Emerald's approach and workflow for Prediction of unconventional reservoir sweet spots

The comprehensive evaluation of unconventional shale oil and gas plays, shale or tight, requires a great understanding of factors controlling both reservoir sweet spot's locations and prediction of their key attributes. Geological elements include depth, thickness, porosity, lithology, lateral and stratigraphic distribution, depositional environments, fractures orientation and density, hydrocarbon saturation, brittleness, TOC content, TOC maturity, type of hydrocarbon generated, and, ultimately, the oil and/or gas in place. Engineering factors consider stress, pressure, fracture distribution, brittleness, and anisotropy, storage capacity, which assist in well drilling/completion and production.

Our workflow combines multi-disciplinary, multi-scales, and multi-layers of interpreted data/maps that allow competent and intelligent exploration/prediction of sweet spots and comprehensive characterization of shale oil and gas reservoirs.

1. Most shale sweet spot parameters (e.g., TOC content, maturity, mineral constituents, brittleness, and faults orientation …) are reliant on laboratory measurement, well-logging data, and seismic. In addition, many of key geological elements (e.g., depositional environments, thickness, porosity, fractures orientation and discontinuities …) need to be interpreted by competent domain experts and simply cannot be predicted by machine learning and artificial intelligence (AI), especially if unsupervised.

2. Geochemical analysis offers key information on TOC content, type of source rock and its maturity; but since this geochemical analysis are only done for a fraction of drilled wells, **we have automated the determination of TOC and thickness from logs** using a modified Passey et al. (1995) ΔlogR technique and GR/Rt techniques. After calibration with lab data in a well where geochemical analysis was previously performed, we calculate the TOC in any well that have log data (GR, Resistivity, Sonic and/or Density). Therefore, not only we can estimate quite accurately the TOC in the well but more importantly **identify the horizons that have source rock potential and their respective thicknesses**.

3. Based on the comprehensive analysis, interpretation, and modeling of geochemical data, we automated a rigorous and very smart workflow to allow rigorous Resources/Reserves estimates of oil and gas expelled and retained within the source rock and adjacent associated tight beds of sandstone/siltstone or carbonate where very early hydrocarbon migration went to. We estimate the oil or gas retained within the source rock and associated tight beds of each analyzed well that have geochemical data *(TOC, S1, S2, S3, HI, and maturity proxy (Tmax, Vitrinite, and or SCI)*. Our methodology was inspired by Jarvie's (2007) and Talukdar (2010) (our paper Madi J.A. & Belhadj E.M., 2015. SPE-172966-MS. https://doi.org/10.2118/SPE-172966-MS) published in Society of Petroleum Engineers. Since then, we have revisited completely our work to address all types of source rocks, geological contexts, elaborated modeling of key parameters to stick as much as possible to the geological setting and source rock type…

4. Gas chromatography analysis of mud gas while drilling assists the identification of pay-zones in conventional reservoirs and (unconventional) tight plays. (a) it does give a strong indication of the type of hydrocarbon present in reservoirs and source rocks; (b) indicate the maturity of these hydrocarbon and source rocks; and (c) identify a Tight Oil/Gas Play when a given bed, with lithology closer to a reservoir than a source rock, shows "higher TOC values" and higher mud gas readings…

5. To better identify a tight oil play, we are finalizing a workflow to predict lithology, which starts from a lithofacies classification based on minerals content and rock/mineral physics, and then set up an estimate of their logs' response, focusing mainly (for now) on key parameters (GR, PEF, Resistivity, Sonic, Density, Neutron). In conjunction with multi-scale information such as geology and logging, we use AI machine learning to calculate the correlation degree between training samples and target of prediction, which can be used to judge the contribution value of each attribute.