Examination of Petrophysical Characteristics of Carbonate Multimodal Porosity Systems*

Mark Skalinski[1], Robert Mallan[1], Paul Theologou[2], and Rafael Salazar[1]

Search and Discovery Article #51282 (2016)**
Posted August 15, 2016

*Adapted from oral presentation given at AAPG 2016 Annual Convention and Exhibition, Calgary, Alberta, Canada, June 16-22, 2016
**Datapages © 2016. Serial rights given by author. For all other rights contact author directly.

[1]ESD, Chevron ETC, Houston, Texas (mtsk@chevron.com)
[2]Chevron Australia, Perth, Western Australia

Abstract

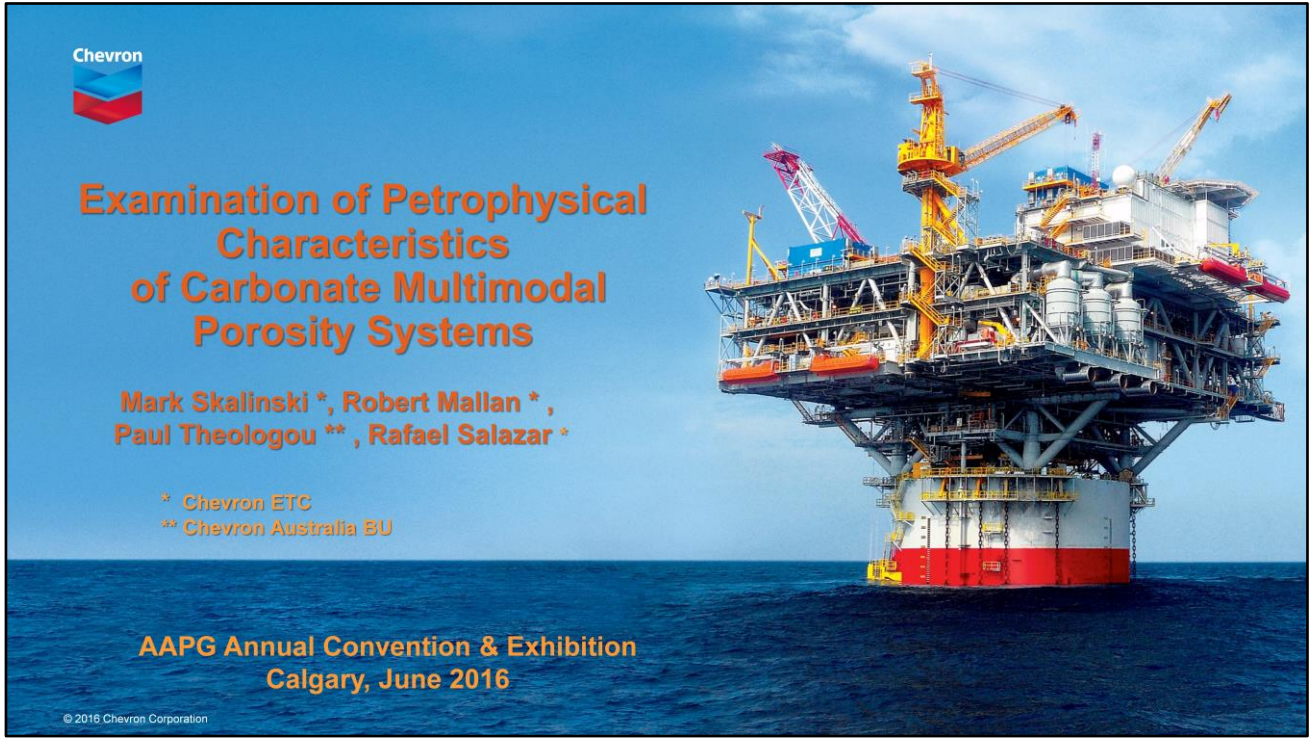
Carbonate petrophysical heterogeneity is generally the result of complex and multi-modal pore systems, including fractures. This complexity is due to a combination of complex depositional rock fabric textures and diagenetic modification of the rocks. Post-depositional processes can modify the original petrophysical properties (e.g., permeability and irreducible water saturation) and result in a disconnection between the original depositional rock fabric and the current reservoir properties. Pore types are a critical element of rock types because they exert a dominant control over petrophysical properties and fluid flow. Conventional pore-typing methods use petrographic observations, including image analysis, to determine pore types, qualitatively or quantitatively, in an attempt to relate the pore system, at least in part, to flow and textural pore types. However, such techniques more than often do not resolve the complexity and multi-modality of the pore system and subsequently result in a misrepresentation of dynamic properties as documented by examples. Pore typing based on mercury porosimetry (MICP) draws on the modality of pore throats accessed by specific pore volumes, which is a strong factor controlling fluid flow in reservoirs. One of the primary parameters in pore typing definitions is the pore system modality. The number of modes is associated with petrophysical properties and depositional or diagenetic processes. However, a more comprehensive link to the recovery factor needs examination of the whole pore system including the pore- size distribution. We have developed a method of automatic modal detection from MICP data, using Gaussian decomposition. It allows an objective estimation of the modality of the pore system. We are also investigating the whole pore system defined by both: pore throats (from MICP) and pore-size distributions (from NMR and image analysis). In this presentation, we describe the integrated pore- typing workflow with examples from several carbonate reservoirs. These case studies show that pore types and pore-system modality are associated with petrophysical properties, depositional facies, and diagenetic modifications. Furthermore, integration of MICP, NMR measurements and 3DBSEM images on the same core plugs enable us to describe the modality of the whole pore system in a more comprehensive way, providing interesting insights on the pore system and drivers of petrophysical properties in carbonates.

References Cited

Clerke, E.A., H.W. Mueller, III, E.C. Phillips, R.Y. Eyvazzadeh, D.H. Jones, R. Ramamoorthy, and A. Srivastava, 2008. Application of

Thomeer hyperbolas to decode the pore systems, facies and reservoir properties of the Upper Jurassic Arab D Limestone, Ghawar field, Saudi Arabia: A “Rosetta Stone” approach: GeoArabia, v/13/4, p. 113-160.

Thomeer, J.H.M., 1960, Introduction of a pore geometrical factor defined by the capillary pressure curve: Journal of Petroleum Technology, v. 12/3, p. 73-77.



Examination of Petrophysical Characteristics of Carbonate Multimodal Porosity Systems

Mark Skalinski *, Robert Mallan * ,
Paul Theologou ** , Rafael Salazar *

* Chevron ETC
** Chevron Australia BU

AAPG Annual Convention & Exhibition
Calgary, June 2016

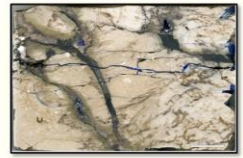
© 2016 Chevron Corporation

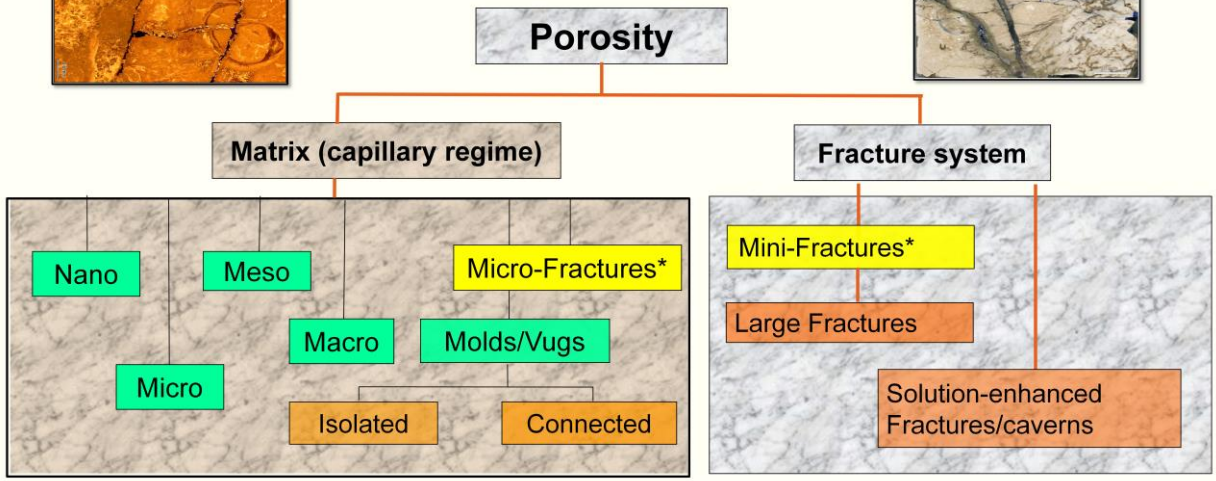
Agenda

- Introduction
- Mercury Injection Capillary Pressure (MICP) Pore Typing Workflow
- Log scale pore types
- Pore types link to petrophysical properties
- Investigation of complex pore systems
- Conclusions

© 2016 Chevron Corporation

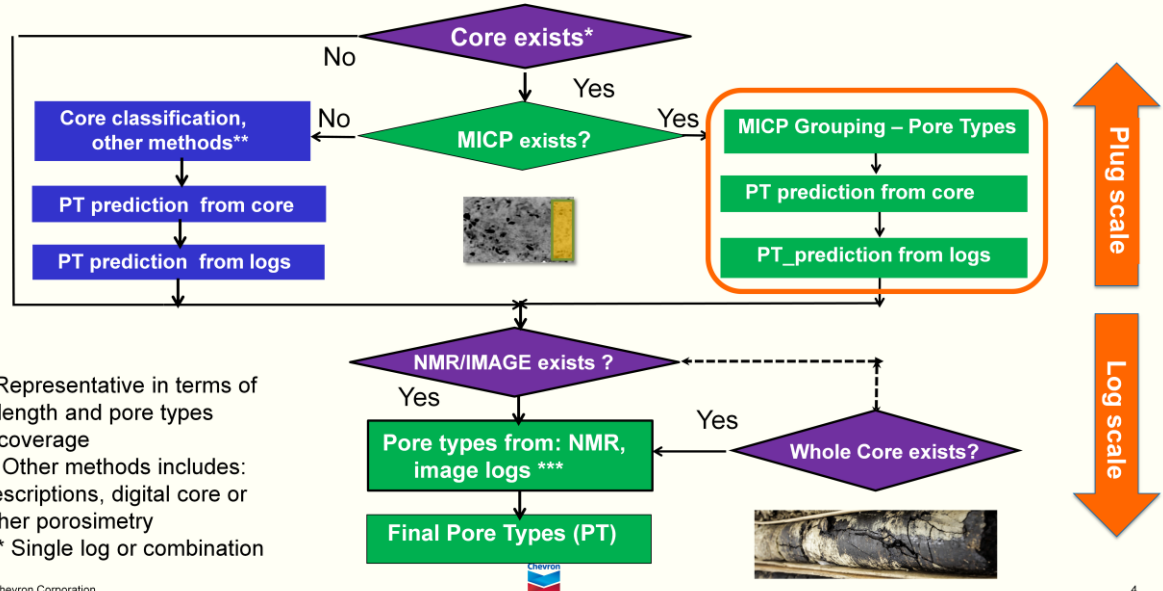
General Dual Porosity Classification





© 2016 Chevron Corporation

Pore Typing Workflow



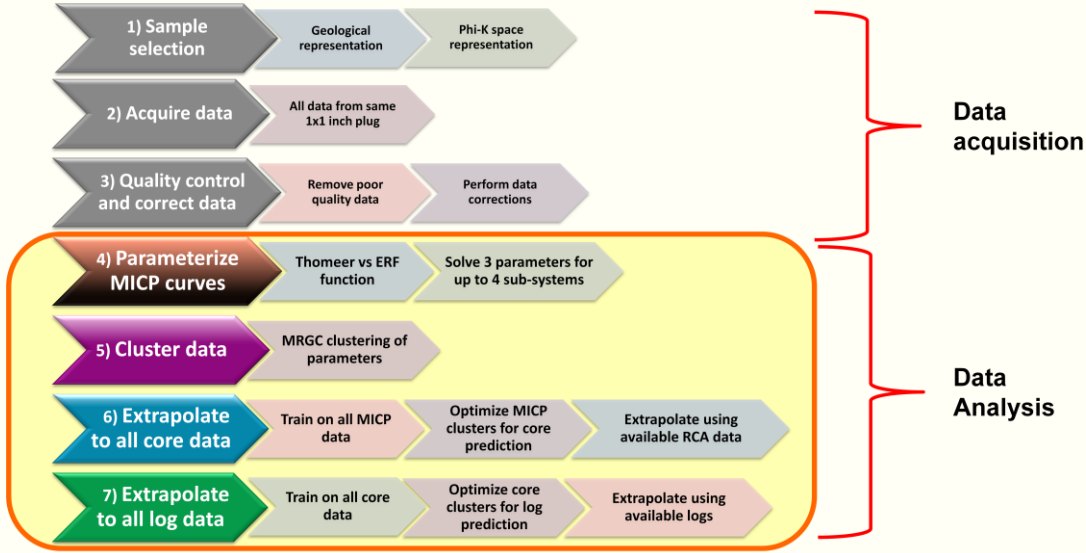
* Representative in terms of length and pore types coverage

** Other methods includes: descriptions, digital core or other porosimetry

*** Single log or combination

© 2016 Chevron Corporation

MICP Pore Typing Workflow



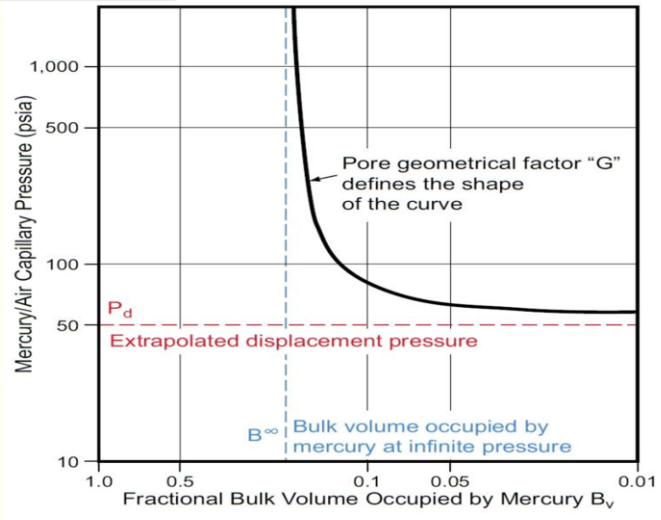
© 2016 Chevron Corporation

Presenter's notes: Our MICP workflow contains 7 steps which are: sample selection, data acquisition, quality control and corrections, parametrization, clustering, extrapolation to core and log domain.

MICP parameterization

4) Parameterize MICP curves → Thomeer vs ERF function → Solve 3 parameters for up to 4 sub-systems

$$\frac{B_v}{B^\infty} = e^{\left[-G/Log\left(\frac{P_c}{P_d}\right)\right]}$$



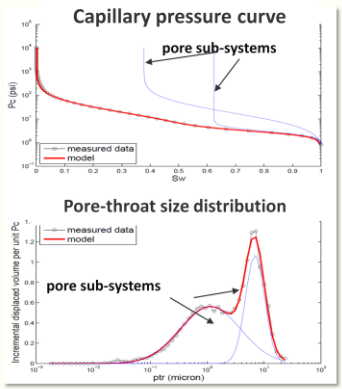
Clerke et al. (2008): Application of Thomeer hyperbolas to decode the pore systems, facies and reservoir properties of the Upper Jurassic Arab D Limestone, Ghawar field, Saudi Arabia: A "Rosetta Stone" approach: *GeoArabia*, v. 13, no. 4 p. 113-160.

© 2016 Chevron Corporation

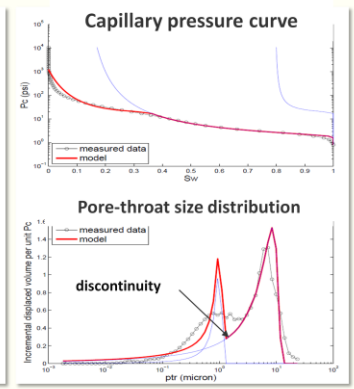
MICP Parameterization

4) Parameterize MICP curves → Thomeer vs ERF function → Solve 3 parameters for up to 4 sub-systems

Gaussian



Thomeer



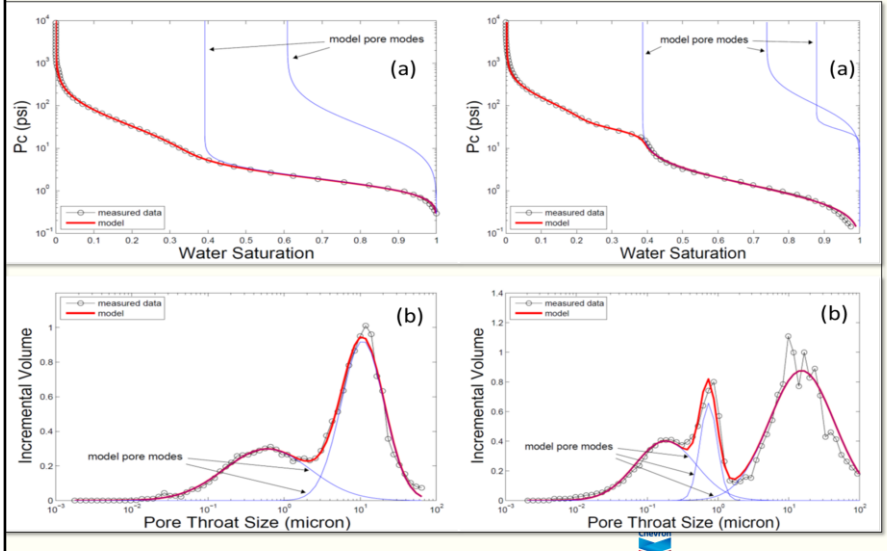
- **Thomeer hyperbola produces discontinuities at sub-system junctions. Evident in pore-throat-size distributions**
- **Thomeer hyperbola is skewed, while error function is symmetrical in log-normal scale**
- **New formulation does not have discontinuities and shows symmetrical shape in log-normal space**

© 2016 Chevron Corporation

Presenter's notes: Step 4 is a parametrization of MICP data. The conventional way is to fit Thomeer function (1960), which defines 3 parameters : entry pressure Pd, shape factor–G, and BVinf. When we apply Thomeers hyperbolic function for the multimodal MICP data, typical for carbonates, we have to define, as presented by Ed Clerke, a separate function for each mode. We started using Thommer but realized that hyperbolic function produces sharp discontinuities at the modal junctions as seen in this picture.
We found that modified Gaussian function provides better fit and accommodates better mode transitions.
Our modified Gaussian function shown here yields parameters similar to Thomeer function : modal porosity- Vp inf, shape factor-S, and Pm. Only difference is that, instead of artificially calculated entry pressure for each mode, we are defining Pm, which is the center of the mode pressure. As result , we have nice smooth transition between the modes, and also the Gaussian fits better natural symmetrrical shape of the modes.

MICP Parameterization

4) Parameterize MICP curves → **Thomeer vs ERF function** → **Solve 3 parameters for up to 4 sub-systems**



New formulation uses three parameters similar to Thomeer:

- $V_{P_{\infty i}}$ =pore sub-system volume
- P_{mi} =pore sub-system pressure
- S_i =pore sub-system geometric factor

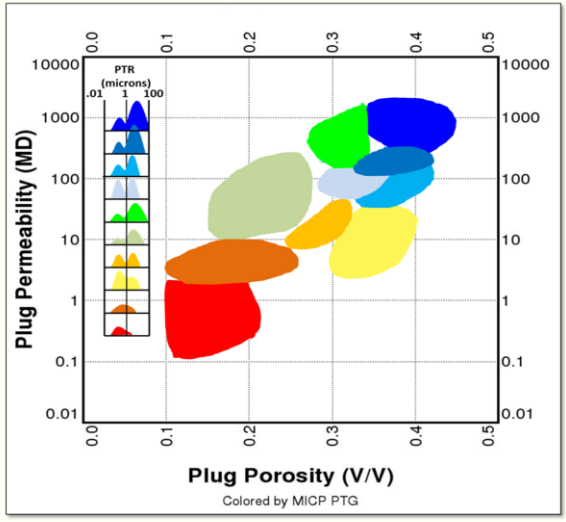
© 2016 Chevron Corporation

Presenter's notes: So we developed application in Matlab which is now linked to GEOLOG which takes cap pressure and performs automatic fit up to 4 modes. Here is an example of application of Gaussian function to bimodal (left) and trimodal (right) pore systems. Each mode will be characterized by 3 parameters.

Clustering of Parameterized Data

5) Cluster data | MRGC clustering of parameters

- Objective clustering using facimage
  - MODEL logs are the parameters derived from multi-modal Gaussian inversion of the MICP data
  - We can also use the whole MICP curve for clustering
- Based on MICP data only
- Looking for definition of clusters in Phi-K space if possible



© 2016 Chevron Corporation

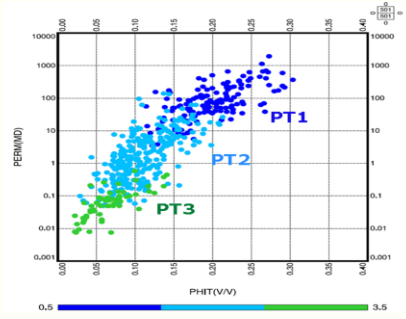
Presenter's notes: In step 5 we take those inversion parameters for the defined pore subsystems and cluster them together with core phi, K data, using Facimage MRGC routine. This picture shows results of the clustering plotted in pki- K crosplot. The color polygons are covering the real data from carbonate reservoir. These clusters are our initial pore types.
Here we can also see corresponding shape of MICP distribution. As we can observe, pore-type clusters are, in general, well separated in Phi-K space, which allow us to predict them from plug data without MICP. For the purpose of prediction from plug and log data, we have to do some lumping, which have to account for the geological information (depositional and diagenetic).

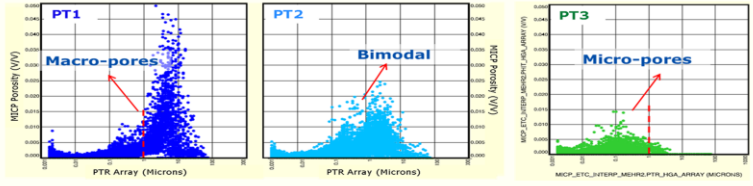
Clustering of Parameterized Data – Pore Types

Case Study – Permian Basin

- After initial cluster definition, supervised lumping is generally needed to reduce the number of Pore Types down to a manageable number – this should be geologically constrained

- Three Pore Types identified by optimizing MICP clusters





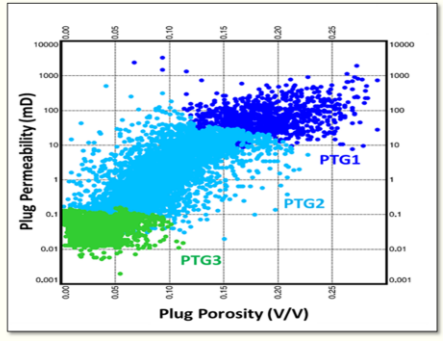
© 2016 Chevron Corporation

Presenter's notes: Here is an example of clustering results from McElroy field.
Original clusters are lumped to 3 groups corresponding roughly to macroporosity, bimodal system, and microporosity.

Pore Type Extrapolation to Core Plugs

6) Extrapolate to all core data → Train on all MICP data → Optimize PTGs for core prediction → Extrapolate using available RCA data

- We usually have limited MICP data
- Much larger dataset of PHI-K
- We can use KNN* log-prediction to assign pore type group to each core plug (using clustered MICP data as the training dataset)
- We make this compromise to build the statistical dataset needed for log prediction



* KNN – K Nearest Neighbor Method

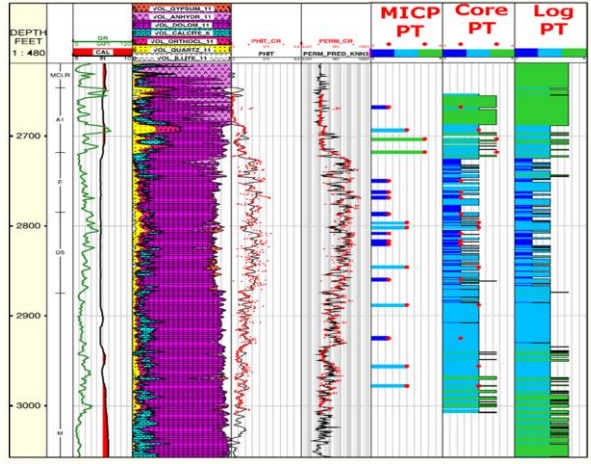
© 2016 Chevron Corporation

Presenter's notes: Because MICP data are limited , we have to extrapolate the MICP pore types groups to all plug data, taking advantage of separation in phi-k space. WE use KNN method (k nearest neighbor) as a method to predict MICP poretypes from plug data. Here is result of extrapolating Mc Elroy MICP pore types shown on previous slide to all plug data.

Pore Type Extrapolation to Log Scale

7) Extrapolate to all log data → Train on all core data → Optimize PTGs for log prediction → Extrapolate using available logs

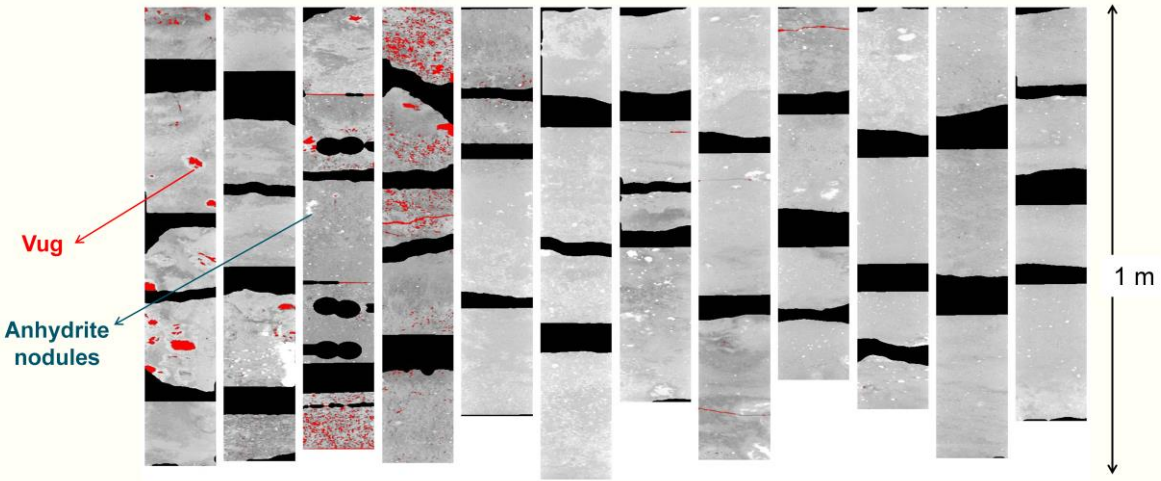
- Use extrapolated pore types from full plug database as training dataset
- Select best logs for prediction; Use log measurements to predict MICP pore type for all log measurements
- Merge pore type groups - in consultation with Geologists – retain geological context



© 2016 Chevron Corporation

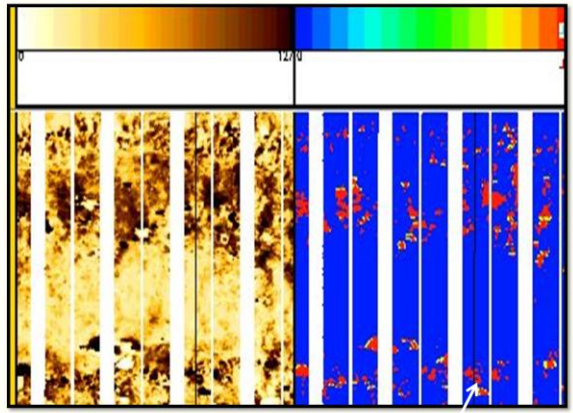
Presenter's notes: In final step, we are predicting pore types from logs. Input data consist of pore types from core domain and all raw and interpreted logs.
We are defining KNN prediction model to populate pore types in log domain, using optimal combination of logs. To define best combination of logs, we can use diagnostic tool in Facimage or stepwise discriminant analysis. On the right we have an example from McElroy field. We have here: GR, core and log Phi, core and log perm, MICP-derived pore types, pore types extrapolated to all plugs, and finally pore types predicted from logs.

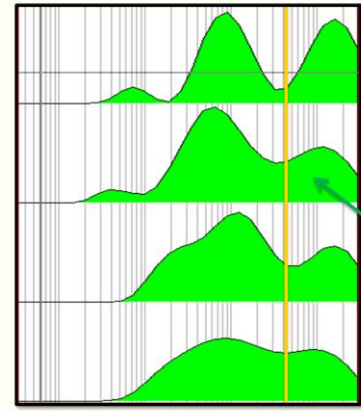
Assessment of vuggy porosity from whole core CT scans



© 2016 Chevron Corporation

Vuggy/Moldic Porosity from FMI & NMR



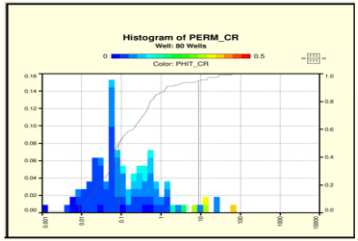


© 2016 Chevron Corporation

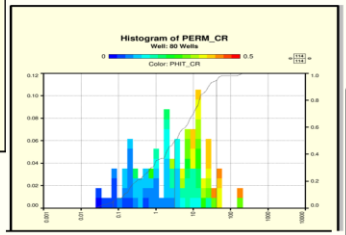
Does modality of pore systems affect petrophysical properties?

Perm Distribution for Bimodal pore systems

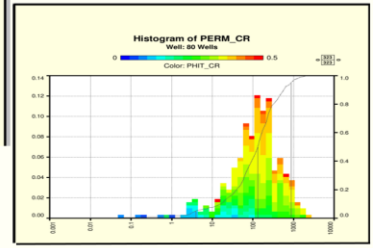
550 samples from 80 wells different carbonate fields



Pres_M1>150 psi



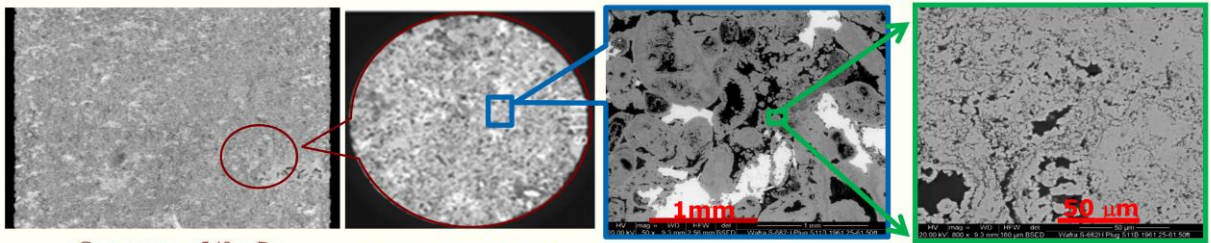
Pres_M1:50-150 psi



Pres_M1<50 psi

© 2016 Chevron Corporation

MICP and 2D NMR compared with Multiscale Images

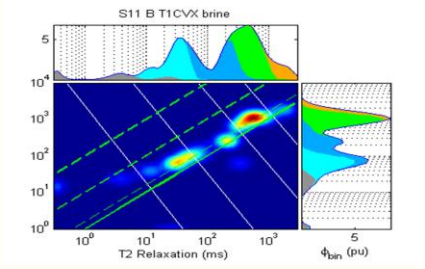


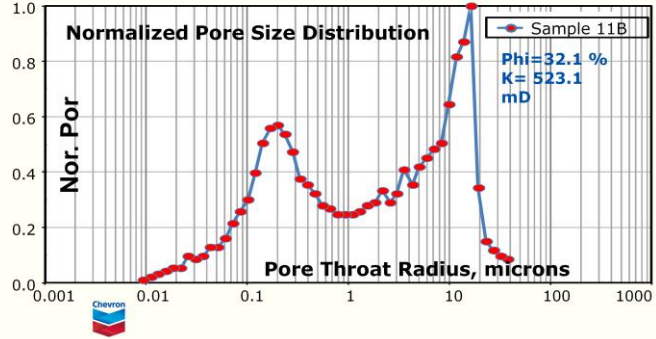
Core perm = 549 mD
Porosity= 30.9

Plug perm = 421 mD
Porosity= 32.12

resolution = 1.25 micron

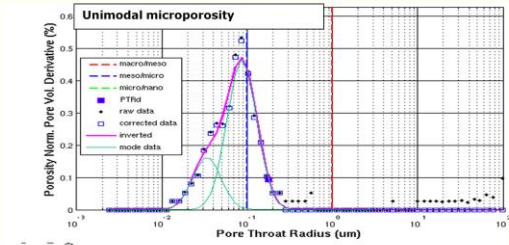
resolution = 0.077 micron

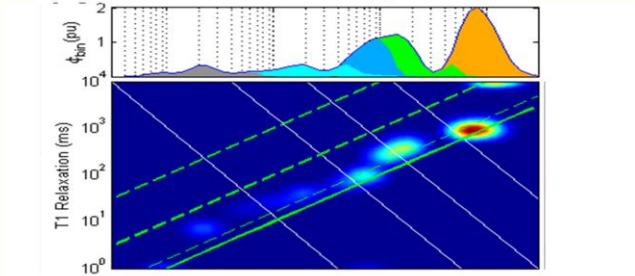


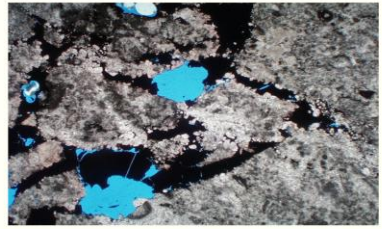


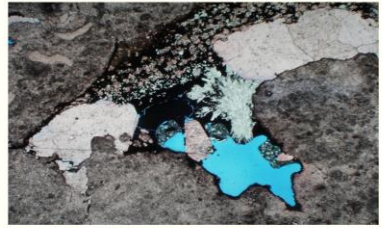
© 2016 Chevron Corporation

NMR-MICP –Image comparison
- Large pores connected by small pore throats









© 2016 Chevron Corporation

Conclusions

- Gaussian inversion fits MICP data better than conventional Thomeer method.
- Our Pore typing workflow defines pore type in core scale and extrapolates them to log scale.
- Pore type in log domain is necessary to provide input to reservoir models and rock typing.
- Pore modality is not a primary driver of petrophysical properties
- Full investigation of complex carbonate pore systems requires multiple tools (MICP, NMR, image analysis).

© 2016 Chevron Corporation

THANKS

© 2016 Chevron Corporation