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Risk Reduction with a Fuzzy Expert Exploration Tool

(Third Semi-Annual Technical Progress Report)

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Table of Contents

Executive Summary 1
Objectives 1
Summary of Progress 2
Progress and Discussion of Results 3
Geology 3
Geophysics. 6
Engineering 6
Database 7
Computational Intelligence. 8
Technology Transfer 16
Tasks for Next Six Months 19
Conclusion 20
References 21

List of Figures

Fig. 1. Map showing the 74 dry holes (circles). 22

Fig. 2. Unsuccessful wells plotted on 10% porosity map. 23

Fig. 3. Unsuccessful wells plotted on 10% porosity map. 24

Fig. 4. Productive and nonproductive sandstone map. 25

Fig. 5. Neural network BVO log training results. 26

Fig. 6. Nonlinear BVO plot of 25 Brushy Canyon wells. 27

Fig. 7. BVO log statistical parameters used to correlate actual production with predicted production. 28

Fig. 8. One hundred random points between 0 and 100. Two sample fuzzy membership functions are illustrated. 29

Fig. 9. The same one hundred random points with a simple trend added, two sample fuzzy membership functions are shown. 29

Fig. 10. Fuzzy curves for the two data distributions illustrated in Figs. 6 and 7. Curves are the summation of the fuzzy membership functions for each point. Value is given to trends with monotonic vertical variations. 30

Fig. 11. Depth error of four time-to-distance transforms. 31

Fig. 12. Expert system; the initial, simple flow chart. 32

Fig. 13. New expert system that expands the initial flow chart shown in Fig. 12. Analysis is broken down into several parallel systems that combine results for output. 33

Fig. 14. Preliminary Java interface showing menus and pool map. 34

Fig. 15. Sample query result. 35

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, including medical diagnostics, have demonstrated beneficial results. A state-of-the-art exploration “expert” tool, relying on a computerized data base and computer maps generated by neural networks, is proposed for development 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 tool will be beneficial in many regions of the US, enabling risk reduction in oil and gas prospecting and 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 US as reserves are depleted. The proposed expert exploration tool will benefit a diverse group in the US, leading to a more efficient use of scarce funds and lower product prices for consumers.

This third of ten semi-annual reports contains an account of the progress, problems encountered, plans for the next quarter, and an assessment of the prospects for future progress.

Summary of Progress

During this six-month period the majority of data acquisition for this project was completed with the compiling and analyzing of well logs, geophysical data, and production information needed to characterize production potential in the Delaware basin. A majority of this data now resides in several online databases on our servers and is in proper form to be accessed by external programs such as web applications.

A new concept was developed and tested in well log analysis using neural networks. Bulk volume oil (BVO) was successfully predicted using wire line logs as inputs, providing another tool for estimating both the potential success of a well, and the interval to perforate.

Regional attributes have been gridded to a 40-ac bin (gridblock) size and our fuzzy ranking procedures have been applied to determine which attributes are best able to predict production trends in the basin, using the average value of the first 12 months of oil production as the value to be predicted.

A study to determine the ability of an artificial intelligence system to predict depth using seismic attributes in a Delaware field was completed and the results published.[1] Significant improvements over standard techniques were found particularly when test wells were on the dataset boundary where extrapolation is required.

An initial step in programming the expert system was undertaken, and a decision tree program was coded in Java Expert System Shell (JESS) that allows development and tabulation of rules and relationships between rules that can be used by our expert system. This important program allows lists of rules to be entered and easily tested and verified.

The design of the expert system itself was clarified and an expanded system was created where several distinct factors such as geologic/geophysical data, trap assessment, and formation assessment will be operated on in parallel to increase efficiency of the overall system.

Coding of the Java interface, which users will utilize to access data in the online databases and run the expert system, has begun. Development of the interface will be an important ongoing project over the next year and will eventually tie together the data and the expert system programs coded in JESS while allowing user customization and informative reports of results to be returned.

The second annual consortium meeting was held November 2, in Hobbs, New Mexico. Research and progress to date was presented to a group of industry and academic professionals.

Progress and Discussion of Results

Geology

During the last half of 2000, further progress was made on geologic data acquisition and synthesis in the Brushy Canyon Formation and on discerning the relationships of these data to the presence of recoverable oil and gas. In order to complement previous work that identified productive areas from the lower Brushy Canyon Formation, 74 wells (shown in Fig. 1) were identified throughout the basin that had unsuccessfully attempted completions in the lower Brushy Canyon. These wells were identified after a thorough search of all wells that have been drilled in the New Mexico part of the Delaware Basin. Unsuccessful completions were defined as wells that penetrated the lower Brushy Canyon, with casing set through the lower Brushy Canyon and subsequently perforated but with no resulting commercial production of hydrocarbons. In many cases, the prospective pay zone in the Brushy Canyon was artificially fractured or otherwise stimulated in an attempt to establish production.

These unsuccessful tests were plotted on maps that show the distribution of reservoir quality sandstones in the lower Brushy Canyon (Figs. 2 and 3). One of these plots revealed that many of the unsuccessful test wells were drilled where there is insufficient reservoir quality sandstone for commercial production to be established (shown in Fig. 2). The other plot revealed that many wells were located to the southeast of major pinchouts and oil accumulations and were therefore drilled into downdip, water-saturated portion of traps seen in Fig. 3. However, in the western part of the basin, there were a substantial number of unsuccessful wells that penetrated thick sections of reservoir quality sandstones in the lower Brushy Canyon. The lack of exploratory success of these wells needs to be incorporated into the fuzzy logic system, so development of a method of identifying these areas via artificial intelligence was begun.

Work was undertaken to differentiate between productive and nonproductive reservoir quality sandstones. Two areas were selected for detailed data acquisition and analysis. These areas are identified by the blue rectangles in Fig. 4. The eastern area is characterized by substantial and lateral contiguous production from the lower Brushy Canyon and is also characterized by an absence of unsuccessful test wells. In this area, production has been obtained where reservoir quality sands are present. Productive areas of small extent that are separated by nonproductive areas where reservoir quality sands are present characterize the western area. Wells with unsuccessful completion attempts are located within the nonproductive areas. The intent is to discern, via the fuzzy expert system, between productive and nonproductive reservoir-quality sands.

Our industrial partners have set forth a variety of explanations for the nonproductive nature of sands that appear (via analysis of porosity logs) to have reservoir quality. Some of these explanations conflict with each other and none have been rigorously proven. It is imperative that the correct explanations be identified and incorporated into our fuzzy logic system if the goal of reducing exploratory risk is to be achieved. The explanations include decreased permeability of sandstones that otherwise have sufficient porosity (>15%) to function as reservoirs. Other explanations include a lack of adequate seals to check the updip (west and northwest) migration of oil or the downdip flushing of reservoirs by fresh waters influent from the west and northwest. The ability to estimate bulk volume oil from conventional well logs should provide insight to the productive/nonproductive sand quandary.

The data acquisition phase of the project is nearly complete. Final maps have been generated for the lower Brushy Canyon using data from 726 wells. Mapped features include Lower Brushy Canyon structure (subsea elevation), Brushy Canyon thickness (isopach) and sand isopachs with 10 and 15% porosity cutoffs. Using a smaller 22-well data set, maps of source parameters were also generated. Of particular interest are maps of Total Organic Content (TOC) and thermal maturity. Final maps of geophysical parameters (aeromagnetic and gravity) were constructed.

Geophysics

For the aeromagnetic, gravity, Brushy Canyon tops, and Brushy Canyon thickness maps, additional data attributes were computed. These attributes include first and second derivatives directionally aligned along latitude and longitude, dip magnitude and azimuth, and curvature magnitude and azimuth.

Engineering

Determining the water saturations in thin-bedded turbidites using wire-line logs is difficult; errors in Sw calculation frequently result in uneconomical completions. Consequently, current Brushy Canyon completion decisions include expensive core information to provide an acceptable indicator of oil saturation to compensate for the Sw calculation problem. Completion decisions can be improved and less core data is needed using a method that correlates wire-line logs with core measured bulk volume oil (ΦS_o).

A neural network was trained and tested using density porosity, neutron porosity, and shallow and deep resistivity logs as input variables. The neural network was trained to predict the BVO product from whole core analysis. A neural network BVO log is shown in Fig. 5.

The trained and tested neural network was then used to estimate BVO in 25 additional Brushy Canyon wells that were not used in the training, but had the same four wire-line logs. A ΦS_o cutoff of 22 units was determined and values greater than the cutoff were summed through the perforated interval in each well. The summed bulk volume oil of the 25 wells was plotted versus the first year's total production, shown in Fig. 6. The plot suggests that $\Sigma\Phi S_o$ greater than 20,000 units will usually result in an economical new well, reentry, or re-completion.

The usefulness of the nonlinear plot in Fig. 6 was improved by calculating the average, sum, and the standard deviation of the BVO log for each of the 25 wells. These statistical parameters were used as input to a neural network that was trained with Nash Draw #23 well information. The trained neural network was used to predict the first-year production values that are plotted versus the actual values in Fig. 7.

Database

In order to relate production data from 2257 Brushy Canyon wells to the regional geophysical, geological and geochemical data, it is necessary to perform some data scaling. In New Mexico, Delaware well spacing is 40 acres. Therefore the minimum size of interest for any given area is 40 acres. The regional data was mapped, then gridded at an interval of one data point every 1320 ft. This resulted in 60,478 data points or 40-ac "bins" for each value or attribute calculated in the 3780-square-mile New Mexico portion of the Delaware basin. With four base values and eight attributes calculated for each base value, the resulting data set contains 2,177,208 individual pieces of information. As we add other regional data this number will double or triple. Each bin has a corresponding location in both latitude/longitude and oilfield xy coordinate systems. Using these locations and the producing well locations it is possible to relate production to the regional data. The average value of the first 12 months of production from each well was selected as the production indicator. Well production from 2257 wells was processed to generate this production indicator. Twelve-month average values were calculated independently for oil, gas, and water production.

Oil is the primary factor in determining Brushy Canyon economics; however, significant gas production does exist and that needs either a separate analysis, or inclusion via a total hydrocarbon equivalent calculation. Water production has a negative economic effect and also may need to be examined.

Computational Intelligence

Regional data analysis

Each of the 36 data and data attributes calculated and loaded into the database were analyzed using fuzzy ranking. Since it is both statistically dangerous and not computationally feasible to use all 36 attributes to form a regression relationship, 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. 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,…,99, and $x_i=0.01*i$, and plot each value (y_I= Random(x_i)) as seen in Fig. 8. Next add a simple trend to the random data ($y_i=(x_i)^{0.5}$+Random (x_i)) and plot those values shown in Fig. 9. 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 Figures 8 and 9. 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 is built up using a summation of all individual fuzzy membership functions in (x_i,

y_i), and this final curve can prioritize a set of inputs for linear or non-linear regressions. The fuzzy curve function is defined below:

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

where N is the size of the data set or the total number of fuzzy membership functions. Figure 10 shows the curves for the data sets shown in Figs. 8 and 9. 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.

Based on the deviation from a flat curve, each attribute is assigned a rank, which allows a direct estimation of which attributes would contribute the most to a particular regression. The fuzzy ranking algorithm was applied to select the optimal inputs (data or attributes) for computing the average value of the first 12 months of oil production in Brushy Canyon wells. The prioritized attributes are:

1. First derivative along latitude of gravity
2. Dip azimuth of gravity
3. First derivative along longitude of magnetism
4. Dip magnitude of magnetism
5. Curvature magnitude of structure
6. First derivative along latitude of subsea elevation
7. Second derivative along latitude of thickness
8. Curvature magnitude of thickness

These attributes will be examined as variables in a regression equation to predict production potential from any bin.

Depth mapping using seismic attributes

Accurate depth maps are useful for reservoir development, particularly for stratigraphic and structural trap location, drilling depth and reservoir modeling. During this reporting period, three velocity-to-depth transforms were evaluated.

Well log and 3-D seismic data were used to construct three depth maps for the top of the target L horizon of the Nash Draw field in southeastern New Mexico. The first two depth maps were made using Landmark™ software packages TDQ and Z-map. The third depth map was made using a multilayer perceptron (MLP) neural network to regress for velocity at each seismic bin. At Nash Draw most of the wells are confined to the central region of the seismic survey, and conventional geostatistics reliably interpolated depths in the region defined by well control. The MLP approach used the best three of 28 “fuzzy” ranked seismic attributes to predict the average velocity field from the surface to the L horizon. Each map was constructed using 15 wells as control points, with three wells excluded for testing. Test wells 1 and 2 were located away from the control wells and had anomalous average velocities/depths.

The three test wells were used to compare the robustness of the computed depth maps, and all depth predictions were compared to the true depths determined from gamma ray logs for each well. TDQ, Z-map and MLP predicted values within 229.4, 104.7 and 7.6 ft, respectively, at test well 1; 129.4, 47.7 and 43.7 ft, respectively, at test well 2; and 12.4, 4.1 and 16.5 ft, respectively, for test well 3. Results are illustrated graphically in the Fig 11 bar chart.

Grid Geostatistical methods underestimate the depths to the top of the L for the test wells lying outside the central clustering of control wells, but the MLP solution calculates a relationship that should be valid in each seismic bin in the field.

Depth filtering of gravity data

Renewed interest in the Delaware Basin and surrounding area gravity and aeromagnetic data sets has been sparked with the advent of new computing tools. Current computing technology (processor speed and memory size) permits larger data sets to be used in combination with advanced modeling software to produce results that offer renewed interest in geophysical prospecting with potential field methods. The goal in this study was to offer an unbiased 3-D differential density model for the Delaware Basin and adjoining Central Basin Platform region covering 31–34° north latitude; -102– -105° east longitude. Tikhonov regularization inverse techniques were applied to solve for the unknown density distribution of a model space described by rectangular blocks of dimension 16 × 16 × 3 (x, y, z). The Tikhonov regularization technique is the most widely used technique for regularizing discrete ill-posed problems. Because of the size of the model space (768 grid blocks) and the data space (1700 surfaces measurements) the system matrix, which relates the data to the unknown model parameters is considered slightly ill-posed. Tikhonov regularization provides a way of performing the inversion in a quick and stable manner, at a low cost.

This method and current computer computing capability allowed this approach to be implemented on large gravity data sets with a sizable model space. Other advantages of the method include:

1) Existing geologic information can be used to constrain the solution by using a starting model.

2) Subjective user input is minimized.

3) No problems are encountered related to wave number domain transforms (as in the upward/downward continuation problem).

Applying this method to a gravity data set covering southeast New Mexico and west Texas showed geologically believable results when compared to previous geologic work describing the basement structure. The method is too coarse for application to the Brushy Canyon interval in the Delaware Sands but the methodology is established with this work.

Expert system advances

In order for the expert system to run more efficiently, clarifications to the procedure have been made. An initial flow chart (Fig. 12) was expanded to reflect the desirability of breaking the analysis down into several parallel systems that combine results for output (Fig. 13). The current working model is built on three tiers. The first tier is data entry and initialization. In this tier an applet is opened in the user's browser. The applet allows the selection of an area of interest (AOI) using latitude/longitude, X/Y, or township-section-range coordinates. Once the AOI has been defined, the applet opens up a link to the online database to determine what information is available in that location. The data may include well logs, log analysis, regional data, and/or regional data analysis. At this stage the user also will be given default values for important analysis parameters that he may accept or alter to reflect personal or corporate philosophy. In tier two, the parameters from tier one are passed to the server and analyses are made using several parallel expert systems. Analyses include such factors as regional indications, trap assessment, formation assessment, applicability of secondary recovery techniques or re-completions and other factors. Once these evaluations are made an overall evaluation, or risk assessment, will be applied and the current/projected price of oil or user input price included. The third tier outputs data from the server back to the client computer via the applet and provides reports, graphs, and tables to support the "expert" opinion made.

JESS (The Java Expert System Shell) has been selected as our expert system software. Aside from being publicly available, the software is versatile and written in the Java programming language, which is already being used in the project to develop the web interface. The final expert system will incorporate all the data gathered, and knowledge obtained for this project in a decision-making program that uses similar processes of elimination and decision that an expert human explorationist familiar with the Delaware basin would use. Therefore a preliminary program was written in JESS to input and test rules for the Fuzzy Expert System. The program, MakeTree, allows the input of crisp decisions in a simple and efficient manner. These "rules" could be entered by anyone with minimal knowledge of computers and the resulting decision tree can easily be tested along all branches by more knowledgeable persons. This program will be very useful in coding the hundreds or even thousands of rules needed for the project.

To reduce the complexity of developing a procedure, Java technology has been selected with development software that includes server-side and user-side program. Pure Java Technology supplies the Java language, Java applet, Java Server Pages (JSP), Java Beans and Java plug-in. All of them obey the Java standard defined by Sun Company.

Coding of Java interface

To date in this project, many kinds of data have been collected, generated and stored into several databases. For convenient user access, we intend to develop web-based application software. With web-based applications, the user simply installs a browser which contains the Java Virtual Machine (Netscape or Internet Explorer), and all of the application software and databases will reside on a host web server. When a user opens the application through the browser (browsing the web site), the requested part of the software will be downloaded into the user's computer (user side) via the Internet and is interpreted or is executed by their browser and Java Virtual Machine.

Both the regional data and production data are managed separately by a relational database system in Microsoft SQL and Microsoft Access on two different servers. Easy-to-use interfaces accessing this data through a web-based application and interactive web interface will be developed.

The application software is divided into three layers:

- Interactive web interface layer
- Server layer
- Database interface layer

The first layer is the man-machine interface, which displays the menu, button, map and data including static data and dynamic data. Through it users can browse, search, access databases and send requests to the server by clicking at menu or button.

The second layer will process the user's request. It will find the relevant software or the data the user requested and display it in a user–side browser window. Software here consists of the HTML file, Java Applets and JSP tags. If Java Applets are contained in the HTML file, they will be downloaded to user side and then executed on the user machine by the Java Virtual Machine. If JSP files are requested or contained in the HTML file, they will initially be compiled by Java Engine on the server side and executed on the server to generate HTML files containing dynamic contents that are sent to the user side.

The third layer is the database interface. Data are stored in tables in several databases. The database manager systems are useful tools for the database administrator to manage huge amounts of data on the server side. When data in the database are requested by the user, the request will be sent to second layer where the query will be translated into the SQL language and sent to the database management system (third layer) that accesses relevant tables in the databases, gets the requested data and sends them back to the second layer.

Data to be accessed in this manner currently include *regional* data such as aeromagnetic, gravity, structure, thickness, source, and correlations and *local* data including production, logs and PredictOnline. Figure 12 shows the working interface as seen on a user-side browser.

Users can initiate operations by clicking on the relevant database seen as a menu on the left side of Fig. 12 to generate requested results. For example operations such as input, edit, delete, and search can be performed, or statistical operations can be applied. When a user's query is a SQL statement, or translated into an SQL statement, the database will be queried and output similar to that seen in Fig. 13 will appear on the user's browser.

Technology Transfer

In addition to the second consortium meeting an aggressive technology transfer effort was undertaken. During the last six months the following papers/posters were presented:

1. Balch, R.S., Weiss, W.W., and Wo, S.: "Core Porosity Prediction Using Wire-Line Logs, Case Study: Dagger Draw Field, New Mexico," paper presented at the AAPG 2000 Rocky Mountain Meeting, Albuquerque, New Mexico, September 17-20, 2000.
2. Hart, D.M., Balch, R.S., Weiss, W.W. and Wo, S.: "Time-to-Depth Conversion of Nash Draw "L" Seismic Horizon Using Seismic Attributes And Neural Networks," paper presented at the AAPG 2000 Rocky Mountain Meeting, Albuquerque, New Mexico, September 17-20, 2000.
3. Weiss, W.W., Sung, A.H., and Broadhead, R.: "Risk Reduction with a Fuzzy Expert Exploration Tool," poster presented at the AAPG 2000 Rocky Mountain Meeting, Albuquerque, New Mexico, September 17-20, 2000.
4. Balch, R.S., Weiss, W.W., Wo, S., and Hart, D.M.: "Regional Data Analysis to Determine Production Trends Using a Fuzzy Expert Exploration Tool," West Texas Geological Society, Fall Symposium Publication 00-109, DeMis, Nelis, and Trentham ed., October 19-20, 2000, p 195-196.
5. Hart, D. M.: “Tikhonov Linear Inversion of Gravity Data to Determine 3-D Differential Density Distribution – Case Study of Southeast New Mexico and West Texas,” West Texas Geological Society, Fall Symposium Publication 00-109, DeMis, Nelis, and Trentham ed., October 19-20, 2000, p 195-196.

The Second Consortium Meeting, presenting research results as well as talks from representatives of industry and government, was held at the end of the project's first year. The following is the Petroleum Recovery Research Center's news story on the meeting.

HOBBS, N.M.--The Reservoir Evaluation and Advanced Computational Technologies (REACT) Group at The Petroleum Recovery Research Center of New Mexico Tech held the Second Consortium Meeting November 2, 2000 for their NPTO-funded project, "Reducing Exploration Risk with the Fuzzy Expert Exploration (FEE) Tool," at New Mexico Junior College in Hobbs, New Mexico. This project employs emerging exploration technologies—fuzzy logic and neural networks—and applies them to finding and developing reservoirs.

Typical data analysis has a primary goal of minimizing errors in input data. This becomes a difficult task when data is sparse, or errors are ill-defined. Fuzzy analysis uses the error as a source of additional data and allows the use of non-crisp inputs such as "high on structure" and "medium porosity." Thus, fuzzy analysis shows great promise for integrating sparse engineering data and geological interpretations.

Area producers and explorationists heard the results of the project's first year expounded by REACT scientists and graduate students. A highlight of the conference was the talk given by Gary Hoose, Exploration Manager at Pogo Production, on the company's experience in exploring the Brushy Canyon formation of southeastern New Mexico.

Hoose encouraged the exploration of unpromising areas and cautioned against having a biased viewpoint, saying "always keep an open mind in exploration." He cited several instances when a crucial moment of decision was reached in exploration, where "we had to trust the model or our hunches and be aggressive."

Project Manager Jim Barnes of the National Petroleum Technology Office (NPTO) of the U.S. DOE followed Hoose with a presentation on the "Technology Development for Independents" Program.

The REACT team presented the results of their first-year research, which included

- Installation of the collected data into the database
- Construction of regional structure, isopach, and thickness-porosity maps
- Training of a neural network to predict the product of porosity and oil saturation (bulk volume oil) based on whole core measurements
- Use of fuzzy ranking to prioritize 3D seismic attributes that were then correlated with depth using a neural network
- Development of a radial basis function neural network for use as a log evaluation tool
- Development of an interactive web-based neural network, PredictOnline, coded in Java and available to consortium members for beta testing
- Completion of a draft design of the Fuzzy Expert Exploration (FEE) Tool system based on readily available software.

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 algorithms is an ongoing problem. The project's graduate students, who gain expertise in developing software, leave for high paying industry jobs following completion of a MS degree. Consideration was given to contracting the work to professional coders. Maintenance of the code is a major drawback to this solution of the web software problem.

Tasks for Next Six Months

Work commenced on detailed geologic and production data acquisition and analysis in commercial and noncommercial areas. The goal of the work is to evaluate the postulated explanations of production versus nonproductives area in a manner that can be rigorously applied to the fuzzy logic system. Initial work includes acquiring data that may be relevant to localized reservoir, seal, and source rock distribution that in turn may relate to commercial oil and gas accumulations. Detailed mapping and analysis of areal variability of porous vs. nonporous sandstones and hydrocarbon seals and source rocks commenced and is approximately 40% complete.

During the next reporting period work will proceed with the acquisition, digital mapping, and digital analysis of these variables. The distribution of these variables will be related to the distribution of production. The acquisition of digital log data will commence and this phase of the project will be integrated with work underway on neural network prediction of bulk volume oil as related to reservoir productivity.

Additional whole core analyses and open-hole logs from Delaware wells other than those in the Nash Draw Unit have been donated to the project. The neural network analysis technique will be tested with the new data.

Additional geophysical and geological attribute maps will be computed for the newly mapped features for the next report.

Based on visual observations (linear correlations) the prospect of developing correlations between regional information and production indicators is good. These correlations alone will reduce the risk of drilling new Brushy Canyon wells. The task of coding of the web interface is proceeding at a deliberate pace with the REACT group developing the expertise required to generate the web software,

Conclusion

During this six-month period the majority of data acquisition for the Brushy Canyon project was completed and now resides in several online databases on our servers in a format that can be accessed by external applications. Regional data were gridded to a 40-ac bin (gridblock) size and fuzzy ranking was used to determine which attributes are best able to predict production trends in the basin. Bulk volume oil was successfully predicted using wire line logs as inputs, providing a new tool for estimating both the potential success of a well, and the interval to perforate. An artificial intelligence system was used to predict depth using seismic attributes in a Delaware field and significant improvements over standard techniques were found.

The design of the expert system itself was clarified, and initial coding of the expert system was undertaken. A decision tree program that allows development, tabulation, and testing of rules and relationships between rules was written. Development of the java interface was initiated and will be an important ongoing project over the next year, eventually tying together the data and the expert system programs coded in JESS.

The second annual consortium meeting was held November 2, in Hobbs, New Mexico. Research and progress to date was presented to a group of industry and academic professionals.

With data and tools prepared, progress towards development and implementation of rules and the web interfaces will move forward. The six months since the last report have seen five papers or presentations given, while industry and academic interest in the project has grown.

References

1. Hart, D.M., Balch, R.S., Weiss, W.W. and Wo, S.: "Time-to-Depth Conversion of Nash Draw "L" Seismic Horizon Using Seismic Attributes And Neural Networks," paper presented at the AAPG 2000 Rocky Mountain Meeting, Albuquerque, New Mexico, September 17-20, 2000.

2. Lin, Y., and Cunningham, G.A.: “A New Approach to Fuzzy-Neural System Modeling,” *IEEE Transactions on Fuzzy Systems* (1995) **v. 3** no 2, 190-198.

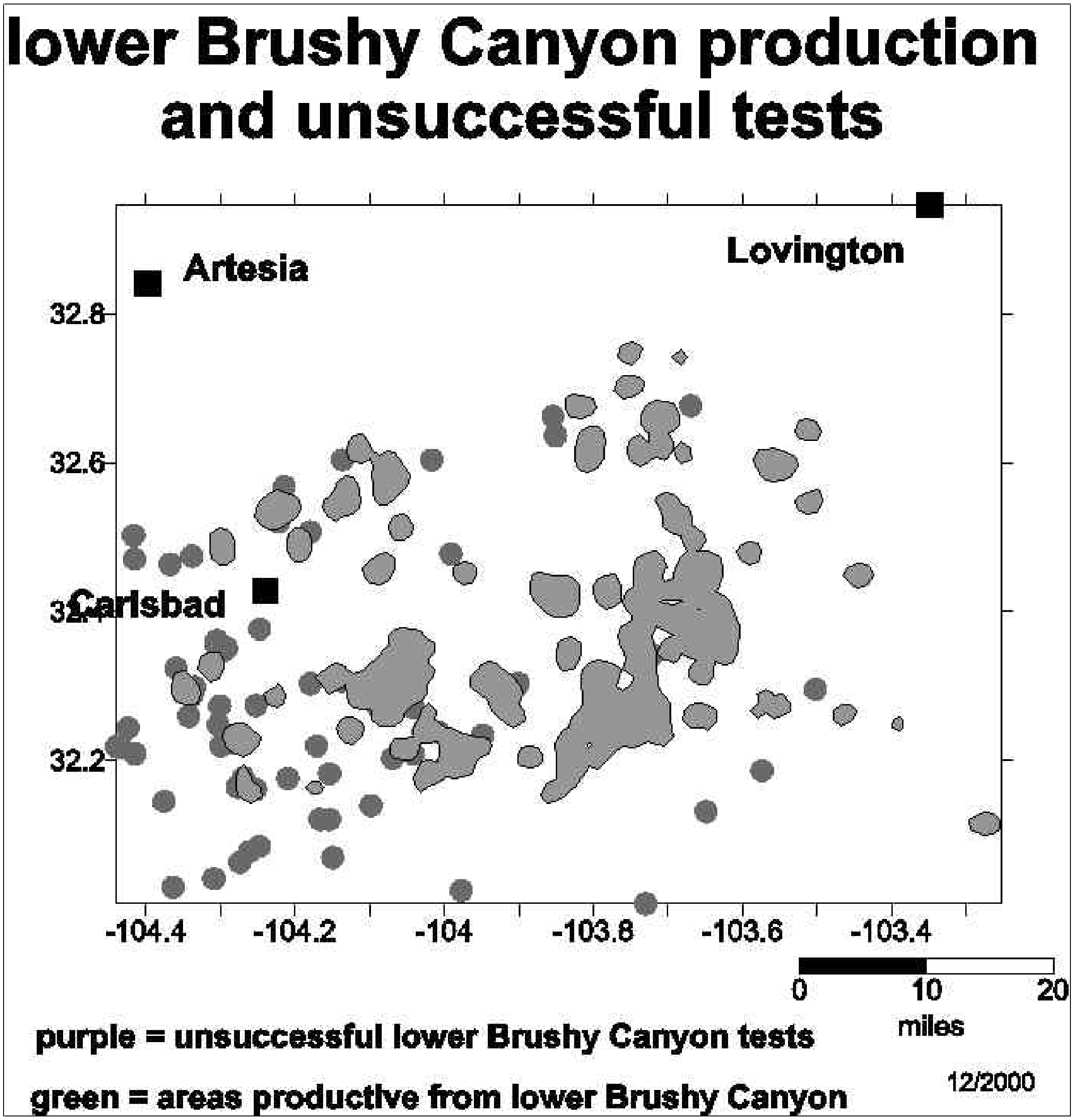


Fig. 1. Map showing the 74 dry holes (circles).

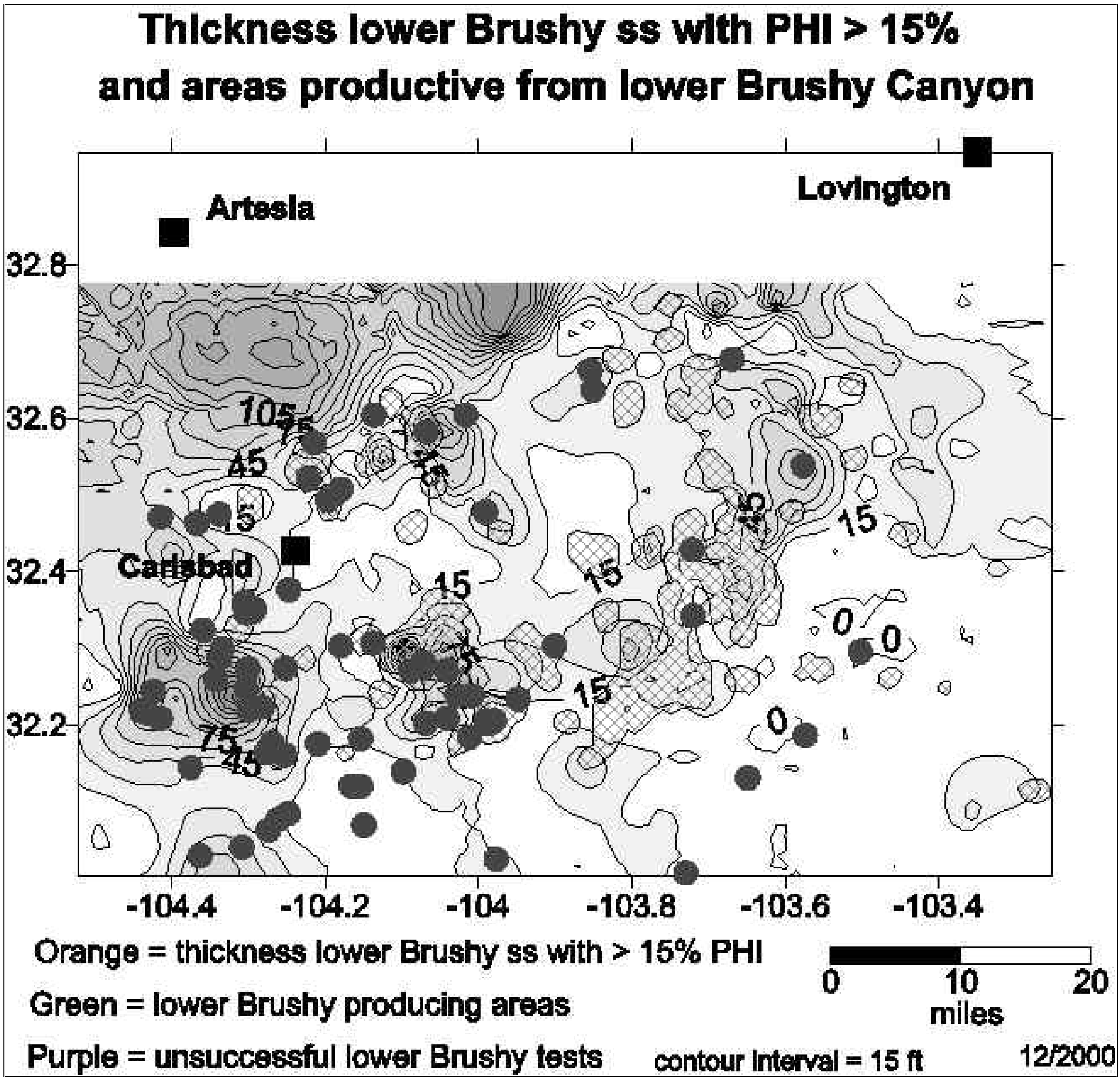


Fig. 2. Unsuccessful wells plotted on 10% porosity map.

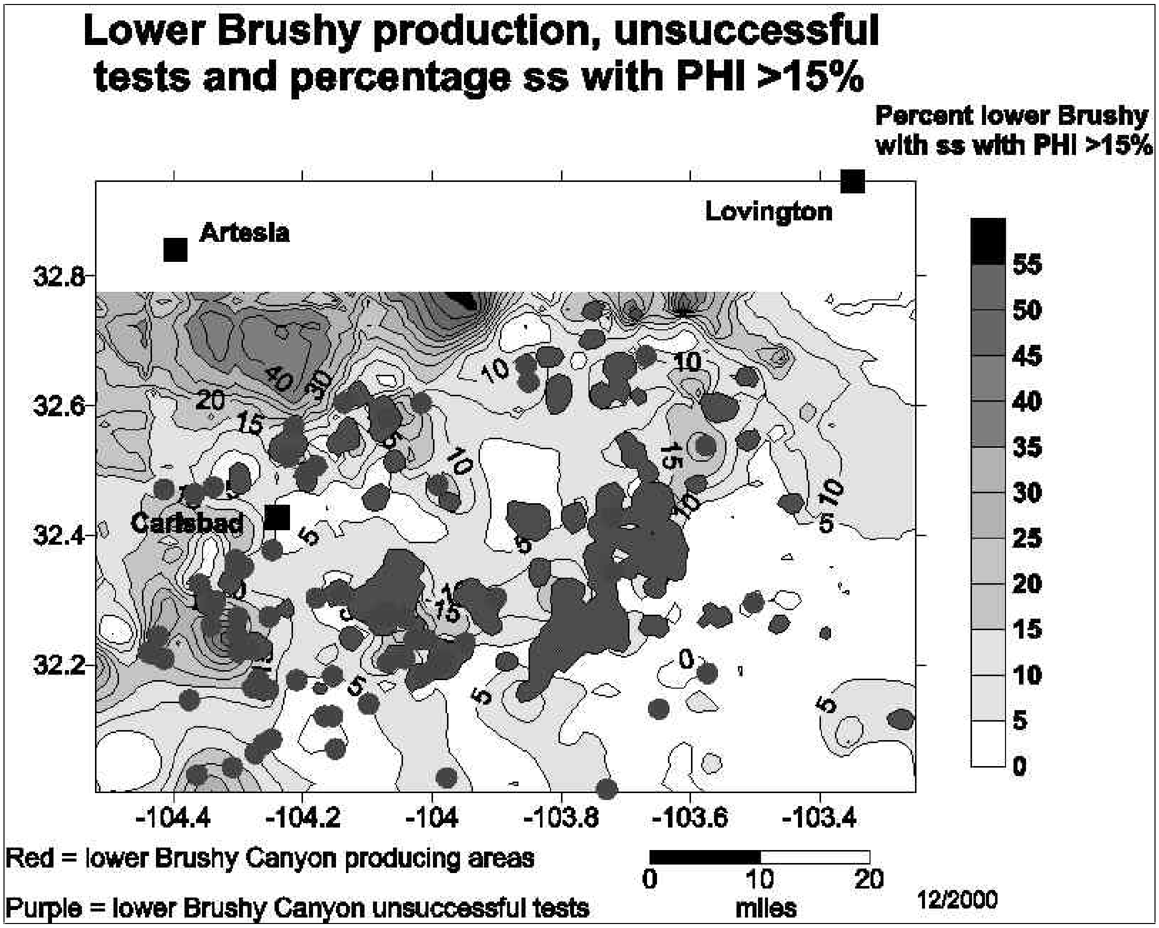


Fig. 3. Unsuccessful wells plotted on 10% porosity map.

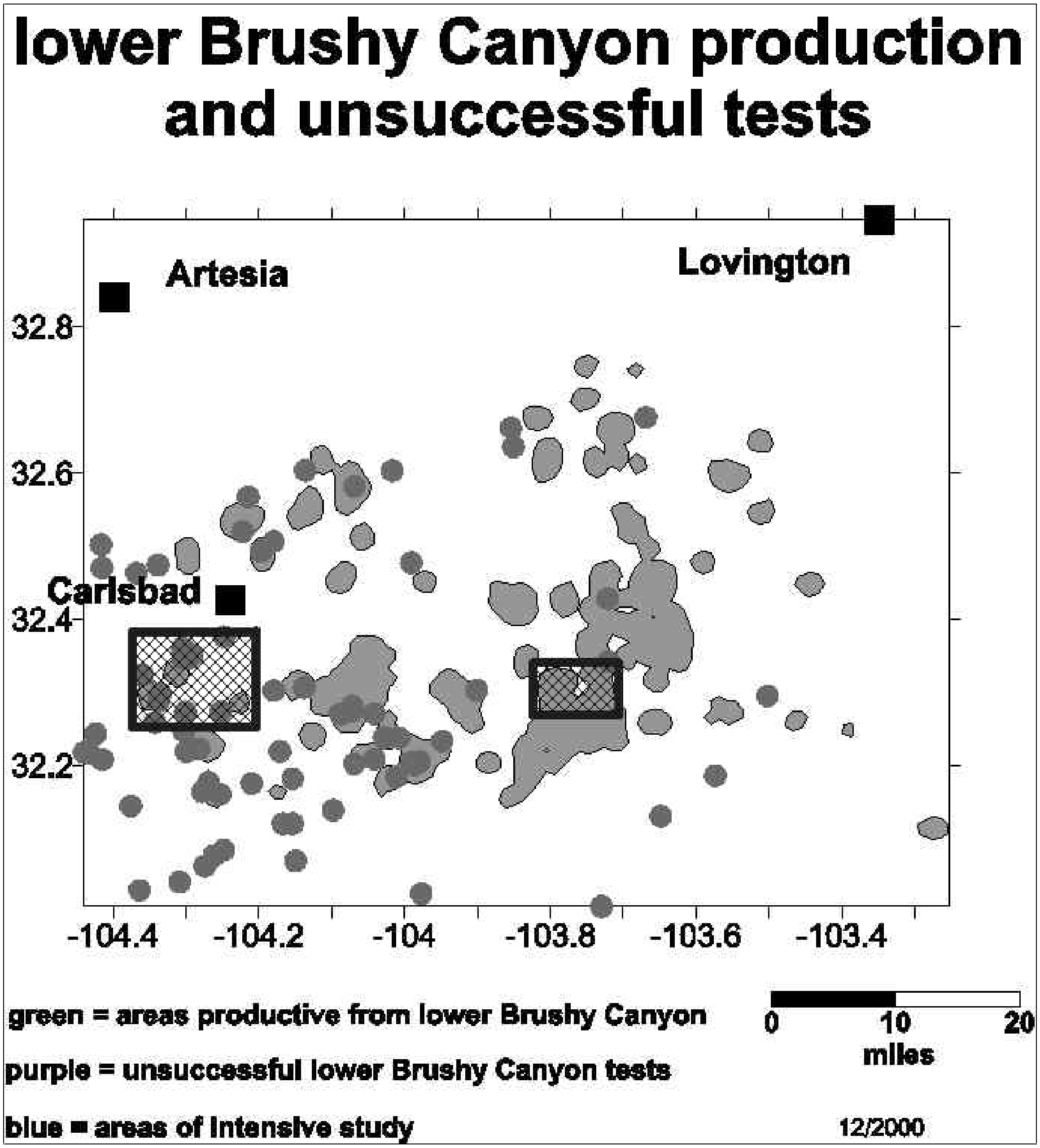


Fig. 4. Productive and nonproductive sandstone map.

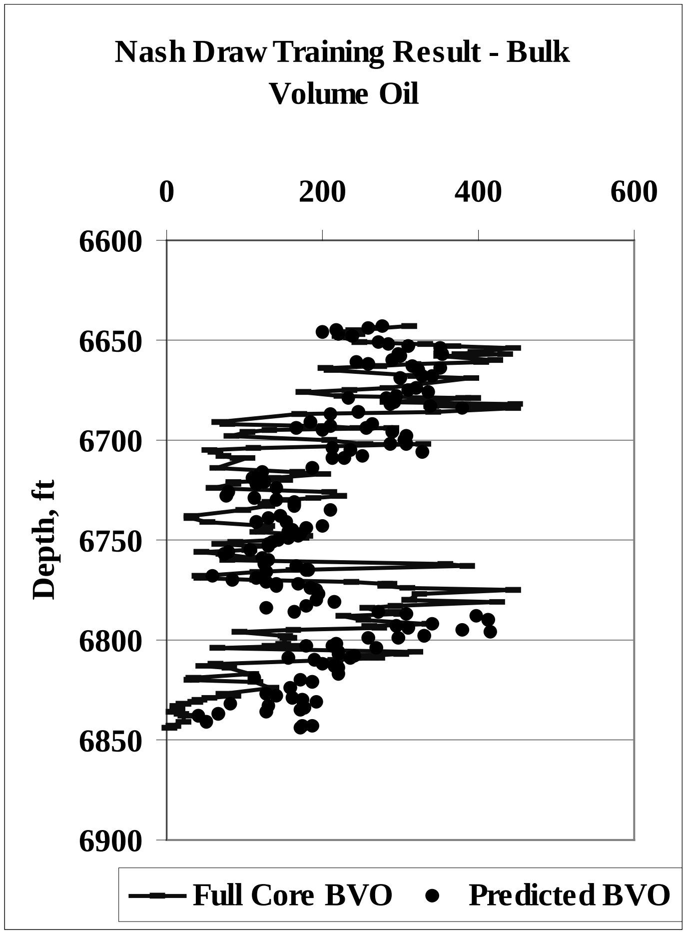


Fig. 5. Neural network BVO log training results.

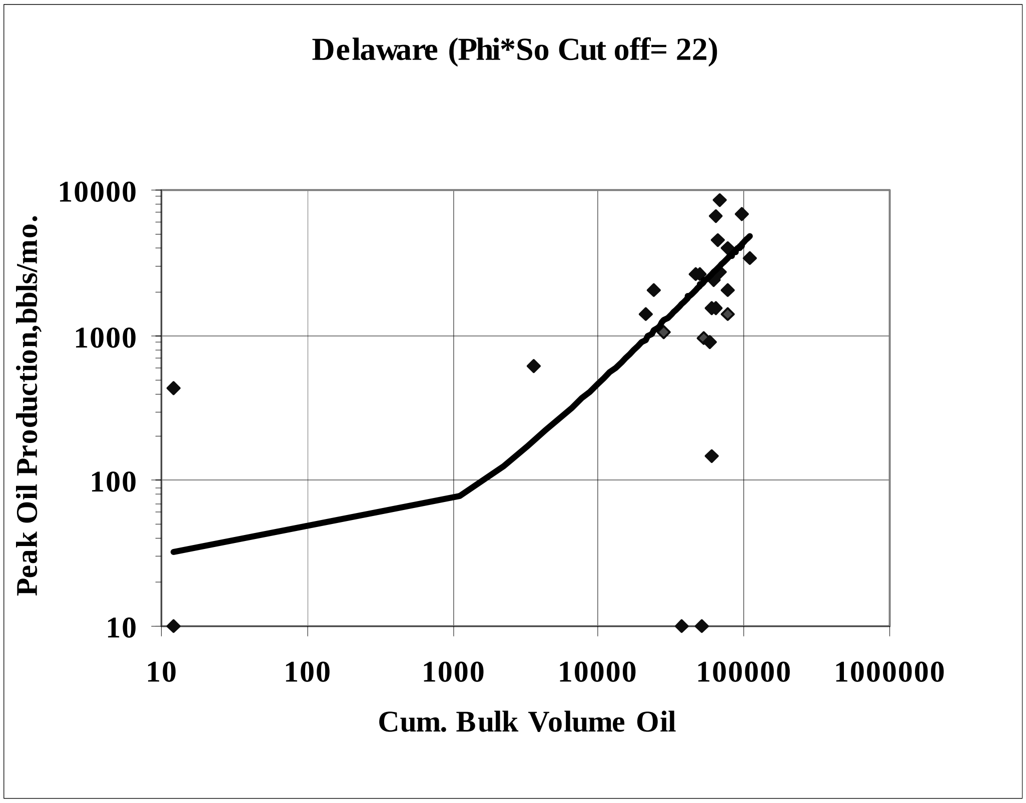


Fig. 6. Nonlinear BVO plot of 25 Brushy Canyon wells.

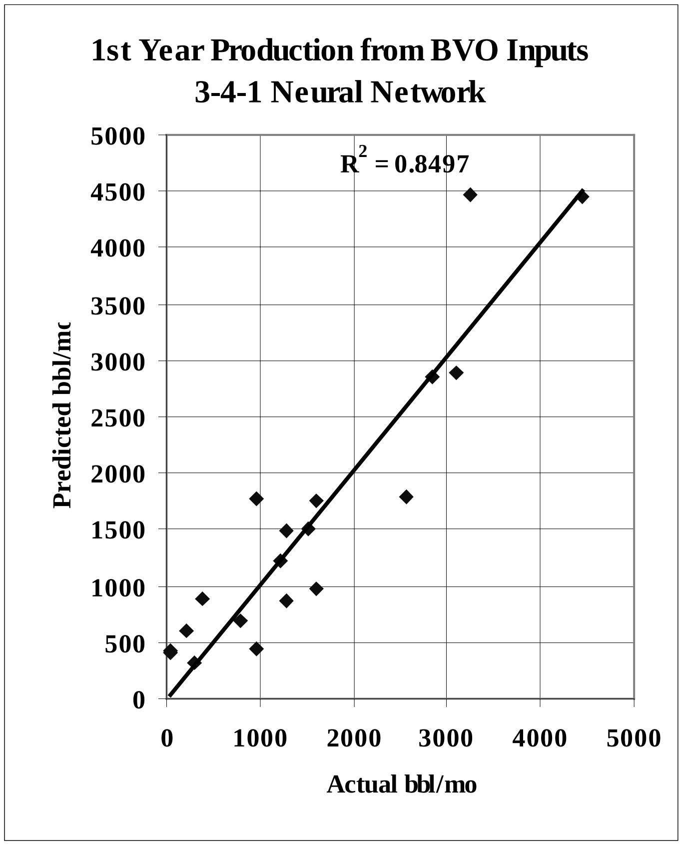


Fig. 7. BVO log statistical parameters used to correlate actual production with predicted production.

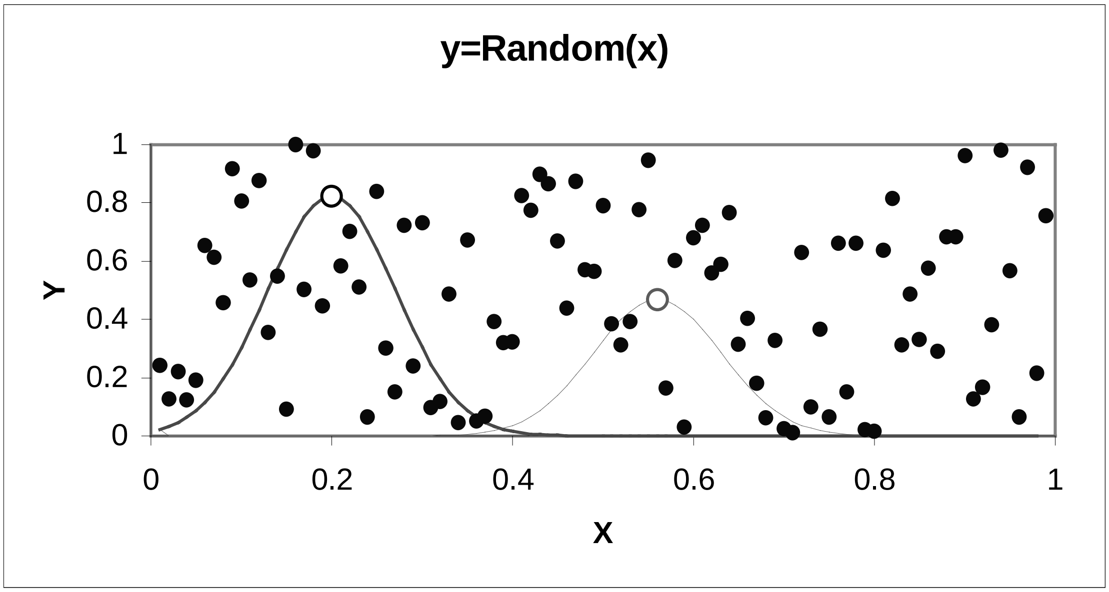


Fig. 8. One hundred random points between 0 and 100. Two sample fuzzy membership functions are illustrated.

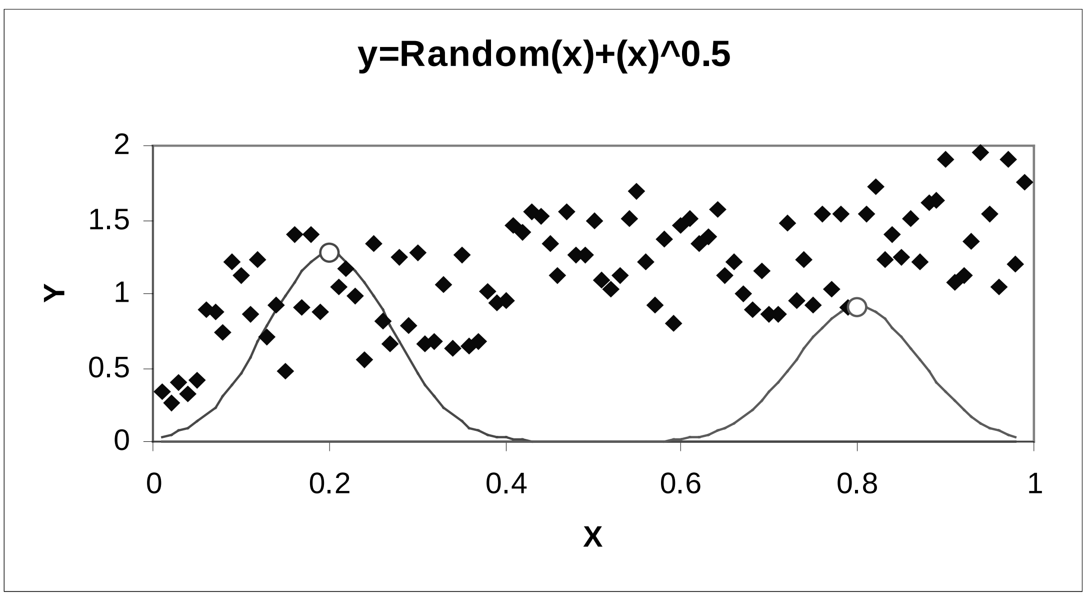


Fig. 9. The same one hundred random points with a simple trend added, two sample fuzzy membership functions are shown.

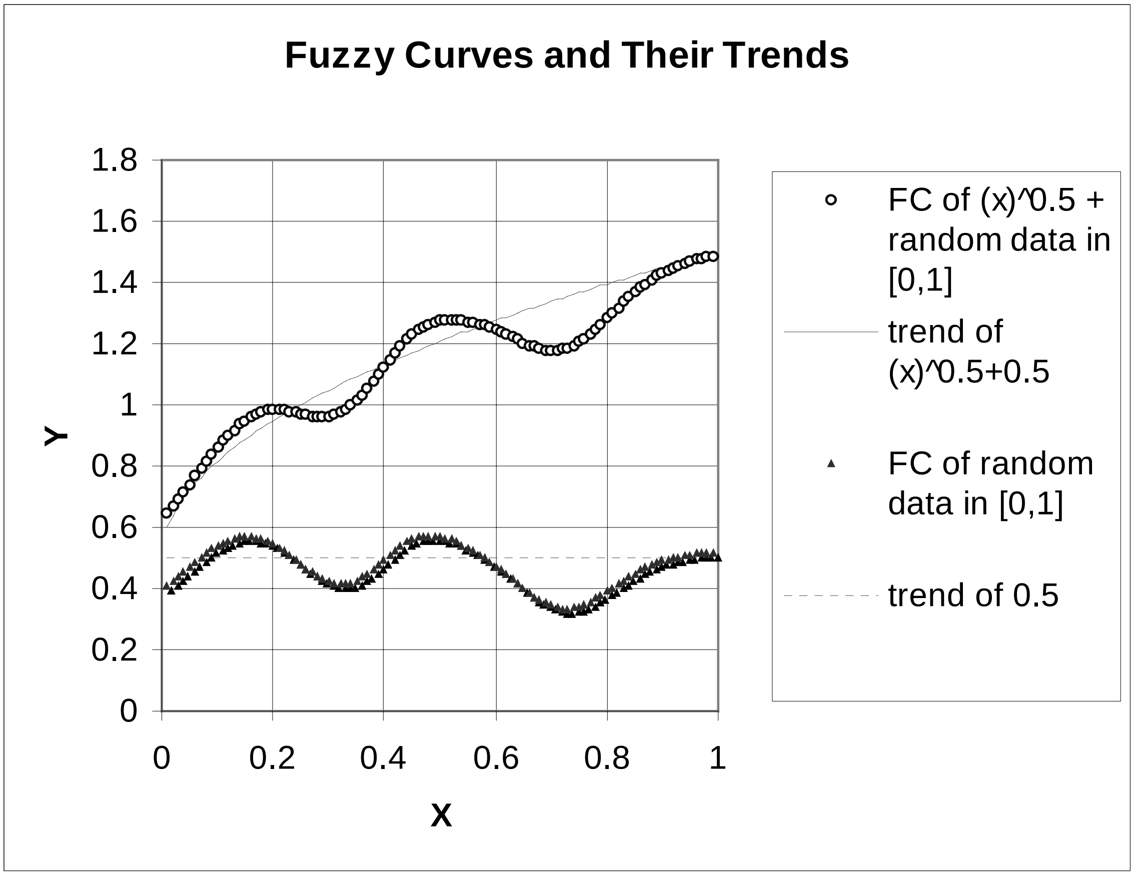


Fig. 10. Fuzzy curves for the two data distributions illustrated in Figs. 6 and 7. Curves are the summation of the fuzzy membership functions for each point. Value is given to trends with monotonic vertical variations.

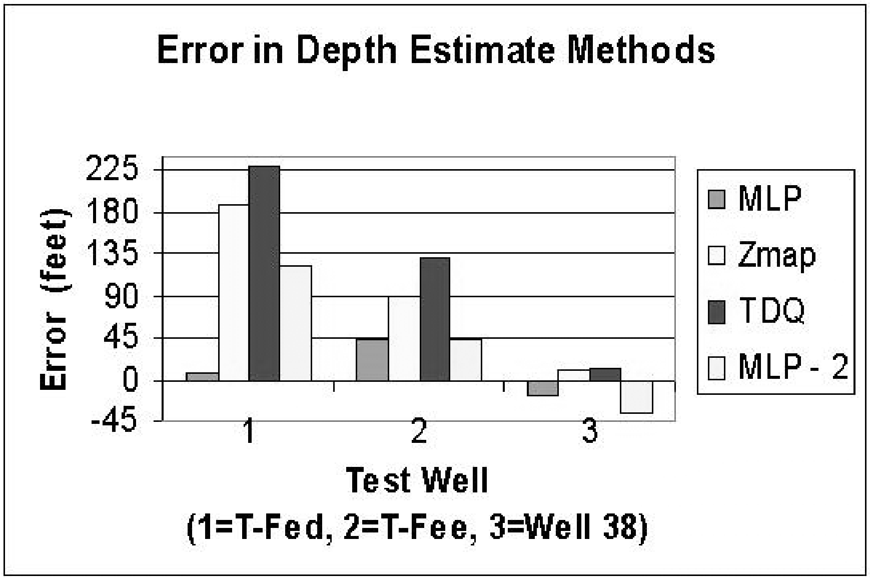


Fig. 11. Depth error of four time-to-distance transforms.

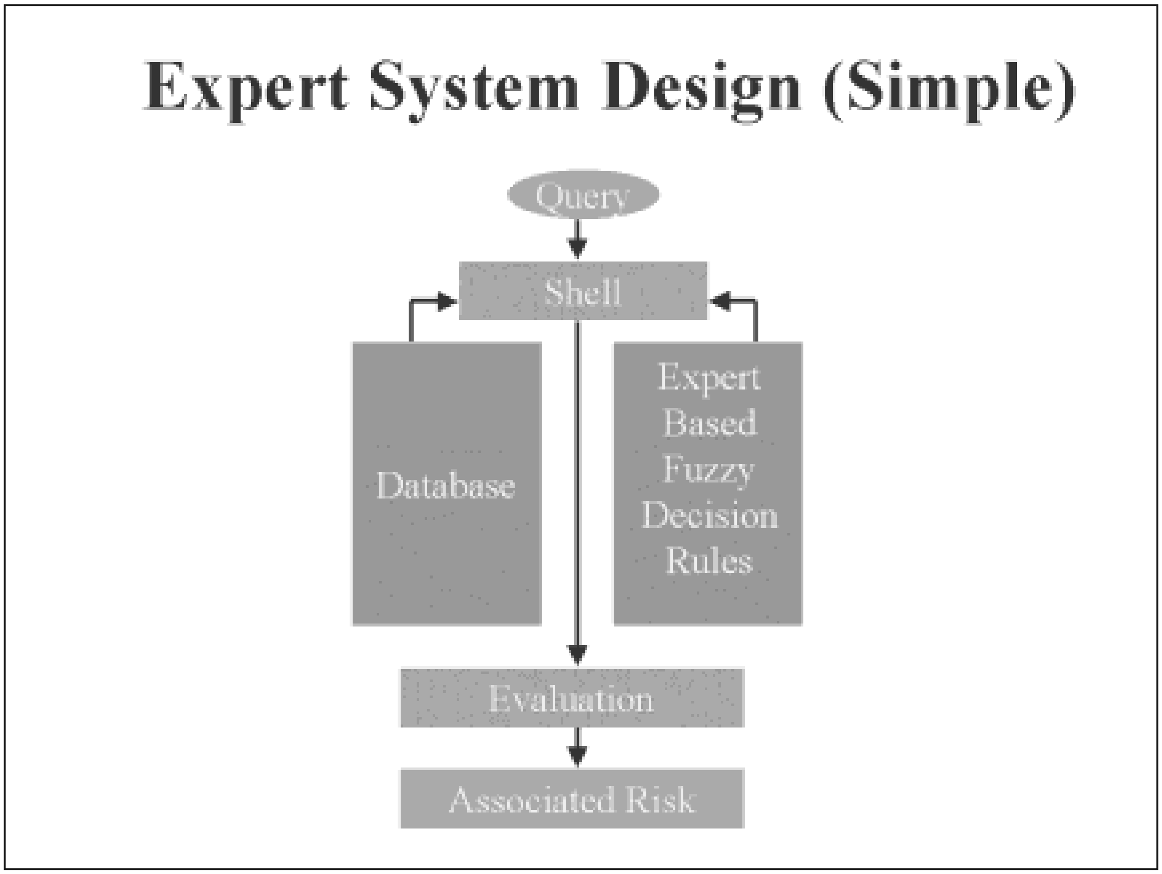


Fig. 12. Expert system; the initial, simple flow chart.

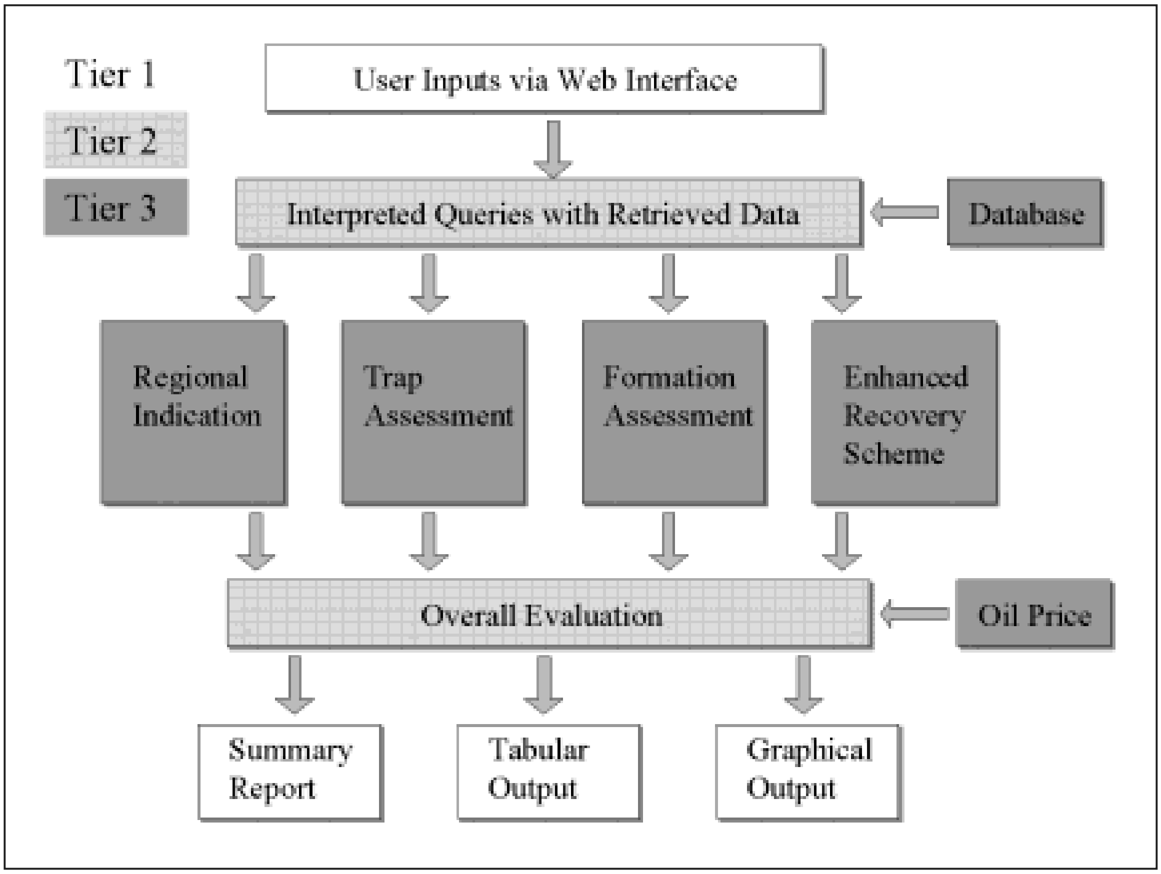


Fig. 13. New expert system that expands the initial flow chart shown in Fig. 12. Analysis is broken down into several parallel systems that combine results for output.

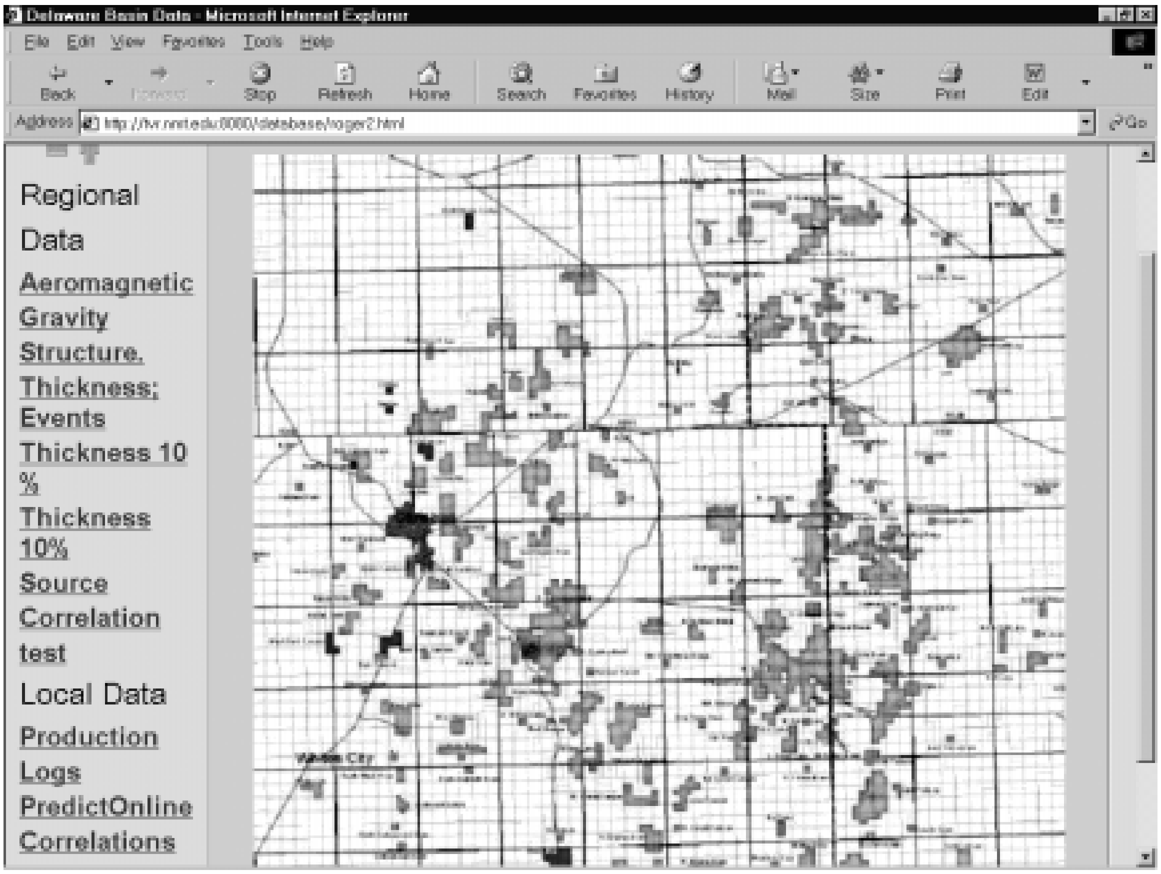
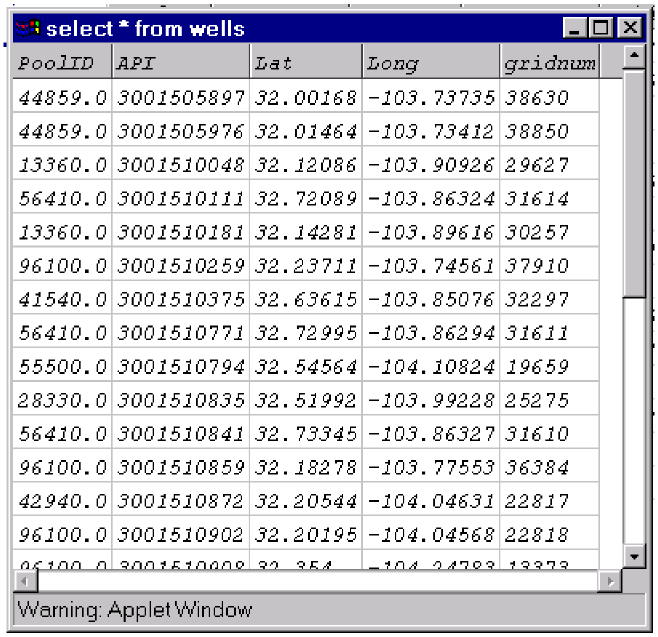


Fig. 14. Preliminary Java interface showing menus and pool map.



PoolID	API	Lat	Long	gridnum
44859.0	3001505897	32.00168	-103.73735	38630
44859.0	3001505976	32.01464	-103.73412	38850
13360.0	3001510048	32.12086	-103.90926	29627
56410.0	3001510111	32.72089	-103.86324	31614
13360.0	3001510181	32.14281	-103.89616	30257
96100.0	3001510259	32.23711	-103.74561	37910
41540.0	3001510375	32.63615	-103.85076	32297
56410.0	3001510771	32.72995	-103.86294	31611
55500.0	3001510794	32.54564	-104.10824	19659
28330.0	3001510835	32.51992	-103.99228	25275
56410.0	3001510841	32.73345	-103.86327	31610
96100.0	3001510859	32.18278	-103.77553	36384
42940.0	3001510872	32.20544	-104.04631	22817
96100.0	3001510902	32.20195	-104.04568	22818

Fig. 15. Sample query result.