Airborne Geophysics

Paper 7

Airborne EM: An Important Exploration Method for Revealing Geological Insights into the Subsurface

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ABSTRACT

Airborne electromagnetics (AEM) is an important exploration method for revealing geological insights into the subsurface. AEM has proven to be particularly useful for mapping geological structures and has played a significant role in places such as the central parts of Africa, South America and Australia, where approximately 80% of the landscape is covered by regolith and sedimentary basins, the outcrop is rare and mineral deposits are hidden beneath barren cover. The method’s non-invasive nature and its extensive ground coverage make it a particularly powerful tool at the early stages of green-field exploration.

Airborne electromagnetic surveys commissioned by exploration companies for mineral exploration purposes are mostly perceived as ‘anomaly detectors’. For further interpretation it is essential to comprehend the main local geological and survey-specific factors that influence the electromagnetic response. The aim of any given observation is to understand the procedures and assumptions used to derive models of conductivity and depth from the measured data, and then develop processes to infer geology, lithology and other characteristics of the subsurface from the models which honour the data.

Geophysicists assessing AEM models are often faced with the conundrum of determining how geologically sensible a proposed model is and how it compares to many other possible solutions. One way is to explore thousands of plausible models that fit the data through stochastic processes. The statistical analysis permits quantification of the degree of uncertainty and a probable distribution of conductivities at depth.

To make the information translatable to other disciplines, it is necessary to process AEM measurements and integrate them with ancillary information. The combination of data integration and AEM's extensive area coverage enables transfer of local geological understanding to a broader region. Previous work has demonstrated there also is great value in reprocessing legacy data that is often abandoned.

INTRODUCTION

The electromagnetic (EM) inductive method was developed mostly in Canada, Russia and Scandinavia (Fountain, 1998). It was engineered to target electrically conductive sulphide ore deposits in resistive hosts, where the first layered inter-phase is typically a resistive overburden of several tens of metres of glacial till. This is a completely different geo-electrical environment to what is encountered in places like Africa and Australia, where old weathered landscapes can be under hundreds of metres of younger cover, and are composed commonly of conductive saprolite, clays and saline ground water. The latter geological settings have meant that in order to "see" under the conductive cover, EM prospecting has to be approached in a different way than in those resistive fresh-rock survey conditions of the northern Hemisphere. The conductive environments have proven to be challenging, but have also played an important role in the development of instrumentation with more powerful transmitters, alternate geometric arrangements amongst the sensors, and better signal-to-noise ratios. To some extent, these environments have also arguably spawned the search of more robust algorithms used for the processing and interpretation of airborne and ground EM data.

Electromagnetic data acquired from aircraft-based platforms cover great extents rapidly and produce high-density datasets that are non-invasive, and do not require land access to the surveyed ground. This is of significant importance in remote regions with thick vegetation where ground access is difficult, and in areas which are culturally or environmentally sensitive. Airborne electromagnetics (AEM) was initially developed as a technology to support the mineral exploration industry, but its use has been extended to other areas such as groundwater resource assessment, geotechnical applications, geohazard prevention and environmental management. Increasingly, AEM is also being applied as a tool for regolith characterization and geological mapping under cover. It is the backbone of large government-based exploration initiatives supported by local and federal government governments in countries like: Ghana, which employed AEM to explore for Uranium (Jordan et al., 2009); Denmark and India, which have flown large areas to map aquifer systems (Thomsen et al., 2004; Chandra et al., 2016); and the Onshore Energy Security Program (GA, 2011) and Exploring for the Future (GA, 2016) initiatives in Australia, aimed at boosting resource exploration and gathering robust data.
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In this paper we present several case studies, which we have used to demonstrate the nature of AEM responses for the different geological conditions and materials under which anomalous responses occur, and are then sought as prospective targets.

Airborne electromagnetic systems are designed to sense conductive bodies; however, conductivity anomalies may result from diverse sources that have similar EM responses (e.g. salt water and clay zones versus graphite- and sulphide-bearing bodies). There are also other physical and chemical effects that influence the AEM response, such as superparamagnetism (Macnae, 2017) and induced polarization (IP; Kaminski and Viezzoli (2017)), which are becoming more prevalent with the more recent higher-powered more sensitive airborne systems.

Improper interpretation of these ‘less-conventional’ sources can lead to false positives, compounding the level of uncertainty that inherently comes with models derived from AEM inversions and other numerical techniques, since they are non-unique solutions. Despite the uncertainty in these models, they are without doubt great tools that allow interpreters to assess the quality of the data and generate meaningful interpretations, but they can also generate a variety of models that may fit the measured data and be numerically correct, but are misleading. Therefore there is a need to discriminate between reasonable and unreasonable models as a way of mitigating the level of uncertainty.

To characterize model uncertainty, we show an example in which AEM data are processed with a Bayesian Markov chain Monte Carlo algorithm that quantifies a range of geophysical models at every station, all of which are consistent with the observed data. We then use a probability estimate of uncertainties which are transformed to lithologies by incorporating prior assumptions about the electrical property distributions for different facies. Results yield quantitative estimates for plausible architecture geometries of the predetermined lithologies.

## DERIVING CONDUCTIVITY-DEPTH MODELS FROM MEASURED DATA

Different modelling approaches to derive conductivity-depth models from AEM data have been developing for over more than two decades. Some of the proposed methods were presented and compiled into a seminal publication by Spies et al. (1998) and more recently a compilation by Davis (2015), but there are many more scattered references throughout the literature. The importance of employing the AEM method beyond bump finding in direct anomaly detection and moving towards a more quantitative analysis has been flagged in several forums e.g., Anderson et al. (1993), Worrall et al. (1998) and Annetts et al. (2004), but still is not of common practice. Gridded contours of channel data are occasionally still the determining factor used to discard AEM surveys, which are considered to be failures because they are anomaly-barren.

Electrical Conductivity, Examples from the Musgrave Province and Northern Eyre Peninsula, South Australia

We refer to work carried out in South Australia to illustrate the importance of reprocessing of AEM data, the use of conductivity derived models and in particular the application of inversion as a process for data assessment (Ley-Cooper and Munday, 2013; Gilfedder et al., 2015). Work from these examples demonstrates the value of reprocessing legacy data acquired from a suite of AEM systems, and the use of the derived models to map geological structures in the near-surface. The map in Figure 1 shows coincident AEM survey lines from the four AEM systems we assessed. The conductivity models have enabled the transfer and extrapolation of local geological knowledge to a broader regional understanding of the area, and have helped define the distribution of the cover sequences that mask the basement geology.

![Figure 1: Coincident flight paths from four different AEM surveys flown with different systems.](image)

![Figure 2: Streamed channel profiles from coincident survey lines of SPECTREM²⁰⁰⁰, TEMPEST, VTEM and Skytem⁵⁰⁸ AEM systems in the Musgrave area of South Australia.](image)
of the bodies that are causing variations in the system response, in a quantitative manner.

Inverting the data from these instruments, acquired over common ground, shows that with proper system characterization, similar conductivity models can be derived despite the differences in the instrumentation. A stack of these sections is shown Figure 3.

Figure 3: Conductivity-depth section comparisons for SkyTEM508, TEMPEST, VTEM, and SPECTREM2000 AEM data along coincident lines. The two soundings S1 and S2 show recovered models from all systems over a conductive (S1) and a resistive site (S2) at two individual locations. The bottom panel shows interpreted geology (from limited off-section drilling). Figure modified from Ley Cooper and Munday (2013).

In order to illustrate the commonality amongst the conductivity sections in Figure 3 we selected conductivity-depth models from two individual soundings at locations S1 and S2. The conductivity sections in Figure 3 show a great degree of agreement between the recovered models despite data being acquired using different instrumentation. The conductivity models were derived using the same model parameterization and the same inversion kernel; Geoscience Australia’s layered Earth sample by sample inversion GA-LEI-SBS-TDEM (Brodie, 2015). With this approach we attempted to mitigate the influence that the different acquisition systems might have on the modelling and final interpretation of the data.

For large-scale regional surveys, AEM methods offer an efficient way of investigating the geo-electrical structure over large areas in a timely manner and at a relatively low cost. Ley Cooper and Munday (2013) show an example that outlines the process of inverting legacy AEM datasets from mineral exploration companies acquired using different systems, which after reprocessing were then used to propose a regional hydrological framework model in the northern Eyre Peninsula, South Australia (Figure 4).

The work in the following example (Ley-Cooper et al., 2015a) showed that mapping conductors and their distribution at varying depths provides an insight to the complexity of aquifers, particularly those that are unconfined and near-surface that are often considered to be formations which have resource potential. The regional map in Figure 4 maps the presence of conductive materials and outlines areas that can be associated with salt water intrusions near coastal aquifers. The map also shows places where transported regolith materials, such as sands and clays, are concentrated in palaeovalleys due to their negative topographic relief.

Figure 4: A regional hydrogeological model for the northern Eyre Peninsula, derived from digital terrain analysis and distribution of conductivity at a depth range of ~50–55 m below the ground surface, derived from different AEM systems. Figure modified from Ley-Cooper et al. (2015a).

CHANGES IN OUR UNDERSTANDING OF AN AEM RESPONSE

Individual AEM soundings can be plotted as EM decays of amplitude (measure of the ground response) versus time with
depth (energy dispersion). The shape and amplitude of the curves reveal information about the subsurface electrical properties including the geometry and potential composition of the source producing the response. The decay curves shown in Figure 5, presented in Ley-Cooper et al. (2015b), shows single soundings acquired over three distinct geological settings, each located approximately 2 km apart, but acquired on the same flight line, therefore with similar instrumentation noise-levels.

In Figure 5, the magenta curve (C) corresponds to a simple, constantly decaying response; its curved shape can be associated with a conductive body which is detected near-surface. The red curve (B) comes from a mineralized conductive body covered by a resistive host. The shapes of the decay curves (C) and (B) are responses that can be modelled in a predictable monotonically decaying manner, and therefore are fairly well understood. However in order to model decay (A) in cyan, we need to challenge what has conventionally been explained as low signal from resistive ground or noise. Where noise is conveyed to have an erratic shape and contain arbitrary changes of sign.

In Figure 5, the alternation in sign of decay curve A could be attributed to airborne induced polarization (AIP) or to erratic late-time superparamagnetic (SPM) effects. These effects are becoming more prevalent in acquisition with the higher-powered and more sensitive AEM systems, which are now able to sense the presence of chargeable sources (Kratzer and Macnae, 2012). Some conductivity responses detectable in the late-time channels can be obliterated by high-amplitude, near-surface responses or from chargeable conductive cover, with amplitudes that can differ by several orders of magnitude.

It is essential that the modelling parameters used in the inversion algorithm are reliable and suitable when seeking to derive quantitative information about the subsurface from AEM data. Inversion algorithms require both quality data and precise system descriptions to try to constrain an already underdetermined problem. There are a wide variety of AEM systems used for acquisition, all of which have intrinsic peculiarities that need to be defined and accurately described in order to reduce the uncertainties in the modelling. Some publications (Christiansen et al., 2011; Ley-Cooper and Munday, 2013; Viezzoli et al., 2013) have tried to exemplify the consequences of inaccurate description of AEM system parameters and how these can hinder the modelling results.

From Purely Inductive Responses to AIP

Induced polarization effects on airborne electromagnetic data (airborne IP—AIP) have been identified for some time now (Smith and West, 1989; Smith and Klein, 1996; Smith and West, 1988). AIP effects are easier to detect in the more recently developed coincident-loop, high-powered, better signal/noise acquisition systems. There are several different locations (e.g., Australia, Canada, Scandinavia, and Central Africa) where AIP effects have been recorded. At these locations the presence of chargeable ground can be attributable to materials such as permafrost, lake sediments, weathered regolith and local alteration associated with mineralization.

The essence of the IP effect is that the conductivity depends on the signal frequency (it is therefore called a dispersive phenomenon). Such behaviour can produce the sign changes in the measured responses that, for central loop systems, are the trademark of AIP. For decades these changes in sign have not been modelled in conventional AEM data processing. Instead they have mostly been regarded as noise, calibration or levelling issues and are dealt with by smoothing, culling or applying DC shifts to the data.

There has been a recent paradigm change on how we deal with changes of sign in AEM data. This has come on the wake of better data quality and increased efforts to retain and model the AIP responses. Most of the recent research (Marchant et al., 2014; Macnab, 2016; Kaminski and Viezzoli, 2017; Viezzoli et al., 2017) adopt the well-known full Cole-Cole model proposed by Pelton et al. (1978) in the forward calculation to model the dispersive conductivity.

The Cole-Cole model is comprised of four parameters; DC conductivity \(\sigma_0\), chargeability \(m\), a relaxation time constant \(\tau\), and a frequency parameter \(c\). According to the model, \(m\) describes the amount of polarizable material; \(\tau\) is linked to the
size of the polarizable sources and \( c \) to the distribution of different polarizable sources.

The need to model AIP is becoming crucial for retrieving useful information from AEM responses. Modelling AIP-affected AEM data provides not only improved resistivity values but also a chargeability model. The potentiality of deriving chargeability from AEM has important implications for interpretation. For example, the derivation of this extra parameter enables the discerning capability of differentiating between a chargeable and a non-chargeable conductor and has implications for interpreting between, for example, sphalerite and other sulphides or brackish groundwater and clays.

**More Details on AIP**

Airborne IP can severely distort the TEM transients at each sounding. A change in sign during the decay is a strong suggestion of IP effects. In other instances AIP “only” determines an increase in dB/dt signal at early times, followed by fast-decaying transient (Figure 6), hence its presence is less evident visually.

![Figure 6: Comparison between a half-space response of a pure EM transient (blue) with a conductivity of \( \sigma = 0.01 \) S/m, and the same half-space but with an IP component (red) with the following Cole-Cole parameters: \( \sigma = 0.01 \) S/m; \( m = 300 \); \( c = 0.5 \); and, \( t=0.001s \), for a coincident-loop waveform.](image)

As shown in Figure 6, if the base frequency, which ultimately determines the response of the latest gate of the AEM system, is not low enough, then the sign change might never be visible. In other instances the signal might fall into noise before it develops a sign change. Figure 7 shows examples of actual AEM survey data acquired with a variety of systems, where IP effects were recorded over several rock types at different locations.

![Figure 7: Measured AIP responses recorded with different AEM systems, over a variety of rock types in different parts of the world (Kaminski and Viezzoli, 2017).](image)

**CORRELATION BETWEEN THE DATA-SPACE METRICS AND ACTUAL PARAMETERS**

The standard approach to modelling AEM, which ignores AIP, is to delete the negative windows and use what is left for modelling. However, opinions in the recent literature are in general agreement that deleting negatives is a rather crude way to go about it, and does not actually solve the issue. This is particularly evident now after seeing that AIP distortion of the transients occurs well before sign changes happen.

In order to thoroughly appreciate the relevance of AIP effects on 1D data, we have calculated thousands of forward responses of half-space models. We varied the combination of Cole-Cole parameters \( \sigma, m, r \) and \( c \) in discrete steps within the following ranges:

\[
1 \leq \sigma < 100,000, \\
0 < m < 900, \\
0.1 < c < 1, \\
10^{-6} < r < 5 \times 10^{-2}
\]

The forward responses were then contaminated with random multiplicative and additive noise to simulate real survey conditions.

The transients were then analysed to quantitatively assess the presence of AIP effects. For this we prepared a series of different AIP metrics (Table 1). The basic idea of these metrics is to summarize the AIP content in the transient array as a set of scalar values, each one capturing a specific aspect of the AIP effect on transients. Some metrics integrate signal, others fit parts of the transients with exponentials, others again flag the time (gate) at which AIP voltages peak or change sign. These metrics can then be imaged in 3D, as a function of the Cole-Cole parameters (varying three parameters at the time and keeping one fixed). Figure 8 shows a view of one of these metrics (i.e., the sum of the negative voltages) of the modelled response for half-spaces with different combinations of Cole-Cole parameters. The figure shows that in significant parts of this
model hyperspace, the Cole-Cole parameters combine to generate strong IP effects which are above the expected noise-levels, hence are detectable under normal survey conditions.

**Table 1**: Types of metrics used to summarize the AIP effects on both synthetic and real data.

<table>
<thead>
<tr>
<th>Metrics on gate numbers</th>
<th>First gate which shows a negative voltage</th>
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<tbody>
<tr>
<td></td>
<td>Gate which shows the maximum negative voltage</td>
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<tr>
<td></td>
<td>Number of gates which show a negative voltage</td>
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<tr>
<td>Metrics on voltages</td>
<td>Maximum negative voltage</td>
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<tr>
<td></td>
<td>Sum of negative voltages</td>
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<tr>
<td></td>
<td>Area below the curve (integral of absolute values)</td>
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<tr>
<td>Metrics on slopes</td>
<td>Straight line best fitting in a log-log plot – Early times</td>
</tr>
<tr>
<td></td>
<td>Straight line best fitting in a log-log plot – Mid times</td>
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<tr>
<td></td>
<td>Straight line best fitting in a log-log plot – Late times</td>
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**Figure 8**: Multidimensional plot showing the combined effects of Cole-Cole parameters (c kept fixed to 0.5) on the transients. Areas in warm colours represent strong negative anomalies (log10 of sum of negative values).

**Figure 9**: Multidimensional plot showing the combined effects of Cole-Cole parameters (c kept fixed to 0.5) on the transients associated with a two layer model (chargeable overburden, resistive bedrock). Areas in warm colours represent strong negative anomalies (log10 of sum of negative values). Zoomed left insert shows the half-space responses, for reference.

**Figure 10**: Multidimensional plot showing the combined effects of Cole-Cole parameters (c kept fixed to 0.5) on the transients associated with a two layer model (non-chargeable, resistive overburden, chargeable bedrock). Areas in warm colours represent strong negative anomalies (log10 of sum of negative values). Zoomed left insert shows the half-space responses, for reference.

**IMPORTANCE OF LAYERING**

The basic response to chargeable half-spaces is severely affected by, for example, layering of the electrical strata that is placing resistive bedrock below the chargeable layer, or burying the chargeable layer under a resistive host.

Figure 9 shows how the AIP effect can be further increased by the presence of resistive bedrock. The maxima of the same metrics used in Figure 8 spreads significantly in all directions. The resistive bedrock, with its small associated induced vortex currents, allows the AIP effect to develop more strongly and more often within the base frequency of the system and above the noise.

Burying the chargeable layers at depth (100 m) reduces AIP (Figure 10). This is expected because the charging starts later in time. However, the AIP does not disappear.

We now illustrate with greater detail the effect of layering and associated possible significant consequences on individual transients. Figure 11 shows how a shallow chargeable layer can, under certain circumstances, distort the transient to very late times, causing a dramatic change in the signature of a deep conductor. In this case, the late time (bedrock) conductor would most likely be missed when inspecting the data. This would happen both if simply plotting gate voltages and if fitting exponentials to the mid/late time gates. In the Lewis Pond case study presented in the next section we show how, when modelling AIP, one can recover the purely EM response for a whole dataset, stripping out the IP effects.
From our investigation with synthetic modelling and calculating responses from different waveforms and datatypes, we confirm that the magnitude and characteristics of AIP:

1) depend to some degree on the type of waveform (more specifically the duration of the ramp down)
2) decrease with higher acquisition height
3) can increase with B field data
4) can increase with lower base frequency
5) are better sampled and resolved with more, shorter, time-gates.

Points 3 and 4 above can increase depth of recoverability of buried chargeable anomalies.

THE RELEVANCE OF MODELLING AIP ON REAL DATA

Airborne IP effects can affect and distort AEM data in different ways. Modelling AIP-affected datasets with standard non-dispersive resistivity model algorithms will produce an erroneous resistivity model. The current conventional approach of just deleting the negatives will not prevent the issue. Not accounting for AIP on AEM data will underestimate overburden resistivity and thickness, overestimate bedrock resistivity, and in some cases miss bedrock conductors. All of these are detrimental effects on further geological mapping and exploration in general. Viezzoli et al. (2017) show some of these examples.

When it comes to inverting an AIP dataset, researchers have taken different approaches. Some take a two-step procedure, e.g., Kang and Oldenburg, (2015); Kwan et al. (2015), Chen et al. (2015), estimating first the non-dispersive resistivity, then the (apparent) chargeability.

It is arguable that one can isolate the purely EM part of the transient affected by AIP. For example, we have shown that early times are also often affected by AIP in a measurable degree. The option of obtaining the non-dispersive resistivity from other sources (e.g., other geophysical techniques) is intriguing, but seldom applicable.

In our view, it is therefore best to model AIP at the same time as the EM response. One way is to use the Cole-Cole model and solve for all Cole-Cole parameters at once. With this modelling we can now recover “AIP corrected” resistivity plus a chargeability of the subsurface.


The AEM inversion problem suffers from large number of unknowns, and great care must be exerted in the regularization and modelling (Viezzoli et al., 2017). Like any other inversion, and arguably even more, the outcome of inverting for chargeability is also dependent on the quality of the data processing prior to inversion.

To illustrate the importance of processing AEM data prior to inversion, in Figure 12 we show an example of the outcome of AIP inversion, where severely AIP-affected data is inverted solely as delivered by the contractor, versus the results obtained with detailed, tailored pre-processing of the data. The latter produces significantly better correlation with drilling information. In our experience proper processing for AIP inversion requires time and visual inspection of the data.

It is important to notice that in the case presented in Figure 12, the vast majority of the survey has transients that are entirely negative, which would have made standard, non-dispersive modelling impossible.
Figure 12: Two soundings shown as decay curves in b) and c) highlight the effects of IP on the AEM data. Sections d) and e) show inversion of HeliTEM data from a Ni-Cu-PGE prospect. Contractor’s delivered data has thoroughly processed before inversion accounting for AIP effects; the modelled and measured data are well fitted. The buried conductive and chargeable body is confirmed by laboratory measurements on diamond drill core a) projected as a black intersecting line on every section. Panels f) and g) show results from inversion, this time on data as delivered by contractor without prior processing. Data are not fitted, the interpreted geology is noisy and there are discrepancies with the diamond drill core measurements. Figure Adapted from Kaminski and Viezzoli (2017).
CASE STUDY: AIP AT LEWIS POND

We now present a case study from a Versatile Time domain EM (VTEM) survey flown over the Lachlan Orogen, in NSW, Australia. The area contains a strata-bound massive-sulphide lens, with lower-grade mineralization in the hanging wall and footwall lenses. Significant chlorite and pyrite alteration extends above the main deposit (Hine and Macnae, 2016). We inverted the data accounting for IP using our standard layered Earth modelling (Viezzoli et al., 2017), which was preceded by careful data processing. Figures 13 to 15 show some of the most relevant results, comparing AIP inversion results with ground IP 3D inversion results and available geological information.

Figure 13 shows chargeability depth slices derived from a ground IP inversion at 25 m and 85 m. Compare this with the same depth slices derived from AIP inversion in Figure 14, and a close-up of the two datasets in Figure 15. The images show that the AIP recovers the weathered alluvium, which has been verified (K. Hine, pers. comm.). Figures 13 and 14 show a deeper correlation between ground IP- and AIP-derived chargeability slices at 85 m depth and that both methods map the general NW-SE trend of pyritic alteration associated with sulphide mineralization. This correlation is also shown in Figure 16, with chargeability local maxima associated with areas of pyrite alteration.

Figure 14: Chargeability slices at different depths (25 m top, 85 m bottom) derived from a Spatially Constrained Inversion (SCI), from a VTEM dataset. Compare to Figure 13.

Figure 15: Close-up of a comparison between (left) ground IP (dipole-dipole) inversion (UBC 3D inversion results, adapted from Hine and Macnae (2016). Compare to Figure 14.

Figure 16: Chargeability local maxima associated with areas of pyrite alteration.
Figure 16: Comparing AIP derived chargeability (c.f. Figure 14 for colour scale) with cross section showing mineralization and alterations. Insert shows measured (error bars) versus modelled (continuous line) transient for the model at distance 1000 m.

It is possible to recover the “pure EM” response by stripping the AIP effects from the AEM data. Figure 17 shows one line of VTEM data flown over mineralization known as Tom’s zone. The comparison is done between the observed AEM data (with IP in it) versus the reconstructed “pure EM” response, by modelling AIP to recover the “IP corrected” resistivity model and an associated chargeability model all at once. We then forward modelled the AEM data associated with the “IP corrected” resistivity model with no chargeability. Data misfit, sensitivity depth of investigation of the resistivity model and adequate noise model on the forward modelled data were all taken into account for this process. The line of “pure EM” response provides clear advantages from the perspective of assessing late time conductors, because the signal-draining IP effect has been taken out of the data. It is, in principle, possible to accurately reconstruct the “pure EM” dataset for the entire survey, and use it for further interpretation (e.g., looking for late time voltage anomalies) and/or modelling (e.g., fitting exponentials, plate modelling).

Figure 17: Windowed amplitude data comparing the observed (top) AEM data from Lewis Pond (which contains IP) versus the reconstructed “pure AEM” response (bottom) for a VTEM line that crosses Tom’s zone (mineralization). The colours and appearance of the different gate voltages are the same in the two plots.

PREDICTION UNCERTAINTY

As seen in the previous sections there are several inaccurate elements that occur during the data acquisition and processing of AEM data which are combined and contribute to the uncertainty of deriving a single solution when inverting and modelling. During the assessment of results, we need to determine which model is suitable or at least representative of the data from which it was derived. Ideally we can use a probabilistic analysis to explore the characteristics of several acceptable models without being concerned about the details of any particular one.

In some situations, we may have prior information which can help restrict models to a smaller set of parameters, but even in these cases different model-parameter values can be altered independently, or may depend themselves on other parameters to explain the observed data. A statistical approach enables us to
estimate uncertainty boundaries on the resulting model and the correlation between different model parameters.

**From Resistivity Values to Lithology Prediction, Case Study Timor-Leste**

To illustrate one way of dealing with uncertainty when modelling AEM data in a stochastic manner, and how this can assist interpretation, we show an example in which a frequency domain helicopter borne EM survey was flown over a karstic plateau in the Baucau province of Timor-Leste (Minsley and Ley-Cooper, 2015).

This example demonstrates how a Bayesian Markov chain Monte Carlo (McMC) algorithm analysis can be used on AEM datasets. It uses a Metropolis algorithm which is a sampling algorithm in which a sample is first drawn from a trial (or proposal) distribution. This sample is then accepted or rejected using the Metropolis criterion. A detailed description of the Trans-dimensional McMC Inversion algorithm used here can be found in Minsley (2011), but in essence the Bayesian McMC algorithm constructs an ensemble of thousands of 1D conductivity models at each AEM sounding location. Each model is described by layer-conductivity and thickness values. It follows McMC sampling rules and uses prior information consistent with the data such as the likely thickness of conductive layer (conductance), and whether a 1D model is a reasonable starting point for the model structure.

The number of layers used to describe each model is a free parameter, allowing for significant flexibility in the model parameterization. By allowing the data to decide the necessary model complexity, errors associated with over- or under-fitting data and incorrect assumptions about model structure are avoided.

After re-calibrating the AEM data following the process described by Ley-Cooper and Macnae (2007) and then inverting the survey with Minsley’s (2011) trans-dimensional McMC algorithm, results successfully led to better constrained resistivity-depth estimates and predictions of stratigraphic variability associated with carbonate-rich rocks. Modelled high resistivities of 1,000 $\Omega$m and over were used to determine the thickness and extent of the carbonate Baucau Formation, with which we mapped an important unconformity between the limestone and the underlying clay rich Viqueque Formation.

Results provided important insights into the architectural features of the carbonate platform (Ley-Cooper and Davies, 2015). We then built a conceptual 3D conductivity structure model. A representative section is shown in Figure 18. In panel A) a cross-section of the mean McMC model for line 19020 was constructed from 50 million models. The flight line was sampled at ~500 locations; for each of those locations 100 thousand models per location were computed, yielding a compiled solid set of statistics at each location.

In Figure 18 a more detailed assessment from results at two locations B) and C), are shown on the top panels. At each location we show the probability distribution of resistivity as a function of depth and a probability-depth histogram. Darker shading in left panels of B) and C) indicates higher probability (i.e. more models sampled with those resistivity-depth values). Discontinuous pink curves enclose models within the 5th and 95th percentile (90% credibility), which spread-out asymmetrically as does the loss of signal resolution at depth. The 'best fitting model' is plotted as a cyan blue curve. The histogram in the right-hand panels of B) and C) represents the sampled layer interface depths from all (100,000) sampled models. In B) there is a sharp (well resolved) interface indicating a single interface around 65 m, whilst in C) we see two peaks, one at around 5 m and another at around 38 m. The red line measures the width of the 90% credibility region.

In Figure 18 the shallower 40 m interface in the right sounding labelled C) is better resolved (both in terms of depth and resistivity values) than the one on the left at location B) at 65 m. Arguably this interface depth and the thickness of the top layer could be resolved and interpreted from a standard deterministic inversion, but the main difference is that through the statistics we have gathered with the McMC process, we can now quantify the uncertainties associated to these derived values of resistivity and depth.

The resistive (1 $\Omega$m) top layer directly relates to the massive Quaternary reefal carbonate Baucau limestone formation, which controls the topography of the plateau (shown as purple/dark blue on the conductivity section). The underlying more conductive values of 10 $\Omega$m and above (green, yellow and red) are associated to clay-rich layers within the Late Miocene-Pliocene molasse Viqueque Formation deposits described in Audley-Charles (1968).
### Resistivity Values to Lithology

One of the by-products of running this computationally intensive algorithm is the generation of enough models to have a set of robust statistics. The probability distribution of resistivity at any depth is extracted from the recovered McMC distribution of models, as shown in the previous section. This distribution is overlain with prior assumptions about uniform resistivity ranges for different facies or lithological groupings, indicated here by different colours (Figure 19). The probability of being within each facies is determined by summing the product of the joint facies and the resistivity probability distributions. Values are normalized so that the sum of all four domains equals one (Minsley and Ley-Cooper, 2015).

It is important to note that the resistivity probability distribution extracted at 40 m is bimodal, it is near a layer interface, i.e., in the proximity of very resistive limestone and a transitional lithology that lies beneath. From our analysis we can say that the resistivity at this depth is attributed to either unit #1 or unit #4, but we cannot determine which. A deterministic inversion would likely recover just a single ‘average’ resistivity value at this depth, but in fact we can see from Figure 19, that an intermediate resistivity value has very low probability at this location.

The cut-off values we have the pre-determined for rock types in this case study range over three orders of magnitude and are listed in Table 2:

<table>
<thead>
<tr>
<th>Lithology</th>
<th>Resistivity Ω·m</th>
</tr>
</thead>
<tbody>
<tr>
<td>very resistive limestone</td>
<td>&gt;1000</td>
</tr>
<tr>
<td>intermediate limestone</td>
<td>100-1000</td>
</tr>
<tr>
<td>intermediate clay</td>
<td>10-100</td>
</tr>
<tr>
<td>conductive clay</td>
<td>&lt;10</td>
</tr>
</tbody>
</table>
CONCLUSIONS

Airborne EM surveys measure geo-electrical contrast in a given area, but the real value comes from extracting useful information from the measurements themselves, and combining the derived conductivity models with ancillary information in order to provide meaningful interpretations and the understanding the subsurface. Through a range of case-histories we show how variability in features such as saline water intrusions, lithological unconformities, chargeable bodies, palaeochannel geometry and transported-cover influence AEM measurements. We also show how these features can be inferred from inversion and interpretation of the measured data.

The need to employ AEM as a method beyond bump finding in direct anomaly detection has been repeatedly flagged over the last few decades, but modelling is still not common practice. Interpretations continue to be drawn from gridded contours of measured channel data, and anomaly-barren surveys are still considered as failures.

A comprehension of all the governing factors which may determine the shape and amplitude of a measured EM response from the air, and an understanding of the instrumentation used for acquisition, are both crucial concepts needed for modelling and interpretation of AEM data. We have shown how modelling AIP-affected AEM data can provide improved resistivity models, and realistic chargeability models, that are consistent with ancillary information. Accounting for AIP effects has enabled the possibility of modelling responses from data that have conventionally been treated as noise; this has important implications for interpretation. Deriving chargeability from AEM enables differentiation between chargeable and non-
chargeable conductors (e.g. some clays and ion-rich groundwater).

When analysed with ancillary information, AEM has the potential to be utilized to plan further mineral exploration, characterize and map clay layers governing groundwater flows and regolith architecture, assist with under-cover lithological and geological mapping, and be used for delineation of structures possibly associated with deeper mineralising structures.

The McMC statistical process we presented as an example here, and other stochastic methods, enable the exploration of a great number of models consistent with measurements and are not focused on one particular model. The McMC algorithms allow the user to assess the associated levels of uncertainty at each location, and to predict lithological variations with depth. This translation from models of conductivity to models of geological significance is crucial to obtain any useful interpretation. Efforts that improve this translation between geophysics and geology will continue to be worthwhile.

ACKNOWLEDGEMENTS

The authors thank the Commonwealth Scientific and Industrial Research Organization (CSIRO), the Goyder Institute for Water Research and BESIK in Timor-Leste, for allowing us to present data and results from projects supported by these organizations. We also thank Ross Brodie (Geoscience Australia), who has facilitated his GA-LEI sample by sample inversion algorithm and Ian Roach (Geoscience Australia) for his review. Burke Minsley (USGS) for the use of his McMC algorithm. Some computational aspects of this research were undertaken on the NCI National Facility (Canberra, Australia), which is supported by the Australian Commonwealth Government, who we also thank. This paper is published with the permission of the CEO, Geoscience Australia.

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