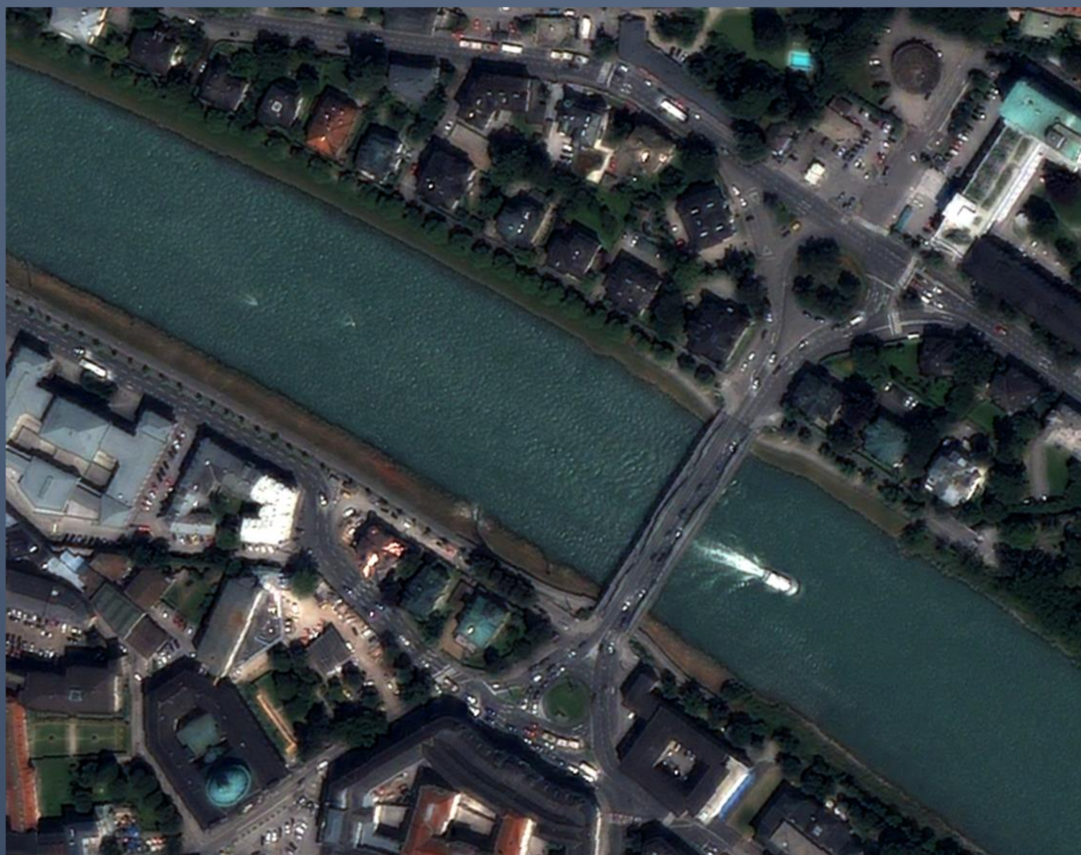
2021



Object Based Image Understanding

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Objective

To get familiarize with the Feature details extraction in eCognition trail version.

Dataset Used

- Quickbird image for a part of Salzburg
- Sample Air-Quality layer

Observations

We know that a feature represents information such as measurements, attached data or values. These features may relate to specific objects or apply globally and in eCognition, details can be extracted from the within available features functionality listed in the Feature View window. Here we have tried in utilizing few of available segmentation methods to extract image object details with the use of several feature-based functionalities.

<u>Adding images to the project</u>

Available Quickbird image along with the given sample raster of air-quality was loaded in the system.

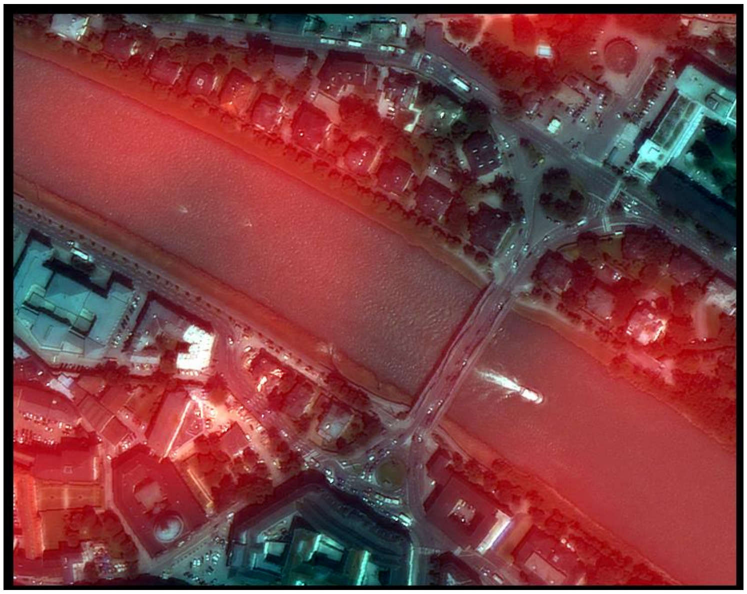


Figure 1: Adding the layer

RGB band combination along with the air-quality (here layer5) was used as shown in the Figure 2 in order to get a visualization of Figure 1. *[Note: Since air quality was a single sample layer it was shown as red layer but can be chosen any.]*

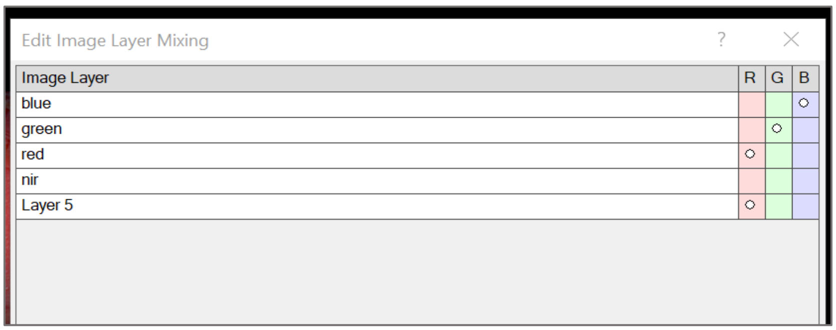


Figure 2: Layer mixing

Performing Chessboard Segmentation

Chessboard Segmentation is fast segmentation process. It splits the image object into equal square of given image objects and is thus, preferred to be used for relatively small image objects which have already been identified.

In the process tree of the project a new rule was set for the segmentation using Chessboard Algorithm setting the object size to 10 which meant that image object was divided into 10x10 pixels as shown in the Figure 3.

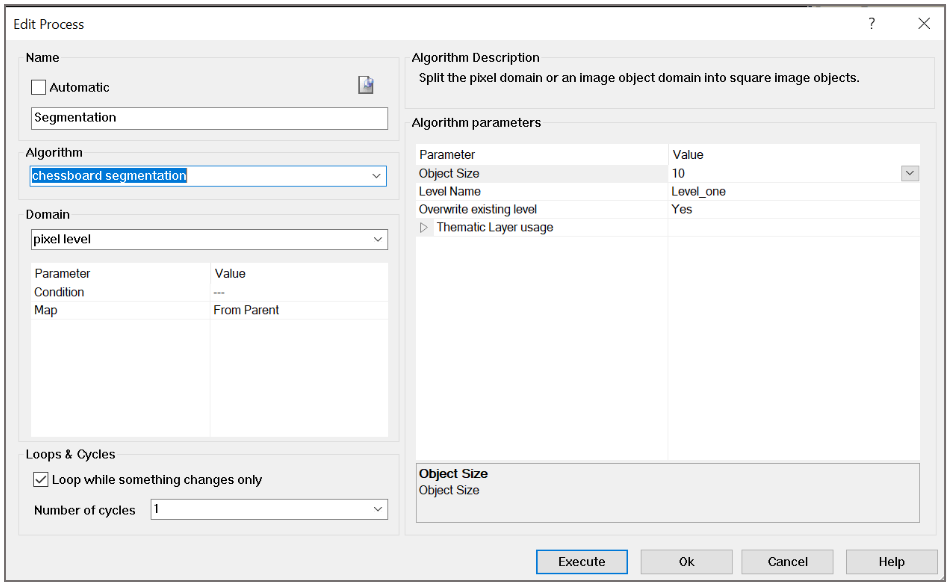
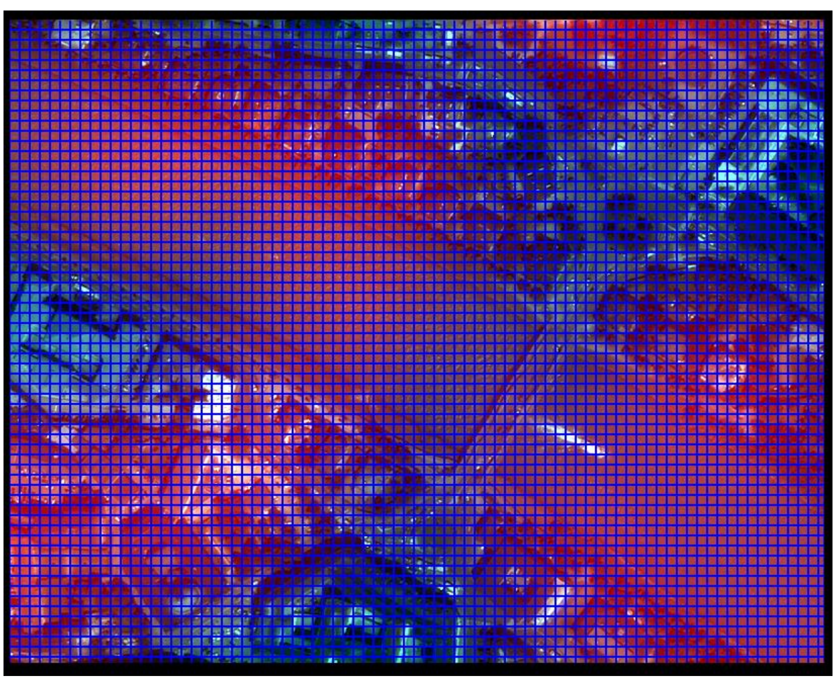


Figure 3: Chessboard Segmentation Algorithm



A simple segmented image as shown in the Figure 4 was obtained when the segmentation was executed.

It was observed that higher the object size set in the ruleset bigger will be the pixel size and vice-versa. Since, this segmentation process does not consider the underlying data, so therefore should be used in more advanced processes where segmentation is undertaken in a number of steps combined with a classification.

Figure 4:Chessboard Segmentation output

Observing Feature Values

To understand the feature values for the newly created image objects, mean was selected from the layer values present under Object Feature in Feature view. It showed that the mean value for the for each band of the image shown in the map view along with the maximum difference of the stacked image.

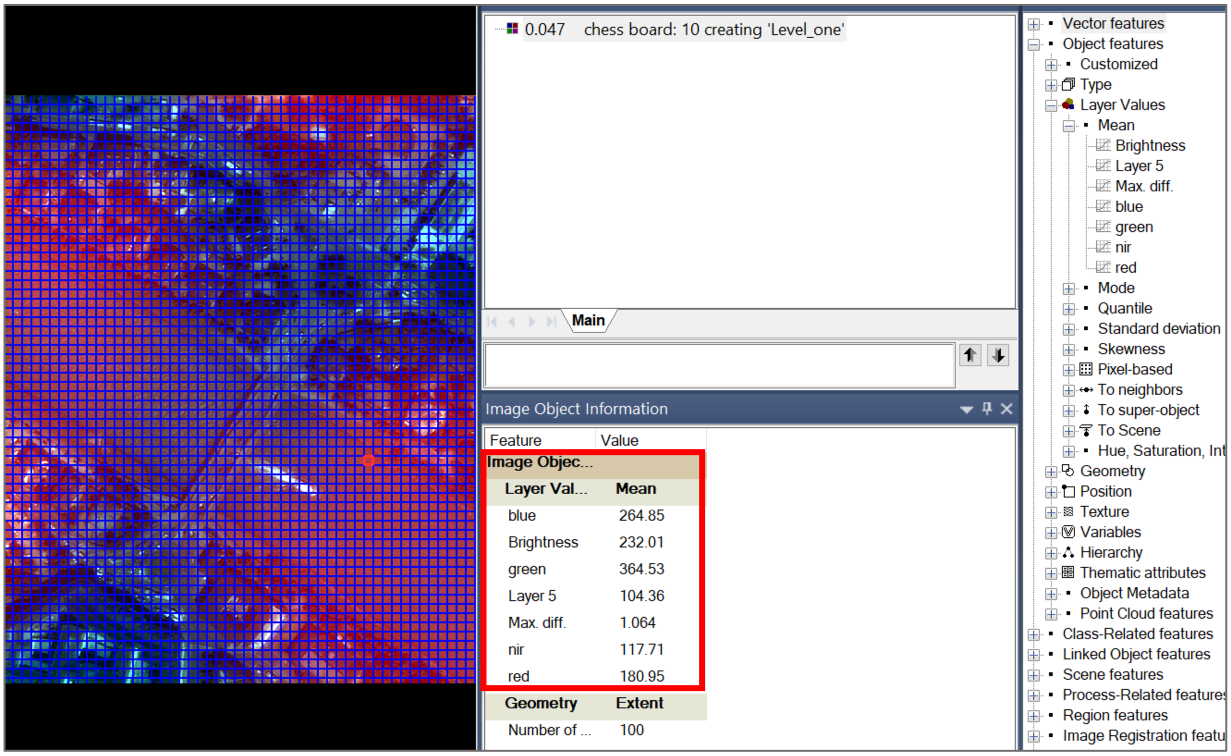


Figure 5: Image object related information

Visually two objects were compared based on their mean values as shown in the Figure 6. It is observed that the pixel with the object boat have higher reflectance than the bridge pixel as shown in the right image.

Figure 6: Comparison of objects in Chessboard Segmentation

Creating Customized Features

Utilizing the functionality provided by the system to create a new relational or arithmetic feature that can adapt to our needs based on the situation we have added NDVI feature with the exiting NIR and Red band using the formula as shown in the Figure 7.

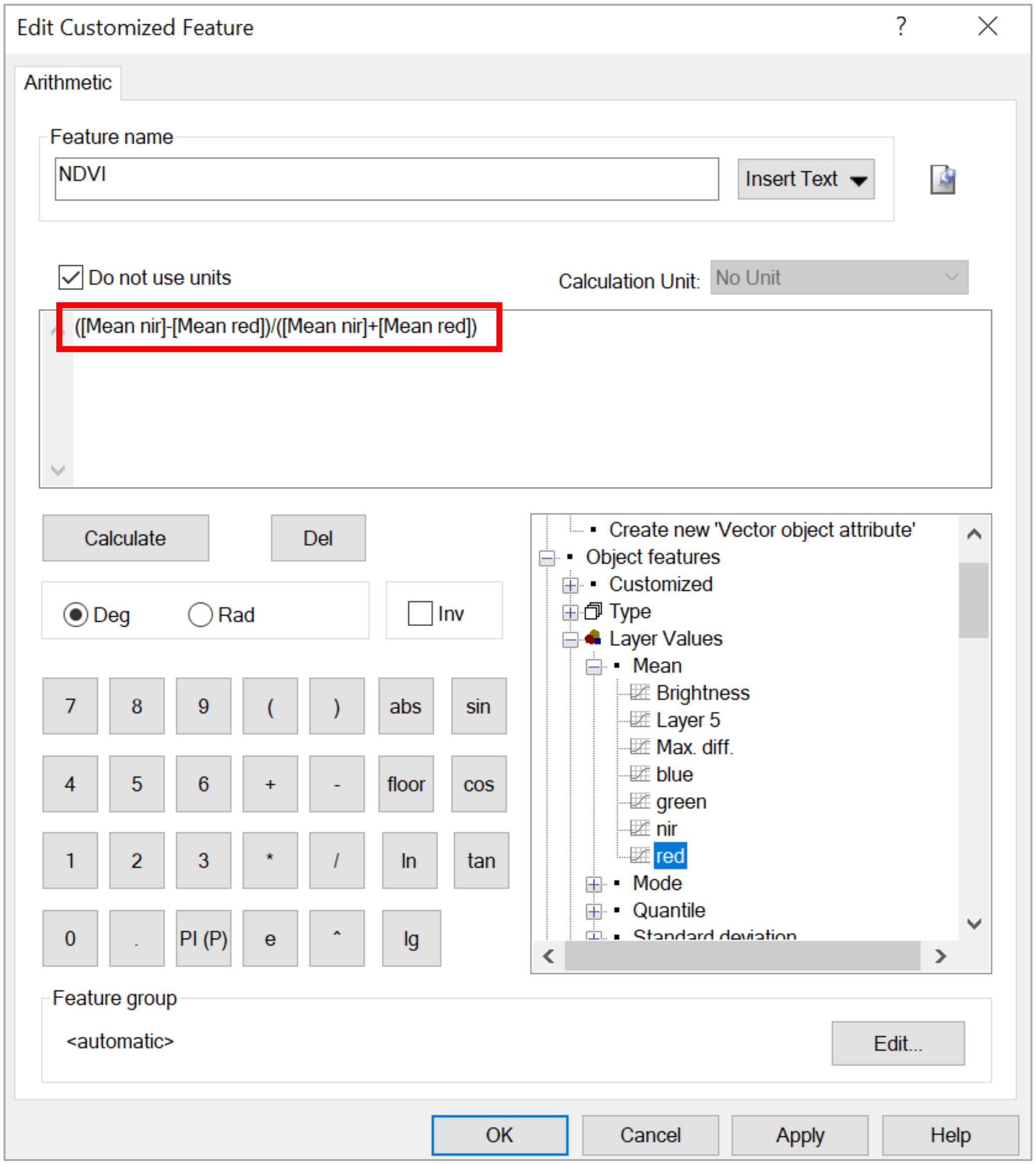


Figure 7: Creating Customized Feature

With the customized feature we can now extract details based on this feature, in this case we can check the vegetation index for each pixel.

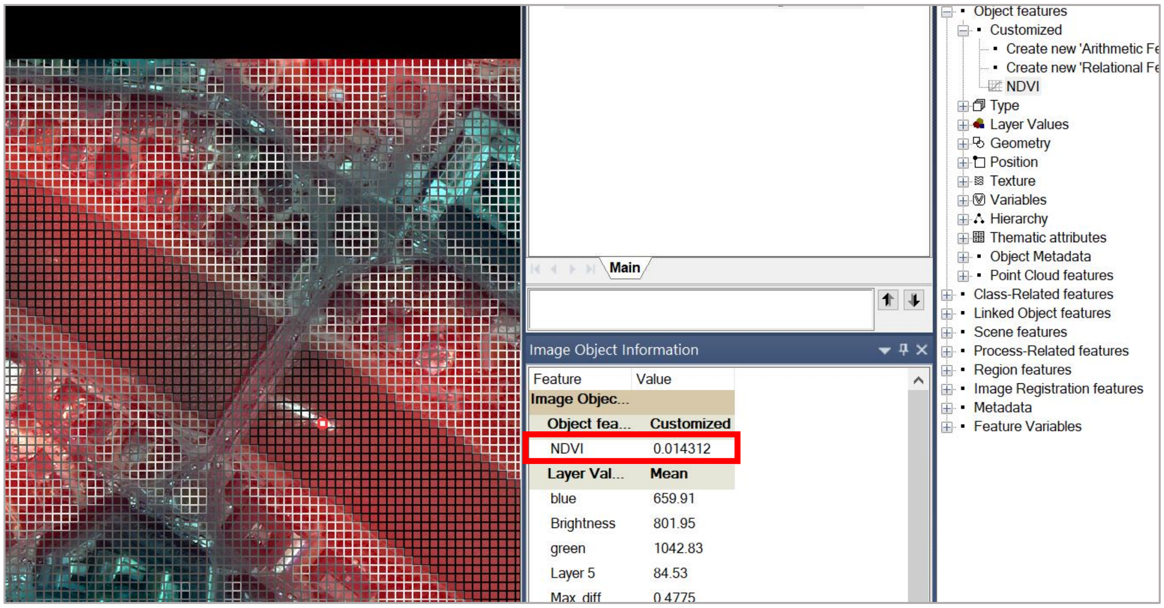


Figure 8: NDVI value for a particular object

When comparing the values for the two objects of the chessboard segmentation, it becomes obvious that the chessboard segmentation cannot segment or delineate the real ground feature because for example if we compare the values of the object both above the water, they have very similar values but they are not classified as same. Furthermore, if there are mixed classes in the chessboard object, it only shows one value (center value) even though it should have completely different values in each band. for example, the case of half boat and half water. So, we must select the object size optimal to segment each feature.

It was studied that Chessboard segmentation maybe useful in the situation when user want to perform classification within the thematic layer or specific area of interest and not in whole image. I think the segmentation feature with varying spectral value distributed highly over a large area doesn't make much sense. As these objects will be assigned with the same reflectance value which make it useless to represent meaningful object.

Performing Multiresolution Segmentation

Multiresolution Segmentation is used in creating image objects and is a bottom-up approach that is used in assembling objects to create large objects. We learned that in this approach a particular object looks around for its best-fitting neighbor for a potential merge. If the best fitting is not mutual, the best candidate object become the new object and finds its best partners. When best fitting is mutual, image objects are created, these loops continue until no further merger is possible.

In this process we are allowed to alter the scale parameters, compactness, smoothness that referred to shape color of for the object. It was mentioned that scale parameter is the homogeneity criterion regarding the spectral and shape of the object. The higher the value of scale parameter, bigger will be the object and vice-versa.

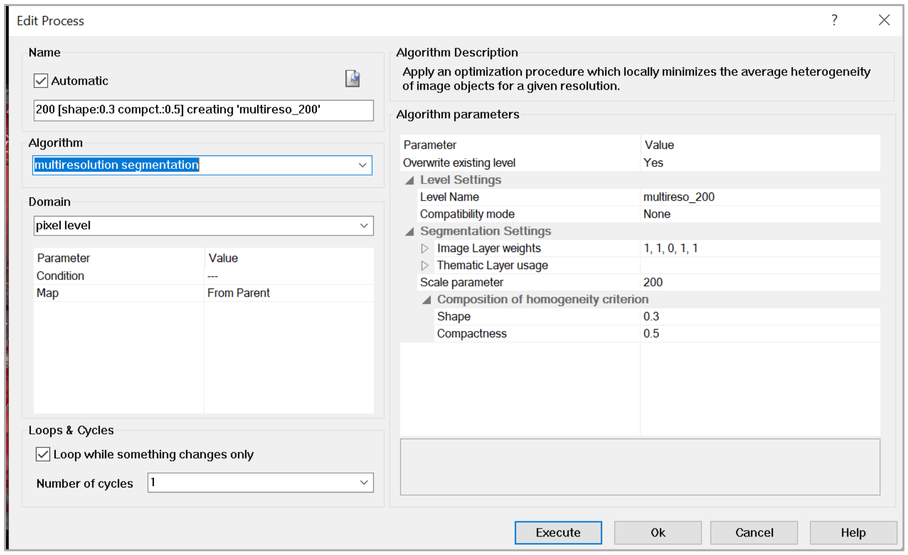


Figure 9: Multiresolution Segmentation

Here, the air-quality band was assigned with weight 0 to avoid the segmentation being influenced by the band. A segmented image as shown in Figure 10 was obtained as output of this process.

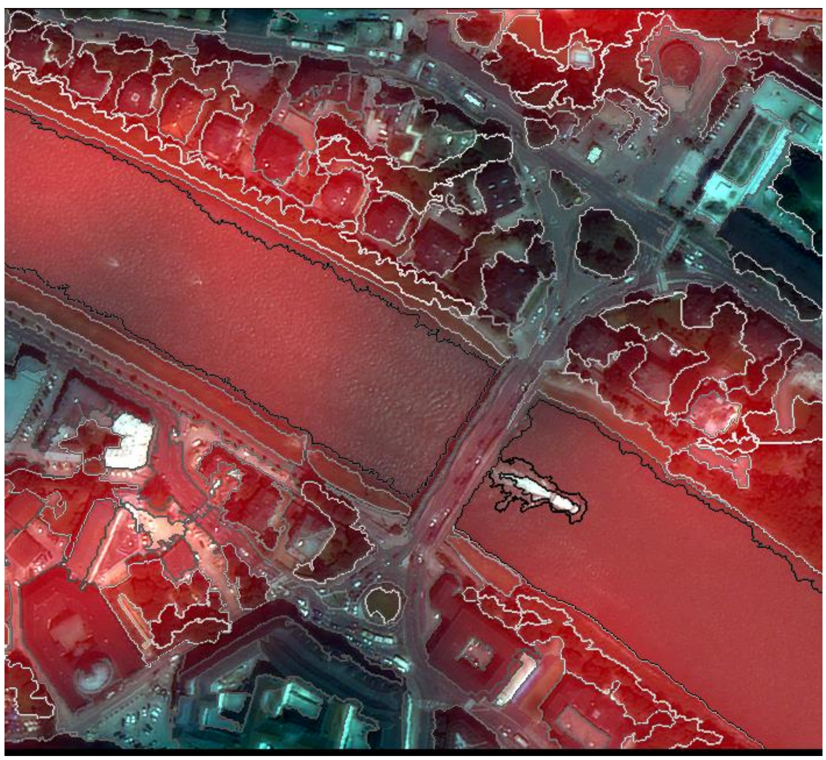


Figure 10: Multiresolution Segmentation Outcome

Visualizing Feature Value Range

Similar to the Chessboard Segmentation method, two different object's feature values we studied by double clicking on them and observing the mean value for each selected object. In this case, left image has boat as selected object and right has the river. Here Shape index has also been selected from the Geometry under Feature View.

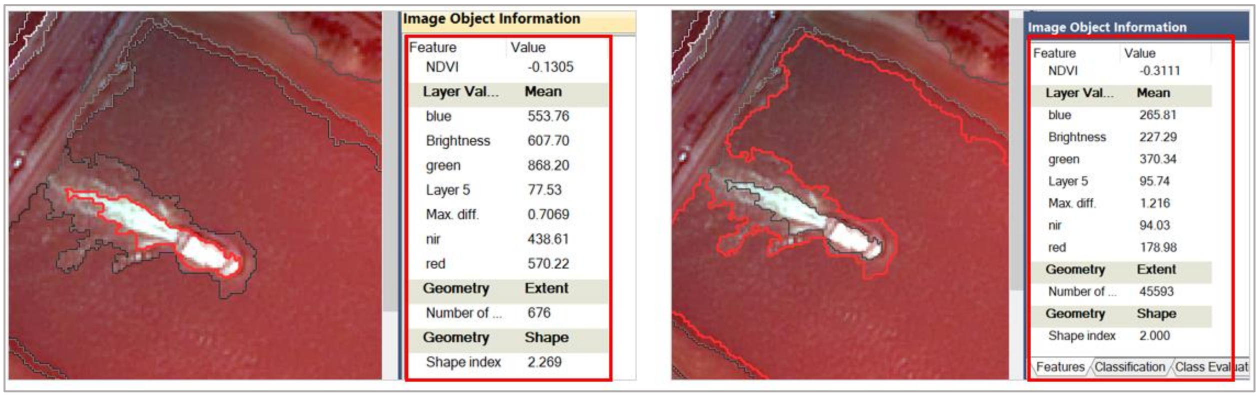


Figure 11: Comparative result from multiresolution

Among the two-segmentation algorithm, I believe that the Multiresolution Segmentation could provide more likely meaningful objects as it takes into account the compactness and shape of the underlying data.

Now to find out the threshold for the new NDVI feature when Multiresolution Segmentation is done, to distinguish between vegetation and non-vegetation areas, we simply update the range by right clicking on previously created Customized Arithmetic Feature. It ranged from -0.311 to 0.7617.

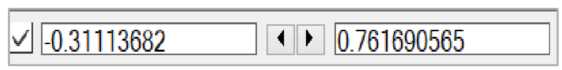


Figure 12: NDVI Range

By switching the object outlines to the object feature view, computed NDVI is visualized as based on Multiresolution Segmentation as shown in Figure 13.

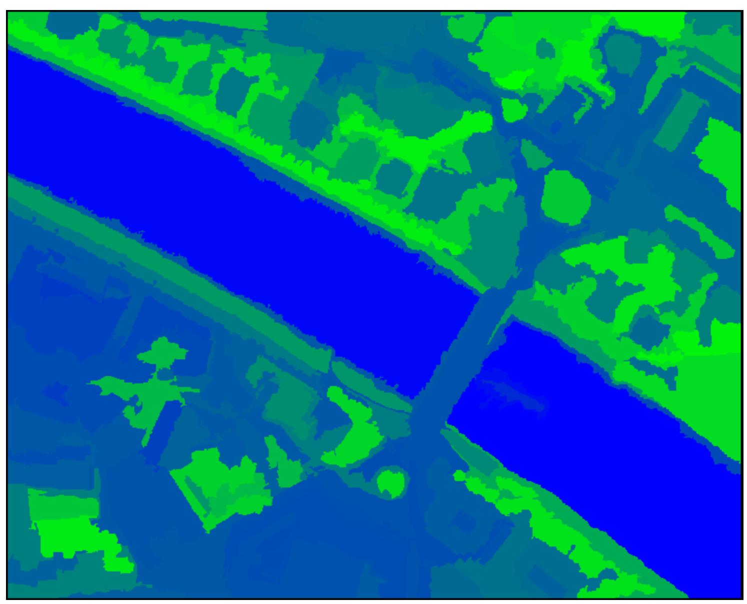


Figure 13: NDVI

Classifications

In order to classify the objects (initially to two classes: vegetation and water), two classes were inserted in the Class Hierarchy. In the Process tree, new process was created with assign class algorithm maintaining the condition of NDVI >= 0.25 and NDVI<= -0.15 for vegetation and water respectively.

An output as shown in Figure 14 was received where segmented objects were classified into either vegetation or water but for the objects whose feature value didn't satisfy the condition were left unclassified.

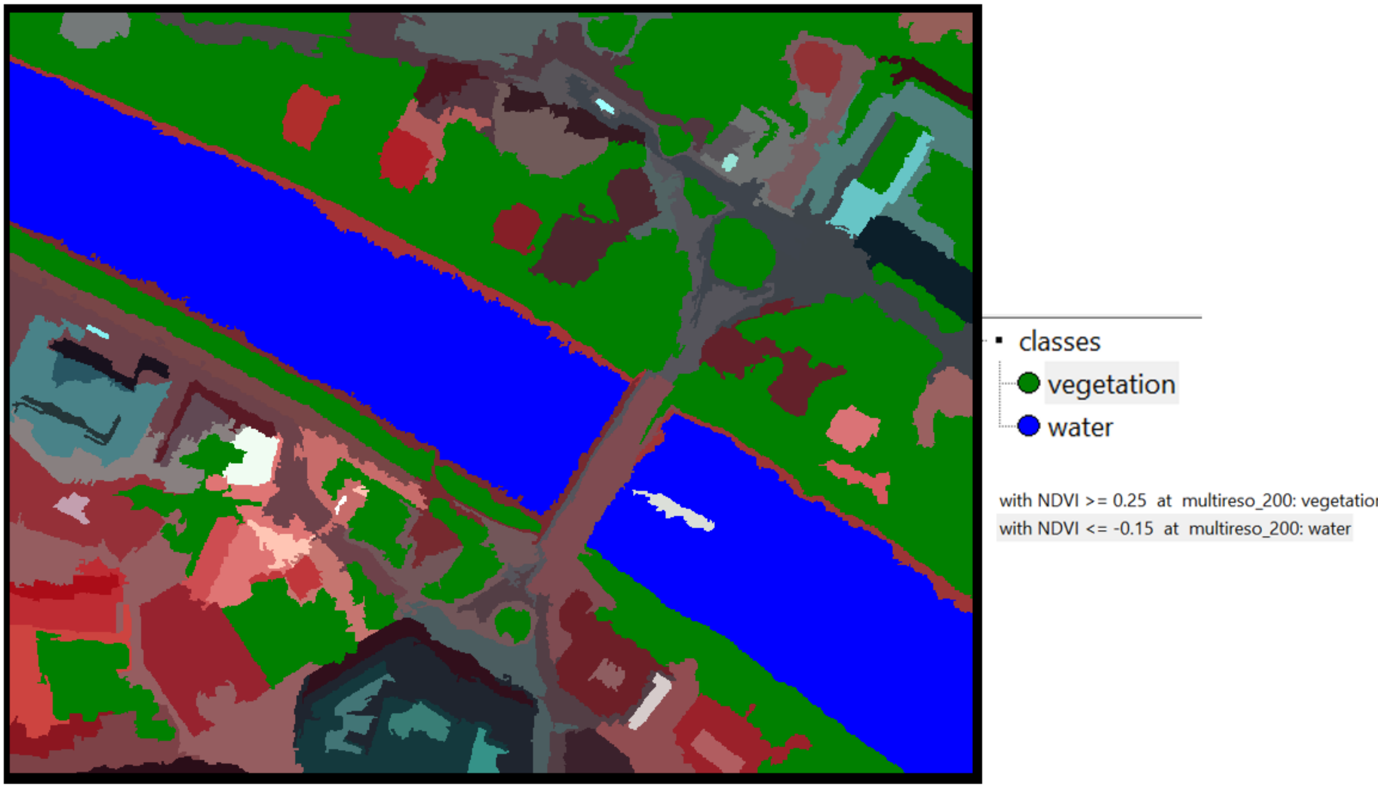


Figure 14: Classified Image

Now, making the use of Class-Related Feature under Feature View to create a new Relative Border to class water feature. Using this to classify boat we use assign class algorithm with a threshold condition that the relative border to water is equal to 1 (it was set as 1, because the object representing the boat is completely surrounded by Class water).

Figure 15 gives the Classified image based on Object feature in 3 different classes including boat maintain the given conditions.

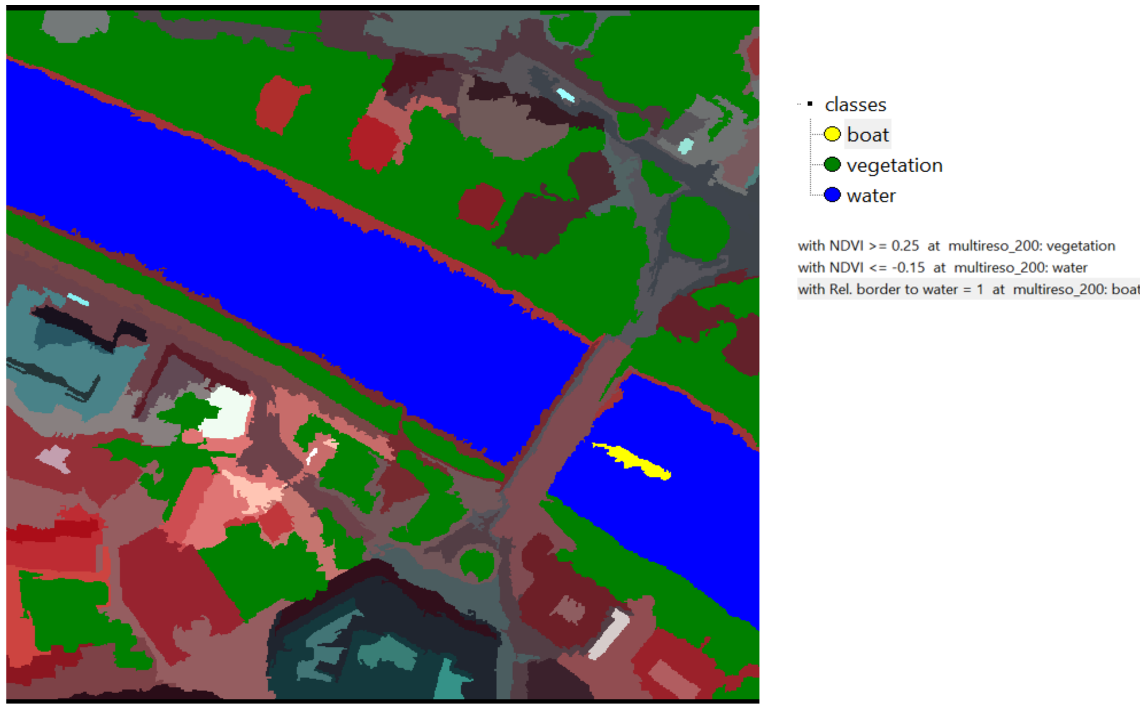


Figure 15: Boat classified with Relative Border Feature

Further, using the air-quality layer as a prior information to refine our classification, we create sub-classes of the class vegetation by dividing it into high and low air-quality area. It was followed by similar technique of assigning the classes with the condition that Mean of Air-Quality layer>=50 and Mean of Air-Quality layer<50 for high air-quality and low-air quality area respectively. The assigning of these classes was limited to the vegetation covered area.

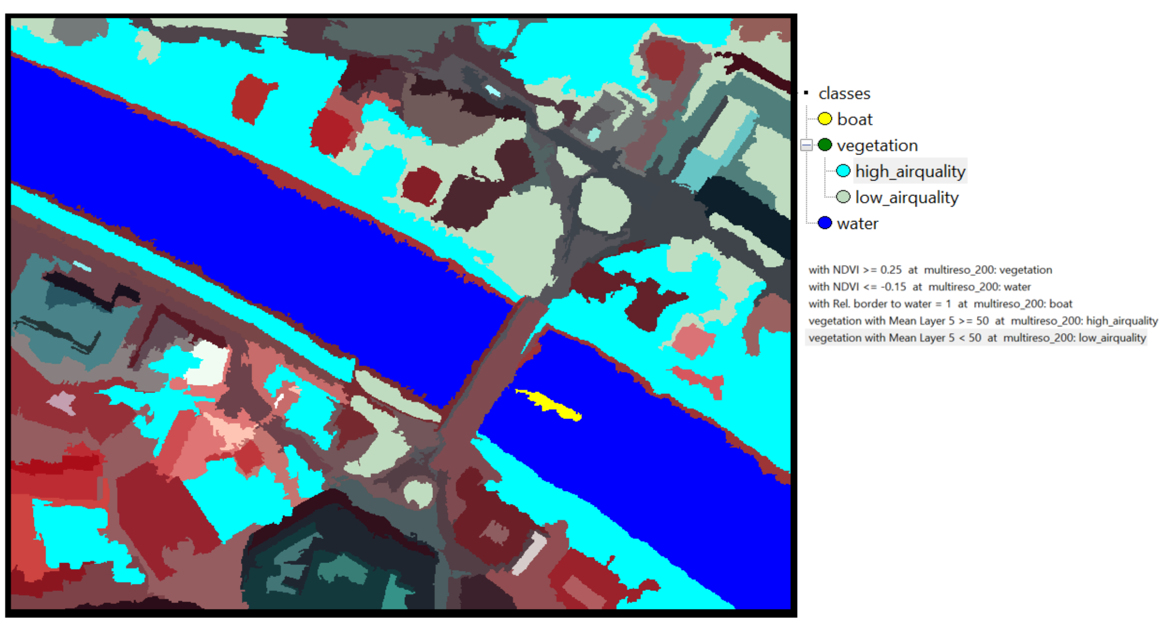


Figure 16: Sub-Classified Image

3 Water Features were identified as classified object for the water class from the Scene Class Related Feature from Feature View. Similarly, for boat and for vegetation, number of classified features were 1 and 47 respectively.

As we know that when we select the vegetation class to generate the feature, it will summarize the values from the grouped sub-classes which obtained as: Area of Vegetation Class was 154321px i.e., 5.556 hectare (55555.56 square meter).

Changing Scale Parameters

As a test, a second attempt was done for performing multiresolution segmentation but with smaller scale parameter, this time 50 and assigning the composition of homogeneity criterion as 50-50 percent. We can see more dense segmentation as compared to the previously created.

A new feature for the Existence of Super Object is created as a container for two separate air quality classes so that it can be directly used to address both sub-classes at once. Relations to Super objects features describe an image object by its relations to other image objects of a given class.

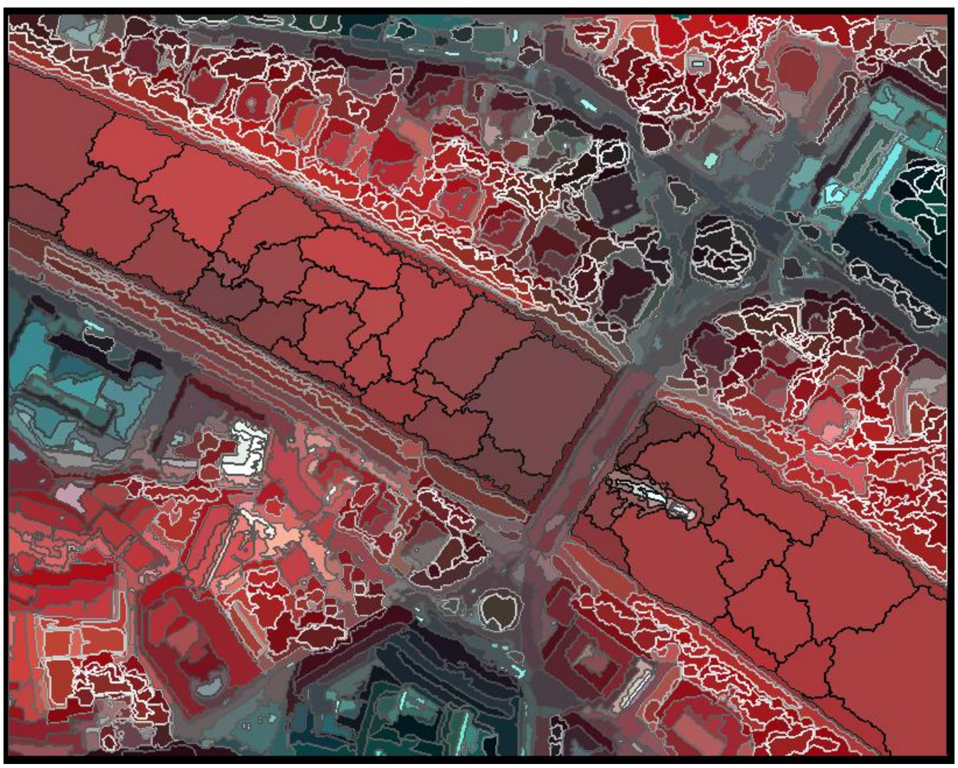


Figure 17: Multiresolution of 50 with vegetation as Superclass

The distance of neighbor objects to the parent image object in feature space. If distance is zero, this refers to image objects that have an exactly same value with the parent in feature space and lie on the same image object level. If a value is specified, it refers to the distance between an object's center of mass and the parent's center of mass, up to that specified threshold. If incase of d=1, it means that the distance is equal to the standard deviation of all features defining that feature space cluster. It is calculated using:

$$d = \sqrt{\sum_f \left(\frac{v_f(s) - v_f(o)}{\sigma_f} \right)^2}$$

d	Distance between sample object s and image object o
$v_f(s)$	Feature value of sample object for feature f
$v_f(o)$	Feature value of image object for feature f
σ_f	Standard deviation of the feature values for feature f

[Source: https://docs.ecognition.com/v9.5.0/eCognition_documentation/User%20Guide%20Developer/6%20About%20Classification.htm]

Conclusion

Outcome of Chessboard and Multiresolution Segmentation was studied with the creation of new customized features. The objects were classified using simple Assign Class algorithm that helped in getting familiar with several functionalities of the eCognition.