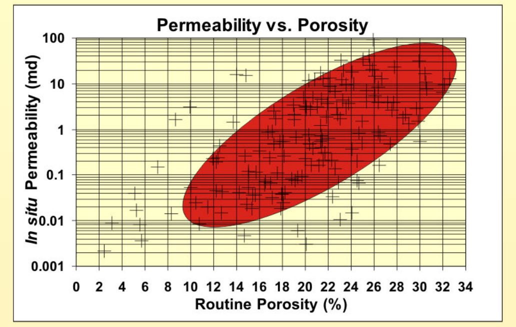
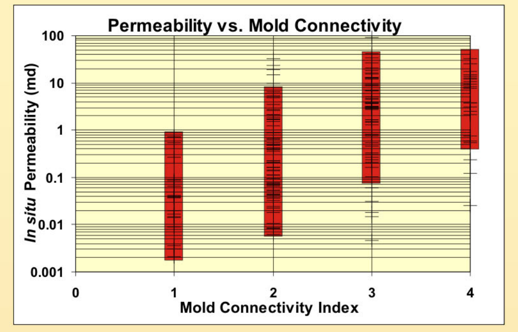
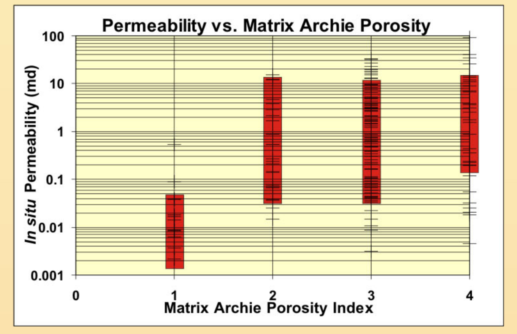
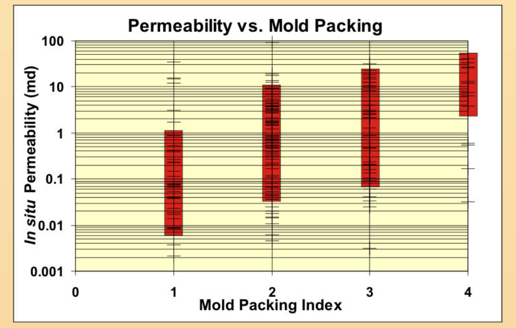
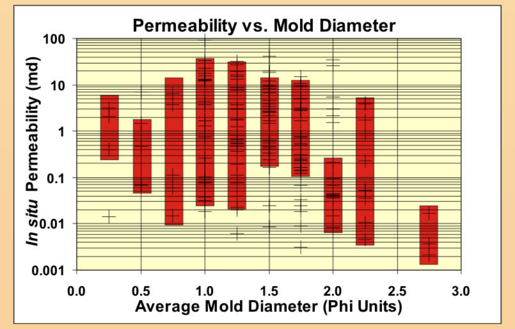










Correlation of Textural Properties with Permeability

To try and improve the prediction of permeability over the standard use of porosity as the independent variable several textural parameters were measured. Indices were created as metrics for measurement using binocular microscope. Metrics using this method were selected since it was assumed that cuttings samples would be the only source of information other than well logs for most wells. It was also believed that this method would provide adequately quantitative data to assess variable influence.

Variables Measured:

Porosity - by helium porosimetry under ambient conditions

Connectivity Index - An index ranging from 1 to 4 representing the degree of connection between oomolds as observed at 10X-20X:
1 - no apparent connection between oomolds, nearly all molds observed have no connection to other molds
2 - Connections are observed but are limited (<10% of molds)
3 - Connections are observed between many molds
4 - A majority of molds display connection to other molds or some percentage of the molds appear to exhibit extensive dissolution and connection

Packing Index - An index from 1 to 4 representing the packing density of oomolds:
1 - Isolated oomolds
2 - Pack-wackestone, Limited contact between oomolds but many portions are wackestone
3 - Extensive contact between oomolds, packstone
4 - Dense packing of oomolds

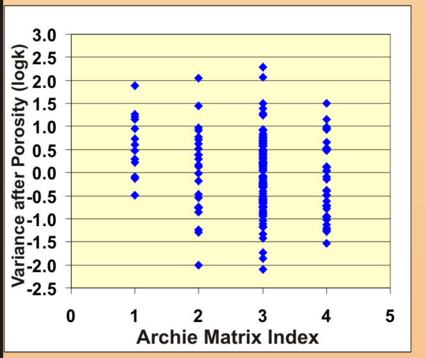
Size - An estimate of the average oomold diameter in phi units

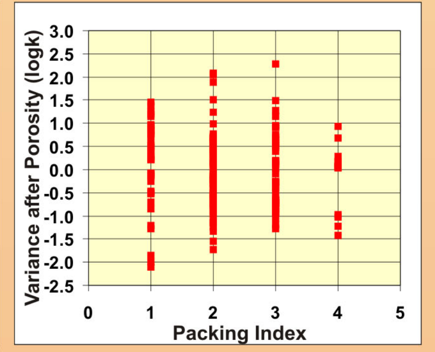
Archie Matrix Porosity Index - base on Archie's (1952) second parameter for describing matrix porosity. Archie's parameter was expressed A-D for matrix porosity. In this study it was expressed as 1 through 4:
1 - No visible porosity in matrix uner 10X examination, pores < 0.01mm
2 - Visible porosity, 0.01mm<pores<0.1mm
3 - Visible porosity, 0.1mm<pores<cutting size
4 - Visible porosity, evident by crystal growth on pores, vuggy

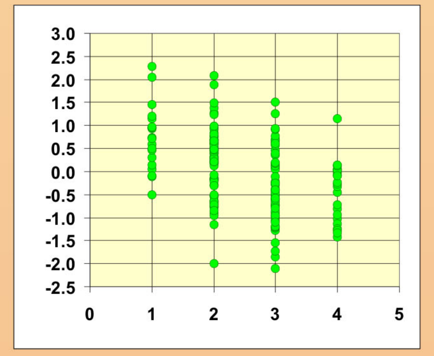
Fracture Index - Index ranging from 0-3 representing influence of fractures on permeability:
0 - No fractures evident
1 - hairline fractures or cracks observed
2 - Fracture present
3 - Samples is heavily fractured

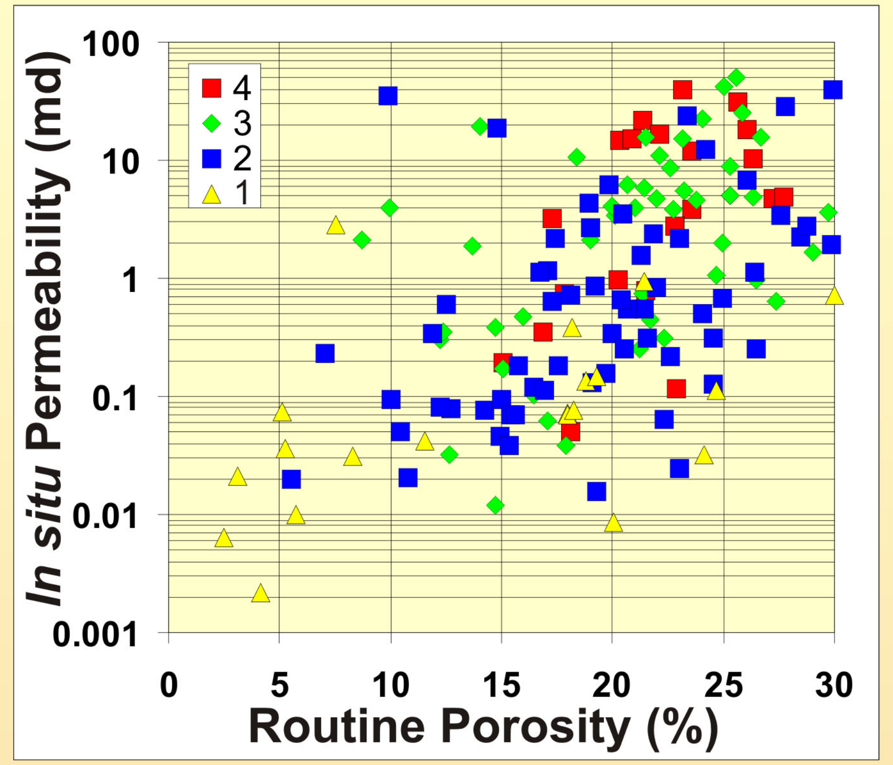
Correlations

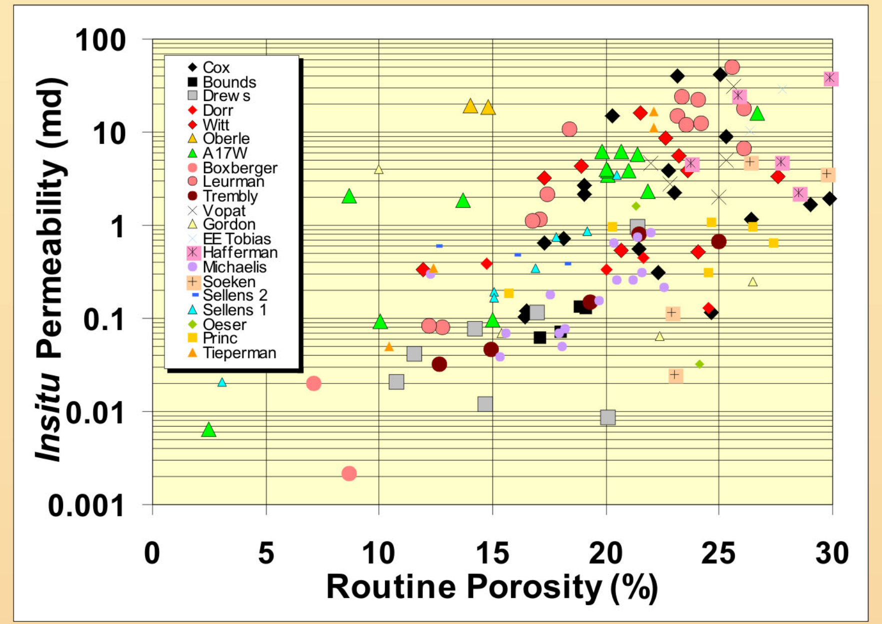
Figures to left indicate that several of the parameters are correlated with permeability and that the nature of the correlation is consistent with what would be anticipated.











Differences Between Wells

Correlation of permeability with porosity separated by well shows that many wells exhibit unique trends that display less variance in the correlation of porosity with permeability than the overall trend for oomoldic limestones. This points up the need for local data.

Remaining Variance After Using Porosity for Prediction

Correlation of permeability with porosity has remaining variance that can be accounted for by one of the other parameters. Examples to left illustrate that remaining variance is most dependent on Connectivity.

Multivariate Linear Regression

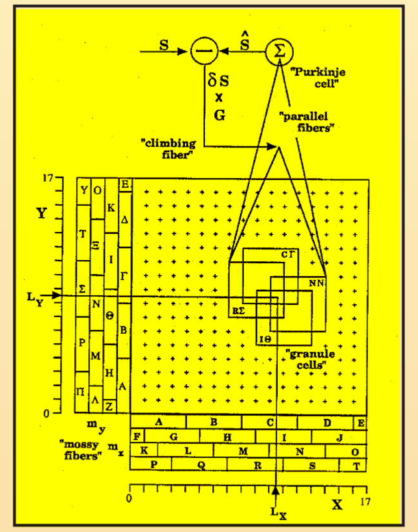
Multivariate linear regression was performed to try and improve permeability prediction. Problems arise in performing LRA using the variables measured because some are correlated with each other creating collinearity problems. This is particularly true for porosity. Factor analysis to separate the relative influences does not significantly improve the overall predictive accuracy.

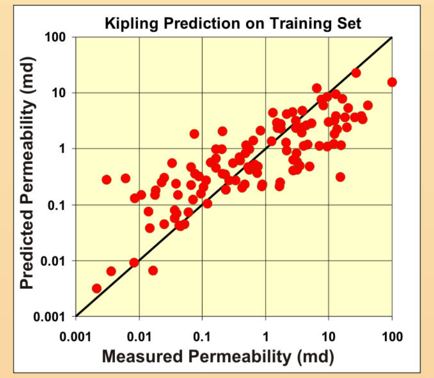
Basic porosity equation:

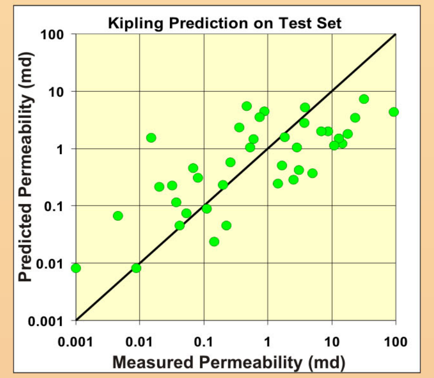
$\log k = 0.112 f - 2.48$ Std. Error = 7X

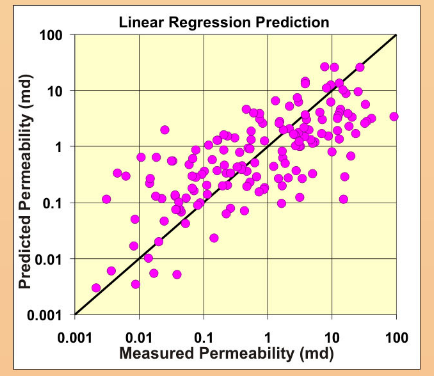
With Connectivity Index:
$\log k = 0.090 f + 0.47$ Connectivity Index - 3.21Std. Error = 5.5X

Addition of any additional variables only improves the standard error of prediction from 5.5X to 5.4X because variance accounted for by porosity is attributed to the actual variable controlling the variance, for example:
$\log k = 0.083 f - 0.40$ Connectivity Index - 0.28 Size
+ 0.11 Archie Index + 0.25 Fracture Index - 2.82Std. Error = 5.4X





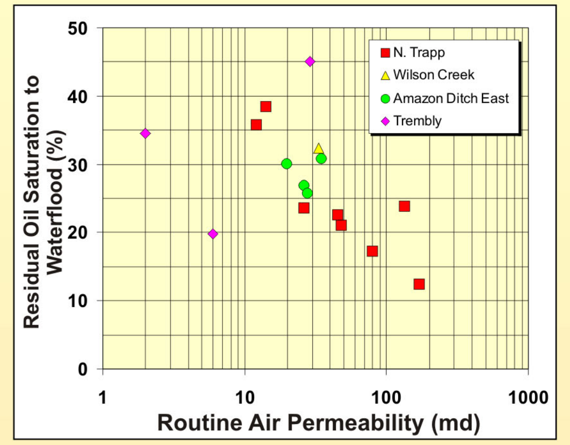




Kipling.xla - Nonparametric Regression

Multivariate linear regression was faced with colinearity issues. In addition, examination of outlier permeabilities indicated that unique traits might account for the measured permeability. For example, tight matirx might significantly lower permeability in a rock that might otherwise have excellent properties. If the population of tight matrix samples is too limited, regression has difficulty handling the variable influence. To see in nonparametric methods might improve prediction an Excel add-in program KIPLING (Bohling and Doveton, 1999 - available from the KGS) was used. KIPLING is an Excel program that is similar to neural network and works by discretizing variable space.

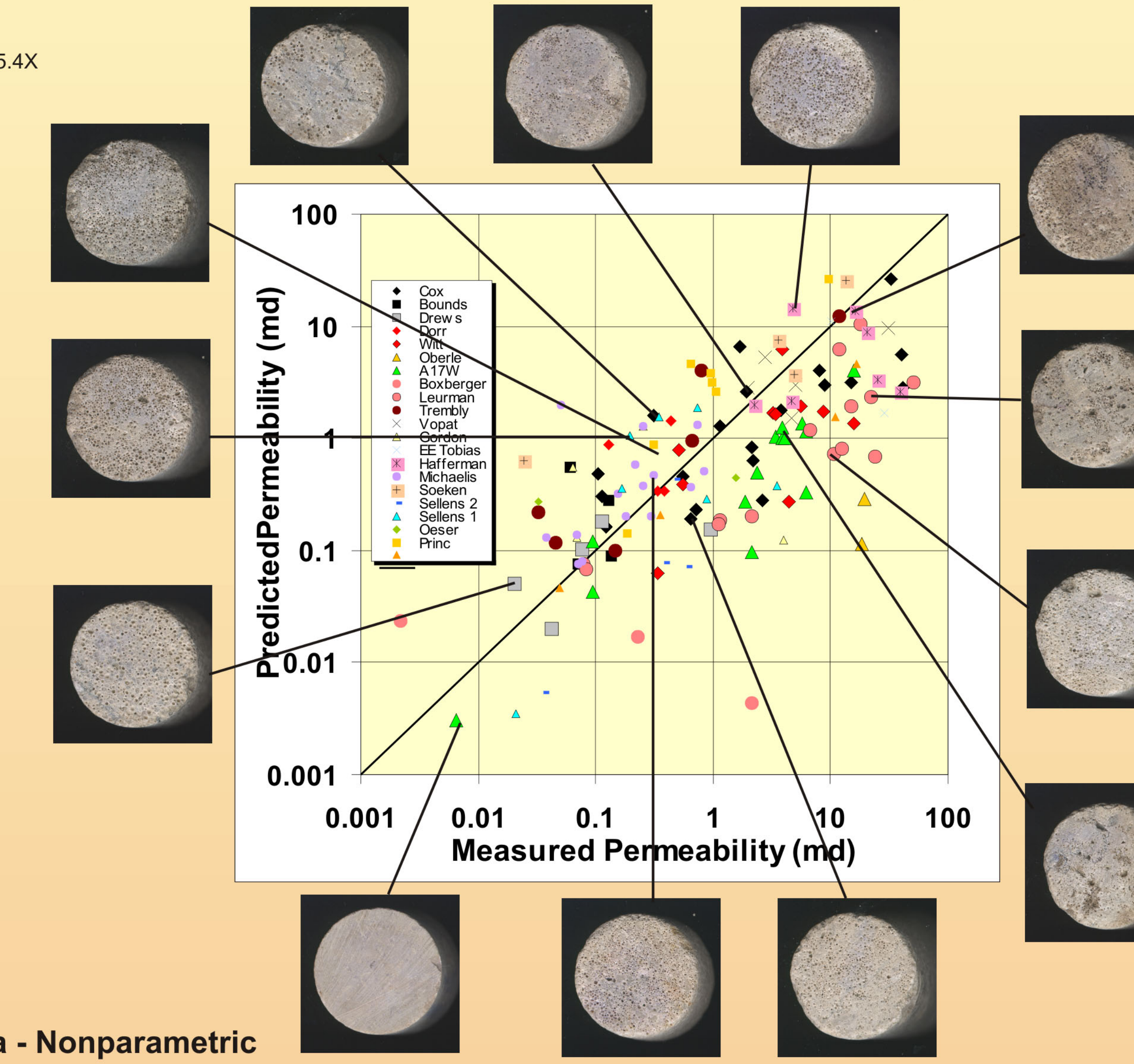
Utilizing 60% of the samples as a training set, KIPLING was able to exhibit a predictive accuracy of a factor of 4.4X on the training set and 5.4X in a test on the remaining data. This is comparable to the MLRA method accuracy. Further analysis is underway to analyze the nature of the analysis and possible directions of improvement.

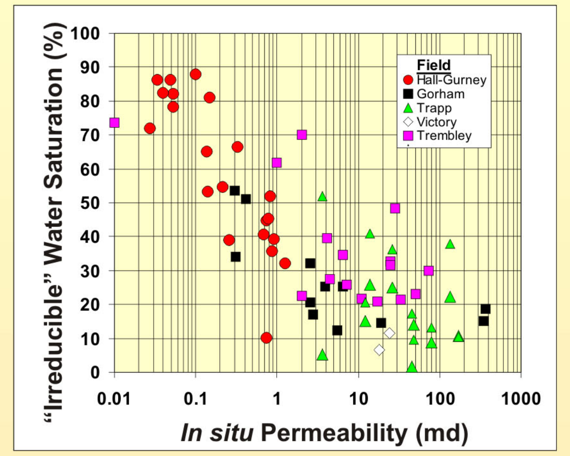


Residual Oil Saturation to Waterflood

Comparison of residual oil saturation to waterflood (S_{orw}) for samples from several fields indicates that S_{orw} increase with decreasing permeability. This may be related to the fact that low permeability rock may still contain large oomoldic pores. High pore body-to-pore throat size ratio has been show to be a strong control on snap-off phenomena and would be expected to result in trapped oil in the large oomoldic pores.

Residual oil saturation can be predicted using the relation:
$S_{orw} = 20.9 \log k + 59$

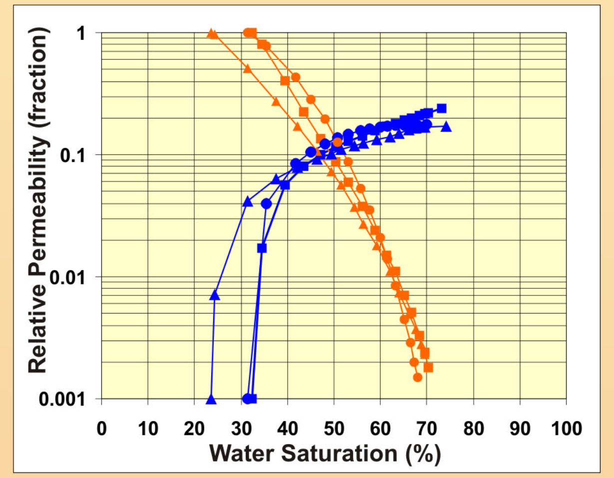




"Irreducible" Water Saturation

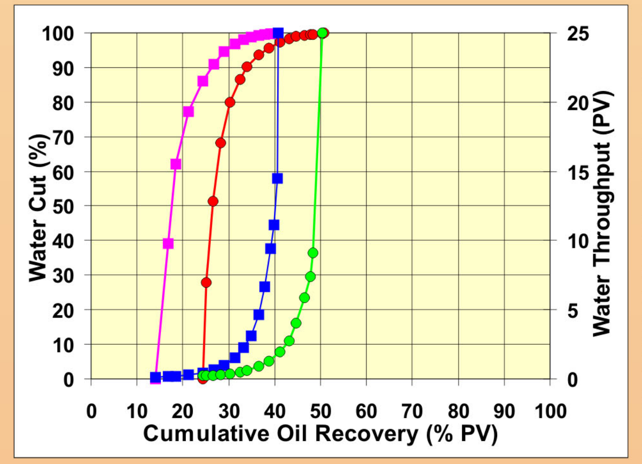
With finer pores in the matrix surrounding large oomolds it is important to understand capillary pressure relationships since high porosity may not be directly associated with effective oil porosity. Correlations of "Irreducible" water saturations (measured at pressures equivalent to 60-120 feet above free water level) indicate that S_{wi} increases with decreasing permeability as exhibited by many rocks. Differences between fields are largely attributable to the samples/wells analyzed and may not reflect true field differences.

Saturation increases with decreasing permeability following the relation:
$S_{wi} = 35.7 \exp(-0.46 \log k)$
\
where S_{wi} is in % and k in md.



Relative Permeability

Imbibition relative permeability curves for oomoldic limestone samples from the Amazon Ditch East Field, Marmaton Formation, exhibit uniformity for three similar samples exhibiting porosities from 24.0 to 25.3%, and permeability from 19.8 to 27.5 md.



Waterflood Susceptibility

Calculated waterflood susceptibility curves for oomoldic limestone samples from the Amazon Ditch East Field, Marmaton Formation, exhibit recovery efficiencies ranging from 56.2 to 66.3% of the oil in place (38.5-50.7% of pore space). These recoveries are for the similar samples exhibiting porosities from 24.0 to 25.3%, and permeability from 19.8 to 27.5 md. The moderately high recovery is consistent with recoveries exhibited by better Lansing-Kansas City oomoldic limestones but many lower permeability rocks exhibit poorer recovery efficiencies.

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Conclusions

Geology and Architecture

Lansing-Kansas City oolitic reservoirs exhibit geometries and architectures similar to modern oolites in the Bahamas although Pennsylvanian oolite reservoirs usually contain multiple stacked, or en echelon shoals which models indicate coalesced in response to sea level fluctuations.

Oolites form across the entire Kansas Pennsylvanian ramp. However, thicker, porous and permeable oolite deposits are commonly associated with the flanks or crests of small and large paleostructural highs. These structural highs may have influenced the intensity of early diagenesis and may have been responsible for development of good reservoir properties. Grain size variation, location on oolite buildups and interbedded carbonate mud (aquitards) influenced the nature and extent of diagenetic overprinting.

Oolite beds with porosity in excess of 8% porosity can reach several tens of feet in thickness, representing cross-bedded stacked shoals.

Subaerial exposure and meteoric water percolation led to cementation around the aragonite ooids and often dissolution of the ooids and variable development of matrix and vuggy porosity. Resulting oomoldic grainstones, the principal reservoir lithofacies, underwent variable degrees of early or later fracturing and crushing, providing connection between otherwise isolated oomolds.

Wireline logs signatures commonly exhibit low gamma ray, porosities ranging to greater than 30% and water saturations in the low teens with bulk volume water (BVW) as low as 0.03 based on an Archie cementation exponent of 2.

Petrophysics

Pay zones typically have BVW <0.05.

permeability (0.01-400 md) is principally controlled by :
Porosity
Oomold connectivity
Other variables that exert influence but are colinear with the above variables or are random include:
Oomold diameter
Oomold packing
Matrix properties
Matrix fracturing/crushing
Although permeability correlates with several of these variables, multivariate linear regression methods only improve prediction from a factor of 6.9X to 5.4X by inclusion of information concerning connectivity index, as measured on rock pieces. Few variable are utilized because of vaiable autocorrelation. The critical role that a single variable may play in controlling permeability hinders linear associations.

Non-parametric Regression analysis, utilizing the variables above, provides a mathematical tool capable of predicting permeability in all oolites studied within a factor of 5.3X, only slightly better than MLRA prediction.

Individual wells exhibit k-f trends with less variance than the overall trend, however, to date, the variables that cause the samples from these wells to exhibit different trends has not been identified. Development of models for specific fields, representing unique associations of conditions, allows the most accurate prediction

Irreducible water saturation (*Siw*) and residual oil saturation after waterflooding (*Sor,w*) are also strongly controlled by connectivity and correlate highly with permeability

The oomoldic reservoirs rocks studied provide insight into the interactions of rock fabric-architecture-diagenesis and better understanding of the universal influence of certain variables on oomoldic reservoir properties. Work is still needed to improve predictive tools.