CARLA JANAINA FERREIRA

METHODOLOGY TO ESTIMATE THE CHANCE OF SUCCESS OF A 4D SEISMIC PROJECT FROM THE RESERVOIR ENGINEERING PERSPECTIVE

METODOLOGIA PARA ESTIMATIVA DA CHANCE DE SUCESSO DE UM PROJETO DE SÍSMICA 4D DO PONTO DE VISTA DA ENGENHARIA DE RESERVATÓRIOS

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2014

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FACULDADE DE ENGENHARIA MECÂNICA
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Thesis presented to the Mechanical Engineering Faculty and Geosciences Institute of the University of Campinas in partial fulfillment of the requirements for the degree of Doctor in Petroleum Sciences and Engineering in the area of Reservoirs and Management.

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Orientador: Prof. Dr. Denis José Schiozer

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DEDICATION

I dedicate this thesis to my dear husband, André for supporting me all the way and who has been a constant source of encouragement and inspiration.

I also dedicate to my mother, Creusa. A strong and gentle soul who taught me to believe in hard work and that so much can be done with little.

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“Do not follow where the path may lead. Go instead where there is no path and leave a trail.”

Muriel Strode

ABSTRACT

Production of hydrocarbons is a high-risk business. The uncertainties inherent to production are related to the uncertainties in the physical state of the reservoir and external variables. Reservoir uncertainty can be reduced as new production and dynamic data become available. 4D seismic technology has been used in the petroleum industry because the integration of geophysics and engineering information increases the predictive capability of reservoir simulations. However, there are technical issues to be addressed before starting a 4D seismic project. Several geophysical studies use the chance of success concept to identify the favorable cases; evaluating the seismic survey and the magnitude of seismic changes. From the engineering point of view, it is important to evaluate the impact of new information on field operations and the consequent monetary benefit. The estimation of 4D seismic data chance of success before its acquisition is a challenge. Therefore, the thesis presents a methodology to estimate the chance of success of a 4D seismic project from the reservoir engineering perspective. The methodology was developed in three phases. The first phase shows that water saturation error can measure the improvement on the fluid behavior understanding due to 4D seismic data. Moreover, it shows that the time for 4D seismic data acquisition affects its value. The second phase presents the methodology to estimate the best time to acquire 4D seismic data. The best time estimation is determined by evaluating time for water breakthrough and the water saturation error curves. Finally, the chance of success methodology is presented. The methodology is simple and an iterative process. It is divided in six steps, in which some of them are well established in the literature. The thesis incorporates the date of 4D seismic data acquisition in the process and assesses the chance of success through the variation in the economic benefit caused by the reservoir uncertainties. The methodology was applied to a synthetic reservoir model, showing a procedure to estimate the expected value of information and the probability of success.

Key Word: 4D Seismic, Reservoir Simulation, Chance of Success, Value of Information.

RESUMO

A produção de hidrocarbonetos é um negócio que envolve muitos riscos. As incertezas inerentes à produção estão relacionadas às incertezas no estado físico do reservatório e variáveis externas. A incerteza do reservatório pode ser reduzida conforme dados de produção e dinâmicos são adquiridos. A sísmica 4D (S4D) tem sido utilizada na indústria de petróleo, pois a integração de informação geofísica e de engenharia aumenta a capacidade preditiva da simulação de reservatórios. Entretanto, há questões técnicas que devem ser avaliadas antes de se iniciar um projeto de S4D. Vários estudos geofísicos usam o conceito de chance de sucesso para identificar os casos favoráveis onde são avaliados o levantamento sísmico e a magnitude das mudanças sísmicas. Porém, do ponto de vista de engenharia é importante avaliar o impacto da nova informação na operação do campo e o consequente benefício financeiro. A estimativa da chance de sucesso de um projeto de S4D é um desafio. Portanto, este trabalho apresenta uma metodologia que estima a chance de sucesso sob a perspectiva da engenharia de reservatórios. A metodologia foi desenvolvida em três fases. A primeira fase mostra que o erro de saturação de água pode ser utilizado para medir a melhora no entendimento da movimentação de fluidos no reservatório devido à aquisição da S4D. Além disso, mostra que o momento em que a sísmica 4D é adquirida impacta no valor da informação. Na segunda fase a metodologia para determinar o melhor momento para a aquisição da S4D é apresentada. O melhor momento é determinado avaliando o tempo para a chegada de água nos poços e as curvas de erro de saturação. Por fim, a metodologia para a estimativa da chance de sucesso é apresentada. A metodologia é um processo iterativo simples. A metodologia é composta por seis etapas, no qual algumas são bem estabelecidas na literatura. A tese incorpora a data que aquisição da sísmica 4D no processo e avalia a chance de sucesso por meio da variação do beneficio econômico ocasionado pelas incertezas do reservatório. A metodologia foi aplicada para um caso sintético para ilustrar o procedimento do cálculo do valor da informação e da probabilidade de sucesso.

Palavras Chave: Sísmica 4D, Simulação de Reservatórios, Chance de Sucesso, Valor da Informação.

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NOMENCLATURE

Latin Letters

4D	time-lapse
4DS	4D seismic
Np	oil production
NRMS	measure of non-repeatable noise
N_{SCN}	specific number of scenarios
P	probability of occurrence
r	discount rate
s	production strategy
Sw	water saturation
trans.	transmissibility
T_{SCN}	total number of scenarios
kr	relative permeability
kz/kx	anisotropy.
x, y, z	Cartesian directions
X	parameter quantity
yr	year
w	weight
Wp	water production

Abbreviation

pdf	probability density function
BHP	bottom-hole pressure
BT	breakthrough
CF	cash flow
COS	chance of success
EMV	expect monetary value
EnKF	ensemble Kalman filter
EVOI	expected value of information
FO	objective Function
HM	history match
NPV	net present value
OBC	ocean-bottom cable
PVT	pressure, volume, temperature
RF	oil recovery factor
SNR	signal-to-noise ratio not repeatable
STL	total surface liquid rate
STW	surface water rate
VOI	value of information
WCUT	water cut

WOC	water oil contact

Superscript

base	base simulation model
n	number of parameters to be adjusted
nRP	number of pressure parameter regions
nRS	number of saturation parameter regions
N	number of production intervals
N_g	number of grid cells
N_{RM}	number of representative models
m	number of wells
model	simulation model analyzed
reference	reference model
RS	saturation parameter region
RP	pressure parameter region
scenario	reservoir scenario model
t	year of production

Subscript

i	cell grid model number
j	specific scenario
r	representative model
M	map
P	production
RM	representative model

Greek Letters

α, β	EVOI coefficients
ε	error
Δ	difference

1. INTRODUCTION

4D seismic is increasingly being used as qualitative and quantitative description of the reservoir behavior for management and decisions making purposes. 4D seismic refers to repeating seismic acquisition over time. It provides unique information regarding the dynamic properties variations (such as pressure and saturation changes) due to production.

4D seismic is used to constrain or update a model of the reservoir, to locate undrained oil, to optimize well planning and minimize the effect of unexpected events, such as an early breakthrough of injected fluids. Knowledge of reservoir connectivity, flow barriers, or bypassed hydrocarbons is the kind of information that is expected from 4D seismic data (Waggoner, 1998 and Kawar *et al.*, 2003).

Such knowledge helps to optimize reservoir investment decisions and increases the average recovery. Due to the actual complexity of the reservoirs, the current average recovery is about 35%. 4D seismic is an important contribution to increase the recovery factor (Oldenziel, 2003).

Statoil states that 4D seismic contributes to reach the ambition of increasing the oil recovery rate to 60% on the Norwegian shelf. A permanent seismic tool will be used to increase the recovery rate; 700 kilometers of seismic cables will be installed on the seabed on the Snorre and Grane fields in the North Sea (Statoil, 2014).

Regarding the Brazilian oil fields, 4D seismic has an important role in the Marlim field management. The integration of 4D seismic and production data provided a more realistic reservoir model and assisted the optimization of well planning: two wells were canceled, five new wells were drilled and many wells were repositioned. The total oil production increased 4.76% and the production per well increased 24%. Most of the improvement can be attributed to the 4D seismic interpretation (Johann *et al.*, 2009).

Several published cases show that 4D seismic can improve reservoir management and increase production efficiency. The following fields can be mentioned: Marlim Sul in Campos Basin; Gulfaks in the North Sea; Oseberg, Heidrun and Ekofisk in Norway (Thedy *et al*., 2007; Roste *et al*., 2006; Sando *et al*., 2009; Smith *et al*., 2010).

However, the use of 4D seismic data to monitor carbonate reservoirs in the published literature is limited. The time-lapse monitoring in carbonate reservoir is a challenge, because the acoustic response is highly variable and there is some debate about the applicability of Gassmann's equation (Chen *et al*., 2008; Guimarães, 2013).

4D seismic can be used with commercial advantage in reservoir monitoring; but it is necessary to identify the favorable cases before starting a project. Many of the existing approaches focus on the geophysical issues of comparing two 3D images. The main objective is to verify if it will be possible to detect changes in the seismic response. Without a meaningful time-lapse change, there is no useful information derived from 4D seismic processing (Waggoner, 1998).

Behrens *et al*. (2001) present the key elements of a successful 4D seismic project: feasibility, acquisition, processing and interpretation. Feasibility analysis is performed to evaluate seismic data ability to identify changes in the reservoir during production. It comprises two factors: detectability and repeatability.

Detectability is the amount of change in the elastic properties of the reservoir associated with production. The detectability is determined by evaluating the following characteristics:

- Reservoir: depth, net pressure, bubble point, temperature, thickness of the reservoir zone to be monitored;
- Rock: dry bulk modulus and porosity;
- Fluid: gas oil ratio, salinity, fluid saturation change, fluid compressibility contrast;
- Seismic: dominant seismic frequency, average resolution, image quality, fluid contact visibility, travel time change, impedance change.

The repeatability is a measure of similarity of the seismic response between two or more seismic surveys. The optimal 4D seismic imaging requires seismic acquisition and processing to be "repeatable" from survey to survey, so that differences between time-lapse images can be "trusted".

Enhanced acquisition repeatability includes using the same acquisition method for each survey, accurate source and receiver positioning, shooting seismic lines in the same direction and using the same bin spacing and offset (Lumley, 1998).

Unwanted differences in the amplitude and timing of seismic reflections can be created by differences in seismic acquisition and processing. In order to interpret amplitude and time differences created by the changes in the reservoir properties it is necessary to minimize these effects.

Some of the acquisition effects on 4D seismic data are reduced by minimized streamer cable feather, improved design of ocean-bottom and land positioning methods, and installation of permanently emplaced receiver arrays. Regarding to the processing phase, the goal is to obtain excellent 3D seismic images for each data set, and simultaneously optimize time-lapse repeatability in regions of no subsurface change (Behrens *et al*.,2001 and Lumley, 2001).

Interpretation of 4D seismic data can be subdivided into qualitative and quantitative. Qualitative interpretation recognizes where changes detected by seismic are happening, but only infers the significance of those changes. Quantitative interpretation attempts to quantify those changes in seismic properties to reservoir properties.

From the moment that 4D seismic is considered feasible in the geophysical approach, it is necessary to evaluate whether the acquisition of new information will be useful for field management.

Two are the benefits that 4D seismic data can bring to the field management. It mitigates the risk and increases the economic value of the project. The combination of 4D seismic and well data enormously reduces reservoir uncertainty; however, the information increases the economic value only if it influences decisions (Pickering, 2003 and Kawar, 2003).

Marques (2012) presents a method to quantify the risk mitigation. The risk is associated with the net present value variability. The variability is measured using the standard deviation.

The value of information (VOI) quantifies the increase in the economic value of the project. The value of 4D seismic data is simpler to determine after data acquisition, because the impact on field operations is known. The VOI estimation before data acquisition is more complex due to the many possibilities that can come from the process; it may require several simplifications to make the process viable.

The literature does not distinguish between the terminologies used to define the value of information calculated before or after data acquisition. Thus, the thesis considers that the value calculated after and before data acquisition are termed: value of information (VOI) and expected value of information (EVOI), respectively. The inclusion of the word expected is necessary because the value calculated is a weighted measure.

The expected value of 4D seismic data depends on four factors presented in Figure 1.1. These factors should be included in the EVOI analysis and are described as follows:

(1) Date of acquisition: the amount of useful information that can be obtained is related to the reservoir fluid flow which is variable over the production period;

(2) Impact on field management: the provided information should impact on field operations and generate more monetary benefit than the cost of its acquisition;

(3) Reservoir uncertainties: if there is a high level of confidence in the reservoir characterization, there is no need of additional costs due to the acquisition of new information;

(4) Other source of data: several potential sources of information can improve the decision making process and reduce the reservoir uncertainty.

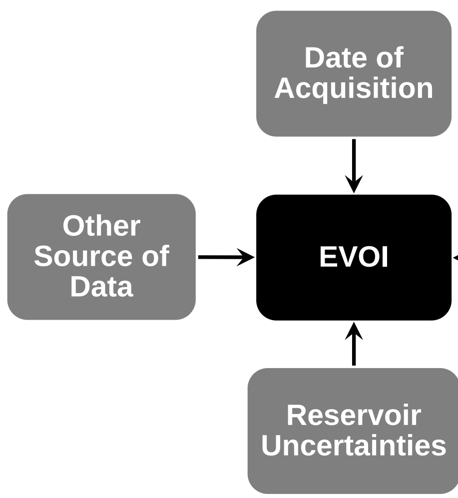


Figure 1.1. Factors that influence the expected value of 4D seismic data.

The first feasibility analysis of a 4D seismic project shall be assessed during the field development phase, due to the high costs involved in the acquisition and processing of 4D seismic data (seabed or towed streamer acquisition).

A 4D seismic project is approved if: the reservoir under analysis is feasible from the geophysical perspective, the new information mitigates the risk of the project and/or the impact on the reservoir management increases the economic return.

The thesis aims to quantify the increase in the economic return due to the acquisition of 4D seismic data and determine the chance that the quantified value is higher than the costs of acquisition and processing.

The EVOI and the probability density function of the increase on the net present value are calculated to incorporate the economic aspect. The methodology to determine the EVOI shall consider all aspects mentioned in Figure 1.1, however the literature does not present a method that considers the “date of acquisition” aspect. Thus, the thesis also improved the EVOI methodology by estimating the best time to acquire 4D seismic data.

1.1. Motivation

Currently, the average recovery is quite low due to the complexity of the reservoirs. Advances in technologies are continuously occurring at several fronts to assist in increasing the production of hydrocarbons. 4D seismic emerged as an important tool because it captures the dynamic behavior of the reservoir and aids reservoir management.

Besides of the many successful reported cases, the feasibility of the acquisition of new information must be evaluated. There are two main motivations for conducting a feasibility study. First, to determine whether the 4D signal generated by production effects in the reservoir is detectable. Second, to assess the impact on field management and the impact on the risk of the project.

There are several methods that assess the feasibility from the geophysical perspective, such as the ones presented by Lumley (1998) and Blonk *et al.* (1998). From the engineering perspective, the evaluation is performed by comparing the EVOI with the acquisition and processing costs.

However, the existing methods to calculate the EVOI do not consider the “date of acquisition” aspect. Another important issue is that the EVOI is a weighted value. It does not show the variability of the increase on the economic return caused by the reservoir uncertainties.

Due to the importance of assessing the feasibility of a new 4D seismic project, the thesis presents a methodology to estimate the chance of success from the reservoir engineering perspective. The methodology includes the “date of acquisition” aspect into the process and determines the probability of the increase on the economic return be higher than the acquisition costs.

1.2. Objectives

The objective of the thesis is to develop a methodology to estimate the chance of success of a 4D seismic project before the information acquisition. The methodology determines the chance of success for the first acquisition of 4D seismic data and uses a probabilistic approach of the economic benefit to assist the decision maker. Moreover, the methodology is applied to a synthetic reservoir model in order to test it in a case with known reservoir.

1.3. Premises

The following assumptions are made in order to apply the proposed methodology to estimate the chance of success of a 4D seismic project:

- Pressure and saturation data without noise can be successfully obtained from 4D seismic. Several studies present methods to map and quantify these changes using different seismic attributes (Tura and Lumley, 1999; Rojas, 2008; Landro, 2001, Trani *et al.*, 2011 and Davolio, 2013);
- All reservoir model uncertainties are identified and quantified;
- The chance of success estimation considers the first acquisition of 4D seismic data.

1.4. Outline of the Thesis

The chance of success methodology is developed in three phases. The first phase evaluates the impact of 4D seismic data on the history match process in comparison to the use of only production data. Chapter 2 discusses the improvement on predicting the production behavior when 4D seismic data is used and evaluates the impact of the date of acquisition on the value of 4D seismic project.

The second phase develops a methodology to estimate the date of acquisition in which the value of 4D seismic data is maximum. Chapter 3 describes the proposed methodology and its application to a synthetic reservoir model.

The last phase develops the methodology to estimate the chance of success. A variety of disciplines are involved: uncertainty and risk analysis, selection of representative models and production strategy optimization. The methodology incorporates the process presented in Chapter 3 and evaluates the number of reservoir model scenarios used to calculate the EVOI.

Chapter 4 describes the methodology to estimate the chance of success and presents the results of its application to a synthetic case. The last chapter presents the conclusions and suggestions for future work.

2. IMPACT OF 4D SEISMIC DATA IN THE HISTORY MATCHING PROCESS

2.1. Introduction

With the advent of 4D seismic surveys in the early 1980`s, the oil industry began using this technology as an indirect tool for monitoring fluid flow (Fahimuddin, 2010). Assuming that 4D seismic signals can be interpreted in terms of reservoir properties, the large amounts of data are integrated with production and other data available to improve the reservoir simulation model.

Constraining the reservoir model to the historical data is referred to as history matching. The objective is to obtain a better match between the observed data and reservoir simulation results by iteratively perturbing the uncertain model parameters. The reservoir model has to correspond to the historical behavior of the actual reservoir, before one may trust production forecasts and handle accordingly.

Reservoir management is a complex task that heavily depends on the reservoir simulation model. A reservoir simulation model is used to analyze the behavior of the reservoir and to forecast future behavior. Constraining the model to all available information raises confidence in its forecasting capabilities.

The combination of 4D seismic data (high lateral resolution) with well data (high vertical resolution) enormously reduces uncertainty and increases the accuracy of the production forecast (Stephen *et al*., 2006). Reservoir management benefits from the reservoir model improvement because decisions can be made to increase the economic return of the project, such as well optimization, identification of remaining oil and drilling potential areas.

Time lapse seismic is available in a qualitative and quantitative form in a number of North Sea, Gulf of Mexico and Campos Basin fields (Johnston *et al.*, 2000; Thedy *et al.* 2007; Roste and Husby, 2006; Smith *et al.*, 2010). The integration of 4D seismic data has been made with different history matching methodologies.

Stephen (2006) presents an automatic history matching method based on an integrated workflow. The method uses a quasi-global stochastic method for choosing new models based on calculated misfits between observed and predicted data.

Fahimuddin (2010) performed 4D seismic history matching of a sector model based on North Sea reservoir in the ensemble Kalman filter (EnKF) framework. The work of Roggero *et al.* (2012) focused on the advance parametrization technique to constrain fine scale geo-statistical model by means of gradual deformation method in the framework of history matching of the Girassol field.

A model conditioned to 4D seismic data has an improved accuracy of the production forecast. Thus, this Chapter evaluates the improvement on the accuracy of the production forecast by including 4D seismic data into the history matching process. Moreover, discuss the utility of 4D seismic regarding to the date of seismic acquisition.

2.2. Objective

Chapter 02 aims to: (1) compare the improvement of the reservoir model obtained using only production data and using production data along with 4D seismic data in the history matching process (2) evaluate the impact of the date of 4D seismic acquisition on the value of time lapse data.

2.3. Assumptions

In order to perform the study some simplifications and assumptions are made:

- The model used is synthetic and simple, representing a specific part of the field, in order to make the analysis simpler;
- Eight simulation models are used: base model, base model history matched using two, four and six years of production data; base model history matched using two, four and six years of production data along with seismic data and the reference model (true earth model);
- The base model is not history matched. It is known that such model gets closer to the reference model as long as the history matching process is done using production data;
- Pressure and saturation data are successfully obtained from 4D seismic. Water saturation and pressure maps are generated from the reference model simulation;
- The time for acquiring and processing the 4D seismic information is not considered in the process.

- The study is performed after the information acquisition to evaluate the impact of the resulting data;
- It is known that the history matching process is a non-unique process. However, the analysis is performed in a deterministic manner to make the analysis simpler.

2.4. Methodology

The study is divided into two cases and the evaluation of both is based on the mismatch in the output of the reference reservoir model and the history matched models. The description of each case is as follows:

(1) Case 1: comparison of the results obtained from the history matched models using only production data and using production data along with seismic data acquired at four years of production;

(2) Case 2: comparison of the results obtained from the history matched models using only production data and using production data along with seismic data at two, four and six years of production.

In order to evaluate how seismic can improve the initial simulation model, pressure and saturation differences are analyzed by generating error maps and calculating the mismatch between the simulated models.

2.4.1. History Matching Methodology

History match is one of the most important activities during petroleum reservoirs development and management. Matched models are fundamental to ensure reliable forecasts, and give an idea of the level of understanding of the geological models. The history match process consists in changing uncertain field simulation model attributes, respecting its uncertainty limits, to match the historical data (Netto *et al.*, 2003).

The history match process aims to improve the reservoir model quality. When performed only with production data, the main objective is to minimize the difference of production data (well pressure, oil, water and gas rate) between observed and simulated data. When performed with seismic data, the objective includes the reduction in the differences of reservoir saturation and pressure maps.

The literature presents some methodologies for history matching using seismic data. The conditioning may be introduced at different levels corresponding to where the mismatch between simulated and measured data is evaluated.

An illustration of the different mismatch levels is shown in Figure 2.1 the levels are: amplitude, elastic parameters and fluid changes domain. Methodologies that evaluate the mismatch in the amplitude and elastic domain are presented by Stephen *et al*. (2006) and Fahimuddin (2010).

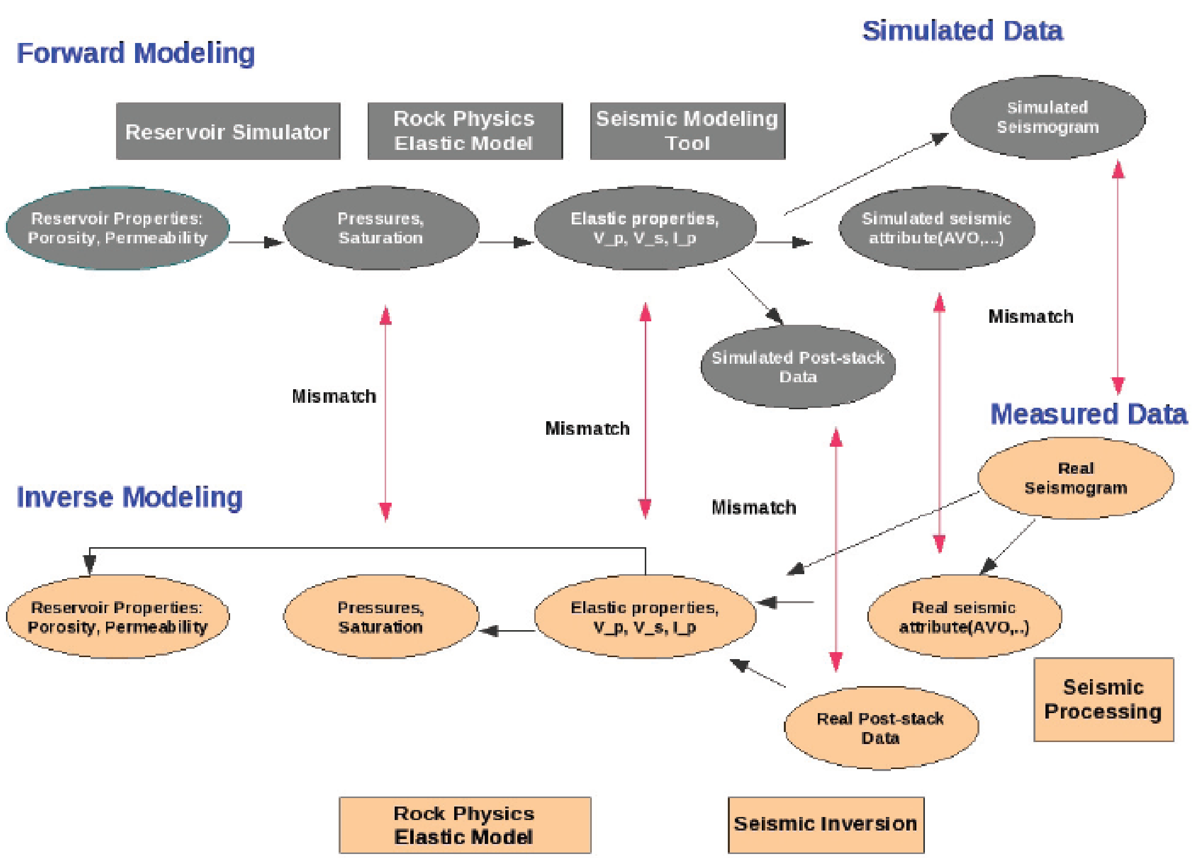


Figure 2.1. Different levels of 4D seismic integration (Skjervheim, 2007).

The present study integrates seismic data in the fluid changes domain, as presented by Machado (2010). The methodology for history matching is shown in Figure 2.2. Real seismic data is not acquired; the saturation and pressure maps are generated from the reference model simulation.

The process remains the same for history matching using only production data, except that water and pressure saturation maps are not included. In both cases, wells are controlled by liquid rate (computed from the reference model) and the parameters to be matched are the water rate and well pressure. It is considered that once the liquid rate is informed and the water rate is matched, the oil rate is matched as a consequence.

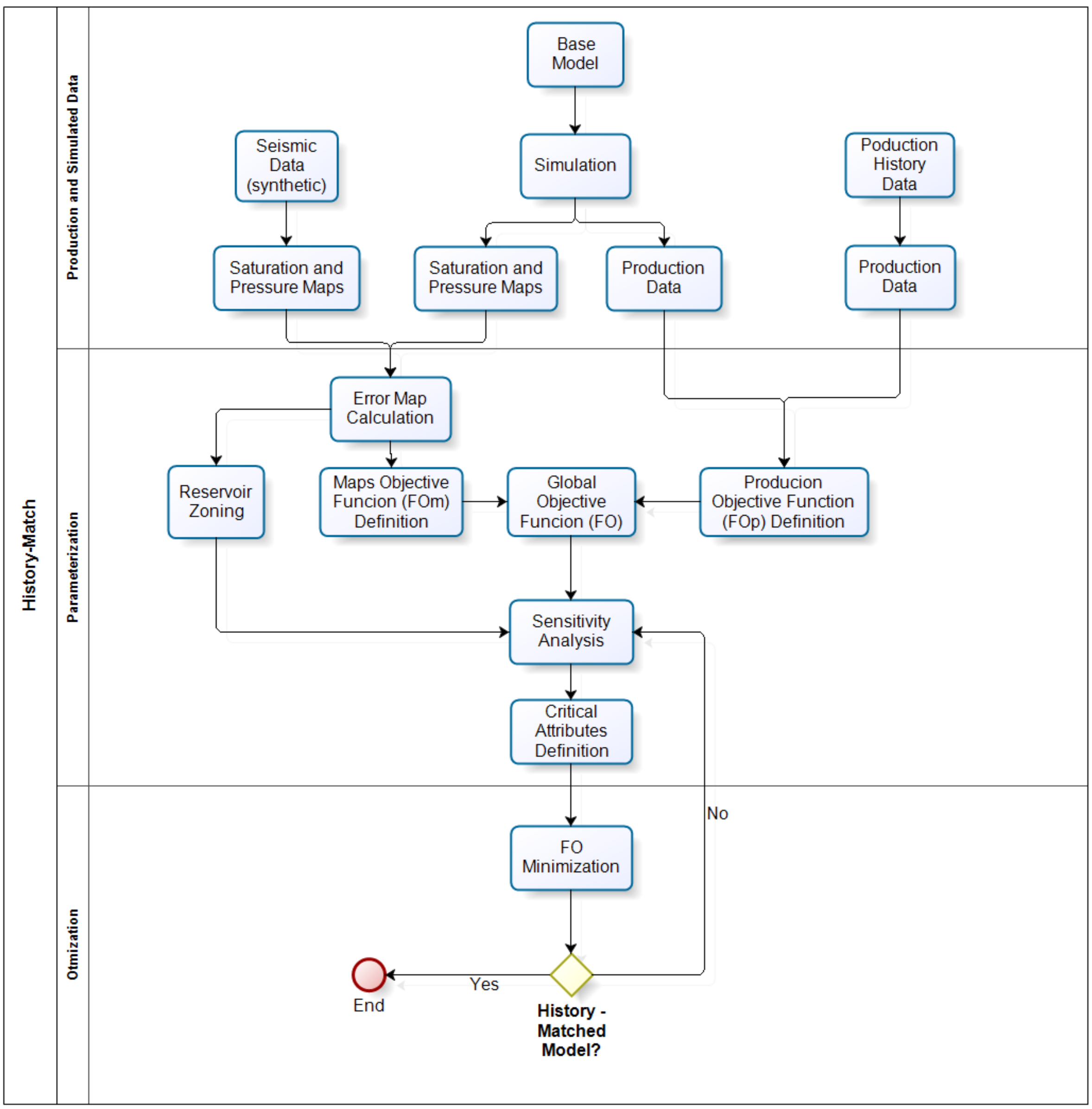


Figure 2.2. History matching process.

The assisted history matching is performed in three steps: data acquisition (historical and simulated data), parameterization and optimization. The parameterization phase stands out for its importance in the process and requires more dedication of the professional involved. The parameterization steps are:

- Reservoir Zoning: the reservoir is divided into regions according to the type of information available. When seismic data is used, two types of regions are considered: attribute regions and parameter regions.

  A parameter region is the reservoir simulation region where the error is measured and its value is incorporated into the objective function. Attribute regions are those where changes in the reservoir model attributes are made in the process. These regions are determined from the analysis of differences in saturation and pressure maps and streamline information;

- Objective Function (FO): the FO is a quantitative evaluation of the history matching. It measures the mismatch between simulated and observed data. The FO used is

$$FO = w_P FO_P + w_M FO_M \quad , \tag{2.1}$$

where, w_P and w_M are the production and maps objective function weights, respectively. To determine FO_P and FO_M the expressions

$$FO = \sum_{i=1}^{m} w_i \sum_{j=1}^{n} \left(w_j \varepsilon_j \right) \quad \text{and} \tag{2.2}$$

$$FO_M = 0{,}5 \sum_{i=1}^{nRS} \left(w_i^{RS} \varepsilon_i^{RS} \right) + 0{,}5 \sum_{i=1}^{nRP} \left(w_i^{RP} \varepsilon_i^{RP} \right) \tag{2.3}$$

are used.

When the process uses production and seismic data, the global function (FO) includes production (FO_P) and maps (FO_M) objective function, otherwise only FO_P is considered.

In Equation 2.2, *m* and *n* represent the number of wells and parameters to be adjusted, w_i and w_j are the well and the parameters weights, ε_j is the parameter measured error.

In Equation 2.3, nRS and nRP are the number of parameter regions in the saturation and pressure error maps, w^{RS} e w^{RP} are the saturation and the pressure parameter region weights, ε_i is the error measured in each parameter region;

- Critical Attributes Definition: because of the model simplicity the sensitivity analyses is not performed. The parameters to be adjusted are the absolute permeability and heterogeneities characteristics.

After the parameterization phase, the search for a combination of attributes that minimizes the error measured can be done through optimization methods. In the present study, the local search algorithm is used; because the history matching is performed to a reservoir specific region and with few parameters. The method uses the algorithm developed by Leitão e Schiozer (1998) and Schiozer (1999) which is based on sequences of exploratory and linear search within a discretized solution space.

2.4.2. Error Map

The error map defines the parameter and the attribute regions. It also analyzes the reservoir model quality. The error map is generated from the water saturation differences between the reference model data and the history matched models data to each simulation grid cell, in accordance with

$$\Delta Sw_i = Sw_i^{\mathrm{model}} - Sw_i^{reference}, \tag{2.4}$$

where the subscript *i* represents the cell grid model number, Δ is the difference between the reference model and the model analyzed, Sw^{model} is the water saturation from the model analyzed and $Sw^{reference}$ is the reference model water saturation. Error values lower than 20% of the highest values are not considered in the definition of the parameter and attribute regions.

2.4.3. Error Function

The error curve over a production period is given by an error function, defined as the quantity that represents the mismatch between real data (reference model) and the simulated data (models studied). The error function used to evaluate the water saturation and pressure maps mismatch is defined as

$$\varepsilon = \sum_{i=1}^{Ng} \left(X_i^{\mathrm{mod}el} - X_i^{reference} \right)^2 , \tag{2.5}$$

where N_g is the number of grid cells, X is the property analyzed (water saturation or pressure); X_i^{model} and $X_i^{reference}$ are the model simulated and reference data, and ε is the error.

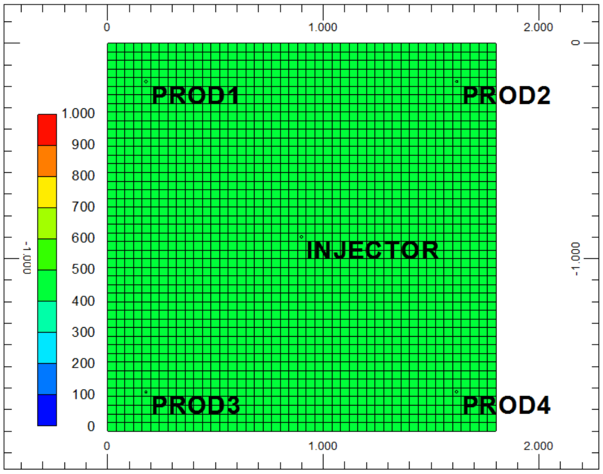
2.5. Application

The base reservoir simulation model and reference model were built by Risso (2007) and modified by Machado (2010). They consist of a five-spot configuration and are structurally represented by a horizontal top at -1000 m, discretized with a 45x45x1 grid in the x, y and z directions, respectively, with a dimension of 40 m in the three orthogonal directions, totaling 2025 blocks.

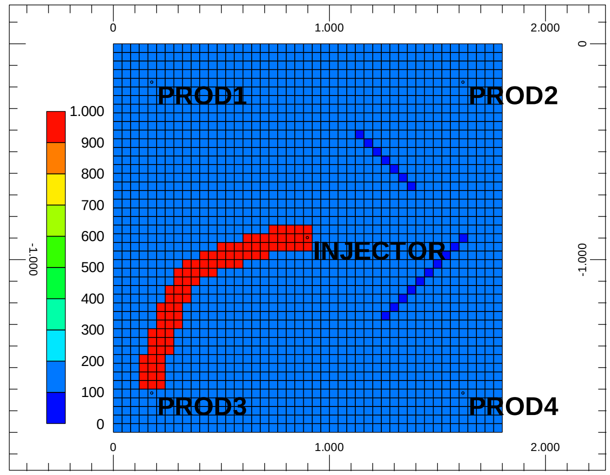
The reservoir permeability (k) and porosity (ϕ) of the models are:

- Base model: k = 500mD, ϕ = 20%;
- Reference model: k = 200 mD, except the channel with high permeability (1000 mD) and the impermeable barriers, ϕ = 20%.

The model permeability maps are shown in Figure 2.3.



(a)



(b)

Figure 2.3. Reservoir model permeability maps: (a) base model and (b) reference model.

The reservoir hydrocarbon fluid is light oil with a viscosity equal to 0.78 cP in the initial reservoir conditions (static pressure equal to 98 kgf/cm² and temperature equal to 50 °C). The initial solubility ratio is equal to 83 m³/m³ and there is no water-oil contact. The Black Oil fluid model is used. The production wells are constrained by the liquid rate and the injector well is constrained by the water rate.

2.6. Results

2.6.1. History Matched Models

Figures 2.4 and 2.5 show the history matched models obtained using only production data (PROD HM model) and using production and seismic data (PROD and 4DS HM model), respectively.

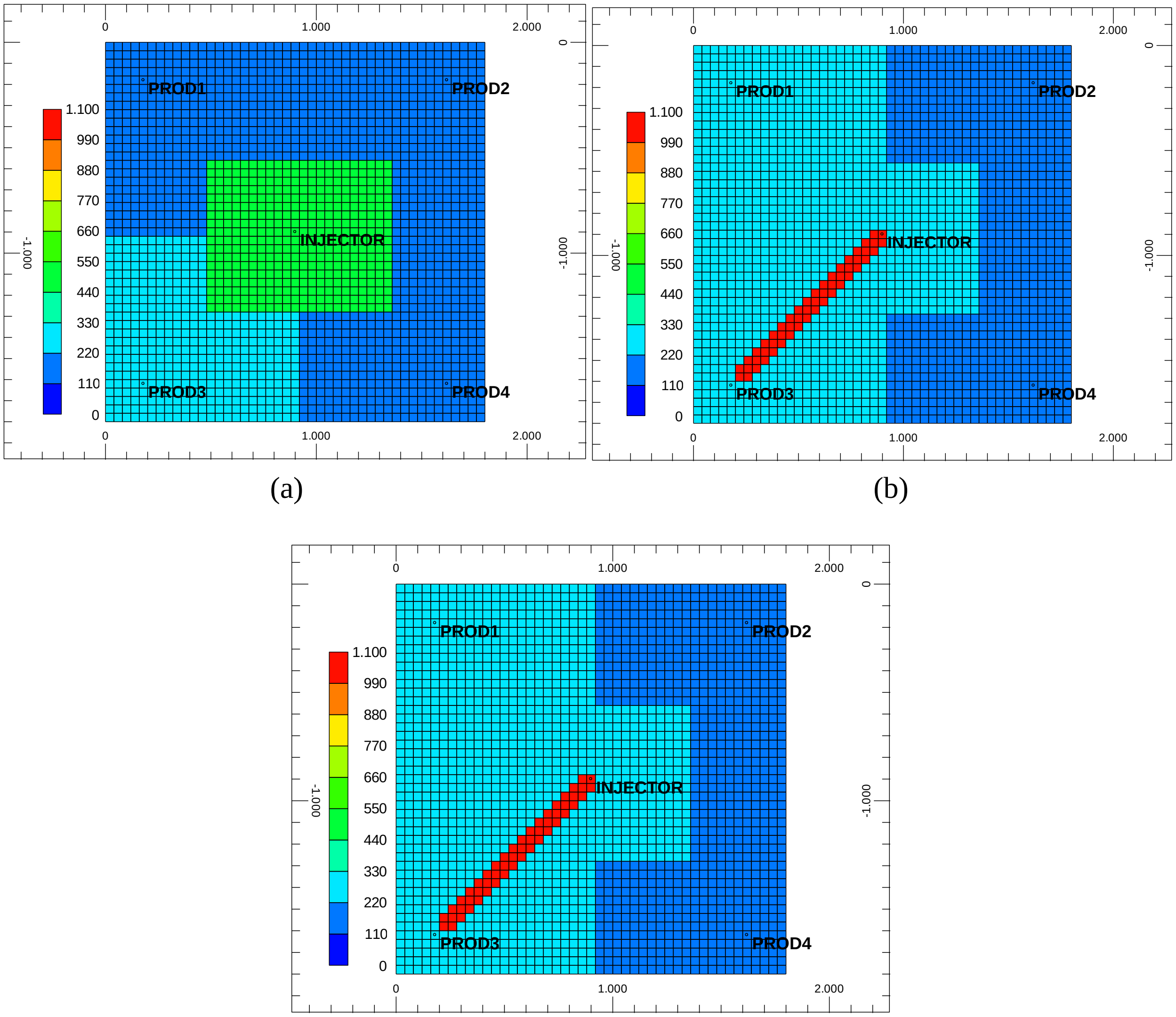


Figure 2.4. Permeability map. PROD HM model: (a) 2 years (b) 4 years (c) 6 years of production.

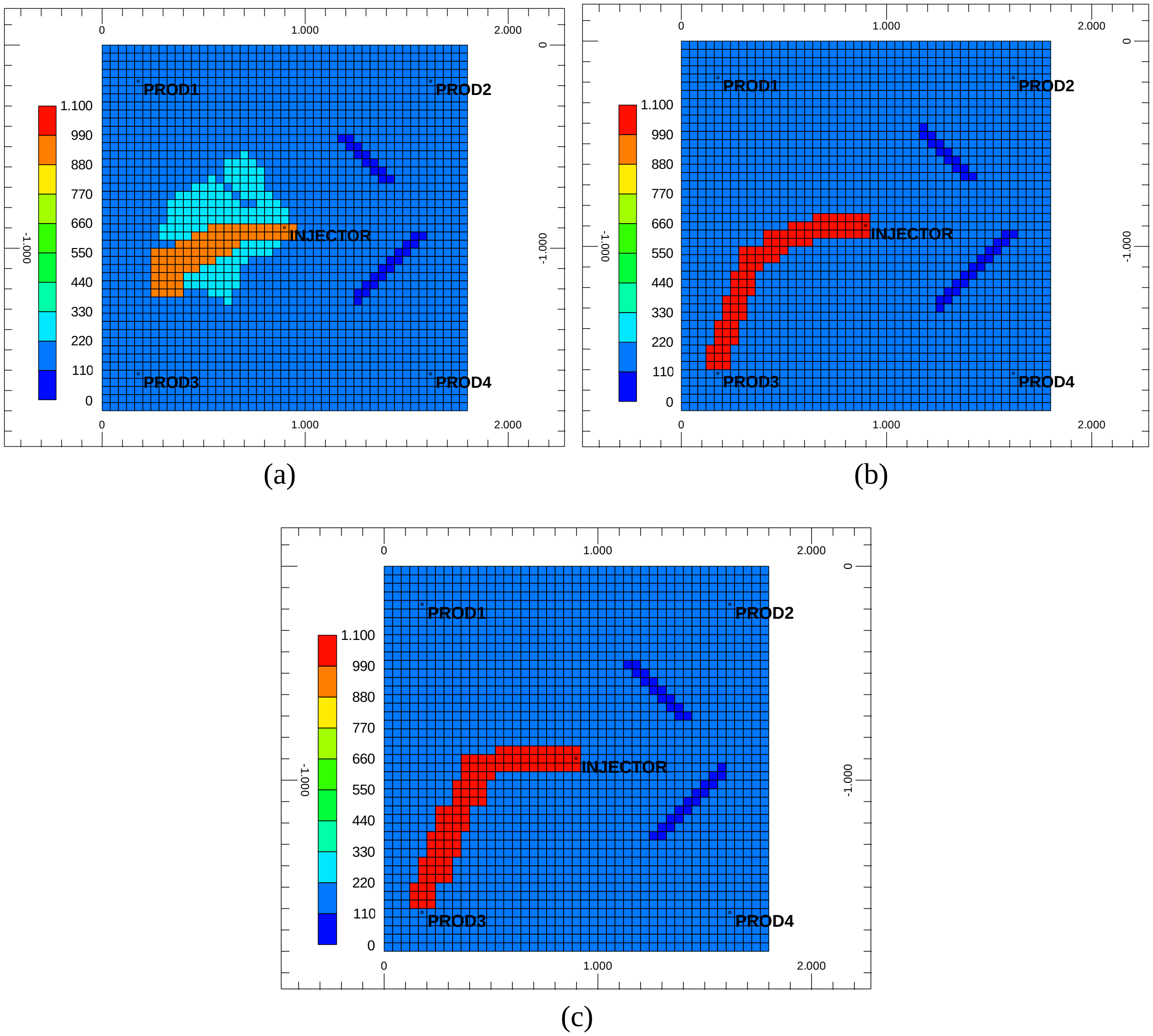


Figure 2.5. Permeability map. PROD and 4DS HM model: (a) 2 years (b) 4 years (c) 6 years of production.

2.6.2. Case 1

Production data and water saturation maps from the history matched models considering 4 years of historical data were compared. This is a production period in which production data itself indicates the existence of a high permeability channel, however the spatial distribution of heterogeneities is better defined with seismic data.

Figures 2.6 to 2.17 show the production results obtained for the base and history matched models. Predictions were obtained after history matching with and without 4D seismic data, to evaluate the impact of time lapse seismic information.

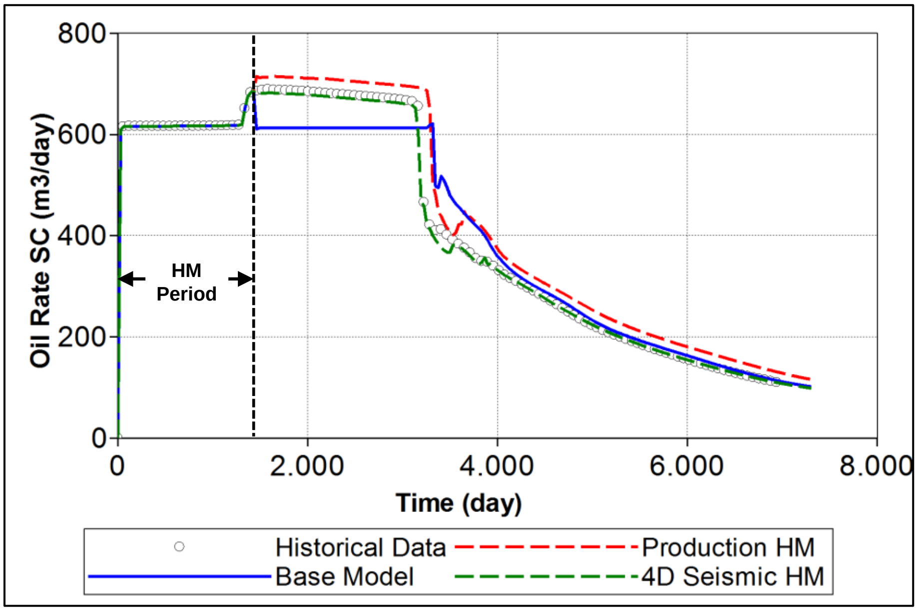


Figure 2.6. Oil rate: PROD 1.

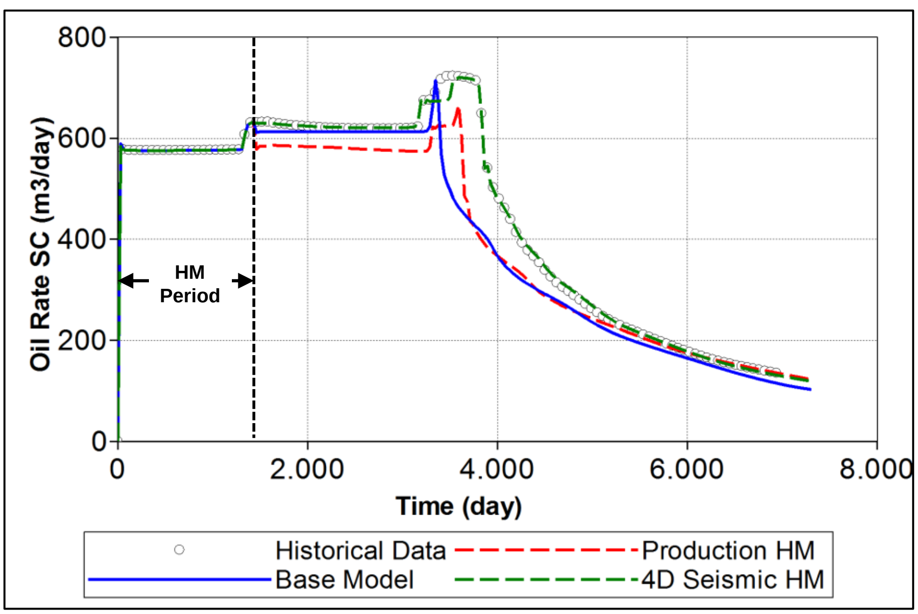


Figure 2.7. Oil rate: PROD 2.

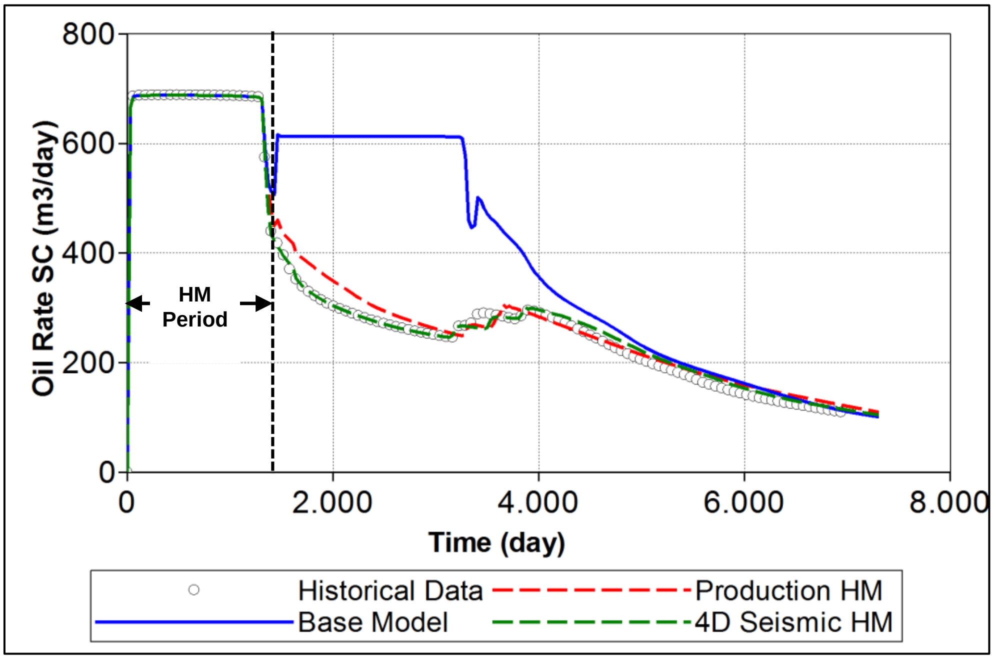


Figure 2.8. Oil rate: PROD 3.

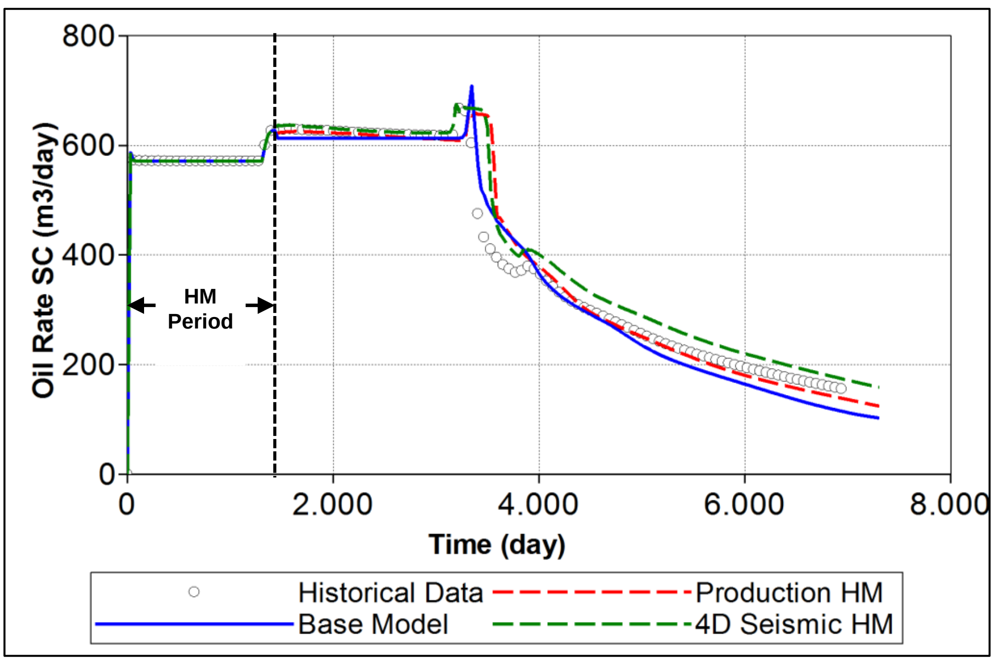


Figure 2.9. Oil rate: PROD 4.

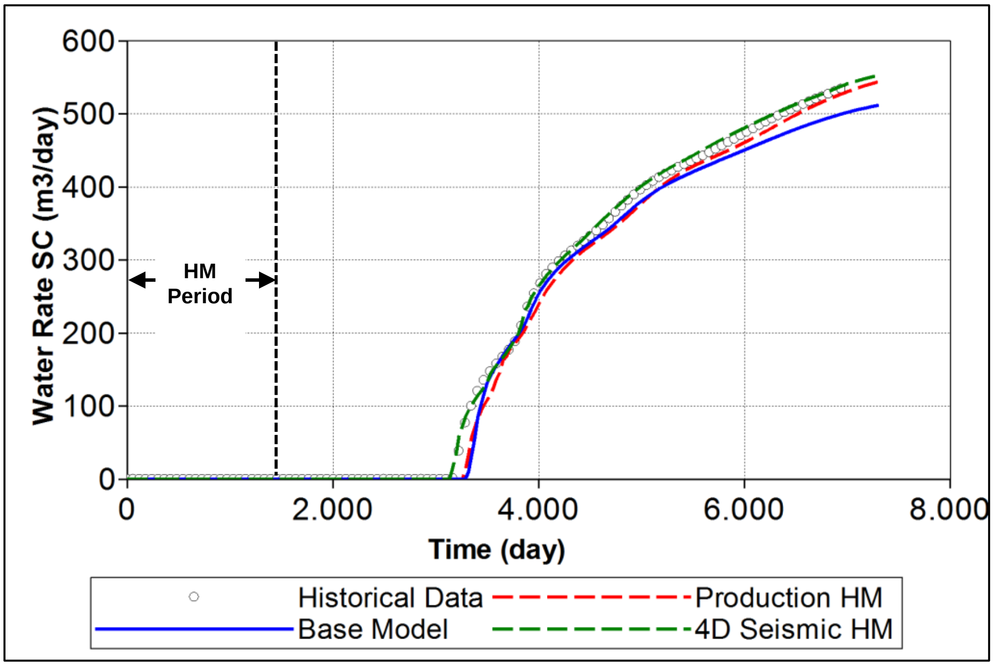


Figure 2.10. Water rate: PROD 1.

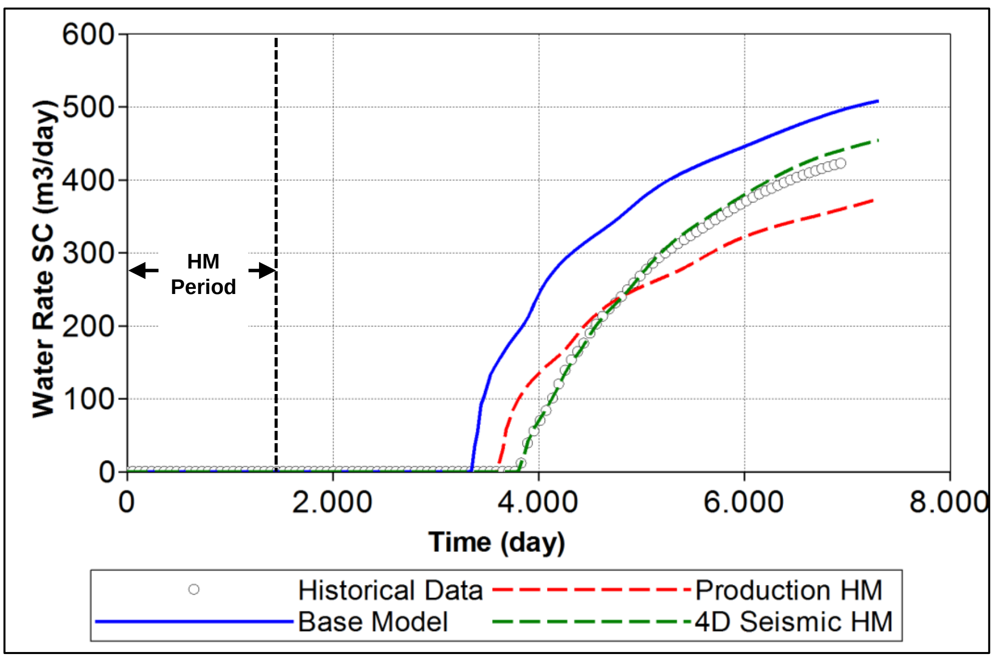


Figure 2.11. Water rate: PROD 2.

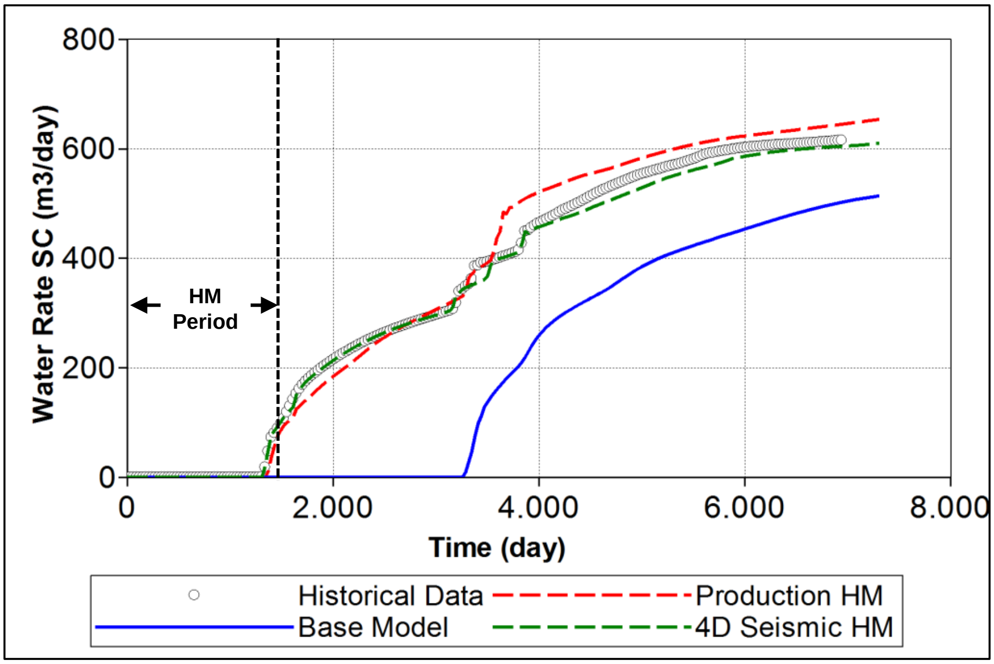


Figure 2.12. Water rate: PROD 3.

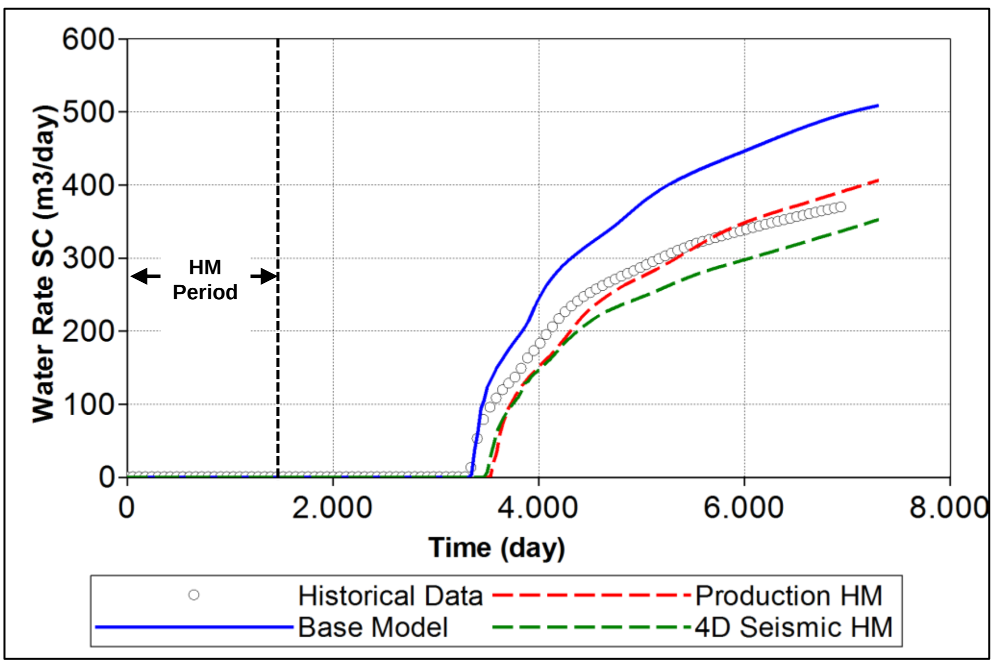


Figure 2.13. Water rate: PROD 4.

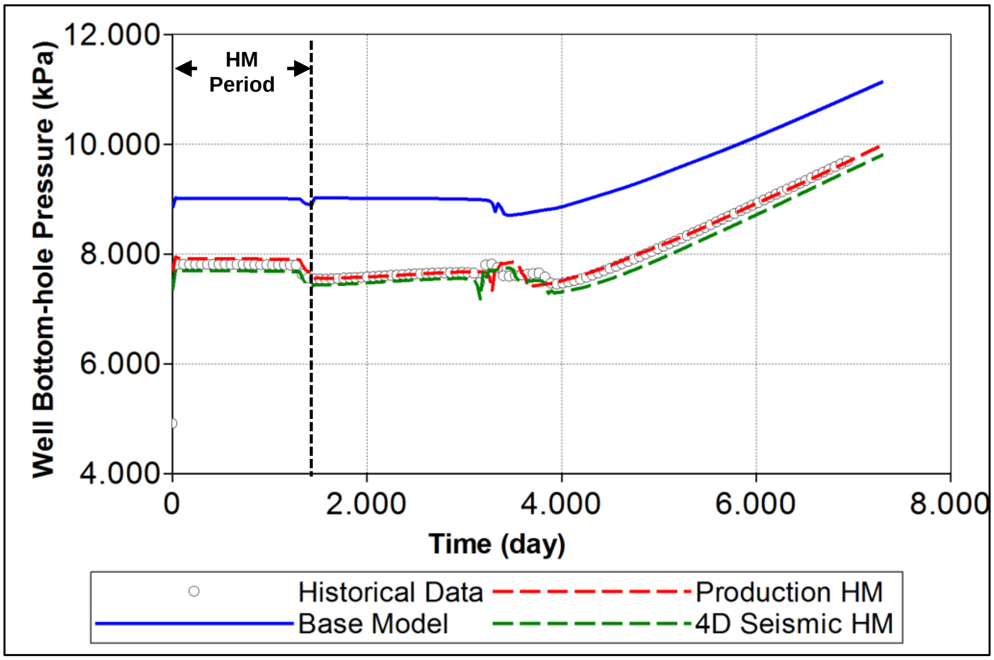


Figure 2.14. BHP: PROD 1.

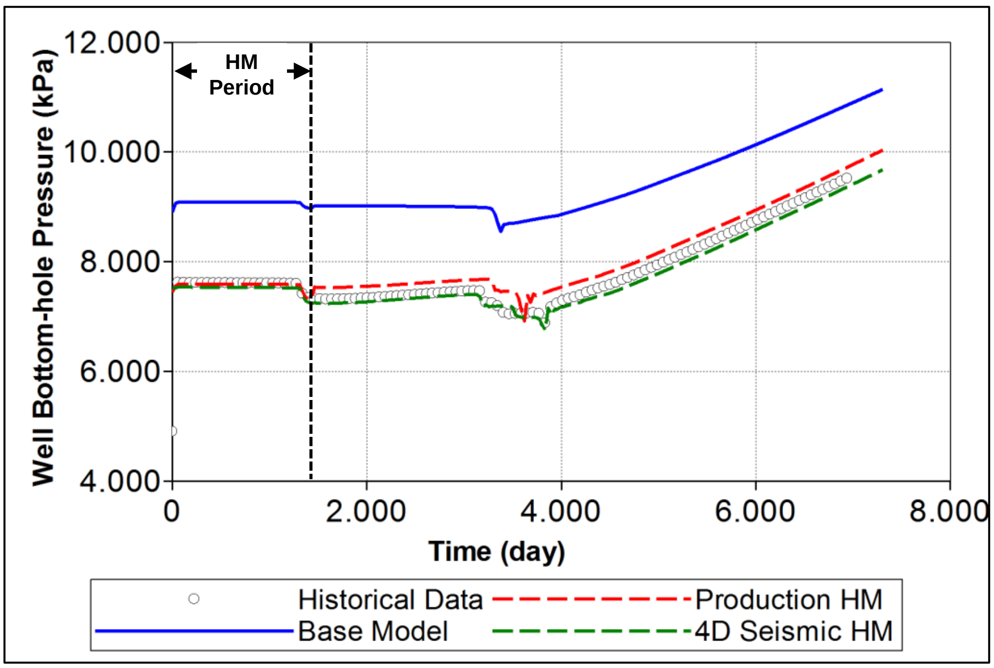


Figure 2.15. BHP: PROD 2.

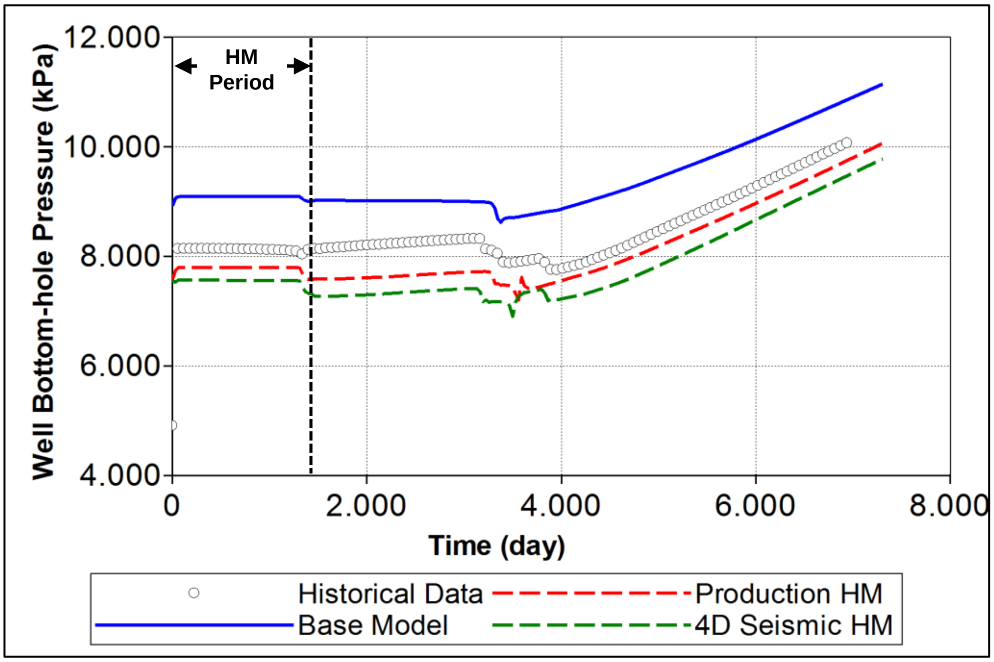


Figure 2.16. BHP: PROD 3.

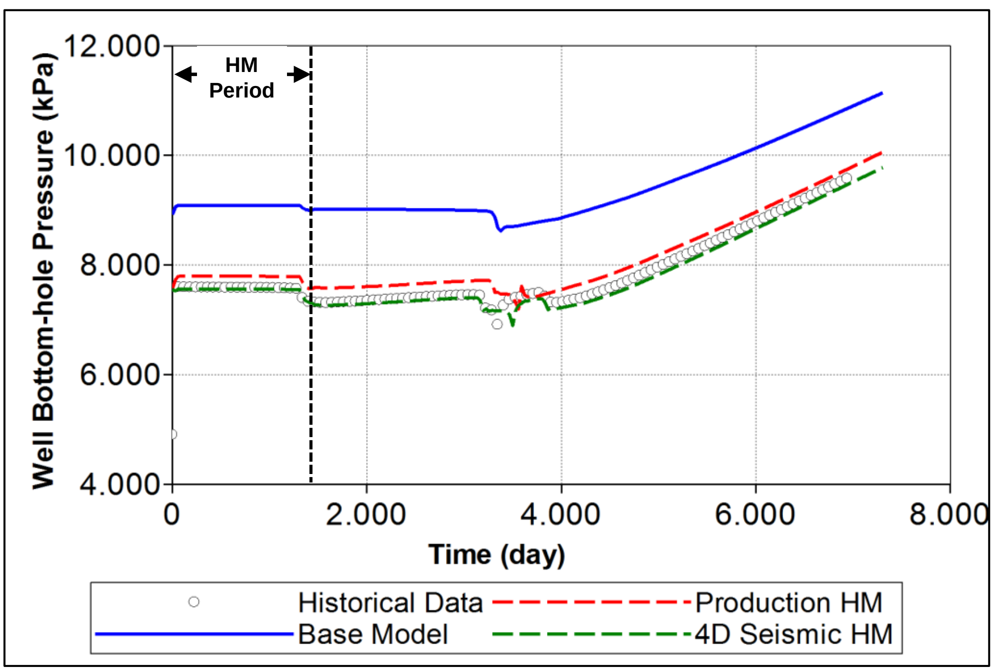


Figure 2.17. BHP: PROD 4.

The base model simulation results showed higher values of oil production than the historical data values and a delay on the time for breakthrough at the production well PROD3 (Figures 2.8 and 2.12). Also the reservoir pressure is higher than the historical data, these are explained by the non-identification of a high permeability channel and barriers by the initial model (Figures 2.14 to 2.17).

Water breakthrough was observed at production well PROD3 during the period considered. The information allowed a good water rate match at production well PROD3 for the history matched model using only production data. However, water rate forecast was not accurate for production wells PROD 2 and PROD 4.

The integration of 4D seismic data with production data increased the accuracy in the production forecasts; especially in the prediction of time to breakthrough for the remaining production wells. The oil rate forecast also presented more accurate results.

An important contribution of 4D seismic data is to better capture the fluid flow behavior during production. Such can be seen by evaluating the water saturation error curves presented in Figure 2.18 and the water saturation maps at different production periods from the history matched models presented in Figure 2.19.

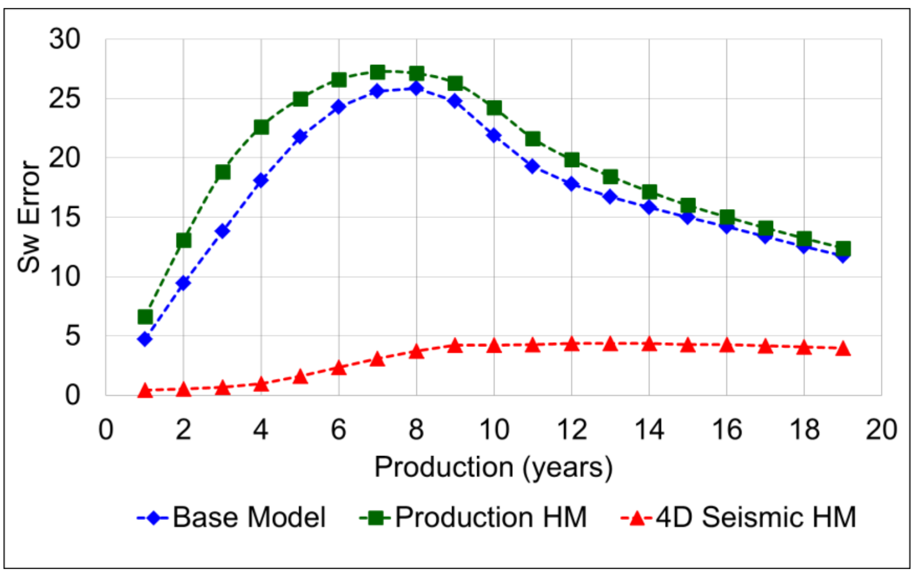


Figure 2.18. Water saturation error for the simulation models analyzed.

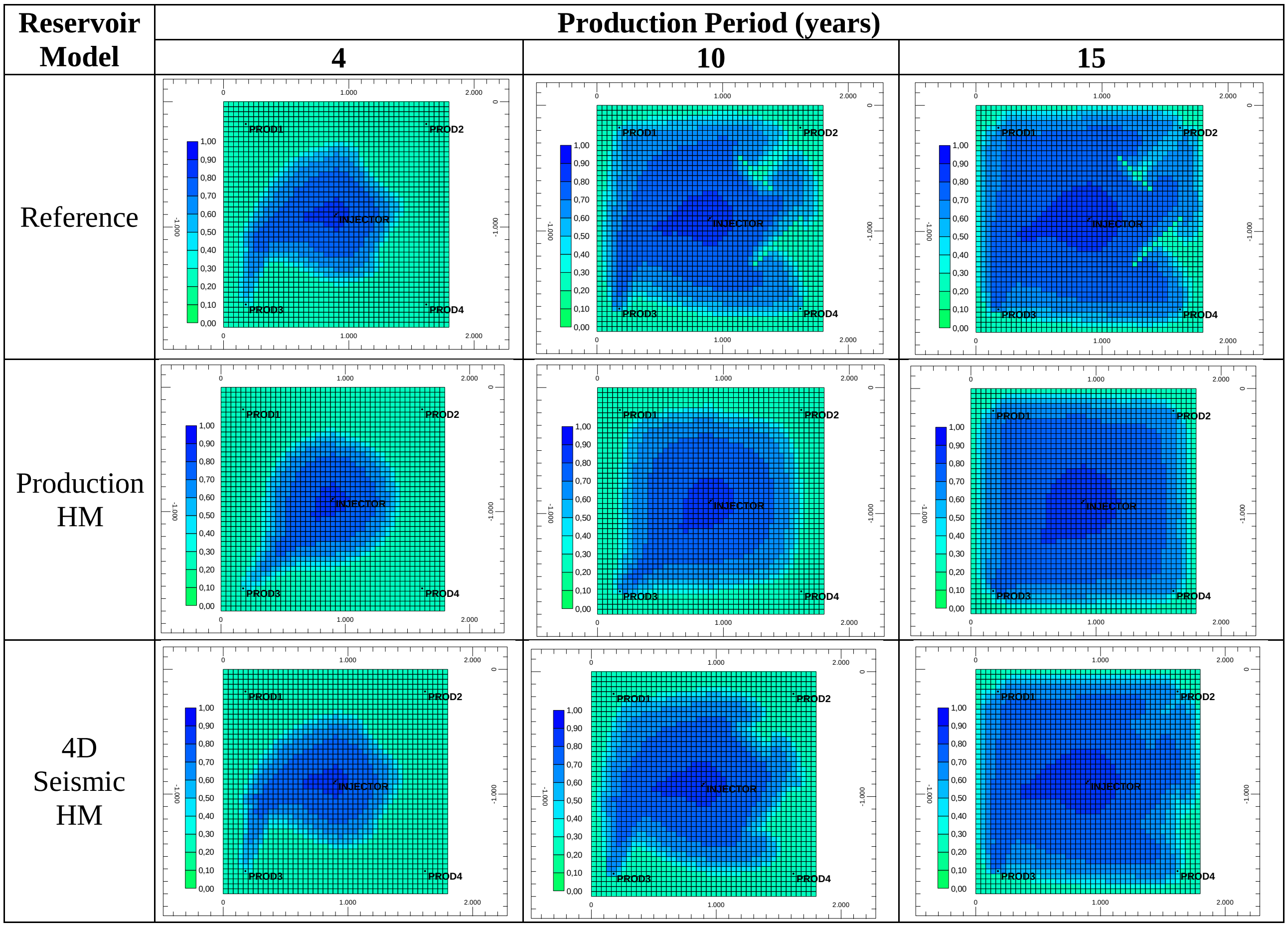


Figure 2.19. Water saturation map from the reference model and the history matched models.

The water saturation error increases up to a peak and then decreases over the production period, since at the beginning of production there is low fluid flow movement and at the end of production the reservoir is almost totally flooded (Figure 2.18).

The water saturation error curve obtained from history matched model using only production data presented higher values than the curve obtained from the base model. Even though production data enabled the identification of the high permeability channel existence, its position and shape are more difficult to determine without spatial data.

The water saturation error decreases significantly when 4D seismic data is used in the history matching process. Seismic data contributed to better characterize the spatial distribution of heterogeneities in the field and consequently the fluid flow movement (Figure 2.19).

Combined with reservoir modeling, time-lapse seismic monitoring enables reservoir engineers to improve reservoir characterization and to reduce uncertainty in production forecasts. The quantification of uncertainty reduction can be performed using the emulator technique.

The emulator was applied to the same synthetic reservoir model in order to quantify the uncertainty reduction due to production data over different production periods. The description of the methodology used and results obtained were published in Ferreira *et al.* (2014a) and are presented in Appendix A.

The emulator was not applied considering 4D seismic data because the main objective of the thesis is to quantify the chance of success based on the EVOI. If the emulator was used, the EMV (expected monetary value) would contain errors inherent to the emulator development. Even if small error values were obtained for the EMV with and without information, this would result in higher errors in the EVOI result.

2.6.3. Case 2

Case 2 evaluates the production results and water saturation errors from the history matched models with and without 4D seismic data. The time lapse data was acquired at 2, 4 and 6 years of production. The assessment of the results obtained is divided according to the type of data considered: production data analysis and water saturation map analysis.

Production Data Analysis

Production well data were analyzed to evaluate the history data mismatch between history matched models and historical data and the prediction accuracy. The water rate of the history matched models using only production date are presented in Figures 2.20 to 2.23, while using 4D seismic data in Figures 2.24 to 2.27.

The pressure results of the history matched models using only production date are presented in Figures 2.28 to 2.31, while using 4D seismic data in Figures 2.32 to 2.35.

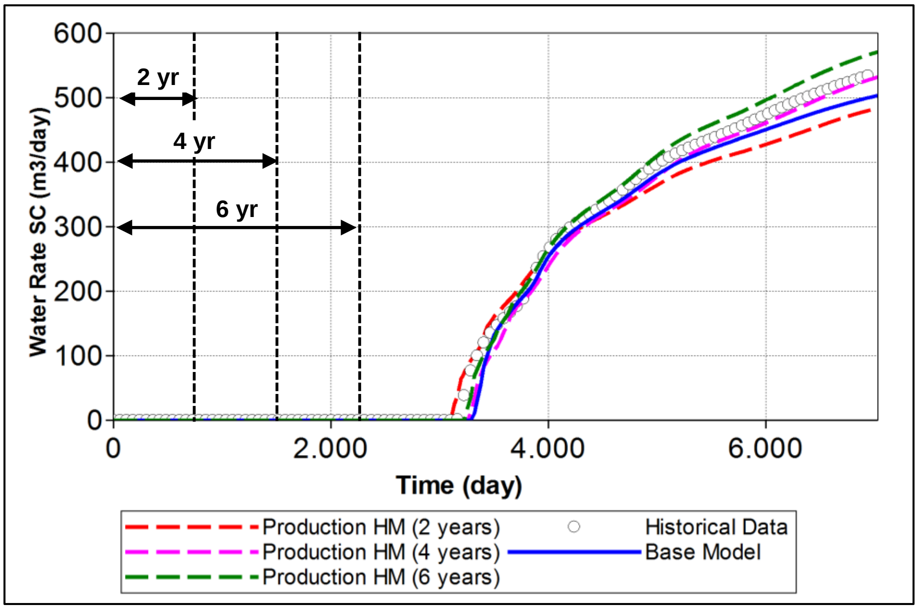


Figure 2.20. PROD 1water rate: production history matched models.

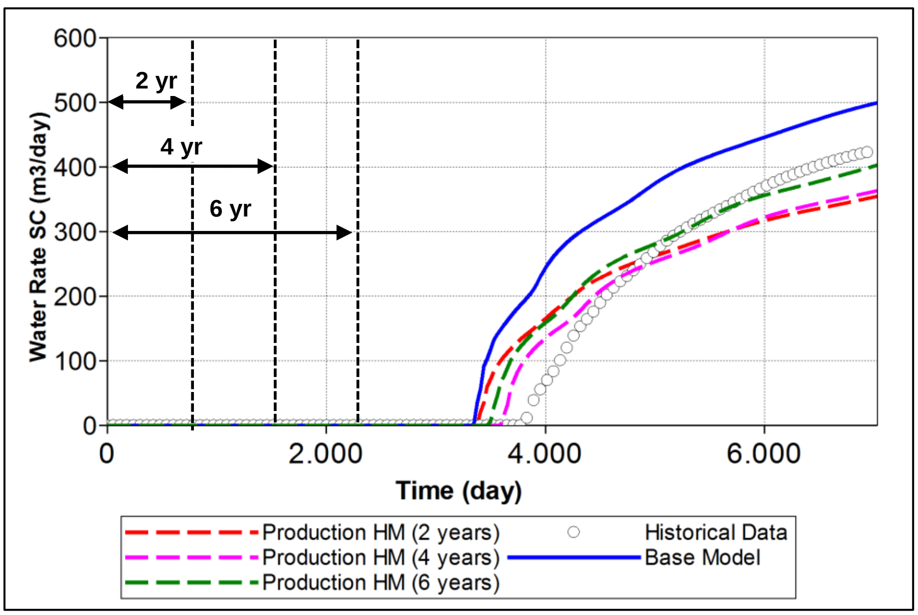


Figure 2.21. PROD 2 water rate: production history matched models.

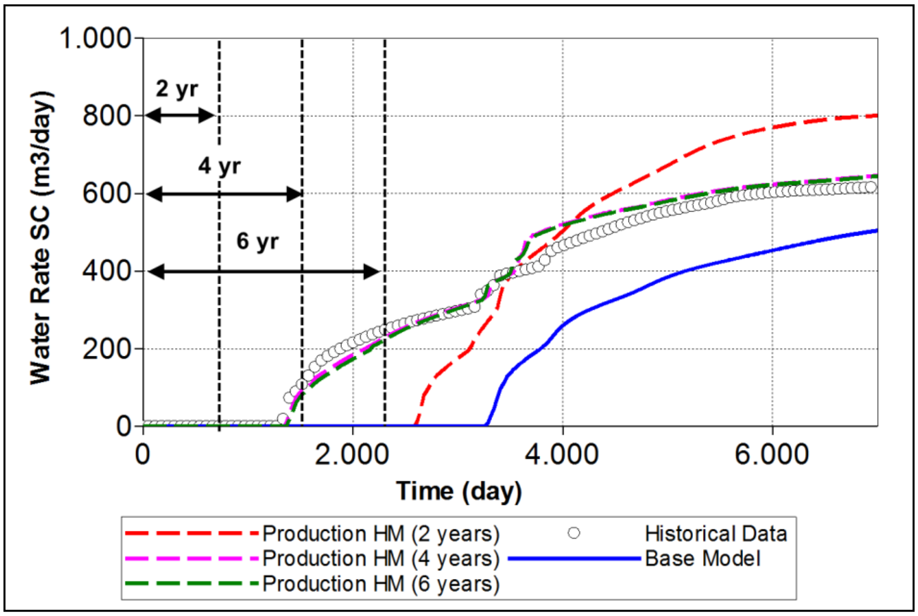


Figure 2.22. PROD 3 water rate: production history matched models.

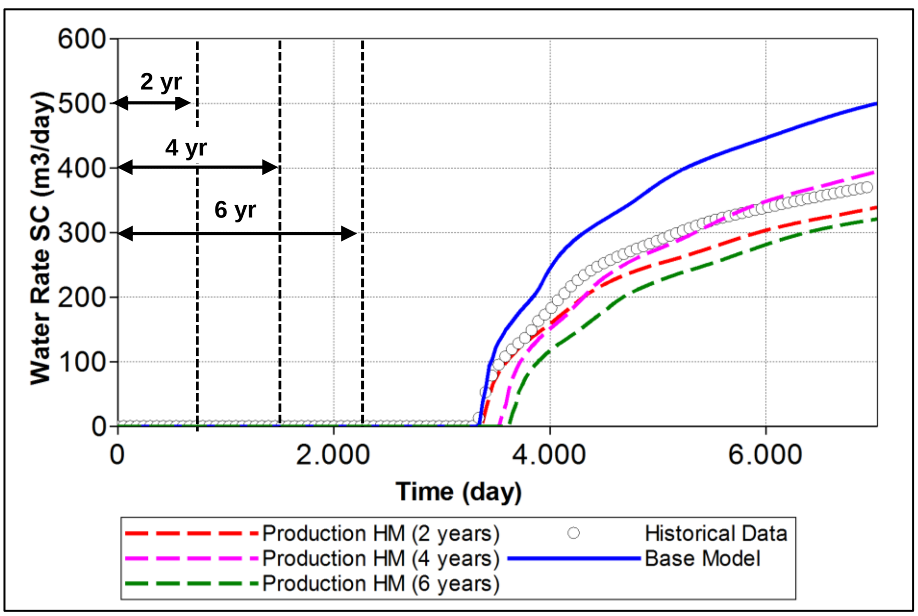


Figure 2.23. PROD 4 water rate: production history matched models.

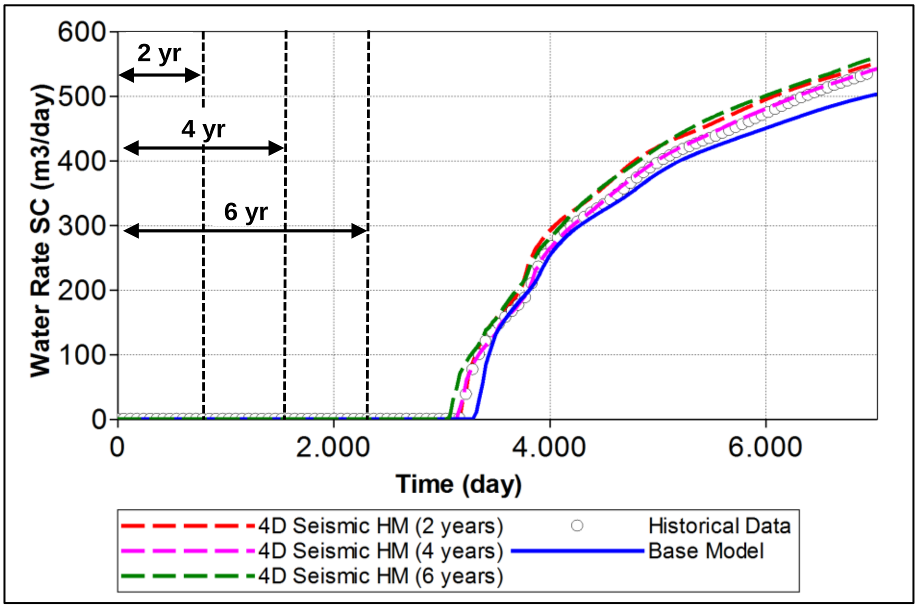


Figure 2.24. PROD 1 water rate: 4D seismic history matched models.

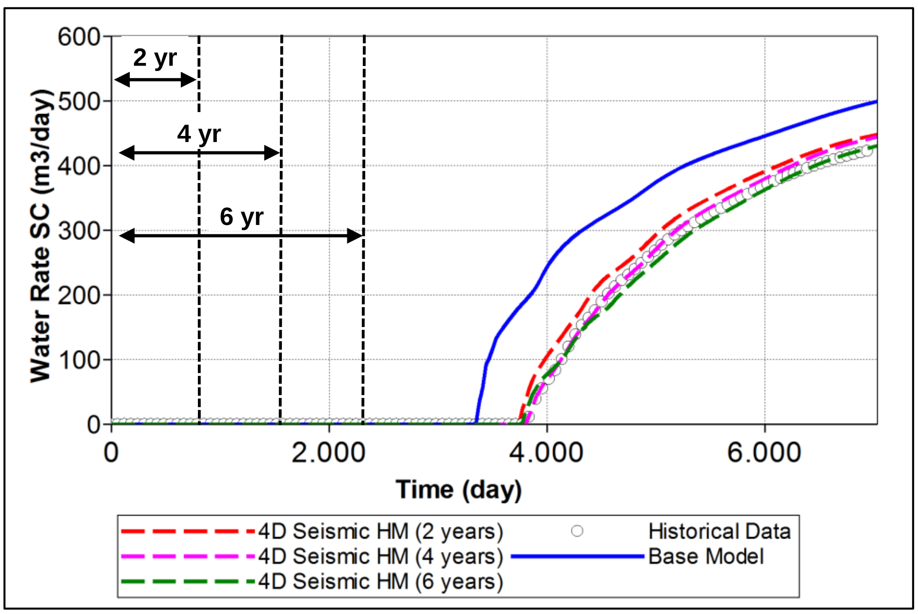


Figure 2.25. PROD 2 water rate: 4D seismic history matched models.

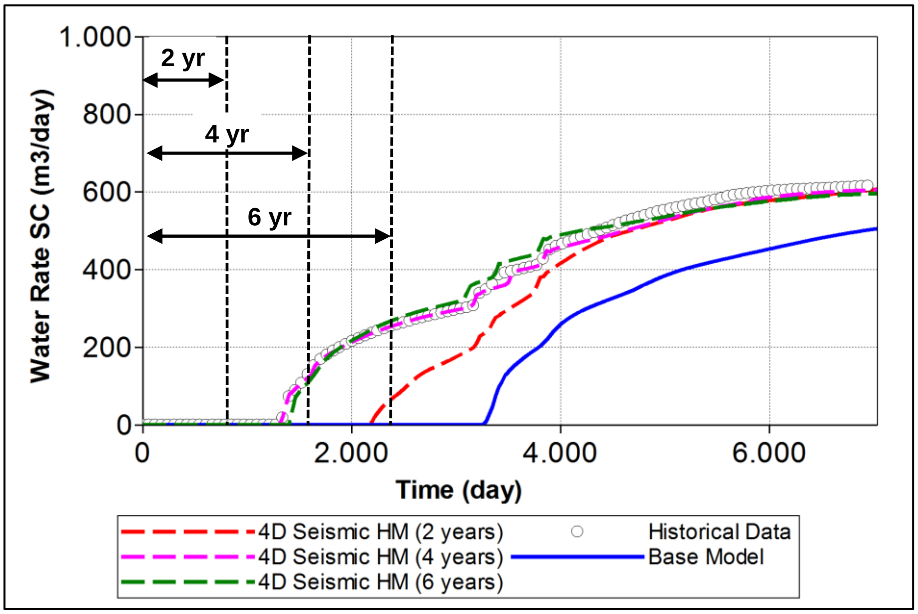


Figure 2.26. PROD 3 water rate: 4D seismic history matched models.

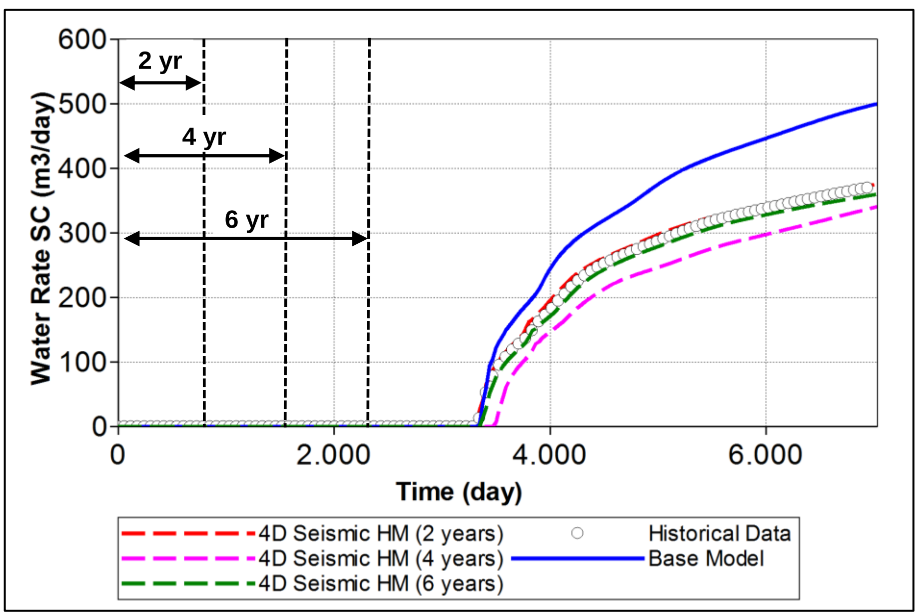


Figure 2.27. PROD 4 water rate: 4D seismic history matched models.

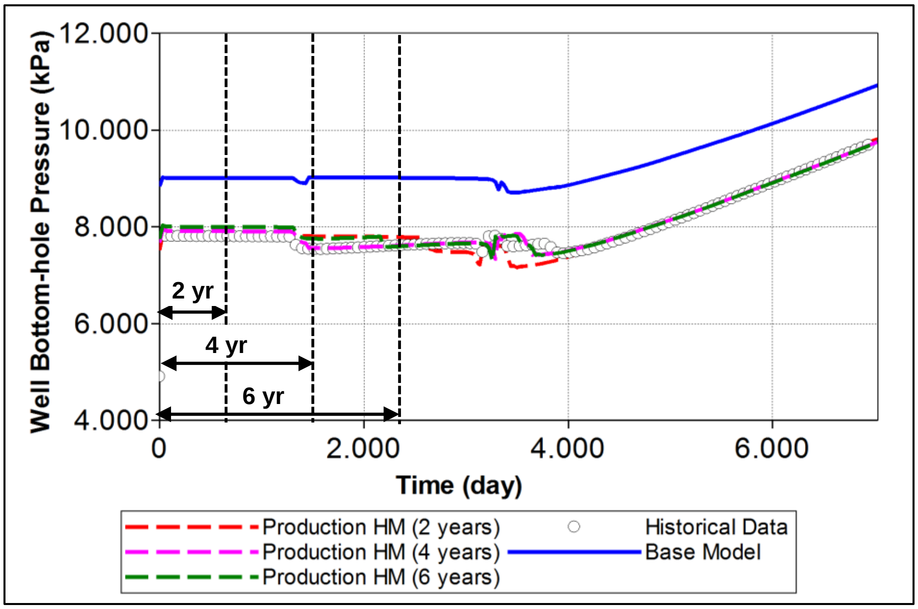


Figure 2.28. PROD 1 BHP: production history matched models.

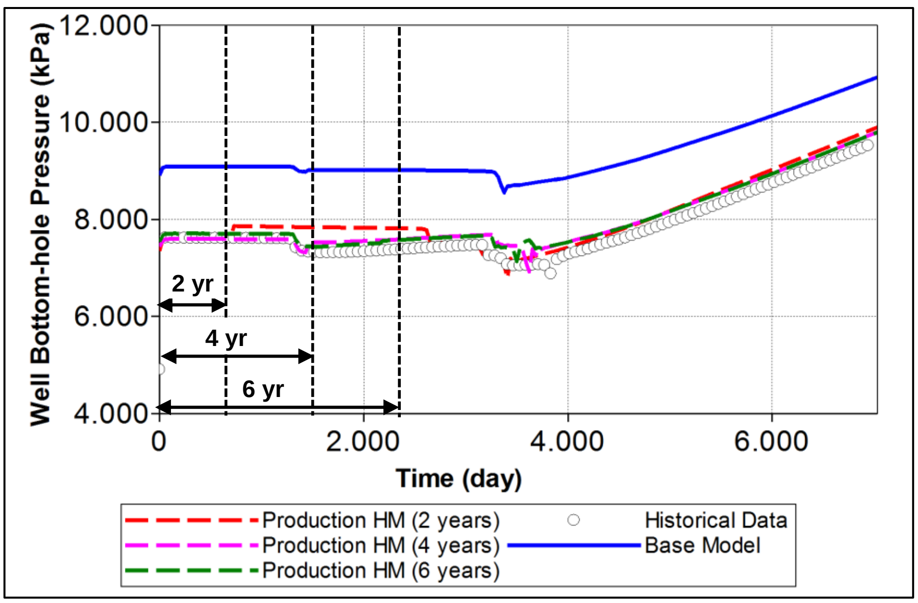


Figure 2.29. PROD 2 BHP: production history matched models.

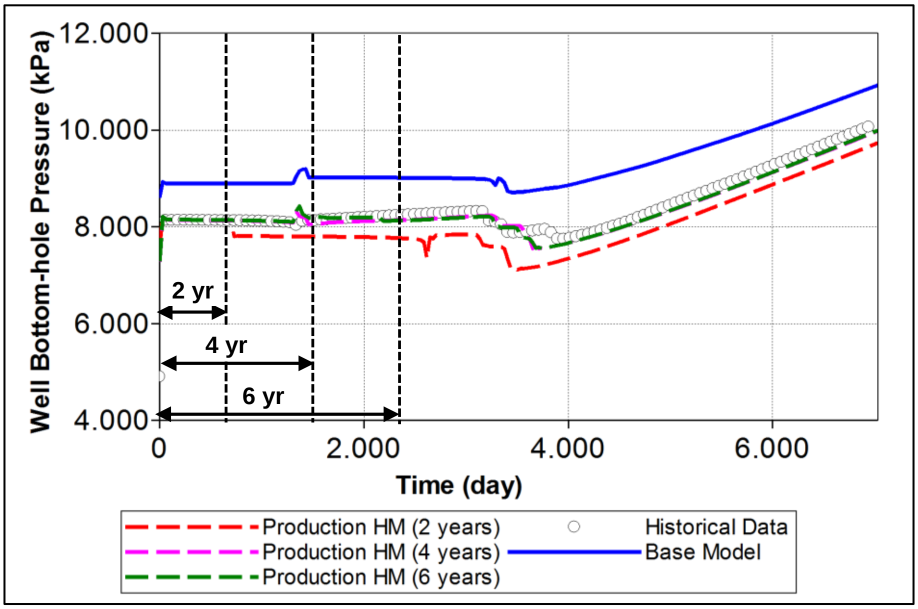


Figure 2.30. PROD 3 BHP: production history matched models.

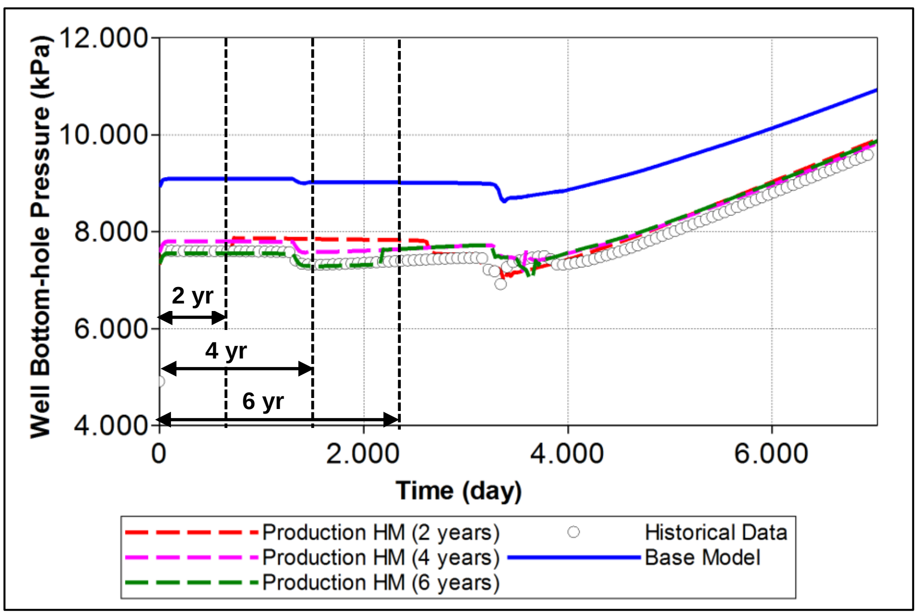


Figure 2.31. PROD 4 BHP: production history matched models.

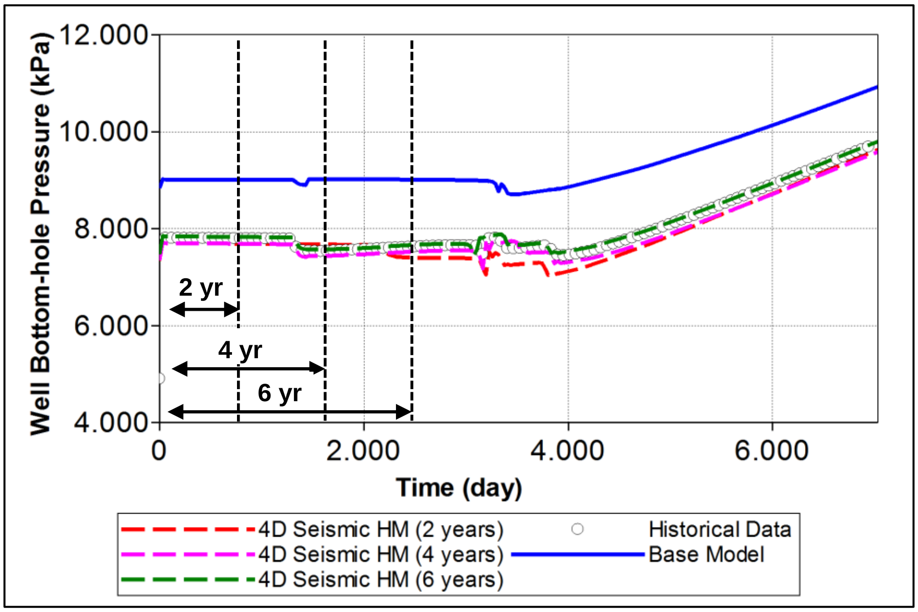


Figure 2.32. PROD 1 BHP: 4D seismic history matched models.

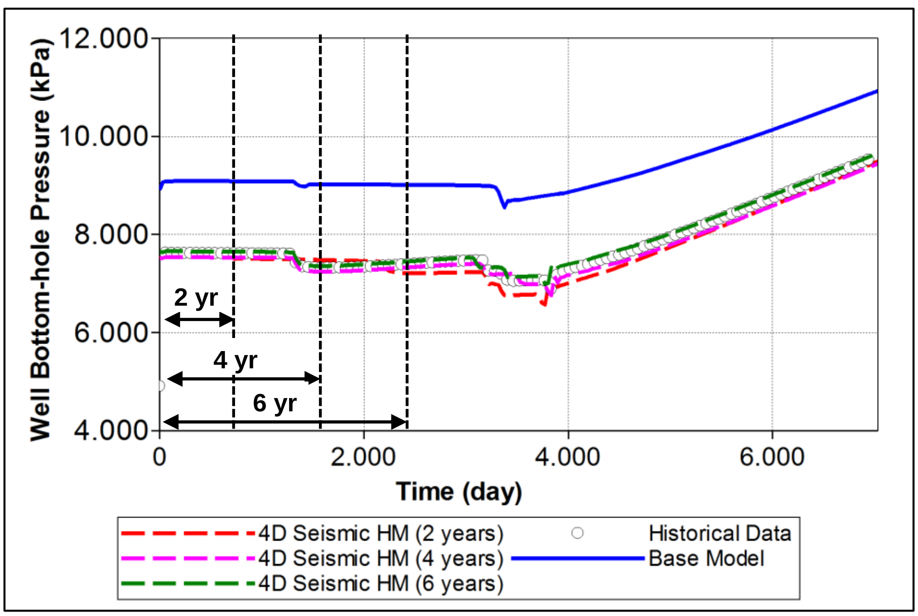


Figure 2.33. PROD 2 BHP: 4D seismic history matched models.

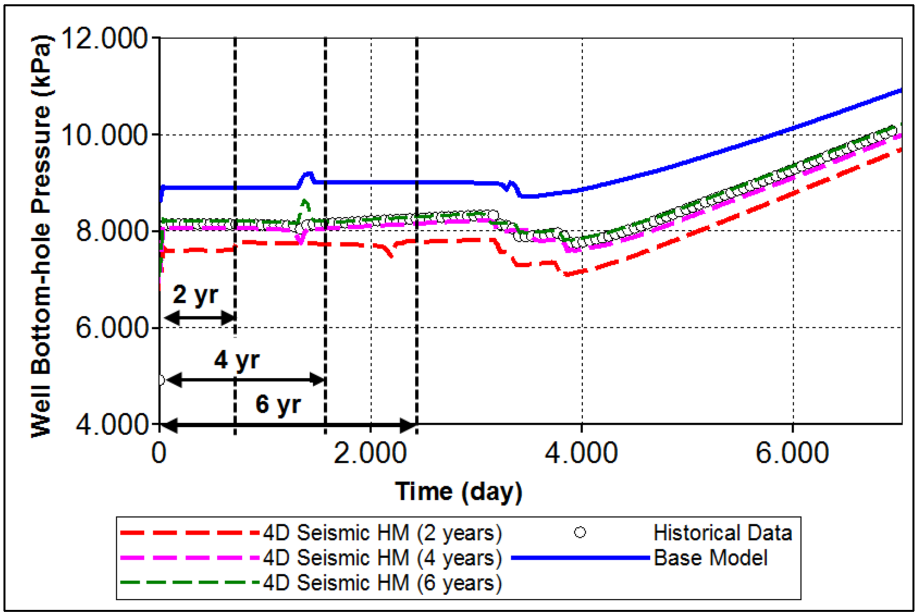


Figure 2.34. PROD 3 BHP: 4D seismic history matched models.

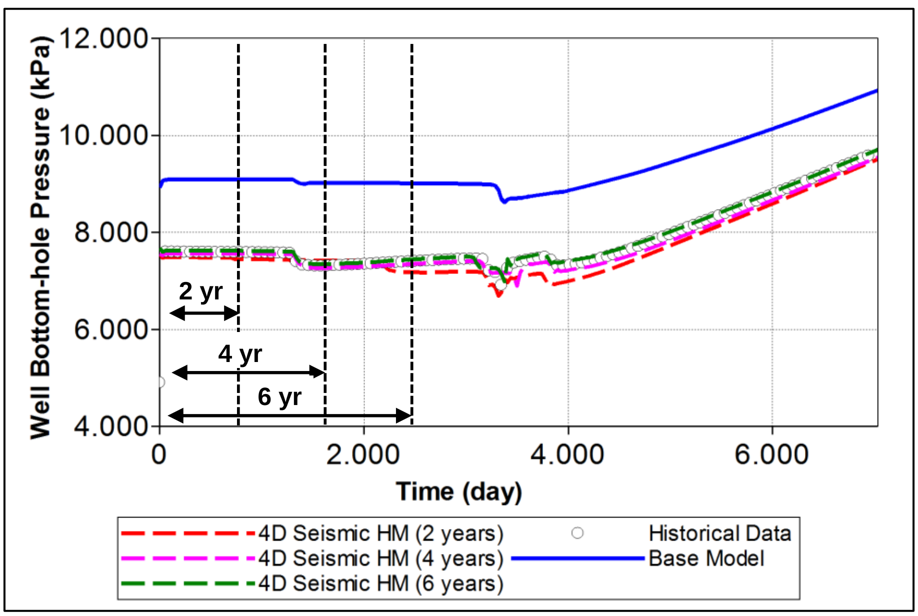


Figure 2.35. PROD 4 BHP: 4D seismic history matched models.

Evaluating the prediction period, 4D seismic data improves water breakthrough prediction for the production wells PROD2 and PROD3 considering two years of historical data (Figures 2.25 and 2.26). The improvement in the production forecast is achieved for the history matched models using production data when breakthrough occurs; this occurs for production well

PROD3 with four years of historical data (Figure 2.22). At this moment, seismic value decreases because production data itself shows that the base model is inadequate.

After four years of production, history matching can be started with the calibration of production well PROD3. However, as production data provides information at a specific reservoir location several alternatives could explain this early breakthrough, such as: high permeability channel, higher permeability of the reservoir near the production well and fractures.

The quantity of data used in history matching increases with six years of production. The production behavior is more accurate for the history matched models using only production data, even though the barriers were not identified in the process. The increase in the amount of available information impacts on the value of 4D seismic data. Other source of data can be used to identify and characterize the uncertain reservoir heterogeneities.

The prediction of the bottom-hole pressure is accurate for most of history matched models. The results obtained for the models history matched with two years of production were lower than the historical data. As the reservoir isn't compartmentalized, pressure is not a critical issue.

Dynamic Data Analysis

Another value derived from the integration of 4DS with production data is the improvement on the simulation model quality, generating more accurate pressure and saturation information. The improvement on the dynamic data from the history matched models were evaluated by computing the water saturation and pressure error curves over the production period

The water saturation error curves are presented in Figures 2.36 and 2.37 while the pressure error curves are shown in Figures 2.38 and 2.39.

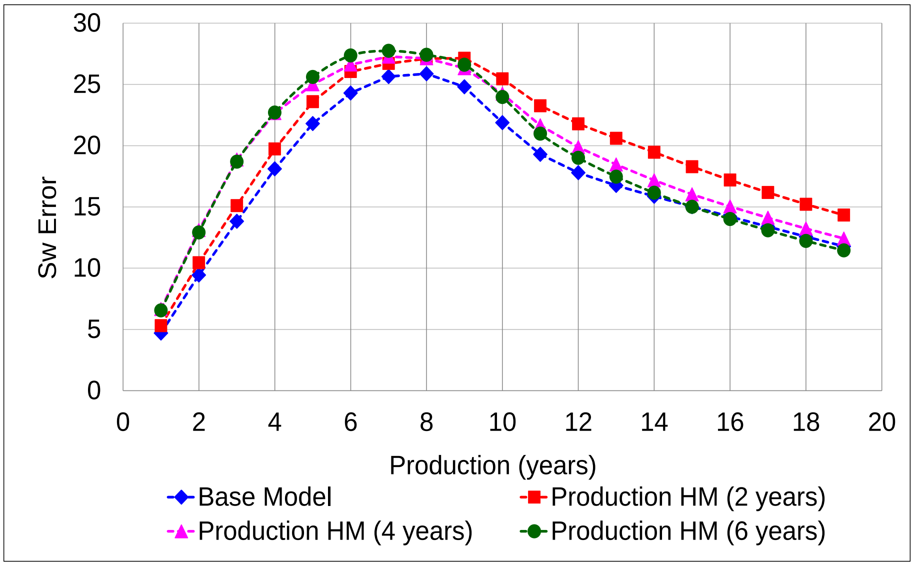


Figure 2.36. Water saturation error: production history matched models.

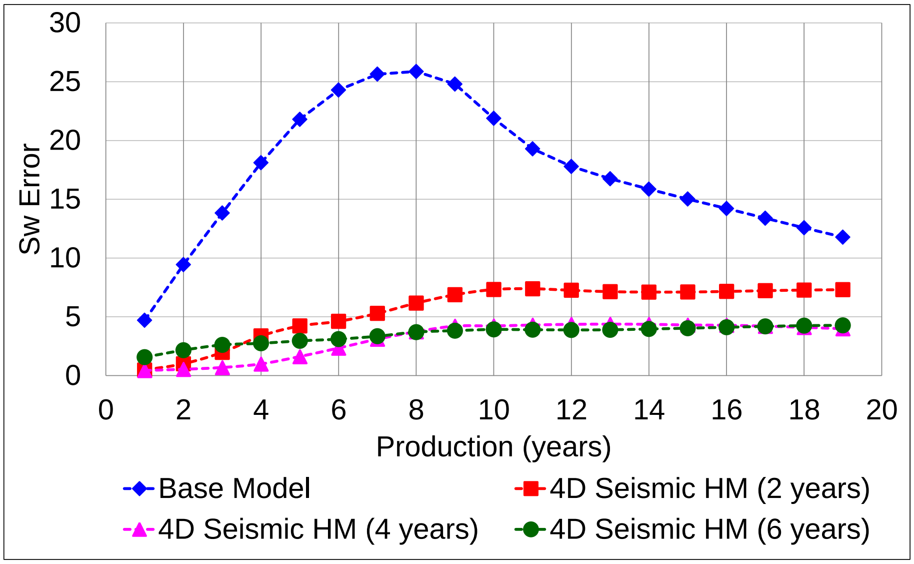


Figure 2.37. Water saturation error: 4D seismic history matched models.

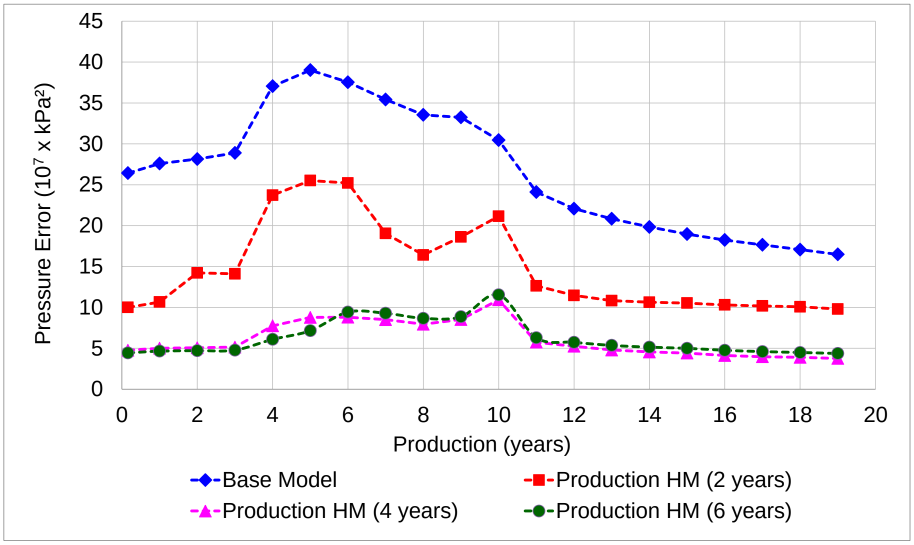


Figure 2.38. Reservoir pressure error: production history matched models.

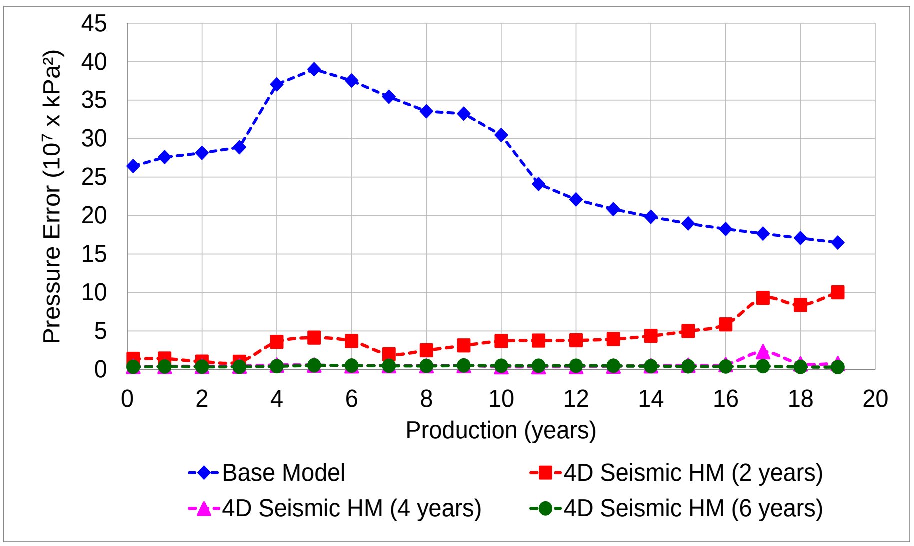


Figure 2.39. Reservoir pressure error: 4D seismic history matched models.

Besides the history matched models with more than four years of only production data presented good prediction results, water saturation error is higher than obtained by the base model. This occurs because well data do not capture the fluid flow behavior during production, making it difficult to identify the correct position and shape of the high permeability channel.

When 4D seismic data is used, water saturation error decreases significantly for the history matched model with two years of historical data. This shows the importance of using 4D seismic; it provides unique information regarding the properties of the reservoir between and beyond the wells. Figures 2.38 and 39 show that the main quality improvement due to 4D seismic data is related to water saturation, since for both history match methods the pressure error decreased.

The improvement on the simulation model quality can also be seen in Figure 2.40. It shows the difference of the water saturation maps between: (1) reference and base model, (2) reference and history matched model using only production data up two years and (3) reference and history matched model using production data and 4D seismic data acquired at two years.

Errors lower than 20% of the highest values were dismissed. The errors obtained over the production period decrease significantly when 4D seismic data is used.

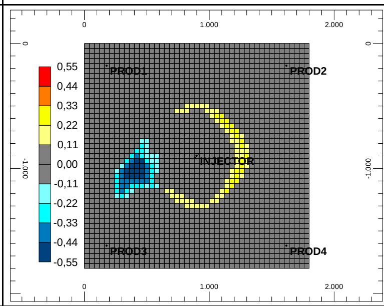
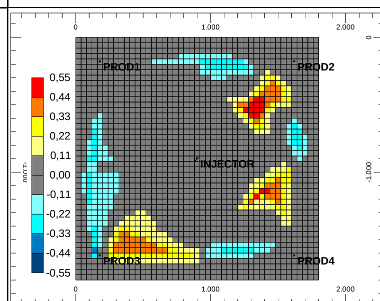
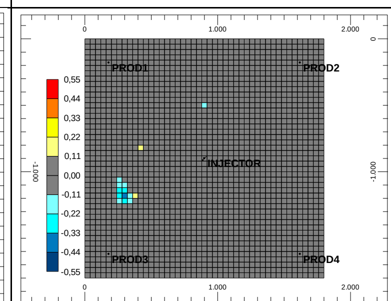
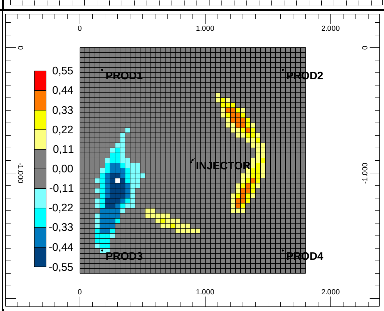
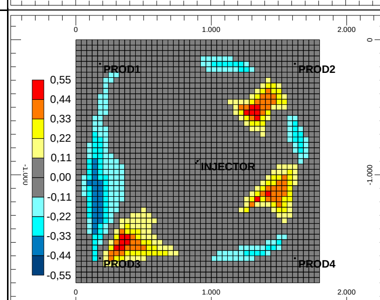
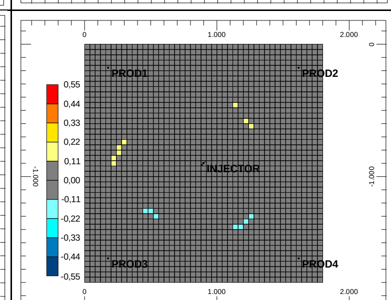
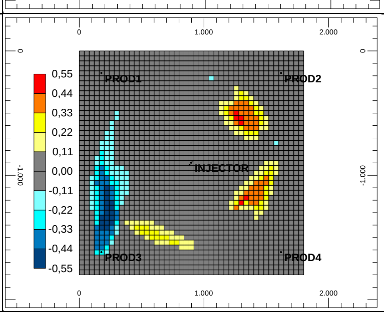
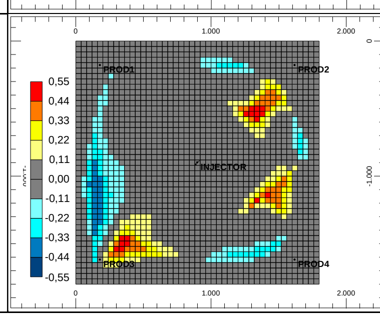
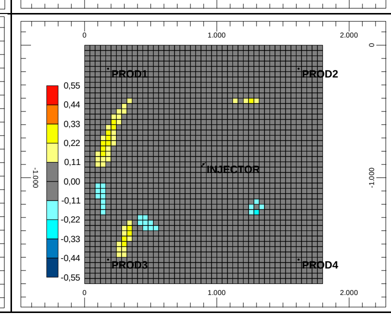
Period (years)	**Base model**	**Production HM (2 years)**	**4DS seismic HM (2 years)**
2			
4			
6			

Figure 2.40. Water saturation error maps.

Acquisition Period Analysis

Production and dynamic data analysis showed that 4D seismic improved production forecasts and captured the fluid flow behavior even for two years of historical data. The history matched models considering the acquisition at four and six years of production showed better results. However, history matched models using only production data with more than four years of historical data also improved the production forecast.

The main value derived from the integration of 4D seismic with production data lies on the improvement of the simulation model quality. History matched models with 4D seismic data decreased the water saturation errors for all production periods analyzed. The understanding of the reservoir fluid flow movement assists the decision maker to improve the production strategy and increase the NPV as a consequence.

The evaluation of the date for 4D seismic data acquisition must consider the economic impact of the new information in the reservoir management. The revenue percentage to be obtained from oil was calculated for the reference model to illustrate how 4D seismic value is related to the production strategy flexibility. The results obtained are presented Figure 2.41.

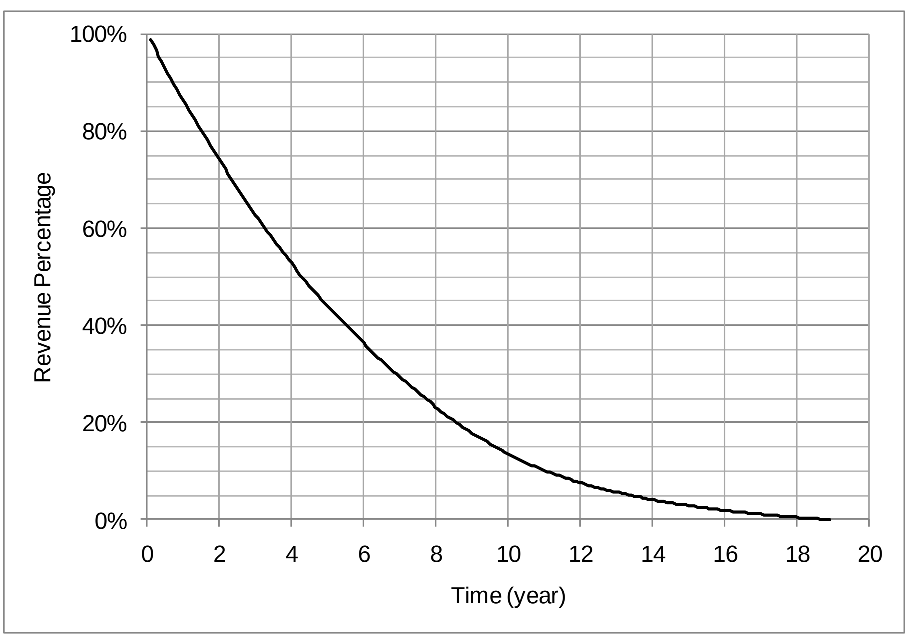


Figure 2.41. Reference model: future revenue (percentage of total) versus time.

At four years of production there is approximately 50% of the revenue to be obtained with the remaining oil. Thus, the improvement of the production strategy at this moment can increase the NPV since there is a significant amount of remaining oil in the reservoir.

However, at eight years of production changes in production strategy are limited, having only 20% of the revenue to be obtained. Thus, the utility of seismic data acquired at this period decreases significantly.

The production period in which the acquisition of 4D seismic data has the highest impact was determined based on the production, dynamic and the simple economic analysis. The acquisition period is between 2 and 4 years of production to the case studied. In summary:

- The history matched model using 4D seismic data acquired at two years of production presented an improvement on the prediction capability;
- After four years of production an improvement on the prediction capability is also presented by the history matched model using only production data, because water breakthrough had occurred;
- The history matched models using only production data for all historical periods analyzed decreased water saturation maps quality;
- The history matched models using production data and 4D seismic data for all historical periods analyzed increased water saturation maps quality;
- If the production strategy was flexible, it would be possible to implement operational changes related to water breakthrough prediction. Between two and four years of production there is a range of approximately 75% to 50% of remaining revenue.

2.7. Conclusions

The use of production data for history matching did not identify the barriers and some channel characteristics such as, angle and width. The history matching performed with four years of production data improved the production forecast. However, the prediction of the movement of fluid flow decreased significantly, because the water saturation errors increased at least 105%.

The acquisition of 4D seismic data at 4 years of production improved the production forecast and reduced the water saturation errors at least 76%. However, at this production period the water breakthrough had occurred. The water breakthrough occurrence reduces the impact on the reservoir management. Thus, it is an important factor that affects the value of 4D seismic data.

The acquisition of 4D seismic data at an early production stage improves the reservoir model. The history matching using 4D seismic data acquired at two years of production provided better production forecast than using only production data, especially for the water rate at production wells PROD 2, 3 and 4.

The water saturation errors decreased at least 38%. The reduction on the water saturation errors shows that the reservoir model better predicts the fluid flow behavior. However, it was not possible to identify the exact moment of water breakthrough at production well PROD 3.

The period of highest impact for 4D seismic acquisition is between 2 and 4 years of production. It would be possible to predict the water breakthrough at production wells and consequently make decisions that would delay the breakthrough. Also, the revenue to be obtained from oil decreases significantly at later times. There would be only 20% of remaining revenue to be obtained after eight years of production.

The water saturation error curve quantifies the quality of the dynamic data from a reservoir simulation model. It also provides important information about the possibility of remaining oil areas.

3. ESTIMATION OF THE BEST PRODUCTION PERIOD FOR 4D SEISMIC DATA ACQUISITION

3.1. Introduction

Chapter 2 showed that the date for 4D seismic acquisition affects the value of 4D seismic data. If seismic data identifies changes in reservoir properties in the initial production phase, the project return increases through improvements in production strategy. On the other hand, if these changes are identified too late, the flexibility in decision making is reduced; consequently, few changes can be made in the production strategy.

Also, the availability of other source of data reduces reservoir uncertainties and improves field development. Thus, the utility of 4D seismic is related to the period for 4D seismic data acquisition and, if done at the appropriate time, this tool has positive impacts on field management.

The analysis of the improvement on the production data and dynamic data forecast, presented in Chapter 02, assumed that the true earth model was known. However, this is not what happens in practice.

The estimation of the value of 4D seismic data shall be determined before its acquisition. Therefore, the best period for 4D seismic acquisition shall be identified without knowing the reference model.

The estimation of the period for 4D seismic acquisition is a challenge task, because it is a problem of decision making under uncertainty. The acquisition of 4D seismic data in different production periods impacts the reservoir management in different manners.

Thus, the present Chapter describes a methodology to estimate the best production period for 4D seismic acquisition. The evaluation process is simple and the methodology is divided in three steps: uncertainty analysis; production data analysis and water saturation error analysis.

The proposed methodology is applied to a simple and synthetic reservoir model is order to exemplify the process. The results obtained are also shown in the present Chapter. The methodology will be incorporated in the chance of success methodology that is presented in Chapter 4.

3.2. Objective

The objective is to describe the methodology that estimates the best production period for 4D seismic data acquisition considering the reservoir uncertainties and to present its application to a simple synthetic reservoir model.

3.3. Assumptions

The following assumptions are adopted:

- The model used is synthetic and simple. It represents a specific part of the field in order to make the analysis simpler;
- The reservoir model uncertainties are properly quantified;
- Pressure and saturation data are successfully obtained from 4D seismic without noise.

3.4. Proposed Methodology

The proposed methodology comprises four stages; as described in the following sections.

3.4.1. Uncertainty Analysis

The base deterministic reservoir model is a simulation model constructed with the most probable values of all input values. The base model is analyzed in order to define the reservoir uncertainties. Depending on the amount of uncertainties, a sensitivity analysis can be performed to identify the most critical attributes to be considered in the process.

The critical attributes must be combined through a statistical technique, among the existing ones: derivation tree, Monte Carlo and Latin Hypercube. Depending on the number of uncertain attributes the use of derivation tree leads to a high number of scenarios. Monte Carlo is a tradition technique to sample randomly within the range of the input distribution. However, a high number of iterations are needed to sample enough quantities to accurately represent the input distribution.

Latin Hypercube sampling is designed to accurately recreate the input distribution through sampling in less iteration when compared to Monte Carlo method. The key is stratification of the input probability distributions.

Stratification divides the cumulative probability curve into equal intervals. A sample is randomly taken from each interval of the input distribution. The technique being used during Latin Hypercube sampling is “sampling without replacement”. The number of stratifications of the cumulative distribution is equal to the number of iterations performed (University of Oslo, 2005).

As more efficient sampling method, Latin Hypercube is used in the methodology to estimate the best time for 4D seismic acquisition. The scenarios generated are then simulated using commercial simulation software to obtain the production outputs.

3.4.2. Production Data Analysis

Chapter 2 showed that production data itself can reduce the reservoir uncertainties and improve the production forecast. Time for breakthrough has indicated to be an important parameter. It increases the production data capability to identify the reservoir heterogeneities and to improve the knowledge of the geological framework.

The acquisition of 4D seismic data before water breakthrough occurs improves the production well operational parameters. Decisions can be made in order to delay the breakthrough and increase the oil production rate as a consequence.

4D seismic data gives information about the evolution in space and time of the fluid distributions inside the reservoir. Thus, the value of 4D seismic data increases when its acquisition is made at a moment in which production data does not provide a good characterization of the reservoir.

Therefore, water rate of each production well for all scenarios must be evaluated. The probability of water breakthrough occurrence at different production periods shall be determined. The acquisition period is determined based on these probabilities, depending on the decision maker risk aversion.

3.4.3. Dynamic Data Analysis

The best time for 4D seismic acquisition is the one that only 4D seismic data is able to identify that the base model does not represent the true earth model and there is enough time to make decision changes in field operations.

The calculation of the water saturation error between each scenario and the base model is necessary to estimate the best period for 4D seismic acquisition. The water saturation error curve over a production period is given by an error function.

The error function is defined as the quantity that represents the mismatch between the reservoir simulation scenario and the base model water saturation maps; each scenario is considered as a true earth model. The error function used is defined as

$$\varepsilon = \sum_{i=1}^{Ng} \left(X_i^{base} - X_i^{scenario} \right)^2 \tag{3.1}$$

and the normalized error function is

$$\varepsilon_{norm} = \frac{\varepsilon}{highest(\varepsilon)}, \tag{3.2}$$

where N_g is the number of grid cells, X is the property analyzed (water saturation); X_i^{base} and $X_i^{scenario}$ are the base and scenario model data, and ε is the error.

The water saturation error graph shows, for each possible scenario, if there is significant information about the reservoir fluid flow to identify that the model considered (base model) is different from the true earth model.

The information is considered perfect, thus the acquisition of information identifies the true earth model represented by each scenario. It is known that in practice history matching would be performed and the resulting reservoir model would be closer to the true earth model.

The normalized water saturation error graph is used to identify the moment in which the water saturation is highest and assists the estimation of the acquisition period. This period shall be between the moment in which there is enough water saturation error and enough time to implement actions that improve the reservoir management.

3.4.4. Acquisition Period Estimation

The results obtained in production and dynamic analyses are evaluated. An upper limit for 4D seismic acquisition is the one that the probability of water breakthrough occurs at any production wells is high. The definition of the probability value depends on the decision maker risk aversion. The lower limit is the one that there is enough water saturation error between the base model and the true earth model to identify that the base model is incorrect.

3.5. Application

The methodology to estimate the best time for 4D seismic acquisition is applied to a synthetic model. The reservoir model description and the reservoir uncertainties are presented in the next sections.

3.5.1. Reservoir Model Description

The reservoir simulation model used is the base model described in the section 2.5 in Chapter 2. The permeability map is presented in Figure 3.1.

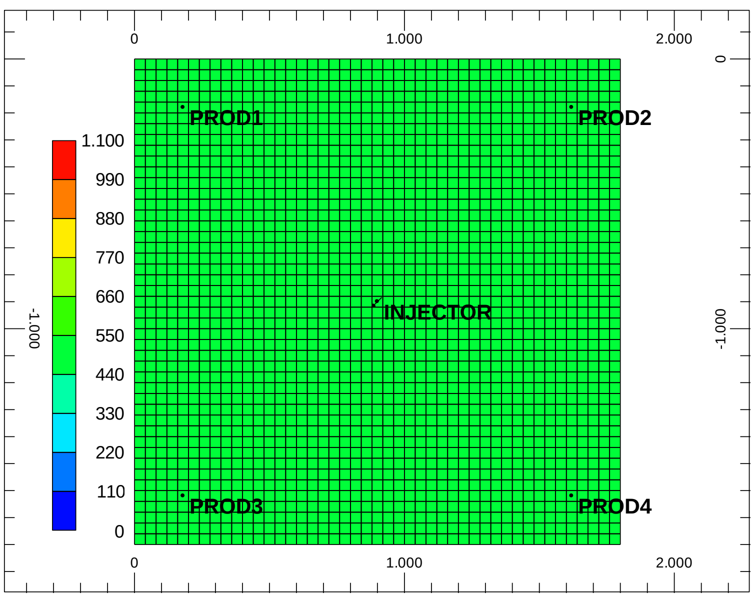


Figure 3.1. Base model permeability map.

3.5.2. Reservoir Model Uncertainties

The reservoir uncertainties description and the range of each variable are presented in Table 3.1 and Figure 3.2. The Latin Hypercube sampling methodology was used to generate the reservoir model scenarios.

Table 3.1. Input parameters and associated ranges.

Uncertain Parameter	Description	Minimum	Maximum
x_c	channel Cartesian x center value	grid cell 5	grid cell 41
y_c	channel Cartesian y center value	grid cell 5	grid cell 41
θ	channel angle	0	π
w_c	channel width	$2\sqrt{2}$	$5\sqrt{2}$
L_c	channel length	0	26 grid cells
k_c	channel permeability	1000mD	3000mD
k	reservoir permeability	200mD	600mD

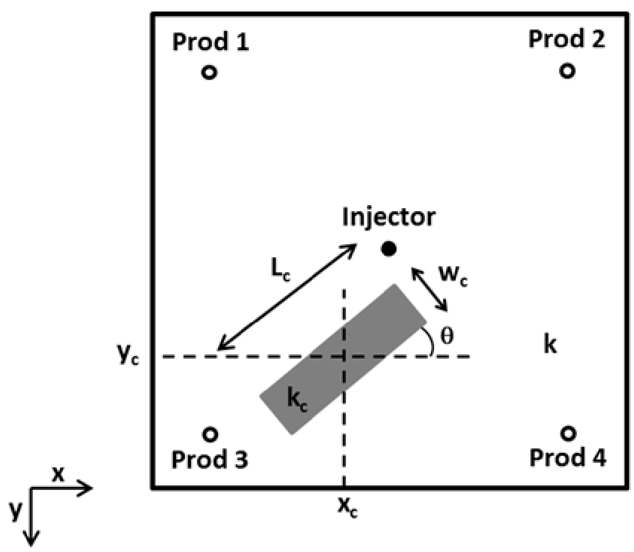


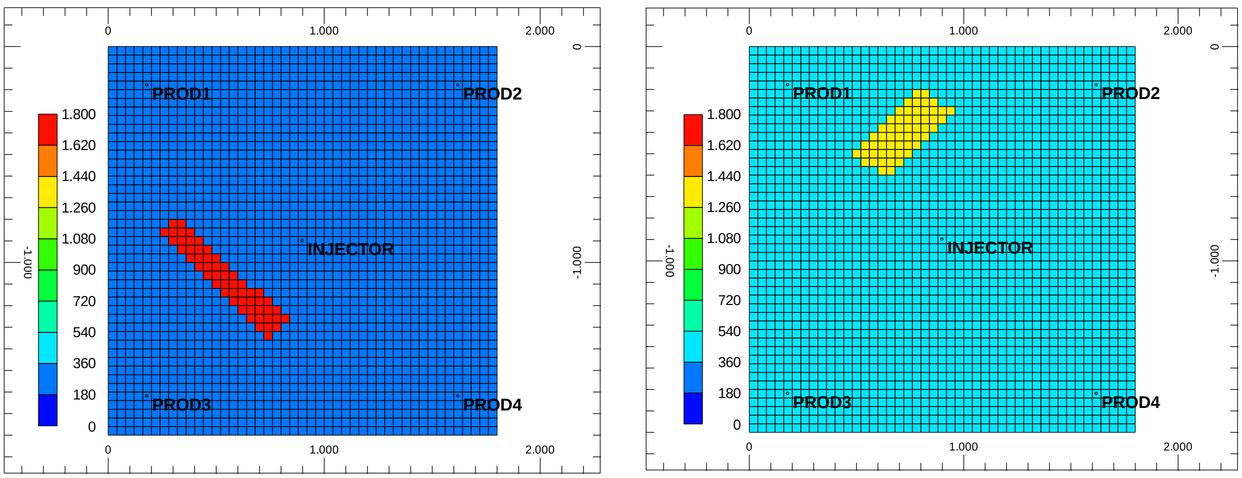
Figure 3.2. Reservoir model uncertainties.

3.6. Results

The results obtained at each methodology step are presented in the next sections.

3.6.1. Uncertainty Analysis

A selection of 200 equiprobable scenarios was generated and simulated using commercial simulation software (IMEX - CMG@). The permeability maps from two different possible scenarios are presented in Figure 3.3. Figures 3.4 to 3.7 shows the cumulative oil production from all scenarios and base model for each production well.



(a) (b)

Figure 3.3. Permeability maps: (a) Scenario 01, (b) Scenario 02

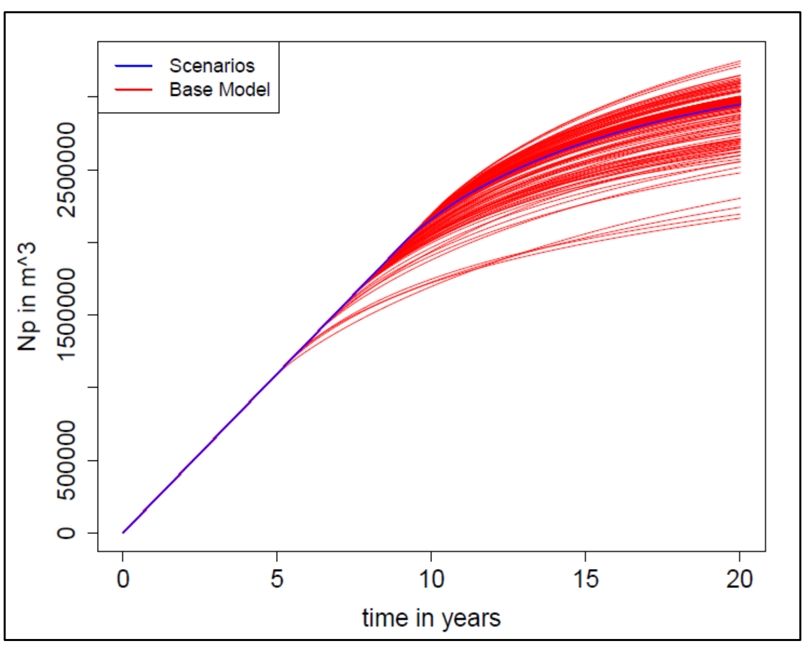


Figure 3.4. PROD1 cumulative oil production.

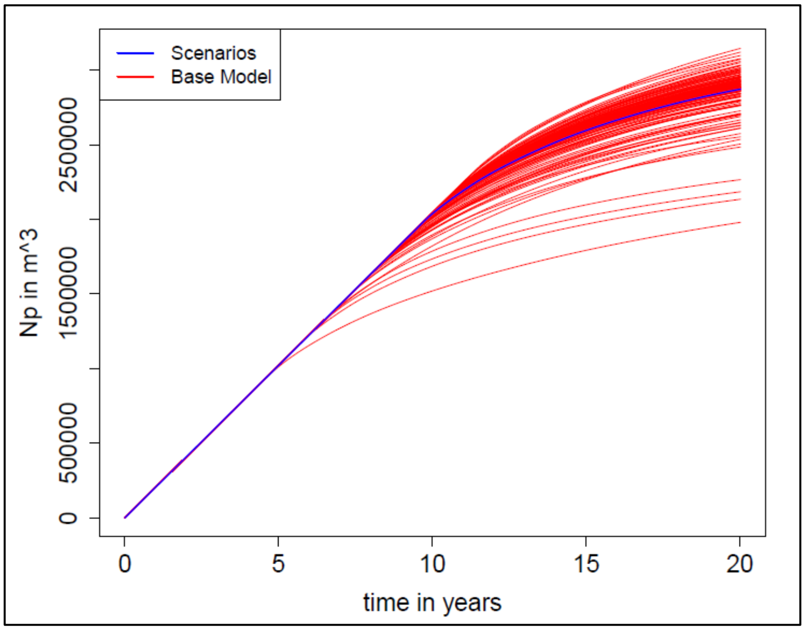


Figure 3.5. PROD2 cumulative oil production.

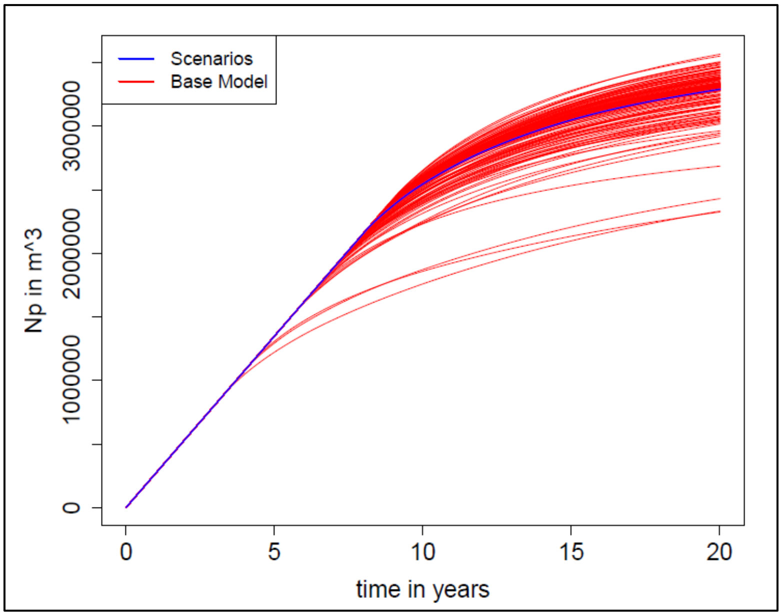


Figure 3.6. PROD3 cumulative oil production.

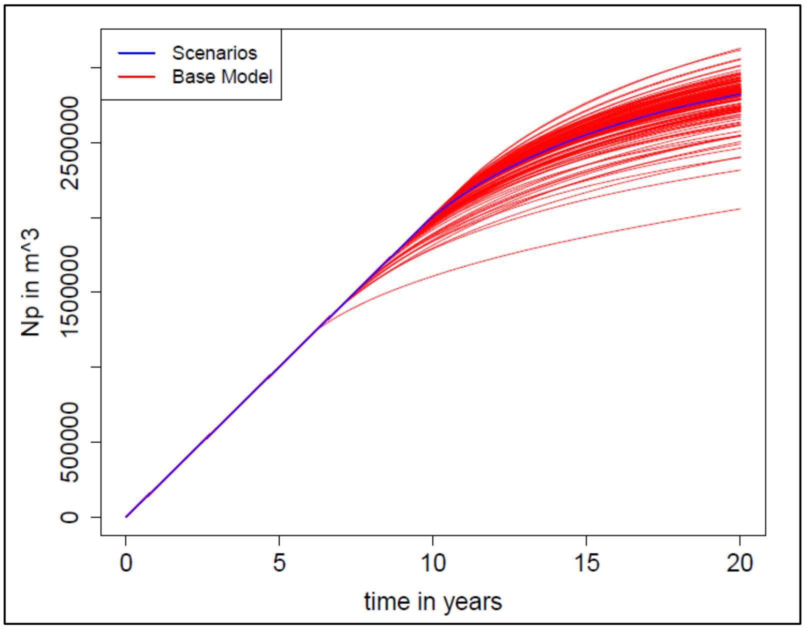


Figure 3.7. PROD4 cumulative oil production.

3.6.2. Production Data Analysis

The date for 4D seismic acquisition is limited to the time for water breakthrough for non-mature reservoirs. The date for water breakthrough at each production well for each scenario was determined. The water rate for each production well is presented in Figures 3.8 to 3.11.

It can be seen that time for BT is highly variable. The probability of water breakthrough at different production periods was determined. Water breakthrough is one of the parameters analyzed to estimate the acquisition period and the estimation is based on BT probabilities, depending on the decision maker risk aversion.

The probabilities were computed by quantifying the number of scenarios in which the BT occurred in any production well at a specific production period. The values obtained are:

- Before four years of production: 1 scenario, 0.5% of probability;
- Before six years of production: 11 scenarios, 5.5% of probability.
- Before eight years of production: 94 scenarios, 47% of probability.

The reduction of the uncertainty of the breakthrough prediction is one of 4DS utility in non-mature fields. Decisions can be made in order to delay the breakthrough and increase the oil production rate as a consequence.

In the case studied, the production strategy is not flexible and only well operational changes can be made to increase field profitability. Assuming that 47% of BT probability is a high level of risk, eight years of production would be the limiting to acquire seismic data.

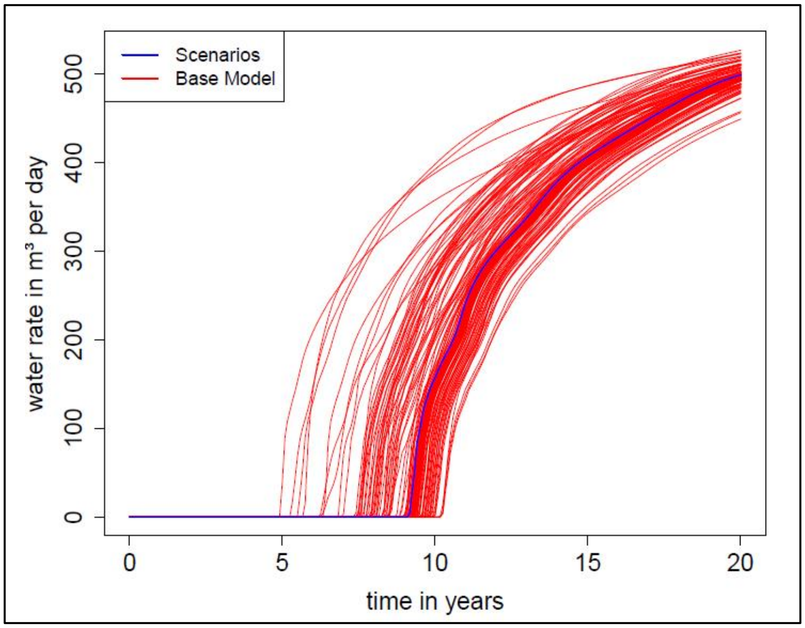


Figure 3.8. PROD1 water rate.

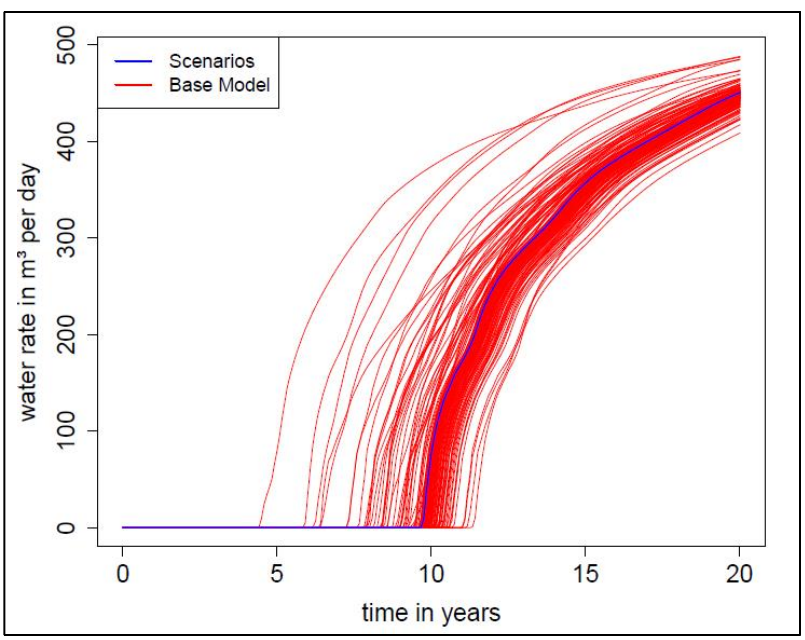


Figure 3.9. PROD2 water rate.

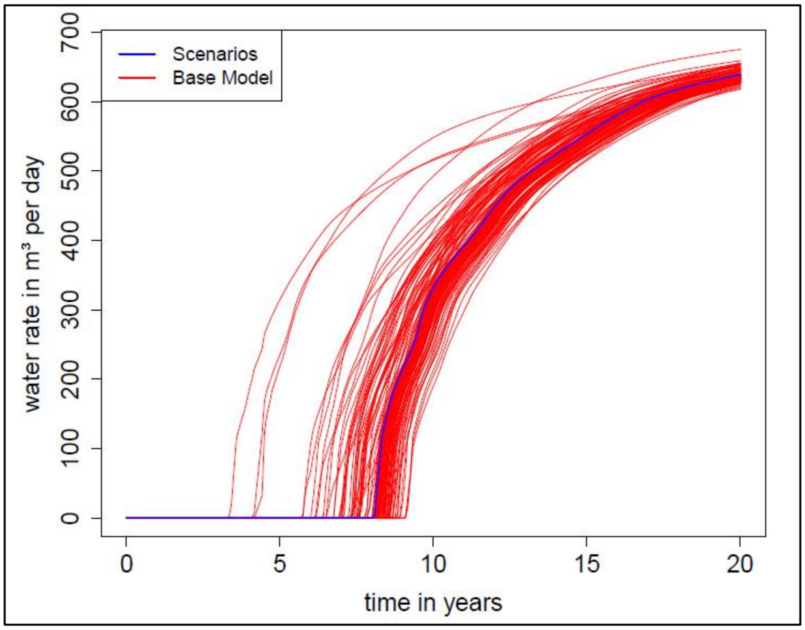


Figure 3.10. PROD3 water rate.

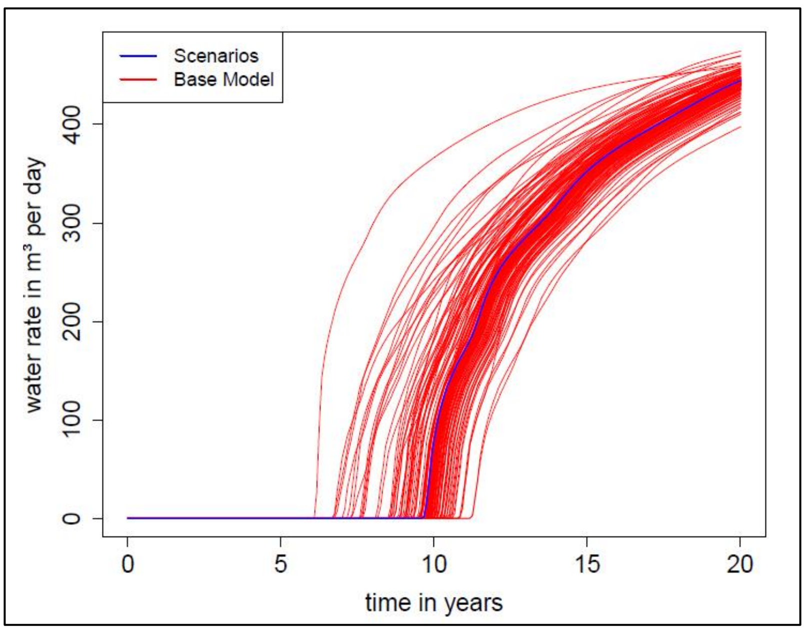


Figure 3.11. PROD4 water rate.

3.6.3. Dynamic Data Analysis

The water saturation error curve was obtained by comparing the water saturation map from the base model and the water saturation map from each scenario; these curves are presented in Figure 3.12.

The graph shows, for each possible scenario, if there is significant water saturation error to identify that the base model is different from the true earth model. It can be seen that there are scenarios with fluid distributions highly different from the base model and scenarios that are geologically similar resulting in low error values.

The water saturation curves were normalized to identify the appropriate acquisition period. The normalized curve identifies the moment in which the water saturation error is highest and are presented in Figure 3.13.

It was considered that 70% of the highest error value would be enough for the true earth model identification. Figure 3.14 shows a histogram of production time in which normalized water saturation error is equal 70%. It can be seen that the highest number of scenarios occurs at five years of production.

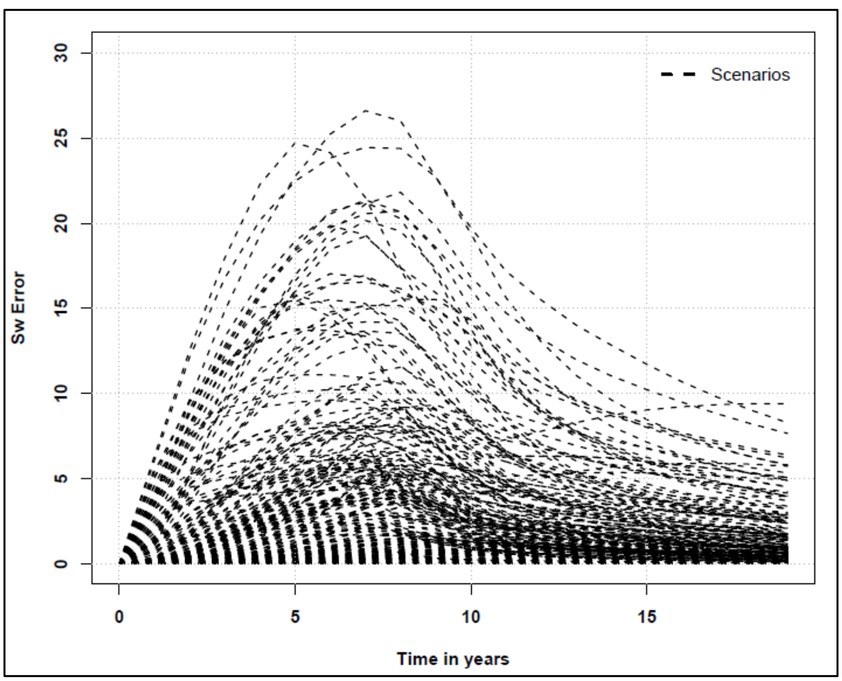


Figure 3.12. Water saturation error curves.

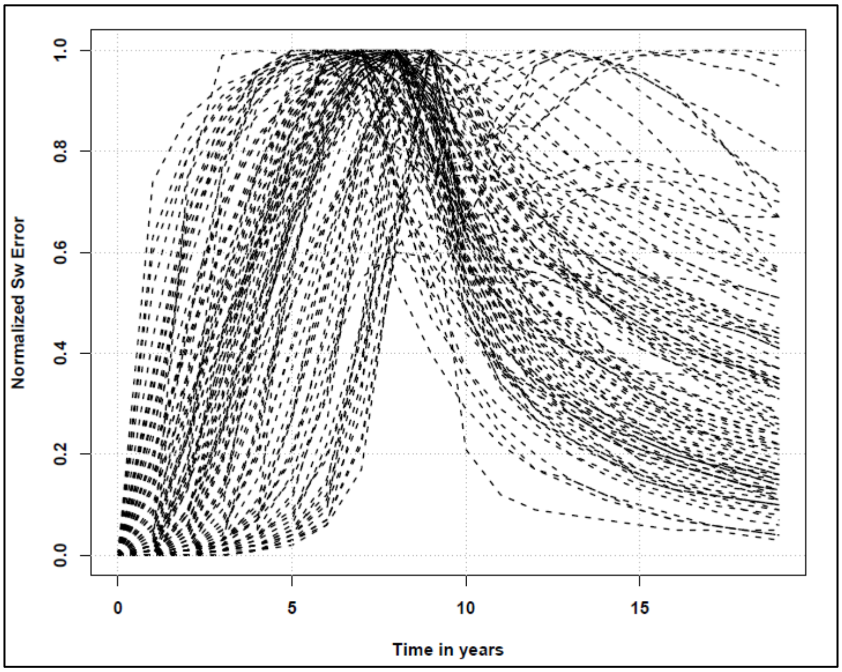


Figure 3.13. Normalized water saturation error curves.

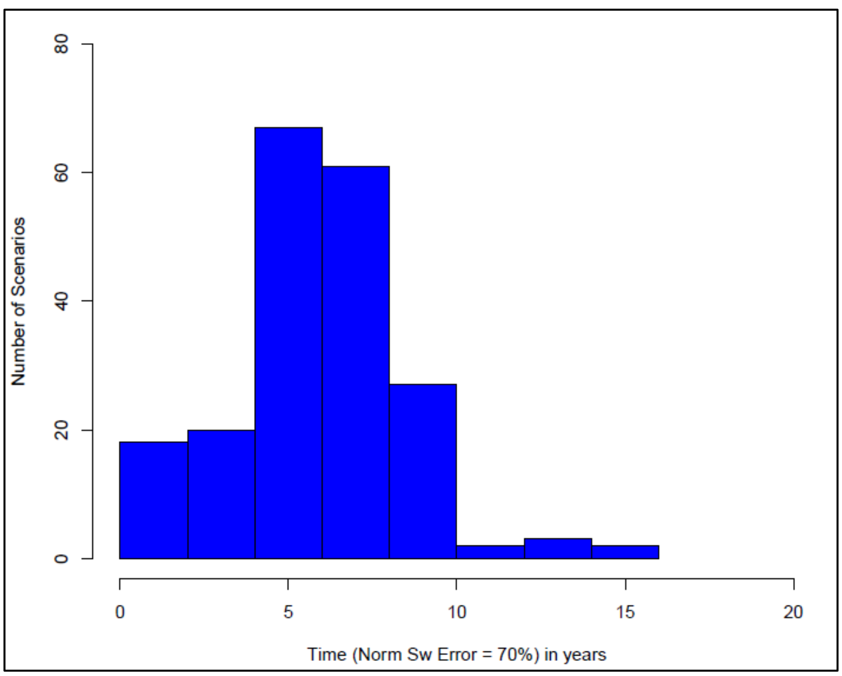


Figure 3.14. Histogram of production time in which normalized Sw error is equal 70%.

3.6.4. Acquisition Period Estimation

The period for the first 4D seismic data acquisition is between five and eight years of production, based on the production and the dynamic data analysis. The period was determined considering a non-mature reservoir without production strategy flexibility.

The inferior limit, five years, is the minimum time at which variations in the reservoir dynamic properties occurred. The superior limit, eight years, indicates the time at which there is a high probability of breakthrough. The production period obtained is different from the one presented in Chapter 2. Such can be justified by the neglected barriers in the scenarios.

3.7. Conclusions

The proposed methodology to estimate the best time for 4D seismic data acquisition incorporates common routines used in the industry, such as uncertainty analysis, and it adds a new procedure through the dynamic data analysis.

Two are the main factors that define the acquisition period: the water breakthrough and the water saturation error. The acquisition of 4D seismic data shall be before water breakthrough. The identification of the water flow path improves the well operational parameters and consequently increases the project economic return.

The appropriate acquisition period is also limited to the time at which 4D seismic data identifies that the base model does not represent the true earth model. The time is defined by considering that 70% of the maximum normalized water saturation error is sufficient to identify the true earth model.

The acquisition period obtained for the synthetic reservoir model is between five and eight years of production. Such period is different from the one presented in Chapter 2 because the barriers were neglected. At five years, the normalized water saturation error is equal 70% for most of the scenarios and at eight years there is 47% of probability of water breakthrough.

4. METHODOLOGY TO ESTIMATE THE CHANCE OF SUCCESS OF A 4D SEISMIC PROJECT

4.1. Introduction

A 4D seismic project is considered successful from the reservoir engineering perspective when 4D seismic data mitigates the risk and/or increases the economic value of the project. Measuring and, especially, predicting the economic impact of new information is complex; within such setting the value of information (VOI) concept rises as an important decision-making tool.

It is simpler to quantify 4D seismic data value after the data acquisition. A deterministic value is calculated by quantifying the impact that the new information had in the field management. Even though the quantification is simpler, it is difficult to define the decisions that would have been taken if no information had been acquired.

In contrast, the quantification of the EVOI before the data acquisition is more complex and must consider the reservoir model uncertainties and the uncertainty in future information (Dunn, 1992; Gerhardt and Haldorsen, 1989).

Currently the concept of EVOI is widespread over the oil and gas literature. The EVOI must take into account the potential benefits. Waggoner (2002) listed and discussed some of the most beneficial and common impacts of 4D seismic acquisition in reservoir management:

- Avoid poor well placement: 4D results can prevent poor well placement by assessing the state of the reservoir at a planned well location. The value of the 4D information saves the cost of an unnecessary well;
- Optimize placement of new wells: when 4D results are used to plan a new well location, it is possible to optimize the placement of that well;
- Locate undrained reservoir compartments: when 4D data indicates no reservoir change in areas expected to be in production, it is likely that those areas of the reservoir are isolated compartments. By locating the compartment, 4D data quantifies the lost reserves and allow placement of a well to access it.

- Identify drained areas/fluid fronts: it is possible to anticipate early breakthrough, potentially in time to adjust field production rates to prevent breakthrough from occurring. 4D seismic information is also important for locating new wells away from fluid fronts to extend the plateau and accelerate production;
- Reduce uncertainty in reservoir models: reservoir models always contain a degree of uncertainty, but 4D results can reduce that. With less uncertainty, there is less risk in many reservoir development and production decisions, which could result in accepting rather than rejecting an economically viable project.

Decision trees, developed as a concept in the 1960's, have gradually become the most widely accepted tool in the petroleum industry to assess the value of information (Ballin *et al.*, 2005). Decision tree models have been used to quantify the economic impact of seismic imaging on reservoir management (Waggoner, 2002) and the key to their successful use is to frame the problem, understand key sensitivities and keep it simple.

A widely used method to determine the VOI calculates the difference between expected monetary value with and without information for possible scenarios through a decision tree. The main differences observed in the literature lies on how the impact of information acquisition is considered in the decision tree, the integration of uncertainty in the process and the estimation of reliability of information.

Waggoner (2002) considered the impact of 4D seismic data acquisition in two different ways: 4D information can (1) increase the net present value and (2) increase the chance of success. The increase on the net present value is included in the decision tree by using a larger value of oil production in the branch considering the information gathering.

Ballin *et al.* (2005) evaluated the impact of 4D seismic data in the compartmentalization risk, the decision is related to drill/recomplete a well or not. The main value comes from changing the probability of the well's economic failure. The uncertainty is included in the process by combining regional database with reserve uncertainty to estimate the risk of well failure.

Coopersmith and Cunningham (2002) and Bratvold *et al.* (2009) include the concept of imperfect information by incorporating the Bayes' theorem in the analysis. Pinto et al (2011) also presented a method to quantify the monetary value of imperfect information provided by time-lapse seismic data acquisition. The proposed method is a simple application of real option analysis in which the value of perfect information is obtained and then the value of imperfect information is determined using a transfer factor.

The method presented by Pinto *et al*. (2011) generates a group of possible scenarios along with all possible production strategies for the reservoir. The scenarios generation considered only three variables: production, cost and oil price. The expected value without information is determined by weighting the net present value obtained from the scenarios using the base production strategy.

4D seismic data identifies the state of nature, therefore a specific production strategy is considered. The expected value with information is determined by weighting the net present value obtained from the scenarios using the specific production strategy. The value of perfect information is the difference between the expected values with and without information.

A transfer factor is used to compute the value of imperfect information. It represents a learning measure and indicates how effective the information is in reducing the uncertainty in the decision making process. The transfer factor is determined through a regression model derived from the technical scoring criteria introduced by Lumley *et al.* (1997).

The EVOI assessment of 4D seismic data is complex and requires several simplifications to make the process viable. However, it should consider the four aspects mentioned in Chapter 1:

- Date of acquisition: Chapter 2 discussed the impact that the date of 4D seismic acquisition has on the value of 4D seismic data. In summary, the acquisition cannot be too early because seismic data may not identify variations in the reservoir dynamic properties, or too late because major changes may no longer be detected and the flexibility in decision making is reduced; i.e., few changes can be made in the production strategy;
- Impact on field management: for a 4D seismic project to be considered an economic success, the provided information should impact field operations and should generate more monetary benefit than its acquisition cost;
- Reservoir uncertainties: the reservoir model used to assist the decision making process is developed under several physical uncertainties. Thus, the VOI should be assessed under uncertainty. The term Expected Value of Information (EVOI) should be used in this context;

- Other source of data: there are several potential sources of information that can improve the decision making process and can reduce the reservoir uncertainty.

A methodology to determine the EVOI that considers all aspects mentioned above is needed. The present chapter describes a methodology that estimates the EVOI considering the "date of acquisition" aspect. The methodology also incorporates a probabilistic approach in the estimation of the chance of success.

The chance of success methodology is applicable to projects in the development phase. The evaluation is performed considering the best production period to acquire 4D seismic data. If the result obtained does not indicate that 4D seismic data would improve the economic return of the project, the use of continuous acquisition also would not be viable.

4.2. Objective

The objective of the present Chapter is to describe the methodology that estimates the chance of success of a 4D seismic project before having 4D seismic data. The methodology uses the concept of EVOI and incorporates the methodology described in Chapter 2. Moreover, present its application to a synthetic reservoir model in order to test the methodology in a case with known answer.

4.3. Assumptions

The following assumptions are made:

- Pressure and saturation data are successfully obtained from 4D seismic data;
- 4D seismic data is considered as perfect information;
- All reservoir model uncertainties are identified and quantified.

4.4. Theoretical Concepts

The process comprises several methodologies used in reservoir engineering which are described in the next sections.

4.4.1. Uncertainty and Risk Analysis

Uncertainty is related to the lack of knowledge about reservoir properties, economics or technology. The uncertain attributes affect the decision-making during reservoir management. The uncertainty and risk analysis involve: identifying the reservoir uncertain attributes, generating scenarios through statistical combination, running the numerical simulation and determining the risk curve.

A team of geologists, geophysicists and engineers is responsible for the definition of the uncertain attributes. The uncertainty concerning the attributes value can be expressed in terms of probabilistic distributions; and each attribute can be discretized into uncertainty levels according to its probability density function (pdf). Usually three uncertainty levels are considered for each attribute: probable, optimistic and pessimistic (Steagall, 2001).

Depending on the quantity of uncertain attributes; it is necessary to perform a sensibility analysis, because not all uncertain attributes generate risk to a project (Becerra, 2011). Thus, the quantity of uncertain attributes can be reduced as soon as an uncertainty generates low or none variation in the reservoir simulation outputs.

The model is evaluated at lower and upper bounds of each uncertainty in turns. The results are traditionally displayed in a tornado plot, also known as Pareto. This type of plot helps the identification of the variables that have the most impact.

The critical attributes must be combined to generate scenarios that represent the reservoir uncertainty. Statistical techniques such as, derivation tree, Monte Carlo and Latin Hypercube are used. Among these techniques, the results obtained using the Latin Hypercube are more accurate (Risso *et al.*, 2011).

The Latin Hypercube Technique is characterized by the division of the uncertainties range into sub-regions, and the sample is realized in each region. The trials number in each region is defined proportionally to the probability of the specific region and each model probability of occurrence is defined by 1/N, where N is the total number of trials.

The risk curve that quantifies the project risk is obtained from the simulation results of the generated scenarios. The curve relates the objective function of each model to a cumulative probability of occurrence. An example of objective function is the net present value (NPV).

4.4.2. Representative Models

It is inefficient to estimate the 4D seismic chance of success considering all scenarios in the process. The number of scenarios generated in the uncertainty and risk analysis is high. Thus, representative models (RM) (that represent the reservoir uncertainties behavior) become necessary to guarantee a reliable analysis,

According to Ligero *et al*. (2005), the selection of representative models consists of choosing, among the simulated reservoir scenarios, the ones that better represent the variability of the attributes and the variability of the objective function. For this, cross plots of the objective function (NPV in the current study) and simulated production results (BHP and oil rate, for example) are obtained.

Reservoir models are chosen close to the scenarios considered as P10, P50 and P90. The percentile P90 means that there is a 90% probability of obtaining higher values than those associated with the index P90. The number of representative models depends on: (1) reliability needed, (2) objective of the analysis needed, and (3) variability of the objective function and the uncertain attributes.

4.4.3. Water Saturation Error Analysis

The concept of water saturation error and its use to evaluate the quality of a reservoir model considered as base model is presented in the section 3.4.3 in Chapter 3. The saturation error curve over a production period is used to identify if scenarios present a reservoir fluid flow movement different from that expected. If the water saturation error is low, the impact of 4D seismic information on the identification of the true earth model decreases.

4.4.4. Economic Analysis.

A parameter used in the economic evaluation of oil and gas projects is the Net Present Value (NPV). NPV is the discounted value of investment cash inflows minus the discounted value of its cash outflows. An investment should have a net present value greater than zero to be adequately profitable. The NPV is expressed as

$$NPV = \sum_{i=1}^{N} \frac{CF_i}{(1+r)^{t_i}}, \tag{4.1}$$

where, CF is the cash flow, *i* is the production period interval, *t* is the time related to the interval considered, *r* is the discount rate and *N* is the number of intervals considered.

Another important economic concept is the Expected Monetary Value (EMV). It is defined as the total of the outcomes multiplied by the corresponding probability of occurrence associated with a decision. The EMV is determined by

$$EMV = \sum_{j=1}^{N} P_j * NPV_j, \tag{4.2}$$

where, N is the number of possible scenarios, j represent a specific scenario and P is the probability of occurrence.

4.4.5. Value of Information

The estimation of the expected value of information (EVOI) is an important tool used in the decision making process. The risk level can be high in the field development phase, depending on the reservoir uncertainties. The acquisition of new information can increase the project's economic return due to the reduction of uncertainty and to the impact on reservoir management.

Bratvold *et al.* (2009) commented that the fundamental question for any information gathering process is whether the likely improvement in decision-making is worth the cost of the information. The EVOI technique is designed to answer this question.

The methodology used to estimate the EVOI is based on Ligero *et al*. (2005), which integrates the decision tree analysis, risk analysis, uncertainty probabilistic approach and the production strategy optimization into the process. As the EVOI methodology is assessed under uncertainty and uses a probabilistic approach, the term Expected Value of Information (EVOI) is used. If the decision maker is risk neutral, EVOI is obtained by

$$\mathrm{EVOI}=\mathrm{EMV}_{\text{with information}} - \mathrm{EMV}_{\text{without information}} . \tag{4.3}$$

The change of the EMV is linked to the impact on the field management due to the acquisition of new information. Moreover, if the decision maker makes the same decision no matter how the test results, then EVOI is equal to zero and the acquisition of new information is worthless.

The $EMV_{without\ information}$ is determined by applying a fixed production strategy, which maximizes the EMV, to all representative models. It is assumed that the base model production strategy maximizes the expected monetary value (EMV). It is represented by

$$EMV_{without\,information} = \sum_{i=1}^{N_{RM}} \left(NPV_{RM_{i,base\,strategy}} \cdot P_{RM_i}\right), \tag{4.4}$$

where, P is the probability of the representative model, N_{RM} is the number of representative models.

The $EMV_{with\ information}$ is determined by applying a specific production strategy developed for each representative model. It is represented by

$$EMV_{with\,information} = \sum_{i,s=1}^{N_{RM}} \left(NPV_{RM_{i,w}} \cdot P_{RM_i}\right), \tag{4.5}$$

where, s is the specific production strategy for each representative model.

Even when the economic parameter EVOI does not indicate that the acquisition of new information can improve the project economic return, the impact on the project risk should be evaluated.

According to Marques et al. (2013), the concept of risk varies depending on the decision makers' profile and objective of the study. The standard deviation normalized by the EMV is used to quantify the risk; however this concept was not applied in the thesis.

4.5. Proposed Methodology

The proposed methodology follows the process described in Figure 4.1. The process comprises six stages in which two of them (highlighted in red) are the main contributions of the thesis.

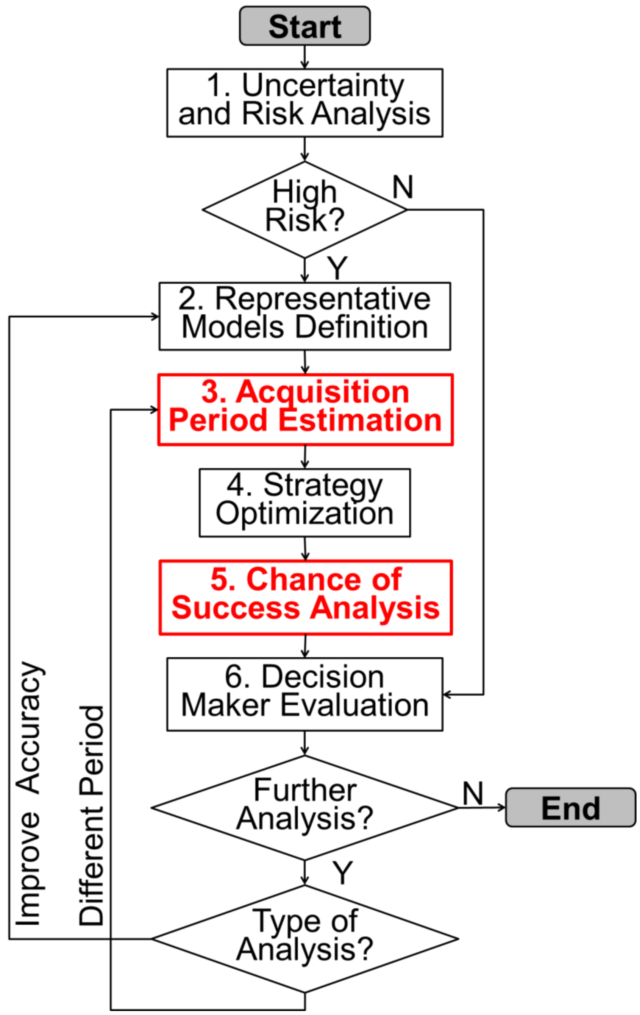


Figure 4.1. Methodology to estimate the 4D seismic chance of success.

4.5.1. Uncertainty and Risk Analysis

This first stage defines the reservoir model uncertainty parameters. Using a statistical procedure to combine these uncertainties, all possible scenarios are generated and the base model is chosen (usually the scenario with a probability of occurrence of 50%).

The production strategy is optimized considering only the base model to determine the base production strategy. With an economic analysis the NPV of each scenario is determined considering the base production strategy.

The range of NPV obtained indicates the projects risk level. The decision maker risk profile defines if the NPV range represents high risk or not. If the project is considered high risk, the acquisition of 4D seismic data would reduce the risk and improve reservoir management, so the estimation process proceeds. For low risk, the decision maker can decide to not acquire 4D seismic data.

4.5.2. Representative Models Definition

The many possible scenarios make the selection of representative models necessary. The chance of success estimation includes the evaluation of the impact on the reservoir management through the strategy optimization. Thus, it would be time consuming to analyze all possible scenarios.

The selection of the representative models is done by plotting the main objective function (e.g. NPV) against the secondary objective function (e.g. RF, Np) and choosing scenarios that represent both values variation. The minimum number of representative models must be the one in which there is no significant variation on the EVOI result (Schiozer *et al.,* 2004; Costa & Schiozer, 2008).

4.5.3. Acquisition Period Estimation (Engineering Perspective)

The utility of 4D seismic data varies depending on the date of 4D seismic data acquisition. The importance of estimating the best time to acquire 4D seismic data was described in Chapter 2 and the methodology to determine the acquisition period was presented in Chapter 3.

The chance of success methodology provides a first estimative of the economic benefits due to 4D seismic data, thus the evaluation is performed considering the best period for 4D seismic data acquisition. The period is such that there is significant variation in the dynamic properties and there is enough time to impact on the reservoir management.

The information that comes from 4D seismic data is evaluated in terms of water saturation map. A production period is considered the best for 4D seismic data acquisition when it is possible to identify that the base reservoir model does not represent the true earth model and enables to anticipate the breakthrough at production wells.

The best production period estimation is done at the development phase and it is assumed that the period is suitable from the geophysical perspective.

4.5.4. Strategy Optimization

The production strategy of each representative model is optimized from the moment of data acquisition and processing to quantify the economic impact of the acquired 4D seismic data. The information is considered perfect, thus 4D seismic data identifies the true earth model represented by the representative models.

The objective of the optimization process is to improve the production strategy and increase the objective function until a predefined criterion is obtained. Net Present Value (NPV) is the objective function considered in this study.

4.5.5. Chance of Success (COS) Analysis

The net present values of each representative model obtained applying the base production strategy and the specific production strategy are compared. The increment on the NPV is the economic benefit due the information acquisition.

In general the impact on the reservoir management is measured by quantifying the expected value of information (EVOI). However, the EVOI is a mean value and does not show the variability of the economic impact on the project.

Thus, the chance of success methodology introduces a new way to analyze the increase on the economic value of the project due to new data. The production strategy optimization of each representative model provides the increase of the NPV and its probability of occurrence, a probability density curve is then calculated. It shows the variability of the economic impact and the probability that the increase on the NPV is higher than the cost of data acquisition and processing.

4.5.6. Decision Maker Evaluation

Based on the data provided in the chance of success analysis stage, the decision maker may take the following actions:

- End the process: the decision maker decides to acquire or to not acquire 4D seismic data;
- Continue the analysis: the decision maker decides to continue the process. Three are the possibilities: (1) to improve the evaluation accuracy by selecting more representative

models, (2) to evaluate a different acquisition period or (3) to improve the strategy optimization procedure.

4.6. Application

The chance of success methodology was applied to a synthetic model. The reservoir model description and uncertainties are presented in the next sections.

4.6.1. Reservoir Model Description

The reservoir model was generated with information from three exploratory wells according to a prior geological and structural interpretation. The reservoir model presents two facies: Facie 1 corresponds to a sandstone type rock and Facie 2 corresponds to a shaly sandstone type. Tables 4.1 and 4.2 show the reservoir model properties and PVT table, respectively. Figure 4.2 shows the relative permeability curves for the oil and water phases for both facies and Figure 4.3 presents the porosity, permeability, NTG and facies for the third layer.

Table 4.1. Reservoir model properties.

Property	**Value**
Reservoir thickness	60m
Grid dimension	90x110x9 (blocks)
Blocks dimension	60x60x6.67 (m)
Number of active blocks	41085
Number of faults	4
Total pore volume	111,321E+03 m^3
Volume of oil in place	88,475E+03 m^3
Volume of water in place	22,267E+03 m^3
Volume of gas in place	6,935E+06 m^3
Oil density	887 kg/m^3
Initial pressure	322 kgf/cm^2
Depth reference	2700 m
WOC	3262 m
Bubble point pressure	210 kgf/cm^2
API	27.9°

Table 4.2. Reservoir model PVT table.

P (kgf/cm^2)	RS (m^3/m^3)	BO (m^3/m^3)	BG (m^3/m^3)	VISO (mPa-s)	VISG (mPa-s)	CO (1/kgf/cm^2)
1.03	0.00	1.060	0.637	5.38	0.0103	0.000181
41.03	30.74	1.197	0.03185	3.18	0.017	0.000161
81.03	48.93	1.245	0.01554	2.65	0.0205	0.000156
121.03	65.98	1.288	0.01013	2.29	0.024	0.00015
161.03	83.84	1.331	0.00745	2.00	0.0243	0.000143
201.1	102.50	1.378	0.00602	1.77	0.0245	0.000142
248.03	126.50	1.439	0.00504	1.57	0.025	0.000134
261.03	133.00	1.448	0.004	1.45	0.0251	0.000131
301.03	153.03	1.494	0.0035	1.32	0.0252	0.000129
341.03	174.06	1.556	0.0031	1.22	0.0253	0.000126
361.03	184.09	1.582	0.0029	1.16	0.0254	0.000123
500.03	271.63	1.763	0.0021	0.80	0.0258	0.000112

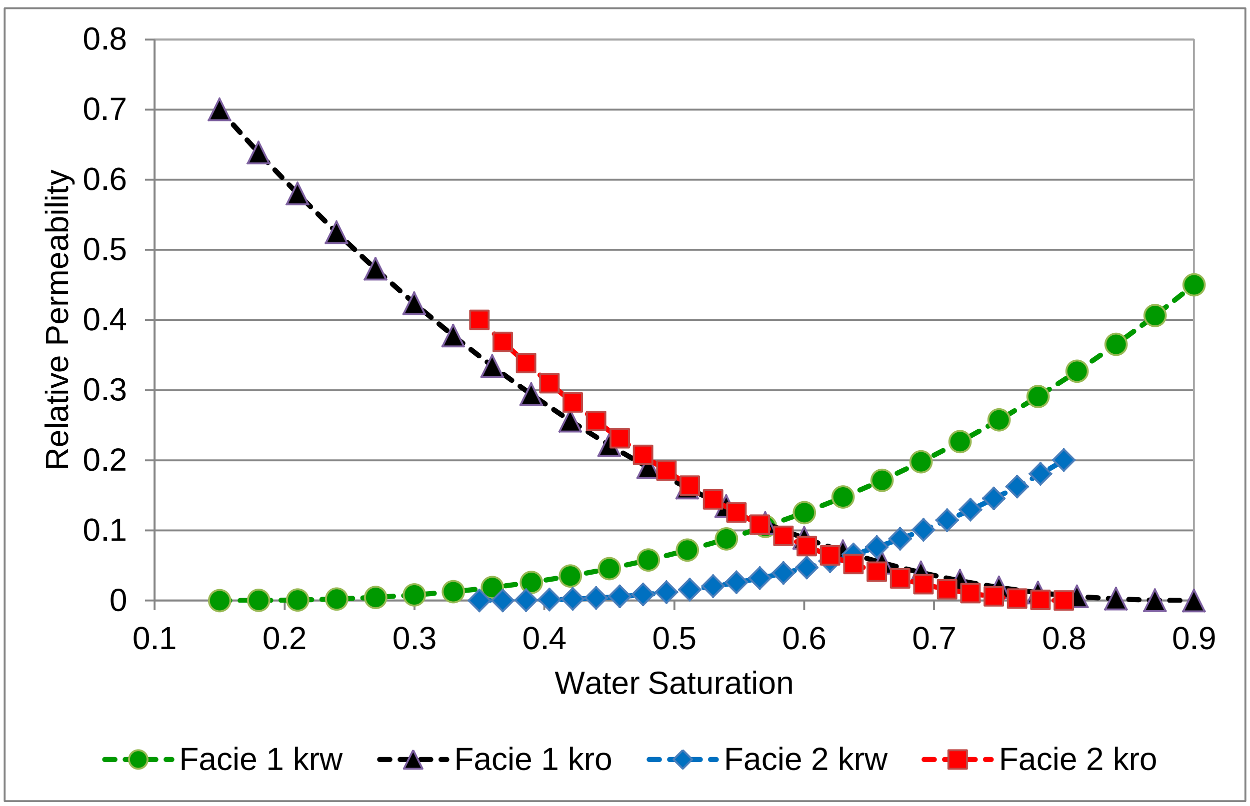


Figure 4.2. Water and oil relative permeability curves for both facies.

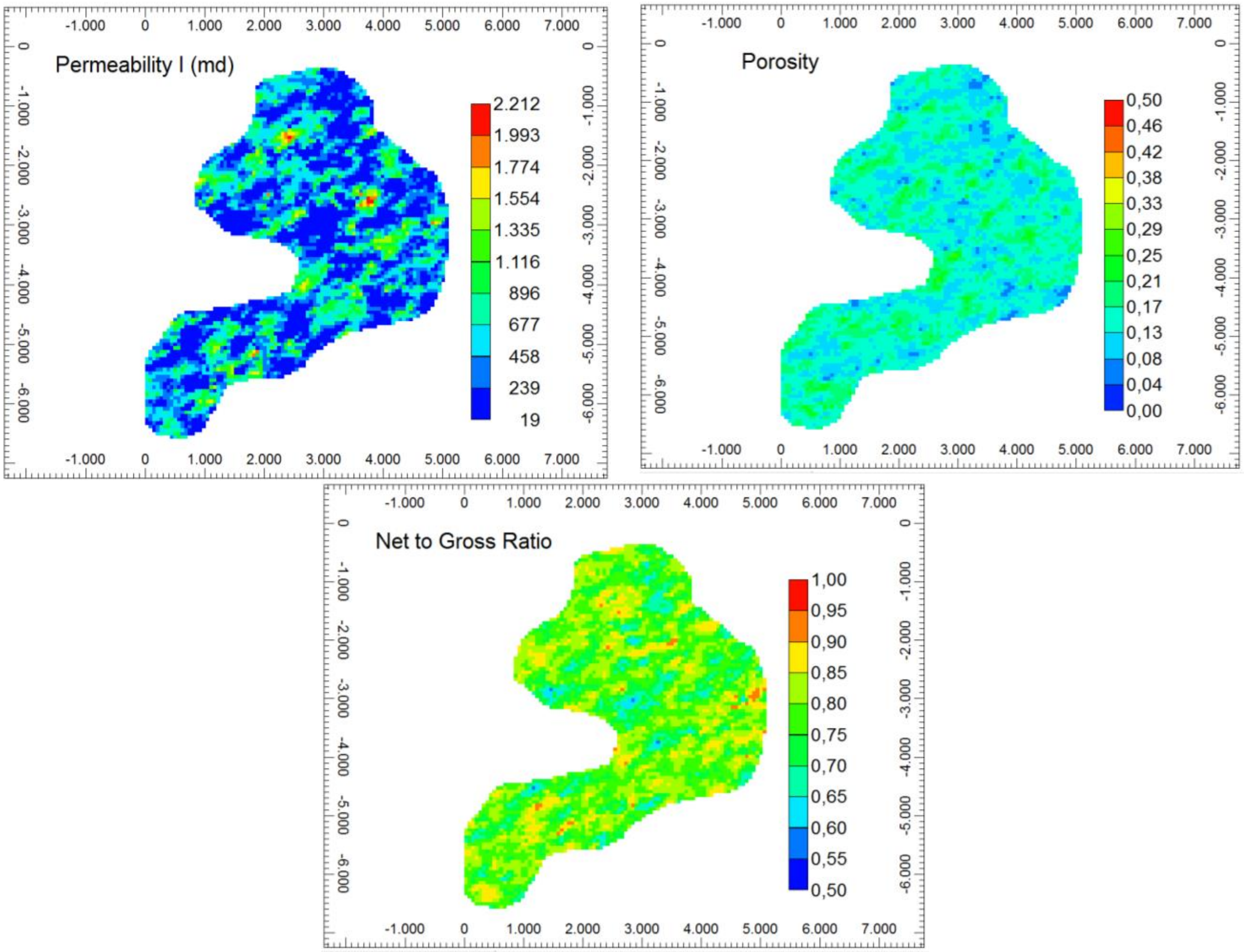


Figure 4.3. Grid properties of the third layer

The reservoir production strategy was defined by optimizing the base model. The reservoir model was simulated in a black oil commercial simulator (IMEX 2010) for 30 years of production with a start date at 01/01/2008. The production strategy consists of fourteen production wells and ten water injector wells. Figure 4.4 shows the base production strategy.

Production wells were completed in layers one to four and the injector wells were completed in layers five to nine. The well and group production constrains are presented in Table 4.3

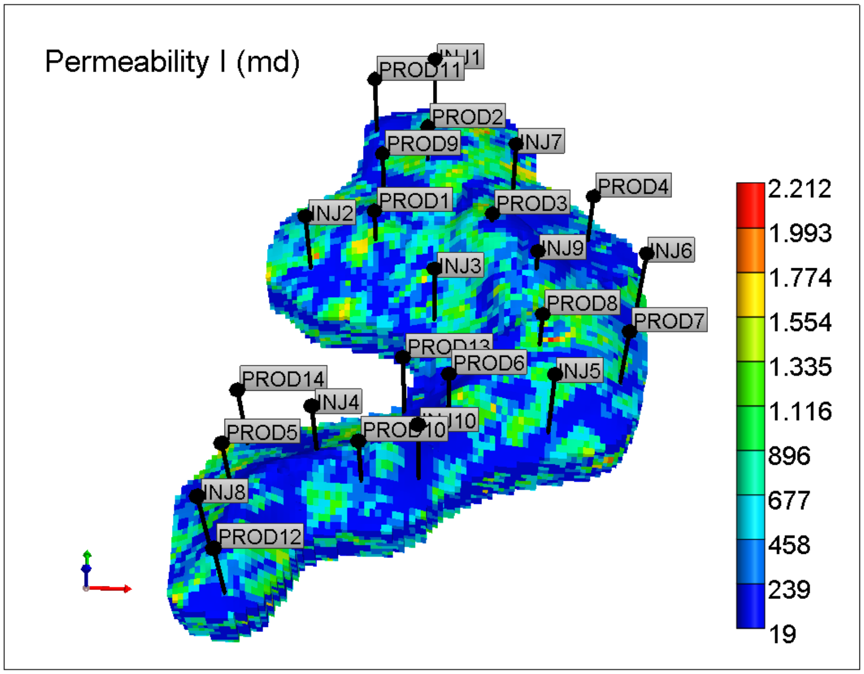


Figure 4.4. Base model production strategy.

Table 4.3. Production constraints

Group	Operational Condition	Value
Production wells	minimum bottom hole pressure (BHP)	215 kgf/cm²
	maximum water cut (WCUT)	0.95
Injector wells	maximum bottom hole pressure (BHP)	215 kgf/cm²
Field	maximum total surface liquid rate (STL)	23000 m³/day
	maximum surface water rate (STW)	23000 m³/day

4.6.2. Reservoir Model Uncertainties

The reservoir model uncertainties definition and quantification is done in the developing phase, so there are many associated uncertainties. The uncertain attributes of the reservoir model under analysis were divided into two groups: discrete attributes and map attributes.

The discrete uncertain attributes were divided into six levels and are presented in Table 4.4; while the maps attributes are: (1) permeability map; (2) porosity map; (3) NTG map and (4) facies distribution. Five hundred maps of each map type (1, 2, 3 and 4) were generated using the Petrel Software.

Table 4.4. Discrete uncertain attributes and level values.

Uncertain Attribute	Level					
	0	1	2	3	4	5
kr (sandstone)	2.50	1.00	2.00	3.00	4.00	5.00
kr (shaly sand)	2.50	1.00	2.00	3.00	4.00	5.00
kz/kx	0.15	0.02	0.09	0.16	0.23	0.30
Trans. (Fault 1)	0.50	0.00	0.001	0.01	0.10	1.00
Trans. (Fault 2)	0.50	0.00	0.001	0.01	0.10	1.00
Trans. (Fault 3)	0.50	0.00	0.001	0.01	0.10	1.00
Trans. (Fault 4)	0.50	0.00	0.001	0.01	0.10	1.00

4.7. Results

The results obtained for each methodology stage applied to the synthetic reservoir model are presented in the next sections.

4.7.1. Uncertainty and Risk Analysis

Due to the many uncertainty attribute levels, the Latin Hypercube was used to generate 500 scenarios. All attributes have a uniform distribution. The field production results from all scenarios and from the base model are presented in Figures 4.5, 4.6 and 4.7. The base model is one combination of all uncertainties.

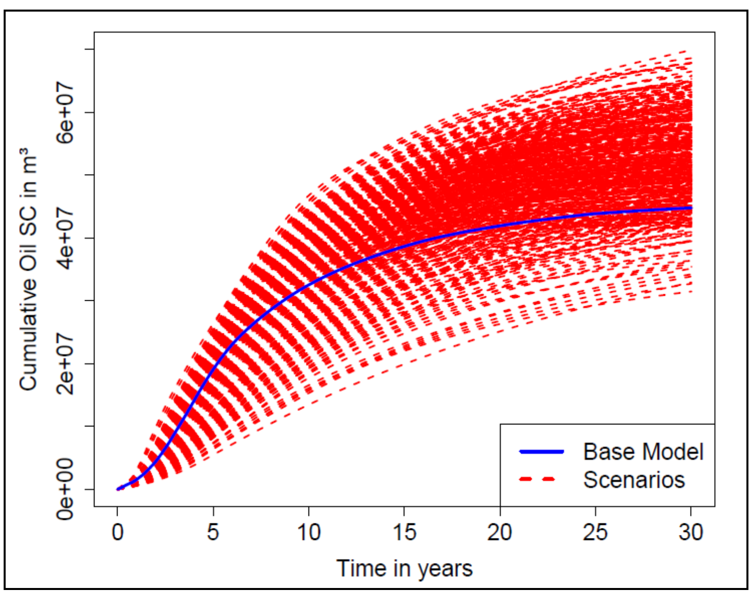


Figure 4.5. Scenarios and base model field cumulative oil.

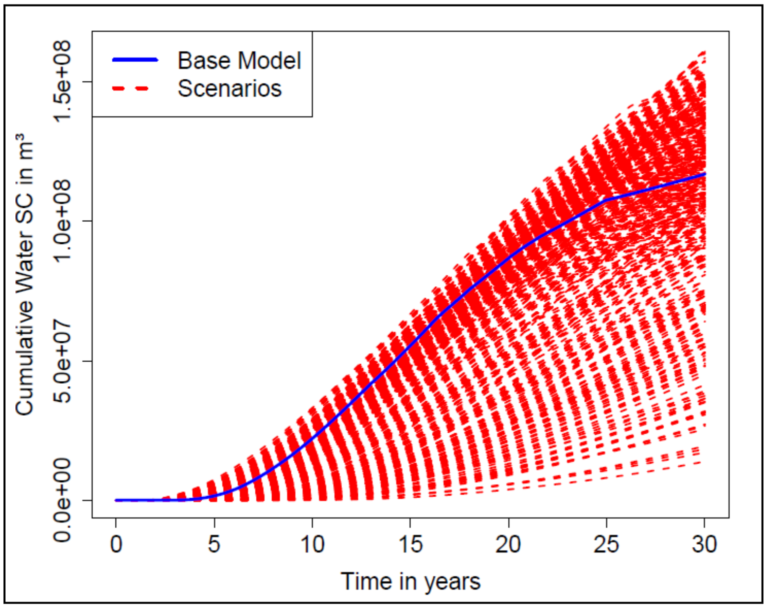


Figure 4.6. Scenarios and base model field cumulative water.

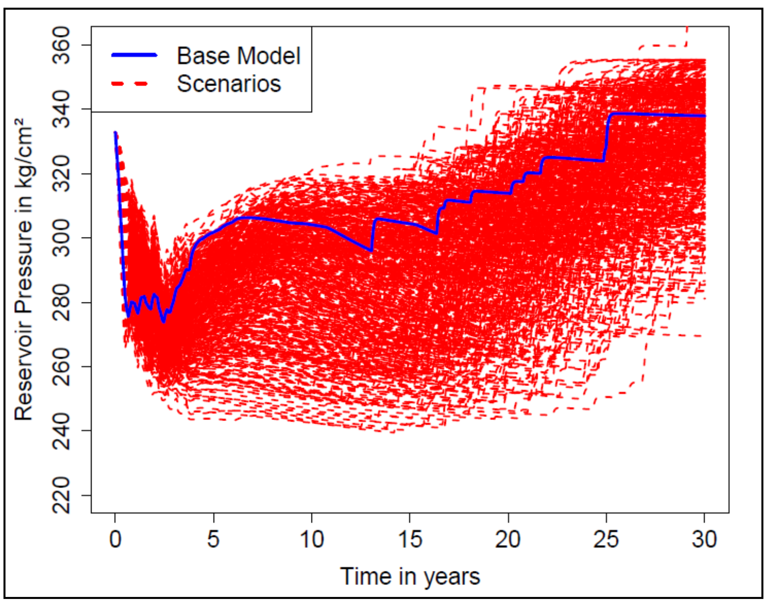


Figure 4.7. Scenarios and base model reservoir pressure.

The NPV was calculated using the UNIPAR-MEC software and the base model production strategy was applied to each scenario. The price context and the costs are presented in Table 4.5. Although the production costs vary with oil prices, this was not considered to keep it simple. The risk curve obtained is shown in Figure 4.8 along with the values of NPV for the representative models.

At the end of the uncertainty and risk analysis stage, the decision maker decides whether to continue or to end the process based on the risk curve. The risk level indicates if the acquisition of new information is necessary to reduce the reservoir uncertainties.

In the case studied, the NPV has a variation of approximately US$ 3 billion. The NPV variation was considered a high value confirming the need for more information. Thus, the process to estimate the chance of success continues.

Table 4.5. Economic scenario.

Index	Value
Royalties	10%
PIS/PASEP + COFINS	9,25%
Income Tax +Social Contribution	34%
Discount Rate	10%
Platform Investment	$740 Million
Abandonment Cost	$74 Million
Well Cost	$35 Million
Brent Value	314.5 US$/m³
Reference Date	01/01/2008

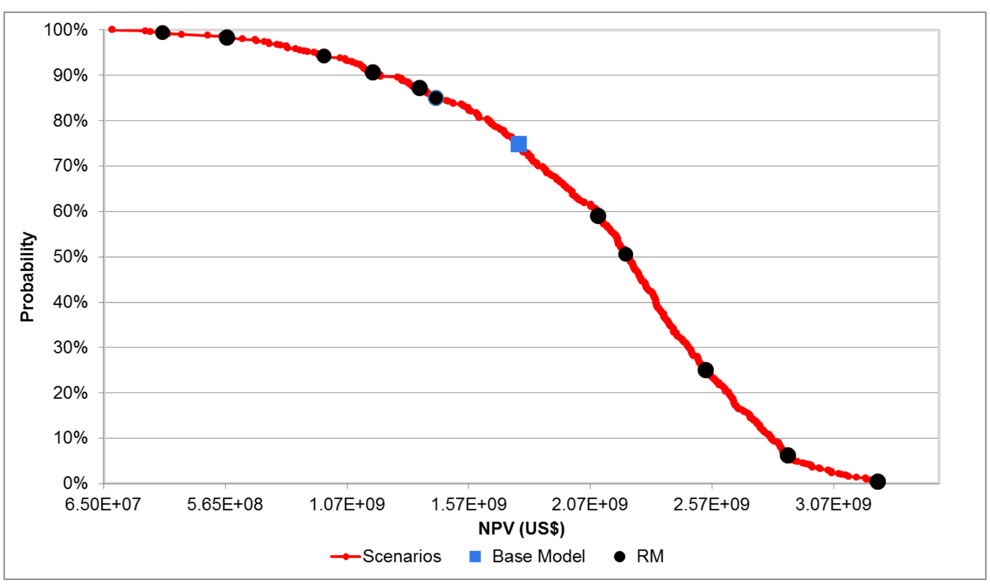


Figure 4.8. Risk curve.

4.7.2. Representative Models Selection

In the case studied the acquisition of 4D seismic data shows which of the possible scenarios represents the true earth model. The chance of success is related to the impact on the reservoir management after the acquisition of the information.

As it would be time-consuming to estimate the impact of 4DS acquisition for all possible scenarios for a specific production period, it is necessary to select simulation models that represent the reservoir uncertainties variation.

The representative models were chosen based on production data (RF, Np and Wp) *versus* economic data (NPV) cross plots. The selection of the representative models can be done several times, with the objective to improve the EVOI accuracy (Figure 4.1). Each loop is called a stage, the number of stages is such that the difference between the EVOI calculated from consecutive stages is less than 5%.

In the current study, the representative models selection was done in four stages. The production and economic results of all representative models are presented in Table 4.6.

Table 4.6. Representative models results using base model production strategy.

Model	NPV (US$ x 10^9)	RF (%)	Np (m^3 x 10^7)	Wp (m^3 x 10^7)
Base	1.770	69.1	4.48	11.70
RM1	1.364	58.6	4.61	8.68
RM2	3.246	72.3	6.70	14.28
RM3	2.877	67.0	6.11	13.72
RM4	2.539	68.5	5.48	12.32
RM5	0.307	47.5	3.39	3.75
RM6	0.970	62.9	3.95	6.97
RM7	2.211	67.7	5.67	10.38
RM8	0.573	52.3	3.80	1.94
RM9	2.096	63.1	5.05	10.44
RM10	1.170	52.8	4.57	3.16
RM11	1.431	58.6	5.00	5.83

The probability of each representative model is determined by

$$P_{RM_r} = \left(\frac{N_{SCNr}}{T_{SCN}}\right) \cdot 100, \quad (4.6)$$

where P_{RMr} is the probability of the representative model *r*, N_{SCNr} is the number of scenarios that has the lowest "distance" value *(d)* with respect to the representative model RM_r and T_{SCN} is the total number of scenarios.

"Distance" is a comparison between the production and economic results from each scenario to each representative model. The distance is calculated by

$$d_{jr} = \left(Np_j - Np_{RM_r}\right)^2 + \left(Wp_j - Wp_{RM_r}\right)^2 + \left(RF_j - RF_{RM_r}\right)^2 + \left(NPV_j - NPV_{RM_r}\right)^2, \quad (4.7)$$

where *d* is the distance of the production and economic results from the scenario *j* to the representative model (RM_r) under analysis.

A schematic example is presented in Table 4.7. The total number of representative models is equal to three and the total number of scenarios (T_{SCN}) is equal to ten.

Table 4.7. Representative model probability: schematic example.

Scenario (j = 1 to 10)	Representative Model RMr (r = 1 to 3)			Lowest Distance
	RM_1	RM_2	RM_3	
	Distance (d_{jr})			
1	$d_{1,1}$	$d_{1,2}$	$d_{1,3}$	$d_{1,1}$
2	$d_{2,1}$	$d_{2,2}$	$d_{2,3}$	$d_{2,2}$
3	$d_{3,1}$	$d_{3,2}$	$d_{3,3}$	$d_{1,1}$
4	$d_{4,1}$	$d_{4,2}$	$d_{4,3}$	$d_{4,3}$
5	$d_{5,1}$	$d_{5,2}$	$d_{5,3}$	$d_{5,3}$
6	$d_{6,1}$	$d_{6,2}$	$d_{6,3}$	$d_{6,2}$
7	$d_{7,1}$	$d_{7,2}$	$d_{7,3}$	$d_{7,2}$
8	$d_{8,1}$	$d_{8,2}$	$d_{8,3}$	$d_{8,1}$
9	$d_{9,1}$	$d_{9,2}$	$d_{9,3}$	$d_{9,3}$
10	$d_{10,1}$	$d_{10,2}$	$d_{10,3}$	$d_{10,2}$

The number of scenarios that presents the lowest "distance" value with respect to:

- Representative model RM_1: $N_{SCN1} = 3$;

- Representative model RM_2: $N_{SCN2} = 4$;
- Representative model RM_3: $N_{SCN3} = 3$.

The probability of each representative model is calculated using Equation 4.6:

- Representative model RM_1: $P_{RM1} = (N_{SCN1} / T_{SCN}) = 0.3$;
- Representative model RM_2: $P_{RM2} = (N_{SCN2} / T_{SCN}) = 0.4$;
- Representative model RM_3: $P_{RM3} = (N_{SCN3} / T_{SCN}) = 0.3$;

4.7.2.1 Stage 1

Three reservoir models were selected: base model, pessimistic model and optimistic model. The pessimistic and optimistic models were selected based on the NPV of all scenarios. The main objective was to verify if the increase on the NPV values, due to information acquisition, for the extreme models would be the maximum that could be obtained.

The pessimistic and optimistic models are called RM2 and RM5, respectively. The production and economic results are presented in Table 4.6, the probability of each representative model is shown in Table 4.8 and the cross plots are presented in Figures 4.9 to 4.12.

Table 4.8. Stage 1: probability of the representative models.

Representative Model	**N_{SCN}**	**Probability (%)**
Base	331	66.2
RM2 (pessimistic)	137	27.4
RM5 (optimistic)	32	6.4
Total	500	100

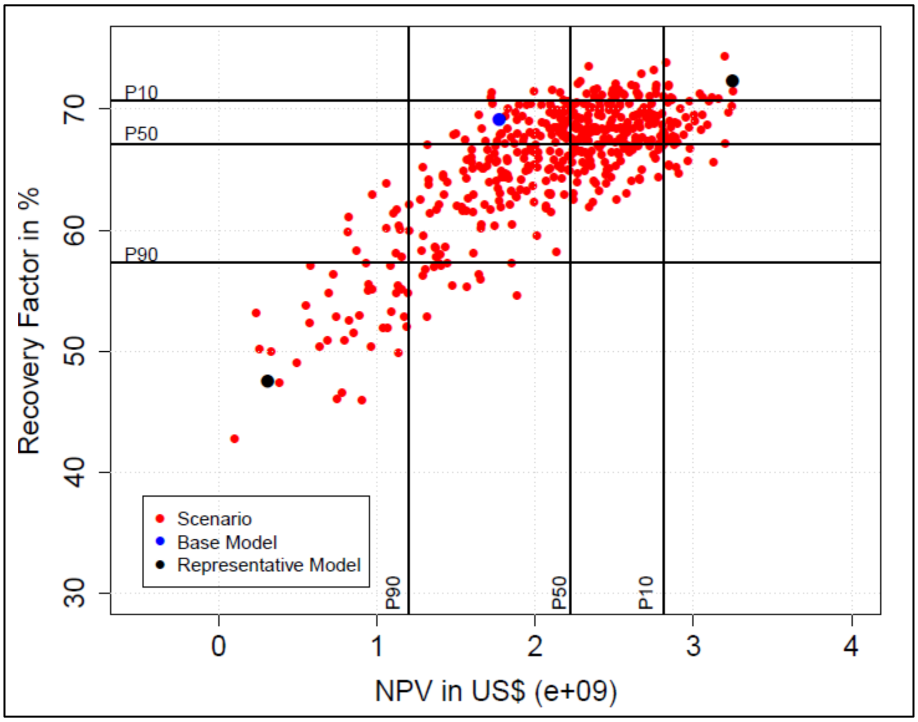


Figure 4.9. Stage 1: RF *versus* NPV.

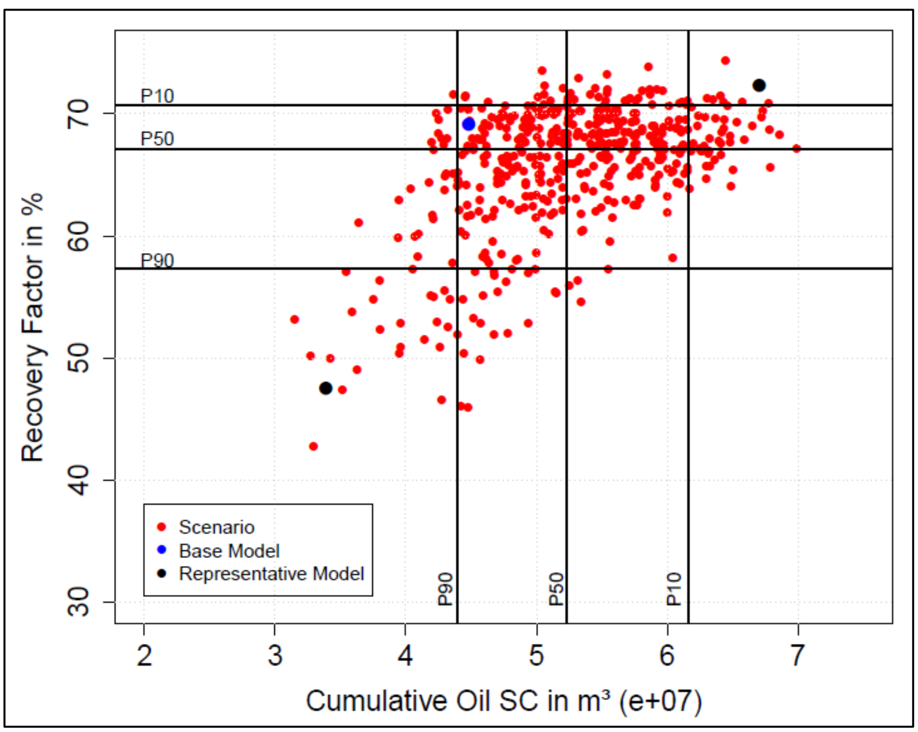


Figure 4.10. Stage 1: RF *versus* NP.

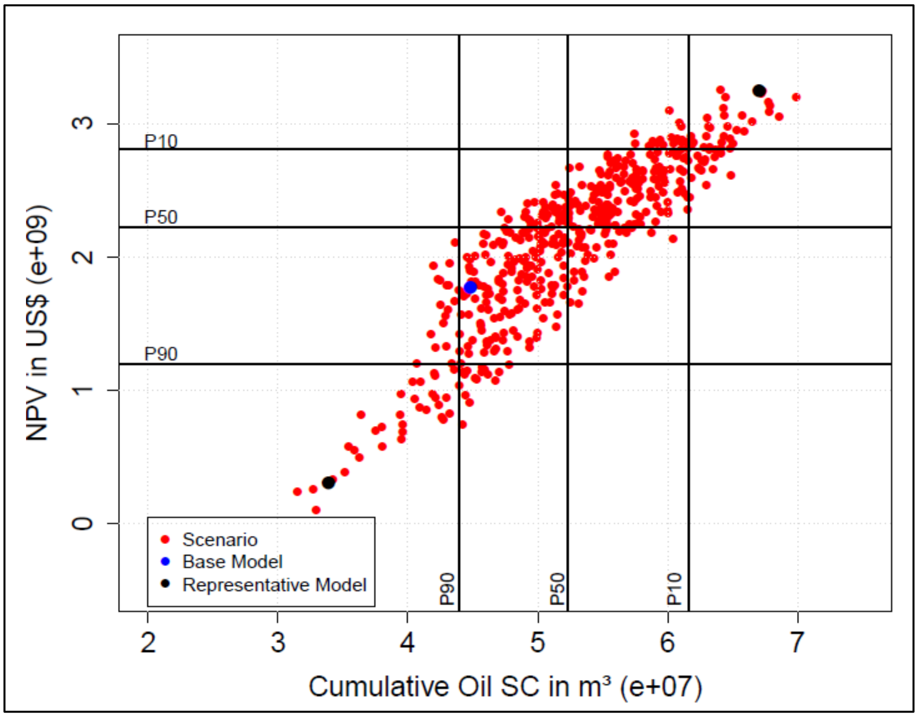


Figure 4.11. Stage 1: NP *versus* NPV.

4.7.2.2 Stage 2

In the second stage two more representative models were selected. The representative models considered were: base model, RM2, RM5, RM7 and RM10. The probability of each representative model is shown in Table 4.9 and the cross plots are presented in Figures 4.12 to 4.15.

Table 4.9. Stage 2: probability of the representative models.

Representative Model	N_{SCN}	**Probability (%)**
Base	101	20.2
RM2	71	14.2
RM5	14	2.8
RM7	250	50.0
RM10	64	12.8
Total	500	100

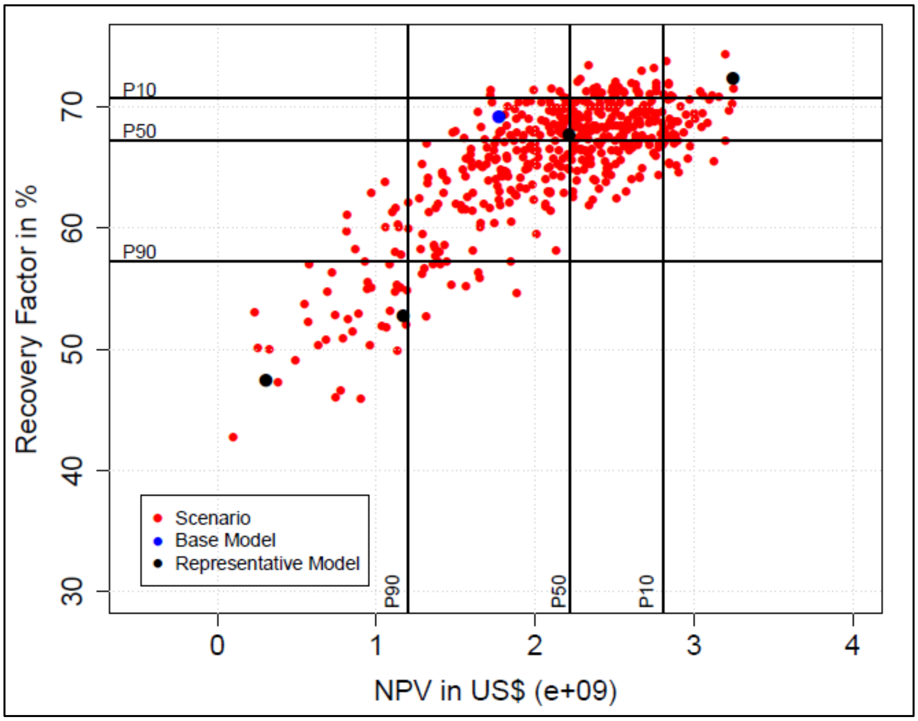


Figure 4.12. Stage 2: RF *versus* NPV.

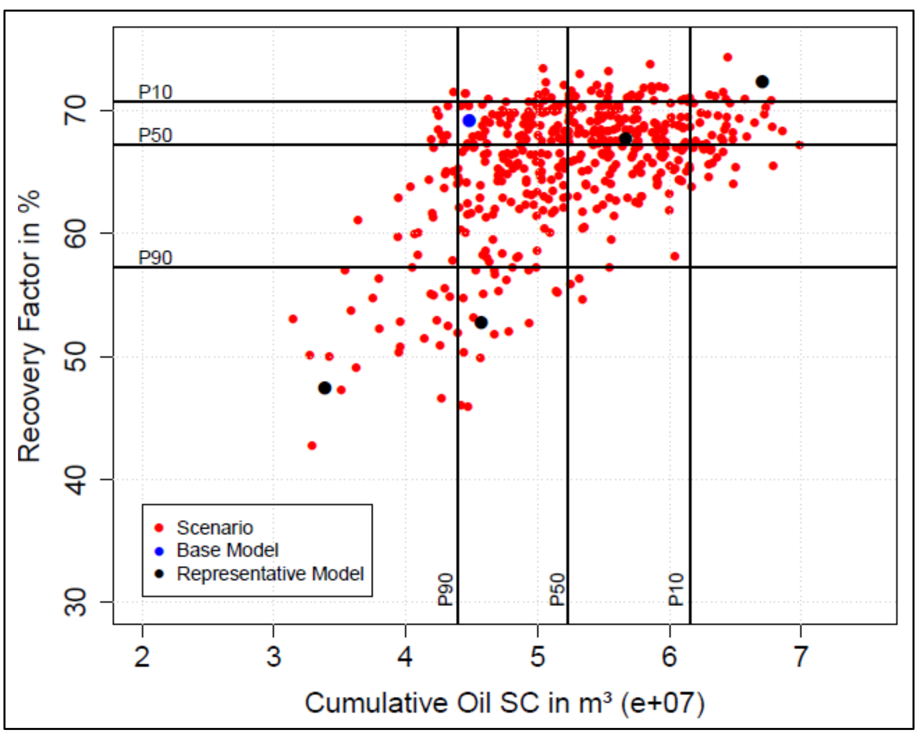


Figure 4.13. Stage 2: RF *versus* NP.

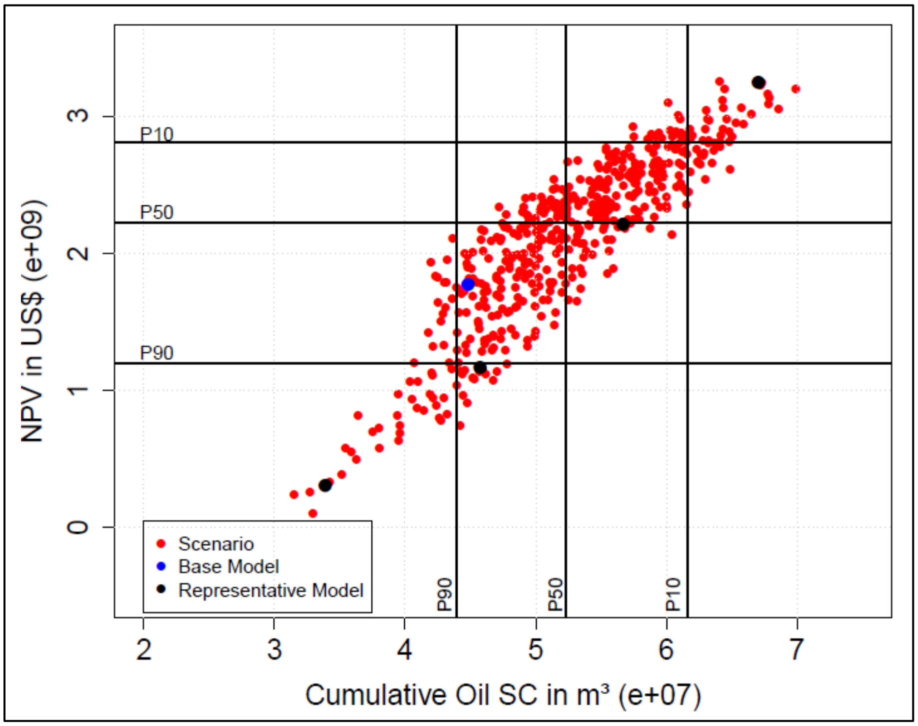


Figure 4.14. Stage 2: NP *versus* NPV.

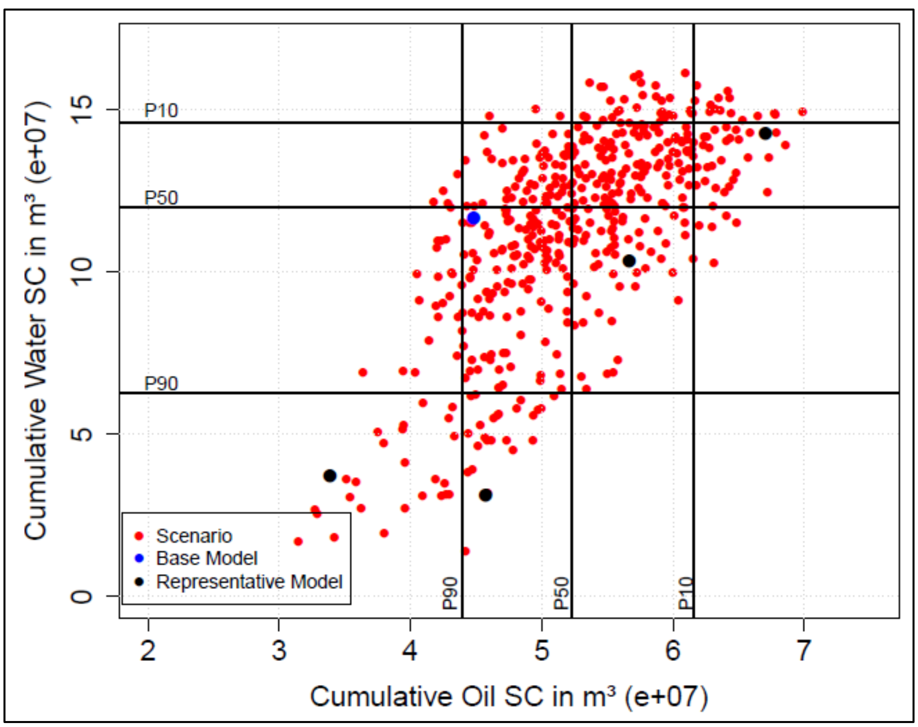


Figure 4.15. Stage 2: WP *versus* NP.

4.7.2.3 Stage 3

In the third stage seven representative models were selected: base model, RM2, RM4, RM5, RM7, RM9 and RM10. The probability of each representative model is shown in Table 4.10 and the cross plots are presented in Figures 4.16 to 4.19.

Table 4.10. Stage 3: probability of the representative models.

Representative Model	N_{SCN}	**Probability (%)**
Base	88	17.6
RM2	27	5.4
RM4	154	30.8
RM5	14	2.8
RM7	96	19.2
RM9	57	11.4
RM10	64	12.8
Total	500	100

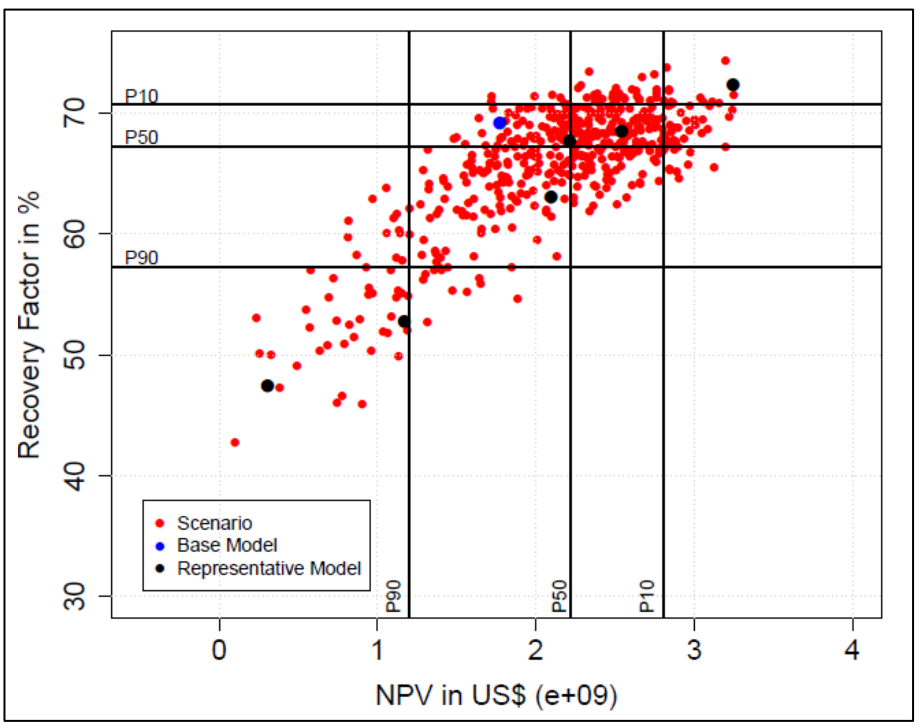


Figure 4.16. Stage 3: RF *versus* NPV.

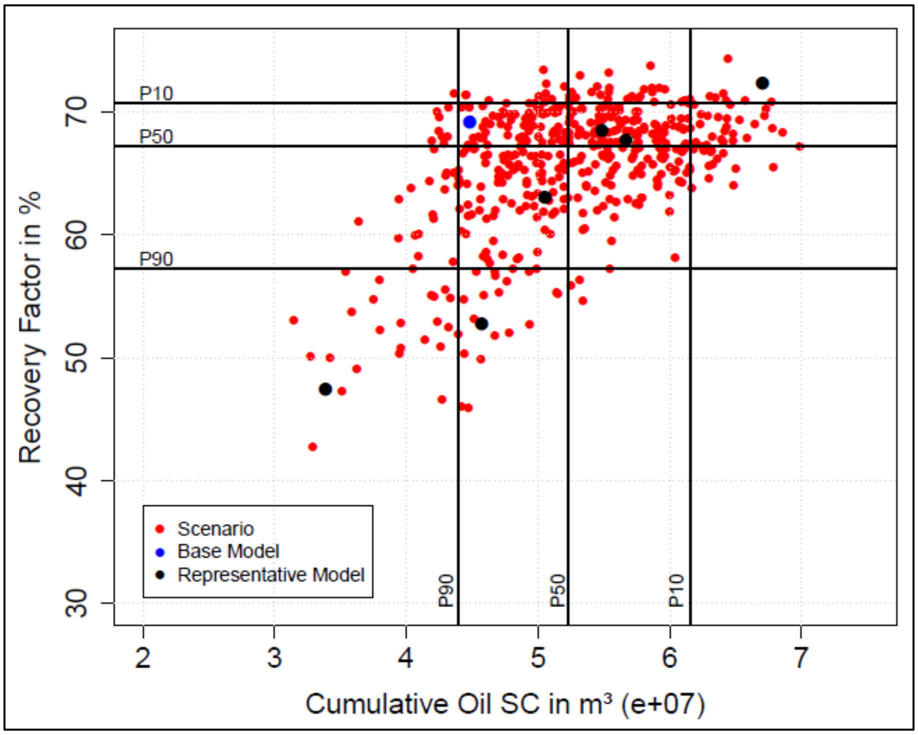


Figure 4.17. Stage 3: RF *versus* NP.

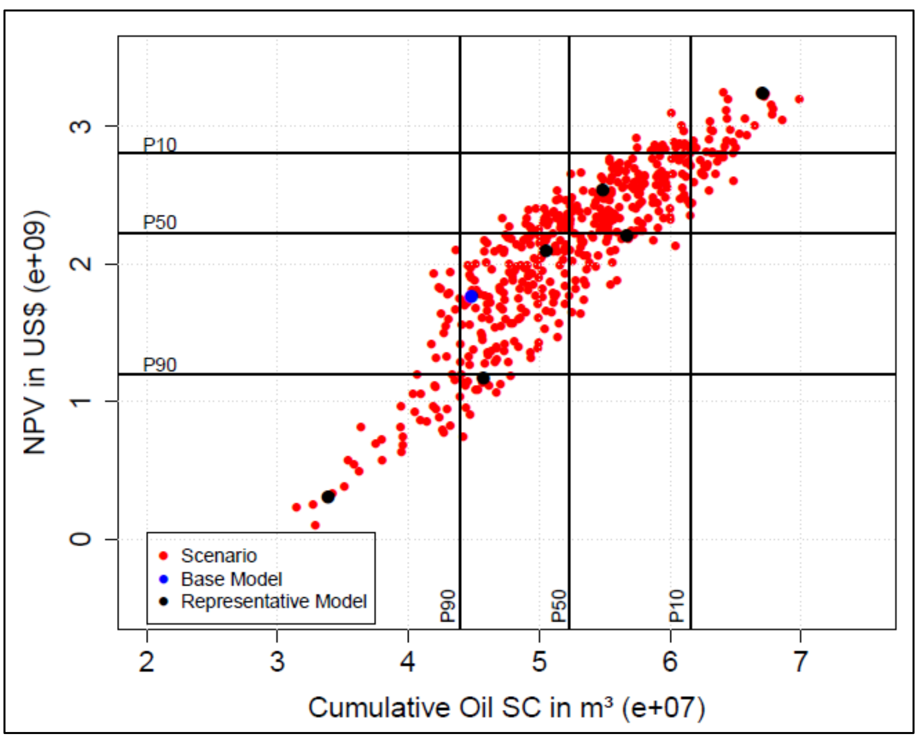


Figure 4.18. Stage 3: NP *versus* NPV.

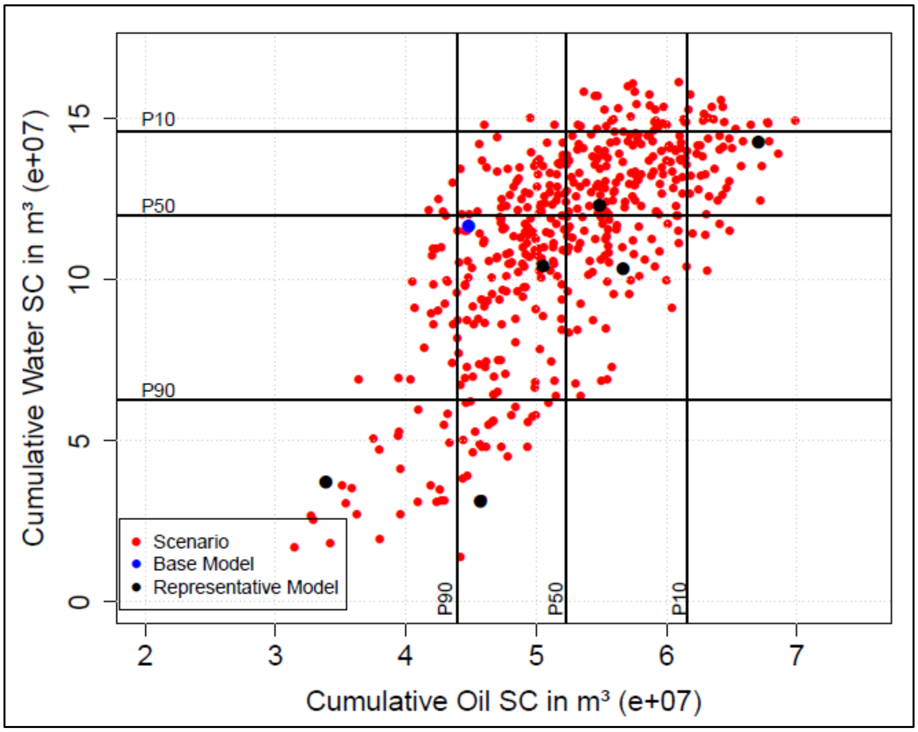


Figure 4.19. Stage 3: WP *versus* NP.

4.7.2.4 Stage 4

Stage 4 is the last stage, because the difference in EVOI obtained in Stage 04 and Stage 03 is less than 5%. The representative models selected were: base model, RM1, RM2, RM3, RM4, RM5, RM6, RM7, RM8, RM9, RM10 and RM11. The probability of each representative model is shown in Table 4.11 and the cross plots are presented in Figures 4.20 to 4.23.

Table 4.11. Stage 4: probability of the representative models.

Representative Model	N_{SCN}	**Probability (%)**	**Representative Model**	N_{SCN}	**Probability (%)**
Base	73	14.6	RM6	19	3.8
RM1	19	3.8	RM7	96	19.2
RM2	11	2.2	RM8	10	2.0
RM3	67	13.4	RM9	57	11.4
RM4	103	20.6	RM10	17	3.4
RM5	6	1.2	RM11	22	4.4

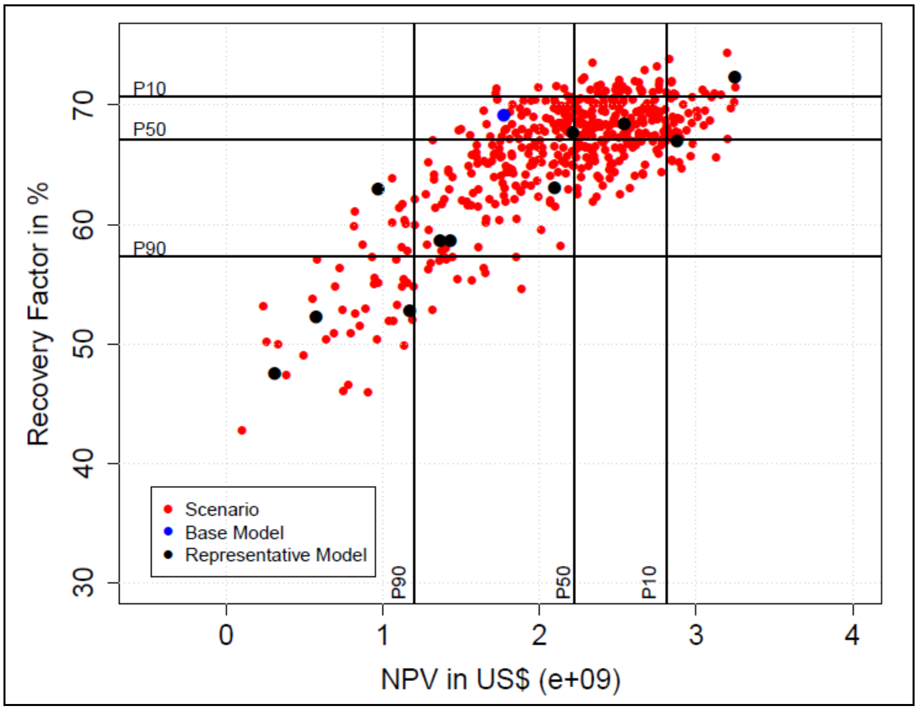


Figure 4.20. Stage 4: RF *versus* NPV.

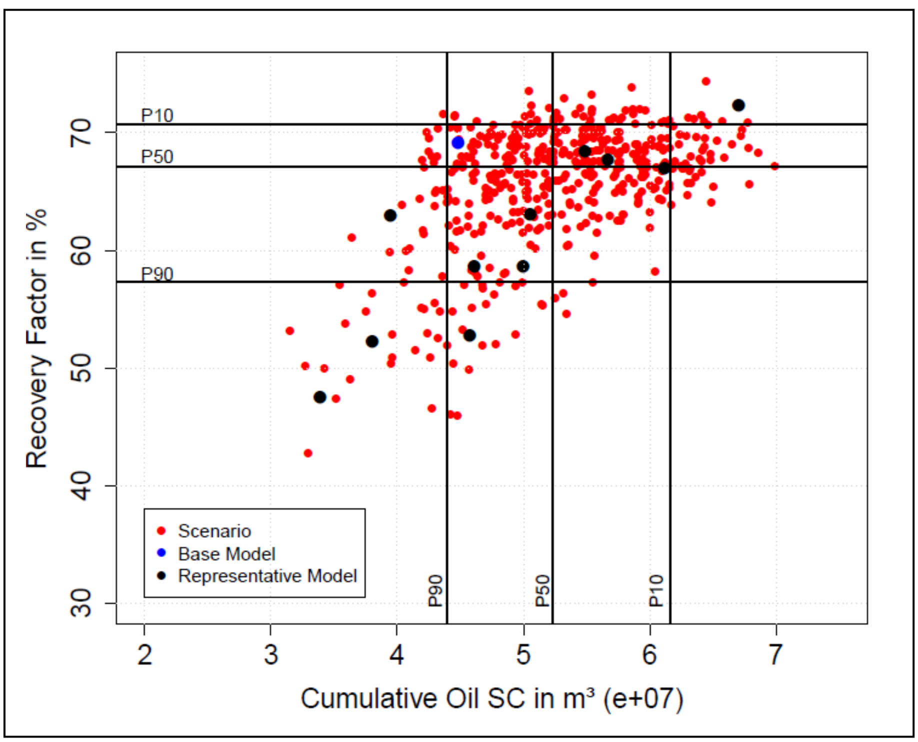


Figure 4.21. Stage 4: RF *versus* NP.

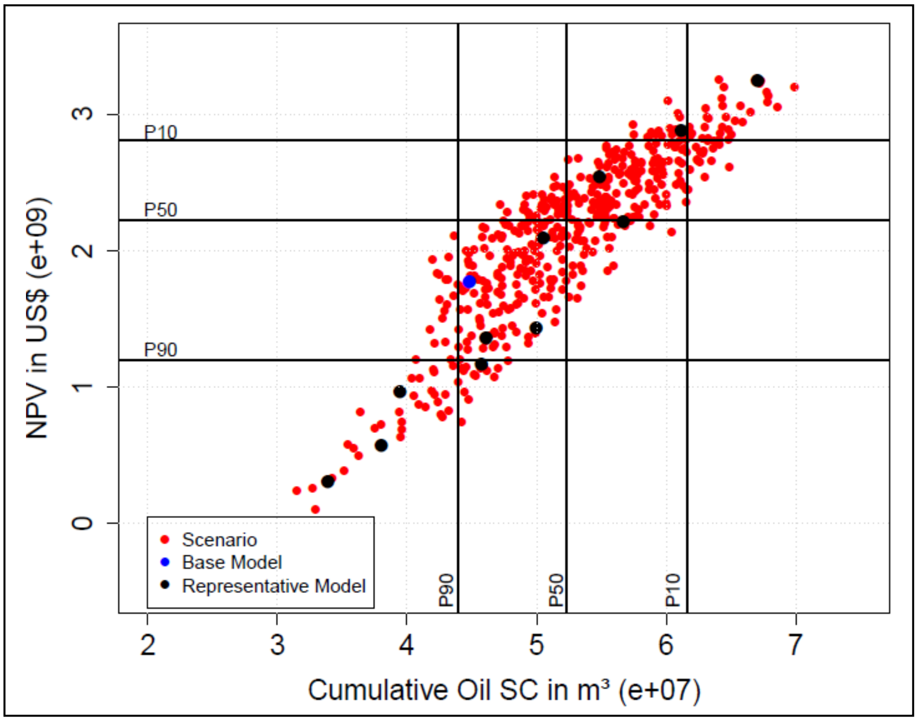


Figure 4.22. Stage 4: NP *versus* NPV.

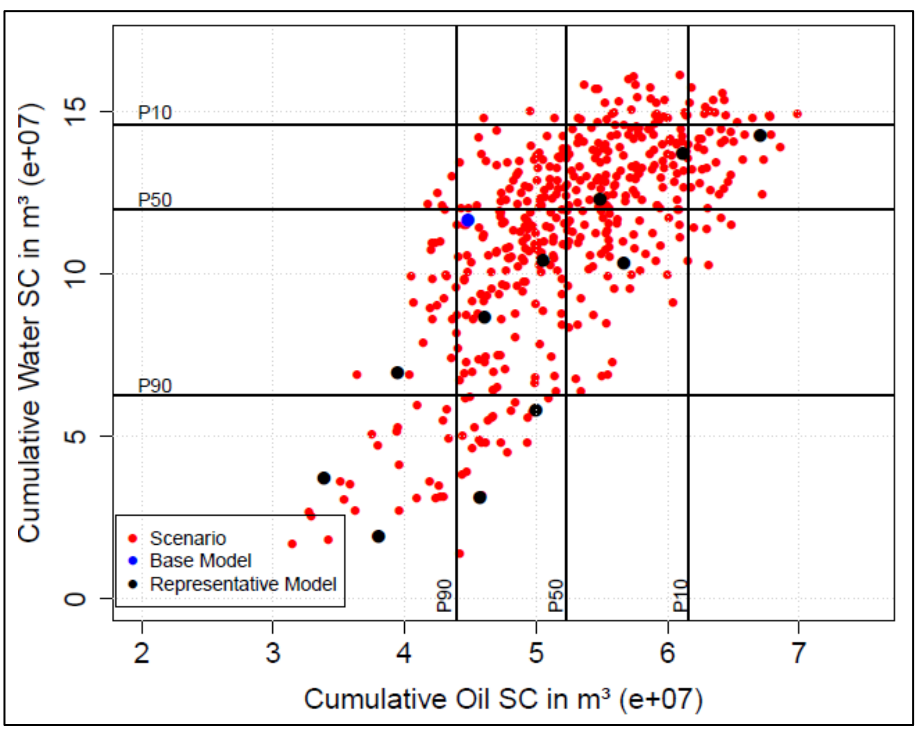


Figure 4.23. Stage 4: WP *versus* NP.

4.7.3. Acquisition Period Estimation

The ability of seismic data to identify heterogeneities and to improve reservoir modeling varies over the production period. The relationship between the reservoir fluid flow and 4D seismic data capacity to improve the reservoir model was described in Chapter 2. A first estimative of the best time for 4D seismic acquisition was obtained applying the methodology described in Chapter 3.

4.7.3.1. Dynamic Data Analysis

The water saturation error was obtained by comparing the water saturation map from each scenario with the water saturation map from the base model. The comparison is made with the base model because the production strategy applied to each scenario is the same as the base model production strategy.

The water saturation curves and the normalized curves were computed using Equation 3.1 and 3.2. The graphs obtained are shown in Figures 4.24 and 4.25. The black curves are the representative models considered in Stage 04.

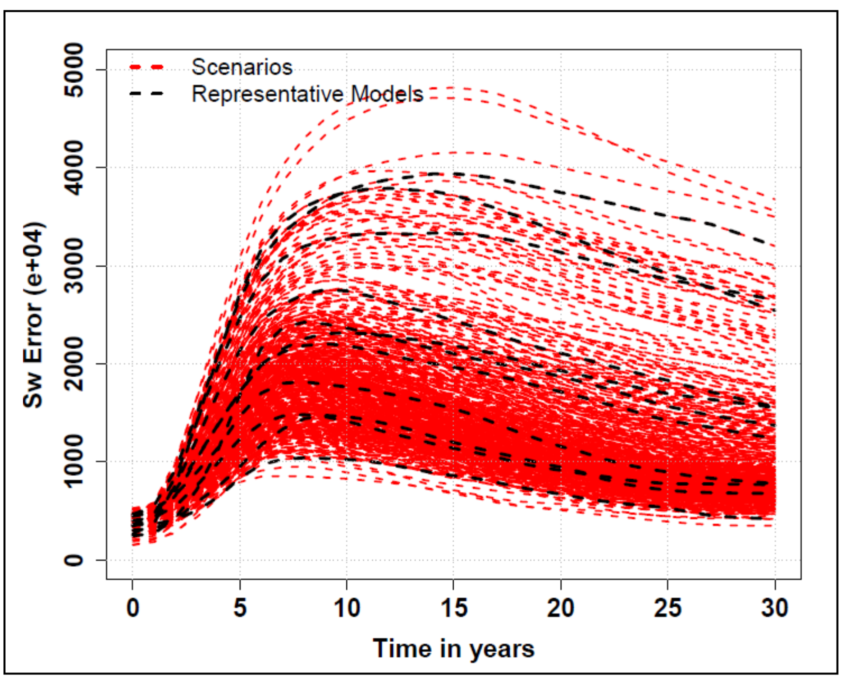


Figure 4.24. Water saturation error.

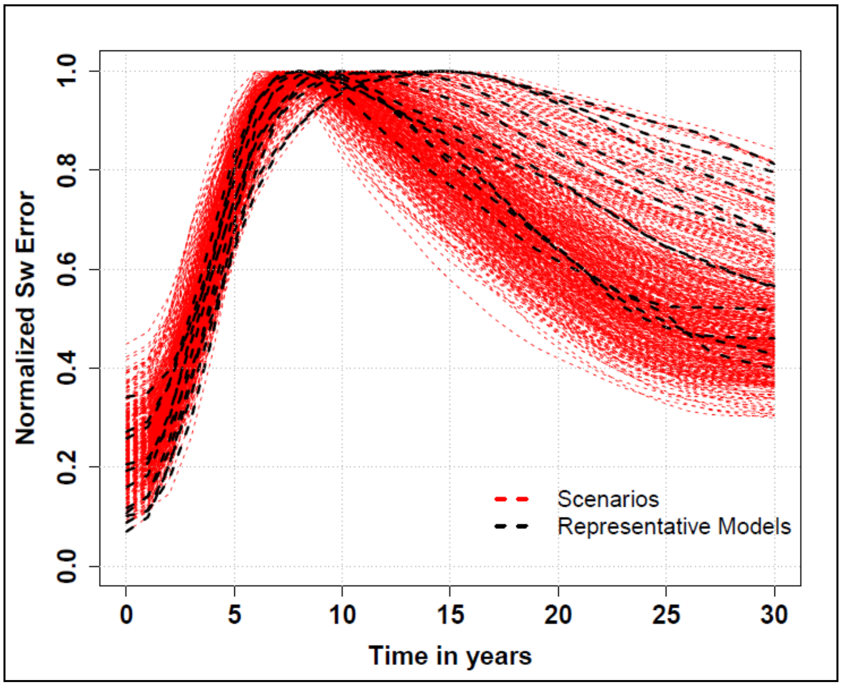


Figure 4.25. Normalized water saturation error.

Figure 4.24 shows if there will be a significant difference between the fluid flow to identify whether the model considered (base model) is incorrect (that is, different from the true earth model).

In practice a history matching process would be performed and the resulting reservoir model would be closer to the true earth model. In this work, as the information is considered perfect, the acquisition of information allows to identify the true earth model represented by each scenario.

There are scenarios in which reservoir characteristics are similar to the base model resulting in low errors and, on the other hand, scenarios highly different from the base model resulting in high errors.

Figure 4.24 also shows that in the initial production phase the errors values are not significant. This occurs due to the low fluid flow and indicates the absence of significant uncertainties, such as a secondary reservoir.

However, at the end of production there are high values of water saturation errors. The high value indicates the existence of remaining oil areas. The identification of remaining oil areas is more difficult to be obtained with other sources of data than 4D seismic data.

In Figure 4.25, the normalized water saturation error identifies when the difference between the base model and each scenario is highest (normalized error equal to one). A first estimative of the period to acquire 4D seismic data would be at 70% of the normalized water saturation error.

Figure 4.26 shows the histogram of normalized errors at five years of production. The error is between 60 and 95%, indicating that the water saturation difference between the scenarios and the base model may be enough to identify that the base model does not represent the true earth model.

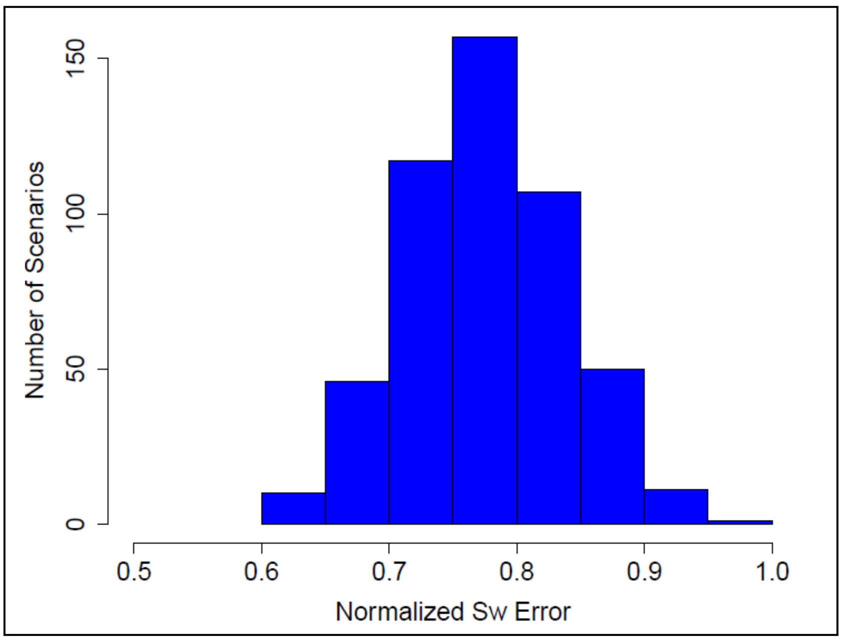


Figure 4.26. Histogram of normalized Sw error at five years of production.

4.7.3.2. Production Data Analysis

The second factor to be analyzed is the time for breakthrough. Figure 4.27 shows a histogram of breakthrough time. The production wells of all scenarios were considered.

Figure 4.28 shows the cumulative distribution of BT: with five years of production, the breakthrough had occurred to approximately 55% of the production wells.

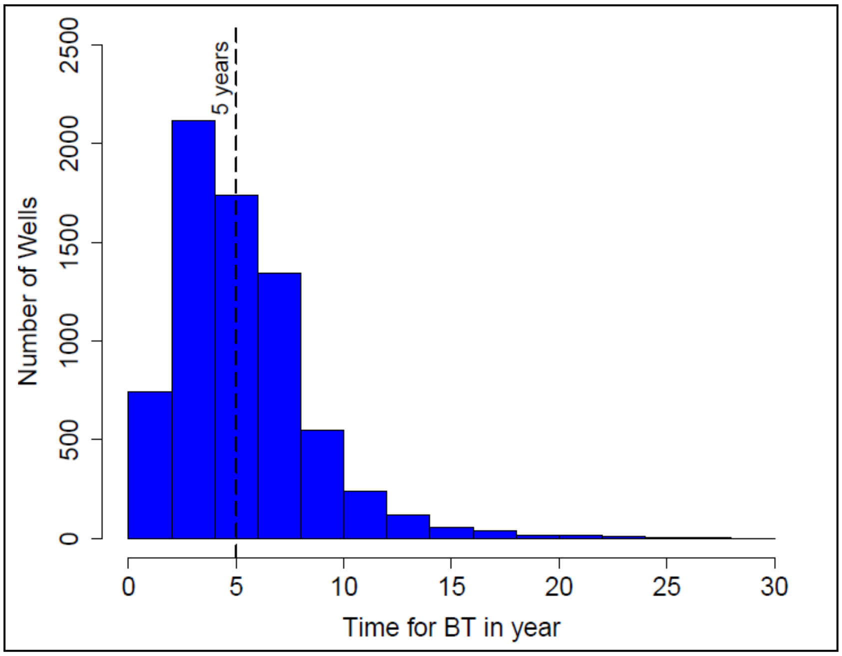


Figure 4.27. Histogram of time for BT.

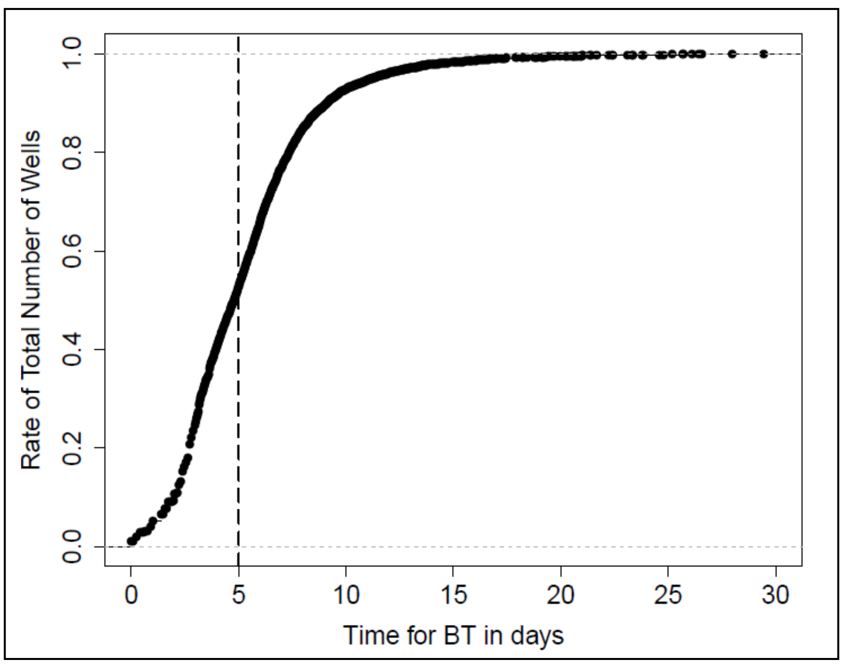


Figure 4.28. Cumulative distribution of time for BT.

4.7.3.3. Acquisition Period Estimation

A first estimate of the acquisition period is before five years of production. The acquisition period was estimated based on: (1) the fluid flow differences between the base model and the reservoir scenarios and (2) the time for breakthrough.

Within this period, the benefits provided by the acquisition of new information depend on the production strategy optimization. The chance of success of 4D seismic data was estimated for five years of production. Such period indicates some potential to mitigate the development risk.

4.7.4. Production Strategy Optimization

The acquisition of new information at the production period defined in the previous step impacts the production strategy. The identification of the true earth model represented by each scenario improves the reservoir management from the moment that information is obtained.

The time to process 4D seismic data was not considered because the case analyzed is synthetic. Thus, the optimization was performed after five years of production.

The objective function was the NPV and the costs considered in the analysis are presented in Table 4.5. The optimization considered the following actions:

- Drilling of a new well (addition or replacement): consists of stopping production or injection wells and drilling a new well to replace it. The drilling of one new well was considered due to the high number of production and injection wells;
- Production or injection wells recompletion: shutting off one or more production or injection periods;
- Production constraints changing: variations on the water cut and maximum surface oil rate values in order to improve the production efficiency.

Appendix C presents the description of the production strategy improvement for the representative models RM1 and RM2. It describes the well control constrains, the objective functions that were evaluated and the results obtained for each action. The same procedure was used to optimize the production strategy from RM3 to RM11.

Figures 4.29 to 4.39 show the final production strategy with the position of the new well drilled after five years of production for all representative models.

Table 4.12 shows the water cut considered in the optimized production strategy for the representative models RM1 and RM5 and maximum surface oil rate considered for RM1.

The water cut considered in the production strategy for the representative models RM2 to RM4 and RM6 to RM11 is equal 0.95. The maximum surface oil rate was not included in the production strategy of the representative models RM2 to RM11.

Table 4.13 presents the economic and production results obtained with the optimized production strategy. The index ΔNPV represents the difference between the NPV using the base production strategy and the NPV using the specific production strategy for each model.

The ΔNPV from the base model is equal to zero; in such case if the information identifies that the base model represents the true earth model the same production strategy would be used in the reservoir management. The results obtained for the remaining representative models vary considerably.

Table 4.12. Well constraints: optimized production strategy.

Production Well	**RM1**		**RM5**
	Maximum Surface Oil Rate (m^3/day)	**Water Cut**	**Water Cut**
PROD 01	600	0.90	0.90
PROD 02	-	0.90	0.90
PROD 03	-	0.90	0.90
PROD 04	250	0.95	0.95
PROD 05	250	0.95	0.95
PROD 06	400	0.95	0.95
PROD 07	400	0.95	0.95
PROD 08	400	0.95	0.90
PROD 09	500	0.90	0.95
PROD 10	-	0.90	0.95
PROD 11	500	0.95	0.85
PROD 12	-	0.90	0.90
PROD 13	75	0.95	0.95
PROD 14	400	0.90	0.95
PROD 15	400	0.90	0.90

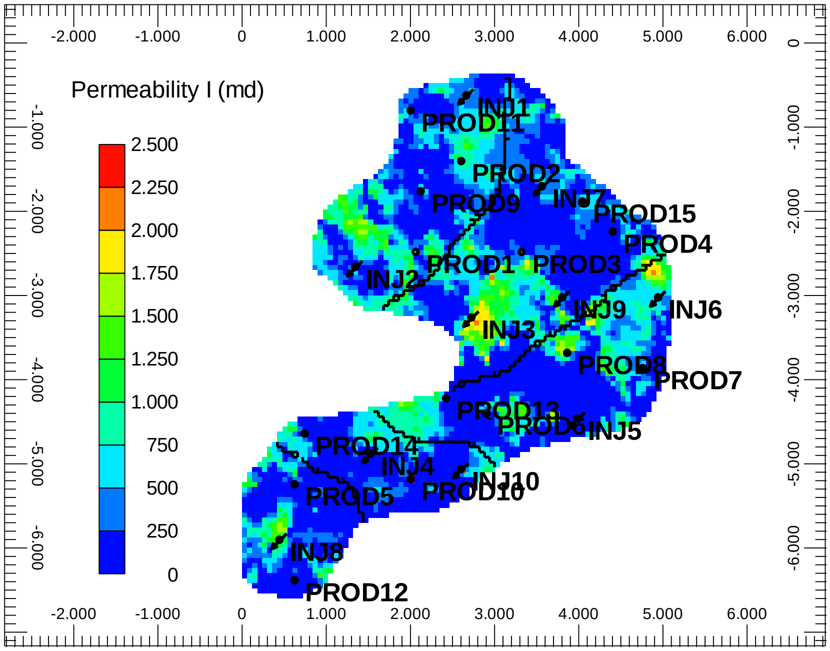


Figure 4.29. RM1: optimized production strategy.

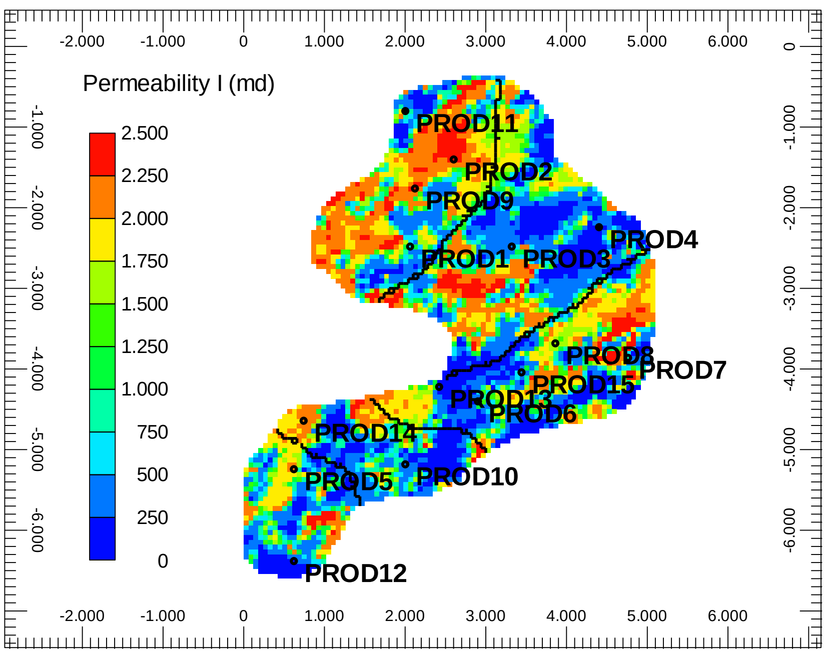


Figure 4.30. RM2: optimized production strategy.

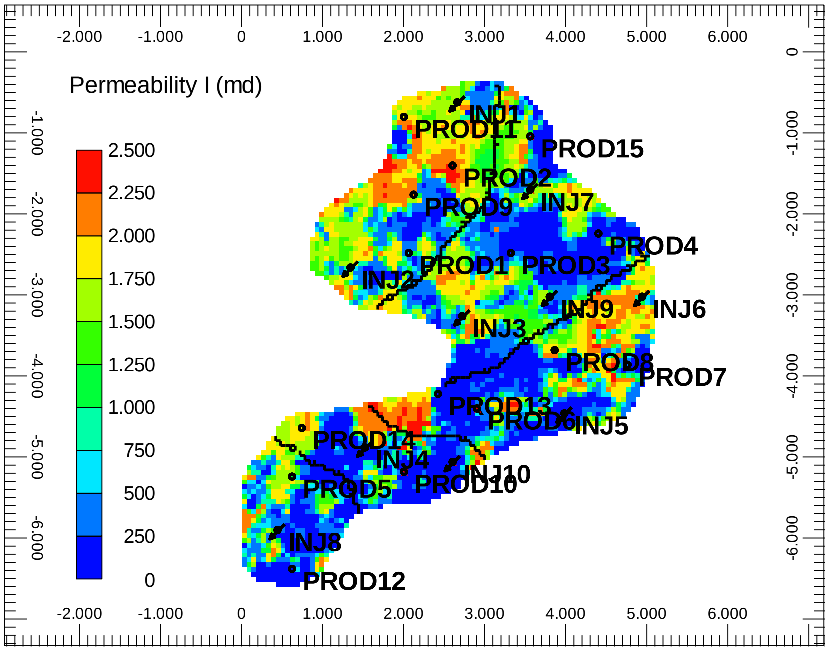


Figure 4.31. RM3: optimized production strategy.

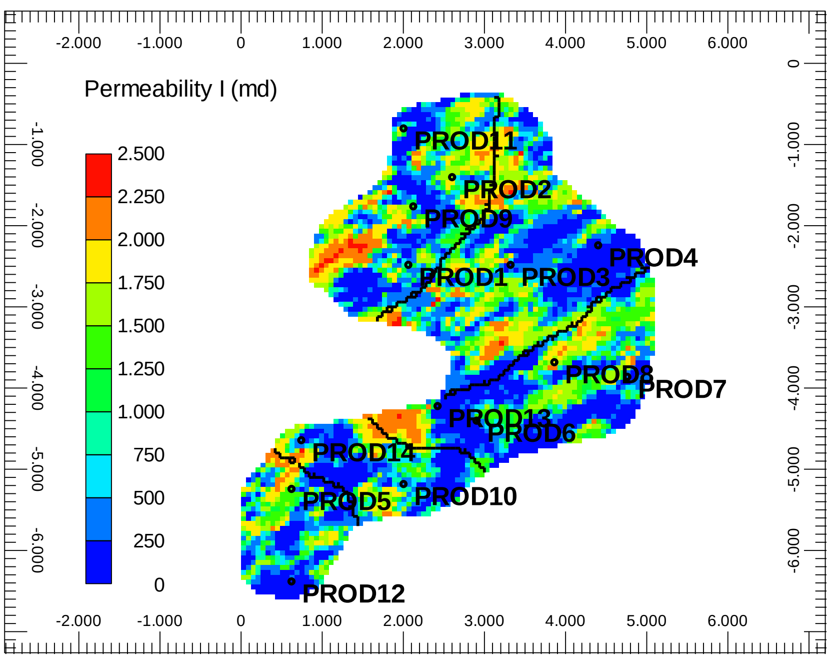


Figure 4.32. RM4: optimized production strategy.

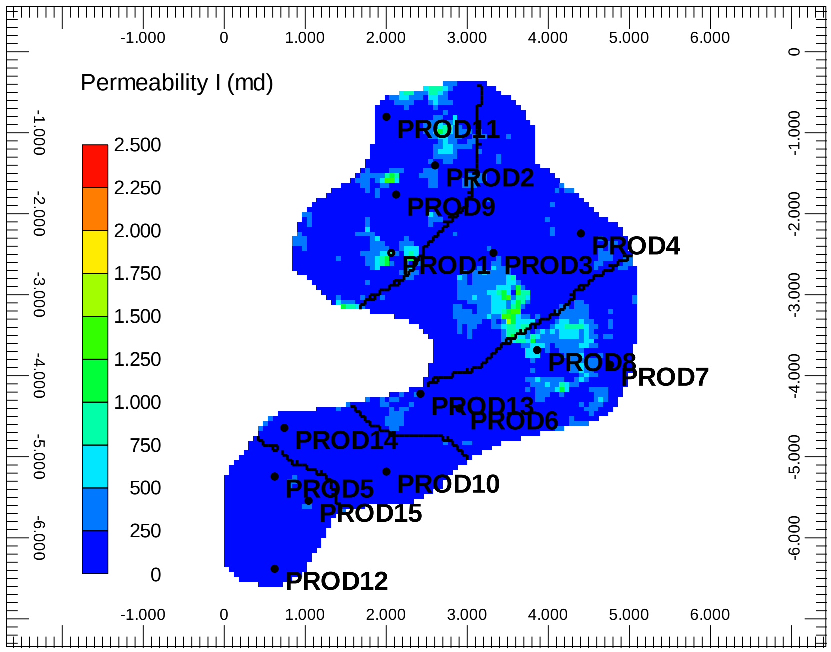


Figure 4.33. RM5: optimized production strategy.

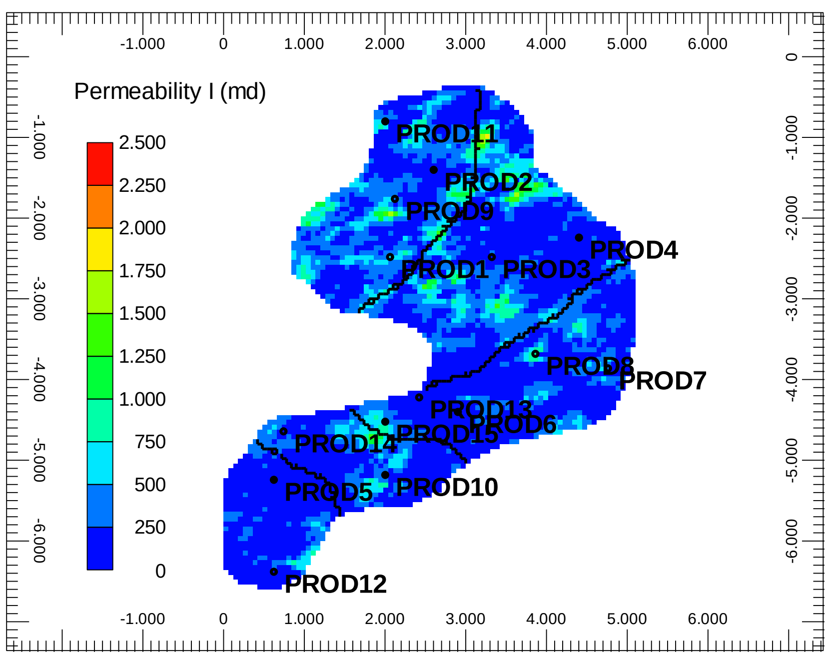


Figure 4.34. RM6: optimized production strategy.

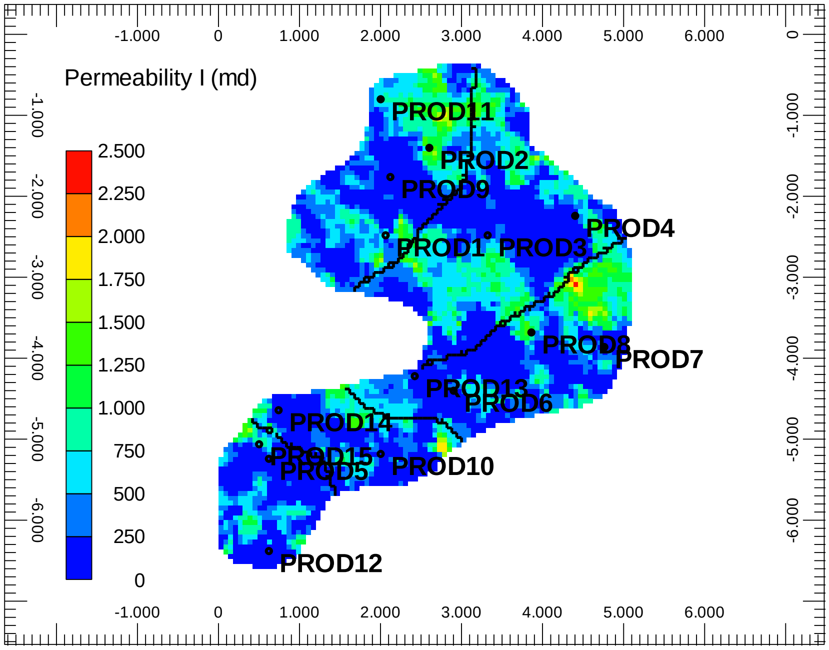


Figure 4.35. RM7: optimized production strategy.

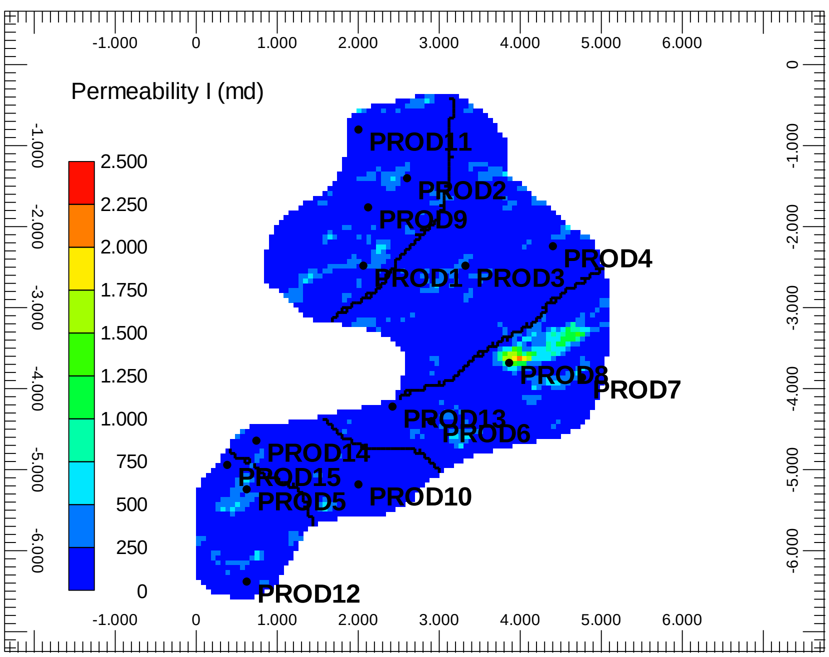


Figure 4.36. RM8: optimized production strategy.

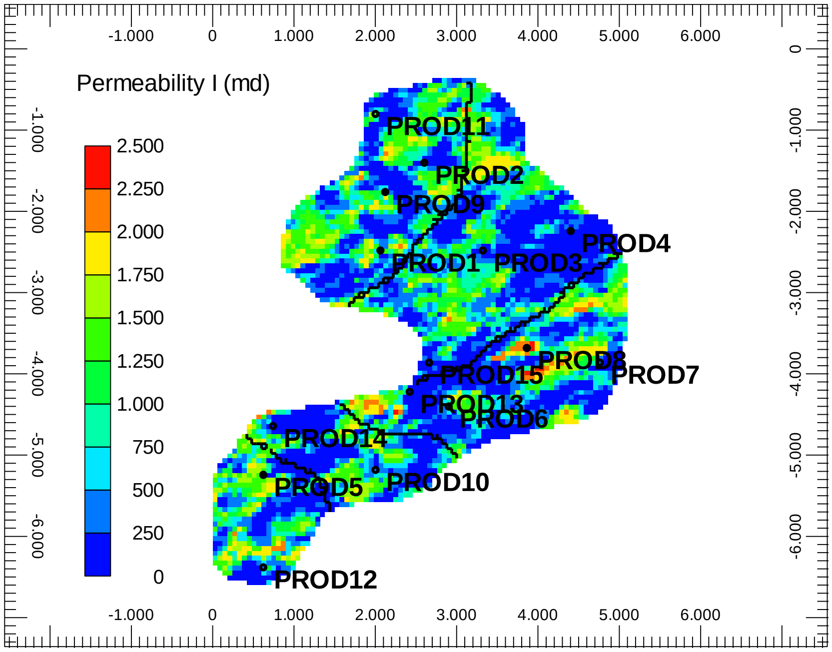


Figure 4.37. RM9: optimized production strategy.

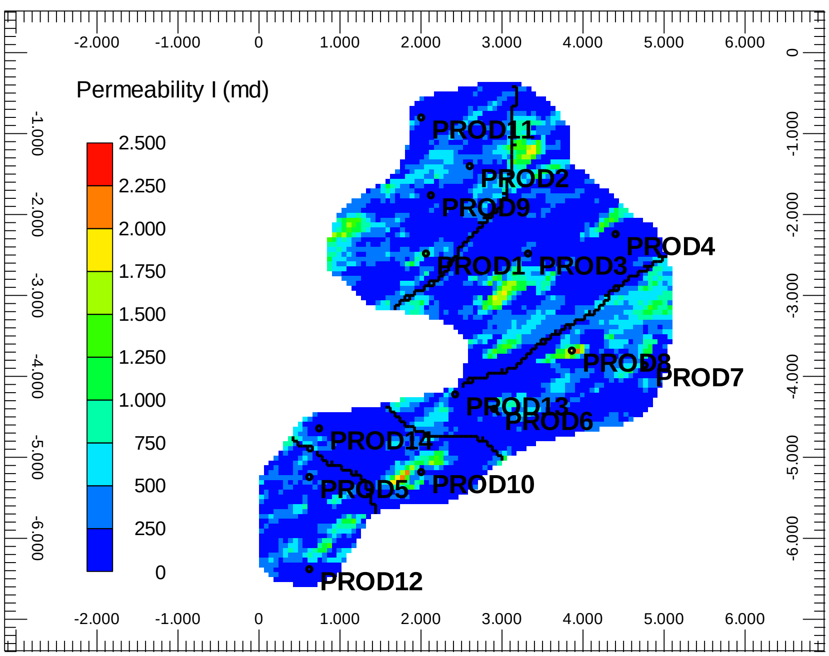


Figure 4.38. RM10: optimized production strategy.

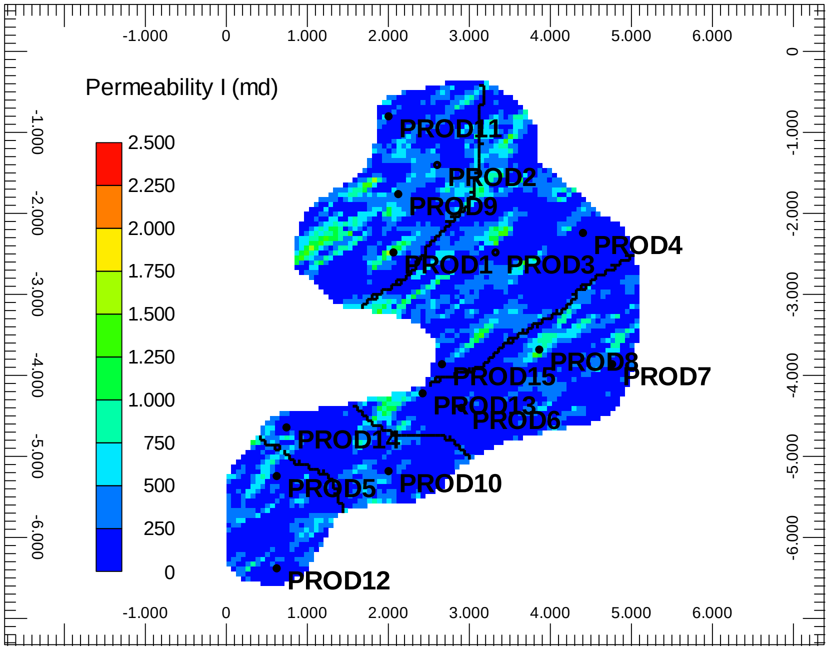


Figure 4.39. RM11: optimized production strategy.

Table 4.13. Representative models results using the optimized production strategy.

Model	NPV (US$ x 10^9)	ΔNPV (US$ x 10^6)	RF (%)	Np (m^3 x 10^7)	Wp (m^3 x 10^7)
Base	1.770	0.0	69.1	4.48	11.70
RM1	1.413	49.2	61.6	4.84	8.16
RM2	3.267	20.7	72.7	6.74	13.98
RM3	2.878	0.9	67.2	6.13	13.25
RM4	2.556	16.9	69.3	5.55	12.09
RM5	0.363	55.8	49.8	3.55	3.52
RM6	0.987	17.0	64.2	4.03	7.07
RM7	2.269	57.7	68.3	5.71	10.23
RM8	0.580	7.4	53.1	3.86	2.03
RM9	2.159	62.9	64.4	5.16	10.46
RM10	1.202	31.7	53.9	4.67	3.39
RM11	1.481	49.9	60.3	5.14	6.38

An important issue that commonly occurs in practice is that when defining the optimal production strategy for a representative model, the optimized production strategy also improves the base model economic return. This issue shows that the base production strategy was not the optimal and the process to estimate the chance of success must be restarted.

The reservoir scenarios must be generated again considering the optimal base production strategy and consequently the following methodology steps. The process of regenerating the reservoir scenarios considering a new base model production strategy occurred in the current study.

However, sections 4.6.1 and 4.6 showed the results obtained considering the optimal base production strategy. The initial base model production strategy description and production data results from the corresponding scenarios are presented in Appendix B.

4.7.5. Chance of Success

The expected value of information and the cumulative probability of the increase on the economic return were determined to estimate the chance of success.

4.7.5.1. Expected Value of Information

A decision tree was used to represent the decision process of whether or not acquire 4D seismic data to estimate the EVOI.

In the decision tree, the branch called "Do not acquire 4DS" represents all possible outcomes if no information is acquired. In such case, it is assumed that the base model production strategy maximizes the expected monetary value (EMV).

Thus, the production strategy applied to obtain all possible outcomes considers the production strategy of the base model, as shown in Equation 4.4. If the true earth model is not represented by the base model, but instead, by any of the representative models, the opportunity of improving the production strategy is lost.

The branch called "Acquire 4DS" represents a decision node. In such case, the decision maker chooses after the information gathering which strategy to use in the reservoir management.

The possible outcomes were determined by applying the production strategy specifically designed for each possible scenario as shown in Equation 4.5. The improvement in the production strategy indicates the impact of new information on reservoir management.

The decision tree for the four stages of representative models selection are presented in Figures 4.40 to 4.43. The EVOI obtained for Stage 1 is much lower than the EVOI obtained using more representative models. Stage 01 was performed as a test to verify if the increment on the

NPV for the extreme models would be the maximum possible values. The verification is done in the Section 4.7.5.2.

The difference in the EVOI values between Stages 2 and 3 is equal 19% and the difference between Stage 3 and 4 is equal 4%. There is a variation on the EVOI as more representative models are added to the process. It was assumed that the maximum difference between the stages was 5%, in order to obtain an accurate EVOI.

The EVOI is equal to US$28.9 million for the acquisition of information at five years of production,. The EVOI obtained was compared to the VOI considering the true earth model. The true earth model is known because the methodology was applied to a synthetic reservoir model.

The VOI obtained was equal to US$25.5 million. The VOI was determined by comparing the NPV applying the base production strategy and the NPV applying a production strategy that maximizes the economic results for the true earth model. The number of representative models used to calculate the EVOI provided an accurate value.

Usually the EVOI is compared to the cost of 4D seismic data acquisition and processing to define whether or not acquire the information. It was considered that the cost of 4D seismic data is equal to US$30 million, with the reference date at 01/01/2008.

However, the EVOI is a weighted measure. It does not show the variation on the NPV increase due to the information acquisition. Thus, a new method of evaluation that considers the NPV increase variation was designed and is presented in the Section 4.7.5.2.

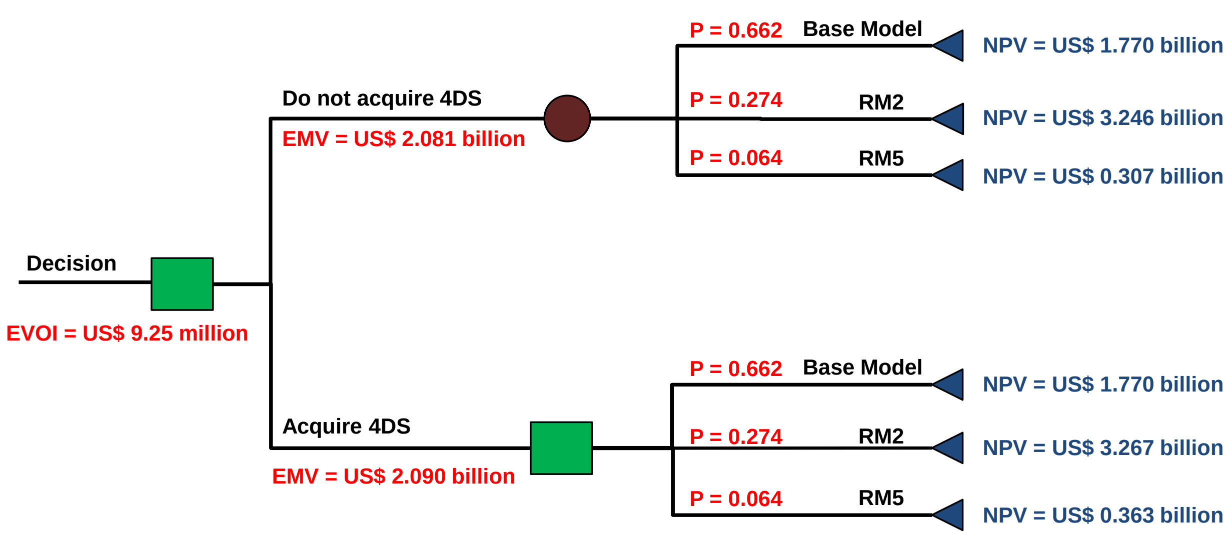


Figure 4.40. Stage 1 decision tree.

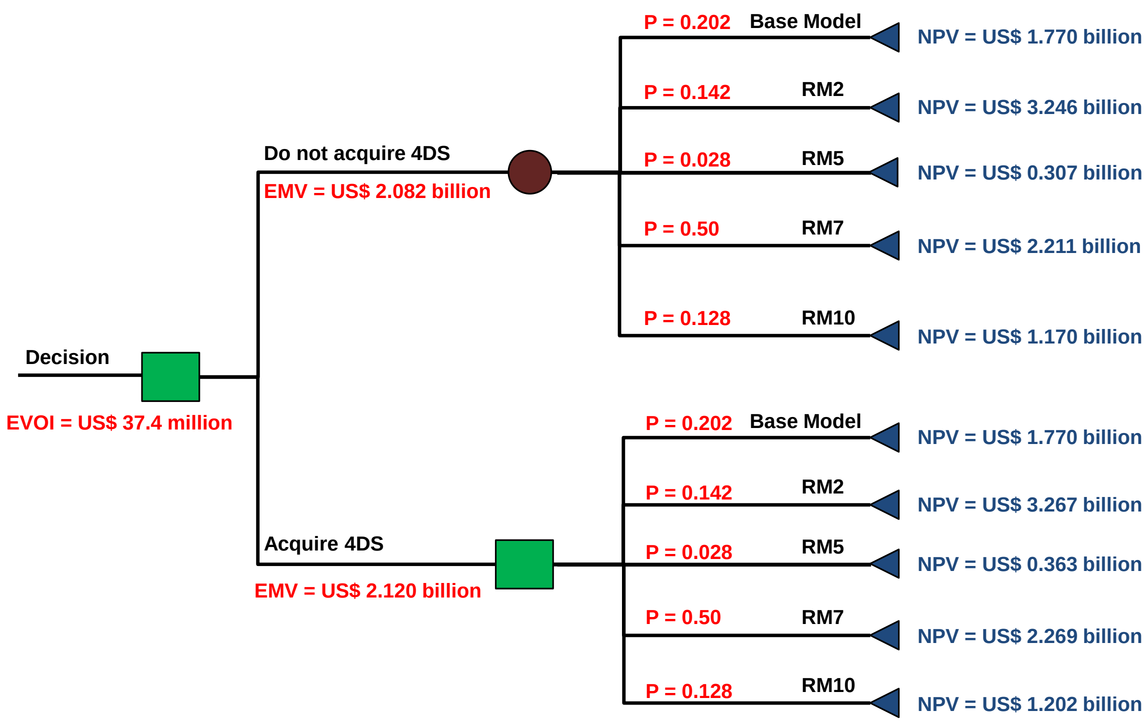


Figure 4.41. Stage 2 decision tree.

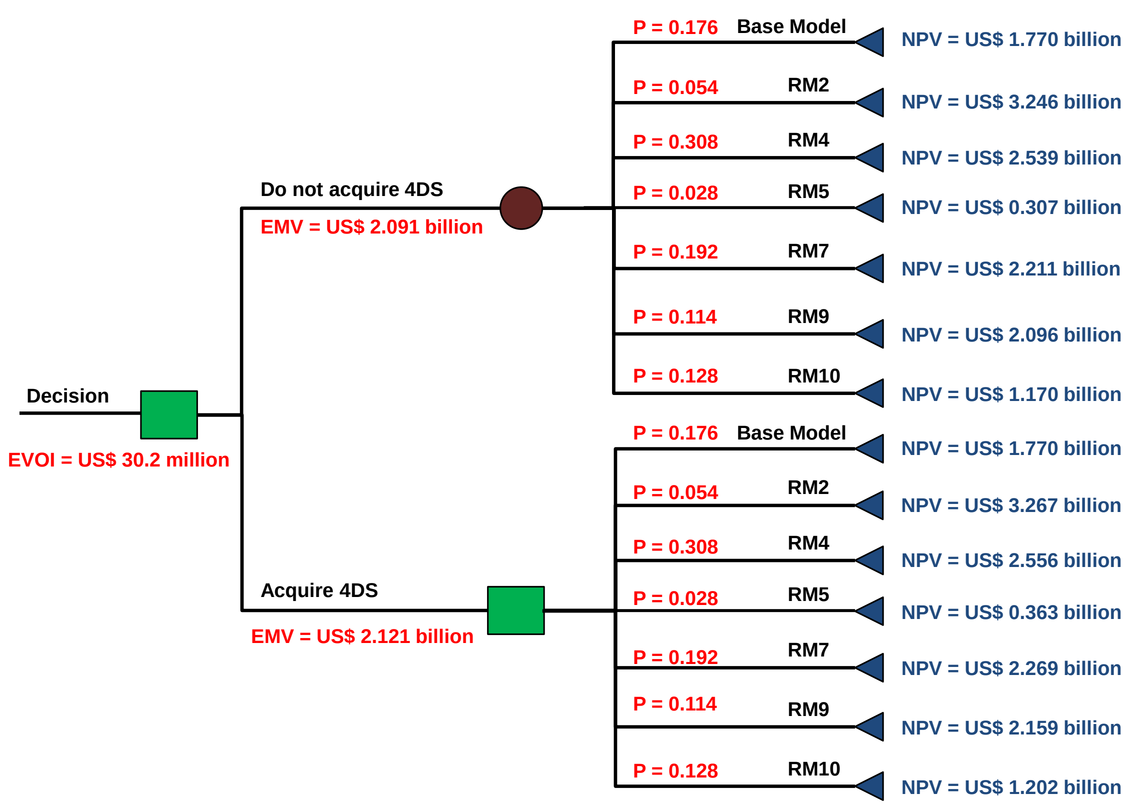


Figure 4.42. Stage 3 decision tree.

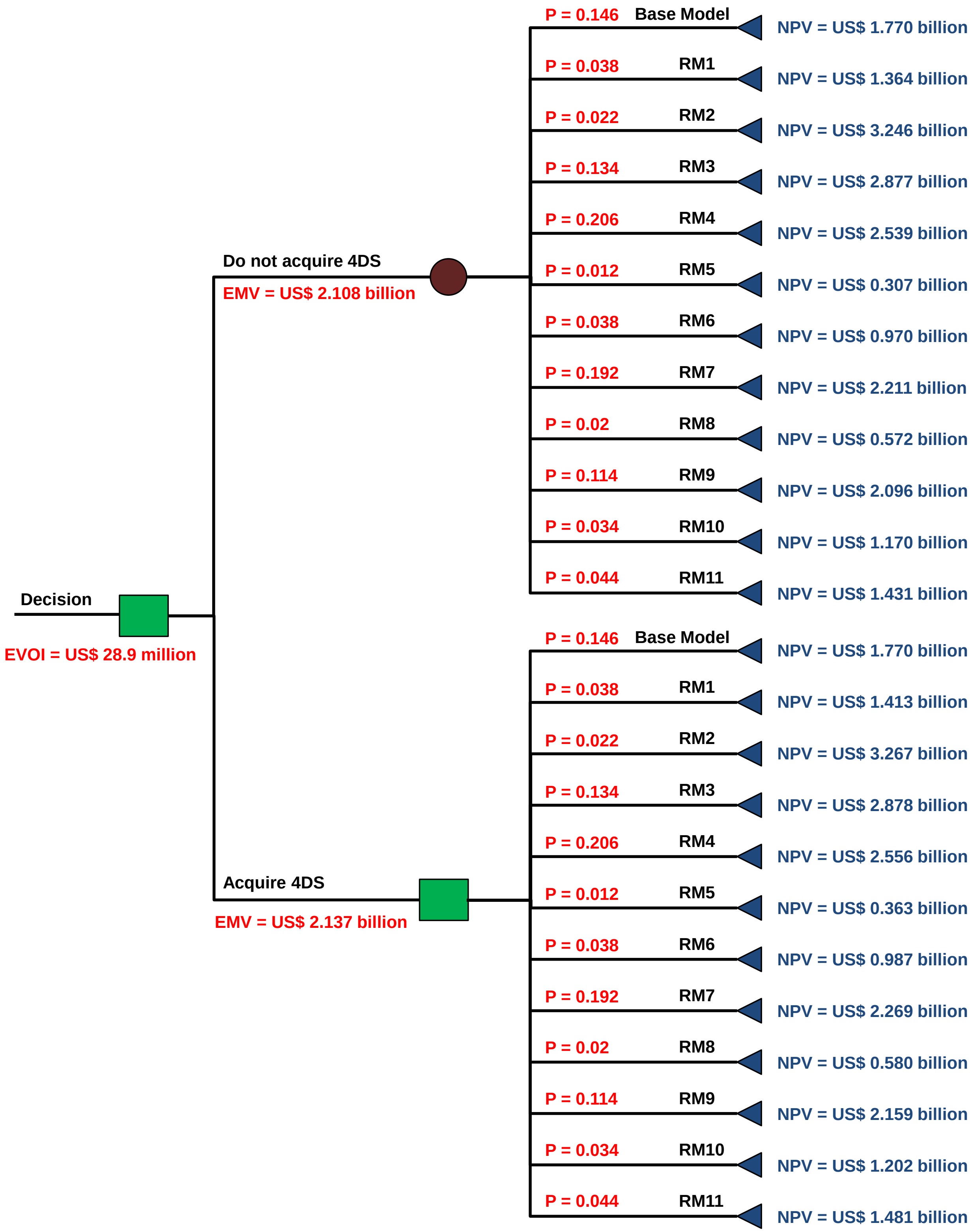


Figure 4.43. Stage 4 decision tree.

4.7.5.2. Increase on the Economic Return

The evaluation of the increase on the economic return is performed through the cumulative probability of the increment on the NPV. The probability distribution curve is determined using inverse cumulative probability and associated ΔNPV values for the representative models. It identifies the minimum and maximum possible increase on the economic return that the acquisition of new information would provide.

The cumulative probability curve was determined for Stages 1 to 4 and is presented in Figure 4.44. Comparing all stages, there is a high variation on the values of ΔNPV for a specific probability value. The more representative models are used, the more accurate is the cumulative probability curve.

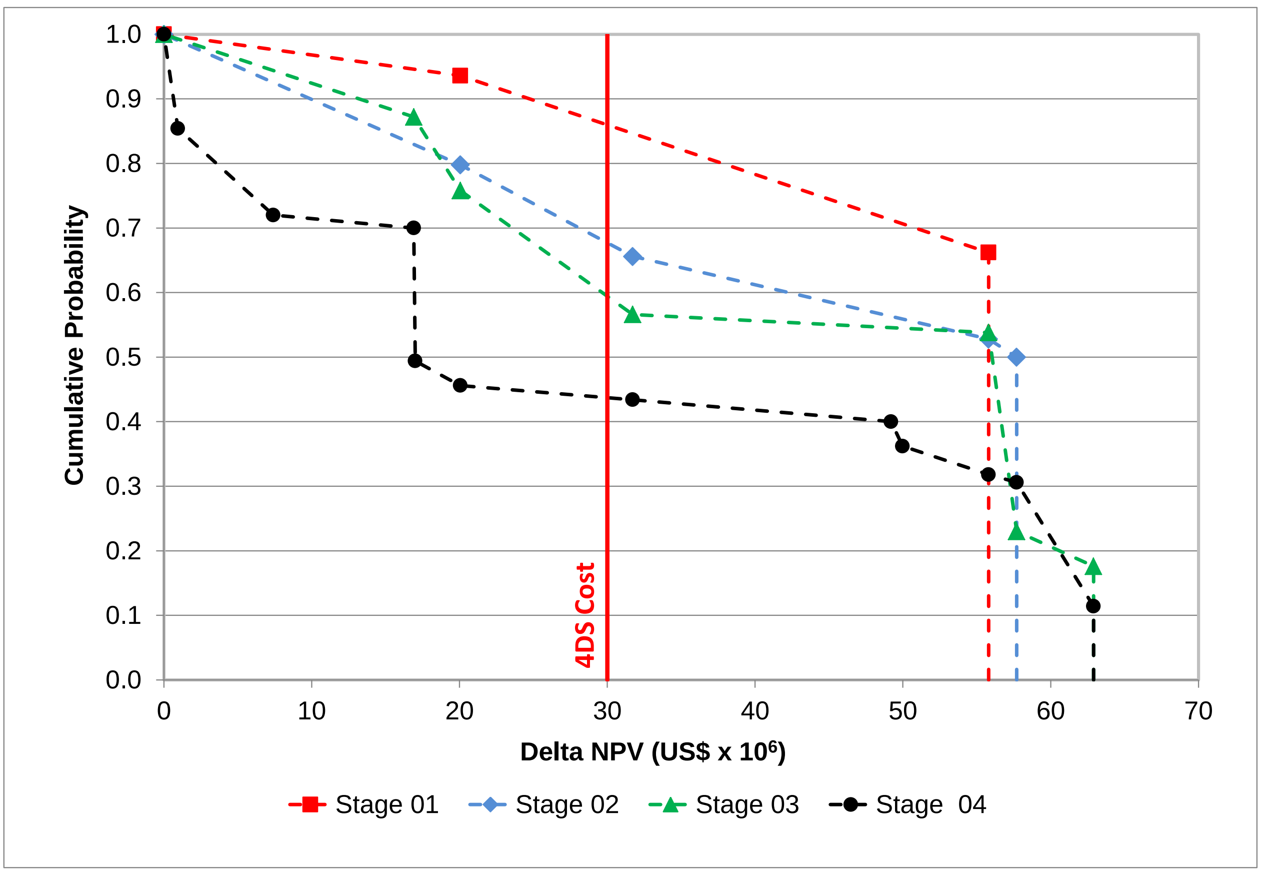


Figure 4.44. Chance of success evaluation.

Stage 1 was performed as a test to verify if the increment on the NPV for the extreme models would be the maximum possible values. However, Stages 2, 3 and 4 showed the existence of representative models with higher values of ΔNPV. It was not possible to define a correlation between the representative models and the increase on the economic return.

Figure 4.44 shows that another Stage should be evaluated, because there is a high variation in the probability density curves. However, it was assumed that Stage 4 can be used to evaluate the chance of success, because the variation on the EVOI was lower than 5%.

Evaluating Stage 4 curve, the probability of the increase on the NPV to be higher than 4D seismic acquisition and processing costs is equal to 44%. Such information better supports the decision maker on whether or not acquire 4D seismic data. The decision depends on the risk aversion of the decision maker.

4.7.6. Decision Maker Evaluation

Based on the data provided by the chance of success analysis, the decision maker can choose the following actions:

- End the evaluation process:
  - Acquire 4D seismic data;
  - Do not acquire 4D seismic data.
- Continue the evaluation process:
  - Select more representative models to improve the estimation accuracy;
  - Evaluate a different acquisition period;
  - Improve optimization process.

In the current study, the EVOI is lower than the acquisition and processing costs and the probability that the increase on the economic return is equal 44%. If the decision maker is risk neutral and the minimum probability acceptance is equal 50%, it could be decided not to acquire 4D seismic data.

Moreover, production data itself could reduce the reservoir uncertainties at the beginning of production. The production results for all scenarios (Figures 4.5 to 4.7) shows that Np and BHP results could be used to reduce reservoir uncertainty.

However, the benefit of risk mitigation was not considered and it can justify the acquisition of new information. Furthermore, other the existence of unknown unknowns can increase the EVOI and the economic return.

4.8. Conclusions

Determine the chance of success of a 4D seismic project before the information acquisition is necessary to support the decision maker on whether or not acquire new data. A methodology is proposed to determine a first estimative and it is applicable to fields in the development phase.

The methodology is simple and is divided into six steps. Some of the procedures used in the methodology are well established in the literature, such as the decision tree technique and value of information calculation. Three are the main contributions provided by the thesis:

- The chance of success analysis is performed at the best time for 4D seismic acquisition. If the result obtained at such period does not indicate that 4D seismic data can improve the economic return of the project, the use of continuous acquisition also would not be viable. The methodology to determine the best time to acquire 4D seismic data is described in Chapter 3 and it is incorporated to the chance of success methodology;
- The chance of success is determined by calculating the probability of the increase on the economic return to be higher than the acquisition and processing costs. The use of only EVOI does not show the variation in the increase on the economic return and does not determine the probability of success;
- It is an iterative process in which the evaluation can be performed to different production periods and the accuracy of the results can be increased with the selection of more representative models.

The number of representative models is an important step in the methodology. The more representative models are selected the more accurate are the results obtained. The selection can be done in stages until the variation of EVOI between the stages is less than 5%. However, further studies are necessary to determine the minimum number of representative models in order to obtain an accurate cumulative probability curve

The methodology was applied to a synthetic reservoir model in order to test its applicability. The chance of success was determined considering the acquisition at five years of production.

The selection of representative models was performed in four stages. The variation on the EVOI due to the number of representative models considered could be verified.

The EVOI obtained is equal US$28.9 million and it is similar to the VOI calculated considering the true earth model that is US$25.5 million.

A better way to evaluate the chance of success is to obtain the cumulative probability curve of the increase on the economic return. The probability of success is equal 44% to the case studied, considering the acquisition and processing costs equal to US$ 30 million,.

The EVOI and probability obtained are low because approximately 98% of the representative models have a recovery factor of more than 50% and there is low flexibility on the production strategy improvement.

The main benefit of 4D seismic data relies on identifying the remaining oil areas. However, other factors that influence on the results obtained should be considered. There are many influence factors that can increase or decrease the value of information.

The quantification of such factors should be subject of further studies. The EVOI can be increased due to the existence of unknown uncertainties and the existence of future uncertainties, such as oil price. The EVOI can be reduced because 4D seismic data is imperfect information and other sources of data can reduce the reservoir uncertainties.

5. CONCLUSIONS

The present thesis describes the development of a methodology to estimate the chance of success of a 4D seismic project from the reservoir engineering perspective. The methodology was developed in three phases, each one described in Chapters 2 to 4.

Chapter 2 evaluated the impact of 4D seismic data in the history matching process. 4D seismic data improved the production forecast and most importantly improved the fluid behavior understanding for all production periods analyzed.

Although production data itself improved the production forecast when breakthrough occurs, the water saturation error increased at least 105% while the use of 4D seismic data reduced the error at least 76%.

The water saturation error quantifies the improvement on the reservoir model dynamic data. Moreover, it identifies which scenarios have a fluid flow different from the base model and the existence of remaining oil areas.

The time for 4D seismic data acquisition affects the value of 4D seismic data. The best period for the information acquisition was between 2 and 4 years of production, for the case studied in Chapter 2.

At such period, it is possible to predict the water breakthrough occurrence and consequently make decisions that could delay it. There is enough water saturation error to identify that the base model is incorrect and the revenue to be obtained from oil is between 70% and 45%.

As Chapter 2 showed the importance of the acquisition period on the 4D seismic value, Chapter 3 treated this task in a more practical condition. It was developed a methodology to obtain a first estimative of the best time for 4D seismic data. The estimative of the best time is determined by evaluating the production and dynamic data of all possible scenarios.

The production data analysis evaluates the time for water breakthrough at production wells. The acquisition of 4D seismic data shall be before water breakthrough occurs because decisions can be made in order to delay the breakthrough and increase the oil production rate as a consequence.

The dynamic data analysis evaluates the water saturation error curves. The acquisition period shall be at the moment in which only 4D seismic data identifies that the base model does not represent the true earth model and there is enough time to make decision changes. It is considered that a normalized water saturation error equal 70% is sufficient to the true earth model identification.

Chapter 3 presented a general methodology to estimate the chance of success of 4D seismic data acquisition. It was designed to perform the evaluation before the data acquisition and at the field development phase.

The methodology is simple and iterative process. It is dived in six steps in which some of them are well established in the literature. The optimization of production strategy is the most time-consuming step. Three are the main contributions provided by the thesis:

- The analysis is performed at the best time for 4D seismic acquisition;
- In general, the decision of whether or not acquire 4D seismic data is based on the EVOI. However, the EVOI is a weighted measure. It does not show the variation in the increase on the economic return and does not determine the probability of success. Thus, the probability of the increase on the economic return to be higher than the acquisition and processing costs is determined;
- It is an iterative process in which the evaluation can be performed to different production periods and the accuracy of the results can be increased with the selection of more representative models.

The number of representative models used in the methodology affects the EVOI and the probability of success results. The representative models selection can be done in stages until the variation of EVOI between the stages is less than 5% and there is no variation on the probability density curve.

The methodology was successfully applied to a synthetic reservoir model. The chance of success was determined considering the acquisition at five years of production. There is no correlation between the representative models and the increase on the economic return due to information acquisition.

The EVOI obtained is equal US$28.9 million and it is similar to the VOI calculated considering the true earth model that is US$25.5 million. The probability of success is equal 44%, considering the acquisition and processing costs equal to US$ 30 million.

The EVOI and probability obtained are low because approximately 98% of the representative models have a recovery factor of more than 50% and there is low flexibility on the production strategy improvement. The main benefit of 4D seismic data relies on identifying the remaining oil areas

Determine chance of success of a 4D seismic project is important to support the decision maker in the industry daily routine. The methodology presented in the thesis was developed considering important assumptions that affect the final results. Below is a list of recommendations for future work:

- Quantify the impact of the existence of unknown uncertainties, the fact that information is not perfect and the capacity of other source of data to reduce the reservoir uncertainties;
- Evaluate the impact of the number of representative models on the cumulative probability curve and define the minimum number to obtain an accurate value;
- Incorporate the risk mitigation benefit into the valuation of the information.

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APPENDIX A: USE OF EMULATOR METHODOLOGY FOR UNCERTAINTY REDUCTION QUANTIFICATION

Abstract

In petroleum engineering, simulation models are used in the reservoir performance prediction and in the decision making process. These models are complex systems, typically characterized by a vast number of input parameters. Usually the physical state of the reservoir is highly uncertain, and thus the appropriate parameters of the input choices. The uncertainty analysis often proceeds by first calibrating the simulator against observed production history and then using the calibrated model to forecast future well production. Most models go through a series of iterations before being judged to give an adequate representation of the physical system. This can be a difficult task since the input space to be searched may be high dimensional, the collection of outputs to be matched may be very large, and each single evaluation may take a long time. As the uncertainty analysis is complex and time consuming; in this appendix, a stochastic representation of the computer model was constructed, called an emulator, to quantify the reduction in the parameter input space due to production data over different production periods. The emulator methodology represents a powerful and general tool in the analysis of complex physical models such as reservoir simulators. Such emulation techniques have been successfully applied across a large number of scientific disciplines. The emulator methodology was applied to evaluate the production data capacity to identify uncertain reservoir physical features over the production period for a synthetic reservoir simulation model. The synthetic model was built to represent a region of an injector and related producers. In the case studied, thousands of realizations were required to identify certain physical reservoir features. This justifies the use of emulation and shows the importance of this technique for the identification of regions of feasible input parameters. Moreover, the impact on the input space reduction due to different production periods was determined. The emulator methodology used assists in carrying out tasks that require computationally expensive objective function evaluation, such as identifying regions of feasible input parameters; making predictions for future behavior of the physical system and investigating the reservoir behavior.

Introduction

Reservoir simulators are important and widely-used in reservoir management. It is used in the reservoir performance prediction and in the decision making process. These simulators are computer implementations of high-dimensional mathematical models for reservoirs, where the model inputs are physical parameters and the outputs are observable characteristics such as well pressure measurements, fluid production and so forth. The uncertainties are always present in the reservoir characterization process, thus the input parameters are usually uncertain so is the simulator output.

The procedure to calibrate the reservoir simulation model is called history matching. Based on observed data, the set of possible input choices for the reservoir model is identified. Two different procedures can be used to perform the history match process: the deterministic and the probabilistic approach.

The deterministic approach involves running the initial simulation model with different input values to obtain one simulation model between many probable matches to the field data. According to Elrafie *et al*. (2009), the conventional procedure does not handle the uncertainty of all model variables and the possibility to identify and carry forward a set of multiple history match model scenarios to predictive forecasting.

In a probabilistic approach, in which several reservoir model scenarios are considered, the uncertainty analysis procedure is used in the process. Identifying the input parameters for which the simulation outputs match the observed data, can be a difficult task because the input space to be searched may be high dimensional, the collection of outputs to be matched may be very large, and each single evaluation may take a long time.

To deal with the large number of iterations and high computational resources commonly encountered in the probabilistic approach, proxy models are used. Zubarev (2009) define proxy models as a mathematically defined function that replicates the simulation model output for selected input parameters. Several papers show the use of different proxy-modeling algorithms in the history matching process (Cullick, 2006; Junker *et al*., 2006 and Slotte and Smorgrav, 2008).

As the history match process and uncertainty reduction quantification is complex and time consuming; the current appendix shows the workflow used to quantify the reduction in the parameter input space due to production data over different production periods. The workflow comprises the construction of a proxy model called an emulator. The emulator technique was applied to a synthetic reservoir simulation model, built to represent a region of an injector and related producers.

The emulator represents a powerful and general tool in the analysis of complex physical models such as reservoir simulators. Such emulation techniques have been successfully applied in reservoir simulation problems, as seen in Cumming & Goldstein (2009), and references therein.

Objective

Describe a workflow to evaluate the production data capacity to identify uncertain reservoir physical features over the production period using the emulation technique. Moreover, show the application for a synthetic reservoir simulation model built to represent a region of an injector and related producers.

Proposed Methodology

The workflow used to construct the emulator is presented. It is important to highlight that a synthetic reservoir model is used. There is no historical data available in the process, thus the production data considered as historical data derived from a hypothetical reality selected from possible scenarios. These scenarios were obtained through an uncertainty analysis performed on the initial reservoir simulation model.

The workflow was designed to quantify the simulation reservoir model uncertainty reduction due to production data. The objective was to identify the inputs of a reservoir simulation model, within a possible input parameter space, whose outputs match to the hypothetical historical production data. The workflow used is shown in Figure A1. Each stage is described as follows.

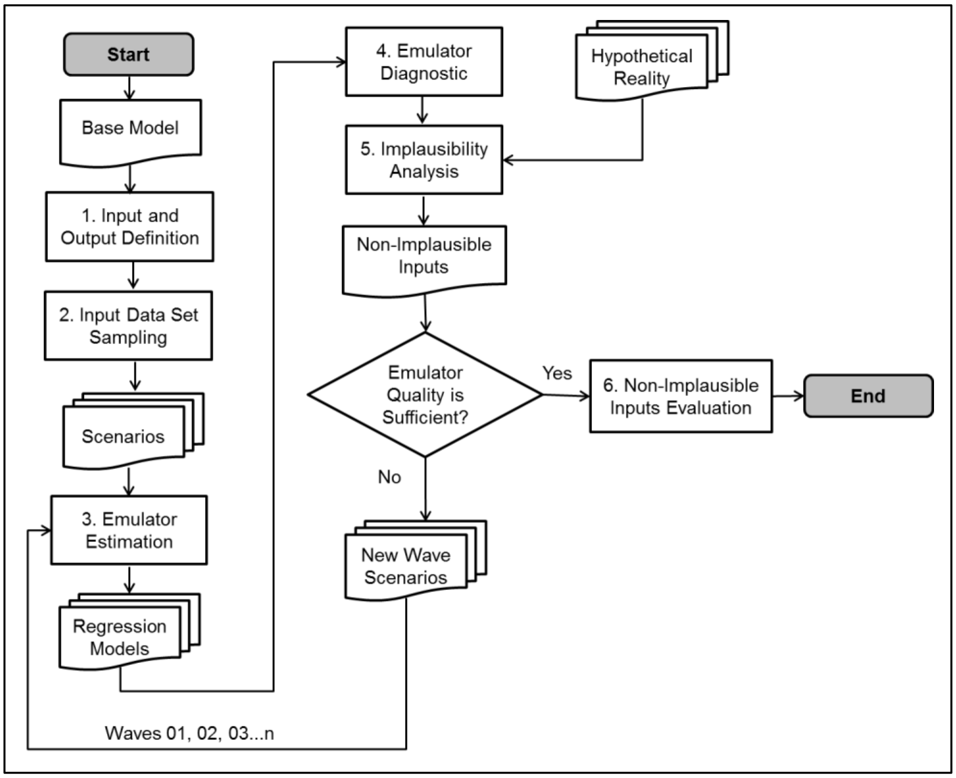

Figure A.1. Process to perform uncertainty reduction quantification.

Input and Output Parameter Definition

In reservoir simulation, uncertain inputs are physical parameters determined through an uncertainty analysis performed on the base model. The outputs of the model are observable characteristics such as well-bottom-hole pressure, water rate at production wells and water saturation maps. The input variable selection depends on the underlying problem and knowledge of the engineer.

The physical state of the reservoir uncertainty varies due to the amount of information available and production period. As in the current study, the analysis is being performed in the field development phase; the uncertainty of the appropriate choices of the input parameters for the reservoir model is high.

Input Data Set Sampling

The input data set sampling is an important stage in creating an adequate emulator. Different sampling methods exist and have been applied in reservoir simulations. The Latin Hypercube Design (LHD) is efficient and was selected as a sampling method to this work. Scenarios were generated based on the input parameter space and sampled using the LHD. The selected scenarios were simulated using commercial simulation software to obtain the production outputs. The sampled input parameters and resulting simulation outputs were used to construct the emulator.

Emulator Estimation

The emulator is an approximation of the existing numerical reservoir model. It should be able to replicate the response of a simulated model. The general structure to develop the emulator was based on Cumming & Goldstein (2009) and Vernon *et al*. (2013) and is as follows.

The simulator is represented by a vector function, taking inputs x which represent the vector of reservoir input parameters, and return the output parameter f(x). The output parameter f(x) intends to represent the real physical system output y. The field observed outputs is represented by z, as field observation is susceptible to measurement errors, the difference between z and y is represented by

$$z=y+e, \tag{A1}$$

where e is the vector of random observational errors, taken to be independent of y. If f(x) was a perfect representation of the system, then an input vector x* only would be accepted as representing the system if $f(x^*) = y$. In practice, however, the simulation reservoir model f simplifies the physics and approximates the solution of the resulting equations. Therefore, the structural discrepancy is represented by

$$y=f(x^*)+\varepsilon, \tag{A2}$$

where ε is the random structural discrepancy vector and is independent of $f(x^*)$. Combining Equation A1 and Equation A2 the input parameters x^* is acceptable if it is probabilistically consistent with the relation

$$z=f(x^*)+\varepsilon+e, \tag{A3}$$

The objective is to identify all choices of x^* which would give acceptable fits to available production data or to identify a wide range of elements x^* belonging to the input parameter space $X(z)$. If the input parameter space was low dimensional, and the function was very fast to evaluate, then it would be possible to estimate $X(z)$ by evaluating the function in the entire space and identify the collection of all x^* choices consistent with Equation A3. However, for a reservoir simulation model it is infeasible to evaluate the simulator at enough choices to search the input space exhaustively. Therefore, a representation of the output uncertainty at each input choice must be constructed. This representation is termed an emulator.

The emulator both suggests an approximation to the function and also contains an assessment of the likely magnitude of the error of the approximation. The form for emulation of output component $\widehat{f_i}$ is

$$\boldsymbol{\hat{f}_i(x) = \textstyle\sum_j \beta_{ij}\, g_{ij}(x) + u_i(x)}, \tag{A4}$$

where x are the input variables, i is the output being emulated, j is the number of function elements, $B = \{\beta_{ij}\}$ are unknown scalars, g_{ij} are known deterministic functions of x and $u_i(x)$ express local variation with constant variance. In this work multiple linear regression was used to determine B, g_{ij} and u_i; therefore the following assumptions must be satisfied:

- Linearity: expected value of $u(x)$ must be equal zero, $E(u)=0$;
- Homoscedasticity and Independence of Errors: $Var(u) = \sigma^2$ and $Cov(u_i,u_j) = 0$.

Emulator Diagnostics

Emulator diagnostics is the process of assessing an emulator's prediction accuracy and quality. The response values predicted by the emulator must comprise the results of the full numerical simulation for the input dataset. Moreover, two measures were evaluated. The first is the squared multiple correlation (R^2); according to Rice (1995) this coefficient is used as a crude measure of the strength of a relationship and the second measure is the standard error (σ) which offers a first handle on how well the fitted equation fits the sample data. These measures are

$$\boldsymbol{R^2 = 1 - \frac{RSS}{RYY}} \text{ and} \tag{A5}$$

$$\boldsymbol{\sigma = \sqrt{\frac{RSS}{n-p}}} \tag{A6}$$

where RSS is the residual sum of squares obtained by calculating the square difference between the fitted and observed value; RYY is the total sum of squares obtained by calculating the square difference between the fitted and mean observed value; n is the number of data points and p is the number of parameters to be estimated (ZUBAREV,, 2005).

Rice (1995) comments that, it is necessary to evaluate the residuals to assess the quality of the fit. Plots of the residuals versus the fitted values were used to find failures of assumptions. Ideally the residual should show no relation to the x values, and the plot should look like a horizontal blur.

Implausibility Analysis

The implausibility analysis is performed to obtain the input parameters whose outputs match the hypothetical historical data. The hypothetical historical data is derived from a hypothetical reality selected from all possible scenarios generated in the uncertainty analysis; moreover these inputs are obtained to improve the emulator reliability and to evaluate the uncertainty reduction at the end of the process.

The range of input parameters that are member of X(z) is determined through the implausibility value calculation (I). For each set of input parameters an emulator output $\widehat{f_i}(x)$ is obtained; with this data the implausibility value is

$$\boldsymbol{I_i^2(x)} = \frac{\left(\boldsymbol{z_i - E[\hat{f}_i(x)]}\right)^2}{\boldsymbol{Var[\hat{f}_i(x)] + Var[\varepsilon_i] + Var[e_i]}}, \tag{A7}$$

where zi is the hypothetical historical output value, $E[\widehat{f_i}(x)]$ is the emulator output expected value and $\mathrm{Var}\left[\hat{f}_i(x)\right]$, $\mathrm{Var}[\varepsilon_i]$ and $\mathrm{Var}[e_i]$ are the variances of the emulator output value, structural discrepancy (ε) and observational errors (e) respectively.

Large values of $I_i^2(x)$ suggest that it is implausible that x ∈ X(z). As for each vector of inputs x there are many implausibility values, one for each output, the implausibilities are then combined. The implausibility value I(x) for a vector of inputs x is considered as being the maximum value among all Ii(x) obtained.

The input parameters x that satisfy x ∈ X(z) are called non-implausible parameters, since in the next iteration the same input may be found to be no longer plausible. If the emulator is not accurate enough or X(z) does not enable a better understanding of the reservoir's physical features, more simulation runs are designed within the 'non-implausible' regions in the input space and the emulation analysis is repeated iteratively; each iteration is called a Wave (Cumming & Goldstein, 2009; Vernon *et al*., 2013)

The maximum acceptable implausibility value cutoff determines whether an input parameter vector (x) is viewed as non-implausible or not. This value can be defined based on various considerations as discussed in Vernon *et al*. (2013), but often the cutoff used is equal to the critical value of some appropriate distribution, for example the standard normal distribution.

Non-Implausible Inputs Evaluation

The 'non-implausible' input parameters obtained at the end of the process represent the input parameters of the reservoir simulation model, whose outputs match to the hypothetical historical production data. These parameters are evaluated to identify how much production data improved the reservoir model understanding.

While carrying out these analysis considering different production periods, it is possible to evaluate the impact of the production period over the reservoir uncertainty reduction.

Results

It is shown the application of the workflow described in the previous topic to a synthetic reservoir model built to represent a region of an injector and related producers. The uncertainty reduction was quantified considering two different production periods: the first at an early stage of production (1000 days) and the second at an intermediate stage of production (3500 days).

Base Model

The reservoir simulation model designed in the field development phase is called base model. In this study the base model consists of a five-spot configuration and is structurally represented by a horizontal top at -1000 m, discretized with a 45 x 45 x 1 grid in the x, y and z directions, respectively, with a dimension of 40 m in the three directions, totaling 2025 blocks. A light oil and Black Oil fluid model was used and presents a constant permeability equal to 500 mD and a constant porosity equal to 20%. The model takes approximately 10 seconds to be simulated. The base model were built by Risso (2007) and modified by Machado (2010). The permeability map is presented in Figure A2.

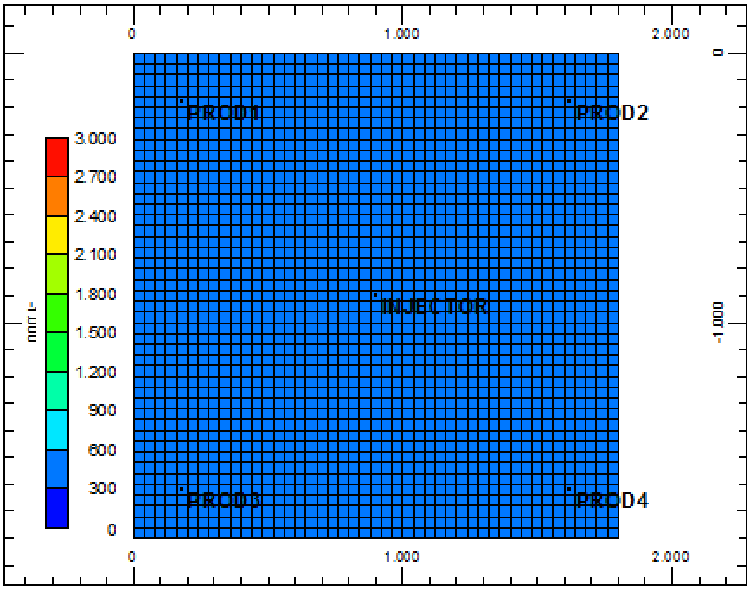

Figure A.2. Base model permeability map.

Input and Output Definition

The reservoir model uncertain input parameters that make up the vector x and that parameterize the reservoir geology containing a channel, are shown in Figure A3; a description and the ranges of these inputs are shown in Table A1.

Table A.1. Input parameters and associated ranges.

Input Parameter (x_i)	**Description**	**Minimum**	**Maximum**
x_c	channel Cartesian x center value	grid cell 5	grid cell 41
y_c	channel Cartesian y center value	grid cell 5	grid cell 41
θ	channel angle	0	π
w_c	channel width	$2\sqrt{2}$	$5\sqrt{2}$
L_c	channel length	0	26 grid cells
k_c	channel permeability	1000mD	3000mD
k	reservoir permeability	200mD	600mD

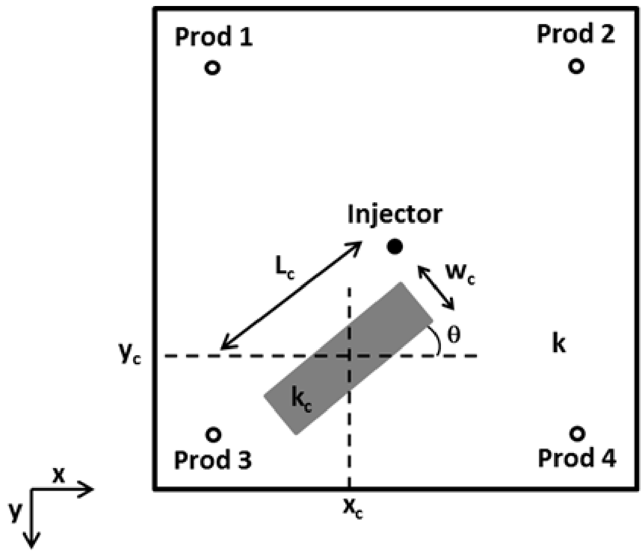

Figure A.3. Uncertainties sketch.

Seventeen production output parameters were selected to evaluate the impact of production data acquisition in the reservoir model uncertainty reduction. The definition of each is as follows:

- $f_1(x)$ to $f_4(x)$: production well 01 to 04 bottom-hole pressure (BHP);
- $f_5(x)$: injector well bottom-hole pressure (BHP);
- $f_6(x)$ to $f_9(x)$: production well 01 to 04 water rate;
- $f_{10}(x)$ to $f_{13}(x)$: production well 01 to 04 time to breakthrough (BT).

Input Data Set Sampling

The selection of the first input data sampling was obtained through the Latin Hypercube sampling method. Two hundred vectors of inputs x, from the initial input space, were sampled generating 200 scenarios. The probability distribution of all uncertainties was considered uniform. Figure A4 shows two dimensional projections of the locations of the 200 input vectors used.

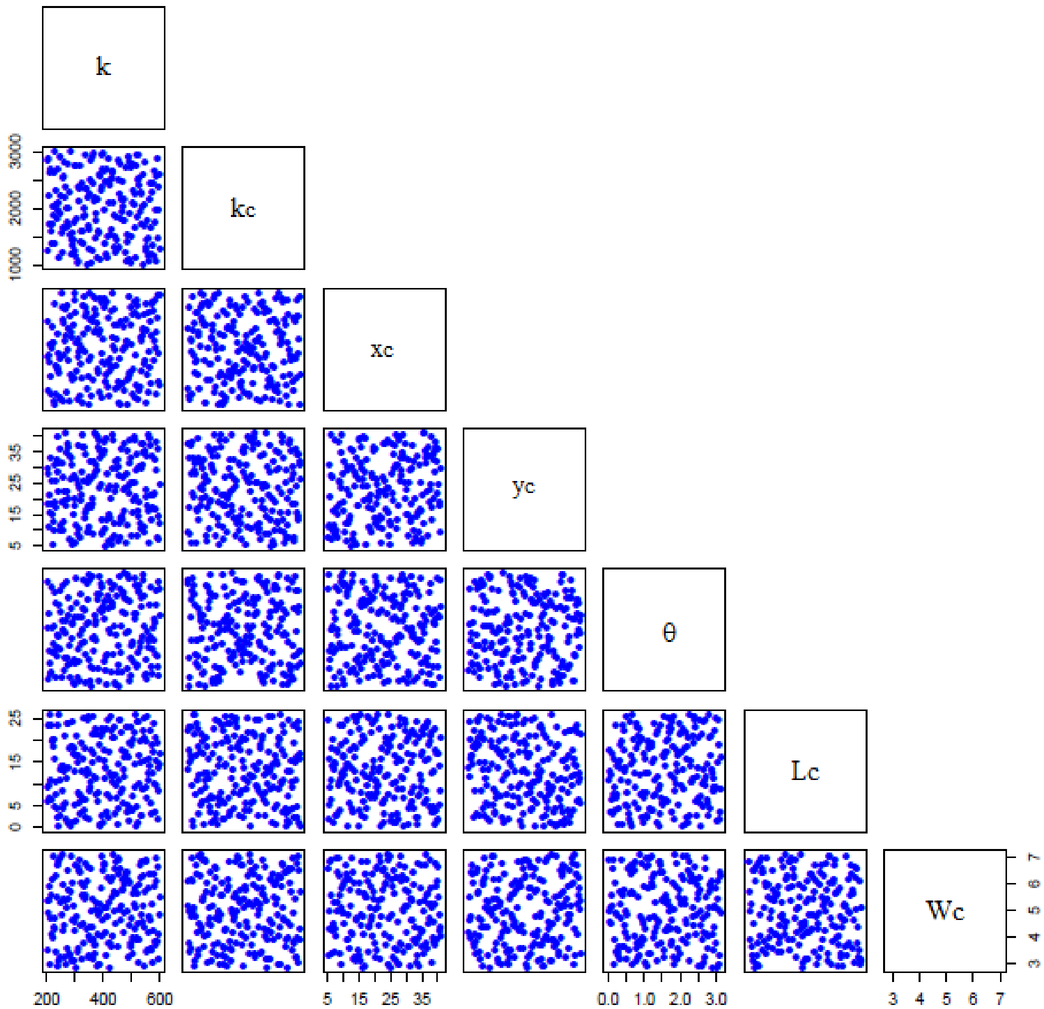

Figure A.4. First set of input data values, generated from a LHD of size 200.

The generated scenarios were simulated to obtain the production outputs f(x). The sampled input parameters and resulted simulation outputs were used to estimate the emulator in the first iteration (Wave 1). The initial input space is reduced at the end of the Wave 1 analysis due to the imposition of the implausibility cutoff; the new input space then consists of the non-implausible input parameters: those whose outputs may match the hypothetical historical data.

In order to improve the emulators' quality and reduce even more the input space, a new data sample is obtained using the LHD from the non-implausible input space derived from the Wave 1 analysis. The Wave 2 analysis consists of estimating new emulators using this new Wave 2 data sample. The quantity of iterations (Waves) depends on the emulator quality needed, reduction in the input parameter space, computational and time resources.

Emulator Estimation and Diagnostic

To estimate the emulator some assumption were adopted:

- As the study is performed with hypothetical historical data, no measurement errors are considered. Therefore, in this study the observational error is equal to zero;
- There is no structural discrepancy between the simulator and real physical system output, thus, ε is equal to zero.

Three interactions (Wave 1, 2 and 3) were needed to obtain the non-implausible input space $X(z)$ for each of the production period analyzed. For the period of production equal 1000 days, the output $f_{10}(x)$ to $f_{13}(x)$ were not used, since there is no water breakthrough at the production wells up to this period. Moreover, in both cases for Wave 1 analysis only BHP outputs were emulated; the water rate linear models obtained were not judged to be accurate enough based on their diagnostics.

Implausibility Analysis

To determine the 'non-implausible' inputs a hypothetical reality was selected from the initial input space. The hypothetical reality used has a high permeability channel; its position and permeability values are shown in Figure A5 and its input values are presented in Table A2.

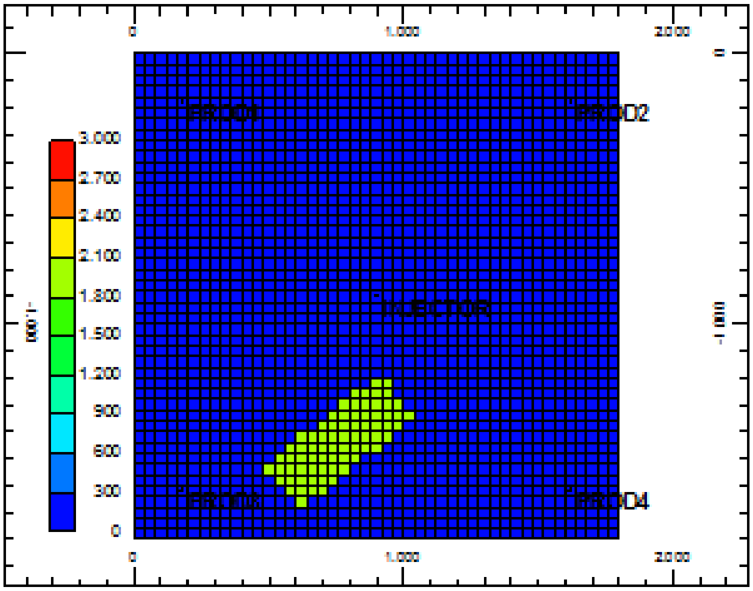

Figure A.5. Hypothetical reality permeability map.

Table A.2. Hypothetical reality input parameters values.

Input Parameter (x_i)	Description	Hypothetical Reality Value	Unit
x_c	channel Cartesian x center value	19.6	grid cell
y_c	channel Cartesian y center value	36.4	grid cell
θ	channel angle	2.47	rad
w_c	channel width	17.7	grid diagonal
L_c	channel length	5.4	grid
k_c	channel permeability	2000.5	mD
k	reservoir permeability	274.7	mD

Each vector from the input parameter space is evaluated to determine if the output parameter obtained using the emulator may match the hypothetical reality output. This evaluation is performed by analyzing the implausibility value obtained. In the case studied the maximum implausibility value cutoff was chose to be equal to the 99% critical value of the corresponding standard normal distribution, and hence set to 2.576.

A vector from the initial input parameter space is considered non-implausible if the implausibility value is less than the cutoff using the emulators obtained in Wave 1, 2 and 3 analyses. Table A3 shows the reduction in the parameter space as the implausibility analysis is performed over the three waves. The results obtained show the importance of using an emulator in the uncertainty quantification reduction. The volume of input parameter space considered non-implausible was found to be a small proportion of the original input space.

Table A.3. Number of input parameters considered non-implausible.

Analysis Phase	**Period of Production Evaluated**	
	1000 days	**3500 days**
Initial Input Space	1,000,000	1,000,000
Wave 1	11,948	49,470
Wave 2	617	790
Wave 3	3	1

Non-Implausible Inputs Evaluation

To obtain a significant number of non-implausible input parameters an initial space of 8e+08 vectors were used. The input space considered non-implausible after all Waves analyses for the production periods equal to 1000 and 3500 days is shown in Figures A6 and A7, respectively.

Each square shows the relation between the corresponding variables; the colors are related to how close the emulator output obtained using a certain input parameter value match the hypothetical output value. Red and pink colors represent values closer and not so close, respectively, to the hypothetical output value.

At an early stage of production, Figure A6, it was possible to identify with high accuracy the field permeability. The range of x and y channel position was narrowed, but channel length values equal to zero was possible to obtain. Zero values to channel length indicate no channel exists. It was not possible to obtain significant information about the channel permeability, angle and width at this stage.

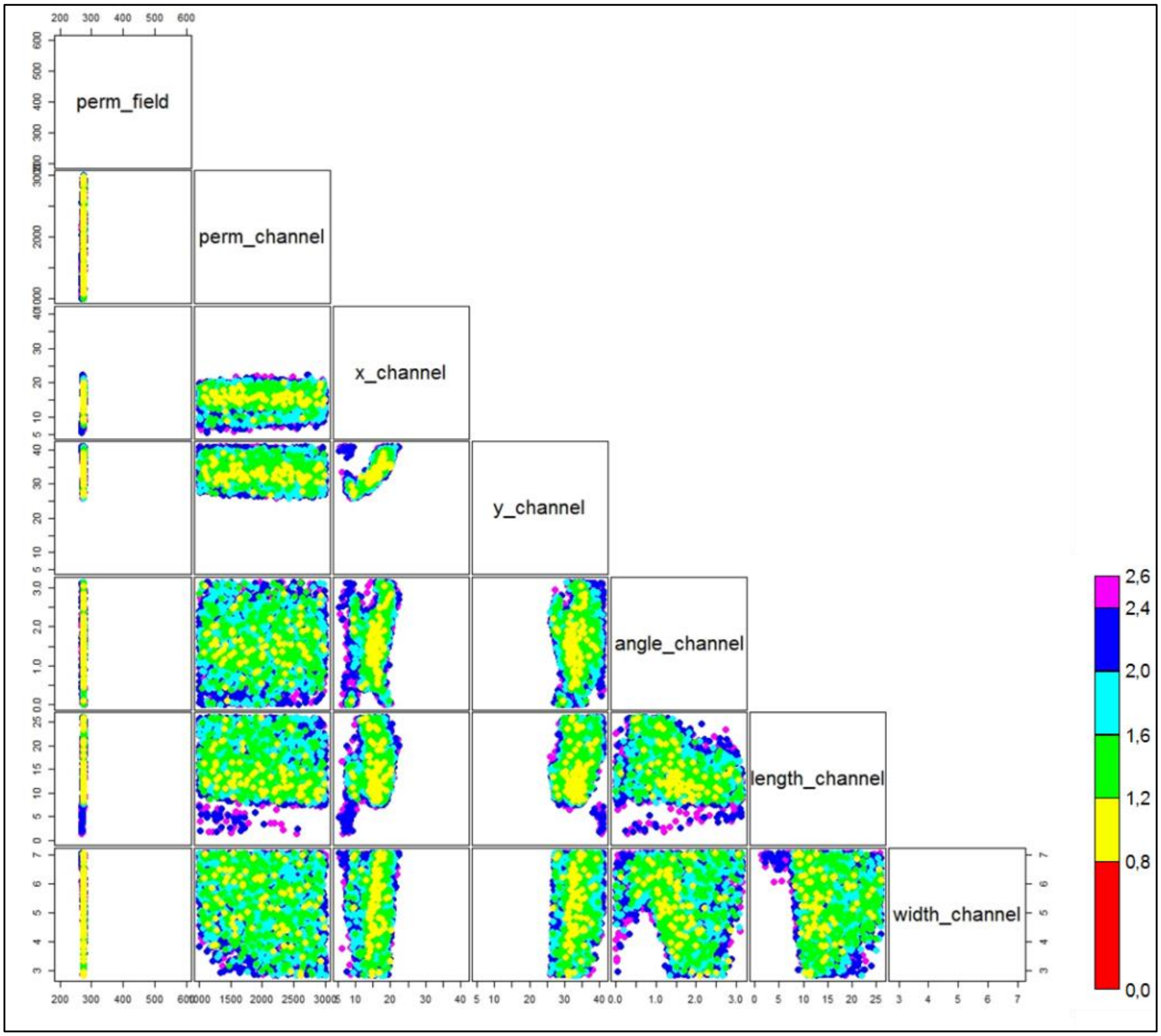

Figure A.6. Non-implausible inputs for period of production equal 1000 days.

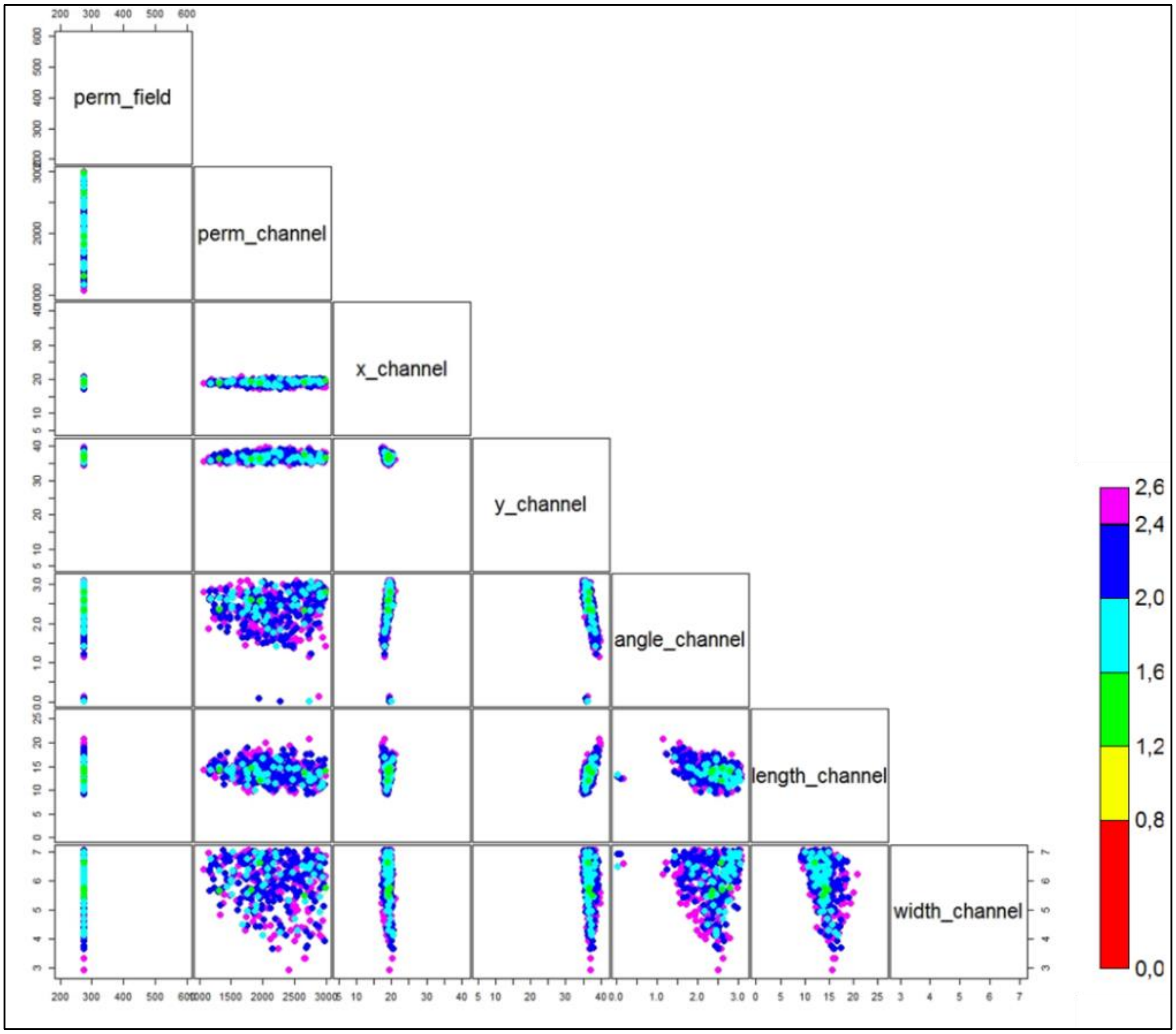

Figure A.7. Non-implausible inputs for period of production equal 3500 days.

For an intermediate production period, Figure A7, a significant uncertainty reduction is obtained using production data. In addition to the field permeability, x and y channel position are close to the hypothetical reality values. It was possible to better understand the channel length, however no significant information was obtained about the channel permeability and width, perhaps suggesting a limit to the amount of information that can be obtained from this production data (or that more waves could be required).

The uncertainty reduction can also be seen in Figures A8, to A19. The cumulative oil production, bottom-hole pressure and water rate for the production wells are presented for the initial input data set (red lines), scenarios obtained after the uncertainty reduction at 1000 (green lines) and 3500 (cyan lines) days, with the reality model shown as a single dark blue line. The production data results were obtained by simulating the scenarios using a simulation software.

There is a significant uncertainty reduction using production data up to 1000 days for most of the wells, however for production well 03 there are still high uncertainty. The uncertainty at production well 03 was reduced using production data up to 3500 days. Note the strong agreement for several outputs between the cyan lines and the dark blue line of the reality model, implying that we have found many locations in input space that are consistent with the observed data. The agreement at late times also implies that we could make accurate predictions of the future behavior of the reality model based solely on the data at 1000 and 3500 days.

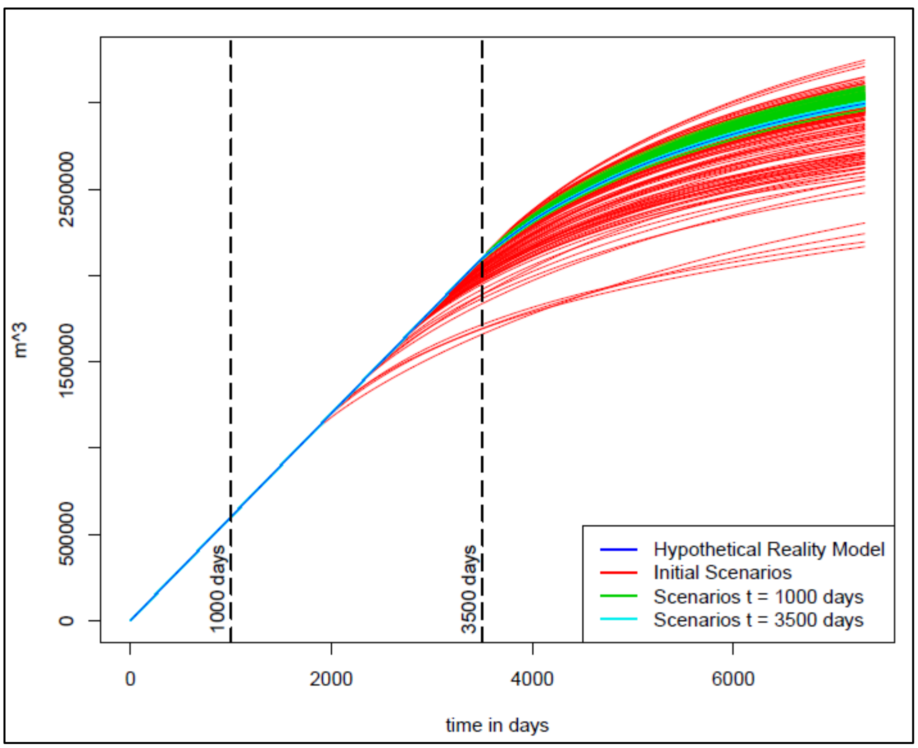

Figure A.8. Uncertainty reduction: PROD 01 cumulative oil.

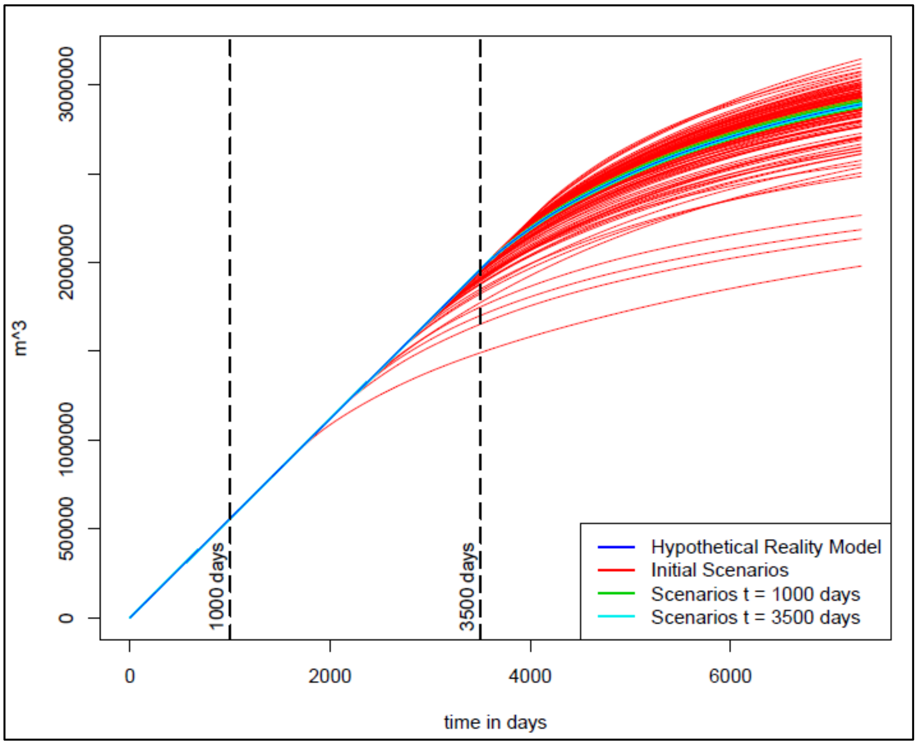

Figure A.9. Uncertainty reduction: PROD 02 cumulative oil.

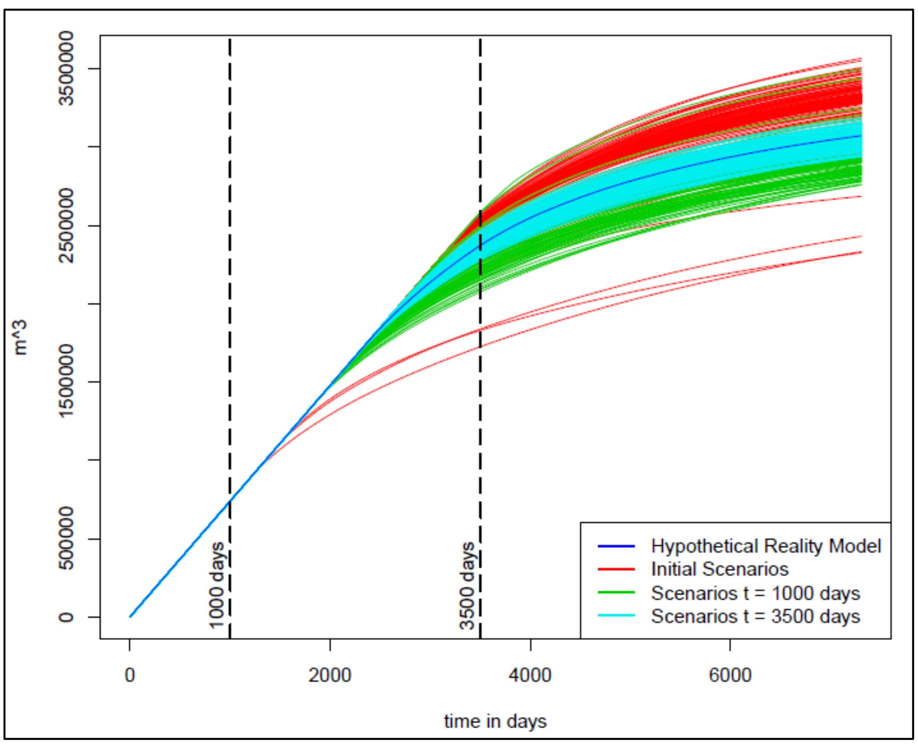

Figure A.10. Uncertainty reduction: PROD 03 cumulative oil.

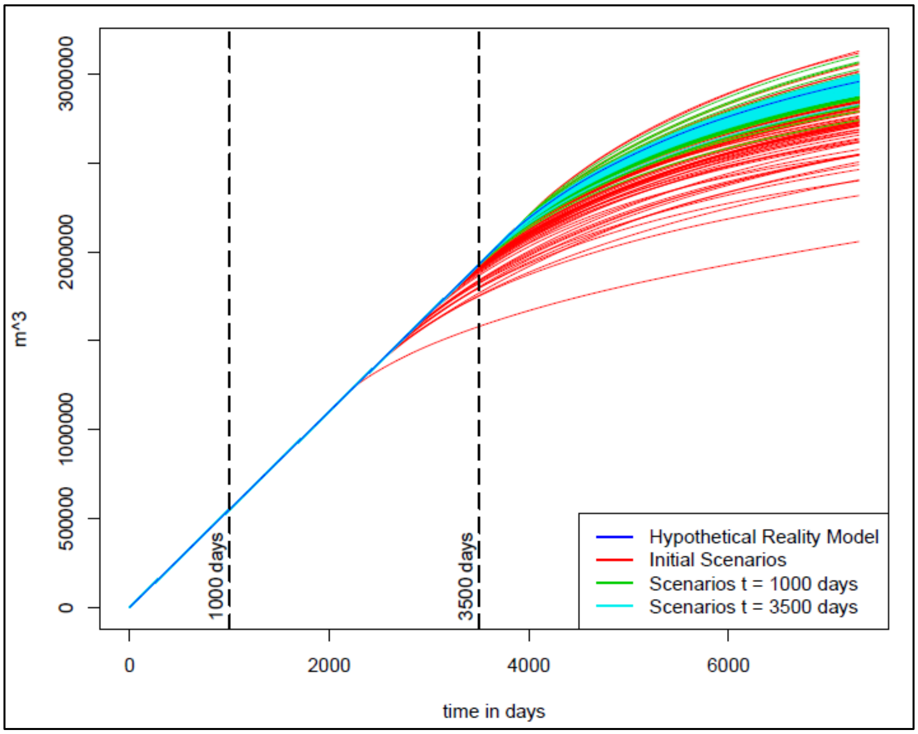

Figure A.11. Uncertainty reduction: PROD 04 cumulative oil.

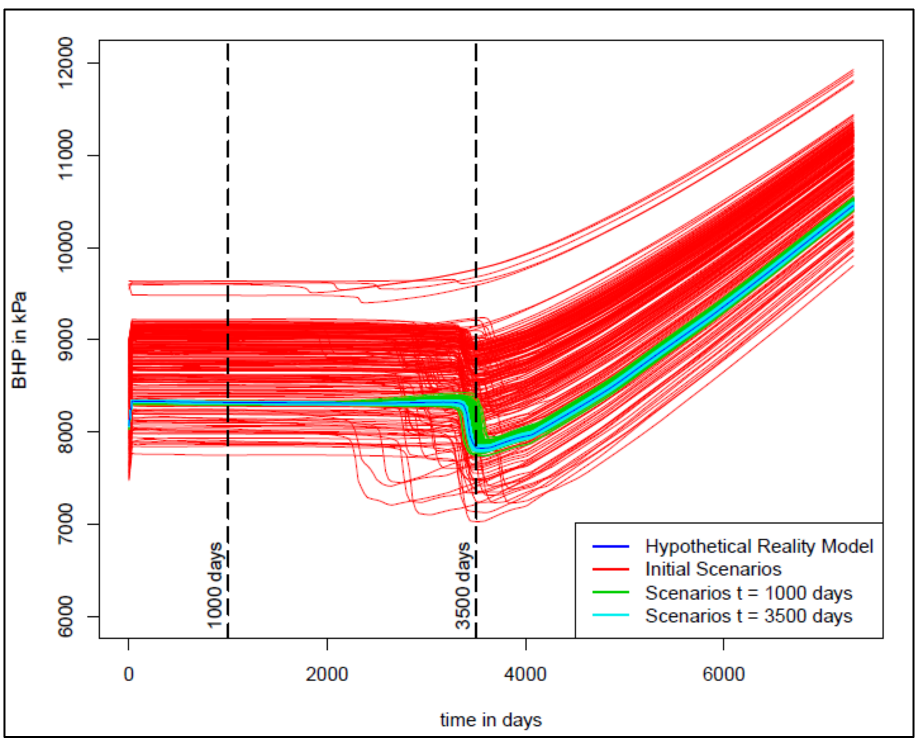

Figure A.12. Uncertainty reduction: PROD 1 bottom-hole pressure.

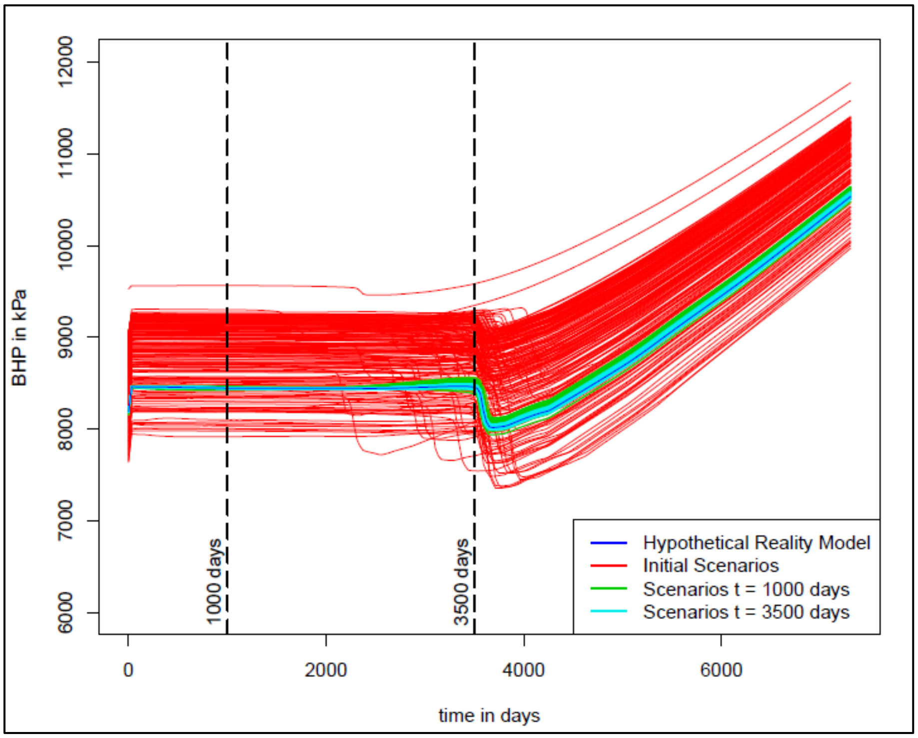

Figure A.13. Uncertainty reduction: PROD 2 bottom-hole pressure.

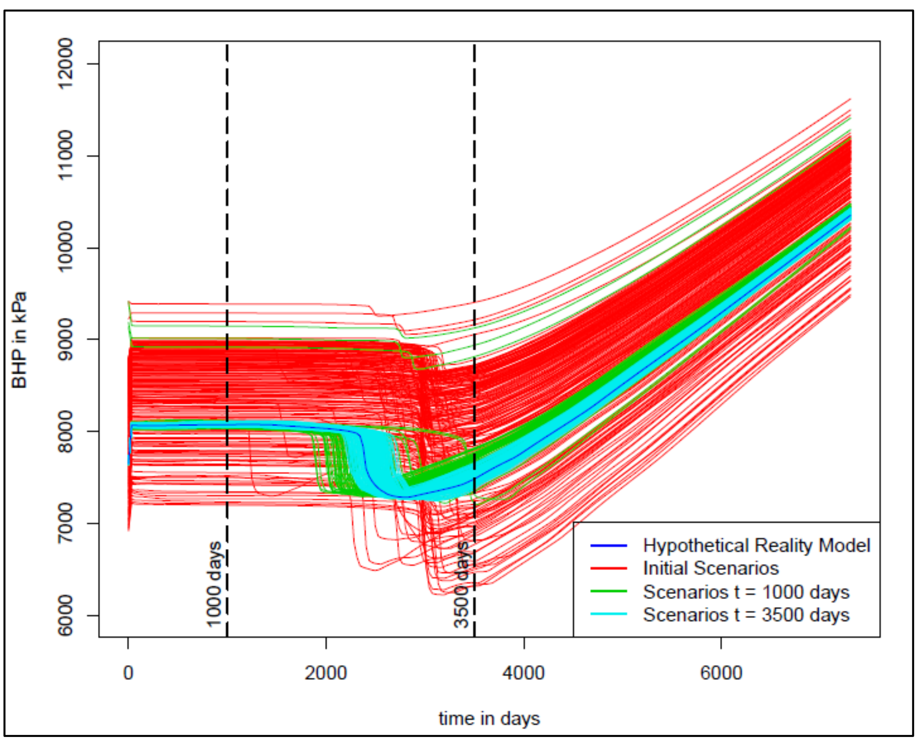

Figure A.14. Uncertainty reduction: PROD 3 bottom-hole pressure.

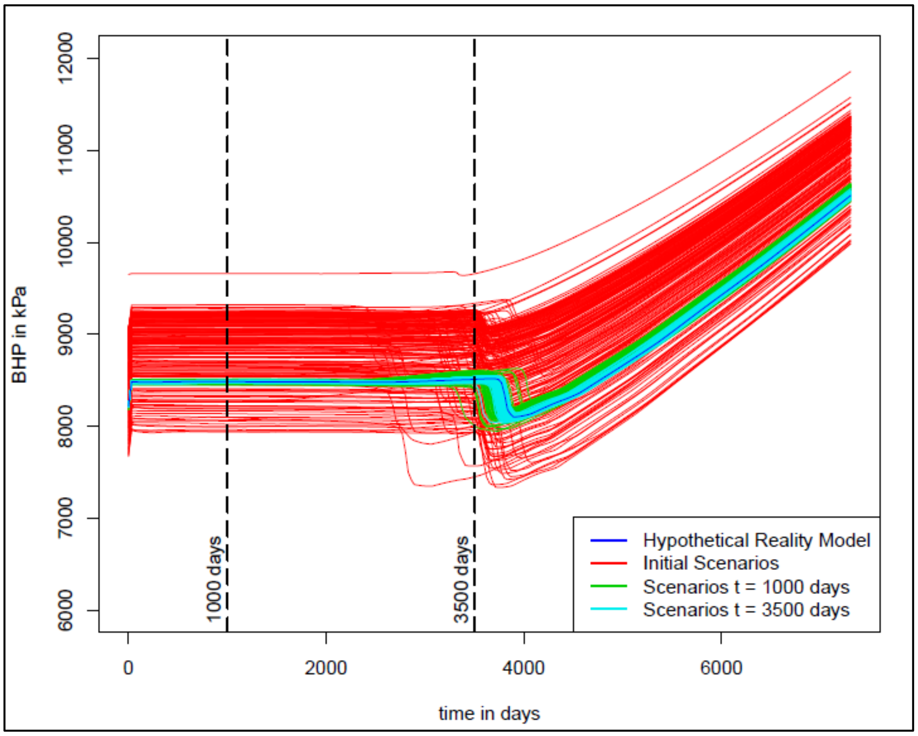

Figure A.15. Uncertainty reduction: PROD 4 bottom-hole pressure.

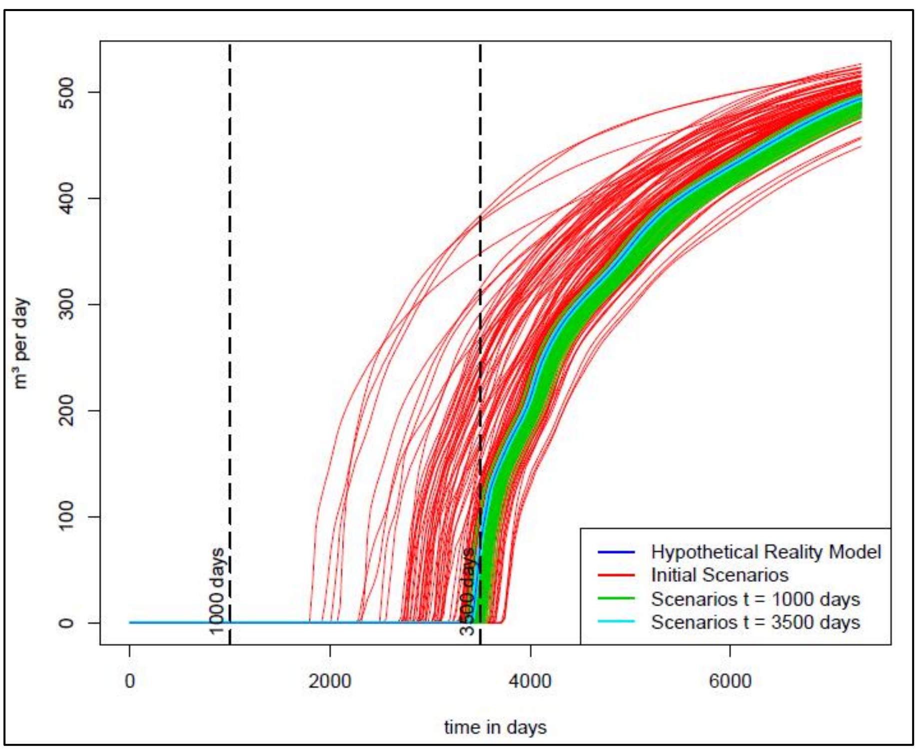

Figure A.16. Uncertainty reduction: PROD 1 water rate.

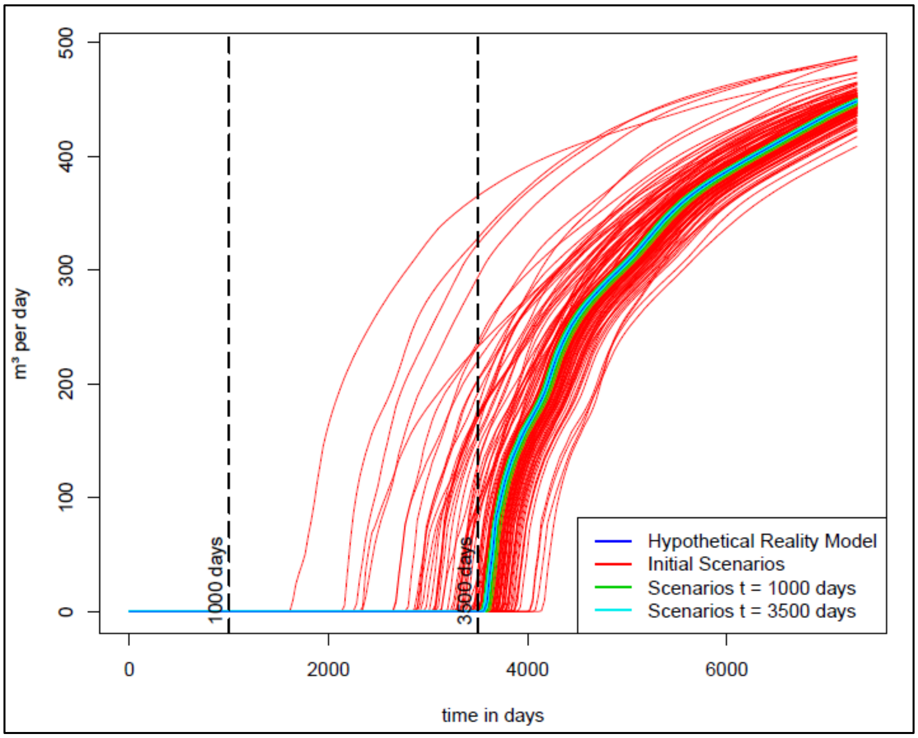

Figure A.17. Uncertainty reduction: PROD 2 water rate.

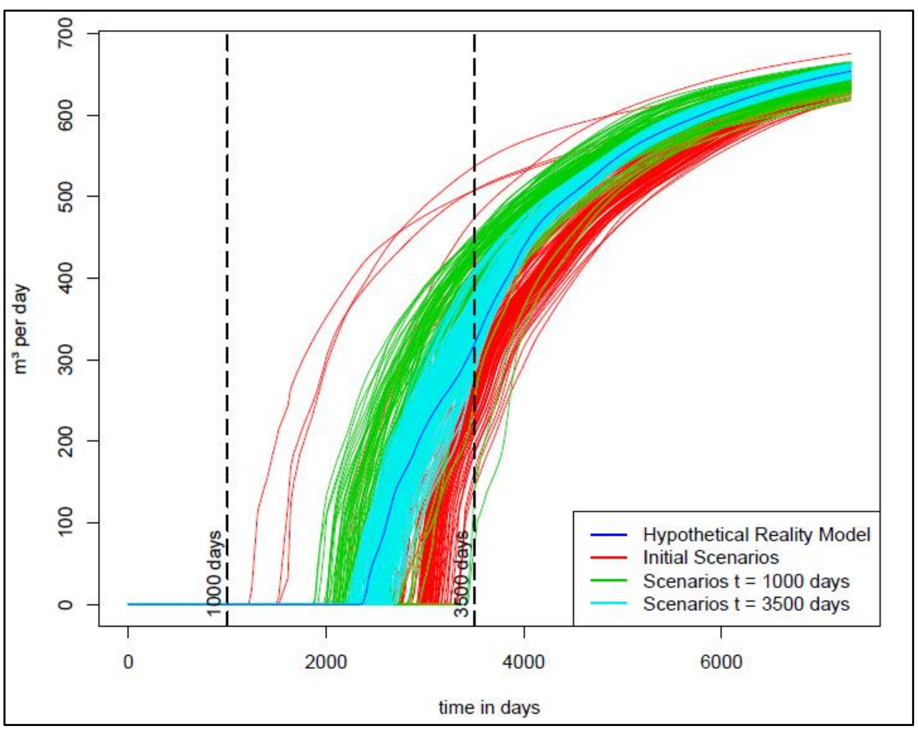

Figure A.18. Uncertainty reduction: PROD 3 water rate.

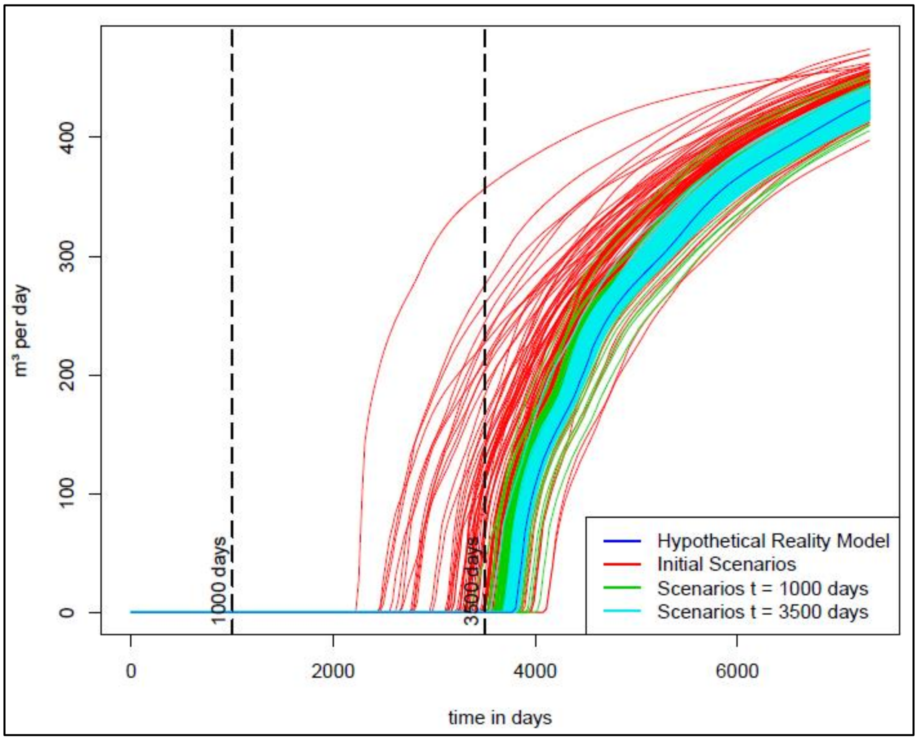

Figure A.19. Uncertainty reduction: PROD 4 water rate.

Conclusions

A workflow to determine the input parameters whose output values match to historical data using emulation techniques was presented. The workflow was successfully applied to a five-spot synthetic case that was built to represent a region of an injector and related producers. The uncertainty reduction of a reservoir model due to new information acquisition for different production periods was quantified. The field production data used was obtained by considering a hypothetical reality among all possible scenarios, since the analysis was performed at the development stage and used a synthetic model. Two periods of production were evaluated: at an early production stage (1000 days) and at an intermediate production stage (3500 days).

The results obtained showed the importance of using emulators in the uncertainty reduction quantification and history matching process. The number of input parameters considered non-implausible was a small set of the initial input space. At an early stage it was possible to reduce the uncertainty by identifying the hypothetical real field permeability and identifying possible values for channel positioning. However, other important physical features were not identified, such as the channel permeability, width and length. At an intermediate stage, the uncertainty reduction was higher. However, still some important physical features that impact on production prediction, such as channel permeability and width were not identified; therefore, further steps of this research will test the application of the emulation technique with seismic 4D data to reduce uncertainty.

Nomenclature

e	random observational errors vector
f(x)	output vector
$\hat{f}(x)$	emulated output
g	deterministic function
i	output emulated
j	number of functions
k_c	channel permeability
k	reservoir permeability
n	number of data points
p	number of parameters to be estimated
u	local variation
x	input vector
x, y, z	Cartesian directions
x_c	channel Cartesian x center value
y_c	channel Cartesian y center value
y	real physical outputs vector
z	field observed outputs vector
w_c	channel width
Cov	covariance
E	expected value
I	implausibility value
L_c	channel length
LDH	Latin Hypercube Design
R^2	squared multiple correlation

RSS	residual sum of squares
RYY	total sum of squares
Var	variance
X(z)	input parameter space
β	scalar
ε	random structural discrepancy vector
σ	standard deviation
θ	channel angle

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APPENDIX B: DESCRIPTION OF THE INITIAL BASE MODEL PRODUCTION STRATEGY

Chapter 4 mentioned that the process to generate the reservoir scenarios needed to be performed again. It occurred because in the phase of production strategy improvement it was found out that the optimal production strategy of the representative model improved the economic results from the base model. The reservoir scenarios were generated again considering the optimal base production strategy and used in the following chance of success methodology steps. The appendix shows the initial base model production strategy description and production data results from the corresponding scenarios.

Initial Base Model Production Strategy Description

The geological and structure of the reservoir model is the same presented in the Item 4.6.1. The initial production strategy used consists of eleven production wells and eight water injector wells. Figure B1 shows a 3D view of the reservoir base model with the injector and production wells.

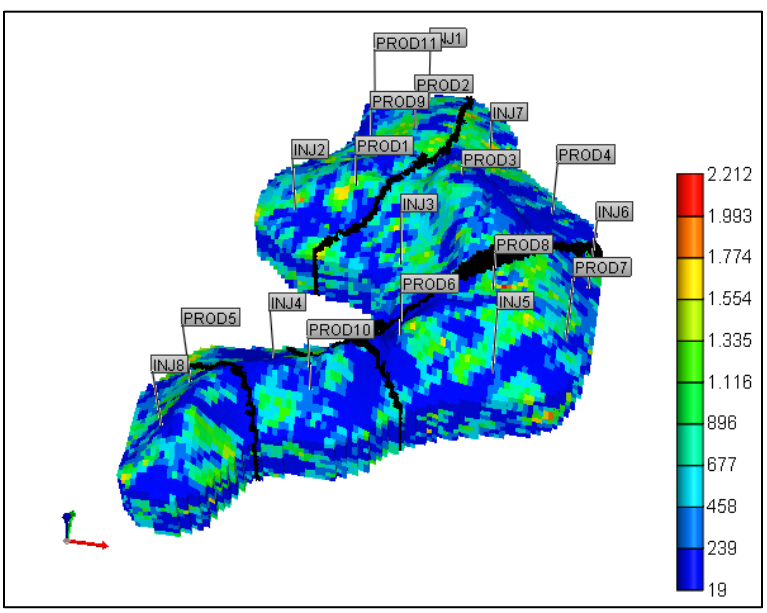

Figure B.1. Reservoir initial base model permeability map 3D view.

Uncertainty and Risk Analysis

The reservoir model uncertainty considered was the same presented in the Item 4.6.2. Discrete Latin Hypercube was used to generate 500 scenarios. It was considered that all attributes have a uniform distribution. The field production results for all scenarios and base model are presented in Figures B2 to B4. The curves pattern remained the same; however the range of the cumulative oil production and reservoir pressure presented lower values to the initial production strategy.

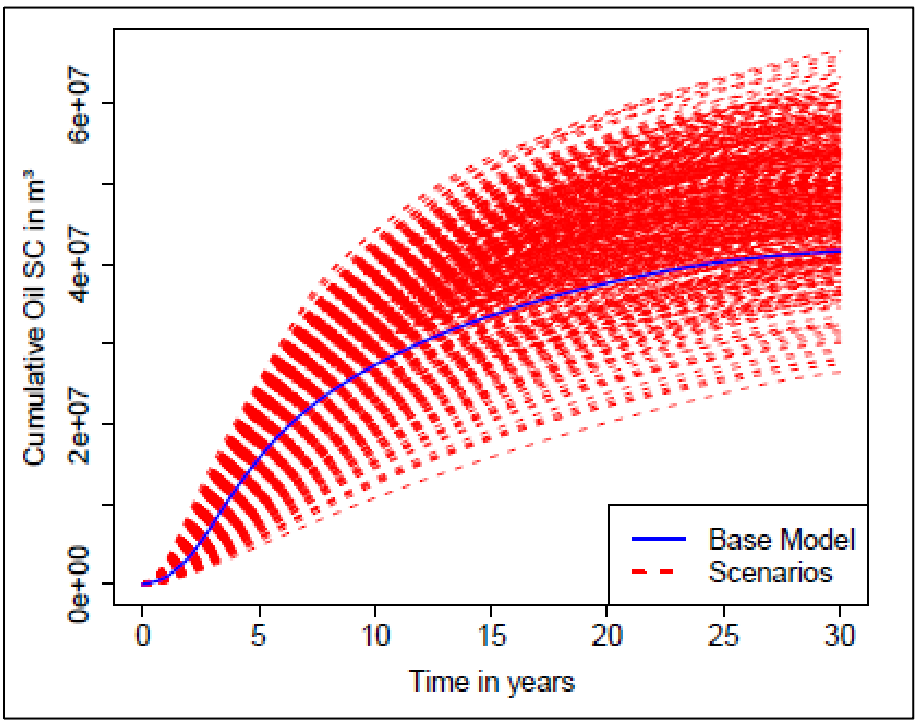

Figure B.2. Production results: field cumulative oil SC.

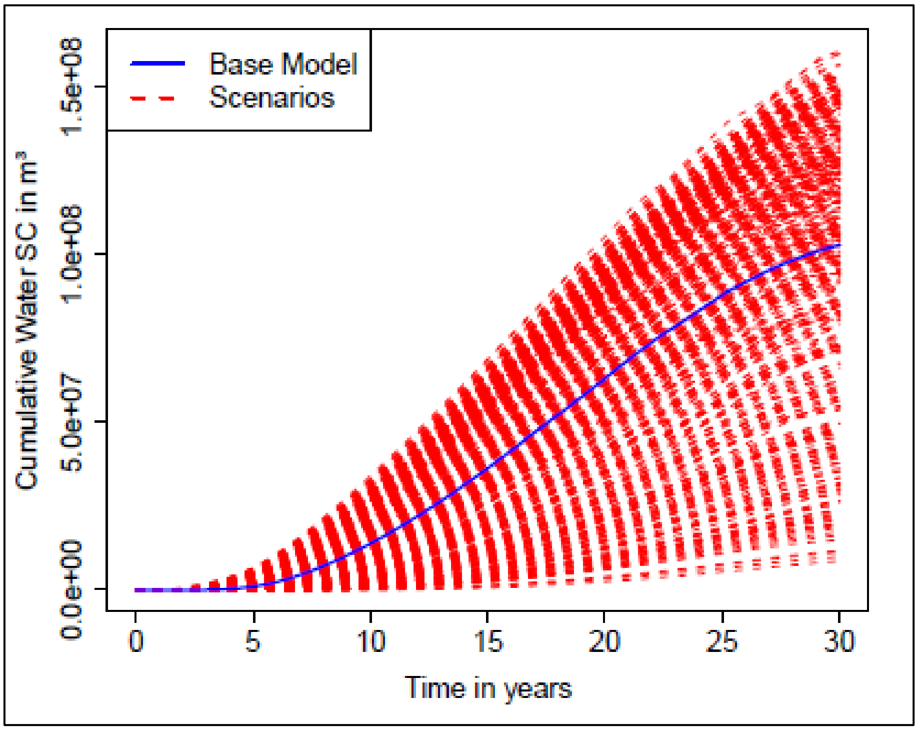

Figure B.3. Production results: field cumulative water SC.

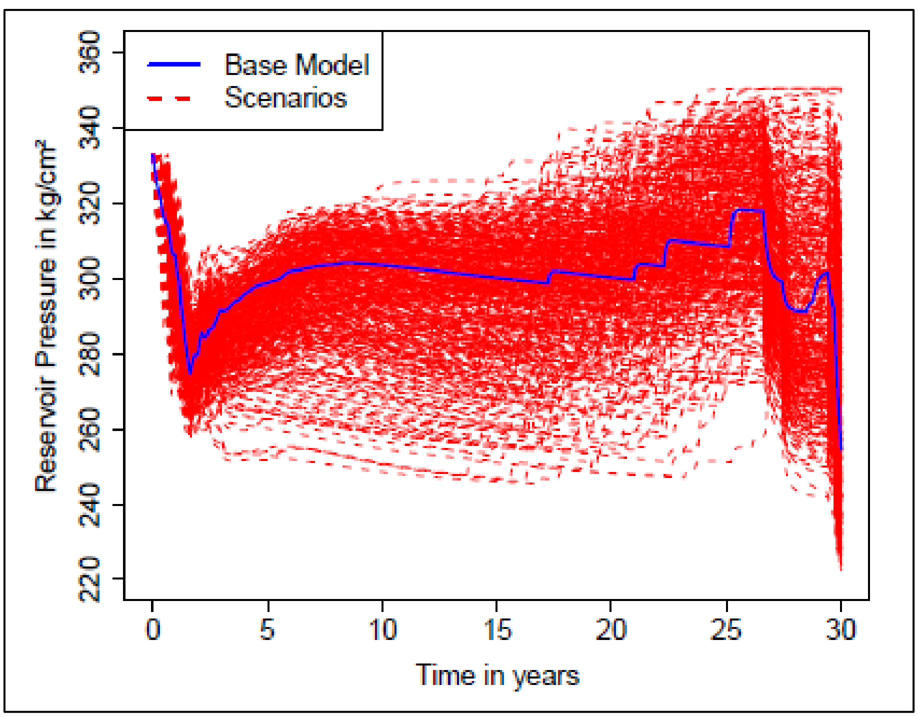

Figure B.4. Reservoir pressure.

Economic Results Comparison

The comparison between the production economic results from the base model using the initial production strategy and the optimal one is presented in Table B1. There was an increase of 21.2% in the NPV and 7.7% of oil production; thus the chance of success methodology presented in Chapter 4 used the base model optimal production strategy.

Table B.1. Production and economic results comparison.

Parameter	**Base Model**	**Optimized Base Model**	**Increase (%)**
Net Present Value (US$)	1.46E09	1.77E09	21.2
Recovery Factor (%)	64.2	69.14	7.7
Cumulative Oil Production (m^3)	4.16E07	4.48E07	7.7

APPENDIX C: DESCRIPTION OF THE OPTIMIZATION PROCESS

Introduction

This item presents the strategy optimization process executed to the representative models RM1 and RM2 after five years of production. The production of the reservoir presents some constraints related to the platform size and reservoir properties. The constraints considered in the reservoir simulation model are:

- Production well minimum bottom-hole pressure (BHP): 215 kgf/cm^2;
- Production well maximum bottom-hole pressure (BHP): 350 kgf/cm^2;
- Platform maximum total production liquid rate (STL): 23.000 m^3/day;
- Platform maximum total injector water rate (STL): 23.000 m^3/day.

The optimization process considered the following actions due to the high number of production and injector wells:

- Drilling of a one new production or injector well;
- Maximum surface oil rate limitation;
- Water rate control.

The performance indicator that defines the best production strategy is the NPV, however other indicators were verified:

- Cumulative Oil Production (Np);
- Recovery Factor (RF);
- Cumulative Water Production (Wp).

RM1 Strategy Optimization

The performance indicators obtained using the base production strategy are presented in Table C1. The RM1 model quality map (total oil per unit area) was evaluated to identify possible drill positions to new production or injector well. The quality maps obtained after 30 years of production from Layers 1 and 6 are presented in Figures C1 and C2.

Table C.1. RM1 Model performance indicator (base production strategy)

Model	**Strategy**	**NPV (US$ x 10^9)**	**RF (%)**	**Np (m^3 x 10^7)**	**Wp (m^3 x 10^7)**
RM1	Base	1.364	58.6	4.61	8.68

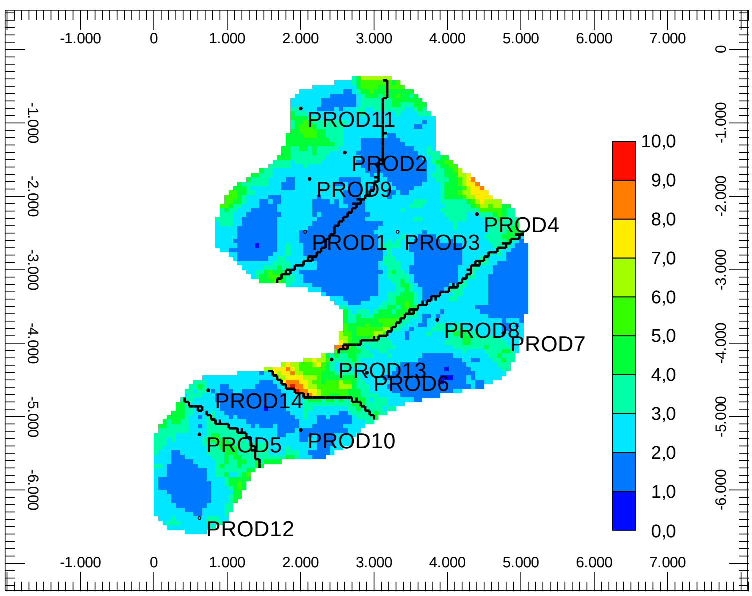

Figure C.1. RM1 model quality maps: Layer 1.

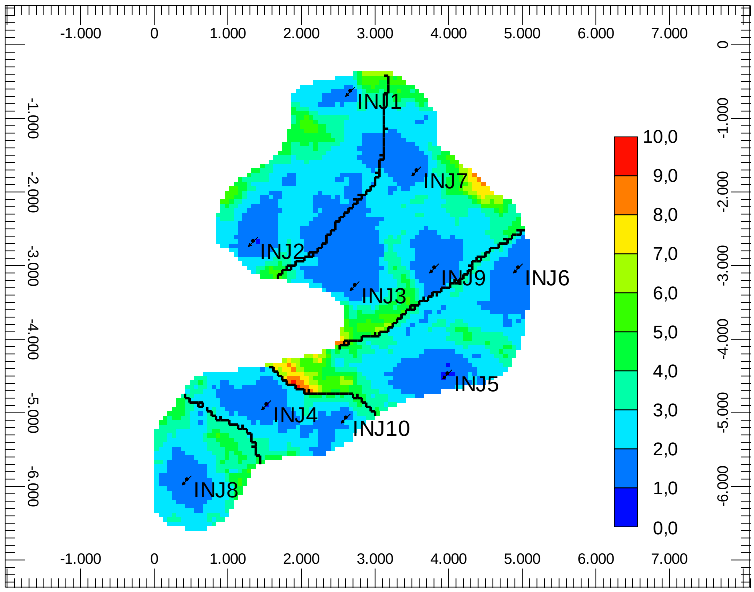

Figure C.2. RM1 model quality maps: Layer 6.

The position of the new well was tested in regions that had the highest values of total oil per area. Four different positions were tested as production or injector wells. The quality maps showing the positions tested are presented in Figure C3. The test description and performance results are presented in Tables C2 and C3.

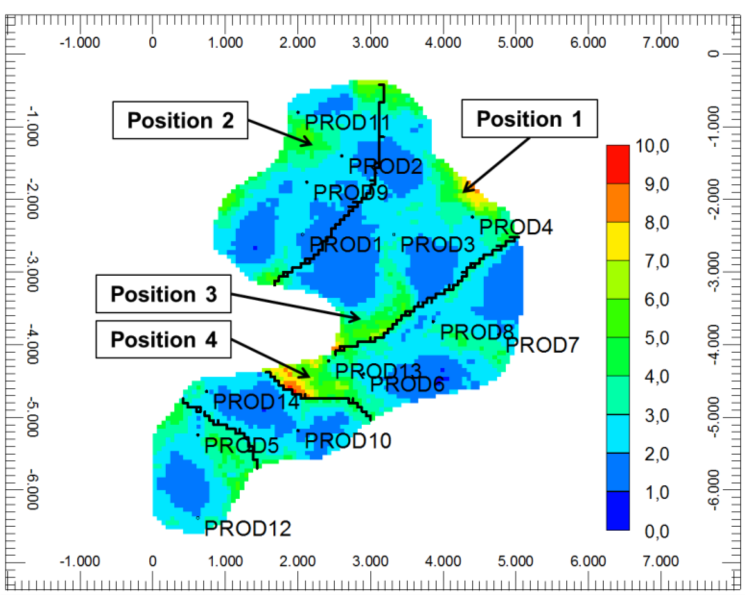

Figure C.3. RM1 model quality map with tested well positions

Table C.2. RM1 optimization tests description.

Model	Test Number	Action
RM1	01	Production well in position 01
	02	Production well in position 02
	03	Production well in position 03
	04	Production well in position 04
	05	Injector well in position 01
	06	Injector well in position 02
	07	Injector well in position 03
	08	Injector well in position 04

Table C.3. RM1 model performance indicators (optimization tests).

Model	Strategy	NPV (US$ x 10^9)	RF (%)	Np (m^3 x 10^7)	Wp (m^3 x 10^7)
RM1	Test 01	1.402	60.0	4.72	9.17
	Test 02	1.382	59.3	4.66	9.23
	Test 03	1.385	59.5	4.67	8.86
	Test 04	1.354	59.2	4.66	8.65
	Test 05	1.369	59.3	4.66	9.08
	Test 06	1.341	58.2	4.57	9.90
	Test 07	1.373	59.2	4.65	8.85
	Test 08	1.401	59.7	4.69	9.53

Test 01 presented the highest value of NPV and RF; thus, the tests related to the reservoir management were performed considering a new production well in position 01 (Test 01). The production wells water and oil rate of Test 01 model are presented in Figures C4 and C5, respectively.

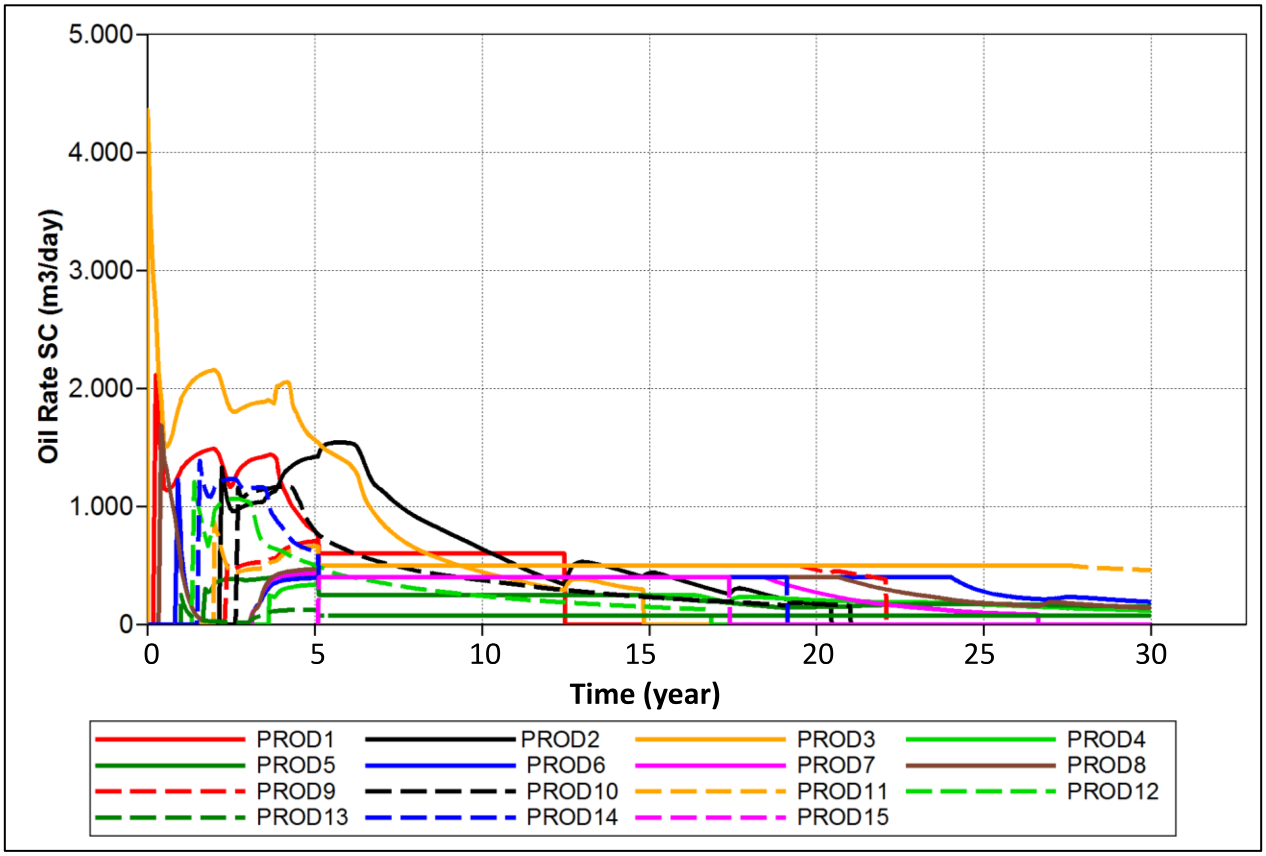

Figure C.4. Test 01 RM1 model production wells oil rate.

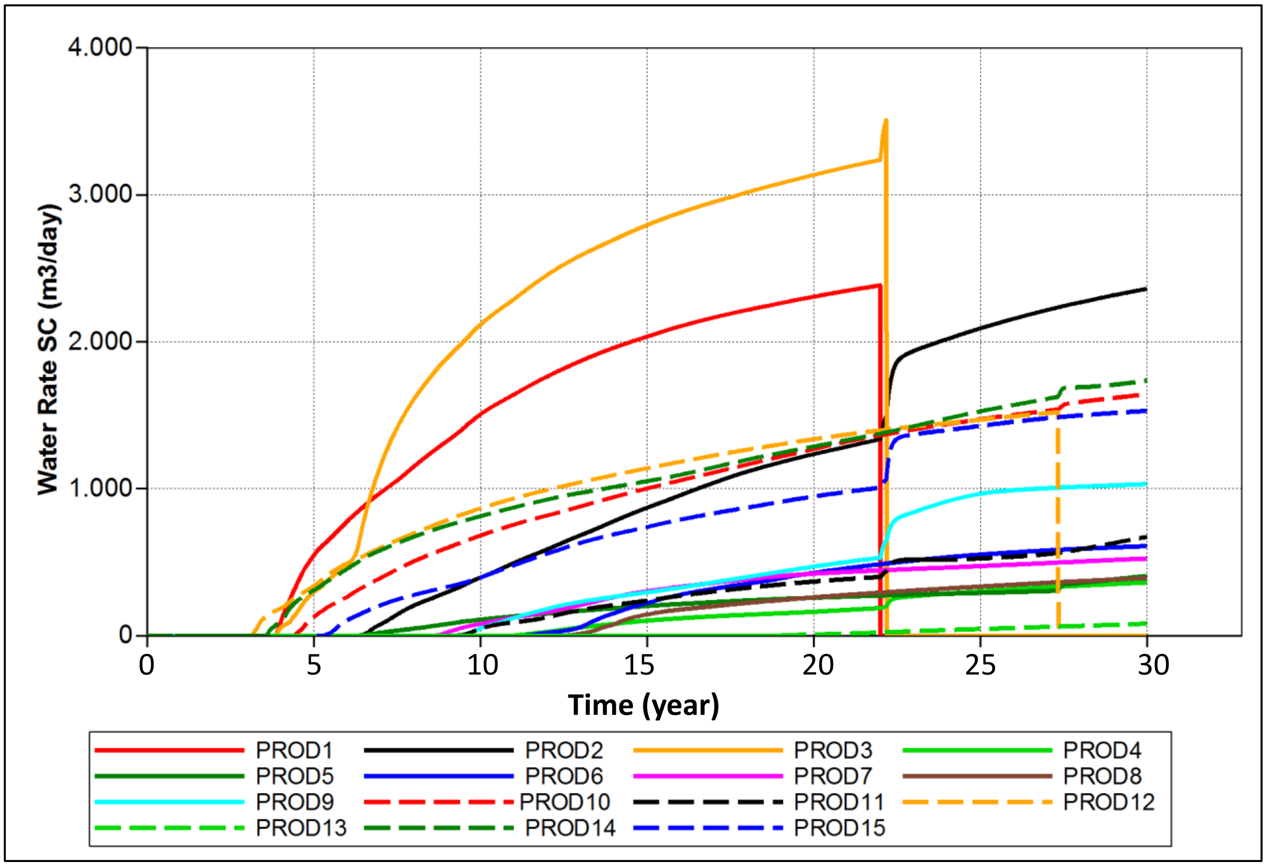

Figure C.5. Test 01 RM1 model production wells water rate.

The reservoir management tests were performed using the software CMOST® to combine all the possibilities. The tests performed considered:

- A limitation on the oil production to extend the production plateau period and increase the efficiency of the production wells. The limit values were defined for each production well based on the results presented in Figure B3;
- The water cut variation for the production wells with highest water rate presented in Figure B4.

The values of maximum surface oil rate tested are presented in Table C4.The water cut variation was tested to the production wells: PROD 01, PROD 02, PROD 03, PROD 09, PROD 10, PROD 12, PROD 14 and PROD 15; the values used are equal to 0.85 and 0.90.

The results of the water cut values and maximum surface oil rate that maximize the NPV obtained using CMOST® are presented in Table C5; a total of 290 tests were performed. In some production wells the inclusion of a limit on the surface oil rate does not improve the performance results; in these cases no value of STO is shown in Table C5.

The comparison between the results obtained to the RM1 model using the base production strategy and the optimized strategy are presented in Table C6. There was an increase in US$ 49.2 million due to the production strategy optimization.

Table C.4. RM1 - values o maximum oil surface used in the tests.

Production Well	**Maximum Surface Oil Rate (m³/day)**		
	STO 01	**STO 02**	**STO 03**
PROD 01	200	400	600
PROD 02	500	750	1000
PROD 03	500	750	1000
PROD 04	100	200	250
PROD 05	100	200	250
PROD 06	200	300	400
PROD 07	200	300	400
PROD 08	200	300	400
PROD 09	200	400	500
PROD 10	200	300	400
PROD 11	200	400	500
PROD 12	200	300	400
PROD 13	50	75	100
PROD 14	200	300	400
PROD 15	200	300	400

Table C.5. RM1 - results of STO and water cut

Production Well	Maximum Surface Oil Rate (m^3/day)	Water Cut
PROD 01	600	0.90
PROD 02	-	0.90
PROD 03	-	0.90
PROD 04	250	0.95
PROD 05	250	0.95
PROD 06	400	0.95
PROD 07	400	0.95
PROD 08	400	0.95
PROD 09	500	0.90
PROD 10	-	0.90
PROD 11	500	0.95
PROD 12	-	0.90
PROD 13	75	0.95
PROD 14	400	0.90
PROD 15	400	0.90

Table C.6. RM1 model performance indicators (base and optimized strategy).

Model	Strategy	NPV (US$ x 10^9)	RF (%)	Np (m^3 x 10^7)	Wp (m^3 x 10^7)
RM1	Base	1.364	58.6	4.61	8.68
	Optimized	1.413	61.6	4.84	8.16

RM2 Strategy Optimization

The performance indicators obtained using the base production strategy are presented in Table C7. The RM2 model quality map (total oil per unit area) was evaluated to identify possible drill positions to new production or injector well. The quality maps obtained after 30 years of production from Layers 1 and 6 are presented in Figures C6 and C7.

Table C.7. RM2 Model performance indicator (base production strategy)

Model	Strategy	NPV (US$ x 10^9)	RF (%)	Np (m^3 x 10^7)	Wp (m^3 x 10^7)
RM2	Base	3.246	72.3	6.70	14.28

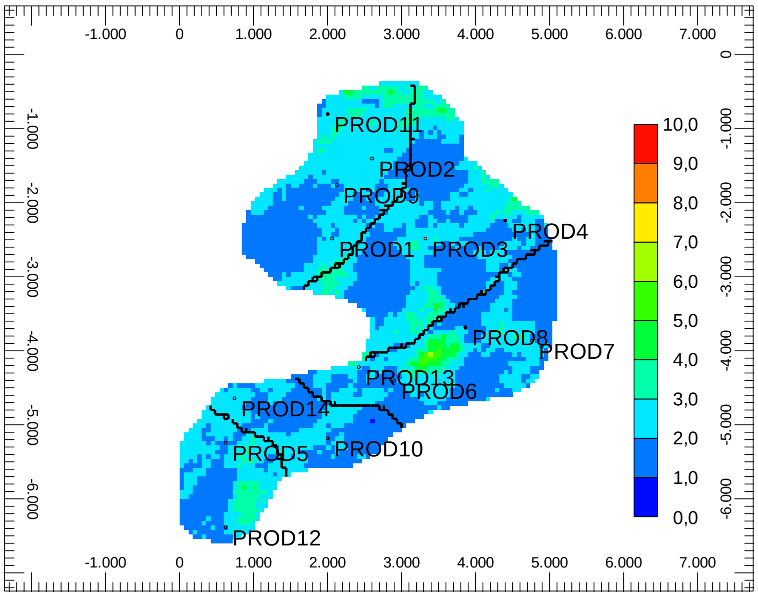

Figure C.6. RM2 model quality maps: Layer 1.

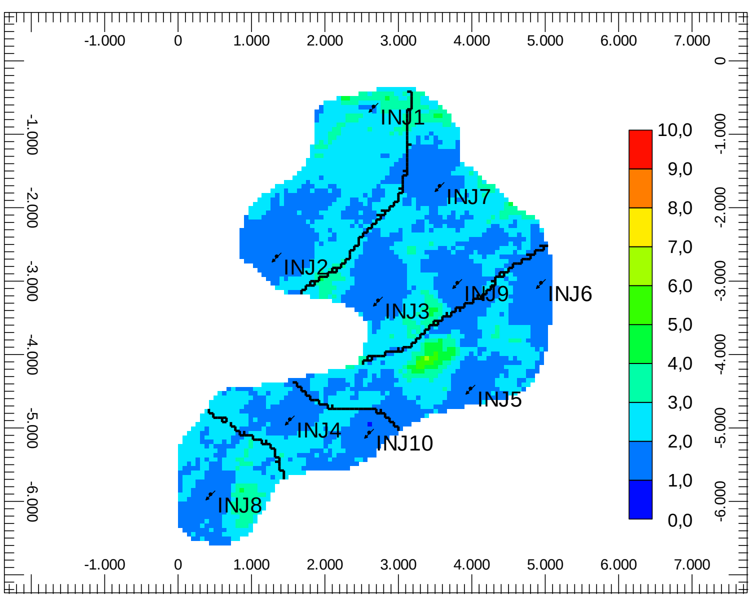

Figure C.7. RM2 model quality maps: Layer 6.

The position of the new well was tested in regions that had the highest values of total oil per area. Three different positions were tested as production or injector wells. The quality maps showing the positions tested are presented in Figure C8. The test description and performance results are presented in Tables C8 and C9.

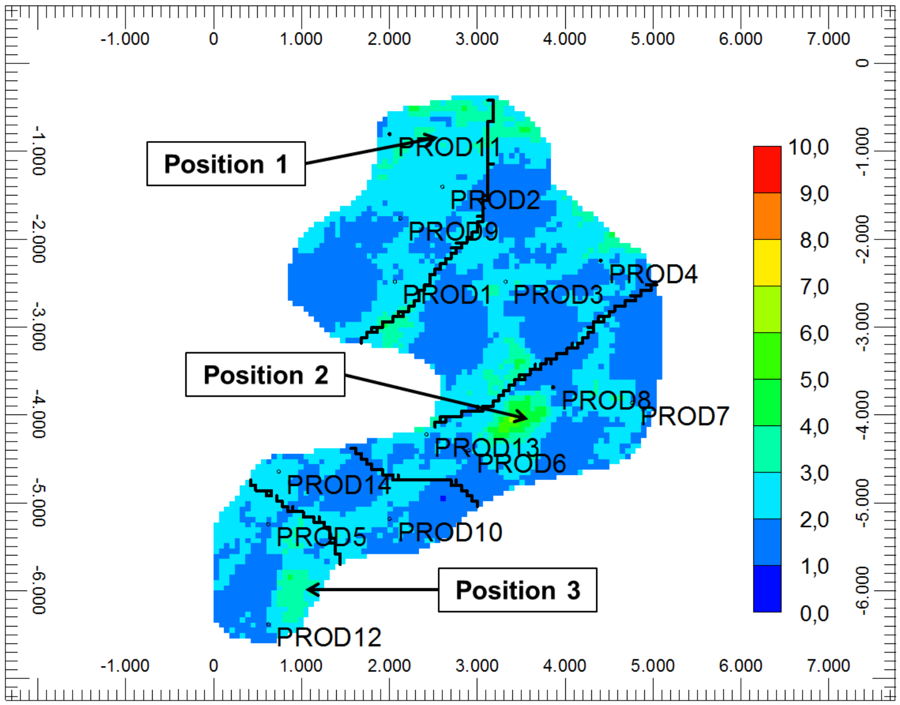

Figure C.8. RM2 model quality map with tested well positions

Table C.8. RM2 optimization tests description.

Model	Test Number	Action
RM2	01	Production well in position 01
	02	Production well in position 02
	03	Production well in position 03
	04	Injector well in position 01
	05	Injector well in position 02
	06	Injector well in position 03

Table C.9. RM2 model performance indicators (optimization tests).

Model	Strategy	NPV (US$ x 10^9)	RF (%)	Np (m^3 x 10^7)	Wp (m^3 x 10^7)
RM2	Test 01	3.247	72.1	6.68	13.88
	Test 02	3.267	72.7	6.74	13.98
	Test 03	3.241	72.4	6.71	13.68
	Test 04	3.180	71.3	6.61	14.76
	Test 05	3.228	72.3	6.70	13.71
	Test 06	3.228	72.3	6.70	13.71

Test 02 presented the highest value of NPV and RF; thus, the tests related to the reservoir management were performed considering a new production well in position 02 (Test 02). The production wells water and oil rate of Test 02 model are presented in Figure C9 and C10, respectively.

The reservoir management tests were performed using the software CMOST® to combine all the possibilities, using the same consideration presented in the RM1 model optimization.

The values of maximum surface oil rate tested are presented in Table C10. The water cut variation was tested to the production wells: PROD 02, PROD 03, PROD 05, PROD 07, PROD 09, PROD 11, PROD 13, PROD 14 and PROD 15; the values used are equal to 0.85 and 0.90. A total number of 230 tests were performed by CMOST®, however the results obtained did not increased the performance indicators.

Test 02 was considered the optimized production strategy. The comparison between the results obtained to the RM2 model using the base production strategy and the optimized strategy are presented in Table C11. There was an increase in US$ 20.7 million due to the production strategy optimization.

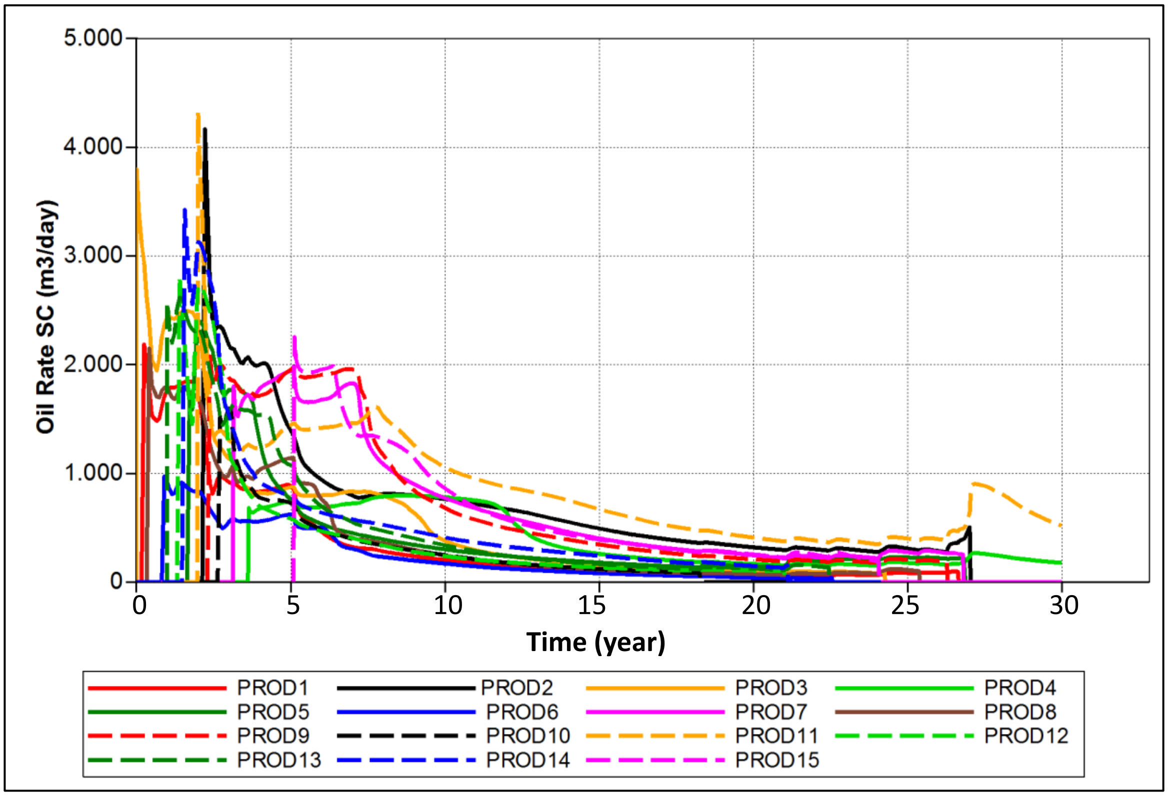

Figure C.9. Test 02 RM2 model production wells oil rate.

Table C.10. RM2 - values o maximum oil surface and water cut used in the tests.

Production Well	**Maximum Surface Oil Rate (STO) in m³/day**		
	STO 01	**STO 02**	**STO 03**
PROD 01	200	400	500
PROD 02	250	500	750
PROD 03	250	500	750
PROD 04	250	500	750
PROD 05	200	400	500
PROD 06	200	300	400
PROD 07	800	1000	1200
PROD 08	250	500	750
PROD 09	800	1000	1200
PROD 10	100	200	300
PROD 11	800	1000	1200
PROD 12	100	200	300
PROD 13	200	400	500
PROD 14	400	500	600
PROD 15	800	1000	1200

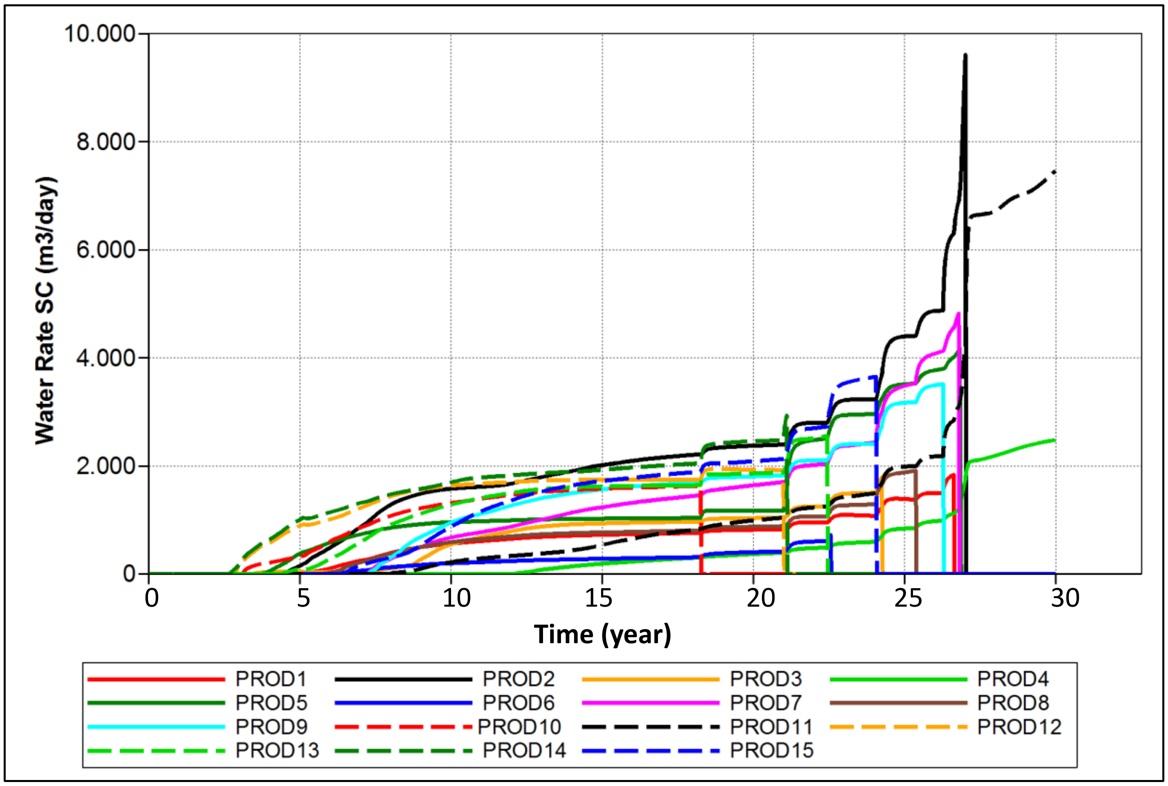

Figure C.10. Test 02 RM2 model production wells water rate.

Table C.11. RM2 model performance indicators (base and optimized strategy).

Model	Strategy	NPV (US$ x 10^9)	RF (%)	Np (m^3 x 10^7)	Wp (m^3 x 10^7)
RM2	Base	3.246	72.3	6.70	14.28
	Optimized	3.267	72.7	6.74	13.98