AN AUTOMATED SPARSE CONSTRAINT MODEL BUILDER FOR UBC–GIF GRAVITY AND MAGNETIC INVERSIONS

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INTRODUCTION

Inversion of geophysical data seeks to extract a model, or suite of models, representing the subsurface physical properties that can explain an observed geophysical dataset. Due to the inherent non-uniqueness of inversion, any recovered property distribution is only one of an infinite number of possible distributions that could explain the observed data. The most desirable solutions are those that can explain the observed geophysical data and also reproduce known geological features; a goal that can only be achieved by including any available geological information into the inversions as constraints.

One approach to achieving this goal of integration is to supply a full 3D model of geological observations and interpretations to the inversion and test the hypothesis that those interpretations are consistent with the geophysical data (McGaughey, 2007; McInerney et al., 2007; Oldenburg and Pratt, 2007). However, in greenfields mineral exploration where limited geological knowledge exists, it may be impossible to define such a 3D model everywhere in the region of interest. An alternate approach is to supply only the available sparse geological observations to the inversion to recover a prediction about the subsurface distribution of geological features that may be required to satisfy both the known geological constraints and the observed geophysical data. This postpones much of the geological interpretation until after the inversions have been performed and reduces the lead time to recover an inversion result and enable the results of inversions to be used in decisions to acquire further geological and geophysical data or to assist with geological interpretation.

We describe a new method for preparing the geological constraints required for this sparse data approach. It is specifically targeted for use with the University of British Columbia – Geophysical Inversion Facility (UBC–GIF) GRAV3D and MAG3D gravity and magnetic inversion programs (Li and Oldenburg, 1996, 1998). The UBC–GIF inversion approach allows constraints to be assigned to each cell using four sets of parameters:

- A reference physical property which provides the best estimate of the arithmetic mean physical property in the cell.
- A smallness weight which provides an estimate of the reliability of the assigned reference physical property. The weight is a unitless value ≥ 1 with increasing values indicating higher confidence.
- Lower and upper physical property bounds indicating the absolute limits on the property range that can be assigned to the cell. These effectively represent a confidence interval on the supplied reference property.
- Smoothness weights controlling the variation in properties between each adjacent cell in each direction. Values > 1 promote smoother property variations between cells. Values < 1 (but > 0) promote discontinuities in properties between cells.

The inversion will recover a physical property model with properties for each cell that lie between the defined bounds and are as close as possible to the supplied reference physical properties, while still reproducing the observed geophysical data. If possible, the reference physical properties will be matched more closely in those cells that have the highest smallness weights.

ASSIGNING OBSERVATIONS TO THE MODEL

There are two main classes of observation that can be utilised in building a physical property model from geological data: physical property measurements; and observations or interpretations of rock types or alteration styles. Physical property measurements are obviously the most directly related to building a physical property model; however they may not be collected systematically. Observations of geology are far more common. Since most geological units and rocks types have characteristic (but not necessarily unique) physical properties, observations of rock types and alteration may be used as a proxy for actual property measurements. A key component of building a physical property model that is partially based on rock type observations is to link the geological observations to appropriate physical property information. This is done early in the model building process via the creation of a physical property database for the model.

Once the physical property database is created, the model building routine can load the various data files containing those observations and extract or calculate the 3D coordinates at which the observations occur. The data that can be used include text files of surface sample property measurements, drill hole and drill core property measurements and geology logs, ArcView shapefile polygon surface and basement geology maps, and 3D models if available. The physical property database is used to convert geological observations into appropriate physical property estimates. Geological models are usually only used to define the default values in different parts of the model. Direct observations provide tighter constraints.

The model cells are populated by combining all of the most reliable property measurements or estimates in each cell. Due to the principle of superposition applying to potential fields, the combined gravity or magnetic response of a collection of sources will be the sum of the responses of each of the individual sources so gravity and magnetic data respond to the arithmetic mean property within each cell. The mean value in each cell therefore provides the best estimate for the reference model. The property bounds are taken as the 100(1 – α) % confidence interval using:

$$\bar{x} \pm Z_{\alpha/2}\frac{\sigma}{\sqrt{n}}, \quad (n \geq 30) \tag{1}$$

where $\bar{x}$ is the sample mean, $Z_{\alpha/2}$ is the critical Z value for the confidence level, σ is the sample standard deviation, and n is the number of samples (Borradaile, 2003; Shi and Golam Kibria, 2007). Modifications of this formula are available for small numbers of observations ($n < 30$). The spatial distribution of observations within a cell is used to assign smallness weights to each cell indicating the reliability of the reference property for that cell so that properties estimated for poorly-sampled cells have a lower reliability than for well-sampled cells.

EXTRAPOLATING PROPERTIES

The constraining model created thus far is based only on the data and is only enforced where data are available. In data-rich areas a significant number of the cells may be constrained. However, in data-poor environments, such as early exploration stages, few cells will have constraints. An option is provided to extrapolate the observed data outwards a short distance into surrounding cells. The method calculates an ellipsoidal buffer zone to represent the zone of influence around each data cell.

The buffers are defined as ellipsoids with three axes radiating from the centre of each data-bearing cell. The axis orientations are derived from geological orientations supplied by the user.

Cells are identified as being inside the ellipsoidal buffer zone if the distance from the centre of the buffer to the cell centre is less than the radius of the ellipsoid in that direction. The radius of the ellipsoid in the direction of each cell is calculated using the standard equation for an ellipsoid in spherical coordinates.

If no other data-bearing cells lie within a buffer, then the reference property of the data-bearing cell is applied as the best available estimate of the reference property for every cell in that buffer zone (Figure 1). Given that the confidence in that property estimate will decrease with distance from the data-bearing cell, the smallness weight assigned to each cell in the buffer is derived from the smallness weight associated with the data-bearing cell but weighted by the squared inverse distance from the data-bearing cell. The same inverse-distance weighting is used to widen the bounds range as the confidence in the bounds decreases with increasing distance from the data-bearing cell until they reach default background values at the edge of the buffer.

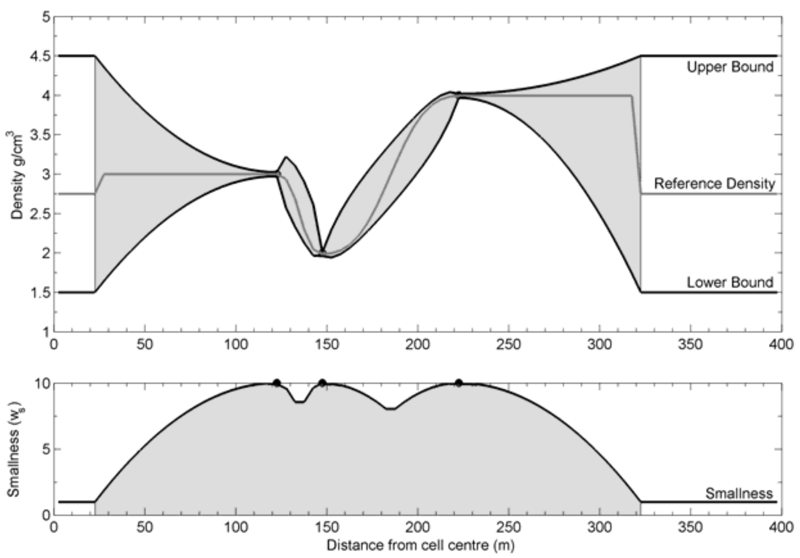

Figure 1: Unidirectional example of property values assigned within buffer zones surrounding three data-bearing cells marked with circles at 122.5 m, 147.5 m, and 222.5 m. At the data points, tight bounds and maximum smallness weights indicate a high confidence in the assigned properties. Between the three data-bearing cells the reference properties, bounds, and smallness weights are distance-squared-weighted averages. Intuitively the bounds and smallness weights reflect a maximum uncertainty in the properties at points halfway between data-bearing cells where it is most unclear which property should apply. To the left and right ends of the profile the bounds widen to default values, and uniform reference properties are assigned.

If multiple data-bearing cells are present within a buffer zone, then the buffers around each of the data-bearing cells will overlap. Any cells that lie between data-bearing cells must take properties that reflect the influence of each of the data-bearing cells; however buffer cells that are closer to one data-bearing cell should more closely reflect the properties of that cell. Weighted averages are used to assign constraint values in those cells lie within overlapping buffer zones. Properties are only extrapolated where no other data is available, and are not extrapolated beyond adjacent data-bearing cells.

SMOOTHNESS WEIGHTS

Smoothness weights define how smoothly the physical properties in the recovered inversion should vary between adjacent cells. There are three main geological scenarios to which smoothness weights can be usefully applied:

1. Allowing sharp changes in properties across geological contacts where they are known;
2. Promoting smooth extrapolation of properties away from observation locations into cells that lack observations, as an alternative to using buffers; and
3. Retaining the natural variability or roughness in physical properties observed in the reference model.

Each of these situations may arise individually, or in combination, and each is handled automatically within the model building program.

EXAMPLE OF DEVELOPING GEOLOGICAL CONSTRAINTS

An example of the constraints that can be built using sparse geological data is shown in Figure 2 for the Perseverance komatiite-hosted nickel sulphide deposit in Western Australia. The example uses all available geological information surrounding the deposit to create density constraints for gravity inversions. The available data includes surface and basement geology map polygon shapefiles, a drilling database with geology logs and density measurements, and density measurements on variably weathered surface rocks. Ellipsoidal buffers with a radius of up to 200 m were used to extrapolate the observations using the dominant north-northwest strike and subvertical dip. The constraint models provide the strongest constraints where cells are well sampled with density measurements or geological observations. Weaker constraints are applied where cells are poorly sampled or where constraints have been extrapolated based on nearby observations. Strong data-based constraints are specified in 2.8 % of the model cells and weaker extrapolated constraints are defined in an additional 17.2 % of the model.

Even prior to running the inversions, the constraint models provide a unique view of some of the geological features at Perseverance. The density reference model in Figure 2 shows several known geological features including a dense dunite core, and maps, in 3D, a fold intersected by only limited drilling at a depth of 1500 m. It also shows patches of the dense massive sulphides and thin subvertical mafic and ultramafic units west of the Perseverance open pit.

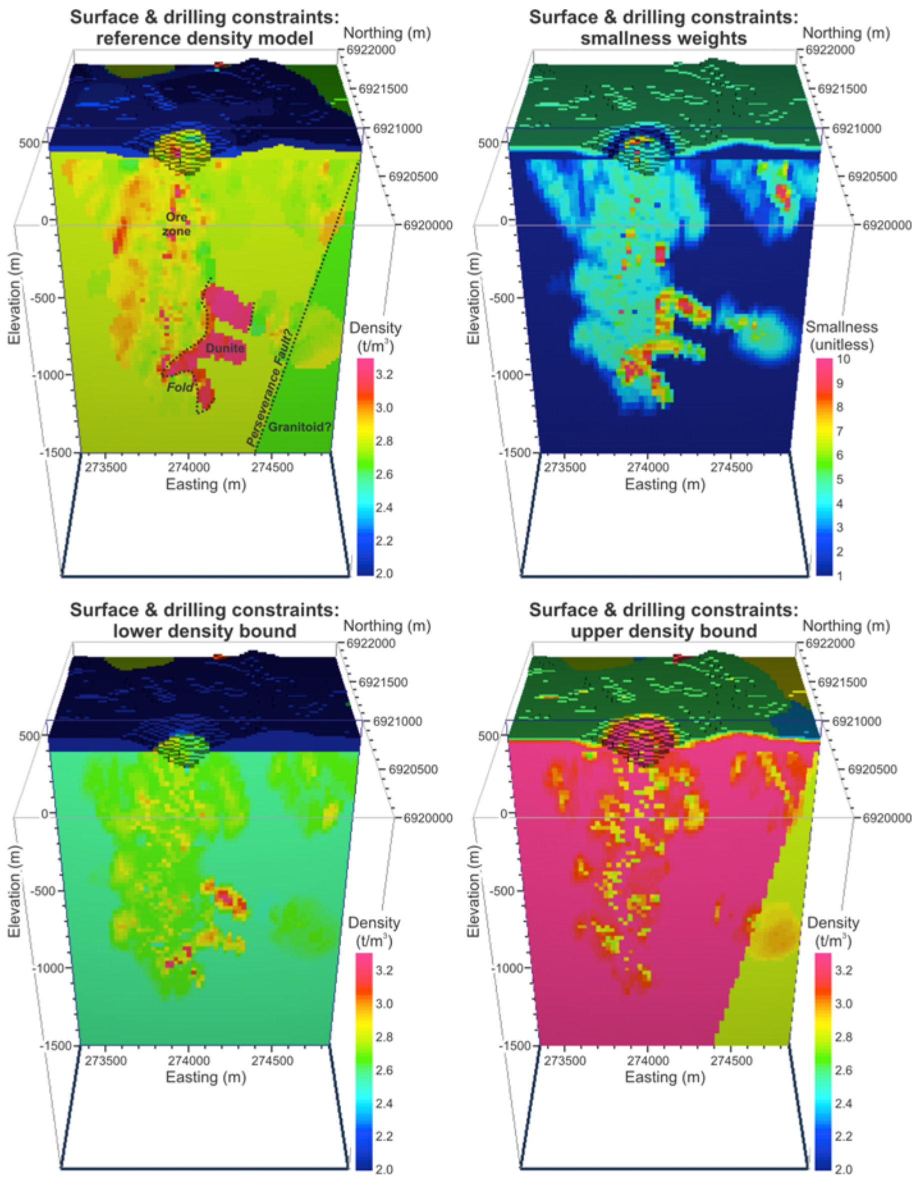

Figure 2: Density constraint models for the core of the Perseverance inversion volume based on drilling geology logs, density measurements and surface information. The observation-based constraints were extrapolated using the ellipsoidal buffers based on the prevalent north-northwest strike and subvertical dip. The models show considerable complexity but reproduce much of the known geology, including: a large dense dunite core at > 1 km depth; thin subvertical mafic and ultramafic bodies west of the open pit: and patches of the massive sulphide ore zone.

SUMMARY

The sparse constraint model builder described here provides a quick and efficient means of automatically producing data-based constraining models for geophysical inversions. Although specifically developed for use with the UBC–GIF inversion programs, the treatment of the different types of geological information could be applied for use in any inversion or modelling algorithm. The procedure itself is primarily a data management routine to provide a systematic and repeatable way of combining geological observations and physical property measurements into a single, self-consistent model. Physical property data is integral to the technique since physical properties provide the critical link between geology and observed geophysical responses and an understanding of the expected physical properties is a necessary component in any geophysical interpretation. By demonstrating an efficient link between physical property measurements and development of a constraining model for inversions, it should provide justification for acquiring more property measurements in the field. When used in inversions, the constraints that are created provide a means to effectively combine geological observations with geophysical data to produce holistic predictive models of the subsurface.

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