Understanding Reservoir Complexity and Heterogeneity: Unique Aspects of Developing Core and Cuttings Based Chemostratigraphic and Lithologic Facies; Examples from Williston, Gulf Coast and Anadarko Basins*

A. Morrell¹, N. Gasner¹, H. Rowe², and J. Mckinney³

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Abstract

While many factors influence reservoir quality and facies, their spatial variability and controls on porosity, permeability, and brittleness are often enigmatic. One of the most important contributions in accessing reservoir quality and heterogeneity is to understand facies and facies-scale variability. Developing a quantitative approach to determining facies-scale heterogeneity in petroleum reservoirs is imperative and particularly difficult in mudrocks and mineralogically complex rocks. The fine-grained nature, lack of visible fabric and complex mineralogy make conventional interpretations difficult. In recent years, scientists have been capable of producing more comprehensive interpretations through the implementation of specific instrumentation. Such methods include Energy Dispersive X ray Florescence (ED-XRF), capturing elemental composition, X ray diffraction (XRD), capturing mineralogical composition, Rock-Eval Pyrolysis, capturing thermal maturity, In situ hydrocarbons and TOC. These techniques integrated together with geologic and petrophysical models are commonly utilized in the evaluation of these complex rocks, producing chemostratigraphic and lithologic facies units. Utilizing XRF spectral data combined with specific methodology and sample preparation, geoscientists are capable of creating high-resolution chemostratigraphic profiles of reservoir facies. Portable XRF aids in resolving micro scale facies and mineralogical variability efficiently at a low cost.

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Reference Cited

Rowe, H., N. Hughes, and K. Robinson, 2012, The quantification and application of handheld energy-dispersive x-ray fluorescence (ED-XRF) in mudrock chemostratigraphy and geochemistry: Chemical Geology, v. 324–325, p. 122–131.

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J. Apache Corp.

Geochemical Techniques

X-Ray Fluorescence (XRF)

X-Ray Diffraction (XRD)

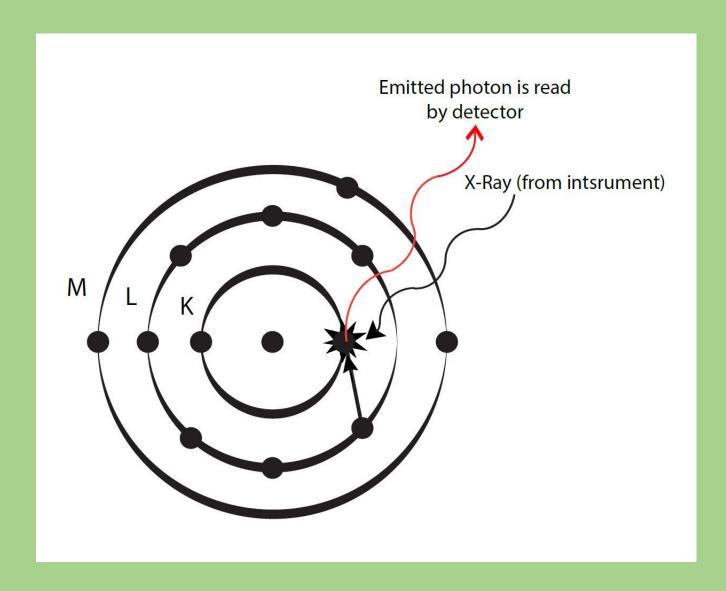
Total Organic Carbon (TOC)

Rock-Eval Pyrolysis

Chemostratigraphy:

The study of rock chemistry in the context of the stratigraphic column

X-Ray Fluorescence



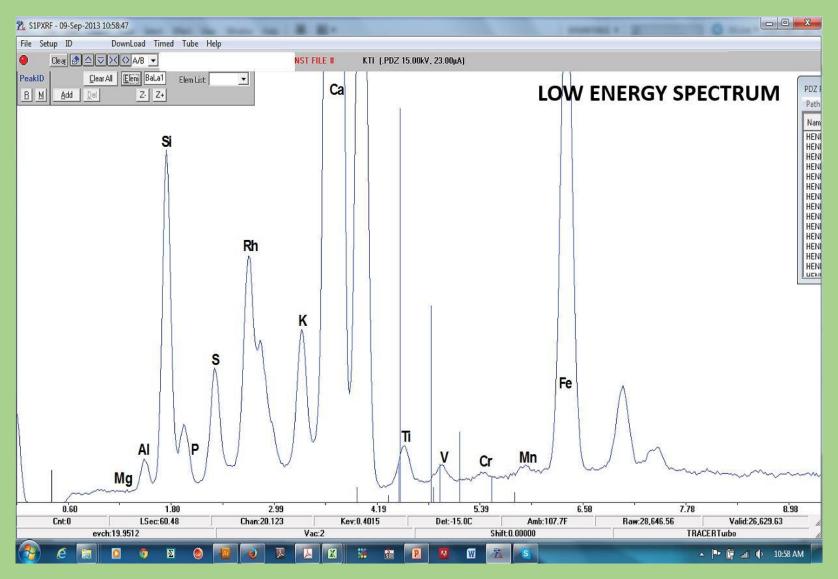
An electron from an outer shell drops into the unoccupied orbital, to fill the hole left behind.

This transition gives off a photon

The emitted photon's energy is unique to the element it came from

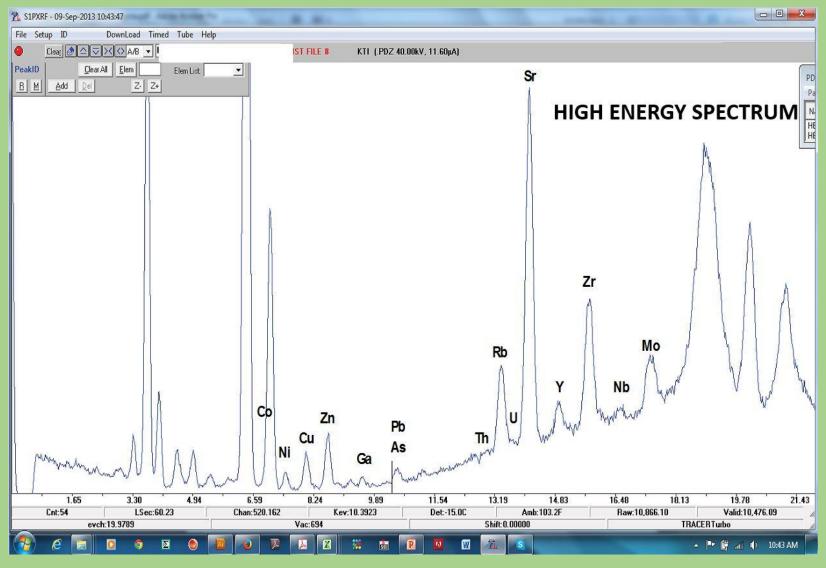
For example Aluminum K-shell energy is 1.47 KeV

Qualitative Real-Time XRF Spectra



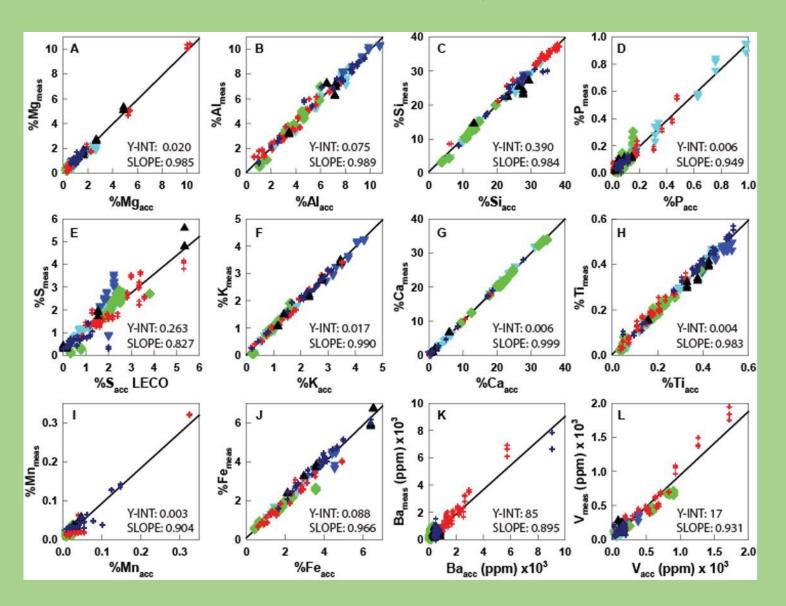
Energy in KeV

Qualitative Real-Time XRF Spectra



Energy in KeV

How to be Quantitative with XRF





Elemental calibration using real geological samples as references

Rowe et al., Chemical Geology, 2012

Goals of Chemostratigraphic Analysis

Integration of Geochemical Data

Different geochemical methods provide a stoichiometric "check" for each other Elemental conversion of XRF results to bulk mineralogy, strengthens petrophysical model Double check interpretations from gamma ray logs using XRF ("pseudo gamma") Find linkages between the different sources of data (Ex: TOC and redox/anoxia indicators)

Quantitative understanding of facies scale variability

Improve core descriptions - observations backed up by hard numbers instead of qualitative descriptions

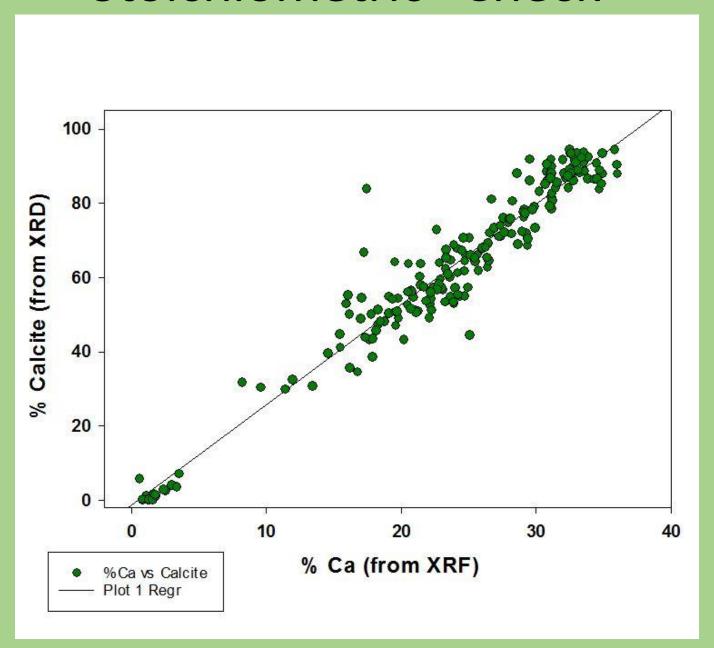
Use geochemical data to create "chemo-facies"

Statistically group samples with similar geochemistry
This can guide sample locations for more expensive "high end" analyses

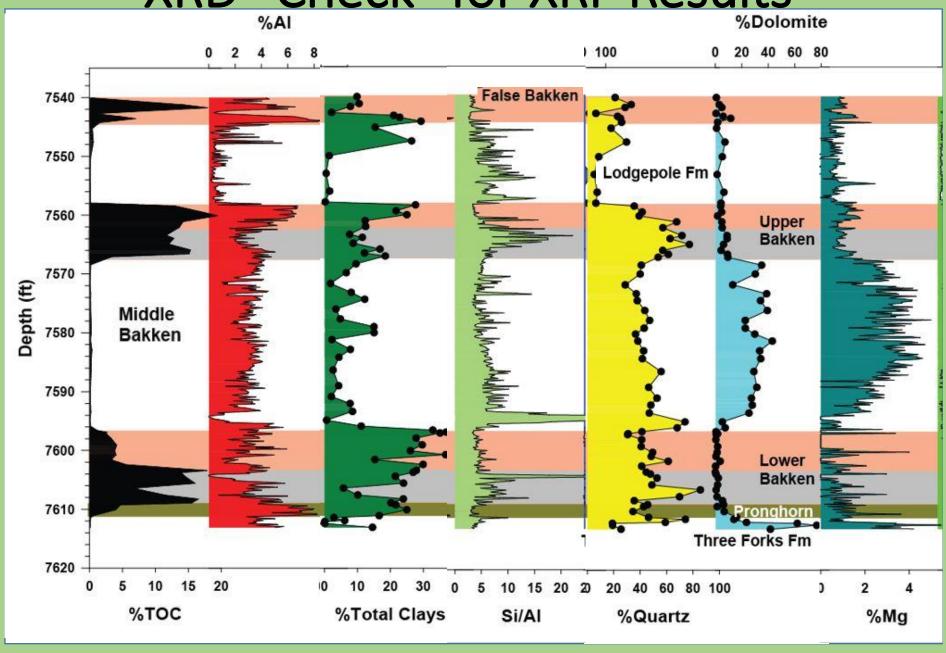
Ability to correlate from well to well

Already have this: well logs, but can be misinterpreted Interpretation can be based on many elemental signatures

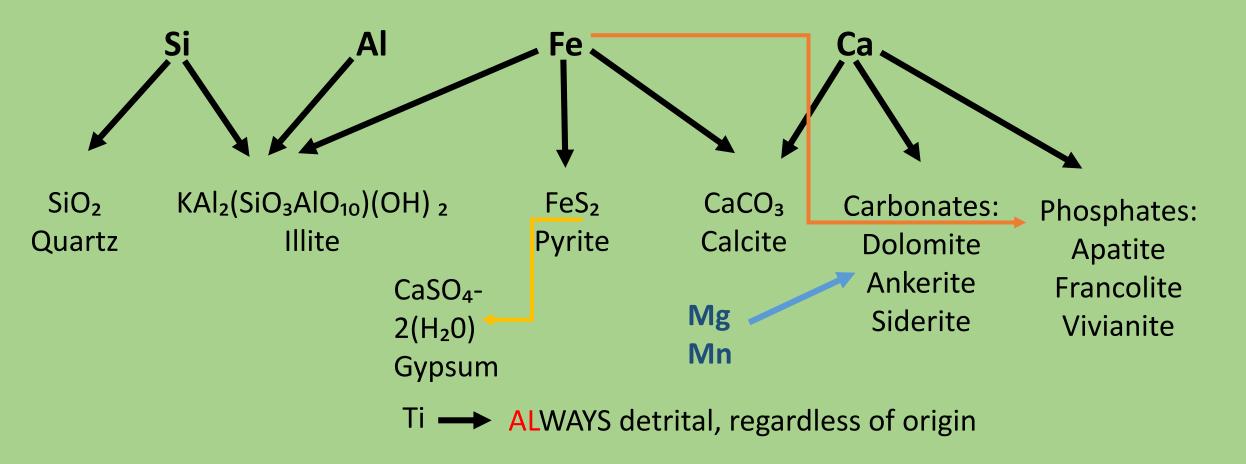
Stoichiometric "Check"



XRD "Check" for XRF Results



Mineral Model from XRF Data



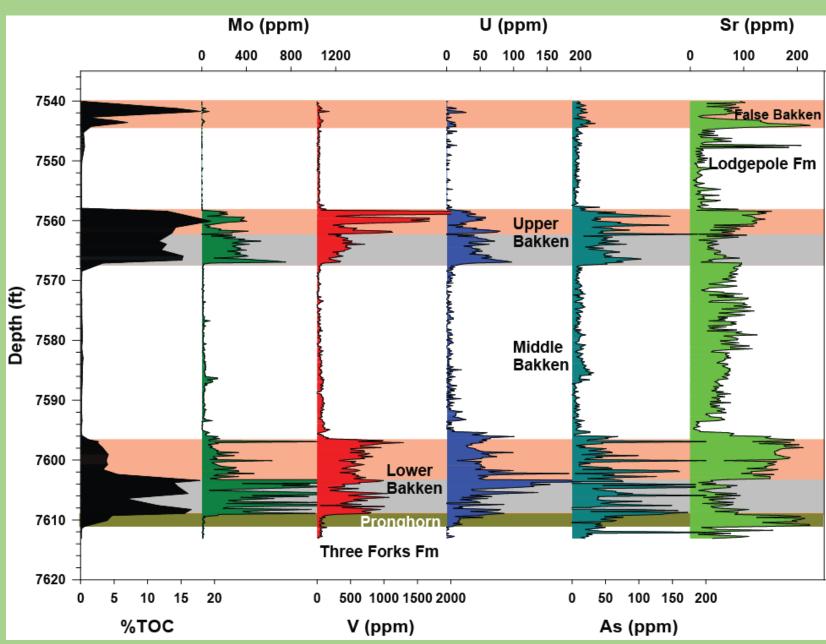
Other complications need to be considered such as mixed clays, feldspars and other sulfides...

Linking Trace Metals from XRF to TOC

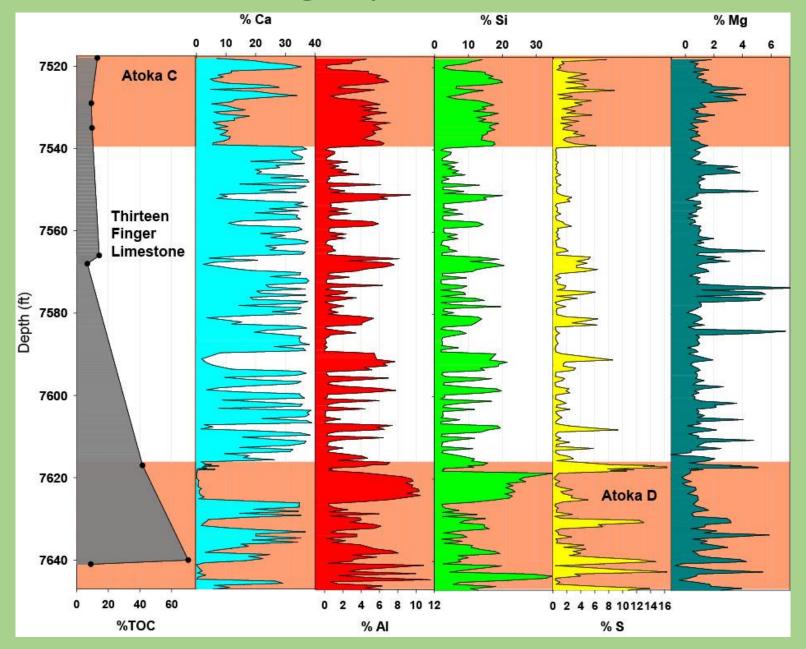
Redox sensitive trace elements can be linked indirectly to the total organic carbon content. (Co and Ni are other examples not shown here)

XRF is a great tool to pre-screen for areas with high TOC

Example shown here is from North Dakota Bakken core

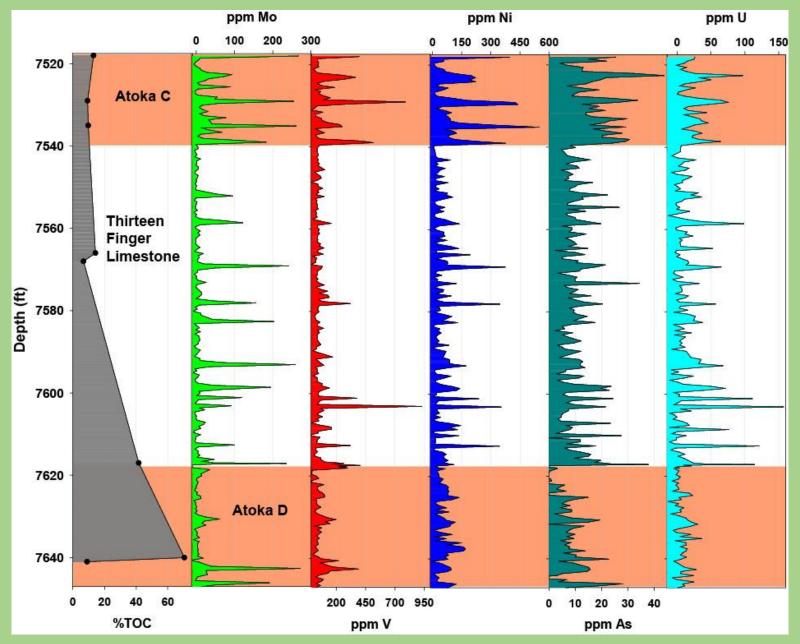


Linking Chemostratigraphic Datasets to Well Logs



Example from Anadarko Basin Core

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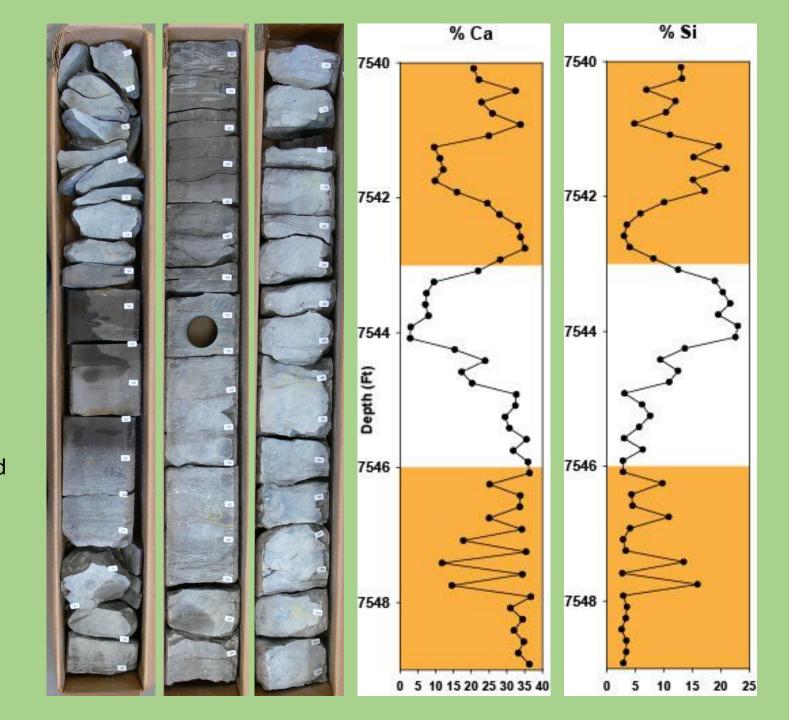
A Quantifiable Aspect of Geochemistry

Core description can be done much more quickly with the aid of elemental data

Observations are backed up by quantitative results

Link geological interpretations with empirical data

Easier to communicate with petrophysicists and engineers

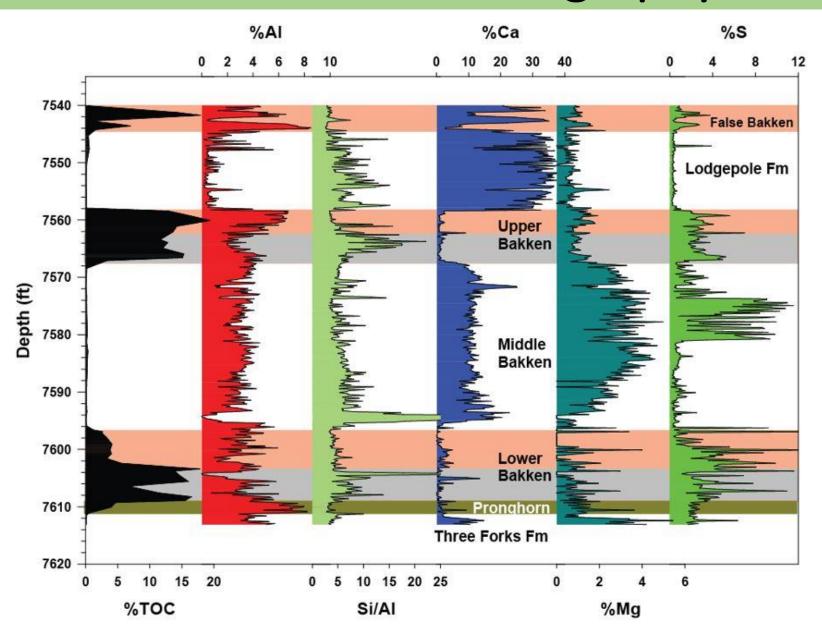


Bakken Chemostratigraphy

Highs in TOC denote Pronghorn Mbr, Lower Bakken, Upper Bakken, and False Bakken.

Lower and Upper Bakken can be subdivided using Si/Al (shift in biogenic silica content).

Si/Al ratio high in lowest Middle Bakken indicates occurrence of channel (high quartz).



Middle Bakken is more dolomitic, as is Three Forks (highs in Mg).

Lodgepole Ls is not dolomitic (%Ca values reaching almost 40%, indicating higher purity limestone.

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Already have this: well logs, but can be misinterpreted Interpretation can be based on many elemental signatures

Generate raw data and calibrate.

| Ni (ppm) | Cu (ppm) | Zn (ppm) | Ga (ppm) | As (ppm) |
|----------|----------|----------|----------|----------|
| 21 | 17 | 18 | 6 | 6 |
| 40 | 34 | 199 | 6 | 9 |
| 30 | 20 | 25 | 8 | 5 |
| 46 | 22 | 25 | 10 | 1 |
| 59 | 31 | 32 | 11 | 7 |
| 74 | 33 | 30 | 14 | 10 |
| 72 | 32 | 30 | 14 | 12 |

(Row Number) * + *

Developing Chemical Facies and Sub-Facies



Use knowledge gained to guide sampling locations and further analysis

Integrate with core descriptions, thin section work, logs, geomechanical properties...



Perform cluster analysis on the data – statistical method to partition multivariate observations into a number of meaningful homogenous groups

User must define number of clusters

Analyze the geochemical characteristics of the clusters, then provide descriptive name.

| SF Cluster | 24 |
|------------|-------|
| n | 32 |
| %P | 24.38 |
| Nb | 3.28 |
| U | 2.55 |
| Υ | 2.21 |
| %S | 2.15 |
| As | 2.09 |
| Со | 2.02 |
| Zn | 1.98 |

Phosphorus Ranked High Artifact? Phosphophile REE-like, Phosphophilic Sulfide enriched Chalcophile Chalcophile Chalcophile

Name: Chalcophilic/Sulfidic Phosphate

Partitioning Index (PI) and Naming of Clusters

| 1 | Cluster 1 | | Cluster 2 | | Cluster 3 | | Cluster 4 | | Cluster 5 |
|----------|-----------|----------|-----------|----------|-----------|----------|-----------|----------|-----------|
| %S | 2.31 | Y (ppm) | 2.28 | %Na | 1.67 | Zn (ppm) | 1.85 | Cu (ppm) | 2.11 |
| Mo (ppm) | 2.27 | %AI | 1.74 | Rb (ppm) | 1.55 | Ni (ppm) | 1.84 | Y (ppm) | 2.07 |
| As (ppm) | 2.20 | %K | 1.58 | Th (ppm) | | %Ca | 1.81 | Sr (ppm) | 1.91 |
| Ni (ppm) | 2.04 | %Ti | 1.49 | U (ppm) | 1.54 | Rb (ppm) | 1.78 | %Si | 1.87 |
| %Fe | 1.78 | Rb (ppm) | 1.48 | V (ppm) | 1.54 | %Ti | 1.49 | Mo (ppm) | 1.79 |
| %P | 1.75 | %Mg | 1.38 | As (ppm) | 1.54 | Ga (ppm) | 1.29 | Th (ppm) | 1.74 |
| V (ppm) | 1.74 | Th (ppm) | 1.34 | Mo (ppm) | 1.52 | U (ppm) | 1.23 | Nb (ppm) | 1.65 |
| U (ppm) | 1.63 | Zr (ppm) | 1.30 | Ni (ppm) | 1.44 | Pb (ppm) | 1.14 | %P | 1.63 |
| Ga (ppm) | 1.30 | %P | 1.17 | Nb (ppm) | 1.37 | %Na | 1.04 | Cr (ppm) | 1.57 |
| Cu (ppm) | 1.30 | Ga (ppm) | 1.13 | Ga (ppm) | 1.25 | V (ppm) | 0.92 | %Fe | 1.28 |
| Nb (ppm) | 1.29 | %Fe | 1.12 | %Fe | 1.02 | Nb (ppm) | 0.60 | %K | 1.24 |
| Co (ppm) | 1.29 | Nb (ppm) | 1.12 | Cu (ppm) | 0.89 | Th (ppm) | 0.56 | %Na | 1.22 |
| Th (ppm) | 1.24 | %Si | 1.11 | %Ti | 0.88 | Mo (ppm) | 0.53 | Pb (ppm) | 1.15 |
| Rb (ppm) | 1.13 | %Mn | 1.07 | Zr (ppm) | 0.86 | %P | 0.45 | %S | 1.14 |
| %K | 1.11 | %Na | 1.00 | %K | 0.85 | As (ppm) | 0.44 | Zr (ppm) | 1.03 |
| %Ti | 1.09 | Cr (ppm) | 1.00 | %Mn | 0.78 | %Si | 0.38 | %Mn | 0.92 |
| %Mg | 1.08 | As (ppm) | 0.98 | Co (ppm) | 0.72 | Sr (ppm) | 0.33 | U (ppm) | 0.91 |
| %AI | 1.06 | %Ca | 0.84 | Cr (ppm) | 0.70 | Zr (ppm) | 0.33 | Ga (ppm) | 0.76 |
| Zn (ppm) | 0.97 | U (ppm) | 0.76 | %S | 0.68 | %Fe | 0.31 | %Ca | 0.50 |
| %Si | 0.84 | Ni (ppm) | 0.75 | %AI | 0.66 | Cu (ppm) | 0.31 | %Ti | 0.48 |
| Pb (ppm) | 0.76 | Co (ppm) | 0.68 | Sr (ppm) | 0.57 | Y (ppm) | 0.22 | As (ppm) | 0.46 |
| Zr (ppm) | 0.74 | %S | 0.65 | %Si | 0.48 | %K | 0.18 | %Mg | 0.40 |
| %Mn | 0.72 | Sr (ppm) | 0.61 | Y (ppm) | 0.37 | %S | 0.17 | V (ppm) | 0.32 |
| Cr (ppm) | 0.62 | Cu (ppm) | 0.59 | %Ca | 0.23 | Cr (ppm) | 0.16 | Co (ppm) | 0.28 |
| %Ca | 0.61 | Zn (ppm) | 0.39 | Zn (ppm) | 0.16 | %Mg | 0.14 | Ni (ppm) | 0.13 |
| %Na | 0.59 | Mo (ppm) | 0.33 | Pb (ppm) | -0.15 | Co (ppm) | 0.09 | Rb (ppm) | 0.11 |
| Sr (ppm) | 0.56 | V (ppm) | 0.18 | %P | -0.20 | %Mn | 0.03 | %AI | -0.42 |
| Y (ppm) | 0.55 | Pb (ppm) | -0.54 | %Mg | -1.65 | %AI | -0.20 | Zn (ppm) | -1.72 |

$$PI_{Element X} = \frac{avg in cluster}{avg in dataset}$$

Naming of cluster is initially based on elemental ranking (enrichment)

Partitioning Index (PI) and Naming of Clusters

| CARBONATES | ANOXIC/EUXINIC | DETRITAL | | PHOSPHATIC | SULFIDIC |
|------------|----------------|-----------|----|------------|----------|
| <u>Ca</u> | <u>Mo</u> | <u>Al</u> | Nb | <u>P</u> | 2 |
| Mg | U | Ti | Th | Ca | Fe |
| Sr | ٧ | K | Cr | U | As |
| Mn | Ni | Rb | Si | Υ | Co |
| | Cu | Zr | Fe | | |
| | Zn | Ga | Na | | |









Limestones Dolomites

Organic Matter
Phosphates
Sulfides

Clays
Quartz
Feldspars
Heavy minerals

Self-Explanatory

As Limestone
Zn Marl
Mo-U Anoxic-Euxinic
Mg Sulfidic
Agrillaceous Detrital

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Thank You