PS Stratigraphic Control on Oil Field Performance in Clastic Reservoirs of the Norwegian Continental Shelf: An Insight from Machine-learning Techniques*

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Abstract

Adequate knowledge of reservoir architecture is key in the placement of injector wells, pressure maintenance, and secondary recovery which in turn can contribute to reserve growth. The main aim of this study is to determine the impact of depositional environment and primary facies architecture on reservoir performance. Fields from the Norwegian Sea, the Norwegian North Sea and the Barents Sea were used to build a database of 91 fields all with more than 11 million barrels of oil in place. A total of 76 clastic reservoirs were classified into three gross depositional environments: continental, paralic/shallow marine and deep marine. 61% of the reservoirs are paralic/shallow marine, 11% are continental and 28% are deep marine. Reservoirs were further classified into eight sub-environments to capture depositional complexity. Representative reservoirs from each sub-environment were analyzed at architectural element scale using logs and core to determine reservoir heterogeneity.

Principal component analysis (PCA) was utilised to identify the importance of stratigraphically dependent variables in the dataset, and to determine the key parameters that have strong effects on the overall variability of the data. PCA reveals that gross depositional environment and sedimentological related parameters dominate the first four principal components. Fluid properties such as API and water saturation are unexpectedly among the less important parameters. A simple box plot of reservoir depositional sub-environment against recovery factor for reservoirs produced via pressure depletion and those supported through water injection reveals weakening recovery with increasing stratigraphic heterogeneity. Delta front, wave-dominated shoreface, tidal non-delta, stacked multistorey fluvial and deep marine reservoirs have relatively good recovery, whereas, offshore/transition zone reservoirs and isolated meandering fluvial channel deposits have low recovery.

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1.0 What Controls Production?

Hydrocarbon production is controlled by a wide range of factors. The goal of this study is to investigate the relative importance of these empirically by applying modern data analytics to the dataset from the Norwegian continental shelf. Some known controlling parameters are;

Geological Complexity

- Substantial amount of oil has been bypassed due to a number of reasons
  - Structural complexity
  - Stratigraphic complexity
- Permeability layering
- Number of reservoir compartments

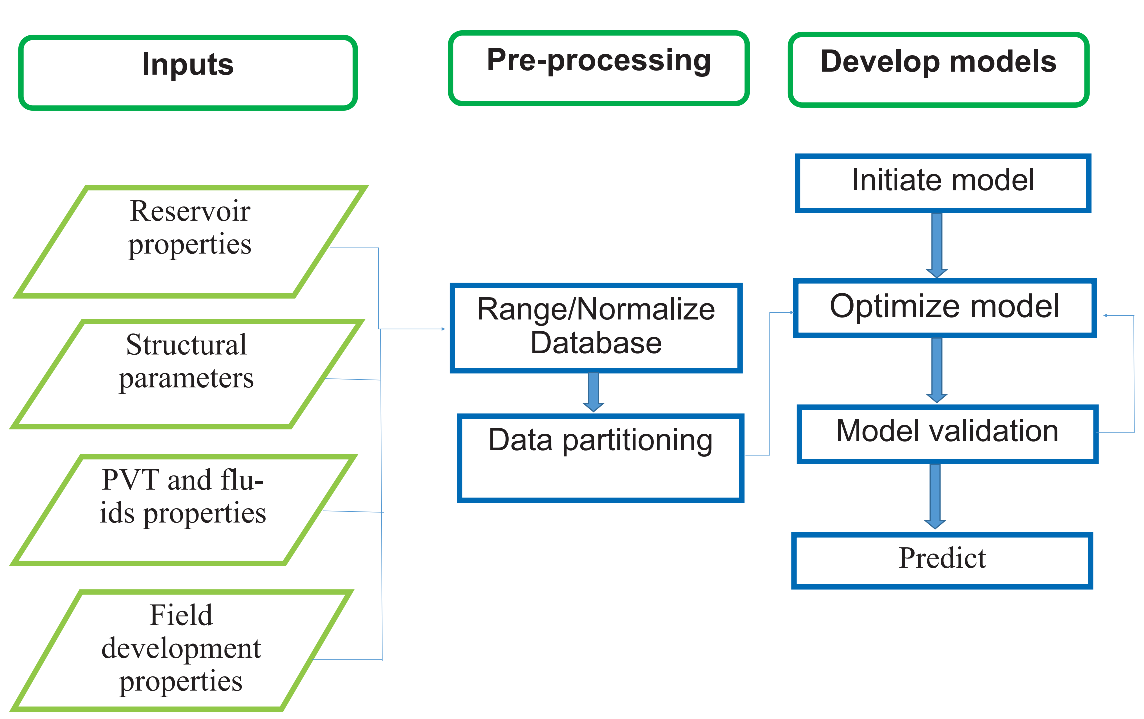
Fluids Properties

- Oil saturation
- Viscosity
- API density

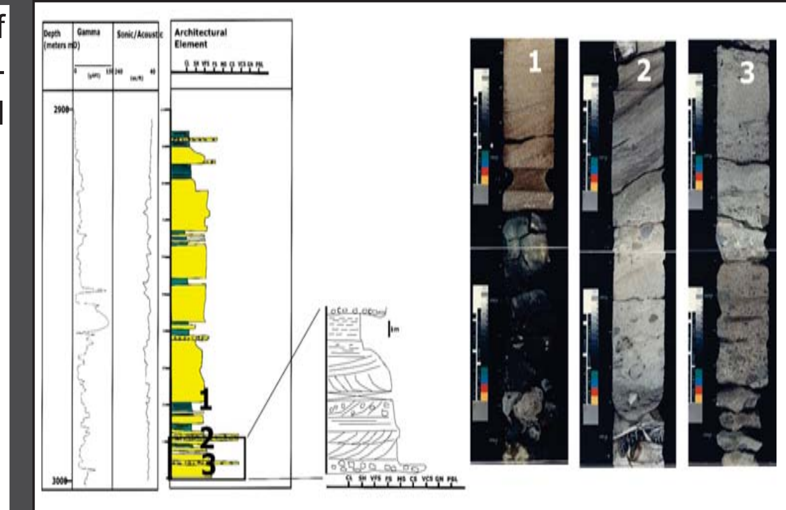
Field Development Strategy

- Onshore or offshore
- Number of wells
- Reservoir drive mechanism
  - Water injection
  - Gas injection
  - Gas/water injection
  - Pressure depletion

2.0 Workflow and Methods

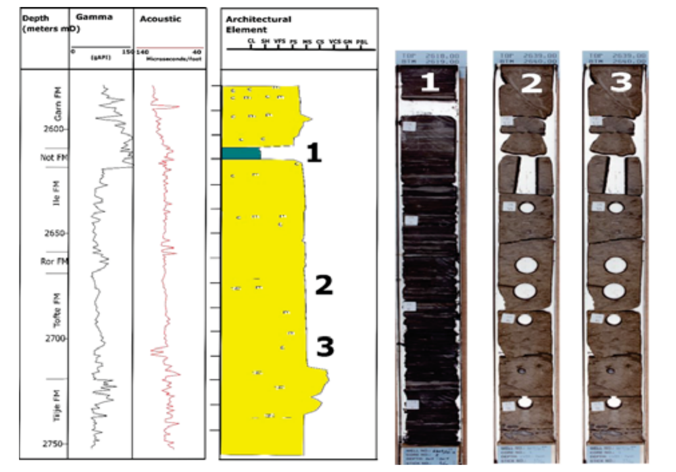


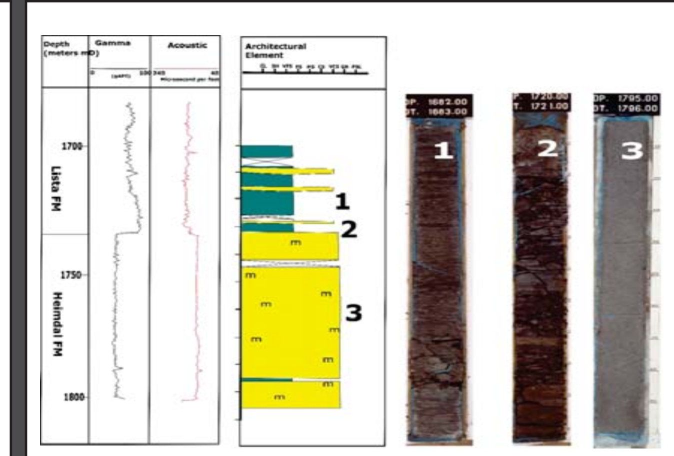
4.0 Initial Analysis



Continental reservoir: Sedimentological log, gamma, sonic logs, and core images of the Skagerrak Formation of the Gaupe field showing sand-body distribution of the reservoir.

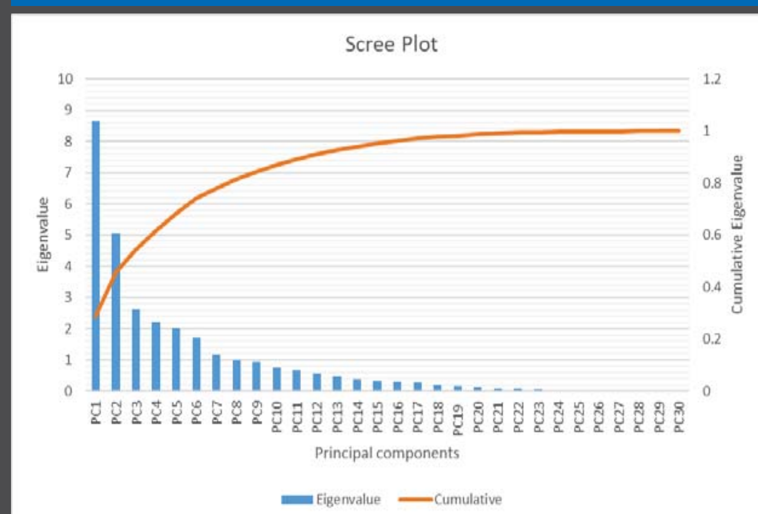
Paralic/shallow marine reservoir: Gamma, sonic, sedimentological logs, and core images of the Ness and Etive section of the Norne reservoir a subtidal deposit.

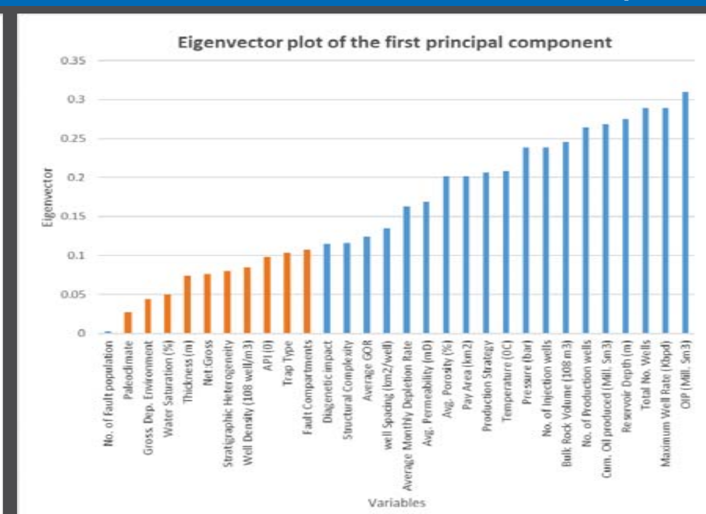


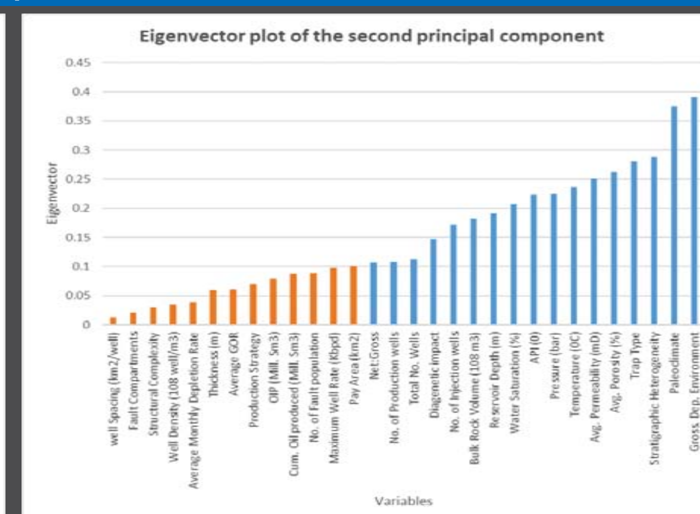


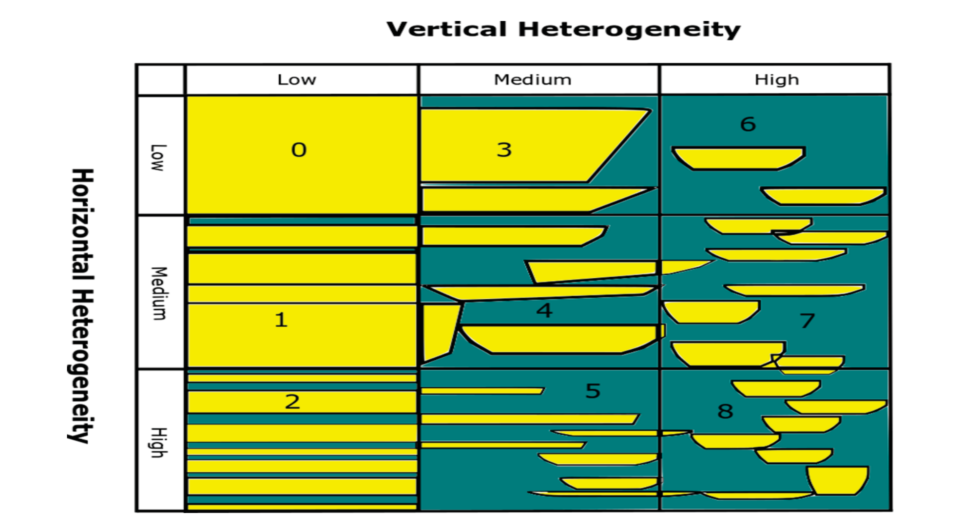
Deep marine reservoir: Gamma, sonic sedimentological logs, and core images of the Lista and Heimdal Formations of the Grane field showing the distribution of the reservoir intraformational fines.

Multivariate Statistical Approach (PCA)

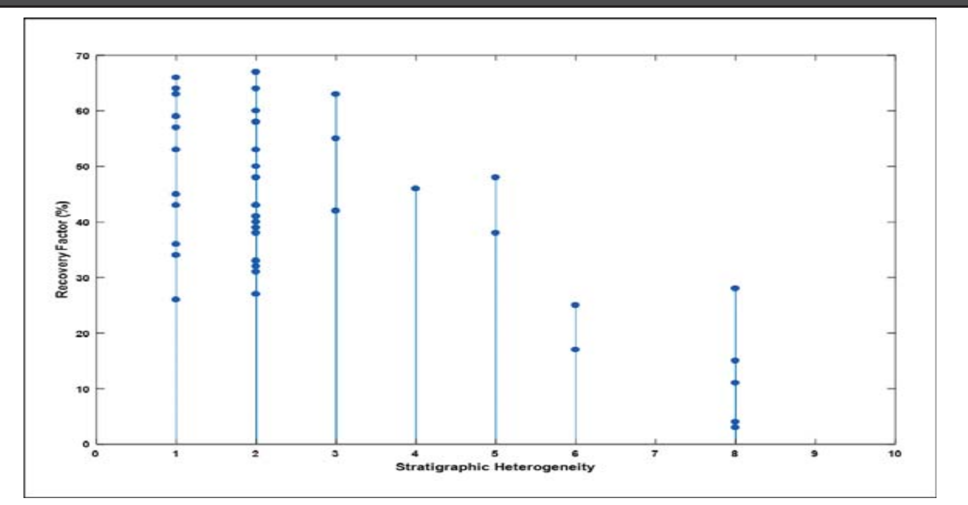








Measure of the degree of depositional heterogeneity/flow units for the different reservoirs using a scale of 0-8.



Stem diagram showing the relationship between recovery against stratigraphic heterogeneity for all the reservoirs

3.0 What's in the database?

Parameters recorded for each field include:

Geological

- Depositional environment (with SAFARI Schema)
- Structural complexity Production profile
- Diagenetic Impact
- Stratigraphic Heterogeneity
- Mean Porosity
- Average Permeability
- Reservoir Depth
- Reservoir Net:Gross
- Total reservoir volume

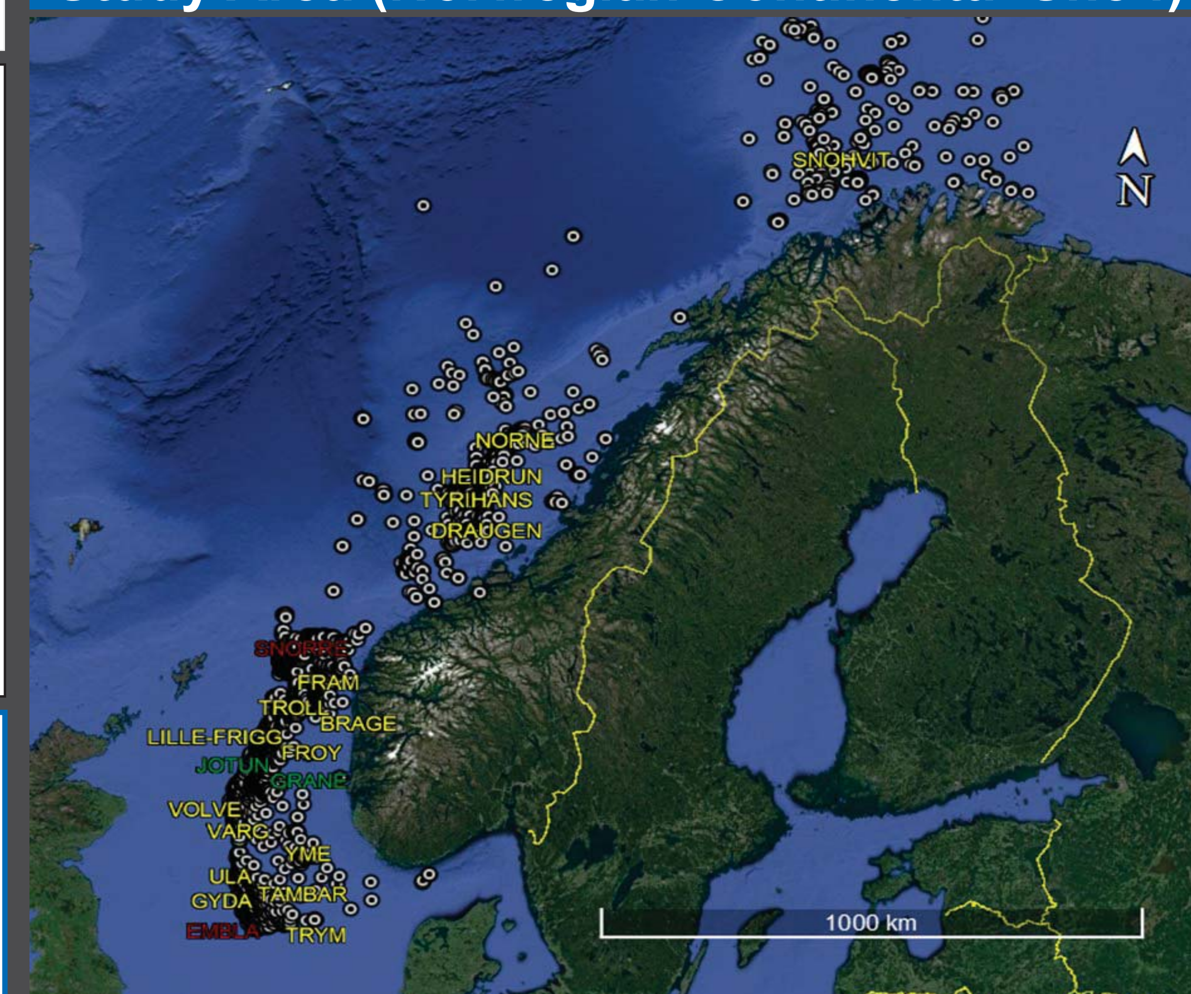
Fluids and Engineering

- Hydrocarbon API
- Drive mechanism
- Number of producing wells
- Wells per unit volume
- GOR

Metrics

- Recovery Factor (estimated for end of field life)
- Average monthly depletion rate
- Maximum oil well rate

Study Area (Norwegian Continental Shelf)



Map of the Norwegian continental shelf showing different wells and field names in the northern North Sea, Norwegian Sea and the Barents Sea. Field names in red have continental reservoir, shallow/parallic reservoirs in yellow and deep marine reservoirs in green.

About SAFARI

SAFARI is an on-going Joint Industry Research Project at UniResearch CIPR and the University of Aberdeen supported by a consortium of currently 14 Oil Companies, the Research Council of Norway and the Norwegian Petroleum Directorate. The goal of the SAFARI project is to develop a fully searchable repository of geological outcrop data from clastic sedimentary systems for reservoir modelling and exploration.

The SAFARI project includes a fully searchable database that is accessed through the website www.safaridb.com The site includes:

Information from 350 outcrops, including descriptions, logs, photos, sections, reservoir models

Over 200 of these sections have photo realistic 3D models (Virtual Outcrops) that allow the user to fly around the outcrop in a purpose built web browser

A tool for identifying modern analogues to reservoirs in GoogleEarth

Over 6500 geometric measurements of reservoir elements from outcrops

Variograms and MPS training images extracted from outcrop analogues

Machine Learning Techniques

5.0 Data Pre-processing

The dataset was normalised using the formula below;

$$Y = \frac{(x - \min(d)) * (\max(n) - \min(n))}{\max(d) - \min(d)} + \min(n)$$

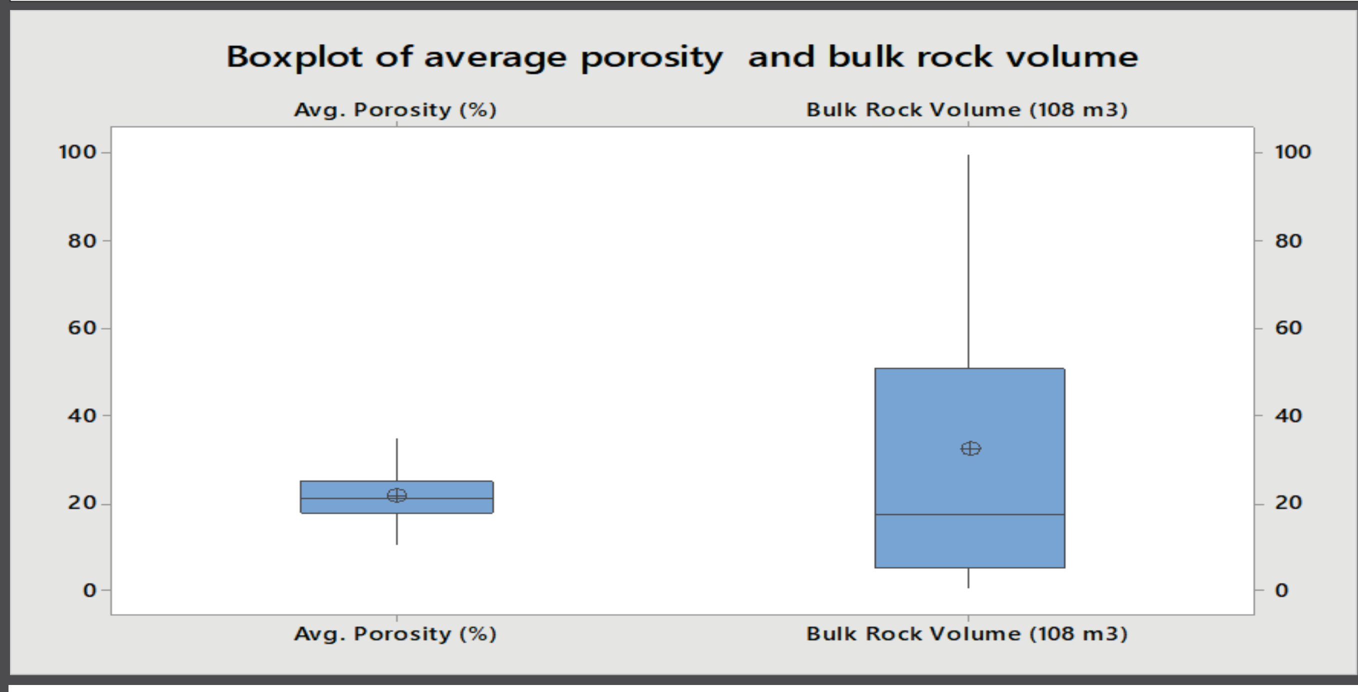
Where,

Min(d)= Minimum or lowest value in data

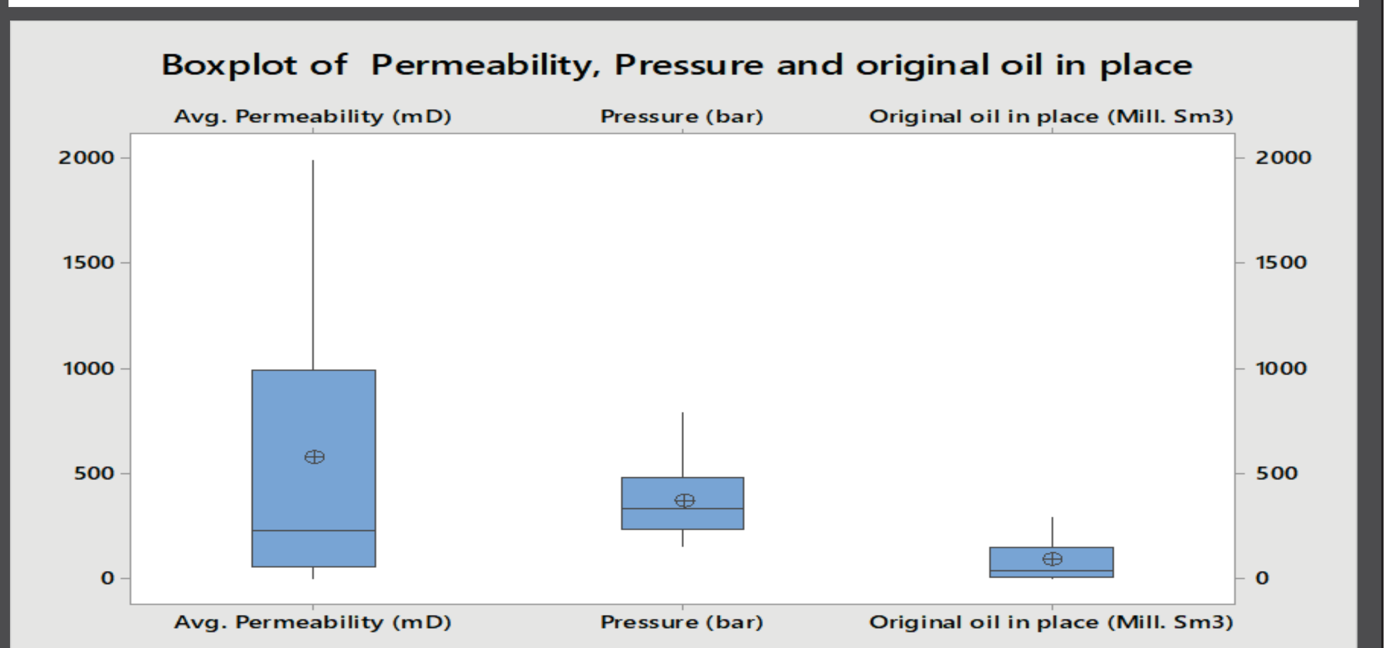
Max(d)= Maximum or highest value in data

Min(n)= Minimum value in new range

Max(n)= Maximum value in new range

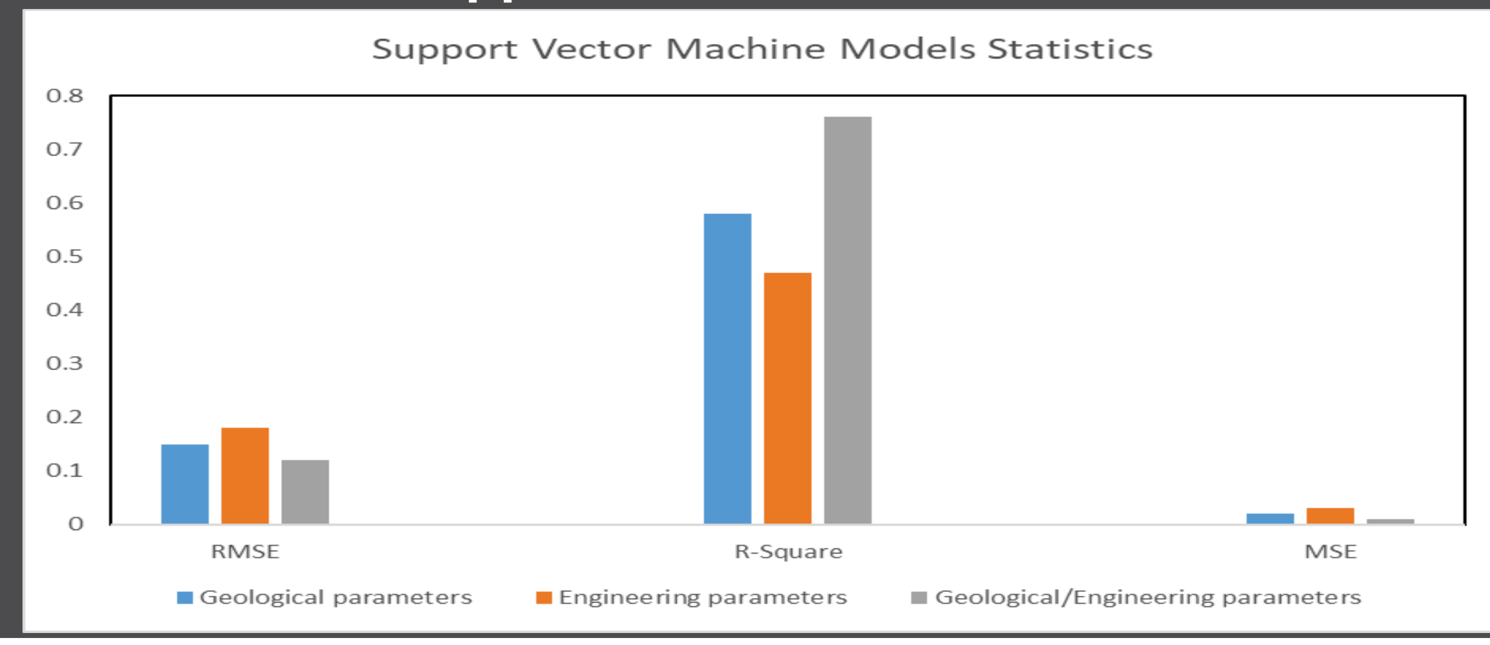


Box plot showing outliers in two parameters (average porosity and bulk rock volume)

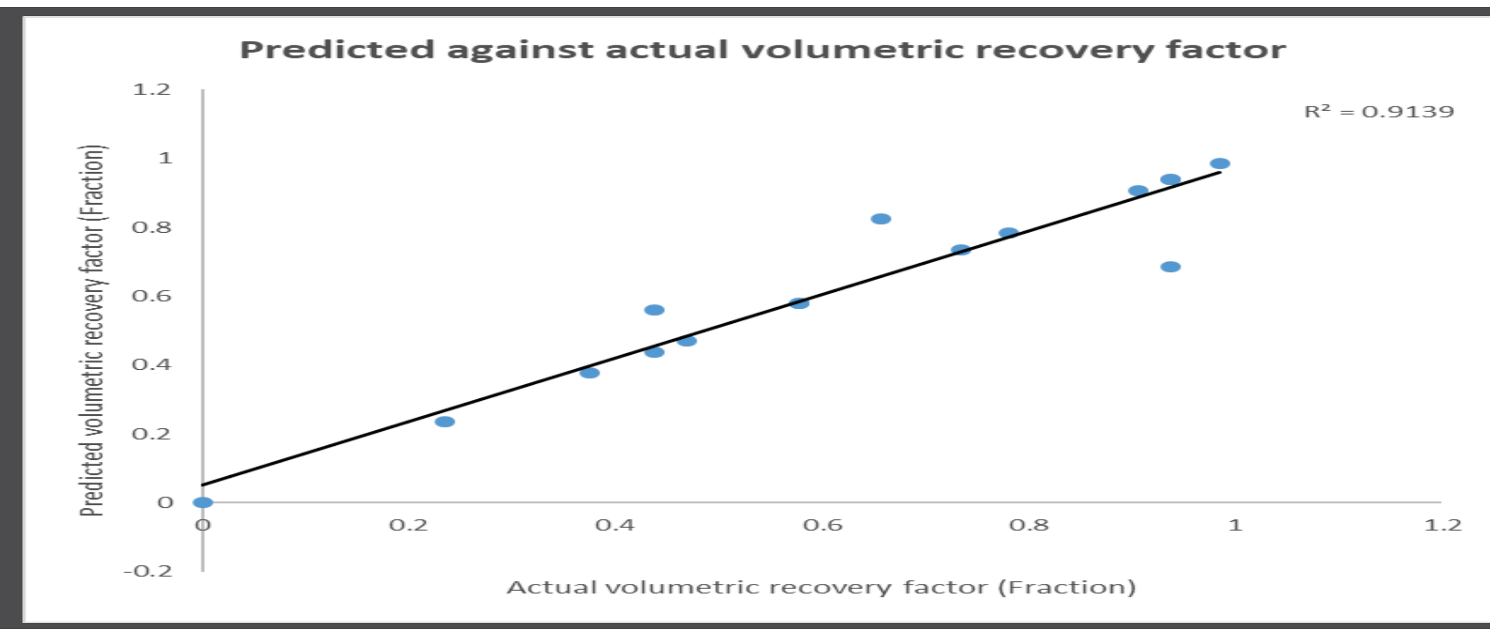


Average permeability, initial pressure and original oil in place have outliers, such observations were eliminated from the database.

6.0 Support vector machine Models



A comparison between the three machine learning models trained with a set of 16 most important parameters in the database categorised into geological, engineering and geological/engineering parameters.



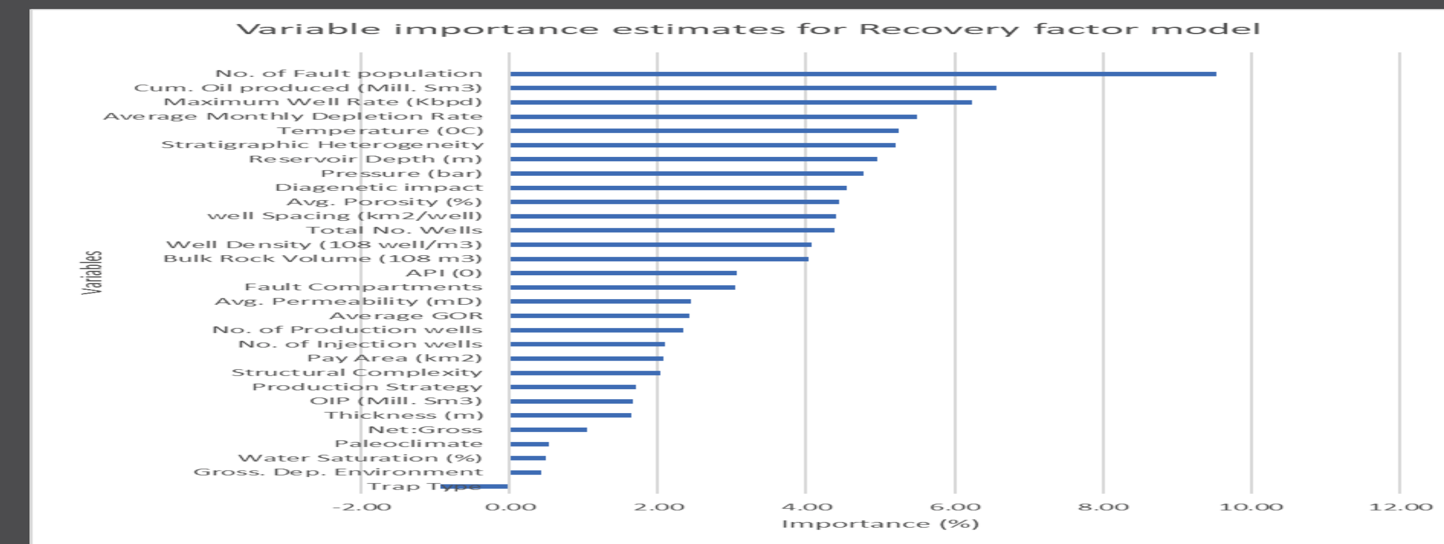
Relationship between recovery factor predicted by machine learning model (SVM model) and volumetrically estimated recovery factor.

Reservoirs	Depositional Environment	Estimated RF (Fraction)	Predicted RF (Fraction)	Estimated RF (%)	Predicted RF (%)	Error
Heather	Paralic/Shallow marine	0.4375	0.4375	31	31	0
Magnus	Deep Marine	0.578125	0.5782	40	40.0048	-7.5E-05
South Brae	Deep Marine	0.46875	0.4687	33	32.9968	5E-05
Staffa	Paralic/Shallow marine	0.234375	0.2344	18	18.0016	-2.5E-05
Strathspey Brent Group	Paralic/Shallow marine	0.90625	0.9061	61	60.9904	0.00015
Strathspey Bank Group	Continental	NaN	NaN			
Thistle	Paralic/Shallow marine	0.734375	0.7344	50	50.0016	-2.5E-05
Glitne	Deep Marine	0.65625	0.8246	45	55.7744	-0.1683
Grane	Deep Marine	0.984375	0.9845	66	66.008	-0.0001
Gungne	Continental	NaN	NaN			
Gyda	Paralic/Shallow marine	0.578125	0.5803	40	40.1392	-0.0021
Heimdal	Deep Marine	0.9375	0.6841	63	46.7824	0.2534
Jotun	Deep Marine	0.78125	0.7824	53	53.0736	-0.0012
Lille Frigg	Paralic/Shallow marine	0.4375	0.5588	31	38.7632	-0.1213
Mime	Paralic/Shallow marine	0	-0.0001	3	2.9936	0.0001
Oseberg 1	Paralic/Shallow marine	0.9375	0.9379	63	63.0256	-0.0004
Oseberg 2	Paralic/Shallow marine	0.9375	0.9378	63	63.0192	-0.0003
Oseberg Sor 2	Paralic/Shallow marine	0.375	0.3768	27	27.1152	-0.0018

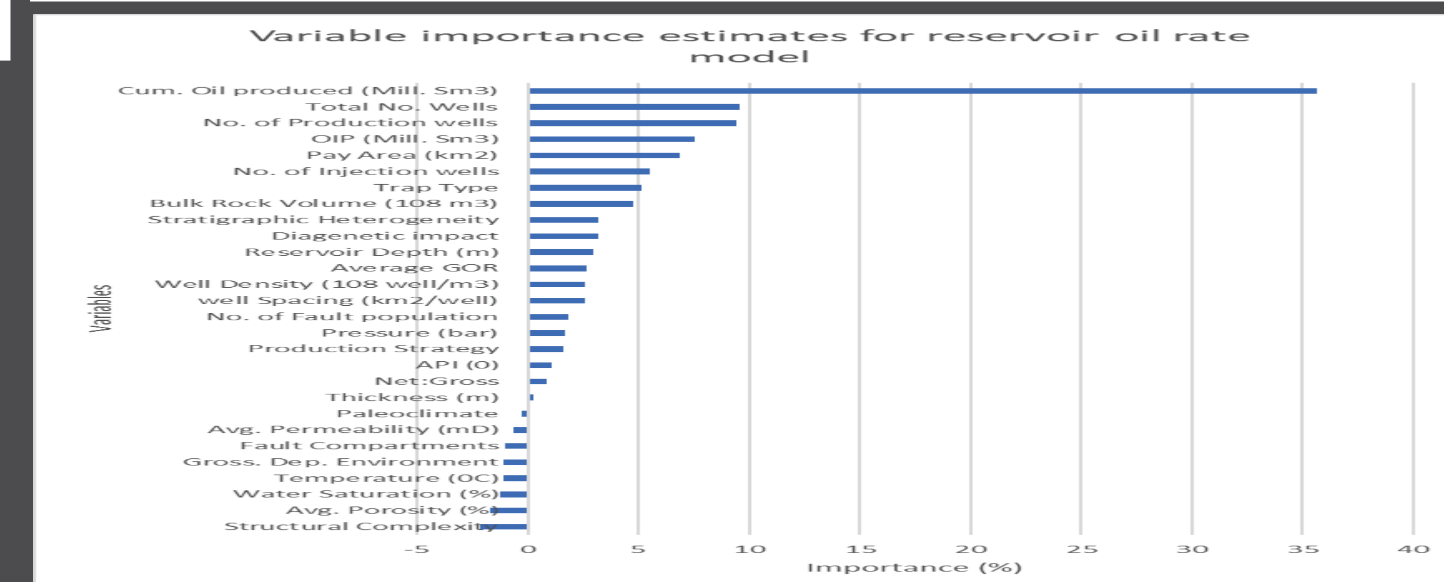
Table showing fields, depositional environments and their recovery factors both predicted and actual. The last coloured column shows good match between prediction by the model and actual recovery in the database

7.0 Random Forest Models

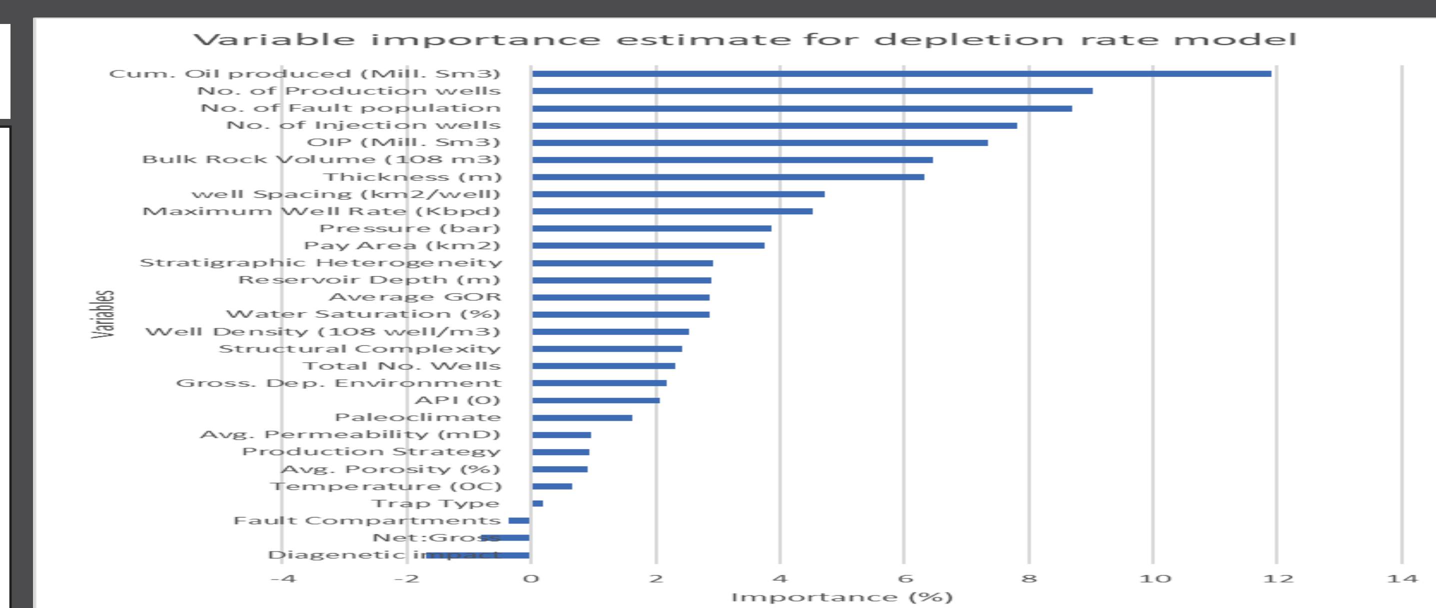
Important parameters in predicting oil recovery factor



Important parameters in predicting oil reservoir rate



Important parameters in predicting oil depletion rate



8.0 Conclusion

A unique database consisting of 32 parameters was developed to evaluate the role of geology in controlling oil field performance.

- The database was used to train and test a set of support vector machine, linear regression and random forest models in order to predict oil fields performance metrics.
- A combination of geological and engineering parameters produced the best predictive models, revealing the importance of some key geology dependent parameters in controlling oil field performance.
- Important geology dependent parameters revealed by these machine learning techniques are; depositional environment, depth of burial, porosity, permeability, initial pressure, stratigraphic heterogeneity, structural complexity and diagenetic impact.

Selected references

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