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A New Look at Analyzing Petrographic Data: The Fuzzy Logic Approach

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ABSTRACT:
The common univariate analysis to evaluate the control of petrographic elements on permeability uses a quasi-quantitative approach. Relying on regression models, this analysis quantifies the behavior of permeability by isolating individual petrographic elements. Though the method does provide an overall picture of the petrographic control, it suffers one serious drawback. Its shortcoming lies in comparing the regression models with best correlation coefficients irrespective of the type of the curve fit—e.g., quadratic versus logarithmic. This inequitable comparison forces the researcher to make qualitative judgments, based on intuition and experience, regarding the petrographic control.

Various multivariate techniques have also been attempted; some as advanced as the Karhunen-Loève transform that examines the covariance matrix and ranks the influence of each petrographic measurement on permeability. These methods tend to be mathematically complex and are not amenable to simple computer programming. In this paper, we present a simple fuzzy logic algorithm which accomplishes the ranking with relative ease. The algorithm uses non-boolean "reasoning" to derive the simultaneous ranking of all the petrographic elements. The primary advantages of this algorithm are speed of processing and elimination of qualitative petrographic interpretations.

Additionally, we demonstrate a novel thin section analysis technique which uses a minipermeameter, to increase the quantity and quality of petrographic data. The investigation volume of the minipermeameter and the proposed thin section analysis are comparable, unlike the larger measurement volume of a core plug. As a result, the measurements—using the new thin-section analysis—result in more reliable correlations. The new method also conserves precious core material. The data collected with the new technique were used in our fuzzy logic analysis of two types of sandstones: the Queen and the Santa Rosa. Results from the conventional petrographic analysis and the fuzzy logic algorithm are in good agreement, while eliminating the individual bias and the tedious regressions associated with the conventional analysis.

INTRODUCTION:
Small-scale permeability heterogeneities affect reservoir performance, especially during secondary and tertiary recovery. These permeability heterogeneities are controlled by variations in petrographic elements such as porosity types, pore morphologies, mineralogy, texture, and type, amount, and distribution of clay and cement. In order to assess the control of each variable on permeability, a comprehensive petrographic study is essential. Conventionally, the influence of each petrographic element on permeability is determined by using core plugs and thin sections, but there is a large difference in the volume of investigation of thin sections and core plugs. Permeability varies at every point within most core plugs. Thus, a thin section prepared from a core plug may not contain the petrographic elements that are representative of the core plug's permeability at that location. As a consequence, correlations developed in this analysis may be misleading. In this paper, we suggest a new simple methodology to improve the quality and quantity of

petrographic data that influence permeability, by making closely-spaced permeability measurements with a minipermeameter. We combine these measurements by making properly oriented thin sections from the surface of the cores on which the permeability was measured.

Once the petrographic data is collected, the second step is analysis. In order to assess the importance (ranking) of each petrographic element in controlling permeability, regression analysis is performed. Linear, power, logarithmic, and exponential models are applied to the data, and the model that yields the best correlation coefficient is chosen. Ranges of the correlation coefficients to evaluate the model as good, moderate, or bad are used—for example: $0 < R^2 < 0.50$ (bad); $0.50 < R^2 < 0.75$ (moderate); $0.75 < R^2 < 1.00$ (good)—where R^2 is the correlation coefficient. It is important to realize that the conventional ranking technique compares the best regression models for different petrographic parameters, while ignoring the type of curve fit. Hence, the comparison is not entirely equitable. Once the best fit curves are obtained, the petrographic elements are ranked in descending order of their correlation coefficients, which also reflects the magnitude of their effect on permeability. At this stage, the petrographer, basing the decision on experience and intuition, supports (or modifies) this ranking of petrographic elements.

In order to reduce this qualitative interpretation and bias introduced by the petrographer, we use a more quantitative approach—the fuzzy logic algorithm—to determine the importance (ranking) of each petrographic elements in controlling permeability. The fuzzy logic algorithm compares all the petrographic parameters on the same basis and hence is superior in that aspect. Depending on the ranking, the permeability may be estimated by using only the most important petrographic elements. In old fields, where the samples are scarce or not suited for making permeability measurements, this, combined thin section and fuzzy logic analysis may be used to estimate the permeability.

NEW METHODOLOGY

To sample the whole permeability range for petrographic analysis without destroying the core, our methodology requires superimposing a fine scale minipermeameter measurement grid on the core. This method allows for improved analysis based on the premises that: (1) the area of investigation of minipermeameter is very small and is comparable to that examined in a thin section, and (2) each thin section contains multiple permeability points (Figure 1). The assumption allows us to make better correlation between petrographic elements and permeability. The second assumption facilitates collection of larger set of dataset. The advantage in collecting a large set of data points is that reliable statistical analysis can be performed and the effects of each petrographic element on permeability can be determined with better accuracy. This methodology helps assess the effects of diagenesis and porosity evolution on permeability more accurately.

According to Goggin *et al.* (1988), the effective radius and depth of investigation of a minipermeameter probe tip is four times the internal radius of the probe tip. However, it was found during the calibration of our minipermeameter, that the area immediately under and around the probe tip exerts the main control over permeability (Ali, 1993). After careful examination, it was concluded that for a probe tip with inner radius of 0.125 inches (3.125 mm), the area of the thin section to be analyzed should have a diameter of 0.4 inches (10 mm). Depending on the number of permeability points present on each thin section, the thin section was divided into that many equal parts and petrographic data were collected for each part separately (Figure 1). Using this new method, we collected on the average, data equivalent to 6 to 14 thin sections from one thin section, which would not have been possible using the conventional core plugs. Because of the comparable areas of investigation of both, the thin section and minipermeameter, the correlations established between permeability and petrographic elements should be more accurate than the correlations obtained from analyzing conventional core plugs.

THE FUZZY LOGIC ALGORITHM:

The correlation coefficient analysis, currently used by petrographers, is the simplest modeling technique for linear systems. This analysis is used to estimate the correlation coefficient for each input parameter (petrographic element) with respect to the output (permeability), and then rank the coefficients in order of their significance.

More sophisticated techniques include the Partial Least Squares method and the Principal Component Analysis (the Karhunen-Loève transform). These techniques seek to identify the most significant inputs that contribute to a given output, and then model the system as a linear combination of the significant inputs. Non-linear systems, on the other hand, require more contemporary modeling techniques like neural networks, fuzzy systems, genetic algorithms, etc., which try to preserve the system's non-linear nature. Although powerful, non-linear techniques are plagued with erroneous solutions generated by the local minima in the solution space. These local minima worsen if the input space is large. Therefore, to efficiently model a non-linear system, it is imperative to reduce the input space by identifying the significant inputs that contribute to a specific output.

In this study, most of the petrographic attributes examined under the thin section contribute to permeability. We are also aware that each attribute alters permeability in a unique manner. It is difficult to accurately quantify this interaction between each of the petrographic parameters and permeability, thus emphasizing its non-linear nature.

Fuzzy logic is useful in analyzing some of these non-linear problems. In fuzzy logic, an element can partially belong to more than one set. For example, the temperature in a room can be "warm" or "cold" depending on a person's perception. Therefore, the perceived "temperature" can belong to both sets "warm" and "cold" at the same time. From a petrographic standpoint, we are trying to answer questions such as: To what extent does a certain petrographic element, such as quartz, affect the permeability of the sandstone? Due to the non-linear effects of the petrographic elements on permeability, such questions may demand fuzzy answers.

Facing the dilemma of not knowing the explicit relationship between each petrographic attribute and permeability, the question of the most significant attributes that contribute to permeability was resolved using a fuzzy logic algorithm. This data-directed algorithm, developed by Lin (1994), compares the effect of each individual input parameter, x_i (the petrographic measurement), on the single output, y (the minipermeameter permeability). Briefly, the algorithm achieves this comparison by building fuzzy membership functions (F_{ik}) for each of the input parameters using:

$$F_{ik}(x_i) = exp\left[-\frac{(x_{ik} - x_i)^2}{b}\right], \quad k = 1, 2, 3 \ldots m$$

for m training data points. b, the normalizing factor, is generally taken as 10% of the length of the input parameter interval. Each fuzzy membership function defines a fuzzy rule. In our case, the rule is "*if* x_i *is*

$F_{ik}(x_i)$*, then* y_i *is* y_k". The fuzzy membership functions are then defuzzified using the centroid defuzzification rule to plot fuzzy curves (c_i) given by:

$$c_i(x_i) = \frac{\Sigma\,\Phi_{ik}(x_i)\cdot y_k}{\Sigma\,\Phi_{ik}(x_i)}$$

The summation is done for all the *m* inputs. The range of each of these fuzzy curves $c_i(x_i)$ on the ordinate reflects the effect of each input parameter x_i on the output permeability. Details of the fuzzy logic algorithm are beyond the scope of this paper and the interested reader is referred to Lin (1994).

Prior to generating the fuzzy curves for these petrographic attributes, histograms were plotted for each attribute after they were normalized based on their representative standard deviations. The histograms ensure that the data have approximately normal distribution. Heavily skewed data may result in erroneous results from the fuzzy logic algorithm and one such cautionary example is illustrated in the following section.

ANALYSIS AND DISCUSSION:

We used a computer controlled scanning minipermeameter (SMP) to make permeability measurements. For details about this minipermeameter see Ali (1993). Core samples of Upper Queen (Shattuck member, Permian age) and Santa Rosa (Triassic age) formations from New Mexico were used in this study. We measured the permeability on a square grid (0.5 inches) on the three available Shattuck member cores. This generated five vertical permeability profiles along the length of the core (Figure 1). Using this technique, we measured 5,000 permeability points, which could be directly examined in the thin sections.

Similar measurements were carried out on the Santa Rosa sandstone core, but on a rectangular grid with horizontal interval of 0.5 inches and vertical interval of 0.2 inches. We based the measurement grids for the two sandstones on the scale of observed lithologic heterogeneity. Approximately 1,200 permeability measurements were made. As an example, the permeability distribution in the Santa Rosa sandstone is shown in Figure 2. We ensured that the samples for petrographic analysis cover the whole range of permeability spectrum. In addition to standard petrographic techniques, we applied fluorescent petrography for the clear delineation of pore geometries and the distribution of micro-pores for improved data collection.

Upper Queen (Shattuck member) Formation:

We made thirty-eight thin sections from the three available cores and total of 267 data points were collected. Petrographic analysis was conducted to establish the ranking of each petrographic element in controlling the permeability. Sixteen petrographic elements were collected for each permeability point. A summary of the correlations and the ranking for top ten petrographic elements is given in Table I. For illustration, regression graphs and the fuzzy curves for the most (High) and least (Low) important petrographic elements are shown in Figures 3 and 4. The results of the fuzzy logic algorithm are in excellent agreement with conventional regression analysis (Table I).

In the Shattuck member, the most important petrographic elements controlling permeability are the porosity types. Among the porosities, the secondary intergranular porosity is the most dominant type and exerts the most influence on the permeability (Table I and Figures 3A, 3B, 4A, & 4B). As the dissolution increases, the secondary intergranular porosity increases and the interconnection between the pores improves.

Quartz and feldspars are the dominant detrital grains, whereas, anhydrite and dolomite are the dominant cements (Figures 3 & 4). Both quartz and feldspar ranked in the middle with respect to controlling the permeability because as their percentage increases, the percentage of anhydrite and dolomite cement decreases (Table I). Detrital clays are present in substantial amounts only in the thinly-laminated, poorly-sorted silty sandstone zones not thicker than 2 inches. This is the reason why clay does not affect the permeability and is close to the bottom of the ranking (Table I) (Figures 3F & 4F). Anhydrite is present in three morphologies: (1) fine crystalline nodules, (2) coarse, pore filling crystals, and (3) large patches of poikilotopic crystals surrounding several grains. It is the poikilotopic morphology which may affect the permeability. Dolomite is present in two morphologies: (1) micritic dolomite, probably formed by the dolomitization of the carbonate mud, and (2) large poikilotopic patches. Dolomite and anhydrite are distributed in the form of irregular patches (2 - 4 mm in diameter) throughout the reservoir zone. This patchy distribution is probably due to the heterogeneous dissolution pattern. Although, based on the correlation coefficient and fuzzy logic, dolomite seems to be more important than anhydrite in controlling permeability, it should be the opposite (Table I) (Figures 3D, 3E, 4D, & 4E). This inverse ranking of dolomite and anhydrite is due to a 1.5 ft. thick low porosity and permeability layer of clastic dolomite at the top of the Shattuck Member which contains as much as 50% dolomite. In the rest of the reservoir zone, the amount of dolomite never exceeded 15 %. Because of this biased distribution, dolomite seems to have more control over permeability (Table I).

All the petrographic elements were represented as a percentage (dimensionless) whereas, the grain and pore sizes were estimated in microns. Therefore, the pore and the grain sizes could not be included in the fuzzy logic analysis because of the incompatibility between units.

Santa Rosa Sandstone:

For the Santa Rosa, we collected 150 data points from twelve thin sections. In this sandstone, quartz is the most abundant detrital grain and dolomite the most abundant cement. Kaolinite occurs as authegenic vermicular pore filling cement. Rock fragments consist of shale fragments and chert. The pore system in the Santa Rosa sandstone consists of the following porosity types: primary intergranular porosity, secondary microporosity, secondary intergranular porosity, secondary intraconstituent porosity (intragranular and intracement), moldic porosity, and secondary oversize pores. Summary of the correlations and ranking for the top eight petrographic elements influencing permeability are given in Table II.

Similar to the Shattuck member, the most important petrographic elements are the porosity types, as determined using both regression and fuzzy logic analysis (Table II). Total porosity and the secondary intergranular porosity are the most dominant petrographic elements controlling permeability. The majority of the primary porosity (reduced primary porosity) consists of pores with polygonal outlines and restricted interconnections due to quartz overgrowths. Secondary intergranular (non-polygonal) pores have better interconnection due to dissolution. Microporosity is mainly present among the kaolinite patches.

Both kaolinite and dolomite show general decreasing trends as the permeability and total porosity increases. As kaolinite is mostly present in areas similar in size and shape to detrital grains, it does not affect pore throats and interconnections between the pores. Kaolinite is only important in thin low and moderate permeability zones, where it is present in considerable amounts and ranked in the middle (Table II). For any given percentage of dolomite there is a wide range of permeability. This scattering of data is due to the presence of two dolomite morphologies. High percentage of dolomite is present in the form of isolated large rhombic crystals. This crystal morphology does not effect permeability considerably, and that is why it ranked at the bottom by both regression and fuzzy logic analysis (Table II).

For the most part, the fuzzy logic and conventional regression analyses are in good agreement, except for microporosity and quartz. As mentioned earlier, to generate fuzzy curves the data distribution should be normal, and skewed data may give erroneous results. This seems to be the case with microporosity and quartz. Even though the data was normalized before creating the fuzzy curves, sometimes the data distribution continues to be skewed. In case of microporosity, the majority of the data dictated a fuzzy range of less than 207, but a single point caused the fuzzy range to jump up to 372 (Figure 6E). This causes microporosity to be ranked in the third place according to fuzzy logic, whereas, the regression analysis ranks it at 7 (Figure 5E, Table II). If we ignore the highest point, the fuzzy range is approximately 207, ranking microporosity in the eight place (Figure 6E, Table II). In case of quartz, the variation in permeability increases rapidly when the quartz percentage exceeds 80% (Figure 5C). This results in a skewed data distribution for quartz. The slightly flat nature of the fuzzy curve is indicative of low influence of quartz on permeability for quartz percentages below 80%. Sometimes, it is difficult to ascertain the effect of one element on permeability, because of their correlation with other elements. Quartz is less effected by dissolution as compared to less resistant mineral species. In the Santa Rosa sandstone, secondary porosity originated mainly by the dissolution of feldspar and dolomitic cement. Because of this correlation of quartz with other petrographic elements, the fuzzy logic algorithm was not able to quantify the effect of quartz on permeability accurately. An alternative has been proposed by Lin (1994) that involves the use of fuzzy surfaces to quantify the effects of strongly correlated variables. Therefore, the distribution and cross-correlation of the data is very important for the correct application of the fuzzy logic algorithm.

CONCLUSIONS:

1. The new technique of combining minipermeameter and thin sections allows the collection of large set of petrographic data with fewer thin sections, thus, conserving valuable core material. With this new technique, the control of different petrographic elements on permeability can be assessed accurately. This methodology also facilitates the understanding of porosity and permeability evolution.

2. The fuzzy logic algorithm is fast, unbiased, and quantative method for establishing the importance of each petrographic element in creating the permeability heterogeneity. The fuzzy logic algorithm should be used with caution for highly skewed data and strongly cross-correlated data.

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Petrographic elements	Amount (Ranges)	Correlation (R^2) with per meability (Regression Models)	Correlation (R^2) with total ϕ (Regression Models)	Ranking based on R^2	Ranking based on Fuzzy Logic (Fuzzy Range)
Secondary intergranular ϕ	0 - 27%	0.75 (Power)	0.91 (Linear)	1	1 (158)
Total Secondary ϕ	0 - 27%	0.71 (Linear)	0.97 (Linear)	2	2 (150)
Total ϕ	0 - 27%	0.70 (Power)	-	3	3 (148)
Pore size (microns)	0 - 70 µm	0.70 (Exp.)	0.81 (Linear)	-	-
Quartz	0 - 75%	0.47 (Exp.)	0.37 (Exp.)	4	4 (97)
Feldspar	0 -26%	0.43 (Exp.)	0.33 (Linear)	5	5 (90)
Dolomite	0 - 55%	-0.36 (Power)	-0.26 (Power)	6	7 (45)
Grain size (microns)	0 - 120 µm	0.30 (Exp.)	0.25 (Linear)	-	-
Anhydrite	0 - 40%	-0.12 (Exp.)	-0.07 (Linear)	7	9 (43)
Micro- ϕ	0 - 5.5%	-0.10 (Linear)	-0.03 (Linear)	8	6 (49)
Clay	0 - 21%	-0.06 (Linear)	-0.13 (Exp.)	9	8 (44)
Rock Fragments	0 - 9%	0.01 (Exp.)	-0.06 (Log.)	10	10 (36)

Table I: Summary of the petrographic elements and their relationship (R^2) with permeability and total porosity for the Shattuck member. The ranking shows the importance of petrographic elements in controlling the permeability as determined by the conventional regression analysis and fuzzy logic. Elements ranked from 6 to 10 essentially have the similar control on permeability.

Petrographic elements	Amount (Ranges)	Correlation (R^2) With per meability (Regression Models)	Correlation (R^2) with total ϕ (Regression Models)	Ranking based on R^2	Ranking based on fuzzy logic (Fuzzy Range)
Total ϕ	2 -30%	0.89 (Power)		1	2 (396)
Secondary intergranular ϕ	0 - 22%	0.81 (Power)	0.80 (Linear)	2	1 (413)
Average pore size (mm)	20 - 200 µm	0.78 (Linear)	0.65 (Linear)	-	-
Quartz	40 - 98%	0.75 (Exp.)	0.62 (Linear)	3	8 (183)
Average grain size (mm)	50 - 200 µm	0.74 (Linear)	0.54 (Linear)	-	-
Clay (Kaolinite)	0 - 25%	0.57 (Exp.)	0.42 (Linear)	4	5 (350)
Rock fragments	0 - 8%	0.42 (Log.)	0.32 (Log.)	5	4 (353)
Primary ϕ	0.5 - 15%	0.32 (Power)	0.5 (Power)	6	6 (297)
Micro-ϕ	0.5 - 4%	0.27 (Power)	0.16 (Linear)	7	3 (372)
Cement (Dolomite)	2 - 40%	0.26 (Exp.)	0.27 (Exp.)	8	7 (222)

Table II: List of the petrographic elements showing their importance in controlling permeability in the Santa Rosa Sandstone.

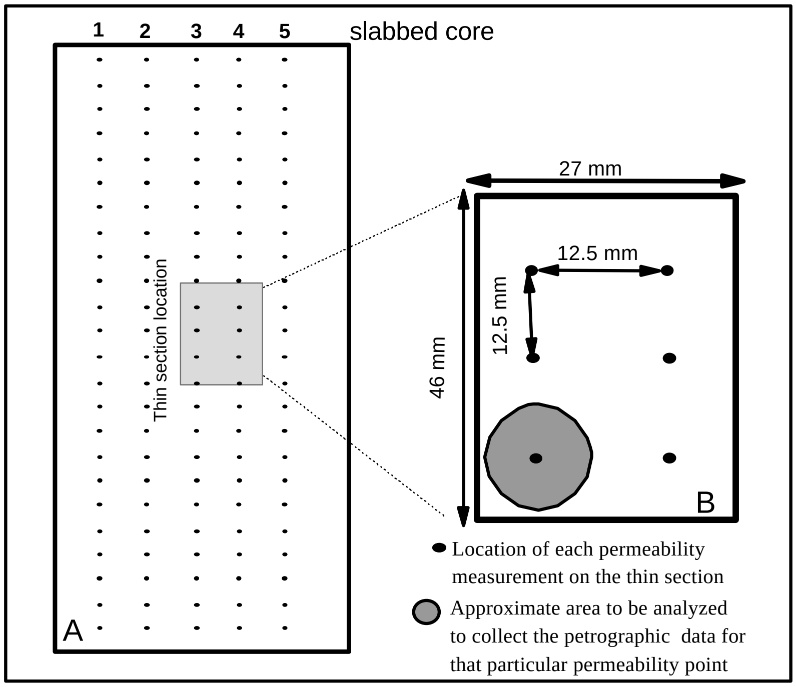

Figure 1: (A) Permeability measurement grid. Five vertical profiles were generated by this grid. Thin section location is also shown. (B) Distribution of permeability measurements on the thin section.

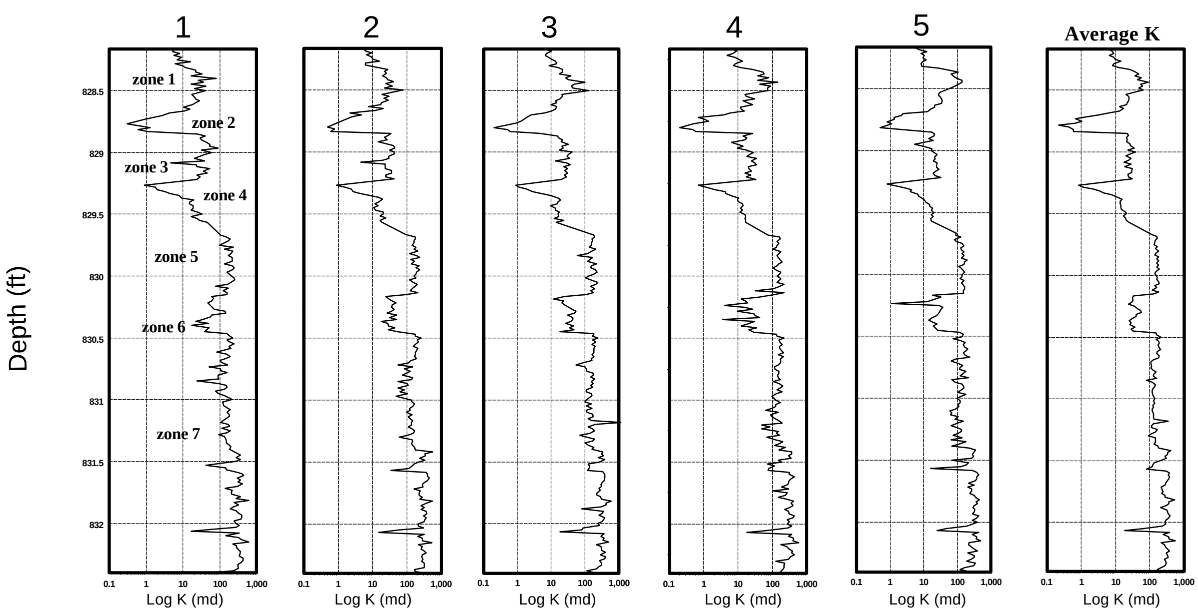

Figure 2: Permeability distribution in Santa Rosa sandstone core. Thin individual permeability zones can be correlated horizontally along the core. The numbers on top of each permeability track correspond to the profiles shown in Figure 1. Similar measurements were performed on the Shattuck member cores.

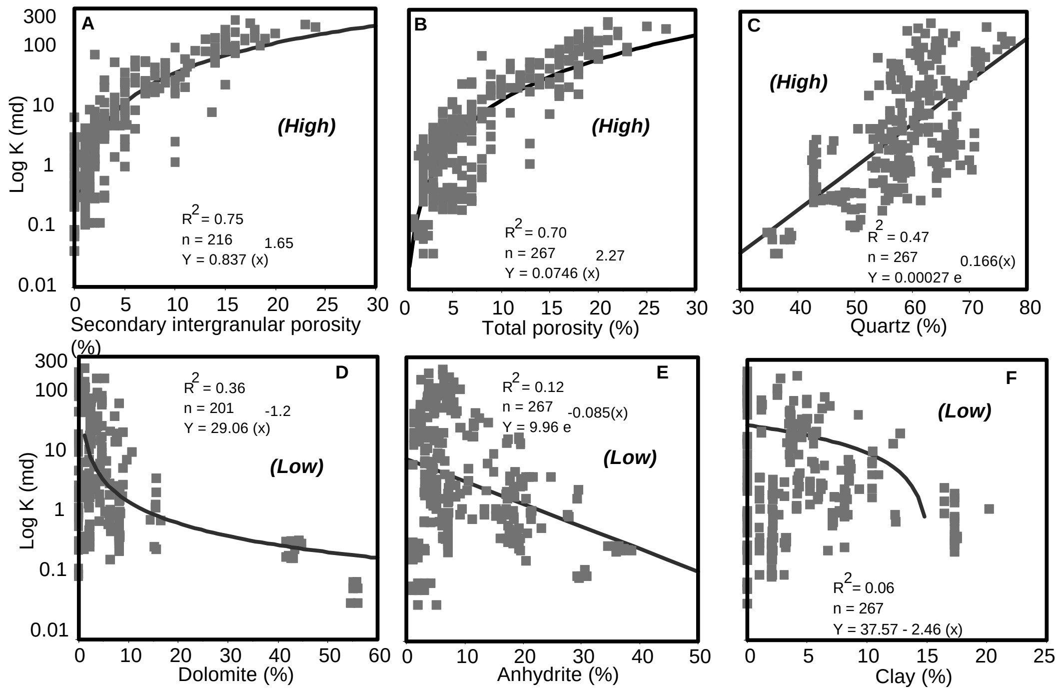

Figure 3: Relationships between permeability and different petrographic elements in the Shattuck Member. Note the different regression models applied to the elements.

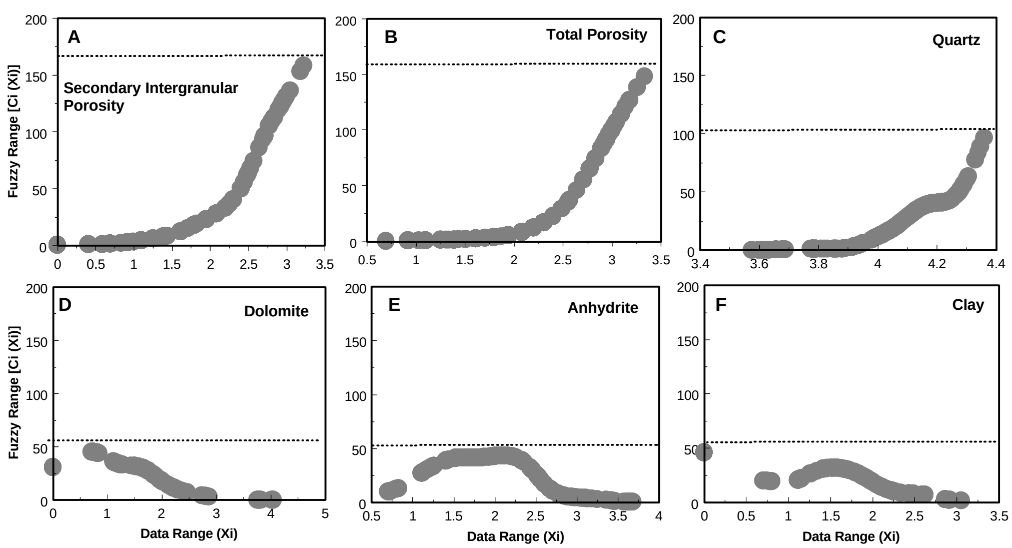

Figure 4: Fuzzy curves for the same petrographic elements shown in Figure 3. The fuzzy range (Y-axis) defines the importance of each petrographic element in controlling the permeability. A higher fuzzy range indicates greater influence on permeability, whereas the flat fuzzy curves depict lesser or no influence.

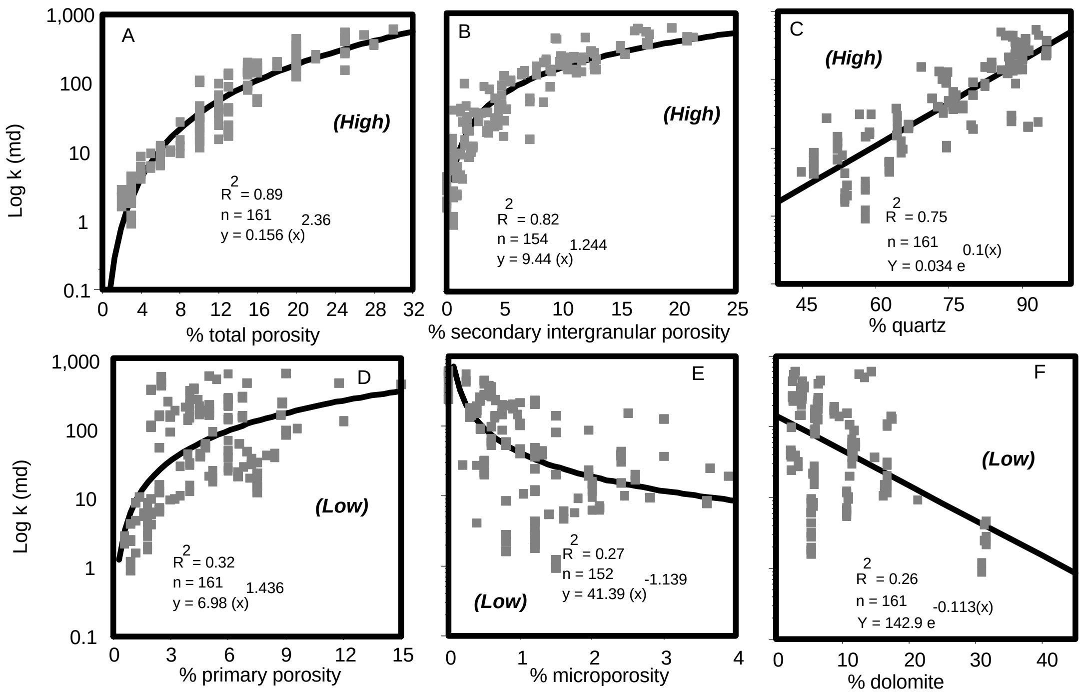

Figure 5: Relationships between permeability and different petrographic elements in the Santa Rosa sandstone.

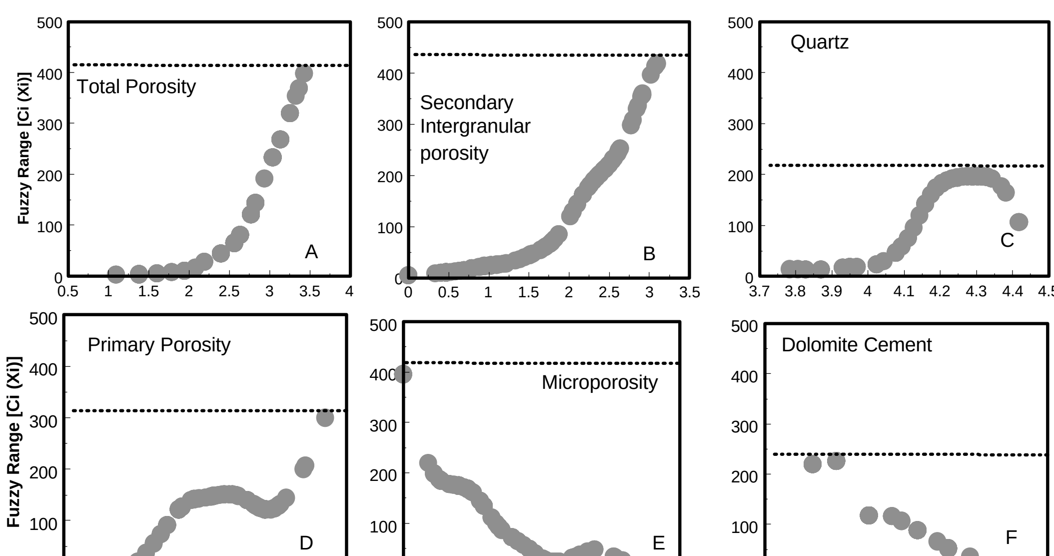

Figure 6: Fuzzy curves for the same petrographic elements shown in Figure 5. Note the flattening of the of the fuzzy curve for quartz (C) reducing its importace. The fuzzy range for microporosity (E) is affected considerably by one data point, which makes it appear to be influential in controlling the permeability.