Making EM systems and bore logs speak the same language

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SUMMARY

Borehole induction logs, together with lithology records, are valuable for inferring geological and geophysical features in the subsurface. They offer insight in the relationship between geology and geophysics, and are an important source of information for determining the success of a planned airborne electromagnetic (AEM) survey for recovering features of interest.

Often, bore logs are used as the 'ground-truth for an AEM system, and are employed for system selection pre-survey and 'validation' post-survey.

We discuss the use of electromagnetic borehole logs for calibrating and validating AEM survey results in a sensible way: by comparing the measurements at the resolution power of the AEM system itself.

Key words: borehole induction logs, AEM, RJ-MCMC, comparison.

INTRODUCTION

Borehole geophysical logs are often the first link between geological and geophysical information that is used in the planning of a geophysical survey. Of the geophysical logs available, electromagnetic induction conductivity logs, coupled with lithological descriptions, are the most useful for airborne electromagnetics (AEM). Not only do the conductivity logs assist us in inferring the relationship between lithology and electrical conductivity, they allow us to construct a model of the expected structure of the subsurface for our survey area of interest.

Increasingly, there is demand for AEM inversions to not only reliably map subsurface electrical conductivity structure, but to provide an estimation of the uncertainty of the inverted parameters (i.e. electrical conductivity and depths of interfaces). In Australia, a lot of attention in Australia is placed on the comparison of electrical conductivity logs obtained from borehole measurements to the inversion results of AEM instruments (e.g. Christensen and Lawrie (2017) and references therein). This is done for two main reasons: AEM system selection and AEM system validation. In other regions, such as Norway, comparisons of AEM to borehole logs are often done to pick out geological features of interest such as depth to bedrock (Christensen et al., 2015). The application of combining AEM to borehole logs is enormous.

AEM surveys conducted in Australia are mostly situated areas that have little or no prior geophysical (or even geological) information. An excellent point source of information can be obtained from a borehole log, especially if it is combined with lithology records. When planning an AEM survey, there is generally a specific purpose (groundwater or minerals exploration) and a specific target (gravel aquifer, thickness of regolith, or zone of mineralisation) in mind. A borehole induction log gives us some information about the specific target we have in mind; and we then use the log to produce a forward model for proposed AEM systems in order to determine which one is 'best' for our particular purpose (e.g. Davis et al., 2013). Alternatively, after a survey is flown, a borehole log in the vicinity of a survey line is used to validate the inversion results (Lane et al., 2001; Lawrie et al., 2012). The question then becomes 'Is my AEM system and inversion 'good enough'?

Borehole induction conductivity logs, rightly or wrongly, are often considered to be the foremost or only source of reliable information; and other datasets must match the induction log in order for it to be acceptable (Ley-Cooper and Davis, 2010). In this paper, we assume that borehole induction log represents an accurate and true measurement of the electrical conductivity of the subsurface down to a certain depth. We also assume that the geological/geophysical features of interest are contained in the log. We present a method that uses borehole induction conductivity information, coupled with the physical parameters of a given AEM system, to give the best possible constrained inversion models available for the AEM system in question. We show that, in general, AEM systems can only produce conductivity models amounting to at most 5 or 6 discrete layers, even with the best constraints; and that the borehole-constrained inversions are better than what we can normally achieve in practice.

METHOD AND RESULTS

We accept the borehole induction conductivity log as an accurate and true measurement of the electrical conductivity structure of the earth. We nominate an AEM system that we wish to model (e.g. TEMPEST or SkyTEM^{304}) and gather the relevant physical parameters of the system. This includes, but is not limited to transmitter (Tx) position, shape, altitude and waveform; receiver (Rx) positions, types, timing gates and filters; and an estimate of the inherent noise of the data acquisition system.

A borehole log, which consists of N recordings of electrical conductivity, is used to generate the N-layer forward response of an AEM system. Noise estimates are then applied to the forward data using a multiplicative error of 3-5% of the measured data. The forward response is then viewed as the 'true-earth' response for the problem at hand.

We compute the inversion of AEM conductivity through the use of the reversible-jump Markov chain Monte-Carlo algorithm (RJ-MCMC). Our variables for the estimation are:

d_i, depths of interfaces (or layer boundaries), and n, the number of layers. Depths d_i are chosen based on the measurement depths of the induction tool itself (e.g. a measurement taken every 0.05 m down the hole). The greatest number of layers allowed in the estimation is limited by N, the number of measurements in the borehole trace: the lowest number of layers is two.

The following models are proposed as part of the Markov chain estimation:

1. Perturb d_i, the depth of interface i, by a Metropolis-type step.
2. Create a new layer at a depth that is randomly chosen from the N - n available depths, where n is the number of layers in the current model.
3. Destroy a randomly chosen layer from the n layers available.

At each step, the conductivity of the model is updated from the borehole induction log. The conductivity of a given layer is calculated from a statistical measure of the conductivity of the borehole trace that is encompassed by the AEM model layer boundaries: thus our AEM inversion is heavily constrained by the borehole information.

Acceptance $\alpha(\boldsymbol{m},\boldsymbol{m}')$ of the proposed model is governed by the usual Metropolis-Hastings-Green method of RJ-MCMC runs (Green, 1995), i.e.:

$$\alpha(\boldsymbol{m},\boldsymbol{m}') = \min\left\{1, \frac{p(\boldsymbol{m}')}{p(m)}\frac{p(\boldsymbol{d}|\boldsymbol{m}')}{p(\boldsymbol{d}|\boldsymbol{m})}\frac{j_m(\boldsymbol{m}')}{j_m(\boldsymbol{m})}\frac{q(\boldsymbol{m}|\boldsymbol{m}')}{q(\boldsymbol{m}'|\boldsymbol{m})}|J|\right\}$$

where $p(\boldsymbol{m}')/p(\boldsymbol{m})$ is the ratio of the likelihood of the prior models, $p(\boldsymbol{d}|\boldsymbol{m}')/p(\boldsymbol{d}|\boldsymbol{m}')$ is the likelihood (data misfit) ratio, $j_m(\boldsymbol{m}')/j_m(\boldsymbol{m})$ is the move-type ratio, $q(\boldsymbol{m}|\boldsymbol{m}')/q(\boldsymbol{m}'|\boldsymbol{m})$ is the proposal ratio of the joint distributions of the random numbers needed to jump between model spaces, and the last term is the Jacobian governing the transformation from state $(\boldsymbol{m})$ to $(\boldsymbol{m}')$.

Figure 1 shows an example of an induction conductivity log from a relatively deep bore. The borehole log is marked in black. The results of three different RJ-MCMC runs are also shown in this panel (median, mean and geometric mean). The solid curves show the posterior mean model for each of the runs, while the shaded areas show the 10th to 90th percentile ranges which are indicative of the spread of the models accepted. All models shown are accumulated from several chains after a sufficient burn-in and appropriate subsampling to remove autocorrelation. All models fit the measured data to within an average of 5% for each of the receiver channels (shown in Figure 2).

A full RJ-MCMC inversion allowing layer thickness, conductivity, and the number of layers to vary, is shown in Figure 3 for comparison. Here, we see that the variation in the model occurs mainly near the surface, within the top 30 m, and that the model results are much more poorly constrained. This result is to be expected, since there is much less constraining information when we are inverting for layer boundaries and conductivity.

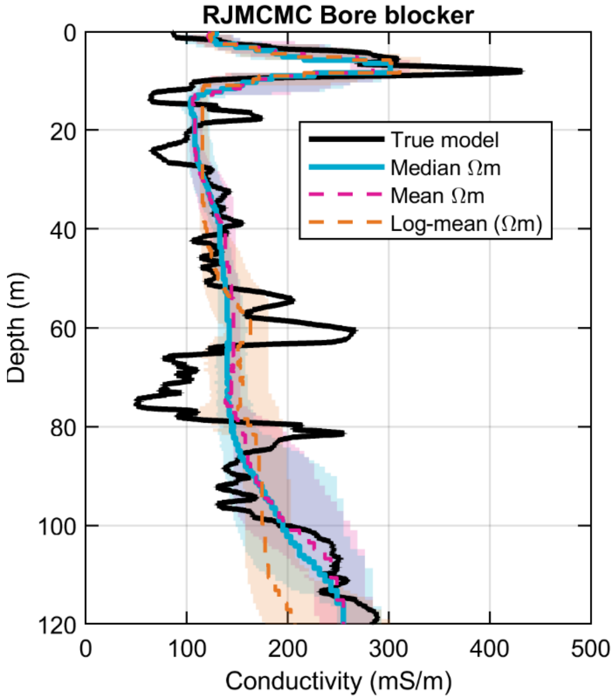

Figure 1. Borehole induction conductivity log (black), with the results of 3 different RJ-MCMC runs using a median (blue), mean (magenta) and geometric mean (orange) statistical function for the blocking. Shaded areas represent the density of acceptable models from the constrained RJ-MCMC inversion.

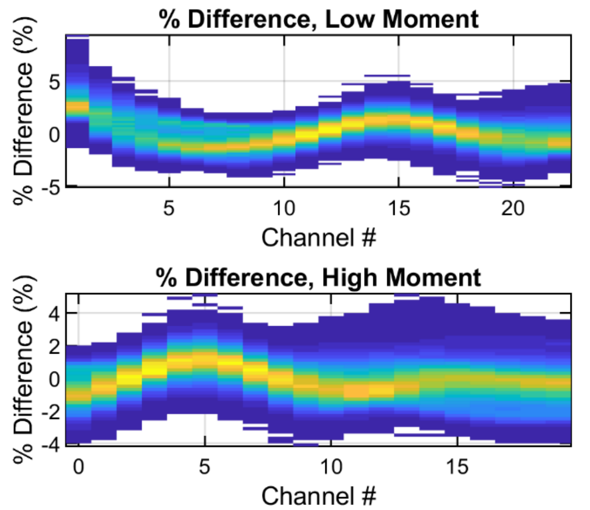

Figure 2. Plots of % difference between the forward model and the RJ-MCMC runs for the low moment (top) and high moment (bottom) transmitter pulses.

CONCLUSIONS

This paper discusses the use of RJ-MCMC methods to investigate the relationships between AEM methods and borehole induction logs. We show, with the TEMPEST system, an example of a deep borehole log and a constrained inversion that uses the borehole conductivity-depth information as ancillary information. We see that, even with such a vast amount of information, the AEM system was not capable of resolving more than four layers. This result does not improve markedly with helicopter or central-loop AEM. This is a sobering thought indeed when we are asked to provide AEM inversions that exactly match borehole logs: we cannot. The diffusive nature of the AEM signal, together with the relatively small amount of secondary response gates, simply means that it is impossible to resolve features on the scale of borehole logs.

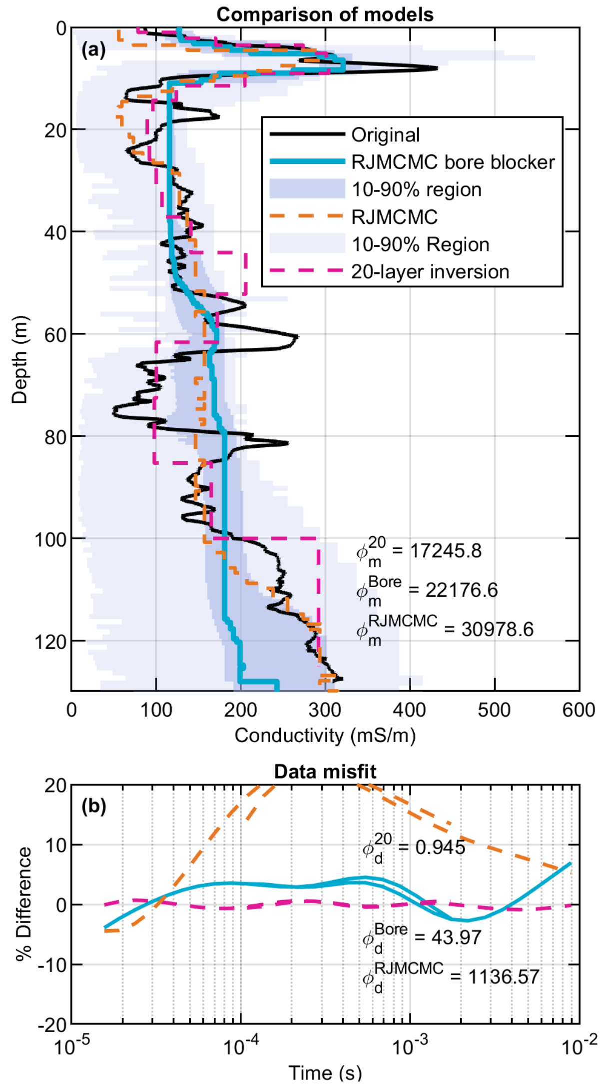

Figure 3. Comparison with a full RJ-MCMC run whereby the number of layers, conductivity and thickness of each layer is allowed to vary. We see that the model is more poorly constrained than in the borehole blocking case. Also shown is the result from a smooth-layer inversion

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