# Image Classification

*Name: Nishit Patel*
*Email: n.t.patel@student.utwente.nl*
*Student No.: s2872129*
*Date: 9th June 2022*

# Contents



# Figures

# 1. Introduction

### Background and Study Area:

Weather Extremes such as ‘Droughts’ are becoming more common in Australia because of climate change. In the face of such extremes, it is critical to keep the geo-information up to date. One such scenario would be to monitor land cover changes in chaotic environments such as Darwin City (NT), where the surrounding environment contains a wide range of habitats and elements, as these changes could potentially impact local or global climate.

Darwin is a city located in the tropical north of Australia. It is also called the Australian gateway to Asia.


*Figure 1: Study Area (Darwin City, NT, Australia)*

# 2. Data

### Data Source:

Sentinel-2 data was used for this assignment. A Sentinel-2 image was obtained from the USGS website. The corresponding tile number of the image is 'T52LGM', and the acquisition date is 14/05/2020. The true color composite of the study area obtained is shown below (the original image is cropped to the study area of Darwin city and its surroundings).

***Figure 2: True Colour composite of Sentinel-2 image over the study area (overlaid on OSM)***

**Data Description:**

The spatial resolution of all Sentinel-2 bands is shown in the following table:

| *Band* | *Resolution (m)* |
|---|---|
| 1 (Coastal Aerosol) | 60 |
| 2 (Blue) | 10 |
| 3 (Green) | |
| 4 (Red) | |
| 5 (Vegetation Red Edge) | 20 |
| 6 (Vegetation Red Edge) | |
| 7 (Vegetation Red Edge) | |
| 8 (NIR) | 10 |
| 8A (Vegetation Red Edge) | 20 |
| 9 (Water Vapor) | 60 |
| 10 (SWIR – Cirrus) | |
| 11 (SWIR) | 20 |
| 12 (SWIR) | |

*Table 1: Sentinel-2 bands and their Spatial Resolution*

As shown in the table, Sentinel data is available at fine resolution, which is suitable for creating products that can be used to monitor land cover changes.

Sentinel-2 has a 12-bit radiometric resolution and high spectral resolution (13 bands). This is sufficient to achieve optimal target separability.

Sentinel-2 has a temporal resolution of 10 days, which is sufficient for monitoring land cover changes because land cover changes are often slow processes. Thus, it is possible to get away with only analyzing one image per season in a year in some cases.

# 3. Filtering

Because the study area is a complex environment with many elements interacting with one another, a combination of filters was used to better define the shape of objects in the defined study area and make them more separable.

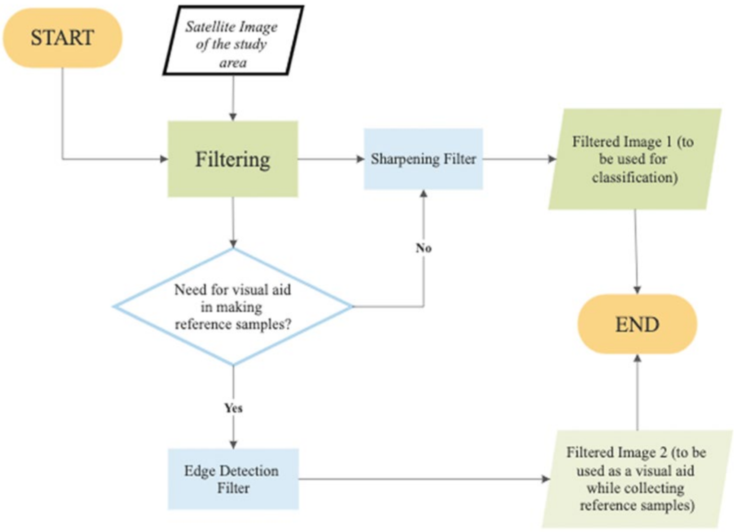


*Figure 3: Flowchart for 'Filtering' process*

## Sharpening Filter:

First, a custom sharpening filter based on inverting the Gaussian blurred image was applied. This filter reduces spectral contrast within objects while also improving shape definition.

*Figure 4: A region in the study area unfiltered (left)*

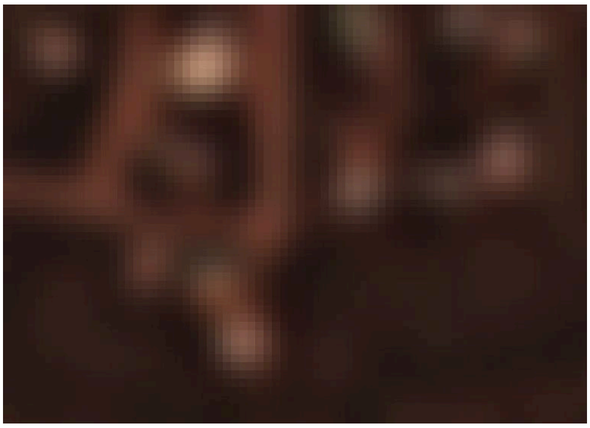

*Figure 5: Same region in the study area sharpened using Gaussian blur filter*

*(Note: The change in colour is due to the change in radiometric values)*

Because this filter was built with the ‘Scikit-Image’ library’s Gaussian filter, the only parameters used were ‘sigma’, which controls the standard deviation of the gaussian kernel. The blurring effect increases as sigma increases. As a result, the sigma value was set to 1 because the image contains no noise and has a high spatial resolution, thus, more blurring could potentially obscure the details. Another parameter that was changed was ‘channel axis’, which tells the algorithm whether the image is multiband or single band.

*Figure 6: Sharpened Image of the study area (to be used for classification)*

**Canny Edge-Detection Filter:**

A canny edge detection filter was also used to assist the analyst in collecting reference samples for the classification, as the sharpened image obtained from the first filter could sometimes cause difficulty in defining the class boundaries.

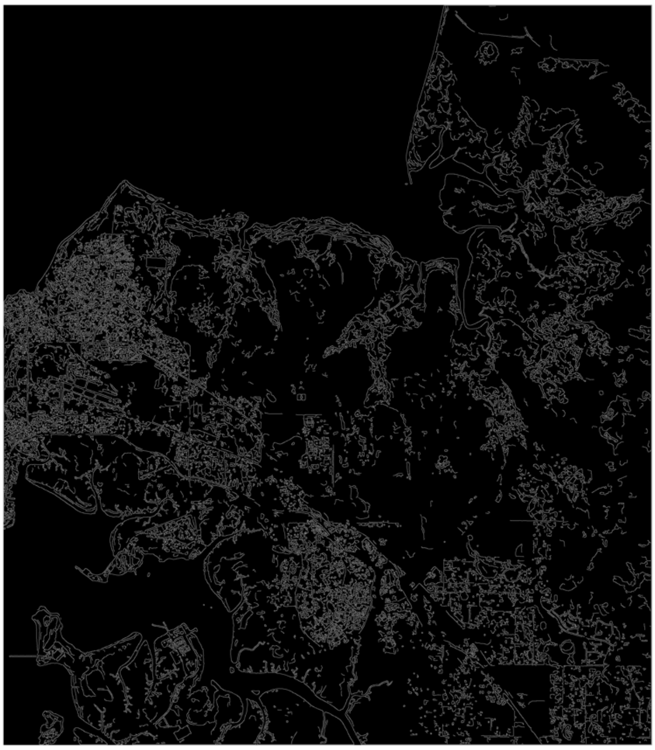

*Figure 7: Canny Filter edge image (sigma = 2)*

## Discussion:

As can be seen from the filtered image results, both sharpened and edge filtered images are appropriate for their respective filtering purposes. However, for the dataset at hand, it would have been preferable to use only the 'canny' filter, as the use of the sharpening filter resulted in some quality and details being lost. On the other hand, one could argue that the spatial resolution of Sentinel-2 data is so good that using low sigma values does not affect the level of detail when looking at classification-related products from a large-scale monitoring perspective. This can be evaluated by comparing the classification results obtained from classifying the filtered image to the results obtained from classifying an unfiltered Sentinel-2 scene. That, however, is outside the scope of this assignment.

# 4. Classification

### Purpose and Algorithm:

We could use both pixel-based and object-based classification to derive crisp land cover information. However, in the case of object-based classification, the accuracy of the classified image is heavily dependent on the parameters of 'Image Segmentation', which are typically tuned using trial and error methods. Thus, if we want to derive classified images for the purpose of regular monitoring, it is preferable to use a pixel-based classification approach to make the classification process more robust. As a result, for this assignment, the image was classified with a pixel-based approach using the 'Decision Tree Classifier'.

Based on certain criteria, the decision tree classifier begins to split into internal nodes from the root node until it reaches individual leaves that represent a specific class label. These nodes can split in a variety of ways, the most common of which are 'Gini Impurity' and 'Information Gain'.

### Process:

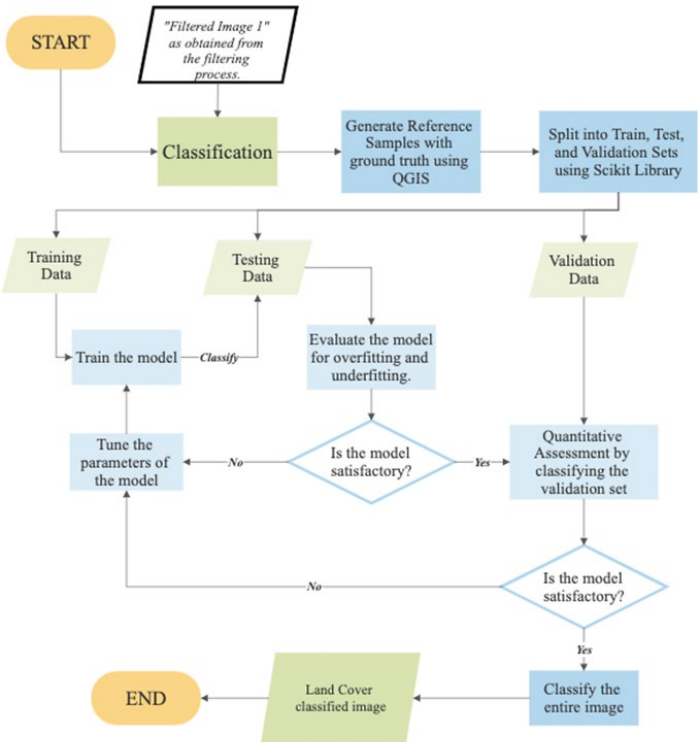


*Figure 8: Flowchart for 'Classification' process*

When creating the reference samples, the class proportions had to be evaluated, i.e., the land cover class in the sample should represent the same percent of area as it does in the population. The study area was divided into five landcover classes for this assignment: 'Water', 'Gray Areas' (which includes both urban and rural areas), 'Green Areas' (which includes anything green – small patches of grasslands, parks, gardens, etc.), 'Mangroves', and 'Bare Surface'.

To achieve 'proportionate samples', an ESRI landcover map of the same area was downloaded. Filtering this reference map with the land cover classes and calculating proportion yields the table below:

| ***Class*** | ***Proportion*** |
|---|---|
| Water | 29% |
| Gray Areas | 5.6% |
| Green Areas | 35.% |
| Mangrove | 12.3% |
| Bare Surface | 17.12% |

***Table 2: Proportion of land cover classes in the study area as obtained from ESRI Landcover Map***

Reshuffling the proportions as it is redundant to have 29% of samples representing the class of 'Water'.

| ***Class*** | ***Proportion*** |
|---|---|
| Water | 9% |
| Gray Areas | 10.6% |
| Green Areas | 40.8% |
| Mangrove | 17.3% |
| Bare Surface | 22.12% |

***Table 3: Reshuffled class proportions in population (entire study area)***

The proportion values of the reference samples were designed to match the population. Furthermore, reference samples were collected from all areas to achieve randomness, ensuring that the final accuracy for different regions within the same study area was consistent.

| *Class* | *Proportion* |
|---|---|
| Water | 6.99% |
| Gray Areas | 9.78% |
| Green Areas | 39.7% |
| Mangrove | 22.21% |
| Bare Surface | 21.26% |

*Table 4:Proportion of land cover classes in the reference samples*

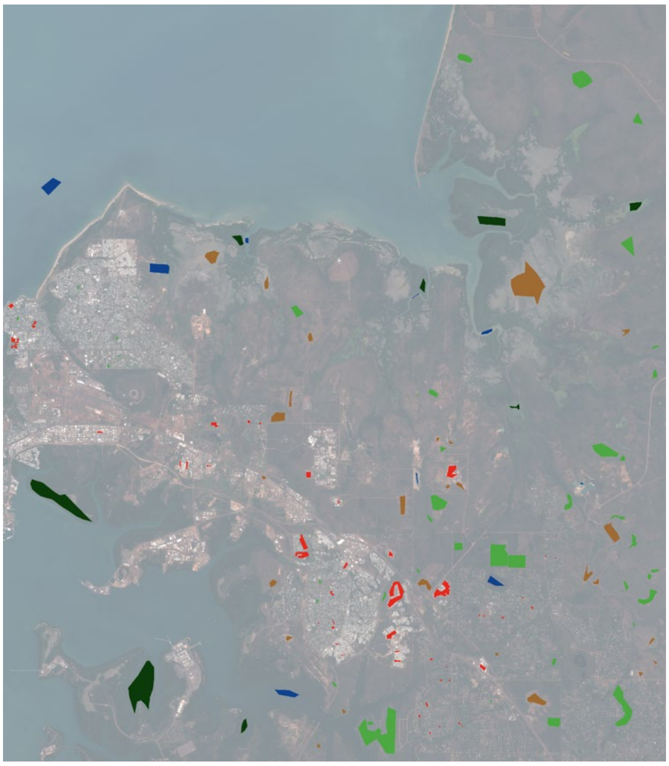

*Figure 9: Distribution of Reference Samples*
*(Note: for Legend, please see the classified image – Figure 11)*

The reference data was then divided into three parts: training, testing, and validation sets (with a 60/20/20 split). The 'stratify' parameter of the 'train_test_split' function (Scikit Library) was used to achieve stratified data while splitting the reference data into train, test, and validation sets to ensure there is no 'class imbalance' in the samples. The samples were now ready for classification.

The Decision Tree Classifier from Python's Scikit Learn Library was used to perform the classification. Overfitting is a well-known characteristic of the Decision Tree algorithm. ‘Pruning’ the tree is one method for controlling overfitting. The ‘max_depth’ parameter can be used to accomplish this.

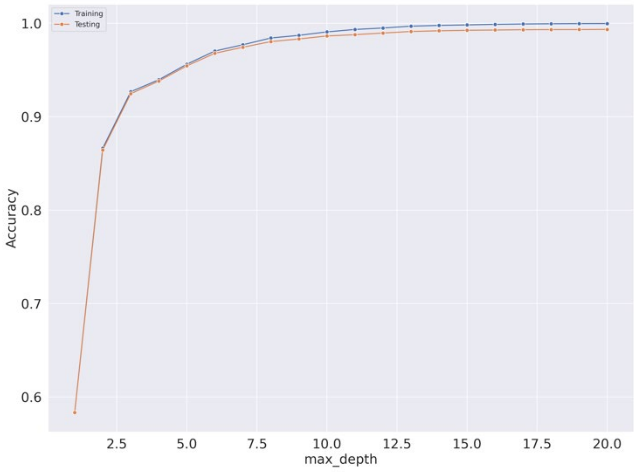


*Figure 10: Accuracy (Training + Testing) v/s ‘max_depth’ parameter*

As one can see, surprisingly, there is only small overfitting in our model. The ‘max_depth’ parameter of 5 was selected to classify the validation set. Other parameters like ‘criterion’, ‘min_samples_split’, and ‘min_samples_leaf’ were kept on default as the results obtained by pruning with ‘max_depth’ were satisfactory.

Now, the model was ready to classify the entire study area. Below is the classified image of the study area.

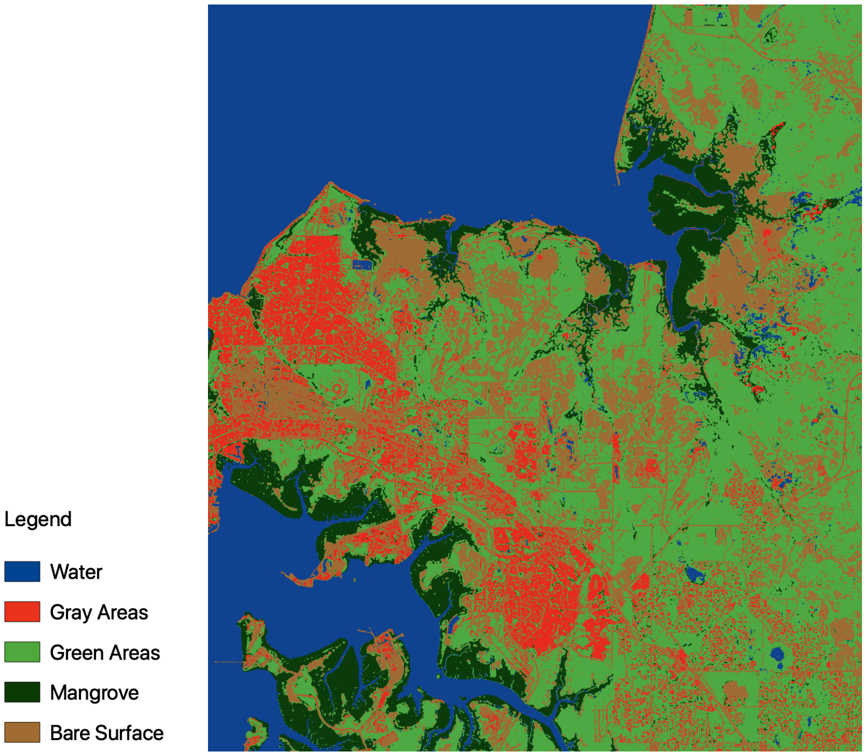


***Figure 11: Classified Image of the study area***

## Quantitative Assessment:

An overall accuracy of 95.24% with a Cohen's Kappa score of 0.93 was achieved while evaluating the model using the validation set. The confusion matrix of the same is given below.

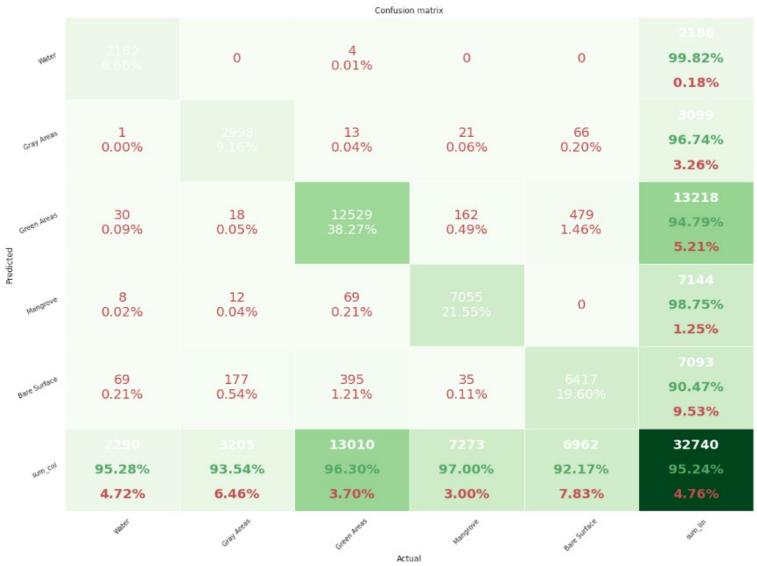


***Figure 12: Confusion Matrix***

In addition to overall accuracy, user and producer accuracies are quite high. One possible explanation for such high accuracy values is that the reference samples only represent 2% of our study area. As a result, one could argue that if the number of training samples was large, the accuracy would suffer. On the other hand, because water covers 29 percent of the area, having many training samples for such classes is unnecessary, and if one only increases samples of a particular class to have reference samples represent 20 percent of the study area, problems with class imbalance may arise. However, the project can undoubtedly be improved by using more reference samples, and the accuracy values may then be reduced to more realistic and practical levels. And whether to do so can be determined by conducting a qualitative analysis of the output.

## Qualitative Assessment:

When the classified map was visually compared to basemaps and the ESRI reference land cover map, it was discovered that the area covered by Mangroves was underestimated. This can be improved by calculating some Mangrove indices and adding them as bands to the raster because these indices would carry more 'feature importance' corresponding to Mangrove class and the Decision Tree algorithm can get pure leaves using these indices. The same technique can be used for other land cover classes, such as NDVI, NDBI, and NDWI, which can assist the algorithm in classifying the classes more accurately.

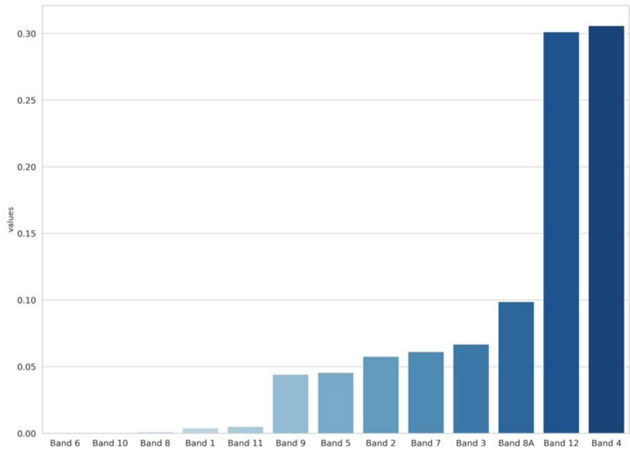


***Figure 13: Feature Importance values of bands***
***(Note: The higher the value the better is the band at classifying the defined land cover classes)***

Aside from that, near the coastline, some of the 'Bare Surface' pixels are misclassified as 'Gray Areas'. There are also minor object shape errors here and there. However, the overall quality of the classified image is good, but it is nowhere near 95.24%, as the quantitative assessment indicates.

# 5. Conclusion

Based on the project's findings, we can conclude that applying filters to fine resolution/noiseless images may not aid in classifying the filtered image. Filters, on the other hand, can assist the analyst in collecting better reference samples. In terms of classification, qualitative analysis is an important task that should be completed to make more sense of the quantitative assessment numbers. This may reveal some sources of uncertainty that are not reflected in quantitative metrics. And as an effort to make better classification, additional information such as indices, textural information, and much more can be added as bands to the input image.

# 6. Resources

The python notebooks are available here