Comparative Assessment of Three-Phase Oil Relative Permeability Models

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Abstract

We assess the ability of eleven models to reproduce three-phase oil relative permeability (k_{ro}) laboratory data obtained in a water-wet sandstone sample. We do so by considering model performance when (*i*) solely two-phase data are employed to render predictions of k_{ro}, and (*ii*) two- and three-phase data are jointly used for model calibration. In the latter case a Maximum Likelihood (ML) approach is used to estimate model parameters. The tested models are selected amongst (*i*) classical models routinely employed in practical applications and implemented in commercial reservoir softwares and (*ii*) relatively recent models which are considered to allow overcoming some drawbacks of the classical formulations. Amongst others, the latter set of models includes the formulation recently proposed by *Ranaee et al.* [2015], which has been shown to embed the critical effects of hysteresis, including the reproduction of oil remobilization induced by gas injection in water-wet media. We employ formal model discrimination criteria to rank models according to their skill to reproduce the observed data and use ML Bayesian Model Averaging to provide model averaged estimates (and associated uncertainty bounds) of k_{ro} by taking advantage of the diverse interpretive abilities of all models analyzed. The occurence of elliptic regions is also analyzed for selected models in the framework of the classical fractional flow theory of displacement. Our study confirms that model outcomes based on channel flow theory and classical saturation-weighted interpolation models do not generally yield accurate reproduction of k_{ro} data, especially in the regime associated with low oil saturations, where water alternating gas injection (WAG) techniques are usually employed for enhanced oil recovery. This negative feature is not observed in the model of *Ranaee et al.* [2015] due to its ability to embed key effects of pore scale phase distributions, such as hysteresis effects and cycle dependency, for modeling k_{ro} observed during WAG.

Keywords: Three-phase oil relative permeability, model comparison, parameter estimation, multimodel analysis, model discrimination criteria.

1. Introduction

Multiphase flow in porous media is inherently affected by uncertainty due to the lack of detailed knowledge of the complex physical processes involved in fluid/fluid and fluid/rock interactions. Several studies highlight the complexity of the mechanisms driving pore scale fluid displacement in three-phase environments [e.g., *Vizika and Lombard*, 1996; *Kalayidjan et al.*, 1997; *Fenwick and Blunt*, 1998; *Blunt*, 2000; *Van Dijke and Sorbie*, 2003; *Piri and Blunt*, 2005; *Van Dijke et al.*, 2006; *Suicmez et al*., 2007; *Sohrabi et al*., 2008]. At the continuum (or macro) scale, the traditional depiction of multiphase flow in porous media is grounded on the Darcy-Buckingham equation where the relative phase permeability, $k_{r\alpha}$, linking the flow rate of the α fluid phase to pressure gradient, is a key parameter to estimate. Reliable experimental studies aimed at providing relative permeability data in three-phase flows are extremely complex to design and perform. An extensive and recent review on this topic is offered by *Alizadeh and Piri* [2014a]. These authors review the effect of fluid saturation, saturation history, wettability, spreading, layer drainage, and interfacial tension on $k_{r\alpha}$. While $k_{r\alpha}$ experimental data in three-phase environments are seldom available, especially in practical applications, three-phase relative permeability estimates are often obtained through empirical/semi-empirical models whose parameters are typically derived from data collected in two-phase settings. In this context, several empirical models have been proposed in the literature to characterize and predict three-phase oil relative permeability, k_{ro}. Here, we consider the suite of eleven models listed in Table 1 and described in details in the supporting information, SI. These models were selected amongst (*i*) classical models routinely used in practical applications and implemented in commercial reservoir softwares [*Stone*, 1970, 1973; *Baker*, 1988] and (*ii*) relatively recent and innovative models [e.g., *Jerauld*, 1997; *Delshad and Pope*, 1989; *Hustad and Hansen*, 1995; *Blunt*, 2000; *DiCarlo et al.*, 2000; *Du et al.*, 2004; *Shahverdi and Sohrabi*, 2013; *Lomeland and Ebeltoft*, 2013; *Ranaee et al.*,

2015] which are considered to allow overcoming, albeit with diverse emphasis, some drawbacks of the classical formulations, as described in the following and in SI.

A first set of models (M_1 - M_4 in Table 1) stems from the work of *Stone* [1970] (i.e., the so-called Stone I model, M_1) and are based on channel flow theory. Model M_4 [*Shahverdi and Sohrabi*, 2013] can include hysteresis effects to characterize k_{ro} values observed during water alternating gas injection, WAG. The channel flow theory assumes that each pore is occupied by a single mobile fluid and k_{ro} at connate (or residual) water saturation, $\bar{S}_{wc}$, is set equal to one. Otherwise, numerical analyses based on pore-network modeling [e.g., *Van Dijke and Sorbie*, 2003; *Piri and Blunt*, 2005; *Van Dijke et al.*, 2006; *Suicmez et al.*, 2007, 2008] and experimental micromodel visualization of pore scale fluid distribution [e.g., *Sohrabi et al.*, 2008] show that more than one mobile fluid is typically found within a single pore. *Spiteri and Juanes* [2006] show that channel flow theory does not yield accurate estimates of k_{ro} for low oil saturations, S_o. In particular, Stone II formulation (M_2 in this study) is prone to provide sometimes severe underestimation of k_{ro}.

A second set of models relies on a saturation-weighted interpolation between two-phase relative permeabilities (models M_5 - M_{11} in Table 1). These models stem from the *Baker* [1988] formulation

$$k_{ro} = \frac{\left(S_w - \bar{S}_{wc}\right)\bar{k}_{row}^{I} + \left(S_g - \bar{S}_{gt}\right)\bar{k}_{rog}^{D}}{\left(S_w - \bar{S}_{wc}\right) + \left(S_g - \bar{S}_{gt}\right)} \quad (1)$$

where S_w and S_g respectively are water and gas saturation in the three-phase environment, $\bar{S}_{gt}$ is the saturation of trapped gas, $\bar{k}_{rog}^{D}$ is oil relative permeability observed during drainage in an oil-gas systems and $\bar{k}_{row}^{I}$ is oil relative permeability observed during imbibition (i.e., water injection) in an oil-water system. Several studies [e.g., *Blunt*, 2000; *Spiteri and Juanes*, 2006; *Ranaee et al.*, 2015] show that (1) fails in reproducing observed k_{ro} values, especially for conditions associated with low oil saturation. In this context, *Blunt* [2000] developed a relatively complex model (model M_8 in

Table1) which allows (*i*) embedding the effect of trapping/remobilization of oil, water and gas on three-phase relative permeabilities and (*ii*) describing k_{ro} at very low oil saturation, corresponding to the so-called layer drainage regime. *Ranaee et al.* [2015] recently proposed to model k_{ro} through a sigmoidal function (model M_{11} in Table 1). This formulation allows reproducing (*i*) oil remobilization induced by gas injection in water-wet media; and (*ii*) a smooth transition towards the layer drainage regime for low oil saturations, including (*iii*) the ensuing reduction of residual oil saturation in a three-phase system. *Ranaee et al.* [2015] developed two simple procedures to estimate k_{ro} during gas and water injections and assessed the strength of their approach by comparisons against two sets of laboratory-scale data (see also the SI). *Ranaee et al.* [2015] tested their model against two published datasets, which comprise a water-wet sandstone sample [*Oak*, 1990] and unconsolidated porous materials associated with diverse wettability conditions [*DiCarlo et al.*, 2000].

All models listed in Table 1, with the exception of M_{10} [*Lomeland and Ebeltoft*, 2013], allow predicting k_{ro} values upon relying solely on observations performed in two-phase settings (i.e., water-oil, oil-gas and/or water-gas) during drainage and/or imbibition, without the strict requirement of three-phase data. However, three-phase data can be used (when available) to estimate the model parameters in a number of cases, including, for example, to provide an estimate of residual oil saturation. As detailed in the SI, almost all models listed in Table 1 describe k_{ro} as a function of oil, S_o, water, S_w, and gas, S_g, saturation, i.e., saturation explicitly appears in the functional relationship employed to compute k_{ro}. The only exceptions are (*i*) M_2 [*Stone*, 1973], where k_{ro} depends on fluids saturation only through the corresponding value of two-phase oil relative permeability and (*ii*) M_9 [*Fenwick and Blunt*, 1998; *DiCarlo et al.*, 2000], where k_{ro} depends only on S_o.

The diversity of models included in our analysis suggests the worth of exploring the possibility of exploiting the relative strength of each of them by employing all of them jointly within the context of a multimodel approach. The latter framework enables us to use jointly multiple models for the

interpretation of observed quantities of interest. It also yields predictions, including the quantification of predictive uncertainty, by taking advantage of a suite of diverse interpretive models which can be used to characterize the system under study. The multimodel approach we consider is grounded on the Maximum Likelihood Bayesian Model Averaging (MLBMA) framework illustrated by *Neuman* [2002, 2003], *Ye et al*. [2004], and *Neuman et al*. [2012]. While applications of multimodel approaches in subsurface environments have mostly studied flow behavior in porous and/or fractured media, with limited analysis of conservative and reactive transport [see, e.g., *Ciriello et al*., 2013, 2015 and references therein], the analysis of the potential of the approach to complex settings of the kind encountered in the characterization of three-phase relative permeabilities has not yet been explored.

In this work we present a detailed analysis of the capability of models M_1 - M_{11} to characterize and predict observed three-phase oil relative permeabilities. We do so by considering as a test bed the recent high quality three-phase oil relative permeability dataset described by *Alizadeh and Piri* [2014b] and acquired on water-wet consolidated Bentheimer sandstone under steady state conditions. In Section 3.1 we estimate k_{ro} by only using the two-phase data provided by *Alizadeh and Piri* [2014b]. As indicated in Table 1, six models (M_1, M_3, M_5, M_6, M_{10}, M_{11}) include parameters that can also be estimated upon relying directly on three-phase oil permeability data. We do so by applying the Maximum Likelihood (ML) approach briefly described in Section 2.1. Then, we treat the models considered as a set of competing alternatives, rank them through model selection (or model discrimination) criteria and evaluate the posterior probability (or weight) associated with each model. Finally, we assess the posterior mean and variance of k_{ro} by considering all models jointly within the framework of a multimodel analysis approach. Key results are summarized in Section 3 which also includes a comparative analysis of the elliptic regions, i.e. regions where the flow problem becomes ill-posed [e.g., *Trangenstein*, 1989; *Shearer and Trangenstein*, 1989; *Jackson and Blunt*, 2002; *Juanes and Patzek*, 2004; *Bianchi Janetti et al.*, 2015], that can occur for selected models.

2. Methodology

2.1 Maximum Likelihood calibration and model discrimination criteria

As mentioned in Section 1, six of the models listed in Table 1 can be calibrated by making use of available three-phase relative permeability data. Table 1 lists the number of parameters (*m*) to be estimated for each of these models (see also SI for additional details). In the following we briefly summarize the Maximum Likelihood (ML) procedure used in Section 3 to estimate model parameters and associated bounds of uncertainty. Then, we describe the model selection criteria we apply to (*i*) rank diverse models, and (*ii*) obtain multimodel predictions through ML Bayesian Model Averaging (MLBMA).

We introduce the vector $\mathbf{Y}$ whose entries are *n* true values of $Y_i = \log k_{ro}\left(S_{o,i}\right) = \log k_{ro,i}$, with $i = 1,\ldots n$, and the vector $\mathbf{Y}^*$ containing *n* available noisy measurements of Y_i, $Y_i^* = \log k_{ro,i}^*$. We treat the prior measurement error vector $\boldsymbol{\varepsilon} = \mathbf{Y} - \mathbf{Y}^*$ as being multivariate Gaussian. A Maximum Likelihood estimate, $\hat{\boldsymbol{\theta}}$, of the parameter vector, $\boldsymbol{\theta}$, of size *m* can be obtained by minimizing the negative log likelihood criterion, *NLL* [*Carrera and Neuman*,1986]

$$NLL = \frac{J}{\sigma_Y^2} + n \ln(2\pi\sigma_Y^2) \tag{2}$$

with respect to $\boldsymbol{\theta}$, where σ_Y^2 represents the measurement error variance. Here, we assume error measurements to be uncorrelated and their statistics to be uniform. Therefore, the covariance matrix of measurement errors, $\mathbf{C}_Y$, can be written as $\mathbf{C}_Y = \sigma_Y^2 \mathbf{I}$, $\mathbf{I}$ being the identity matrix. The quantity J in (2) is equivalent to the least square criterion

$$J = \sum_{i=1}^{n} \varepsilon_i^2 \quad \text{with} \quad \varepsilon_i = Y_i - Y_i^* \tag{3}$$

where Y_i are evaluated according to models M_1 (with $m = 1$), M_3 (with $m = 6$), M_5 (with $m = 1$), M_6 (with $m = 2$), M_{10} (with $m = 7$) and M_{11} (with $m = 2$). Note that σ_Y^2 is generally unknown and the ML estimate of σ_Y^2 can be obtained as

$$\hat{\sigma}_Y^2 = \frac{J_{\min}}{n} \tag{4}$$

$J_{\min}$ being the minimum value of J, i.e., $J_{\min} = J\left(\hat{\boldsymbol{\theta}}\right)$. The covariance matrix of the estimation error is approximated by its Cramer-Rao lower bound as

$$\mathbf{Q} = \hat{\sigma}_Y^2 \left(\mathbf{J}^T \mathbf{J}\right)^{-1} \tag{5}$$

where the superscript T denotes transpose and $\mathbf{J}$ is the $n \times m$ Jacobian matrix whose entries are the derivatives of the target variable, Y_i, with respect to the model parameters evaluated at $\hat{\boldsymbol{\theta}}$. Approximation (5) obviates calculation of second order derivatives of *NLL* (2). The diagonal entries of $\mathbf{Q}$ provide lower bound estimates of parameter estimation variance. In this work, minimization of (3) is achieved through the gradient method [e.g., *Nocedal and Wright*, 2006], as implemented in the Matlab® environment.

Various model information (known also as model selection or discrimination) criteria, IC, have been proposed in the literature to discriminate amongst models which are formulated with the aim of interpreting a target quantity of interest. These include the information criterion AIC_c [*Hurvich and Tsai*, 1989] and the Bayesian criteria BIC [*Schwarz*, 1978] and KIC [*Kashyap*, 1982], respectively defined as

$$AIC_c = NLL + 2m + \frac{2m(m+1)}{n-m-1} \tag{6}$$

$$BIC = NLL + m \ln n \tag{7}$$

$$KIC = NLL - m \ln(2\pi) - \ln|\mathbf{Q}| \tag{8}$$

All these criteria consider the goodness of fit between available measurements and ML estimates (through NLL) and tend to penalize models with a large number of parameters (parsimony principle). KIC also includes a quantitative metric of the quality of the parameter estimates, as rendered by |**Q**|, as an additional term assisting in discriminating amongst model performance. AIC_c tends to select more complex models as n increases while KIC reduces to BIC when $n >> m$ (see e.g., *Ye et al*. [2008] for a detailed discussion on these points). In the context of nonlinear geostatistical inverse problems of single phase flow in porous media, *Ye et al*. [2008] and *Riva et al*. [2011] demonstrated the unique ability of KIC to estimate the parameters of the variogram of randomly heterogeneous log conductivity fields.

Maximum Likelihood Bayesian Model averaging, MLBMA [*Neuman*, 2003; *Ye et al*., 2004], stands out as a robust and computationally efficient way to combine the predictive capabilities of a suite of distinct models. Following *Neuman* [2003], the posterior model weight (for AIC_c) or the posterior model probability (for BIC and KIC) of model M_k comprised in the collection of N_M candidate models analyzed is given by

$$p\left(M_k \mid \mathbf{Y}^*\right) = \frac{\exp\left(-\tfrac{1}{2}\Delta IC_k\right) p\left(M_k\right)}{\sum_{i=1}^{N_M} \exp\left(-\tfrac{1}{2}\Delta IC_i\right) p\left(M_i\right)} \tag{9}$$

Here IC_k is any criterion from (6)-(8), $\Delta IC_k = IC_k - IC_{\min}$ with $IC_{\min} = \min\left\{IC_k\right\}$ evaluated over all N_M competing models and $p\left(M_k\right)$ is the prior probability of model M_k. The multimodel posterior mean and variance of $\mathbf{Y}$ are respectively evaluated as

$$E\left(\mathbf{Y} \mid \mathbf{Y}^*\right) = \sum_{k=1}^{N_M} E\left(\mathbf{Y} \mid \mathbf{Y}^*, M_k\right) p\left(M_k \mid \mathbf{Y}^*\right) \tag{10}$$

$$Var\left(\mathbf{Y} \mid \mathbf{Y}^*\right) = \sum_{k=1}^{N_M} Var\left(\mathbf{Y} \mid \mathbf{Y}^*, M_k\right) p\left(M_k \mid \mathbf{Y}^*\right) + \sum_{k=1}^{N_M} \left[E\left(\mathbf{Y} \mid \mathbf{Y}^*, M_k\right) - E\left(\mathbf{Y} \mid \mathbf{Y}^*\right)\right]^2 p\left(M_k \mid \mathbf{Y}^*\right) \tag{11}$$

$E\left(\mathbf{Y}\,|\,\mathbf{Y}^*, M_k\right)$ and $Var\left(\mathbf{Y}\,|\,\mathbf{Y}^*, M_k\right)$ respectively being the posterior mean and variance of $\mathbf{Y}$ computed for model M_k. We provide the application of MLBMA to our suite of multiple models in Section 3.2.

2.2 Analysis of elliptic regions

In Section 3 we investigate the possibility of occurrence of elliptic regions, as embedded in the classical fractional-flow theory of displacements [*Jackson and Blunt*, 2002], in (*i*) two classical models typically used in black-oil reservoir simulators (i.e., the Stone I and Baker models, respectively identified as M_1 and M_5 in Table 1) and (*ii*) the very recent sigmoid-based model presented by *Ranaee et al*. [2015] (model M_{11} in Table 1). The analysis of elliptic regions is critical to modeling of three-phase flows at the macro- (Darcy-) scale because the flow problem becomes ill-posed for saturations at which the governing system of equations is elliptic.

Darcy-scale three-phase flow of immiscible and incompressible fluids in a porous medium in one dimension is governed by

$$\partial_t \mathbf{u} + \partial_x \mathbf{f} = 0 \quad \text{where} \quad \mathbf{u} := \begin{Bmatrix} S_g \\ S_w \end{Bmatrix}; \mathbf{f} := \begin{Bmatrix} f_g \\ f_w \end{Bmatrix} \tag{12}$$

where f_w and f_g respectively are the fractional flows of water and gas phases and x and t are rescaled space and time variables. If gravity and capillary forces are neglected, fractional flow of each phase is defined as the phase mobility ratio ($\lambda_\alpha = k_{r\alpha}/\mu_\alpha$ with $\alpha = w, g$; μ_α being the dynamic viscosity of the α-phase) divided by the total mobility ratio, $\lambda_T = \lambda_w + \lambda_o + \lambda_g$. In the following, we focus our study on the occurrence of elliptic regions associated with k_{ro} models. Thus, we neglect hysteresis effects in the prediction of water, k_{rw}, and gas, k_{rg}, relative permeabilities. The latter are respectivly approximated by water, $\bar{k}^I_{rwo}$, and gas, $\bar{k}^I_{rgo}$, relative permeabilities in two phase (oil-water and oil-gas) systems under imbibition [*Corey and Rathjens*, 1956], i.e

$$k_{rw} \approx \bar{k}_{rwo}^{I} = \bar{k}_{rwo}^{M} \left(\frac{\bar{S}_{wo} - \bar{S}_{wc}}{1 - \bar{S}_{wc}} \right)^{ewo} \tag{13}$$

$$k_{rg} \approx \bar{k}_{rgo}^{I} = \bar{k}_{rgo}^{M} \left(\frac{\bar{S}_{go} - \bar{S}_{gt}}{1 - \bar{S}_{wc} - \bar{S}_{rog} - \bar{S}_{gt}} \right)^{ego} \tag{14}$$

$\bar{k}_{rwo}^{M}$ and $\bar{k}_{rgo}^{M}$ respectively being the maximum water and gas relative permeabilities in two-phase environments. Here, $\bar{S}_{wo}$ is water saturation in oil-water systems, $\bar{S}_{go}$ and $\bar{S}_{rog}$ respectively are gas and residual oil saturation in oil-gas systems, and *ewo* and *ego* are model parameters. The latter are here obtained through ML estimation on the basis of the two-phase relative permeability data of *Alizadeh and Piri* [2014b] (see also Section 3.1). All remaining quantities have been defined above.

When gravity and capillarity effects are considered, the fractional flows can be evaluated as [*Juanes and Patzek,* 2004; *Bianchi Janetti et al*., 2015]

$$f_w = \frac{\lambda_w}{\lambda_T}\left[1 - N_d \mu_o \left(\rho_d - 1\right)\lambda_o + \rho_d \lambda_g\right] \tag{15}$$

$$f_g = \frac{\lambda_g}{\lambda_T}\left[1 + N_d \mu_o \left(\rho_d \lambda_w + \lambda_o\right)\right] \tag{16}$$

where $\rho_d = \left(\rho_w - \rho_g\right)/\left(\rho_o - \rho_g\right)$ is the density ratio and $N_d = \left(\rho_0 - \rho_g\right) K g_x / \left(\mu_o q \phi\right)$ is the gravity number, ρ_α being density of fluid phase α; K, ϕ, g_x and q are intrinsic permeability and porosity of the medium, the component of gravity along the flow direction and the total volumetric flow rate. The nature of (12) can be determined by analyzing the behavior of the eigenvalue problem

$$\mathbf{A}\mathbf{r} = \nu\mathbf{r} \quad with \quad \mathbf{A} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} \partial f_g/\partial S_g & \partial f_g/\partial S_w \\ \partial f_w/\partial S_g & \partial f_w/\partial S_w \end{bmatrix} \tag{17}$$

where $\mathbf{A}$ is the Jacobian matrix of (12), ν is an eigenvalue and $\mathbf{r} = \left[r_{i,Sg}, r_{i,Sw}\right]^T$ (i = 1, 2) is a right eigenvector. The eigenvalues $\nu_{1,2}$ and $\mathbf{r}$ are evaluated as

$$\nu_{1,2} = \frac{1}{2}\left[a + d \pm \sqrt{\left(a - d\right)^2 + 4bc}\right] \tag{18}$$

$$\frac{r_{1,Sg}}{r_{1,Sw}} = \frac{\nu_1 - a}{b} = \frac{c}{\nu_1 - d}; \qquad \frac{r_{2,Sg}}{r_{2,Sw}} = \frac{b}{\nu_2 - a} = \frac{\nu_2 - d}{c} \tag{19}$$

For any combination of S_g and S_w, the system (12) is elliptic when $v_{1,2}$ are complex conjugates. Regions identified in the saturation space to correspond to this state are termed elliptic regions. When $v_{1,2}$ are real and distinct, the system (12) is hyperbolic and $v_{1,2}$ represent the characteristic speed at which waves describing changes in saturation propagate throughout the domain. In this case there are two real and linearly independent eigenvectors that, when viewed in the saturations space, correspond to the directions of admissible changes in fluid saturations and identify so called fast and slow rarefaction curves.

3. Results

In this section we assess the capability of the collection of models listed in Table 1 to characterize and predict three-phase oil relative permeability data. We do so by grounding our study on the data presented by *Alizadeh and Piri* [2014b]. These authors provide oil relative permeability data under steady state conditions during two- (gas/oil, oil/brine, gas/brine) and three-phase (gas/oil/brine) coreflooding experiments in (water-wet) Bentheimer sandstone core samples. The dataset presented by the authors include experiments of primary gas injection (*G*1 in Table 1) performed with two initial oil saturations ($S_{oi(1)} = 65\%$ and $S_{oi(2)} = 45\%$) followed by the waterflooding experiments (*W*2 in Table 1), representing the behavior of oil relative permeability, k_{ro}, under a WAG cycle. The dataset of *Alizadeh and Piri* [2014b] is here classified as follows (see Table 1 for nomenclature, which we employ hereinafter):

- Dataset *G*1 with $S_{oi(1)} = 65\%$ comprises 8 data points from experiment A and 12 data points from experiment B;
- Dataset *G*1 with $S_{oi(2)} = 45\%$ comprises three sets of 9 data points, respectively associated with experiments C, E, G.

- Dataset *W*2 includes all data points for which decreasing gas saturation is reported, i.e., 9 points from experiment A and 8 points from experiment F.

Note that from each experiment we select only data corresponding to three-phase flow (i.e., all three fluid saturations are larger than zero) and for which $k_{ro} > 0$. Experiment D-1 in *Alizadeh and Piri* [2014b] is associated with measurements performed in a gas-oil environment at connate water saturation. Following a common practice [e.g., *Spiteri and Juanes*, 2006], we employ experiment D-1 to characterize the two-phase oil relative permeability $\bar{k}_{rog}^{D}$.

3.1 Predictions of k_{ro} relying only on two-phase data

We estimate k_{ro} in all three settings (e.g., *G*1 with $S_{oi(1)}$, *G*1 with $S_{oi(2)}$, and *W*2) considered by *Alizadeh and Piri* [2014b] by relying only on their two-phase data and applying all models listed in Table 1. We do not consider in this analysis model M_{10}, whose parameters need to be estimated on the basis of three-phase data (see SI for details). When needed (i.e., for M_1, M_3, M_4, M_5), we evaluate residual oil saturation, S_{or}, by making use of (A.3). The need for a proper estimate of S_{or} to accurately predict k_{ro} has been recently discussed by *Kianinejad et al*. [2015] and *Kianinejad and DiCarlo* [2016]. Note that M_{11} requires estimating two distinct parameters for each of the three settings (see also SI).

Table 1 lists the values of $LMSE = J / n$, where J is calculated according to (3) and n is the number of experimental data available, resulting by considering each of the three experimental sets individually and merging all data into a unique dataset. We note that M_{11} [*Ranaee et al*., 2015] renders the smallest $LMSE$ values for all three sets of experiments, followed by M_6, M_8 or M_9 (in an order which depends on the setting analyzed). This high quality performance of M_{11}, as quantified in terms of *LMSE* values, with respect to the other investigated models can be due to its inherent capability of embedding (*i*) impact of hysteresis, due to the two diverse strategies developed for the prediction of k_{ro} under gas injection or waterflooding, and (*ii*) cycle dependency effects, because the model

directly considers the influence of initial oil saturation and/or the initialization of the experiment (see SI for details).

As an example, Figure 1 depicts the graphical comparison amongst three-phase oil relative permeabilities predicted by two of the models which are commonly implemented in commercial software (M_1 and M_5) and those obtained by M_4 and M_{11}, together with experimental data. The Baker model (M_5) yields quite good predictions of k_{ro} data collected during gas injection when initial oil saturation is high (see Figure 1a). These results are explained upon observing that values of $\overline{k}_{row}^{I}$, $\overline{k}_{rog}^{D}$ and k_{ro} are very similar for high S_{oi} values, so that all saturation-weighted interpolation models lead to acceptable results under these conditions. Moreover, differences between displacement of oil under gas and water injection are very limited when S_{oi} is large (this condition corresponding to piston type configuration, *Piri and Blunt* [2005]) and saturation-weighted interpolation based models that do not account for hysteresis effects can be successfully employed in this regime. The Baker model fails in reproducing experimental data associated with gas injection and small initial oil saturation values (see Figure 1b), a condition for which WAG techniques are usually employed. The general underestimation of k_{ro} obtained with M_5 in these conditions is likely linked to the observation that the coexistence of a considerable amount of all three phases in the system tends to increase the occurrence of oil remobilization from small pores through spreading layers [*Suicmez et al.*, 2007; 2008]. Additionally, one should note that $\overline{k}_{row}^{I}$ vanishes for $S_o < \overline{S}_{row}$ and by using (1) leads to k_{ro} values which are slightly smaller than $\overline{k}_{rog}^{D}$. This result is in contrast with experimental coreflooding observations [e.g., *Oak*, 1990; *DiCarlo et al.*, 2000; *Alizadeh and Piri*, 2014b] showing that oil recovery increases shifting from two- to three- phase environments. Similar to what observed above for M_{11}, also the saturation-weighted interpolation based models M_6 - M_9 are associated with values of k_{ro} under gas injection experiments initiated in low oil saturations ($G1$ dataset with S_{oi} = 0.45) of relatively improved quality with respect to the Baker model (see Table 1). This results is consistent

with the observations that (*i*) M_6 and M_7 are characterized by an increased weight of $\bar{k}_{rog}^{D}$ since they disregard the effect of trapped gas, (*ii*) M_8 considers remobilization of oil under layer drainage configurations, and (*iii*) M_9 somehow takes into account nonlinear variations of k_{ro} with S_o at low oil saturations.

The models based on the channel flow theory (M_1 - M_4) generally do not accurately reproduce the k_{ro} data considered. In particular, model M_1 tends to overestimate k_{ro} for high oil saturations and to underestimate k_{ro} when S_o decreases (see Figure 1a-b). This result can be explained upon noting that M_1 requires the use of $\bar{k}_{row}^{I}$ and $\bar{k}_{rog}^{D}$ values evaluated for oil saturation levels different from those observed under three-phase environments (see Section S1 of the SI), a similar consideration holding also for M_2 and M_4. Figure 1 shows that M_4, which includes hysteresis effects, tends to overestimate k_{ro}. This is consistent with the observation that M_4 was developed on the basis of data collected in the presence of low interfacial tension, where oil relative permeability tends to be relatively large [*Harbert*, 1983; *Fatemi et al*., 2011; *Chukwudeme et al*., 2014].

3.2 ML estimate of k_{ro} based on three- and two-phase data

For six (M_1, M_3, M_5, M_6, M_{10}, M_{11}) of the eleven models analyzed, it is possible to constrain model parameters through the use of available three-phase oil relative permeability data. We do so by applying the approach described in Section 2 to compute ML estimates of model parameters. Results of this analysis are listed in Table 1 in terms of $LMSE_{\min} = J_{\min} / n = \hat{\sigma}_Y^2$, as given by (4). Similar to what has been presented in Section 3.1, $LMSE_{\min}$ has been evaluated by considering each of the three experimental sets individually and merging all data into a unique dataset. As expected, values of $LMSE_{\min}$ for M_1, M_3, M_5, M_6, and M_{11} are generally smaller than those of the corresponding *LMSE* since three-phase data are considered in the model calibration procedure. We note that $0.01 < LMSE_{min}/LMSE < 0.6$ (depending on the model and experimental setting considered) for models M_1

and M_5, where only residual oil saturation is calibrated. This type of result is in agreement with the main findings of *Kianinejad et al*. [2015].

Figure 2 provides a graphical depiction of three-phase experimental data and the corresponding ML estimates of k_{ro} (i.e., k_{ro} computed with the ML estimate, $\hat{\boldsymbol{\theta}}$, of the parameter vector, $\boldsymbol{\theta}$) based on M_1, M_3, M_{10} and M_{11} for the three experimental scenarios considered. Comparison of Figures 1 and 2 evidences the general improvement in the quality of model results emerging from constraining model parameters through ML calibration on three-phase data.

When all available data are jointly considered in the ML analysis, models M_{10} and M_{11} provide the smallest values of $LMSE_{\min}$, equal to 0.06 and 0.03, respectively (see Table 1). Remarkably, calibrated models M_1, M_3, M_5, M_6 are seen to be associated with values of $LMSE_{\min} > 0.08$, the latter being the value of $LMSE$ associated with M_{11} when solely two-phase data are employed (see Section 3.1), i.e. without model calibration. In other words, model M_{11} is conducive to estimates of k_{ro} of higher quality (when assessed in terms of *LMSE*) than those rendered by all other tested models, even in cases where three-phase data are included in these and are not considered in M_{11}. This result provides evidence of the superior predictive capability of M_{11} in the settings analyzed. Figure 3 shows estimates of k_{ro} obtained with a set of models upon (*a*) relying only on two-phase data (Figure 3a) or (*b*) making also use of three-phase data (Figure 3b) versus all (*G*1 and *W*2) experimental data considered jointly. These results allow appreciating the generally superior performance of M_{11} in reproducing k_{ro}, as compared to all other models considered.

Figure 4 depicts the values of the model selection criteria (*IC*s) (6)-(8) for each model. Models M_3, M_{10} and M_{11} are identified as best depending on the experimental setting (Figures 4a-c) and the model discrimination criterion, *IC*, adopted. Model M_{11} is unambiguously selected as the best model by all *IC*s when all data are jointly considered (see Figure 4d). The latter finding can be explained upon considering the structure of models M_3 and M_{10}. In particular, these models do not consider (*i*)

the impact of initialization of phase saturations at the onset of each experiment (cycle dependency) and (*ii*) hysteresis effects yielding differences in the system and model behavior under gas injection and water flooding scenarios, while M_{11} is designed to embed these physical features.

We then evaluate the posterior model weight (for AIC_c) or the posterior model probability (for *BIC* and *KIC*), $p\left(M_k \mid \mathbf{Y}^*\right)$, according to (9) for each candidate model and for each model *IC*, including *NLL* as a term of comparison. We assign an equal prior probability $p\left(M_k\right)$ = 1/6 = 16.7% to each model (k = 1, 3, 5, 6, 10, 11). Table 2 lists these results for M_3, M_{10} and M_{11} (M_1, M_5 and M_6 are associated with virtually zero posterior probabilities). In all cases $p\left(M_k \mid \mathbf{Y}^*\right)$ is markedly different from the prior probability, reflecting the relevant impact of conditioning on the available three-phase data. The value of $p\left(M_k \mid \mathbf{Y}^*\right)$ associated with M_{11} is equal to 1 when all data are jointly considered, independent of the discrimination criterion adopted. Model M_{10} is assigned (*a*) a unit weight when only $G1$ experiments initiated with low oil saturation ($S_{oi(2)}$) are considered and (*b*) the largest weight for experiments $W2$ according to all model discrimination criteria.

Interpretation of the results of experiments $G1$ initiated with large oil saturation ($S_{oi(1)}$) is not straightforward. While M_{10} provides the best match against the data (as quantify by *NLL*), AIC_c and *BIC* favor M_{11} (with $p\left(M_k \mid \mathbf{Y}^*\right)$ respectively equal to 97.8% and 98.8%), and *KIC* selects M_3 ($p\left(M_k \mid \mathbf{Y}^*\right)$ equal to 97.2%) as best model. This difference between model rankings stems from the characteristics of the diverse model information criteria analyzed. We start by noting that M_3, M_{10}, and M_{11} lead to very similar results in this case (see Figure 2a). Therefore, while *NLL* (that considers only the quality of the fit) tends to prefer the model with the largest number of parameters (i.e., M_{10}, with m = 7), AIC_c and *BIC* favor the model with the smallest m value (i.e., M_{11}, with m = 2). As discussed in Section 2.1, *KIC* also includes a metric quantifying the quality of the parameter estimate

as discriminant amongst models. Figure 5 depicts uncertainty bounds, as quantified by $(\hat{\theta}+\hat{\sigma}_\theta)/\hat{\theta}$, $\hat{\sigma}_\theta$ being the square root of the parameter estimation error variance, associated with each estimated parameter of models M_3, M_{10}, M_{11}. We note that the ML estimate of θ_5 of M_3 obtained for $G1$ with initial large oil saturation ($S_{oi(1)}$) is associated with a large estimation uncertainty (see Figure 5a), consistent with *KIC* favoring M_3 in this case. We further note that according to *Tsai and Li* [2008] *BIC* should be preferred to *KIC* when comparing models embedding considerably different types of characteristic uncertain parameters, as is the case here.

Finally, we apply MLBMA to provide a multimodel analysis of the oil relative permeability data. We do so by (*i*) selecting a model M_k (with k = 3, 10 or 11); (*ii*) generating $NMC = 10^7$ Monte Carlo (MC) realizations of each model parameter θ_i (with i = 1,..,m), assuming the estimation error associated with θ_i to be Gaussian with mean and variance respectively given by $\hat{\theta}_i$ and $\hat{\sigma}_{\theta_i}$; (*iii*) use model M_k to obtain $NMC = 10^7$ MC realizations of $\mathbf{Y}$; (*iv*) computing mean, $E\left(\mathbf{Y}\,|\,\mathbf{Y}^*, M_k\right)$, and variance, $Var\left(\mathbf{Y}\,|\,\mathbf{Y}^*, M_k\right)$, of $\mathbf{Y}$ across realizations evaluated at step (*iii*); and (*v*) use (10)-(11) to compute MLBMA estimates $E\left(\mathbf{Y}\,|\,\mathbf{Y}^*\right)$ and variance $Var\left(\mathbf{Y}\,|\,\mathbf{Y}^*\right)$. Figure 6 depicts a scatterplot of MLBMA estimates, $E\left(\mathbf{Y}\,|\,\mathbf{Y}^*\right)$, versus observed three-phase oil relative permeabilities, $\log k_{ro}^*$, for experiments $G1$ with $S_{oi(1)}$ and replacing *IC* in (9)-(11) with *NLL* (Figure 6a) AIC_c (Figure 6b) *BIC* (Figure 6c) and *KIC* (Figure 6d). As an additional term of comparison, Figure 6 also depicts intervals of width $E\left(\mathbf{Y}\,|\,\mathbf{Y}^*\right)\pm\sqrt{Var\left(\mathbf{Y}\,|\,\mathbf{Y}^*\right)}$, characterizing the uncertainty associated with MLBMA estimates. To highlight the relevance of the uncertainty associated with a given model, Figure 6 includes values of $E\left(\mathbf{Y}\,|\,\mathbf{Y}^*, \tilde{M}_k\right)$ and $E\left(\mathbf{Y}\,|\,\mathbf{Y}^*, \tilde{M}_k\right)\pm\sqrt{Var\left(\mathbf{Y}\,|\,\mathbf{Y}^*, \tilde{M}_k\right)}$, $\tilde{M}_k$ being the model associated with the largest $p\left(M_k\,|\,\mathbf{Y}^*\right)$ for each selected *IC*. The ML estimates of $\log k_{ro}$ (i.e., $\log k_{ro}$

computed with $\hat{\boldsymbol{\theta}}$) associated with $\tilde{M}_k$ are also shown. Note that the ML estimates of $\log k_{ro}$ are very close to $\log k_{ro}^*$ in all subplots of Figure 6. This result, when considered by itself, could imbue one with an unjustified sense of confidence about the predictive capabilities of model $\tilde{M}_k$ because it does not consider the uncertainty linked to (*i*) the ML model parameter estimates and (*ii*) the model choice (when viewed in the context of a pool of alternative model possibilities). These aspects are fully included in the MLBMA. It is noted that here the model averaging procedure has a limited effect on the average value of estimated relative permeability, i.e., $E\left(\mathbf{Y}\,|\,\mathbf{Y}^*\right) \approx E\left(\mathbf{Y}\,|\,\mathbf{Y}^*, \tilde{M}_k\right)$, consistent with the observation that $p\left(\tilde{M}_k\,|\,\mathbf{Y}^*\right) > 95\%$ for all considered cases. Otherwise, we find that the uncertainty associated with the model choice is in general not negligible, as $Var\left(\mathbf{Y}\,|\,\mathbf{Y}^*\right) > Var\left(\mathbf{Y}\,|\,\mathbf{Y}^*, \tilde{M}_k\right)$, a finding which is particularly evident when *NLL*, *BIC* and AIC_C are considered as model averaging criteria (see Figure 6a-c).

The results of the corresponding analysis for experiments *W*2 are illustrated in Figure 7 for *IC* = AIC_c (Figure 7a) and *KIC* (Figure 7b). Note that in this case *NLL* and *BIC* favor M_{10} with posterior probability equal to 1. Consistent with the results in Figure 6, we observe that $E\left(\mathbf{Y}\,|\,\mathbf{Y}^*\right) \approx E\left(\mathbf{Y}\,|\,\mathbf{Y}^*, \tilde{M}_k\right)$ while the effect of model averaging on the quantification of uncertainty is particularly important when *KIC* is considered as information criterion.

3.3 Occurrence of elliptic regions

Here we compare the results of our study on the occurrence of elliptic regions for (*i*) two classical models typically used in black-oil reservoir simulators (Stone I, M_1, and Baker, M_5) and (*ii*) model M_{11}, which was selected as best to jointly interpret the complete dataset of *Alizadeh and Piri* [2014b] in Section 3.2 (see Table 2).

Figure 8a illustrates the 351 sampling points used to calculate the rarefaction paths in the saturation space. The saturation domain where elliptic regions are studied is bounded by the

maximum ($\overline{S}_{\alpha}^{M}$) and residual ($\overline{S}_{r\alpha}$) saturation of fluid phase α. Figure 8b depicts the distribution of the sampling points mapped within the ternary diagram of reduced saturations $S_{\alpha}^{Norm} = \left(S_{\alpha} - \overline{S}_{r\alpha}\right) / \left(\overline{S}_{\alpha}^{M} - \overline{S}_{r\alpha}\right)$, where $\overline{S}_{r\alpha} = \overline{S}_{wc}$ for $\alpha = w$, $\overline{S}_{r\alpha} = \overline{S}_{rog}$ for $\alpha = o$ and $\overline{S}_{r\alpha} = \overline{S}_{gt}$ for $\alpha = g$ (w, o, and g respectively denoting water, oil and gas). At each sampling point we evaluate the eigenvalues (18) of the Jacobian matrix $\mathbf{A}$ (17) associated with the flow equations (12). Values of fluids viscosities and densities are taken from *Alizadeh and Piri* [2014b]. In order to have a detailed definition of the elliptic regions, when the radicand in (18) is negative (at least) at one of the 351 sampling points depicted in Figure 8a we increase the number of sampling points up to 30000. In a water-wet system, fast rarefactions correspond to situations in which gas or/and water saturation increases (corresponding, e.g., to oil production during primary gas injection and/or secondary waterflooding), slow rarefactions being related to increasing oil saturation (corresponding, e.g., to oil generation) [*Shearer and Trangenstein*, 1989; *Jackson and Blunt*, 2002]. Here, we are mailnly concerned with the fast rarefactions corresponding, for example, to oil productions under WAG injection scenarios.

Figure 9 depicts the distribution of eigenvectors evaluated with the selected models and associated with fast rarefaction waves in the saturation space in the absence of gravity (Figures 9a-d) and for three selected values of the gravity number N_d (Figures 9e-p). Results related to M_{11} for primary gas injection (Figures 9a, e, i, m) have been obtained by setting $\overline{S}_{row} = 38.5\%$. Qualitatively similar results have been obtained by using diverse $\overline{S}_{row}$ values in the range $38.5\% \leq \overline{S}_{row} \leq 65\%$ (not shown).

Figures 9a-d clearly show that the system (12) is hyperbolic within the entire saturation space when gravity forces are neglected, regardless the model selected. Use of M_{11} for primary gas injection (Figure 9a) yields eigenvectors which are mostly parallel to the gas-water edge, i.e., most of the eigenvectors are oriented along directions of constant oil saturations. The use of M_1 (Figure 9d) results

in eigenvectors that rotate near the vertex $S_g^{Norm} \approx 1$ (i.e., $S_o \approx \overline{S}_{rog}$ and $S_w \approx \overline{S}_{wc}$), the latter constituting an umbilic point [*Shearer and Trangenstein*, 1989]. This umbilic point is seen to shift towards smaller S_g^{Norm} values along the oil-gas edge when M_{11} (for waterflooding) and M_5 are considered. Comparison of Figures 9b and 9c shows that implementation of M_{11} (for waterflooding) or M_5 yields very similar changes in the saturation states across the ternary diagram. This is likely related to the observation that both models are based on saturation-weighted interpolation techniques. Eigenvectors are oriented along directions of constant oil saturations for the regions of high gas content ($S_g^{Norm} \geq 0.8$) where estimates of k_{ro} are proportional to $\overline{k}_{rog}^{D}$ (see (1)).

When gravity effects are included (Figures 9e-p), all models are characterized by the occurrence of elliptic regions, where the directions associated with the eigenvectors coincide, the only notable exception being model M_{11} for gas injection (Figures 9e, i, m), because in this case k_{ro} evaluated through (A.46) is a function of oil saturation [*Shearer and Trangenstein*, 1989]. The fraction of the saturation space covered by elliptic regions is also listed (when present) in Figures 9e-p. We observe that the elliptic regions tend to extend to zones characterized by low gas saturations as N_d is increased from 0.1 to 1.0. A futher increase of N_d does not change dramatically the shape of the elliptic regions. While the Stone I model (M_1) leads to elliptic regions which cover about 3% of the entire saturation space regardless of the value of N_d, the extent of the elliptic regions observed for M_{11} (for water injection) and M_5 tends to decrease with increasing N_d.

4. Conclusions

We analyze a suite of 11 three-phase oil relative permeability models and compare the ability of describing three-phase oil relative permeability, k_{ro}, data when (*i*) only two-phase data are employed and (*ii*) two- and three-phase data are jointly used for model calibration. The study is based

on a recently published dataset [*Alizadeh and Piri*, 2014b] which reports data aquired in a water-wet Bentheimer sandstone sample. Our study leads to the following major conclusions.

1. The model proposed by *Ranaee et al*. [2015] (identified as M_{11} in Table 1) provides reasonably accurate estimates of k_{ro} data, supporting its ability to embed the role of hysteresis effects for the characterization of oil displacement in three-phase systems. All model selection criteria analyzed select M_{11} as the best model to interpret the considered dataset, when all data (gas injection and waterflooding) are jointly considered for model parameter estimation.
2. Model M_{11} renders high quality estimates of k_{ro} even when three-phase data are not included and the model is employed to provide predictions of three-phase relative permeabilities by relying solely on two-phase data, thus supporting its predictive capability. Remarkably, estimates of k_{ro} obtained by M_{11} solely on the basis of two-phase data are of same or higher quality (in terms of mean square error) than their counterparts obtained with all other tested models calibrated on the basis of three-phase oil permeability data. On the bases of these results, additional testing of model M_{11} against experimental data is foreseen. In this context, a possible candidate data-base is, for example, the one recently presented by *Moghadasi et al*. [2016], or others, as they become available.
3. Multimodel analyses based on Maximum Likelihood Bayesian Model Averaging provide an efficient way of combining the predictive power of a collection of competitive k_{ro} models to render high quality results.
4. The use of the classical Stone I and Baker models induces elliptic regions when the gravity effects are included in the analysis. Employing the sigmoid-based model (M_{11}) of *Ranaee et al*. [2015] does not lead to elliptic regions under gas injection conditions, while no elliptic regions arise under waterflooding only in the absence of gravity effects. The location of elliptic regions in

the saturation space tends to vary only minimally when the gravity number $1 \leq N_d \leq 10$ for these models.

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Figure captions

Figure 1 Three-phase oil relative permeability versus oil saturation. Curves represent values calculated through models M_1, M_4, M_5, and M_{11} and are based solely on information from two-phase data. Figures (a, b) include analysis of experiments performed following primary gas injection; (c) considers secondary waterflooding experiments.

Figure 2 ML estimates of three-phase oil relative permeability versus oil saturation for models M_1, M_3, M_{10}, and M_{11} and are based on information from two- and three- phase data. Subplots (a, b) include analysis of experiments performed following primary gas injection; (c) considers secondary waterflooding experiments.

Figure 3 Estimates of k_{ro} obtained (a) relying only on two-phase and (b) making also use of three-phase data, versus experimental values (data from primary gas injection and secondary waterflooding are jointly considered).

Figure 4 Model selection criteria evaluated on the basis of ML calibration of models M_1, M_3, M_5, M_6, M_{10}, and M_{11} on the three-phase oil relative permeability data obtained under primary gas injection ($G1$) with initiation at (a) high, $S_{oi(1)}$, and (b) low, $S_{oi(2)}$, oil saturations; (c) secondary waterflooding ($W2$); and (d) complete data set ($G1$ + $W2$ experiments).

Figure 5 Normalized uncertainty bounds, as quantified by $(\hat{\theta}+\hat{\sigma}_\theta)/\hat{\theta}$, for all parameter estimates $\hat{\theta}$ resulting from ML calibration of models M_3, M_{10}, and M_{11}; experiments $G1$ initiated with (a) $S_{oi(1)}$ and (b) $S_{oi(2)}$; (c) experiment $W2$.

Figure 6 Estimates of k_{ro} versus experimental values observed during $G1$ with $S_{oi(1)}$ and IC = (a) *NLL*; (b) AIC_c; (c) *BIC and* (d) *KIC*.

Figure 7 Estimates of k_{ro} versus experimental values observed during $W2$ and IC = (a) AIC_c and (b) *KIC*.

Figure 8 (a) Original and (b) reduced (normalized) saturation space. Circles represent the 351 sampling points at which eigenvectors of (18)-(19) are calculated.

Figure 9 Distributions of eigenvectors associated with fast rarefaction waves in the reduced saturation space. Results are illustrated (a)-(d) in the absence and (e)-(p) in the presence of gravity effects with selected values of N_d. Elliptic regions are depicted as black areas. The percentage of the saturation space covered by elliptic regions is indicated where relevant.

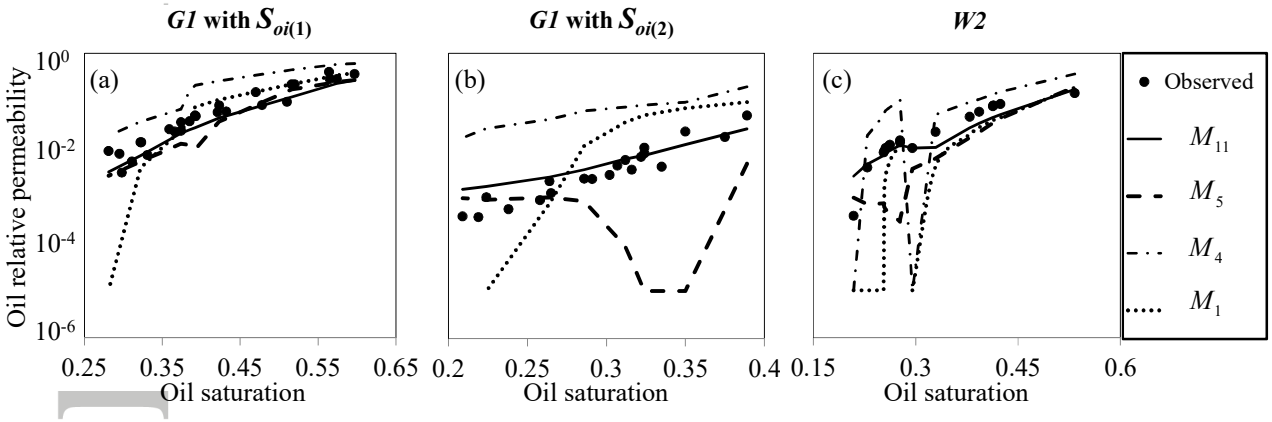


Figure 1

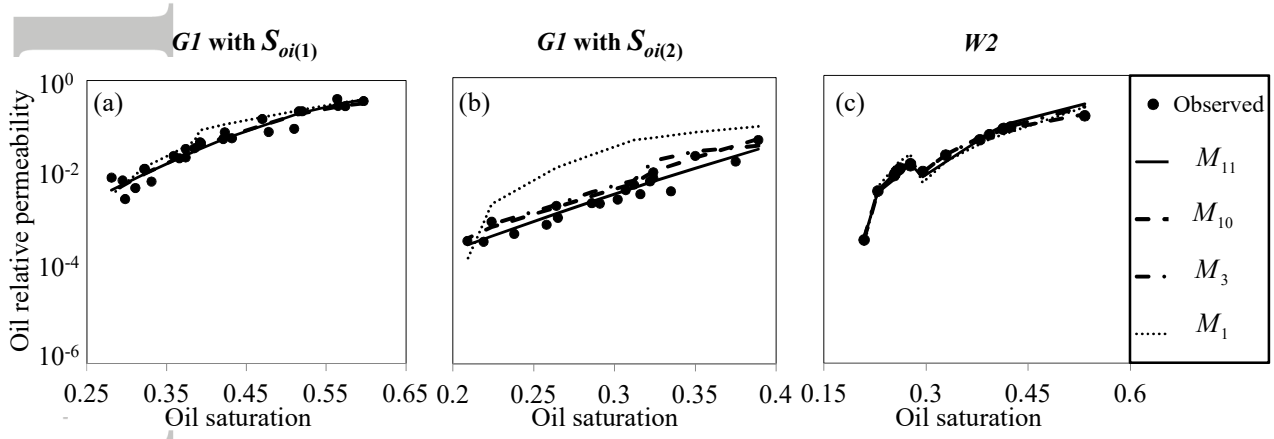
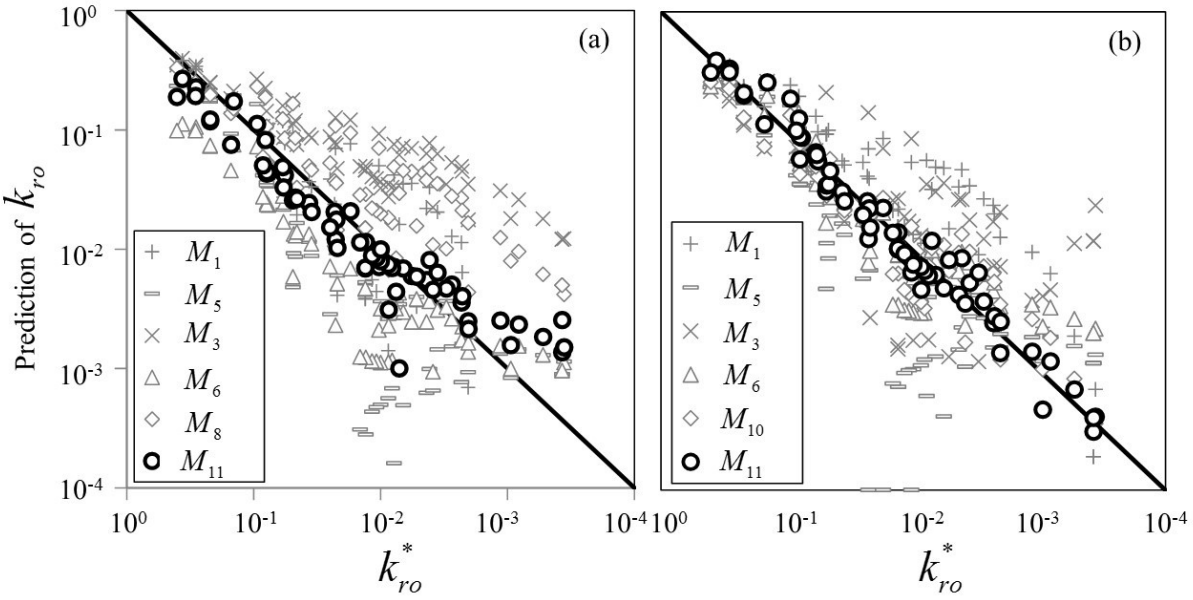


Figure 2



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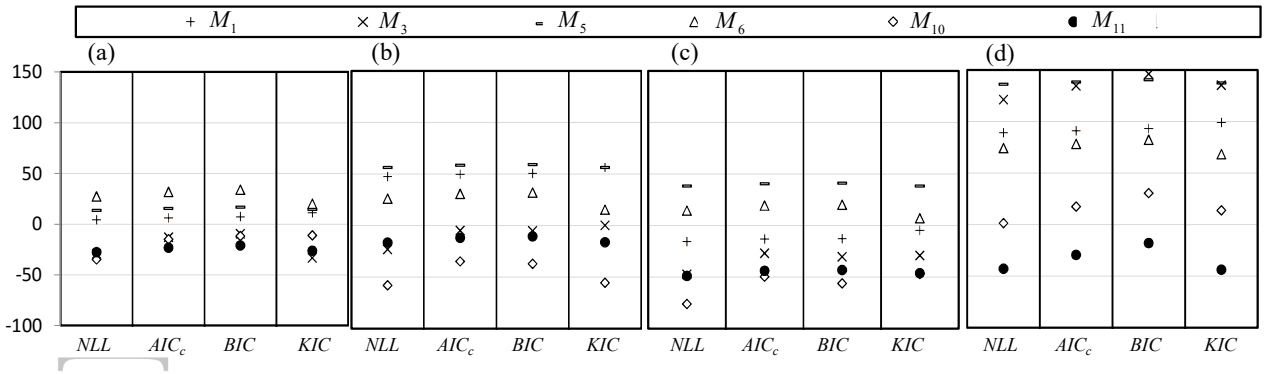

Figure 4

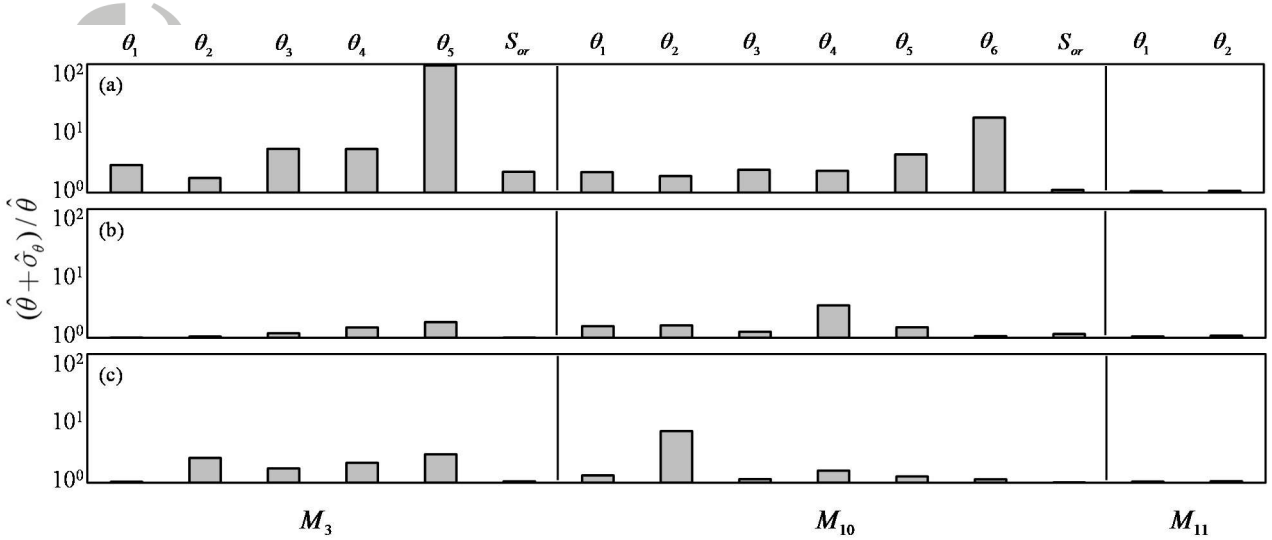

Figure 5

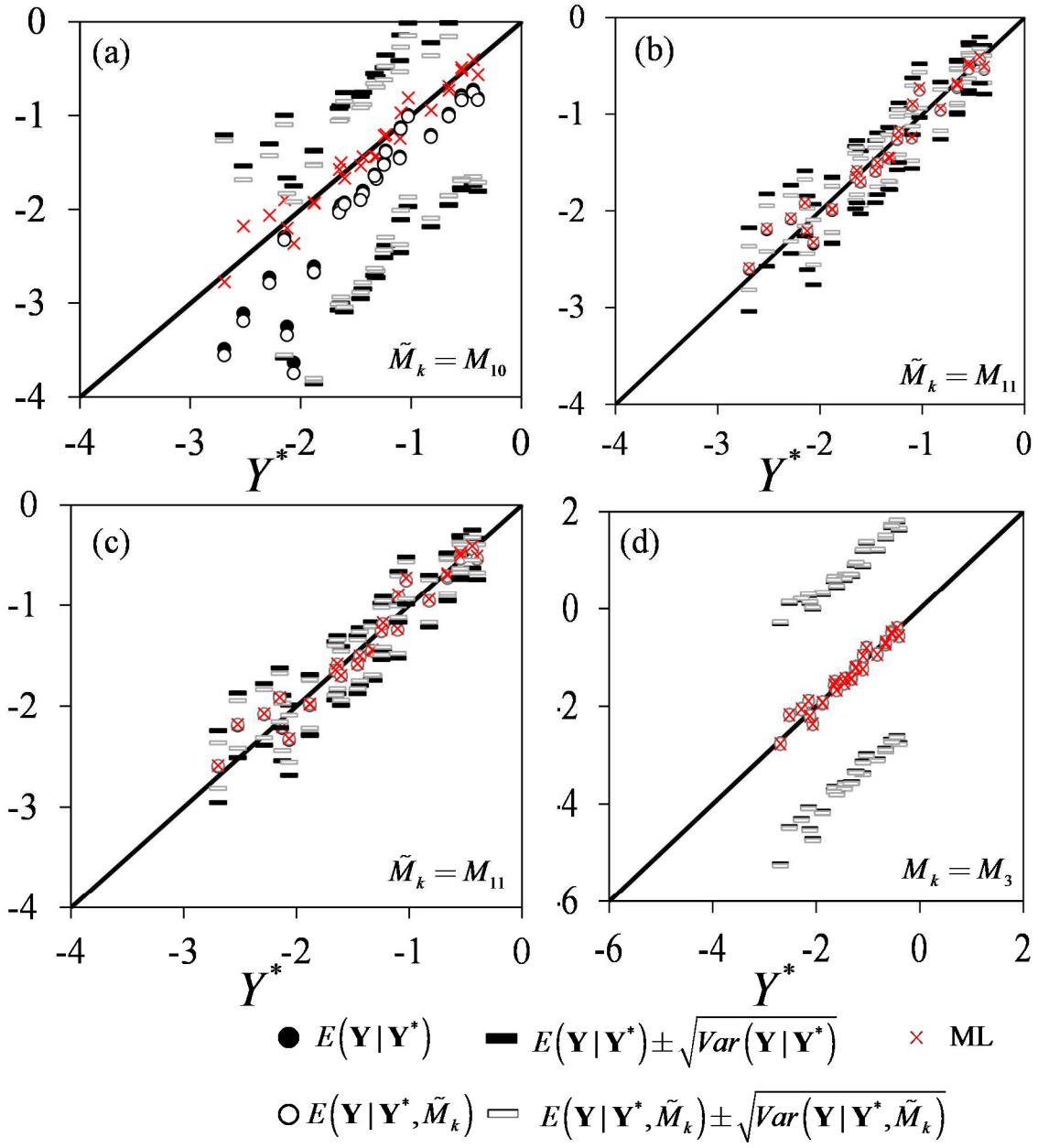

Figure 6

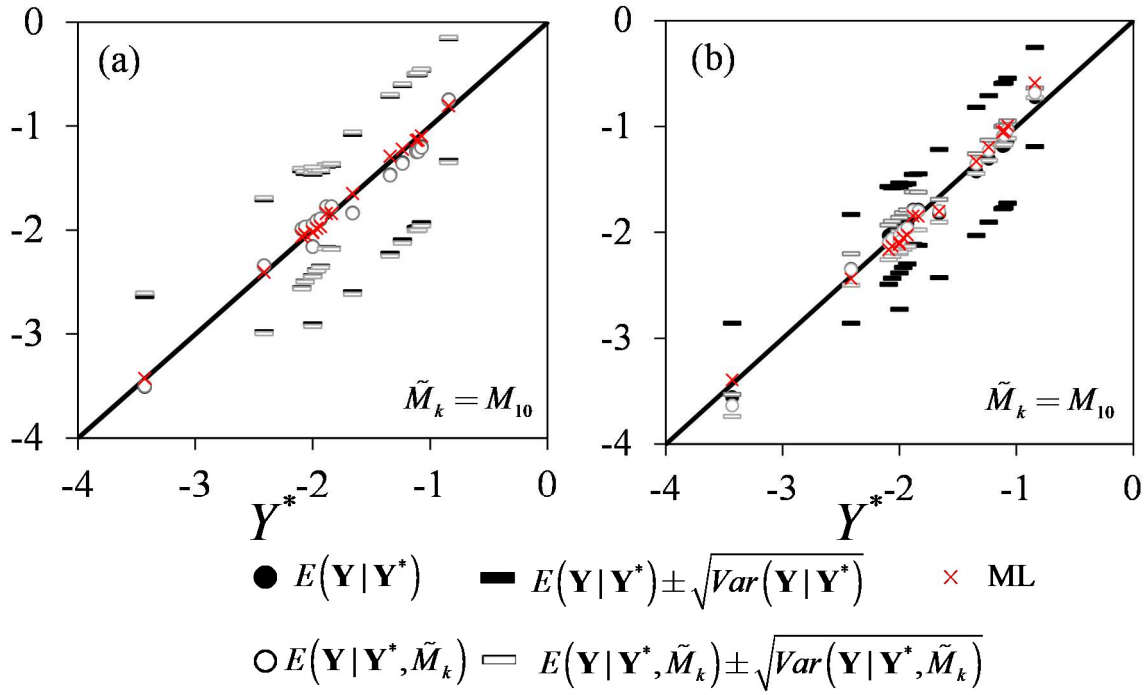

Figure 7

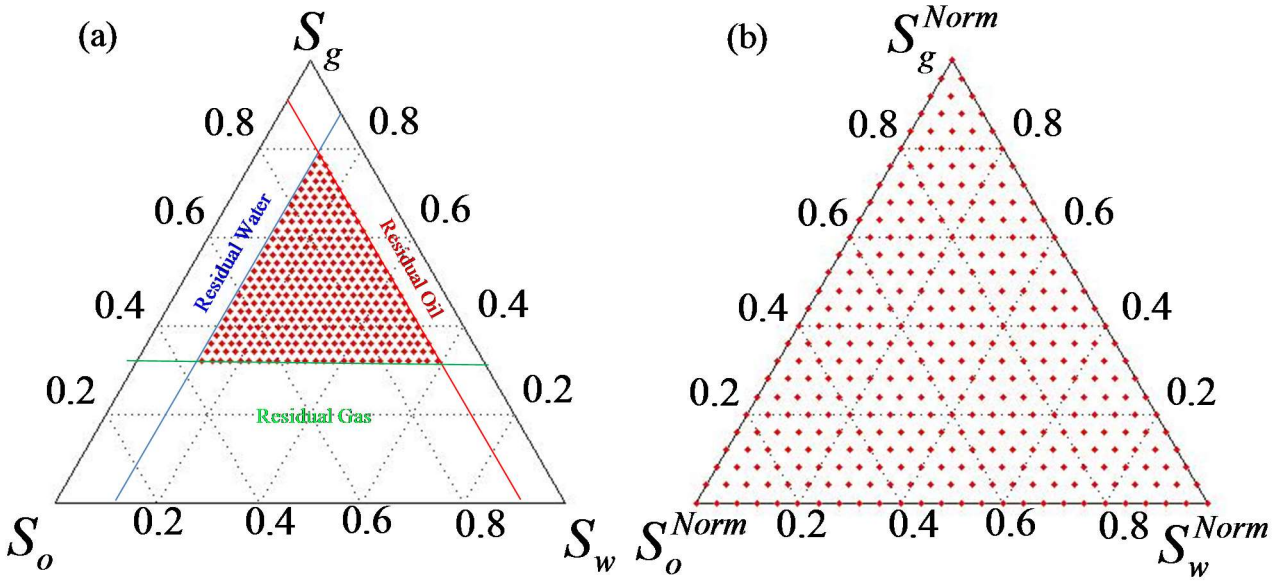

Figure 8

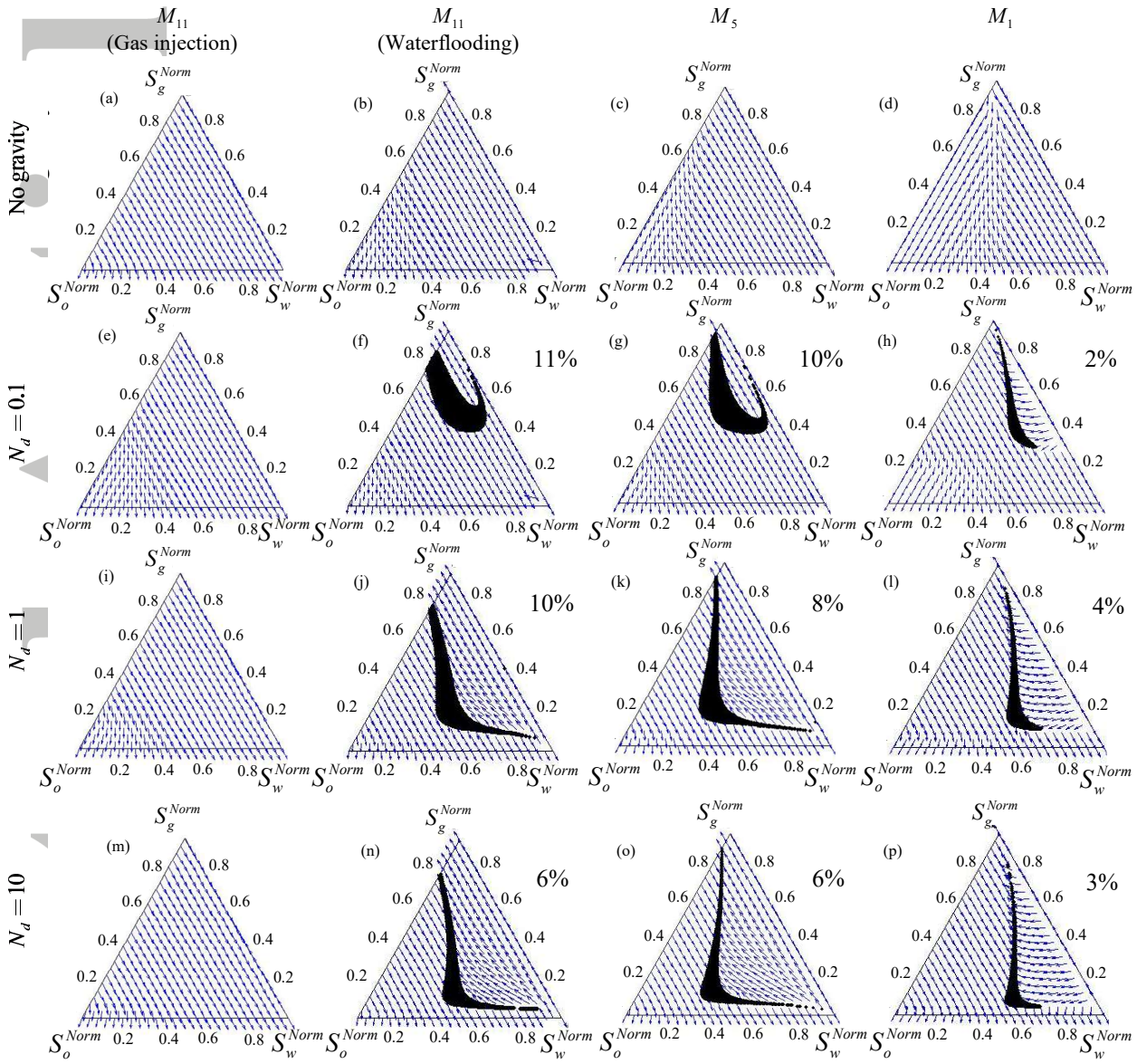

Figure 9

Model	Model requirements for application (Y: yes; N: no)				Model based on Channel flow theory	Number of model parameters (m)	Consideration of hysteresis effects	Model results obtained through two-phase data ($LMSE$)				ML model calibration through three-phase data ($LMSE_{\min} = \hat{\sigma}_Y^2$)			
	Saturation of all three fluid phases	Two-phase relative permeabilities	Saturation ending points	Initial condition of the experiment				$G1$		$W2$ ($n = 17$)	All ($n = 64$)	$G1$		$W2$ ($n = 17$)	All ($n = 64$)
								$S_{oi(1)} = 0.65$ ($n = 27$)	$S_{oi(2)} = 0.45$ ($n = 20$)			$S_{oi(1)} = 0.65$ ($n = 27$)	$S_{oi(2)} = 0.45$ ($n = 20$)		
M_1 [*Stone*, 1970]	Y	Y	Y	N	Y	1	N	0.97	1.29	1.70	1.26	0.07	0.62	0.02	0.23
M_2 [*Stone*, 1973]	N	Y	N	N	Y	–	N	1.42	1.60	1.12	1.40	–	–	–	–
M_3 [*Delshad and Pope*, 1989]	Y	Y	Y	N	Y	6	N	0.27	1.49	0.33	0.67	0.02	0.02	0.003	0.39
M_4 [*Shahverdi and Sohrabi*, 2013]	Y	Y	Y	Y	Y	–	Y	0.33	1.02	1.01	0.91	–	–	–	–
M_5 [*Baker*, 1988]	Y	Y	Y	N	N	1	N	0.15	2.08	0.93	0.96	0.09	0.97	0.56	0.51
M_6 [*Du et al*., 2004]	Y	Y	Y	N	N	2	N	0.18	0.18	0.54	0.28	0.16	0.21	0.14	0.11
M_7 [*Hustad and Hansen*, 1995]	Y	Y	Y	N	N	–	N	0.15	0.47	3.44	1.12	–	–	–	–
M_8 [*Blunt*, 2000]	Y	Y	Y	N	N	–	Y	0.81	0.88	0.13	0.65	–	–	–	–
M_9 [*Fenwick and Blunt*, 1998; *DiCarlo et al*., 2000]	N	N	Y	N	N	–	N	0.13	0.56	0.15	0.27	–	–	–	–
M_{10} [*Lomeland and Ebeltoft*, 2013]	Y	Y	Y	N	N	7	N	–	–	–	–	0.02	0.003	7×10^{-4}	0.06
M_{11} [*Ranaee et al*., 2015]	Y	Y	Y	Y	N	2×3	Y	0.07	0.10	0.07	0.08	0.02	0.02	0.003	0.03

Table 1 Characteristics of the analyzed three-phase oil relative permeability models together with results based on modeling outputs obtained by relying solely upon two-phase data and making joint use of two- and three-phase data (i.e., obtained through ML parameter estimation).

Model	Posterior model weight based on *NLL*				Posterior model weight based on AIC_c				Posterior model probability based on *BIC*				Posterior model weight based on *KIC*			
	*G*1		*W* 2 (*n*=17)	*All* (*n*=64)	*G*1		*W* 2 (*n*=17)	*All* (*n*=64)	*G*1		*W* 2 (*n*=17)	*All* (*n*=64)	*G*1		*W* 2 (*n*=17)	*All* (*n*=64)
	$S_{oi(1)} = 0.65$ (*n*=27)	$S_{oi(2)} = 0.45$ (*n*=20)			$S_{oi(1)} = 0.65$ (*n*=27)	$S_{oi(2)} = 0.45$ (*n*=20)			$S_{oi(1)} = 0.65$ (*n*=27)	$S_{oi(2)} = 0.45$ (*n*=20)			$S_{oi(1)} = 0.65$ (*n*=27)	$S_{oi(2)} = 0.45$ (*n*=20)		
M_3	5.6%	0%	0%	0%	0.6%	0%	0%	0%	0.3%	0%	0%	0%	97.2%	0%	0%	0%
M_{10}	91.8%	100%	100%	0%	1.6%	100%	94.4%	0%	0.9%	100%	100%	0%	0%	100%	59.4%	0%
M_{11}	2.6%	0%	0%	100%	97.8%	0%	5.6%	100%	98.8%	0%	0%	100%	2.8%	0%	40.6%	100%

Table 2 Posterior weights/probability calculated from (9) using *NLL* (2), AIC_c (6), *BIC* (7) and *KIC* (8) for candidate models M_3, M_{10} and M_{11}