IMPROVED RESERVOIR CHARACTERIZATION THROUGH CORE AND LOG DATA INTEGRATION

EMA JAKUPEC, INA d.d.
Ph.D. ŽELJKA MARIĆ ĐUREKOVIĆ, INA d.d.
PATRICIJA IVAK, INA d.d.
RENATA VIDAČEK, INA d.d.
Visegrad, 2017

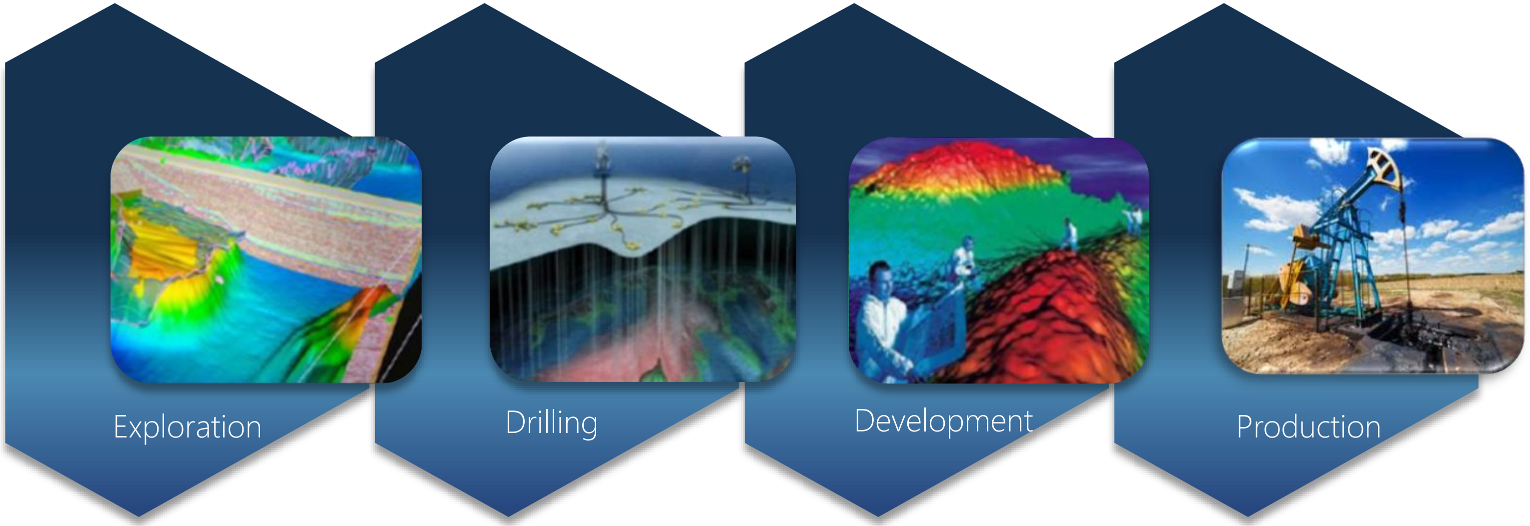
AGENDA

GENERAL INTRODUCTION

- APPLICATION OF ARTIFICIAL NEURAL NETWORKS AND FUZZY LOGIC ARE COMMON IN RESERVOIR CHARACTERIZATION, SIMULATION, PRODUCTION AND DRILLING OPTIMIZATION
- GOAL: OPTIMIZE PRODUCTION PERFORMANCE AND REDUCING THE COST OF PRODUCTION PER BARREL

METHODOLOGY & SIGNIFICANCE IN UPSTREAM

- APPLICATION OF MATHEMATICAL CONCEPTS, PRIMARILY STATISTICS AND LINEAR ALGEBRA, TO PROCESS, ANALYZE AND PREDICT FUTURE COURSES OF ACTION BASED ON PAST DATA
- NEURAL NETWORKS ARE UTILIZED TO PREDICT FORMATION CHARACTERISTICS (POROSITY, PERMEABILITY AND FLUID SATURATION) FROM CONVENTIONAL WELL LOGS AND CORE DATA
- FINDING CORREALTIONS IN ALL AVAILABLE DATA AND GIVING NEW INPUTS WITHOUT ADDITIONAL COST



SUMMARY

- CASE STUDY WAS MADE AS A PART OF THE IRS CONDUCTED FOR UPDATING GEOLOGICAL AND NUMERICAL MODEL OF MATURE FIELD FOR EOR PROJECT
- IMPLEMETNTING CO_2 EOR PROJECT REQUIRES **SIGINIFACNT CAPITAL**
- **POTENTIAL RISK** OF UNEXPECTED **GEOLOGIC HETEROGENITY**: SIGINIFACNTLY REDUCING THE EXPECTED INJECTION RESPONSE
- **RISK MITIGATION** – CREATING ROBUST MODEL

- **LIMITATIONS:** MATURE FIELD WITH LIMITED CORE AND LOG DATA
- **OPPORTUNITY:** OPTIMIZING PREDICTION OF CO_2 INJECTION THROUGH APPLICATION OF NEURAL NETWORKS
- **SOLUTION:** USING WELL LOGS AS INPUT DATA COUPLED WITH CORE DATA ON THE CORRESPONDING DEPTH TO PREDICT RESERVOIR CHARACTERISTICS IN UNCORED AREAS

CORE DATA

Scarce in mature fields
Expensive
Very limited distribution

WELL LOG DATA

Continous vertical measurement
Wide distribution of data
Function of the lithology and permeability

RESERVOIR MODEL

Integration of seismic, petrophysical and production data
Depends on the quality of the rock property inputs

OBJECTIVES

1. INTEGRATE AND UTILIZE AVAILABLE WELL LOG AND CORE DATA — HIGHER PRECISION OF CORE DATA AND LARGER SCALE OF INVESTIGATION OF LOG DATA
2. ESTABLISH CORELATION BETWEEN CORE DATA AND LOG BEHAVIOR — CREATING MODEL WITH THE NEURAL NETWORK
3. PROPAGATE THE CLASSIFICAITON ON UNCORED INTERVALS AND WELLS — APPLYING MODEL DEFINED WITH NEURAL NETWORK
4. CREATE NEW INPUT FOR RESERVOIR MODELING — CREATING ELECTROFACIES CURVES FOR EACH WELL
5. PROPAGATE CHARACTERISTICS FROM LOG DOMAIN TO RESERVOIR LEVEL — FACIES MODELING

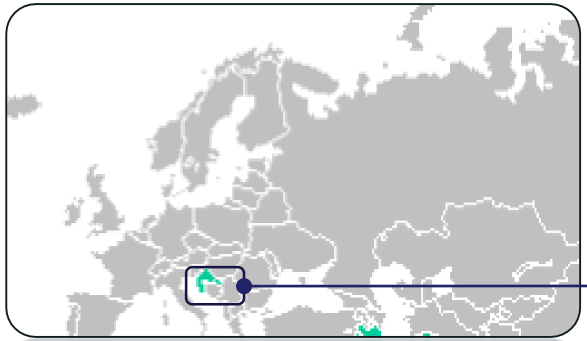
- ✓ SUCCESSFUL ELECTROFACIES CLASSIFICATION OF MORE THAN 70 WELLS
- ✓ INTEGRATING NEW METHODOLOGIES INTO EXISTING PRACTICES GAVE US NEW INPUTS FOR RESERVOIR MODELING

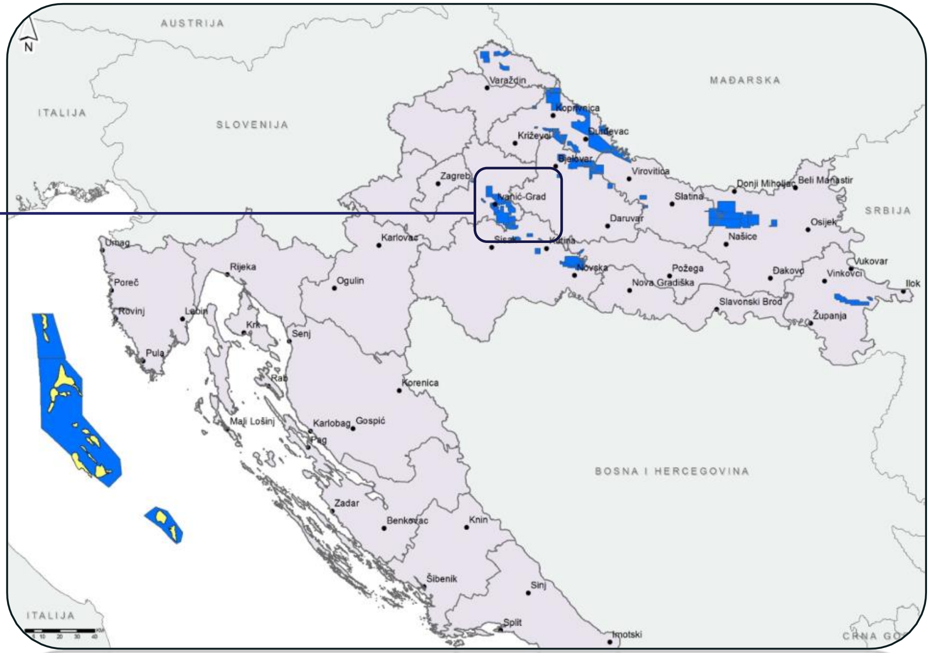
GEOGRAPHICAL SETTING

- PANNONIAN BASIN – BACK ARC BASIN
- CENTRAL CROATIA
- FIELD IN THE SAVA DEPPRESION IN CPBS

GEOLOGICAL SETTING

- LATE MIOCENE: UPPER PANNONIAN TO LOWER PONTIAN THERMAL SUBSIDENCE TRIGGERED BY THE COOLING OF THE LITHOSPHERE
- SEDIMENTS DEPOSITED BY TURBIDITIC MECHANISM IN RESPONSE TO GRAVITATIONAL AND TECTONIC INSTABILITY IN UPPER PANNONIAN





LITHOSTRATIGRAPHIC UNIT

- IVANIC GRAD FORMATION
- DEEPWATER SANDSTONES

LITHOLOGY

- ALTERATION OF MARLS, SILTSTONES AND SAND

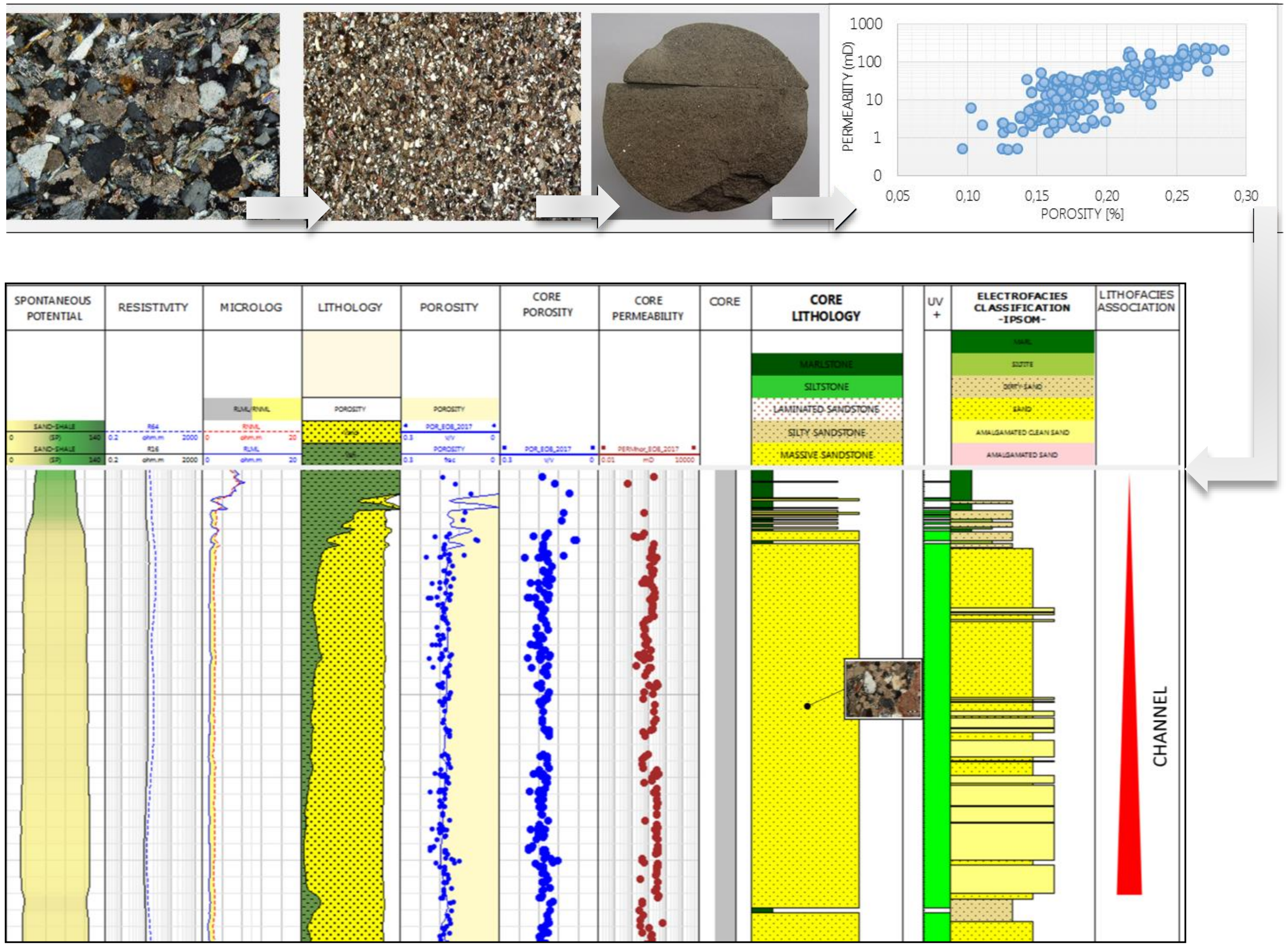
FIELD DATA

- IN PRODUCTION SINCE 1966
- CHOSEN FOR EOR PROJECT: CO_2 INJECTION

CORE DATA

- ROUTINE CORE ANALYSIS – 20 WELLS
- SPECIAL CORE ANALYSIS – 3 WELLS
- PETROGRAPHIC ANALYSIS
- SEM ANALYSIS

CORE AND LOG DATA INTEGRATION



LOGGING DATA

- CONVENTIONAL WELL LOGS
- PETROPHYSICAL ANALYSIS
- MORE THAN 70 WELLS

WHAT IS ELECTROFACIES?

- FACIES REFERS TO A DISTINCTIVE GROUP OF CHARACTERISTICS WITHIN A ROCK UNIT THAT ALLOWS IT TO BE DISTINGUISHED FROM OTHER ADJACENT ROCK UNITS
- THE OBSERVABLE CHARACTERISTICS OF A ROCK IN TERMS OF WELL LOG RESPONSE ARE CALLED ELECTROFACIES - DETERMINED BY THE PHYSICAL PROPERTIES OF ROCKS

IPSOM provides automatic classification solutions based on neural network technology (The Kohonen algorithm)

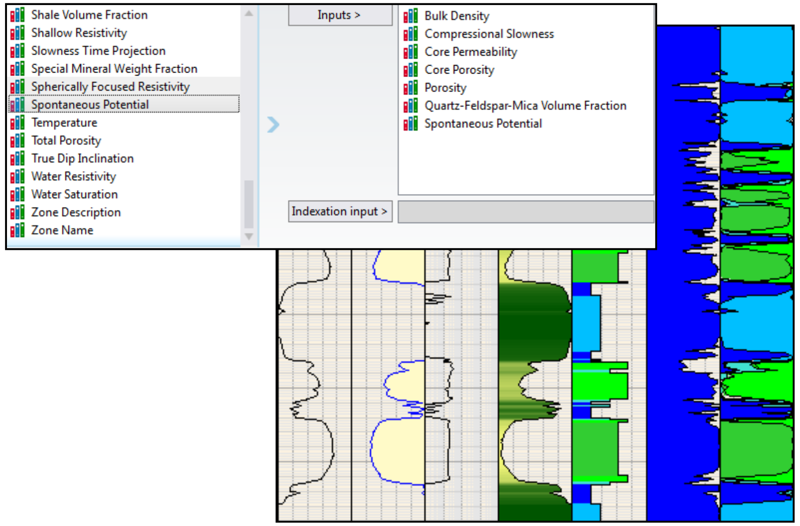
Techlog

TYPICAL FACIES MODELING WORKFLOW

INPUT

- INPUT DATA SELECTION

Selection of a set of properties representative of the facies



MODEL DEFINITION

- NEURAL ANALYSIS

Clustering of the inputs to get a downsampled but representative set of nodes

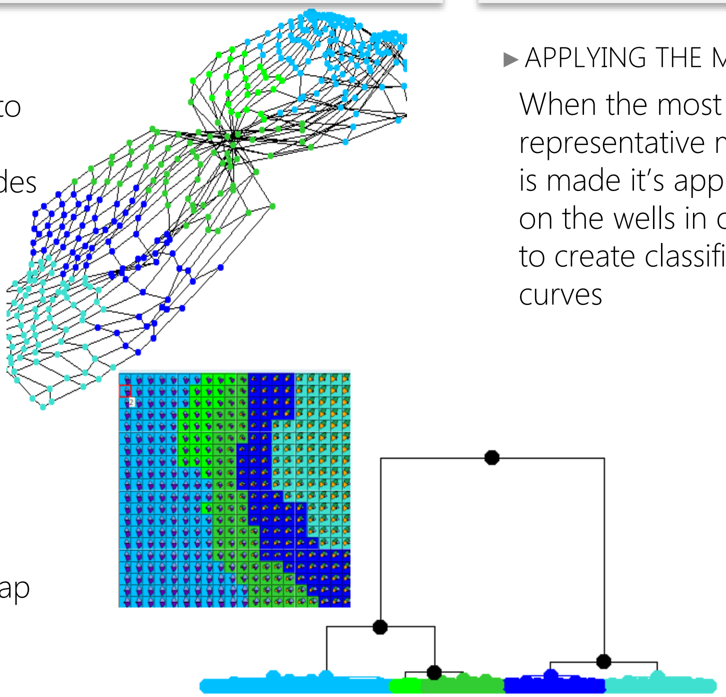
- INDEXATION

Regroup of nodes with similar petrophysical properties

- MODEL REFINEMENT

Manual editing of the map

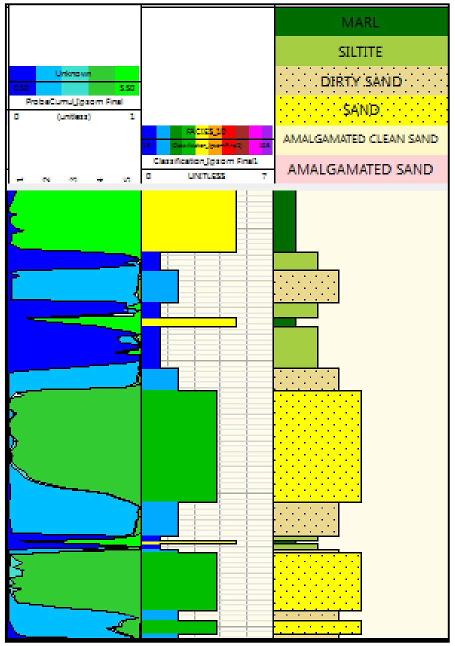
Defining the optimal number of groups (Dendogram)



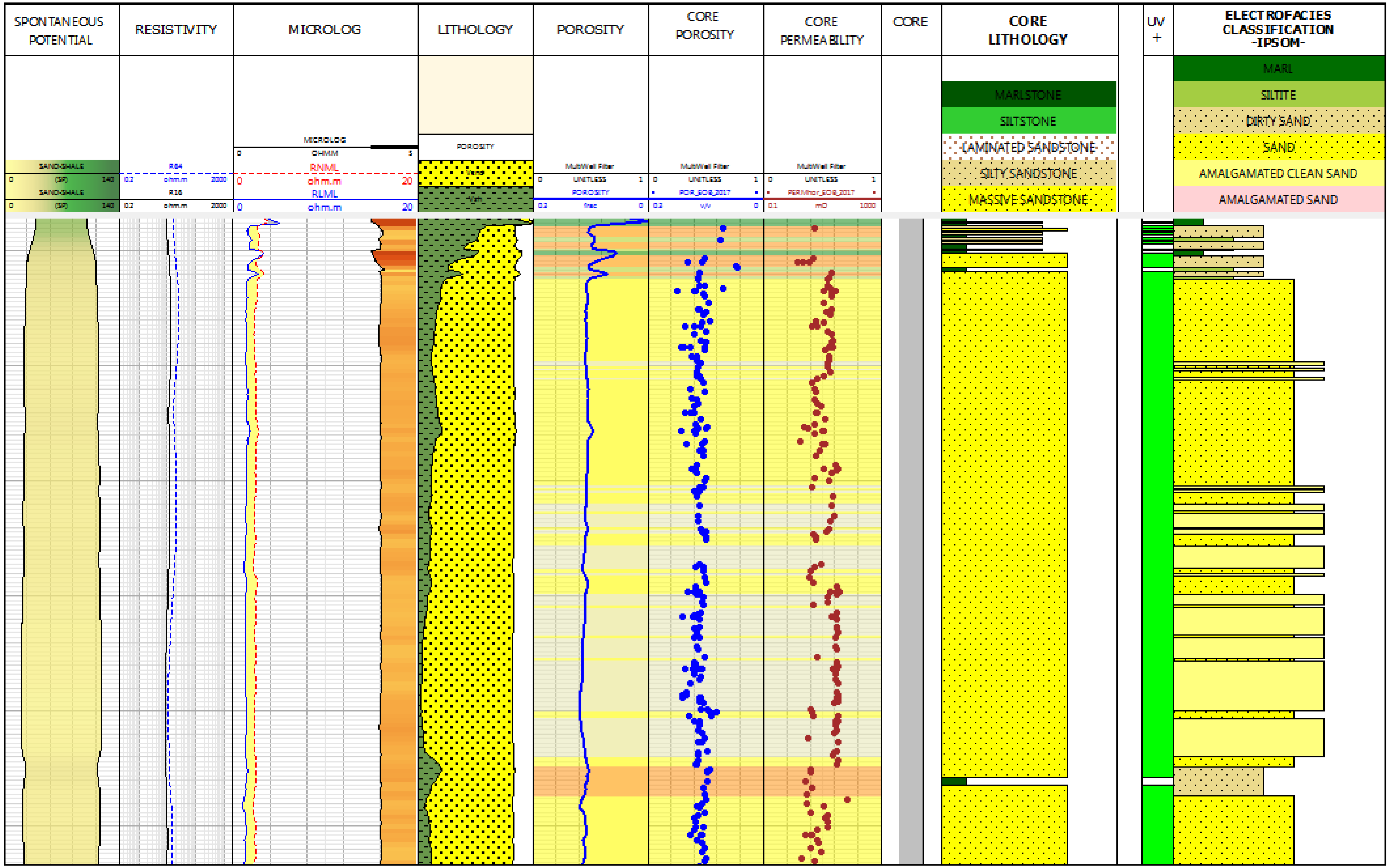
MODEL APPLICATION

- APPLYING THE MODEL

When the most representative model is made it's applyed on the wells in order to create classification curves



MODEL APPLICATION RESULTS

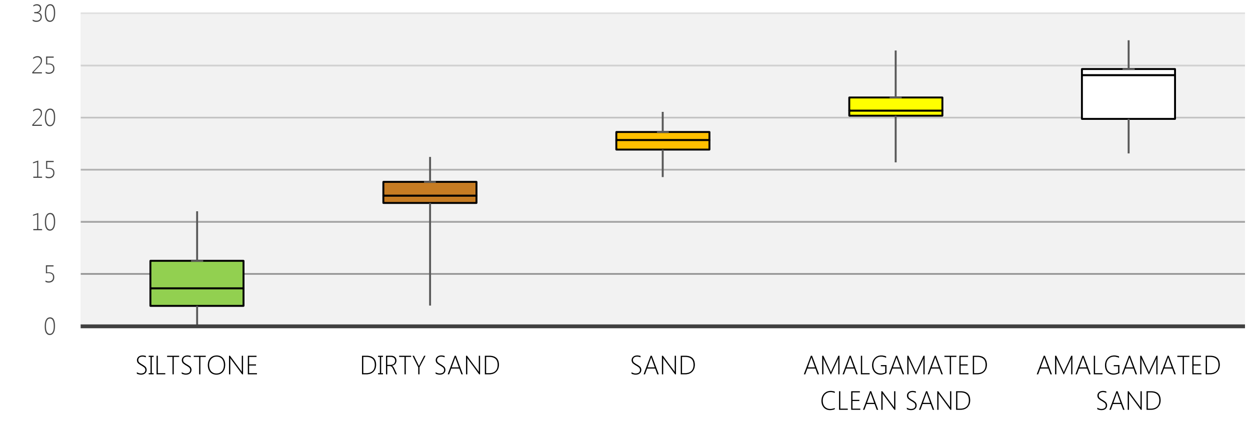


- SIX IDENTIFIED ELECTROFACIES
  - MARL
  - SILTITE
  - DIRTY SAND
  - SAND
  - AMALGAMATED CLEAN SAND
  - AMALGAMATED SAND
- MORE DETAILED CLASSIFICATION
  - HIGHER RESOLUTION
  - MORE AFFECTED BY CHANGES IN PETROPHYSICAL PROPERTIES
  - APPLIED TO UNCORED INTERVALS

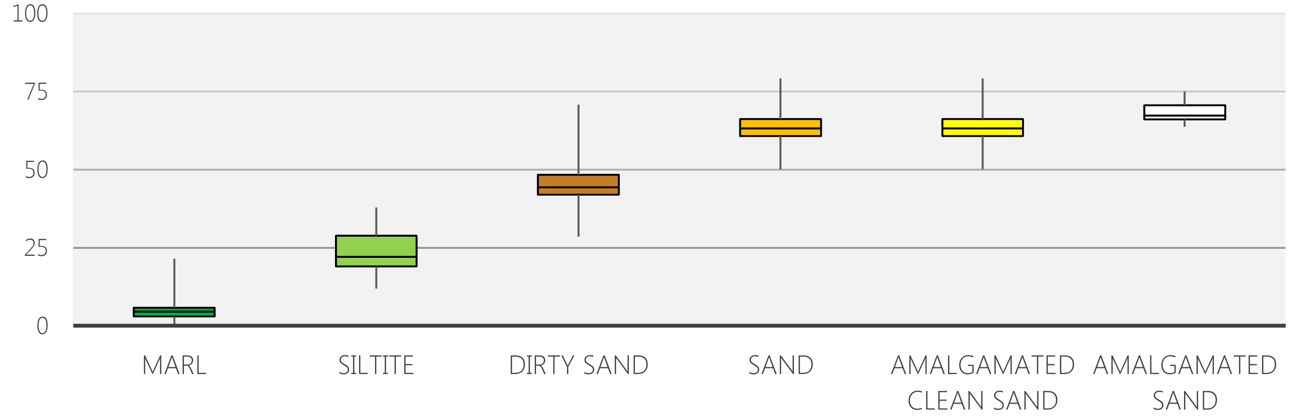
MODEL APPLICATION RESULTS

SIX IDENTIFIED GROUPS: CLEAR DISTRIBUTION OF RESERVOIR PROPERTIES

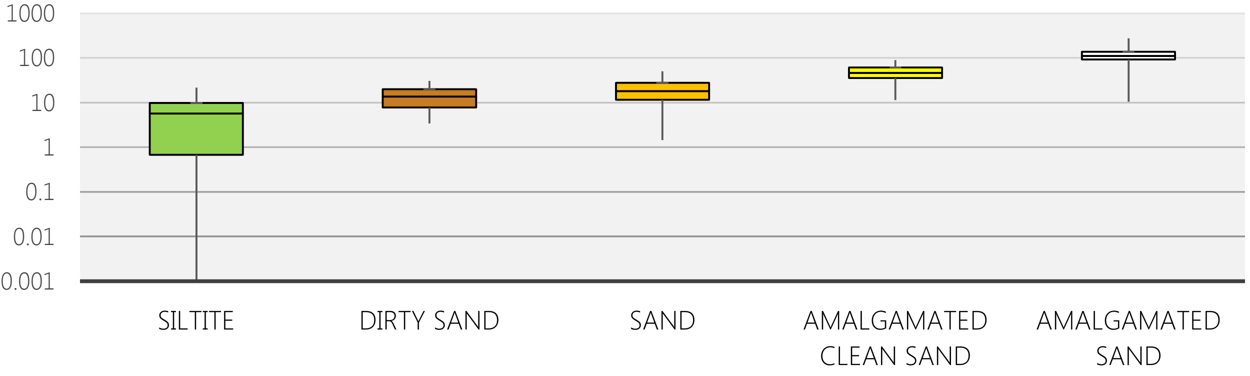
POROSITY



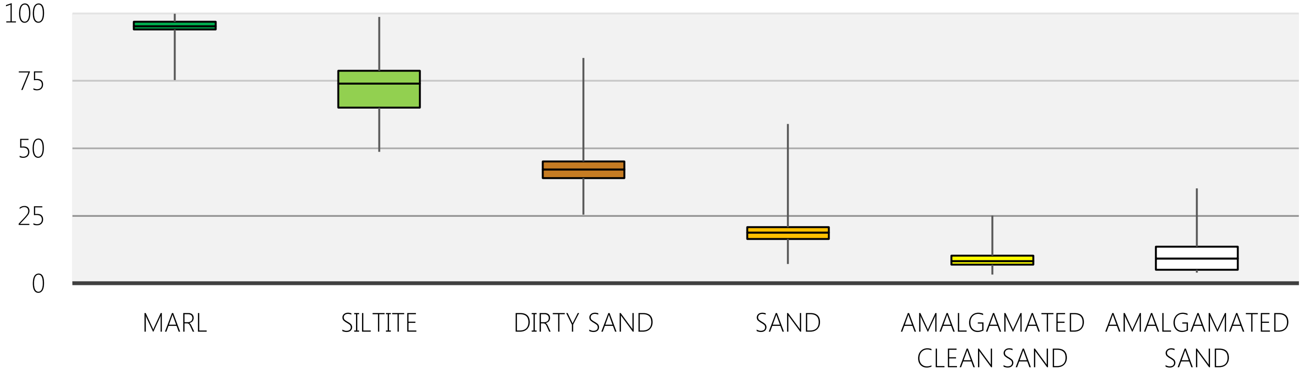
SAND CONTENT



PERMEABILITY



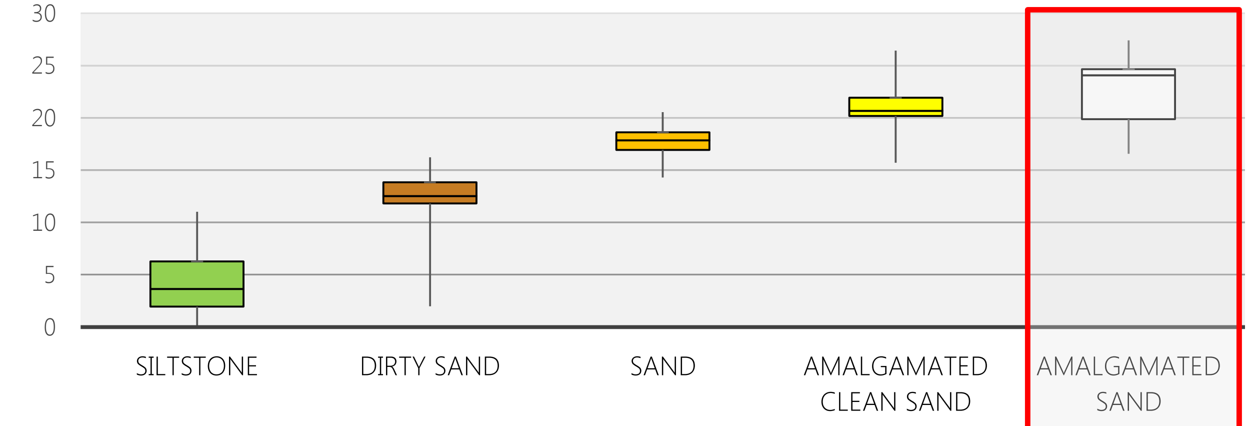
SHALE CONTENT



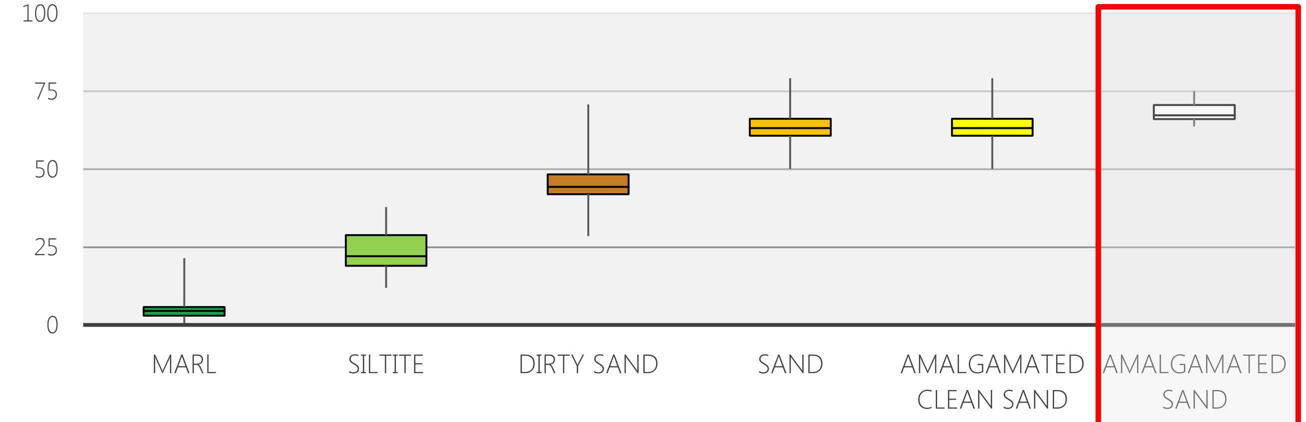
MODEL APPLICATION RESULTS

SIX IDENTIFIED GROUPS: CLEAR DISTRIBUTION OF RESERVOIR PROPERTIES

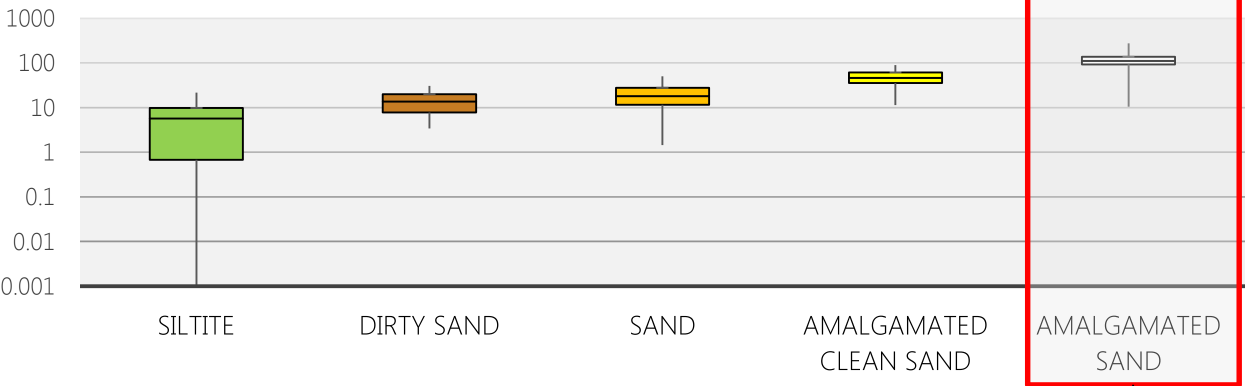
POROSITY



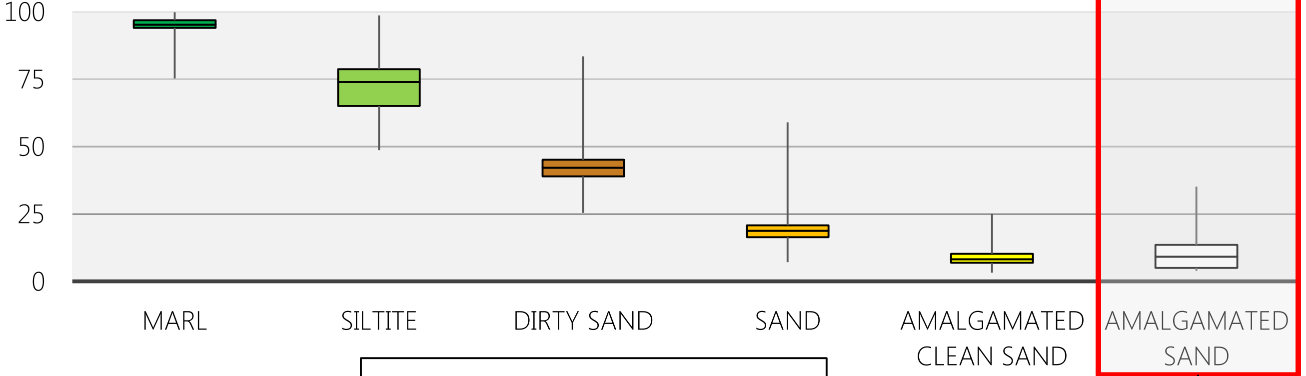
SAND CONTENT



PERMEABILITY



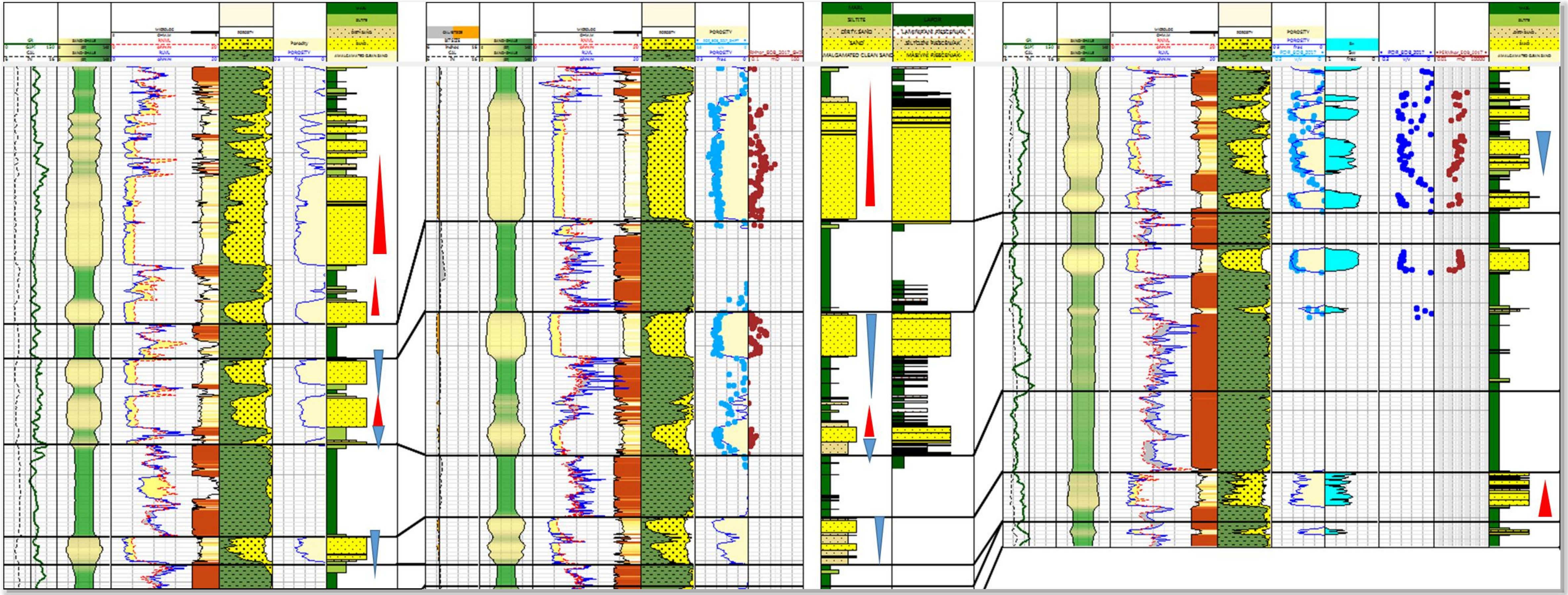
SHALE CONTENT



ELECTROFACIES GROUP WITH THE BEST RESERVOIR PROPERTIES

INTERPRETATION & CORRELATION

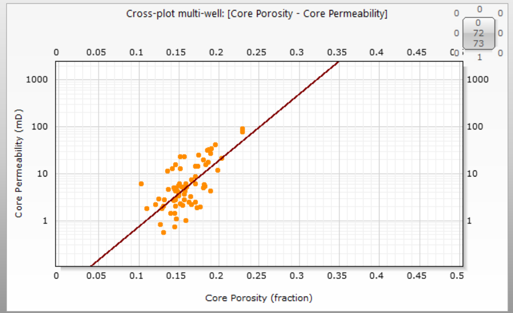
RESERVOIR CORRELATION –ZONATION DETERMINATION



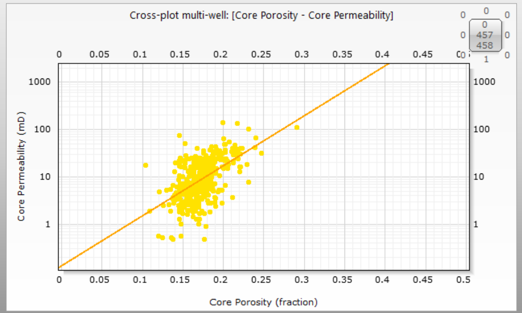
PERMEABILITY CALCULATION FROM CORE DATA

REGRESSIONS AND EQUATIONS

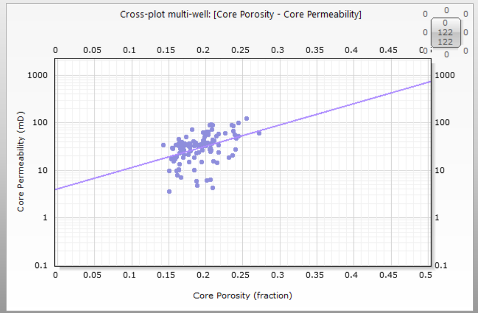
GROUP	EQUATION	CORRELATION	R^2	R^2 ADJUSTED	RMSE	COLOR	DESCRIPTION
DIRTY SAND	llog10(Core Permeability) = + 43.63462 * Core Porosity - 6.867689	0.722617	0.522175	0.517249	1.478		Regression type: Y/X; Fixed constant: no; Fixed slope: no; With selection: no
SAND	log10(Core Permeability) = + 20.88645 * Core Porosity - 2.735167	0.603791	0.364563	0.363203	0.689		Regression type: Y/X; Fixed constant: no; Fixed slope: no; With selection: no
AMALGAMATED CLEAN SAND	log10(Core Permeability) = + 5.349179 * Core Porosity + 0.4399292	0.462954	0.214326	0.207833	0.278		Regression type: Y/X; Fixed constant: no; Fixed slope: no; With selection: no
AMALGAMATED SAND	log10(Core Permeability) = + 21.68502 * Core Porosity - 3.348007	0.737765	0.544297	0.536303	0.776		Regression type: Y/X; Fixed constant: no; Fixed slope: no; With selection: no
GLOBAL	log10(Core Permeability) = + 14.1819 * Core Porosity - 1.46681	0.673952	0.454212	0.453482	0.918		Regression type: Y/X; Fixed constant: no; Fixed slope: no; With selection: no



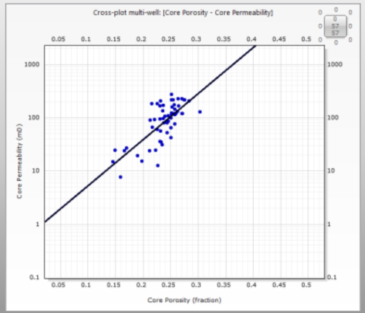
DIRTY SAND



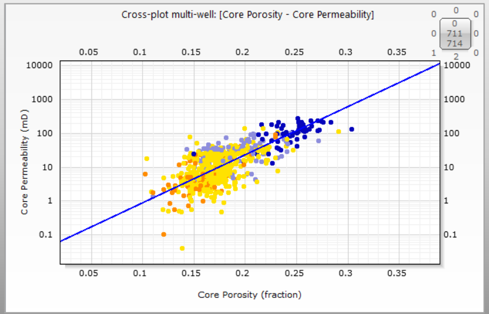
SAND



AMALGAMATED CLEAN SAND



AMALGAMATED SAND

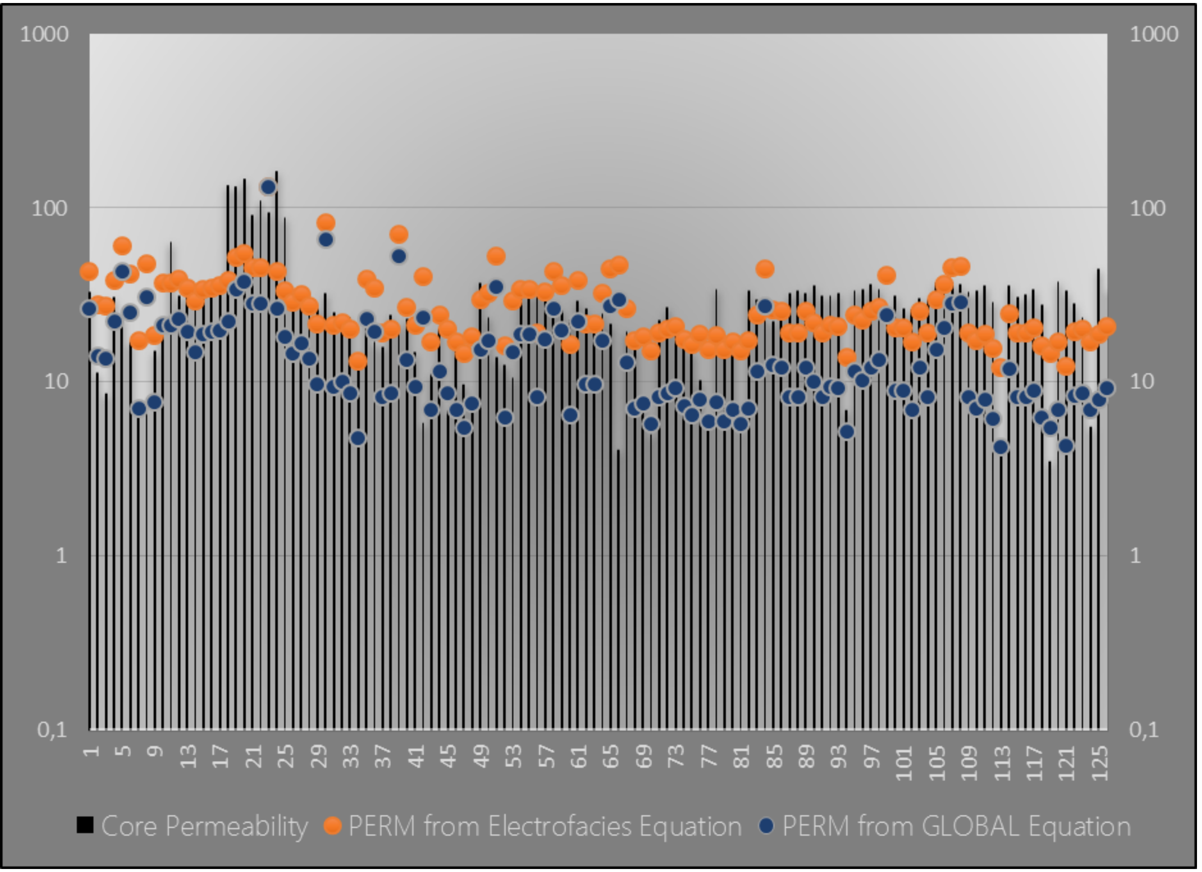


ALL DATA (GLOBAL)*

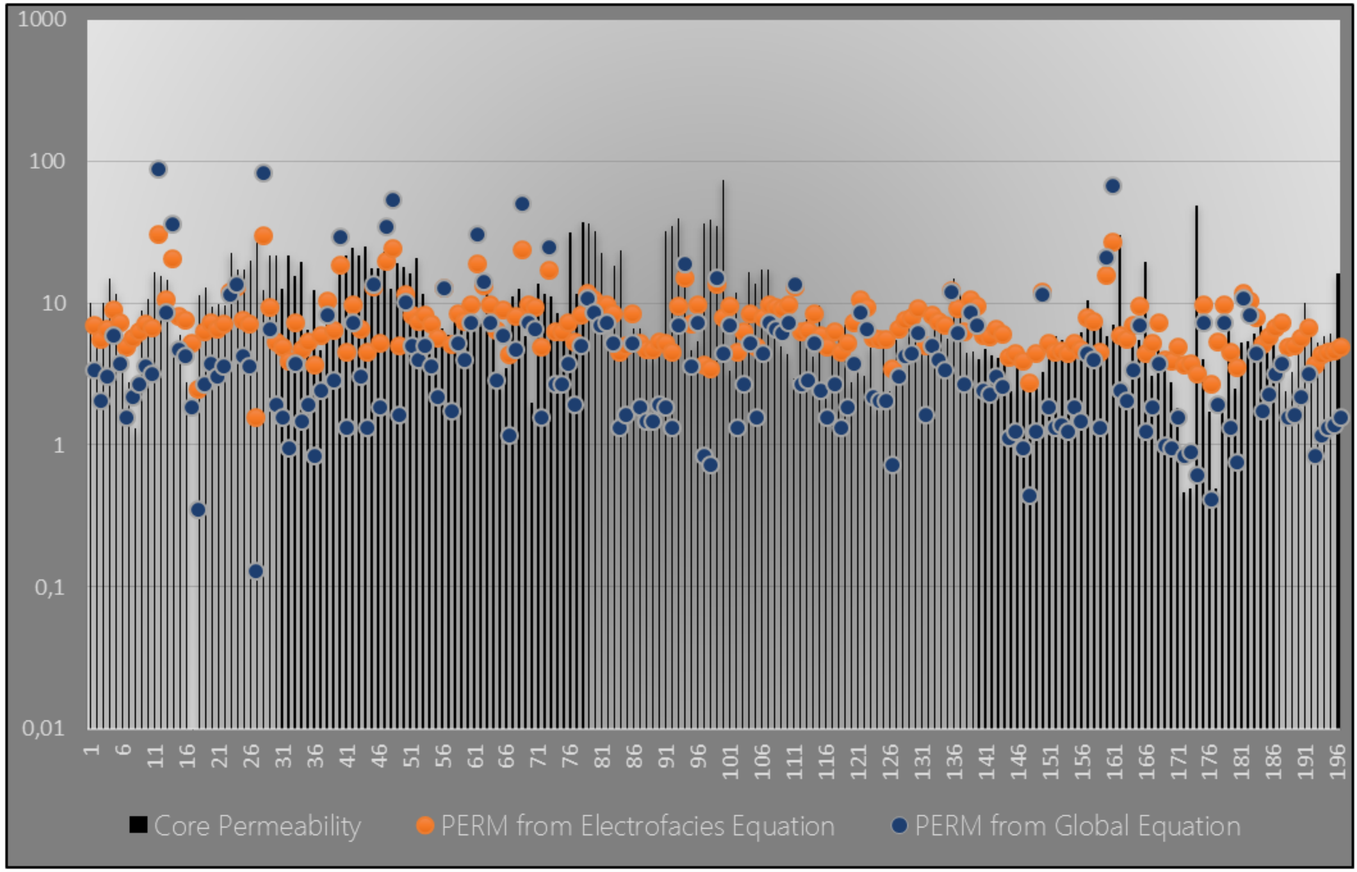
* GENERAL PRACTICE

RESULTS VALIDATION

Permeability calculated with different equations and compared with permeability measured on cores



AMALGAMATED SAND

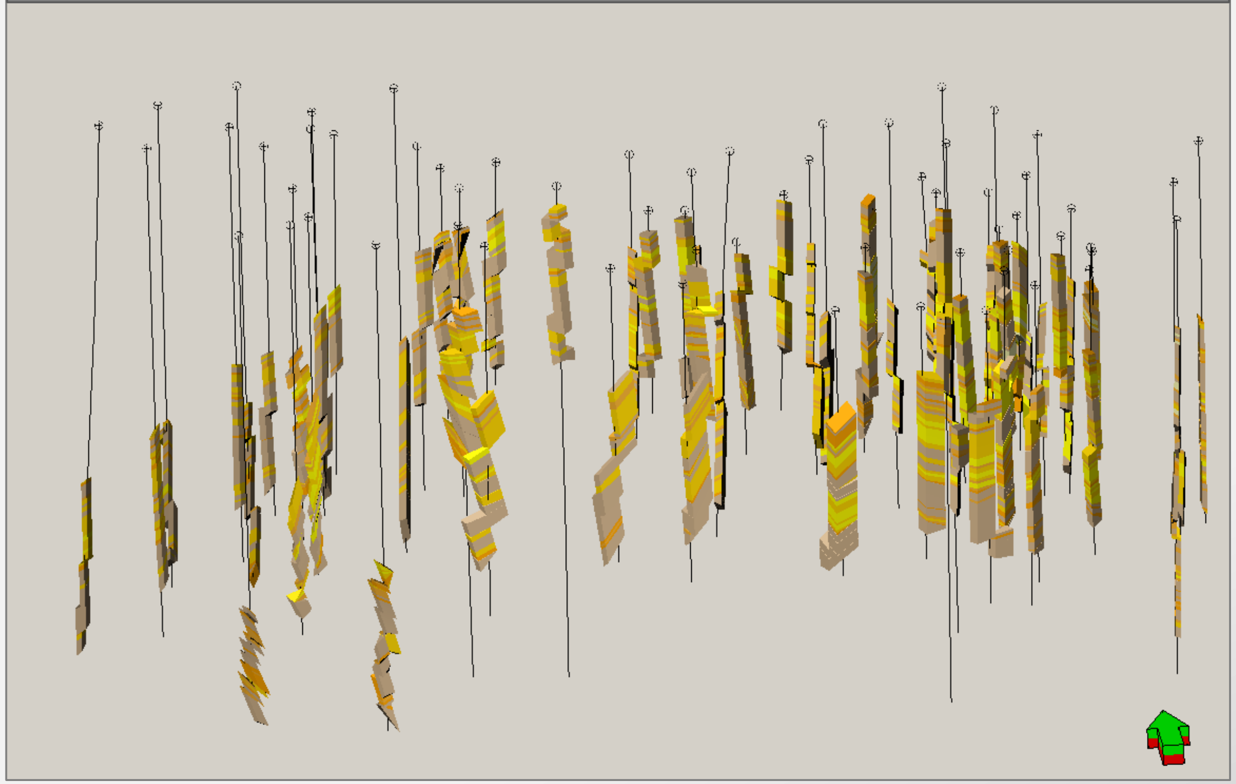


SAND

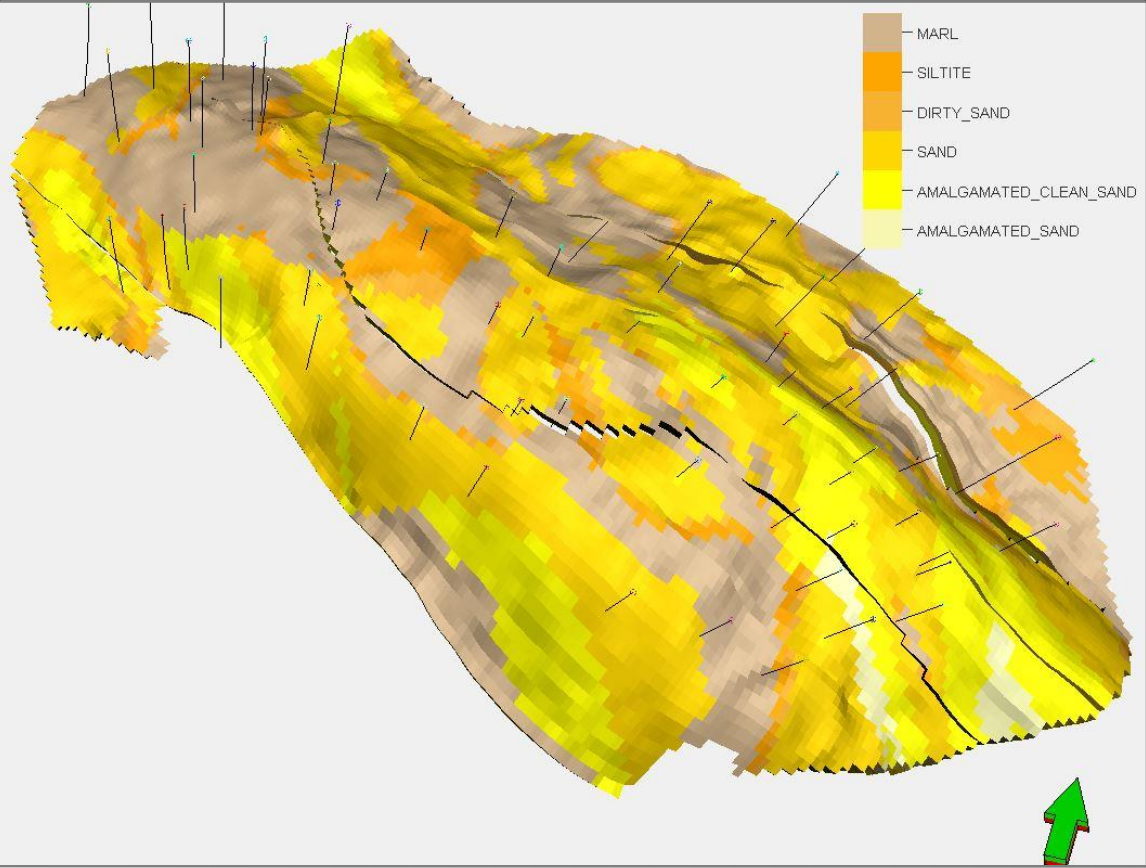
PERMEABILITY CALCULATED FROM ELECTROFACIES EQUATIONS IS MORE RELIABLE

FACIES MODELING

VERTICAL ELECTROFACIES ASSOCIATION



LATERAL ELECTROFACIES ASSOCIATION

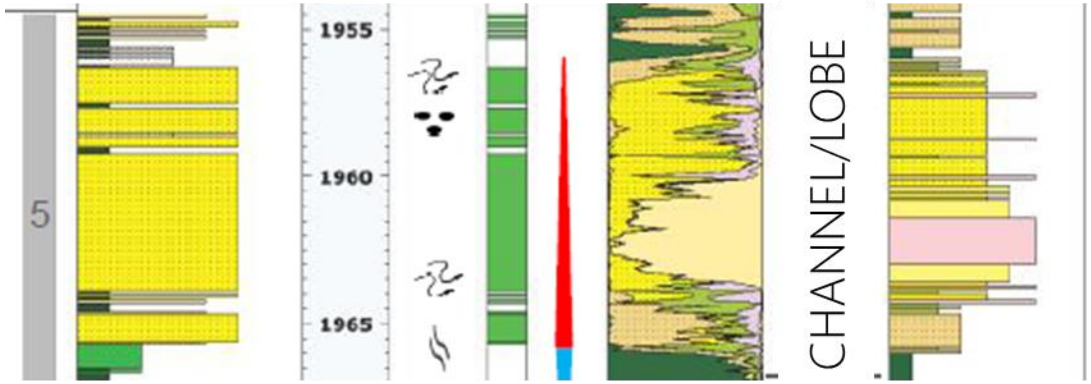


- 3D FACIES MODEL IS USED TO CONTROL SPATIAL DISTRIBUTION OF RESERVOIR PROPERTIES – POROSITY, PERMEABILITY AND INITIAL WATER SATURATION
- MORE ROBUST MODEL

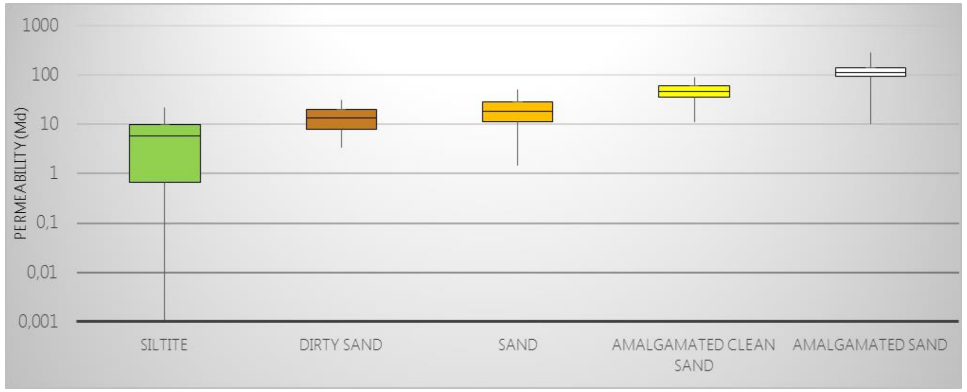
CONCLUSION

SUCCESSFUL ELECTROFACIES CLASSIFICATION OF MORE THAN 70 WELLS

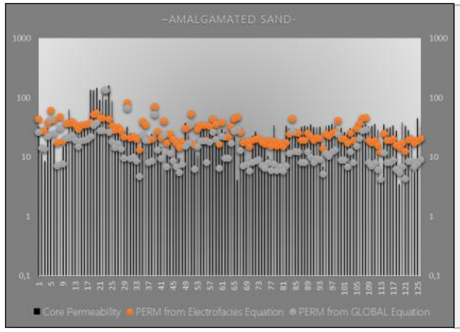
VERTICAL ELECTROFACIES ASSOCIATION INDICATES POSITION IN DEPOSITIONAL ENVIROMENT -FOR SEDIMENTOLOGICAL INTERPRETATION-



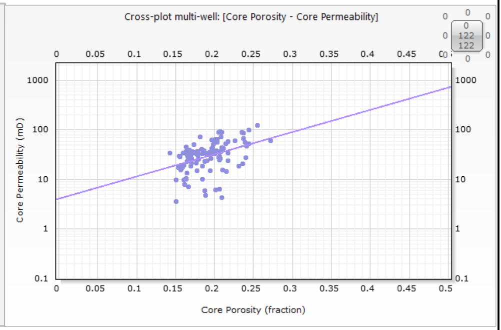
SIX ELECTROFACIES IDENTIFIED - IN A WAY TO OPTIMIZE THE DISRIBUTIONS OF POROSITY AND PERMEABILITY ASSOCIATED WITH EACH GROUP



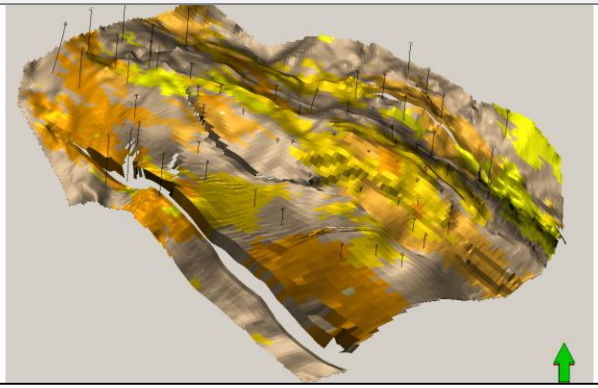
NEW EQUATIONS FOR PERMEABILITY CALCULATIONS EACH ELECTROFACIES SEPARATELY



log10=5.349179*Porosity + 0.4399292



NEW INPUT FOR RESERVOIR MODELLING HAS BEEN MADE WITH IDENTIFIED ZONES OF DIFFERENT PERMEABILITES AND POROSITIES



MAXIMUM UTILIZATION OF AVAILABLE DATA – WITHOUT ADDITIONAL COST

SIGNIFICANCE

- MORE **ROBUST MODEL** – HIGHER CONTROL OVER DISTRIBUTION PROPERTIES
- PREDICTS RESERVOIR **HETEROGENETIES**
- ELECTROFACIES ARE DEFINED BASED ON ALL AVAILABE DATA AND IN DEPTH REFLECT RESERVOIR PROPERTIES
- INCREASES THE TEAM EFFICIENCY

POSSIBLE OUTCOMES

- PREVENTING **UNNECESSARY WORKOVERS** DUE TO MORE PRECISE RESERVOIR CHARACTERIZATION
- BASED ON MORE ACURATE MODEL, **OPTIMAL PATTERN OF INJECTORS AND PRODUCERS** CAN BE DETERMINED
- BETTER PREDICITON OF **FLUID DYNAMICS**
- OPTIMIZING PREDICTION OF CO_2 INJECTION QUANTITIES
- BETTER **ESTIMATION OF RECOVERY** (POSSIBLY BOTH HIGHER AND LOWER)
- ALL LEADS TO **BETTER PROJECT EFFICIENCY** AND **LOWER PRODUCTION COST PER BARREL**

NEURAL NETWORK APPLICATION SIGNIFICANTLY IMPROVED RESERVOIR CHARACTERIZATION FROM WELL LOGS AND CORE DATA

QUESTIONS...

BEST PRACTICES

IMPLEMENTING SOLUTIONS BASED ON MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE FROM MASSIVE AMOUNT OF DATA IN:

RESERVOIR CHARACTERIZATION

CORE AND LOG DATA INTEGRATION[1]

- ELECTROFACIES DETERMINATION THROUGH CORE AND LOG DATA INTEGRATION
- CORRELATING GEOLOGICAL DATA WITH ELECTROFACIES
- CALIBRATION OF ELECTROFACIES WITH SEISMIC DATA TO UPSCALE IT TO FIELD LEVEL
- ACHIEVED DEEPER UNDERSTANDING OF THE DYNAMIC RESPONSES OF THE RESERVOIRS

FIELD DEVELOPMENT

ELECTROFACEIS MODELING IN CARBONATES[2]

- DEFINING PERMEABILITY AND FACIES CHANGES RELATED TO ROCK QUALITIY THROUGH CORE DATA, CONVENTIONAL LOGS, NMR AND IMAGE LOGS INTEGRATION
- APPLYING THE MODEL TO PREDICT CHANGES IN WELLS WITHOUT CORE DATA

EXPLORATION

INTEGRATED DATA ANALYSIS USING ELECTROFACIES AND SEISMIC ATTRIBUTE FOR RESERVOIR MODELING[3]

- EXTENDING THE MEASURED PROPERTIES FROM THE WELLBORE TO THE ENTIRE STUDIED AREA
- PRACTICAL METHOD BASED ON THREE STEPS:
  - DETECTING AND CLASSIFYING ELECTROFACIES FROM WELL LOGS
  - ESTIMATING PETROPHYSICAL PROPERTY USING WELL LOGS AND CORE DATA
  - ELECTROFCIES SPATIAL MODELING FROM SEISMIC ATTRIBUTE

1 CORE AND WELL LOG DATA INTEGRATION, THE KEY FOR DETERMINING ELECTROFCIES (L. P. STINCO)
2 ELECTROFACIES MODELING: USING MULTI-RESOLUTION GRAPH BASED CLUSTERING (MRCG), ANALYSIS IN CARBONATE FIELD, VENEZUELA (PARADIGM CUSTOMER STORY)
3 INTEGRATED DATA ANALYSIS USING ELECTROFACIES AND SEISMIC ATTRIBUTE FOR RESERVOIR MODELING (CHEOLKYUN JEONG, STANFORD)

APPENDIX

McKINSEY STUDY[1]

IN UPSTREAM ONLY, THERE IS AROUND USD 50bn AT STAKE THROUGH IMPLEMENTATION OF AI PRACITES

NOT EXHAUSTIVE — (orange) CAPEX reduction potential — (blue) EBIT increase potential

EBIT pool/ CAPEX pool

~280 Billion/ ~180 Billion			~40 Billion/~20 Billion			
Upstream			**Midstream**		**Downstream**	
Exploration	**Development**	**Production**	**Transport and storage**	**Trading**	**Refining**	**Marketing & retail**
						

	Exploration	Development	Production
Connectivity	Real time comparisons with well characteristics logs from well repository to assess prospectively — 2% (EBIT)	~20% faster delivery of large capital projects from coordinated planning and communication — 4% (CAPEX)	Improve communication across shift and between on- and offshore to remove unnecessary well work-overs — 0,5% (EBIT)
Automation	Speed up, automate and improve quality of seismic analysis to reduce the number of dry exploration wells by 10% — 1% (CAPEX)	1-2 % higher rig, crew and equipment availability (logistics and maintenance) — 0,2% (CAPEX)	Optimize logistics operations to reduce stock-levels, faster maintenance, and reduced cost — 1,5% (EBIT)
Decisioning		Lower CAPEX through “rightsizing” of well and top-side design — 3% (CAPEX)	Predictive maintenance of top-side and wells, increasing up-time of the asset by 4-5% — 5% (EBIT)
Innovation	▪ Analytic engine to better evaluate M&A targets (fields and companies) ▪ “Crowd sourcing” of seismic analysis based on open data ▪ Continuous deterministic and probabilistic concept choice analyses to optimize investment vs. revenue — 3-5% (CAPEX), 3-5% (EBIT)		

Total: ~10% = USD 20 bn (CAPEX) — ~10% = USD 30 bn (EBIT)

1 http://insights.globalspec.com/article/2772/the-growing-role-of-artificial-intelligence-in-oil-and-gas