UNIVERSITY OF CAMPINAS
FACULTY OF MECHANICAL ENGINEERING

Final Report
Course Completion Assignment

SELECTION OF INDICATORS TO ESTIMATE THE QUALITY OF RESERVOIR SIMULATION MODELS IN THE PRODUCTION FORECAST PROCESSES

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Course: Mechanical Engineer

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Dedication

I dedicate this work to my parents, Claudia and Alessandro, and to my aunt, Chrislaine, who were directly responsible for all my achievements and made this graduation possible.

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Abstract

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Reservoir simulation is a technique widely used in petroleum engineering in several steps of the field exploration, such as history matching, selection of production strategy and production forecast, which impacts the decision-making processes. The reliability of the simulation models is crucial to ensure the accuracy of the production forecast, allowing the development of consistent and efficient strategies for maintaining or increasing petroleum production. Besides, the feasibility of an analysis is directly related to the CPU time required by the study – which is greatly influenced by the amount of detail and complexity of the simulation model. Several works that proposes techniques to reduce the CPU time keeping an acceptable accuracy for the analysis can be found in the literature. However, we observed a lack of studies related to the correlation between the quality of solution and the invested effort in applying such techniques mentioned above.

Thus, the objectives of this work are: (1) select relevant indicators, through a literature review, capable of estimating the quality of a risk curve regarding a defined reference, applying the selected indicators to observe the evolution of the quality of a risk assessment compared to the applied computational effort (simulation time) and (2) select the most suitable indicator for the study.

Four quality indicators were studied, and we concluded that the most suitable for assessing quality of forecast production is the Normalized Quadratic Deviation with Signal (NQDS), which is capable of measuring the quality of the analysis and setting limits of acceptance for a decision taker.

Key Words: Numerical Simulation, Quality Indicator, Production Forecast.

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Nomenclature

Latin letters		Unit
b_l	Block structure	-
C_p	Rock compressibility	$\left(\frac{kgf}{cm^2}\right)^{-1}$
ff	Multiplication factor in completed wells	-
K_r	Relative permeability	-
K_z	Vertical continuity	-
S_o	Oil saturation	
S_{or}	Residual oil saturation	
S_w	Water saturation	
S_{wc}	Critical water saturation	
Np	Cumulative oil production	m^3
Wp	Cumulative water production	m^3
Abbreviations		-
AAPE	Absolute arctangent percentage error	-
APE	Absolute percentage error	-
AQD	Acceptable Quadratic Deviation	-
DLHG	Discretized Latin Hypercube sampling method combined with geostatistical techniques	-
HFM	High Fidelity Model	
LHS	Latin Hypercube Sampling	-
LFM	Low Fidelity Model	-
MAAPE	Mean Arctangent Absolute Percentage Error	-
MAE	Mean Absolute Error	-
MAPE	Mean Absolute Percentage Error	%
MSE	Mean Squared Error	-
NMSE	Normalized Mean Squared Error	-
NQDS	Normalized Quadratic Deviation with Signal	-
OF	Objective function	-
OGR	Oil group	-
OIW	Oil injector well	-
OPL	Oil platform	-
OPW	Oil producer well	-
PI	Productivity Index	-
QDS	Quadratic Deviation with Signal	-
RFo	Oil Recovery Factor	%
RMSE	Root Mean Squared Error	-
SMAPE	Symmetric Mean Absolute Percentage Error	-
SD	Simple Deviation	-

1 INTRODUCTION

Reservoir simulation is a technique widely used in petroleum engineering in several steps of the field exploration, such as history matching, selection of production strategy and production forecast, which impacts the decision-making processes.

The simulations models are built and constantly updated and optimized so that they can reproduce the physical conditions of the real reservoir. This process is represented by the Closed Loop Reservoir Management and Development (Figure 1.1), which is divided in three steps: model construction (green), application of real observed data for history matching and uncertainty reduction (red) and the selection of production strategy aligned with the decision-making process (blue).

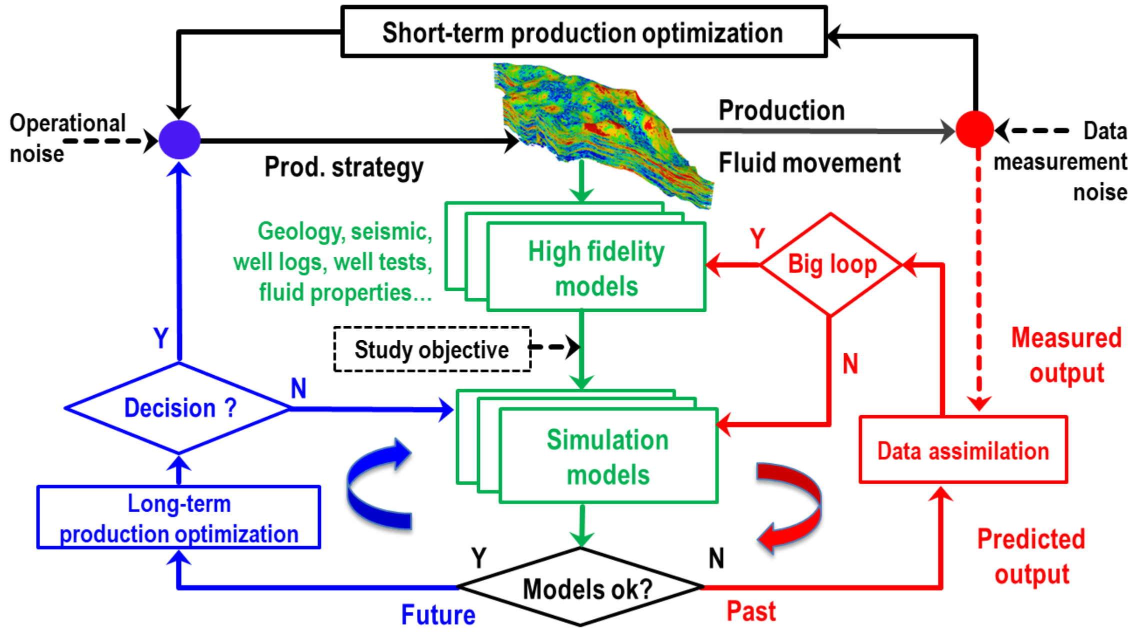


Figure 1.1: Closed Loop Reservoir Management and Development (Schiozer et al., 2015)

The reliability of those models is crucial to ensure the accuracy of the production forecast, allowing the development of consistent and efficient strategies for maintaining or increasing petroleum production. However, all parameters that are used as input for the simulation models (such as porosity and permeability) carries a level of uncertainty, once they are estimated from the available data, that are limited most of times. Under these conditions, it is necessary that strategy decisions of production and exploitation should be based on a consistent risk analysis.

Risk assessment requires a more comprehensive analysis of the generated scenarios (a simulation model that consists in a combination of technical, economic and geological uncertainties), based on a range of uncertainties about the volume of hydrocarbons in place and the performance of the reservoir, such as the cumulative productions and pressures. This assessment requires the simulation of several different models, which is expected to compose an impartial sampling of the reservoir characteristics. However, the idea of simulating several scenarios are often faced with resistance, due to constrains of time and processing resources.

The accuracy of the models is also related with the grid that is built and other parameters. Usually, the more discretized the grid is, the greater the capacity of the model to produce reliable results, but it also depends on the heterogeneity level of the reservoir. Nevertheless, models that have a high level of complexity and heterogeneity lead to higher CPU time, making the probabilistic approach a problem to be solved.

Based on this context, many researchers have been focusing their effort to develop methods and techniques that can speed up processes which demands a high computational effort in the petroleum industry. Several techniques are presented in the literature – Emulators, Response Surface Methodology, Sampling methods (such as the Latin Hypercube sampling), Upscaling techniques and others that can be applied in several steps of an oil reservoir study.

We observed, though, that there is a lack of studies related to the correlation between the quality of solution and the invested effort in applying such techniques mentioned above. Thus, this work aims to define a methodology that allows measuring the quality of the solutions versus applied effort in models with different levels of fidelity in the risk analysis step of a petroleum field study. Additionally, use this methodology to calibrate a low-fidelity model using few simulations of high-fidelity ones, increasing the accuracy to obtain higher accuracy then just using high-fidelity versions.

2 OBJECTIVES

In this work, we aim to:

(1) select relevant indicators, through a literature review, capable of estimating the quality of a risk curve regarding a defined reference;

(2) apply the selected indicators to observe the evolution of the quality of a risk assessment compared to the applied computational effort (simulation time) and select the most suitable indicator for the study, based on six factors: (1) Interpretation, (2) Finite Boundary, (3) Physical Significance, (4) Ease of Calculation, (5) Acceptance Limits and (6) Presence in the Oil & Gas Literature.

The studies are conducted using a benchmark case created by the UNISIM group – a synthetic model based on Campos Basin, Namorado Field: UNISIM-I-D. Considering the following objective functions: cumulative oil production (Np), cumulative water production (Wp) for the whole field and wells, and oil recovery factor (RFo).

3 LITERATURE REVIEW

The literature review is divided in two main topics. The first addresses to methods of risk analysis and production forecast of petroleum fields and the second topics deals with quality indicators used in the field of study.

3.1 Risk analysis and production forecast

Due to high complexity of the processes that are responsible to mold oil reservoirs, any description of its structure and properties carries a significant level of arbitrariness and, despite the evaluation of all observed data, there are infinite possible descriptions of where the hydrocarbons are contained. Once there is possible to generate nearly endless realizations for a same dataset, this problem ceases to be deterministic and began to be probabilistic.

The development phase of a petroleum field is characterized for high investments, substantial uncertainties in the oil recovery with direct impact in the economic performance of the projects. In this phase, coexist: (1) geological uncertainties, associated with the recoverable volumes and characteristics of the flow, (2) operational uncertainties, related to the system's availability, and (3) economic uncertainties, such as oil price, investments and operational costs. The production forecast under a probabilistic approach allows quantifying the impact of the uncertainties and their interaction. Thus, risk assessment is a necessary analysis that may assist the decision-making process.

Though the risk analysis does not guarantee the success of a decision, its systematic application ensures remarkable advantages. The main one is the quantification of losses and sub-optimal development when the performance of a field is different from the expected.

Risk analysis based on a probabilistic approach started to be widely applied in the 80's, when oil prices began to decrease, the projects became less profitable and the initial investments became higher (due to the discovery of petroleum fields in greater depths, for example). Schuyler (1998) recommends the application of probabilistic techniques in the estimative of reserves, highlighting that probabilistic tool improves the uncertainties characterizations, producing more precise results.

Ovreberg et al. (1990) proposed a procedure based on 3 steps: sensitivity analysis; subjective evaluation of uncertainties' probabilities and Monte Carlo simulation. The structural uncertainties are quantified through the adoption of three conceptions of the rock volume, obtained from the interpretation of seismic and geological data: a probable, a pessimistic and an optimistic model. The relation between the recovery and the total volume of hydrocarbons is obtained through the simulation of the optimistic and the pessimistic model, using average parameters of characterization. The application of the methodology is easy and inexpensive, but its major problem is the impossibility of considering probable non-linearity of correlated variables, as well their spatial dependencies.

Loschiavo (1999) sought to develop a methodology that allows estimating probabilistic profiles of hydrocarbon production parameters, considering geological uncertainties on the field's development. In addition, the basis of that methodology is the decision tree technique. The author concludes that in case the most critical attribute is much more expressive than the others (conclusion obtained from the sensitivity analysis), it is recommended an increase in the number of levels for this attribute.

Steagall (2001) developed an enhancement of Lochiavo's methodology, by studying the development and application of this new method in the analysis of the impact of reservoir uncertainties in production forecast and risk analysis of an oil field. The methodology is based on the use of the flow simulator, generating scenarios through a decision tree with some critical parameters selected in a sensitivity analysis study. The application was made in a real field of Campos Basin, with available data obtained in the delimitation step, with few drilled wells, 2D seismic and the strategy of production was fixed. The methodology showed a reduction in the risk of the estimative of the NPV, due to the reduction of structural, volumetric and horizontal permeability uncertainties.

Steagall and Schiozer (2001) applied the derivation tree methodology in a real case of Campos Basin, obtaining the risk of the forecast of cumulative oil production and net present value. The authors proposed the use of representative models of the geological uncertainties to integrate the risk analysis with the production strategy of the field.

Santos (2002) studied the influence of the production strategy in the risk analysis processes. The risk methodology consists in defining the uncertain parameters, building a base model to simulation, selecting the critical attributes through sensitivity analysis, simulate all possible models, express the risk using the net present value as objective function and choosing some models to represent the geological uncertainties. Optimization procedures are applied in the base model and in the other models. The author verified that the gain in the net present value is inexpressive regarding the uncertainties and changes in the production strategy is not relevant, concluding that the adoption of an only production strategy can be applied in that case.

Costa (2003) observed that the complexity of the risk analysis processes is due to three main factors: (1) a high investment, (2) a high number of uncertain variables and (3) a strong dependence of the results with the definition of the production's strategy. To mitigate this complexity and reduce the required computational effort, some simplifications are performed. Although, the author pointed the lack of methodologies that can quantify the impact of the uncertainties and of those simplifications.

Because of this, the researcher developed a methodology through a detailed study about risk analysis in the development's phase through the quantification of simple techniques to accelerate the processes without lose its precision. It is substantiated in treatment of attributes, gradual combination, and aggregation of attributes and use of representative models to integrate the effects of different types of uncertainties with the definition of the production strategy.

The methodology has proven to be able to give support to the decisions with higher reliability, showing the critical points of the process and quantifying the impact of the simplifications that can be done to make standardized and user-friendly processes.

Ligero et al. (2003) used the methodology developed by Loschiavo (1999) and applied by Steagall (2001) to perform risk analysis in the development phase of an oil field. To improve the computational performance, they used an automated procedure to elaborate the simulation models, combined with parallel processing, which allowed the simulation of many scenarios simultaneously. Three representative geological models were proposed and they were applied to integrate geological and economic uncertainties to perform the risk assessment.

The techniques described before (Monte Carlo and Derivation tree) attempt to perform a probabilistic analysis of the geological model, considering of all the possible scenarios considering their uncertainties and associated probabilities. These methods usually require many simulation models to cover all the solution space, leading to excessive computational effort and sometimes rendering such analysis impractical. Due to this, many works are developed aiming to study methods capable of reducing the computational effort required by these techniques or even applying new ones. We present some solutions proposed by researchers to solve those problems.

Zabalza-Mezghani et al. (2004) proposed several statistical methods, mainly based on the experimental design technique, to solve practical problems throughout the field life: evaluating geological scenarios; comparing and ranking impact of uncertain parameters on production profiles; assessing production forecast under uncertainties; selecting relevant parameters for production scheme optimization and performing an economic risk evaluation. The authors showed the effectiveness of these methodologies both in real and synthetic fields.

Another way to reduce the computational effort required by a simulation of a model is to apply upscaling techniques to reduce the grid size of the geological model, transforming into a coarser model. Although, it is difficult to select a grid size that could represent an adequate balance between precision of risk assessment and computational effort. Ligero et al. (2004) studied the effect of the grid size on this process. The authors developed a methodology (1) to select an adequate grid size and (2) to speed up the risk analysis process. They showed practical applications of upscaling in a probabilistic risk assessment using a model of a petroleum field with geological uncertainties represented in a fine grid.

Madeira (2005) performed a comparison between some techniques used to accelerate and simplify the risk analysis process – the simulation of Monte Carlo, derivation tree, experimental design with the development of fast models (also known as proxy models) associated with the response surface methodology and some combinations of these techniques. The author performed this study in an offshore field and showed it is possible to significantly reduce the number of simulations using statistical models and exalted that some simplifications may change the decision process.

Lechner et al. (2005) investigated an approach that uses Artificial Neural Networks (ANN) to integrate the reservoir simulation to speed up processes which requires excessive computational time. As a first step, the authors selected the most sensitive parameters which affect the performance of the simulation using a limited number of runs. By training the ANN, they developed a model capable of interpolating between the individual simulation scenarios. In this way a large variety of realizations can be approximated by a limited number of reservoir simulation models. The ANN were used in Monte Carlo simulation to generate the probability distribution of all possible outcomes.

Due to the very low computational cost of the ANN, many realizations can be calculated in a short amount of time.

Reis (2006) proposed three methodologies based on Experimental Design and Response Surface Modeling to model flow simulations. The first method uses two different RSM: one to represent the decision variable and other to represent an objective function that consider dynamic data, enabling the risk analysis with history matching. In the second methodology, a maximum tolerance of the objective function is used as a filter to select the models taken on risk analysis. The last one is similar to the previous method, but the ANN replaces the RSM to model the flow simulation. These methodologies were applied to two different reservoirs: a semi-synthetic case and a real case. The author showed that it is possible to improve the quality of the risk analysis, constraining the possible range of the uncertainty variables by taking into account dynamic data.

Risso et al. (2008) compared the precision of three methods in the risk assessment of oil fields: Derivation Tree Technique, Monte Carlo simulation and Response Surface Methodology associated with the Box-Behnken and central composite designs. Two cases representing a development field with five uncertain attributes were studied, and the objective functions analyzed were net present value and cumulative oil production. The response surface methodology was capable of efficiently substitute the reservoir simulation to obtain the risk curves. The use of this technique allowed a reduction in approximately 83% of the number of simulations while maintaining the precision of the risk curves. However, the authors emphasize the importance of the correctly use of the statistical design methodology, because the different possible surface responses that can be obtained may affect the results significantly.

Arinkoola et al (2015) performed a study to examine several Design of Experiments (DoE) methods for uncertainty quantification of production forecast during reservoir management. Considering all uncertainties for analysis can be time consuming and expensive. Uncertainty screening using experimental design methods helps reducing number of parameters to manageable sizes. The authors studied three families of designs (sensitivity be one factor at-a-time, fractional experiment, and Plackett-Burman design) used for screening and four (Box-Behnken, central composite, D-optima and full factorial) used for response surface modeling. For screening, the authors concluded that there was no added advantage using fractional factorial instead of Plackett-Burman design. The best model for uncertainty quantification must be selected based on the reservoir management objectives. BB method was adequate to determinate P10/P50/P90 and associated models. On the other hand, to evaluate future development strategies, stimulation and the needs for acquiring additional information, full factorial and central composite design are more efficient predictors.

Jablonowski et al. (2016) described the method and results of a probabilistic risk analysis used to provide a quantitative basis for a complex and high-stakes design decision for a subsea oil project. The available geological information (obtained from a small number of exploration and appraisal wells) was coupled to a wellbore fluid dynamics model (defined as “system model”) to simulate operational outcomes for potential well kill operations. The authors compared two methods of probabilistic approach: the full probabilistic and the design of experiments approach, which are used to obtain a surrogate equation that are used in place of the system model.

The authors showed that the system model could be used to specify a risk analysis to support risk-based design and that the surrogate models that are based on the experimental designs yield very good fits to the system model results, with a 99% reduction in the number of iterations.

Polizel et al. (2016) used proxy models associated with the Latin Hypercube Sampling technique to perform the risk assessment of four objective functions: cumulative oil production, cumulative water production, oil recovery factor and net present value. The authors also compared to design of experiments: full factorial and Box-Behnken design. The application was performed in a medium-complexity synthetic case with rock, fluid and operational uncertainties without geostatistical realizations. It was shown that (1) the Box-Behnken Design can reduce the number of realizations and keep the accuracy of the results and (2) the proxy models can perform a risk analysis with reduced computational effort and substitute the reservoir simulator on this application.

Naderi et al. (2016) studied the impact of engineer and geological uncertainties in the recovery factor of a gas reservoir. The authors used four DoE (Box-Behnken, full factorial, central composite and uniform design) to develop the recovery response function, through the RSM. Then, the genetic algorithm (GA) were applied to optimize the combination of these DoE for prediction of final recovery factor distribution. They showed that (1) the uncertainty associated with ultimate recovery factor depends mostly on average reservoir permeability, permeability anisotropy, tubing head pressure and aquifer size and (2) the application of the GA allowed achieving a higher performance over the conditional uncertainty assessment methods.

Another important technique that can reduce the number of simulations needed to perform a risk analysis is the Latin Hypercube. Risso et al. (2009) sought the best way to perform the distribution of trails and verify the influence in the variation of this number when acquiring the risk curves, through the Latin Hypercube Sampling technique. This methodology was also compared to the derivation tree technique, aiming to reduce the number of simulation keeping the accuracy of the results. A complex and a high-heterogeneity model were used, and three objective functions (cumulative oil production, oil recovery factor and net present value) were studied. The authors used 9000, 3000 and 200 trials. The results showed that the number of trials did not influence the results, once the curve obtained with 200 trials had almost no difference from the obtained with 9000. This works showed the efficiency of the method, which can be used with a reduced number of simulations, saving computational effort.

Santos et al. (2014) compared two methods of risk analysis of oil fields: The Monte Carlo sampling technique combined with joint proxy models (JMM) and the Discretized Latin Hypercube sampling method combined with geostatistical techniques (DLHG) in terms of (1) accuracy of the results, (2) computational cost, (3) difficulty in the application, and (4) limitations of the methods. The application was performed in a synthetic model containing geologic and operational uncertainties and the reference response were obtained using the classic Monte Carlo simulation with a very high sampling number. Both methodologies were able to produce reliable results when applied to a complex reservoir comprising a large set of geostatistical realizations. However, the JMM presented a limitation due to the way it captures the effect of a geostatistical uncertainty, making the number of simulation runs growing exponentially. The DHLG method showed advantages as it obtained the same results from less than half of the simulation runs and presented smaller deviations from the reference curves. The application of this method is fast and direct, surpassing the other methodology in all used criteria.

Schiozer et al. (2016) presented a methodology that combines different types or uncertainties, such as geostatistical realizations, reservoir structure and fluid characterization, using the fewest possible simulation runs through a Discretize Latin Hypercube sampling. Applying this methodology in a complex synthetic case, the authors showed that it was possible to produce reliable results using 100 or more simulations, presenting insignificant variation regarding the reference curve (obtained with 3000 scenarios using the Monte Carlo sampling). This work showed the main characteristics of this method: (1) it preservers the geostatistical consistency of parameters that vary spatially in the reservoir, (2) it needs few simulations runs to obtain reliable results, (3) it is easy to implement, and (4) it is flexible for use in cases with different requirements of precision, computational times and types of uncertainties.

3.2 Quality indicators

In this work, we intend to compare high, medium and low fidelity models and proxy models in terms of their capacity of prediction. Once risk assessment is the step to be accomplished using these models, we must choose a method that allows comparing the accuracy of the generated risk curves, once tiny errors can lead to a wrong decision taking. Thus, this topic presents the most common indicators to measure the quality of forecasting methods. Since this subject represents a whole field of study, we will only present methods that may be adequate for the reservoir simulation area.

The history of the evaluation of forecast accuracy goes along with time-series analysis. The first tests for forecasting models were developed in 1939 by Tinbergen, in response to Keynes, who stated that theories must be confirmed if the data and statistical methods are employed correctly (Woschnagg et al, 2004).

Given the importance of the statistical validation (defined as a comparison of the model's predictions with the real world to determine whether the model is suitable for its intended purpose), Mayer et al. (1993) performed a research around statistical validation of time-series. The authors grouped validation techniques into four main categories:

- **Subjective assessment**, which involves an evaluation by a number of experts in the field of interest;
- **Visual techniques**, performing graphical displays of data feature, typically plots of both simulated data and observe data against a common independent variable;
- **Deviance measures** applied when observed and simulated data can be paired according to time, location, treatment and so on. Deviance measures are based on the difference between simulated and observed data.
- **Statistical tests**, which comprehends t-test, F-test and others, depending on the type of the model, the nature of variables and their complexity.

Since this work is looking for methods that measure the accuracy of the model based on the difference of risk curves, we must focus on deviance measures. In the previous study, Mayer pointed the three commonly used measures for numerical data – Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), presented in Equation 3.1, 3.2 and 3.3.

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}\left(\left|Y_i - \widehat{Y}_i\right|\right)$$ Equation 3.1

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left(\frac{\left|Y_i - \widehat{Y}_i\right|}{\left|Y_i\right|}\right)$$ Equation 3.2

$$\mathrm{RMSE} = \left(\frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2}{n}\right)^{0.5}$$ Equation 3.3

where Y_i represents observed values, $\widehat{Y}_i$ predicted values and n the number of pairs.

As MAE is in the same unit as the data and MAPE is relative, both can be informative measures, and MAE may be used for mean algebraic error. Algebraically, RMSE > MAE (due to the influence of squaring larger values). With squared deviations, RMSE can be useful in deriving statistical properties. We also observe that for these three indicators, as close they are to zero, the better is the results.

Some authors define limits of acceptability for these indicators but given that the model validity depends very much on both the type of the model and its intended uses, i.e., it is impractical to set a single absolute limit.

For Makridakis (1993), MAPE is the best choice for general use. It is a relative measure that incorporates the best characteristics among the various accuracy criteria. Moreover, it can be used for both evaluating large-scale empirical studies and for presenting specific results. With this, the author studied ways of correcting some problems that can influence MAPE, such as:

1. Equal errors above the actual value result in a greater APE (Absolute Percentage Error, Equation 3.4) than those below the actual value (e.g. when the observed value is 150 and the forecast is 100, MAPE results 33.33%, when the observed value is 100 and the forecast is 150, MAPE results 50%);

2. When the observed value is too small (usually less than 1), it can provide large percentage errors;
3. In case of unusually large errors, when the value of Y_i is small, some absolute percentage error (APE) can become extremely large (outliers) and distort the comparison in forecasting competitions or empirical studies.

$$APE = \frac{\left|Y_i - \widehat{Y_i}\right|}{|Y_i|} \qquad \text{Equation 3.4}$$

The author solved the first problem by defining the symmetric Mean Absolute Percentage Error (sMAPE) as follows in Equation 3.5:

$$sMAPE = \frac{100}{\mathrm{n}} \sum_{i=1}^{n} \left(\frac{\left|Y_i - \widehat{Y_i}\right|}{\frac{|Y_i| + \left|\widehat{Y_i}\right|}{2}} \right) \qquad \text{Equation 3.5}$$

In this study, the second and third problem should not be an issue, once the studied objective functions, such as oil and water production, presents high output values.

Chen et al. (2004) evaluated forecast accuracy measures. The authors distinguished between stand-alone and relative accuracy. Stand-alone accuracy measures are those that can be obtained without additional reference forecast. The idea of relative measures is to evaluate the performance of a relative forecast to a benchmark forecast (specifically, the random walk). Since the reference forecast is a deterministic simulation, we cannot apply the random walk, which is a characteristic of a stochastic process. Thus, this work must focus on stand-alone accuracy measures.

Besides the previously mentioned indicators, the authors proposed three others indicators that could be used in this work: Mean Squared Error (MSE, Equation 3.6), Normalized Mean Squared Error (NMSE, Equation 3.7) and the KL-N, based on the Kullback-Leibler (KL) divergence, presented in Equation 3.8.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(\widehat{Y_i} - Y_i\right)^2 \qquad \text{Equation 3.6}$$

$$NMSE = \left(\frac{\sum_{i=1}^{n} \left(\widehat{Y_i} - Y_i\right)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \right)^{\frac{1}{2}} \qquad \text{Equation 3.7}$$

where $\bar{Y}$ is the mean of observed values.

$$KL-N=\left(\frac{1}{n}\sum_{i=1}^{n}\frac{\left(\widehat{Y_{i}}-Y_{i}\right)^{2}}{S_{i}^{2}}\right)^{\frac{1}{2}}$$ Equation 3.8

where

$$S_i^2=\frac{1}{i-1}\sum_{k=1}^{i-1}(Y_k-\bar{Y}_{i-1})^2\,,\bar{Y}_{i-1}=\frac{1}{i-1}\sum_{k=1}^{i-1}Y_k$$ Equation 3.9

Among these indicators, the authors identified the same condition about MAPE and sMAPE as Makridakis: a major flaw when the true value of the forecast is close to zero. In addition, they concluded that the KL divergence-based measures achieved the best results in the study.

Willmott el at. (2005) stated the advantages of MAE over RMSE. The authors pointed that although RSME is widely report in several studies, including in the climatic and environmental literature, it is inappropriate because it is a function of three characteristics of a set of errors, rather than one (the average error). RSME tends to became increasingly larger then MAE as the distribution of error magnitudes becomes more variable, and, it tends to grow larger than MAE with $n^{\frac{1}{2}}$. The authors observe there is no clear interpretation of RMSE or related measures, once it is an unambiguous measure of average error magnitude and they recommend that such measures should not be reported in the literature anymore.

Kim et al. (2016) proposed another modification in MAPE measurement to overcome the problem of close-to-zero observed values, defined as Mean Arctangent Absolute Percentage Error (MAAPE). In this approach, they consider a triangle with adjacent and opposite sides that are equal to $|Y_i|$ and $|Y_i-\widehat{Y_i}|$ respectively. The slop of the hypotenuse can be measure either as a ratio of $|Y_i-\widehat{Y_i}|$ to $|Y_i|$, ranging from zero to infinity; or, as an angle, varying from 0 to $90°$. The authors saw the potential to use the slope as an angle as a measure of the forecast accuracy, overcoming the mentioned problems, and defined the MAAPE as follows in Equation 3.10.

$$MAAPE=\frac{1}{n}\sum_{i=1}^{n}\left(\arctan(\frac{\left|Y_i-\widehat{Y_i}\right|}{|Y_i|})\right)=\frac{1}{n}\sum_{i=1}^{n}(\mathrm{AAPE}_i)$$ Equation 3.10

where AAPE is the Absolute Arctangent Percentage Error.

For the authors, MAAPE preserves the advantages of MAPE; thus, MAAPE is scale-independent, can be interpreted intuitively as an absolute percentage error (as closer to zero, the better the result) and is simple to calculate. In addition, the bounded range of the arctangent function (0 to $\pi/2$) allows the MAAPE to overcome the MAPE's limitation of going to infinity as the actual value goes to zero. MAAPE is also more robust than MAPE due to the bounded influences of outliers; thus, it can be particularly useful when extremely large errors are due to mistaken or incorrect observations.

Another indicator that could be useful four our work is the Normalized Quadratic Deviation with Signal – NQDS (Maschio and Schiozer, 2016), which is a method to quantify the quality of the adjust of production data and maps data. Forlan et al (2014) incorporated the NQDS in a methodology of multi-objective assisted history matching and uncertainties reduction using it for: (I) filter the best models considering well's history matching and (II) optimize the history matching of these models through a iterative process to minimize NQDS function.

Saalfeld et al (2016) used the NQDS indicator to perform a numerical adjust of the productivity of a simple porosity model using as reference a double porosity one and to make a sensitivity analysis of pseudo properties' parameters in a work with naturally fractured reservoirs. Usually this indicator is used to quantify the quality of the simulated values regarding the history data. On the other hand, this indicator can be used to quantify the misfit between risk curves. As a result, we can use them to verify the misfit between the studied curve and the defined reference. It is important to notice that this study does not assume possible inconsistencies between the history data and the simulator.

To obtain the NQDS indicator, some definitions must be made:

- Simple Deviation (SD)

$$\mathrm{SD} = \sum_{i=1}^{n} (Est_i - Sim_i) \qquad \text{Equation 3.11}$$

where Est_i is the i estimated OF, given by the studied model and Sim_i is the i reference case OF.

- Quadratic Deviation with Signal (QDS)

$$\mathrm{QDS} = \frac{\mathrm{SD}}{|SD|} \sum_{i=1}^{n} (Est_i - Sim_i)^2 \qquad \text{Equation 3.12}$$

Acceptable Quadratic Deviation (AQD)

$$\mathrm{AQD} = \sum_{i=1}^{n} (Tol * Sim_i)^2 \qquad \text{Equation 3.13}$$

where Tol is the tolerance of acceptance regarding the reference OF, usually defined with the researcher's experience. Then, the normalized quadratic deviation with signal (NQDS) is defined as shown in Equation 3.14.

$$\mathrm{NQDS} = \frac{\mathrm{QDS}}{AQD} \qquad \text{Equation 3.14}$$

In resume, this indicator calculates the distance between the curves point to point, i.e., for each generated scenario that is used to build the risk curves. It can be noticed that the adjust is considerable acceptable when the NQDS value is between the interval of -1 and +1 and the closer NQDS is to 0, the smaller is the difference between the curves.

4 METHODOLOGY

The methodology is summarized in Figure 4.1.

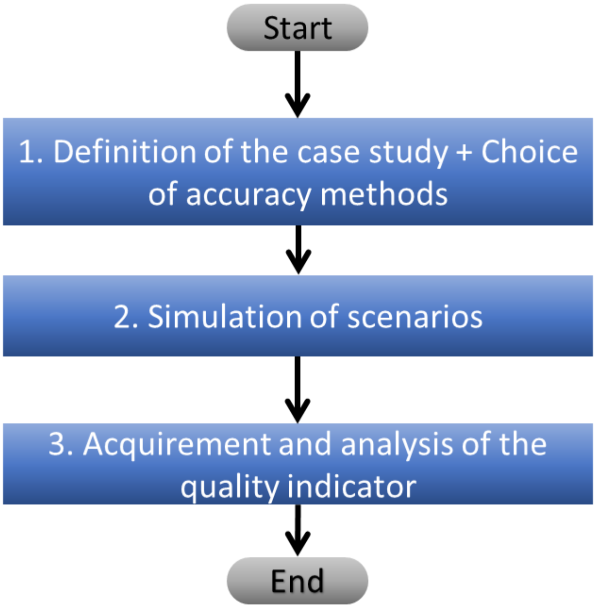


Figure 4.1: Proposed methodology for acquisition and study of the selected quality indicators.

The proposed methodology is described as following:

1) Definition of the case study + choice of accuracy methods

This step aims to define the geomodel that the study will be carried out and to select, among several indicators which one (maybe ones) fits our work objective.

2) Simulation of scenarios

In this step, we simulate several scenarios in different sets of simulations (sets with 50, 100, 200 until 2000 scenarios), using the DLHG (Discretized Latin Hypercube with Geostatistical Realizations, Schiozer et al. 2017) as sampling technique.

3) Acquirement and analysis of quality indicator

With all data generated in the previous step, the indicators are calculated for the defined OF (for both field and well) and then analyzed.

5 CASE STUDY

UNISIM-I case study, described by Avansi and Schiozer (2015), is based on real dataset from Namorado field at Brazil (Guardado et al., 1989a; Guardado et al., 1989b). This case was designed as a benchmark for research studies on risk analysis, optimization of production strategy and history matching problems.

A simulation model with uncertainties (UNISIM-I-D) was created in a process of reservoir studies in an initial field development plan under uncertainties. The model was built in a medium numerical grid resolution after the upscaling of a geo-model and with some information of UNISIM-I-R (Avansi and Schiozer, 2015) as illustrated in Figure 5.1. This model consists in an offshore oil field, 80km from the coastline, and represents a field project in 05-31-2013, including 4 years of production data (2013-2017) using the information from four production wells. The reservoir depth varies between 2900 to 3400m. There are well log measurements, core description, and seismic data to build the structural, facies and petrophysical models based on the previous steps of the reference model. The grid block is defined as 100 x 100 x 8 m discretized into a corner point grid with 81 x 58 x 20 cells (36,739 active cells). The exploitation strategy for the production forecast comprised 14 production wells (4 verticals from the history period and 10 horizontals) and 11 horizontal water injection wells. The maximum time defined for field abandonment is 30 years (10967 days).

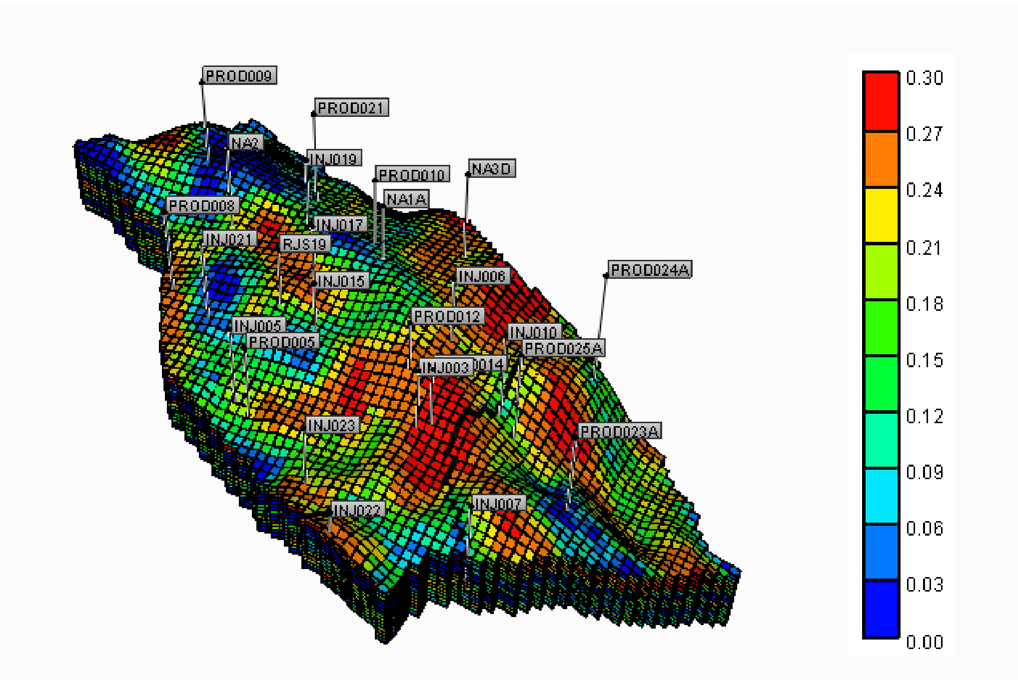


Figure 5.1: Porosity map from UNISIM-I-D Low fidelity model.

5.1 Rock and fluid uncertainties

The considered rock and fluid uncertainties are: relative permeability of water (K_{rw}), rock compressibility (c_p), PVT table (PVT), oil-water contact (OWC), vertical continuity (k_z) and the east block structure (bl). The uncertainties are shown in Table 5.1.

Table 5.1: Rock and fluid uncertain parameters, type of uncertainties and levels/pdf considered in this study.

Uncertainties	Type of Uncertainties	Levels/pdf*
East block structure (bl), dimensionless	Discrete	Presence (0.70); Absence (0.30)
Relative permeability of water (K_{rw}), dimensionless	Discrete	$K_{rw}0$ (0.34); $K_{rw}1$ (0.33); $K_{rw}2$(0.33)
PVT table (PVT)	Discrete	$PVT0$ (0.34); $PVT1$(0.33); $PVT2$ (0.33)
oil-water contact (OWC), m	Continuous (triangular)	$\begin{cases} 0, & x < 3024 \\ (x-3024)/22500, & 3074 \le x \le 3174 \\ (3324-x)/22500, & 3174 \le x \le 3324 \\ 0, & x > 3324 \end{cases}$
Rock compressibility (c_p), $\left(\frac{10^6 kgf}{cm^2}\right)^{-1}$	Continuous (triangular)	$\begin{cases} 0, & y < 10 \\ (y-10)/1849, & 10 \le y \le 53 \\ (96-y)/1849, & 53 \le y \le 96 \\ 0, & y > 96 \end{cases}$
Vertical continuity (k_z), dimensionless	Continuous (triangular)	$\begin{cases} 0, & z < 0 \\ (2z)/4.5, & 0 \le z \le 1.5 \\ (6-2z)/4.5, & 1.5 \le z \le 3.0 \\ 0, & z > 3.0 \end{cases}$

*Probability density function

5.2 Operational uncertainties

A set of five discrete operational uncertainties were considered, and they are presented in Table 5.2.

Table 5.2: Operational uncertainties and their probabilities distribution.

Uncertainties	Type of Uncertainties	Levels/pdf*
Multiplication factor in completed wells (ff)	Discrete	0.70 (0.33); 1 (0.34); 1.40 (0.33)
Oil producer well (opw)	Discrete	0.91 (0.33); 0.96 (0.34); 1 (0.33)
Oil injector well (oiw)	Discrete	0.92 (0.33); 0.98 (0.34); 1 (0.33)
Oil platform (opl)	Discrete	0.90 (0.33); 0.95 (0.34); 1 (0.33)
Oil group (ogr)	Discrete	0.91 (0.33); 0.96 (0.34); 1 (0.33)

5.3 Geostatistical realizations

Geostatistical realizations (also called images) are stochastic uncertainties, this is, they correspond to a variable that has a non-linear impact on the response and can take infinite equiprobable discrete values.

The geostatistics allows obtaining a more realistic reservoir description, which honors geological properties and considers rock heterogeneities (Zabalza-Mezghani et al., 2001). They represent spatially correlated reservoir properties (e.g. porosity, permeability and net-to-gross ratio). In this study, we used 500 equiprobable images to model the properties. We can observe in Figure 5.2 an example of the variability introduced by the images in porosity distribution of the reservoir.

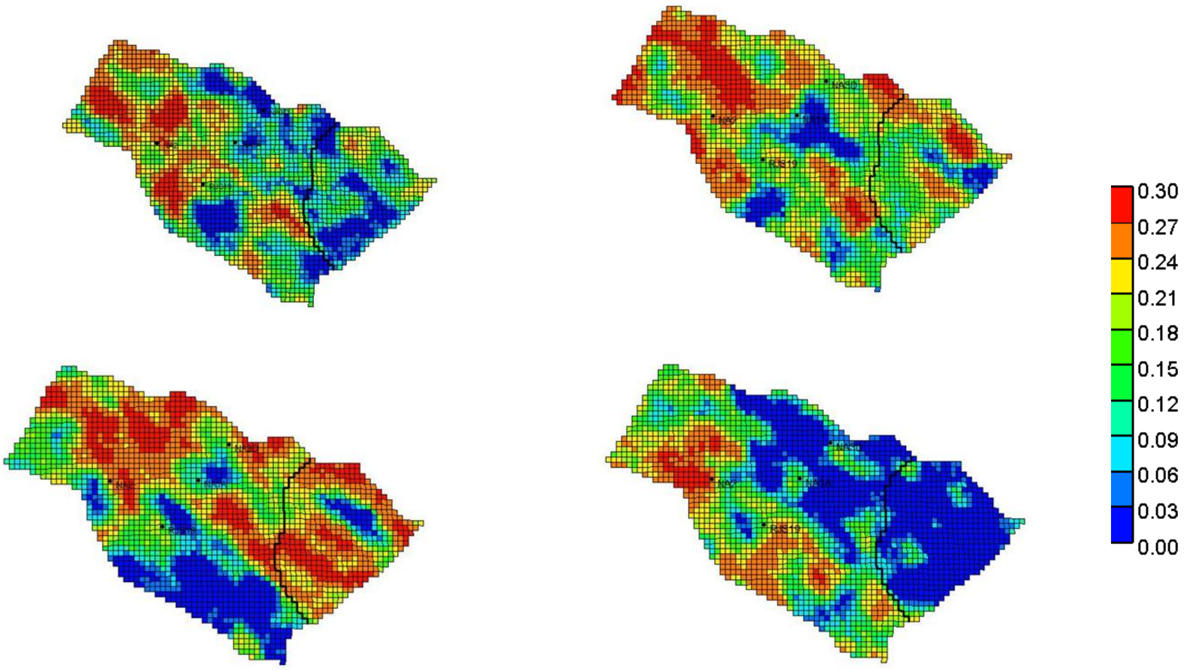


Figure 5.2: Porosity distribution given by four different images (UNISIM-I-D LFM).

5.4 Objective Functions

The objective functions studied within this case are:

- Np – Cumulative oil production;
- Wp – Cumulative water production;
- RFo – Oil recovery factor.

In the maximum time defined for field abandonment, which is 30 years.

6 RESULTS

In this topic, we present the results obtained following the presented methodology.

6.1 Methods and threshold

The first step of the methodology was accomplished through the literature review presented in the Section 3 of this work – we chose to compare four indicators: MAE, RMSE, MAPE and NQDS due to the reasons showed in the Section 4.

6.2 Definition of the case Study

The case study is the UNISIM-I-D model, representing the low fidelity model – LFM (this case is detailed in the Section 5).

6.3 Simulation of scenarios

In this step, we simulated and gathered data from our LFM. A total of 63.500 simulations were made. They were separated in sets of 50, 100, 200, 300, 500, 700, 1000, 1500 and 2000 scenarios, each one being sampled and simulated 10 times in one processor taking approximately 20 minutes per scenario (the risk curves for each field OF are available at Appendix A). As said in Section 4, these scenarios are sampled throughout the DLHG technique and are totally random.

6.4 Generate graph of quality of the solution vs effort

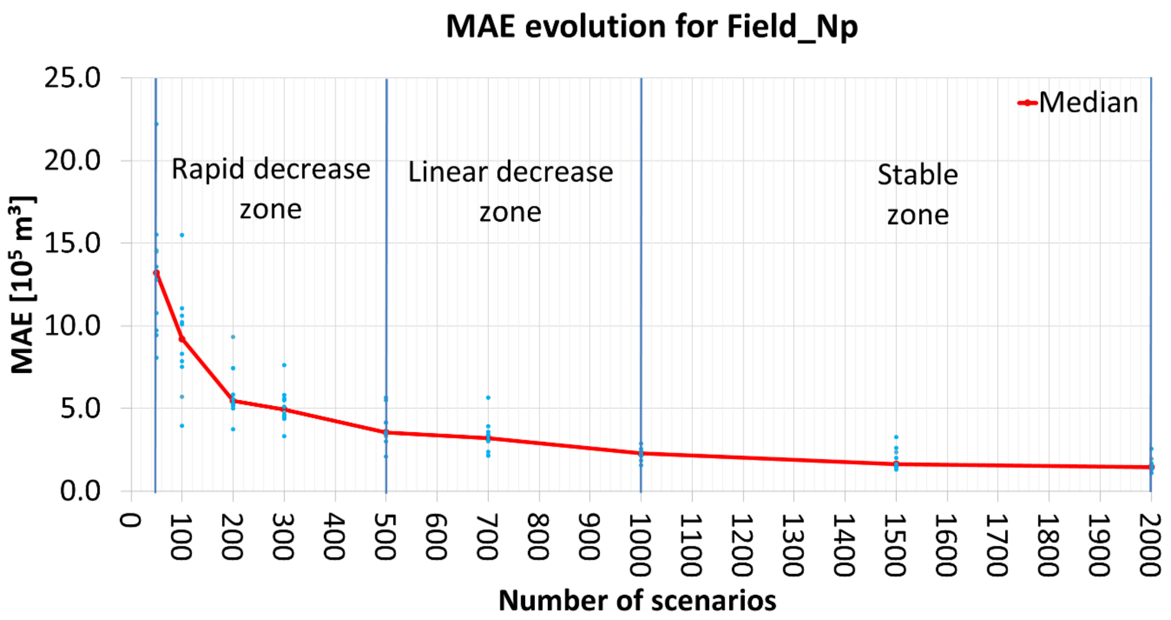
With the results from the previous step we calculated the four indicators using as reference the average result from the 20000 simulations performed within the 2000 set of scenarios. They were calculated for each OF through a linear interpolation (once it is a point-to-point analysis), considering both field and wells.

Therefore, we can head to the analysis of each one. First, we will separate them in two groups: Indicators that cannot reach a negative number – Group I (MAE, RMSE and MAAPE) and indicators that can reach a negative number – Group II (NQDS).

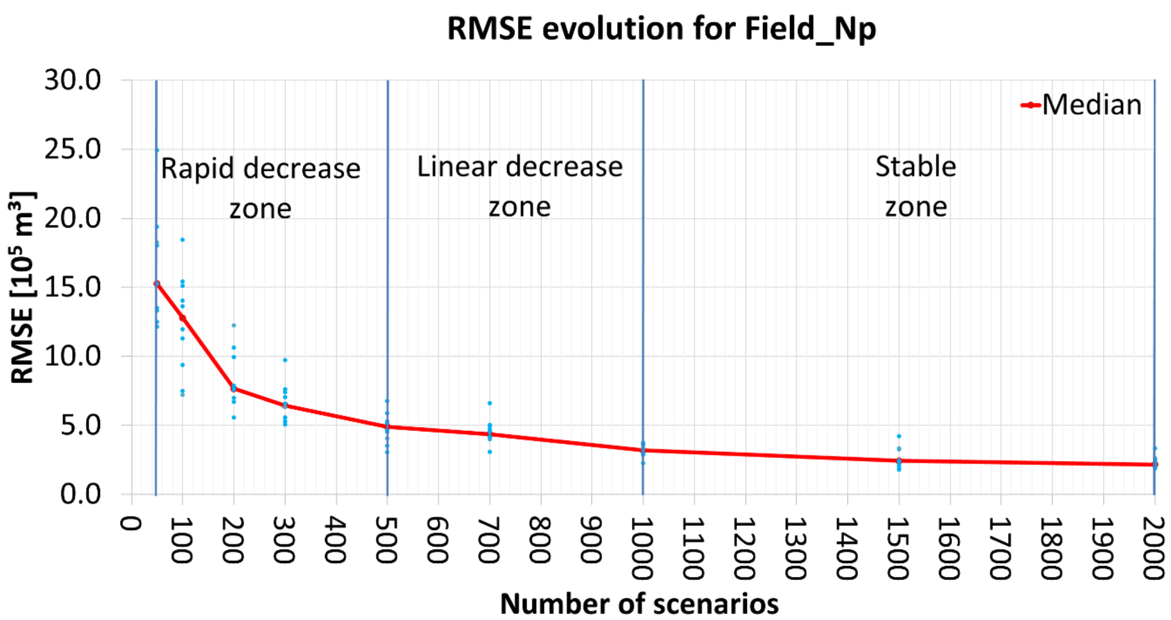
- **Group I**

Figure 6.4 shows the three indicators calculated for the field Np (Wp and RFo OF can be found in Appendix B). We can observe the behavior of the indicators regarding the number of scenarios – which we consider the most time-consuming parameter of our work.

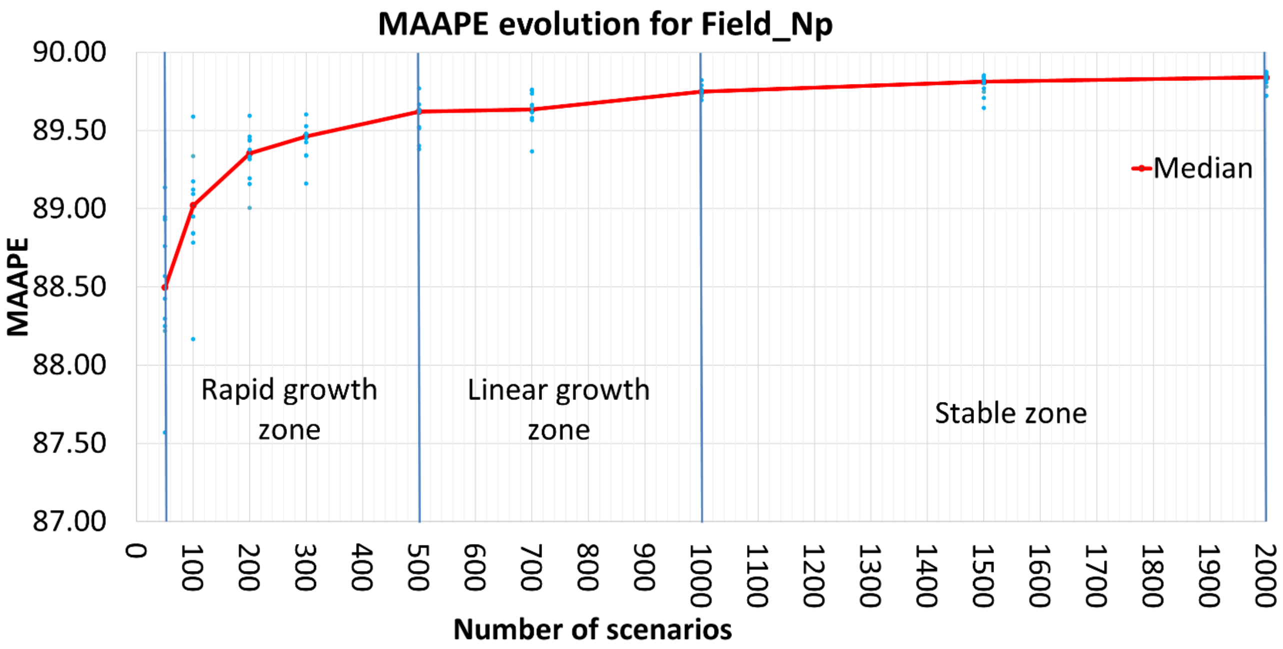
For all three indicators and field OF we can distinguish three phases of evolution, even MAE and RMSE having a decreasing behavior and MAAPE an increasing behavior: rapid growth (or decrease) zone, linear growth (or decrease) zone and stable zone, as shown below (Figure 6.1).



(a)



(b)

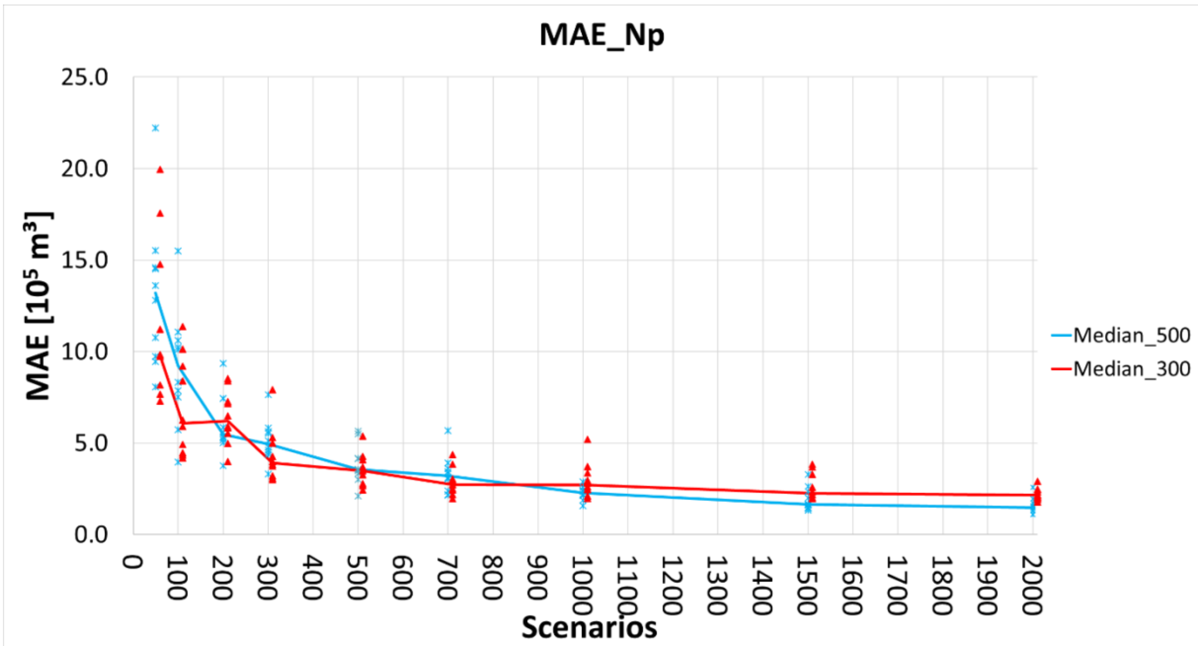


(c)

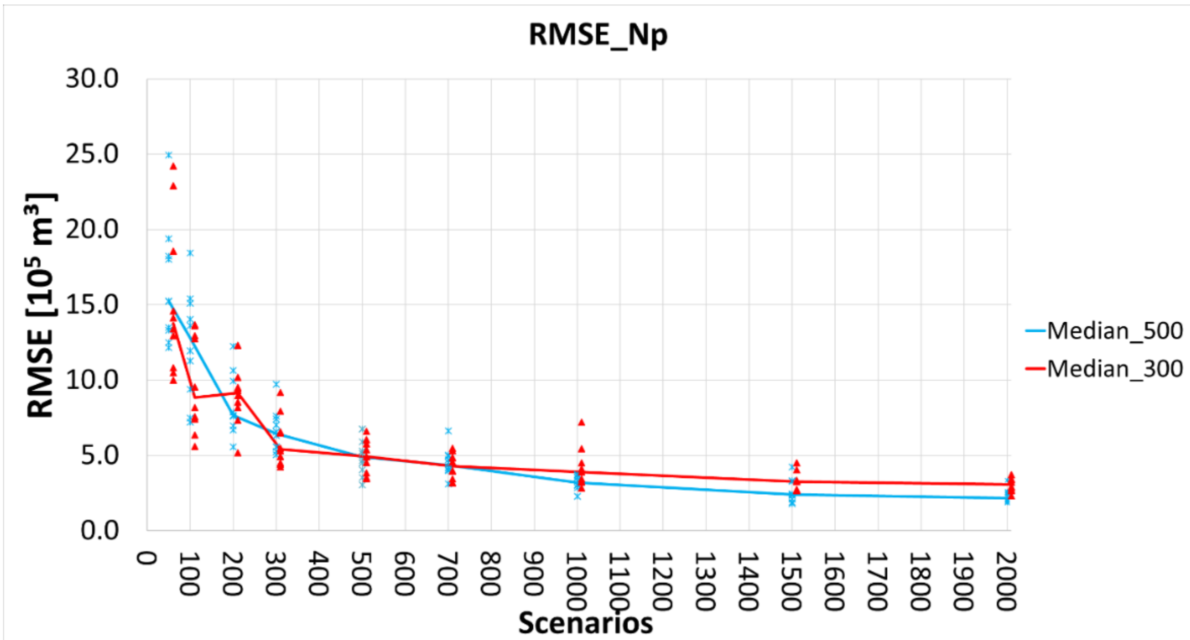
Figure 6.1: Highlight of the different evolution zones for each indicator in Group I – (a) MAE (b) RMSE and (c) MAAPE.

Analyzing the graphs in Figure 6.1, we can observe that the evolution has higher change rates between 50 and 500 scenarios and from there it gets smoother, stabilizing in 1,000 scenarios. The fact that the variation decreases when the number of scenarios reaches the number of geostatistical images (500) raised a doubt: Was this phenomenon due to the number of images used or due to the statistical distribution and the sampling technique?

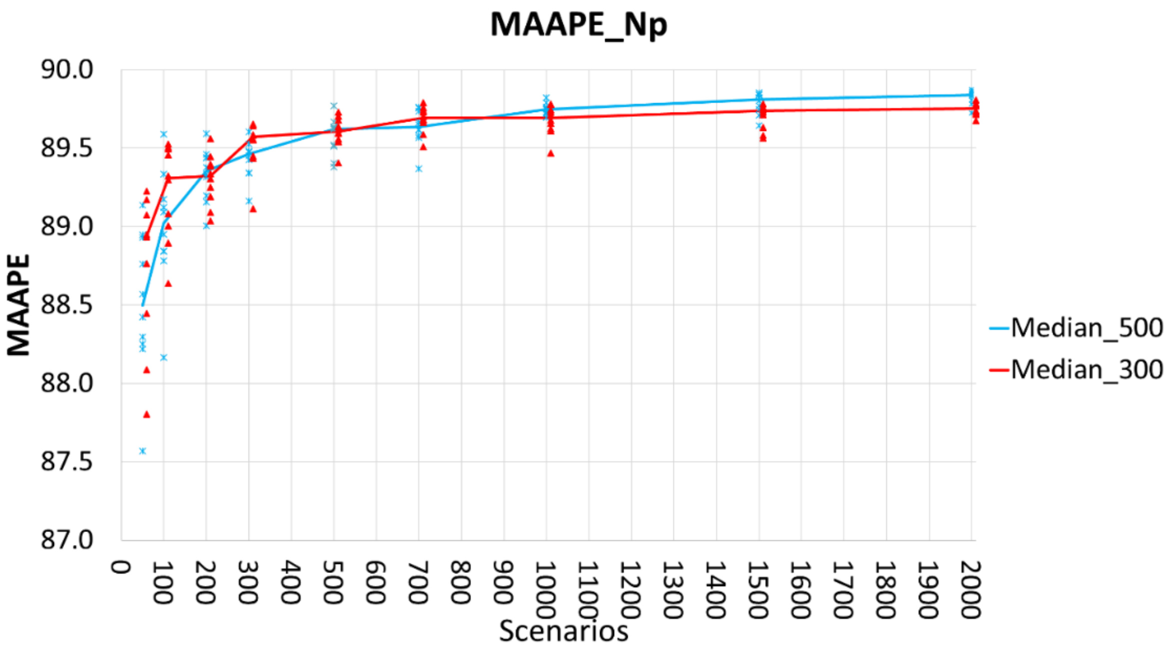
To understand this behavior, we repeated the previous analysis considering only 300 images, and using the same reference as before. Figure 6.2 present the same functions as Figure 6.1, comparing the evolution of our Group I indicators with different number of images.


MAE_Np
MAE [10^5 m^3]
25.0
20.0
15.0
10.0
5.0
0.0
0 100 200 300 400 500 600 700 800 900 1000 1100 1200 1300 1400 1500 1600 1700 1800 1900 2000
Scenarios
Median_500
Median_300

(a)


RMSE_Np
RMSE [10^5 m^3]
30.0
25.0
20.0
15.0
10.0
5.0
0.0
0 100 200 300 400 500 600 700 800 900 1000 1100 1200 1300 1400 1500 1600 1700 1800 1900 2000
Scenarios
Median_500
Median_300

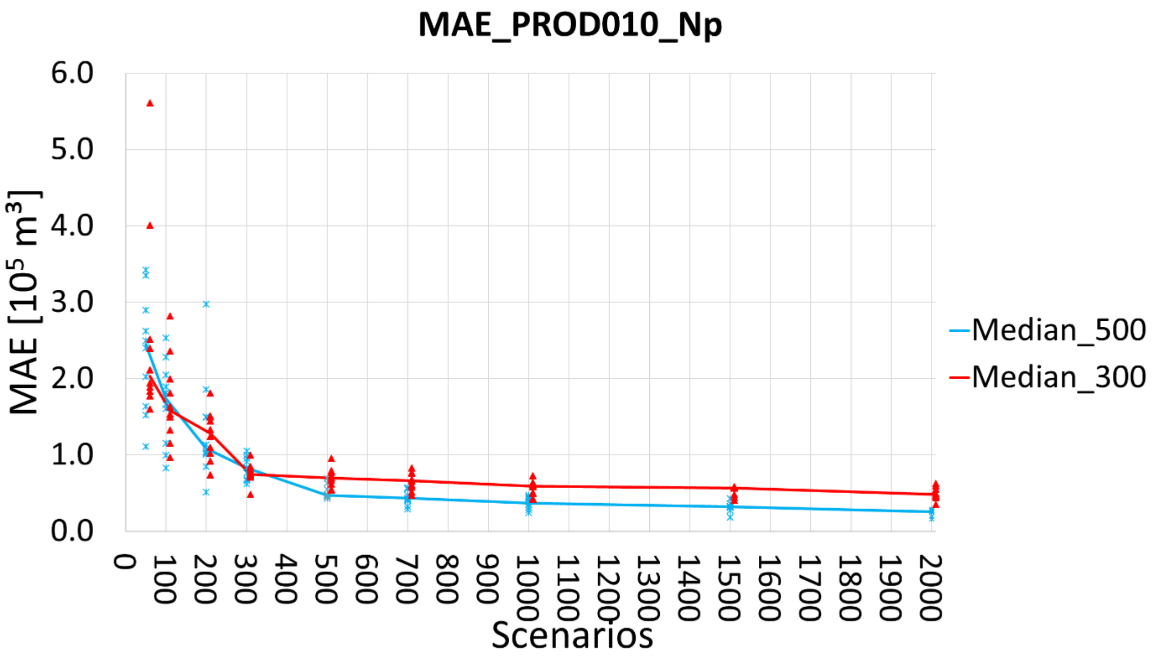
(b)



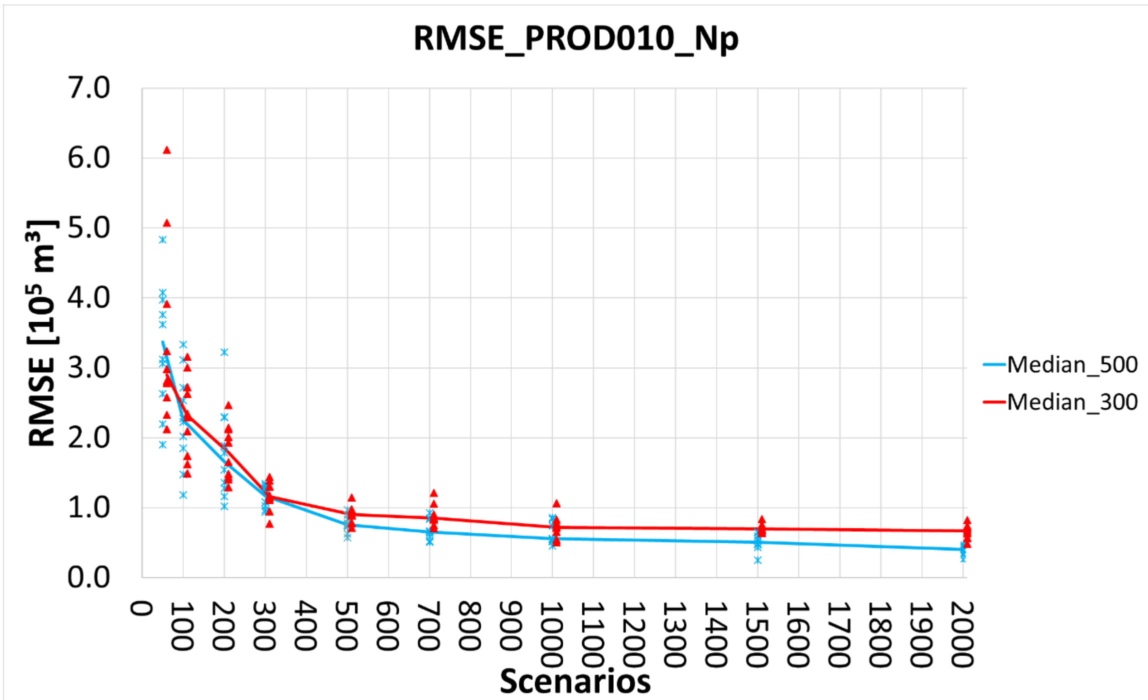
(c)

Figure 6.2: Comparison of quality indicators generated by cases with 500 and 300 images for (a) MAE_Np (b) RMSE_Np and (c) MAAPE_Np

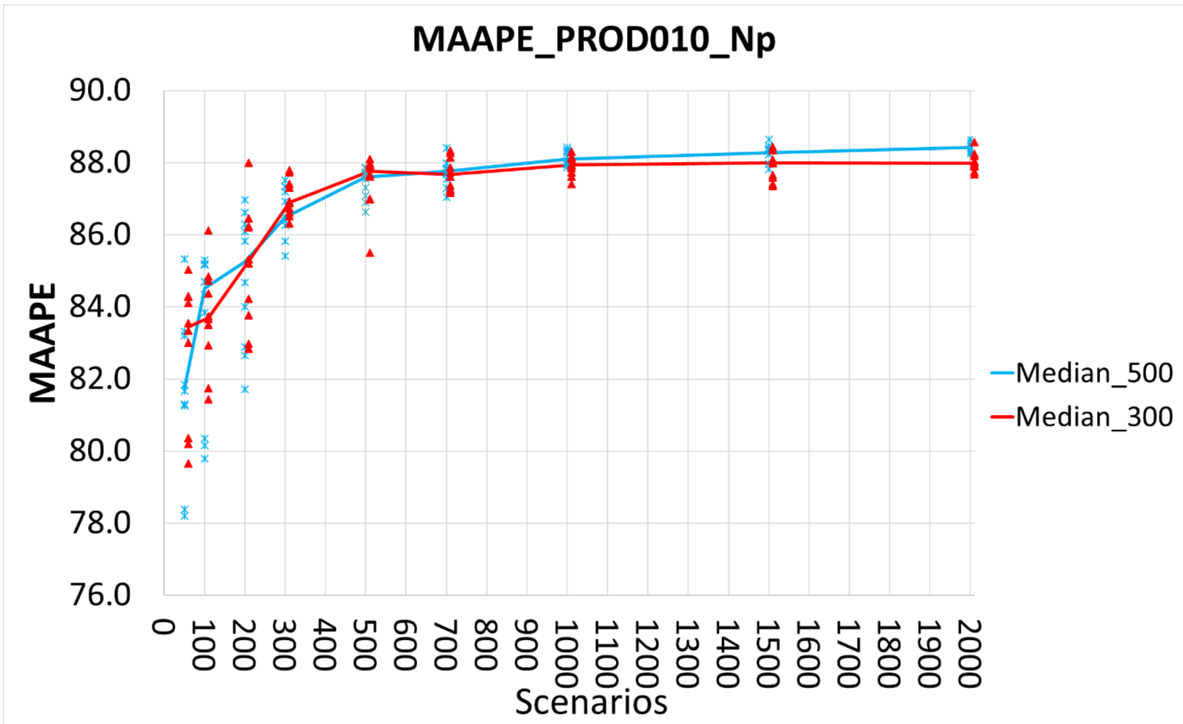
As we expected, the case with 500 images showed better indicators, once those additional 200 images increase the range of possible results. In addition, for our new case (300 images), it is possible to observe a difference in the behavior of the indicator after it reaches the total number of images. In some cases, for well functions, such as the example below (Figure 6.3), this behavior is intensified:


MAE_PROD010_Np
MAE [10^5 m^3]
6.0
5.0
4.0
3.0
2.0
1.0
0.0
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300
1400
1500
1600
1700
1800
1900
2000
Scenarios
Median_500
Median_300

(a)


RMSE_PROD010_Np
RMSE [10^5 m^3]
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300
1400
1500
1600
1700
1800
1900
2000
Scenarios
Median_500
Median_300

(b)



(c)

Figure 6.3: Comparison of quality indicators generated by cases with 500 and 300 images for (a) MAE_PROD010_Np (b) RMSE_PROD010_Np and (c) MAAPE_PROD010_Np

This behavior, though, is not observed for all functions, but we have strong evidence that the stabilization point is directly related to the number of images being simulated.

Another discussion point is the dimensions and physical significance of those indicators. Both MAE and RMSE take the same dimensions as the OF and their range goes from 0 to ∞. However, as shown in Equation 3.1, MAE simply indicates the absolute difference between a reference and a studied parameter, which makes the decision-maker interpretations easier, while taking the square of this error (RMSE - Equation 3.3) makes the results more difficult to understand, once it is not influenced proportionally by the absolute value of each error, as in MAE. MAAPE, though, have a fixed dimension (degrees) and a range from 0 to 90° - this may be interesting when comparing different OF, but it fails in physical interpretation, once it isn't clear for the decision maker the meaning of a MAAPE of 93°, for example. We could overcome this problem by setting limits of acceptance and rejection, but it would be difficult to generalize this value, since it would depend on several variables (geo-model, decision-maker profile, uncertainty levels and others).

- **Group II**

As NQDS can reach both negative and positive values, a Boxplot is the most suitable plot to study its behavior, once is a method for graphically depicting groups of numerical data through their quartiles – we can observe the median, the variability and the outliers, as shown in Figure 6.4. For the NQDS indicator, we defined a tolerance – *tol* – of 1% for field functions and 2,5% for well functions.

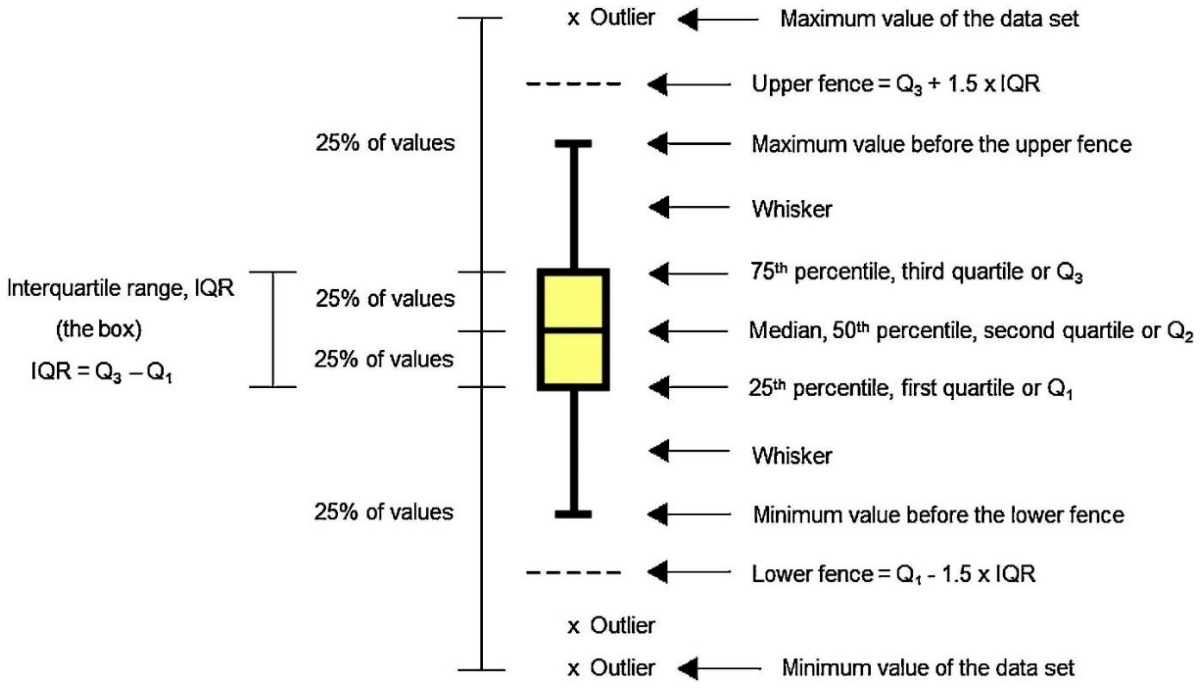
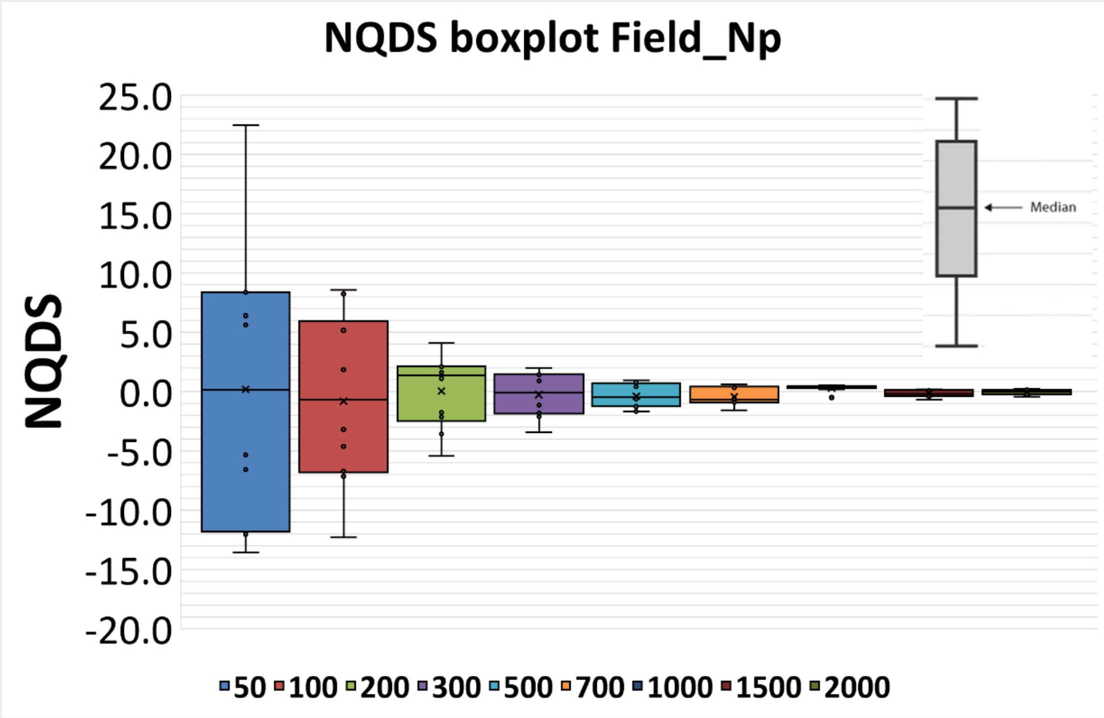
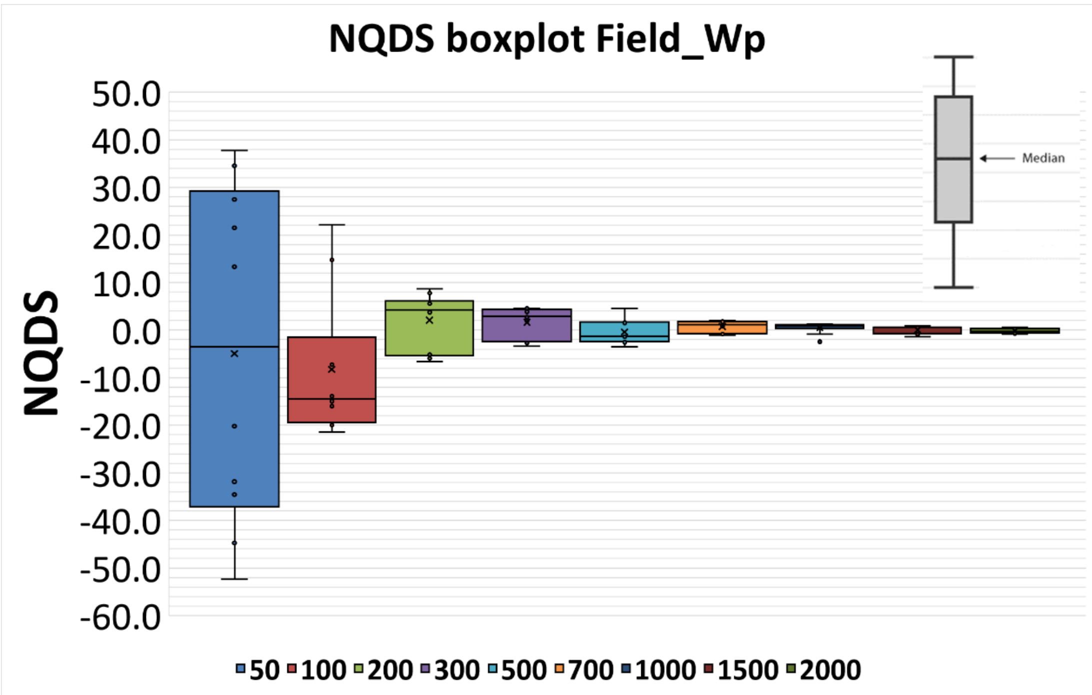


Figure 6.4: Scheme of construction of a boxplot.

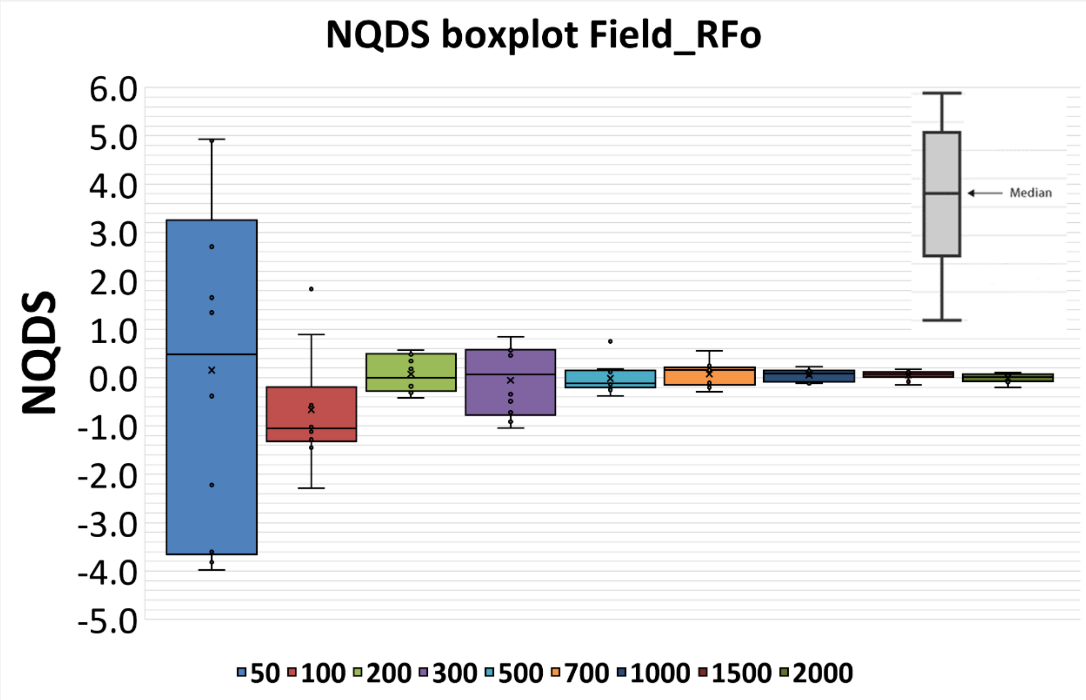
For all field OF (Figure 6.5), the NQDS median values resides in the [-1 +1] interval since the set of 50 simulations, but we can see a decrease in the dispersion of the values and the approximation to zero when the number of simulations increases.


NQDS boxplot Field_Np
25.0
20.0
15.0
10.0
5.0
0.0
-5.0
-10.0
-15.0
-20.0
NQDS
Median
50 100 200 300 500 700 1000 1500 2000

(a)


NQDS boxplot Field_Wp
50.0
40.0
30.0
20.0
10.0
0.0
-10.0
-20.0
-30.0
-40.0
-50.0
-60.0
NQDS
Median
50 100 200 300 500 700 1000 1500 2000

(b)



(c)

Figure 6.5: NQDS indicator for all field OF.

As MAAPE, this indicator has a different dimension regarding the OF and may be suitable to compare different OF. The big advantage of this method the defined acceptance region (intervals -1 and +1), which relies on the tolerance factor (Equation 3.14), defined by the user's experience and/or objective, which also helps the decision maker to define what action to take.

For optimization purposes or situations where the negative values are not desirable, we could use a modification of NQDS, removing the $\frac{SD}{|SD|}$ term of the equation, thus assuming only positive values.

In this type of study, it is interesting to analyze each well separately since results combine to mold our field functions, and, therefore, they can compensate each other's "problems" delivering an untrue "well-behavior" field function

Figure 6.6 and Figure 6.7 shows the four indicators for a vertical well and horizontal well, respectively.

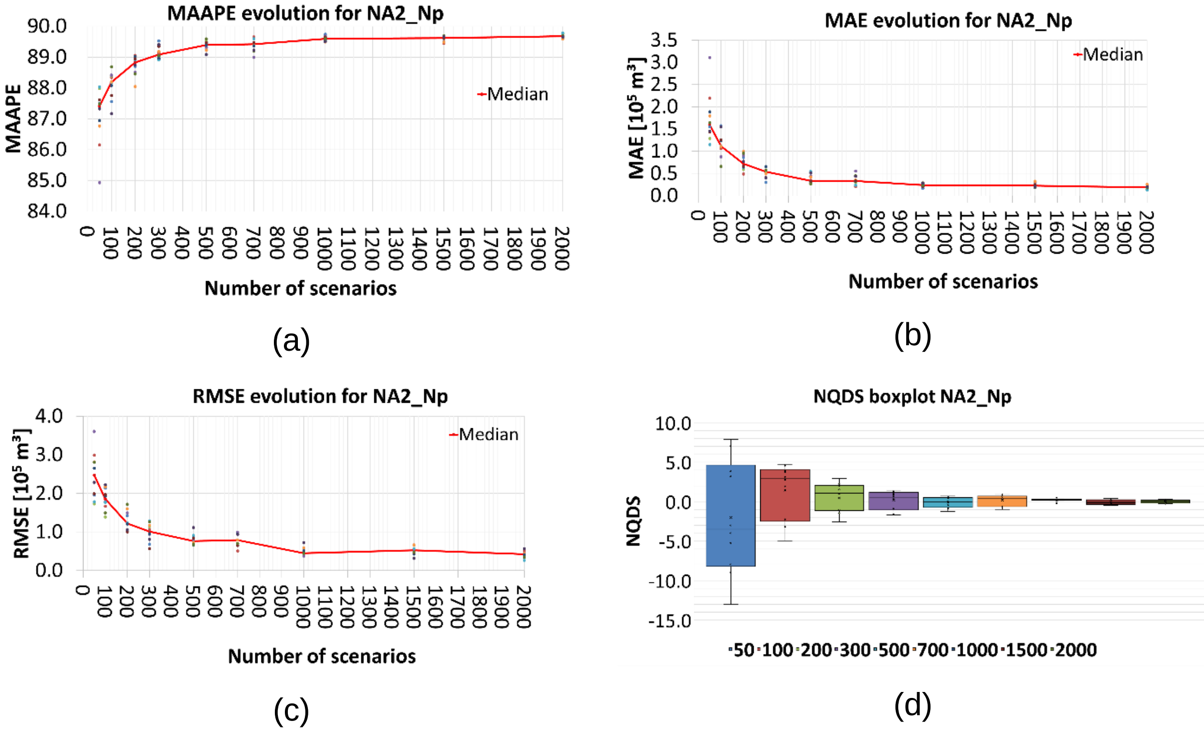


Figure 6.6: Quality indicators for NA2D vertical well - (a) MAAPE (b) MAE (c) RMSE (d) NQDS.

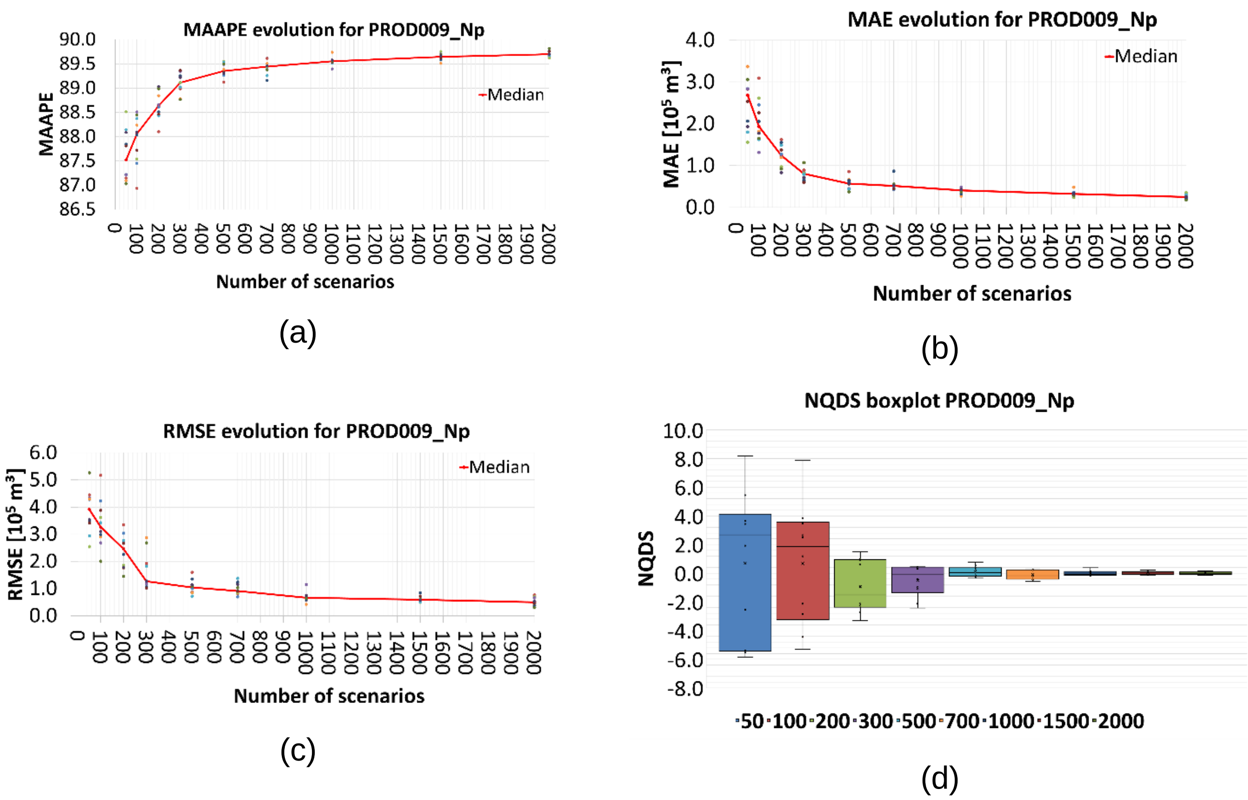
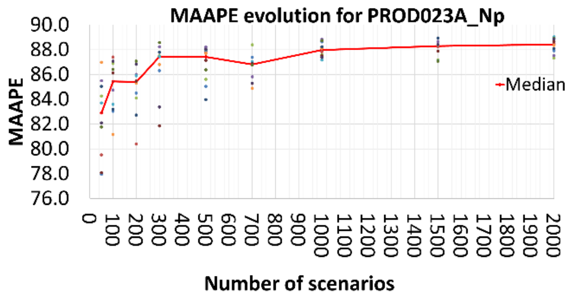
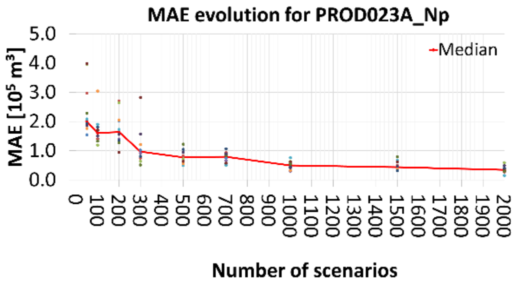


Figure 6.7: Quality indicators for PROD009 horizontal well - (a) MAAPE (b) MAE (c) RMSE (d) NQDS.

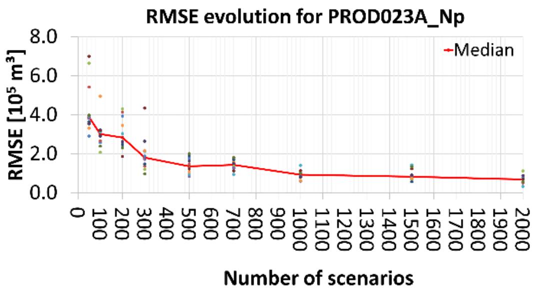
We can observe that the trends for the wells are less regular than field functions – Group I show more abrupt steps and Group II show a bigger dispersion, but we still can conclude the same previous points for almost all wells – excepting PROD0023A (Figure 6.8), PROD0024A and PROD0025A (Appendix B), for the reason pointed below.



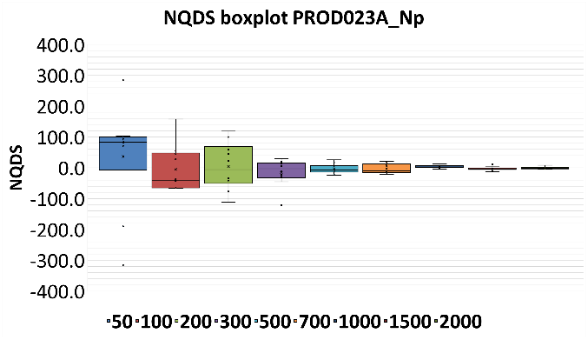
(a)



(b)



(c)



(d)

Figure 6.8: Quality indicators for PROD023A horizontal well - (a) MAAPE (b) MAE (c) RMSE (d) NQDS.

These wells presented very irregular trends for Group I. Figure 6.9 may explain this behavior:

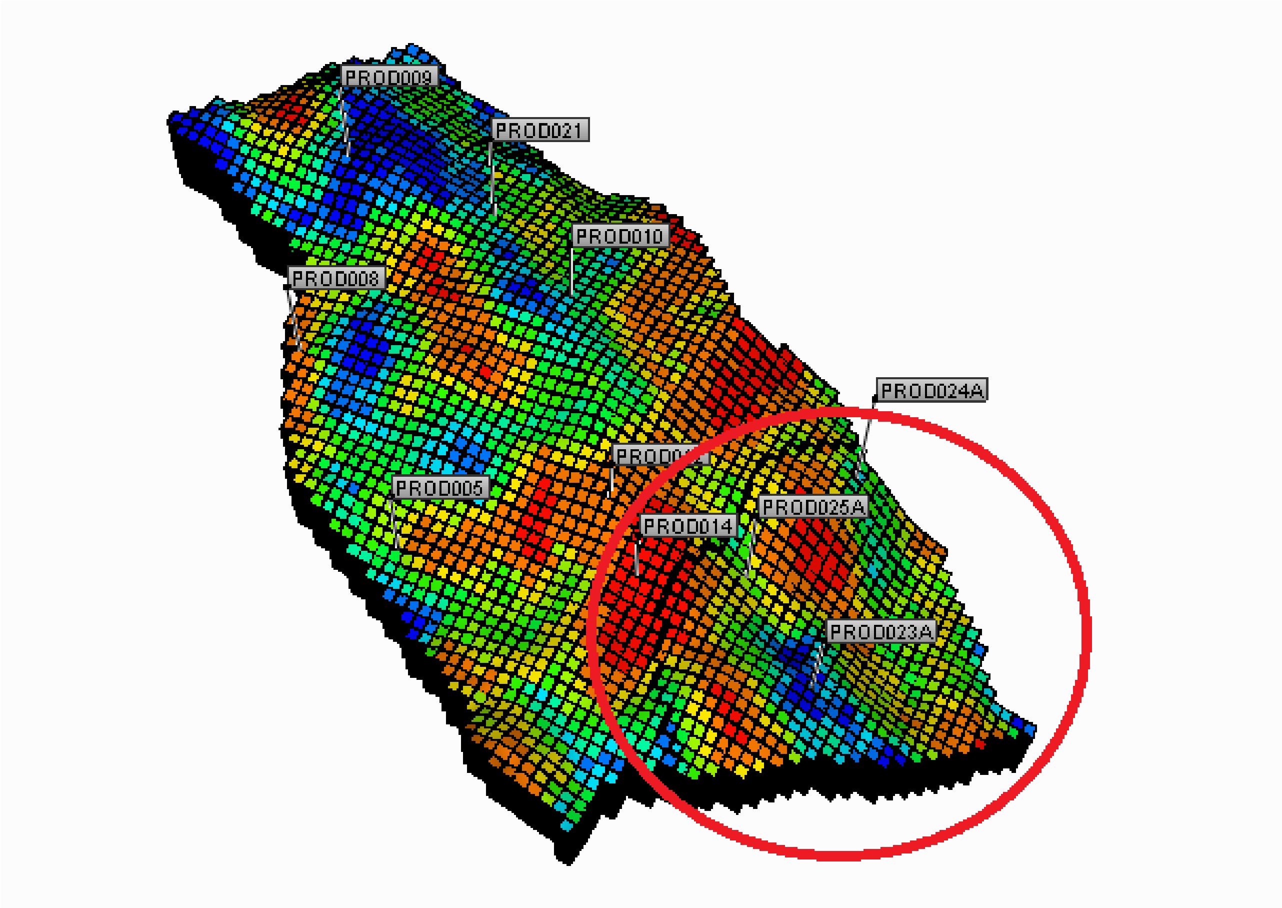


Figure 6.9: Top view of the producer wells of UNISIM-I-D LFM (porosity map). The red circle highlights the location of three wells: PROD0023A, PROD024A and PROD025A.

As we can see inside the red circle, those three wells are the only ones inside the East-Block zone which is an uncertainty in the model – it either can or cannot exist (Section 5). This uncertainty introduces a significant impact in the model's response (Polizel, 2016) and it appears that this is leading to a higher deviation in the results. Nevertheless, even there is a bigger variance in those trends, the data still accompany those shown previously and stabilize when closer to 1000 scenarios

Finally, we must choose, based on the results, the indicator that better measures the quality of a solution regarding a reference. We present a decision matrix in Table 6.1, each column shows an aspect of interested (advantage) in a quality indicator, and they can assume values of 1 to 3. The indicator that cumulate more points will be that suits best our study:

Table 6.1: Decision matrix.

	Interpretation	Finite boudary	Physical significance	Ease of calculation	Acceptance limits	Oil & Gas literature	Total
MAAPE	1	3	1	1	1	1	8
MAE	3	1	3	3	1	2	13
RMSE	1	1	2	2	1	2	9
NQDS	2	3	1	2	3	3	14

As we can see, NQDS is the indicator that, given our parameters, fits best as quality measurement in risk analysis processes. However, it does not disqualify the others to be tested in other methodologies, analysis and applications, each one has their advantages and should be explored as well.

7 CONCLUSIONS AND RECOMMENTADIONS FOR FUTURE WORK

In this work, we analyzed and selected an indicator that can estimate the quality of the production forecast process of an oil field. This study allowed the following conclusions:

- Through the literature review, we were able to select four potential indicators – MAE, RMSE, MAAPE and NQDS that could assess quality of the production forecast processes.
- The NQDS indicator was the most useful for the application: the biggest advantage is the existence of boundaries of acceptance, leading to an easier decision making.
- Other indicators, such MAE, received a high rating in the decision matrix, showing its potential use in other studies.
- For future works, we could test the capacity of our discussed indicator (NQDS) in model calibration – trying to calibrate the LFM using the HFM as reference, in a probabilistic approach, that is, calibrate some models and use this calibration for all other models. Some information about this subject can be found in Appendix C.

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9 APPENDIX A – RISK CURVES FOR WP, RFO AND NP

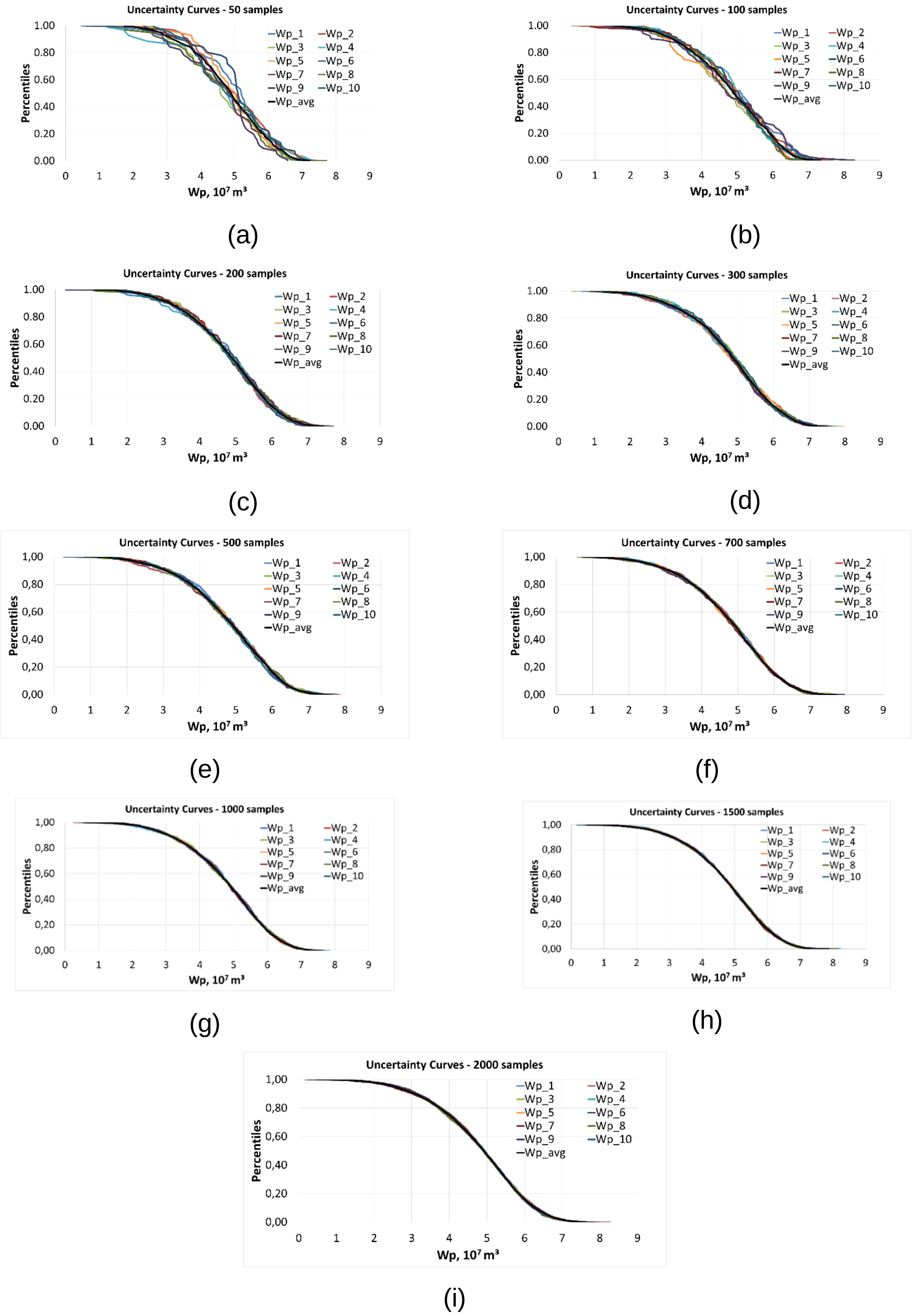
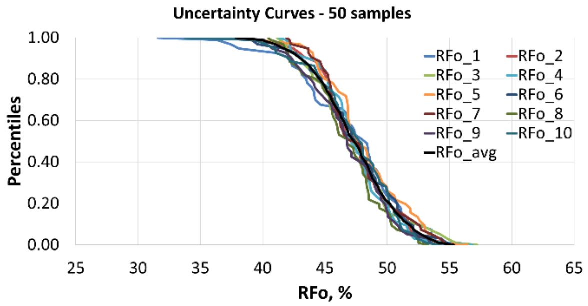
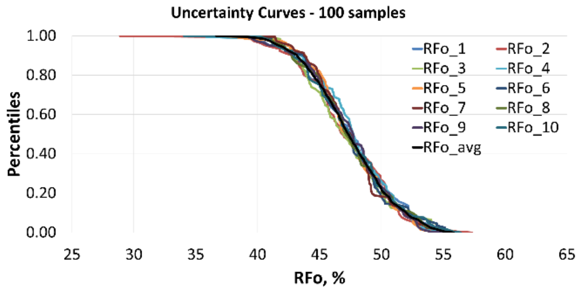


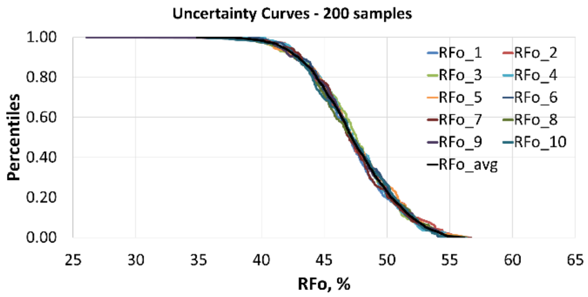
Figure 9.1: Risk Curves for the Wp function containing 10 samples and the average curve for (a) 50 scenarios (b) 100 scenarios (c) 200 scenarios (d) 300 scenarios (e) 500 scenarios (f) 700 scenarios (g) 1000 scenarios (h) 1500 scenarios and (i) 2000 scenarios.


Uncertainty Curves - 50 samples
Percentiles
RFo, %
RFo_1 RFo_2 RFo_3 RFo_4 RFo_5 RFo_6 RFo_7 RFo_8 RFo_9 RFo_10 RFo_avg

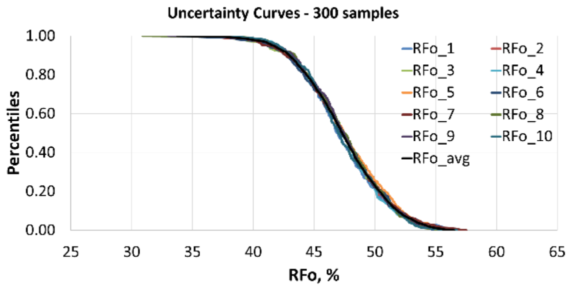
(a)


Uncertainty Curves - 100 samples
Percentiles
RFo, %
RFo_1 RFo_2 RFo_3 RFo_4 RFo_5 RFo_6 RFo_7 RFo_8 RFo_9 RFo_10 RFo_avg

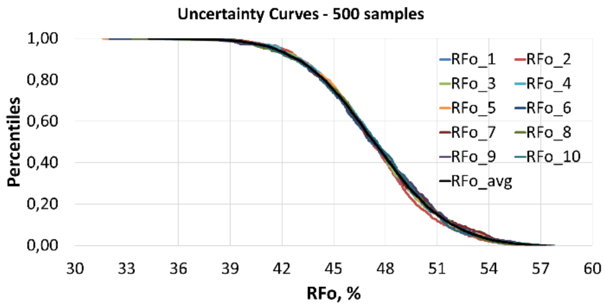
(b)


Uncertainty Curves - 200 samples
Percentiles
RFo, %
RFo_1 RFo_2 RFo_3 RFo_4 RFo_5 RFo_6 RFo_7 RFo_8 RFo_9 RFo_10 RFo_avg

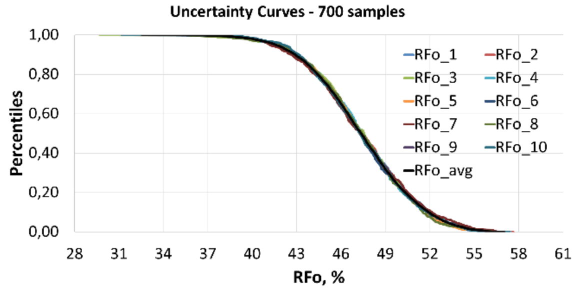
(c)


Uncertainty Curves - 300 samples
Percentiles
RFo, %
RFo_1 RFo_2 RFo_3 RFo_4 RFo_5 RFo_6 RFo_7 RFo_8 RFo_9 RFo_10 RFo_avg

(d)


Uncertainty Curves - 500 samples
Percentiles
RFo, %
RFo_1 RFo_2 RFo_3 RFo_4 RFo_5 RFo_6 RFo_7 RFo_8 RFo_9 RFo_10 RFo_avg

(e)


Uncertainty Curves - 700 samples
Percentiles
RFo, %
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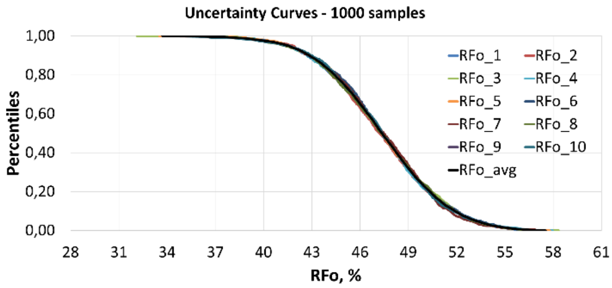
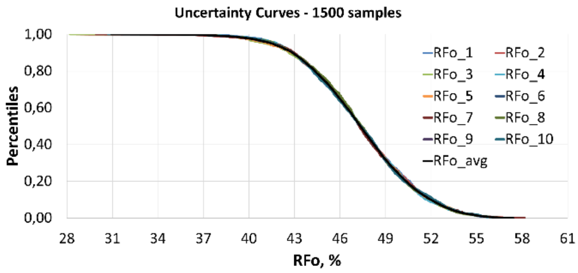
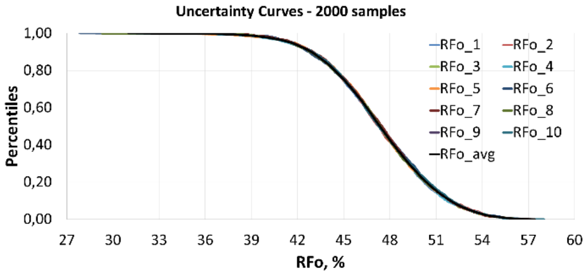
(f)


Uncertainty Curves - 1000 samples
Percentiles
RFo, %
RFo_1 RFo_2 RFo_3 RFo_4 RFo_5 RFo_6 RFo_7 RFo_8 RFo_9 RFo_10 RFo_avg

(g)

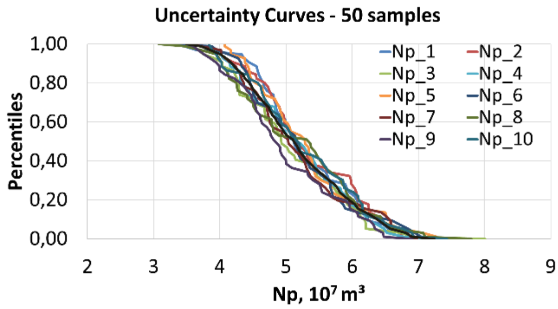

Uncertainty Curves - 1500 samples
Percentiles
RFo, %
RFo_1 RFo_2 RFo_3 RFo_4 RFo_5 RFo_6 RFo_7 RFo_8 RFo_9 RFo_10 RFo_avg

(h)

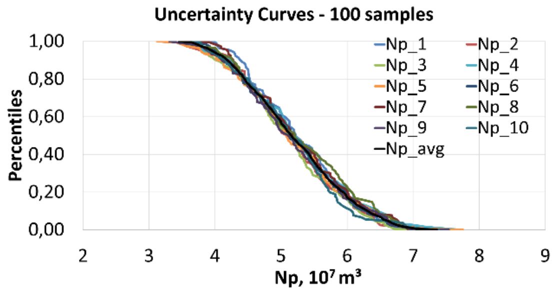


(i)

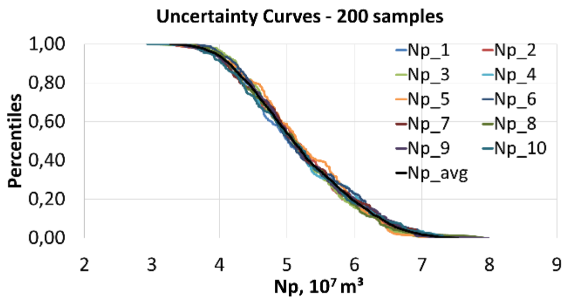
Figure 9.2: Risk Curves for the RFo function containing 10 samples and the average curve for (a) 50 scenarios (b) 100 scenarios (c) 200 scenarios (d) 300 scenarios (e) 500 scenarios (f) 700 scenarios (g) 1000 scenarios (h) 1500 scenarios and (i) 2000 scenarios.



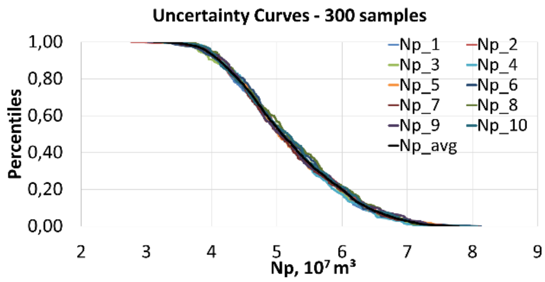
(a)



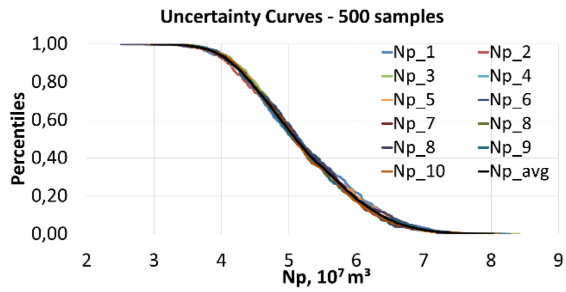
(b)



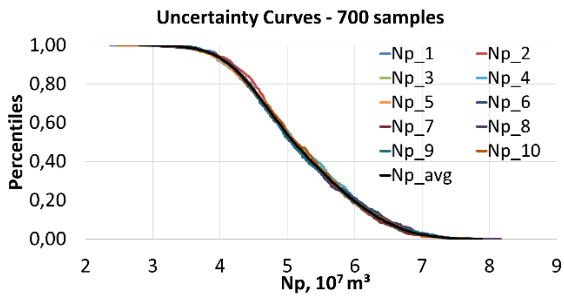
(c)



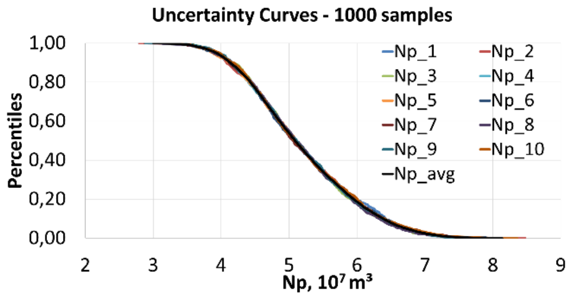
(d)



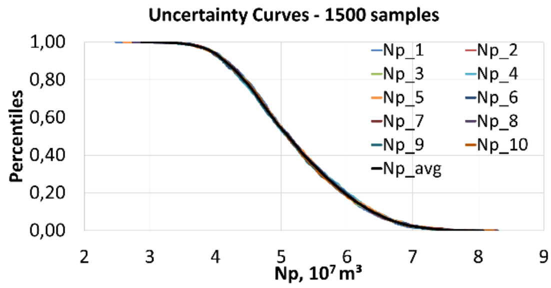
(e)



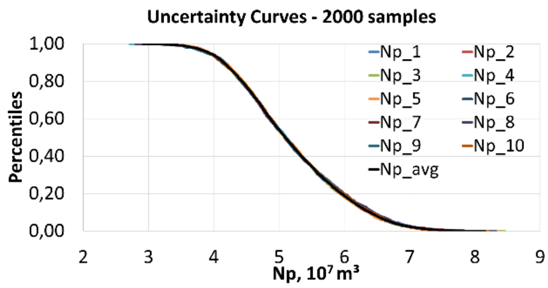
(f)



(g)



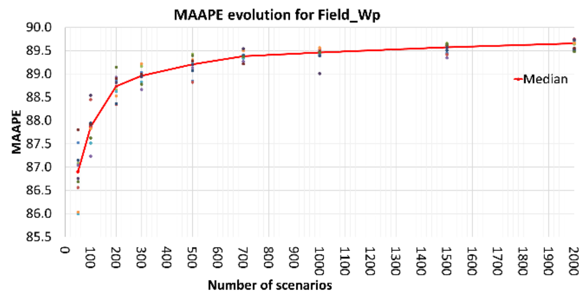
(h)



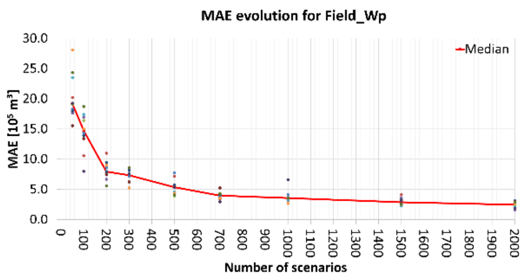
(i)

Figure 9.3: Risk Curves for the Np function containing 10 samples and the average curve for (a) 50 scenarios (b) 100 scenarios (c) 200 scenarios (d) 300 scenarios (e) 500 scenarios (f) 700 scenarios (g) 1000 scenarios (h) 1500 scenarios and (i) 2000 scenarios.

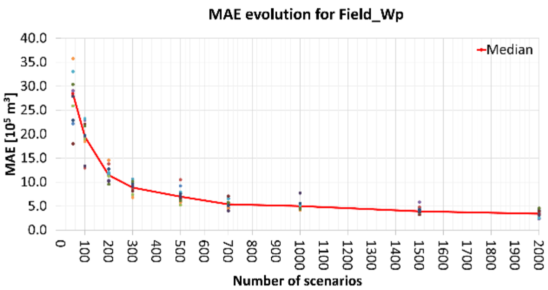
10 APPENDIX B – QUALITY INDICATORS FOR FIELD AND WELL OBJECTIVE FUNCTIONS



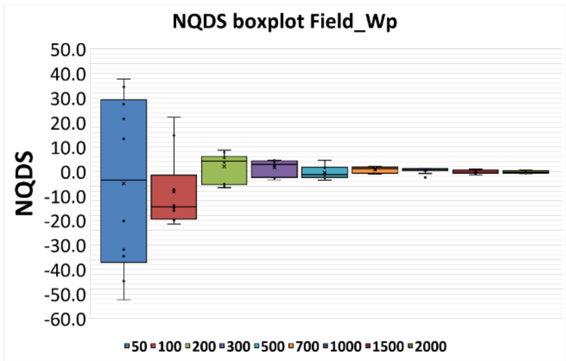
(a)



(b)



(c)



(d)

Figure 10.1: Indicators for field cumulative water production - (a) MAAPE (b) MAE (c) RMSE (d) NQDS.

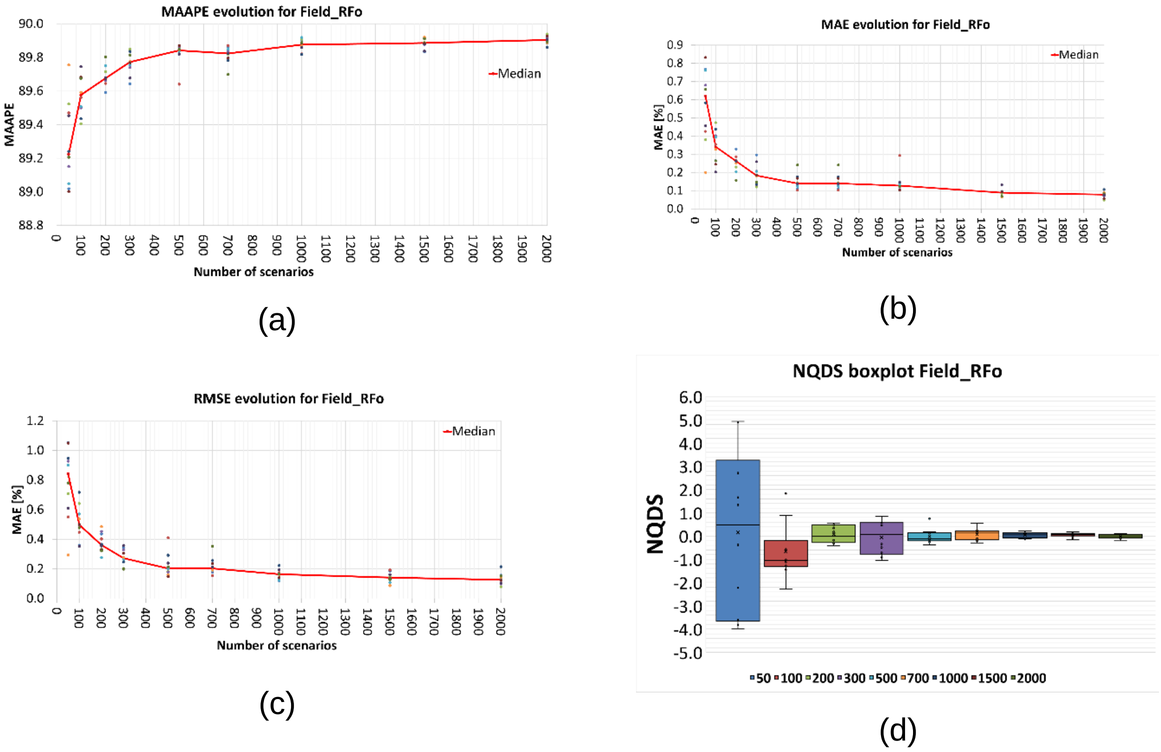


Figure 10.2: Indicators for field RFo - (a) MAAPE (b) MAE (c) RMSE (d) NQDS.

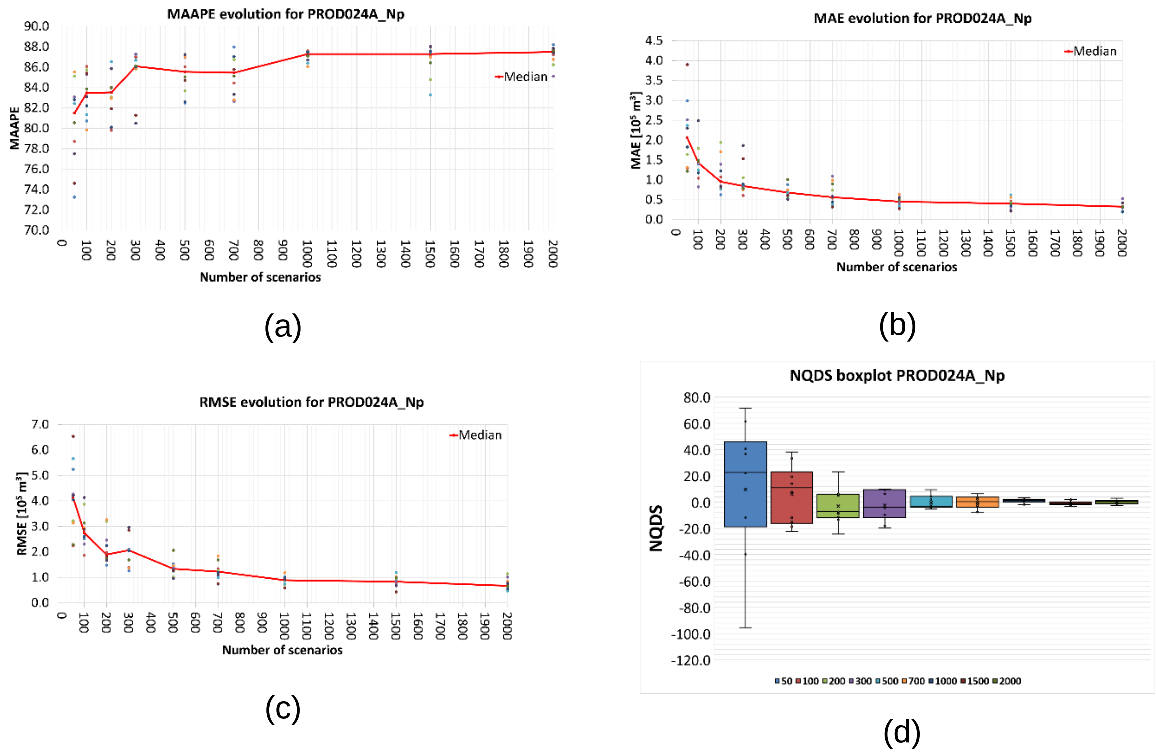
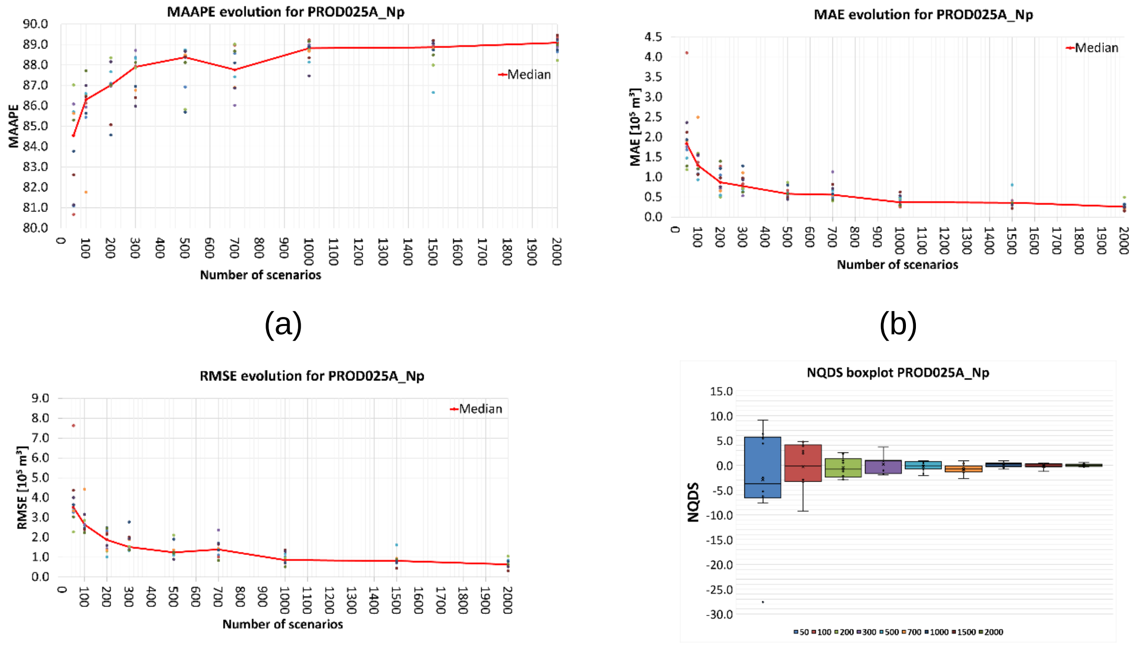


Figure 10.3:Indicators for PROD024A cumulative oil production - (a) MAAPE (b) MAE (c) RMSE (d) NQDS



(a) (b) (c) (d)

Figure 10.4: Indicators for PROD025A cumulative oil production - (a) MAAPE (b) MAE (c) RMSE (d) NQDS

11 APPENDIX C: SUGGESTION FOR FUTURE WORK (MODEL CALIBRATION)

During this work, we ran some tests trying to calibrate the LFM with the HFM as reference. The methodology was based in the work of Ligero *et al* (2004), as showed in Figure 11.1.

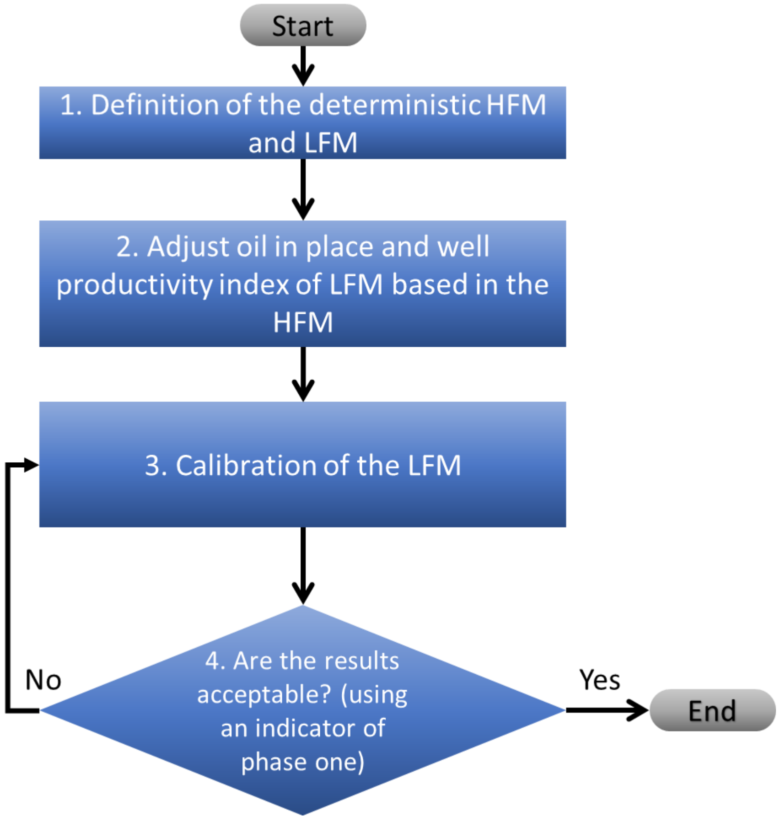
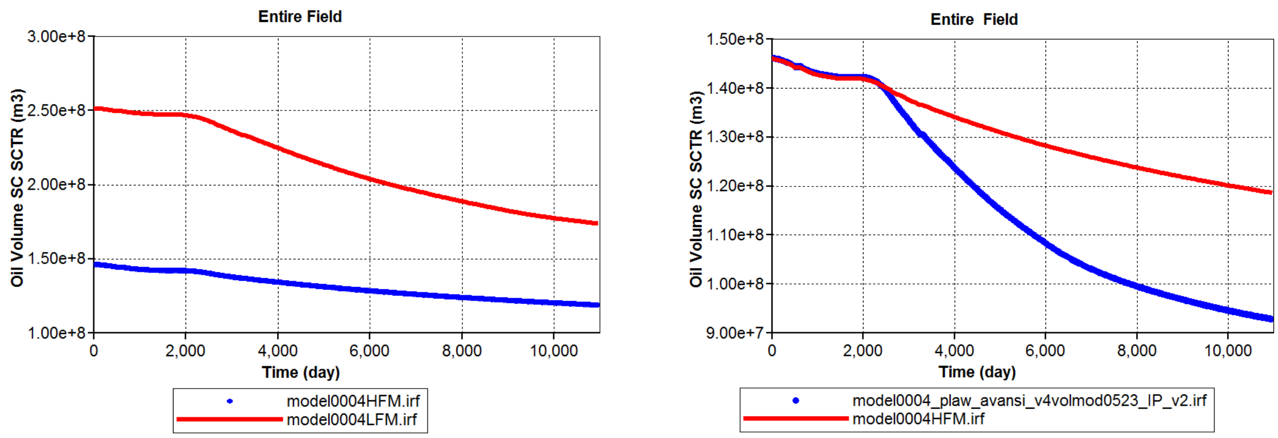
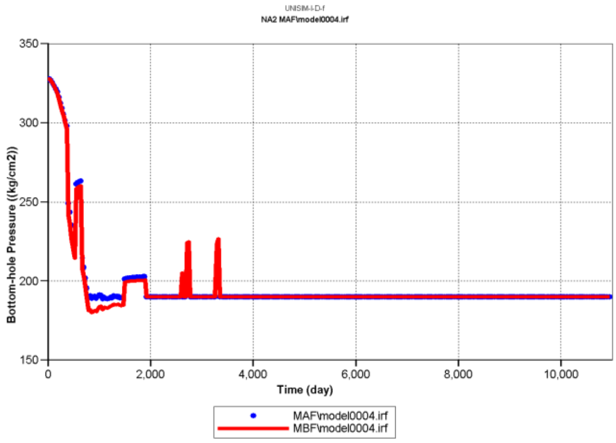


Figure 11.1 – Proposed methodology for model calibration using the NQDS.

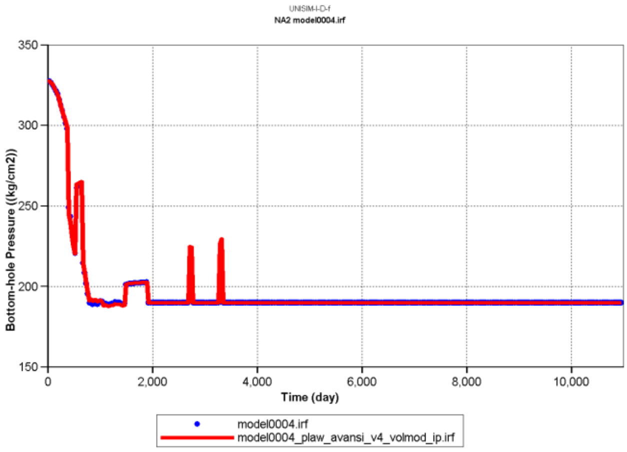
First, the model was chosen based the model oil in place of the HFM (the LFM was generated using the same geostatistical realization). Then, we adjusted the oil in place and productivity index based on the HFM (Figure 11.2).



(a)



(b)

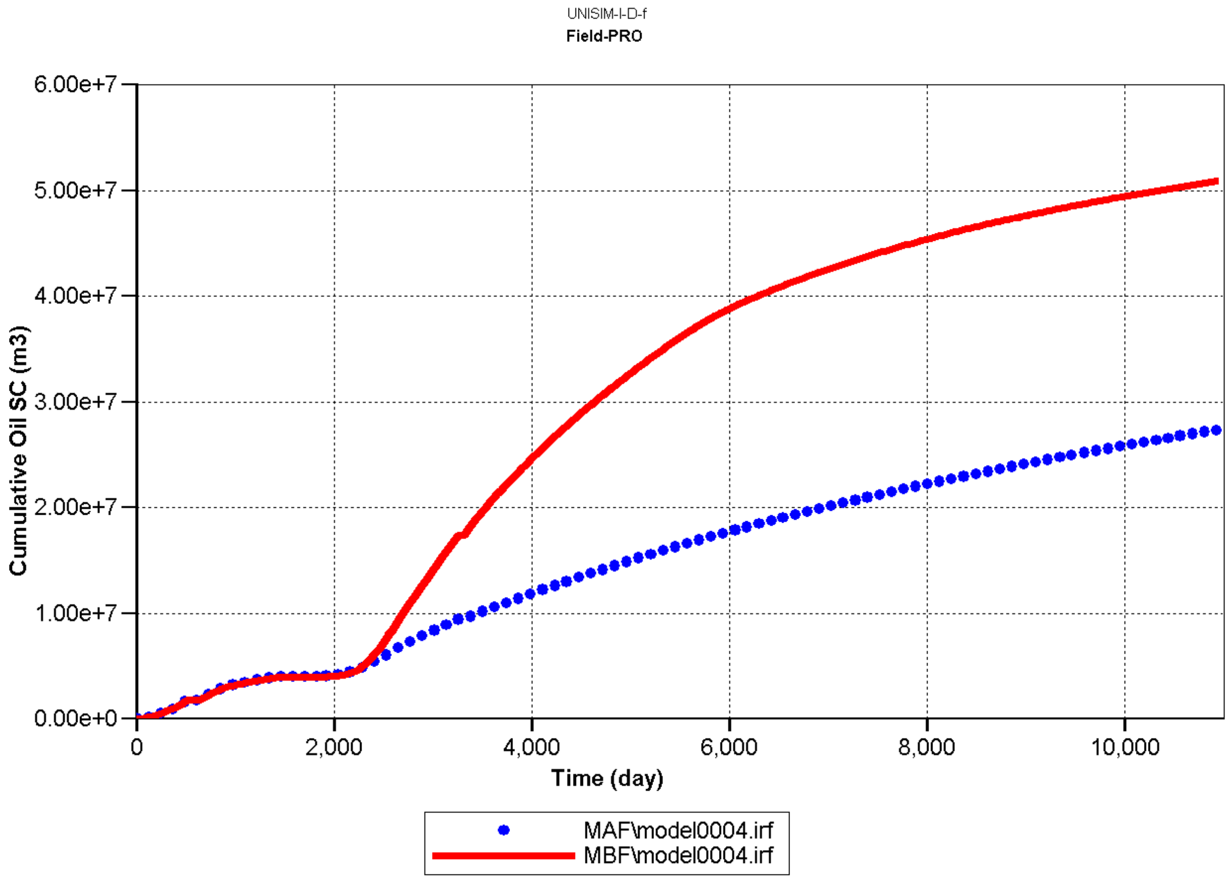


(c)

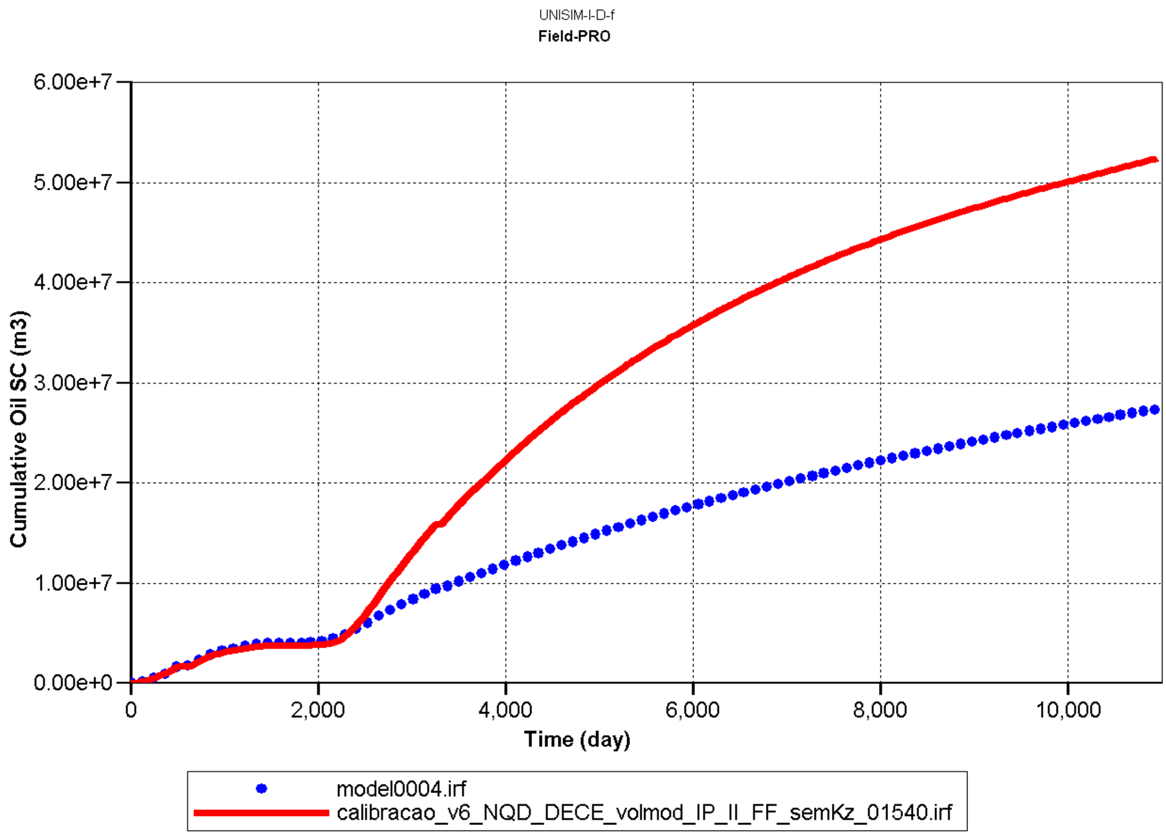
(d)

Figure 11.2: Comparison of oil in place and well productivity (highlighting BHP of NA2) before (a) and (b) and after (c) and (d) the adjust.

The next step, which consists in an optimization step, is to adequate the production of the LFM (calibrate) using the NQD (NQDS without signal) of oil and water production (field and wells) through adjustments of the pseudo relative permeability, using the Corey Coefficients (Corey, 1954), and the result is shown in Figure 11.3.



(a)



(b)

Figure 11.3: Comparison of oil in place before (a) and after (b) the adjust.

As observed, this first approach did not succeed as expected, but some points could be investigated:

- We could study which FOs are the most suitable to calibrate our model, instead of only using oil and water production;
- We should verify the calibration method itself, and test new approaches;
- Perform the calibration in a probabilistic study, involving several scenarios.