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Risk Reduction with a Fuzzy Expert Exploration Tool

(Third Semi-Annual Technical Progress Report)

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New Mexico Petroleum Recovery Research Center
New Mexico Institute of Mining and Technology
Socorro, NM 87801
(505) 835-5142

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Project Manager:	James Barnes, NPTO
Principal Investigator:	William W. Weiss
Contributors:	Ron Broadhead,
Contracting Officer's Representative:	William R. Mundorf, FETC
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Executive Summary

Objectives

Incomplete or sparse information on types of data such as geologic or formation characteristics introduces a high level of risk for oil exploration and development projects. “Expert" systems developed and used in several disciplines and industries have demonstrated beneficial results. A state-of-the-art exploration “expert” tool, relying on a computerized database and computer maps generated by neural networks, is being developed through the use of “fuzzy” logic, a relatively new mathematical treatment of imprecise or non-explicit parameters and values. Oil prospecting risk can be reduced with the use of a properly developed and validated “Fuzzy Expert Exploration (FEE) Tool.”

This FEE Tool can be beneficial in many regions of the U.S. by enabling risk reduction in oil and gas prospecting as well as decreased prospecting and development costs. In the 1998-1999 oil industry environment, many smaller exploration companies lacked the resources of a pool of expert exploration personnel. Downsizing, low oil prices, and scarcity of exploration funds have also affected larger companies, and will, with time, affect the end users of oil industry products in the U.S. as reserves are depleted. As a result, today’s pool of experts is much reduced. The FEE Tool will benefit a diverse group in the U.S., leading to a more efficient use of scarce funds and lower product prices for consumers.

This fifth of ten semi-annual reports contains a summary of progress to date, problems encountered, plans for the next year, and an assessment of the prospects for future progress. The emphasis during the May 2001 through September 2001 was directed toward development of rules for the fuzzy system.

Progress and Discussion of Results

Geology

The following tasks were addressed during the reporting period on the Brushy Canyon petroleum system.

1. *Logging and stratigraphic description of productive and non-productive cored sandstone intervals of the lower Brushy Canyon Formation.* Previous work on this project determined that some thick sections of Brushy Canyon sandstones in trap configuration are productive while others are non-productive despite having been extensively tested. One hypothesis for this phenomenon is that grain size and/or pore size may be larger in the productive sandstones, thereby resulting in lower capillary entry pressures that permitted entry of migrating hydrocarbons while the finer sandstones, with higher capillary entry pressures effectively acted as seals for the hydrocarbons. Productive and nonproductive sandstones from core in the Nash Draw field (Fig. 1) were described macroscopically in order to provide baseline data on productive and nonproductive sandstones.

2. *Correlation of petrographic properties of sandstones with log properties in the lower Brushy Canyon Formation.* Several petrographic properties related to capillary pressure properties and oil migration and emplacement were analyzed and related to log properties. The purpose of this work is to determine if factors affecting and/or limiting hydrocarbon migration/emplacement can be mapped in order to establish

areal limits to potentially productive thick accumulations of sandstone. Such properties as percent macroporosity, percent microporosity, grain size, and clay content were quantitatively related to log properties (Figs. 2, 3). Similar work has proven successful in the Cherry Canyon Formation.[1] We show that the gamma-ray intensity of lower Brushy Canyon sandstones relates linearly to clay content (Fig. 2). The difference in porosity given by the neutron logs and the density logs (phi_n - phi_d) also shows correlation to gamma ray intensity (Fig. 3). Where the density logs reads a higher porosity than the neutron log (gas effect = hydrocarbon-filled reservoir), the gamma-ray intensity is low, signifying a low clay content. Where the neutron log gives a significantly higher porosity than the density log (no gas effect = water-filled reservoir), the sandstones have a high gamma-ray reading, and therefore high clay content. Petrographic examination of Brushy Canyon sandstones reveals that the clays are mostly present in pores and will act to inhibit migration and emplacement of oil in the reservoir. During the next quarter we will verify these results on additional core and will map clay content via gamma ray logs in productive and nonproductive porous sandstones that are in trap configuration. The additional cores come from the Poker Lake field in the southern part of the basin and from a nonproductive well adjacent to the Parallel field in the northern part of the basin (Fig. 1). These observations may result in development of rules in the overall expert system.

3. *Detailed subsurface mapping of depositional elements of lower Brushy Canyon sandstones in areas proven to be productive and areas proven to be nonproductive.* These maps show sandstones, in trap configuration, for which a distinction cannot be

made between thick, productive sands and thick, non-productive sands. Therefore, steps 1 and 2 above were undertaken to acquire additional data that should be relevant to oil prediction.

Engineering

Fuzzy log analysis techniques were applied to a Lower Brushy Canyon log/core dataset from the Poker Lake field. The results to date demonstrate the value of the Nash #23 dataset with its 203 records for training a neural network to predict bulk volume oil. The maximum number of contiguous whole core records in the Poker Lake field is 79 from well #80. Limited records can lead to a neural network over-training problem. The problem manifests itself by testing trained neural network with data not included in the development of the neural network architecture. An example of "blind testing" is seen in Fig. 4 where the Nash #23 neural network is used to predict the Poker Lake #80 core measurements. Overtraining is minimized by maintaining the neural network records to weights ratio greater than two.

Additional work with the carbonate log/core data set reported in the Second Annual Report suggests that core-measured aspect ratio (porosity/permeability) may correlate well logs. These preliminary results may prove useful when the direction of the project shifts to Devonian carbonate reservoirs.

Computational Intelligence

Regional data analysis

A key component of this study is the analysis of the regional data to provide baseline data to correlate with production potential, but also to provide a source of heuristic rules for the expert system. Four major categories of regional data (gravity, aeromagnetic, structure, and thickness) were selected, compiled and finalized during the last six months. Regional gravity surveys covering the entire area of the Delaware basin have been compiled with an accuracy of a few milligals. The survey measurements are on the order of a few thousand feet apart, but sample point locations are highly variable as gravity is measured in easily benchmarked locations, such as along roadways. Gravity measures variations in density and tends to highlight large-scale regional structures in basement materials, so if structure has an impact on maturation, migration or trapping of hydrocarbons in the basin, useful information can be obtained. Regional aeromagnetic data, primarily collected via over-flights with one-mile spacing re-gridded to 0.296 miles longitude and 0.346 miles latitude, also exist for the region. Aeromagnetic data highlights contrasts in the magnetic susceptibility between rocks and can help indicate basement blocks, large-scale faults, and possible large-scale alluvial deposits. The structure of the lower Brushy Canyon was picked on 700 wells in the basin covering a geographically large area. Large-scale maps of structure covering the region were constructed with a kriging algorithm using this data. Structure can play more than one role in trapping and migration of hydrocarbons. Two potentially helpful attributes for this study are structural highs and flexures that may induce fracturing along the flanks of structures or be caused by subsurface faulting. Finally, the wells used to compute structure were used to generate an isopach map for the Brushy Canyon in the region. Thickness may indicate areas of greater potential production and can indicate pinch-outs and other nonstructural features that may form hydrocarbon migration pathways or traps.

A number of attributes were calculated from the four regional data types. These attributes are first and second derivatives along latitude and longitude, dip azimuth and magnitudes, and curvature azimuths and magnitudes. These values were computed to expose finer scale features in the basic data types, which might be useful for correlating back to a production indicator. A total of 36 maps were generated using the Zmap tool of Landmark Graphics Release 98 plus interpretation package.

Each of these maps was gridded at a scale of 1320-ft (quarter section) because that is the regulatory spacing for wells in the Brushy Canyon in New Mexico. The gridded data was exported and loaded into the project production database. Our current production database is a subset of the Oil and Natural Gas Administration and Revenue Data (ONGARD) database used by the State of New Mexico (supplied courtesy of the SW PTTC) containing production information on all New Mexico wells. In this database we have also identified Brushy Canyon wells and, using grid locations from the Zmap maps, we were able to correlate producing wells with grid numbers. This essentially allows regressions to be formed using the production data as control points (training and testing) and the attribute data as variables. Any regression formed in this manner could then be used to predict production in all other 40-ac bins in the basin.

There are two primary considerations when trying to form regressions: the first involves the quality of the data you are attempting to predict with the generated regression model; the second deals with the choice of attributes or variables that will be used in forming the regression model. An optional consideration is the application of linear models (least squares regression) or more complicated non-linear solutions such as polynomial regressions or neural networks. An average of the first 12 producing months' hydrocarbon equivalent (BO + MCF/6) calculated at each well was chosen as the data to be modeled. Figure 5 shows a histogram of average hydrocarbon equivalent produced per month in barrels (BEPM) for the 2257 identified Brushy Canyon wells. The trend of the histogram is approximately an exponential decay function. A more ideal data distribution that simplifies modeling follows a Gaussian distribution. The production data was conditioned with a log10 filter, and Fig. 6 shows a histogram of the production indicator after log10 conversion. The bulk of the data now follows a roughly Gaussian distribution with some notable outliers on the low end. It is desirable to remove outliers from the training data if those data are not significant to the solution. In this case, a cutoff of 50 barrels of oil per month was applied to remove the outliers. The data can then be unfiltered once the outliers are removed and used as normal in regression analysis as the filtered data is well conditioned for either linear or non-linear regression analyses.

There are a number of ways to determine which of a set of inputs (attributes) would best be used to form a regression for a particular output. Simply crossplotting each input against the output can give an indication of the quality of linear or multiple linear regression models that could be formed. For this study each of the 36 data and data attributes calculated and loaded into the database were analyzed using fuzzy ranking.[2] It is both statistically dangerous and not computationally feasible to use all 36 attributes to form a regression relationship, so software was developed based on a fuzzy-ranking algorithm[2] to select attributes best suited for predicting production indicators. The algorithm statistically determines how well a particular input (regional data or data attribute) could resolve a particular output (production indicator) with respect to any number of other inputs using fuzzy curve analysis. Using a newly refined fuzzy ranking tool (described in subsequent paragraphs) each data attribute was ranked for its ability to predict production potential at these well locations. The highest ranked attributes are gravity dip-azimuth, gravity second derivative north-south, gravity first derivative north-south, gravity first derivative east-west, magnetism second derivative east-west, and magnetism first derivative north-south. These attributes are being used to generate a production potential map for the Delaware basin, using neural networks and expert systems, at the scale of 40 acres. Such a map will be a useful tool for evaluating infill, step out, and wildcat wells in the Delaware basin, both at reservoir and regional scales, and will provide valuable heuristic rules for the expert system.

Fuzzy Ranking Revisited

A fuzzy curve solution to the problem of identifying important neural network input variables from large sparse database was discussed in the second annual report. For completeness the fuzzy ranking concept is reviewed.

There are a number of ways to select the best set of inputs to be used to form a regression for a particular output. Simply crossplotting each input against the output can give an indication of the quality of linear or multiple linear regression models that could be formed. Software was developed based on a single stage fuzzy-ranking algorithm to select inputs best suited for predicting the desired output. The algorithm statistically determines how well a particular input could resolve a particular output with respect to any number of other inputs using fuzzy curve analysis.

To illustrate the technique a simple example is given. Consider a set of random numbers in the range {0,1} using $x=\{x_i\}$, $i=1,2,\ldots,99$, and $x_i=0.01*i$, and plot each value (y_I= Random(x_i)). Next add a simple trend to the random data ($y_i=(x_i)$^0.5+Random (x_i))

and plot those values. For each data (x_i, y_i) a "fuzzy" membership function is defined using the following relationship:

$$F_i(x) = \exp(-(\frac{x_i - x}{b})^2) * y_i$$

Sample fuzzy membership functions are shown in Figs. 7 and 8. Here, b=0.1, since b is typically taken as about 10% of the length of the input interval of x_i. A fuzzy curve was constructed using a summation of all individual fuzzy membership functions in (x_i, y_i). This final curve can prioritize a set of inputs for linear or non-linear regressions. The fuzzy curve function is defined below:

$$FC(x) = \frac{\sum_{i=1}^{N} F_i(x) * y_i}{\sum_{i=1}^{N} F_i(x)}$$

where N is the size of the data set or the total number of fuzzy membership functions. Figure 9 shows the curves for the data sets shown in Figs. 7 and 8. This simple example illustrates the ability of the fuzzy ranking approach to screen apparently random data for obscure trends such as the correlation between seismic attributes and reservoir properties.[3]

More information is needed to advance this analysis from the art of reading these fuzzy curves to a more robust and systematic elimination of less useful inputs. Therefore, work began on a two-stage fuzzy ranking code.[4] The two-stage fuzzy ranking (TSFR) has two improvements: 1) reduction of input variable space through random characterization and 2) establishment of hard rules for selection of best-input variables. TSFR introduces second stage fuzzy curves, with first and second stage fuzzy surfaces to select the most important and independent input variables for modeling, while removing the input variables that show random characteristics.

TSFR uses first and second stage fuzzy curves to generate the fuzzy curve performance index:

$$P_c = \frac{P_{stage1}}{1+P_{stage2}}.$$

With the addition of a known random variable into the input space, P_c is normalized by the random $P_{c,R}$ to produce the normalized fuzzy curve performance index:

$$P_{c,N} = \frac{P_c}{P_{c,R}}.$$

The input variable with the smallest $P_{c,N}$ value the most important variable. Input variables with $P_{c,N}$ greater than one are eliminated from the selection process. Once the most important variable is determined, fuzzy surface analysis is performed.

Analogously, for fuzzy surfaces a performance index exists that uses the first and second stage fuzzy surfaces:

$$P_s = \frac{P_{stage1}}{1+P_{stage2}}.$$

A similar normalization procedure produces the normalized fuzzy surface performance index:

$$P_{s,N} = \frac{P_s}{P_{s,R}}.$$

The input variable with the smallest $\boldsymbol{P_{c,N}}$ is considered the next most important and independent input. In an iterative process, the input variables with $\boldsymbol{P_{c,N}}$ above 1.0 are eliminated from the pool of potential independent inputs. The fuzzy surface analysis continues until no input variables remain. Therefore, two-stage fuzzy ranking can be used to automatically and quickly identify the important and independent inputs needed to model the system of interest.

Expert System Rules

Basic Design Changes. The original design entailed the use of a single massive expert system to make decisions about a prospect's potential as a well site (Fig. 10). As we have investigated the process of designing and running expert systems, it has become apparent that a multi-tiered system, with components running in parallel would be both more efficient and more versatile in actual usage. Figure 11 shows the current design structure for implementing and accessing the various expert systems needed to evaluate production potential. The new design is more efficient for several reasons. First, it will be faster to code the rules and the resulting code will run faster. Second, parallel expert systems will allow the user to consider only the data types they feel are most influential, and ease customization to their personal philosophies. Third, database IO from the system will occur in numerous small packets instead of large chunks and extraneous data transfers will be reduced.

Implementation

Figure 11 shows the basic layout of the Fee Tool project. Tier 1 is a user interface that allows selection of an area or prospect of interest. Users can select the types of data they are interested in, and can review that data online with their browser. Tier 2 in Fig. 11 represents the access of the user's browser with our online database. Advanced users can manipulate the transferred data for their personal use. This data will reside on their computer and will not be generally available, or affect the permanent database in any way. This allows the use of proprietary information with the system. Once the data is accepted or modified, the next step is to run the appropriate expert systems using the available data to answer heuristic questions and accepting user input to answer other questions that "experts" tend to ask when evaluating Brushy Canyon prospects. In tier three there are five expert systems that can be applied based on user wishes. These address regional indications, trap assessment, formation assessment, improved recovery, and oil price. Specifics and starting rules for these five systems are discussed below. Some users may elect to not factor in certain aspects, or to hard wire their own values for future oil price.

Scoring of rules. Each of the sub-expert systems will assign a numerical score based on the answers to individual questions. The score can come in several varieties, including binary, or off/on flagging, assigned percentage values, or fuzzy based distributions. Most rules in the subsystems will likely be assigned numerical values based on analysis of training data or fuzzy distributions based on data analysis. When combined to form the global relationship, fuzzy distributions or other functions will be applied.

Trap assessment–rules. Initial trap assessment rules as programmed into the initial system are graphically illustrated in Figs. 12–14 in flowchart form.

Formation assessment–rules. Initial source rock assessment rules as programmed into the initial system are graphically illustrated in Figs. 15–19 in flowchart form.

Regional indication–rules. Initial regional assessment rules as programmed into the initial system are graphically illustrated in Figs. 20–21 in flowchart form.

Improved recovery–rules. As the Brushy Canyon sands comprise a relatively new play, there is not a lot of information available on improving existing production. Also, as the play is believed to be water-wet, waterfloods are high-risk anywhere in the basin. One possible advanced recovery technique is CO_2 flooding, but Brushy Canyon field data are scarce. Horizontal wells appear to be the most likely candidate technology for improved recovery.

Oil price – rule. Oil price will be available in three main formats:

- *User- entered*, the user enters a fixed price per barrel based on internal projections or company philosophy.
- *Predicted by neural network*, projects the price of oil using the futures markets (a neural network is being developed).
- *Standard posted price,* for the day the calculation is made.

Database notes and concerns. The final database has to consider what heuristic rules are going to be used. For example if the prospect in question is within 2 km of TOC >1.0% source rock, the database will need to be populated with data of this sort for each bin or be able to calculate such data on the fly. Also note that these are examples of very basic and simple rules intended to illustrate the process and provide a starting point for developing the system and linking it to the various databases. More rules will be added as the system is trained and as more expert information becomes available.

Numerical Fuzzy Rules

Introduction. Fuzzy set theory is a mathematical approach for working with imprecise data and measurements. In exploration, relevant data such as porosity is sometimes approximated or interpolated from data collected at nearby wells. The following example shows how principles of fuzzy set theory are used with expert opinions to compute a value for a well's potential. The steps involved are: determining the input parameters and obtaining approximate numerical values, developing the linguistic values, fuzzifying the input parameters, firing the appropriate expert defined rules, and defuzzification of the output parameter. Each of these steps is discussed in detail below.

Input parameters. In this example, two variables will be used as input parameters. The variables, total organic carbon (TOC) and porosity, are variables for which it is sometimes difficult to get a precise value, and measurements may have to be used from nearby wells. For each of these variables, linguistic values will be defined based on the following criteria:

T=Total Organic Carbon

T: ZERO if $0 \le T < 0.5$
T: LOW if $0.5 \le T < 1.0$
T: MEDIUM if $1.0 \le T < 1.5$
T: HIGH if $1.5 \le T$

P=Porosity (percentage)

P: ZERO if $0 \le P < 5$
P: LOW if $5 \le P < 10$
P: MEDIUM if $10 \le P < 15$
P: HIGH if $15 \le P$

For this example, 0.72 will be used as the best available value for TOC, and 13% will be used for the best available porosity. These two inputs will be used to develop a value for R, the prospect potential on a scale of 1 to 100.

Fuzzification of input parameters. The next step in the process is to “fuzzify” the input parameters. In order to do this, we will define fuzzy membership values for each of the sets; zero, low, medium and high, using a set diagram called a fuzzy membership curve that graphically defines each of the linguistic values. There are many curves that can be used in this process, the simplest being a trapezoidal graph, which we will use here. The process is done for each of the input parameters. Figure 22 illustrates the process for the variable T. The value of 0.72 is plotted on the x-axis, corresponding to the following values of membership in each of the linguistic sets:

T (Zero)=0
T (Low)=56
T (Medium)=44
T (High)=0

The process is repeated for the porosity (Figure 23), using the best value of 13%.

Φ (Zero)=0
Φ (Low)=0
Φ (Medium)=40
Φ (High)=60

Rules. Once the input parameters have been fuzzified, the linguistic sets with non-zero membership can be used to fire a set of rules determined by an expert. The rules for this example are:

1. If T is zero then R is zero.
2. If P is zero then R is zero.
3. If T is low and P is low or medium, then R is low.

4. If T is low and P is high then R is medium.
5. If T is medium and P is low then R is low.
6. If T is medium and P is medium or high, then R is medium.
7. If T is high and P is low or medium then R is medium.
8. If T is high and P is high then R is high.

We use the non-zero memberships from the fuzzification process to determine that rules 3, 4 and 6 are applicable.

Defuzzification. The next step in the process is to determine the strength of each of the fired rules using the set theory operators min for "and" and max for "or". Beginning with rule 3, T is low with membership value of 56, P is low with membership value of 0 and P is medium with membership value of 40. Thus, P is low ***or*** medium with a membership value of 40. Rule 3 is then "fired" with a strength of 40, using min(56,40) to arrive at this value.

Following this process for the two other rules, rule 4 and 6, we have rule 4 fired with a strength of 56 and rule 6 fired with a strength of 44. Rule 4 and 6, however, both result in R being medium, so we combine the two using the max operator. The final results are that R is medium with a strength of 56 and low with a strength of 40.

To obtain a numerical value for R, on a scale of 1 to 100, we consider the median values of 10 for low, 50 for medium and 90 for high. Then using the strengths computed above, we calculate R as follows:

$$R = 0.40*(10)+0.56*(50) = 32$$

Summary. This is a simple example of how the fuzzy set theory approach can be used to determine potential. In a more complex example, multiple input parameters may be used, and the curves used to determine the memberships may be more complex than the trapezoidal curves used here. The basic ideas are the same, however, and can be used to build the framework for computer codes that compute potential based on rules written by experts in the field.

A Web-Based Database Management System (WDMS)

Advances in the web system. A key component to the success of this project is the development of a dynamic web-accessible database for storing, managing, accessing, and analyzing data, including the development of heuristic fuzzy rules and operation of the inference engine. As the data files can be quite large, the system must be efficient and useable by persons with varying degrees of computer literacy.

Several important advances in the web system have taken place in this semi-annual period. Key data definitions, data flows, data processing methods and user interfaces with WDMS have all progressed. A new version of *PredictOnline* has been coded, user management software has been developed and debugged, and a beta version of a fuzzy ranking code, *FuzzyOnline*, utilizing the more advanced two-stage algorithm, has been developed.

Considerations of security for both users and potentially proprietary data, as well as the integrity of the databases led to the development of web-based account management. Users can now register, login, create and delete accounts, change user's privilege and see statistics on their personal usage of the system in a secure environment. In addition system administrators can locally or remotely manage all accounts.

Improvements to *PredictOnline* include the removal of the Java policy file. In the previous version, a Java policy file was needed on the user's computer to allow *PredictOnline* to access data via applets. Upload and download functions without Java policy files have been developed in JSP. In addition, an alternate version of the neural network algorithm was installed, which, for some problems, improved efficiency by nearly an order of magnitude for a test case.

Java applet codes were designed to implement the user-side interface for a new *FuzzyOnline* software package. JSP codes were designed to implement the server-side functions. JSP codes called Fortran executable codes have been successfully tested, though the overall program still requires development.

Technology Transfer

During this six-month period (May 01-Sept. 01) the following five papers or presentations were made to disseminate the results of the project:

1. Weiss, W.: "Mining Regulatory Files with Artificial Intelligence to Predict Waterflood Recovery," presented to the City Different Petroleum Club, Santa Fe, NM, May 3, 2001.
2. Weiss, W. W., Stubbs, B.A. Balch, R.S.: "Estimating Bulk Volume Oil in Thin-Bedded Turbidites," paper SPE 70041 presented at the SPE Permian Basin Oil & Gas Recovery Conference, Midland, Texas, 14-17, May 2001.
3. Weiss, W.: "Risk Reduction with a Fuzzy Expert Exploration Tool," SPE 70054, Poster presented at the SPE Permian Basin Oil & Gas Recovery Conference, Midland, Texas14-17, May 2001.
4. Weiss, W. W., Wo, S., Weiss, J.: "Data Mining at a Regulatory Agency to Forecast Waterflood Recovery," paper SPE 71057 presented at the 1999 SPE Rocky Mountain Technical Conference, Keystone CO, 21-23 May 2000.
5. Weiss, W.W.: "Neural Networks and Geostatistics Used to Characterize a Reservoir in a Coastal Dune Environment," Short Course Presented at the Annual Petroleum Engineering Summer School, Workshop No. 8 *Geomodeling In Exploration and Production of Oil and Gas*, Dubrovnik, Croatia, 4-8 June, 2001.

Problems

The acquisition of regional seismic lines continues to be a problem due to the value of the data. Local datasets are available such as those from the DOE-funded Nash Draw project. The processed data from this 3D data set was used to develop new methods of interpreting the distribution of thickness, porosity, water saturation and depth throughout the survey area. The methodology can be applied throughout the Delaware Basin.

Coding of the required web interface algorithms is an ongoing problem. New graduate students are in place and continue to support development of the software.

Next Year's Tasks

September 2001 marks the halfway point in the project schedule when the geologic focus of the project becomes the Devonian carbonate. The Devonian petroleum system of southeastern New Mexico consists of carbonate reservoirs in the Fusselman Formation and source rocks and regional seals in the overlying Woodford Shale.

Devonian and Siluro-Devonian carbonates produce from numerous oil and gas fields in southeastern New Mexico (Fig. 24). The 122 Siluro-Devonian fields in southeast New Mexico had produced a cumulative 443 MMBO by 1995,[5] 10% of the oil produced in southeast New Mexico. Production is from a number of zones within the Silurian and Devonian sections (Fig. 25). A variety of mechanisms form traps, most notably anticlines, faulted anticlines, and sub-unconformity pinchouts.[6]

Geologic data acquisition began on the Devonian carbonates during the reporting period. One thousand six hundred wells in southeast New Mexico that have penetrated the Devonian were identified and entered into a database; longitude and latitude have been calculated for these wells. Work also began on a regional network of cross sections in order to establish correlation control and to provide quality assurance of data.

As in our earlier work on the Brushy Canyon Formation, we will use our correlated data to produce geologic structure maps, and isopach (thickness) maps of Devonian carbonate strata and relate these to production/non-production in both visual and artificial intelligence settings. The goal is to use our artificial intelligence system to predict trap configurations in Devonian strata.

We will also construct regional maps of source rocks. The chief source rock unit is the Devonian Woodford Shale, which directly overlies the Devonian carbonates (Fig. 25). The Silurian Simpson shales are source rocks that underlie the Siluro-Devonian carbonate section. The Woodford is thought to be the chief source unit for lower Paleozoic reservoirs in the Permian Basin and the Simpson is a secondary but still important source unit.[7,8] As with the Brushy Canyon, we will map regional distributions of source rock maturity and quality and relate these to oil and gas distribution. With the depth of the Woodford varying from less than 7000 ft in the northern part of the basin in Chaves County to more than 15,000 ft in the southern part in Lea and Eddy Counties, we expect to encounter thermal maturity variations across the oil window/gas window boundary that will relate to the distribution of oil reservoirs and gas reservoirs. The map of Siluro-Devonian oil and gas fields (Fig. 24) indicates that most gas fields are located in the more deeply buried southern parts of the basin where thermal maturity of source rocks should be higher. These relationships will be quantified for use in the artificial intelligence system. Thermal maturity variations may also help in the prediction of gas-oil ratios and therefore, relate to aspects of recovery efficiency.

During the next 12 months, we expect to:

1. Finish correlating significant Siluro-Devonian marker beds in wells throughout the Permian Basin in southeastern New Mexico.
2. Produce appropriate computer-contoured structure and thickness maps of variables that should be relevant to the accumulation and entrapment of oil (for example, structure on top of the Devonian carbonates, thickness of significant productive, porous units).
3. Select appropriate wells for source rock analysis of the Woodford Shale and, to a lesser extent, the Simpson shales and perform source rock analyses.

Anticipating that log interpretation in carbonates may be amenable to neural network technology, a study of open-hole logs and cores from a vuggy carbonate reservoir was undertaken and preliminary results were reported in the Second Annual. The initial objective was to correlate bulk volume oil measured in cores with the available logs. Additional work done during the past six months indicates that aspect ratio (porosity divided by permeability can be estimated from "fuzzy" log analysis.

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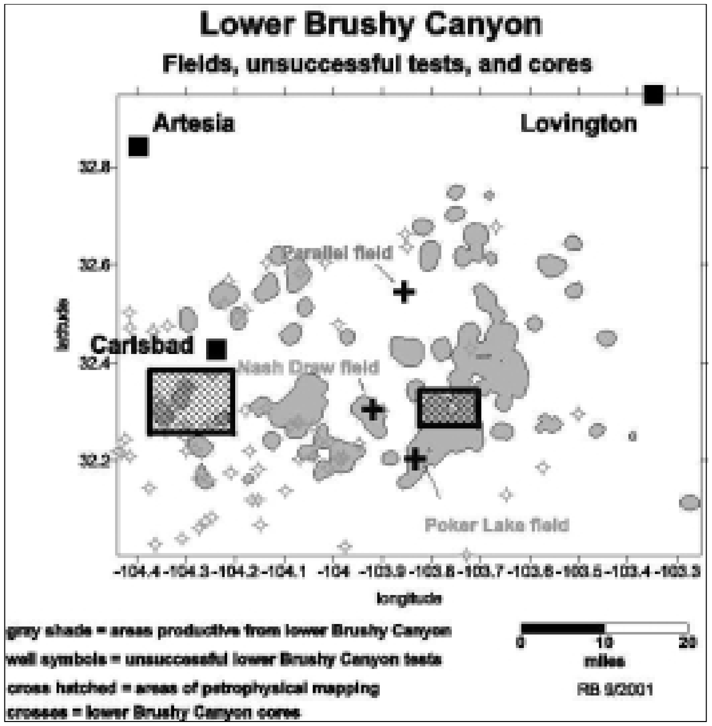


Fig. 1. Location of Brushy Canyon oil fields, fields with core utilized for petrographic and petrophysical study, and areas designated for mapping of clay content of lower Brushy Canyon sandstones. Well symbols indicate wells that unsuccessfully tested lower Brushy Canyon sandstones.

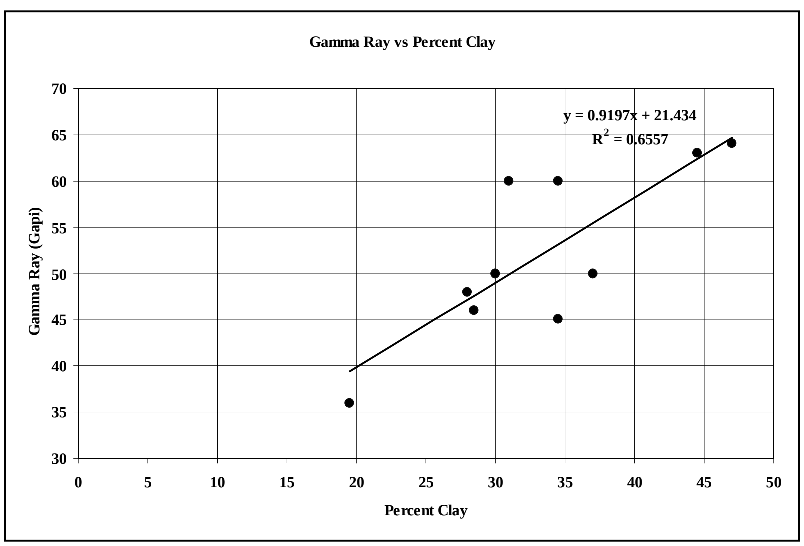


Fig. 2. Gamma-ray intensity as measured from gamma-ray log plotted against petrographically-determined clay content of lower Brushy canyon sandstones. Core located in Nash Draw field.

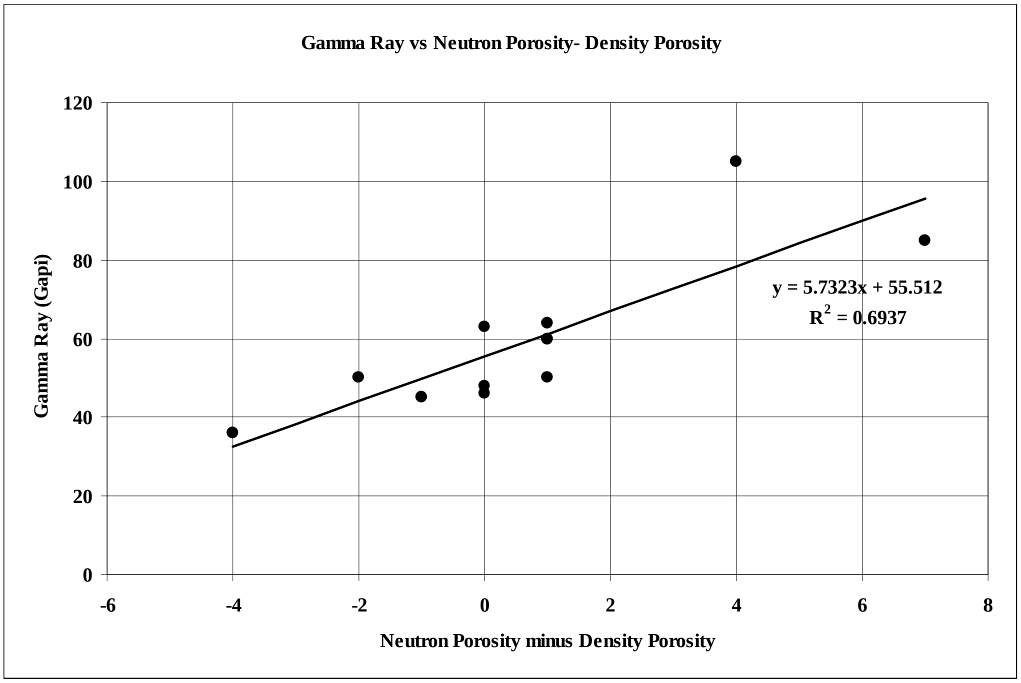


Fig. 3. Gamma-ray intensity as measured from gamma-ray log plotted against the difference between neutron log porosity and density log porosity (phi_n - phi_d).

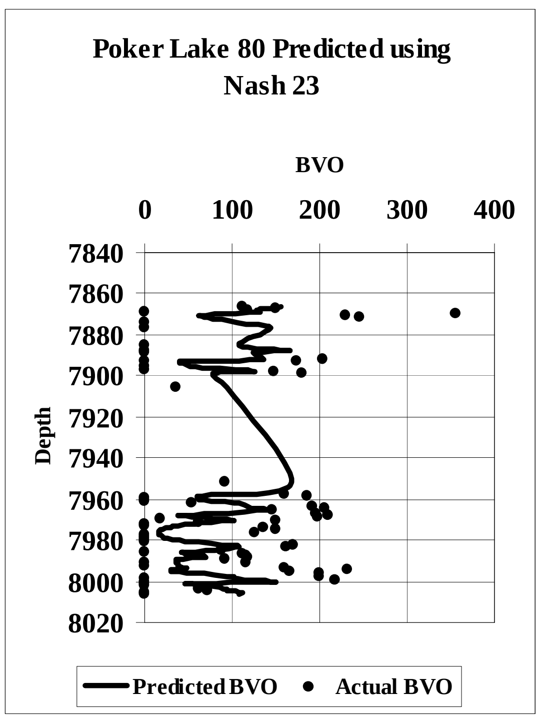


Fig. 4. Poker Lake #80 predicted with Nash 23.

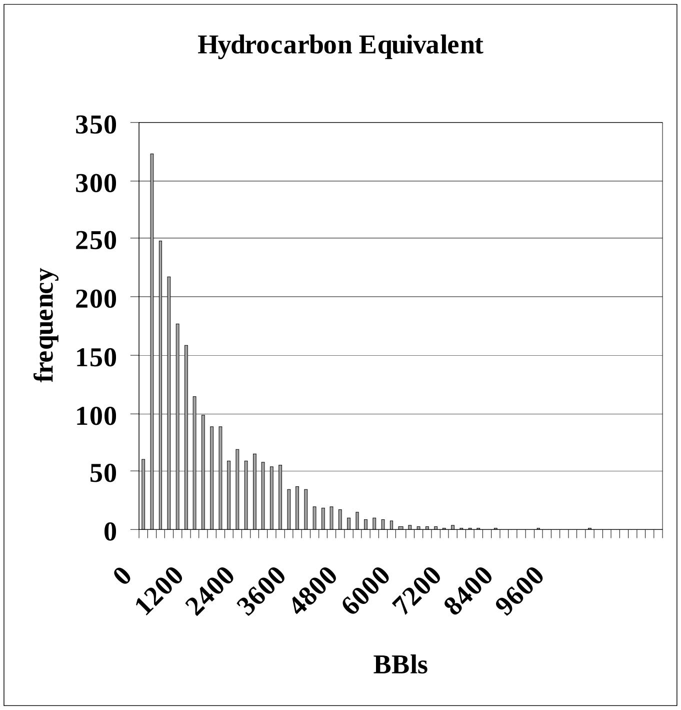


Fig. 5. Barrels equivalent per month histogram.

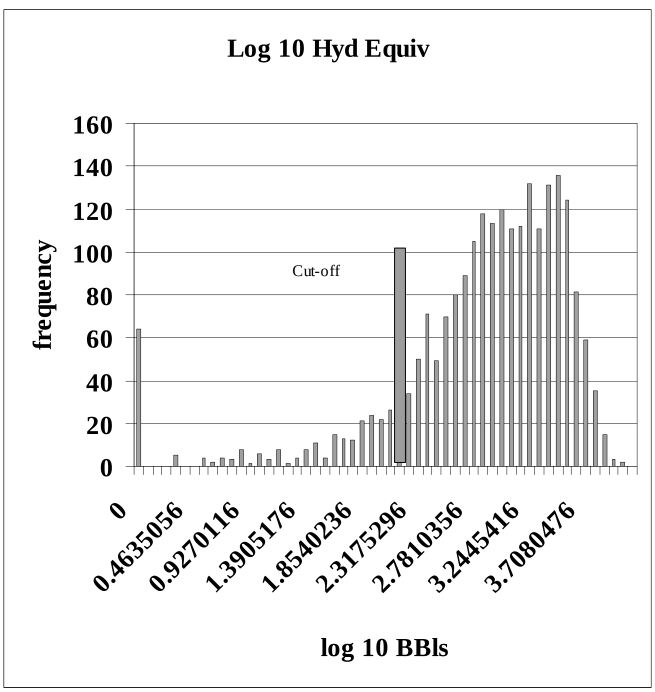


Fig. 6. Barrels equivalent per month filtered histogram.

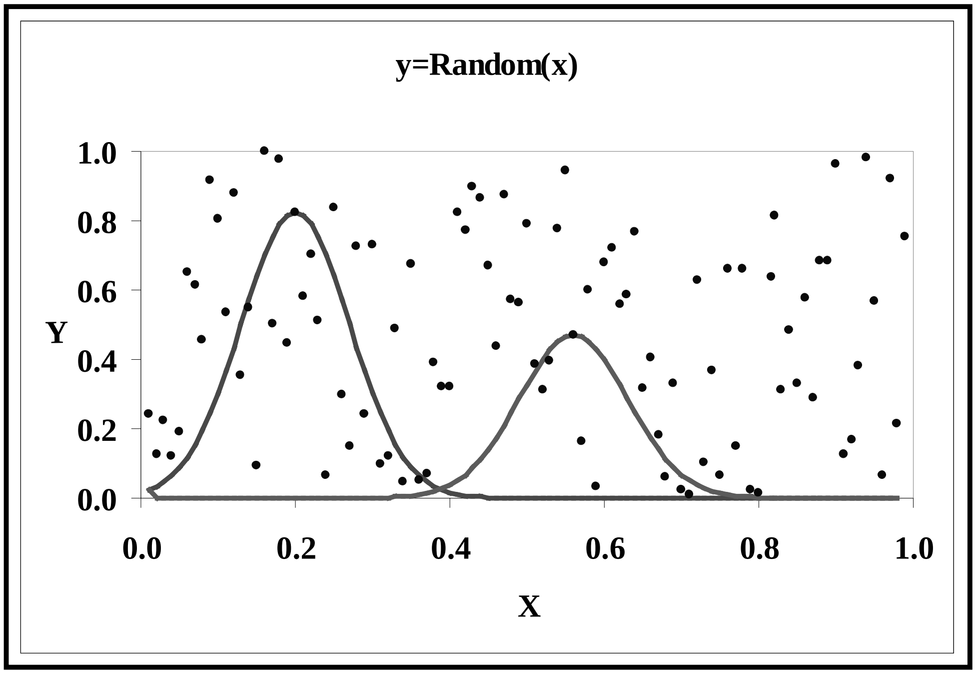


Fig. 7. Fuzzy membership function-random.

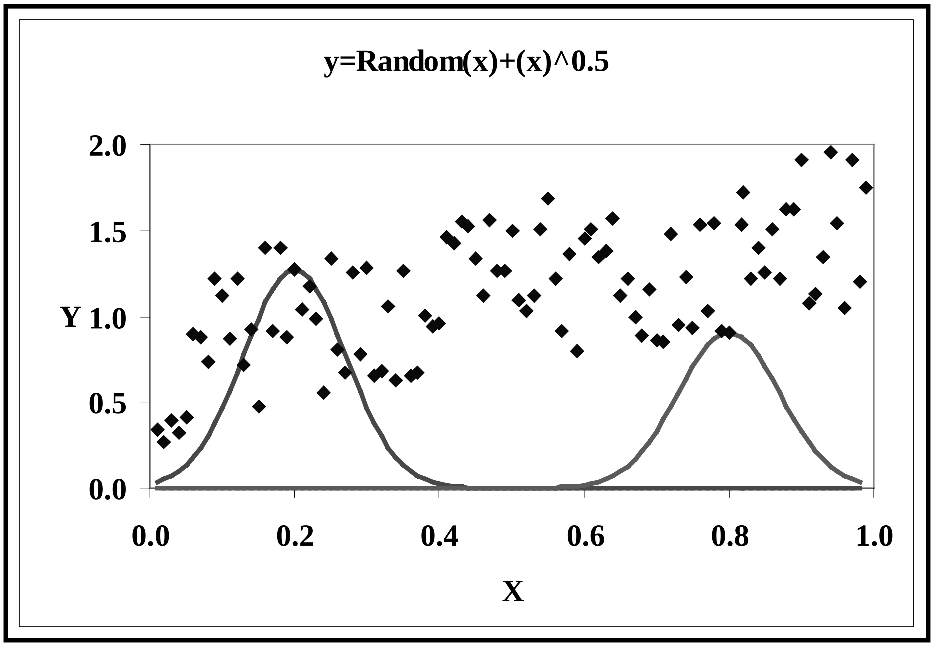


Fig. 8. Fuzzy membership function-trend.

Fig. 9. Fuzzy curves.

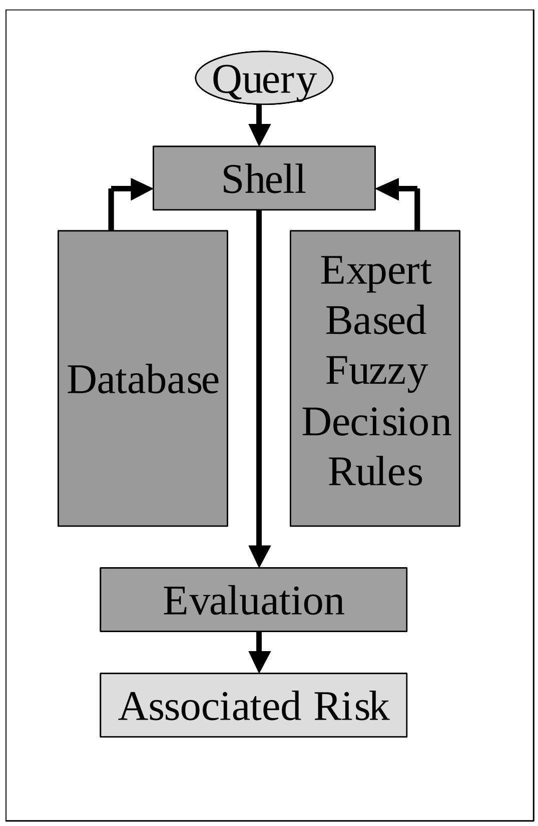


Fig. 10. Single expert system.

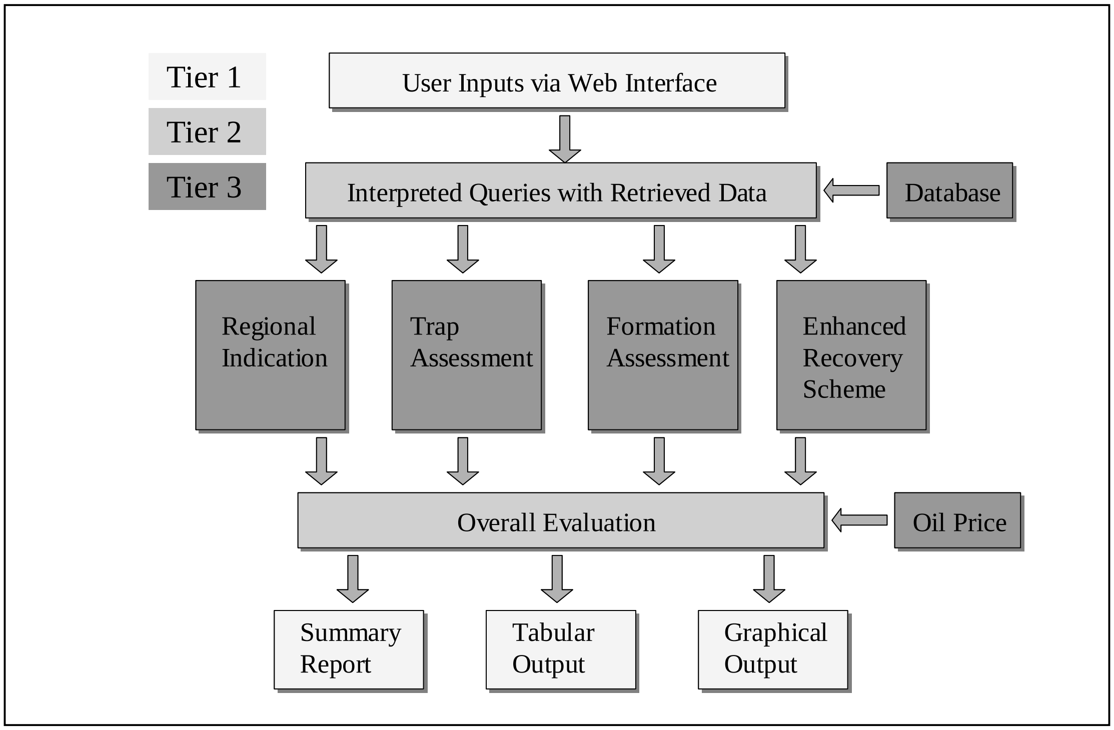
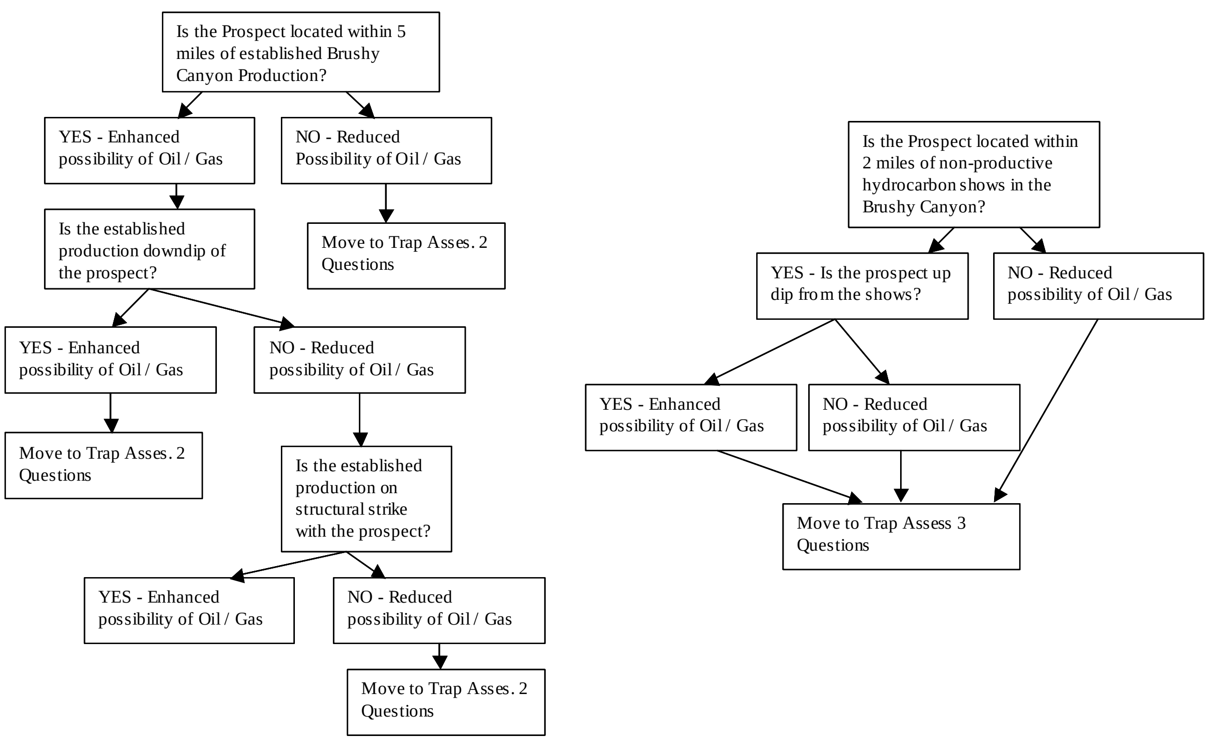
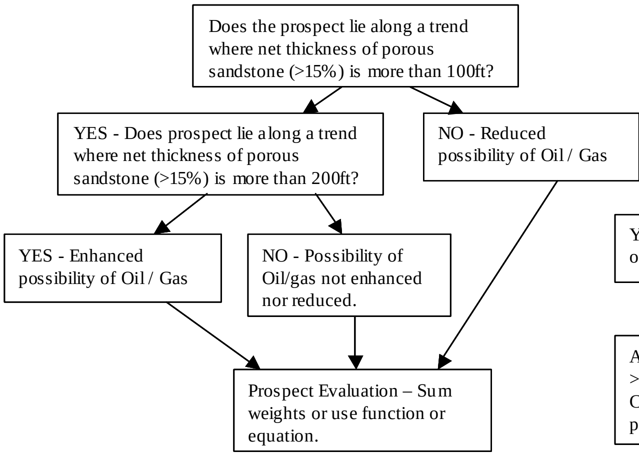
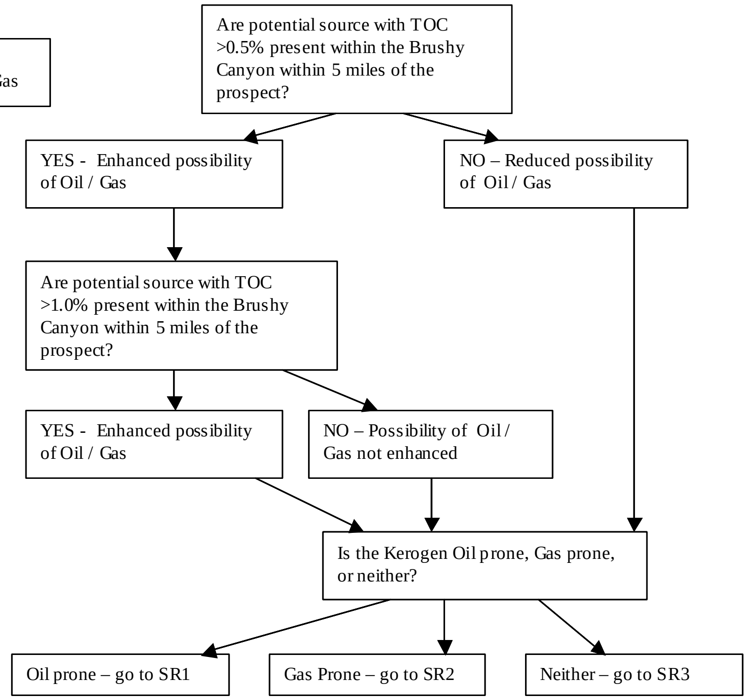


Fig. 11. Current expert system design.

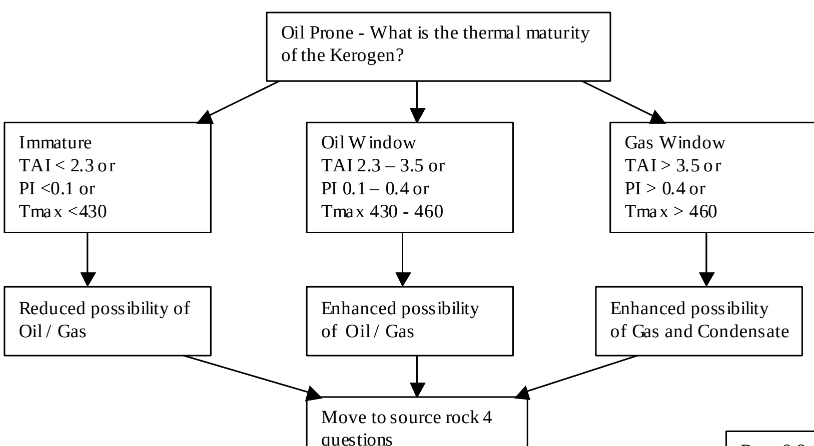


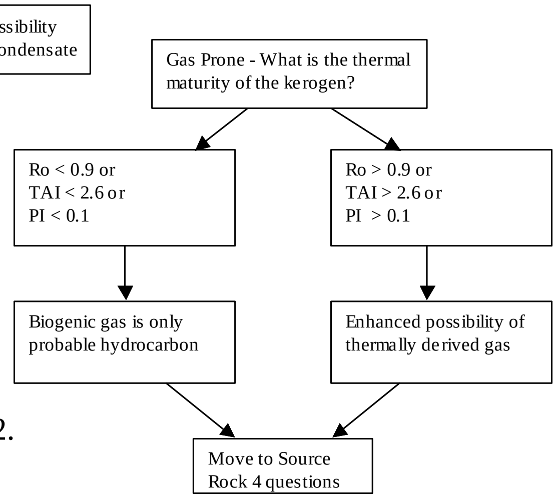
Figs. 12 & 13. Trap assessment rules 1 and 2.



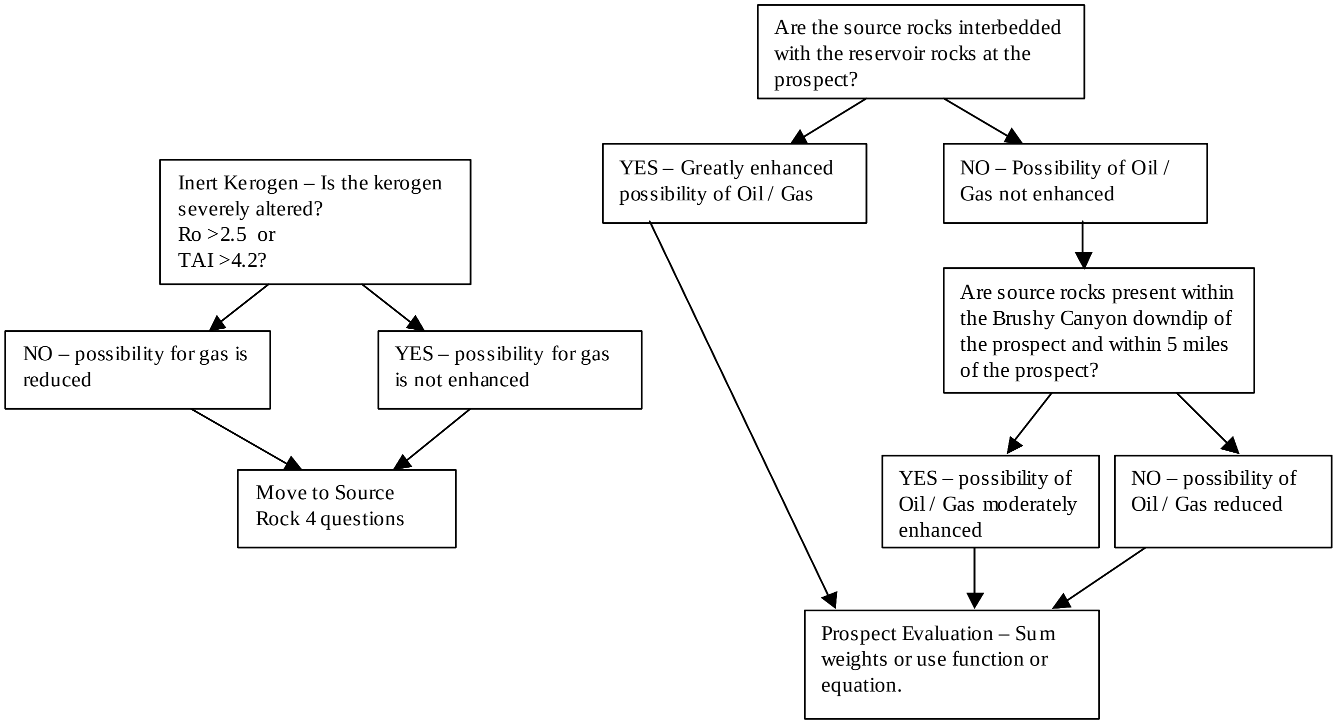


Figs. 14 & 15. Trap assessment rules 3 and source rock assessment main.





Figs. 16 & 17. Source rock assessment rules 1 and 2.



Figs. 18 & 19. Source rock assessment rules 3 and end.

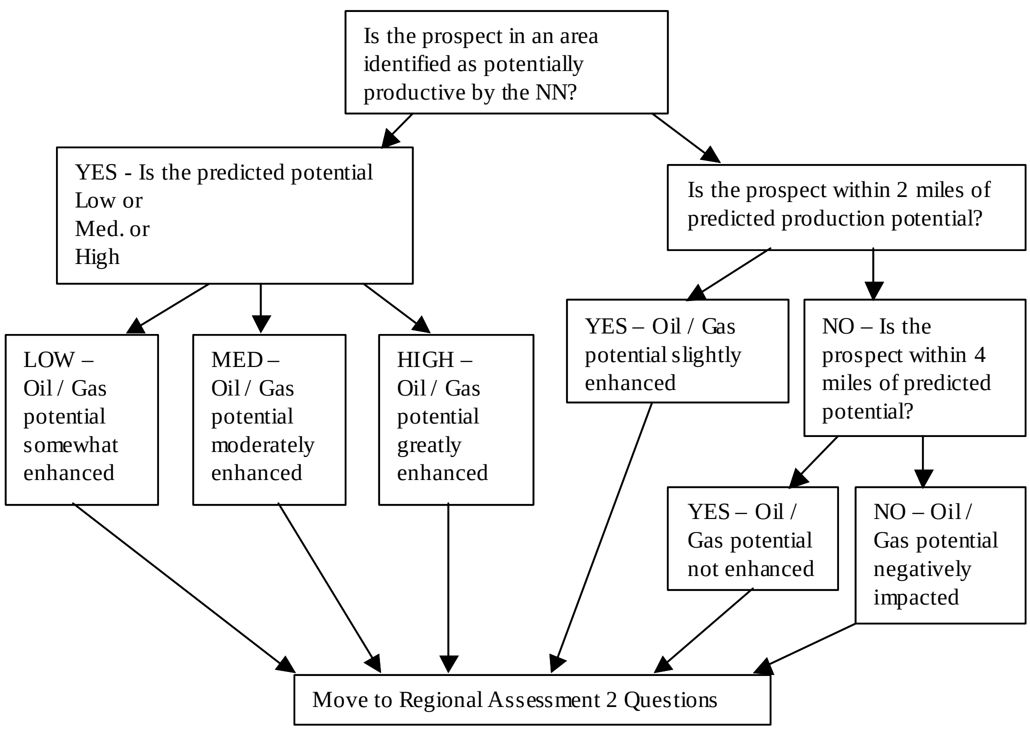


Fig. 20. Regional assessment rules 1.

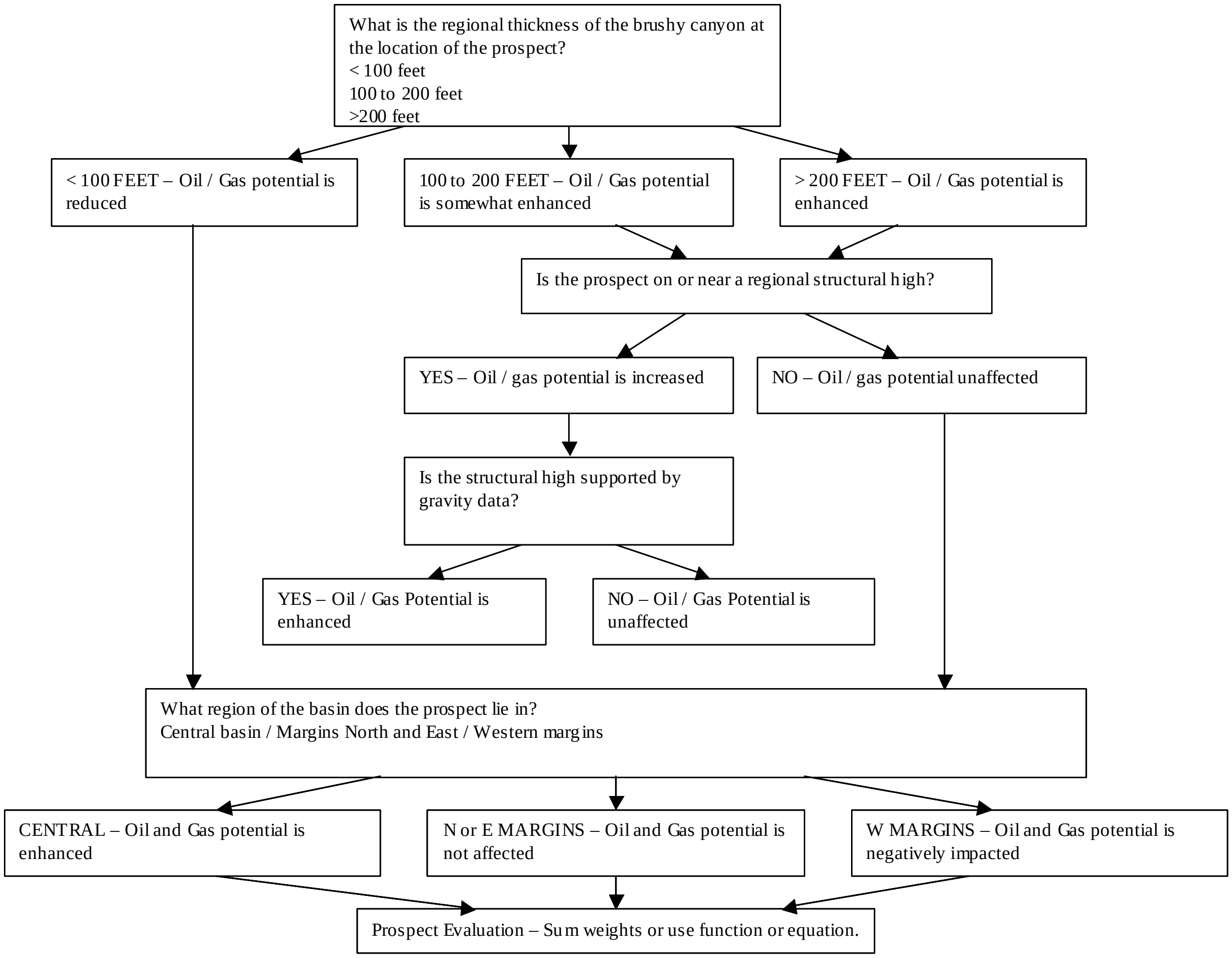
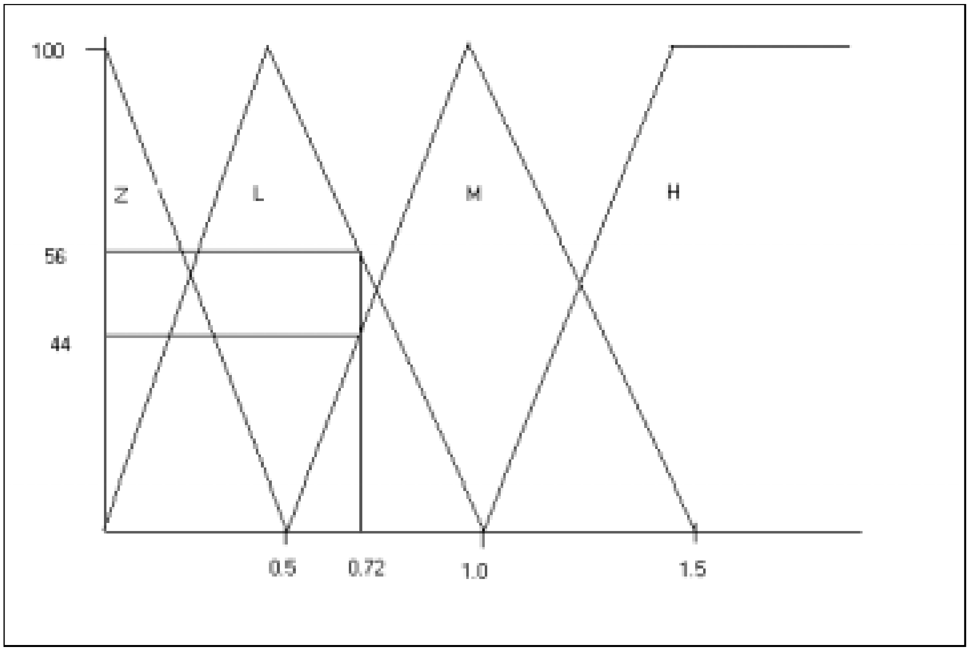
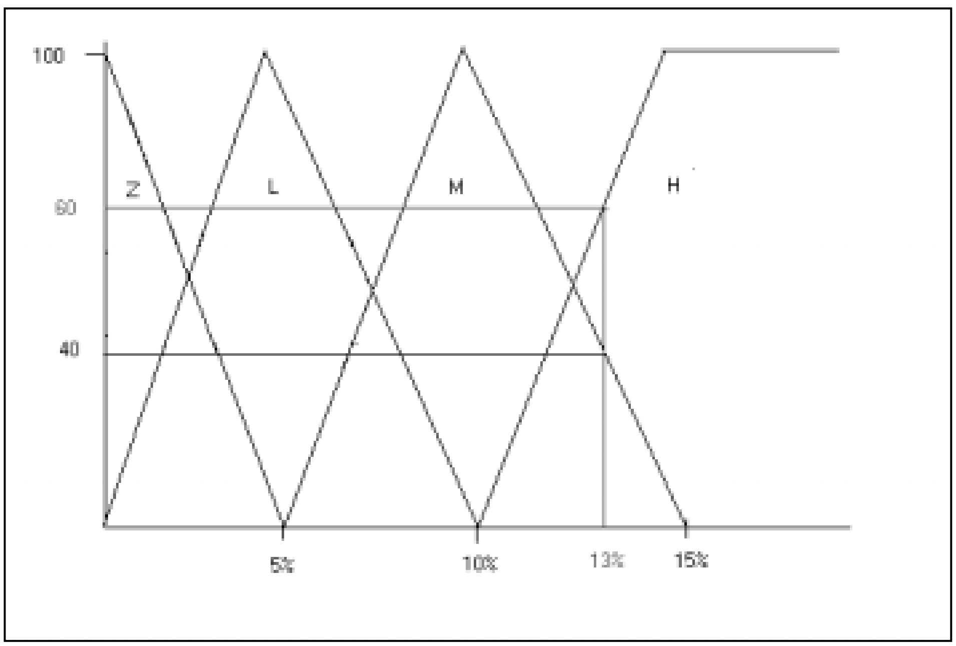


Fig. 21. Regional assessment rules 2.





Figs. 22 & 23. TOC and porosity fuzzy curves.

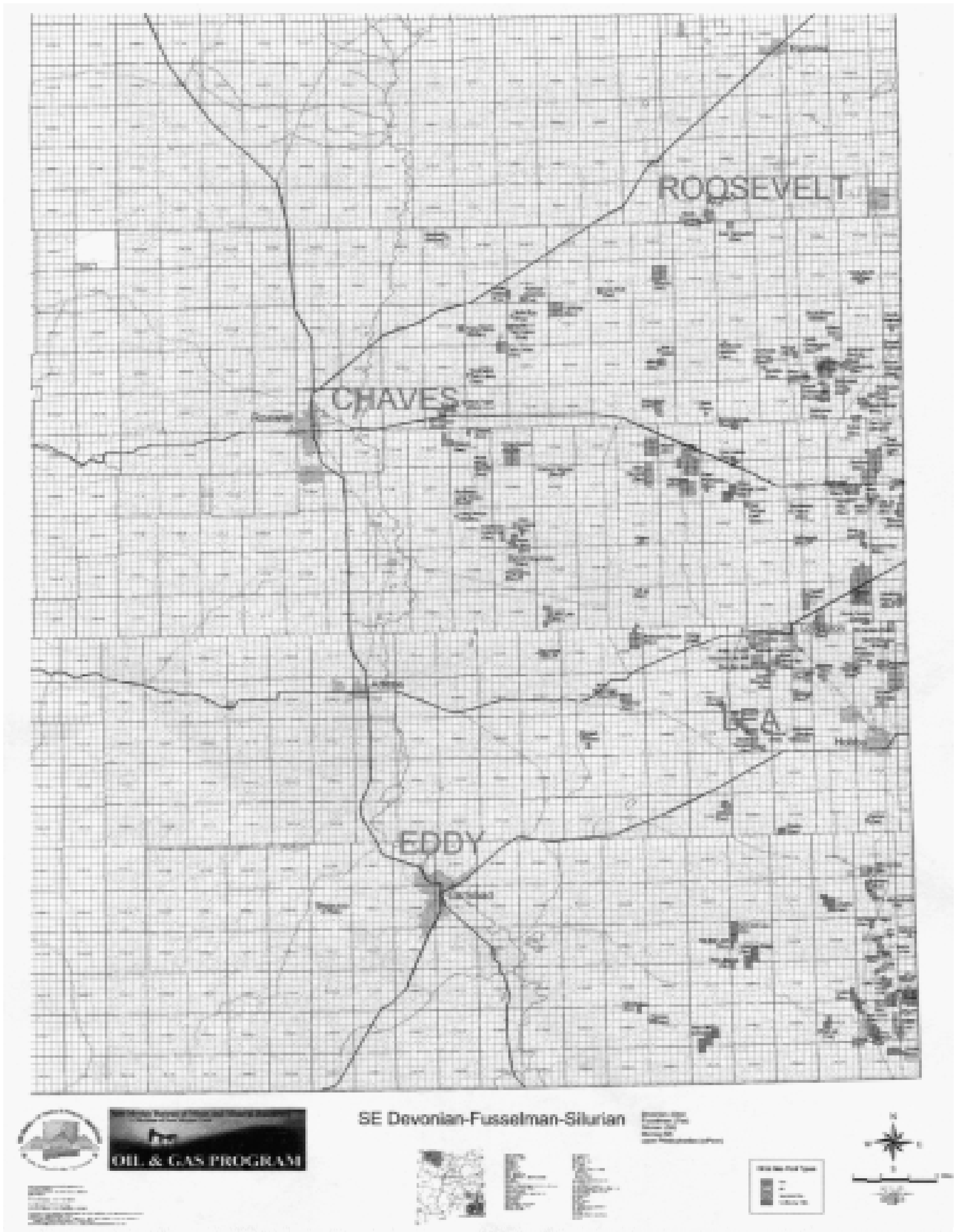


Fig. 24. Oil and gas fields productive from Siluro-Devonian carbonate reservoirs in southeast New Mexico.[10]

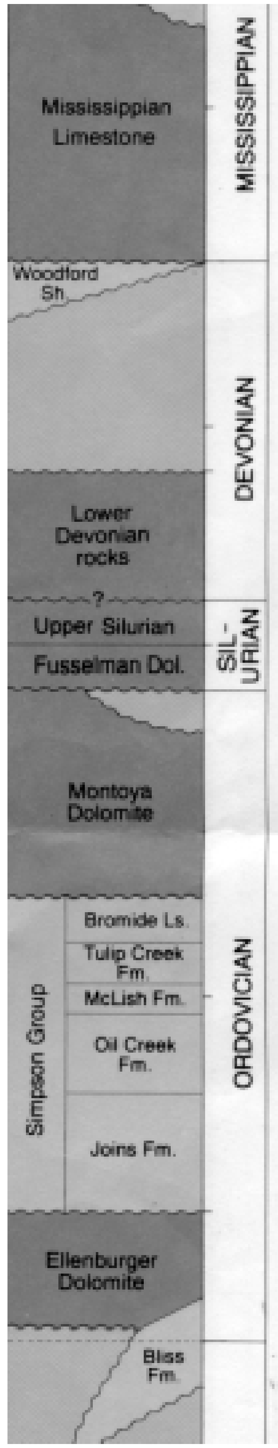


Fig. 25. Stratigraphic column of Ordovician, Silurian and Devonian strata in southeastern New Mexico.[11]