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# Comparison of full-tensor manetic gradiometry with conventional magnetic data: Implications for kimberlite exploration

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## Introduction

Many of the historical kimberlite discoveries in the Slave geological province were initially identified by magnetic lows caused by remanently magnetized bodies. Paleomagnetic analyses show that the remanence is often antiparallel to the current Earth field. It was expected that utilizing a technique like $QMAG^T$, capable of recovering the full tensor of the magnetic field, would identify more subtle anomalies generated by remanence with directions oblique to that of the current field.

Over 2022 to 2023, a $QMAG^T$ survey was conducted by Dias Airborne over the majority of tenure held by Diavik Diamond Mines. The logistics of operating this survey in a remote, arctic climate are discussed (including pre-mobilization and planning). The technical specifications for the survey, including quality assurance and control steps, are also reviewed.

A semi-automated, supervised learning method for utilizing 1D convolution of $QMAG^T$ data to predict kimberlite occurrences was also tested. The large amount of drilling on the property has been leveraged to provide a labelled dataset that was used to train several different 1D CNN architectures. Though outputs from the models were broadly similar, differences in performance and efficiency of differing architectures are evaluated.

## Comparison of TMI and tensor data

While the $QMAG^T$ system directly measures the independent tensor components of the magnetic field, there is a method available (Yin et al., 2016) to calculate the magnetic gradient tensor from total magnetic intensity (TMI) data. A comparison of the two tensor components, i.e. measured and calculated, shows that there are implications for survey design.

Airborne magnetic data from a late 1990s Dighem survey were subset and processed to produce calculated magnetic field tensors, i.e. $B_{xx}$, $B_{xy}$, $B_{xz}$, $B_{yy}$ and $B_{zz}$. These were compared to $QMAG^T$ tensor data over the same area. The $B_{zz}$ component is illustrated in Figure 1 and shows that, while, large-scale features are faithfully reproduced, there are significant differences on the scale of smaller, kimberlite-sized features. Differences are attributable, in part, to acquisition settings between the two surveys. Dias' use of tensor-consistent gridding also produces a smoother product.

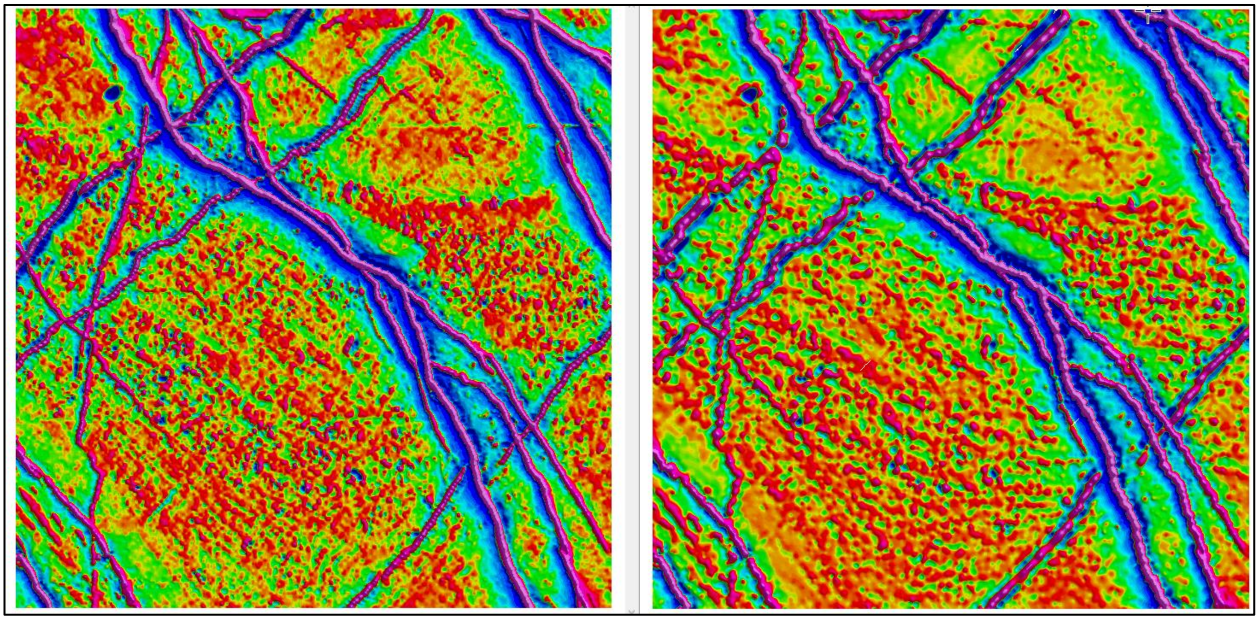

Figure 1. Comparison of FTMG $B_{zz}$ component (left) and $B_{zz}$ calculated from Dighem magnetic data.

Despite its relative novelty, there are several modelling packages capable of inverting tensor magnetic data collected with the $QMAG^T$ to recover a model of subsurface magnetic susceptibility. A subset of the $QMAG^T$ data over a known Diavik kimberlite was inverted using SimPEG, VPmg, and ModelVision packages. The results are variable but most produced compact bodies with varying levels of agreement with drillhole data. The application of constraints is critical

**Convolutional Neural Network**

Training data were created by leveraging the existing drilling across the property. A radial buffer of 250m was applied around each drillhole and labelled either non-kimberlite (0) or kimberlite (1). These buffer areas were utilized as a mask for the raw $QMAG^T$ data, which was extracted into a separate database. Flight lines were preserved during this process to maximize data fidelity. Any of the truncated flight lines less than 80 fiducials in length were discarded, and those longer were padded with 0s to create a training set of 934 lines of an exact length of 533 fiducials each. Approximately 40% of the resultant lines were labelled to the positive class (kimberlite). Data were split into training and validation datasets.

Several network architectures were evaluated, but all relied upon a hierarchy of 1d simultaneous convolutions (e.g. 8 fid → 16 fid → 32 fid) of the six $QMAG^T$ channels. The output of these convolutions were then fed into a series of dense layers with the final classification sigmoid placed at the end of the network. Model loss during training was quite noisy, Figure 2, and the very low loss is suggestive of overfitting (despite the equal loss in the validation set).

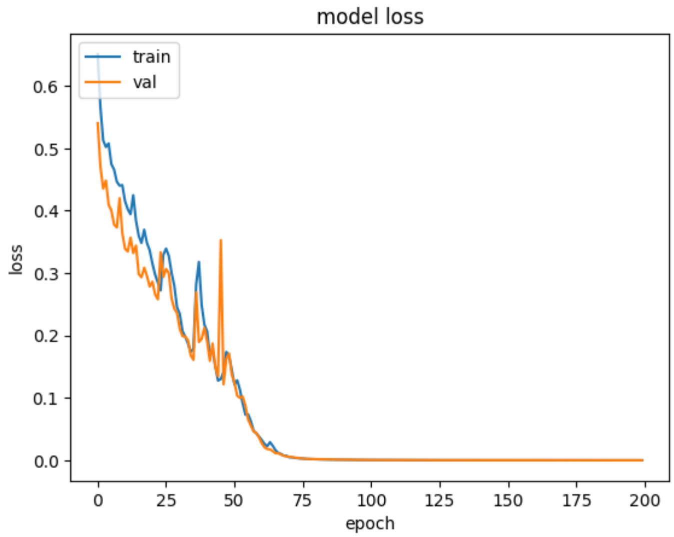


Figure 2. Model loss curve for selected training run.

After training, the network was applied to the entire QMAG$^T$ dataset, providing a prediction value (ranging 0-1) for each data measurement. The results are shown below in Figure 3.

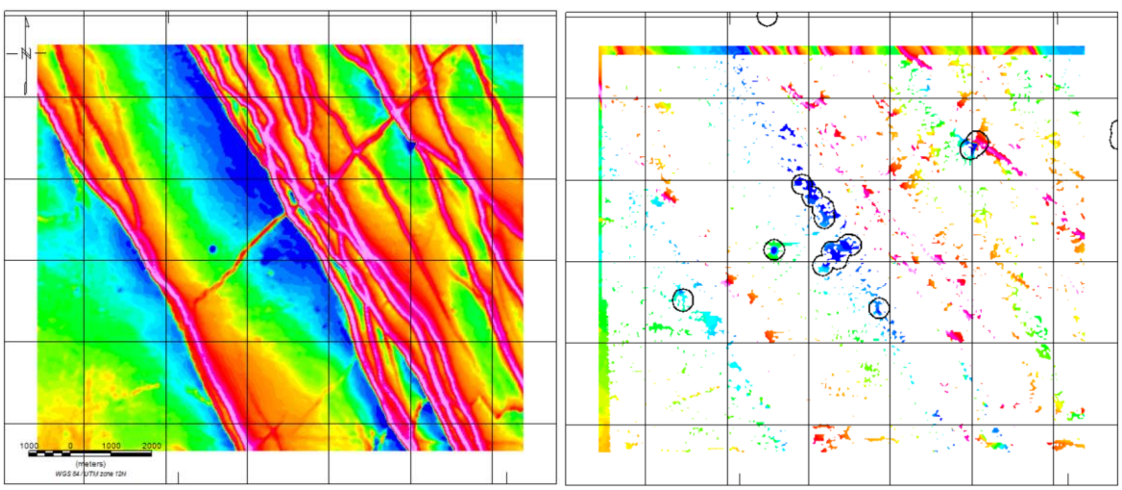

Figure 3. Left: Gridded TMI image over selected portion of Diavik tenure. Right: Prediction map applied over TMI image at 95% probability, with areas with drillholes that intersected kimberlite outlined in black.

## References

Yin G, Zhang Y, Mi S, Fan H, Li Z (2016) Calculation of the magnetic gradient tensor from total magnetic anomaly field based on regularized method in frequency domain. Journal of Applied Geophysics 134:44-54