Datarock.

Textural analysis of large scale geophysical data sets with computer vision algorithms

Dr. Thomas Ostersen

Who are Datarock?

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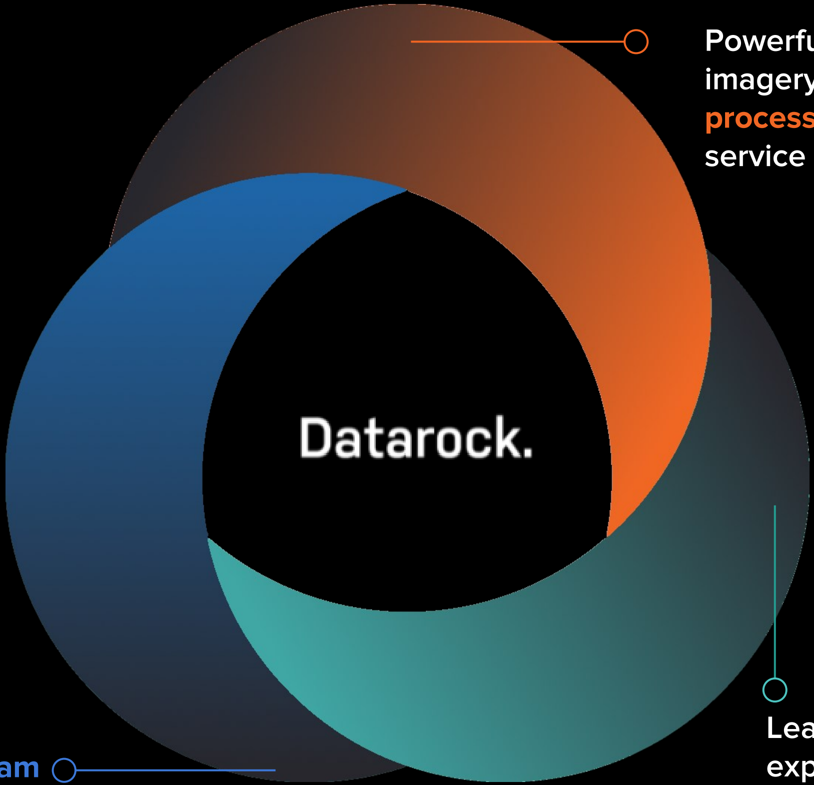
- Datarock is a mining technology company
- We build productionised machine learning solutions for the mining industry
- These solutions extract valuable geological and geotechnical information from imagery, video and point clouds



Powerful cloud-based imagery and video **processing platform** service

Leading industry experts in **leveraging AI** to solve geoscience challenges

Renowned **Applied Science team** made up of experienced geoscientists and data scientists

Prospectivity Mapping 101

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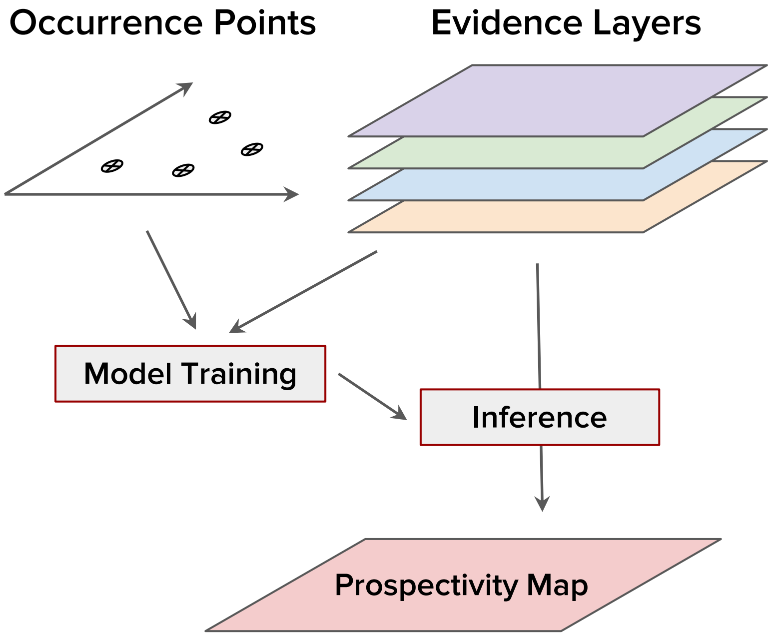
- Mineral prospectivity is a function of geological, geochemical and geophysical data quantified in evidence layers
- We approximate this function with a statistical model trained on known mineral occurrences
- Running inference with model allows us to derive a map delineating the spatial distribution of ‘prospectivity’
- Important to select evidence layers that are sensitive to the mineral system being targeted



NE Tasmania Sn-W Prospectivity Mapping

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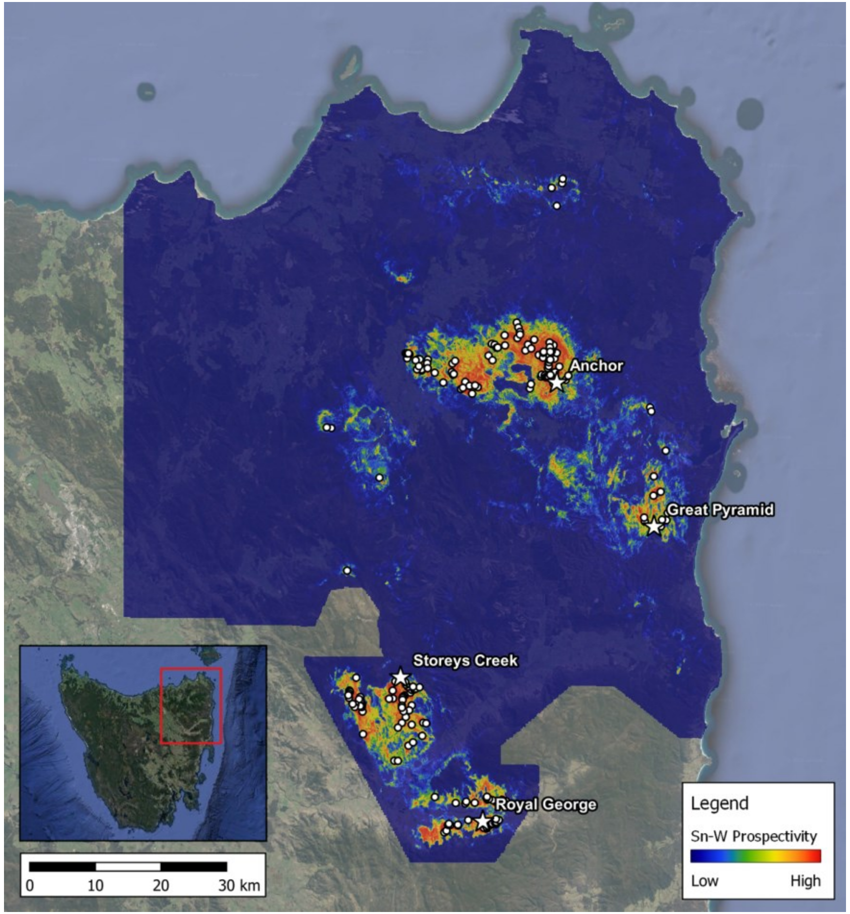
- Pixel-wise modelling using various geophysical and remote sensing data sets as evidence layers
  - Gravity data sensitive to low density granites
  - Radiometrics sensitive to evolved granites at surface
  - Magnetics sensitive to ‘quiet’ response of evolved granites
- Key limitation of the method is that pixels are treated as isolated data points
  - This is not how humans interpret geoscientific maps!
  - We interpret the absolute values as well as ***texture*** (the relationship between pixels)
  - Computer vision algorithms can help us

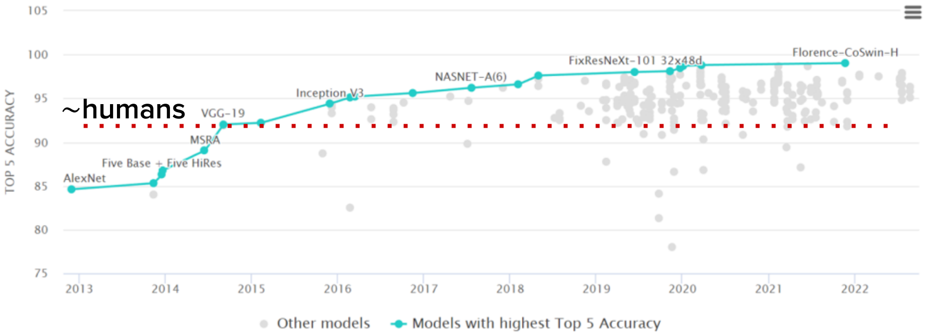


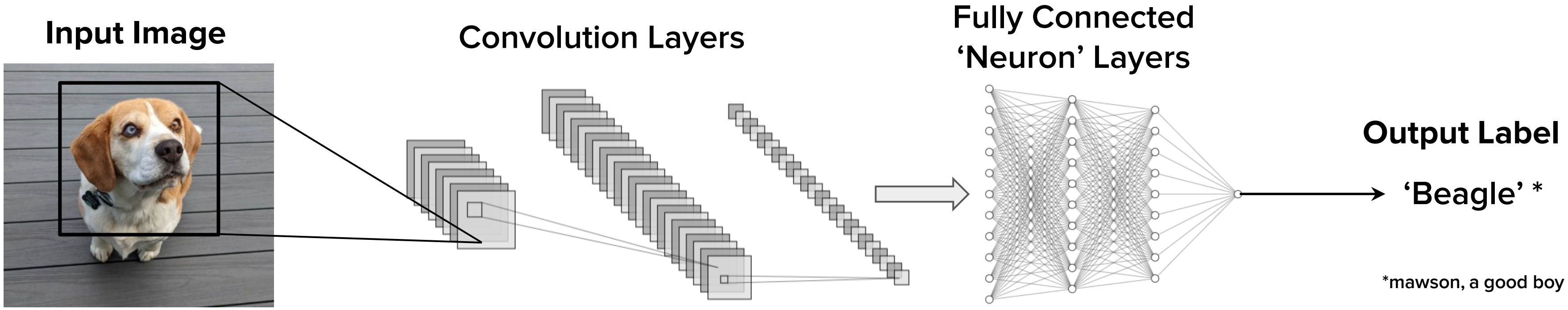
Computer Vision 101

- Computer science field concerned with algorithms that interpret and understand visual data
- ImageNet → long running image classification competition
- Convolutional neural network models bested human performance in ~2015

ImageNet Examples

ImageNet Competitor Scores vs. Time





Convolutional Image Features

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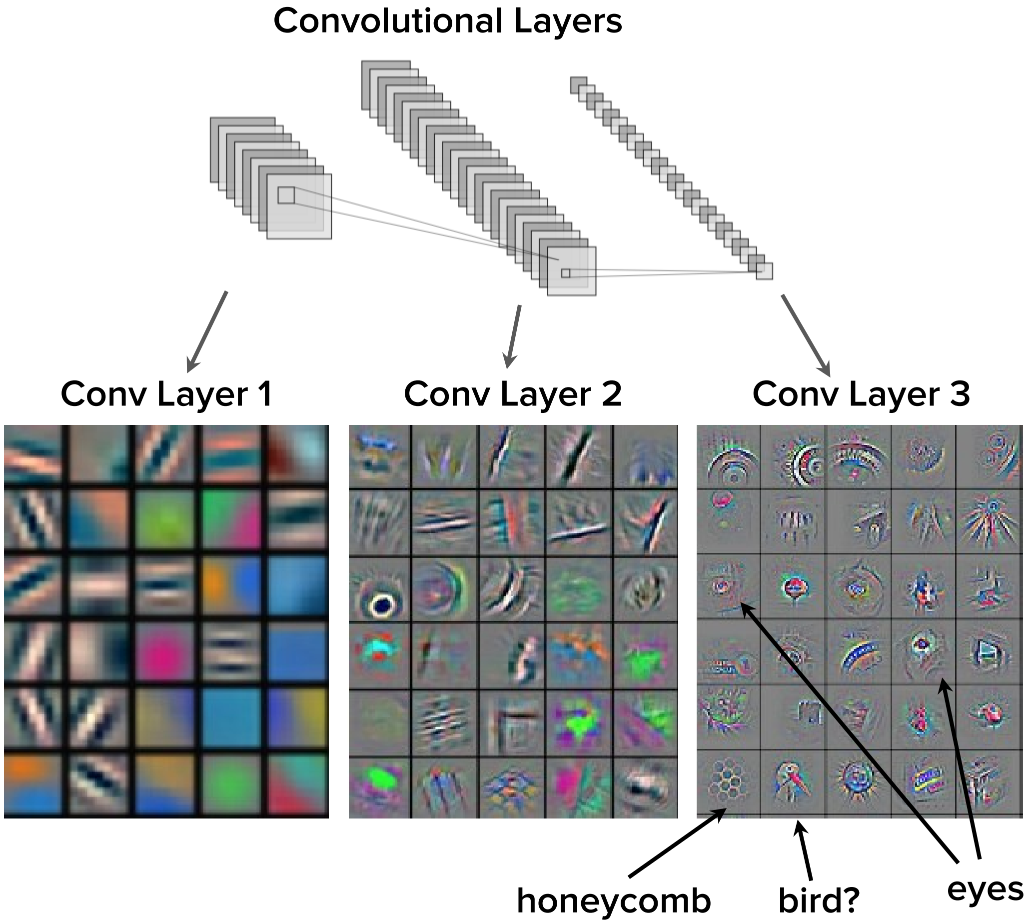
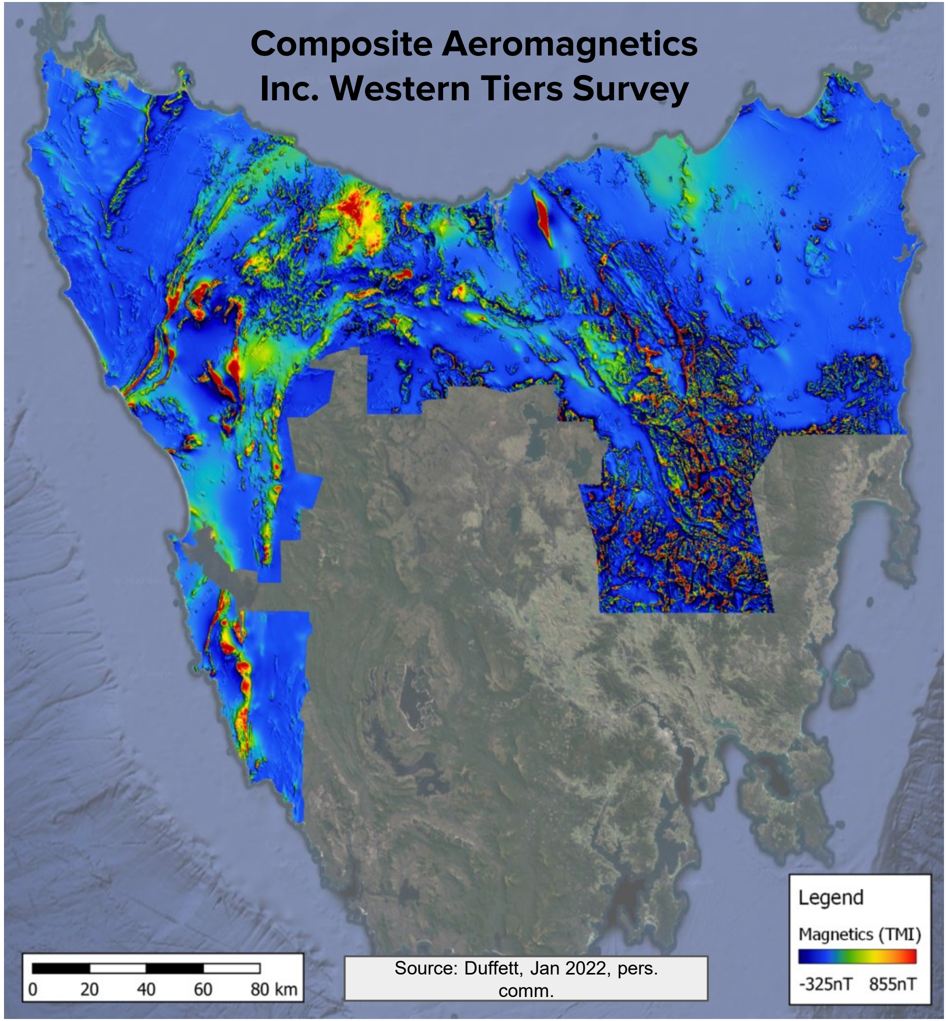
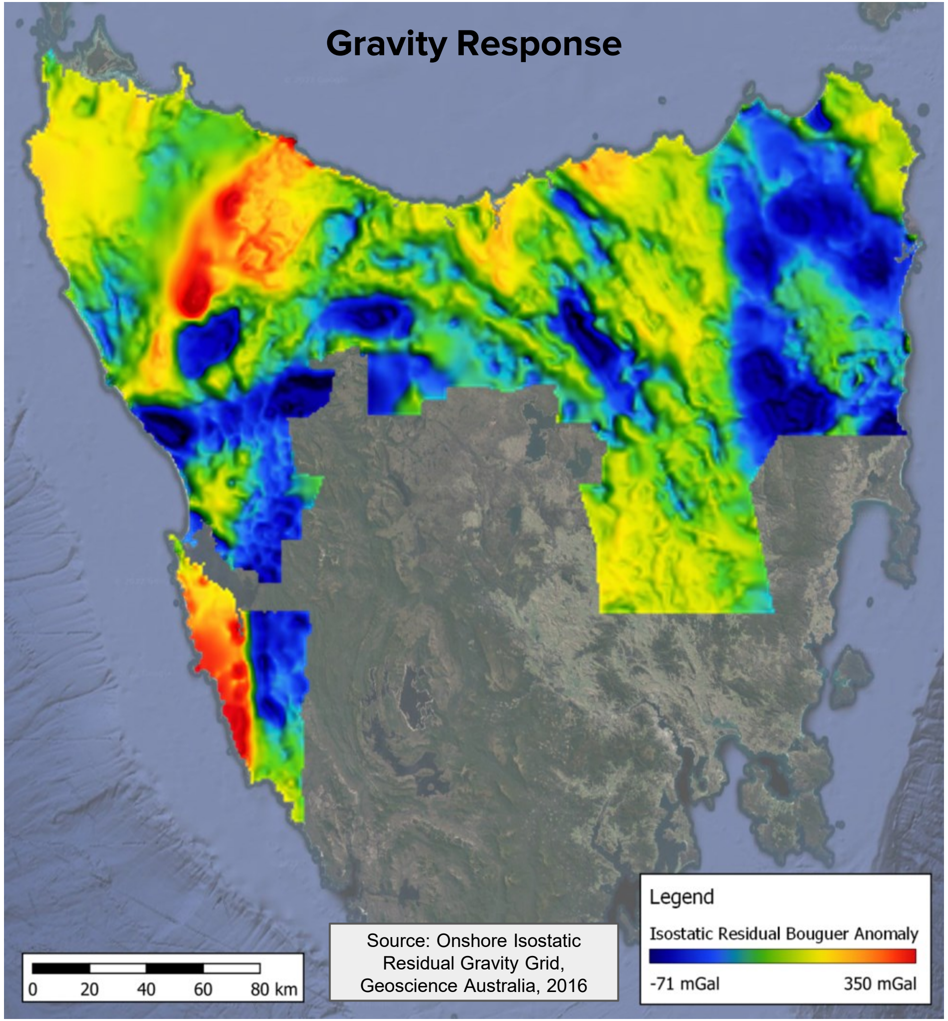
- Convolutional layers learn textural features in the image
- The complexity of features captured increases with number of layers in the model
- Training NN models requires a lot of computing power and data
- Models trained on generic ImageNet photos and their corresponding labels are sensitive to a wide range of textures with varying complexity



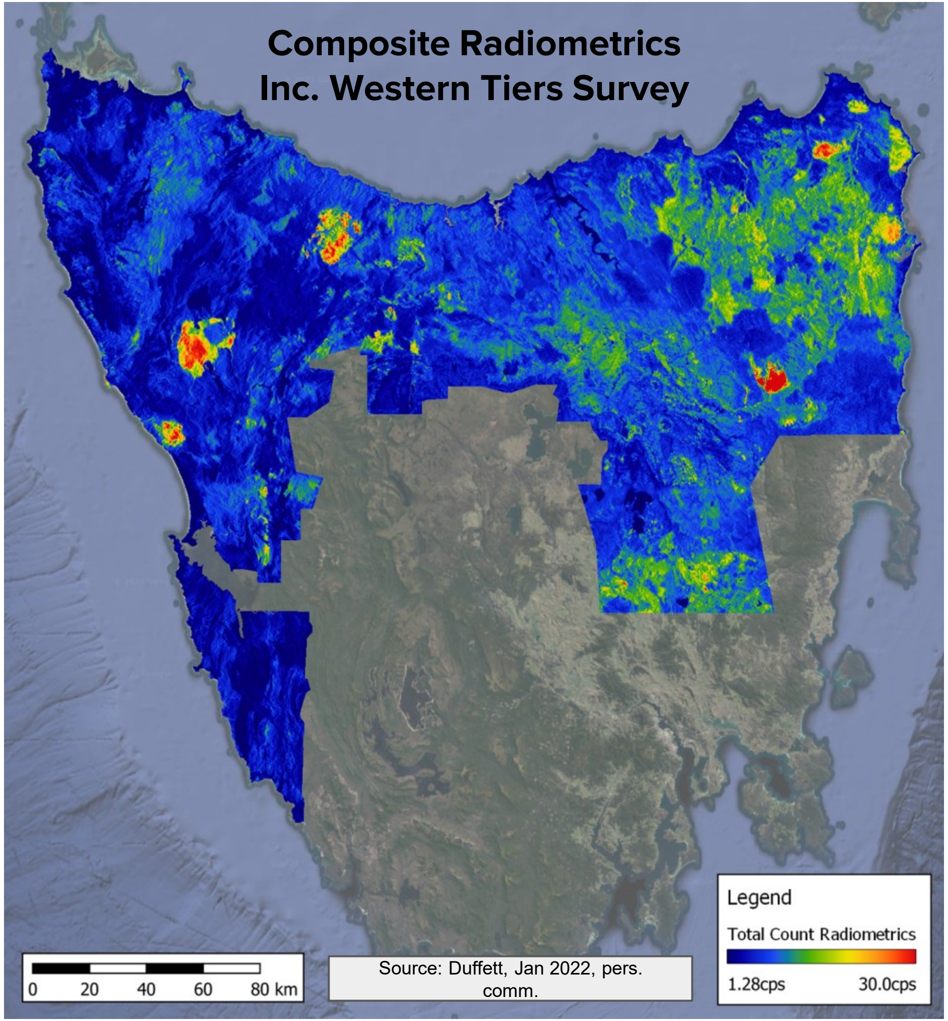
Geophysical Imagery

- Human interpretation of this data focuses on texture
    - Eg: dolerite dykes and sills in Tasmania basin have distinctive magnetic texture
- We can use pre-trained networks to quantify image texture
    - This is *transfer learning*
    - Using insights gained from one machine learning task (classifying ImageNet) to inform a different task (quantifying geophysical texture)
- This requires a degree of data preparation as models ingest 3-band RGB imagery





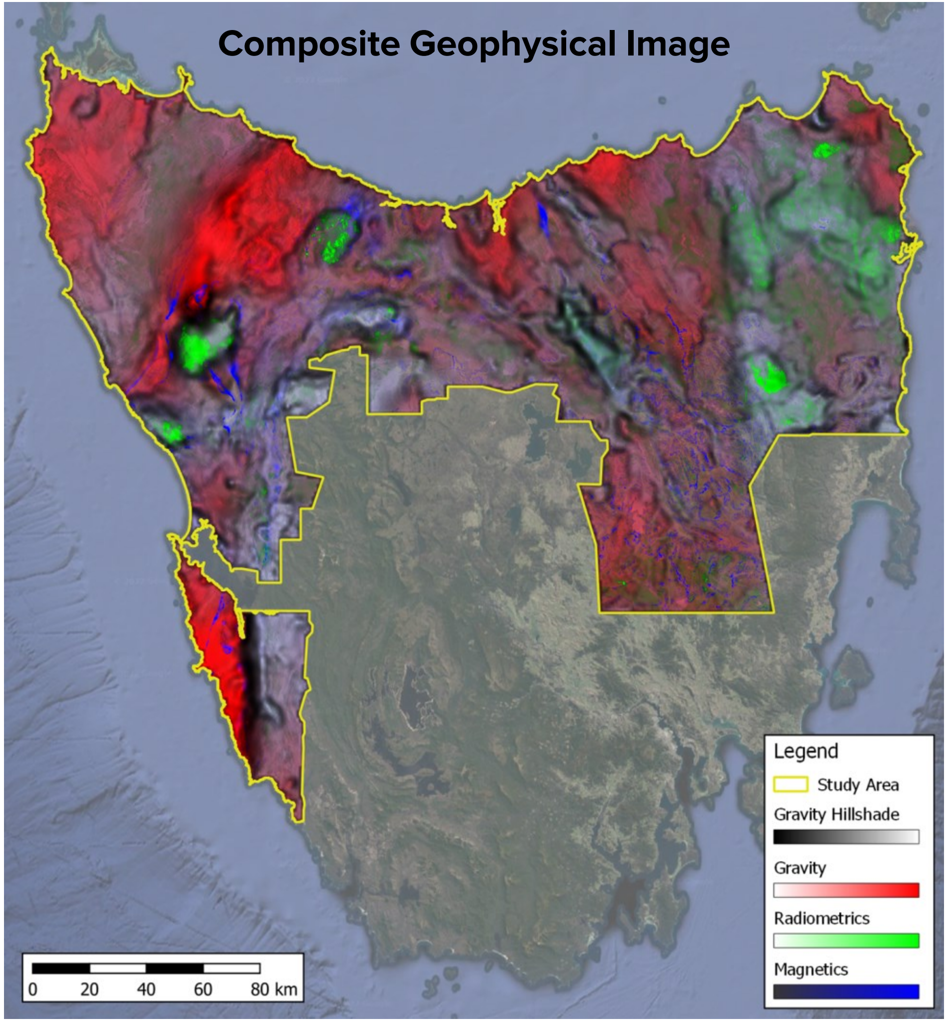
Gravity Response
Source: Onshore Isostatic Residual Gravity Grid, Geoscience Australia, 2016
Legend
Isostatic Residual Bouguer Anomaly
-71 mGal
350 mGal
0 20 40 60 80 km



Composite Radiometrics Inc. Western Tiers Survey
Source: Duffett, Jan 2022, pers. comm.
Legend
Total Count Radiometrics
1.28cps
30.0cps
0 20 40 60 80 km

Geophysical Imagery Compositing

- Used QGIS to stack magnetics, gravity and radiometrics data into a composite image
- Added a gravity vertical hillshade layer to highlight gravity gradients in the image
- This is a *completely* subjective process
- Devonian granites are distinctive with low gravity pale blues ± greens
- Data now ready for texture feature extraction



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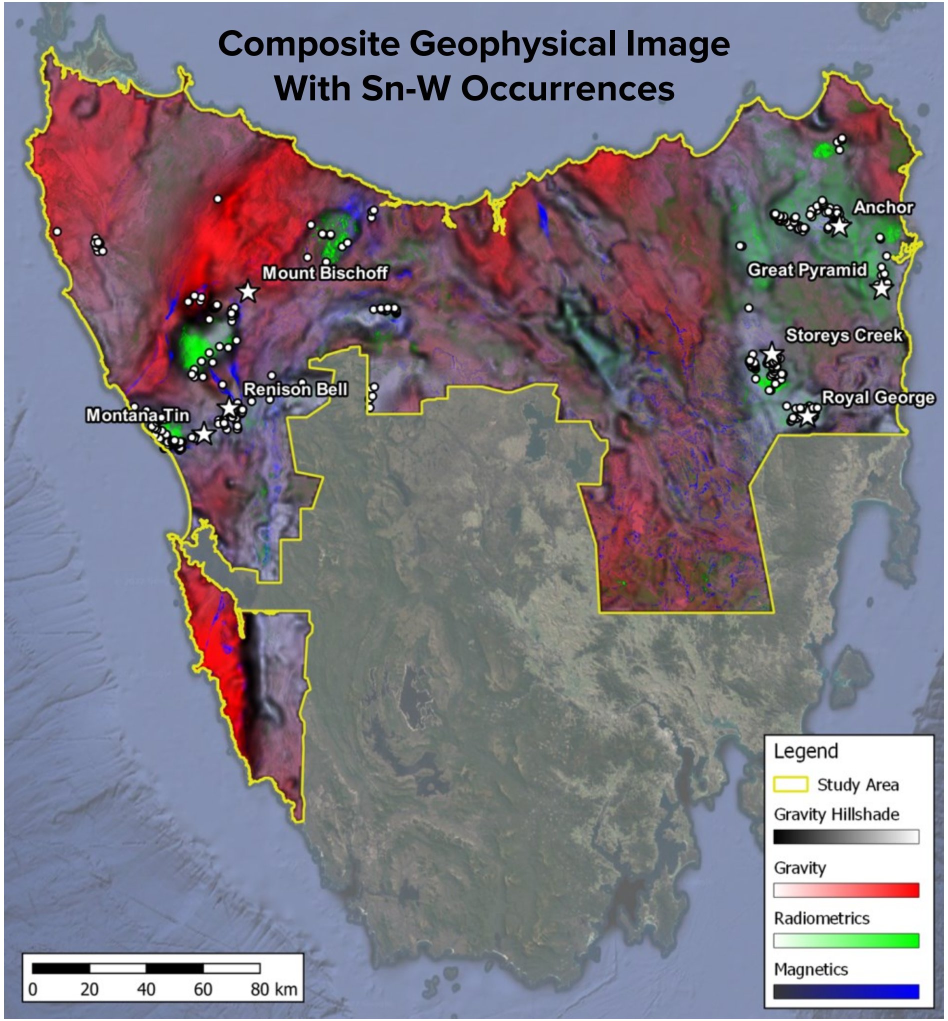

Image Tiling

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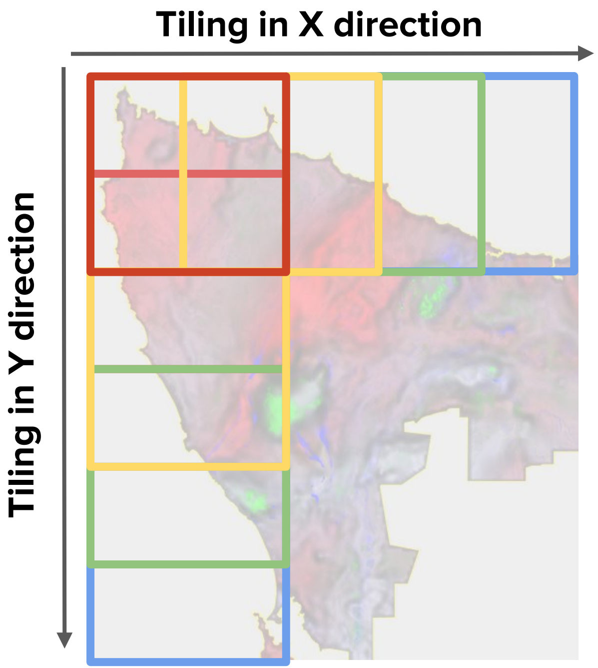
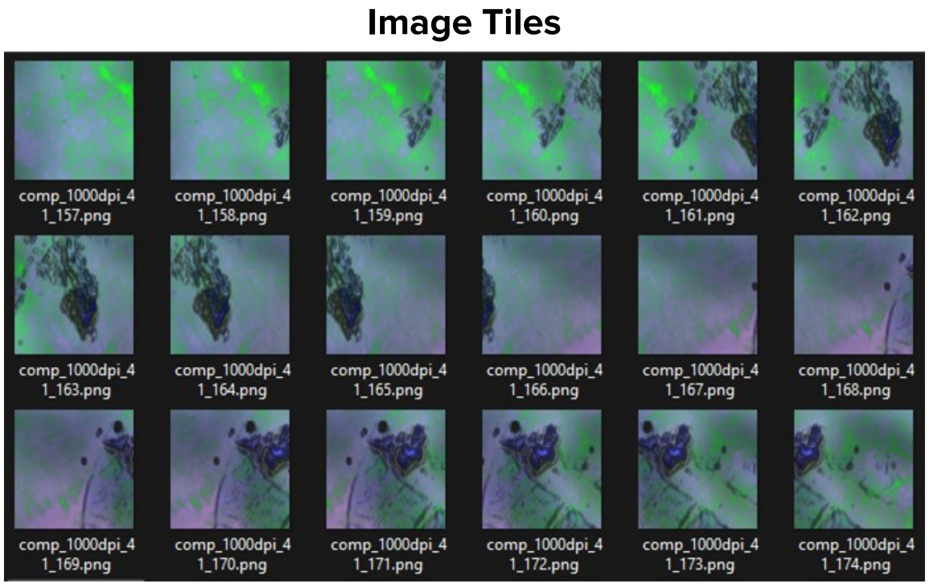
- Geophysical composite image sliced into square tiles with 80% overlap
- Also generated a tile centred on all Sn-W mineral occurrences
- This can be done at different scales of investigation - using 4km in this example





Feature Extraction

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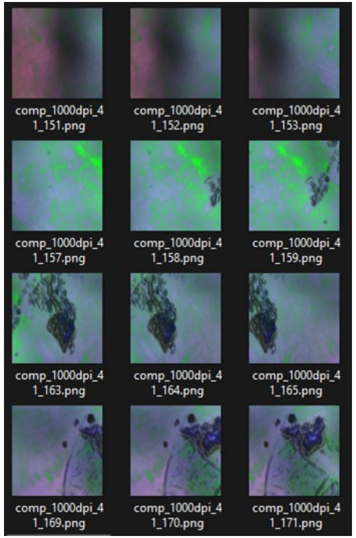
- Image tiles fed through pre-trained ResNet-50 model
- 512 feature vectors describing textural information extracted for each tile
- Values are completely arbitrary
  - Feature **X0** may represent presence of dog ears or car tyres ➔ details irrelevant

Image Tiles



Feature Extraction with Pretrained ResNet-50 Model

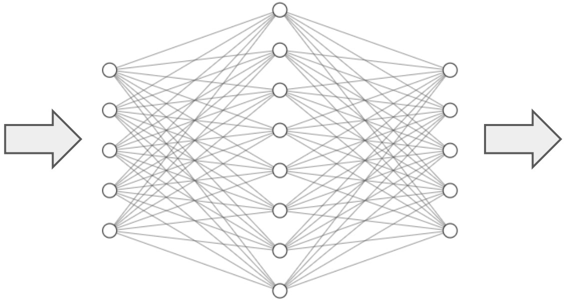


Table of Feature Vectors for All Image Tiles

	img	X0	X1	...	X510	X511
0	snw_minocc_depid_1286.png	0.552817	0.443831	...	1.063608	2.338869
1	snw_minocc_depid_5382.png	3.037738	1.088314	...	2.007402	0.304402
2	snw_minocc_depid_2409.png	0.424897	1.445704	...	2.057926	6.006111
3	snw_minocc_depid_1275.png	4.598716	2.969924	...	1.977413	1.056619
4	snw_minocc_depid_2713.png	3.033064	5.163166	...	1.276369	5.133771
...	...	...	...	...	...	...
13837	comp_500dpi_60_69.png	2.445644	0.692269	...	0.236308	1.511673
13838	comp_500dpi_1_100.png	2.445644	0.692269	...	0.236308	1.511673
13839	comp_500dpi_8_101.png	2.610287	3.666613	...	2.538560	0.667721
13840	comp_500dpi_60_28.png	3.035514	3.928397	...	2.200748	1.255313
13841	comp_500dpi_5_108.png	2.445646	0.692269	...	0.236311	1.511677

13842 rows × 517 columns

Textural Similarity Measures

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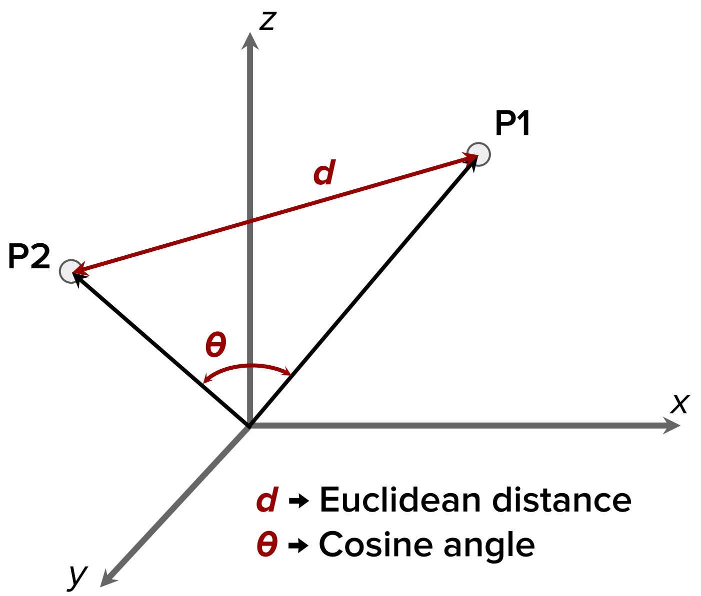
- Images with similar textures will have similar feature vectors
- We use cosine distance to quantify similarity
  - Small cosine angle between images → similar
  - Large cosine angle between images → dissimilar
- Calculating cosine distance in 512-dimensional feature space allows us to quantify textural similarity

Similarity Metrics - 3D Example



Similarity to Royal George

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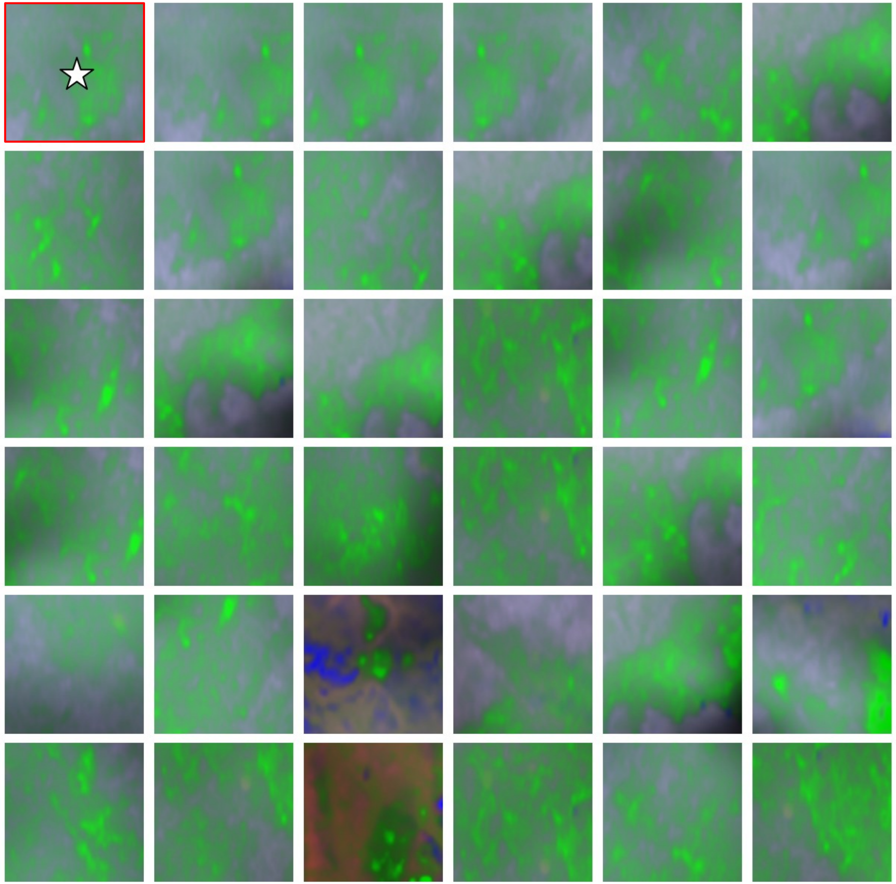
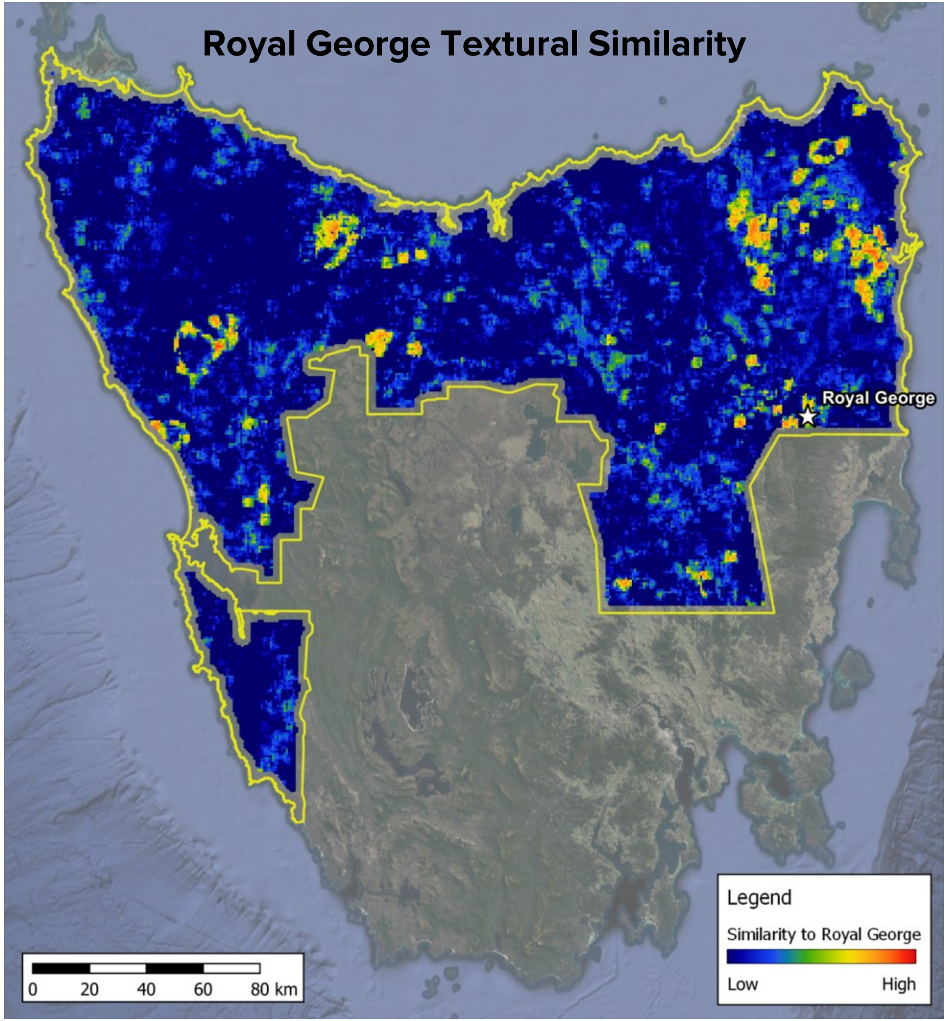
- Calculate cosine distance in feature vector space to all tiles from the Royal George Sn-W occurrence tile
- Similar tiles tend to be dominated by a mottled green texture from the radiometric layer
- Broad scale brightness gradients reflects gravity hillshade layer
  - This is sensitive to granite edges

35 Most Similar Tiles to Royal George Sn-W Occurrence Tile



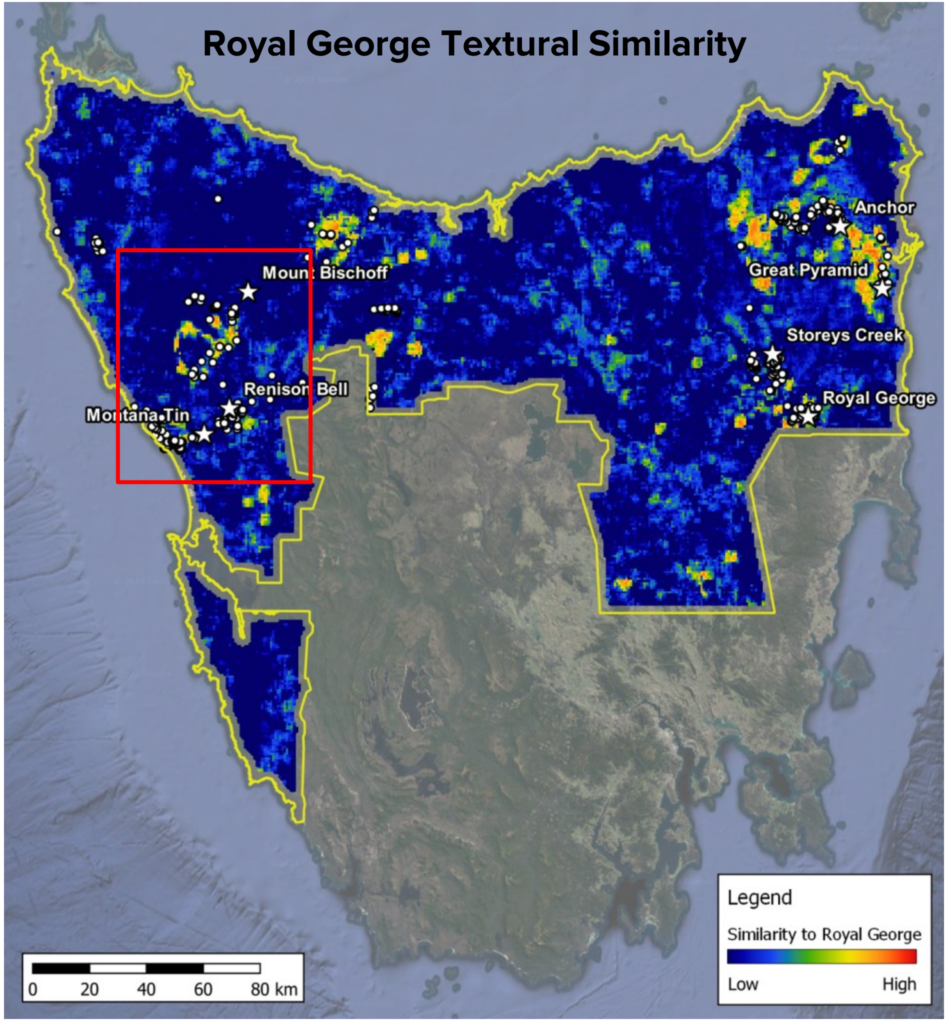
Similarity to Royal George

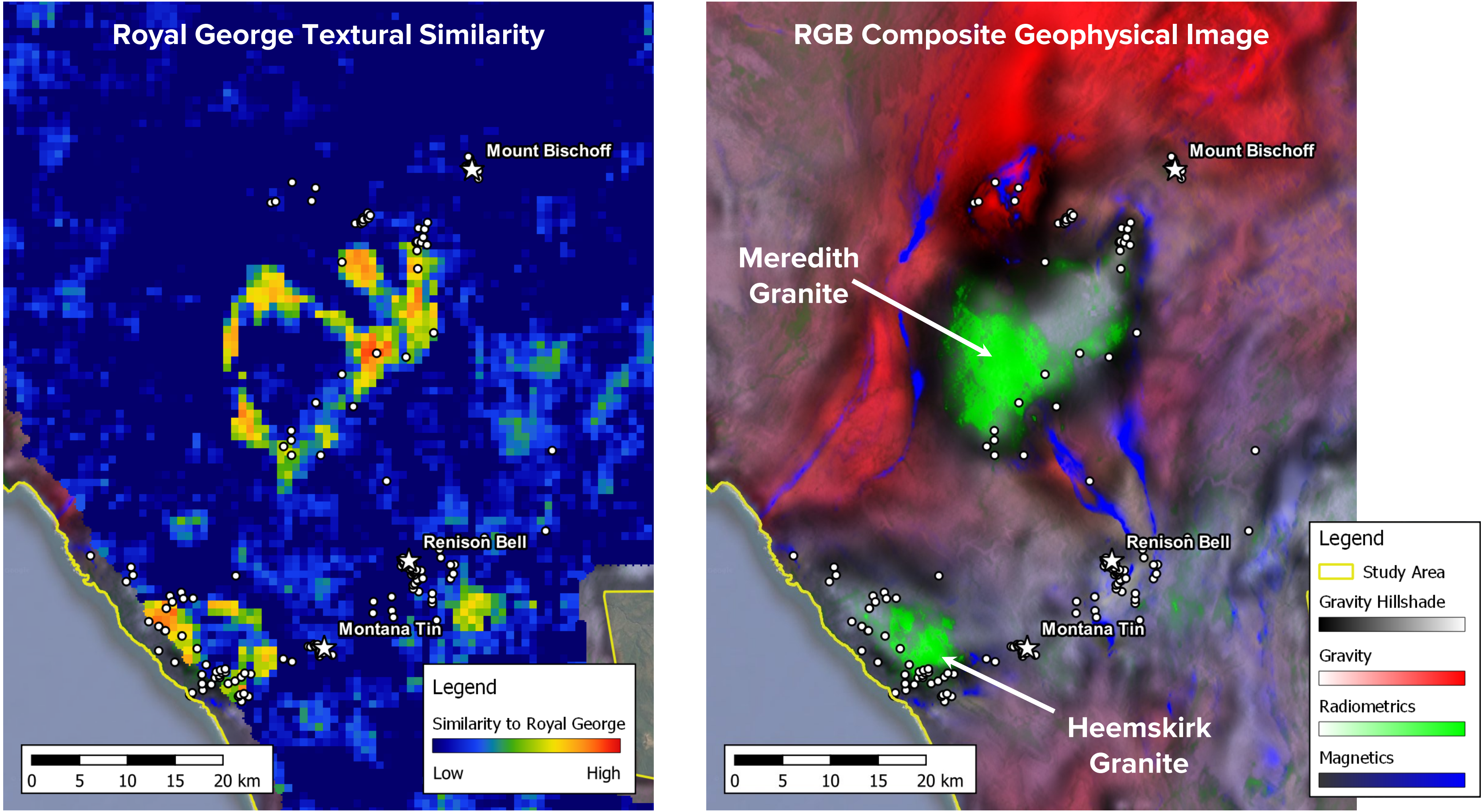
- Similarity to Royal George Sn-W occurrence tile plotted as a grid
- A number of tiles in Tasmania basin have high similarity
    - Isolated areas with strong radiometric responses



Similarity to Royal George

- Similarity to Royal George Sn-W occurrence tile plotted as a grid
- A number of tiles in Tasmania basin have high similarity
  - Isolated areas with strong radiometric responses
- Reasonable 1st order spatial correlation between Royal George similarity and other Sn-W occurrences
- Next slide: Meredith Granite area




Royal George Textural Similarity
Mount Bischoff
Renison Bell
Montana Tin
Legend
Similarity to Royal George
Low
High
0
5
10
15
20 km
RGB Composite Geophysical Image
Mount Bischoff
Meredith Granite
Renison Bell
Montana Tin
Heemskirk Granite
Legend
Study Area
Gravity Hillshade
Gravity
Radiometrics
Magnetics
0
5
10
15
20 km

Similarity to Renison Bell

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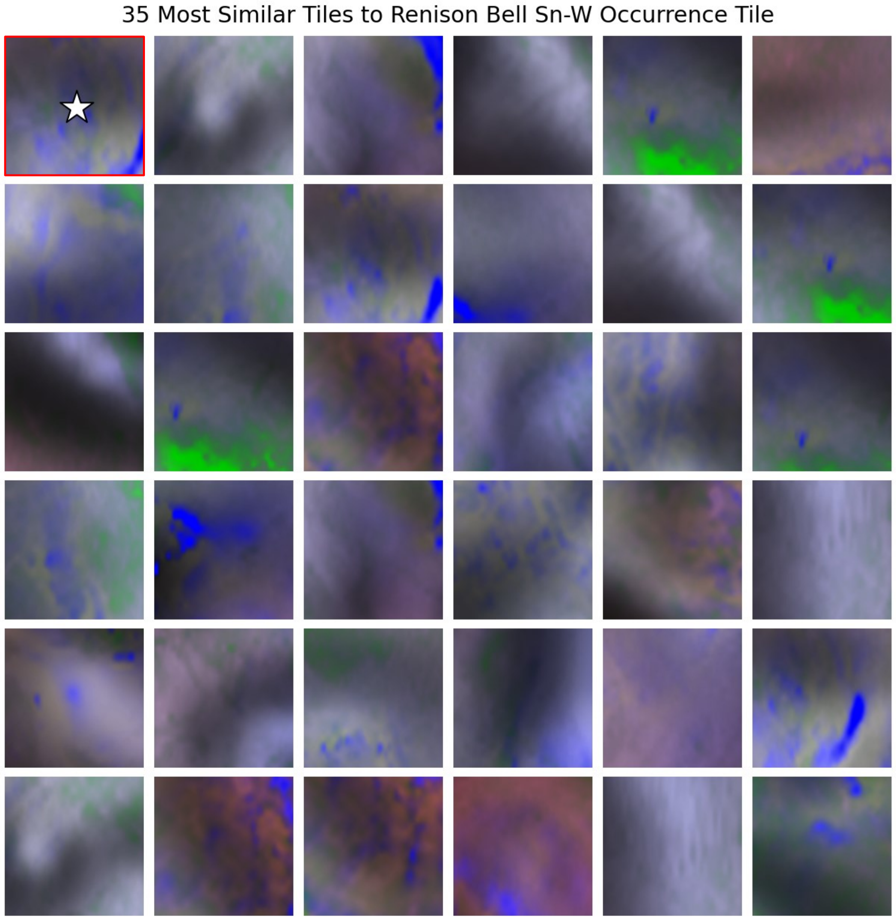
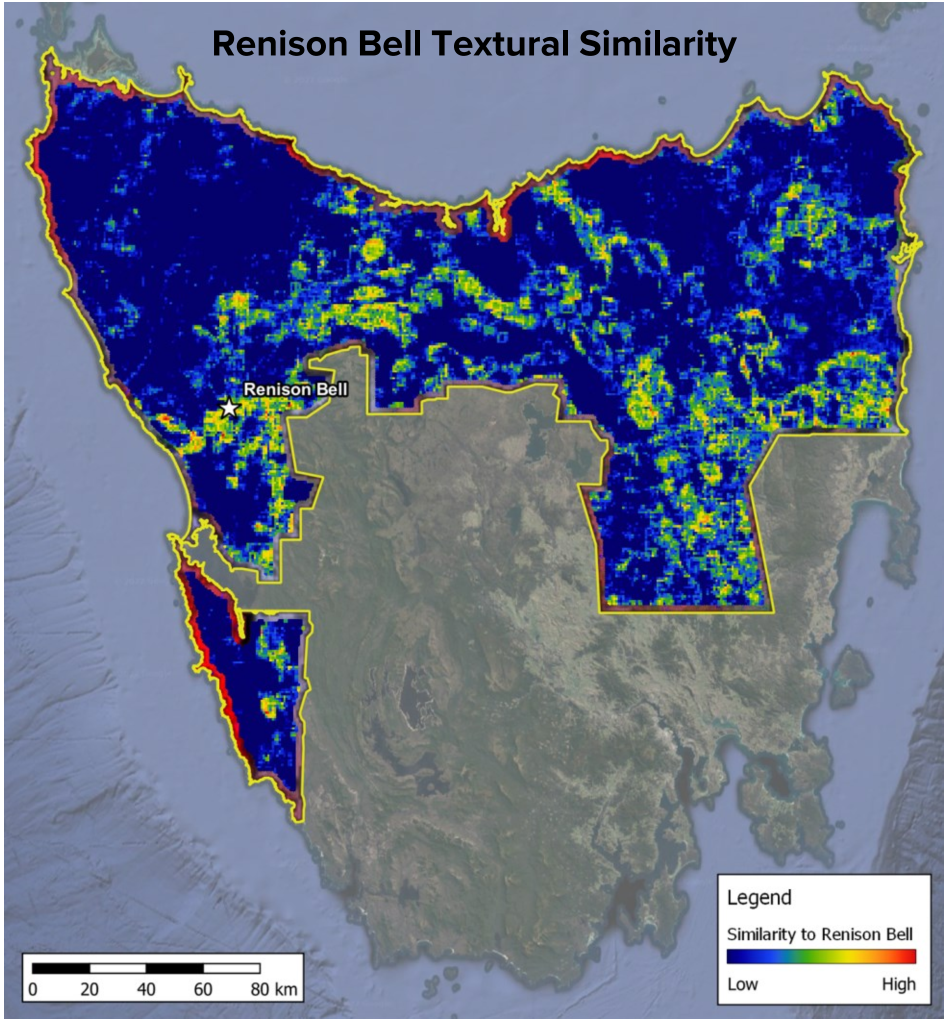
- Renison Bell tile has strong broad-scale brightness gradient effect from gravity hillshade layer
- Also has some linear blue textures from the magnetic layer
- Minor radiometric signature



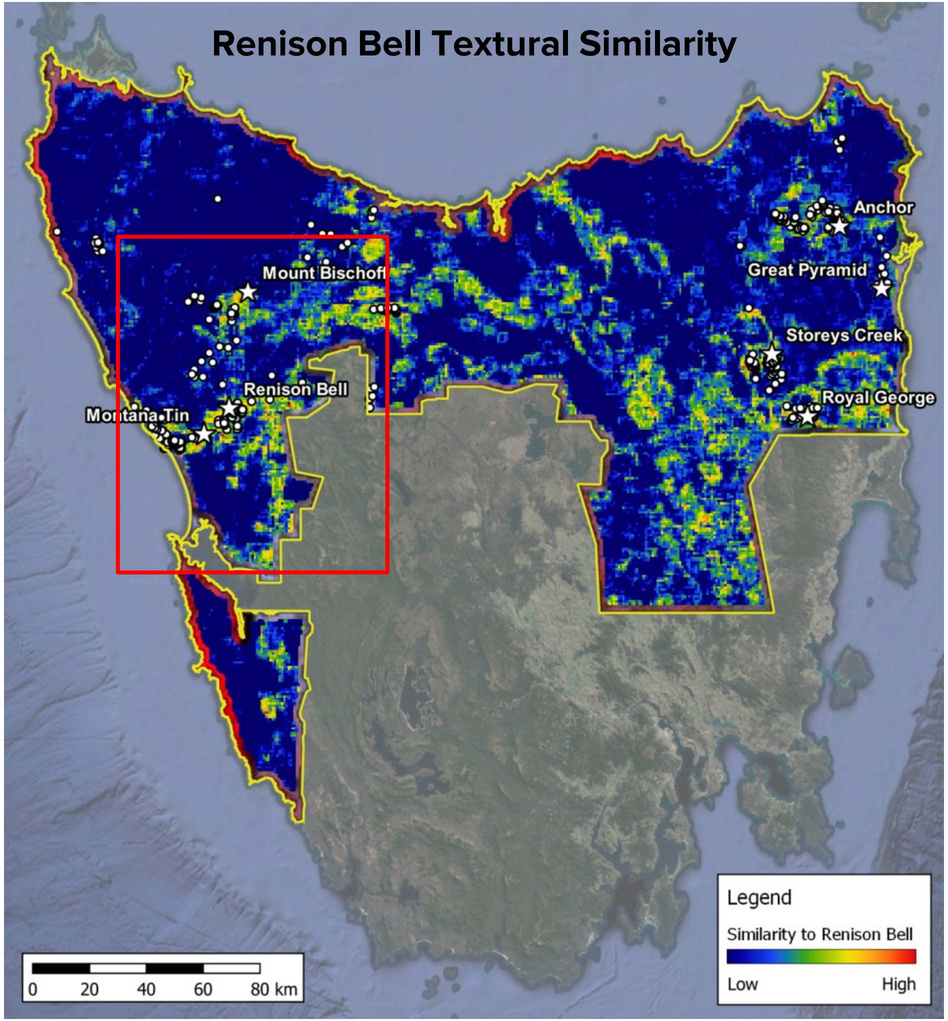
Similarity to Renison Bell

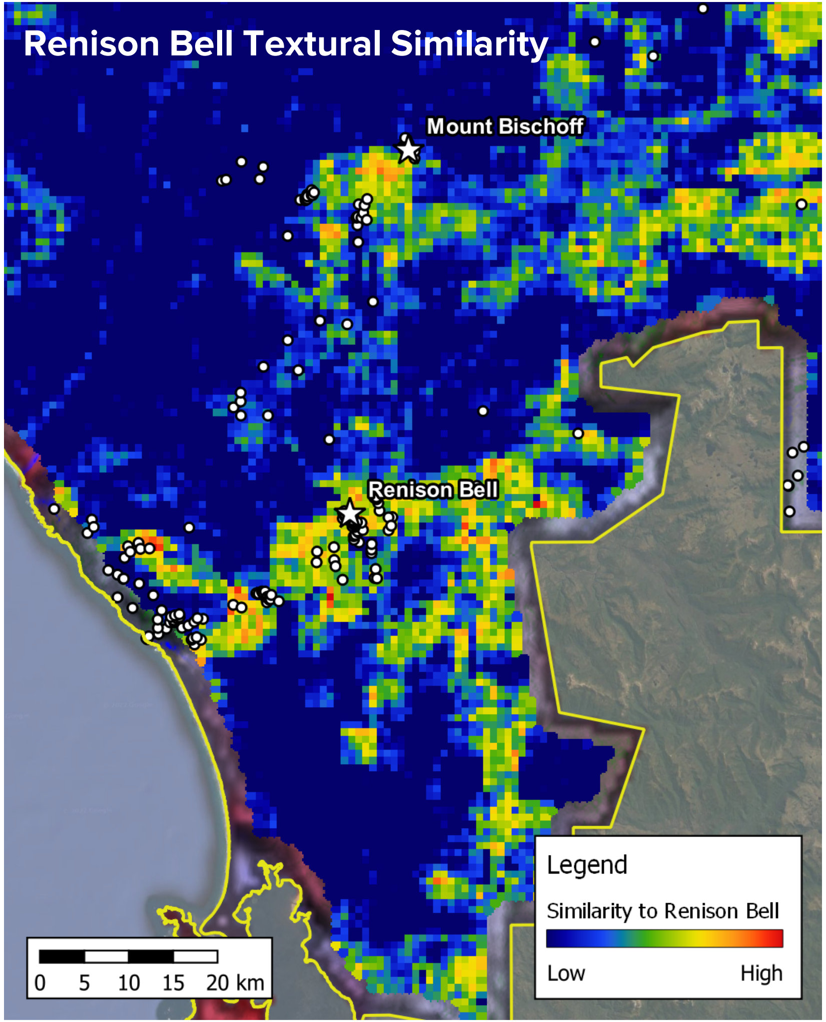
- Renison Bell tile has many lookalikes in non-prospective areas
    - Tasmania basin, inc. Tamar graben
- Blue linear textures and gravity gradients are present everywhere



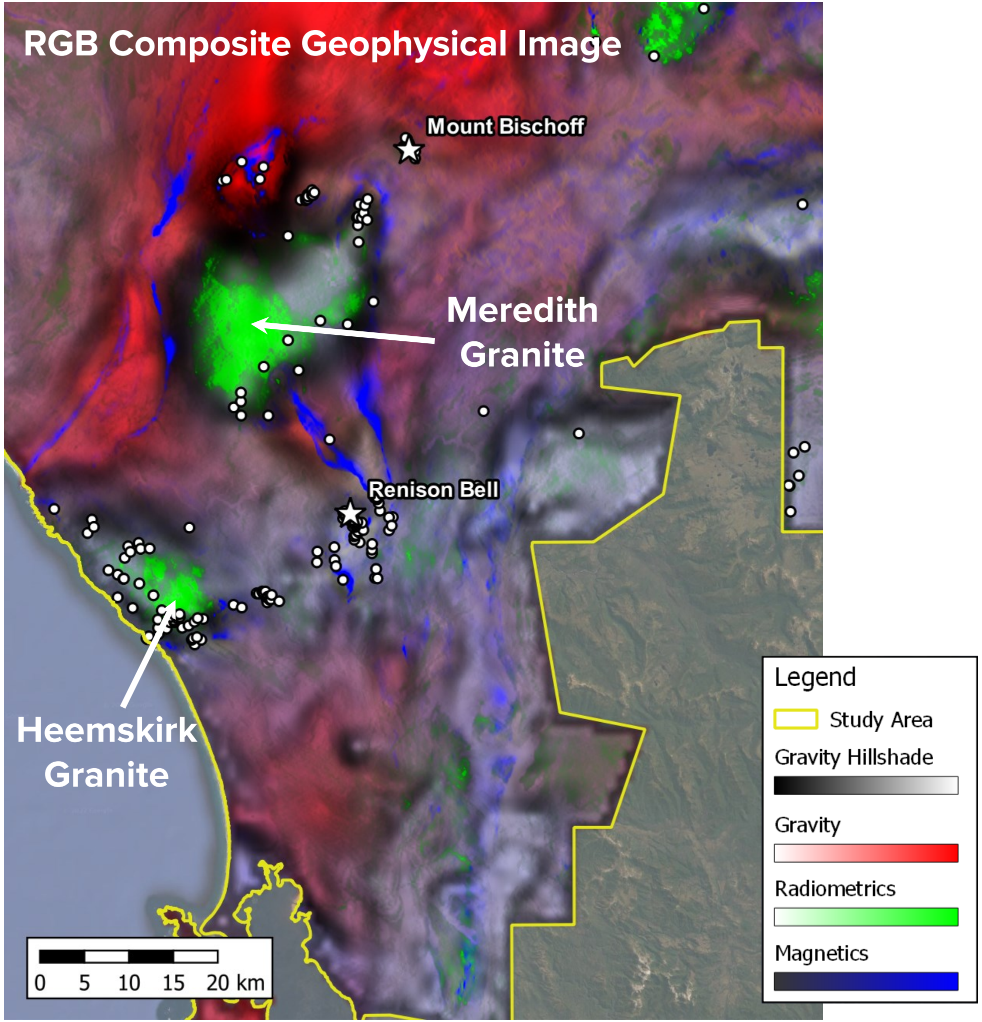
Similarity to Renison Bell

- Renison Bell tile has many lookalikes in non-prospective areas
    - Tasmania basin, inc. Tamar graben
- Blue linear textures and gravity gradients are present everywhere
- Similarity map is poorly correlated with other Sn-W occurrences
- Next slide: West Coast





Renison Bell Textural Similarity
Mount Bischoff
Renison Bell
Legend
Similarity to Renison Bell
Low
High
0 5 10 15 20 km



RGB Composite Geophysical Image
Mount Bischoff
Meredith Granite
Renison Bell
Heemskirk Granite
0 5 10 15 20 km
Legend
Study Area
Gravity Hillshade
Gravity
Radiometrics
Magnetics

Summary & Conclusion

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- Prospectivity modelling workflows often ignore *texture* in evidence layers
- Computer vision algorithms are optimised for analysing texture
- Generic computer vision models can extract meaningful texture information from new, previously unseen imagery
  - Computationally cheap & highly scalable (eg: whole Australian continent)
  - Allows for textural similarity searching in an unbiased, or at least *consistently* biased way
- Have <u>not</u> found the next Renison Bell here
- Need to be conscious of limitations in the input data sets
  - Spatial resolution differences?
  - Depth sensitivity differences?
  - Overall appropriateness of data for the task?
  - <u>Geology is king</u>

Acknowledgements

- Mark Duffett for providing early access to Western Tiers aeromagnetic and radiometric data sets 👍
- Geoscience Australia for onshore Isostatic Residual Bouguer Anomaly data
- Colleagues Mark Grujic, Harvey Nguyen & Dr. Yasin Dagasan for assistance with feature vector extraction code

Link to 2020 Sn-W Prospectivity Blogpost