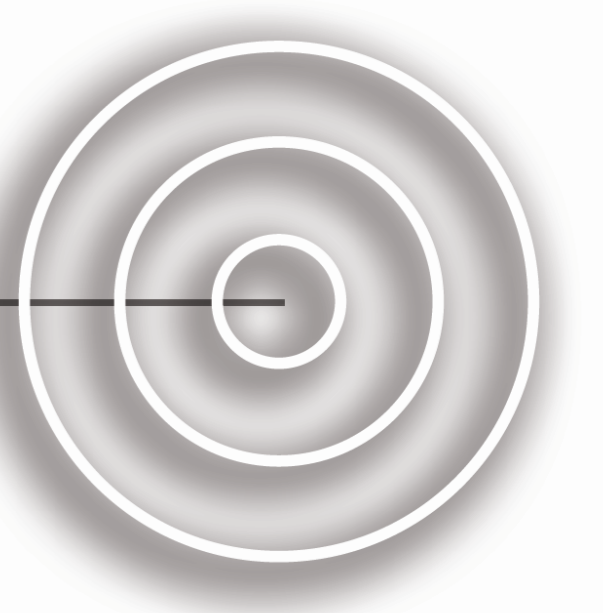


# Magnetic grid resolution enhancement using deep learning super-resolution



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## High-resolution geophysical grids are a critical tool for mineral exploration across all scales

- Western Australia has extensive open-file airborne magnetic data at 400 m line spacing or better
- High-resolution surveys over targets of interest are undertaken by industry at closer line spacing
- High resolution refers to the inclusion of higher frequency information in a grid with finer cell size
- High frequency content is necessary for more detailed interpretation of structures in gridded geophysics
- Optimal grid cell size is determined by survey line spacing
- Closer line spacing increases survey cost
- Existing grids in merged grid products have different resolutions, which can create artifacts during further processing

## Increased grid resolution may be achieved without performing higher resolution surveying

- Recent computer science research has seen vast improvement in convolutional neural network *super-resolution* upsampling techniques using deep learning
- Two techniques were applied to TMI data over the Eastern Goldfields Superterrane, the best result shown in Figure 1
- TMI data were extracted from the 80 m and 20 m magnetic merged grid of Western Australia 2020 (Brett, 2020)
- The 80 m low-resolution grid data used are *interpolated* high-resolution grid data
- Follow-on research will be conducted into using low-resolution survey data, in its optimal resolution

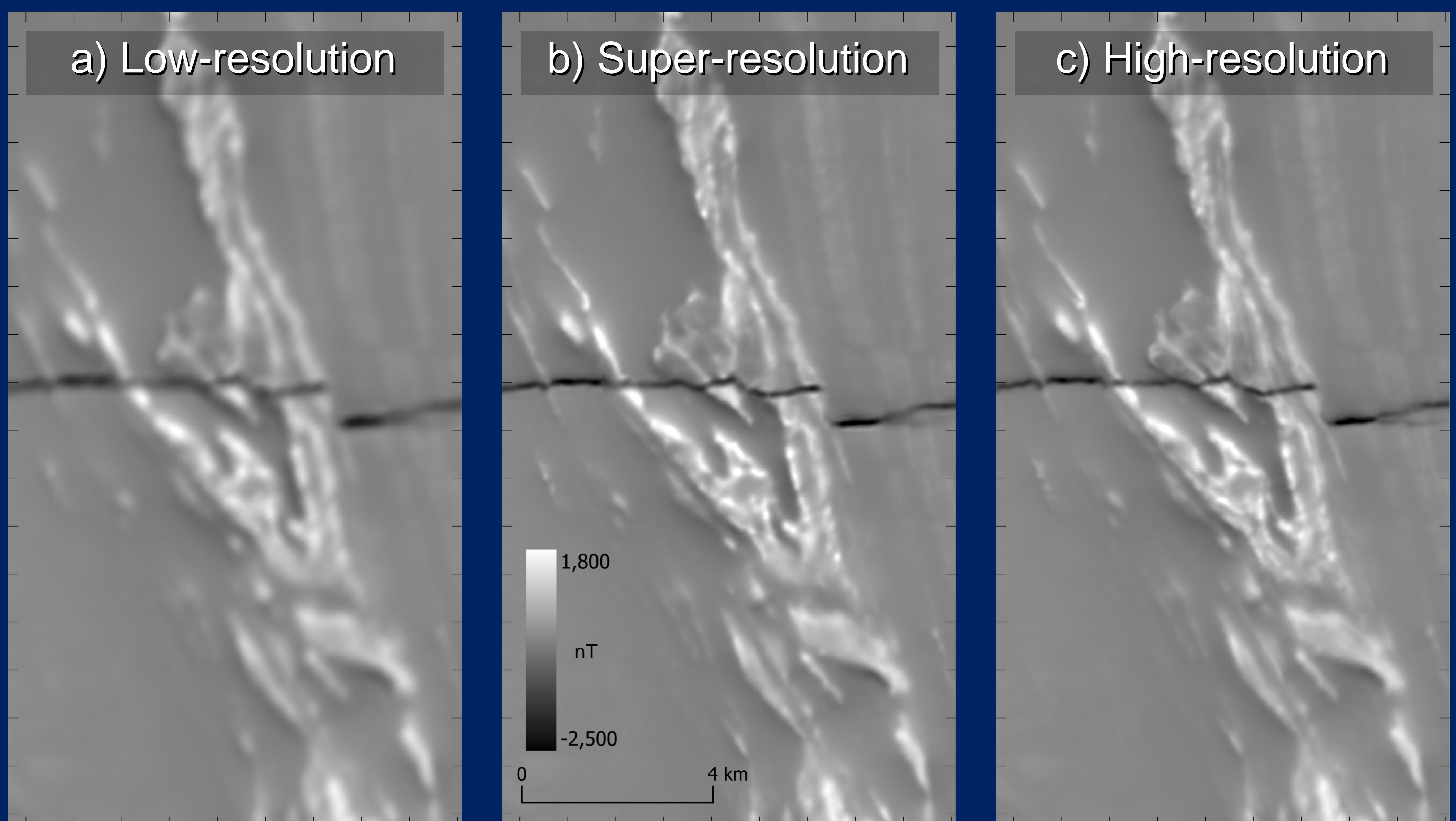


Figure 1 - Super-resolution successfully restores lost high-frequency content in downsampled TMI grids

- a) Low-resolution 80 m cell size extent from the state grid
- b) Super-resolution 20 m cell size prediction, using a) as the input
- c) High-resolution 20 m ground truth from the state grid

- All sub-figures share the same extent and linear colour map
- The low-resolution grid has been bicubically filtered for visualisation
- This extent was not seen during training
- The high-resolution target was not seen during inference
- The additional frequency content is predicted using information learnt by the network during training, accurate against high-resolution targets for similar TMI features in a nearby extent

## Methods, Discussion, and Conclusion

- *ESRGAN+* (Rakotonirina and Rasoanaivo, 2020), a current state-of-the-art super-resolution network, was trained with and without the assistance of a GAN discriminator network
- Training data take the form of 5290, 32x32 pixel 80 m low-resolution and 128x128 20 m high-resolution TMI patches from the merged state grid, min-max normalised between 0 and 1
- Validation and Test patches were held independent of the training patches, to identify the best model and measure its performance
- The most accurate result was achieved with the unassisted method
- This result shows super-resolution can be used to predict high frequency content for features and textures present in TMI grids
- The same training process could be used with grids generated from surveys at different line spacing

## References

Brett, J., 2020. 80 m magnetic merged grid of Western Australia 2020 version 1. Geological Survey of Western Australia, [www.dmp.wa.gov.au/geophysics](http://www.dmp.wa.gov.au/geophysics).  
*ESRGAN+*: Further improving enhanced super-resolution generative adversarial network, in: ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Presented at the ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, Barcelona, Spain, pp. 3637-3641.

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