Using machine learning to classify landforms for minerals exploration

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Introduction

Geomorphology, the study of landforms, can tell us about the evolution of topographic features and how they were shaped by the interplay of physical and biological processes with the underlying geology. Minerals prospecting, as an early stage of exploration for minerals, can make use of anomalies in topographic patterns as indicators of underlying geological processes that may favour the concentration of economic deposits.

Landscape Classification

Common indicators to characterise geomorphological features operate on the scale of several kilometres. This scale is adequate to characterise single elements, like a single river valley, but cannot adequately describe entire geomorphological regions. We, therefore, set out to test whether machine learning (ML) algorithms can be used to classify landforms based on data derived from a digital elevation model (DEM).

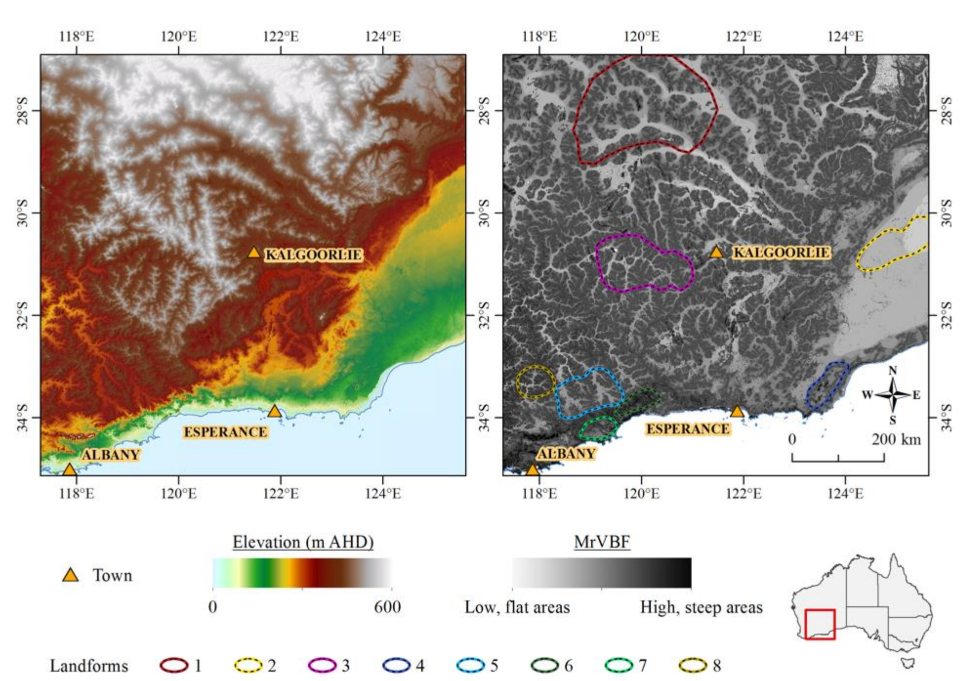

Figure 1: DEM of the southwest Yilgarn Craton and Albany-Fraser Orogen (left). Valley bottom flatness map derived from the DEM and characteristic landscapes (right).

Spatial feature aggregation

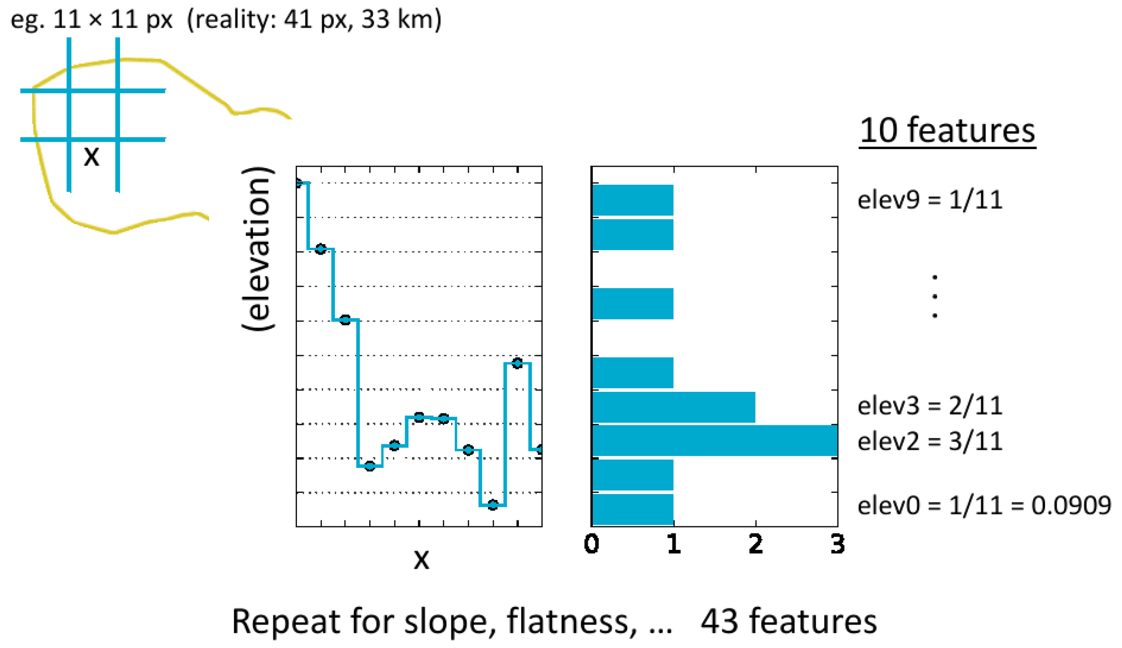

Figure 2: Derivation of features for machine learning from a digital elevation model (DEM) and parameters derived from the DEM.

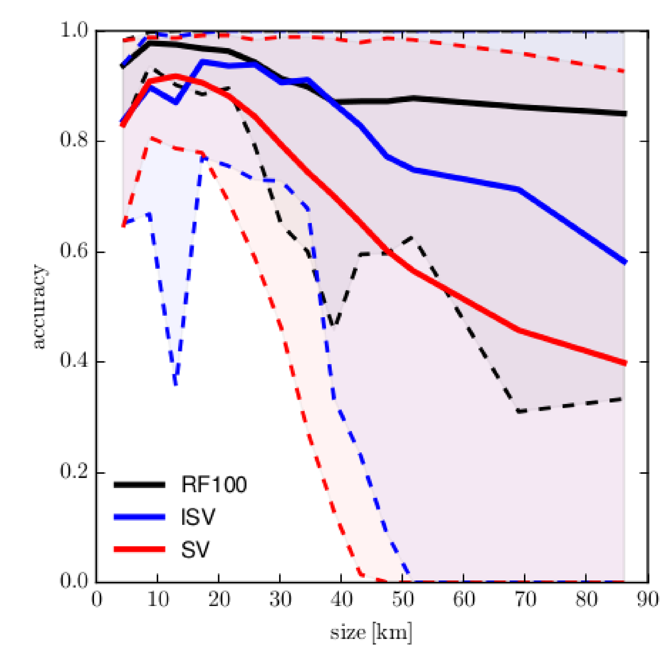

Figure 3: The prediction accuracy varies with tile-size. Large tile sizes result in a low prediction accuracy for small-scale landscape features.

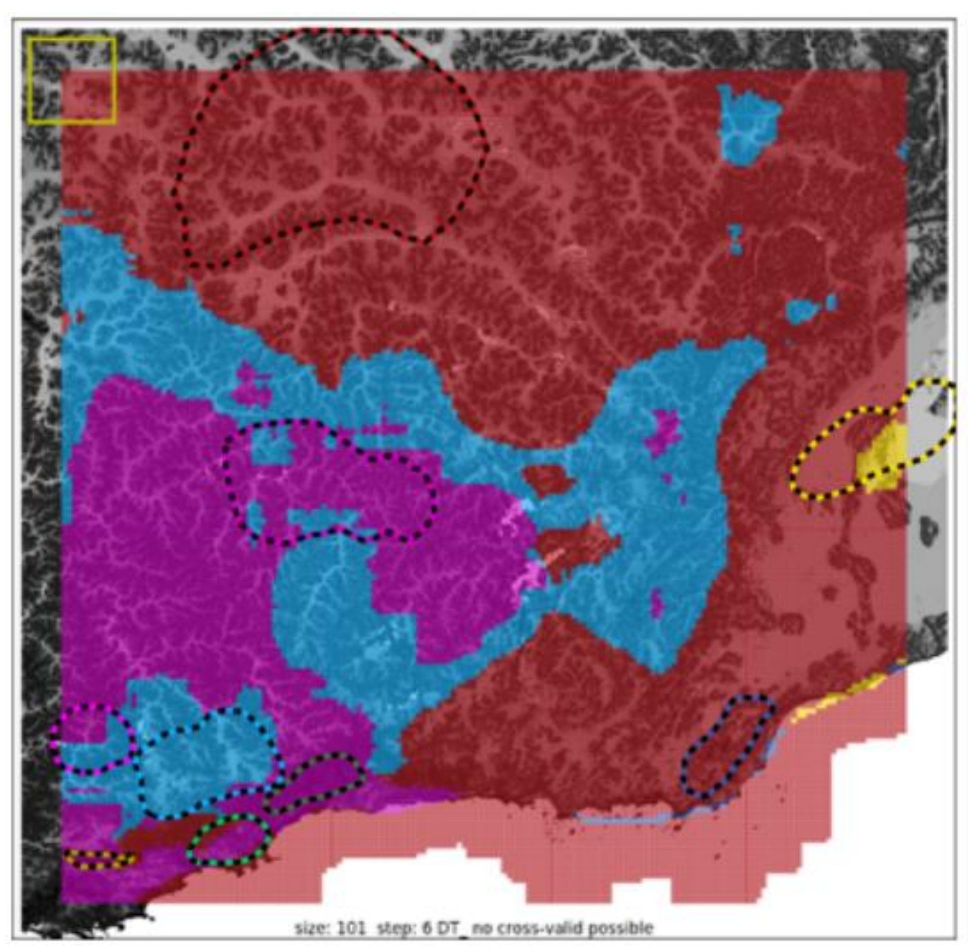

Figure 4: A large tile size (100 x 100 km) results in a very broad characterisation of the landscape elements with low prediction accuracy on smaller landscape features.

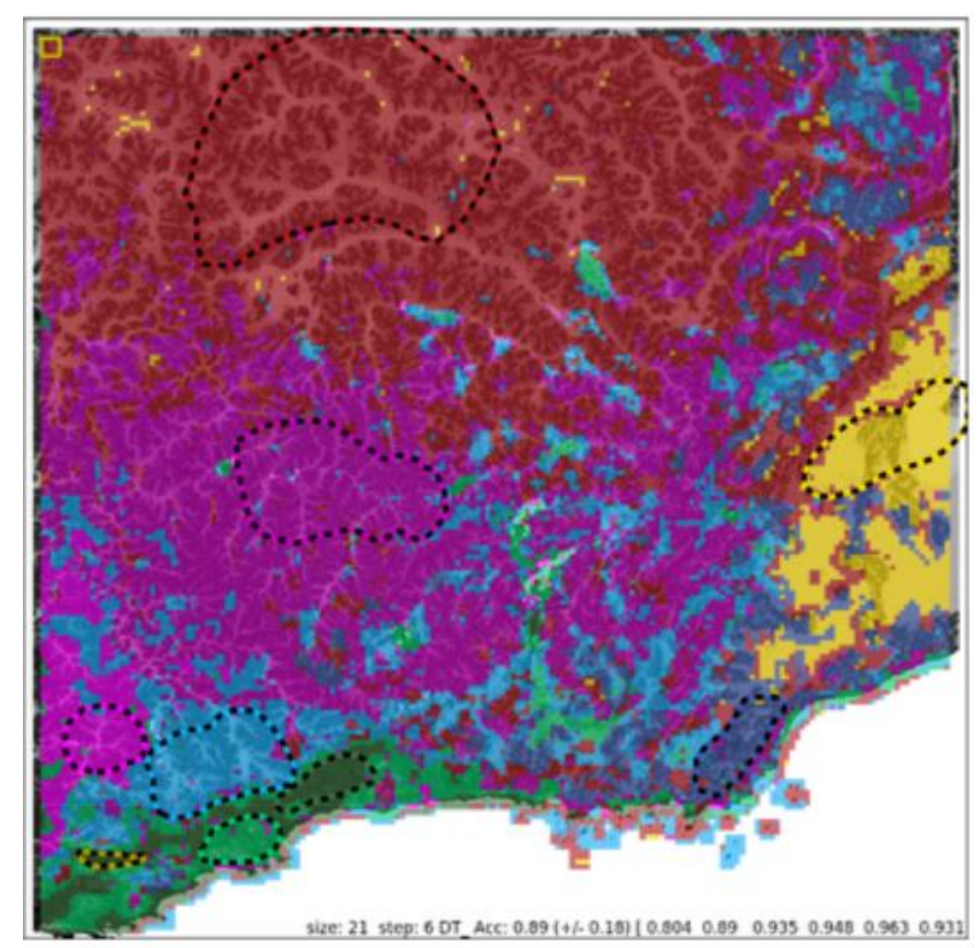

Figure 5: A small tile-size (10x10 km) results in a noisy map with parts of large landscape features being potentially misclassified as elements of small landscape features.

Method

We used topographical data derived from a DEM and applied supervised and unsupervised ML methods to classify landforms on a regional scale. We evaluated the performance of a range of ML algorithms, including support vector machines, decision trees, and random forests.

Results and Conclusions

With an accuracy of 98%, a support vector machine yielded the best results. An application of these methods to the south-eastern Yilgarn Craton (Western Australia) was verified in the field, and the field observations were in turn used to refine the input to supervised classification.

Did it work?

Machine learning was able to classify landscapes on a regional scale based on its digital elevation model (DEM) and parameters derived from the DEM.

Care must be taken in choosing a tile-size to match the size of the landscape elements and the amount of data available from the training dataset.

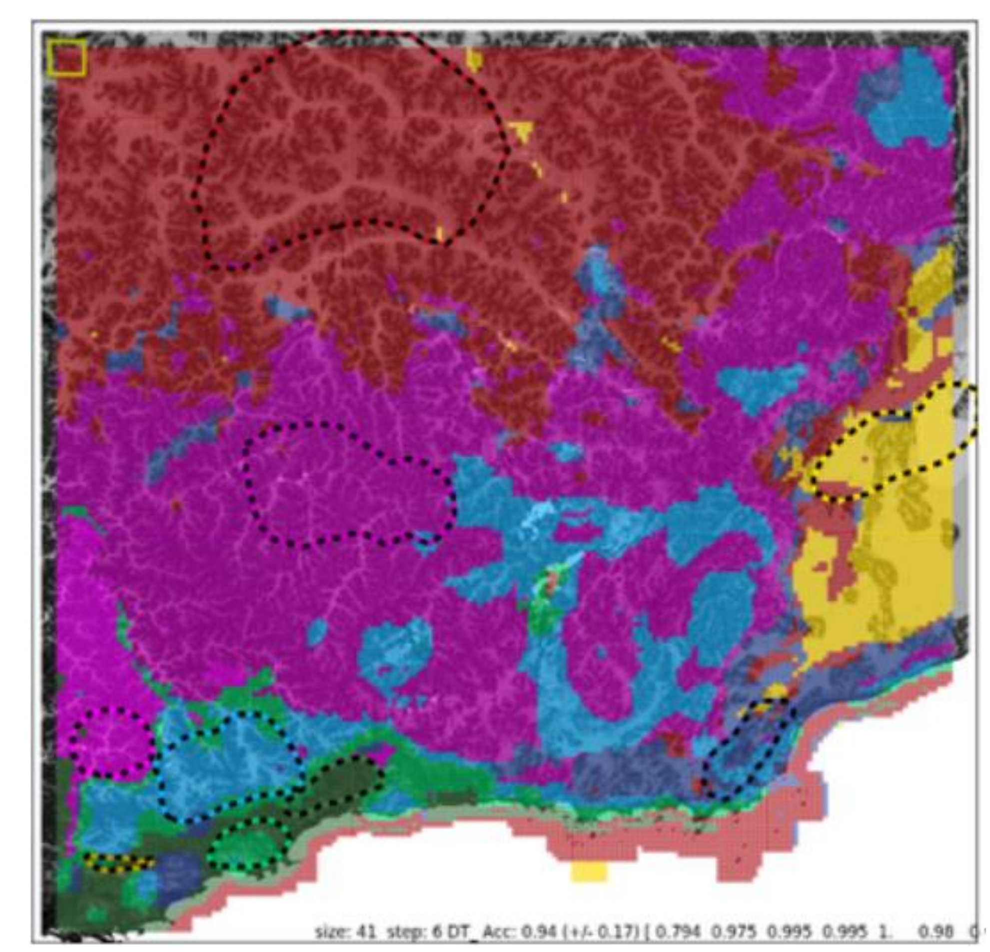

Figure 6: Choosing a tile-size of 15x15 km resulted in a good balance of prediction accuracy for both small and large landscape features.

FOR FURTHER INFORMATION
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