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Field Performance Prediction under Uncertainty – Thriving on Automation

Ralf Schulze-Riegert
Schlumberger Norwegian Technology Center

Society of Petroleum Engineers
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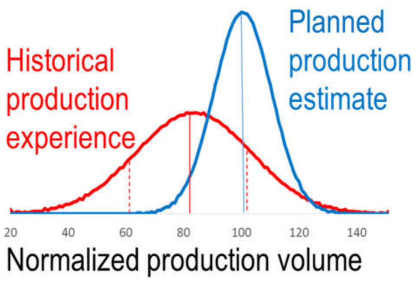
Uncertainty Management in Upstream Projects

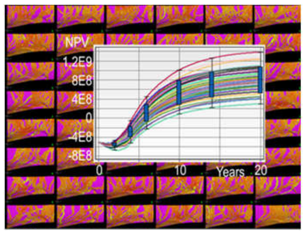
Concern:

- Majority of the industry projects never deliver planned production volumes*).



Solutions:

- Holistic uncertainty assessment to challenge optimism**)
- Ensemble-based reservoir modelling



Challenges:

- Efficient use of digital strategies for fast execution and concept selection

*) Nandurdikar and Wallace, SPE-145437 (2011)
**) Scott Meddaugh, SPE-175009 (2015), SPE DL (2018)

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Overview

- Short introduction to a framework for uncertainty management
- Practical solution strategies and examples
- Impact on result presentation for decision support under uncertainty

1
- Geothermal – Hotspot assessment

2
- Brownfield model maturation

3
- Field development under uncertainty

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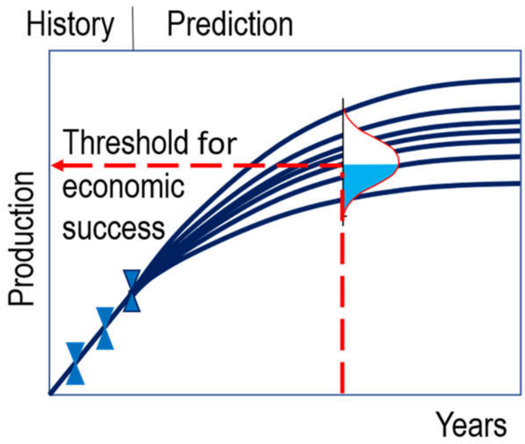
Overview

- Short introduction to a framework for uncertainty management
- Practical solution strategies and examples
- Impact on result presentation for decision support under uncertainty



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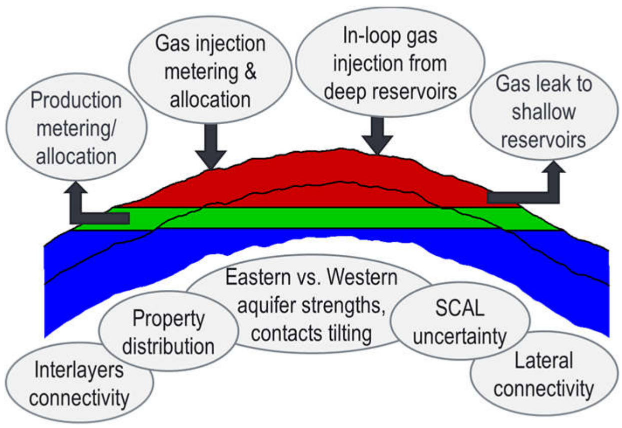
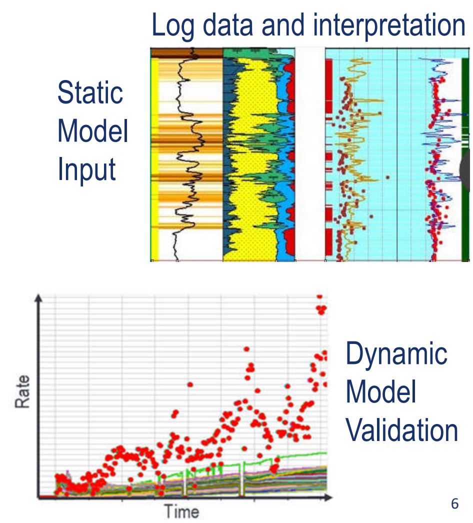
Data Quality – Managing Uncertainties



Oil rim development project*)



*) M. Elharith et al. JPEPT (2019)

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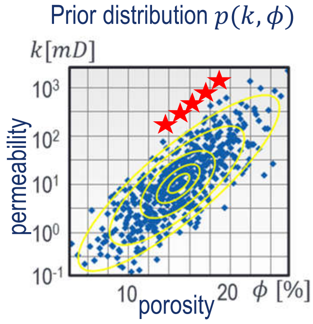
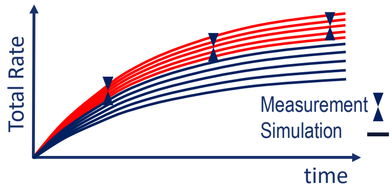
Uncertainty Framework in Geoscience

A probabilistic formulation combines the
- belief – prior model $p(m)$ and
- evidence – difference between model and measurement D

$$p(m|D) = p(m) \times p(D|m)$$

Alternative conclusions drawn for cases outside prior range
1. Model falsification*) – exclude cases ★ not consistent with prior model
2. Model maturation – revise prior model assumptions, learn from data





*) Quantifying Uncertainty in Subsurface Systems, C. Scheidt, L. Li, & J. Caers, Wiley (2018)

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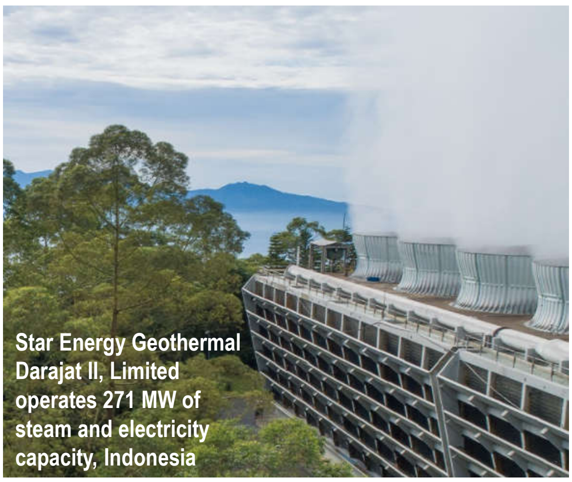
1. Geothermal: Natural Fracture Modelling and Sweet Spot Maps

Challenge
- Identify sweet spots for well targeting and optimization for robust drilling decisions under subsurface uncertainty

Solution
- Create alternative structural models and geo-mechanical drivers to explain natural fractures
- Automate multiple realization workflow to capture subsurface uncertainty



Innovative technical strategies in natural fracture characterization for well placement: Case Study from Darajat Field, J.P. Joonnekindt at al., accepted for publication at the IPTC 2022

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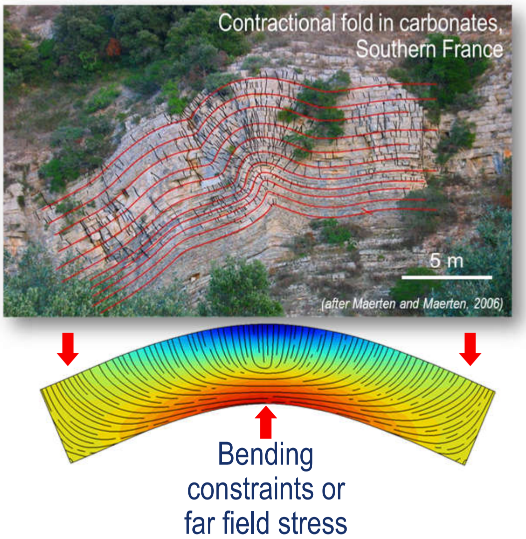
Modelling Natural Fractures using Geomechanics

Geomechanical forward modelling

- Enhance classical approaches
- Based on a structural model
- Estimate stress perturbations due to Fault sliding during paleo tectonic events etc.

Natural fracture characteristics (type, orientation, location)

- at the time of their development
- dependent on the local state of stress and rock type



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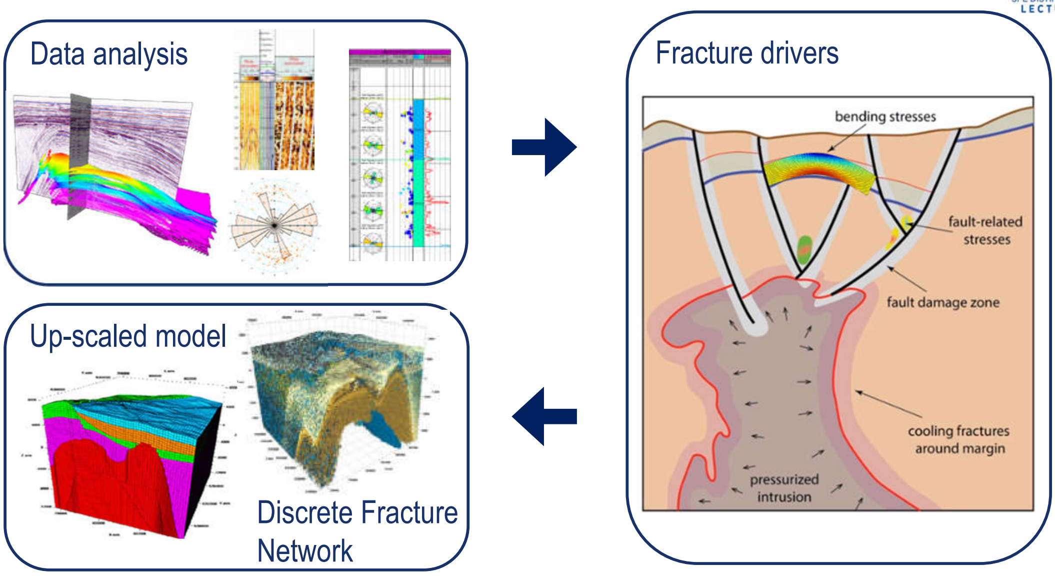
Modelling Natural Fractures in Reservoirs



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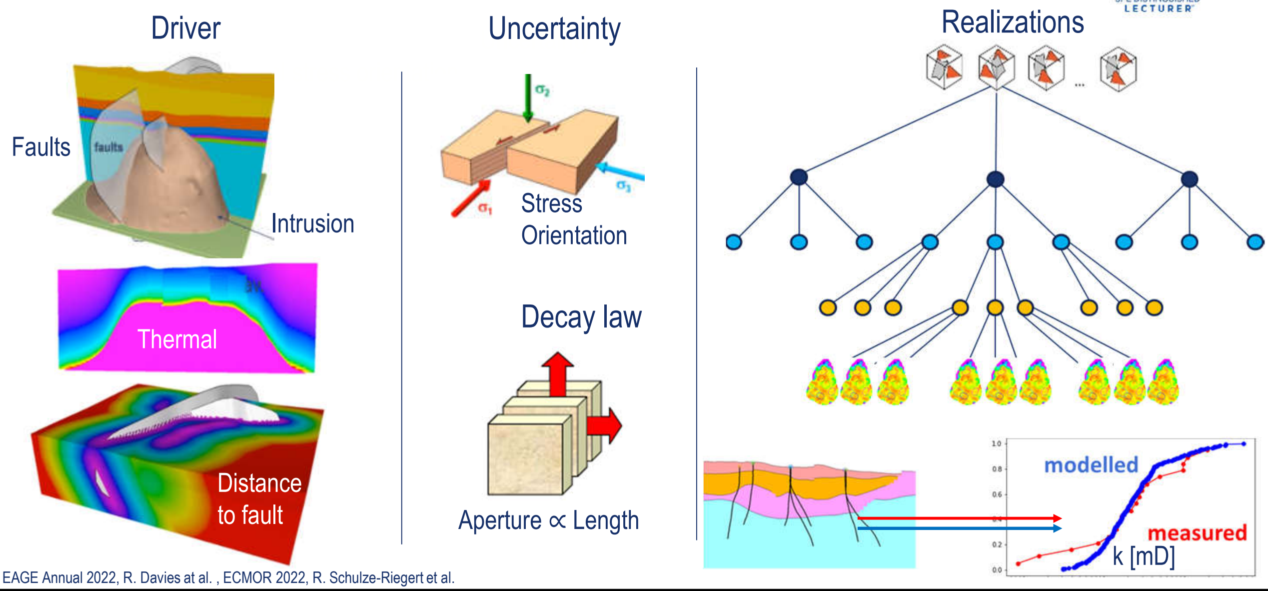
Multiple-Realization Workflow



EAGE Annual 2022, R. Davies at al. , ECMOR 2022, R. Schulze-Riegert et al.

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Result Preparation

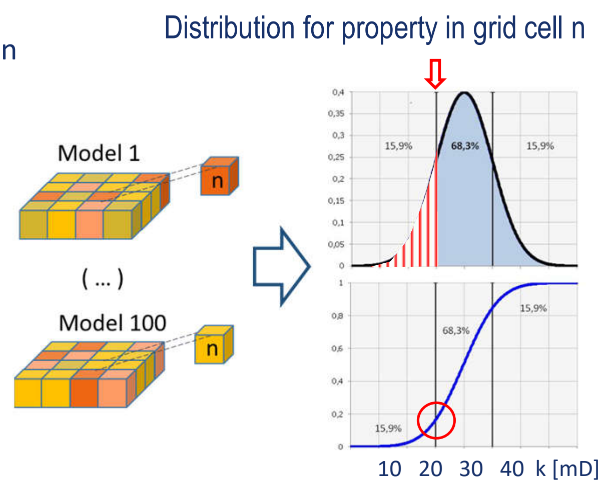
Probability maps deliver a combined view on multiple-realizations for robust host spot identification

Question to ask:

- Which area shows a high probability finding permeability above a defined threshold level, e.g., k > 20 [mD]

Answer, e.g.:

- Probability for area “n” finding
  - k < 20 [mD] is ~ 16%
  - k > 20 [mD] is ~ 84%



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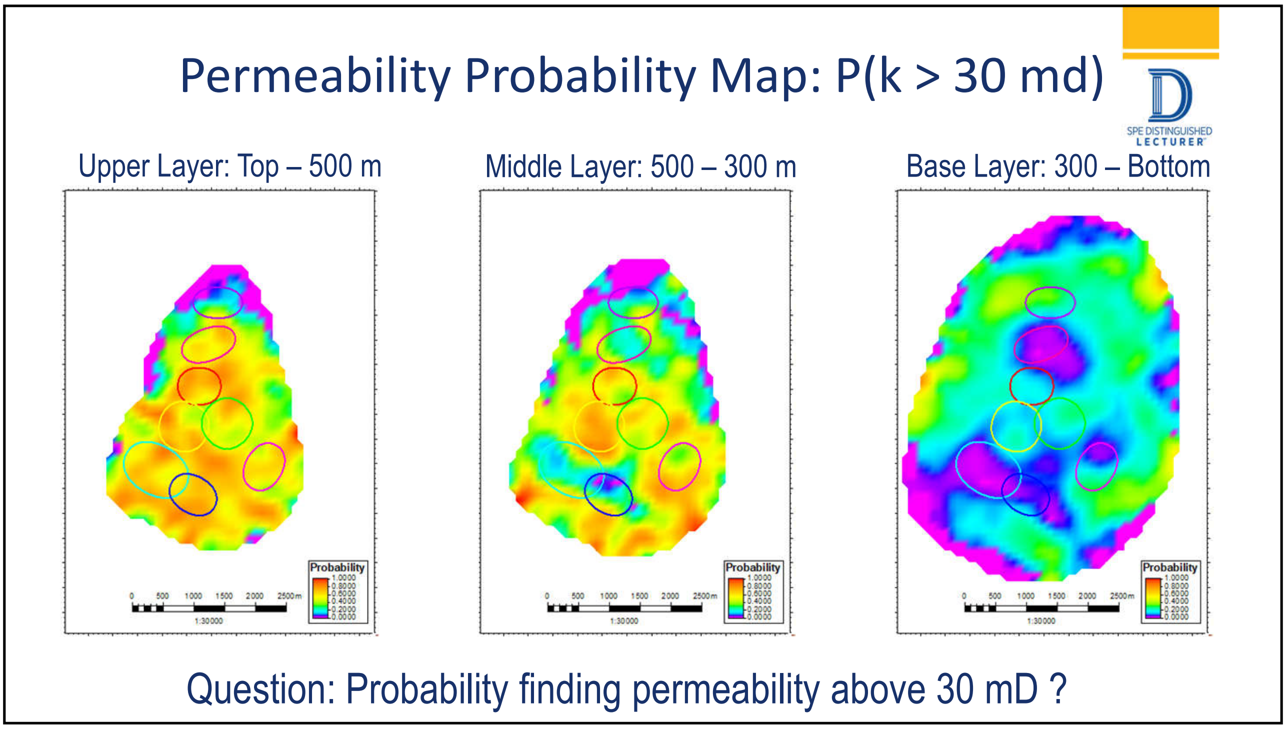
Permeability Probability Map: P(k > 30 md)
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Upper Layer: Top – 500 m
Middle Layer: 500 – 300 m
Base Layer: 300 – Bottom
Probability
Question: Probability finding permeability above 30 mD ?

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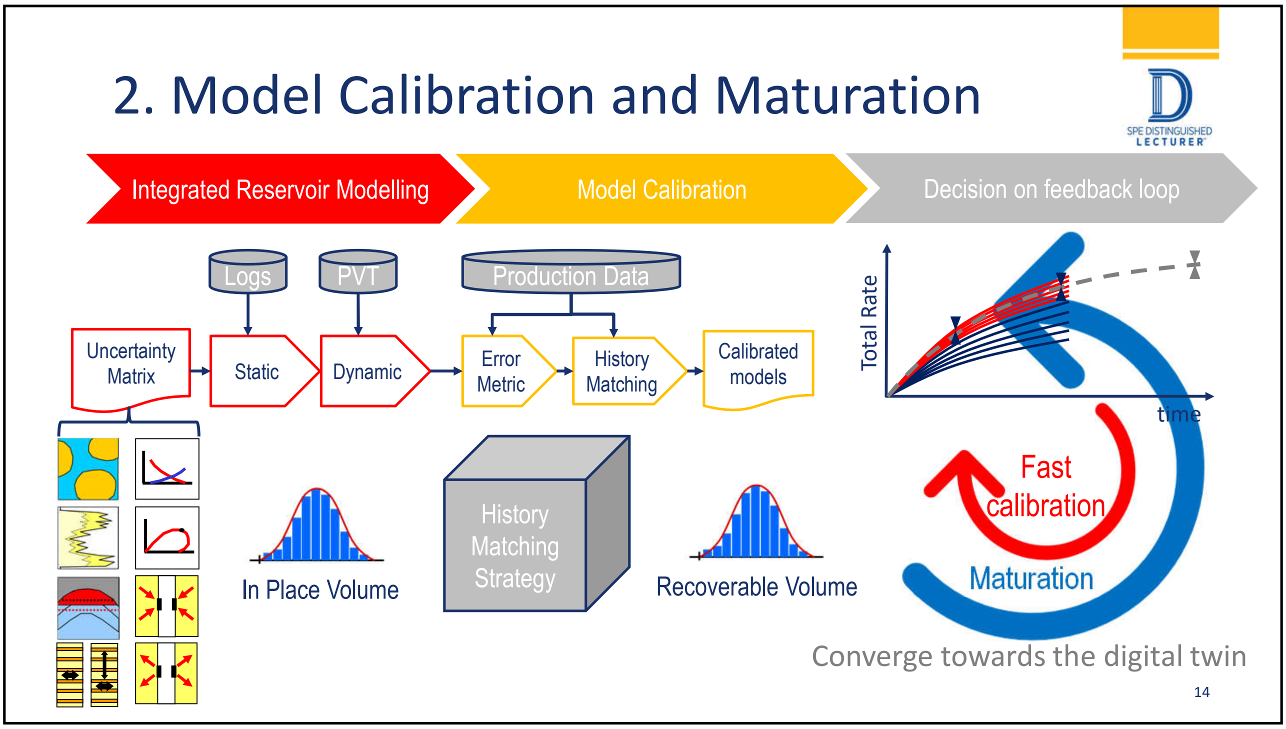
2. Model Calibration and Maturation
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Integrated Reservoir Modelling
Model Calibration
Decision on feedback loop
Logs
PVT
Production Data
Uncertainty Matrix
Static
Dynamic
Error Metric
History Matching
Calibrated models
Total Rate
time
In Place Volume
History Matching Strategy
Recoverable Volume
Fast calibration
Maturation
Converge towards the digital twin
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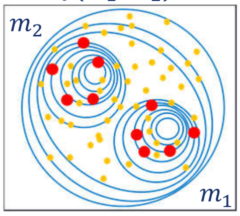
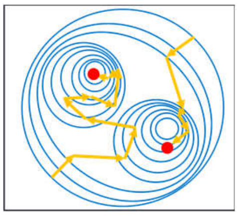
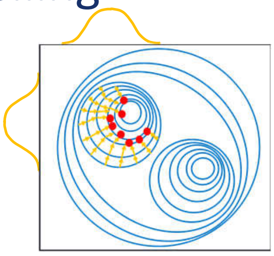
Ensemble-based History Matching Strategies and Probabilistic Modelling







Falsification
- Extensive sampling of geological models, scenarios, realizations
- Model selection using Multi-dimensional scaling, distance matrices, etc.
- No inverse modelling

Markov Chain Monte Carlo
- Structured approach to history matchinig
- Sampling from approximated posterior distribution
- ML-based predictive modelling

Ensemble-based (Smoother)
- Initial prior ensemble
- Data assimilation
- Evolve prior ensemble to posterior ensemble

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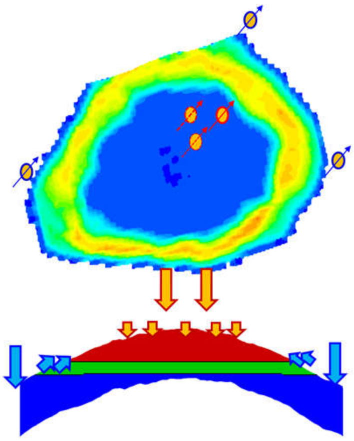
Oil Rim Field Development Assessment

Challenge
- History match an oil-rim reservoir*), offshore Malaysia with 40 years production history.
- Uncertainty assessment of an infill drilling strategy.

Solution
- Multiple history matched models
- Probability maps for revised well placement strategy

Results
- Automation of repetitive integrated modelling processes
- Robust incremental increase across ensemble of matched simulation cases – revised infill design



*) M. Elharith et al. JPEPT (2019)

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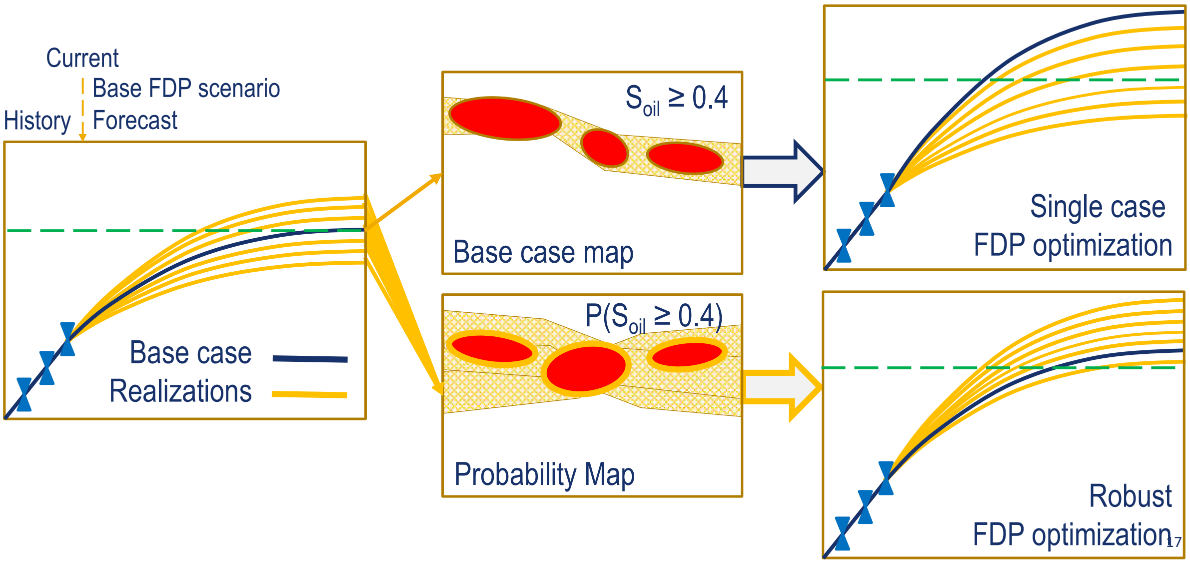
Probabilistic Framework for Result Analysis



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Uncertainty Management Contributions

Uncertainty matrix

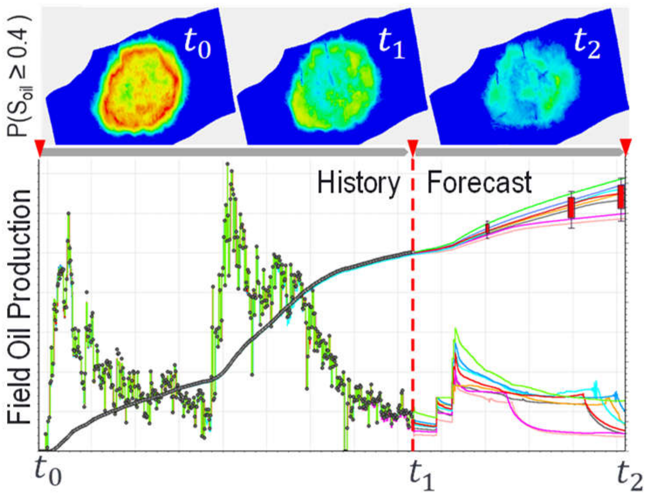
- Identify key subsurface uncertainties

Multiple history matched solutions

- Trusted prediction candidates

Forecast and probabilistic result analysis

- Probability maps for infill well design support under subsurface uncertainty



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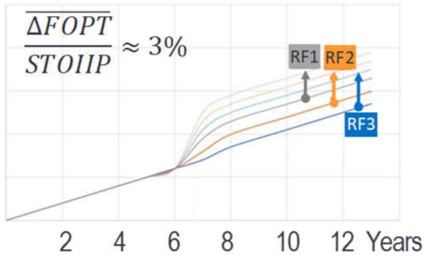
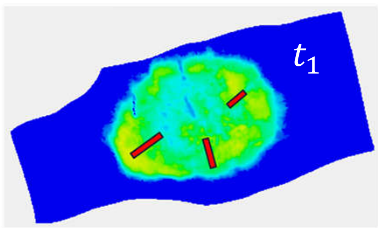
Result presentation and analysis

- Prediction candidate selection of 8 trusted history matched solutions
- Optimize infill well locations based on probability maps
- For infill redesign prove robust incremental increase of production

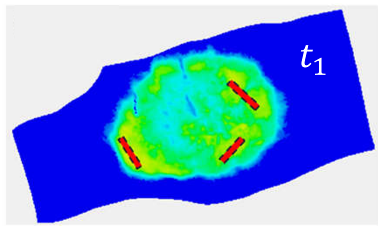


Probability map end of history

Horizonal well



Baseline infill producer location



Optimized infill producer location 20

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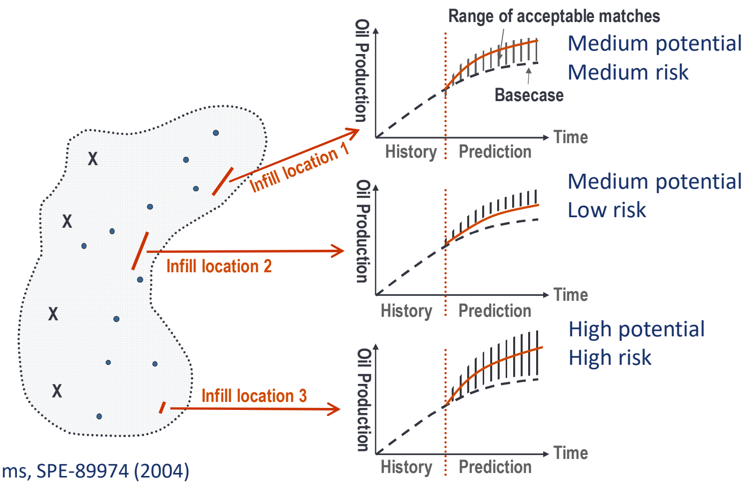
3. Field Development Planning under Subsurface Uncertainty

FDP under Uncertainty

1. Optimize economic success criteria
2. Identify potential and address risk

Input to decision support



G. Williams, SPE-89974 (2004)

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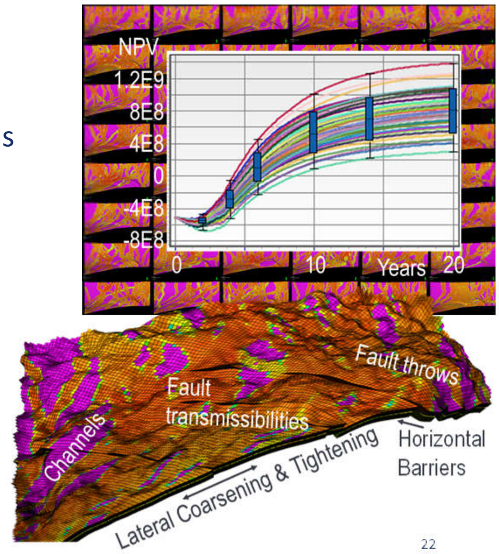
The Olympus Challenge*)

Reservoir
- Inspired by a virgin oil field in the North Sea
- Two formations with fluvial channel sands and
- Alternating layers of coarse, medium and fine sands

Production
- 7 Injectors, 11 Producers
- Voidage replacement strategy

Challenges
- Optimize field development plan
- Consider 50 equiprobable subsurface realizations
- Compare solution to reference case



*) Initiative of the “Integrated Systems Approach to Petroleum Production“ research consortium; R. Fonseca et al., COMG (2020)

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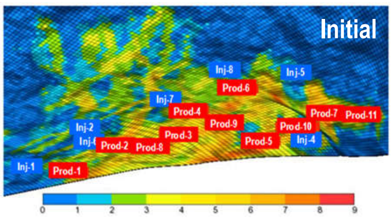
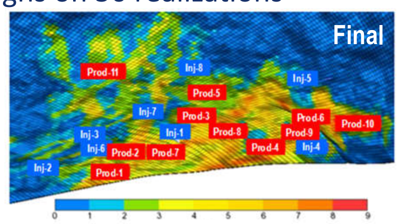
Solution Strategies

Parameterization design*)
- Coordinates heel and toe, Well type, Status (on/off)

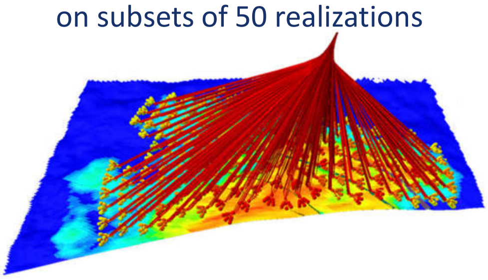
Execution:
- **105 000** simulations
- **2 100** tested designs on 50 realizations





Parameterization design**)
- Preconfigured well designs: 100+ well location candidates

Execution:
- **23 000** simulations
- **2 000** tested designs on subsets of 50 realizations



*) V.L.S. Silva et al. EAGE (2018)

**) S. Tanaka et al. EAGE (2018)

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Automation using Machine Learning

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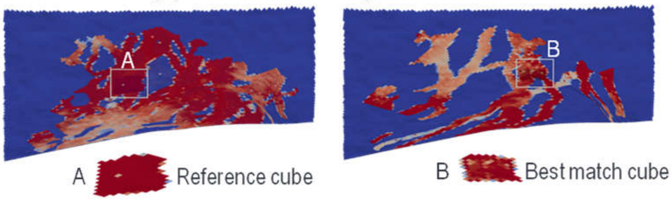
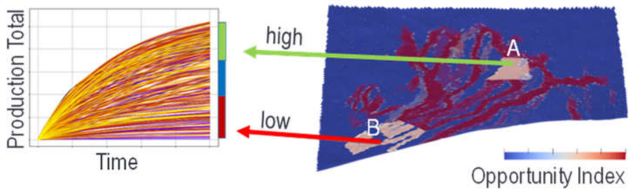
Scope:
- Optimization of well drilling targets
- Predictive machine learning model to capture subsurface structure

Machine learning application support:
- Identification of production targets
- Classification of production targets – low, mid, high performance

Identify production targets



Classify production targets



P. Lang, T. Adeyemi, R. Schulze-Riegert, ECMOR (2020)

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Application of Machine Learning (ML)

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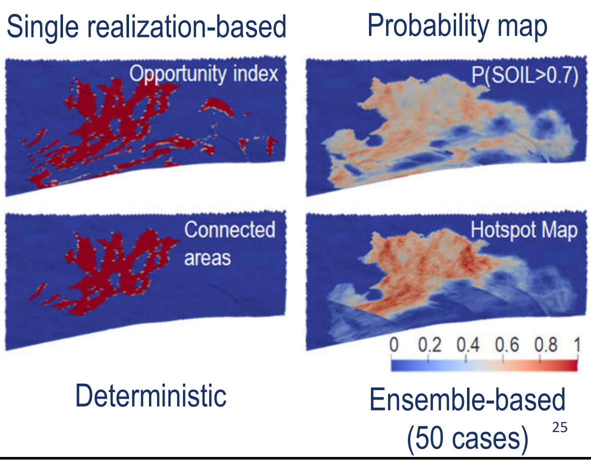
Execution:
- Automatic well target selection

Simulation results → Opportunity index → Connected volumes → Target candidates → ML model → Target

Robust well location selection among 100s target candidates



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Decision Criteria

Success criteria are based on economic objectives and deliver a “yes or no”

Deterministic:

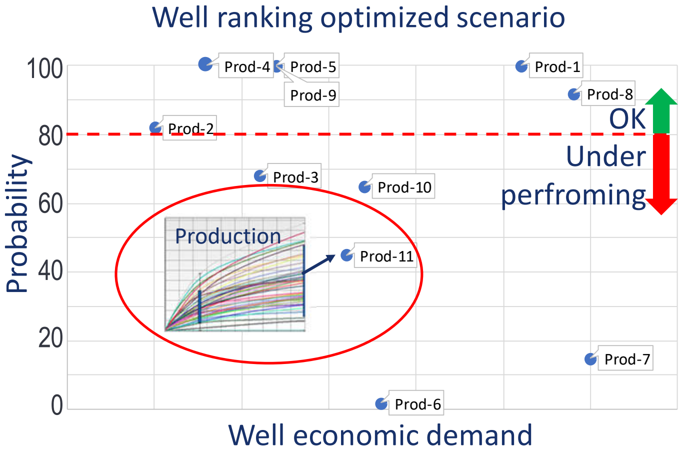
- Recoverable Volume > MEFS*)

Probabilistic:

- P_{80} (Well NPV) > Economic Demand

Target:

- 90% of all wells deliver the economic demand at an 80% probability level or higher**)



*) MEFS: Minimum economic field size
**) R. Schulze-Riegert et al. COMG (2020)

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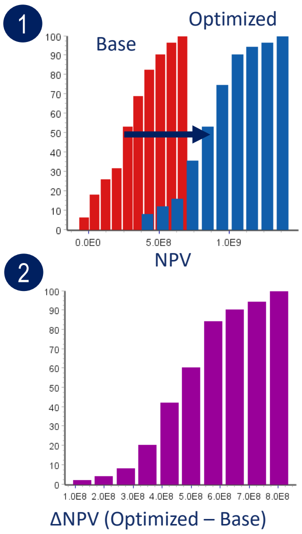
Probabilistic Result Presentation

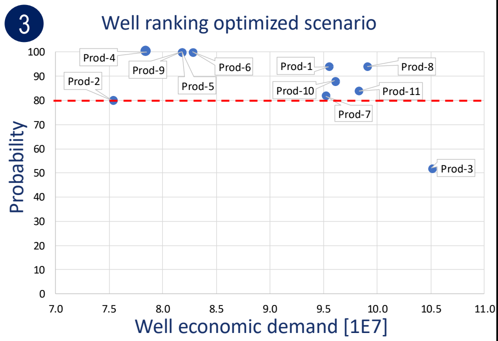
One plot – full ensemble view

- ensemble performance
- differences of optimized and reference scenario

Robust optimization and probabilistic ranking

- Wells moved from loss to profitable
- Identify problematic wells
- Highlight and justify low risk scenarios





“High performing scenario”: More than 90% of all wells deliver the economic demand at an 80% probability level or higher

R. Schulze-Riegert et al. SPE-202660 (2020)

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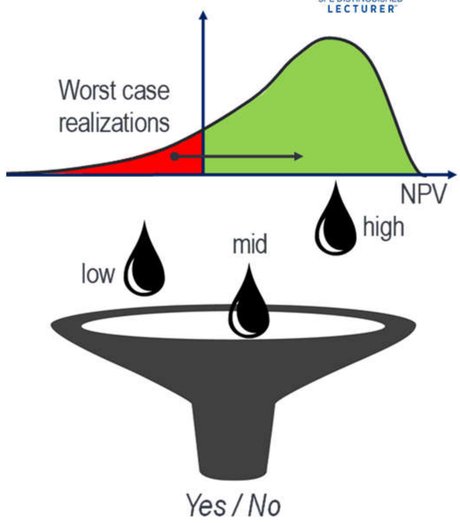
Conclusion

- Ensemble-based reservoir modelling provides a basis for a forecast uncertainty assessment
- Ensemble-result deliveries thrive on automation;
  - execution and
  - analysis services
- Economic success criteria for maturing projects require a “Yes” or “No” to pass decision gates. Uncertainty management will be measured to support this objective.



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Take Away

- Subsurface uncertainty assessment of production forecasts impacts all modelling domains from static to dynamic
- Uncertainty management services rely on well defined success criteria for substantial decision support
- Major technology contributions are expected from analytics and machine learning applications – guided by domain expertise

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References and Acknowledgement

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- EAGE/TNO Workshop on OLYMPUS Field Development Optimization, ISBN: 978-94-6282-261-0, Published: Sept. 2018 and
Comput. Geosci, 24, issue 6, December 2020, Overview of OLYMPUS Optimization Benchmark Challenge, Issue editors, R.M. Fonseca, E. Della Rossa, A.A. Emerick, R.G. Hanea, J.D. Jansen

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