Lab Assignment #8 – Mapping Land-cover Changes

1. Logistics

Date assigned:	Monday, January 06, 2025
Date due:	Monday, January 27, 2025 (via Moodle)
Points:	90 points

Please submit all homework as a single PDF file via Moodle.

In this lab, we will work use or knowledge of supervised classification techniques to detect changes in land cover over time.

2. Supervised Classification of Multiple Time Steps

There are many areas of the world that have drastically changed in the last few decades. The classic example is the Amazon, where deforestation and urban development is striking. However, many large lakes have shrunk dramatically (ie. Lake Chad, the Aral Sea), urban centers have grown enormously (e.g., West Africa, China), and natural disasters have occurred (e.g., hurricanes and tsunamis).

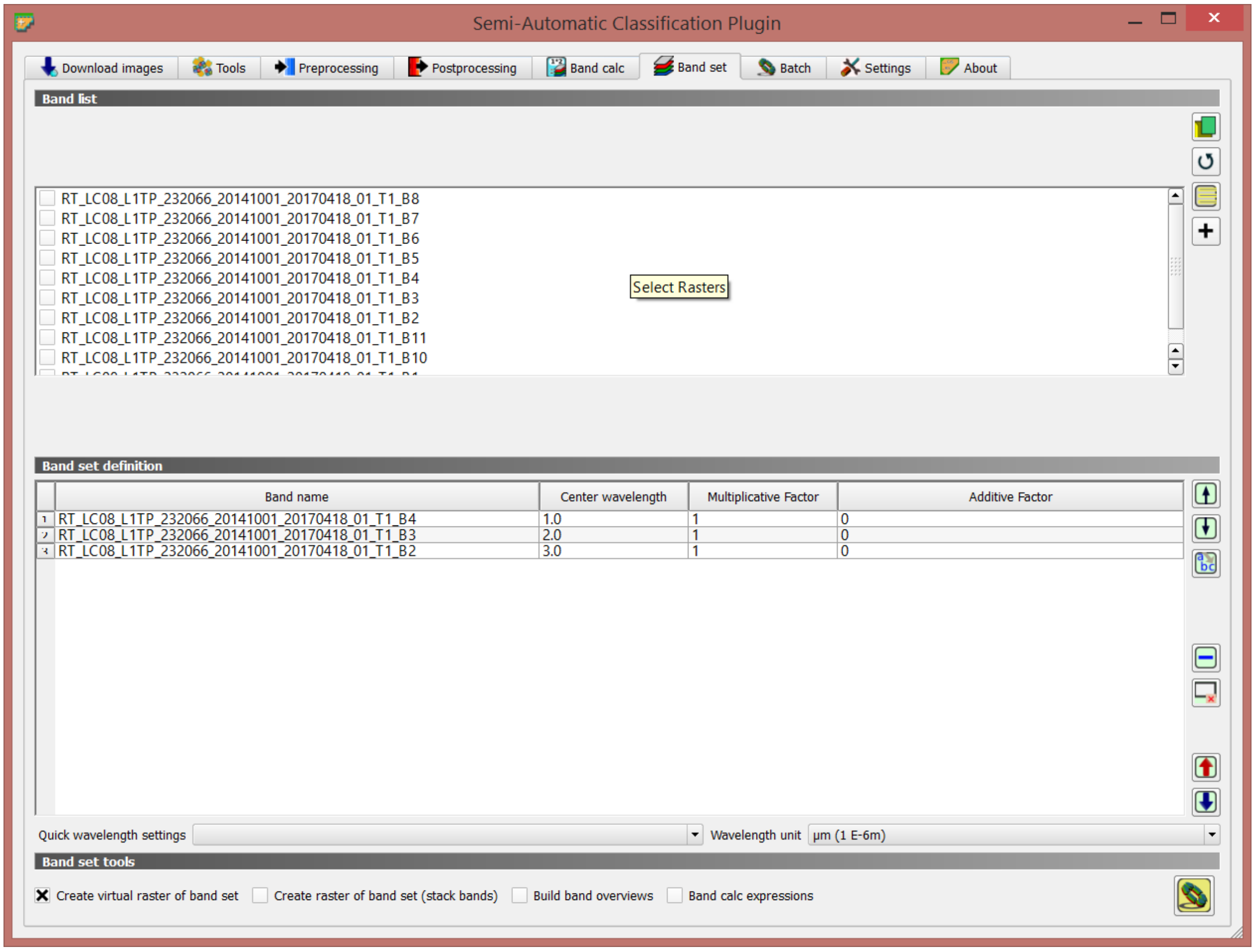
In this lab, we will classify the land-use types of two different images through time. If you are interested (or are using this data for another project), feel free to use several images. This portion of the lab will provide an outline to the approach, **but you should use your own location of interest.** You should already have two images of the same area from previous labs, which you are welcome to use. Otherwise, download two images from EarthExplorer to use in the second half of this lab. **You are also welcome to use Sentinel-1 or Sentinel-2 data if you prefer**.

In this example, I've downloaded two Landsat scenes of Rodonia (around the town of Porto Velho,
Lat: 08° 43' 51" S, Lon: 063° 53' 27" W). The first scene is from Landsat 5, in October 1993. The second is from October 2014. **Note: it is important to choose two images during the same season if you want to compare changes across years. This helps control for differences in growing season in plants, solar illumination, etc**.

The first step is to classify both images with training data. In this example, I am doing a simple classification into (4) classes (water, urban, forest, and agriculture). **Note: it is best if you can find images without clouds, but often there simply aren't any cloud-free images available. This is a particular problem in the tropics and in high mountains which see frequent storms.**

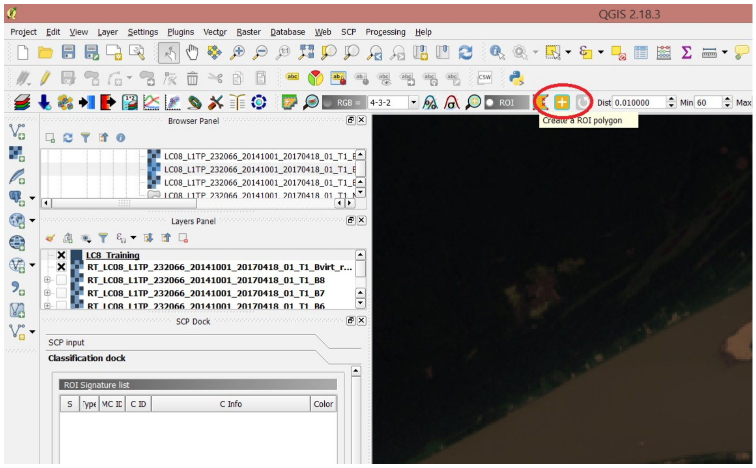
Open your corrected Landsat bands in QGIS. We want to select areas which are representative of our different land-use classes. For example, take big areas of forest, big areas of water, etc. You can either create a single multi-band raster which holds all of the Landsat bands you will use for classification, or you can build a 'virtual raster' in QGIS which simply lets you access all of the data bands without saving out a new (giant) file.

Use the *'Band Set'* tool to select which raster bands you want to be in your virtual raster, and run the tool by clicking the button on the bottom right.

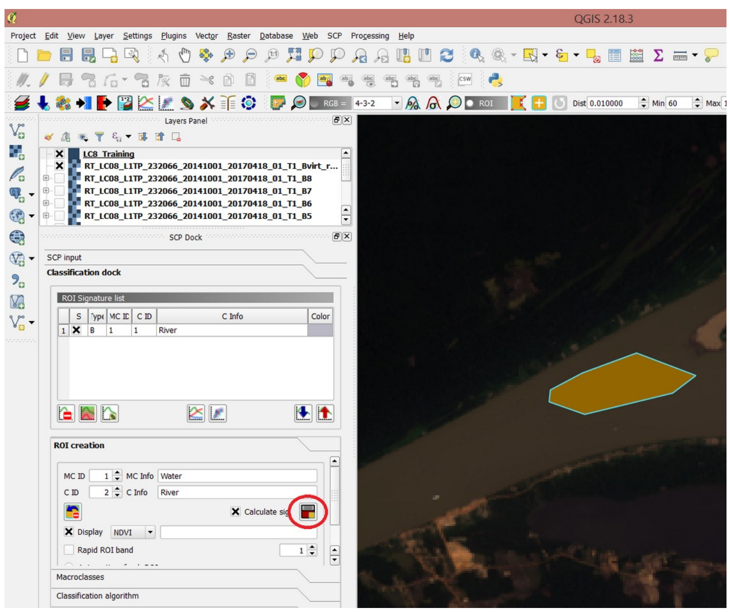


Next, we want to create our training data zones. Right below the 'band set' tool is the 'Training Input' tools. First we want to create an empty training dataset. Click 'Create new training input'. **Note: we will have to create a separate training dataset for each scene that we classify, as our 'training' zones might have changed land-cover type between the time periods.**

Below the SCP input tools there is a 'Classification' tab. This should show up below your file browser. This is where we will assign labels to our training data.

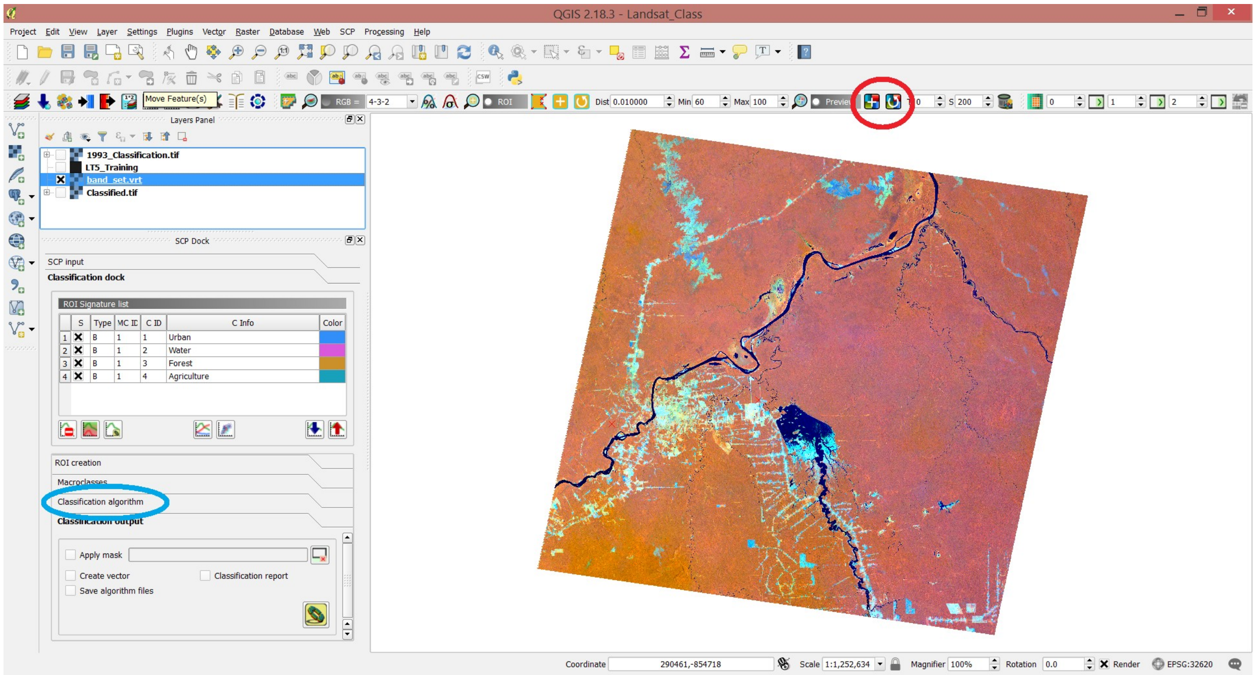


We can now create polygons defining our different land-cover types. Click points around the edges of your polygon, and right click to close the shape. Once you are happy with your polygon, add attributes and save the polygon to the training dataset (button circled in red in the image below).



Continue selecting training areas until you are satisfied with the spread of training areas. **Note: it is important to select examples of the same land cover type from multiple areas in your image! This helps prevent too-tight of a classification**. For example, if you have both rivers and lakes, and only select water pixels from the lake, you will likely miss some river areas due to different colors, suspended sediment loads, etc.

You can preview your classification with this button (main toolbar):



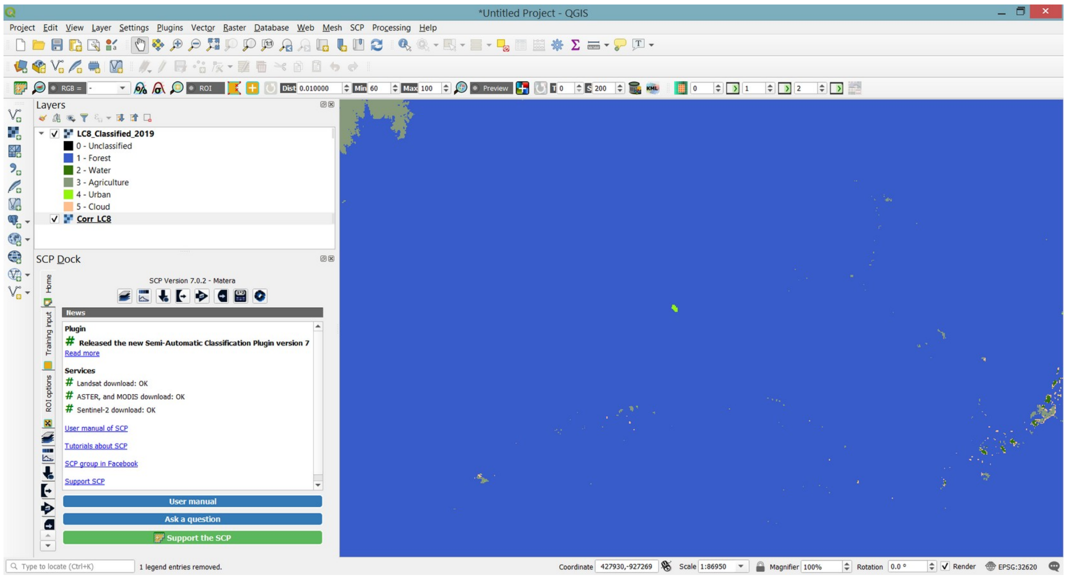
This will show you the classification results over a small window so you can see how well the algorithm does with your current settings. If the results look questionable, try adding additional polygons of whichever zones seem to be misclassified. You can also try different algorithms (maximum likelihood, spectral distance, etc), which are accessed on the bottom panel of the SCP toolbox (bottom left, circled in blue).

> **<u>Question 1:</u>** Which landcover types in your selected area are the most difficult to correctly classify? What strategies did you use to try to fix these classes? (10 points).

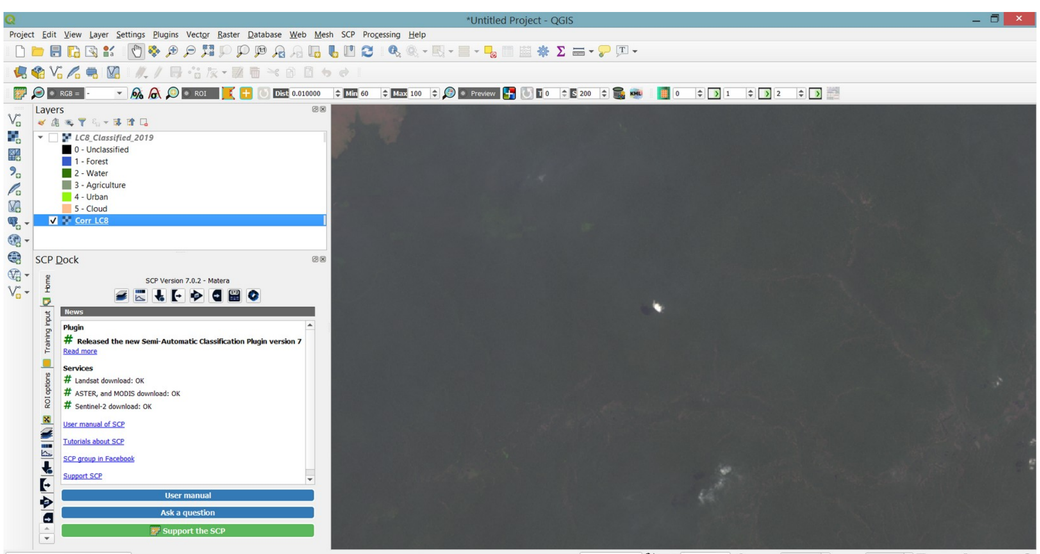
Once you are satisfied with your classification, repeat this process with a second image of the same area.

3. Refining Classification Results

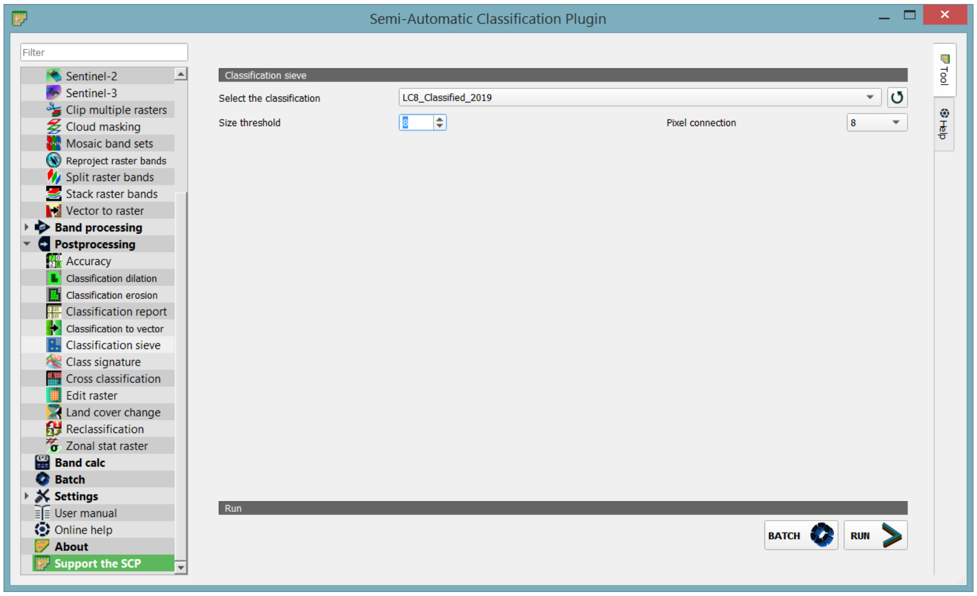
Often, classifications end up with isolated pixels – for example, one ‘water’ pixel in the middle of a large area of ‘forest’. Depending on how accurate your classification is – and how well separated your classes are – it is sometimes helpful to refine or generalize your classification results. For example, look at this isolated forest region of my 2014 image:



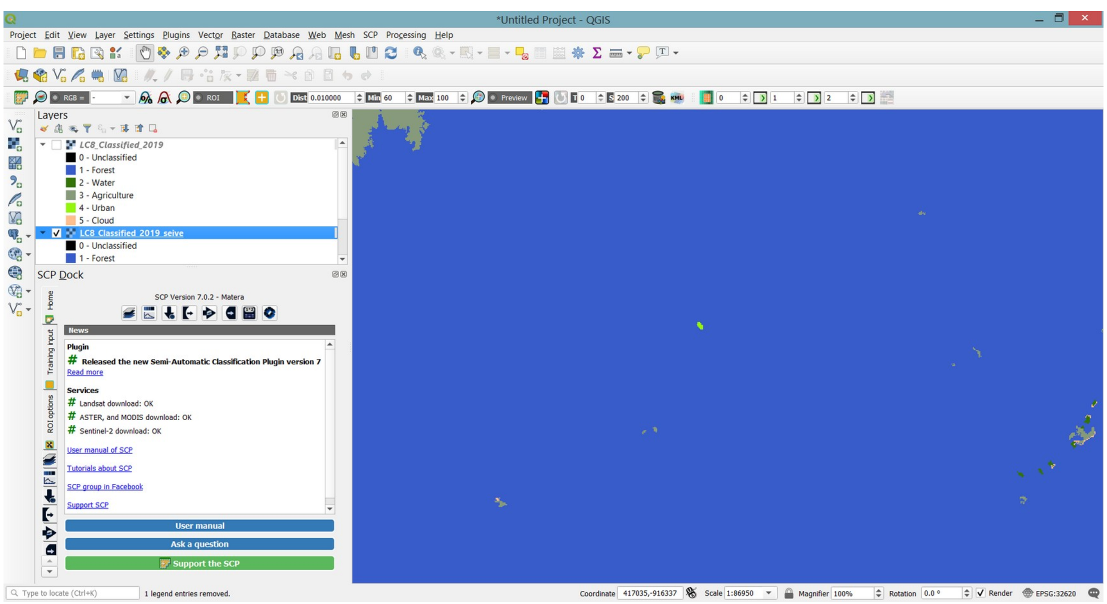
While most of the area is correctly classified as ‘forest’, there are some ‘urban’ areas in there. If I look back at the original image, I can see that that small area is actually a misclassified cloud/cloud shadow.



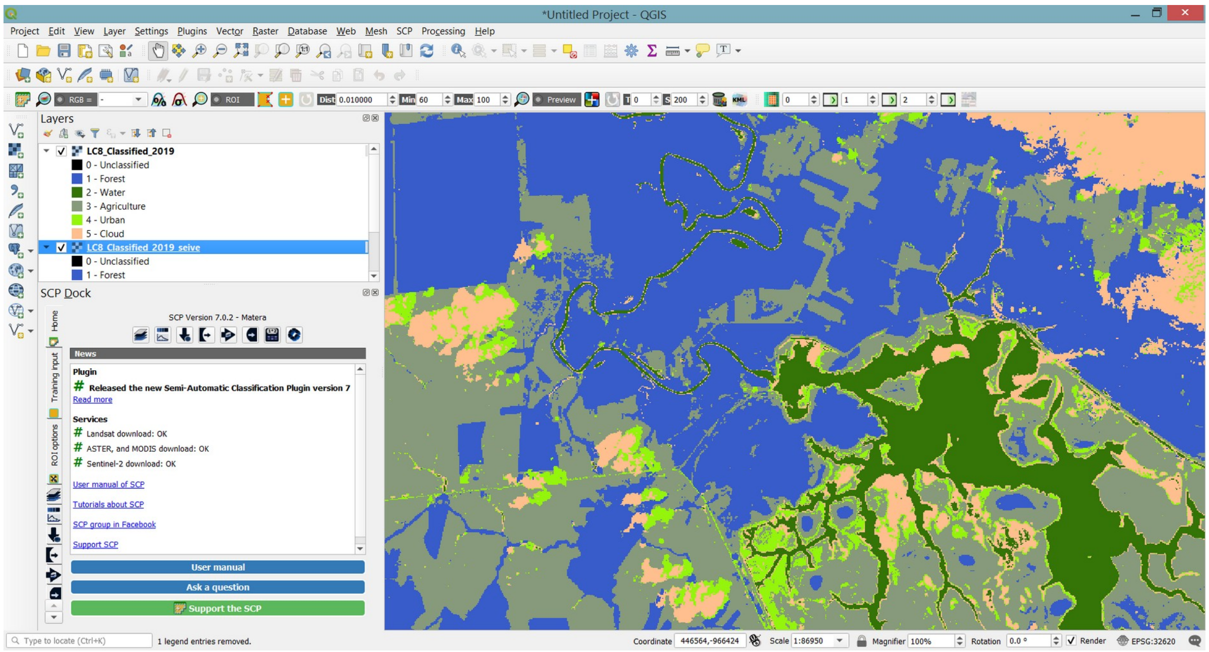
We can attempt to remove some of these small and isolated misclassified pixels using the **Classification Sieve** tool:



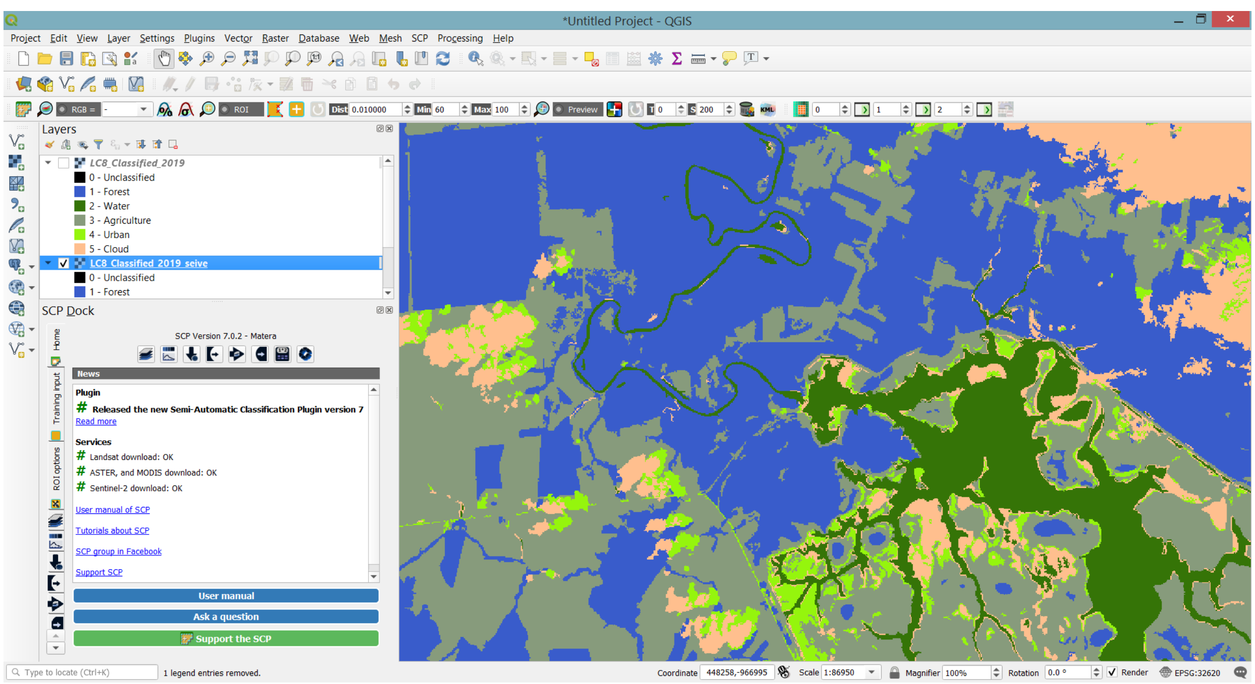
Unfortunately, in this case it did not eliminate that large cloud area – there were too many connected pixels to be removed. It did, however, remove some of the smaller pixels just south of the cloud:



In this instance, the classification became **WORSE** by dropping those small pixels. In other parts of the image, however, it became **BETTER** by removing small edges/noise.



Before Image



After Image

Notice particularly how much cleaner the classification borders are, and how many small regions have disappeared.

Using the **Accuracy Report** tool, check which of the classifications performs better. What impact does the size of the window/connectivity used in the **Sieve Tool** have on the accuracy?

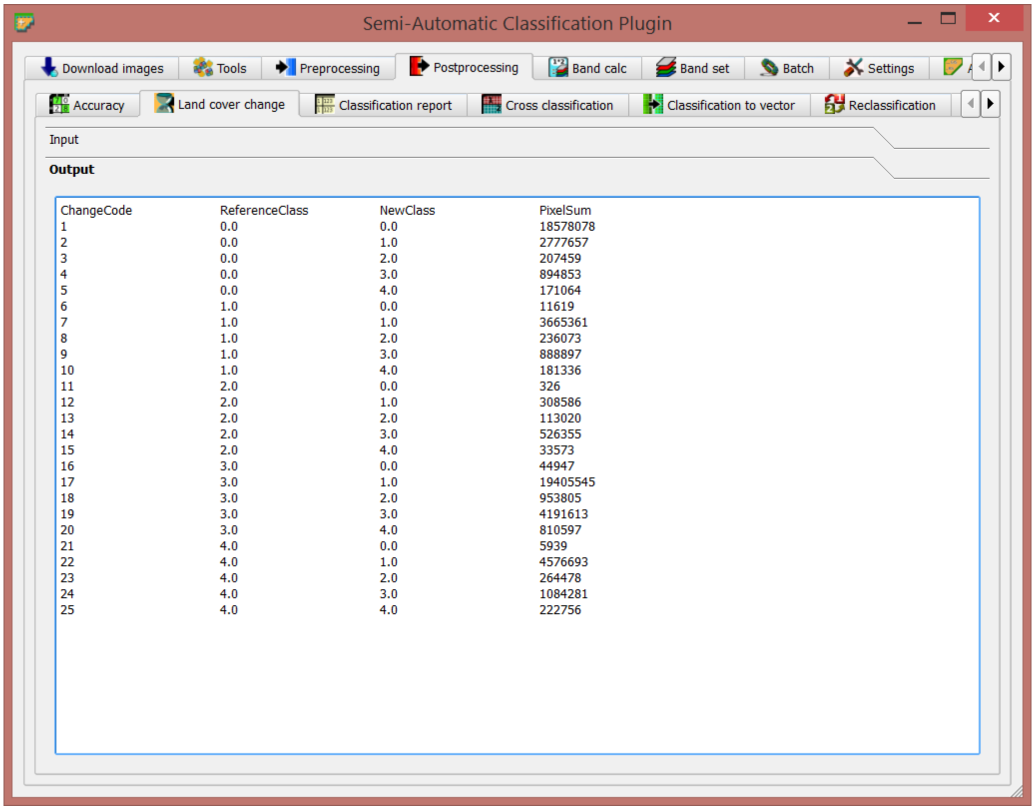
> **Question 2:** Compare the Accuracy of one of your classifications before and after Sieving. Try at least two different sieve thresholds. How does your accuracy change when you remove small/isolated pixels? (20 points)

It is important to consider both your application and your audience when refining a classification – is it more important to have a noisy but overall more accurate result, or a more generalized/smoother result? This will depend on what further analysis you want to do with your classification and how you will present your final results.

4. Multi-temporal Change Detection

Once you are satisfied with our classification results on both images, we can do a change analysis. In order for this to work, the **class labels must be the same between both images!** For example, in both your earlier and later image Water should be classified by the same number.

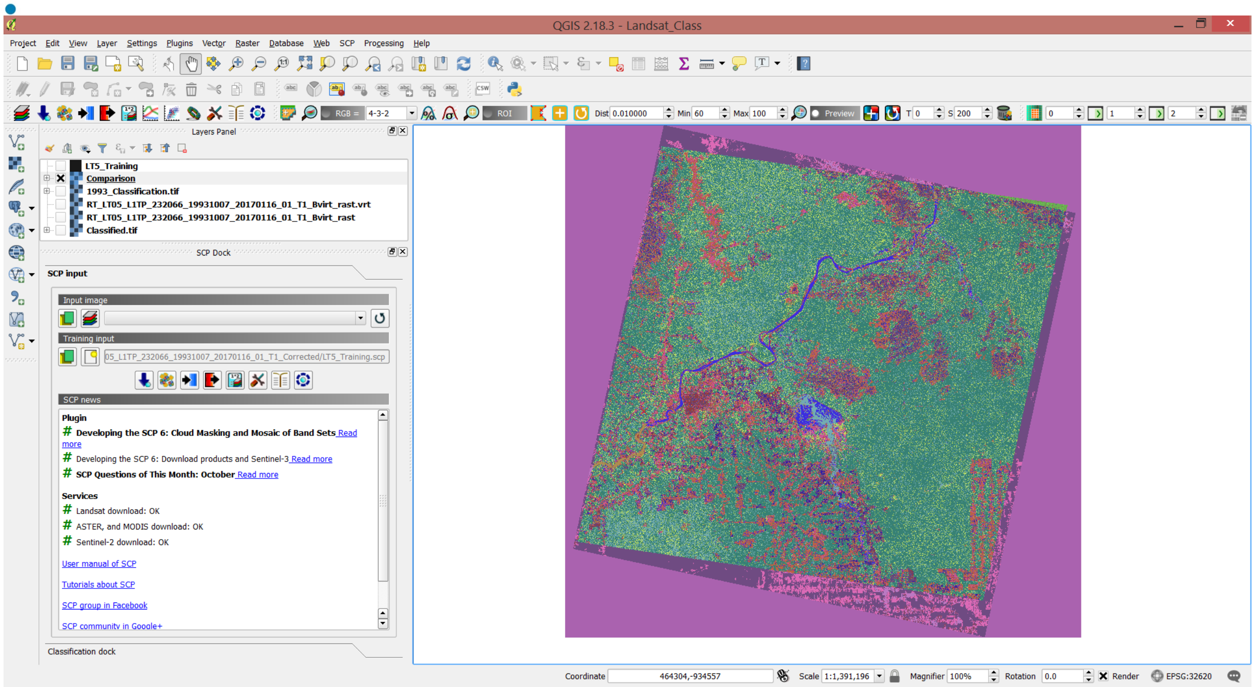
For this last step, we will use the ‘Land cover change’ tool. This tool will compare every pixel in both images and see which classes changed and which remained the same.



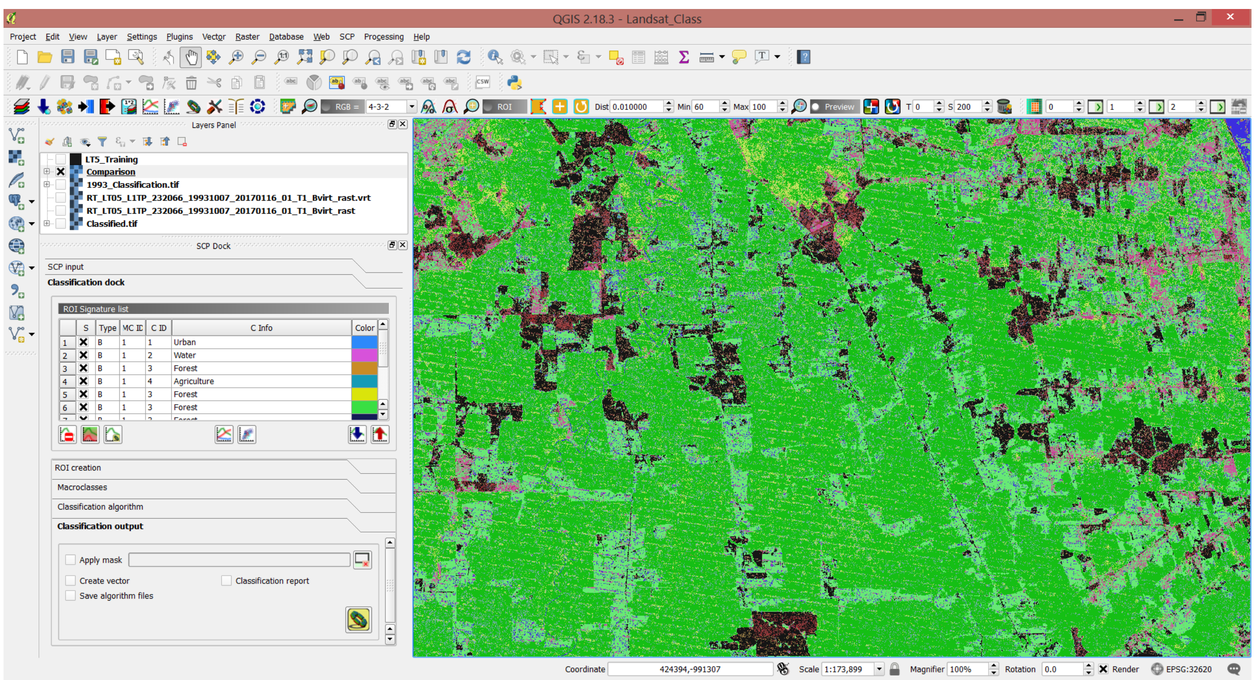
ChangeCode	ReferenceClass	NewClass	PixelSum
1	0.0	0.0	18578078
2	0.0	1.0	2777657
3	0.0	2.0	207459
4	0.0	3.0	894853
5	0.0	4.0	171064
6	1.0	0.0	11619
7	1.0	1.0	3665361
8	1.0	2.0	236073
9	1.0	3.0	888897
10	1.0	4.0	181336
11	2.0	0.0	326
12	2.0	1.0	308586
13	2.0	2.0	113020
14	2.0	3.0	526355
15	2.0	4.0	33573
16	3.0	0.0	44947
17	3.0	1.0	19405545
18	3.0	2.0	953805
19	3.0	3.0	4191613
20	3.0	4.0	810597
21	4.0	0.0	5939
22	4.0	1.0	4576693
23	4.0	2.0	264478
24	4.0	3.0	1084281
25	4.0	4.0	222756

<u>Question 3:</u> Attach the land-cover change detection results to your lab. It is fine to include this as a screenshot (20 points).

This will also result in a map showing the classification differences between each pixel. If the numbers don't make much sense, you should use the land cover change matrix (ie, the output shown in the image above) to interpret the class numbers. In this case, ChangeCode 1 represents pixels that started in class zero and ended in class zero.



This is my example classification in the Amazon. Even without doing extensive change statistics, it is clear that urban areas have grown significantly into the rainforest in this area.



As an example, the black areas are areas which changed from Forest to either Urban or Agriculture over the last 20 years.

Question 4: Attach a map showing the results of your land-cover change detection. Change the legend labels to be something useful (ie, labeled as Forest -> Urban instead of ‘Class 17’. Include a scale bar, north arrow, and grid. (20 points).

Question 5: Which land cover classes changed the most? What are the likely drivers of these changes in your area? Do these changes seem reasonable? (20 points).