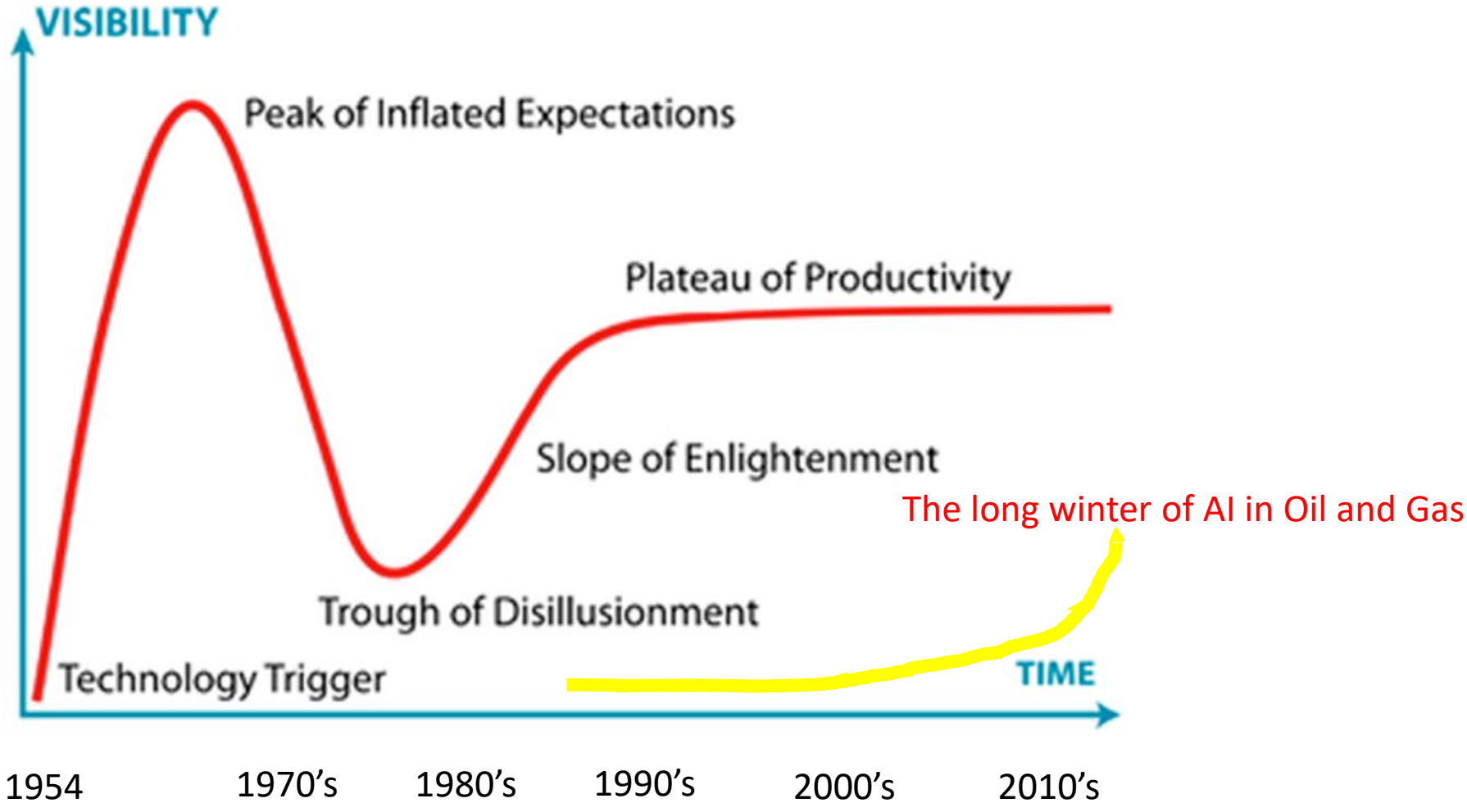
Three Decades of Reservoir Modeling using Artificial Intelligence: Lessons Learned and Future Trends for Unconventionals

Ahmed Ouenes

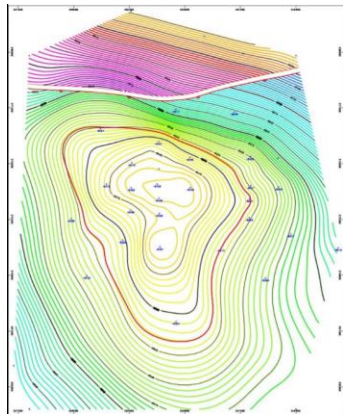
The Winters and Summers of AI (Tad Gonsalves, 2018)



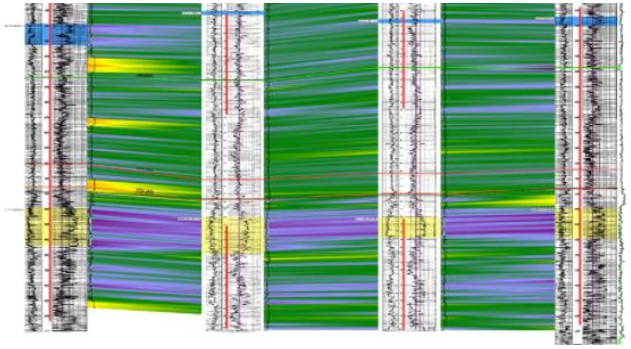
Evolution of Reservoir Modeling

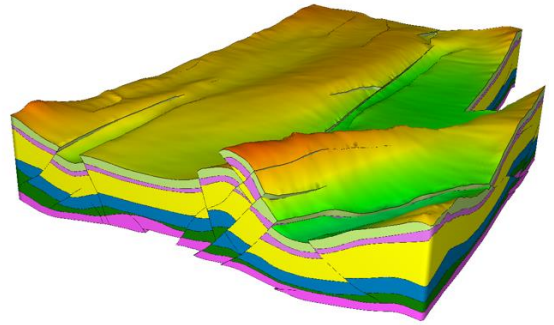
- Geostatistics transformed reservoir modeling in the late 80's to 90's to better represent the reservoir framework and its rock properties

maps

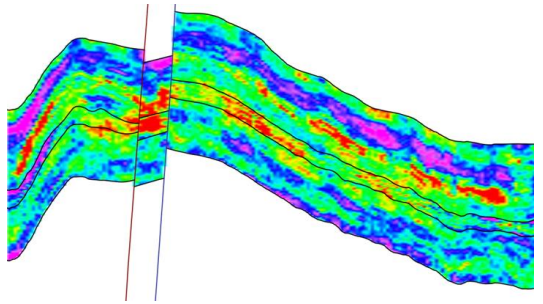


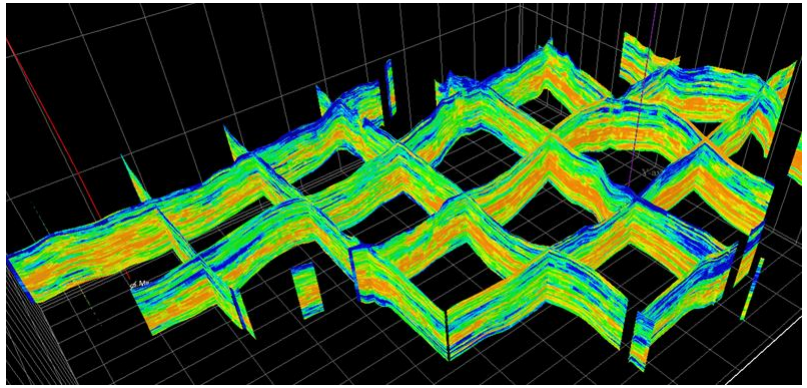
Cross sections





Container: Complex structural frameworks

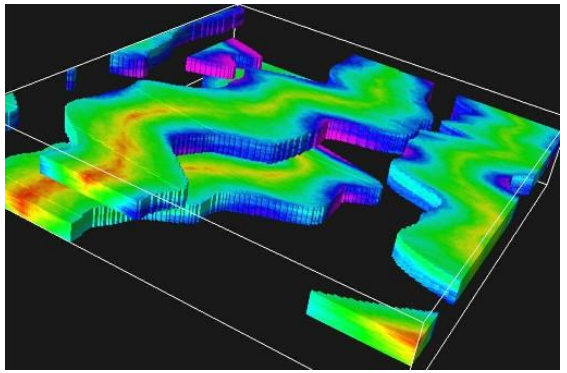


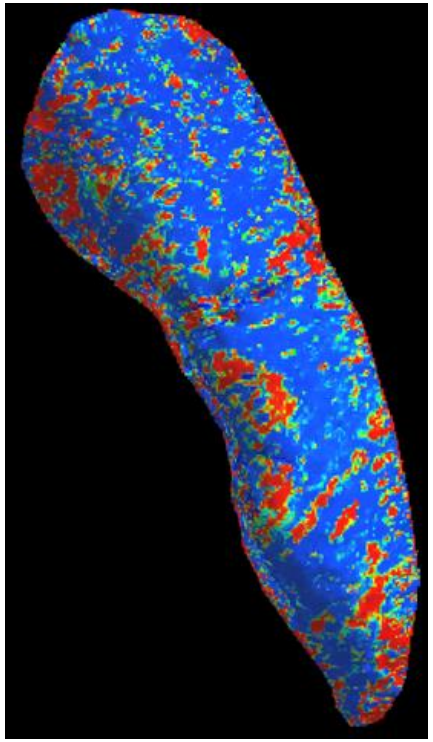


Seismic attributes and complex geologic models

Why AI in reservoir Modeling ?

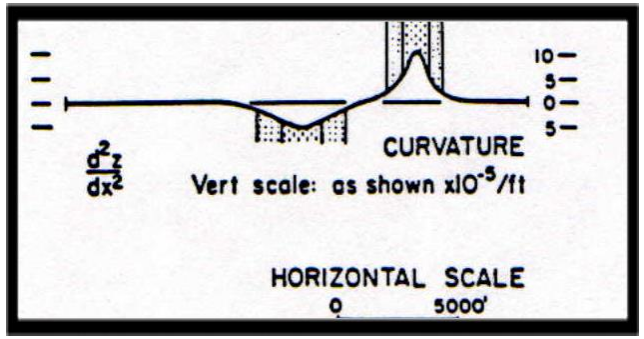
- Geostatistics uses many assumptions that are better suited to rock properties controlled mainly by deposition
- Many rock properties are affected by processes that occur AFTER deposition (diagenesis, tectonics, etc.)
- Statistical methods have performed very poorly since the “statistics” of these reservoirs will always remain elusive.
- Carbonate and naturally fractured reservoirs are some of the examples where AI could provide better modeling approaches. We use the case of naturally fractured reservoirs to illustrate this point



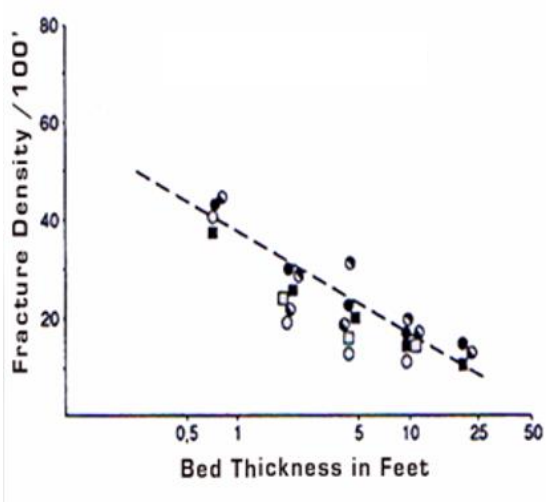


Why AI in Reservoir Modeling ?

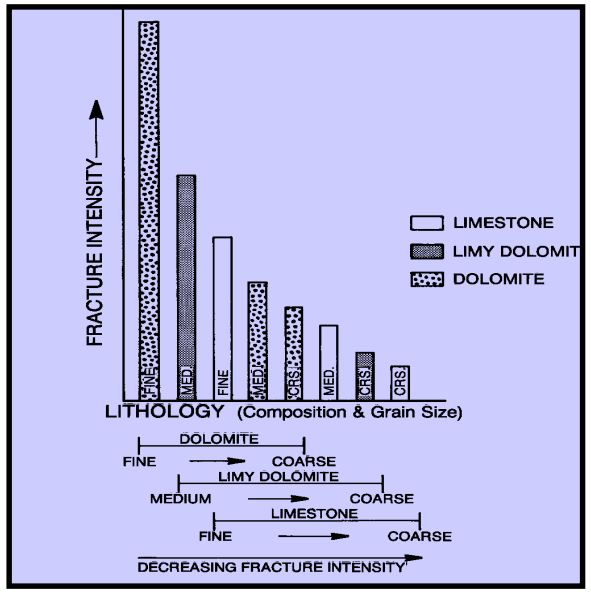
We understand how each geologic, and geomechanical factor affects density and orientation of the natural fractures
But we cannot understand how their combined effect works to create the resulting complexity



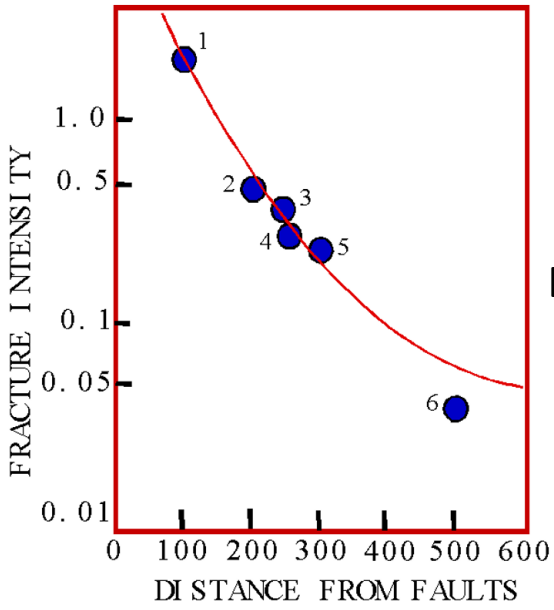
curvature



Bed thickness



Lithology



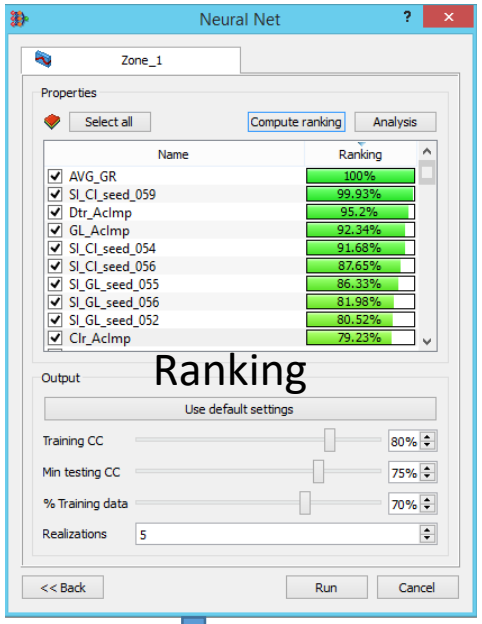
ETC ……

Faults

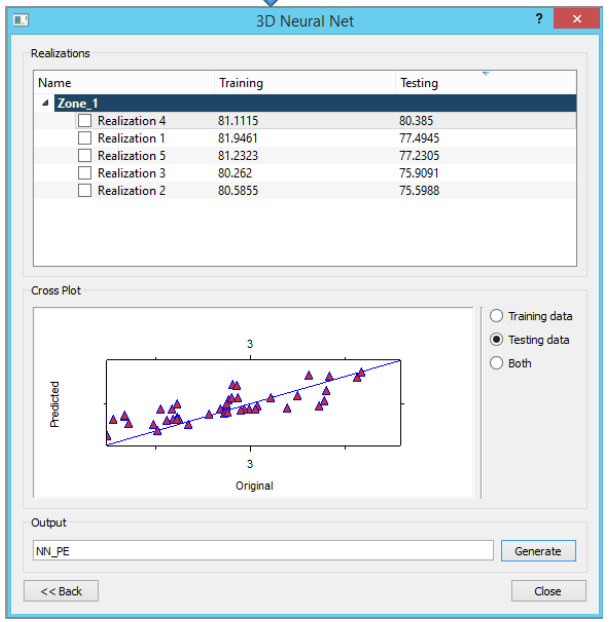
In every naturally fractured reservoir, there is a unique relationship between its geologic drivers and the final complex distribution of the fractures that can be estimated and modeled very accurately with AI tools

Why AI tools ?

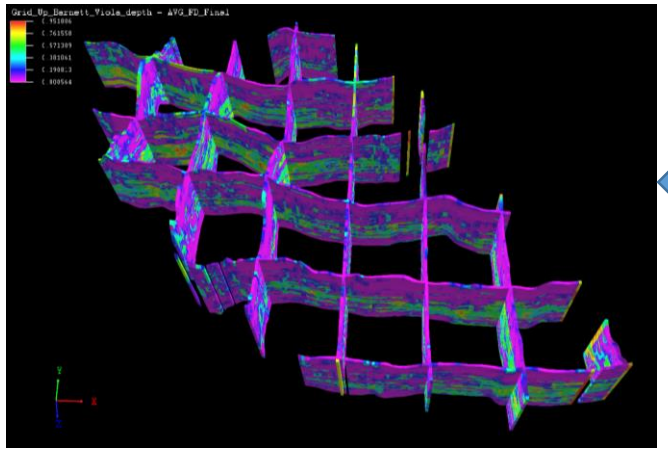
- We have very poor understanding of the drivers that control reservoir complexity ➔ AI Classifications and ranking tools allow us to understand the drivers
- We need predictive models using limited data ➔ Modeling tools such as Neural Networks allow us to capture the intricate relationship that exist between the target reservoir property and its drivers with sometimes as little as one or two wells



Ranking

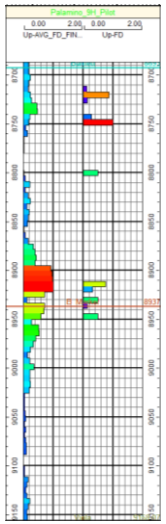


Neural Net Modeling



3D Distribution

Blind well validation



AI Provides Tools - Domain Expertise Provides the Solution

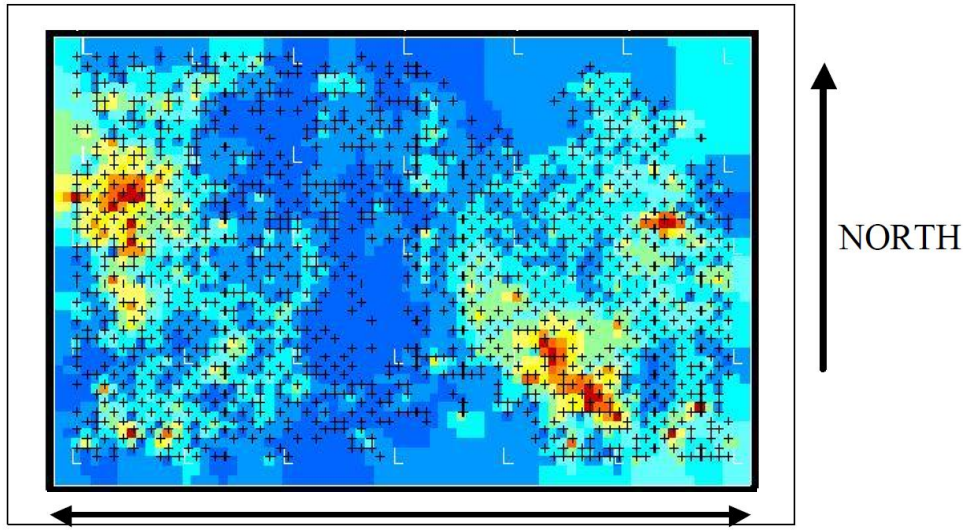


Fig. 2: EUR map for the 24 township area.
The dark areas represent "sweetspots"

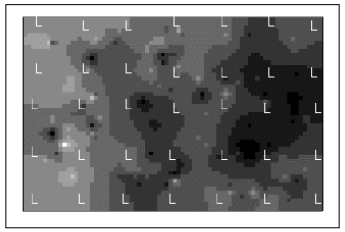


Fig. 5: Thickness of Sand A over the 24 townships.
The dark parts represent the thicker sand.

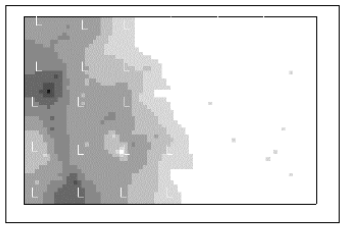
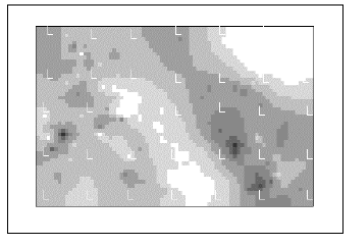


Fig. 6: Thickness of Sand B over the 24 townships.
The dark parts represent the thicker sand.



4 people spent 2 years (8 man years) trying to figure out the right drivers !!!

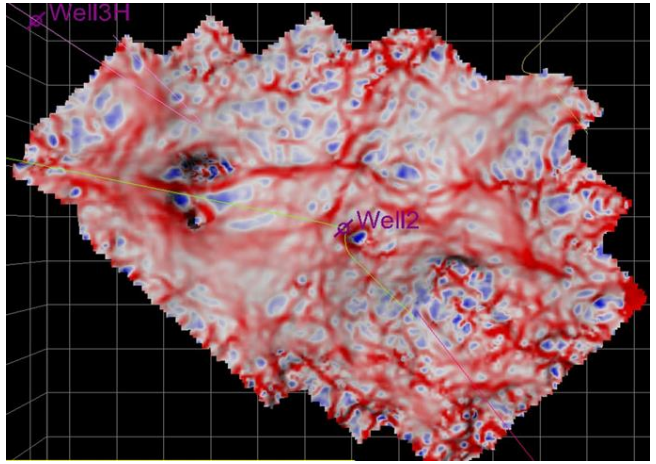
SPE 39965

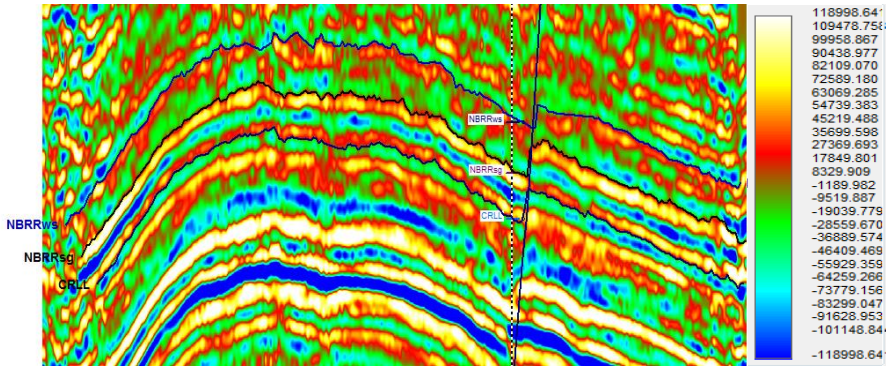
Practical Use of Neural Networks in Tight Gas Fractured Reservoirs: Application to the San Juan Basin

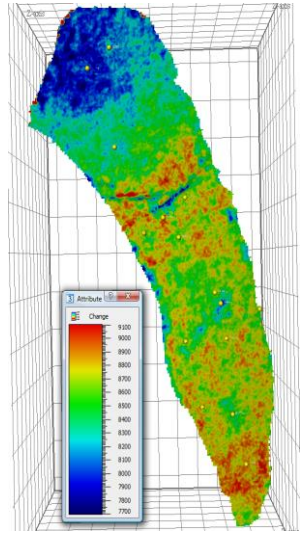
A. Ouenes, A. Zellou, Terra Nova, P. M. Basinski, and C. F. Head, Burlington Resources

Focus on the drivers not on AI tools

- What we learned during these 3 decades using AI in reservoir modeling ?

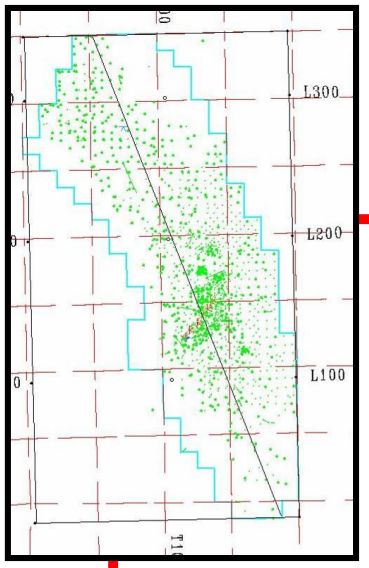




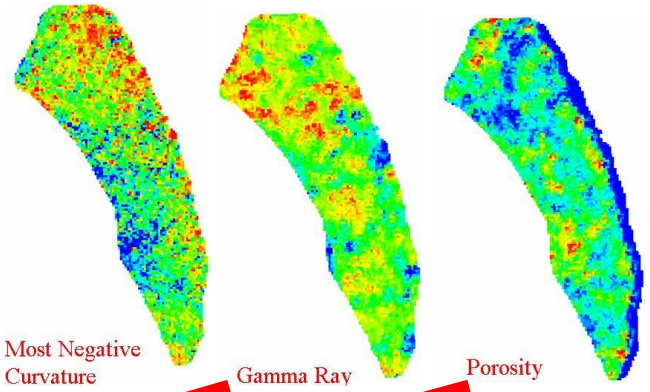


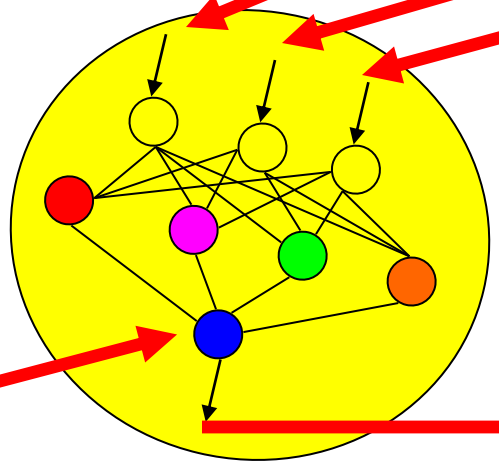
- FOCUS ON THE DRIVERS especially advanced high resolution seismic attributes
- Focus on many ways to compute the target reservoir property at the wells

Linking the Drivers to Cumulative Oil with AI tools

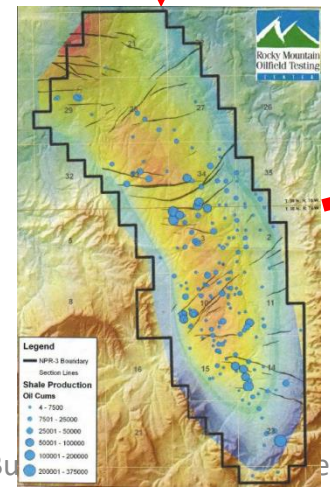


Seismic and Geologic
2D Attribute Maps

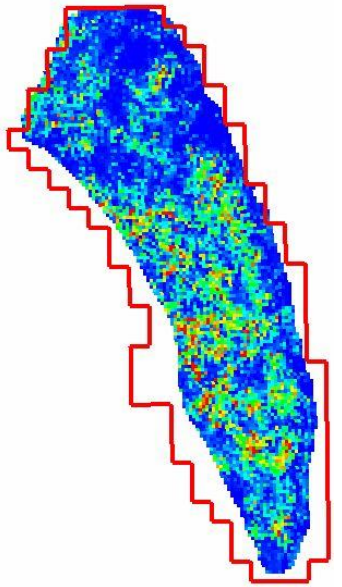




Neural Net



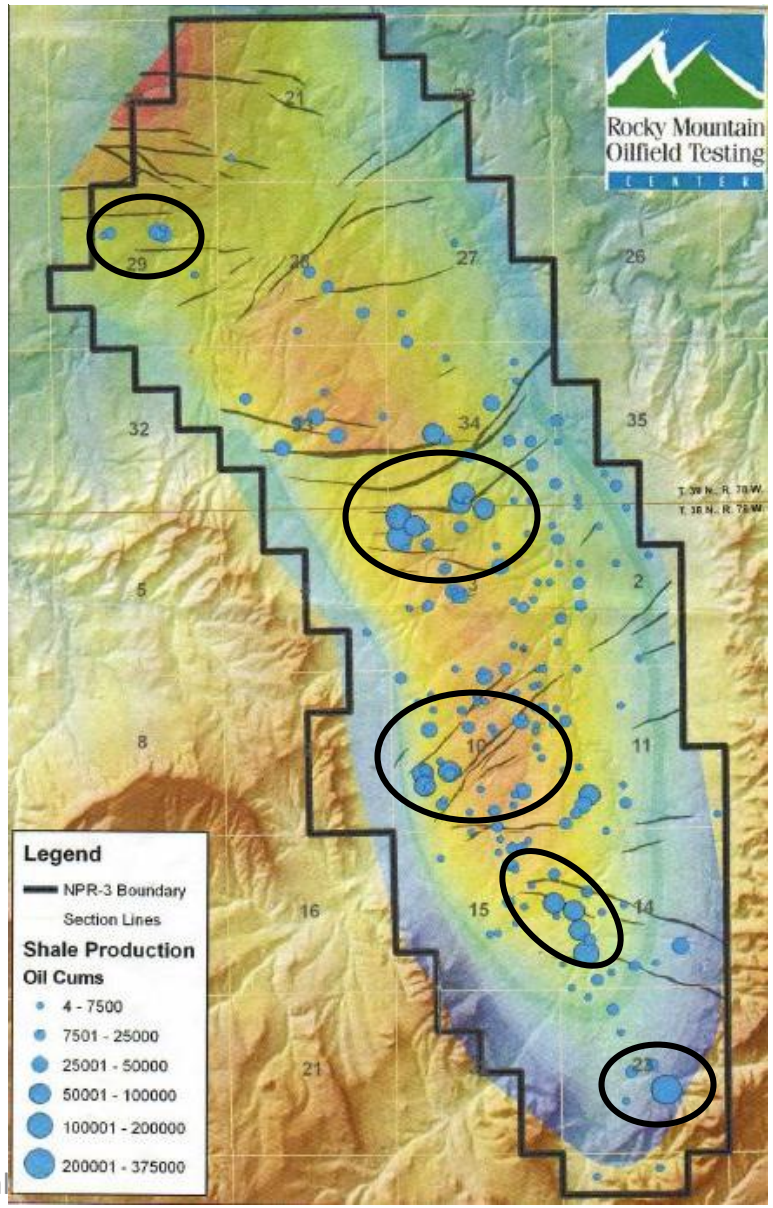
Cumulative oil
at the wells



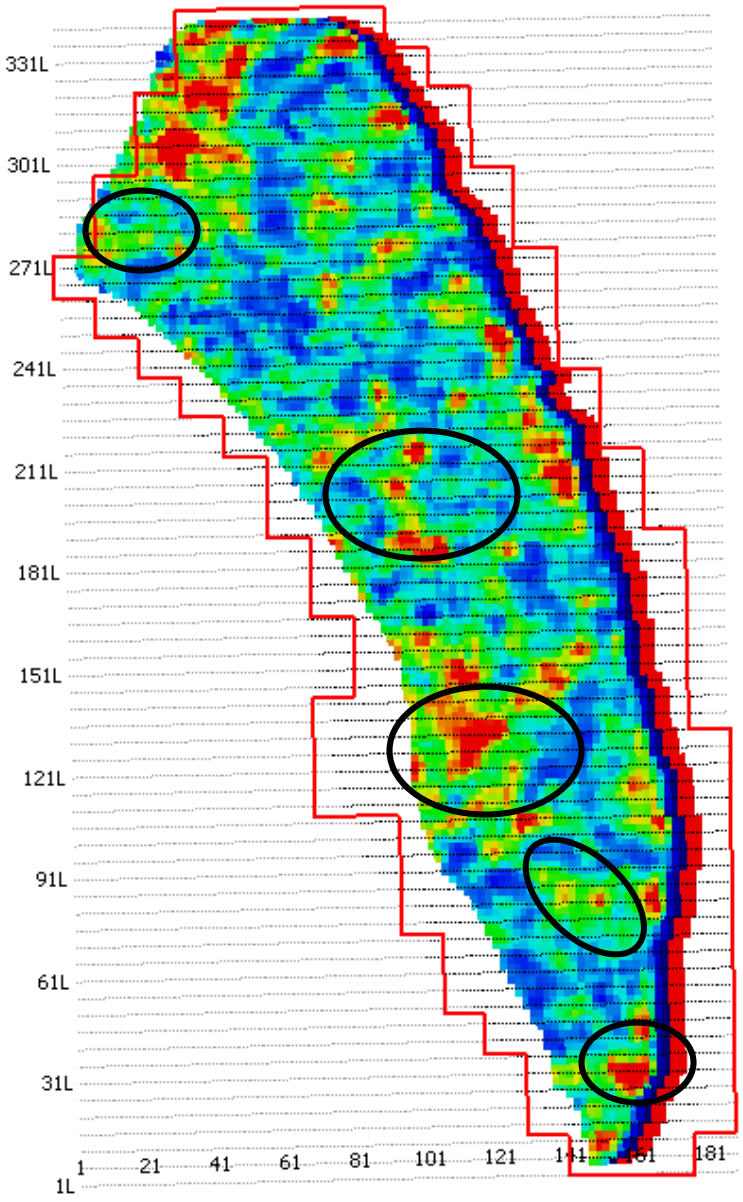
Cumulative Oil 2D Maps

Comparison between Average Permeability map and Cumulative Shale Oil Production

Cumulative Shale Oil Production



Average permeability



Combining Multiple AI Derived Reservoir Models: Definition of Shale Capacity "SC"

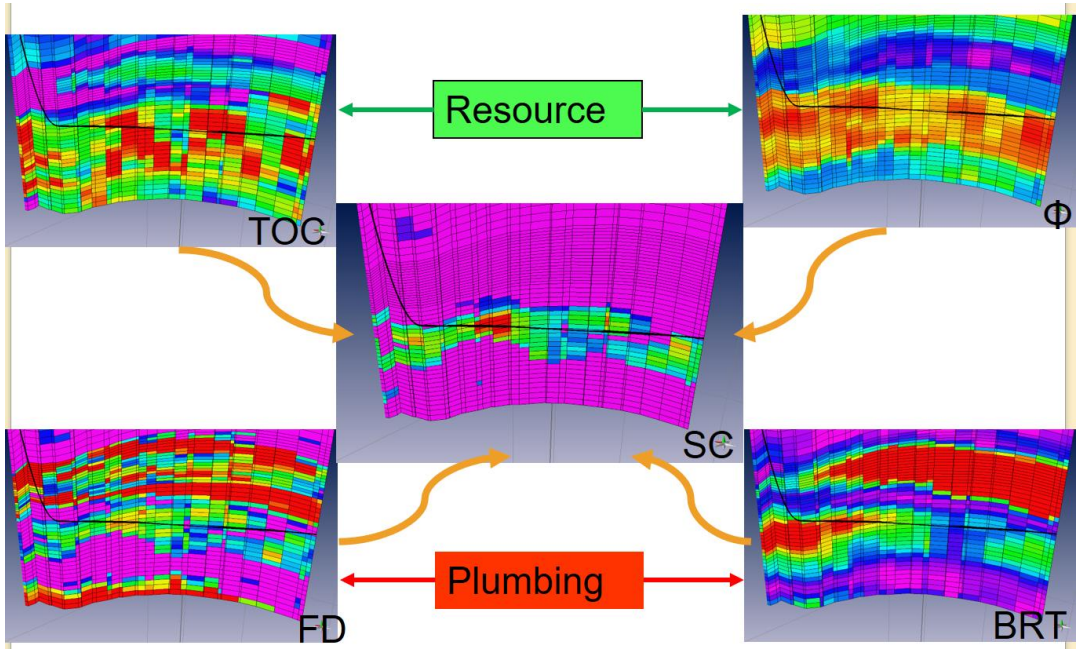
- The four shale drivers are used to define the SHALE CAPACITY SC ➔ Geologic "Sweet Spots" for landing and geosteering

- $SC = TOC_{net} \times \Phi_{net} \times BRT_{net} \times FD_{net}$

resource

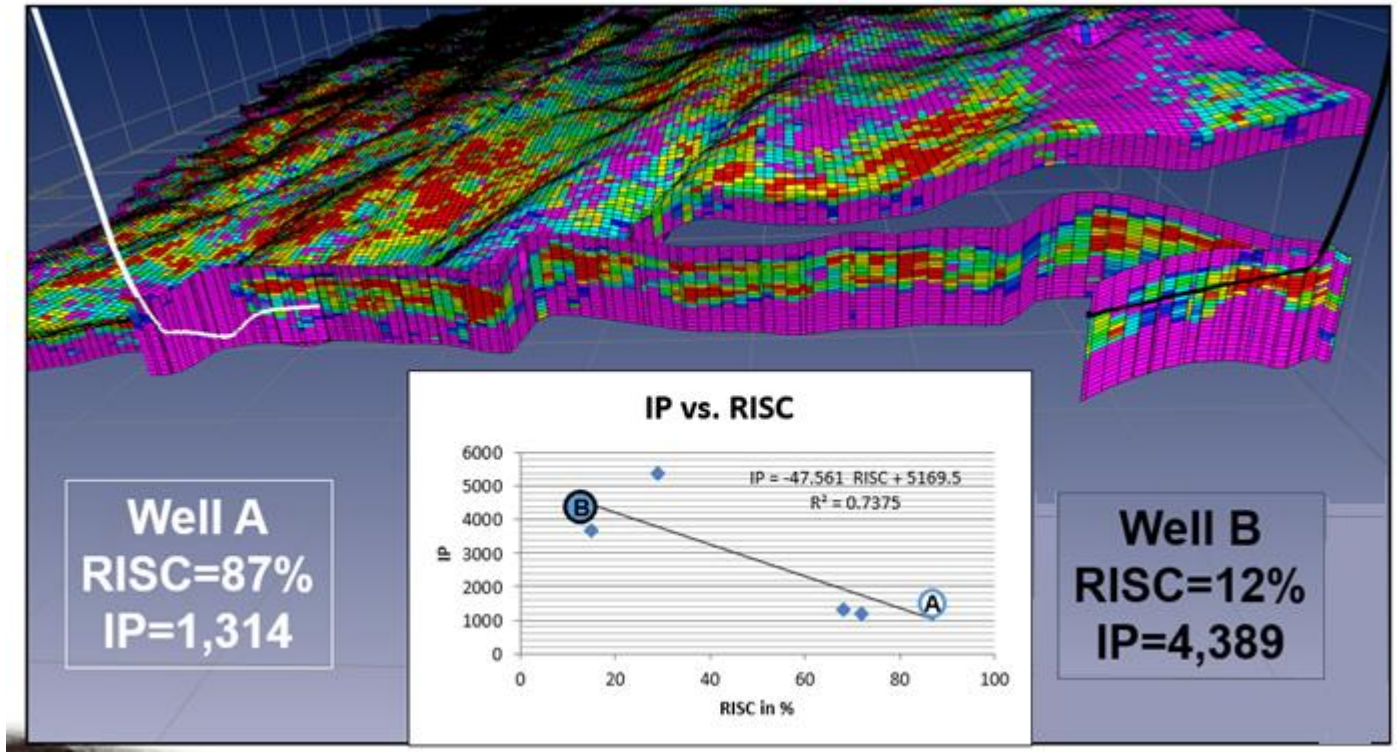
Plumbing needed to turn resource into reserves

  - Where $TOC_{net} = TOC > \text{cut-off}$ else 0
  - $BRT_{net} = BRT > \text{cut-off}$ else 0
  - $FD_{net} = FD > \text{cut-off}$ else 0
  - $\Phi_{net} = \Phi > \text{cut-off}$ else 0

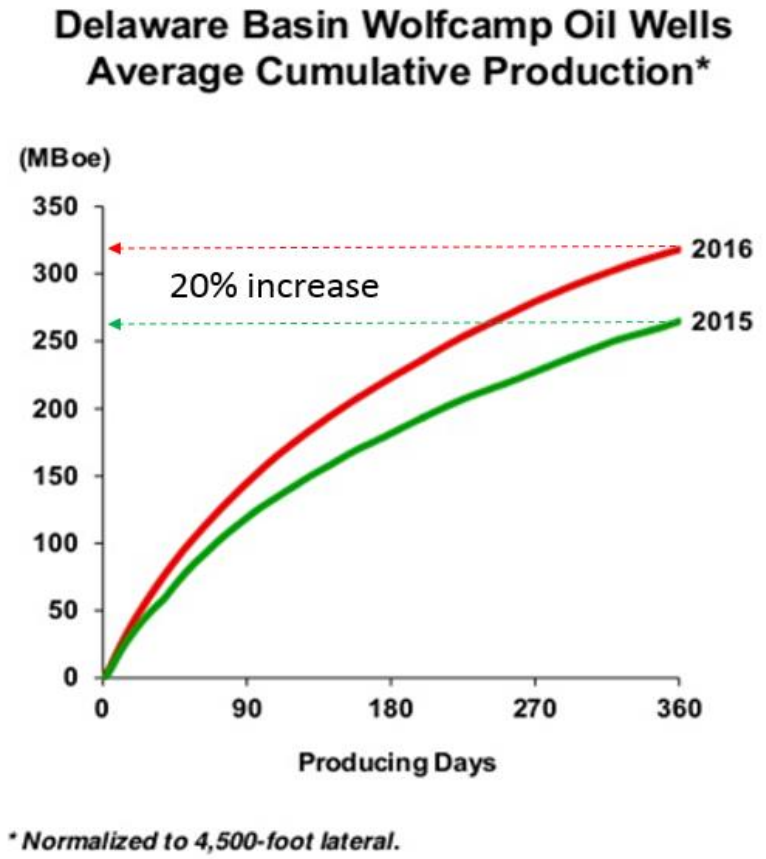


SPE 167779, (2014)

Landing Zone Selection and Geosteering based on AI Tools



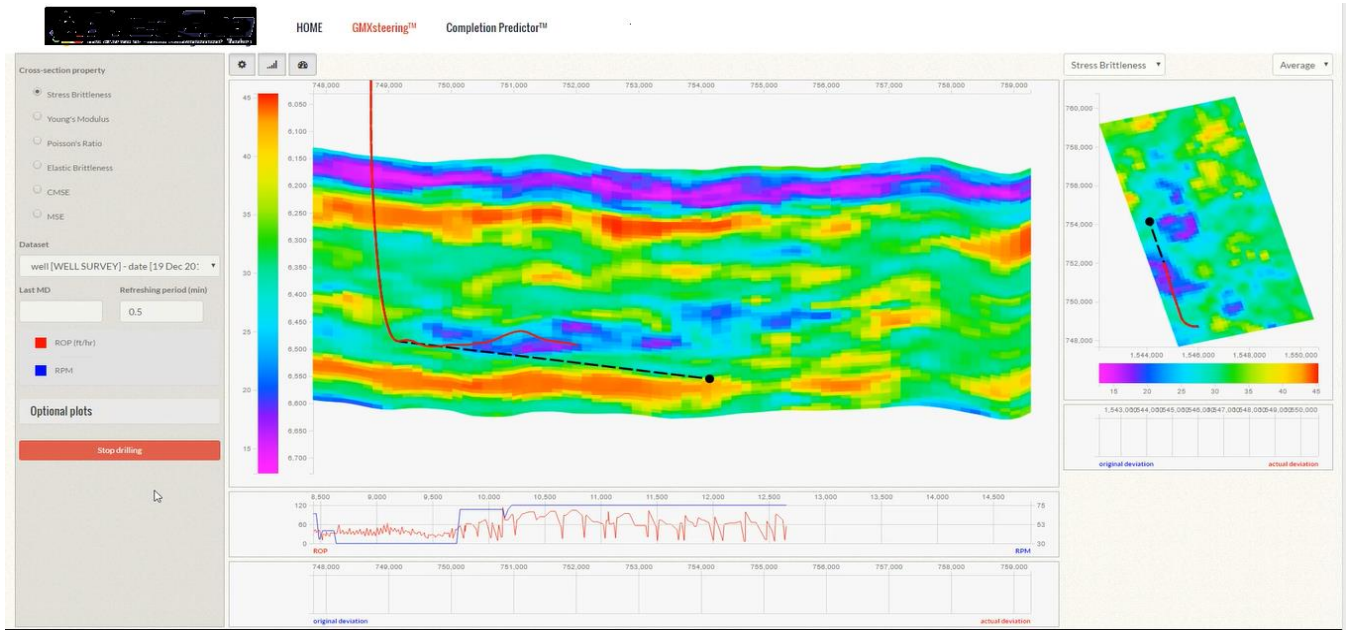
SPE 175055, (2015)



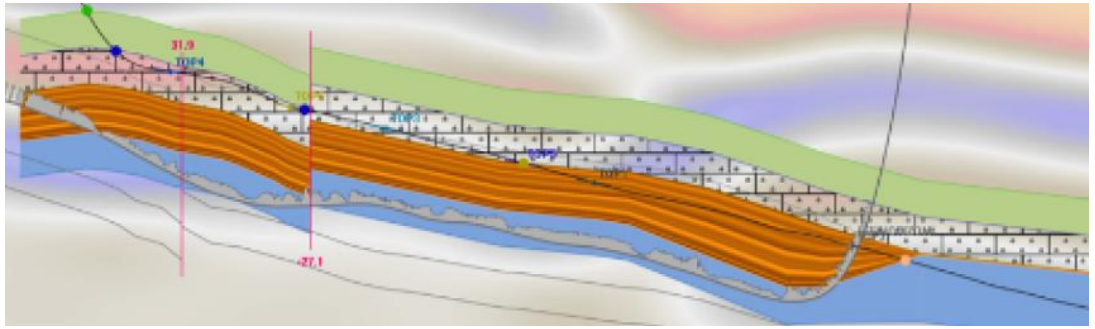
Geosteering technology increased production by 20% in one year for this shale operator

URTEC 2693870, (2017)

Real Time Live Geomechanical Models Derived Using AI Tools



AI derived real time 3D reservoir models using real time Logs derived from surface drilling data SPE 188087, (2017)

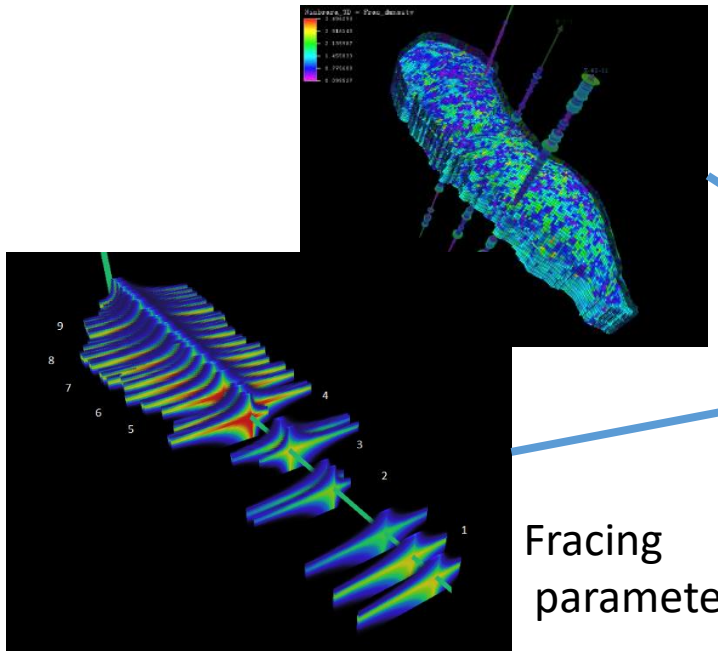


Conventional geosteering with 2D cross sections And GR logs

Using surface drilling data to create real time geomechanical logs, pore pressure, stresses and fracture index, AI tools are used to build real time 3D reservoir models that help geosteer the shale wells in the target zones

AI Tools help when the reservoir interacts with a complex physics

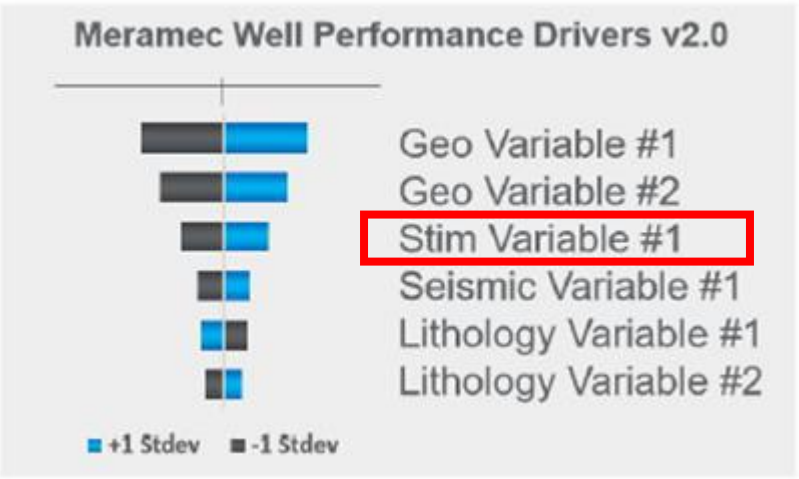
- Adding to the reservoir properties, the fracing parameters (proppant loading, number of clusters, stage length, etc..) to better predict performance of unconventionals



Reservoir parameters

Fracing parameters

Well performance

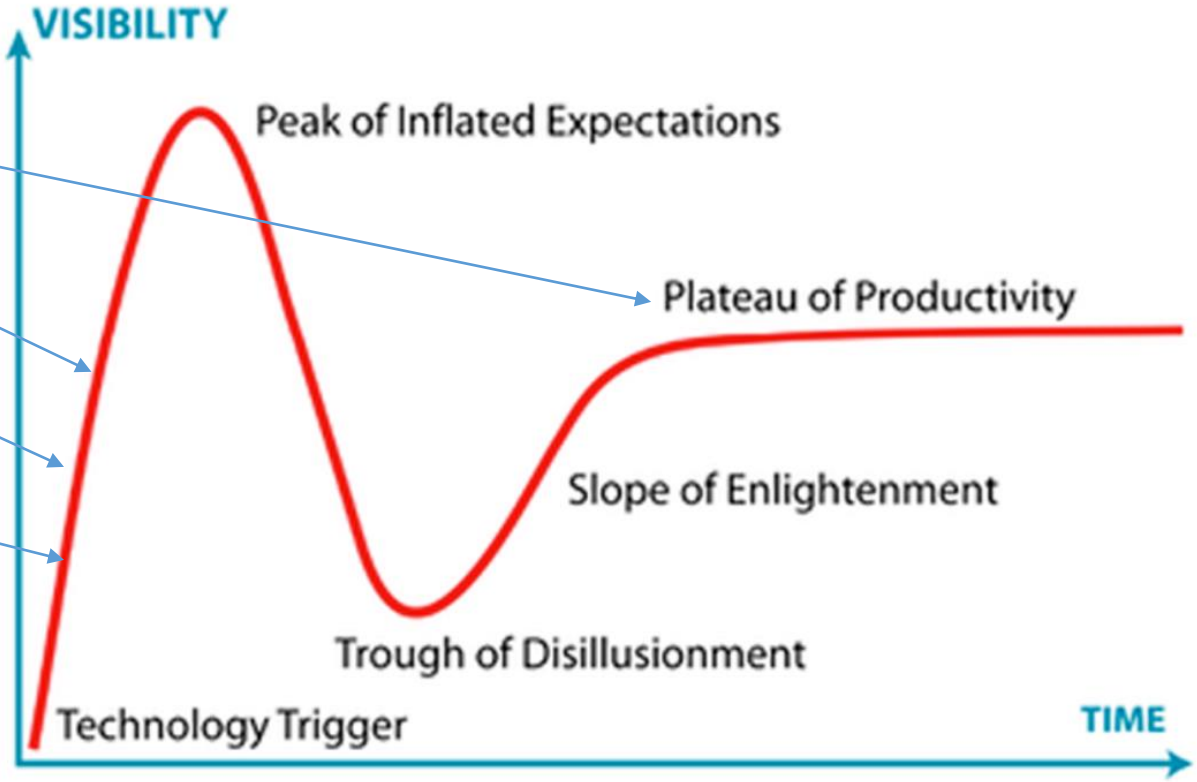


MRO investor presentation, 2017

The Future of AI Tools in Reservoir Modeling

- Reservoir modeling
- Drilling and geosteering
- Refrac candidate selection
- Adaptive Fracing &

Geoengineered completions



Will the Oil and Gas Industry Seize the Opportunity ?

7-August-2017 | **Digital Supply Networks (http://www.digitalistmag.com/./digital-supply-networks)**

Artificial Intelligence: The Future Of Oil And Gas

Anoop Srivastava (http://www.digitalistmag.com/author/anoopsrivastava)

Few individuals and firms will be extremely successful using AI and Data Analytics
But the industry as a whole may not. Time will tell

Discussion