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**Statistical Analysis And Chemostratigraphy Of The Lower Rus Formation,
Eastern Saudi Arabia: Implications For Chemosteering In Dolomite
Reservoirs**

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ABSTRACT

Conventional stratigraphic correlation using well logging data provides constraints to geo-steer directional drilling. However, this method has limitations when drilling in thinly bedded and highly heterogeneous reservoirs, which is the case of many carbonates in the Middle East. One alternative approach that has provided cheap, quick, and real-time prediction is geochemical steering (chemo-steering). The improvement of geochemical data, therefore, for chemo-steering to build accurate forward statistical geochemical models that predict and classify lithofacies help optimize hydrocarbon production using directional drilling. In this study, we examine the viability of using forward statistical geochemical models to differentiate between two thin, interbedded, and compositionally similar but significantly different petrophysical properties beds in the Lower Rus Member of the Rus Formation, Dhahran, eastern Saudi Arabia. These two beds mainly comprise dolomites with minor calcite and quartz, chert nodules, and accessory minerals - with varying proportions of constituents between the two lithofacies. These two beds show different pore system and porosity values based on laboratory results. Advanced statistical techniques (principle component analysis, factor analysis, and logistic regression modeling) applied to elemental and mineralogical data of these two beds provided proxies to differentiate between the better reservoir bed geochemically. Methods and results of this study can be used to distinguish between flow zones in dolomite reservoirs in subsurface in such complex strata elsewhere in similar settings.

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EXTENDED ABSTRACT

Introduction

Currently, due to the real-time monitoring nature of geosteering – to keep the drilling within the targeted producing interval -alternative methods that offer cheap, quick, and real-time prediction were applied to precisely detect lithological variations and identify reservoir layers. According to Estarabadi et al. (2013) and Carpenter (2015), one of the alternative methods that has satisfied these requirements is geochemical geosteering as it has a high sensitivity to compositional changes and, therefore, can efficiently guide drilling trajectory through reservoir layers according to the detected geochemical signals.

In this framework, this research aims to build forward statistical geochemical models for strata in the Lower Rus Formation, Dhahran, eastern Saudi Arabia to aid in accurately quantifying and predicting the chemical properties of two compositionally similar lithofacies. These two lithofacies mainly comprise dolomites with minor calcite and quartz occurring as geodes, chert nodules, and accessory minerals. Moreover, based on laboratory results, both lithofacies show exceptional reservoir properties. However, the two lithofacies display highly contrasting textures in the outcrop. The recessive (relatively soft and easily eroded) strata have better reservoir properties than the resistive (relatively hard and hardly eroded) strata. Although the petrophysical attributes of the studied outcrop would collectively represent, if preserved, a reservoir interval in the subsurface, the success of using forward statistical geochemical models in differentiating between the two compositionally similar lithofacies will imply that it is a reliable guide for geosteering even for highly intricate successions.

Tectonic settings

The Early Eocene Rus Formation constitutes the central part of the NW-SE trending Dammam Dome of Dammam Peninsula, eastern Saudi Arabia. The exposed part of the Dammam Dome is comprised of gently dipping strata (average slope $< 2^\circ$) of Tertiary formations (from oldest: Rus Formation, Dammam Formation, Hadruk Formation, and Dam Formation) overlain by Quaternary sediments (coastal, sabkha, and eolian) and some minor reclaimed land (Figure 1). The Dammam Dome has three local topographic highs, those are Jebel Umm Er Rus (150 m) located at the highest point of the dome and above which King Fahd University of Petroleum and Minerals (KFUPM) was built, Jebel Midra Ash Shamali (125 m) in the northern margin of the dome, and Jebel Midra Al-Janubi (92 m) located west of Jebel Umm Er Rus (Weijermars, 1999).

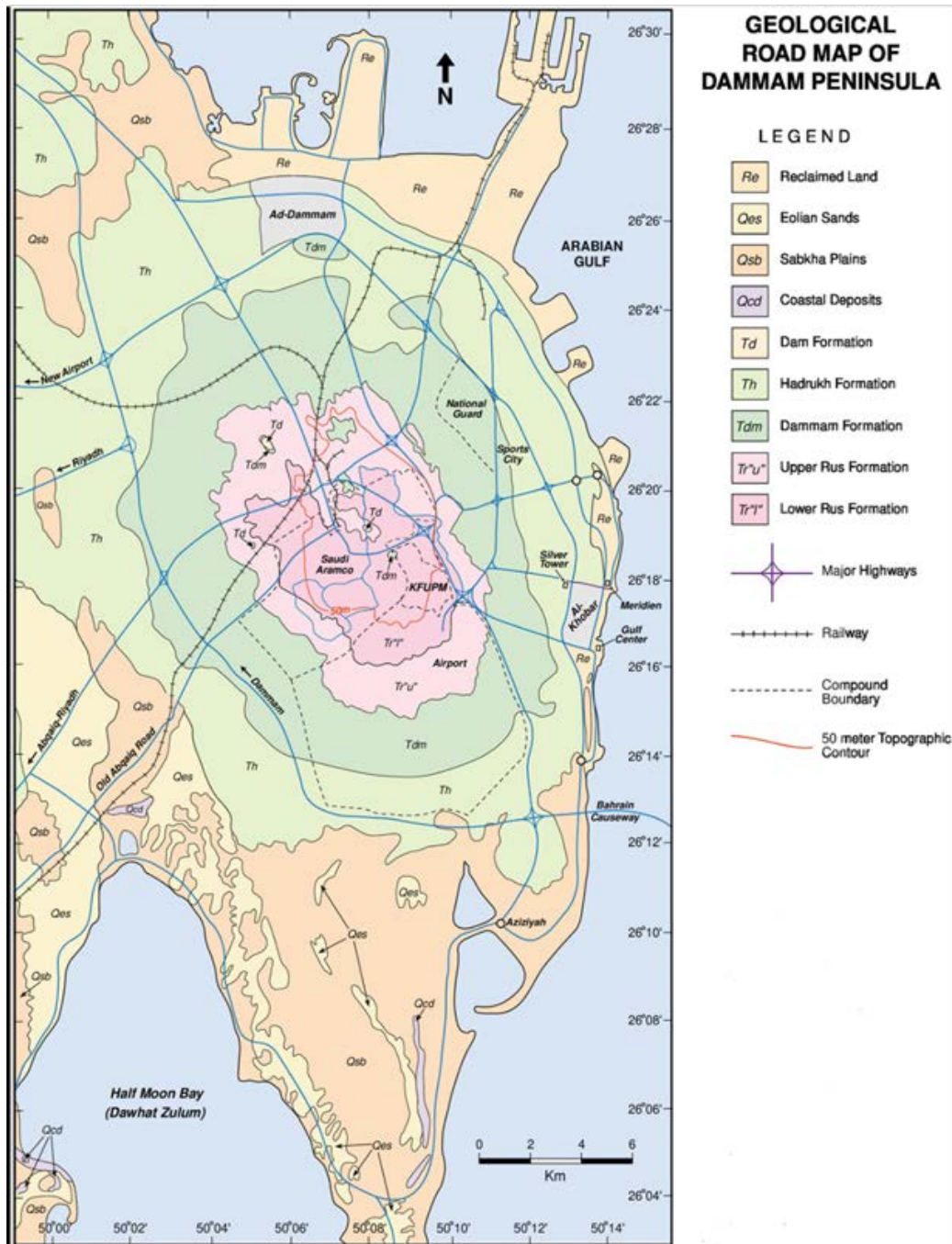


Figure 1. A geological map of the Dammam Peninsula. Geology was partly mapped by Weijermars (1999) and generalized from previous sources (Steineke et al., (1958); Tleel, (1973); Roger, (1985)). Indicated geological boundaries are between the Tertiary formations, Quaternary sediments and reclaimed land. From Weijermars (1999).

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Methods

A total of 120 samples were collected from the study area (Figure 2). Firstly, 51 powdered samples were obtained by performing systematic sampling every 10cm of the 5m studied outcrop. secondly, 60 hand specimens and 9 (1.5 inch) core samples were collected. These samples are then utilized to analyze their petrophysical, petrographic, and chemical properties. Finally, a systematic statistical approach is then used to produce geochemical models that distinguish and predict two compositionally similar dolomitic facies.

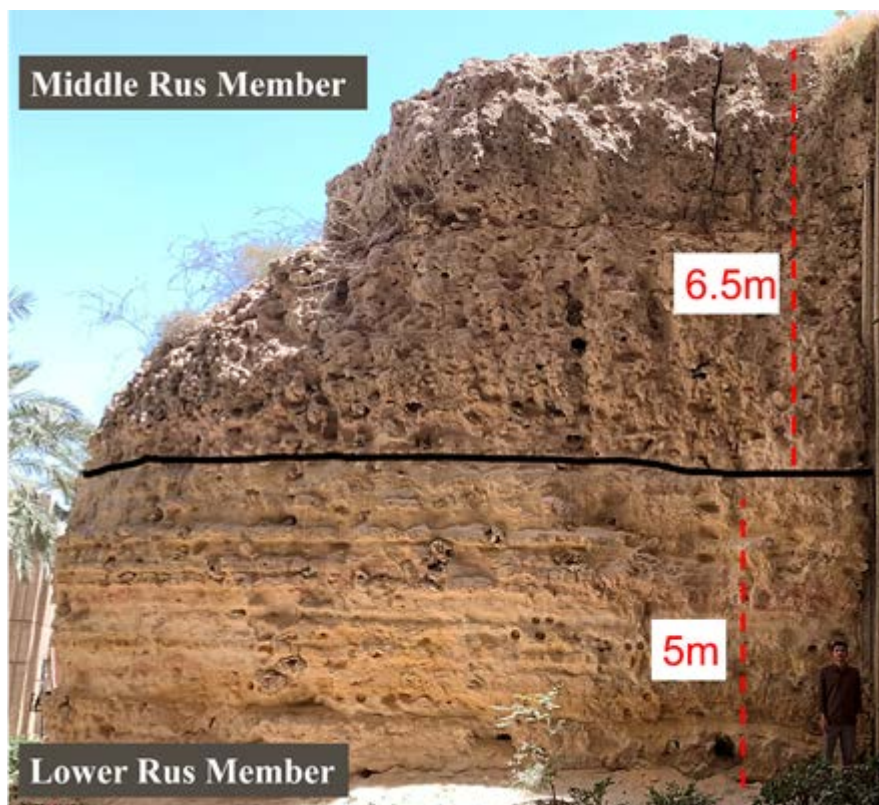


Figure 2 The outcrop of the study area showing the contact between the Lower Rus and Middle Rus members. Note the cm-scale alteration between the recessive and resistive dolomitic units which constitutes an authentic test for predicting the lithofacies.

I. Petrophysical analysis

porosity was measured using two methods. The first method calculated the porosity via the Helium Porosimeter device, which requires 1.5-inch core samples to operate. Second, the wax method uses Archimedes' principle to calculate the porosity. The wax seals the samples to prevent water contamination, then measuring the samples weight in air and after

submerging it in water to determine the sample's volume. From the sample's volume, pore volume is then calculated -assuming that density is known- and from it, porosity is measured.

II. Petrographic Analysis

15 thin sections to describe texture, composition, framework, and porosity. Using AXIO scan device, digital copies of the thin sections were analyzed by the Zeiss ZEN Blue software.

III. Chemical Analysis

51 powdered samples were investigated to identify their chemical composition. The X-ray fluorescence (XRF) was applied to define the elemental composition by using the M4 Tornado device. Also, X-ray diffraction (XRD) was used to define the mineralogical composition by using the PANalytical EMPYREAN device.

IV. Statistical Analysis

The first trial to build a prediction model has been applied to both, the minerals and elements as individuals. However, after applying regression analysis on the chemical data as individuals with facies as dependent variables, the resulted statistical significance has shown numbers higher than 0.05 (as shown in Table 4) so the decision was not to use them to make prediction model.

In order to resolve the statistical significance restriction, a principal component analysis has been applied, where it is testing if the relationship between the independent variables could produce factors that are statistically significant.

The final step of building prediction model is applying binary logistic regression modeling on the generated principal component factors.

Results & Discussion: Part 1

I. Porosity Analysis

The porosity results obtained from the wax method showed two distinct clusters. The scatter plot (Figure 3) shows two major clusters in red and blue. The resistive units represented by red show porosity that ranges from 13 – 33% with 23.73% average. The recessive units represented by blue show porosity that ranges from 35 – 50% with 43.15% average.

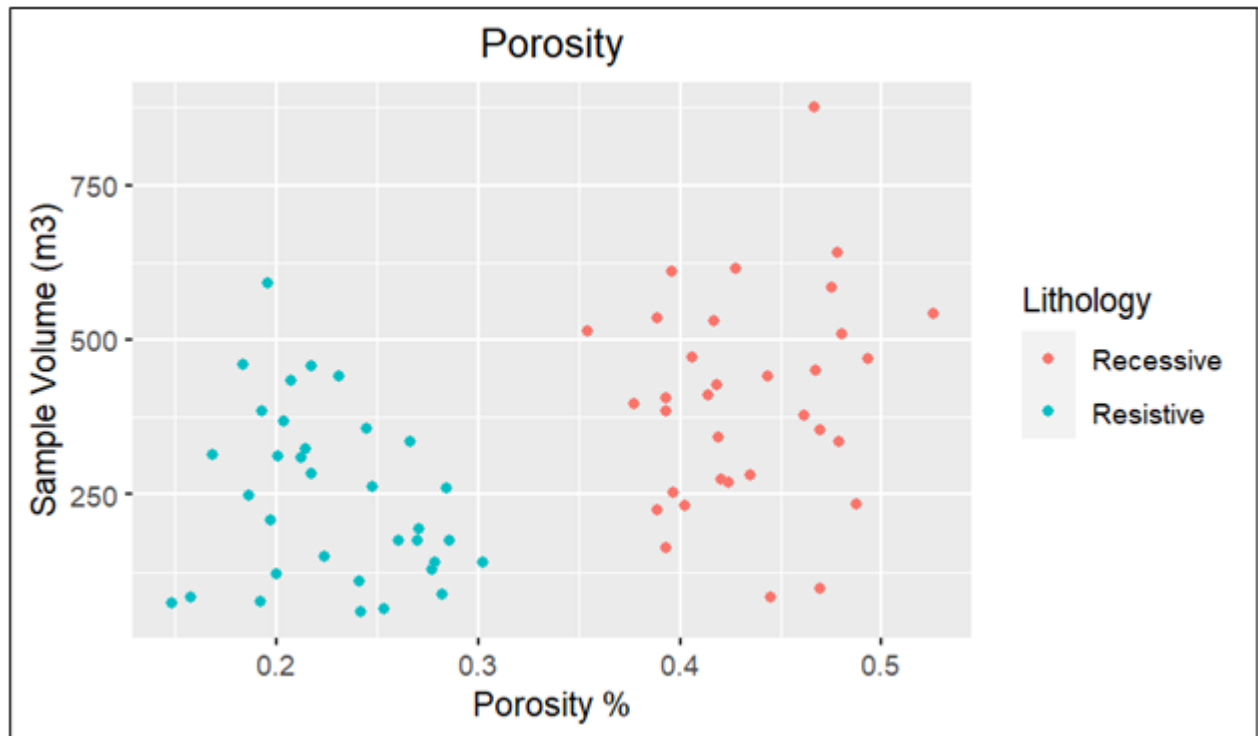


Figure 3 scatter plot of samples porosity

II. Petrographic Analysis

thin sections show fabric destroying dolomite and intercrystallite porosity in both samples, however the degree of alteration is the reason to create different facies (Figure 4). And a major difference between the two units is that in the resistive unit has dolomite crystals that are euhedral to subhedral while in the recessive the dolomite crystals are rounded, altered and anhedral.

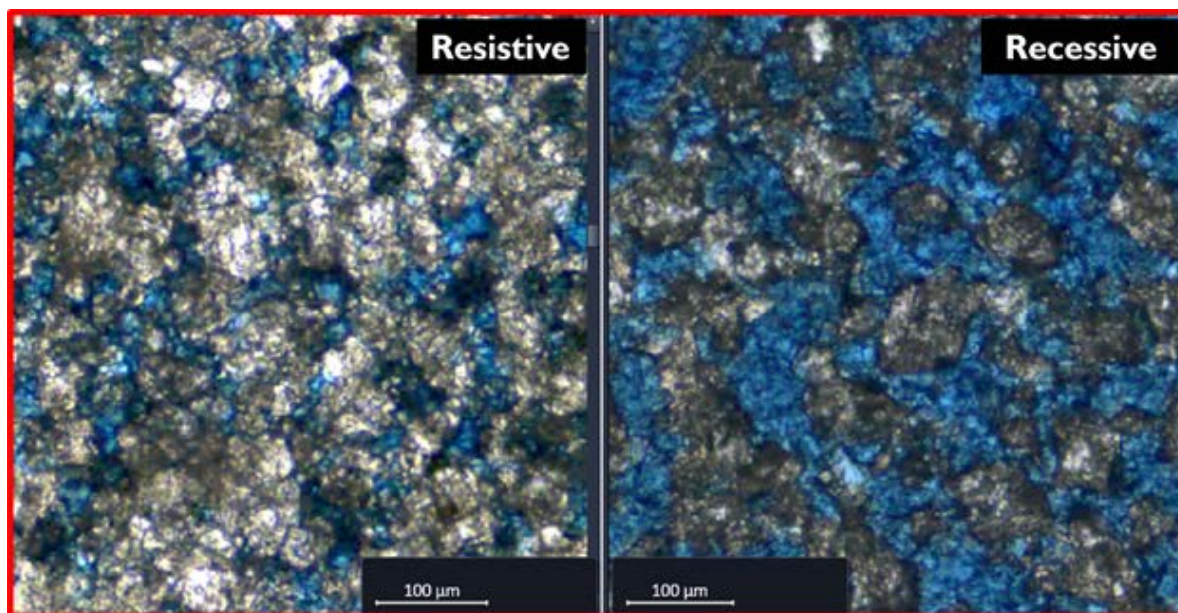


Figure 4 thin sections of two samples representing Resistive and Recessive.

The previous results show a clear difference between the resistive and recessive unites. A possible explanation is that it could be attributed to dissolution effects, where recessive beds has originally higher permeability than the Resistive beds. This permeability variations resulted in high degree of dissolution by meteoric water on the recessive and relatively low degree of dissolution on the resistive.

III. Chemical Analysis

the 51 powder samples show dominant dolomite composition, which is not unusual. The elemental results obtained from the XRF indicate two dominant elements (Table 1). Magnesium (Mg) with 52.16% and Calcium (Ca) with 26.09%. Both are account for more than 75% compared to other elements. The mineralogical results support the elemental results with 95.09% dolomite compared to other minerals (Table 2). Mineralogical logs were constructed using the mineralogical data (Figure 5). These logs show a clear mirror image and reverse relationship between the dolomite in on hand and the quartz and halite on the other hand. Logs are consistent below 2m and starter to fluctuate between 2 – 4m, and intensely fluctuate when approaching the top of the Lower Rus member.

Hosted by	Mg	Ca	Na	Si	Al	Others
	Dolomite	Quartz	Halite	Gypsum	Others	
	95.09%	2.12%	1.46%	0.95%	0.38%	

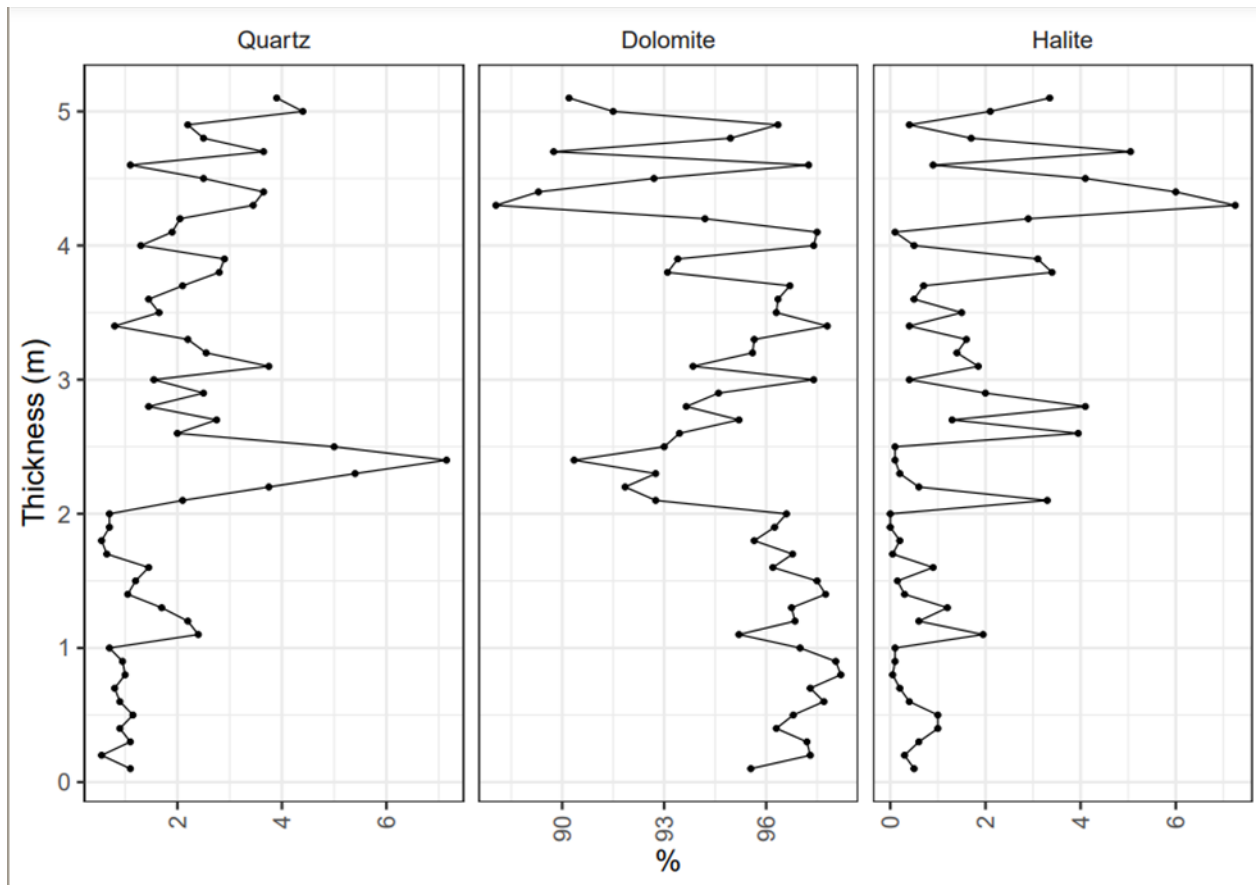


Figure 5- mineralogical log constructed against the thickness of the outcrop

Comparison between the mineralogical logs and the constructed stratigraphic column could explain the logs fluctuations and behavior (Figure 6). There is an obvious trend relate the increasing trend of the dolomite and the opposite decreasing trend of both quartz and halite with the resistive units, for example at 4.5m. The reverse behavior can also be noted at 4.3m. These trends can be explained as a diagenesis process. Nevertheless, this trend between the units and the chemical signature is not always consistent, for instance, at 2.5m and 3m.

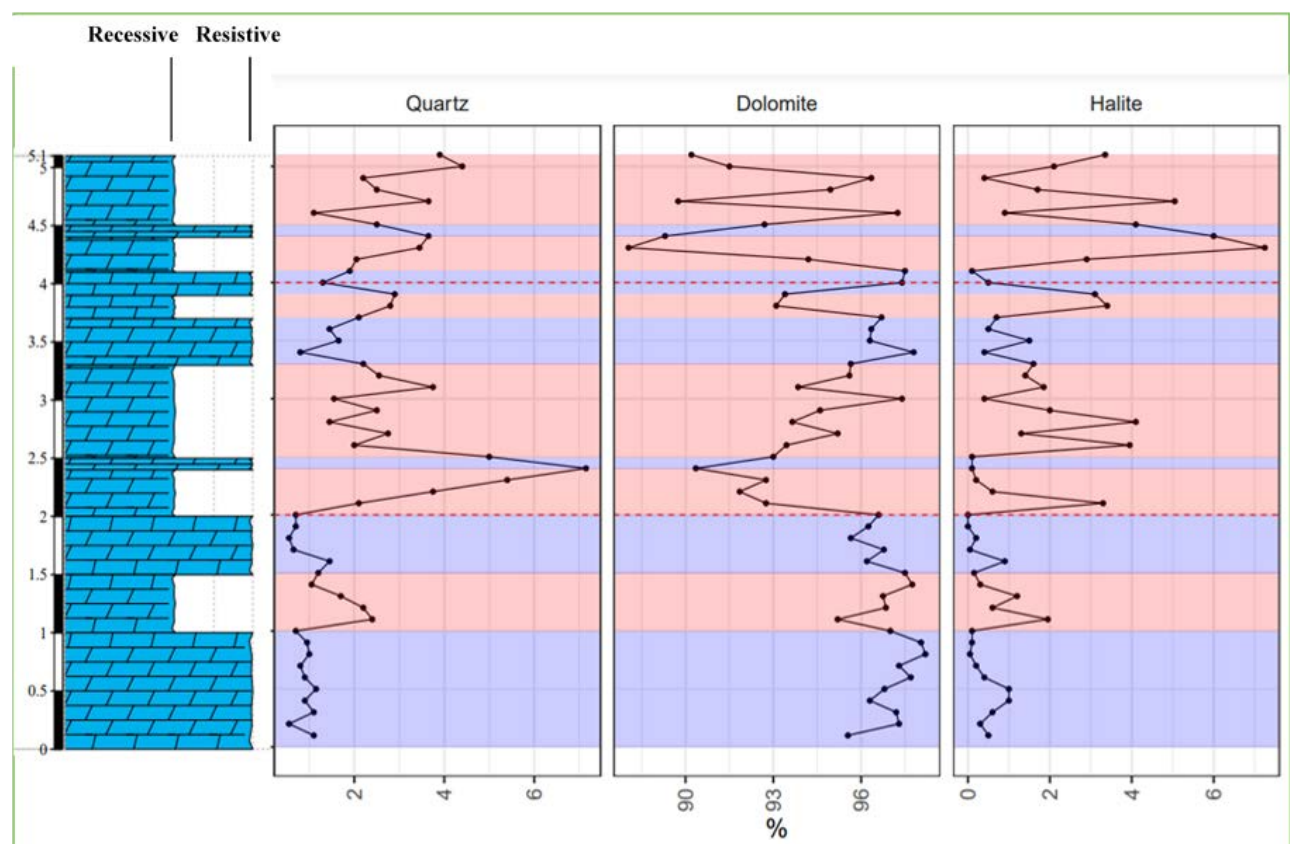


Figure 6- facies stratigraphic column constructed along with mineralogical composition, Red representing Recessive, and Blue representing Resistive.

Results & Discussion: Part 2

Advance statistics is a reliable tool to build a prediction model, and in this study the goal is to predict of the dolostone facies using the elemental and mineralogical data. In terms to predict a variable, the right statistical tool must be chosen, for this study logistic regression analysis is the perfect tool to measure the probability of having two different dolomite facies, which are recessive and resistive.

The first trial to build a prediction model has been applied to all the minerals and elements as individuals. However, after applying regression analysis on the chemical data as individuals with facies as dependent variables, the resulted statistical significance has shown numbers higher than 0.05 (as shown in Table 4) so the decision was not to use them to make prediction model.

In order to resolve the statistical significance restriction, a principal component analysis has been applied, where it is testing if the relationship between the independent variables could produce factors that are statistically significance. The results of principal component analysis produced three factors, these factors may represent geological process by analyzing the relationship of the minerals and the elements. Looking at component 1 in Table 3, the inverse relationship of both quartz and halite with dolomite could represent diagenetic process as the precipitation of halite and quartz will be faced by dolomite dissolution. Also looking at component 2 in Table 3, a positive number of quartz, silica, aluminum, and potassium together may represent detrital input. Finally, with component 3 in Table 3, inverse relationship of both dolomite and magnesium with halite could represent the effect of dissolution of dolomite and precipitating of halite.

Component Matrix^a

	Component		
	1	2	3
Quartz	-.699	.523	
Dolomite	.750		-.572
Halite	-.570		.576
Mg	-.686		-.639
Na	-.627	-.566	
Al	-.552	.808	
Si		.947	
Ca	.926		
Cl			
S	.697		
K	.604	.502	
Fe	.661		

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Table 3 Results of principle component analysis

After preforming regression analysis on the three factors, the resulted significance has shown values lower than 0.05 for factor 1 and factor 6 as illustrated in table 6, while factor 2 resulted in significant value higher than 0.05.

The final step of building prediction model is applying binary logistic regression modeling on the generated principal component factors. The model was applied using the probability equation, the results of the predicted facies has reached 88% rate of success with 45 correct predictions out of 51 facies. In Figure 7 the actual stratigraphic column versus the predicted is showing the similarity between them, there is small variations in the thickness of the beds and a 10 cm bed has not been detected.

$$\text{Dependent} = \frac{1}{1 + e^{-(b_0 + (b_1 * F1) + (b_2 * F2))}}, \text{ (probability equation)}$$

Actual VS Predicted

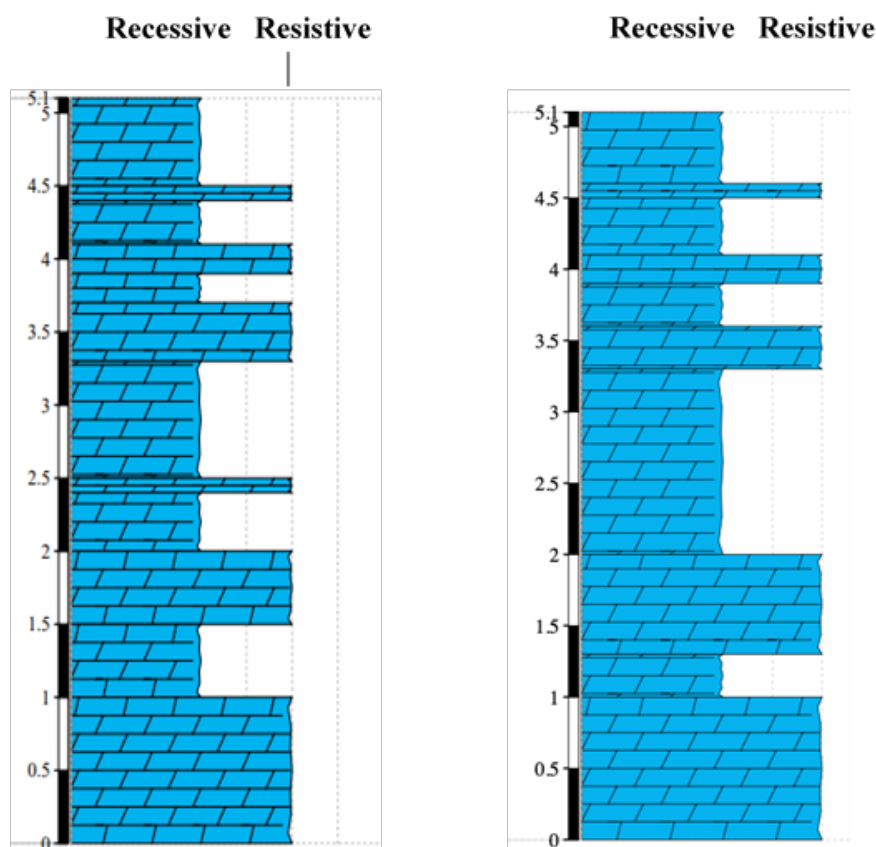


Figure 7 Actual stratigraphic column versus predicted stratigraphic column

To check the diagnostic ability of the generated prediction model, a receiver operating characteristic curve has been produced where the area under the curve reached 0.884 as shown in Figure 8. The curve is indicating that the prediction model is a good predictor.

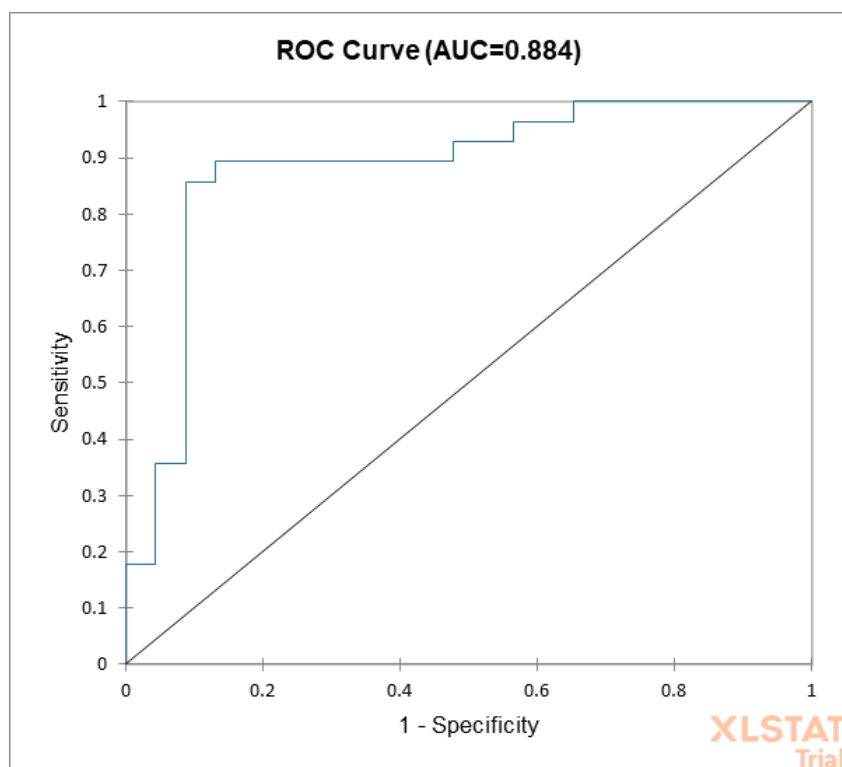


Figure 8, ROC curve of the prediction model

Implication:

Although many scientists have shown the ability of mineralogical and elemental data to differentiate between carbonates, this study has proven that geochemical data could be further used as predictors to differentiate between dolomite facies. The interbedding cycles in the studied outcrop is a crucial feature that provide advance implication to this study. Implying that the methodology used in Lower Rus outcrop could be used as a guidance while drilling in subsurface is one of the important findings in this study. As the surface outcrop is representing the same succession of a subsurface rocks for a certain formation, it is important to analyze an outcrop to test a certain methodology prior to testing subsurface. However, it is known for subsurface rocks to undergo diagenetic alterations that are different from surface conditions, hence differences in chemical composition is a possibility between subsurface and surface outcrop, this study is illustrating that if reliable prediction factors are generated from elemental and mineralogical data, then the alternating facies in subsurface could be predicted and mapped as well, which will be an enhancing technique for Chemo-steering.

Conclusion:

Performing this study in Lower Rus Formation interbedding dolomites has demonstrated the following:

- The Lower Rus Formation has two distinct units, varies in their petrophysical characteristics while having the same lithology
- Mineralogical and elemental data can be used as predictors in indistinguishable beds by performing statistical approach
- Chemo Steering could be a useful tool to identify different dolomite facies using Geochemical data

The results have shown that predicting dolomite facies is possible using geochemical data. However, to further prove the ability of this technique, testing wellbore geochemical data has to be performed in order to be used as gaudier in subsurface drilling process.

Acknowledgment

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References

- Allouche, E. N., Ariaratnam, S. T., and Lueke, J. S. (2000). Horizontal Directional Drilling: Profile of an Emerging Industry. ASCE Library. [https://ascelibrary.org/doi/abs/10.1061/\(ASCE\)0733-9364\(2000\)126:1\(68\)](https://ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9364(2000)126:1(68))
- Carpenter, C. (2015). Drilling of Multilateral Wells in Kuwait Aided with Geochemical Analysis. Journal of Petroleum Technology, 67(02), 79-82.
- Cooper, G. A. (1994). Directional Drilling. Scientific American, 270(5), 82-87. <http://www.jstor.org/stable/24942698>
- Estarabadi, J., Gezeeri, T., Padhy, G. S., Silambuchlvyan, J., Ferroni, G., Al-Anezi, K. K., ... & Latif, A. A. (2013, May). Innovative Geosteering Technology Utilized in Drilling Smart Multilateral Wells, Kuwait. In Offshore Technology Conference. OnePetro.
- Hartenergy. (2005). History of horizontal directional drilling. <https://www.hartenergy.com/news/history-horizontal-directional-drilling-52314>
- Palmer, A.R. (1983). The Cenozoic Time Scale. Geology, v. 11, p. 504.

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Powers, R.W., L.F. Ramirez, C.D. Redmond, and E.L. Elberg Jr. (1966). Geology of the Arabian Peninsula, Sedimentary Geology of Saudi Arabia. United States Geological Survey Professional Paper 560-D, 147 p.

Roger, J. (1985). Industrial Mineral Resources Map of Ad-Dammam, Kingdom of Saudi Arabia. Scale 1:100,000. GM-111.

Steineke, M., T.F.Harris, K.R.Parsons and E.L.Berg. (1958). Geologic Map of the Western Persian Gulf Quadrangle, Kingdom of Saudi Arabia. United States Geological Survey Miscellaneous Geological Investigations . Map 1-208A, Scale 1:500,000. Reprinted in 1977 as GM-208B.

Tleel, J.W. (1973). Surface Geology of the Dammam Dome, Eastern Province, Saudi Arabia. American Association of Petroleum Geologists Bulletin , v. 57, no. 3, p. 558–576.

Weijermars, R. (1999). Surface Geology, Lithostratigraphy and Tertiary Growth of the Dammam Dome, Saudi Arabia: A New Field Guide. GeoArabia 4 (2): 199–226.

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