Continuous Mineral Mapping of Core Using Hyperspectral Imaging: Example from the Upper Cretaceous Austin Chalk Marathon 1 Robert Todd Core, Central Louisiana*

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Abstract

Hyperspectral imaging (HI) is a method of observing and enhancing geological rock properties that are not readily apparent visually. Originally developed for the mining industry, HI uses a combination of short-wave infrared light (SWIR) and long-wave infrared light (LWIR) to create a visual ‘map’ of the minerals on the surface of a core that respond to reflectance principles. HI, which requires no special preparation other than that the core be slabbed, clean, and dry, can be rapidly obtained and provides mineralogical and chemical results related to various energy emitted in wavelength spectrum by either halogen bulb reflectance (short-wave quantification) or heat reflectance spectra (long-wavelength quantification). We collected hyperspectral core imaging data of the Austin Chalk Robert Todd core in central Louisiana to obtain detailed, high-resolution mineralogical and textural information and investigate the application of hyperspectral imaging as an integrative tool. Digital HI-derived single mineral curves calibrated to X-ray diffraction (XRD) data were imported as curves to display mineralogical variations with depth alongside overlays showing the textural relationships of the mineralogical assemblages, rock typing models, X-ray fluorescence (XRF) data, and rock-mechanics data. We integrated the hyperspectral data with core description, thin-section, XRF and XRD to identify Milankovitch cycles and aid in quantification and property ‘up-scaling’ from SEM and thin-section scales to understand the mechanical stratigraphy.

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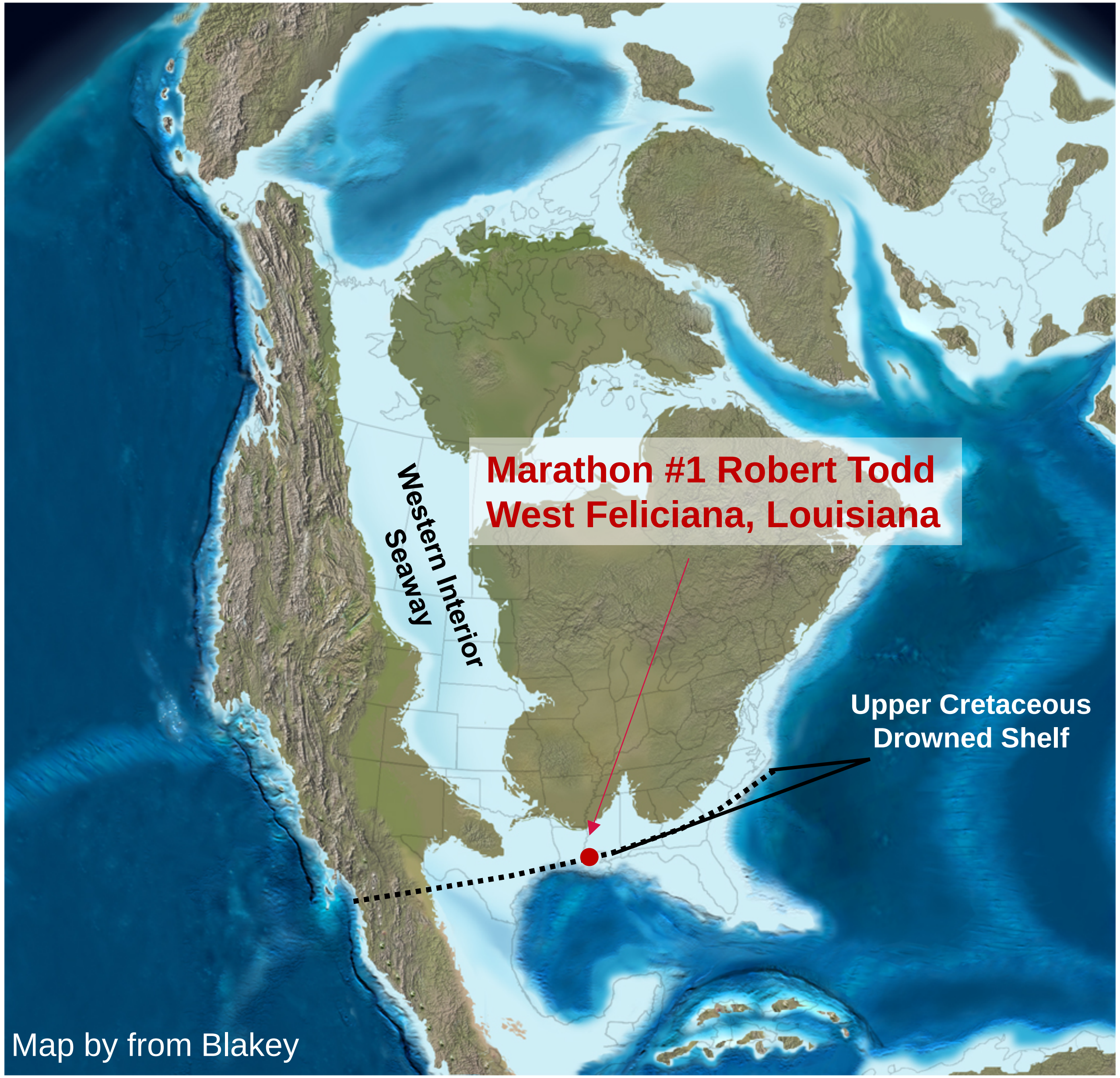
Case Study

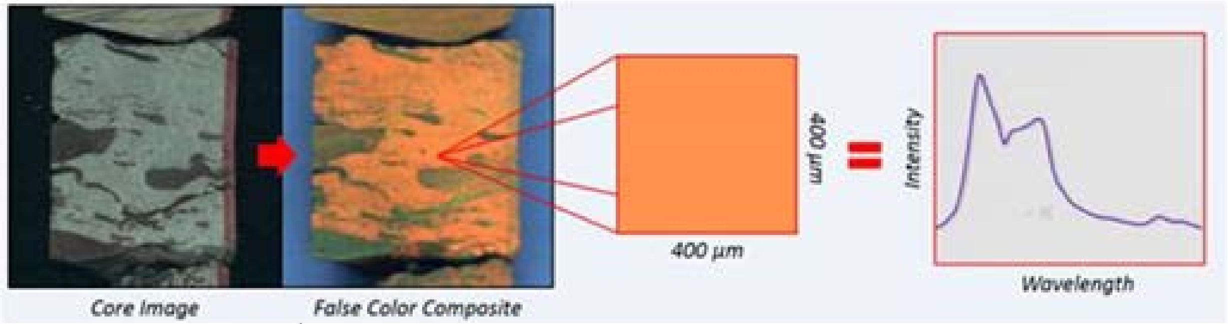
- We collected hyperspectral core imaging data of the Marathon 1 Austin Chalk Robert Todd core in central Louisiana to obtain detailed, high-resolution mineralogical and textural information and investigate the application of hyperspectral imaging as an integrative tool.

- Digital HI-derived single mineral and TOC curves calibrated to X-ray diffraction (XRD) and TOC data, respectively, were imported as curves to display mineralogical variations with depth alongside overlays showing the textural relationships of the mineralogical assemblages, rock typing models, X-ray fluorescence (XRF) data, TOC data and rock-mechanics data.

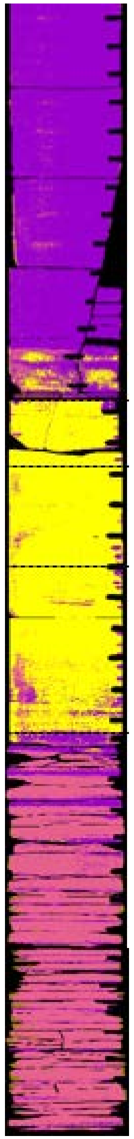


What is Hyperspectral Imaging?

- Hyperspectral core imaging is a non-destructive analytical technique
- Uses infrared light to produce a visual ‘map’ of the minerals in a core
- New long-wave infrared (LWIR) spectrometer: the first in the United States; contains a specialized lens to obtain data at a high resolution of 300-500 µm pixels
- LWIR measure responses from tectosilicates, carbonates and some clays, as well as hydroxides, sulfates and phosphates
- New short-wave infrared (SWIR) spectrometer: also uses a specialized lens for a high resolution of 300-500 µm pixels
- SWIR identifies carbonates, hydroxides, sulfates, hydrocarbons, other silicate minerals, and clays

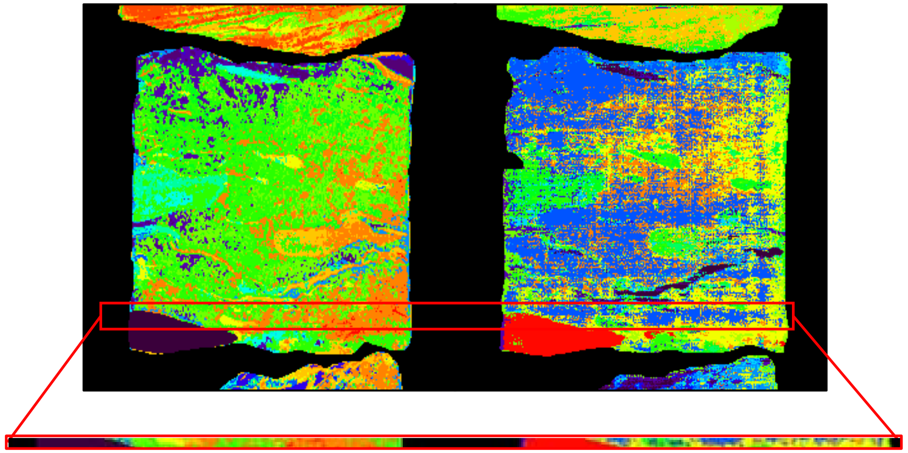


	Structure	Mineral Group	Example	VN IR Response	SWIR Response	LWI R Response
Silicates	Inosilicates	Amphibole	Actinolite	Non-Diagnostic	Good	Moderate
		Pvroxene	Diopside	Good	Moderate	Good
	Cvclosilicates	Tourmaline	Elbaite	Non-Diagnostic	Good	Moderate
	Nesosilicates	Garnet	Grossular	Moderate	Non-Diagnostic	Good
		Olivine	Forsterite	Good	Non-Diagnostic	Good
	Sorosilicates	Epidote	Epidote	Non-Diagnostic	Good	Moderate
	Phyllosilicates	Mica	Muscovite	Non-Diagnostic	Good	Moderate
		Chlorite	Clinochlore	Non-Diagnostic	Good	Moderate
		Clay Minerals	Illite	Non-Diagnostic	Good	Moderate
			Kaolinite	Non-Diagnostic	Good	Moderate
	Tectosilicates	Feldspar	Orthoclase	Non-Diagnostic	Non-Diagnostic	Good
			Albite	Non-Diagnostic	Non-Diagnostic	Good
		Silica	Quartz	Non-Diagnostic	Non-Diagnostic	Good
Non-Silicates	Carbonates	Calcite	Calcite	Non-Diagnostic	Moderate	Good
		Dolomite	Dolomite	Non-Diagnostic	Moderate	Good
	Hvdroxides		Gibbsite	Non-Diagnostic	Good	Moderate
	Sulphates	Alunite	Alunite	Moderate	Good	Moderate
			Gvpsum	Non-Diagnostic	Good	Good
	Borates		Borax	Non-Diagnostic	Moderate	Uncertain
	Halides	Chlorides	Halite	Non-Diagnostic	Uncertain	Uncertain
	Phosphates	Apatite	Apatite	Moderate	Non-Diagnostic	Good
	Hvdrocarbons		Bitumen	IUncertain	Moderate	Uncertain
	Oxides	Hematite	Hematite	Good	Non-Diagnostic	Non-Diagnostic
		Spinel	Chromite	Non-Diagnostic	Non-Diagnostic	Non-Diagnostic
	Sulphides		Pvrite	Non-Diagnostic	Non-Diagnostic	Non-Diagnostic

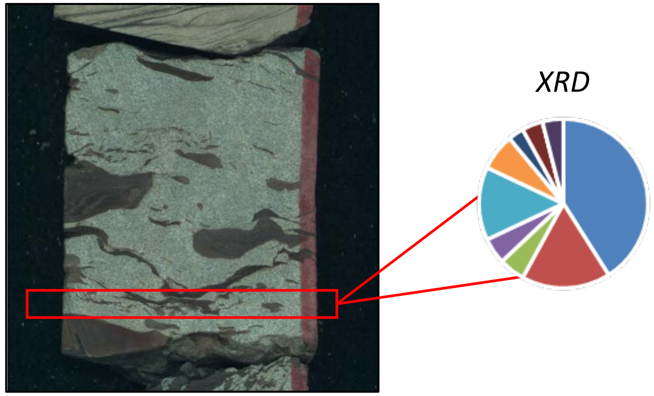


Single Mineral Logs

- Objective approach to extracting single mineral components from multi-mineral spectra
- Different composition and textural attributes contribute to different spectral responses → self-organizing map (SOM) classes represent different rock compositions and textures
- Determine relationships between SOM classes and known composition (XRD) → predict mineralogy
- A similar approach was used to produce a continuous TOC curve from discrete TOC data



9,875.45 ft = 17% LWIR Class 1, 3% SWIR Class 1, etc.



9,875.45 ft = 38% Quartz, 17% Illite, 5% Kaolinite, etc.

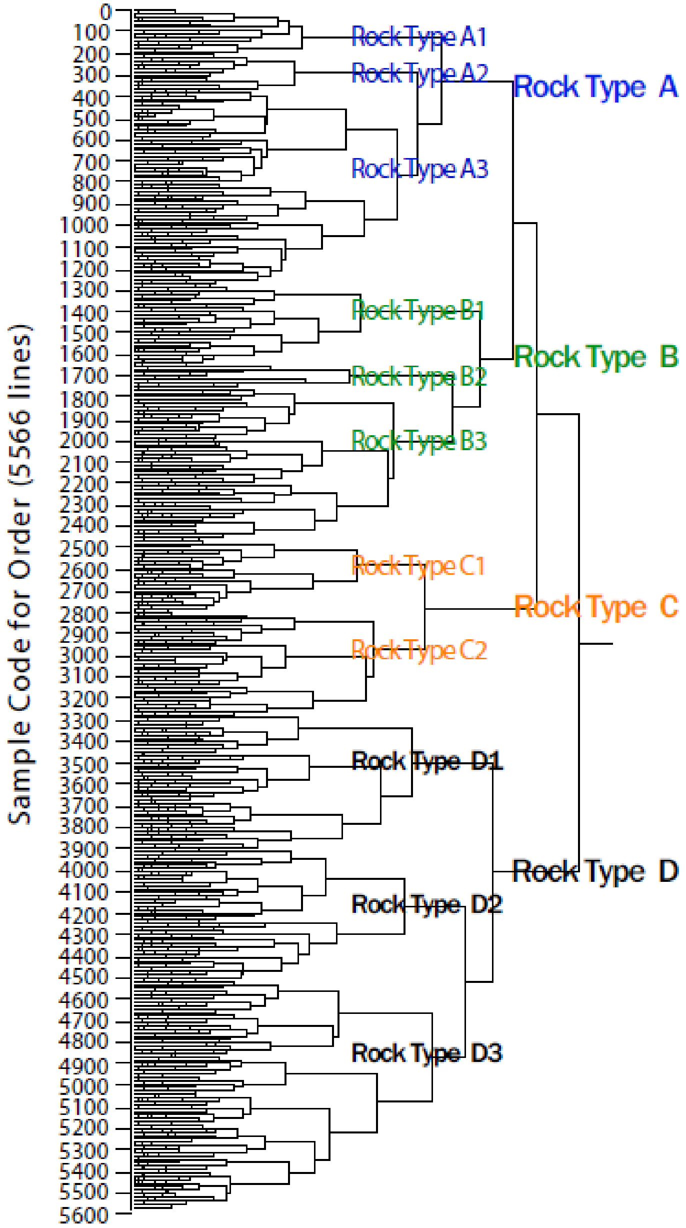
Rock typing

Cluster analysis was performed on the raw, uninterpreted hyperspectral imaging SOM data to obtain rock types

Robert Todd

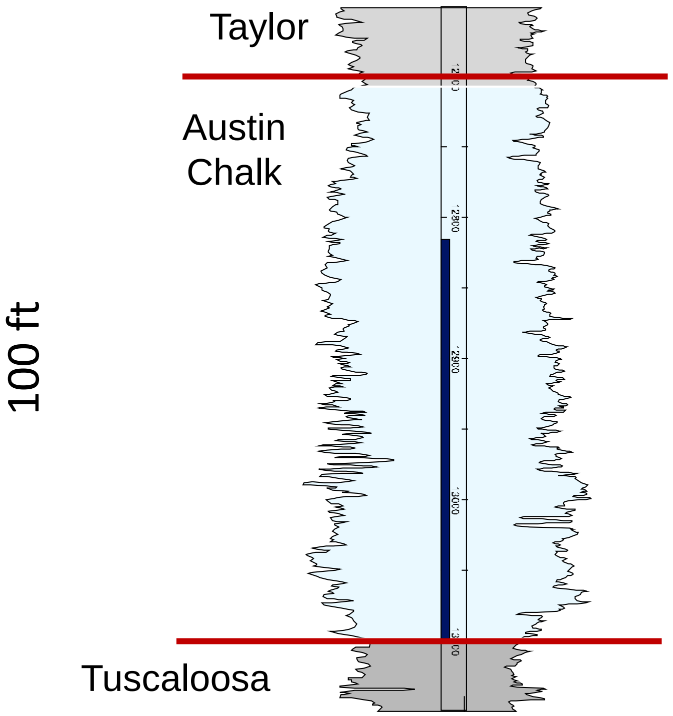
Cluster using Hyperspectral Imaging "Class" data

(for rock typing)

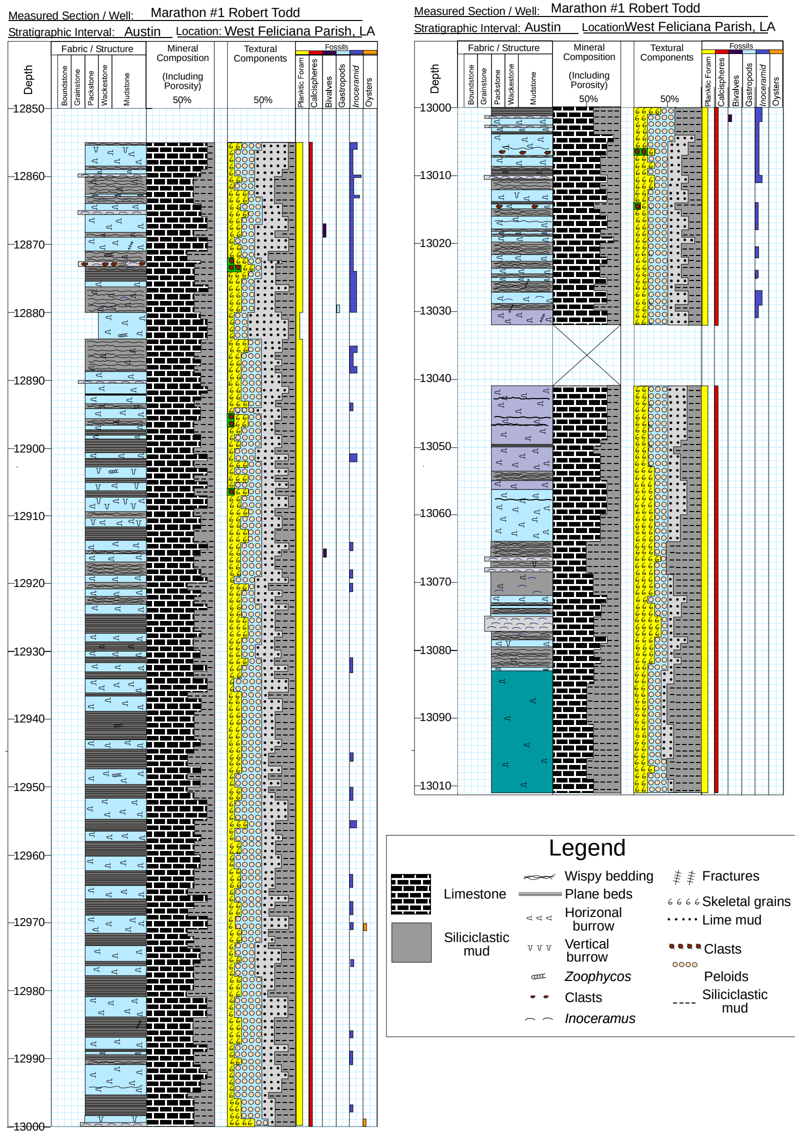


Stratigraphic Section and Core Description

Marathon #1 Robert Todd
West Feliciana Co., Louisiana



Marathon
#1 Robert Todd
West Feliciana,
Louisiana
245 ft of core



- Section displays abundant aerobic to anaerobic cycles
- Of the cored section, 66% is anaerobic and high TOC

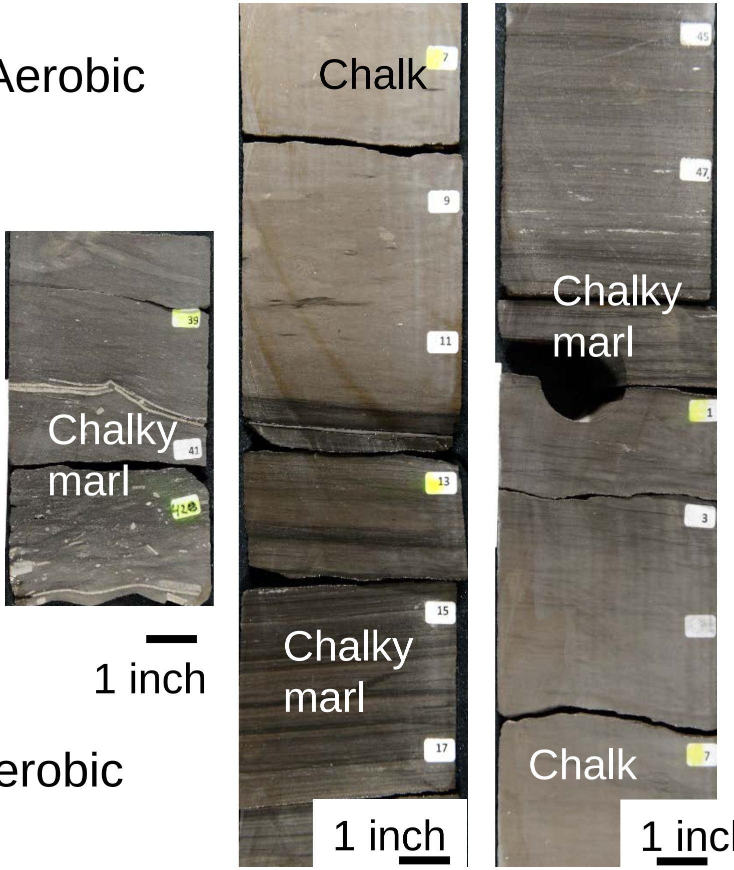
Lithofacies

Marathon #1 Robert Todd
West Feliciana Co., Louisiana

- The chalk environment of deposition is aerobic and chalky marls are anaerobic
- Carbonate productively is believe to be the variable with siliciclastic sediment being relatively constant
- Chalks have very Low TOC (~0.24%) whereas chalky marls have moderate to high TOC (~1.4%)

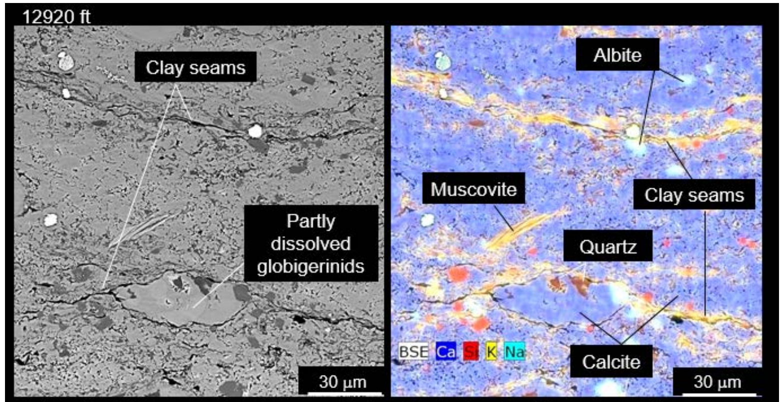
Aerobic

Anaerobic



Chalky marl

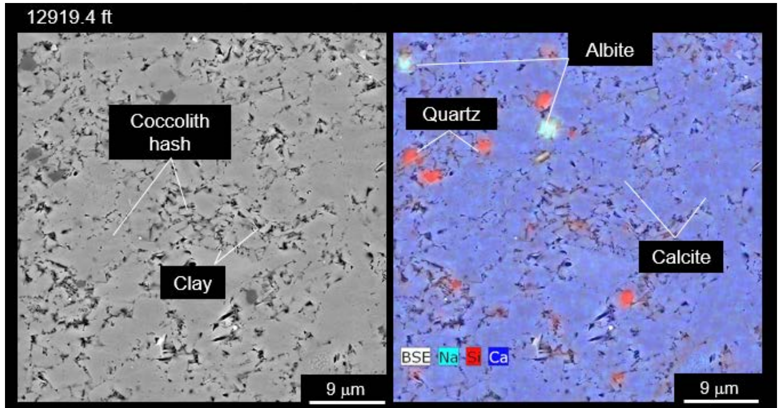
Anaerobic



- Argillaceous and organic laminae (mats) in coccolith matrix
- Carbonate = 85.4%, Quartz/feldspar = 7.0%, Clay = 7.6%
- TOC = 1.83%

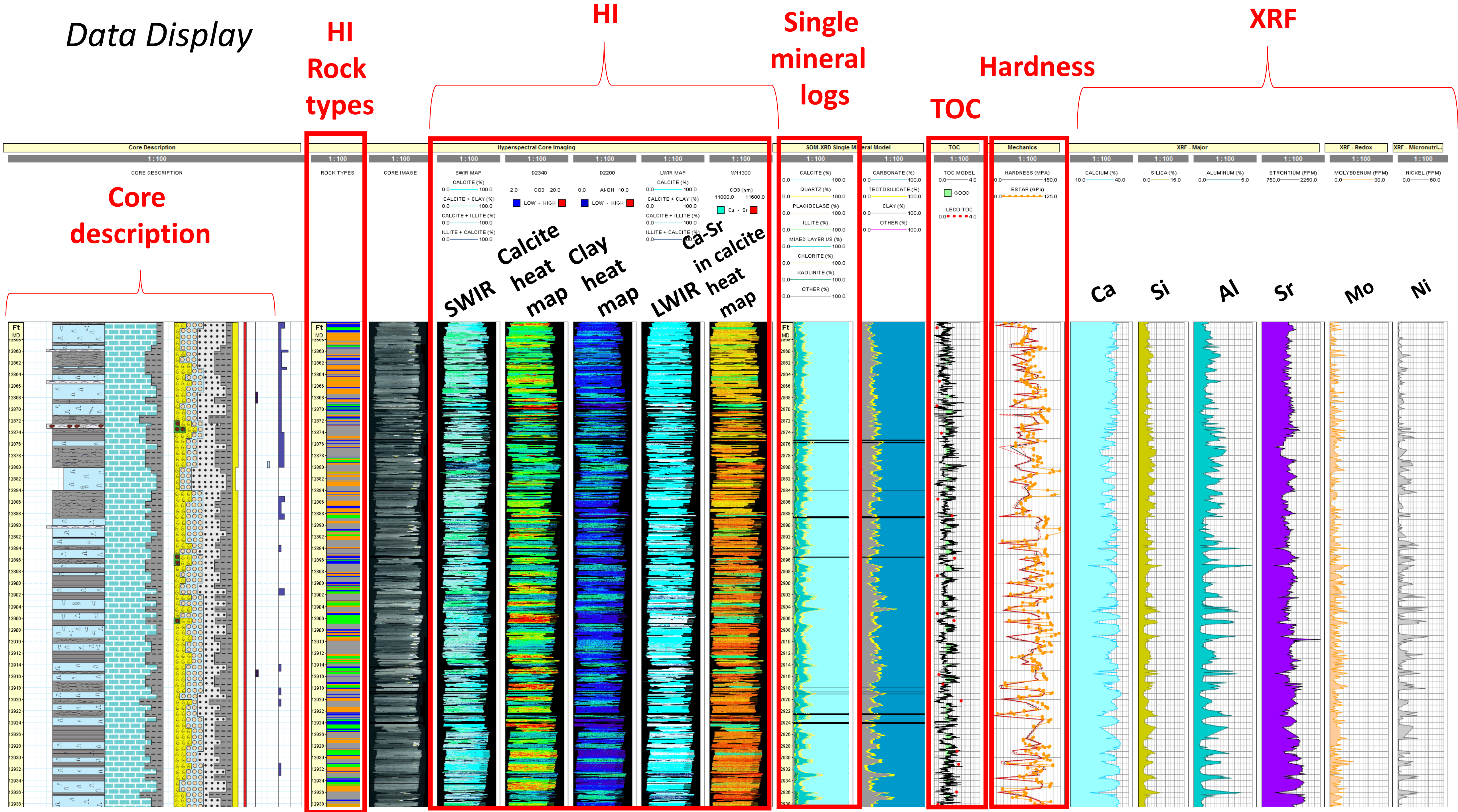
Chalk

Aerobic

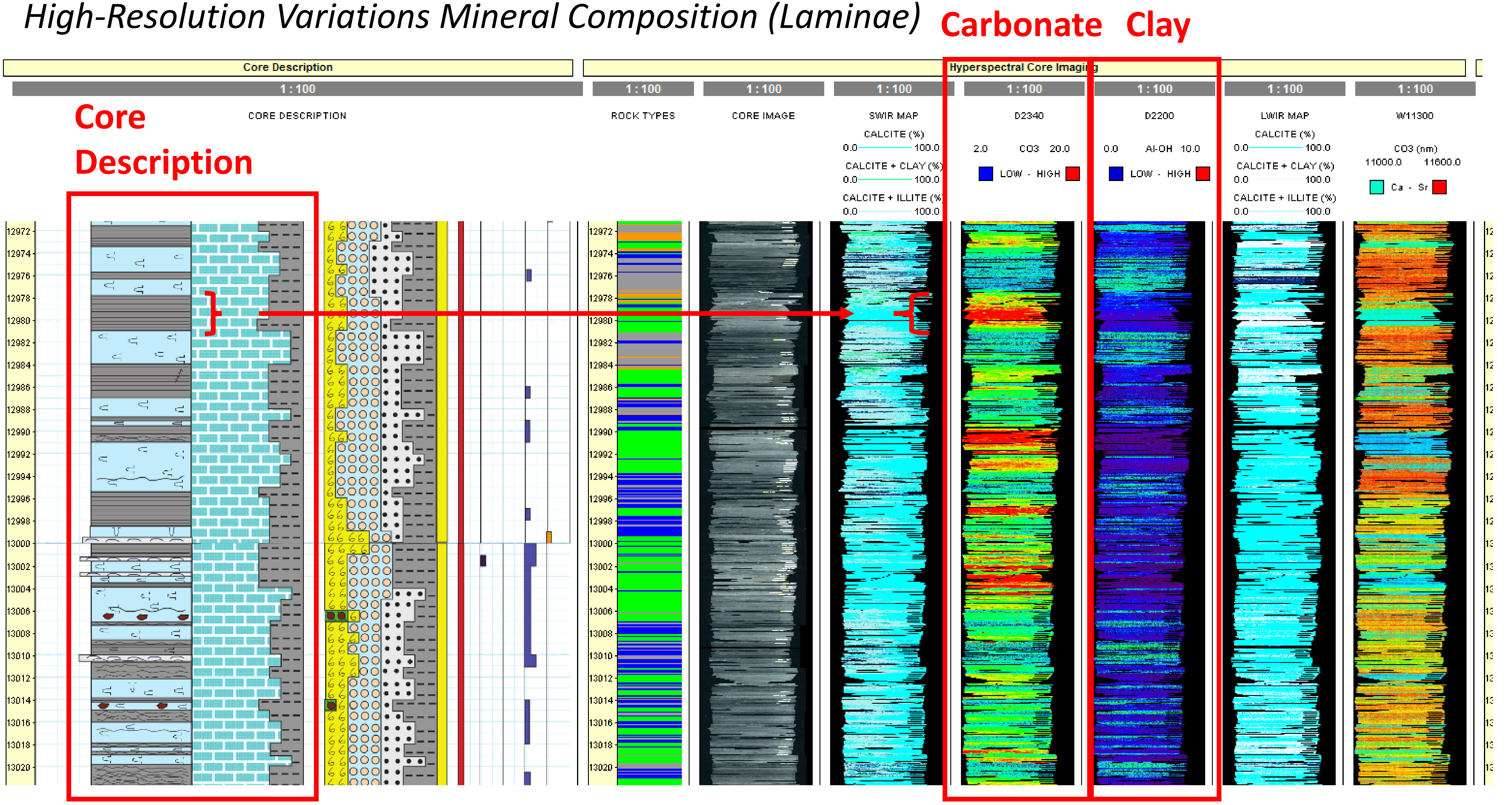


- Quartz and albite silt in cemented coccolith matrix
- Carbonate = 95.4%, Quartz/feldspar = 2.8%, Clay = 1.8%
- TOC = 0.20%

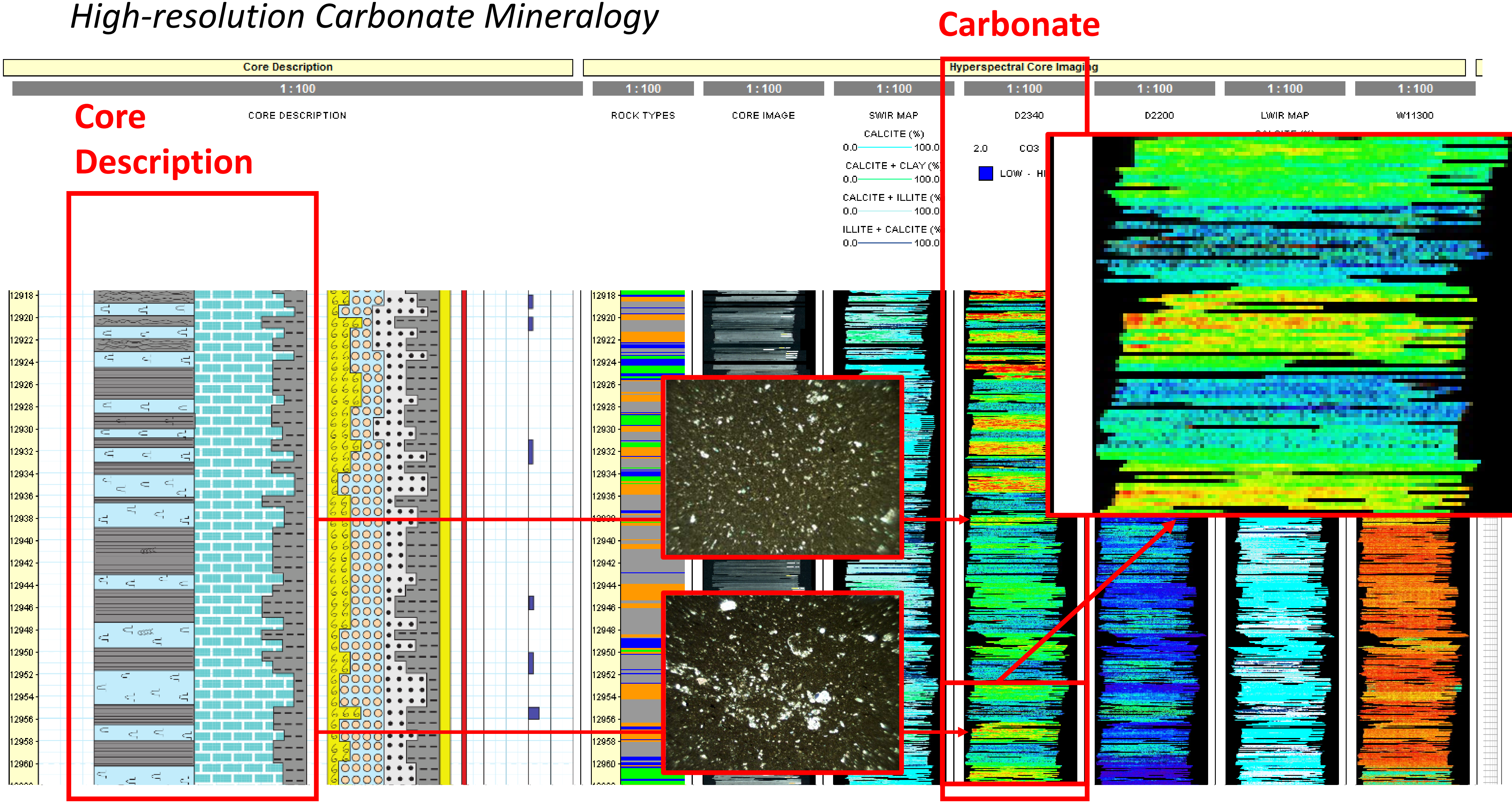
Data Display



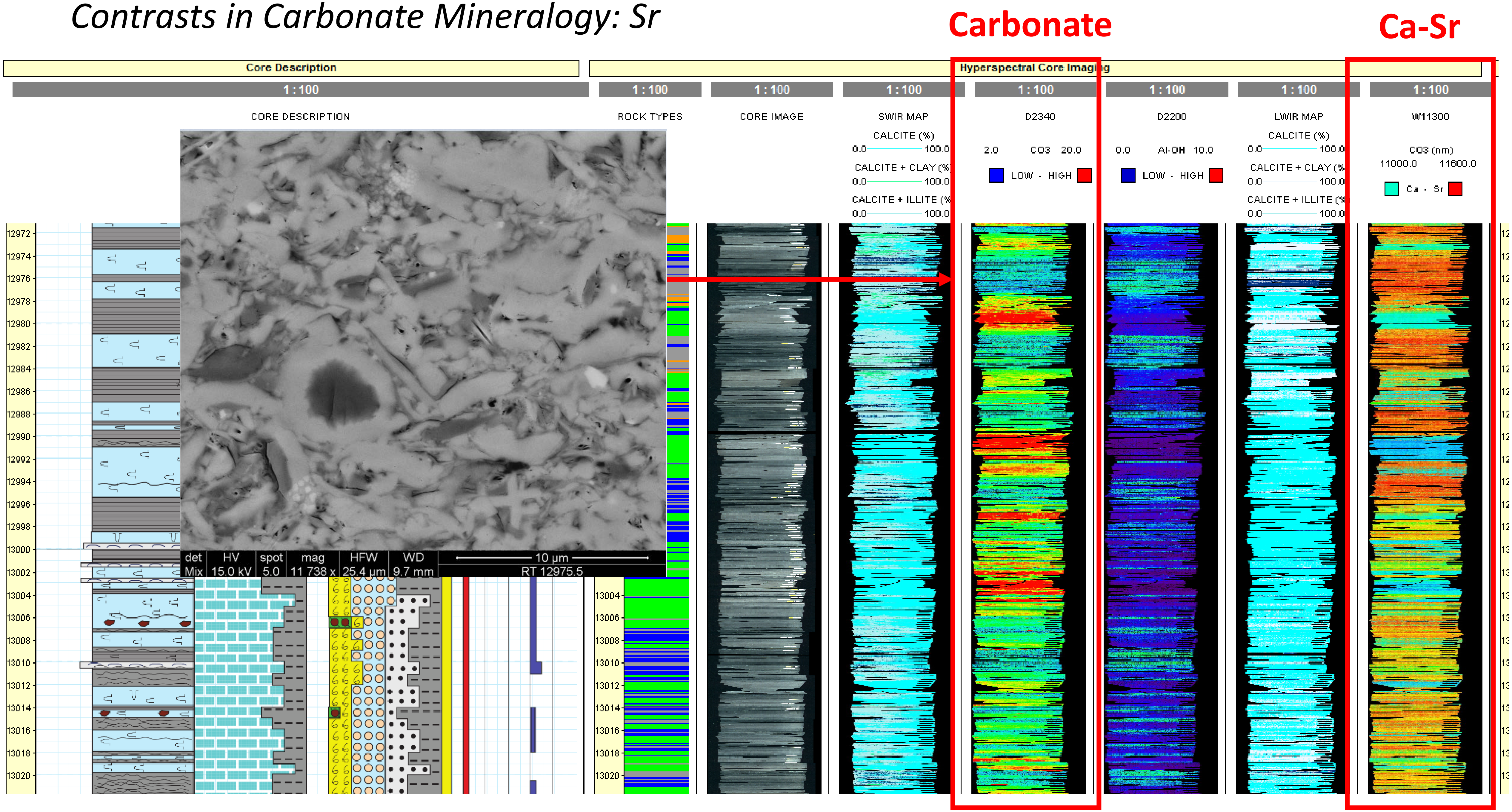
High-Resolution Variations Mineral Composition (Laminae)



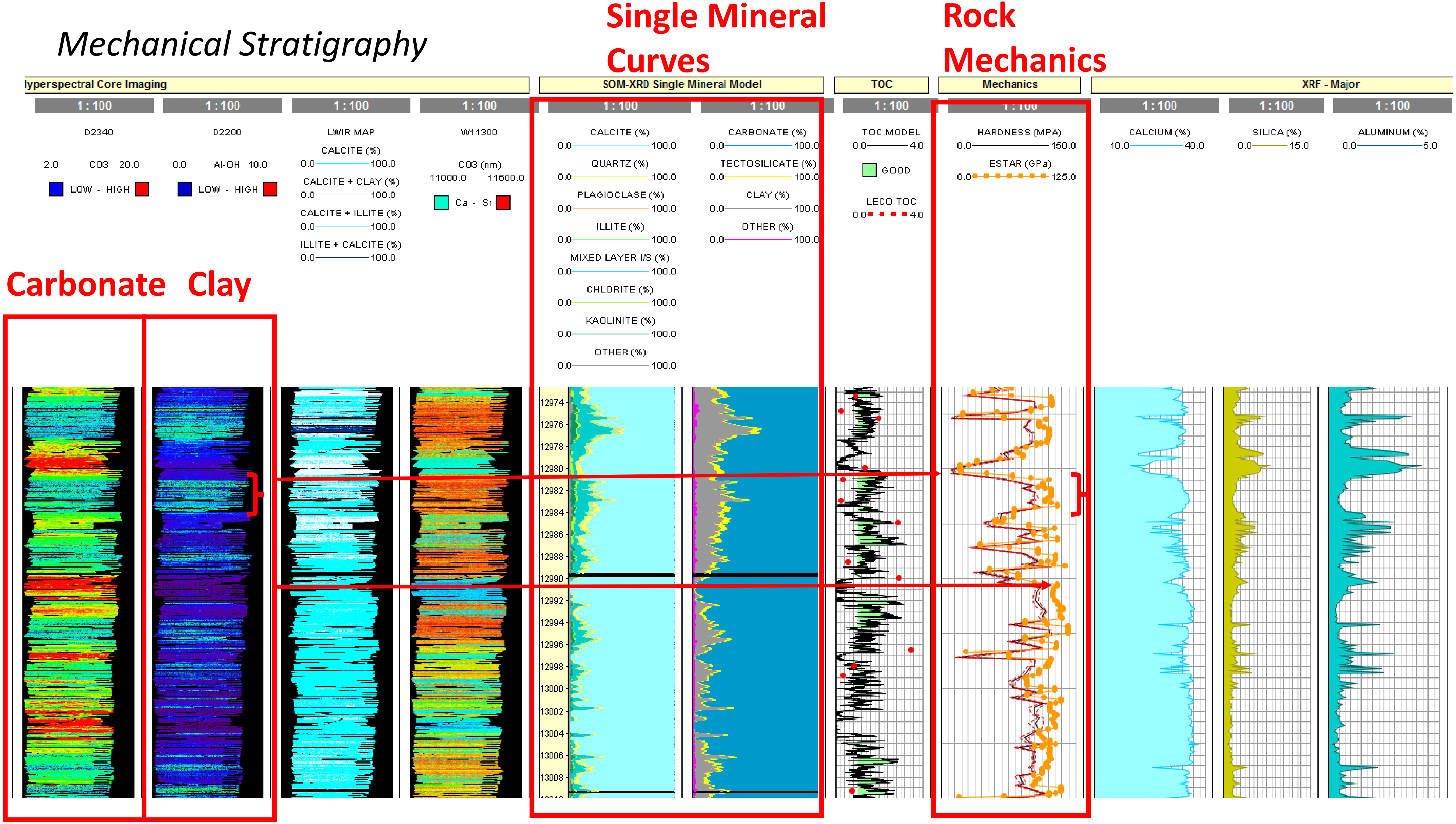
High-resolution Carbonate Mineralogy

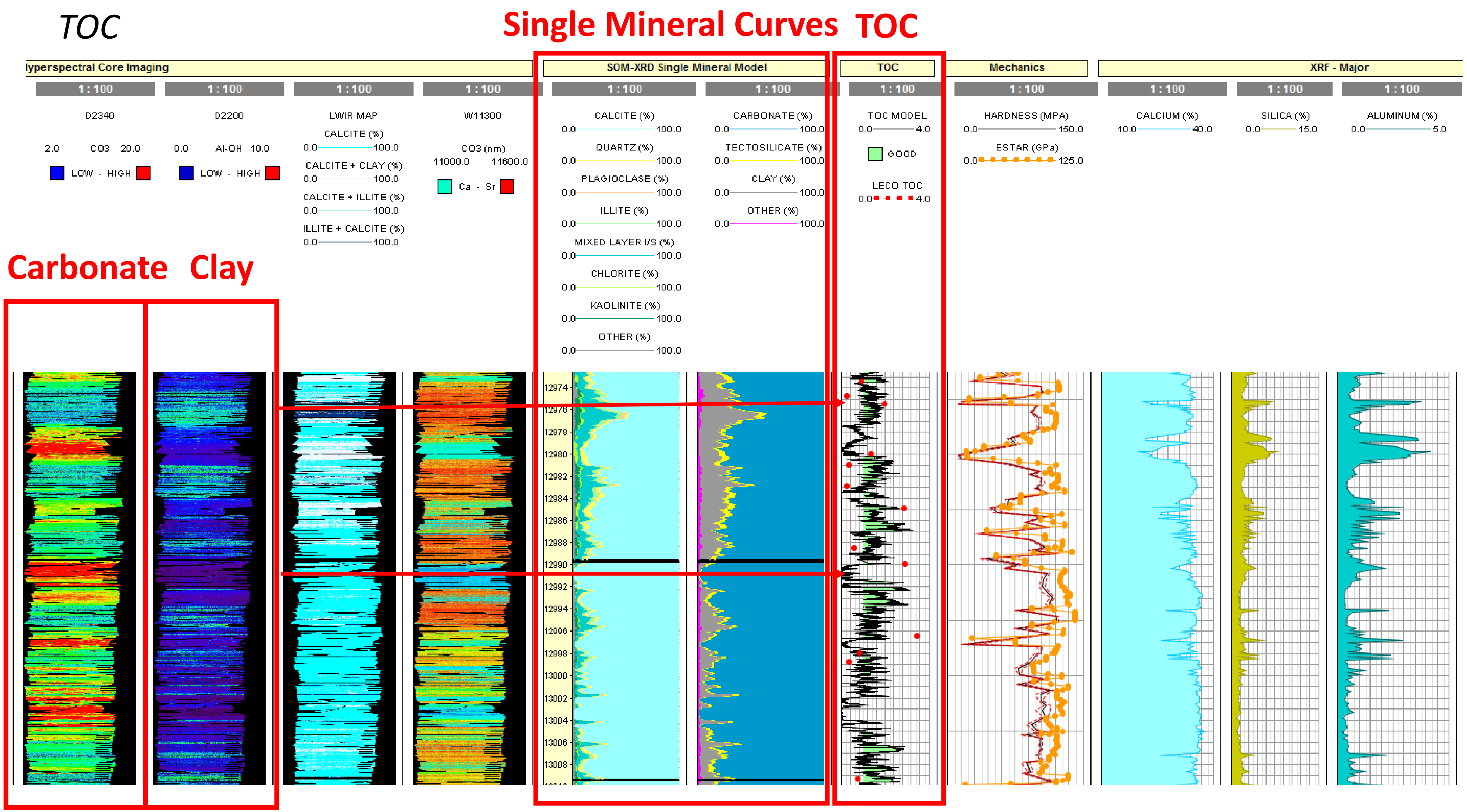


Contrasts in Carbonate Mineralogy: Sr



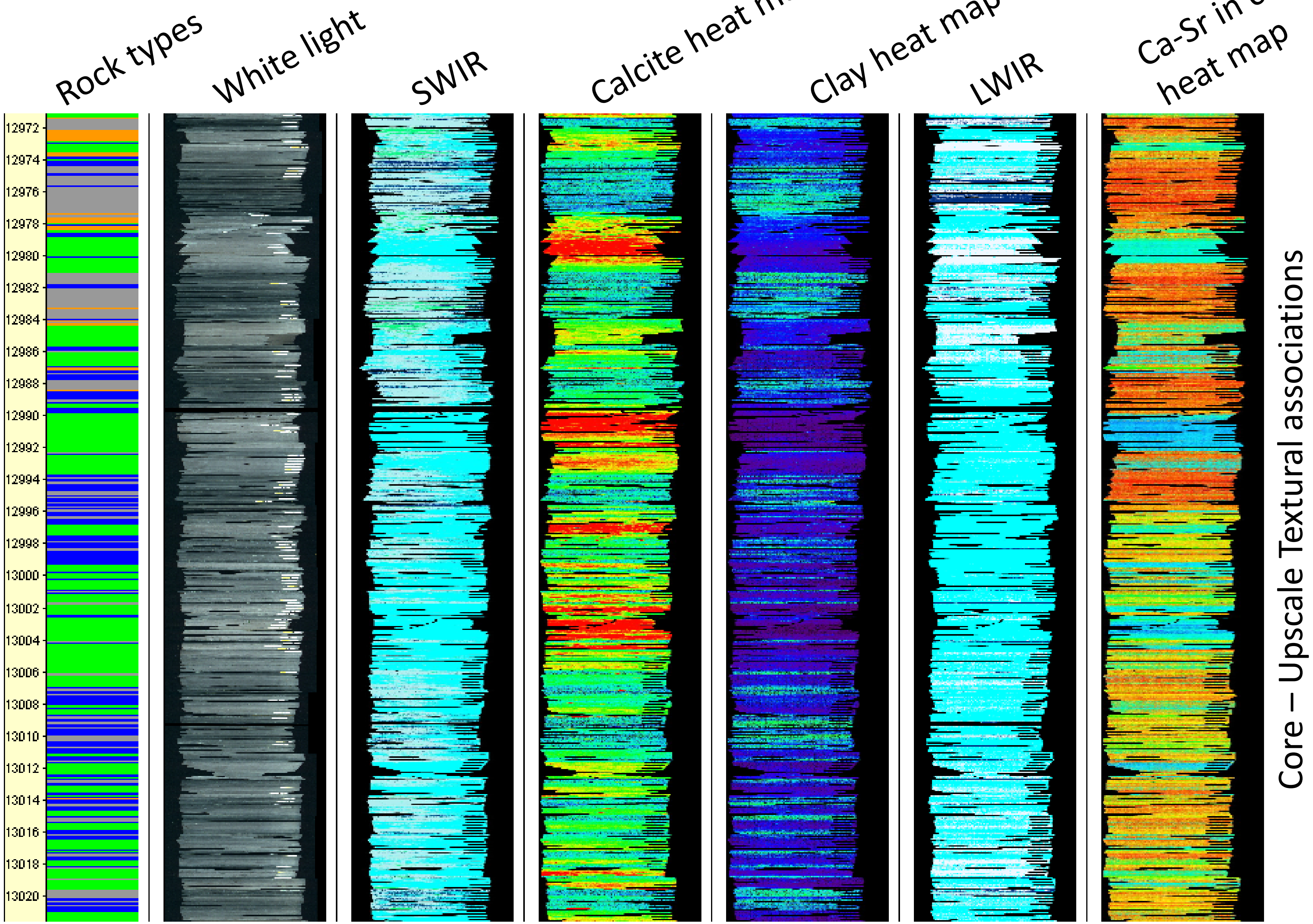
Mechanical Stratigraphy



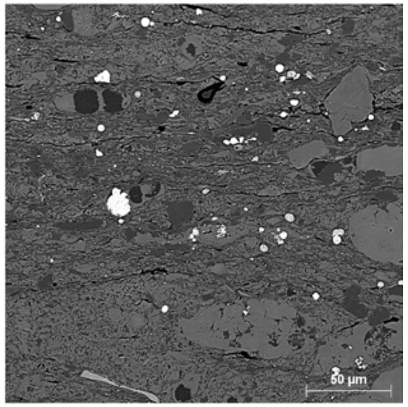


TOC
Single Mineral Curves
TOC
Carbonate
Clay
lyperspectral Core Imaging
SOM-XRD Single Mineral Model
TOC
Mechanics
XRF - Major
1 : 100
D2340
2.0 CO3 20.0
LOW - HIGH
D2200
0.0 Al-OH 10.0
LOW - HIGH
LWIR MAP
CALCITE (%)
0.0 100.0
CALCITE + CLAY (%)
0.0 100.0
CALCITE + ILLITE (%)
0.0 100.0
ILLITE + CALCITE (%)
0.0 100.0
W11300
CO3 (nm)
11000.0 11600.0
Ca - Sr
CALCITE (%)
0.0 100.0
QUARTZ (%)
0.0 100.0
PLAGIOCLASE (%)
0.0 100.0
ILLITE (%)
0.0 100.0
MIXED LAYER I/S (%)
0.0 100.0
CHLORITE (%)
0.0 100.0
KAOLINITE (%)
0.0 100.0
OTHER (%)
0.0 100.0
CARBONATE (%)
0.0 100.0
TECTOSILICATE (%)
0.0 100.0
CLAY (%)
0.0 100.0
OTHER (%)
0.0 100.0
TOC MODEL
0.0 4.0
GOOD
LECO TOC
0.0 4.0
HARDNESS (MPA)
0.0 150.0
ESTAR (GPa)
0.0 125.0
CALCIUM (%)
10.0 40.0
SILICA (%)
0.0 15.0
ALUMINUM (%)
0.0 5.0
12974
12976
12978
12980
12982
12984
12986
12988
12990
12992
12994
12996
12998
13000
13002
13004
13006
13008

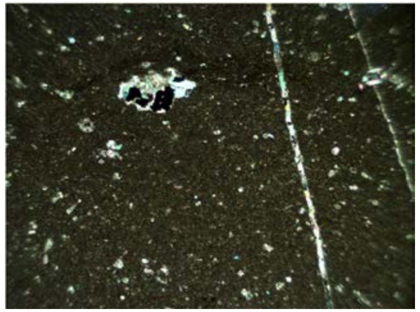
Upscaling



SEM – Pore Scale



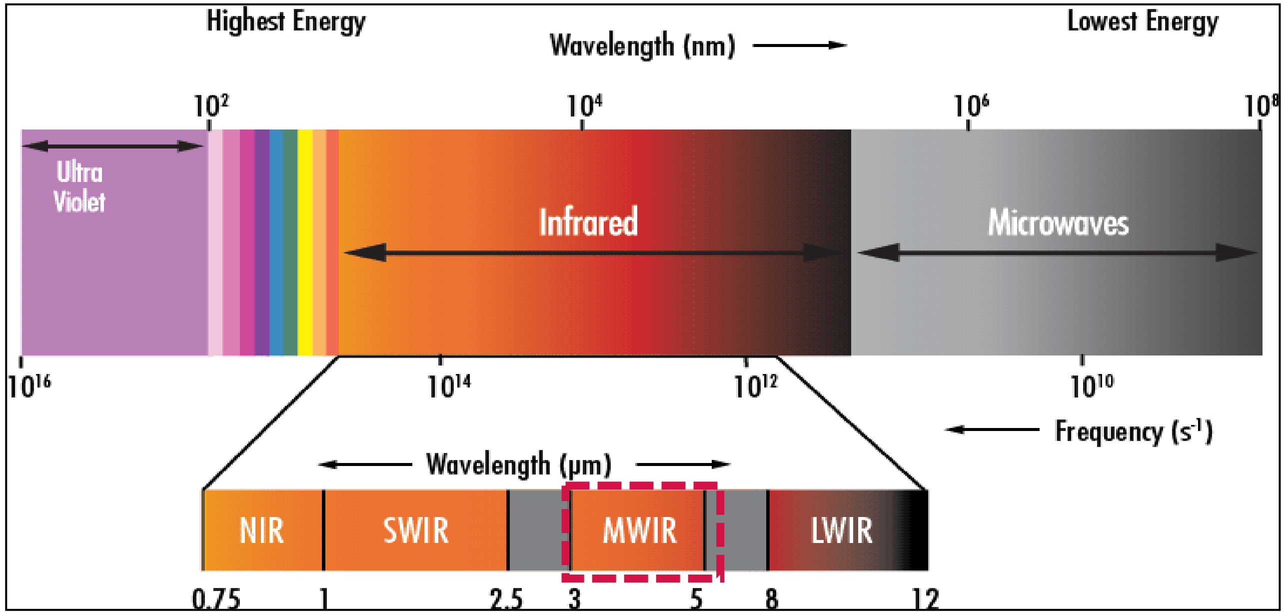
Thin section - Texture



Accurate representation of pore- and textural-scale heterogeneity to the depositional (cyclic) scale is aided by hyperspectral imaging.

Conclusions

- Hyperspectral imaging provided detailed, high-resolution mineralogical and textural information of a whole core from the Austin Chalk.
- Interpreted SWIR and LWIR data identified textural associations not visually identified or distinguished by the human eye, especially in dark core such as the Austin Chalk.
- Can be utilized to display mineralogical variations with depth alongside mechanical data to understand mechanical stratigraphy.
- Reveals a relationship between total organic content and mineralogy and identification of ‘sweet spots’.
- Accurate representation of pore- and textural-scale heterogeneity to the depositional (cyclic) scale is aided by hyperspectral imaging.
- This technique adds a wealth of data that other methods are unable to provide because of time and cost.
- Future work will include evaluation of the mid-range infrared spectra (MWIR) to identify minerals and hydrocarbons in cores from unconventional resources.



Acknowledgments

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