Petrophysics in Inversion

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ABSTRACT

Petrophysics provides the link between geology and geophysics, since it is the physical properties of rocks which govern their geophysical response. Knowledge of petrophysics is therefore a key driver for integrated interpretation of geology and geophysics. In particular, given that inversion generates petrophysical models from geophysical data, understanding of rock properties is an important determinant of the effectiveness of inversion. The aim of this paper is to briefly review the roles of petrophysics in inversion.

The two main types of petrophysical data are measurements on core samples or in situ *measurements recorded downhole. This reliance on boreholes means that petrophysical data is generally scarce and not necessarily representative in greenfields exploration. Even in advanced projects and at mines, data coverage is often sparse and irregular. In addition, the scale (volume support) of a petrophysical measurement is extremely small relative to the volume of a typical inversion model cell. Linear upscaling is valid for density and (low) susceptibility, but rigorous upscaling of electrical properties can be problematic. The combination of scarcity and scale complicate interpretation and exploitation of petrophysical data.*

Petrophysical data can expedite inversion in three main ways: by increasing confidence in forward modelling, by constraining inversions, and by underpinning interpretation of inversion results. Forward modelling, to compute synthetic data, is a pre-requisite for inversion and also plays a key role in survey design and in hypothesis testing after drilling. The validity and relevance of the synthetic data rest on the geometry and physical properties of the model to which they refer. The need for geological and petrophysical constraints during inversion arises because there are usually an infinite number models which are acceptable in terms of data fit; the models which conflict with what is already known about the geology and petrophysics of the area must be rejected. Property bounds imposed on geological units or on individual model cells are the most common form of constraint. Fixed (upscaled) values can be assigned to cells containing property measurements. If inversion is performed on a geological model rather than a pure property model, a richer set of options is available, both for inversion style and for constraints. For example, a probability distribution or variogram model can be imposed on the physical properties within geological domains. After inversion, it is desirable to update the geological model, and define exploration targets, via analysis of the inverted property model(s). Supervised or unsupervised computer algorithms can be brought to bear to infer rock type from physical properties. The result is an integrated interpretation, consistent with the available geological, geophysical, and petrophysical data.

INTRODUCTION

Geophysical methods map variations in the physical properties of rocks. Petrophysics, therefore, provides the link between geology and geophysics. In metalliferous exploration and mining, the properties of prime interest are usually density, magnetic susceptibility and remanence, conductivity, resistivity, and chargeability.

In mineral exploration inversion is generally understood as a computational process used to find a petrophysical model, i.e. a sub-surface distribution of a physical property, which explains a geophysical data set. Unfortunately, there are usually an infinite number of rock property models satisfying the geophysical data acceptably well, owing to the limitations imposed by physics, logistics, and experimental error. One valid response to this issue of non-uniqueness is to endeavour to characterise the entire suite of possible models in statistical fashion, e.g. Bosch et al (2001), Minsley (2011). Probabilistic approaches to constrained inversion are computationally onerous and are themselves subject to uncertainties. Philosophically, there is also a limit as to the utility of probability-based decision-making in exploration, an endeavour driven more by possibility than probability. We largely restrict attention to a single "best information" model here, but recognise that a deterministic methodology carries additional risk.

The pre-requisites for geophysical inversion are a physical property model defined over some volume, a forward algorithm which predicts the geophysical response from the model, and a geophysical data set. "Geophysical data" here refers to measurements influenced by a large and poorly defined volume of rock; geophysical data are often recorded remotely, e.g. from the air. By contrast, "petrophysical data" are recorded in close proximity to the small rock volume to which they refer;

petrophysical data are directly affected by the mineral composition and texture within that localised volume. There are two main types of petrophysical measurements: those recorded on rock samples and those recorded downhole. Measurements on core samples are clearly petrophysical, while aeromagnetic data are clearly geophysical. Wireline logs are petrophysical, but downhole TEM measurements are geophysical.

Petrophysical data serve three main roles before, during, and after inversion (Mitchinson, 2013):

1. Forward modelling

With knowledge of physical properties, synthetic geophysical data can be computed for geological scenarios of interest using an appropriate forward algorithm. Forward modelling is undertaken for survey design, for assessing fit to measured data during inversion, and for auditing targets post-drilling.

2. Constraining inversions

Geophysical data sets usually admit a wide range of possible interpretations, or in mathematical terms the solution of the geophysical inverse problem is said to be non-unique. Therefore it is desirable to honour geological and petrophysical information during inversion, in order to produce models which are consistent with what is already known about the geology. The integration of petrophysical, geological and geophysical information reduces uncertainty (Giraud et al, 2016).

3. Interpreting inversions

Interpreting geology from inverted models demands a knowledge of physical properties. Sometimes orebodies exhibit strong physical property contrasts with respect to their host rocks, e.g. VMS mineralisation. However, geophysics is increasingly deployed as a geological mapping tool first and foremost, to define favourable ore settings. Targets may be expressed as subtle variations in physical properties related to alteration.

These three roles are illustrated schematically in Figure 1. This paper aims to describe these roles more fully, and hence to demonstrate the benefits of collecting and analysing petrophysical data. The remainder of the paper is comprised of five sections. Factors influencing petrophysical data are briefly reviewed, and then the three main applications of petrophysical data in inversion are considered in turn, followed by conclusions.

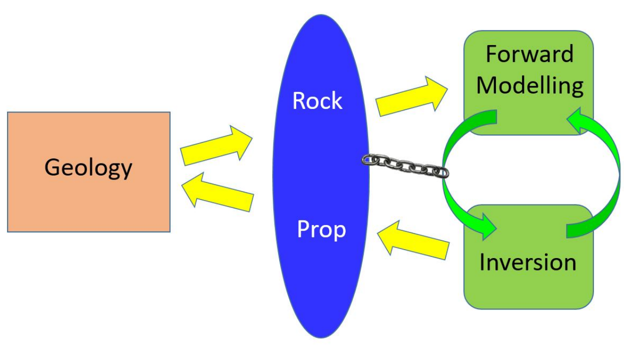

Figure 1: Schematic to illustrate central role of petrophysics in integrated interpretation. Geology and geophysics relate through the "lens" of rock properties. The chain signifies constraints.

FACTORS INFLUENCING PETROPHYSICAL DATA

Before illustrating the role of petrophysical properties in forward modelling and inversion, it is important to introduce several key factors that affect physical property measurements.

Rock samples versus downhole data

Although physical properties can be measured on rock faces or hand samples, the great bulk of the data is recorded either on drill cores samples or in drill holes. These two types of measurements are starkly different in terms of sample volume and experimental conditions. Consequently it is often difficult to reconcile reading(s) from a small volume of core in air with reading(s) from the rock enclosing a downhole probe, even if the two instruments are consistent in terms of underlying principle and calibration.

In the context of inversion, downhole logs are almost always preferable to readings on core because they provide an almost continuous record of *in situ* properties, are generally more accurate, and are more representative (by virtue both of their greater spatial density and larger "support" volume). Downhole logs do not rely implicitly on core recovery, and indeed can be recorded in percussion holes. On the other hand, wireline logging is not always feasible, even when planned, e.g. if holes collapse or conditions are unsuitable (such as a dry hole for resistivity logging).

Core samples, removed from their natural environment, can differ from the rock *in situ* in terms of groundwater (salinity, temperature, and degree of saturation), fracturing, magnetisation, and oxidation. In particular, sulphides oxidise and become more resistive, and magnetite can oxidise to hematite, becoming much less susceptible. Therefore petrophysical determinations on mineralised core samples sourced from historic holes should be treated with suspicion. Drying may also lead to cracking, or even complete disintegration of the sample. In general the deviation between core and *in situ* properties is most significant for electrical properties (conductivity, resistivity, chargeability), somewhat significant for magnetic properties (susceptibility, remanence), and least significant for mass properties (density, porosity).

Core samples do offer one big advantage over downhole measurements: certainty in terms of support. The physical properties can be attributed to a particular core sample unequivocally, and hence related to its mineralogy, assays, and geotechnical characteristics with confidence. In mines core samples provide an opportunity for establishing correlations between physical properties and lithology, alteration, assays, and geotechnical and geometallurgical parameters. Better understanding of these relationships at mine scale expands the role of downhole logging at mines, and develops petrophysical insights which can be applied in exploration.

Effect of scale

Most rocks are by their very nature heterogeneous at the scale of their constituent grains or crystals. Therefore, petrophysical properties are always dependent to greater or lesser degree on the sample size or the "support" volume of the measurement.

Physical properties can be measured at the scale of individual crystals (e.g. Roach et al, 1997), but core sample measurements are usually the highest resolution data available. Core sample volume is normally at least 100 times smaller than the "volume of influence" of a downhole probe, e.g. 0.5m radius sphere, which is in turn orders of magnitude smaller than typical cell volumes in inversion models. Model cell volumes generally range from ~10^3 m^3 at mines to ~10^7 m^3 for regional interpretations, i.e. are at least 10^5 times larger than core samples. Thus a core sample could differ in volume from a regional model cell by 9 or more orders of magnitude!

Taking account of differences in support volume is a familiar consideration in mining geostatistics (Journel & Huijbregts, 1978). However, the underlying assumption of additivity (which, strictly speaking, does not even apply to grade) is untenable for some petrophysical properties. Consequently, while density, porosity, and (low) susceptibility are amenable in principle to conventional geostatistics, others (notably the electrical properties) are not: the conductivity of a rock volume cannot always be reliably estimated from the average conductivity of its constituent parts. In general, conductivity increases as sample volume increases, since additional conduction pathways become available, be they electronic or ionic. Similarly, mineralised core samples are often more resistive than their parent rock *in situ* by virtue of their small scale, e.g. Close et al (2001). However, there are exceptions: for core samples containing conductive particles uniformly dispersed in an insulating matrix, conductivity is proportional to $1/D^2$, where D is the core diameter (Yang & Emerson, 1997).

For petrophysical data recorded downhole, the support volume itself is difficult to define: the "range of influence" for a downhole probe is fuzzy, and often property dependent. These points are illustrated in Figure 2, showing the effect of conductivity on the support volume of an inductive conductivity probe.

The non-linear nature of the "support effect" on some physical properties is well appreciated in the petroleum industry, e.g. Frykman & Deutsch (2002), Dubrule (2003). In seismic velocity models the cells are much larger than the volume associated with downhole sonic log measurements, in part because of a large difference in frequency. A range of "upscaling" algorithms has been developed to estimate seismic velocity, at ~100 Hz, from sonic logs, at ~2 kHz (e.g. Tiwary et al, 2009). In principle, analogous upscaling algorithms could be developed for, say, resistivity. This would be feasible in sedimentary environments, e.g. when Archie's Law applies, but is technically daunting in general: the resistivity of rocks spans a huge range, and is sensitive to mineralogy, texture, permeability, saturation, salinity, and temperature.

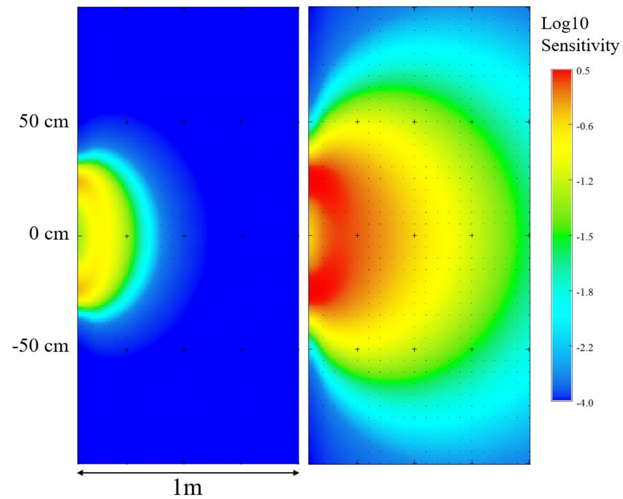

Figure 2: Effect of conductivity on support volume of a two-coil inductive conductivity probe, operating at 20kHz in a homogeneous medium. Conductivity is 1000 S/m (left) and 0.1 S/m (right). Based on the formulations of Moran & Kunz (1962) and Anderson (1968).

In practice, it is not uncommon to upscale petrophysical data linearly in mines or at advanced exploration projects when data coverage warrants 3D interpolation of one or more physical properties. Kriging is often employed for interpolation of the upscaled data within the inversion model volume, even for electrical properties, notwithstanding the underlying conceptual difficulties. Kriging offers convenience and flexibility, plus estimates of variance. In most cases density and/or susceptibility are interpolated, in which case no serious technical objections arise.

In grassroots exploration, sparsity and scale of petrophysical data generally conspire against upscaling in the normal sense. The available rock property data guide selection of starting values assigned to model cells, but inversion itself constitutes the best means for upscaling and interpolation.

Effect of mineral abundance and texture

In general physical properties are governed by mineralogy (silicate, oxide, sulfide), mineral abundance (modal composition, proportions), texture (porosity, grain size, foliation), and fluid content and composition.

A simple linear relationship links mineral abundance with density and (low) susceptibility. However, conductivity is usually non-linearly related to mineral abundance by virtue of its sensitivity to rock texture. In a low sulphide situation, the higher porosity associated with alteration mineralogy (micas and clay minerals) can exert a stronger effect on the conductivities than sulphide mineral abundance, e.g Bell porphyry Cu-Au deposit, British Columbia (Mitchinson et al, 2013) .

Some minerals, notably pyrrhotite and chalcopyrite, exhibit a greater propensity to develop networks through the rock mass than cubic minerals such as pyrite and galena. A low concentration of chalcopyrite can produce a higher conductivity than massive pyrite. Consequently as chalcopyrite or pyrrhotite content increases, the bulk conductivity can increase very rapidly when continuous electrical connection is established. This critical mineral concentration, or "percolation threshold", can be as low as 1 vol%. On the other hand, the conductivity of rock with disseminated sulphide mineralisation can be low, even at relatively high mineral concentrations.

Calibration and data dynamic range

For some applications of petrophysical data, calibration is not critical as long as the readings are repeatable. In other words, precision can be more important than accuracy. An uncalibrated susceptibility probe can be used to log boundaries between magnetic and non-magnetic formations, provided its data are repeatable and provided its sensitivity is adequate to detect the susceptibility contrast. Calibration becomes important when multiple different instruments are employed, or when petrophysical measurements are used for quantitative purposes, e.g. density in a resource model or conductivity in a starting model for inversion. In the case of susceptibility, for example, the unit (cgs or SI) and "range" (defining the power of ten) may not matter unless the data are intended to constrain forward modelling and inversion.

Conductivity and resistivity of rocks span an enormous range, over 20 orders of magnitude. Although conductivity and resistivity are generally treated as equivalent (reciprocals), in fact they are different: conductivity is measured inductively, with coils, whereas resistivity is measured galvanically, via direct injection of current. Resistivities are very unreliable for highly conductive samples, e.g. fresh massive sulphides, because the measured voltage differences are very small. Conversely, inductive conductivity is very insensitive to variations in resistivity between highly resistive rocks. Thus a large resistivity data base may be of limited value when interpreting EM data. The sensitivity will be instrument and parameter dependent. Operating frequency is an important consideration for inductive conductivity, as is electrode separation for galvanic resistivity. The enormous range of conductivity/resistivity, and the calibration issues that arise as a result, complicate reconciliation of electrical data from different sources.

FORWARD MODELLING

Forward modelling is the calculation of geophysical data on, above, or inside a petrophysical model. Synthetic geophysical data can be predicted at actual or proposed measurement locations. A forward modelling capability is a pre-requisite for inversion and also plays a key role in survey design and in "ground-truthing" after drilling.

If the starting point is a geological model, either conceptual or real, each geological unit must be attributed with physical properties. Geological units are usually assumed homogeneous initially. In an ideal world, a comprehensive petrophysical data base would be available, comprising downhole logs and/or measurements on core samples. In that case the petrophysical characteristics of each rock type could be analysed statistically, to yield suitable starting values and ranges (upper and lower bounds). In practice reliable physical property data are often scarce, especially for greenfields exploration. Consequently starting values are often assigned on the basis of published compilations, or drawing on experience, or by accessing on-line petrophysical databases managed by government mines departments or private companies, e.g. Mira Geoscience (Parsons & McGaughey, 2007),.

At mines or advanced exploration projects, wireline logs may be available from several drill holes in a reasonably compact area. In such cases the petrophysical data can be upscaled to the model cell size and then interpolated in 3D to create a heterogeneous property distribution. Kriging is commonly used for interpolation, based on an assumed simple variogram model. However, objectives and data density may justify variography in each of the geological domains, e.g. Schetselaar et al (2017). It may be possible to increase the spatial extent or resolution of a petrophysical model by exploiting a correlation with another data set. For example, a positive correlation between density and FeO concentration at the Lalor Zn-Cu-Au deposit, Manitoba, enabled Schetselaar et al (2017) to generate higher resolution density and P-wave velocity models via collocated cokriging. The seismic response from Lalor was then predicted from these density and velocity models, and compared with the measured seismic data. In general, the available petrophysical data are usually too sparsely distributed, or too localised, to support 3D interpolation over a sufficiently large volume for forward modelling. However, a detailed petrophysical model volume can be blended into a larger model (Figure 3).

Knowledge of physical properties can influence choice of forward modelling software; in the context of magnetics, for example, self-demagnetisation should be taken into account when susceptibility is high (e.g. Fullagar & Pears, 2013a), and not all programs allow specification of remanent magnetisation in individual geological units.

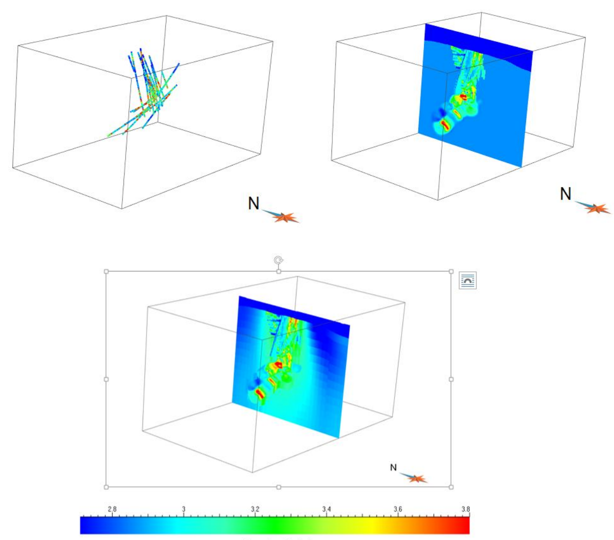

Figure 3: Density modelling at Prominent Hill IOCG deposit, South Australia. (a) Selected drill holes, coloured by core density; (b) Section through density model based on interpolation of core

measurements; (c) Same after constrained gravity inversion (after Fullagar & Pears, 2013b).

If the purpose of the forward modelling is survey design, calculated responses can be assessed with respect to expected noise levels to determine whether the proposed survey specifications (frequency, flying height, line spacing, etc.) are likely to prove effective. Physical properties also influence choice of methods. For example, a strong density contrast at Platreef level in the Bushveld, South Africa, (Figure 4) provides a strong case for mapping the ore horizon with gravity and reflection seismic methods (Williams et al, 2016).

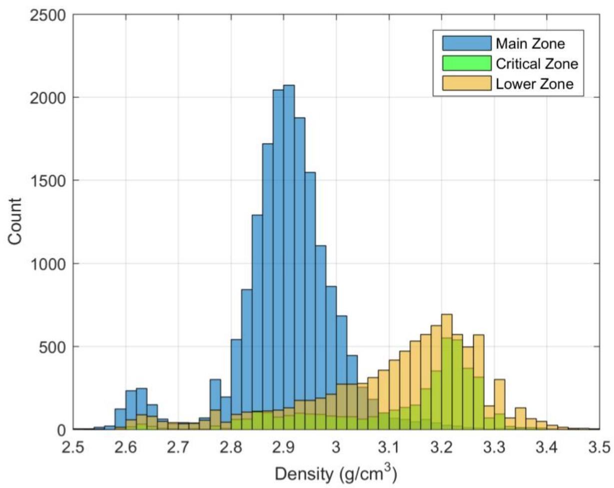

Figure 4: Density histograms for Bushveld formations. The Critical Zone (or Platreef) hosting PGE-Ni-Cu mineralisation lies between lower density gabbronorites of the Main Zone, and higher density rocks of the Lower Zone (after Williams et al, 2016).

In the ground-truthing application, forward modelling is undertaken to determine whether the material intersected in drill hole(s) is sufficient to explain the geophysical data. Drilling constrains the target geometry, and petrophysical data from the new holes characterise the relevant properties, albeit with the usual caveats about the effect of scale.

Forward modelling is the first step towards quantitative interpretation of field data. Comparing the starting model calculated responses with the measured data is always worthwhile prior to launching inversion. It allows the user to confirm that the model and data are correctly located with respect to one another, and to verify that the synthetic data are consistent with expectations, both in terms of amplitude and qualitative appearance. Forward modelling can flag calibration problems with either geophysical data or physical properties.

Trial and error manual adjustment of models, guided by forward modelling, is a form of inversion. If the physical properties (or contrasts) are more reliable than the model geometry, then adjustment of size and shape of geological units is warranted in order to improve the data fit. If the geological boundaries are more reliable than the physical properties, then forward modelling can drive manual adjustment of property values.

CONSTRAINING INVERSIONS

The aim of inversion is to define one or more petrophysical models which satisfy a geophysical data set. There is usually an infinite number of rock property models which satisfy the geophysical data acceptably well, i.e. to an accuracy consistent with the uncertainties. Imposing geological and petrophysical constraints focusses the inversion on the subset of models which is consistent with all the available information. Petrophysical constraints ensure that the inverted model reproduces individual measurements at specific locations and/or conforms to data-based statistical models within geological domains.

Ideally, inversion is performed on a geological model. Geological models are comprised of rock type domains, confined between structural and formational boundaries. Physical property starting values must be assigned to the domains prior to inversion.

Inverting geological models delivers flexibility and control not available with pure property models (Fullagar & Pears, 2007). In particular, geological models permit *geometry inversion*, to alter the shape of boundaries, as well as *property inversion* (Figure 5). Property inversion can be either homogeneous, to optimise the physical properties of uniform geological units, or heterogeneous. Assigning different remanent magnetisation within rock type domains, or constraining a physical property to conform to a statistical condition, is natural when inverting on geological models. A sequence of inversions can be performed, assuming homogeneous geological units initially, and only permitting heterogeneity to develop later on in selected units as required to fit the data. Maximising the homogeneity of units is consistent with the reasonable working assumption that geological structural and formational boundaries are the primary control on geophysical data (McGaughey et al, 2014).

Geophysical inversion is often performed on purely petrophysical models, in which cells are assigned one or more physical properties, but are not attributed to a rock type. In "unconstrained" inversion, the starting model is a homogeneous half-space, and the choice of initial property value may or may not exert a strong influence on the inverted model. Cell boundaries are entirely artificial, i.e. bear no relation to geological contacts and structures. After unconstrained inversion, the geological meaning of the (usually smooth) property distribution may not be obvious.

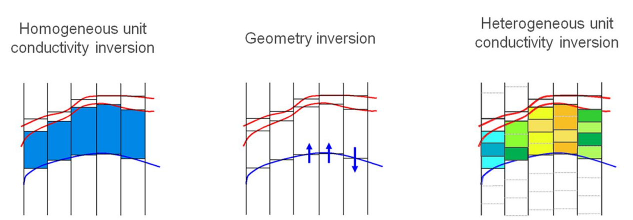

Figure 5: Schematic to illustrate different styles of inversion available on geological models (Fullagar & Pears, 2007)

During any property inversion, the value assigned to a particular cell may not be a reliable estimate of the actual property in that location. An extreme case is apparent density or susceptibility inversion, used to derive initial property estimates from gravity and magnetic data: the model top honours topography, but property variations are purely lateral. Similarly, apparent resistivity and conductivity are commonly used as a basis for first-pass interpretation of electrical and EM data; the values are "apparent", not real. Thus individual cell properties should not be regarded as "true" (upscaled) values unless the cell is fixed, i.e. contains petrophysical measurements.

Uncertainty in physical properties can exert a strong influence on size and shape of elements of inverted models. Whereas geophysical data can sometimes prescribe the "strength" of an anomalous body quite well, a great deal of ambiguity remains in terms of body size if its physical property is unknown. Examples of interplay between volume and property (contrast) include anomalous mass associated with a gravity anomaly, magnetic moment associated with a magnetic anomaly, and in EM the conductance of a layer and the time constant of a compact body. In depth-to-basement inversion, the property contrast at the basement contact controls the amplitude of the topographic relief of that contact required to explain the geophysical data. Therefore, petrophysical constraints can strongly influence inversion models and the conclusions drawn from them.

If a geological model is comprised of homogeneous units, as is often the case at the start of an inversion, the property of each unit can be optimised readily. For example. Fullagar & Pears (2007) optimised the susceptibility of "mineralisation classes" at the Cannington Ag-Pb-Zn mine, Queensland, via bulk property inversion of ground magnetic data collected pre-mining. The shapes of the mineralised units were well defined by drilling, but forward modelling revealed that their susceptibilities were poorly determined (too low) initially. Optimisation of the homogeneous susceptibilities delivered a fast and dramatic improvement to the data fit. Inversion was rapid because only 24 susceptibilities were allowed to vary, even though the model itself was quite complex (82500 cells). The remanent magnetisation of each unit could be optimised in similar fashion (Fullagar & Pears, 2013a).

In pure property models, geological constraints must always be imposed indirectly, via property values. Deviation of model properties from "reference" model properties can be included in the inversion objective function (e.g. Li & Oldenburg, 1996). A commonality of boundaries can be imposed by assuming that petrophysical gradients are coincident (e.g. Leon-Sanchez et al, 2016). This "structure coupling" is a convenient way to formulate joint inversion of disparate data sets, since it avoids scaling issues which arise when parameters with different units are inverted simultaneously (e.g. Gallardo et al, 2012).

Constraints are termed "hard" (objective) here, if honouring observations directly or indirectly, and termed "soft" (subjective), if favouring or penalising certain characteristics. In practice the nature of constraints is often mixed, influenced by both data and user preferences.

Hard Constraints

The most common petrophysical constraints applied during inversion are upper and lower property bounds, based on analysis of the relevant petrophysical data. The bounds may be imposed on all model cells or on subsets of cells belonging to a particular geological unit. If a large number of cells attain an upper or lower bound during inversion, it may be a sign that something unexpected is needed to explain the data. On the other hand, it may simply be an indication that the bound is inappropriate, e.g. based on inadequate or unrepresentative petrophysical data.

In principle, (upscaled) downhole or drill core property measurements can be honoured during inversion by fixing the property in the cells to which they belong. For advanced exploration projects or in mines the petrophysical data density can justify upscaling and fixed cell constraints. However, in greenfields exploration the sparsity of petrophysical data and the huge disparity between measurement and model cell volumes generally preclude fixed cell constraints, or render them subjective, i.e. "soft".

If inversion is performed on a geological model, a wider range of constraint options becomes available than on pure property models. For example different remanent magnetisation can be assigned to individual geological units. If property measurements are available in sufficient quantity to define the probability distribution for a physical property, stochastic inversion becomes viable. A simple form of stochastic inversion is illustrated in Figure 6. In this synthetic example the density in a limestone is constrained to honour a statistical distribution as well as to reproduce gravity data. The model shown is just one realisation; the inversion algorithm produces a new solution each time it is run. All forms of stochastic inversion directly illustrate non-uniqueness: not only do individual realisations differ from one another, but their erratic property variations are in stark contrast to conventional smooth models.

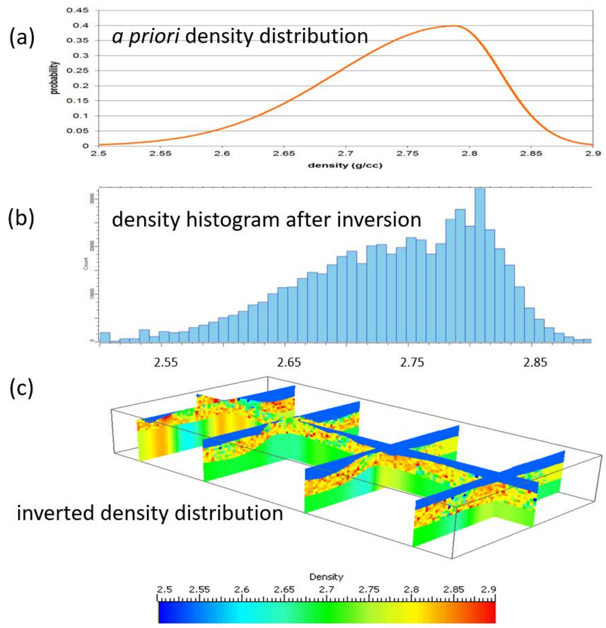

Figure 6: VPmg stochastic inversion of a limestone unit has produced a density distribution which satisfies a gravity data set and honours a statistical distribution.

In geostatistical inversion, the spatial variation of a physical property (not just its amplitude) is statistically constrained. For example Chasseriau & Chouteau (2003) describe a 3D gravity inversion algorithm conditioned by parameter (i.e. cell density) covariances determined via variography of density measurements. The approach is closely allied to kriging, and includes the desirable feature that cells with fixed (known) density are honoured by virtue of their zero variance. Thus petrophysical trends, e.g. a preferred dip, can be incorporated into the modelled rock volumes as well as coarser scale variations required to achieve a fit to the geophysical data.

Algorithms which invoke kriging generate a single smooth model which is "optimal" in some sense. It is instructive to examine less smooth solutions in order to gauge the variability that is permitted by the data and the variography. This can be achieved via stochastic inversion which, as noted above, produces a different, somewhat erratic, property model every time it is run on the same geophysical data, e.g. Shamsipour et al (2010, 2011). To be accepted as a valid solution, a stochastic simulation must satisfy the geophysical data and the (upscaled) petrophysical data, and conform to the variogram model(s). Stochastic inversion of surface and downhole gravity data, constrained by density logs, has been demonstrated at Lalor, Manitoba, by Schetselaar et al (2014).

Soft Constraints

The spatial distribution of physical properties is always conditioned mathematically during property inversion. Smoothness is imposed commonly, and depth weighting is often employed in potential field inversion to counteract the tendency for property variations to concentrate near the ground surface (e.g. Li & Oldenburg, 1996, 1998). Combinations of mathematical norms and weights can be employed to favour other characteristics. For example, the number of cells with non-zero property can be minmised if compact sources are sought (Portniaguine & Zhdanov, 2002; Fournier et al, 2016).

Sun & Li (2011, 2015) have extended conventional property inversion using fuzzy c-mean clustering to generate solutions with cell properties close to a one of a small number of preferred values. The user nominates the number of clusters and the target property value for each, e.g. based on petrophysical measurements for a specific geological unit. After inversion each cell has both a property and a class (cluster membership). Assuming the geological significance of the individual clusters is well understood, the inversion produces a geological model.

Joint property distributions can be used to impose correlations between petrophysical parameters during stochastic inversion. For example, Bosch et al (2001) enforce correlations between density and susceptibility for each of eight lithologies (Figure 7). Whether this qualifies as an application of "hard" or "soft" constraints depends on the origin and reliability of the joint distributions: are they based on substantial quantities of petrophysical data for the formations in question, or estimated using global compilations or conventional wisdom?

If property values in some cells are fixed during inversion, it is desirable to suppress changes in adjacent cells. Otherwise, an implausible "string of beads" could develop along drill hole traces in the inverted model, with the fixed cells as the "beads" contrasting with their neighbours. In order to reduce the likelihood of such artefacts, the solution can be conditioned with weights, to penalise changes in a "neighbourhood of influence" around each fixed cell, e.g. the ellipsoidal neighbourhoods defined by Williams (2008). This is effective provided the starting model properties in the vicinity of the drill holes have been interpolated in a manner consistent with the petrophysical data. The weighting attenuates with increasing distance from the fixed cell(s). If the petrophysical data have been kriged, the weights could be based on the kriging variances.

The merging of hard (wireline) and soft (kriging) constraints is illustrated using downhole resistivity from the Decar Ni-Fe Alloy project in central British Columbia, Canada. Resistivity logs recorded at 10 cm intervals were upscaled into 25 m model cells. Variography was performed separately in peridotite and meta-sediment domains. An areal variogram was generated from a near-surface horizontal section extracted from a pre-existing unconstrained DC resistivity inversion. The vertical variogram was derived from downhole resistivity logs. 3D resistivity inversion was constrained using the kriged resistivity, with model cell changes weighted according to proximity to drill holes. Sections through the unconstrained and constrained resistivity models reveal significant differences (Figure 8). More detail has been incorporated in the constrained model, especially along its western margin where the unconstrained model was indicating conductive sedimentary rocks over its entire length.

INTERPRETING INVERSIONS

Inversion delivers one or more models which fit geophysical data acceptably well, i.e. to an accuracy consistent with expectations.

After parametric inversion, interpretation of a causative body reproducing a particular anomaly may entail an assessment of its physical properties, size, and depth in order to reach a judgement, given the geological context, as to whether or not it warrants a drill hole or further geophysical work. The interplay between size and contrast is often an important consideration.

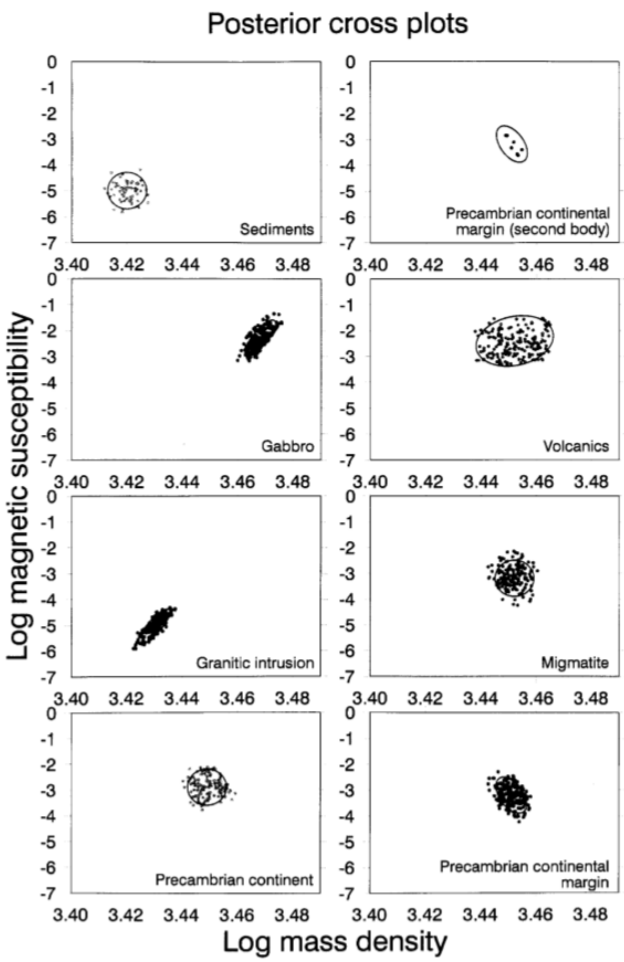

Figure 7: Cross-plots of density and susceptibility after 2D stochastic joint inversion of gravity and magentic data. The ellipses denote 2 standard deviation limit of the underlying marginal distributions (Bosch et al, 2001).

After general 3D inversion some potential targets may be obvious by virtue of their anomalous physical properties, e.g. highly conductive massive sulphides, but usually the inverted property model(s) must be interpreted in geological terms before exploration targets can be defined.

Initial interpretation after an unconstrained 3D property inversion usually involves a fairly qualitative "domainal" analysis. 3D iso-surfaces may be defined to isolate volumes with anomalously high or low inverted properties. The geological significance of the domains is assessed on the basis of their petrophysical characteristics. If the inverted model is geological, the initial domainal analysis can be focussed on the units of prime interest. The existence and possible significance of subtle features, e.g. alteration effects, may therefore become apparent more quickly in geological models. For geometry inversions, the focus is, of course, on the revised shapes of the active surfaces.

The next level of interpretation is quantitative prediction of rock type from the available inverted property models, thereby closing the circle: geology → petrophysics → geophysics → petrophysics → geology. Predicting rock type from a single property is sometimes possible, but often ambiguous in the absence of other information. When two or more inverted properties are available, computer algorithms can be brought to bear, either supervised (e.g. Perron et al, 2011; Chalke et al, 2012) or unsupervised (e.g. Hodgkinson et al, 2012).

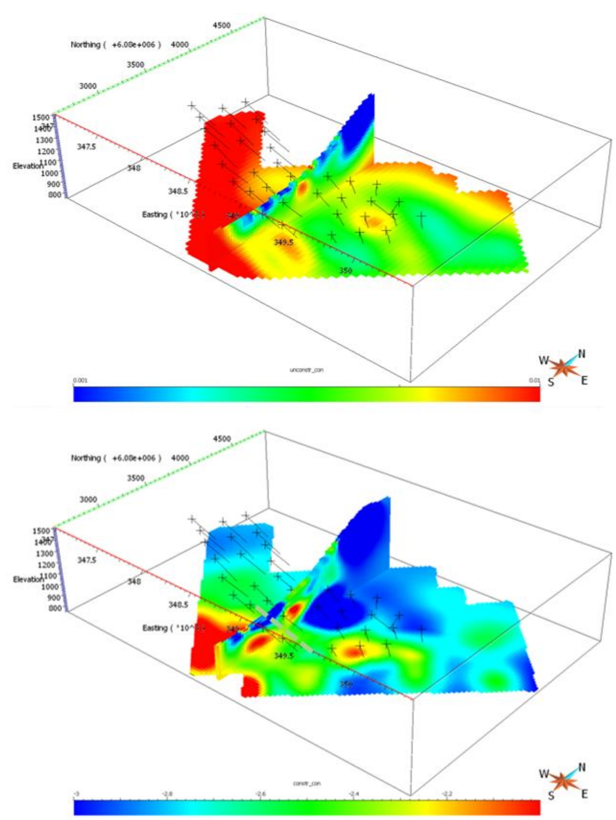

Figure 8: Vertical and horizontal sections through inverted DC resistivity models at Decar, British Columbia. Lower model is constrained by resistivity logs recorded in the drill holes (traced in black); upper model is unconstrained. (per favour FPX Nickel).

In supervised schemes, the physical property distributions of the key rock types are assumed known *a priori*. In unsupervised schemes, rock classes are postulated via analysis of the inverted property values; the geological significance of the inferred classes is then subject to interpretation. In either case, inverted petrophysical models can be transformed into categorical "rock type" models. An example of supervised inversion-based revision of a geological model is described in more detail below.

The demarcation between supervised and unsupervised approaches is often blurred. New rock types can emerge in notionally supervised analysis, and prior knowledge can inform decisions about both number and nature of classes in unsupervised analysis. A hybrid scheme is employed in the example described below.

Possible targets can be identified in the "inverted geology" model, either on the basis of their anomalous physical properties or their favourable litho-structural settings. For example, at the Victoria property, near Sudbury, Canada, new occurrences of quartz diorite host rocks for Ni-Cu-PGE mineralisation were interpreted from analysis of inverted density and susceptibility values by Perron et al (2011). Depending on geological context, petrophysical rules may exist to guide discrimination between prospective and unprospective host rocks, e.g. Hanneson (2003), Williams & Dipple (2007).

Revision of a geological model on the basis of inverted physical property models

Geological revision after geophysical inversion has been demonstrated in the course of an integrated regional interpretation of the Mt Dore area, Queensland, Australia (Geological Survey of Queensland, 2011; Chalke et al, 2012). The ultimate aim was to advance iron oxide copper gold (IOCG) exploration in the area. The underlying methodology has wider applicability, and indeed was used by Perron et al (2011) for integrated interpretation at a Ni-Cu-PGE sulphide property, as noted above.

The workflow can be summarised as follows:
1. traditional 2D interpretation, based on geological mapping and domain and lineament interpretation of magnetic and gravity images;
2. 3D model construction, using implicit geological modelling and some localised inversion, e.g. for dip or thickness estimation of individual geological units;
3. petrophysical data compilation, hence assignment of starting values to geological units;
4. bulk property inversion, to optimise properties of geological units (assumed homogenous at this stage);
5. separate heterogeneous inversion of available data sets, i.e. magnetics, gravity, +/- EM or resistivity/IP;
6. reconciliation of inversions with geology via lithology prediction based on inverted properties and rock property statistics; and
7. targeting.
The procedure is summarised schematically in Figure 9.

A geological starting model was constructed from maps, interpreted sections, and 2D gravity and magnetic interpretations. Density and susceptibility measurements from the project area were very limited, and conductivity measurements were unknown. Best-information starting densities were assigned on the basis of values provided by the Geological Survey of Queensland (GSQ) for units in the Eastern Succession of the Mount Isa Inlier.

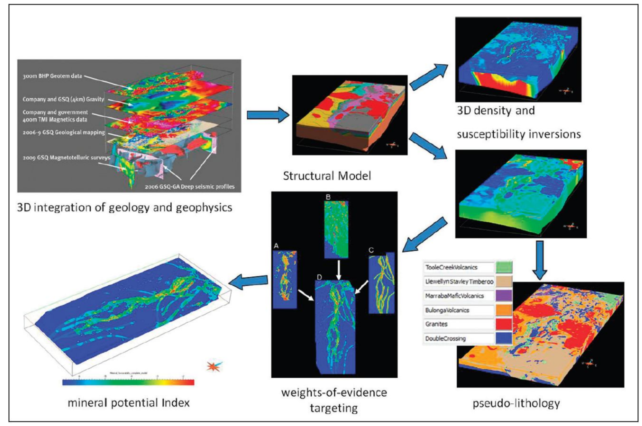

Figure 9: Schematic illustrating the workflow for integrated interpretation and targeting in the Mt Dore area of Queensland. After inversion, lithology is interpreted from density, susceptibility, and conductivity models. (Chalke et al, 2012).

A sequence of inversions (homogeneous, geometry, and heterogeneous) was applied to the gravity data at a coarse resolution (900 x 900 x 500m). Heterogeneous inversion was applied to the magnetic data at a higher resolution (300 x 300 x 150m). In addition, conductivities generated from CDI processing of GeoTEM data (Fullagar & Reid, 2001) were interpolated onto the higher resolution (300m) mesh.

The geological implications of the geophysical data were examined by predicting lithology from the inverted physical property models. The motivation for creating an inverted lithology was twofold. The first objective was to update the geological model, both lithology and structure, in light of the geophysical data. The second objective was to highlight anomalous zones or structurally complex zones demanded by the geophysical data which could prove significant in terms of exploration.

Mt. Dore lithology was predicted from density, susceptibility, and conductivity using LogTrans (Fullagar et al, 1999), a supervised classification algorithm. The available petrophysical data were inadequate for reliable statistical characterisation of all units in the model. Therefore, statistics were generated by superimposing the starting model domains on the 3D physical property models. Histograms were created for inverted density, log{susceptibility}, and log{conductivity} values assigned to cells lying within each of the geological domains in the starting model. Logarithms of conductivity and susceptibility were used since the distributions of these properties are often approximately log-normal.

Characterising rock property distributions on the basis of inverted results is somewhat circular, but is an attractive option when petrophysical data are scarce and/or unrepresentative, as is often the case in greenfields exploration. Although LogTrans is notionally a supervised algorithm, the methodology adopted here was a hybrid, neither truly supervised nor truly unsupervised.

LogTrans does not explicitly rely on conformity of parameter distributions to a particular statistical model, but it does assume that each property follows a unimodal distribution in every rock type. Examination of histograms revealed bimodal distributions in certain units. Therefore several rock types were split into sub-populations, i.e. new geological sub-classes were introduced. On the other hand three sedimentary formations, virtually indistinguishable in terms of density, susceptibility, and conductivity, were amalgamated into a single super-class. These are both examples of development of a classification, which is characteristic of unsupervised approaches.

The resulting inverted lithology model is compared with the geological starting model in Figure 10. Of all 2.26 million cells in the model, 72% were assigned to their original (starting model) rock types. It is encouraging that coherent volumes have been assigned to new classes, not isolated cells. This demonstrates the potential for the inverted lithology to delineate zones which were originally assigned to an incorrect rock type, or which have undergone considerable change in physical properties owing to alteration or metamorphism.

Interpretation of the inverted lithology can be undertaken in various ways, e.g. focussed on variation within a particular rock type. Sediment cells re-assigned as metamorphics could have undergone alteration which increased the magnetite content, for example. As a final stage in the GSQ project, targeting for IOCG mineralisation was performed using Weights of Evidence, yielding a 3D mineral potential map for the project area.

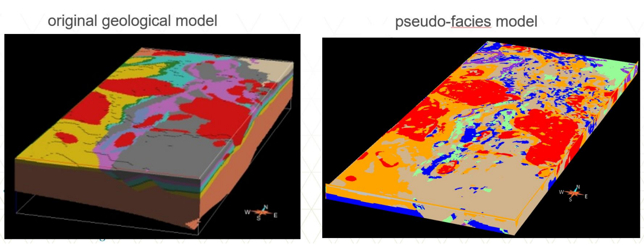

Figure 10: Comparison of Mt Dore geological starting model (left), and revised geology based on inverted density, susceptibility, and conductivity models (after Chalke et al, 2012).

CONCLUSIONS

Petrophysics provides the link between geology and geophysics, since it is the physical properties of rocks which govern their geophysical response. Therefore all forms of interpretation of geophysical data, not least inversion, must involve some judgements about petrophysics.

The two main types of petrophysical data are measurements on core samples and *in situ* measurements taken downhole. Although acquisition of petrophysical data is more common today than it was 10 years ago, it is often still the case that little or no local physical property data is available. Lack of petrophysical data increases the uncertainty in interpretation.

The volume support of petrophysical data is very small (usually at least 4 orders of magnitude) relative to the volume of inversion model cells. In greenfields exploration, this huge disparity in scale combined with the sparsity of data usually means that attributing model cells with upscaled and interpolated physical property values is not viable. It is rare for cells to be held fixed during inversion, even if downhole logs or core sample properties have been recorded within the volume they enclose. Inversion itself is the best upscaling and interpolation tool.

Upscaling is warranted in mines and advanced exploration projects when petrophysical data density is much higher. Conventional linear upscaling is valid for some properties (notably density and low susceptibility). However, upscaling of electrical properties can be problematic. Upscaled data are interpolated, often by means of kriging. Kriging is convenient and flexible, and yields estimates of variance. However, its application to electrical properties is not always justifiable. This is an area for additional research.

The aim of inversion is to modify a starting model in order to achieve a satisfactory fit to geophysical data. When available, petrophysical data can expedite inversion in three main ways: forward modelling, providing constraints, and aiding interpretation.

A forward modelling capability is a pre-requisite for inversion and also plays a key role in survey design and in "hypothesis-testing" after drilling. If the starting point is a geological model, each unit must be attributed with physical properties prior to modelling and inversion. After forward modelling, the calculated data can be compared with the measured data, in preparation for inversion. In the ground-truthing application, forward modelling is undertaken to determine whether the material intersected in the hole(s) is sufficient to explain the data.

The need for geological and petrophysical constraints during inversion arises because, owing to the limitations imposed by physics, logistics, and experimental error, there are usually an infinite number models which are acceptable in terms of data fit. The purpose of constraints is therefore to focus the inversion on the models which are consistent with what is already known about the geology and petrophysics of the area.

If inversion is performed on a geological model rather than a pure property model, a richer set of options is available, both for inversion style and for constraints. In particular, a specific remanent magnetisation can be assigned to individual geological units, or the variability of a property within a domain can be controlled to conform to a prescribed variogram model.

Petrophysical constraints can be "hard", if based on actual measurements, or "soft", if imposing a subjective preference. The most common form of petrophysical constraints are bounds, restricting the range of permissible property values allowed for individual model cells or entire geological units. In pure property models, minimising the deviation from a "reference" model is implemented as a petrophysical constraint; this is in essence a geological constraint if the reference model is based on geology.

After inversion, the geology must be interpreted from the inverted property models in order to gain new insights and to identify exploration targets. Initial interpretation of 3D models is usually a fairly qualitative "domainal" analysis to delineate volumes with anomalously high or low inverted properties. If the inverted model is geological, the domainal analysis is focussed on units of prime interest, expediting recognition of subtle features, e.g. alteration effects.

Rock class can be predicted quantitatively from inverted property models on the basis of petrophysical characteristics. In this way a revised geological model consistent with geophysics and petrophysics, i.e. an integrated interpretation, can be produced. Possible targets can be identified in the "inverted geology" model on the basis of their anomalous physical properties and/or their favourable litho-structural settings. Either supervised or unsupervised, or hybrid, computer algorithms can be brought to bear. Revision of a geological model from Mt Dore, Queensland, has been described in some detail. Rock type prediction was based on inverted density, susceptibility, and conductivity models. Petrophysical data were very limited, so a hybrid supervised/unsupervised methodology was adopted; property distributions for each rock type were estimated by overlaying the inverted property models on the geological starting model.

Petrophysics is already playing important roles in inversion, and there have been considerable advances in both computer algorithms and interpretational methodologies during the past decade. However, there is still plenty of scope for improvement. Lack of local petrophysical data is still more the rule than the exception in mineral exploration. Petrophysical data will always be limited at the outset of greenfields projects, but should be abundant at operating mines. Further integration of petrophysical data into workflows at operating mines is the key challenge. When the relationships between physical properties and lithology, alteration, assays, and geotechnical and geometallurgical parameters are better understood at mine scale, the rationale for acquisition and analysis of petrophysical data at all stages of exploration will become more and more compelling.

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