Magnetic inversion constrained by probabilistic magnetotellurics models: methodology and application

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SUMMARY

We introduce a sequential inversion workflow where we integrate magnetotelluric and magnetic data. We first perform probabilistic MT inversions, from which we derive 2D or 3D probabilities of observing an interface between rock units of contrasting electrical resistivity. Secondly, we use these probabilities to partition the model into domains where different rock units, or combinations thereof, can be observed. Using these domains, we define constraints for magnetic data inversion where the corresponding intervals (joint or disjoint) of magnetic susceptibility are used as spatially varying bound constraints for inversion. After introducing the methodology, we investigate the proof-of-concept using a geologically realistic synthetic model and conclude that the proposed methodology is applicable to field data. We then present ongoing investigations in the Cloncurry area (Queensland) on a 2D line to image the thickness of the sedimentary cover and to reduce interpretation uncertainty.

Key words: potential fields, magnetotellurics, constraints, inversion, integration.

INTRODUCTION

The development of techniques exploiting the complementarities between geoscience disciplines connected by a common goal, i.e, characterizing the subsurface, has become one of the workhorses of academia and industry alike over the past two decades or so (see reviews of Lelièvre and Farquharson, 2016, Moorkamp et al., 2016).

On the geophysical side of the exploration geosciences, much of the data integration effort has focused on introducing new algorithms capable of connecting geophysical techniques obeying different physics through multi-physics modelling codes. This includes linking the models inverted jointly using well-known principles introduced in Haber and Oldenburg (1997) and Gallardo and Meju (2003), to enforce structural similarity, or the use of petrophysical relationships (e.g., Lelièvre et al., 2012, Sun and Li, 2015, Giraud et al., 2017 and others).

On the contrary, there remains a relative paucity of studies focusing on leveraging the interoperability between existing modelling approaches to exploit the complementarities that exist between different disciplines. The cost effectiveness and the flexibility such approach may offer motivated us to develop a cooperative workflow where the inversions of different datasets can run in a standalone, sequential fashion. Here, we develop a workflow where information from magnetotelluric (MT) inversion can be automatically passed on to magnetic data inversion to take advantage of the respective strengths of these two geophysical techniques. More specifically, we use probabilistic 1D MT inversions, which are sensitive to vertical resistivity variations, to constrain magnetic data inversion, which is more sensitive to lateral magnetic susceptibility changes.

The process can be summarised as follows:

1) We run probabilistic 1D MT inversions and use the resulting ensemble of models to calculate the probability of observing an interface between specified rock units in 2D or 3D using a Bayesian estimate fusion method (see Seillé and Visser, 2020, Visser and Markov, 2019).

2) Using such MT-derived probabilities, we subdivide the modelled area into domains where different geological units can be observed (i.e., two or more rock units with a probability of occurrence superior to zero). Using prior knowledge about the rocks' magnetic susceptibilities, we use these domains to derive ranges of plausible magnetic susceptibility values across the studied area.

3) We perform magnetic data inversion using bound constraints allowing multiple, disjoint intervals as defined by these MT-derived domains (extending Ogarko et al., 2021, to the magnetic data case). This allows us to differentiate the rock units allowed by probabilistic 1D MT inversions by confronting the different possibilities to magnetic data and to reduce the range of possible interpretations.

The remainder of this abstract is organised as follows. In the methodology section, we provide essential background information about MT inversion, the domaining approach and magnetic data inversion. Following this, we introduce the synthetic model and present preliminary results of a field application case in the region of Cloncurry (Queensland).

METHODOLOGY

In this section, we introduce the different elements of the workflow in the same order as they are performed and listed in the Introduction.

MT modelling (1st stage)

The 1D MT inversions are run separately for each MT site using the approach developed by Seillé and Visser (2020), who employ a trans-dimensional Markov chain Monte Carlo sampler. The 1D MT inversion code is robust to 2D and 3D effects present in the MT measurements thanks to a dimensionality error modelling procedure. It translates phase tensor parameters into dimensionality uncertainties that are accounted for during 1D inversion. Interface probabilities are then derived across the survey combining the posterior ensembles derived from the MT inversion using a Bayesian estimate fusion algorithm (Visser and Markov, 2019), and translated into the observation probability of each rock units.

Domaining using MT inversion results (2nd stage)

Starting from the rock units probabilities derived for the complete model, we first calculate the projection of such probabilities on the mesh used to model magnetic data inversion in 2D or 3D. We then define domains for magnetic data inversion from such interpolated probabilities by applying a transform as explained below.

Considering the probability of occurrence of the rock units as a matrix $\boldsymbol{\psi} \in \mathbb{R}^{N \times M}$ (with N the total number of rock units and M the number of model cells), the domain d a given cells with index j belongs to is determined by identifying all probabilities $\psi_{i=1..N}^{j} > 0$. This allows us to uniquely define each combination of rock units in a given model-cell. After calculating d for each model-cell, we can assign the corresponding ranges of magnetic susceptibility to constrain gravity inversion. Conceptually, such constraints are illustrated in Figure 1 for the sediments – basement case (2 rock units).

Magnetic data inversion (3rd stage)

We invert magnetic data consisting of the reduced to the pole (RTP) magnetic anomaly using the Tomofast-x inversion platform (Giraud et al., 2021). The implementation used here extends the disjoint interval bound constraints using the alternating direction method of multipliers (ADMM) introduced in Ogarko et al. (2021) to the magnetic data inversion case constrained by MT information. Using such constraints, magnetic susceptibility is encouraged to remain within intervals defined by domains that are input to the inversion algorithm.

Note that unconstrained inversion and the application of constrains with a single domain allowing the magnetic susceptibilities of all rock units everywhere in the model may be used to identify features sensitive to MT and magnetic data without quantitative integration of the two methods and areas where it may be necessary to reconcile the different disciplines in the next stage of the workflow.

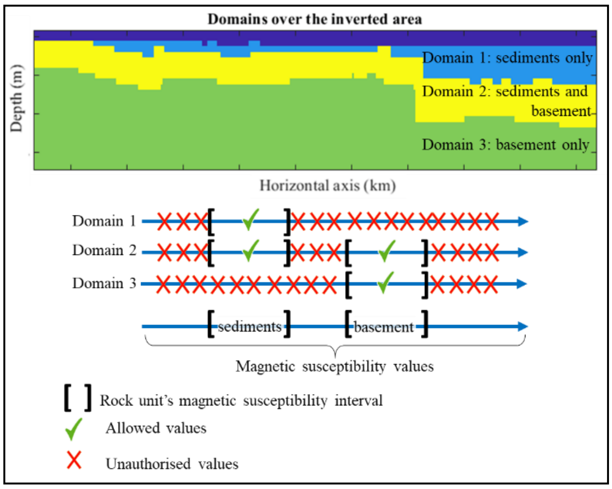

Figure 1. Conceptual representation of domaining to constrain magnetic data inversion in 2D.

PROOF-OF-CONCEPT

We test our methodology using an idealised model derived from geological data from the Mansfield area (Victoria) made available by Pakyuz-Charrier (2018) and populated with literature resistivity and magnetic susceptibility values.

The true magnetic susceptibility model is shown in Figure 2a. The shallow, low magnetic susceptibility areas correspond to the sedimentary cover while the deeper units with high magnetic susceptibility values correspond to the basement. In the simulation of MT data, we assume a conductive sedimentary cover and resistive basement. We simulate a realistic acquisition setup of airborne magnetic measurements and MT data in terms of noise contamination and data spacing.

After performing MT modelling, we calculate domains from the rock units probabilities. The domains that can be derived from MT modelling are shown in Figure 2b. Inverted magnetic susceptibilities are shown in Figure 2c (unconstrained inversion) and Figure 2d (inversion using MT-derived domains). Note that in the constrained case, the only constraints applied to inversion pertain to the utilisation of the disjoint interval bound constraints. While possible, the utilisation of prior information such as a prior model derived from MT or the utilisation of MT uncertainty to derive spatially varying smoothness constraints in the same fashion as geological uncertainty in Tomofast-x (e.g., Giraud et al., 2019), lies beyond the scope of this abstract and is the object of future work.

The comparison of Figure 2c with Figure 2d indicates clearly that the utilisation of domains derived from MT inversion results to define spatially varying bound constraints for magnetic inversion results in a magnetic susceptibility model that:

1) is closer to the true model (Figure 2a) in terms of the depth of the sediment – basement interface and in terms of the magnetic susceptibility histograms;
2) is easier to interpret and to feed back to geological or MT modelling for another iteration.

From the tests performed on synthetic data discussed above and shown in Figure 2, we conclude that the proposed methodology can be applied to field data and complement existing modelling approaches.

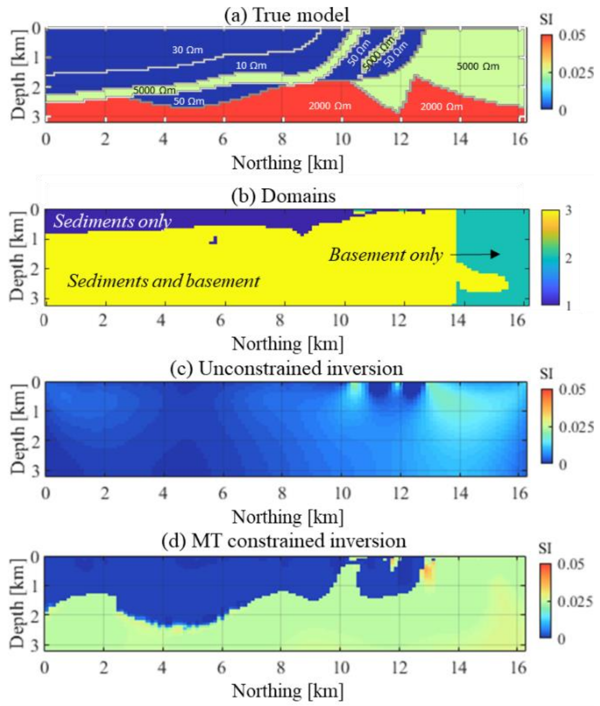

Figure 2. Synthetic tests. (a) shows the true magnetic susceptibility model, (b) shows the domains derived from probabilistic MT modelling, (c) shows the unconstrained inversion results and (d) the case with MT-derived bound constraints.

FIELD APPLICATION

In this section, we introduce ongoing investigations in the Cloncurry region (Queensland), in a district that is gaining interest for its prospectively in economic minerals. We apply the workflow presented above to a 2D line where magnetic data suggests the presence of complex geological features. Here, we use the combination of geophysical techniques to reduce uncertainty and improve our understanding of the geology of the area. The study area is shown in Figure 3a and the magnetic data map is shown in Figure 3b below. It consist of the RTP data freely available on the Queensland geological survey. Prior MT information consists of the probabilities of observing the sediment units (Figure 3c), the complementary of which is the probability of observing non-sedimentary units.

In Figure 3 is indicated the profile where the 1D probabilistic inversions and the fusion of the MT data (Seillé et al. 2020) were performed. . To confront the results obtained (Figure 3c)with magnetic data, we first performed unconstrained magnetic data inversion, as shown in Figure 4a. Following this, we estimate a magnetic-only derived basement interface model. To this end, we apply the ADMM constraints to cluster the inverted magnetic susceptibilities within prescribed intervals without applying any domaining. Such constraints encourage the magnetic susceptibilities to lie within the following interval (in SI):

$$[-0.005, 0.005] \cap [0.015\ 0.085] \quad \text{(eq. 1)}$$

The results of such inversion is shown in Figure 4b. It shows that many subvertical anomalies are present in the model. The comparison of inversion results shown in Figure 4a and 4b with MT-derived probabilities (Figure 3c) suggests that constraining the top of the basement using the MT results could allow to locate more accurately the depth and extent of these magnetic anomalies and to refine their geometry.

Our preliminary results also suggest that the constrained inversion could highlight possible discrepancies between the magnetic data and the constraints used, and therefore allow for adjustment of the geological hypotheses and the MT-derived constraints in the areas highlighted in Figure 4b.

CONCLUDING REMARKS

We have presented a cooperative workflow leveraging complementarities between probabilistic MT modelling and magnetic data inversion by ensuring the interoperability between codes that otherwise run in a standalone fashion. We have demonstrated the applicability of the methodology to field data through a synthetic study and introduced current investigations in a region that is prospective for economic minerals.

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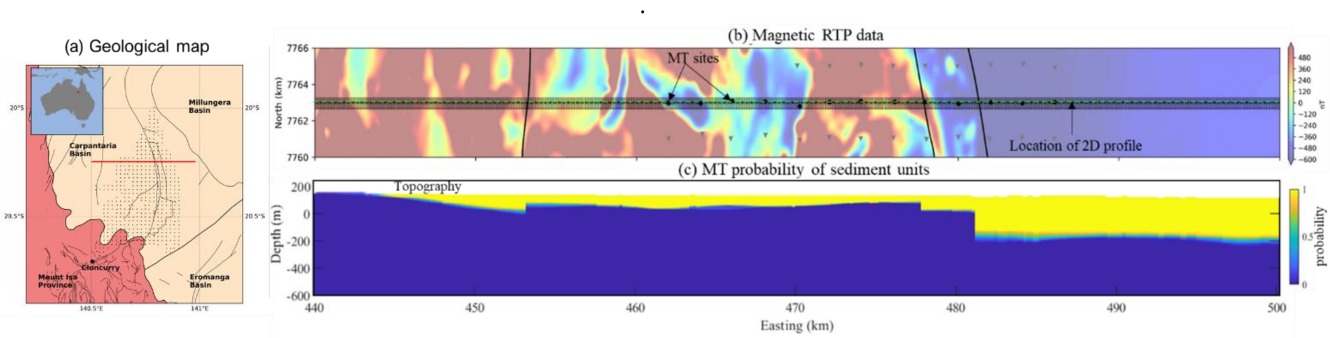

Figure 3. Study area and context. (a) Geological map of the of the area . In red the Proterozoic rocks of the Mt Isa Province, in pale yellow the cover sequences of the sedimentary basins. Red line is the location of the profile. (b) shows the magnetic data map and the location of the MT sites (black dots), and 2d profile along the green dashed line that we focus our modelling effort on. Note that the area constrained by MT data does not extend to the east of west beyond the location of MT sites. (c) shows the probabilities of observing the sedimentary units derived from MT inversions.

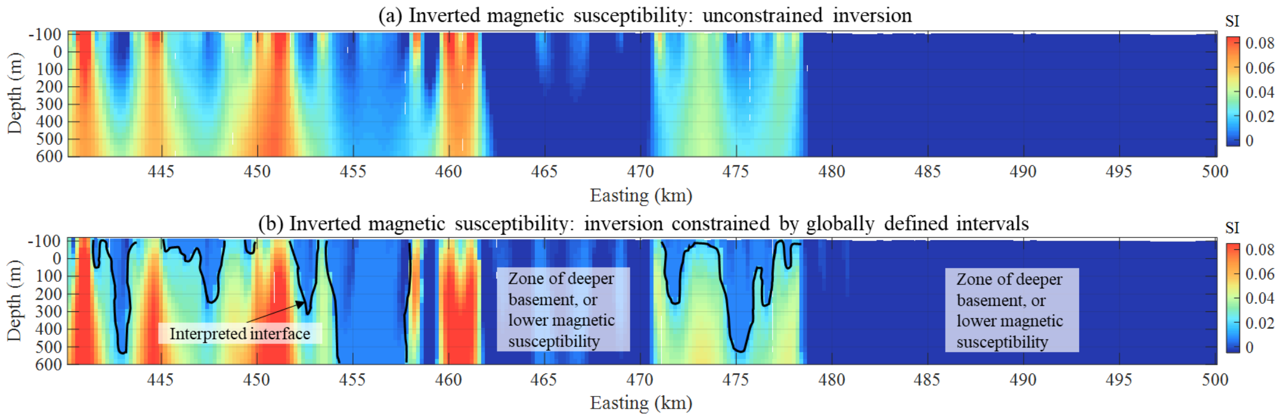

Figure 4. (a) unconstrained magnetic data inversion results (b) results of magnetic data inversion constrained by global, disjoint interval bound constraints (without use of MT inversion results)