Applying Machine Learning and GPM for Gaining Efficiency and Improved Predictability on the Cheviot Asset

Paul Armitage
Subsurface Manager

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Outline

1. The Cheviot Development Project
2. Current GeoModelling Workflows
3. Study Objectives
4. ML Workflow
5. Results
7. Next Steps
Cheviot Field Overview

- Redevelopment of the Emerald Oil Field (renamed Cheviot)
- Conventional Oil
- Reservoir Depth around 5500 ft
- Excellent Jurassic Reservoir with 25 to 30% Porosity
- High Water Cut Development
Cheviot Field Existing Geomodels

- **Structural uncertainty analysis and model build automation**
- **Geo screening workflow to select ~50 representative models**
- **Screen models then history match ensemble of 3-9 representative cases**
- **Prediction simulation of ensemble using current reference strategy**
- **Document project structure and workflows**

**Base Case Workflow**
- 300 lines
- ~10-12 mins to rebuild geomodel from input surface

**Base Case Workflow with uncertainty parametrisation**
- 500 lines
- 2-3 days to build over 300 realisation, and run volumetrics and flow connectivity calculation on each
## Cheviot Field: Objectives and Challenges

<table>
<thead>
<tr>
<th>Challenge</th>
<th>Is there an improved petrophysical properties correlation to be incorporated into Cheviot Field Geomodels?</th>
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<tbody>
<tr>
<td>Solution</td>
<td>Improving properties correlation using a random forest regression workflow. Also, use additional training feature inputs (seismic and geometrical properties) to check for correlation coefficient improvements</td>
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<tr>
<td>Innovation</td>
<td>Integrating Geological Process Modeling workflow to be used as a training feature in the ML Property Modeling workflow for conditioning porosity and permeability.</td>
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<td>Results</td>
<td>Increased correlation percentage for porosity from 61 to 94% on the blind testing validation workflow.</td>
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Cheviot Field: Machine Learning Property Modeling Workflow
Cheviot Field: Correlation Coefficients for Predicted Porosity

*Comparison of Correlation Coefficients for Porosity predictions with and without ML Property Modeling Workflow*
Cheviot Field: Porosity Blind Testing Validation

- QA/QC Blind testing

- Several sets of wells selected in a random order to check for variability on model prediction

- Blind Testing for ML Property Model porosity showed a correlation coefficient of 94.5% vs. 61% for the geostatistical model.
Cheviot Field: Integrating Forward Stratigraphic Modeling

- Additional training feature integrated into the workflow
- Forward Stratigraphic Model generates a property model conditioned to facies framework
- Porosity correlation coefficient improved by additional 5%.
Next Steps

Better statistics for correlations achieved, but so what?
1. Improved confidence in model results?
2. Better development plan?

1. **Updated Geological Model** with refined validated reservoir properties distributions on Porosity, Permeability, VShale & Permeability and hence updated NTG property

2. **Updating Base Case Volumetrics** with refined validated Net to Gross properties and an update on the Base Case Volumes may be observed

3. **Update on Uncertainty Volumetric Assessment** with possibility of refined Base Case Volumes as a result of model update the uncertainty assessment for the volumes would also be updated and validated

**Final Geological Model for History Matching & Dynamic Simulation**

**The Dynamic Modeling History Matching and update on the Predictions and Forecasting Scenarios**