Final Examination

1. Object-based classification

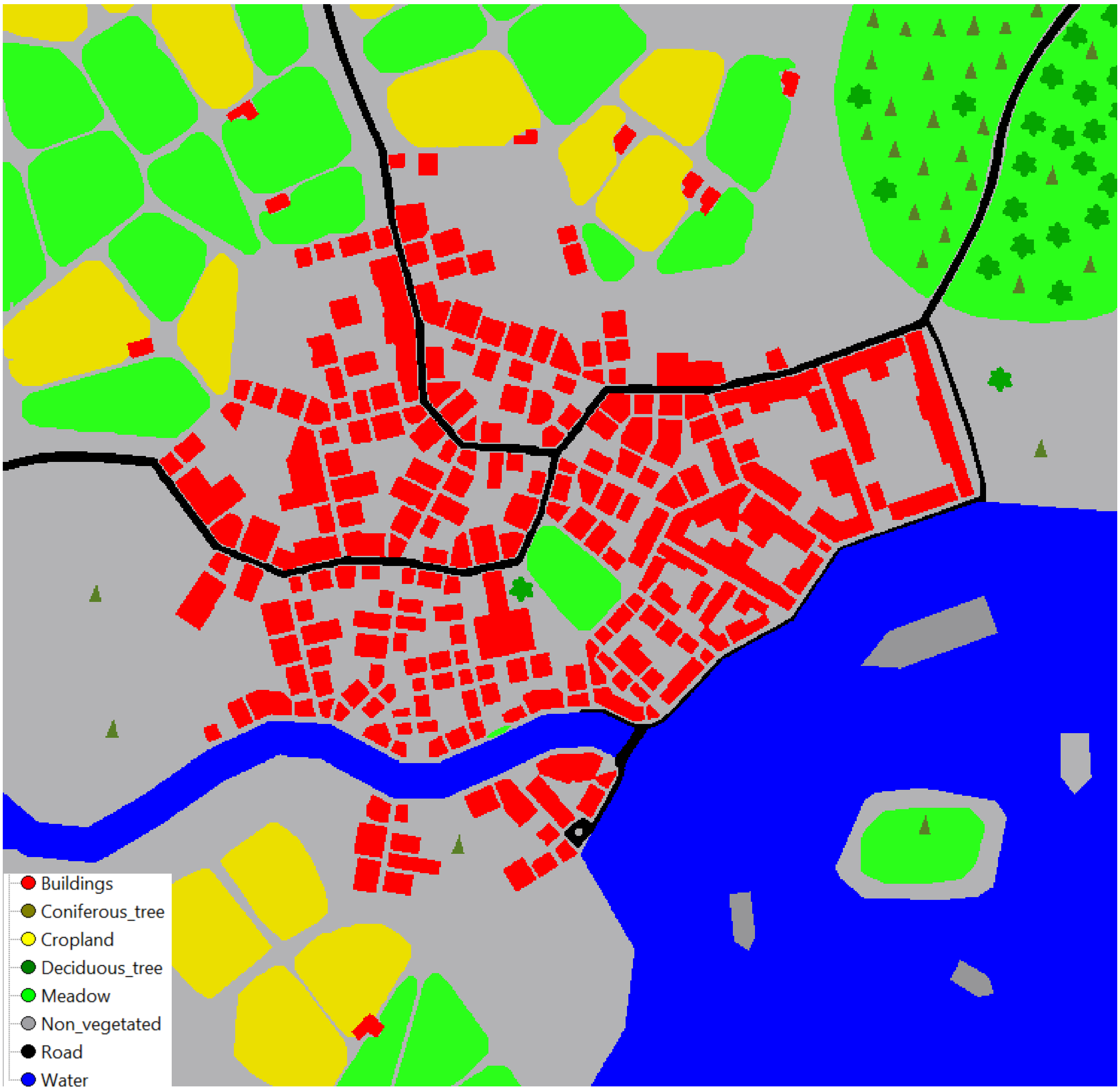

Figure 1. Results of the sample-based (supervised) image classification using SVM.

See file: *Kiefer_sample_based.dpr*

2. Knowledge-based classification

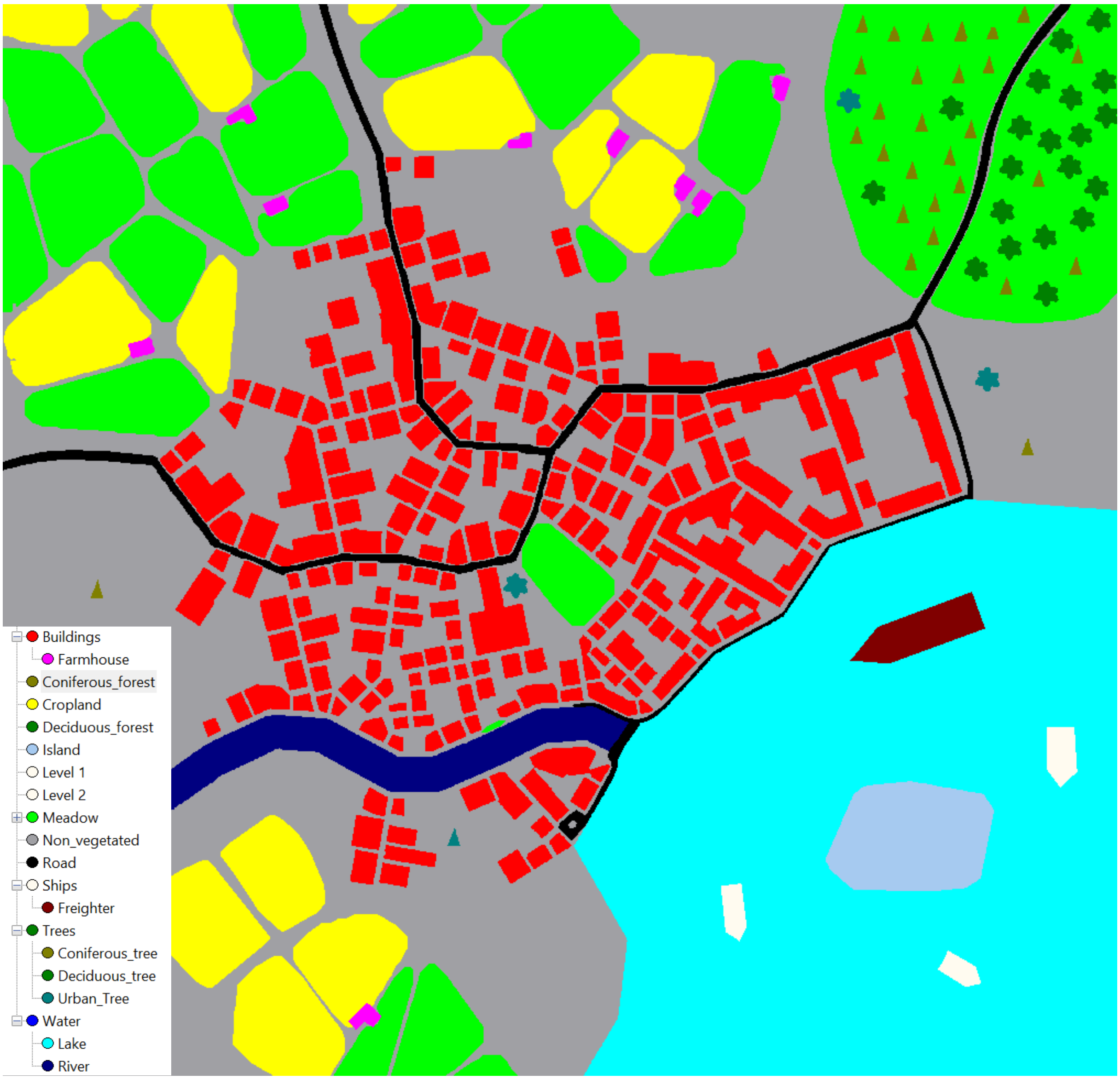

Figure 2. Results of the knowledge-based/rule-based classification.

See file*: Kiefer_expert_based.dpr*

3. Hierarchical classification

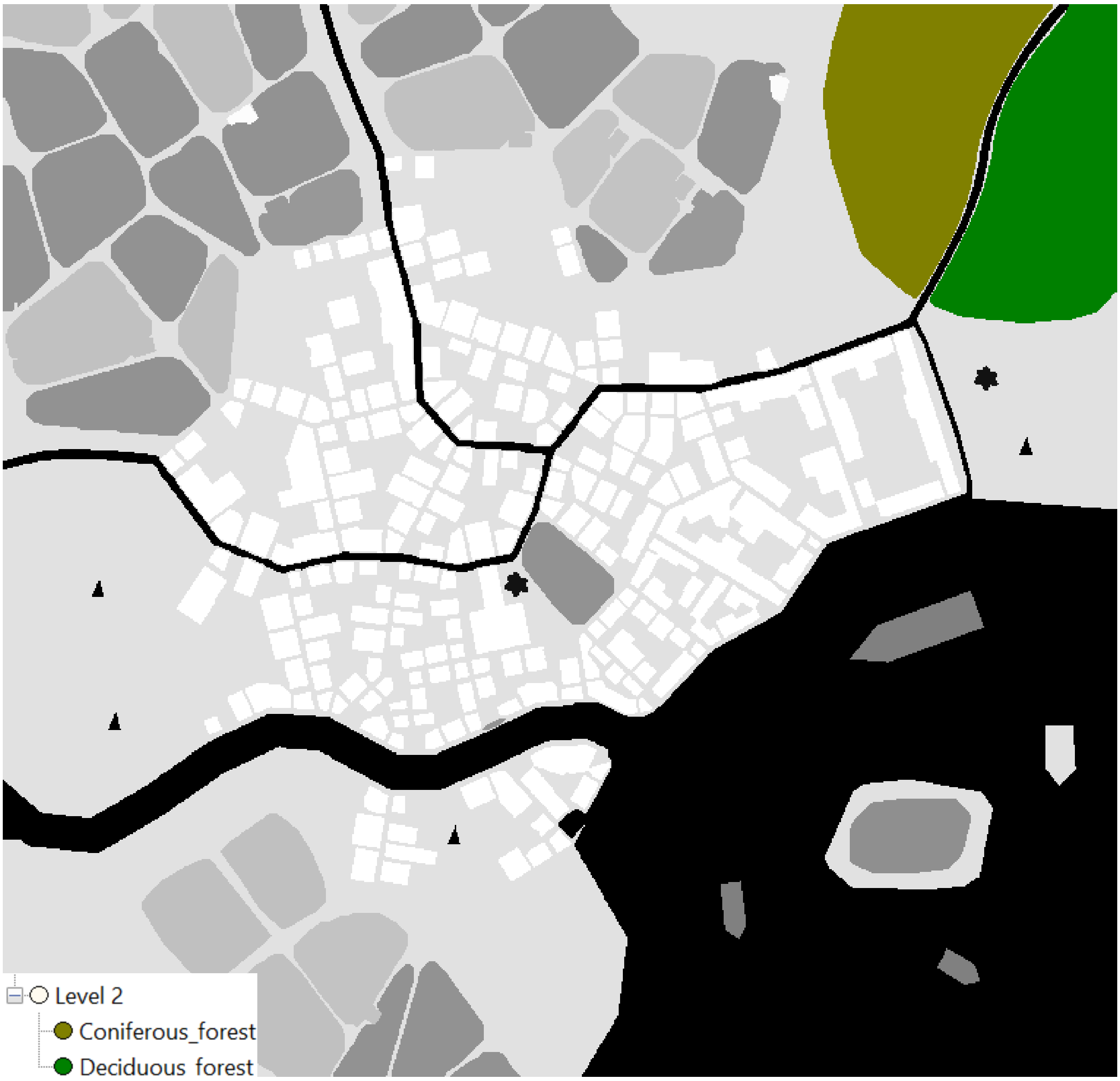

Figure 3. Results of the hierarchical classification using hierarchical relationships between the two levels.

See file*: Kiefer_expert_based.dpr*

4. Object statistics

4.1 Describe shortly (3-5 sentences), why most of the classes of the knowledge-based classification cannot be addressed in a pixel-based approach, give three specific examples of your solution.

While pixel-based approaches mainly consider color in the form of spectral reflectance, knowledge-based classification enables the inclusion of expert knowledge and thus defines a specific spatial context as well as forms and shapes. It becomes possible to use class-related features when the classification of an object depends on its surroundings (neighboring objects, sub objects & super objects). In this particular classification, the knowledge-based approach provided the opportunity to further classify the superficial classes derived from the pixel-based approach into more meaningful classes. Specifically, we were able to further differentiate water by recognizing different shapes of water objects, buildings by defining those in close neighborhood to agricultural areas as farmhouses, as well as defining the object of an island determined by being surrounded by water, which would not be possible with a pixel-based approach.

4.2 Select the appropriate Feature in your final project and figure out the length (in map coordinates - not in pixels, check the context menu for the feature to change the units) for the class: Freighter

Length [m] freighter: **75.42 m**

Select the appropriate Object Feature in your final project and figure out the Elliptic fit values (geometry feature) for the classes River and Lake. Describe briefly how the Elliptic fit is calculated and what the meaning of the values is. Consult the eCognition User Guide for a more comprehensive understanding. Write down the values in your text document and explain the value differences between the two objects. In which case the value gets 0?

Elliptic fit river: **0**

Elliptic fit lake: **0.6591**

The elliptic fit is a geometry-based object feature that measures how closely an object fits into an ellipse of a similar area. It is calculated by fitting an ellipse to the shape of the object and then determining how closely the object's shape matches that ideal ellipse. It ranges from 0 to 1, where 1 stands for perfect circles. In this example, the elliptic fit of the lake is higher and closer to 1 than that of the river, as the lake has a compact, round shape. In contrast, the value 0 for the elliptic fit of the river shows it is very irregular and that it is impossible to fit an ellipse around it, especially because of the meandering of the river.

Source: Trimble (2024). Advanced Rule Set Concepts. Retrieved from: https://docs.ecognition.com/eCognition_documentation/User%20Guide%20Developer/7%20Advanced%20Rule%20Set%20Concepts.htm *(Accessed 09.02.2025).*

4.3 Create a customized feature reflecting the following formula for an $REDNESS$ index in your final project. What threshold of the $REDNESS$ index could be used to differentiate between buildings and the other classes/objects? For this you can make use e.g. of the "update range" view in eCognition, as explained in the "objects features" exercise. • Can you explain why the "water" and "road" objects have an undefined REDNESS value?

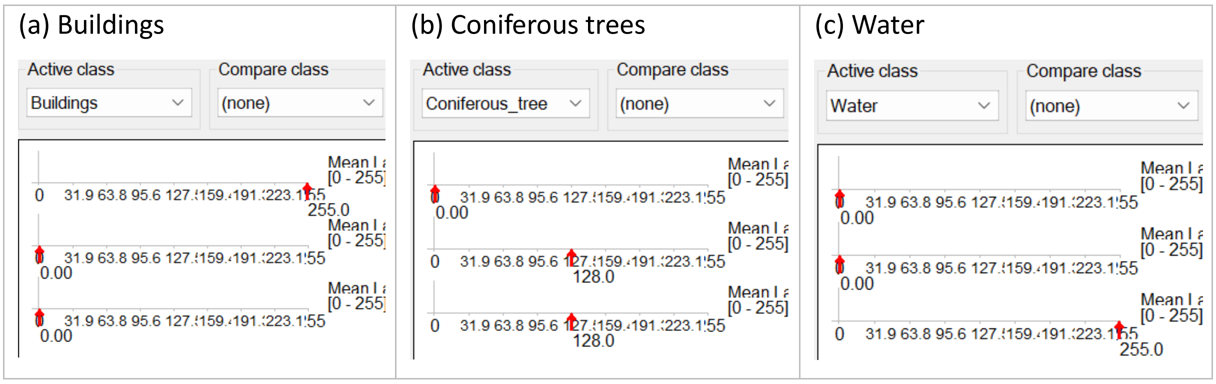

Figure 4. Comparison of the mean reflectance values for Layer 1 to 3 for the different objects (a) buildings, (b) coniferous trees and (c) water.

In general, the REDNESS index considers the first two layers, i.e. the red and green bands. It should be noted that in this case we can’t speak of reflectance values, but rather of DNs representing colors, since we are dealing with an artificial landscape image. The index ranges from -1 to 1, with values close to -1 representing high DNs in the second layer (green) and close to 1 representing high DNs in the first layer (red). This makes it quite easy to differentiate between buildings and other objects. Since buildings are shown in red in the image, this results in high DN values in the red band and no values in the green band (see figure 4 (a)) and correspondingly in a REDNESS index of 1. Thus, to distinguish between buildings and other objects, you can create a threshold that defines all objects with a REDNESS index of 1 as buildings and those with a REDNESS index below 1 as non-buildings.

Water has an undefined REDNESS index, as not all three RGB bands are taken into account, but only the red and green ones. This is illustrated in figure 4 (b) & (c). Although coniferous trees have medium DNs in both the green and blue bands, only the green band is considered in the REDNESS index, resulting in a value of -1 for coniferous trees. Similarly, water has high DNs in the third band (blue), but no values in the first two bands, resulting in undefined REDNESS values. This could be avoided if all three layers were considered. Lastly, the roads are represented in the color black, indicating that they have zero DNs in all three bands, resulting in an undefinable REDNESS index. Similarly, gray objects which have the same DN in all three bands are given a REDNESS index of 0.