Uncertainty in subsurface interpretation: a new workflow

Garrett M. Leahy and Arne Skorstad explain a new interpretation workflow that focuses on the measurement of uncertainty and combines the interpretation and modelling phases.

Current interpretation and geomodelling workflows are ageing and, constrained by conventional wisdom, developed in an era where reservoirs were structurally less complex. In particular, the conventional workflow suffers from an overreliance on a single product: a deterministic reservoir model that is difficult to update and does not accurately represent the full spectrum of geologic risk. In order to meet the increasing technical challenges provided by the structurally complex reservoirs of today and tomorrow, we propose a new interpretation workflow that focuses on the measurement of uncertainty and combines the interpretation and modelling phases. This workflow provides quantitative, risk-based decision-making support to help integrated asset teams achieve the best possible reservoir management and recovery.

The geosciences community faces significant challenges through the rise in increasingly remote and geologically complex reservoirs. However, most upstream organisations and workflows are optimised around conventional oil paradigms developed in the 1980s and 1990s. Broadly speaking, the typical practice in subsurface geoscience is for geophysicists to handle the data and interpretation, and to hand off the interpretation product (i.e., a configuration of subsurface faults and horizons representing their impression of the data) to a geomodeller, who then integrates the interpretation products with other geologic data (well logs and picks, inversion products, etc.) to produce a reservoir model.

The reservoir model is the central focus for decision-making in reservoir management – it provides a common representation of the reservoir to facilitate integration of all subsurface disciplines and workflows (Figure 1). The reservoir model can be used to compute a wide range of quantitative decision support products, from volumetric estimates to simulation and production estimates.

With increasingly complex tectonics resulting in more commercially complex business decisions, the reservoir model has never been more critical – and it is becoming clear that the current paradigm needs to evolve to meet the future needs of the oil and gas industry. Conventional interpretation and reservoir modelling workflows fail to meet these challenges for three key reasons.

First, conventional interpretation and reservoir modelling workflows are typically disjointed and independent within organisations. This leads to a constrictive lack of agility on the part of the typical asset team, whether it is via a difficulty in adapting and responding to new data, or challenges correcting errors in existing data.

Second, conventional workflows are geared to producing a single, deterministic, ‘best estimate’ model. This model becomes the quantitative support for all business decisions for reservoir management. This mode of thought becomes a liability when developing prospects that are challenging to image, or when the tectonic setting (or style of faulting) is poorly constrained.

Third, and perhaps most fundamental, is that conventional workflows are not equipped to quantify uncertainty. Every piece of geologic data has an associated uncertainty (whether from resolution, sensitivity, or noise), and for good or for ill, all of these uncertainties are carried into the reservoir model. As uncertainties in static reservoir properties (i.e., spatial description and volume) tend to be the key driver for the economics of a prospect, this challenge is becoming increasingly relevant to operators worldwide.

Here, we describe a new workflow for subsurface interpretation and modelling to meet these and future challenges. We focus on the development and quantification of ‘measurement uncertainty’ associated with seismic interpretations, and integrating this into subsurface modelling workflows. With uncertainty collected at the most fundamental stages of the interpretation process, the interpretation becomes not a single configuration but a means for generating an ensemble of reservoir models that can be used to risk and improve decision making. Furthermore, we believe that the reservoir model is the interpretation, and therefore that these workflows should be tightly integrated to provide ultimate flexibility to asset teams. We call the concept model-driven interpretation.

Theory & Methods

Interpretation can be a catch-all term that encompasses a variety of subsurface mapping and analysis activities – and it starts with a seismic image. While many interpreters feel that the seismic image is primary data (i.e., a direct picture of the
subsurface), the best interpreters recognise and understand the limits of the data, particularly when it comes to noise and processing artifacts.

The seismic image is impacted by the survey acquisition parameters (e.g., sources, receivers, geometry); the material response (wave physics, e.g., finite frequency effects, anelasticity, anisotropy, multiples); noise (environmental, e.g., weather, or electronic, e.g., instrument); and migration (e.g., modelled physics, starting assumptions). While properly tuned migration and stacking procedures can mitigate the impact of these effects, lateral variations in physical properties imply that it is virtually impossible to correct these errors over the footprint of a typical 3D seismic survey.

These effects directly impact the waveform of the seismic image: the amplitudes, locations, and shapes of seismic events that are critical to decision-making workflows. For example, poor migration or ground-roll removal can decrease seismic amplitudes used to calculate AVO anomalies. Or, the presence of noise can change the shape of a seismic event, leading to a miscalibrated tuning thickness of a reservoir.

However, these effects pale in comparison to the limitations imposed by the seismic bandwidth. The seismic band-limitation problem is a well-studied technical challenge in seismic acquisition. Briefly, it stems from challenges in both putting energy into the ground (e.g., size of sources impact the low frequencies, attenuation impacts the high frequencies) and getting the returning energy on tape (e.g., instrument response, receiver-side ghosting). Missing low frequencies impact on the ability to accurately assess material properties, whereas missing high frequencies impact on the ability to resolve features. These missing frequencies directly impact the ability to locate a geologic feature in the subsurface. While new acquisition technologies are continuing to improve both ends of the spectrum, the reality today is that much of the seismic data available can provide vertical resolution of at best tens of metres.

From an interpreter’s point of view, a detailed understanding of the physics is not necessary – what is important is to understand how predictive a measurement of a geologic feature is. For example, while the peak of a seismic event can be measured precisely to within the sample rate (order of metres), seismic band-limitation effects imply that inaccuracy exists in this measurement at the scale of tens of metres. Therefore, a precisely picked seismic event can be precisely wrong in practice.

The canny interpreter will therefore appreciate that there is a ‘null space’ associated with an interpretation: a set of all interpretations that are indistinguishable (within a specified tolerance) using only the seismic image. An interpretation should therefore be not merely a collection of mapped seismic events, but also a description of the variability tolerated within the data. This article focuses on how interpreters can quantify this zone of ambiguity during their interpretation, and, how to use it to improve decision-making in the oil and gas industry.

We call the underlying concept of quantifying the ambiguity in the prediction the ‘measurement uncertainty.’

This is distinctly different from ‘configurational’ or ‘conceptual’ uncertainty, a challenge that has drawn much atten-
tion recently (e.g., Bond et al., 2007). For these sources of uncertainty, a probability could be attached to a higher-level geologic concept, for example, style of deformation, geologic setting, or whether or not a fault or horizon is present in the interpreted data. These uncertainties are not directly derived from the measured data, and therefore can be treated separately from measurement uncertainty.

Collecting measurement uncertainty data during the interpretation, as this new workflow will demonstrate, adds a new dimension to analysis workflows by giving the interpreter the ability to ‘simulate’ an interpreted surface; that is to say, individual realizations of fault or horizon surfaces may be generated to create an ensemble of interpretations that satisfy the data. These realizations can be created subject to externally imposed constraints to narrow the focus of modelling: surfaces can be tested for plausibility, truncation relationships, stratigraphy, smoothness, or other application-specific value judgments.

In practice, there are two ways to quantify measurement uncertainty: automatically or manually. Automatic uncertainty estimation requires a detailed understanding of the data, acquisition, and processing of the seismic image. While theoretically straightforward (and an obvious direction for technical development), manual uncertainty measurement is more realistic for near-term applications – mainly due to logistical and training challenges (for example, uncertainty estimation would need to be incorporated fully into subsurface workflows for an automated system to be successful).

Today, we expect the interpreter to be best placed to estimate the uncertainty manually during the interpretation phase. The interpreter can make an integrated assessment of all sources of uncertainty in the measurement, encompassing broad characteristics from wavelet shape to data quality issues in poorly imaged parts of the survey. Manual estimation further gives the interpreter the flexibility to vary the uncertainty spatially depending on changing conditions.

This kind of workflow leads directly to an interpreter mapping a probability distribution function (PDF) rather than single measurements (or estimates) of a subsurface location’s position. This distribution is conceptually equivalent to the Bayesian ‘prior’, a representation of the input uncertainty that can be used to estimate the probability of outcomes or ‘posterior’ distribution.

The mechanics of interpreting such a distribution, as illustrated in our new workflow, are quite simple: the interpreter looks at the data, estimating the spatial dimensionality associated with the probability density function at a given point, and then digitizes the ‘best estimate’ value (Figure 2). Rather than focusing on a single horizon or fault, uncertainties are represented by an uncertainty envelope that changes size based on the uncertainties of individual measurements. Conceptually, the exact functional form of the distribution is not relevant – it could be changed or altered after the interpretation. Given the nature of seismic data, a Gaussian PDF is usually suitable, but skewed distributions or arbitrary distributions could be used given more knowledge about a specific reflector.

A key aspect of the proposed workflow is that it is not limited to the interpretation of seismic data. An interpreter should be able to make an estimate of subsurface structure based on any geophysical data – for example, velocity models derived from travel times, and gravity or CSEM inversion volumes. Different data types all carry different sources of uncertainty, and this should be reflected in the way best practices can be set for interpreters to measure uncertainty.

These best practices will certainly be application specific. For seismic data, the size of the envelope might reflect the peak frequency of the data in a window near the pick; for gravity or other potential field data the envelope might reflect the sensitivity/resolution kernels at depth. Lateral uncertainties could be derived from acquisition parameters, such as shot/receiver spacing or bin size. Users could also specify uncertainty manually based on the proximity to the well data, the signal-to-noise ratio (SNR) data and the interpreter’s confidence and experience in geological setting.

The next step for interpreted data is typically structural modelling. A reservoir’s structure is frequently mentioned as one of the most critical components of the reservoir model and can account for the greatest uncertainty in reserves assessment.

Structural modelling involves solving a set of geologic surfaces (fault planes and horizons) that satisfy all available data (e.g., interpretation fault or horizon data, well picks, isochores, and zone logs) in a geologically consistent fashion. Key challenges include representing complex structures – from thrust faults to salt domes – while honouring stratigraphic relationships (depositional and erosional) and fault geometries.

Structural models can be used to generate grids for facies or petrophysical property modelling, and these fully integrated reservoir models can be used directly for decision-making (data acquisition or well placement), or passed to reservoir engineers for simulation or history matching.

The large inefficiencies created by having more or less independent interpretation and modelling stages can lead to problems – new data is frequently left out of the reservoir model, and errors are difficult to catch and correct. We propose a new method in which the interpretation and modelling steps are combined.

In this workflow, a geologically consistent structural model is created (and updated) every time the interpreter makes a measurement of a subsurface feature. The fault and horizon surfaces created in this manner are the interpretation, ie, the interpretation is not merely a collection of control points, but the integrated geological representation of a structural model satisfying those measurements. The interpretation process therefore becomes a ‘constructive’ process rather than the time-consuming mapping process it is today. The interpreter uses control points to guide the
Consider instead a horizon interpreted with uncertainty. Given an interpreted point $x_0$, with associated Gaussian uncertainty envelope $G(t_0, \sigma_0)$, the expected AVO amplitude anomaly may be computed at that position:

$$\langle AVO(x_0, y_0, t_0) \rangle = \int \int G(t_0, \sigma_0) F(x_0, y_0, t, \theta) dt$$

This is immediately a more robust estimate of the expected AVO anomaly, in that it accounts for the possible uncertainty in surface location. This also allows the effects of tuning and noise on amplitudes to be averaged out over the width of the uncertainty envelope, resulting in improved confidence in the result.

Consider also that the uncertainty envelopes can be used to generate many realizations of the structural model. These realizations can be used to compute sets of outcomes for each surface, i.e., the set of possible AVO outcomes for a surface geologic model, and has the power to add detail and complexity where the model and the data require it. The ability to construct an interpretation that shows geologic relationships immediately provides a huge advantage over traditional serial approaches: for example, the traditional approach requires extensive iteration when trying to construct a geologic model near a fault. This is because the interpretation measurements typically become lower quality as a horizon nears a fault due to imaging effects, resulting in changes to the interpretation where geologic rules cannot be satisfied. Our workflow sidesteps this intensive QC process by giving the interpreter direct control over the modelling process (Figure 3). Finally, this workflow can help to closely integrate geologists and geophysicists working together on asset teams via the central focus on uncertainty in the interpretation.

**Applications**

An obvious application of this method involves the calculation of surface-based attributes. Because the measurement includes both a best estimate and its uncertainty, statistical analysis can be performed on attributes that were previously completely deterministic. As an illustration, consider the application to the well-known amplitude-vs-offset horizon attribute (AVO, a sample functional form can be obtained from Aki and Richards, 1980):

$$AVO(x, y, t) = F(x, y, t, \theta)$$

In the conventional approach, AVO is calculated on a surface, and regions are classified according to their behaviour. This workflow is used primarily to discriminate between fluid types (oil, gas, or brine) – but at the end of the day the outcome of such an analysis is only a spatially varying map of amplitudes. Those amplitudes depend heavily on the accuracy of the horizon, and the critical assumption that differences in amplitude between offsets is only affected by the fluid response (and not noise, tuning, or migration effects).

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perturb the model and generate volumetric statistics for each realization.

Figure 4 shows the sequential process where the displacement field is calculated, modified and then used to update the horizon model. In this case, the new approach allows the displacement field to be modified by scaling, adding or subtracting displacement. Changes can also be distributed differently on the hanging wall (HW) and footwall (FW) sides and uncertainty loops then run.

Faults can vary within the fault uncertainty envelope and generate realistic structural scenarios. Furthermore, horizons can also be extrapolated to ensure realistic results.

Once you have an initial model, interpreters can then update the model with new deviated wells. Figure 5, for example, illustrates the initial structural model, the new well drilled and the model then adjusted to include the new well path. In this way, the model-driven interpretation is ideal for QC’ing zonation. Other applications include simply how to incorporate uncertainty into the well planning process itself (e.g., Rivenæs et al., 2005).

The most important input to reservoir modelling decision making and investment returns, however, is the ability to quantify volumetric uncertainty. In this case, the input data includes a combination of velocity, isochore and fault uncertainties.

The workflow consists of running horizon uncertainty modelling (Abrahamsen, 1993, 2005) with time interpretation, Where \( \{AVO_i\} = \{F(x_i, y_i, t_i, \theta)\} \)

Aside from quantitative geophysical methods, this workflow can also be used to provide direct input to existing structural uncertainty workflows. For example, Stenerud et al. (2012) use uncertainty estimates associated with horizon location to condition structural surfaces to zone logs in horizontal wells using Bayesian Kriging techniques (Abrahamsen, 1993, 2005; Abrahamsen and Benth, 2001). Our method would improve the robustness of this method by providing spatially variable uncertainty input to use as an extra constraint.

As a proof of concept, we have applied the proposed workflow to a seismic data set from the Norwegian Continental Shelf.

Through fault uncertainty modelling (e.g., Georgsen et al., 2012), we initially estimated fault displacement by calculating a 3D displacement field for faults based on an existing horizon model. We then used the uncertainty in the faults to perturb the model and generate volumetric statistics for each realization.

Figure 4 A fault configuration implies a displacement field that can be inspected for matches with other data. Modifying the displacement field can then be done, with the date being honoured and a direct and consistent update of the combined fault/horizon model.
Figure 5 Using spatially varying uncertainty in interpretations, an ensemble of structural models can be generated that satisfy well zonation data.

Figure 6 Volume distribution for 50 realizations of the structural model (as shown in Figure 5). Both relative frequency for a given volume and a cumulative probability distribution can be obtained, allowing for quantitative, risked decision-making.

Figure 7 Parameter sensitivities of GIIP for 50 realizations of the structural model (as shown in Figure 5). Blue indicates positive correlation, and red indicates negative correlation. Uncertainty in the gas-water contacts and net/gross are the most important factors controlling reservoir volume.
velocity, isochores and well paths. Depth convert faults can be developed with updated velocities and uncertainty modelling then run on these fault positions.

The result is that simulated structural and grid models are developed. Gas Initially In Place (GIIP) is identified and net-to-gross (NTG) uncertainty as well as uncertainties on contacts and porosity are all generated.

In the Norwegian Continental Shelf example, 50 realizations of the structural model are run with changing fault positions (Figure 5). Figure 6 shows the 50 gridded realizations of bulk volume and Figure 7 the GIIP distribution.

Conclusions
The model-driven interpretation approach can have a significant impact on decision-making support in a number of areas.

For example, the new workflow can generate a more complete representation of the data – no matter what the data quality. By capturing uncertainty and building models directly from the data, the new model-driven interpretation approach generates a more complete representation of the data in less time. Model-driven interpretation also does not allow poor data quality to cause unnecessary delays with the uncertainty staying with the interpretation throughout the modelling workflow.

Similarly, the new workflow can provide early distributions of reservoir volumes. By increasing productivity and streamlining workflows, model-driven interpretation allows geoscientists to quickly build risked models of static reservoir volumes, providing the best possible estimates to support commercial decisions.

In addition, the workflow can help to generate risk estimates for drilling decisions. Combined with logging-while-drilling data and precision steering the captured interpretation uncertainty can also lead to real-time risk assessments and hazard avoidance.

In summary, the new approach places the model and risk analysis at the centre of the decision-making process – whether it is bid valuations, new field development and operational plans, drilling programmes, or production estimates or divestments.

References