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First Palynological Results from GSQ Roma 2, Surat Basin, QLD

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Palynology of the Jurassic–Cretaceous transition, Surat Basin

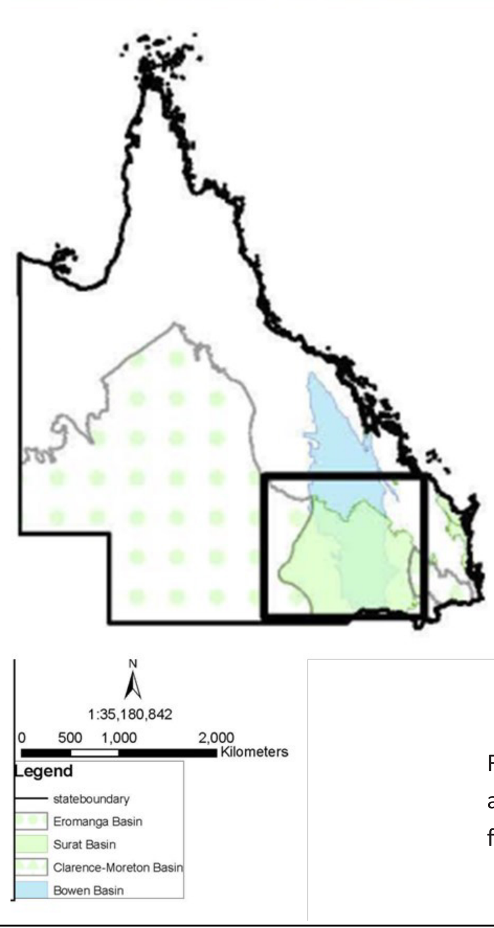
The formations around the Jurassic–Cretaceous transition in the Surat Basin are the last of that basin to undergo systematic palynological study. They represent the most complete record of deposition for the period in the state and contain a number of important aquifers.

This project will result in

- A systematic description of the palynomorphs from the strata and the description of several new species
- Conformation of how well the pan Australian palynostratigraphic zones (Fig. 1) work for this region and possible new units alowing for a finer subdivision of the strata
- An improved understanding of the flora and climate of the period of deposition.

Work to date

- Sample for palynology have been taken from 3 GSQ Stratigraphic holes (Fig. 2)
- A systematic survey of palynomorphs has been conducted for DRD 26 and Roma 2 finding 237 species across 111 genera.
- Species counts have begun for samples from Roma 2



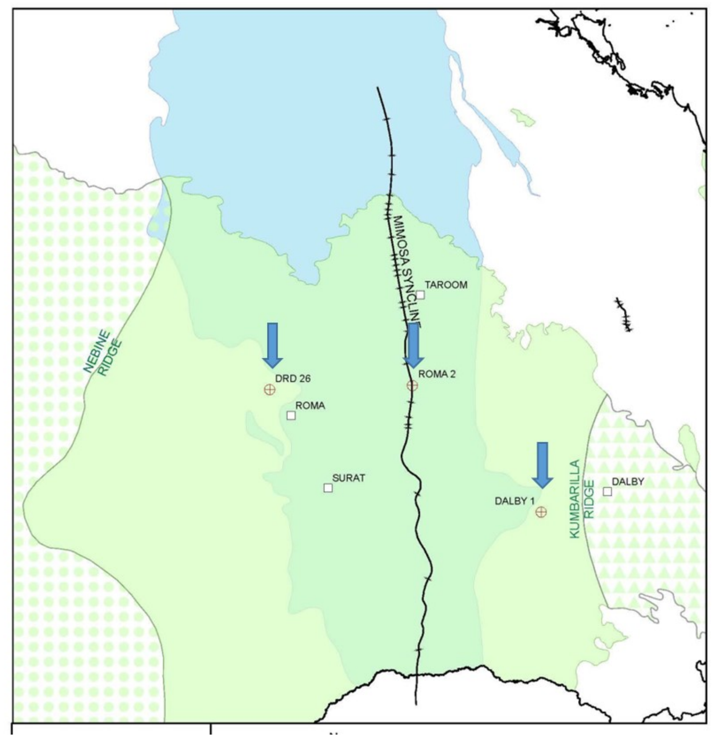


Figure 1: Map of Queensland to the left showing area of the map above. Above map shows the three GSQ Stratigraphic holes sampled for this project. GSQ DRD 26, GSQ Roma 2 and GSQ Dalby 1.

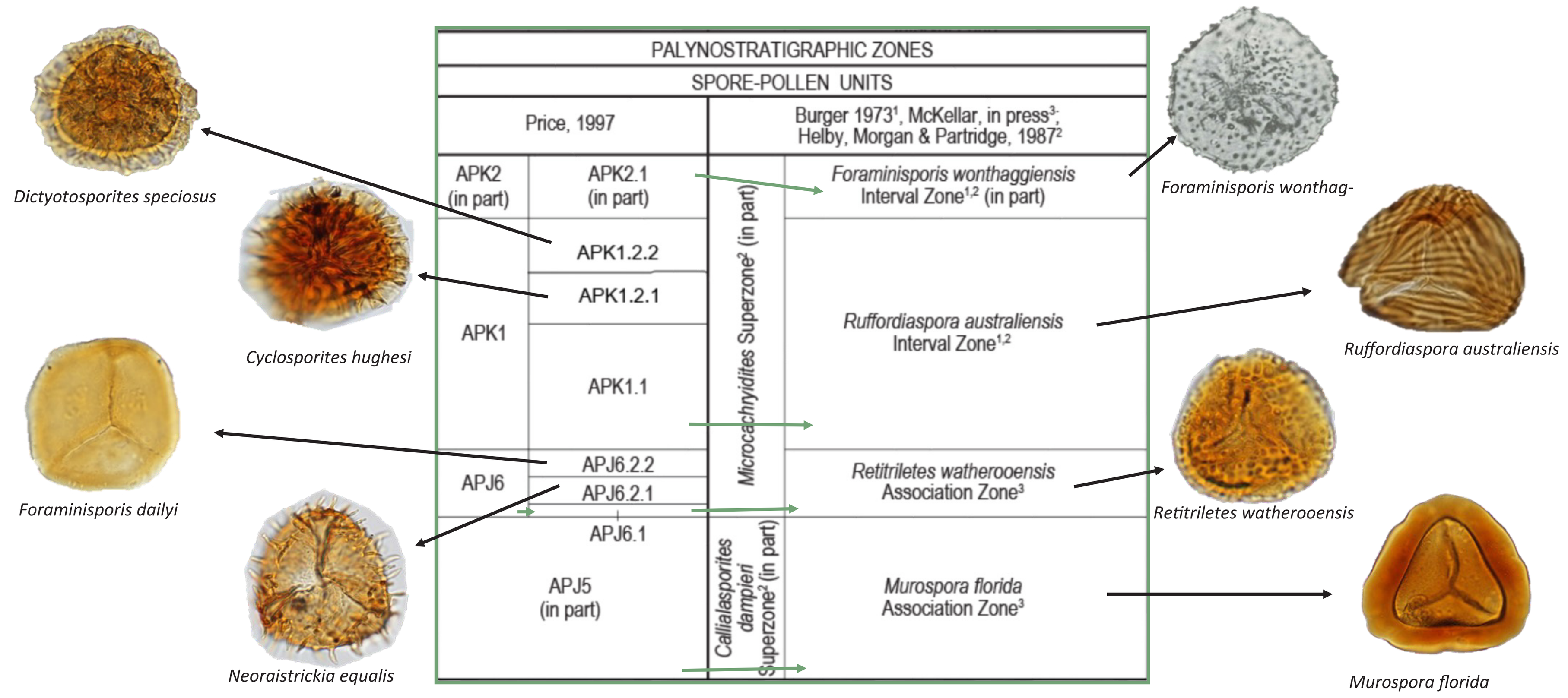


Figure 3: The pan-Australian palynostratigraphic zones covering the Late Jurassic and Early Cretaceous shown with their index fossils. The first appearance of the index fossil in a section corresponds with the base of the palynostratigraphic zone.

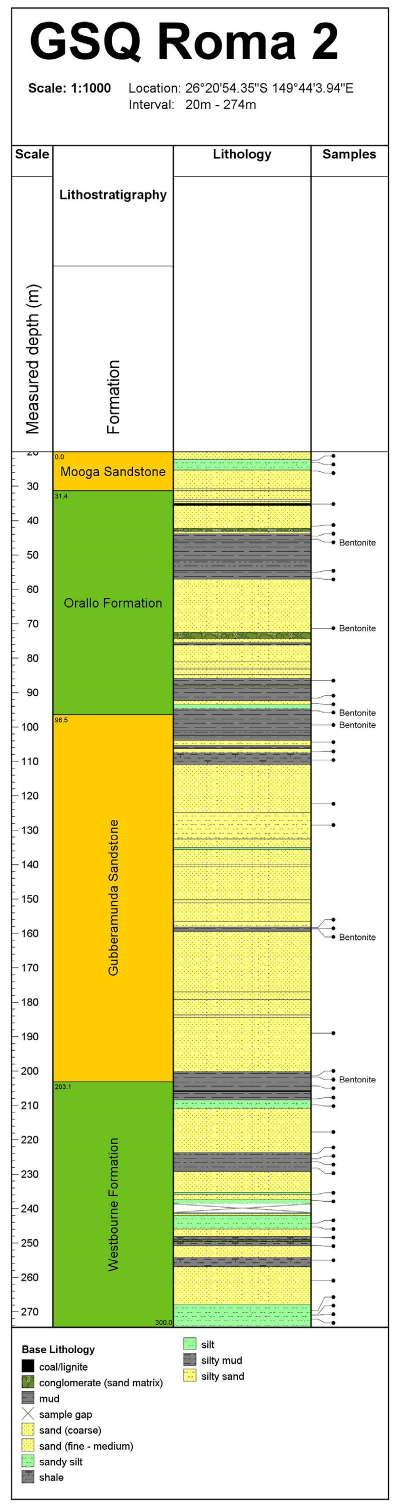


Figure 2: The complete set of samples taken from Roma 2. Bentonite samples are for zircon dating.

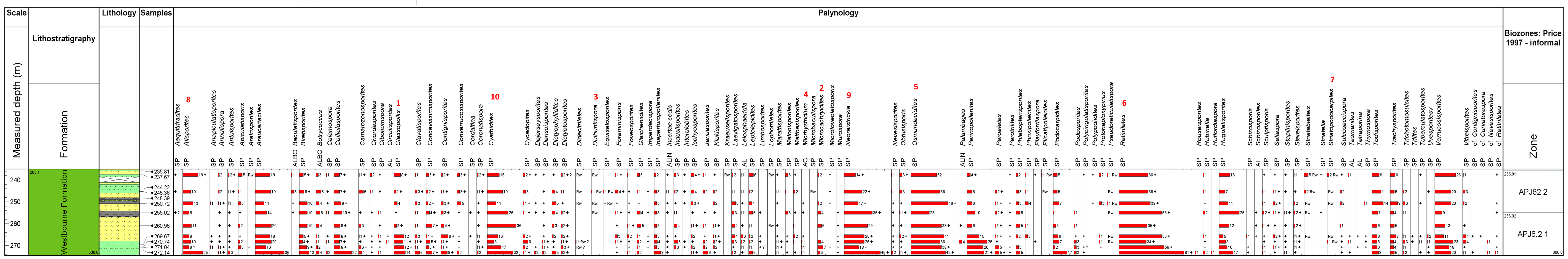


Figure 4: Preliminary Palynological data from Roma 2. Figure shows depths, lithology, samples, genera level occurrences with counts of 300 per sample and interpreted biozones as per the Price, 1997 scheme.

Significance of selected palynomorphs from figure 4

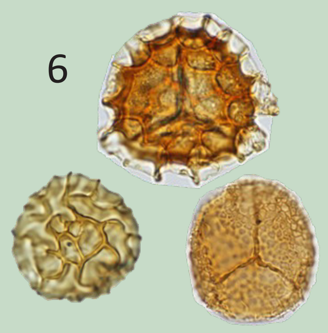
1  The *Classopollis* are a globally distributed genus and associated with warm or hot climates.

2  The *Michrystridium* genus and other tri-saccate pollen are associated with cool climates.

3  The *Dulhuntispora* are an iconic Permian genus, their appearance here indicates reworking of Permian sediments.

4  The *Michrystridium* are fresh or brackish water acritarchs.

5  The *Osmundacidites* are one of the most abundant spores in these samples. Possibly for taphonomic reasons.

6  The *Retitriletes* are one of the most diverse genera from the Late Jurassic and Early Cretaceous.

7  The *Striatopodocarpites* and other striped bisaccate pollen are reworked from Permian sediments.

8  The *Alisporites* are bisaccate pollen native to the Jurassic and Cretaceous.

9  The *Neoraistrickia* are another very diverse group of spores. Like the *Retitriletes* this variation can be used to identify changes in time.

10  The *Cyathidites* are characteristic of Mesozoic sediments in many parts of the world.

11  The *Matonisporites* are another indicator of warmer climates.

12  *Converrucosisporites parvitumulus* is just here because I think it looks cool.

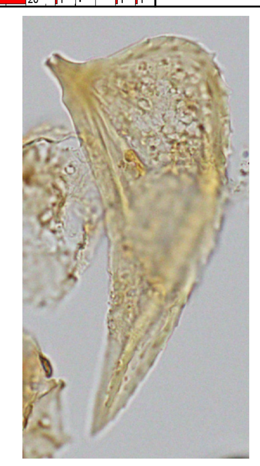


Figure 5: Weirdest palynomorph. Possible insect scale.

Acknowledgements

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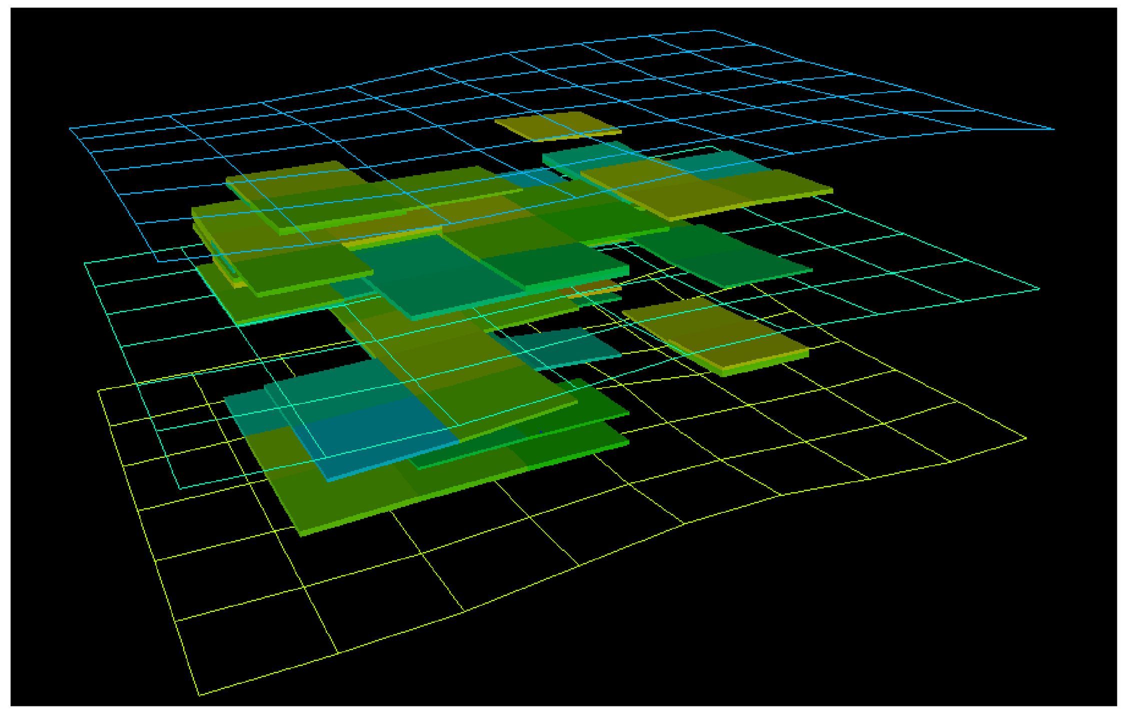
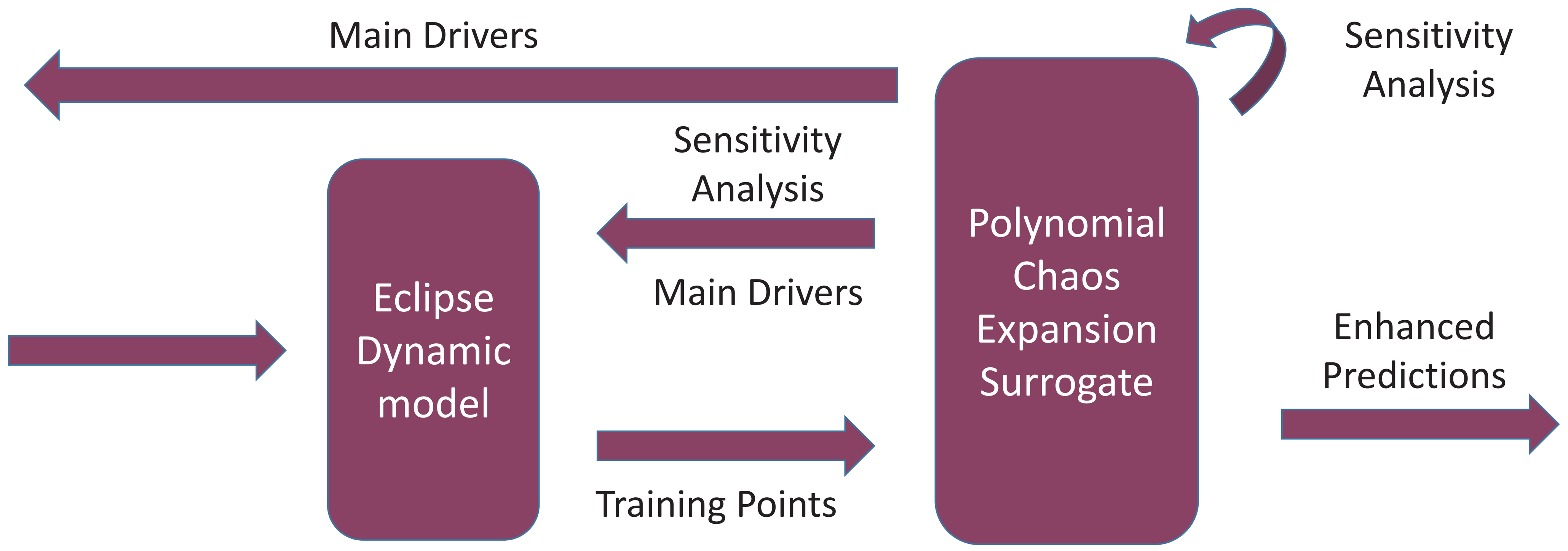
Machine Learning for Coal Seam Gas Production

Diane Donovan, Suzanne Hurter, Thomas McCourt, Iain Rodger, Bevan Thompson and Ryan Blackmore

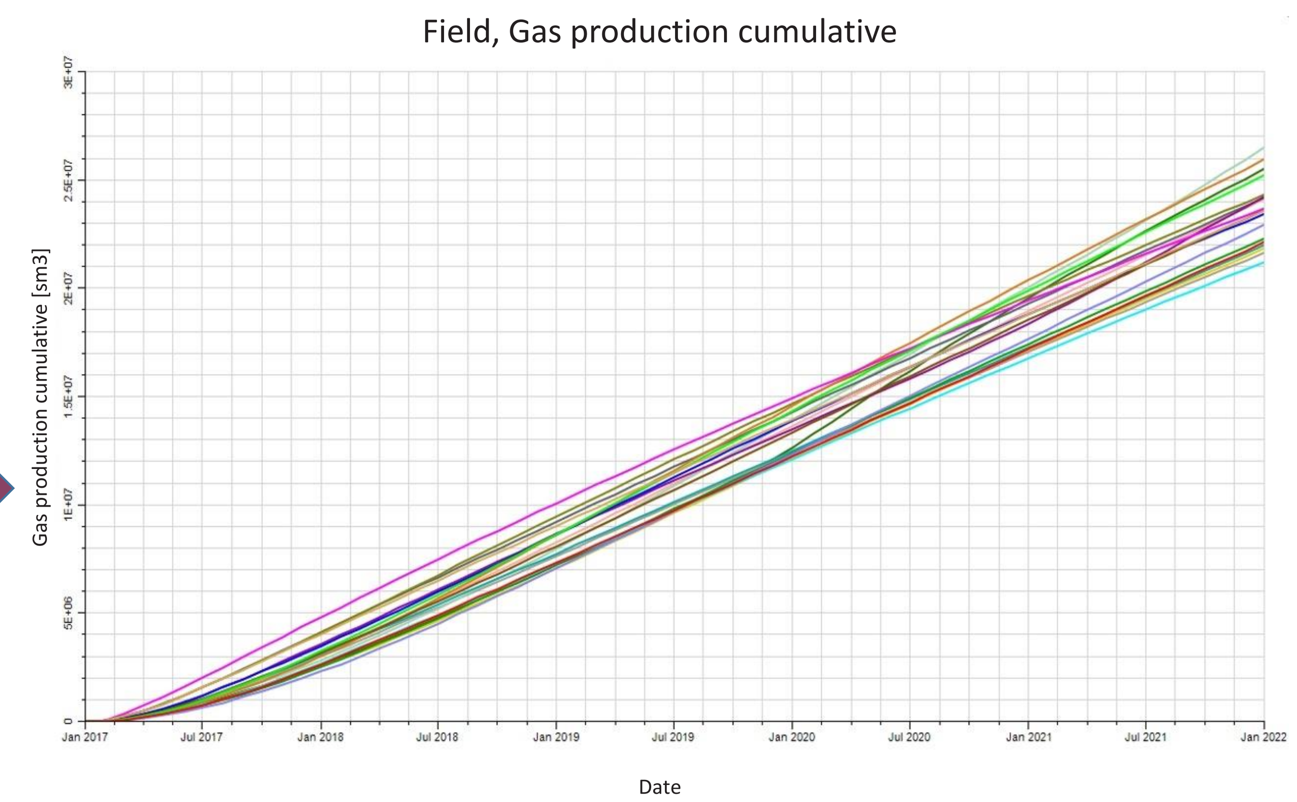


Static Reservoir Simulation Model: QDEX data
4.2km x 3km x 300m, with 5 wells



87 – 174 Active Parameters

Fast and Efficient Machine Learning



How do we apply machine learning?

- A **surrogate model** is built to approximate a computationally expensive model.
- It emulates the behaviour of the original model, honouring the underlying physics.
- It accurately and efficiently performs:
  - uncertainty propagation; and
  - sensitivity analysis.
- It facilitates processes such as EUR calculations and history matching.

What are the desirable properties?

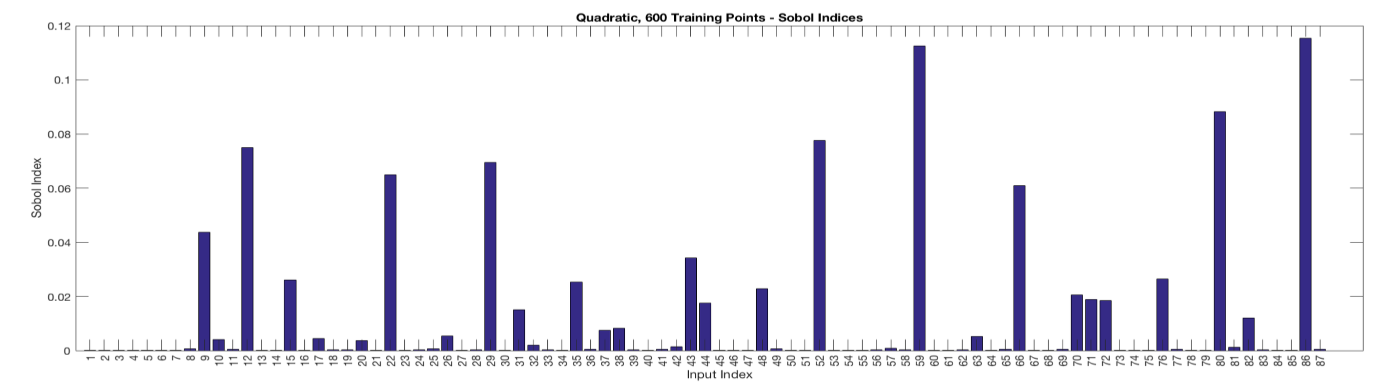
- Accurate predictions using small sets of training and validation data.
- Fast evaluations across the entire parameter space.
- Respects the statistical distributions of uncertain input parameters.
- Direct access to sensitivity analysis.

What is the pay off?

- Statistical information and uncertainty propagation: mean, variance and higher moments, and cumulative distribution functions.
- Sensitivity analysis – identifying key inputs and parameter variance.
- History matching through fast and comprehensive exploration of the response surface.

Example – Identifying the sources of uncertainty.

Sobol' Indices are used to rank the impact of the porosity and permeability of the various coal bodies (see figure top left).



How do you construct a PCE surrogate model?

- A PCE represents the model as a sum of carefully chosen polynomials each individually **weighted** to give an accurate approximation.

$$\mathcal{M}(x) = \underbrace{c_0 \,\cdot}_{\text{The mean}} \underbrace{+\, c_1 \,\cdot + c_2 \,\cdot + c_3 \,\cdot + \cdots}_{\text{Capturing how the model varies}}$$

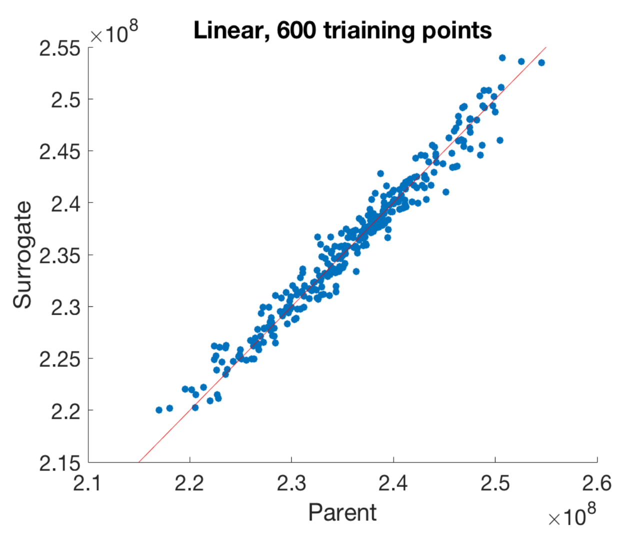
- The method naturally generalises to multiple input parameters.
- The polynomials are **orthogonal** with respect to the input parameters' statistical distributions:
  - reducing the complexity;
  - capturing the uncertainty in the input parameters;
  - allowing for efficient identification of key parameters and key parameter interactions.

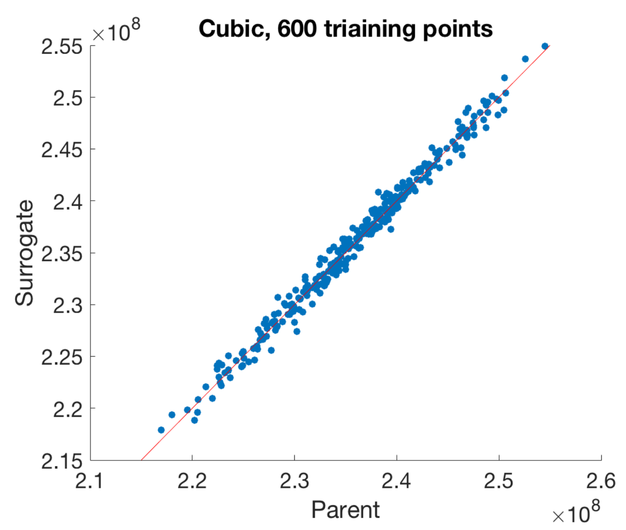
How does it honour the geophysics?

- The weights $c_0, c_1, c_2, \ldots$ are derived from the underlying data (often via evaluations of the original model).

Example – Using a surrogate to predict cumulative gas production.

Order	Number of coefficients	RMSE x 10^6	Relative RMSE x 10^{-3}	Mean APE x 10^{-1} %	Median APE x 10^{-1} %
1	88	1.3967	5.9249	4.5627	3.6436
2	175	1.1634	4.9325	3.8976	3.2392
3	300	0.8599	3.6569	2.8667	2.3450





How do we optimise the construction process?

- Construct surrogate models using moments or approximations of the moments for the inputs, thus allowing for unknown distributions.
- Use regression techniques for approximating key coefficients, thus reducing the required number of training points.
- Two types of regression techniques to solve the same minimum argument equation; Ordinary Least Squares (OLS) and Least Angle Regression (LARS).
- LARS is preferred for higher dimensionality cases as it preferences the 'most important' coefficients and hence can generate a higher order surrogate model.

Future directions.

1. Exploring the relationship between the size of the training set, the number of input parameters and the accuracy of the surrogate model.
2. Machine learning from field data, *cutting out the middleman*, i.e. no requirement for an established model.

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