

RESERVOIR MANAGEMENT DECISION-MAKING IN THE PRESENCE OF GEOLOGICAL UNCERTAINTY

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I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a dissertation for the degree of Doctor of Philosophy.

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Abstract

The investments to develop a reservoir are very large, so any improvement in the development plan could represent millions of dollars in additional profit. However, the decisions about the development plan are made in the presence of many sources of uncertainty. Geological uncertainty about the reservoir geometry and petrophysical properties, due to sparse sampling of the reservoir, is one of the uncertainties that could influence the reservoir management decisions significantly.

This research introduces a so called *Full* approach to incorporate the geological uncertainty in the selection of the best production scenario among a set of predefined scenarios. This approach makes use of multiple geostatistical realizations and presents the advantage of including the profit seeking and risk aversion profile of the company.

Different reservoir management problems were considered, with that related to location of a moderate number of wells being retained as the problem for which the geological uncertainty is most critical. The benefits of accounting for geological uncertainty in the well location decision are evaluated by comparing the results of the decisions made with the *Full* approach to those made with the conventional approach of using a single deterministic model.

The influence of the level of uncertainty is investigated, showing that the larger the number of available data, the smaller the uncertainty, the better the decisions and the smaller the benefits of modeling uncertainty. Nonetheless, the potential gains of including uncertainty are always on the order of millions of dollars, which is much higher than the computational costs required to incorporate multiple realizations into the decision-making.

This work introduces the concept of a quality map to locate wells. An L-optimal

quality map, obtained by averaging the individual realization quality maps through a loss function, allows locating the wells accounting for the geological uncertainty as well as for the profit seeking and risk aversion profile of the company. This quality map is used within the *Full* approach to decide on the best number of wells with the corresponding optimized spatial configuration.

Because it is built from flow simulations, the quality map integrates all the three-dimensional geological variables and the fluid variables into a single two-dimensional characterization of the reservoir. Besides well locations, this two-dimensional characterization of the flow responses can be used to visualize productivity areas, to rank realizations, to identify a most representative realization and to compare different reservoirs.

50 synthetic yet realistic reservoirs and more than 450,000 flow simulations were generated in the course of this research to develop and evaluate the potentials of the *Full* approach and quality map.

Acknowledgments

I dedicate this work to my wife Fátima, my daughter Gabriella and my son Bráulio.

Contents

Abstract	v
Acknowledgments	vii
1 Introduction	1
1.1 Problem statement	1
1.1.1 Sources of uncertainty	1
1.1.2 Decision-making	3
1.2 Literature review	5
1.2.1 Traditional petroleum decision-making	5
1.2.2 Uncertainty modeling in heterogeneous reservoirs	7
1.2.3 Transfer of geological uncertainty	8
1.2.4 Decision-making without accounting for uncertainty	10
1.2.5 Decision-making accounting for uncertainty	10
1.2.6 Benefit of accounting for the uncertainty	13
1.3 Research undertaken	13
2 The <i>Full</i> Approach	19
2.1 Introduction	19
2.2 Methodology	20
2.3 Case study	26
2.3.1 Settings	26
2.3.2 Results	32
2.3.3 Conclusions	41

2.4	Discussion	42
2.4.1	Alternative use of multiple realizations in decisions	42
2.4.2	Influence of the uncertainty level	42
2.4.3	Inclusion of other types of uncertainty	43
2.4.4	Limitations of the case study	44
2.4.5	Reducing the computational effort of the <i>Full</i> approach	47
3	The Quality Map	53
3.1	Definition	53
3.2	Methodology	54
3.2.1	Generation of a quality map	54
3.2.2	Types of quality map	55
3.2.3	Uses of the quality maps	60
3.3	Case study	66
3.3.1	Settings	66
3.3.2	Results	69
3.3.3	Conclusions	86
3.4	Discussion	88
3.4.1	Uncertainty level	88
3.4.2	Limitations of the quality map	89
3.4.3	Modifications of the quality map	90
3.4.4	Alternative algorithm for well location	90
4	Sensitivity Analysis of the Uncertainty Level	93
4.1	Need and types of the analysis	93
4.2	Description of the cases	95
4.2.1	Base Case	95
4.2.2	Case 1: more realizations	96
4.2.3	Case 2: more uncertainty	96
4.2.4	Case 3: prior knowledge of anisotropy	97
4.2.5	Case 4: different numbers of sampling wells	97
4.3	Results of the analysis	99

4.3.1	Indices	99
4.3.2	Analysis 1	103
4.3.3	Analysis 2	108
4.3.4	Analysis 3	114
4.4	Conclusions of the analysis	118
5	Other Reservoir Management Decisions	121
5.1	Other types of reservoir management decisions	122
5.1.1	Well location for different types of reservoirs	122
5.1.2	Vertical or horizontal well?	122
5.1.3	Intervals to complete a well	123
5.1.4	Number of platforms	124
5.1.5	Type of enhanced oil recovery	125
5.1.6	Time to start water injection	126
5.1.7	Time to start water treatment	127
5.1.8	Direction of a horizontal well	127
5.1.9	The best injection scenario	128
5.2	Methodology to define the injection scenario	128
5.3	Case study with water injection	131
5.3.1	Settings	131
5.3.2	Results	135
5.3.3	Conclusions	144
5.4	Discussion	146
5.4.1	Relevance of accounting for the geological uncertainty	146
5.4.2	Fine adjustment of the locations of injector wells	146
5.4.3	Hierarchical decisions	148
6	Contributions, Conclusions and Future Work	149
6.1	Contributions	149
6.2	Conclusions	150
6.3	Future work	150

A	Generation of the True Reservoirs	161
A.1	General characteristics	161
A.2	Top	164
A.3	Thickness	166
A.4	Facies	168
A.5	Porosity and permeability	170
B	Generation of the Models	177
B.1	Sampling the true reservoirs	177
B.2	Stochastic simulations	180
B.3	Kriging	191
B.4	Upscaling	200
C	Flow Simulation and Economic Function	209
D	Automation	215

List of Tables

2.1	Reducing the number of scenarios	48
2.2	Reducing the number of realizations	50
4.1	Average results and indices over ten reservoirs of the cases involved in Analysis 1.	104
5.1	Generic relevance of the consideration of the geological uncertainty for reservoir management problems.	147
A.1	Characteristics of the 50 true reservoirs.	163
A.2	Probability distributions used to generate thickness.	166
A.3	Probability distributions of the parameters used in ELLIPSIM to gen- erate shales.	168
A.4	Probability distributions of the parameters used in SISIM to generate sandstone porosity.	170
A.5	Probability distributions of the parameters used in SISIM to generate sandstone permeability.	172
C.1	Fluid and rock properties used in flow simulation.	210

List of Figures

2.1	<i>Full</i> approach methodology.	21
2.2	Three types of loss function and probability distribution of profit for two scenarios.	25
2.3	Configuration 1 for eight different numbers of wells.	30
2.4	The seven configurations for 15 wells.	31
2.5	Scenario profits obtained from each approach and from the true reservoir.	33
2.6	Comparison between the approaches for 50 reservoirs.	36
2.7	True profits averaged over 50 reservoirs.	39
3.1	Presentation of the quality map.	56
3.2	Three types of loss function and probability distribution of quality in two cells.	58
3.3	Types of quality map.	59
3.4	Optimization procedure to locate wells.	62
3.5	Quality maps of eight realizations and of the kriged model.	68
3.6	Definition of the weighting formula to evaluate total quality.	70
3.7	Examples of location of wells using quality map and oil volume map.	72
3.8	Comparison between quality map and oil volume map to locate wells for 50 reservoirs.	73
3.9	Example of comparison between the location of wells using three different quality maps.	76
3.10	Comparison between the location of wells using three different quality maps for 50 reservoirs.	77

3.11	Comparison between the results of <i>Conv-1</i> , <i>Conv-k</i> and <i>Full</i> for 50 reservoirs.	77
3.12	Correlation coefficient between the rank of 20 realizations obtained using profit and using total quality.	83
3.13	Correlation coefficient between the rank of 20 realizations obtained using profit and using oil volume.	83
3.14	Reserve versus average value of the mean quality map.	85
3.15	Reserve versus original oil in place.	85
3.16	Reserve uncertainty versus quality uncertainty.	85
3.17	Reserve uncertainty versus original oil in place uncertainty.	85
4.1	Location of the sampling wells.	98
4.2	Maps used to check the correlation between the index “correlation with true quality map” and the mean true profit.	101
4.3	Correlation between the index “correlation with true quality map” and true profit.	102
4.4	Average results of <i>Conv-1</i> , <i>Full</i> and true reservoir in the Base Case and Case 1.	104
4.5	Example of model accuracy and model efficacy in the Base Case and in Case 2.	106
4.6	Example of upscaled vertical permeability for the true reservoir, and for Realization 1 and the kriged model in the Base Case and in the Case 2.	107
4.7	Example of upscaled vertical permeability for the true reservoir, and for two realizations and the kriged model in the Base Case and Case 3.	109
4.8	Uncertainty in the profits with the realizations, for different numbers of sampling wells.	110
4.9	Results of <i>Full</i> , <i>Conv-1</i> and <i>Conv-k</i> , for different numbers of sampling wells.	110

4.10	Average over 20 reservoirs of the correlation coefficient between the true quality map and the quality maps of the models, for different numbers of sampling wells.	110
4.11	Example of upscaled vertical permeability for the true reservoir, and for Realization 1 and the kriged model for different numbers of sampling wells.	112
4.12	Example of the quality map of the true reservoir, and of Realization 1 and the kriged model for different numbers of sampling wells.	113
4.13	Average over 50 reservoirs of the correlation coefficient between the true quality map and the quality maps of the models, for different numbers of sampling wells.	115
4.14	Comparison between quality map and oil volume map for well location, for different numbers of sampling wells.	117
5.1	Types of injection quality map.	134
5.2	Configurations for six injector wells with the injection quality map. .	136
5.3	Configurations for six injector wells with the composite permeability map.	138
5.4	Results of the locations of injector wells using the injection quality map and the composite permeability map.	139
5.5	Injection scenarios defined with the three types of injection quality map.	142
5.6	Mean true profits over the locations of six numbers of wells with three types of injection quality map.	143
5.7	Results of the decision of the best injection scenario with <i>Full</i> , <i>Conv-1</i> and <i>Conv-k</i>	143
5.8	Best scenario, including production and injection, for ten reservoirs. .	145
A.1	Top depth of true Reservoir 1, 2 and 3.	165
A.2	Thickness over the six layers of true Reservoir 1.	167
A.3	Cross-sections showing the distribution of shale and sandstone of true Reservoir 1.	169
A.4	Scattergrams between porosity and permeability for true Reservoir 1.	173

A.5	Porosity over the six layers of true Reservoir 1.	174
A.6	Permeability over the six layers of true Reservoir 1.	175
A.7	Permeability cross-sections of true Reservoir 1.	176
B.1	“Seismic” surfaces of the structural top of Reservoir 1, 2 and 3. . . .	179
B.2	Top depth of Realization 1 of Reservoir 1, 2 and 3.	181
B.3	Thickness over the six layers of Realization 1 of Reservoir 1.	183
B.4	Vertical porosity semivariograms over the six layers of Reservoir 1. . .	184
B.5	Vertical permeability semivariograms over the six layers of Reservoir 1.	185
B.6	Scattergrams between porosity and permeability from well data and Realization 1.	187
B.7	Porosity over the six layers of Realization 1 of Reservoir 1.	188
B.8	Permeability over the six layers of Realization 1 of Reservoir 1.	189
B.9	Permeability cross-sections of Realization 1 of Reservoir 1.	190
B.10	Top depth of the kriged model of Reservoir 1, 2 and 3.	193
B.11	Thickness over the six layers of the kriged model of Reservoir 1. . . .	194
B.12	Porosity over the six layers of the kriged model of Reservoir 1.	196
B.13	Permeability over the six layers of the kriged model of Reservoir 1. . .	197
B.14	Permeability cross-sections of the kriged model of Reservoir 1.	198
B.15	Histograms of permeability with the true reservoir, well data, the kriged model and Realization 1 of Reservoir 1.	199
B.16	Upscaled top depth of true Reservoir 1, 2 and 3.	202
B.17	Upscaled thickness of true Reservoir 1.	203
B.18	Upscaled porosity of true Reservoir 1.	204
B.19	Upscaled vertical permeability of true Reservoir 1.	205
B.20	Upscaled vertical permeability of Realization 1 of Reservoir 1.	206
B.21	Upscaled vertical permeability of the kriged model of Reservoir 1. . .	207
C.1	Production curves of Configuration 1 of 11 numbers of wells with true Reservoir 1.	213
C.2	Production curves of Configuration 1 of 15 wells with true reservoir, 20 realizations and the kriged model of Reservoir 1.	214

Chapter 1

Introduction

1.1 Problem statement

This research addresses the problem of how to make decisions on petroleum reservoir management in the presence of uncertainty.

The type of uncertainty considered is the geological uncertainty about static reservoir geometry and petrophysical properties due to the sparse sampling of the reservoir. This uncertainty is modeled by multiple geostatistical realizations.

The type of reservoir management decision considered relates to the definition of a development plan to maximize the profitability of the reservoir resource.

1.1.1 Sources of uncertainty

Petroleum exploration and production are inherently risky activities. Decisions regarding those activities depend on the forecast of the future hydrocarbon production revenue. Such forecasts are uncertain because of:

- uncertainty about the reservoir geometry and the spatial distribution of petrophysical properties,
- uncertainty about the fluid properties,
- measurement errors,

- uncertainty about the actual behavior of the rock and fluid when subjected to external stimuli,
- modeling limitations,
- uncertainty about the future prices of the product.

Reservoirs lie under thousands of feet of rock and water (in the offshore case) and cannot be seen directly or measured accurately. Reservoirs can only be modeled.

If too few data from the reservoir are available, data borrowed from nearby or analogous reservoirs are used in the modeling. However each reservoir is unique and inappropriate “analogous” data may lead to an invalid picture of the reservoir and result in erroneous predictions.

Even actual reservoir data have error. It is difficult to measure initial saturations, porosity, capillary pressure, absolute and relative permeability using well cores or electric logs. Moreover, the upscaling laws from the measurement scale to the scale used in the flow models are not well known.

There are problems obtaining representative fluid samples and measures of fluid properties such as viscosity, formation factor and gas in solution with varying pressure and temperature. Even if such measures were accurate, the true process inside the reservoir may be different from that simulated in the laboratory.

Well tests may provide estimates of the averaged permeability of the volume that contributes to the production during the test, but well test data do not constrain the shape or heterogeneity of this volume since the averaging laws are poorly known.

When historical production data are available, they can reduce the uncertainty in the reservoir model; however individual well data usually have errors and the determination of their inverse relationship to rock and fluid properties is a difficult and ill-posed problem.

Seismic data give reasonable information about reservoir boundaries, but the resolution of seismic interpolation usually is much larger than the internal heterogeneities. Moreover, the correlations between geophysical measurements and rock and fluid properties are subject to error.

Flow simulation provides a reasonable approach to predict reservoir behavior; however, the equations and software used for flow simulation consider the input data without any error or uncertainty and give a single deterministic response. The equations and numerical solution schemes are themselves based on approximations and assumptions that add to the uncertainty of the production forecasts.

Future prices of oil and gas are uncertain, which further increases uncertainty in the revenue forecasts.

The sources of uncertainty in revenue forecasts are many. In this research the uncertainty scope was restricted to that of the geological model due to sparse sampling of the reservoir. Geostatistical techniques were used to model this uncertainty through multiple stochastic realizations.

For heterogeneous reservoirs, the lack of data away from the wells is the largest source of uncertainty in the geological model. That geological uncertainty, related to the reservoir geometry and the distribution of petrophysical properties, has the most direct effect on the production forecasts, which constitute the basis for reservoir management decision-making.

1.1.2 Decision-making

Exploration and production are done in sequence. First, exploration finds a promising geologic structure, making use of seismic responses and knowledge of the sedimentary basin. Then, a well is drilled to prove the existence of a hydrocarbon reservoir. If this first exploratory well succeeds in finding hydrocarbon, depending on the field size, other exploratory wells are drilled to delimit the deposit. Next, a development plan is generated to provide the necessary data for the production cash flow analysis. If the company decides to invest in that project, the development plan is implemented and hydrocarbons are produced.

There are three main types of decisions involved in the exploration and production process:

1. the decision to drill or not to drill an exploratory well,

2. the technical decision of selecting the best development plan to optimize the profitability of the reservoir production and
3. the business decision to invest in a project or not.

Decision-making in exploration typically makes use of decision tables which relate alternative actions to various outcomes. Estimates of the probabilities attached to each outcome are necessary. Most exploratory wells are dry or noncommercial, resulting in substantial losses. In order to evaluate the expected monetary value of an exploration well, it is necessary to know the probability of a dry hole and its complement, the probability of a producer at various levels of production. A regional “success ratio” is a useful starting point for estimating the dry hole probability. Success ratio represents the proportion of the all exploratory wells that were successful in a specific region. The outcome of a dry hole is just the cost of drilling the well, while the outcome of the producer is a probability distribution associated to the spectrum of sizes for the field that might be discovered. The production curves for each size can be estimated from “analogous” reservoirs, or by modeling the reservoir geometry, rock and fluid properties and then using a flow simulator.

Since a methodology already exists to consider the uncertainty in the decision of drilling or not drilling an exploratory well, this problem is not addressed in this work.

After the exploratory reservoir delimitation, reservoir management becomes the activity of planning and controlling the reservoir production. The main goal of this activity is the development plan, which determines the number, type and location of additional wells and presents the rig work schedule and the curves for injection and production of fluids.

Once the development plan is defined, it is possible to transfer some aspects of data uncertainty to the production forecasts. Ballin [2] presented a methodology to transfer the geological uncertainty to the production forecasts by considering multiple equally-probable geostatistical realizations, all of them respecting the available data from wells and seismic. These different realizations provide a measure of the geological model uncertainty. For each realization a flow simulator is run and a production curve is obtained, using the number, location, type and production schedule of the wells as

defined in the plan. The differences in the production curves provide a measure of the uncertainty in the forecasts. The probability distribution of the discounted cash flow calculated over each curve is used to evaluate the expected monetary value of the project and to guide the business decision to invest in a particular project or not.

The “conventional” way to define the development plan is: (a) build a deterministic (no uncertainty) geological model of the reservoir (this may be done by traditional geological modeling, by kriging, or by generating just one stochastic realization), (b) define the possible production scenarios (numbers of wells, configuration for each number of wells, types of wells - vertical or horizontal, producer or injector, fluid to inject, etc.), (c) run a flow simulator for each scenario to generate the respective production/injection curves, (d) perform a cash flow analysis for each scenario and (e) select the scenario that provides the maximum profit.

This “conventional” approach does not guarantee that the selected scenario is optimal for the actual field because geological uncertainty was not taken into account. An alternative equally-probable geological model, although respecting the same available data, could lead to a different best production scenario.

This work addresses the question of how to account for geological uncertainty in the second type of decision, that is, the technical decision of selecting the best development plan to optimize the reservoir resources. This is by far the most important decision in reservoir management.

1.2 Literature review

1.2.1 Traditional petroleum decision-making

In the petroleum business, the need to account for uncertainty in decision-making was identified very early, in the 1930s [29]. Probability theory, decision trees, Monte Carlo simulation and economic models were introduced for decision analysis in exploration [25, 55] and in development [52, 63], for cases where the uncertainty was characterized by probability distributions of the parameters involved, such as oil in place or production curve.

To use a decision tree, the financial outcomes and their probabilities need to be known. Then expected monetary value can be calculated to aid in making choices to maximize profit. Expected monetary value analysis involves multiplying financial outcomes by probabilities and summing the products to obtain a “risk-weighted” financial estimate. The time value of money must be accounted for in the alternatives. Discounted cash flow is used to calculate the present value of each alternative. In addition, each organization may have a different reaction to losses or gains, i.e. different desires for financial gains and aversion to losses. A utility function can be built to translate monetary values to utility values. Dollars can be substituted for utilities in the decision table and an expected utility value can be calculated, instead of an expected monetary value. An expected utility value table thus combines risk, expressed as probabilities, with risk aversion, expressed by the utility function [27, 28].

For independent variables, if their probability distributions can be modeled as simple distributions, such as the uniform or triangular distribution, a final probability distribution of linear combinations of these variables can be evaluated analytically [47]. That would be the case, for example, for transferring the uncertainty in mean thickness and mean porosity to the estimation of oil in place. The method of combining simple distributions through analytical formulas is called the parametric method and gives the mean and variance but not the shape of the final distribution [62].

For more generic probability distributions of independent variables, Monte Carlo simulation may be applied to combine different types of uncertainty [6]. The basic steps of a Monte Carlo simulation are:

1. Determine the cumulative distribution function (CDF) of the variables.
2. For each variable:
 - (a) Draw a random number between 0 and 1.
 - (b) Enter the y-axis of the CDF for the variable with this number and read off the corresponding value of the simulated variable.
3. Assign the combination of simulated variables to one realization.

This step requires that the variables be independent one from another.

4. Repeat items 2 and 3 until the specified number of realizations is obtained.

Another sampling technique is Latin hypercube sampling [66], which is suitable for risk analysis problems that involve events with very small probabilities but large effects on the final solution.

1.2.2 Uncertainty modeling in heterogeneous reservoirs

For heterogeneous reservoirs, sampling techniques, such as Monte Carlo simulation or Latin hypercube sampling, can not be used directly to transfer the uncertainty in the geological variables to production forecasting through a flow simulator because the variables are not independent. The flow simulation model calls for discrete geological attributes over a grid and even if the cross correlation between different types of attributes, such as porosity and permeability, could be ignored, the variables related to the same attribute have a spatial correlation.

These spatially-correlated geological variables generate different types and scales of geological heterogeneities that affect oil recovery. Weber [72] classified those heterogeneities and showed that they must be quantified for modeling purposes and field development decision-making.

Geostatistics provides a theoretical foundation for the quantification and integration of different scales and types of spatially-correlated variables into geological models. The concept of the variogram as a measure of spatial variability was first applied to evaluate mining block properties through the interpolation technique called kriging. The first applications in petroleum exploration occurred in the early seventies [51] to generate kriging-based maps.

During the 1980s, other techniques such as conditional simulations were developed and Journel [38, 39, 40, 41] played an important role in spreading their potential applications.

In the 1990s, geostatistical packages such as GSLIB [15] became widely distributed, and the use of geostatistical techniques spread in the oil industry. Good collections and compilations of the theories and available techniques were published by Isaaks and Srivastava [32], Goovaerts [24] and Deutsch [14].

More than just a mean of interpolating values of an attribute at unsampled locations, geostatistics is a tool for modeling the uncertainty of that attribute through stochastic simulations [26, 42, 50]. Stochastic simulation is the process of generating alternative, equally-probable, images (realizations) of the spatial distribution of an attribute, all of them honoring the data available. In general, values of the attribute are generated at a large but finite number of locations or nodes that are distributed in a grid over the domain of interest.

There are several stochastic simulation techniques [15]. Sequential simulation is possibly the most frequently used. In sequential simulation, a random path to visit all the grid nodes is defined and at each grid node a conditional distribution is constructed by kriging using all original and previously simulated data available in a neighborhood. Then, a simulated value of the attribute is drawn from that conditional distribution. Changing the random path, different realizations are obtained. Most often only the path is changed, while the same set of model parameters is kept.

Model parameters include expected mean values, variance, spatial dependence of each geological attribute and interdependency among the attributes. Freezing these model parameters reduces the global geological uncertainty [57]. In order to model not only the variability but also the representativeness of the observed data (model parameter uncertainty), the number of stochastic models resulting from the parameter combinations could be very large.

Ding et al. [19] and Sandsdalen et al. [60] presented applications of Latin hypercube sampling for reducing the number of realizations to represent the global geological uncertainty. Morelon and al. [53] applied experimental design to model the geostatistical parameter uncertainties.

1.2.3 Transfer of geological uncertainty

Once the development plan is defined, one way to transfer the geological uncertainty modeled by stochastic simulation to production forecasting is by running a flow simulator on each geological realization with the specifications of the plan. This approach was proposed by Omre et al. [57] and by Ballin [2].

Reducing the number of realizations

Depending on the number of realizations, the flow problem complexity, the number of grid cells and available computational facilities, processing all the realizations through a flow simulator may be very time-consuming.

Ballin et al. [3] suggested fast simulations, such as tracer, simplified flow model and simulation over a cross section or over a coarse grid to rank and to select the realizations to be processed through a comprehensive (full field) flow simulator. The final probability distribution of the production response is constructed using the results from the fast simulation (with a few realizations) and the ranking of the results from the fast simulation (with all realizations).

Production data, if available, may be incorporated into the generation of conditional realizations, decreasing the uncertainty in the geological characterization [13, 30, 45, 73]. Although this area of research is now very active, it is important to notice that the inverse problem is difficult, ill-posed and substantial uncertainty usually remains even after long periods of production [22, 46].

Production data may also be used to reduce the number of realizations to process through a flow simulator by retaining only those that match history [33, 43, 56].

Another way to reduce the number of realizations is by ranking them somehow. Deutsch and Srinivasan [17] presented several ranking techniques, showing that there are limitations in all of them but the best results are obtained with techniques based on flow simulation.

Economic criteria may be used to estimate the value (or realization) that minimizes some objective loss function [64], once the conditional probability distribution has been established.

The development of stream-tube simulators made the approach of running a full field simulator for all the realizations much faster [68] for certain type of flow problems, such as ones with negligible gravitational effects.

1.2.4 Decision-making without accounting for uncertainty

When no uncertainty is considered, decisions are made using a deterministic geological model, a flow simulator, an economical model and an optimization algorithm [5, 7, 59].

Bittencourt and Horne [7] used a hybrid algorithm based on the genetic algorithm, polytope and tabu search to define a development plan where the wells can be placed anywhere in the reservoir and can be vertical or horizontal and, if horizontal, any direction in the same layer can be considered.

Vasantharajan and Cullick [70] presented the concept of a quality measure of the reservoir to be used with integer programming optimization for locating wells. The measure is a combination of static characteristics of the reservoir and does not account properly for the dynamic and nonlinear interaction between the parameters, nor does it incorporate any geological uncertainty.

Another approach is to train a neural network to replace the flow simulator for faster evaluations of the objective function inside the optimization algorithm [35]. The training needs to be repeated for each model of the reservoir.

1.2.5 Decision-making accounting for uncertainty

Geological uncertainty is unavoidable and it ought to be taken into account for decision-making.

With simple models of geological uncertainty

For homogeneous reservoirs or for heterogeneous reservoirs where the heterogeneity can be summarized by a single number, Monte Carlo-type techniques can be applied with some optimization method to model the uncertainty and make decisions. One example is the uncertainty modeling of homogeneous fields and the use of Latin hypercube sampling together with simplified flow models to select the best enhanced oil recovery project [49]. Another example is the representation of uncertainty by a probability distribution of the Dykstra-Parson coefficient and the use of Monte Carlo simulation and Newton-Greenstadt optimization method together with an analytical

flow model to select the best operational parameters for a surfactant flooding project [4].

Without flow simulation

Direct measures taken from stochastic models of the static parameters can be used for some decision-making without performing any flow simulation. One example is the decision of whether to inject gas in a fluvial channel reservoir based on estimates of the connected pore volume between injector and producer wells taken over several realizations of the sandstone/shale sequence within a meander-belt environment [65]. Another example is the definition of optimum high-angle development wells based on the statistical analysis of the genetic unit strings extracted from each well trajectory over several realizations of genetic unit distributions [61].

With flow simulation

For most of the reservoir decisions, however, the value of each reservoir development option needs to be predicted using a flow simulator.

Only sensitivity analysis about the uncertainty

A simple but incomplete way to account for uncertainty is to perform sensitivity analysis on some selected development scenarios and evaluating the flow response for all these scenarios, using only one realization.

Stripe et al. [67] presented an example of defining the best recovery method using only three geological realizations built from a pessimistic, a most likely and an optimistic set of parameters, and carrying out the majority of the flow simulations on the most likely realization.

Ovreberg et al. [58] presented an application of Monte Carlo simulation to obtain the base, upside and downside cases of production forecasts to compare development scenarios.

Experimental design

Reservoir management problems involving large numbers of uncertain parameters

and full field flow simulations have been analyzed using experimental design techniques to reduce the number of necessary simulations [1, 10, 11, 12, 20, 36, 71].

Experimental design is a statistical technique where several parameters are varied simultaneously. With this technique it is possible to obtain the same information as the “one parameter at a time” method with significantly fewer simulation runs and to obtain some understanding of possible interactions between the parameters [8]. D-optimality is a mathematical procedure to select the optimal runs from a large set of possible runs to get most information at the lowest experimental cost [21, 34].

The response surface methodology [54] may be applied together with experimental design to approximate a regression model over the region of interest. With this model, analytical predictions can be made for any value of the input uncertain parameters over the domain. Monte Carlo simulation may be used then to assess the global uncertainty in the final response and to guide the decisions.

One drawback of the response surface methodology is that it requires the input parameters to be continuous over the domain. The variables are normalized and only three levels are used at maximum. Normally these levels are -1 (minimum or pessimistic case), 0 (mean or base case) and +1 (maximum or optimistic case). In order to use multiple realizations as an input uncertain parameter for the response surface methodology, the realizations need to be ranked somehow. Aanonsen et al. [1] presented an example with eight realizations whose rankings were determined based on low, base and high cases of geological interpretations.

If discrete input parameters are used, as in Jones et al. [36], a regression model can not be obtained and experimental design is then just a sampling tool for sensitivity analysis about uncertainty. The authors could have obtained a separate model for each of the discrete production scenarios (waterflood patterns), though, at the cost of carrying out more experiments (flow simulations).

From the literature examples, it is clear that experimental design, response surface methodology and Monte Carlo simulation are good tools to be used together to integrate and to transfer different sources of uncertainty to the production response. But that must be done for each production scenario, if the purpose is to decide the best scenario.

The optimization applications presented are basically for locating wells [1, 12, 71] and are limited to the location of only two wells at most and considering separate regions for each well. Moreover, the optimality of the well locations is questionable since there is no way to identify the best location in a particular area (one with very high permeability, for example) with the response surface methodology unless the well has been placed in that area in at least one of the experiments. However, for selection of the well locations to use in the experiments (flow simulations), experimental design uses only the well coordinates without any consideration of the reservoir properties inside the grid.

1.2.6 Benefit of accounting for the uncertainty

Although the example relates to mining, Deutsch et al. [18] presented a rare study with quantification of the benefit of using several realizations in decision-making as opposed to using just one deterministic model.

They discussed that the use of synthetic reservoirs is the only way to assess the true results (for example profits) of different decisions. With real reservoirs only the true result of the implemented decision is known and it is impossible to find out if a different decision would have had a better result.

1.3 Research undertaken

The problem addressed in this research is how to define the best development plan in the presence of geological uncertainty.

Previous works showed how to model geological uncertainty and how to transfer this uncertainty to the flow responses for a specific development scenario.

The cases presented in the literature to define the development scenario in the presence of uncertainty used experimental design and response surface methodology to obtain the distribution of flow responses for each scenario. However, the use of a reduced number of realizations required by those methodologies probably leads to an incomplete assessment of the uncertainty in the flow responses. Moreover, no clear

procedure to choose the best development scenario, after obtaining the distribution of flow responses for each one of them, was presented.

Reliable techniques for optimization of scenarios were presented only for cases where no uncertainty was considered.

No quantification of the benefits of incorporating the uncertainty into reservoir management decision-making has ever been presented.

Therefore, this research aims at developing a more complete and clear methodology to incorporate geological uncertainty into the definition of the best development plan and to quantify the “worth” of this incorporation. An optimization technique to find the best spatial configuration for each number of wells accounting for uncertainty was also developed.

The techniques necessary to apply the proposed methods are two basic skills in petroleum engineering: geostatistics to generate the geological models and flow simulation to obtain the flow responses. The optimization algorithm to locate wells is very simple and does not require any special knowledge besides basic programming.

Chapter 2 presents the *Full* approach, the approach proposed to define the reservoir development plan in a manner that is robust with respect to the inherent geological uncertainty.

The geological uncertainty is modeled with multiple geostatistical realizations. Alternative development plans (production scenarios) are predefined. A probability distribution of profit is obtained for each scenario by processing all the realizations through a flow simulator. An estimate of profit is retained for each scenario based on the minimization of a specified loss function. The best scenario is defined as the one that has the maximum profit estimate.

A very large case study was undertaken to quantify the benefits of modeling the uncertainty. The reservoir management problem addressed was the definition of the best number of producer wells and their spatial configuration. The decision criterion was the maximization of the expected value of profit.

In order to assess and to compare the true profit results of the scenarios defined with the *Full* approach and with the conventional approach of using a single deterministic model, 50 synthetic yet realistic “true” reservoirs were generated. In the *Full*

approach, 20 realizations were generated for each reservoir by sequential simulation and considering the uncertainty in the horizontal range of continuity. Two conventional approaches were used: (a) *Conv-1*, where the single deterministic model is one of the simulated realizations, and (b) *Conv-k*, where that deterministic model is generated by kriging. Data for the modeling were obtained from the “true” reservoirs by a smooth image of their top structure, imitating seismic data, and by five sampling wells.

The results of the case study show that the production scenario defined using multiple realizations (*Full* approach) is on average better (higher profit) than the scenario defined using just one deterministic model. Between the two conventional approaches, *Conv-1* using a simulated realization is just slightly better than *Conv-k* using the kriged model. The quantification of the gains, which is an important contribution of this chapter, is presented.

The limitations of the method, and some suggestions for decreasing the computational effort of the *Full* approach and for incorporating different types of uncertainty are discussed.

Chapter 3 introduces the concept of a quality map, which is a representative two-dimensional characterization of the reservoir flow responses. The map is built using a flow simulator to integrate all the parameters that affect the flow of fluids through the heterogeneous reservoir and to ensure the proper dynamic interactions between them.

The quality map is generated by running a flow simulator with a single well and varying the position of that well in each run to provide coverage of the entire horizontal grid. Kriging is used to interpolate quality over a two-dimensional grid. The quality value for a grid cell is defined as the cumulative oil production after a specified time of production for a single well producing in that cell.

The geological model uncertainty is transferred to production uncertainty by generating multiple stochastic realizations and a quality map for each realization. With the probability distribution of quality for each cell, three other maps are obtained: (a) the mean quality map, with the mean value for each cell; (b) the uncertainty quality map, with the standard deviation for each cell and (c) the L-optimal quality

map, with the value that minimizes a specified loss function for each cell.

The same 50 synthetic reservoirs and models presented in Chapter 2 were used again in a second case study to check the benefits and to demonstrate the following uses of the quality map: (1) definition of the best configuration for each number of wells, accounting for the geological uncertainty through the lower quartile quality map and using an optimization algorithm that does not require any further flow simulation, (2) reduction of the number of realizations in the *Full* approach to just one, by identifying a representative realization for each scenario, (3) ranking of realizations for several purposes using the quality map of all realizations and (4) comparison of reservoirs using the average values of the mean quality and uncertainty quality maps.

The goodness of the well locations obtained using the quality map was compared to the locations obtained using the oil volume map for several different numbers of wells and for all the 50 reservoirs.

Chapter 4 presents an analysis of the sensitivity to the level of uncertainty. The following effects were evaluated using a representative selection of 20 reservoirs among the 50 available: (a) number of realizations, by running a case with 40 realizations instead of 20; (b) more geological knowledge, by running a case where the true horizontal direction of anisotropy is assumed known within a small degree of error; (c) more uncertainty, by running a case where uncertainty in other model parameters is considered and (d) number of sampling wells, by running three new cases with three, nine and 25 sampling wells as opposed to the previous case with five wells.

The results of this sensitivity analysis show that the more data or knowledge available, the smaller the uncertainty and consequently the smaller the benefit of modeling it. The smaller the uncertainty, the more similar the results between the various approaches, yet the *Full* approach is always justified for the levels of uncertainty expected during the definition of a development plan.

Chapter 5 discusses the value of modeling the geological uncertainty for other types of reservoir management problems and concludes that the main problem addressed in this research - choosing well locations - is the most important problem. To complement the analysis of the well location problem, since only producer wells were

considered in the three previous chapters, a methodology for locating injector wells is presented.

The methodology is based on the generation of a quality map for injection after the number and configuration of producer wells are defined. The producer wells might exist already. If not, their optimal number and configuration must be determined first, using the methodology presented in Chapter 3 but considering the presence of a water drive during the generation of the quality maps for production.

The quality map for injection is obtained similarly using a flow simulator and kriging. For each evaluation of quality, a single injector well and all the producer wells are used. The position of the injector well is changed in each run to provide coverage of the entire horizontal grid. The injection quality of a cell is the cumulative oil production with all the producer wells after a long time of production with the single injector well located in that cell.

A case study to demonstrate the methodology and to show the location of injector wells is presented for ten different reservoirs.

Chapter 6 presents the major conclusions and contributions of this research and suggests possible future extensions. An important conclusion is that with the ever increasing advance of fast, inexpensive and reliable computers, methods based on an intensive use of computer CPU, like the ones suggested in this research, that would have been impracticable a few years ago, can now be applied. Although the CPU time involved in those methods is still high, the potential gains are much higher than the computer costs.

Appendix A presents the methodology for generating the 50 “true” reservoirs that were used in all the case studies. Their principal characteristics are also presented.

Appendix B presents the methodology used to generate the models of the reservoirs, including sampling of the “true” reservoirs, simulation, kriging and upscaling.

Appendix C presents the flow simulation problem, that is, the fluid properties, the controls of the wells, etc. and the economic function used for evaluation of the profits in all the case studies.

Appendix D presents the structure and gives some examples of UNIX script files, which are very usefull tools to execute repetitive tasks. In this research several script files were developed to automate the generation of different reservoirs, their sampling, the generation of the models, the generation of the quality maps, the flow simulations, the evaluation of the economic function, etc. Automation is necessary to ensure that the work gets done in a reasonable time without requiring extensive engineer interaction.

Chapter 2

The *Full* Approach

2.1 Introduction

This chapter presents the *Full* approach, the approach proposed to define the reservoir development plan in a manner that is robust with respect to the geological uncertainty.

With this approach, the best development plan or production scenario is chosen among a set of possible alternative scenarios with the geological uncertainty modeled by multiple geostatistical realizations. The name “full” relates to the fact that the flow responses are obtained for each scenario by running a flow simulator on every realization; no shortcuts are taken. This is in contrast to the conventional approach of defining the development plan by examining the flow responses of a single reservoir model (or realization) to different production scenarios.

The decision criterion for selecting the best scenario is economic. After each simulation run, a measure of profit is evaluated, integrating all the production/injection curves through an economic function. From the probability distribution of profit for each scenario, an estimate of profit is retained based on the minimization of a specified loss function. The best scenario is defined as the one that has the maximum retained estimate of profit.

This chapter describes a general methodology that can be applied with any type of reservoir management problem and then presents a case study to demonstrate the application of that methodology to the important reservoir management problem of

defining the number of producer wells and their spatial configuration. The case study involved 50 different reservoirs to quantify the expected benefit of accounting for the geological uncertainty in this kind of decision-making. The benefit is evaluated by comparing the results of the *Full* approach, which uses multiple models of the reservoir, with the results of the conventional approach, which uses a single deterministic model.

The approach defined here requires the prior specification of all the alternative production scenarios; the solution is one of the specified scenarios. Optimization of the spatial configuration for each number of wells together with the definition of the best number of wells is presented in **Chapter 3**.

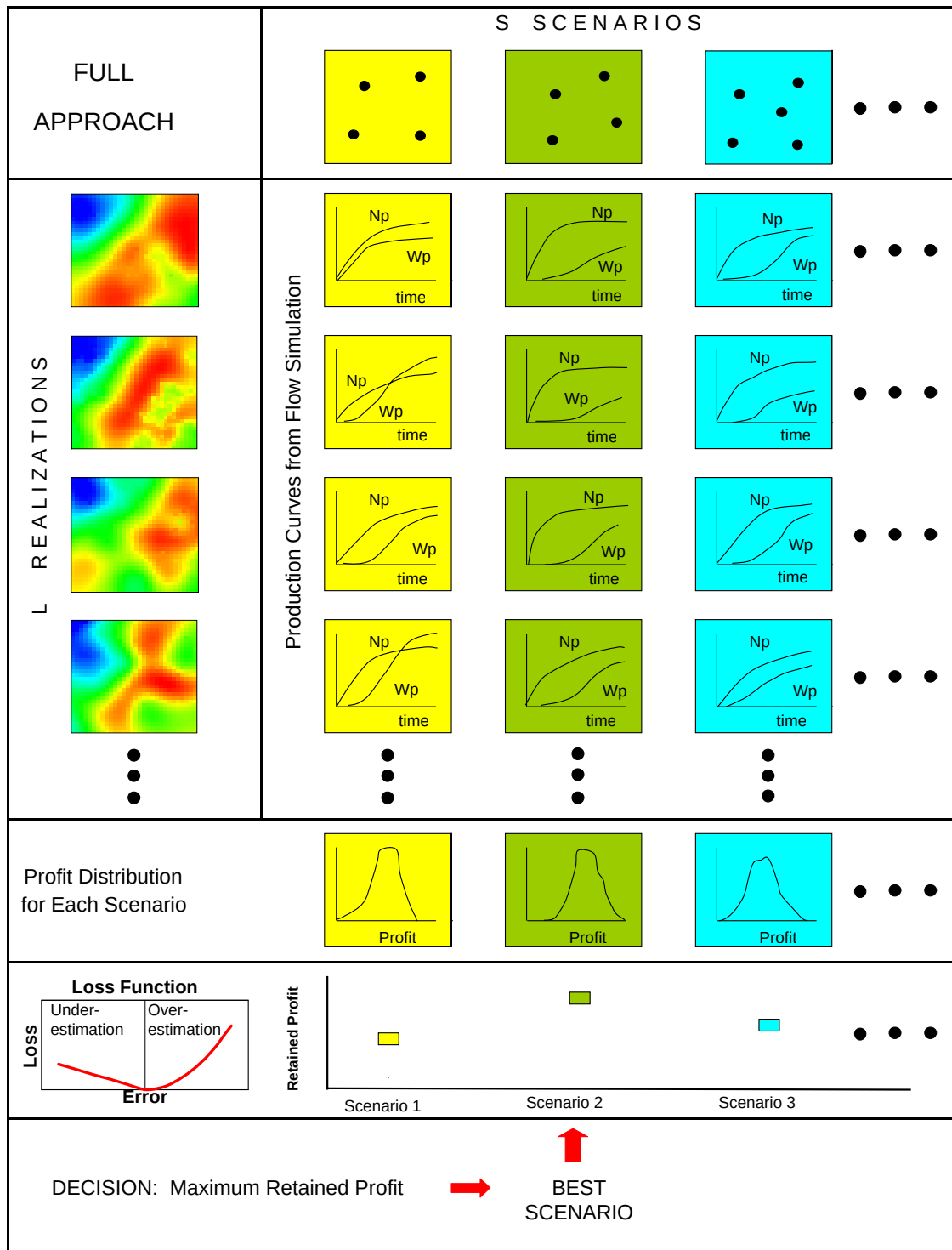
Although only geological uncertainty was considered in the *Methodology* and in the *Case study* sections, the inclusion of other types of uncertainty is addressed in the *Discussion* section (Section 2.4.3).

2.2 Methodology

The steps of the proposed *Full* approach, as illustrated in **Figure 2.1**, are:

1. Generate L geostatistical realizations of the geological model $l = 1, \dots, L$. The notation for the geological model “ l ” was intentionally simple but actually l is a spatially distributed vector of numerical models representing top structure, lithology, thickness, porosity, permeability and fluid saturations.

Depending on the representativeness of the available data, the geostatistical modeling parameters can be randomized to define a larger and possibly more realistic space of geological uncertainty. Examples of modeling parameters are: facies proportions, correlation between variables or between core and log measurements, probability distribution of the variables and variogram parameters. Sampling techniques such as Monte Carlo simulation, Latin hypercube sampling or experimental design (see Section 1.2, *Literature Review*) should then be applied to choose the combination of parameters to be used for each geostatistical simulation in order to: (a) have a good sampling of the uncertainty

Figure 2.1: *Full* approach methodology.

range and (b) keep the total number of realizations L small enough to afford their processing through a flow simulator. The practical number of realizations L depends on the time available for the study, the number of production scenarios, the CPU time needed for each flow simulation run, the computational resources and the precision with which the uncertainty assessment is required.

2. Define the possible reservoir management scenarios: $s = 1, \dots, S$. Each scenario is a complete specification of one possible solution for the problem. For example, for an initial development plan, one scenario would define the number of wells, their locations, the completion intervals, the surface facilities, etc.; for an enhanced oil recovery project, one scenario would define the locations, type, amount, concentration, timing, etc. of injection.

The initial total number S of scenarios could be very large (hundreds) but an inspection of the L realizations and/or some prior sensitivity flow analysis based on just one realization may reduce this number substantially.

3. Establish a quantitative measure of profit P to be maximized. The measure of profit would increase with increased hydrocarbon production and would decrease as more wells and facilities are required. The profit depends on the related costs, hydrocarbon prices and taxes. A good unit to measure the profit is the present value of the discounted cash flow.
4. Calculate the profit for each scenario and each realization: $P_{s,l}$, $s = 1, \dots, S$; $l = 1, \dots, L$. The fluid production and injection curves are obtained by running a flow simulator and the profit measure is calculated from the scenario specifications and curves for each case (s and l).
5. Determine the best estimate of profit $\hat{P}_s$ for each scenario, based on minimization of a specified loss function. This summary estimate is retained to compare the scenarios instead of the distribution of profits over all the realizations.

A loss function [64, 40] quantifies the impact or loss of estimating the unknown profit by a single value p^* with a given error $e = p^* - P$. The function $Loss(e)$

must be specified by the organization or person in charge of the economic decisions in the company and thus is known, but the argument e is not. Therefore, for each scenario s , an expected loss value can be determined using the distribution of P and the formula:

$$E\{Loss\}_s = \frac{1}{L} \sum_{l=1}^L Loss(p_s^* - P_{l,s}) \quad (2.1)$$

The best estimate of profit for the scenario s is $\widehat{P}_s$ such that the expected loss is minimum when taking $p_s^* = \widehat{P}_s$.

For the following particular loss functions, the determination of the best estimate is straightforward and does not require the numerical evaluation of the previous sum:

- If $Loss(e) = \alpha e^2$, where α is just a constant conversion factor, the best estimate is the expected value of the probability distribution, that is in our case the mean of the L profit realizations $P_{l,s}$ for each scenario s .
- If $Loss(e) = \alpha|e|$, the best estimate is the median of the distribution.
- If

$$Loss(e) = \begin{cases} 0 & \text{for } e = 0 \\ \alpha & \text{otherwise} \end{cases}$$

the best estimate is the mode of the distribution.

- If

$$Loss(e) = \begin{cases} \omega_1 e & \text{for } e \geq 0 \text{ (overestimation)} \\ \omega_2 |e| & \text{for } e < 0 \text{ (underestimation)} \end{cases}$$

the best estimate is the p -quantile [15] of the distribution with

$$p = \frac{\omega_2}{\omega_1 + \omega_2} \in [0, 1].$$

For example, if the loss function is linear with $\omega_1 = 3$ and $\omega_2 = 1$, that is, the loss of overestimating the profit is three times greater than the loss

of underestimating the profit for the same absolute error, then the best estimate of profit is the lower quartile of the distribution ($p = 0.25$).

Figure 2.2 presents an example of the distribution of profits for two scenarios and three different types of loss function that lead to different values of the retained profit value for each scenario and to different decisions of the best scenario. The two scenarios have the same mean value, but scenario 1 has a smaller uncertainty than scenario 2. For a loss function that penalizes underestimation more than overestimation (such as the loss function in the right), the profit value that minimizes the expected loss is above the mean (for example the upper quartile of the distribution). Between the two scenarios presented in the figure, an “aggressive” company using this type of loss function would prefer the one with greater probability of high profit values (scenario 2). For a quadratic loss function where the loss due to underestimation is the same as the loss due to overestimation (loss function in the center), the profit value that minimizes the expected loss is the mean. A company using this type of loss function would prefer scenarios with high expected profit, without consideration of uncertainty (no preference between scenario 1 and scenario 2). For a loss function that penalizes overestimation more than underestimation (loss function in the left), the profit value retained would be below the mean (for example the lower quartile of the distribution). Between two scenarios with the same mean profit, a “conservative” company using this type of loss function would prefer the one with smaller uncertainty (scenario 1).

6. Define the optimal scenario s^* as the scenario that has the maximum optimal estimate of profit $\hat{P}_s$.

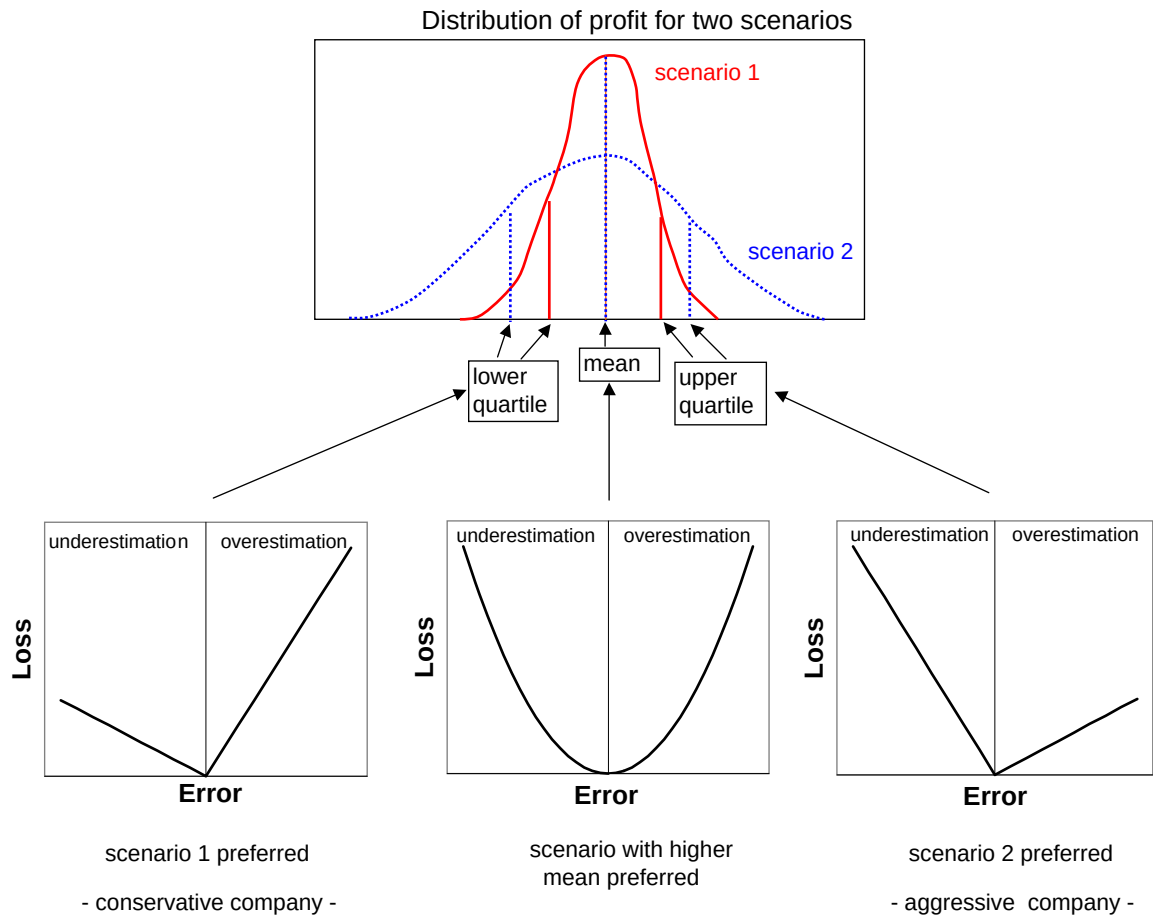


Figure 2.2: Example of probability distribution of profit for two scenarios and three types of loss function that yield different values of the retained profit value for each scenario and different decisions about the best scenario.

2.3 Case study

2.3.1 Settings

The best scenario defined with the *Full* approach takes into account the uncertainty in the geological model by using multiple models, but is it better than the scenario that would be defined with the conventional approach of using a single deterministic model? In order to quantify the “goodness” of the *Full* approach, we must compare the “true” results (profits) of the decisions made different ways.

A very large case study was undertaken to demonstrate the value of considering uncertainty in reservoir decision-making. Since in practice only one development plan can be implemented, and there is no access to the “true” reservoir, we must work with synthetic reservoirs and moreover, we must consider multiple “true” (synthetic) reservoirs because, by chance, the “conventional” or the “full” method could appear better in any one particular case. The *Full* approach and two conventional approaches - kriging and one single realization - were applied to each “true” reservoir and the resulting true profits of the approaches were compared.

Using stochastic simulation algorithms, 50 “true” reservoirs were generated. No attempt was made to cover all the possible types of hydrocarbon reservoirs, but careful attention was given to the generation of reservoirs different enough to validate the conclusions of this research.

Each reservoir is defined over a $90 \times 90 \times 60$ grid. There are six main stratigraphic layers, each with ten sublayers. The reservoir volumes, productivity and lithology represent medium size offshore reservoirs with sandstone/shale lithology. No faults or fractures were considered. Two phases (oil and water) were considered and the initial saturation of the fluids was determined by the position of the oil/water contact. The position of this contact was the same for all the reservoirs but the different elevations of the top structure and the different thickness and porosity of the layers resulted in different volumes of oil and water for each reservoir. The bottom layer was generated thicker than the other layers to ensure a strong bottom aquifer for all the reservoirs. The details of the reservoir generation, the main characteristics and some images of the reservoirs are presented in **Appendix A**.

Each “true” reservoir was sampled by five vertical wells to obtain data for the top elevation and thickness of all six layers, the lithology, porosity and permeability. A smooth image of the “true” structural top was also generated to mimic seismic data. The availability of five sampling wells and a good seismic representation of the structural top can be considered realistic for the development plan phase of an offshore reservoir.

The sample data were used to generate a kriged reservoir model and 20 simulated realizations, using geostatistical techniques different from those used to create the “true” reservoirs. Using such different algorithms protects from a recursive argument.

Each model involved the generation of one top surface and for each layer: a map of thickness, a three-dimensional grid of porosity and a three-dimensional grid of permeability. The layers were then assembled into one reservoir model. No combination of the realizations was considered, that is, a realization of any particular variable was used only once.

No explicit modeling of the facies (shale/sandstone) was done. Porosity and permeability were modeled directly. For the realizations, the reproduction of the high contrast between shale and sandstone values was guaranteed by the histogram of porosity and permeability, which reflected low and high values related to these different facies. A normal-score transform of the variables was followed by sequential Gaussian simulation.

For the kriged models, kriging was performed on the log transform of permeability as a way to propagate further the small permeability values of shale data. In this work, preservation of the small values of permeability around shale data was assumed more important than a possible introduction of bias due to kriging log-transformed variables and back-transforming with antilog [37].

Since horizontal variogram modeling is not possible with only five vertical wells, the horizontal ranges of porosity and permeability were modeled from the experimental vertical range using a triangular distribution for the horizontal to vertical anisotropy coefficient. Monte Carlo simulation was used to sample the anisotropy coefficients from the triangular distribution. The other model parameters were assumed constant, without any further consideration of uncertainty.

The original grid of the “true” reservoirs and models was upscaled to a $30 \times 30 \times 6$ grid in order to be processed faster by a flow simulator.

Appendix B presents the detailed methodology used for sampling the “true” reservoirs, generating the kriged and simulated realizations and upscaling the models, and gives some images of the models.

Although the details of the generation of the true reservoirs and models were placed in appendices to avoid interrupting the flow of the ideas in this chapter, they are very important for the generality of the conclusions of this research and the reading of these appendices is recommended.

The type of reservoir management problem chosen for the case study was the definition of the best number of producer wells to maximize the profitability of the reservoir resources. A smaller number of wells, even with smaller production, may give a higher profit if the profitability of the additional production does not pay for the cost of the additional wells. Moreover, to decide the best number of wells, different spatial configurations must be considered for each number of wells, because a number of wells in good locations may produce more than a greater number of wells in bad locations.

A total of 77 different production scenarios were defined, comprised of 11 different numbers of wells and seven different configurations for each number of wells. The particular numbers in the range of 11 numbers of wells varies depending on the “true” reservoir to account for the variable oil in place and productivity of each reservoir. For example, for a “bad” reservoir, the range of numbers may go from six to 16 wells while for a “good” reservoir the range may go from 13 to 23 wells. The five original wells used for data sampling were always considered for production.

The configurations for each given number of wells were defined using a **geometric** criterion to ensure a good spacing between wells and to avoid the boundaries. No inspection of any variable of the reservoirs was done for this definition. This case study is not intended to find the optimum location of the wells, but to compare the “goodness” of each approach in identifying the best scenario among a set of predefined scenarios.

To illustrate the production scenarios considered in this case study, two figures are

presented: **Figure 2.3**, which shows Configuration 1 for eight different numbers of wells and **Figure 2.4**, which shows the seven configurations for a particular number of wells (15).

The scenarios are the same for all three approaches: *Full*, *Conv-1* (conventional with just one realization) and *Conv-k* (conventional with the kriged model).

A flow simulator was run for each combination of model and scenario to obtain the production curves. For this case study the flow simulator ECLIPSE [48] was run 84,700 times, corresponding to (one true reservoir + 20 realizations + one kriged model) x 77 scenarios x 50 reservoirs.

Fluid properties, well conditions, and shut-in criteria were chosen to be realistic and they were kept the same for all the runs. With these specified production conditions, the greater the horizontal permeability values of the producer cells and the more difficult the communication between those cells and the aquifer, the better the position of a well.

The measure of profit was defined as the present value of the net oil production for 20 years of production, minus the cost of the wells. The net oil production for each period of time is the incremental oil production for that period minus the cost of processing the produced water. The economic units were expressed in volumes of oil to avoid the uncertainty in oil price, yet some results are also expressed in dollars to allow a better appreciation of the results. The price of oil used was \$100 per m^3 of oil, that is, \$15.89 per barrel.

The details of the flow simulation problem and the economic function to evaluate profit are presented in **Appendix C**.

With the two conventional approaches, the best scenario was defined as the one with maximum profit. For the definition of the best scenario with the *Full* approach, a quadratic loss function was considered, that is, the expected (mean) profit over all the realization results was retained for each scenario and the best scenario was defined as the one with maximum expected profit.

The comparison between the approaches was done using the actual profit (calculated from the “true” reservoir) of the scenario determined as best with each approach. Access to the “true” (synthetic) reservoir permits this comparison here, although such

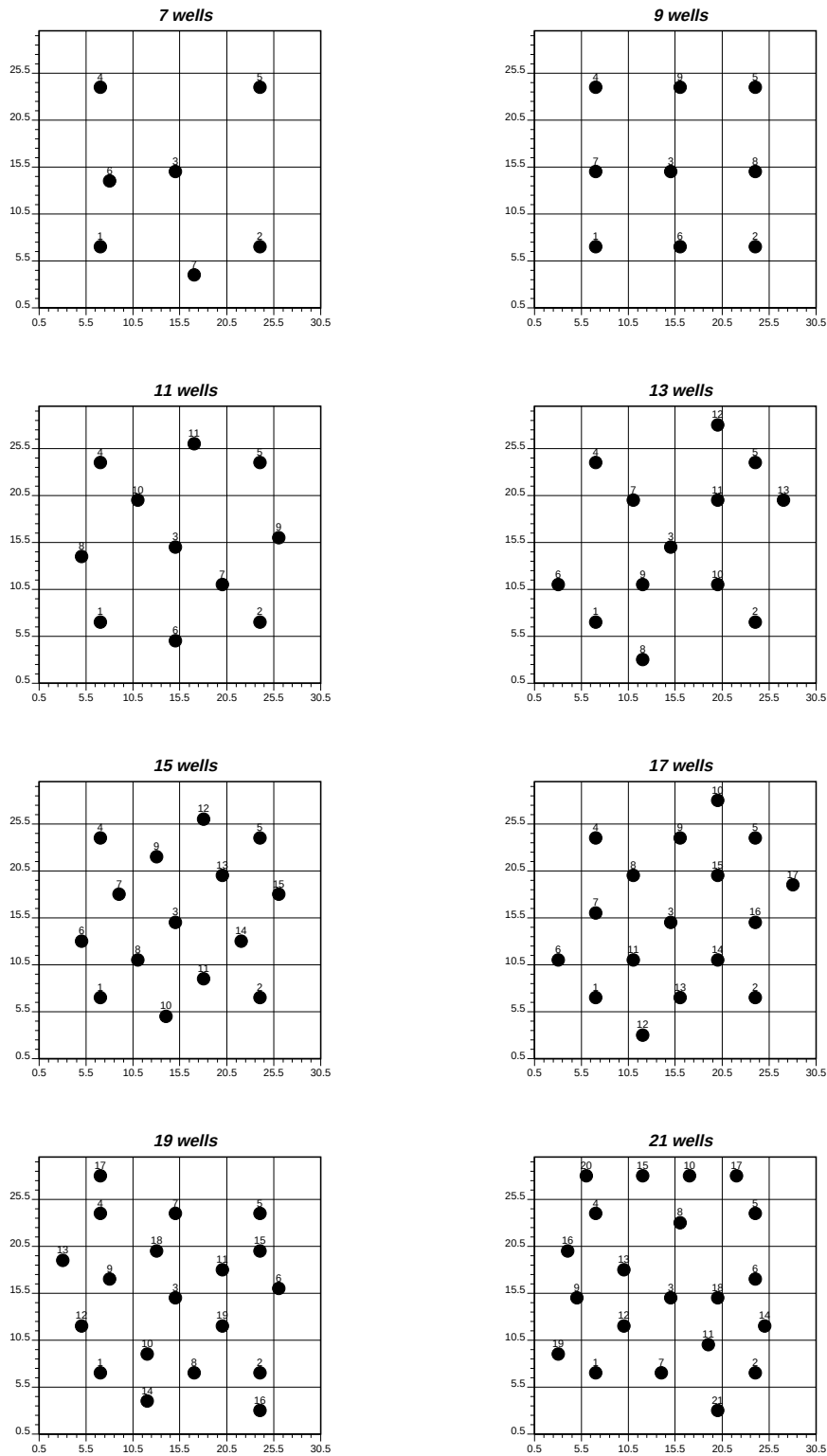


Figure 2.3: Configuration 1 for eight different numbers of wells.

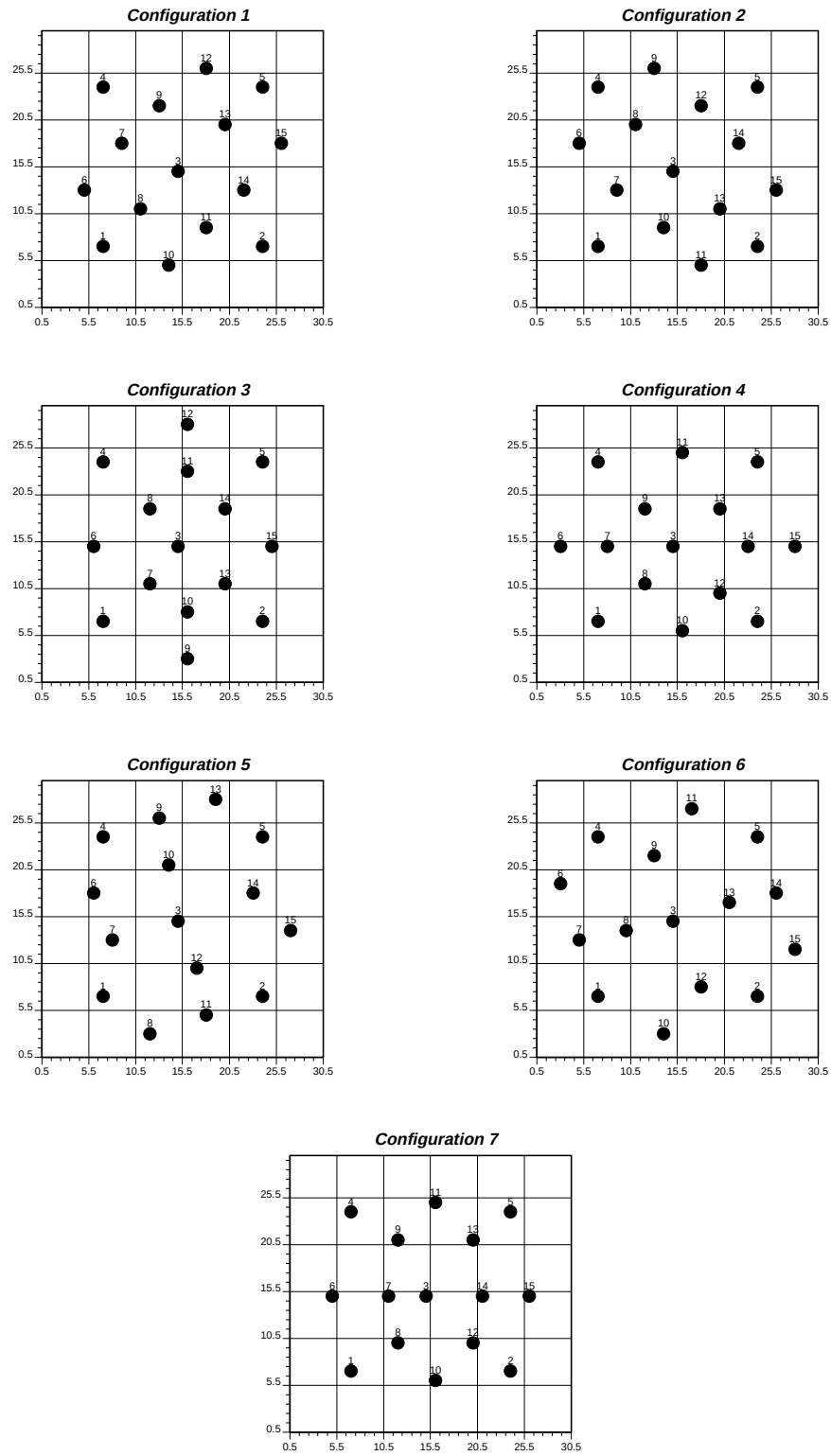


Figure 2.4: The seven configurations for 15 wells.

a comparison would be impossible in practice.

Several FORTRAN programs were developed and run in combination with GSLIB and ECLIPSE programs, using UNIX script files in order to create different reservoirs, sample them, model the variograms, generate the kriged and simulated models, up-scale, prepare the files for the flow simulator, run the flow simulator and evaluate the profit function automatically. UNIX script files are very useful tools, without them this research would not have been possible. **Appendix D** presents the structure and gives some examples of these files.

2.3.2 Results

The results of the three approaches are summarized here: (1) *Conv-k* denotes the conventional approach with a reservoir model built by kriging, (2) *Conv-1* denotes the conventional approach using a single geostatistical realization, and (3) *Full* denotes the *Full* approach using the expected value of profit calculated over all 20 realizations.

In the *Conv-1* approach, each realization could lead to a different definition of the best scenario with resulting different true profits. Instead of just presenting the result corresponding to one arbitrary realization, three results are presented for the *Conv-1* approach: the worst, the expected (mean) and the best result.

Figure 2.5 illustrates the comparison between the three approaches for one particular reservoir. The top four pictures of the figure show the mean profit calculated over all the realizations for each scenario (*Full*) and the profit of each scenario calculated with the kriged model (*Conv-k*), with Realization 1 (given as an example of *Conv-1*) and with the “true” reservoir. These pictures presents a color-coded table where the abscissa axis gives the seven possible spatial configurations and the ordinate axis gives the 11 different total numbers of wells. A scenario is found in these tables at the intersection of the number of wells row and the configuration column, with the profit values given by the color legend.

For each approach, the best scenario is defined as the one with the maximum profit. The corresponding true profits are then obtained for each scenario by using the values evaluated from the “true” reservoir. The comparison between the three

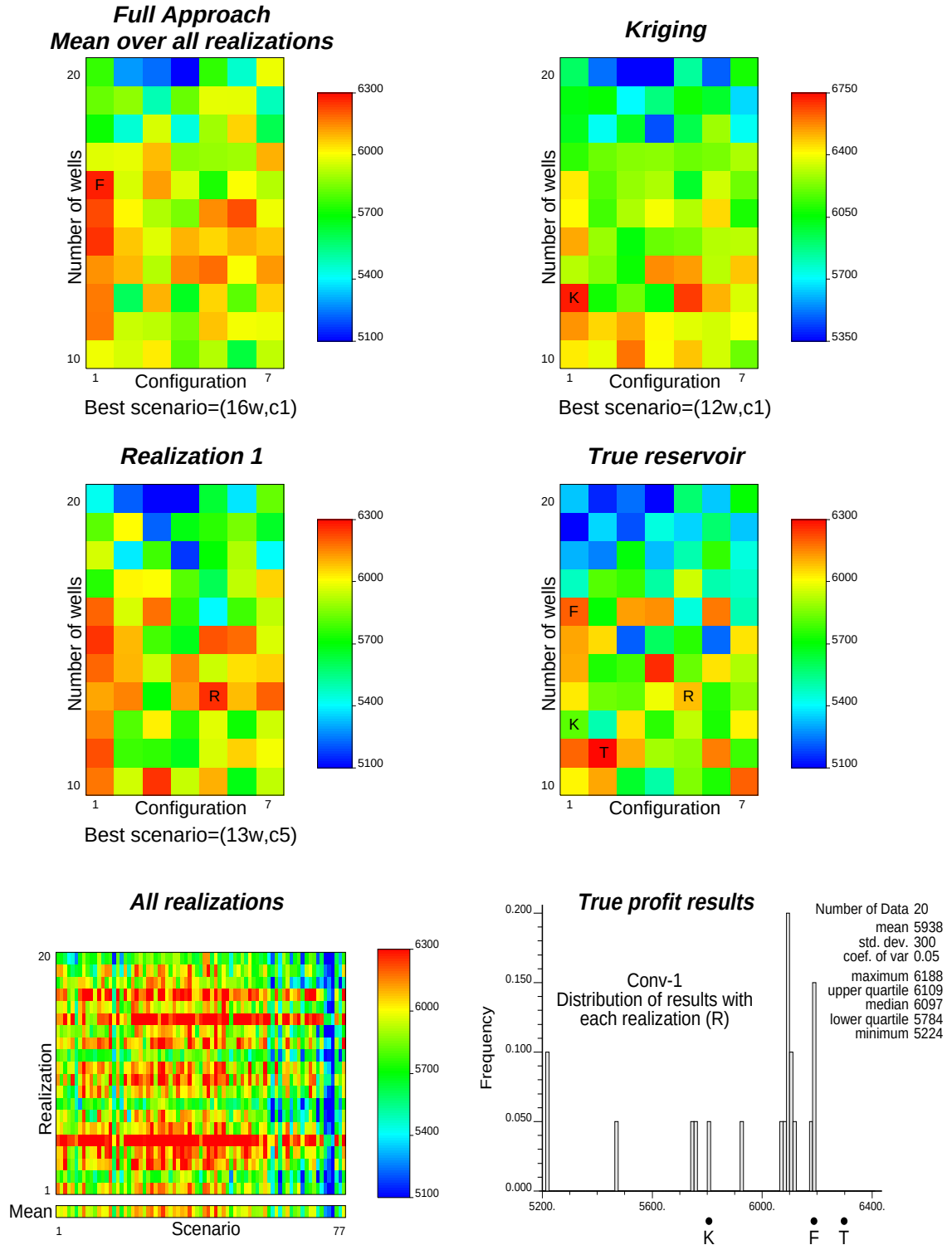


Figure 2.5: Scenario profits (Mm^3) obtained from each approach and from the true reservoir. Best scenario and corresponding true profit from: F=*Full* approach, K=*Kriging*, R=*Realization 1*, T=*True reservoir*.

approaches is made using these true profits.

For the particular reservoir used in the example of Figure 2.5, the optimal scenario defined using the *Full* approach (**F**) consists of 16 wells with Configuration 1, which has a true profit P of $6,188Mm^3$ of oil. The optimal scenario defined using Realization 1 (**R**) consists of 13 wells with Configuration 5, which has a true profit P of $6,074Mm^3$ of oil. The optimal scenario defined with the kriged model (**K**) consists of 12 wells with Configuration 5, which has a true profit P of $5,805Mm^3$ of oil. None of the approaches, however, yielded the “true” best scenario (**T**), which consists of 11 wells with Configuration 2, which has profit $P = 6,291Mm^3$ of oil. A good scale to compare those profit values is the equivalent cost of $150Mm^3$ of oil for one offshore well as considered in the economic function.

Realization 1 was used in the center left picture of Figure 2.5 just as an example of the *Conv-1* approach. The realization could be any one of the other 19. The bottom left picture of the figure gives the (20×77) profit results calculated over the 20 realizations (ordinate axis) for each of the 77 scenarios (abscissa axis), showing that the decision of the best scenario could be different for each realization retained for the *Conv-1* approach. The set of mean values over all the realizations presented at the bottom of this picture represents the *Full* approach. In order to present all the results in the same picture, the 77 scenarios shown in the abscissa axis were ordered increasing first the configuration number and then the number of wells, i.e. Scenario 1 is Configuration 1 of ten wells (the first number of wells in the range for this reservoir), Scenario 7 is Configuration 7 of the same number (ten) of wells and Scenario 77 is Configuration 7 of 20 wells (the 11th number of wells in the range).

The distribution of true profits using *Conv-1* with each one of the realizations is shown in the bottom right picture of Figure 2.5, as well the true profits (dots) of the other two approaches and the “true” best result. The worst result obtained from two of the realizations corresponds to a scenario of 16 wells with Configuration 5 yielding a true profit P of $5,224Mm^3$ of oil, while the best result obtained from three realizations corresponds to the same optimal scenario obtained with the *Full* approach, with a true profit P of $6,188Mm^3$ of oil. The expected true profit of the *Conv-1* approach is $5,938Mm^3$ of oil.

In this example, the worst result of the *Conv-1* approach is much poorer than the result of the *Conv-k* approach, itself poorer than the expected result of *Conv-1*, which is poorer than the result of the *Full* approach. That latter result is the same as the result of the best realization of *Conv-1*. The *Full* approach result is only slightly poorer than the ideal true best result (if the “true” reservoir was known).

These comparisons are valid only for the particular reservoir utilized for Figure 2.5; for a different reservoir the relative results of the three approaches considered could vary. To compare the approaches more reliably, different reservoirs should be considered: the previous exercise was repeated over 50 different reservoirs.

Since the absolute profit values are very different for each reservoir, in order to better compare the relative result of each approach and present all results in a single figure, the values were scaled as follows:

$$P_{approach} = \frac{P_{approach} - P_{worst\ realization}}{P_{best\ realization} - P_{worst\ realization}} \quad (2.2)$$

Figure 2.6 presents the comparisons between the three approaches for the 50 reservoirs using the scaled true profits. The mean results over all the reservoirs are given in the right column of the figure. The following observations can be made:

- The *Full* and the *Conv-k* results are almost always bracketed by the worst and the best realization of the *Conv-1* approach. There were just three exceptions: *Conv-k* was worse than the worst realization for Reservoir 43, *Conv-k* was better than the best realization for Reservoir 4 and *Full* was better than the best realization for Reservoir 5.
- On average over 50 reservoirs, *Full* is better than *Conv-k* and than the expected value of *Conv-1* taken over 20 realizations, and this latter is just a little better than the *Conv-k* approach.
- Models generated either by kriging or by stochastic simulations using data from only five wells do not lead to the true best decision for most of the reservoirs.

Since the best approach varies for each reservoir, an extensive attempt was made to find characteristics of the reservoirs that could be used to predict the best approach for

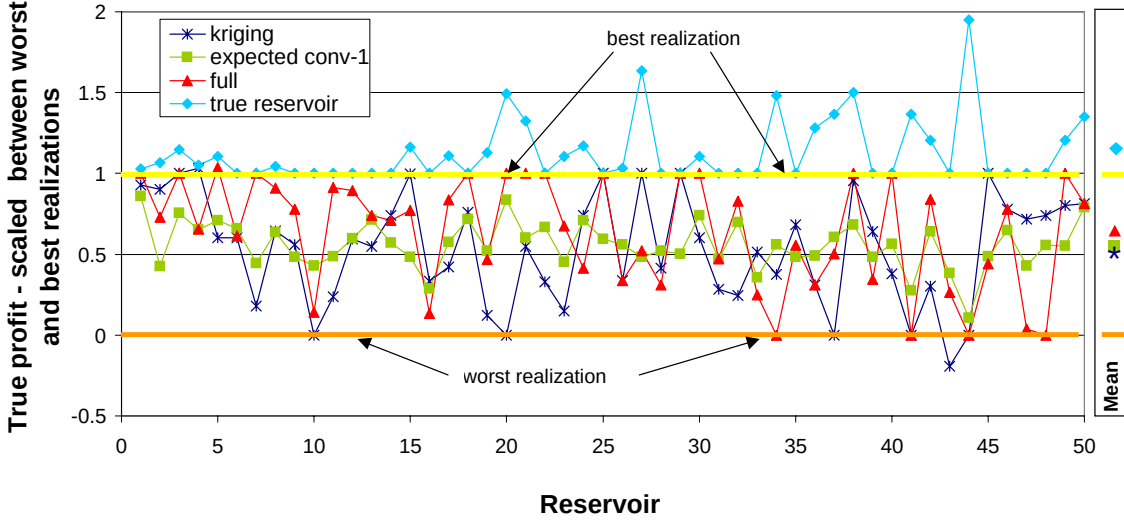


Figure 2.6: Comparison between the approaches for 50 reservoirs.

any particular reservoir, but no reasonable correlation between approach suitability and model parameters or modeled variables could be found.

The probability of an approach to be better than the others is given by the number of reservoirs (in percentage) for which that approach was better than the others. Using the expected value of the *Conv-1* approach over the 20 realizations to represent the conventional approach of using a single realization taken at random, the following scores between the approaches are observed:

- Comparing the three approaches together:
 - The *Full* approach was the best approach for 52% of the reservoirs.
 - The *Conv-k* approach was the best approach for 36% of the reservoirs.
 - The expected result of the *Conv-1* approach was the best result for 22% of the reservoirs.
 - There were reservoirs yielding the same results with two approaches.
- Comparing the approaches two by two:

- The *Full* approach had better results than the expected result of the *Conv-1* approach for 64% of the reservoirs.
 - The *Full* approach was better than the *Conv-k* approach for 52% of the reservoirs.
 - The *Full* approach was equal to the *Conv-k* approach for 18% of the reservoirs.
 - The *Full* approach was worse than the *Conv-k* approach for 30% of the reservoirs.
 - The *Conv-k* approach had better results than the expected result of the *Conv-1* approach for 48% of the reservoirs.
- Compared with the best realization (probability of occurring = $\frac{1}{20} = 5\%$) of the *Conv-1* approach:
 - The *Full* approach had better results for 2% of the reservoirs.
 - The *Full* approach had equal results for 26% of the reservoirs.
 - The *Conv-k* approach had better results for 2% of the reservoirs.
 - The *Conv-k* approach had equal results for 14% of the reservoirs.
 - Compared with the worst realization (probability of occurring = $\frac{1}{20} = 5\%$) of the *Conv-1* approach:
 - The *Full* approach had worse results for none of the reservoirs.
 - The *Full* approach had equal results for 8% of the reservoirs.
 - The *Conv-k* approach had worse results for 2% of the reservoirs.
 - The *Conv-k* approach had equal results for 10% of the reservoirs.

Since Figure 2.6 does not show the entire distribution of the *Conv-1* results, it is useful to know the number of realizations that have better, equal or worse results than the *Full* or the *Conv-k* approach. For example, for the reservoir presented in Figure 2.5, the result using the *Full* approach (**F**) was better than the result obtained from

17 (85%) of the realizations and equal to the results obtained from three (15%) of the realizations, while the result with *Conv-k* (**K**) was better than the result obtained from five (25%) of the realizations and equal to the result obtained from one (5%) realization; using any of the other 14 (70%) realizations yield result better than using *Conv-k*.

This exercise of evaluating the number of realizations in the *Conv-1* approach for which the *Full* or the *Conv-k* approach had better, equal or worse result was repeated for all the 50 reservoirs and the following average scores are observed:

- The *Full* approach when compared with the *Conv-1* approach led to:
 - better decisions than 45% of the realizations.
 - equal decisions in 24% of the realizations.
 - worse decisions than 31% of the realizations.
- The *Conv-k* approach when compared with the *Conv-1* led to:
 - better decisions than 40% of the realizations.
 - equal decisions in 13% of the realizations.
 - worse decisions than 47% of the realizations.

Each reservoir has its own distribution of results (true profits) corresponding to its 20 realizations. To obtain an average distribution of these results over the 50 reservoirs, the results of the 20 realizations were ranked for each reservoir and the results with the same rank order were averaged across the 50 reservoirs. **Figure 2.7** shows the distribution of these 20 average profit results together with the average result of the *Full* (**F**) and *Conv-k* (**K**) approaches. For reference, the average result of the best scenario obtained with the true reservoirs (**T**) is also presented.

Based on these results, the following comments can be made:

- Comparing *Full* and *Conv-1*.
 - *Full* was better than 60% of the realizations and worse than 40% of the realizations.

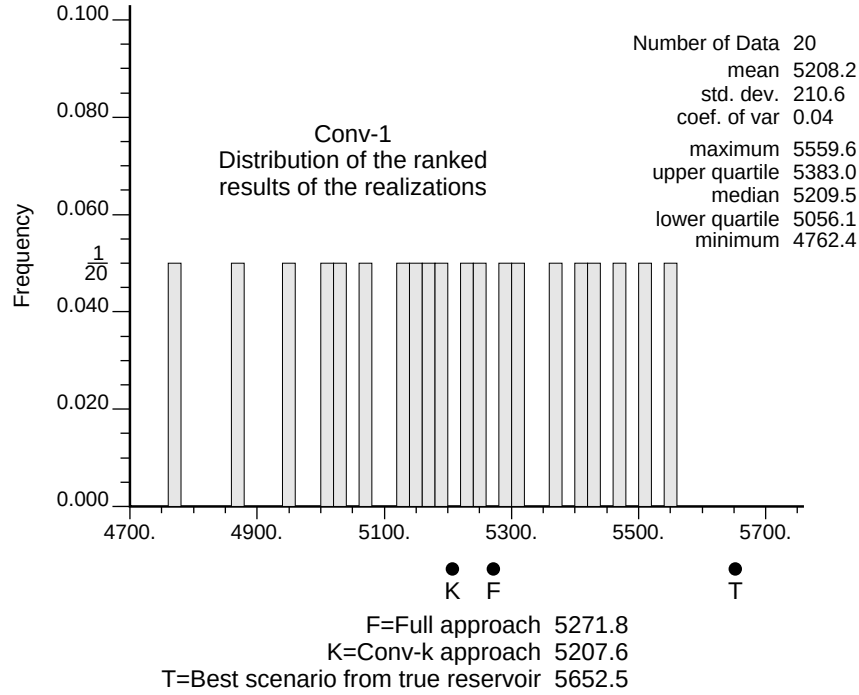


Figure 2.7: True profits (Mm^3) averaged over 50 reservoirs.

- The average gain of *Full* over the expected result of *Conv-1* was $63.6Mm^3$ of oil, which represents an increment of 1.22% in profit or \$6.37 million.
- The average gain of *Full* if only a single realization worse than *Full* was used (probability = 60%) would be $202.4Mm^3$ of oil (this is the mean of the difference between the *Full* result and the results of the realizations worse than *Full*).
- The average loss of *Full* if one realization better than *Full* was used (probability = 40%) would be $144.5Mm^3$ of oil (this is the mean of the difference between the results of the realizations better than *Full* and the *Full* result).
- Comparing *Conv-k* and *Conv-1*.
 - *Conv-k* was better than 50% of the realizations and worse than 50% of the realizations.

- The average loss of *Conv-k* over the expected result of *Conv-1* was $0.6Mm^3$ of oil.
 - The average gain of *Conv-k* if one realization worse than *Conv-k* was used (probability = 50%) would be $172.2Mm^3$ of oil.
 - The average loss of *Conv-k* if one realization better than *Conv-k* was used (probability = 50%) would be $173.3Mm^3$ of oil.
- Comparing *Full* and *Conv-k*.
 - The average gain of *Full* over *Conv-k* was $64.2Mm^3$ of oil, which represents an increment of 1.23% in profit or \$6.42 million.

For the quadratic loss function used in this case study, the value of profit retained from the distribution of profits over all the 20 realizations for each scenario is the mean of that distribution. Although only the results of the *Full* approach using this quadratic loss function were used to compare the approaches, the influence of the specific loss function used in the *Full* approach was investigated by evaluating also the results of the *Full* approach with two other loss functions: (a) a conservative loss function for which the retained profit value is the lower quartile of the profit distribution over all the 20 realizations, and (b) an aggressive loss function for which the retained profit value is the upper quartile of that distribution.

The results of the *Full* approach with different loss functions varied for some reservoirs, yet the average result over the 50 reservoirs changed very little. Retaining the lower quartile value of the profit distribution over the 20 realizations for each scenario, the average result with the *Full* approach over the 50 reservoirs was $5,275.7Mm^3$ of oil. Retaining the upper quartile, the average result of the *Full* approach was $5,263.3Mm^3$ of oil. Recall that the average result of the *Full* approach when retaining the mean (quadratic loss function) was $5,271.8Mm^3$ of oil.

Although the absolute values used in the comparisons between the *Full* approach and the two other approaches would have been a little different, the qualitative comparisons between the approaches made based on the average results over the 50 reservoirs do not depend on the particular loss function used in the *Full* approach.

2.3.3 Conclusions

The principal conclusions are:

1. On average over many reservoirs, the *Full* approach provides better results than the *Conv-k* approach and than the expected result of the *Conv-1* approach.
2. There is no way to predict which approach would give the best result for a particular reservoir because the suitability of the approach depends ultimately on the true reservoir. However, since the truth is unknown, the use of multiple realizations for decision-making decreases the risk of very bad decisions.
3. The decision of which approach to use, between *Conv-1* and *Full* or between *Conv-1* and *Conv-k*, depends on the profit desire and risk aversion profile of the company.

Although the results of this case study show that on average over many reservoirs the *Full* approach provides higher profits than the expected profit obtained with one realization taken at random (*Conv-1* approach), an aggressive company (profit desire greater than the risk aversion) may decide to use a single realization for a particular reservoir, expecting to have a realization that would lead to a profit higher than the one obtained using all the realizations.

Between the *Conv-k* approach and the *Conv-1* approach, a conservative company (risk aversion greater than the profit desire) would prefer the *Conv-k* to decrease the risk of a very bad decision, while an aggressive company would prefer to use a single realization taken at random, expecting to have a realization that would lead to a profit higher than the one obtained using the kriged model.

4. The expected gain of using multiple geostatistical realizations in decision-making through the *Full* approach (approximately \$6 million in this case study) more than justifies the additional computational costs.

2.4 Discussion

In this section, the following aspects of the *Full* approach and of the case study are discussed:

- Alternative use of multiple realizations in decisions.
- Influence of the uncertainty level.
- Inclusion of other types of uncertainty.
- Limitations of the case study.
- Reducing the computational effort of the *Full* approach.

2.4.1 Alternative use of multiple realizations in decisions

Once the profits are evaluated for each scenario with every realization, one could think of different ways to define the best scenario. For example, an idea could be to retain the best scenario defined with every realization independently and define the best scenario as that most frequently retained scenario (mode).

The main drawback of this way to use multiple realizations to define the best scenario is that there is no incorporation of the profit desire and risk aversion profile of the company. The distribution of the scenario profits over all the realizations would not be used for the definition of the best scenario. For example, a particular scenario s may be the best for five among 20 realizations, but for the other 15 realizations this scenario may be very bad. If this “mode” procedure was applied and no other scenario had been the best for more than four realizations, the scenario s would be defined as the best even with an expected value smaller than several other scenarios.

2.4.2 Influence of the uncertainty level

It is reasonable to expect that as the uncertainty in the geological model decreases, that is, as the various realizations become more alike, the benefits of the *Full* approach would decrease. At the limit of zero uncertainty, all the realizations are the same and

just one needs to be used for decision-making, and that one is best (more quickly) obtained by kriging.

This remark could not be confirmed with the case study undertaken because just one level of uncertainty was used for each reservoir. The variation of the level of uncertainty and the influence on the relative goodness of each approach will be shown in **Chapter 4**.

2.4.3 Inclusion of other types of uncertainty

Other uncertainty types, besides geological, affect the responses of the flow simulation. These could be included in the *Full* approach by increasing the number of models. The term “model” is understood here as the geological specifications given to the geostatistical realizations plus the fluid and rock/fluid interaction properties. For example, if three different curves of relative permeability were possible with specified probabilities of occurring, the number of models would be multiplied by three, considering the three different curves for every realization.

If the number of other uncertain parameters (such as relative permeability, capillary pressure, PVT properties, etc.) that needs to be considered is large, then sampling techniques such as Monte Carlo simulation, Latin hypercube sampling or experimental design (see Section 1.2, *Literature Review*) must be applied to choose the models to be used in the *Full* approach, provided that all such uncertainties are independent one from another.

Those uncertainties that affect the definition of the best scenario only after obtaining the production curves can be incorporated easily because no further flow simulation is necessary. For example, the parameters of the economic function, such as oil and gas prices, cost of wells, operational costs, taxes, internal rate of return, etc. could have their uncertainty modeled by some kind of probability distribution. Then a Monte Carlo simulation could be used to sample each parameter to obtain a distribution of profits instead of just one value for each production response. The final distribution of profits for each scenario would be obtained simply by averaging all the distributions of profit for that scenario (one distribution per model).

2.4.4 Limitations of the case study

Some reasonable questions about the case study and the answers provided are:

Question: A conclusion from the case study is that on average over many reservoirs the results of decisions made accounting for the geological uncertainty are better than the results of decisions made without accounting for the geological uncertainty. This conclusion was based on the specific decision problem and reservoirs used in the case study. Can this conclusion be extended to all types of reservoir management problems and all types of reservoirs?

Answer: No. There are situations where the consideration of the geological uncertainty is not relevant for the decision of the best scenario.

The relevance of considering geological uncertainty for different types of reservoirs and different types of reservoir management decisions is discussed in **Chapter 5**.

However, the case study and its conclusions are representative of a very important problem where the consideration of geological uncertainty is relevant: the definition of the best number and spatial configuration of wells for medium size offshore reservoirs.

Question: Are the results dependent on the algorithms used for modeling the reservoir?

Answer: Yes, everything in geostatistics is algorithm dependent, but the algorithms used here are the widely used SGSIM [15], for sequential Gaussian simulation and KT3D [15] for kriging. Although the absolute results may be different with different algorithms, the conclusions about the comparison of the approaches are unlikely to have changed.

Question: Are the flow responses obtained with the realizations and with the kriged model affected differently by the upscaling?

Answer: Yes. Recall that each upscaled layer has ten sublayers in the original grid and that the upscaled vertical permeability is affected strongly by small values. Consider only one layer and two different situations for the five sampling wells: Situation A, where shale is present in only one sublayer in all the wells and Situation B, where shale is present in all the sublayers but in only one well.

In Situation A, kriging would generate one sublayer with small permeability everywhere and the upscaled vertical permeability would be small everywhere too. In the same situation, if the horizontal continuity of the variogram is small, simulation would generate some permeabilities different from the shale permeability, even for the sublayer where all the wells sampled shale, and the upscaled layer would have some points with reasonable vertical communication.

In Situation B, with kriging the upscaled layer would have small vertical permeability only around one well. With simulation, points with small permeability would be generated between the wells for each sublayer. If the vertical continuity of the variogram is small, those points with small permeability could be in different positions for each sublayer and then the upscaled layer would have small vertical permeability almost everywhere.

Question: How does upscaling affect the comparison between the approaches?

Answer: Between *Full* and *Conv-1*, the absolute values used in the comparisons could change but, since both approaches are based on simulation, the conclusion that *Full* is better than *Conv-1* would be the same.

The effects of upscaling on the comparison between *Conv-k* and the simulation-based approaches depends on the truth. If the true reservoir has an upscaled layer with small permeability almost everywhere (even if no sublayer is a complete barrier), kriging would be a better model than the simulated realizations and it would probably provide a better decision in Situation A, while the realizations would be closer to the truth in Situation B.

Upscaling may favor kriging or simulation for a particular layer but since 50 different reservoirs were used in the case study and six layers were upscaled for each reservoir, the effects of upscaling each layer over the goodness of the kriged or the simulated models became random effects.

Question: How does the decision of not explicitly modeling the shales affect the comparison between *Conv-k* and the simulation based approaches?

Answer: The histograms of the petrophysical parameters containing the small

values of the shale and the high values of the sandstone were reproduced in the simulations by the use of a normal-score transform and the sequential Gaussian simulation but those histograms were smoothed by kriging, despite the use of a log transform of permeability (refer to **Appendix B** for details).

However, the contrast between facies is just another component of the basic differences between simulation and kriging: simulation provides the reproduction of the variable histograms while kriging smoothes them, simulation provides better reproduction of the flow pattern while kriging provides local accuracy. Depending on the available data, the flow paths generated by simulation may or may not be in the correct places.

An analysis of the influence of the number of available data on the results of the approaches is presented in **Chapter 4**.

Question: How does the type of problem affect the comparison between *Conv-k* and the simulation-based approaches?

Answer: For some types of problems, reproduction of the correct flow pattern is less important than for other problems where the communication between wells and/or the time of breakthrough affects the decision. Examples of problems where it is important to reproduce the flow pattern correctly are the definition of the amount of tracer to inject and the timing to install a water treatment plant.

The problem presented in the case study was the definition of the best number of wells and their spatial configuration to maximize the profit of the production over 20 years. For this kind of problem, a correct reproduction of the flow pattern, as ideally given by the simulated realizations, may be worse than the smooth model of the reservoir given by kriging, if the “channels” and barriers are simulated in wrong places.

However, it will be shown in **Chapter 5** that the problem of locating wells, chosen for this case study, is one of the most critical reservoir management problems for which modeling of the geological uncertainty makes a difference.

2.4.5 Reducing the computational effort of the *Full* approach

The benefits of the *Full* approach were shown unambiguously with the case study. But the computational (CPU) time involved is at least 20 (the number of realizations) times greater than with the conventional approach where just one model is used.

As an example of the computational effort, each flow simulation run in the case study took approximately 1.2 minutes of CPU on a DEC Alpha 600MHz workstation; thus the total CPU time to run all the flow simulations involved in the *Full* approach using 20 realizations and 77 scenarios for one reservoir was approximately 31 hours.

Depending on the computational resources available and on the time allocated for the decision, it may be a necessity to reduce the computational effort of the *Full* approach. This reduction may be obtained by decreasing the number of realizations and/or the number of scenarios to process through a flow simulator.

An exercise was performed to show how this reduction could be implemented and to quantify the differences between the results with a reduced approach and with the *Full* approach. Two ways to reduce the total number of flow simulation runs were investigated for the case study shown in Section 2.3:

I) Reducing the number of scenarios

Procedure:

- Take one realization randomly.
- Run the flow simulator for all the scenarios with that realization.
- Select some scenarios to keep and exclude the others based on the profits evaluated from that realization.
- Apply the “*Full*” approach with all the realizations and the selected scenarios.

For this analysis, after deriving the profits for all the scenarios over one single realization, a reference number of wells was defined as the one with maximum mean profit over all the configurations. Starting with a range of just one number of wells (the reference number), several alternative numbers of wells were considered, adding

wells to and subtracting wells from the reference number. For example, for a range of three numbers of wells, the reference number, the reference number minus one and the reference number plus one were considered.

Table 2.1 presents, for each range of numbers of wells, the number of reservoirs where the result of the *Full* approach was the same as the original result with 11 numbers of wells, the number of reservoirs where the result of *Full* was worse, the number of reservoirs where the result of *Full* was better, the mean loss for the reservoirs where *Full* was worse and the mean gain for the reservoirs where *Full* was better. The number of reservoirs is expressed as a percentage of the 50 reservoirs.

Table 2.1: Reducing the number of scenarios

Range of number of wells	Range of numbers of wells (%)	Number of reservoirs with same result (%)	Number of reservoirs with worse result (%)	Number of reservoirs with better result (%)	Mean difference: reservoirs with worse result (Mm^3 oil)	Mean difference: reservoirs with better result (Mm^3 oil)
1	9	32	50	18	-260.2	307.7
3	27	58	26	16	-205.2	399.5
5	45	84	12	4	-241.6	425.6
7	64	94	4	2	-188.9	381.7
9	82	96	2	2	-74.2	381.7

The range of numbers of wells, given as a percentage of the original range of 11 numbers of wells, is a measure of the reduction in the computational effort, discounted the previous runs to select the scenarios. The numbers of reservoirs in percentage are measures of the probabilities of having the same, worse and better results with less numbers of wells than with the original 11 numbers of wells. For example, the probability of having the same result with only 45% (five wells) of the original 11 numbers of wells is 84%, if the procedure described above were to be applied.

The probability of loss due to the exclusion of a true good scenario is higher than the probability of gain due to the exclusion of a scenario that is truly bad but that

appears as the best on average over all the realizations. For this case study, though, the average loss of excluding a true good scenario was smaller than the average gain of excluding a true bad scenario. This indicates that, for this case study, the amount by which a scenario is truly worse is greater than the amount by which a scenario is truly better.

II) Reducing the number of realizations

Procedure:

- Take one scenario from the middle of the range of scenarios.
- Run the flow simulator for all the realizations with that scenario.
- Rank the realization based on the profits evaluated with that scenario.
- Select a limited number of realizations in the high side, middle and low side of the ranking.
- Apply the “*Full*” approach with all the scenarios and the selected realizations.

The scenario used in this analysis was Configuration 1 with the number of wells in the middle of the range of 11 numbers of wells, for each reservoir. Starting with three realizations (the best, the worst and the middle one), several different numbers of realizations were considered, just increasing the number of realizations on each side of the ranking. For example, with nine realizations, the realizations are the three best, the three worst and the three in the middle of the ranking.

Table 2.2 presents, for each number of realizations, the number of reservoirs (in percentage) where the result of the *Full* approach was the same as the original result with 20 realizations, the number of reservoirs where the result of *Full* was worse, the number of reservoirs where the result of *Full* was better, the mean loss for the reservoirs where *Full* was worse and the mean gain for the reservoirs where *Full* was better.

The number of realizations, given as a percentage of the original 20 realizations, is a measure of the reduction of the computational effort, not counting the previous runs to rank the realizations.

The probability of loss due to the exclusion of good realizations, i.e. realizations where a scenario that appears to have a good profit is truly good, is slightly higher than the probability of gain due to the exclusion of bad realizations, i.e. realizations where a scenario that appears to have a good profit is truly bad.

Table 2.2: Reducing the number of realizations

Number of realizations	Number of realizations (%)	Number of reservoirs with same result (%)	Number of reservoirs with worse result (%)	Number of reservoirs with better result (%)	Mean difference: reservoirs with worse result (Mm^3 oil)	Mean difference: reservoirs with better result (Mm^3 oil)
3	15	42	30	28	-278.9	220.4
6	30	54	24	22	-167.9	224.7
9	45	64	20	16	-167.0	270.2
12	60	72	14	14	-153.5	197.6
15	75	84	10	6	-110.3	230.7
18	90	92	4	4	-210.6	308.0

For this case study, the average loss of excluding good realizations was smaller than the average gain of excluding bad realizations. This can be explained by a negative skewness of the distribution of the true profits obtained with the realizations. In Figure 2.7, this negative skewness, i.e. a longer tail towards the low outcome values, can be observed. In other words, the amount by which a bad realization is worse is greater than the amount by which a good realization is better.

Between the two ways to reduce the number of flow simulation runs for this problem, the reduction of the number of scenarios is more effective than the reduction of the number of realizations. For example, in reducing the computational effort to 45% of the original effort, the probability of having the same result is 64% if reducing

the number of realizations and is 84% if reducing the number of scenarios. For the 84% probability of having the same result that could be obtained by reducing the number of scenarios to 45% of the original, the computational effort would be reduced to only 75% of the original effort, if decreasing the number of realizations.

Also, the absolute values of the losses and gains due to the reduction of number of realizations are smaller than due to the reduction of number of scenarios, indicating that there is more similarity between the realizations than between the scenarios. Thus it is easier to identify bad scenarios to exclude than to identify bad realizations to exclude.

Combinations of both types of reduction could be considered. It is important to notice, though, that the approach obtained by reducing the number of scenarios and/or reducing the number of realizations is not “full” any more and differences between the results with this reduced approach and with the *Full* approach are expected, being the probability of worse results with the reduced approach greater than the probability of better decisions.

Neither experimental design nor optimization techniques can be applied to reduce the number of flow simulation runs for this kind of problem because neither the realizations nor the scenarios are continuous variables.

The quality map introduced next in **Chapter 3** can be used to reduce the computational effort of the *Full* approach by: (a) optimizing the configuration for each number of wells and then using just one configuration for each number of wells, (b) identifying a representative realization for each scenario and then using just one realization for each scenario, and (c) ranking the realizations for each scenario and then using a smaller number of realizations.

Chapter 3

The Quality Map

3.1 Definition

The parameters that govern fluid flow through heterogeneous reservoirs are numerous and most of them uncertain. Even when it is possible to visualize all the parameters together, the complex and nonlinear interaction between them makes it difficult to predict the dynamic reservoir responses to production. A flow simulator may be used to evaluate the responses for each production scenario given the geological model. The *Full* approach uses the results of flow simulations over multiple realizations to account for the geological uncertainty in the decision-making.

With the *Full* approach, the scenario defined as the best in one of the predefined scenarios. For some reservoir management problems, the number of predefined scenarios to ensure that the selected scenario is optimal would be too large.

For the problem of well location, for example, the number of possible configurations for nw wells in a horizontal grid of nc cells is $\frac{nc!}{(nc-nw)!}$. For ten wells ($nw = 10$) in a 30×30 grid ($nc = 900$), for example, the number of possible configurations is 3.3×10^{29} . It would be impractical to optimize the configuration for several numbers of wells considering multiple geological models, even with the help of sophisticated optimization algorithms.

The quality map, introduced in this chapter, provides a way to optimize the configuration of a given number of wells, accounting for the geological uncertainty, with

a reasonable number of flow simulations and using a simple optimization algorithm. The use of just one configuration for each number of wells reduces the computational effort of the *Full* approach significantly for the problem of defining the best number of wells and their spatial configuration.

The quality map is, by construction, a map of “how good the area is for production”. The quality at a location is a measure of the expected oil production if a well was to be placed at that location (with no other wells in the reservoir). The use of a flow simulator to evaluate quality ensures that the nonlinear and dynamic interactions between the parameters are taken into account. The use of multiple realizations ensures that the geological uncertainty is taken into account.

Besides the optimization of the configuration of a given number of wells, the integration of all the rock and fluid characteristics into a single two-dimensional visualization and characterization of a reservoir model allows other uses for the quality map, such as identification of a representative realization, ranking of realizations and comparison between reservoirs.

This chapter presents the methodology for building different types of quality map, the procedures for using them, and a case study based on the same 50 reservoirs used in Chapter 2 to check the benefits and to demonstrate the uses of the quality maps.

3.2 Methodology

3.2.1 Generation of a quality map

The quality map is generated by running a flow simulator multiple times with just one producer well and varying the position of the well in each run to provide a coverage of the entire horizontal grid. Each run evaluates the quality for the horizontal cell where the well is located.

The quality unit is the cumulative oil production (N_p) after a certain time of production. The total time of production depends on the size of the reservoir but must be long enough to allow the well to approach likely economic abandonment.

In the flow simulation, the well is completed in all oil layers with automatic shut

down of the layer when some water (or gas) cut limit is reached. No rate limits are imposed. Only a minimum bottom hole pressure (BHP) and a minimum oil rate must be specified in accordance with the expected limitations of the wells during actual production.

Considering the cumulative production of a vertical well placed in different positions, the three-dimensional characterization of a reservoir, involving multiple parameters, is translated into a single two-dimensional grid of values. The flow simulator accounts for all the interactions between variables and returns one single value of quality (N_p) for each position of the single well. The larger the horizontal transmissibility around the well, the higher the initial rate, the longer the production time before the minimum BHP is reached and the greater the quality value (total N_p). Also, the smaller the transmissibility between the aquifer (and/or gas cap) and the well, the smaller the water (and/or gas) production and the greater the total N_p for the same final BHP.

Figure 3.1 shows, as an example, some of the parameters that affect the oil production and presents the quality map (lower right corner), which integrates all the parameters. The higher the structural top, the greater the final cumulative oil production because the thicker the oil column. The larger the oil volume, the better. The greater the horizontal permeability in the upper layers where most of the oil production occurs the better. The lower the vertical permeability between the aquifer and the production layers (k_z - Layer 3 in the figure) the better. Several other parameters also affect the flow of fluids inside the reservoir and only a flow simulator is capable of accounting for all the interactions between these parameters.

3.2.2 Types of quality map

A full quality map may be built for a particular model with the well in each cell of the horizontal grid, as was the case of the quality map in Figure 3.1. However, when dealing with multiple models, it would be too CPU demanding to evaluate quality for each cell of each model. The alternative is to obtain only some points for every realization and then to interpolate the maps by kriging. The number of necessary

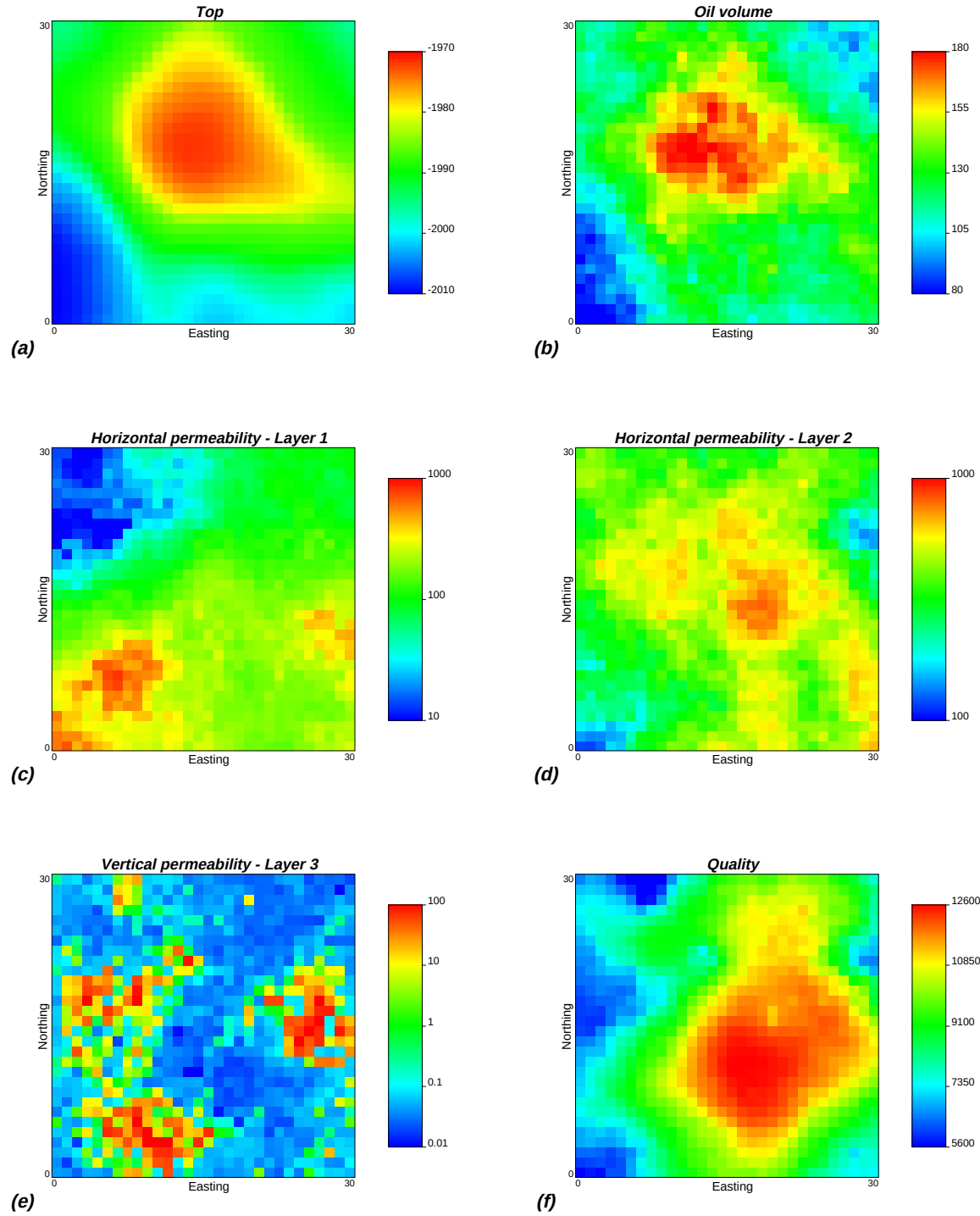


Figure 3.1: Presentation of the quality map. Several variables, including: (a) top (m), (b) oil volume (Mm^3), (c)(d) horizontal and (e) vertical permeabilities (md), are integrated into (f) the quality map (Mm^3).

points depends on the reservoir heterogeneity and on the grid size of the model, however between five and ten percent of the total number of cells should be sufficient, provided the points are evenly distributed over the entire grid. The sampling positions must vary for every realization in order to sample each cell at least once.

The quality maps of all the realizations provide a distribution of quality values for each cell. The expected value may be taken for each cell to generate a mean quality map and the standard deviation of the distribution may be taken for each cell to generate a map of quality uncertainty.

For well location purposes, an L-optimal quality map can be generated if a loss function is specified. The quality value that minimizes the expected loss is retained for each cell, generating the L-optimal quality map.

Figure 3.2 presents an example of the distribution of quality in two cells and three different types of loss function that lead to different values for the L-optimal quality map in each cell and to different decisions for the best cell in which to locate a well. The two cells have the same mean value, but cell 1 has a smaller uncertainty than cell 2. For a loss function that penalizes underestimation more than overestimation (like the loss function in the right of the figure), the quality value that minimizes the expected loss is above the mean (for example the upper quartile of the distribution). Between the two cells presented in the figure, an “aggressive” company using this type of loss function would prefer the cell with greater probability of high quality values (cell 2). For a quadratic loss function where the loss due to underestimation is the same as the loss due to overestimation (loss function in the center), the quality value that minimizes the expected loss is the mean. A company using this type of loss function would prefer to locate wells in cells with high expected quality, without consideration of the quality uncertainty (no preference between cell 1 and cell 2). For a loss function that penalizes overestimation more than underestimation (loss function in the left), the retained value of quality is below the mean (for example the lower quartile of the distribution). Between two cells with the same mean value, a “conservative” company using this type of loss function would prefer the cell with smaller uncertainty (cell 1).

Figure 3.3 presents the quality maps of two realizations (with the positions of the

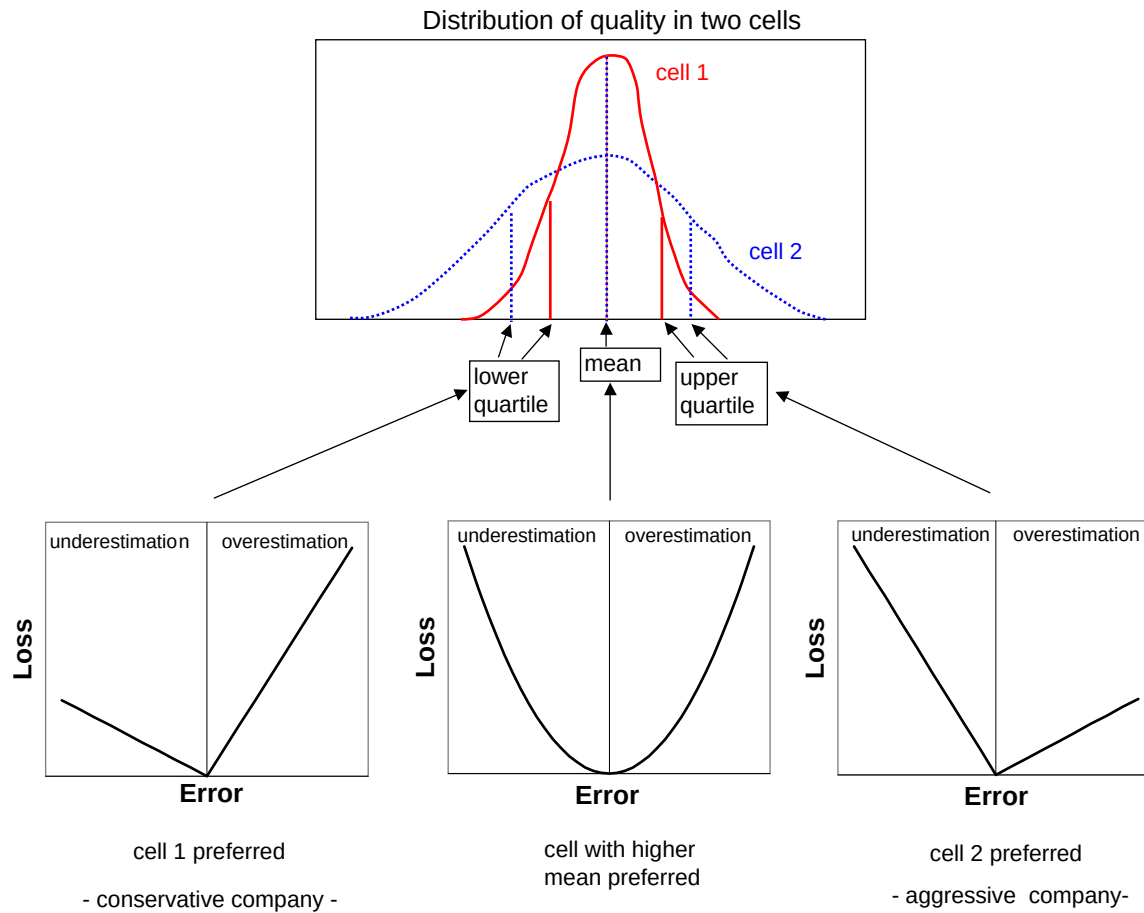


Figure 3.2: Example of probability distribution of quality in two cells and three types of loss function that yield different values for the L-optimal quality map in each cell and different decisions about the best cell to locate a well.

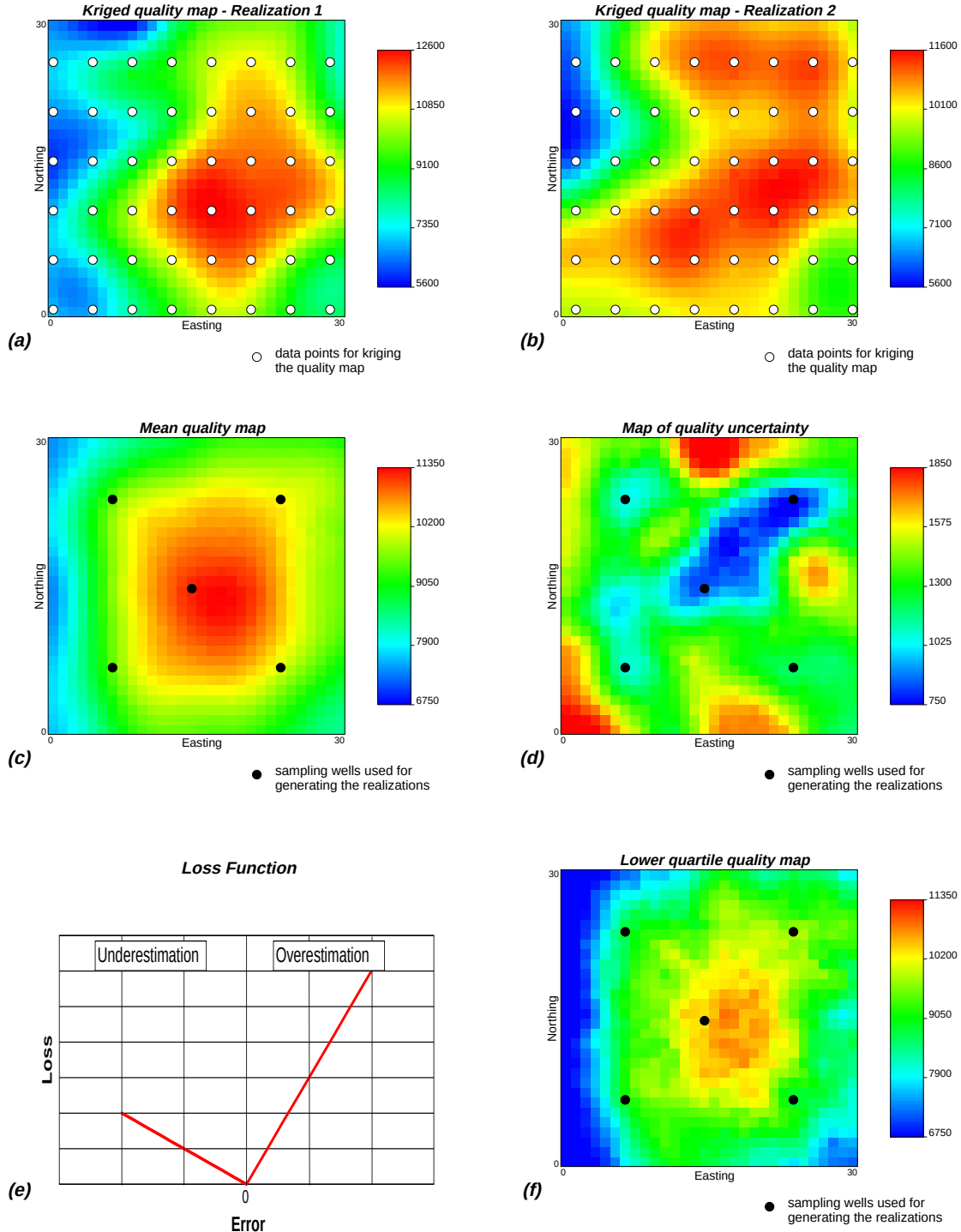


Figure 3.3: Types of quality map: kriged quality map of the first two realizations (a)(b), mean quality map (c), map of quality uncertainty (d) and lower quartile quality map (f). The loss function (e) was used to define the L-optimal quality map as the lower quartile quality map. The unit of quality is Mm^3 of oil.

data points that were used in the kriging), the mean quality, the quality uncertainty and the lower quartile quality maps. The lower quartile map is the L-optimal map for a “conservative” linear loss function where the loss due to underestimation is three times smaller than the loss due to overestimation. This loss function is also presented in the figure, at the bottom left corner.

The kriged quality map of Realization 1 is very similar to the full quality map of the same realization shown in Figure 3.1. That full quality map was built exhaustively, evaluating quality for every cell of the horizontal grid.

The positions of the sampling wells that provided data for the generation of the realizations are shown in the mean quality, quality uncertainty and lower quartile quality maps. As expected the uncertainty is small close to the sampling wells and increases away from the wells. The greater the uncertainty (quality standard deviation) the greater the relative difference between the mean quality value and the lower quartile quality value for the same cell.

3.2.3 Uses of the quality maps

The uses of the quality maps include: (1) location of wells; (2) optimizing the *Full* approach to determine the best number of wells; (3) identification of a representative realization; (4) ranking of realizations; (5) characterization and comparison of reservoirs.

Location of wells

An optimization program was developed to find the best configuration for a given number of wells. The objective function to be maximized is the total quality associated with the wells as defined hereafter. The evaluation of this function is very quick because it is based on the quality map and does not require any further flow simulation.

For each evaluation of the total quality, the program first visits each cell c and allocates the cell to the closest well. Then the program evaluates the quality of each well (Q_w) by adding all the quality values of the cells (Q_c) allocated to that

well, weighting the quality of each cell by an inverse distance weight (w_c). The total quality (Q_t) is the sum of all the well qualities.

$$w_c = \frac{1}{(d_c + 1)^b} \quad (3.1)$$

$$Q_w = \sum_{c=1}^{nc_w} Q_c \cdot w_c \quad (3.2)$$

$$Q_t = \sum_{w=1}^{nw} Q_w \quad (3.3)$$

where: d_c = distance from the cell c to the nearest well

nc_w = number of cells allocated to the well w

nw = total number of wells

The initial configuration for each additional well is obtained sequentially by searching the entire grid for the best position (maximum Q_t) of that well given the location of the previous wells. The optimization of the configurations is made taking two wells at a time and trying all the possible combinations for the positions of these two wells within an area defined by one cell on each side of the previous well location (total of nine possible locations for each well and total of 81 possible combinations).

All the combinations of wells taken two at a time are tried. Every time a change in a well location occurs, the combination of two wells is revisited because, for two wells that were tried before without any change, a better location may be found for at least one of the wells if a change has occurred for a third well location. A configuration is final when no further improvement in Q_t is possible after trying all the combinations of two wells at a time.

Figure 3.4 illustrates the steps of this optimization algorithm, showing the allocation of the cells to the wells for a particular configuration, the positions that are tried for each pair of wells taken at a time and the changing of the pair of wells.

The weights w_c affect the well location and the resulting profit. The higher the exponent b , the more clustered the wells in the high quality area, but wells too

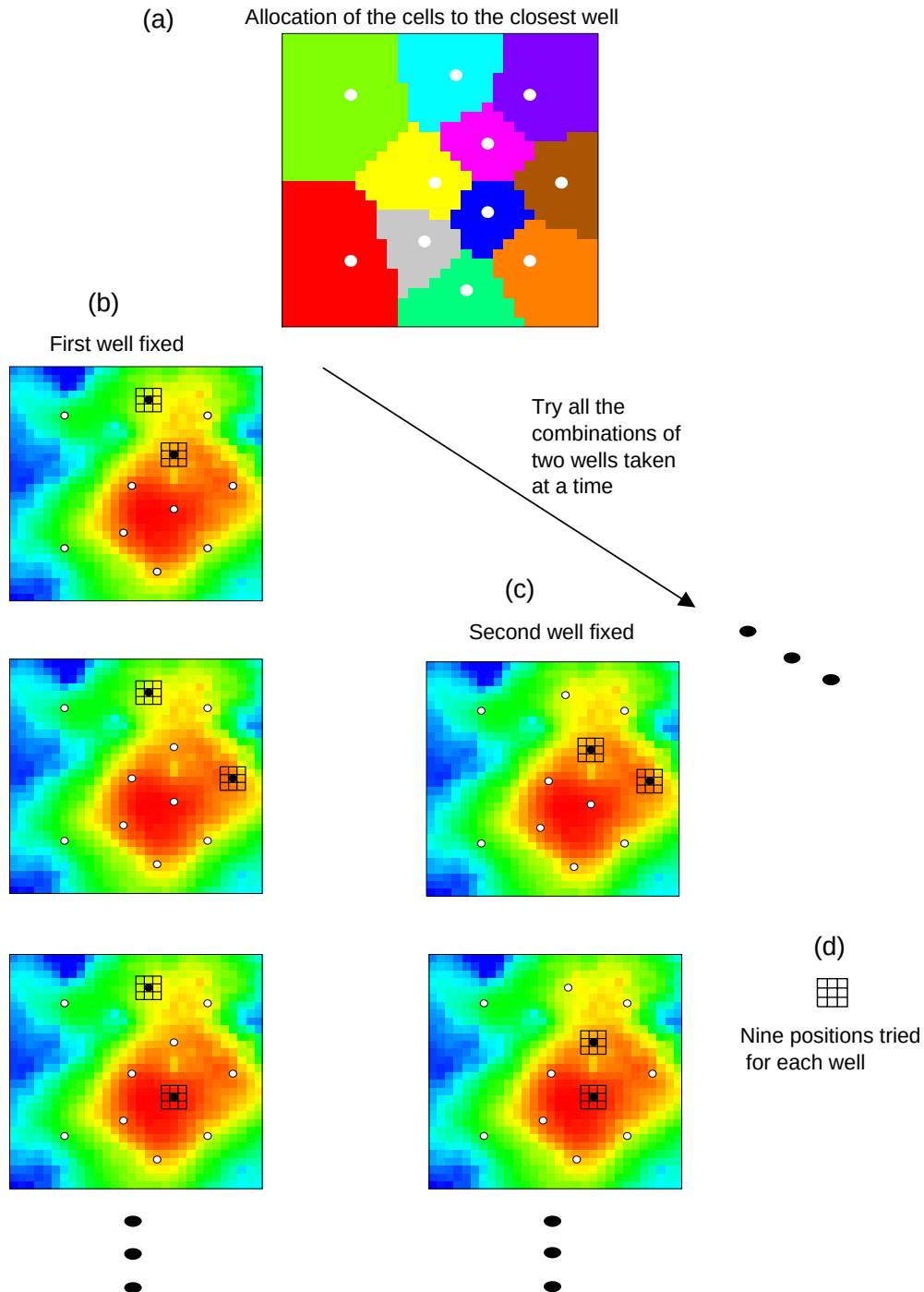


Figure 3.4: Optimization procedure to locate wells. For each evaluation of the objective function “total quality”, the cells are allocated to the closest well (a). For all the combinations of two wells taken at a time (b)(c) ..., the nine positions around each well (d) are tried, seeking better locations for these two wells.

clustered in the same area would not be optimal. A sensitivity analysis, with different exponents and flow simulator runs with the resulting configurations, may be necessary to define an appropriate exponent for each reservoir. Just one realization and just one number of wells need to be used in such analysis. A value that is good enough for many reservoirs and represents a good start point for the sensitivity analysis has been found to be $b = 3$. This value was obtained from an analysis made with the 50 reservoirs of the case study, as shown later in Section 3.3.1.

Optimizing the *Full* approach to determine the best number of wells

When using the quality maps, the steps of the *Full* approach for the definition of the best number of wells and their spatial configuration, are the same as presented in Chapter 1. Here the only difference is that instead of predefining different configurations for each number of wells, the best configuration for each number of wells is found using the L-optimal quality map.

Finding the optimal configuration for each number of wells with the L-optimal quality map ensures that the configuration is the best not only for a particular realization but is the best, in loss function sense, over all realizations. Using just one configuration for each number of wells greatly decreases the number of scenarios to be considered in the *Full* approach.

Identification of a representative realization

The representativeness mentioned here is in terms of flow responses and two types of representative realization may be identified based on the quality maps of all the realizations:

- 1) *A single representative realization independent of the scenario.*

A single representative realization may be selected from a set of realizations for decision-making with the *Conv-1* approach, for visualizing the geological model or for any other analysis.

The concept of representativeness calls for a specified loss function. Indeed, depending on the loss function, the single representative realization may be that which

gives the median, the mean, or the lower quartile flow response over the flow responses of all the realizations.

Since the quality map is a two-dimensional characterization of the flow responses of a realization, it is an appropriate “measure” to use for identifying the single representative realization. The single representative realization is identified as the realization whose quality map is the closest one to the L-optimal quality map.

The “closeness” is measured by the correlation coefficient between the quality map of each realization and the L-optimal quality map.

2) *A scenario-dependent representative realization.*

A scenario-dependent representative realization may be used to reduce the computational effort of the *Full* approach and for presenting just one flow simulation result (for example reserve or the production curve forecast) for a specific scenario, instead of the probability distribution of results obtained with the use of multiple realizations.

This type of representative realization should be that which gives the flow response closest to the response retained by the minimization of the expected loss from the distribution of responses over all the realizations.

The idea is to use only the response of the scenario-dependent representative realization within the *Full* approach. Ideally, the best scenario defined using only this representative realization per scenario would be the same scenario defined with the *Full* approach.

One “measure” to identify a scenario-dependent representative realization, without running the flow simulator with that scenario for all realizations, is provided by the total quality associated with that scenario.

The scenario-dependent representative realization is then identified by: (a) finding the value to be retained from the distribution of total qualities over all realizations for a specific scenario, by minimizing the expected loss; (b) finding the realization whose total quality value is closest to that retained value.

Recall though that when reducing the number of realizations within the *Full* approach, some losses in the results are expected when compared with the results obtained using the complete *Full* approach, since the probability of worse results with

this reduced approach is greater than the probability of better results.

Ranking of realizations

A methodology for ranking realizations is useful for reducing the computational effort of the *Full* approach and for transferring the uncertainty in the geological model to the flow responses of a particular scenario, without having to run the flow simulator over all realizations.

Any ranking of realization is scenario-dependent. Consider a simple case with only two realizations, the first with the best production area in the North and the second with the best area in the South. Considering only one producer well, a scenario with the well in the North would rank the first realization as the best, while a scenario with the well in the South would give a different rank with the second realization as the best.

The quality maps of the realizations along with the weighting system of the cell quality values for a specific scenario may be used for ranking realizations. For a given scenario, the total quality (Q_t) associated with the wells is evaluated for each realization and the realizations are ranked according to Q_t .

Characterization and comparison of reservoirs

The average value of the mean quality map is a good number to characterize the production potential and the average value of the map of quality uncertainty is a good number to characterize the uncertainty in the flow responses of a reservoir. Those two numbers may help comparing reservoirs.

Typically reservoirs are compared by their original oil in place (OOIP) and reserves, as well as by the present value of the profit due to the production of the reserves. The volumes are classified into different categories according to the uncertainty in their existence, but typically no uncertainty is associated with the values resulting from flow simulation. The addition of a measure that characterizes the uncertainty in the flow responses may increase the significance of reserve and profit values when comparing reservoirs.

There are two ways to calculate reserves. When the development plan is defined or already implemented, the reserves are the expected additional cumulative production of the current or planned production scenario. When the development plan is not defined yet (new reservoirs), the reserves are evaluated based on the OOIP and on a recovery factor borrowed from some analogous reservoir.

A regression between reserves and the average value of the mean quality map (production potential) could be derived from reservoirs for which the reserves are known with small uncertainty (depleted reservoirs, for example). This regression could be a better way to estimate the reserves of a new reservoir than a guessed recovery factor. This regression could also be used to identify reservoirs where the production potential is high but the expectation of production based on the current production scenario (reserves) is low. Such reservoirs would be candidates for a development plan review.

3.3 Case study

3.3.1 Settings

In order to explore the applications of the quality map and to determine its benefit, a case study was undertaken using the same 50 true reservoirs and models already generated, as described in Chapter 2, Appendix A and Appendix B.

One quality map was built for each of the 20 realizations and for the kriged model. Approximately 45 quality data were obtained for each model (whether a realization or the kriged model), running the flow simulator with just one well and varying the position of that well in each run. Then a map was obtained, interpolating quality for all the cells using kriging. An isotropic Gaussian variogram, with no nugget effect and horizontal range modeled from quality data was used for that kriging.

For the realizations, the locations of the sampling points, where the quality was evaluated, varied in order to provide a good coverage of the horizontal grid and to have each cell of the 30×30 grid sampled at least once. Since there are 20 realizations, the sampling scheme was obtained using a spacing between the sampling points of four

cells in the X direction and five cells in the Y direction and changing the origin of the sampling grid for each realization. With this sampling scheme, the construction of the quality maps for all the realizations of each reservoir required 900 flow simulations.

The locations of the sampling points for the quality map of the kriged model were the same as that taken for one of the realizations (Realization 11).

Figure 3.5 presents eight (the first four and the last four) out of the 20 realization quality maps and the quality map of the kriged model, for a particular reservoir. The locations of the sampling points, where the quality was evaluated by a flow simulation, are shown in each map.

In this case study, no sensitivity simulation runs were necessary to define the weighting formula for the evaluations of total quality, because the reservoirs and models are the same as in the previous case study (Chapter 2) and, therefore, hundreds of profit evaluations associated with different scenarios were already available.

These available results were used to find the best weighting formula. First the best b value for the formula $w_c = \frac{1}{(d_c+1)^b}$ was determined by the following steps: (a) a total quality was calculated for each scenario and each one of the quality maps using the following b values: 0.5, 1.0, 2.0, 3.0, 4.0 and 6.0; (b) for each number of wells, a correlation coefficient was determined between total quality and profit of the seven configurations; (c) the best b value, to be used for all the reservoirs, was defined as the one with the greatest expected value for the correlation coefficient, considering all the 11 numbers of wells for all the 20 realizations and all the 50 reservoirs (total of 11,000 values of correlation coefficients). The best b value was 3.0.

A slightly different weighting formula was tried and the mean correlation coefficient over the 50 reservoirs between total quality and profit with this formula was found to be a little better than with the previous formula. The new formula is:

$$w_c = \begin{cases} \frac{1}{a \cdot d_c^b} & \text{for } d \geq 1 \\ 1 & \text{for } d=0 \end{cases} \quad (3.4)$$

and the two coefficients are $a = 2.0$ and $b = 2.0$. This new formula was used in this case study for all the total quality evaluations involved in location of wells, identification of scenario-dependent representative realization and ranking of realizations.

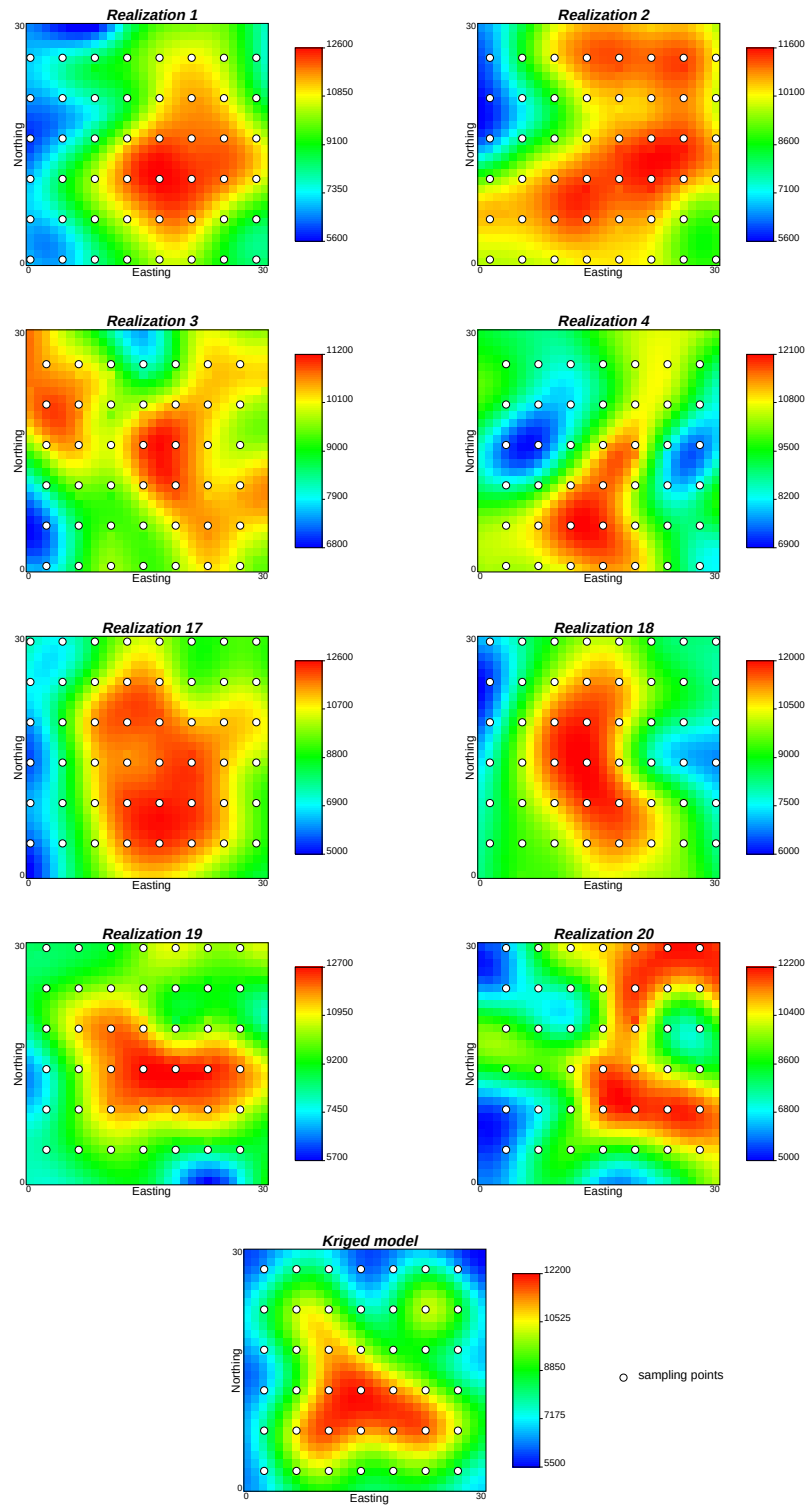


Figure 3.5: Quality (Mm^3) maps of eight realizations and of the kriged model with the location of the sampling points that were used for kriging the maps.

Figure 3.6 gives (top graph) the weight values as function of the distance to the well for the original formula and different b values and for the new formula with $a = b = 2.0$. The center graph shows the comparison between the expected values of the correlation coefficients for the different formulas and coefficients. The bottom graph shows the distribution of correlation coefficients for the chosen formula.

The main difference between the formulas appears to be the higher weights given by the new formula to the cells contiguous to the well. For $d_c = 1$, with the original formula $w_c = 0.125$ if $b = 3$ and $w_c = 0.25$ if $b = 2$, while with the new formula $w_c = 0.5$.

The high correlation between total quality and profit for most of the 11,000 cases gives confidence to the optimization procedure based on the maximization of total quality to find the best configuration for a given number of wells.

The loss function considered in this case study was linear with the loss due to underestimation three times smaller than the loss due to overestimation. In the *Full* approach the profit retained for each scenario was the lower quartile of the distribution of profits over all realizations. The L-optimal quality map was obtained by retaining the lower quartile quality value from the distribution of qualities over all realizations for each cell.

3.3.2 Results

Location of wells

The goodness of the well locations using the quality map was checked by comparing the results with locating the wells using a map of oil volume. The map of oil volume is obtained by summing the oil volume of all the layers for each cell of the horizontal grid.

For this check no uncertainty was considered. Only the first realization (Realization 1) of each reservoir, taken as a deterministic model, was used for both methods (quality and oil volume). The methods were compared with respect to the profit obtained from production of the wells located with each map.

For all the reservoirs, 11 different numbers of wells were located using both maps

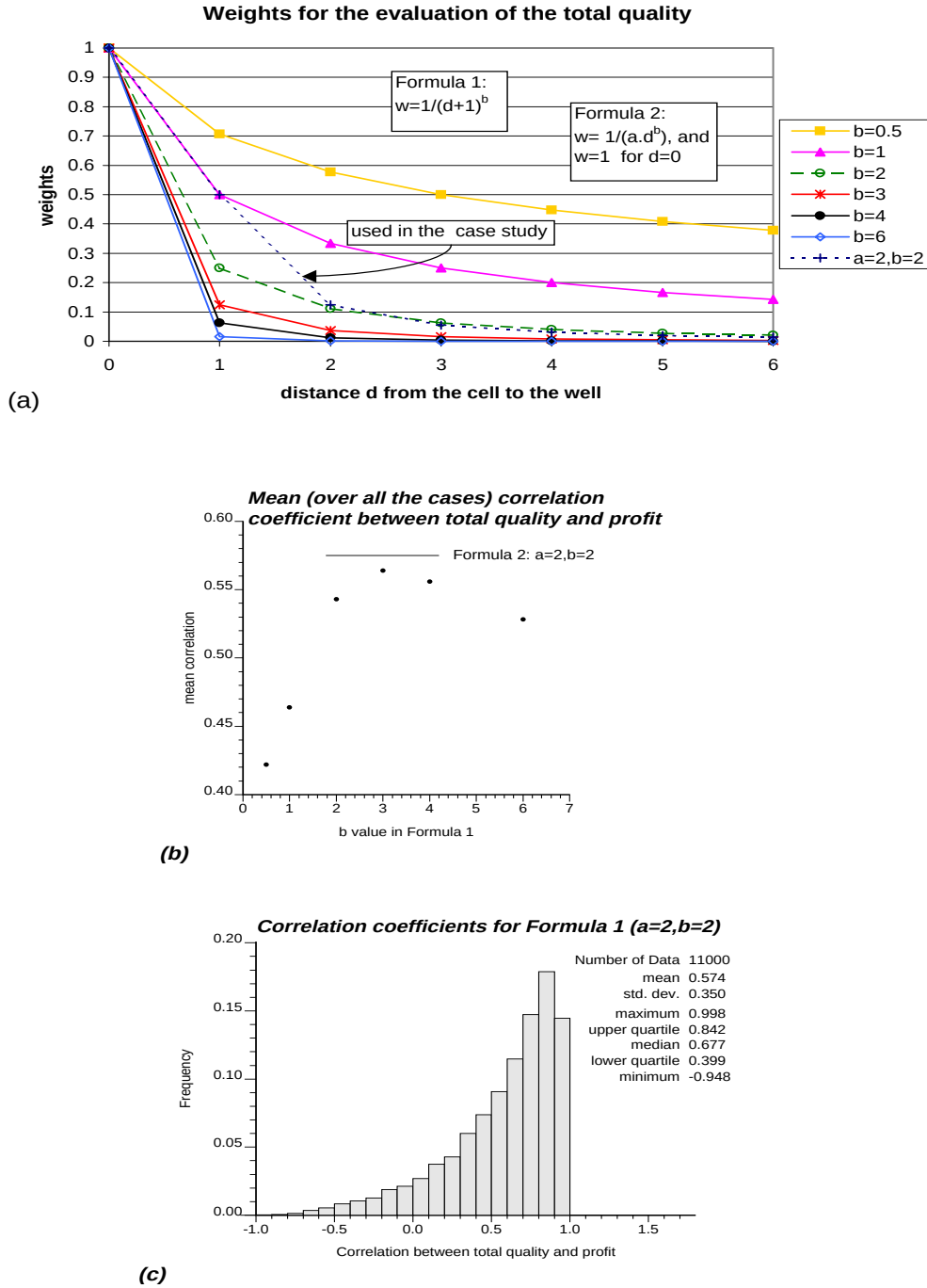


Figure 3.6: Definition of the weighting formula to evaluate total quality. (a) gives the weight values as function of the distance to the well for two formulas and different exponents b in Formula 1. (b) shows that Formula 2 yields a higher mean correlation coefficient between total quality and profit. (c) gives the distribution of correlation coefficients for Formula 2.

and the comparison between the two methods was made using the mean profit over the 11 results. The five sampling wells were always used for production too. Hence for a total number of 17 wells for example, only 12 wells needed to be located.

The same optimization program was used to locate wells with the oil volume map, just replacing quality by oil volume.

Figure 3.7 shows the locations of three different numbers of wells obtained using the quality map and with the oil volume map of Realization 1 for a particular reservoir. The profits evaluated for this realization and with each one of the scenarios are also given, showing the superiority of the quality map over the oil volume map for well locations. For the particular reservoir shown in the figure, the average (over 11 numbers of wells) gain of using the quality map instead of the oil volume map was $653Mm^3$ of oil.

Figure 3.8 compares the results (mean profit over 11 numbers of wells) of locating the wells with the quality map and with the oil volume map for the 50 reservoirs.

The quality map provides better well locations than the oil volume map for 88% of the reservoirs. Over the 50 reservoirs, the average gain per reservoir when using the quality map instead of the oil volume map was $309Mm^3$ of oil. That gain is more than two times the cost considered for one offshore well and represents an increment of 4% in the reserves.

The fact that for 12% of the reservoirs the oil volume map worked better than the quality map for locating wells is explained by the setting of the same well controls (*rate limit = none*, *BHP limit = $50 \frac{Kgf}{cm^2}$* and *water cut limit = 97%*) and total time of production (*20 years*) when generating the quality map, and by the use of the same weighting formula ($a = 2$ and $b = 2$) in the optimization program for every reservoir.

Through sensitivity analysis, it would be possible to find the appropriate parameters to use when generating the quality map and for the optimization program, in order to get better locations with the quality map than with the oil volume map for any reservoir. However, the effort for such further improvement in the cases where it has been observed that the oil volume map is giving better results, may not be worth it, considering that the oil volume map is already doing a good job and it may be used for well location in those cases.

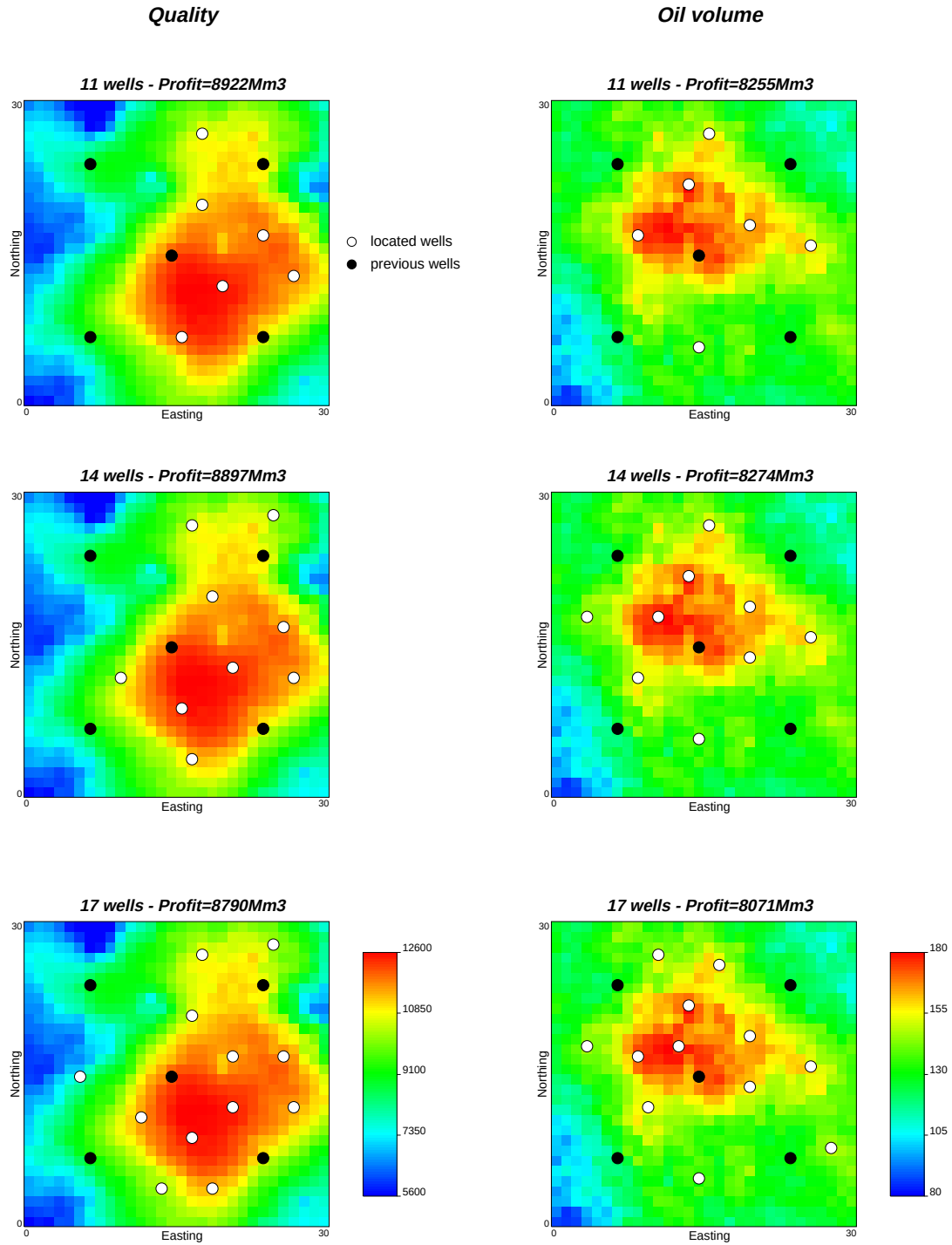


Figure 3.7: Examples of location of wells and resulting profits using quality map (left) and oil volume map (right) of Realization 1, for 11, 14 and 17 wells. Unit in the maps = Mm^3 .

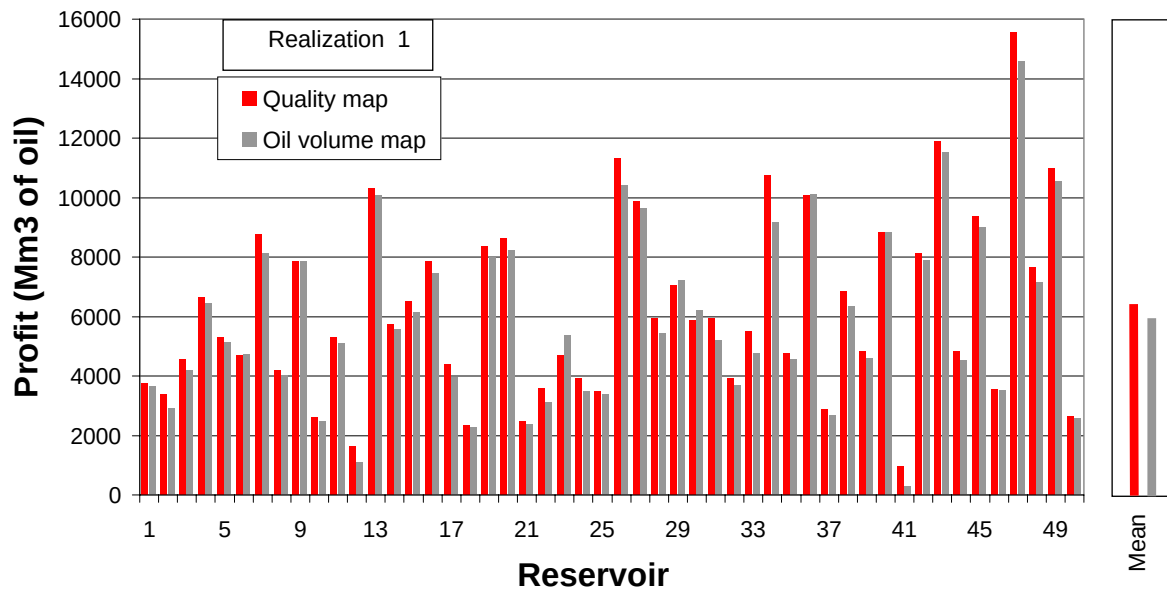


Figure 3.8: Comparison between quality map and oil volume map to locate wells for 50 reservoirs, using Realization 1.

Optimizing the *Full* approach to determine the best number of wells

The two goals of this case study are:

- To compare the results of decision-making with and without accounting for uncertainty.
- To compare the results and the computational effort of the *Full* approach done in the first case study (Chapter 2), where seven configurations were predefined for each number of wells with the results and computational effort of the *Full* approach performed in this case study, where one quality map is built for each realization but just one optimized configuration is used for each number of wells.

The decision-making here relates to the definition of the best number of wells. The same range of 11 different numbers of wells was used here but only the best configuration for each number of wells was retained. The same three approaches (*Full*, *Conv-1* and *Conv-k*) are compared, but each approach is evaluated not only by its ability to determine the best number of wells but also by its ability to find the best configuration for each number of wells.

Full is the approach to account for uncertainty. The lower quartile quality map was used to find the best configuration for each number of wells. A flow simulator was run over all the realizations for each number of wells and the best number of wells was defined as that with maximum expected profit over all the realizations.

Conv-1 and *Conv-k* are the two conventional approaches for deciding the best number of wells without accounting for uncertainty, i.e. using only one deterministic model.

For the *Conv-1* approach, only Realization 1 was used. The best configuration was found for each number of wells, using the quality map of that realization and the best number of wells was defined as that with maximum profit, using the flow simulation results for each number of wells.

For the *Conv-k* approach, a quality map was built using the kriged model and the best configuration was found with this map for each number of wells. The same procedure as in *Conv-1* was followed to define the best number of wells.

Each scenario, defined by the number of wells and its best configuration, was applied to the true reservoir generating the true profits. The goodness of each quality map for well location is evaluated by the average value of the true profits obtained from the 11 numbers of wells. The goodness of each decision-making approach is evaluated by the true profit of the best number of wells defined with each approach.

Figure 3.9 (left column) presents, for a particular reservoir, the best scenario (best number of wells with its best configuration) defined with the three approaches. The true profit of that best scenario is a measure of the goodness of the approach. The distribution of true profits for the 11 numbers of wells is given in the right column. The corresponding expected value is a measure of the goodness of each of the three quality maps for well location.

For the particular reservoir considered in Figure 3.9, the quality map of Realization 1 was the best for locating the wells (higher expected value over the 11 numbers of wells), while the best approach was *Conv-k* (higher true profit of the decision). This example was chosen on purpose to show that a certain quality map may provide better locations on average when considering different numbers of wells, but the associated approach may not yield the best profit.

The comparison between the true profits obtained for well locations using the three types of quality map for all the reservoirs is presented in **Figure 3.10**. The comparison between the true profits obtained with the three approaches for all the reservoirs is presented in **Figure 3.11**. In both figures, all results were divided by the result obtained with the kriged model to provide an easier comparison.

- Comparing the three approaches together:
 - The *Full* approach was the best for 48% of the reservoirs.
 - The *Conv-1* approach was the best for 24% of the reservoirs.
 - The *Conv-k* approach was the best for 30% of the reservoirs.
 - *Full* and *Conv-k* had the same result for 2% of the reservoirs.
- Comparing *Full* and *Conv-1*:

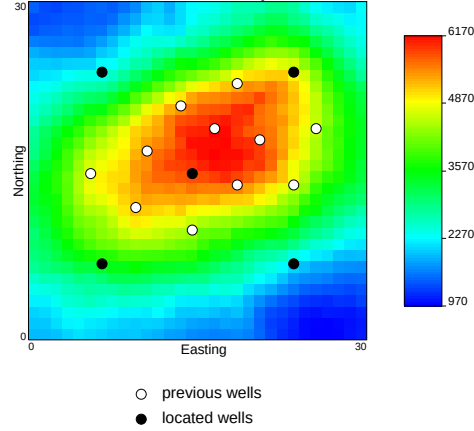
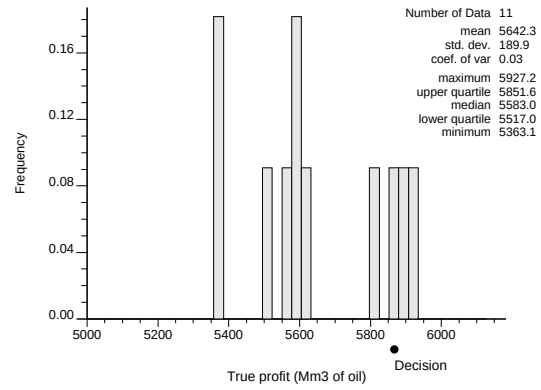
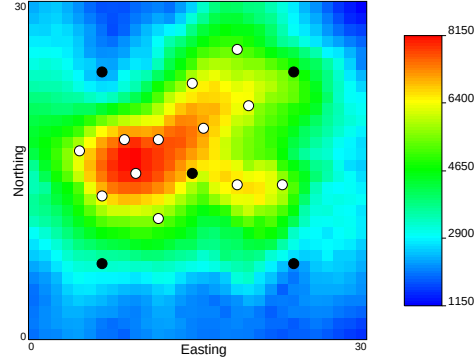
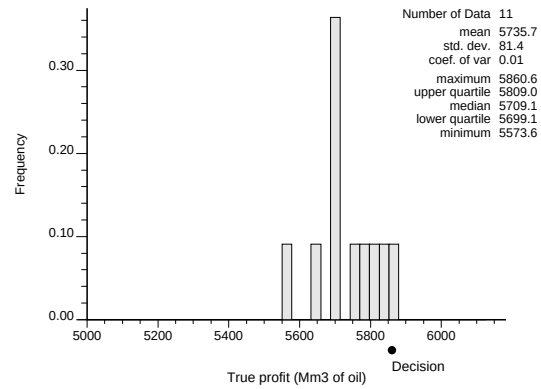
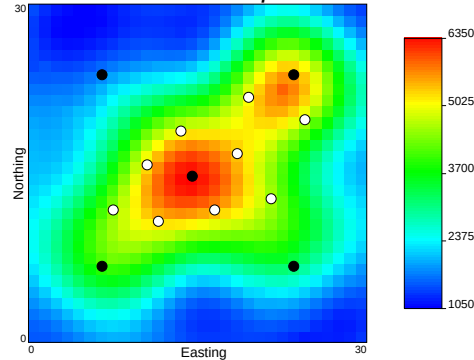
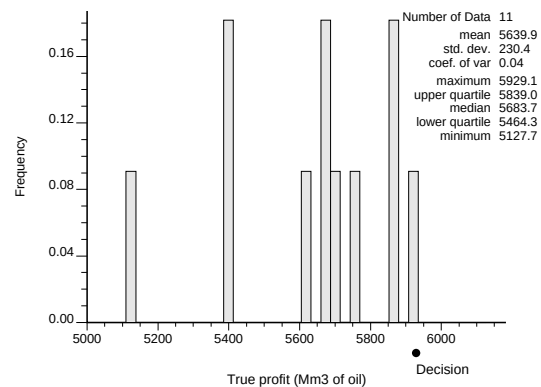
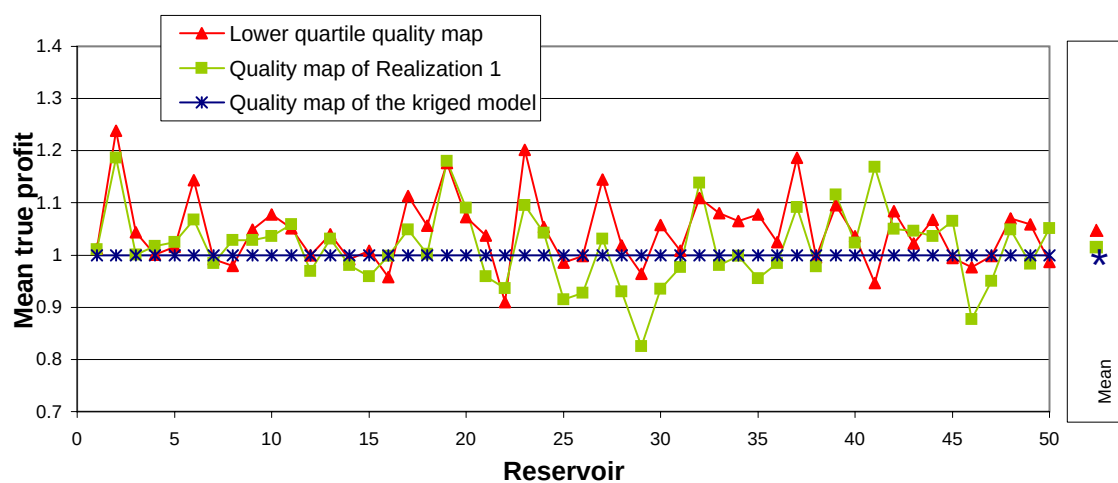
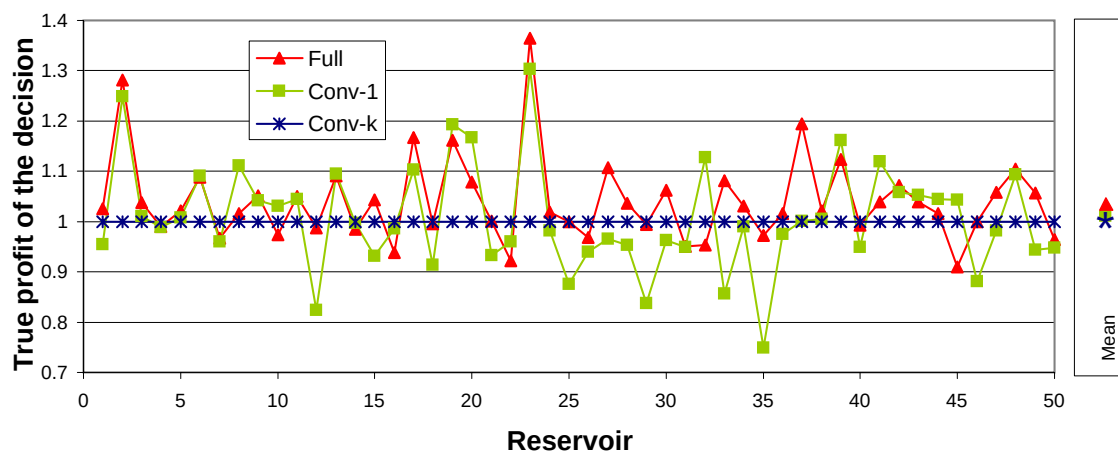
Lower quartile quality map**Best scenario=16 wells - True profit=5868 Mm³****Distribution over 11 numbers of wells****Quality map of Realization 1****Best scenario=17 wells - True profit=5861 Mm³****Distribution over 11 numbers of wells****Quality map of the kriged model****Best scenario=14 wells - True profit=5929 Mm³****Distribution over 11 numbers of wells**

Figure 3.9: Example of comparison between the location of wells using three different quality maps. Left column: best scenario defined with the three associated approaches. Right column: distribution of true profits (Mm^3) for 11 numbers of wells. Unit in the maps = Mm^3 .



Average values over the 50 reservoirs:
 Lower quartile = 5274.1Mm3, Realization 1 = 5121.1Mm3, Kriged model = 5066.6Mm3

Figure 3.10: Comparison between the location of wells using three different quality maps for 50 reservoirs. The results in the figure are divided by the result using the quality map of the kriged model.



Average values over the 50 reservoirs:
 Full = 5386.4Mm3, Conv-1 = 5228.0Mm3, Conv-k = 5198.5Mm3

Figure 3.11: Comparison between the results of the decisions with *Conv-1*, *Conv-k* and *Full* for 50 reservoirs. The results in the figure are divided by the result of *Conv-k*.

- The *Full* approach had better results than *Conv-1* for 70% of the reservoirs.
 - The average loss of using *Full* in the cases *Conv-1* led to better decisions (probability=30%) was $256.4Mm^3$ of oil, while the average gain in the opposite cases (probability= 70%) was $336.2Mm^3$ of oil.
 - The expected gain per reservoir of *Full* over *Conv-1* was $158.4Mm^3$ of oil, which represents an increment of 3.0% in profit or 15.84 millions of dollars.
- Comparing *Full* and *Conv-k*:
 - The *Full* approach had better results than *Conv-k* for 64% of the reservoirs and equal results for 2% of the reservoirs.
 - The average loss of using *Full* in the cases *Conv-k* led to better decisions (probability=34%) was $172.7Mm^3$ of oil, while the average gain in the opposite cases (probability= 64%) was $385.4Mm^3$ of oil.
 - The expected gain per reservoir of *Full* over *Conv-k* was $187.9Mm^3$ of oil, which represents an increment of 3.6% in profit or 18.79 millions of dollars.
 - Comparing *Conv-1* and *Conv-k*:
 - Although the quality map of Realization 1 provided better well locations in general (considering the mean result over 11 numbers of wells) than the quality map of the kriged model for 58% of the reservoirs, *Conv-1* had better results than *Conv-k* for only 46% of the reservoirs.
 - The average loss of using *Conv-1* in the cases *Conv-k* led to better decisions (probability=54%) was $298.2Mm^3$ of oil, while the average gain in the opposite cases (probability= 46%) was $414.2Mm^3$ of oil.
 - The expected gain per reservoir of *Conv-1* over *Conv-k* was $29.5Mm^3$ of oil.

Since just one realization (Realization 1) was used in *Conv-1*, it was not possible to compare the results of *Full* and *Conv-k* with the distribution of results of *Conv-1* that would be generated if every realization had been used to locate the wells and to

decide the best number of wells. This comparison will be presented in **Chapter 4** based on an index that will be introduced there, yet preempting what will be shown there, Realization 1 is a better realization than the mean over all the realizations. It is important also to notice here that using the same realization number (1) for all the reservoirs amounts to a random selection of the realization, because Realization 1 may be the best one for a particular reservoir but it may be the worst for another reservoir and there are 50 different reservoirs.

A comparison was made between the results of the *Full* approach of this case study, where just one optimized configuration is used for each number of wells, and the results of the *Full* approach of the previous case study (Chapter 2) where seven configurations were defined using a geometric criterion for each number of wells.

Three measures were used in this comparison:

- *Measure 1*: the mean profit over all configurations, numbers of wells and realizations, using the profits from the realizations (not the true profits). This measure is useful to evaluate the goodness of the well locations with the lower quartile quality map.
- *Measure 2*: the mean profit over all configurations and numbers of wells, using the profits from the true reservoir. This measure is useful to evaluate the influence of uncertainty on the goodness of the well locations.
- *Measure 3*: the true profits from the defined best scenario. This measure is useful to evaluate the goodness of the decisions.

For the previous case study, this measure uses the results of the *Full* approach obtained using the same loss function that was used in this case study, that is, the profit value retained for each scenario is the lower quartile of the distribution of profits over all realizations.

The average value of *Measure 1* over all the reservoirs was $442.1Mm^3$ of oil greater when using the optimized configuration for each number of wells (this case study) than when using seven configurations for each number of wells (previous case study). *Measure 1* was greater in this case study than in the previous study for all the reservoirs,

giving confidence in the use of the lower quartile quality map to locate wells.

The average value of *Measure 2* over all the reservoirs was $330.0Mm^3$ of oil greater in this case study than in the previous case study. *Measure 2* was greater in this case study than in the previous case study for 78% of the reservoirs, showing that most often the goodness of locating the wells with the lower quartile quality map was transferred to the true reservoirs. In some cases, though, due to unrepresentative models, it was better to consider a set of geometric configurations for each number of wells than to use a single optimized configuration.

The average value of *Measure 3* over all the reservoirs was $110.7Mm^3$ of oil greater in this case study than in the previous case study. *Measure 3* was greater in this case study than in the previous case study for 62% of the reservoirs, showing that most often the goodness of the location of wells was transferred to the true results of the decision of the best number of wells, but not always.

Even though 900 flow simulations were necessary to build the quality maps for all the realizations and then the lower quartile quality map, the total number of flow simulations in this case study was only 73% of the number of flow simulations in the previous case study. Moreover, the flow simulations to build the quality maps, where only one well is used, are simpler and faster than the flow simulations required to compare the scenarios, where all the wells are used.

Identification of a representative realization

For each of the 50 reservoirs, the two types of representative realization were identified.

The single representative realization was identified as the realization whose quality map had higher correlation coefficient with the lower quartile quality map. The scenario-dependent representative realization was identified for as the realization whose total quality value associated with that scenario is closest to the lower quartile value of the distribution of total qualities over all realizations.

The single representative realization was used to find the best configuration for each number of wells (using its quality map) and to decide the best number of wells as in the conventional approach. This representative realization only replaces the Realization 1 in the *Conv-1* approach.

The identification of the single representative realization is illustrated by the comparison between the quality maps of the eight realizations presented in Figure 3.5 with the lower quartile quality map presented in Figure 3.3. In this example, the single representative realization is Realization 17, with a correlation coefficient with the mean quality map of 0.900. The correlation coefficient between the quality map of Realization 1 and the mean quality map, in this case, was 0.816.

The scenario-dependent representative realization was used to reduce the computational effort of the *Full* approach by using just one realization (instead of 20) for each number of wells to define the best number of wells, once the best configuration was found for each number of wells using the lower quartile quality map.

The true profit obtained with the defined best scenario was used to compare the results:

- Between *Conv-1*, with the single representative realization, and *Full*:
 - *Full* had a better results for 56% of the reservoirs (recall that *Full* had better results than *Conv-1* with Realization 1 for 70% of the reservoirs).
 - The expected loss per reservoir of using just the single representative realization instead of all the realizations was $33.3Mm^3$ of oil (recall that the expected loss with Realization 1 was $158.4Mm^3$ of oil).
- Between the two types of *Conv-1*, i.e. using a random realization (Realization 1) or the single representative realization:
 - The single representative realization had the same results as Realization 1 (single representative = Realization 1) for 4% of the reservoirs and better results for 68% of the reservoirs.
 - The expected gain per reservoir of using a representative realization instead of a random realization was $125.1Mm^3$ of oil.
- Between the two types of *Full*, i.e. the complete *Full* approach, using all the realizations, and the “*Full*”, using only the representative realization for each scenario to define the best number of wells:

- Using the representative realization for each scenario gave the same results for 44% of the reservoirs, better results for 20% of the reservoirs and worse results for 36% of the reservoirs.
- The expected loss (over all reservoirs) of using only the representative realization for each scenario instead of all the realizations was $11.6Mm^3$ of oil.

Considering that the quality maps of all the realizations need to be built for the identification of both types of representative realization, the number of flow simulations is the same in both cases. For the decision of the best number of wells using their optimal spatial configuration, the principal reason for the differences between the results obtained with the two types of representative realization is the difference in the well locations. With the single representative realization, the wells are located using the quality map of that realization, while with the scenario-dependent realization the wells are located using the lower quartile quality map, which provides better well locations on average over many reservoirs.

Ranking of realizations

Ideally a ranking methodology should lead to the same rank as obtained with the flow response of interest. Typically, there is good correlation between different types of flow responses and the profit is a good summary of all of them.

A ranking of the 20 realizations was done using the total quality associated with the wells (Q_t) for each of the 11 scenarios for all the 50 reservoirs. The same weighting formula used for well locations was applied here. Another ranking of the 20 realizations was obtained using the profits, and the correlation coefficient between the two ranks was evaluated for each case. Just for comparison and to provide a feeling of the goodness of ranking with total quality, the same exercise was repeated using the oil volume maps and ranking the realizations by the total oil volume associated with the wells.

Figure 3.12 shows the distribution of the correlation coefficients between the rank using total quality and the rank using profits. **Figure 3.13** shows the correlation

coefficients between the rank using total oil volume and the rank using profits.

The distribution of correlation coefficients between the rank using quality shows a mean of 0.578, a median value of 0.627 and the most frequent value is between 0.70 and 0.75. None of the cases displayed a negative correlation. These numbers indicate that, for most of the cases, the ranking of realizations using total quality is good enough to choose low-side, expected and high-side for the realizations (see Deutsch and Srinivasan [17]).

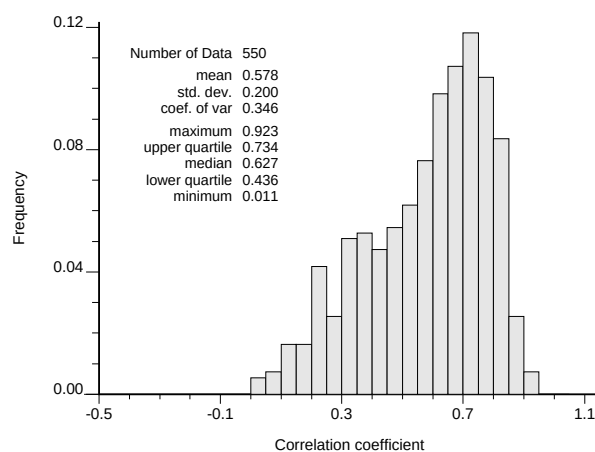


Figure 3.12: Correlation coefficient between the rank of 20 realizations obtained using profit and using total quality.

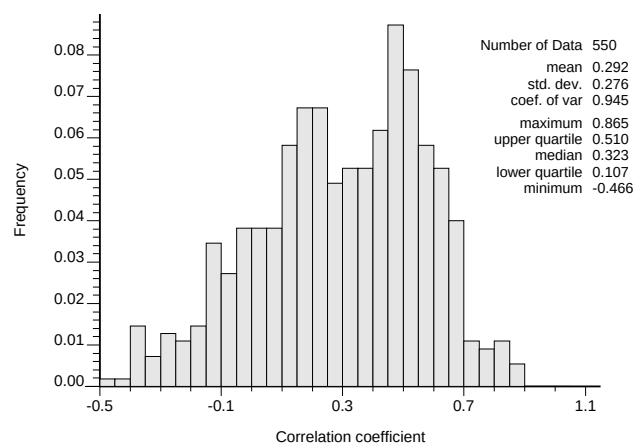


Figure 3.13: Correlation coefficient between the rank of 20 realizations obtained using profit and using oil volume.

Using the total oil volume associated with the wells to rank the realizations, the mean correlation coefficient with the correct ranking (using profit) was just 0.292, with negative correlation in several cases, indicating that static parameters work poorly to approximate ranking from flow responses.

Characterization and comparison of reservoirs

The goodness of the average value of the mean quality map to characterize the production potential of a reservoir was checked by its correlation with reserves. The reserves were defined as the mean over all realizations of the cumulative oil production after 20 years for the best scenarios chosen with the *Full* approach. **Figure 3.14** shows the scattergram for the 50 reservoirs; the corresponding correlation coefficient is 0.833.

Figure 3.15 presents the comparison between reserves and OOIP to show that the previous quality measure is better correlated with reserves than OOIP. The correlation coefficient between reserves and OOIP is only 0.592.

The goodness of the average value of the map of quality uncertainty to characterize the uncertainty in flow responses was checked by its correlation with the uncertainty in reserves. The uncertainty in reserves was defined as the standard deviation over the 20 realization reserves. **Figure 3.16** presents the comparison between these two evaluations of uncertainty, showing that the correlation coefficient is high at 0.719.

Figure 3.17 shows that the standard deviation of OOIP is a much poorer estimation of the uncertainty in reserves; the correlation coefficient is only 0.418.

The correlation between the uncertainty estimated with the quality maps and the uncertainty in flow responses “in general” was also calculated showing a correlation coefficient of 0.711, very similar to the result with reserves. The uncertainty in flow responses “in general” was evaluated by calculating the standard deviation of the distribution of realization profits for each scenario and then taking the expected value of the standard deviations over all the scenarios.

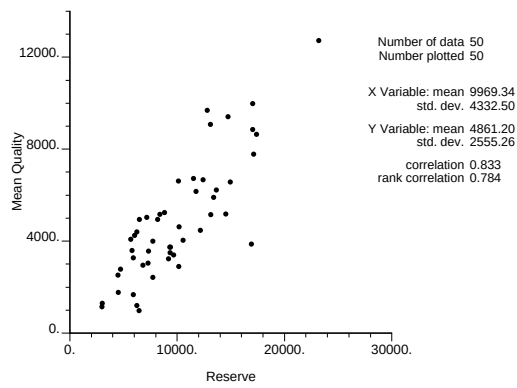


Figure 3.14: Reserve (Mm^3) versus average value of the mean quality map (Mm^3).

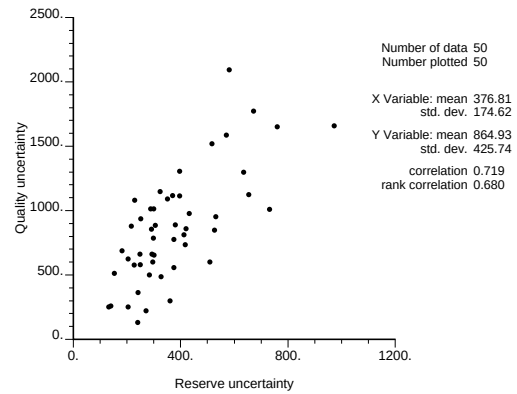


Figure 3.16: Reserve uncertainty (Mm^3) versus quality uncertainty (Mm^3).

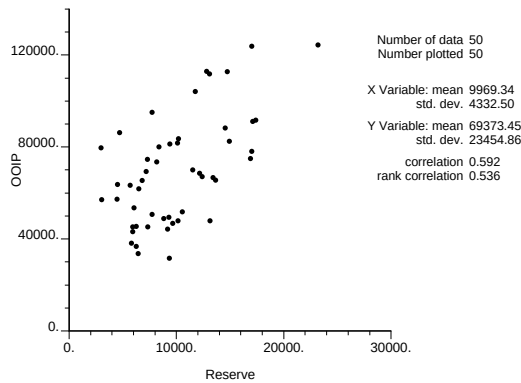


Figure 3.15: Reserve (Mm^3) versus original oil in place (Mm^3).

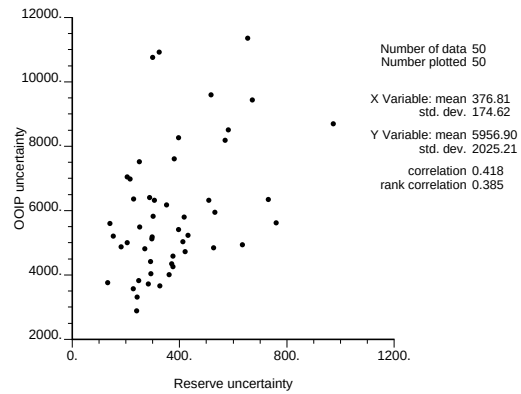


Figure 3.17: Reserve uncertainty (Mm^3) versus original oil in place uncertainty (Mm^3).

3.3.3 Conclusions

1. The quality map integrates all the variables involved in the flow of fluids through a heterogeneous reservoir into a two-dimensional visualization of “how good the area is for production”
2. The quality map along with a simple optimization algorithm can be used to determine good locations for vertical producer wells.
3. The L-optimal quality map, obtained by building a quality map for each realization and integrating all of them with a loss function, can be used for well location accounting for the geological uncertainty and for the profit desire and risk aversion profile of the company.
4. Comparing different types of quality map for well location based on the average results over 50 reservoirs, it was found that:
 - The L-optimal (lower quartile, in this case study) quality map is better than the quality map of a realization taken at random and than the quality map of the kriged model.
 - The quality map of a realization taken at random is better than the quality map of the kriged model.
5. Comparing the three approaches to define the best number of wells, finding the best configuration with the associated quality map and using only the optimized configuration for each number of wells, it was found that:
 - Taking the results obtained using either Realization 1 or the single representative realization as representatives of *Conv-1*, the following comparisons between this approach and the other two approaches can be made: (a) between *Full* and *Conv-1*, *Full* is better; (b) between *Conv-k* and *Conv-1*, *Conv-k* has a higher probability of better decisions but the expected result of *Conv-k* is smaller than *Conv-1* because *Conv-k* has a higher risk of very poor decisions.

- *Full* is clearly better than *Conv-k*.

6. Between the two ways to apply the *Full* approach:

- Using the lower quartile quality map and finding the best configuration for each number of wells provides better results and requires less computational effort than using several configurations for each number of wells, for the definition of the best number of wells and their spatial configuration.

7. About the representative realization:

- A single representative realization can be identified after obtaining the quality map of all the realizations. The use of that single realization to locate the wells and to decide the best number of wells provides better results than the expected result of using a single realization taken at random and needs less computational effort than the application of the *Full* approach but, as expected, there is a loss in expected profit by taking this reduced approach when compared with the *Full* approach.
- A scenario-dependent representative realization can be identified, for the purpose of reducing the computational effort of the *Full* approach, by using the total quality associated with the wells of a specific scenario. The best configuration for each number of wells is found *a priori*, using the lower quartile quality map. With less CPU expense, the use of just that representative realization for each scenario allows comparisons of scenarios with results similar to the ones obtained by using all the realizations and retaining one value from the distribution of profits. The probability of a loss in the quality of the decision needs to be compared with the gain in the speed of the decision.
- The use of a scenario-dependent representative realization to define the best number of wells after finding the best configuration for each number of wells using the lower quartile quality map provides better results than using a single representative realization to locate the wells and to define the best number of wells, and the computational effort is the same. However,

the identification of the single representative realization does not require the prior definition of any scenario and may have other uses, such as the selection of a realization to represent the geological model.

8. The realizations can be ranked using the total quality (Q_t) associated with the wells. This ranking permits low-side, expected and high-side realizations to be identified for each production scenario.
9. The average value of the mean quality map has good correlation with the production potential of the reservoir and the average value of the map of quality uncertainty has good correlation with the uncertainty in flow responses. These two average values may be used to help comparing reservoirs.

3.4 Discussion

In this section, modifications and limitations of the quality map and its uses as well as the limitations of the conclusions of the case study are discussed.

3.4.1 Uncertainty level

The following comparisons may be affected by the level of uncertainty:

- between quality map and oil volume map for well location;
- between the three types of quality map for well location;
- between the three types approaches for decision of the best number of wells.

In this chapter only a high level of uncertainty, defined by the use of data from only five wells and a “seismic” image of the structural top, was considered. The effects of different levels of uncertainty will be shown in **Chapter 4**.

3.4.2 Limitations of the quality map

- The only decision-making problem for which the quality map applies directly is the definition of the best number of vertical wells and their spatial configuration.

The term “vertical well” used in this work does not exclude deviated wells as long as the horizontal distance between the position of the well in the top and in the bottom of the reservoir is smaller than the horizontal grid size.

In this chapter only producer wells were considered. In **Chapter 5** an application of the quality map for locating injector wells will be presented.

- Depending on the computational resources available and on the number of cells in the discrete grid of the reservoir, the time and computational effort to build a quality map for all the realizations may be overwhelming.

In cases where the flow simulation model requires a very fine grid, upscaling can be applied to generate a coarser grid for building the quality maps, since there is no need for a high resolution quality map. However, if necessary, a first selection of the well sites may be obtained with a quality map built on a coarse grid, and then additional flow simulations can be run to refine the quality map and to provide more accurate well locations.

For this case study, 45 simulations, on average, were necessary to obtain the data points for kriging the quality map of each realization. Each flow simulation run, with two phases on a three-dimensional grid of $30 \times 30 \times 6$ blocks, took approximately one minute CPU time on a DEC Alpha 600MHz workstation. Thus, approximately 900 minutes (15 hours) of CPU were necessary to generate the quality maps for all 20 realizations.

However, it is important to realize that computational resources are just a matter of money and the potential gain involved in the use of the quality map more than justifies investing in more and faster computers.

3.4.3 Modifications of the quality map

For problems different from that of locating vertical wells, different ways to build the quality map and/or the consideration of different quality units can be considered.

As an example, for the problem of horizontal well location, two or three quality maps may be necessary, fixing the layer for the single well completion when building each map.

The quality unit may be a direct measure of profit, instead of cumulative oil production, to incorporate different costs of wells in different areas of the reservoir or to account for the discounted value of the production. Although this idea seemed attractive for well location, that is, between two positions with the same cumulative oil production, the one with faster oil production at early times would be preferable, the resulting “quality” would not be an intrinsic characterization of the reservoir any more; it would depend on the particular economic function and completion schedule being considered.

3.4.4 Alternative algorithm for well location

Each quality value is obtained by running a flow simulator with just one well. Thus, by construction, there is no consideration of the interferences between more than one well producing at the same time in the quality map.

For well location, however, those interferences are considered in the optimization algorithm. Allocating the cells to the closest well (using a kind of Voronoi grid [9]), weighting the quality values with an inverse distance to the well, and seeking the maximum total quality associated with the wells ensures that interference between the well locations is taken somewhat into account. The results of the case study showed that this methodology provides good results for the joint location of several wells.

A more explicit way to account for the interference between wells could be tried following the alternate methodology:

1. Record the pressure drop (ΔP) after certain time in all the cells due to the production of the single well during the generation of one quality value.

2. Average, somehow, the pressure drops of all the layers to obtain just one value of pressure drop for each position i, j of the horizontal grid due to the production of the well in the cell i_w, j_w ($\Delta P_{i,j}^{i_w, j_w}$).
3. Use the following formula to evaluate the total quality, weighting the quality value of each cell by the ratio of the total pressure drop in that cell due to the production of the total number of wells (nw) and the pressure drop in that cell due to the production of the well in that cell, without any necessity to allocate the cells to the closest well:

$$Q_t = \sum_{i=1}^{nx} \sum_{j=1}^{ny} Q_{i,j} \frac{\sum_{w=1}^{nw} \Delta P_{i,j}^{i_w, j_w}}{\Delta P_{i,j}^{i_w, j_w}} \quad (3.5)$$

Although this methodology seems attractive, because it uses the superposition concept [31] to add up the effects of the production of several wells in the pressure drop of a particular cell, there are points that still need investigation, such as the time to record the pressures of all the cells and the pressure averaging formula over all the layers.

An additional drawback would be the storage of a matrix with $(nx \times ny \times nz)$ results (pressures) for each position of the well. Considering the grid $(nx \times ny)$ of a quality map and nz cells in the vertical direction, each map would require the storage of $(nx \times ny) \times (nx \times ny \times nz)$ values. With the grid used in the case studies ($nx=30$, $ny=30$ and $nz=6$), each map would require the storage of 4,860,000 values. This is why this methodology was not tried here, recalling that this research used 50 reservoirs and 22 models (20 realizations, one kriged model and one true reservoir) for each reservoir.

Chapter 4

Sensitivity Analysis of the Uncertainty Level

4.1 Need and types of the analysis

Just one level of uncertainty was used in the case study presented in Chapter 2 to compare the three approaches (*Full*, *Conv-1* and *Conv-k*) to define the best production scenario. The level of uncertainty was determined by:

- the use of five sampling wells,
- the use of a “seismic” information with good correlation with the structural top,
- the use of 20 realizations,
- the consideration of uncertainty only in one model parameter, namely the horizontal range in the variogram.

This same single level of uncertainty was used in the case study presented in Chapter 3 to compare the three types of quality map (lower quartile quality map, quality map of one realization and quality map of the kriged model) to locate wells and the three associated approaches (*Full*, *Conv-1* and *Conv-k*) to defined the best production scenario.

No uncertainty was considered in the case study presented in Chapter 3 to compare the quality map and the oil volume map for locating wells. There was no uncertainty consideration because Realization 1 was used as a deterministic model (as if it was the true reservoir) in that comparison.

Therefore an investigation about the effects of the level of uncertainty in those previous comparisons is needed. This chapter presents the cases, the results and the conclusions of this investigation.

Three cases were used to investigate the effects of number of realizations, uncertainty in other model parameters and inclusion of a prior geological knowledge about the horizontal anisotropy. Three other cases were used to investigate the effects of different numbers of sampling wells.

The number of flow simulations necessary to compare the approaches and to generate the quality maps for all the cases and all the 50 reservoirs would have been impracticable. Therefore, the investigations were grouped in the following three analyses:

- **Analysis 1:** Analysis of the effects of number of realizations, uncertainty in other model parameters and inclusion of a prior geological knowledge about the horizontal anisotropy in the *results* of the *Full*, *Conv-1* and *Conv-k* approaches to define the best production scenario.

Only ten reservoirs sampled randomly from the 50 available reservoirs were used in this analysis. The *result* considered was the true profit of the scenario defined from each approach. The same 77 “geometric” scenarios used in the case study presented in Chapter 2 were considered in this analysis.

- **Analysis 2:** Analysis of the effects of different numbers of sampling wells in the *results* of the *Full*, *Conv-1* and *Conv-k* approaches to define the best production scenario.

Another ten reservoirs were chosen to be added to the first ten reservoirs randomly selected for Analysis 1, in order to have 20 reservoirs with a good representation of the 50 reservoirs in the case with five sampling wells. The *result*

considered was the true profit of the scenario defined from each approach. The 77 “geometric” scenarios were also used.

- **Analysis 3:** Analysis of the effects of different numbers of sampling wells in the *results* of well locations with the three different types of quality map and with the oil volume map, and analysis of the effects of different numbers of sampling wells in the results of the approaches (*Full*, *Conv-1* and *Conv-k*) to define the best production scenario.

All 50 reservoirs were used in this analysis, however the *result* considered was not the true profit of the scenario but an index that has a good correlation with the true profits obtained from the wells located with each map. This index has also a reasonable correlation with the true profits of the scenarios chosen with each approach. This index is the correlation coefficient between a given map (any of the quality maps or the oil volume map) and the quality map of the true reservoir.

4.2 Description of the cases

4.2.1 Base Case

The Base Case is the case with the same level of uncertainty used in the case studies of the previous chapters. The specifications of this case are:

- Number of sampling wells = 5.
- Number of realizations = 20.
- Horizontal nugget effect equal to the experimental vertical nugget effect.
- Horizontal range of the petrophysical variables obtained from the experimental vertical range and with a ratio of horizontal/vertical anisotropy drawn from the uniform distribution $U \in (5, 25)$ for each model.
- No horizontal anisotropy.

- No uncertainty in any other model parameters.

Although the results of the 50 reservoirs are available for the Base Case, only the results of ten reservoirs were used in Analysis 1 and only the results of 20 reservoirs were used in Analysis 2, to be coherent with the number of reservoirs used in the other cases for each analysis.

4.2.2 Case 1: more realizations

The only difference with the Base Case was the number of realizations. In this case, 20 additional realizations were generated and a total of 40 realizations were used in Analysis 1.

4.2.3 Case 2: more uncertainty

In this case, uncertainty in other model parameters was considered. The specifications of this case, additional to the ones of the Base Case, are:

- The correlation between the primary variable and the secondary variable (“seismic” image) used for cokriging the structural top was drawn from the uniform distribution $U \in (0.5, 0.6)$ for each model. Considering that in the Base Case, the correlation was always higher than 0.8, the specification of a correlation between 0.5 and 0.6 increased the uncertainty in the structural top.
- The horizontal ranges of the top, thickness, porosity and permeability variables were drawn from $U \in (30, 60)$ for each model. Recalling that the total dimension of the field is 90 (cell units), the specification of a horizontal range between one third and two thirds of the total field dimension increases the differences between the realizations. This effect is explained in geostatistical modeling by two observations: (1) for very small horizontal ranges, the variables in the realizations are randomly distributed and the realizations are globally alike, and (2) for very large horizontal ranges, the data influence are extended to almost the entire field given again a global similarity to the realizations.

- An error was considered for the experimental vertical range and the experimental vertical nugget effect. The error was drawn from a triangular distribution $T \in (-20\%, 0\%, +20\%)$ for each model. In this notation for the triangular distribution, the left number represents the minimum value, the central number represents the most likely value and the right number represents the maximum value.

4.2.4 Case 3: prior knowledge of anisotropy

Since only five sampling vertical wells were used in the Base Case, no horizontal modeling was possible. But, there are situations where prior geological knowledge of the sedimentary basin and/or seismic data may allow the prediction of the main direction and the ratio of horizontal anisotropy.

For this case, the true direction and the true ratio of horizontal anisotropy plus an error were used in the modeling of the petrophysical properties. The error in the direction was drawn from $T \in (-10\%, 0\%, +10\%)$ while the error in the ratio was drawn from $T \in (-20\%, 0\%, +20\%)$.

4.2.5 Case 4: different numbers of sampling wells

Besides the Base Case with five sampling wells, three other numbers of wells were used to sample the true reservoirs and to condition all models: three, nine and 25 wells.

Figure 4.1 shows the locations of the four different numbers of sampling wells. The wells that are used in the smaller sample are used for the larger sample too.

In the case with three wells, the same modeling procedure and specifications as in the Base Case were applied; only the number of data points decreased.

In the case with nine wells, the horizontal nugget effect and range were modeled based on the experimental variogram and they were used for the generation of all the models; no uncertainty in the horizontal range was considered. No modeling of the direction of anisotropy was possible, though, and as in the Base Case, no horizontal anisotropy was considered.

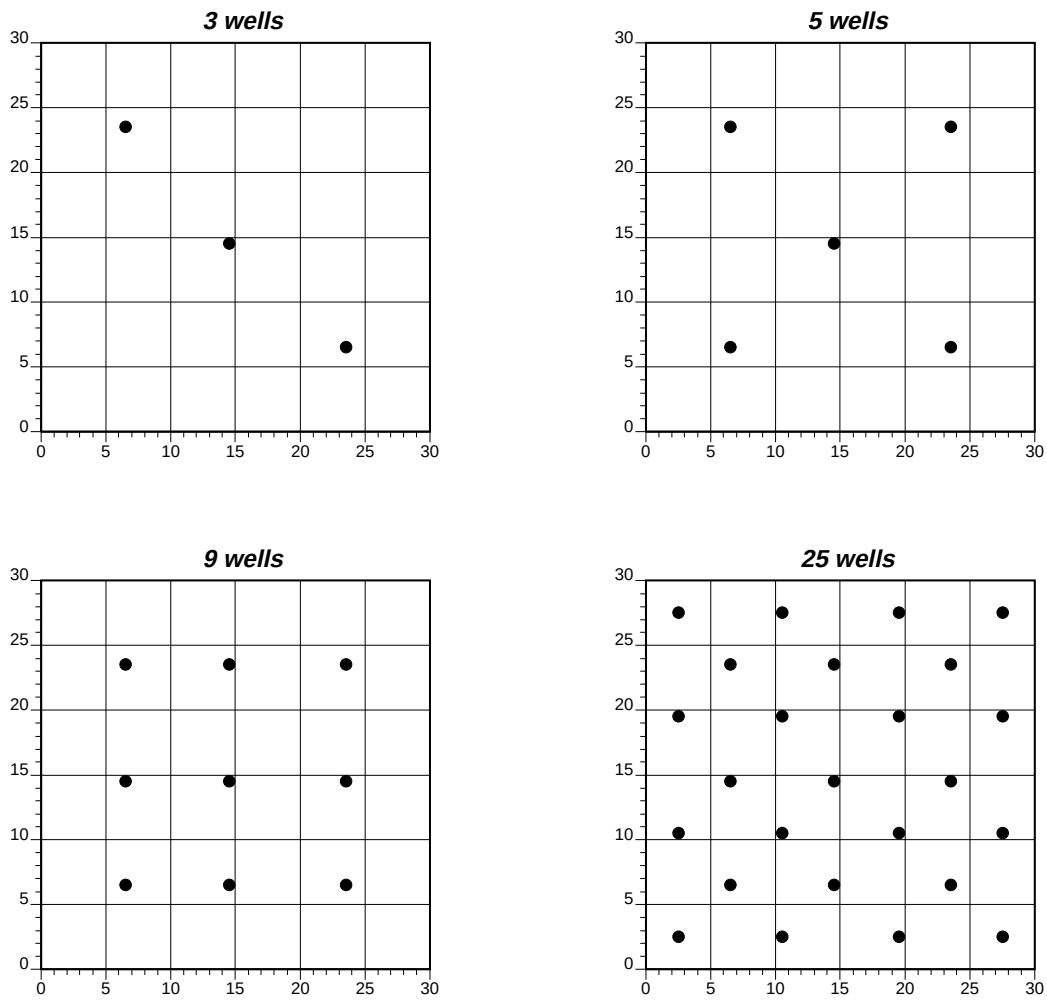


Figure 4.1: Location of the sampling wells.

In the case with 25 wells, a complete horizontal variogram modeling was possible, providing the direction and ratio of horizontal anisotropy.

The different numbers of sampling wells were used only for modeling purposes; for the definition of the best production scenario, the same 77 scenarios used in the case study of Chapter 2 were considered here. In these scenarios, the five sampling wells of the Base Case are always present and the locations of the other wells vary in each scenario. For example, although 25 wells were used for sampling the true reservoir in the case with 25 wells, only five of them were used for production in the scenarios. The reason for this was to permit direct comparison of results between the cases.

4.3 Results of the analysis

4.3.1 Indices

To limit the computational effort to a practical level, the correlation between the quality map of the models and the true quality map was used as the *result* in Analysis 3, as a substitute for the true profit. This index was evaluated for all the reservoirs in the three additional cases of different numbers of sampling wells. For each case and every reservoir, a quality map and an oil volume map were built for the true reservoir, for each of the realizations and for the kriged model.

The correlation between this index and true profit was checked based on the results available in the case study of Chapter 3, which is the Base Case (five sampling wells) of Analysis 3, and some additional flow simulations.

In Chapter 3, 11 numbers of wells were located for every reservoir with each of the following maps: (1) quality map of the kriged model, (2) quality map of Realization 1, (3) quality map of the representative realization, (4) lower quartile quality map and (5) oil volume map of Realization 1. Since the true profit obtained with each well configuration was also evaluated in that case study, there were five available points for each reservoir to evaluate the correlation coefficient between the index “correlation with the true quality map” and the mean true profit over the eleven numbers of wells. A sixth point was generated to increase the number of data available to evaluate that

correlation coefficient for each reservoir. This point was obtained by considering the lower quartile oil volume map and carrying out the well locations and profit evaluations for this map.

Figure 4.2 presents the true quality map and the six types of map for one of the reservoirs. The correlation with the true quality map and the mean profit are shown for each of the maps.

Figure 4.3 presents, in the top left corner (a), the correlation between the index “correlation with the true quality map” and the mean profit, for the reservoir shown in Figure 4.2. In the top right corner (b), the distribution of correlation coefficients for the 50 reservoirs is presented. This distribution shows that for most of the reservoirs, the index “correlation with the true quality map” is a good predictor of the goodness of the map for well location. To have good correlation with the true profit of the decision is more difficult, though. Even the correlation between the mean true profit over 11 numbers of wells and the true profit of the best number of wells is not very good, as can be seen at the bottom left corner of the figure (c). Thus, the correlation between the index “correlation with the true quality map” and the true profit of the decision is only reasonable, as presented at the bottom right corner of the figure (d).

Besides the correlation with the true quality map, other indices were defined, evaluated and used to help understand the results in Analysis 1 and 2.

The coefficient of variation (in percentage) of the distribution of profits obtained with all the realizations was defined as a measure of the uncertainty for each scenario. The global measure of uncertainty of the model was taken as the average value of the coefficient of variation over the 77 scenarios. Since this index is based on profits, it could not be evaluated in Analysis 3 and was used only in Analysis 1 and 2.

In Analysis 2, the correlation with the true quality map was used as a measure of the model goodness, but in Analysis 1 two other indices had to be defined as substitutes for the model goodness measure, because the quality maps were not built for the cases involved in Analysis 1.

The inverse of the absolute difference between the true profit and the profit of the model, divided by the true profit, was defined as a measure of the *model accuracy* for each scenario. The global model accuracy was taken as the expected value of this

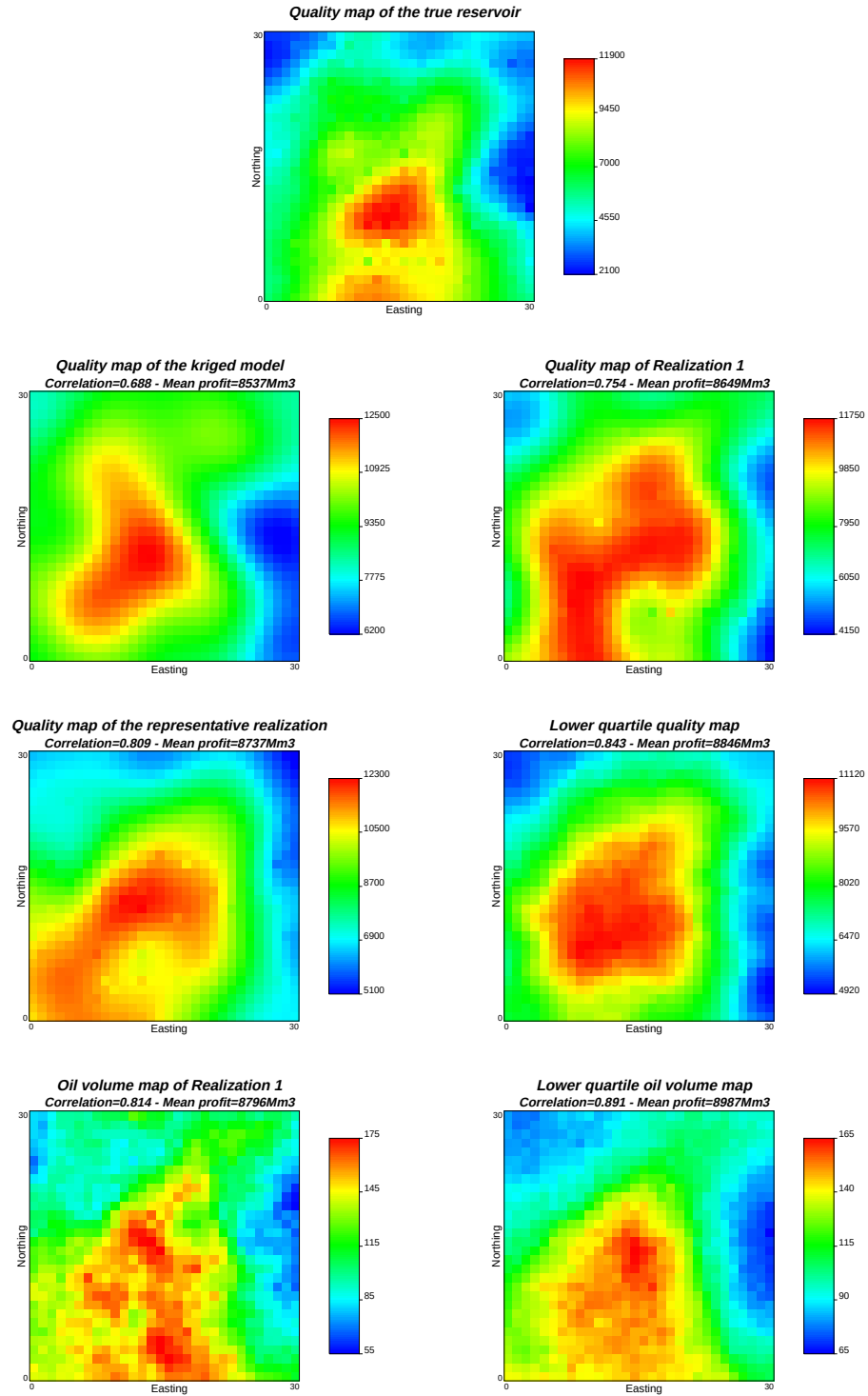


Figure 4.2: Example of true quality map and maps of the models used to check the correlation between the index “correlation with true quality map” and the mean true profit. Unit= Mm^3 .

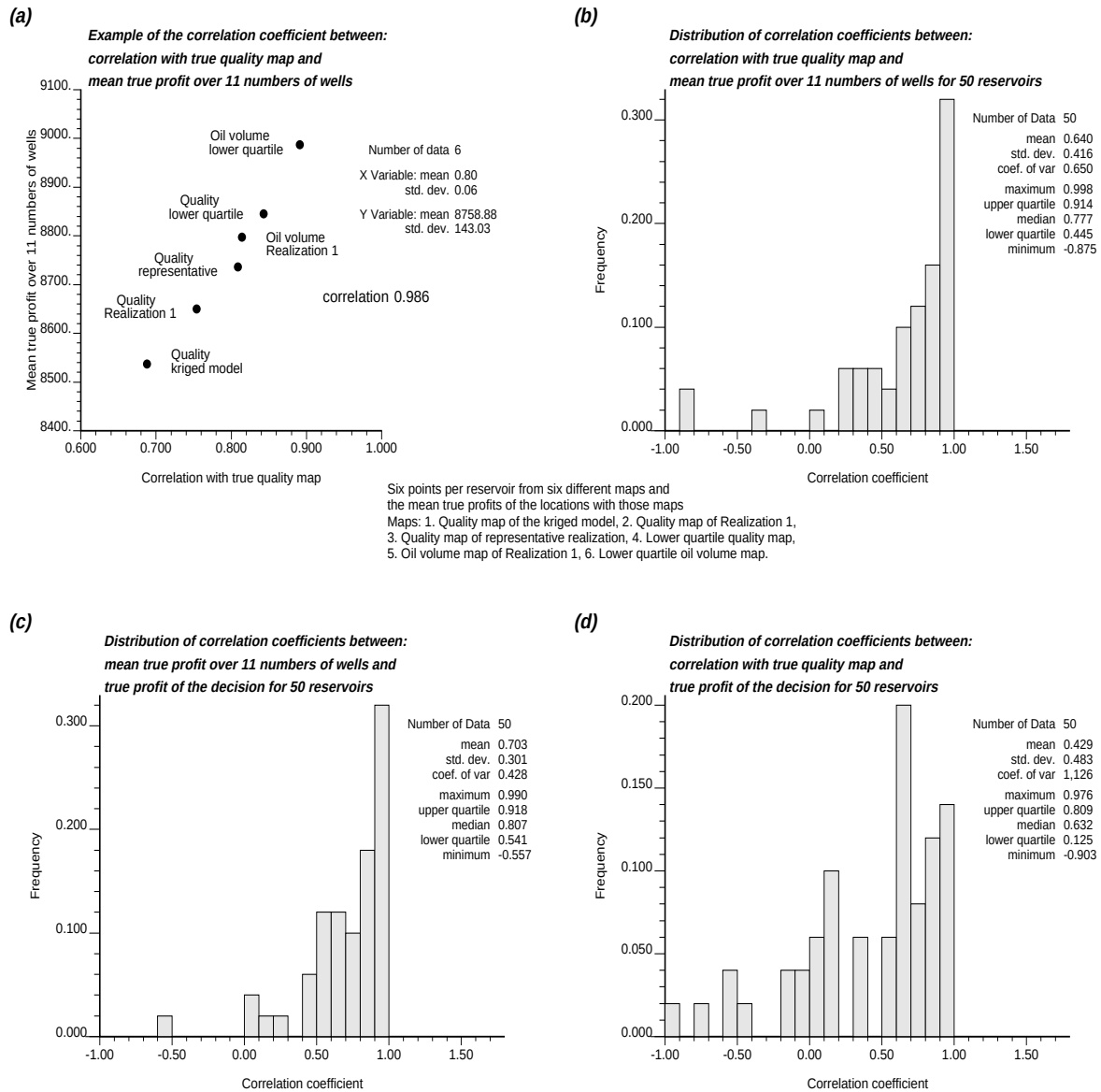


Figure 4.3: Correlation coefficient between the index “correlation with true quality map” and mean true profit for a particular reservoir (a), distribution of these coefficients over 50 reservoirs (b), correlation between mean true profit and the true profit of the decision (c) and correlation between the index and the true profit of the decision (d).

measure over the 77 scenarios. This index is evaluated by:

$$\text{Model accuracy} = \frac{1}{S} \sum_{s=1}^S \frac{P_s^o}{|P_s^o - P_s^m|} \quad (4.1)$$

where P_s^o is the profit of the true reservoir and P_s^m is the profit of the model for scenario s . For the realizations, P_s^m is the expected profit over all the realizations ($P_s^m = \frac{1}{L} \sum_{l=1}^L P_s^l$), while for the kriged model there is just one value for each scenario s .

The correlation coefficient between the true profits and the profits of the model, considering all the scenarios, was defined as a measure of the *model efficacy*.

Although they carry valuable information about the model goodness, these other two indices are not as well correlated with true profits as the index “correlation with the true quality map”. A good model should have high accuracy and high efficacy, but to decide the best scenario, the right (true) ranking of the scenarios (efficacy) is more important than the closeness between the model results and the true results (accuracy).

4.3.2 Analysis 1

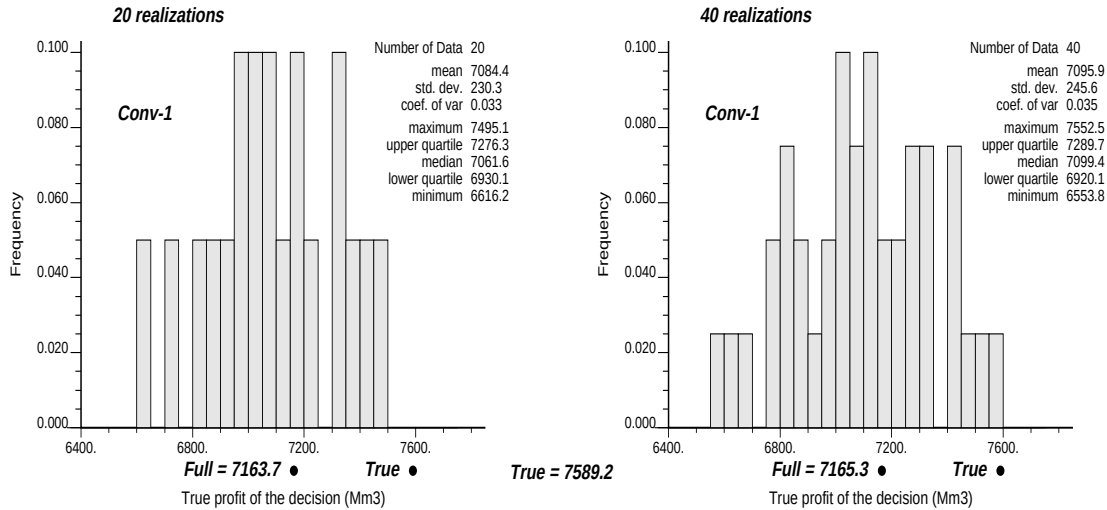
Table 4.1 presents the results and indices of the three approaches in the Base Case, Case 1 (more realizations), Case 2 (more uncertainty) and Case 3 (knowledge of anisotropy). The values are the average values over the ten reservoirs selected randomly for this analysis.

Figure 4.4 shows the average result of the decision, over ten reservoirs, for the Base Case (20 realizations) and Case 2 (40 realizations). The distribution of results and the expected value of the *Conv-1* approach are presented, as well as the result of the *Full* approach and the decision that would be made if the true reservoir was known.

Doubling the number of realizations, in Case 1 (more realizations) (see Table 4.1 and Figure 4.4), includes good and bad realizations but, in general, the new realizations are similar to the previous realizations and increasing their number did not

Table 4.1: Average results and indices over ten reservoirs of the cases involved in Analysis 1.

Case	Approach	Profit of the decision (Mm^3 oil)	Model accuracy (fraction)	Model efficacy (correlation)	Uncertainty (%)
Base	<i>Full</i>	7163.7	7.19	0.600	4.82
	<i>Conv-1</i>	7084.3	6.92	0.470	
	<i>Conv-k</i>	7255.4	8.11	0.585	
1. More realizations	<i>Full</i>	7165.3	8.40	0.605	5.70
	<i>Conv-1</i>	7095.9	7.71	0.475	
2. More uncertainty	<i>Full</i>	7137.0	8.21	0.562	5.36
	<i>Conv-1</i>	7023.3	7.52	0.406	
	<i>Conv-k</i>	7095.7	8.13	0.559	
3. Knowledge of anisotropy	<i>Full</i>	7249.4	9.12	0.616	5.07
	<i>Conv-1</i>	7100.3	8.46	0.480	
	<i>Conv-k</i>	7225.2	8.12	0.591	

Figure 4.4: Average results over ten reservoirs of the decision with *Conv-1*, *Full* and true reservoir in the Base Case (20 realizations) and Case 1 (40 realizations).

change the average results of the decisions significantly. On average, the uncertainty increases, but the inclusion of a few good realizations improved the model accuracy reasonably and the model efficacy a little bit. The final effect was a small improvement on the results of the decisions for both approaches. With 40 realizations, the result of the *Full* approach was the same for 90% and better for 10% of the reservoirs. The expected result of *Conv-1* was better for 70% and worse for 30% of the reservoirs.

The average results of Case 2 (more uncertainty) (see Table 4.1) show that the inclusion of uncertainty in other model parameters increased the uncertainty and the accuracy of the models, but the model efficacy was reduced. The final effect was a worsening in the results for all the three approaches. Moreover, the worsening in the *Conv-k* approach was greater than in the simulation-based approaches. Compared with the Base Case, the results of the *Full* approach were better for 20%, equal for 40% and worse for 40% of the reservoirs. The results of *Conv-1* were better for 30% of the reservoirs and worse for 70% of the reservoirs. The results of *Conv-k* were better for 10% of the reservoirs, equal for 40% of the reservoirs and worse for 50% of the reservoirs.

Figure 4.5 illustrates the situation of a reservoir where the model accuracy improved and the model efficacy worsened in Case 2 (more uncertainty) compared with the Base Case. Although the results were closer to the results of the true reservoir, the smaller correlation between the true results and the model results led to a worse decision about the best scenario in Case 2 (more uncertainty).

Figure 4.6 illustrates a situation of a reservoir where the inclusion of uncertainty in other model parameters had a worse effect in kriging than in simulation. The figure shows the upscaled vertical permeability of one of the six layers. Besides the kriged and simulated models in the Base Case and in Case 2 (more uncertainty), the figure shows the true upscaled vertical permeability of that layer to serve as reference for the comparison of the goodness of the models. The loss of horizontal continuity caused both the models to be more different from the true reservoir in Case 2, but the effect was more significant in the kriged model.

The results of Case 3 (knowledge of anisotropy) (see Table 4.1) show that the inclusion of the knowledge of direction and ratio of horizontal anisotropy increased the

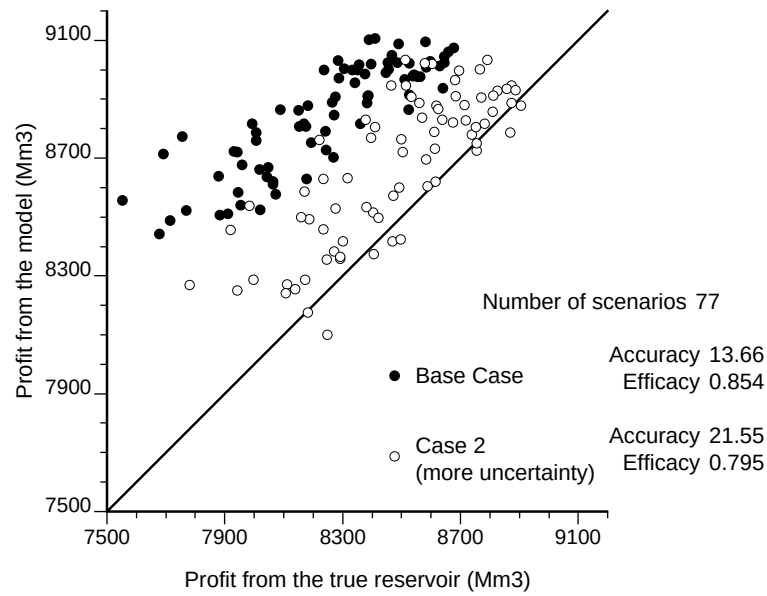


Figure 4.5: Example of model accuracy and model efficacy in the Base Case and in Case 2 (more uncertainty).

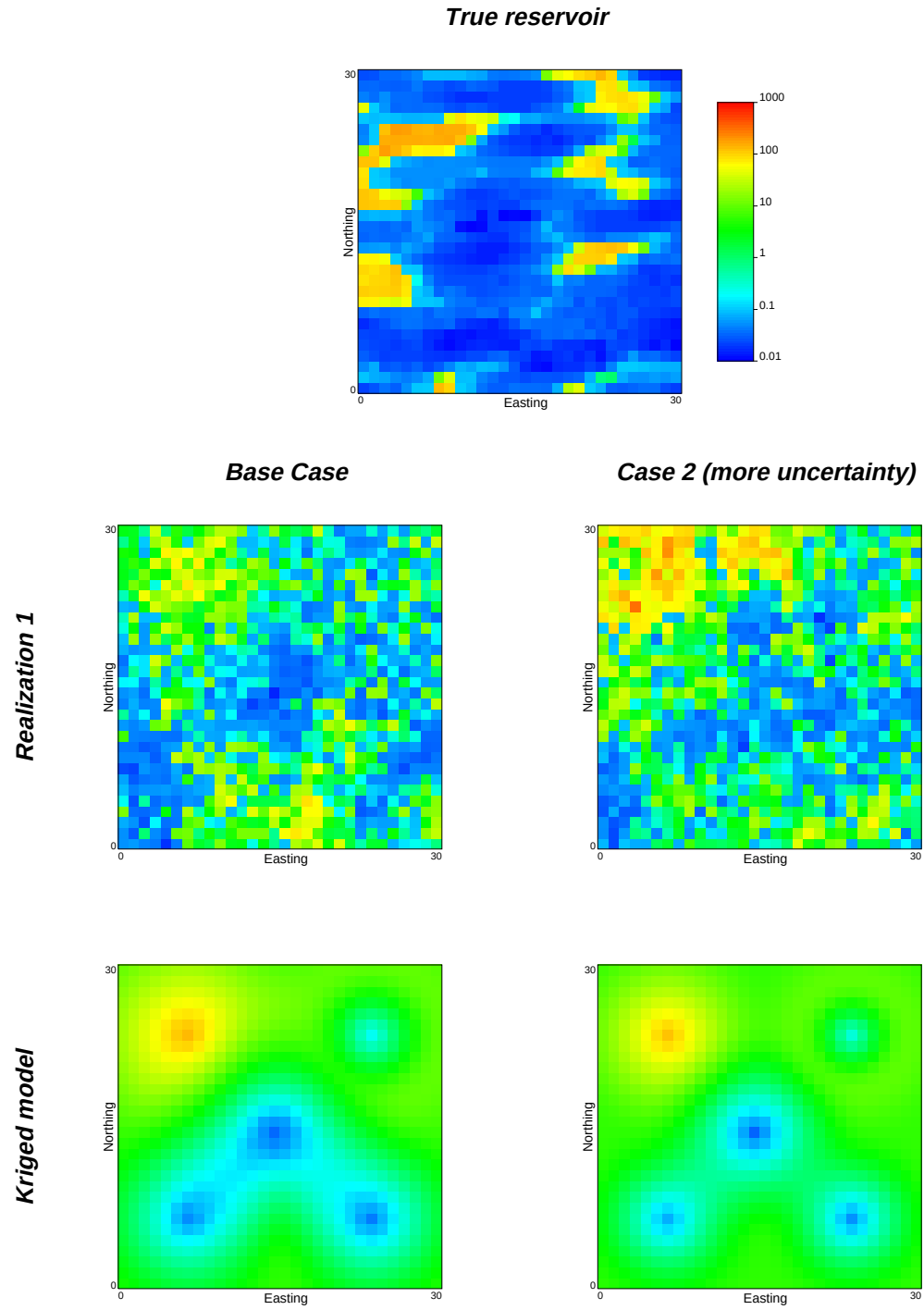


Figure 4.6: Example of the upscaled vertical permeability (md) of one layer for the true reservoir (top), and for Realization 1 (center) and the kriged model (bottom) in the Base Case (left) and Case 2 (more uncertainty) (right).

uncertainty among the realizations and the model accuracy and efficacy of the three approaches. The improvement of model accuracy and efficacy was smaller for *Conv-k* compared with *Full* and *Conv-1*, though. The average effect was an improvement in the decisions of *Full* and *Conv-1* and a worsening of the decisions of *Conv-k*.

Compared with the Base Case, the results of the *Full* approach in Case 3 (knowledge of anisotropy) were better for 20%, equal for 70% and worse for 10% of the reservoirs. The results of *Conv-1* were better for 70% and worse for 30% of the reservoirs. The results of *Conv-k* were better for 10%, equal for 80% and worse for 10% of the reservoirs.

Figure 4.7 presents the upscaled vertical permeability of one of the six layers for one of the ten reservoirs. The true reservoir is presented and also two realizations and the kriged model for the Base Case and for Case 3. Comparing the two simulated models of each case, it can be seen that the differences (uncertainty) between the two realizations increased in the anisotropic case compared with the isotropic case. Comparing the simulated models and the kriged model with the true reservoir, it can be seen that the horizontal anisotropy knowledge provided better simulated models of the channels and barriers but did not improve the kriged model significantly.

4.3.3 Analysis 2

The average results and indices over 20 reservoirs of the four different numbers of sampling wells are presented in the following three figures:

Figure 4.8 shows the uncertainty in the profits with the realizations.

Figure 4.9 shows the true profit of the decision with the *Full*, *Conv-1* (expected value) and *Conv-k* approaches.

Figure 4.10 shows the correlation between the true quality map and: (a) the lower quartile quality map, (b) the quality map of the realizations (mean value over all the realizations) and (c) the quality map of the kriged model.

Comparing Figure 4.9 with Figure 4.10, it can be seen that, on average, the correlation with the true quality map is a good index to represent the results of the approaches. The lower quartile quality map correlates well with *Full*, the mean value

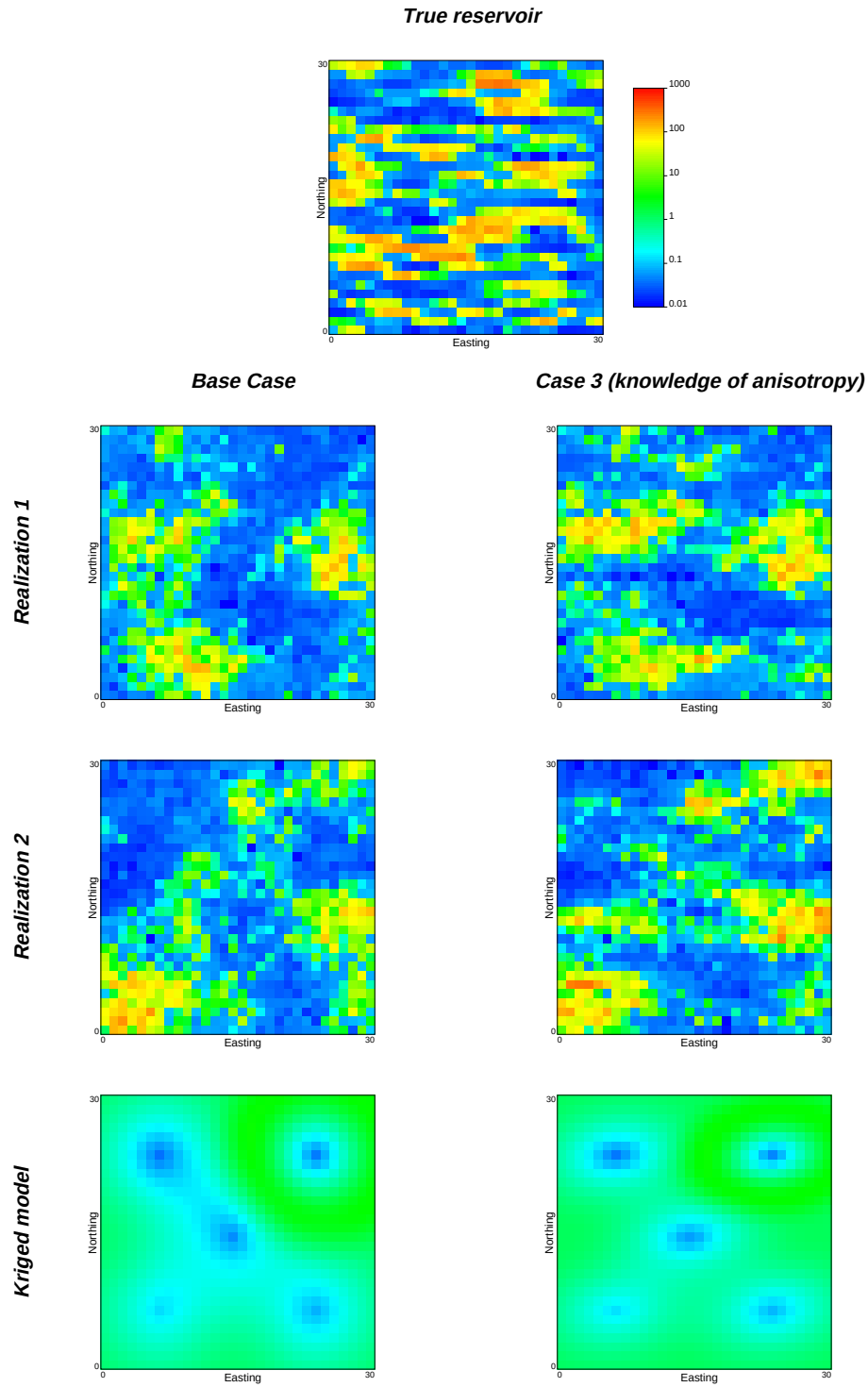


Figure 4.7: Example of the upscaled vertical permeability (md) of one layer for the true reservoir, and for two realizations and the kriged model in the Base Case (left) and Case 3 (knowledge of anisotropy) (right).

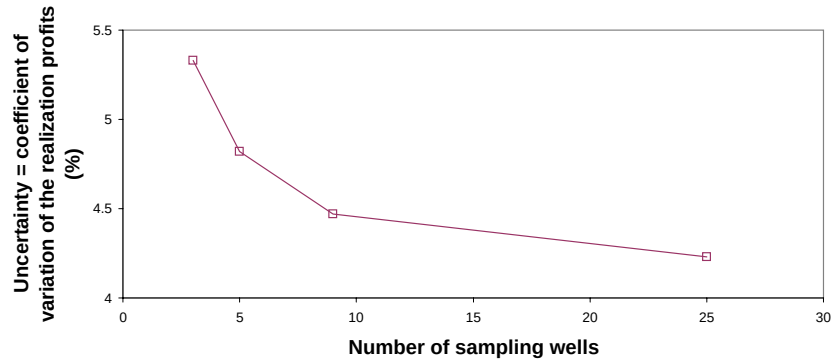


Figure 4.8: Average value over 20 reservoirs of the uncertainty in the profits with the realizations, for different numbers of sampling wells.

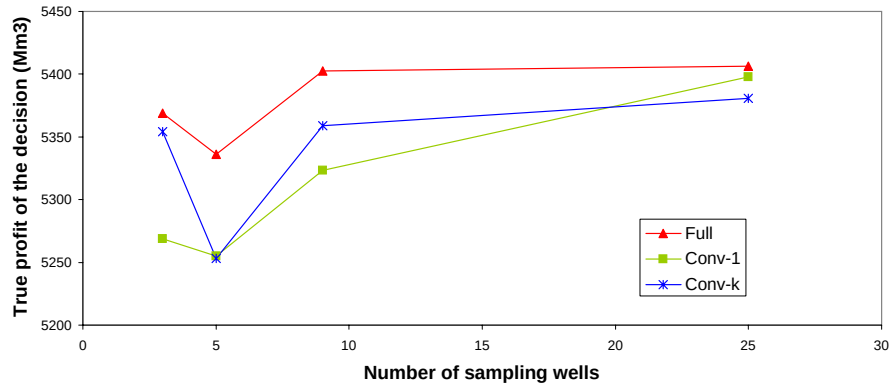


Figure 4.9: Average results over 20 reservoirs of the decisions with *Full*, *Conv-1* and *Conv-k*, for different numbers of sampling wells.

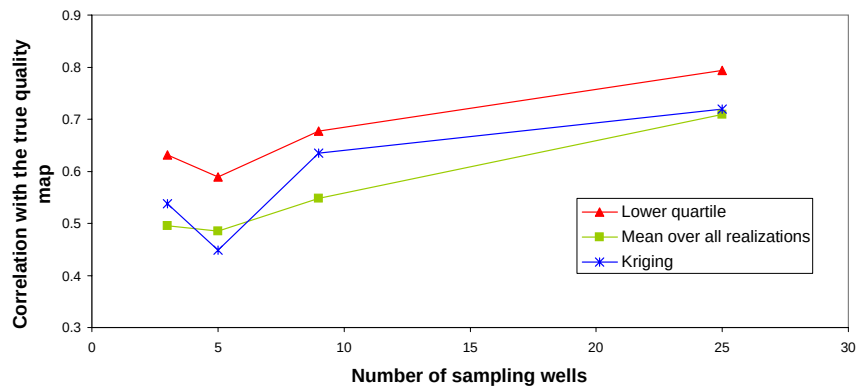


Figure 4.10: Average over 20 reservoirs of the correlation coefficient between the true quality map and the quality maps of the models, for different numbers of sampling wells.

of the index over all the realizations correlates well with the expected value of *Conv-1* and the quality map of the kriged model correlates well with *Conv-k*.

The relative positions of the results for the Base Case (five wells) in Figure 4.9 show that the 20 reservoirs used in this analysis, are representative of the 50 reservoirs used in the case studies of Chapter 2 and 3: the *Full* approach (or the lower quartile quality map) is better than the expected value of the *Conv-1* approach (or the mean value of the quality map of the realizations), which is slightly better than the result of the *Conv-k* approach (or the quality map of the kriged model).

However, both results, the true profit (in Figure 4.9) and the correlation with the true quality map (in Figure 4.10), showed unexpectedly better values with three wells than with five wells for simulation and kriging. Moreover, kriging was better than the mean value of the realizations with three and five wells. The correlation with the true quality map was better for kriging than for simulation with 25 wells too. Comparing the relative positions of the curves in Figure 4.9 and 4.10, it seems that for kriging the index was pessimistic with three and five wells and optimistic with 25 wells.

In general, as the number of sampling wells increases, the uncertainty decreases, the results of the approaches improve and the differences between the results of the approaches decrease.

Figure 4.11 presents the upscaled vertical permeability of one of six layers for one of the 20 reservoirs. The true reservoir, Realization 1 and the kriged model are shown for the cases with three, five, nine and 25 wells.

Figure 4.12 presents the quality maps of the true reservoir and models for the same cases and same reservoir presented in Figure 4.11. The correlations with the true quality map are also shown in the quality maps of the models.

Based on these two figures, some observations, which help understanding the results, can be made:

- The additional data from the bottom left well in the Five Wells Case made the model worse than in the Three Wells Case (notice smaller correlation with the true quality map with 5 wells than with 3 wells in Figure 4.12). Although correct at the specific location of the well, the information of good vertical permeability, brought by this well, should not have been extended so much to the bottom left

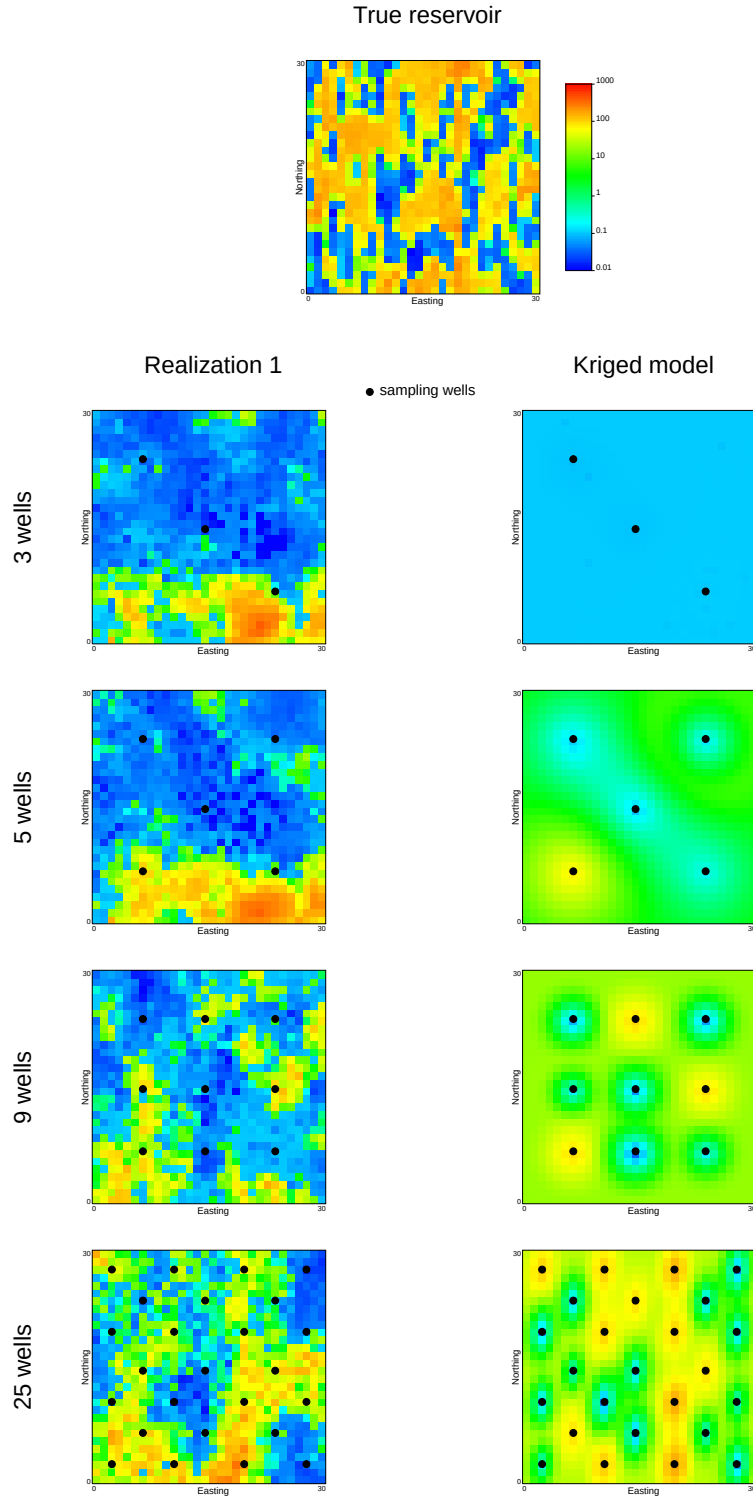


Figure 4.11: Example of the upscaled vertical permeability (md) of one layer for the true reservoir, and for Realization 1 and the kriged model for different numbers of sampling wells.

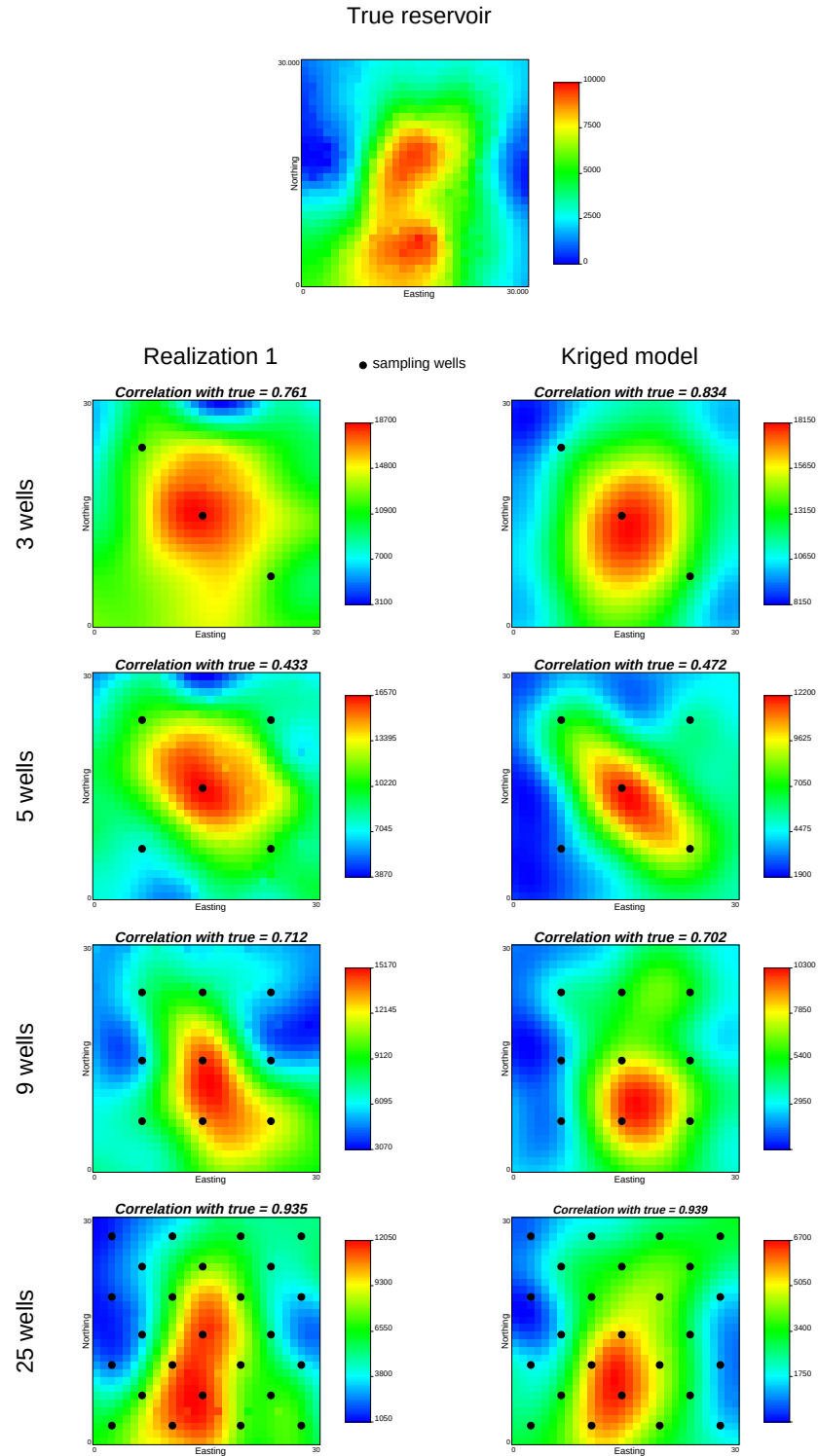


Figure 4.12: Example of the quality (Mm^3) map of the true reservoir, and of Realization 1 and the kriged model for different numbers of sampling wells.

corner of the layer. The production in that corner was affected strongly by the good communication with the bottom aquifer, making the quality in that area smaller than the truth.

- The effect of very bad or very good data is more important for the kriged model than for the simulated one, because in kriging only the hard data are used while in simulation some “data” are created, decreasing the impact of not representative data.
- The quality map is a smooth map. Note that the heterogeneity in the vertical permeability map is much higher than in the quality map of the true reservoir. Although the quality map is interpolated by kriging, a very fine grid (2×2) was used to evaluate the quality points with a flow simulator for the true reservoir, ensuring good resolution for the true quality map. Although there are five other layers, the vertical permeability of the layer presented is important to prevent water production from the bottom aquifer and the specific locations of the barriers and points of good communication were not reflected in the final cumulative oil production (quality).
- As the number of sampling wells increases, the correlation with the true quality improves faster for the kriged model than for the simulated one, because the kriged model has sufficient definition of the important flow paths and the need for simulated features decreases.

4.3.4 Analysis 3

Figure 4.13 shows the average value, over the 50 reservoirs, of the index “correlation with the true quality map” with three, five, nine and 25 sampling wells for the following quality maps: (a) worst realization, (b) best realization, (c) lower quartile, (d) kriged model, (e) representative realization and (f) Realization 1. The mean index over all the realizations is also presented.

As was discussed in Section 4.3.1, when presenting Figure 4.3, this index measures the goodness of each map for use in well locations. The index can also be related to

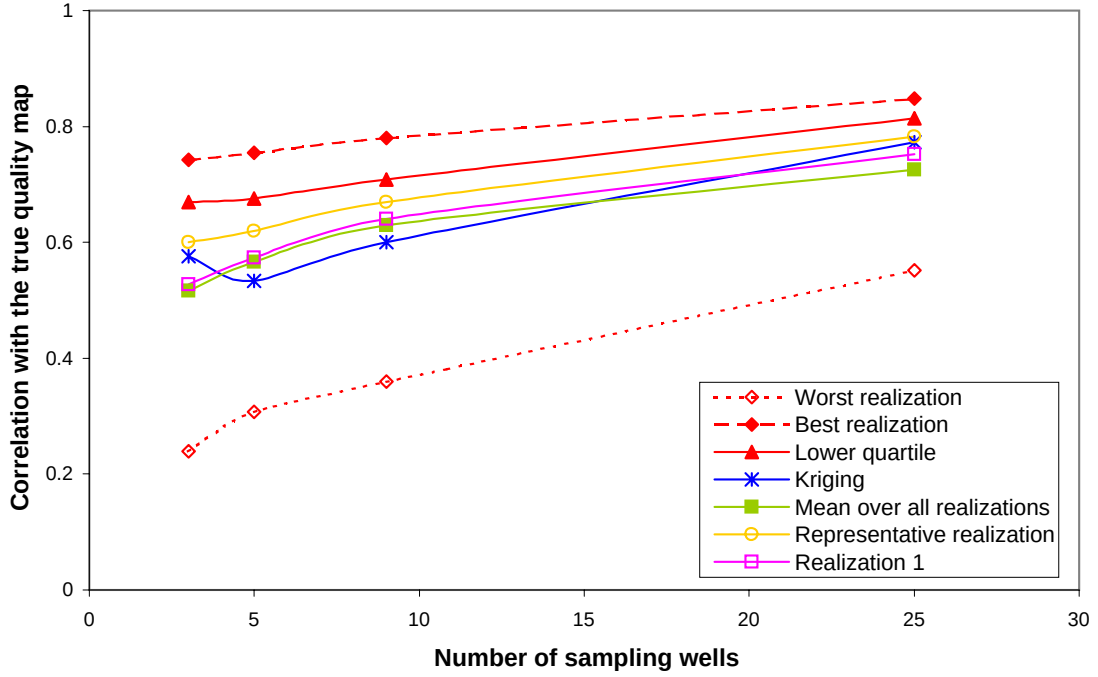


Figure 4.13: Average over 50 reservoirs of the correlation coefficient between the true quality map and the quality maps of the models, for different numbers of sampling wells.

the goodness of the approaches to define the best production scenario. The indices for the realizations are related to *Conv-1*, the indices for the kriged model are related to *Conv-k* and the indices for the lower quartile quality map are related to the *Full* approach.

Based on Figure 4.13, the following observations can be made:

- Although the differences between the results decrease with more sampling wells, the lower quartile (or *Full* approach) is always better than the mean over all the realizations (expected value of *Conv-1*), than the representative realization and than the kriged model (*Conv-k*).
- With more sampling wells, the results with kriging increase faster than with the realizations. Up to 25 wells, although kriging becomes better than the mean value over all the realizations, kriging remains worse than the representative realization and than the lower quartile quality map.

- Realization 1, which represented the case of just one realization in the comparisons between the quality maps and between the decision approaches in the case study of Chapter 3, is better than the mean over all the realizations.
- The representative realization is better than the mean over all the realizations independent of the number of sampling wells.
- With the average over 50 reservoirs, the realizations no longer showed the unexpected better results with three wells than with five wells, as had been observed in Figure 4.10 with 20 reservoirs. The kriged model still shows better results with three wells than with five wells, but the difference decreases. This indicates that additional data may worsen the model for particular reservoirs, if the additional data is bad, but in general increasing the number of data improves the models.
- The position of the results of the quality maps (or approaches) relative to the worst and best realization may be used to decide which map (or approach) to use, considering the profit desire and risk aversion profile of the company. An aggressive company may decide to use just one realization, expecting to have a realization better than the lower quartile (or *Full*). From the figure, though, it is clear that, picking one realization randomly, the probability that the results would be worse than with the lower quartile is much greater than the probability that the results would be better.

Figure 4.14 shows the index “correlation with the true quality map” with the quality map of the worst and the best realization, the lower quartile quality map, the oil volume map of the worst and the best realization and the lower quartile oil volume map. The values are the average over the 50 reservoirs. This figure is intended to compare the goodness of the quality map and the oil volume map for well location.

To standardize the figure, the number of sampling wells was divided by the total number of cells in the upscaled horizontal grid. The extreme points for no data and for data in all the cells were also included. If there were no data, the correlation with the true quality map would be very small, or zero or even negative. If there were data

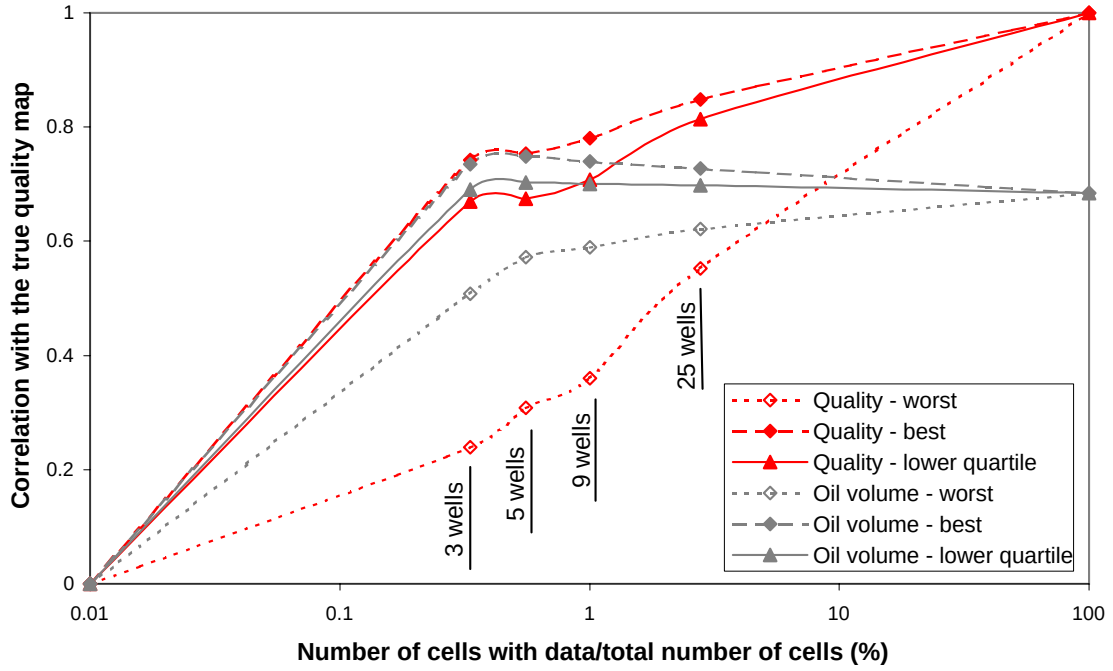


Figure 4.14: Comparison between quality map and oil volume map for well location, using the average value over 50 reservoirs of the index “correlation with the true quality map”, for different numbers of sampling wells.

for every cell, all the models would be equal to the true reservoir and the correlation between the true quality map and the quality map of any model would be 1.0, but the correlation between the true quality map and the oil volume map would be less than 1.0. This correlation with the oil volume map, for the situation where the models are equal to the true reservoir (zero uncertainty), was evaluated by using the oil volume map and the quality map of the true reservoirs.

The following observation could be made:

- The situation of zero uncertainty (100% of the cell with data) was the one used in the comparison between quality and oil volume map presented in Chapter 3, where Realization 1 was used as it was the true reservoir and it was shown that the quality map provides better well locations than the oil volume map.
- The uncertainty in the quality map is greater than in the oil volume map. Besides the uncertainty in the top, thickness and porosity of the oil zone that

are considered in the oil volume map, the quality map incorporates also the uncertainty in the permeability and in the aquifer.

- Although there was always at least one quality map better than the best oil volume map, for high level of uncertainty (small number of sampling wells), the probability to locate wells better with the oil volume map than with the quality map is high. The explanation is that the flow paths are placed badly in most of the realizations and/or the aquifer is modeled badly.
- As the number of data increases, the models of permeability and aquifer improve and the quality becomes a better map to locate wells than the oil volume. For the reservoirs used in this research, the existence of data in at least 1% of the cells (nine sampling wells) was necessary to make the lower quartile quality map better than the lower quartile oil volume map. This level of uncertainty reflects the minimum amount of data necessary to start extracting some information from a horizontal variogram modeling.

4.4 Conclusions of the analysis

Based on the average results over many reservoirs, the conclusions from the sensitivity analysis undertaken in this chapter are:

1. 20 realizations are sufficient to apply the *Full* approach for the settings of this case study. Increasing the number of realizations may improve the results in some cases, but the expected improvement is small.
2. Considering uncertainty in the data and in additional model parameters, besides the horizontal range, may bring the results from the models closer to the truth for some scenarios, but the decision of the best scenario may be worse than without considering additional uncertainty. The decision depends more on the ranking of the scenarios than on the accuracy of the individual results and that ranking may deviate further from the truth with additional uncertainty.

3. Information about the direction and magnitude of horizontal anisotropy is very valuable to improve the quality of the models and the decisions made with them. In this case study, this information was more important for simulation than for kriging.

Some investment may be made to evaluate the horizontal anisotropy, but the expected gain in the decisions would not pay the cost of one offshore well.

4. By increasing the number of sampling wells, the results of the decisions made with the three approaches improve and the differences between the approaches decrease, but the *Full* approach is always better than *Conv-k* and the expected value of *Conv-1*.

However, when the number of sampling wells is small, it is possible for an additional well to include “bad” data, which may have strong negative influence in the models, in which case the decision with more data may be worse than the decision with less data, for a particular reservoir. In this case study, the influence of discordant data was more important for kriging than for simulation.

5. Even with a large increase in the number of sampling wells, for example from three to 25, the expected gain in the decisions, due to the availability of additional data, does not pay the cost of even one offshore well.
6. For a small number of sampling wells, the expected gain of *Full* over the expected value of *Conv-1* or over *Conv-k* is greater than the gain obtained with data from additional wells.
7. Increasing the number of sampling wells, the results of the well location decisions improve with any of the quality maps and the differences between the results decrease, but in this case study with a maximum number of 25 sampling wells, the lower quartile quality map was always better than the expected value of the quality map of one realization and than the quality map of the kriged model.
8. The lower quartile oil volume is a better map to locate wells than the lower quartile quality map when there is insufficient data to obtain good horizontal

variogram models.

If the realizations are generated based on good horizontal variograms, the lower quartile quality map provides better well locations than the oil volume map. In this case, the expected gain of the quality map over the oil volume map may be as much as the cost of two offshore wells.

Chapter 5

Other Reservoir Management Decisions

The *Full* approach, presented in Chapter 2, is generic and can be applied to account for geological uncertainty in the selection of the best scenario from a set of predefined scenarios, for any type of reservoir management decision.

However, so far the benefits of considering the geological uncertainty in reservoir management decision-making have been evaluated only for a specific type of problem, the selection of the best number and spatial configuration of vertical producer wells for offshore reservoirs of moderate size.

Moreover, although the quality map presented in Chapter 3 has other applications, its principal use is also the location of vertical producer wells.

This chapter presents a discussion about the relevance of accounting for the geological uncertainty in other types of reservoir management decision. Some ways to incorporate that uncertainty into the decision-making are suggested for those decisions where this incorporation is relevant.

Among the different types of problems discussed, the definition of the best injection scenario using vertical wells was selected to be examined in this chapter.

A methodology to generate an injection quality map and to use it to locate injector wells is presented. The benefits of accounting for the geological uncertainty in the definition of the best injection scenario are evaluated in a case study using ten different

reservoirs.

The methodology and comparison between approaches, presented in this chapter, complement the ones presented in Chapter 2 and 3 for the definition of the best scenario considering producer and injector wells.

5.1 Other types of reservoir management decisions

5.1.1 Well location for different types of reservoirs

The reservoirs and the well cost used in all previous the case studies represent the situation of a development plan for medium-size offshore reservoirs. If the well cost was much smaller (as in onshore reservoirs) or the size of the reservoirs was much bigger, the optimal number of wells would be much larger and the modeling of the geological uncertainty could be less relevant for the decision of the best number of wells and their spatial configuration.

Modeling the geological uncertainty between the conditional data is only relevant for the decision of the best scenario if that decision varies depending on the realization. For a very large number of wells, the scenarios are defined by different grids (or patterns) of wells with regular spacing between the wells and the particular behavior of a few wells would not change the overall response of a scenario. The overall response of a scenario is determined by the spacing between the wells in the regular grid defined in the scenario and by the average properties of the reservoir, instead of by any local characteristic.

If the average properties of a reservoir do not change from one realization to another, because they are correctly depicted by the conditional data which are honored by all realizations, the decision of the best scenario (grid of wells) would be the same with any realization.

5.1.2 Vertical or horizontal well?

The decision to drill a well vertically or horizontally is governed by the differences in cost and in production (or injection) of the two types of well. Since a horizontal

well is more expensive, it must produce (or inject) more and/or longer than a vertical well.

The final oil recovery with a horizontal well may be higher than with a vertical well because of two characteristics of a horizontal well: (1) higher productivity (or injectivity) due to a greater length of the interval completed in the well, and (2) better location of the completed intervals.

In general, the reservoirs in which a horizontal well is expected to work better than a vertical well have a small oil column and good vertical permeability. Some common situations where a horizontal well may be preferred are:

- Small oil column with gas cap and/or bottom aquifer.
- Thin oil layer with good permeability embedded in other layers with much smaller permeability.
- Naturally fractured reservoirs, with the direction of the horizontal well normal to the fractures.

The geological characterization necessary to determine if a reservoir is appropriate for horizontal wells is typically performed at the macroscale and this kind of characterization does not change from one realization to another. For example: if there is a gas cap in one realization it would be present in all the realizations; if the average oil column is five meters in one realization, it is not likely to be 50 meters in any other; if the average ratio of vertical permeability over horizontal permeability is 0.5 in one realization, it is not likely to be 0.1 in any other, etc.

Therefore, in general, the consideration of multiple realizations to decide between vertical and horizontal wells is not likely to be relevant.

5.1.3 Intervals to complete a well

The decision as to which intervals to complete in a well is made after the drilling of the well and is based on: (1) the overall recovery strategy for the field and (2) the specific electric logs of that well.

The overall recovery strategy for the field is determined using geological characterization at a macroscale, which is the same for all the realizations. For example, if the oil column is thick with homogeneous permeability, if there is an active bottom aquifer and if no gas cap is expected to be formed during production, the strategy may be to complete only the upper intervals for production. In another example, if the reservoir is multilayered with small hydraulic communication between the layers and if there is a lateral aquifer or waterflood, the strategy may be to complete all the good layers to start producing and to return to the well in the future to close some intervals with very high water cut.

The definition of the specific intervals to complete in a well is made based on the electric logs, which show the good and bad intervals for that well. Typically, the data from the well are considered deterministically, the well information is assumed laterally continuous around the well and no uncertainty is considered in the definition of the specific intervals to complete in the well.

Therefore, in general, the consideration of multiple realizations to decide the intervals to complete a well for production is not likely to be relevant.

5.1.4 Number of platforms

The definition of the number of platforms is not really a problem different from the definition of the optimal number of wells and their spatial configuration; the number and location of the platforms must be part of the scenario definition. The profit function used to compare the scenarios must incorporate the costs of different numbers of platforms and the costs of the flow lines to connect the wells to the platforms.

Even for the case where just one platform is considered in all the scenarios, the location of the platform must be known to allow the incorporation of the costs of the flow lines into the profits resulting from the production of different numbers and locations of wells. For example, it may happen that an additional well gives sufficient additional production to pay the additional drilling cost, but that well may be very far from the platform and the inclusion of its flow line costs may lead to a lesser profit.

Considering geological uncertainty may be relevant to decide between one, two or three platforms when the number of wells is moderate (less than 50). The necessity to consider scenarios with different number of platforms depends on:

- The maximum number of wells within the range of possible numbers of wells defined by the scenarios.
- The expected total length of the production lines with different number of platforms.
- The cost of the flow lines by unit of length.
- The cost of the platforms with different sizes (number of wells).

Using the maximum number of wells, if the cost of increasing the number of platforms increases more than the decrease in the cost of the flow lines, then there is no necessity to consider different numbers of platforms in the scenarios.

However, if the cost of increasing the number of platforms is similar to or smaller than the decrease in the costs of the flow lines, then different numbers of platforms need to be considered in the scenarios.

Note that the assessment of the necessity to consider different numbers of platforms in the scenarios is not influenced by the geological uncertainty, for a moderate number of wells.

For a very large number of wells, the scenarios are defined by regular grids of wells and the number of platforms is defined based on the costs of platforms, costs of flow lines and multiphase flow constraints; the eventual difference of production between the realizations does not affect the decision of the number of platforms.

5.1.5 Type of enhanced oil recovery

Lake [44] defines enhanced oil recovery as oil recovery by the injection of materials not normally present in the reservoir. The common types of enhanced oil recovery and their recovery mechanisms are:

- Chemical

- Polymer - improvement of volumetric sweep by mobility reduction.
- Micellar polymer - same as polymer plus reduction of capillary forces.
- Alkaline polymer - same as micellar polymer plus oil solubilization and wettability alteration.
- Thermal
 - Steam (drive and stimulation) - reduction of oil viscosity and vaporization of light ends.
 - In-situ combustion - same as steam plus cracking.
- Solvent
 - Immiscible - reduction of oil viscosity and oil swelling.
 - Miscible - same as immiscible plus development of miscible displacement.

Based on the physical mechanisms of the recovery, it is clear that the fluid properties are more important than the rock properties in the selection of the type of enhanced oil recovery to apply in a reservoir. Although geological uncertainty may have some influence in the selection of the type of enhanced oil recovery, the uncertainty that is really important is the uncertainty in the fluid properties.

5.1.6 Time to start water injection

For reservoirs with original gas cap, a good practice is to start injecting water at the same time the production starts.

For reservoirs with original pressure above the saturation pressure, a company may have a financial gain in delaying the water injection until the pressure drops to a value just above the saturation pressure. This “just above the saturation pressure” point in time is determined by material balance.

Material balance uses the average properties of the reservoir and, therefore, the modeling of geological uncertainty is not necessary to decide the time to start injecting water.

5.1.7 Time to start water treatment

This is not a very common decision, because most of the platforms already have a water treatment plant when they are set up in the location. But, in some cases (on-shore, for example), a company may have a financial gain in delaying the investment in a plant to treat the water produced.

The breakthrough time, that is the time when the first water is produced in any of the wells, is determined by the relative mobility between oil and water and by the easiest communication path between the aquifer (or injector wells) and the producers.

This is probably the type of decision where geological uncertainty has the most influence. Modeling the correct patterns of flow is essential in the determination of the break-through time and kriging should not be applied, because kriging smoothes the high and low values of permeability, delaying the break-through time.

The *Full* approach can be applied to decide the best time to start the produced water treatment, considering scenarios with different starting times.

5.1.8 Direction of a horizontal well

If the reservoir is naturally fractured, the horizontal well should be drilled normal to the main direction of fracture to induce the flow to be in the direction of higher permeability and to communicate a large area of the reservoir with the well. Typically, the definition of the main direction of fractures is made based on seismic data without modeling of the geological uncertainty.

If the reservoir is clearly elongated in one direction, the direction of the horizontal well may be determined without any consideration about the geological uncertainty. Depending on the dimensions of the reservoir, a few horizontal wells aligned with the reservoir length or several horizontal wells aligned with the reservoir width may be defined.

For other reservoirs, though, the definition of the direction of a horizontal well is basically the same problem of the definition of the number and spatial configuration of vertical wells and the consideration of the geological uncertainty is relevant. The *Full* approach can be applied to decide the direction of horizontal well, considering

scenarios with different directions, start positions and lengths for the well.

5.1.9 The best injection scenario

The most common action taken to improve the oil recovery of a reservoir is to inject water (or gas). Unless the reservoir is known to have a very large aquifer (and/or gas cap), injection is always considered in the development plan.

Similarly to a producer well, the performance of an injector well depends on the specific properties of the reservoir around the well and the consideration of the geological uncertainty through multiple realizations may lead to different definitions of the best number and configuration of injector wells.

Among the other types of reservoir management decisions, this problem of defining the best injection scenario was selected to be examined in the remainder sections of this chapter, because: (a) consideration of injection is common and important in the definition of the development plans, (b) the benefits of accounting for the geological uncertainty in the definition of the best injection scenario needed to be quantified, and (c) this problem complements the example used in the previous case studies for the definition of the best scenario including producer and injector wells.

5.2 Methodology to define the injection scenario

The best injection scenario determination must be integrated with the definition of the best production scenario. The best number of injector wells depends on the number of producer wells and the best spatial configuration of injectors depends on the spatial configuration of producers. Therefore, any injection scenario is associated with a production scenario.

Ideally, both scenarios should be defined at the same time and their definition should consider the geological uncertainty. Two ways to do that would be:

1. Define integrated scenarios considering several production scenarios and several injection scenarios for each production scenario, and apply the *Full* approach to decide the best scenario.

The problems with this way are the large number of predefined scenarios and the non-optimality of the decision, since the solution is one of the predefined scenarios.

2. Use an optimization algorithm to determine the best scenario, considering jointly production and injection, for each realization, then retain only the optimum scenarios of each realization in the *Full* approach.

The problem with this way is the large computational time required to obtain the best scenario for each realization. The use of flow simulation to evaluate the response of each scenario and the extremely large number of scenarios defined by all the combinatorial positions of several producer wells and several injector wells, would make the optimization process required for each realization very time-consuming. Moreover, despite all the computational effort, the decision would be optimum only for one realization.

An alternate methodology is proposed below to define the production scenario first, substituting water injection by a simulated strong aquifer, and then to define the best injection scenario, considering the production scenario defined previously.

Considering that: (a) the objective of water injection is to create the same effects as a strong aquifer, (b) the injector wells are never located very close to the producers, (c) the water injected tends to go to the bottom of the reservoir by gravity and (d) the main effect of water injection is pressure maintenance, the representation of the water injection by a strong aquifer in the definition of the production scenario is reasonable.

Although not ideal, this methodology incorporates geological uncertainty, considers optimization of the scenarios and is faster than the joint optimization of both scenarios for every realization.

The steps of this methodology are:

1. Define the best production scenario using the L-optimal quality map and the *Full* approach, as presented in Chapter 3. The difference here is that the best number and locations of the producer wells need to be defined considering that water is being injected in the reservoir.

Since the location of the injector wells is not known yet, the effects of the water injection from wells are represented by the consideration of a strong aquifer. The aquifer can be simulated by considering an analytical water influx or by artificially increasing the size of the cells below the oil/water contact.

2. Build an injection quality map using the production scenario defined previously, a single injector and varying only the position of the injector well in each flow simulation run.

The injection quality for each cell is the resulting cumulative oil production in all the producer wells. The injection quality values near a producer well are expected to be small, unless there is some local barrier between the water injection location and the producer locations.

The same constraints (layers completed, maximum bottom hole pressure and maximum rate) that will be imposed on the actual injector wells are considered for the injector well used to build the injection quality map.

The case study in the next section will analyze the necessity of generating either: (a) an injection quality map for each realization and then the L-optimal injection quality map or (b) just an injection quality map from a deterministic model, either a single realization or the kriged model.

3. Define the range of possible numbers of injector wells.

A material balance, using the total initial production rate and the maximum injection rate per well, gives one of the numbers in the range, as a reference.

The other numbers in the range are defined by adding and subtracting to the reference one determined by material balance. Sensitivity analysis with flow simulation, using the production scenario and different numbers of injector wells can reduce the range of numbers of injector wells that comprises the best solution. The configuration of the injector wells in the sensitivity analysis just has to ensure that none of the injectors are too close to any producer and that there is a reasonable spacing between the injectors.

4. Determine the best configuration for each number of injector wells, using the same procedure used to optimize the configurations of producer wells. In the injection case, the total injection quality associated with the injector wells is maximized instead of the total quality associated with the producer wells.
5. Define the best number of injector wells, using only the best configuration for each number of wells.

The choice of which of the three approaches (*Full*, *Conv-1* or *Conv-k*) should be used to decide the best number of injector wells was investigated in the case study described in the next section.

5.3 Case study with water injection

5.3.1 Settings

A case study with ten reservoirs was undertaken to: (a) illustrate the methodology proposed to define the best scenario including production and injection, (b) check the goodness of the location of injector wells using an injection quality map, and (c) evaluate the benefits of accounting for geological uncertainty to define the best injection scenario after definition of the production scenario.

Reservoirs used

The same ten reservoirs selected randomly for Analysis 1 in Chapter 4 were used here. However, the thickness of the bottom layer was modified to make the reservoirs suitable for waterflooding.

The reservoirs were generated originally with a very thick bottom layer, to ensure the existence of a strong bottom aquifer in the previous case studies without water injection. The presence of a strong aquifer was necessary because, in addition to the local permeability around the well, the production of water is what makes the difference between two well locations.

The thickness of the original bottom layer was reduced by a factor of 25 in this case study, making the injection of water necessary for a better recovery in the ten reservoirs.

Production scenario

The first step of the proposed methodology is to find the best production scenario, considering the presence of a strong aquifer in the reservoir, using the L-optimal quality map to locate the wells, and using the *Full* approach to define the best number of wells.

One way to consider the presence of a strong aquifer is to increase the thickness of the cells below the oil/water contact. In this case study, a strong aquifer was simulated by moving the base of the bottom layer back to its original position, that is using the original reservoirs for the definition of the production scenario. Before moving the base of the reservoirs to a lower position, it was verified that in none of the reservoirs the oil volume would be increased too, indeed the oil/water contact was always above the base of bottom layer.

An analytical water influx could have been considered instead of increasing the aquifer thickness, but the second option was preferred here because the best production scenario, using the lower quartile quality map and the *Full* approach, had already been determined in the case study of Chapter 3 for the original reservoirs.

In all the other steps of the proposed methodology, the actual (reduced) thickness of the aquifer was used.

Injection quality maps

An injection quality map was built for each realization and for the kriged model, using the defined production scenario and just one injector well for each evaluation of the injection quality. The same sampling scheme used in Chapter 3 (see Figure 3.5) was repeated here to select the points where the injection quality was evaluated by a flow simulation. The maps were generated by interpolating injection quality to all the cells, using kriging.

The L-optimal map considered was the lower quartile injection quality map, obtained with the distribution of injection qualities (from the 20 realizations) for each cell. The injection quality map of Realization 1 was selected to represent the case of just one realization.

Figure 5.1 shows the injection quality maps (of one of the reservoirs) used to check the benefits of accounting for geological uncertainty in the location of injector wells after definition of the production scenario. The maps are the lower quartile injection quality map, the injection quality map of Realization 1 and the injection quality map of the kriged model. The mean injection quality map and the map of injection quality uncertainty (quality standard deviation over all realizations for each cell) are also presented at the bottom of the figure to show how the uncertainty around the producer wells further decreases the lower quartile values, making the location of an injector well near a producer well very improbable using the lower quartile injection quality map. The production scenario used to build the injection quality maps is shown in all the maps.

Range of numbers of injector wells

One of the numbers of wells in the range of possible numbers of injector wells was determined by material balance. The total injection rate, under reservoir conditions, was made equal to the total initial production rate, considering the production scenario. Then the number of injector wells was determined by dividing the total injection rate by the maximum injection rate allowed in each injector well.

Five other numbers of wells were defined for each reservoir through sensitivity analyses with different numbers around the number determined by material balance. For these analyses, the injector wells were distributed over the grid, making sure that they were not too close to any producer nor to any other injector.

The range of six numbers of injector wells was found wide enough to comprise the best solution for all the ten reservoirs.

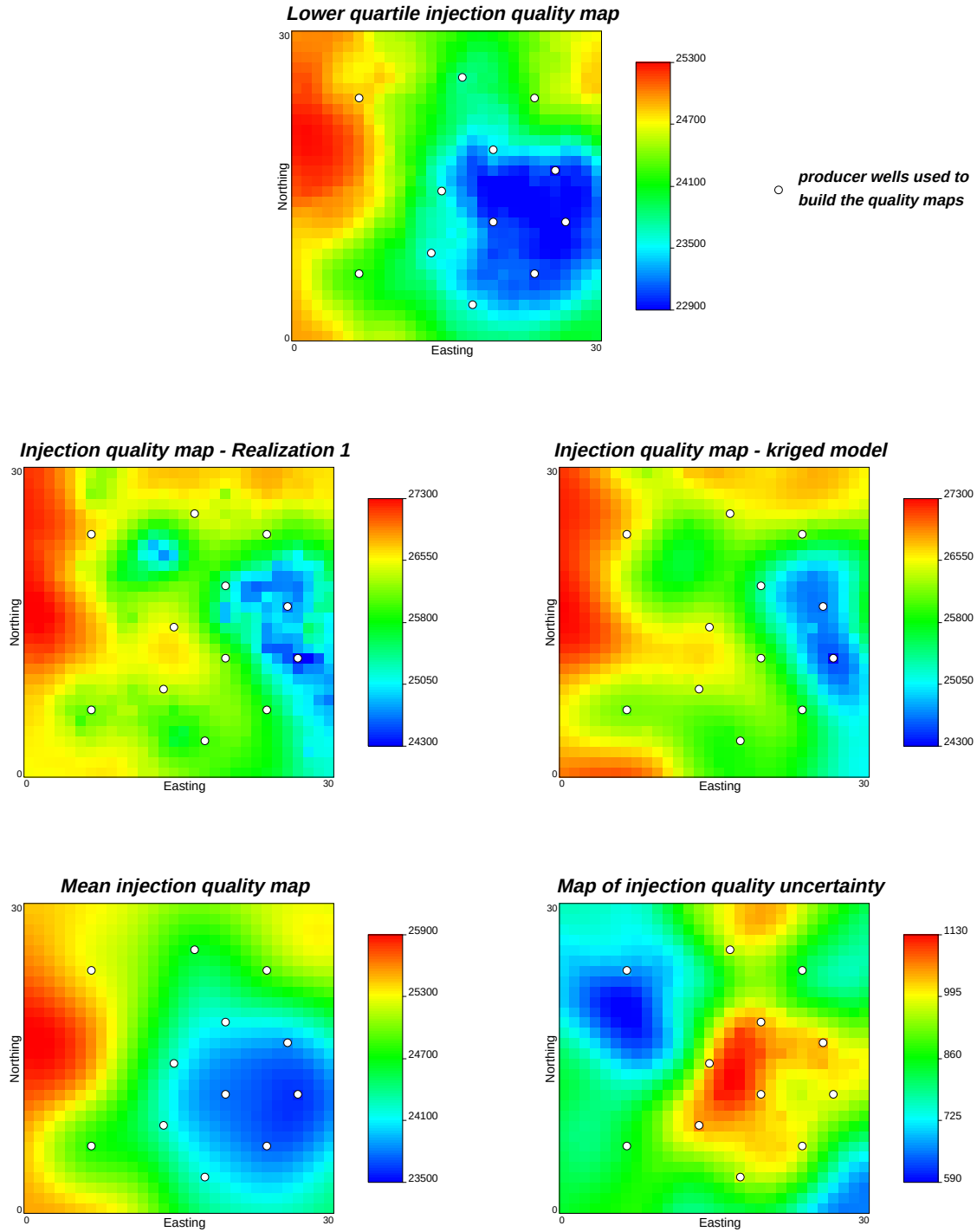


Figure 5.1: Types of injection quality (Mm^3) map with the positions of the producer wells used to build the maps.

Best configuration for each number of injector wells

The best configuration was found for each number of wells and for each of the three injection quality maps considered (lower quartile injection quality, injection quality of Realization 1 and injection quality of the kriged model).

The same procedure used to locate the producer wells was used here. However, an analysis was made to find the best exponent b in the weighting formula ($w_c = \frac{1}{d^b}$). This analysis used Realization 1 of the ten reservoirs, six numbers of injector wells and three different values for the b exponent ($b = 0.5$, $b = 2$ and $b = 6$).

Figure 5.2 shows an example of the best configuration for just one number (six) of injector wells, obtained with different b values and the profits resulting from the production (in the producer wells) with water injection in the locations presented. It can be seen that the higher the exponent b , the more clustered the injector wells in the high injection quality regions and the more separated the injector wells are from the producers.

On average over the six numbers of injector wells and over the ten reservoirs, the b value that resulted in higher profits was $b = 6$. This value was retained to find the best configuration for each number of injector wells with the three types of injection quality map.

5.3.2 Results

Checking the goodness of the locations of injector wells

It is difficult to check how good the locations of the injector wells are. A configuration for a certain number of wells could be declared the best only if all the combinatorial positions of wells were tried using a flow simulator. Since the number of possible configurations is extremely large, the determination of the actual best configuration was never done in this exercise.

The goodness of the well locations was checked by comparing the results of the locations with the injection quality map and with a different map generated only for this purpose. This new map is a composite permeability map and is intended to represent the common procedure to select the well locations looking at the permeability

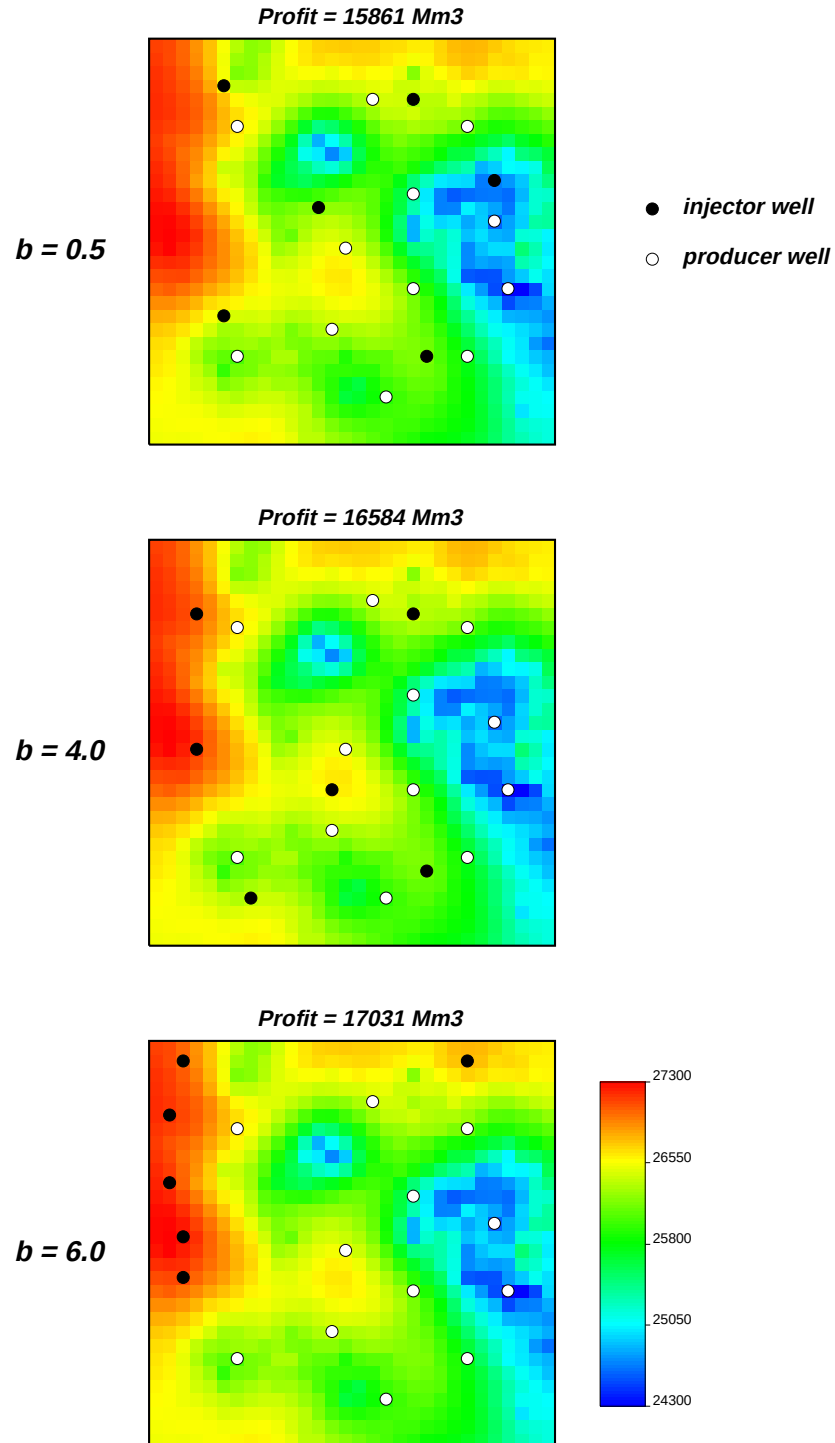


Figure 5.2: Different configurations for six injector wells in function of the values of the exponent b in the weighting formula. The injection quality maps and the profits are for Realization 1. The unit in the maps is Mm^3 .

maps of the layers.

Considering that there are six layers and most of the production occurs in the two upper layers, a good location for a injector well should have good horizontal transmissibility in Layers 6 (bottom), 5 and 4 to ensure good injectivity, and a Layer 3 that is thick and/or has small vertical permeability to delay the water production. Thus, the composite permeability value for each cell was determined by the formula:

$$\text{composite permeability} = \ln \left((k_{x_6}h_6 + k_{x_5}h_5 + k_{x_4}h_4) \cdot \frac{h_3}{k_{z_3}} \right) \quad (5.1)$$

where: h = thickness,

k_x = horizontal permeability and

k_z = vertical permeability

Since the composite permeability map does not account for the positions of the producer wells, an additional constraint was imposed in the well location algorithm in order to have a certain number of blocks n around a producer well where an injector well can not be placed.

Using two different values for n ($n = 2$ and $n = 4$) and three different values for the exponent b ($b = 0.5$, $b = 2$ and $b = 6$), six different configurations for each number of wells were obtained with the composite permeability map to be compared with the configuration obtained with the injection quality map.

The six different configurations for each number of injector wells were intended to represent injection schemes with different levels of importance attributed to the composite permeability map, different spacings between the injectors and different separations between injectors and producers. Moreover, only the best result from the six configurations was used in the comparisons with the result using the injection quality map.

Figure 5.3 shows the six configurations obtained for six injector wells (for a particular reservoir), using the composite permeability map and the two n values and the three b values. The higher the b value, the more concentrated the wells in the high composite permeability regions. The higher the n value, the more separated the injector wells from the producers. The profits from each configuration are also

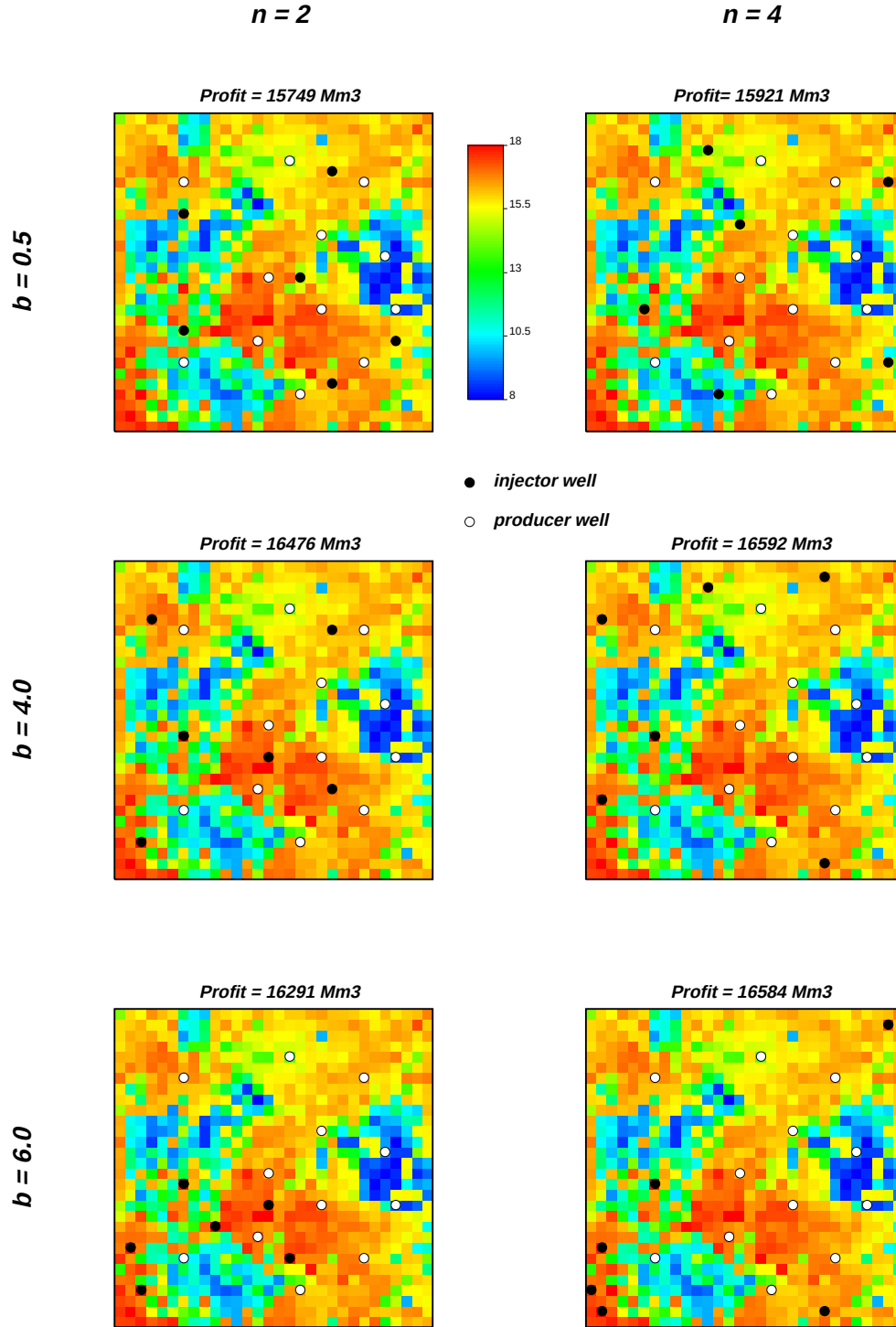


Figure 5.3: Different configurations for six injector wells with the composite permeability map and different values for the minimum number n of blocks between an injector and a producer and for the exponent b in the weighting formula. Unit= m^2 .

given, showing that for the reservoir used in the figure, the best result was obtained for $n = 4$ and $b = 4$.

Six different numbers of injector wells were located with the injection quality map and with the composite permeability map. The comparisons were made with the average results over the six different numbers of wells.

Figure 5.4 presents the results of the locations of injector wells using the injection quality map or the composite permeability map for Realization 1 of ten reservoirs. The differences between the results with the injection quality map and the results with the composite permeability map are presented at a different scale. It can be seen that the results with the injection quality map were better than those with the composite permeability map for all the reservoirs.

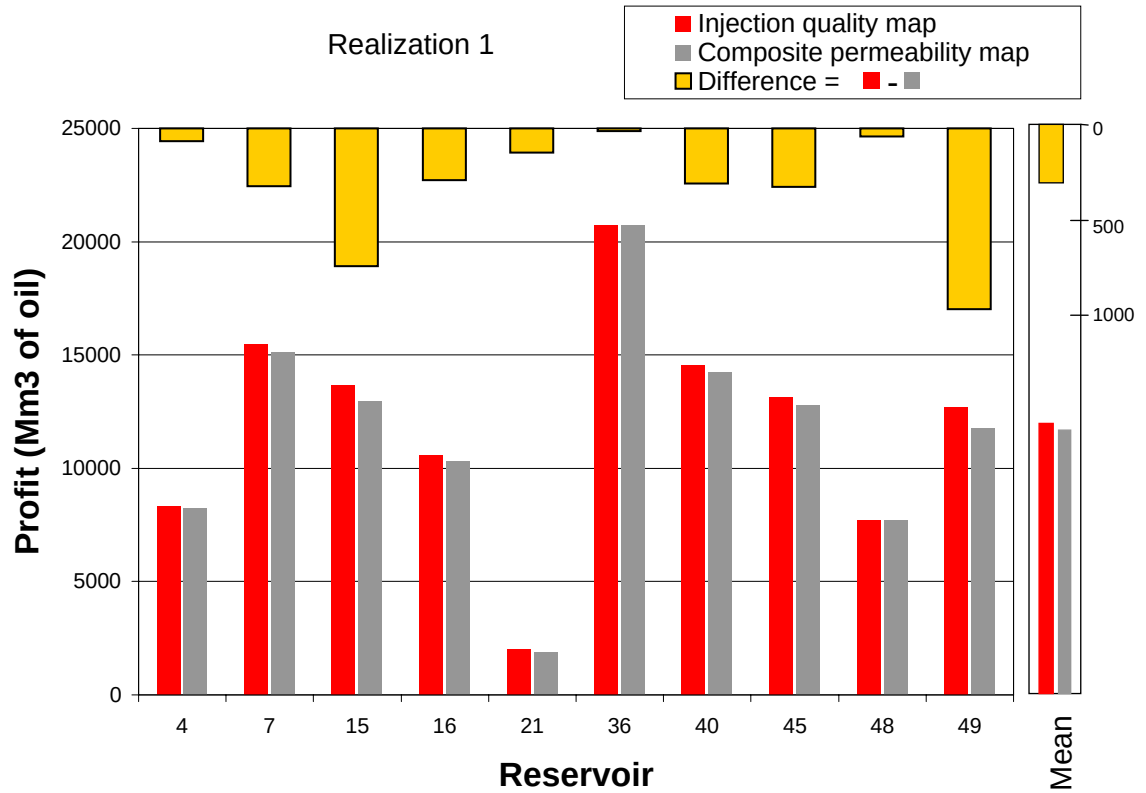


Figure 5.4: Results of the locations of injector wells using the injection quality map and the composite permeability map for Realization 1 of ten reservoirs.

Only Realization 1 was used in both maps because the comparison between the goodness of the well locations was made intentionally without consideration of uncertainty; we wanted to know which map would provide better well locations if the reservoir was exactly that one. However, it was also verified that applying the locations of the wells in the true reservoirs, the true profits obtained with the injection quality maps were higher than the true profits with the composite permeability maps for all the reservoirs.

The goodness of the locations of injector wells with an injector quality map was also checked using the differences in profit and in the final oil recovery of the true reservoirs with and without water injection.

Without injection, the mean profit over the ten reservoirs was $2,268 \text{ Mm}^3$ of oil, while with injection the mean profit was $11,876 \text{ Mm}^3$ of oil. Without injection, the final recovery (mean over the ten reservoirs) was 7.36 %, while with injection the mean recovery was increased to 47.24 %.

Although this is not a check of the optimality of the locations, it gives an idea about how good the locations are. Note that: (a) 47.24 % is a good oil recovery with water injection, and (b) the recovery could have been higher if more wells had been used but the profit would have been lower.

Definition of the best injection scenario

After obtaining the best configuration for each number of injector wells using the three types of injection quality map (lower quartile injection quality map, quality map of Realization 1 and quality map of the kriged model), the best number of wells was determined by applying the associated approaches (*Full*, *Conv-1* and *Conv-k*).

The number of injector wells and their optimal spatial configuration determines the injection scenario. The best injection scenario defined from each map and the associated approach was applied to the true reservoir yielding true profit, which was used for the comparisons.

Note that the production scenario is the same for the three types of injection quality map and that, by the proposed methodology, geological uncertainty is taken into account for the definition of that production scenario. Only the additional benefit

of accounting for geological uncertainty in defining the best injection scenario, *after* the definition of the production scenario, are being evaluated in this section.

Two types of comparisons were made: (1) using the mean true profit over the results with six different numbers of injector wells, and (2) using the true profit attached to the number of injector wells defined as the best. The first comparison relates to the goodness of the injection quality map to locate injector wells. The second comparison relates to the goodness of each approach in defining the best injection scenario.

Figure 5.5 presents, for one of the reservoirs, the best scenarios defined with the three types of injection quality map (left side) and the corresponding distribution of the true profits for the six numbers of wells (right side). For the reservoir presented in the figure, the lower quartile injection quality map provided better locations of wells on average (higher mean true profit over six wells) while the injection quality map of Realization 1 and the *Conv-1* approach provided a better definition of the best injection scenario.

Using Figure 3.9, which shows the same comparisons as Figure 5.5 (although for a different reservoir) as a reference for the case of production wells, note that the differences between well locations using the three types of quality map are smaller in the case of injector wells. The locations of the injector wells are influenced strongly by the production scenario, which is the same for the three types of injection quality maps.

Figure 5.6 presents the comparison between the goodness of the three types of injection quality map to locate wells for ten reservoirs. The goodness of the maps is evaluated by the mean true profit over the results of the locations of six different numbers of injector wells. All the results were divided by the result of the injection quality map of the kriged model to better compare them in the same figure. It appears that none of the maps was clearly better than the others.

Figure 5.7 presents the comparison between the results of the best injection scenario for ten reservoirs. The best injection scenarios were defined using the three associated approaches to select the best number of injector wells among six different numbers of wells, after finding the best configuration for each number of wells with

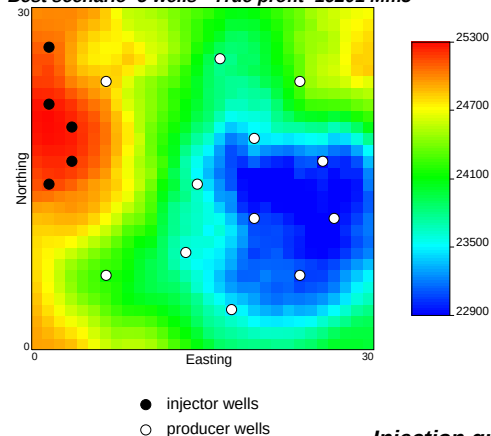
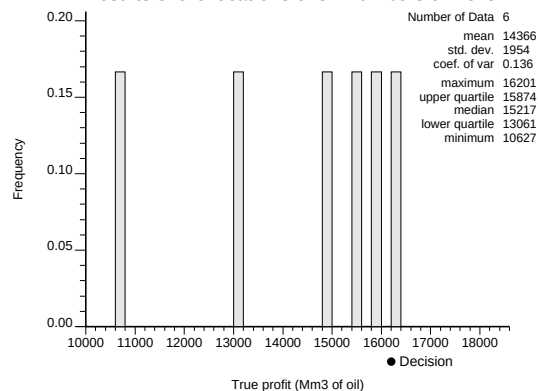
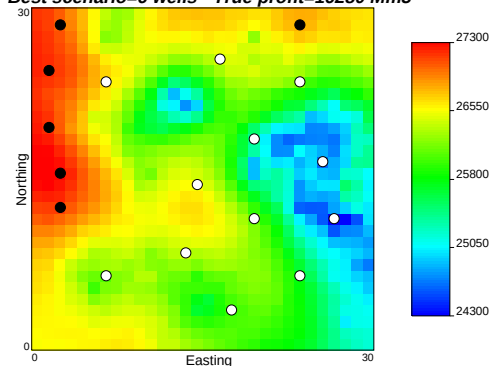
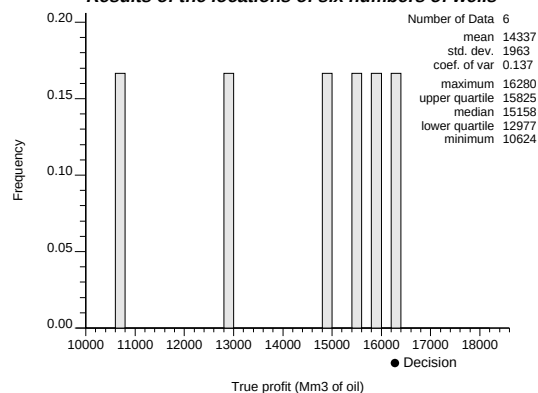
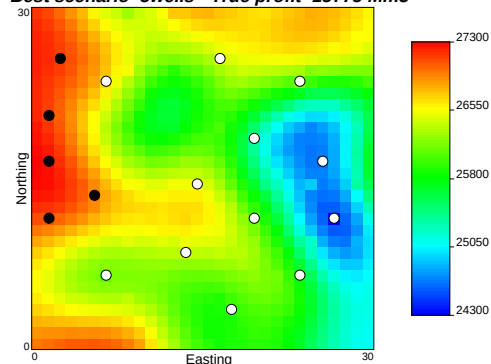
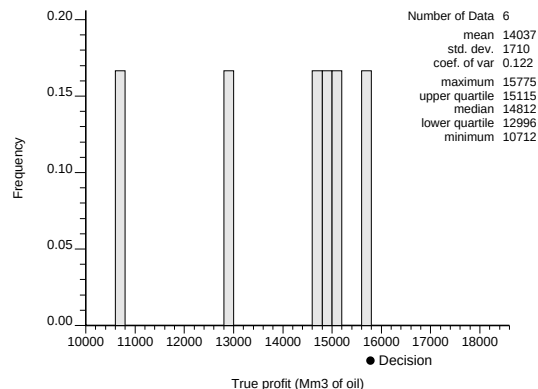
Lower quartile injection quality map**Best scenario=5 wells - True profit=16201 Mm³****Results of the locations of six numbers of wells****Injection quality map of Realization 1****Best scenario=6 wells - True profit=16280 Mm³****Results of the locations of six numbers of wells****Injection quality map of the kriged model****Best scenario=5wells - True profit=15775 Mm³****Results of the locations of six numbers of wells**

Figure 5.5: Best injection scenarios defined with the three types of injection quality map (left side) and the distribution of true profits for six numbers of wells located with each map (right side). Unit= Mm^3 .

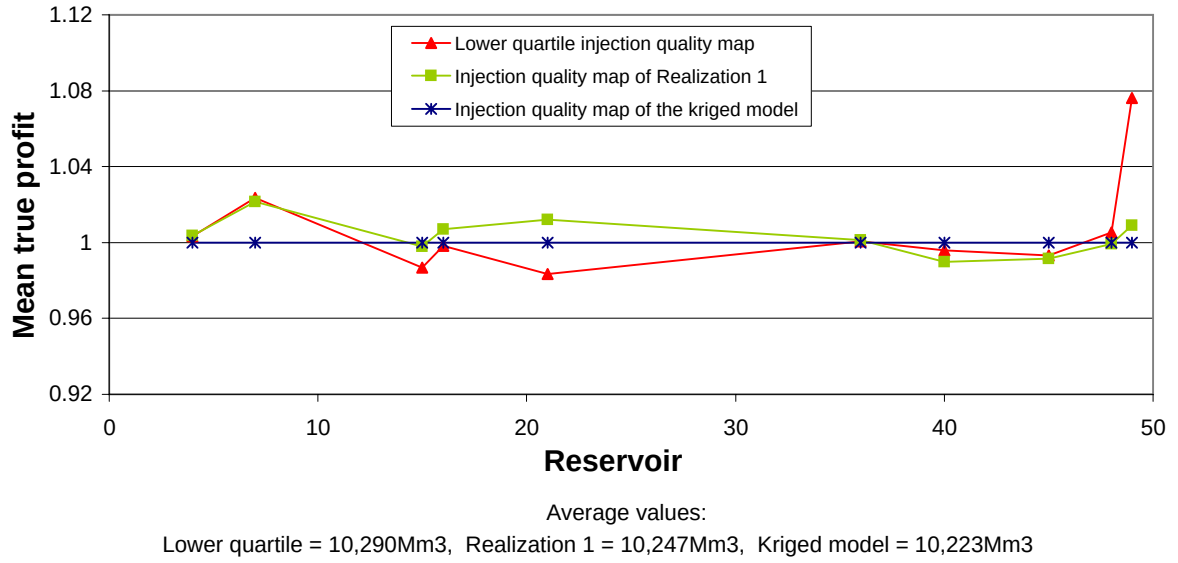


Figure 5.6: Mean true profits over the locations of six numbers of wells with three types of injection quality map for ten reservoirs. All the results are divided by the result of the injection quality map of the kriged model.

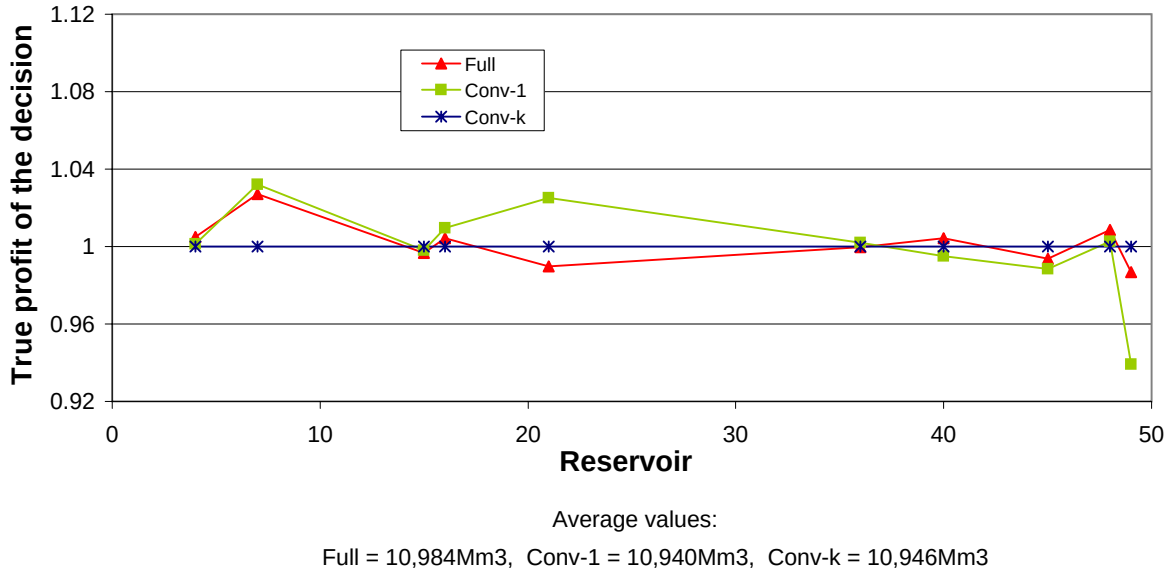


Figure 5.7: Results of the decision of the best injection scenario with the approaches associated with the three types of injection quality map for ten reservoirs. All the results were divided by the result of the *Conv-k* approach.

the three types of injection quality map. All the results are divided by the result of the *Conv-k* approach. It appears again that none of the approaches was clearly better than the others.

The differences between the approaches are due mainly to the differences between the locations of the wells with the associated injection quality maps. The use of 20 realizations in the *Full* approach to decide the best injection scenario was not relevant, because in almost all the realizations the decision was the same.

The variety of scenarios that are obtained with the proposed methodology can be visualized in **Figure 5.8**, which shows the best scenario, including production and injection, for ten reservoirs. The production scenarios were obtained locating the wells with the lower quartile quality map and deciding the best number of wells with the *Full* approach. The injection scenarios were obtained locating the wells with the injection quality map of Realization 1 and deciding the best number of wells with the *Conv-1* approach.

5.3.3 Conclusions

1. The proposed methodology yields good integrated scenarios, which include both production and injection. With this methodology the production scenario is defined first, assuming the presence of a strong aquifer, and then the injection scenario is defined, considering the previously defined production scenario and using an injection quality map to locate the wells.
2. Through the proposed methodology, geological uncertainty is considered in the definition of the production scenario. However, for the definition of the injection scenario, after definition of the production scenario, the consideration of the geological uncertainty is not likely to be relevant and just one geological model can be used.
3. Using one realization is preferred over using the kriged model to define the best injection scenario, since the realizations have to be generated in advance to define the production scenario.

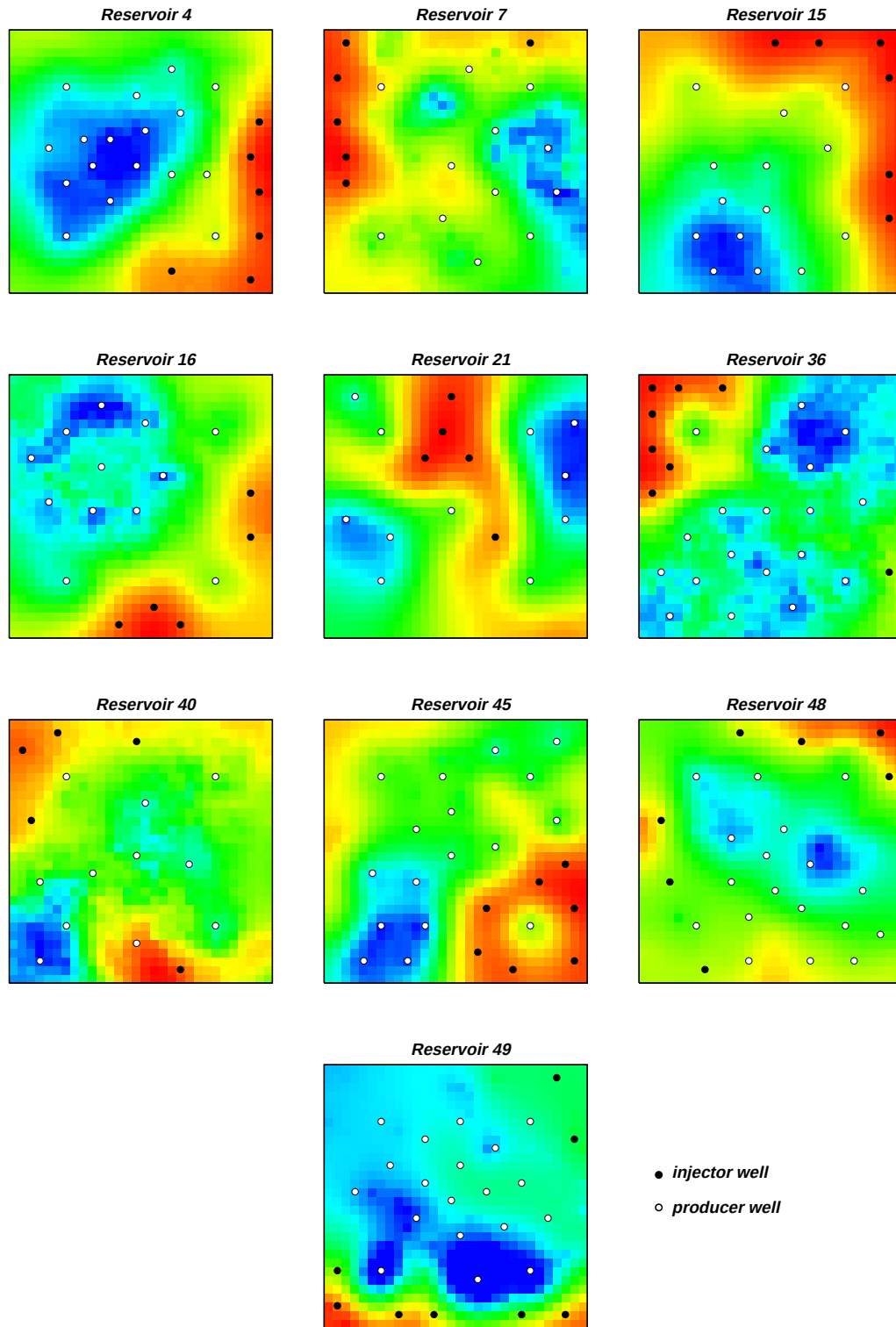


Figure 5.8: Best scenario, including production and injection, for ten reservoirs. The maps are the injection quality maps of Realization 1 of each reservoir.

5.4 Discussion

5.4.1 Relevance of accounting for the geological uncertainty

Table 5.1 summarizes the analyses made about the relevance of considering geological uncertainty for several reservoir management problems. This table presents very generic rules. The solution of a specific problem may be realization-dependent, even though the generic class of that problem was presented otherwise in the table. That could be the case, for example, of the location of a single injector well after the definition of the production scenario.

From the table, it is clear that Problem 1 (location of a small number of producer wells), is the problem for which consideration of geological uncertainty is most relevant. That was the reservoir management problem used in the case studies of Chapter 2, 3 and 4.

It is important to note that the term “vertical well” used in the classification of problems does not exclude wells that are drilled deviated due to some drilling strategy. The only requirement for a well to be considered vertical in this research is that the horizontal cell, where the well is located, needs to be same in all the layers.

5.4.2 Fine adjustment of the locations of injector wells

The algorithm to determine the best configuration for each number of wells accounts for the interaction between the wells through the evaluation of total quality. However, for the case of injector wells, the interaction between the wells to generate a good displacement of the oil is also important and this kind of interaction is not captured explicitly by the algorithm.

This may result in non-optimal configurations, in terms of displacement. It is possible, for example, to have an injector just behind another injector well, in a situation where the two wells located side by side would provide a better displacement front and a final higher oil recovery, even with a smaller total injection quality.

Table 5.1: Generic relevance of the consideration of the geological uncertainty for reservoir management problems.

Problem			Geological uncertainty relevant?	Comments
1)	Location of small number of producer wells		yes	Problem used in the case studies of Chapters 2, 3 and 4
2)	Location of large number of wells in regular grid		no	Overall response of the scenario is determined by the well spacing and average properties of the reservoir
3)	Vertical or horizontal well?		no	Uses a macro characterization of the reservoir, which is the same in all realizations
4)	Intervals to complete a well		no	Uses overall recovery strategy (which does not depend on the realization) and the specific electric logs of the well
5)	Number of platforms	small number of wells	yes	Problem should be integrated with Problem 1
		large number of wells	no	Same as Problem 2 plus greater importance of the costs of platforms and lines and of the multiphase constrains than eventual production differences
6)	Type of EOR		no	Fluid properties are more important
7)	Time to start water injection		no	Time is determined by material balance
8)	Time to start water treatment		yes	Not a common problem
9)	Direction of a horizontal well	naturally fractured reservoirs	no	Main direction of fracture determined by seismic
		stretched reservoirs	no	Overall shape of the reservoir does not change with realizations
		other reservoirs	yes	Problem similar to Problem 1
10)	Location of injector wells after the definition of the production scenario		no	Location of the injectors are strongly affected by the production scenario

Instead of adding constraints in the algorithm to account for displacement interactions, it is preferable to use the algorithm as it is and to inspect the final configurations. If situations of non-optimal displacement are found in the configurations, a fine adjustment of the well locations may be necessary to relocate one or two wells, thereby improving the global displacement of oil by the injected water.

An example of this type of non-optimal configuration may be seen in Figure 5.5, in the injection quality map of the kriged model. If the injector well located towards the East was brought more to the West, the injector wells would be more aligned and the profit would be higher, as suggested by the results of the configurations resulting from the other two injection quality maps.

5.4.3 Hierarchical decisions

Some reservoir management problems are very complex. For example, a scenario may involve the definition of number and position of platforms; number and type of producer wells; number and type of injector wells; direction, start position and length of the horizontal wells; different times to start producing or injecting in each well; different layers completed in each well; etc.

Theoretically the *Full* approach can always be applied to select the best scenario among a set of predefined scenarios, but the number of predefined scenarios necessary to cover all the possibilities in a very complex problem may make the the *Full* approach impracticable.

One possible solution is to split a complex problem into simpler problems, to sort the simpler problems in order of importance and to solve them from the most important to the least important. In the solution of each problem, simplifications of the impacts of the variables of the other problems may be necessary.

An example of this kind of hierarchical decisions is the definition of the integrated scenario (involving production and injection) that was presented in this chapter.

Chapter 6

Contributions, Conclusions and Future Work

6.1 Contributions

The principal contributions of this research have been:

1. Introduction of the *Full* approach, which is a comprehensive method to incorporate geological uncertainty and the profit desire and risk aversion profile of the company into reservoir management decision-making.
2. Introduction of the quality map, which integrates all the three-dimensional geological variables and the fluid variables into a single two-dimensional characterization of a reservoir model. This two-dimensional characterization can be used to visualize good and bad areas for production, to locate wells, to rank realizations, to identify a representative realization and to help comparing reservoirs.
3. Presentation of an optimization algorithm that can be used to locate wells based on any two-dimensional property of the reservoir.
4. A better understanding of the benefits of modeling the geological uncertainty through multiple realizations for reservoir decision-making purposes.

The results and conclusions of the case studies are based on 50 reservoirs and more than 450,000 flow simulations.

5. The application of the methods presented in this research does not require any specific training nor the assimilation of any new theory; the methods require only two basic skills in reservoir management: geostatistical modeling and flow simulation.

6.2 Conclusions

1. Location of a moderate number of wells (less than 50) is the reservoir management problem for which consideration of geological uncertainty is most relevant.
2. On average over several reservoirs, the consideration of geological uncertainty, through multiple realizations using the *Full* approach, provides better decisions regarding the best number and spatial configuration of wells than the use of a deterministic model, either a single realization or the kriged model.
3. The L-optimal quality map, obtained by building a quality map for each realization and by integrating all of them with a loss function, allows well locations to be decided accounting for geological uncertainty and for the profit desire and risk aversion of the company.
4. The larger the number of available data, the smaller the uncertainty, the better the decisions and the smaller the benefit of modeling uncertainty, but the potential gains are always much higher than the computational costs required to incorporate multiple realizations into the decision-making.

6.3 Future work

1. For complex reservoir management problems, which involve decisions about several development plan parameters, the solutions presented in this research may not be ideal.

The *Full* approach could be used, but the number of scenarios to consider would be too large and, since these scenarios are predefined, the solution may not be optimal.

The hierarchical approach suggested in Section 5.4.3 to split the problem and to solve each one of the smaller problems in order of importance, considering simplifications for the interactions between the problems, is a way to optimize each individual problem, but the global solution is not guaranteed to be optimal.

Global optimization algorithms presented in the literature are typically very slow because they call for flow simulation for the evaluation of the objective function. Moreover, they use only one deterministic model.

Thus, an algorithm to consider geological uncertainty and to optimize jointly all the parameters involved within a reasonable computational time would be useful.

2. The idea presented in Section 3.4.4, to use pressure superposition to account for interference between the wells in the optimization algorithm to locate wells, needs to be developed, implemented and tested.

The following points need to be defined to test the idea:

- the time to record the pressures of all cells,
- the formula to average the pressures of all the layers in each cell of the horizontal grid.

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Appendix A

Generation of the True Reservoirs

A.1 General characteristics

A total of 50 “true” or reference reservoirs were generated to be used in the case studies of this research. Several FORTRAN programs were developed and run together with GSLIB [15] programs, using a UNIX script file, in order to automatically generate reservoirs that were as realistic and different from each other as possible. Probability distributions for all the necessary parameters were defined and values were drawn from these distributions using seed numbers based on the reservoir number. Thus, given the reservoir number, a unique reservoir was generated using the script file.

The reservoirs are defined on a $90 \times 90 \times 60$ grid. They all include six main stratigraphic layers with ten sublayers in each. The reservoir volumes, productivity and lithology represent medium size offshore reservoirs with sandstone/shale lithology. No faults or fractures were considered.

Two phases (oil and water) were considered and the initial saturation of the fluids was determined by the position of the oil/water contact. That contact was the same for all the reservoirs but the different top structure and the different thickness and porosity of the layers resulted in very different volumes of oil and water for each reservoir.

The number of layers is the same (six) for all reservoirs but the thickness for each layer is drawn from uniform probability distributions with realistic values. The

bottom layer is thicker than the other layers to ensure a strong bottom aquifer for all the reservoirs. The presence of such strong aquifer was necessary because, besides the local permeability around the well, the production of water is what makes the difference in overall reservoir performance in a choice between two well locations.

All the simulations are nonconditional (there were no data) since these reservoirs are all synthetic. The horizontal grid was the same for all reservoirs ($nx = 90, ny = 90$), with dimensionless grid-block size $dx = dy = 1$. For flow simulation, the dimensions were drawn from a triangular probability distribution $T \in (90, 120, 150)$ to give realistic and different horizontal dimensions for each reservoir. In the previous notation for the triangular distribution, the left number represents the minimum value, the central number represents the most likely value and the right number represents the maximum value.

All reservoirs are composed of sandstone and shale, but shale is present only in Layers 2, 4 and 6. The other three layers have a single lithology (sandstone). Even though the presence of shales was considered in the same layers for all reservoirs, the differences in layer thickness, shale proportion and shale continuity make the final shale distribution very different from one reservoir to another.

To generate the shale lithology (Layers 2, 4 and 6) and the petrophysical fields (porosity and permeability), each layer was modeled with ten sublayers. The total number of grid-blocks is therefore $90 \times 90 \times 6 \times 10 = 486,000$. The main horizontal direction of anisotropy is the same for lithology, porosity and permeability.

Table A.1 gives some global characteristics for the 50 reservoirs. In the table: (a) the original volumes in place are expressed at reservoir conditions, (b) the unit length of the cells are for the horizontal grid after upscaling from the original grid to the 30×30 grid that was used in the flow simulations, (c) the shale proportion is the average proportion over the six layers even though only three layers have shale, (d) the porosity and permeability values are for sandstone only; the values for shale are constant: porosity = 0.01% and permeability = 0.01 md.

Re- ser- voir	Original oil in place (M Rm3)	Original water in place/ Original oil in place (m3/m3)	Mean top (m)	Mean thickness with oil (m)	Unit length of the cells in the 30x30 grid (dx=dy) (m)	Shale proportion (%)	Sandstone porosity		Sandstone permeability	
							Mean	Standard deviation	Mean	Standard deviation
							(%)	(%)	(md)	(md)
1	69346	4.78	2024.4	32.28	128	7.55	17.07	8.41	397.13	535.11
2	77915	3.44	2011.9	49.02	111	7.80	16.89	7.83	344.86	527.33
3	84613	9.94	1997.8	51.31	110	12.59	17.95	8.00	368.54	421.52
4	48818	15.88	2025.4	34.87	101	8.83	17.98	7.35	365.22	577.89
5	49979	8.72	2028.1	28.19	115	7.89	17.63	7.23	332.55	370.56
6	46165	9.96	2025.3	29.81	107	11.91	17.78	7.55	374.93	563.02
7	113256	4.10	1991.0	62.42	114	12.74	18.31	8.15	412.93	592.05
8	54819	5.76	2032.4	24.47	134	9.44	16.39	6.77	344.62	721.34
9	54800	19.28	2029.6	24.95	125	11.41	18.40	7.68	386.09	437.49
10	58582	2.39	2020.3	35.03	117	10.41	15.96	7.67	411.17	938.45
11	81698	3.53	2013.2	42.57	120	9.55	17.50	7.56	368.43	582.91
12	53130	2.57	2018.8	37.90	109	7.18	15.46	6.76	337.30	801.56
13	67523	4.57	2016.6	42.90	108	9.76	17.81	6.96	373.64	717.78
14	71703	3.90	2001.4	51.55	102	9.70	17.38	7.42	366.26	596.20
15	81857	6.92	2003.9	52.11	108	8.58	17.54	7.42	396.27	742.65
16	68752	10.22	2018.1	38.07	116	11.91	17.68	7.75	344.29	383.45
17	69484	5.20	2003.3	54.06	99	8.34	17.11	7.69	455.06	926.87
18	55068	2.29	2021.0	35.78	109	9.58	17.02	7.55	423.73	834.84
19	104249	5.07	1993.9	59.53	112	10.75	18.31	7.93	444.07	707.11
20	64882	14.41	2031.2	28.50	127	9.55	18.56	7.73	389.94	467.82
21	32533	22.48	2038.7	20.58	112	4.83	16.42	7.64	392.20	837.90
22	45690	10.12	2028.6	28.02	108	9.08	18.24	8.05	450.17	759.60
23	43549	32.73	2037.7	19.92	125	10.14	18.37	7.67	396.41	590.56
24	50719	5.40	2016.2	40.75	99	7.77	16.71	7.73	402.38	788.87
25	32625	11.37	2031.5	23.83	101	13.72	17.54	7.52	370.35	588.63
26	122255	5.03	2016.6	42.74	145	9.15	17.83	8.03	398.09	614.89
27	64971	28.56	2032.8	25.17	133	8.65	19.03	7.83	424.64	563.24
28	67884	10.02	2029.7	31.92	124	5.55	18.17	8.36	427.99	620.38
29	59201	17.79	2029.4	27.71	123	10.70	18.48	7.68	419.40	655.10
30	46306	16.76	2022.8	31.37	104	8.10	17.82	6.89	441.59	888.16
31	45483	13.45	2021.6	32.01	103	11.89	17.62	7.45	388.23	647.63
32	56159	5.93	2023.0	32.70	112	11.04	17.98	7.37	353.57	396.47
33	38873	21.60	2034.1	20.12	117	11.24	18.44	7.51	364.41	379.81
34	77097	11.58	2009.5	47.48	110	8.85	17.48	7.75	375.15	535.93
35	37903	29.28	2036.6	19.17	119	10.73	18.41	7.39	359.06	370.48
36	104509	6.70	2004.2	53.78	117	9.52	18.65	7.59	411.64	617.48
37	79159	2.26	2017.7	47.88	114	5.54	16.52	7.77	416.34	885.87
38	73036	7.12	2010.3	44.51	109	9.67	17.95	7.55	390.35	641.62
39	49669	11.60	2021.5	35.85	105	6.38	16.40	7.41	367.68	730.07
40	109179	5.14	1995.4	57.85	116	11.79	18.34	8.23	397.10	464.19
41	82902	2.24	2007.9	56.93	112	6.23	15.07	7.18	442.01	1087.93
42	65905	12.69	2019.5	34.43	121	10.03	17.02	7.49	377.72	711.37
43	92727	11.61	2003.9	50.08	116	9.86	18.15	7.58	345.35	363.33
44	32009	38.05	2039.2	17.16	115	11.10	18.47	6.97	399.60	668.81
45	82140	10.73	2011.2	45.75	113	8.10	18.45	7.47	379.53	506.87
46	43246	7.77	2025.2	34.21	97	10.24	17.57	7.97	422.42	759.75
47	114938	11.50	2013.8	43.72	136	9.56	18.62	7.60	384.37	476.02
48	54694	21.07	2021.1	32.45	111	9.53	17.81	7.69	388.37	609.30
49	73505	17.37	2020.9	35.48	119	9.86	19.08	8.35	419.90	456.24
50	24339	34.58	2043.7	14.66	113	7.26	16.98	7.65	381.48	659.83
Mean	59983	11.71	1858.2	37.27	105	8.70	16.25	6.98	360.98	585.21
Standard deviation	23898	9.16	12.7	12.36	10	1.92	0.90		31.00	

Table A.1: Characteristics of the 50 true reservoirs.

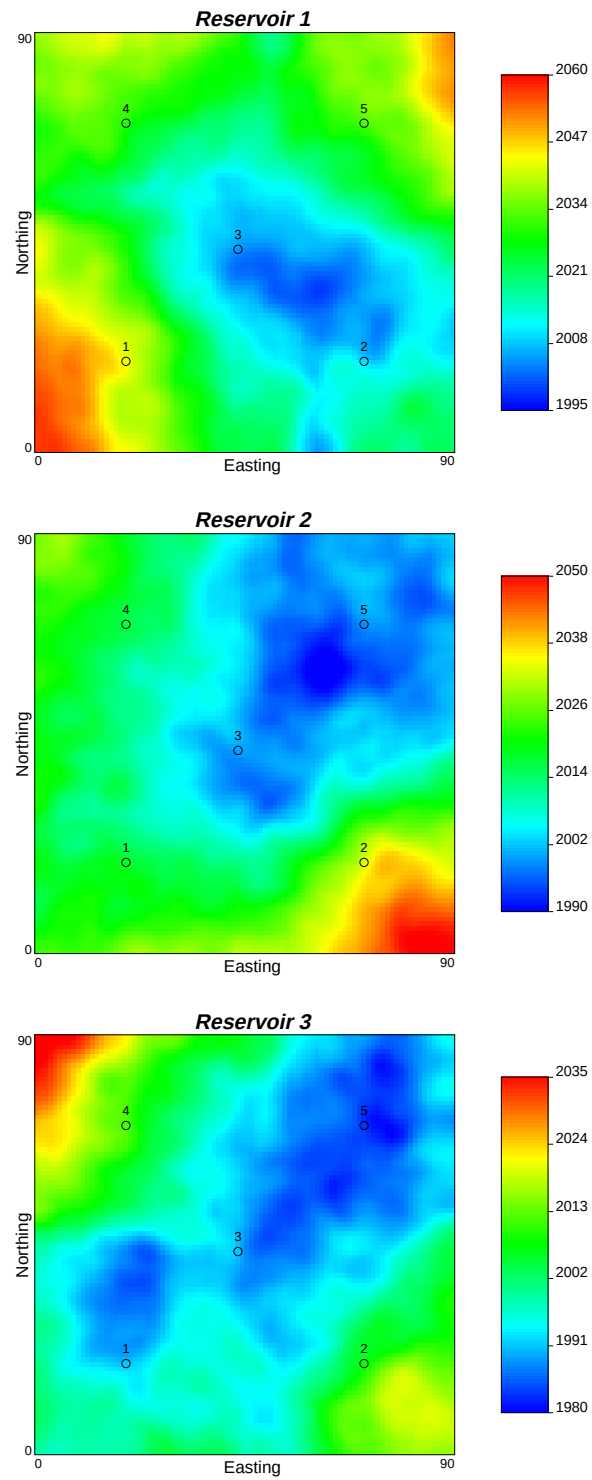
A.2 Top

The top sealing structures of the reservoirs are such that there is closure, that is, the depth is shallower in the center and deeper at the margins. Multiple top-of-structure maps were obtained by first establishing a deterministic surface with minimum depth (2000 m) at the center point and then adding a stochastic component obtained from a nonconditional sequential Gaussian simulation (SGSIM) with Gaussian semivariogram and a relatively long range.

The deterministic surface was established by: (a) drawing a center position, (b) drawing a main direction and magnitude of anisotropy, (c) drawing the increment in top depth for each grid-block away from the center position in the main direction of anisotropy, (d) evaluating top depth for a set of points across the grid using these drawn parameters, and (e) interpolating (using kriging) that set of points to the entire grid. The stochastic component was obtained by transforming the zero mean and unit variance distribution from SGSIM to depth units, multiplying each value by 15.

Figure A.1 shows the top surfaces of the three first reservoirs.

The positions of the sampling wells are shown in Figure A.1 and in all the subsequent figures related to the true reservoirs in this appendix to serve as reference for the comparisons with the figures of the models shown in the next Appendix B.

Figure A.1: Top depth (m) of true Reservoir 1, 2 and 3.

A.3 Thickness

For each reservoir, six isochore maps were generated and added to the top structure to define the geometry of the layers. For each layer, a simulated annealing simulation algorithm (SASIM) was used to generate a field with a triangular histogram and zero mean ($sa_{i,j}, i = 1, \dots, nx; j = 1, \dots, ny$). These SASIM fields were smoothed, redefining the value for each grid-block as the average value within a certain number of blocks (nb) on each side:

$$sa_{i,j} = \frac{1}{(2nb + 1)^2} \cdot \sum_{x=i-nb}^{i+nb} \sum_{y=j-nb}^{j+nb} sa_{x,y} \quad (\text{A.1})$$

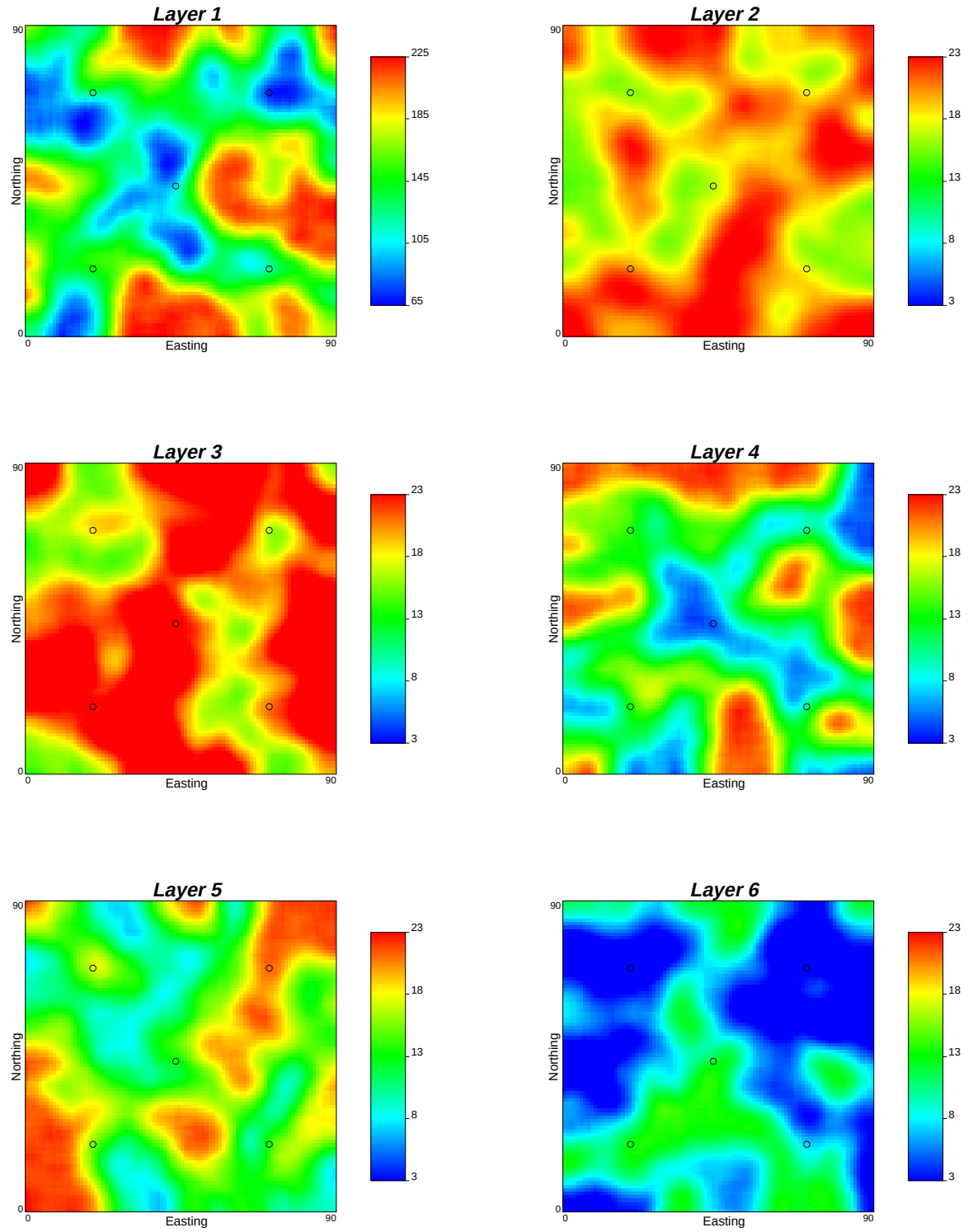
Realistic values of thickness were obtained from the smoothed field using the formula: $t_{i,j} = \bar{t} + sa_{i,j} \cdot \bar{t}v, i = 1, \dots, nx; j = 1, \dots, ny$. Values for mean thickness ($\bar{t}$) and mean thickness variation ($\bar{t}v$) were drawn from the distributions presented in **Table A.2**. In the table, the uniform distribution is defined by (a, b) , with a being the minimum value and b the maximum value, and the triangular distribution is defined by (a, b, c) , with a being the minimum value, b the most likely value and c the maximum value.

Table A.2: Probability distributions for mean thickness and thickness variation used to generate the six layers thicknesses of the true reservoirs.

Parameter	Distribution type	Layer	a	b	c
Mean thickness (m)	Uniform	1	30	330	
		2, 3, 4, 5, 6	2	22	
Thickness variation (m)	Triangular	1	10	50	90
		2, 3, 4, 5, 6	1	5	9

Figure A.2 displays the thickness for the six layers of Reservoir 1.

For each reservoir, the same main horizontal direction of anisotropy was used for shale, porosity and permeability, but some variation was allowed from that main direction for each layer. Thus two different distributions were used for direction: the first uniform $U \in (-90, 90)$ for the average direction which is a property of the

Figure A.2: Thickness (m) of the six layers of true Reservoir 1.

reservoir (the corresponding seed number is defined from the reservoir number), the second triangular $T \in (-10, 0, 10)$ for the variation of each layer about the average direction (the corresponding seed number is a function of the reservoir number and the layer number). The final main horizontal direction of anisotropy for each layer is obtained by adding the values drawn from both distributions.

A.4 Facies

The shale lithology was simulated for Layers 2, 4 and 6 using ELLIPSIM, which is a program that generates three-dimensional ellipsoids. Each layer is itself a three-dimensional grid and was modeled independently. The parameters necessary to run the program for each layer were drawn from the probability distributions presented in **Table A.3**.

Table A.3: Probability distributions of the parameters used in program ELLIPSIM to generate shales for Layers 2, 4 and 6 of the true reservoirs. The lengths are in grid units.

Parameter	Distribution type	Layer	a	b	c
Shale proportion (fraction)	Triangular	2	0.05	0.25	0.45
		4, 6	0.01	0.16	0.31
Major axis radius	Triangular	2	9	18	27
		4, 6	3	9	15
Minor axis radius	Triangular	2	3	6	9
		4, 6	2	3	4
Vertical radius	Triangular	2, 4, 6	1	2	3

Figure A.3 shows six vertical cross-sections in the direction W-E with the facies distribution in the six layers of Reservoir 1.

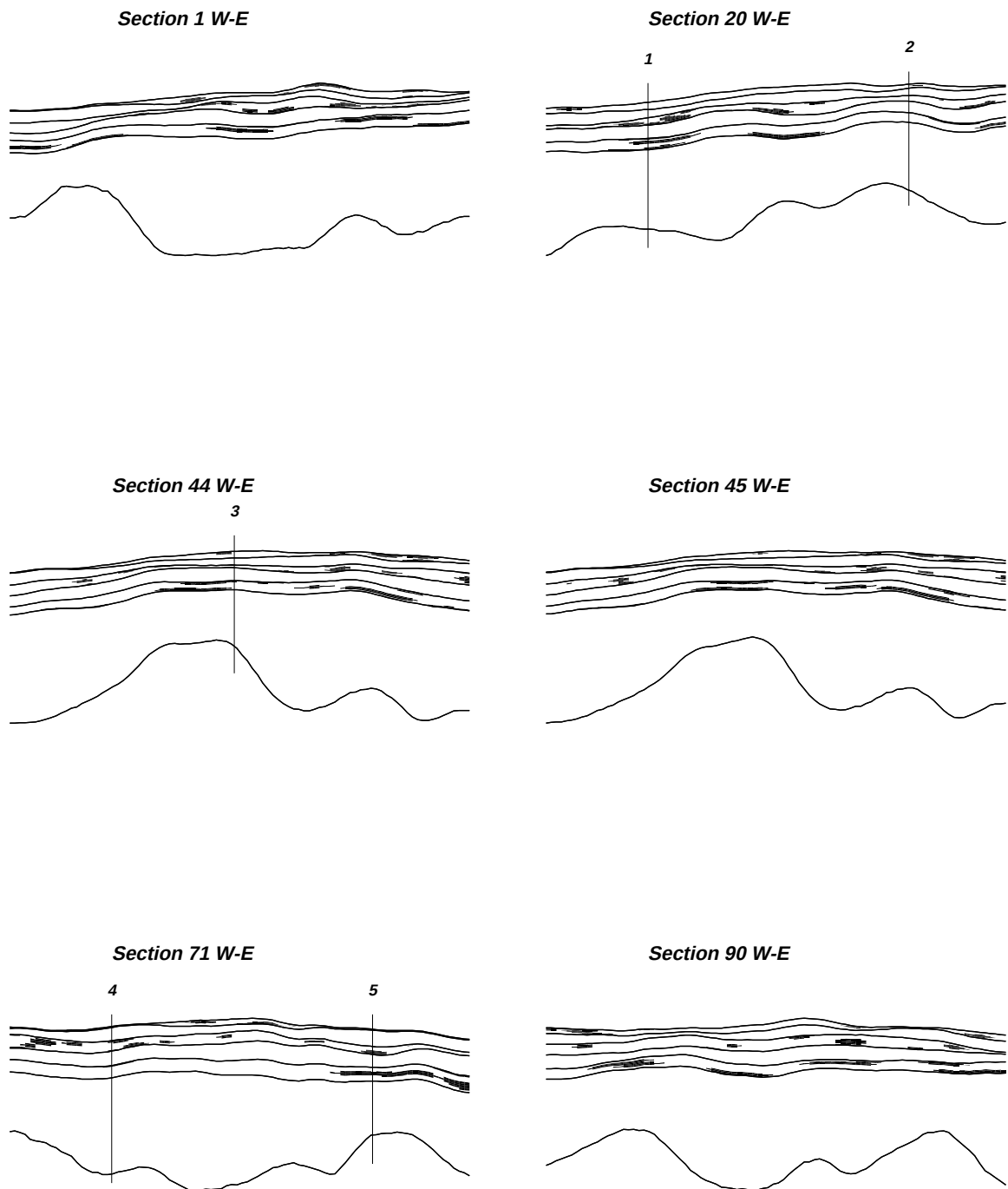


Figure A.3: Cross-sections showing the six layers and distribution of shale (black) and sandstone (white) of true Reservoir 1.

A.5 Porosity and permeability

The three-dimensional sandstone porosity field of each layer was generated using sequential indicator simulation (program SISIM). The cumulative distribution function (cdf) values for the thresholds $z_k, k = 1, \dots, 9$ were fixed: $F(z_1) = 0.1, F(z_2) = 0.2, \dots, F(z_9) = 0.9$. Mean porosity ($\bar{\phi}$) and porosity coefficient of variation (CV_ϕ) were drawn from the distributions presented in **Table A.4**, with the thresholds determined as $z_k = G^{-1}(F(z_k)) \cdot \sigma_\phi + \bar{\phi}$, where $G^{-1}(F(z_k))$ is the inverse Gaussian cdf and $\sigma_\phi = CV_\phi \cdot \bar{\phi}$.

Table A.4: Probability distributions of the parameters of program SISIM used to generate sandstone porosity fields for all the layers of the true reservoirs. The lengths are in grid units.

Parameter	Distribution type	Layer	a	b	c
Mean ϕ (%)	Triangular	1, 3, 5	15	20	25
		2	10	14	18
		4, 6	10	14	18
ϕ coefficient of variation	Triangular	1, 3, 5	0.15	0.30	0.45
		2	0.35	0.50	0.65
		4, 6	0.25	0.40	0.55
Nugget effect	Triangular	1, 3, 5	0.10	0.25	0.40
		2	0.00	0.10	0.20
		4, 6	0.05	0.15	0.25
Maximum horizontal range	Triangular	1, 3, 5	10	20	30
		2	45	60	75
		4, 6	30	40	50
Minimum horizontal range	Triangular	1, 3, 5	8	11	14
		2	30	40	50
		4, 6	15	25	35
Vertical range	Triangular	1, 3, 5	4	6	8
		2	0	2	4
		4, 6	1	3	5

The semivariogram parameters (nugget effect, maximum horizontal range, minimum horizontal range, vertical range) were drawn from their distributions, which are

also presented in **Table A.4**. The semivariogram parameters were assumed the same for every threshold and the program SISIM was run for each layer.

The procedure to generate the sandstone permeability fields was essentially the same as for porosity, except that porosity (ϕ) was used as soft data when simulating permeability (k) to induce a correlation between the two fields. The relationship between ϕ and k was taken as log-linear with a log-normal stochastic component, i.e. $\log(k) = a + b \cdot \phi + N(0, c)$. The values of $a = 1.375$, $b = 0.055$ and $c = 0.10$ were chosen to provide reasonable values for k . After obtaining the bivariate distribution $\phi/\log(k)$, the program BICALIB was used to prepare the data for SISIM, computing the soft (porosity) indicator values (the prior distributions) and the $B(z)$ calibration parameters.

Table A.5 gives the probability distributions used to draw the mean value of $\log(k)$, its coefficient of variation and all the semivariogram parameters necessary to simulate $\log(k)$. After the simulation of the $\log(k)$ field, the k field was recovered from $\log(k)$.

Figure A.4 shows the scattergrams of porosity and permeability for the six layers of Reservoir 1, indicating a good correlation between the two fields.

The shales were set to a low porosity (0.01%) and permeability (0.01 md) and merged with the sandstone petrophysical properties (porosity and permeability), i.e. a grid-block receives a fixed shale value for porosity and permeability if it is simulated as a shale grid-block; otherwise it keeps the simulated sandstone value.

Figure A.5 shows the bottom sublayer of porosity for the six layers of Reservoir 1 after merging with the shales, and **Figure A.6** shows the same sublayers with permeability. Recall that there are ten sublayers for each layer.

The vertical distribution of permeability after merging with the shales is illustrated by the vertical cross-sections presented in **Figure A.7**. In this figure only the upper five layers are presented to enhance the visualization of the permeability contrast within the layers.

Table A.5: Probability distributions of the parameters used in the program SISIM to generate sandstone $\log(\text{permeability})$ fields for all the layers of the true reservoirs. The lengths are in grid units.

Parameter	Distribution type	Layer	a	b	c
Mean $\log(k)$ (<i>md</i>)	Triangular	1, 3, 5	2.0	2.7	3.4
		2	1.3	2.0	2.7
		4, 6	1.6	2.3	3.0
$\log(k)$ coefficient of variation	Triangular	1, 3, 5	0.15	0.30	0.45
		2	0.35	0.50	0.65
		4, 6	0.25	0.40	0.55
Nugget effect	Triangular	1, 3, 5	0.10	0.25	0.40
		2	0.00	0.10	0.20
		4, 6	0.05	0.15	0.25
Maximum horizontal range	Triangular	1, 3, 5	10	20	30
		2	45	60	75
		4, 6	30	40	50
Minimum horizontal range	Triangular	1, 3, 5	8	11	14
		2	30	40	50
		4, 6	15	25	35
Vertical range	Triangular	1, 3, 5	4	6	8
		2	0	2	4
		4, 6	1	3	5

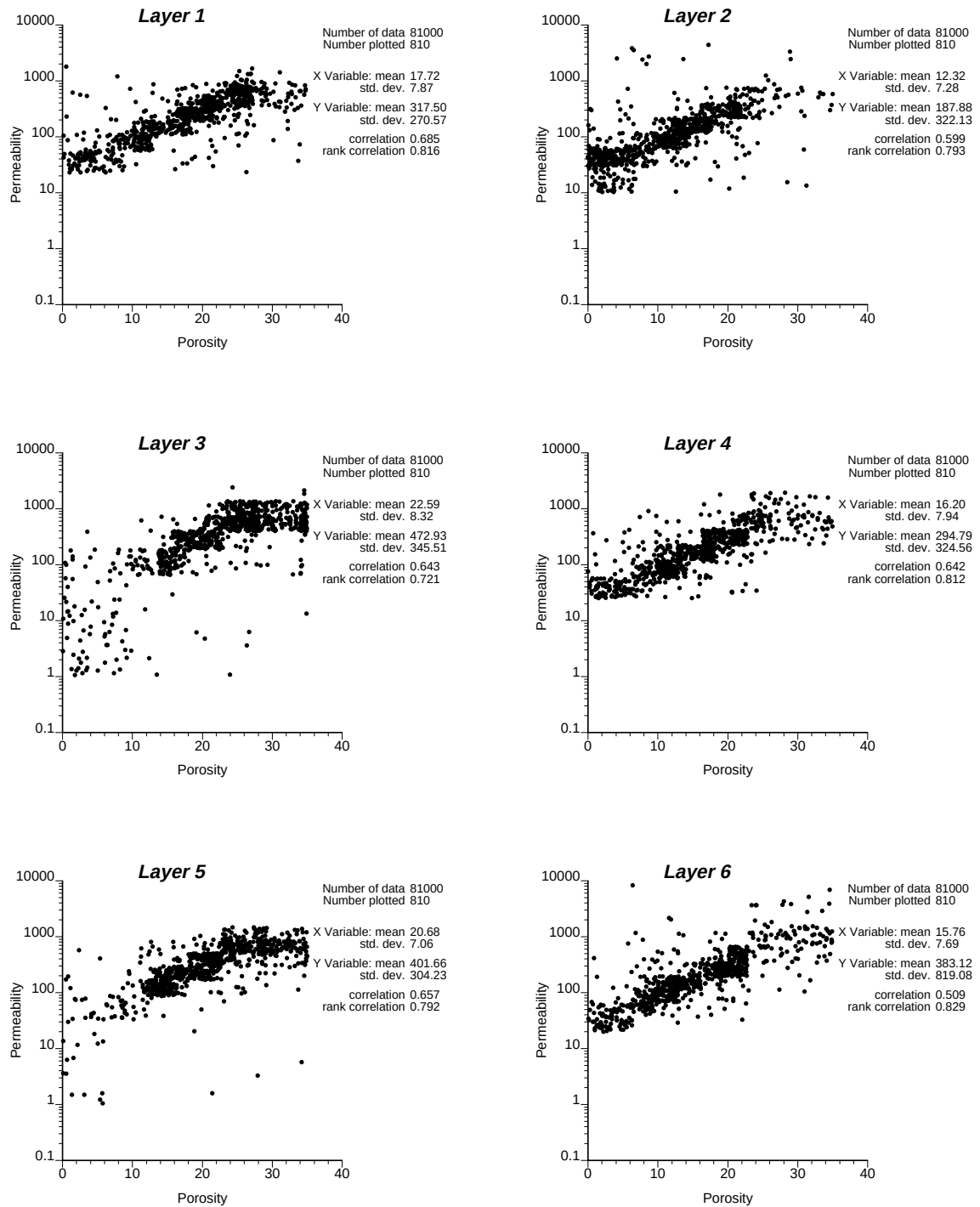


Figure A.4: Scattergrams between porosity (%) and permeability (md) in the six layers of true Reservoir 1.

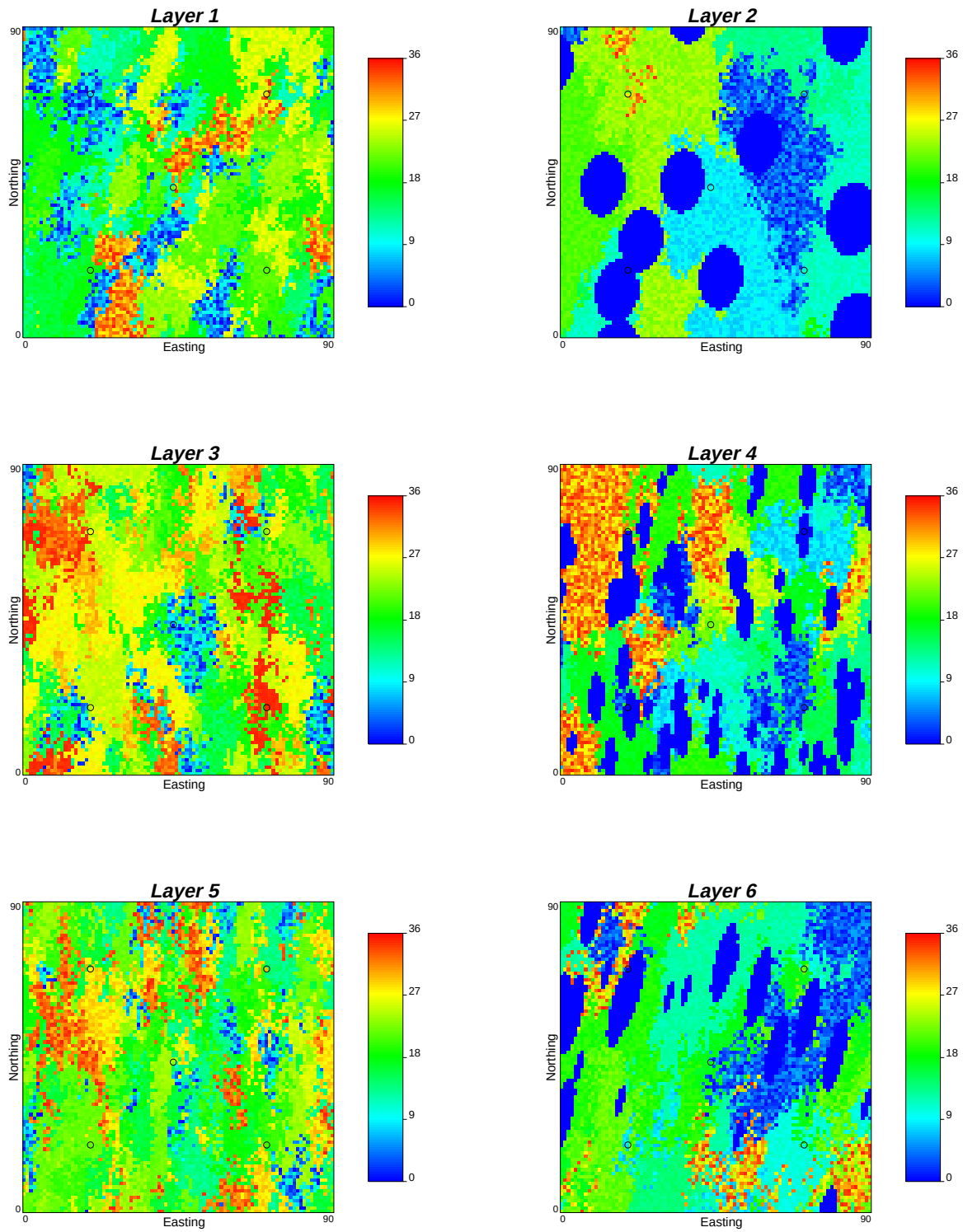


Figure A.5: Porosity (%) over the six layers of true Reservoir 1. Only the bottom sublayer of the ten sublayers of each layer is shown.

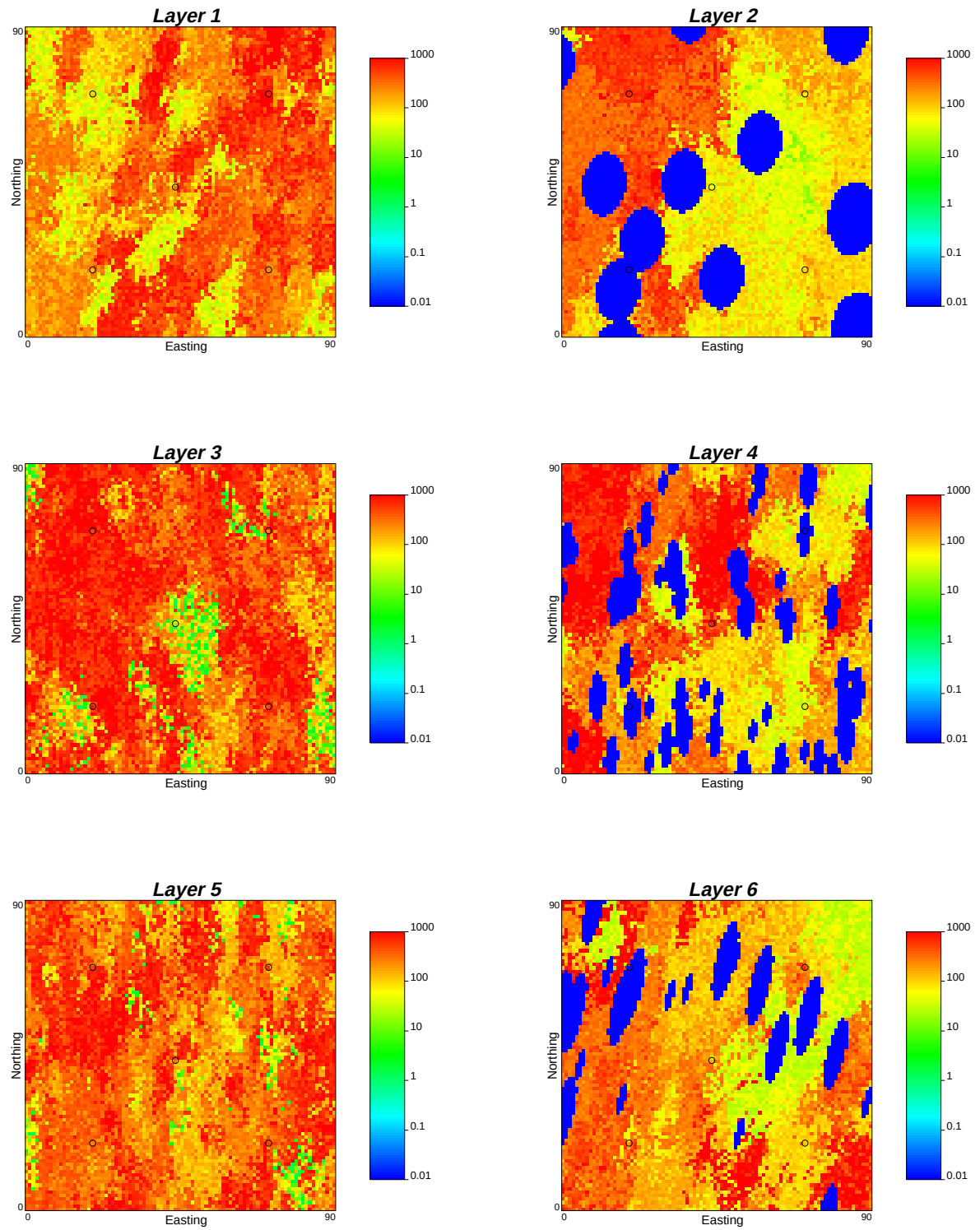


Figure A.6: Permeability (md) over the six layers of true Reservoir 1. Only the bottom sublayer of the ten sublayers of each layer is shown.

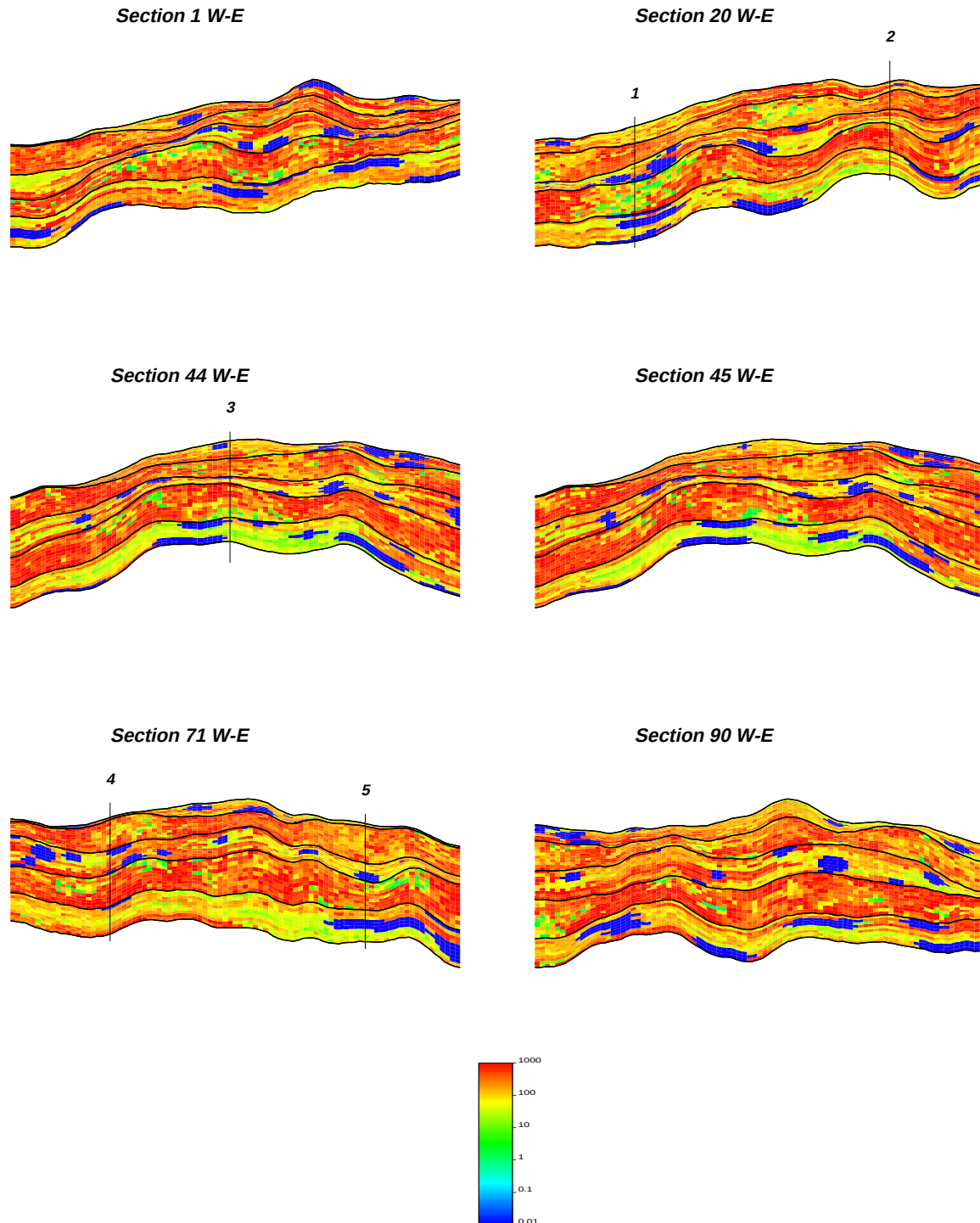


Figure A.7: Cross-sections of permeability (md) over the five upper layers of true Reservoir 1.

Appendix B

Generation of the Models

B.1 Sampling the true reservoirs

Since the reservoirs were “created”, the exhaustive true distribution of rock properties is available. However, in order to imitate a real acquisition of data, only data from a few sampling wells and a smoothed image of the true reservoir top (as would be obtained from seismic data) were used to generate the reservoir models.

The number and position of the sampling wells were the same for all reservoirs. Only five wells were used, this being a realistic number of exploratory wells in the kind of reservoirs (offshore) under investigation. The data kept from each well are the horizontal coordinates (x and y), depths, facies types, porosity and permeability for each of the ten sublayers of the six layers. From these well data, data files were prepared for the geostatistical modeling: one file with the overall top, one file per layer with the layer thickness, and one file per layer with the stratigraphic depth, facies type, porosity and permeability for each sublayer.

A stratigraphic vertical coordinate for each sublayer was defined as

$$z_c = \frac{bottom - z}{bottom - top} \cdot 10 - 0.5 \quad (\text{B.1})$$

where bottom and top are respectively the bottom and top depth of the layer, z is the depth of the sublayer top and $z_c \in (0.5, 9.5)$ corresponds to the middle of the sublayer and decreases with depth to be consistent with the GSLIB system of

coordinates. The z_c stratigraphic coordinate was used for all the three-dimensional simulated realizations and for the upscaling; the real z depth was recovered only for flow simulation.

Seismic data for the top of the structure are correlated with the real top (from wells). However, the seismic surface is typically smooth due to the restricted vertical definition of seismic data. In order to imitate the acquisition of seismic data, a smoothed image of the “true” top was obtained by taking the value for each cell as the average top value of ten grid-blocks on each side of that cell.

The locations of the wells were presented in the previous Appendix (for example, Figure A.1) and will be shown in all the maps and cross-sections in this section.

Figure B.1 gives the “seismic” surfaces for Reservoir 1, 2 and 3. The comparison with Figure A.1 shows that the “seismic” surfaces are indeed smooth images of the true tops.

Different geostatistical programs were used to create the true reservoirs and to generate the models (realizations or the kriged model). This care was necessary to make the case studies more realistic since the geological processes that created the real reservoirs are not known and using such different algorithms protects from a recursive argument.

The GSLIB [15] programs used to create the true reservoirs were SASIM, ELLIPSIM and SISIM (see Appendix A). The models were generated using two different techniques: 1) stochastic simulation, to generate the realizations and 2) kriging, to generate the kriged model. Program SGSIM was used for the stochastic simulations of all the variables, program KT3D for kriging and program COKB3D for cokriging.

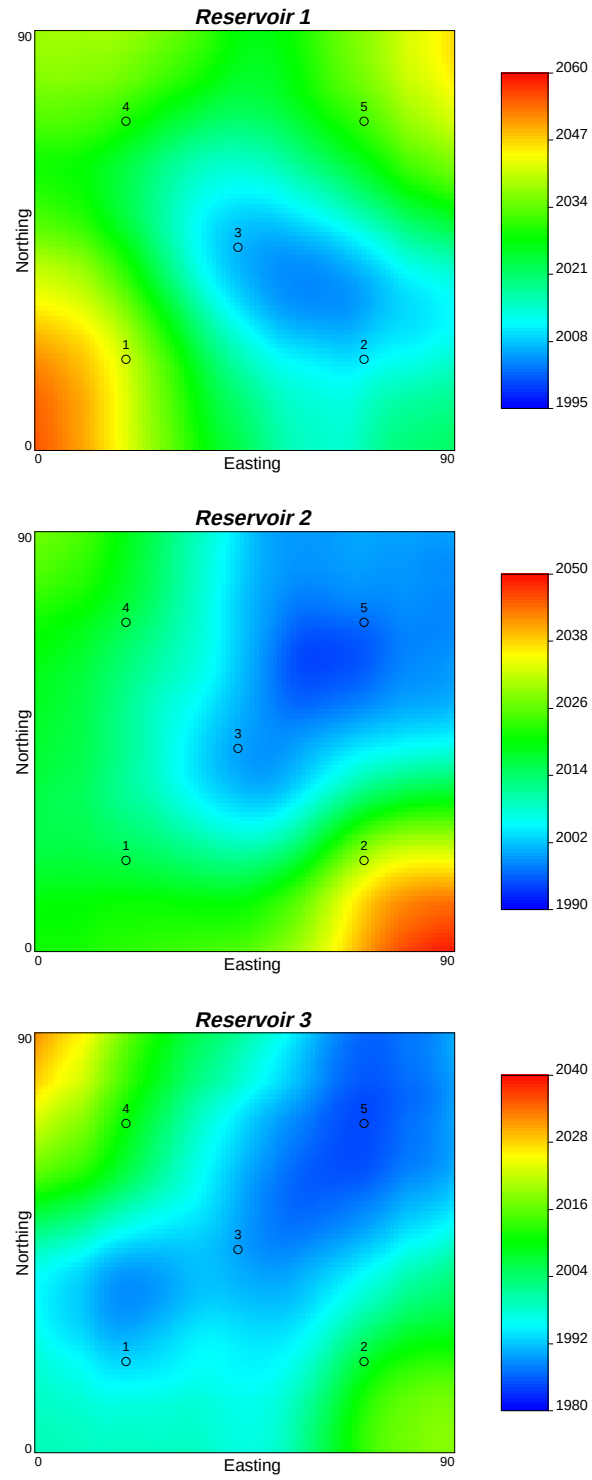


Figure B.1: “Seismic” surfaces of the structural top (m) of Reservoir 1, 2 and 3.

B.2 Stochastic simulations

A geological model is defined by its top surface, the thickness of each layer and the petrophysical parameters (porosity and permeability) of each sublayer.

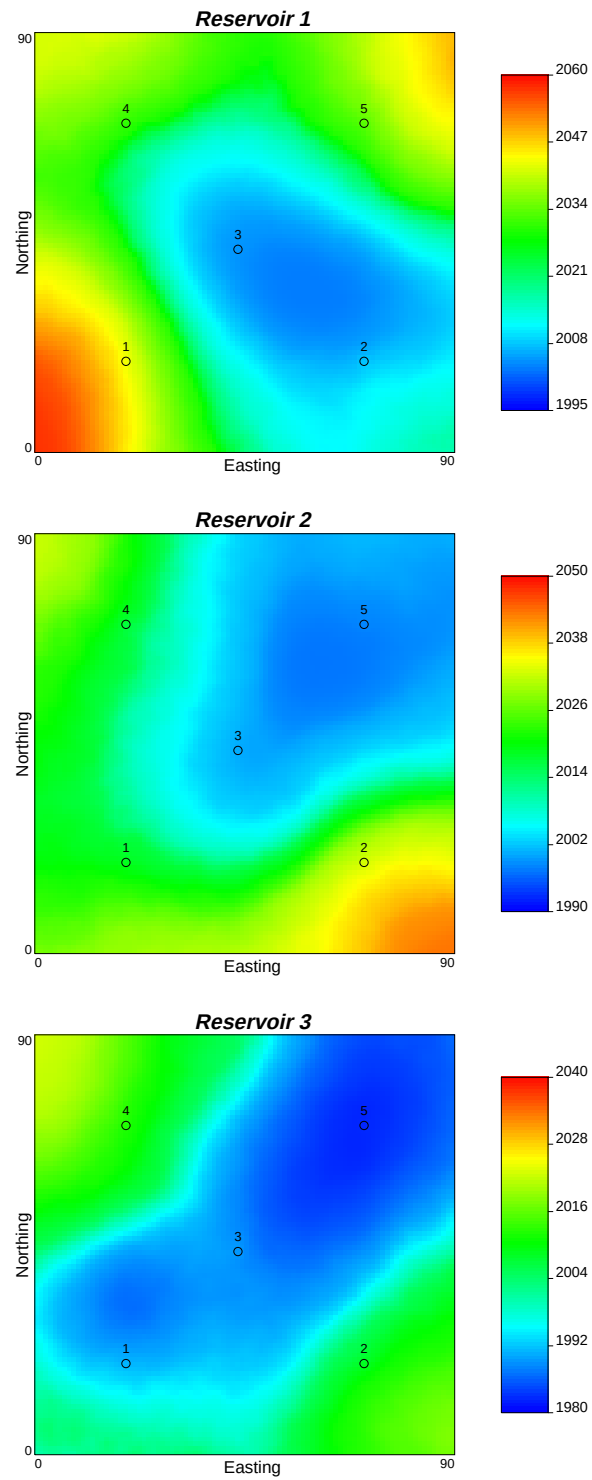
Simulated realizations of the top surface were generated using the well data as primary variable and the “seismic” data as secondary variable.

With only five hard data available from well data, no variogram modeling was possible for the primary variable; only three points would appear in the omnidirectional semivariogram, with the first one already beyond the range. Sensitivity analyses, using several semivariogram models based on seismic data of different reservoirs, showed that the results of the simulations were not very sensitive to the semivariogram parameters because there is a collocated seismic datum for every grid-block. Thus the semivariogram parameters were fixed for all the reservoirs.

The semivariogram was fixed to be of Gaussian type because this provides greater small scale continuity as expected for a top surface. The semivariograms were isotropic with very small nugget effect (0.001) and relatively large range (range of 60 for a total field length of 90 - in grid-block units). The coefficient of correlation between seismic and top data, necessary for the collocated option of program SGSIM, was calculated from the collocated pairs of well data and seismic data. Since there was only five data from the five wells, a smoothed histogram was generated and taken as the reference distribution for the SGSIM runs. The seed numbers for the program were generated from the reservoir and the realization id numbers.

Figure B.2 displays the top surface of Realization 1 for the first three reservoirs. Comparing these surfaces with the true and seismic surfaces of Figures A.1 and B.1 respectively, it can be seen that the realizations reproduce the true reservoirs. However, the simulated surfaces are smoother than the truth, as expected from the smooth nature of seismic data.

For the thickness modeling of each layer, again only five data were available and no variogram modeling was possible. Hence, there was no option but to assume the same semivariogram model for all reservoirs and layers. After some analysis, an isotropic Gaussian semivariogram with no nugget effect and a range equal to the

Figure B.2: Top depth (m) of Realization 1 of Reservoir 1, 2 and 3.

smallest distance between the wells (35 grid-block units) was retained. As for the simulation of tops, a smooth histogram of thickness was also generated and used in SGSIM for each layer based on the well data. The seed number was generated from the reservoir, realization and layer id numbers.

Figure B.3 displays the simulated thickness of Realization 1 for the six layers of Reservoir 1. Comparing with the true thickness of Figure A.2, it can be seen that the reproduction of the mean values is satisfactory but the reproduction of the spatial distribution is poor, as a consequence of the realistic shortage of well data (only five data per layer).

For the petrophysical parameters, 50 data (5 wells $\times$ 10 sublayers) are available for each layer, thus variogram modeling was possible along the vertical direction. In the horizontal direction only three points would appear in the variogram and no modeling was attempted.

The variogram was modeled in the vertical direction and a horizontal/vertical anisotropy ratio was drawn from a uniform distribution $U \in (5, 25)$. In the horizontal direction the variogram was assumed isotropic. The seed number is the same as that used previously for thickness. This seed number was used to generate the random number necessary to draw the horizontal/vertical anisotropy ratio, and in program SGSIM to define the random sequential path.

One single spherical structure was considered and a program was written to calculate the nugget effect and the vertical range. The program uses the Gauss-Newton method [23] to find the nugget effect and the range that minimizes the quadratic differences between the variogram model and the data.

The porosity was simulated first and then the permeability, using porosity as a collocated data. The purpose is to generate porosity and permeability fields with correlation similar to that evaluated from wells. The simulation was done after normal-score transform and then back-transformed to recover the variable values.

Figure B.4 shows the vertical semivariograms of porosity for Reservoir 1. For each layer, there are four curves showing the well data, the fitted model, the data after simulation (Realization 1) and the true reservoir (given as a mere reference since the true reservoir is considered unknown).

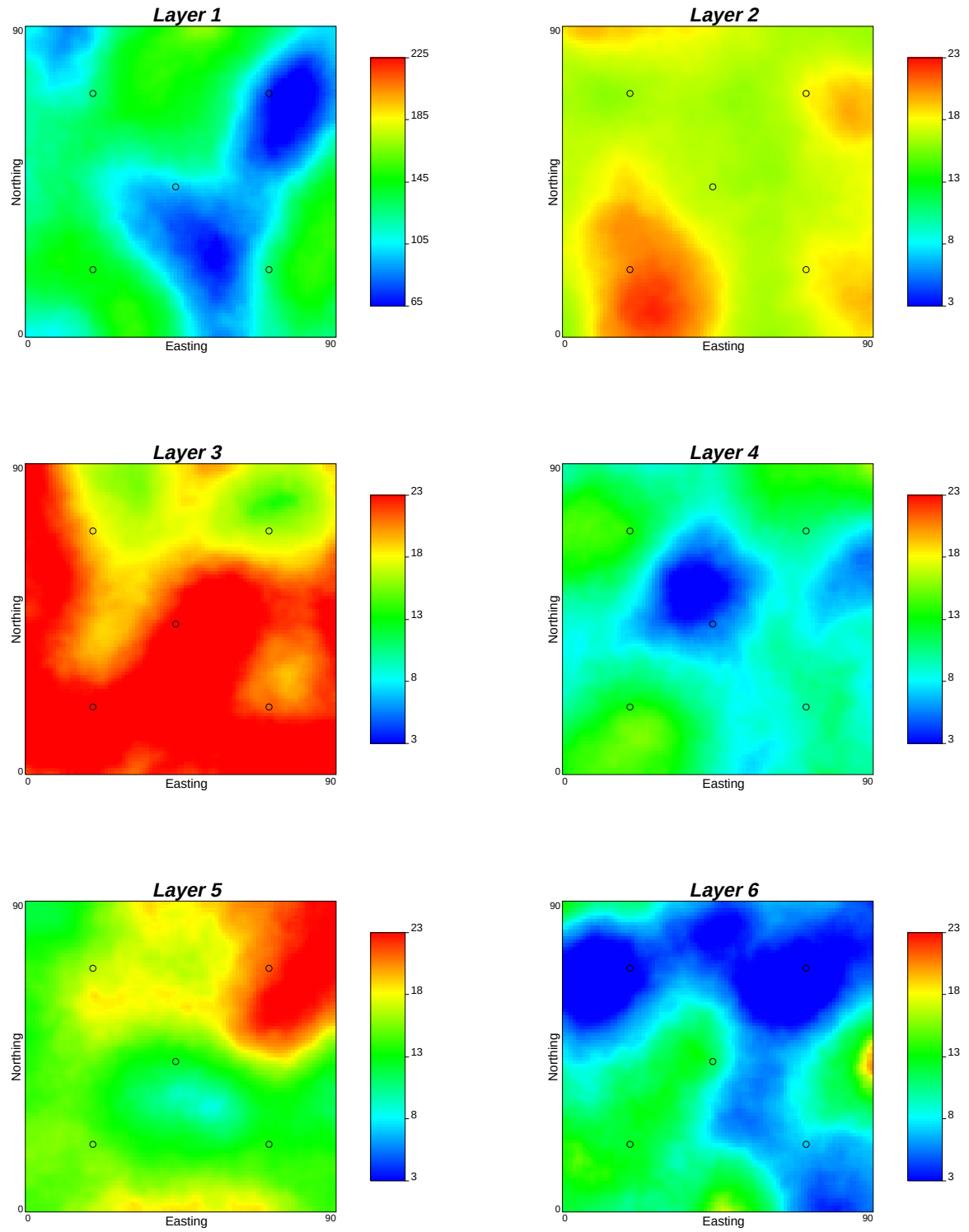


Figure B.3: Thickness (m) over the six layers of Realization 1 of Reservoir 1.

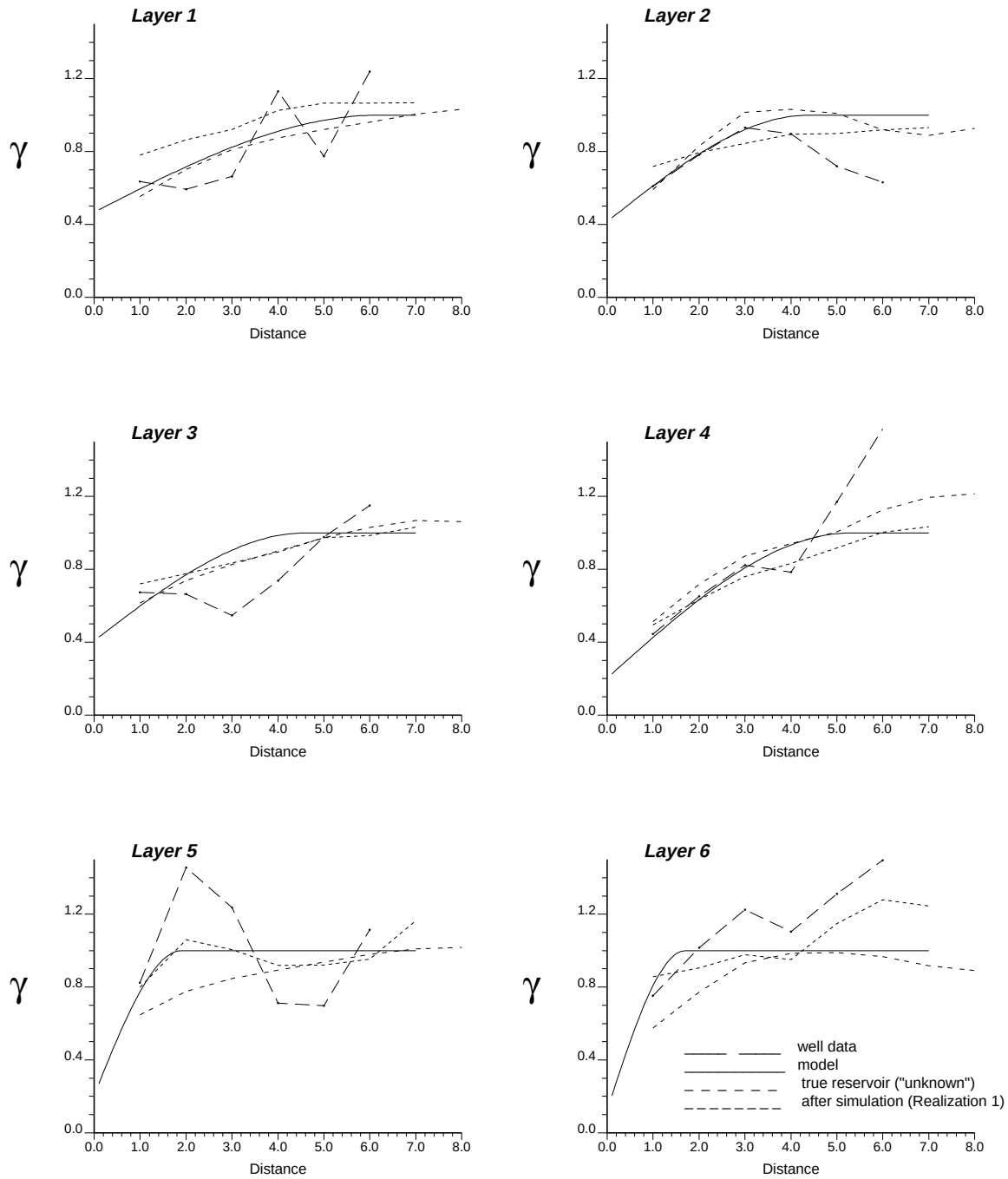


Figure B.4: Vertical porosity semivariograms over the six layers of Reservoir 1. The following semivariograms are shown for each layer: from well data, model used in the simulations, the true reservoir (unknown) and Realization 1.

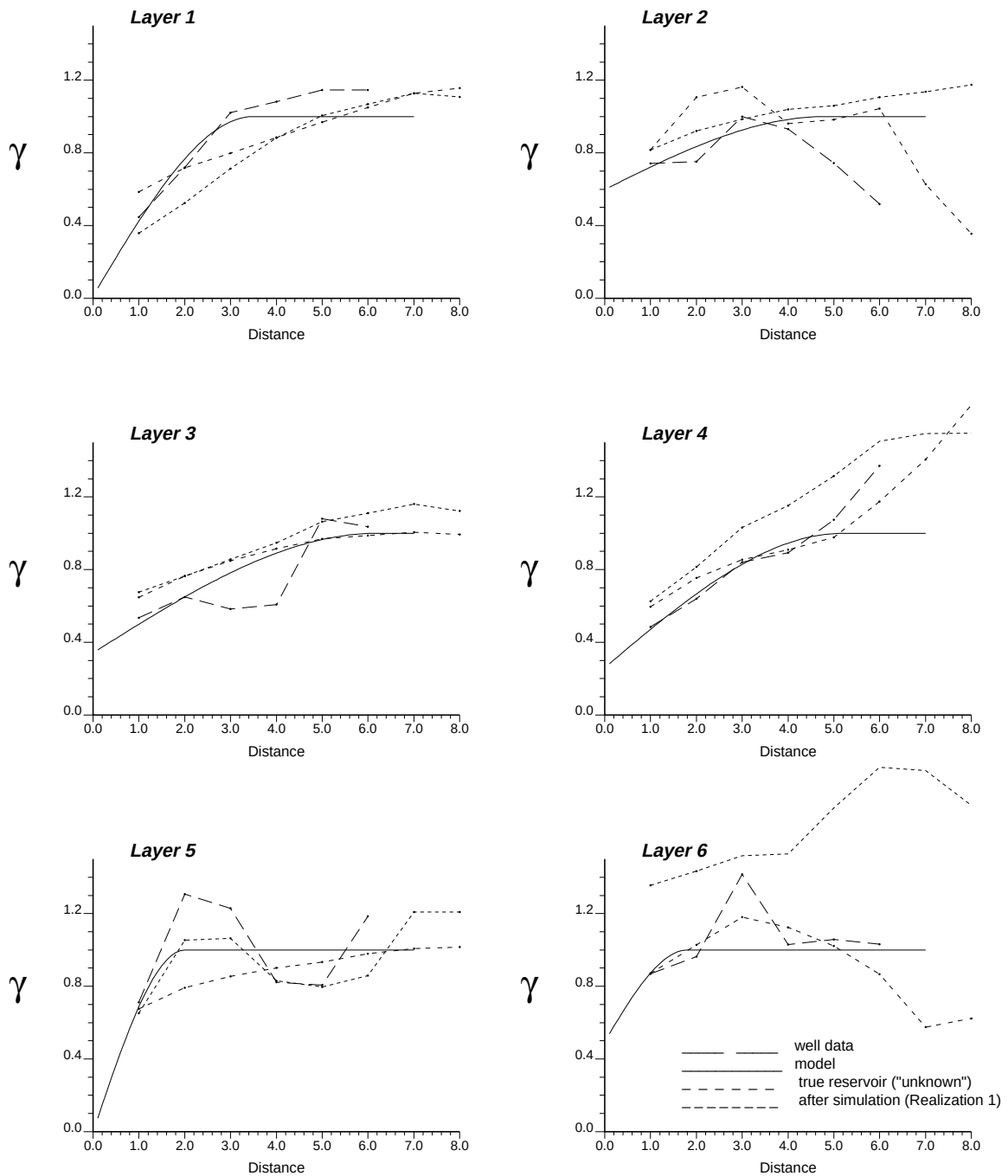


Figure B.5: Vertical permeability semivariograms over the six layers of Reservoir 1. The following semivariograms are shown for each layer: from well data, model used in the simulations, the true reservoir (unknown) and Realization 1.

Figure B.5 gives the vertical semivariograms of permeability for each layer of Reservoir 1. The higher simulated variance (sill) is a common problem associated to collocated cokriging using the Markov Model 1 as a simplification of the linear model of coregionalization. Although this problem was detected in some cases (as in the simulated layer 6 shown in this figure), no reduction factor was used in the program SGSIM because a better understanding of the impacts of this factor is still being studied (see GSLIB [16] page 174).

Figure B.6 shows the scattergrams of porosity and permeability of the four upper layers for the well data and for the simulated results (Realization 1). The reproduction after simulation of the well data correlation between the two variables was good due to the use of the collocated cokriging option.

Figure B.7 shows the bottom slice (sublayer 1) of the simulated porosity (Realization 1) for all layers of Reservoir 1 and **Figure B.8** shows the same for permeability. The good correlation between porosity and permeability is evident when comparing the two figures.

Figure B.9 shows six vertical cross-sections along the W-E direction with the permeability values of Realization 1 and the position of the five sampling wells. The thicker bottom layer is not shown to enhance the visualization of permeability contrast within the upper five layers.

Comparison with the true reservoir (Figure B.7 to Figure A.5, Figure B.8 to Figure A.6 and Figure B.9 to Figure A.7) shows how different from the truth a model built with data from only a few wells could be. One important difference is due to the true elliptical shape of the shales, which is unknown and could not be captured with SGSIM and so few data.

The difficulty in reproducing the truth with few data is a reality in reservoir modeling and is the principal source of the uncertainty under analysis in this research.

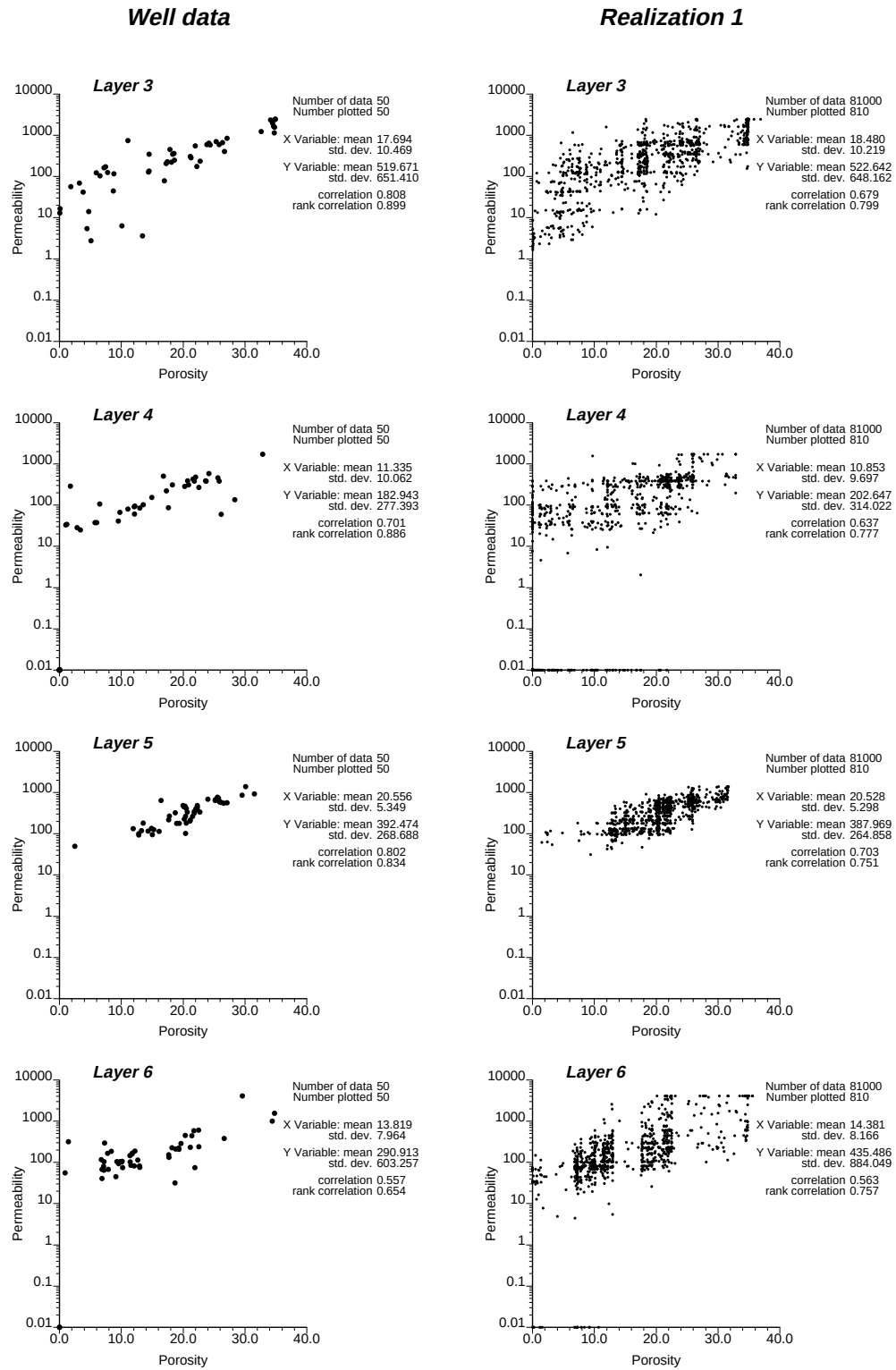


Figure B.6: Scattergrams between porosity (%) and permeability (md) from well data (left) and Realization 1 (right) over the four upper layers of Reservoir 1.

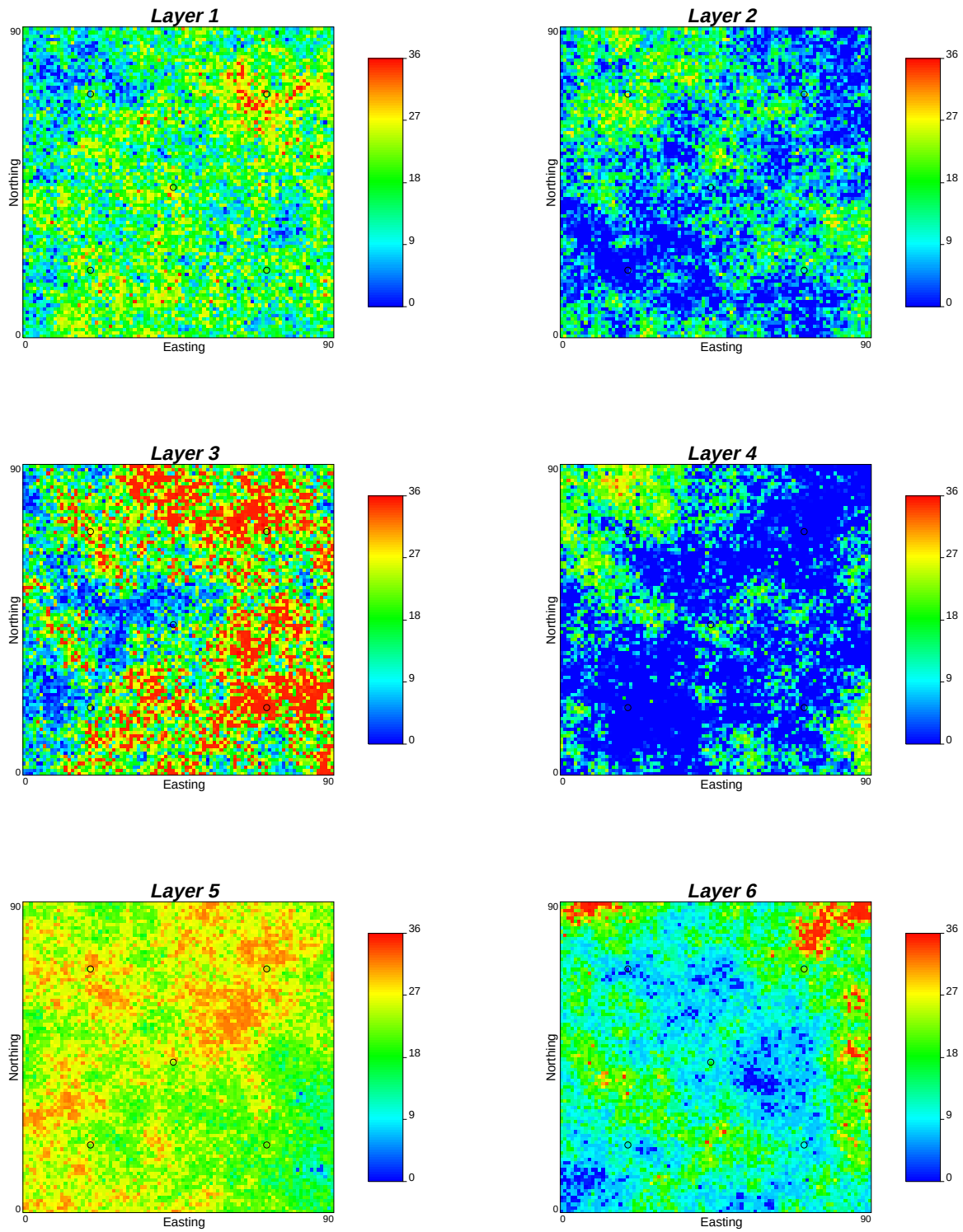


Figure B.7: Porosity (%) over the six layers of Realization 1 of Reservoir 1. Only the bottom sublayer from the ten sublayers of each layer is shown.

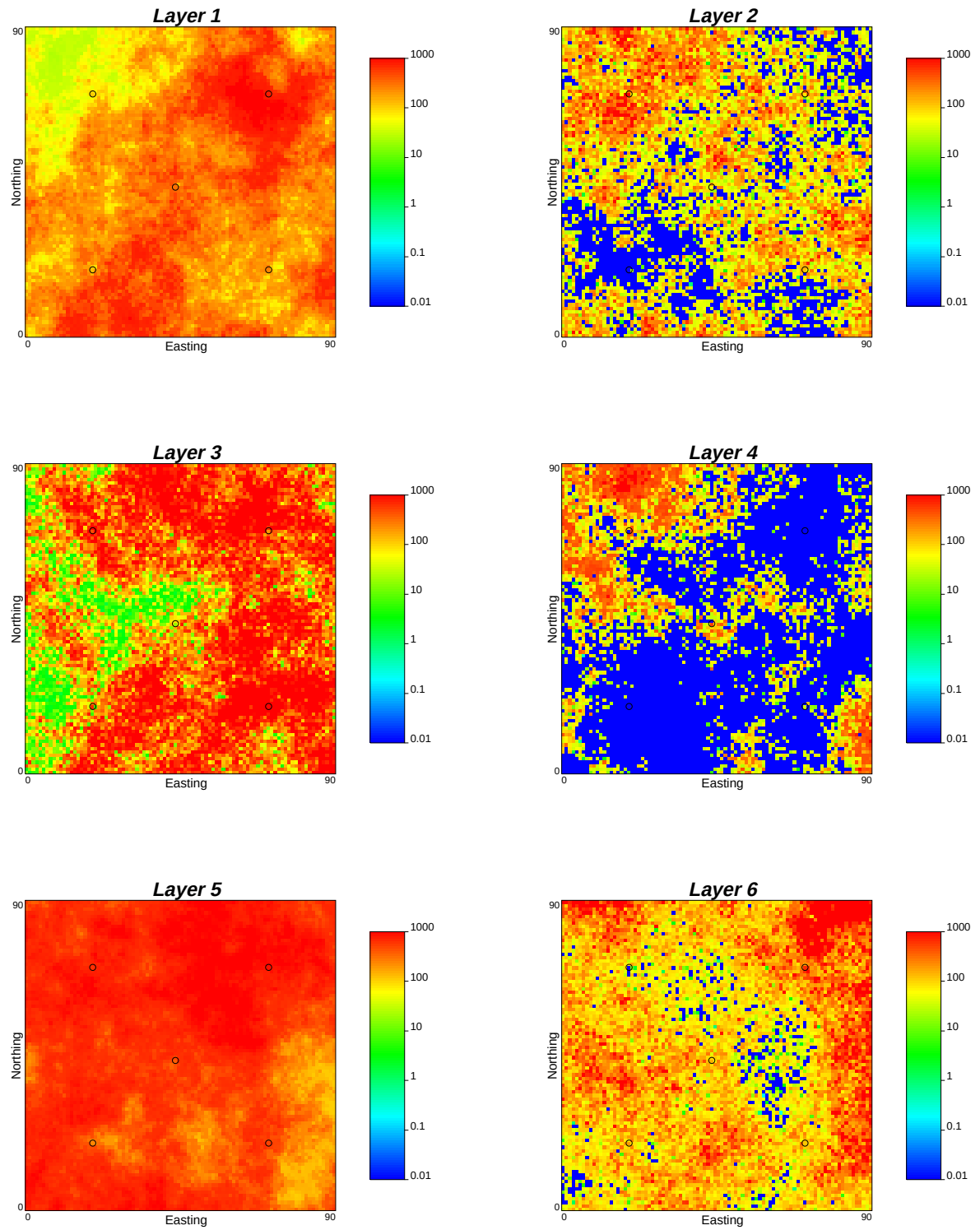


Figure B.8: Permeability (md) over the six layers of Realization 1 of Reservoir 1. Only the bottom sublayer from the ten sublayers of each layer is shown.

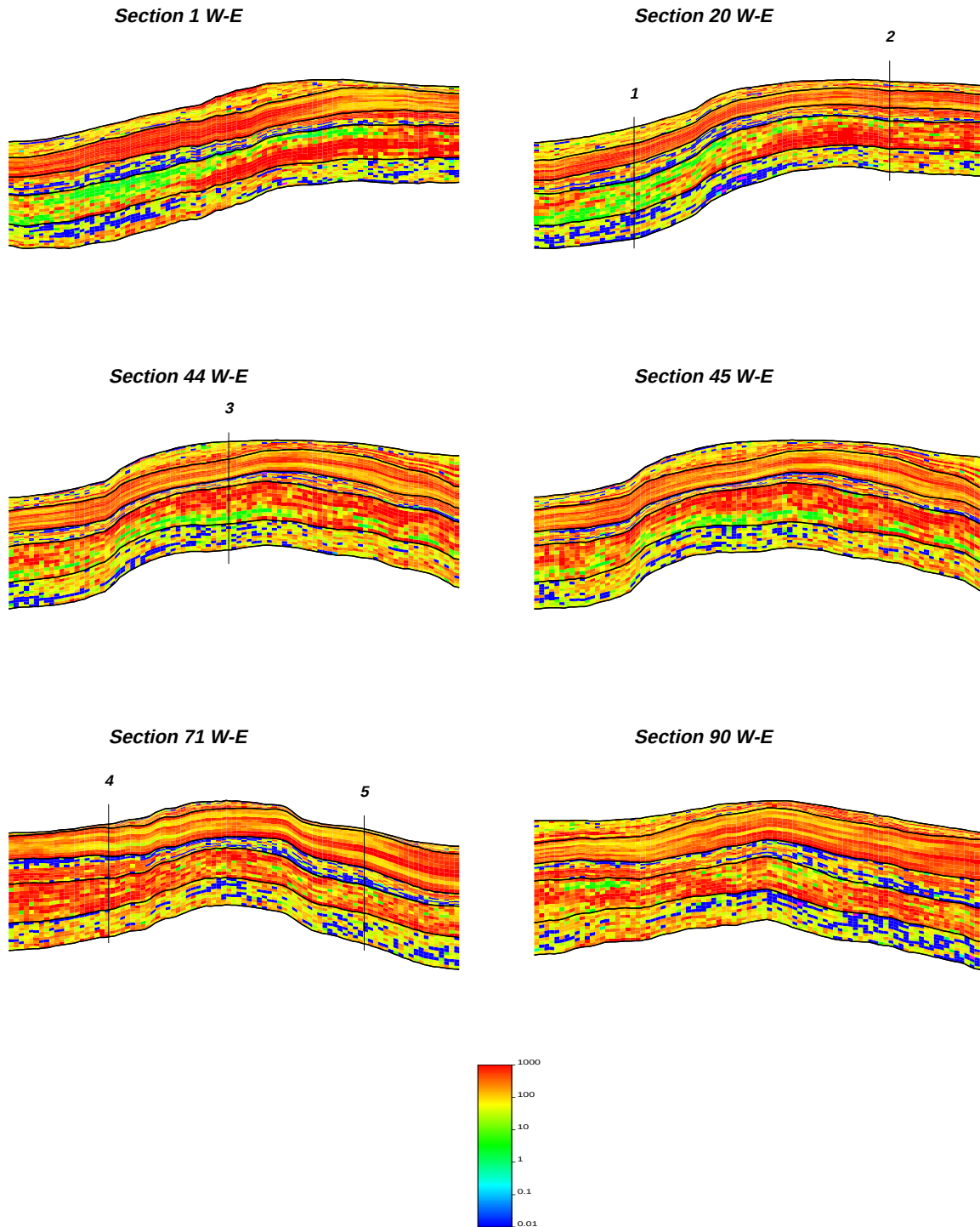


Figure B.9: Cross-sections of permeability (md) over the five upper layers of Realization 1 of Reservoir 1.

B.3 Kriging

The top surface was generated by cokriging using the well data as the primary variable and seismic as a collocated secondary datum. Before modeling, both variables were transformed into a distribution with zero mean and unit variance, by subtracting the mean of the original distribution from each value and dividing the difference by the standard deviation of the original distribution. After cokriging, the top values were transformed back, to real values.

The collocated option was implemented with COKB3D by writing the seismic data (as a secondary variable) together with the well data in the same file and by defining a secondary horizontal search radius smaller than the distance between cells. To use the program this way, a complete linear model of coregionalization was necessary to solve the cokriging system.

The semivariograms for the primary and secondary variables were the same and equal to that retained for the stochastic simulations of the top. To meet the positive-definiteness requirement of the cokriging system, the cross-semivariogram was defined with a nugget effect and sill smaller than the square root of the product between the respective values of the primary and secondary variables. The nugget effect was fixed at 0.0001 and the sill was taken equal to the coefficient of correlation between well and seismic data (making sure it would never be greater than 0.998). Only one structure with range equal to 60 (grid-blocks) was considered. That linear model of coregionalization is:

$$\gamma_{11}(h) = 0.001 + 0.999 \cdot \gamma_G \left(\sqrt{\frac{h_x}{60} + \frac{h_y}{60}} \right) \quad (\text{B.2})$$

$$\gamma_{12}(h) = 0.0001 + \rho_{12}(0) \cdot \gamma_G \left(\sqrt{\frac{h_x}{60} + \frac{h_y}{60}} \right) \quad (\text{B.3})$$

$$\gamma_{22}(h) = 0.001 + 0.999 \cdot \gamma_G \left(\sqrt{\frac{h_x}{60} + \frac{h_y}{60}} \right) \quad (\text{B.4})$$

where γ_G is a Gaussian structure, $\rho_{12}(0)$ is the coefficient of correlation between collocated primary and secondary variables and $\rho_{12}(0) \leq 0.998$.

Figure B.10 shows the cokriged tops for the first three reservoirs. Comparison with the simulated tops of Figure B.2 reveals a similar smoothing effect of kriging because a smoothed image (the seismic data) was also used in the simulations. Comparing the cokriged tops with the true and seismic tops in Figure A.1 and B.1, it can be seen that the use of abundant and good seismic data ensured correct reproduction of the true top surfaces.

The thickness of each of the six layers was generated by simple kriging using the data available within each layer and the variogram model utilized for the stochastic simulations. **Figure B.11** presents the results for the six layers of Reservoir 1. Comparing these values with the simulation results of Figure B.3 and the true thickness of Figure A.2, the smoothing effect of kriging appears evident, but the mean values are reasonable considering that only five data values were available.

For the petrophysical parameters, the same procedure as used for the stochastic simulations to model the variograms was applied; the only difference was that the seed number used to draw the horizontal/vertical ratio of anisotropy was a function of the reservoir and layer numbers only.

Porosity was kriged using actual porosity data, but a log transform of permeability was applied to propagate further the small permeability values of shale data. After kriging, the real values of permeability were recovered from the log values. Ordinary kriging was used.

To see how the log transform works to preserve small values, imagine kriging the permeability for a cell using two data, one datum with shale near the cell and the other datum with sandstone far away from the cell. Assume $k = 0.01\text{md}$ for the shale permeability datum with a kriging weight of 0.95 and $k = 1000\text{md}$ for the sandstone datum with a kriging weight of 0.05. Kriging the log-transformed permeabilities and then back-transforming, the estimated value for the permeability of the cell near the shale datum would be $k = 0.0178$, while using the actual values of permeability, the estimated value for the permeability of the cell near the shale datum would be $k = 50\text{md}$. In this work, preservation of the small values of permeability from shale data was assumed more important than a possible introduction of bias due to kriging log-transformed variables and back-transforming with antilog [37].

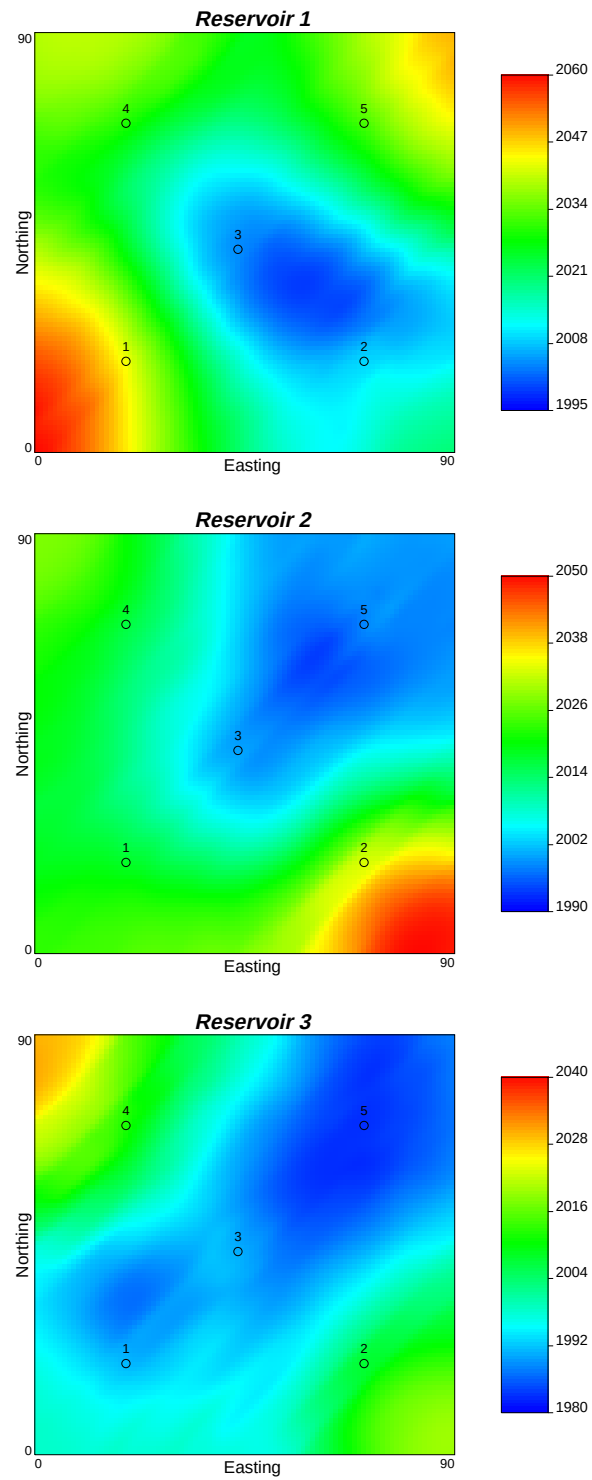


Figure B.10: Top depth (m) of the kriged model of Reservoir 1, 2 and 3.

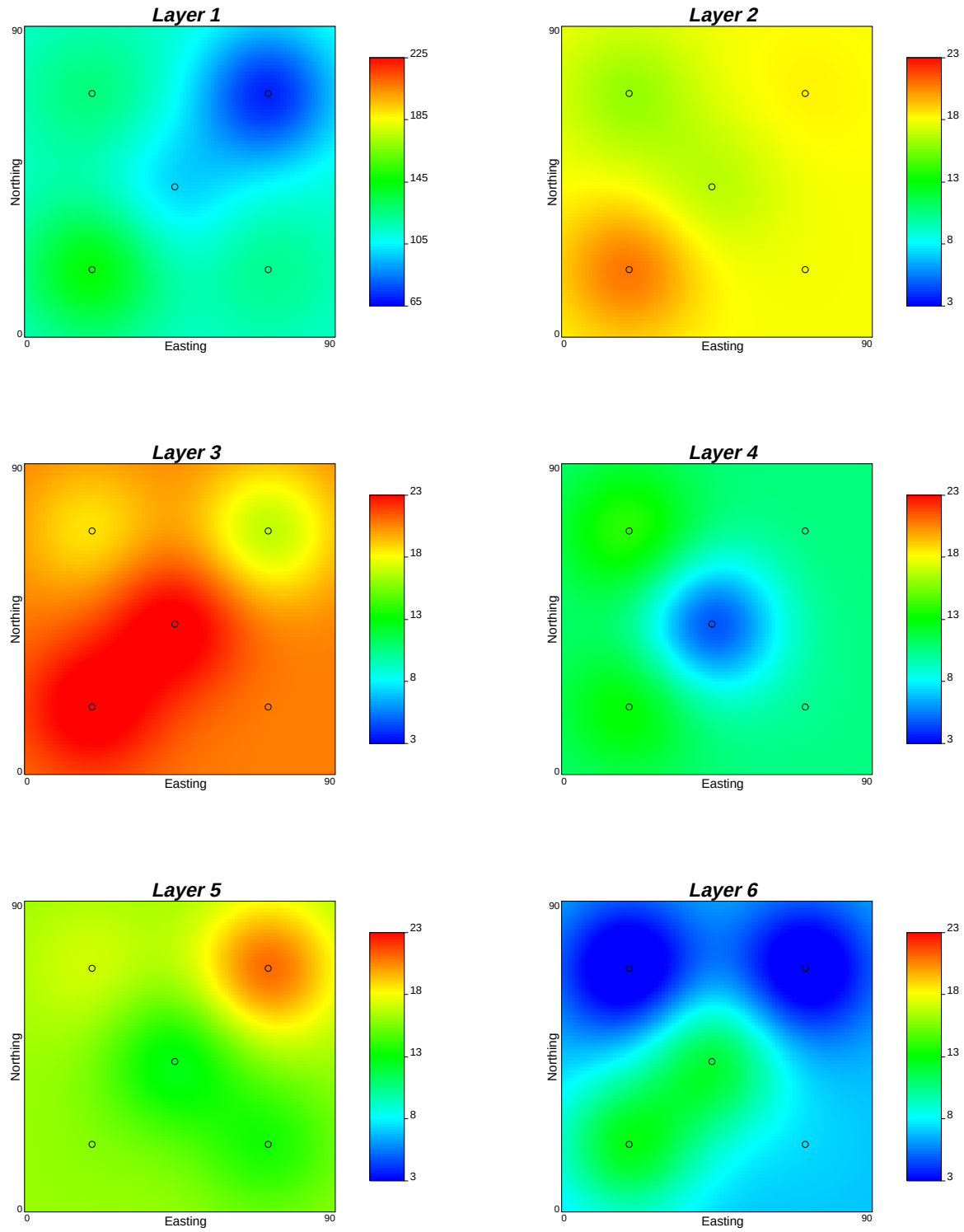


Figure B.11: Thickness (m) over the six layers of the kriged model of Reservoir 1.

Permeability was kriged independently of porosity since cokriging would not ensure better reproduction of the sample correlation between porosity and permeability.

For each layer of Reservoir 1, **Figure B.12** shows the bottom slices of porosity obtained by kriging and **Figure B.13** shows the same slices for permeability.

Figure B.14 presents six vertical cross-sections in the direction W-E with the permeability values of the kriged model for the five upper layers and the position of the five sampling wells.

Comparing these figures of the kriged model to the figures of the true reservoir (Figure B.12 to Figure A.5, Figure B.13 to Figure A.6 and Figure B.14 to Figure A.7), the smoothing effect of kriging is evident. Nevertheless, the well data are reproduced and are propagated laterally.

The differences between stochastic simulation and kriging can be seen by comparing Figure B.12 to Figure B.7, Figure B.13 to Figure B.8 and Figure B.14 to Figure B.9. The kriged fields are smoother than the simulated fields because kriging interpolates values for all the cells using only the well data while simulation “creates” high and low values in order to reproduce the data histogram.

Figure B.15 shows the histograms of permeability for the true reservoir, the well data, the kriged model and a simulated model (Realization 1) of Reservoir 1. It can be seen that the well data histogram was reproduced with simulation even though the shales were not modeled explicitly. With kriging the high and low values were smoothed despite the use of the log transform. Without the log transform, more of the small values of permeability related to shales would have been lost.

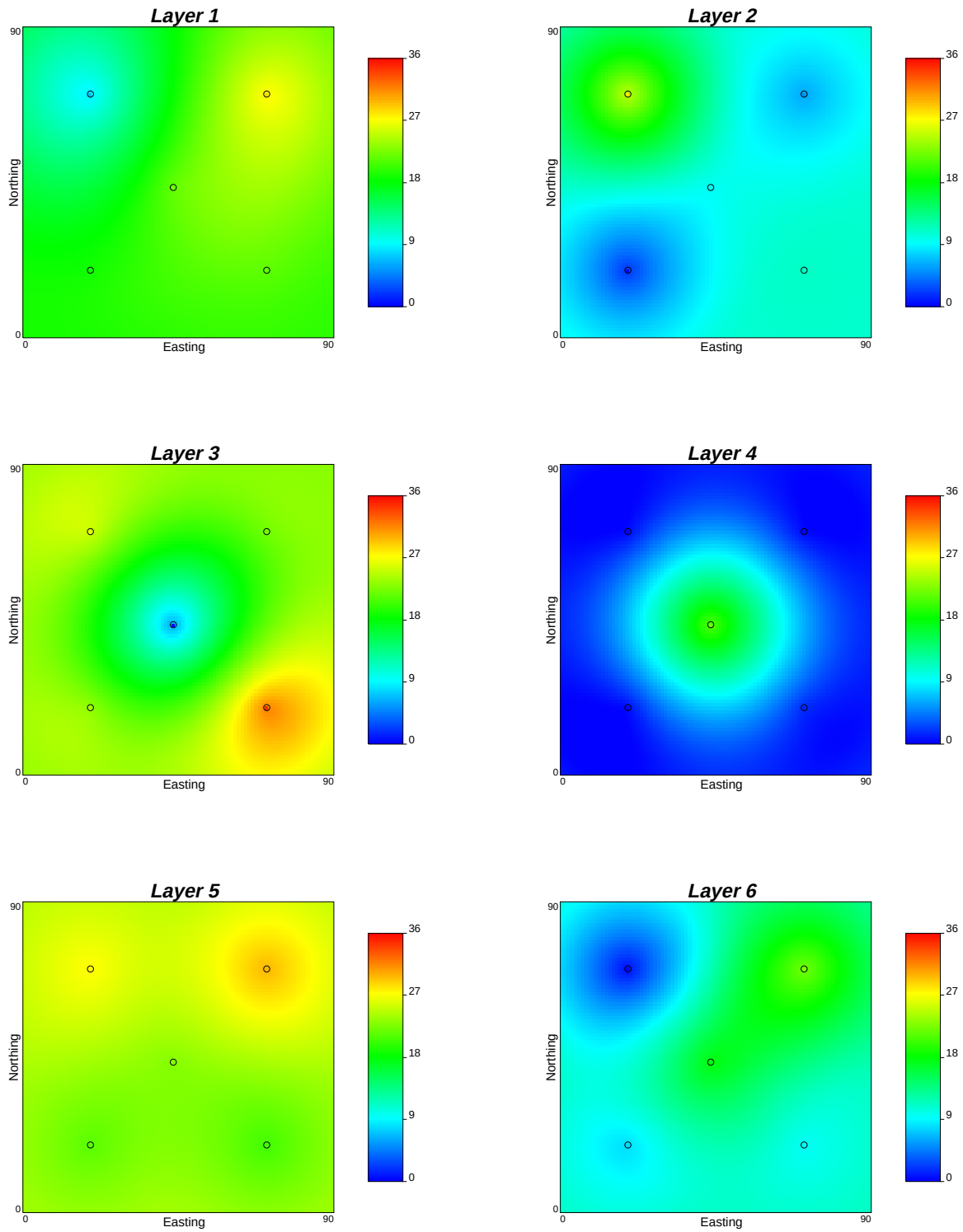


Figure B.12: Porosity (%) over the six layers of the kriged model of Reservoir 1. Only the bottom sublayer from the ten sublayers of each layer is shown.

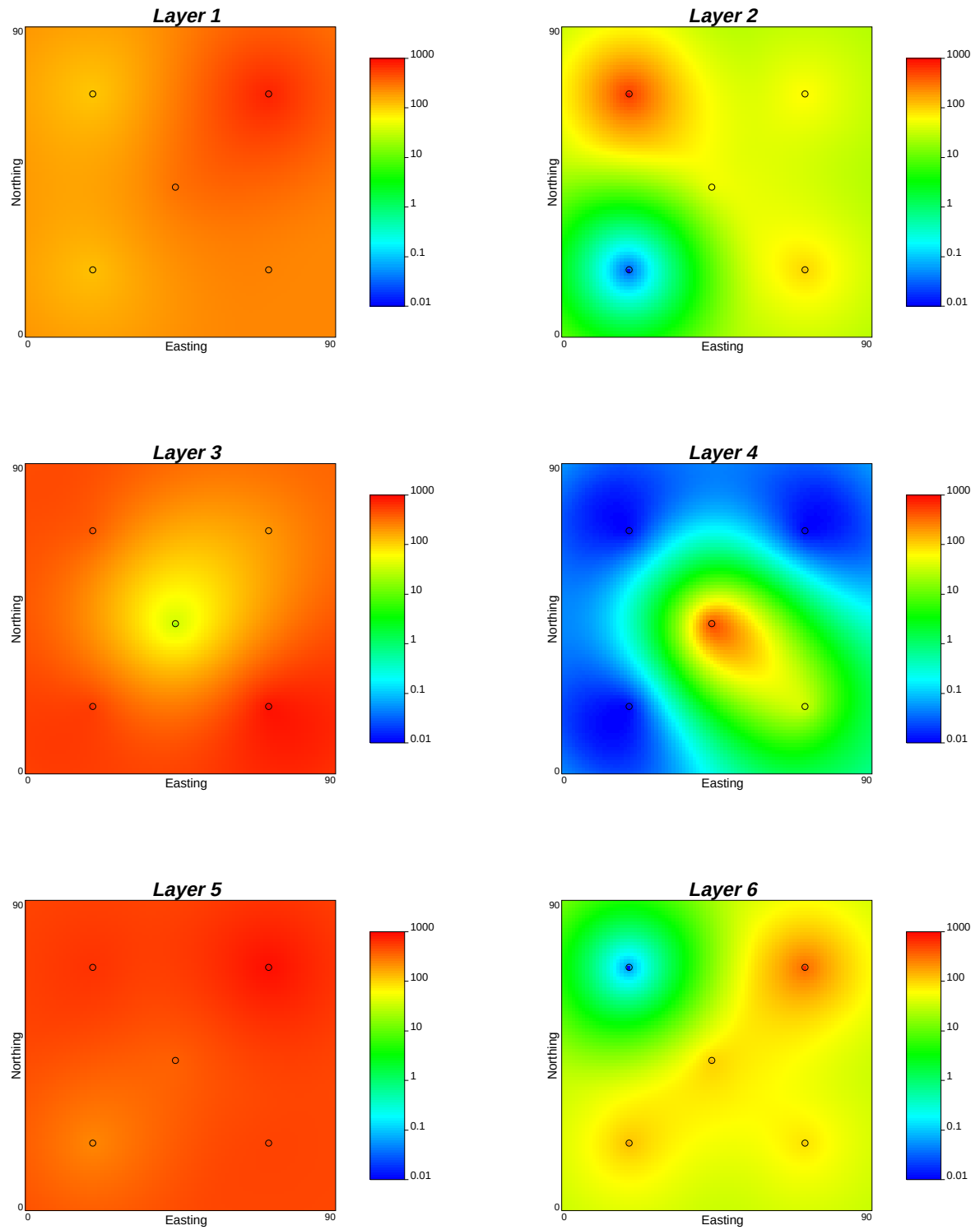


Figure B.13: Permeability (md) over the six layers of the kriged model of Reservoir 1. Only the bottom sublayer from the ten sublayers of each layer is shown.

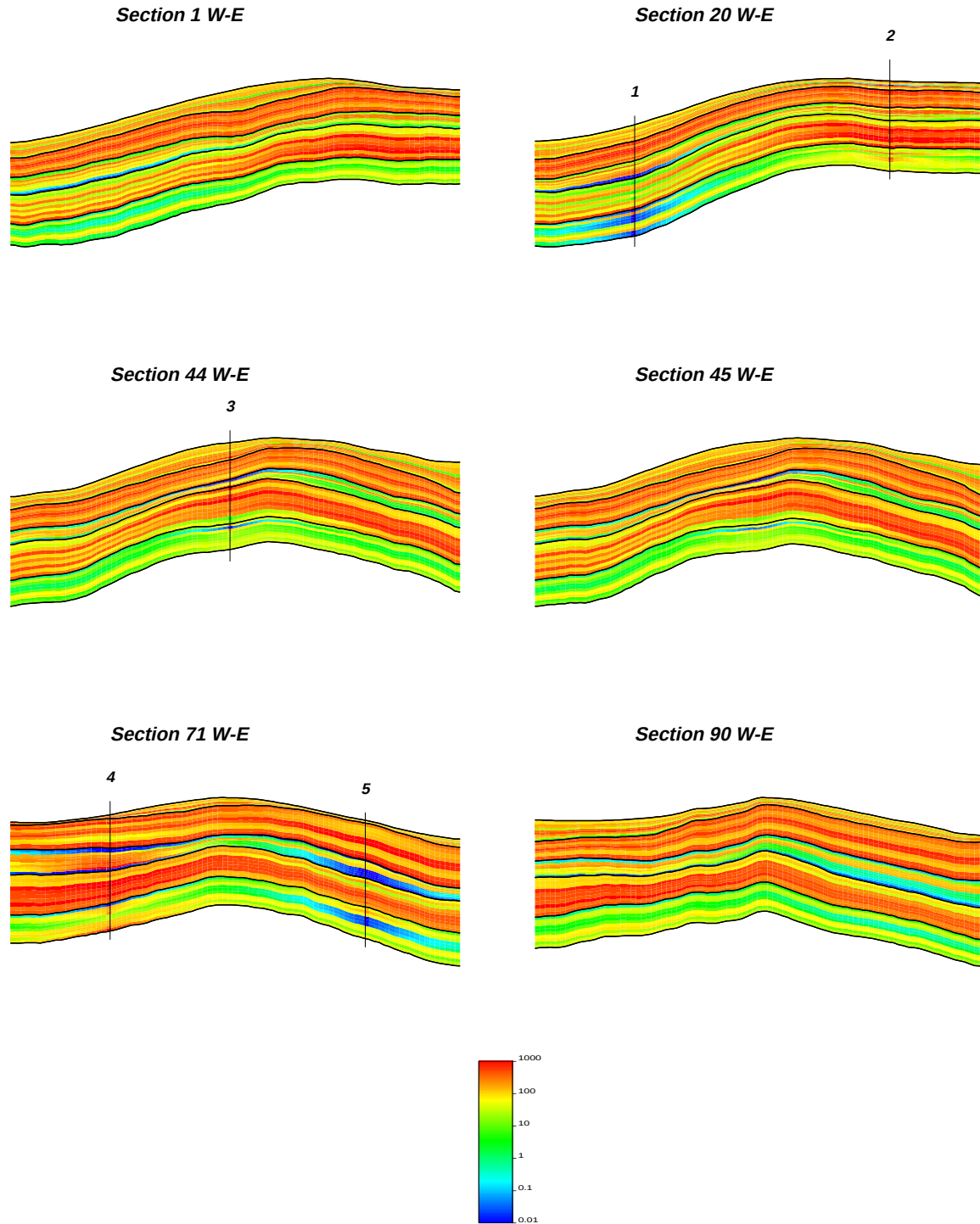


Figure B.14: Cross-sections of permeability (md) over the five upper layers of the kriged model of Reservoir 1.

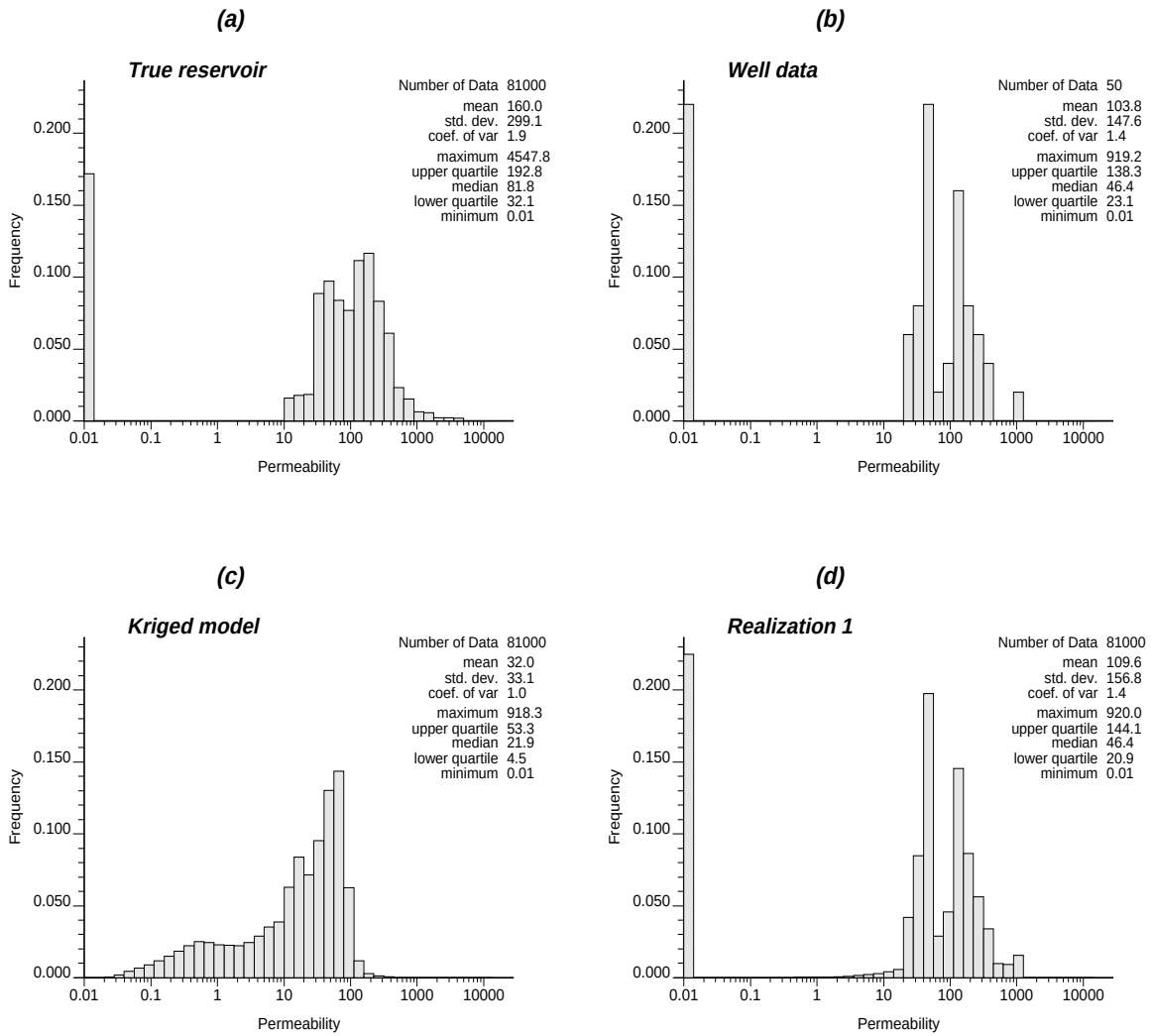


Figure B.15: Histograms of permeability (md) of Layer 2 with the true reservoir (a), well data (b), the kriged model (c) and Realization 1 (d) of Reservoir 1.

B.4 Upscaling

The reservoirs and their models were generated over a $n_x=90$, $n_y=90$ and $n_z=60$ grid (6 layers with 10 sublayers each), which is a reasonable grid in terms of geostatistical modeling. For a reservoir with average dimensions of $4500m \times 4500m \times 60m$, for example, each grid block would be $50m \times 50m \times 1m$. This geostatistical scale is much larger than the data support dimensions and a large part of the uncertainty due to the sparse sampling is hidden. This problem is called “the missing scale” [69] and is out of the scope of this research.

Even with this $90 \times 90 \times 60$ grid, to run a flow simulator for thousands of times that were required by this research would take too much time. All variables had to be upscaled to a coarser grid. After some analysis of the time required for each flow simulation run, the upscaled grid was defined as $n_x=30$, $n_y=30$ and $n_z=6$. In the vertical direction all ten sublayers of each main stratigraphic layer were upscaled to just one and in the horizontal plane nine cells (3×3) were regrouped into a single block.

Although upscaling can have different effects on the flow results with a simulated or a kriged model, the comparison between the approaches was fair since the same upscaling methodology was also used for the true reservoirs and all models, and since 50 different reservoirs were used (see the discussion in Section 2.4.4).

The upscaled top and thickness were obtained from the arithmetic mean of the nine fine grid values for each coarse grid block. Porosity and permeability were upscaled in each layer, using the 90 ($3 \times 3 \times 10$) fine grid values for each coarse grid block. For porosity a simple arithmetic mean was used. To evaluate the coarse grid effective permeability, single-phase steady-state flow simulations were run for each coarse grid block. The program used (FLOWSIM) calculates different permeability values along the three directions (k_x, k_y, k_z) using appropriate boundary conditions. For k_x , for example, a constant difference of potential is applied at the boundaries in the x direction and a no-flow condition is applied at the boundaries in the other two directions. After the simulation, the coarse permeability is evaluated using the following concept: “the equivalent permeability of a heterogeneous medium is the permeability

of a homogeneous medium that would provide the same flow when subjected to the same boundary conditions”.

Figure B.16 shows the upscaled top of the first three true reservoirs. **Figure B.17** presents the upscaled thickness for the six layers of true Reservoir 1. These should be compared to the fine grid images in Figure A.1 and A.2 to see the modest smoothing effect of the upscaling on these two variables.

Although the positions of the sampling wells are presented in all the upscaled maps, the true values at the well locations do not need to be honored exactly in the models, because the conditioning to the data was done at the fine scale.

Figure B.18 shows the upscaled porosity images for the six layers of true Reservoir 1. These can be compared to the fine grid slices in Figure A.5 recalling that ten of the fine grid slices were upscaled into each of the coarse grid images.

The upscaled vertical permeability (k_z) of each layer of Reservoir 1 is given in **Figure B.19** (true reservoir), **Figure B.20** (simulated Realization 1) and **Figure B.21** (kriged model). The comparison between the coarse k_z images and the fine grid slices of permeability in Figures A.6 (true reservoir), B.8 (simulated Realization 1) and B.13 (kriged model) indicates that the upscaling reduces the differences between the true reservoir and the models, yet preserves the main features.

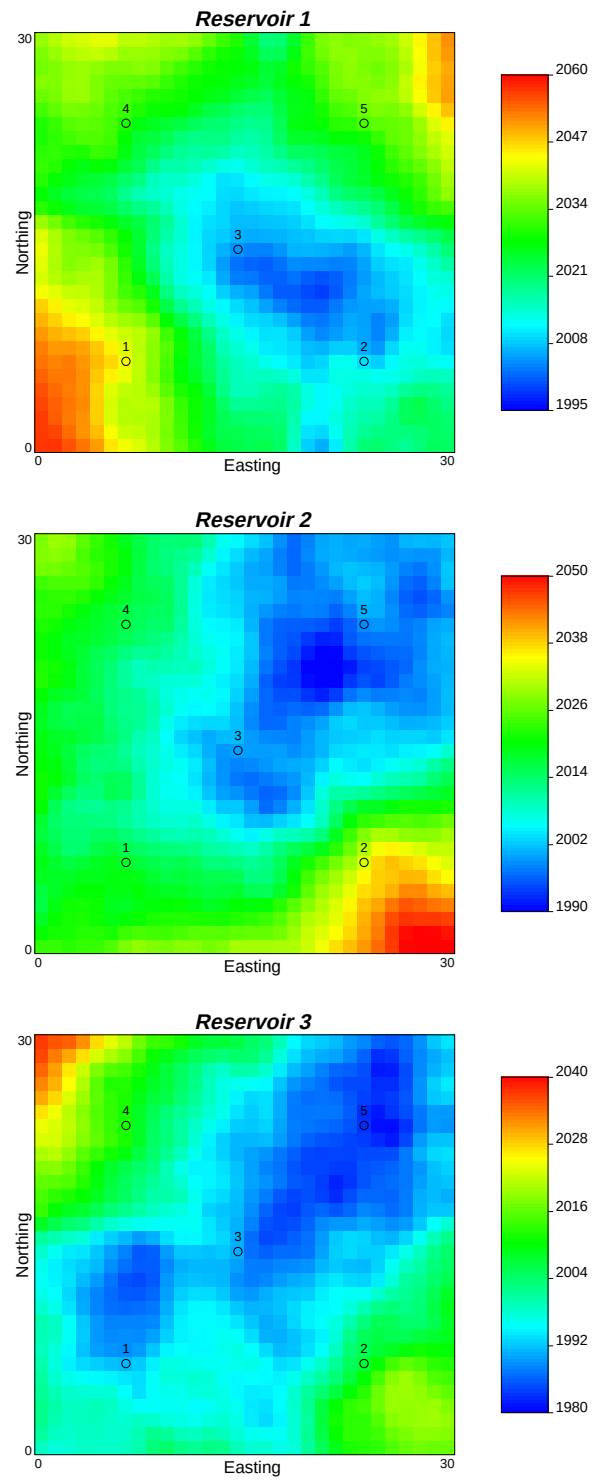
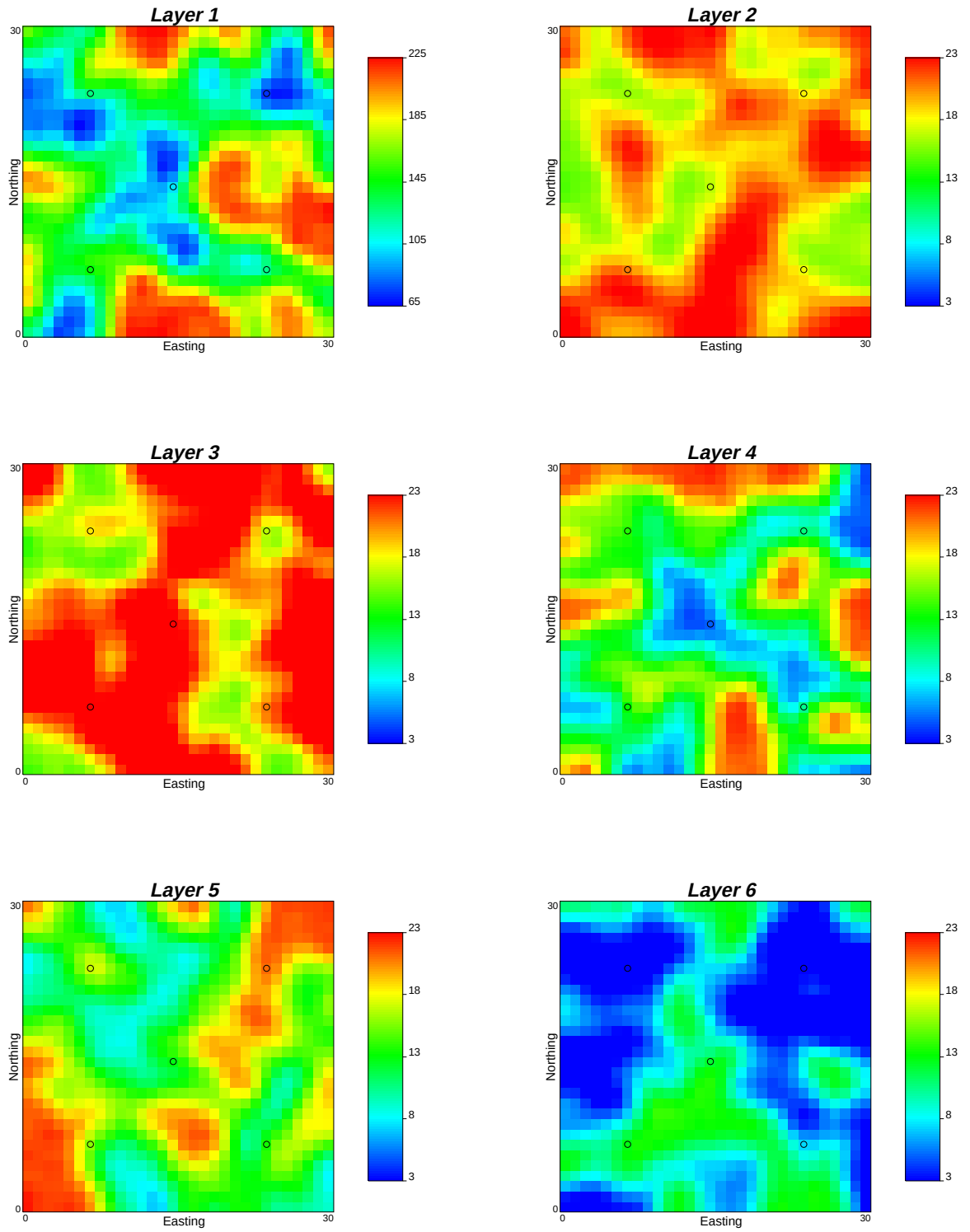


Figure B.16: Upscaled top depth (m) of true Reservoir 1, 2 and 3.

Figure B.17: Upscaled thickness (m) over the six layers of true Reservoir 1.

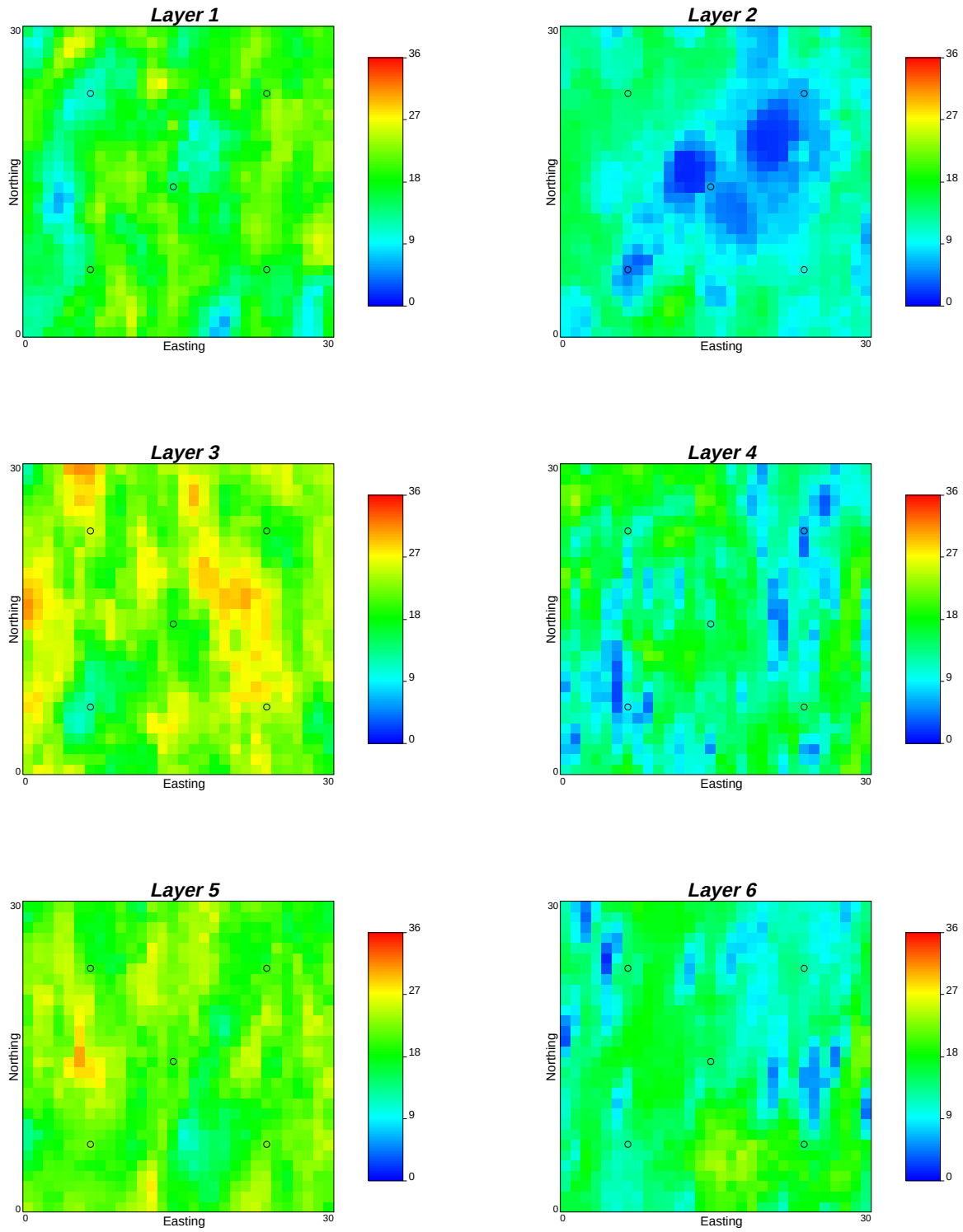


Figure B.18: Upscaled porosity (%) over the six layers of true Reservoir 1.

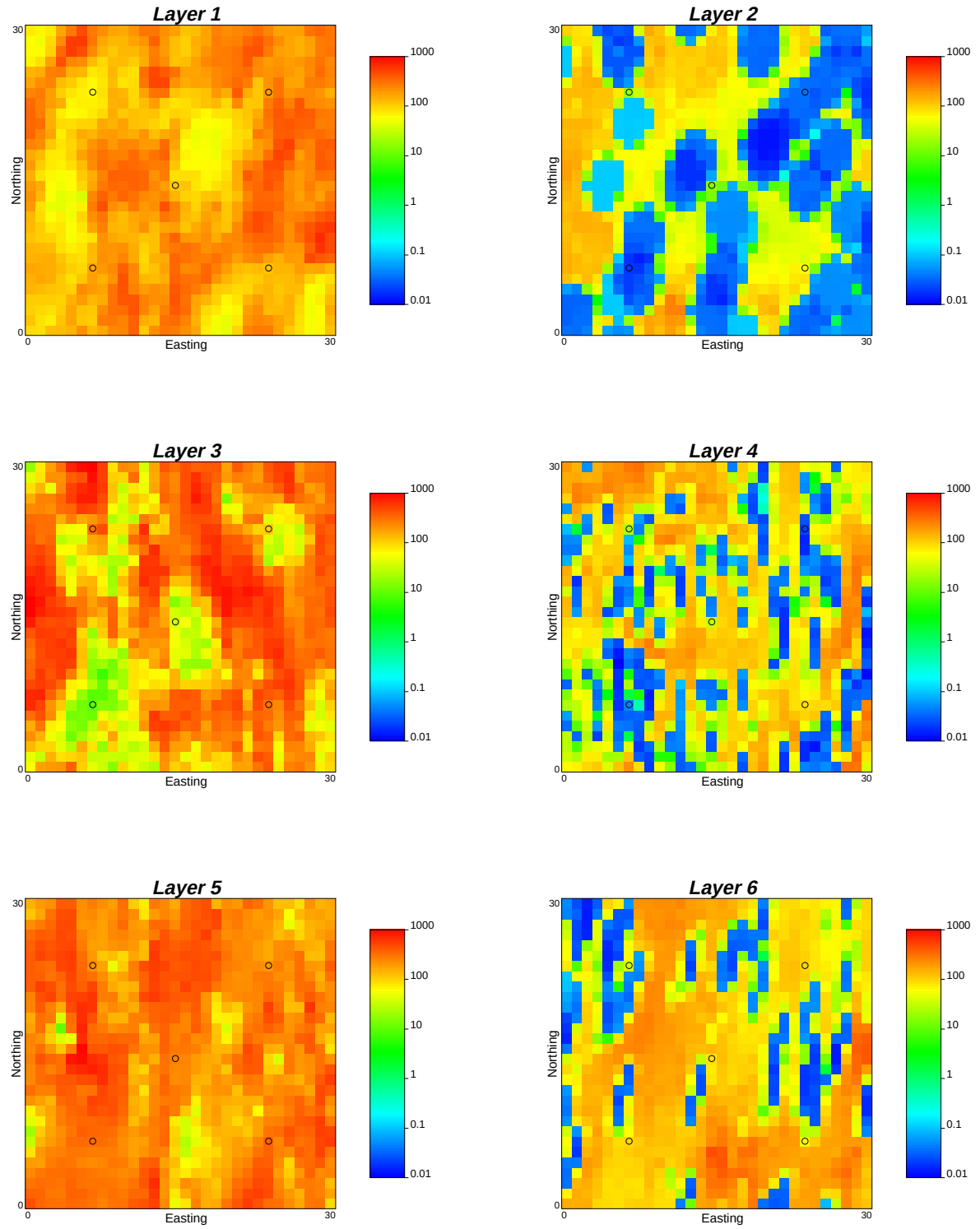


Figure B.19: Upscaled vertical permeability (md) over the six layers of true Reservoir 1.

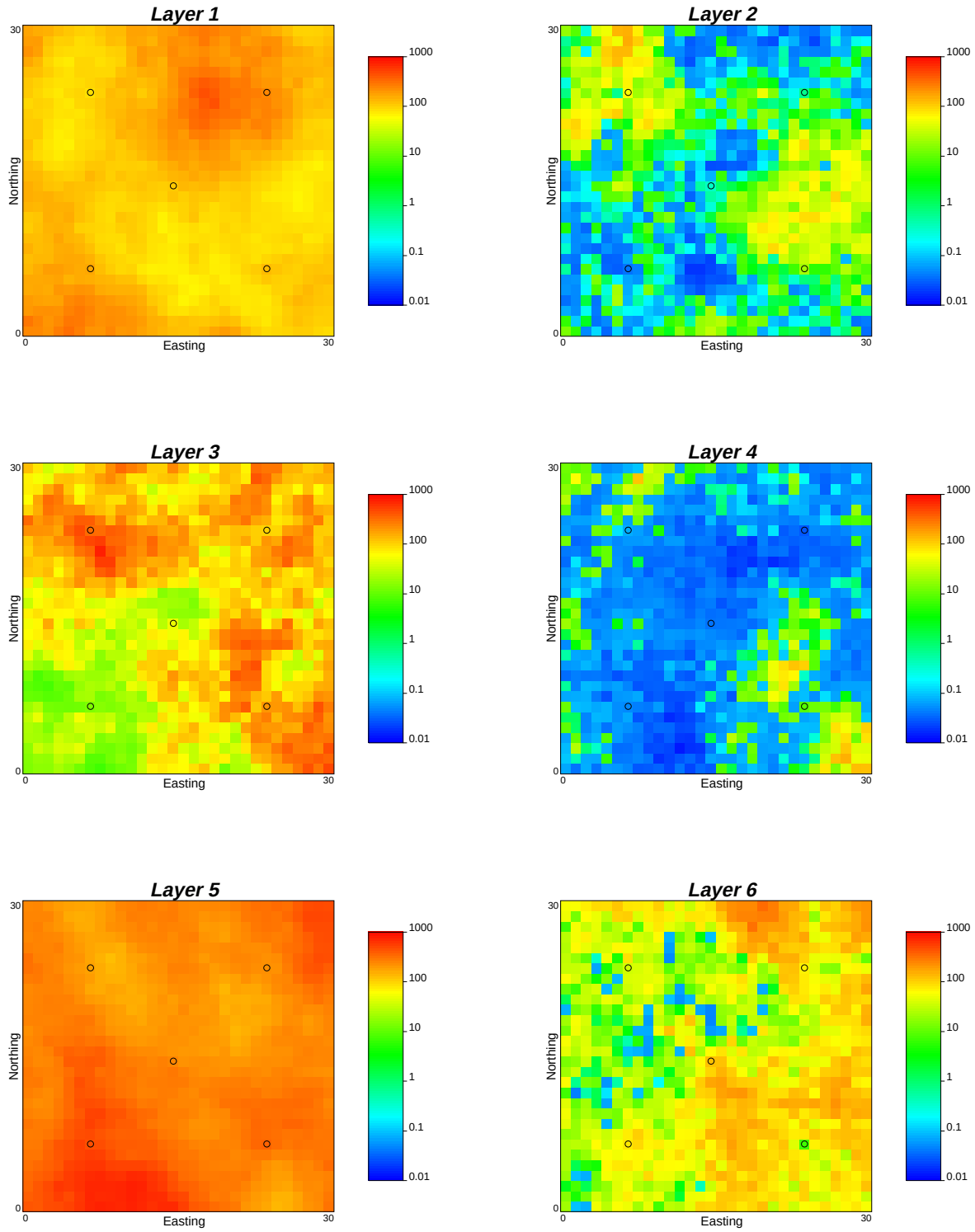


Figure B.20: Upscaled vertical permeability (md) over the six layers of Realization 1 of Reservoir 1.

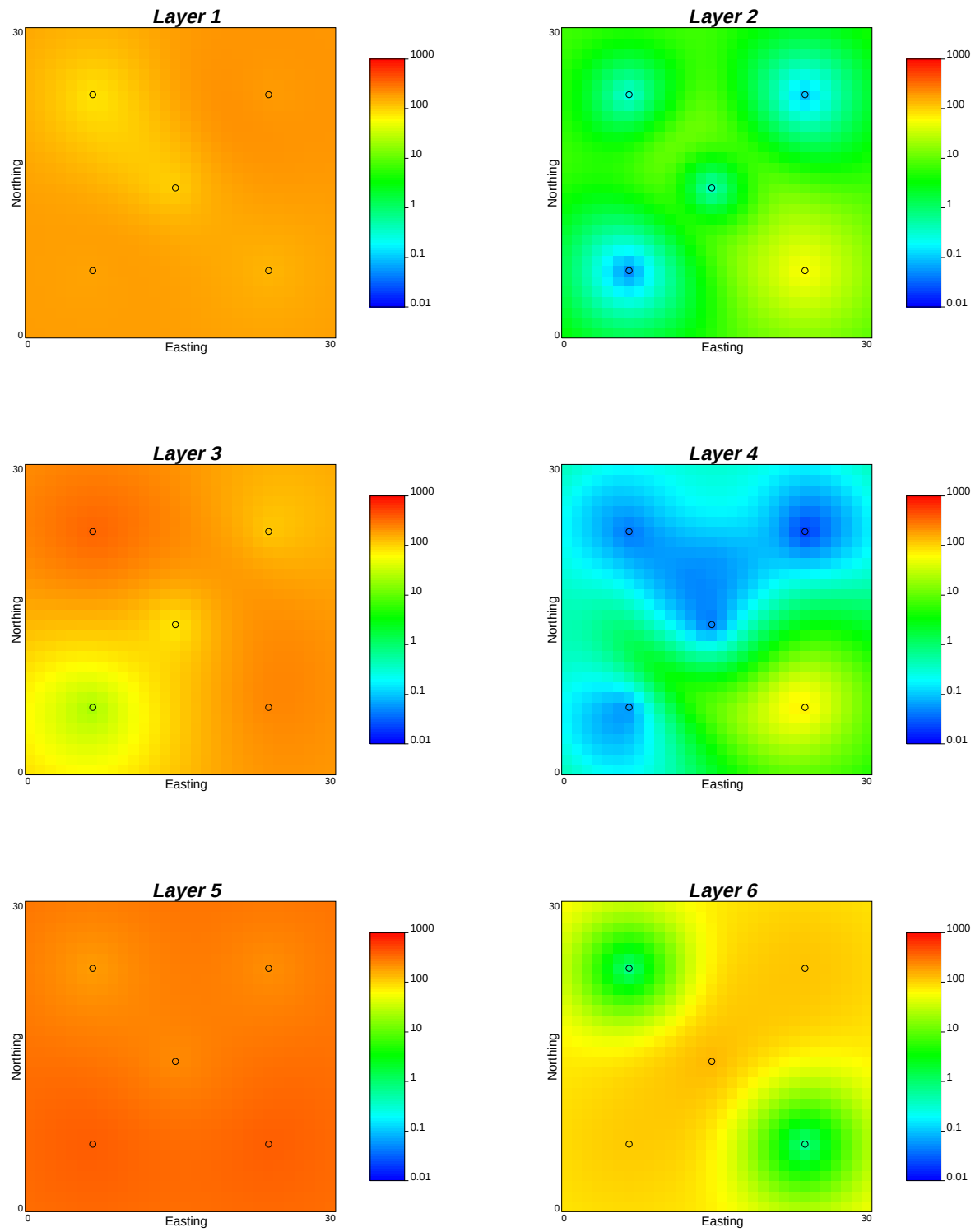


Figure B.21: Upscaled vertical permeability (md) over the six layers of the kriged model of Reservoir 1.

Appendix C

Flow Simulation and Economic Function

In addition to the geological model and the well locations, several other parameters must be defined in order to run a flow simulator. An economic function is also necessary to evaluate profit, which is used to quantify the results of each case for the comparison of the approaches.

The flow simulator ECLIPSE [48] was used because it is a commonly used commercial simulator and because it was available.

The required rock and fluid properties are presented in **Table C.1**. The relative permeability curves were defined at the flow simulation scale to avoid upscaling errors. The initial pressure was taken as 210 bar at the water/oil contact (which was fixed at 2060 m for all reservoirs) and the minimum bottom hole pressure (BHP) as 50 bar. Notice that given the PVT data and pressure limits specified, no free gas was allowed in the reservoir.

The wells were controlled by maximum liquid rate ($600 \text{ STD } m^3/day$) until the BHP reached the minimum and then they were controlled by this minimum BHP. The two upper layers were opened jointly for production but they were closed selectively whenever either of them reached the maximum water-cut (97%). When the economic limit of minimum oil rate ($5 \text{ STD } m^3/day$) was reached, the well was closed.

All economic units were expressed in terms of cumulative oil production (STD

Table C.1: Fluid and rock properties used in flow simulation.

Relative permeability and capillary pressure			
S_w	k_{rw}	k_{ro}	P_c
0.00	0.000	1.000	0.0
0.15	0.000	1.000	0.0
0.20	0.029	0.838	0.0
0.30	0.096	0.540	0.0
0.40	0.175	0.326	0.0
0.52	0.280	0.161	0.0
0.60	0.368	0.086	0.0
0.70	0.500	0.000	0.0
1.00	0.500	0.000	0.0

Density (Kg/m ³)	
Oil	Water
876.2	1024

PVT oil		
Pressure	B_o	Viscosity
(bar)	(Rm ³ /Sm ³)	(cp)
0	1.30	1.30
400	1.15	1.30

Water		
C_w	B_w	Viscosity
(bar ⁻¹)	(Rm ³ /Sm ³)	(cp)
0.00001	1.05	0.5

Formation	
C_f (bar ⁻¹)	0.000053

Initial pressure (bar)	210
Datum (m)	2060

Notation	
S_w = water saturation	B_o = oil formation volume factor
k_{ro} = oil relative permeability	B_w = water formation volume factor
k_{rw} = water relative permeability	C_w = water compressibility
P_c = capillary pressure	C_f = formation compressibility

m^3) to avoid having to define oil price. The measure of profit (P) was defined as the present value of the net oil production for each period of time (t) during 20 years of production less the cost of the wells. The net oil production for each period of time is the incremental oil production (ΔN_p) for that period less the cost of processing the produced water (ΔW_p). This cost for the produced water was estimated by calculating a percentage (3%) of ΔW_p and then transforming it into an effective oil volume. All other operational costs were assumed constant independent of the number of wells. The present value of the net oil production was obtained by bringing the value of each period of time back to the present, discounting them by an internal rate of return (i) of 7.5% per year and adding the values for all the periods of time (nt). The cost of drilling and completing each well (wc) was assumed to be equivalent to 150,000 STD

m^3 of oil and the total cost of wells was obtained just multiplying wc by the total number of wells (nw). The formula used was:

$$P = \sum_{t=1}^{nt} \frac{\Delta Np_t - 0.03 \cdot \Delta Wp_t}{(1+i)^t} - nw \cdot wc \quad (C.1)$$

The parameter values to control the wells, the costs and the internal rate of return will have a great impact on the absolute values of the economic results, but since they were the same for all the approaches, they did not affect the comparison between the approaches. Moreover, these values were defined to be realistic and consistent with an offshore operation to give meaning to the absolute economic results.

As an example of the ECLIPSE results, **Figure C.1** shows the curves of “cumulative oil production (N_p) versus time”, “oil rate versus time”, “cumulative water production (W_p) versus N_p ” and “reservoir pressure versus time” for Configuration 1 of all 11 numbers of wells for true Reservoir 1. It can be seen that, since the wells are initially controlled by maximum liquid rate, the greater the water production the smaller the oil production. After reaching the BHP limit (50 bars) the total liquid rate drops. A good well location is such that the water production is minimum and the permeabilities of the completed cells are large enough to cause a small pressure drop and to delay the BHP limit. The greater the number of wells the greater the initial oil rate, the faster the drop in pressure and the sooner the BHP limit is reached. The optimal number of wells is determined by the economic function. For a certain number of wells (for example 12) to be better than the next smaller number (11), the incremental present value of the net oil production has to be greater than the cost of the additional well.

As an example of the differences between the responses of the true reservoir and the models, **Figure C.2** shows the previous set of production curves for Configuration 1 of 13 wells for the true reservoir, the 20 realizations and the kriged model of Reservoir 1. The explanation for the greater total N_p obtained with the true reservoir despite its greater water production is that the fluid volumes (oil and water) are greater in the true reservoir than in the models for this particular reservoir. It can be seen that the envelope of responses from the models does not include the true reservoir response for this reservoir. This shows that flow uncertainty may be larger than that represented

by the spread of responses from realizations generated using a specific well data set, changing the random path in the sequential simulation and considering uncertainty only in the horizontal variogram range. The analysis of the worth of using more realizations, different numbers of sampling wells and consideration of other sources of uncertainty in model parameters is the scope of Chapter 4.

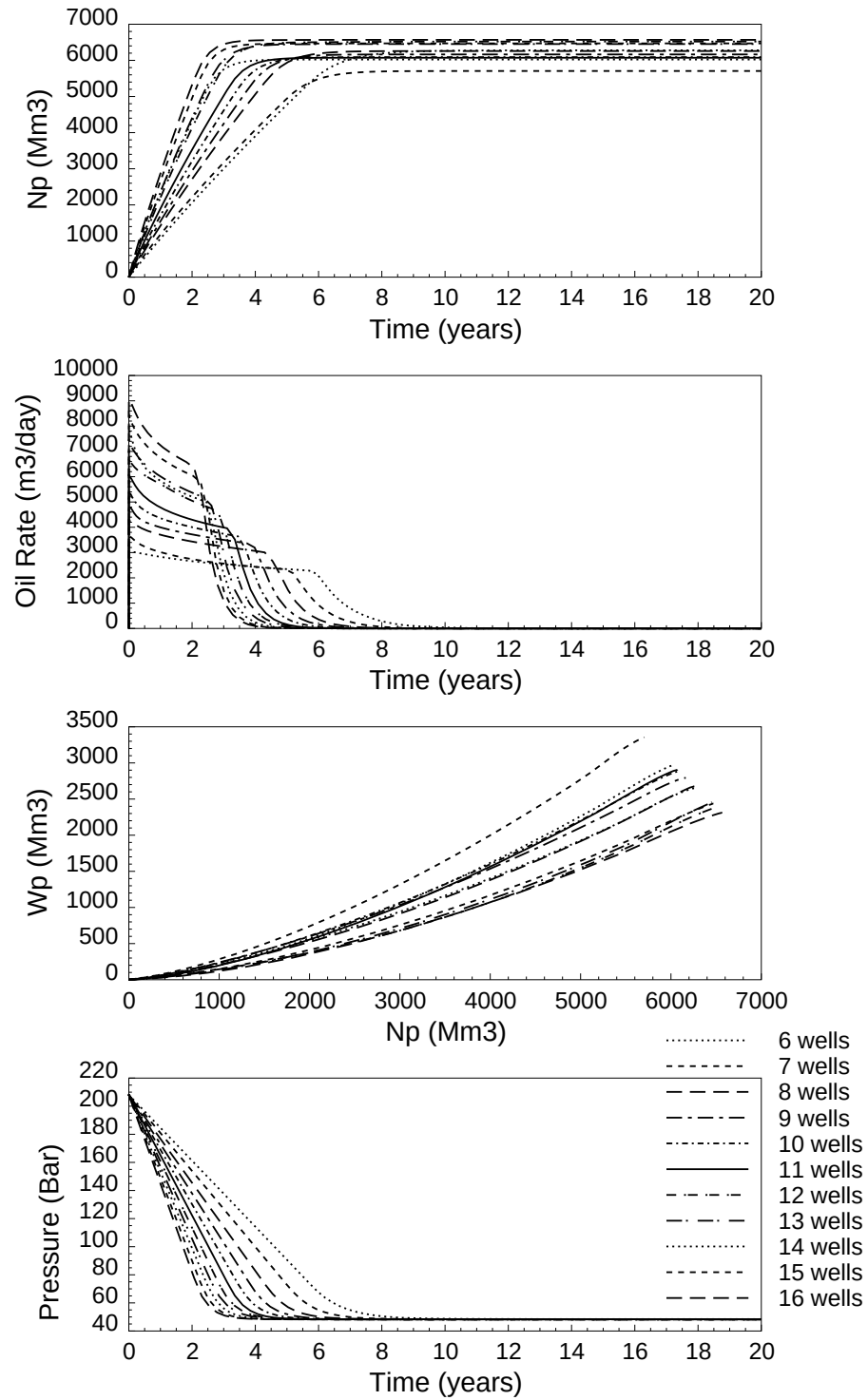


Figure C.1: Production curves of Configuration 1 of 11 numbers of wells with true Reservoir 1.

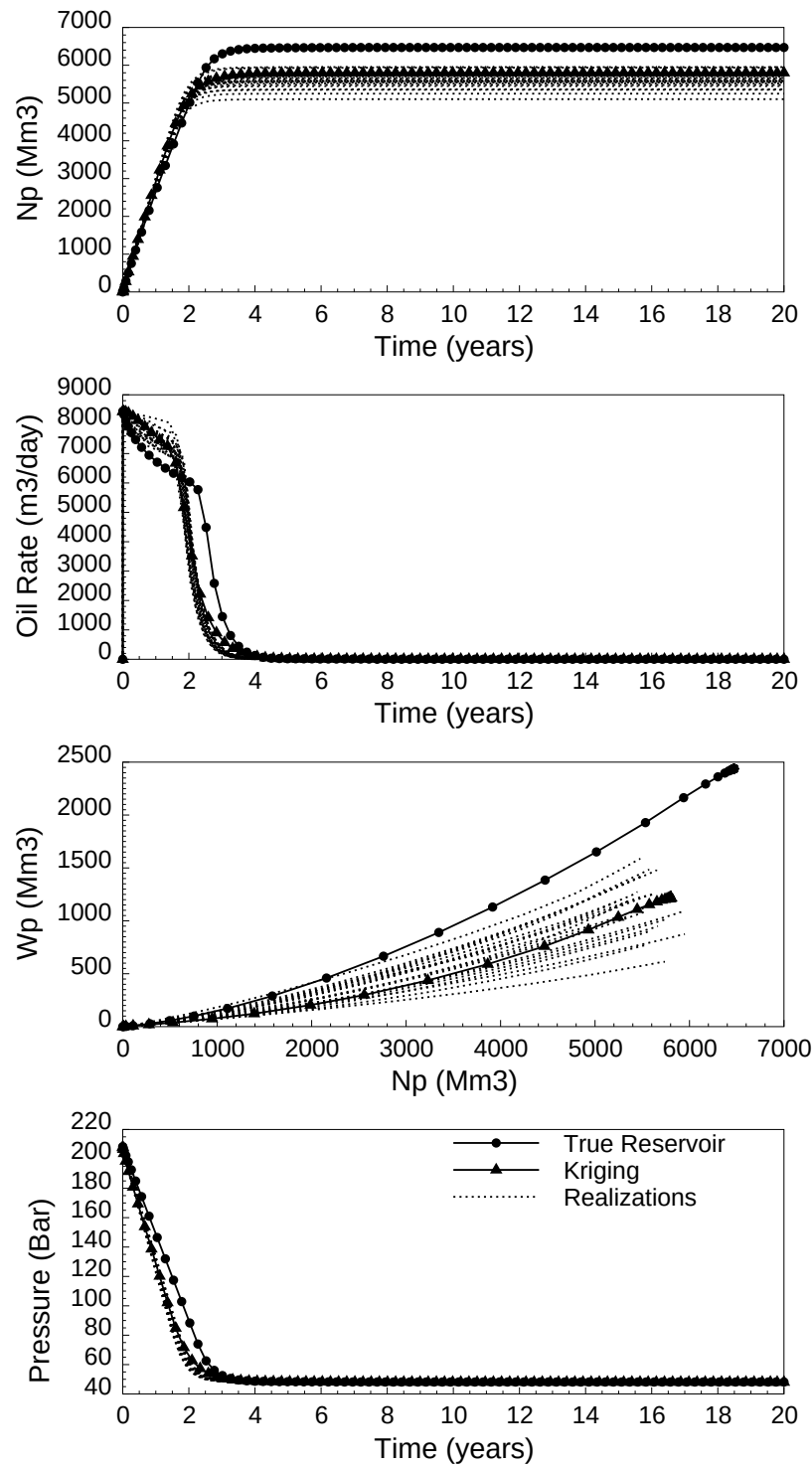


Figure C.2: Production curves of Configuration 1 of 15 wells with true reservoir, 20 realizations and the kriged model of Reservoir 1.

Appendix D

Automation

A UNIX script file is a very useful tool to execute repetitive tasks. The script must be an executable file, which can be ensured by the command:

```
chmod +x file
```

where *file* is the name of the script file.

Long script files can be written using the following few commands and notations:

- “set”, to set values for variables.

Example: `set var1 = 3` sets the value of the variable named *var1* as 3.

- “\$”, to access the value of a variable.

Example: `$var1` has the value 3 in the previous example.

- “@”, to set values for variables using another variable initialized previously.

Example: `@ var2 = $var1` sets the value of the variable *var2* as the value of the variable *var1*.

- “sed”, to make editing changes in a file.

Example: `sed -e “s/VAR1/$var1/g” -e “s/VAR2/$var2/g” file1 > file2` changes the strings *VAR1* and *VAR2* written in the input file *file1* to the values of the variables *var1* and *var2* and writes the results into a new file *file2*.

- “**cat**”, to concatenate files.

Example: **cat file1 file2 > file3** writes *file1* followed by *file2* into a new file *file3*.

- “**cp**”, to copy files.

Example: **cp file1 file\$var1** copies *file1* to the file whose name is formed by the string *file* followed by the value of the variable *var1*.

- “**if (expression) then**”, to condition the execution of some commands to the fulfillment of a certain expression.

Example: **if (\$var1 == 2) then** conditions the execution of the commands between this line and the line with the corresponding “**endif**” to the cases where *var1* has the value 2.

- “**while**”, to implement loops with variables.

Example: **while (\$var1 <= \$var2)** starts a loop for the variable *var1*, executing all the commands between this line and the line with the corresponding **end**, as long as the value of *var1* is less than or equal to the value of *var2*. The increment of the *var1* is made right before the “*end*” command using

@ var1 = @var1 + \$increment.

Other usages are: **while (\$var1 == \$var2)** and **while (\$var1 >= \$var2)**.

- “**< file**” or “**> file**”, to redirect the standard (screen) input or output to a file.

Example: **sgsim < sgsim.inp > sgsim.out** runs the program SGSIM [15] using the file *sgsim.inp* as input and the file *sgsim.out* as output. Most of the GSLIB [15] programs call for the name of the parameter file and write some information on the screen while running. For the case of the example, *sgsim.inp* has the name of the parameter file for the program SGSIM and the run summary is written in *sgsim.out*.

- the symbol “\” must be placed at the end of a line to allow the command in that line to be continued in the following line.

- everything in a line after the symbol “#” is just a comment.

The following example prepares the parameter file for the program PIXELPLT [15], runs the program for three different layers using the corresponding minimum, maximum and increment values, and then uses the program PLOT3 to plot the three resulting postscript files into a single file named *three.layers.ps*.

```
set inilayer = 1
set finlayer = 3
#
@ layer = $inilayer
while ($layer <= $finlayer)
#
    if ($lay == 1) then
        set min = 5
        set max = 25
        set incr = 4
    endif
    if ($lay == 2) then
        set min = 10
        set max = 110
        set incr = 20
    endif
    if ($lay == 3) then
        set min = 50
        set max = 250
        set incr = 40
    endif
#
    sed -e "s/LAYER/$layer/g" -e "s/MIN/$min/g" -e "s/MAX/$max/g" \
        -e "s/INCR/$incr/g" pixelplt.ini > pixelplt.par
    pixelplt < pixelplt.inp
#
    @ layer = $layer + 1
end
#
plot3 1.ps 2.ps 3.ps three.layers.ps
```

The *pixelplt.ini* file in this example could be the following:

```

Parameters for PIXELPLT
*****

START OF PARAMETERS:
../data/layLAY.dat      -file with gridded data
1                        -column number for variable
-1.0e21  1.0e21         -data trimming limits
LAY.ps                  -file with PostScript output
1                        -realization number
30   0.5   1.0          -nx,xmn,xsiz
30   0.5   1.0          -ny,ymn,ysiz
1    0.0   1.0          -nz,zmn,zsiz
1                        -slice orientation: 1=XY, 2=XZ, 3=YZ
1                        -slice number
Layer LAY               -Title
East                    -X label
North                   -Y label
0                        -0=arithmetic, 1=log scaling
1                        -0=gray scale, 1=color scale
0                        -0=continuous, 1=categorical
MIN  MAX  INCR          -continuous:  min, max, increm.
1                        -categorical: number of categories
1    3    Code_One      -category(), code(), name()

```

The *pixelplt.inp* file would have the name of the parameter file to be used, i.e.:

pixelplt.par

The following example runs the flow simulator ECLIPSE [48] for each situation of different configuration, number of wells, realization and reservoir. Besides the steps that are shown in this example, the initial and final number of wells should be defined a priori for each reservoir and their values set inside the script file. Also in this example, all the realizations of each reservoir would have been generated, upscaled and formatted to be used in ECLIPSE. The scenarios, composed by number of wells

and configuration, would have been predefined and stored in ECLIPSE format. The ECLIPSE input file would have “INCLUDE” commands to read the files with the realization properties and the file with the production scenario.

```
#-----
# SET THE LIMITS AND INCREMENTS FOR THE VARIABLES
#
set startr = 1      # initial reservoir
set finshr = 50     # final reservoir
set incr = 1        # reservoir increment
set stareal = 1     # initial realization
set finreal = 20    # final realization
set increal = 1     # realization increment
set startc = 1      # initial configuration
set finshc = 7      # final configuration
set incrm = 1       # configuration increment
#-----
# INITIALIZE THE FILE FOR THE FLOW RESPONSES
#
cp response.ini response.out
#-----
# LOOP OVER ALL RESERVOIRS
#
@ reserv = $startr
while ($reserv <= $finshr )
#-----
# INFORM THE INITIAL AND FINAL NUMBER OF WELLS FOR EACH RESERVOIR
#
if ($reserv == 1) then
    set startw = 6
    set finshw = 16
endif
if ($reserv == 2) then
    set startw = 8
    set finshw = 18
endif
#
```

```

# INFORM NUMBER OF WELLS FOR THE REMAINING RESERVOIRS
#
#-----
# LOOP OVER ALL REALIZATIONS
#
@ realiz = $stareal
while ($realiz <= $finreal )
#-----
# LOOP OVER ALL NUMBERS OF WELLS
#
@ wellnum = $startw
while ($wellnum <= $finshw )
#-----
# LOOP OVER ALL CONFIGURATION NUMBERS:
#
@ wellcon = $startc
while ($wellcon <= $finshc )
#-----
# COPY THE CORRESPONDING FILES WITH THE REALIZATION AND THE SCENARIO
#
cp ../data/R$reserv.r$realiz.top.dat top.dat
cp ../data/R$reserv.r$realiz.thickness.dat thickness.dat
cp ../data/R$reserv.r$realiz.porosity.dat porosity.dat
cp ../data/R$reserv.r$realiz.permeability.dat permeability.dat
cp ../conf/w$wellnum.c$wellcon.dat wellconf.dat
#-----
# RUN ECLIPSE FLOW SIMULATOR
#
@eclipse < eclipse.inp
#-----
# EXTRACT THE VARIABLES OF INTEREST FROM THE ECLIPSE .RSM FILE
#
sed -e "s/RESER/$reserv/g" -e "s/REAL/$realiz/g" \
    -e "s/WELL/$wellnum/g" -e "s/CONF/$wellcon/g" rsmdat.ini > rsmdat.inp
rsmdat < rsmdat.inp
#-----

```

```

# STORE THE RESULT FOR THIS CASE
#
cat response.out rsmdat.out > temp
mv temp response.out
#-----
# END LOOP OVER CONFIGURATIONS
#
@ wellcon = $wellcon + $incrm
end
#-----
# END LOOP OVER NUMBERS OF WELLS
#
@ wellnum = $wellnum + $incrm
end
#-----
# END LOOP OVER REALIZATIONS
#
@ realiz = $realiz + $increal
end
#-----
# END LOOP OVER RESERVOIRS
#
@ reserv = $reserv + $incr
end
#-----

```