CLASSIFICATION ASSIGNMENT: PART II – OBJECT FEATURES

FELIPE CAMACHO HURTADO

SALZBURG UNIVERSITY

ADVANCED REMOTE SENSING

SALZBURG, AUSTRIA

JANUARY 7, 2023

CONTENTS

1. OBJECTIVES

1. Learn how to address specific object-features in eCognition for rule-based classification purposes.

2. USED SOFTWARE

1. eCognition Developer Trial 9

3. USED DATA

1. Quickbird image of Salzburg
2. Air Quality Layer

4. EXAMPLE I

4.1 Adding Project Data

As an initial step, the Quickbird data of Salzburg (with blue (1), green (2), red (3), and nir (4) bands) was loaded into the project. The "**airquality_sb.tif**" data was assigned as layer number 5 of the image layers to be added (Figure 1). As result, an image layer with 5 bands was successfully loaded (Figure 2).

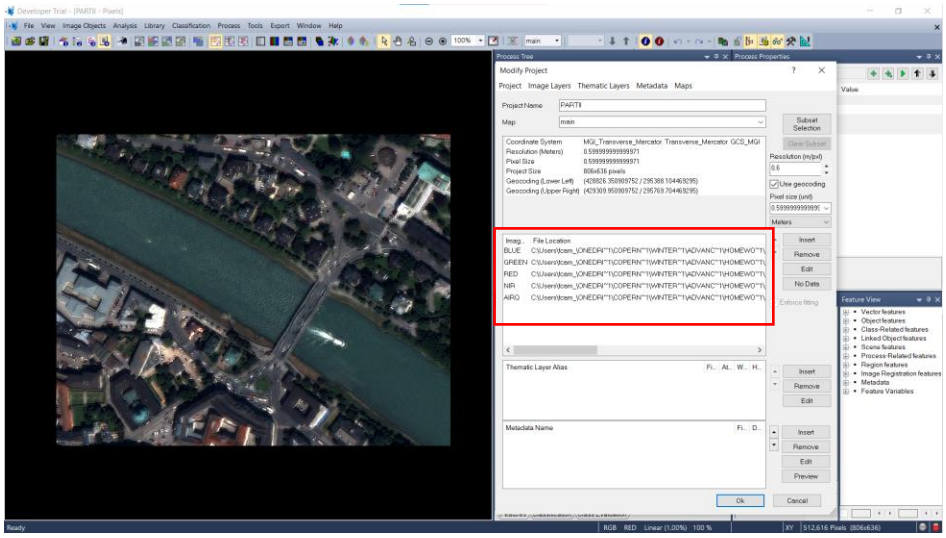

Figure 1. Loading Image into eCognition (Version 9 – Trial).

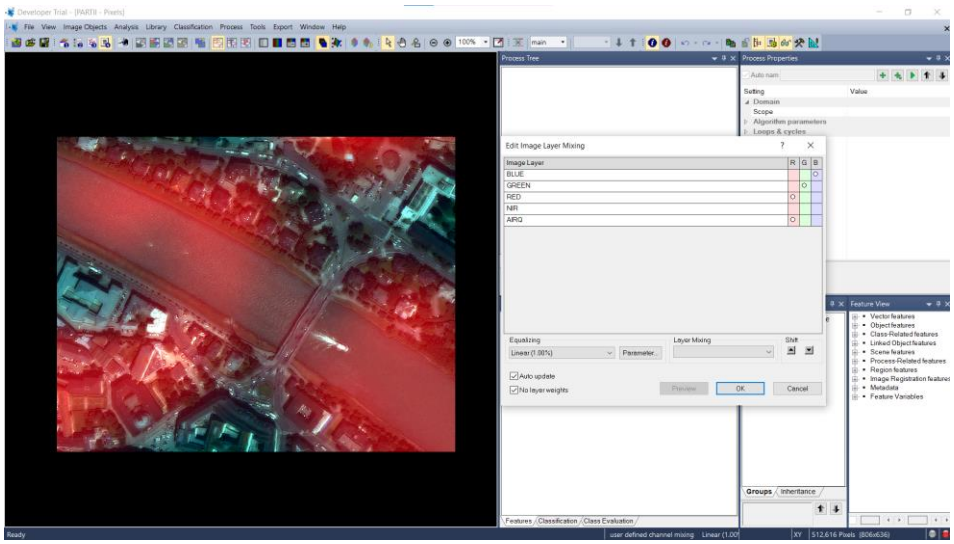

Figure 2. Image layer visualized with a Natural Color composite and the Air Quality layer in red channel.

4.2 Chessboard Segmentation

With the objective of creating a pixel-level segmentation, in the Process Tree, the parent process "**Segmentation**" was created. The "chessboard segmentation" child process was inserted. This algorithm was executed using an "Object Size" of 10 and the new level name was assigned as "**L1_CB**". (Figure 3)

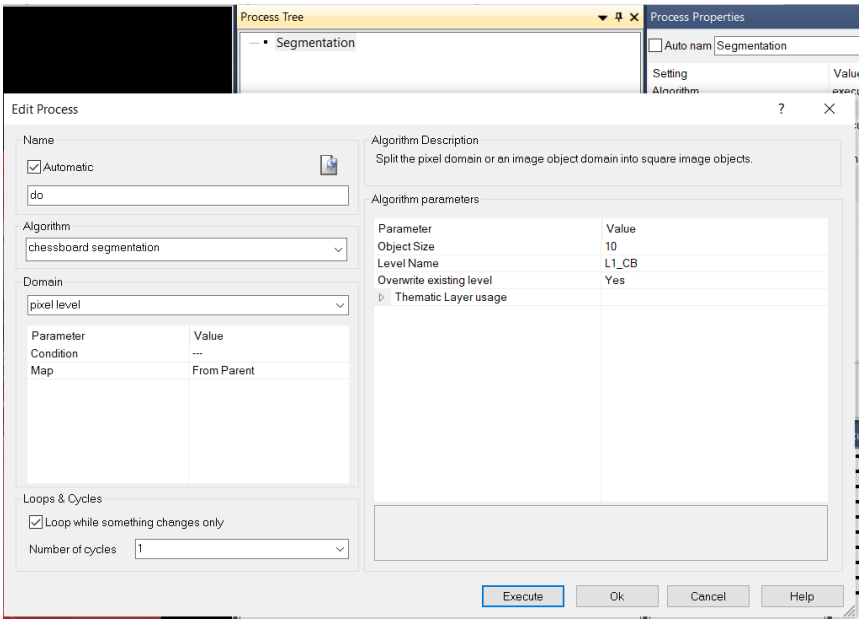

Figure 3. The "chessboard segmentation" algorithm configuration.

Additionally, in the “Image Object Information” panel, several features were displayed, including the mean values for all five layers and the number of pixels for the scene (100). To show how those features work dynamically, two objects were selected. For the first one (Figure 4), in the Salzach river, the biggest value was the green layer (396.76) and the lower the Air Quality layer (54.95). For the second object (Figure 5), corresponding to a rooftop, the highest value was the green layer (997.82), and the lowest was the Air Quality layer (81.34).

Moreover, another group of features was displayed for additional objects. The new features included: Mean value of the blue band, Max pixel value of the blue, Area of the object, Shape Index of the object, and NDVI index.

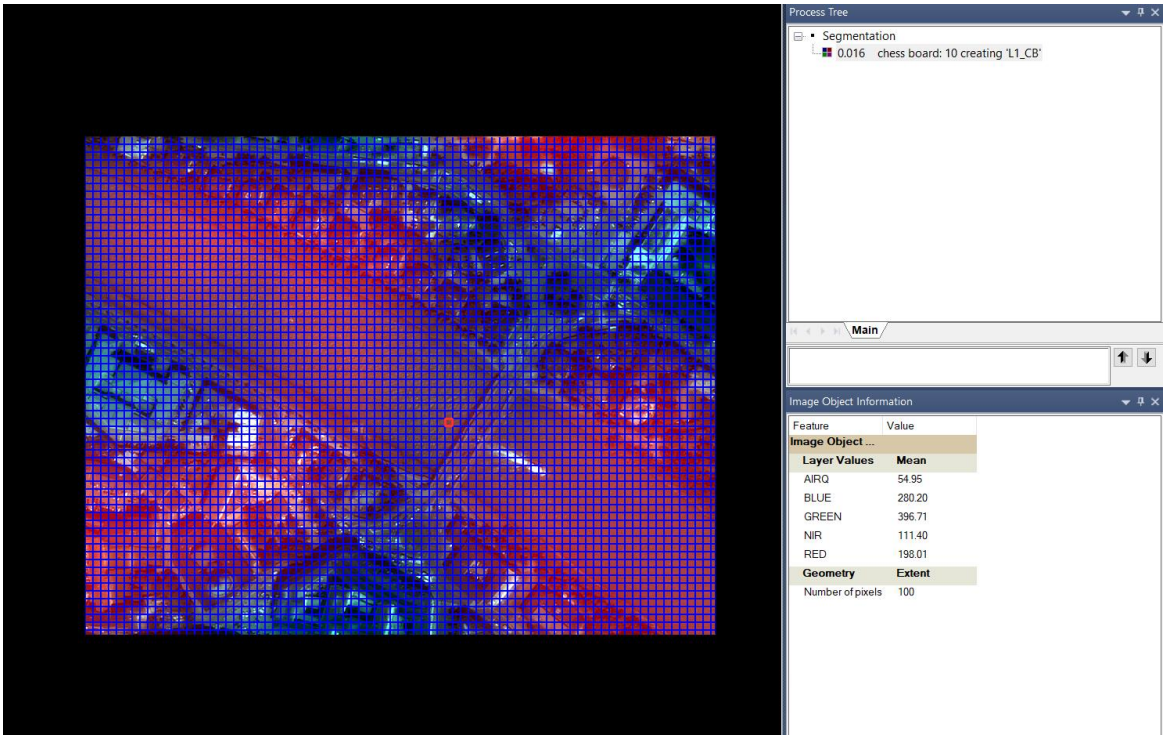

Figure 4. Features Displayed for Object #1 - Salzach River.

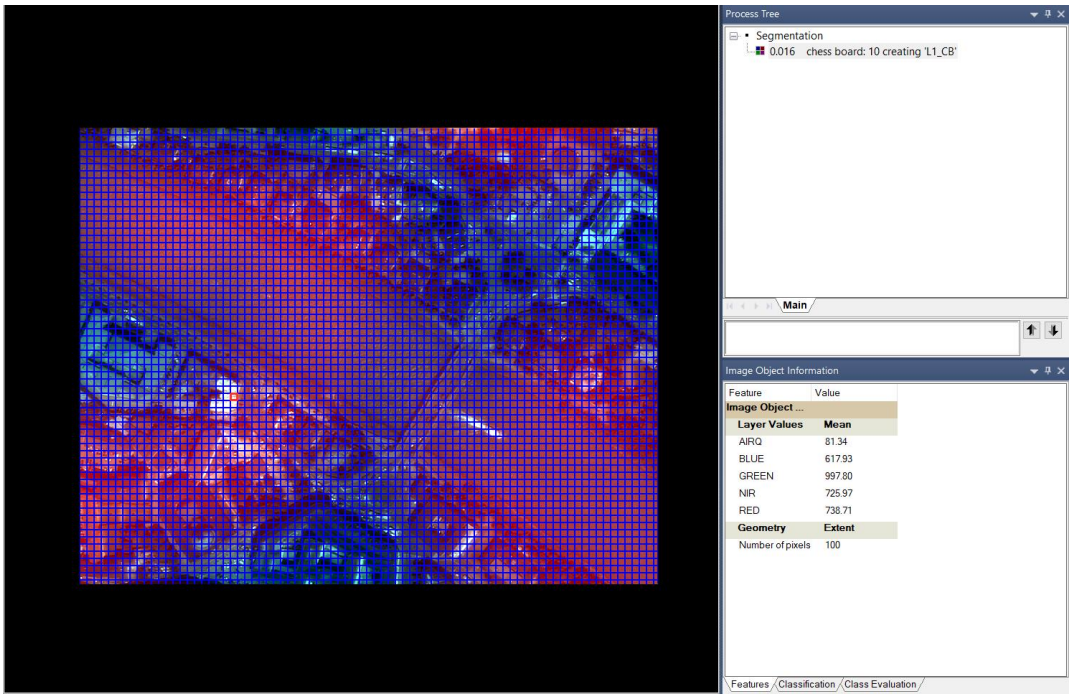

Figure 5. Features Displayed for Object #2 – House Rooftop.

All the previously mentioned features were already created by default. However, the NDVI index had to be created. This was achieved by creating a customized feature (Figure 6) with the NDVI formula: ([Mean NIR] – [Mean Red] / [Mean NIR] + [Mean Red]).

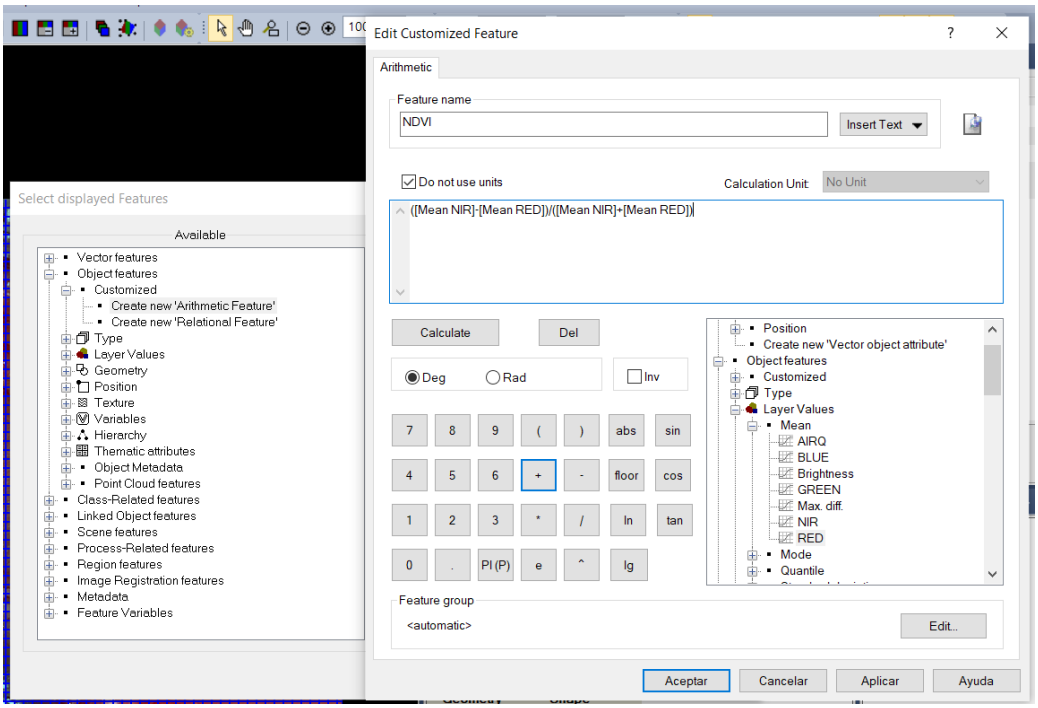

Figure 6. NDVI Customized Feature.

As result, an object in the Salzach river (Figure 7), returned a value of -0.3384 for the NDVI index, and a Mean of 270.34 for the blue band. On the other hand, an object corresponding to a boat (Figure 8), returned an NDVI value of 0.014312, and a Mean of 659.91 for the blue band. In this case, the Area and shape index was constant.

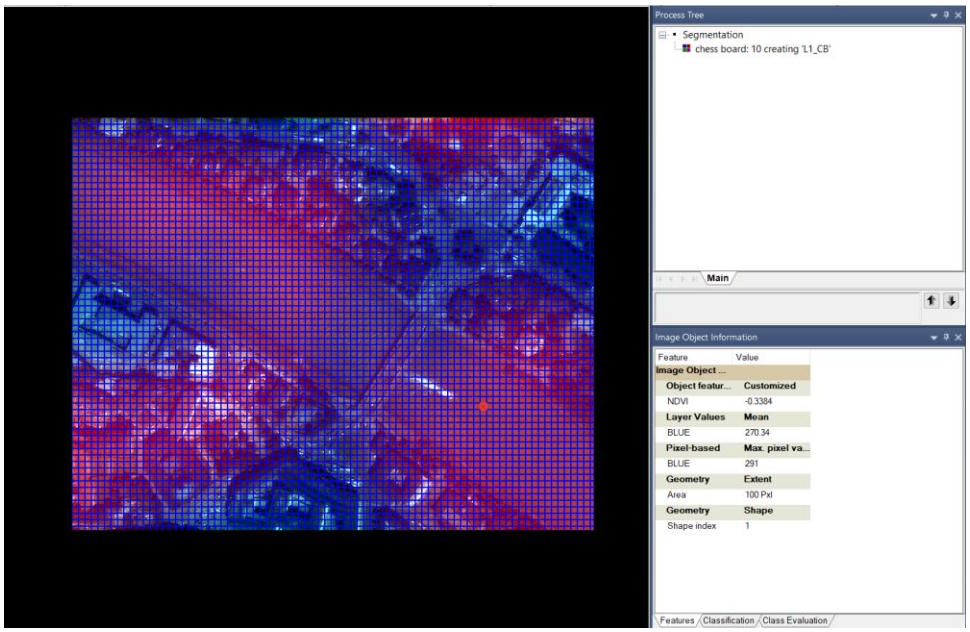

Figure 7. Features Displayed for Object #3 – Salzach River.

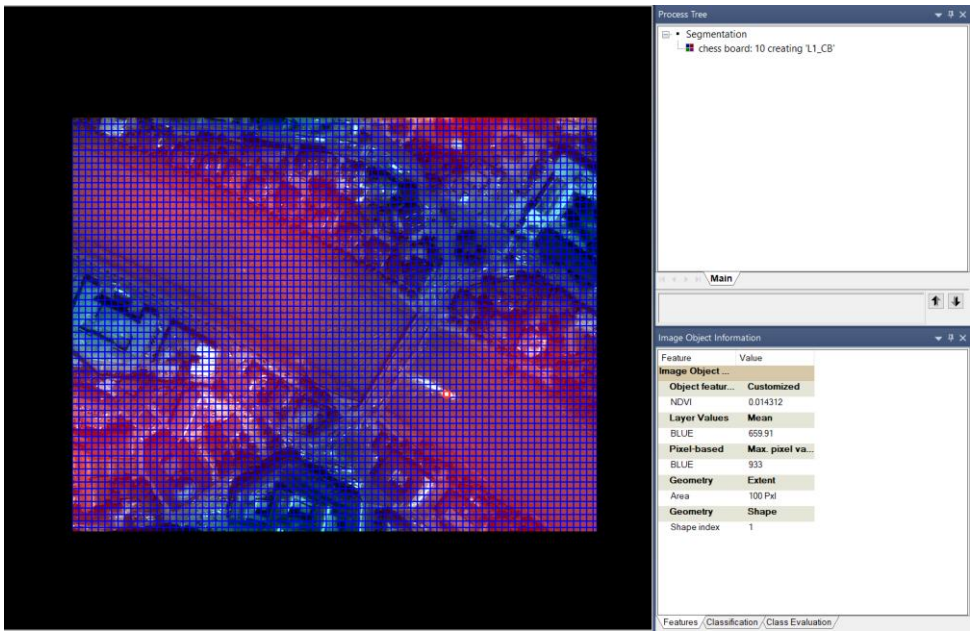

Figure 8. Features Displayed for Object #4 – Boat.

4.3 Questions

- **What becomes obvious if you compare the values for the two objects of the chessboard segmentation?**

Considering Object #3 and Object #4, it can be observed that the NDVI index feature is displaying the expected values. For water features, it's returning negative values close to zero. For the boat, we have also values close to zero which is evidence of a lack of vegetation. In this case, the chessboard segmentation performed well for the selected objects, as they had the same type of class.

However, when selecting objects with mixed classes, the chessboard segmentation will not be useful to delineate the real ground objects, as within the same object, different types of classes may be contained. For example, in a square of 100 pixels, you can have different classes like vegetation, water, and artificial surfaces, and if you perform a classification based on the mean value of a band, the object will be mistakenly classified, as the mean will be influenced by all the type of classes.

- **Which features don't make that much sense in this case**

With the "Chessboard Segmentation" algorithm, it makes not so much sense to display the "Area" and the "Shape Index" features. The reason is that the "Chessboard Segmentation" algorithm creates fixed-size square objects aligned from the left and top borders of the image. As result, most of the objects (excluding the bottom and right border objects) will have the same area. For our configuration, the regular squares will have an Area of 100 pxl or 36m2.

Regarding the "Shape Index", considering the objects created by the "Chessboard Segmentation" and the "shape index" expression and parameters (Figure 9), each of the squares will have the same border length and area, and consequently, will display the same Shape index value (1 for a chessboard segmentation with an object size of 10).

Parameters

- b_v is the image object border length
- $4\sqrt{\#P_v}$ is the border of a square with area $\#P_v$

Expression

$$\frac{b_v}{4\sqrt{\#P_v}}$$

Figure 9. "Shape Index" formula (eCognition).

5. EXAMPLE II

5.1 Multiresolution Segmentation

Using the "multiresolution segmentation" process, a new object segmentation level was created. The "multiresolution segmentation" algorithm was run after assigning a weight of "0" to the Air quality layer, a scale parameter of 200, and a shape of 0.3 and compactness of 0.5. (Figure 10).

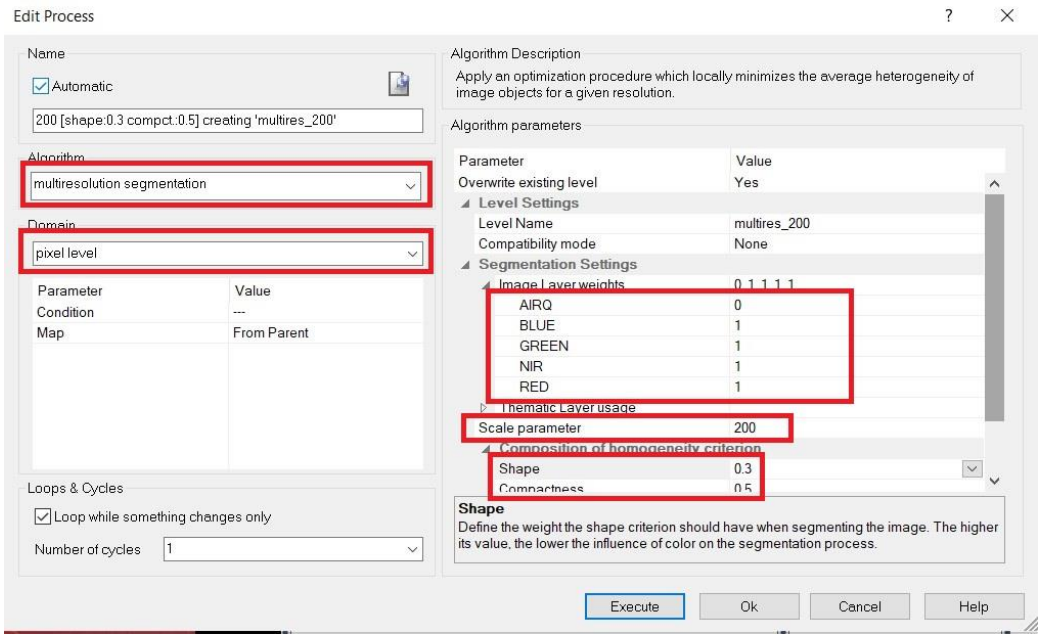

Figure 10. Multiresolution Segmentation.

Using the “multiresolution segmentation” process, a new object segmentation level was created. The “multiresolution segmentation” algorithm was run after assigning a weight of “0” to the Air quality layer, a scale parameter of 200, and a shape of 0.3 and compactness of 0.5. (Figure 10).

In comparison to the Chessboard segmentation, we can observe that the Salzach river (Figure 11) is better delineated. This same enhancement is evidenced for the boat object (Figure 12). With this segmentation, the “Area” and “Shape Index” features become useful, as now the objects have different sizes, lengths, and forms. Additionally, as the created objects will now represent one type of class (not always), displayed features like the mean of the bands, are now representative of those objects and can be used to correctly classify them.

Because of the above, for creating “meaningful objects”, the “multiresolution segmentation” will be a better option, compared to the “chessboard segmentation”.

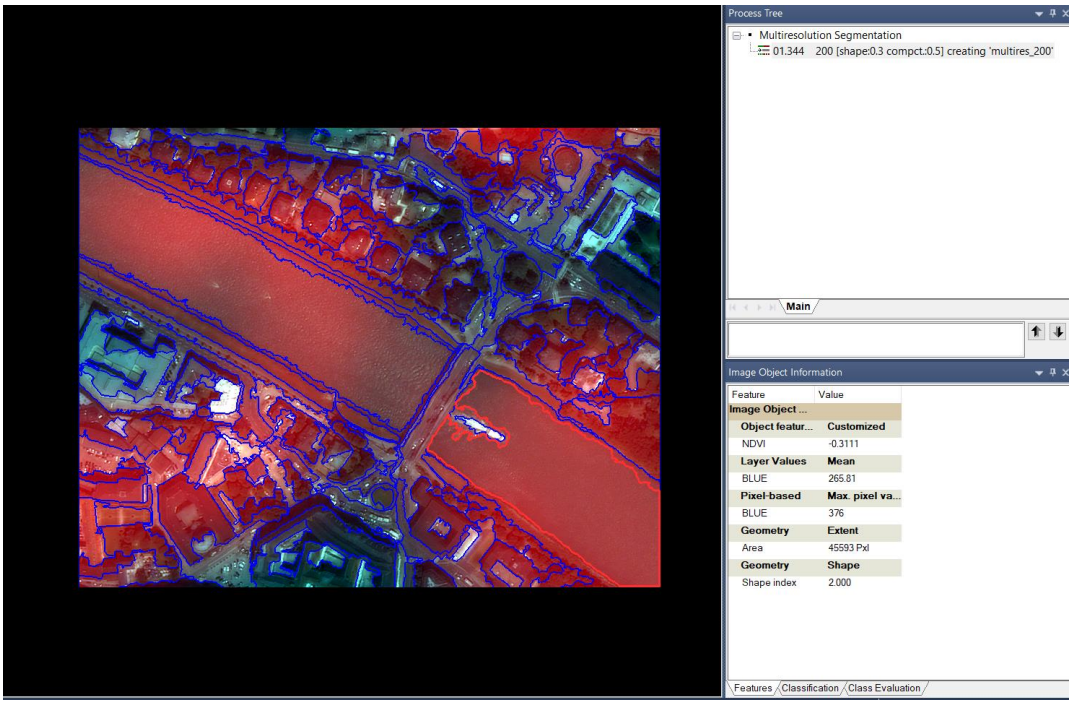

Figure 11. Multiresolution Segmentation – Salzach Object

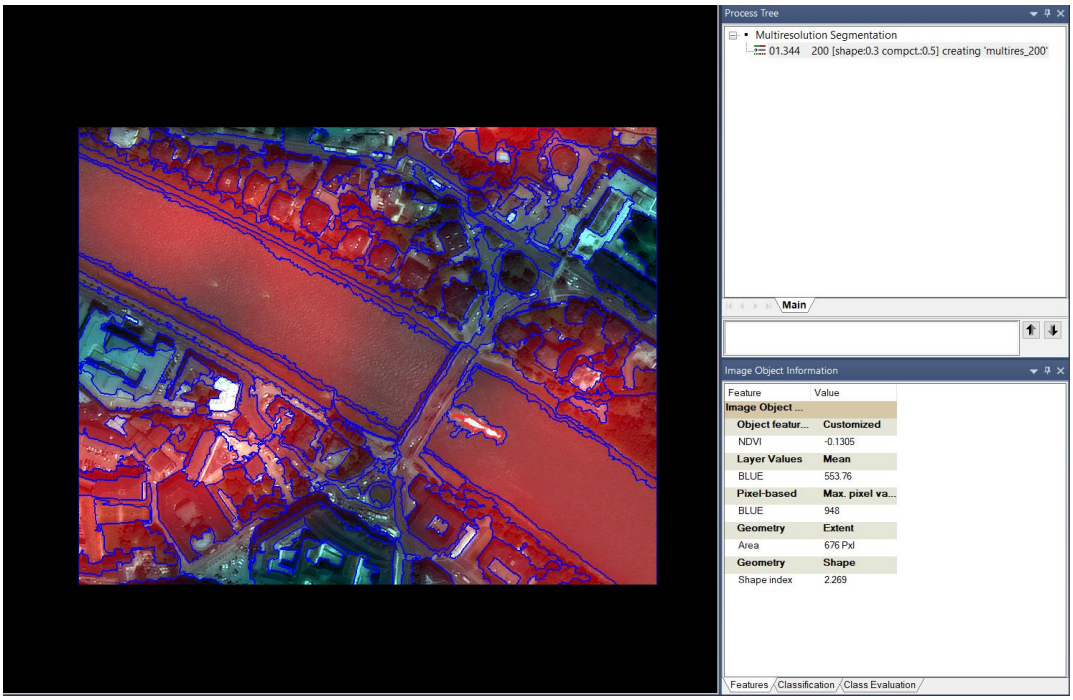

Figure 12. Multiresolution Segmentation – Boat Object

6. EXAMPLE III

6.1 NDVI Index Range

To find a threshold for the created NDVI feature and differentiate between water and vegetation objects, the NDVI range was updated. As result, the image (Figure 13) evidenced an NDVI range between -0.311 and 0.761. Considering the obtained image NDVI Index range, a threshold was established, to display only the water features (Figure 14), this range was between -0.311 and -0.2. The same process was carried out for the vegetation objects, and the resulting threshold was between 0.36 and 0.761 (Figure 15).

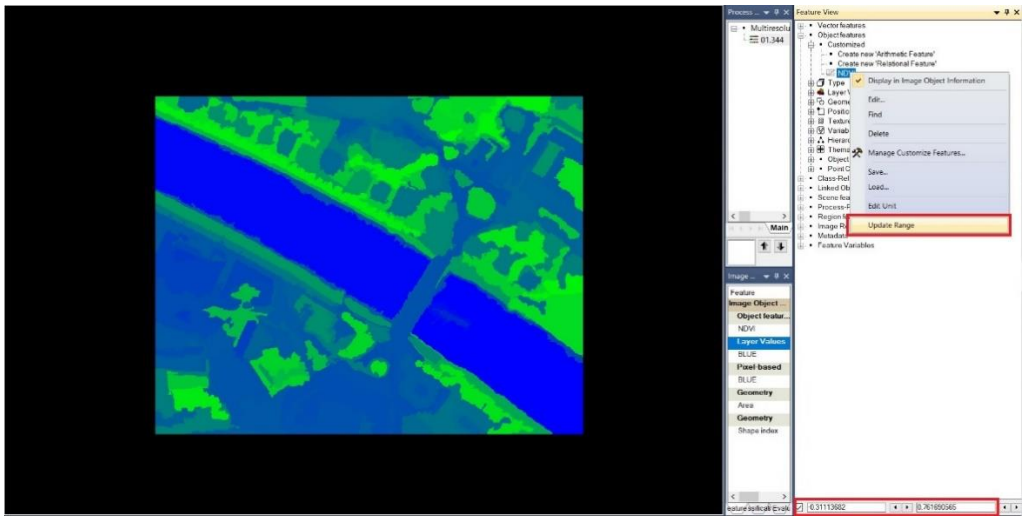

Figure 13. Image NDVI Index Range

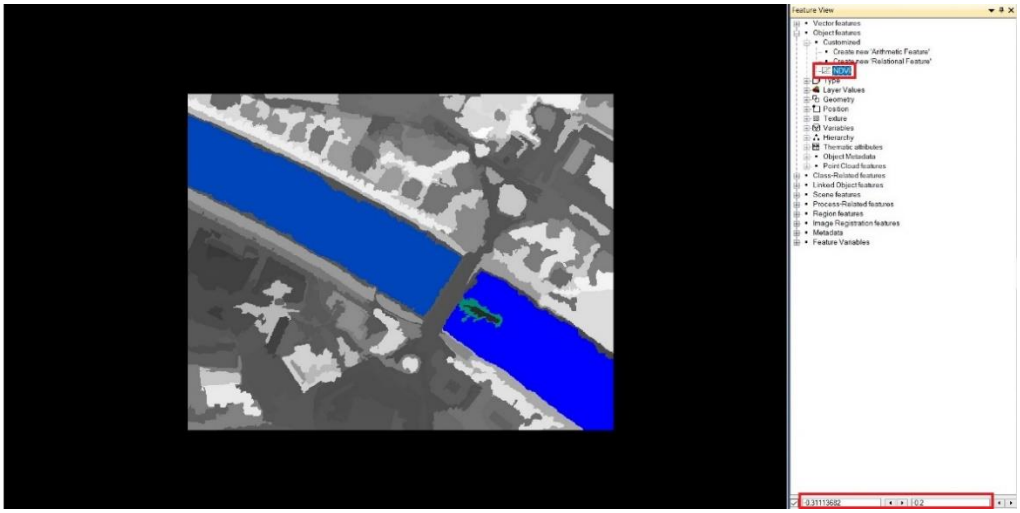

Figure 14. Water NDVI Index Range

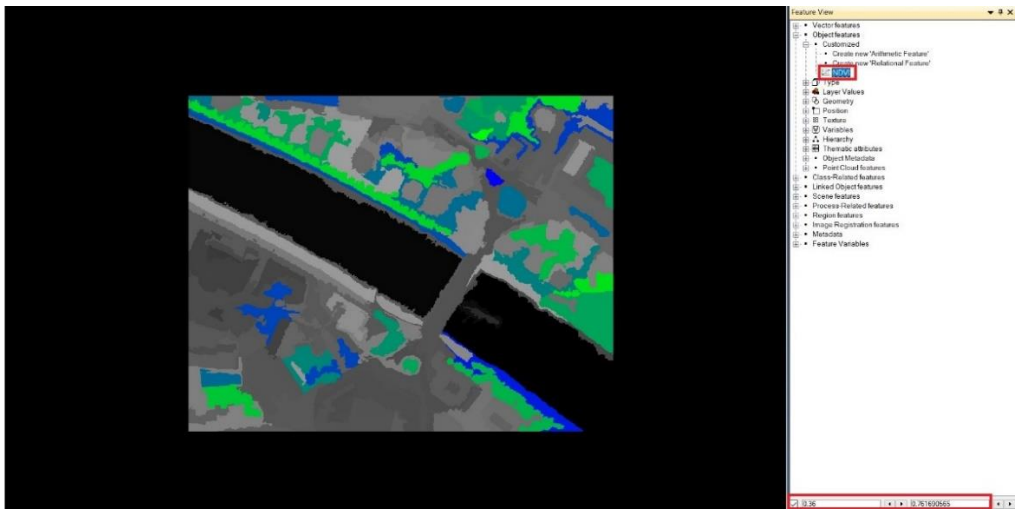

Figure 15. Vegetation NDVI Index Range

7. EXAMPLE IV

7.1 Class creation and Assignment (NDVI Threshold)

After having created two new classes (Vegetation and Water), two "assign class" algorithms were created, one for each class. For the Vegetation Class (Figure 16), the following condition was configured: NDVI >= 0.36. While for the Water Class (Figure 17), the condition was configured as NDVI <= -0.2. Both conditions were created based on the identified NDVI threshold in the previous section.

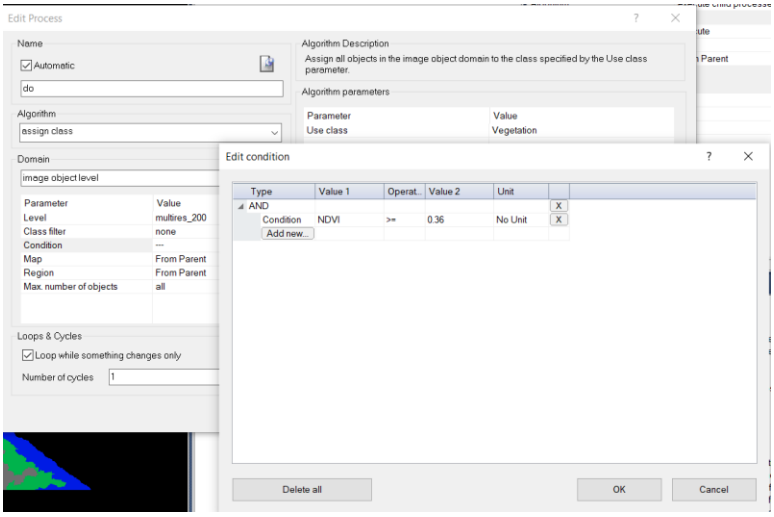

Figure 16. Vegetation Class Assignment

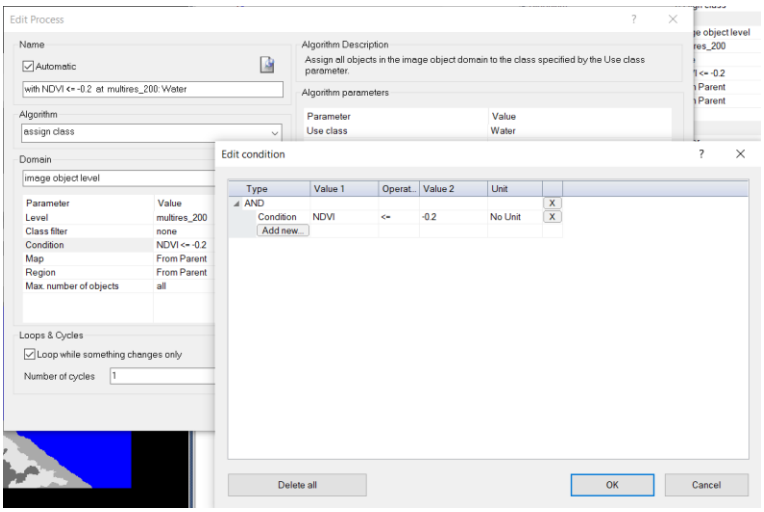

Figure 17. Water Class Assignment

Below you will find the class assignment result (Figure 18).

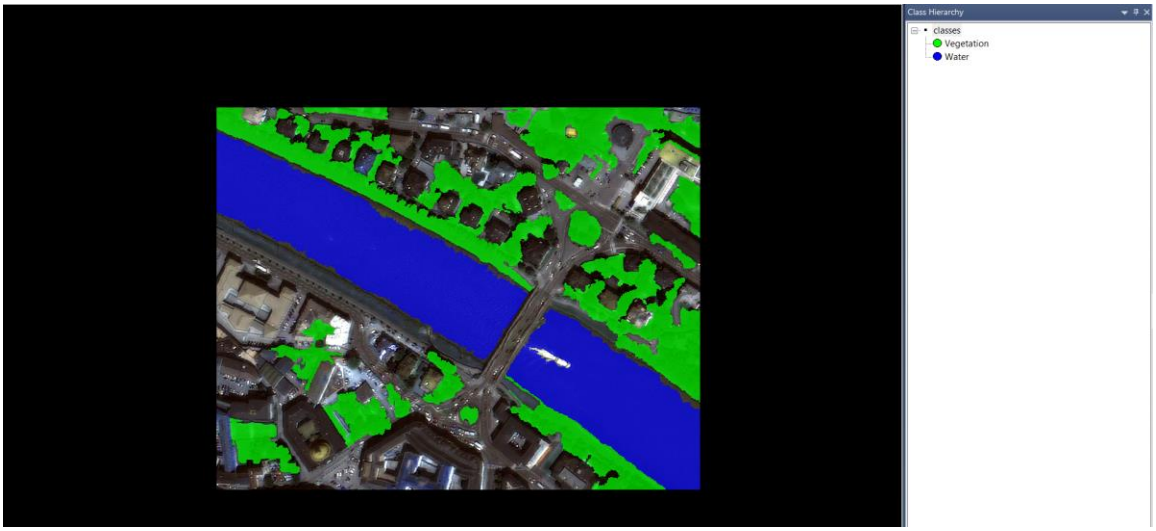

Figure 18. Class Assignment Result

As can be observed in the resulting classification, the boat inside the Salzach river could be classified based on its object relationship with the water objects. For that purpose, the feature "relative to border to" was created for the border relationship of the objects with the Water class (Figure 19). The resulting feature returns values between 1 (100% of the selected object it's surrounded by water) or 0 (0% of the selected object it's surrounded by water). For the boat object, the result was 1 as expected (Figure 20).

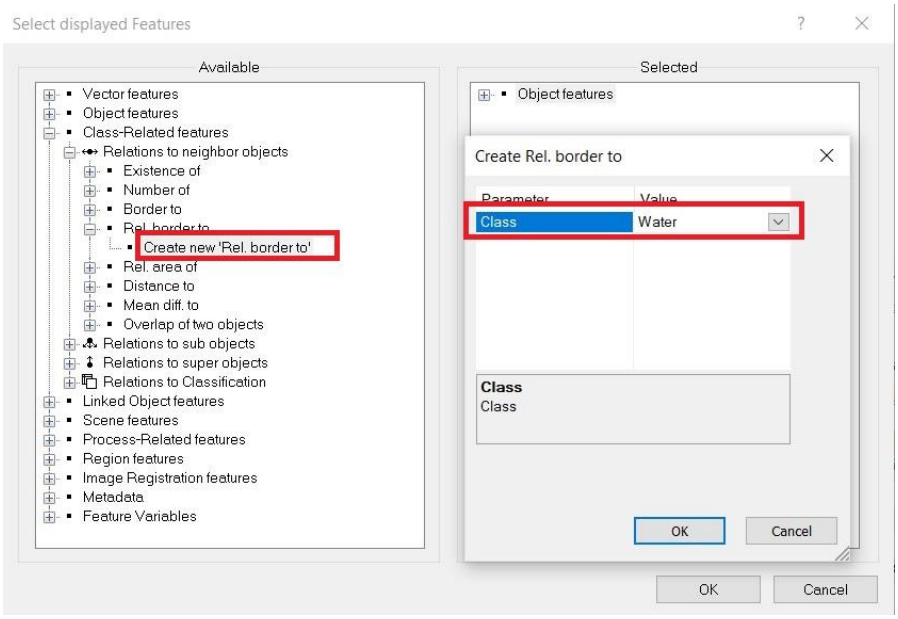

Figure 19. Feature: "Ref. border to"

Figure 20. Boat Object – Border relationship to water class.

Then, a new "Boat" class was created, and using a new "assign classification" algorithm, that class was assigned to objects whose Ref. border to the class water was 1 (Figure 21). The result was an image with three classifications, Vegetation, Water, and Boat. Being the Boat correctly delineated and classified (Figure 22).

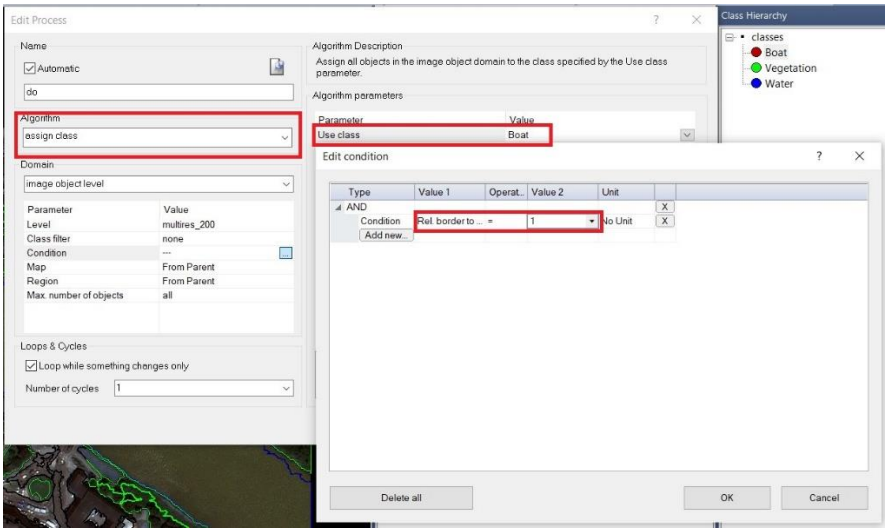

Figure 21. Boat Classification – "Ref. Border to" conditional expression.

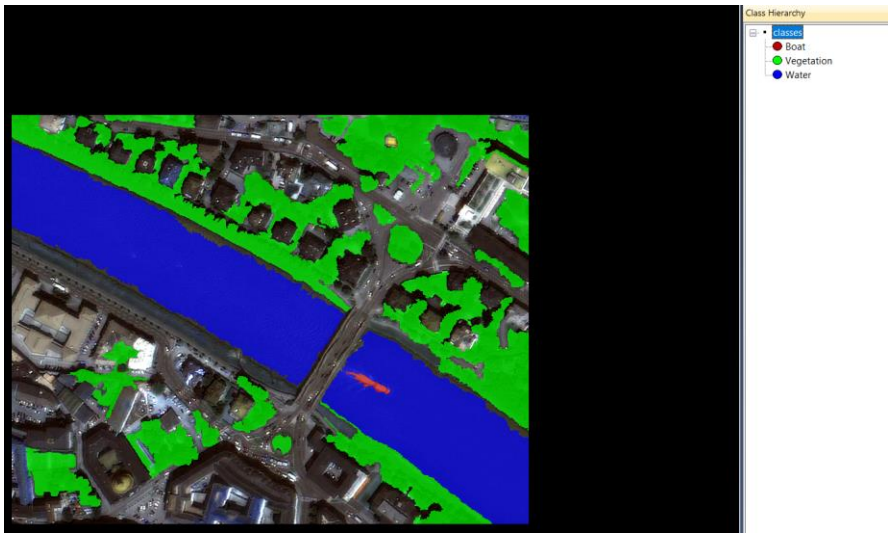

Figure 22. Final Image classification (3 Classes).

7.2 Class creation and Assignment (Air Quality)

To provide a detailed classification, the air quality layer was used. For that purpose, two new classes were created: High Air Quality and Low Air Quality, as part of the Vegetation class. Subsequently, two now "assign class" processes were created based on the air quality values. The "High Air Quality" classification was assigned to objects with a Mean value (Air Quality) higher or equal to 50 (Figure 23), while the "Low Air Quality" classification was assigned to objects with a Mean value (Air Quality) lower than 50 (Figure 24).

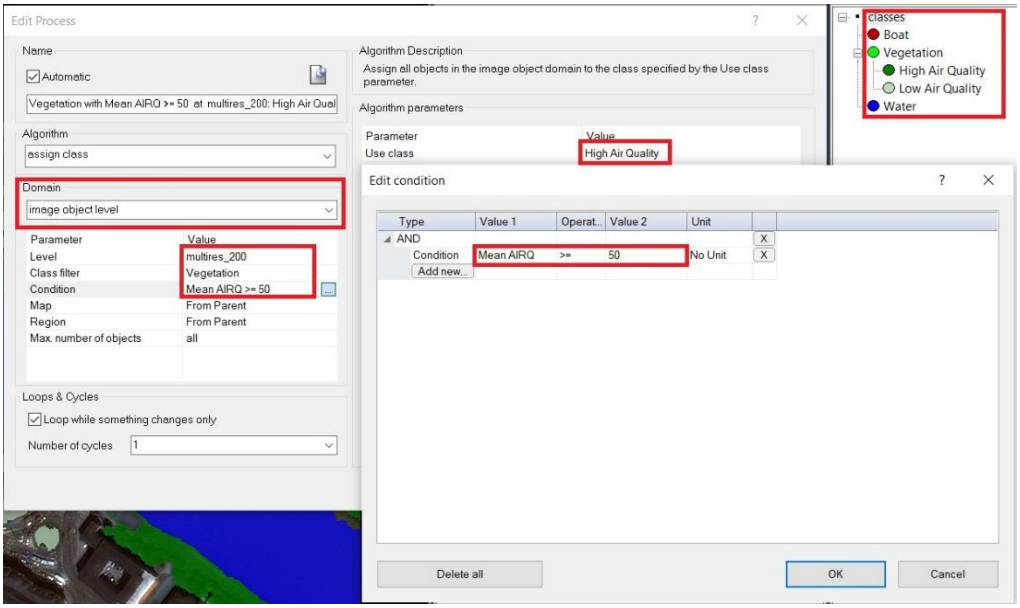

Figure 23. High Air Quality Class Assignment.

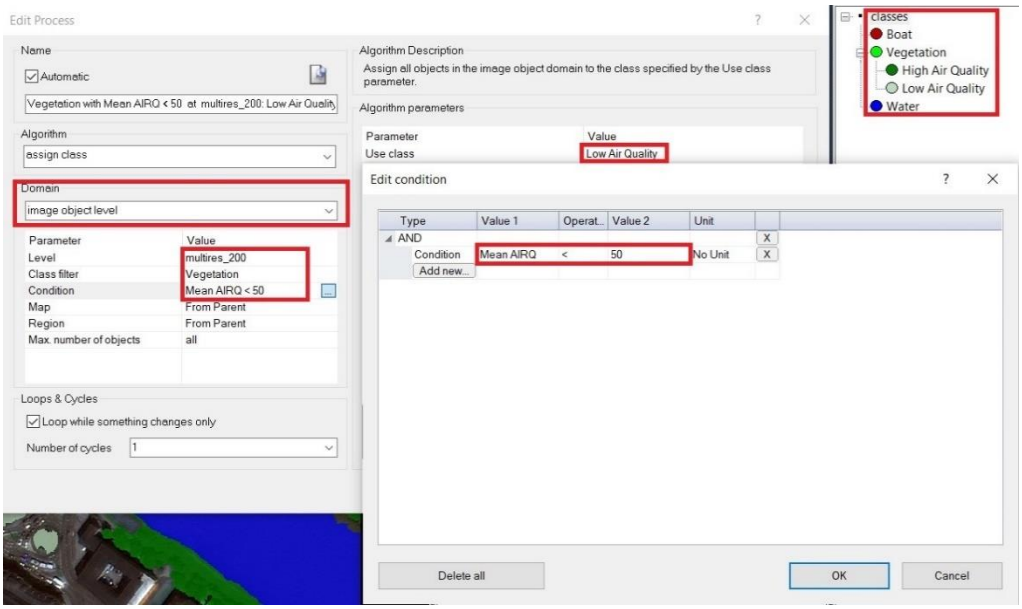

Figure 24. Low Air Quality Class Assignment.

As result, a new classification was implemented (Figure 25), including the classes Boat, Vegetation (with High Air Quality and Low Air Quality), and Water. For visualization purposes, the Vegetation super-class can be collapsed, in that case, the objects classified as High Air Quality and Low Air Quality sub-classes will be now assigned to the Vegetation superclass and displayed with its symbology.

Figure 25. Final Image Classification (5 Classes).

7.3 Questions

- **How many objects were classified as "Water"?**

To determine how many objects were classified as water in the image, the "Number of classified objects" feature was displayed, for the Water class. (Figure 26). As result, the previous feature returned that just 3 objects were identified to be part of the Water class. (Figure 27)

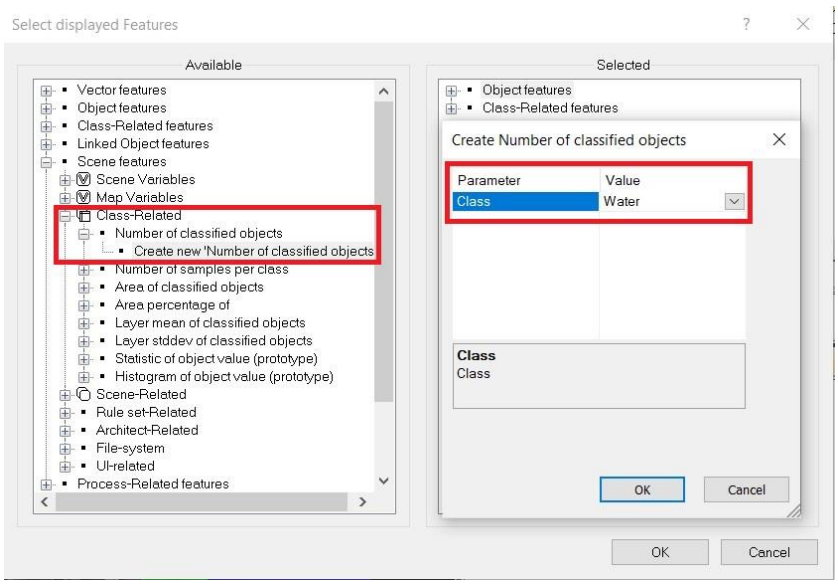

Figure 26. "Number of classified Objects" feature.

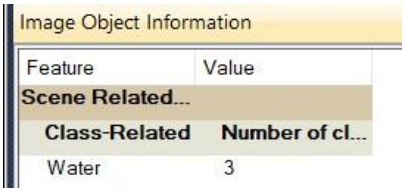

Figure 27. Number of objects classified as Water.

- **What is the area of the whole vegetation class (if you select the vegetation class to generate the feature, it will summarize the values from the grouped sub-classes?**

To determine the area of the whole vegetation class, the "Area of classified objects" feature was displayed for the Vegetation class (Figure 28), and for the related subclasses.

As result, the Vegetation class has an extent of 40853.12 m2, the High Air Quality class 29469.96 m2, and the Low Air Quality class 11383.20 m2. (Figure 29)

Moreover, with the previous area values, we can confirm that if the "Area of classified objects" it's displayed for a superclass, it will summarize the values from the grouped sub-classes, as the sum of our sub-classes area extent, it's equal to the super class area extent.

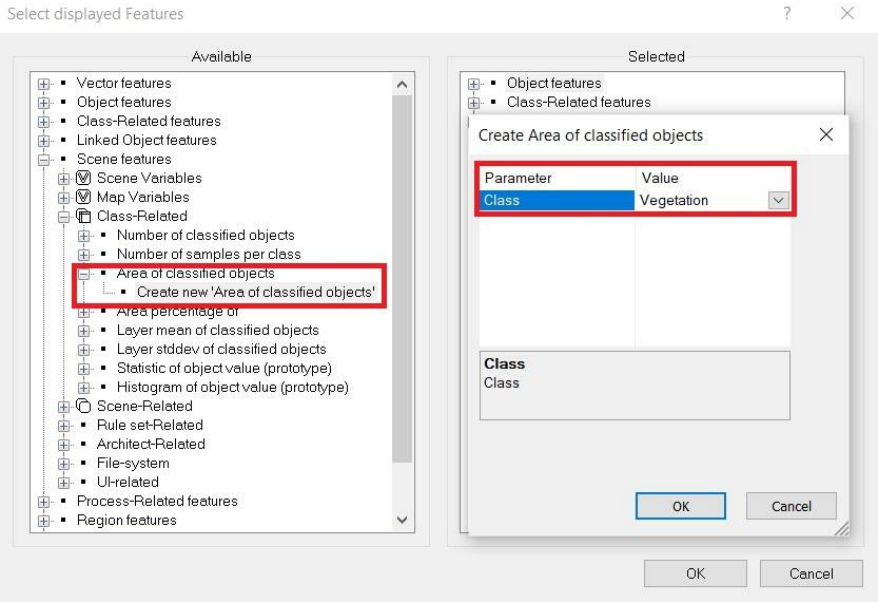

Figure 28. "Area of classified objects" feature.

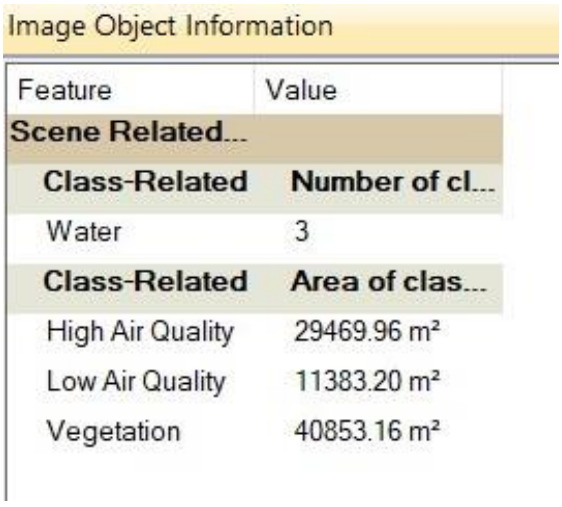

Figure 29. Vegetation Area (with sub-classes).

8. EXAMPLE V

8.1 Class Assignment based on Level Distance

To create a new level below the existing "multires_200" level, the "multiresolution segmentation" process was carried out, with a "Scale parameter" of 50, Shape and Compactness of 0.5, and considering all the layers except the Air Quality one. (Figure 30)

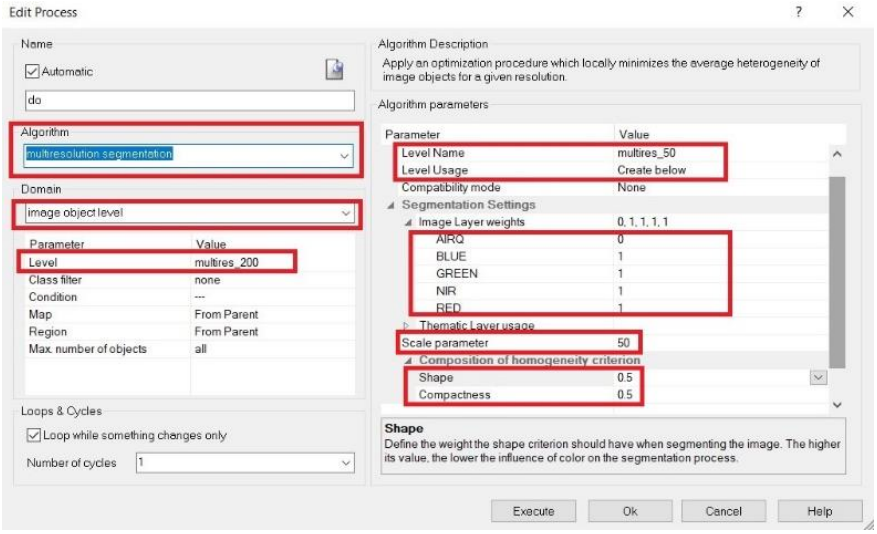

Figure 30. "Multiresolution Segmentation" process for a level below.

As result, a segmentation with smaller objects was created, considering that this time the Scale parameter was four times smaller than the original level. (Figure 31)

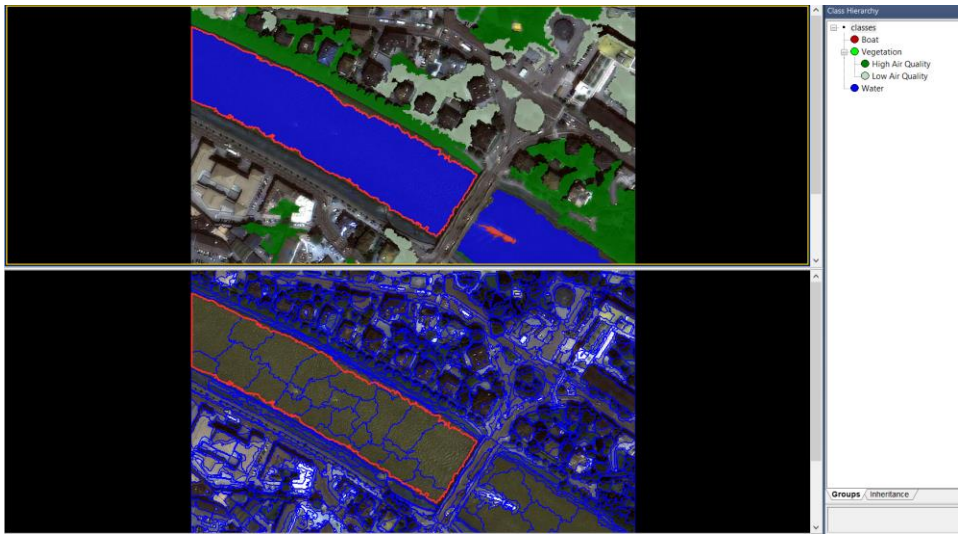

Figure 31. Comparison of object segmentations. (Above: Scale Parameter of 200 | Below: Scale Parameter of 50)

Then, to classify the new level segmentation, based on the existing classification in the super object level, the “Existence of” feature was displayed (Figure 32), this will return a 1 if the object in the current level has a super object assigned to the vegetation class. (Figure 33)

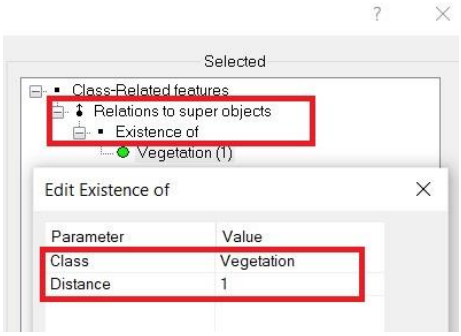

Figure 32. “Existence of” Feature.

As a bonus step, using the “assign class” process and the previously created “Existence of” feature, the “Vegetation” class was assigned to the sub-objects (Level: multires_50) for which a super object (Level: multires_200) has assigned the Vegetation class (or the “Existence of” feature is equal to 1). (Figure 34)

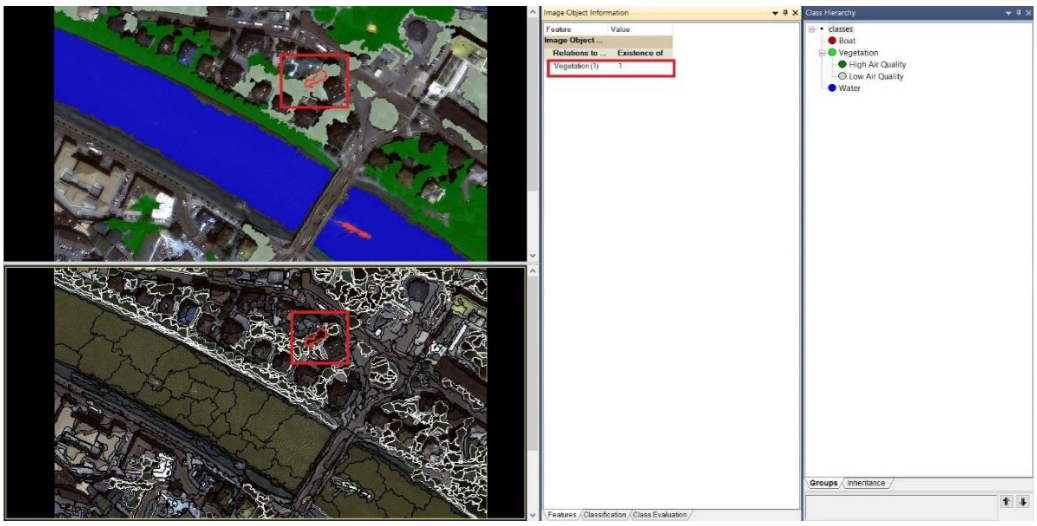

Figure 33. Example of the “Existence of” Feature functionality.

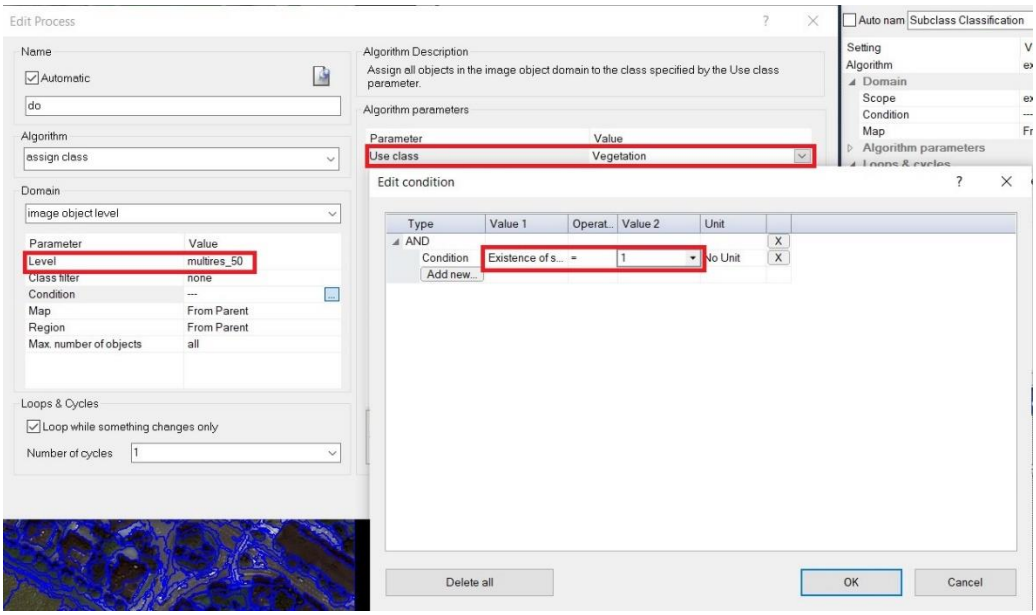

Figure 34. "Assign Class" process for sub objects.

As result, below you will find a comparison between the super objects classified as "Vegetation" and the sub-objects classified as "Vegetation" with the "Assign class" process. (Figure 35)

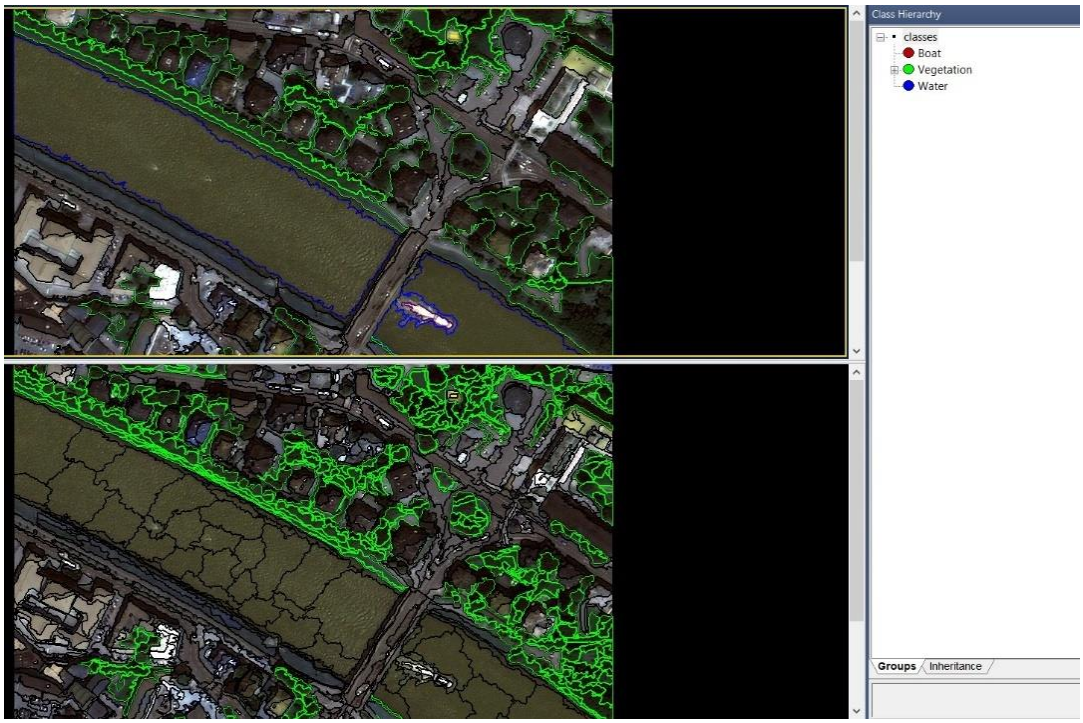

Figure 35. Comparison of object classifications. (Above: Super object | Below: Sub object)

8.2 Questions

- **What is the meaning of the distance value when you create the feature?**

The Distance value parameter for the “Existence of” feature, refers to the hierarchical distance to super-objects. In other words, it is a level distance that represents the hierarchical distance between image objects on different levels (E-cognition). In the case of the “Existence of” feature, having a distance value of 1, means that it will check the relationship of the sub-objects (current level) with the objects one level above (super objects), in case the number was 2, it would not check the relationships with the super objects one level above, but two levels above.

9. CONCLUSIONS

After carrying out an Object-Based classification workflow using eCognition software, we could evidence the advantages of working with objects instead of pixels for classification purposes. Moreover, we learn how to perform a correct classification using some of the basic object, classes and spatial relationships like thresholds, super/sub object, borders percentages among others.

10. REFERENCES

Advanced Rule Set Concepts. Documentation eCognition Suite (Developer User Guide) (n.d.). Retrieved January 6, 2023, from https://docs.ecognition.com/v9.5.0/eCognition_documentation/User%20Guide%20Developer/4%20Basic%20Rule%20Set%20Editing.htm

Basic Rule Set Editing. Documentation eCognition Suite (Developer User Guide). (n.d.). Retrieved January 6, 2023, from https://docs.ecognition.com/v9.5.0/eCognition_documentation/User%20Guide%20Developer/4%20Basic%20Rule%20Set%20Editing.htm

Features - Overview. Documentation eCognition Suite (Developer Reference Book) (n.d.). Retrieved January 6, 2023, from https://docs.ecognition.com/#eCognition_documentation/Reference%20Book/03%20Features/2%20Object%20features/8%20Relations%20to%20objects/5%20Super-objects/To%20super-objects.htm?TocPath=Documentation%2520eCognition%2520Suite%257CDeveloper%2520Reference%2520Book%257CFeatures%2520and%2520Feature%2520View%257CFeatures%2520-%25C2%25A0Overview%257C2%2520Object%2520features%257C8%2520Relations%2520to%2520objects%257C5%2520Super-objects%257C_____1