GEE classification report

Introduction

The study area encompasses Yunlin County and the western portion of Nantou County in central–western Taiwan, covering the period from June through the end of September 2023. This study area includes diverse terrain, ranging from the cropland and built-up plains of Yunlin County to the forested hills and mountain ranges of Nantou County. The objective of the study was to compare the performance of land cover classification by the three different machine learning classifiers available on Google Earth Engine Javascript: Random Forest, Support Vector Machine (SVM), and Classification and Regression Trees (CART).

Methods

Landsat 8/9 Surface Reflectance imagery variables such as blue, green, red, near-infrared, shortwave infrared 1, and shortwave infrared 2 bands, along with the derived Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) from the aforementioned bands were used as input features to guide the three machine learning classifiers in classifying pixels as one out of nine land cover types. The European Space Agency (ESA) WorldCover 10 m 2021 product, based on Sentinel-1 and Sentinel-2 data, outputs eleven landcover types, nine of which were used as ground truth for land cover classification of the study area.

Clouds remaining in the Landsat 8/9 imagery were further masked to improve calculation accuracy. The Landsat bands and derived indices were then randomly split into train and test subsets: 70% of data was used for training and the remaining 30% was used for testing. The random forest classifier used a random seed of 42 for training. The SVM classifier used a gamma of 0.5 and cost of 10 for training. The CART classifier used a max of 100 nodes for training. Each classifier was evaluated based on its overall accuracy, kappa score, producer's accuracy, user's accuracy, and confusion matrix on test data in Fig. 6. and Fig. 7. For each classifier, the total area that it classified as each of the nine land cover classes was summed in Fig. 8.

The three classifiers used were Random Forest, Support Vector Machine (SVM), and Classification and Regression Trees (CART) classifiers. The nine land cover types present in the outputs were the tree cover, shrubland, grassland, cropland, built-up, bare/sparse, water, and herbaceous wetland classes.

Results

The best classifier was the Random Forest classifier with an overall accuracy of ~0.63 and kappa score of ~0.57. The worst classifier was the CART classifier with an overall accuracy of ~0.56 and kappa score of ~0.49. The SVM classifier had an overall accuracy of ~0.59 and kappa score of ~0.52. The hardest classes to distinguish were cropland (3) and built-up (4) classes. All classifiers had a tendency to mislabel them as one another. The CART classifier tended to classify cropland as built-up in Fig. 5

whereas the random forest classifier classified correctly as cropland. The random forest classifier was also the only classifier to detect shrubland land cover in the study area as shown in Fig. 8.

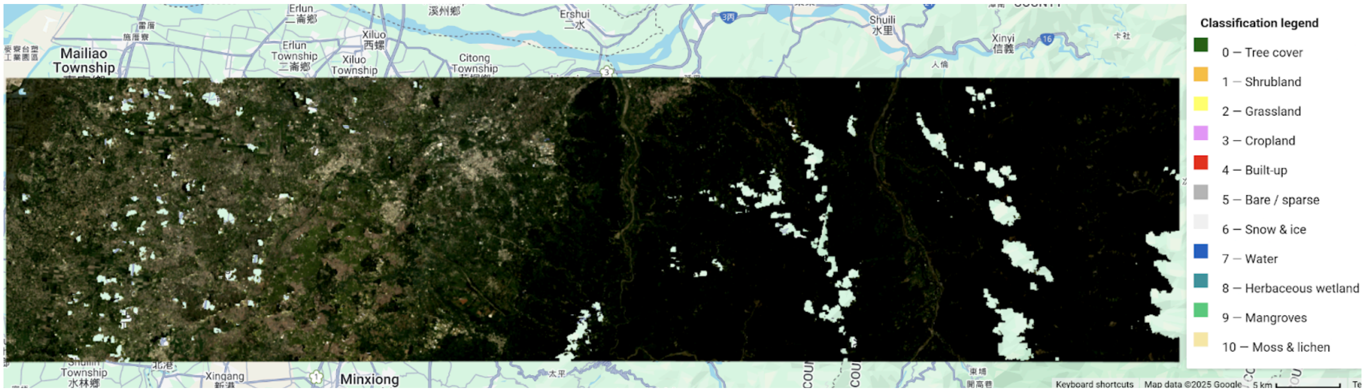

Fig. 1. Color-composite map from Landsat 8/9 in Yunlin and Nantou County

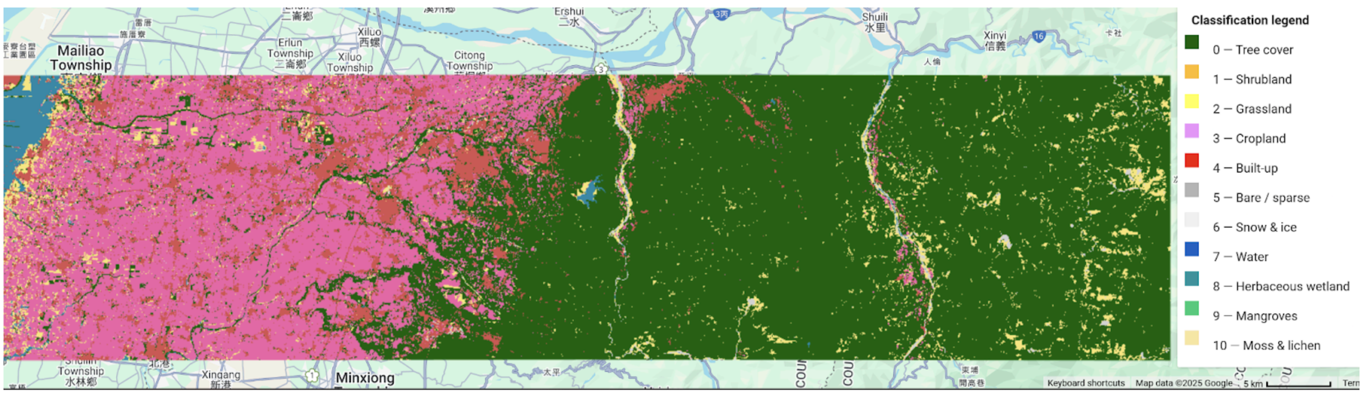

Fig. 2. Reference (ground truth) land cover map from ESA WorldCover in Yunlin and Nantou County

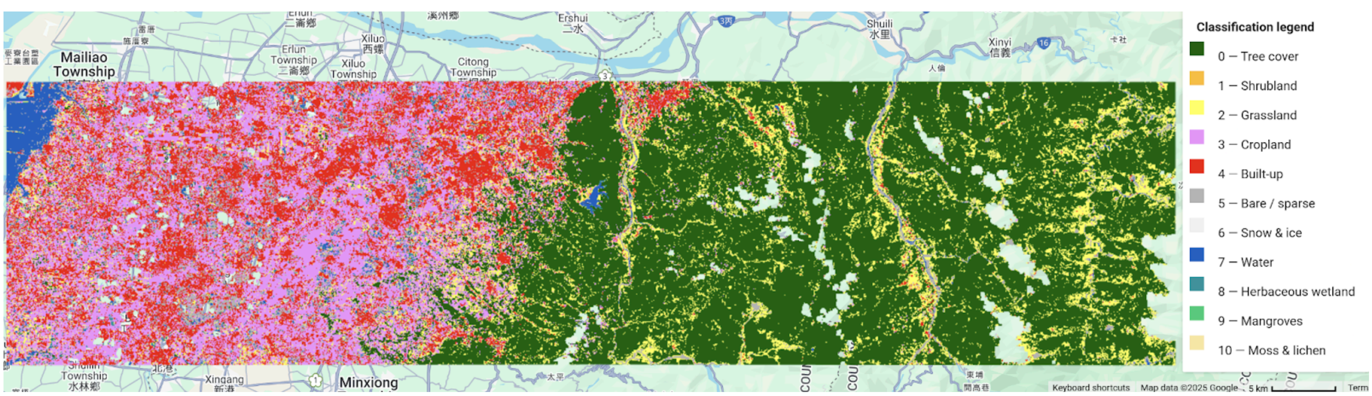

Fig. 3. Random Forest land cover classification in Yunlin and Nantou County

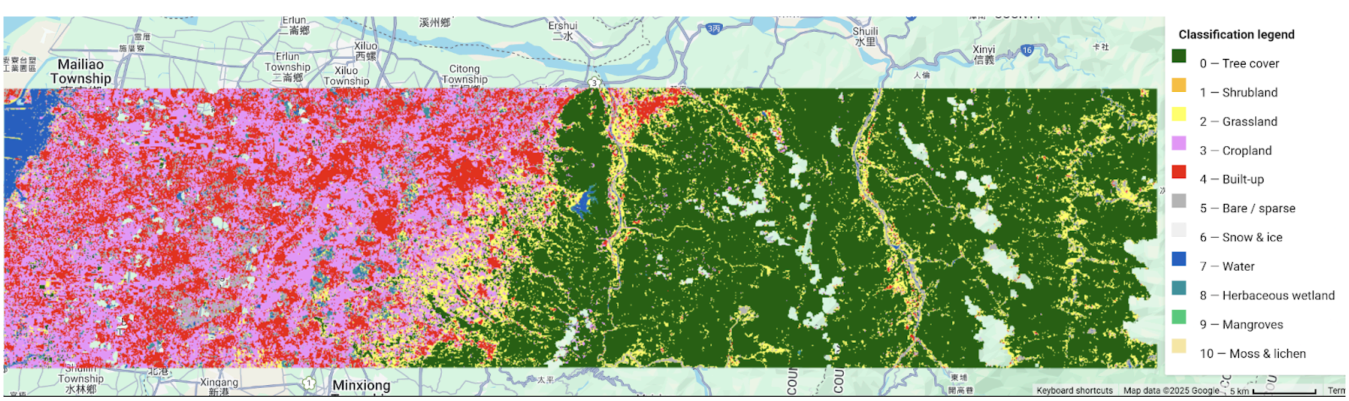

Fig. 4. Support Vector Machine land cover classification in Yunlin and Nantou County

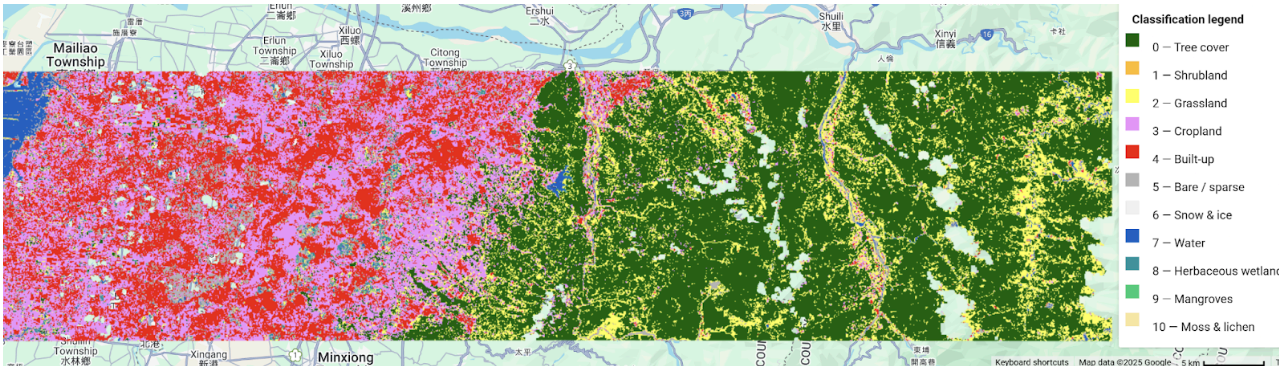

Fig. 5. Classification And Regression Trees (CART) land cover classification in Yunlin and Nantou County

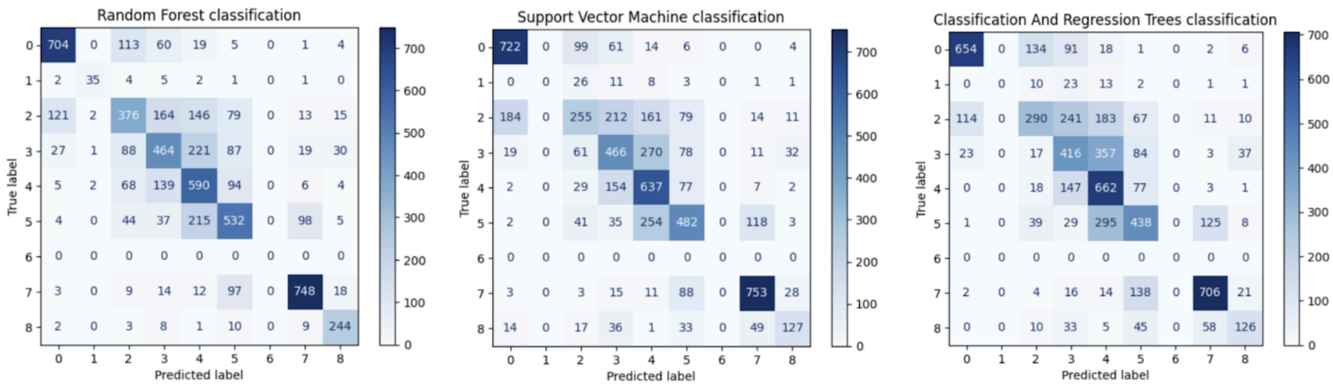

Fig. 6. Confusion Matrices on test data for classifiers in Yunlin and Nantou County

Random Forest

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Overall accuracy: 0.6334476843910806
Kappa: 0.5686577986314512
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	Class	Producer's Accuracy	User's Accuracy
0	0	0.777042	0.811060
1	1	0.700000	0.875000
2	2	0.410480	0.533333
3	3	0.495197	0.520763
4	4	0.649780	0.489221
5	5	0.568984	0.587845
6	6	0.000000	0.000000
7	7	0.830189	0.835754
8	8	0.880866	0.762500

Support Vector Machine

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Overall accuracy: 0.5903945111492281
Kappa: 0.5162476492194678
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	Class	Producer's Accuracy	User's Accuracy
0	0	0.796909	0.763214
1	1	0.000000	0.000000
2	2	0.278384	0.480226
3	3	0.497332	0.470707
4	4	0.701542	0.469764
5	5	0.515508	0.569740
6	6	0.000000	0.000000
7	7	0.835738	0.790136
8	8	0.458484	0.610577

Classification And Regression Trees

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Overall accuracy: 0.5646655231560892
Kappa: 0.4858680907837088
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	Class	Producer's Accuracy	User's Accuracy
0	0	0.721854	0.823678
1	1	0.000000	0.000000
2	2	0.316594	0.555556
3	3	0.443970	0.417671
4	4	0.729075	0.427925
5	5	0.468449	0.514085
6	6	0.000000	0.000000
7	7	0.783574	0.776678
8	8	0.454874	0.600000

Fig. 7. Evaluation scores for classifiers in Yunlin and Nantou County

Random Forest

	Class	Area
0	0	8.822031e+08
1	1	1.514920e+06
2	2	2.522130e+08
3	3	3.848761e+08
4	4	2.765021e+08
5	5	9.447798e+07
6	6	0.000000e+00
7	7	3.967403e+07
8	8	1.838242e+07

Support Vector Machine

	Class	Area
0	0	9.100764e+08
1	1	0.000000e+00
2	2	1.917967e+08
3	3	3.959107e+08
4	4	3.074311e+08
5	5	8.889982e+07
6	6	0.000000e+00
7	7	3.504102e+07
8	8	2.068787e+07

Classification And Regression Trees

	Class	Area
0	0	7.974387e+08
1	1	0.000000e+00
2	2	2.476542e+08
3	3	3.962640e+08
4	4	3.634256e+08
5	5	9.191529e+07
6	6	0.000000e+00
7	7	3.048472e+07
8	8	2.266115e+07

Fig. 8. Sum of area in each predicted class for each classifier in Yunlin and Nantou County

Discussion

SVM and CART classifiers failed to classify minority shrubland class, both classified them as either grassland or cropland as shown in Fig. 6. In contrast, the random forest classifier was able to classify the minority shrubland class with 0.77 in producer's accuracy and 0.81 in user's accuracy. Although the accuracies weren't high among all three classifiers, all three classifiers provided a more detailed land cover classification than the ground truth ESA landcover classification map shown in Fig. 2. When I zoomed in using a plain Google Earth Engine Satellite image, I did see smaller residential houses in pixels where machine learning classifiers marked as built-up but ground truth ESA landcover classification map did not. This may indicate that ESA landcover classification is too broad and can't account for the finer-grain mix land cover that is present in the study area. Additionally, the ESA landcover classification is from 2021, whereas the studied time range was 2023, therefore, there could be changes within the 2 years that become potential sources of error in classification. Classification can be improved by obtaining higher quality Landsat imagery with less cloud coverage and more detailed and recent land cover classification map for ground truth. Classifier parameters such as random seed in random forest classifier or gamma in support vector machines can also be fine-tuned to improve classification results. For future work perhaps train-test data can be split on a 80-20% basis instead of by 70-30%.

Conclusion

In conclusion, the random forest classifier achieved the highest overall accuracy at approximately 0.63, while the CART classifier produced the lowest accuracy at around 0.56. All classifiers struggled to differentiate cropland from built-up land cover, likely due to Taiwan's landscape where agricultural fields often include scattered built structures. Overall, the classifiers showed relatively low classification performance, indicating that substantial improvement is needed—either through parameter fine-tuning or by enhancing the quality of the ground-truth data.