Practical Environmental Measurement Techniques

Lab Report

Satellite Image Analysis

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Group A

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1 Introduction

This experiment was conducted to acquire an understanding of the methods of analysis of the images captured by the earth observation satellite in lower earth orbit(LEO) Landsat 8. It has been in service since 2013 and orbits the earth at an altitude of 705km with a high inclination sun synchronous near-polar orbit. The Thermal Infrared Sensor(TIRS) and the Operational Land Imager(OLI) are its two primary sensors. In this experiment we analyse images taken with the OLI. The OLI is a push broom sensor that operates passively in the near-infrared and visible spectrum region and has a 185km swath at which it maps most of the earth's surface with a 16-day repeating cycle[1].
The sensor in the focal plane has a total of 9 respective channels or bands, each covering a different part of the observed spectrum. They are listed below(see table 1).

Even though the channels of the sensor are given 12-bit quantisation, a 16-bit quantisation is used for the images provided by the Landsat operator. The data is then sequentially stored in subdivided scenes of which each one possesses a row and a path number as well as a timestamp and is available for download on the earth explorer website. Each scene is stored in a 3-D Matrix with two dimensions being the respective sensor channels.

Table 1: Operational Land Imager (OLI) sensor channels, wavelengths and spatial resolution and their typical applications.

Channel	Colour	Wavelength	Resolution	Typical Application
1	Ultra Blue	0.435 - 0.451μm	30 m	Coastal/Aerosol
2	Blue	0.452 - 0.512μm	30 m	
3	Green	0.433 - 0.590μm	30 m	green reflectance of heavy vegetation
4	Red	0.636 - 0.673μm	30 m	chlorophyll absorption of plants
5	NIR	0.851 - 0.879μm	30 m	biomass surveys and water bodies
6	SWIR1	1.566 - 1.651μm	30 m	
7	SWIR2	2.107 - 1.294μm	30 m	
8	Panchromatic	0.503 - 0.676μm	15 m	
9	Cirrus	1.363 - 1.384μm	30 m	Clouds

2 Experiment

The scene from the Landsat Imager was analysed in *JupyterNotebook* with the *python* programming language. A worksheet was provided with the essential code functions and directions on the procedure of the analysis.

2.1 Loading the Scene

From the collection of scenes from the Landsat[2], a data-set was chosen and loaded onto the *JupyterNotebook*. Areas with low vegetation and forest cover were among the criteria for selecting the scene in order to better distinguish between these features. The total scene has the shape (8051, 7971, 8), where the initial two numbers are the number of pixels in x and y directions respectively. The 8 represents the 8 different channels. The size of the image is $\approx$ 533 MB and the data is given as *unit* 16.Figure 1. shows the scene through the NIR. After loading the scene, eight channels are obtained.

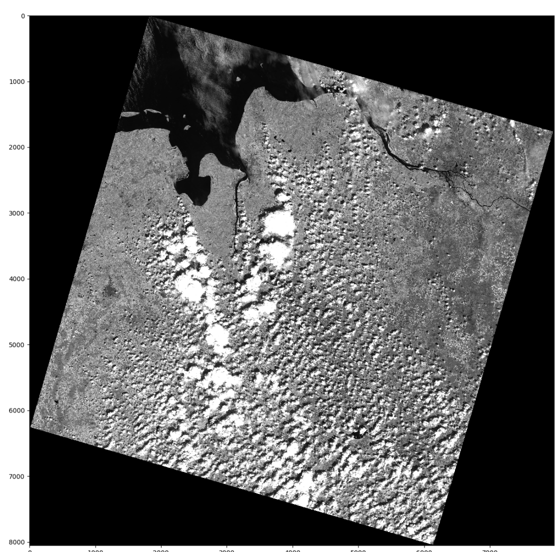


Figure 1: Full-size image of channel 5 (NIR). It has the scene identifier - $LC08\_L1TP\_196023\_20180712\_20200831\_02\_T1$.

2.2 Cropping into Hamburg and surroundings

A scene with sufficient pastures, forest cover and low vegetation was identified for analysis and cropped accordingly. Moreover, additional care was taken to ensure that parts of downtown Hamburg, industrial areas as well as the two airstrips were also included.
While viewing these images from the different channels it is observable that terrain features are barely distinguishable and only water bodies and some cloud features are distinctly identifiable. This is an issue that arises due to the poorly chosen black and white points in the histograms of these images where most of the intensity range is unused. These histograms are refined accordingly to enhance their respective images.

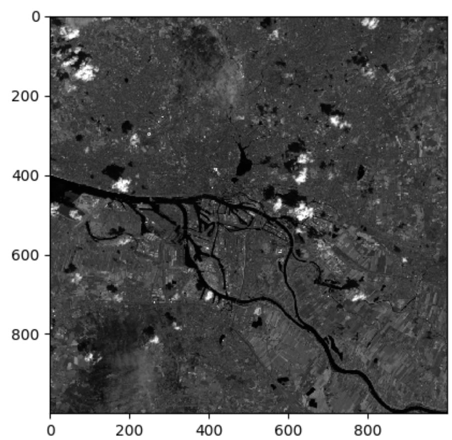


Figure 2: Channel 6 (SWIR1) of the cropped image matrix of Hamburg and it's surrounding with a size of 1000x1000 Pixels.

2.3 Histogram Refinements and Contrast setting

The contrast range is adjusted to refine the visibility in each channel and to prepare the data for further analysis by changing the histogram. Taking a look at the histogram of all the channels in Figure 3., it is observed that distribution only uses a narrow band of the entire available contrast range between absolute black(0) and absolute white(65535) points.

Extracting the mean value and standard deviation for each of the unedited channel images lead to those findings. The mean value refers to the mid-tone value in the histogram and the standard deviation gives us an idea of the contrast within the image. The smaller the standard deviation is the more the

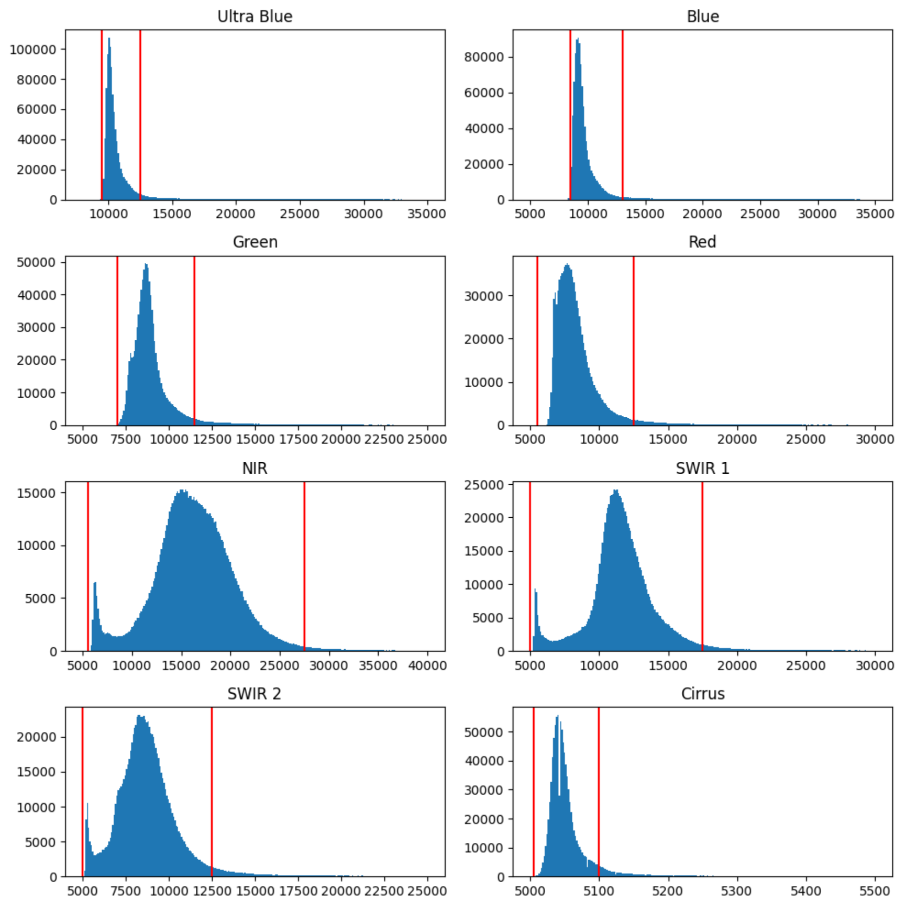


Figure 3: Refined Histograms (All Channels)

tendency of the histogram to pile up at a certain narrow range and the flatter the image looks and vice versa.
A predefined scaling function is used to scale the unedited histogram to a contrast range that results in an enhanced image. For each of the channels the range is manually & appropriately selected. After executing the command the output is a stretched histogram.

After scaling the images of each of the 8 channels, it is evident that there exists a clear difference between the scaled and unscaled images. In the contrast-enhanced scenes the surface features like forests and urban areas are now clearly visible.

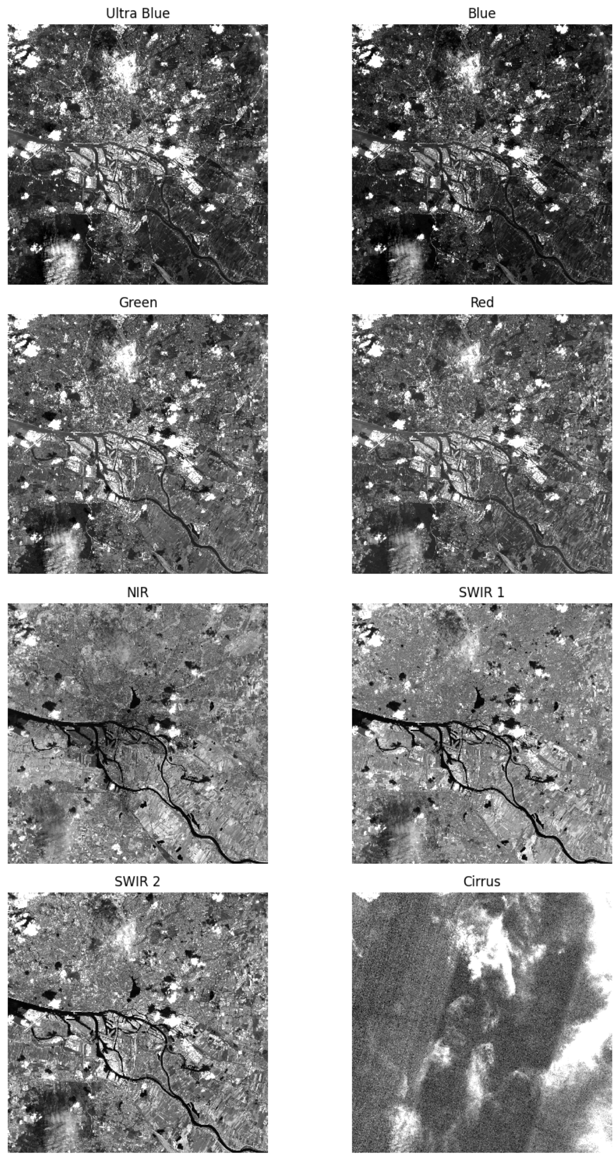


Figure 4: Contrast enhanced scenes of all the channels.

2.4 False Colour Images

A colour image has three channels whose respective grey-scale brightness levels are displayed as a red, green and blue composite (RGB). A true colour image assigns those red, green and blue colour channels to the same wavelength regions that the human eye perceives as those colours. To understand the relationships

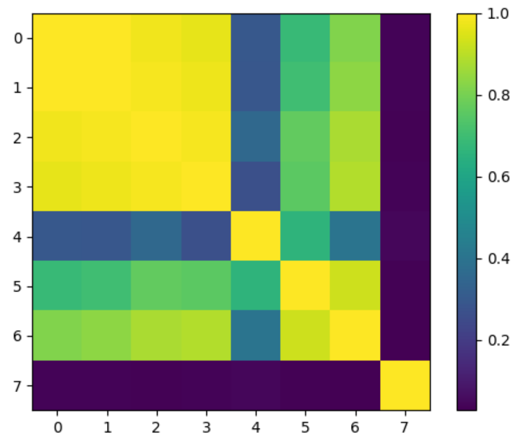


Figure 5: Matrix plot of the correlation coefficient analysis

between the different spectral bands used in this study, a correlation analysis was performed. The correlation plot(see figure 5) visually represents the degree of correlation between the channels.
High correlation, indicated by yellow regions, suggests strong interdependence between channels, such as between visible green channel and red bands. Moderate correlation, represented by green regions, indicates a moderate level of interdependence, as seen between NIR and SWIR2. Low correlation, indicated by blue and purple regions, shows weak or no correlation, such as between Red channel and SWIR2 channel, reflecting their distinct reflectance properties for different surface types.
This correlation information is crucial for selecting channels that maximize the information content in false colour images. High correlation suggests redundancy, whereas low correlation indicates complementary information. Understanding these correlations aids in better interpreting the false colour images. For instance, combining channels with low correlation, such as NIR and SWIR2, can enhance the contrast between different land cover types, improving classification accuracy.
When different channels for these red, blue and green colour channels are used a False Colour Image is generated. False colour images are crucial in satellite image analysis as they enhance the visibility of features not readily apparent in true colour images. By utilizing spectral bands beyond the visible range, false colour composites can highlight specific land cover types such as vegetation, water bodies, and urban areas. For this experiment 2 such false colour images were generated.Plants absorb strongly the red and blue wavelength, therefore they appear green. At the same time, they reflect even more in the NIR which is why vegetation appears red in the false colour image. Whereas water absorbs

strongly in longer wavelengths and less in shorter wavelengths, therefore it appears blue in our eyes. Instead in the false colour image, it will appear very dark, nearly black.

(a) False Colour Image 1 (b) False Colour Image 2

Figure 6: False Colour Images.

For the false colour image 1 (Figure 6.(a)), the red channel was assigned to the Near-Infrared (NIR) Band 5, the green channel to the Red Band 4, and the blue channel to the Green Band 3. In this combination, vegetation appears red due to high NIR reflectance, water bodies appear dark because of absorption of NIR and visible light, and urban areas show up in shades of cyan and blue.
In contrast, the false colour image 2 (Figure 6(b)) used the Cirrus channel Band 9 for the red channel, the Red Band 4 for the green channel, and the Green Band 3 for the blue channel. In this combination, vegetation appears in various shades of green and water bodies remain dark. One particulary noteworthy observation is that cirrus clouds which appear blue are profoundly identifiable.

2.5 Spatial Resolution

The Landsat 8 Data Users[1] Handbook states that the satellite images contain a uniform spatial resolution of 30 meters. To verify this, the dimensions of the scaled image of Hamburg and its surroundings were matched to a map from an open-source map software called OpenStreetMap[3].

In the scene from Channel 3, a few geographical features are identified and using these features as landmarks the same area is identified on the map from OpenStreetMap(see figure 7). These features are:

- The end of the north facing runway of the Hamburg Airport.
- The motorway intersection *Kreuz-Hamburg Ost* in the east
- The *Neßsand* landmass in the middle of the Elbe in the west.
- The straight part of the A1 just north of the *Maschener Kreuz* in *Seevetal* in the south.

Figure 7: Open street map showing the matched rectangle (left) and the cropped scene from channel 3 (right). The geographic features determining the scaling dimensions are highlighted in red boxes.

The map software then outputs us a latitudinal and longitudinal extension of the box as xmin, xmax, ymin and ymax. Knowing those and taking our picture size of 1000x1000 pixels into account we can calculate:

$$res_x = \frac{\Delta x \times cos(53.5°) \times 1.11 \times 10^5 m/°}{1000p} = \frac{0.449° \times cos(53.5°) \times 1.11 \times 10^5 m/°}{1000p} = 29.68 m/p \tag{1}$$

$$res_y = \frac{\Delta y \times 1.11 \times 10^5 m/°}{1000p} = \frac{0.264 \times 1.11 \times 10^5 m/°}{1000p} = 29.36 m/p \tag{2}$$

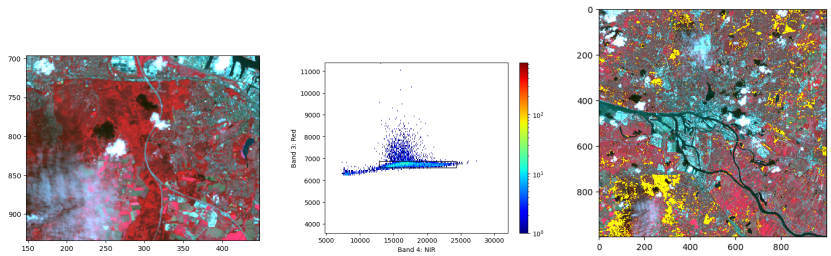
In the analysis, an estimated uncertainty of approximately 2 km in the extent of the cutout region was considered. This uncertainty could arise from potential mismatches or slight misalignments between the geographic features in the satellite image and the map. To ensure accuracy, this 2 km uncertainty was propagated into the spatial resolution estimate.
This 2 km uncertainty translates into a 2-meter uncertainty in the calculated spatial resolution, as the footprint calculation involves a scaling factor of 1/1000. Thus, both the latitudinal (Δy) and longitudinal (Δx) extents, as determined by the software, are subject to this estimated uncertainty. Taking this into account, the spatial resolution estimates are adjusted as follows:

$$res_x = 29.682 m/pixel$$
$$res_y = 29.362 m/pixel$$

This adjustment reflects the potential error due to uncertainties in the geographic cutout, ensuring that the final resolution estimate is both accurate and robust. Hence, it can be concluded that this method does in fact provide evidence that the spatial resolution of the images from Landsat 8 is 30 meters.

2.6 Manual Surface Classification

Manual surface classification is done to identify different surface types. This is done using an interactive image analyser tool in $JupyterNotebook$. Representative areas of a single surface type were marked by selecting rectangular patches in the scatter plot of the image using the analyzer tool.

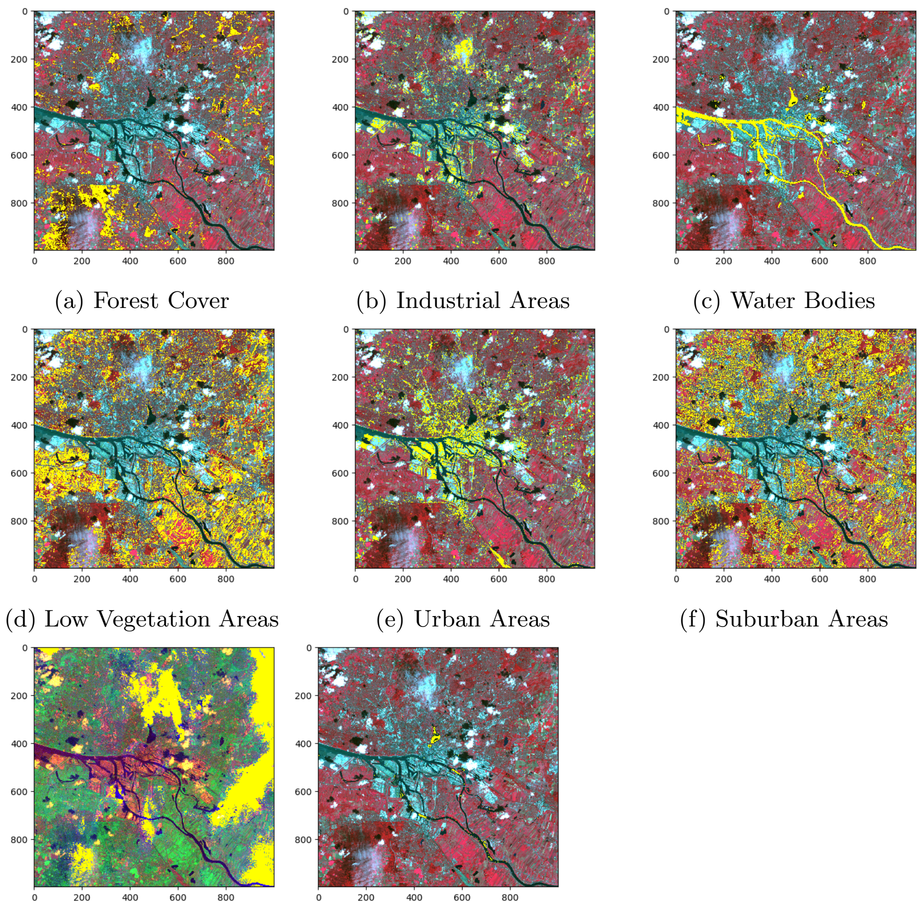


(a) (b) (c)

Figure 8: Backscatter signature of forest cover and its areal distribution. In (a) the areas where forest cover is visible were zoomed into in the original cropped image. (b) is the scatter plot from all values of the pixels that were selected. With a rectangle, the densest part of the plot was marked and then the pixels with the same values are shown in yellow over the entire image (c).

Areas with dense forest cover were chosen to be identified in figure 8(a). All these areas were marked and the analyser tool extracted their brightness levels in figure 8(b). The densest parts of this scatter signature were chosen and these pixels appear yellow across the image(see figure 8(c)). Seven other surface types were identified in a similar fashion(see figures 9 & 10). They are Industrial areas, urban areas, water bodies, Suburban areas, Cirrus clouds, the Außenalster and Low vegetation areas. Dense forest cover is distinguishable from meadows, grass cover and farmland. It is assumed that this is a phenomenon that occurs as a result of trees having more diffusive reflections than grass and farm crops. On the other hand meadows, grass and farm areas are not easily distinguishable as they appear to be approximate of the same height and their reflection and absorption properties are almost similar. A more obvious indicator of farming areas would be the linear farming lines along the field. Industrial areas are made identifiable with the help of their large shiny roofs which become much more evident as they appear a slight blue in the image. The motorway A7 also seemed to be included while identifying these areas.

While identifying water bodies, the *Elbe* is quite evident and along with it, the *Außenalster* is also identified. Since the $Wilstedter$ lake and $Stadtparksee$ lake in Norderstedt are relatively large water bodies, they also appear in the classification. Hence the water-filled areas are quite significantly identifiable.

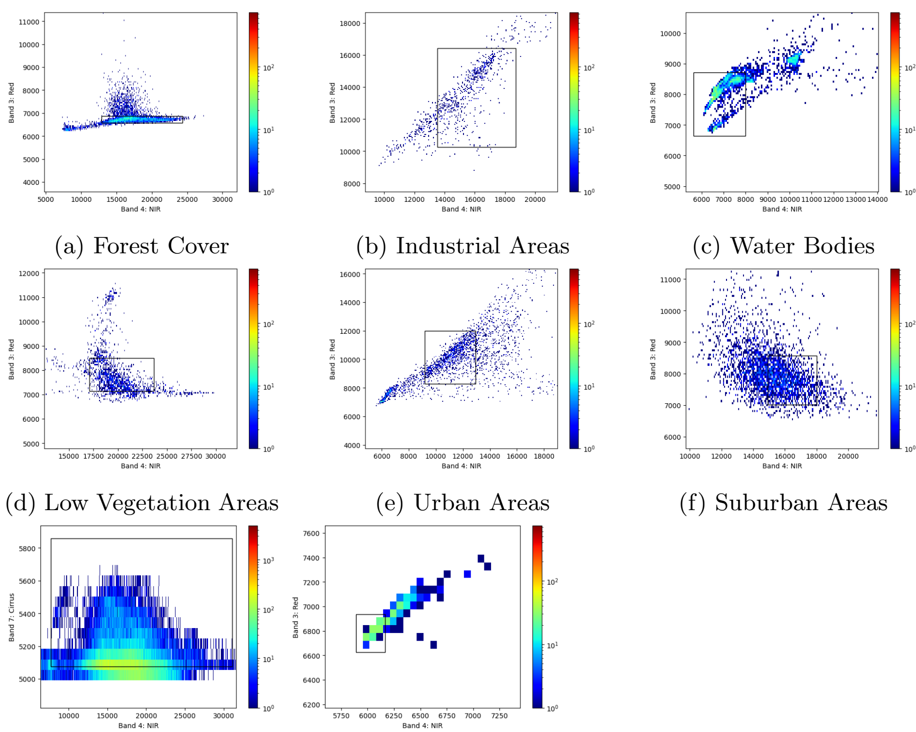


(a) Forest Cover (b) Industrial Areas (c) Water Bodies

(d) Low Vegetation Areas (e) Urban Areas (f) Suburban Areas

(g) Cirrus Clouds (h) The Außenalster

Figure 9: The manually identified surface types shown up in yellow(called the range display) after the densest parts in their respective scatter plots were marked.



(a) Forest Cover (b) Industrial Areas (c) Water Bodies

(d) Low Vegetation Areas (e) Urban Areas (f) Suburban Areas

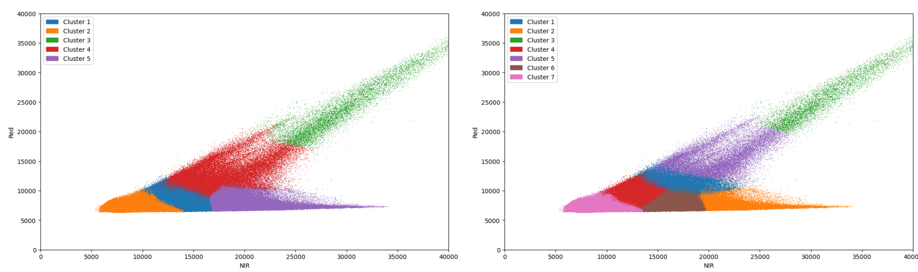
(g) Cirrus Clouds (h) The Außenalster

Figure 10: Scatter plots of the pixel values for different surface types. The rectangles show the refined selection of the pixels. Mostly the densest part was marked to obtain a good selection for the surface types.

2.7 Automatic Surface Classification

In the final part of the experiment, the computer is made to identify different surface types. It is done with the help of an algorithm called the K-Means algorithm. This algorithm identifies different clusters by taking pixels with similar brightness across all channels and assigns them to a number of desired clusters. A flat version of the image is created and all channels are stored into single vectors and a scatter plot is plotted.

This K-Means algorithm is made to search for five and seven different clusters



(a) Classified scene with 5 clusters (b) Classified scene with 7 clusters

Figure 11: Scatter plot showing the Classified scenes using the K-means cluster algorithm. The algorithm searched for five(a) and seven different(b) clusters and marked their associated wavelength regions in the right scatter plot.

and produces the outputs as plots for the Red/NIR Blue channels on the y- and x-axis respectively (see figure 11). Marking the respective clusters in yellow on the false colour image produces automatically generated images similar to the ones created manually.

Cluster 2 in figure 12 & Cluster 7 in figure 13 depicts the water bodies in the image and it is evident that they are very distinctively identifiable for the algorithm especially the *Elbe* and the *Außenalster*. Parts of the *Stadtparksee* lake were identified but not in their entirety. Also included were some of the cloud shadows, whereas Cluster 3 in fig. 13 identifies cloud clusters accurately by avoiding all other water bodies.

Cluster 1 in fig. 11 represents the low vegetation areas and they are also identified by the algorithm particularly avoiding the thick forest cover areas.

Cluster 1 in fig.12 identified what can be classified as populated areas (suburbs and urban areas) as well as some of the crop fields. Notably it avoided some of the industrial areas south of the *Elbe* unlike Cluster 5 which avoided the densely populated part of Hamburg and just identified green vegetation and forestry similar to Cluster 2 in fig.13 .

While distinctive parts of the various landscape features were identified with precision by manual surface classification(however time consuming and labour intensive it may have been), the algorithm, on the other hand, could manage to distinctively identify water bodies, vegetation areas and cloud clusters in specific clusters(Clusters 7, 4 & 2 in fig. 13 Clusters 3 & 1 in fig.12 . Some of the

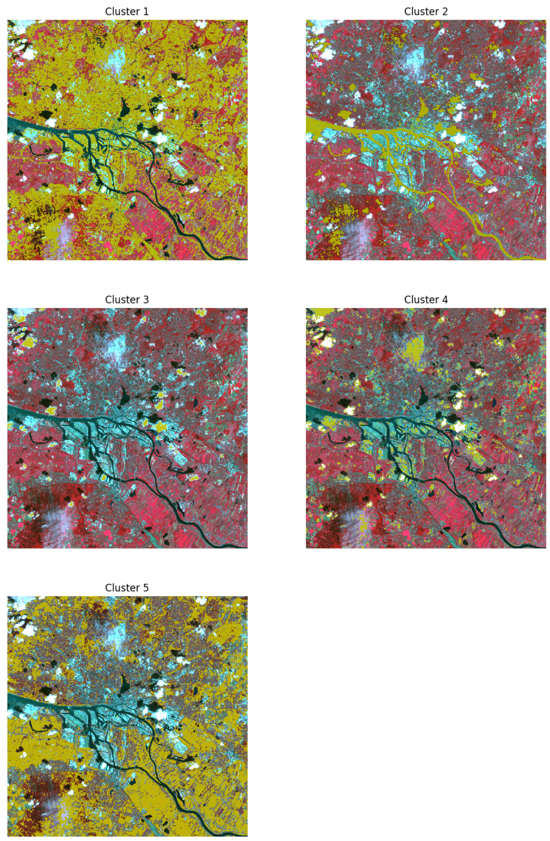


Figure 12: K-Means 5 Cluster Algorithm results. Every cluster output is shown in one image with the determined pixel coloured in yellow in the false colour image. Cluster 2 is the best identification of the five clusters as it correctly identifies water bodies.

features were overlapped with each other like cloud shadow and water bodies in Cluster 2 in fig 12.
In Summary it can be interpreted that the K-Means Cluster Algorithm is a reliable tool for automated classification of surface types with distinct scattering signatures and for those surface types with scattering signatures that overlap, manual classification would be considered accurate.

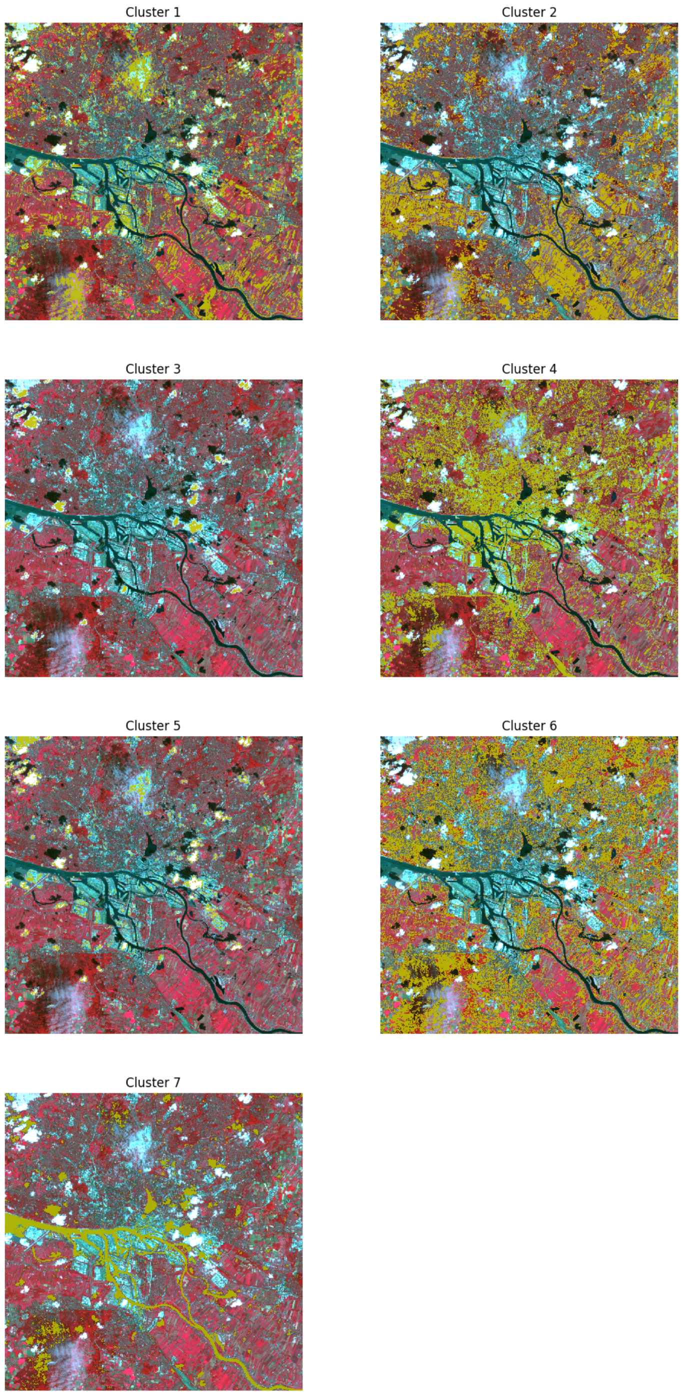


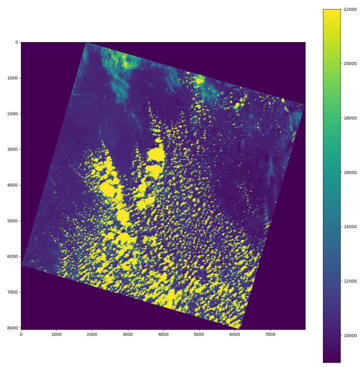
Figure 13: K-Means 7 Cluster Algorithm results. Every cluster output is shown in one image with the determined pixel coloured in yellow in the false colour image. Cluster 4 is the best identification of the seven clusters as it correctly identifies suburban & urban areas.

3 Conclusion

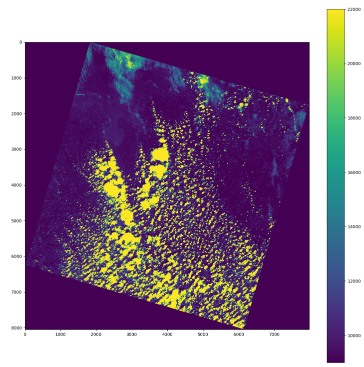
This experiment highlights the significance of fitting a contrast range and cropping into desirable areas to efficiently analyse images, especially for images from large Field of View sensors. Fitting a contrast range can enhance different surface features for better visibility.
In the next part of the experiment, the spatial resolution of the sensor images as stated in the Landsat 8 Data Users Handbook was verified through graphical methods. The area in the image was estimated with the help of topographic features on the map and the dimensions of the resultant area were measured manually with which the spatial resolution was calculated.
Generating False Colour Images was a remarkable procedure that helped to identify and distinguish different surface features. Urban and Industrial areas, Forest cover and low vegetation are distinctively identifiable. The same cannot be said when it comes to differentiating between farmlands, grass cover and meadows. They can be estimated by their geometry.
The main task of the experiment was to manually identify surface types with the help of the false colour images. Identifying industrial areas, low vegetation and forest cover was elementary. Water bodies were also easily identifiable from the scatter plots. Distinguishing the *Himmelmoor* swamp from the forest cover areas was not possible and it was identified only after referring to the map.
The K-Means algorithm was successful in distinguishing between a few surface features like water bodies and forest cover areas but not very effective in identifying urban areas and low vegetation.
To summarize, thorough raw data preparation, as well as an exact understanding of the scatter plots and impression of the surface feature of interest, are critical for both manual and automatic analysis of satellite images.

Appendix

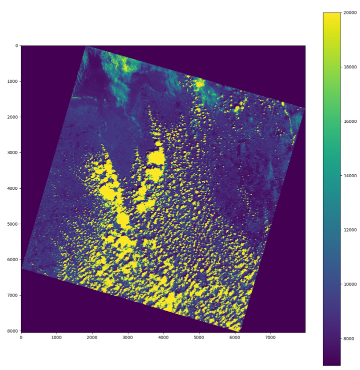
A.1 Full Size Scenes



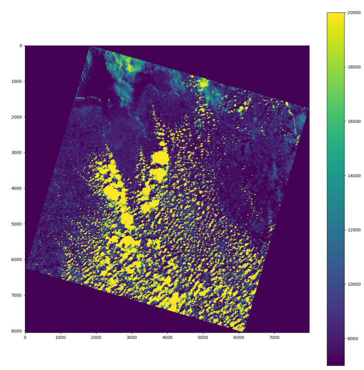
(a) Channel 1



(b) Channel 2

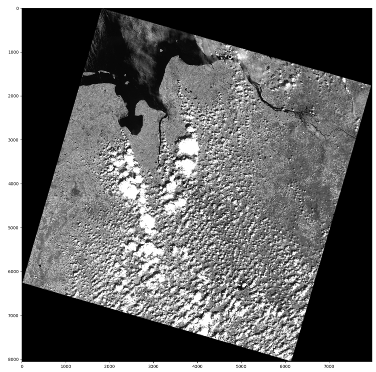


(c) Channel 3

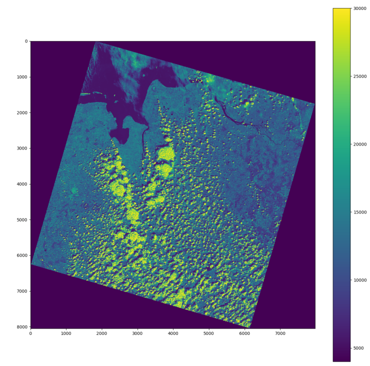


(d) Channel 4

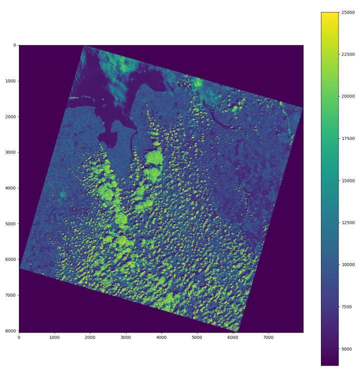
Figure 14: Full size scenes channels 1 - 4



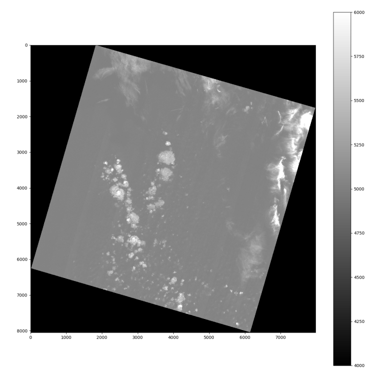
(a) Channel 5



(b) Channel 6



(c) Channel 7



(d) Channel 9

Figure 15: Full size scenes channels 5 - 9

A.2 Unscaled Histograms

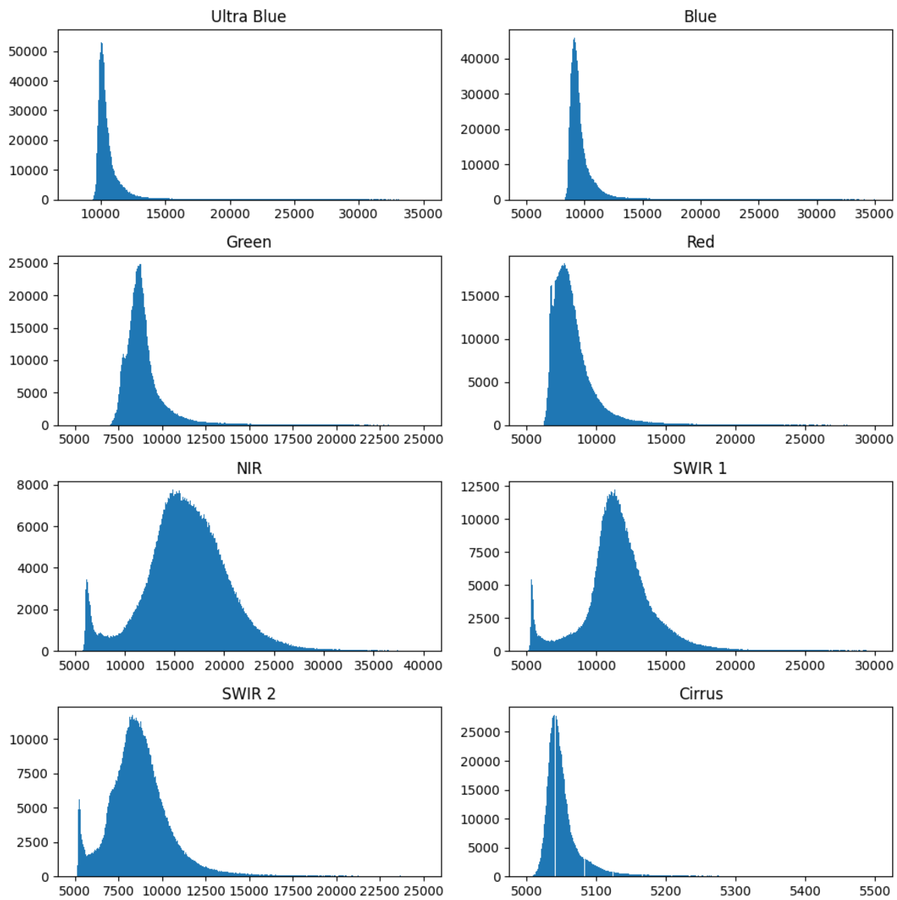


Figure 16: Unscaled Histograms (All Channels)

A.3 True Colour Image

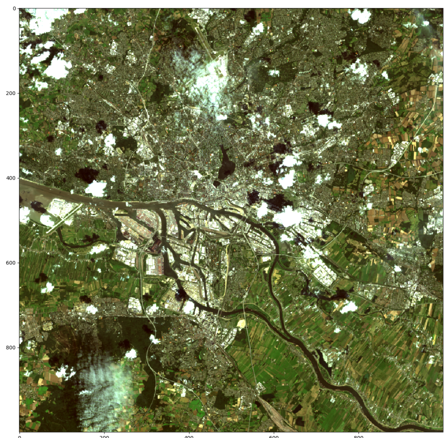


Figure 17: True Colour Image of the Cropped scene

References

[1] U. G. S. L. P. S. Office, “Landsat 8 data users handbook,” 2013, [Online; accessed 22-June-2024]. [Online]. Available: https://www.usgs.gov/landsat-missions/landsat-8-data-users-handbook

[2] ——, “Earth explorer,” 2013, [Online; accessed 19-June-2024]. [Online]. Available: https://earthexplorer.usgs.gov/

[3] S. Coast, “Openstreetmap,” 2004, [Online; accessed 24-July-2024]. [Online]. Available: https://www.openstreetmap.org/=11/53.5470/9.9797