UPSTREAM

# THE CERTAINTY IN UNCERTAINTY:
# Quantifying coreflood data errors

Multiphase flow in porous media systems is a critical element of many processes in the energy industry. The characteristics of the simultaneous flow of the immiscible phases can be quantified using relative permeability relations. In geoscience applications, these relations are determined in coreflooding studies that often comprise coreflood tests of oil–water mixtures performed on centimetre-scale rock samples. The outcomes of these are subject to uncertainty, which ultimately influences how accurately the parameters from small-scale tests translate to the upscaled estimations. To assess this uncertainty, Shell researchers have developed an inverse modelling workflow for the uncertainty analysis of relative permeability functions derived from coreflood tests. The results suggest that, even at a small scale, the uncertainty can be significant.

## Corefloods

Multiphase flow is prevalent in many natural phenomena and a wide range of processing technologies, from papermaking to fuel cells, involve it in some form. In the oil and gas industries, multiphase flow often implies the simultaneous flow of oil, water and gas. Understanding such flow is important for predicting reservoir flow and hydrocarbon production.

Managing uncertainty is key to delivering Upstream projects within the estimated recovery range and closer to the cost estimate. Special core analysis (SCAL) studies play an important role in determining

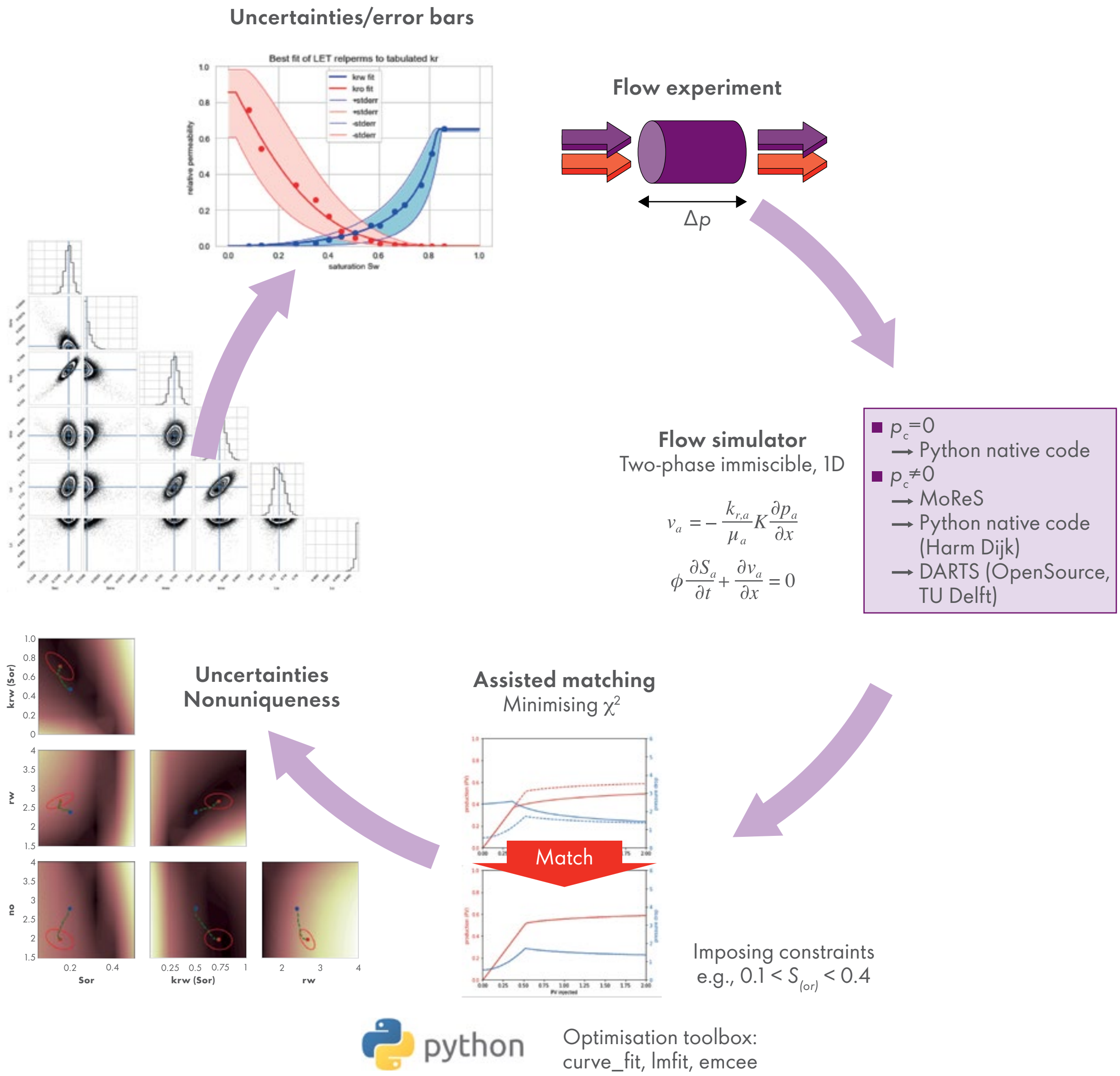



FIGURE 1
Inverse modelling workflow to assess uncertainties in relative permeability.

the input parameters for the reservoir models that are used for evaluating probabilities of success and mitigating risk. Therefore, the analysis of uncertainty should start with the interpretation of laboratory SCAL measurements.

SCAL experiments seek values for petrophysical parameters, such as the porosity of the reservoir, and flow parameters, such as permeability. Essential to SCAL are coreflood tests. In these, a fluid or combination of fluids is injected into a sample of rock to measure its permeability, the relative permeability of the injected fluids, the saturation distribution and the interactions between the fluid and the rock.

The core material often comes from an oil reservoir, but some tests use outcrop rock. The fluid in place at the start of the test is typically either a simulated formation brine, crude or refined oil, or a combination of brine and oil. Injected fluids may include crude oil, simulated reservoir brine, refined fluids, drilling mud filtrate, acids, foam or other chemicals used in the oil field.

Depending on the purpose of the test, the conditions may be either ambient temperature and low confining pressure or the high temperature and pressure of a subject reservoir. Pressures and flow rates at both ends of the core are measured. A coreflood is typically used to determine the optimum development option for an oil reservoir and often helps to evaluate the effect of injecting fluids specially designed to improve or enhance oil recovery.

Shell's best practices in SCAL require that (1) coreflood experiments be conducted with restored-wettability cylindrical rock samples taken from cores and (2) the measured pressure drop, production data and saturation profiles be interpreted with the aid of numerical models that also take the (independently measured) capillary pressure into consideration. In the past, the match between the modelled data and the experimental data from the second step was achieved by manually varying the relative permeability value. This ultimately gave a best-fit relative permeability value, but it did not provide its associated uncertainty, at least not in a representative way.

**Uncertainty assessment workflow**

This workflow described here can systematically assess the uncertainty of the relative permeability derived from assisted history matching of coreflood experiments. In the workflow (Figure 1), coreflood experiments are interpreted with the aid of a two-phase Darcy flow model that numerically simulates the experiment. A match between the measured values and the model parameters is achieved using the Python optimisation toolbox, which uses gradient-based methods to find a minimum of the mismatch between measured and modelled values expressed by the $\chi^2$ function, which is the sum of the squared differences.

Hyperplanes through the multidimensional parameter space reveal the nonuniqueness of the solution and whether the inverse model-matching converges to the global minimum. Respective error ranges for all the parameters in the relative permeability model can then be obtained from the covariance matrix of the $\chi^2$ fit with respect to the local optimum and, more globally, from Markov chain or Monte Carlo methods.

## Darcy's law and multiphase flow

The flow of a fluid in a porous medium is macroscopically described using Darcy's law, which relates the flux to the pressure gradient. Specifically, the law states that the flux, *v*, is inversely proportional to the viscosity of the fluid, *μ*, and the constant of proportionality, *k*, is the permeability of the porous medium:

$$v_{Darcy} = -\frac{K}{\mu}\nabla p \qquad \text{[Eq 1]}$$

For describing multiphase flows, Darcy's law is extended with the introduction of two phenomenological parameters that are ▸▸▸

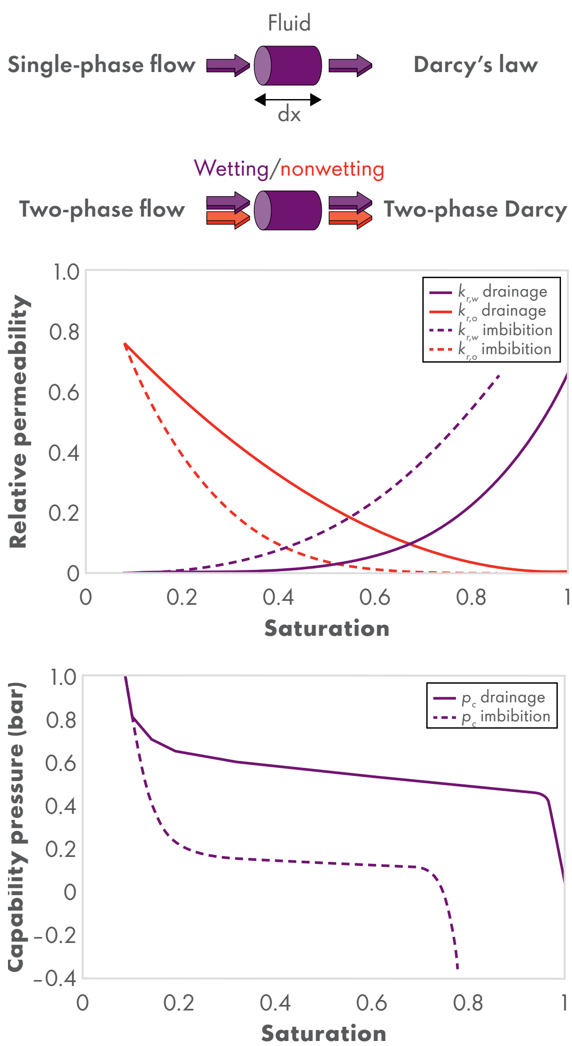



FIGURE 2
Darcy's law for single-phase flow and its phenomenological extension to two-phase flow.

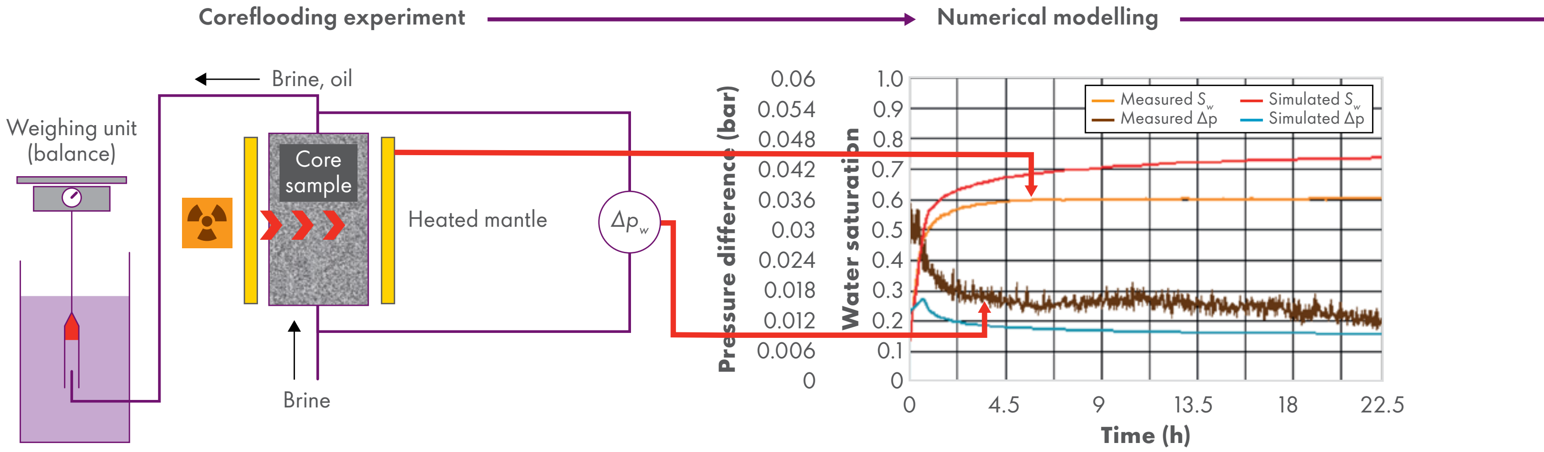



FIGURE 3
Workflow for deriving the relative permeability functions for the wetting (blue) and nonwetting (red) phases.

considered as functions of saturation: relative permeability, $k_{r,\alpha}$, and capillary pressure, $p_c(S_w)$, such that

$$k_{r,\alpha} = k_{r,\alpha}(S_w)$$

$$p_c(S_w) = p_{nw} - p_w \text{ and}$$

$$v_\alpha = -k_{r,\alpha}\frac{K}{\mu_\alpha}\nabla p_\alpha \qquad \text{[Eq 2]}$$

where $\alpha$ is the phase (wetting or nonwetting).

These parameters cannot be predicted within the framework of two-phase Darcy flow; they need to be derived empirically (or computed using digital rock methods) (Figure 2).

Indeed, coreflood experiments are routinely used to determine relative permeability functions [Ref 1, 2]. Although the most common experiments involve the so-called unsteady-state method, the Shell-recommended practice is to use the steady-state method. Both types of experiments are discussed here; the unsteady-state method is somewhat more illuminating, however, and it will be used to demonstrate the workflow, from conducting the experiment, to interpreting the results and, finally, deriving the relative permeability (Figure 3).

Many analytical approaches exist to interpret these experiments, but they all ignore capillary effects, which can significantly influence the resulting relative permeability. The Shell-recommended practice is to use numerical

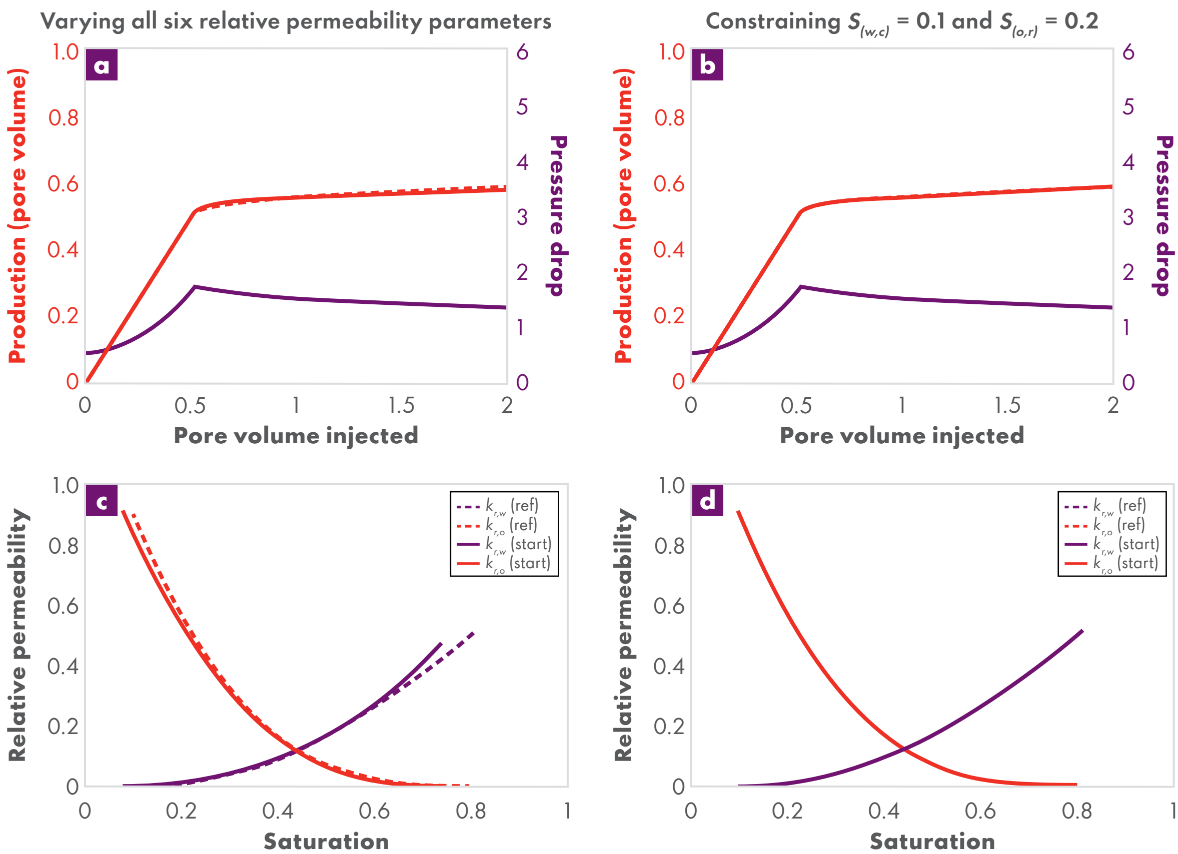
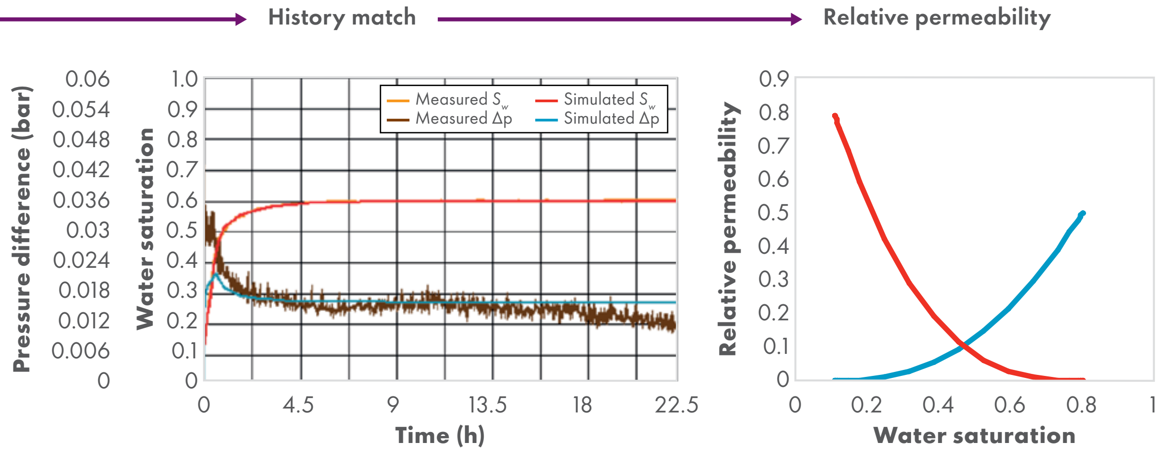



FIGURE 4
Nonuniqueness of the relative permeability derived from an unsteady-state experiment using synthetic data.

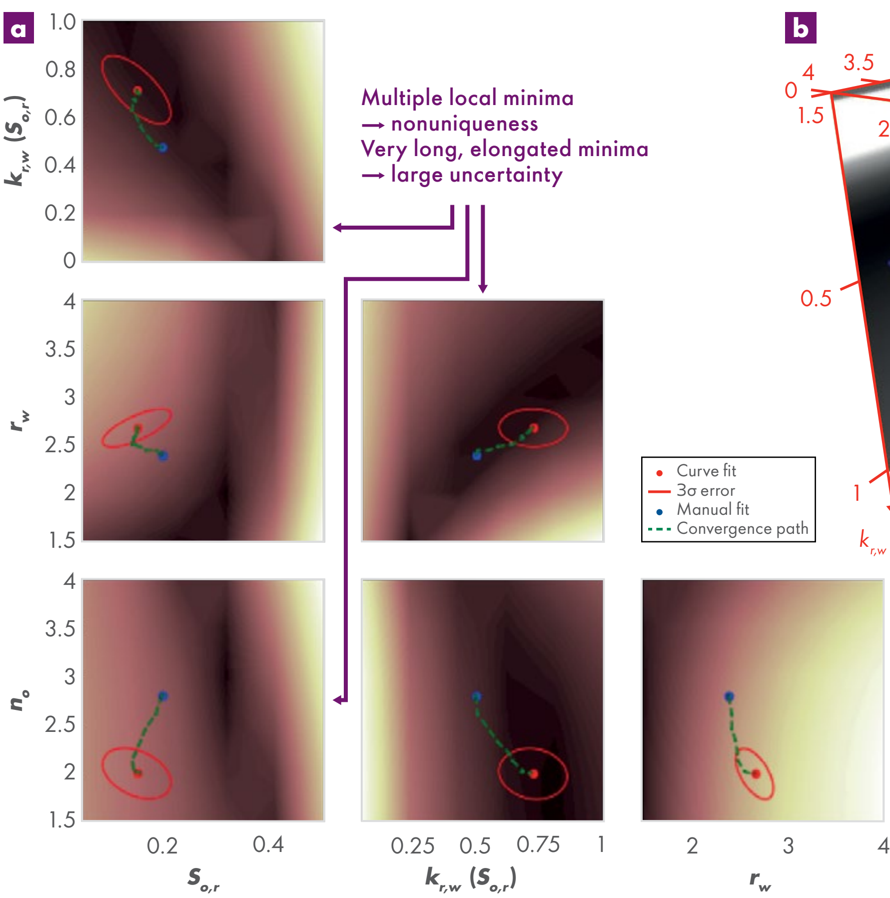



interpretation to compensate for these effects. The data from the experiment (pressure-drop and production data for an unsteady-state experiment) are therefore matched against the numerical simulation by varying the relative permeability curves. Figure 3 shows a high-level representation of the assisted-history-matching workflow in which experimental data are matched to the numerical solution of the governing equations (the two-phase extension of Darcy's law) so that the relative permeability functions for the wetting and nonwetting phases can be derived.

## How unique is the match?

The big question is, what is the uncertainty of the relative permeability curves? Before that question can be addressed, it is necessary to understand whether the match obtained in the workflow outlined in Figure 3 is, in fact, unique.

To address this question, it is necessary to go beyond the workflow of manual matching, as depicted in Figure 3, and to automate the matching of the model to the experimental data. To this end, the curve_fit and lmfit functions from the Python optimisation toolbox are used. Both of these are based on the Levenberg–Marquardt algorithm (which is a gradient-based $\chi^2$ minimisation method) and coupled with a numerical flow simulator that computes the numerical solution of the two-phase, 1D Darcy equations with capillarity.



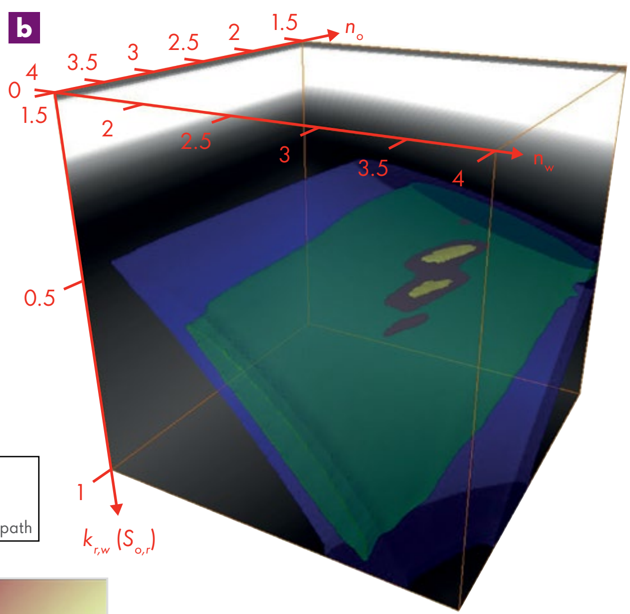




FIGURE 5
Cuts through the $\chi^2$ parameter space for the history match of an unsteady-state experiment.

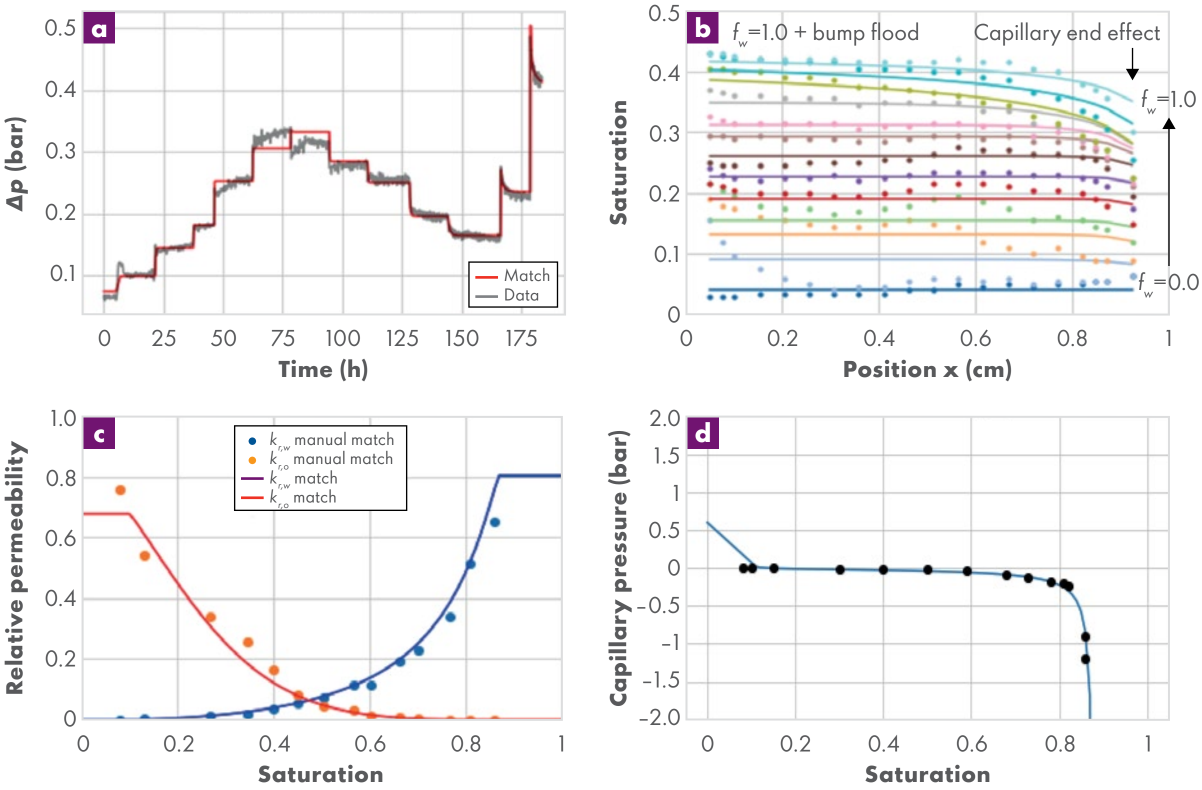



FIGURE 6
Experimental data from a steady-state coreflood experiment.

The study team used three different types of flow simulators: a 1D explicit numerical scheme with $p_c = 0$ coded in Python, Shell's reservoir simulator Dynamo/MoReS (with a Python wrapper) and a 1D implicit numerical scheme with $p_c \neq 0$ and timestep control. The last turned out to be the main tool used in the study, because it captures all the essential flow physics and is a factor of 400 faster than calling Dynamo/MoReS via the wrapper.

When testing the workflow on a synthetic data set, it became apparent that, even in the simplest case of a 1D unsteady-state displacement with $p_c = 0$, the ground truth is not automatically recovered. Figure 4 shows the known, ground-truth production curve, pressure drop and relative permeability (labelled as "ref") plotted as broken lines. Without applying any constraints, that is, varying all six parameters of the Corey function used to represent relative permeability, even in the most idealised situation (i.e., data without any noise), the ground-truth relative permeability is not recovered, even though the matches with the production and pressure drop curves are almost perfect (Figures 4(a) and (b)). However, when constraints for connate water $S_{(w,c)}$ and residual oil saturation $S_{(o,r)}$ are applied, the ground truth is recovered (Figures 4(c) and (d)).

Thus, even though the match in terms of production curve and pressure drop is practically indistinguishable from the ground-truth data, the relative permeability of the match is not the ground truth. That is a clear sign of nonuniqueness. The same behaviour is observed for the inverse matching of an experimental data set from an unsteady-state experiment in which multiple $\chi^2$ minima can be seen. Light colours represent large values of $\chi^2$ and dark colours small values (Figure 5(a)). The $\chi^2$ parameter space exhibits multiple minima, which a 3D contour plot of the $\chi^2$ landscape for a three-parameter match shows (Figure 5(b)).

This problem is one reason why Shell does not recommend using unsteady-state corefloods to determine relative permeability, and especially not at only one fixed rate. SCAL experts have known this for many years, which is why they have relied on additional data to constrain the solution.

**Choice of input and flow model**

After assessing the fundamental problems of interpreting coreflood experiments by means of inverse modelling [Ref 1, 2], the team went on to demonstrate that a match can be sufficiently constrained with the right choice of data and the right relative permeability model. As an example, the team used a steady-state relative permeability experimental data set that is part of Shell's internal SCAL training course.

The data set comes from a constant flow rate experiment with varying fractional flow, $f_w$, and a so-called "bump flood" at the end, when the flow rate is increased in two steps. This can be clearly seen as the increase in pressure drop at the end of the experiment from about 170 h onwards (Figure 6(a)).

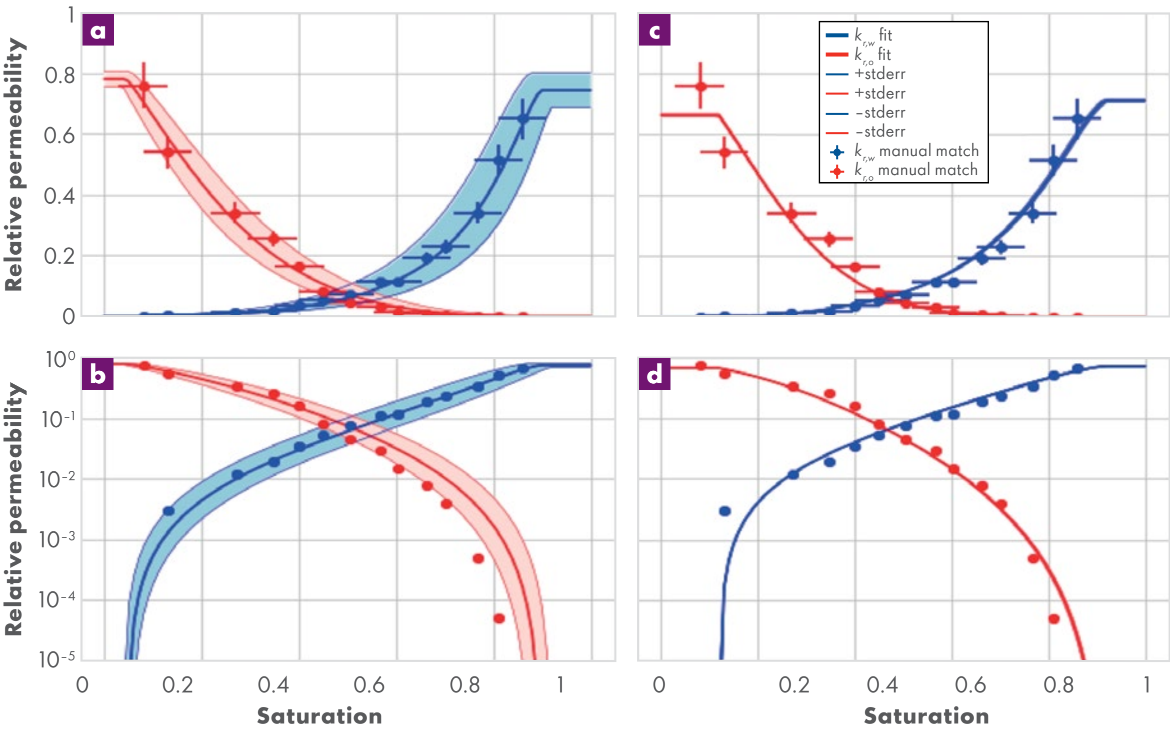



FIGURE 7
Comparison of the uncertainty associated with the relative permeability curves from the manual match, **(a)** and **(b)**, and the automated match, **(c)** and **(d)**.

In the experiment, for a series of flow, $f_w$, values, the pressure drop (Figure 6(a) and saturation profiles (Figure 6(b)) are matched using the LET model of relative permeability. The resulting relative permeability curves are shown in Figure 6(c), which also plots the results of the manual match.

The automated match also includes the independently measured capillary pressure function, $p_c(S_w)$, which was parameterised with an analytical function, as shown in Figure 6(d). In the match, all the parameters were allowed to vary, including $S_{(w,c)}$ and $S_{(o,r)}$. The experimental data, including the bump flood and saturation profiles $S_{w(x)}$, constrained the match sufficiently well that consistency with $S_{(o,r)}$ from the capillary pressure data was achieved.

The model matches both the pressure drop and the saturation profiles reasonably well at about the same level of quality that a SCAL expert can achieve with manual matching.

In Figure 7, the uncertainty associated with the relative permeability curves of the manual match is compared with that of the automated match. The uncertainty was assessed with a Markov chain–Monte Carlo approach [Ref 1, 2]. When the tabulated relative permeability values obtained from the manual match were fitted to a LET model, the resulting uncertainty ranges were of about the same magnitude as the experimental uncertainty-based error bars (Figures 7(a) and (b)). The automated match, in which the flow model is matched directly to the whole pressure drop and saturation profile data set, results in different relative permeability curves (Figures 7(c) and (d)) with significantly less uncertainty.

The reason is that, in the fit of the tabulated data, only 14 individual data points were available to constrain the match and there were significant correlations between the fit parameters, all of which led to significant errors in the individual parameters of the relative permeability model. In contrast, when the model is directly matched to the experimental data, $S_{(o,r)}$ is very well constrained (particularly by the bump floods), thereby effectively decoupling the water and oil relative permeability parameterisations and resulting in much lower uncertainty.

One last point to note is that the manual-match and the automated-match curves differ in terms of endpoints, crossover points and shape. These differences in relative permeability would have implications in practice.

## What next?

The workflow presented in this article provides evidence that it is feasible to history match coreflood experiments by coupling numerical flow simulators with optimisation methods. Using Python provides a convenient platform for rapid prototyping without needing a software licence. This software is freely available, and its optimisation toolbox provides methods sufficiently well suited to achieving assisted matches of models with at least 10 parameters. Despite Python being predominantly interpreted code, the use of the Numba just-in-time compiler has made the code significantly faster. ▸▸▸

The implementation of the 1D implicit flow simulation code is a factor of 400 faster than wrapping a reservoir simulator. This made the code fast enough to run a full Markov chain–Monte Carlo model with 10 parameters using 20,000 iterations in an acceptable time, even on a laptop computer. This opens the door to further refinement of the team's approach.

Before optimising the code further, however, the study team plans to extend the interpretation methodology to centrifuge experiments used for the independent measurement of the capillary pressure, $p_c(S_w)$, and to match the raw data from centrifuge and steady-state experiments simultaneously.

Although the LET relative permeability model does provide a satisfactory match, the residuals show a systematic non-Gaussian distribution and are significantly larger than the experimental error. Possible reasons for this are shortcomings in either the flow model or the relative permeability parameterisation. Alternatively, there may be an unexplained phenomenon at play in the experimental data. These aspects will be investigated in future research.

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