Guangzhou Satellite Image Classification Report
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I. Introduction

The purpose of this lab is to use supervised classification methods to sort a satellite image by land cover types. Supervised classification needs the user to provide the training data, which is the groups of pixels in the region of interest from classes of land cover picked by the user. Different from unsupervised classification, the supervised method required the user to define the number and category of classes. The collected sample data created a signature file for the algorithm process. The algorithm the user chooses would compare the unclassified pixel with the sample data for the classification, and each algorithm has different methods to classify. After the process of classification, I will conduct a quantitative accuracy assessment to test the accuracy of classified results with the original real image.

II. Methods

I used two common supervised classification methods. The first one is the maximum likelihood algorithm, which calculates the similarity statistics, including the means, variance, and covariance. Pixels in the largest similarity with the training data would be classified in the same class. The advantages of maximum likelihood classification are that it provides results with the largest accuracy, and it takes the most variable conditions into consideration. However, it restricted the training data to be normally distributed. It is non-spatial and sensitive to the data variance. If The data samples are not large enough, the algorithm will be biased. Also, this algorithm is computationally intensive and requires a large amount of computation. The second one is Support Vector Machine classification, which is to use the maximum margin distance among the points in different classes to generate the most optimized hyperplane and differentiate the classes. This algorithm is efficient and has better results if the margin between classes is clear in high dimensional spaces and when the training data is small. It also has broad applications, such as the fire burning area detection. The Support Vector Machine algorithm does not perform very well when there are a lot of classes, and the results would be negatively impacted if the data sources are noisy. Based on the characteristics of Guangzhou city and the comparison of Google Earth, I defined the land cover classes as forest, water, urban area, fish farm and cropland. Rather than water and forest features that are clear to differentiate, urbanized areas are always combined with the farmlands. Therefore, I picked 50 pixels for each land cover type for the training purpose.

The accuracy assessment is in the evaluation step to calculate the correctness of the classification results. To reduce the bias and ensure the equity of data representation, I created a random noise image first, and chose the band threshold as 0.057 to generate 51 pixels for the test use. Once I got the test pixels, I labeled the test sites by identifying the corresponding land cover type, and it is used to generate the confusion matrix and compute the overall accuracy, producer's accuracy, and user's accuracy. The accuracy assessment is important because it shows the quality of a classification map more directly, and the result can be prepared for the revision, especially for those classes with slight differences.

III. Results

Figure 1 is the map result using the Maximum Likelihood classification method, and Figure 2 uses the Support Vector Machine classification method. Table 1 and Table 2 are the confusion matrices using ground truth regions of interests. Overall, both two maps classify the land cover types in a good shape so that we can clearly see the colored rivers, forests, urban areas, fish farms and croplands. However, the maximum likelihood method produces more fish farms. If you pay attention to the forests on the top right corner (Figure 3), you will notice that the shape of the forest mountains is delineated and identified as fish farms, which are incorrect from the original image. On the contrary, the Support Vector Machine method handled this condition better that the according part is classified as urban areas (Figure 4). Another point that both maximum likelihood and Support Vector Machine did not generate accurate results is that when we zoomed into the center of the image (Figure 5, Figure 6), we can see the narrow and light green lines of fish farms in an organized pattern. It is unreasonable that fish farms can go across the rivers and are not concentrated as bounded areas, and in the real satellite image, the narrow lines should be the roads.

The overall accuracy of Maximum Likelihood classification is 68.63% (Table 1), while that of the Support Vector Machine classification is 64.71% (Table 2). The overall accuracy of the Maximum Likelihood classification is higher than SVM classification. Producer's accuracy refers to the probability that a land cover type is classified correctly among all the sample test data in this type. Therefore, it is calculated from the column of each type of test data. The producer's accuracy indicates error of omission that pixels classified as other land cover types should be this specific type. User's accuracy refers to the rate of a land cover type with correct results over the total number of pixels classified in this type, which is calculated from each row in the error matrix. It indicates error of commission that pixels belonging to other types are wrongly classified as this land cover type. Several classes have high user's and producer's accuracy in our results. For example, in Maximum Likelihood classification, water and urban areas have the top highest producer's accuracy, which is 80% and 74%. They also have the top highest user's accuracy, and they are 88.9% and 87.5% each. One exception is the forest. Its producer's accuracy is relatively low, which is 61.54%, but it has 100% of the user's accuracy. However, two classes contain a high amount of error. Cropland and fish farms only have 60% and 50% accuracy, and their user's accuracy is as low as 0.3 and 0.2. There are huge differences between these two classes and others.

In Support Vector Machine classification, only water type has a higher producer's accuracy, which is 90%, and other types have an average accuracy of 60%. For user's accuracy, forest, water, and urban areas have the highest accuracy, which are 88.9%, 1 and 91.7%. However, similar to Maximum Likelihood classification, SVM classification does not perform very well in fish farms and croplands, which have only 25% and 22% accuracy. Analyzing the case is important because it can help me specify which class has a good quality and which does not. Furthermore, it directs me to consider why croplands and fish farms fail the accuracy test and make further improvements.

IV. Discussion

For the accuracy test results, Maximum Likelihood worked better than Supporting Vector Machine, but the advantage is not obvious, which is 4% higher than SVM method. Both methods show a higher user's accuracy than producer's accuracy in forest, water, and urban areas, which are all higher than 80%. That indicates a lower error of commission, which means fewer pixels are classified into other classes. Specifically, In the relationship of forest and fish farms, low producer's accuracy generates higher error of omission, which is also corresponding to higher error of commission in the row of fish farms. For example, in Table 1, it means that the 3 pixels that should be in the forest are wrongly classified as fish farms, and the actual classification results included those three pixels as fish farms. Similar conditions happen in urban areas in Table 2, too. 5 pixels that should be in urban areas are wrongly identified as croplands.

Based on the results above, croplands and fish farms are the classes difficult to map and had confusion. First, the farmlands in the real world are divided into relatively small parts, but the spatial resolution in the original image is low. Therefore, each pixel in the fish farms is sometimes mixed up with forests and urban areas. Second, the pixel value of fish farms is also close to water, and fish farms do contain the water from the rivers, which causes the pixel value similar with water and urban features and some narrower rivers are identified as fish farms. To solve this problem, I corrected and redefined the region of interests of water and fish farms, especially for small areas, before running the classification algorithms to make them equally distributed. Rather than making any changes to the parameters in the algorithm, I added the pixels of the road features as the urban areas. The algorithm generated better results, but it did not correct all the errors.

V. Appendix

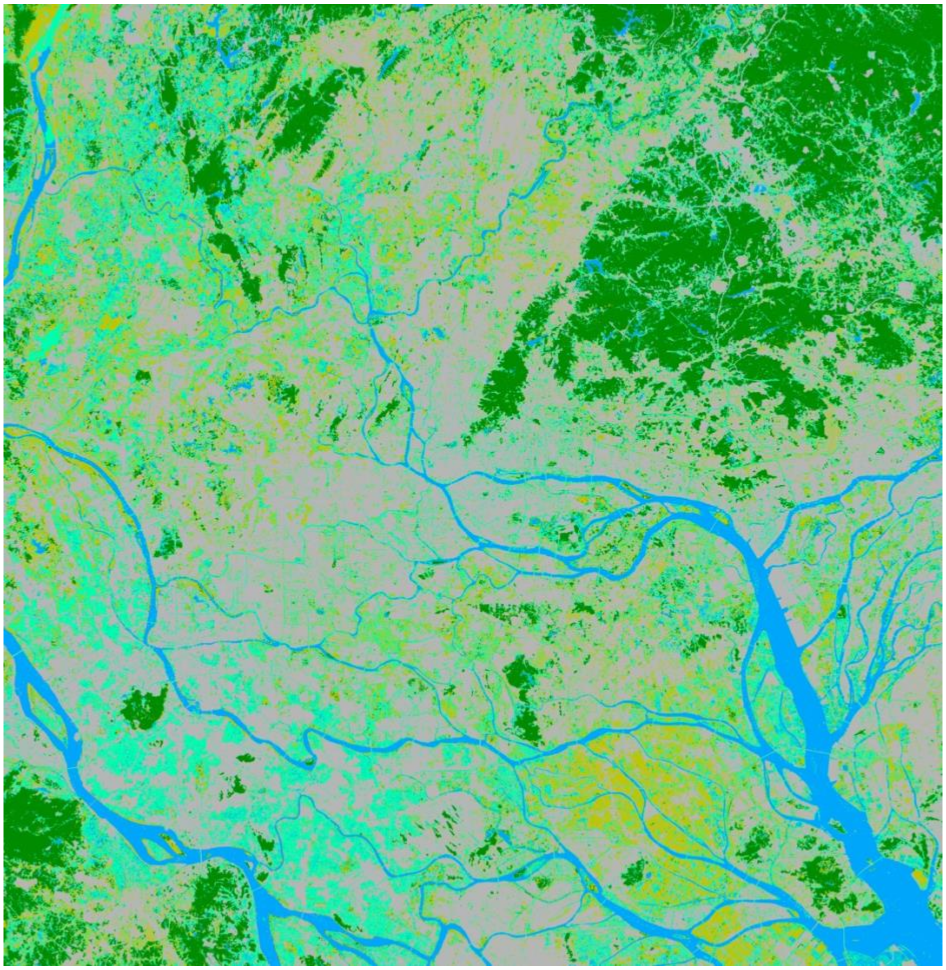

Figure 1. The whole-area map of the city of Guangzhou in the south of China produced suing a supervised classification with Maximum Likelihood procedure. The satellite image is in WGS_1984_UTM_Zone_49N projected coordinate systems retrieved from Oct 21, 2022, with Landsat 8 path/row 122 044. In the map, water is shown in blue, urban areas in grey, fish farm in greener cyan, forests in darker green, and cropland in yellow.

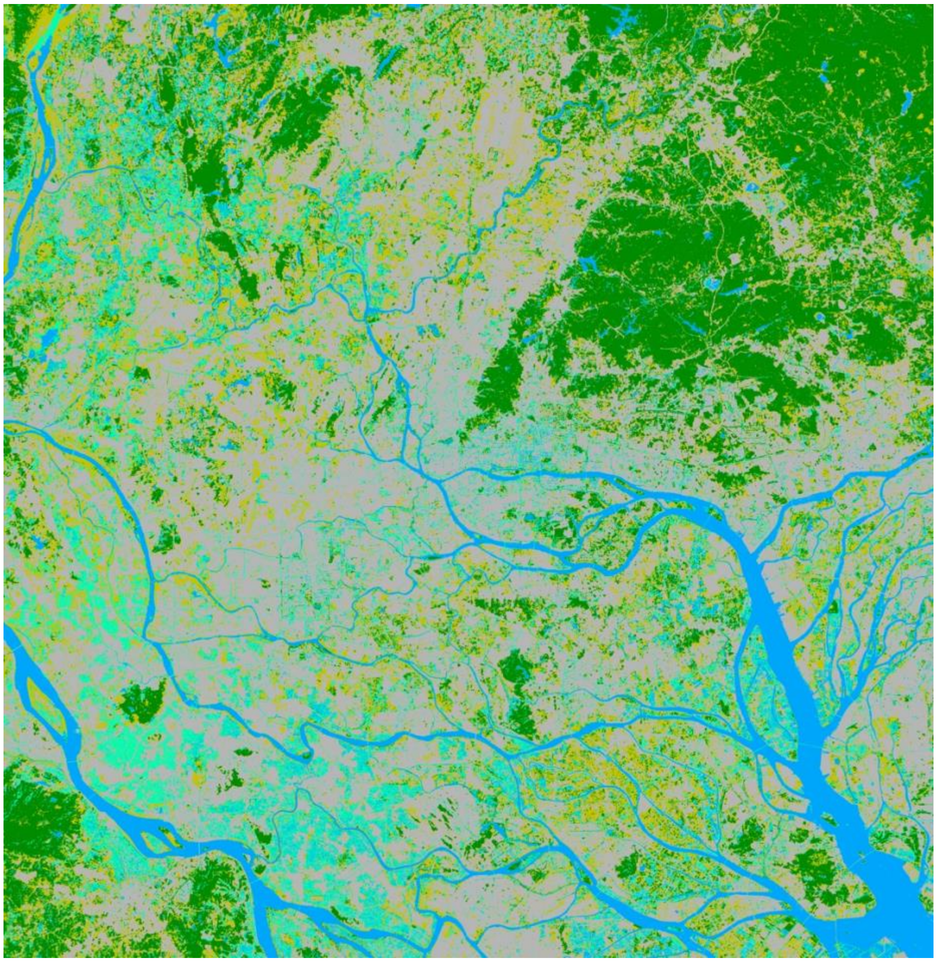

Figure 2. The whole-area map of the city of Guangzhou in the south of China produced suing a supervised classification with Support Vector Machine procedure. The satellite image is in WGS_1984_UTM_Zone_49N projected coordinate systems retrieved from Oct 21, 2022, with Landsat 8 path/row 122 044. In the map, water is shown in blue, urban areas in grey, fish farm in greener cyan, forests in darker green, and cropland in yellow.

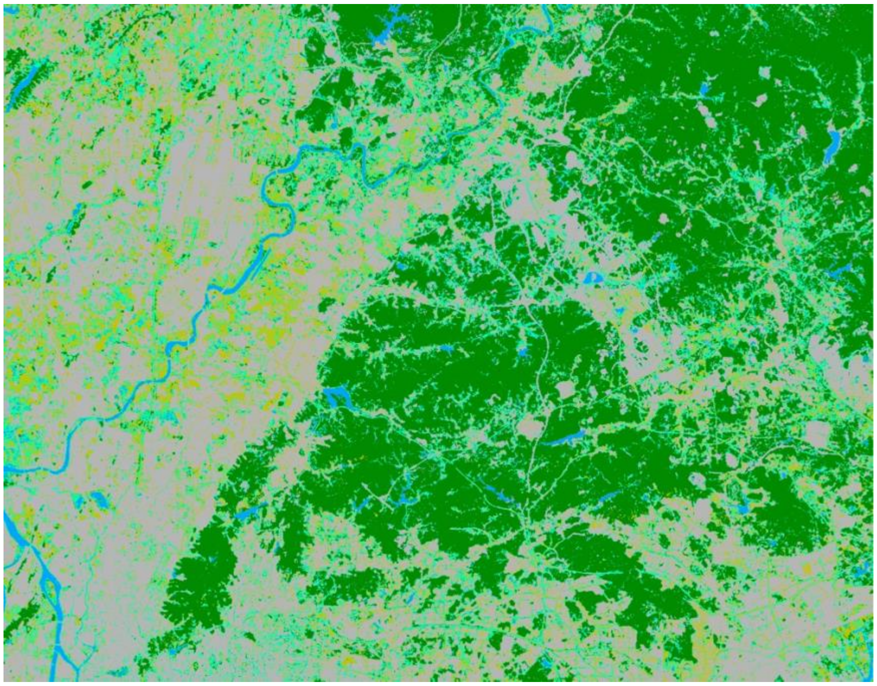

Figure 3. The detailed forest map of the city of Guangzhou in the south of China produced suing a supervised classification with Maximum Likelihood procedure. In the map, water is shown in blue, urban areas in grey, fish farm in greener cyan, forests in darker green, and cropland in yellow.

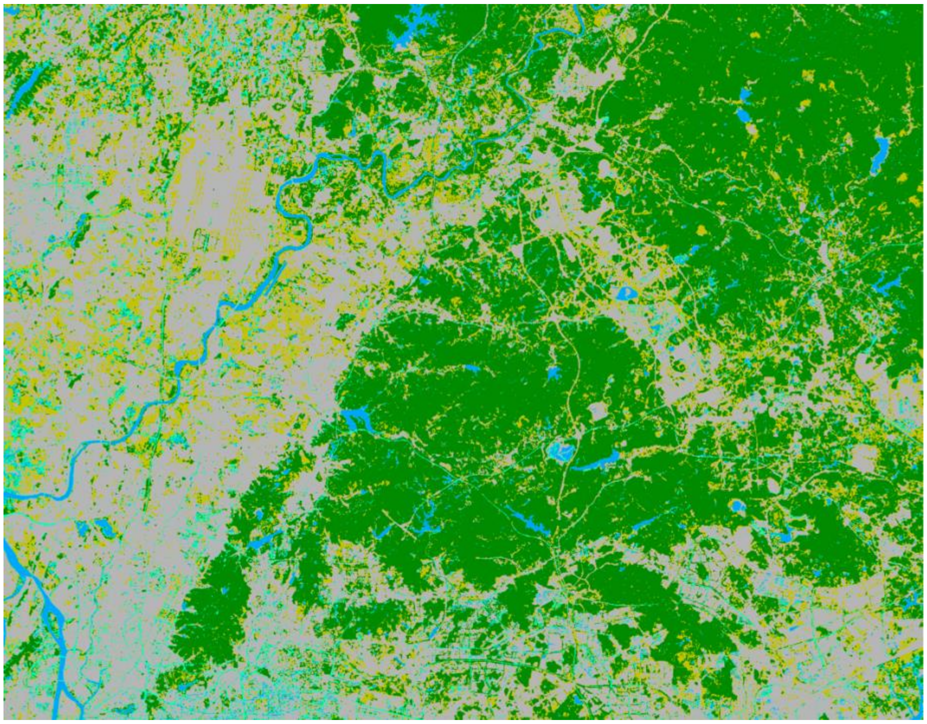

Figure 4. The detailed forest map of the city of Guangzhou in the south of China produced suing a supervised classification with Support Vector Machine procedure. In the map, water is shown in blue, urban areas in grey, fish farm in greener cyan, forests in darker green, and cropland in yellow.

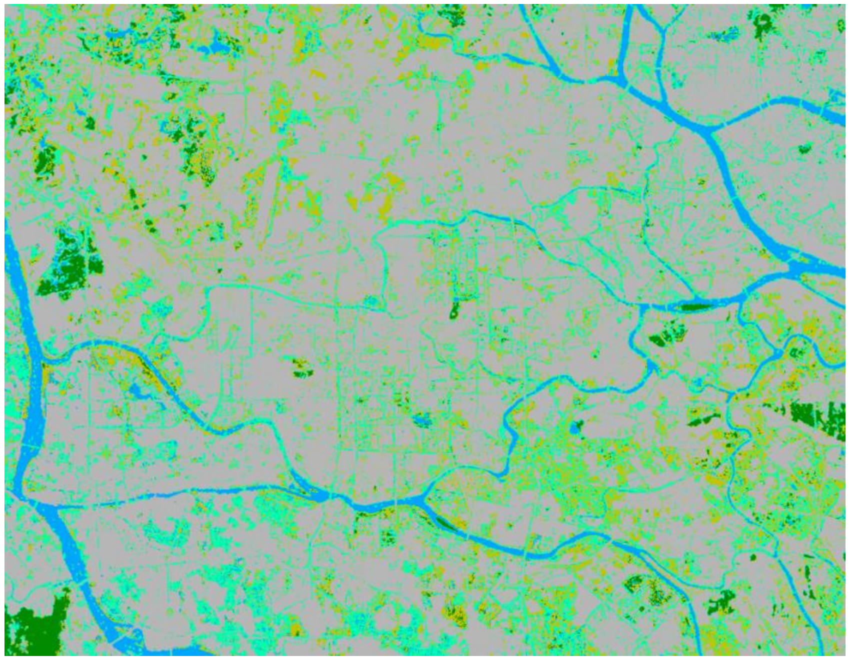

Figure 5. The detailed urban map of the city of Guangzhou in the south of China produced suing a supervised classification with Maximum Likelihood procedure. In the map, water is shown in blue, urban areas in grey, fish farm in greener cyan, forests in darker green, and cropland in yellow.

Figure 6. The detailed urban map of the city of Guangzhou in the south of China produced suing a supervised classification with Support Vector Machine procedure. In the map, water is shown in blue, urban areas in grey, fish farm in greener cyan, forests in darker green, and cropland in yellow.

Class	ForestTest	WaterTest	UrbanTest	CroplandTest	FishFarmTest	Total	User's Accuracy
Forest	8	0	0	0	0	8	1
Water	0	8	0	0	1	9	0.888889
urban	1	0	14	1	0	16	0.875
cropland	1	0	4	3	1	9	0.333333
FishFarm	3	2	1	1	2	9	0.222222
Total	13	10	19	5	4	51	
Producer's accura	0.615384615	0.8	0.736842105	0.6	0.5		
Overall Accuracy	0.68627451						

Class	Total
Unclassified	0
Forest	8
Water	9
urban	16
cropland	9
FishFarm	9
Total	51

Table 1. Maximum Likelihood Classification Accuracy Assessment Error Matrix

Class	ForestTest	WaterTest	UrbanTest	CroplandT	FishFarmT	Total	User's Accuracy
Forest	8	0	0	1	0	9	0.888889
Water	0	9	0	0	0	9	1
urban	1	0	11	0	0	12	0.916667
cropland	2	0	5	3	2	12	0.25
FishFarm	2	1	3	1	2	9	0.222222
Total	13	10	19	5	4	51	
producer's accura	0.615385	0.9	0.578947	0.6	0.5		
Overall Accuracy	0.647059						

Class	Total
Unclassified	0
Forest	9
Water	9
urban	12
cropland	12
FishFarm	9
Total	51

Table 2. Support Vector Machine Classification Accuracy Assessment Error Matrix