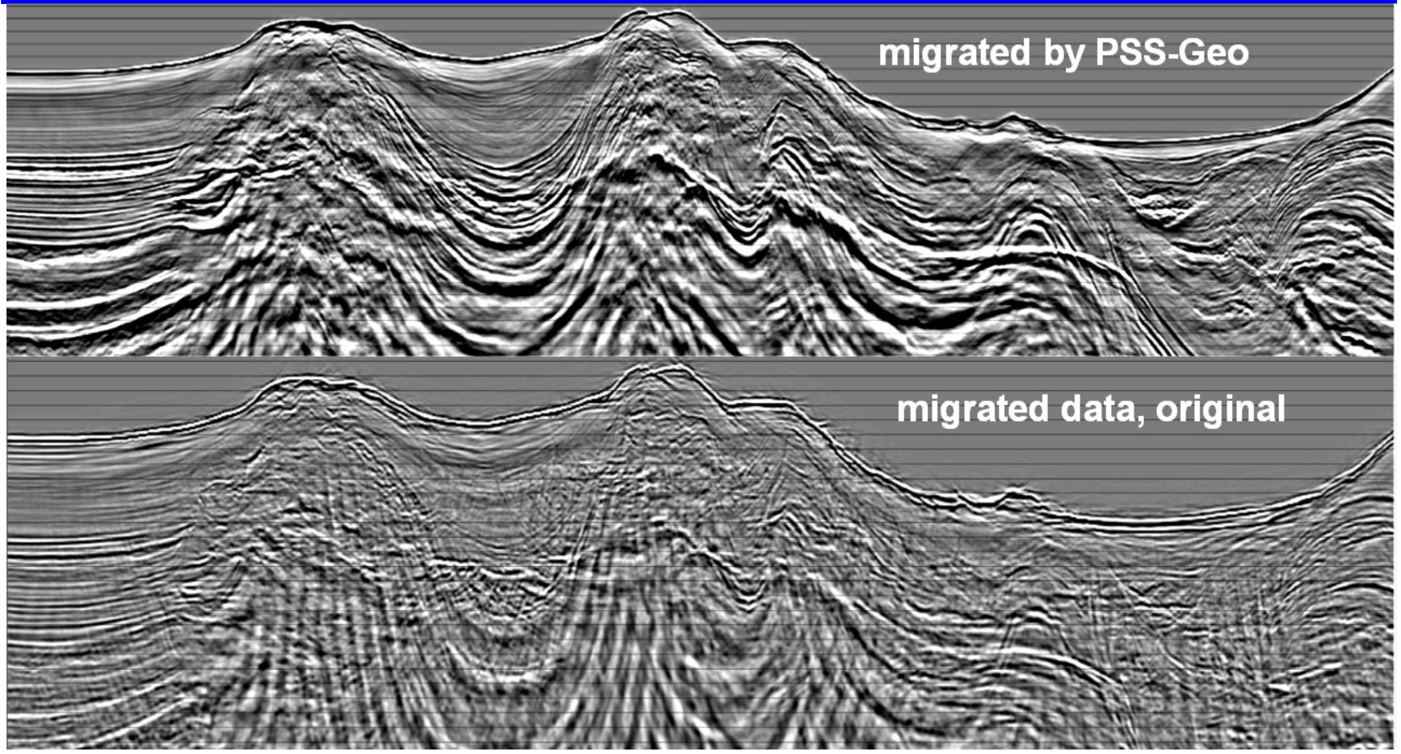
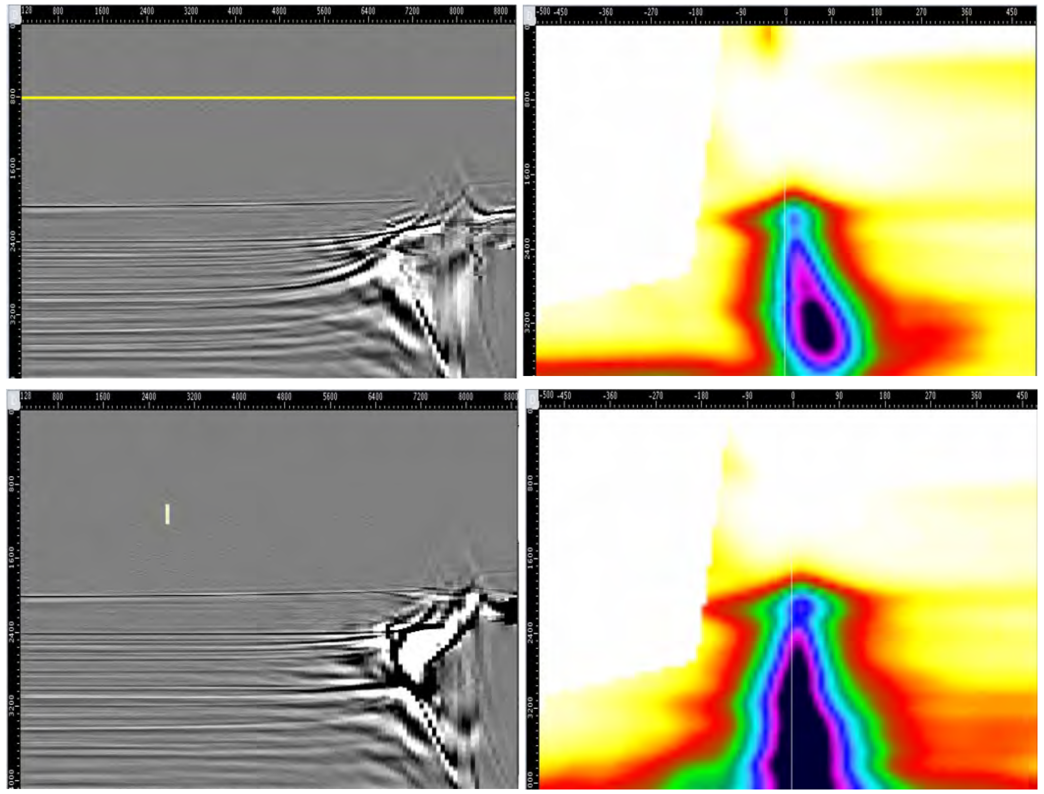


Top picture is seismic data processed by PSS-Geo AS. Migration algorithm is old known Kirchhoff Anisotropic Wavefront Propagation Depth migration. Velocity model is corrected velocity model built by using logs data and anisotropic VTI/TTI gridded tomographic solution trough iterations approach. Bottom picture is the same seismic data migrated by modern algorithm with simplified velocity model.

to ensure correct depth in well positions is maintained.

2) Iterative tomographic inversion

- On progressively deeper volumes the data is depth-migrated using Kirchhoff migration, to an appropriate depth, using the current velocity model.
- Residual moveout are auto-picked on gathers. Such pick must be representative of primary energy: a Hi-Res Radon demultiple, or other process, might be used to increase moveout measure quality. Events must be geologically meaningful as displayed on imaged stack.
- The residual moveout picked on the velocity analyses is inverted to update the interval velocity field using an anisotropic VTI/TTI gridded tomographic solution.
- The number of iterations required defined by the complexity of the area involved and the consistency of results.



Top two pictures show a cdp gather and semblance scan of PSDM data migrated with the initial velocity model. Bottom pictures show the same cdp location this time migrated with the updated velocity model

The 3D Pre-Stack Depth Migration is tied to the key wells to confirm the accuracy of the velocity field and anisotropy parameters.

Our approach is flexible and can allow for continuous update of vertical and anisotropic velocity models and aim at a depth image consistent with well data.

Whether it is a new or old migration algorithm, PSS-Geo AS recommend to use presented above sequence for velocity model building. Variations of this algorithm can be used effectively for depth conversion and time migration.

In spite of the chain of process, the algorithm is still cheap and has reasonably quick velocity model building solution.

Prospectivity evaluation with 3D CSEM

by Daniel Baltar and Neville D Barker, EMGS

Daniel Baltar
Global Exploration Advisor,
Electromagnetic Geoservices ASA
dbaltar@emgs.com

Neville Barker
Product Champion,
New Technology,
Electromagnetic Geoservices ASA
nbarker@emgs.com

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Evaluation of the prospectivity potential of hydrocarbon exploration ventures is an integration process. Information provided by different technologies needs to be integrated into a single evaluation. This article details a method for embedding the additional information provided by 3D Controlled Source Electromagnetic (CSEM) surveys into existing (or independently-generated) prospect evaluations. The approach is based on a Bayesian update to the risk assessment (as widely used in industry for AVO, fluid seeps and other direct hydrocarbon indicators), extended into a coupled risk/volume update in order to account for, and leverage the additional volumetric sensitivity of the CSEM information.

CSEM-embedding workflows

Three related workflows are described in the article (Figure 1):

1. The “EM Negative” workflow is used to assess the range of the original volume distribution and probability of success (PoS) that is consistent with a negative CSEM survey outcome (the case where no resistive anomaly is identified to be associated with the prospect).
2. The “EM Positive” workflow is used to assess the total range of the original volume distribution and PoS that is consistent with positive CSEM outcomes (the cases where a resistive anomaly is identified to be associated with the prospect).
3. The “Constrained EM Positive” workflow is used to assess the volume distribution, and corresponding PoS, that are compatible with a specific CSEM-identified resistor. We will focus on this workflow in the case study example.

CSEM sensitivity

The ability of CSEM to detect a hydrocarbon accumulation depends not only on the presence of hydrocarbons in the reservoir, but also on the size of the accumulation, and the surrounding resistivity structure. The dominant parameters determining the strength of the CSEM response are the Anomalous Transverse Resistance (ATR = Total Pay Thickness x Pay Vertical Resistivity) and the area of the accumulation, and thus a cross-plot of these parameters is key to the sensitivity assessment (Figure 2).

Detectability is established using a sensitivity threshold, which divides the ATR and target area domain into detectable and undetectable regions (solid black line). Additional factors which affect the ability to reliably recover or interpret a target resistor include dataset quality, and background complexity and uncertainty. These can be thought of as affect-

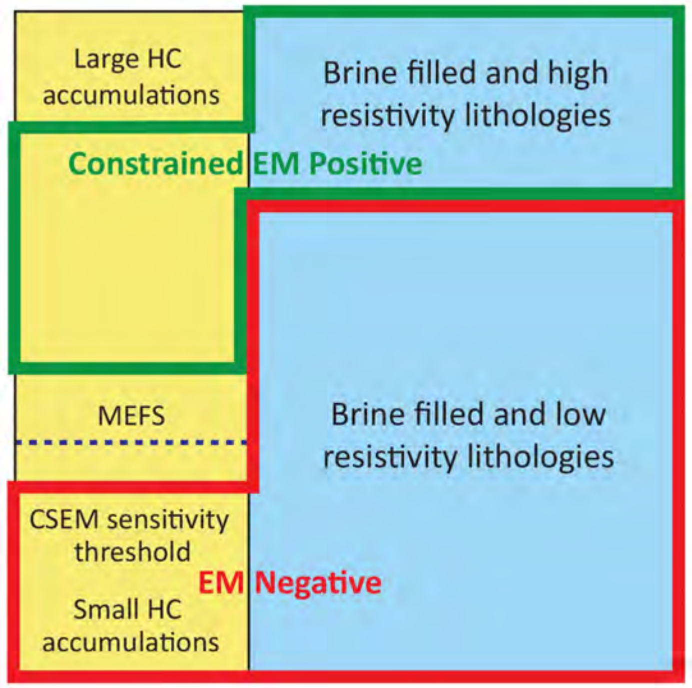

*Figure 1: Graphic representation of a prospect evaluation, and its partitioning with CSEM information. Blue region: brine outcomes (some with high resistivity; some with low resistivity). Yellow region: hydrocarbon (HC) outcomes, ranging from small to large accumulations. The Minimum Economic Field Size (MEFS) and CSEM sensitivity threshold to hydrocarbon outcomes are simplified as horizontal volume lines. From this arrangement, prior PoS corresponds to the area of the yellow region divided by the total area; the Probability of Economic Success, Pe = PoS * P(Recoverable volume > MEFS), is the area of the yellow region above the MEFS line, again relative to the total area*

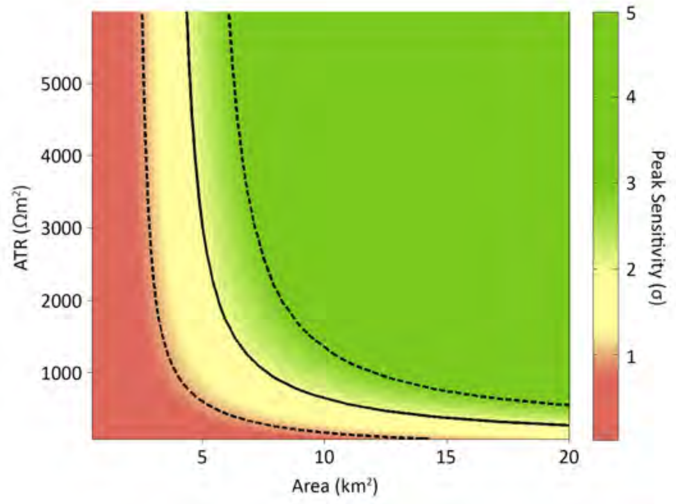

Figure 2: CSEM sensitivity assessment for a single prospect

ing the level of sensitivity below which we would not expect a resistor to be reliably identified from the data; two examples are illustrated in Figure 2 as dashed lines.

Updating volumetric assessments with information from 3D CSEM data

For volumetric updates, we broadly follow the approach detailed in Baltar and Roth, 2013, combining this with the more advanced CSEM sensitivity assessment detailed above. Given an existing probabilistic volume evaluation, only background and charged reservoir resistivity distributions, along with a CSEM-sensitive criteria, need to be added. A Monte Carlo simulation is carried out, with each realization classified as either detectable or undetectable by CSEM. In this way, two updated volume assessments are generated, corresponding either to the cases where we would expect an appropriate resistor to be identified in the CSEM data (EM Positive), or the cases where no such resistor could be identified (EM Negative).

With a specific EM Positive outcome, Baltar and Roth, 2013 describe how the characteristics of the identified resistor can be used to directly constrain the volume estimation, by the substitution of a new EM-derived net rock volume distribution (NRVem); we follow this approach in the Constrained EM Positive workflow.

Bayes' theorem applied to EM

According to Bayes' theorem, given an existing (prior) probability of finding hydrocarbons, P(HC) = PoS, and a certain CSEM outcome, EM, the new probability of finding hydrocarbons, P(HC|EM), can be calculated by applying:

(1)

$$P(HC\,|\,EM)=\frac{P(HC)}{P(HC)+R(1-P(HC))}$$

In order to evaluate P(HC|EM), the likelihood ratio, R, of each of the two possible EM outcomes is needed. The R for EM Positive (Rp) and EM Negative (Rn) outcomes are:

(2)

$$Rp=\frac{P(EMp\,|\,nHC)}{P(EMp\,|\,HC)}$$

(3)

$$Rn=\frac{P(EMn\,|\,nHC)}{P(EMn\,|\,HC)},$$

where EMp is an EM positive case, EMn is an EM negative case, HC denotes the case where hydrocarbons exist in the reservoir, and nHC the case where no hydrocarbons exist.

Evaluation of EM response probability in the absence of hydrocarbons

We can evaluate P(EMp|nHC) and P(EMn|nHC) together, since they are complementary: P(EMn|nHC) + P(EMp|nHC) = 1. P(EMp|nHC) is the probability of obtaining an EM positive outcome in the absence of hydrocarbons, an important interpretation pitfall to be considered when using resistivity data for hydrocarbon detection. Buland et al., 2011, from their experience estimate this probability to be 0.2 for a typical prospect; this probability will primarily depend on the geologic setting, and can be better-estimated from large-scale surveys.

Evaluation of EM response probability in the presence of hydrocarbons

We can also evaluate P(EMp|HC) and P(EMn|HC) as complementaries. They are estimated in different ways, depending on which volumetric workflow is followed.

For the EM Positive and EM Negative workflows, P(EMp|HC) can be calculated directly from the outcome of the Monte Carlo simulation described in Baltar and Roth, 2013, and corresponds to the ratio of detectable volume cases to the total number of Monte Carlo iterations.

For the Constrained EM Positive workflow, P(EMp|HC) no longer relates to the entire range of potential positive outcomes, but is specific to the positive outcome obtained. Its value, the proportion of the prior net rock volume (NRV) that could produce a CSEM anomaly similar to the one actually measured, can be estimated from the overlap between the prior NRV and NRVem distributions:

P(EMp|HC) = Percentile of prior NRV at P01(NRVem) - Percentile of prior NRV at P99(NRVem).

For example, assume that the prior NRV P99 and P01 values are 80 m.km2 and 9000 m.km^2 respectively, and the corresponding NRVem values are 500 m.km^2 and 9000 m.km^2, then it follows that there is approximately a 70 percent (P99 NRVem = P70 NRV, and P01 NRVem = P01 NRV) chance of having an NRV that generates a resistive anomaly consistent with the 3D CSEM data.

Coupling of P(EMp|HC) to volumes in this way has three key benefits over stand-alone risk and volume assessments, which help reduce the risk of inappropriate use of the new information:

1. Likelihood ratio estimates in EM Positive and Negative workflows depend upon the data sensitivity: high sensitivity to a scenario, increases the data's R in that scenario, and vice versa.
2. Very precise NRVem estimates (narrow P10 – P90 range relative to the prior) require correspondingly high confidence in the information, or PoS to that outcome will be penalized.
3. Confidence in NRVem ranges partially (or wholly) outside the prior's range is partially (or wholly) penalized as being inconsistent with the original evaluation. By reducing (zeroing) PoS in such cases, the interpreter is forced to re-evaluate prospect risk factors to this new volume range.

Real-life Constrained EM Positive example: Pingvin

Fanavoll et al., 2014, used the NRV workflow from Baltar and Roth, 2013, to generate a pre-drill net rock volume prediction from a CSEM anomaly associated with an existing prospect in the Barents Sea (Figure 4). The Pingvin prospect was located in production license 713, approximately 65 km northwest of the 7220/8-1 Johan Castberg oil and gas discovery and 300 km northwest of Hammerfest. Subsequently, the operator, Statoil Petroleum AS, tested the prospect with wildcat well 7319/12-1 and encountered gas in the reservoir interval, announcing drilling results and preliminary volume estimates (NPD Drilling Announcement, 2014). We use this case to illustrate the practical application of the Constrained EM Positive workflow.

Prior evaluation

To consider the impact of CSEM in the evaluation of this prospect, and given that we do not have access to Statoil's pre-CSEM evaluation, we must first generate a reasonable prior.

In Fanavoll et al., we can observe two clear flat spots, naturally interpreted as GOC and OWC. Taking into account that prior to drilling this was a frontier setting and an unproven play, the probability of success must be low. On the other hand, the seismic indicators were good (flat spots and bright spots). We therefore con-

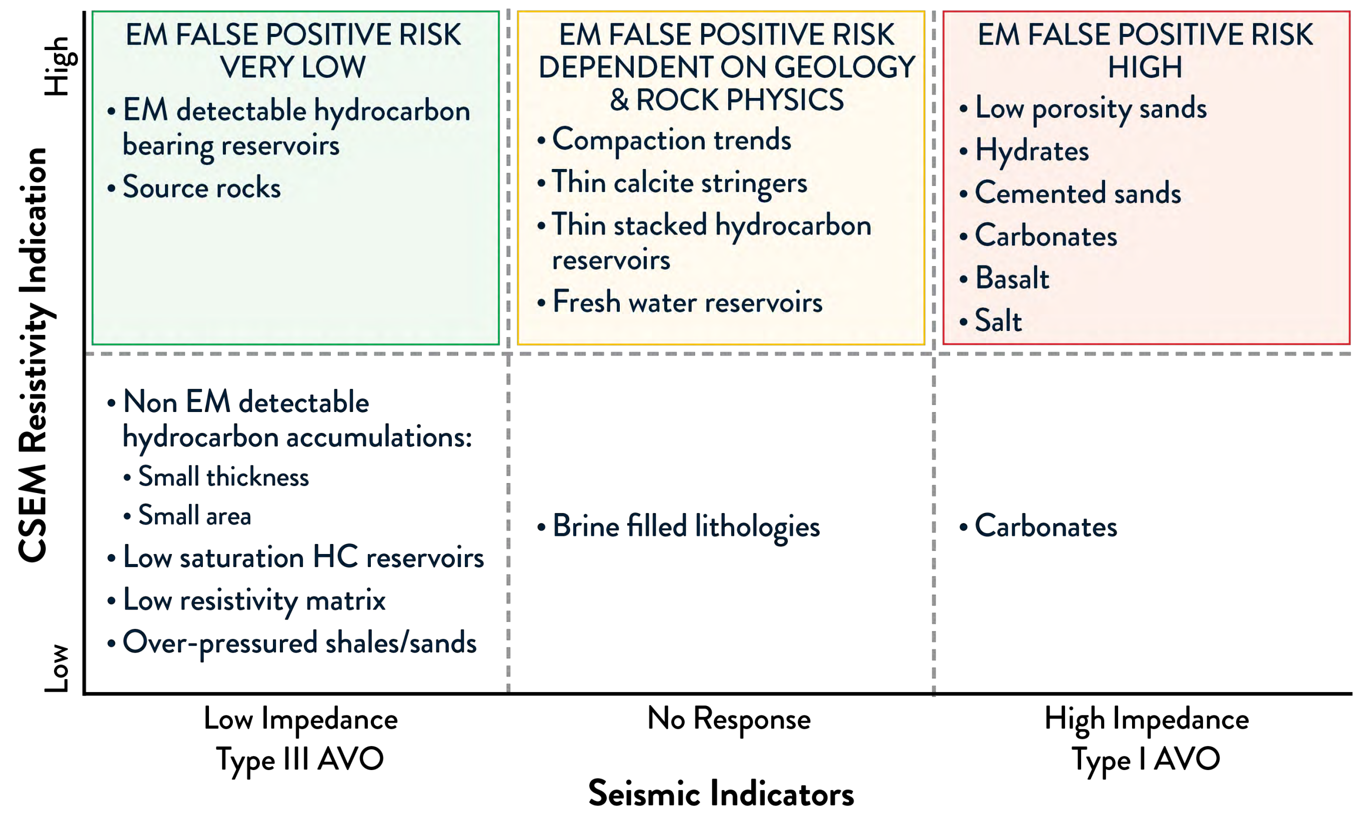

Figure 3: Various geological scenarios as a function of their typical relative electrical and acoustic characteristics. A joint analysis is a useful de-risker for the "false-positives" possible from both resistivity DHI and seismic DHI in isolation

clude PoS would have been at the high end of the unproven play range, and use a value of 0.33.

We assess the area from available information: the area inside the first flat spot will be used as P90 and the area inside the second flat spot will be used as P10, thus P90 = 20 km², P10 = 60 km². For the thickness we use the same source of information, leading to P90 = 10 m, P10 = 35 m, and an NRV distribution as Table 1.

All other parameters (porosity, hydrocarbon saturation, recovery factor and formation volume factor) will be considered unaffected by the new CSEM information and will therefore be set aside for the rest of the example.

Fit of CSEM to prior

This CSEM case is a clear positive response, therefore the positive likelihood ratio, Rp, (comprising P(EMp|HC) and P(EMp|nHC)) needs to be assessed. P(EMp|HC) can be calculated by the ratio between the prior NRV and NRVem. The calculation performed in Fanavoll et al. yields the NRVem probability distribution listed in Table 1. We graphically compare the overlap between both NRV distributions in Figure 5. P01 of the NRVem corresponds approximately to P25 of the prior NRV, therefore we estimate P(EMp|HC) = 0.75.

Now we estimate the false positive risk. The excellent fit between the area distribution of CSEM and seismic DHI places this case in the upper left corner of Figure 3, leading us to conclude that P(EMp|nHC) is quite low. The limited number of similar cases (one example would be "Case A" in Escalera et al., 2013) limits our ability to narrow-down this number in a statistically sound way, so we use Buland et al.'s reference P(EMp|nHC) = 0.2, and reduce it to account for the fit to seismic DHI information, estimating P(EMp|nHC) as 0.1.

Computing Rp from Equation 2, and applying Bayes' theorem in Equation 1 gives an updated probability of success of 0.79.

It can be seen that, compared to the prior, the CSEM data and their good fit to seismic DHI information are pointing to a higher likelihood of finding hydrocarbons in the reservoir, but severely limiting the upper side of the NRV distribution. The announced discovery (NPD Drilling Announcement, 2014) comprised a gas column of "about 15 metres", and "Preliminary estimates place the size of the discovery at between 5 – 20 billion standard cubic metres of recoverable gas". Using reasonable estimates for the

	Net Rock Volume (m.km²)			Probability of Success
	P90	P50	P10	
Prior evaluation (before EM)	280	600	1300	33%
With EM results	50	150	450	79%

Table 1: A reasonable prior (before CSEM) NRV distribution and PoS for the Pingvin prospect, along with an NRVem distribution calculated directly from the CSEM results by Fanavoll et al., 2014, and the updated PoS from the Constrained EM Positive workflow

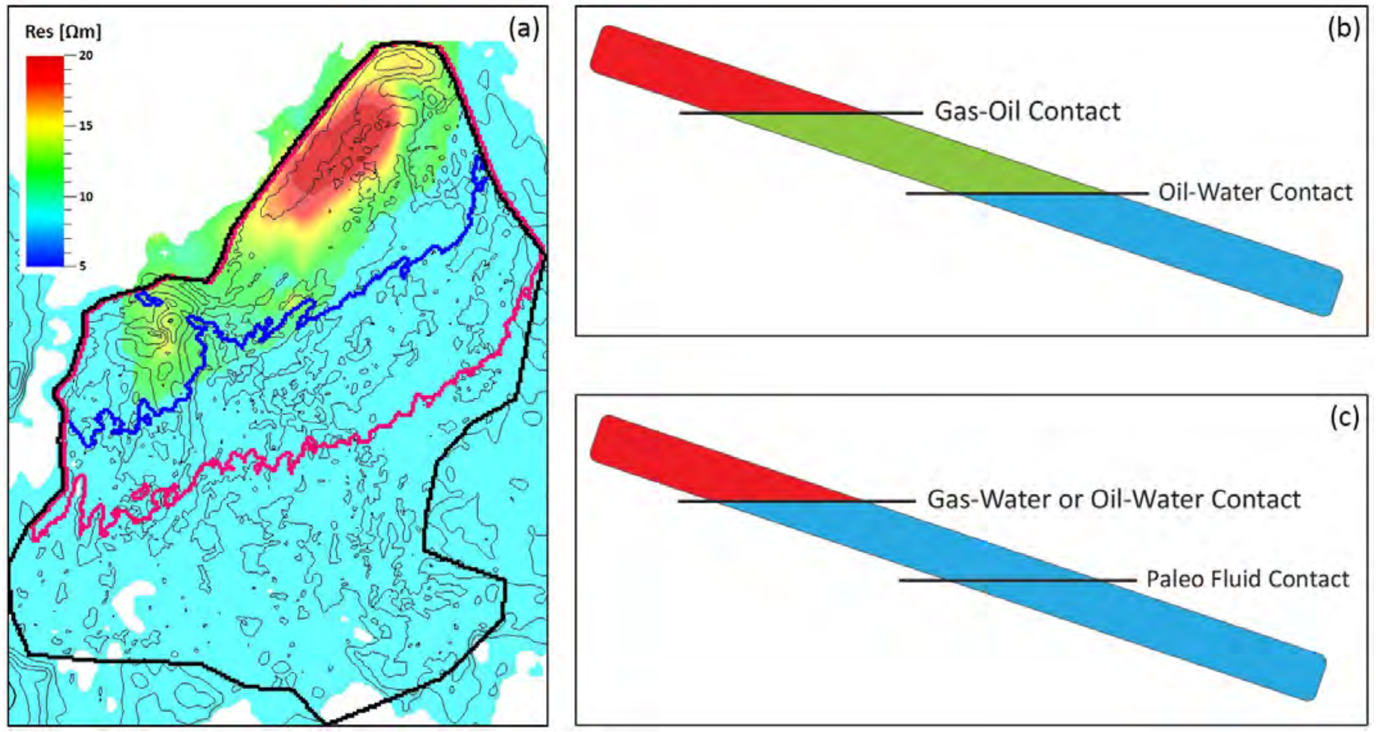

Figure 4. (a): Pingvin prospect average resistivity map from CSEM inversion displayed with contoured reservoir thickness. Minimum (blue), medium (red), and maximum (black) scenarios based on seismic data are given by the three polygons. Reproduced from Fanavoll et al. (2014), Figure 7(b). (b) and (c): two competing interpretations of the double flat spot identified in seismic data. In scenario (b), the prospect is fully charged; the flat spots corresponding to gas-oil and oil-water contacts. In scenario (c), the prospect is only charged to the uppermost flat spot. CSEM information provides compelling evidence in support of scenario (c), as turned out to be the case

other reservoir properties (porosity, saturation, recovery factor, and expansion factor), it can be shown that CSEM-predicted volume range is in line with the reported discovered volumes.

Impact on a portfolio, and large-scale application of CSEM

While described here in terms of a single prospect, the greatest value has been obtained from 3D CSEM data when the information is available at the portfolio scale and early in the exploration process: as well as reducing false-positive risk, spatially-extensive information can also be used to identify new exploration leads in known plays, aid in the development of new play concepts, or upgrade untested concepts (e.g., Escalera et al., 2013, Fanavoll et al., 2014). Within an existing CSEM-sensitive portfolio, the typical behaviors of individual prospects are summarized in Figure 6. These changes naturally lead to greater portfolio polarization, and the potential for significant changes in exploration decision-making.

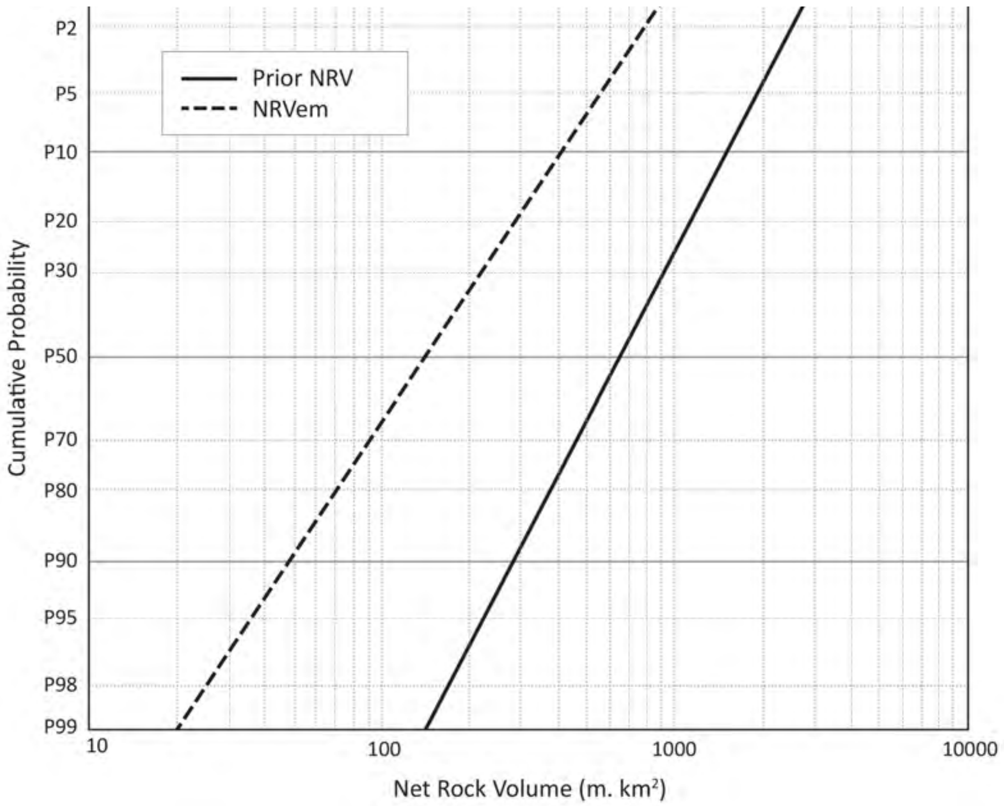

Figure 5: The CSEM-derived NRV distribution (NRVem) from Fanavoll et al., compared to a reasonable NRV prior estimate for the Pingvin prospect, Barents Sea.

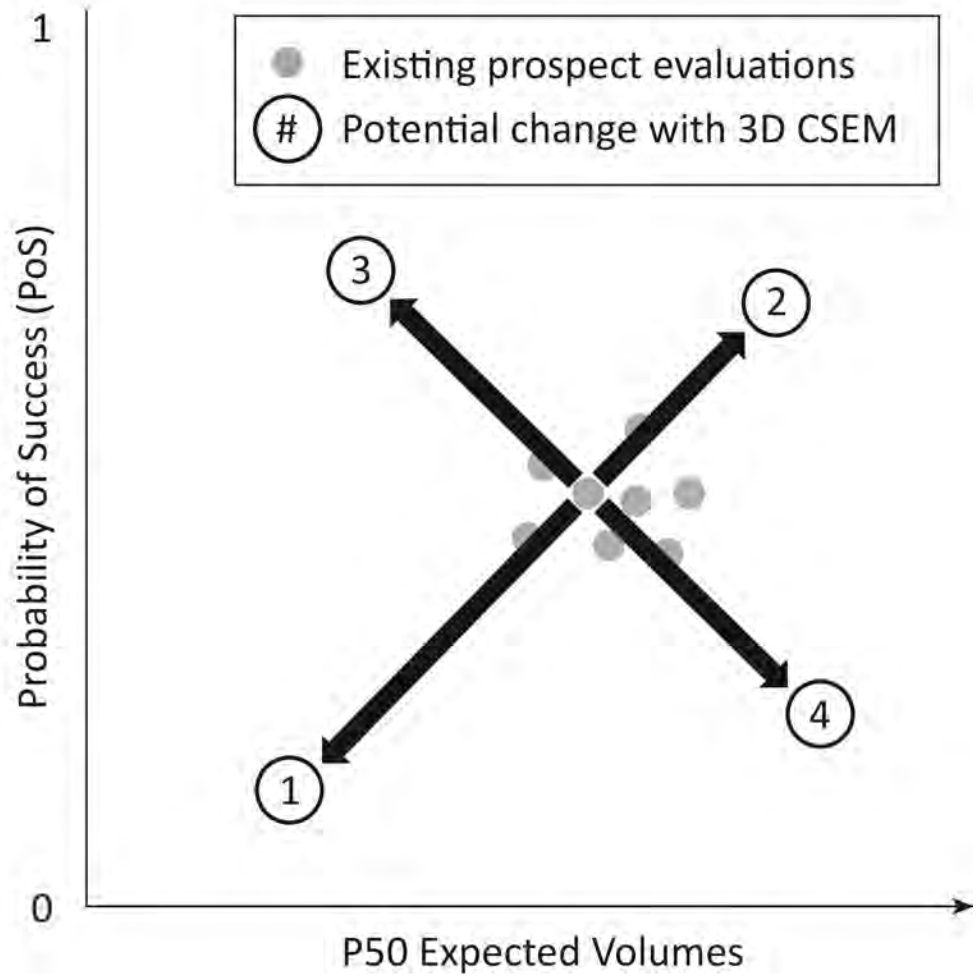

Figure 6: A summary of the typical end-member outcomes seen after the addition of information from 3D CSEM to an existing prospect portfolio. (1) EM Negative. Reduction in expected volumes to below the level of EM sensitivity, removing potential upside, and corresponding reduction in PoS. (2) Large Resistor. When consistent with prior, the large resistor increases both potential volumes and PoS, especially in the presence of other supporting evidence from seismic or absence of false positive potential. (3) Very Small Resistor. Again, consistent with the prior, the small resistor has increased the PoS, but removed the upside, potentially pushing the expected volumes to sub-commercial levels. (4) Unexpectedly Large Resistor. Increase in volumes, but potential decrease in PoS if volumes are largely incompatible with prior (increased risk of false positive). Increased potential may, or may not, outweigh increased risk.

Conclusions

The workflows presented here have been designed to leverage the primary strengths of the CSEM measurement, while keeping to a minimum the disruption and potential increase in risk associated with the adoption process. This has been achieved through:

1. A focus on updating existing evaluations, rather than proposing more fundamental changes to evaluation components
2. The use of data-driven (unconstrained) 3D CSEM inversion results as input, rather than more complex joint imaging products. This provides a more independent information source, from which in practice it is easier to estimate uncertainties and minimize interpreter bias
3. Adoption of industry-standard performance tracking methodologies. In the early stages of adoption, the logical approach is to start with a conservative estimate for the R parameters, making larger evaluation updates as experience with, and confidence in, the information increases.

Many further refinements are possible; these can be more easily developed and applied once a core CSEM-embedding framework, such as the one presented in this article, is in place. Variants may include coupling to additional lower-uncertainty volumetric parameters, such as the recovery factor (reservoir resistivity is linked to reservoir permeability), rock porosity, and hydrocarbon saturation.

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