

Use of Geostatistically-constrained Potential Field Inversion and Downhole Drilling to Predict Distribution of Sulfide and Uranium Mineralisation

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ABSTRACT

The Basil Cu/Co deposit comprises a 26.5 Mt Inferred Resource of copper and cobalt, grading 0.57 per cent Cu and 0.05 per cent Co. It lies in the Harts Range, Central Australia, within the Riddock Amphibolite of the Irindina Province. Analysis of drilling within the mineralised zone of the deposit determined a spatial association between pyrrhotite with high magnetic susceptibility and chalcopyrite, following a strong magnetic trend as determined from airborne geophysics. A study was commissioned to examine if geophysical inversion could predict the distribution of sulfide mineralisation based on pyrrhotite from drill hole intersections, as well as predicting further mineralisation at depth or in the vicinity of the deposit. Petrophysical and geostatistical analysis of drilling susceptibility and mineralisation provided a basis of property distribution inside the model. This was followed by 3D geological modelling of mineralisation based on domain kriging of drill hole susceptibility sensitivity testing of signal to source depth, and distribution was performed using 3D forward modelling. Stochastic inversion generated alternative 3D geological models, which were tested for behaviour and adherence to observed drilling data and geostatistical limitations using GeoModeller software. Predicted mineralisation distribution was compared with conventional geostatistical modelling and found to be in agreement in planar behaviour but exhibiting possibly isoclinally folded trends, with reliability increasing closer to the surface. Predictions of mineralisation at greater depth and beneath weaker anomalies were more diffuse due to small model cell size having limited influence on the signal at depth.

The Blackbush uranium deposit comprises a 64.5 Mt Inferred Resource, grading 230 ppm U in the Pirie Basin south of Whyalla, South Australia. It directly overlies the radiogenic Saphire Granite and is considered a tertiary unconformity deposit. Sensitivity modelling was performed using high-resolution ground gravity to see if a deposit signature could be detected using gravity. This required 3D implicit modelling of the geology and mineralisation from drill hole data and characterisation of an associated physical property model using domain kriging in GeoModeller. Density models relied on exploiting an observed relationship between logged density and measured uranium oxide percentage. The residual gravity response of the background geology model identified the location of the uranium deposit. Stochastic inversion of the litho/property 3D model has refined the known distribution of uranium from drilling and provided structural insights into the deposit.

These projects have become excellent case studies for exploiting the relationship between mineralisation and potential fields and for testing the applicability of using domain kriging of properties determined from drilling to build robust 3D geological models for stochastic geophysical inversion, leading to robust methods for exploration targeting and mineral deposit prediction.

INTRODUCTION

The purpose of this paper is to demonstrate practical examples of maximising drill hole petrophysical and geochemical log data together with geological data for ideally constrained *a priori* geological models, to be used for inversion with magnetics, gravity and gravity gradients. These *a priori* (initial) models, together with the results of geophysical

inversion, can be used to improve the understanding of mineral deposits. They may also provide practical pathways for exploration and maximising geophysical and geological data sets for interpretation, as well as providing alternative ways to improve resource modelling.

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INVERSION PREPARATION

Inversion background

The majority of inversion algorithms currently in use for potential fields rely on deterministic methods similar to those of Parker and Huestis (1974) and Li and Oldenburg (1996, 1998a). These types of computations can be made very rapidly in 2D and 3D with modern computing methods, but often lack *a priori* knowledge of the geology and petrophysical properties, leading to high degrees of geological uncertainty. Solutions can be refined by drilling data, seismic horizon picks, rock sample analysis, iterative property weighting (Geosoft, 2013) and fast automated depth solutions such as Euler deconvolution (Reid *et al.*, 1990) or tilt-depth (Salem *et al.*, 2007).

More recent stochastic inversion techniques (Guillen *et al.*, 2008) have advantages in that they typically use 3D voxel models of predefined geology or geological rock properties as input, which provide far better initialisation conditions. Probabilistic geological and geophysical misfit conditions are used to discard less likely solutions. With the advent of more powerful processors and the multithreading of computations, it is now possible to construct very detailed input 3D geological models and retrieve and review modelling process in very reasonable time frames. More plausible geological starting models means that inversion has a much greater success in predicting lithological and petrophysical changes and testing model hypotheses. This paper will demonstrate that taking advantage of geostatistical analysis of downhole drilling logs to generate and constrain geological models can significantly enhance the reliability of input geological models and provide a testing framework for inversion results in most geological scenarios.

Geological and geostatistical methods

The methodology outlined here is intended to be generally prescriptive for advanced inversion case studies. For these case studies, the primary software used for geostatistical and geological modelling and subsequent geophysical forward and inverse modelling is GeoModeller, developed by Intrepid Geophysics. GeoModeller interpolates between geological boundaries, structural data and drill holes to generate easily adaptable 3D geological models. Geological information supplied for this type of modelling comes from field mapping and geographical information systems (GIS), digital elevation and geophysical grid interpretation, structural cross-sections and drill hole logs. GeoModeller uses a geostatistical method involving co-kriging of spatially-related variables to interpolate the geology in 3D, using observed geology contacts and geology gradients (dip and strike) (Calcagno *et al.*, 2008).

Geostatistics has long been used in resource modelling work and, more recently, hydrocarbon studies. However, the use of these techniques for more general 3D geological modelling has been less common. Understanding of the subsurface, for all geological studies, is marred by low data density in the horizontal domain between known observations, hence the requirement for implicit modelling of the type described previously. In addition, interpolation of virtually any type of drill hole log data (eg geochemical logs, density, susceptibility, impedance, conductivity and temperature, amongst others) can be used to predict, with an estimate of uncertainty, a great deal more information about the subsurface. It can be used to verify or identify geological and geophysical trends, provide the basis for 3D petrophysical models and provide

links and substitution models for linked physical, chemical and geological inferences.

GeoModeller has several tools for data interpolation, including nearest neighbour analysis, inverse distance and kriging. The method is to import the measured property or geochemical logs and intervals into the program, where they are associated with the input drill holes and downhole formation changes. From this point, bulk property analysis to characterise the statistical behaviour of the downhole data can be performed. In the case of magnetic susceptibility (and much more subtly, with density), property values tend to follow a log-normal distribution. Both bulk property analysis and kriging need to be performed on normally distributed data to work, so susceptibility values were converted to their logarithmic equivalents. This allows the correlation between high susceptibility and mineralisation intercepts to be viewed directly for each drill hole (as illustrated in Figure 1, which comes from the Basil case study). Property values then need to be regularised over a specified interval before kriging can be performed. In practice, measurements are made over different intervals that are often biased by the appearance or

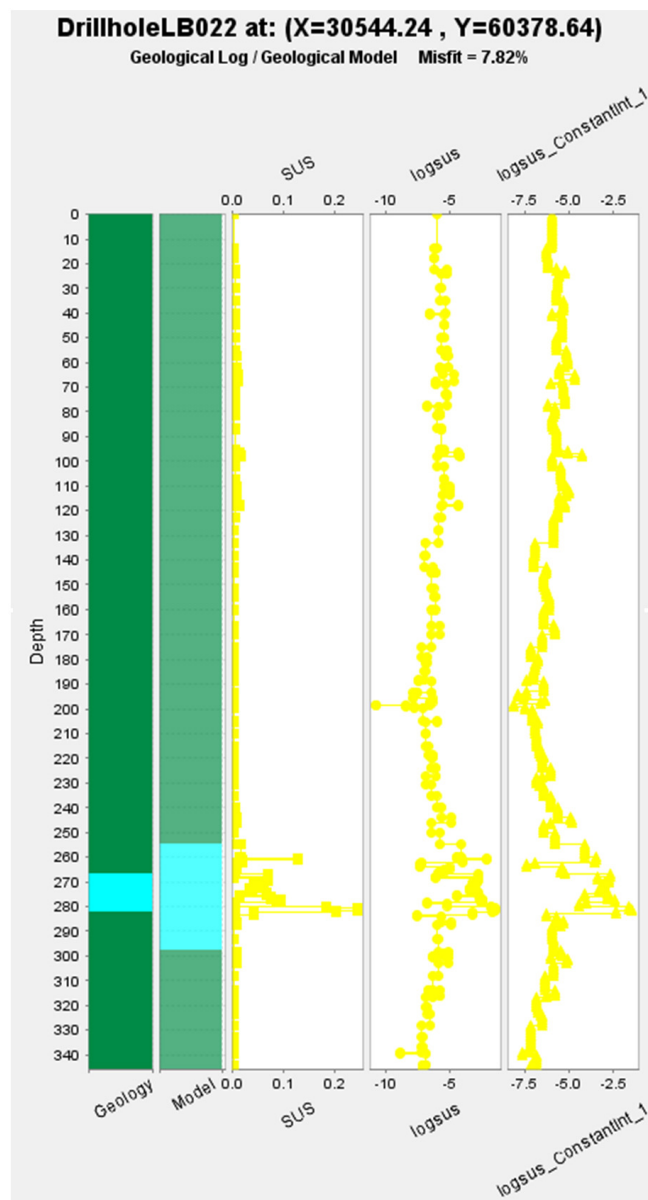


FIG 1 – Drill hole property plots showing original, log and regularised values of susceptibility.

not of sulfide mineralisation. This is also observed in Figure 1. In the Basil case study, an interval of 1 m was used as many sulfide bands were quite thin.

Domain kriging

The modelling techniques involved in these studies included simple inverse distance modelling, radial 1D and 2D kriging and domain kriging. Of these, attention is drawn to domain kriging, which exploits a set of geological pseudo-potential trends generated by implicit modelling functions (Guillen, Courrioux and Bourguine, 2011). Instead of classical kriging – which is performed in one, two or three fixed directions or by radial basis functions – the interpolation function follows the pseudo-potentials defining the shape, direction and thickness of specific geological units or series (Figure 2). When interpolating measured or derived data, the grid is filled according to the variogram function pertaining to each geological unit. This has a clear advantage in defining a 3D input petrophysical grid in areas of more complexly-defined geology without having to resort to inferences about anisotropy as the predicted geological trends inform the property interpolator. Where information about an important physical or chemical parameter is limited but related to another that has been more reliably measured by logging or chemical analysis of log samples, domain-based interpolation can suddenly become critically important. An example of the effect of using domain potential estimation is illustrated in Figure 3, where two cross-validation plots of a variogram calculated on Fe per cent from an iron ore deposit are shown.

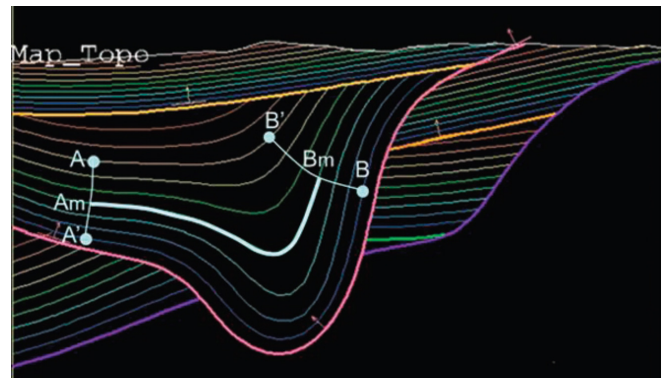


FIG 2 – Curvilinear distance between two points, A and B. Point A is on the isovalue potA, point B is the isovalue potB. The distance $dg(A, B)$ is the length of the arc AmBm (in blue) at isovalue $potM = (potA + potB)/2$. The distance $dg(A, B)$ is therefore defined as $dg(Am, Bm)$.

The domaining estimation shows much higher correlation with observed data than a radial basis variogram.

Model sampling

For the purposes of potential field inversion, the geological model is discretised into a 3D structured grid or block model with dimensions that reflect the target spatial resolution of the potential field grid. This stage is very important as the inversion will not be able to resolve wavelength changes that are smaller than the X, Y, Z cell size. The input observed grid(s) and possibly digital elevation grid should also be sampled at

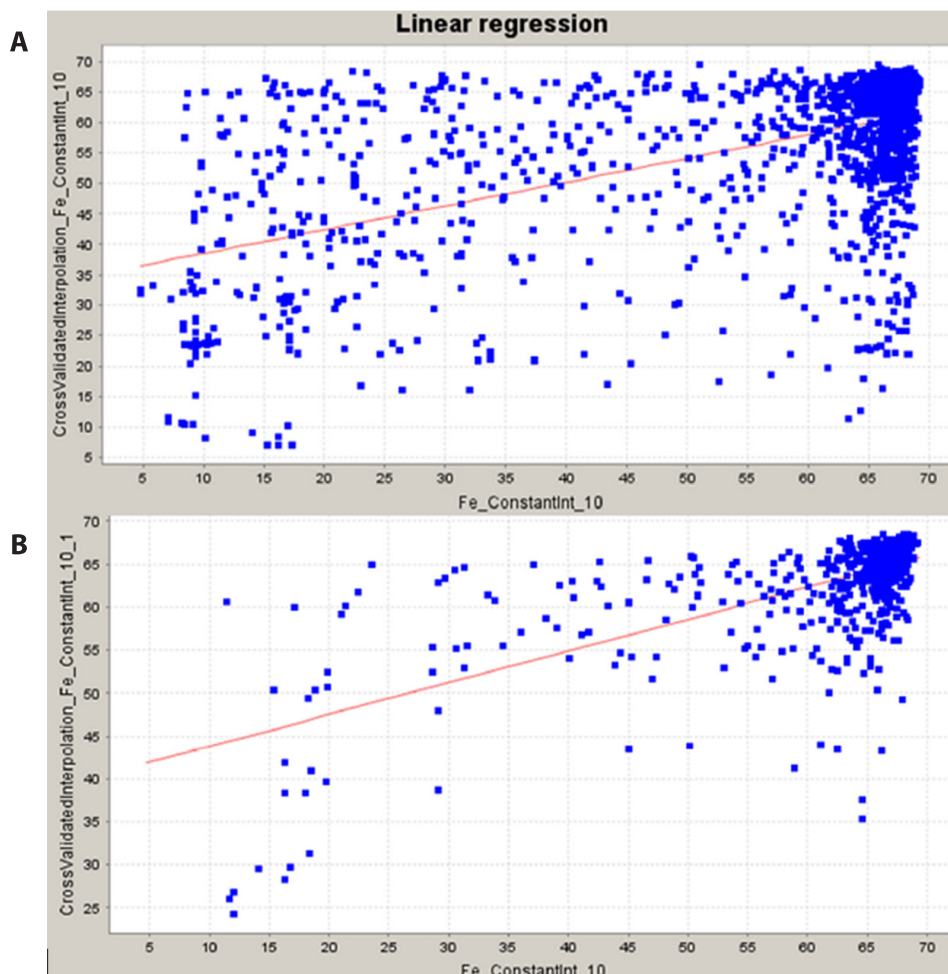


FIG 3 – Scatterplot of cross-validation between radial variogram of (A) Fe per cent and (B) domain variogram.

the same horizontal wavelength as the discretised model. If necessary, coarse 3D models should be used in inversion to resolve gross wavelength changes and geological effects first, before the desired changes are applied and the model is re-sampled at higher resolution.

INVERSION CASE STUDIES

Basil Cu-Co deposit

The first example is from the Basil copper deposit modelling project in Central Australia (Figure 4). The Basil Cu/Co deposit comprises a 26.5 Mt resource of copper and cobalt, grading 0.57 per cent Cu and 0.05 per cent Co (Sharrad *et al*, 2013). It lies in the Harts Range, Northern Territory, within the Riddock Amphibolite of the Irindina Province. Sulfide mineralisation was found outcropping in a linear-trending series of gossans within amphibolite. Diamond drilling discovered chalcopyrite mineralisation at depth in intimate association with pyrrhotite, extending in a series of faulted dipping sheets from surface. A densely spaced helicopter magnetic survey identified a series of linear magnetic anomalies associated with the pyrrhotite. All drill holes were logged for susceptibility as well as Cu and sulfide abundance. A study was commissioned to investigate if 3D inversion of the susceptibility data could predict the distribution of sulfide mineralisation at depth. Although it was perhaps not realised at the time, this study became possibly the first fully geologically-, petrophysically- and geostatistically-constrained stochastic geophysical inversion performed for practical purposes in Australia, so an evolution of practical processes took place during the course of the study.

Pre-inversion model preparation

Initial models were built using drilling data intersections and an estimated ore deposit shell provided from another consulting company, which was also developed through standard mining geostatistical modelling (Figure 5). There was general agreement that mineralisation was confined within a dipping plane extending from gossanous surface outcrop to the deep drill hole intersections. However, even though initial geological modelling honoured the general nature of the deposit, it was realised very quickly after inversion scenario testing that attempting to use simple

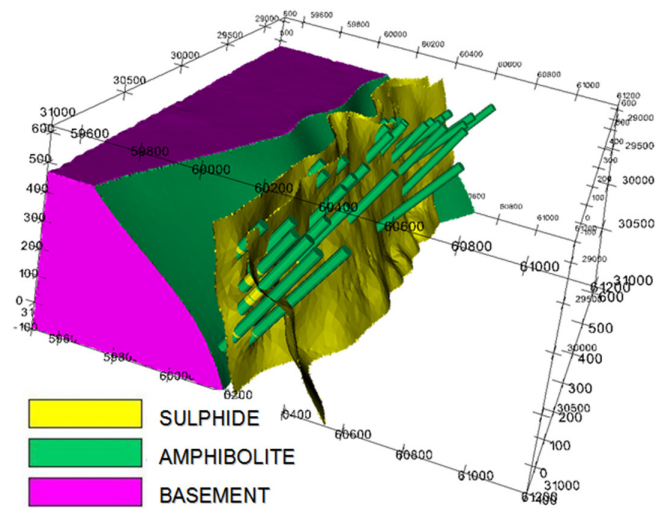


FIG 5 – Original three-dimensional geological model of dyke-like sulfide mineralisation at Basil Cu-Co deposit.

predictive inversion would fail due to the tendency for results to immediately shift to clustered anomalies close to surface. If inversion prediction is to be truly constrained, it must begin with known observations at depth.

A subsequent thought process was to realise that it was both simpler and more accurate to interpolate in small radius around each drill hole and then allow the inversion itself to propagate property values. This also led to the notion that it was much better to initialise the geology model based on this property interpolation so that the starting model reflects the interpolation. Two steps of geostatistical interpolation followed. Simple radial kriging out to a grid distance of 50 m was performed on the drill hole data, creating a voxel mesh grid containing log susceptibility property values. Examination of the bulk susceptibility histogram (Figure 6) shows that pyrrhotite susceptibility is clearly visible as a distinct population above ~ -4 logSI (log magnetic susceptibility index). This value was used to clip the 3D voxel to show only cells with an SI greater than this value. These clipped voxels were used to create a sulfide mineralisation ‘ribbon’ as a proxy for the mineralisation geology (Figure 7) by adding in geological model contact points and orientations into the implicit modelling program around the margins of the clipped values, and recomputing the implicit model. Domain kriging was then used on the log-susceptibility data from the drilling logs to populate this sulfide ribbon of mineralisation to create a 3D pyrrhotite property voxel body at depth (Figure 8). Log susceptibility values were exponentiated back to true susceptibility. The distribution of interpolated values shows a significant cluster of high-susceptibility values closer to surface at the western edge of the model. Away from this area, high-susceptibility values are more thinly spread at depth in a fairly analogous fashion compared to the actual observed magnetic response, giving the impression that this is a good point at which to start the inversion.

Inversion

Magnetic inversion needs to be a carefully controlled process. There is a very high degree of sensitivity to both distance from the source measurement (ie depth of target) and the property values themselves, as well as the voxel size. In general, property changes tend to create stronger responses than lithology changes and therefore tend to dominate inversions where both property and lithology are allowed to change. Early testing with the first geological model, as has been explained, showed that the

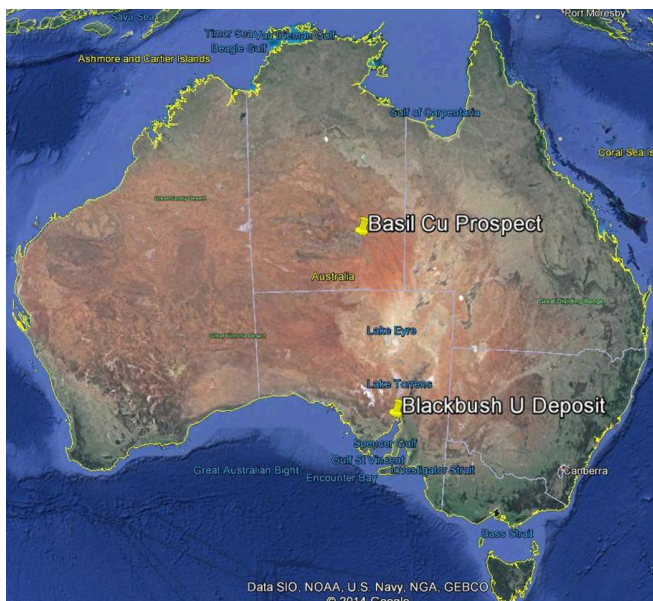


FIG 4 – Location map of case modelling studies in Australia.

Histogram of logsus

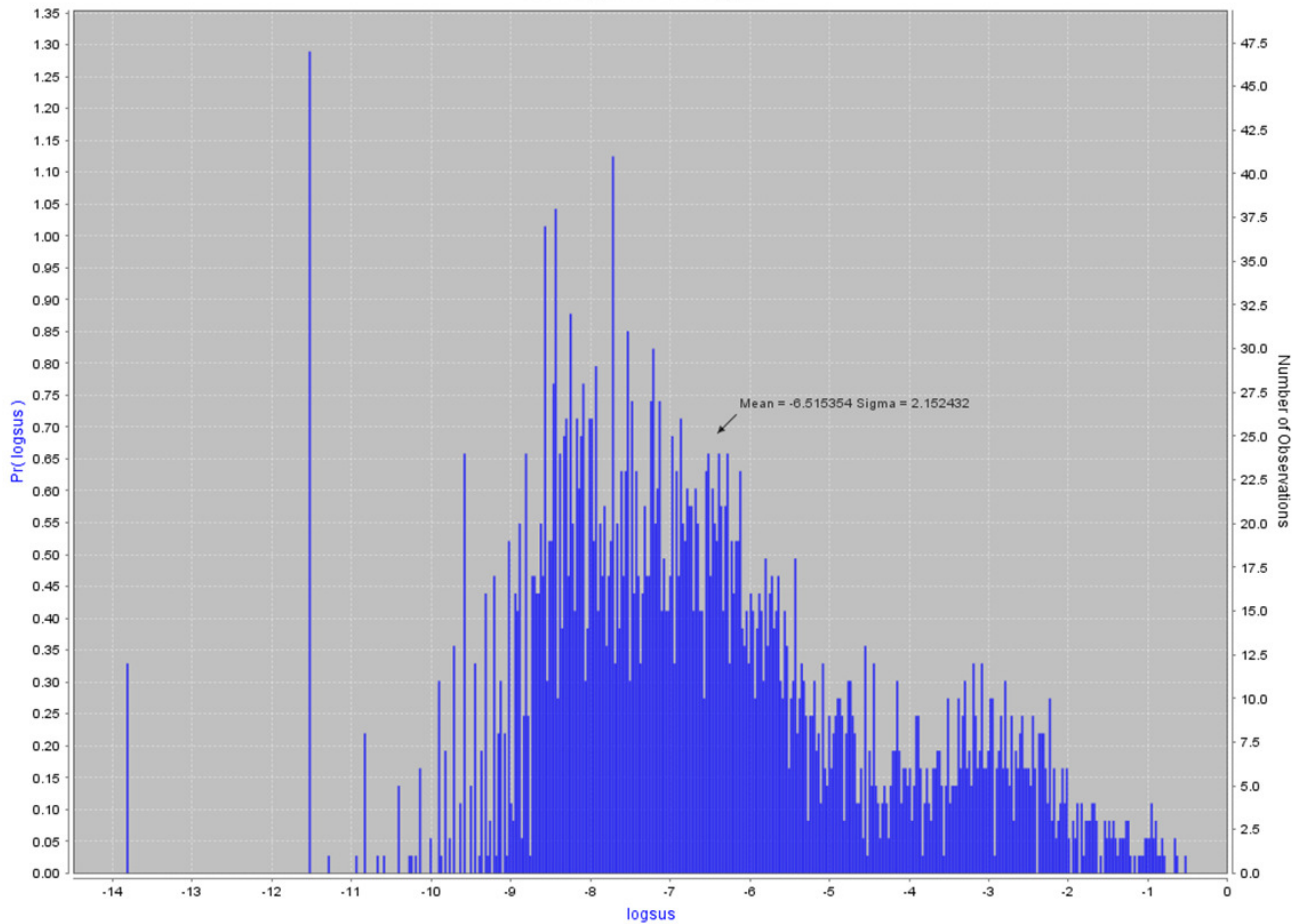


FIG 6 – Histogram of log-susceptibilities from downhole drilling.

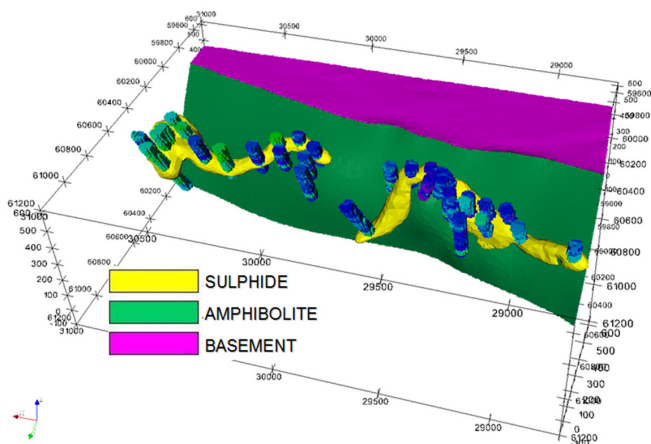


FIG 7 – Geostatistically-defined sulfide model 'ribbon' with radially kriged drill hole susceptibilities.

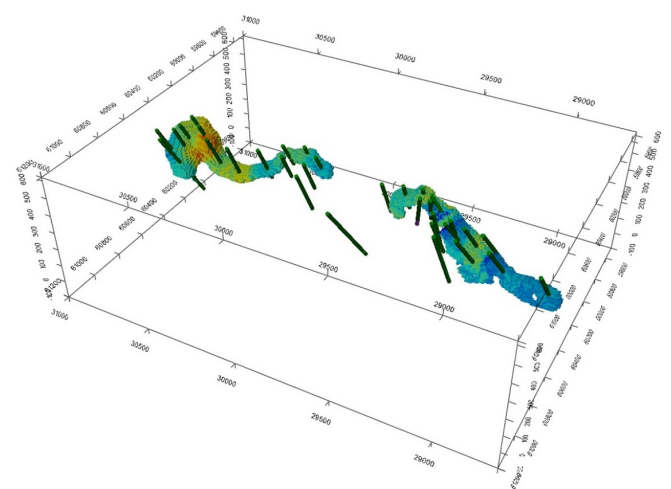


FIG 8 – Domain kriged initial sulfide susceptibility model with drill holes.

inversion was not likely to honour the deep sulfide intercepts, in favour of a shallow solution, particularly where very strong susceptibility values will dominate the response behaviour. GeoModeller performs optimisation to minimise inversion misfit by proposing changes to either property or lithology, with a percentage ratio favouring one process or another. By default, the process is 50/50, so after every proposed lithology change on a cell, a property change will be proposed with the bounds set by the standard deviation of physical property measurements for a given lithological unit. Further controls on lithology changes can limit changes in overall volume, shape

and commonality with the starting model, with options to fix drill hole observations or prevent changes to a given lithology based on criteria.

Therefore, bearing these factors in mind, it was decided that the best approach to the inversion in this situation was to alternately invert for property and lithology in separate inversions, limiting the number of total changes (inversion iterations) each time. At each stage, fix the changes that had previously been made. A gradually declining misfit between observed and computed responses should eventually limit the progressive growth of the defined initial sulfide formation,

along with property changes, until a reasonably low misfit between the observed and the computed responses was reached. Although more time consuming, this was deemed to be the best approach. Inversion was computed on reduced to pole total magnetic intensity (TMI) data due to operating on a local grid, at $10 \times 10 \times 10$ m on eight CPUs for 2 815 200 cells.

Results

The resulting final 3D body, shown in Figure 9, resembles the gross geometry of the dipping sheet expected from resource modelling, with some predictions of extensions at depth and into previously unknown areas, but suggests that the distribution of the mineralisation is likely to be determined by folding in the plane of mineralisation. Examining the physical property distribution in 3D shows that predictions of higher response susceptibility were limited by depth and still remain biased toward the near surface, although this has been partially controlled by the stepwise process. Further improvements to this modelling are possible through revision of physical property and inversion parameters and the acquisition of detailed ground gravity for density inversion.

Blackbush uranium deposit

The second example shown is from a shallow uranium deposit in South Australia, the Blackbush deposit (Figure 4). Uranium was discovered from drilling into tertiary sediments above a strongly radiogenic basement granite between 60 m and 80 m depth. The uranium lies in a palaeochannel flanking a local basement high in the granite. Although the mineralisation had been defined principally by pattern aircore drilling, gravity data had also been collected across the area at spacings between 100 m and 25 m. A study was commissioned to determine if gravity was able to play any role in defining either the deposit

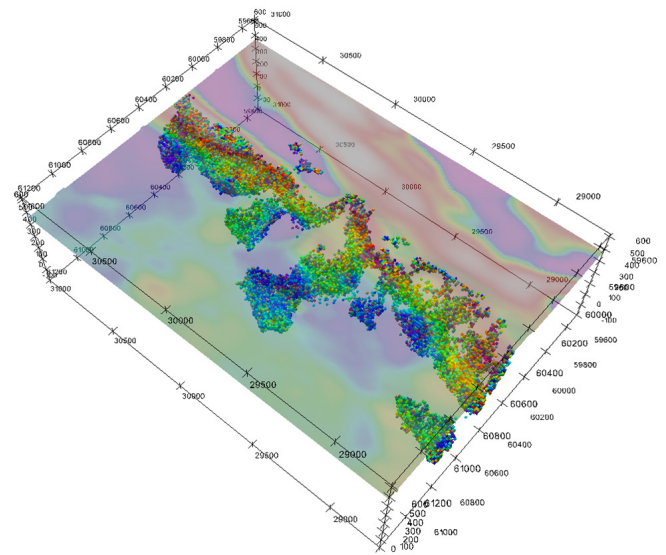


FIG 9 – Final sulfide model susceptibilities after two-dimensional magnetics as transparent overlay.

itself or at least the geometry of the basin and density contrasts defining palaeochannels and basement highs.

Pre-inversion model and grid preparation

Bouguer gravity data were terrain corrected, gridded with variable density techniques (Intrepid V5.0, 2013) and then residual filtered using power spectrum techniques (Spector and Grant, 1970) to create a residual Bouguer gravity grid containing shallow signals representative of the upper 200 m. A 3D geological model (Figure 10) was created over the

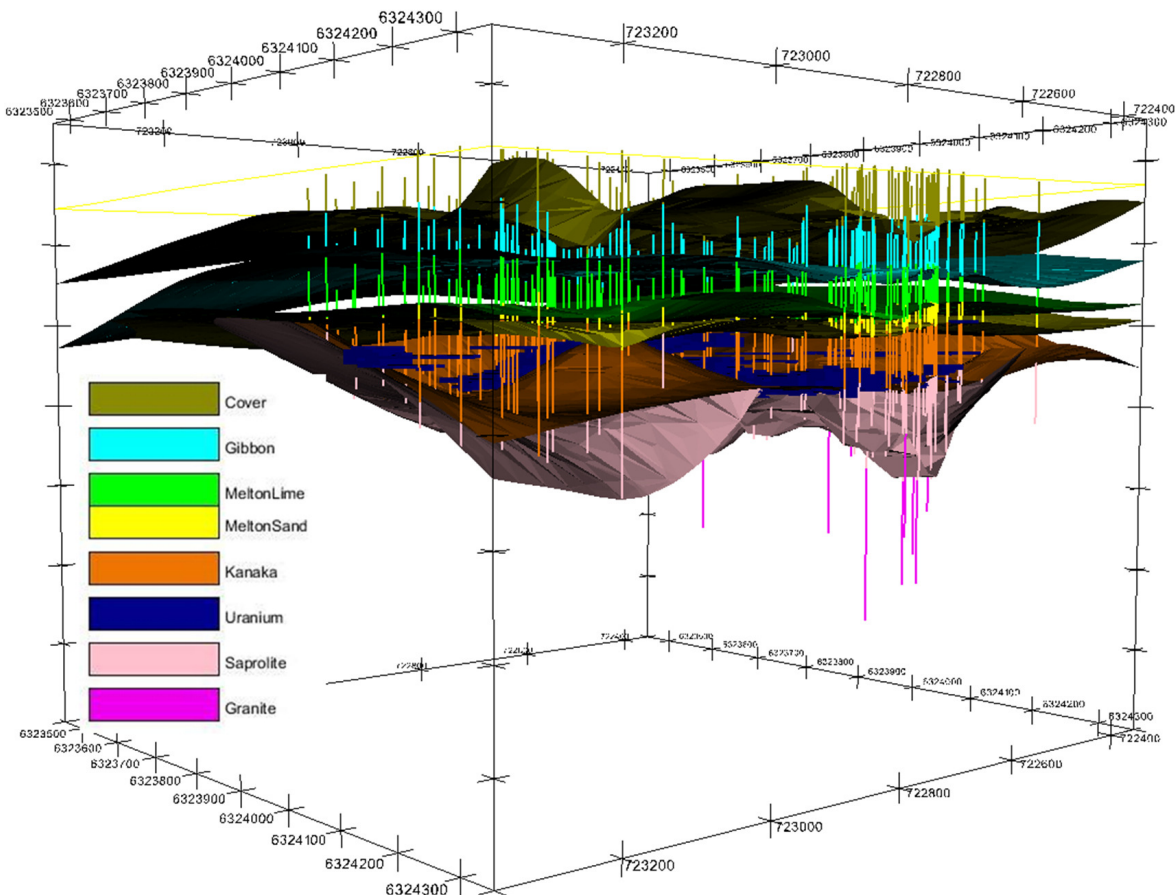


FIG 10 – Three-dimensional geological model of Blackbush showing drill holes and uranium mineralisation.

deposit area using data from ~120 drill holes, all of which were logged for U₃O₈ abundance but only a dozen were logged for density. Statistical analysis of the limited density logs identified average density distributions for the individual formations, but, although density spikes were present at the uranium mineralisation intersections, there was not enough information to model the uranium density. Comparison of the density logs with U₃O₈ ppm (Figure 11) revealed consistent correlation of density spikes where U₃O₈ was greater than 1000 ppm. Domain kriging of the U₃O₈ data above 1000 ppm generated a 3D grid of uranium mineralisation. This was converted to a 3D grid of assumed density using a linear regression function from correlation with the density logs. A separate domain kriging of the downhole densities for the sedimentary formations populated the background property model, except for the basement where a random distribution was used.

Inversion and anomaly identification

In addition to these processes, a forward gravity model was computed from the 3D geological model generated from drilling, using the identified formation and granite densities, but not taking into account the uranium density model. The misfit between the forward model and the residual gravity used as input for modelling revealed a prominent positive gravity anomaly in the centre of the model (Figure 12), which

when compared to the 3D kriged U₃O₈/density models showed a near-identical shape and distribution (Figure 13). This was a clear identification of the uranium deposit from the gravity data.

Stochastic inversion of the model used the residual Bouguer gravity data as the geophysical input. The domain kriged uranium density voxets were used to replace the background sedimentary voxets at the same spatial locations using a grid calculator to generate the final input 3D property model. Inversion was run on a 12.5 × 12.5 × 1 m grid for 10 million iterations of ~1.4 million cells using a 50/50 bias between property and lithology changes. Only a single final inversion was required due to the reliability of the source model and largely homogenous response of the basement. The optimised output from the inversion reorganised and distributed the uranium mineralisation in a consistent manner to that predicted from resource modelling, as well as making subtle changes the basement and sedimentary formation boundaries and densities.

Results

The redistributed uranium mineralisation optimised by the residual gravity signal in the inversion, is shown in Figure 14. It was realised that, possibly for the first time, a subtle signature of a shallow uranium deposit of moderate size can

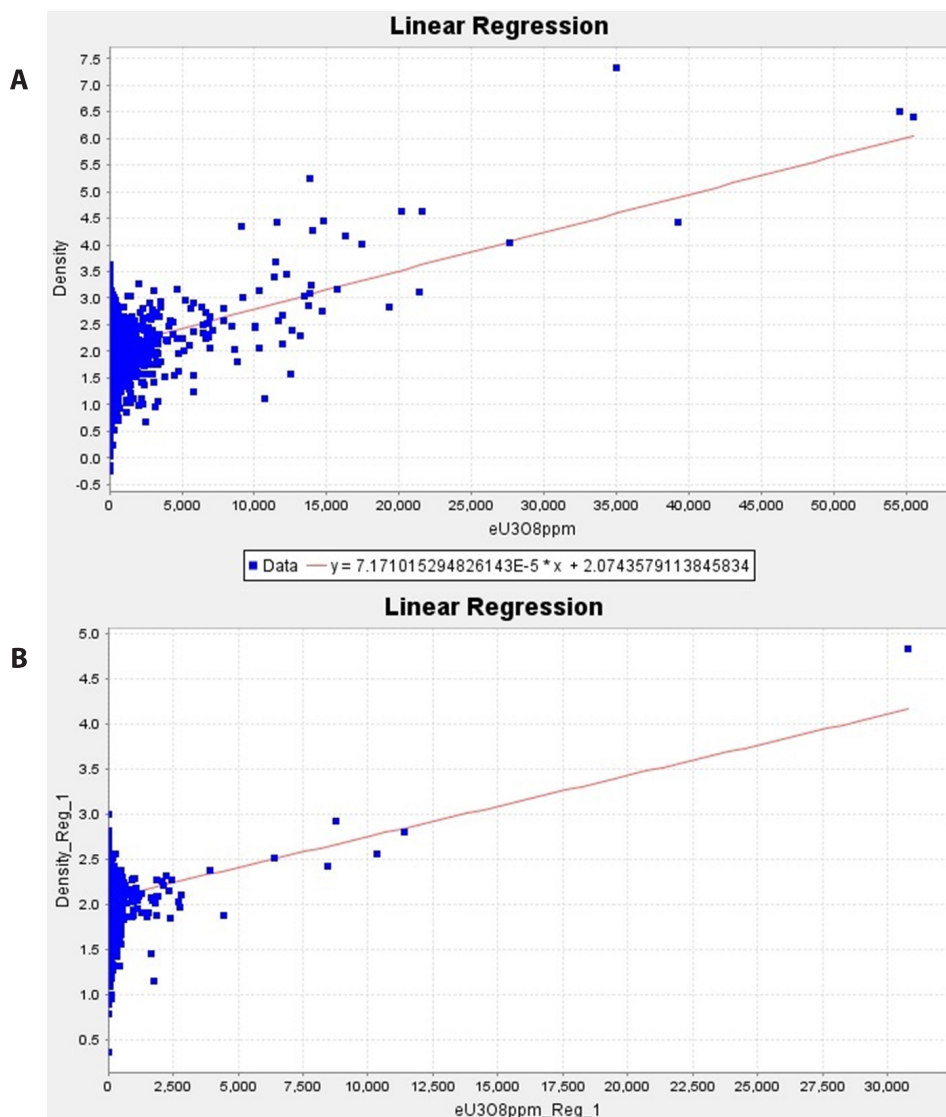


FIG 11 – Correlation plot between drilling density and U₃O₈ ppm.

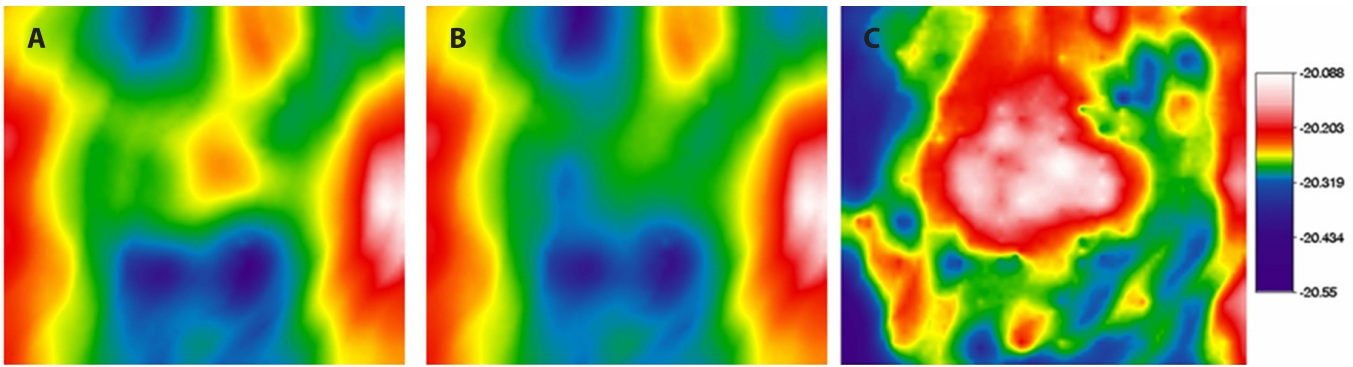


FIG 12 – (A) Observed residual Bouguer gravity; (B) forward modelled Bouguer gravity; (C) misfit residual Bouguer anomaly from difference of previous grids.

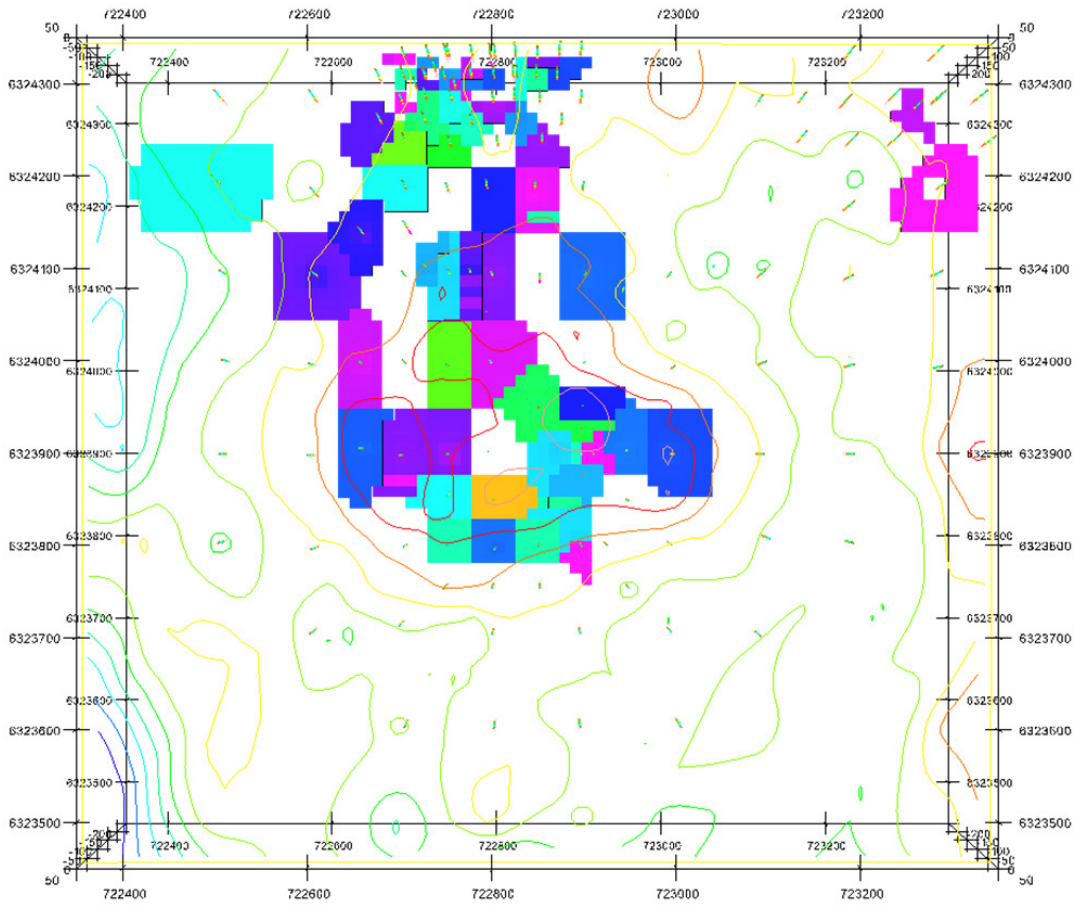


FIG 13 – Top view of three-dimensional uranium pre-inversion domain kriged density with residual gravity contours.

be detected from appropriately collected and treated gravity data if the 3D geology is modelled first. The residual gravity data may then be used to optimise both the mineralisation distribution and the background geological changes. Results from the 3D inversion showed sensitivity to subtle structural changes implied by both the drilling and residual gravity signal. Extracts from the model also generated depth horizon surfaces. The products of the process have led to a concept for future pathways for exploration for shallow uranium using gravity and pattern drilling.

CONCLUSIONS

These examples serve to illustrate that there are many ways to exploit downhole drilling data for the purpose of potential field modelling. Whilst this paper is not an examination of inversion techniques, it suggests very strongly that even if data is fairly sparse, creating an initial 3D geological model

and populating it with petrophysical properties will lead to a far more reliable set of solutions from inversion. At worst, it can be used for hypothesis testing. At best, it can extend as far as predicting mineralisation or geology related to in a well-constrained fashion, or even identify approaches to deposit detection and general exploration. Geostatistical property modelling can add significant quantitative evidence to geological scenarios and initial geological models where geometries and lithologies were previously unknown. It can also be used in the petroleum industry to assist in identifying impedance contrasts due to stratigraphic or facies changes in 3D, and provide geometrical and domain-bounded petrophysical models with more accurate trends. With some imagination and recognition of correlations between geochemical and geophysical log parameters, mathematical treatment of voxel grids can lead to much improved model initialisations. The future of 3D potential field (and other

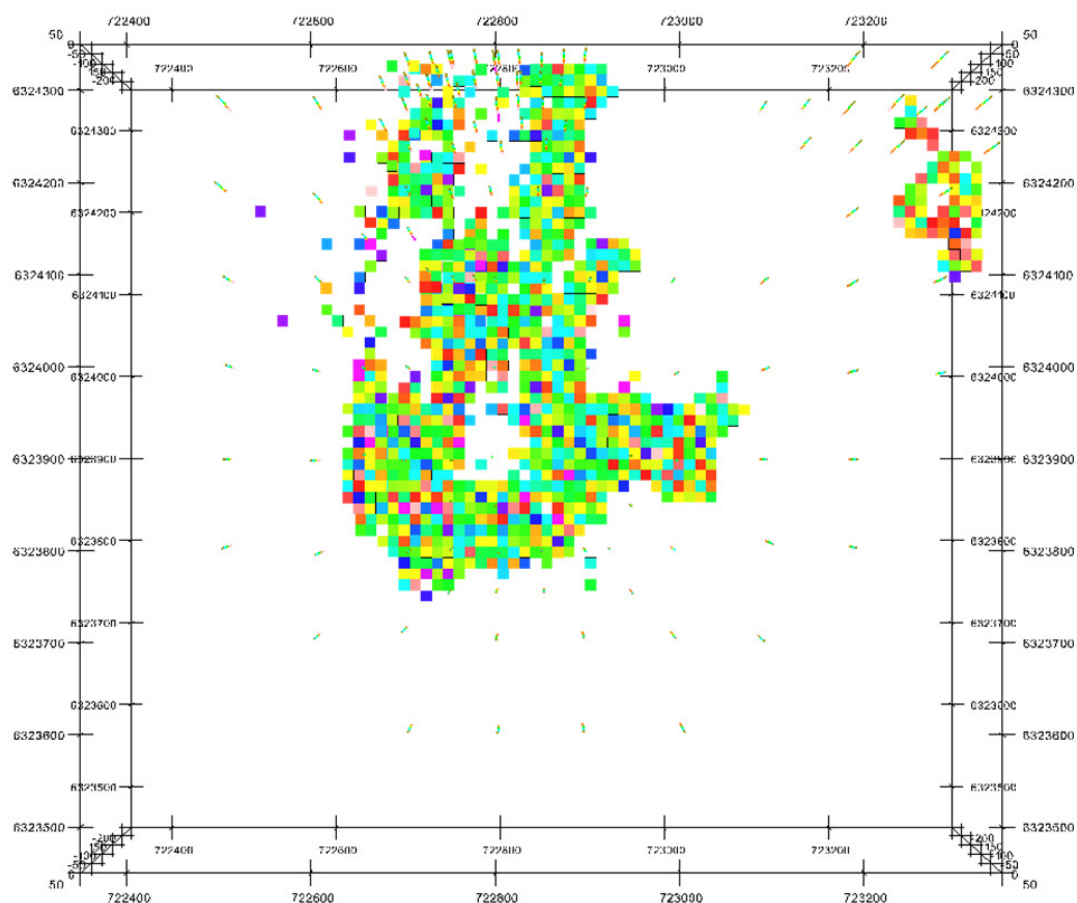


FIG 14 – Optimised uranium mineralisation distribution after inversion.

geophysical) inversion modelling best practice is intimately linked to creating good 3D geology models and taking advantage of geostatistical interpolation to construct 3D property models for much more powerful constrained inversion. Relations of measured physical properties and geochemistry need to be routinely logged and compared during exploration. The result from the Blackbush case study has illuminated a potential exploration technique for uranium using gravity and pattern drilling, whilst the optimised final 3D model for the Blackbush deposit after inversion is being explored for structural behaviour to aid further drilling. Magnetic susceptibility from drilling together with airborne magnetics have been used to predict the distribution of sulfides in the Basil case study. Property volumes also do not necessarily have to be sourced from drilling, but can be optimised using good lithology models, or as a corollary, a good physical property model may itself imply the lithology. Future 3D inversions for mineral exploration are recommended to follow these inversion techniques as they will lead to more robust constrained pathways.

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