Enhancing Reservoir Modeling with Machine Learning to Integrate Static and Dynamic Calibration Data in Stratigraphic Forward Simulation

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Abstract

Traditional reservoir modeling workflows often rely on geostatistical techniques, such as kriging or multipoint statistics, to construct geological models. While these methods can incorporate a wide range of data, they tend to oversimplify critical geological features, failing to fully represent the spatial and temporal complexities of sedimentary systems. This simplification can lead to inaccuracies in dynamic reservoir simulations and suboptimal predictions. In contrast, Stratigraphic Forward Modeling (SFM) offers a more detailed, physically grounded representation of sedimentary processes such as erosion, transport, and deposition. However, SFM-based models are often challenging to calibrate, typically representing only geological knowledge without ensuring compatibility with dynamic field behaviors.

To address these limitations, we propose a novel workflow that integrates static geological data and dynamic production data into the calibration process of SFM, enhancing the geological realism of reservoir models while ensuring they are consistent with field performance.

This approach leverages SFM's capacity to simulate sedimentary processes, offering a geologically grounded alternative to conventional stochastic methods. Constructing models that adhere to physical sedimentary principles produces geological representations closely aligned with subsurface realities. Furthermore, a robust procedure for converting SFM outputs into flow simulation grids ensures an accurate representation of geological structures and associated reservoir properties, such as porosity, permeability, and capillary pressures.

The workflow employs a multi-objective calibration strategy. The first objective function focuses on static geological data, such as facies derived from well logs, while the second accounts for dynamic data, including field pressures and connectivity indicators. These objective functions are integrated into a unified optimization framework that balances geological fidelity with dynamic accuracy. Cutting-edge machine learning surrogate models are also incorporated, enabling the generation of multiple realizations that are both geologically and dynamically consistent. This reduces computational demands while capturing the diversity of acceptable geological scenarios.

The proposed methodology holds significant promise for the oil and gas industry, particularly for reservoirs with high geological uncertainty, such as Brazil's pre-salt carbonates. By overcoming the limitations of traditional geostatistical models, this workflow offers a more accurate,

flexible, and scalable approach to reservoir modeling.

A case study on a Brazilian Aptian carbonate reservoir of the Campos Basin demonstrates the methodology’s potential to bridge the gap between geological processes and reservoir performance. By integrating static and dynamic data in a unified framework, this workflow sets a new benchmark for generating geologically realistic and dynamically consistent reservoir models, paving the way for improved production forecasts and more effective resource optimization.

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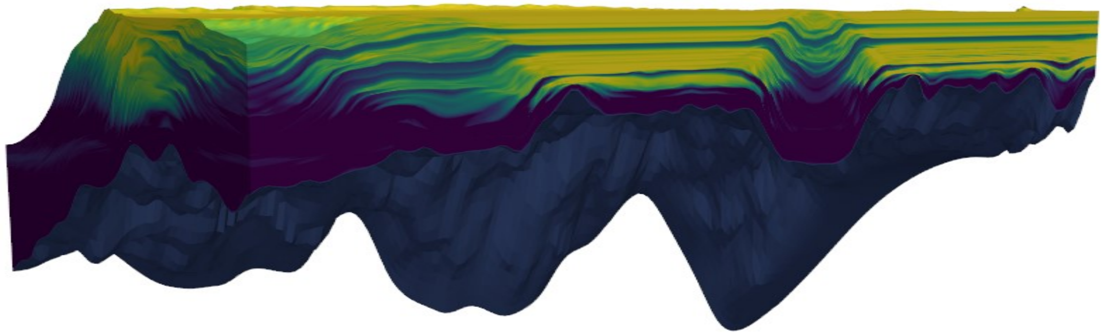
INTEGRATING STATIC AND DYNAMIC DATA FOR CALIBRATION OF STRATIGRAPHIC FORWARD MODELING

Mathieu Ducros

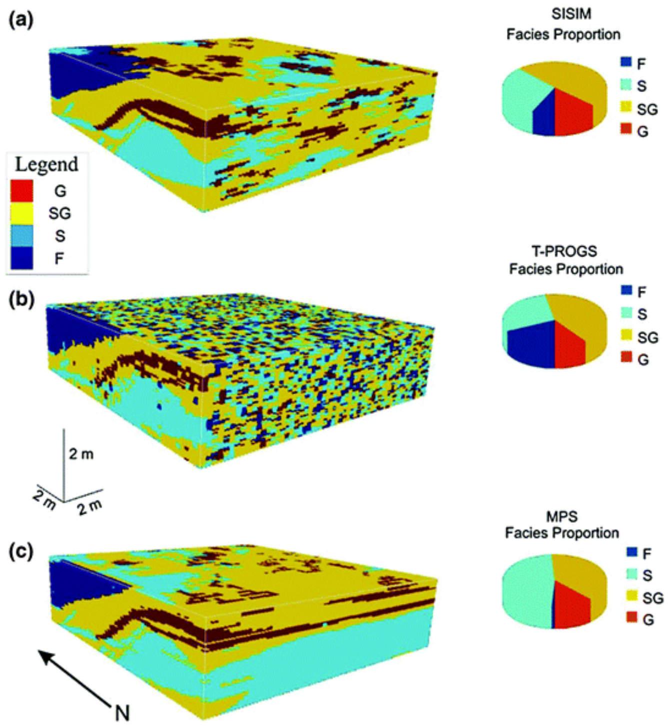
Introduction

From geostatistics to processes simulation

- **Geostatistical models**: not realistic geological models, difficult to perform history matching with predictive results.
- **Simulations of geological processes**: geologically realistic, explanatory models but calibration usually focuses on geological data only.



Example of sediment distribution using geological processes



Examples of geostatistics facies models (Maliva, 2016)

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Introduction

Objectives and challenges

Objectives:

- Generate geological models with **process simulations.**
- Calibrate the models using **geological and dynamic data.**

Challenges:

- Efficiently **adjust the model** with the two types of data.
- Generate **various adjusted realizations** corresponding to different geological scenarios.

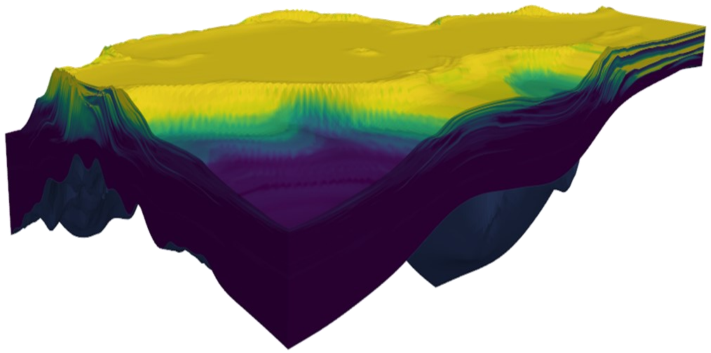
Methodology
Technical solutions

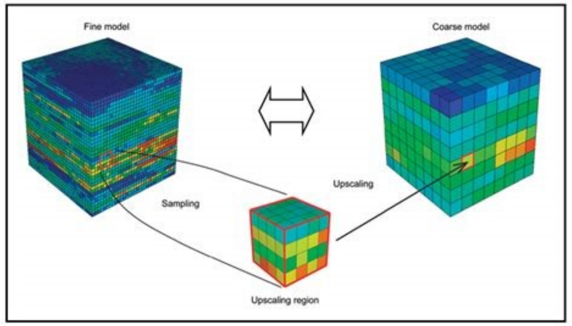
- **Machine learning** models to provide multidimensional results instantaneously (e.g., distribution of sediments, production curves).
- **Multi-objective optimization** methods to adjust on both the geological and dynamic data.
- **Clustering methods** in the multi-objective optimization space, to extract models corresponding to different geological configurations.

Methodology

From geological processes to flow simulation

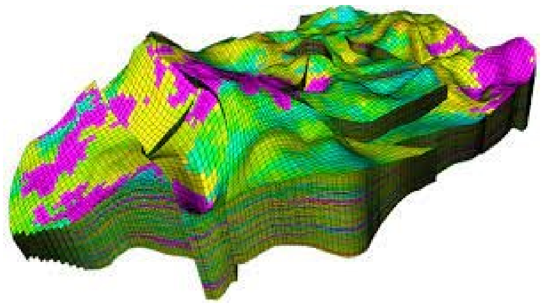
1. Forward stratigraphic modeling
(geological processes)





2. Deterministic grid conversion
based on sediment proportions
in each cell

3. Reservoir simulation



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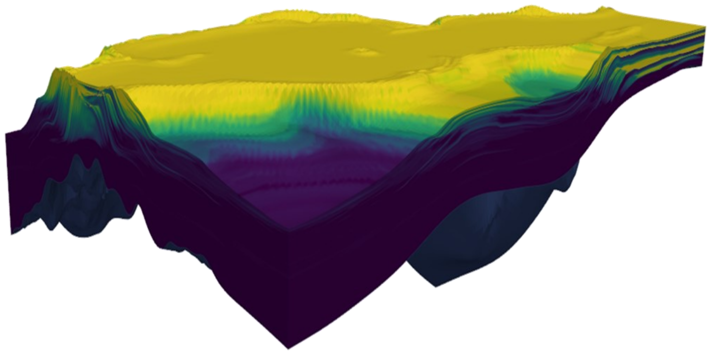
Methodology

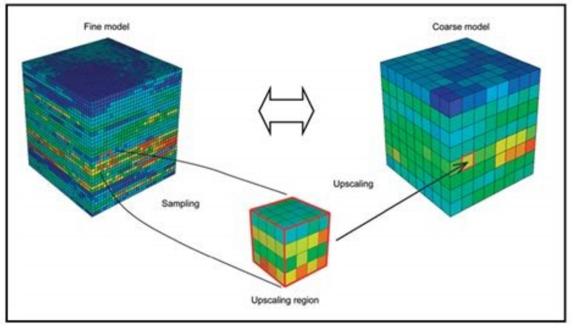
Account for uncertainties along the process

1. Forward stratigraphic modeling
(geological processes)



Machine Learning

Uncertainties:
- Sediment supply
- Basin deformation
- Transport
- Carbonate production
- ...

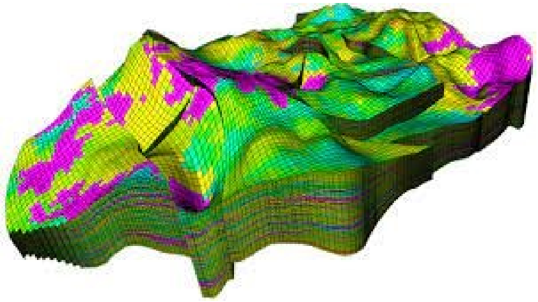


2. Deterministic grid conversion
based on sediment proportions
in each cell

Machine Learning

Uncertainties:
- Porosity
- Permeability
- Kr/PC
- ...

3. Reservoir simulation



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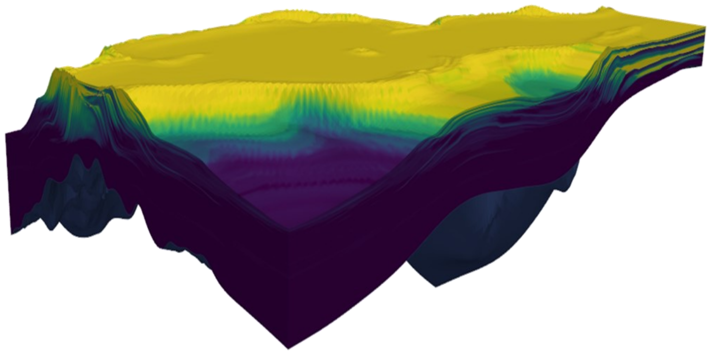
Methodology

Multi-objective optimization

1. Forward stratigraphic modeling (geological processes)



Machine Learning

Uncertainties:
- Sediment supply
- Basin deformation
- Transport
- Carbonate production
- …

Objective function

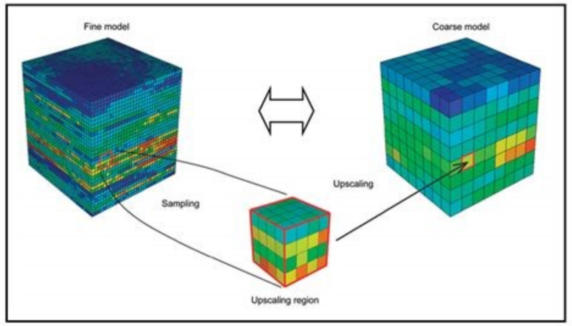
Multi-objective optimization

Pareto front (geological and dynamic data)

Objective function

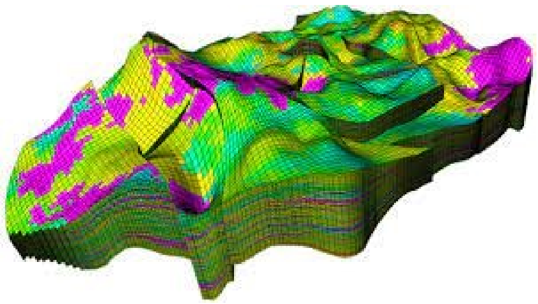
Machine Learning

Uncertainties:
- Porosity
- Permeability
- Kr/PC
- …



2. Deterministic grid conversion based on sediment proportions in each cell

3. Reservoir simulation



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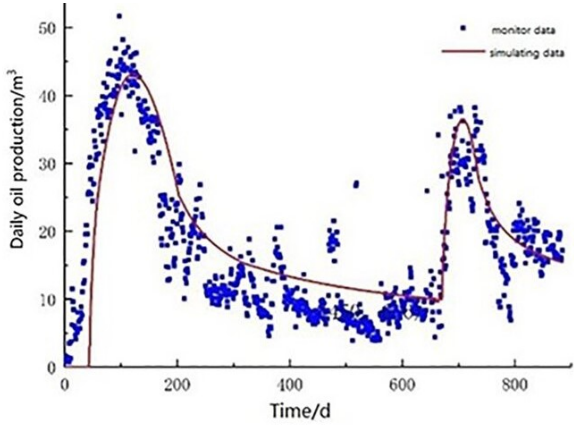
Methodology

Objective functions

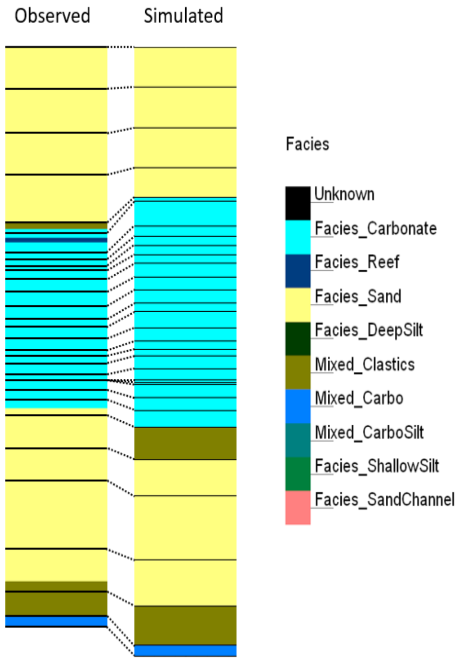
Objective function of dynamic data:

- Classical objective function like RMSE



Objective function of geological data:

- Function inspired by techniques of automated well correlation (correlation of the observed sequence with the simulated sequence)



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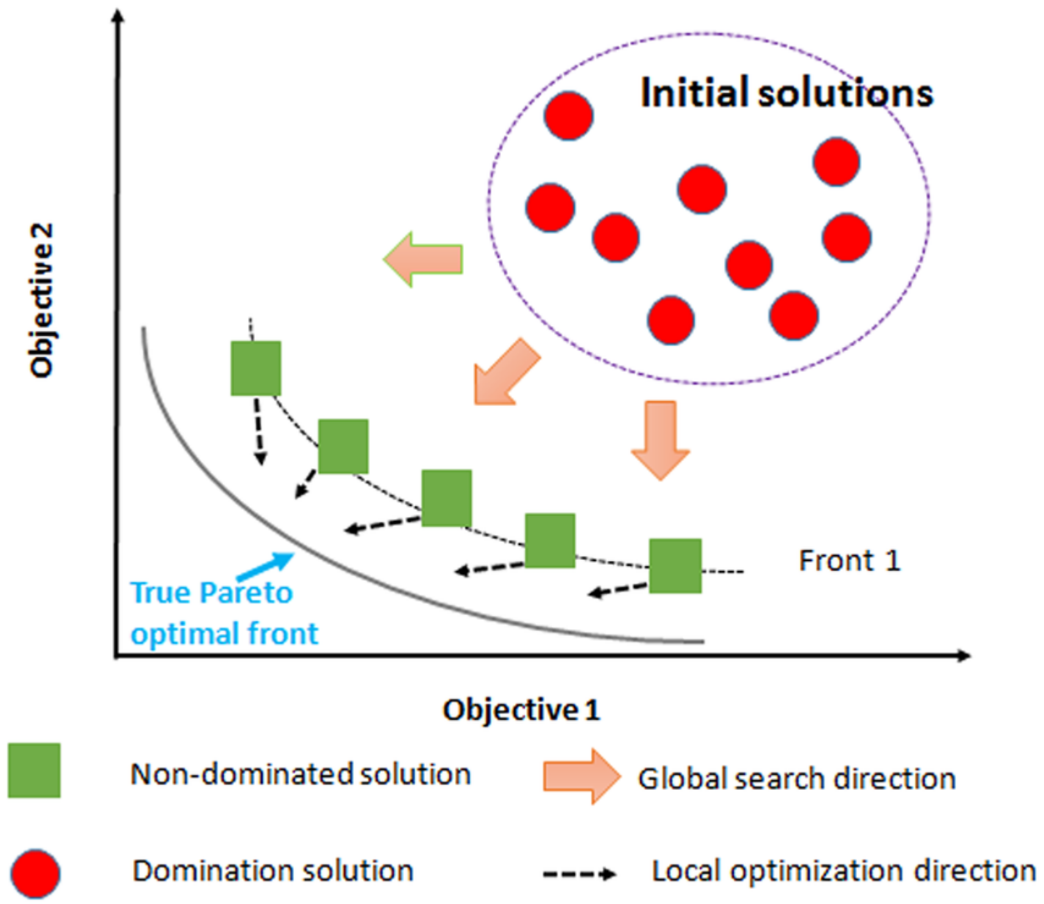
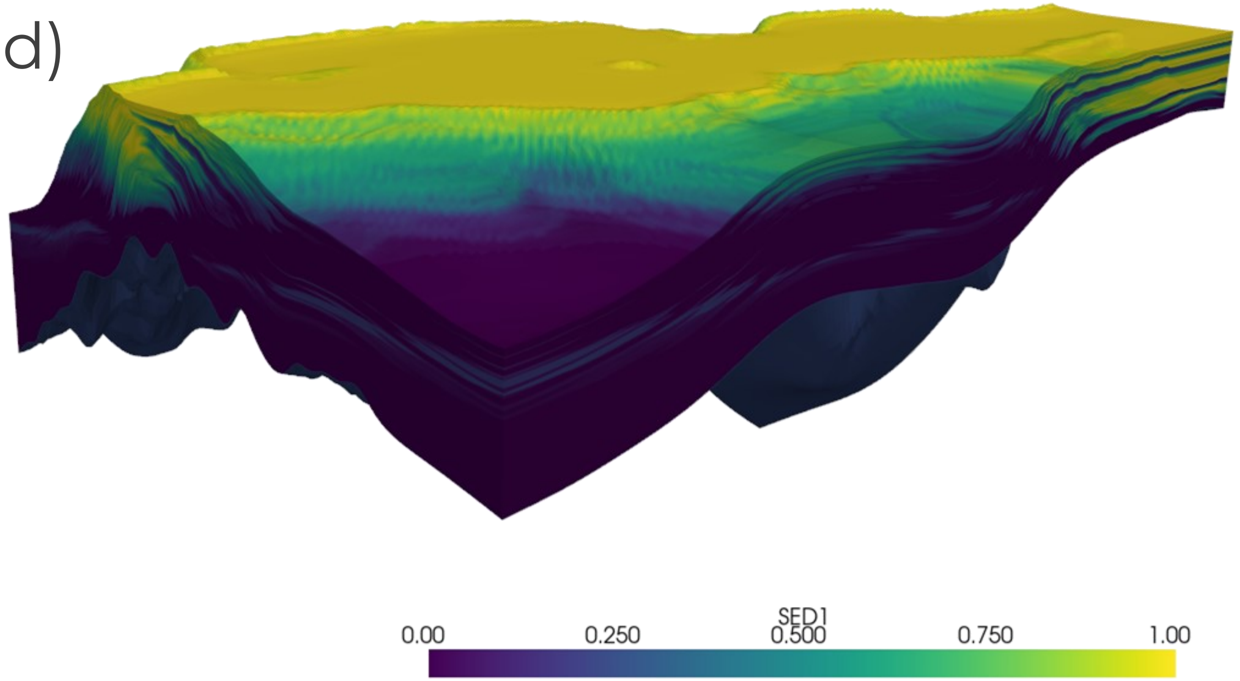
Case study
Multi-objective optimization



- Global optimization
- No competition between the different objectives
- Set of optimal solutions as a result (Pareto front)

Case study
Aptian carbonates reservoir of the Campos Basin

- SedSimple open-source SFM simulator
- 4 sediments (stromatolites, spherulites, laminites and mud)
- 100 layers representing 3Ma
- 200m resolution
- NX = 205, NY = 112
- More than 2.2M active cells



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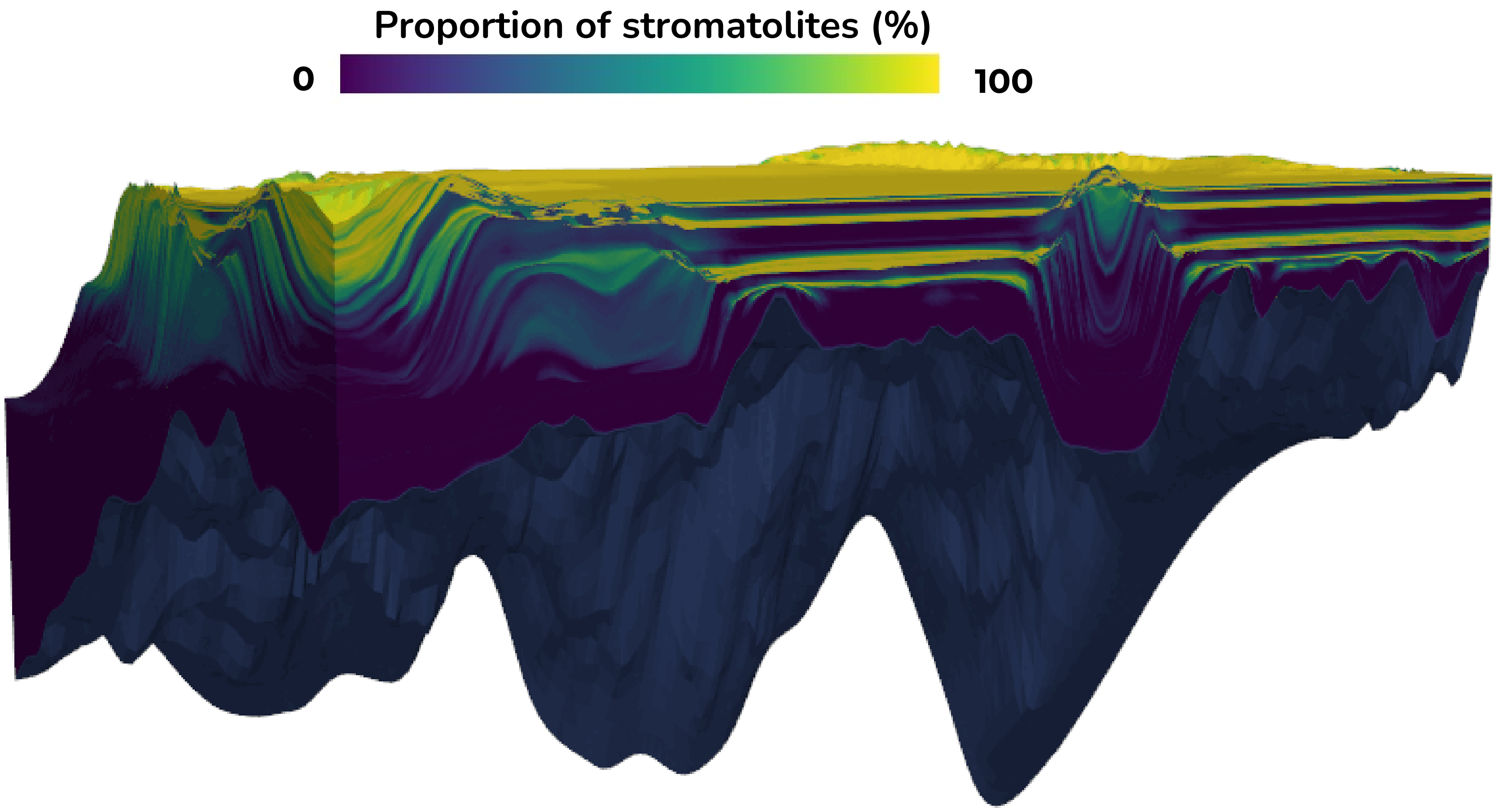
Case study

Machine learning results



Sea level variations

Stromatolites production rate

5 uncertain parameters

- Sea-level
- Carbonate growth rates
- Porosity
- Permeability

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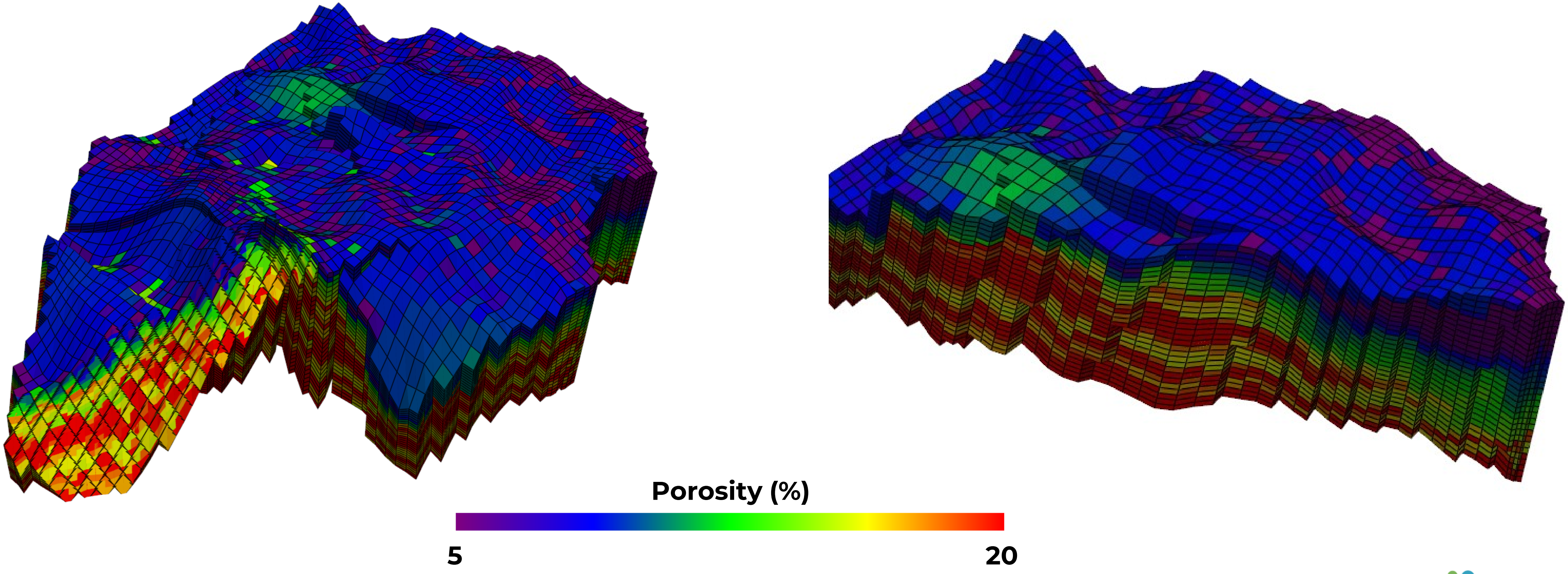
Case study
Grid conversion results

Possible to keep the heterogeneities in the reservoir



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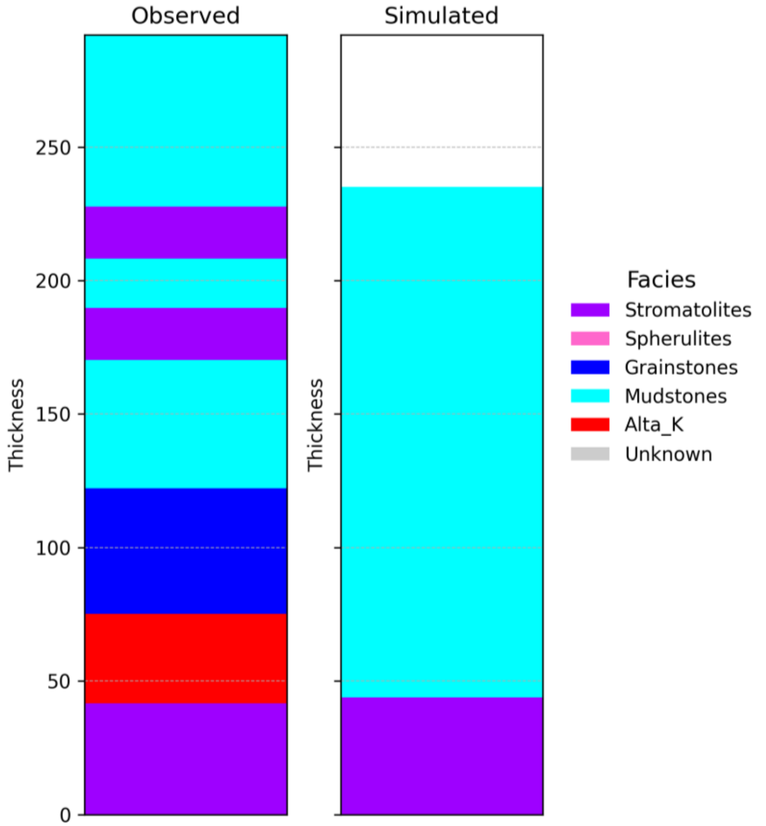
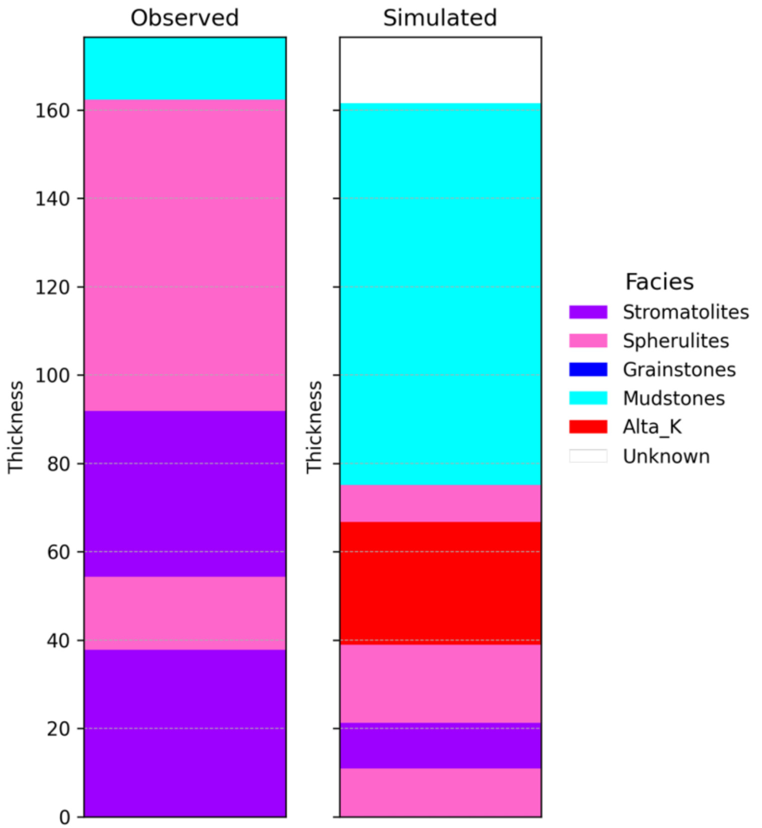
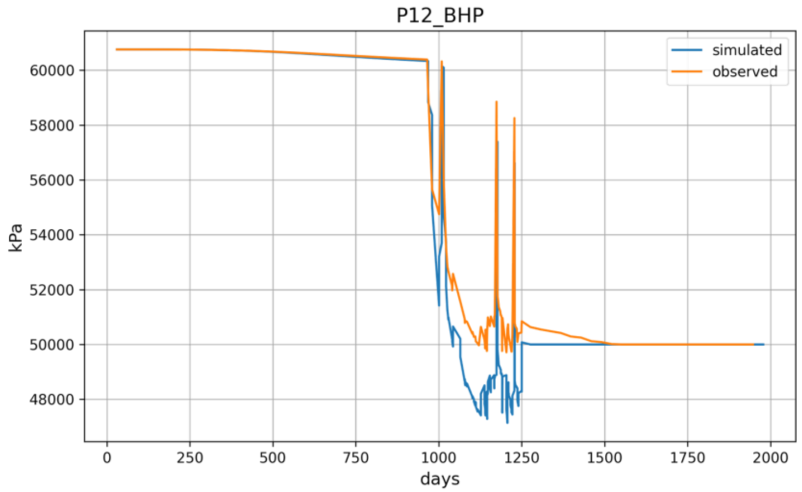
Case study

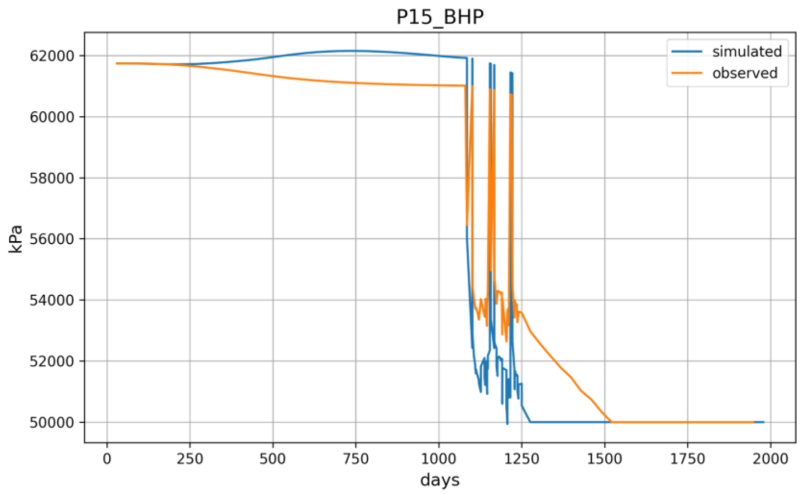
Multi-objective optimization



Initial model







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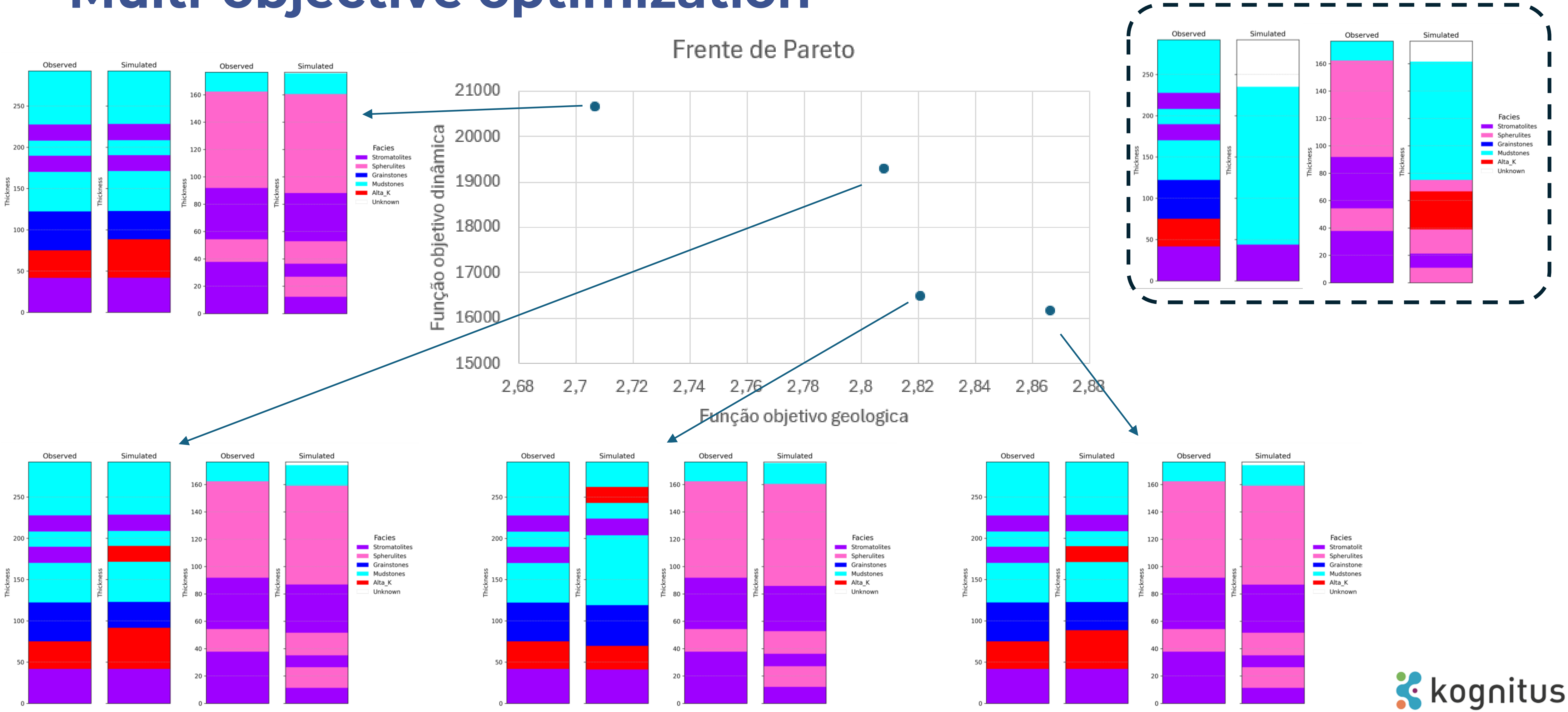
Case study

Multi-objective optimization

Initial model



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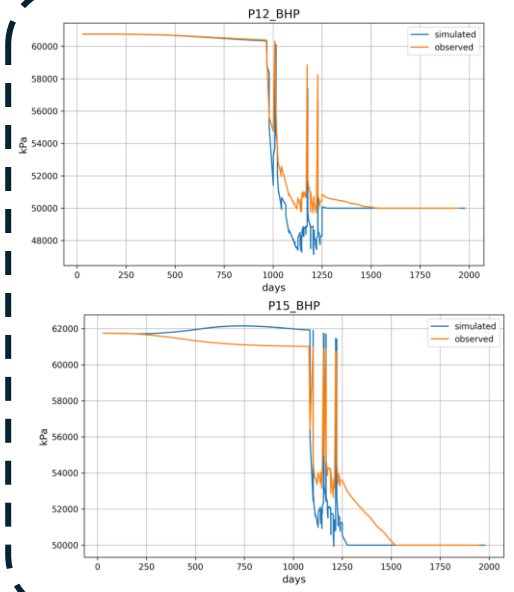
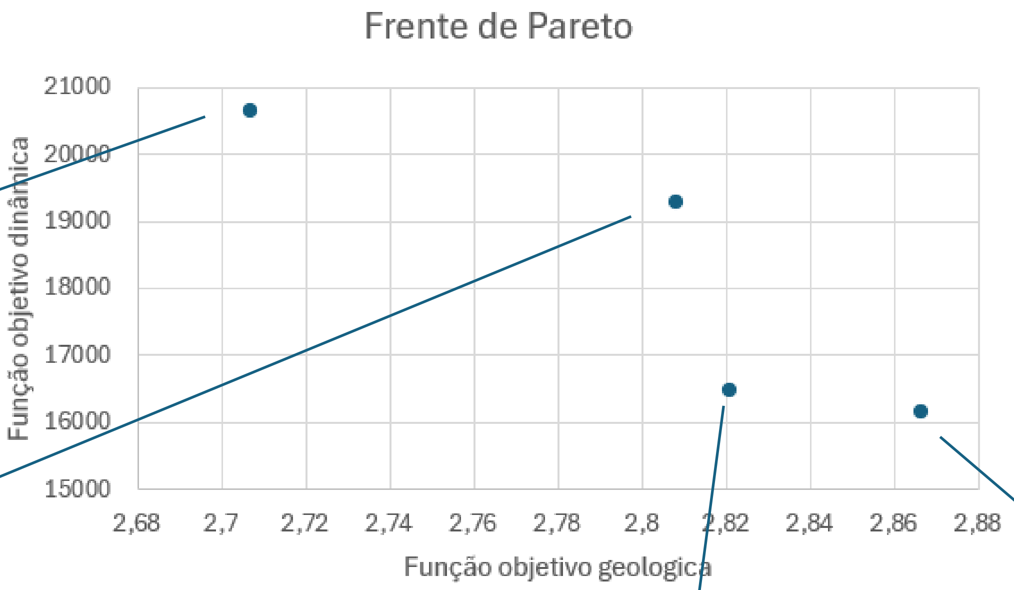
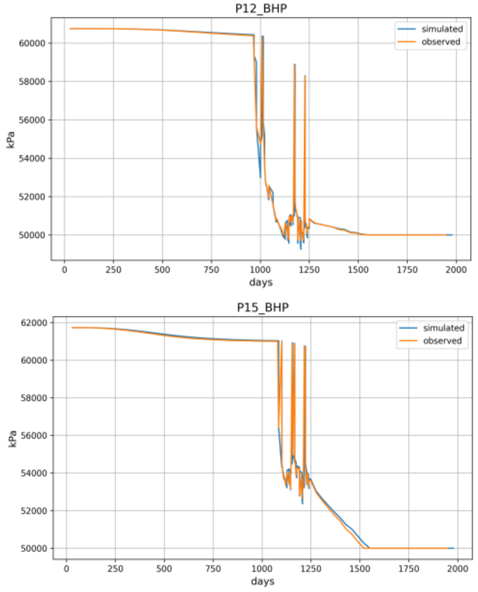
Case study

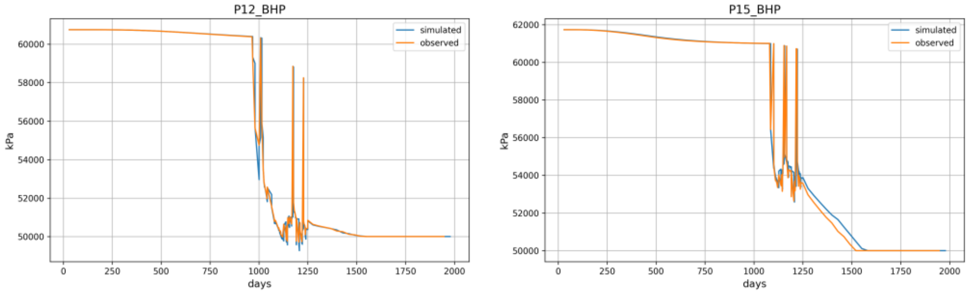
Multi-objective optimization

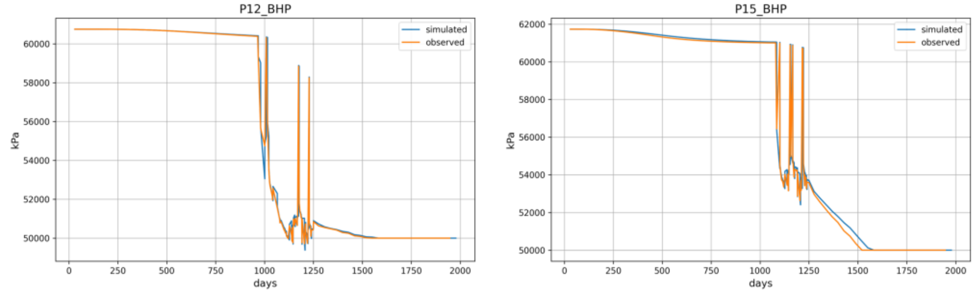
Initial model

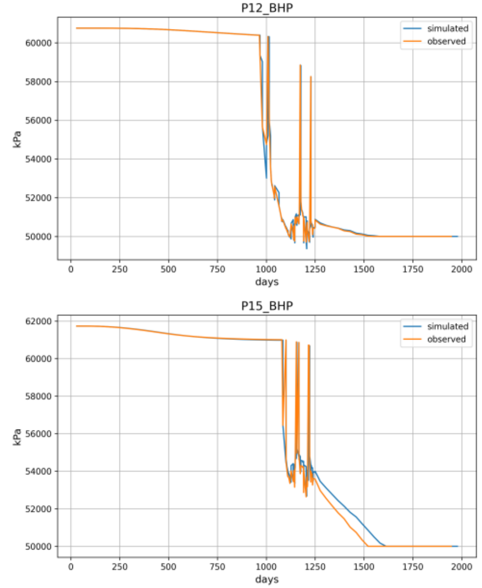












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Conclusions

Very promising results!

- The machine learning enables the **instantaneous generation of 3D models** corresponding to any value of the input parameters
- The geological grid for the reservoir simulation **present heterogeneities important for the flow simulation**
- **The multi-objective optimization**, performed using the machine learning models, gave access to **multiple realizations of calibrated models** for both geological and dynamical data.

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Thank you!

Funding of the project

PETROBRAS

Providers of numerical simulators

COMPUTER MODELLING GROUP LTD.

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