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Waterflood Optimization by Data Analytics on Mature Fields

Accelerate the Field Developing Process from Months to Weeks

Babak Moradi

THRE360 ENERGY

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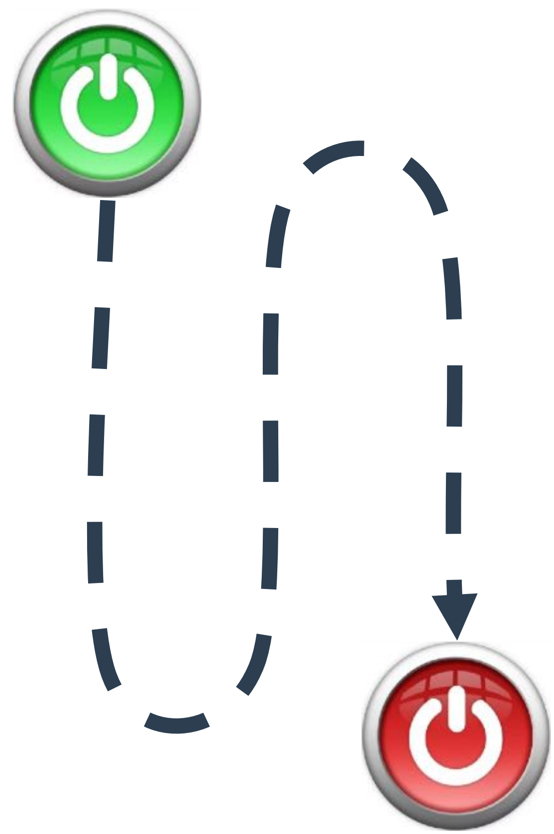
Outline

- ❑ Introduction
- ❑ Classical Analytics
- ❑ Machine Learning
- ❑ Hybrid Workflows
- ❑ Case studies
- ❑ Conclusions



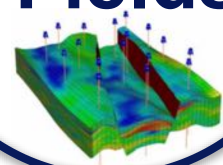
Mature Fields

A significant amount of information is available in a mature field

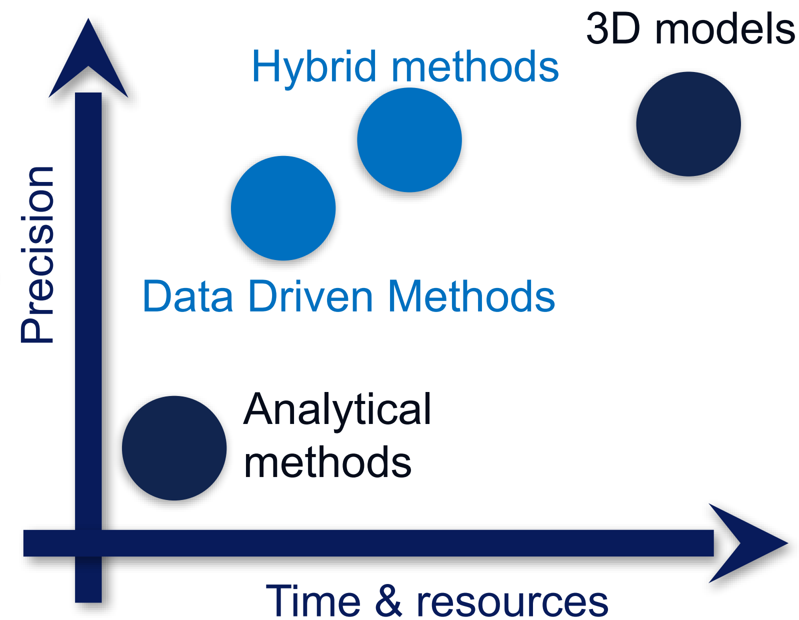
70 % of global oil production

High well count

Mature Fields



Years of historical data



Decline Curve Analysis

A set of empirical techniques to forecast production data

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Arps Production Decline Equations

Exponential

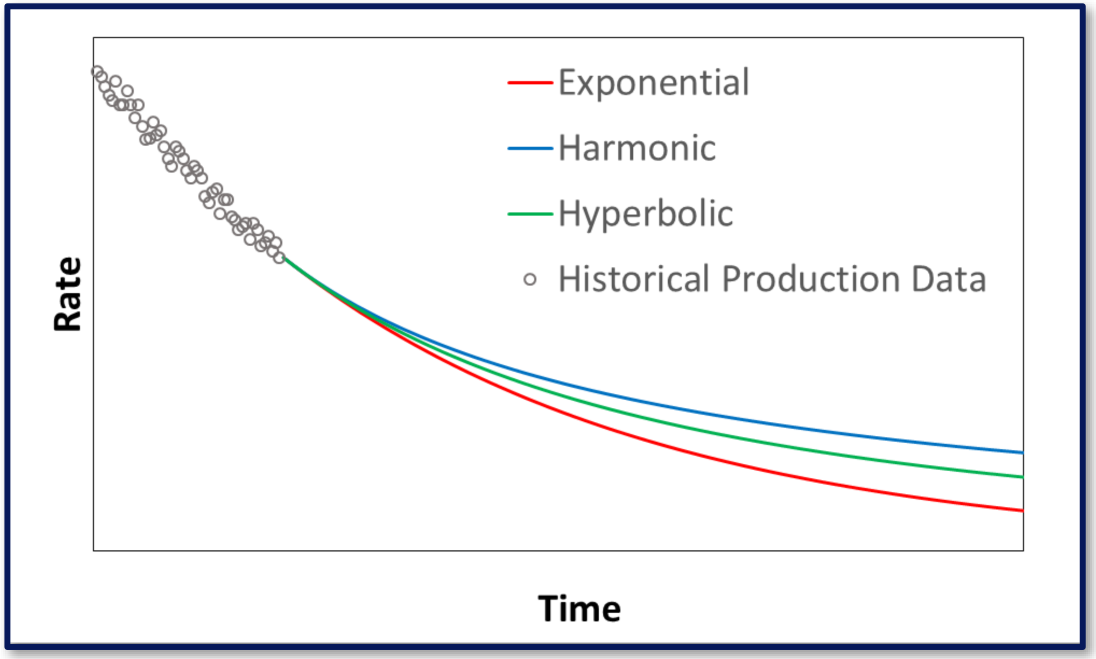
$$q(t)=q_i exp(-D*t)$$

Harmonic

$$q(t)=\frac{q_i}{1+D*t}$$

Hyperbolic

$$q(t)=\frac{q_i}{(1+b*D*t)^{1/b}}$$



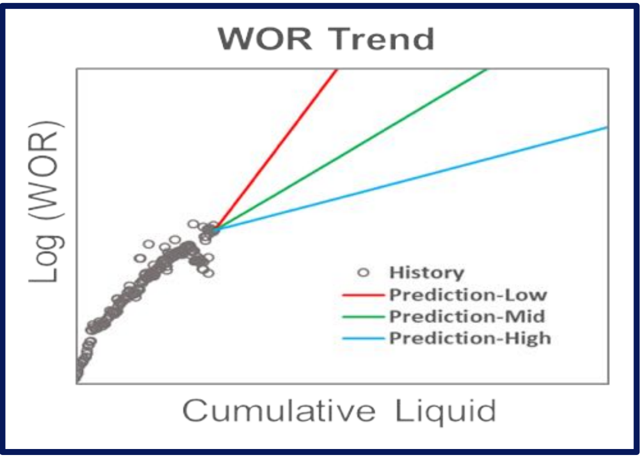
q = Production rate
q_i = Initial production rate
t = Cumulative time since start of production
D = Initial decline rate
B = Hyperbolic decline constant

Type Curve –WOR* vs Cumulative Liquid

A simple tool to predict waterflood performance

- ❑ Onstream > 6 years; RF>30 %
- ❑ 3 producers and 2 water injectors

STEP 1

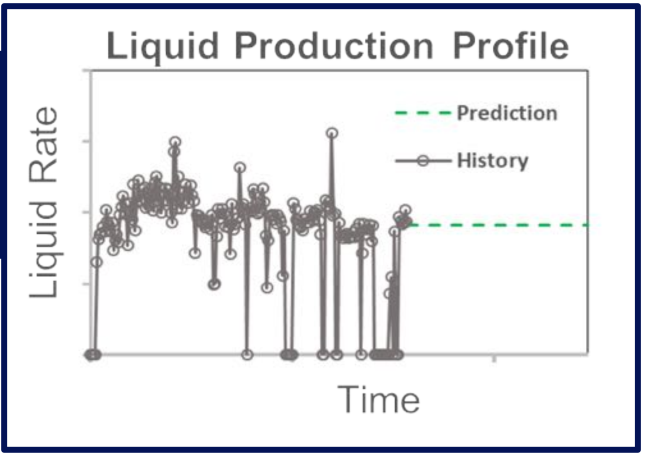


STEP 1
Find WOR vs Cumulative liquid trend

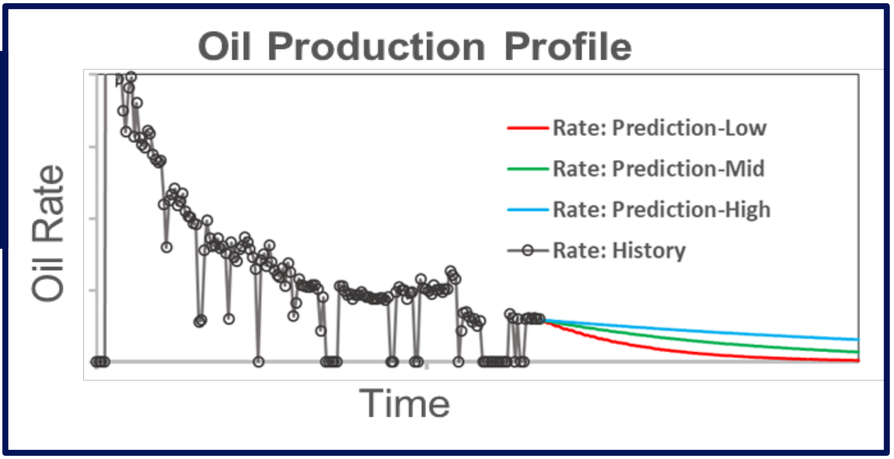
STEP 2
Assume a constant liquid rate

STEP 3
Calculate oil and water rate

STEP 2



STEP 3

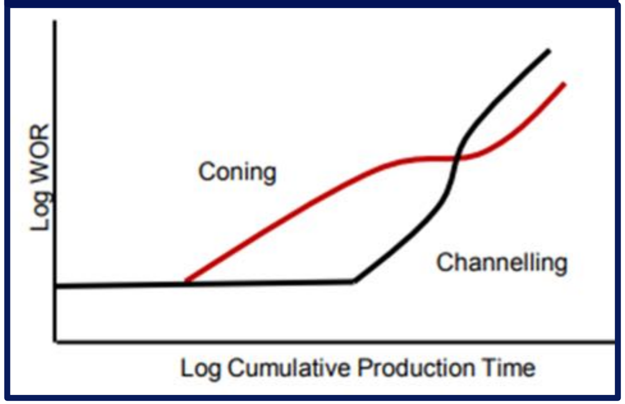


*. WOR = Water Oil Ratio

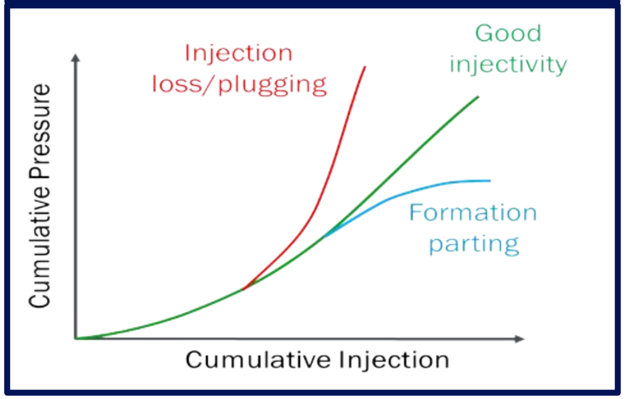
Classical Analytics

Simple (and fast!) diagnostics and predictive tools

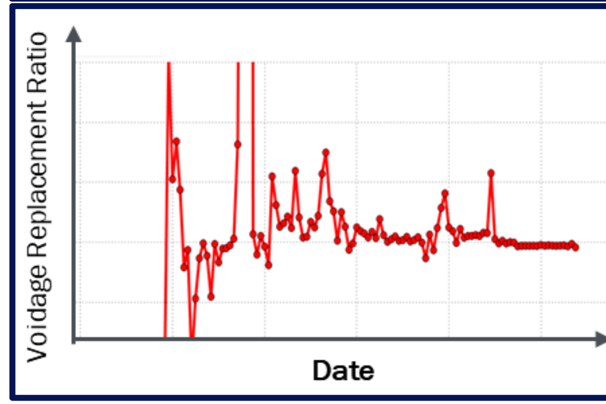
Chan Plot



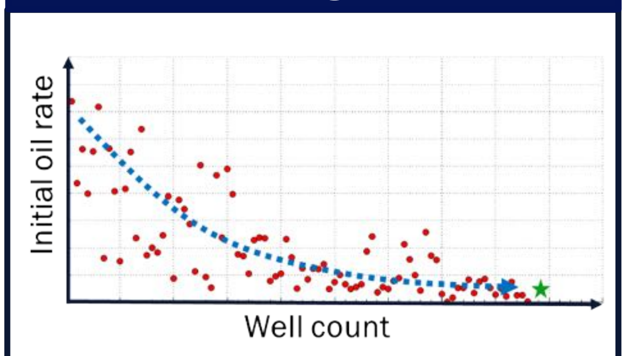
Hall Plot



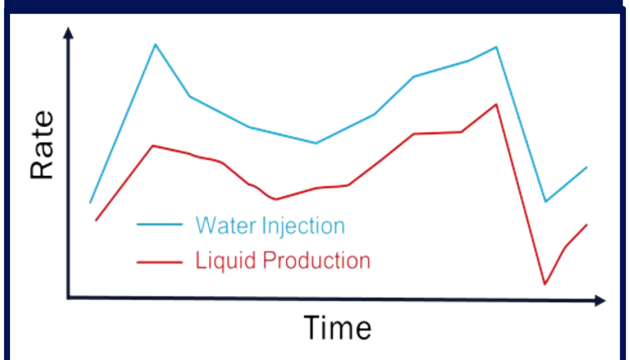
Voidage Replacement Ratio



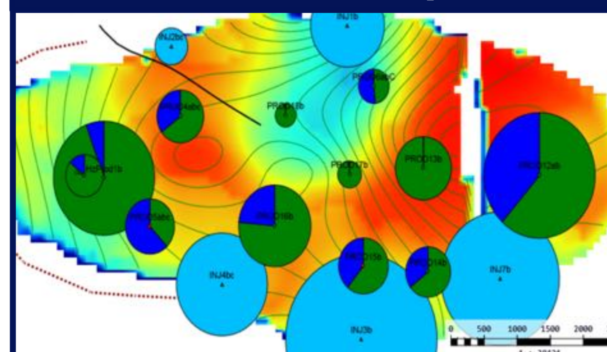
Creaming Curve



Well Interaction



Bubble Map



Machine Learning

Applied methods are now ubiquitous around us

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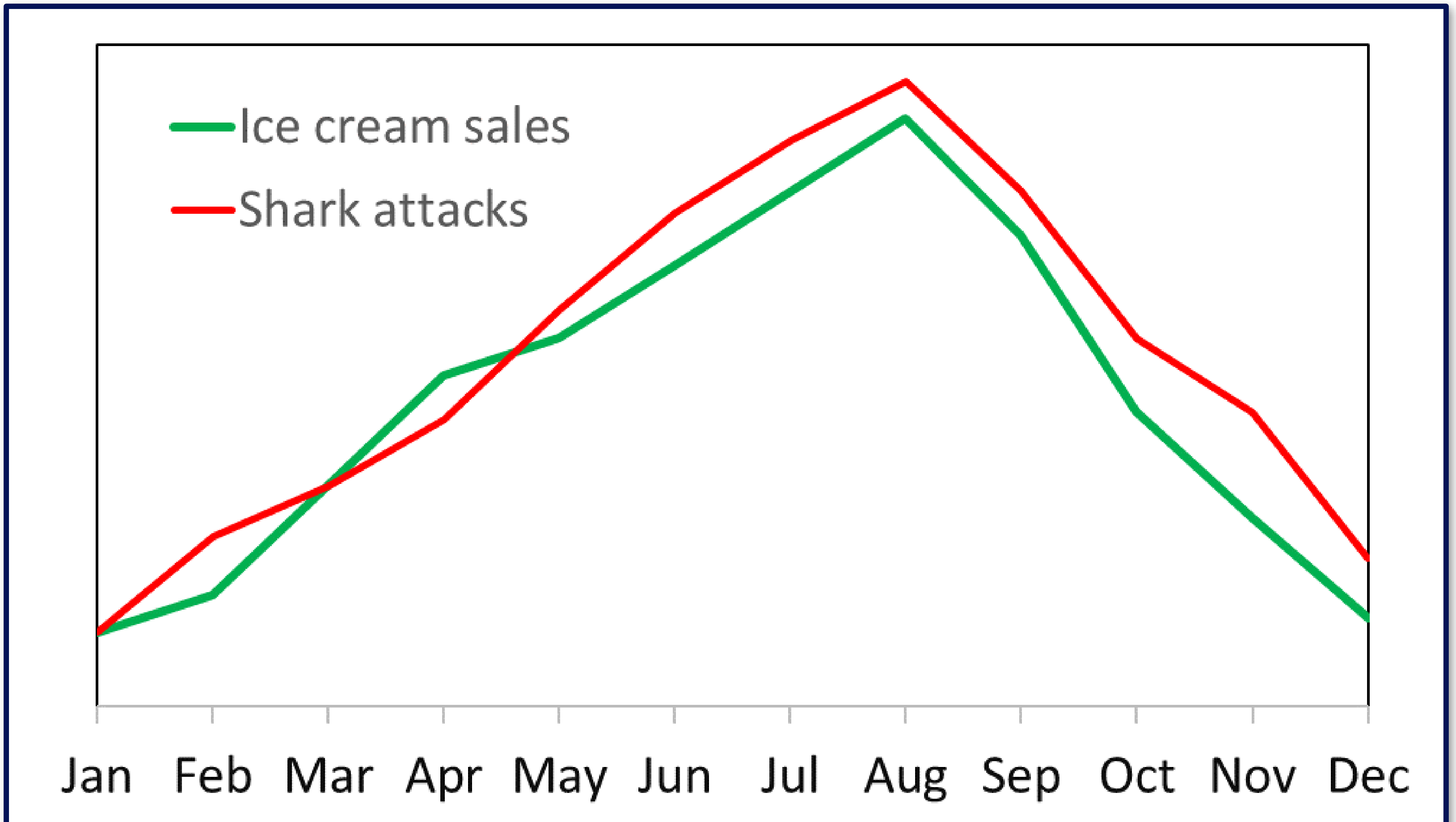
'Social' sciences

- Data-driven methods widely used
- Massive datasets, no discernible physics
- Ie. physics is within the data

Data Driven Models

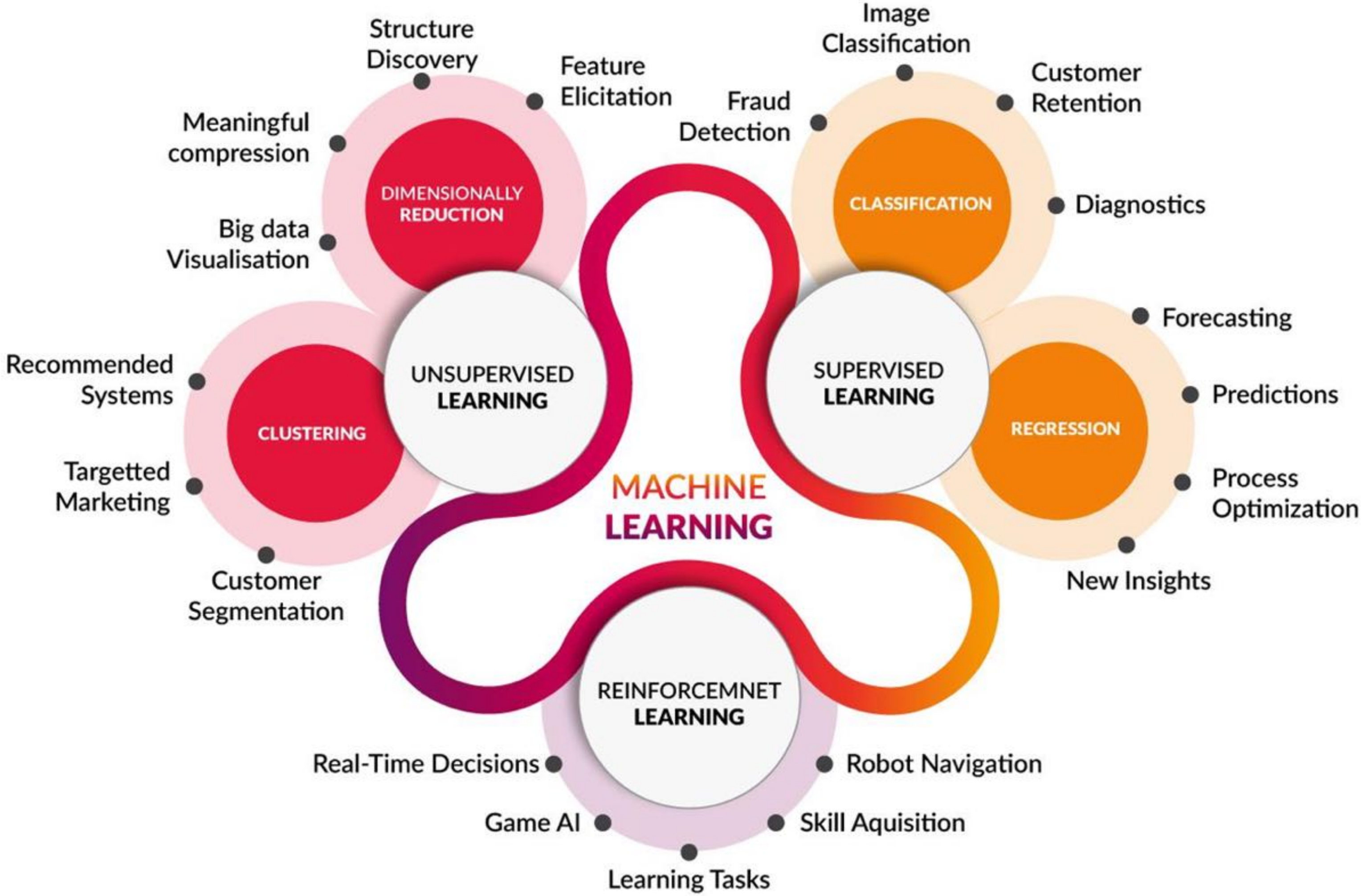
"Black-box" models learn patterns solely from data.

…. Assuming "the physics is in the data" ….



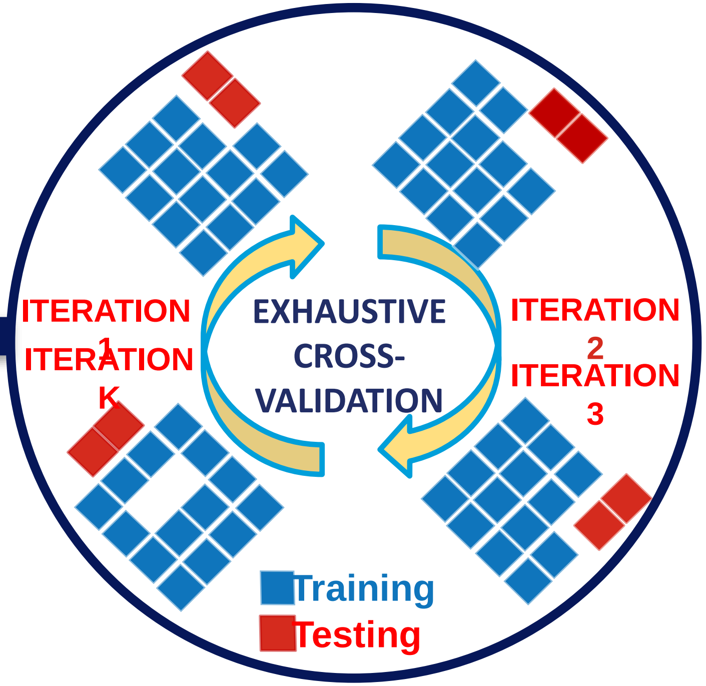
Data Driven Algorithms

Turn data into knowledge



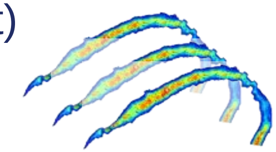
Reference: https://twitter.com/ltdrpa/status/1239446198131417096

Machine Learning Workflow



Input Dataset

- **STATIC INPUTS**
  - Porosity
  - Permeability
  - Well location (x,y)
  - Net to gross
  - …
- **DYNAMIC INPUTS**
  - ΔSw(t) within k-neighbors
  - OIP(t) within k-neighbors
  - Perforation length (t)
  - Distance from the contact (t)
  - …



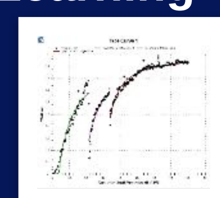
Selected infill or existing wells

Train ML Models

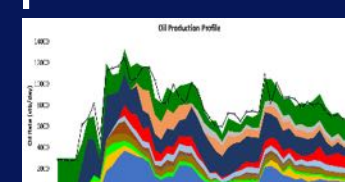
Forecast

Machine Learning Outputs

EUR[1] and Initial WCT[2]



Type Curves



Production Profiles

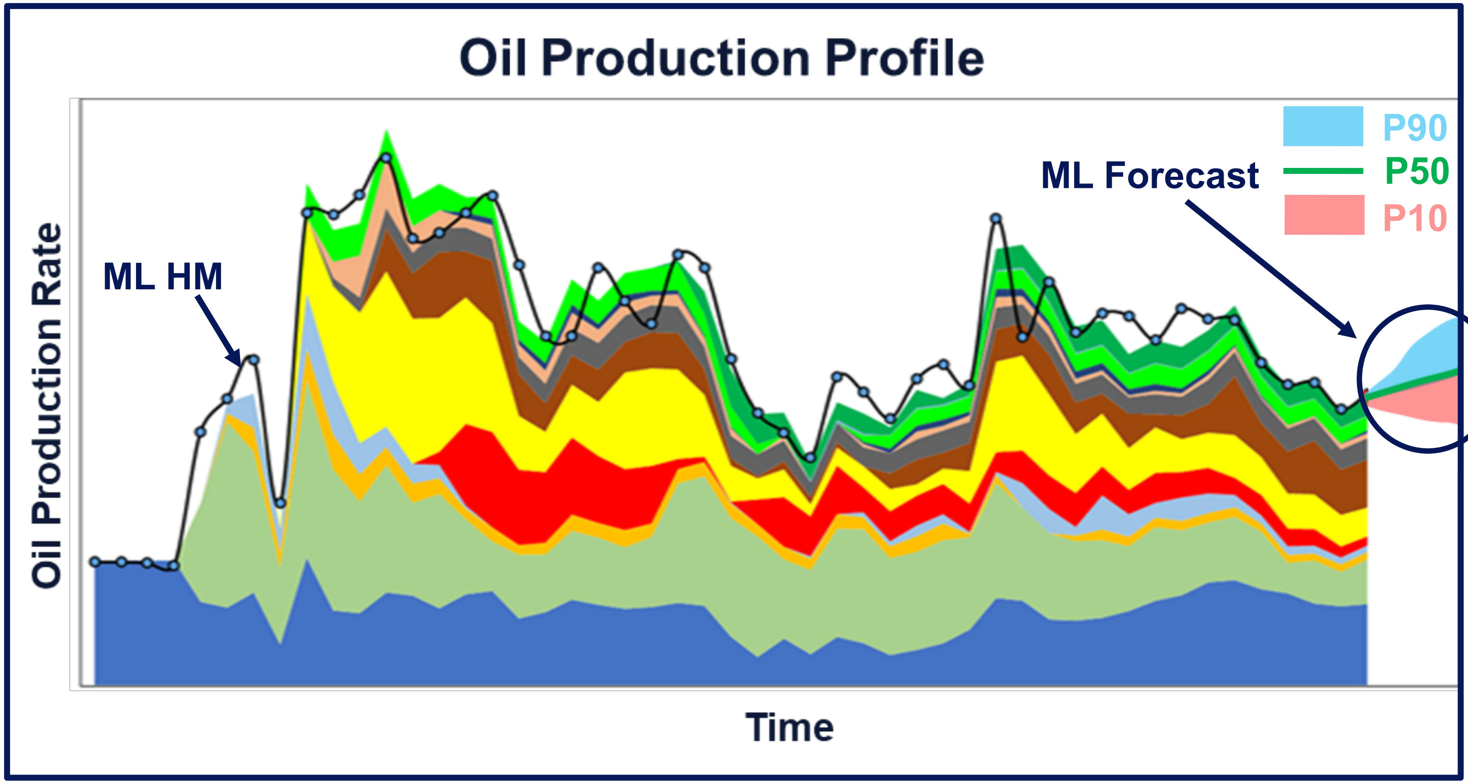
1. EUR = Estimated Ultimate Recovery
2. WCT= Water-cut

Waterflood Optimization by Machine Learning

An offshore field located in Asia Pacific

- 4 Water Injectors
- 14 Producers
- 5+ years of production History

- The forecasted oil production rate varied between – 6% to + 8%
- The ML model concludes the injection efficiency of each water injector



Physics-Compliant Data Driven Models

Can we have the 'best of both worlds'

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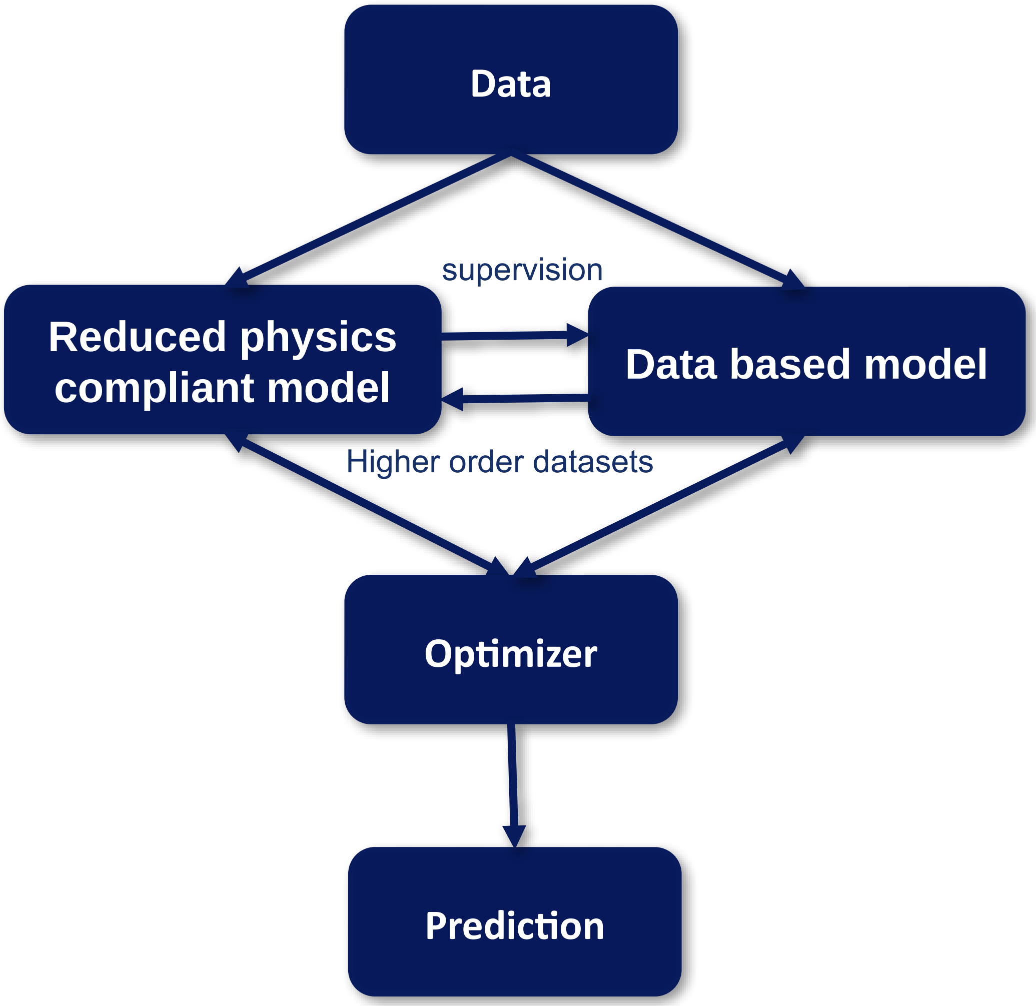

Popular approaches to develop hybrid models

Physics-guided model⇔ Data-driven model

- Physics-guided loss function
- Physics-inspired feature engineering
- Physics-based model initialized data-driven model

A Hybrid Algorithm for LTRO* Studies

Data-driven but physics-compliant and time-step based process

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Inputs

Constraints

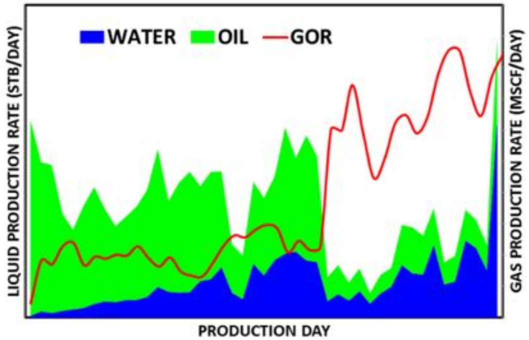
Flow Potential

Saturation Mapping

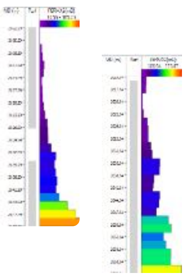
Outputs

- ❑ inputs are analogous to conventional numerical simulators

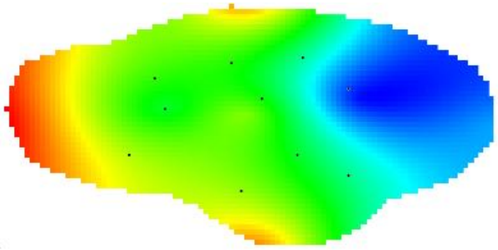
PRODUCTION DATA



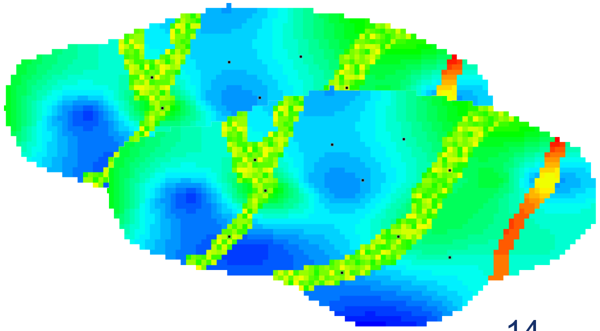
LOGS



GEOLOGY



4D-SEISMIC CONSTRAINTS



* LTRO = Locate The Remaining Oil

A Hybrid Algorithm for LTRO* Studies

Data-driven but physics-compliant and time-step based process

- Inputs
- **Constraints**
- Flow Potential
- Saturation Mapping
- Outputs

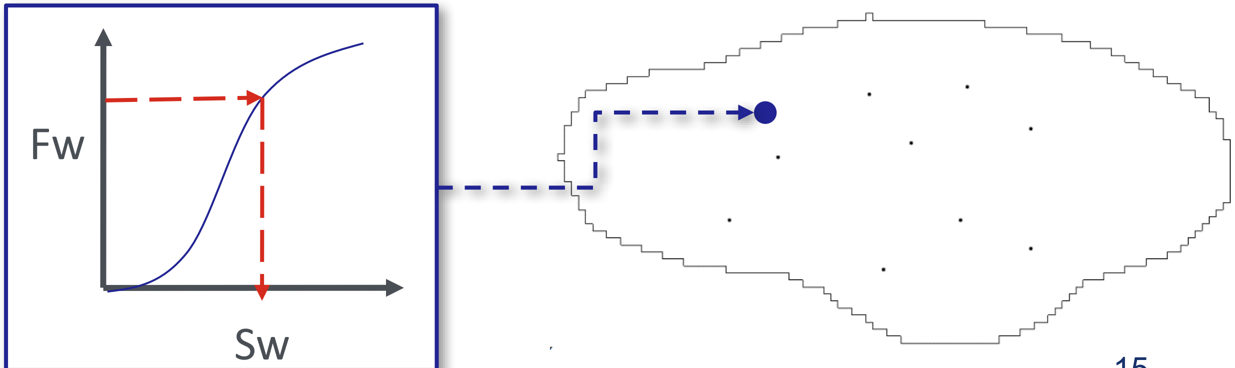
Local Constraints

A. Saturation at well locations

Step 1. Calculate watercut from historical production data

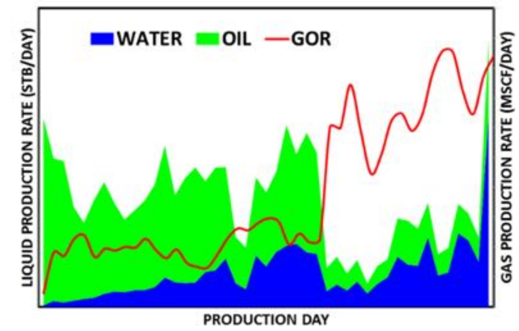
Step 2. Fractional flow inversion

- Well fractional flows taking into account the vertical heterogeneity at wells.



B. 4D Seismic Survey

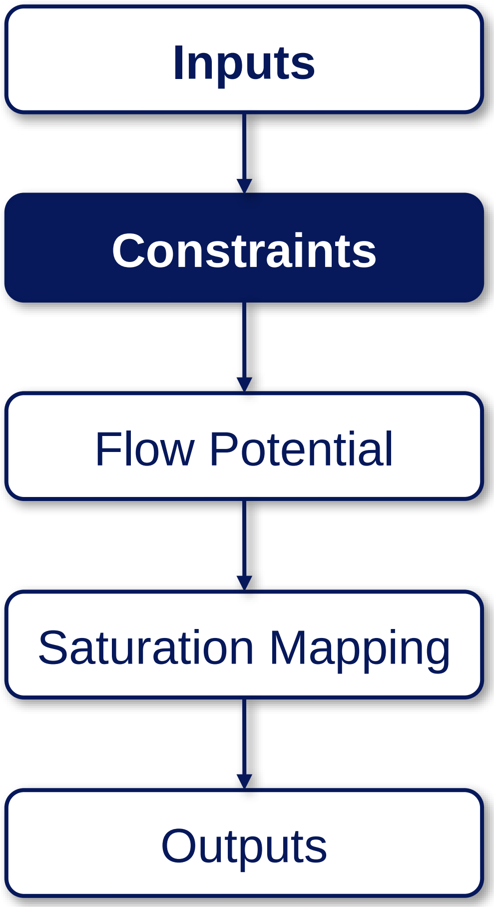
Historical data



* LTRO = Locate The Remaining Oil

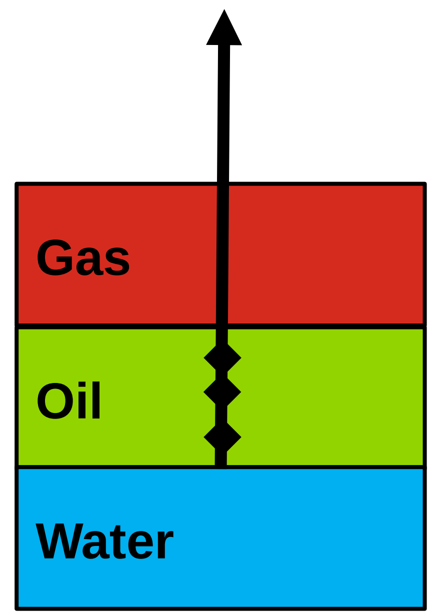
A Hybrid Algorithm for LTRO* Studies

Data-driven but physics-compliant and time-step based process



Global Constraint

- ❑ Material Balance



Remaining oil in place = STOIIP - Cumulative production

* LTRO = Locate The Remaining Oil

A Hybrid Algorithm for LTRO* Studies

Data-driven but physics-compliant and time-step based process

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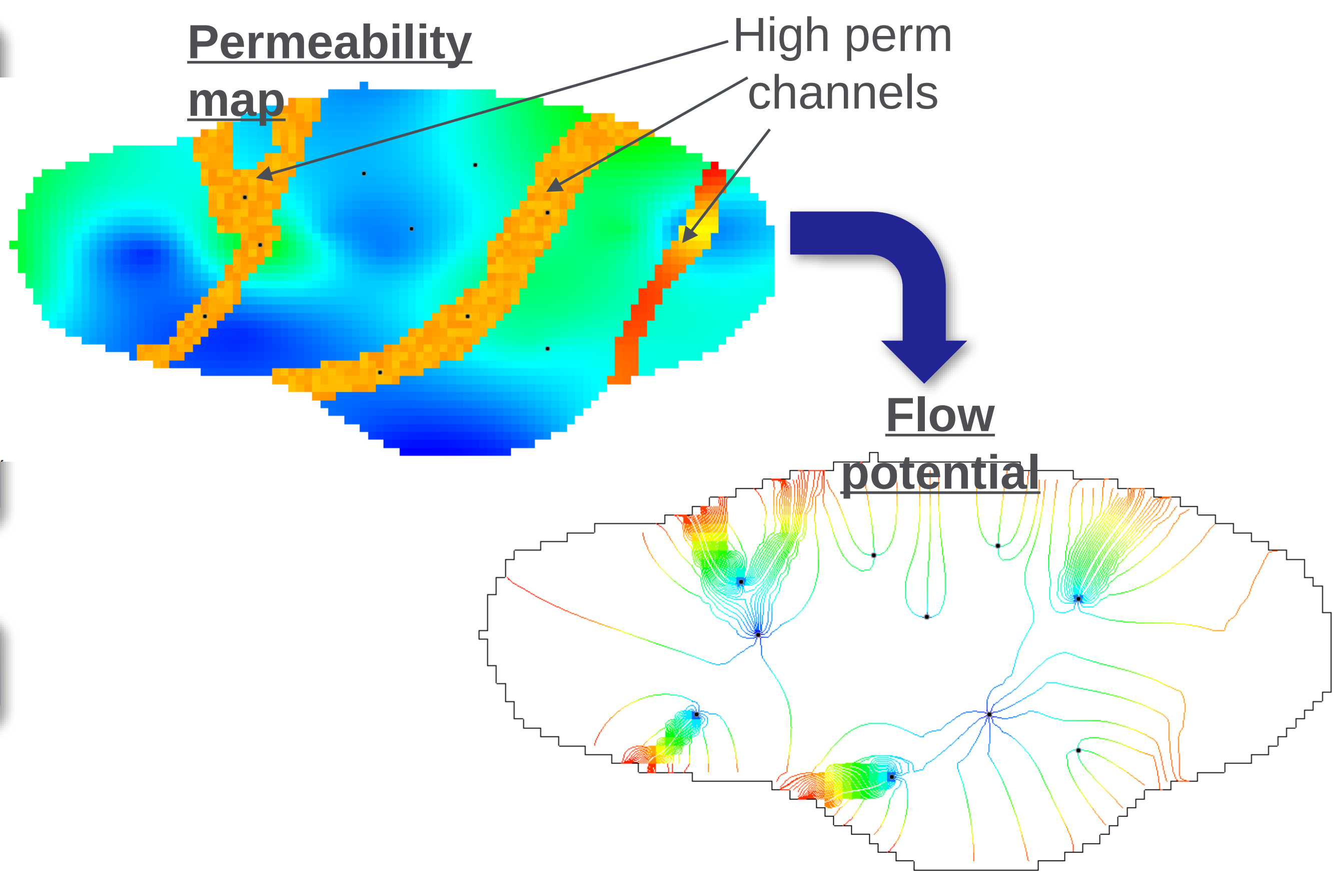
Inputs → Constraints → **Flow Potential** → Saturation Mapping → Outputs

- ❑ Fast-marching method
- ❑ Estimating flow potential taking into account geology, injections, aquifers and withdrawal



* LTRO = Locate The Remaining Oil

A Hybrid Algorithm for LTRO* Studies

Data-driven but physics-compliant and time-step based process

Inputs

↓

Constraints

↓

Flow Potential

↓

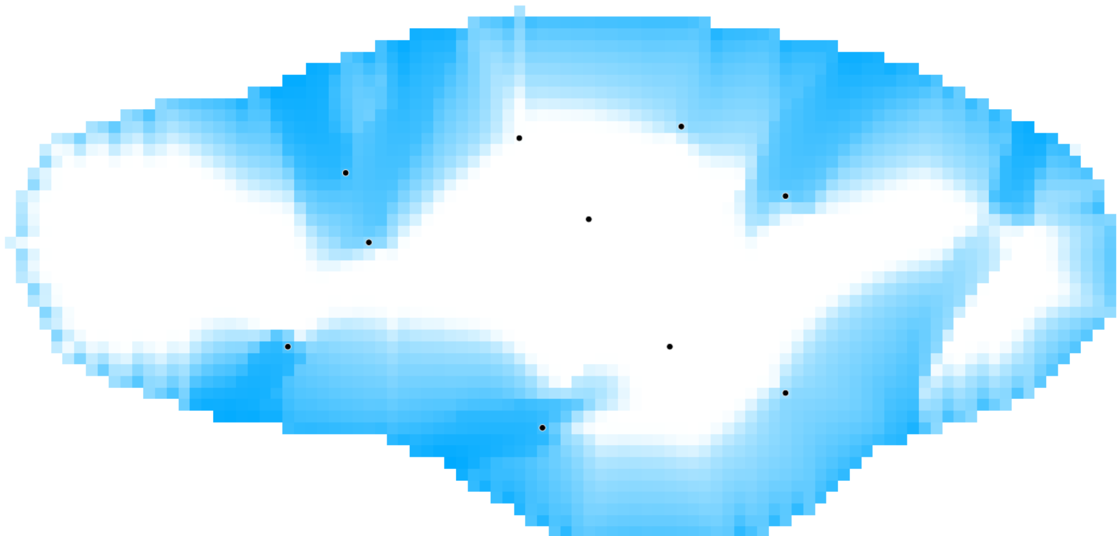
Saturation Mapping

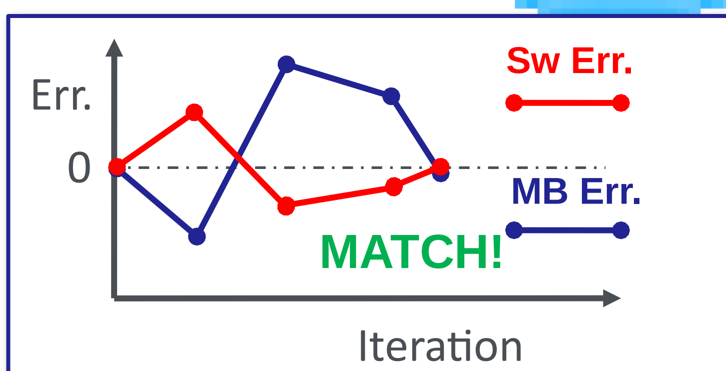
↓

Outputs

Water Saturation

Iteration 4





Err. = Error
Sw = Water Saturation
MB = Material Balance

* LTRO = Locate The Remaining Oil

A Hybrid Algorithm for LTRO* Studies

Data-driven but physics-compliant and time-step based process

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Inputs

↓

Constraints

↓

Flow Potential

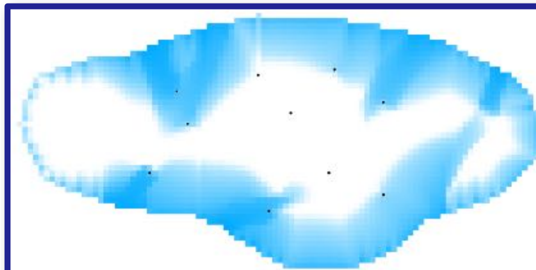
↓

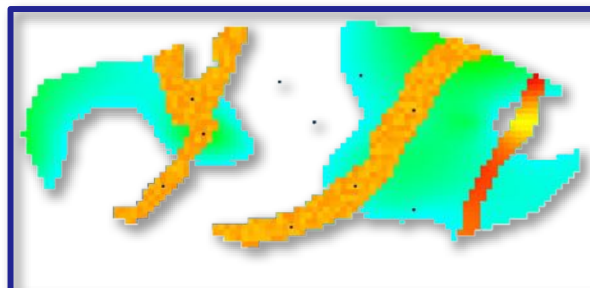
Saturation Mapping

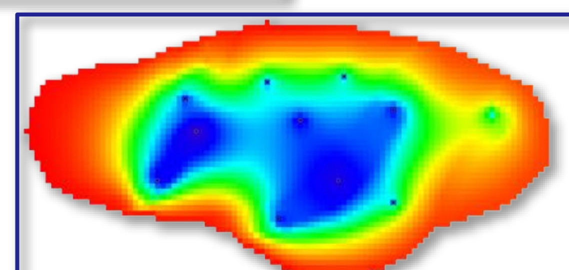
↓

Outputs

- ❑ Outputs are analogous as conventional numerical simulator:
- ❑ Forecasts, Sw, Delta Sw, STOIP[1], MOIP[2], Sweep Efficiency, and...







1. STOIP = Stock Tank Oil in Place
2. MOIP = Movable Oil in Place

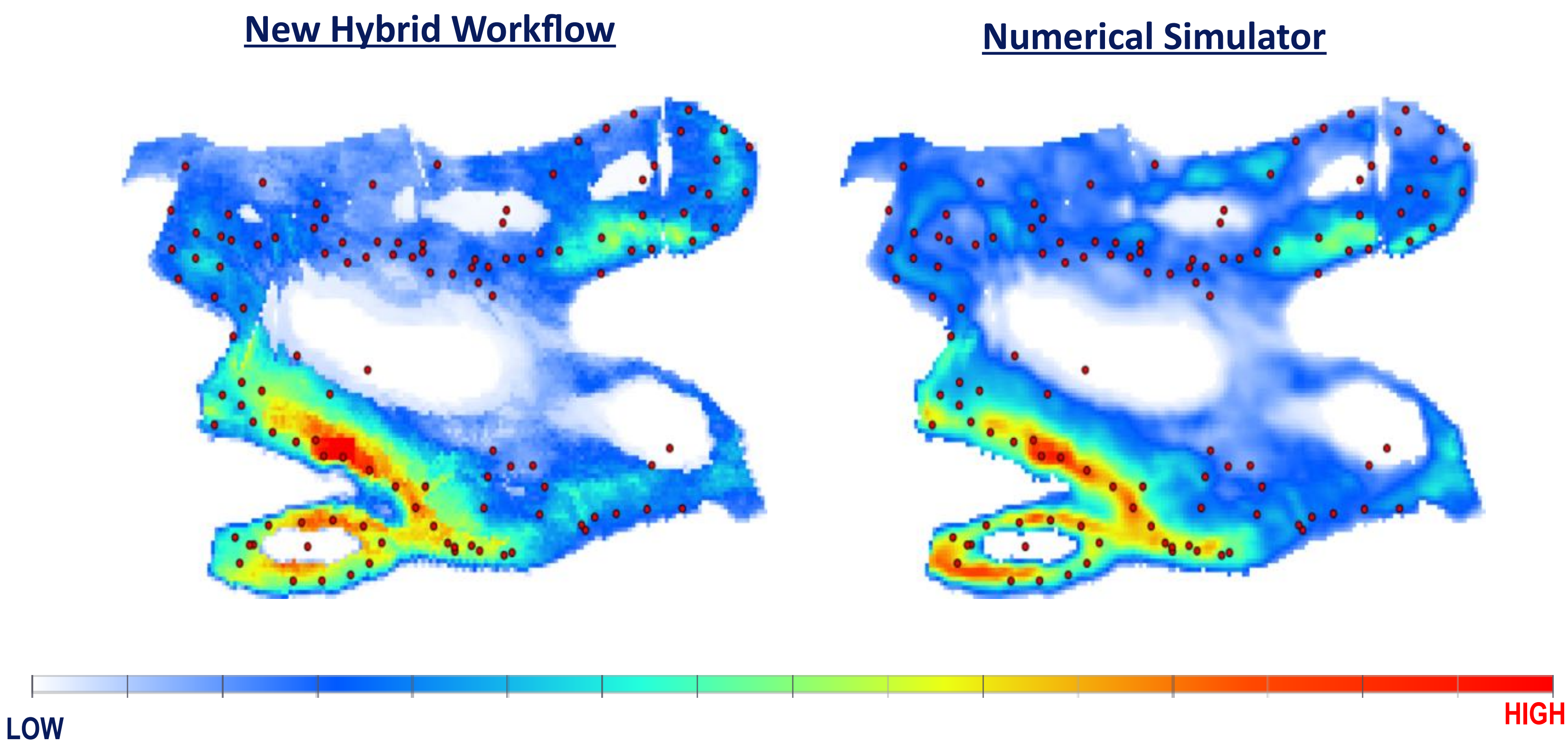
*** LTRO = Locate The Remaining Oil**

Validation- Full Physics Comparison

Case study 1: Mature field with >100s active oil producers

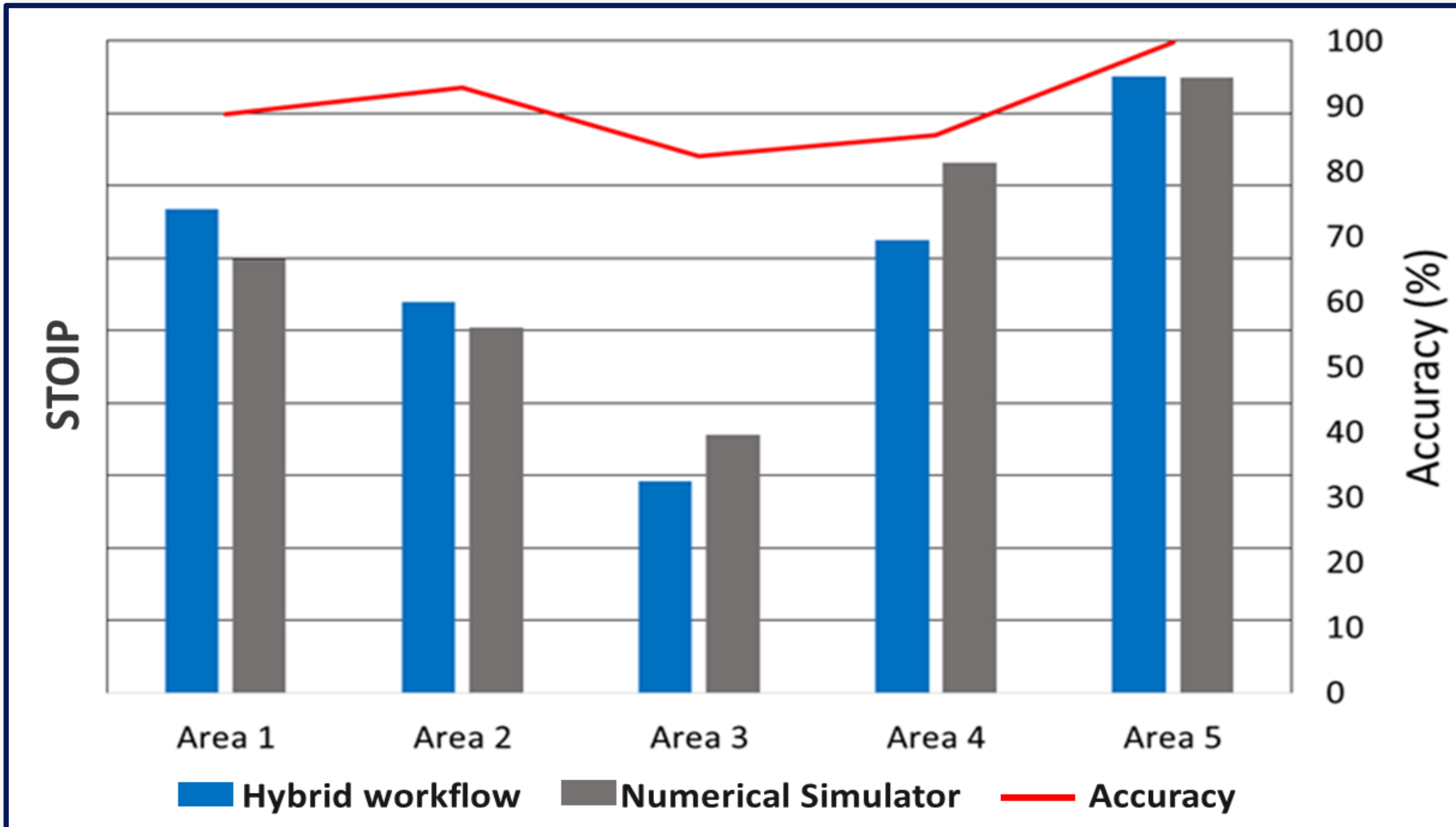
Stock Tank Oil in Place

Time Step: 4



Validation- Evolving Oil Resource Distribution

Case study 1: Mature field with >100s active oil producers



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Integrating 4D Seismic into the Hybrid Data-Physics Saturation Mapping Workflow

Case study 2: Offshore oil field located in the North Sea

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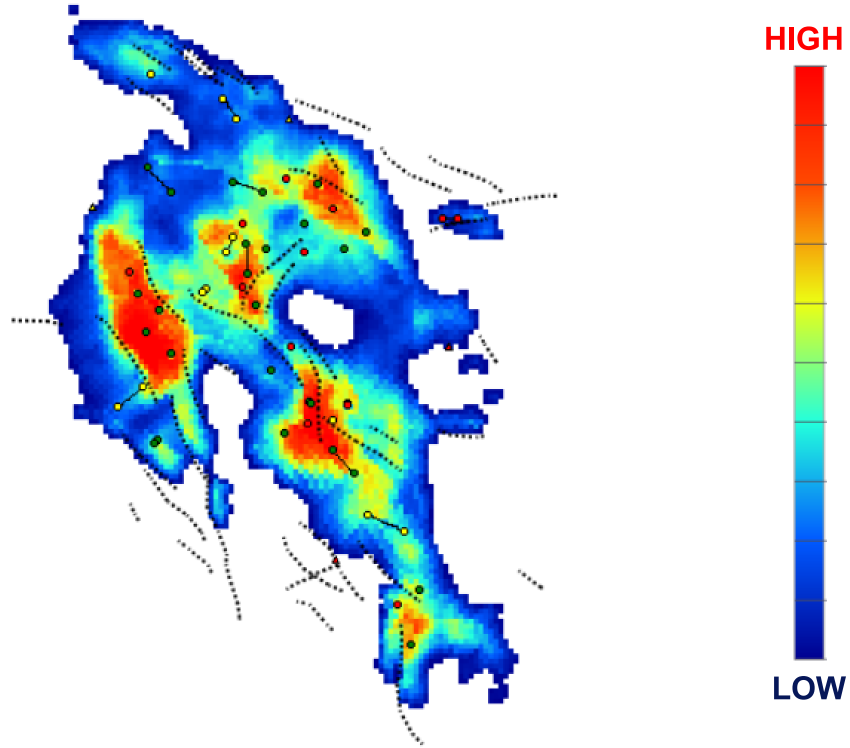
Year: 2018

Stock Tank Oil in Place

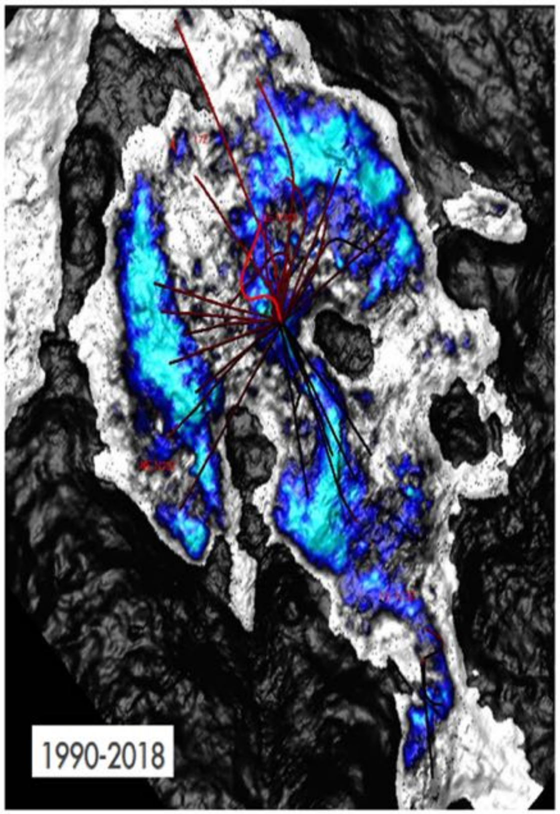


- 40+ producers and injectors
- Vertical, deviated and near-horizontal wells
- Onstream > 25 years
- RF > 50%

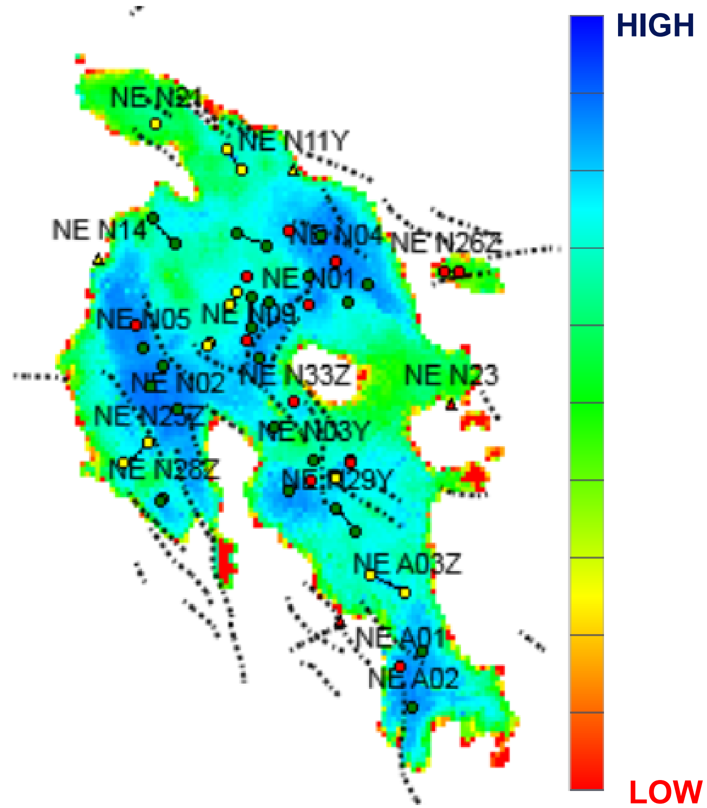
Incorporating 4D Seismic into the Compliant Saturation Mapping Algorithm

Illustration of conformance

4D Seismic Contact Movement
1990-2018



Hybrid workflow
Saturation change (Delta Sw)
End of HM – Initial time step



Combine Saturation Maps with Machine Learning for Infill Drilling

Case study 3: Onshore field located in the Middle East

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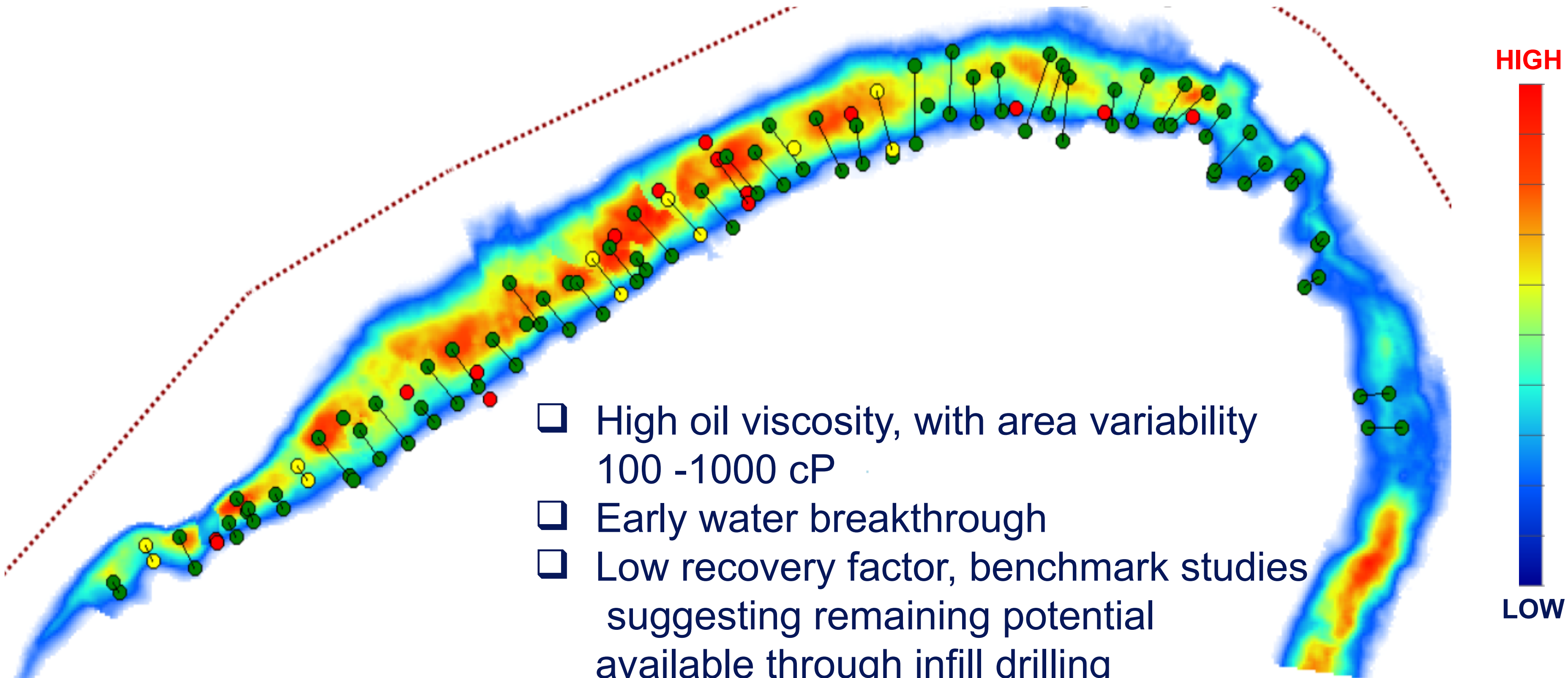
Year: 2016

Stock Tank Oil in Place



- High oil viscosity, with area variability 100 -1000 cP
- Early water breakthrough
- Low recovery factor, benchmark studies suggesting remaining potential available through infill drilling

Workflow – Define Uncertainty Parameters

Generating and testing multiple realization in a resource-efficient manner

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- **Define Uncertainty Parameters**
- Define Control Areas
- Analyze Tornado Diagrams
- Create Subsurface Realizations
- Quantify Risk
- Identify / Rank Infill Targets
- Generate Forecasts

Sensitivity Analysis- One variable at time

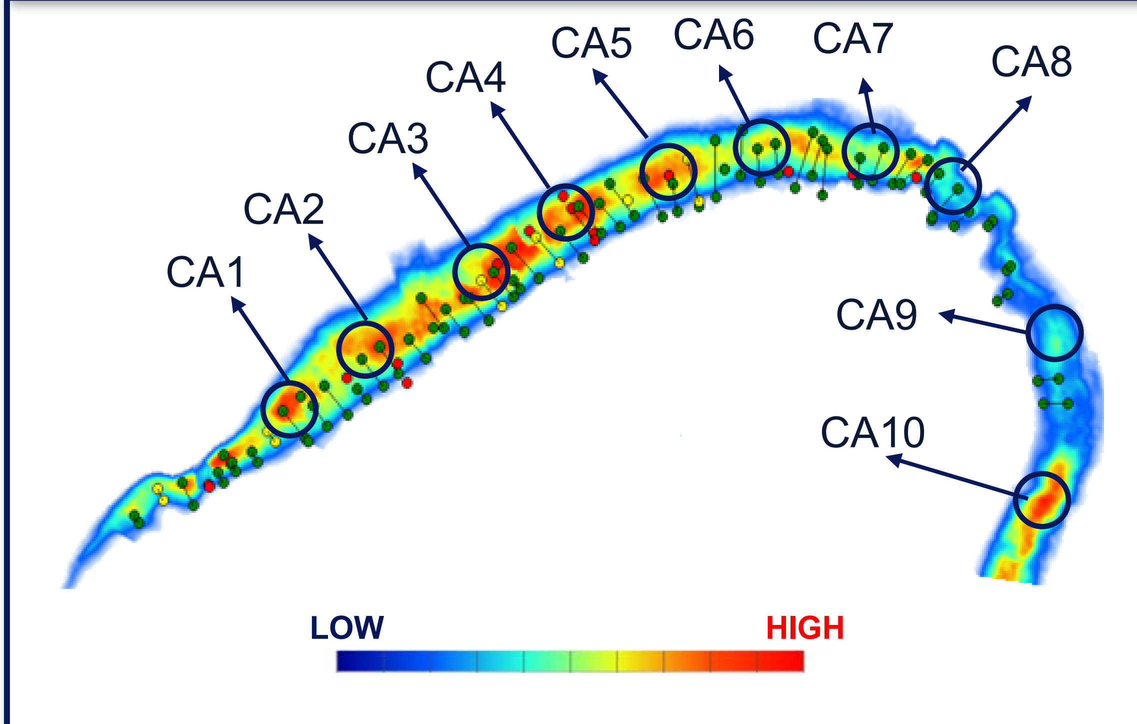
- **Define a list of uncertain parameters**
  - Static
    - Poro/Perm
    - Contacts
    - …
  - Dynamic
    - Production allocation
    - Relative permeability
    - …
- **Define L/M/H values of each parameter**
- **Run LTRO cases (one variable at time)**

Workflow - Define Control Areas

Generating and testing multiple realization in a resource-efficient manner

- Define Uncertain Parameters
- **Define Control Areas**
- Analyze Tornado Diagrams
- Create Subsurface Realizations
- Quantify Risk
- Identify / Rank Infill Targets
- Generate Forecasts

Stock tank oil in place at the end of history match



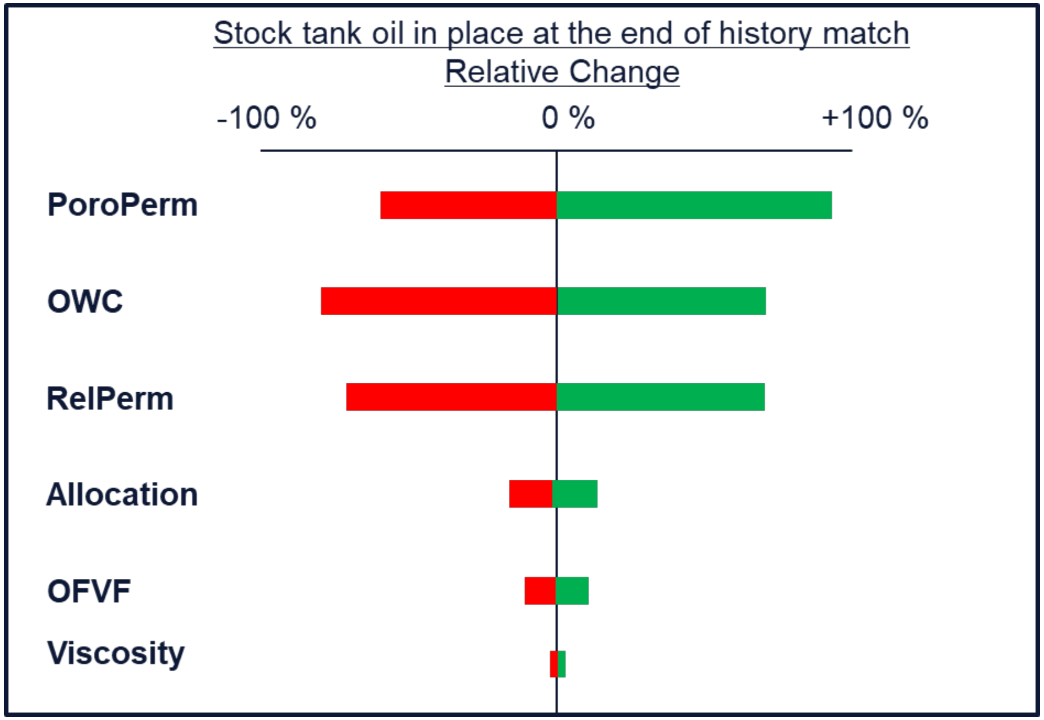
Workflow – Analyze Tornado Diagrams

Generating and testing multiple realization in a resource-efficient manner

SPE DISTINGUISHED LECTURER

- Define Uncertain Parameters
- Define Control Areas
- **Analyze Tornado Diagrams**
- Create Subsurface Realizations
- Quantify Risk
- Identify / Rank Infill Targets
- Generate Forecasts

One Variable at a Time

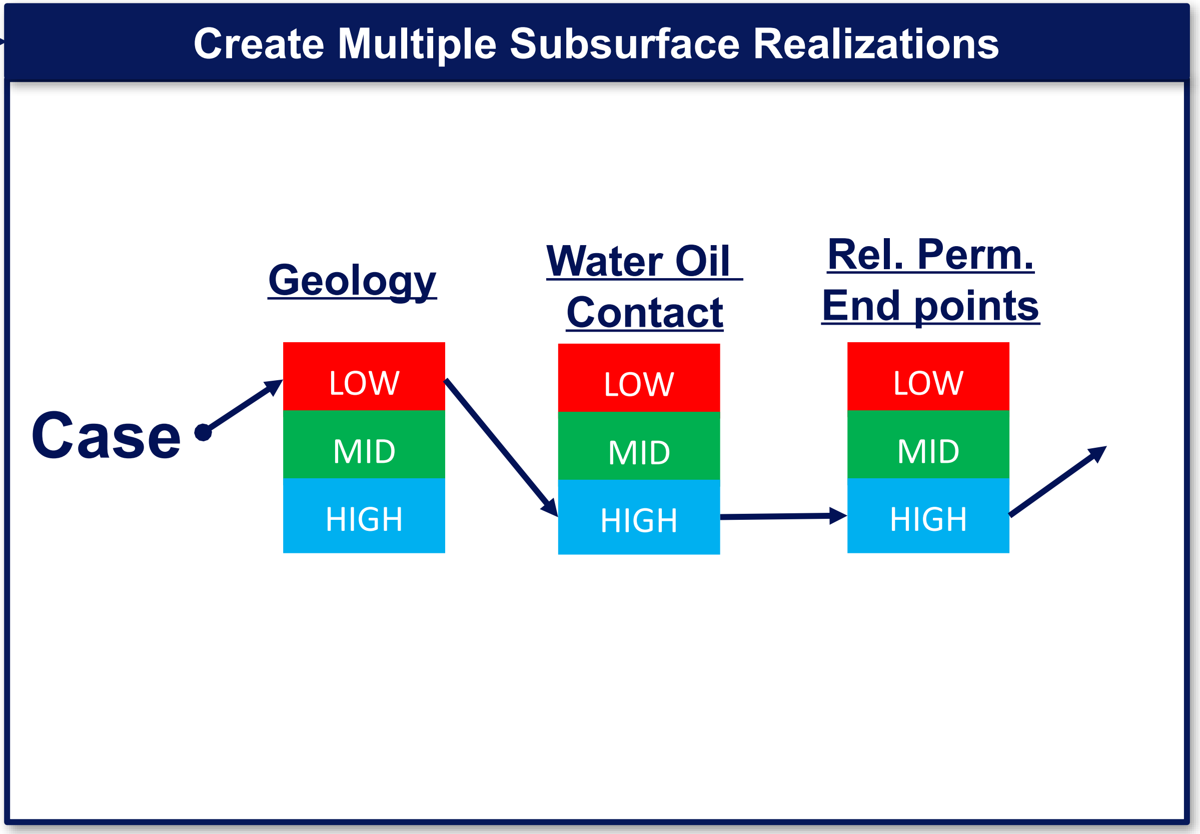


- ❑ Identifying main parameters

Workflow - Create Subsurface Realizations

Generating and testing multiple realization in a resource-efficient manner

- Define Uncertain Parameters
- Define Control Areas
- Analyze Tornado Diagrams
- **Create Subsurface Realizations**
- Quantify Risk
- Identify / Rank Infill Targets
- Generate Forecasts



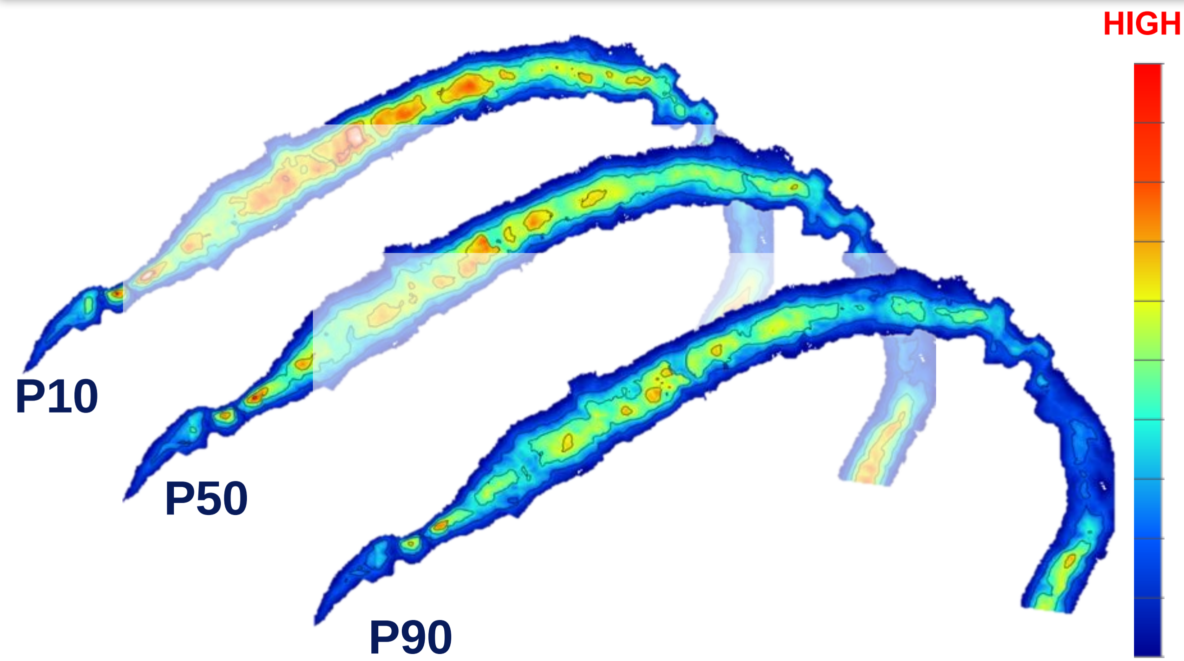
Workflow – Quantify Risk

Generating and testing multiple realization in a resource-efficient manner

- Define Uncertain Parameters
- Define Control Areas
- Analyze Tornado Diagrams
- Create Subsurface Realizations
- **Quantify Risk**
- Identify / Rank Infill Targets
- Generate Forecasts

❑ Covering range of uncertainties

Define Range of Outcomes: Quantify Risk



Stock tank oil in place at the end of history match

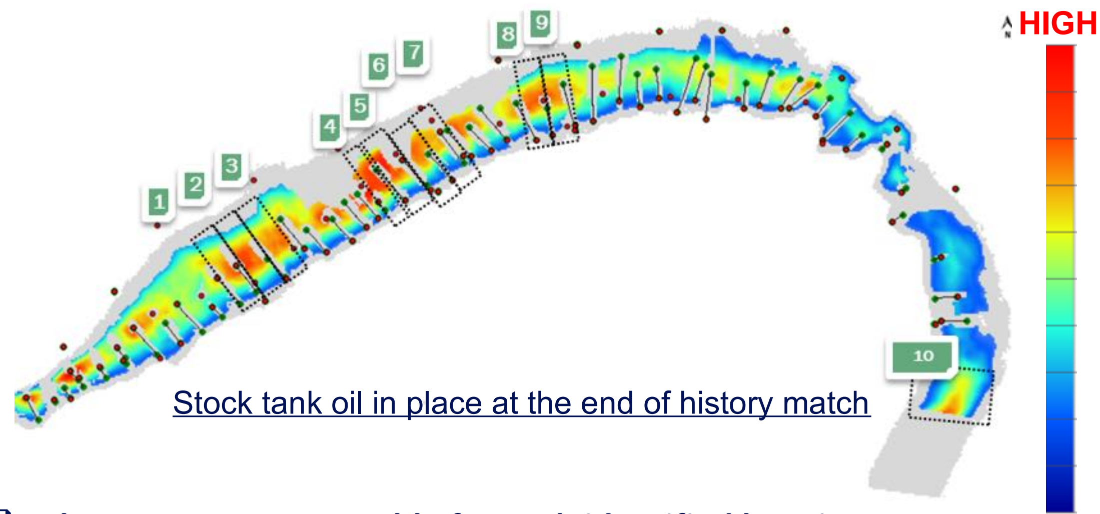
Workflow – Identify / Rank Infill Targets

Generating and testing multiple realization in a resource-efficient manner

SPE DISTINGUISHED LECTURER

- Define Uncertain Parameters
- Define Control Areas
- Analyze Tornado Diagrams
- Create Subsurface Realizations
- Quantify Risk
- **Identify / Rank Infill Targets**
- Generate Forecasts

Infill Target Identification



Stock tank oil in place at the end of history match

- The target summary table for each identified location

Target	P50 Remaining Oil	Base Case Remaining Oil	Risk Remaining Oil	Upside Remaining Oil	Downside Remaining Oil
Target 1					
…					
Target N					

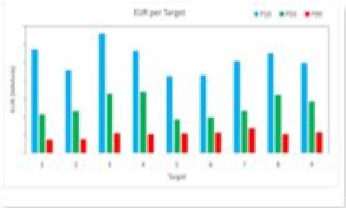
Workflow - Generate Forecasts

Generating and testing multiple realization in a resource-efficient manner

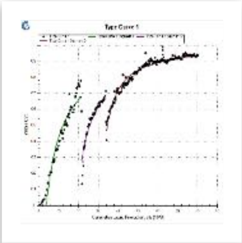
1. Define Uncertain Parameters
2. Define Control Areas
3. Analyze Tornado Diagrams
4. Create Subsurface Realizations
5. Quantify Risk
6. Identify / Rank Infill Targets
7. **Generate Forecasts**

Machine Learning

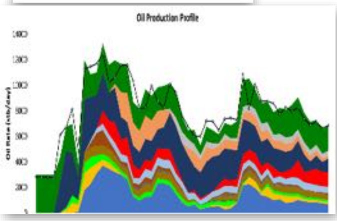
- EUR and Initial WCT



- Type Curve



- Production Profiles

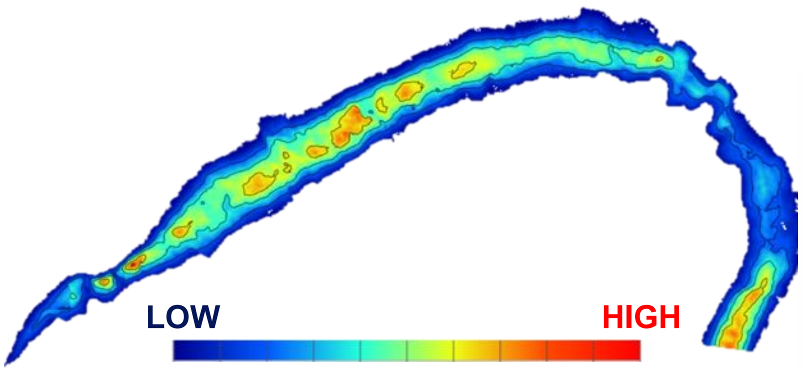


Post drilling results

Proof by the drill bit SPE-196631 (2019, onshore Z field)

- 4 Infill wells drilled using hybrid workflow
- Successful outcome, fairly consistent with forecasts

P50- STOIP Map



Society of Petroleum Engineers

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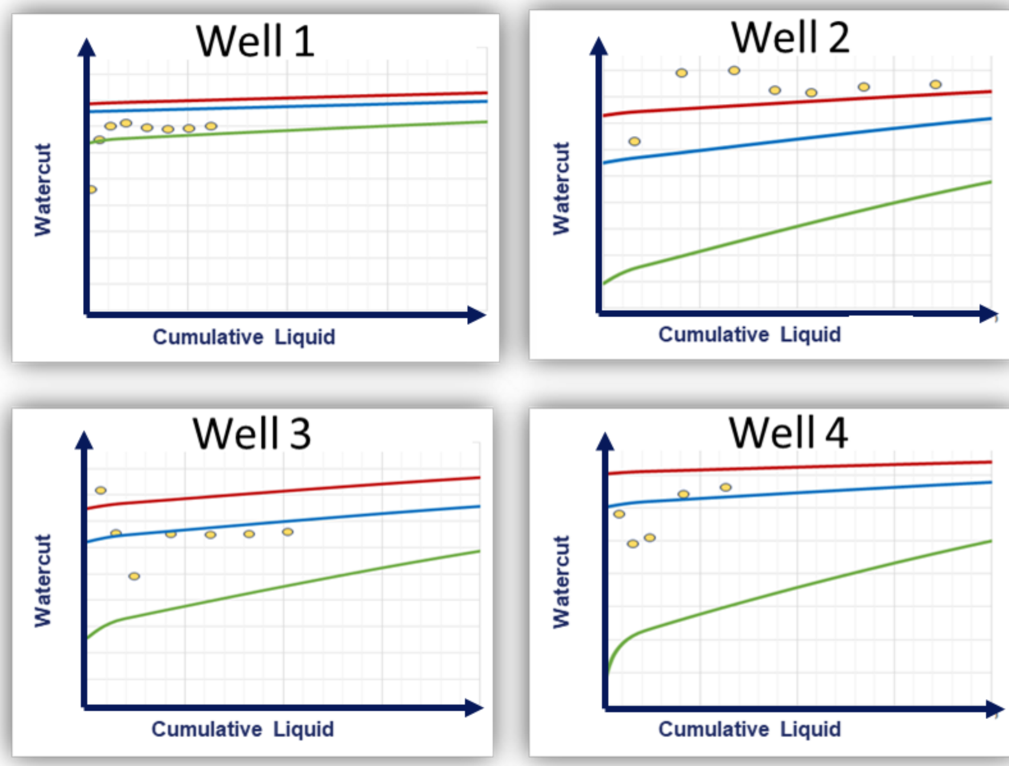
P10
P50
P90
Actual

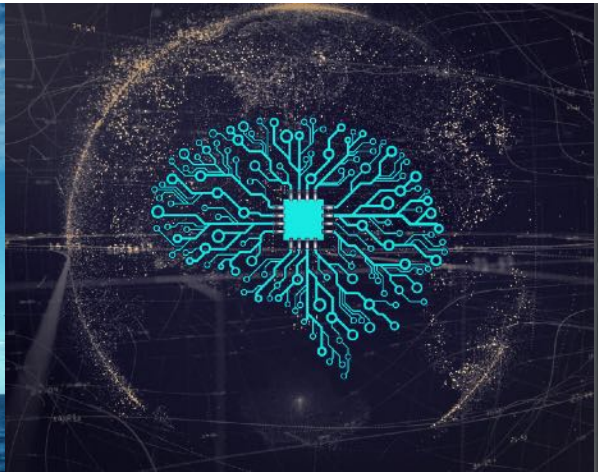
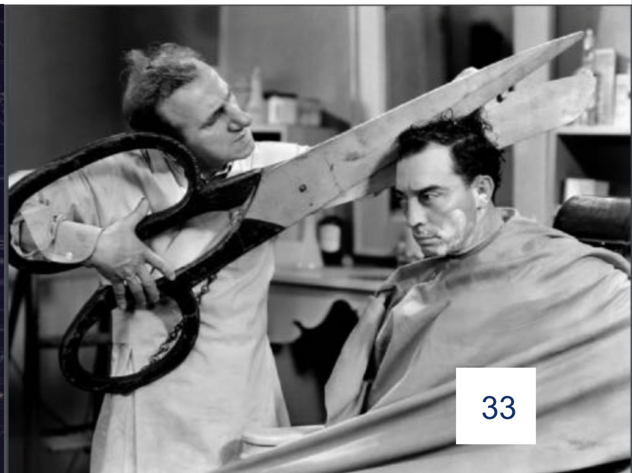
Type Curve- WCT vs. Cumulative Liquid



Conclusions

Hybrid physics-guided data-driven approaches are a powerful tool for the E&P industry

- ❑ Unlock remaining potential of mature fields in a shorter time-frame and cost-effectively compared to the standard integrated modelling workflows
- ❑ Ensure uncertainty and risks are captured within the identification of opportunities
- ❑ Hybrid workflows leverage benefits of both approaches: data-driven (inherent calibration to history) and physics-based (understand/explain what's going on)

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