GENERALIZED CORRELATIONS TO ESTIMATE OIL RECOVERY AND PORE VOLUMES INJECTED IN WATERFLOODING PROJECTS

A Dissertation

by

ARNALDO LEOPOLDO ESPINEL DIAZ

Submitted to the Office of Graduate Studies of Texas A&M University in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2010

Major Subject: Petroleum Engineering

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Approved by:

Chair of Committee,	Maria A. Barrufet
Committee Members,	Stephen A. Holditch
	Daulat Mamora
	Charles Glover
Head of Department,	Stephen A. Holditch

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ABSTRACT

Generalized Correlations to Estimate Oil Recovery and Pore Volumes Injected in Waterflooding Projects.

(December 2010)

Arnaldo Leopoldo Espinel Diaz, B.S., Universidad Jose Maria Vargas; M.S., Texas A&M University

Chair of Advisory Committee: Dr. Maria A. Barrufet

When estimating a waterflood performance and ultimate recovery, practitioners usually prepare a plot of log of water-oil ratio vs. cumulative production or recovery factor and extrapolate the linear section of the curve to a pre-established economic limit of water production. Following this practice, engineers take the risk of overestimating oil production and/or underestimating water production if the economic limit is optimistic. Engineers would be able to avoid that risk if they knew where the linear portion of the curve finishes. We called this linear portion the "straight-line zone" of simply SLZ.

In this research, we studied that "straight-line zone" and determined its boundaries (beginning and end) numerically using mathematics rules. We developed a new procedure and empirical correlations to predict oil recovery factor at any water/oil ratio.

The approach uses the fundamental concepts of fluid displacement under Buckley-Leverett fractional flow theory, reservoir simulation, and statistical analysis from multivariate linear regression. We used commercial spreadsheet software, the Statistical Analysis Software, a commercial numerical reservoir simulator, and Visual Basic Application software.

We determined generalized correlations to determine the beginning, end, slope, and intercept of this line as a function of rock and fluid properties, such as endpoints of relative permeability curves, connate water saturation, residual oil saturation, mobility ratio, and the Dykstra-Parsons coefficient. Characterizing the SLZ allows us to estimate the corresponding recovery factor and pore volumes injected at any water-oil ratio through the length of the SLZ.

The SLZ is always present in the plot of log of water-oil ratio vs. cumulative production or recovery factor, and its properties can be predicted. Results were correlated in terms of the Dykstra-Parsons coefficient and mobility ratio. Using our correlations, practitioners can estimate the end of the SLZ without the risk of overestimating reserves and underestimating water production. Our procedure is also a helpful tool for forecasting and diagnosing waterfloods when a detailed reservoir simulation model is not available.

DEDICATION

To God, for giving me the opportunity and the privilege of living, studying, and working in Aggieland for a second time.

To my wife and kids, for their dedication, support, and sacrifice giving me always a reason to work out this degree.

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CHAPTER I

INTRODUCTION

For many years petroleum engineers plotted data on graph paper, and with a straightedge or a curve, drew average lines through the points or extrapolated those linear trends to estimate future performance. Now they use the same technique electronically.

A straight-line correlation is a linear correlation of several variables. Extrapolating a straight line in plots can be useful, especially when dealing with oil and water production data and recovery factors, but also may be dangerous, because recoverable oil may be overestimated.

Observing field data or simulation results from waterflooding projects, we can see that when no more movable oil is left in the reservoir, the curve of the widely used log of water-oil ratio (WOR) vs. oil recovery factor (RF) plot abruptly bends up. Therefore, extrapolating the zone before the curve bends up to a pre-established economic limit may drive the practitioner to overestimate recoverable oil and underestimate water production.

The log WOR vs. RF plot is an important, powerful and reliable diagnostic and forecasting tool because its shape is affected by very important factors that determine a waterflooding project performance, such as areal (E_A) and vertical (E_i) sweep efficiencies, displacement efficiency (E_D) , rock properties, reservoir heterogeneity, fluid properties, and fluid saturations.

This dissertation follows the style of the SPE Journal.

In this chapter we discuss briefly these important factors, the most relevant previous works related to the WOR vs. oil production and RF plots, our objectives, and our contributions with this research. In the following chapters we will discuss our methodology, results, conclusions and recommendation.

 E_A is the fraction of the reservoir area contacted by injected water. This efficiency will depend upon the oil and water relative permeabilities (k_{ro} and k_{rw}), Mobility Ratio (M), injection pattern, pressure distribution between the injector and the producer, and areal heterogeneity (including fractures and directional permeability). Experimental correlations have been published to estimate E_A for different mobility ratios (Craig, 1971).

 E_i is the fraction of the reservoir's vertical plane contacted by water. Vertical heterogeneity will determine this efficiency. Published correlations are available to estimate E_i for different mobility ratio values (Dykstra and Parsons, 1950). E_{ν} , or volumetric sweep efficiency, is the product of E_A and E_i . E_i can be expressed in terms of the Dykstra-Parsons coefficient (VDP). This coefficient indicates the degree of heterogeneity of a reservoir. VDP equal to 0 would correspond to an ideal, completely homogeneous reservoir, and 1 to a completely heterogeneous reservoir. Most reservoirs have VDPs between 0.8 and 0.95.

The Dykstra-Parsons coefficient is determined following these steps:

- 1. Divide permeability samples into layers of equal thickness.
- 2. Arrange the permeability data in decreasing order.

- 3. Determine for each value the percent of values with greater permeability and express each number as cumulative percentage, or "percent greater than."
- 4. Plot the data on log-probability scale, with permeability in the log scale and percent in the probability scale.
- 5. Estimate the best fit for a straight line and determine permeability values at 84.1% and at 50%.
- 6. Determine the Dykstra-Persons coefficient using the expression:

$$VDP = \frac{k_{50} - k_{84.1}}{k_{50}}.$$
 (1)

 E_D is the ratio of displaced oil to the total flooded portion of the reservoir and can be estimated as function of water and oil saturation:

$$E_{D} = \frac{\overline{S_{w}} - S_{wc} - S_{g}}{1.0 - S_{wc} - S_{g}} , \qquad (2)$$

where

 $\overline{S_w}$ = average water saturation behind the water front, fraction

 S_{wc} = connate water saturation, fraction

 S_g = gas saturation, fraction

and recovery efficiency (E_R) will be defined as:

$$E_R = E_A \times E_i \times E_D. \tag{3}$$

Relative permeability is the ratio of effective permeability (permeability to water, oil, or gas when more than one phase is present in the reservoir) to some reference permeability. The most used reference permeability is the effective permeability to oil measured at the irreducible water saturation $(k_o)_{Swi}$. In this case, the value of the relative permeability of oil at S_{wi} will always be 1.0. Sometimes we may find that the base permeability used is the permeability to air (k_{air}) . This procedure is not incorrect, but makes comparison of different relative permeability curves more difficult.

Other very important concepts to take into account when planning or analyzing a waterflooding project follow. These concepts are basic knowledge for our research.

Based on the reservoir continuity, especially considering continuity of the floodable pore volume, the injection scheme may be peripheral or have a specific injection pattern. If the reservoir is continuous and no permeability barrier is present between injectors and producers, peripheral water injectors can begin in the reservoir flanks, which can be an excellent way of displacing oil with water while saving investments by minimizing the number of injection wells.

The injected water will move from the edges of the reservoir to the center, and oil will be displaced toward the producer wells. Initial peripheral injection usually is expanded to interior reservoir injection to either reach symmetry or not. If the existing well density is high and/or sealing faults or permeability barriers are present, the peripheral scheme may not work efficiently, so an injection pattern should be applied to achieve a better sweep efficiency.

Large rock permeability is desired to ensure adequate injectivity and productivity and, if feasible, to accelerate the production response with a higher injection rate. However, large permeability variation or large contrast between layers will increase the oil volumes within zones of lesser permeability.

Mobility ratio (M) is defined as the ratio of the mobility of the displacing phase to the mobility of the displaced phase. M may be estimated using k_{rw} evaluated at the maximum water saturation (1- S_{or}), and the oil relative permeability evaluated at the connate water saturation (S_{wc}) (unflooded zone). This M is called the "endpoint" mobility ratio (see Eq. 4).

$$M = \frac{\lambda_{\text{Displacing}}}{\lambda_{\text{Displaced}}} = \frac{\frac{(k_{rw})_{S_{wmax}}}{\mu_w}}{\frac{(k_{ro})_{S_{we}}}{\mu_o}}, \qquad (4)$$

where

 $\lambda_{displacing} =$ mobility of the displacing phase (water)

 $\lambda_{displaced}$ = mobility of the displaced phase (oil)

 $(k_{rw})_{Swmax}$ = relative permeability to water at the maximum water saturation, fraction $(k_{ro})s_{wc}$ = relative permeability to oil at the connate water saturation, fraction

$$\mu_w$$
 = water viscosity, cp

 μ_o = oil viscosity, cp

This "endpoint" definition is used for simplicity in this work. Another definition for M uses k_{rw} evaluated at the average water saturation in the flooded zone at the water breakthrough, instead of the k_{rw} evaluated at the maximum water saturation (1- S_{or}). This definition better explains the fluid behavior in the porous media (Craig, 1971) but is less practical to use in developing our correlations. *M* will remain constant before water breakthrough but will begin to increase after that point with the increase of average water saturation in the water-swept zone.

Unfavorable M (M >> 1) may create some problems that may be handled with peripheral injection schemes. Large M values mean that water will move faster than oil; therefore, water fingering (water bypassing oil due to the higher mobility of the displacing phase) can occur and may cause early water breakthrough in producing wells. When the mobility ratio is much larger than one, injectivity will be larger than productivity, because water will flow through the porous medium easier than oil. To balance voidage and maintain pressure, more producers may be required than injectors. For very favorable mobility ratios (M<<1), productivity will be larger than injectivity because oil will be more mobile than water, and more injectors will be required than producers (Craig, 1971). Assuming steady-state, incompressible fluid behavior, and after gas fill-up is completed, we may neglect this effect in our forecasting since we will have one unit of produced liquid for each unit of injected water.

Initial free gas saturation may delay injection response due to the gas fill-up where injected water and displaced oil will fill the spaces previously occupied by free gas. To estimate oil and gas saturations at the beginning of the waterflood, the following expressions can be used (Craft and Hawkins, 1991):

$$S_{o} = \left(1.0 - \frac{N_{pp}}{N_{ob}}\right) \left(\frac{B_{o}}{B_{ob}}\right) \left(1.0 - S_{wc}\right) \dots (5)$$

and

$$S_g = 1.0 - S_o - S_{wc},$$
(6)

where

- S_o = oil saturation at the beginning of the waterflood, fraction
- N_{pp} = primary oil production from the bubblepoint pressure to the current reservoir pressure, STB
- N_{ob} = original oil in place at the bubblepoint pressure, STB
- B_o = oil formation volume factor at current average reservoir pressure, RB/STB
- B_{ob} = oil formation volume factor at the bubblepoint pressure, RB/STB
- S_{wc} = connate water saturation, fraction
- S_g = gas saturation at the beginning of the waterflood, fraction

During the last 50 years, several attempts have been made to forecast waterflood performance and ultimate oil recovery by modeling the sweeping process of water displacing oil through the porous medium.

The accuracy of the prediction is mostly affected by the knowledge about effects of reservoir heterogeneity, fluid saturations, and mobility ratio. These factors affect displacement and areal and vertical sweep efficiencies. Water channeling that bypasses mobile oil remaining within the rock, causing low displacement and early breakthrough in producing wells, will reduce ultimate recovery.

Reasonable forecasts of waterflood performance can improve decisions regarding a waterflooding candidate and project feasibility. Waterflood performance can be estimated by various analytical and empirical methods based upon several assumptions that many times are ignored or violated. Reservoir simulation is now one of the most comprehensive and widely used waterflood prediction tools. When used properly, it can be a very useful tool for waterflood design, planning, and surveillance. Simulation is especially useful when used to develop forecasts of a complex reservoir, varying fluid properties, and a no uniform well pattern.

However, while simulation can yield results that are superior to and more detailed than other methods, it also generally requires a lot more data and time. A range of uncertainty in the input data leads to a resulting band of uncertainty in the output. A good understanding of the uncertainties, multiple realizations, and sensitivity analysis will significantly increase the value and usefulness of the simulation results.

Since reservoir simulation requires more data and time to produce good forecasts, we focused our research in analytical and empirical methods used to develop more general but reasonable waterfloods forecasts.

Baker et al. (2003) showed that in the plot of log WOR vs. cumulative production, a linear extrapolation can be made of the linear region of the curve obtained up to a value of log WOR = 2 (WOR = 100). The authors highlighted the possibility of errors (underestimation of ultimate recovery) if exponential decline is used. However, they did not offer a procedure to extrapolate the curve in terms of the linear portion boundaries, giving only rules of thumb based on observations made from simulation results.

Ershaghi and Omoregie (1978) developed a procedure to extrapolate watercut curves to estimate recovery after injected water breakthrough, using the "X-function"

(defined in Eq. 7) in an approach similar to the one used for the plot of log WOR vs. cumulative production:

$$X = -\left[\ln(\text{WOR}) - \frac{1}{\text{WOR} - 1}\right].$$
(7)

In Ershaghi and Omoregie's (1978) approach, the straight-line relationship between the "X" factor and cumulative production (N_p) on a Cartesian plot may be extrapolated after WOR is equal to 1. This plot assumes a 1D Buckley-Leverett model, does not consider stratification, and assumes E_A constant after water breakthrough. For values of WOR between 0.5 and unity, a linear relationship may be expected, but the abrupt increase of the WOR when oil saturation approaches S_{or} is not considered, so extrapolations to the economic limit should be done with extreme caution.

Lo (1990) presented a procedure to estimate recovery for mature fields using relative permeability curves and production data. The method is used to calculate the slope of the log WOR vs. N_p curve from the relative permeability curve data and determine ultimate recovery by extrapolating that curve. However, the end of the SLZ and the capability to predict reservoir behavior before breakthrough is not defined. This method assumes homogenous reservoirs.

Lo (1990) demonstrated that for 1D, linear, immiscible, and incompressible displacement, log WOR is linearly proportional to the cumulative oil production; therefore, a straight line will appear in a semilog plot of these variables. Lo used the 1D Buckley-Leverett analytical method and derived the slope of the curve from the relative permeability data, S_{wc} , B_o , and hydrocarbon pore volume (HCPV), using the expression:

$$Slope = \frac{(1 - S_{wc})bB_o}{\text{HCPV}},$$
(8)

where:

 S_{wc} = connate water saturation

b = slope of the log of the best fit of the curve of water/oil relative permeability ratio vs. water saturation

HCPV = hydrocarbon pore volume $(V_P(1-S_{wc})/V_P)$

Lo (1990) did not consider reservoir stratification (VDP), M, or sweep efficiencies in his study.

Despite all of the progress made by later researchers, Lo's work seemed to offer the best basis.

For our project, we incorporated the best contributions of other authors, as we modified Lo's approach to account for different reservoir and fluids properties and reservoir heterogeneity.

After studying the different authors and reviewing published information and case studies, we wanted to answer the following questions: How accurate is the extrapolated procedure using the log WOR vs. RF curve to estimate RF and WOR? Is the SLZ always present? How long it is? Is it always correct to extrapolate it to find ultimate recovery at an assumed economic limit? What are the SLZ boundaries (where does the SLZ begin and where does it end)?

The specific objectives of this research are:

1. To prove or disprove the existence, formation, and boundaries of the linear (SLZ) portion of the log WOR vs. RF plot as a function of reservoir

parameters, and to use this SLZ to estimate oil recoveries and water injection needs.

- To develop generalized correlations using fractional flow theory, reservoir simulation, and field data to predict expected recovery factors for any WOR value.
- To create a unique analytical and statistical tool that helps the user develop plans to maximize oil recovery and minimize water production and operating costs.
- 4. To validate our correlations and the tool developed in this project using field data from more than 80 reservoirs, including rock and fluid properties, production and injection rates, and recovery factors. That way we can ensure that our correlations and results are data driven. In this research we show two examples of forecasts using field cases results.

In summary, the purpose of our research is to characterize the linear portion (SLZ) of the plot of log WOR vs. RF in terms of its beginning and end so that practitioners can predict oil recovery at any WOR with a reasonable degree of accuracy.

Using fractional flow theory, we determined the slopes and intercepts of the SLZ when linear behavior is maintained in the plots of log WOR vs. RF for reasonable combinations of M, VDP, S_{wc} , S_{orw} , and k_{roe} , k_{rwe} for oil- and water-wet rocks. We applied reservoir simulation to create a database of results for different heterogeneous cases, we developed multiple linear correlations to predict waterflood performance using

basic production data, and we built a computer code to apply our newly developed correlations.

Our correlations estimate the beginning and the end of the SLZ to obtain recovery forecasts while avoiding the risk of extrapolating the WOR vs. RF line and overestimating reserves.

Our methodology includes recovery correlations that account for reservoir heterogeneity based on the VDP in a range of values from 0.5 to 0.99.

All results were compared with field data and results obtained from the reservoir simulator to perform a control check with all estimates.

CHAPTER II

METHODOLOGY

A waterflood oil production profile considering only production due to water injection—that is, injecting from the first day of operation—will present four typical basic stages that we can identify using the plot of log WOR vs. RF. These stages can be defined as (see Fig. 1):

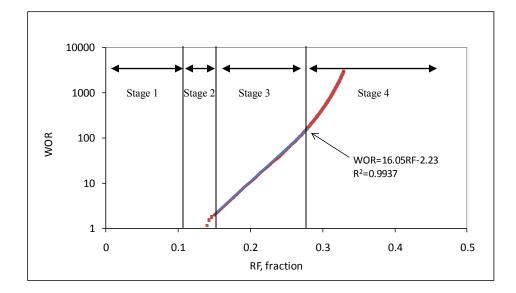


Fig. 1—Data from simulation. The plot shows a log WOR vs. RF plot, the curve stages, the SLZ zone, and the calculated slopes and intercepts for an example taken from the simulation runs with VDP = 0.9, M = 3, $S_{oi} = 0.6$, $S_{or} = 0.35$ and $S_{wi} = 0.4$.

- Beginning of injection to water breakthrough: During this stage, oil banks are formed around the injection well. A water front is formed and advances through the reservoir layers.
- 2. Breakthrough to SLZ: This stage is the period of time from when injected water is first produced to when the SLZ begins to form. After a short period of stabilization, that according to our observations usually occurs between WOR = 0 and WOR = 1.5, the SLZ appears and the water production increases slowly, creating the SLZ in a semilog plot.
- 3. SLZ: Period when the change in the log of WOR with respect of the RF is constant. Water cut is increasing relatively slowly.
- 4. Incline WOR: The SLZ ends and WOR begins to increase above the SLZ trend.

By applying linear regression, we can determine that the SLZ in the example has a slope of 16.05 and an intercept of -2.23, with a regression coefficient (R2) higher than 0.99.

From the SLZ analysis, we can see that when producing the well after a value of WOR equal to 110, corresponding to a RF of approximately 28%, the water production will abruptly. The slope and the intercept of the SLZ will depend upon the reservoir and fluid characteristics.

From the example discussed above, we can see that an increase of more than one order of magnitude in WOR would be needed to obtain only 4% of additional recovery (32%), with a large amount of additional water injected and produced, which may

increase costs and decrease economics of the project if this water production is not expected or planned.

Fig. 2 shows real data from an actual well in a field where waterflooding was conducted from the beginning of the field development. A sharp increase in WOR begins after the SLZ ends, just before reaching an RF of about 42%, as can be seen in the plot. This well is an example of the SLZ application.

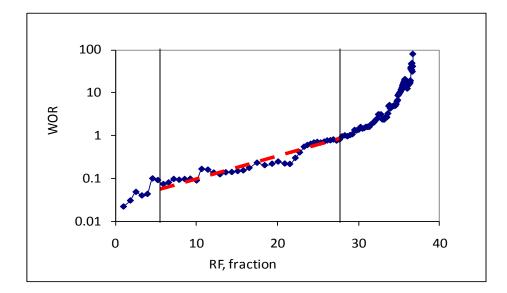


Fig. 2—Data from a real well. The SLZ is highlighted in red. This example shows the beginning of the SLZ between log WOR -1.5 and -1 and the end of the SLZ close to 0.1, with a RF = 42%. WOR increases abruptly after this point.

Table 1 presents a summary of the characteristics for each stage in a typical waterflooding project.

STAGES	CHARACTERISTICS
Beginning of injection	Oil banks formation.
to water breakthrough	Gas fill-up occurs.
(Stage 1).	Pre-breakthrough stage.
	Secondary production begins.
Water breakthrough to	Injection reaches the producer.
SLZ(Stage 2).	Water breakthrough occurs.
SLZ (Stage 3).	Oil rate peak. Water production
	increases constantly.
incline WOR (Stage 4).	Oil production decreases and
	water production increases fast.
	High water cut is obtained.

Table 1—Stages in the waterflooding life cycle and their characteristics.

The steps during this research can be summarized as follows:

- Perform literature review of worldwide oil industry experiences and lessons learned from real waterflooding projects including waterflooding performance estimation.
- 2. Build a database using a computer spreadsheet, including proprietary data available from existing fields consisting on permeability, porosity, fluid viscosity, *M*, voidage ratio, PVI, relative permeability curves, and all other

available parameters that can contribute to evaluate waterflooding performance.

- Identify waterflood performance estimation methods that can be used for heterogeneous reservoirs with unfavorable mobility ratios.
- 4. Develop a set of correlations based on fractional flow theory to accurately evaluate reservoir performance under waterflood including the effect of initial fluid saturations, wettability, heterogeneity, and different viscosity ratios.
- 5. Build up this automated procedure in the Statistical Analysis Software (SAS) to create correlations to estimate the beginning and the end of the SLZ for homogeneous reservoirs, using reservoir and fluid properties, including recovery factors and pore volume injected. Prove the theoretical existence of the SLZ in all cases.
- Build simple reservoir simulation models using commercial reservoir simulation systems to create multiple heterogeneous cases and to determine the existence of the SLZ in these runs for several combinations of M and VDP.
- Develop an easy-to-use, user-friendly tool in VBA that includes the new methodology.

We used field data to test our correlations. Reservoir and fluids properties of more than 100 reservoirs and fields were used. Among those properties, we collected oil rate (q_o) , water production rate (q_w) , N, N_p primary, N_p secondary, PV, processing rates

(PVI/year), μ_o , μ_w , S_{or} , S_{wc} , relative permeability curves, cumulative water injection, wettability, PVT data and VDP.

Data quality check was performed. We tabulated all data collected and built log WOR vs. RF plots for each reservoir. To avoid the effects of errors in production measurements and specific operational problems in the data, we used a correlation coefficient (R^2) cutoff of 0.95 for the SLZs obtained from actual field data to select the curves to be used to calibrate our procedure. 84 reservoirs were used.

Data used is proprietary and restricted by Intellectual Property policies, therefore we did not obtain permission to publish all the results. However, we obtained permission to show two sets of data of two fields that we called Field A and Field B, both described in the Results section.

The Module for Homogeneous Reservoirs

We programmed and applied the conventional Buckley-Leverett (Buckley and Leverett, 1942) procedure using the Statistical Analysis Software (SAS) to calculate and differentiate the fractional flow (df_w/dS_w) . Corey's relative permeability functions were used to estimate reasonable combinations of relative permeability curves using oil and water exponents (Molina, 1980). We called that code the "homogeneous module."

Corey's type functions (Molina, 1980) are expressed as:

$$k_{rw} = k_{rwe} \left[\frac{S_w - S_{wc}}{\left(1 - S_{wc} - S_{or}\right)} \right]^{n_w}$$
(9)

and

$$k_{ro} = k_{roe} \left[\frac{1 - S_w - S_{or}}{\left(1 - S_{wc} - S_{or}\right)} \right]^{n_o}$$
(10)

where k_{rwe} and k_{roe} are the water and oil relative permeability curves endpoints and n_w and n_o are the water and oil Corey exponents (Molina, 1980). The base relative permeability used to develop the calculations to define a range for the oil relative permeability endpoint was the air permeability.

For normalized relative permeability curves, the program uses the following expression for dimensionless water saturation:

$$S_{wD} = \frac{(S_w - S_{wc})}{(S_{w\max} - S_{wc})}.$$
 (11)

and the following expressions for relative permeability values:

$$k_{rw} = k_{rwe} [S_{wD}]^{n_w}(12)$$

$$k_{ro} = k_{roe} [1 - S_{wD}]^{n_o}.$$
 (13)

Calculations at and after water breakthrough are computed to estimate the conditions at the flood front for all possible combinations of viscosity ratios (VR), M, and Corey's exponents for oil and water relative permeability endpoints, and S_{wc} and S_{orw} (see the homogeneous module's code in Appendix A).

For homogeneous cases, we differentiated fractional curves to calculate slopes for each saturation step:

$$f_{w}' = \left(\frac{df_{w}}{dS_{w}}\right). \tag{14}$$

We calculated the water/oil ratio as the ratio of water rate to oil rate. Using Darcy's law for 1D, linear flow, we can express water and oil rate as follows:

$$q_{w} = -0.001127 \frac{k_{w}A}{\mu_{w}} \left[\frac{\partial P_{w}}{\partial s} + 0.00694 \rho_{w} \sin \alpha \right].$$
 (15)

and

$$q_o = -0.001127 \frac{k_o A}{\mu_o} \left[\frac{\partial P_o}{\partial s} + 0.00694 \rho_o \sin \alpha \right], \qquad (16)$$

so an expression for WOR will be:

WOR =
$$\frac{q_w}{q_o}$$
,(17)

or substituting Eq. 15 and 16 into Eq. 17, ignoring capillary pressure, assuming a horizontal reservoir, and solving, we have:

WOR =
$$\frac{k_{rw}}{k_{ro}} \frac{\mu_o}{\mu_w}$$
. (18)

Recovery factor and cumulative production can be expressed as dimensionless functions of average oil and connate water saturations. Using these values, we can generate the plot of log WOR vs. RF and analyze the SLZ.

where

N = original oil in place, STB

or

$$RF = \frac{1 - \overline{S_o} - S_{wc}}{1 - S_{wc}} \frac{B_o}{B_{oi}} \qquad (20)$$

where $\overline{S_o}$ is average oil saturation, determined as:

$$\overline{S_o} = 1 - \overline{S_w} \,. \tag{21}$$

Dimensionless PVI in fractional flow theory is calculated as the inverse of the slopes for each saturation step as shown in Eq. 14.

This PVI is related to the well's floodable pore volume and is equivalent to the ratio of the quantity of water injected to the total floodable pore volume associated to the well when no gas is present in the reservoir:

$$PV = \frac{NB_o}{(1 - S_{wi})} \dots (22)$$

where

N = original oil in place, STB

 B_o = oil formation volume factor, RB/STB

 S_{wi} = irreducible water saturation, fraction

Since PVI is related to the well floodable pore volume, we assume an analysis on a well-by-well basis. As long as the producer is receiving the complete effect of the injector, regardless the injection scheme, the method will produce a good forecast since it works according to the fractional flow equation for homogeneous reservoirs only.

Since our basic calculations are dimensionless, we can use the processing rate (PVI/year) and the following equations to calculate reservoir performance in terms of production rates and cumulative production in barrels:

where

t = time, years

PVI = pore volume injected, fraction

PVI/*y* = Pore Volume Injected per year

where

 i_w = water injection rate, STB/day

 W_i = total water injected at the evaluated time step, STB

 W_{i-1} = total water injected at previous time step, STB

 Δt = time difference, days

where

PV = reservoir pore volume, RB

 B_w = water formation volume factor, RB/STB

$$q_o = \frac{i_w B_o}{\text{WOR} \times B_w + B_o} \quad$$
(26)

where

 $q_o = \text{oil rate, STB/D}$

 $B_o = oil$ formation volume factor, RB/STB

and

$$q_{w} = \frac{(i_{w}B_{w}) - (q_{o}B_{o})}{B_{o}} \quad$$
(27)

where

 q_w = water rate, STB/D

The assumptions and limitations of this module are the following:

- 1. Buckley-Leverett displacement, 1D linear flow
- 2. Horizontal, homogeneous, isotropic reservoir
- 3. Incompressible fluids
- 4. Initial gas saturation is zero
- 5. Neglect capillary pressure (*Pc*)

Flow performance at and after breakthrough for recovery factors and water/oil ratio for each saturation step were calculated. All ranges and steps used in the homogeneous module to calculate each fractional flow case and each straight line are shown in Table 2.

RANGES – FRACTIONAL FLOW			RUNS
Input data	Range	Steps	Combinations
Viscosity ratio	0.1 to 1	0.2	5
Oil exponent	1 to 5	1.0	5
Water exponent	1 to 5	1.0	5
Residual oil sat	0.1 to 0.5	0.1	5
Connate water sat	0.1 to 0.5	0.1	5
Oil relative permeability endpoint	0.3 to 1.0	0.1	8
Water relative permeability endpoint	0.3 to 1.0	0.1	8
Total runs (SLZ)			200,000

Table 2—Parameters and ranges used in SAS to generate SLZs for homogeneous reservoirs in the homogeneous module.

Our homogeneous module performs all the fractional flow calculations. A total of 200,000 different runs were made with SAS to generate the same number of SLZs for homogeneous cases.

All the SLZs were correlated, and general correlations for all the possible combinations of reservoir and fluid properties shown in Table 2 were obtained.

After all SLZs from the statistical model and all correlations for the homogeneous module were obtained, we needed to validate these results with reservoir simulation results and ensure that the SLZ was also present in simulation results and that its characteristics were reasonably similar to those estimated with the Buckley-Leverett 1D procedure. If results were consistent and similar in terms of RF at the end of the SLZ, and in terms of slopes and intercepts, we would be able to continue using reservoir simulation to estimate SLZs for different VDPs and build our heterogeneous module.

Fractional flow is a 1D model, where areal and vertical sweep efficiencies are assumed to be unity. In a reservoir simulator, we built a 3D model with an injection scheme of a 5-spot pattern. Comparing 1D model results with 3D model results would not be consistent, and 1D model results will overestimate recovery. However, we analyzed SLZ results from simulation for homogeneous cases (VDP = 0), and checked that areal sweep efficiency at the end of the SLZ was already unity in all cases. From simulation results, EA at the breakthrough was between 0.70 and 0.72.

Since our objective in this comparison (1D vs. 3D) was only to test the existence of the SLZ and not to produce RF estimates including VDP (we developed correlations for heterogeneous reservoirs later) we recognized our results as consistent, concluding that the SLZ existence was theoretically proved.

We compared fractional flow and reservoir simulation results in terms only of ultimate recoveries (recovery at the end of the SLZ), and slopes and intercepts, just to ensure that SLZs obtained from simulation were consistent with those obtained from fractional flow theory—in other words, just to be sure that the SLZ s was present in all cases and that the SLZs finished at the same points (same WOR and same RF), and they did. Consistency in results is shown later in Chapter III.

Thus, reservoir simulation models were built to validate the SAS results, for M of 0.6 to 5, for water- and oil-wet reservoirs, and for combinations of other variables. We made 720 runs for the homogeneous reservoir cases using reservoir simulation. These runs are summarized in Table 3.

RANGES – SIMULATION RUNS			RUNS
Input Data	Range Steps		Combinations
Mobility ratio	0.6 to 5	1	5
Oil exponent	2 to 5	3	2
Water exponent	2 to 5	3	2
Residual oil sat	0.0 to 0.5	0.25	3
Connate water saturation	0.25 to 0.5	0.25	2
Oil relative permeability endpoint	0.3 to 1.0	0.7	2
Water relative permeability endpoint	0.3 to 0.5	0.1	3
Total runs (SLZ)			720

Table 3—Variables and ranges used to generate reservoir simulation cases for homogeneous reservoirs and validate results from our new correlations.

All straight lines were correlated together to obtain the final expressions for the slope- and-intercept generalized correlations. Water saturation steps for all calculations are taken as $\Delta S_w = 0.001$.

Analysis of the log WOR vs. RF Plot

The application of the fractional flow equation and the frontal advance theory permits us to estimate waterflood performance, including the construction of the log WOR vs. RF plot.

We propose that calculating slopes and intercepts for all possible log WOR vs. RF plots from our correlations and generating a statistical solution for slopes and intercepts as a function of mobility and viscosity ratios, endpoints of oil and water relative permeability curve, Corey's function exponents for oil and water, and oil and water saturations, we can predict ultimate recovery and PVI for any combination of reservoir and fluid properties with a single equation for homogenous reservoirs, and we can use simulation runs to generate correlations to calculate RF and PVI for heterogeneous reservoirs as well, using different VDP and *M* ranges.

Prior to determining the correlations, we estimated the extent of the SLZ in a general form. For that purpose we used the definition of a straight line knowing that the slope (first derivative) of a line is constant and its second derivative is zero. We computed the first and second derivatives numerically and excluded points that had second derivatives greater than |0.01| using an automated instruction on the computer code. Our set of correlations provides the RF at the end of the SLZ, when the second derivative is greater than |0.01| and advises the user to avoid extrapolations of the SLZ and overestimation of reserves. Fig.3 shows an example plot of the first derivative vs. RF. The first derivative is called DWOR in the plot, which is expressed as:

$$DWOR = \frac{d \log(WOR)}{d(RF)}.$$
 (28)

Using this set of correlations, we can forecast the expected behavior of the waterflood performance for a homogeneous reservoir in terms of the SLZ by predicting the curves' slopes and intercepts as functions of the variables defined earlier. Once each slope and intercept is calculated, recovery factors may be determined using the straight-line properties as shown in the next section.

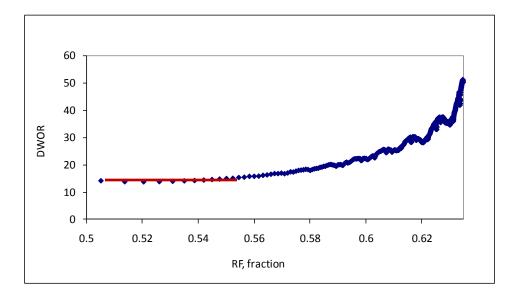


Fig.3—Plot of the first derivative of WOR with respect to RF showing the constant slope zone. RF range from 0.5 to 0.57 indicates the boundaries for the SLZ.

Applying the fractional flow theory and the frontal advance equation, we can forecast the expected behavior of the log WOR vs. RF plot for a homogeneous reservoir in terms of the SLZ by predicting the curves' slopes and intercepts and using only the same five rock and fluid parameters. In the next section, we present the statistical principles used to develop the correlations for any homogeneous reservoir using simple linear and multiple regressions. We also calculate water saturation at the water breakthrough (S_{wBT}), water cut at the breakthrough (f_{wBT}), and PVI correlations and represent them in tables and graphically. We can determine PVI for any RF provided that both variables are within the SLZ.

Multiple Linear Regression Application

Regression analysis establishes a mathematical relation between two or more variables that can determine a response, or set of dependent variables, from a given set of independent (or control variables). This statistical technique is useful to construct correlations for predicting trends of physical phenomena.

Using multiple linear regressions, we can analyze linear relationships among several variables, determining the slope and the intercept (numbers also called *regression coefficients*) of a straight line. The mean value of the data will be a function of the predictor (independent variable, usually plotted in the x axis in a graph and called x). We need to describe the expected value of the mean of that independent variable, called Y, as the mean value of the function plus a random error term, as:

 $Y = \beta_o + \beta_1 x + \varepsilon , \qquad (29)$

where

 β_0 = intercept (unknown regression coefficient)

 β_1 = slope (unknown regression coefficient)

x = independent variable, or "regressor"

 ϵ = random error term

When the set of correlations has only one regressor, it is called a "simple linear regression model." In this research, since we are using several regressors to understand the SLZ behavior, we will be using a "multiple linear regression model."

Technically, if we assume normal distribution of errors and that the mean and the variance of the random error term ε , are 0 and σ^2 respectively, we can say:

$$E(Y,x) = \beta_o + \beta_1 x, \qquad (30)$$

and

$$V(Y,x) = \sigma^2, \qquad (31)$$

with *E* being the expected value of the mean of *Y* for each *x*, and *V* the variance of *Y* with respect to *x*.

So the regression model can be defined as:

$$\mu_{Y,x} = \beta_o + \beta_1 x. \tag{32}$$

The model is a line of mean values where the height of the regression line at any value of x is the expected value of Y for that x. The slope β_1 is the change in the mean of Y for a unit change of x, and the variability of Y at a particular value of x is defined by the error variance σ^2 . So there is a distribution of values of Y at each x value, and the variance of this distribution is the same at each x. If σ^2 is small, the observed values of Y will fall close to the straight line. Is σ^2 is large, the observed values may deviate too much from the straight line. Since σ^2 is constant, the variability of Y at any value of x is the same (Montgomery and Runger, 2007).

In real-world problems, the values of slopes, intercepts, and error variance must be estimated from data, and future observations of Y from possible values of x are estimated using the statistical model. Regression relationships are only valid for values of the regressor within the range of the original data, so large extrapolations are usually not accurate, or at least, more uncertainty is introduced in the process. For that reason, we developed a set of correlations using the SLZ boundaries to avoid extrapolations.

To estimate the unknown regression coefficients, or the slope and the intercepts for our log WOR vs. RF curves, we need to obtain the "best fit" of the data available, obtained from the application of the fractional flow equation and frontal advance theory, which are the first results from our SAS correlations.

Estimating these parameters is easy if we minimize the sum of the squares of the vertical deviations of the variance for each data set. This is the method of the "least squares."

If we use Eq. 29 to express n observations in the sample, we may define the following equations to determine the least-squares estimates as:

$$\hat{\beta}_{o} = \overline{y} - \hat{\beta}_{1} \overline{x}$$
(33)

and

$$\hat{\beta}_{1} = \frac{\sum_{i=1}^{n} y_{i} x_{i} - \frac{\left(\sum_{i=1}^{n} y_{i}\right) \left(\sum_{i=1}^{n} x_{i}\right)}{n}}{\sum_{i=1}^{n} x_{i}^{2} - \frac{\left(\sum_{i=1}^{n} x_{i}\right)^{2}}{n}},$$
(34)

where

$$\overline{y} = \left(\frac{1}{n}\right) \sum_{i=1}^{n} y_i \quad \dots \tag{35}$$

$$\bar{x} = \left(\frac{1}{n}\right) \sum_{i=1}^{n} x_i .$$
(36)

So using these equations, we can determine the fitted or estimated regression line as:

$$\overline{y} = \hat{\beta}_o + \hat{\beta}_1 x \dots (37)$$

and the residual, which describes the error in the fit of the correlations to the i^{th} observation y_i and helps to determine the adequacy of the fitted model is described by

$$e_i = y_i - y_i, \qquad (38)$$

which is used to estimate σ^2 as

$$\hat{\sigma}^{2} = \frac{\sum_{i=1}^{n} \left(y_{i} - \hat{y}_{i} \right)^{2}}{n-2}.$$
(39)

Application of these formulas is really tedious, particularly for multiple regressions, and the possibilities for mistakes are really high, but they are all built into the SAS system and are the basis of our approach.

Using SAS we not only determined the best fit but also the estimated standard error of the slope and the intercept, which provides good guidance to examine the accuracy of the correlations.

Another important parameter to be taken into account is the P_{-value} , which is the lowest value that would lead to rejection of the null hypothesis H_0 of a given data, if H_1

and

is the hypothesis to be tested. In other words, the $P_{\text{-value}}$ is the probability that the test statistic will take on a value that is at least as extreme as the observed value of the statistic when the null hypothesis is true. The $P_{\text{-value}}$ gives information about the weight of evidence against H_0 and it allows us to make conclusions about the level of significance. In summary, the data used will be significant if the null hypothesis is rejected. Based on that, we may give a clearer definition of $P_{\text{-value}}$, saying that this is the smallest level at which the data is significant. The $P_{\text{-value}}$ must be as low as possible so we can ensure a good fit of the model.

The *P*-value is computed with the expression:

$$P_{-\text{value}} = 1 - P(x_1 < \overline{X} < x_2), \qquad (40)$$

where

P = probability

 x_1 = lower value of the range analyzed

 x_2 = higher value of the range analyzed

 \overline{X} = mean of the distribution

If the probability that the mean value within the observed values is high, 1-*P* will be small; therefore, our correlation is making good predictions.

The $P_{\text{-value}}$ is calculated for each regressor, and a high $P_{\text{-value}}$ will mean that that specific regressor is not necessary to improve the accuracy of the correlation. Good regressors will show $P_{\text{-values}}$ less than 0.0001.

We used the $P_{\text{-value}}$ as our main indicator for significance for each parameter estimator, since a low value (P < 0.0001) tells us that the slope and the intercept are good

values. We rejected any parameter estimator with a *P*-value over the degree of confidence used (95% or α =0.05).

Finally, we used the correlation coefficient, or coefficient of determination, R^2 , which is the square of the correlation coefficient between x and Y. This value may be dangerous, since it will increase artificially if more terms are added to the correlations, although some of these terms may exhibit low standard errors but may not be significant or necessary. In this case, their inclusion will increase the error. We used the adjusted R^2 , which increases only if a new variable reduces the error mean square. This indicator penalizes the user for adding unnecessary terms to the correlations, trying to over-fit the model.

Further applications and details regarding these estimators can be found in Montgomery and Runger (2007) and Bain and Engelhardt (1992).

In this research we wanted to measure the effects of several parameters on the determination of the slope and intercept of the general correlations, so we now needed to consider the multiple linear correlation procedure.

For a multiple regression model, we built our correlation using a relationship with the following form:

$$Y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon, \quad \dots$$
(41)

where the subscripts 1 to *n* represent the number of variables used as regressors. This model describes a hyperplane in the *n*-dimensional space of the regressor variables. The multiple regression model developed here is used as an approximating function since the true functional relationship between Y and $x_1, x_2, x_3, ..., x_n$ will remain unknown, but over an adequate range of independent variables, the linear regression model is an adequate approximation.

Our correlations include interaction effects, represented as cross-products of two or more variables, where applying the linear regression principles requires a variable transformation.

The regression coefficients can also be estimated from the method of least squares, where the parameter solution vector is obtained from a matrix of equal numbers of rows and columns.

The next step was to determine which variables were good for the correlations. We first selected those variables that were used to perform the fractional flow calculations. Based on the initial correlation coefficients (around 0.86), we tested some transformed variables, using those that intervene in the calculation of other variables such as mobility ratio and relative permeability curves, (for example, oil viscosity divided by Corey's oil exponent), until we obtained good initial R^2 results (above 0.9). However, we needed to improve the correlations methodically, so we used some built-in SAS procedures.

Four procedures are available: the stepwise regression, the forward selection, the backward elimination, and the *R*-squared selection. Use of the four methods is recommended so the analyst can compare results and make the best choice regarding which variables better fit the new model (Montgomery and Runger, 2007).

We used step-wise regression to build a sequence of regression models by adding and removing variables one at a time, finding the highest R^2 and the smallest *P*-value that define the strongest model.

The forward selection method will add variables like in the previous method, trying to maximize R^2 , but will not eliminate added variables.

The backward elimination method begins with all variables included and will delete the worst regressors one at a time.

The *R*-squared method selects the combination of variables that reaches the highest correlation coefficient (R^2).

We ran all four methods and also checked our correlations for the lowest *P*-value for each statistic and with the covariance matrix (see outputs in Appendix G).

Correlation coefficients measure the extent of the association between two variables. Each such coefficient must lie between -1 and +1, inclusive. A positive coefficient indicates a positive association: a greater-than-expected outcome for one variable is likely to be associated with a greater-than-expected outcome for the other, while a smaller-than-expected outcome for one is likely to be associated with a smaller-than-expected outcome for the other. A negative coefficient indicates a negative association: a greater-than-expected outcome for one variable is likely to be associated with a smaller-than-expected outcome for one variable is likely to be associated with a smaller-than-expected outcome for one variable is likely to be associated with a smaller-than-expected outcome for the other, while a smaller-than-expected outcome for the other. A coefficient of zero indicates no correlation at all.

The covariance matrix in our analysis indicated that all the variables could be used to develop the different correlations, but the variable selection procedures helped us to define the improvement of R^2 we can obtain with each variable. Both procedures were complementary.

The determination of influential points (outlier observations that do not improve the model and a few values too far from the mean) and possible variable transformations were studied.

All possible combinations for the input variables used were run and analyzed using variable selection procedures in SAS. Each SLZ boundary was defined, and for each SLZ, a slope and an intercept were obtained. All correlations presented a R^2 value around 0.99 with a maximum difference of about 2%.

Once each slope and intercept is calculated, recovery factors may be determined using the straight line properties as:

$$\log WOR = RF \times m + I \tag{42}$$

where *m* is the slope and *I* is the intercept.

Also, we can define these slopes and intercept as $m = f_I(M, n_o, n_w, S_{wc}, S_{or}, k_{roe}, k_{rwe})$ and $I = f_2(M, n_o, n_w, S_{wc}, S_{or}, k_{roe}, k_{rwe})$. Eq. 42 can be used to determine RF, and solving for RF we have:

$$RF = \frac{LogWOR - I}{m} .$$
(43)

Therefore, to obtain the calculated recovery factor, only the WOR value was necessary as an input, since the correlations will give the boundaries of the SLZ from the second derivative analysis described before and the maximum WOR value to keep the RF results within the SLZ boundaries.

However, our objective was to obtain a generalized correlation to calculate *unique* slope and intercept expressions as functions of the previously determined variables to be used in all cases, so all obtained slopes and intercepts were correlated again to determine a general set of correlations to be used in any kind of reservoirs and conditions. Regressors used for correlations were viscosity ratio (VR), endpoint mobility ratio (M), Corey's oil and water exponents (n_o and n_w), connate water saturation (S_{wc}), and residual oil saturation (S_{or}).

Many combinations were tested with the different correlation variables to optimize the correlation coefficient R^2 and obtain a value over 0.99 for the general correlation.

After analyzing and trying several variables that might affect the correlation coefficients, we realized that for combinations of n_o , S_{or} , and S_{wc} parameters, the correlation coefficients we obtained were not acceptable values ($R^2 < 0.80$). Therefore, we decided to separate the calculations and build two different correlations for waterand oil-wet rocks, suspecting that the oil-wet rocks would not be able to produce a good correlation because of the wettability effects in sweep efficiency discussed above. We analyzed the wettability impact based on the effects of each calculated variable.

Using the rules of thumb published by Craig (1971) that consider rocks waterwet when relative permeability curves cross each other after water saturation values of 0.5, and oil-wet when the curves cross before that value, our correlations separate and correlate SLZs based on wettability. To consider each type of rock, we created two codes: One code performs calculations for water-wet rocks and the other for oil-wet rocks, based on the values of S_{wc} , S_{or} , k_{rwe} , k_{roe} , n_o , and n_w that affect the point where the relative permeability curves cross each other. If they crossed after $S_w = 0.5$, we considered the rock to be water-wet. If the crossing point was before $S_w = 0.5$, we considered the rock to be oil-wet.

The correlation variable x_1 considering VR and n_o is defined as:

$$x_1 = \frac{\mathrm{VR}}{n_o}, \qquad (44)$$

where

VR = viscosity ratio (μ_{water}/μ_{oil})

 n_o = oil exponent from Corey's function

We used the variables described earlier and the log of mobility ratio to generate the correlations for homogeneous, water- and oil-wet reservoirs, and to calculate f_{wBT} and S_{wBT} , slopes and intercepts, for the general log WOR vs. RF plot. Tables in Chapter III present the SAS output for the obtained correlations.

Putting it all together, the partial set of correlations for a homogeneous reservoir has the form:

$$\log WOR = RF \times m(M, \text{VR}, n_o, n_w, S_{or}, S_{wc}, k_{ro}, k_{rw}) + I(M, \text{VR}, n_o, n_w, S_{or}, S_{wc}, k_{ro}, k_{rw}),$$
(45)

Reservoir Simulation Model for Homogeneous Reservoirs

A simple, synthetic reservoir simulation model was built to control and calibrate our correlations. A general description of the simulation model can be seen in Table 4 (see Appendix C).

Our simulation two-phase model (oil and water) has grid dimensions of $19 \times 19 \times 10$ with 3,610 cells. The lengths are 20 ft in the *x* and *y* directions, and 10 ft in the *z* direction. It is ¹/₄ of a 5-spot pattern with one producer and one injector, completed in all layers. Production and injection rates are constant at 2,000 STB/D. The production control method is by reservoir voidage, and the waterflood strategy is pressure maintenance. The solution method is fully implicit. OOIP, PV, and production and injection in barrels need to be multiplied by four to obtain the total pattern area values.

Reservoir and fluid properties were changed and tested according to the ranges shown before in Table 2, corresponding to each run evaluated in our new correlations. Fig. 4 shows a 3D screen example for the homogeneous reservoir model.

PROPERTY	VALUE/DESCRIPTION
Grid dimensions, number (x,y,z)	19, 19, 10-50
Grid size, cells	3610
Dx, Dy, Dz, feet	20, 20, 10
Layers	10
Number of wells (i/p)	1/1
Producer completions	19 19 1-10 (all layers)
Injector completions	1 1 1-10 (all layers)
Production rate, BBL/D (not critical)	2000
Injection rate, BBL/D (not critical)	2000
Production control methods	Reservoir voidage (RESV)
Waterflood strategy	Pressure maintenance
Relative permeability curves	Variable – Corey's functions
Solution method	Implicit (AIM)
Porosity, fraction	0.3
Ave layer permeability, md	200
Phases(oil and water)	2
Water viscosity, cp	Variable
Oil viscosity, cp	Variable
Sor, fraction	Variable
Swi, fraction	Variable
kv/kh	0.1-1
Pattern	5-spot
Reservoir pressure, psi (constant)	3665

Table 4—Generalized model description for the reservoir (homogeneous and heterogeneous cases).

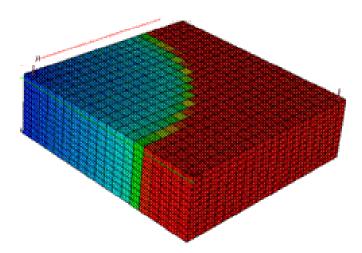


Fig. 4—Example of an oil saturation profile for a homogeneous reservoir at time 500 days, showing effective sweeping.

Once our correlations from the homogeneous module were determined, we applied those correlations to the same input we used in the simulation runs for each corresponding SLZ case to compare ultimate recovery results using both approaches for homogeneous reservoirs. Comparisons are shown in Chapter III.

To determine if a linear relationship existed between the two recovery factor calculations, we also compared ultimate recovery factor results (at the end of the SLZ) from the homogeneous module with the ultimate recovery factors estimated from the end of the SLZ obtained from the simulation results.

As we can see in the example shown in Fig. 5, we obtained straight lines in all cases. These lines however, had different slopes, intercepts, and lengths than those of corresponding homogeneous cases.

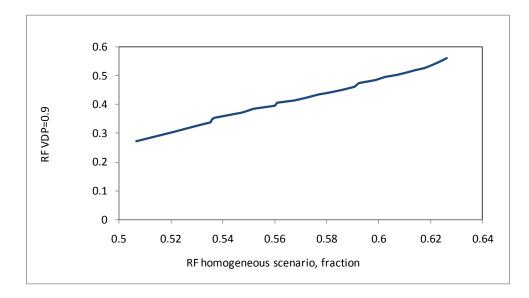


Fig. 5—Comparison of ultimate recovery factors for a homogeneous case vs. the same reservoir including VDP = 0.9 (including heterogeneity). A linear behavior is present. The case for VDP = 0.9 presents lower RF.

Reservoir Simulation Model for Heterogeneous Reservoirs

Since the fractional flow equation applies for homogeneous reservoirs only, we used the reservoir simulation model to generate results with different VDP values and correlated them linearly with their correspondent model's results for the homogeneous reservoir case for input data set. The observations included the whole length of each SLZ.

Permeability values were changed to provide different VDP cases and a new data file was built with recovery factors, PVI, and log WOR values calculated for different *M*.

Fig. 6 is a 3D capture of the new model. See details of data files in Appendix D.

Heterogeneous module results will be discussed in Chapter III and in the module for heterogeneous reservoir section, later in this chapter. Runs for heterogeneous cases are shown in Fig. 7 and Fig. 8.

Injection expressed as PVI has an economic significance, since maximized recovery with a minimum of water injected will maximize net present value (NPV).

In this research, even when the log WOR vs. RF curve is independent of the injection rate, we wanted to understand the effect of different water injection rates on the ultimate recovery, so several exercises were run, in different scenarios of homogeneous and heterogeneous systems, with favorable and unfavorable mobility ratios.

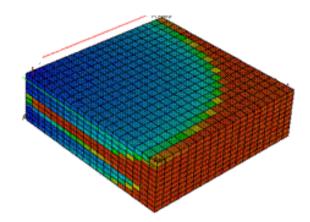


Fig. 6—Oil saturation profile for a heterogeneous reservoir with a VDP = 0.9. This figure shows irregular displacement at 500 days.

In Appendix H we include simulation run results where total fluid production and injection rates for each case were kept constant during the simulation runs to maintain reservoir pressure. Different scenarios were analyzed to determine if injecting more water per unit of time would affect the ultimate recovery and the correlations to be determined for heterogeneous reservoirs. Injection rates do not affect results in terms of plots of RF vs. PVI or log WOR vs. RF. The only important effect we found is the acceleration of recovery when higher rates are used.

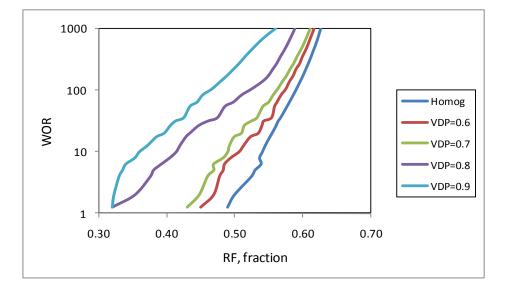


Fig. 7—Example of SLZs observed from reservoir simulation for different degrees of heterogeneity expressed by the Dykstra-Parsons coefficient. These results were correlated with our correlations for homogeneous reservoirs to generate the heterogeneous correlations for RF.

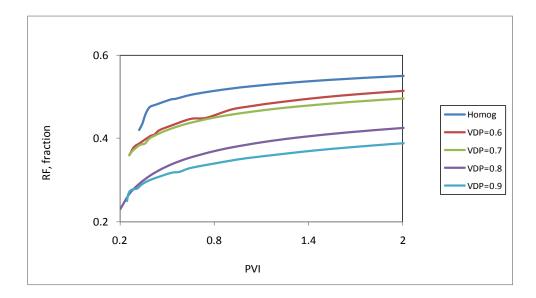


Fig. 8—Example of PVI observed from reservoir simulation for different degrees of heterogeneity expressed by the Dykstra-Parsons coefficient. These results were also correlated with our correlations for homogeneous reservoirs to generate the heterogeneous correlations for PVI.

For a homogenous reservoir, in the presence of a favorable *M*, we expected that increasing the injection and production rate [using a higher processing rate, but maintaining a voidage replacement ratio (VRR) close to one] should not affect the ultimate recovery, so an acceleration of production instead of an increase of reserves would take place in the field. However, we wanted to investigate if the higher probability of water fingering and oil left behind by high injection rates in the presence of a high VDP and/or an unfavorable M would lead to different results.

The same reservoir model used for each of the heterogeneous cases was used to determine the effect of different injection rates in the waterflood performance. We used

a base injection rate of 200 STB/D as the lower rate, and 2,000 STB/D (one order of magnitude higher) as the higher rate.

Responses for all analyzed cases were similar in terms of the recovery factors and PVI obtained. Injection and production rates, VDP, and M were changed, one at a time, and compared to determine possible impacts. The base case has the following combination of properties: $n_o=3$, $n_w=5$, $S_{or}=0.2$, $S_{wc}=0.4$, $k_{roe}=0.9$, $k_{rwe}=0.55$, VR=0.06 (for M=10) and VR=0.6 (for M=1). Cases with the same values of VDP and mobility ratio were compared to each other to isolate the effect of injection rate change. We needed to avoid including the already known heterogeneity and mobility ratio effects in this analysis. Keeping all other parameters unchanged, we changed the injection rates and compared recovery factors with PVI and log WOR values.

We can conclude that the most important effect of a higher injection rate, assuming no injectivity problems, is the acceleration or delay in production (see higher recovery for the same period of time for injection rate of 2,000 STB/D), which is not always favorable, because the impact of water injection costs must be taken into account.

However, at M = 10 and VDP = 0.9, a higher recovery can be seen in the 200-B/D injection rate curve, a difference of less than 2%, if enough time is provided for that case. In this run, we allowed 135,000 days, which is an extremely long period of time for this kind of project.

After approximately 10 PVI, we can see recoveries of 0.414 for water injection rates (i_w) of 2,000 STB/D and 0.430 for water injection rates (i_w) of 200 STB/D. Also,

for a recovery factor of 0.48 using i_w of 200 STB/D, a log WOR of 3.0 is reached, while for the higher injection rate, a similar log WOR is obtained faster. (See Appendix H.)

In practice, at unfavorable M and high VDP, low injection rates may help to increase recovery and avoid the risk of water fingering, applying a sound reservoir management strategy. PVI would be smaller in time, so economics can also be improved.

The difference in recoveries using different injection rates may not be considered a limitation of the new procedure presented here, since the deviation is small and the impact is reached after very large amounts of water have been injected and when the WOR is away from the SLZ.

For areal heterogeneity, lower injection rates may be beneficial, but we will consider this issue as a design matter, due to the high degree of uncertainty and complexity involved.

The effect of high heterogeneity and mobility ratio are manifested in the lower recovery and earlier breakthrough times. Rate dependency of water coning was not studied.

Another variable we wanted to evaluate is the effect of the number of layers on the new correlation's results.

We used the same approach of comparing simulation results for different layer models, and we determined that no effect was important enough to consider. Ultimate recovery factors (URF) and slopes and intercepts of SLZ had no change. We used VDP = 0.9 and M = 10 to account for unfavorable effects and ran cases for 10 and 50 layers (see Appendix H for more details).

Another important variable we wanted to assess was the effect of crossflow in the recoveries of waterflood performance.

Craig (1971) discussed some experimental approaches regarding incremental recovery due to crossflow between layers. For homogeneous systems and at favorable mobility ratios (M), the results show that only a very small amount of additional recovery is obtained in those experiments. At unfavorable M, the same crossflow will produce less recovery than the one obtained when no or lower crossflow is present. As expected, high M will produce fingering and bypassed oil in the rock that will reduce recovery. Under this situation, crossflow will hold back the advance of the front in the low-permeability layers.

At favorable *M*, crossflow values will tend to increase recovery efficiency, but at unfavorable *M*, efficiency will be reduced.

Thakur and Satter (1998) analyzed several crossflow levels in terms of vertical to horizontal permeability ratios. Simulation shows that ultimate recovery increases slightly with crossflow, about 0.5%; PVI may be slightly lower and breakthrough may occur later than in no-crossflow scenarios.

Even when these conclusions seem to be enough to understand the phenomenon, we wanted to use our reservoir simulation model to evaluate the effect of heterogeneity and the presence of "thief zones" in the system and determine if those situations could limit the applicability of our correlations. We performed runs for several scenarios to model crossflow effects. We used M = 1.0 since the effects of fluctuations in that parameter had been discussed in previous works.

We used the same data file presented in Table 4 but we changed values for k_v and k_h . Crossflow values ranged from 0 to 1. The value selected for *M* was 1.0. Again, no important effect was found when considering crossflow in the reservoir. Results and some published references are shown in Appendix H.

For a homogeneous reservoir with a favorable *M*, crossflow will not affect performance or ultimate recovery. For the case of high VDP but low- to moderate-permeability values in all layers, the difference in oil and water rates, breakthrough time, and ultimate recovery will not affect estimates from our correlations with the log WOR vs. RF plot. However, when high-permeability layers are present, even when the VDP may be not too high, the system with no crossflow will present an earlier breakthrough in "thief zones," a higher watercut in early times, delayed production peak, and possibly a negative effect on the net present value due to the delayed production and water cycling, together with some oil left behind in the rock, especially in low-permeability zones.

Thief zones will reduce vertical sweep efficiency, so gel slugs may be used in the wellbore to divert flow and reduce permeability on thief zones, and/or to isolate thief zones. Water will bypass oil in high-permeability layers with high *M*.

The Module for Heterogeneous Reservoirs

The new correlations for heterogeneous reservoirs were built using multiple

linear regression to create specific correlations for heterogeneous cases. Correlations were developed for VDP, M, RF, and WOR obtained from the simulation models for heterogeneous reservoir cases, for two scenarios of water-wet rocks (extreme and medium), two scenarios of oil-wet rocks, and their corresponding recovery factors obtained from the homogeneous reservoir model. Table 5 shows the variables and ranges used to estimate a total of 144 SLZs.

Table 5-Variables and ranges used to generate simulation cases for heterogeneous				
reservoirs using 2 scenarios for water-wet rocks and 2 scenarios for oil-wet rocks.				

RANGES			RUNS
Variables	Range	Steps	Number
M (water-wet)	0.6 to 5	1	12
VDP (water-wet)	0.5 to 1	0.1	6
Total cases (SLZ) water-wet			72
M (oil-wet)	0.6 to 5	1	12
VDP (oil-wet)	0.5 to 1	0.1	6
Total cases (SLZ) oil-wet			72
Total runs (SLZ)			144

We used transformed variables to improve correlation coefficients, and determined the best correlation variables using "Stepwise", "Backward", and "Forward" variable analysis procedures.

Two multiple linear correlations were developed, one for water-wet systems and other for oil-wet rocks. These correlations do not use fractional flow theory for the heterogeneous cases, but calculate recovery factors and PVI for any value of VDP and M using correlated results from the simulator model and fractional flow results from the homogeneous cases (see Appendix E).

The program generated the correlations using two data files, one for water-wet and another for oil-wet systems, which contains all data to be correlated for both sets.

Each data file had the following fields: mobility ratio, log WOR, recovery factor for homogeneous reservoir (output from the homogeneous correlations), PVI correspondent to the correlated homogeneous reservoir recovery factor, and recovery factors for VDPs of 0.5, 0.6, 0.7, 0.8, 0.9 and 0.99 with their corresponding PVI, all for each value of log WOR. (See Appendixes B and C for the programs and result tables and examples of data files, respectively.)

Mobility ratio and WOR are independent variables, or predictors, because they are usually known (measured or calculated); and we set recovery factor and PVI as dependent variables. The regressors we used are M and log WOR, but we needed transformed variables to better fit the correlations, since the log WOR curve has an exponential behavior when plotted against PVI, and a linear behavior (in the SLZ) when compared to RF for each VDP case. To determine the heterogeneous cases' recovery factors, we defined the new transformed variables (regressors) as:

$$x_{11} = RF^2_{\text{hom}},$$
 (46)

where

 RF_{hom}^2 = square of the correlated recovery factor for homogeneous reservoirs,

 $x_{12} = e^{LogWOR},$ (47)

and

 $x_{13} = 10^{\log WOR}$ (48)

The correlations we obtained (Appendix B) all show R^2 higher than 0.99. Results and all variables are shown and discussed in the next chapter.

Fig. 9 shows the workflow we used to generate our correlations using SAS, reservoir simulation, and VBA. Fig.10 shows how the codes work for each module.

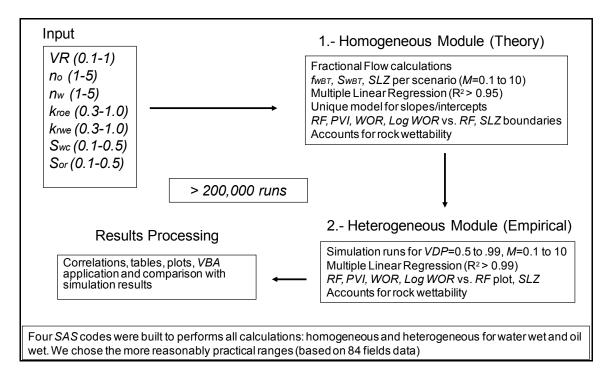


Fig. 9—Workflow used to generate our more than 200,000 runs for different cases, including correlations to estimate boundaries of the SLZs.

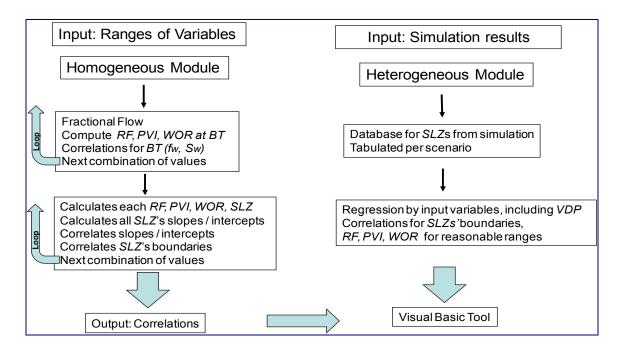


Fig.10—Structure and workflow of the regression codes.

Assumptions and limitations for the heterogeneous module are:

- Confined ¹/₄ of a 5-spot pattern
- Multilayered reservoir
- No crossflow between layers
- Uniform permeability per layer
- Permeability *k* changes with each layer
- Relative permeability curves are the same for all layers and are estimated using Corey-type equations
- Constant injection and production volumetric rates, $q_i = q_p$
- Initial $S_g = 0$

CHAPTER III

RESULTS

A new procedure and statistical correlations have been developed to predict oil recovery at any WOR and ultimate recovery for reservoirs under water injection, using the fractional flow equation and multiple linear regressions. We developed correlations to estimate the slopes and intercepts of the SLZs in the log WOR vs. RF plots for all reasonable combinations of S_{or} , S_{wc} , n_o , n_w , M, and VR, including the SLZ boundaries for homogenous reservoirs, and also correlations to estimate recovery for heterogeneous reservoirs within a range of VDP from 0.5 to 0.99 and M from 0.1 to 10.

Limitations include that no dip angle, no capillary pressure, no initial gas saturation, and no gravity effects were considered. However, this methodology can be extended to include these cases and other special cases such as extra-heavy oil reservoirs and naturally fractured reservoirs.

After applying our correlations to cases with initial gas saturations from 1% to 16%, we observed that for waterfloods with small initial gas saturations ($S_{gi} < 0.04$), RF results are reasonably acceptable, with error less than 2% compared with recovery factors at the end of the SLZ found in simulation runs.

SLZ Characteristics and Correlations

The log WOR vs. RF plot shows an SLZ that is present in all studied cases. The correlations produced parameter estimates that multiply rock and fluid properties values used for regressions to calculate RF, WOR, and PVI for any value of VDP.

Typical behaviors relative to the effect of different values of rock and fluid properties in the SLZ are shown in Table 6.

Compensation can be seen if crossed effects. Descriptions of each variable and parameter estimates of correlations for homogeneous (ideal) cases are included in Table 7, Table 8 and Table 9. These correlations calculate water cut (f_{wBT}) and water saturation (S_{wBT}) at the water breakthrough and the slope and the intercept of each SLZ for homogeneous reservoirs. Parameters are slightly different for oil-wet rocks but having different correlations improves the correlation coefficients for both types of rock.

Correlation for Homogeneous Reservoirs

Four correlations were obtained for the homogeneous module to estimate the beginning and the end of the SLZ in terms of the minimum and maximum WOR corresponding to each SLZ boundary (WOR at the beginning and at the end of the SLZ), both estimated as functions of the input data used.

PROPERTY	WATER	SLZ	SLOPE	RF	WOR @
CHARACTERISTIC	BREAKTHROUGH	LENGTH			GIVEN
					RF
Water-wet rock	late	short	steep	high	low
Oil-wet rock	early	long	moderate	low	high
High viscosity ratio	late	short	steep	high	low
(μw/μo)					
Low viscosity ratio	early	long	moderate	low	high
(μw/μo)					
High VDP	early	long	moderate	low	high
Low VDP	late	short	steep	high	low
High mobility ratio	early	long	moderate	low	high
Low Mobility ratio	late	short	steep	high	low
High Sor	early	long	moderate	low	high
Low S _{or}	late	short	steep	high	low
High S_{wc}	early	long	moderate	low	high
Low S_{wc}	late	short	steep	high	low

Table 6—Qualitative and relative comparison of the expected shapes and characteristics of the SLZ for different reservoir and fluid parameters combinations.

Table 7—Parameter estimates for homogenous reservoirs (water-wet rocks).

GUIDE		WATER-WET ROCKS						
Regressor	Variable	f_{wBT}	S _{wBT}	Slope	Intercept			
Independent	Intercept	0.71084	0.64301	1.29383	-1.56680			
x ₁	VR/n_o	0.20212	0.23901	27.81540	-30.39900			
x ₂	VR	-0.08234	-0.10030	-6.79110	8.83008			
x ₃	n _o	0.01779	-0.0302	0	0			
x ₄	n_w	0.03932	0.03722	2.08358	-1.50080			
x ₅	S_{wc}	0	0.34619	4.76521	-0.10520			
x ₆	Sor	0	-0.65380	22.31420	-0.58340			
X ₇	log M	-0.09479	-0.15480	-4.7940	4.03107			

GUIDE			OIL-WET	ROCKS	,
Regressor	Variable	$f_w BT$	$S_w BT$	Slope	Intercept
Independent	Intercept	0.65980	0.56187	0.77519	-3.42540
x ₁	VR/n_o	0.11888	0.16777	8.93439	-11.94000
x ₂	VR	-0.04844	-0.06870	-3.36470	4.78633
x ₃	n _o	0.02099	-0.02200	0	0
x ₄	n_w	0.05127	0.04494	2.67364	-1.41670
x ₅	S_{wc}	0	0.41472	0	-0.33000
x ₆	Sor	0	-0.58530	28.23280	-0.06060
X ₇	log M	-0.09342	-0.14540	-8.40360	5.30721

Table 8—Parameter estimates for homogenous reservoirs (oil-wet rocks).

Table 9—Parameter estimates for PVI in homogeneous reservoirs. This correlations work for water and oil-wet rocks.

REGRESSOR	VARIABLE	WATER-WET	OIL-WET
Independent	Intercept	-0.81246	-0.86240
X ₈	М	0.35196	0.41381
x ₁₂	$e^{\log WOR}$	0.21624	0.24178
x ₁₃	$10^{\log WOR}$	0.00800	0.00194

The correlations for maximum and minimum WOR to estimate the beginning and the end of the SLZ, for water-wet and oil-wet rocks in homogeneous reservoirs are the following. Water-wet

 $R^2 = 0.98$

Oil-wet

R2 = 0.99

Different runs were made to test the correlation results and compare against simulator results to ensure that the fractional flow theory supported the procedure. Applying our correlations to the simulation results would support the quality of predictions and the results from the heterogeneous module. Correlations to estimate the end of the SLZ were always more accurate, presenting an error less than 2% compared to errors up to 4% in the beginning of the SLZ. However, determining the end of the SLZ was the main objective because we wanted to avoid overestimation of reserves and underestimation of the WOR through the extrapolation of the plot's curve.

Table 10 shows examples of input variables used to run this test. Table 11 shows the matches obtained for ultimate recovery, since at the end of the SLZ, E_A is one in all results from the simulation runs.

RESERVOIR	VR	n _o	n_w	S_{or}	S_{wc}	k _r
		-				

Table 10-Reservoir data used for comparison.

RESERVOIR	VR	n _o	n_w	S_{or}	S_{wc}	k _{roe}	k _{rwe}	М
1	1.0	3	5	0.20	0.40	0.90	0.55	0.6
2	1.0	2	2	0.50	0.25	0.90	0.90	1.0
3	0.06	3	5	0.20	0.40	0.90	0.55	10.2
4	0.2	2	2	0.50	0.25	0.90	0.90	5.0

	RESULTS COMPARISON									
	Water-wet, M=0.6			Oil-wet, M=1.0		Water-wet, M=10.0		Oil-wet, M=5		
	Correlations	Simulator	Correlations	Simulator	Correlations	Simulator	Correlations	Simulator		
RF	0.62	0.63	0.41	0.40	0.57	0.57	0.31	0.30		
Log WOR	2.3	2.3	1.7	1.7	1.7	1.7	2.0	2.0		
Slope	22.5	22.0	21.0	23.0	15.4	15.4	15.0	15.3		
Intercept	-11.8	-11.9	-6.8	-6.0	-6.3	-6.5	-2.6	-2.6		
PVI.	2	2	1	1	4	4	3	3		

Table 11—Comparison of results using correlations and simulation for the homogeneous module.

Bigger differences in RF are obtained for oil-wet reservoirs but only are about 1% of ultimate recovery. Different wettabilities and M were run for two different homogeneous, synthetic reservoirs. The correlations matched the simulator, and trends for less recovery for unfavorable M are present. Fig.11 presents one of the examples in the form of an SLZ plot.

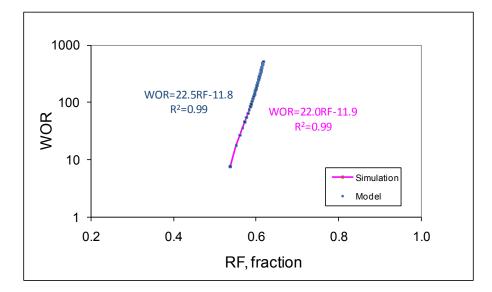


Fig.11—Comparison of SLZ estimated with our correlations almost perfectly matched one obtained from simulation results for a hypothetical water-wet, homogeneous reservoir (VDP = 0) and M=1.

Comparisons of results for homogeneous reservoirs were made for RF, slopes, and intercepts for four different reservoirs—with favorable and unfavorable mobility ratios and water-wet rocks, and with favorable and unfavorable mobility ratios but oilwet rocks.

When comparing our correlations results with the reservoir simulation results, excellent matches were obtained with our new model results, as can be seen in Fig.12. In that figure, we compare only the ultimate recovery (RF at the end of the SLZ) obtained with our correlations with the one obtained from the SLZ in the corresponding simulation.

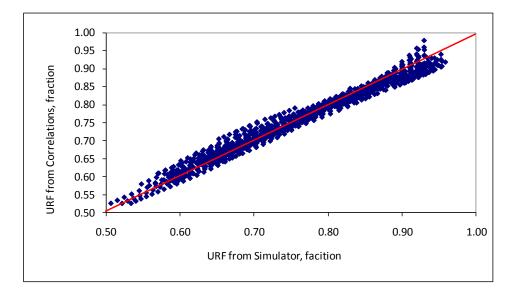


Fig.12—Estimated ultimate recovery at the end of 720 SLZ obtained from our correlations and from the simulation runs. Results matched very well.

The objective of this comparison is to verify that the SLZ obtained using fractional flow, the theoretical basis behind the SLZ, applies to the 3D simulation results. Since results matched, we can feel confident applying the correlations developed for heterogeneous reservoirs using only simulation.

We can see in Fig.12 that results from correlations developed for homogeneous reservoirs using fractional flow are reasonably close to those obtained for the same cases with simulation for homogeneous (SLZ = 0) reservoirs. Some outlier observations are located a little far from the Slope-1 trend line (in red) because of their oil-wet nature. The maximum error was 3% for water-wet systems and 4% for oil-wet systems. The same trend was found for the corresponding PVI.

The same comparison was made between the correlated slopes and intercepts of all SLZs calculated with our correlations for all combinations of cases and those calculated with the simulator. Fig.13 and Fig.14 show those results. Slope trends close to 1 can be seen in both plots.

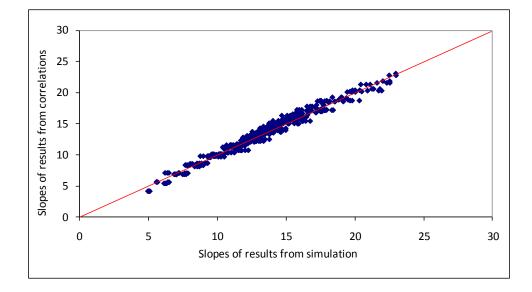


Fig.13—Our correlations reproduced the slopes determined from reservoir simulation (720 SLZs).

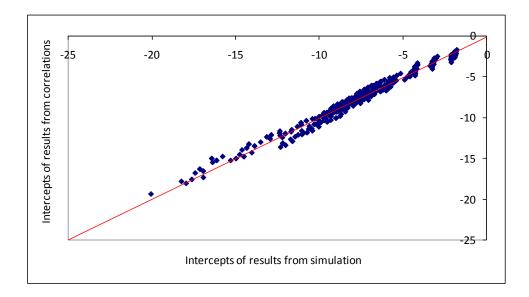


Fig.14—Our correlations captured intercepts determined from reservoir simulation (720 SLZs).

More results are shown in Fig.15, Fig.16, and Fig.17. As can be seen, the correlation matches the simulator runs results.

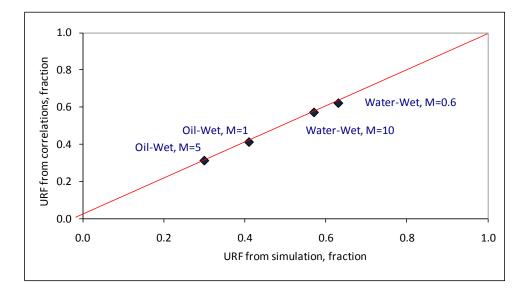


Fig.15—Final RF correlation from correlations and simulator for specific cases.

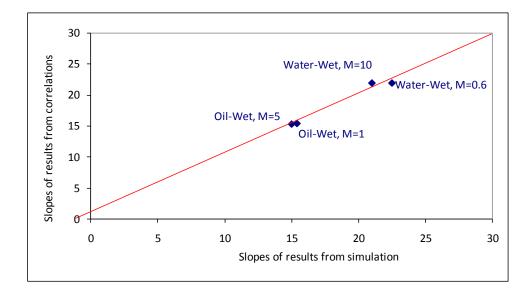


Fig.16—Slope correlations from correlations and simulator for specific cases.

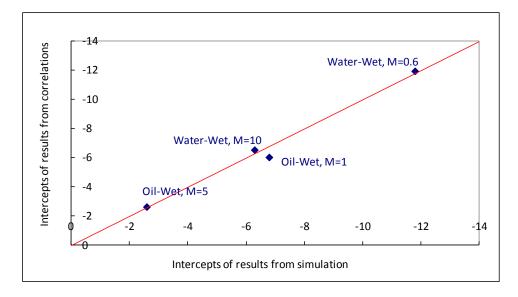


Fig.17—Intercept correlation from correlations and simulator for specific cases.

Correlation for Heterogeneous Reservoirs

Regressors and parameter estimates for heterogeneous reservoirs are shown in Table 12 and Table 13.

Table 12—Parameter estimates for heterogeneous reservoirs for water-wet rocks.

GUIDE			WATER-WET ROCKS						
Regressor	Variable	VDP	= 0.6	VDP	= 0.7	VDP	= 0.8	VDP	9 = 0.9
		RF	PVI.	RF	PVI.	RF	PVI.	RF	PVI.
Indepe	endent	- 0.1802	- 1.05462	0.19068	-1.2156	0.09829	-2.0651	0.1718	-0.4536
x ₈	М	0	0.46384	-0.0037	0.47344	-0.0075	0.58703	-0.0144	0.08084
X9	<i>RF</i> hom	1.2751 1	0	0	0	0	0	0	0
x ₁₀	log WOR	0	0	0.02336	0	0.05354	0	0.0722 7	0
x ₁₁	RF^2_{hom}	0	0	0.91971	0	0.88719	0	0.4411 7	0
x ₁₂	$e^{\log WOR}$	0	0.28413	0	0.31097	0	0.57103	0	0.19269
x ₁₃	$10^{\log WOP}$	0	0.00912	0	0.01136	0	0.01217	0	0.02353

GUIDE			OIL-WET ROCKS						
Daamaaaaa	Variable	VDP	= 0.6	VDP	= 0.7	VDP	= 0.8	VDP = 0.9	
Regressor	Variable	RF	PVI.	RF	PVI.	RF	PVI.	RF	PVI.
Indepe	endent	-0.0988	- 1.2680 5	0.09036	-1.1147	0.06727	-1.2674	0.0748	-0.6497
X ₈	М	0	0.4976 9	-0.0023	0.43417	-0.0049	0.45081	-0.0054	0.18524
X9	<i>RF</i> hom	1.27817	0	0	0	0	0	0	0
x ₁₀	log WOR	0	0	0.01459	0	0.03839	0	0.04112	0
x ₁₁	RF^2_{hom}	0	0	1.78812	0	1.27549	0	0.88482	0
x ₁₂	$e^{\log WOR}$	0	0.3737 6	0	0.30144	0	0.32235	0	0.22142
x ₁₃	$10^{\log WOR}$	0	0.0023 8	0	0.00691	0	0.01279	0	0.0137

Table 13—Parameter estimates for heterogeneous reservoirs for oil-wet rocks.

We developed different correlations for RF and PVI to simplify application of our correlation.

Parameter estimates for water-wet and oil-wet rocks were correlated independently; therefore, a better R^2 (higher than 0.9) is obtained using the two different correlations. Bigger differences are observed in values corresponding to higher SLZ, because oil-wet rocks show lower RF and higher PVI with higher heterogeneity than water-wet rocks. Using the tables above, application of the correlations can be easily programmed in a spreadsheet. However, a basic VBA program is provided in Appendix G for immediate application of the correlation.

Correlations to estimate RF and PVI for different VDPs in water-wet and oil-wet, heterogeneous reservoirs are the following.

Water-wet and heterogeneous calculations:

VDP > 0.55 and VDP <= 0.65

$$RF = -0.18015 + 1.27511(x_9)$$
 (53)

$$PVI = -1.05462 + 0.46384(x_8) + 0.28413(x_{12}) + 0.00912(x_{13}) \dots (54)$$

VDP > 0.65 and VDP <= 0.75

$$RF = 0.19068 - 0.00368(x_8) + 0.02336(x_{10}) + 0.91971(x_{11}).....(55)$$

$$PVI=-1.2156 + 0.47344(x_8) + 0.31097(x_{12}) + 0.01136(x_{13}) \dots (56)$$

VDP > 0.75 and VDP <= 0.85

$$RF = 0.09829 - 0.00751(x_8) + 0.05354(x_{10}) + 0.88719(x_{11})....(57)$$

$$PVI = -2.06505 + 0.58703(x_8) + 0.57103(x_{12}) + 0.01217(x_{13}) \dots (58)$$

VDP > 0.85 and VDP <= 0.99

$$RF = 0.1718 - 0.0144(x_8) + 0.07227(x_{10}) + 0.44117(x_{11}) \dots (59)$$

$$PVI = -0.45357 - 0.08084(x_8) + 0.19269(x_{12}) + 0.02353(x_{13}) \dots (60)$$

Oil-wet and heterogeneous calculations:

VDP > 0.55 and VDP <= 0.65

$$RF = -0.0988 + 1.27817 (x_9) \dots (61)$$

$$PVI = -1.26805 + 0.49769(x_8) + 0.37376(x_{12}) + 0.00238(x_{13}) \dots (62)$$

VDP > 0.65 and $VDP \ <= 0.75$

$$RF = 0.09036 - 0.00226(x_8) + 0.01459(x_{10}) + 1.78812(x_{11}) \dots (63)$$

$$PVI = -1.11471 + 0.43417(x_8) + 0.30144(x_{12}) + 0.00691(x_{13}) \dots (64)$$

VDP > 0.75 and VDP <=0.85

$$RF = 0.06727 - 0.00489(x_8) + 0.03839(x_{10}) + 1.27549(x_{11}) \dots (65)$$

$$PVI = -1.26744 + 0.45081(x_8) + 0.32235(x_{12}) + 0.01279(x_{13}) \dots (66)$$

$$VDP > 0.85 \text{ and } VDP <= 0.99$$

$$RF = 0.0748 - 0.00535(x_8) + 0.04112(x_{10}) + 0.88482(x_{11}) \dots (67)$$

$$PVI = -0.64968 + 0.18524(x_8) + 0.22142(x_{12}) + 0.0137(x_{13}) \dots (68)$$

ANOVA Tables for Correlations

Analysis of variance (ANOVA) is a powerful technique to check for adequacy of correlations, which is determined by the information provided from four statistical indicators: correlation coefficient (R^2), mean square error (σ^2), *F*-statistic, and *P*_{-value}. A high value for R^2 (higher than 0.9) means that an accurate explanation of the behavior of the dependent variable will be obtained by studying the behavior of the independent variable. Our goal was to obtain R^2 as close as possible to 0.99. The mean square error is a measure of the error between the predicted value and the mean of the dependent variable, so a small value of the error means that the calculated value is closer to the mean. The *P*_{-value} is related to the adequacy of the correlation to be used to predict values of the dependent variable within the range of investigation (sample). When the *P*_{-value} is small, the correlation is also adequate (see explanations in Chapter II). Analysis of variances (ANOVA) tables follow.

ANOVA TAB	LE			
RF variable	f_{wBT}	S_{wBT}	Slope	Intercept
\mathbb{R}^2	0.8537	0.9408	0.9223	0.9444
σ^2	0.00053	0.00045	1.19005	0.54696
P _{-Value}	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Table 14—ANOVA for RF calculation for homogeneous, water-wet rocks.

For homogeneous, water- and oil-wet reservoirs, Table 14 and Table 15 show R^2 numbers for f_{wBT} and S_{wBT} , the slope and intercept correlations. These correlations are strong and can be used to calculate water cuts and saturations at breakthrough and slopes and intercepts to determine recoveries at any WOR, including ultimate recovery.

Table 15—ANOVA for RF calculation for homogeneous, oil-wet rocks.

ANOVA TAB	BLE			
RF variable	f_{wBT}	\mathbf{S}_{wBT}	Slope	Intercept
\mathbb{R}^2	0.8751	0.9516	0.8627	0.9352
σ^2	0.00057	0.00051	1.07414	0.20607
P _{-Value}	< 0.0001	< 0.0001	< 0.0001	< 0.0001

For heterogeneous reservoirs, statistics are shown in Table 16 and

Table 17.

ANOVA TABLE				
RF variable	VDP = 0.6	VDP = 0.7	VDP = 0.8	VDP = 0.9
\mathbb{R}^2	0.9836	0.9966	0.9953	0.9987
σ^2	6.6E-05	0.000017	4E-06	0.000001
P-Value	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Table 16—ANOVA for RF calculation for heterogeneous, water-wet rocks.

Table 17—ANOVA for RF calculation for heterogeneous, oil-wet rocks.

ANOVA TABLE				
RF variable	VDP = 0.6	VDP = 0.7	VDP = 0.8	VDP = 0.9
\mathbb{R}^2	0.971	0.9881	0.9926	0.9938
σ^2	0.00008	0.00003	0.00003	0.00002
P-Value	< 0.0001	<0.0001	< 0.0001	< 0.0001

Table 18—ANOVA for PVI correlation statistics, water-wet rock.

ANOVA TABLE	HETEROGENEOUS-WATER-WET ROCK				
PVI variable	Homog	VDP = 0.6	VDP = 0.7	VDP = 0.8	VDP = 0.9
\mathbb{R}^2	0.9727	0.9691	0.965	0.9503	0.9963
σ^2	0.30927	0.50905	0.81395	2.11876	0.19934
P-Value	<.0001	<.0001	<.0001	<.0001	<.0001

Table 19—ANOVA for PVI correlation statistics, oil-wet rock.

ANOVA TABLE	HETEROGENEOUS-OIL-WET ROCK				
PVI variable	Homog	VDP = 0.6	VDP = 0.7	VDP = 0.8	VDP = 0.9
\mathbb{R}^2	0.9149	0.9239	0.9486	0.9511	0.9919
σ^2	0.33022	0.61156	0.65109	1.33752	0.18589
P-Value	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Table 18 and Table 19 present very good correlation coefficients for the PVI correlations.

Consistently with previous results, four correlations were obtained to estimate the beginning and the end of the SLZ for the heterogeneous module. The expressions shown below are called "WOR_{min}" and "WOR_{max}" variables, referring to the minimum and maximum log WOR acceptable to ensure that the results are still within the SLZ area for heterogeneous reservoirs. These expressions are functions of *M* and SLZ:

Water-Wet – SLZ beginning:

WOR_{min} =
$$4.91690 + 0.01738(M) - 10.83657(VDP)$$

+ $9.73473(VDP^2) - 0.33856(10^{VDP})$ (69)

Oil-Wet – SLZ beginning

WOR_{min} =
$$2.37473 + 0.02337(M) - 2.99912(VDP)$$

+ $2.88892(VDP^2) - 0.22364(10^{VDP})$ (70)

Water-Wet-SLZ end

WOR_{max} =
$$5.15914 + 0.13366(M) - 9.6964(VDP) + 0.62073(10^{VDP})$$
(71)

Oil-Wet - SLZ end

WOR_{max} =
$$1.93449 + 0.02621(M) - 0.45239(VDP) - 0.00594(10^{VDP})$$
 (72)

Minimum and maximum WOR value ranges within the different SLZs were determined with our correlations for the homogeneous and heterogeneous modules. We obtained a range of minimum WOR values (beginnings of the SLZ) for water-wet rocks from WOR = 1 to WOR = 15, and maximum WOR values (ends of the SLZ) from WOR = 30 to 489, all for SLZ values between 0.5 and 0.99. The mean values were WOR = 5

and WOR = 72, respectively. We defined ranges for oil-wet zones between WOR = 1 and WOR = 251 for heterogeneous cases.

For homogeneous cases, WOR ranges between 4 and 59 (min WOR) and 87 and 3090 (max WOR). Such extreme, unrealistic values for max WOR were obtained because the homogeneous module only considers the ideal case of SLZ = 0.

Fig. 18 presents ranges for each minimum and maximum WOR for homogeneous and heterogeneous cases for water-wet rocks. Fig. 19 shows ranges for oil-wet rocks. Table 20 shows minimum, maximum, and mean values for beginnings and ends of all SLZs for water- and oil-wet rocks, for both homogenous and heterogeneous reservoirs.

As can be seen, WOR ranges tend to be shorter for oil-wet rocks, as expected. Also, SLZs will finish earlier for heterogeneous rocks since they show shorter max WOR than the homogeneous cases.

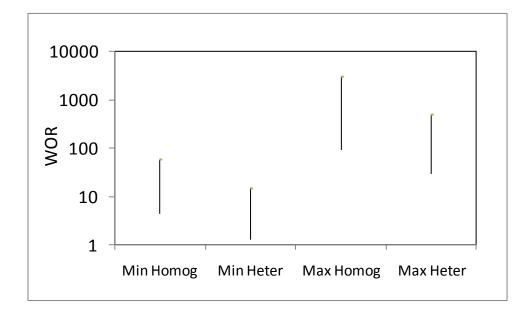


Fig. 18—Ranges for WOR determined with our correlations for both the homogeneous and the heterogeneous modules for water-wet rocks.

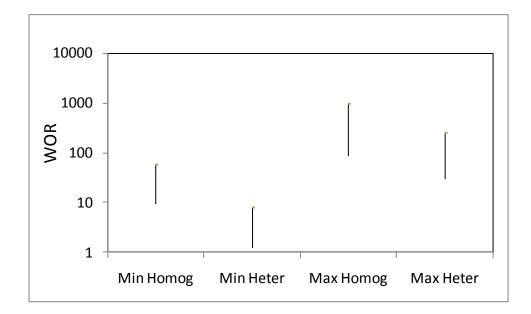


Fig. 19—Ranges for WOR determined with our correlations for both the homogeneous and the heterogeneous modules for oil-wet rocks.

WOR	WATER-WET		OIL-WET			
	Min	Mean	Max	Min	Mean	Max
Min Homogeneous	4	17	58	9	22	59
Min Heterogeneous	1	5	15	1	3	8
Max Homogeneous	93	308	3090	87	352	977
Max Heterogeneous	30	72	489	29	58	251

Table 20—Minimum, maximum and mean values of WOR for different cases for water-wet and oil-wet reservoirs.

Comparisons of results for heterogeneous reservoirs are shown for ultimate RF (at the end of the SLZ) and its corresponding PVI for two different reservoirs—with favorable and unfavorable mobility ratios and water-wet rocks, and with favorable and unfavorable mobility ratios but oil-wet rocks. Results are shown in Fig. 20 and Fig. 21. As can be seen, using these extreme reservoir property values, and for all SLZs used, the correlations again match the simulator runs results for URF (at the end of the SLZ) and PVI.

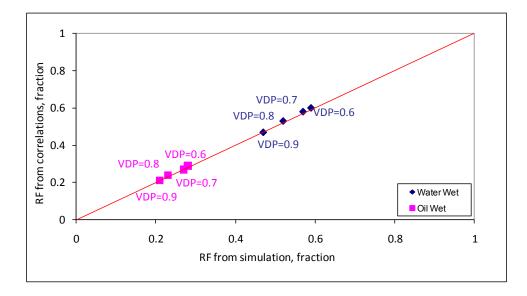


Fig. 20—URF for different wettabilities and SLZ from our correlations and from reservoir simulation.

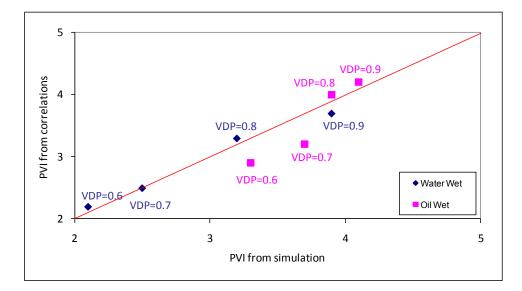


Fig. 21—Ultimate PVI for different wettabilities and SLZ from our correlations and from reservoir simulation.

Since comparing the correlations results with the simulator results was successful, we wanted to validate the correlations using field data to ensure the applicability of the correlations in real-life situations.

Two extreme cases were run to ensure that the correlations for the heterogeneous module were consistent with the reservoir simulation results in terms of predicting the SLZ behavior.

The first case presented is for an oil-wet rock reservoir with M = 5 and variations of SLZ from 0.7 to 0.9. These results permitted us to corroborate the accuracy of the correlations, as we can see in Fig. 22, Fig. 23 and Fig. 24.

The second case is for another oil-wet rock reservoir with M = 30 and variations of SLZ from 0.7 to 0.9. Results can be seen in Fig. 25, Fig. 26, and Fig. 27.

Results show that our correlations reproduced the SLZ behavior; therefore, the beginning and end of the SLZ can be predicted reasonably accurately.

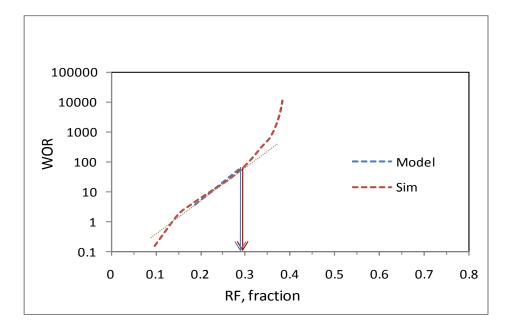


Fig. 22—Comparison of results from simulation and our correlations for an oil-wet rock with M = 5 and SLZ = 0.7.

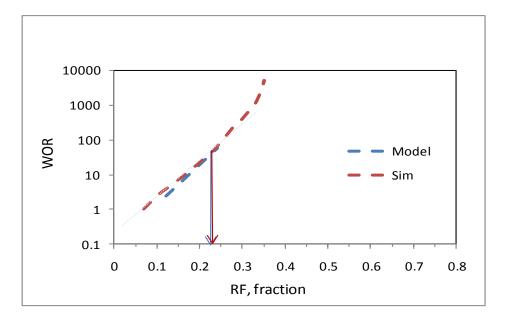


Fig. 23—Comparison of results from simulation to our correlations for an oil-wet rock with M = 5 and VDP = 0.8.

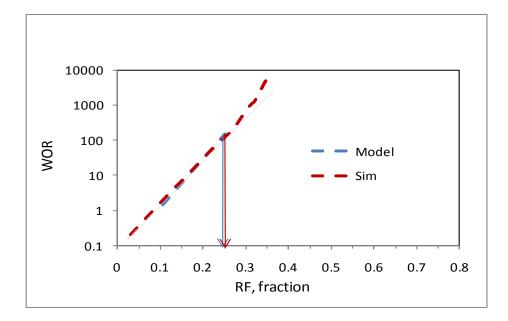


Fig. 24—Comparison of results from simulation and our correlations for an oil-wet rock with M = 5 and VDP = 0.9.

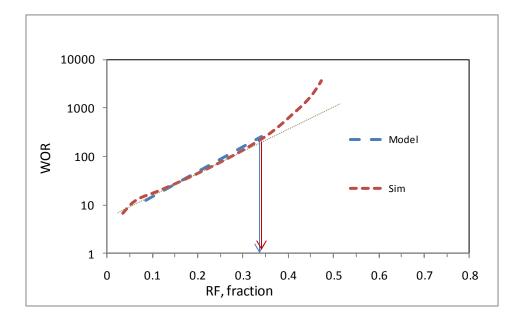


Fig. 25—Comparison of results from simulation to our correlations for an oil-wet rock with M = 30 and VDP = 0.7.

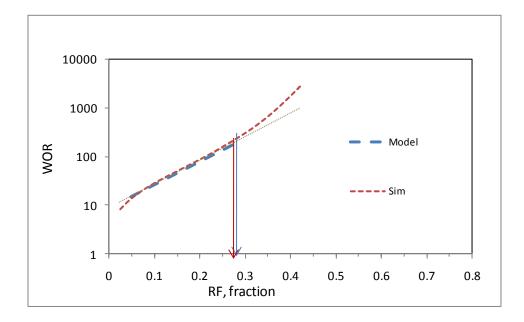


Fig. 26—Comparison of results from simulation with our correlations for an oil-wet rock with M = 30 and VDP = 0.8.

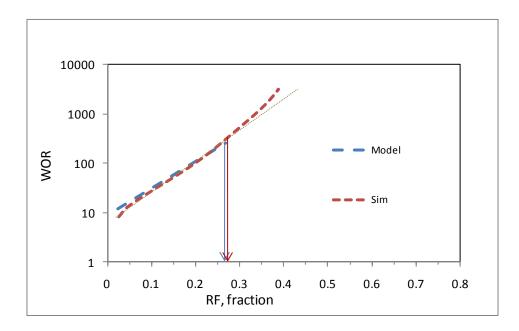


Fig. 27—Comparison of results from simulation with our correlations for an oil-wet rock with M = 30 and VDP = 0.9.

Field Cases

Eighty-four field cases were analyzed with our correlations. Two different field cases (called Field A and Field B) and several well performances are presented. Reservoir properties for the Field A case are shown in Table 21 and Table 22.

These reservoir data correspond to infill wells with no primary production. Runs were made with the original reservoir simulator and our new correlations. This example has a favorable M value of 0.76.

To apply our methodology, we developed a computer program in VBA that simplifies the correlation application (see Appendix F). A screen shot of the program illustrates the interface used by our code with input and output for all variables in Fig. 28.

DATA FOR FIELD A	VALUE	UNITS
Connate water saturation, S_{wc}	0.38	011110
Residual oil saturation, S _{or}	0.23	
Residual gas saturation, S_{gr}	0.01	
Initial gas saturation, S_{gi}	0.01	
Water viscosity, μ_{w}	0.9	ср
Oil viscosity, μ_0	1.2	cp
Oil formation factor, B_0	1.15	RB/STB
Water formation factor, B _w	1	RB/STB
Area	35	Acres
Injection pressure	2500	psi
Reservoir pressure	1200	psi
Wellbore radius, r _w	0.3	ft
End-point oil relative perm, k _{roe}	0.96865	
End-point water relative perm, k _{rwe}	0.551	
Oil Corey's function exponent, n _o	3.017	
Water Corey's function exponent, n _w	1.8045	
Oil in place (from simulation) OOIP	4,633,054	STB
N _p (from simulation)	1,861,397	STB
URF – end of the SLZ (from simulation)	40.18	fraction
VDP	0.8	

Table 21—Field A case. Real and simulation model data.

LAYERS DATA					
Net h, ft	k,md	Porosity, %			
85	175	0.19			
41	44	0.14			
10.5	190	0.15			
15	43	0.17			
9.5	31	0.13			
12	13	0.12			
48	15	0.12			
Totals:					
221	73	0.15			

Fig. 28 presents the input module where the user inputs the fluid and rock properties, the SLZ, and the WOR. The user must input the first 12 items requested (cells colored in white in Fig. 28) and run the case. When the program runs, it calculates the slope, the intercept, M, f_{wBT} , S_{wBT} , PVI, and RF for homogeneous cases, and the max WOR recommended, RF, and PVI for heterogeneous cases. A warning will be given if the user approaches the recommended max WOR or obtains a PVI higher than 2.5 for homogeneous cases, but the calculation will still be allowed so the user can adapt the program for any case and sensitivity.

A final RF of 39.6% is calculated at the end of the SLZ, based on the given log WOR. If a higher log WOR is used, PVI will increase rapidly while the RF will increase slowly. Since the correlations will calculate the end of the SLZ, the program will warn the user when too-high WOR values are used and linear extrapolation is are being done or when high PVI is required to obtain RF values.

Input your data before running:	Enter Data here:
Reservoir Name	Field A
Oil Viscosity, cP	1.2
Water Viscosity, cP	0.9
Corey exponent for oil(no)	3.017
Corey exponent for water(nw)	1.8045
Oil rel perm curve end-point (kroe)	0.96865
Water rel perm curve end-point (krwe)	0.551
Residual oil saturation (Sor)	0.23
Connate water saturation (Swc)	0.38
Dykstra-Parsons coeff. (VDP)	0.8
Water wet=1 or Oil wet=2	1
Estimated max operational WOR	26.3
Results:	
Slope	14.39
Intercept	-5.87
fwBT	0.835
SwBT	0.603
Max WOR	26.3
Min WOR	0.360
Mobility Ratio	0.758
RF	0.396
PVI	1.062

Fig. 28—Screen shot of the VBA program to apply the new correlations. Run for Field A well case.

One of the most important observations we can make at this point is that other analytical methods and the new methodology will offer reasonably similar results, with the difference that the traditional methods need more data and perform more calculations than the new correlations.

To compare our estimates with other analytical methods, we calculated and present results from all the methods, including our new correlations and field data (Fig. 29). We included Craig-Geffen-Morse (CGM), modified Buckley-Leverett (BL) to account for E_A at the breakthrough, Dykstra-Parsons (DP), and Stiles (see Appendix J for definitions, assumptions and limitations of these methods).

Our new methodology shows an end of the SLZ similar to the field data's. Our ultimate recovery factor (at the end of the SLZ) is 39.6% (less than 1% different from the field data).

In Fig. 29 we can see that the two wells have an abrupt water production increase at the end of our SLZ and water production for both wells are far from the other analytical methods in terms of WOR or RF. Also, the SLZs found in the field data have slopes and beginnings similar to the one estimated with our correlations. Results from other analytical methods are too optimistic.

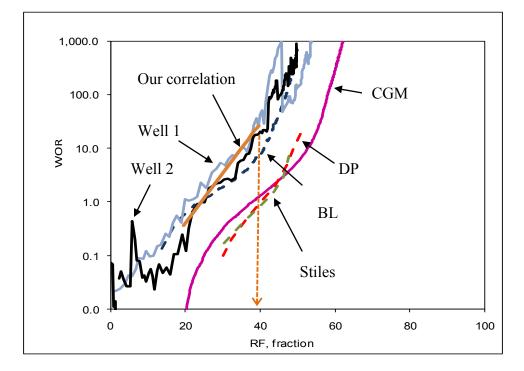


Fig. 29—Comparison of performance of two different wells from Field A with our new correlations and with four different analytical methods: Craig-Geffen and Morse (CGM), Dykstra-Parsons (DP), Modified Buckley-Leverett (BL), and Stiles.

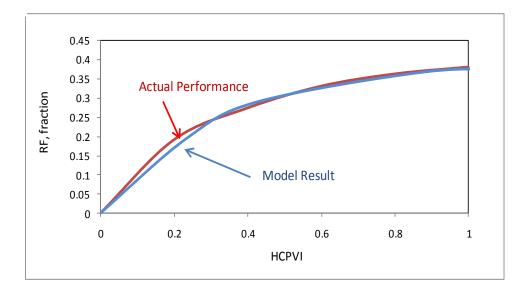


Fig. 30—RF calculated using our correlations and compared with the actual performance of Field A.

Comparing actual field performance with our correlations results, we see that our predictions match the actual behavior in terms of RF vs. hydrocarbon pore volumes injected (HCPVI), as seen in Fig. 30.

Fig. 31 shows a comparison of calculated and actual HCPVI and PVI estimated with the correlations, and Fig. 32 presents calculations of oil and water production rates using our correlations.

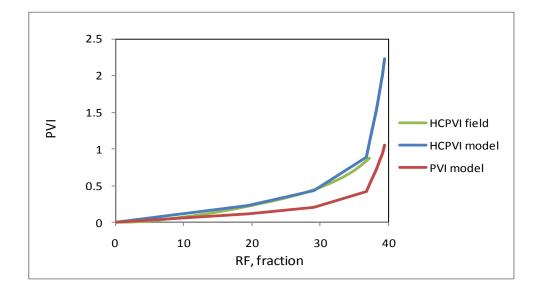


Fig. 31—Comparison of hydrocarbon pore volumes injected and total pore volume injected, estimated with the correlations and actual performance in Field A.

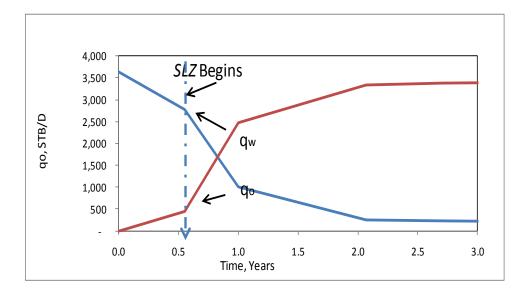


Fig. 32—Oil and water production rates per well estimated with the correlations. Field A.

Case 2, called Field B, presents a reservoir with unfavorable M and medium heterogeneity or SLZ (see Table 23 and Table 24). RF from simulation is 41.5% with high water cut, since the operator can handle water cuts above 98%. Layer data are average values.

DATA FOR FIELD A	VALUE	UNITS
Connate water saturation, S _{wc}	0.17	
Residual oil saturation, Sor	0.25	
Residual gas saturation, S _{gr}	0	
Initial gas saturation, S _{gi}	0	
Water viscosity, μ_w	0.25	ср
Oil viscosity, μ_0	2.54	ср
Oil formation factor, B _o	1.108	RB/STB
Water formation factor, B _w	1	RB/STB
Area	340	Acres
Injection pressure	1540	psi
Reservoir pressure	500	psi
Wellbore radius, r _w	0.583	ft
End-point oil relative perm, kroe	1.0	
End-point water relative perm, k _{rwe}	0.25	
Oil Corey's function exponent, n _o	3	
Water Corey's function exponent, n _w	2	
Oil in place (from simulation) OOIP	45,000,000	Bbls
N _p (from simulation)	18,660,768	Bbls
URF - end of the SLZ (from simulation)	41.47	fraction
VDP	0.8	

Table 23—Field B Case. Real and original simulation model data.

Table 24—Field B Case. Average data for the only layer where the well is completed, taken from the original simulation model.

LAYERS DATA				
Net h, ft k,md Porosity, %				
55.5	340	0.17		

Fig. 33 shows the tool's input and output for this case. High initial oil saturation and medium SLZ help to obtain good recovery at high production rates.

Using our methodology, recovery at 2.98 PVI is 37%. Fig. 34 shows data from two different wells, and even when the curves may be slightly different, the reservoir and fluid properties are similar and the SLZ estimated from our correlations matched the real data observations reasonably well. Results from other analytical methods are too optimistic.

Fig. 35 and Fig. 36 show performance estimations and oil and water production rates per well estimated from our correlation results.

In general, our methodology presents more realistic results than other methods, and can be used as an additional tool to support more detailed reservoir studies and simulations in later stages of planning and development.

Input your data before running:	Enter Data here:
Reservoir Name	Field B
Oil Viscosity, cP	2.54
Water Viscosity, cP	0.25
Corey exponent for oil(no)	3
Corey exponent for water(nw)	2
Oil rel perm curve end-point (kroe)	1
Water rel perm curve end-point (krwe)	0.25
Residual oil saturation (Sor)	0.25
Connate water saturation (Swc)	0.17
Dykstra-Parsons coeff. (VDP)	0.8
Water wet=1 or Oil wet=2	1
Estimated max operational WOR	45.5
Results:	
Slope	10.15
Intercept	-3.23
fwBT	0.803
SwBT	0.458
Max WOR	45.50
Min WOR	0.360
Mobility Ratio	2.540
RF	0.373
PVI	2.977

Fig. 33—Screen shot of the VBA program applying the new correlations to Field B well.

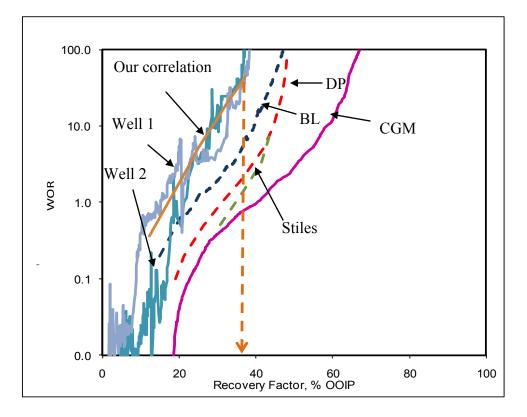


Fig. 34— Comparison of performance of two different wells from Field B with our new correlations and with four different analytical methods: Craig-Geffen and Morse (CGM), Dykstra-Parsons (DP), Modified Buckley-Leverett (BL), and Stiles.

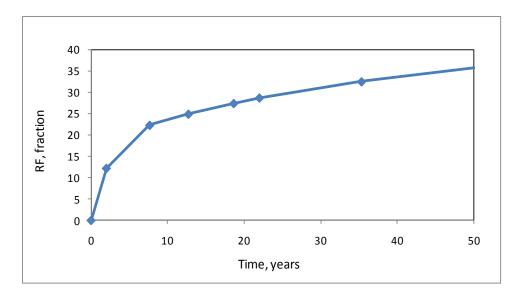


Fig. 35—RF vs. time calculated with our correlations for Field B.

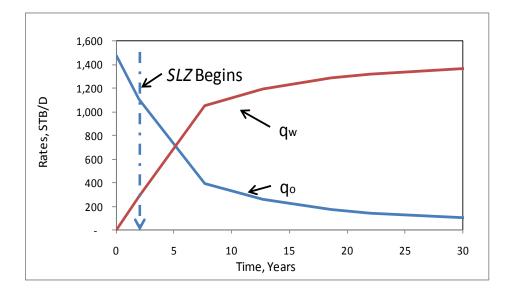


Fig. 36—Oil and water production rates per well estimated with the correlations. Field B.

CHAPTER IV

CONCLUSIONS AND RECOMMENDATIONS

On the basis of these research results, we offer the following conclusions and recommendations.

- 1. The plot of log WOR vs. RF always presents an SLZ for all reasonable combinations of *M*, fluid saturations, and relative permeability curves developed using Corey-type functions.
- 2. We characterized the SLZ by developing generalized empirical correlations using fractional flow theory and numerical reservoir simulation. These correlations may be used to estimate reservoir performance, ultimate recovery factors, water/oil ratio, and pore volumes injected for reservoirs under a waterflood. This procedure is faster than reservoir simulation and other analytical methods.
- The correlations were developed using multivariate linear regression analysis. Our correlations provide the boundaries, slopes, and intercepts of the SLZ. The software also produces results in plots and tables, all in one report and query.
- 4. Using the automated tool we developed in this research that calculates the SLZ for any combination of mobility ratio, fluid saturations, and oil and water Corey exponents, we can estimate RF and PVI up to the ultimate recovery, avoiding the risks of extrapolating the SLZ beyond its boundary, overestimating reserves, and underestimating WOR.

- 5. This analysis must be performed on a well-by-well basis since production data will be affected by different operational problems such as well stimulations, infill drilling, and pattern changes. These may all mask net injection effects in performance and recovery. However, by detecting these deviations of the estimated SLZ, we can determine the effects of interference from one well to another, so the correlations can be used as a diagnostic tool.
- Our correlations can be used accurately with multilayered or heterogeneous reservoirs, with or without crossflow, and with any value of injection rates. Initial gas saturation should not be higher than 4% to avoid overestimation of reserves.
- 7. Our procedure estimates results that can be compared and benchmarked with other analytical methods and simulation results. Also, these results can be used in most companies to support reserves calculation processes, to benchmark simulation results, and to generate first estimates of water injection requirements and production rates, facilities, and costs.
- This procedure simplifies early identification of opportunities for the oil industry and supports existing reservoir simulation models.
- 9. Using our correlations as a diagnostic tool, the user may compare actual performance with the expected performance for the parameters given (for example, too-early breakthrough may indicate higher heterogeneity, water channeling, fractures, or thief zones). Other problems such as water loss or completions problems may be inferred.

- 10. This procedure may be used to generate correlations for special cases: extraheavy oil fields and dip-angled, naturally fractured reservoirs. Cases with high initial gas saturations may be analyzed with this procedure, when good quality, comprehensive databases are available. Using the software, the practitioner can develop adjusted correlations based on the specific databases and analogies the practitioner may want to analyze.
- 11. Data required to use the correlations are usually available production data. This makes the analysis easy and fast to achieve, and results will be accurate and reliable without the need of additional and more expensive and timeconsuming processes, such as reservoir simulation, at early stages of planning, contributing to cost and time efficiency.

NOMENCLATURE

- A = area, acres
- B_o = oil formation volume factor, RB/STB
- B_{ob} = oil formation volume factor at the bubblepoint pressure, RB/STB
- B_w = water formation volume factor, RB/STB
 - e = base of the natural logarithm (≈ 2.71828)
- E(Y,x) = expected value of the mean of variable Y for each value of x
 - $E_A = a$ real sweep efficiency, percentage
 - E_D = Displacement Efficiency, fraction
 - e_i = residual, or error in the fit of the correlations
 - E_i = Vertical Sweep Efficiency, fraction
 - E_R = Recovery Efficiency, fraction
 - E_v = volumetric sweep efficiency after waterflood, fraction
 - f_w = water fraction on the fractional flow calculation, fraction
 - f_{wBT} = water fraction at breakthrough, fragment
 - H_1 = hypothesis to be tested
- HCPV = hydrocarbon pore volume, fraction of PV
- HCPVI = hydrocarbon pore volume injected, fraction of PV
 - H_o = null hypothesis
 - I = intercept, dimensionless
 - i_w = injection rate, STBW/D
 - k_{air} = Permeability to air, mD

- k_i = permeability to oil in a percentile (*i*) in the log-probability plot of permeability to estimate VDP, cp (as in Eq. 1)
- k_o = effective permeability to oil, fraction
- k_{ro} = oil relative permeability
- k_{roe} = oil relative permeability endpoint
- k_{rw} = water relative permeability
- k_{rwe} = water relative permeability endpoint
- k_w = effective permeability to water, fraction
- M = mobility ratio
- m = slope of the SLZ, fraction
- N = original oil in place, RB
- n_o = Corey oil exponent

 N_{ob} = original oil in place at the bubblepoint pressure, STB

 N_p = cumulative production, STB

- N_{pp} = primary cumulative production, STB
- NPV = Net Present Value,\$
 - n_w = Corey water exponent
 - P = probability
 - P_o = pressure in the oil phase, psi
 - PV = reservoir pore volume, fraction
- P_{-value} = smallest level of data significance
 - PVI = pore volume injected, dimensionless

- P_w = pressure in the water phase, psi
- q_o = oil production, bbl/day
- q_p = total fluid production rate, STB
- q_w = water production, bbl/day
- R^2 = statistical correlation coefficient, fraction
- RF = recovery factor, dimensionless
- RF_{heter} = recovery factor for heterogeneous reservoirs, dimensionless
- RF_{homog} = recovery factor for homogeneous reservoirs, dimensionless
 - s = fluids saturation, fraction
 - S_g = gas saturation, fraction
 - S_{gi} = initial gas saturation, fraction
 - SLZ = Straight-line zone in the logwor vs. RF plot
 - S_{or} = residual oil saturation after waterflood, fraction
 - S_w = water saturation, fraction
 - $S_{w max}$ = max water saturation, fraction
 - S_{wBT} = water saturation at the breakthrough, fraction
 - S_{wc} = connate water saturation at the moment of discovery, fraction
 - S_{wD} = dimensionless water saturation
 - S_{wi} = irreducible water saturation, fraction
 - $\overline{S_o}$ = average oil saturation, fraction
 - $\overline{S_w}$ = average water saturation in the flooded zone, fraction
 - t = time, days

URF = Ultimate Recovery Factor, fraction

V(Y,x) = variance of Y with respect to x

VDP = Dykstra-Parsons Coefficient

VR = viscosity ratio, μ_w / μ_o

VRR = Voidage Replacement Ratio, fraction

 W_i = total water injected, STB

WOR = water/oil ratio, ratio

 x_i = correlation regressor (*i* =1 to 14, in tables in Chapter III)

- ε = random error term
- $\Delta t =$ time difference, days

 α = reservoir dip angle, degrees

 β_l = intercept as an unknown regression coefficient in statistics notation

 β_o = slope as an unknown regression coefficient in statistics notation

 $\lambda_{displaced}$ = mobility of the displaced phase

 $\lambda_{displacing}$ = mobility of the displacing phase

 μ_o = oil viscosity, cp

- μ_w = water viscosity, cp
- $\mu_{Y,x}$ = mean of Y with respect to x
 - $\rho_o = \text{oil density}$
 - ρ_w = water density

 σ = standard error

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APPENDIX A

BASIC PROGRAMS FOR HOMOGENEOUS RESERVOIRS

SAS general program to estimate homogeneous reservoir waterflood performance. This example is for water-wet systems. For oil-wet systems, only change section 4. For the following lines:

```
data BT;
* for BT:
begin counter for saturation and evaluation of relative permeabilities
and fractional flow;
 dsw= 0.001;
  bo= 1;
  boi= 1;
       e=2.7182818284590452353603;
*ranges estimated from the relative perm curves analized and the Craig
approximation for wettability;
   Do uwuo= 0.1 To 1 by 0.2;
     Do po= 2 To 3.0 by 1;
       Do pw= 2 To 5.0 by 1;
         Do swc= 0.15 To 0.4 by 0.1;
           Do sor= 0.1 To 0.2 by 0.1;
           Do kroe=0.7 to 1 by 0.1;
           Do krwe=0.55 to 0.8 by 0.1;
 swmax= 1 - sor;
 sw=swc;
 do sw=swmax To swc by -dsw;
  *normalized water saturation;
  swd = (sw - swc) / (swmax - swc);
  If swd = 1 Then
 kro = 0.00000001;
      else kro = kroe*(1 - swd) ** po;
 If swd = 1 Then
      krw = krwe*(swd) ** pw;
      else krw = krwe*(swd) ** pw;
If swd = 1 Then
     fw = 1;
      else fw = 1 / (1 + (kro / krw) * (uwuo));
If swd = 1 Then
      dfw 1 = 1;
      else dfw 1 = (fw - 0) / (sw - swc);
if swd=1 then
  dfw 2 = 0;
  krod = kroe*(1 - (swd + 0.0001)) ** po;
  krwd = krwe*(swd + 0.0001) ** pw;
```

```
fwd = 1 / (1 + krod / krwd * uwuo);
  dfw 3 = (fwd - fw) / 0.0001;
*Compare two successive slopes;
  diff = dfw 1 - dfw 2;
  If diff <= 0 Then</pre>
  fwbt = fw;
      If diff <= 0 Then
  swbt = sw;
      If diff <= 0 Then
  p_inj1 = 1 / (dfw_3+00000.1);
      If diff <= 0 and p_inj1>0 or p_inj1<1 Then</pre>
  swav1 = (1 - fw) / dfw 1 + sw;
      If diff <= 0 and p inj1>0 or p inj1<1 Then</pre>
  soav1 = 1 - swav1;
      If diff <= 0 and p_inj1>0 or p_inj1<1 Then
  RF a = ((1 - soav1 - swc) / (1 - swc)) * bo / boi;
      WOR = (krw/kro) * (1/uwuo);
      LWOR =log10(WOR o+0.0000001);
      WOR o=WOR ;
      M=(krwe/kroe)/uwuo;
      lM=log10(M);
      output;
If diff <= 0 and p inj1>0 Then
sw = swc;
*If diff <= 0 Then;
      dfw 2 = dfw 1;
      *output;
      end;
        end;
               end;
                         end;
                               end;
                                      end;
                                            end;
                                                   end;
data Work.BT;
set Work.BT;
rename po=no pw=nw uwuo=VR;
if diff>=0 then delete;
if p inj1<=0 then delete;</pre>
if p inj1>1 then delete;
proc sort; by VR no nw swc sor kroe krwe M;
data Work.BT;
set Work.BT;
e=2.7182818284590452353603;
x1=(VR/no);
x2=VR;
x3=no;
```

```
x4=nw;
x5=swc;
x6=sor;
x7=log10(M);
proc reg;model fwbt= x1 x2 x3 x4 x7 ;
*proc reg; *model fwbt= no nw lM /vif;
output out=front P=Predicted R=Residual;
proc reg;model swbt= x1 x2 x3 x4 x5 x6 x7 ;
*proc reg;*model swbt= no nw swc sor lM /vif;
output out=satur P=Predicted R=Residual;
*proc gplot; *plot fwbt*lM;*by VR no nw swc sor ;
*plot swbt* lM;*by VR no nw swc sor ;
*plot fwbt * swbt;*by VR no nw swc sor;*run;
data recovery1;
* This program performs Fractional Flow Theory calculations to
determine recovery factors and
WOR values based upon the LogWOR vs. RF plot. The staight line zone is
determined fron the "nose" region to the
beginning of the change in slope more than 1%, using the second
derivative approach.
Following module (data recovery1) performs the calculation described
above.;
* Loop for different water saturation values, relative perm curves, and
fractional flow curve:;
   dsw= 0.001;
   bo= 1;
   boi= 1;
       e=2.7182818284590452353603;
*ranges estimated from the relative perm curves analized and the Craig
approximation for wettability;
   Do uwuo= 0.1 To 1 by 0.2;
     Do po= 2 To 3.0 by 1;
       Do pw= 2 To 5.0 by 1;
         Do swc= 0.15 To 0.4 by 0.1;
           Do sor= 0.1 To 0.2 by 0.1;
            Do kroe=0.7 to 1 by 0.1;
               Do krwe=0.55 to 0.8 by 0.1;
   swmax= 1 - sor;
   sw=swc;
   do sw=swc To swmax by dsw;
   *normalized water saturation;
   swd= (sw - swc) / (1 - sor - swc) + 0.0000001;
   kro= kroe*(1 - swd) ** po;
   krw= krwe*(swd) ** pw;
   *evaluates incremental for derivatives;
   krod= kroe*(1 - (swd + 0.0001)) ** po;
```

```
krwd= krwe*(swd + 0.0001) ** pw;
  fwd=1 / (1 + krod / krwd * uwuo);
 *evaluates fractional flow curve;
   fw= 1 / (1 + kro / krw * uwuo);
 *Evaluates derivative of the fractional flow curve as well as
derivative from Swc;
 If sw = swc Then
  dfw 1 = 100;
           Else dfw 1= (fwd - fw) / 0.0001;
      If sw = swc Then
   dfw 2 = 0.1;
           Else dfw 2 = (fw - 0) / (sw - swc);
      If sw= swc Then
   swav1= 100;
           Else swav1= (1 - fw) / dfw 2 + sw;
      If sw= swc Then
  nose= 100;
            Else nose= (RF a - RF a1) / (WOR - WOR o+.0001);
      If sw= swc Then
      RF a = 0;
           Else RF a= ((1 - soav1 - swc) / (1 - swc)) * bo / boi;
      soav1= 1 - swav1;
      WOR = (krw / kro) * (1 / uwuo);
     RF a= ((1 - soav1 - swc) / (1 - swc)) * bo / boi;
     RF a2 = RF a - RF a1;
      * PVI SLZ ::
     LWOR = log10 (WOR o + 0.000001);
      LWOR 2 = LWOR - LWOR 1;
      dzero = LWOR 2 / (RF a2+.00001);
      SLZ = dzero - dzero1;
      SLZ 2 = SLZ / (dzero + 0.001);
     p_inj1= 1 / (dfw 1 + 0.000001);
 p inj2= 1 / dfw 2;
 p inj12 = p inj1-PVI.;
      dzeroPVI. = p inj12 /(RF a2 + 0.00001);
      SLZ PVI = dzeroPVI. - dzero1PVI. ;
      SLZ PVI.2 = SLZ PVI / (dzeroPVI. + 0.001);
 LWOR = log10 (WOR o + 0.000001);
     nose= (RF a - RF a1) / (WOR - WOR o);
      M=(krwe/kroe)/uwuo;
      1M=log10(M);
   *stores old value of recovery factor to evaluate nose derivative and
increase counter
   *write all other values in generic results spreadsheet;
  RF al= RF a;
  WOR o= WOR ;
   LWOR 1= LWOR ;
      PVI = p inj1;
   dzero1= dzero;
```

dzero1PVI. = dzeroPVI.; output ; end; end; end; end; end; end; end; end; *proc print; *var nose RF RF 1 1WOR 1WOR 1 1WOR 2 dzero dzero1 SLZ SLZ 2 p inj1 RF 2; *by uwuo po pw sor swc; * This module deletes negative noses and fixes the tolerance for the SLZ region; data Work.recovery1; set Work.recovery1; rename po=no pw=nw uwuo=VR; if nose < 0 or nose > 50 then delete; if RF a > 1 then delete; IF SLZ 2<-0.01 or SLZ 2>0.01 then delete; * Activate the following instruction to determine the optimim RF vs PVI only. If not activated, the program will determine the critical RF and PVI.; *IF SLZ PVI.2<-0.01 or SLZ PVI.2>0.01 then delete; proc sort; by VR no nw swc sor kroe krwe M; data Work.bt; set Work.bt; proc sort; by VR no nw swc sor kroe krwe M; data merged; merge Work.recovery1 Work.Bt; by VR no nw swc sor kroe krwe M; * This module calculates and creates a table with the slopes and intercepts for LWOR vs. RF plots for each VR, no, nw, sor, swc case; proc reg data= merged outest=slopes; by VR no nw swc sor kroe krwe M; model LWOR = RF a; run; data Work.slopes; set Work.slopes; *rename RF =Slope; e=2.7182818284590452353603; x1=(VR/no);x2 = VR;x3=no; x4=nw; x5=swc; x6=sor; x7=log10(M); *proc reg; *model Slope= x2 x3 no nw sor swc lM /vif;;* kroe krwe M/vif; proc reg; model Slope= x1 x2 x4 x5 x6 x7 ;* kroe krwe M/vif;

```
output out=sloperes P=predicted1 R=residual1;
*This procedure performs the regression for the intercepts and creates
a table for calculated values;
proc reg; model Intercept= x1 x2 x4 x5 x6 x7 ;* kroe krwe M/vif;
*proc reg; *model Intercept= x2 x3 no nw sor swc lM /vif;
output out=interres P=predicted2 R=residual2;
run:
data merged2;
merge
            Work.merged
            Work.interres;
by VR no nw swc sor kroe krwe M;
data Work.merged2;
set Work.merged2;
x1=VR/no;
slopecalc=predicted1;
interceptcalc=predicted2;
logWOR calc=slopecalc*RF a1+interceptcalc;
RF acalc=(lWOR -interceptcalc)/slopecalc;
diflogWOR = (logWOR calc-lWOR ) / lWOR ;
difRF = (RF acalc-RF a1) /RF a1;
output;
run;
data Work.merged2;
set Work.merged2;
x1=VR/no;
if difRF > 0.05 then delete;
proc reg; model Slope= x1 x2 x4 x5 x6 x7 ; * kroe krwe M/vif;
output out=sloperes P=predicted3 R=residual3;
*This procedure performs the regression for the intercepts and creates
a table for calculated values;
proc reg; model Intercept= x1 x2 x4 x5 x6 x7 ;* kroe krwe M/vif;
*proc req; *model Intercept= x2 x3 no nw sor swc lM /vif;
output out=interres P=predicted4 R=residual4;
run;
data Work.merged2;
set Work.merged2;
proc reg; model Slope= x1 x2 x4 x5 x6 x7 /selection=forward slentry=0.05
details; run;
proc reg; model Slope= x1 x2 x4 x5 x6 x7 /selection=backward slstay=0.05
details; run;
proc reg;model Slope= x1 x2
                                  x4 x5 x6 x7 /selection=stepwise
slentry=0.08 details; run;
proc reg; model Slope= x1 x2 x4 x5 x6 x7 /selection=rsquare cp mse; run;
proc corr data=merged2 cov out=outcov (type=cov)nocorr noprint;
var x1 x2 x4 x5 x6 x7;
run;
proc print data=merged2(obs=12);
run;
proc mianalyze data=merged2 edf=30 mult;
var x1 x2 x4 x5 x6 x7;
run;
```

Results from the Water-wet model:

The REG Procedure Model: MODEL1	
Dependent Variable: fwbt	
Number of Observations Read Number of Observations Used	2880 2880

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	$\Pr \rightarrow F$
Model Error Corrected Total	5 2874 2879	8.84325 1.51503 10.35828	1.76865 0.00052715	3355.12	<.0001

Root MSE	0.02296	R-Square	0.8537
Dependent Mean	0.86652	Adj R-Sa	0.8535
Coeff Var	2.64964	• •	
	2.04304		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > [t]
Intercept	1	0.71084	0.00543	130.99	<.0001
x1 .	1	0.20212	0.01815	11.14	<.0001
×2	1	-0.08234	0.00858	-9.60	<.0001
×3	1	0.01779	0.00174	10.24	<.0001
x4	1	0.03932	0.00038266	102.76	<.0001
x7	1	-0.09479	0.00330	-28.71	<.0001

The REG Procedure Model: MODEL1 Dependent Variable: swbt

Number of Observations Read 2880 Number of Observations Used 2880

Analysis of Variance

Source		DF	Sum of Squares	Mean Square	F Value	Pr → F
Model Error Corrected To	tal	7 2872 2879	20.51846 1.29146 21.80993	2.93121 0.00044967	6518.51	<.0001
	Root MSE Dependent Coeff Var		0.02121 0.64132 3.30654	R-Square Adj R-Sq	0.9408 0.9406	

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	$\Pr \rightarrow \{t\}$
Intercept	1	0.64301	0.00529	121.54	<.0001
x1 .	1	0.23901	0.01676	14.26	<.0001
x2	1	-0.10025	0.00792	-12.65	<.0001
x3	1	-0.03016	0.00161	-18.79	<.0001
x4	1	0.03722	0.00035343	105.30	<.0001
x5	1	0.34619	0.00484	71.53	<.0001
×6	1	-0.65383	0.00790	-82.73	<.0001
x7	1	-0.15479	0.00305	-50.75	<.0001

The REG Procedure Model: MODEL1 Dependent Variable: slope

Number of Observations Read 226977 Number of Observations Used 226977

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr→F
Model Error Corrected Total	6 226970 226976	3205594 270106 3475700	534266 1.19005	448942	<.0001
D+	MOE	1 09090	B_Course	0 0999	

ROOT MSE	1.03030	R-Square	V.9223
Dependent Mean	12.30964	Adj R-Sq	0.9223
Coeff Var	8.86212		

Variable	DF	Parameter Estimate	Standard Error	t Value	$\Pr \rightarrow t $
Intercent	1	1.29383	0.02174	59.51	<.0001
Intercept					
x1	1	27.81540	0.05745	484.14	<.0001
x2	1	-6.79106	0.03085	-220.16	<.0001
x4	1	2.08358	0.00209	995.21	<.0001
x5	1	4.76521	0.02929	162.68	<.0001
×6	1	22.31418	0.04731	471.61	<.0001
x7	1	-4.79404	0.01729	-277.35	<.0001

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Number of Observations Number of Observations		226977 226977
--	--	------------------

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr → F
Model Error Corrected Total	6 226970 226976	2109903 124144 2234047	351651 0.54696	642917	<.0001
Dep	ot MSE Dendent Mean eff Var	0.73957 -6.21398 -11.90168	R-Square Adj R-Sq	0.9444 0.9444	

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	$\Pr \rightarrow \{t\}$
Intercept x1 x2 x4 x5 x6	Intercept	1 1 1 1	-1.56684 -30.39889 8.83008 -1.50075 -0.10520 -0.58337	0.01474 0.03895 0.02091 0.00142 0.01986 0.03208	-106.30 -780.46 422.26 -1057.4 -5.30 -18.19	<.0001 <.0001 <.0001 <.0001 <.0001 <.0001
x7		i	4.03107	0.01172	344.00	<.0001

Results from the Oil-wet model:

The REG Procedure Model: MODEL1 Dependent Variable: fwbt

Number of Observations Read 8441 Number of Observations Used 8441

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr → F
Model Error Corrected Total	5 8435 8440	33.95133 4.84563 38.79696	6.79027 0.00057447	11820.1	<.0001

Root MSE	0.02397 F	R-Square	0.8751
	0.84045 A 2.85183	ndj R-Sq	0.8750

Variable	DF	Parameter Estimate	Standard Error	t Value	$\Pr \rightarrow \{t\}$
Intercept x1	1	0.65980 0.11888	0.00374 0.01107	176.61 10.74	<.0001 <.0001
×2	1	-0.04844	0.00494	-9.81	<.0001
×3	1	0.02099	0.00122	17.15	<.0001
x4	1	0.05127	0.00023332	219.74	<.0001
x7	1	-0.09342	0.00177	-52.75	<.0001

The REG Procedure Model: MODEL1 Dependent Variable: swbt

Number	of	Observations	Read	8441
Number	of	Observations	Used	8441

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr → F
Model Error Corrected Total	7 8433 8440	84.21711 4.28149 88.49860	12.03102 0.00050771	23696.8	<.0001

Root MSE	0.02253	R-Square	0.9516
Dependent Mean	0.41177	Adj R-Sq	0.9516
Coeff Var	5.47210		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr→ [t]
Intercept	1	0.56187	0.00360	156.00	<.0001
×1	1	0.16777	0.01040	16.12	<.0001
×2	1	-0.06865	0.00464	-14.79	<.0001
×3	1	-0.02195	0.00115	-19.08	<.0001
x4	1	0.04494	0.00021935	204.86	<.0001
x5	1	0.41472	0.00417	99.42	<.0001
×6	1	-0.58525	0.00208	-281.07	<.0001
x7	1	-0.14536	0.00166	-87.31	<.0001

The REG Procedure Model: MODEL1 Dependent Variable: slope

Number	of	Observations	Read	9600
Number	of	Observations	Used	9600

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	$\Pr \rightarrow F$
Model Error Corrected Total	5 9594 9599	241628 38449 280077	48326 4.00765	12058.3	<.0001

Root MSE	2.00191	R-Square	0.8627
Dependent Mean	15.56270	Adj R-Sq	0.8626
Coeff Var	12.86352		

Variable	DF	Parameter Estimate	Standard Error	t Value	$\Pr > t $
Intercept	1	0.77519	0.17979	4.31	<.0001
x1	1	8.93439	0.36963	24.17	<.0001
×2	1	-3.36474	0.20697	-16.26	<.0001
x4	1	2.67364	0.01827	146.30	<.0001
×6	1	28.23280	0.18275	154.49	<.0001
х7	1	-8.40355	0.13878	-60.55	<.0001

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept Number of Observations Read 9600

Number	of	Ubservations	Kead	9600
Number	of	Observations	Used	9600

Analysis of Variance

Source		DF	Sum of Squares	Mean Square	F Value	$\Pr \rightarrow F$
Model Error Corrected To	tal	6 9593 9599	51074 3536.24062 54610	8512.33172 0.36863	23092.0	<.0001
	Root MSE Dependent Coeff Var	Mean	0.60715 -5.59580 -10.85005	R-Square Adj R-Sq	0.9352 0.9352	

Variable	Labe I	DF	Parameter Estimate	Standard Error	t Value	$\Pr \rightarrow \{t\}$
Intercept x1 x2 x4 x5 x6 x7	Intercept	1 1 1 1 1 1	-3.42537 -11.94031 4.78633 -1.41665 -0.33004 -0.06060 5.30721	0.05516 0.11210 0.06277 0.00554 0.11085 0.05542 0.05542	-62.10 -106.51 76.25 -255.60 -2.98 -1.09 126.09	<.0001 <.0001 <.0001 <.0001 0.0029 0.2742 <.0001

APPENDIX B

EXAMPLE OF BASIC PROGRAMS FOR HETEROGENEOUS RESERVOIRS

Water-wet system program:

```
Recovery:
data allMandVDP;
set allMandVDP;;
x2=homo**2;
proc reg;model vdp06= homo /vif r clm cli alpha=.05;
run;
proc reg;model vdp07= M lwor x2 /vif r clm cli alpha=.05;
run:
proc reg; model vdp08= M lwor x2 /vif r clm cli alpha=.05;
output out=vdp08i P=predicted8i R=residual8i;
run;
proc reg;model vdp09= M lwor x2 /vif r clm cli alpha=.05;
run;
*proc gplot;
*plot vdp08 * predicted8i;
*plot lwor * predicted8i;by M;
*plot lwor * (vdp06 vdp07 vdp08 vdp09);
*run;
PVI:
option ls=120 ps=75 nocenter nodate;
title 'Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and
0.6';
data allMandVDPandPVI;
infile "c:\0001 My Research\Tesis Total\Writings and Calculations\ Nov
19\heterwaterwetPVIdata";
input M lwor rfhomo PVIhomo rf06 PVI06 rf07 PVI07 rf08 PVI08 rf09 PVI09;
*cards;
data allMandVDPandPVI;
set allMandVDPandPVI;
e=2.7182818284590452353603;
x9=M;
x13=e**(lwor);
x14=10**(lwor);
proc reg;model PVIhomo= x8 x12 x13 /r clm cli alpha=.05;
output out=homo P=predictedh R=residualh;
run;
proc reg;model PVI06= x8 x12 x13 /r clm cli alpha=.05;
output out=vdp06 P=predicted6 R=residual6;
run;
proc reg;model PVI07= x8 x12 x13 /r clm cli alpha=.05;
output out=vdp07 P=predicted7 R=residual7;
run;
proc reg;model PVI08= x8 x12 x13 /r clm cli alpha=.05;
output out=vdp08 P=predicted8 R=residual8;
run;
proc reg;model PVI09= x8 x12 x13 /r clm cli alpha=.05;
output out=vdp09 P=predicted9 R=residual9;run;
```

Results from the Water-wet model, Recovery Factors:

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 $125\,$

The REG Procedure Model: MODEL1 Dependent Variable: vdp06

Number	of	Observations	Read	82
Number	of	Observations	Used	82

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	1 80 81	0.31629 0.00527 0.32156	0.31629 0.00006587	4801.35	<.0001

Root MSE	0.00812	R-Square	0.9836
Dependent Mean	0.52645	Adj R-Sq	0.9834
Coeff Var	1.54170		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-0.18015	0.01024	-17.60	<.0001
homo	1	1.27511	0.01840	69.29	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 129 $\,$

The REG Procedure Model: MODEL1 Dependent Variable: vdp07

Number	of	Observations	Read	82
Number	of	Observations	Used	82

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	3 78 81	0.37584 0.00129 0.37713	0.12528 0.00001657	7560.63	<.0001
Root MSE Dependent Mean	0.00407 0.50843	R-Square Adj R-Sq	0.9966 0.9964		

0.80063

Parameter Estimates

		Parameter	0	Standard		
Variable	DF	Estimate		Error	t Value	Pr > t
Intercept	1	0.19068		0.01494	12.76	<.0001
X8	1	-0.00368		0.00127	-2.89	0.0050
X10	1	0.02336	(0.00354	6.59	<.0001
X11	1	0.91971		0.06093	15.10	<.0001
Gral corr	behavior,	Homo, VDP	0.6,	0.7, 0.8,	and 0.9 wi	th M= 1, 3

Gra⊥ 133

Coeff Var

and 0.6

The REG Procedure Model: MODEL1 Dependent Variable: vdp08

Number	of	Observations	Read	82
Number	of	Observations	Used	82

Analysis of Variance

Source D	F Squa	ares Square	e F Value	Pr > F
Model Error 7 Corrected Total 8		0.0000407		<.0001

Root MSE	0.00638	R-Square	0.9953
Dependent Mean	0.45022	Adj R-Sq	0.9951
Coeff Var	1.41814		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	0.09829	0.02344	4.19	<.0001
X8	1	-0.00751	0.00200	-3.76	0.0003
X10	1	0.05354	0.00556	9.64	<.0001
X11	1	0.88719	0.09556	9.28	<.0001
Sum of Resi	duals		0		
Sum of Squa	red Res	iduals	0.00318		
Predicted R	esidual	SS (PRESS)	0.00350		

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 137 The REG Procedure Model: MODEL1 Dependent Variable: vdp09 Number of Observations Read 82

Number	ΟĪ	Observations	Read	82
Number	of	Observations	Used	82

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	3 78 81	0.58779 0.00077325 0.58856	0.19593 0.00000991	19763.9	<.0001

Root MSE	0.00315	R-Square	0.9987
Dependent Mean	0.40614	Adj R-Sq	0.9986
Coeff Var	0.77525		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	0.17180	0.01156	14.86	<.0001
X8	1	-0.01440	0.00098386	-14.64	<.0001
X10	1	0.07227	0.00274	26.37	<.0001
X11	1	0.44117	0.04712	9.36	<.0001

Results from the Water-wet model, PVI:

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 161 $\,$

The REG Procedure Model: MODEL1 Dependent Variable: PVIhomo

Number	of	Observations	Read	81
Number	of	Observations	Used	81

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	3 77 80	849.00414 23.81351 872.81765	283.00138 0.30927	915.07	<.0001

Root MSE	0.55612	R-Square	0.9727
Dependent Mean	2.73765	Adj R-Sq	0.9717
Coeff Var	20.31364		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-0.81246	0.18097	-4.49	<.0001
X8	1	0.35196	0.05886	5.98	<.0001
X12	1	0.00800	0.00076159	10.50	<.0001
X13	1	0.21624	0.03685	5.87	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 165 $\,$

The REG Procedure Model: MODEL1 Dependent Variable: PVI06

Number of Observations Read 81 Number of Observations Used 81

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	3 77 80	1230.20736 39.19689 1269.40425	410.06912 0.50905	805.56	<.0001

Root MSE	0.71348	R-Square	0.9691
Dependent Mear	3.36284	Adj R-Sq	0.9679
Coeff Var	21.21653		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-1.05462	0.23218	-4.54	<.0001
X8	1	0.46384	0.07551	6.14	<.0001
X12	1	0.00912	0.00097710	9.34	<.0001
X13	1	0.28413	0.04727	6.01	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 169 The REG Procedure Model: MODEL1 Dependent Variable: PVI07

Number of Observations Read81Number of Observations Used81

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	3 77 80	1725.72439 62.67400 1788.39839	575.24146 0.81395	706.73	<.0001

Root MSE	0.90219	R-Square	0.9650
Dependent Mean	3.81432	Adj R-Sq	0.9636
Coeff Var	23.65272		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-1.21560	0.29359	-4.14	<.0001
X8	1	0.47344	0.09548	4.96	<.0001
X12	1	0.01136	0.00124	9.20	<.0001
X13	1	0.31097	0.05978	5.20	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 173 $\,$

The REG Procedure Model: MODEL1 Dependent Variable: PVI08

Number of Observations Read 81 Number of Observations Used 81

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	3 77 80	3120.38902 163.14421 3283.53322	1040.12967 2.11876	490.92	<.0001

Root MSE	1.45559	R-Square	0.9503
Dependent Mean	5.17494	Adj R-Sq	0.9484
Coeff Var	28.12777		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-2.06505	0.47368	-4.36	<.0001
X8	1	0.58703	0.15405	3.81	0.0003
X12	1	0.01217	0.00199	6.10	<.0001
X13	1	0.57103	0.09645	5.92	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 $177\,$

The REG Procedure Model: MODEL1 Dependent Variable: PVI09

Number of Observations Read 81 Number of Observations Used 81

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	3 77 80	4122.74491 15.34892 4138.09384	1374.24830 0.19934	6894.11	<.0001

Root MSE	0.44647	R-Square	0.9963
Dependent Mean	5.29914	Adj R-Sq	0.9961
Coeff Var	8.42536		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-0.45357	0.14529	-3.12	0.0025
X8	1	0.08084	0.04725	1.71	0.0911
X12	1	0.02353	0.00061143	38.48	<.0001
X13	1	0.19269	0.02958	6.51	<.0001

Oil-wet system program:

```
Recovery:
data allMandVDP;
set allMandVDP;;
x2=homo**2;
proc reg;model vdp06= homo /r clm cli alpha=.05;
run;
proc reg;model vdp07= M lwor x2 /r clm cli alpha=.05;
run;
proc reg;model vdp08= M lwor x2 /r clm cli alpha=.05;
run;
proc reg;model vdp09= M lwor x2 /r clm cli alpha=.05;
run;
*proc gplot;
*plot homo * (vdp06 vdp07 vdp08 vdp09);
*run;
PVI:
option ls=120 ps=75 nocenter nodate;
title 'Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and
0.6';
data allMandVDPandPVI;
infile "c:\0001 My Research\Tesis Total\Writings and Calculations\Ultimos a Nov
19\heterwaterwetPVIdata";
input M lwor rfhomo PVIhomo rf06 PVI06 rf07 PVI07 rf08 PVI08 rf09 PVI09;
data allMandVDPandPVI;
set allMandVDPandPVI;
e=2.7182818284590452353603;
x9=M;
x11=e**(lwor);
x12=10**(lwor);
proc reg;model PVIhomo= x8 x12 x13 /r clm cli alpha=.05;
run:
proc reg;model PVI06= x8 x12 x13 /r clm cli alpha=.05;
run;
proc reg;model PVI07= x8 x12 x13 /r clm cli alpha=.05;
run;
proc reg;model PVI08= x8 x12 x13 /r clm cli alpha=.05;
run;
proc reg;model PVI09= x8 x12 x13 /r clm cli alpha=.05;
run;
*proc gplot;
*plot homo * (vdp06 vdp07 vdp08 vdp09);
*run;
```

Results from the Oil-wet model, Recovery Factor:

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 197 $\,$

The REG Procedure Model: MODEL1 Dependent Variable: vdp06

Number	of	Observations	Read	84
Number	of	Observations	Used	84

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	1 82 83	0.21885 0.00653 0.22538	0.21885 0.00007967	2746.83	<.0001

Root MSE	0.00893	R-Square	0.9710
Dependent Mean	0.26381	Adj R-Sq	0.9707
Coeff Var	3.38349		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-0.09880	0.00699	-14.14	<.0001
homo	1	1.27817	0.02439	52.41	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 201 $\,$

The REG Procedure Model: MODEL1 Dependent Variable: vdp07

Number	of	Observations	Read	84
Number	of	Observations	Used	84

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error Corrected Total	3 80 83	0.21292 0.00257 0.21549	0.07097 0.00003217	2206.41	<.0001

Root MSE	0.00567	R-Square	0.9881
Dependent Mean	0.25536	Adj R-Sq	0.9876
Coeff Var	2.22102		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	0.09036	0.01160	1.06	0.2907
X8	1	-0.00226	0.00052347	-6.90	<.0001
X10	1	0.01459	0.00217	10.92	<.0001
X11	1	1.78812	0.04889	15.37	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 205 $\,$

The REG Procedure Model: MODEL1 Dependent Variable: vdp08

Number	of	Observations	Read	84
Number	of	Observations	Used	84

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model Error	3 80	0.30137 0.00226	0.10046 0.00002820	3562.41	<.0001
Corrected Total	83	0.30362			

Root MSE	0.00531	R-Square	0.9926
Dependent Mean	0.22262	Adj R-Sq	0.9923
Coeff Var	2.38536		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	0.06727	0.00627	10.73	<.0001
X8	1	-0.00489	0.00055858	-8.76	<.0001
X10	1	0.03839	0.00260	14.77	<.0001
X11	1	1.27549	0.11041	11.55	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 209 $\,$

The REG Procedure Model: MODEL1 Dependent Variable: vdp09

Number	of	Observations	Read	84
Number	of	Observations	Used	84

Analysis of Variance

		Sum of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
Model	3	0.24670	0.08223	4306.13	<.0001
Error	80	0.00153	0.00001910		
Corrected Total	83	0.24823			
Root MSE	0.00437	R-Square	0.9938		

Root MSE	0.00437	R-Square	0.9938
Dependent Mean	0.20143	Adj R-Sq	0.9936
Coeff Var	2.16950		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Variable	DF	ESCIMALE	FILOL	t value	PI > L
Intercept	1	0.07480	0.00516	14.50	<.0001
X8	1	-0.00535	0.00045967	-11.63	<.0001
X10	1	0.04112	0.00214	19.23	<.0001
X11	1	0.88482	0.09086	9.74	<.0001

Results from the OIL-wet model, PVI:

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 The REG Procedure Model: MODEL1 Dependent Variable: PVIhomo

Number	of	Observations	Read	87
Number	of	Observations	Used	87

Analysis of Variance

Source Pr > F	DF	Sum of Squares	Mean Square	F Value
Model <.0001	3	294.48907	98.16302	297.26
Error	83	27.40850	0.33022	
Corrected Total	86	321.89757		
Root MSE	0.57465	R-Square	0.9149	

		-	
Dependent Mean	1.75655	Adj R-Sq	0.9118
Coeff Var	32.71468		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-0.86243	0.17016	-5.07	<.0001
X8	1	0.41381	0.05868	7.05	<.0001
X12	1	0.00194	0.00075435	2.57	0.0119
X13	1	0.24178	0.03561	6.79	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 9610 The REG Procedure Model: MODEL1 Dependent Variable: PVI06

Number	of	Observations	Read	87
Number	of	Observations	Used	87

Analysis of Variance

Source Pr > F	DF	Sum of Squares	Mean Square	F Value
Model <.0001	3	616.55169	205.51723	336.05
Error	83	50.75989	0.61156	
Corrected Total	86	667.31158		
Root MSE	0.78203	R-Square	0.9239	
Dependent Mean Coeff Var	2.45954 31.79562	Adj R-Sq	0.9212	

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-1.26805	0.23157	-5.48	<.0001
X8	1	0.49769	0.07986	6.23	<.0001
X12	1	0.00238	0.00103	2.32	0.0228
X13	1	0.37376	0.04846	7.71	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 9614 Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 9617 The REG Procedure Model: MODEL1 Dependent Variable: PVI07 Number of Observations Read Number of Observations Used 87

Analysis of Variance

87

Source Pr > F	DF	Sum of Squares	Mean Square	F Value
Model <.0001	3	997.31606	332.43869	510.59
Error Corrected Total	83 86	54.04059 1051.35665	0.65109	
Root MSE	0.80690	R-Square	0.9486	

Dependent Mean 2.77621 Coeff Var 29.06492 2.77621 Adj R-Sq 0.9467

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-1.11471	0.23894	-4.67	<.0001
X8	1	0.43417	0.08240	5.27	<.0001
X12	1	0.00691	0.00106	6.52	<.0001
X13	1	0.30144	0.05001	6.03	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 The REG Procedure Model: MODEL1 Dependent Variable: PVI08 Number of Observations Read 87

Number	ΟI	Observations	Read	8 /
Number	of	Observations	Used	87

Analysis of Variance

Source Pr > F	DF	Sum of Squares	Mean Square	F Value
Model <.0001	3	2157.88326	719.29442	537.78
Error	83	111.01378	1.33752	
Corrected Total	86	2268.89704		
Root MSE	1.15651	R-Square	0.9511	
Dependent Mean Coeff Var	3.77747 30.61598	Adj R-Sq	0.9493	

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-1.26744	0.34246	-3.70	0.0004
X8	1	0.45081	0.11810	3.82	0.0003
X12	1	0.01279	0.00152	8.42	<.0001
X13	1	0.32235	0.07167	4.50	<.0001

Gral corr behavior, Homo, VDP 0.6, 0.7, 0.8, and 0.9 with M= 1, 3 and 0.6 9625 The REG Procedure Model: MODEL1 Dependent Variable: PVI09 Number of Observations Read 87 Number of Observations Used 87

Analysis of Variance

Source Pr > F	DF	Sum of Squares	Mean Square	F Value
Model <.0001	3	1888.85706	629.61902	3387.07
Error	83	15.42881	0.18589	
Corrected Total	86	1904.28586		
Root MSE	0.43115	R-Square	0.9919	
Dependent Mean Coeff Var	3.44690 12.50832	Adj R-Sq	0.9916	

		Parameter	Standard		
Variable	DF	Estimate	Error	t Value	Pr > t
Intercept	1	-0.64968	0.12767	-5.09	<.0001
X8	1	0.18524	0.04403	4.21	<.0001
X12	1	0.01370	0.00056597	24.20	<.0001
X13	1	0.22142	0.02672	8.29	<.0001

APPENDIX C

EXAMPLE OF BASIC DATA FILES FOR HETEROGENEOUS RESERVOIRS

М	LogWOR	RFhomo	PVI homo	RF 0.6	PVI 0.6	RF 0.7	PVI 0.7
0.6	0.0	0.49	0.30	0.45	0.35	0.43	0.30
0.6	0.3	0.50	0.32	0.47	0.38		
0.6	0.6	0.53			0.39	0.46	0.37
0.6	0.7	0.53	0.35	0.48	0.41	0.47	0.39
0.6	0.8	0.54	0.37	0.49	0.42	0.47	0.42
0.6	0.9	0.54	0.39	0.49	0.46	0.48	0.46
0.6	1.0	0.54	0.42	0.51	0.52	0.49	0.49
0.6	1.1	0.55	0.46	0.51	0.59	0.49	0.55
0.6	1.2	0.55	0.52	0.52	0.65	0.50	0.59
0.6	1.3	0.56	0.55	0.53	0.79	0.51	0.72
0.6	1.4	0.56	0.65	0.54	0.85	0.51	0.79
0.6	1.5	0.56	0.71	0.54	0.92	0.52	0.98
0.6	1.6	0.57	0.78	0.55	1.18	0.53	1.18
0.6	1.7	0.58	1.04	0.56	1.31	0.54	1.44
0.6	1.8	0.58	1.18	0.56	1.44	0.55	1.77
0.6	1.9	0.59	1.44	0.57	1.71	0.56	2.10
0.6	2.0	0.59	1.70	0.57	2.10	0.56	2.50
0.6	2.1	0.60	2.09	0.58	2.50	0.57	3.03
0.6	2.2	0.60	2.49	0.59	3.03	0.58	3.62
0.6	2.3	0.60	3.01	0.59	3.55	0.58	4.28
0.6	2.4	0.61	3.53	0.60	4.34	0.59	5.07
0.6	2.5	0.61	4.32	0.60	5.13	0.59	6.06
0.6				0.60	6.19	0.60	
0.6	2.7	0.62	6.15	0.61	7.37	0.60	8.63
0.6	2.8	0.62	7.33	0.61	8.69	0.61	10.21
0.6			8.64		10.41	0.61	12.05
0.6	3.0	0.63	9.56	0.62	11.46	0.61	13.24

Table 25—Data for heterogeneous reservoirs, example for water-wet systems.

M	LogWOR	BE home	PVI homo			RF 0.7	PVI0.7
							-
0.6							0.18
0.6		0.23					
0.6							
0.6		0.25					
0.6					0.23		0.22
0.6		0.27					0.26
0.6			0.30				
0.6		0.28					
0.6		0.28					
0.6		0.28					
0.6		0.29					
0.6	1.3	0.29	0.52	0.27	0.65		0.65
0.6		0.30			0.78	0.27	0.71
0.6		0.30	0.65				0.84
0.6	1.6	0.31	0.78	0.29	1.04	0.28	0.97
0.6	1.7	0.31	0.91	0.30	1.30	0.28	1.10
0.6	1.8	0.31	1.04	0.30	1.43	0.29	1.30
0.6	1.9	0.31	1.17	0.30	1.69	0.29	1.56
0.6	2.0	0.32	1.30	0.31	1.95	0.29	1.88
0.6	2.1	0.32	1.43	0.31	2.21	0.30	2.33
0.6	2.2	0.32	1.69	0.31	2.46	0.30	2.79
0.6	2.3	0.32	1.95	0.32	2.85	0.31	3.37
0.6		0.32	2.21		3.24		4.02
0.6		0.32	2.46	0.32	3.63		4.73
0.6			2.85				
0.6		0.33			4.67		
0.6		0.33			5.32	0.32	7.33
0.6					6.10	0.32	
0.6					-		

Table 26—Data for heterogeneous reservoirs, example for oil-wet systems.

APPENDIX D

SIMULATION MODEL FOR HOMOGENEOUS RESERVOIR

-- Black Oil model for waterflooding process.

-- This model is only for WATER INJECTION.

-- Grid 19x19x10 = 3610 cells

RUNSPEC TITLE 350204 homogeneo vs heterogeneo VR=0.1 DIMENS -- NX NY NZ 19 19 10 /

NONNC

-- NOSIM

OIL

WATER

FIELD

IMPLICIT

EQLDIMS 1 100 50 1 50 /

TABDIMS

--# of sat #of PVT max # sat max # press max # of max # Rs --tables tables nodes nodes FIP regions nodes 1 1 100 100 1 100 /

WELLDIMS --max # #of conn max # max # wells --wells per well groups per group 5 50 2 5 /

START 19 'JUL' 2006 /

-- Specifies the size of the stack for Newton iterations NSTACK 10 /

UNIFOUT

UNIFIN

```
GRID
__=
-- PERMX,Y CONSTTE = 120
EQUALS
'DX' 20 /
'DY' 20 /
'DZ' 10 /
'PORO' 0.3 /
'TOPS' 8325 1 19 1 19 1 1 /
'PERMX' 200 1 19 1 19 1 1 /
'PERMX' 200 1 19 1 19 2 2 /
'PERMX' 200 1 19 1 19 3 3 /
'PERMX' 200 1 19 1 19 4 4 /
'PERMX' 200 1 19 1 19 5 5 /
'PERMX' 200 1 19 1 19 6 6 /
'PERMX' 200 1 19 1 19 7 7 /
'PERMX' 200 1 19 1 19 8 8 /
'PERMX' 200 1 19119 9 9 /
'PERMX' 200 1 19 1 19 10 10 /
/
COPY
 'PERMX' 'PERMY' 1 19 1 19 1 10 /
 'PERMX' 'PERMZ' 1 19 1 19 1 10 /
/
MULTIPLY
-- Kv/Kh
PERMZ 0.1 1 19 1 19 1 10 /
/
INIT
PROPS =======
SWOF
                              PCwo
-- Sw Krw Kro
-- Sat water int = 0.4
0.40000
                       0.00000
                                      0.90000 0.00000
0.40667
                       0.00000
                                      0.85575 0.00000
                                      0.81297 0.00000
0.41333
                       0.00000
0.42000
                       0.00000
                                      0.77164 0.00000
0.42667
                       0.00000
                                      0.73173 0.00000
0.43333
                       0.00000
                                      0.69323 0.00000
0.44000
                       0.00001
                                      0.65610 0.00000
```

DEBUG 200001/

0.44667	0.00001	0.62032 0.00000
0.45333	0.00002	0.58587 0.00000
0.46000	0.00004	0.55271 0.00000
0.46667	0.00007	0.52083 0.00000
0.47333	0.00011	0.49020 0.00000
0.48000	0.00018	0.46080 0.00000
0.48667	0.00026	0.43260 0.00000
0.49333	0.00038	0.40557 0.00000
0.50000	0.00054	0.37969 0.00000
0.50667	0.00074	0.35493 0.00000
0.51333	0.00100	0.33128 0.00000
0.51555	0.00100	0.30870 0.00000
0.52667	0.00175	0.28717 0.00000
0.53333	0.00226	0.26667 0.00000
0.54000	0.00289	0.24716 0.00000
0.54667	0.00365	0.22863 0.00000
0.55333	0.00455	0.21105 0.00000
0.56000	0.00563	0.19440 0.00000
0.56667	0.00691	0.17865 0.00000
0.57333	0.00840	0.16377 0.00000
0.58000	0.01015	0.14974 0.00000
0.58667	0.01217	0.13653 0.00000
0.59333	0.01451	0.12413 0.00000
0.60000	0.01719	0.11250 0.00000
0.60667	0.02025	0.10162 0.00000
0.61333	0.02373	0.09147 0.00000
0.62000	0.02768	0.08201 0.00000
0.62667	0.03214	0.07323 0.00000
0.63333	0.03715	0.06510 0.00000
0.64000	0.04277	0.05760 0.00000
0.64667	0.04905	0.05070 0.00000
0.65333	0.05604	0.04437 0.00000
0.66000	0.06382	0.03859 0.00000
0.66667	0.07243	0.03333 0.00000
0.67333	0.08195	0.02858 0.00000
0.68000	0.09244	0.02430 0.00000
0.68667	0.10398	0.02047 0.00000
0.69333	0.11665	0.01707 0.00000
0.70000	0.13052	0.01406 0.00000
0.70667	0.14568	0.01143 0.00000
0.71333	0.16222	0.00915 0.00000
		0.00913 0.00000
0.72000	0.18022	0.00720 0.00000
0.72667	0.19980	
0.73333	0.22103	0.00417 0.00000
0.74000	0.24404	0.00304 0.00000
0.74667	0.26892	0.00213 0.00000
0.75333	0.29579	0.00143 0.00000
0.76000	0.32477	0.00090 0.00000
0.76667	0.35598	0.00052 0.00000
0.77333	0.38954	0.00027 0.00000
0.78000	0.42558	0.00011 0.00000
0.78667	0.46424	0.00003 0.00000
0.79333	0.50567	0.00000 0.00000

0.80000 0.55000 0.00000 0.00000 -- Sat oil res = 0.2-- PVT PROPERTIES OF WATER -- REF. PRES. REF. FVF COMPRESSIBILITY REF VISCOSITY VISCOSIBILITY **PVTW** 4014.7 1.0 3.13D-6 1.0 0/ ROCK -- REF. PRES COMPRESSIBILITY 14.7 3.0D-6 / DENSITY -- OIL WATER GAS 49.1 62.428 0.06054 / **PVDO** --to be updated --Press Bo Visc 400 1.0004 5.160 1200 1.0003 5.164 2000 1.0002 5.167 2800 1.0001 5.550 3600 1.0000 5.000 4400 0.9999 5.0001 5200 0.9998 5.0002 6000 0.9997 5.0003 7000 0.9996 5.0004 8000 0.9995 5.0005

9000 0.9994 5.0006 /

/

SOLUTION ========

-- DATA FOR INITIALISING FLUIDS TO POTENTIAL EQUILIBRIUM ---- DATUM DATUM OWC OWC GOC GOC RSVD RVVD SOLN -- DEPTH PRESS DEPTH PCOW DEPTH PCOG TABLE TABLE METH EOUIL 8400 3665.3518 15000 0 / RPTRST BASIC=2 / SUMMARY =======

--REQUEST PRINTED OUTPUT OF SUMMARY FILE DATA

```
RUNSUM
```

```
-- FIELD OIL PRODUCTION, Cumulative oil prod. for field and for every well
FOPR
FOPT
WOPT
WOPR
/
-- FIELD WATER INJ. RATE, Cumulative water inj. for field and for every well
FWIR
FWIT
WWIT
/
WWIR
/
--INSTANTANEOUS WATER CUTS FOR FIELD AND FOR EVERY WELL.
FWCT
WWCT
FWPR
WWPR
/
--OIL IN PLACE for field and for every FIP Region
FOIP
ROIP
/
--Water in place for field and for every FIP region
FWIP
RWIP
/
--Average PRESSURE for field and for every FIP region
FPR
RPR
/
-- WELL BOTTOM-HOLE PRESSURE
WBHP
/
TCPU
ELAPSED
SEPARATE
RPTONLY
SCHEDULE ======
```

```
------ THE SCHEDULE SECTION DEFINES THE OPERATIONS TO BE SIMULATED
_____
-- WELL SPECIFICATION DATA
--WELL GROUP LOCATION BHP PI
--NAME NAME I J DEPTH DEFN
WELSPECS
'INJ1' 'G' 1 1 1* 'WATER' 1* 'STD' 'SHUT' 'NO' /
'PROD1' 'G' 19 19 1* 'WATER' 1* 'STD' 'SHUT' 'NO' /
/
-- COMPLETION SPECIFICATION DATA
---
--WELL -LOCATION- OPEN/ SAT CONN WELL
--NAME I J K1 K2 SHUT TAB FACT DIAM
COMPDAT
'PROD1' 19 19 1 10 'OPEN' 2* 0.5 /
'INJ1' 1 1 1 10 'OPEN' 2* 0.5 /
/
-- SELECCIONAR WCONPROD Y WCONINJE SEGUN LA SENSIBILIDAD QUE QUERA (PCTTE
O DECL)
WCONPROD
--WELL OPEN/ CNTL OIL WATER GAS LIQU RES BHP
--NAME SHUT MODE RATE RATE RATE RATE RATE
'PROD1' 'OPEN' 'RESV' 4* 2000 4* /
/
WCONINJE
-- PARA RECORDAR: PARA MANTENER PRESION CONTROLAR RESV. SI CONTROLO LRAT O
RATE Y OUIERO MANTENER PRESION
-- DEBO AJUSTAR POR FACTORES VOLUMETRICOS BW Y BO.
--WELL INJ OPEN/ CNTL SURF . FLOW RESV. FLOW BHP
--NAME TYPE SHUT MODE RATE RATE RATE
                                            UPPER
'INJ1' 'WATER' 'OPEN' 'RESV' 1* 2000 4* /
/
-- WCONPROD
-- 'PROD1' 'OPEN' 'LRAT' 3* 20 5* /
-- /
-- WCONINJE
-- 'INJ1' 'WATER' 'OPEN' 'RATE' 20 5* /
-- /
RPTSCHED
FIP=2 WELLS=4 /
TUNING
1*10/
/
```

TSTEP -- 25 years 900*50 /

/

END ============

APPENDIX E

EXAMPLE OF SIMULATION MODEL FOR HETEROGENEOUS RESERVOIR

----Black Oil model for waterflooding process.

-- This model is only for WATER INJECTION.

-- Grid 19x19x10 = 3610 cells

RUNSPEC TITLE 350204 homogeneous vs. heterogeneous VR=0.1 DIMENS -- NX NY NZ 19 19 10 /

NONNC

OIL

WATER

FIELD

IMPLICIT

EQLDIMS 1 100 50 1 50 /

TABDIMS --# of sat #of PVT max # sat max # press max # of max # Rs --tables tables nodes nodes FIP regions nodes 1 1 100 100 1 100 /

WELLDIMS --max # #of conn max # max # wells --wells per well groups per group 5 50 2 5 /

START 19 'JUL' 2006 /

-- Specifies the size of the stack for Newton iterations NSTACK 10 /

UNIFOUT

UNIFIN

DEBUG

```
EQUALS
'DX' 20 /
'DY' 20 /
'DZ' 10 /
'PORO' 0.3 /
'TOPS' 8325 1 19 1 19 1 1 /
'PERMX' 200 1 19 1 19 1 1 /
'PERMX' 140 1 19 1 19 2 2 /
'PERMX' 110 1 19 1 19 3 3 /
'PERMX' 80 1 19 1 19 4 4 /
'PERMX' 60 1 19 1 19 5 5 /
'PERMX' 40 1 19 1 19 6 6 /
'PERMX' 10 1 19 1 19 7 7 /
'PERMX' 5 1 19 1 19 8 8 /
'PERMX' 1 1 1911999/
'PERMX' 0.2 1 19 1 19 10 10 /
/
COPY
 'PERMX' 'PERMY' 1 19 1 19 1 10 /
 'PERMX' 'PERMZ' 1 19 1 19 1 10 /
/
MULTIPLY
-- Kv/Kh
PERMZ 0.1 1 19 1 19 1 10 /
/
INIT
PROPS =======
SWOF
-- Sw Krw Kro
                             PCwo
-- Sat water int = 0.4
0.25
                       0
                             0.9
                       0.00025
0.254166667
                       0.001 0.841
0.258333333
                       0.00225
0.2625
0.266666667
                       0.004 0.784
0.270833333
                       0.00625
0.275
                       0.009 0.729
0.279166667
                       0.01225
```

0.283333333

0.291666667

0.2875

0

0

0

0

0

0

0.016 0.676

0.025 0.625

0.02025

0.87025 0

0.81225 0

0.75625 0

0.70225 0

0.65025 0

200001/

GRID

148

0.295833333	0.03025	0.60025 0
0.3	0.036 0.576	0
0.304166667	0.04225	0.55225 0
0.308333333	0.049 0.529	0
0.3125	0.05625	0.50625 0
0.316666667	0.064 0.484	0
0.320833333	0.07225	0.46225 0
0.325	0.081 0.441	0
0.329166667	0.09025	0.42025 0
0.333333333	0.1 0.4	0
0.3375	0.11025	0.38025 0
0.341666667	0.121 0.361	0
0.345833333	0.13225	0.34225 0
0.35	0.144 0.324	0
0.354166667	0.15625	0.30625 0
0.358333333	0.169 0.289	0
0.3625	0.18225	0.27225 0
0.366666667	0.196 0.256	0
0.370833333	0.21025	0.24025 0
0.375	0.225 0.225	0
0.379166667	0.24025	0.21025 0
0.383333333	0.256 0.196	0
0.3875	0.27225	0.18225 0
0.391666667	0.289 0.169	0
0.395833333	0.30625	0.15625 0
0.4	0.324 0.144	0
0.404166667	0.34225	0.13225 0
0.408333333	0.361 0.121	0
0.4125	0.38025	0.11025 0
0.416666667	0.4 0.1	0
0.420833333	0.42025	0.09025 0
0.425	0.441 0.081	0
0.429166667	0.46225	0.07225 0
0.433333333	0.484 0.064	0
0.4375	0.50625	0.05625 0
0.441666667	0.529 0.049	0
0.445833333	0.55225	0.04225 0
0.45	0.576 0.036	0
0.454166667	0.60025	0.03025 0
0.458333333	0.625 0.025	0
0.4625	0.65025	0.02025 0
0.466666667	0.676 0.016	0
0.470833333	0.70225	0.01225 0
0.475	0.729 0.009	0
0.479166667	0.75625	0.00625 0
0.483333333	0.784 0.004	0
0.4875	0.81225	0.00225 0
0.491666667	0.841 0.001	0
0.495833333	0.87025	0.00025 0
0.5	0.9 0	0
Sat oil res = 0.2		
/		

-- PVT PROPERTIES OF WATER -- REF. PRES. REF. FVF COMPRESSIBILITY REF VISCOSITY VISCOSIBILITY **PVTW** 4014.7 1.0 3.13D-6 3.0 0/ ROCK -- REF. PRES COMPRESSIBILITY 14.7 3.0D-6 / DENSITY -- OIL WATER GAS 49.1 62.428 0.06054 / **PVDO** --to be updated --Press Bo Visc 400 1.0004 5.160 1200 1.0003 5.164 2000 1.0002 5.167 2800 1.0001 5.550 3600 1.0000 5.000 4400 0.9999 5.0001 5200 0.9998 5.0002 6000 0.9997 5.0003 7000 0.9996 5.0004 8000 0.9995 5.0005 9000 0.9994 5.0006 / SOLUTION ========= -- DATA FOR INITIALIZING FLUIDS TO POTENTIAL EQUILIBRIUM --

-- DATUM DATUM OWC OWC GOC GOC RSVD RVVD SOLN -- DEPTH PRESS DEPTH PCOW DEPTH PCOG TABLE TABLE METH EQUIL 8400 3665.3518 15000 0 /

RPTRST BASIC=2 /

SUMMARY ========

--REQUEST PRINTED OUTPUT OF SUMMARY FILE DATA

RUNSUM

-- FIELD OIL PRODUCTION, Cumulative oil prod. for field and for every well FOPR

FOPT WOPT / WOPR / -- FIELD WATER INJ. RATE, Cumulative water inj. for field and for every well FWIR FWIT WWIT WWIR / --INSTANTANEOUS WATER CUTS FOR FIELD AND FOR EVERY WELL. FWCT WWCT FWPR WWPR / --OIL IN PLACE for field and for every FIP Region FOIP ROIP / --Water in place for field and for every FIP region FWIP RWIP / --Average PRESSURE for field and for every FIP region FPR RPR / -- WELL BOTTOM-HOLE PRESSURE WBHP / TCPU ELAPSED SEPARATE RPTONLY SCHEDULE ===== ----- THE SCHEDULE SECTION DEFINES THE OPERATIONS TO BE SIMULATED

-- WELL SPECIFICATION DATA

```
--WELL GROUP LOCATION BHP PI
--NAME NAME I J DEPTH DEFN
WELSPECS
'INJ1' 'G' 1 1 1* 'WATER' 1* 'STD' 'SHUT' 'NO' /
'PROD1' 'G' 19 19 1* 'WATER' 1* 'STD' 'SHUT' 'NO' /
/
-- COMPLETION SPECIFICATION DATA
--WELL -LOCATION- OPEN/ SAT CONN WELL
--NAME I J K1 K2 SHUT TAB FACT DIAM
COMPDAT
'PROD1' 19 19 1 10 'OPEN' 2* 0.5 /
'INJ1' 1 1 1 10 'OPEN' 2* 0.5 /
/
WCONPROD
--WELL OPEN/ CNTL OIL WATER GAS LIQU RES BHP
--NAME SHUT MODE RATE RATE RATE RATE RATE
'PROD1' 'OPEN' 'RESV' 4* 2000 4* /
/
WCONINJE
--WELL INJ OPEN/ CNTL SURF. FLOW RESV. FLOW BHP
--NAME TYPE SHUT MODE RATE RATE RATE UPPER
'INJ1' 'WATER' 'OPEN' 'RESV' 1* 2000 4* /
/
-- WCONPROD
-- 'PROD1' 'OPEN' 'LRAT' 3* 20 5* /
-- /
---
-- WCONINJE
-- 'INJ1' 'WATER' 'OPEN' 'RATE' 20 5* /
-- /
RPTSCHED
FIP=2 WELLS=4 /
TUNING
1*10/
/
TSTEP
-- 25 years
900*50 / END
```

APPENDIX F

APPLICATION IN VBA FOR QUICK SLZ AND RECOVERY CALCULATIONS

Arnaldo Espinel ' This procedure calculates Waterflooding projects performance ' Part one: ' Declaration of Variables Option Explicit

' Fractional Flow Calculations

Sub homogeneous()

Dim i, j, moil, mwater, no, nw, kroe, krwe, sor, swc, M, x8, VDP, WOR, logM, lWOR, e, x1, x12, x13, VR, Slope, Intercept, RF, RFprev, RFheter, PVI, PVIhomo, PVIhomorev, PVIrev, fwBT, SwBT, maxlog, wet As Double

Dim maxlog05, maxlog06, maxlog07, maxlog08, maxlog09, maxlog05a, maxlog06a, maxlog07a, maxlog08a, maxlog09a, minwor As Double

Dim points, sw(10000), kro(10000), krw(10000), swd(10000), fw(10000), pointsVDP(10000), RFheter2, RFhetery, PVI2 As Double

Dim x2, x3, x4, x5, x6, x7, x9, x10, x11, x120, x130, lwor2, RFprev2, RF2, worhomomin, worhomomina, worhomomaxa As Double

' Data Table construction

With ThisWorkbook.Worksheets("Calculations") Range("d1,d200:n1,n200").ClearContents Cells(1, 1) = "Input your data before running:" Cells(2, 1) = "Reservoir Name" 'Name = .Cells(2, 2)Cells(3, 1) = "Oil Viscosity, cP"moil = Cells(3, 2)Cells(4, 1) = "Water Viscosity, cP" mwater = Cells(4, 2)Cells(5, 1) = "Corey exponent for oil(no)" no = Cells(5, 2)Cells(6, 1) = "Corey exponent for water(nw)"nw = Cells(6, 2)Cells(7, 1) = "Oil rel perm curve end-point (kroe)"kroe = Cells(7, 2)Cells(8, 1) = "Water rel perm curve end-point (krwe)" krwe = Cells(8, 2)Cells(9, 1) = "Residual oil saturation (Sor)" sor = Cells(9, 2)Cells(10, 1) = "Connate water saturation (Swc)" swc = Cells(10, 2)Cells(11, 1) = "Dykstra-Parsons coeff. (VDP)" VDP = Cells(11, 2)Cells(12, 1) = "Water-wet=1 or Oil-wet=2" wet = Cells(12, 2)Cells(13, 1) = "Estimated max operational WOR" WOR = Cells(13, 2)

'wettability according to kr's plot: points = 10For i = 1 To points + 1If i = 1 Then sw(i) = swcElse sw(i) = swc + (1 - swc - sor) * (i - 1) / pointsEnd If 'normalizing swd(i) = (sw(i) - swc) / (1 - sor - swc) $kro(i) = kroe * (1 - swd(i)) ^ no$ $krw(i) = krwe * swd(i) ^ nw$ If krw(i) = 0 Then fw(i) = 0Else fw(i) = 1 / (1 + kro(i) * mwater / (krw(i) * moil))End If Cells(1, 10) = "Sw"Cells(1, 11) = "SwD"Cells(1, 11) = "Kro"Cells(1, 12) = "Krw"Cells(1, 13) = "fw"Cells(i + 1, 10) = sw(i)'Cells(i + 1, 11) = swd(i)Cells(i + 1, 11) = kro(i)Cells(i + 1, 12) = krw(i)Cells(i + 1, 13) = fw(i)Next i ' Parameters calculations M = (krwe / mwater) / (kroe / moil)x8 = M $\log M = Log(M) / Log(10)$ e = 2.71828182845905 x1 = (mwater / moil) / nox2 = (mwater / moil)x3 = nox4 = nwx5 = swcx6 = sor $x7 = \log M$ 'Homogeneous oil-wet: If wet = 2 Then Slope = 0.77519 + 8.93429 * x1 - 3.36474 * x2 + 2.67364 * x4 + 28.2328 * x6 - 8.40355 * x7 Intercept = -3.4254 - 11.94 * x1 + 4.78633 * x2 - 1.4167 * x4 - 0.33004 * x5 - 0.0606 * x6 + 5.30721 * 1.4167 * x4 - 0.33004 * x5 - 0.0606 * x6 + 5.30721 * 1.4167 * x4 - 0.33004 * x5 - 0.0606 * x6 + 5.30721 * 1.4167 * x4 - 0.33004 * x5 - 0.0606 * x6 + 5.30721 * 1.4167 * x4 - 0.33004 * x5 - 0.0606 * x6 + 5.30721 * 1.4167 * x4 - 0.33004 * x5 - 0.0606 * x6 + 5.30721 * 1.4167 * 1.

x7

fwBT = 0.6598 + 0.11888 * x1 - 0.04844 * x2 + 0.02099 * x3 + 0.05127 * x4 - 0.09342 * x7

SwBT = 0.56187 + 0.16777 * x1 - 0.0687 * x2 - 0.022 * x3 + 0.04494 * x4 + 0.41472 * x5 - 0.5853 * 0.x6 - 0.1454 * x7 'Homogeneous water-wet Else Slope = 1.29383 + 27.8154 * x1 - 6.7911 * x2 + 2.08358 * x4 + 4.76521 * x5 + 22.3142 * x6 - 4.794 * x7 Intercept = -1.5668 - 30.399 * x1 + 8.83008 * x2 - 1.5008 * x4 - 0.5834 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x4 - 0.5834 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x4 - 0.5834 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008 * x6 - 0.1052 * x5 + 4.03107 * 1.5008x7 fwBT = 0.71084 + 0.20212 * x1 - 0.08234 * x2 + 0.01779 * x3 + 0.03932 * x4 - 0.09479 * x7 SwBT = 0.64301 + 0.23901 * x1 - 0.1003 * x2 - 0.0302 * x3 + 0.03722 * x4 + 0.34619 * x5 - 0.6538 * x6 - 0.1548 * x7 End If 'All max log general: 'If wet = 2 Then ' maxlog = 1.82775 + 0.0629 * x8 - 0.47157 * VDP 'Else $\max \log = 5.15914 + 0.13366 * x8 - 9.6964 * VDP + 0.62073 * (10 ^ VDP)$ 'End If 'All max log with constrains for case dependent cases VR = mwater / moil'maxwor and minwor homo: 'water-wet: If wet = 1 Then worhomomina = $10 \land (0.10547 + 0.31449 * VR + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * 0.08504 * no + 0.18375 * nw + 0.56262 * sor + 0.08504 * 0$ 0.15521 * swc + 0.10024 * kroe + 0.11893 * krwe - 0.01843 * Mworhomomaxa = $10 \wedge (1.31556 - 0.24884 * VR + 0.60999 * no + 0.06739 * nw - 0.66761 * sor - 1.25442$ * swc - 0.0454 * kroe - 0.24884 * krwe + 0.06416 * M) Else 'oil-wet: worhomomina = $10 \land (-0.10923 + 0.36546 * VR + 0.06644 * no + 0.18869 * nw + 0.41633 * sor + 0.10923 + 0.$ 0.17015 * swc + 0.23567 * kroe - 0.04279 * krwe + 0.01746 * M) swc - 1.29377 * kroe + 0.74267 * krwe - 0.12195 * M) End If If wet = 2 Then $\max\log_{10} 05 = 1.93449 + 0.02621 * x8 - 0.45239 * (0.5) - 0.00594 * (10^{(0.5)})$ Else $maxlog05 = 5.15914 + 0.13366 * x8 - 9.6964 * (0.5) + 0.62073 * (10^{(0.5)})$

End If

If wet = 2 Then $maxlog06a = 1.93449 + 0.02621 * x8 - 0.45239 * (0.6) - 0.00594 * (10^{(0.6)})$ Else $max \log 06a = 5.15914 + 0.13366 * x8 - 9.6964 * (0.6) + 0.62073 * (10^{(0.6)})$ End If If wet = 2 Then $maxlog07a = 1.93449 + 0.02621 * x8 - 0.45239 * (0.7) - 0.00594 * (10^{(0.7)})$ Else $\max \log 07a = 5.15914 + 0.13366 * x8 - 9.6964 * (0.7) + 0.62073 * (10^{(0.7)})$ End If If wet = 2 Then $maxlog08a = 1.93449 + 0.02621 * x8 - 0.45239 * (0.8) - 0.00594 * (10^{(0.8)})$ Else $\max \log 0.08a = 5.15914 + 0.13366 * x8 - 9.6964 * (0.8) + 0.62073 * (10^{(0.8)})$ End If If wet = 2 Then $maxlog09a = 1.93449 + 0.02621 * x8 - 0.45239 * (0.9) - 0.00594 * (10^{(0.9)})$ Else $\max\log 0.9a = 5.15914 + 0.13366 * x8 - 9.6964 * (0.9) + 0.62073 * (10^{(0.9)})$ End If If $maxlog06a \ge maxlog05$ Then maxlog06 = maxlog05 - (maxlog05 * 0.1)Else maxlog06 = maxlog06aEnd If If maxlog07a >= maxlog06a Then maxlog07 = maxlog06a - (maxlog06a * 0.1)Else maxlog07 = maxlog07aEnd If If maxlog08a >= maxlog07a Then maxlog08 = maxlog07a - (maxlog07a * 0.1)Else maxlog08 = maxlog08aEnd If If maxlog09a >= maxlog08a Then maxlog09 = maxlog08a - (maxlog08a * 0.1)Else maxlog09 = maxlog09aEnd If If VDP ≤ 0.5 Then maxlog = maxlog05Else If VDP > 0.5 And $VDP \le 0.65$ Then maxlog = maxlog06End If If VDP > 0.65 And VDP ≤ 0.75 Then maxlog = maxlog07

End If If VDP > 0.75 And VDP ≤ 0.85 Then maxlog = maxlog08End If If VDP > 0.85 And VDP ≤ 1 Then maxlog = maxlog09End If End If If VDP > 0.5 Then If wet = 1 Then 'minwor = $10^{(5.14786 * (VDP^2) - 8.44063 * (VDP) + 3.81754)}$ minwor = 10 ^ (0.01738 * M + 9.73473 * (VDP ^ 2) - 10.83657 * (VDP) + 4.9169 - 0.33856 * (10 ^ VDP)) Else 'minwor = 10 ^ (1.27008 - 1.27427 * (VDP ^ 2)) minwor = 10 ^ (2.37473 + 0.02337 * M - 2.99912 * VDP - 0.22364 * (10 ^ VDP) + 2.88892 * VDP ^ 2) End If Else If wet = 1 Then minwor = $10 \land (0.01738 \ast M + 9.73473 \ast (0.5 \land 2) - 10.83657 \ast (0.5) + 4.9169 - 0.33856 \ast (10 \land 0.5))$ Else minwor = $10^{(2.37473 + 0.02337 * M - 2.99912 * 0.5 - 0.22364 * (10^{(0.5)} + 2.88892 * 0.5^{(2)})$ End If End If

```
If VDP = 0.9 And wet = 2 Then
minwor = 5
End If
```

If worhomomina > $(10 \land (2.37473 + 0.02337 * M - 2.99912 * 0.5 - 0.22364 * (10 \land 0.5) + 2.88892 * 0.5 \land 2))$ Then worhomomin = worhomomina Else worhomomin = $(10 \land (2.37473 + 0.02337 * M - 2.99912 * 0.5 - 0.22364 * (10 \land 0.5) + 2.88892 * 0.5 \land 2))$ * 1.3 End If

If worhomomaxa > $10 \land (maxlog05)$ Then worhomomax = worhomomaxa Else worhomomax = $10 \land (maxlog05) * 1.3$ End If

Cells(26, 1) = "WOR homo min" Cells(26, 2) = worhomomin Cells(27, 1) = "WOR homo max" Cells(27, 2) = worhomomax 'Recovery Calculations |WOR = Log(WOR) / Log(10)RFprev = (|WOR - Intercept) / Slope 'RF constrain If RFprev > (1 - x6) Then RF = (1 - x6) Else RF = RFprev End If

```
\begin{array}{l} x12 = e^{(1WOR)} \\ x13 = 10^{(1WOR)} \\ 1wor2 = Log(0.1) / Log(10) \\ x120 = e^{(1Log(worhomomax) / Log(10)))} \\ x130 = 10^{((Log(worhomomax) / Log(10)))} \end{array}
```

```
Cells(14, 4) = "Message:"
Cells(14, 1) = "Results:"
Cells(15, 1) = "Slope"
Cells(15, 2) = Slope
Cells(16, 1) = "Intercept"
Cells(16, 2) = Intercept
Cells(17, 1) = "fwBT"
Cells(17, 2) = fwBT
Cells(18, 1) = "SwBT"
Cells(18, 2) = SwBT
Cells(19, 1) = "Max WOR"
Cells(19, 2) = 10^{n} maxlog
Cells(20, 1) = "Min WOR"
Cells(20, 2) = minwor
Cells(21, 1) = "Recovery Factor homogeneous"
Cells(21, 2) = RF
Cells(22, 1) = "PVI homogeneous"
Cells(23, 1) = "Mobility Ratio"
Cells(23, 2) = x8
```

' Calculation of SLZ end:

If VDP < 0.5 Then RFheter = RF Else 'water-wet and heterogeneous calculations If VDP >= 0.5 And VDP <= 0.65 And wet = 1 Then RFheter = -0.18015 + 1.27511 * RF PVI = -1.05462 + 0.46384 * x8 + 0.00912 * x13 + 0.28413 * x12 End If If VDP > 0.65 And VDP <= 0.75 And wet = 1 Then RFheter = 0.19068 - 0.00368 * x8 + 0.02336 * 1WOR + 0.91971 * RF ^ 2 $\begin{array}{l} PVI = -1.2156 + 0.47344 * x8 + 0.01136 * x13 + 0.31097 * x12 \\ End If \\ If VDP > 0.75 And VDP <= 0.85 And wet = 1 Then \\ RFheter = 0.09829 - 0.00751 * x8 + 0.05354 * IWOR + 0.88719 * RF ^ 2 \\ PVI = -2.06505 + 0.58703 * x8 + 0.01217 * x13 + 0.57103 * x12 \\ End If \\ If VDP > 0.85 And VDP <= 1 And wet = 1 Then \\ RFheter = 0.1718 - 0.0144 * x8 + 0.07227 * IWOR + 0.44117 * RF ^ 2 \\ PVI = -0.45357 - 0.08084 * x8 + 0.02353 * x13 + 0.19269 * x12 \\ End If \\ End If \\ End If \end{array}$

'oil-wet and heterogeneous calculations If VDP ≤ 0.5 Then RFheter = RFElse If VDP > 0.5 And VDP ≤ 0.65 And wet = 2 Then RFheter = -0.0988 + 1.27817 * RF PVI = -1.26805 + 0.49769 * x8 + 0.00238 * x13 + 0.37376 * x12 End If If VDP > 0.65 And VDP ≤ 0.75 And wet = 2 Then RFheter = 0.09036 - 0.00226 * x8 + 0.01459 * IWOR + 1.78812 * RF ^ 2 PVI = -1.11471 + 0.43417 * x8 + 0.00691 * x13 + 0.30144 * x12 End If If VDP > 0.75 And VDP ≤ 0.85 And wet = 2 Then $RFheter = 0.06727 - 0.00489 * x8 + 0.03839 * IWOR + 1.27549 * RF^{2}$ PVI = -1.26744 + 0.45081 * x8 + 0.01279 * x13 + 0.32235 * x12 End If If VDP > 0.85 And VDP ≤ 1 And wet = 2 Then RFheter = 0.0748 - 0.00535 * x8 + 0.04112 * IWOR + 0.88482 * RF ^ 2 PVI = -0.64968 + 0.18524 * x8 + 0.0137 * x13 + 0.22142 * x12 End If End If

```
If wet = 1 Then

PVIhomo = -0.81246 + 0.35196 * x8 + 0.008 * x13 + 0.21624 * x12

Else

PVIhomo = -0.86243 + 0.41381 * x8 + 0.00194 * x13 + 0.24178 * x12

End If

If PVIhomo < 0.2 Then

PVIhomorev = 0.2

Else

PVIhomorev = PVIhomo

End If
```

Cells(22, 2) = PVIhomorev

If VDP <= 0.5 Then PVIrev = PVIhomorev

Else PVIrev = PVIEnd If If PVI < 0.1 Then PVIrev = 0.1Else PVIrev = PVIEnd If If RFheter > RF Then RFheterx = RF * 0.9Else RFheterx = RFheter End If If RFheter < 0 Then RFhetery = RF * 0.9Else RFhetery = RFheter End If

If RFheter < 0 Then Cells(24, 1) = "RF heterogeneous" Cells(24, 2) = RFhetery Else Cells(24, 1) = "RF heterogeneous" Cells(24, 2) = RFheterx End If

Cells(25, 1) = "PVI Heterogeneous" If VDP <= 0.5 Then Cells(25, 2) = PVIhomorev Else Cells(25, 2) = PVIrev End If

If PVIhomo >= 3 Or IWOR > maxlog Then Cells(15, 4) = "Warning: due to the high WOR used, your RF value may be close to or beyond he end of the SLZ" Cells(16, 4) = "Correlations are defined only for the SLZ so higher values of max WOR must be ingnored" Cells(17, 4) = "If you obtain recovery factors for heterogeneous reservoirs higher than the correspondent" Cells(18, 4) = "homogeneous recovery factor, you are extrapolating the SLZ and overestimating reserves" Cells(19, 4) = "if that is the case, please try a lower WOR value (please check suggested Max Log WOR)" Else Cells(15, 4) = "No problem has been detected. Please continue your evaluation"

End If

Cells(24, 1) = "RF heterogeneous" Cells(24, 2) = RFheter

End With

End Sub

APPENDIX G

VARIABLES SELECTION PROCESSES AND COVARIANCE MATRIX RESULTS

Variable Selection and Covariance Matrix for the water-wet homogeneous model (Slope)

The REG Procedure Model: MODEL1 Dependent Variable: slope

Number of Observations Read226977Number of Observations Used226977

Forward Selection: Step 1

Statistics for Entry DF = 1,226975

Model

Variable Tolerance R-Square F Value Pr > F

x1	1.000000	0.4993 226317 <.0001
x2	1.000000	0.4417 179557 <.0001
x4	1.000000	0.3137 103754 <.0001
x5	1.000000	0.0042 964.74 <.0001
x6	1.000000	0.0127 2919.78 <.0001
x7	1.000000	0.4748 205174 <.0001

Variable x1 Entered: R-Square = 0.4993 and C(p) = 1235459

Analysis of Variance

Model 1 1735328 1735328 226317 <.0001 Error 226975 1740372 7.66768 Corrected Total 226976 3475700

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1, 1

Forward Selection: Step 2 The SAS System 09:56 Saturday, October 3, 2009 2888

The REG Procedure Model: MODEL1 Dependent Variable: slope

Forward Selection: Step 2

```
Statistics for Entry
DF = 1,226974
```

Model Variable Tolerance R-Square F Value Pr > F

x2	0.121152	0.4993	17.78 <.0001
x4	0.999971	0.8173	394957 <.0001
x5	0.990126	0.4993	12.16 0.0005
x6	0.977372	0.5483	24657.2 <.0001
x7	0.222493	0.5188	9233.19 <.0001

Variable x4 Entered: R-Square = 0.8173 and C(p) = 306744.1

Analysis of Variance

 $\begin{array}{ccc} Sum \mbox{ of } Mean\\ Source & DF \mbox{ Squares } Square \mbox{ F Value } Pr > F \end{array}$

 Model
 2
 2840550
 1420275
 507543
 <.0001</th>

 Error
 226974
 635150
 2.79834
 <.0001</td>

 Corrected Total
 226976
 3475700

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1, 4.0001

Forward Selection: Step 3

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Forward Selection: Step 3

Statistics for Entry DF = 1,226973

Model Variable Tolerance R-Square F Value Pr > F

x2	0.120862	0.8177	566.47 <.0001
x5	0.985080	0.8193	2606.96 <.0001
x6	0.972575	0.8857	135979 <.0001
x7	0.221813	0.8291	15755.4 <.0001

Variable x6 Entered: R-Square = 0.8857 and C(p) = 106791.5

Analysis of Variance

 $\begin{array}{ccc} Sum \mbox{ of } Mean\\ Source & DF \mbox{ Squares } Square \mbox{ F Value } Pr > F \end{array}$

3 3078507 1026169 586397 <.0001 Model 226973 397193 1.74996 Error Corrected Total 226976 3475700 Parameter Standard Variable Estimate Error Type II SS F Value Pr > F Intercept -1.63770 0.01350 25755 14717.4 <.0001 x1 25.42569 0.02435 1908473 1090583 <.0001 $2.06667 \quad 0.00252 \quad 1172641 \quad 670097 < .0001$ x4 x6 20.77006 0.05633 237957 135979 <.0001 Bounds on condition number: 1.0282, 9.1697

Forward Selection: Step 4

The SAS System 09:56 Saturday, October 3, 2009 2890

The REG Procedure Model: MODEL1 Dependent Variable: slope

Forward Selection: Step 4

Statistics for Entry DF = 1,226972

x2	0.120806	0.8865	1458.51	<.0001
x5	0.950012	0.8951	20208.0	<.0001
x7	0.221782	0.8969	24655.3	<.0001

Variable x7 Entered: R-Square = 0.8969 and C(p) = 74090.55

Analysis of Variance

Model 4 3117425 779356 493733 <.0001 Error 226972 358275 1.57850 Corrected Total 226976 3475700

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 4.537, 44.33

Forward Selection: Step 5

The SAS System 09:56 Saturday, October 3, 2009 2891

The REG Procedure Model: MODEL1 Dependent Variable: slope

Forward Selection: Step 5

Statistics for Entry DF = 1,226971

Model Variable Tolerance R-Square F Value Pr > F

Variable x2 Entered: R-Square = 0.9132 and C(p) = 26468.81

Analysis of Variance

 Model
 5
 3174100
 634820
 477738
 <.0001</th>

 Error
 226971
 301600
 1.32880

 634820
 477738
 <.0001</td>

Bounds on condition number: 14.523, 164.04

Forward Selection: Step 6

The SAS System 09:56 Saturday, October 3, 2009 2892

The REG Procedure Model: MODEL1 Dependent Variable: slope

Forward Selection: Step 6

Statistics for Entry DF = 1,226970

x5 0.949089 0.9223 26463.8 <.0001

Variable x5 Entered: R-Square = 0.9223 and C(p) = 7.0000

Analysis of Variance Sum of Mean $DF \quad Squares \quad Square \ F \ Value \ Pr > F$ Source Model Error Corrected Total 226976 3475700 Parameter Standard Variable Estimate Error Type II SS F Value Pr > F Intercept 1.29383 0.02174 4214.70878 3541.61 <.0001 27.81540 0.05745 278940 234393 <.0001 x1 -6.79106 0.03085 57684 48472.0 <.0001 x2 x4 2.08358 0.00209 1178686 990447 <.0001 x5 4.76521 0.02929 31493 26463.8 <.0001 22.31418 0.04731 264688 222417 <.0001 x6 x7 -4.79404 0.01729 91544 76924.2 <.0001 Bounds on condition number: 14.526, 203.73 _____

All variables have been entered into the model.

The SAS System 09:56 Saturday, October 3, 2009 2893

The REG Procedure Model: MODEL1 Dependent Variable: slope

Summary of Forward Selection

Variable Number Partial Model Step Entered Vars In R-Square R-Square C(p) F Value Pr > F

> The REG Procedure Model: MODEL1 Dependent Variable: slope

Number of Observations Read 226977 Number of Observations Used 226977

Backward Elimination: Step 0

All Variables Entered: R-Square = 0.9223 and C(p) = 7.0000

Analysis of Variance

 Sum of
 Mean

 Source
 DF
 Squares
 Square F Value
 Pr > F

 Model
 6
 3205594
 534266
 448942
 <.0001</td>

 Error
 226970
 270106
 1.19005
 Corrected Total
 226976
 3475700

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 14.526, 203.73

Backward Elimination: Step 1

The SAS System 09:56 Saturday, October 3, 2009 2895

The REG Procedure Model: MODEL1 Dependent Variable: slope

Backward Elimination: Step 1

Statistics for Removal DF = 1,226970

Partial Model Variable R-Square F Value Pr > F

x1	0.0803	0.8420	234393	<.0001
x2	0.0166	0.9057	48472.0	<.0001
x4	0.3391	0.5832	990447	<.0001
x5	0.0091	0.9132	26463.8	<.0001
x6	0.0762	0.8461	222417	<.0001
x7	0.0263	0.8959	76924.2	<.0001

All variables left in the model are significant at the 0.0500 level. The SAS System 09:56 Saturday, October 3, 2009 2896

> The REG Procedure Model: MODEL1 Dependent Variable: slope

Number of Observations Read 226977 Number of Observations Used 226977

Stepwise Selection: Step 1

Statistics for Entry DF = 1,226975

Model

Variable Tolerance R-Square F Value Pr > F

x1 1.000000 0.4993 226317 <.0001

 x2
 1.000000
 0.4417
 179557
 <.0001</th>

 x4
 1.000000
 0.3137
 103754
 <.0001</td>

 x5
 1.000000
 0.0042
 964.74
 <.0001</td>

 x6
 1.000000
 0.0127
 2919.78
 <.0001</td>

 x7
 1.000000
 0.4748
 205174
 <.0001</td>

Variable x1 Entered: R-Square = 0.4993 and C(p) = 1235459

Analysis of Variance

Parameter Standard

Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1, 1

Stepwise Selection: Step 2 The SAS System 09:56 Saturday, October 3, 2009 2897

The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 2

Statistics for Entry DF = 1,226974

Model

Variable Tolerance R-Square F Value Pr > F

x2	0.121152	0.4993	17.78 <.0001
x4	0.999971	0.8173	394957 <.0001
x5	0.990126	0.4993	12.16 0.0005
x6	0.977372	0.5483	24657.2 <.0001
x7	0.222493	0.5188	9233.19 <.0001

Variable x4 Entered: R-Square = 0.8173 and C(p) = 306744.1

Analysis of Variance

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F Bounds on condition number: 1, 4.0001

Stepwise Selection: Step 3

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 3

Statistics for Removal DF = 1,226974

Partial Model Variable R-Square F Value Pr > F

> Statistics for Entry DF = 1,226973

Model Variable Tolerance R-Square F Value Pr > F

x2	0.120862	0.8177 566.47 <.0001
x5	0.985080	0.8193 2606.96 <.0001
x6	0.972575	0.8857 135979 <.0001
x7	0.221813	0.8291 15755.4 <.0001

Variable x6 Entered: R-Square = 0.8857 and C(p) = 106791.5

Analysis of Variance

Source Sum of Mean DF Squares Square F Value Pr > FModel 3 3078507 1026169 586397 <.0001

Error 226973 397193 1.74996 Corrected Total 226976 3475700

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Intercept -1.63770 0.01350 25755 14717.4 <.0001 x1 25.42569 0.02435 1908473 1090583 <.0001 x4 2.06667 0.00252 1172641 670097 <.0001 x6 20.77006 0.05633 237957 135979 <.0001 The SAS System 09:56 Saturday, October 3, 2009 2899 The REG Procedure

Model: MODEL1 Dependent Variable: slope Stepwise Selection: Step 3

Bounds on condition number: 1.0282, 9.1697

Stepwise Selection: Step 4

Statistics for Removal DF = 1,226973

Partial Model Variable R-Square F Value Pr > F

x1	0.5491	0.3366	1090583 <.0001
x4	0.3374	0.5483	670097 <.0001
x6	0.0685	0.8173	135979 <.0001

Statistics for Entry DF = 1,226972

 $\begin{array}{c} Model\\ Variable & Tolerance & R-Square & F Value & Pr > F \end{array}$

Variable x7 Entered: R-Square = 0.8969 and C(p) = 74090.55

Analysis of Variance

Bounds on condition number: 4.537, 44.33

Stepwise Selection: Step 5

Statistics for Removal

DF = 1,226972

> Statistics for Entry DF = 1,226971

ModelVariableToleranceR-SquareF ValuePr > Fx20.0688540.913242651.0<.0001</td>

x5 0.949226 0.9057 21107.9 <.0001

Variable x2 Entered: R-Square = 0.9132 and C(p) = 26468.81

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 5

Analysis of Variance

 Model
 5
 3174100
 634820
 477738
 <.0001</th>

 Error
 226971
 301600
 1.32880

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 14.523, 164.04

Stepwise Selection: Step 6

Statistics for Removal DF = 1,226971

Partial Model Variable R-Square F Value Pr > F

 $0.3320 \quad 0.5812 \quad 868479 \ < .0001$ x4 0.0690 0.8442 180500 <.0001 x6 $0.0268 \quad 0.8865 \ 70030.7 \ < .0001$ x7 The SAS System 09:56 Saturday, October 3, 2009 2902 The REG Procedure Model: MODEL1 Dependent Variable: slope Stepwise Selection: Step 6 Statistics for Entry DF = 1,226970 Model Variable Tolerance R-Square F Value Pr > F x5 0.949089 0.9223 26463.8 <.0001 Variable x5 Entered: R-Square = 0.9223 and C(p) = 7.0000 Analysis of Variance Sum of Mean Source DF Squares Square F Value Pr > F 6 3205594 534266 448942 <.0001 Model 226970 270106 1.19005 Error Corrected Total 226976 3475700 Parameter Standard Variable Estimate Error Type II SS F Value Pr > F -6.79106 0.03085 57684 48472.0 <.0001 x2 x4 2.08358 0.00209 1178686 990447 <.0001

-4.79404 0.01729 91544 76924.2 <.0001 Bounds on condition number: 14.526, 203.73

4.76521 0.02929 31493 26463.8 <.0001 22.31418 0.04731 264688 222417 <.0001

Stepwise Selection: Step 7

x5 x6 x7

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 7

Statistics for Removal DF = 1,226970

Partial Model Variable R-Square R-Square F Value Pr > F

x1	0.0803	0.8420	234393	<.0001
x2	0.0166	0.9057	48472.0	<.0001
x4	0.3391	0.5832	990447	<.0001
x5	0.0091	0.9132	26463.8	<.0001
x6	0.0762	0.8461	222417	<.0001
x7	0.0263	0.8959	76924.2	<.0001

All variables left in the model are significant at the 0.1500 level.

All variables have been entered into the model.

Summary of Stepwise Selection

Variable Variable Number Partial Model Step Entered Removed Vars In R-Square R-Square C(p) F Value Pr > F

1 x1	1 0.4993 0.4993 1235459 226317 <.0001
2 x4	2 0.3180 0.8173 306744 394957 <.0001
3 x6	3 0.0685 0.8857 106792 135979 <.0001
4 x7	4 0.0112 0.8969 74090.5 24655.3 <.0001
5 x2	5 0.0163 0.9132 26468.8 42651.0 <.0001
6 x5	6 0.0091 0.9223 7.0000 26463.8 <.0001
	The SAS System 09:56 Saturday, October 3, 2009 2904

The REG Procedure Model: MODEL1 Dependent Variable: slope

R-Square Selection Method

Number of Observations Read 226977 Number of Observations Used 226977

Number in

Model R-Square C(p) MSE Variables in Model

1	0.4993	1235459	7.66768 x1
1	0.4748	1307009	8.04283 x7
1	0.4417	1403672	8.54964 x2
1	0.3137	1777411	10.50920 x4
1	0.0127	2656558	15.11866 x6
1	0.0042	2681290	15.24833 x5
2	0.8173	306744.1	2.79834 x1 x4
2	0.7724	437832.0	3.48565 x4 x7
2	0.7466	513178.3	3.88070 x2 x4
2	0.5483	1092158	6.91636 x1 x6
2	0.5188	1178295	7.36799 x1 x7
2	0.5161	1186372	7.41034 x6 x7
2	0.4993	1235346	7.66712 x1 x2
2	0.4993	1235382	7.66731 x1 x5
2	0.4833	1281987	7.91166 x2 x6
2	0.4782	1297127	7.99104 x2 x7
2	0.4749	1306603	8.04072 x5 x7
2	0.4417	1403500	8.54877 x2 x5
2	0.3366	1710476	10.15828 x4 x6
2	0.3144	1775494	10.49918 x4 x5
2	0.0149	2650073	15.08471 x5 x6
3	0.8857	106791.5	1.74996 x1 x4 x6
3	0.8299	269723.4	2.60423 x4 x6 x7
3	0.8291	272103.0	2.61671 x1 x4 x7

```
3 0.8193 300685.6 2.76657 x1 x4 x5
3 0.8177 305417.4 2.79138 x1 x2 x4
3 0.8051 342254.6 2.98453 x2 x4 x6
3 0.7773 423370.6 3.40983 x2 x4 x7
3 0.7730 435871.8 3.47537 x4 x5 x7
3 0.7475 510399.1 3.86613 x2 x4 x5
3 0.5674 1036418 6.62413 x1 x6 x7
3 0.5505 1085862 6.88337 x1 x5 x6
3 0.5483 1092145 6.91632 x1 x2 x6
3 0.5205 1173480 7.34277 x2 x6 x7
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```

Model: MODEL1 Dependent Variable: slope

R-Square Selection Method

Number in

Model R-Square C(p) MSE Variables in Model

3	0.5189	1178284	7.36795 x1 x5 x7
3	0.5167	1184622	7.40119 x5 x6 x7
3	0.4993	1235273	7.66676 x1 x2 x5
3 3	0.4842	1279493	7.89861 x2 x5 x6
3	0.4783	1296864	7.98969 x2 x5 x7
3	0.3366	1710478	10.15833 x4 x5 x6
4	0.8969	74090.55	1.57850 x1 x4 x6 x7
4	0.8951	79507.26	1.60690 x1 x4 x5 x6
4			1.73879 x1 x2 x4 x6
4	0.8442	228011.3	2.38553 x1 x2 x4 x7
4	0.8364	250790.2	2.50496 x2 x4 x6 x7
4	0.8350	255078.8	2.52745 x4 x5 x6 x7
4	0.8309	266771.3	2.58876 x1 x4 x5 x7
4	0.8198	299222.5	2.75890 x1 x2 x4 x5
4	0.8110	325047.6	2.89431 x2 x4 x5 x6
4	0.7782	420941.5	3.39710 x2 x4 x5 x7
4	0.5812	996202.7	6.41329 x1 x2 x6 x7
4	0.5693	1030980	6.59563 x1 x5 x6 x7
4	0.5505	1085860	6.88338 x1 x2 x5 x6
4	0.5317	1140627	7.17053 x1 x2 x5 x7
4	0.5213	1171244	7.33107 x2 x5 x6 x7
5			1.32880 x1 x2 x4 x6 x7
5	0.9057	48476.95	1.44420 x1 x4 x5 x6 x7
5	0.8959	76929.19	1.59338 x1 x2 x4 x5 x6
5	0.8461	222422.2	2.35623 x1 x2 x4 x5 x7
5	0.8420	234398.2	2.41902 x2 x4 x5 x6 x7
5	0.5832	990452.4	6.38316 x1 x2 x5 x6 x7

6 0.9223 7.0000 1.19005 x1 x2 x4 x5 x6 x7

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The CORR Procedure

6 Variables: x1 x2 x4 x5 x6 x7

Covariance Matrix, DF = 226976

x1 x2 x4 x5 x6 x7

x1 0.013310993 0.030600508 -0.000682703 -0.000919871 -0.000867544 -0.037908526 x2 0.030600508 0.080044782 0.003738304 -0.001959494 -0.001905864 -0.098515099 x4 -0.000682703 0.003738304 1.215603899 -0.006237114 -0.003772409 -0.008763795 x5 -0.000919871 -0.001959494 -0.006237114 0.006438250 -0.000661045 0.002311448 x6 -0.00867544 -0.001905864 -0.003772409 -0.000661045 0.002498730 0.002401774 x7 -0.037908526 -0.098515099 -0.008763795 0.002311448 0.002401774 0.138854170

Simple Statistics

Varia	ıble	N	Mean	Std Dev	Sum	Minimum	Maximum
x1 x2						0.03333	
x4	2269	77	3.18472	0.28292 1.10254	722859	2.00000	5.00000
x5 x6	2269 2269		0.23984 0.15113	0.08024 0.04999	54439 34303	0.15000 0.10000	
x7	22697	77	0.40354	0.37263	91594	-0.21388	1.02996

Pearson Correlation Coefficients, N = 226977 Prob > |r| under H0: Rho=0

x1 x2 x4 x5 x6 x7

The CORR Procedure

6 Variables: x1 x2 x4 x5 x6 x7

Covariance Matrix, DF = 226976

x1 x2 x4 x5 x6 x7

Simple Statistics

Variable N Mean Std Dev Sum Minimum Maximum x1 226977 0.16623 0.11537 37731 0.03333 0.45000

 $226977 \quad 0.41589 \quad 0.28292 \quad 94397 \quad 0.10000 \quad 0.90000$ x2 226977 3.18472 1.10254 722859 2.00000 5.00000 x4 226977 0.23984 0.08024 54439 0.15000 0.35000 x5 226977 0.15113 0.04999 34303 0.10000 0.20000 x6 x7 226977 0.40354 0.37263 91594 -0.21388 1.02996 Pearson Correlation Coefficients, N = 226977 Prob > |r| under H0: Rho=0 x1 x2 x4 x5 x6 x7 x1 1.00000 0.93747 -0.00537 -0.09937 -0.15043 -0.88176 <.0001 0.0106 <.0001 <.0001 <.0001 x2 0.93747 1.00000 0.01198 -0.08632 -0.13476 -0.93445 <.0001 <.0001 <.0001 <.0001 <.0001 x4 -0.00537 0.01198 1.00000 -0.07050 -0.06845 -0.02133 0.0106 <.0001 <.0001 <.0001 <.0001 x5 -0.09937 -0.08632 -0.07050 1.00000 -0.16481 0.07731 <.0001 <.0001 <.0001 <.0001 <.0001 x6 -0.15043 -0.13476 -0.06845 -0.16481 1.00000 0.12894 <.0001 <.0001 <.0001 <.0001 <.0001 x7 -0.88176 -0.93445 -0.02133 0.07731 0.12894 1.00000 <.0001 <.0001 <.0001 <.0001 <.0001

Variable Selection and Covariance Matrix for the water-wet homogeneous model (Intercept)

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Number of Observations Read 226977 Number of Observations Used 226977

Forward Selection: Step 1

Statistics for Entry DF = 1,226975

x1	1.000000	0.6227	374538	<.0001
x2	1.000000	0.4955	222965	<.0001
x4	1.000000	0.2717	84678.4	<.0001
x5	1.000000	0.0133	3062.80	<.0001
x6	1.000000	0.0225	5212.99	<.0001
x7	1.000000	0.5333	259349	<.0001

Variable x1 Entered: R-Square = 0.6227 and C(p) = 1314262

Sum of Mean Source DF Squares Square F Value Pr > F

 Model
 1
 1391052
 1391052
 374538
 <.0001</th>

 Error
 226975
 842995
 3.71404

 Corrected Total
 226976
 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1, 1

Forward Selection: Step 2 The SAS System 09:56 Saturday, October 3, 2009 5795

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 2

Statistics for Entry DF = 1,226974

x2	0.121152	0.6332 654	5.48 <.0001
x4	0.999971	0.8988 619	9402 <.0001
x5	0.990126	0.6240 833	3.80 <.0001
x6	0.977372	0.6237 598	8.29 <.0001
x7	0.222493	0.6280 325	9.17 <.0001

Variable x4 Entered: R-Square = 0.8988 and C(p) = 186344.4

Analysis of Variance

 Model
 2
 2007980
 1003990
 1008016
 <.0001</th>

 Error
 226974
 226067
 0.99601

 Corrected Total
 226976
 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > FIntercept 2.12789 0.00709 89644 90003.7 <.0001

Bounds on condition number: 1, 4.0001

Forward Selection: Step 3

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 3

Statistics for Entry DF = 1,226973

Model Variable Tolerance R-Square F Value Pr > F

Variable x2 Entered: R-Square = 0.9154 and C(p) = 118706.2

Analysis of Variance

Model 3 2044976 681659 818308 <.0001 Error 226973 189071 0.83301 Corrected Total 226976 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 8.2739, 52.648

Forward Selection: Step 4

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 4

Statistics for Entry DF = 1,226972

x5	0.984545	0.9154	30.18 <.0001
x6	0.972117	0.9154	177.11 <.0001
x7	0.126408	0.9443	118198 <.0001

Variable x7 Entered: R-Square = 0.9443 and C(p) = 337.3204

Analysis of Variance

Model 4 2109721 527430 962883 <.0001 Error 226972 124327 0.54776 Corrected Total 226976 2234047

Bounds on condition number: 14.518, 126.9

Forward Selection: Step 5

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 5

Statistics for Entry DF = 1,226971

Model Variable Tolerance R-Square F Value Pr > F

x5 0.984346 0.9444 3.57 0.0590 x6 0.972108 0.9444 306.22 <.0001

Variable x6 Entered: R-Square = 0.9444 and C(p) = 33.0606

Analysis of Variance

 Model
 5
 2109888
 421978
 771403
 <.0001</th>

 Error
 226971
 124159
 0.54703

 Corrected Total
 226976
 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 14.523, 164.04

Forward Selection: Step 6

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 6

Statistics for Entry DF = 1,226970

x5 0.949089 0.9444 28.06 <.0001

Variable x5 Entered: R-Square = 0.9444 and C(p) = 7.0000

Analysis of Variance

Sum of Mean Source DF Squares Square F Value Pr > F

Model 6 2109903 351651 642917 <.0001 Error 226970 124144 0.54696 Corrected Total 226976 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 14.526, 203.73

All variables have been entered into the model.

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept Summary of Forward Selection

Variable Number Partial Model Step Entered Label Vars In R-Square R-Square C(p) F Value Pr > F1 0.6227 0.6227 1314262 374538 <.0001 1 x1 $2 \quad 0.2761 \quad 0.8988 \quad 186344 \quad 619402 \quad <.0001$ 2 x4 3 x2 3 0.0166 0.9154 118706 44413.1 <.0001 4 0.0290 0.9443 337.320 118198 <.0001 4 x7 5 0.0001 0.9444 33.0606 306.22 <.0001 5 x6 6 x5 $6 \quad 0.0000 \quad 0.9444 \quad 7.0000 \quad 28.06 \quad <.0001$ The SAS System 09:56 Saturday, October 3, 2009 5801 The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept Number of Observations Read 226977 Number of Observations Used 226977 Backward Elimination: Step 0 All Variables Entered: R-Square = 0.9444 and C(p) = 7.0000Analysis of Variance Sum of Mean Source DF Squares Square F Value Pr > F 6 2109903 351651 642917 <.0001 Model 226970 124144 0.54696 Error Corrected Total 226976 2234047 Parameter Standard Variable Estimate Error Type II SS F Value Pr > F Intercept -1.56684 0.01474 6181.05193 11300.7 <.0001 -30.39889 0.03895 333163 609116 <.0001 x1 x2 8.83008 0.02091 97524 178302 <.0001 -1.50075 0.00142 611502 1118000 <.0001 -0.10520 0.01986 15.34805 28.06 <.0001 x4 x5 -0.58337 0.03208 180.90739 330.75 <.0001 x6 x7 4.03107 0.01172 64724 118334 <.0001

Bounds on condition number: 14.526, 203.73

Backward Elimination: Step 1

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Backward Elimination: Step 1

Statistics for Removal DF = 1,226970

x1	0.1491	0.7953	609116 <.0001
x2	0.0437	0.9008	178302 <.0001
x4	0.2737	0.6707	1118000 <.0001
x5	0.0000	0.9444	28.06 <.0001
x6	0.0001	0.9444	330.75 <.0001
x7	0.0290	0.9155	118334 <.0001

All variables left in the model are significant at the 0.0500 level. The SAS System 09:56 Saturday, October 3, 2009 5803

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Number of Observations Read 226977 Number of Observations Used 226977

Stepwise Selection: Step 1

Statistics for Entry DF = 1,226975

 $\begin{array}{c|ccccc} Model \\ Variable & Tolerance & R-Square & F Value & Pr > F \\ x1 & 1.000000 & 0.6227 & 374538 & <.0001 \\ x2 & 1.000000 & 0.4955 & 222965 & <.0001 \\ x4 & 1.000000 & 0.2717 & 84678.4 & <.0001 \\ x5 & 1.000000 & 0.0133 & 3062.80 & <.0001 \\ \end{array}$

Variable x1 Entered: R-Square = 0.6227 and C(p) = 1314262

Analysis of Variance

 Model
 1
 1391052
 1391052
 374538
 <.0001</th>

 Error
 226975
 842995
 3.71404

 Corrected Total
 226976
 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1, 1

Stepwise Selection: Step 2 The SAS System 09:56 Saturday, October 3, 2009 5804

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 2

```
Statistics for Entry
DF = 1,226974
```

Model Variable Tolerance R-Square F Value Pr > F

x2	0.121152	0.6332	6545.48 <.0	001
x4	0.999971	0.8988	619402 <.0	001
x5	0.990126	0.6240	833.80 <.0	001
x6	0.977372	0.6237	598.29 <.0	001
x7	0.222493	0.6280	3259.17 <.0	001

Variable x4 Entered: R-Square = 0.8988 and C(p) = 186344.4

Analysis of Variance

 Model
 2
 2007980
 1003990
 1008016
 <.0001</th>

 Error
 226974
 226067
 0.99601

 Corrected Total
 226976
 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1, 4.0001

Stepwise Selection: Step 3

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 3

Statistics for Removal DF = 1,226974

Partial Model Variable R-Square F Value Pr > F

> Statistics for Entry DF = 1,226973

Model Variable Tolerance R-Square F Value Pr > F

x2	0.120862	0.9154	44413.1 <.0001
x5	0.985080	0.8988	0.28 0.5970
x6	0.972575	0.8988	63.73 <.0001

x7 0.221813 0.9008 4451.07 <.0001

Variable x2 Entered: R-Square = 0.9154 and C(p) = 118706.2

Analysis of Variance

Model 3 2044976 681659 818308 <.0001 Error 226973 189071 0.83301 Corrected Total 226976 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 3

Bounds on condition number: 8.2739, 52.648

Stepwise Selection: Step 4

Statistics for Removal DF = 1,226973

Partial Model Variable R-Square F Value Pr > F

x1	0.1568	0.7586	420530	<.0001
x2	0.0166	0.8988	44413.1	<.0001
x4	0.2821	0.6332	756648	<.0001

Statistics for Entry DF = 1,226972

Model Variable Tolerance R-Square F Value Pr > F

Variable x7 Entered: R-Square = 0.9443 and C(p) = 337.3204

Analysis of Variance

```
Model
           4 \quad 2109721 \quad 527430 \quad 962883 \ <.0001
        226972 124327 0.54776
Error
Corrected Total 226976 2234047
        The SAS System 09:56 Saturday, October 3, 2009 5807
        The REG Procedure
        Model: MODEL1
    Dependent Variable: Intercept Intercept
       Stepwise Selection: Step 4
    Parameter Standard
 Variable Estimate Error Type II SS F Value Pr > F
 Intercept -1.69538 0.01209 10767 19655.7 <.0001
       -30.33430 0.03877 335280 612090 <.0001
 x1
       8.82201 0.02092 97393 177801 <.0001
 x2
      -1.49834 0.00141 617349 1127040 <.0001
 x4
 x7
       4.03128 0.01173 64744 118198 <.0001
    Bounds on condition number: 14.518, 126.9
                                            _____
       Stepwise Selection: Step 5
       Statistics for Removal
        DF = 1,226972
       Partial Model
  Variable R-Square R-Square F Value Pr > F
         0.1501 0.7943 612090 <.0001
  x1
         0.0436 0.9008 177801 <.0001
  x2
  x4
         0.2763 0.6680 1127040 <.0001
        0.0290 0.9154 118198 <.0001
  x7
       Statistics for Entry
        DF = 1,226971
           Model
  Variable Tolerance R-Square F Value Pr > F
        0.984346 0.9444 3.57 0.0590
  x5
        0.972108 \quad 0.9444 \quad 306.22 \ < .0001
  x6
  Variable x6 Entered: R-Square = 0.9444 and C(p) = 33.0606
        The SAS System 09:56 Saturday, October 3, 2009 5808
        The REG Procedure
        Model: MODEL1
    Dependent Variable: Intercept Intercept
       Stepwise Selection: Step 5
       Analysis of Variance
         Sum of Mean
```

Source DF Squares Square F Value Pr > F

Model 5 2109888 421978 771403 <.0001

226971 124159 0.54703 Error Corrected Total 226976 2234047 Parameter Standard Variable Estimate Error Type II SS F Value Pr > F x2 8.82875 0.02091 97509 178252 <.0001 x4 -1.50009 0.00141 615684 1125512 <.0001 x6 -0.55121 0.03150 167.51209 306.22 <.0001 x7 4.03193 0.01172 64764 118394 <.0001 Bounds on condition number: 14.523, 164.04 -----

Stepwise Selection: Step 6

Statistics for Removal DF = 1,226971

Partial Model Variable R-Square F Value Pr > F

x1	0.1498	0.7947	611638 <.0001
x2	0.0436	0.9008	178252 <.0001
x4	0.2756	0.6688	1125512 <.0001
x6	0.0001	0.9443	306.22 <.0001
x7	0.0290	0.9154	118394 <.0001

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 6

Statistics for Entry DF = 1,226970

Model Variable Tolerance R-Square F Value Pr > F

 $x5 \qquad 0.949089 \quad 0.9444 \quad 28.06 < .0001$

Variable x5 Entered: R-Square = 0.9444 and C(p) = 7.0000

Analysis of Variance

Model 6 2109903 351651 642917 <.0001 Error 226970 124144 0.54696 Corrected Total 226976 2234047

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 14.526, 203.73

Stepwise Selection: Step 7

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 7

Statistics for Removal DF = 1,226970

Partial Model Variable R-Square F Value Pr > F

x1	0.1491	0.7953	609116 <.0001
x2	0.0437	0.9008	178302 <.0001
x4	0.2737	0.6707	1118000 <.0001
x5	0.0000	0.9444	28.06 <.0001
x6	0.0001	0.9444	330.75 <.0001
x7	0.0290	0.9155	118334 <.0001

All variables left in the model are significant at the 0.1500 level.

All variables have been entered into the model.

Summary of Stepwise Selection

Variable Variable Number Partial Model Step Entered Removed Label Vars In R-Square R-Square C(p) F Value Pr > F

> The REG Procedure Model: MODEL1 Dependent Variable: Intercept

R-Square Selection Method

Number of Observations Read 226977 Number of Observations Used 226977

Number in

Model R-Square C(p) MSE Variables in Model 1 0.6227 1314262 3.71404 x1 1 0.5333 1679313 4.59374 x7 0.4955 1833463 4.96521 x2 1 1 0.2717 2747720 7.16837 x4 1 0.0225 3765798 9.62172 x6 1 0.0133 3803119 9.71165 x5 -----_____ 2 0.8988 186344.4 0.99601 x1 x4 2 0.7891 634398.7 2.07572 x4 x7 0.7586 759162.2 2.37638 x2 x4 2 2 0.6332 1271063 3.60996 x1 x2 2 0.6280 1292446 3.66148 x1 x7 2 0.6240 1308623 3.70047 x1 x5 0.6237 1310212 3.70430 x1 x6 2 0.5369 1664351 4.55770 x2 x7 2 0.5368 1665044 4.55937 x5 x7 2 2 0.5364 1666439 4.56273 x6 x7 2 0.4986 1820893 4.93493 x2 x6 0.4986 1821186 4.93564 x2 x5 2 2 0.2848 2694241 7.03952 x4 x6 2 0.2779 2722338 7.10723 x4 x5 2 0.0426 3683411 9.42322 x5 x6 _____ 3 0.9154 118706.2 0.83301 x1 x2 x4 0.9008 178397.0 0.97685 x1 x4 x7 3 0.8988 186230.4 0.99573 x1 x4 x6 3 0.8988 186345.9 0.99601 x1 x4 x5 3 3 0.7943 613321.7 2.02494 x2 x4 x7 3 0.7897 632002.7 2.06996 x4 x5 x7 3 0.7896 632299.9 2.07067 x4 x6 x7 3 0.7590 757374.4 2.37208 x2 x4 x6 3 0.7589 757672.1 2.37279 x2 x4 x5 0.6680 1129025 3.26768 x1 x2 x7 3 3 0.6345 1266022 3.59782 x1 x2 x5 3 0.6341 1267479 3.60133 x1 x2 x6 3 0.6295 1286306 3.64670 x1 x5 x7 3 0.6290 1288245 3.65137 x1 x6 x7 The SAS System 09:56 Saturday, October 3, 2009 5812 The REG Procedure Model: MODEL1 Dependent Variable: Intercept **R-Square Selection Method** Number in Model R-Square C(p) MSE Variables in Model 3 0.6256 1302430 3.68556 x1 x5 x6 0.5414 1646347 4.51433 x5 x6 x7 3 3 0.5402 1651197 4.52602 x2 x5 x7 3 0.5398 1652556 4.52929 x2 x6 x7 3 0.5030 1803208 4.89233 x2 x5 x6 3 0.2948 2653561 6.94152 x4 x5 x6 _____ 4 0.9443 337.3204 0.54776 x1 x2 x4 x7 0.9154 118438.7 0.83236 x1 x2 x4 x6 4 0.9154 118662.3 0.83290 x1 x2 x4 x5 4 4 0.9008 178304.6 0.97663 x1 x4 x6 x7 4 0.9008 178396.4 0.97685 x1 x4 x5 x7 4 0.8988 186224.6 0.99572 x1 x4 x5 x6 4 0.7947 611473.9 2.02049 x2 x4 x5 x7 4 0.7947 611741.9 2.02113 x2 x4 x6 x7 4 0.7905 628903.6 2.06249 x4 x5 x6 x7

4	0.7595	755145.2	2.36671 x2 x4 x5 x6
4	0.6694	1123323	3.25395 x1 x2 x5 x7
4	0.6688	1125677	3.25962 x1 x2 x6 x7
4	0.6358	1260526	3.58459 x1 x2 x5 x6
4	0.6311	1279824	3.63109 x1 x5 x6 x7
4	0.5444	1633980	4.48454 x2 x5 x6 x7
5	0.9444	33.0606	0.54703 x1 x2 x4 x6 x7
5 5		33.0606 335.7502	0.54703 x1 x2 x4 x6 x7 0.54776 x1 x2 x4 x5 x7
-	0.9444		
5	0.9444 0.9155	335.7502	0.54776 x1 x2 x4 x5 x7
5 5	0.9444 0.9155 0.9008	335.7502 118339.3	0.54776 x1 x2 x4 x5 x7 0.83212 x1 x2 x4 x5 x6
5 5 5	0.9444 0.9155 0.9008 0.7953	335.7502 118339.3 178306.5	0.54776 x1 x2 x4 x5 x7 0.83212 x1 x2 x4 x5 x6 0.97663 x1 x4 x5 x6 x7

6 0.9444 7.0000 0.54696 x1 x2 x4 x5 x6 x7

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The CORR Procedure

6 Variables: x1 x2 x4 x5 x6 x7

Covariance Matrix, DF = 226976

x1 x2 x4 x5 x6 x7

x1 0.013310993 0.030600508 -0.000682703 -0.000919871 -0.000867544 -0.037908526 x2 0.030600508 0.080044782 0.003738304 -0.001959494 -0.001905864 -0.098515099 x4 -0.000682703 0.003738304 1.215603899 -0.006237114 -0.003772409 -0.008763795 x5 -0.000919871 -0.001959494 -0.006237114 0.006438250 -0.000661045 0.002311448 x6 -0.00867544 -0.01905864 -0.003772409 -0.00661045 0.002498730 0.002401774 x7 -0.037908526 -0.098515099 -0.008763795 0.002311448 0.002401774 0.138854170

Simple Statistics

Varia	ıble	Ν	Mean	Std Dev	Sum 1	Minimum	Maximum
x1	2269	77	0.16623	0.11537	37731	0.03333	0.45000
x2	2269	77	0.41589	0.28292	94397	0.10000	0.90000
x4	2269	77	3.18472	1.10254	722859	2.00000	5.00000
x5	2269	77	0.23984	0.08024	54439	0.15000	0.35000
x6	2269	77	0.15113	0.04999	34303	0.10000	0.20000
x7	2269	77	0.40354	0.37263	91594	-0.21388	1.02996

Pearson Correlation Coefficients, N = 226977 Prob > |r| under H0: Rho=0

x1 x2 x4 x5 x6 x7

x6 -0.15043 -0.13476 -0.06845 -0.16481 1.00000 0.12894

```
<.0001 <.0001 <.0001 <.0001 <.0001
x7 -0.88176 -0.93445 -0.02133 0.07731 0.12894 1.00000
<.0001 <.0001 <.0001 <.0001
```

Variable Selection and Covariance Matrix for the oil-wet homogeneous model (Slope)

The REG Procedure Model: MODEL1 Dependent Variable: slope Number of Observations Read 804144

Number of Observations Used 804144

Forward Selection: Step 1

Statistics for Entry DF = 1,804142

Model Variable Tolerance R-Square F Value Pr > F

 x1
 1.000000
 0.1396
 130519
 <.0001</th>

 x2
 1.000000
 0.1680
 162387
 <.0001</th>

 x4
 1.000000
 0.3387
 411943
 <.0001</th>

 x5
 1.000000
 0.0025
 1977.47
 <.0001</th>

 x6
 1.000000
 0.2200
 226815
 <.0001</th>

Variable x4 Entered: R-Square = 0.3387 and C(p) = 5475160

Analysis of Variance

 Model
 1
 3455232
 3455232
 411943
 <.0001</th>

 Error
 804142
 6744864
 8.38765

 10200095

 3455232
 411943
 <.0001</td>

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1, 1

Forward Selection: Step 2 The SAS System 11:24 Saturday, October 3, 2009 9654

The REG Procedure Model: MODEL1 Dependent Variable: slope

Forward Selection: Step 2

	Statistics for Entry DF = 1,804141					
Vorie	Model	naa D. Sauara E.Valua Dr. E.				
vana	ible Toleral	nce R-Square F Value $Pr > F$				
x1	0.999919	0.4745 207755 <.0001				
x2	0.999585	0.4972 253513 <.0001				
x5	0.999993	0.3414 3180.42 <.0001				
x6	0.915514	0.5758 449401 <.0001				

x7 0.999529 0.5472 370089 <.0001

Variable x6 Entered: R-Square = 0.5758 and C(p) = 3224002

Analysis of Variance

 $\begin{array}{ccc} Sum \ of & Mean \\ Source & DF & Square & Square & F \\ Value & Pr > F \end{array}$

 Model
 2
 5873298
 2936649
 545780
 <.0001</th>

 Error
 804141
 4326797
 5.38064

 Corrected Total
 804143
 10200095

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1.0923, 4.3691

Forward Selection: Step 3

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Forward Selection: Step 3

Statistics for Entry DF = 1,804140

Model Variable Tolerance R-Square F Value Pr > F

x1	0.963891	0.7962	869279 <.0001
x2	0.964070	0.8246	1141135 <.0001
x5	0.995161	0.5830	13964.4 <.0001

x7 0.954563 0.9039 2746752 <.0001

Variable x7 Entered: R-Square = 0.9039 and C(p) = 108082.3

Analysis of Variance

Sum of Mean

Source DF Squares Square F Value Pr > F

 Model
 3
 9220243
 3073414
 2522273
 <.0001</th>

 Error
 804140
 979853
 1.21851

 Corrected Total
 804143
 10200095

 Parameter
 Standard

 Variable
 Estimate
 Error
 Type II SS F Value Pr > F

 Intercept
 2.10594
 0.00702
 109601
 89947.1 < .0001</td>

 x4
 2.40763
 0.00115
 5313344
 4360526 < .0001</td>

 x6
 23.48963
 0.01359
 3639193
 2986593 < .0001</td>

 x7
 -7.23629
 0.00437
 3346944
 2746752 < .0001</td>

Bounds on condition number: 1.1437, 9.8566

Forward Selection: Step 4

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Forward Selection: Step 4

Statistics for Entry DF = 1,804139

Model Variable Tolerance R-Square F Value Pr > F

x1	0.391421	0.9059	16448.8	<.0001
x2	0.265209	0.9044	3784.50	<.0001
x5	0.994818	0.9131	84836.7	<.0001

Variable x5 Entered: R-Square = 0.9131 and C(p) = 21029.47

Analysis of Variance

Source DF Squares Square F Value Pr > F

 Model
 4
 9313752
 2328438
 2112486
 <.0001</th>

 Error
 804139
 886343
 1.10223

 Corrected Total
 804143
 10200095

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

 Intercept
 1.62404
 0.00688
 61412
 55715.9 <.0001</th>

 x4
 2.41514
 0.00110
 5343579
 4847987 <.0001</td>

 x5
 6.50617
 0.02234
 93509
 84836.7 <.0001</td>

 x6
 23.76092
 0.01296
 3704509
 3360933 <.0001</td>

 x7
 -7.25876
 0.00415
 3366599
 3054362 <.0001</td>

Bounds on condition number: 1.1497, 17.191

Forward Selection: Step 5

```
The SAS System 11:24 Saturday, October 3, 2009 9657
        The REG Procedure
        Model: MODEL1
       Dependent Variable: slope
       Forward Selection: Step 5
        Statistics for Entry
        DF = 1,804138
            Model
  Variable
           Tolerance R-Square F Value Pr > F
         0.391415 0.9150 17900.7 <.0001
  x1
  x2
         0.265179 0.9135 3789.78 <.0001
   Variable x1 Entered: R-Square = 0.9150 and C(p) = 3062.767
        Analysis of Variance
          Sum of Mean
           DF \quad Squares \quad Square \ F \ Value \ Pr > F
Source
Model
            5 9333053 1866611 1731187 <.0001
Error
         804138 867042 1.07823
Corrected Total 804143 10200095
     Parameter Standard
  Variable Estimate Error Type II SS F Value Pr > F
 Intercept 0.72599 0.00956 6220.21933 5768.94 <.0001
       2.03790 0.01523 19301 17900.7 <.0001
 \mathbf{x1}
       2.41858 0.00109 5355805 4967239 <.0001
 x4
       6.49437 \quad 0.02209 \quad 93169 \ 86409.5 < .0001
  x5
       23.82882 0.01283 3719881 3450002 <.0001
 x6
  x7
       -6.59415 0.00645 1128375 1046511 <.0001
     Bounds on condition number: 2.5803, 41.936
                                                 _____
____
       Forward Selection: Step 6
        The SAS System 11:24 Saturday, October 3, 2009 9658
        The REG Procedure
        Model: MODEL1
       Dependent Variable: slope
```

Forward Selection: Step 6

Statistics for Entry DF = 1,804137

Model Variable Tolerance R-Square F Value Pr > F

x2 0.119539 0.9153 3057.77 <.0001

Variable x2 Entered: R-Square = 0.9153 and C(p) = 7.0000

Analysis of Variance

Sum of Mean DF Squares Square F Value Pr > F Source 6 9336338 1556056 1448650 <.0001 Model 804137 863758 1.07414 Error Corrected Total 804143 10200095 Parameter Standard Variable Estimate Error Type II SS F Value Pr > F Intercept 1.01676 0.01089 9357.77363 8711.85 <.0001 2.96582 0.02264 18428 17155.8 <.0001 x1 -0.65198 0.01179 3284.47749 3057.77 <.0001 x2 x4 2.42011 0.00108 5359086 4989175 <.0001 6.50844 0.02205 93561 87102.5 <.0001 x5 x6 23.84656 0.01281 3723084 3466099 <.0001 -6.83971 0.00782 822256 765500 <.0001 x7 Bounds on condition number: 8.3655, 126.58

All variables have been entered into the model.

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Summary of Forward Selection

Variable Number Partial Model Step Entered Vars In R-Square R-Square C(p) F Value Pr > F1 0.3387 0.3387 5475160 411943 <.0001 1 x4 $2 \quad 0.2371 \quad 0.5758 \quad 3224002 \quad 449401 \ < .0001$ 2 x6 3 x7 3 0.3281 0.9039 108082 2746752 <.0001 4 0.0092 0.9131 21029.5 84836.7 <.0001 4 x5 5 x1 5 0.0019 0.9150 3062.77 17900.7 <.0001 6 x2 $6 \quad 0.0003 \quad 0.9153 \quad 7.0000 \ \ 3057.77 \ < .0001$ The SAS System 11:24 Saturday, October 3, 2009 9660 The REG Procedure

Model: MODEL1 Dependent Variable: slope

Number of Observations Read 804144 Number of Observations Used 804144

Backward Elimination: Step 0

All Variables Entered: R-Square = 0.9153 and C(p) = 7.0000

Analysis of Variance

Sum of Mean DF Squares Square F Value Pr > F Source $6 \quad 9336338 \quad 1556056 \ 1448650 \ < .0001$ Model 804137 863758 1.07414 Error Corrected Total 804143 10200095 Parameter Standard Variable Estimate Error Type II SS F Value Pr > F Intercept 1.01676 0.01089 9357.77363 8711.85 <.0001 2.96582 0.02264 18428 17155.8 <.0001 x1 -0.65198 0.01179 3284.47749 3057.77 <.0001 x2 2.42011 0.00108 5359086 4989175 <.0001 x4 6.50844 0.02205 93561 87102.5 <.0001 x5 23.84656 0.01281 3723084 3466099 <.0001 x6 -6.83971 0.00782 822256 765500 <.0001 x7 Bounds on condition number: 8.3655, 126.58

Backward Elimination: Step 1

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Backward Elimination: Step 1

Statistics for Removal DF = 1,804137

x1	0.0018	0.9135	17155.8 <.0001
x2	0.0003	0.9150	3057.77 <.0001
x4	0.5254	0.3899	4989175 <.0001
x5	0.0092	0.9061	87102.5 <.0001
x6	0.3650	0.5503	3466099 <.0001
x7	0.0806	0.8347	765500 <.0001

All variables left in the model are significant at the 0.0500 level. The SAS System 11:24 Saturday, October 3, 2009 9662

> The REG Procedure Model: MODEL1 Dependent Variable: slope

Number of Observations Read 804144 Number of Observations Used 804144

Stepwise Selection: Step 1

Statistics for Entry DF = 1,804142

 $\begin{array}{c} Model\\ Variable & Tolerance & R-Square & F & Value & Pr > F \end{array}$

x1	1.000000	0.1396	130519	<.0001
x2	1.000000	0.1680	162387	<.0001
x4	1.000000	0.3387	411943	<.0001
x5	1.000000	0.0025	1977.47	<.0001
x6	1.000000	0.0880	77621.3	<.0001
x7	1.000000	0.2200	226815	<.0001

Variable x4 Entered: R-Square = 0.3387 and C(p) = 5475160

Analysis of Variance

 Model
 1
 3455232
 3455232
 411943
 <.0001</th>

 Error
 804142
 6744864
 8.38765

 3455232
 3455232
 3455232

 343765

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1, 1

Stepwise Selection: Step 2 The SAS System 11:24 Saturday, October 3, 2009 9663

The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 2

Statistics for Entry DF = 1,804141

Model

 $Variable \quad Tolerance \quad R\text{-}Square \ F \ Value \ Pr > F$

x1	0.999919	0.4745	207755	<.0001
x2	0.999585	0.4972	253513	<.0001
x5	0.999993	0.3414	3180.42	<.0001
x6	0.915514	0.5758	449401	<.0001
x7	0.999529	0.5472	370089	<.0001

Variable x6 Entered: R-Square = 0.5758 and C(p) = 3224002

Analysis of Variance

 Sum of DF
 Mean Squares
 Square F Value
 Pr > F

 Model
 2
 5873298
 2936649
 545780
 <.0001</td>

 Error
 804141
 4326797
 5.38064
 <.0001</td>

 Corrected Total
 804143
 10200095

Parameter Standard

Variable Estimate Error Type II SS F Value Pr > F

Intercept -0.37485 0.01442 3637.70377 676.07 <.0001 x4 2.32777 0.00242 4975388 924683 <.0001 x6 18.71166 0.02791 2418067 449401 <.0001

Bounds on condition number: 1.0923, 4.3691

Stepwise Selection: Step 3

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 3

Statistics for Removal DF = 1,804141

Partial Model Variable R-Square F Value Pr > F

> Statistics for Entry DF = 1,804140

> > Model

Variable Tolerance R-Square F Value Pr > F

x1	0.963891	0.7962	869279 <.0001
x2	0.964070	0.8246	1141135 <.0001
x5	0.995161	0.5830	13964.4 <.0001
x7	0.954563	0.9039	$2746752 \ <.0001$

Variable x7 Entered: R-Square = 0.9039 and C(p) = 108082.3

Analysis of Variance

 Model
 3
 9220243
 3073414
 2522273
 <.0001</th>

 Error
 804140
 979853
 1.21851

 Corrected Total
 804143
 10200095

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F Intercept 2.10594 0.00702 109601 89947.1 <.0001

x4 2.40763 0.00115 5313344 4360526 <.0001 x6 23.48963 0.01359 3639193 2986593 <.0001 x7 -7.23629 0.00437 3346944 2746752 <.0001 The SAS System 11:24 Saturday, October 3, 2009 9665

The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 3

Bounds on condition number: 1.1437, 9.8566

Stepwise Selection: Step 4

Statistics for Removal DF = 1,804140

Partial Model Variable R-Square F Value Pr > F

x4	0.5209	0.3830	4360526	<.0001
x6	0.3568	0.5472	2986593	<.0001
x7	0.3281	0.5758	2746752	<.0001

Statistics for Entry DF = 1,804139

 $\begin{array}{c} Model\\ Variable & Tolerance & R-Square & F Value & Pr > F \end{array}$

x1 0.391421 0.9059 16448.8 <.0001 x2 0.265209 0.9044 3784.50 <.0001 x5 0.994818 0.9131 84836.7 <.0001

NO 0.991010 0.9151 01050.7 .0001

Variable x5 Entered: R-Square = 0.9131 and C(p) = 21029.47

Analysis of Variance

 Sum of
 Mean

 Source
 DF
 Squares
 Square F Value Pr > F

 Model
 4
 9313752
 2328438
 2112486
 <.0001</td>

 Error
 804139
 886343
 1.10223

Corrected Total 804143 10200095 The SAS System 11:24 Saturday, October 3, 2009 9666

> The REG Procedure Model: MODEL1 Dependent Variable: slope

> Stepwise Selection: Step 4

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Bounds on condition number: 1.1497, 17.191

Stepwise Selection: Step 5

Statistics for Removal DF = 1,804139Partial Model Variable R-Square R-Square F Value Pr > F $0.5239 \quad 0.3892 \ 4847987 \ < .0001$ x4 0.0092 0.9039 84836.7 <.0001 x5 0.3632 0.5499 3360933 <.0001 x6 0.3301 0.5830 3054362 <.0001 x7 Statistics for Entry DF = 1,804138Model Variable Tolerance R-Square F Value Pr > F 0.391415 0.9150 17900.7 <.0001 x1 x2 0.265179 0.9135 3789.78 <.0001 Variable x1 Entered: R-Square = 0.9150 and C(p) = 3062.767 The SAS System 11:24 Saturday, October 3, 2009 9667 The REG Procedure Model: MODEL1 Dependent Variable: slope Stepwise Selection: Step 5 Analysis of Variance Sum of Mean DF Squares Square F Value Pr > F Source Model Error Corrected Total 804143 10200095 Parameter Standard $Variable \ Estimate \ Error \ Type \ II \ SS \ F \ Value \ Pr > F$ Intercept 0.72599 0.00956 6220.21933 5768.94 <.0001

 x1
 2.03790
 0.01523
 19301
 17900.7 < 0001</th>

 x4
 2.41858
 0.00109
 5355805
 4967239
 <0001</th>

 x5
 6.49437
 0.02209
 93169
 86409.5
 <0001</th>

 x6
 23.82882
 0.01283
 3719881
 3450002
 <0001</th>

 x7
 -6.59415
 0.00645
 1128375
 1046511
 <0001</th>

Bounds on condition number: 2.5803, 41.936

Stepwise Selection: Step 6

Statistics for Removal DF = 1,804138

Partial Model Variable R-Square F Value Pr > F

x1 0.0019 0.9131 17900.7 <.0001

x4	0.5251	0.3899 49	67239 <.	0001	
x5	0.0091	0.9059 86	409.5 <.0	001	
	x6	0.3647	0.5503	3450002	<.0001
	x7	0.1106	0.8044	1046511	<.0001

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 6

Statistics for Entry DF = 1,804137

Model Variable Tolerance R-Square F Value Pr > F

x2 0.119539 0.9153 3057.77 <.0001

Variable x2 Entered: R-Square = 0.9153 and C(p) = 7.0000

Analysis of Variance

Sum of Mean Source DF Squares Square F Value Pr > F 1556056 1448650 <.0001 Model 6 9336338 804137 Error 863758 1.07414 Corrected Total 804143 10200095

 $\begin{array}{ccc} Parameter & Standard \\ Variable & Estimate & Error & Type II SS \ F \ Value \ Pr > F \end{array}$

Intercept	1.01676	0.01089	9357.77363 8711.85 <.0001
x1	2.96582	0.02264	18428 17155.8 <.0001
x2	-0.65198	0.01179	3284.47749 3057.77 <.0001
x4	2.42011	0.00108	5359086 4989175 <.0001
x5	6.50844	0.02205	93561 87102.5 <.0001
x6	23.84656	0.01281	3723084 3466099 <.0001
x7	-6.83971	0.00782	822256 765500 <.0001

Bounds on condition number: 8.3655, 126.58

Stepwise Selection: Step 7

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The REG Procedure Model: MODEL1 Dependent Variable: slope

Stepwise Selection: Step 7

Statistics for Removal DF = 1,804137

 $\begin{array}{ccc} Partial & Model \\ Variable & R-Square & R-Square & F Value & Pr > F \end{array}$

x1	0.0018	0.9135	17155.8	<.0001
x2	0.0003	0.9150	3057.77	<.0001
x4	0.5254	0.3899	4989175	<.0001
x5	0.0092	0.9061	87102.5	<.0001
x6	0.3650	0.5503	3466099	<.0001
x7	0.0806	0.8347	765500	<.0001

All variables left in the model are significant at the 0.1500 level.

All variables have been entered into the model.

Summary of Stepwise Selection

Step		Variable N Removed			Model re R-Squa	are C(p)	F Value	Pr > F
1	x4	1	0.3387	0.3387	5475160	411943	<.0001	
2	x6	2	0.2371	0.5758	3224002	449401	<.0001	
3	x7	3	0.3281	0.9039	108082	2746752	<.0001	
4	x5	4	0.0092	0.9131	21029.5	84836.7	<.0001	
5	x1	5	0.0019	0.9150	3062.77	17900.7	<.0001	
6	x2	6	0.0003	0.9153	7.0000	3057.77	<.0001	
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The REG Procedure Model: MODEL1 Dependent Variable: slope

R-Square Selection Method

Number of Observations Read	804144
Number of Observations Used	804144

Number in Model R-Sa

Number	in			
Model	R-Squ	are C(p) MSE	Variables in Model
1	0.3387	5475160	8.38765	x4
1	0.2200	6602729	9.89382	x7
1	0.1680	7096460	10.55332	x2
1	0.1396	7365841	10.91315	x1
1	0.0880	7855962	11.56784	x6
1	0.0025	8668600	12.65333	x5
2	0.5758	3224002	5.38064	x4 x6
2	0.5472	3496078	5.74407	x4 x7
2	0.4972	3970051	6.37719	x2 x4
2 2	0.4745	4185944	6.66557	x1 x4
2	0.3830	5054671	7.82599	x6 x7
2	0.3414	5450425	8.35462	x4 x5
2	0.3122	5727555	8.72480	x2 x6
2	0.2780	6052382	9.15869	x1 x6
2 2	0.2226	6577904	9.86067	x5 x7
2	0.2202	6600531	9.89089	x2 x7
2	0.2202	6601186	9.89177	x1 x7
2	0.1703	7074330	10.52377	x2 x5
2	0.1680	7096284	10.55310	x1 x2
2	0.1420	7343123	10.88282	x1 x5
2	0.0928	7810505	11.50713	x5 x6
3	0.9039	108082.3	1.21851	x4 x6 x7
3	0.8246	861021.0	2.22426	x2 x4 x6

3	0.7962	1131535	2.58560	x1 x4 x6
3	0.5830	3155247	5.28881	x4 x5 x6
3	0.5499	3469833	5.70902	x4 x5 x7
3	0.5476	3492287	5.73901	x1 x4 x7
3	0.5473	3494410	5.74185	x2 x4 x7
3	0.4997	3946501	6.34574	x2 x4 x5
3	0.4975	3967227	6.37342	x1 x2 x4
3	0.4771	4161801	6.63333	x1 x4 x5
3	0.3892	4995766	7.74731	x5 x6 x7
3	0.3837	5047906	7.81696	x1 x6 x7
3	0.3835	5050579	7.82053	x2 x6 x7
3	0.3176	5676075	8.65604	x2 x5 x6
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The REG Procedure Model: MODEL1 Dependent Variable: slope

R-Square Selection Method

Number in

Number	in			
Model	R-Squ	are C(p)	MSE	Variables in Model
3	0.3125	5724356	8.72054	x1 x2 x6
3	0.2834	6000599	9.08953	x1 x5 x6
3	0.2228	6575874	9.85796	x2 x5 x7
3 3 3	0.2228	6576446	9.85873	x1 x5 x7
3	0.2202	6600487	9.89084	x1 x2 x7
3	0.1704	7074144	10.52354	x1 x2 x5
4	0.9131	21029.47	1.10223	x4 x5 x6 x7
4	0.9059	89798.73	1.19409	x1 x4 x6 x7
4	0.9044	103811.2	1.21280	x2 x4 x6 x7
4	0.8328	783788.8	2.12110	x2 x4 x5 x6
4	0.8265	843183.3	2.20043	x1 x2 x4 x6
4	0.8044	1053550	2.48143	x1 x4 x5 x6
4	0.5503	3466177	5.70414	x1 x4 x5 x7
4	0.5501	3468315	5.70700	x2 x4 x5 x7
4	0.5476	3492239	5.73895	x1 x2 x4 x7
4	0.5000	3943632	6.34191	x1 x2 x4 x5
4	0.3899	4989181	7.73852	x1 x5 x6 x7
4	0.3896	4991999	7.74229	x2 x5 x6 x7
4	0.3837	5047888	7.81694	x1 x2 x6 x7
4	0.3179	5672741	8.65160	x1 x2 x5 x6
4	0.2228	6575825	9.85791	x1 x2 x5 x7
5	0.9150	3062.767	1.07823	x1 x4 x5 x6 x7
5	0.9135	17160.85	1.09706	x2 x4 x5 x6 x7
5	0.9061	87107.50	1.19049	x1 x2 x4 x6 x7
5	0.8347	765505.2	2.09667	x1 x2 x4 x5 x6
5	0.5503	3466104	5.70405	x1 x2 x4 x5 x7
5	0.3899	4989180	7.73853	x1 x2 x5 x6 x7
6	0.9153	7.0000	1.07414	x1 x2 x4 x5 x6 x7

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The CORR Procedure

6 Variables: x1 x2 x4 x5 x6 x7

Covariance Matrix, DF = 804143

x1 x4 x5 x6 x7 x2

x1	0.014765359	0.031255086	0.001222166	0.000010498	-0.002168265	-0.027338461
x2	0.031255086	0.080380462	0.006449020	0.000045538	-0.005114094	-0.070126382
x4	0.001222166	0.006449020	1.247236758	-0.000152301	-0.031440474	-0.006994508
x5	0.000010498	0.000045538	-0.000152301	0.002761387	-0.000334695	0.000051812
x6	-0.002168265	-0.005114094	-0.031440474	-0.000334695	0.009380917	0.005847031
x7	-0.027338461	-0.070126382	-0.006994508	0.000051812	0.005847031	0.083268051

Simple Statistics

Variable	Ν	Mean	Std Dev	Sum	Minimum	Maximum
x1	804144	0.22587	0.12151	181635	0.06667	0.50000
x2	804144	0.55709	0.28351	447984	0.20000	1.00000
x4	804144	3.28964	1.11680	2645347	2.00000	5.00000
x5	804144	0.05796	0.05255	46606	0 0	.15000
x6	804144	0.34562	0.09686	277931	0.20000	0.50000
x7	804144	0.60734	0.28856	488388	0.05799	1.22185

Pearson Correlation Coefficients, N = 804144 Prob > |r| under H0: Rho=0

x1 x2 x4 x5 x6 x7

Variable Selection and Covariance Matrix for the oil-wet homogeneous model (Intercept)

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Number of Observations Read804144Number of Observations Used804144

Forward Selection: Step 1

Statistics for Entry DF = 1,804142

Model

Variable	Tolerance	R-Squar	re F Value Pr > F
x1	1.000000	0.3622	456589 <.0001
x2	1.000000	0.3171	373441 <.0001
x4	1.000000	0.4968	793944 <.0001
x5	1.000000	0.0001	50.51 <.0001
x6	1.000000	0.1311	121300 <.0001
x7	1.000000	0.4244	592931 <.0001

Variable x4 Entered: R-Square = 0.4968 and C(p) = 8087357

Analysis of Variance

Sum of Mean DF Square F Value Pr > FSource Squares 1809024 793944 <.0001 1809024 Model 1 Error 804142 1832260 2.27853 Corrected Total 804143 3641284

Parameter Standard

Variable Estimate Error Type II SS F Value Pr > F

 $\begin{array}{ccccc} Intercept & -0.50232 & 0.00524 & 20969 & 9202.79 < .0001 \\ x4 & -1.34302 & 0.00151 & 1809024 & 793944 < .0001 \end{array}$

Bounds on condition number: 1, 1

Forward Selection: Step 2 The SAS System 11:24 Saturday, October 3, 2009 9674

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 2

Statistics for Entry DF = 1,804141

Model

 $Variable \qquad Tolerance \qquad R-Square \quad F \ Value \quad Pr > F$

x1	0.999919	0.8514	1918851 <.0001
x2	0.999585	0.7981	1199963 <.0001
x5	0.999993	0.4968	59.39 <.0001
x6	0.915514	0.5238	45559.8 <.0001
x7	0.999529	0.9017	3312667 <.0001

Variable x7 Entered: R-Square = 0.9017 and C(p) = 932648.9

Analysis of Variance

Sum of Mean DF Source Squares Square F Value Pr > F2 1641693 3688633 <.0001 Model 3283387 357898 Error 804141 0.44507 Corrected Total 804143 3641284

Bounds on condition number: 1.0005, 4.0019

Forward Selection: Step 3

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 3

Statistics for Entry DF = 1,804140

 $\begin{array}{c|cccc} Model \\ Variable & Tolerance & R-Square & F Value & Pr > F \\ x1 & 0.392046 & 0.9269 & 276818 & <.0001 \\ x2 & 0.265256 & 0.9018 & 378.32 & <.0001 \\ x5 & 0.999982 & 0.9017 & 128.12 & <.0001 \\ x6 & 0.874328 & 0.9026 & 7418.51 & <.0001 \\ \end{array}$

Variable x1 Entered: R-Square = 0.9269 and C(p) = 487884.8

Analysis of Variance

	Su	um of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
Model	3	3375039	1125013	3397876	<.0001
Error	804140	266245	0.33109		
Corrected Tota	al 8041-	43 364	1284		

Parameter Standard Variable Error Type II SS F Value Pr > F Estimate Intercept -1.53964 0.00435 41395 125024 <.0001 -4.43726 0.00843 91652 276818 <.0001 x1 x4 -1.32052 0.00057474 1747821 5278941 <.0001 3.23636 0.00355 274849 830126 <.0001 x7

Bounds on condition number: 2.5517, 18.309

Forward Selection: Step 4

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 4

Statistics for Entry DF = 1,804139

Variable x2 Entered: R-Square = 0.9541 and C(p) = 7248.815

0.9274 6201.80 <.0001

Analysis of Variance

0.872932

x6

	Su	m of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
Model	4	3474084	868521	4177085	<.0001
Error	804139	167201	0.20793		
Corrected Tota	l 80414	3 364	1284		

 $\begin{array}{ccc} Parameter & Standard \\ Variable & Estimate & Error & Type II SS & F Value & Pr > F \end{array}$

Intercept	-3.17965	5 0.00419	119759 575970 <.0001
x1	-9.52673	0.00995	190529 916333 <.0001
x2	3.57900	0.00519	99044 476347 <.0001
x4	-1.32651	0.00045554	1763070 8479352 <.0001
x7	4.57904	0.00342	372360 1790836 <.0001

Bounds on condition number: 8.3594, 75.147

Forward Selection: Step 5

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 5

Statistics for Entry DF = 1,804138

____,.....

 $\begin{array}{c} Model\\ Variable & Tolerance & R-Square & F \ Value & Pr > F \end{array}$

x5	0.999840	0.9541	206.53	<.0001
x6	0.872418	0.9545	6824.93	<.0001

Variable x6 Entered: R-Square = 0.9545 and C(p) = 422.3553

Analysis of Variance

Sum of Mean

Source DF Squares Square F Value Pr > F

 Model
 5
 3475491
 695098
 3371391
 <.0001</th>

 Error
 804138
 165794
 0.20618

 Corrected Total
 804143
 3641284

Parameter Standard Error Type II SS F Value Pr > FVariable Estimate Intercept -3.36277 0.00472 104464 506674 <.0001 -9.49002 0.00992 188683 915159 <.0001 x1 98414 477331 <.0001 x2 3.56864 0.00517 -1.31499 0.00047456 1583102 7678420 <.0001 x4 x6 0.46240 $0.00560 \quad 1407.13254 \quad 6824.93 \ <.0001$ 4.55087 0.00342 364145 1766189 <.0001 x7

Bounds on condition number: 8.3644, 100.41

Forward Selection: Step 6

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Forward Selection: Step 6

Statistics for Entry DF = 1,804137

 $\begin{array}{c} Model\\ Variable & Tolerance & R-Square & F Value & Pr > F \end{array}$

x5 0.994669 0.9545 417.36 <.0001

Variable x5 Entered: R-Square = 0.9545 and C(p) = 7.0000

Analysis of Variance

 $\begin{array}{ccc} Sum \ of & Mean\\ Source & DF & Squares & Square & F \ Value & Pr > F \end{array}$

 Model
 6
 3475577
 579263
 2811017
 <.0001</th>

 Error
 804137
 165708
 0.20607

 2811017
 <.0001</td>

ParameterStandardVariableEstimateErrorType II SSF ValuePr > FIntercept-3.376600.00477103204500823<.0001</td>

mercept	5.57000	0.00477	105204 500025 4.0001
x1	-9.48883	0.00992	188630 915372 <.0001
x2	3.56742	0.00516	98334 477189 <.0001
x4	-1.31476	0.00047457	1581662 7675406 <.0001
x5	0.19733	0.00966	86.00390 417.36 <.0001
x6	0.47064	0.00561	1450.20388 7037.47 <.0001
x7	4.54955	0.00342	363805 1765456 <.0001

Bounds on condition number: 8.3655, 126.58

All variables have been entered into the model.

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Summary of Forward Selection

	Variable	Number Partial M			del			
Step	Entered	Label	Vars In	R-Square	R-Square	C(p)	F Value	Pr > F
1	x4	1	0.4968	0.4968	8087357	793944	<.0001	
2	x7	2	0.4049	0.9017	932649	3312667	<.0001	
3	x1	3	0.0252	0.9269	487885	276818	<.0001	
4	x2	4	0.0272	0.9541	7248.82	476347	<.0001	
5	x6	5	0.0004	0.9545	422.355	6824.93	<.0001	
6	x5	6	0.0000	0.9545	7.0000	417.36	<.0001	
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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Number of Observations Read804144Number of Observations Used804144

Backward Elimination: Step 0

All Variables Entered: R-Square = 0.9545 and C(p) = 7.0000

Analysis of Variance

	Su	m of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
		-	-		
Model	6	3475577	579263	2811017	<.0001
Error	804137	165708	0.20607		
Corrected Tota	al 80414	43 364	1284		

$\begin{array}{ccc} Parameter & Standard \\ Variable & Estimate & Error & Type II SS \ F \ Value \ Pr > F \end{array}$

Intercept	-3.37660	0.00477	103204 500823 <.0001
x1	-9.48883	0.00992	188630 915372 <.0001
x2	3.56742	0.00516	98334 477189 <.0001
x4	-1.31476	0.00047457	1581662 7675406 <.0001
x5	0.19733	0.00966	86.00390 417.36 <.0001
x6	0.47064	0.00561 1	450.20388 7037.47 <.0001
x7	4.54955	0.00342	363805 1765456 <.0001

Bounds on condition number: 8.3655, 126.58

Backward Elimination: Step 1

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Backward Elimination: Step 1

Statistics for Removal DF = 1,804137

Partial Model Variable R-Square R-Square F Value Pr > F 0.9027 915372 <.0001 0.0518 x1 x2 0.0270 0.9275 477189 <.0001 x4 0.4344 0.5201 7675406 <.0001 x5 0.0000 0.9545 417.36 <.0001 0.0004 0.9541 7037.47 <.0001 x6 x7 0.0999 0.8546 1765456 <.0001

All variables left in the model are significant at the 0.0500 level. The SAS System 11:24 Saturday, October 3, 2009 9682

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Number of Observations Read804144Number of Observations Used804144

Stepwise Selection: Step 1

Statistics for Entry DF = 1,804142

Model					
Variable	Tolerance	R-Squar	re F Value	Pr > F	
x1	1.000000	0.3622	456589 <	.0001	
x2	1.000000	0.3171	373441 <	.0001	
x4	1.000000	0.4968	793944 <	.0001	
x5	1.000000	0.0001	50.51 <.0	0001	
x6	1.000000	0.1311	121300 <	.0001	
x7	1.000000	0.4244	592931 <	.0001	

Variable x4 Entered: R-Square = 0.4968 and C(p) = 8087357

Analysis of Variance

	Sur	n of	Mean		
Source	DF	Squares	Square	F Value	Pr > F

 Model
 1
 1809024
 1809024
 793944
 <.0001</th>

 Error
 804142
 1832260
 2.27853

 </t

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F

Intercept	-0.50232	0.00524	20969	9202.79	<.0001
x4	-1.34302	0.00151	1809024	793944	<.0001

Bounds on condition number: 1, 1

Stepwise Selection: Step 2 The SAS System 11:24 Saturday, October 3, 2009 9683

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 2

Statistics for Entry DF = 1,804141

Model

Variable Tolerance R-Square F Value Pr > F

x1	0.999919	0.8514	1918851 <.0001
x2	0.999585	0.7981	1199963 <.0001
x5	0.999993	0.4968	59.39 <.0001
x6	0.915514	0.5238	45559.8 <.0001
x7	0.999529	0.9017	3312667 <.0001

Variable x7 Entered: R-Square = 0.9017 and C(p) = 932648.9

Analysis of Variance

Sum of Mean DF Source Squares Square F Value Pr > F

2 3283387 1641693 3688633 <.0001 Model Error 804141 357898 0.44507 Corrected Total 804143 3641284

Parameter Standard Variable Estimate Error Type II SS F Value Pr > F Intercept -3.43947 0.00282 661458 1486194 <.0001 -1.31669 0.00066631 1737991 3905000 <.0001 x4 x7

4.69352 0.00258 1474362 3312667 <.0001

Bounds on condition number: 1.0005, 4.0019

Stepwise Selection: Step 3

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 3

Statistics for Removal DF = 1,804141

Partial Model Variable R-Square R-Square F Value Pr > F

x4	0.4773	0.4244	3905000	<.0001
x7	0.4049	0.4968	3312667	<.0001

Statistics for Entry DF = 1,804140

	Мо	del		
Variable	Tolerance	R-Squar	re FVa	lue $Pr > F$
	0.000046	0.00		
x1	0.392046	0.9269	276818	<.0001
x2	0.265256	0.9018	378.32	<.0001
x5	0.999982	0.9017	128.12	<.0001
x6	0.874328	0.9026	7418.51	<.0001

Variable x1 Entered: R-Square = 0.9269 and C(p) = 487884.8

Analysis of Variance

	Su	ım of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
		-	-		
Model	3	3375039	1125013	3397876	<.0001
Error	804140	266245	0.33109		
Corrected Tota	al 80414	43 364	1284		

Par	rameter	Standard			
Variable	Estimate	e Error	Type II SS	F Value	Pr > F

Intercept	-1.53964 0.00435	41395 125024 <.0001
x1	-4.43726 0.00843	91652 276818 <.0001
x4	-1.32052 0.00057474	1747821 5278941 <.0001
x7	3.23636 0.00355	274849 830126 <.0001
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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 3

Bounds on condition number: 2.5517, 18.309

Stepwise Selection: Step 4

Statistics for Removal DF = 1,804140

Partial Model

Variable R-Square R-Square F Value Pr > F

x1	0.0252	0.9017	276818	<.0001
x4	0.4800	0.4469	5278941	<.0001
x7	0.0755	0.8514	830126	<.0001

Statistics for Entry DF = 1,804139

 $\label{eq:model} \begin{array}{c} Model\\ Variable & Tolerance & R-Square & F \ Value & Pr > F \end{array}$

x2	0.119625	0.9541	476347	<.0001
x5	0.999935	0.9269	279.86	<.0001
x6	0.872932	0.9274	6201.80	<.0001

Variable x2 Entered: R-Square = 0.9541 and C(p) = 7248.815

Analysis of Variance

 $\begin{array}{ccc} Sum \mbox{ of } Mean\\ Source & DF \mbox{ Squares } Square \mbox{ F Value } Pr > F \end{array}$

 Model
 4
 3474084
 868521
 4177085
 <.0001</th>

 Error
 804139
 167201
 0.20793

 </td

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 4

Parameter
VariableStandard
EstimateError
ErrorType II SSF Value
Pr > FIntercept-3.179650.00419119759575970<.0001</td>

x1	-9.52673	0.00995	190529 916333 <.0001
x2	3.57900	0.00519	99044 476347 <.0001
x4	-1.32651	0.00045554	1763070 8479352 <.0001
x7	4.57904	0.00342	372360 1790836 <.0001

Bounds on condition number: 8.3594, 75.147

Stepwise Selection: Step 5

Statistics for Removal DF = 1,804139

Variable	Partial M R-Square	Model R-Sqi	iare FV	alue	Pr > F
x1	0.0523	0.9018	916333	<.0	001
x2	0.0272	0.9269	476347	<.0	001
x4	0.4842	0.4699	8479352	<.0	0001
x7	0.1023	0.8518	1790836	<.(0001

Statistics for Entry DF = 1,804138

Model								
Variable	Tolerance	R-Squar	re FVa	lue $Pr > F$				
x5	0.999840	0.9541	206.53	<.0001				
x6	0.872418	0.9545	6824.93	<.0001				

Variable x6 Entered: R-Square = 0.9545 and C(p) = 422.3553

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 5

Analysis of Variance

Sum of Mean Source DF Squares Square F Value Pr > F 695098 3371391 <.0001 Model 5 3475491 804138 165794 0.20618 Error Corrected Total 804143 3641284 Parameter Standard Error Type II SS F Value Pr > F Variable Estimate Intercept -3.36277 0.00472 104464 506674 <.0001 -9.49002 0.00992 188683 915159 <.0001 x1 98414 477331 <.0001 3.56864 x2 0.00517

Bounds on condition number: 8.3644, 100.41

Stepwise Selection: Step 6

0.00342

-1.31499 0.00047456

0.46240

4.55087

x4

x6 x7

Statistics for Removal DF = 1,804138

Variable	Partial I R-Square	Model R-Squ	are FVa	alue Pr > F
x1	0.0518	0.9027	915159	<.0001
x2	0.0270	0.9274	477331	<.0001
x4	0.4348	0.5197	7678420	<.0001
x6	0.0004	0.9541	6824.93	<.0001
x7	0.1000	0.8545	1766189	<.0001

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1583102 7678420 <.0001

364145 1766189 <.0001

 $0.00560 \quad 1407.13254 \quad 6824.93 \quad <.0001$

The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 6

Statistics for Entry DF = 1,804137

Model Variable Tolerance R-Square F Value Pr > F

x5 0.994669 0.9545 417.36 <.0001

Variable x5 Entered: R-Square = 0.9545 and C(p) = 7.0000

Analysis of Variance

Sum of Mean DF Square F Value Pr > F Source Squares Model 3475577 579263 2811017 <.0001 6 804137 165708 0.20607 Error Corrected Total 804143 3641284 Parameter Standard Variable Estimate $Error \quad Type \ II \ SS \quad F \ Value \quad Pr > F$ Intercept -3.37660 0.00477 103204 500823 <.0001

x1	-9.48883	0.00992	188630 915372 <.0001
x2	3.56742	0.00516	98334 477189 <.0001
x4	-1.31476	0.00047457	1581662 7675406 <.0001
x5	0.19733	0.00966	86.00390 417.36 <.0001
x6	0.47064	0.00561	1450.20388 7037.47 <.0001
x7	4.54955	0.00342	363805 1765456 <.0001

Bounds on condition number: 8.3655, 126.58

Stepwise Selection: Step 7

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The REG Procedure Model: MODEL1 Dependent Variable: Intercept Intercept

Stepwise Selection: Step 7

Statistics for Removal DF = 1,804137

Variable	Partial R-Square	Model R-Sqi	iare F	Value	Pr > F
x1	0.0518	0.9027	915372	2 <.00	001
x2	0.0270	0.9275	47718	9 <.00	001
x4	0.4344	0.5201	767540	6 <.0	001
x5	0.0000	0.9545	417.36	5 <.00	01
x6	0.0004	0.9541	7037.4	7 <.00	001
x7	0.0999	0.8546	176545	6 <.0	001

All variables left in the model are significant at the 0.1500 level.

All variables have been entered into the model.

Summary of Stepwise Selection

Variable Variable	Number	Partial Model
Step Entered Remove	d Label Va	Its In R-Square R-Square $C(p)$ F Value $Pr > F$
1 x4	1 0.4968	0.4968 8087357 793944 <.0001
2 x7	2 0.4049	0.9017 932649 3312667 <.0001
3 x1	3 0.0252	0.9269 487885 276818 <.0001
4 x2	4 0.0272	0.9541 7248.82 476347 <.0001
5 x6	5 0.0004	0.9545 422.355 6824.93 <.0001
6 x5	6 0.0000	0.9545 7.0000 417.36 <.0001
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The REG Procedure Model: MODEL1 Dependent Variable: Intercept

R-Square Selection Method

Number of Observations Read	804144
Number of Observations Used	804144

Number Model	in R-Sqı	iare	C(p)		MSE	Variable	es in Model
1	0.4968 8083		7357	2.27	853	x4	
1	0.4244				637	x7	
1	0.3622	1046	6608		8823	x1	
1	0.3171	1126	2427	3.0	9217	x2	
1	0.1311	1455	0014	3.9	3464	x6	
1	0.0001	1686	4986	4.5	2788	x5	
2	0.9017		48.9	0.44	507	x4 x7	
2	0.8514	182	1656	0.67	288	x1 x4	
2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2	0.7981	276	3550	0.91	425	x2 x4	
2	0.5238	761	0608	2.15	636	x4 x6	
2	0.4968	808	5702	2.27	836	x4 x5	
2	0.4777	8424	4946	2.36	504	x6 x7	
2	0.4469	896	9616	2.50	0462	x1 x7	
2	0.4275	931	2710	2.59	254	x1 x6	
2	0.4245	936	5198	2.60	1599	x2 x7	
2	0.4244	936	5109	2.60	622	x5 x7	
2	0.3856	1005	1877	2.7	8196	x2 x6	
2	0.3638	1043	7196	2.8	8070	x1 x2	
	0.3622	1046	5206	2.8	8788	x1 x5	
2	0.3172	1126	0785	3.0	9175	x2 x5	
2	0.1321	1453	2145	3.9	3007	x5 x6	
3	0.9269	4878	84.8	0.33	109	x1 x4 x7	
3	0.9026	9167	74.8	0.44	100	x4 x6 x7	
3 3	0.9018		34.1		486		
3	0.9017	9323		0.44	500	x4 x5 x7	
3 3	0.8541	177			6056	x1 x4 x6	
3	0.8518		4215		098	x1 x2 x4	
3 3	0.8515	182			266		
3	0.8019		5840		690	x2 x4 x6	
3 3	0.7982		2476		398	x2 x4 x5	
3	0.5241		5164		6497	x4 x5 x6	
3	0.4979		8522		371	x1 x6 x7	
3	0.4782		5824		5296		
3	0.4777		4313		488	x2 x6 x7	
3	0.4699		2982	2.40		x1 x2 x7	
		The SA	AS Syst	em	11:24	Saturday,	October 3, 2009

The REG Procedure Model: MODEL1 Dependent Variable: Intercept

R-Square Selection Method

Number in

Model	R-Squa	are	C(p)	MSE	Variables in Model
3	0.4469	896	8818	2.50442	x1 x5 x7
3	0 4283	020	7873	2 58873	v1 v2 v6

9691

 3
 0.4283
 9297823
 2.58873
 x1 x2 x6

 3
 0.4281
 9300776
 2.58948
 x1 x5 x6

3	0.4245	9364605	2.60584	x2 x5 x7
3	0.3864	10038927	2.77864	x2 x5 x6
3	0.3639	10435745	2.88033	x1 x2 x5
4	0.9541	7248.815	0.20793	x1 x2 x4 x7
4	0.9274	477998.5	0.32856	x1 x4 x6 x7
4	0.9269	487437.3	0.33098	x1 x4 x5 x7
4	0.9027	916053.0	0.44082	x2 x4 x6 x7
4	0.9026	916113.5	0.44083	x4 x5 x6 x7
4	0.9018	931548.3	0.44479	x2 x4 x5 x7
4	0.8545	1767524	0.65901	x1 x2 x4 x6
4	0.8542	1771502	0.66003	x1 x4 x5 x6
4	0.8519	1813309	0.67075	x1 x2 x4 x5
4	0.8021	2693222	0.89623	x2 x4 x5 x6
4	0.5197	7682816	2.17487	x1 x2 x6 x7
4	0.4984	8059903	2.27150	x1 x5 x6 x7
4	0.4782	8416141	2.36279	x2 x5 x6 x7
4	0.4699	8562496	2.40029	x1 x2 x5 x7
4	0.4290	9285872	2.58567	x1 x2 x5 x6
5		422.3553	0.20618	x1 x2 x4 x6 x7
5		7042.474	0.20787	x1 x2 x4 x5 x7
5		477194.0	0.32835	x1 x4 x5 x6 x7
5		915376.7	0.44064	x2 x4 x5 x6 x7
5		1765461	0.65849	x1 x2 x4 x5 x6
5	0.5201	7675411	2.17297	x1 x2 x5 x6 x7
6	0.9545	7.0000	0.20607	x1 x2 x4 x5 x6 x7

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The CORR Procedure

6 Variables: x1 x2 x4 x5 x6 x7

Covariance Matrix, DF = 804143

	x1	x2 x4	x5	x6 x7		
x1	0.014765359	0.031255086	0.001222166	0.000010498	-0.002168265	-0.027338461
x2	0.031255086	0.080380462	0.006449020	0.000045538	-0.005114094	-0.070126382
x4	0.001222166	0.006449020	1.247236758	-0.000152301	-0.031440474	-0.006994508
x5	0.000010498	0.000045538	-0.000152301	0.002761387	-0.000334695	0.000051812
x6	-0.002168265	-0.005114094	-0.031440474	-0.000334695	0.009380917	0.005847031
x7	-0.027338461	-0.070126382	-0.006994508	0.000051812	0.005847031	0.083268051

Simple Statistics

Variable	e N	Mean	Std Dev	Sum	Minimum	Maximum
x1	804144	0.22587	0.12151	181635	0.06667	0.50000
x2	804144	0.55709	0.28351	447984	0.20000	1.00000
x4	804144	3.28964	1.11680	2645347	2.00000	5.00000
x5	804144	0.05796	0.05255	46606	0 0.	15000
x6	804144	0.34562	0.09686	277931	0.20000	0.50000
x7	804144	0.60734	0.28856	488388	0.05799	1.22185

Pearson Correlation Coefficients, N = 804144 Prob > |r| under H0: Rho=0

x1 x2 x4 x5 x6 x7

x1	1.00000	0.9072	.4 0.00	901	0.00164	4 -0.	18423	-0.77967
	<.	0001	<.0001	0.14	04 <	<.0001	<.00	01

APPENDIX H

EVALUATION OF THE INJECTION RATES, CROSSFLOW AND LAYERS NUMBER IN THE RECOVERY FACTOR AND PVI RESULTS USING THE SIMULATION MODEL

Injection Rates Effect

Table 27—Example cases to evaluate the effect of different injection							
rates using the reservoir simulator characteristics as described in							
Table 2.							
	Cons. #	II	M - 1- 11:4	T	Data		

Case #	Heterogeneity	Mobility	Injection Rate
	(VDP)	Ratio	(B/D)
1	0.0	1	200
2	0.0	10	200
3	0.0	1	2000
4	0.0	10	2000
5	0.9	1	200
6	0.9	10	200
7	0.9	1	2000
8	0.9	10	2000

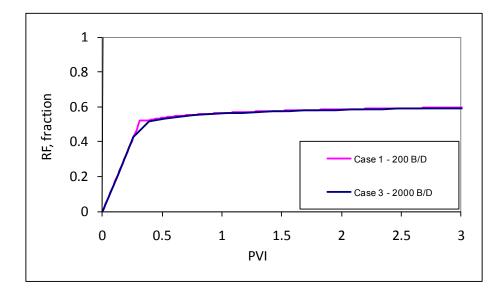


Fig. 37—Comparison of recovery factors obtained using different injection rates and M=1 for homogeneous reservoirs.

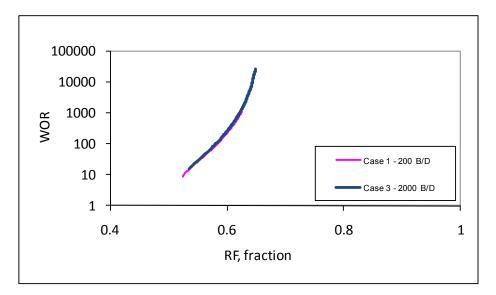


Fig. 38—Comparison of SLZs obtained using different injection rates and M=1 for homogeneous reservoirs.

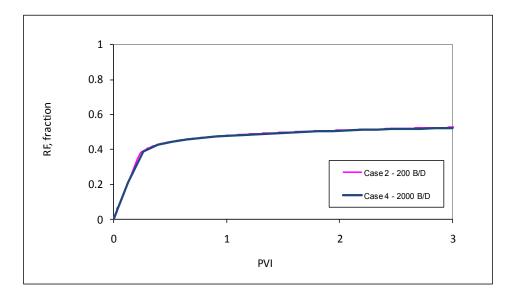


Fig. 39—Comparison of recovery factors obtained using different injection rates and M=10 for homogeneous reservoirs.

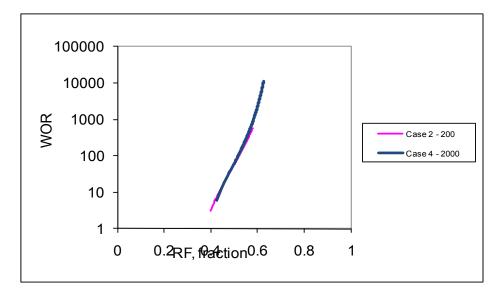


Fig. 40—Comparison of SLZs obtained using different injection rates and M=10 for homogeneous reservoirs.

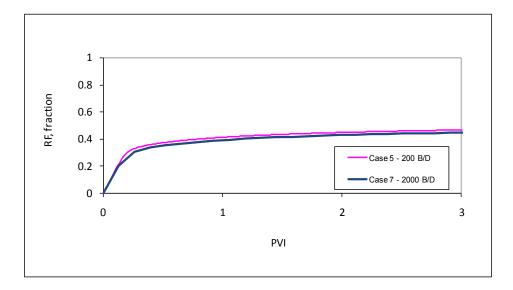


Fig. 41—Comparison of recovery factors obtained using different injection rates and M=1 and VDP=0.9.

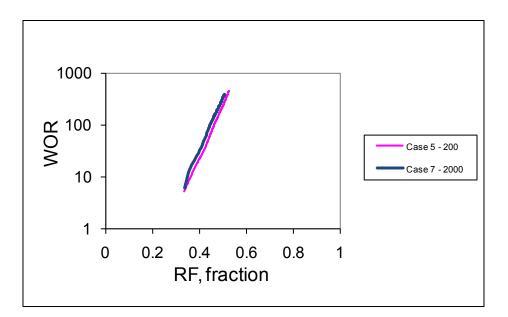


Fig. 42—Comparison of SLZs obtained using different injection rates and M=1 and VDP=0.9.

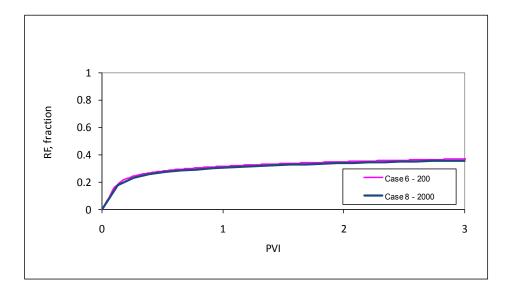


Fig. 43—Comparison of recovery factors obtained using different injection rates and M=10 and VDP=0.9.

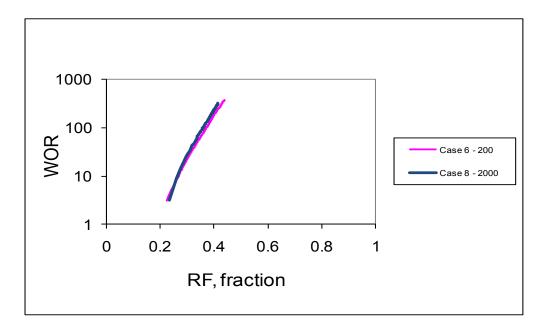


Fig. 44—Comparison of SLZs obtained using different injection rates and M=10 and VDP=0.9.

Number of Layers Effect

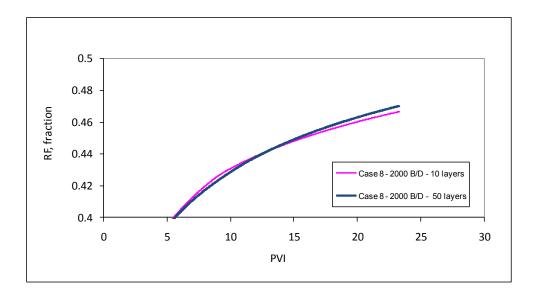


Fig. 45-Recovery comparison for different number of layers in the same reservoir.

Fig. 45 shows the same behavior for both cases, so we can infer that not an important effect is observed, considering that only at high PVI a difference will be obtained. Also, Fig. 46 shown the SLZ behavior and no important effect is noticed.

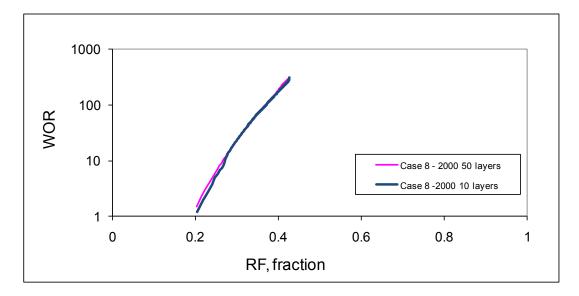


Fig. 46—SLZ plot for heterogeneous cases (VDP=0.9) with M=10. No difference in behavior is shown for the number of layers used.

Crossflow Effect

Three scenarios of the same 10-layers reservoirs in Table 28 were evaluated:

<u>Scenario 1</u>: Homogeneous reservoir (VDP=0), no crossflow $(k_v=0)$ and crossflow $(k_v=k_h)$.

<u>Scenario 2</u>: Heterogeneous reservoir (VDP=0.93), no extreme values of permeability (*k* from 0.1 to 200 mD), no crossflow and crossflow.

<u>Scenario 3</u>: Heterogeneous reservoir (VDP=0.85), 3 theft zones (*k* from 10 to 3000 mD), no crossflow and crossflow.

Layer	Scenario 1	Scenario 2	Scenario 3
1	200	200	2000
2	200	100	100
3	200	80	800
4	200	60	60
5	200	0.1	2000
6	200	0.2	100
7	200	10	10
8	200	150	150
9	200	100	3000
10	200	50	50
VDP	0	0.93	0.85

Table 28—Permeability values per layer used in the crossflow exercise.

Table 28 shows the VDP input data and figures present the simulation runs results. In Fig. 47, RF vs. PVI curve behavior for the homogenous reservoir is presented. We cannot see any difference in performances. Fig. 48 presents a plot of WOR vs. RF . In any of them we can see a difference. We can conclude that crossflow will not affect homogeneous reservoir behavior.

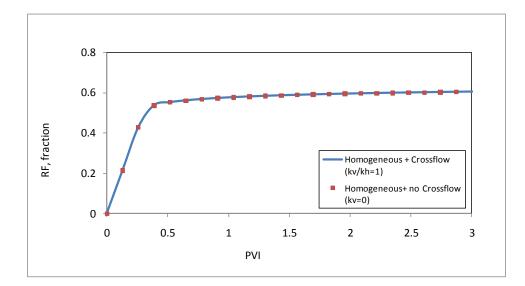


Fig. 47-Crossflow effect in homogeneous reservoir.

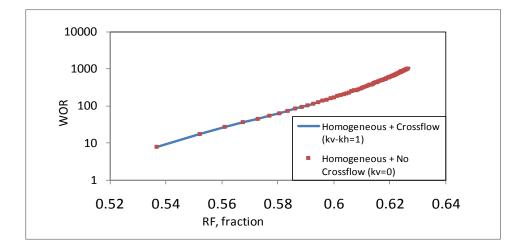


Fig. 48—Log WOR vs. RF plot for homogeneous reservoir with and without crossflow.

Same set of plots are presented for Scenario 2, with a VDP of 0.93 but with relatively low permeability values in all layers. No important difference can be detected in the plots due to crossflow effects.

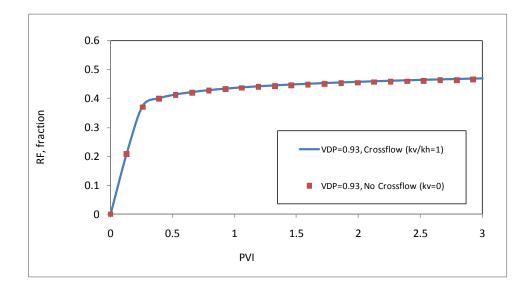


Fig. 49—Crossflow effect in heterogeneous reservoir (VDP=0.93).

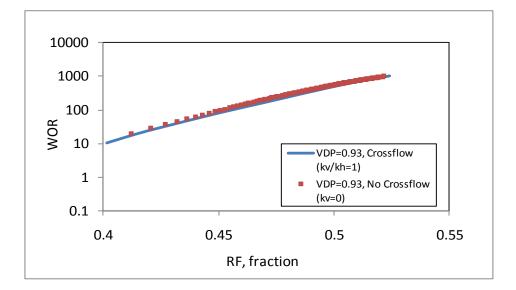


Fig. 50—WOR vs. RF plot for heterogeneous reservoir with and without crossflow (VDP=0.93).

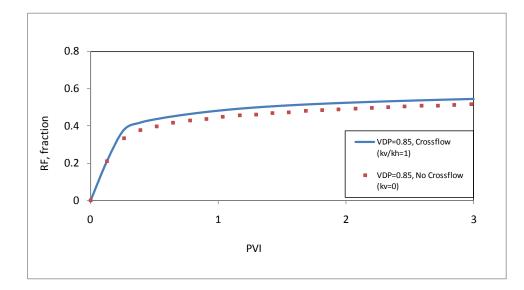


Fig. 51—Crossflow effect in heterogeneous reservoir (VDP = 0.85). For larger VDP, if there is a "thief zone", the effect will be stronger.

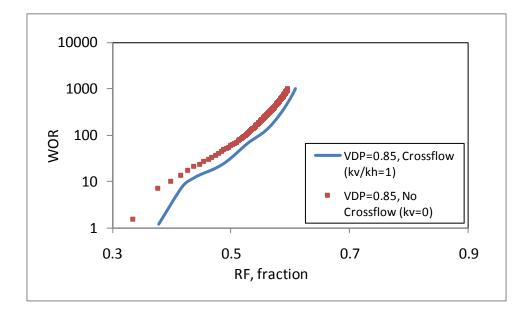


Fig. 52—WOR vs. RF plot for heterogeneous reservoir with and without crossflow (VDP = 0.85).

In Fig. 52 we can see a little difference in the two SLZs. However ultimate recovery does not show an important difference that may affect results in our statistical model. This case has "thief zones". Vertical permeability contrast is less than Scenario 2, but high permeability layers represent a sort of "channels" that are expected to take most of the water injected since horizontal permeability values are extremely high. This situation can be seen in many reservoirs. Thief zones with higher permeability will increase the difference in recovery, WOR and PVI.

In these cases, earlier breakthrough may happen for the no-crossflow case. High permeability layers are acting as theft zones, taken more water and bypassing oil in the reservoir, leaving low permeability zones with less sweep efficiency (red in Fig. 53 and Fig. 54) showing oil saturation profiles at a water cut of 99%.

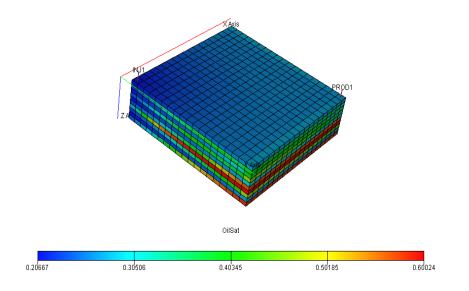


Fig. 53—Oil saturation profile for no crossflow reservoir, with VDP = 0.85.

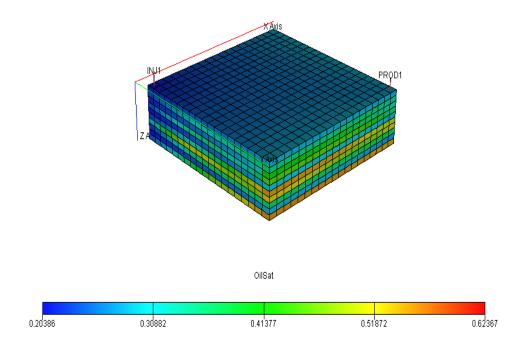


Fig. 54—Oil saturation profile for reservoir with crossflow and VDP = 0.85.

Some Published Works Regarding Crossflow Effect

According to Kumar (2005), factors controlling recovery and fingering are high average permeability and M. In these cases, depletion will cause important increments of M since at lower pressures the oil will be more viscous, so the presence of thief zones may affect recovery and water cycling. Heterogeneity affects recovery more for high M(less resistance to flow for water) so thief zones will contribute to recovery mostly during primary depletion. Accurate M and relative permeability measurements for each layer will be essential to optimize operations and maximize recovery. Highly correlated (continuous), thin, thief zones will reduce recovery for high *M*. Mechanical or chemical blocking of thief zones on the injection or production side may be a remedy needed in these cases (Yang and Ershaghi, 2005).

Willhite (1986) explains that oil and water can move between layers depending on relative permeability relationships and potential differences, but because permeability differences, the front in the high permeability zone (*HPZ*) will move faster than in the low permeability zone (*LPZ*). Viscous crossflow can occur from *LPZ* to *HPZ* because mobility ratio may be higher in the *HPZ*.

Also, capillary forces can cause crossflow: if the rock is water-wet, water from *HPZ* can imbibe into *LPZ* and *some* oil from *LPZ* can go to *HPZ* where is displaced.

Craig (1971) explains that when $k_v \ll k_h$: Reservoir can perform as one with very little or no crossflow (30 mD vs. 3000 mD = 0.01).

Ahmed (2002) says that "substantial reservoir uniformity is one of the major physical criterions for successful waterflooding. For example, if the formation contains a stratum of limited thickness with a very high permeability (i.e., thief zone), rapid channeling and bypassing will develop. Unless this zone can be located and shut off, the producing water–oil ratios will soon become too high for the flooding operation to be considered profitable. The lower depletion pressure that may exist in the highly permeable zones will also aggravate the water-channeling tendency due to the high permeability variations".

Ultimate recovery in previous plots in this section are very similar, including same slopes and intercepts in both trend lines, which may drive us to conclude that our model will still Work properly in those cases. Also, all these findings confirm conclusions from other authors commented above.

For cases with extremely high Mobility Ratios, the user must be careful applying any prediction method, including reservoir simulation, because even simulators may have problems accounting for high Mobility Ratio effects (Avery et al., 1987). Techniques such as simulators based on nine-point finite difference, or the use of a preselected grid orientation, will improve forecast when an unfavorable *M* is present.

APPENDIX I

Fractional Flow and Frontal Advance Theory

In waterflooding projects, water displaces oil through the rock in an immiscible process. This process is desired to *be* efficient, meaning that we want the water to displace as much oil as possible. The term "Displacement Efficiency" (E_D) is then referred to the fraction of oil saturations swept by water from the reservoir that can be explained using the principles of the Frontal Advance Theory and the Fractional Flow (Buckley-Leverett) Equation as a 1-D process.

Beginning with the Darcy's law, and following the derivation process shown by Craig (1971), we can write this expression in consistent units, for oil and water separately as follows:

$$u_o = -\frac{k_o}{\mu_o} \left(\frac{\partial P_o}{\partial x} + g\rho_o \sin \alpha \right).$$
 (I.1)

and

$$u_{w} = -\frac{k_{w}}{\mu_{w}} \left(\frac{\partial P_{w}}{\partial x} + g\rho_{w} \sin \alpha \right).$$
 (I.2)

where:

 $u_o = \text{oil phase velocity}$

- u_w = water phase velocity
- k_o = effective permeability to oil
- k_w = effective permeability to water

- μ_o = oil viscosity, cP
- μ_w = water viscosity, cP
- P_o = pressure in oil phase
- P_w = pressure in water phase
- x = distance along direction of movement
- g = acceleration due to gravity

 $\rho_o = \text{oil density}$

$$\rho_w$$
 = water density

 α = angle of the reservoir dip with the horizontal

. .

Rearranging Eq. I.1 and I.2 and substituting, we obtain:

and

$$u_{w}\frac{\mu_{w}}{k_{w}} = -\frac{\partial P_{w}}{\partial x} - g\rho_{w}\sin\alpha...$$
(I.4)

Subtracting Eq. I.3 from Eq. I.4 we obtain:

$$u_{w}\frac{\mu_{w}}{k_{w}}-u_{o}\frac{\mu_{o}}{k_{o}}=-\left(\frac{\partial P_{w}}{\partial x}-\frac{\partial P_{o}}{\partial x}\right)-g(\rho_{w}-\rho_{o})\sin\alpha$$
 (I.5)

Since the difference of the pressure in the oil phase minus the pressure in the water phase is defined as Capillary Pressure (P_c), and the density difference is the difference between the water density and the oil density, we can write:

but we can express Eq. I.6 in terms of the total velocity (u_t) as:

and solving Eq. I.7 and dividing both members by u_t :

$$u_{w}\left(\frac{\mu_{w}}{k_{w}}+\frac{\mu_{o}}{k_{o}}\right)-u_{t}\frac{\mu_{o}}{k_{o}}=\frac{\partial P_{C}}{\partial x}-g\Delta\rho\sin\alpha$$
 (I.8)

and solving for the fraction of water velocity of the total velocity (*fw*):

$$\frac{u_w}{u_t} = f_w = \frac{\frac{\mu_o}{k_o} + \frac{1}{u_t} \left(\frac{\partial P_C}{\partial x} - g\Delta\rho\sin\alpha\right)}{\frac{\mu_w}{k_w} + \frac{\mu_o}{k_o}}....(I.10)$$

or

$$f_{w} = \frac{1 + \frac{k_{o}}{u_{t}\mu_{o}} \left(\frac{\partial P_{c}}{\partial x} - g\Delta\rho\sin\alpha\right)}{1 + \frac{\mu_{w}}{\mu_{o}}\frac{k_{o}}{k_{w}}}....(I.11)$$

Which is the Fractional Flow Equation including Capillary Pressure, fluids density and dip angle of the reservoir.

We assumed Capillary Pressure negligible and a horizontal reservoir. We simplify our equation as:

With the Fractional Flow Equation, we can determine the water cut (f_w) at any point in the reservoir where water saturation is known.

Frontal Advance Equation (Craig, 1971), makes two main assumptions: mass transfer between phases does not exist and fluids are incompressible. We also consider an infinitesimal element of rock with a constant porosity (ϕ) and area (A) in the direction of flow with distance x. Applying the Mass Conservation and Material Balance principles we can define the water mass rate entering and leaving the element at point x, and the water accumulation in the element as:

$$(q_w \rho_w)_x....(I.13)$$

$$(q_w \rho_w)_{x+\Delta x}....(I.14)$$

$$A\phi\Delta x \frac{\partial}{\partial t} (S_w \rho_w)....(I.15)$$

and we can express water accumulation = water in – water out as:

or

$$\frac{\partial}{\partial x} (q_w \rho_w) + A \phi \frac{\partial}{\partial t} (S_w \rho_w) = 0.....(I.17)$$

eliminating density difference:

$$\frac{\partial}{\partial x}(q_w) + A\phi \frac{\partial}{\partial t}(S_w) = 0.$$
 (I.18)

and solving for changes in water saturation with time:

but q_w is a function of both water saturation and time, so:

$$dq_{w} = \left(\frac{\partial q_{w}}{\partial S_{w}}\right)_{t} dS_{w} + \left(\frac{\partial q_{w}}{\partial t}\right)_{S_{w}} dt \dots (I.20)$$

Taking the derivative with respect to x at a fixed time and solving for the change of water saturation with respect to length:

$$\left(\frac{\partial S_{w}}{\partial x}\right)_{t} = \frac{\left(\frac{\partial q_{w}}{\partial x}\right)_{t}}{\left(\frac{\partial q_{w}}{\partial S_{w}}\right)_{t}}....(I.21)$$

Water saturation is a function of x and t, so giving the same treatment we gave to q_w we have:

$$dS_{w} = \left(\frac{\partial S_{w}}{\partial x}\right)_{t} dx + \left(\frac{\partial S_{w}}{\partial t}\right)_{x} dt = 0.$$
 (I.22)

We made $dS_W = 0$ because we are looking at a plane of constant *x* where S_W changes. Thus

and substituting Eq. I.19 into Eq. I.21 we have:

but we also have that

and differentiating with respect to $S_W at a constant t$:

but the change of velocity with respect to S_W at any time is zero because the fluids are incompressible, so we finally have, substituting Eq. I.26 into Eq. I.24 :

$$\left(\frac{\partial x}{\partial t}\right)_{S_w} = \frac{q_t}{A\phi} \left(\frac{\partial f_w}{\partial S_w}\right)_t.$$
(I.27)

This is the linear Frontal Advance Equation for water, based upon conservation of mass and assuming incompressible fluids. It states that the rate of advance (velocity= distance /time) of the saturation front inside the reservoir will be equal to superficial velocity of the total fluid, times the change of the fractional flow with water saturation. We can also say that particular water saturation propagates through a porous rock at a constant velocity. To determine that velocity, we need to apply the Fractional Flow Equation.

Some limitations of the frontal advance solution are related to the basic assumptions, such as:

- 1. The two immiscible fluids are considered incompressible.
- 2. Linear or radial flow in only one direction is assumed.

- 3. Initial fluids saturations are uniform.
- 4. Applies only to stabilized displacement processes.
- Layers are assumed to be homogeneous and isotropic. Constant rock properties except permeability per layer, layer thickness and porosity in the reservoir.
- 6. Layer-cake mode with no crossflow between layers.
- 7. Steady State flow.
- 8. Gravity segregation, dip angle and capillary pressure are neglected.
- 9. The vertical efficiency is unity within each layer.

General Application

In this section, we summarize a typical application of the fractional flow equation and the Frontal Advance Theory. In later sections we will show the approach developed in this research.

Rewriting Eq. I.12 in terms of the oil and water relative permeabilities ratios we have:

$$f_{w} = \frac{1}{1 + \frac{\mu_{w}}{\mu_{o}} \frac{k_{ro}}{k_{rw}}}$$
(I.28)

Since the relative permeabilities are functions of the water saturation (S_w) , f_w is also a function of the water saturation. It is used to construct a plot of water front (f_w) vs. water saturation (S_w) to determine displacement performance. To construct the plot, we need a set of relative permeability curves generated from a model or determined by special core analysis and oil and water viscosity values.

For computation of performance at water breakthrough, the plot needed is shown in Fig. 55, where an example of a fractional flow performance with water saturation can be seen. According to Welge procedure, a tangent drawn from the initial water saturation (S_{wc}) touches the curve at S_w =0.69 and at f_w =0.93. These are the values of those variables at the water front, and will be the values at the water breakthrough when the injected water front reaches the producer well.

The stabilized zone includes all water saturations from S_{wc} to S_{WBT} =0.69 and water saturations will increase after breakthrough up to the maximum water saturation (1- S_{or}). Reading the point where the tangent reaches f_w =1, we can determine the average water saturation behind the front. In Fig. 55, this value is 0.72.

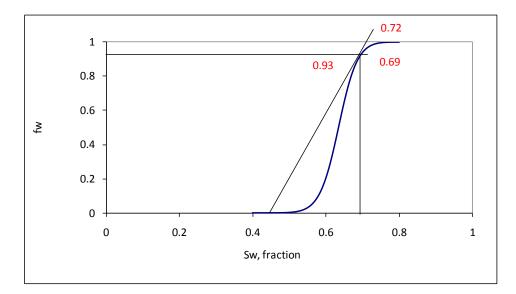


Fig. 55—Example of fractional flow curve showing the breakthrough at a f_w of 0.93 and a S_w of 0.69. The average water saturation at the breakthrough is 0.72.

To determine performance after breakthrough (the non-stabilized portion of fractional flow curve), several tangents to the portion of the fractional flow curve after breakthrough can be determined to identify the f_w value for each water saturation value, until we reach the maximum water saturation $(1-S_{or})$. The extrapolation of these tangents to the value of f_w =1 provide the values of S_{Wave} .

Even when the Welge's graphical method is useful, in some cases it may be difficult to determine where the tangent intersects the curve. High viscous oils can present a stepped curve where the tangent cannot be identified properly. A numerical approach is better than the graphical method and using Fractional Flow Theory we obtain Eq. I.29:

$$\overline{S_w} = S_{Wf} + \frac{1 - f_{wf}}{\left(\frac{df_w}{dS_w}\right)_{S_{wf}}} \qquad (I.29)$$

Using this information (just the appropriate water-oil relative permeability curves and the oil and water viscosities), cumulative oil production and water injection, injection and production rates, and WOR can be computed.

Wettability is an important factor that control displacement efficiency in the waterflooding process. A decrease of water-wetness will make water permeability increase (more water flow) and oil permeability decrease (less oil flow). The fractional flow curve for an oil-wet rock is steeper than the water-wet one. That will make displacement of oil by water in an oil-wet rock less efficient than that in a water-wet rock, or more PVI will be needed to achieve an equivalent recovery factor.

The viscosity ratio will also affect displacement since the more viscous the oil, the stepper the slope of the fractional flow curve after breakthrough, so more PVI will be required to produce oil, because the expression for PVI for linear systems is:

The same effect will be obtained for high or unfavorable mobility ratio, since water mobility will be higher than oil mobility and this parameter is affected by the oil viscosity (see Fig. 56).

Gravity forces will affect also when the dip angle is high. In that case, the dip angle component in the fractional flow curve must be considered. Usually oil density is less than water density, so water should move slower or faster than oil, depending on where the water is injected in the reservoir, down dip or up dip, respectively.

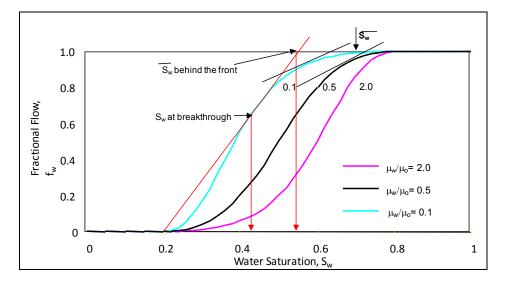


Fig. 56—Effects of viscosity ratio in fractional flow curves, maintaining the same relative permeability curves, S_{wi} and S_{or} .

APPENDIX J

ANALYTICAL METHODS FOR ESTIMATING WATERFLOOD RECOVERY

Analytical and Empirical Forecasting Procedures

During the last 50 years, several attempts have been made to forecast waterflood performance and ultimate oil recovery by modeling the sweeping process of water displacing oil through the porous medium.

The accuracy of the prediction is mostly affected by the knowledge about effects of reservoir heterogeneity, fluid saturations, and mobility ratio. These factors affect displacement and areal and vertical sweep efficiencies. Water channeling that bypasses mobile oil remaining within the rock, causing low displacement and early breakthrough in producing wells, will reduce ultimate recovery.

Reasonable forecasts of waterflood performance can improve decisions regarding a waterflooding candidate and project feasibility. Waterflood performance can be estimated by various analytical methods based upon several assumptions that many times are ignored or violated.

A brief description of the most used analytical and empirical forecasting methods follows:

Craig-Geffen-Morse Method

The Craig-Geffen-Morse prediction method (CGM) can be used to estimate waterflood performance (Craig, 1971). It is based on the Buckley-Leverett theory that is

concerned with displacement mechanisms and considers oil displacement by water in either a linear or a radial system. The method estimates oil recovery with the required volume of water injected for that recovery in a waterflood system as a function of time. CGM considers multilayered systems, variable injection rate, and areal sweep efficiency as main parameters.

In addition to displacement in the swept area, CGM uses experimental correlations that account for areal sweep efficiency at water breakthrough and relates the areal sweep efficiency after breakthrough to the cumulative injected water. The method accounts for a gradual improvement in areal sweep efficiency with continued water injection and for increasing displacement of oil behind the front in the contacted zone until areal sweep efficiency is equal to unity.

The method performs all calculations for a single layer. Results of injection and production rates for the other layers can be extrapolated in proportion to the flow capacity (kh) values and pore volumes of the other layers. The vertical sweep efficiency is considered unity. The summation process accounts for vertical sweep of the multilayered system.

The total oil production is the sum of the oil displaced from the initial swept region and the additional oil produced as a result of the increase in areal sweep. Oil production begins before water breakthrough, just after gas fill-up. The water production is then the water injected minus the oil produced.

The method discussed in the original paper (Craig, 1954) did not consider multilayer reservoirs, but a revised version was extended to stratified reservoirs (Craig 1971).

The main assumptions of the CGM method are:

1. Multilayered reservoirs with no crossflow between layers. Each layer is homogeneous but the method accounts for vertical heterogeneity.

2. Linear or radial flow can be explained using Darcy's law. Applies for , incompressible fluids and isothermal process.

3. Steady-state flow.

4. Only rock properties that change per layer are permeability, layer thickness, and porosity.

5. Gravity segregation between oil and water, dip angle, and capillary pressure are neglected.

6. Gas fill-up per zone is completed before production begins.

7. Areal sweep efficiency is calculated with experimental correlations and increases up to 100%. Also 100% vertical sweep efficiency is assumed for each layer.

Dykstra-Parsons Method

Dykstra-Parsons' method (Dykstra and Parsons, 1950) is concerned mostly with reservoir stratification. Used for predicting waterflood behavior in stratified systems, the method combines laboratory results with theoretical studies. This method requires the use of VDP, M, the initial or connate water saturation (S_{wc}), and fractional oil recovery at

a specified water/oil ratio. Dykstra and Parsons introduced the vertical coverage (C_v) parameter, determined experimentally, to account for vertical sweep efficiency. This parameter is determined using VDP, *M*, and C_v correlations, and later C_v is multiplied times the areal sweep efficiency, determined using Craig's correlations (1971). The main assumptions of this method are:

1. Multilayered reservoirs with no crossflow between layers.

2. Linear flow; incompressible fluids; isothermal process; can be explained using Darcy's law.

3. Steady-state flow.

4. Only rock properties that change per layer are permeability, layer thickness, and porosity.

5. Gravity segregation between oil and water is ignored.

6. Piston-like displacement with no oil production from behind the front, ignoring relative permeability effects.

The results obtained from this method tend to be optimistic, related mainly to the assumption of piston-like displacement, but the method is accurate for highly heterogeneous reservoirs with any M.

Stiles Method

The Stiles method handles reservoir heterogeneity and is used in stratified reservoirs. The method is subject to the following assumptions (Stiles, 1949):

1. Multilayered reservoirs with no crossflow between layers.

2. Linear flow; incompressible fluids; isothermal process; can be explained using Darcy's law.

3. Steady-state flow.

4. Only rock properties that change per layer are permeability, layer thickness, and porosity.

5. Gravity segregation between oil and water is ignored.

6. Piston-like displacement with no oil production from behind the front.

7. Flood front penetration into each layer is proportional to the capacity of the layer (thickness \times permeability). This is equivalent to assuming the mobility ratio is unity.

Stiles' method is more realistic for multilayered reservoirs. The method calculates permeability distribution from capacity distribution and considers the physical structure of the reservoir better than Dykstra-Parsons, which is based on statistical and experimental correlations. Running both methods and comparing results can be a good approach to estimate recovery when high VDP and M are present. Input data and reservoir characteristics will dictate which method should be used in each case.

Other practical approaches include the work published by Craig (1971), which presents different graphic correlations for areal sweep efficiencies as a function of M. Graphic, experimental correlations are used to determine areal and vertical sweep efficiency and to determine displacement efficiency and cumulative production (N_p) . This method provides accurate results for more favorable M (M<1).

VITA

Name: Arnaldo Leopoldo Espinel Diaz Address: Department of Petroleum Engineering c/o Dr. Maria Barrufet Texas A&M University College Station, TX 77843-3116

Email Address: arnaldo_e@hotmail.com

Education:

- Petroleum Engineering, Instituto Universitario de Nuevas Profesiones, Caracas, Venezuela, 1984
- B.S., Business Administration, Universidad Jose Maria Vargas, Caracas, Venezuela, 1993
- M.S., Petroleum Engineering, Texas A&M University, 1998
- Certification, Higher Education Professional Post-Graduate Program, Universidad de Oriente, Barcelona, Venezuela, 2004.
- Ph.D., Petroleum Engineering, Texas A&M University, 2010