Analysis of Time-Lapse Seismic and Production Data for Systematic Reservoir Model Classification and Assessment

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SUMMARY

The heterogeneous distribution of reservoir properties is one of the most important uncertainties in static and dynamic reservoir modelling. Petrophysical properties are usually interpolated within reservoir models from sparse well-log data, which can lead to highly uncertain estimates at inter-well locations that directly affect the reliability of fluid-flow model predictions of reservoir behavior. To address this issue, we build an ensemble of equiprobable models that combine different geostatistical realizations of reservoir properties to span the range of potential outcomes. While this process captures the impact of reservoir property distributions on the model response, a major challenge is classifying the subset of models in the ensemble best representing reservoir fluid-flow behavior. Thus, we introduce a methodology combining 4D seismic amplitude attributes and reservoir production data to classify fluid-flow models. This classification is based on applying thresholds for independent seismic and production objective functions. We test our methodology on the benchmark case UNISIM-I developed from observations from the Namorado Field, Campos Basin, Brazil. By comparing injection and production rates in relation to 4D seismic amplitude trends, we identify nine models out of an ensemble of 100 that judged optimal via the required seismic and production objective function thresholds and obtain an improved quantitative evaluation of the impact of reservoir production on the 4D seismic signal. Ultimately, combining seismic and production data offers interpretation scenarios that automatically identify realistic fluid-flow models that can assist the update of permeability and porosity distributions within the reservoir.

Keywords: 4D seismic, fluid-flow model classification, reservoir property uncertainties.

INTRODUCTION

Fluid-flow models have long been used to assist in reservoir development and management acitivities (Aziz, K. and Settari 1979; Oliver et al. 2008; Oliver & Chen 2011). These models simulate the dynamics of fluid flow in porous media, which is used to predict future hydrocarbon reservoir behaviour. Flow models have been developed based on a wide range of different data sources including well-logs, field seismic data, and laboratory measurements of rock and fluid properties (Fanchi 2006). However, because each data source has its own characteristic scale length, horizontal and vertical resolution and areal coverage, it is unlikely that a single fluid-flow model will adequately capture the heterogeneity of reservoir properties. One key fluid-flow model building challenge is reliably extrapolating information derived from geographically sparse well logs to provide estimates of porosity and permeability distributions throughout a reservoir. Accordingly, in static and dynamic reservoir modelling, property heterogeneity is a source of errors, such as the number, locations and hydraulic properties of faults, which altogether can lead to highly uncertain production forecasts.

Even though uncertain production forecasts increase reservoir management risks, deterministic approaches using a single model are often the initial (and final) choice for static and dynamic reservoir modelling. Deterministic approaches cannot capture the full range of expected reservoir response to development activity as they do not account for the significant uncertainties associated with reservoir property heterogeneity. To examine the impact of reservoir property heterogeneity, one increasingly common strategy is to follow a stochastic approach and build an ensemble of equiprobable models that combine different geostatistical realisations of reservoir properties that ideally span the range of potential outcomes (Doyen 2007; Schiozer et al. 2016). By sampling the parameter space one can generate posterior statistics that help quantify uncertainties on the model response due to variable reservoir property realisations, which provides invaluable information for reservoir development and management engineers (Mesquita et al. 2015). However, a major challenge with this approach is selecting the subset of stochastic models that optimally represent reservoir behaviour. Effectively and efficiently addressing this issue requires developing an automated assessment procedure for identifying and classifying fluid-flow models that are both physically realisable and consistent with all available geophysical, production and geological data.

Current model classification procedures typically use criteria based on a combination of production data, such as bottom hole pressure, water production rates and water cut values (G.D. Avansi & Schiozer 2015; Avansi et al. 2016). While this approach can identify models that reasonably reconstruct production history, the absence of geological information poses a challenge for identifying models consistent with the observed geological settings. In addition, inferring distributions of reservoir properties remains highly uncertain where no 4D seismic attributes are available to indicate fluid-movement trends (Lumley 1995; Lumley & Behrens 1998;

Kjelstadli et al. 2005; Ullmann et al. 2011; Barkved 2012). This suggests that incorporating additional information obtained from 4D seismic data, where present, should improve the model classification process.

Incorporating seismic data in a quantitative manner requires transforming the information content into a format compatible with fluid-flow modelling outputs. One of the main associated challenges is that 4D seismic amplitude information exists in volumes acquired at a few sparse points in calendar time, which is in contrast to the relatively continuous production time-series data. A number of approaches extract, filter and segment 4D seismic attribute maps to quantify time-lapse reservoir changes (Tillier et al. 2012). These methods binarize 4D attribute maps to calculate a local modified Haussdorff distance quantifying the (dis)similarity of two images (e.g., modelled and observed 4D seismic amplitude maps). Tillier (2012) successfully applies this method in a synthetic steam-assisted gravity drainage production scenario, and improves objective function convergence in a history matching (HM) procedure when compared to a conventional least-squares optimisation approach (Gosselin et al. 2003).

The goal of our study is to define quantitative criteria for use in classifying fluid-flow models from an ensemble of equiprobable realisations, according to their consistency with both 4D seismic amplitude maps and production data. Our approach accepts (or rejects) models based on acceptance thresholds defined independently for seismic and production objective functions. For our seismic objective function, we reformulate the binarisation method developed by Tillier (2012) introducing a new "informative" ILDM that identifies the source of the differences (e.g., observed or modelled seismic data). We define our production objective function following the normalized quadratic deviation with signal (NQDS) approach (Schiozer et al. 2016). Thus, the suite of models that optimally satisfy both objective functions are likely to be those most consistent with the available geological, geophysical and engineering data, and thereby offer the most physically consistent insights about fluid-flow, porosity and permeability distributions as well as fault locations and fluid-flow characteristics.

METHODS

Figure 1 presents our methodology to classify fluid-flow models according to their consistency with both seismic and production data. We defined consistency as satisfying independent acceptance thresholds for both seismic and production objective functions. We divide our methodology into four steps:

- (1) generate an ensemble of equiprobable fluid-flow models;
- (2) apply a 4D seismic workflow;
- (3) apply a production modelling workflow;
- (4) assert the model classification routine.

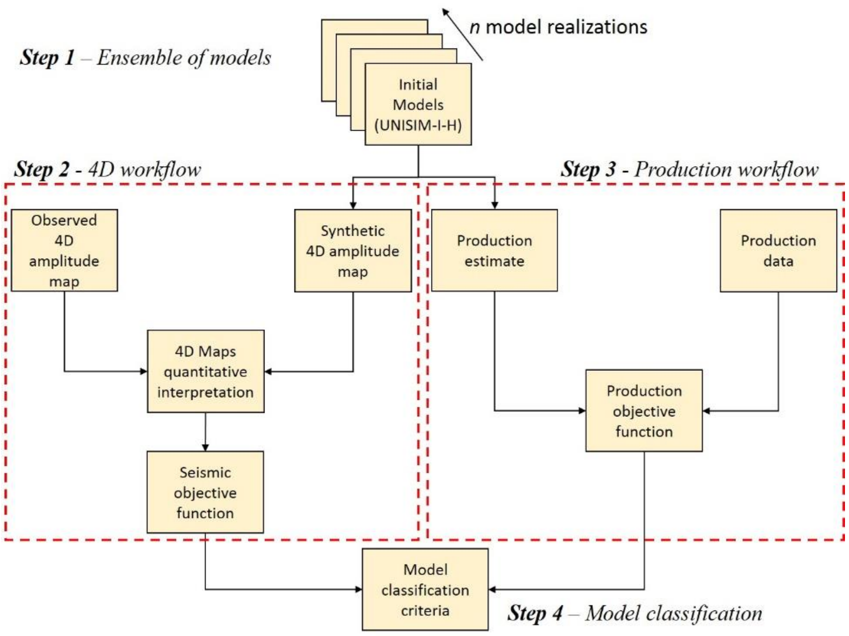

Figure 1: Workflow steps to define the model selection criteria. Step 1 generates the ensemble of models. Step 2 involves seismic forward modelling and interpreting the 4D amplitude changes maps and evaluating the seismic objective function OF_S. Step 3 estimates the production objective function (OF_P). Step 4 selects the optimal models by applying our criteria to the OF_S and OF_P.

The model classification step combines the measures calculated in Steps 2 and 3 to classify the models in the ensemble. We define our model classification criterion by applying independent seismic and production acceptance thresholds, T_S and T_P on OF_S and OF_P, respectively. The value of each acceptance threshold is determined on a case-by-case basis. These criteria allow us to identify models with an acceptable match between seismic and production data that satisfy both $OF_S < T_S$ and $OF_P < T_P$.

To facilitate understanding of our model classification procedure we introduce four model classes:

- Type 1 models that satisfy both seismic and production data
- Type 2 models that are acceptable by seismic constraints, but are rejected by production data
- Type 3 models that are rejected by seismic data, but are acceptable by production data constraints.
- Type 4 models are rejected by both seismic and production data.

Models falling in each type are important as they offers a different perspective of the results. For example, Type 2 models could suggest an unconsidered interpretation hypothesis that may be overlooked due to rejection based on production data. Similarly, a better correlation with the 4D seismic amplitude map may indicate that away from the wells, the property distribution (e.g., porosity and permeability) is closer to the true model than a model selected by the production data alone. Similar benefits arise when interpreting Types 3 and 4.

RESULTS

In this study, we validate our methodology using the synthetic UNISIM-I benchmark model (G. D. Avansi & Schiozer 2015) consisting of the UNISIM-I-R reference model and a suite of derivative models. UNISIM-I-R is a fluid-flow model built in a high-resolution grid using publicly available data (e.g., core descriptions, well logs, 2D/3D seismic data) from the Namorado field, Campos Basin, Brazil. While the original structural interpretation is used to define the top and bottom reservoir surfaces and fault locations, sequential indicator simulation (SIS) was used to model the facies distribution. The UNISIM-I-R performance evaluation accounts for small-scale heterogeneities distributed within these facies using a [Δx, Δy, Δz]=[25,25,1] metres grid-cell size discretised into a corner point grid with 326x234x157 active cells (approximately 3.4 million in total). The high level of detail offers both a reliable geological model and suitable derivative models for simulations that honour production history data. For a detailed description of the UNISIM-I-R model we refer the reader to Avansi (2015).

Figure 2 shows the partitioned region of interest on which we focus during this investigation. This region contains three producer (PROD023, PROD024 and PROD025) and two injector (INJ007 and INJ010) wells, and is isolated from the rest of the reservoir by the known sealing fault FB. INJ007 and INJ010 are completed in Layers 9 and 10 and commence water injection after approximately 2000 and 2200 days of production, respectively. The injection strategy focuses on sustaining reservoir pressure and thereby supporting the oil production rate. PROD023A is completed in Layer 8 and starts producing water after 3167 days of production (Figure 3b). Note that the models in the ensemble predict a much earlier water breakthrough arrival time in comparison with production history, indicating that these models require further property updates in the vicinity of the well in order to delay the arrival of water. PROD024A is completed at Layer 2 and starts producing water after approximately 2600 days of production (Figure 3c). Conversely to observations at PROD023A, the majority of the models in the ensemble predict water arrivals much later than expected, again highlighting a need for reservoir model updating. Finally, PROD025 completed at Layer 3 starts producing water after approximately 2500 days of production (Figure 3d). The variation on these predictions highlights that this ensemble of models represents only an initial attempt to model the correct reference model UNISIM-I-R response. Thus, our goal is to identify those models out of the full ensemble that are the most consistent with both seismic and production data that could form the basis of a subsequent round of fluid-flow reservoir model updating.

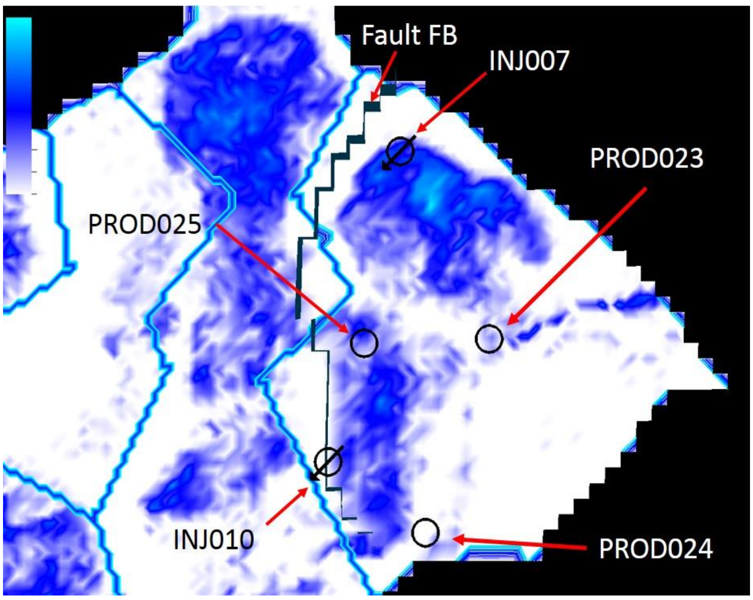

Figure 2: Boundaries of the region of interest for model classification defined at the 4D seismic amplitude map superimposed with three producers (PROD023 and PROD024 and PROD025) and two injectors (INJ007 and INJ010).

To classify the models according to the methodology described above we first calculate OF_S and OF_P and then apply the T_S and T_P thresholds. We use a value of T_S=0.44 that is half of the OF_S range, while OF_P values within T_P = ±300% are deemed acceptable according to previous evaluations (Schiozer et al. 2016). While a 300 % threshold may seem somewhat high, we stress that the ensemble of models require further updating, as they do not yet present high-quality matches (Figure 3a-d). In fact, using a lower T_P would likely discard models broadly consistent with both seismic and production data.

By examining the 4D seismic amplitudes in Figure 2 we identify two major 4D anomalies associated with INJ010 and INJ007. To quantitatively assess and classify the models, we estimate OF_S using the ILDM within the region of interest for the entire ensemble. Figure 4 shows a crossplot of the OF_S and OF_P for Region 6 (see Figure 2) colour coded by type, where again each marker represents one model of the ensemble. This plot shows the classified model Types 1-4, as well as the four models (m_1, m_2, m_3 and m_4, respectively) used as examples of Types 1-4 in the ensuing discussion (indicated by the red-cross). When enforcing both seismic and production selection criteria we classify nine Type 1, 49 Type 2, 11 Type 3 and 25 Type 4 models.

Figure 6a present the ILDM of the representative model Type 2. We observe that the quality of the match varies within the region, the ILDM have zero values at locations where the input attributes are well matched; thus, the area nearby INJ007 exhibits a better match than around INJ010. Figure 6b shows the water rate production curves for all models presented in Figure 4 and highlights PROD025 OF_P values provided by the m_1, m_2, m_3 and m_4 models. Similarly to the OF_S values, the computed OF_P increase once the quality of the match between the production history and the simulated water rate deteriorates.

Figure 6c-d show the RMS map (i.e., averaged to the seismic resolution) of the permeability distribution extracted from the UNISIM-I-R and m_2 model, respectively. A qualitative comparison between these maps shows locations that correlate in magnitude and/or pattern with the true reference permeability distribution (Figure 6c). Model m_2 offers a reasonable visual match at the north of the area of interest while any correlation seems unlikely towards the south. Note the major permeability anomaly located at the south added in earlier attempts to improve the match between simulated and observed production rates (Figure 6b) (Mesquita et al. 2015). As a result, the water injected by INJ010 moves southward along the high permeability anomaly, decreasing the synthetic 4D seismic amplitudes in the area. The m_2 ILDM in Figure 6a shows extended areas in blue in the region where the synthetic 4D RMS map indicates no 4D signal. Further, this high permeability structure may be the cause of the delay in the predicted time of water arrival (Figure 6b) as the water saturation front moves from INJ010 to the south instead of northeast towards PROD025.

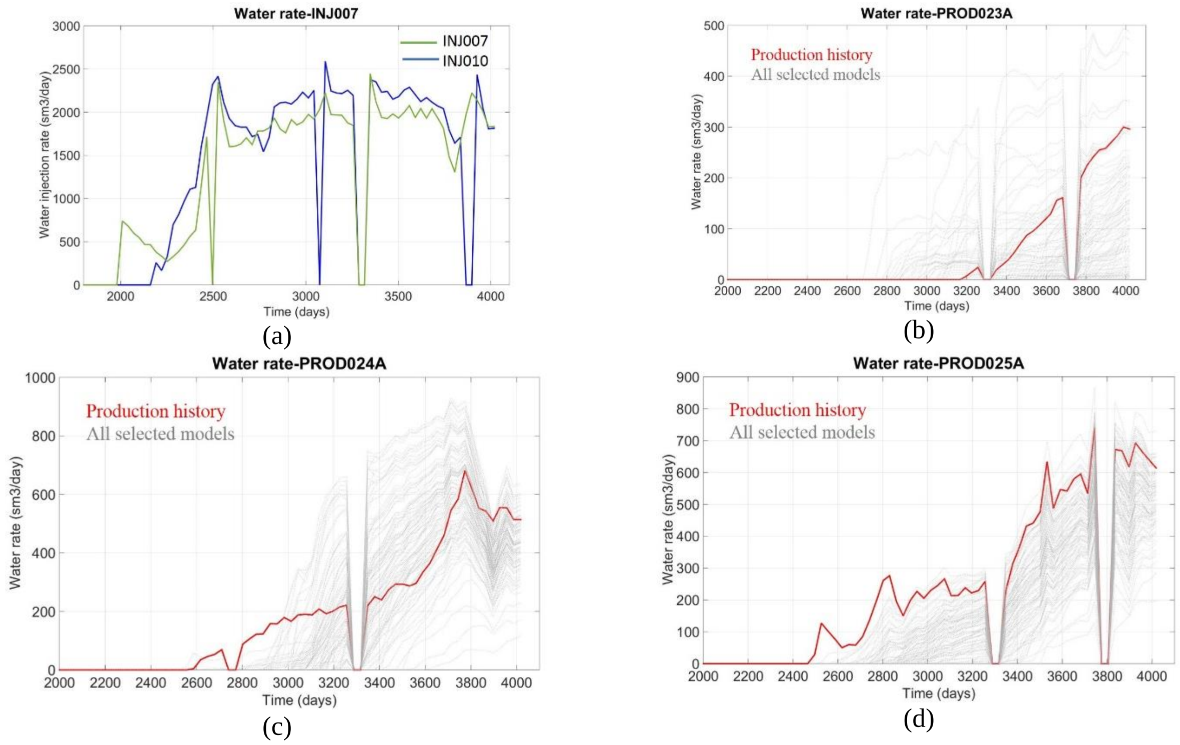

Figure 3: (a) Water injection rate of the wells INJ007 and INJ010 and water rate production history (in red) superimposed with the flow simulation response of the models in the ensemble for the producer wells: (b) PROD023; (c) PROD024A and (d) PROD025.

In Figure 6a-d we crossplot model Types 1-4 versus the true permeability within the 4D Mask 2. This area, located to the north of our region of interest, presents a better visual match between the observed and modelled permeability distributions than the region in the vicinity of the INJ010 nearby the permeability anomaly. The m_1 and m_2 RMSE are 267.96~mD and 164.29~mD, while the m_3 and m_4 are 167.89 mD and 215.39mD. Note that m_1 presents the highest error in relation with the other model Types. The differences between the reference and m_1 permeabilities illustrate these higher errors. Rather than being the best, a Type 1 model indicates the optimal compromise between the quality of seismic and production data predictions as a function of T_S and T_P. Illustrating this further, in Figure 4 we observe that m_2 has a lower OF_S than m_1, which justifies the smaller error of the m_2 permeabilities; however, m_1 outperforms m_2 water rate predictions at PROD025 (Figure 5b), highlighting the impact of the permeability distributions in deeper layers, where the extracted 4D seismic amplitude maps could not provide any information. Note that the Mask 2 is located in the vicinity of the permeability anomaly in the fluid-flow models (Figure 6d) and therefore offers a less accurate match between the reference and modelled 4D seismic amplitudes.

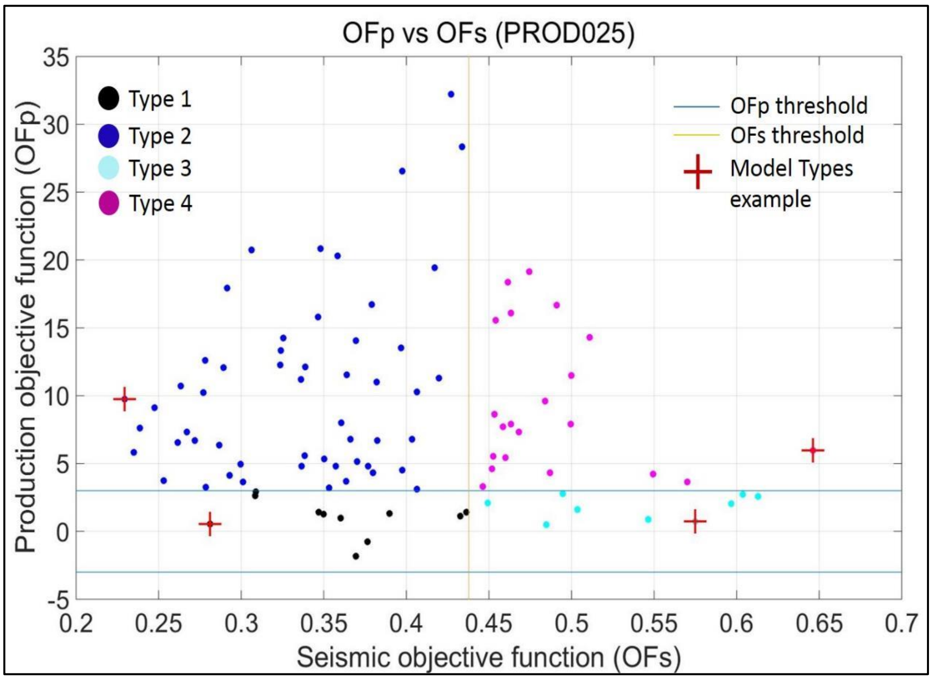

Figure 4: PROD025 production objective function (OF_P) versus seismic objective function (OF_S) colour coded by the classification type. The classified model Types 1-4 in Figure 3 are indicated by the red crosses.

DISCUSSION

By categorizing the fluid-flow models in the ensemble regarding their consistency between seismic and production data, our methodology offers a systematic approach to an often overwhelming task. Systematically and automatically analysing the different models by considering their (in)consistency with seismic and production data allows us to better understand water saturation movement trends within the reservoir and the permeability distribution.

When analysing RMS maps of 4D seismic attributes, it is important to remember that the 4D seismic amplitude map is a vertically limited "snapshot" of the reservoir fluid distribution at the time of the monitor survey. This means that the 4D amplitude changes at the top layers of the reservoir results from the up-dip water movement trend highlighted by the fluid-flow models. The poor ILDM match in the vicinity of the INJ010 indicates that the 4D seismic amplitude information does not comply with the permeability anomaly found in that area. In this scenario, we could confirm that there is no anomaly because we have the true permeability distribution; however, this is not the case in practice and it becomes invaluable to know where to add permeability trends within the fluid-flow model.

Our approach offers quantitative insights about the permeability distributions and, by applying 4D seismic techniques, avoids the uncertainties associated with estimating permeability based on the inversion of seismic attributes. Further, by classifying and selecting models in the ensemble we estimate permeability distributions that are consistent with both 4D seismic amplitude and production data that can be directly used as inputs in future simulation runs to streamline model calibration processes.

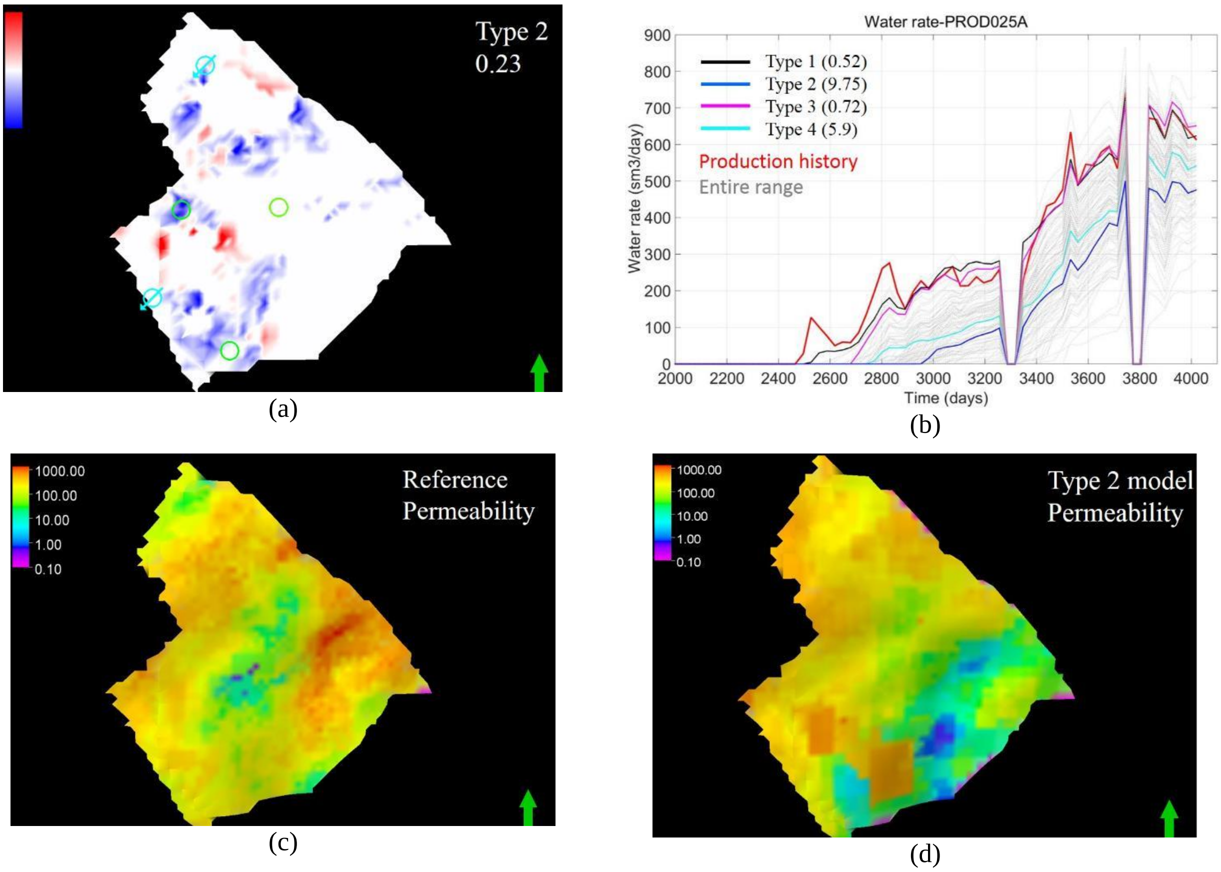

Figure 5: (a) ILDM between the reference and the model Type 2 (b) Water rate of the PROD025A for the models in the ensemble; and the Reference and model Type 2 permeability distributions (c-d).

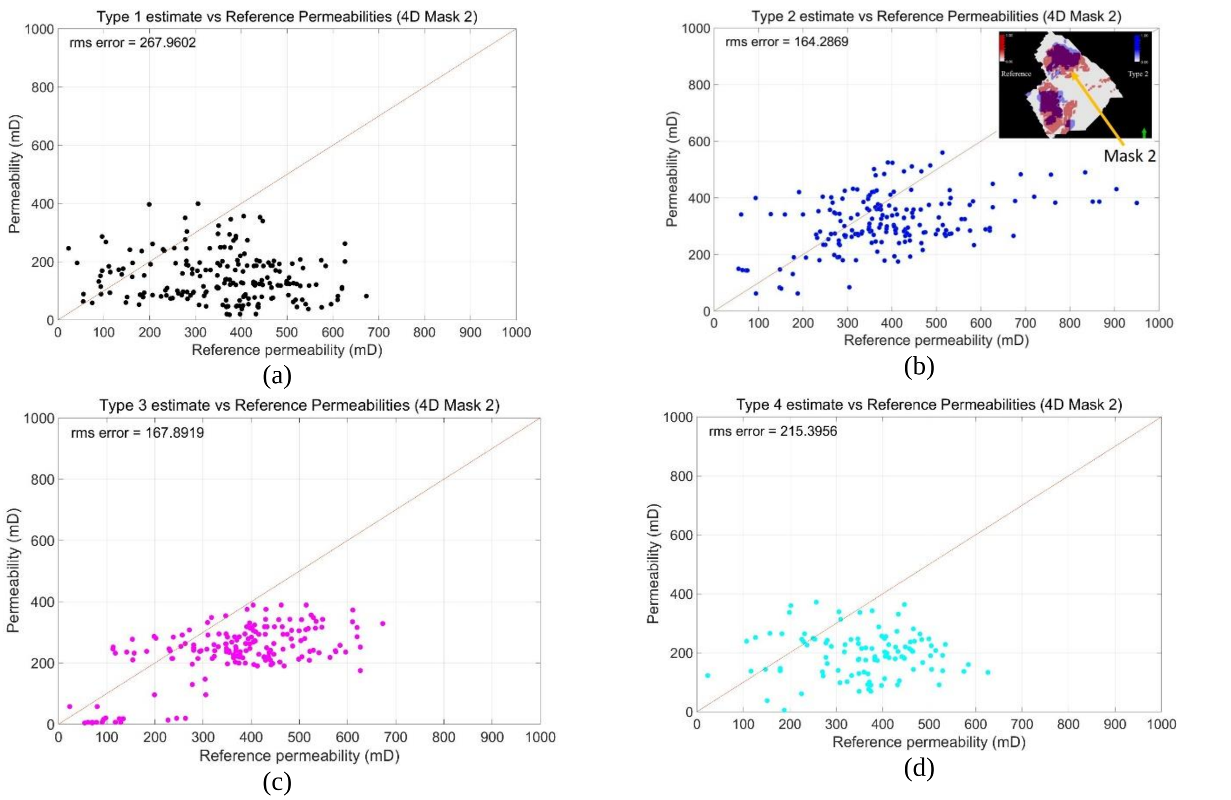

Figure 6: Cross-plots between the reference and modelled permeability distributions within the 4D Mask 2 (see sub-Figure 6b) and their respective RMSE values for: (a) m_1; (b) m_2; (c) m_3; and (d) m_4.

CONCLUSIONS

We present a new methodology combining 4D amplitude and production data to select a preferred subset of models out of an ensemble of equiprobable fluid-flow model realisations. We develop informative local dissimilarity maps ($ILDM$) that allow us to quantify differences between observed and modelled 4D seismic amplitude maps in an independent seismic objective function. When combined with a standard production objective function, this leads to an automated and systematic methodology to classify fluid-flow model response and to provide insights about delays and advances in the predicted water arrival-times at productions wells. Classifying fluid-flow models by types with respect to their consistency with seismic and production data is viewed as a good integration approach that leads to estimates of fault locations and hydraulic and reservoir property distributions such as permeability and porosity. The cross-plot analysis shows that identified models can contain physically coherent permeability estimates and therefore validates our methodology for real data applications. By introducing a quantitative interpretation integrating 4D seismic attributes and fluid-flow models, this methodology offers a rapid and systematic approach for the time-consuming task of interpreting a large number of fluid-flow models.

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