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Accuracy Improvement For Remote Sensing Based Lithological Mapping By Using Randomisation And Categorical Coincidence

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ABSTRACT

Remote sensing based lithological mapping is commonly applied in the field of earth science as it requires less resource in contrast with real field work. Limitation regarding low accuracy is a challenge that should be tackled in applying remote-sensing based classification. In this paper, an attempt to improve overall accuracy of image classification using randomisation and categorical coincidence analysis was performed. It yielded final majority classification map which has higher overall accuracy compared to the overall accuracy of the population average and the overall accuracy of the map created by including all training data.

Keywords: *Remote sensing, Randomisation, Categorical coincidence*

ABSTRAK

Pemetaan berbasis pengindraan jauh umum digunakan di bidang ilmu kebumian karena metode ini membutuhkan sumber daya lebih sedikit dibadingkan dengan pekerjaan lapangan. Batasan metode pengindraan jauh terkait rendahnya akurasi merupakan hal yang perlu ditangani. Pada paper ini disajikan upaya peningkatan akurasi keseluruhan klasifikasi citra menggunakan pengacakan dan analisis categorical coincidence. Metode ini menghasilkan akurasi keseluruhan dari peta klasifikasi mayoritas final yang lebih tinggi dibandingkan akurasi keseluruhan dari rerata populasi dan akurasi keseluruhan dari peta yang dihasilkan dengan menggunakan seluruh data latihan.

Kata kunci: *Pengindraan jauh, Pengacakan, Categorical coincidence*

1. INTRODUCTION

Remote sensing has been widely utilised as a tool on the field of remote earth sciences. The application ranges from basic aerial photograph delineation to more advanced machine-learning based land cover analysis [1–4]. In more specific use, remote sensing method is commonly used in preliminary or wide-scaled surface geological due to its relatively lower budget compared to field-based geological mapping [5–8]. This approach is possible to be conducted because each mineral absorbs and reflects electromagnetic wavelength differently.

As an indirect approach, remote sensing based mapping faced several issues which may lower its accuracy, such as vegetation, cloud cover, and similarity in lithological characteristics of different rock units. This paper is aimed to inspect how randomisation and categorical coincidence analysis can improve accuracy.

2. GEOLOGICAL UNITS

According to geological map of Alice Springs [9], there are many formal rock units. The strata are folded with east-west trend. For simplification, the rock units in the area were regrouped into 4 classes as appears on Figure 1. It can be seen that there are several places where real measurement of structural geology data were performed. These points were assumed to contain data points of the outcrops.

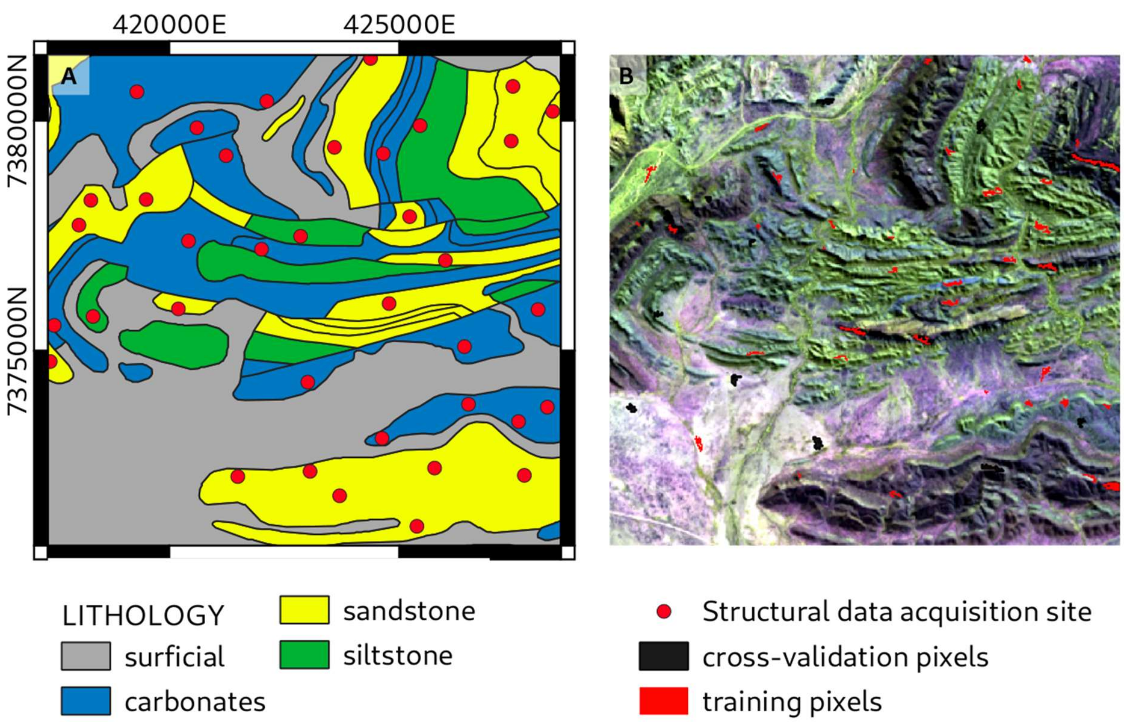

Figure 1. (A) Geological map of the area of interest with red points showing site for structural data acquisition [9]; (b) true colour map of the area of interest with pixels used for training input and cross validation.

3. DATA AND METHOD

3.1 Data

For this paper, one set of cloud-free Level-1 Landsat 8 image of Alice Springs area, Australia (Figure 1B) was used. It was acquired from EarthExplorer (https://earthexplorer.usgs.gov). The data were taken during winter season of 2017 where the cloud cover is minimum. For reference, digital GIS (Geographic Information System) data of Alice Springs area [9] which contains locations of structural data acquisition were used. The interpreted geologial map was utilised as guide for rock type grouping, while the structural data acquisition sites were used for training data and cross-validation data locations.

3.2 Method

The image processing in this paper was conducted using SAGA tools and Semi-automatic Classification Plugin (SCP) [10] in QGIS. Prior to the classification, pre-processing was performed to produce at-surface reflectance value using DOS1 algorithm [11] provided in the SCP. This step will make the pixel values closer to the real reflectance of the object.

Classification in this study follows remote predictive mapping method developed by [12] as also has been performed by [13, 14]. In principle, collected training data were separated into two groups which were used for training input and cross validation on 20 repetitions of classification using maximum likelihood algorithm. The first group contains one-third or one-quarter of the whole population of training data from each class. This group were collected from location at or near to structural data acquisition points. The data were reserved for cross-validation. The second group contains the rest of the training data. In each repetition, 50% of the data were randomly selected to be used for training data for the classification. The results were cross validated using data from the first group.

After the 5th, 10th, 15th, and 20th repetition, categorical coincidence analysis of the classification maps were performed to produce majority classification map and variability map. This process assigns the most commonly occurred class to a pixel. It also counts how many type of classes found for a pixel from each classification map. The more classes counted to present in a pixel, the less reliable the majority class is for the pixel. Later, these majority classification maps were cross-validated using the training data of the first group. The overall accuracy of these maps were then compared to the overall accuracy of the randomised classification maps.

4. RESULT AND DISCUSSION

From 20 repetition, it can be found that each repetition produced maps with varied distribution of classed but still within similar pattern (Figure 2). Cross validation of the maps resulted range of 55%-89% with average value of 75.58% (Table 1). Two extremely low accuracy values were observed from 12th and 17^{thr} repetitions. It may be caused by deviation of randomised training data which may cause misassignment of the pixels.

After categorical coincidence analysis, four majority classification maps with their variability maps were produced (Figure 3). It can be seen that the variability maps show that majority of the pixels have low variability which may indicate relatively high reliability of the majority maps. However, it can also be observed that several area have high variability. It may be accounted to heterogeneity of the rock unit referred from the geological map or similarity in mineralogy such as those in siltstone unit and in surficial sediment which often contains clay minerals.

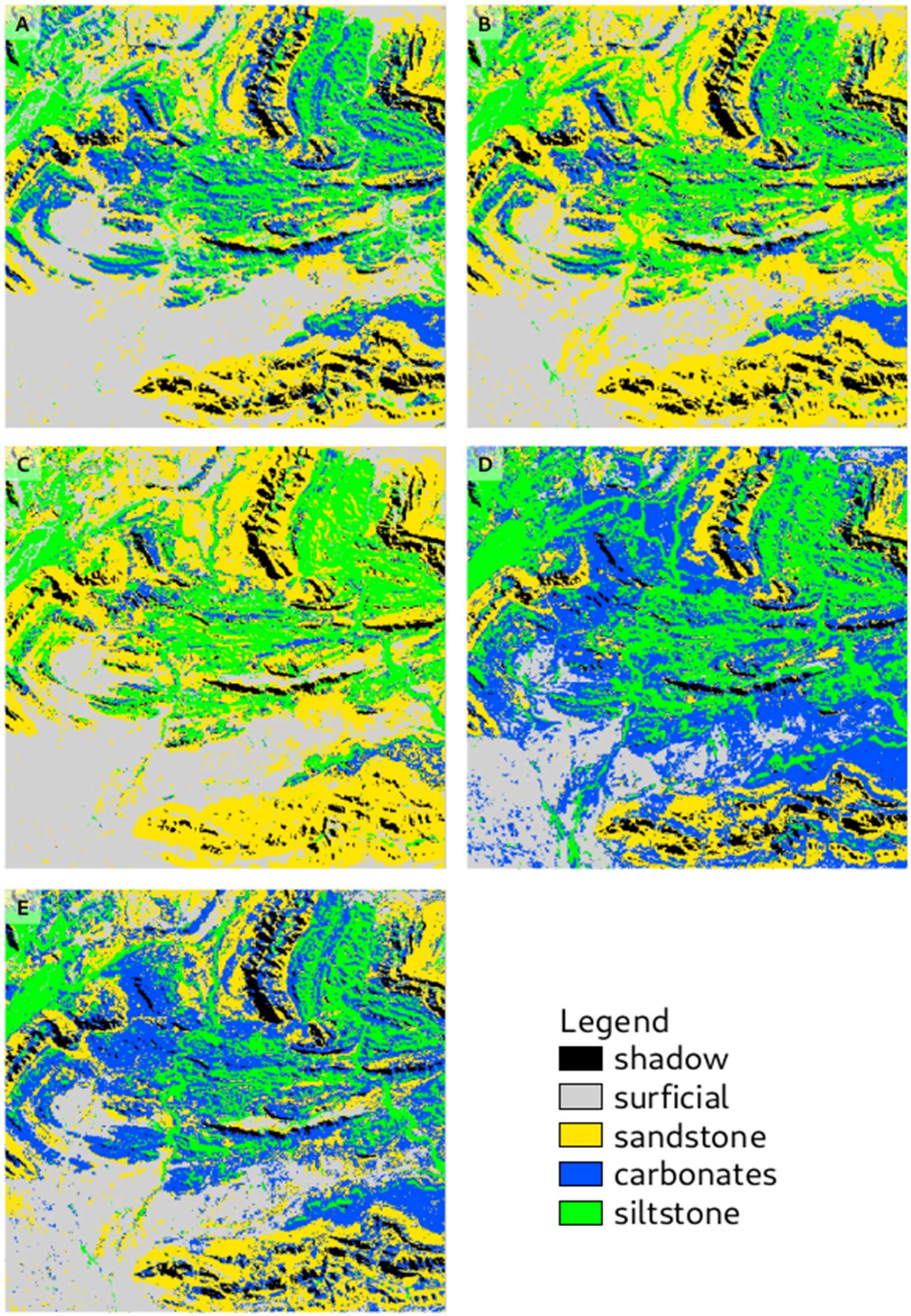

Figure 2. (A-F) Examples of the repeated classification map showing the 1st, 2nd, 8th, 17th, and 20th classification maps respectively.

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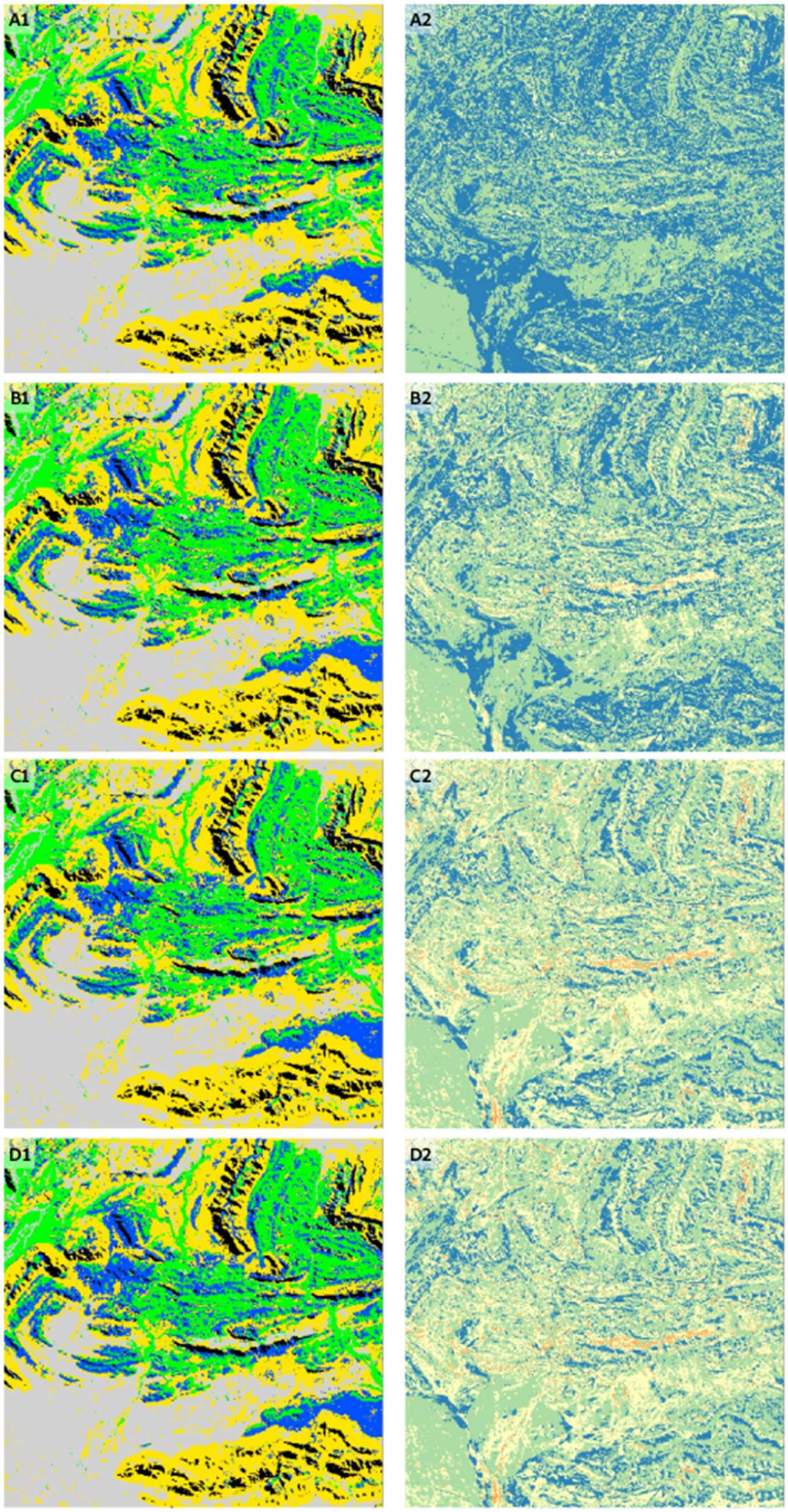

Figure 3. (A-D) Majority classification maps and their variability maps showing 5th, 10th, 15th, and 20th majority classification maps.

Cross-validation of the four majority classification maps shows >80% accuracy (Table 1 and Figure 4) except for the 10th majority classification map. The variability map shows high variability trend near the fold axis (Figure 3) which may cause the low accuracy. However, the final majority classification map (the 20th) shows higher overall accuracy compared to the average of the repetition maps and the map generated using all training data (Table 1). It suggests that the categorical coincidence analysis removed pixels assigned with wrong classes due to overlapping of spectral signature generated from training data randomisation. The process replaced the pixel values with ones more commonly assigned which in this experiment shows less overlapping. It should be noted that incorrect class assignment caused by incorrect training data collection (i.e. population with large range or overlapping classes) may be amplified as it would occur more often.

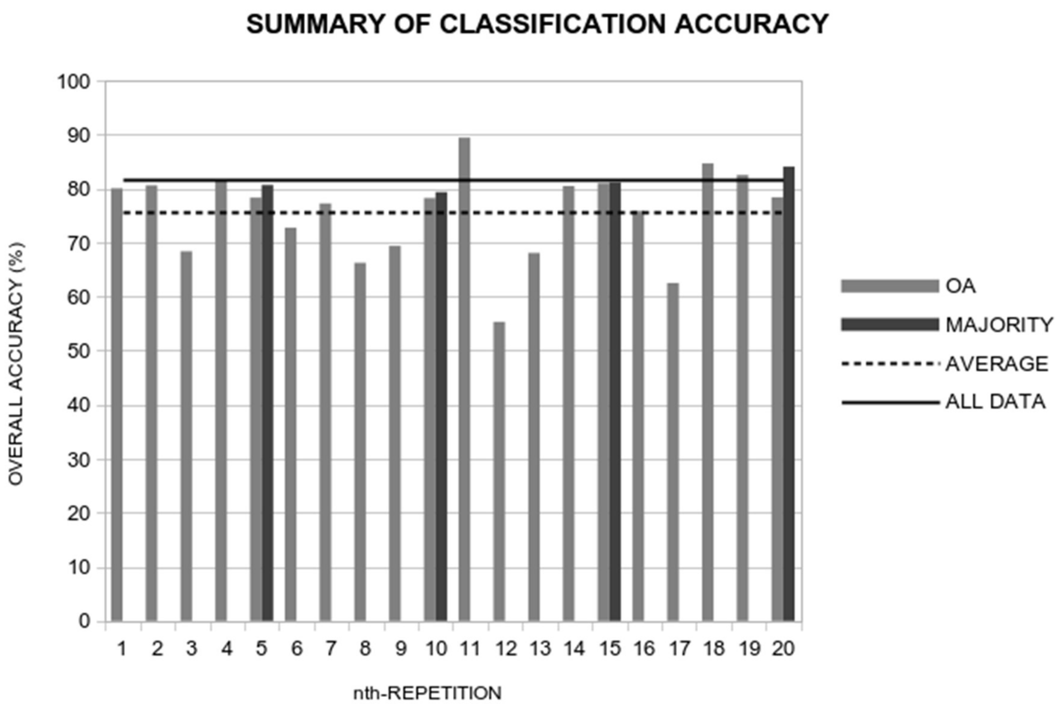

Figure 4. Comparison of overall accuracy between repeated classification and the majority classification. The overall classification of majority classification always higher than the average of repeated classification and the overall accuracy of the final majority classification is higher than the overall accuracy of the classification using all training data. Abbreviation: OA – Overall.

Table 1. Summary of overall accuracy for all classification.

n^{th}-REPETITION	OVERALL ACCURACY (%)	MAJORITY	OVERALL ACCURACY (%)
1	80.1044	**5th majority**	**80.7182**
2	80.6684		
3	68.3523		
4	81.652		
5	78.3871		
6	72.7221	**10th majority**	**79.3955**
7	77.287		
8	66.2423		
9	69.3654		
10	78.3073		
11	89.4673	**15th majority**	**81.2047**
12	55.3336		
13	68.0507		
14	80.5128		
15	81.0419		
16	75.9119	**20th majority**	**84.1056**
17	62.5094		
18	84.707		
19	82.5562		
20	78.4429		
Average	**75.5811**		
All Training Data	**81.7314**		

5. CONCLUSION

Based on the experiment, in can be concluded randomisation and categorical coincidence analysis can improve the overall accuracy. It is caused by elimination of the less frequently assigned class to a certain pixel.

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