Probabilistic 3D geological modelling from AEM data in Fregon, SA

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Introduction

Airborne electromagnetics (AEM) is a powerful and low-cost tool for imaging the conductivity structure of the near subsurface across large areas. AEM is a mature geophysical technique and is used in a range of fields including mineral exploration, groundwater studies and geological mapping. With further advancements in AEM inversions algorithms and the ever-decreasing cost of computing, it is now possible to rapidly invert large surveys. The deterministic AEM inversion approach involves inverting soundings using a 1D layered earth model, with regularisation used to penalise sharp vertical gradients within the models. Uncertainty in AEM bulk conductivity is considerable and arises from data errors, data bias, poor data fits, conceptual uncertainty relating to assumptions underpinning the inversion procedure and model non-uniqueness, where an infinite set of models can adequately fit the data. Given that the relationship between measurements and model is often non-linear, probabilistic approaches are the preferred way of understanding AEM conductivity model uncertainty. Probabilistic modelling involves inverting the data hundreds of thousands of times to find the ensemble of models that fit the AEM data.

The task of integrating AEM conductivity models with other datasets to model geology and infer subsurface properties is difficult, time consuming and itself a major source of uncertainty. The uncertainties in AEM models and other geological datasets are a major reason for what we will term 'interpretational uncertainty'. Other significant sources of uncertainty include the quality of the data with respect to the property under investigation, data sparsity, errors introduced during interpolation and extrapolation from spatial datasets and errors in model conception. The salience of the adage that if you 'ask 50 geologists for the answer you will get 50 different answers' becomes clear when we understand how poorly constrained most geological modelling problems are and how inadequate the data typically are.

Rigorously quantifying the uncertainties from all the sources described above is an interesting area of research but not always tractable for geological interpreters working on real world problems and real-world timeframes. The purpose of this paper is to consider the uncertainties relating to interpreting geological structure from AEM and other datasets with a real world example and suggest practical solutions for uncertainty handling.

Geological setting

This geological modelling exercise was undertaken in a 900 square km area around the remote community of Fregon in the central Musgraves Province in NW South Australia (Figure 1). This area was the focus of an investigation into groundwater resources for remote Indigenous communities undertaken by the CSIRO (Costar et al., 2019). As part of this survey a SkyTEM312 AEM survey was flown, with line spacing of 2000m (regional lines) and 250m (infill) (Soerensen et al., 2018) and a number of bores were drilled. The region is characterised by Cenozoic palaeovalleys incised into Neoproterozoic basement rocks. The palaeovalley fill is comprised of Eocene fluvial sediments of the Pidinga Formation, marine, lacustrine and fluvial deposits of the Mangatitja Formation and fluvio-aeolian quarternary sands and calcretes. The basement material is granitic or metasedimentary and has a thick weathering zone which can be difficult to differentiate from the palaeovalley material.

The CSIRO study found that the palaeovalley fill is well-resolved from the bedrock using AEM, and these data were used to estimate palaeovalley fill thickness. They also found that the area is heavily faulted which has disrupted the palaeovallies and has controlled palaeovalley incision geometries.

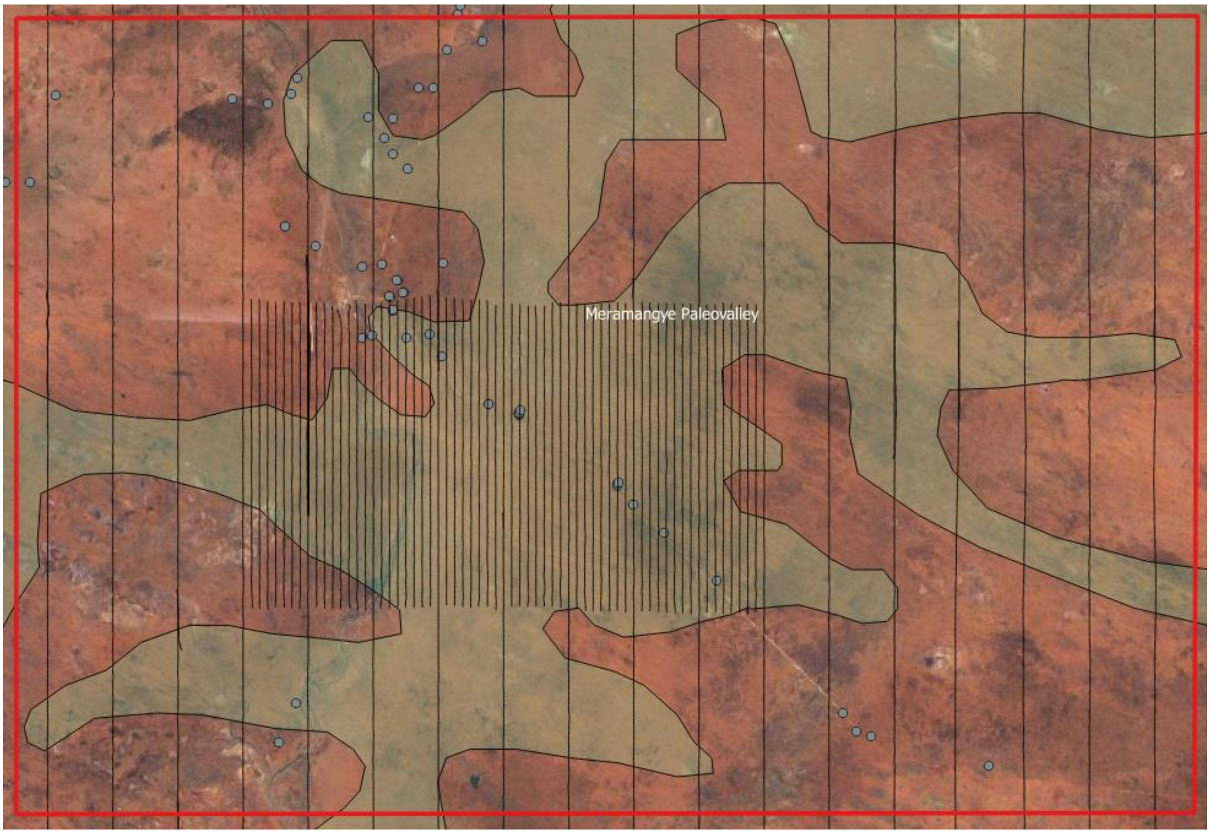

Figure 1 A map of AEM flightlines, bores and an outline of palaeovalley extent within the project area (red box).

Method

Borehole data for this area were loaded from the NGIS database. The hydrostratigraphic log data were unsuitable for interpretation and instead used the lithological log table to classify logged intervals as ‘Cenozoic’, ‘weathered basement’ or ‘basement’ lithologies. This approach has issues due to ambiguity in the logs and variable quality and errors were probably introduced.

I inverted the SkyTEM312 data using the deterministic GA-LEI algorithm, which is part of the GA-AEM package. I also inverted every tenth sounding from seven flightlines using the probabilistic transD-GP AEM inversion code. Additionally AEM fiducials within 250m of a borehole were inverted using transD-GP. I used the GA-LEI inversions for the interpretation while, I used the transD-GP to assess the GA-LEI inversion, visualise model uncertainties and develop an interpretation uncertainty model. A number of approaches for estimating uncertainty were trialled and assessed visually by plotting the uncertainty bars on the percentile model sections from the transD inversion. The simplest approach that yielded reasonable results are summarised in table 1. In general, I assigned the uncertainties conservatively, which is appropriate for environmental studies where there may be low-probability models may have disproportionately significant outcomes.

Table 1 A definition of how I picked the base of palaeovalley from the AEM and how I estimated the upper and lower uncertainty.

	Definition	Method

Interpreted interface (P)	The interpreted most likely depth of base palaeovalley at a point	Picking on the 0.005 S/m transition while filtering artefacts with my eyes
Upper uncertainty	The shallowest depth that would be a reasonable interpretation given the ensemble of models subtracted by the interpreted interface at that point.	Upper uncertainty = ga-lei layer thickness of three layers above interpreted interface at that point
Lower uncertainty	The deepest depth that would be a reasonable interpretation given the ensemble of models subtracted by the interpreted interface at that point.	Lower uncertainty = ga-lei layer thickness of three layers below interpreted interface at that point

I interpreted the interface between the basement and AEM interpretation using python based AEM interpretation tool. Three-dimensional geological modelling was done using the Geomodeller software using ~1700 interface picks and 42 boreholes with classified lithologies. For the uncertainty assessment, I generated a ‘shallow’, ‘average’ and ‘deep’ model, which can be thought of as encapsulating most of the variance in geological modelling given my understanding of the uncertainties.

Results

The AEM inversions revealed that this area is characterised by very resistive basement with a more conductive cover, up to ~100m thick (Figure 2). The 3D distribution of the conductivity body is highly coherent and spatial patterns suggest it strongly correlates with palaeovalley fill (Figure 2). In general, data fits from the GA-LEI model were poor, reflecting the very low data values with some potential induced polarisation (IP) and/ or superparamagnetic effects (SPM). The probabilistic inversion revealed that the palaeovalley geometries were resolved across at least 90% of all the models (Figure 3), indicating high confidence.

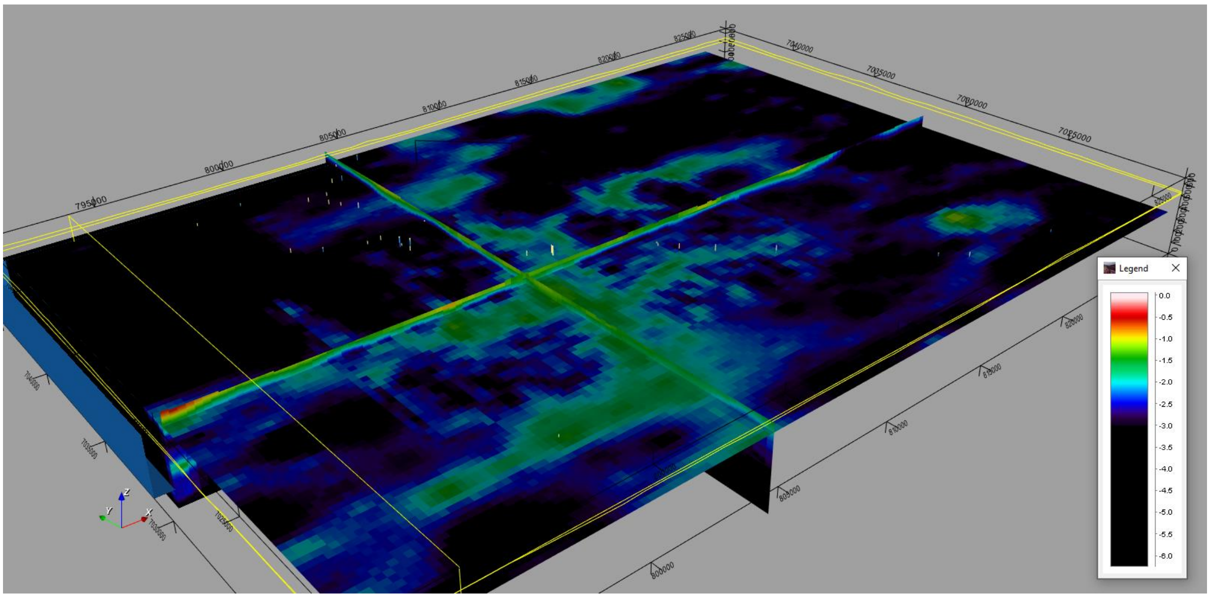

Figure 2 A 3D visualisation of the AEM bulk conductivity grid interpolated onto a 250x250x10m voxel grid using kriging. The elevation slice is at ~430mAHD and the vertical exaggeration is 5. This image demonstrates that conductive palaeovalley fill (greens) are clearly resolved from the highly resistive basement (black).

It is critical that AEM models are first compared with borehole data to ensure a consistency of understanding between the datasets. Unfortunately, I did not have access to induction logs, which would have allowed more meaningful comparison between datasets. Instead I used the lithology logs plotted against the AEM conductivity models for the nearest fiducial (e.g. Figure 4). The borehole data were unable to definitively confirm or reject that 'geo-electric' features modelled using AEM map onto actual geological features. The reason for this is that few bores intersected the both the palaeovalley and basement lithologies and those that did typically only encountered weathered basement. The borehole log in Figure 4 demonstrates this point. While there is undoubtedly a reduction in conductivity in all models towards the base of the palaeovalley, the transition in gradual and as we do not know the properties of the weathered basement, it is not possible to know if this is accurate or an artefact of the AEM inversion. This is a source of conceptual uncertainty as I don't truthfully know what I am picking, the top of the weathered zone, the top of the fresh basement, or more likely a combination of both. Another source of uncertainty are errors in the interpretation of the boreholes by me or whomever did the logging. These errors are not explored here due to insufficient supporting data.

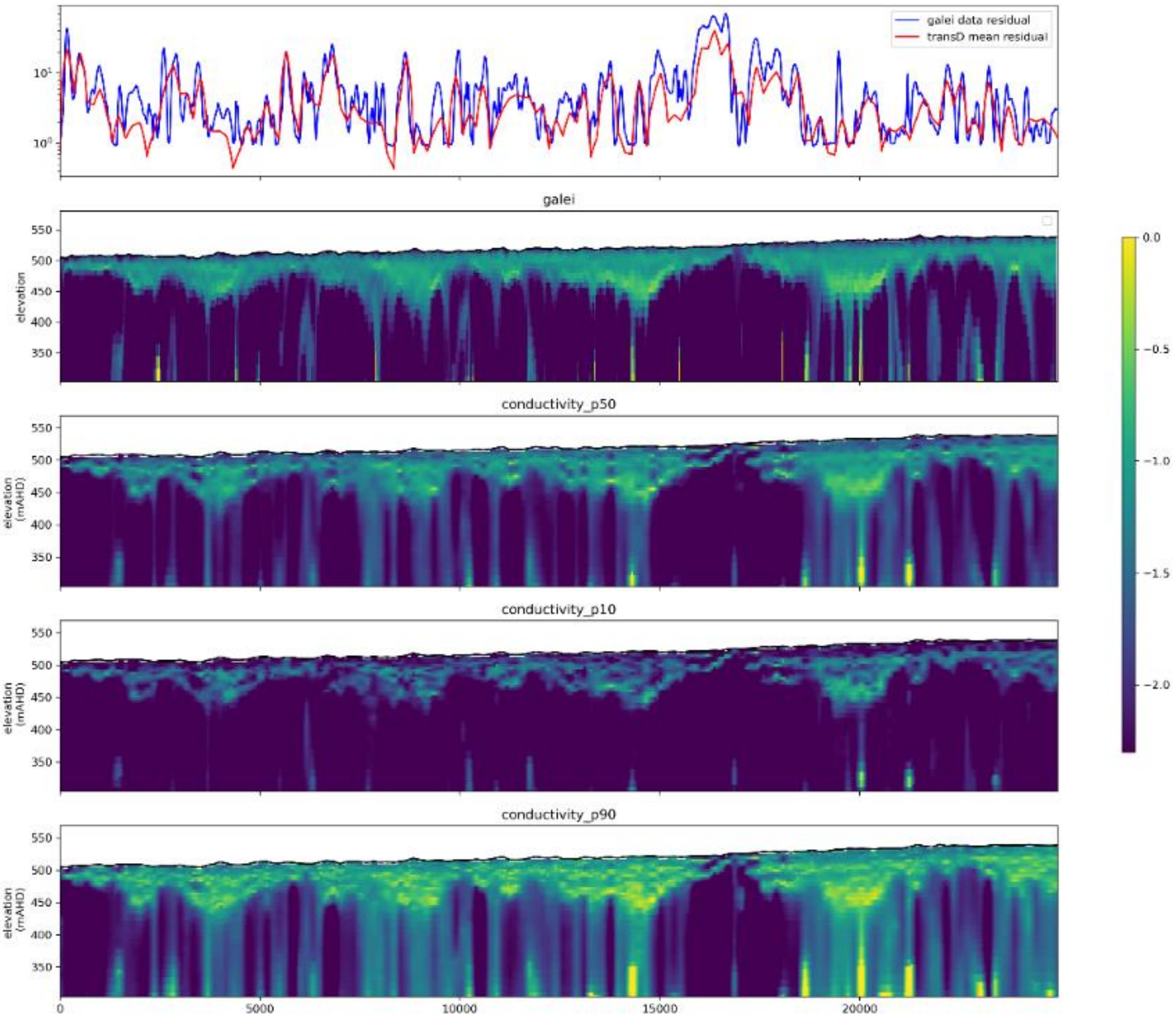

Figure 3 A section plot revealing the GA-LEI bulk conductivity model compared with the 50th, 10th and 90th percentile, bulk conductivity models (panels 3-5). Importantly the major features, the U-shaped conductors at the surface, are evident in all models indicating high-confidence that these features are 'real'.

I interpreted GA-LEI conductivity model using a python based app in dash. My approach was to pick boundaries as the modelled conductivity approached the 0.005 S/m (**Error! Reference source not found.**). As is typical with AEM modelling for all the reasons previously mentioned, there is considerable noise and adjacent models are not always consistent with each other. To overcome this issue I ‘filtered the section with my eyes’ by avoiding features that I judged to be artefacts. This introduces interpreter bias which is often unavoidable given the noisy, diffuse nature of AEM inversions. However, given the objective was to model the base of the palaeovalley, this approach is justified as our prior model assumes a relatively smooth surface.

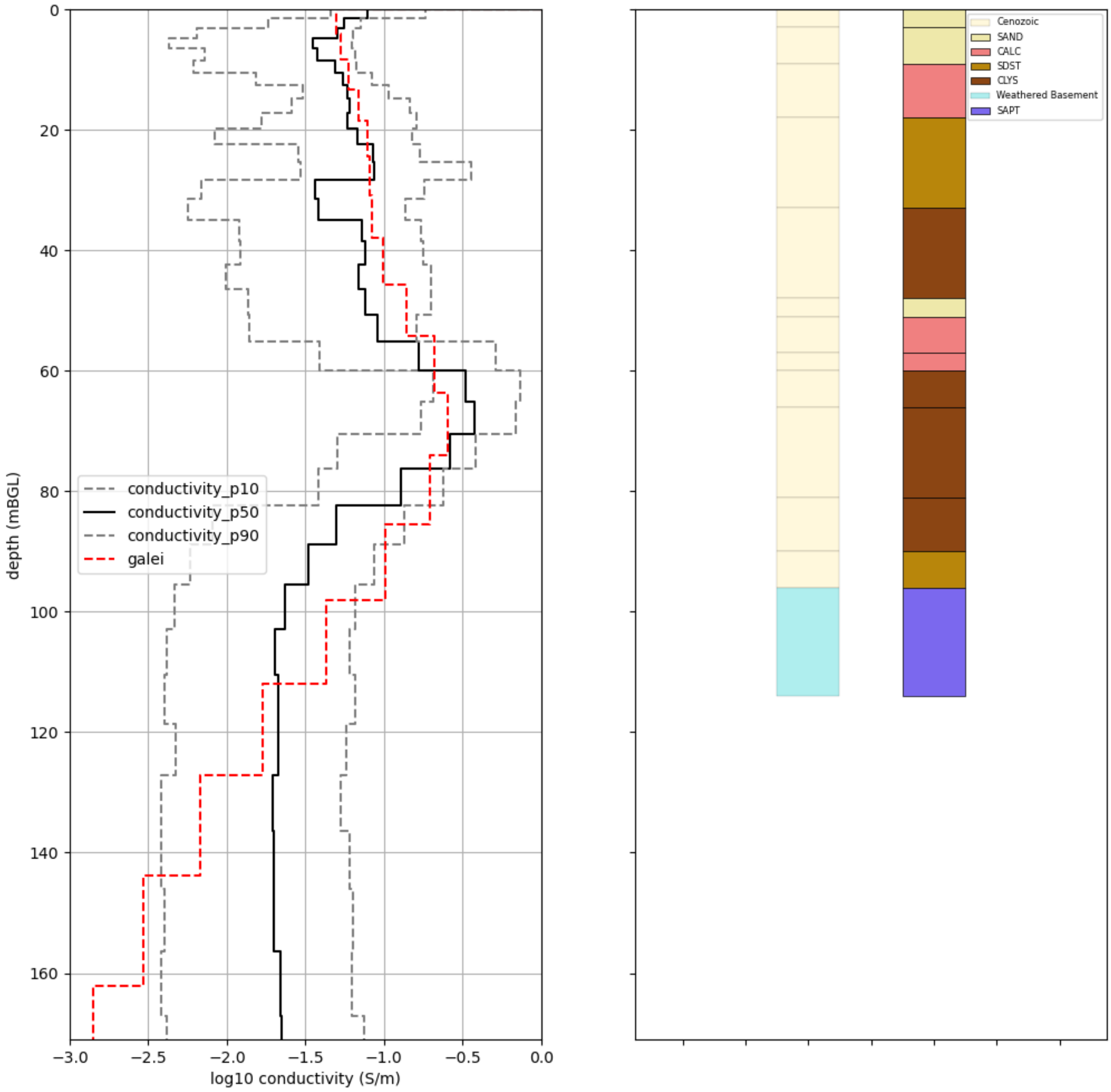

Figure 4 Hydrostratigraphy and lithology logs for borehole DH1A2 (right panel) and nearest AEM conductivity models (left panel). Here we have plotted the galei conductivity models as well as the percentile conductivity models from the transD inversion. This plot shows that the AEM in general can only resolve the larger scale features within the palaeovalley such as the marine claystone from ~60-95m depth. The base of the palaeovalley is gradational in both the GA-LEI and transD percentile models suggesting that this contact may well be gradational. This is supported by the borehole logs which suggest that ‘fresh’ bedrock was never drilled at this site.

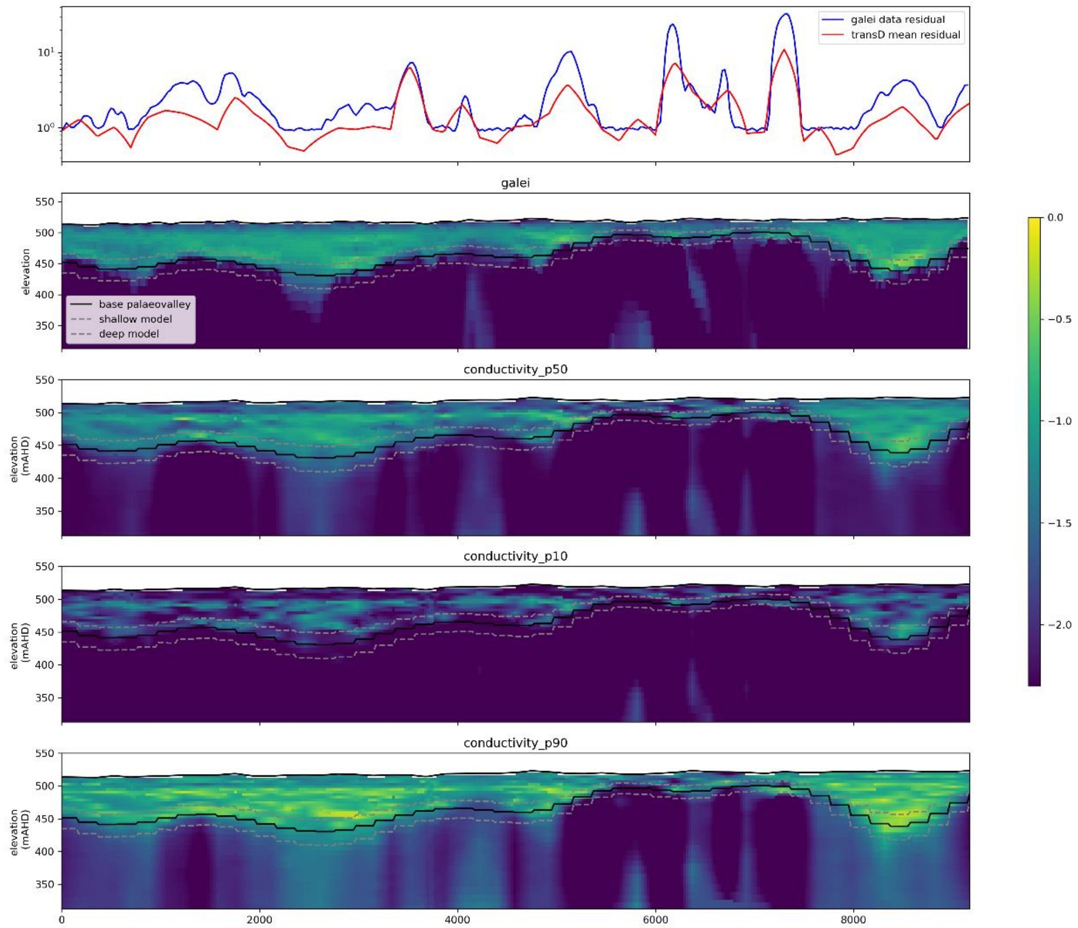

Figure 5 A conductivity section plot revealing the GA-LEI bulk conductivity model compared with the 50th, 10th and 90th percentile, bulk conductivity models and the interpreted interface for the base palaeovalley average, shallow and deep models.

The interpretational uncertainty model generated as part of this study is defined in Table 1. To assess the uncertainty model, we generated a simple base of palaeovalley surface using minimum curvature gridding and used the uncertainty model to generate a 'shallow' and 'deep' model by subtracting and adding the uncertainties from this model. The method I chose ensured that the magnitude of uncertainty was proportional to layer thickness and depth. A desirable characteristic of this uncertainty model is that uncertainties are asymmetrically distributed around the interpreted base of palaeovalley surface, with the deeper uncertainty greater than the shallower. This is consistent with our observations from the probabilistic conductivity model ensemble. An example conductivity section is shown in Figure 5. After some trial and error, I was satisfied with the uncertainty model and used it to calculate an upper and lower uncertainty for each interpretation. Finally, I used the upper and lower uncertainties to produce three sets of interpreted points, an 'average' model, a shallow model and a deep model.

The AEM interpretations and borehole data were imported into Geomodeller for 3D modelling. To produce a geometrically sensible model, I needed to generate orientation observations deterministically. Although no data were available, I used the assumption that orientation of the palaeovalley fill was orthogonal to the palaeovalley-basement interface. To stabilise the model I also added some 'dummy' features, including interfaces above the ground surface. The resulting model is consistent with our current understanding of the palaeovalley geometry (Costar et al., 2019) displaying a large trunk palaeovalley, smaller fault-controlled tributary valleys and the palaeovalley being offset in the north and west by faults (Figure 6). The model did a good job of fitting the observations and the level of model smoothness was consistent with my expectations.

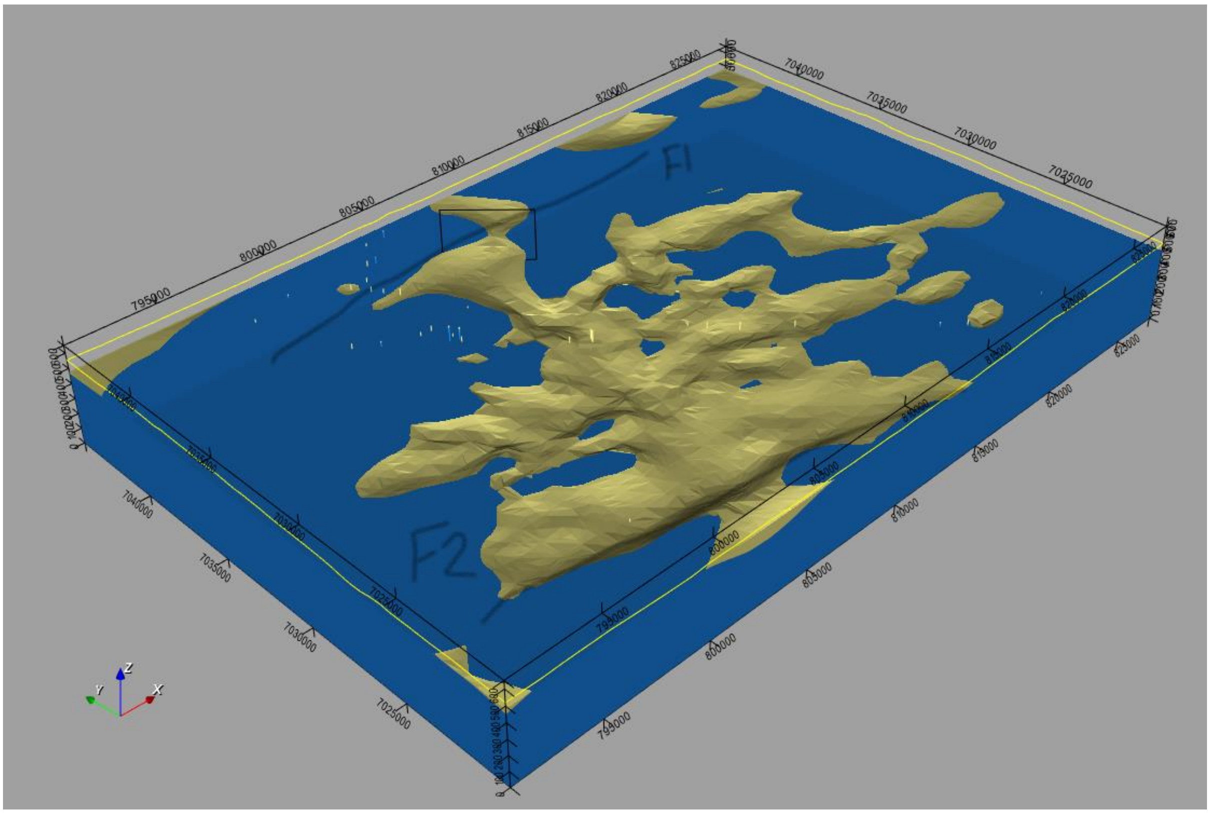

Figure 6 A 3D visualisation of the 'average' base of palaeovalley surface (yellow) sliced at 481mAHD with the two major fault annotated on the volume. The vertical section outlined in black was used to estimate the cross-sectional area of the palaeovalley at its thinnest (Table 2).

For the uncertainty analysis, I generated a shallow, average and deep base of palaeovalley model. I reviewed the modelled interface against the interpreted borehole data though for the reasons the ambiguity of the response of the weathered basement precluded a thorough assessment of model performance using boreholes. From the models, I produced surfaces representing the elevation of the basement-paleovalley interface and a voxel model (200x220x5m). For a rapid and easy to communicate comparison, I used four model statistics that may be of interest for an assessment into groundwater resources. These statistics are the palaeovalley material volume, the lowest elevation, the mean elevation and the saturated cross-sectional area across the thinnest part of the valley (Figure 6). The results are summarised in Table 2 and show that the different models yield significantly different statistics. As expected, the 'deep' model yields a larger volume of aquifer material and a significantly larger saturated cross-sectional area compared to the shallow model.

Table 2. Some important statistics calculated from the shallow, average and deep base of palaeovalley 3D models.

	Palaeovalley material volume (km^3)	Minimum elevation (mAHD)	Mean elevation (mAHD)	Saturated cross sectional area (m^2)
Shallow model	29.3	414	493	62,768
Average model	38.9	401	486	102,868
Deep model	50.2	369	470	154,730

Discussion

In this investigation, I have explored how one might approach uncertainty analysis when interpreting airborne electromagnetics within a data sparse area in Australia. I also probed the sensitivity of model attributes such as palaeovalley volume, area and depth by producing three models, a shallow, average and deep model. Here I will discuss the implications of this work for future modelling efforts using AEM and other geoscientific data.

The key finding from this investigation is the importance of assessing interpretation uncertainty. There is a significant difference in the properties of the 3D models (Table 2). For example, the palaeovalley volume of the deep model is almost 30% greater compared with the average model. Importantly, different model attributes have different sensitivities to uncertainty. To demonstrate this I investigated the saturated cross-sectional area of the narrowest part of the palaeovalley, which might have significant implications for understanding how groundwater flowing into the system. For this question, the deep model has a saturated cross-sectional area that is 50% greater than the average model and 147% greater than the shallow section. This demonstrates that understanding model uncertainties may be more important for some questions, particularly relating to smaller scale features, which often have a disproportionate effect on groundwater flow systems.

One finding from this study, which I have experienced in the past when interpreting AEM, was the difficulty of using boreholes as validation. This area is much richer in borehole information relative to rest of the Musgrave Province and much of Australia. Borelogs were of mixed quality we few bores intersecting the basement and when they did, it was generally into the weathered zone. Without a good handle on the properties of the weathering zone, it is hard to validate the useability of the AEM with respect to interpreting the base of the Cenozoic. The boreholes thus offer little more than a qualitative check that our interpretation strategy was not inconsistent with borehole information.

An important choice that I made during this investigation was to use an uncertainty model, where uncertainty was calculated based on the depth of the interpretation. This heuristic greatly improved the efficiency of the modelling and appeared to be appropriate given the consistent conductivity of the overlying palaeovalley fill. The simpler approach is also justified given the complexity of estimating uncertainty given the range of sources involved including model non-uniqueness, data errors, poor model fits and diffuse relationship between conductivity and geology. However, this approach may not be viable in a complex environment with multiple model layers and great variation in conductivity and more manual, time-consuming approaches may be necessary.

Another simplifying choice I made was to assess uncertainty with three models, a 'best' model and two end-member models (shallow and deep). A more scientifically rigorous approach would have been to estimate the uncertainty at every point, derive a probability density function (PDFs) and generate an ensemble of 3D models by sampling from these PDFs. The reason I did not pursue this approach is not only is it a lot more work, but also it assumes the uncertainties are uncorrelated. However, given the heuristics used to estimate uncertainty and other likely biases, such as what conductivity threshold to use during interpretation and lateral data averaging, uncertainties are certainly correlated. While covariance can be handled in probabilistic 3D modelling methods, this requires some understanding of parameter covariance, which we do not have and would be very difficult to ascertain.

The implications for using a three-model approach is that we are not ask probabilistic questions of the model ensemble. For example, we cannot ask what that probability of the palaeovalley having more than 35 km^3 of material in our modelling domain. Instead we have to be content with asking, is questions such as; is it likely that the saturated cross-section area of palaeovalley is less than 50 m^2 given the three models. Nonetheless, I believe that these questions are still useful and justify the effort in uncertainty analysis.

Recommendation

This work demonstrates a single example of uncertainty handling in AEM interpretation. My recommendation is not that we use this exact approach, as each investigation will have its own objective, data characteristics and limitations. Having said this, I recommend all AEM interpretation projects should at least try to characterise interpretation uncertainty. At a minimum, I recommend inverting the AEM data from a few lines and near existing drillholes, using probabilistic methods. The conductivity ensemble should be queried to find the range of models that fit the data and a relationship between conductivity and lithology/ stratigraphy should be described and uncertainties qualitatively explored.

If uncertainties are to be propagated into the modelling, the approach should be specific to the question. For example, if one is only interested in the saturated cross-sectional area of the narrowest part of the channel, there is no need to model the entire area with all uncertainties. Finally, it is worth keeping in mind that there are no correct uncertainties and whatever approach we have to estimate them is merely an expression of the interpreters understanding of their ignorance. Hence, any uncertainties derived by any method will be bias and yield correlated uncertainties. For this reason, I recommend simpler approaches to propagating uncertainty such as those used in this study.