Depth to basement mapping in Mount Isa using 2D MT constrained inversions

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SUMMARY

Many Australian metallogenic provinces are buried under thick post-mineralization cover. Imaging the depth to prospective basement in this type of geological environment is challenging and improving the reliability of the geophysical images requires incorporating constraints within the geophysical data inversions. In this study, we propose to derive structural depth constraints using a probabilistic magnetotelluric (MT) data driven workflow, to constrain a deterministic 2D MT inversion. The workflow is applied to a profile in the Mount Isa region in Queensland. The results show that a geologically realistic model with sharp resistivity boundaries associated with the depth to basement transition can be recovered even in presence of a conductive sedimentary cover of thickness greater than 500 meters.

Key words: Magnetotellurics, constrained inversion, Bayesian inversion, depth to basement.

INTRODUCTION

Magnetotelluric (MT) data is sensitive to changes in the resistivity of the subsurface to great depths, making it suitable for mineral exploration in the presence of thick sedimentary cover. Of particular interest is the estimation of the depth to the basement, which helps driving exploration strategies. A reliable estimation of the sedimentary cover thickness requires a precise detection of sharp geological boundaries such as the one existing at the transition between a conductive sedimentary cover and a resistive basement. However, traditional deterministic inversions of MT data impose significant smoothness constraints generally resulting in smooth models which are not geologically realistic. On the other hand, it has been showed that 1D probabilistic inversion of MT data coupled with a Bayesian interpolation approach can accurately estimate depth to basement (Seillé et al, 2021, Seillé et al., 2022a). Therefore, combining an inversion approach that considers physics of the MT problem in 2D with structural constraints derived from a probabilistic 1D workflow suggests that an improved and more realistic image of the subsurface can be obtained.

A typical regularized inversion algorithm optimizes the following cost function Φ:

$$\Phi = \Phi_d + \lambda\Phi_m \qquad with \qquad \Phi_m = \|\mathbf{Rm}\|^2$$

where Φ_d is the data misfit term, Φ_m the roughness term, λ the regularization parameter, **m** the vector of model parameters and **R** the roughness operator. The roughness operator **R** usually penalizes large gradients in the model and drives the solution towards smooth models. Therefore, at specific boundaries between model parameters the smoothness constrain can be removed or reduced and sharp boundaries can develop in the model without penalizing the global cost. Prior information has been incorporated in the cost function in different ways to constrain the inverse problem. For example, Brown et al. (2012) and Yang et al. (2017) have defined the roughness operator based on seismic velocity gradients and seismic envelope attributes, respectively, to enforce a correlation between EM and seismic models. Mackie et al. (2020) incorporated a cross gradient term to the cost function to enforce correlation with seismic gradients derived from a seismic image. Constraints derived from seismic data are generally preferred because of its high resolution and capability to image sharp interfaces. However, seismic data are not necessarily acquired alongside MT data, especially as part or early exploration projects, and little prior information is available to constrain MT inversions.

In this paper we present the result of a workflow developed to inform a 2D inversion of MT data with depth constraints derived from a probabilistic workflow using 1D MT inversions, to map a sharp sediment basement interface along a profile in the Mount Isa province in Queensland. The capability of the 1D probabilistic method to detect discrete horizontal resistivity interfaces, coupled with a clustering approach to classify interfaces and a probabilistic interpolation algorithm, allow to derive a probabilistic depth to basement surface along the profile. This surface is used to constraint a 2D MT inversion, specifying within the roughness operator which model parameter boundaries should have the smoothness constrain relaxed. The results are discussed in comparison with an unconstrained 2D inversion, and some limitations of the workflow are discussed.

METHOD AND RESULTS

The workflow we apply here to regularize a 2D inversion using geometrical constraints was described and applied on synthetic data in Seillé and Visser (2022b). It consists in 4 successive steps: 1) For each MT site, a 1D trans-dimensional Markov chain Monte Carlo inversion (Seillé and Visser, 2020) is performed, to which solution is a probability density function approximated by an ensemble of 1D resistivity models. 2) A resistivity-lithology relationship is then derived fitting a Gaussian mixture model (GMM) to all the MT probability density functions summed together and integrated over all depths. 3) The GMM is then used to classify all the 1D models from each MT sites into lithologies, from which probability distributions on transitions between the different lithologies is derived. The transitions probabilities for each geological interface are then interpolated laterally across the profile using a Bayesian Estimate Fusion algorithm (Visser and Markov, 2019). 4) Finally, these transitions probabilities are used to derive the geometric constraints for a 2D deterministic inversion. The 2D inversion is carried out using the code MARE2DEM (Key, 2016). This code parametrizes the model using unstructured grids, making the inclusion of complex geometries such as the constrains previously derived possible.

Dataset

The workflow described is applied to an MT profile located in Mount Isa, in Queensland, Australia (Figure 1). In this study we use 41 audio MT (AMT) sites, with a separation of 500 meters. The frequency range is between $1-10^4$ Hz. A previous modelling of this MT dataset (Simpson and Heinson, 2020) imaged the basement topography in the area and located it at depth greater than 500 meters beneath the surface. In this study we are interested in mapping the precise and sharp boundary between the sedimentary layers and the basement.

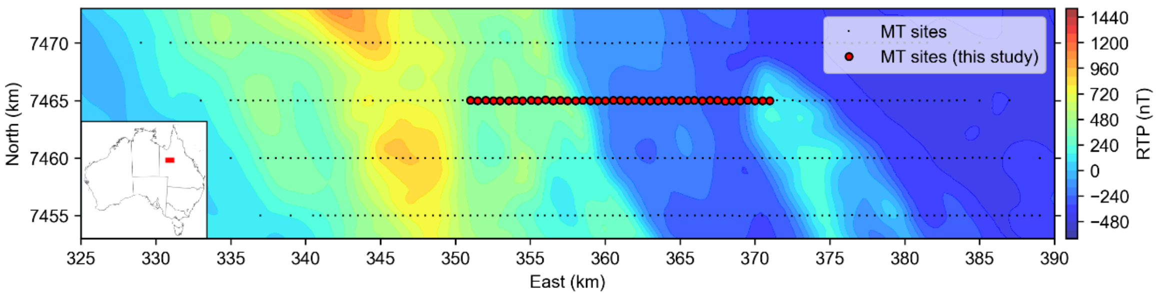


Figure 1. Reduced to pole magnetic map with location of the MT sites along the studied profile.

2D MT unconstrained inversion

We first ran a 2D unconstrained inversion using the MARE2DEM inversion algorithm, which uses an Occam regularization approach, solving for the smoothest model that fits the data. A general NS strike was determined for the MT sites of the profile, and the XY and YX polarizations were assigned to the TE and TM polarizations, respectively. We assigned to the TE and TM data error floors of 10% and 5%, respectively. The starting model had a homogeneous resistivity of 100 Ωm. The inversion converged to an RMS of 1.0 after 13 iterations. The model (Figure 2a) obtained shows the succession of 4 layers, from top to bottom: a thin conductive layer / a resistive sedimentary layer / a conductive sedimentary layer / a resistive basement. This succession is dipping towards the west.

1D Bayesian MT inversion

The 1D Bayesian inversions were ran using a Bayesian MT inversion, where input data errors were replaced by likelihood functions dependent on the MT phase tensor and specific for each MT site, to account for 2D and 3D effects existing in the data (Seillé and Visser, 2020). The inversions were run for each MT sites using 40 chains of 10^6 iterations each. The medians of the posterior probability distribution obtained for each MT site are shown in Figure 2b. A similar pattern with 4 successive lithologies of varying resistivity is observable.

Generation of structural constraints

We first define a resistivity-lithology relationship for the entire profile, using the resistivity model ensemble. An empirical resistivity probability density function (ρPDF) is derived recording resistivity values across all sites, for all models, across all depths (Figure 3). A classification algorithm similar to the one proposed by Minsley et al. (2021) is then used to find a Gaussian mixture model (GMM) that fits the empirical resistivity pdf. It uses a least square minimization, iteratively fitting one Gaussian at a time guided by the local maxima in the empirical ρPDF, given a set of bounds on the model parameters. The resulting GMM (Figure 3) is comprised by 3 components, each one being associated to a resistivity-lithology class c, with $c \in \{GM_1, GM_2, GM_3\}$.

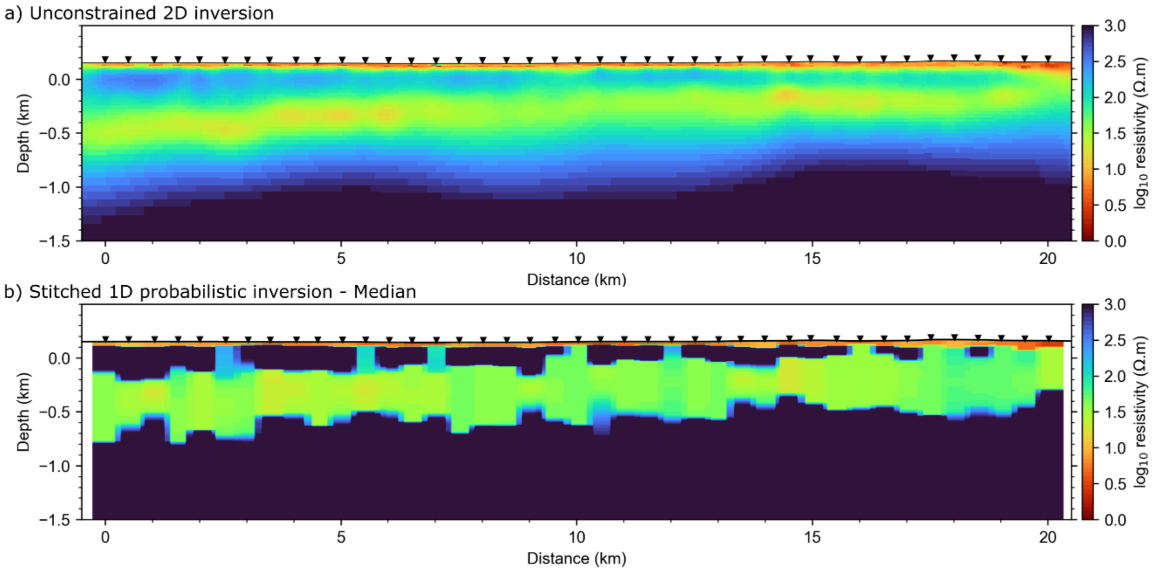
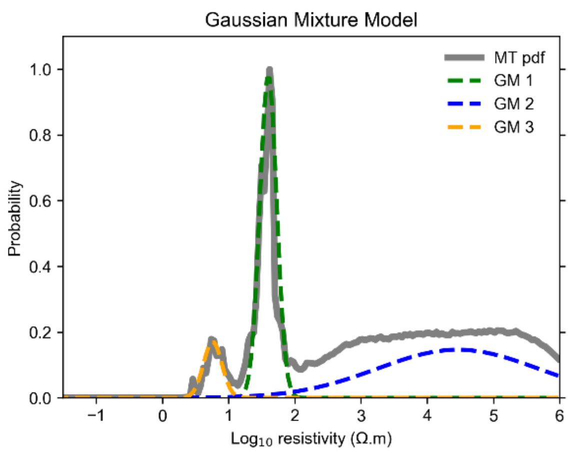


Figure 2. a) Unconstrained 2D MT inversion. b) Stitched median of the 1D probabilistic inversions.

Then, using the GMM, for each layer l_k of each model of the MT ensembles we denote the probability of l_k to belong to class *c* given its resistivity ρ_k as $p(l_k = c \mid \rho_k)$.



The most probable lithology of layer l_k is defined as $argmax_c\ p(l_k = c|\rho_k)$. Having classified the most probable lithology for each layer, we can derive probabilities on the depth at which transitions between the different lithologies occurs. In this study, we focus on the transitions between lithology 1 and lithology 2 (Figure 3), which define the sediment-basement boundary probability distribution for each MT site. In a final step, these depth to basement probabilities are interpolated laterally using a Bayesian estimate fusion algorithm (Visser and Markov, 2019) to produce a depth to basement probabilistic surface (Figure 4a). The median (50^{th} percentile) of this distribution is the used as the depth constraint for the 2D constrained inversion.

Figure 3. Empirical MT resistivity distribution fitted by the Gaussian mixture model.

2D MT constrained inversion

The depth to basement surface derived is incorporated into the MARE2DEM inversion. The algorithm allows to relax the roughness penalty along parameter boundaries defined by the depth to basement surface. We used the same homogeneous starting model and inversion parameters as for the unconstrained inversion. The inversion converged to an RMS of 1.0 after 11 iterations. The model (Figure 4b) shows similar structures as the unconstrained model, but the top of the resistive basement appears well depicted, contrasting with the overlying sediments.

CONCLUSIONS

The workflow that was presented showed that the structural constraints derived through the lithological classification of the 1D MT model ensembles are compatible with the 2D MT data, resulting in a 2D constrained model that fits well the data while defining a sharp boundary at the sediment basement interface. This type of model is geologically more interpretable. Along this short profile in Mt Isa, the basement appears to be very resistive and dipping to the west. However, it is important to note that due to the non-uniqueness of the inversion of noisy MT data, inaccurate structural constraints could provide models with acceptable data fit (Brown et al., 2012). Performing 2D inversions with a set of constrains would allow in that case to define the range of solutions that are compatible with the data, using for example the 10^{th} and 90^{th} percentiles of the posterior distribution on the depth to basement as constraints. Also, the workflow would beneficiate from the use of lithological and petrophysical information extracted downhole close to the modelling area.

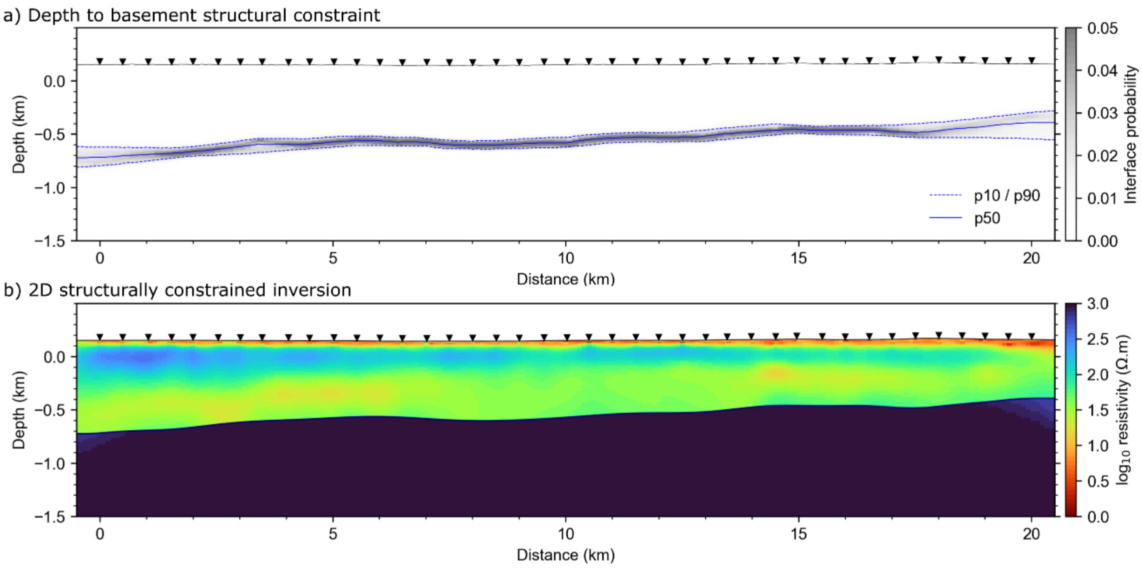


Figure 4. a) Depth to basement probabilistic surface. Blue dashed and solid lines represent the 10th/90th and 50th percentiles. The 50th percentile is used as the structural constrain for the 2D inversion. b) Structurally constrained 2D MT inversion.

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