SMT201: Geographical Information Systems for Urban Planning

AY2023-24 Term 1

Group Project on Land Cover Change Analysis in Libya 2023

Project Report

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Introduction

Tropical-like cyclones typically occur once a year in the Mediterranean. This year's (2023) storm, named Storm Daniel, is the deadliest seen. Derna, a city in Libya was significantly affected by the storm as the Storm resulted in the collapse of two dams, resulting in a flood. The flood washed people out to sea and led to the displacement of around 40,000 people (according to estimates by the UN International Organization of Migration). There were also major impacts infrastructure wise; entire neighbourhoods were swept out to sea, roads were destroyed, and over 3,100 buildings were destroyed (as per estimates by the United Nations satellite centre indicate that around). Floods can also result in long term impacts on the economy as infrastructure and inventory may need a substantial amount of time to be rebuilt. As such, planning is essential to allocate resources effectively so as to maximise recovery and resilience in the future.

Geospatial Analysis can support planning decisions in the process of recovery to rebuild and strengthen the society against future incidents. Due to the difficulty of accessing on the ground data in areas without established on-the-ground sensing infrastructure, satellite data is the main source of data for post-flood management and planning. Satellite data can be used for land use/ land cover change detection which is useful for analysing the impact of the flood on different areas and selecting suitable sites for emergency response facilities and to inform recovery and rebuilding efforts.

This project aims to investigate the changes in land cover after the flooding of Derna City in Libya on 10 September 2023, due to Storm Daniel and the collapse of the dam. Statistical learning and Machine learning methods will be used to classify land cover before and after the storm respectively. Using land cover change analysis, the extent and types of damage caused by the flood can be identified and analyzed for identifying suitable sites for healthcare facilities.

In this project report, showcases the analysis conducted and insights from the project. Sections 1 - 11 outlines the step-by-step GIS processes and functions used, and Section 12 outlines the analysis and results with maps. Lastly, the report ends with discussions of recommendations in Section 13, limitations and extensions in Section 14.

Section 1: Downloading the required data

The data required is as follows:

- Pre-Flood and Post-Flood Satellite Data: Maxar's Open Data Program

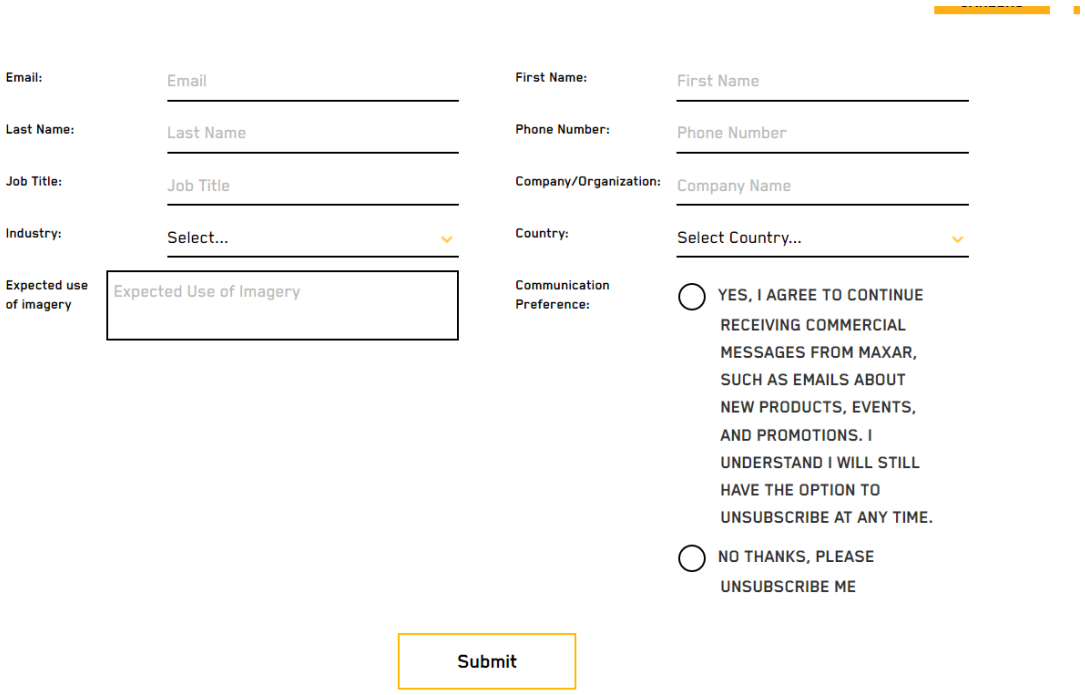
Our study area is composed of the following satellite images. You will be required to download the datasets corresponding to the following codes for both Pre-Event and Post-Event.

  - 120200213121
  - 120200213130
  - 120200213131
  - 120200213123
  - 120200213132
  - 120200213133

- 250m Study Area Hexagon of Derna city
- Libya Health Facilities (OpenStreetMap Export) - Humanitarian Data Exchange (humdata.org) (Polygon file)

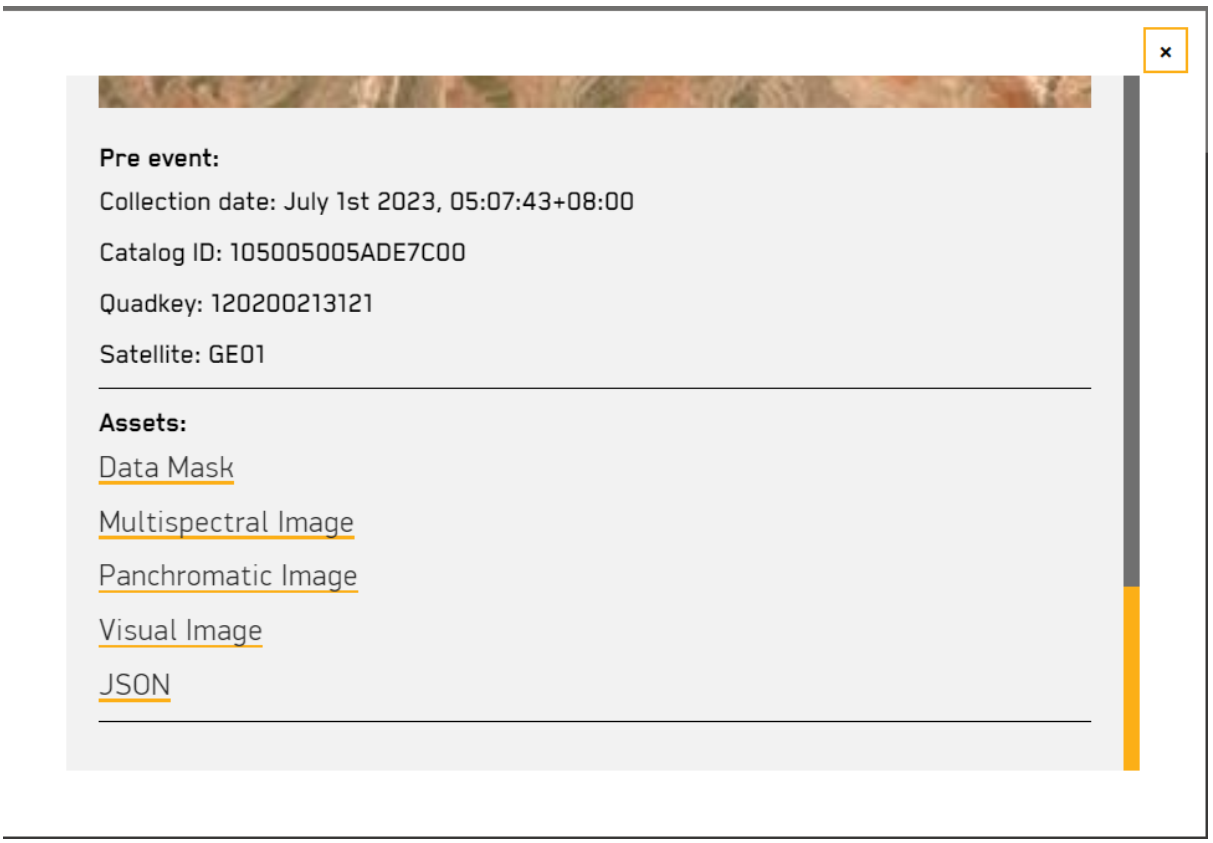
Download the datasets and save it into a folder named 'Data' under the project directory. In the Data folder, have a folder named '*Derna'* for the 250m Study Area Hexagon of Derna city and folder *Maxar Geoeye* for the satellite images.

Note on Downloading the Maxar satellite images:
On the web page above, scroll down until you see a sign up form. Note that you will need to sign up for an account to access and download the data.



After signing up, you should see a grid of codes. You can Filter by Pre-Event or Post-Event and also search for a specific code.

Search for each of the codes listed above. Upon finding the code of interest, click on it. Do a quick check that the dataset covers Derna city. When you are ready to download the dataset, scroll down and click on the Multispectral image on the bottom left.



Repeat for all the datasets (both Pre Event and Post Event for each code)
After downloading the dataset, do rename to pre and post flood respectively for easy identification.

Section 2: Data preparation

Before we start, change the Project Coordinate System of QGIS to EPSG:3197

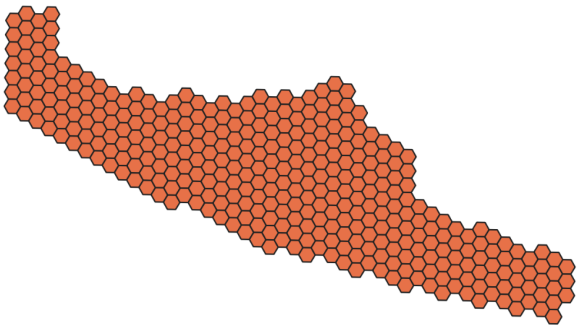
2.1: Data preparation for 250m Study area

1. Load in the 250m Study Area Hexagon of Derna City in QGIS.

From the menu bar, go to ***Layer*** → ***Add Layer*** → ***Add Vector layer***
The Data Source Manager would appear.

Click on the ***Browse*** icon to select the files
Select Derna_city_250m_hexagon.shp
Click on ***Open*** → ***Add*** to add the layer in

The layer should look like the following:



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2. Save the layer into a GeoPackage

- Right click on the layer in the **Layers panel** → ***Export*** → ***Save Features As***

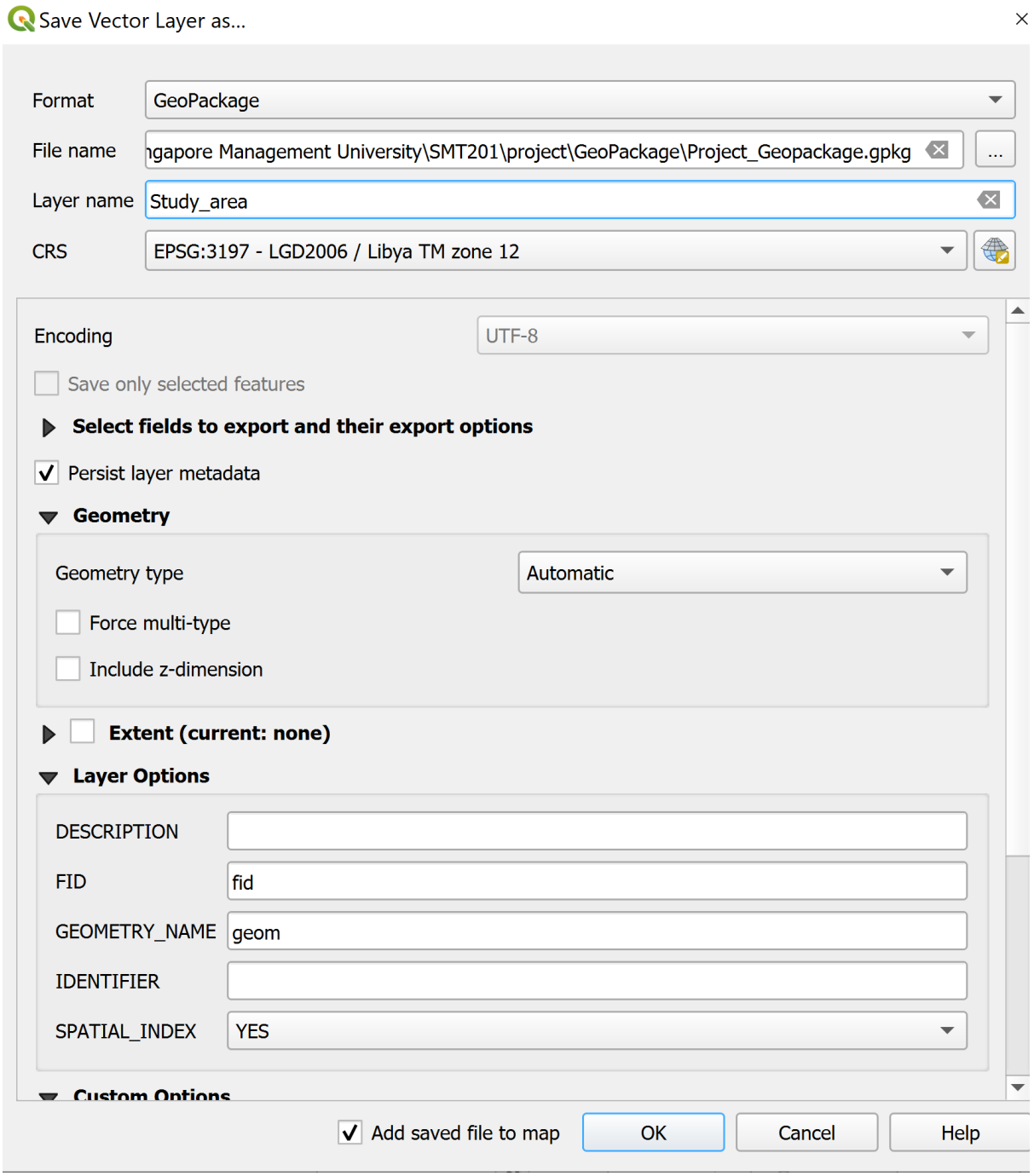
The dialog window to save the Vector layer would appear.

- Click the browse icon and create a new Geopackage named *Project_Geopackage* under the *GeoPackage* folder
- Enter the Layer name '*Study_area'*

For the CRS, choose EPSG:3197 as we will be using this CRS for this project. We will be using the EPSG 3197 Coordinate Reference System (CRS) for the subsequent analysis. This CRS covers Derna City, Libya.

- Ensure that the "Add saved file to map" checkbox is checked.

The dialog window would look like this:



Click on **OK** to save the study area into the geopackage.

3. Remove the *Derna_city_250m_hexagon* layer by **right clicking** → **Remove Layer**
4. Rename the newly added layer as *Study_area* instead of *Project_Geopackage* — *Study_area* by right clicking → **Rename Layer**

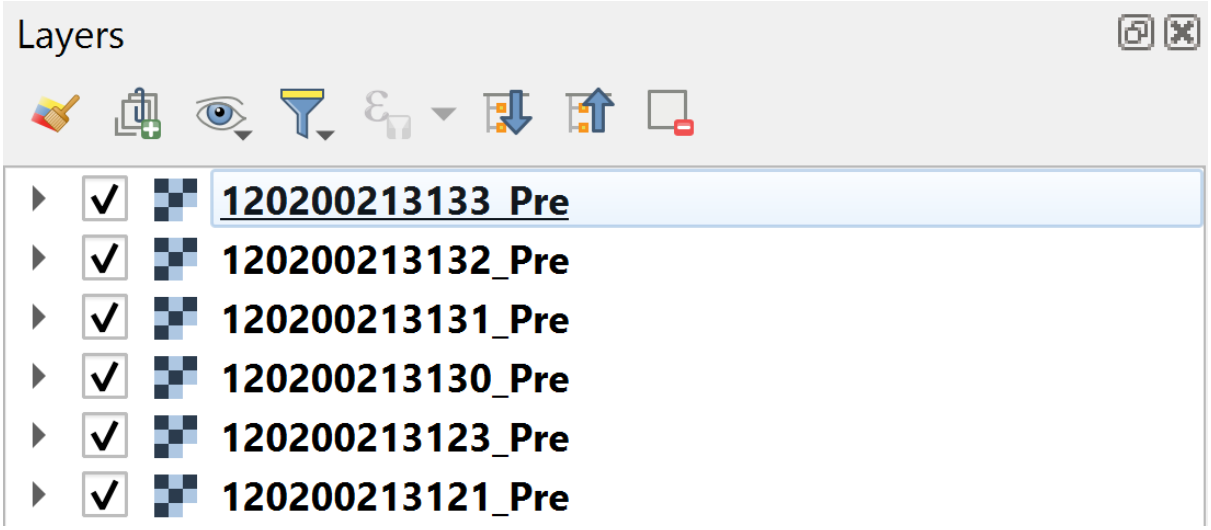
2.2: Data preparation for Pre flood layer

1. Load the six raster images corresponding to the Pre-Flood satellite data into QGIS.

From the menu bar, go to ***Layer*** → ***Add Layer*** → ***Add Raster layer***

The Data Source Manager window would appear.

- Click on the *browse* icon ... to select the pre flood satellite data from the *Maxar Geoeye* folder
- Select 6 raster files corresponding to the Pre-Flood maps
- Click on ***Open*** → ***Add*** to add the layer in. Click on *Close* to close the Data Source Manager window.



2. Merge the 6 raster layers

From the menu bar, go to **Raster** → **Miscellaneous** → **Merge**

The Merge dialog window would appear.

Under Input layer, select on the browse icon ... to select the 6 pre flood raster layers. Click on **OK** before returning to save the selection.

- Click on **Run** to merge the layers.

Notice that a temporary Merged layer is created.

- Close the merge dialog window.

3. Save the pre flood layer as a GeoTiff

Right click on the temporary Merge layer in the Layers panel → ***Export*** →***Save Features As.*** The dialog window to save the Raster layer would appear.

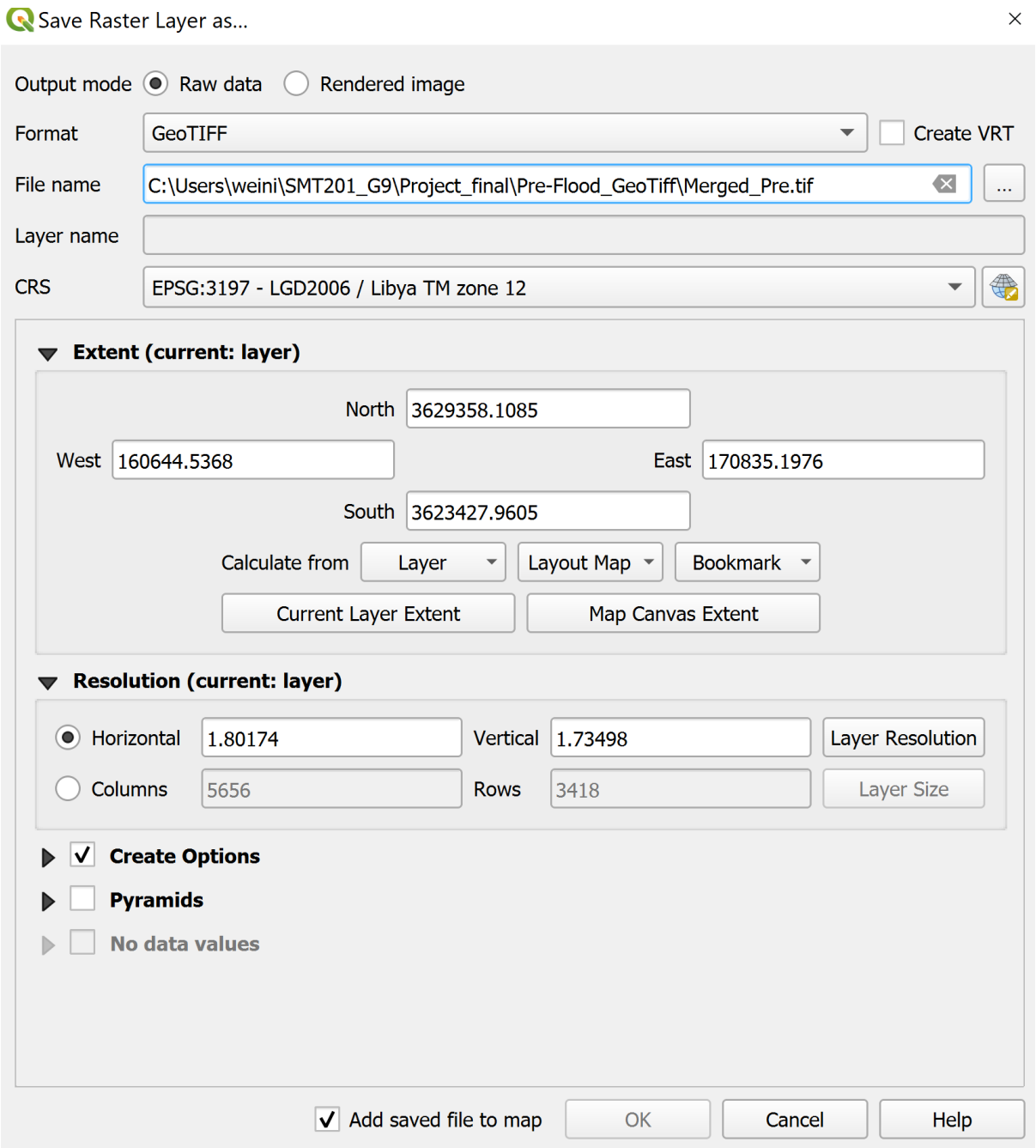
Click the browse icon and navigate to the *Pre-Flood_GeoTiff* folder to save the layer into, save the filename as *Merged_Pre*

Under the Extent, select **Calculate from Layer**, and select the *Study Area*

Ensure that the “Add saved file to map” checkbox is checked.

The dialog window would look like this:

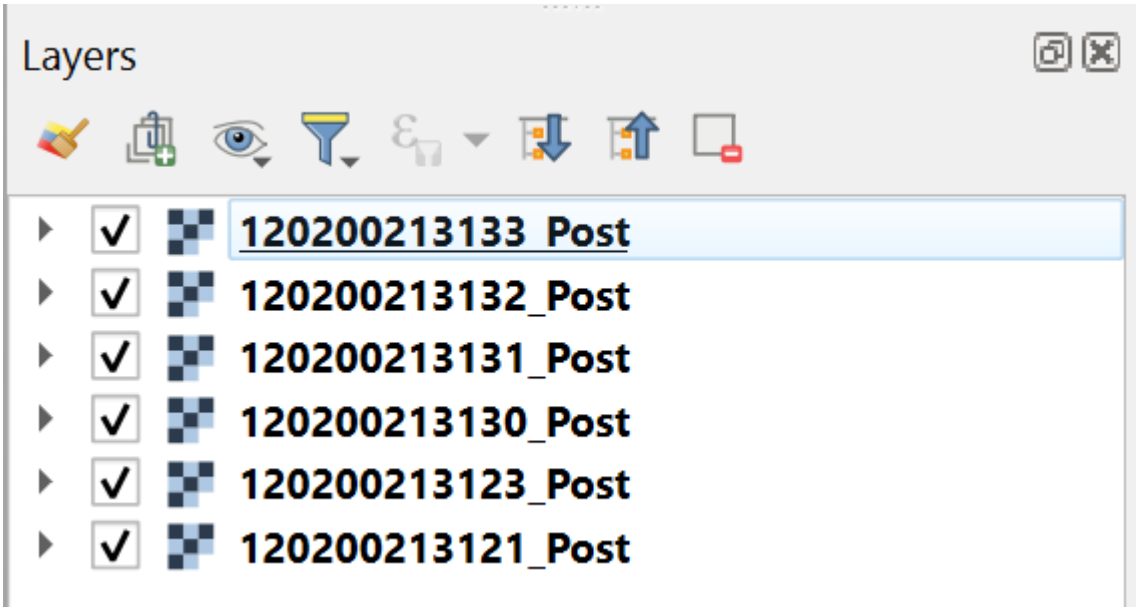
\



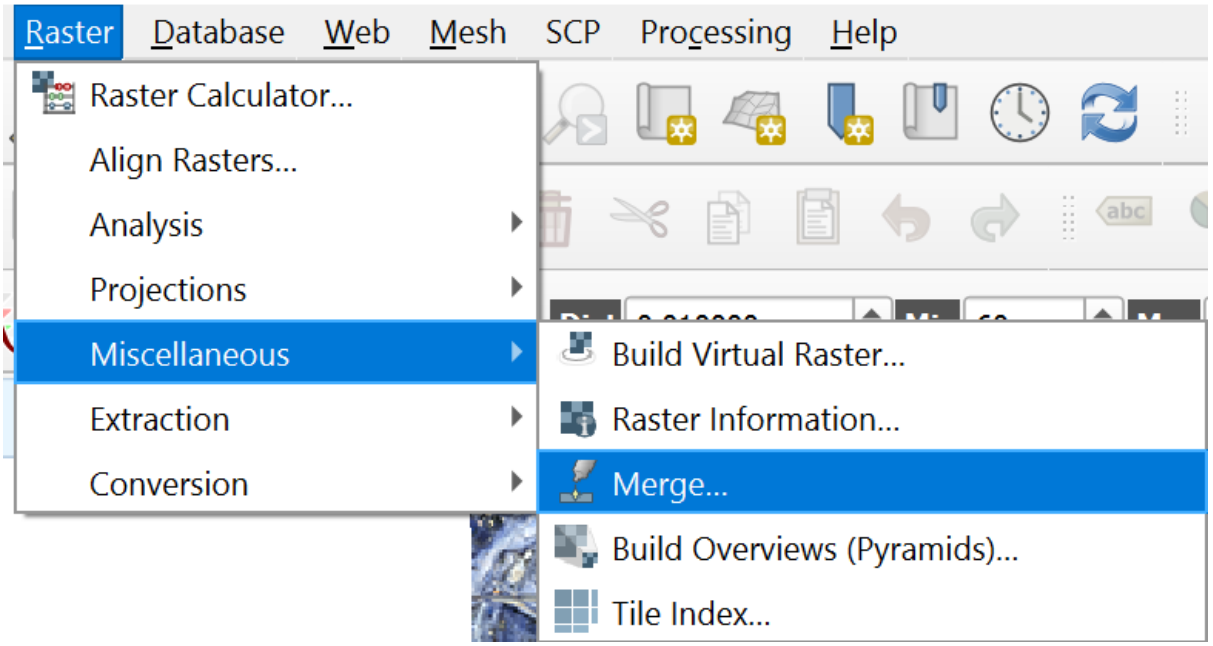
Remove the 6 original raster layers and the **temporary Merged layer → right click on the layer → Remove Layer.**

2.3: Data preparation for Post flood layer

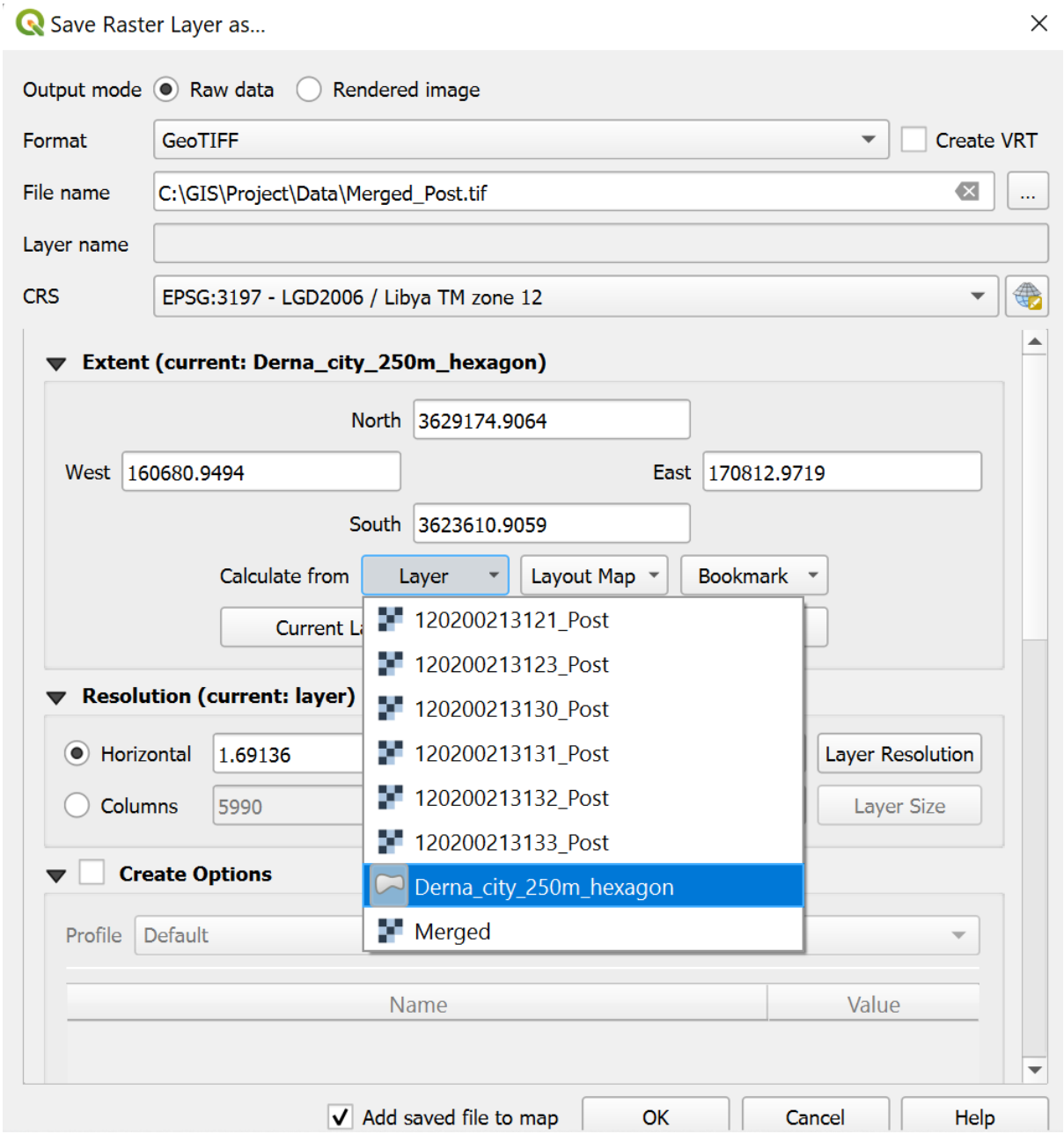
1. Load the six raster images corresponding to Post-Flood satellite data into QGIS



2. Now we are going to merge the six layers. Select all six layers and go to **Raster → Miscellaneous → Merge**



3. Save the merged layer



- Click **Ok**

Now we are going to train and evaluate the classification models for Pre-Flood and Post-Flood

Section 3: [Pre] Creating TCC and FCC

1. Create a Bandset

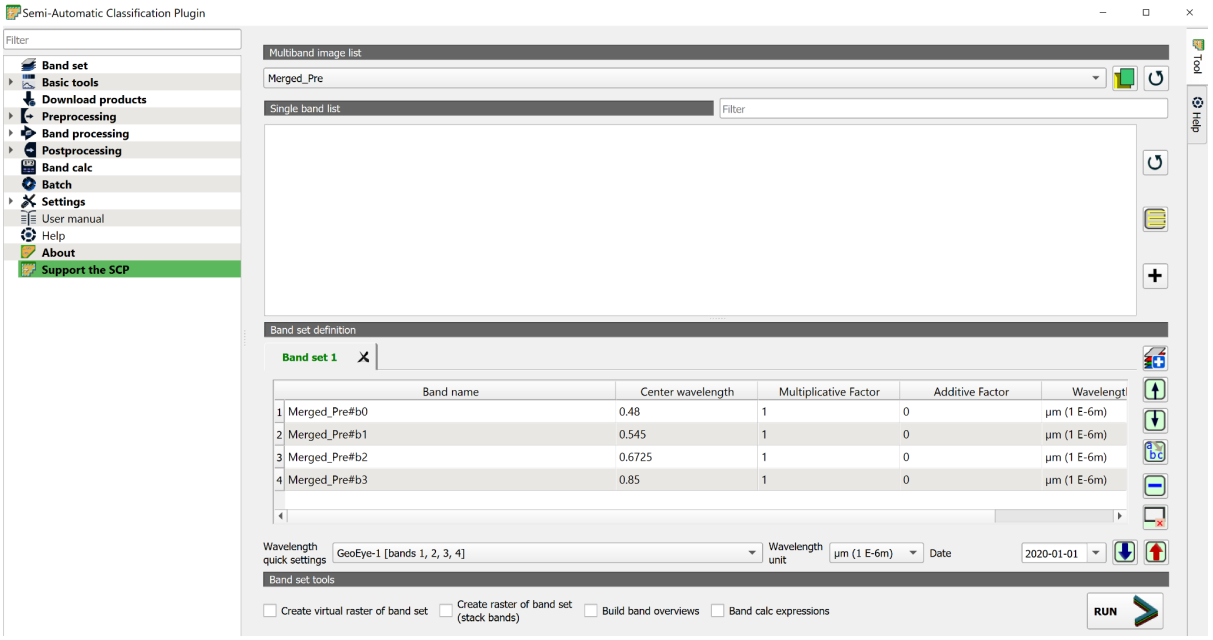
From the menu bar, select the Semi-Automatic Classification Plugin , the dialog window would appear.

Select Band set on the left column selection.

Under multiband image list, refresh and select the Pre-flood layer.

Under Wavelength quick settings, select GeoEye-1.

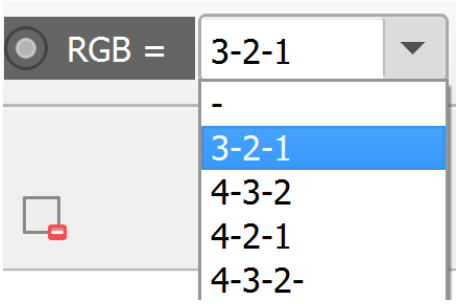
The dialog window would look similar to this:



Click on **Run** then minimise the window.

2. Create True Colour Composite (TCC) Image

- Return to the QGIS window.
- Under the menu bar, Click on the drop-down list beside the RGB pane.
- Select 3-2-1 from the drop-down list. If it is not available, type directly onto the pane.



Your screen should look similar to the screenshot below, a true colour composite of Derna pre-flood is created.

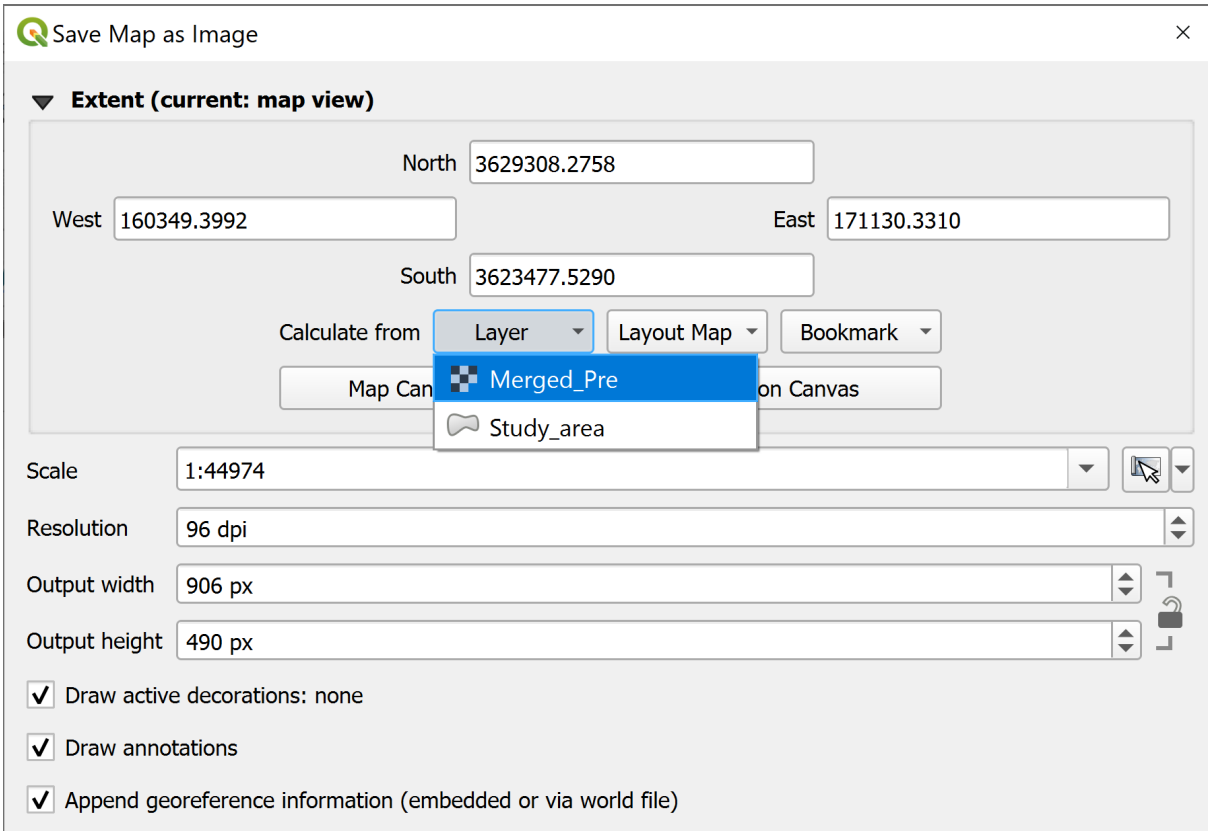
3. Save the TCC image

- From the **menu bar** → **Project** → **Import/Export** → **Export Map to Image**.

The dialog window to Save Map as Image would appear.

- Under Extent, select calculate from **Layer** → **Merged_Pre layer**

- Click on **Save** to save the image.



A dialog window would appear to select the directory and filename to save as.

- Save the image as TCC_prefloods in a folder named “images” in the project folder.

4. Create False Colour Composite (FCC) Image

For the false colour composite image, under the RGB panel, select or type 4-3-2

Your screen should look similar to the screenshot below, a false colour composite of Derna Preflood is created, where it is able to allow us to identify vegetation easily

Save the FCC image as FCC_prefloods.

Section 4: [Pre] Training the Supervised Classification Models

For both pre and post layers, the following classes are chosen for the analysis:

- Built-up area
- Bare land
- Impervious surfaces
- Water body
- Vegetation
- Cloud
- Cloud shadow

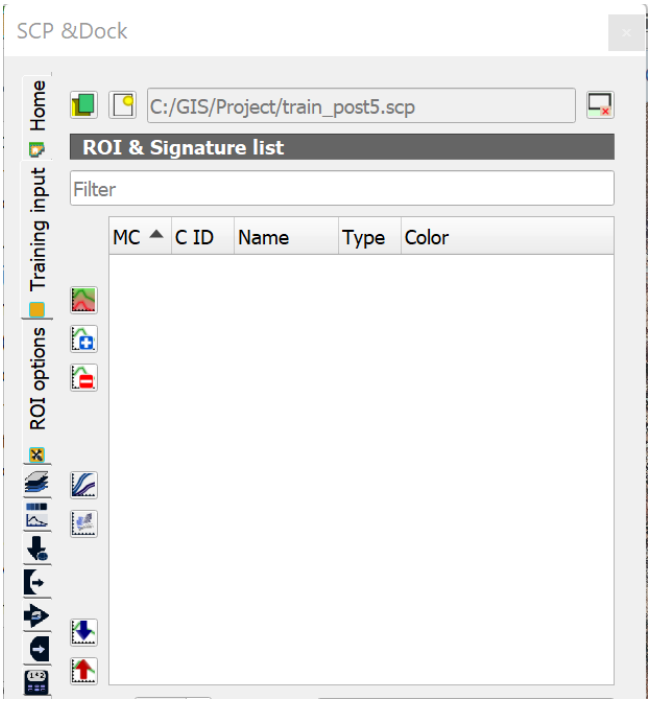
4.1: Digitising the training samples

1. Show SCP Dock

- Go to **SCP** → **Show Plugin**

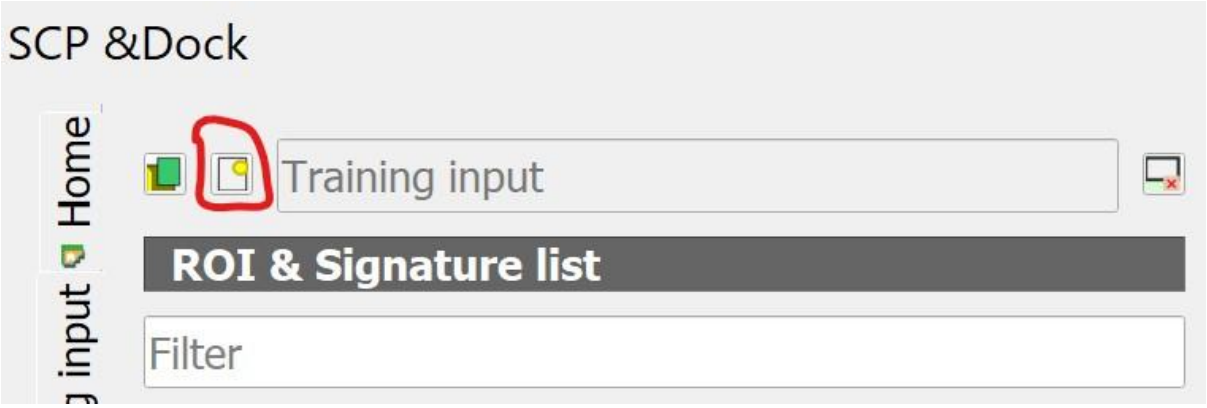
The SCP & Dock window should appear

- Click on Training input on the left hand side



2. Create a new training input to save ROI

At the top of the SCP & Dock panel, click on the second icon to the left



Navigate to the location you want to save your training file. Call the output file Train_Maxar_Pre.

When you are ready, click on the **Save** button.

Notice that a temporary layer called Train_Maxar_Pre has been added to your Layer panel. The Training input layer is called Train_Maxar_Pre.scp.

3. Defining the training samples

Note that we will be defining multiple ROIs for most of the Macroclasses. This is because the spectral signatures within a Macroclass may be varied and not able to

be represented by a single ROI.

Ensure that the layer you are seeing is the Pre-Flood GeoEye1 Raster Layer

We will be manually drawing a polygon using the SCP Plugin to define the ROI for each class.

From the SCP Working toolbar, click on Create a ROI polygon button.

- The first Macroclass we are going to define is Built-up area
- To do this, left click the following sample site in the View Window to define the ROI vertices and right click to define the last vertex closing the polygon.

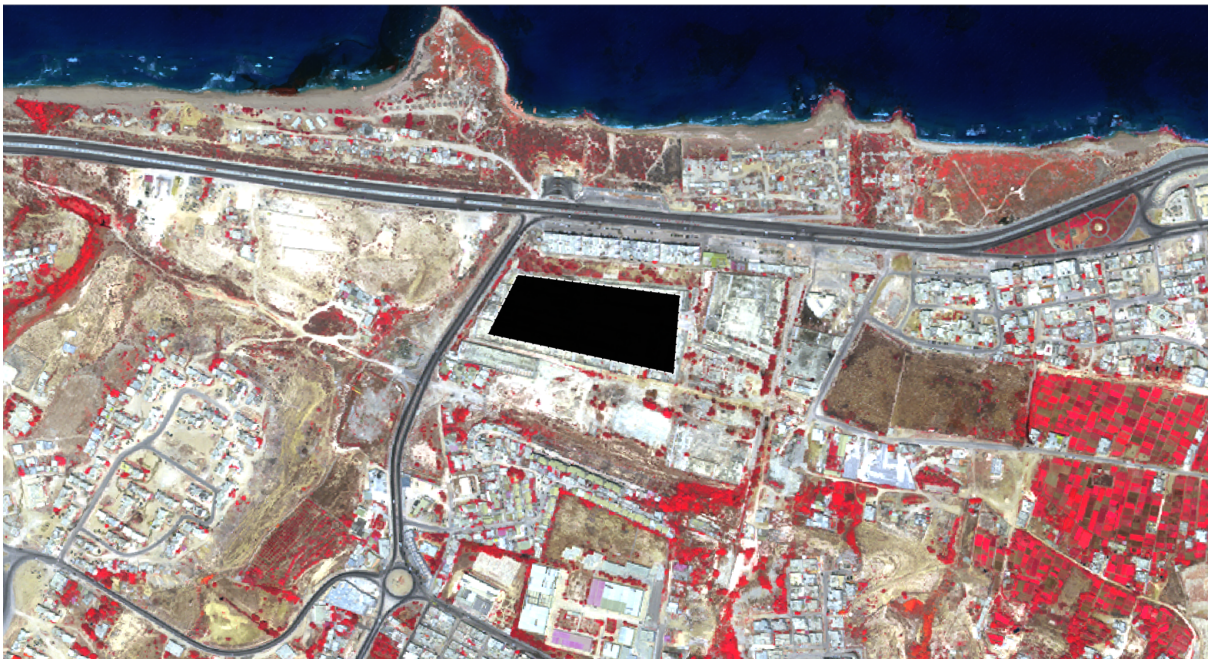
An orange semi-transparent polygon will appear over the defined ROI. This is a temporary polygon which is not saved as a Training input yet.

When we are satisfied with the site, we can save it to the Training input layer.

- Set *MC ID = 1* and *MC Info = Built-up area*, *C ID = 1* and *C Info = Built-up area*
- Now click on the Save temporary ROI to training input button to save the ROI in the Training input.

The saving will take a while if you have left the Spectral Signature checkbox checked.

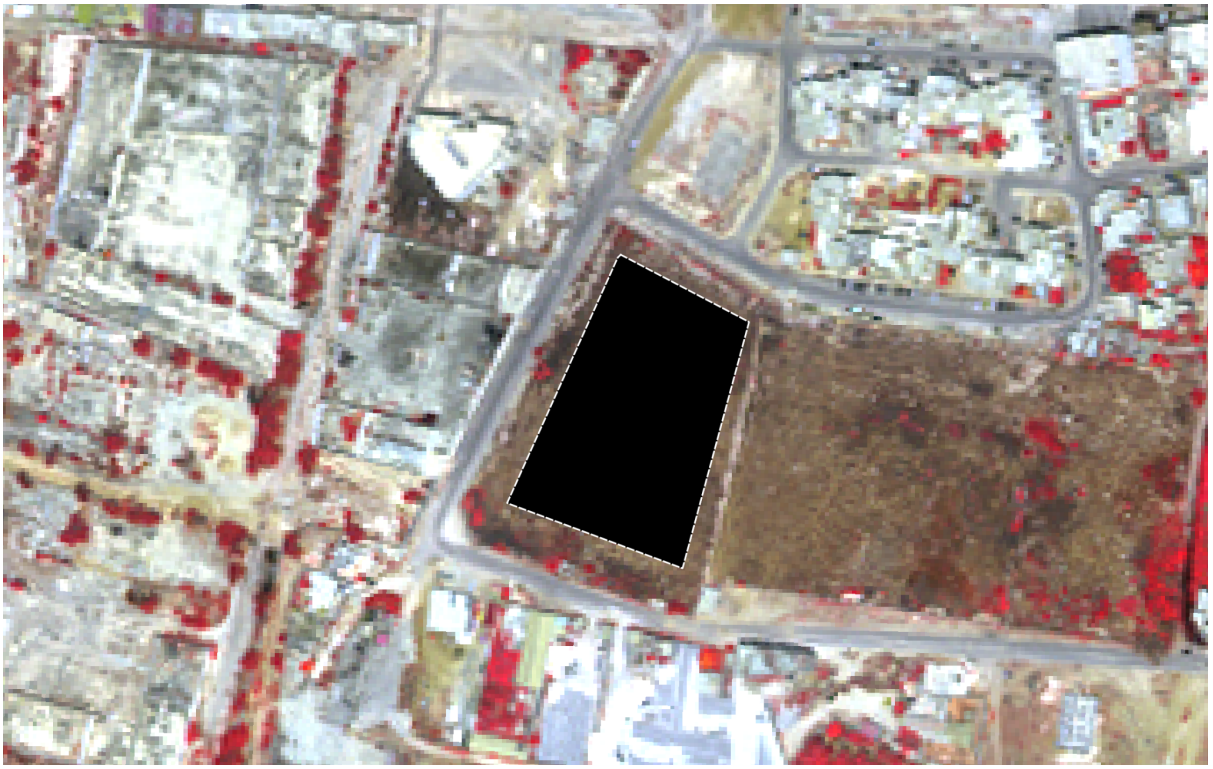
Repeat the steps to define the following ROIs for the following Built-up area.

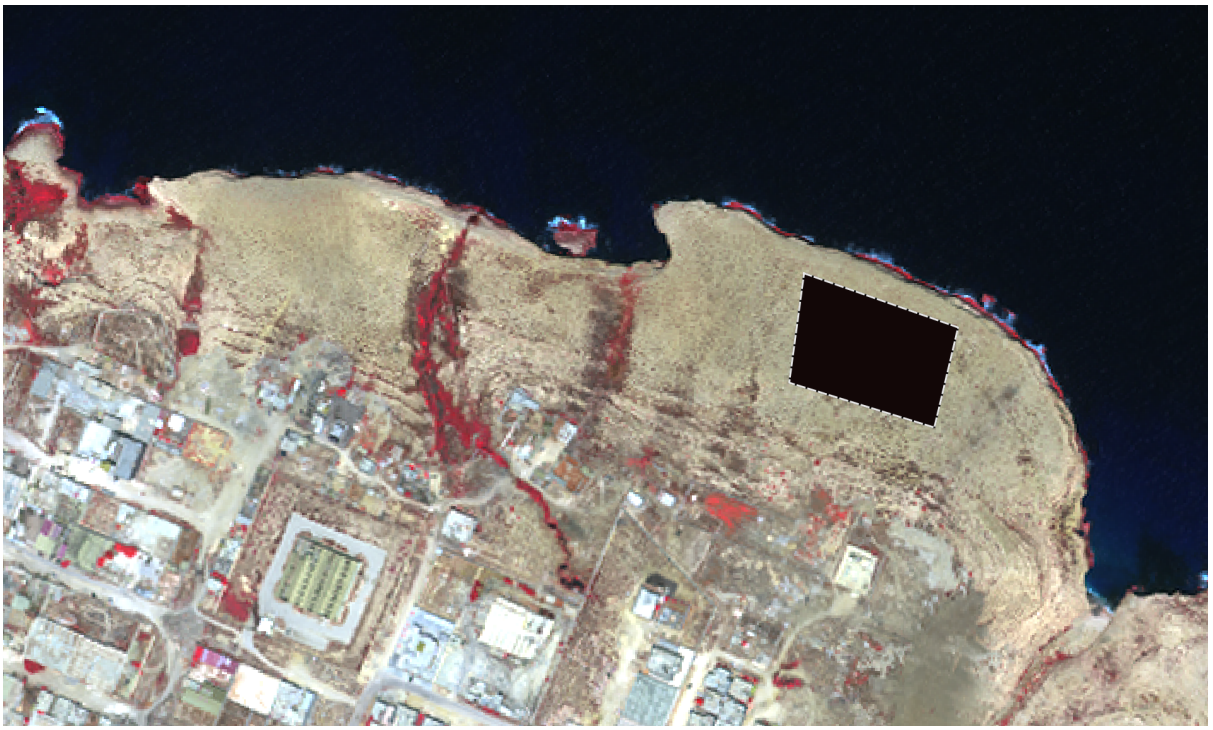


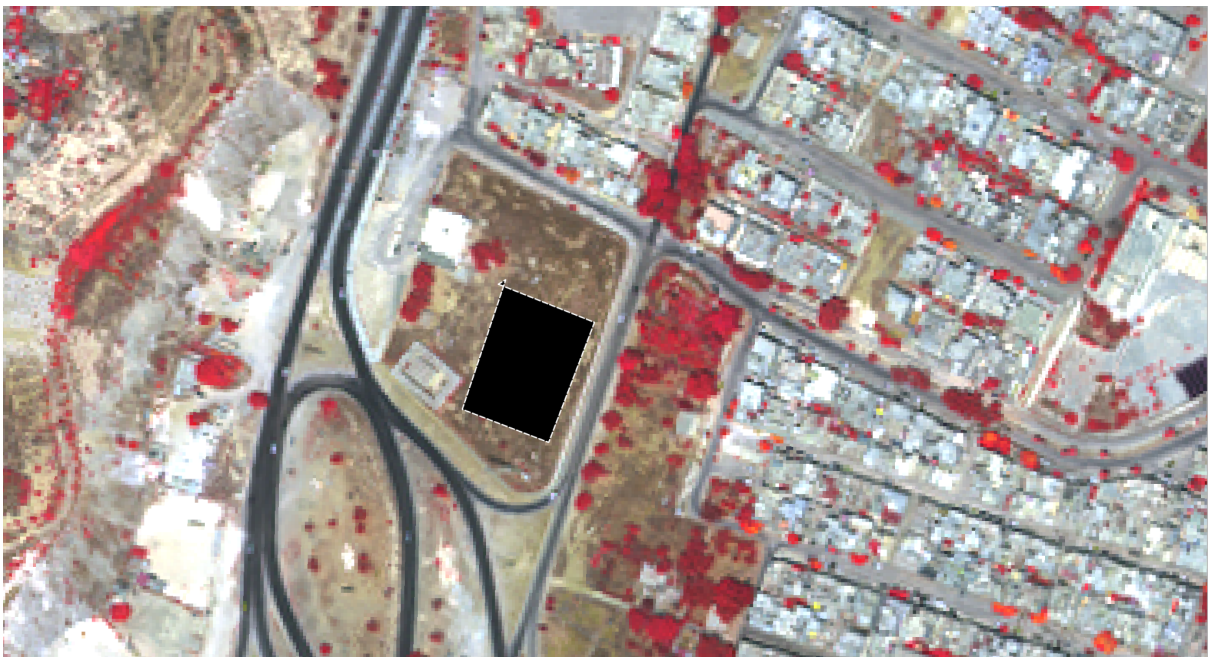
Note: The type of the ROI is R&S, meaning that the ROI spectral signature was calculated and saved in the Training input.

Macroclass 2: Bare land

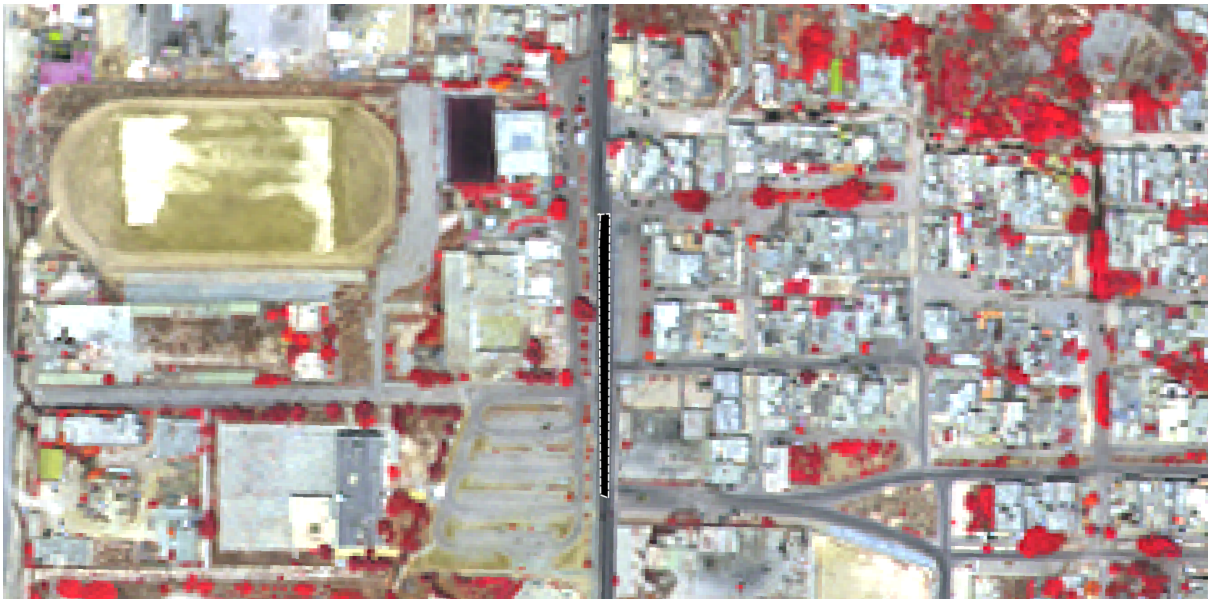
Repeat the steps to define another ROI for the following areas. Remember to increment the Macroclass ID, set the Macroclass to Bare land, increment the Class ID, and set the Class to Bare land.

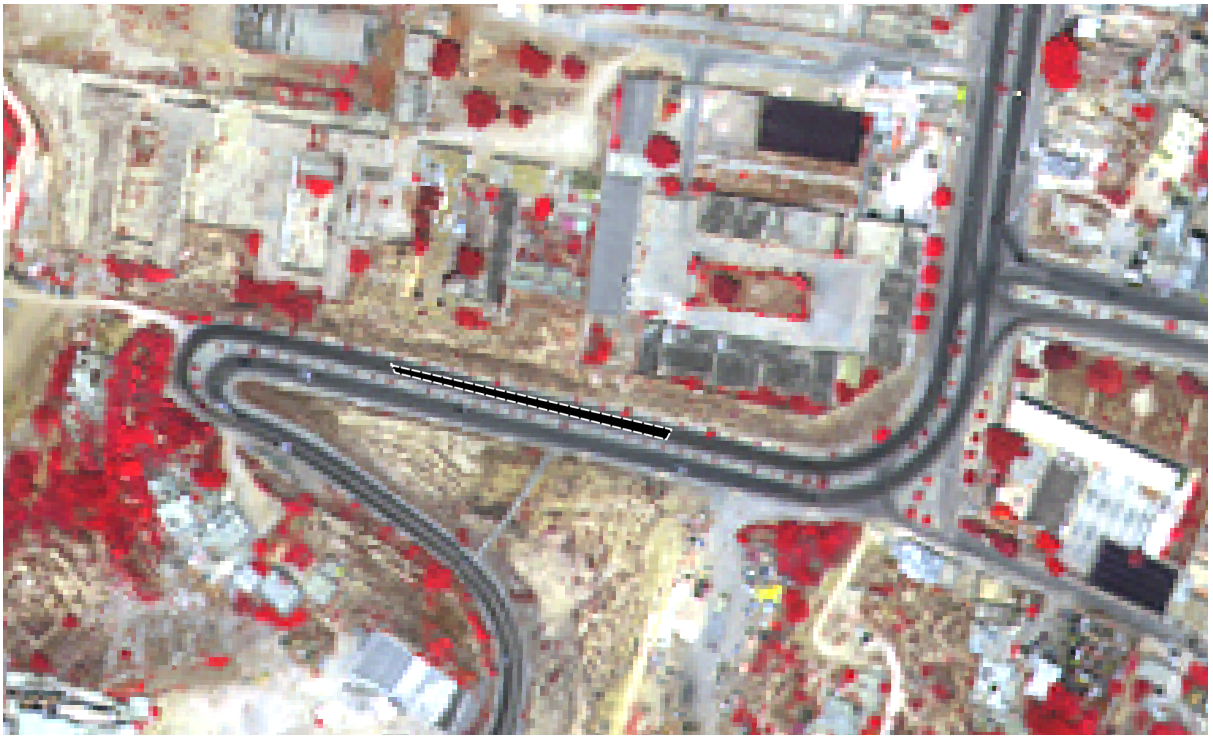




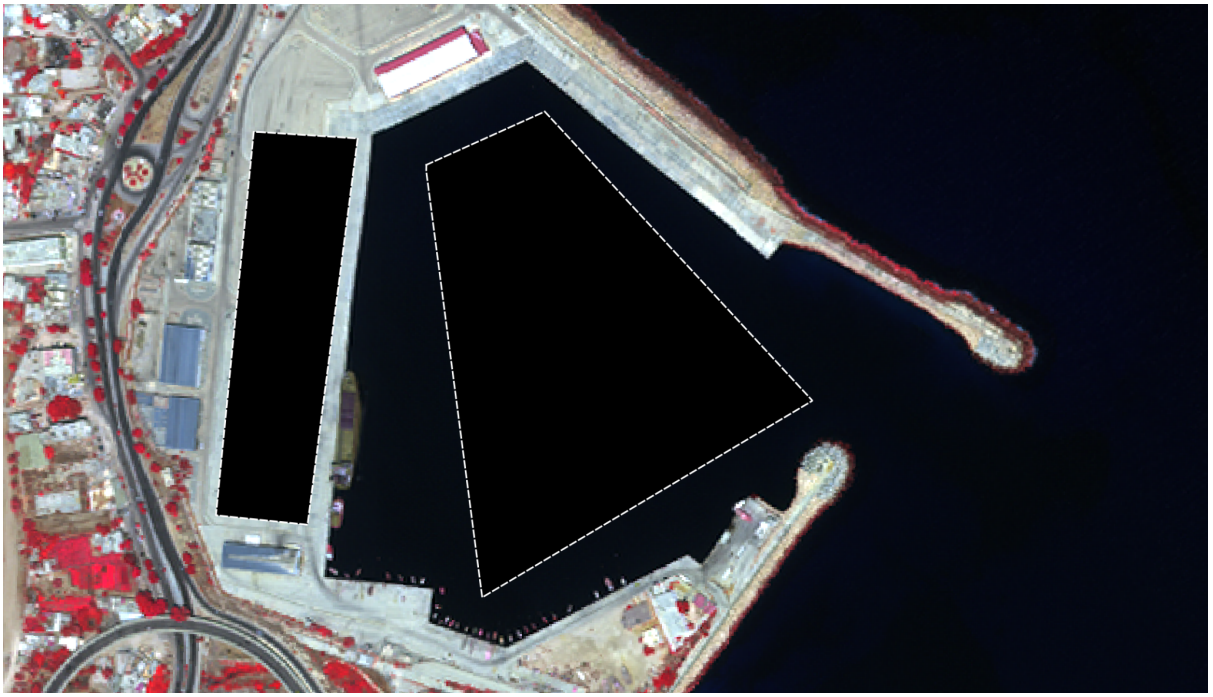


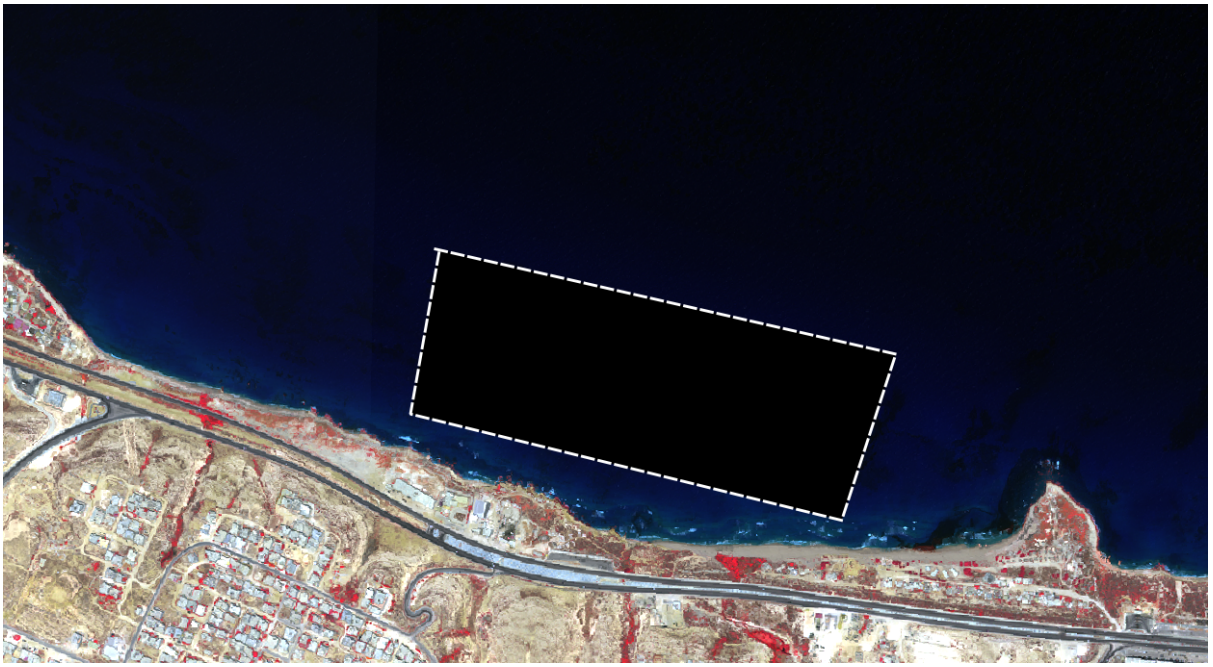
Macroclass 3: Impervious surfaces



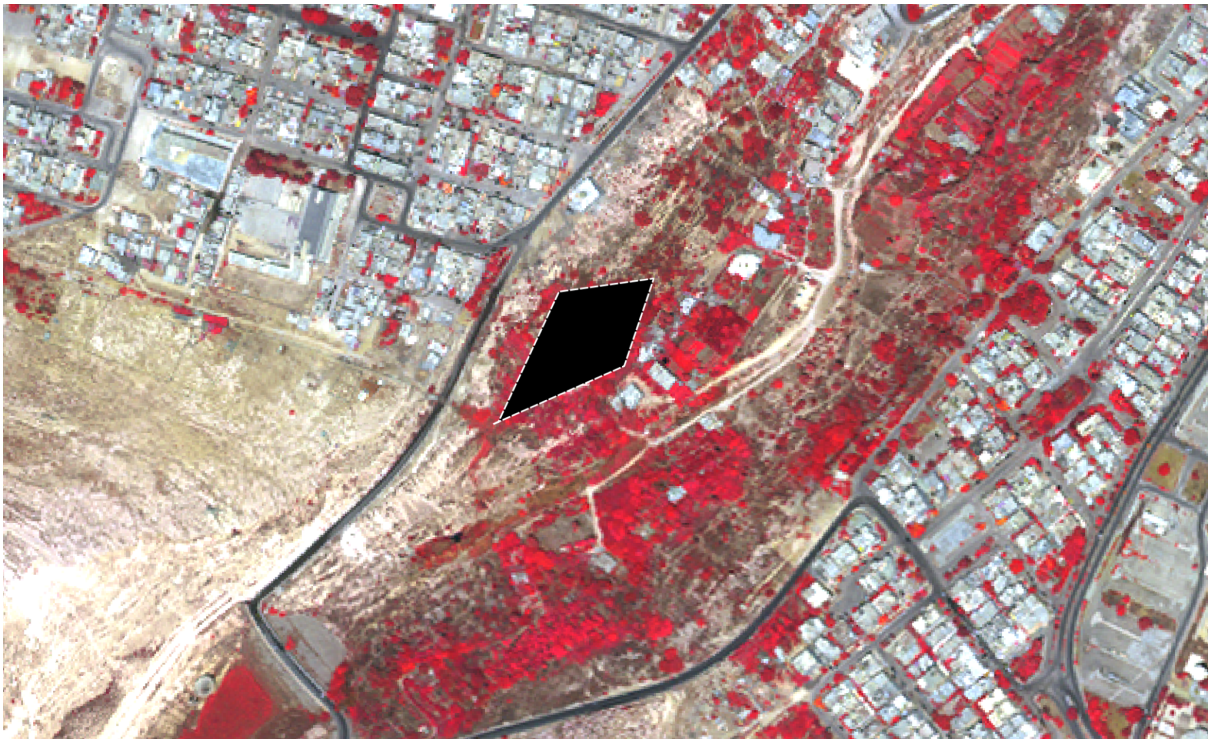


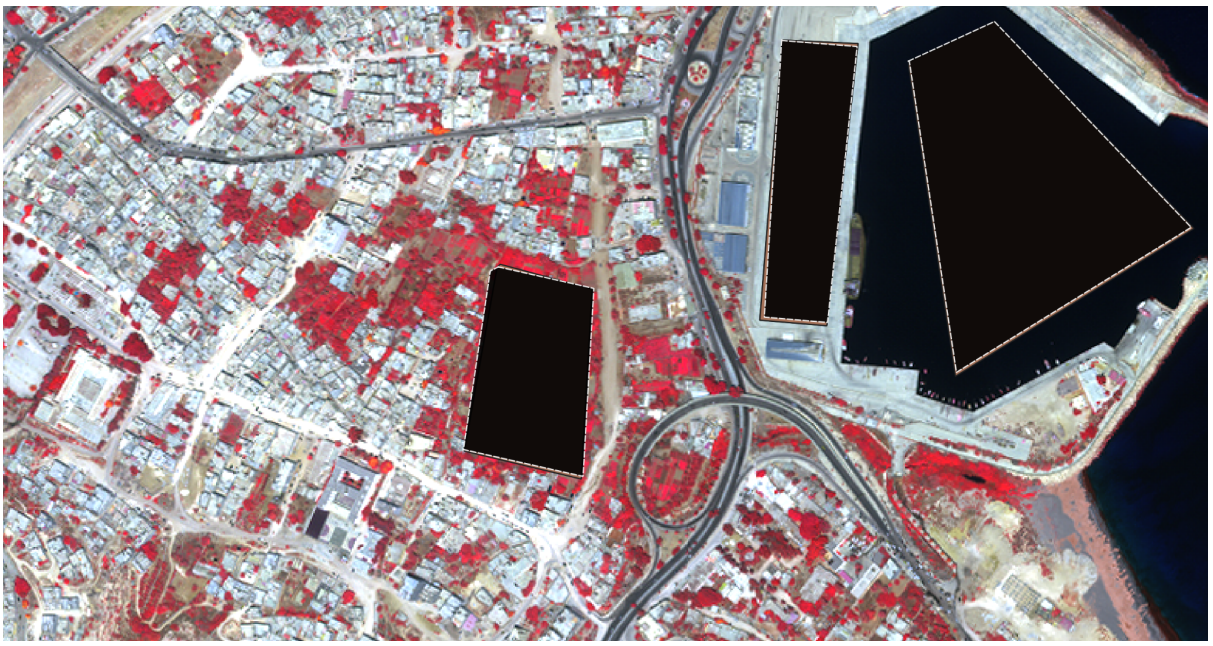
Macroclass 4: Water body





Macroclass 5: Vegetation





Overview of the areas selected are as follows:

There are no clouds for the Pre-flood raster layer, hence there will be no cloud and cloud shadow class.

Double click the colour (in the column Colour) of each ROI to choose a representative colour of each class. Set the colour for Macroclasses in table Macroclasses as well.

4.2: Assessing the Spectral Signatures

Next, assess the Spectral Similarities using the Spectral Signature Plot
Different land use types may have similar spectral signatures. This may lead to misclassification of some classes. This is why we look at the Spectral Signature Plot to check for overlaps before performing classification.

To display the signature plot, select the spectral signatures within the table, then click on the Spectral Signature Plot button.

Interpreting the plot:
The minimum and maximum of each band represents the minimum and maximum values of the pixels in each class. If there are significant overlaps between classes, it is worth considering combining the classes as there might be significant misclassification otherwise.

Once done selecting the training inputs, we are going to check the Spectral Signature Plot and Signature Details to see if there is a notable difference between the band signatures of each class. If a band does have notable differences between all classes, it is a good idea to remove it as it will not add to the accuracy of classification.

SCP: Spectral Signature Plot

Signature list

	S	MC ID	MC Name	C ID	C Name	lap M	Min B1	Max B1	Min B2	Max B2	Min B3	Max B3	Min B4	
1	✓	1	Built-up area	1	Built-up area	2-...	616.0	3762.0	821.0	4521.0	707.0	5939.0	1075.0	6470.0
2	✓	1	Built-up area	1	Built-up area	2-...	724.0	4090.0	873.0	4876.0	762.0	5969.0	877.0	7808.0
3	✓	1	Built-up area	1	Built-up area	2-...	1021.0	2441.0	1227.0	3187.0	1625.0	4610.0	1625.0	5050.0
4	✓	2	Bare land	2	Bare land	1-...	676.0	1844.0	862.0	2362.0	781.0	3292.0	1456.0	3896.0
5	✓	2	Bare land	2	Bare land	1-...	1101.0	1992.0	1479.0	2808.0	2157.0	4277.0	2828.0	5126.0
6	✓	2	Bare land	2	Bare land	1-...	872.0	1742.0	1031.0	2494.0	1356.0	3953.0	1995.0	4681.0
7	✓	3	Imprevious ...	3	Imprevious ...	1-...	941.0	1606.0	1062.0	1808.0	1274.0	2211.0	1091.0	2314.0
8	✓	3	Imprevious ...	3	Imprevious ...	1-...	1317.0	1508.0	1435.0	1731.0	1763.0	2061.0	1768.0	2128.0
9	✓	3	Imprevious ...	3	Imprevious ...	1-...	1047.0	1829.0	1151.0	2346.0	1368.0	2429.0	1414.0	2656.0
10	✓	4	Water body	4	Water body		444.0	574.0	442.0	602.0	275.0	411.0	108.0	239.0
11	✓	4	Water body	4	Water body	5-5;	438.0	1167.0	381.0	1341.0	230.0	824.0	82.0	444.0
12	✓	5	Vegetation	5	Vegetation	1-...	508.0	2079.0	773.0	2540.0	400.0	3701.0	1466.0	7671.0
13	✓	5	Vegetation	5	Vegetation	1-...	451.0	3279.0	626.0	3766.0	439.0	5324.0	1662.0	6272.0
14	✓	5	Vegetation	5	Vegetation	1-...	480.0	3667.0	607.0	4807.0	342.0	6489.0	106.0	7508.0

4.3: Generate Classification

Once the training samples are ready, classification can be done. Two types of classification are conducted - Minimum Distance and Random Forest.

4.3.1: Land cover classification with Minimum Distance

From the menu bar, go to **SCP** → **Band Processing** → **Classification**

In the Classification dialog window,

Under Use, check MC ID

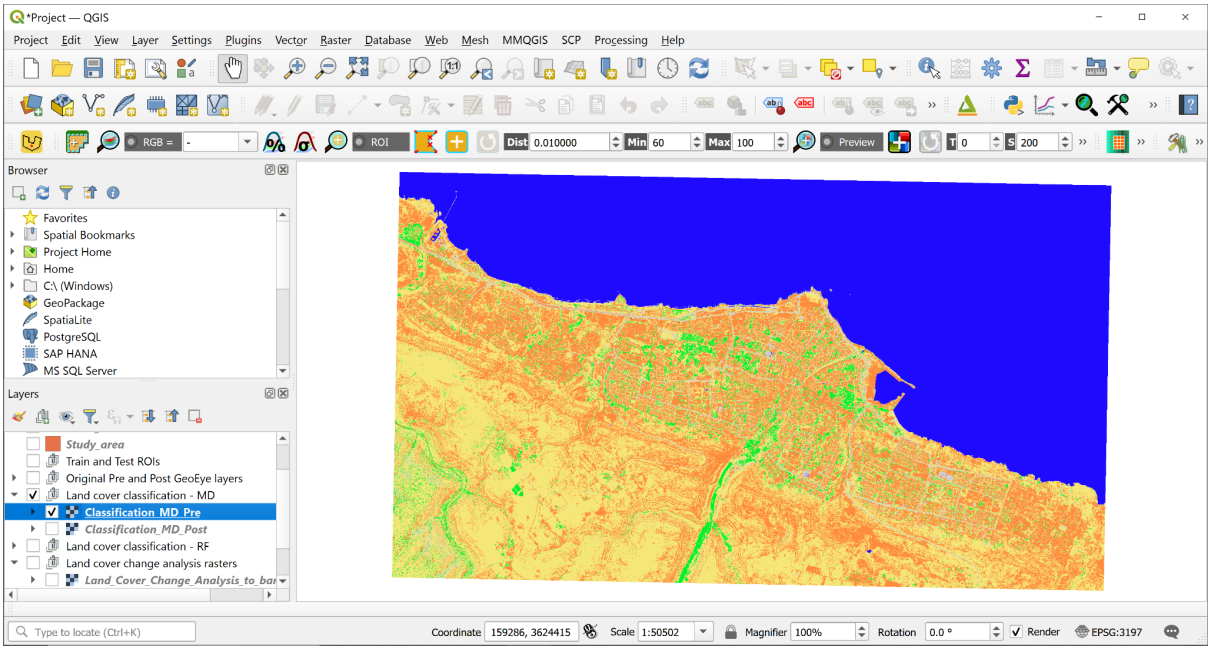
Select Minimum Distance under the Algorithm

Click on the **Run** button.

The Save classification output dialog window appears.

Navigate to the Pre-flood GeoTiff sub-folder of this project, give the name the output file *Classification_MD_Pre*. Notice that the output file will be saved in geotiff file format.

When the classification process is completed, a sound is played. At the same time, a land cover image called *Classification_MD_Pre* is added into the Layers panel and displayed in the view window of QGIS as shown in the figure below.



4.3.2: Land cover classification with Random Forest

From the menu bar, go to **SCP** → **Band Processing** → **Random forest**

In the Random Forest Classification dialog window,

Under Use, check MC ID

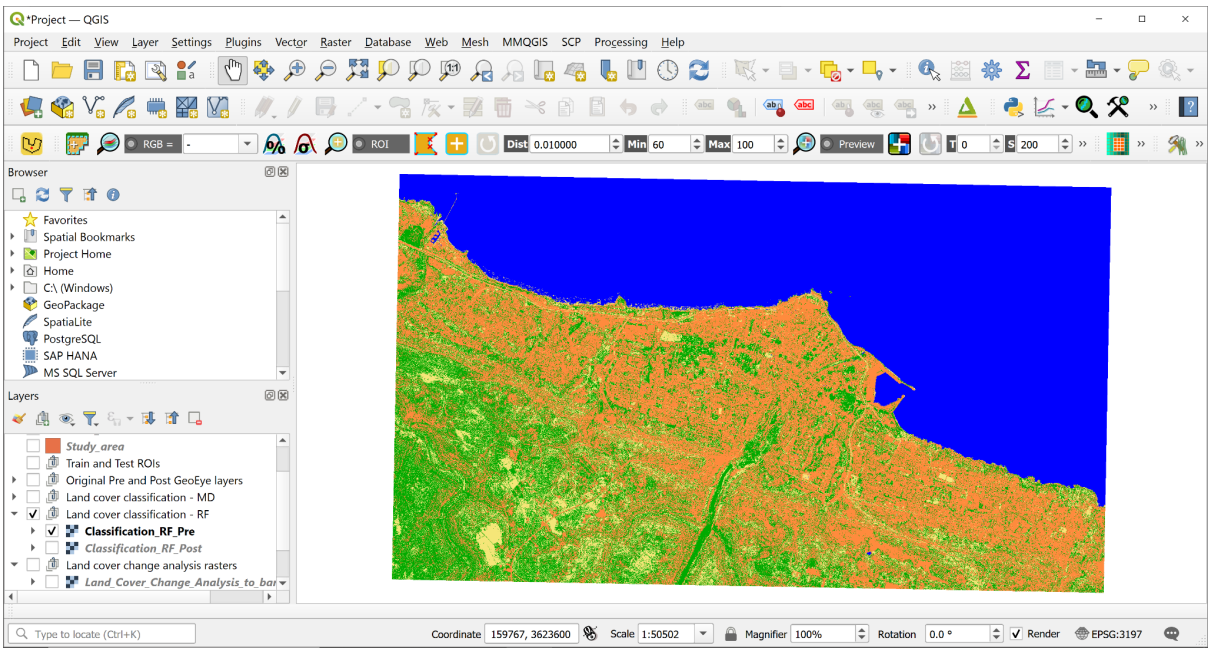
Set the number of training samples as 5000, number of trees as 10

Click on the **Run** button.

The Save classification output dialog window appears.

Navigate to the Pre-flood GeoTiff sub-folder of this project, give the name the output file *Classification_RF_Pre*. Notice that the output file will be saved in geotiff file format.

When the classification process is completed, a sound is played. At the same time, a land cover image called *Classification_RF_Pre* is added into the Layers panel and displayed in the view window of QGIS as shown in the figure below. A confidence raster is also created which assess the reliability (from 0 minimum to 1 maximum) of the model at pixel levels.

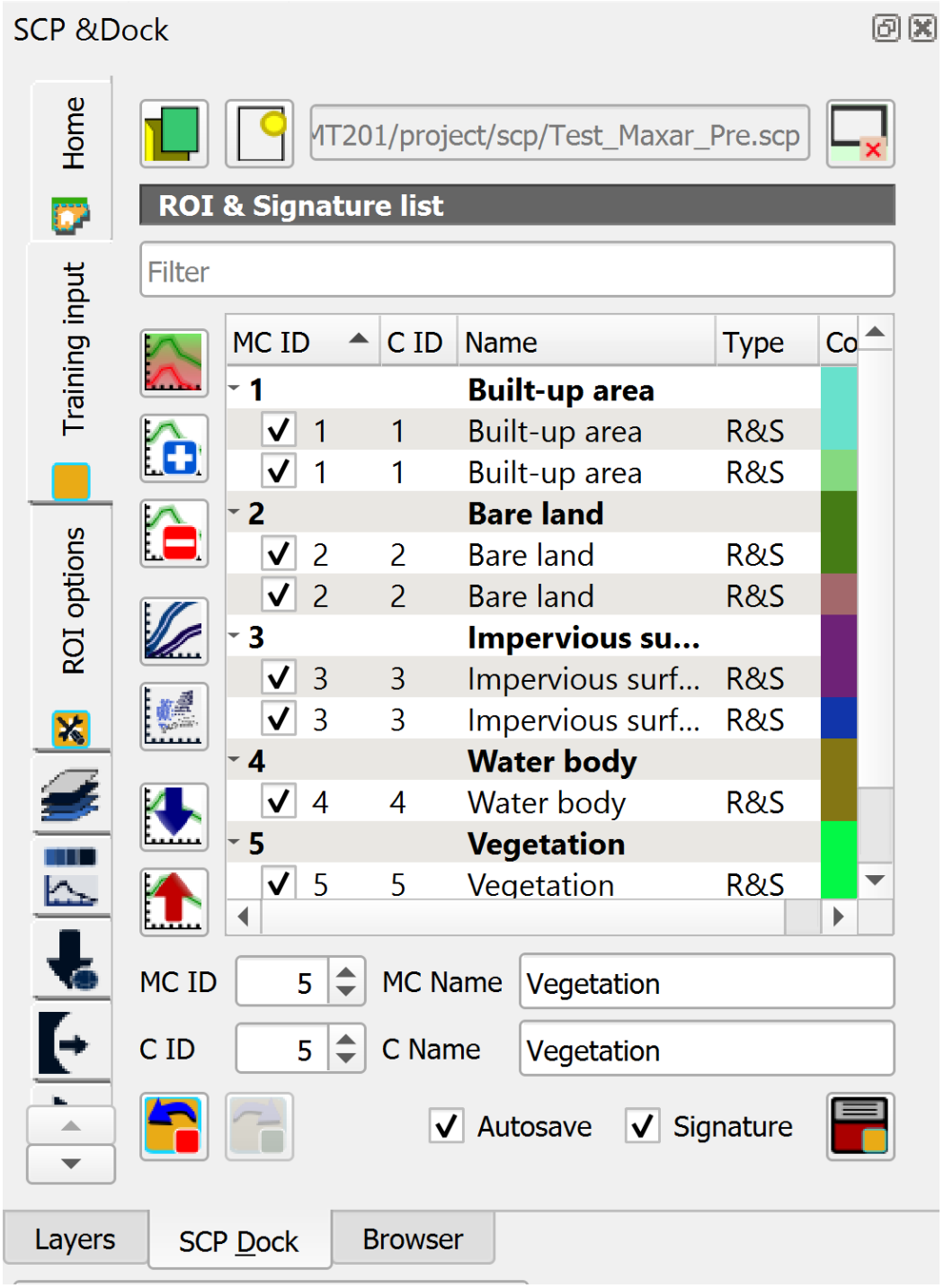


Section 5: [Pre] Evaluating the classification

1. Create testing data

To evaluate the classification, digitise a new layer with ROIs and set again ROIs for the 5 classes to have a reference ground. Do not use the ROIs that were used for the classification because the classification has to be compared with undependable training input.

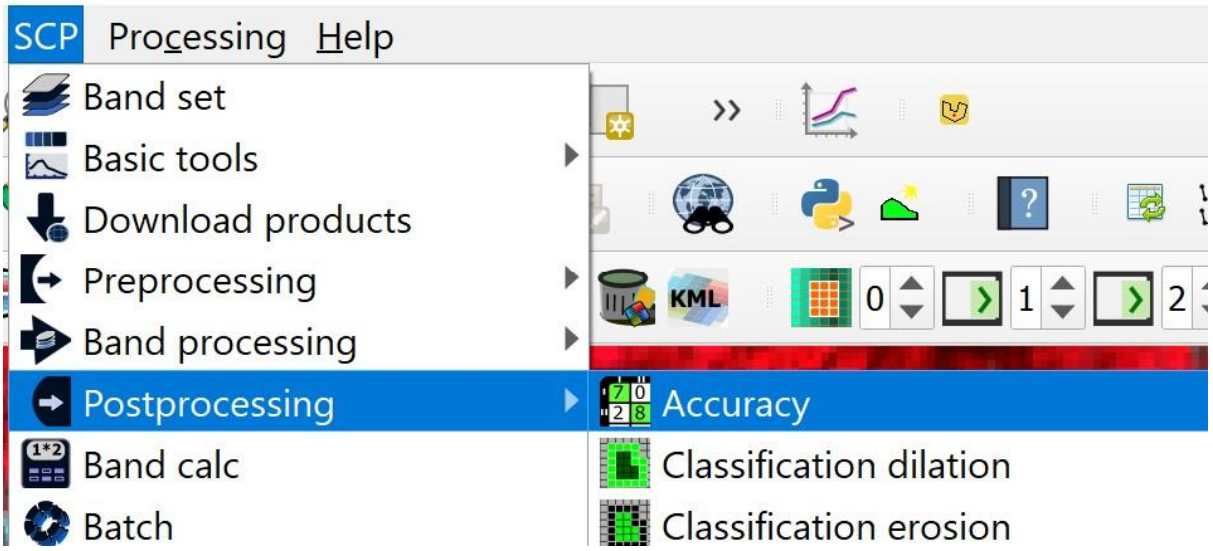
We are now going to create a testing layer to evaluate the accuracy of our classification.
As with the Training input, define ROIs for the Testing input. Define at least one for each class. Name it *Test_Maxar_Pre*



Once the Test_Maxar_Pre ROI is ready, the accuracy assessment analysis can be performed.

2. Evaluate accuracy

From the menu bar go to **SCP** → **Postprocessing** → **Accuracy**.



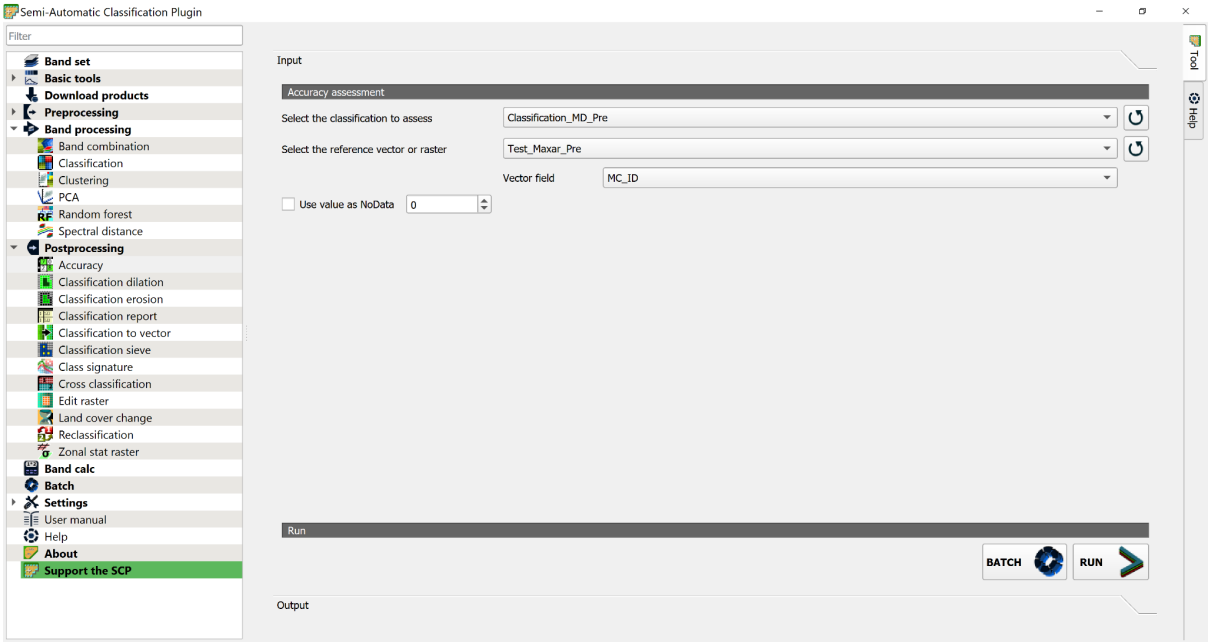
The Accuracy assessment dialog window appears.

Under the Select the classification to assess, select the classified image Classification_MD_Pre from the drop-down list (If there are no layers appearing, click on the refresh button located at the end of the selection before clicking on the drop-down list)

Under the Select the reference vector or raster, select the newly created test samples, Test_Maxar_Pre from the drop-down list (Similarly here, If there are no layers appearing, click on the refresh button located at the end of the selection before clicking on the drop-down list

Under the Vector field, select MC_ID from the drop-down list.

The screen should look similar to the screenshot below.



Click on the **Run** button.

The Save error matrix raster output dialog window appears, naming the output file Classification_Accuracy_MD_Pre.

Click on the **Save** button.

The Accuracy assessment report appears. It consists of three sub-section.

1. The long pairwise error list.

ErrMatrixCode	Reference	Classified	PixelSum
1	1	1	1427
3	1	2	314
6	1	3	57
10	1	4	3
15	1	5	3
2	2	1	177
5	2	2	2262
9	2	3	112
19	2	5	1
8	3	2	8
13	3	3	411
21	4	4	100750
16	5	2	453
20	5	3	192
25	5	5	2506

2. Confusion Matrix

3. Kappa hat matrix

> ERROR MATRIX (pixel count)
> Reference

V_Classified	1	2	3	4	5	Total
1	1427	177	0	0	0	1604
2	314	2262	8	0	453	3037
3	57	112	411	0	192	772
4	3	0	0	100750	0	100753
5	3	1	0	0	2506	2510
Total	1804	2552	419	100750	3151	108676

> AREA BASED ERROR MATRIX
> Reference

V_Classified	1	2	3	4	5	Area	Wi
1	0.1870	0.0232	0.0000	0.0000	0.0000	12165774.0107	0.2102
2	0.0334	0.2405	0.0009	0.0000	0.0482	18688075.6553	0.3229
3	0.0018	0.0035	0.0129	0.0000	0.0060	1406981.8117	0.0243
4	0.0000	0.0000	0.0000	0.4087	0.0000	23654032.8811	0.4087
5	0.0000	0.0000	0.0000	0.0000	0.0339	1964801.7245	0.0339
Total	0.2222	0.2672	0.0138	0.4087	0.0881	57879666.0834	
Area	12862416	15466527	798282	23653329	5099114	57879666	
SE	0.0024	0.0031	0.0005	0.0000	0.0021		
SE area	141088	176770	30683	407	122806		
95% CI area	276532	346468	60138	797	240700		
PA [%]	84.1466	89.9953	93.8333	100.0000	38.4708		
UA [%]	88.9651	74.4814	53.2383	99.9970	99.8406		
Kappa hat	0.8581	0.6518	0.5258	0.9999	0.9983		

Overall accuracy [%] = 88.2978
Kappa hat classification = 0.8320

Area unit = metre^2
SE = standard error
CI = confidence interval
PA = producer's accuracy
UA = user's accuracy

Repeat Step 2 of Section 5 for the classification layer by Random Forest (Classification_RF_Pre) with the same testing ROIs. The results are as follows:

ErrMatrixCode	Reference	Classified	PixelSum
1	1	1	1694
3	1	2	35
8	1	4	1
12	1	5	74
2	2	1	528
5	2	2	1353
15	2	5	671
4	3	1	206
7	3	2	212
17	3	5	1
16	4	4	100750
13	5	2	347
20	5	5	2804

> ERROR MATRIX (pixel count)
> Reference

V_Classified	1	2	3	4	5	Total
1	1694	528	206	0	0	2428
2	35	1353	212	0	347	1947
3	0	0	0	0	0	0
4	1	0	0	100750	0	100751
5	74	671	1	0	2804	3550
Total	1804	2552	419	100750	3151	108676

> AREA BASED ERROR MATRIX
> Reference

V_Classified	1	2	3	4	5	Area	Wi
1	0.2041	0.0636	0.0248	0.0000	0.0000	16931943.1528	0.2925
2	0.0018	0.0679	0.0106	0.0000	0.0174	5656459.4671	0.0977
3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.4075	0.0000	23587074.1025	0.4075
5	0.0042	0.0382	0.0001	0.0000	0.1597	11704189.3610	0.2022
Total	0.2101	0.1698	0.0355	0.4075	0.1771	57879666.0834	
Area	12159199	9825087	2055768	23586840	10252772	57879666	
SE	0.0028	0.0030	0.0018	0.0000	0.0016		
SE area	161223	171768	103817	234	93887		
95% CI area	315997	336666	203482	459	184019		
PA [%]	97.1553	40.0074	0.0000	100.0000	90.1674		
UA [%]	69.7694	69.4915	nan	99.9990	78.9859		
Kappa hat	0.6173	0.6325	nan	1.0000	0.7446		

Overall accuracy [%] = 83.9251
Kappa hat classification = 0.7768

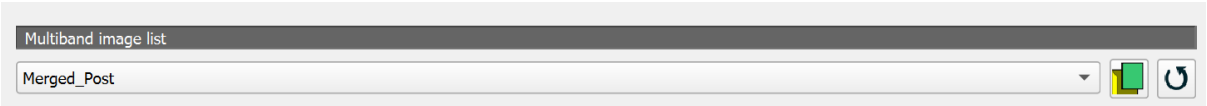
Area unit = metre^2
SE = standard error
CI = confidence interval
PA = producer's accuracy
UA = user's accuracy

Section 6: [Post] Creating TCC and FCC

1. Create a Bandset

From the menu bar, select the Semi-Automatic Classification Plugin , the dialog window would appear.
Select Band set on the left column selection.

Under multiband image list, refresh and select the Post-flood layer.

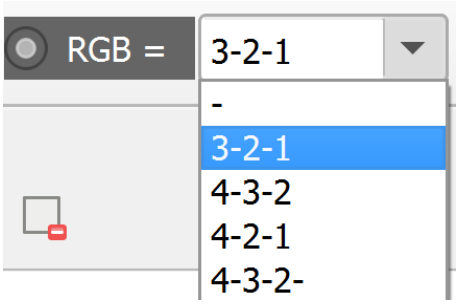


Under Wavelength quick settings, select GeoEye-1.

Click on **Run** then minimise the window.

2. Create True Colour Composite (TCC) Image

- Return to the QGIS window.
- Under the menu bar, Click on the drop-down list beside the RGB pane.
- Select 3-2-1 from the drop-down list. If it is not available, type directly onto the pane.



Your screen should look similar to the screenshot below, a TCC of the Post-flood map is created.

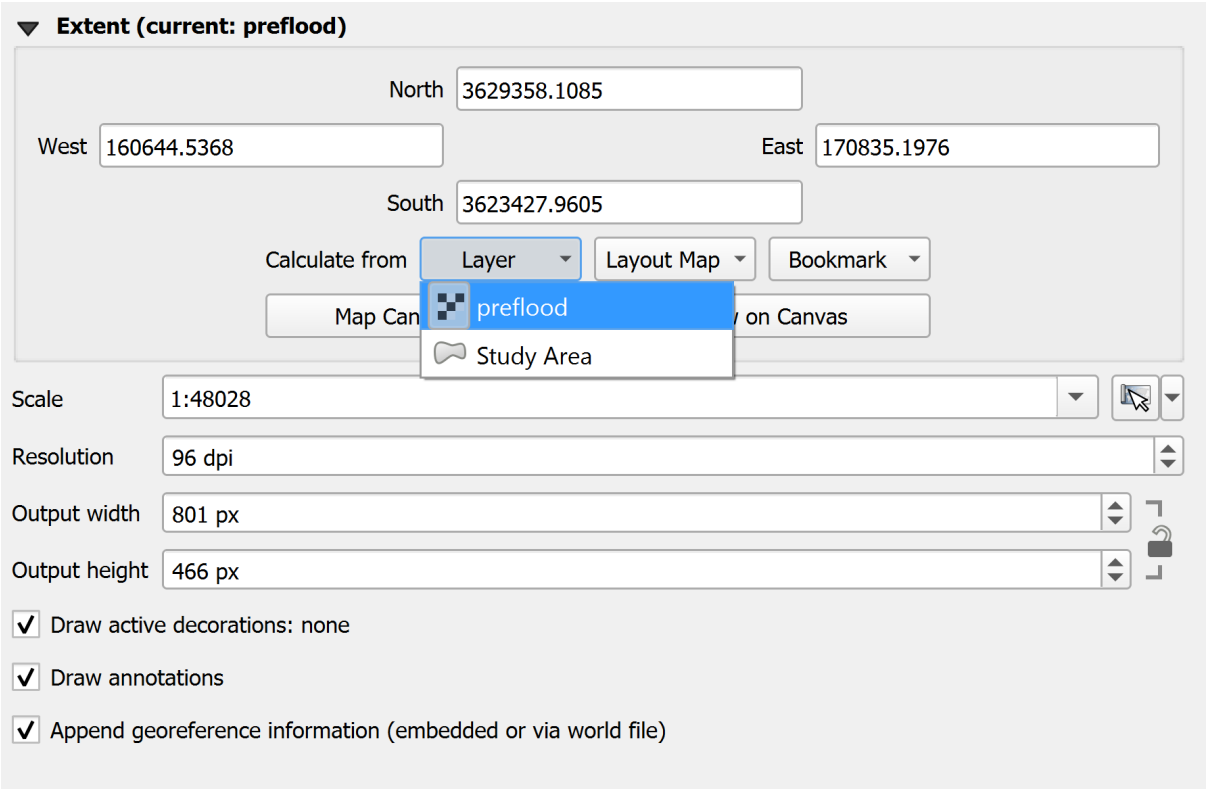
3. Save the TCC image

From the **menu bar** → **Project** → **Import/Export** → **Export Map to Image**.

The dialog window to Save Map as Image would appear.

Under Extent, select calculate from **Layer** → **preflood layer**

Click on **Save** to save the image.



A dialog window would appear to select the directory and filename to save as. Save the image as TCC_preflood in the project folder.

4. Create False Colour Composite (FCC) Image

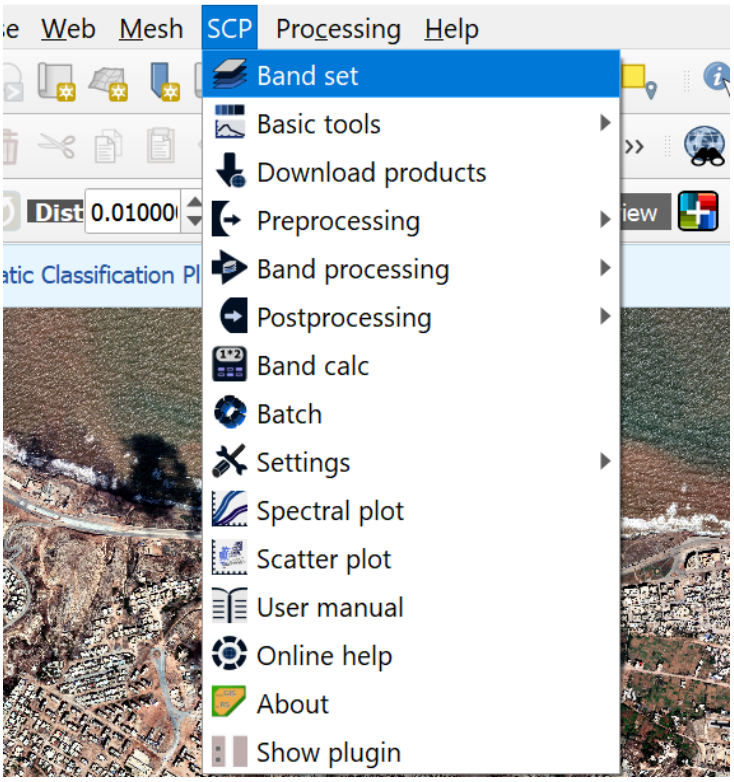
For the FCC image, under the RGB panel, select or type 4-3-2

Your screen should look similar to the screenshot below, a FCC for the Post-flood map is created, allowing us to identify vegetation easily

Section 7: [Post] Training the Supervised Classification Models

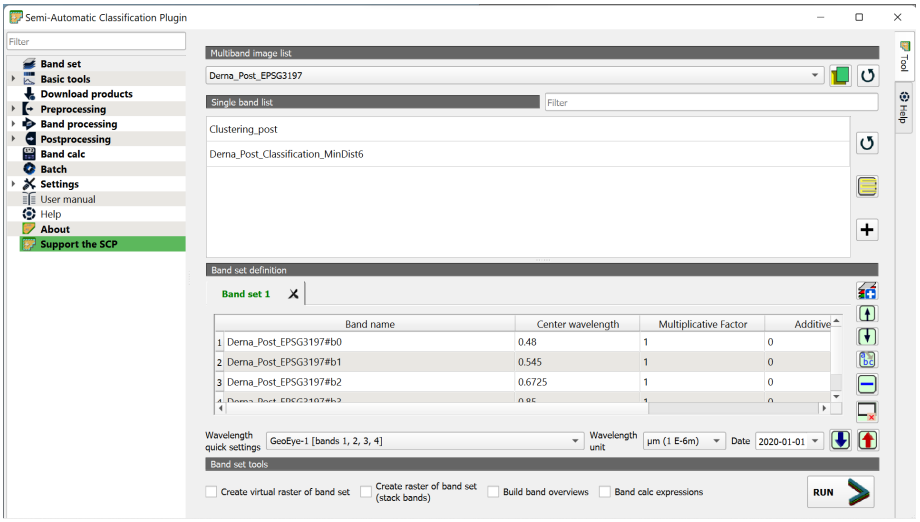
7.1: Digitising the training samples

On the top Menu Bar go to **SCP** → **Band set**



- Under Multiband image list, select the Post-Flood raster layer from the dropdown menu
- For Wavelength quick settings, select **GeoEye-1 [bands 1,2,3,4]**

The configurations should look like this:

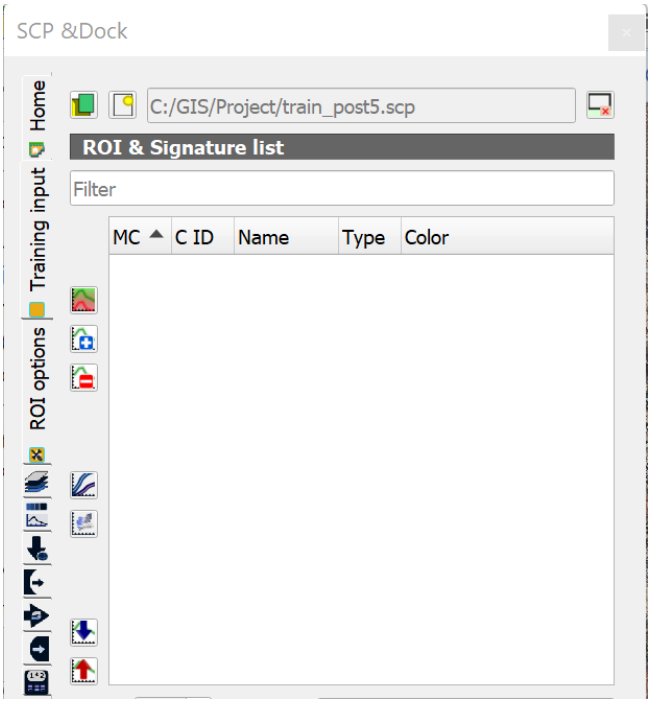


Close the SCP window

- Go to **SCP → Show Plugin**

The SCP & Dock window should appear

Click on Training input on the left hand side



Next we will be defining and labelling the ROIs that will be used for training.

- At the top of the SCP & Dock panel, click on the second icon to the left

- Navigate to the location you want to save your training file. Call the output file Train_Maxar_Post.
- When you are ready, click on the Save button.

Notice that a temporary layer called Train_Maxar_Post has been added to your Layer panel. The Training input layer is called Train_Maxar_Post.scp.

Note that we will be defining multiple ROIs for most of the Macroclasses. This is because the spectral signatures within a Macroclass may be varied and not able to be represented by a single ROI.

Ensure that the layer you are seeing is the Post-Flood GeoEye1 Raster Layer

We will be manually drawing a polygon using the SCP Plugin to define the ROI for each class.

- From the SCP Working toolbar, click on **Create a ROI polygon button**.

- The first Macroclass we are going to define is Built-up area
- To do this, left click the following sample site in the View Window to define the ROI vertices and right click to define the last vertex closing the polygon.

An orange semi-transparent polygon will appear over the defined ROI. This is a temporary polygon which is not saved as a Training input yet.

When we are satisfied with the site, we can save it to the Training input layer.

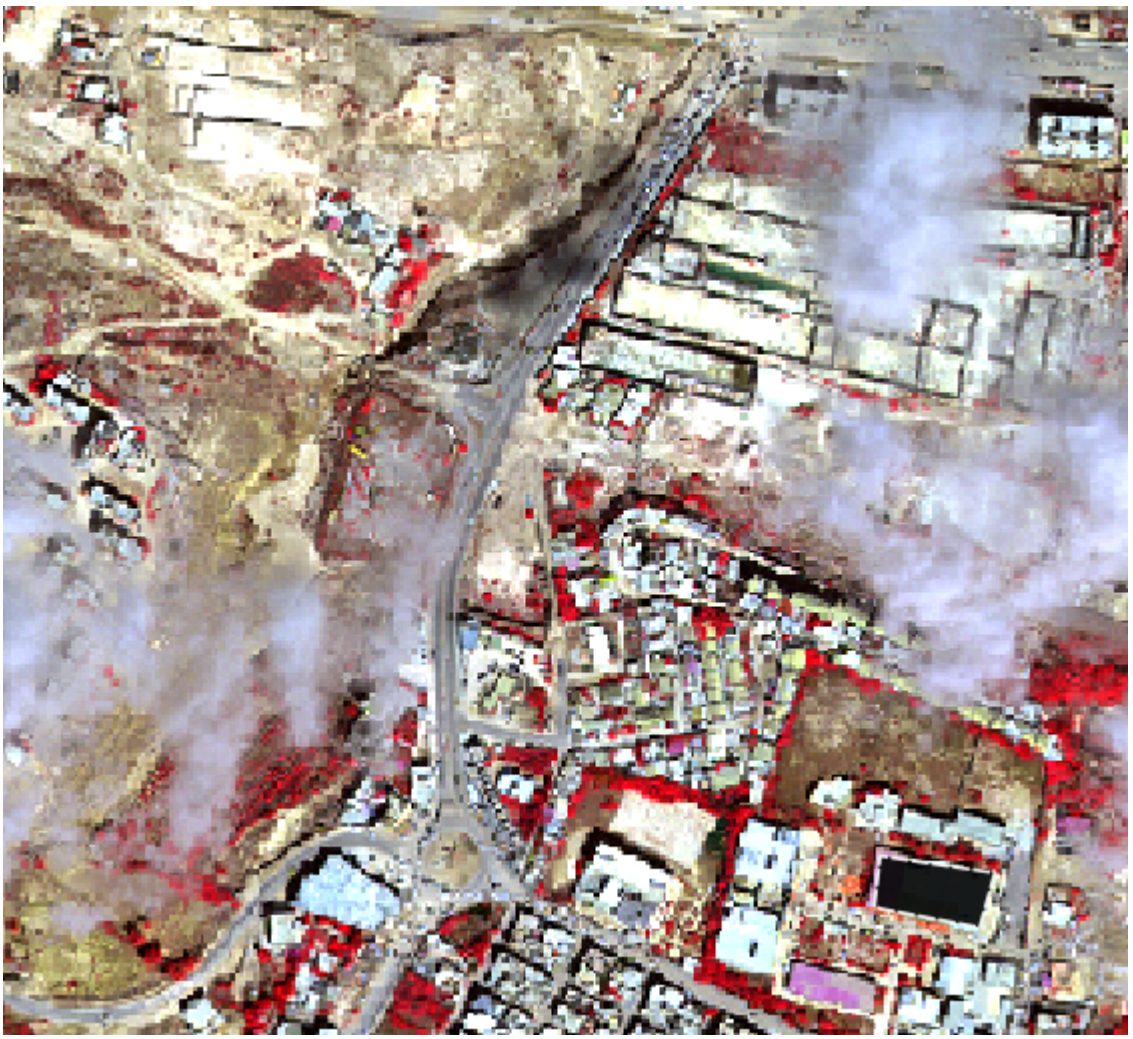
- Set *MC ID = 1* and *MC Info = Built-up area*, *C ID = 1* and *C Info = Built-up area*

Your screen should look similar to the figure below:

- Now click on the Save temporary ROI to training input button to save the ROI in the Training input.

The saving will take a while if you have left the Spectral Signature checkbox checked.

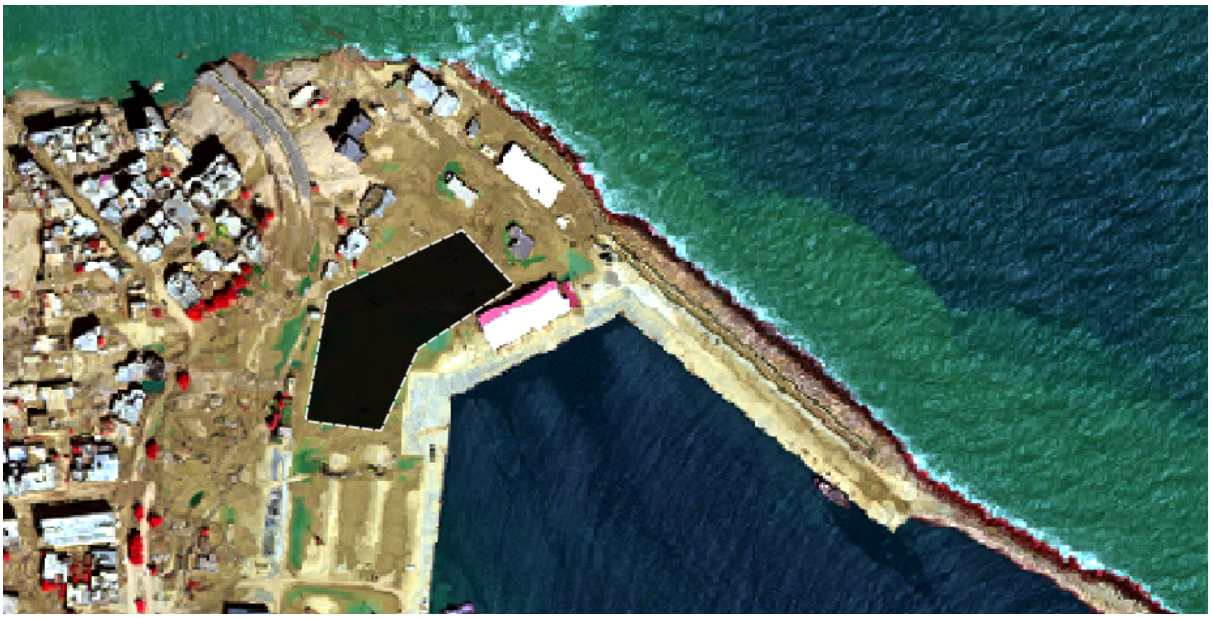
Repeat the steps to define the following ROIs for the following Built-up area.

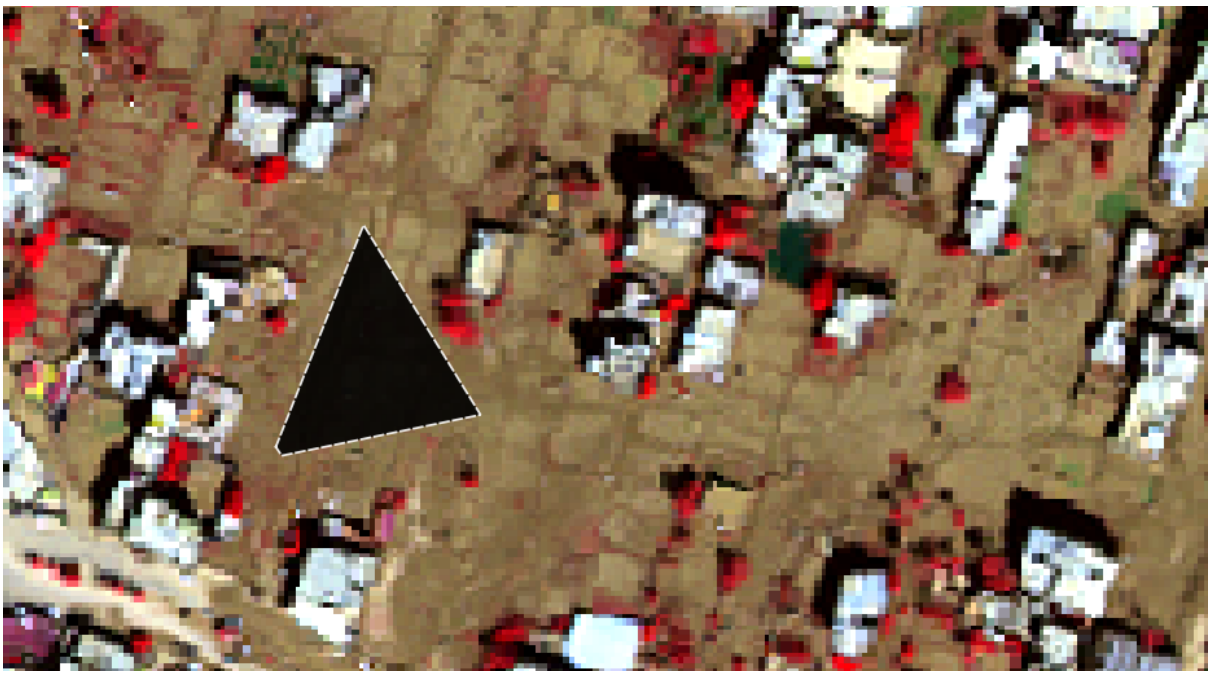


Note: The type of the ROI is R&S, meaning that the ROI spectral signature was calculated and saved in the Training input.

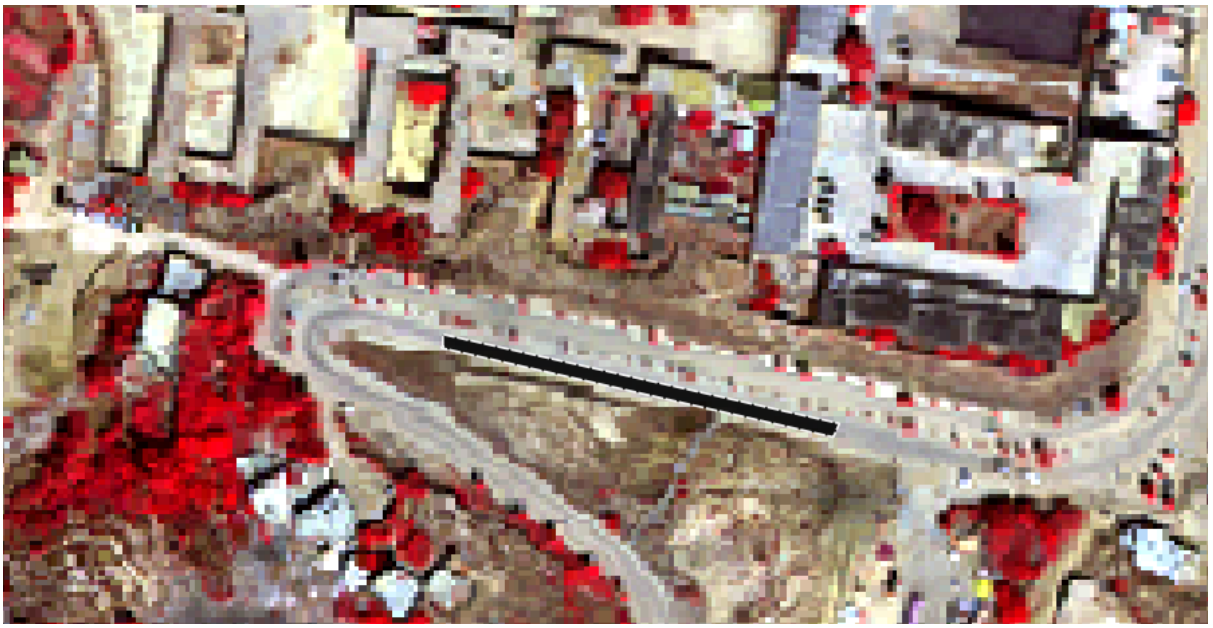
Macroclass 2: Bare land

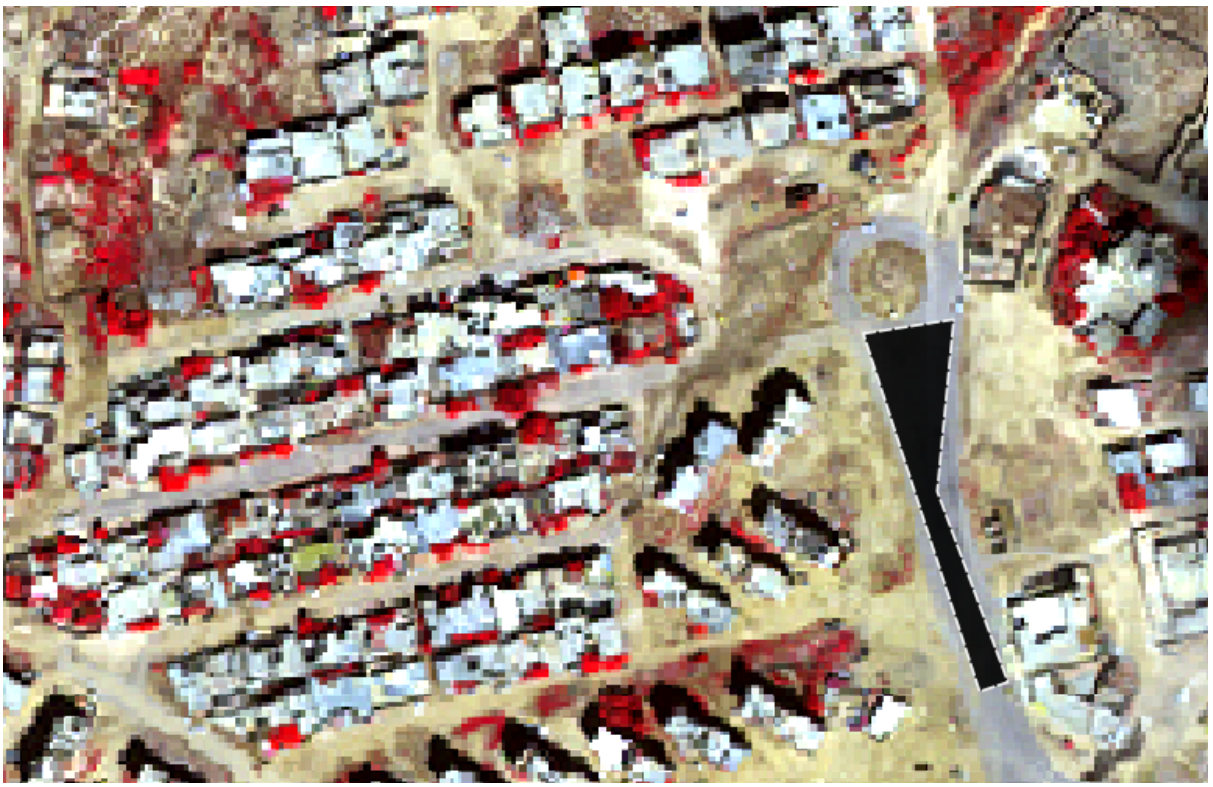
Repeat the steps to define another ROI for the following areas. Remember to increment the Macroclass ID, set the Macroclass to Bare land, increment the Class ID, and set the Class to Bare land.



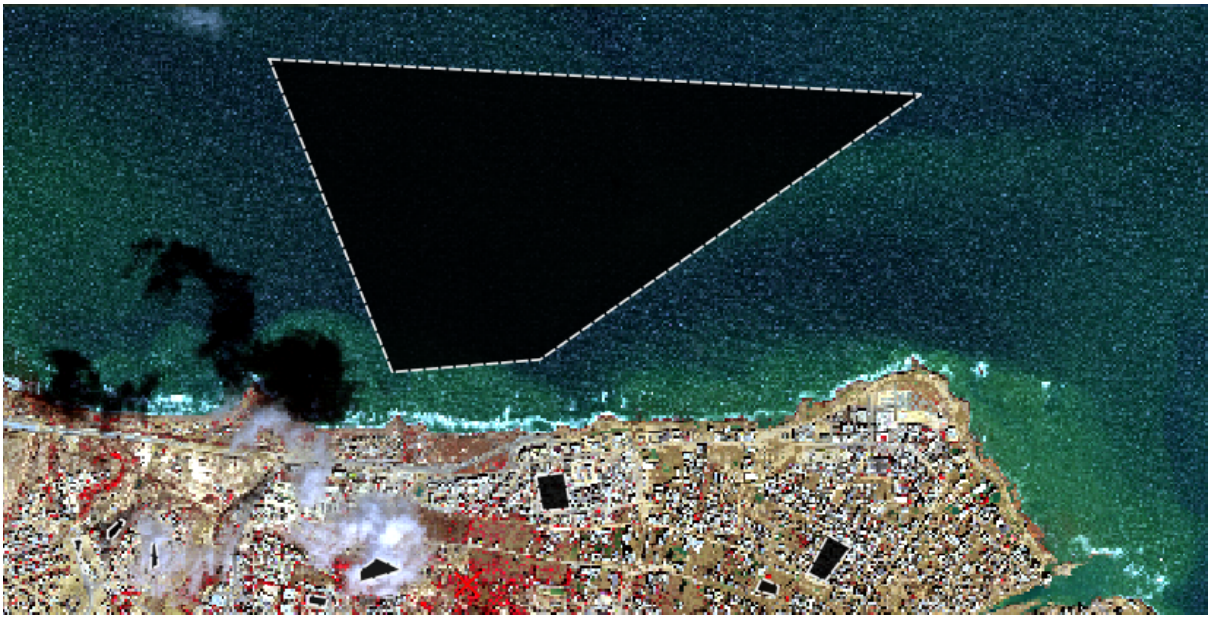


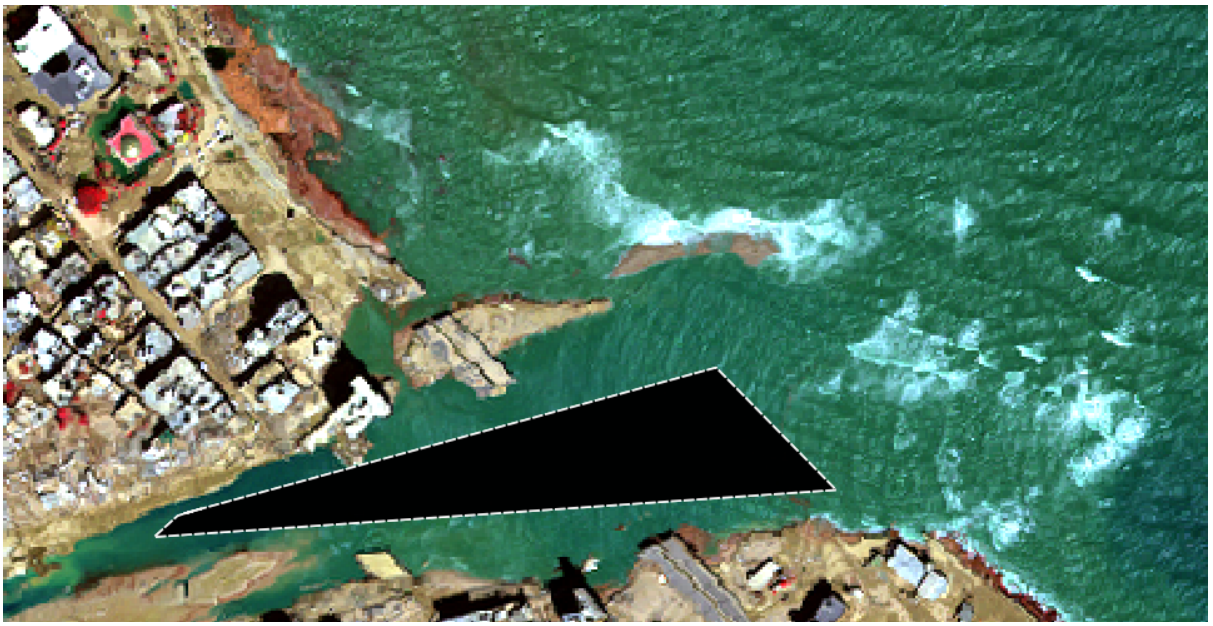
Macroclass 3: Impervious surfaces



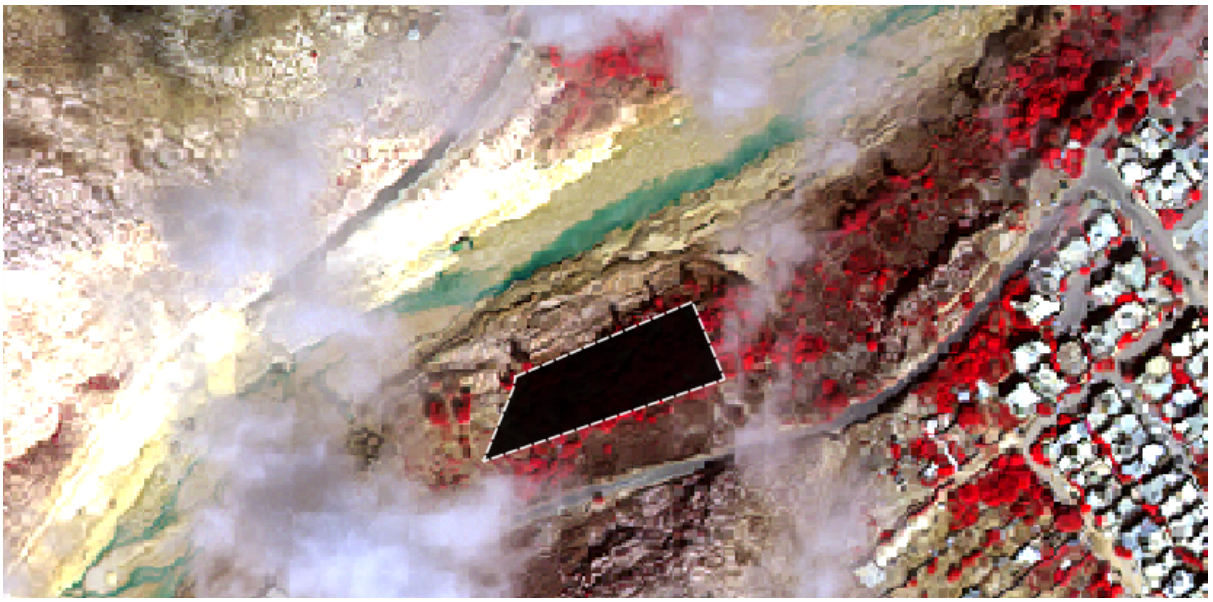


Macroclass 4: Water body

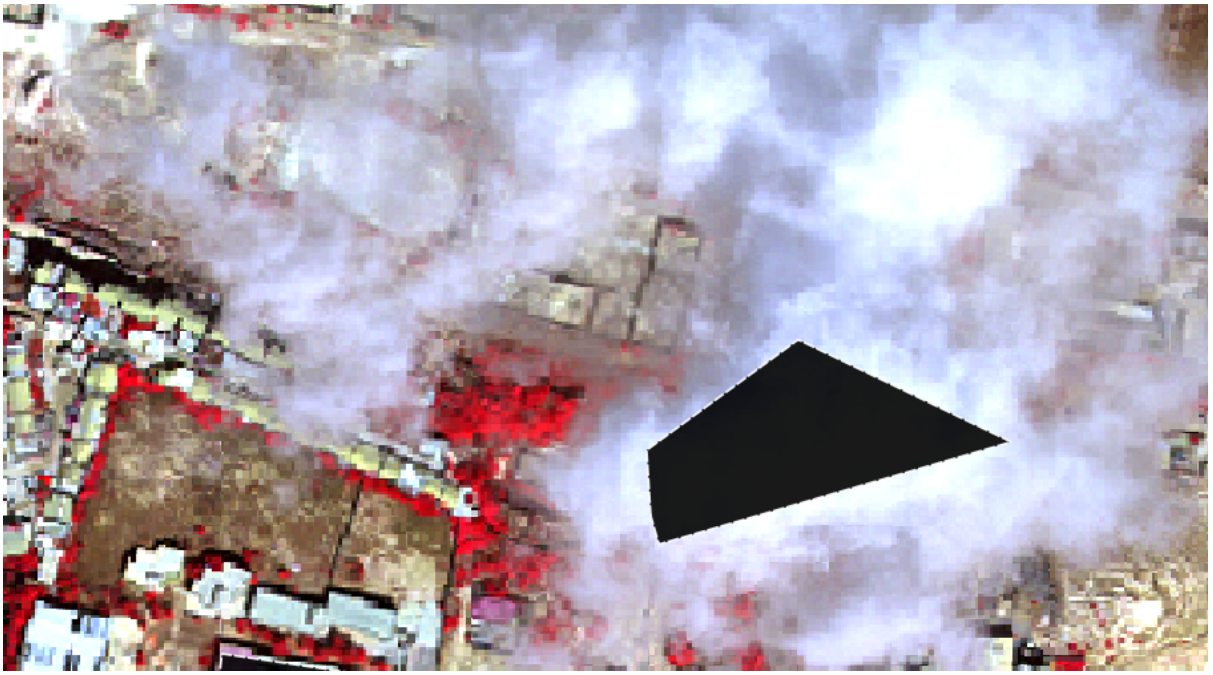


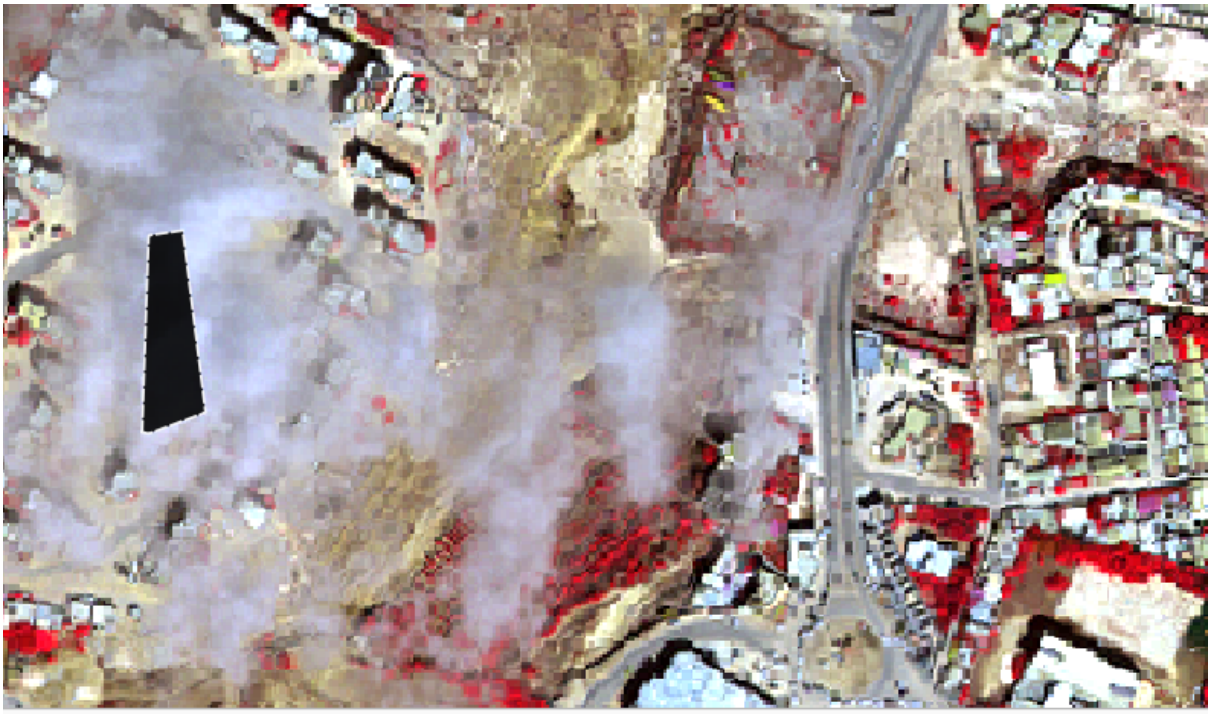


Macroclass 5: Vegetation

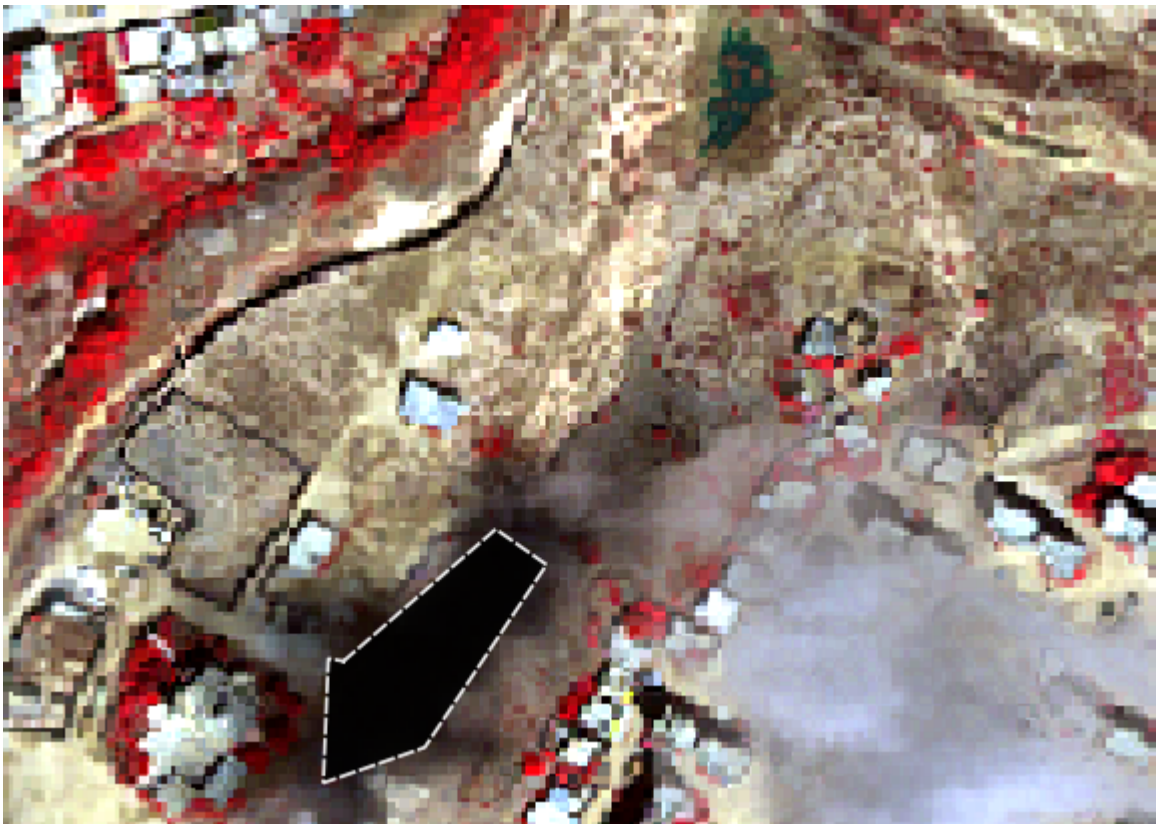


Macroclass 6: Cloud





Macroclass 7: Cloud shadow



Overview of the areas selected are as follows:

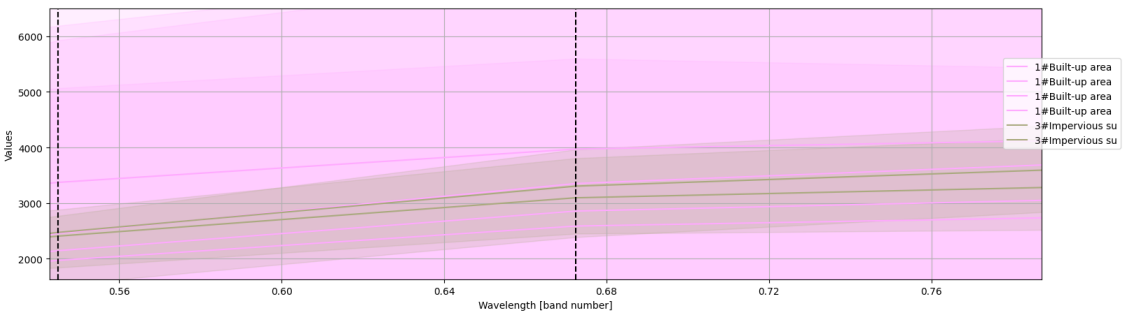
7.2 Assessing Spectral Similarities using the Spectral Signature Plot

Once done selecting the training inputs, we are going to check the Spectral Signature Plot and Signature Details to see if there is a notable difference between

the band signatures of each class. If a band does have notable differences between all classes, it is a good idea to remove it as it will not add to the accuracy of classification. Different land use types may have similar spectral signatures. This may lead to misclassification of some classes. This is why we look at the Spectral Signature Plot to check for overlaps before performing classification.

- To display the signature plot, select two or more spectral signatures within the table, then click on the Spectral Signature Plot button.

Interpreting the plot:
The minimum and maximum of each band represents the minimum and maximum values of the pixels in each class. If there are significant overlaps between classes, it is worth considering combining the classes as there might be significant misclassification otherwise. It is good to interpret the plot in conjunction with the table as the table.
For example, selecting the built-up areas and impervious surfaces, we get the following plot and table. There are significant overlaps on the plot, however, the table shows that while there are overlaps, there is a much smaller range of values for impervious surfaces than built-up areas.



	S	MC ID	MC Name	C ID	C Name	lap M	Min B1	Max B1	Min B2	Max B2	Min B3	Max B3	Min B4	Max B4
1	✓ ...	1	Built-up area	1	Built-up area	3-3;...	1.0	5504.0	1.0	6182.0	1.0	7198.0	1.0	8058.0
2	✓ ...	1	Built-up area	1	Built-up area	3-3;...	1.0	7552.0	1.0	7779.0	1.0	8208.0	1.0	8219.0
3	✓ ...	1	Built-up area	1	Built-up area	3-3;...	1.0	4682.0	1.0	5921.0	1.0	7090.0	1.0	7946.0
4	✓ ...	1	Built-up area	1	Built-up area	3-3;...	1.0	4470.0	1.0	5060.0	1.0	5592.0	1.0	5342.0
5	✓ ...	3	Impervious surfaces	3	Impervious surfaces	1-1;...	1197.0	2147.0	1522.0	2764.0	2382.0	3958.0	3077.0	4611.0
6	✓ ...	3	Impervious surfaces	3	Impervious surfaces	1-1;...	1605.0	2478.0	1834.0	2875.0	2444.0	3802.0	2551.0	4342.0

Signature list

	S	MC ID	MC Name	C ID	C Name	verlap MC_I	Min B1	Max B1	Min B2	Max B2	Min B3	Max B3
1	✓	1	Built-up area	1	Built-up area	2-2;2-2;2...	1.0	5504.0	1.0	6182.0	1.0	7198.0
2		1	Built-up area	1	Built-up area	2-2;2-2;2...	1.0	7552.0	1.0	7779.0	1.0	8208.0
3		1	Built-up area	1	Built-up area	2-2;2-2;2...	1.0	4682.0	1.0	5921.0	1.0	7090.0
4		1	Built-up area	1	Built-up area	2-2;2-2;2...	1.0	4470.0	1.0	5060.0	1.0	5592.0
5	✓	2	Bare land	2	Bare land	1-1;1-1;1...	618.0	1176.0	917.0	1701.0	1437.0	3072.0
6		2	Bare land	2	Bare land	1-1;1-1;1...	159.0	1923.0	219.0	2567.0	432.0	3987.0
7		2	Bare land	2	Bare land	1-1;1-1;1...	243.0	1697.0	279.0	2531.0	366.0	4137.0
8		2	Bare land	2	Bare land	1-1;1-1;1...	1.0	3349.0	1.0	4240.0	1.0	5808.0

Click on Signature details on the left hand side.

Plot | Signature details | Spectral distances

MC_ID = 1 MC_name = Built-up area C_ID = 1 C_name = Built-up area ROI_size = 688 pixels				
Wavelength [E-6m]	0.48	0.545	0.6725	0.85
Values	1642.1757	2144.9563	2857.3901	3155.4036
Standard deviation	810.3897	1036.9615	1344.8372	1449.0425

MC_ID = 2 MC_name = Bare land C_ID = 2 C_name = Bare land ROI_size = 53 pixels				
Wavelength [E-6m]	0.48	0.545	0.6725	0.85
Values	867.42456	1341.8257	2478.0	3146.4968
Standard deviation	76.39336	130.5583	254.97333	286.25894

MC_ID = 3 MC_name = Impervious surfaces C_ID = 3 C_name = Impervious surfaces ROI_size = 32 pixels				
Wavelength [E-6m]	0.48	0.545	0.6725	0.85
Values	1940.6238	2473.4429	3305.8713	3749.7761
Standard deviation	130.473	153.05275	187.83598	234.61597

MC_ID = 4 MC_name = Water body C_ID = 4 C_name = Water body ROI_size = 49590 pixels

If a band doesn't add to the classification, you can remove it. Once you are satisfied with the Spectral signatures for each class, you are ready to perform the classification.

7.3: Generate Classification

Once the training samples are ready, classification can be done.

7.3.1: Land cover classification with Minimum Distance

From the menu bar, go to **SCP** → **Band Processing** → **Classification**

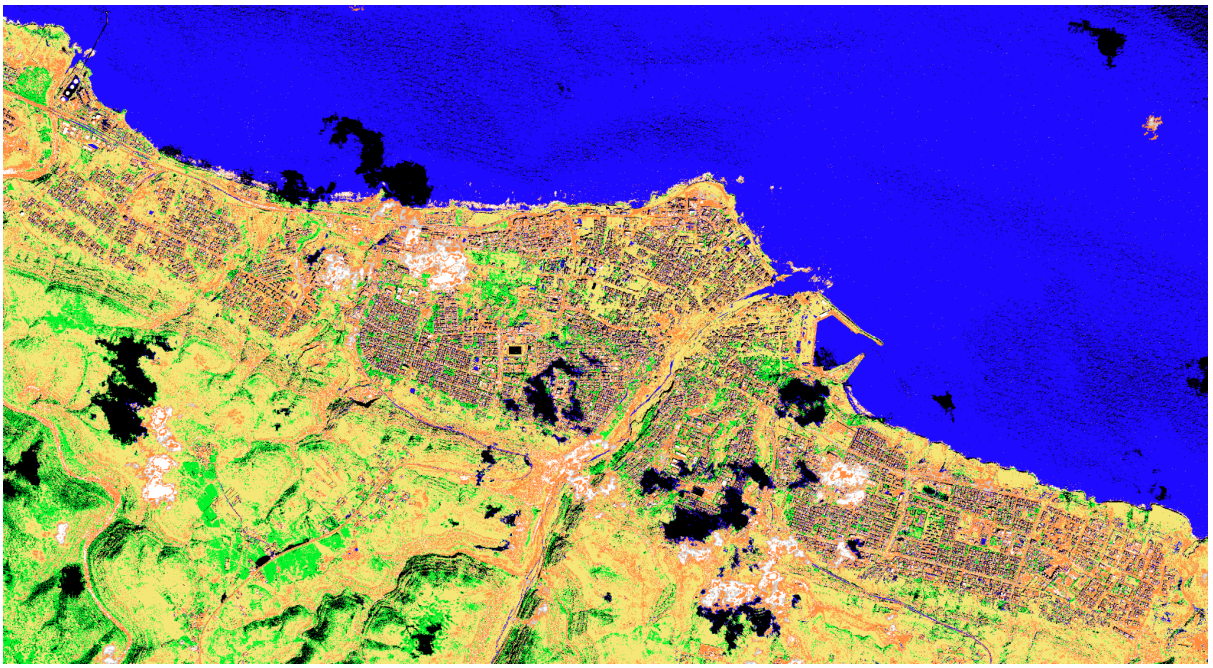
In the Classification dialog window,

- Under Use, **check MC ID**
- Select **Minimum Distance** under the Algorithm
- Click on the **Run** button.

The Save classification output dialog window appears.

Navigate to the Post-Flood GeoTiff sub-folder of this project, give the name the output file *Classification_MD_Post*. Notice that the output file will be saved in Geotiff file format.

When the classification process is completed, a sound is played. At the same time, a land cover image called *Classification_MD_Post* is added into the Layers panel and displayed in the view window of QGIS as shown in the figure below.



7.3.2: Land cover classification with Random Forest

From the menu bar, go to **SCP** → **Band Processing** → **Random forest**

In the Random Forest Classification dialog window,

Under Use, check MC ID

Set the number of training samples as 5000, number of trees as 10

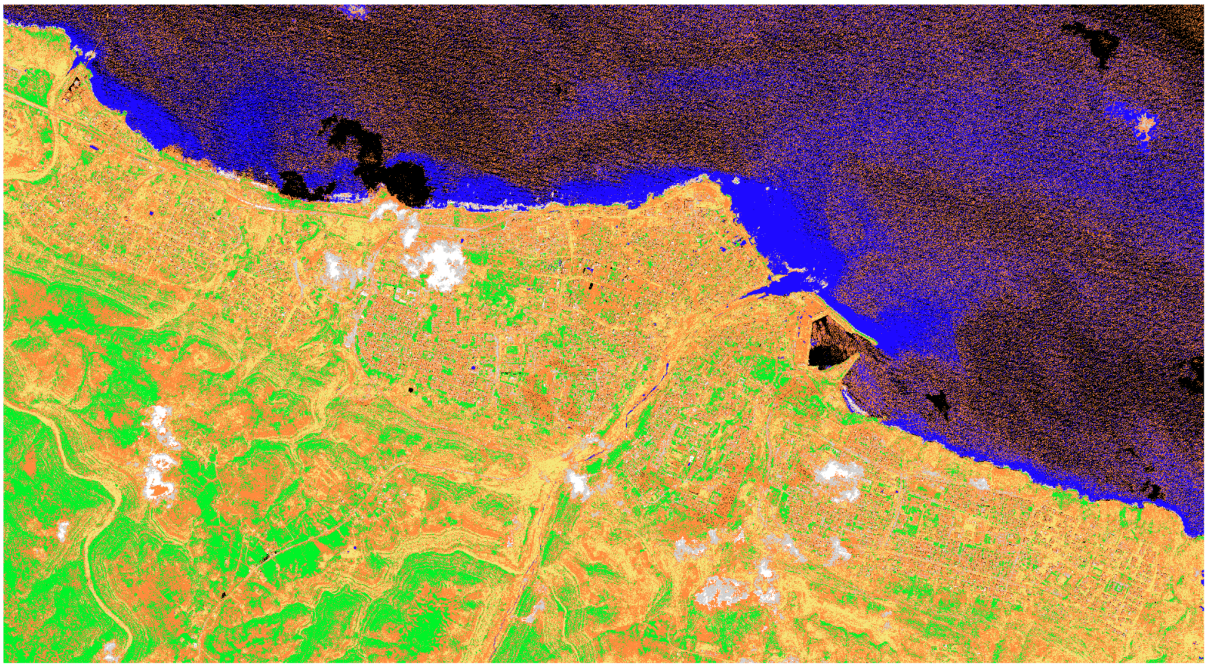
Click on the **Run** button.

The Save classification output dialog window appears.

Navigate to the Post-flood GeoTiff sub-folder of this project, give the name the output

file *Classification_RF_Ppst*. Notice that the output file will be saved in geotiff file format.

When the classification process is completed, a sound is played. At the same time, a land cover image called *Classification_RF_Post* is added into the Layers panel and displayed in the view window of QGIS as shown in the figure below. A confidence raster is also created which assess the reliability (from 0 minimum to 1 maximum) of the model at pixel levels.

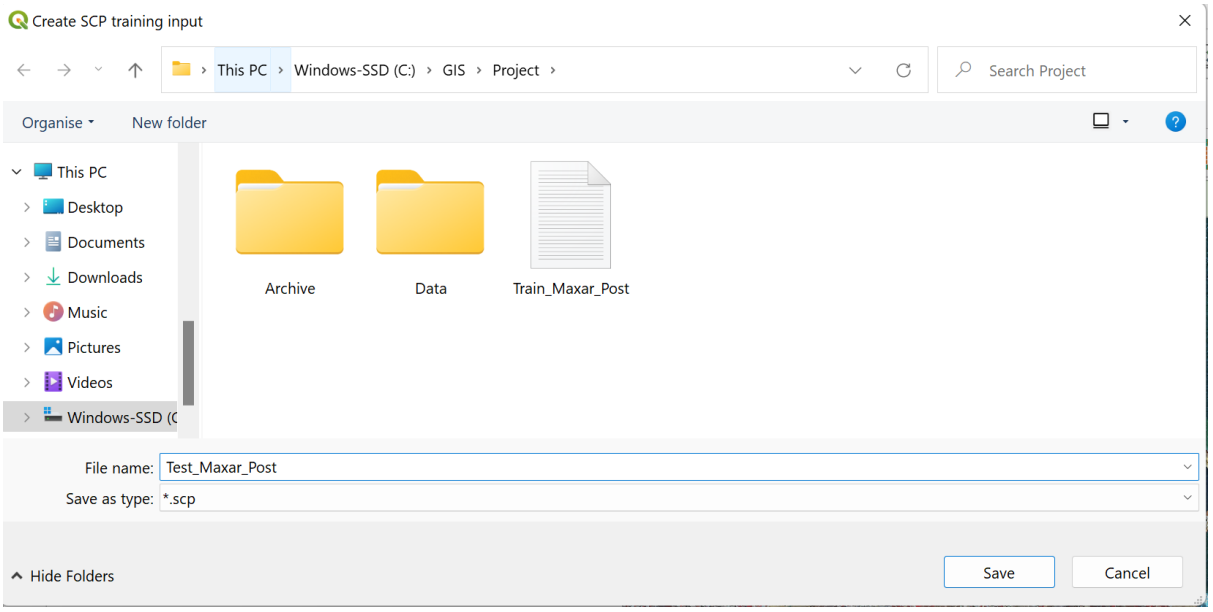


Section 8: [Post] Evaluating the classification

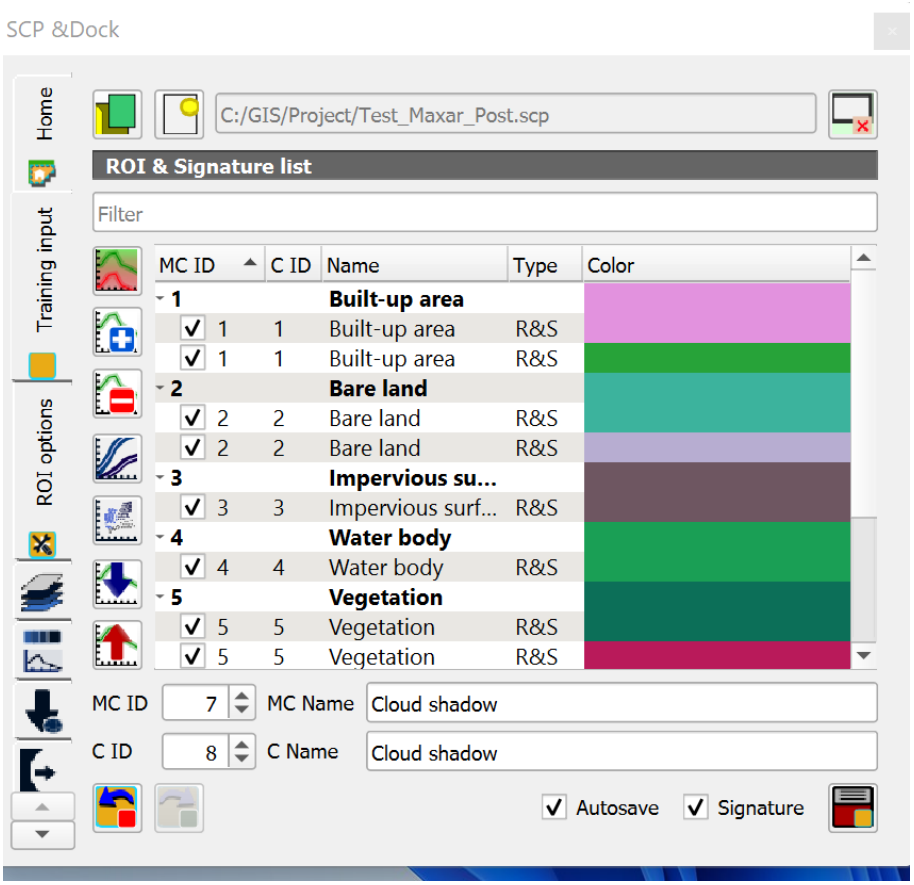
We are now going to create a testing layer to evaluate the accuracy of our classification.

1. Create testing data

As with the Training input, define ROIs for the Testing input. Define at least one for each class. Name it Test_Maxar_Post

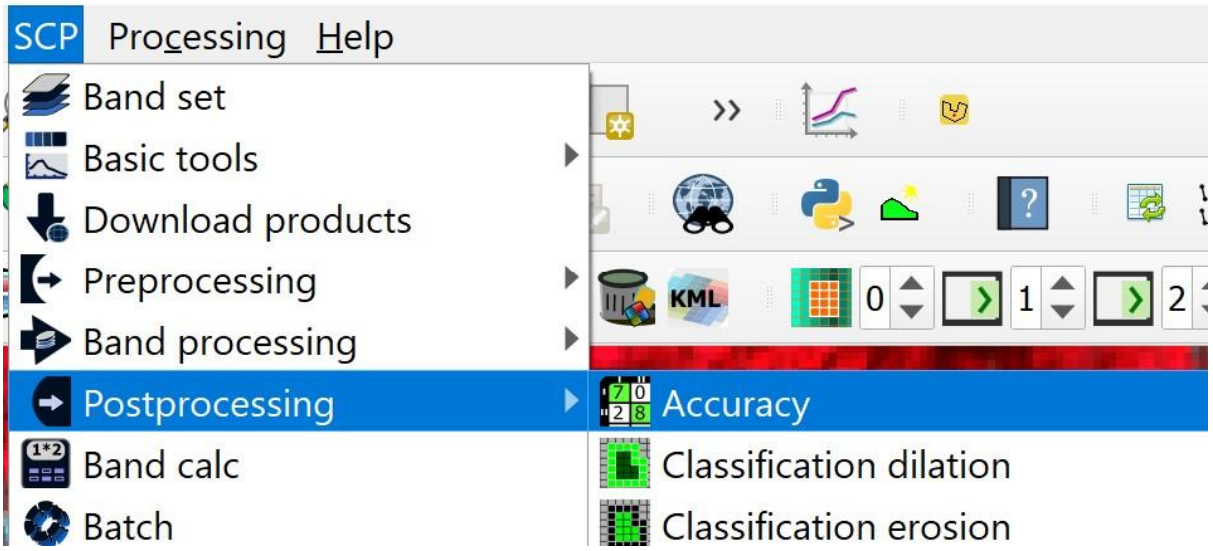


Ensure that the ROIs do not overlap with any of your training ROIs



2. Evaluate accuracy

From the menu bar go to **SCP** → **Postprocessing** → **Accuracy**.



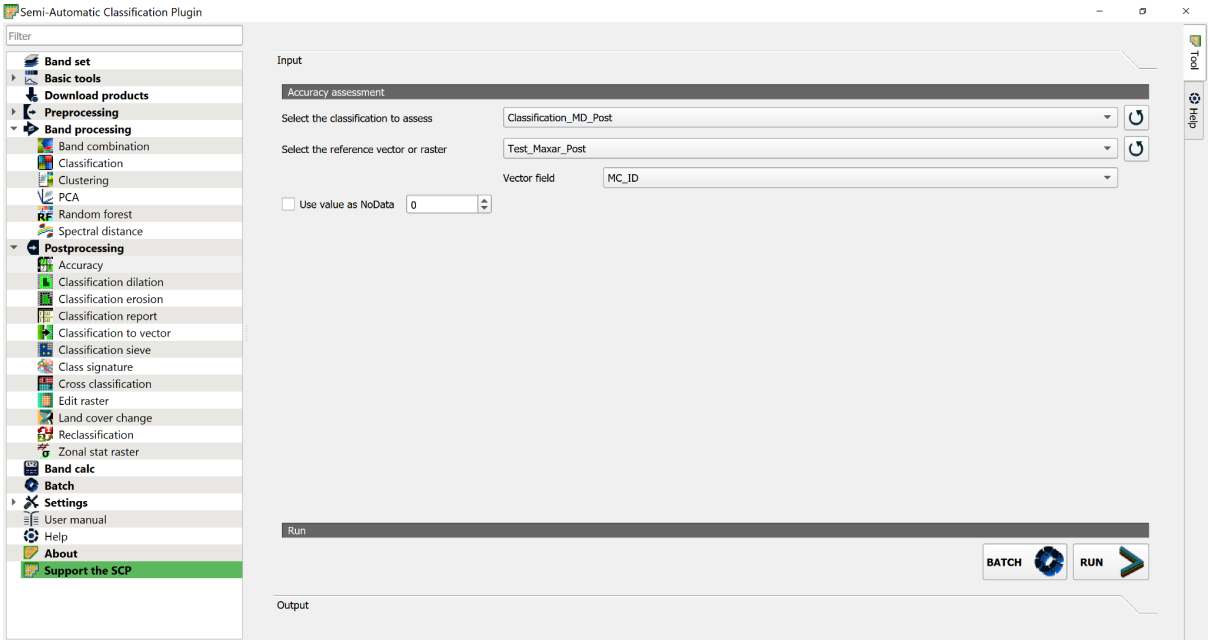
The Accuracy assessment dialog window appears.

Under the Select the classification to assess, select the classified image Classification_MD_Post from the drop-down list (If there are no layers appearing, click on the refresh button located at the end of the selection before clicking on the drop-down list)

Under the Select the reference vector or raster, select the newly created test samples, Test_Maxar_Post from the drop-down list (Similarly here, If there are no layers appearing, click on the refresh button located at the end of the selection before clicking on the drop-down list

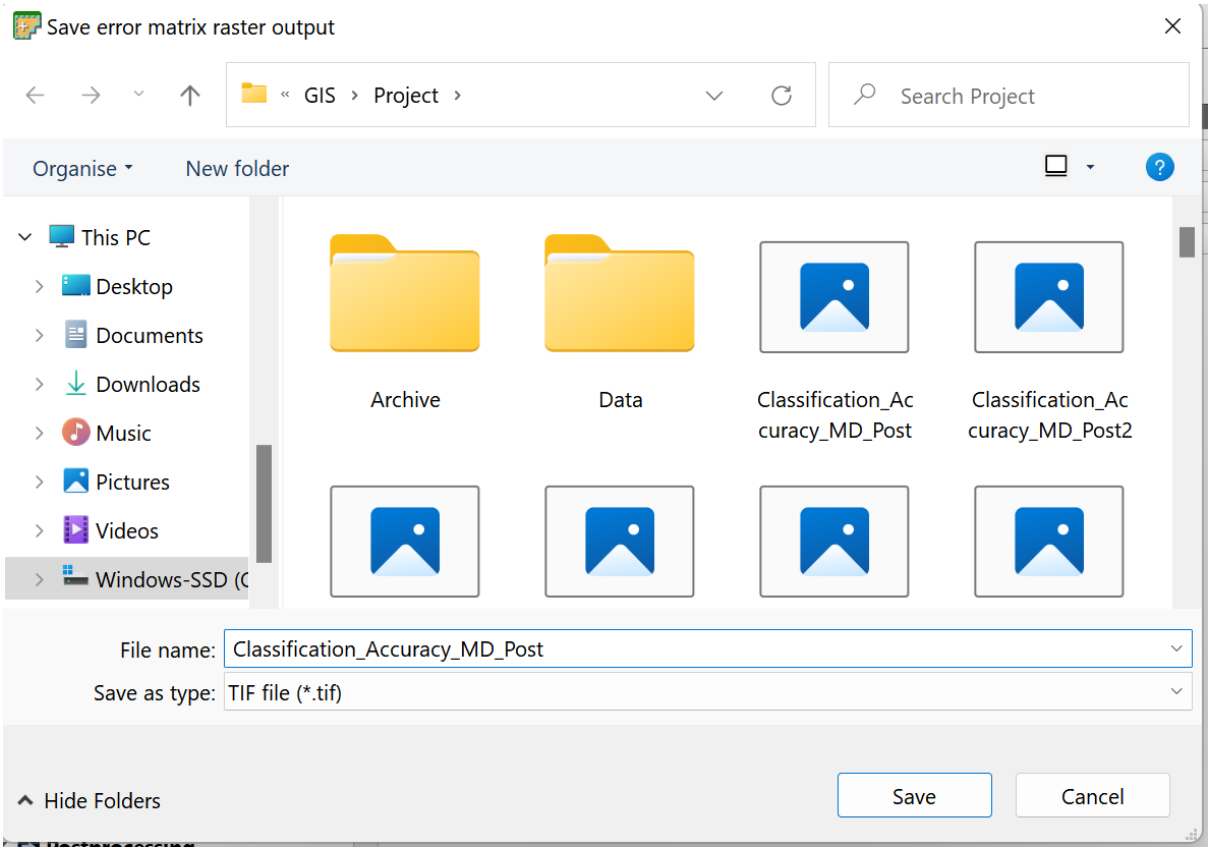
Under the Vector field, select MC_ID from the drop-down list.

The screen should look similar to the screenshot below.



- Click on the **Run** button.

The Save error matrix raster output dialog window appears, name the output file **Classification_Accuracy_MD_Post**



- Click on the **Save** button.

Results from the classification are as follows:

ErrMatrixCode	Reference	Classified	PixelSum
1	1	1	2914
3	1	2	1798
6	1	3	2585
10	1	4	1767
15	1	5	759
21	1	6	2117
28	1	7	2634
2	2	1	1447
5	2	2	8428
9	2	3	1234
14	2	4	36
20	2	5	1917
27	2	6	1038
34	2	7	87
4	3	1	735
8	3	2	46
13	3	3	733
19	3	4	27
26	3	5	3
33	3	6	12
39	3	7	7
7	4	1	186
18	4	3	27
25	4	4	34485
38	4	6	10
43	4	7	2726
11	5	1	3
17	5	2	252
24	5	3	3
31	5	4	3
37	5	5	3039
46	5	7	261
16	6	1	10
30	6	3	712
45	6	6	2972

> ERROR MATRIX (pixel count)
> Reference

V_Classified	1	2	3	4	5	6	7	Total
1	5065	4212	1054	86	9	848	0	11274
2	864	6595	21	0	291	0	0	7771
3	1367	139	417	12	1	298	0	2234
4	1472	72	33	36407	1	0	700	38685
5	637	1163	3	0	2926	0	0	4729
6	1743	1775	21	6	0	2548	0	6093
7	3426	231	14	923	333	0	17395	22322
Total	14574	14187	1563	37434	3561	3694	18095	93108

> AREA BASED ERROR MATRIX
> Reference

V_Classified	1	2	3	4	5	6	7	Area	Wi
1	0.0580	0.0482	0.0121	0.0010	0.0001	0.0097	0.0000	7273567.6671	0.1290
2	0.0289	0.2208	0.0007	0.0000	0.0097	0.0000	0.0000	14666153.2429	0.2602
3	0.0113	0.0012	0.0035	0.0001	0.0000	0.0025	0.0000	1043880.0998	0.0185
4	0.0151	0.0007	0.0003	0.3746	0.0000	0.0000	0.0072	22438263.2056	0.3980
5	0.0096	0.0176	0.0000	0.0000	0.0443	0.0000	0.0000	4035775.8132	0.0716
6	0.0094	0.0096	0.0001	0.0000	0.0000	0.0137	0.0000	1852022.1421	0.0329
7	0.0138	0.0009	0.0001	0.0037	0.0013	0.0000	0.0700	5064916.0854	0.0898
Total	0.1462	0.2990	0.0168	0.3794	0.0555	0.0259	0.0772	56374578.2560	
Area	8241716	16855293	945747	21389312	3128692	1460832	4352985	56374578	
SE	0.0013	0.0013	0.0004	0.0005	0.0008	0.0004	0.0004		
SE area	71798	73981	23714	28382	42798	22800	20711		
95% CI area	140724	145002	46480	55628	83884	44688	40593		
PA [%]	39.6489	73.8444	20.6029	98.7267	79.8122	53.0169	90.6727		
UA [%]	44.9264	84.8668	18.6661	94.1114	61.8735	41.8185	77.9276		
Kappa hat	0.3550	0.7841	0.1728	0.9051	0.5963	0.4027	0.7608		

Overall accuracy [%] = 78.4836
Kappa hat classification = 0.7093

Area unit = metre^2
SE = standard error
CI = confidence interval
PA = producer's accuracy
UA = user's accuracy

Repeat Step 2 Section 8 for the classification layer using Random Forest (Classifcation_RF_Post layer)

Results are as follows:

ErrMatrixCode	Reference	Classified	PixelSum
1	1	1	9110
3	1	2	1350
6	1	3	2300
10	1	4	5
15	1	5	1040
21	1	6	384
28	1	7	385
2	2	1	6065
5	2	2	5628
9	2	3	337
20	2	5	2098
27	2	6	59
4	3	1	394
8	3	2	40
13	3	3	1085
26	3	5	4
33	3	6	38
39	3	7	2
7	4	1	9763
12	4	2	205
18	4	3	89
25	4	4	12240
38	4	6	6
43	4	7	15131
11	5	1	359
17	5	2	20
24	5	3	1
37	5	5	3181
16	6	1	38
30	6	3	519
45	6	6	3137
22	7	1	959
29	7	2	2
40	7	4	7
49	7	7	17127

> ERROR MATRIX (pixel count)
> Reference

V_Classified	1	2	3	4	5	6	7	Total
1	9110	6065	394	9763	359	38	959	26688
2	1350	5628	40	205	20	0	2	7245
3	2300	337	1085	89	1	519	0	4331
4	5	0	0	12240	0	0	7	12252
5	1040	2098	4	0	3181	0	0	6323
6	384	59	38	6	0	3137	0	3624
7	385	0	2	15131	0	0	17127	32645
Total	14574	14187	1563	37434	3561	3694	18095	93108

> AREA BASED ERROR MATRIX
> Reference

V_Classified	1	2	3	4	5	6	7	Area	Wi
1	0.1339	0.0891	0.0058	0.1435	0.0053	0.0006	0.0141	22108730.2527	0.3922
2	0.0260	0.1082	0.0008	0.0039	0.0004	0.0000	0.0000	7851024.5199	0.1393
3	0.0178	0.0026	0.0084	0.0007	0.0000	0.0040	0.0000	1888822.1191	0.0335
4	0.0001	0.0000	0.0000	0.1269	0.0000	0.0000	0.0001	7161310.7933	0.1270
5	0.0201	0.0405	0.0001	0.0000	0.0614	0.0000	0.0000	6876407.8343	0.1220
6	0.0011	0.0002	0.0001	0.0000	0.0000	0.0090	0.0000	585628.5030	0.0104
7	0.0021	0.0000	0.0000	0.0814	0.0000	0.0000	0.0922	9902654.2337	0.1757
Total	0.2009	0.2406	0.0151	0.3564	0.0670	0.0136	0.1064	56374578.2560	
Area	11325637	13561231	854026	20093934	3778921	764755	5996076	56374578	
SE	0.0015	0.0014	0.0004	0.0013	0.0008	0.0002	0.0007		
SE area	81773	80066	21765	72464	46222	11134	37262		
95% CI area	160275	156930	42660	142029	90595	21822	73033		
PA [%]	66.6352	44.9721	55.4066	35.6043	91.5449	66.2867	86.6461		
UA [%]	34.1352	77.6812	25.0520	99.9021	50.3084	86.5618	52.4644		
Kappa hat	0.1758	0.7061	0.2390	0.9985	0.4674	0.8638	0.4681		

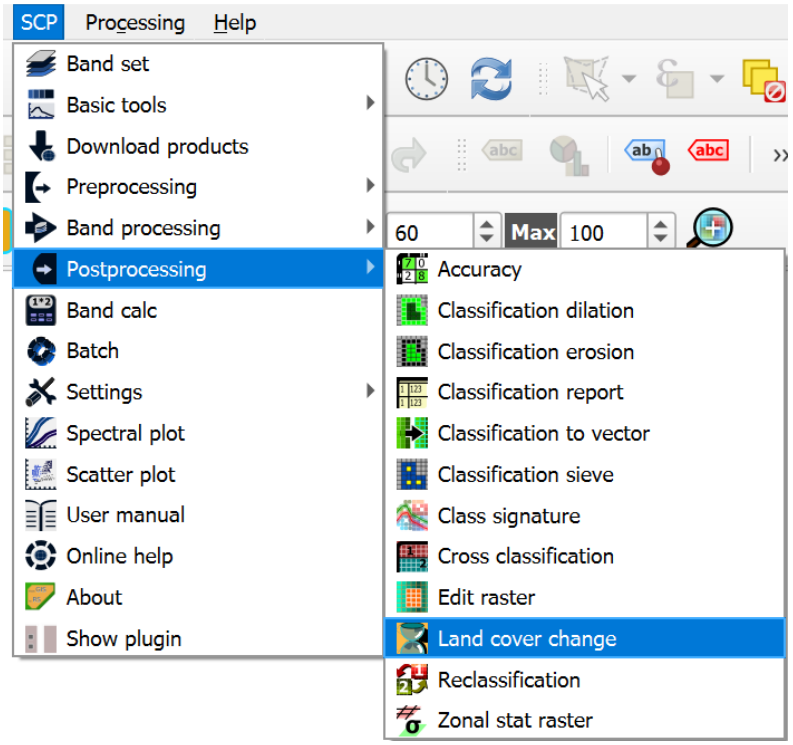
Overall accuracy [%] = 53.9868
Kappa hat classification = 0.4354

Area unit = metre^2
SE = standard error
CI = confidence interval
PA = producer's accuracy
UA = user's accuracy

Since the accuracy for Minimum Distance is higher, the land cover classification layer for Minimum Distance is used for subsequent analysis of land cover change.

Section 9: Change Detection

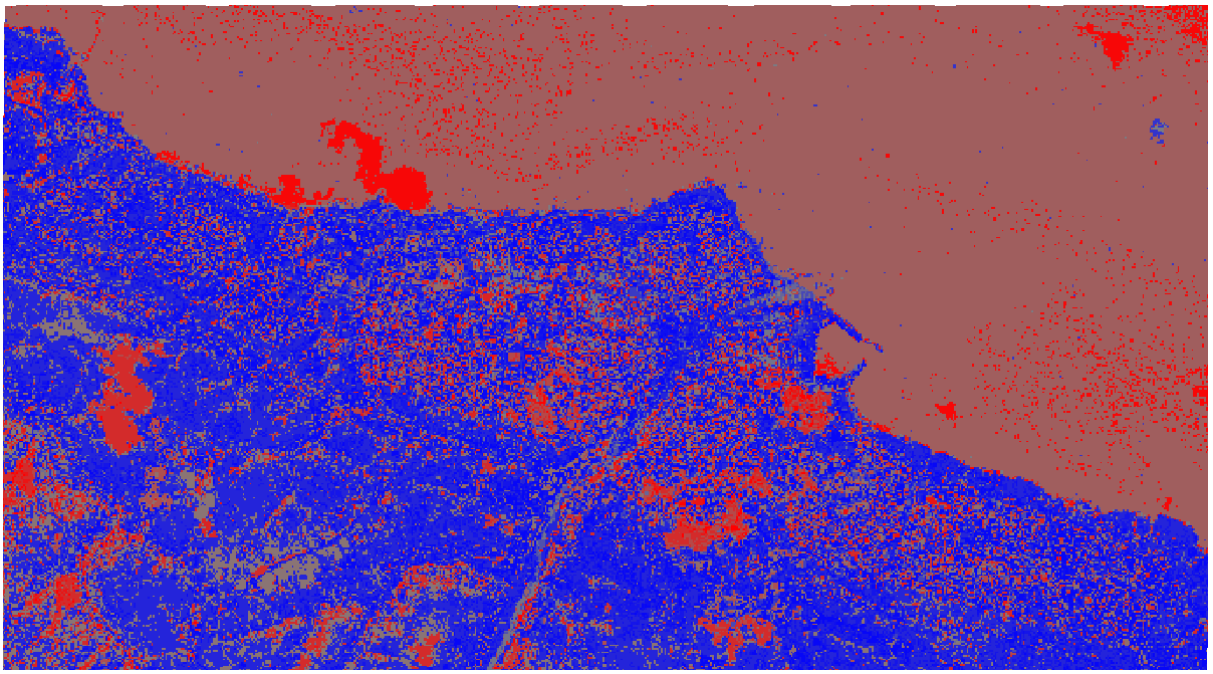
On the top toolbar, go to **SCP** → **Postprocessing** → **Land cover change**



Select the Pre-flood classification and Post-flood classification for reference classification and new classification respectively.

- Click **Run**

For the new raster layer, you should see that 35 classes have been created, each representing a change between two classes from Pre-flood to Post-flood.



Initially, it may not look like there are 35 classes. But this is due to the display configuration of the raster layer. We will be changing this later.

There will also be a CSV file created with information on the number of pixels that changed between classes for the two rasters.

Now we are going to change the display configurations to only display the classes of interest, (1) change from other land cover types to Bare Land and (2) change from other land cover types to Water Body

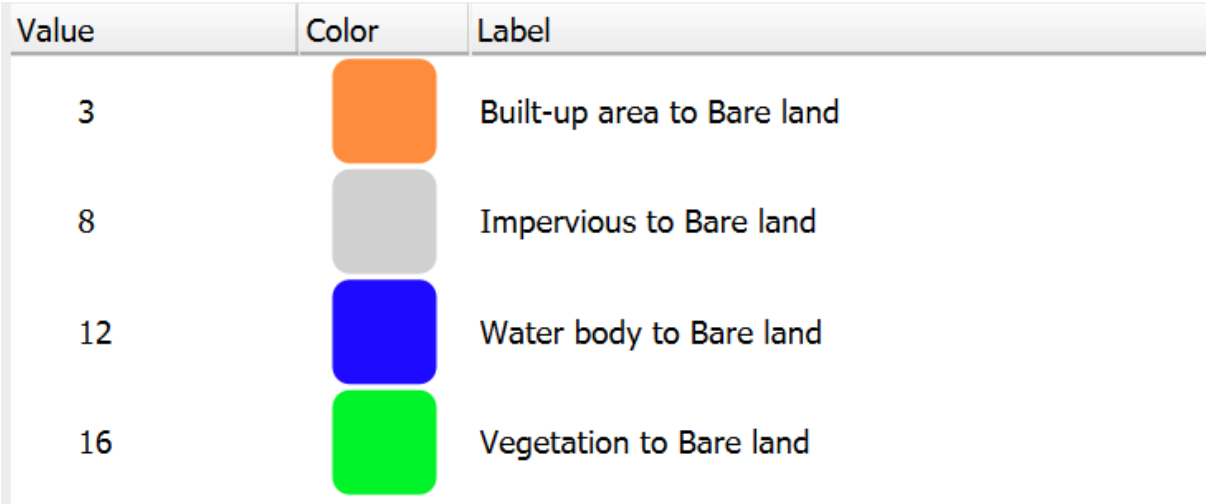
Create a copy of the original Land Cover change analysis raster layer. Name it 'Land_Cover_Change_Analysis_to_Bare_Land'. Right click the layer and click on Properties. Go to the Symbology tab. Make sure 'Paletted/unique values' is selected for Render Type. Next change the Colour to black for all Values that correspond to classes that are not of interest and change the colour of the Values that correspond to the classes of interest according to the table below.

Table 1. Class-Colour Mapping

Built up	ff8b3d
Bare land	f5e678
Impervious surface	d0d0d0
Water body	1e0aff

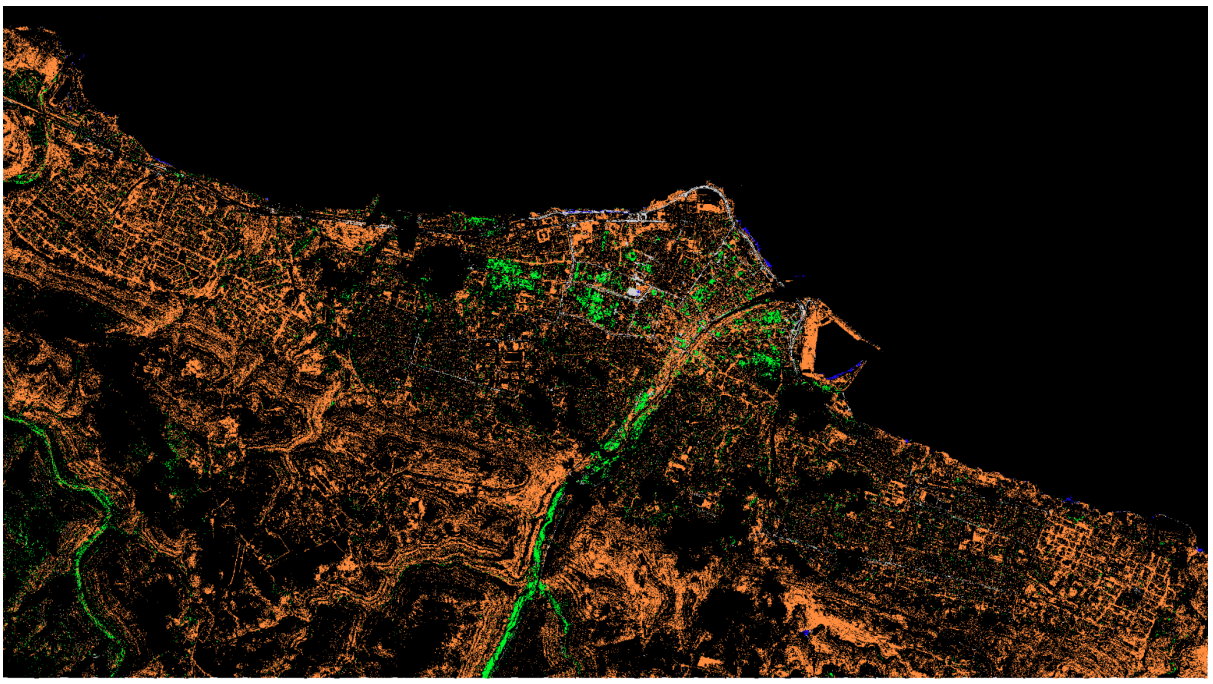
Vegetation	00f328
Cloud cover	white
Cloud shadow	black

For example, if 3 corresponds to the ‘Built-up area to Bare land’ class, change the Colour to orange.



The rest of the Change Classes should be Black.

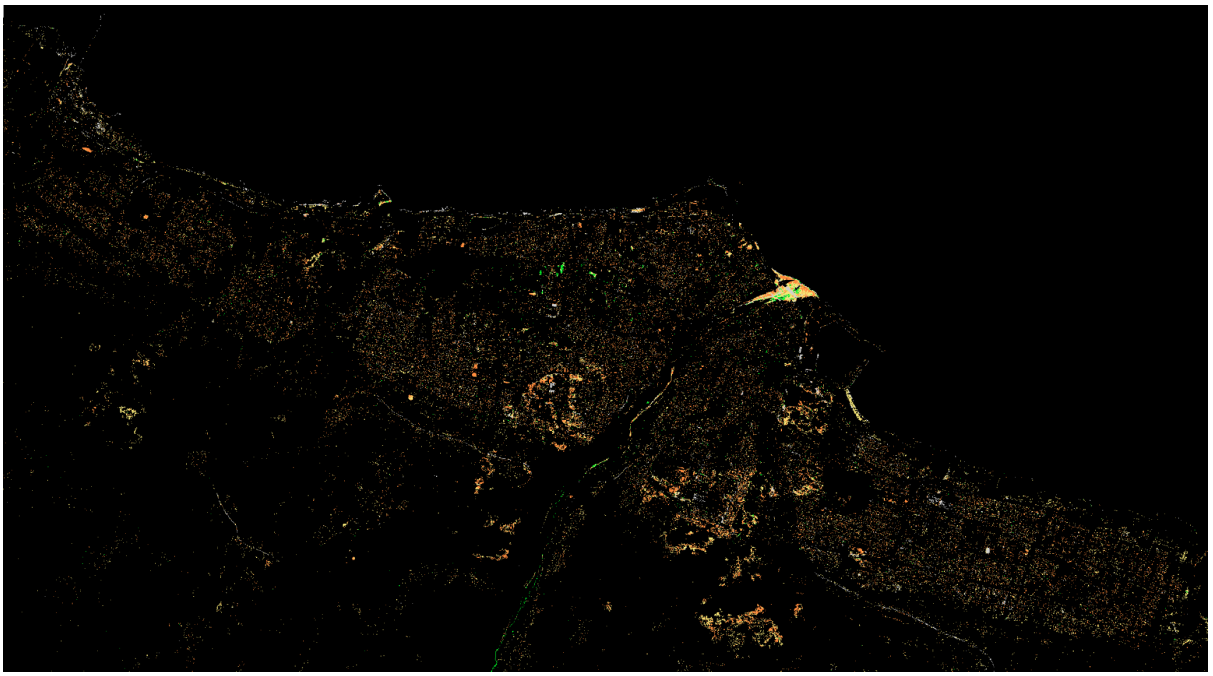
The resulting raster layer should look like this



The land cover change map shows that for the land in closer proximity to the dam, there are generally more changes from other land types to bare land.

Additionally, nearer to the coast and the dam, there seems to be denser regions of Built-up areas that became bare land after the flood.

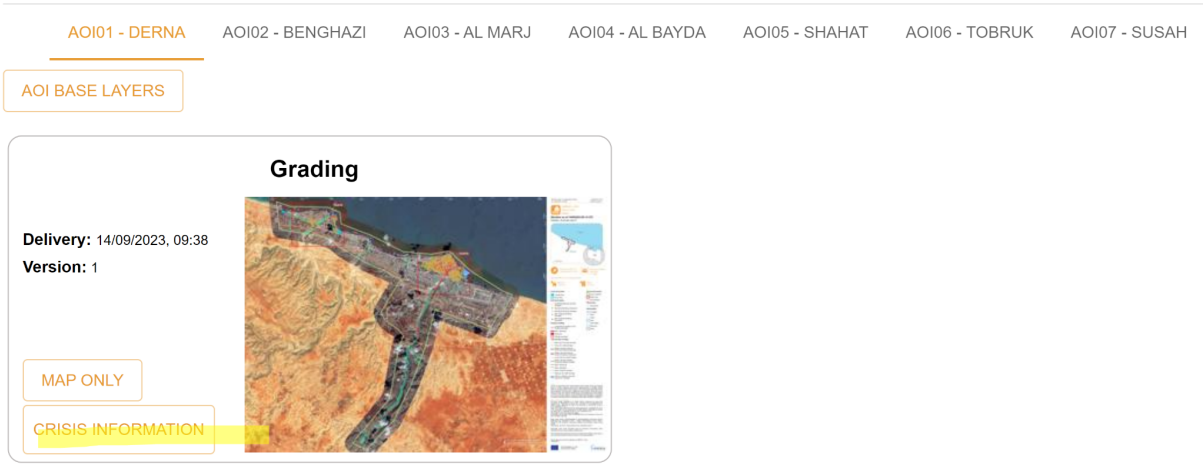
Repeat the steps for change from other land cover types to Water body, naming it Land_Cover_Change_Analysis_to_Water_Body. The resulting map should look like this:



Section 10: Cross Checking our Results with other Sources

10.1: Downloading the data

Go to [COPERNICUS Emergency Management Service - Mapping]() and download flooding information about the Libya floods.



Select the tab for Derna, and click on crisis information to download the data.

A zipped folder with various *shp* files is downloaded. Our file of interest is EMSR696_AOI01_GRA_PRODUCT_observedEventA_v1

10.2: Clipping data to study area

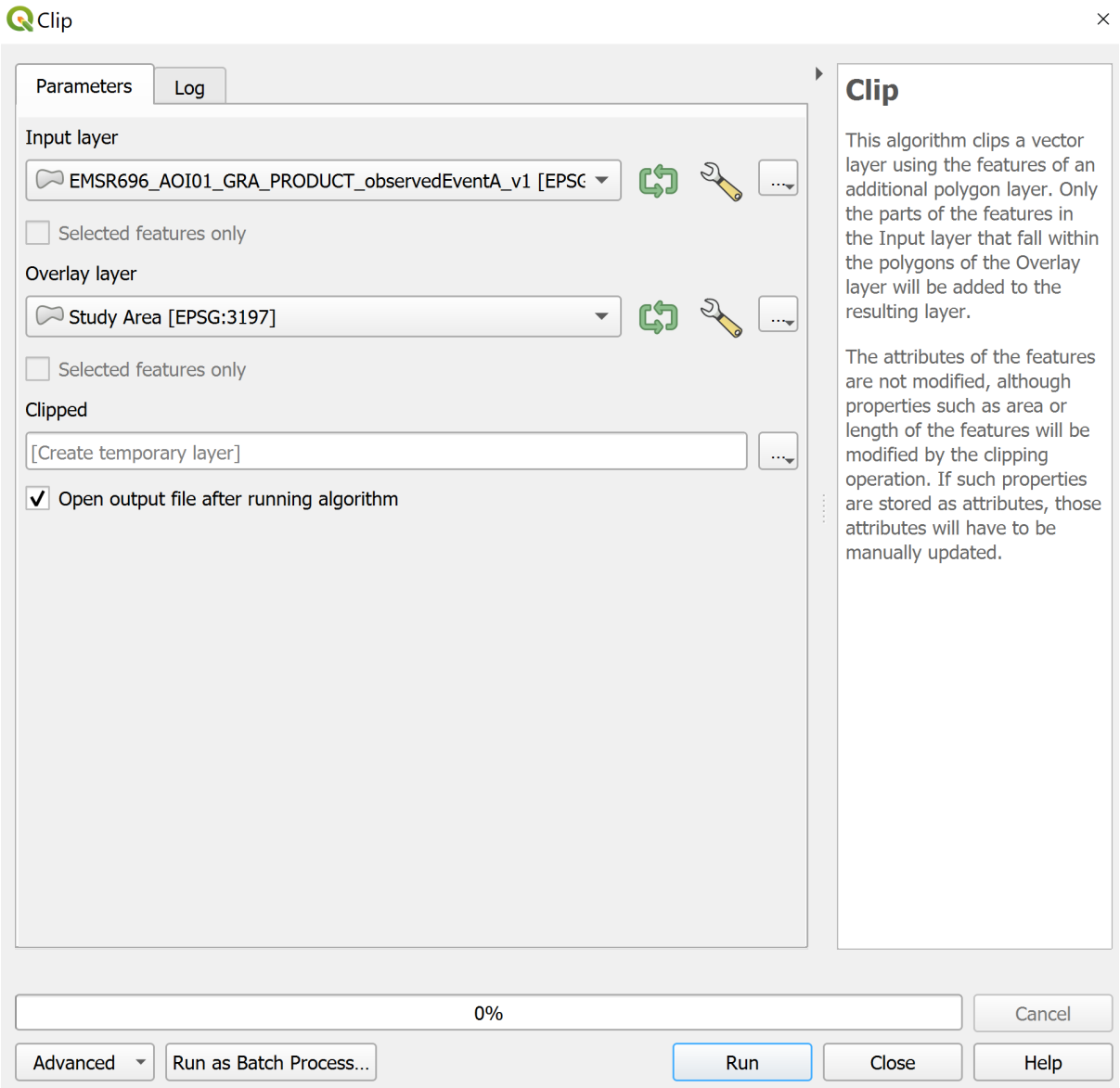
1. In QGIS, load in the shp file for EMSR696_AOI01_GRA_PRODUCT_observedEventA_v1
2. Clip the data to study area

Go to the menu bar, under Vector → Geoprocessing Tools → **Clip**

The clip dialog window would appear.

- Select EMSR696_AOI01_GRA_PRODUCT_observedEventA_v1 for the input layer
- Select Study Area for the Overlay layer.

The clip dialog window should look like the following:



Click on **Run**

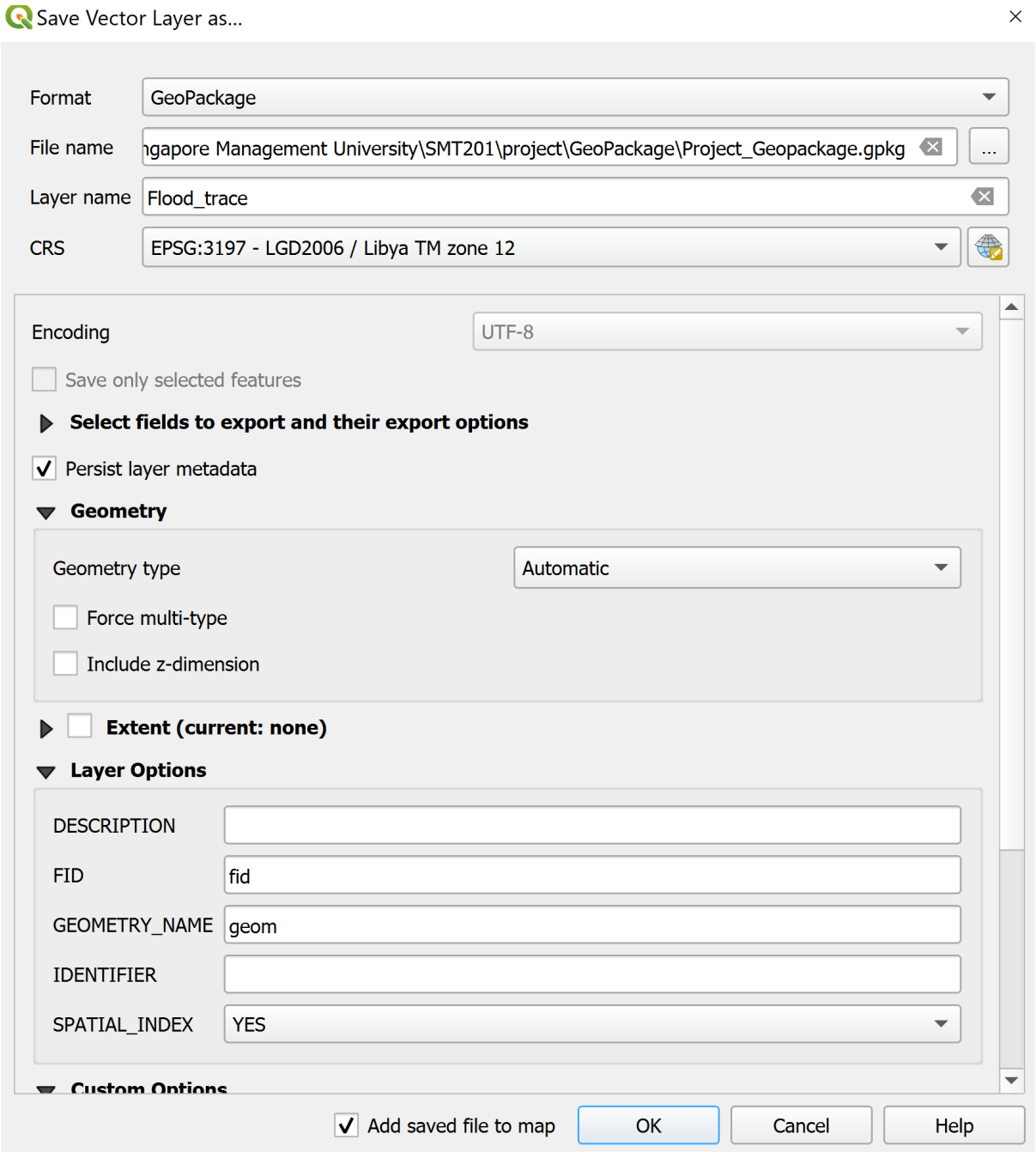
3. Save the temporary clipped layer to the project Geopackage

Right click on the temporary Clipped layer in the Layers panel → *Export* → *Save Features As.* The dialog window to save the Vector layer would appear.

Click the browse icon ... and select *Project_Geopackage* under the *GeoPackage* folder.

- Enter the Layer name as *"Flood_trace'*
- For the CRS, choose the project CRS EPSG:3197.
- Ensure that the "Add saved file to map" checkbox is checked.

The dialog window would look like this:



Click on **OK** to save the layer into the Geopackage.

4. Remove the *EMSR696_AOI01_GRA_PRODUCT_observedEventA_v1* and temporary *Clipped* layer by right clicking → Remove Layer
5. Rename the newly added layer as *Flood_trace* instead of *Project_Geopackage* — *Flood_trace* by right clicking → Rename Layer

10.3: Style the data

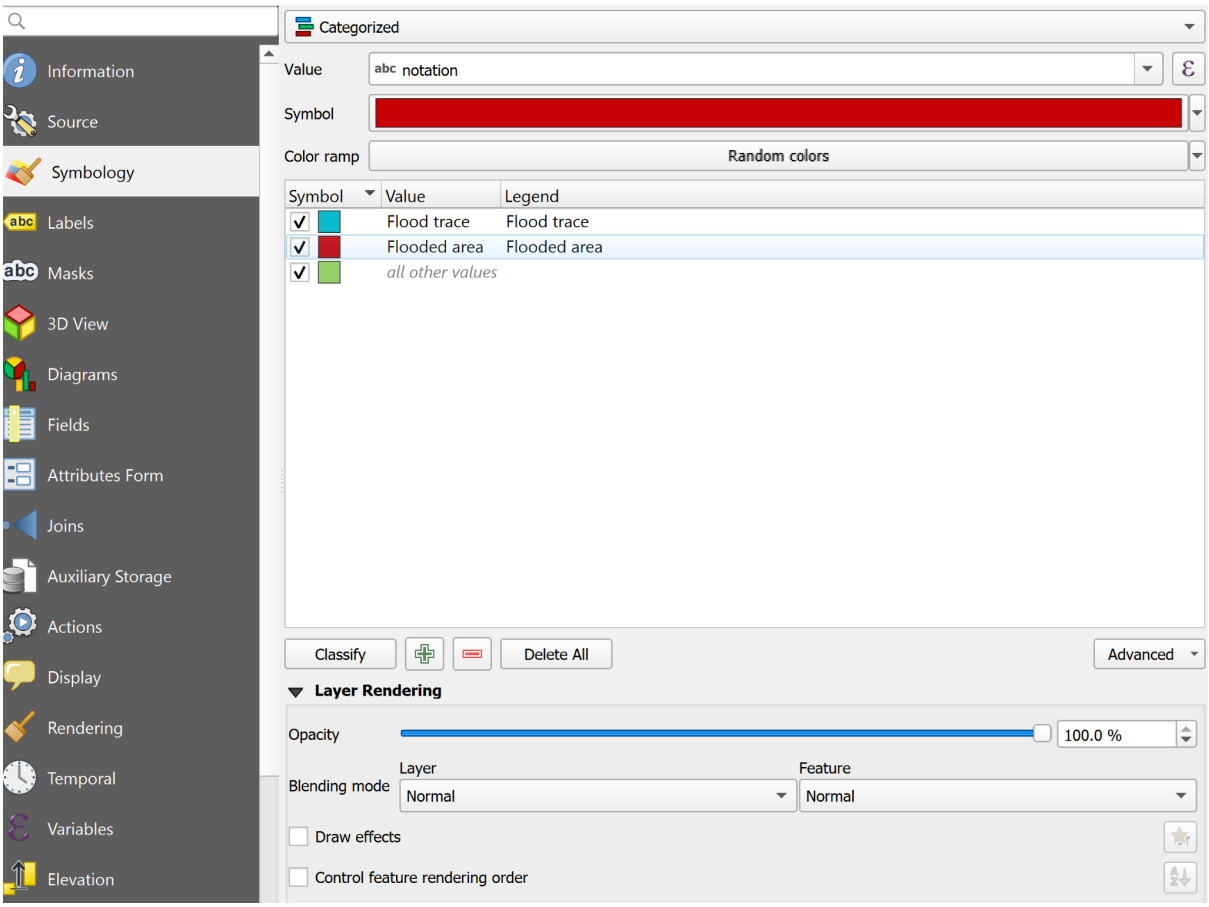
The data outlines the area of floods and flood trace for the event on 14 September 2023. We can visualise the different areas and cross check with our remote sensing for flooded areas.

- Right click on the Observed Event layer → **Properties**

The Properties window would appear.

- Select the **Symbology** tab
- Select **Categorised** for the dropdown bar.
- Under Value, select notation.
- Click on the **Classify** button.

The Properties window should look similar to the following:



Click on **Apply** and close the window.

The QGIS window should look like the above, the blue area shows flood trace and red shows flooded areas as of 14 September.

Section 11: Suitable Healthcare Facility Locations

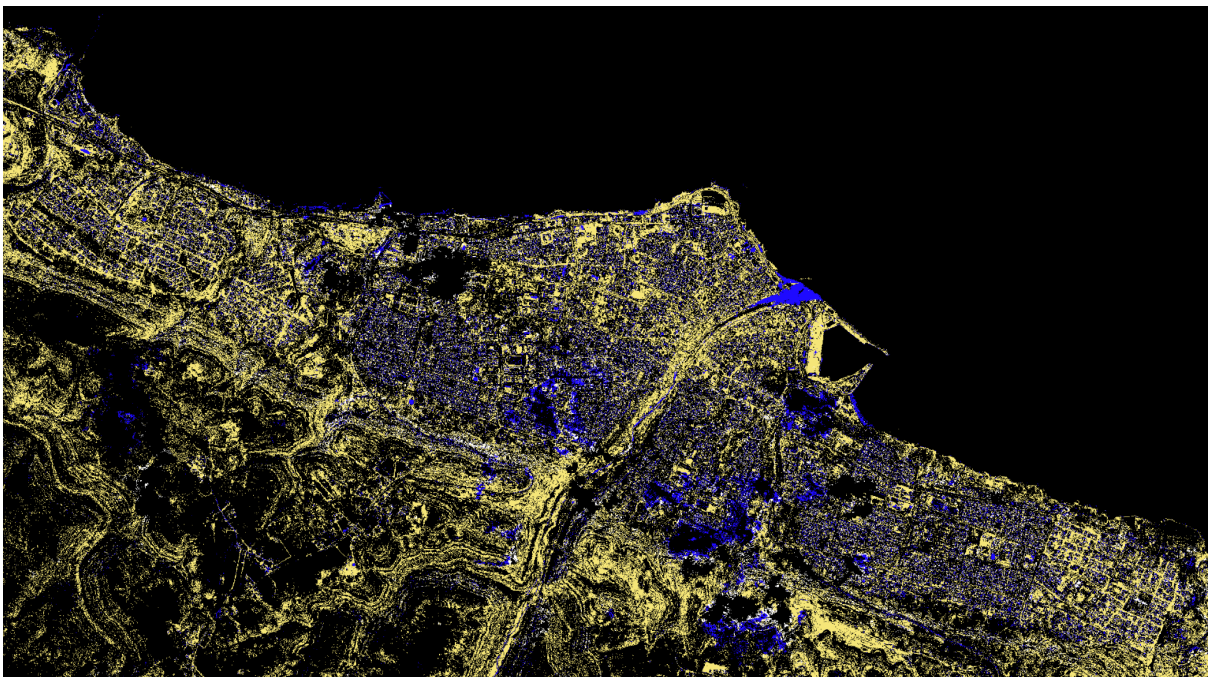
The purpose of this analysis is to identify suitable locations for temporary healthcare facilities given the damage identified in the land cover change map from the previous section. Underlying the identification of suitable sites for a temporary healthcare facility is the assumption that less damaged built-up areas can act as suitable sites for a temporary healthcare facility.

If you haven't already done so, download the Shapefile for Healthcare facilities from [Libya Health Facilities (OpenStreetMap Export) - Humanitarian Data Exchange (humdata.org)](#) and save it into the GeoPackage. Note: Download the Polygon File.

We will now check the damage to each healthcare facility using the Land cover change analysis map. Using the steps from above, change the colouring of the layer so that

1. Other land use types to bare land: f5e678
2. Other land use types to water body: 1e0aff

You should see a map that looks like this:

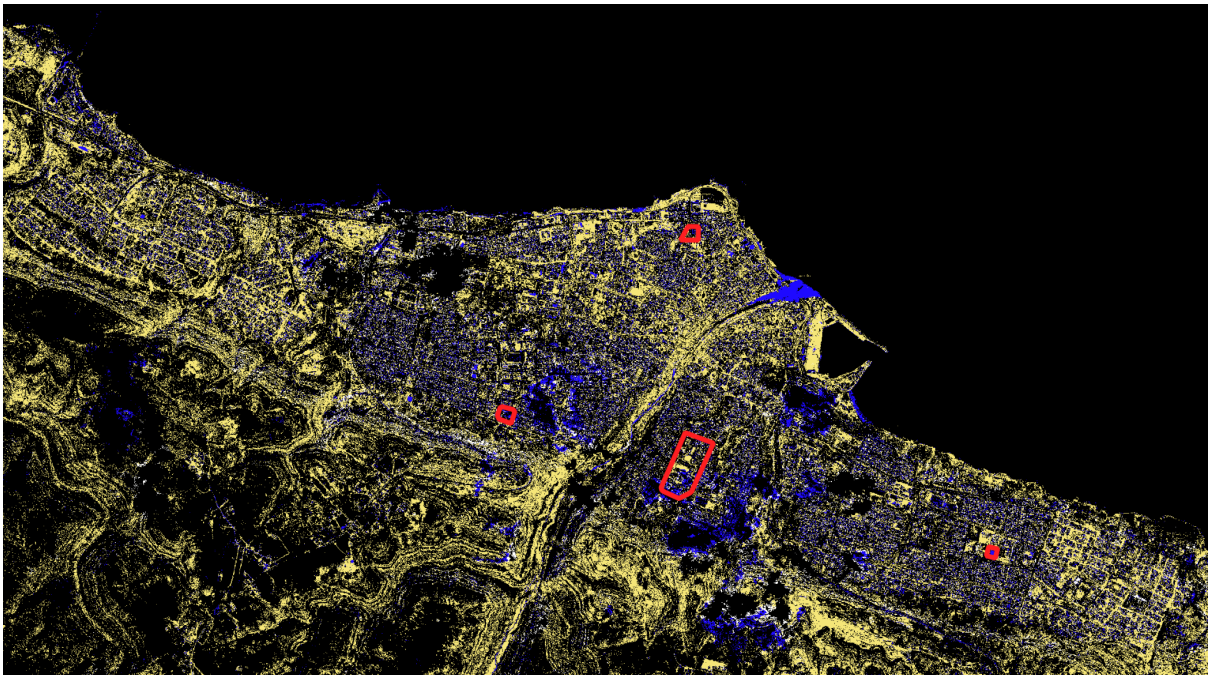


- Load the healthcare facilities layer into QGIS

You should see four healthcare facilities in Derna city.

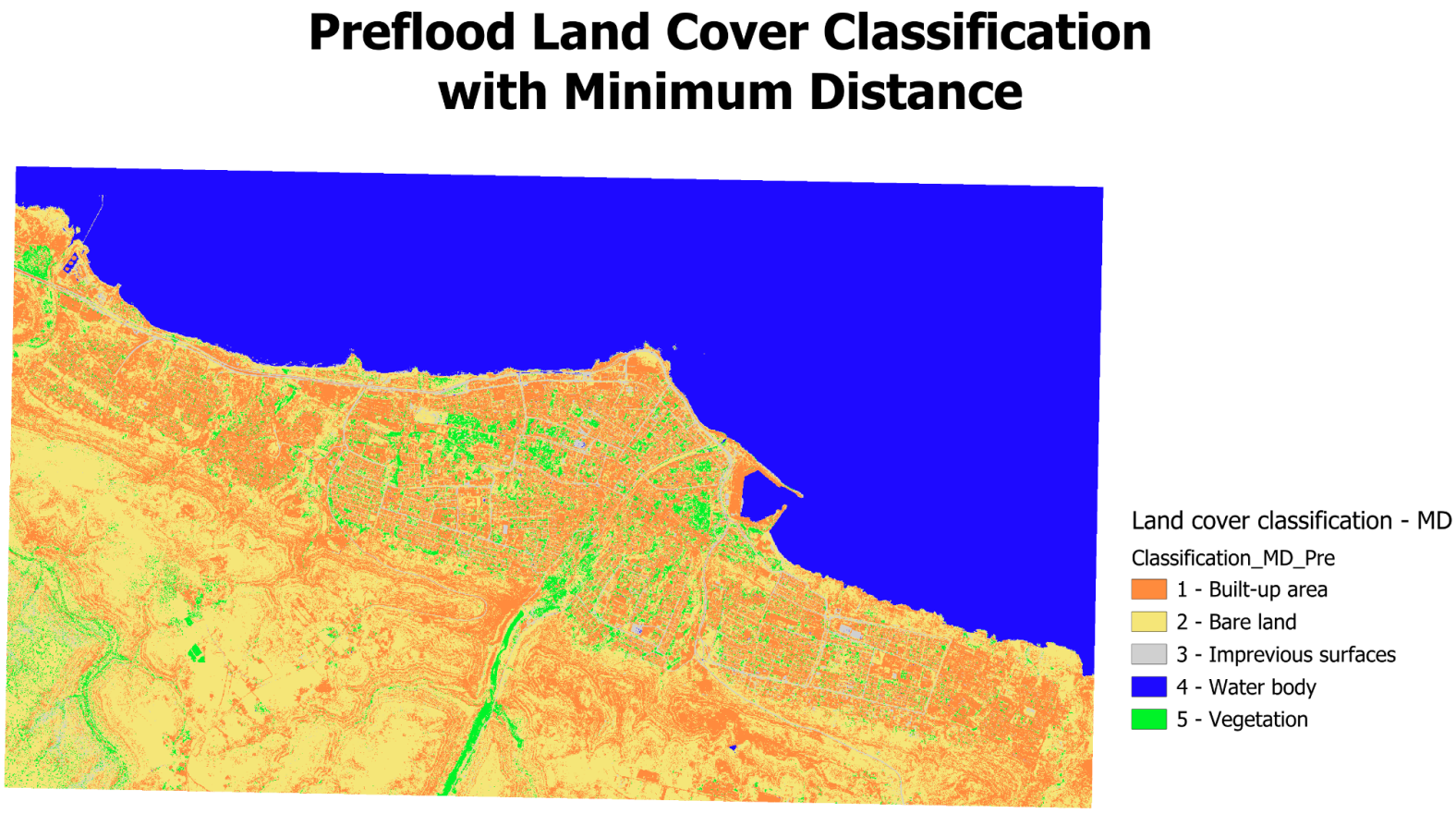
- Right click the layer and click Properties. Choose Outline: Simple Line

You may also want to change the colour to red.

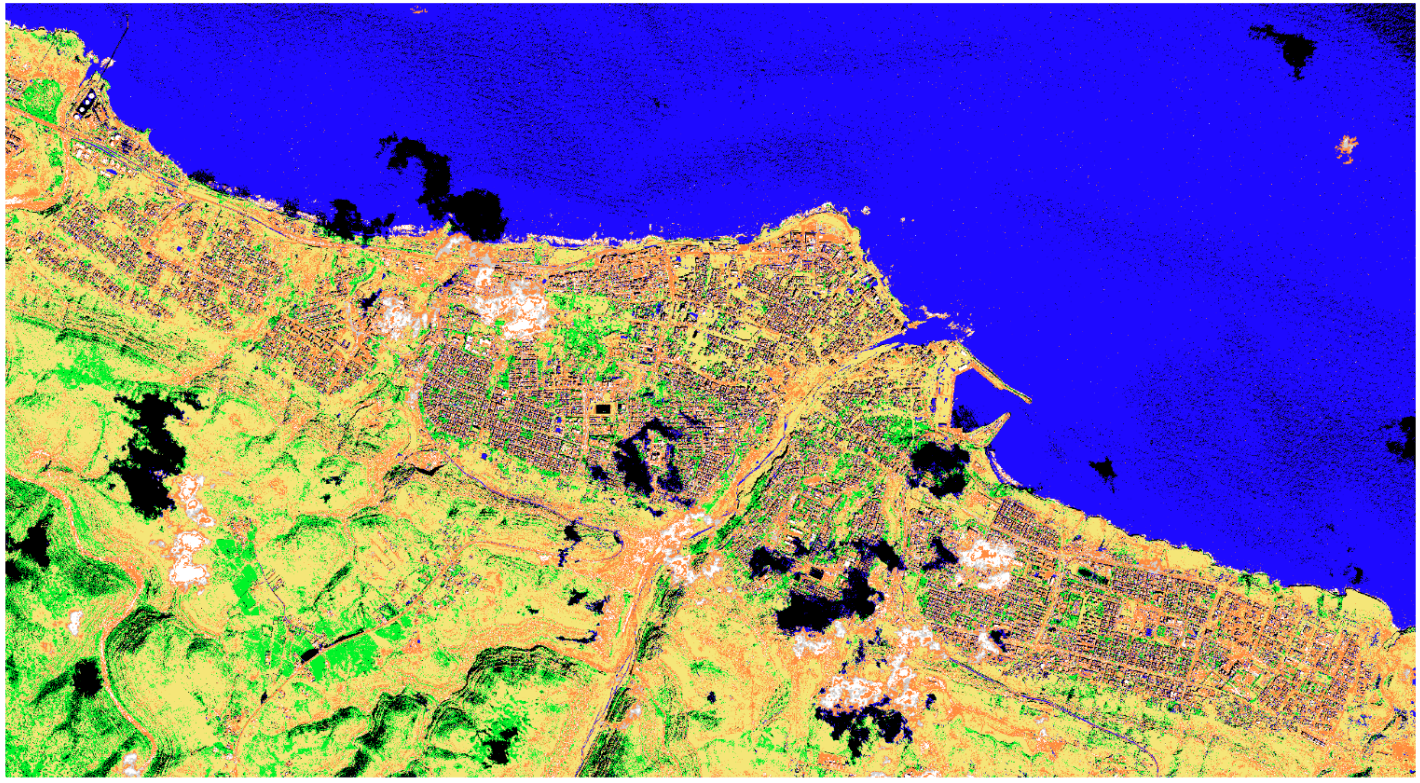


Section 12: Analysis and results

12.1: Land cover classification



Postflood Land Cover Classification with Minimum Distance



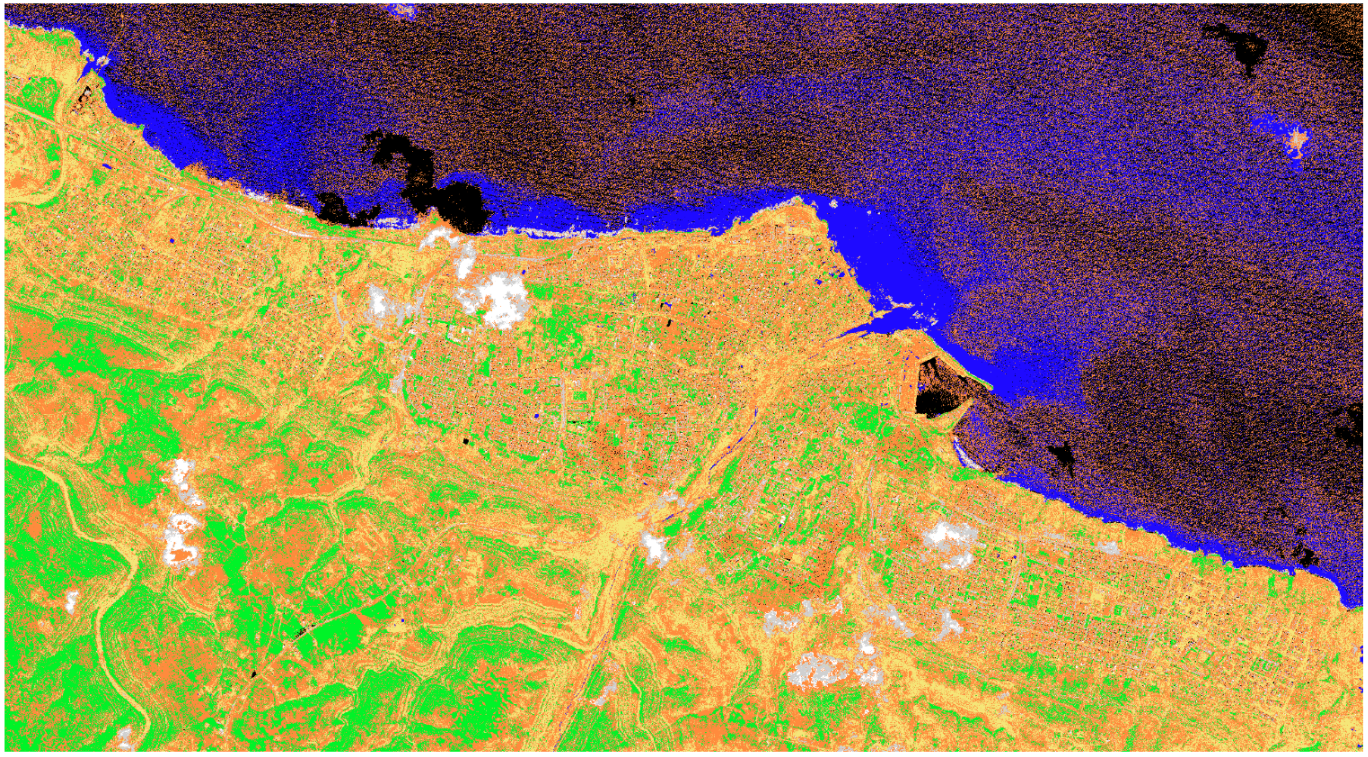
Land cover classification - MD

Classification_MD_Post

- 1 - Built-up area
- 2 - Bare land
- 3 - Impervious surfaces
- 4 - Water body
- 5 - Vegetation
- 6 - Cloud
- 7 - Cloud shadow

Preflood Land Cover Classification with Random Forest

Postflood Land Cover Classification with Random Forest



Land cover classification - RF

Classification_RF_Post

- 1 - Built-up area
- 2 - Bare land
- 3 - Impervious surfaces
- 4 - Water body
- 5 - Vegetation
- 6 - Cloud
- 7 - Cloud shadow

12.2: Accuracy of classification

Overall Accuracy and Kappa Hat Classification is used to evaluate the accuracy of classifications. The Overall Accuracy is a measure of the proportion of correctly classified pixels over the total number of pixels, whereas Kappa Hat Classification is a discrete multivariate technique used in accuracy assessments, with values ranging from 0 - 1. The closer to 1, the better the strength of agreement or accuracy. A summary of the Overall Accuracy and Kappa Hat Classification score for Minimum Distance and Random Forest algorithms on the 2 layers can be seen in the table below.

Classification Method	Minimum Distance		Random Forest	
Layer	Preflood	Postflood	Preflood	Postflood
Overall Accuracy (%)	88.30	78.48	83.93	53.99
Kappa hat	0.823	0.7093	0.7768	0.4354

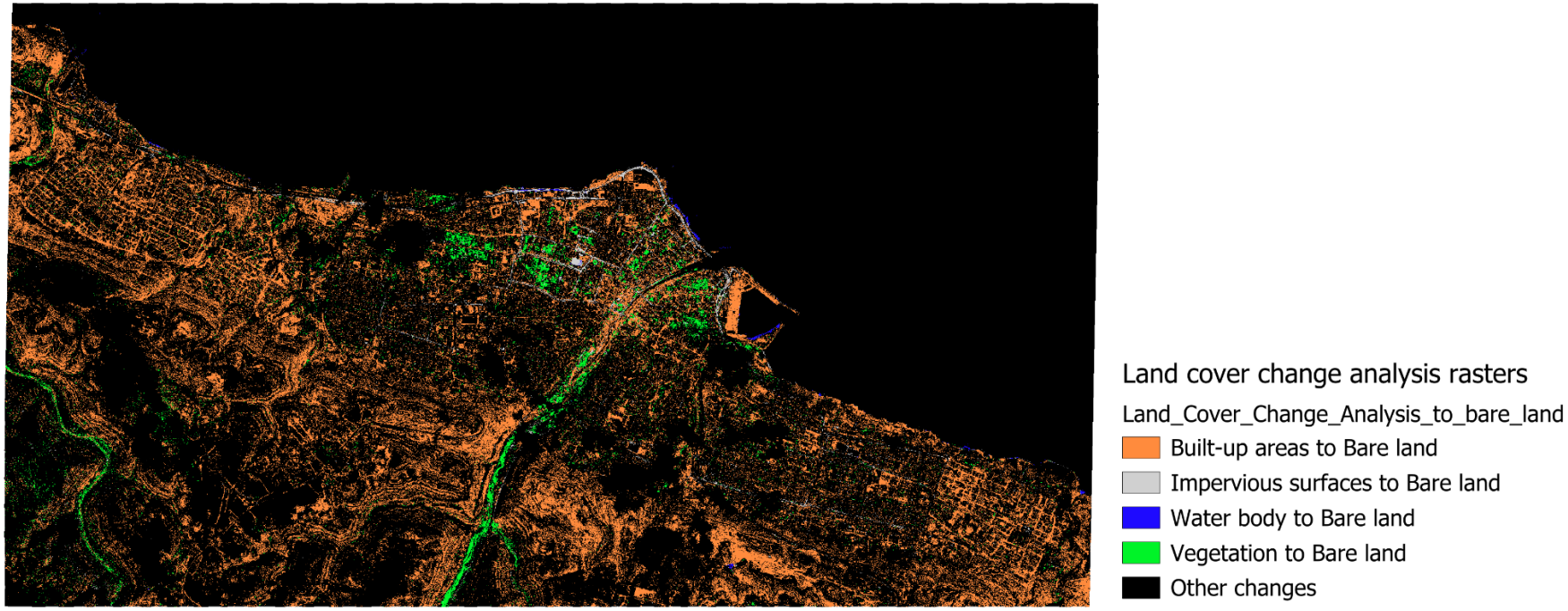
We also looked into the finer details of the per-class accuracy using the Producer's and User's Accuracy metrics (PA & UA) and noted that the differences in PA and UA were quite different among classes. This may be a result of spectral similarities between some classes, resulting in misclassification between the classes. Even after trying to vary and increase the training input ROIs for the classes, PA and UA still remained low for some classes. This is a limitation of our classification that might result in an inaccurate classification and change detection map.

Since the Overall Accuracy and Kappa Hat Classification of Minimum Distance is better than Random Forest, the results of classification from the Minimum Distance is used for analysis of change in land cover in the subsequent sections

12.3: Change in land cover classification

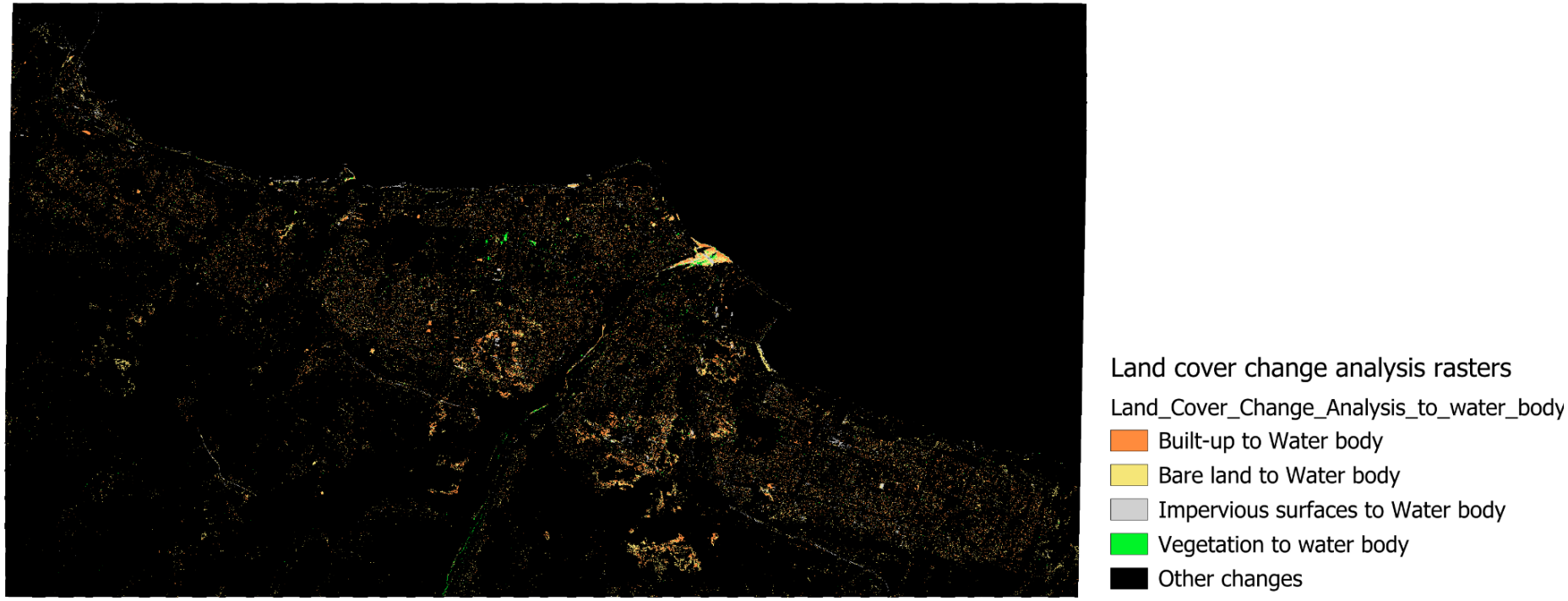
Using SCP's land cover change function, we conduct land cover change analysis of pre and post flood layers classified with the Minimum Distance algorithm in Section 9. We sieved out areas that changed to Bare land and Water body to identify areas of damage and flooding respectively. Results can be seen in figures below

Land Cover Change to Bare Land of Derna City after Flooding



Observations: The map above for the land cover change to bare land shows that for the land in closer proximity Wadi Derna and the mouth of Wadi Derna (where the river meets the ocean) have generally more changes from other land types to bare land. It also appears that there was more damage to Built-up areas to the East of Wadi Derna, indicating that the East part of Derna may be more prone to flood damage.

Land Cover Change to Water Body of Derna City after Flooding



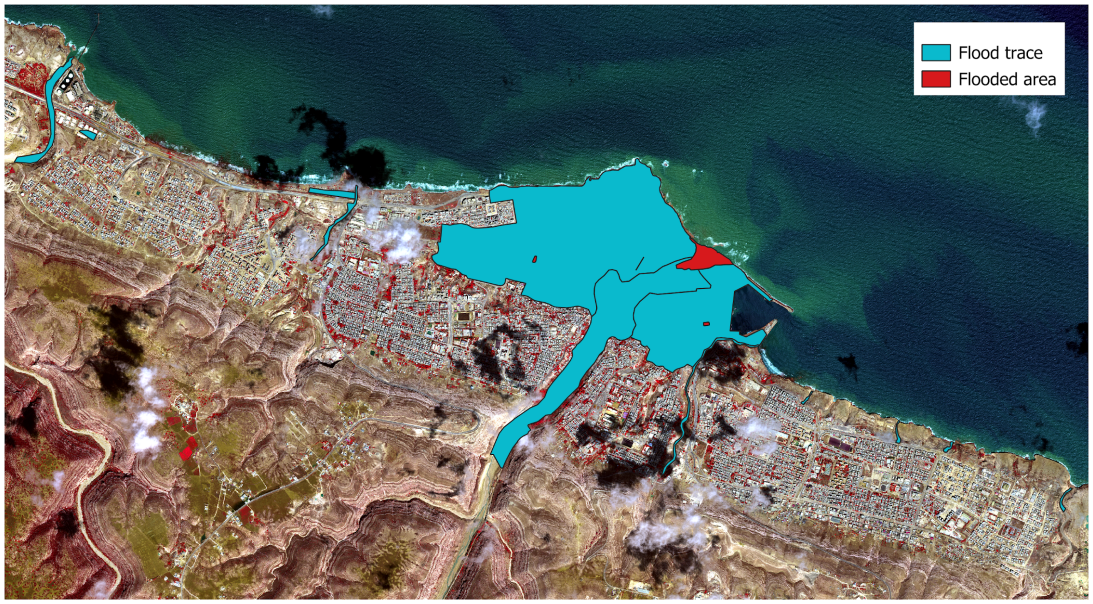
Observations: The map above for land cover change to Water body shows that the flooded areas as of 13 September (one day after the flood) are near the mouth of Wadi Derna where the river met the ocean. It shows that the flood had subsided in most areas, though some previously vegetated areas remain inundated. This may be because vegetated areas contained higher

amounts of moisture before the flood, making them unable to absorb all the flood water that inundated that area. Other areas, however, were likely drier and thus were able to absorb flood waters.

12.4: Cross checking with other sources

We have also cross checked our analysis with other sources about the Libya floods, from COPERNICUS Emergency Management Service - Mapping as outlined in Section 10. The data shows flood trace and flooded areas as of 14 September 2023, shown in the figure below.

Flood Trace and Flooded Areas of Derna City



By comparing the above figure with the land cover change to water body of Derna City after flooding, we are able to observe that reported flooding areas at the mouth of Wadi Derna (in red) corresponds to the water body areas identified from land cover change

Section 13: Recommendations

13.1: General Recommendations

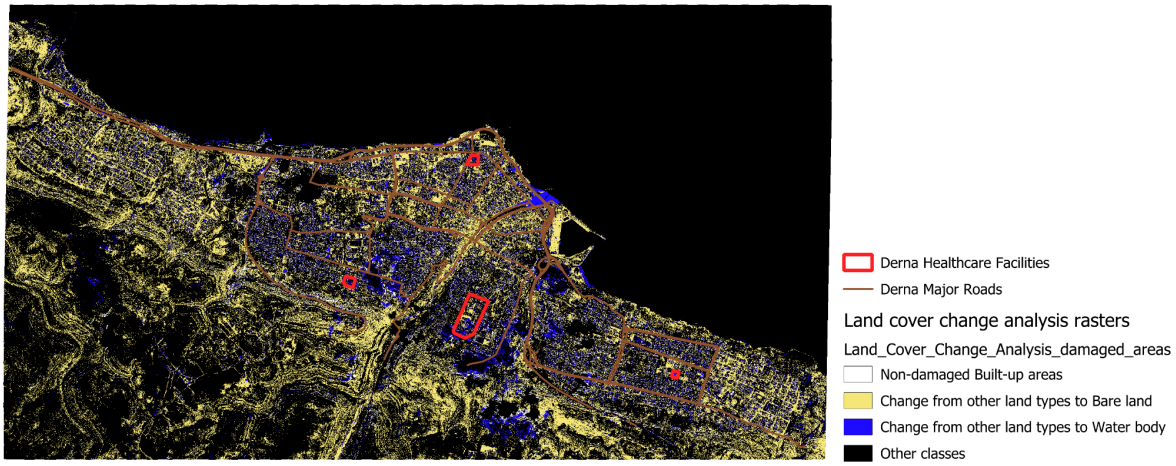
Given the observations above on the land cover change, there should be measures in place to avoid disastrous impact of floods in the future, some of which include:

- Avoid building settlements and buildings near the Wadi Derna and areas that were heavily impacted by this flood (flooded areas and areas with flood trace)
- Rebuild the dams using an asphalt-concrete core
- Build flood walls along Wadi Derna

13.2: Recommendations for Emergency relief facilities

In addition, areas that were turned into Bare land and Water body after the flood (damaged areas), non-damaged areas and Derna's healthcare facilities and major roads were identified for recommendations to locate emergency relief facilities.

Damaged areas of Derna City after Flooding



All the healthcare facilities appear to have suffered damage from the flood (is currently bare land or flood waters). In light of this damage and the flood, there might need to be temporary healthcare facilities set up. Our group recommends setting up temporary healthcare facilities in non-damaged built-up areas as there may not be enough time and resources to set up new facilities due to the urgency of treating injuries.

However, it must be noted that closer inspection should be done on the ground before selecting this area as temporary healthcare facilities as not all factors determining suitability can be seen from this map.

Overall, as can be seen by the above map, Derna suffered widespread damage that didn't spare any area in particular. Due to the damage on road networks, transportation across Derna may be difficult. Therefore, emergency relief facilities such as healthcare facilities and food banks should aim to be distributed across the city and make use of existing built-up areas before evacuation and/or rebuilding efforts are in place.

Section 14: Limitations and extensions

There are limitations to our analysis including the inaccuracy of Classification using SCP. Even for the more accurate minimum distance algorithm, the Pre-Flood and Post-Flood classification had accuracy of 88.3% and 78.48% respectively. There is a notable number of pixels that are misclassified. This may be because the classification algorithm classifies each pixel without taking in contextual information, resulting in classification where there is incorrectly classified "noise" amongst correctly classified pixels. Therefore, the extent of change for each land type may not be accurate. However, when drawing insights from the land cover change map visually, this noise may not affect the eventual conclusions significantly as our eyes see the bigger picture.

In the future, other tools such as LSMSSegmentation using the Orfeo Toolbox plugin can be experimented with. Segmentation may provide more accurate results and overcome the noise issue as it draws out regions from the raster before classification is performed by region (instead of by pixel).

A limitation to the recommendation of suitable sites for temporary healthcare facilities is that we do not know all the challenges Derna is facing or the exact situation on the ground. Recommendations for location of healthcare facilities should take into account factors such as safety of the location and the need at the location. Therefore, more research could be done on the needs and challenges Derna is facing before making these recommendations. Additionally, closer inspection should be done on the ground before selecting this area as temporary healthcare facilities as not all factors determining suitability can be seen from the maps.