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„OBIA in the Neusiedlersee region“

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ABSTRACT

This work is about how can Object-based image analysis (OBIA) can be performed in the eCognition Developer software - it is described how a satellite image could be segmented and classified, using different tools of the program.

Categorizing of outcomes of research, providing users with overview of existing segmentation techniques becomes more and more in-demand task. The program eCognition Developer is one of rather few software suitable to fulfil this task. OBIA can provide a more meaningful source of information than pixel-based image analysis due to less well-defined edges and borders between different classes. Here a formal definition of OBIA is proposed and demonstrated how it works in the eCognition Developer software step by step.

OBIA in eCognition Developer software consists of two parts: segmentation and classification. In this work, different techniques intended for image segmentation and classification applied to optical remote sensing images has been studied and reviewed. The RapidEye satellite image of the Neusiedlersee region has been selected for the goals of demonstration. The selection of samples is based on a classification of a land cover map which was taken from Spatial Indicators for Land Use Sustainability (SINUS) and which is based on a visual interpretation. Multi-resolution segmentation and classification of the nearest neighbor as the most convenient methods were implemented by mapping of the RapidEye satellite image in eCognition Developer. The most convenient methods - multi-resolution segmentation and classification of the nearest neighbour - were implemented by mapping of the RapidEye satellite image in eCognition Developer.

At last, to analyze OBIA pro-s and contra-s in eCognition Developer Software it has been provided a comparison of the segmented and classified satellite photo in eCognition Developer with the other one taken from SINUS.

Keywords: Object-based image analysis, OBIA, image segmentation, multi-resolution segmentation, image classification, remote sensing, satellite image, Rapid Eye, land cover mapping, eCognition Developer.

ZUSAMMENFASSUNG

In dieser Arbeit geht es darum, wie die objektorientierte Bildanalyse (OBIA) in der eCognition Developer Software durchgeführt werden kann - es wird beschrieben, wie das Satellitenbild mit verschiedenen Werkzeugen des Programms segmentiert und klassifiziert werden kann.

Es ist immer wichtiger geworden, die Forschungsergebnisse zu kategorisieren und die Leser mit einem Überblick über die existierenden Segmentationstechniken in jeder Kategorie und mit der ständig wachsenden Forschung über die Bildsegmentierung zu versorgen. Das Programm eCognition Developer ist eines der komfortabelsten Programme, die für diesen Ansatz verwendet werden können. Die OBIA kann aufgrund weniger gut definierter Kanten und Grenzen zwischen verschiedenen Klassen eine aussagekräftigere Informationsquelle als die pixelbasierte Bildanalyse darstellen. Hier wird eine formale Definition von OBIA vorgeschlagen und demonstriert, wie es in der eCognition Developer Software funktioniert.

OBIA in der eCognition Developer Software besteht aus zwei Teilen: Segmentierung und Klassifizierung. In dieser Arbeit werden verschiedene Bildsegmentierung und Klassifikationstechniken für optische Fernerkundungsbilder untersucht. Zur Demonstration wurde das RapidEye-Satellitenbild der Region Neusiedler See ausgewählt. Die Auswahl der Stichproben basiert auf der Klassifizierung einer Landbedeckungskarte, die von Spatial Indicators for Land Use Sustainability (SINUS) genommen wurde und auf einer visuellen Interpretation basiert. Die Multi-Resolution-Segmentierung und Klassifizierung des nächsten Nachbarn als die bequemsten Methoden wurde durch die Abbildung des RapidEye-Satellitenbildes in eCognition Developer realisiert.

Um alle Vor- und Nachteile von OBIA in der eCognition Developer Software zu sehen, wurde schließlich einen Vergleich unseres segmentierten und klassifizierten Satellitenfotos im eCognition Developer mit der Karte, die von SINUS genommen wurde gemacht.

Schlagwörter: Objektorientierte Bildanalyse, OBIA, Bildsegmentierung, Multi-Resolution-Segmentierung, Bildklassifizierung, Fernerkundung, Satellitenbild, Rapid Eye, eCognition Developer.

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INTRODUCTION

Object-based image analysis

It was found that capabilities of a traditional pixel-based image analysis is rather restricted due to the following reasons: image pixels are not true to geographical objects, so the pixel topology is limited; pixel-based image analysis mostly neglects the spatial photo-interpretive elements such as texture, context, and shape; the increased variability implicit within high spatial resolution imagery confuses traditional pixel-based classifiers resulting in lower classification accuracy (Hay and Castilla, 2006).

Satellite remote sensing provides essential data like paired images (mostly in the band of optical or radar) for preparing updated maps which are widely used in environmental monitoring, three-dimensional planning or crisis management.

Remote sensing data are obtained mostly for the next process stages and not just because of the limitations of weather (cloud cover satellite scenes) but also technological (the size of the collected data sets).

Therefore, a major challenge that is currently faced by satellite remote sensing and GIS systems is automation the process of selection and classification of remote sensing data archives (Benz et al., 2004).

Probably, the most dynamically developing method for automatic classification of remote sensing data is Object Based Image Analysis (acronym OBIA).

Majority of OBIA developers used to use a term ‘object based’. A few authors used ‘object oriented’ (Blaschke et al., 2000; Blaschke and Hay, 2001; Benz et al., 2004), some of them later switched to ‘object-based’ (with or without a hyphen), whilst others still keep using ‘object-oriented’ (Navulur, 2007). Those authors which prefer using ‘based’ since ‘oriented’ term could be too closely related to the object-oriented programming paradigm (Hay and Castilla, 2008). Kettig and Landgrebe in 1976 pioneered incorporating of contextual information in the classification of remote sensing images, with emphasize on importance of incorporating texture increases with increasing resolution. Overcoming of so called ‘salt and pepper effect’ was a major target of grouping pixels into image objects (Blaschke et al., 2000). Since that ttime many researchers claimed that OBIA methods are suitable for overcoming this situation, e.g. ‘‘Thanks to the recent improvements in image segmentation, object-based approaches can be used to delineate and classify land cover efficiently'' (Duveiller et al., 2008). Latter articles stated that ''Object-oriented processing techniques are becoming more popular compared to traditional pixel-based image analysis'' (Gamanya et al., 2009).

OBIA substantially transformed the approach to the traditional method of processing of remote sensing images. It offered a quick and fully automated technique of classification of images, the quality of which is similar to the human visual image interpretation (Blaschke, Strobl, 2001; Benz et al., 2004; Liu, Wang, 2005). New and recognized quality of the remote sensing and geographic information systems was provided to analysis of Object-images (Adamczyk, Będkowski, 2006). Contrary to earlier image classification techniques, OBIA is based on pixels groups rather than on single individual pixels, forming a homogeneous, and logical conceptual NYM segments (objects) that reflect real-world entities much better than sets of single pixels (Benz, 2004; Aldred, Wang, 2007). This ideology of analysis provides better algorithmic processing to the perception of objects or dimensional units for human perception. It makes possible designing more intuitional objects in the course of images segmentation (Blaschke, Strobl, 2001).

It allows using, on top to spectral (brightness value) characteristics, also the extensional characteristics, like texture, relations between segments, surface, shape, topology, etc., to make up knowledge. With OBIA, an newly designed object contains by far more useful information than a single pixel; it in turn substantially enhances quality of the final results of the classification.

An additional advantage of the object technique is a possibility to exploit fuzzy logic during the classification process. A segment can belong to the system with a probability varying from 0 to 1, so complexity of the real world is mirrored much better comparatively to the usual binary system.

One more valuable useful feature of the object-oriented analysis is its ability to create different levels of objects hierarchy simultaneously, reaching a network of horizontal and vertical connections between different hierarchy objects.

OBIA operates with image segmentation and classification verification techniques. Image segmentation is the first OBIA step. Essence of the process of segmentation is grouping the pixels in order to form objects. This is by far the most critically important aspect of object-oriented analysis, as its quality pre-determined the correctness of the final classification (Jiang et al., 2008). Sections are made up by combining smaller objects (with similar characteristics) with larger ones based on the criterion of homogeneity of the local one (Baatz, Schap, 2000). Creation of the sizeable objects is restricted by a predefined user parameter, e.g. the scale parameter (eCognition Developer 8.7 User Guide, 2011). Thus, designed segments represent individual objects (roads, buildings, lakes, etc.). This classification is based on the previously created objects, using general values of the individual characteristics of the object. This reduces the spectral variation within an object and allows usage of the object's extended characteristics. As an object is a group of pixels, the group's characteristics such as mean value, standard deviation, ratio, etc. can be calculated; on top of this, other available object features like shape and texture can be used for differentiating land cover classes with similar spectral information. This promotes usage the OBIA techniques for production land cover thematic maps with accuracies higher than those produced by traditional pixel-based method.

Animal distributions and abundance is affected with the cover and composition of ground vegetation which influence habitat selection and provide critical resources for survival and reproduction. Thus, it is of high importance to use sampling techniques which provides close to unbiased estimators of vegetation cover and composition to avoid deceptive recommendations for conservation. Well known techniques for measuring ground cover and composition used to be based on the Daubenmire (1959) approach, which is exploits visual estimating of either percent cover or percent cover categories (e.g. 0–5, 5–25, 25–50, 50–75, 75–95, and 95–100%).

However, subjective methods which are based upon visual estimation are subject to a bias and are not repeatable (e.g. different observers will almost certainly record different measurements for the same quantity; Kercher et al. 2003). Available Published estimates of observer bias affecting visual estimation have ranged published earlier (Hatton et al. 1986; Kennedy and Addison, 1987) vary from 13% to 90% variance, depending on percent cover category and plot size (Klime, 2003).

A number of attempts have been made to account for an observer's bias in visual estimation techniques, but none could have in full been removed a subjectivity factor. Tilman's technique (1997) uses visual aids, such as cardboard cutouts of specific shapes and sizes to improve estimates. However, interpretation of these cutouts is still subject to bias.

Others have used known levels of ground cover to train observers (Anderson and Kothmann 1982), but training alone will also not completely remove observer bias (Sykes et al., 1983).

Recent developments in Geographic Information System (GIS) and image analysis software and technology offer great potential for using digital images of habitat to quantify ground cover and composition of vegetation in a repeatable and timely manner. So below I shall evaluate the usage of image analysis software "eCognition" (Definiens Imaging, GmbH, München, Germany), for analyzing digital photographs of the Neusiedlersee region.

The eCognition is a software extensively used for OBIA solutions. However, the open source products like GRASS and Opticks OBIA plugins have reached a stage which can now be used for OBIA to further extent.

In this study I will be concentrating on analysis of the region using the eCognition Methods of Segmentation and Classification.

General information about the Neusiedlersee Region

Neusiedlersee is a well-known "green tourism" and recreation area (Oberleitner, I., 2006). It is also a popular place for water sports (sailing, surfing), with a ban for using combustion engines.

The Neusiedler See - Seewinkel is located in the area "Eastern shore of Lake Neusiedl" until the border of Hungary. The largest in Austria salt lakes (ca. 26 sq. km area) are located in "Lacke" area at south of Seewinkel. Water flows are of ca. 50 cm of depth. Drain-free inflowing lacquers on the surface are a subject to severe seasonal fluctuations.

Neusiedlersee is a part of region "Ramsar". ¾ of the lake area is located in Austria, ¼ - in Hungary. The lake's total area accounts for app. 44,230 ha.

Neusiedlersee is a so called "landscape conservation" area. It was formally signed as "Natura-2000" having included some parts of National Park as well. Some parts of Neusiedlersee are natural reservations. Most of Ramsar area is internationally protected as of 1983, because of a national park Neusiedler See - Seewinkel. In 2001 UNESCO awarded the cultural landscape of the Neusiedlersee with a cross border World Cultural Heritage (Austria / Hungary).

The Neusiedler See - Seewinkel National Park is bordering with Fertö-Hanság Nemzeti Park. The Nemzeti park was founded in 1998 on in Hungary, on a that side of Neusiedl lake. The Seewinkel National park happened to be the first national park in Austria located in two countries. The park is the first protected area in the country recognised by IUCN. A half of National park area is located in the zone closed for visitors, Total National park area is almost three hundred sq.km., out of which 1/3 is "Austrian" part, and the rest (app. 200 km2) is "Hungarian" one (Zechmeister T., 2010).

The National park is subdivided by two zones:

- "Nature" zone. The major part of the Park. Total area is ca. 4500 ha. It is not allowed to use it for any business or agricultural activities. The nature is left to itself there, as mentioned, no access for visitors is allowed.
- "Preservation" zone. A "cultural" which thus is exploited tourists and agricultural measures to develop. Six areas can be defined as sub-zones:
    - Apetlon. Long lacquers of area ca. 1750 ha.
    - Illmitz-Hell. Total area – ca. 1550 ha.
    - Podersdorf – Karmazik; area app. 160 ha.
    - Sandeck – Neudegg, with ca. 460 ha area.
    - Waasen / Hanság – app. 140 ha.
    - Zitzmannsdorfer meadows with the area around 650 ha.

The whole land was in long-term leasing from more than 1,200 land owners.

Landscape preservation and protection zones as well as "natural" area have been established to preserve the Lake Neusiedl fauna and flora as well as its original landscape.

Lakes of Neusiedl and its lacquers are a place for breeding and resting of many birds coming there often from all across Europe. Breeding birds find their food there in shallow parts of the lake and can restore their reserves to fly further to the South.

Thus, Neusiedler See-Seewinkel National Park is known as one of if not the most important sanctuary for birds in Europe. In total, there are 300+ bird species which inhabit in the areas of salty varnishes, reeds and swampy meadows. The major species are graugans, bladders and sows. Saber buffoons, kite-whistles, caterpillars, great-traps and silver- and purple-horses can be mentioned among other birds species which can be found there.

The Park is also a breeding zone for such species as Purple Heron (100% of national breeding stock); Eurasian Bittern - 90%, Common Little Bittern 70%, Red-crested Pochard 80%, Eurasian Spoonbill 100%, Ferruginous Duck (65%), Garganey 20%, Common Redshank (8%) (Dvorak, Karner, 1995)

Among EU common species living in the Park the following could be mentioned: Sandpiper (*Himantopus himantopus*), Bluethroat (*Luscinia svecica*), Stilt Baillon's crake (*Poriana porzana*), Little crake (*Porzana parva*) and Moustached Warbler (*Acrocephalus melanopogon*). (Dick et al., 1994)

Neusiedlersee is a resting particularly important for many water birds, particularly in Fall. In 1990 – 1991 the following numbers of birds were registered there (max.): Caspian Gull (*Larus cachinnans*: 282), Common Teal (*Anas crecca*: ca. 7,000), Gadwall (*Anas strepera*: ca. 2,000), Mallard (*Anas platyrhynchos*: app. 2,545), Northern Shoveler (*Anas clypeata*: 2,300 and more), Black-headed Gull (*Larus ridibundus*: app. 1600). (Dvorak, Karner, 1995):

Mammals: in 2007 Gold jackal firstly was observed there. A few rather rare species, such as Root Vole, Southern Water Shrew, Eurasian Pygmy Shrew and Tundra Vole were found there as well.

Insects: on top to several rare butterflies' species, many species insects and 40 plus dragonfly species are found.

Amphibians species observed: substantial numbers of Smooth Newt (*Triturus vulgaris*), Moor Frog (*Rana arvalis*), Fire-bellied Toad (*Bombina bombina*), Levant Water Frog (*Rana esculenta*) and European Tree Frog (*Hyla arborea*).

Fish species: Tench (*Tinca tinca*), Pike-perch (*Stizostedion lucioperca*), Nothern Pike (*Esox lucius*) and others.

Plants species: *Iris sibirica*, *Succisa pratensis, Serratula tinctoria, Cyprinodonus cumulus*. Very rare species like *Cyprus pannonicus, Aster canus, Iris spuria, Pholiurus pannonicus, Camphorosma annua, Plantago tenuifolia* have been observed among others (Fischer, Fally, 2000)

Like in several other EU-located preservation areas, several elements of the Lake Neusiedl landscape are particularly important to be protected.

The steppe Seewinkel landscape has been substantially shaped by human beings. Such activities like forests clearing, haymaking, grazing and gradual drainage have been resulted in considerable changes happened to the area's landscape during the several centuries.

So, a major goal of establishing the National Park was to restore and preserve the landscapes as unique complex ecological systems.

People which have been living in Seewinkel should adapt their activities to dry as well as wet seasons. Extensive agricultural areas were set up because of available dewatering technologies via drainage ditches. This badly affected and eventually resulted in disappearing of many valuable habitats of this area.

Fast implementation of intensive agriculture technologies aggravated the situation further: a lot of endangered plant species which used to live at fields and vineyards were forced to leave them. Declining livestock in 60s/70s reduced a need in pastures and hay lands; subsequently, it resulted in abundant vegetation (mostly – reeds) in this area.

So, a major target for the land management system in the Park preservation area is maintenance and enhancement of biotypes quality in the cultivated landscape.

Purpose of the study

Selection of segmentation and classification techniques makes a major impact on later content classification satellite image. Therefore, the aim of this study is the demonstration of the chosen methods (multiresolution segmentation and NN classification), as the most convenient methods by mapping of the RapidEye (RE) satellite image rather than comparison of different methods available in the software company eCognition Developer.

The targets of the work are:

1. Review and analysis of OBIA advantages versus pixel-oriented picture analysis using a comparison of two land cover maps of the same region
2. Study of types of segmentation available in the eCognition Developer software for the selected type of satellite image (high resolution satellite images, RapidEye) and selected types of land cover (settlement, agriculture, water, reed, etc.).

Satellite photos of Neusiedlersee region were chosen to use for these purposes because of wide range of their uses. It is important that the samples for segmentation were not taken locally, but were chosen, based on a classification of a land cover map which was taken from Spatial Indicators for Land Use Sustainability (SINUS).

MATERIALS

Satellite system Rapid Eye

General information about the satellite system

This study uses the RapidEye (RE) satellite picture as an input to the eCognition project.

The work on the concept of the satellite system dates back to 1996, Germany, where a company Kayser-Threde GmbH raised the idea of building satellites for the German Space Agency DLR (Deutsches Zentrum für Luft- und Raumfahrt). Two years later the company RapidEye managed to raise substantial investment which enabled it to convert the concept into commercially available proposal.

RapidEye satellite sensor was launched successfully by the DNEPR-1 Rocket at Baikonur Cosmodrome in Kazakhstan on August 29th 2008. RapidEye was created by MacDonald Dettwiler, Ltd. (MDA); it offers image users a new data source which brings an unprecedented earlier set of large-area coverage, frequent revisit intervals, of high resolution and multispectral capabilities.

The RapidEye constellation uses five satellites meaning it stands apart from other satellite based geospatial information providers. It is uniquely capable in acquiring high quality, large-area image data on a day to day basis.

RapidEye's imaging capabilities may have numerous applications providing the system with high importance within a broad range of industries - forestry, agriculture, mining, power and engineering and construction, oil and gas exploration, cartography, etc.

The system collects rather substantial amount of data, on average 4 million square kilometers per day, with a nominal ground resolution of 6.5 meters. This impressive result is achieved with each single satellite less than one cubic meter and weighing approximately 150 kg. The satellites are designed for at least 7 years mission life. All 5 of the satellites have identical sensors located in the same orbital plane.

5 channels - one each in the blue, green, red, red edge, and near infrared regions of the spectrum – are made up the data set.

RapidEye is also offered in two levels of processing:

Level 1B - RapidEye Basic Product: images after radiometric correction without geometric correction (pixel size field is 6.5 m at nadir; five single-channel files in TIFF format).

Level 3A - RapidEye Ortho: image after radiometric and geometric correction. Down perform orthorectification is used for Digital Terrain Model spatial resolution of 30 to 90 meters, usually 90m SRTM (Shuttle Radar Topographic Mission) and points adapt GCP (Ground Control Points). These source points are used by the manufacturer to perform adjustments with these adjustment tolerances varying as such: GeoCover 2000 Landsat mosaic error circular position (0.9) of 50m and GLS 2000 Landsat mosaic error circular position (0.9) of 30 meters. Images level 3A - TIFF file size 25km x25km. (RapidEye, 2013).

Table 1: RapidEye Satellite Sensor Specifications (Source: Satellite Image Corporation, https://www.satimagingcorp.com/ . Access on June 2017.)

Number of Satellites	5	
Spacecraft Lifetime	7 years	
Orbit Altitude	630 km in Sun-synchronous orbit	
Equator Crossing Time	11:00 am local time (approximately)	
Sensor Type	Multi-spectral push broom imager	
	Capable of capturing any of the following spectral bands	
Spectral Bands	Type	Wavelength (nm)
	Blue	440 - 510
	Green	520 - 590
	Red	630 - 685

	Red edge	690 - 730
	NIR	760 - 850
Ground sampling distance (nadir)	6.5 m	
Pixel size	5 m	
Swath Width	77 m	
On board data storage	1500 km of image data per orbit	
Revisit time	Daily (off nadir) / 5.5 m (at nadir)	
Image capture capacity	4 million sq km/day	
Dynamic Range	12 bit	

The interpretation of False-color image

Many sensors are carried on the satellite's instruments, with each tuned to a narrow range ("band") of wavelengths. Looking at the output from just one band will only give one portion of the whole spectrum like viewing the world in shades of grey. Brighter spots are areas that reflect/emit a lot of the wavelength of light with the band, while darker areas contrastingly reflect or emit little if there are any at all.

In creating a full satellite image, researchers will choose three bands and represent them in tones of red, green or blue. This is understandable as most visible colors can be created by a combination of red, green and blue light. These red, green and blue images when combined together form a full-color representation of the world.

In a natural or true-color image combinations of actual measurements of red, green and blue light are used, the resulting image looks like the world as humans would see it.

While false-color images use at least one nonvisible wavelength, this band will still be represented in either red, green or blue. Because of this some colors in the final image may not be as expected. An example is grass which is not always green. These false-color band combinations are used to reveal unique aspects in the data image that might not be visible otherwise.

This natural-color image (Fig.1) showing a human perception shows dark green forest areas, light green agriculture land, brown wetlands, silver or grey urban areas and turquoise for offshore reefs and shallows.

Figure 1: Naturally colored satellite image of the Neusiedlersee region. Screenshot adopted from eCognition Developer 8.7.

The same area shown in green, near-infrared (NIR) and shortwave-infrared (SWIR) light would cause plant-covered lands to become bright green,; areas of water appears in black; earth would range from tan to pink; urban areas are in purple. Other interesting data such as freshly burned farmland are shown in dark red, while farmland suffering from older burns appears in a light red. The farmland in this area is mostly used for cane sugar growing. This means that burned land looks different in this kind of false-color image. It makes possible to notice how extensively farmers rely on fire in this region. The false-color view also demonstrates water flows in the region. Making it is easier to see the full extent of the wetlands compared to the surrounding land, as areas of water are dark and plant-covered land is bright green allowing a greater contrast within the image.

True- or false-color images and select wavelength bands are made by scientist to highlight the featuresmost interested in data visualizers and remote sensing. E.g., blue light (450 to 490 nanometers) is one of the few wavelengths reflected by water while the rest are absorbed. So the blue bands are useful to see water surface features, as well as to identify the bottom of shallower bodies of water.

It can be seen that water will reflect some blue light in the image Neusiedlersee – Seewinkel. Water appears lighter in the blue band than in either the red or green bands, however the lake is too deep to reveal shallow features. Human-beings constellations (like towns and roads) are also shown up strongly in the blue light band. This wavelength is most scattered by gas molecules and particles in the atmosphere (so the sky is seen as being blue by human beings because of this).

Green light (490 to 580 nanometres) can be used to monitor phytoplankton in oceans and plants on land. Chlorophyll present in these organisms absorbs red and blue light while reflecting green light. This is also the case for sediment in water, meaning a muddy or sandy body of water will show up as brighter because it reflects both blue and green light.

Red light (620 to 780 nanometres) can be used to help distinguish minerals and soils types that contain high concentrations of iron or iron oxides, meaning it can have value in geology studies. Also, because chlorophyll absorbs red light, this band is commonly used in monitoring the health and growth of various plant life. Red light bands can be used to help distinguish between different types of plants on a broad scale.

NIR light wavelengths are between 700 and 1,100 nanometres. NIR is absorbed by water, so can be useful for defining land-water boundaries that may not be so obvious in ordinary visible light. Plants contrastingly reflect NIR light strongly, especially healthy plants more so than stressed plants. NIR light can also penetrate haze, so this band can used to show the finer details in a scene that may be smoky or hazy.

SWIR light sits at wavelengths between 1,100 and 3,000 nanometres. SWIR light is absorbed by water in three regions of this band: 1,400, 1,900 and 2,400 nanometres. If there are higher quantities of water, even in soil, the image will appear darker at these wavelengths. Meaning SWIR measurements can be used to help scientists when estimating amounts of water present in plants and soil. SWIR bands can also be used to distinguish between cloud types (water clouds vs. ice clouds) and between clouds themselves and ground cover of snow or ice (All would appear as white on the visual spectrum).

Midwave-infrared (MIR) light fall in the range between 3,000 and 5,000 nanometers. It is most often used to study thermal radiation emitted during the night. MIR energy can also be useful when trying to measure sea-surface temperatures, as well as clouds and fires.

Between 6,000 to 7,000 nanometers we find Infrared light. It is of utmost importance to observing atmospheric water vapour. Despite water vapour is only making up 1-4 percent of the atmosphere, it is a major “greenhouse gas”, being also a basis for clouds and rainfall. As water vapour absorbs and re-emits energy within this range infrared satellite observations can track water vapour. This is a reason why these observations are essential to accuracy of modern weather forecasts.

Thermal light (otherwise known as longwave-infrared light) falls in wavelengths between 8,000 and 15,000 nanometres. Most energy in this area of the spectrum is emitted by Earth as heat and can be observed at either day or night. Thermal-infrared radiation is used to help gauge surface temperatures of both land and water; it is particularly useful for those interested in geothermal mapping and detecting such heat sources as fires, gas flares or power plants. Thermal-infrared light can also be used to monitor crops. This can be seen as growing plants cool the air above them by evapotranspiration which is a release water, with this in mind thermal-infrared light can also help scientists to assess how much water the plants use.

A lot of possible combinations wavelength bands exist. Usually NASA’s Earth Observatory selects one of four combinations depending on which event or a feature is to be observed or illustrated. For example, floods are being viewed in SWIR, NIR with green light (just because muddy water would blend with brown land in a natural-color image). SWIR light can highlight the differences between clouds, ice and snow (all of which seem white in visible light.)

4 most common false-color band combinations used by the site are:

1. NIR (red), green (blue) and red (green). A traditional band combination used to see changes in plant health.

2. SWIR (red), NIR (green) and green (blue). The combination used mostly to show floods or newly burned land.

3. Blue (red) and two different SWIR bands (green and blue). A combination used to differentiate snow, ice and clouds.

4. Thermal infrared. Usually used to illustrate temperature shown in grey tones.

Probably the most frequently published combination uses NIR light as red, green light as blue and red light as green (Fig.2). Under such conditions, plants will reflect NIR and green light while absorbing red. As they will reflect more NIR than green, plant-covered land appears in a deep red. The band combination is valuable when gauging plant health.

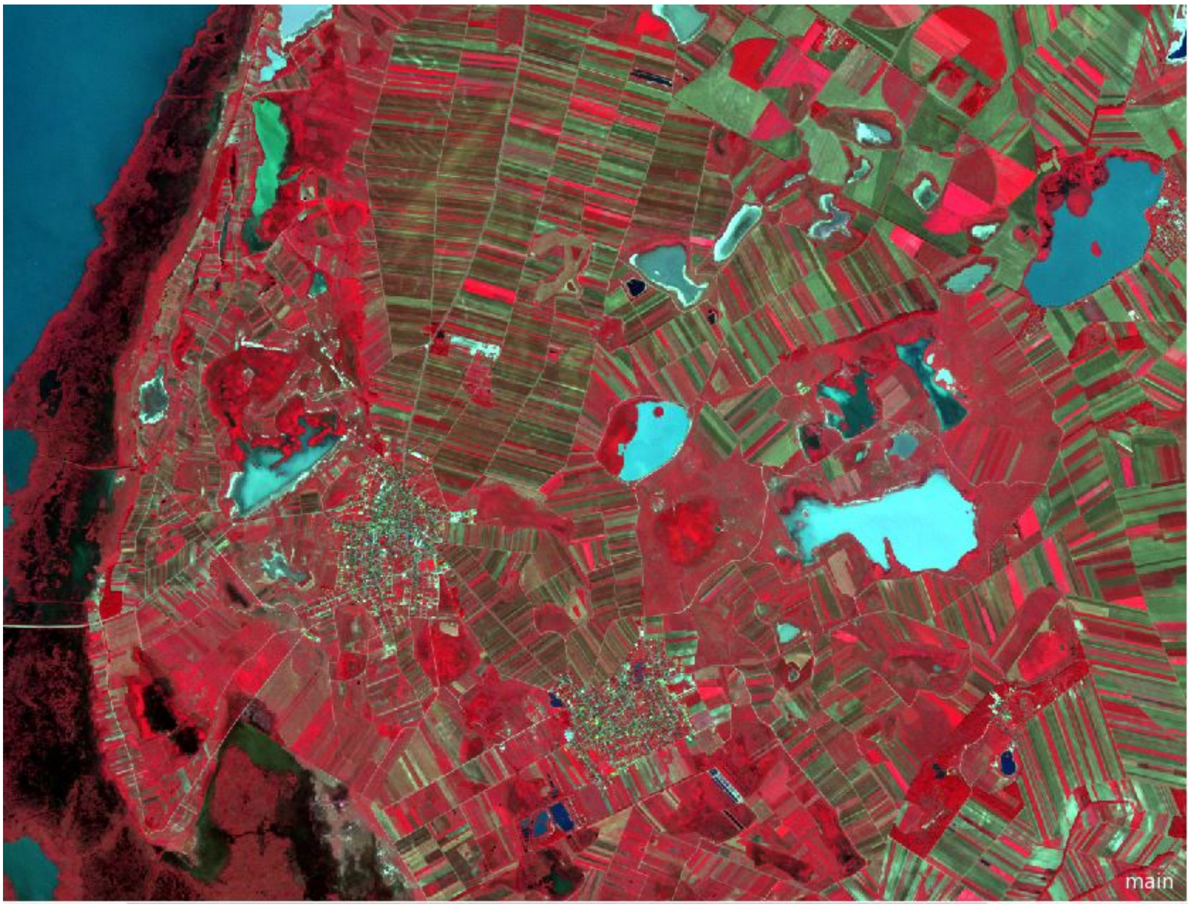


Figure 2: False colored (NIR light as red, green light as blue and red light as green) satellite image of the Neusiedlersee region. Screenshot adopted from eCognition Developer 8.7.

Urban areas and cleared ground appear grey or tan, while clear water looks black. In the image above, the water bodies are muddy, and so the sediment reflects light. This causes the water to look blue.

This combination will mostly be used during the segmentation of Neusiedlersee region.

Landcover map: for simulation of sampling and comparison

Map of Landcover (Project SINUS) for comparison: The automated evaluation of satellite images for the delimitation of landcover classes, whose results were introduced into the present study, was conducted at the Institute of Surveying, Remote Sensing and Land Information of the University of Natural Resources and Applied Life Sciences, Vienna. In addition to the LandsatTM images being Processed, the image material was segmented and classified (Steinwendner et al., Schneider & Suppan 1998). The methodological approach employed for the classification was a combination of knowledge-based and statistical classification. The knowledge was formulated in the form of rules. In the knowledge-based classification, comprehensive general knowledge about the interrelations between remote-sensing features (signatures), collateral data, and the assignment to classes play a decisive role. The result of the computer-assisted satellite image interpretation is an all-encompassing data record of Austria's landcover classes. In this context, on the level of the segments (= land units), 20 different landcover classes were identified.

But for other projects this map was corrected for the Neusiedlersee-Region by visual interpretation based on "in situ exploration" — therefore this map fulfils the requirements for so called "visual interpreted Map" in the context of this work.

METHODS

eCognition Developer

Object based image analysis (OBIA) is a dedicated technique intended to analyse digital images. It is a relatively recent development comarstively to the traditional pixel-based image analysis (Burnett and Blaschke 2003). While pixel-based image analysis is using the information from & within each single pixel, the object-based image analysis is based on information from a set of similar pixels (which are called “image obects” or just “objects”). More specifically, the image objects are defined as groups of pixels similar one to another based on a measurement of certain spectral properties as well as upon the context from a neighbourhood surrounding the pixels.

eCognition software suite is applied for the solving of the delineation task. The software contains a few of proprietary built-in segmentation procedures different from those presented in the last section. But theoretical knowledge of segmentation and the experience gained from its implementation aids in the proper use of this software suite.

The input consists of raster images for the delineation of scattered trees; color infrared (CIR) ortho-photos with sub-meter resolution are applied. Very high resolution (VHR) satellite images can also be used. The major output is a thematic vector (shapefile) with the classification results, which can be used in other GIS programs.

As eCognition deals with a hierarchical system of images and image objects, the images could consist of several different levels, but do not always fall into a hierarchical structure. The image object levels are virtual copies of the image, containing information regarding specific components of the image. Thus, neighbouring objects on the same level are getting linked, making up super-objects of higher (coarser scale) levels, or linking to sub-objects of lower (finer scale) levels. While it is in principle possible to have many object levels, it is not always necessary as it often complicates the classification with a higher number of image object levels.

The figure below is taken from the Definiens Developer 8.7, User Guide 2011, p. 26. It presents links between objects on the same as well as different levels. Thick blue lines are the links between samples “image object” (orange box with the black border) on the same level (“neighbours”), and at multiple levels (“super-” or “sub-objects”).

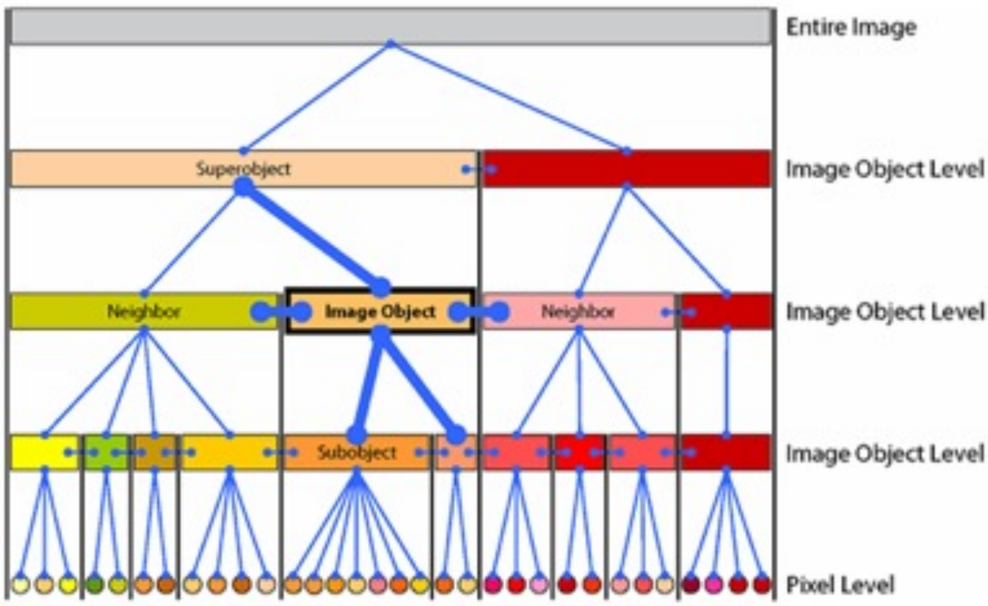


Figure 3: Object image hierarchy in eCognition Developer (Definies Developer 8.7, User Guide, 2011)

Segmentation and classification steps are executed to derive objects from the level of pixels. Depending on the complexity of the task, this process can consist of several steps.

The eCognition suite provides quite a few of procedures which are in turn made up of elementary algorithms. Selection of the procedures and their parametrization mandates deep knowledge of segmentation and photogrammetry techniques. Several publicly available and/or proprietary segmentation algorithms are implemented under the names “Chessboard”, “Contrast Split”, “Quadtree”, “Multiresolution”, “Spectral Difference”, etc. Segments combined in a system under certain criteria are taken as inputs for the classification. Except of regular statistical measures, also available are such features as geometrical and textural ones, membership functions in class hierarchy and statistical distributions. Commands and functions are combined into so called “Rule Sets” (Definiens AG, 2011).

While processing large images, a “divide and conquer” philosophy is applied by eCognition: the image is getting splitted into smaller equal-sized sub-images which may in turn be processed in parallel; the results of these tiles are eventually “stitched” together (Definiens AG, 2011)..

OBIA Processes

Segmentation

As segmentation process starts, it initially recognizes each individual pixel on the image as one segment. These single-pixel segments are successively merged then into larger segments by using a pair-wise clustering process (Definiens AG, 2011). The algorithm consists of three parameters: scale, shape weighting, and compactness weighting. Scale parameters determine the size of the area within generated segments; the shape and used compactness weighting values just determine the shape of the segments. Small scale values (e.g., 10) produce smaller segments while large scale values (e.g., 300) produce larger segments. Shape and compactness parameter values range from 0 to 1. A low shape value (e.g., 0.1) will place a higher emphasis on color which would normally be the most important feature when creating meaningful objects (Definiens AG, 2011). On the other hand, higher compactness weightings (e.g., 0.9) will result in more compact object boundaries. This is typical for crops in fields or urban buildings (Dobrowski et al., 2008).

Initial boundaries generated from the image segmentation process sometimes are referred to as “object primitives” or “object candidates” to distinguish them from true objects (Blashke, 2010). In OBIA segmentation and classification is an iterative process; quite a few iterations are needed to achieve the final boundaries. A 100% automated method may not be achievable in some cases; manual corrections then are required (Dobrowski et al., 2008).

The best settings for segmentation parameters may vary considerably. Usually they are determined through experience and a trial and error approach. The settings which work well for one image, may be useless for others even if the images seem to be similar. Tools like estimation of scale parameter (ESP) have recently become available for identifying the suitable scale parameters based on the concept of the local variance of the object heterogeneity (Dobrowski et al., 2008).

Color/shape parameters

When it comes to how objects are created during segmentation it is the color and shape parameters that affect the objects appearance (Definiens AG, 2011). Higher values of color or shape criteria result in better objects optimization for spectral or dimensional homogeneity. The shape criteria (could be modified by a user) can alter the degree for smoothness of the objects borders as well as their compactness. (Blaschke, 2010).

The color and shape parameters balance each other. If one has a high value (high impact on segmentation) the another should be low with less influence. If color and shape parameters are equal they should have close to equal amounts of impact over the segmentation outcome (Definiens A.G. User Guide, 2011).

Scale Parameter

Values of the scale parameter affect image segmentation and determine the size of the image objects. If the scale value is high, the variabiliy which allowed within each object is high and the image objects is relatively large. On the other hand, small scale values allow for less variability within the segments, making them smaller (Blaschke, 2010).

According to the User Guide (2011), here is a variety of methods to generate image objects, with pros and contras of each.

In general, image segmentation methods are split into two main domains: knowledge-driven methods (top-down) and data-driven methods (bottom-up).

In top-down approaches the user already knows what he wants to extract from the image, but does not know how to perform the extraction. Whilst making up a model of the desired objects the system attempts to determine the most efficient techniques for processing images to get them exracted. The generated object model gives the objects' meaning implicitly (Definiens A.G. User Guide, 2011).

In bottom-up approaches the segments are created using a set of statistical methods and parameters needed for processing an image as a whole. Bottom-up methods as such might also be presented as a sort of data abstraction or data compression. But, as with clustering methods, in the very beginning the generated image segments have little meaning, and they are better referred to as image object primitives (Definiens A.G. User Guide, 2011)..

- Top-down segmentation examples:
  - Chessboard Segmentation
  - QuadTree Based Segmentation

- Contrast Filter Segmentation
- Contrast Split Segmentation)

➢ Bottom-up segmentation examples:

- Multiresolution Segmentation; MRS
- Multi-Threshold Segmentation; MRS

➢ Spectral Difference Segmentation

➢ Multiresolution Segmentation + *Region Grow*

A brief overview of all of these types of Segmentation in eCognition Developer is presented below.

Chessboard Segmentation

The simplest kind of top-down segmentation. It divides an image into squares sets by pixels size (Definiens A.G. User Guide, 2011).

According to Object-Oriented Classification Course by Landmap Geoknowledge, this approach may be realized on both the entire image and selected areas (already classified segments). The most common use of Chessboard Segmentation is division of an image into identical parts. In addition, the segmentation may be used to optimize already classified objects. Such objects may be subject to additional division, in order to create a more accurate analysis (Definiens A.G. User Guide, 2011).

Using this segmentation to set the *Object Size,* which defines the size of created objects (the number of pixels forming the side square). The minimum value which can be administered to is 1 - it means that every object created has a size of one pixel. The work on classification segmentation in this parameter will resemble the classifications pixel (Definiens A.G. User Guide, 2011).

QuadTree Based Segmentation

This is a type of "Top-down " segmentation that, like the previous algorithm, creates the board-shaped objects squares. The objects created are to the contrary are not of the same size. The image is divided into four objects so the resulting objects are iteratively subdivided into four parts. (Object-Oriented Classification Course by Landmap Geoknowledge. Access on 6. June 2017)

The maximum size of a segment created by the algorithm is 65,536 pixels (a square object with a side equal to 256 pixels) (Definiens A.G. User Guide, 2011).

In accord to User Guide, homogeneity criterion is based on a parameter of *Scale,* which is s subject to define by the user. This parameter, at first, determines maximum difference in the variability of pixels color; it will be a boundary built between the pixels then.

At second, the *Scale* parameter of the segmentation tree is a selection of spectral channels that are to be analyzed by the creating of segments. As in the case of Chessboard segmentation, a vector layer imported earlier into the project can be included in the process.

Contrast Filter Segmentation

"Contrast filter" is another "top-down" segmentation algorithm. The "good performance" segmentation is done in a way allowing rejection in the initial process of those image elements which will not be taken into account in the further process of classification. In accord to Landmap Geoknowledge Object-Oriented Classification Course, this is particularly important to analyse long-distance taken images. At such time of "initial rejection" as a result total number of segments in the subsequent segmentation will be much lower than if the process would be subjected to the whole image's potential objects.

According to User Guide 2011, application of the "Contrast filter" segmentation procedure assumes:

1. Choice of two spectral channels which will be analysed during objects search process (*First Layer Second Layer). If* only one channel is needed, an option for *No Layer* in the field exists for the choice of classification parameters of the second channel.

2. Ranging pixel values in the two pre-selected channels; they will be then classified as a mask layer (*Lower Threshold Upper Threshold).*

3. Up to four distance values of the analyzed pixel (*Scale).* The resulting square viewed will assess gradient (difference in contrast between pixels).

4. Determination of the size of the gradient, which modify the base ranges of spectral reflection (point 2) objects.

5. Improving the shape of objects by removing narrow (beacons) fragments.

The result of the segmentation layer is classified on the basis of the above parameter objects. In addition, segmentation is automatically performed in a "matrix" for the resulting objects.

Contrast Split Segmentation

The algorithm is the last segmentation methods similar to other "top-down" ones used in this work. In accord to User Guide 2011, this process of dividing the image into segments is based on comparing dark and light objects on the basis of spectral range pixels set by the operator. These values are not final, because the division of images takes into account the difference in contrast between objects. Alike to the previous segmentation, allocation algorithm uses the contrast segmentation of the board type to produce the initial objects. It also creates pre-classified objects. However, in case of segmentation division, the contrast split segmentation creates two classes of objects: light and dark objects.

Assessing the applicability of this type of segmentation for imaging RapidEye satellite uses an indicator of vegatation NDVI (*Normalized Difference Vegetation Index)* to test the accuracy of segmentation of the objects to “bright” and “dark” ones by the algorithm (RapidEye, 2016).

Multiresolution Segmentation

This is the first algorithm from "Bottom-up" group, one of the most frequently used procedures for the classification of aerial or satellite imagery (Object-Oriented Classification Course by Landmap Geoknowledge. Access on 20. June 2017)

It is based on minimizing the “average heterogeneity” in a single object extracted from the image (Baatz et al., 2000). According to Introductory course to the fundamental concepts of remote sensing, Multi-level segmentation consistently combines either pixels or existing facilities. According to the following rules are used by the procedure (eCognition Segmentation and Supervised Classification, 2013. Access on 22. June 2017):

1. The algorithm for operation on the image layer commences with its individual pixels having them combined until maximum homogeneity and heterogeneity between the inside segments is achieved.

2. Initial pixels (*Seeds)* are searched for a location based on homogeneity candidates.

3. If none of the candidates meets the required homogeneity criteria, the closest to this criterion pixel becomes the next initial pixel; then the procedure is performed again.

4. When the pixel-candidate meets the criterion of homogeneity it is connected to the initial pixel and forms the nucleus of the object.

5. The process is repeated until the further merging of pixels ceases to be possible.

The heterogeneity criterion has a number of factors (parameters), connected to each of the dependencies, linked in turn in the form of equations (Benz et al. 2004):

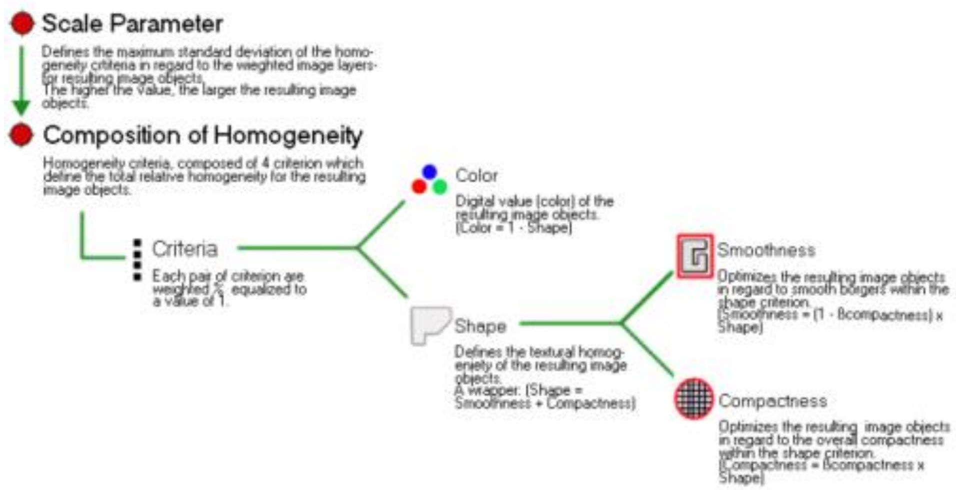


Figure 4: Schematic diagram of a multi-level segmentation parameters (Source: eCognition Developer 8.7 User Guide, 2011)

According to User Guide, scale parameter (defined by the user) determines which objects are not merged with each other. Values assumed by this parameter vary depending on the type of source data, the methodology adopted and the work of the classification.

The “dialog tiered” segmentation includes a set of scale and individual factors. It also implies the selection of spectral channels which the software then will consider while creating segments. A smoothness parameter is not pre-defined because total compactness and smoothness rates are both equal to 1. So only one of them could be provided (Definiens A.G. User Guide, 2011).

Parameter	Value
Overwrite existing level	Yes
⊟ **Level Settings**	
Level Name	New Level
⊟ **Segmentation Settings**	
⊟ Image Layer weights	1, 1, 1, 1, 1
Blue	1
Green	1
NIR	1
Red	1
Red-edge	1
⊞ Thematic Layer usage	
Scale parameter	10
⊟ **Composition of homogeneity criterion**	
Shape	0.1
Compactness	0.5

Figure 5: Dialog multi-level segmentation. Screenshot adopted in eCognition Developer 8.7.

Multi-Threshold Segmentation

A new segmentation type, appearing in "eCognition" starting from version 8.7. It represents a simple process of dividing the image into classes based on the pre-defined values of pixels (Definiens A.G. User Guide, 2011). Multi-Threshold Segmentation is used mostly for initial classification of items on images which can be distinguished easily.

Spectral Difference Segmentation

It has been shown so far that segmentation algorithms can be successfully used as stand-alone processes forming objects for further analysis (classification).

None of the segmentation of the image analysis processes can begin performing algorithm differences in Spectral Difference Segmentation. According to User Guide, this segmentation is not able to create new objects within the pixel display; it only works on previously created objects. This process examines the contiguous segments by the differences in average intensity values. In the case where the difference is less than the threshold set by the operator, the segments are bonded together. As segmentation is often used after a multi-level segmentation it primarily aims improving borders and reducing number of segments (usually in cases of small pre-segmentation). Analysing impact of segmentation differences in the spectrum, multi-level segmentation is performed; then the algorithm combining segments accordingly to the rules of segmentation spectral differences is launched (Object-Oriented Classification Course. Land map Geoknowledge. Access on 6. June 2017).

Multiresolution Segmentation Region Grow

The other segmentation type can be activated only in eCognition objects created using the multi-level version of "Enlargement of regions" segmentation process, or in short MRS-Region-Grow. This process works using the same specifications as the multi-resolution segmentation; the only difference is that it is capable in linking pre-existing segments. (Tilton J., Tarabalka Y., 2012) This segmentaton technique is offered in eCognition v 4.0.6 object-oriented image analysis software.

Now let us have a look at different Classification techniques.

Classification

After an image has been segmented into it's appropriate image objects, the image then should be classified by assigning each object to a class, this is based on features and criteria which will be set by the user.

“Classification” features are those OBIA features (different from GIS features) which measure (in relative or absolute terms) a variety of characteristics (size, shape, color, texture, context) of image objects (Definiens A.G. User Guide, 2011). The efficacy of the different features can also vary widely, depending on objectives, object size, texture, color and shape properties, and the location within the object hierarchy structure.

Normally, the upper and lower limits of the range of characteristics measured in the image objects are to be defined. Image objects inside the defined limits are assigned to a specific class. Those image objects which fall outside of the pre-determined feature range are either assigned to a different class, or left unclassified.

Below is presented a list (not exhaustive) of commonly used classification features, according to User Guide:

- Color: mean or standard deviation of each band, mean brightness, band ratios
- Size: length to width ratio, relative border length, area
- Shape: asymmetry, roundness, rectangular fit
- Class level: relation to neighbors, relation to sub-objects and super-objects
- Texture: smoothness, local homogeneity

Classification methods

A few different image classification methods exist, e.g., subpixel, unsupervised, or supervised classification. Below is a summary of each type of Classification, before turning all attention to the Supervised Classification.

Subpixel classification

Spectral Mixture Analysis (SMA) is a technique used while estimating to what extent each of the pixels is covered by a series of known cover types (Schuckman K. et al. 2017). In other words, it sets out to determine what the likely composition of each image pixel is. Pixels which contain multiple cover types are called mixed pixels (while "pure" pixels contain only one class or feature). For example, a mixed pixel could contain bare ground, vegetation, and soil crust whereas a pure pixel would only contain one feature, such as bare ground. Mixed pixels can cause problems when using traditional image classifications (e.g., supervised or unsupervised classification). A reason is simple - the pixel belongs to more than one class but it must be assigned to only one class. A way of addressing this issue would be using the SMA along with hyperspectral imagery (Schuckman K. et al. 2017).

SMA determines component parts contained in mixed pixels by forecasting a proportion of a pixel belonging to a particular class or feature based on the spectral characteristics of the class end members. It is done by converting radiance to fractions of spectral end members.

Unsupervised classification

Grouping pixels together is based on their reflectance properties. These groupings are referred to as “clusters”. The user will identify how many clusters should be generated and which bands are to be used. This information allows clusters generating by the image classification software (Schuckman K. et al. 2017).

The user manually identifies each cluster with land cover classes. Multiple clusters could represent a single land cover class. The user should merge clusters into their land cover type. This unsupervised classification image classification technique is most commonly used when there are no sample sites in existence.

Unsupervised Classification Steps:

- Generate clusters
- Assign classes

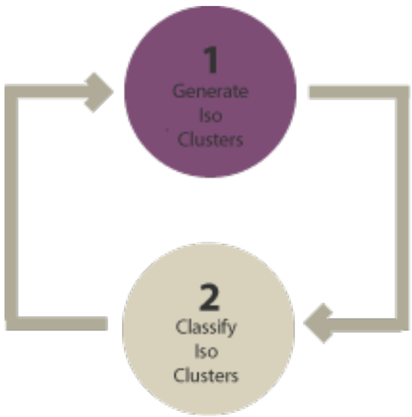


Figure 6: Unsupervised Classification Steps. (Source: Supervised and Unsupervised Classification in ArcGIS http://gisgeography.com/)

During unsupervised classification, an image is classified by the image processing software based on natural groupings of the spectral properties of the pixels. The user does not have to specify a procedure for classification of each portion of the image (Schuckman K. et al. 2017) . Conceptually, unsupervised classification has a lot of similarities to cluster analysis when observations (in this case, pixels) are placed in the same class due to them having similar values. However, the user must specify a few other pieces of basic information, such as which spectral bands should be used in the classification, the number of categories to be used in the classification, etc., otherwise the software could confusingly generate any number of classes based solely on natural groupings. Commonly used clustering algorithms include K-means clustering, ISODATA clustering, and Narenda-Goldberg clustering.

Supervised classification

The user first selects representative samples for each class of land cover within the digital image. According to ARSET Advanced Land Cover Classification Webinar Series - these sample land cover classes are known as "training sites"**.** The image classification software uses the training sites as an identifying feature for the land cover classes in the entire image.

This classification of land cover is based on the spectral signature defined in the training set. Digital image classification software determines then each class based on what it resembles most in the training set. The common supervised classification algorithms are set at maximum likelihood and minimum-distance classification (ARSET Webinar, 2017).

Supervised Classification Steps:

- Select training areas
- Generate signature file
- Classify

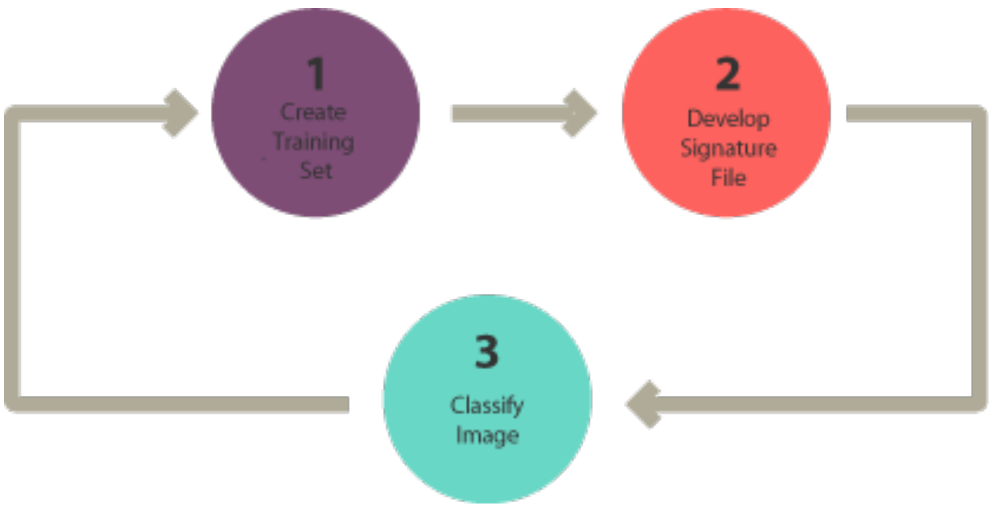


Figure 7: Supervised Classification Steps. (Source: Supervised and Unsupervised Classification in ArcGIS http://gisgeography.com/)

The user specifications on the land cover classes of interest guide the image processing software. For each of the land cover types of interest a user defines the "training sites" – areas of the map known to represent a particular land cover type. The software then determines the spectral signature of each pixel, within each training area, and is using this to define the mean(average) and variance of classes in relation to all input bands or layers. Each of the pixels in the image will then be assigned to a class it best matches, based on its spectral signature (ARSET Webinar, 2017). Choosing training areas that will cover the full range of variability within each of the land cover types, is important. This allows the software to be accurate when it classifies the rest of the image. Some of the more common classification algorithms that can used in supervised classification are: the Minimum-Distance to the Mean Classifier, Parallelepiped Classifier, and the Gaussian Maximum Likelihood Classifier (Definiens A.G. User Guide, 2011).

Supervised classification is an effective and accurate way to classify satellite images. According to User Guide 2011, it can be applied down to individual pixel level or to image objects (groups of adjacent, similar pixels). However, for this to work properly, the user processing the image needs to have a previous knowledge (aerial photographs, field data, or other knowledge) to define classes of interest (e.g., land cover types) locations, or to be able to directly identify them from the imagery (Schuckman K. et al. 2017) .

This method can also be used together with unsupervised classification in a process known as "hybrid classification" (Definiens A.G. User Guide, 2011). Unsupervised classification is exploited first to determine the spectral class composition of the image, and then - to see how well the initially intended land cover classes can be defined from the image. Upon this, supervised classification should be used to properly classify the image into the land cover types of interest.

Successful Rangeland Uses

Satellite images may be classified based on different distinguishable cover types as specified by the user, including but not limited to (Xie Y., Sha Z., Yu M., 2008):

- Land cover classes
- Vegetation condition

- Major vegetation types
- Distinguishing native vs invasive species cover
- Disturbed areas (eg. fire)
- Land use change, etc.

Similar to segmentation process, it is impossible to define “the best” method, or the best combination of methods. Selection of the most appropriate method will heavily depend on objectives, image characteristics, a prior knowledge, as well as experience and preference of the user (Xie Y., Sha Z., Yu M., 2008) .

Nearest neighbor (NN)

Nearest neighbor (NN) classification is a type of supervised classification. After multi-resolution segmentation, the user identifies sample sites for each land cover class. The statistics to classify image objects are defined. The object based image analysis software then classifies objects based on their resemblance to the training sites and the statistics defined (Definiens A.G. User Guide, 2011).

Figure 8:Nearest neighbor Classification Steps. (Source: Supervised and Unsupervised Classification in ArcGIS http://gisgeography.com/)

Object-Based Nearest Neighbor Classification (Nearest Neighbor Classification Guide, 2017):

- Perform multiresolution segmentation

- Select training areas
- Define statistics
- Classify

The Nearest Neighbor (NN) classifier is a supervised classification approach whereby each of the classes required, training samples are located and used to classify all remaining (unknown) objects in the image. The NN classifier has been used successfully for many classification problems (e.g., tree species; Leckie et al., 2005).

- User chooses sample image objects for each class
- Samples are usually based on prior knowledge of the plant community, and should represent the range of characteristics within a single class
- Software finds objects similar to the samples, then assigns those objects to their proper class
- Classification improves through iterative steps
- Appropriate for describing variation in fine resolution images

Selection of classification approach

In general, supervised classifications could be considered more accurate ones (in comparison to unsupervised classification) as regard to the prior knowledge, skillset of the user processing the image, and classes distinctiveness (Blaschke T., 2010). If the designated training sites do not represent the range of variables found in a certain land cover type, the classification can be less accurate. As mentioned above, a combination of supervised and unsupervised classification (hybrid classification) seems to be the most efficient option to employ.

RESULTS

Segmentation is always the first step of any process within Definiens Developer, it generates image objects the classification process will be performed with.

The important outcome of the segmentation process is to identify objects which are representative of the features you wish to classify and are distinct in terms of the features available within Definiens (e.g. spectral values, shape, texture).

After starting a new Project, open the *Image File* and type the right names of bands for the RapidEye satellite photo (Fig. 9)

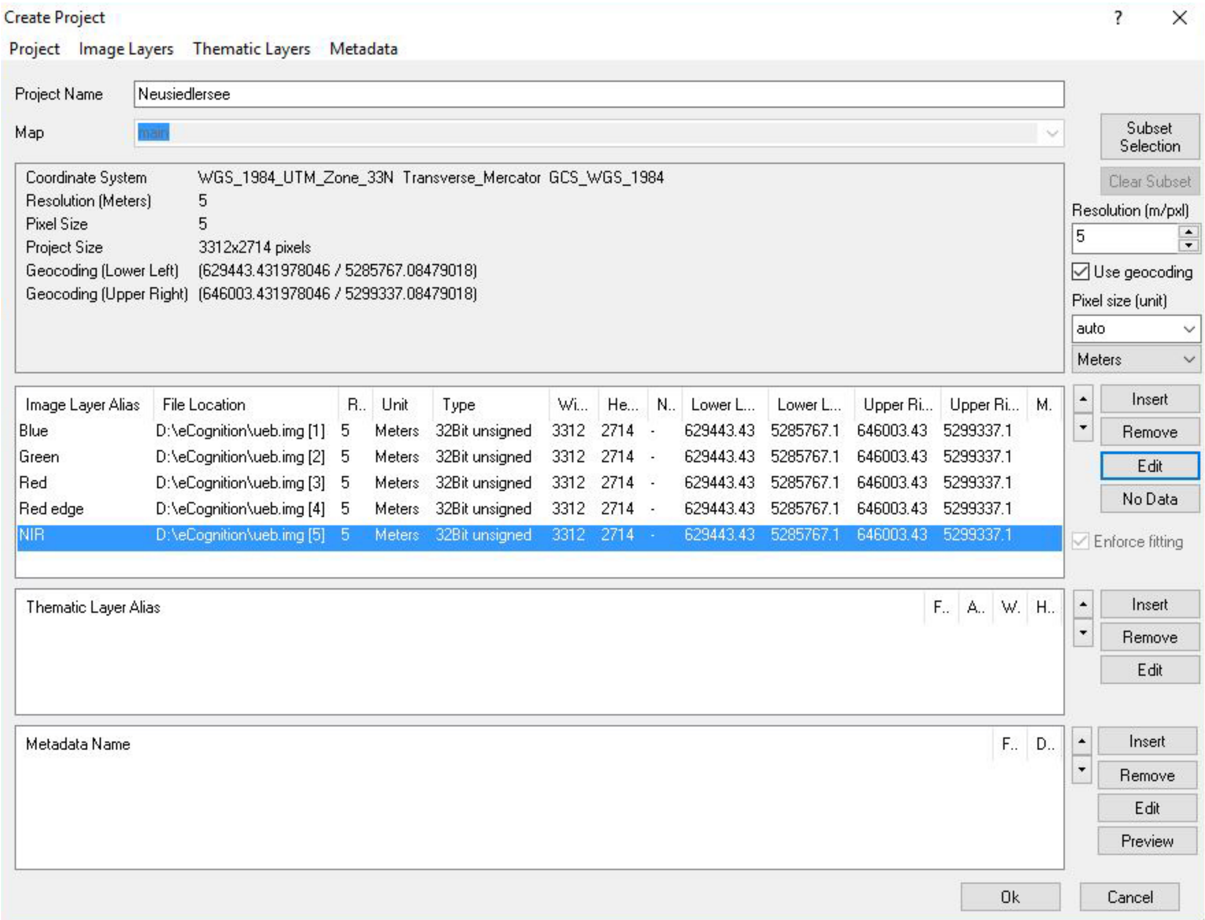


Figure 9: Create Project window. Screenshot adopted from eCognition Developer 8.7

Then change True colors to False colors (e.g. NIR (red), green (blue) and red (green), which is a traditional band combination used to see changes in plant health) (Fig. 10).

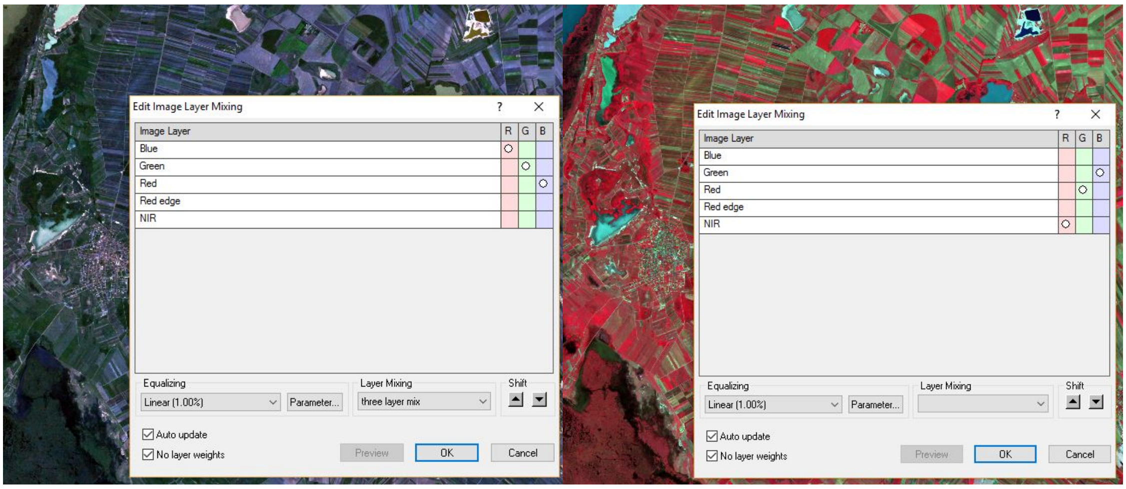


Figure 10: True vs False band colors. Screenshot adopted from eCognition Developer 8.7.

As with all classifications in eCognition Developer, the first task is to perform segmentation. In this case, the use of a multi-resolution segmentation is recommended, although others could also be used. After a right click in the *Process Tree* click on *Append New* and type "Segmentation", as a new process. To create the process that performs the segmentation, right-click on the *Segmentation process* which was already created before, select *Insert Child Process*, choose *"multiresolution segmentation"* in the drop-down menu for *Algorithm*, then click *Execute* as shown below (Fig.11).

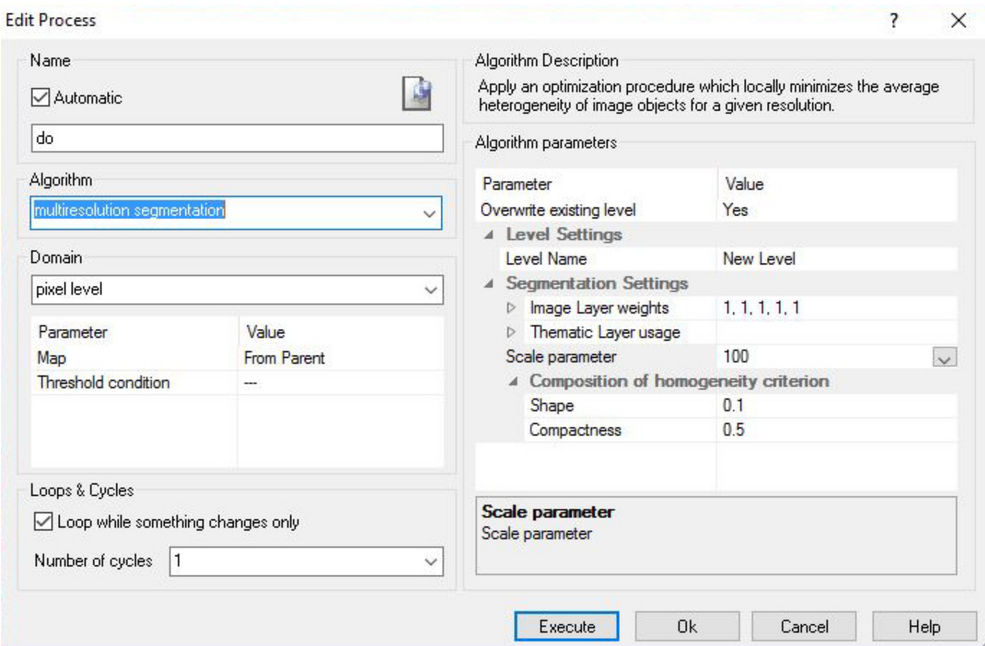


Figure 11: Multiresolution Segmentation (Scale Parameter = 100, Shape = 0.1, Compactness = 0.5). Screenshot adopted from eCognition Developer 8.7.

Some different segmentations in this case were performed with varying scale, shape and compactness parameters. Having started with Scale Parameter = 100, Shape = 0.1 and Compactness = 0.5, continue increasing the Scale Parameter. The object sizes get bigger until they come to the optimal scale - the objects begin to represent real objects on the ground so that settlement areas, vegetated areas, and water bodies begin to form distinct objects.

From the table below (Tab. 2) it can be deduced what each parameter means, for better understanding what has been changed.

Table 2: Parameters of Segmentation Process.

Parameter	**Description**
Level name	Name of the level in the hierarchy crated by the segmentation
Image layer Weights	Increases the weighting of the layer when calculating the heterogeneity measure, is used to decide whether pixels/objects are merged. Zero ignores the layer.
Thematic layer usage	If any thematic layers are available, allows thematic layers to be turned on and off individually for use within the segmentation process.
Scale parameter	Controls the amount of spectral variation within objects and therefore their resultant size. Has no unit.
Shape - color	A weighting between the objects shape and its spectral color whereby if 0, only the color is considered whereas if > 0, the objects shape along with the color are considered and therefore less fractal boundaries are produced. The higher the value, the more that shape is considered.
Compactness	A weighting for representing the compactness of the objects formed during the segmentation.

(Source: Dr Peter Bunting, Object-Oriented Classification Course - http://learningzone.rspsoc.org.uk/index.php/Learning-Materials/Object-oriented-Classification/2.5.-Multi-Resolution-Segmentation)

One more table (Tab. 3) shows all the segmentation parameters which were tried out before getting the most representative one.

Table 3: Parameters of Segmentation were tried out to find the most appropriate one.

Scale	100	130	150	160	170	180	190	200	180
Shape	0.1	0.1	0.5	0.5	0.6	0.8	0.8	0.9	0.9
Compactness	0.5	0.6	0.7	0.8	0.8	0.9	0.8	0.8	0.8

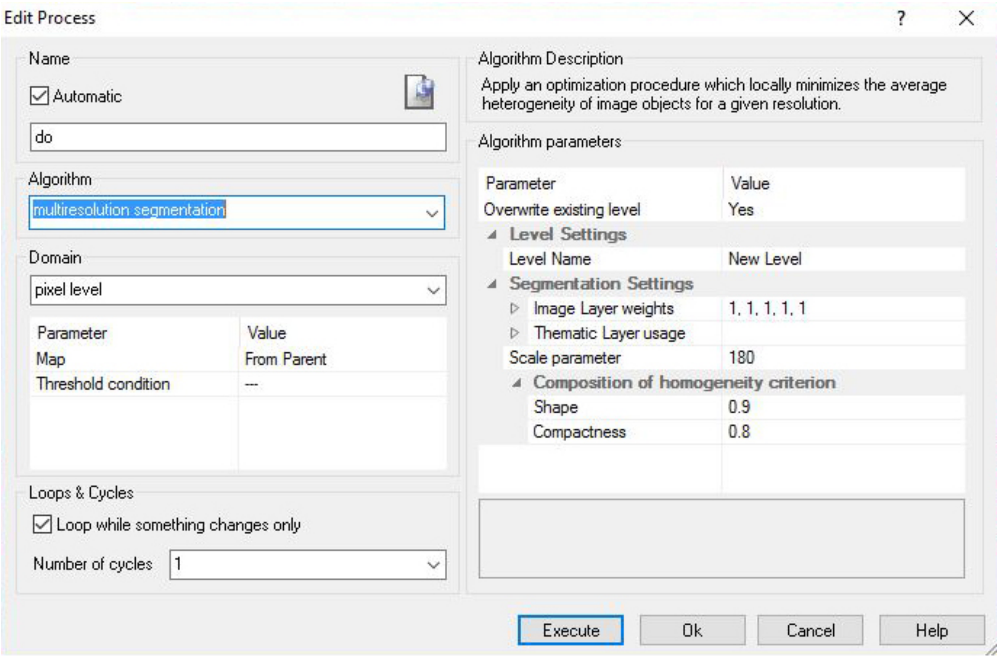


Figure 12: Segmentation Edit Process. Screenshot adopted from eCognition Developer 8.7.

On the images below (Fig 13 a, b and Fig.14) the screenshots with the most appropriate Segmentation are presented, with Scale Parameter = 180, Shape = 0.9, Compactness = 0.8.

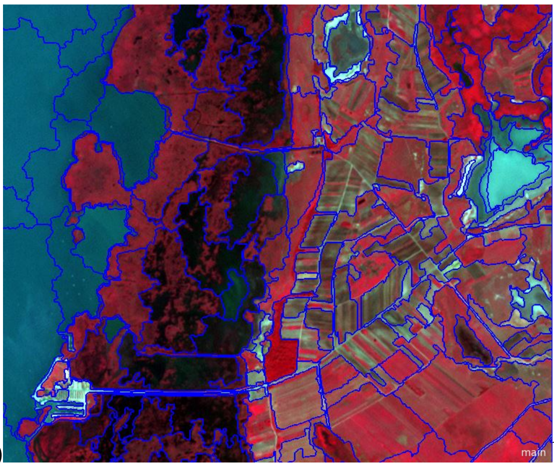
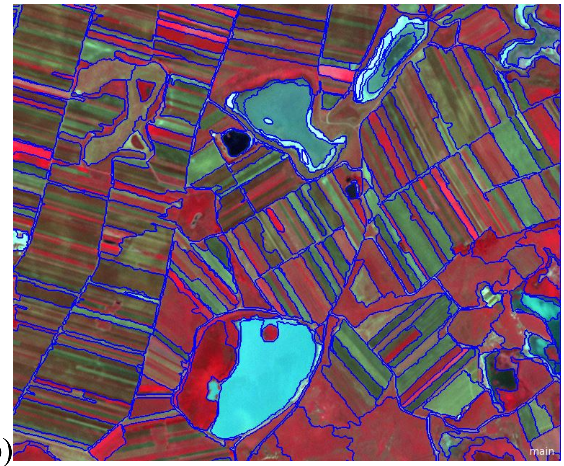
a)  b) 

Figure 13: Segmentation a) and b) (Scale Parameter = 180, Shape = 0.9, Compactness = 0.8). Screenshots adopted from eCognition Developer 8.7.

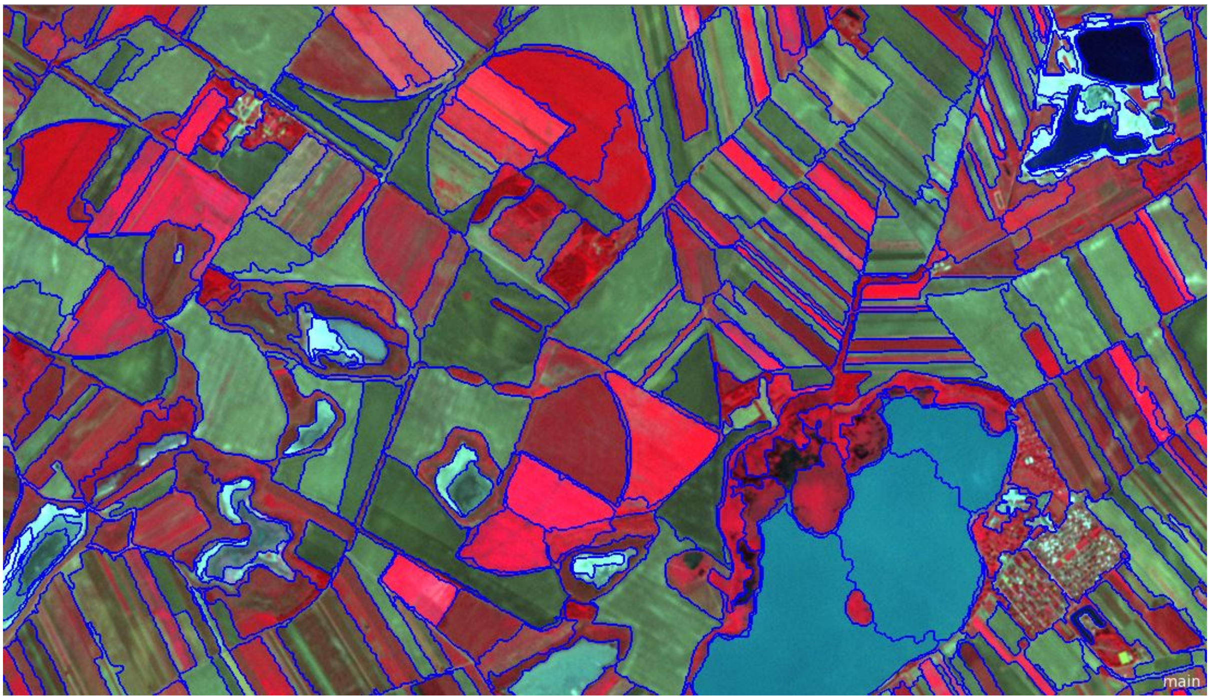


Figure 14: Segmentation (Scale Parameter = 100, Shape = 0.1, Compactness = 0.5). Screenshot adopted from eCognition Developer 8.7.

Having achieved the most representative segmentation (as mentioned before in this case it is Scale: 180, Shape: 0.9, Compactness: 0.8) classification of the segments with a Nearest Neighbor Classification instrument can be started.

With a right click in the *Process Tree* a new process named "Classification" is created. Then a right click on it *Insert a Child Process,* for the *Algorithm* drop down menu select "classification".

The Nearest Neighbor (NN) classifier is a supervised classification approach whereby for each of the classes required, training samples are located and used to classify all remaining (unknown) objects in the image. The NN classifier has been used successfully for many classification problems (e.g., tree species; Leckie et al., 2005).

For NN classification, the first task is to create the classes we require and (in this case) to insert the Nearest Neighbor Feature into each class. To create a class, the *Class Hierarchy* window has to be opened. With a right click inside the Class Hierarchy box, *Insert Class* is selected and name of the represented class is typed. As many classes as needed can be created.

After giving each class a name, select an appropriate color for each class. This can be anything you wish, although the final classification will be easier to understand and interpret if a logical color will be chosen (e.g. Green for Forest) (Fig. 15)

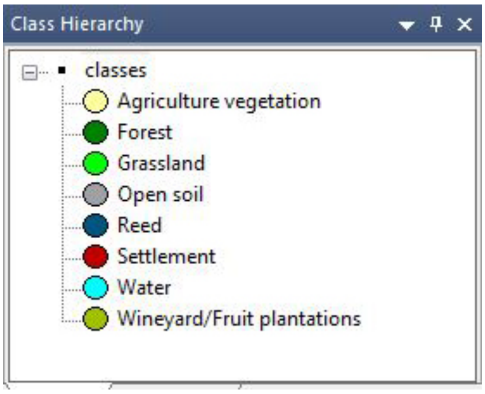


Figure 15: Class Hierarchy. Screenshot adopted from eCognition Developer 8.7.

Then appropriate samples should be selected before performing our classification. On the toolbar go to *Classification –> Samples –> Select Samples*. Then go to the *Class Hierarchy* box and click on the selected class and make sure it is highlighted. This makes sure that our selections go to the class we wanted to.

Next step is to zoom down to an area and double click inside the segments that overlay our areas or hold the shift key and click once in the segment. This will turn the segment to the color of the class that is selected. Now at least 10 samples for each class should be selected. In this case, it was taken about 20-30 for each class.

Since the aim of this work is to evaluate the method, the samples were not taken locally on Neusiedlersee. The selection of samples is based on a classification of a land cover map which was taken from SINUS and which is based on a visual interpretation.

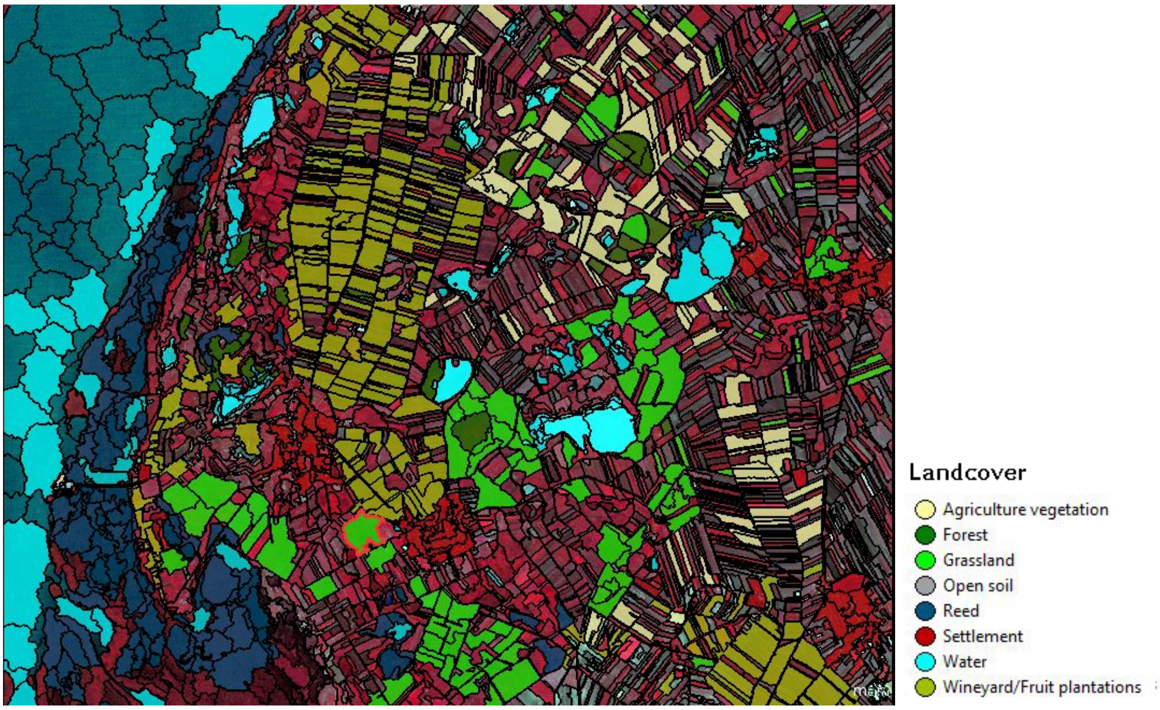


Figure 16: Classification Samples. Screenshot adopted from eCognition Developer 8.7.

Once finished with selecting samples (Fig.16) go up to *Classification –> Nearest Neighbor –> Edit Standard NN Feature Space*. Open up '*Object features*' and double click on '*Layer Values*' and then click on OK.

Next step is to apply Standard NN to Classes. Going back to *Nearest Neighbor* and select Apply *Standard NN to Classes* (Fig.17). Click the All —> then click Ok.

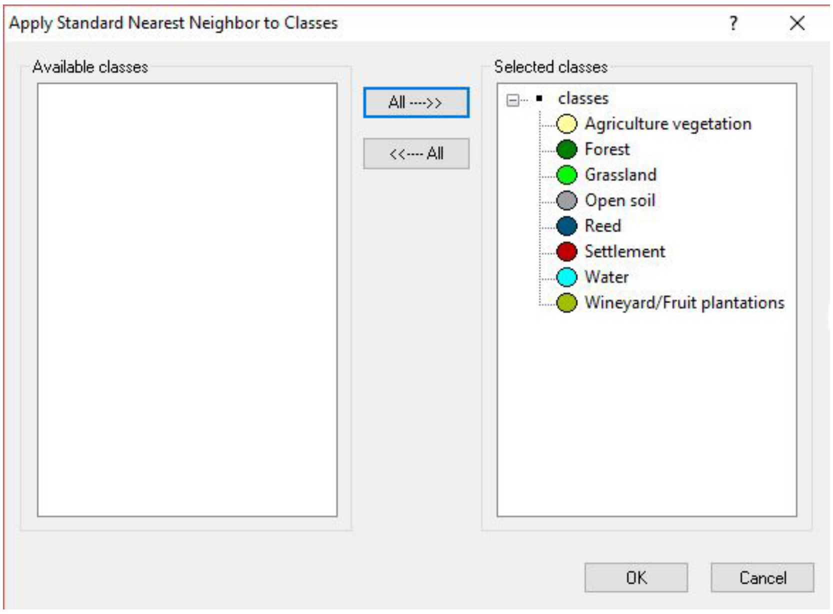


Figure 17: Standard Nearest Neighbor to Classes. Screenshot adopted from eCognition Developer 8.7.

Then for *Active classes* under change the classes from *None* selected by clicking in the box then on the three dots or double clicking on the field and make sure that every class besides Unclassified is checked and click Execute. This Process will be observed in our *Process Tree* (Fig. 18)

Figure 18: Process Tree – Classification. Screenshot adopted from eCognition Developer 8.7.

In case of an unsatisfactory result with the classification, the procedure should be repeated, but it should be selected some more or alternative samples before reclassifying the image. To re-run the classification, open the process and simply click on execute or select the process and press F5 or right-click on the process and select *Execute.*

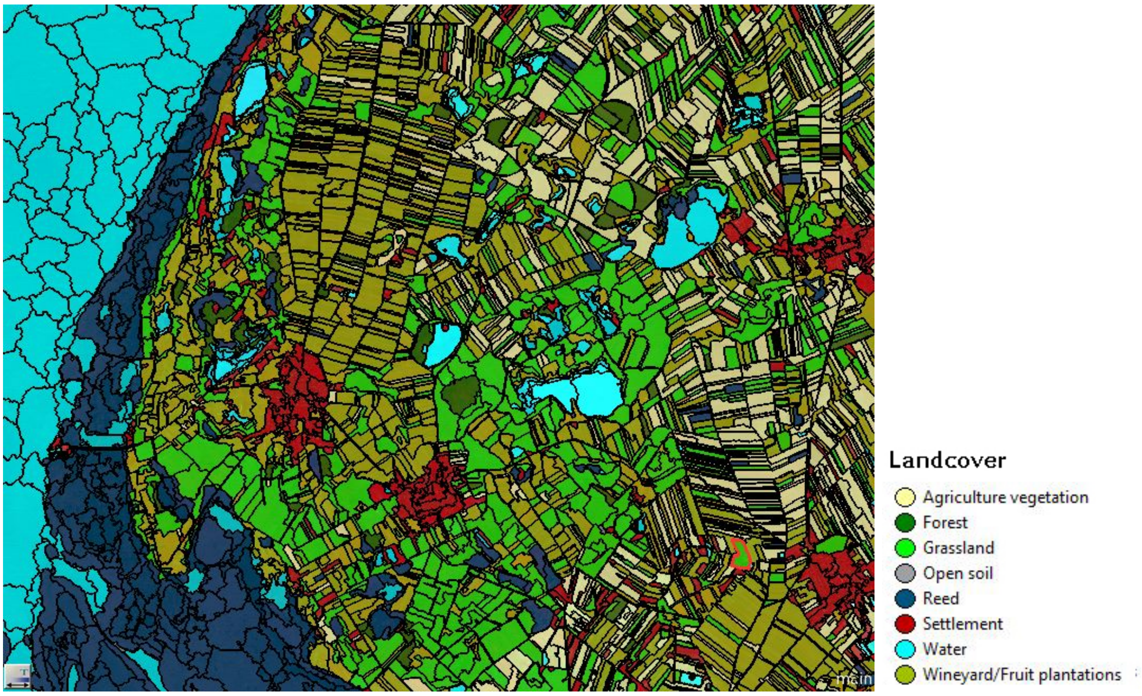


Figure 19: Classification executed. Screenshot adopted from eCognition Developer 8.7.

Once our classification fulfills our expectations, previously created image objects have to be executed (Fir. 7.19). Next step is to set up the processes which will merge our classification so that all neighboring objects of the same class will form single objects. It is important to merge the classification to identify complete objects.

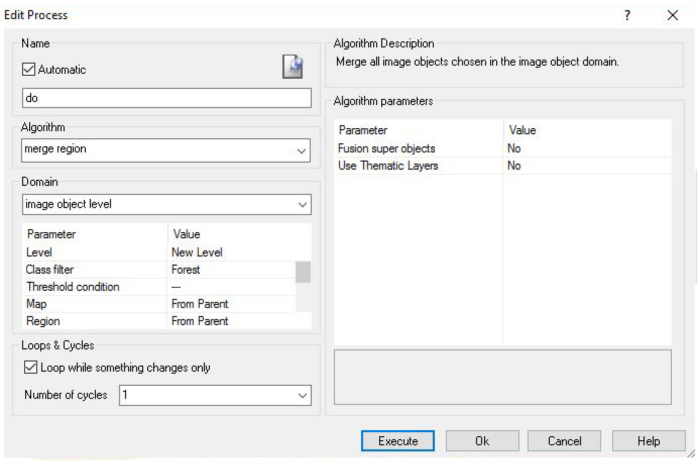


Figure 20: Edit Merge Process. Screenshot adopted from eCognition Developer 8.7.

For example, once merged the lake can be quarried to find its complete area. To merge the results, a merge process for each class should be entered. On the Fig. 21 it is shown how the Process Tree looks after running the Merge process for each class.

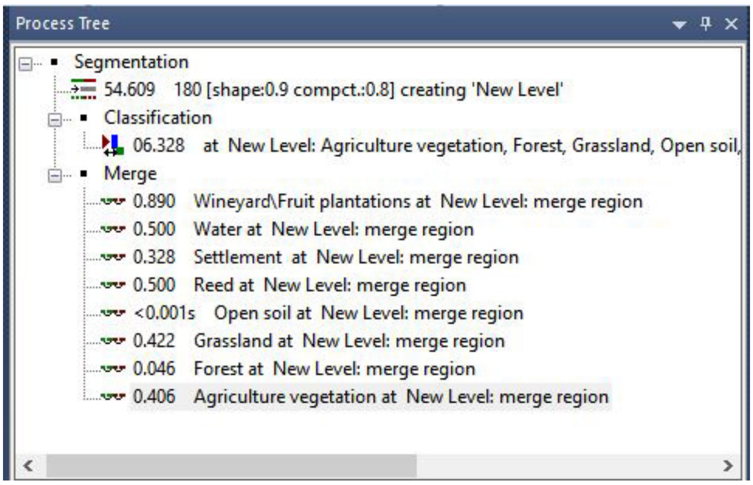


Figure 21: Process Tree. Screenshot adopted from eCognition Developer 8.7.

The class for merging is defined using the *Image Object Domain* where the class of interest is defined, if *multiple classes* is selected, all the selected classes would be merged, removing the boundaries and classification of these objects.

Figure 22: Merged classification of Landcover map.

Before the results are exported for further analyze they need to be reviewed to make sure that everything worked correctly, to do this it could be experimented with the visualization options by clicking the *Classification View* button.

Figure 23: Classification View field. Screenshot adopted from eCognition Developer 8.7.

The purpose of merging is to create a final classification which is a closer representation to the objects in the scene. For example, it will allow calculating the area of the whole lake. But it is important to remember that merging the image objects removes the selected samples, as the segmentation will have changed.

Finally, the results of the classification should be exported from Definiens. At first, they can be exported by clicking on *Export –> Export Results*. Leave the buttons on the left default and change the Export File Name to 'Classification'. Click on *Select Classes* and select all except for unclassified. Then click on *Select Features* to add all the attributes.

As mentioned before, the output of OBIA is usually a classified image, which often then becomes part of a map used, for example, to illustrate different vegetation types in an area. The segmentation itself can be an output, and is often imported into a GIS as a raster (e.g., image file), or a polygon vector layer (e.g., shapefile), to summarize and statistically analyze data.

The first feature, that could be added to the attribute table is the area of each class. Follow this path to add the area: *Object Features –> Geometry –> Extent –> Area* and then double click on *Area* to add it to the space to the right. The unit for the area can also be changed by right clicking on it *–> Edit Unit –>* change to Meters. This keeps us from having to calculate the area from pixels in ArcMap.

The second feature that could be added to the attribute table is class name. Follow this path to add the name: *Class-Related features –> Relations to Classification –> Class name* and double click on *Class Name*. This will add it to the selected box.

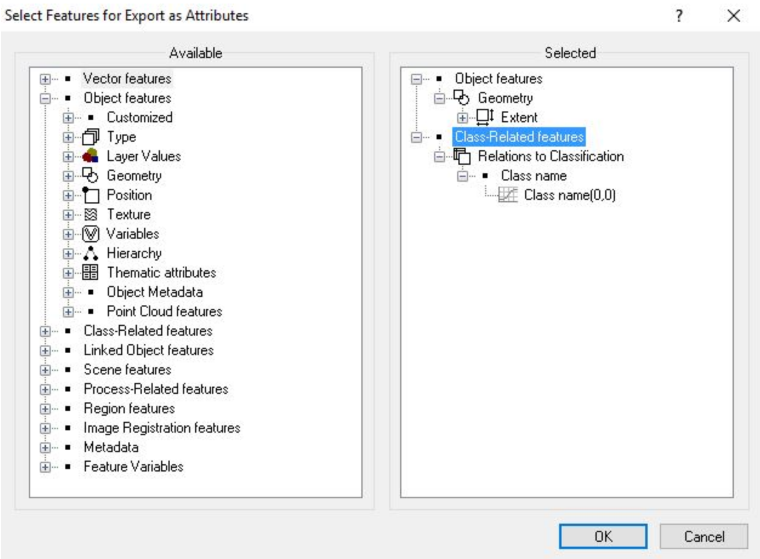


Figure 24: Features for Export as Attributes. Screenshot adopted from eCognition Developer 8.7.

Finally, run the process by clicking O*k* to export the results. This will result in an ESRI shapefile and allow the creation of a map (Fig. 25).

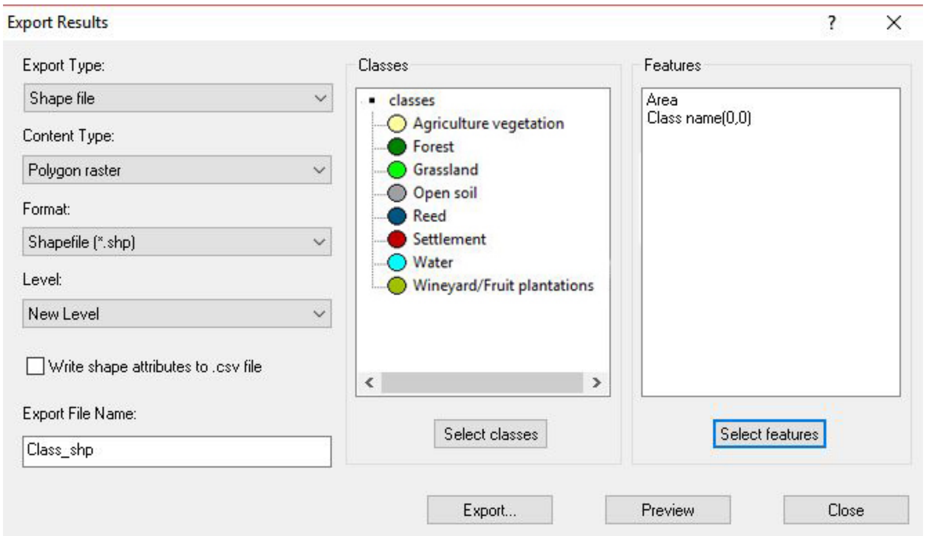


Figure 25: Export results. Screenshot adopted from eCognition Developer 8.7.

Another possible output of OBIA is an accuracy assessment such as an error matrix indicating the classification quality and amount of uncertainty associated with each class.

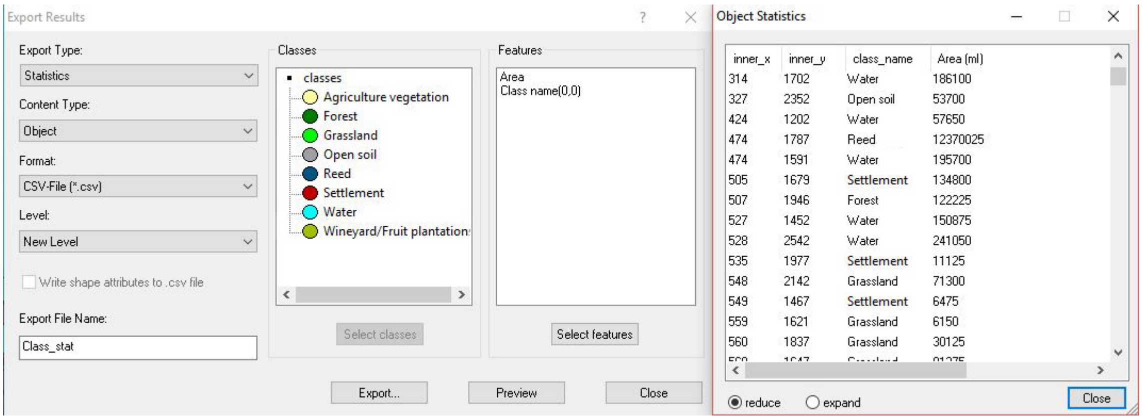


Figure 26: Export results – Object Statistics. Screenshot adopted from eCognition Developer 8.7.

In our case after rewiewing of classification results (Fig. 26) it was found that all unclassified polygones should be signed as “settlement”. To solve this problem, it will be made manually in an exported Excel table.

Another possible Table could be exported is shown on the screenschot below (Fig.27):

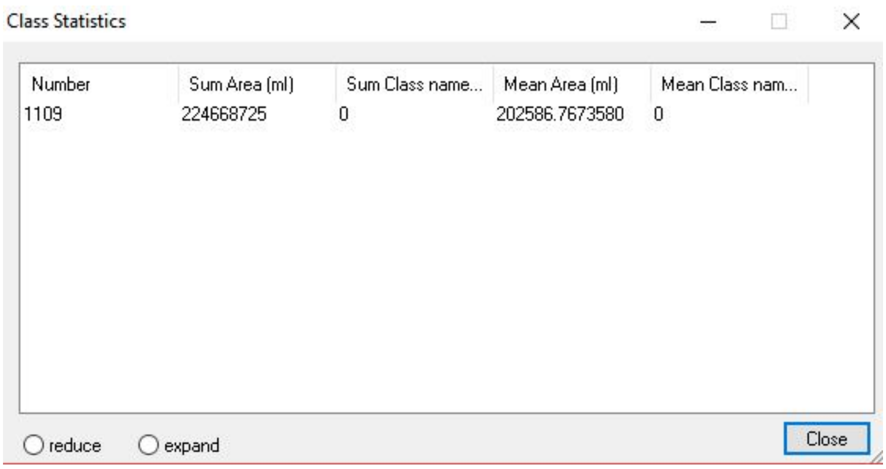


Figure 27: Class Statistics table export - Screenshot adopted from eCognition Developer 8.7.

To refine the classification further, Definiens Developer offers also an automated feature, the *Feature space optimization* tool to identify automatically the features which best separate the classes for which samples have been selected. To use this feature, the classification has to be deleted and the segmentation process - re-run. Also, new samples should be re-selected as these will be deleted each time the segmentation is changed.

To use this tool, select the features to compare, e.g. for mean, standard deviation and the pixel ratio, but it could also be chosen any parameters depending on what is needed. An example is shown below on the Fig. 28.

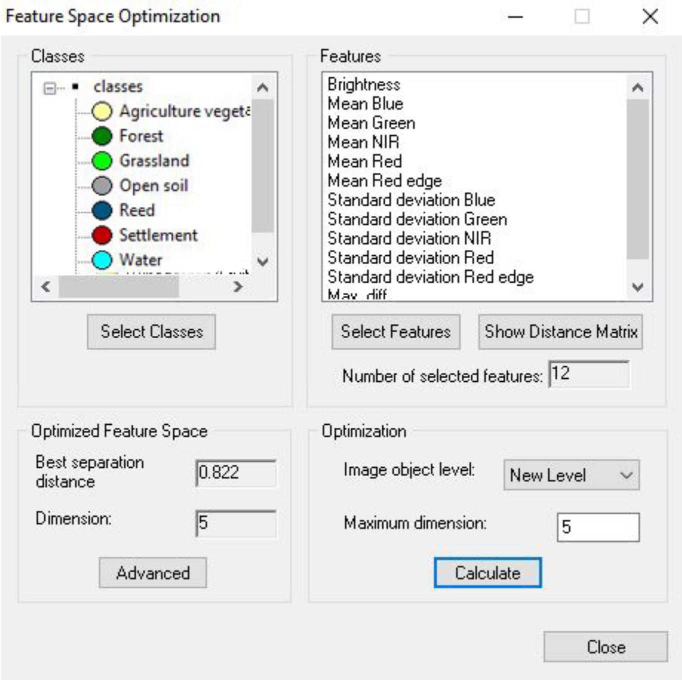


Figure 28: Feature Space Optimization Tool. Screenshot adopted from eCognition Developer 8.7.

Then select *Calculate*. Once the calculation is finished, select *Advanced* to see which features offered the best separation, and at last *Apply to the Std NN* to use within the classification.

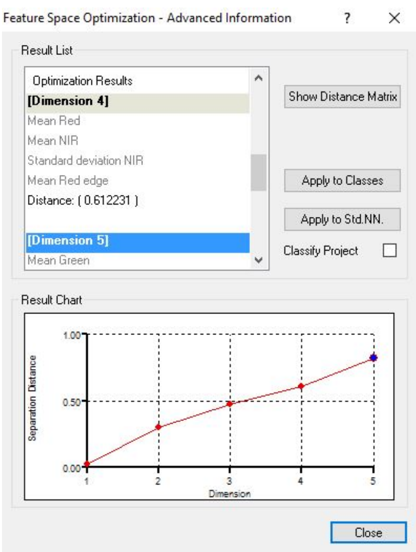


Figure 29: Feature Space Optimization Tool – Advanced Information. Screenshot adopted from eCognition Developer 8.7.

Now the Classification step can be run again, and then *Merge* and compare the results with the previous classification.

After the Project had been finished, it was decided to compare our results with the existed land cover map I got from the SINUS archive.

It was decided to add the existing segmentation to the satellite image in eCognition Developer and see the difference between the performed segmentation and the existing segmentation based on visual interpretation. Unfortunately, there is currently no option allowing to import a shape file as a segmentation layer in eCognition. But it could still be done by using chessboard segmentation in eCognition project.

After starting the project with the satellite picture, the shapefile with the existing segmentation should be imported as an extra *Thematic layer* (Fig. 30).

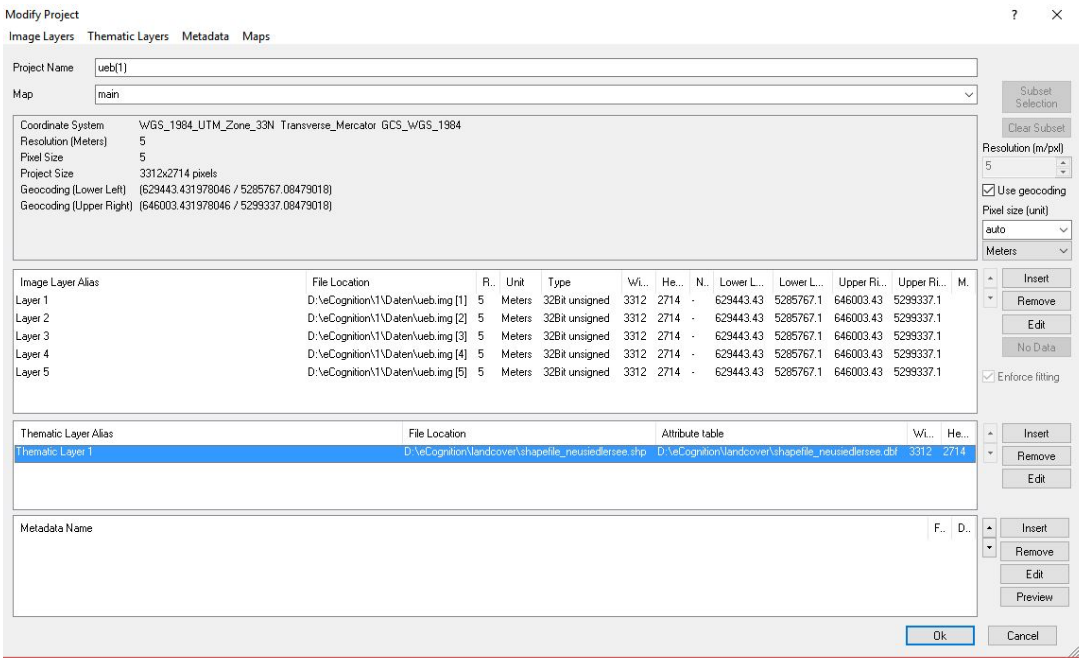


Figure 30: Modifying project, adding an extra Thematic layer. Screenshot adopted in eCognition Developer 8.7.

Then use *chessboard segmentation* with the object size bigger than our image file (Fig. 31) and select the shapefile as thematic layer. *Execute* the process.

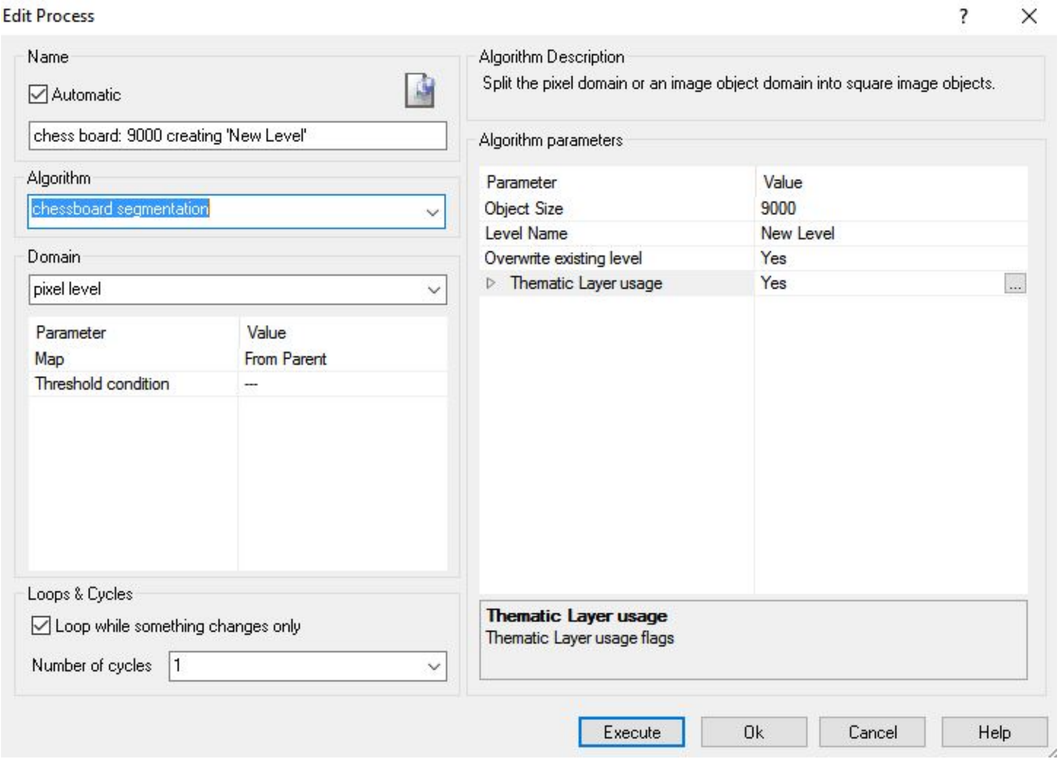


Figure 31: Chessboard segmentation – Edit process. Screenshot adopted in eCognition Developer 8.7.

This algorithm creates identical objects like in our imported segmentation (Fig. 32).

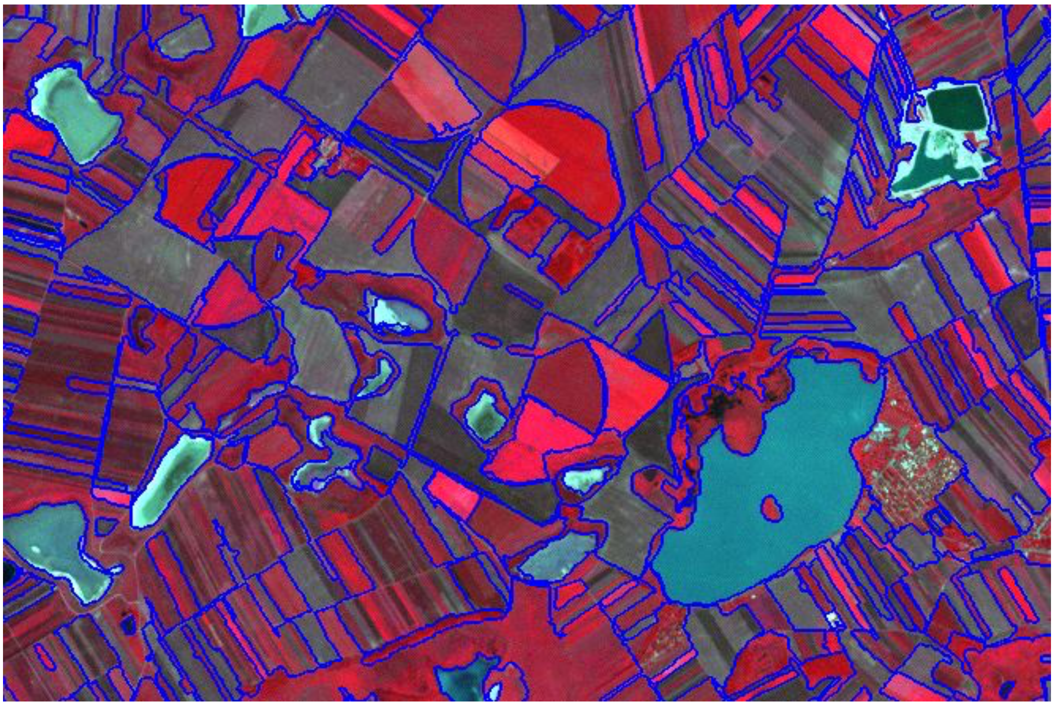


Figure 32: Chessboard segmentation using the Thematic layer(shapefile). Screenshot adopted in eCognition Developer 8.7

After the segmented image appears, it can be classified with already described Nearest Neighbor classification method.

On the screenshot (Fig. 33) it is shown how the Process Tree should look like:

Figure 33: Process Tree – Chessboard segmentation and Classification. Screenshot adopted in eCognition Developer 8.7.

Next step will be to compare two maps. Having opened the existing shapefile of land cover map of the region Neusiedlersee in ArcMap 9, colors for each class were changed to make the map more visual. The similar colors as in eCognition were given while making the classification (Fig. 34) and creating a map with the legend (Fig. 35).

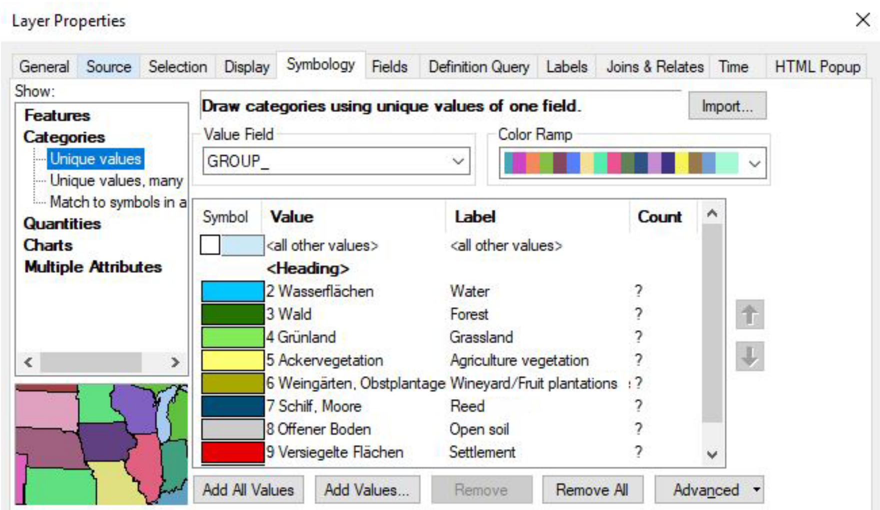


Figure 34: Layer Properties. Screenshot adopted from ArcMap 9

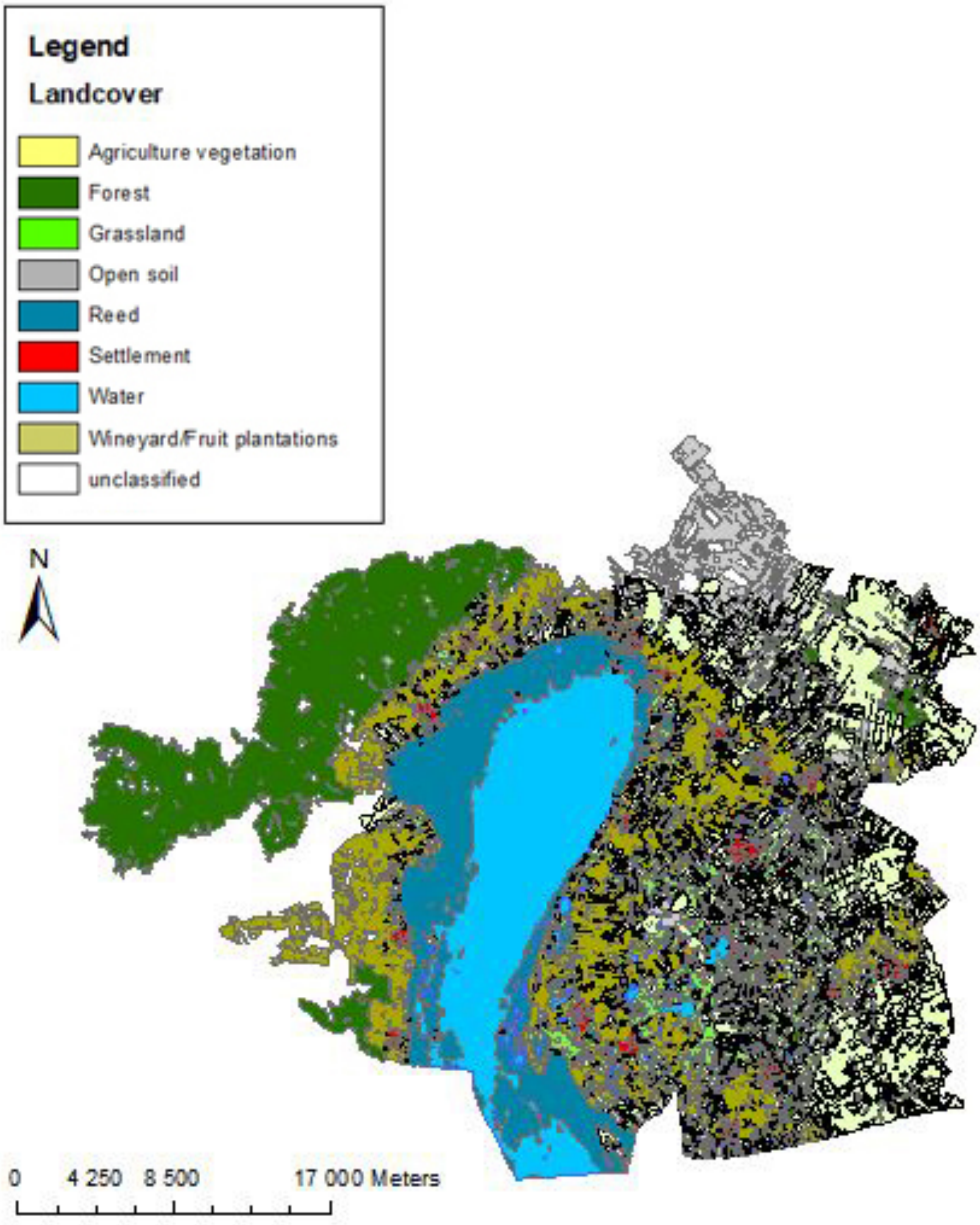


Figure 35: Land cover map of the Neusiedlersee region. Made in ArcMap 9. (Land cover map is taken from: SINUS)

For the further analyze it is needed to zoom the map to the region that was analyzed in eCognition. The same detail of map, taken from SINUS as the satellite image that was used in this work should be created. The segmentation based on satellite image was imported to a land cover map in ArcMap as a new layer. Than using *Dissolve* and *Intersect* tools (Fig. 36) the map was cut to the size of satellite image and appeared as a new layer (Fig. 37). This layer contains the information about the polygons from a map taken from SINUS and boarders from a satellite image we imported as a shapefile.

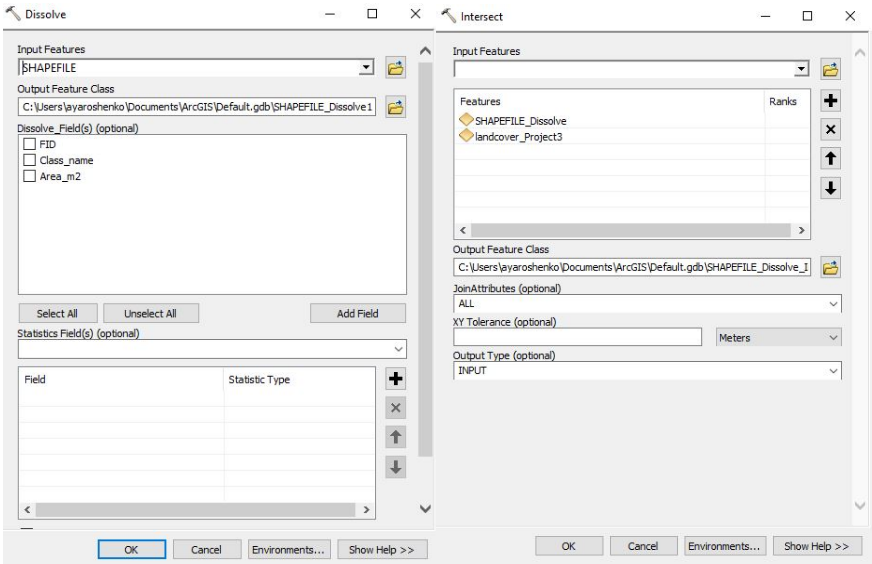


Figure 36: Dissolve and Intersect tools. Screenshot adopted in ArcMap 9.

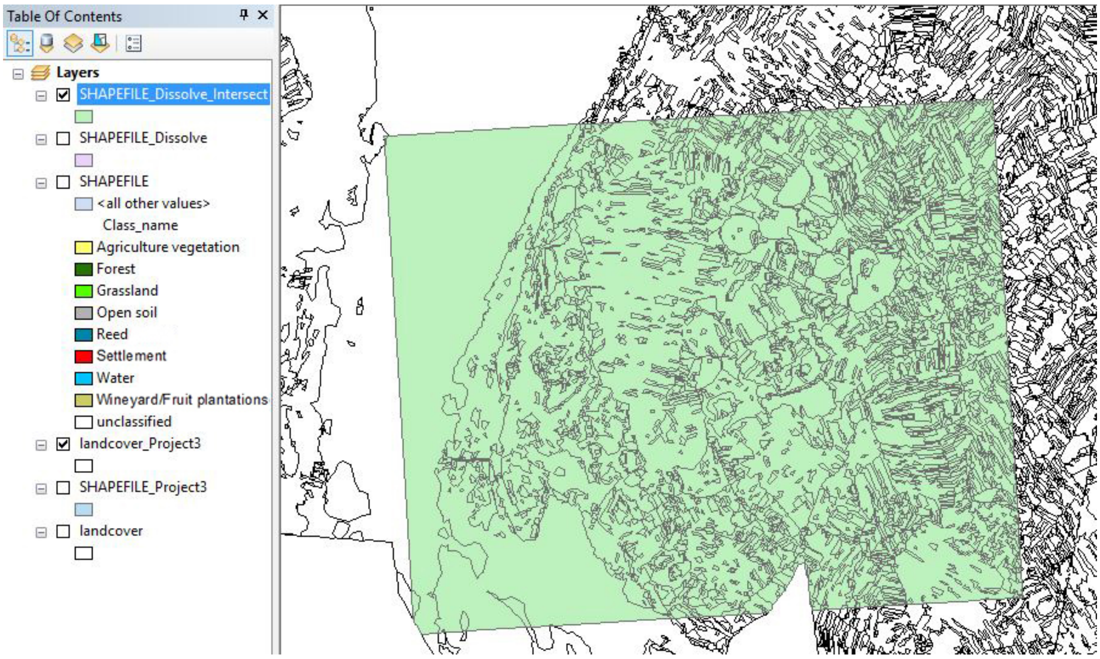


Figure 37: New layer to analyze. Screenshot adopted in ArcMap 9.

If we add again all values and give them the same colors - the difference between two maps will be clearly visible. (Fig. 38, 39).

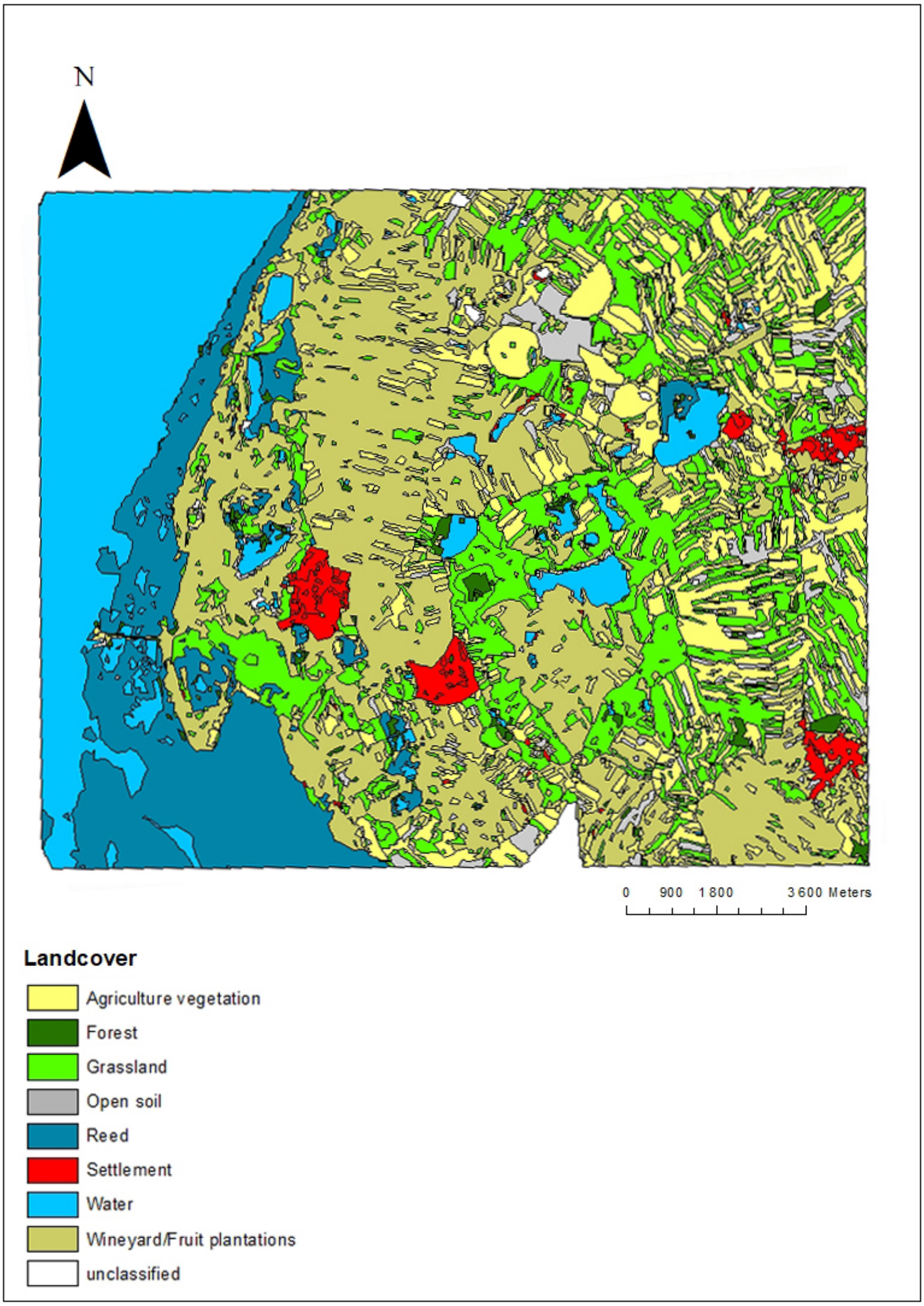


Figure 38: Land cover map of the Neusiedlersee region based on a visual interpretation made in ArcMap 9. (Source: SINUS)

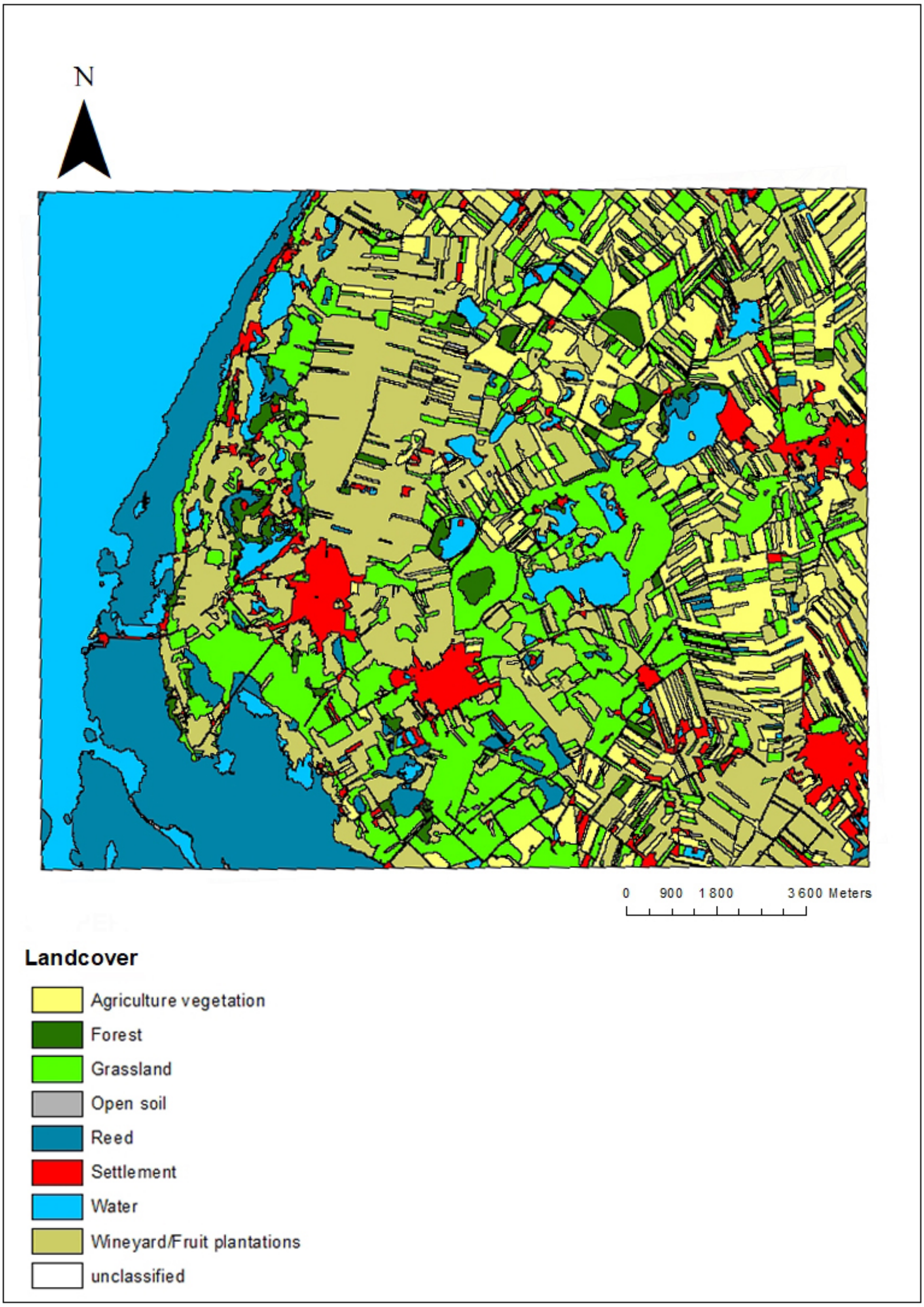


Figure 39: Land cover map of the Neusiedlersee region based on OBIA and made in eCognition Developer 8.7.

DISCUSSION

Comparing the results with the existing land cover map.

Here comes the visual comparison of two maps – one was segmented and classified in eCognition Developer Software (Fig. 40 a) and the other was provided by SINUS (Fig. 40 b). Both of them were opened in ArcMap.

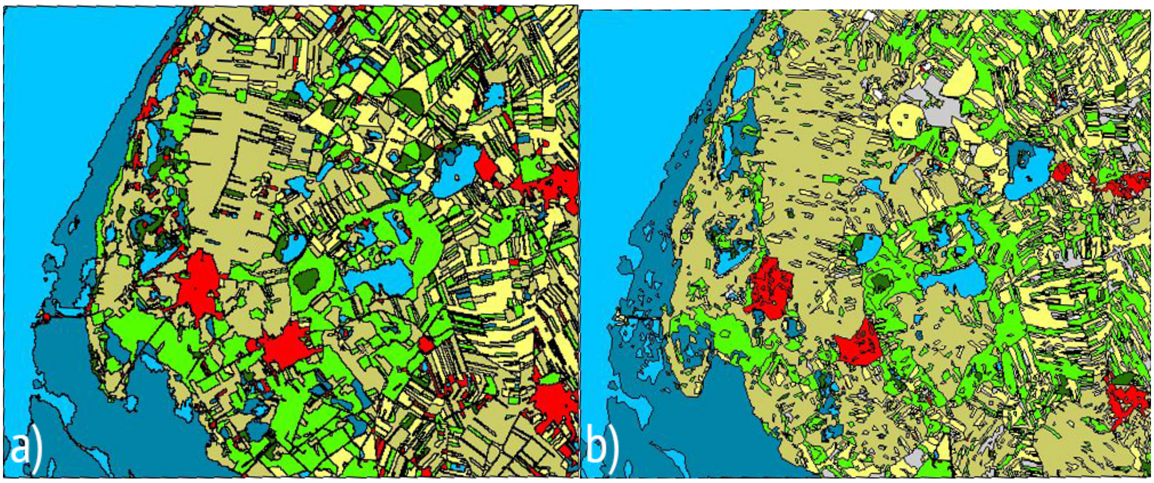


Figure 40: Land cover map of the Neusiedlersee region. a) Segmented using Multiresolution segmentation, b) Segmented by Visual interpretation

Afterwards the attribute tables of both maps were exported as .csv files and compared in the Table below (Tab.4):

Table 4: Land cover area comparison of two maps: map, based on visual interpretation (Source: SINUS) and a map, based on OBIA.

LAND COVER	AREA (m2)	
	Automated classified and visual corrected (ArcMap)	OBIA (eCognition)
Water	36451506	38758475
Forest	2704808	5120200
Greenland	41460197	45007675
Agriculture vegetation	39645121	31843875
Reed	25086236	26512875
Wineyard/Fruit plantation	65033577	63651225
Open soil	6223069	240475
Settlement	4796519	12844575
Not defiend	2376309	50475
Other	64010	0
Total area	223841352	224029850

Two maps look quite different, a lot of land cover territory has changed. The first map – map, segmented in eCognition Developer with a multiresolution segmentation - is made from much "younger" satellite picture than the second one taken from the archive.

First of all, it could be mentioned that nowadays there is much more settlement territory around the lake and less open soil than on the second map (the older one). Also, there are not much undefined territory, it seems that the land is getting more explored and used. On the other hand, wine garden territory has a bit decreased and grassland, as well as forest territory, on the contrary has grown.

But it should not be forgotten that there is always a chance of error in classifying objects because samples in eCognition have to be chosen on our own. That means it comes each time to a bit different result by choosing different samples.

That's why first of all let us compare land cover maps at the stage of segmentation in the eCognition viewer (before choosing samples).

By means of comparison of two segmentations in the same software (Fig. 41 a,b) – the one (a) made in eCognition Developer Software and the other (b) made in ArcMap by my colleagues earlier – it becomes clear that the segmentation made with a Multiresolution tool in eCognition Developer is more detailed and exact than the other one, made manually in ArcMap. But once more - don’t forget, that the land cover has definitive a bit changed since the first map was created, that’s why the segmentation was made in eCognition is different and represents the actual land cover objects.

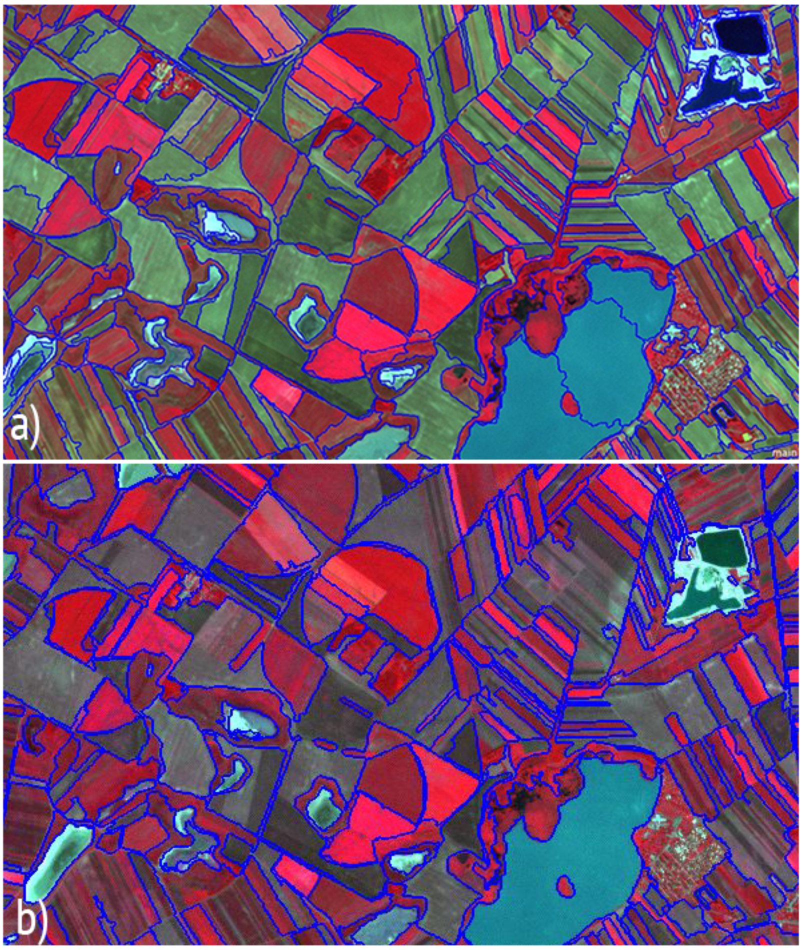


Figure 41:a) Segmentation made in eCognition Developer 8.7. b) Segmentation carried out in the SINUS. Screenshots adopted in eCognition Developer 8.7.

After the classifying of our maps in the eCognition Developer was finished, they could be compared. The first one (Fig. 42) is based on the segmentation made in eCognition Developer and the second one (Fig. 43) is based on the segmentation made in ArcGIS.

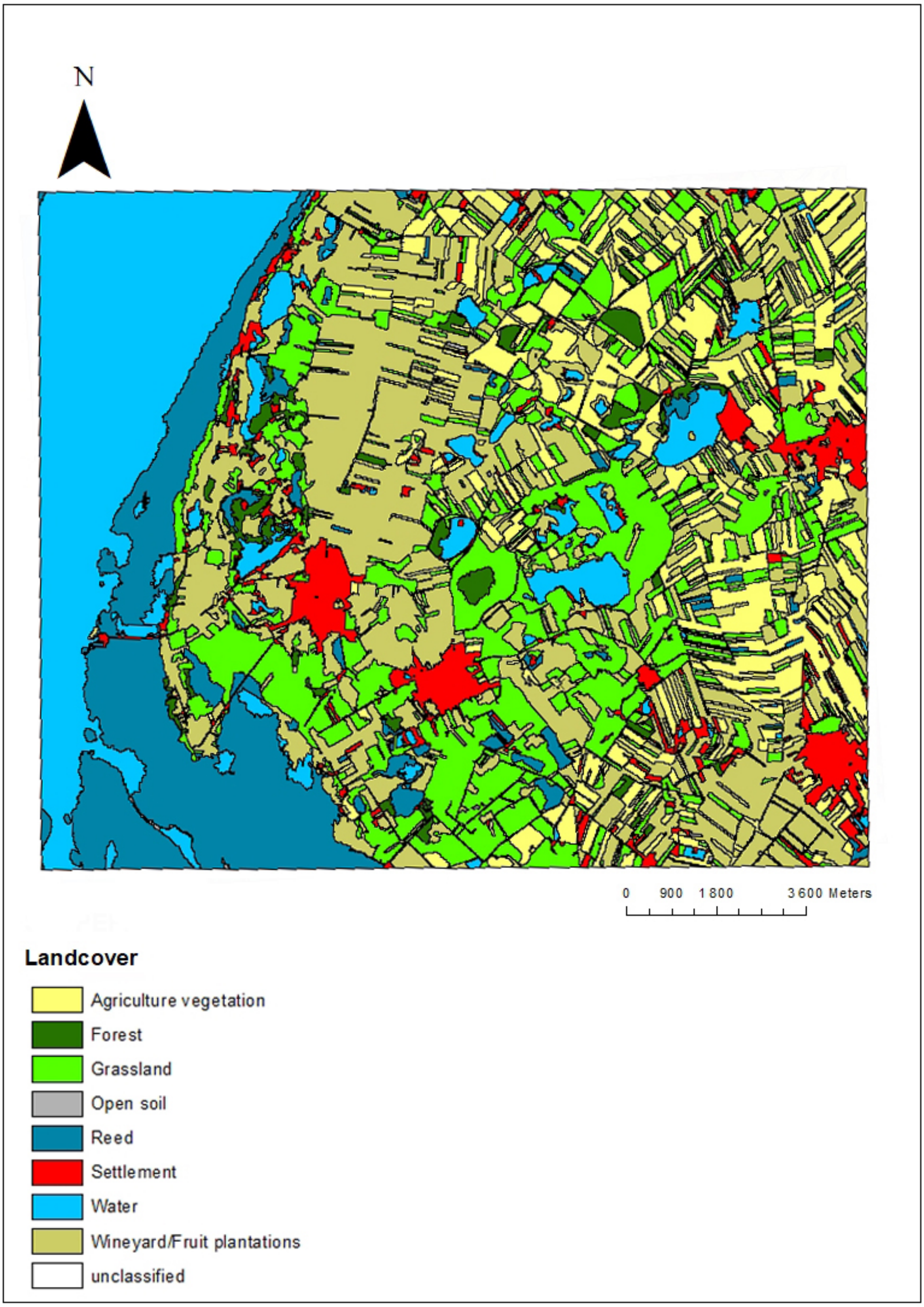


Figure 42:Map, segmented and classified in eCognition Developer 8.7 based on OBIA.

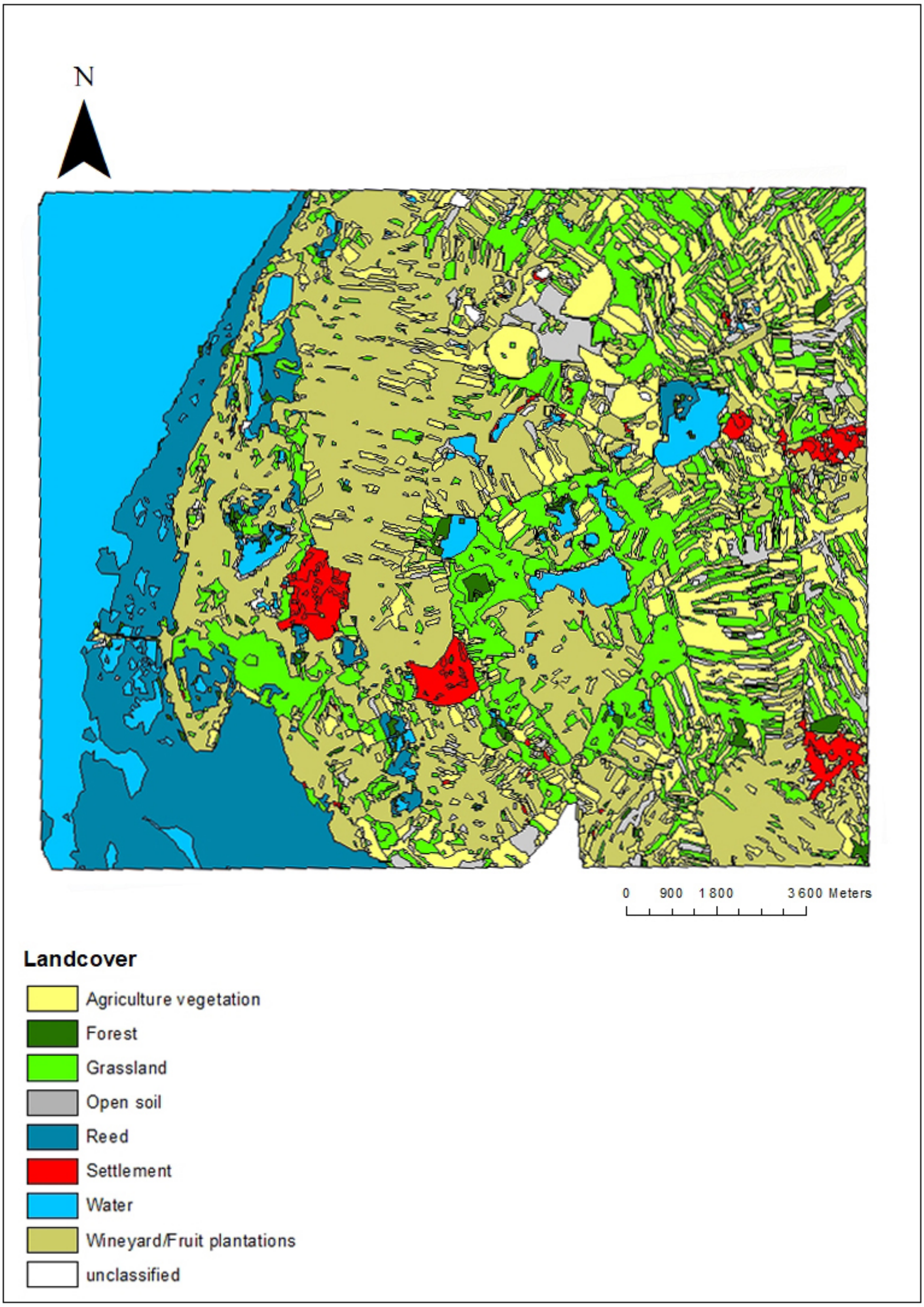


Figure 43: Map, segmented by visual interpretation and classified in ArcMap 9. (Source: SINUS)

Similarly, as was mentioned above by describing the table with data, by opening both maps in ArcMap it looks like some reed/moor polygons have been dissolved (instead of them we see forest polygons), and the settlement cover is getting definitely bigger with a time.

Interpretation of results

Spatial relationship information held in an image object allows for multiple levels of analysis. This is of top importance to the accuracy of image analysis of the landscape scale as the analysis would require multiple related levels of scale levels or segmentation. In the pixel based image analysis, the pixels are expected to cover a meaningful at the landscape scale area, however it is often not the case. The objects within the OBIA should provide a complex amount of information on various scales (through multiple segmentations with different parameter settings), and thus making OBIA more suitable to landscape scale analyses.

The RapidEye satellite picture of selected region was segmented with multi-resolution segmentation. The first segmentation was created with a scale factor of 100, color factor of 0.1 and compactness of 0.5. But after some different combinations it was found that the most representative combination based on visual checking is a scale factor of 180, color factor of 0.9 and compactness of 0.8. Next, this level was classified by Nearest Neighbor (NN) into 5 different classes, each colored with a different and most representative colors. After a couple of different sample selections, the most appropriate result was got and exported it in a shapefile (.shp), image file (.jpg) and an excel table with statistics (.csv).

Output of OBIA is usually a classified image which then might become a part of a map used, for example, to illustrate different vegetation types in the area. The segmentation itself can be an output, and it is often then imported into a GIS as a raster (e.g. image file), or a polygon vector layer (e.g. shapefile), to summarize and to statistically analyse the data.

It was not the aim for us to make a distinction between tree species. The definition of target categories is based on spectral properties extracted from samples of different areas with trees, independently of species. Classification are based on maximum-likelihood decision. Results can be improved using geometric properties. Then it can be imported into a GIS for the further analyze.

Another possible output of OBIA is an accuracy assessments, such as an error matrix indicating the classification quality and amount of uncertainty associated with each class. This can be presented in the final report about the current state of usage in the region.

OBIA is able to filter out useless information and assimilate other pieces of information into a single object. This is analogous to how the human eye filters information that is then translated by the brain into an image that makes sense. For example, the pixels in an image are filtered and grouped to reveal a pattern, like that of an orchard or tree plantation.

There are some difficulties which could occur when classifying in eCognition:

Unclean criteria. If conditions are not clearly defined when an object belongs to a class and when does not, it becomes difficult or impossible to classify an object. This happens quite frequently in the everyday use of classification: Which criteria distinguishes between good and bad? Clearly formulated and objectively measurable criteria are required for an unequivocal classification. In order to achieve a clear formulation, mathematics is usually sought.

Wrong features It is only possible to classify objects into classes if the characteristics considered actually allow a distinction of the classes. For example, it is not possible to classify creatures by their hair color into the classes of humans and monkeys; the hair color has generally no importance regarding the class membership of a living being.

Flowing crossings. Flowing transitions between classes contradict the idea of sharp class boundaries. For example, the class boundaries of the red class in the color spectrum are very difficult to determine. In order to enable classification, a sharp dividing line can be artificially introduced. Instead, by using the fuzzy logic, it is possible to operate on these fuzzy sets and to make a sharp decision by the de-fuzzification.

Non-separability. Non-separability occurs mainly when there are too few or non-predictive features. The objects appear mixed from this angle and a clear separation seems impossible. If apples or oranges were to be distinguished by their color, size and weight, many apples and oranges could be so similar in these traits that a clear separation is almost impossible. Although the features are clearly chosen, there remains a gray area in which the decision is uncertain.

Runaway Unpredictable measurement errors or unusually pronounced single copies may cause an object to be misclassified.

Rest objects. At the end of the classification, a group of residual objects can be left which does not fit into any of the existing classes and for which no new class can be created which would not make the entire classification system incoherent. For these objects an unsatisfactory residual category has to be established.

CONCLUSION

OBIA can provide a more meaningful source of information than pixel-based image analysis because it allows for less well-defined edges and borders between different classes. On maps, divisions between differing types of vegetation, for example where a grassland meets a shrubland, would generally represented by a single line. While in nature there is no such abrupt change. Instead the area where the shrubland meets the open grassland is a transitional area, this is known as an ecotone, which contain characteristic of species from each community, and sometimes species unique to the ecotone itself.

Nowadays there are many applications using object-based image analysis. eCognition Developer is one of the most convenient software which can be used for this approach. OBIA in eCognition comprises of two parts: multi-resolution segmentation and context-based classification. Multi-resolution segmentation allows the generating of image objects on an arbitrary number of scales, taking into account criteria of homogeneity in color and shape. Additionally, the created segments are embedded into a hierarchical network in which each object knows its neighboring objects in horizontal and vertical directions (Baatz and Schape, 1999).

To gain useful information from an image, the segmentation process divides an image into unclassified "object primitives" that form the base of the image objects as wells as the rest of the image analysis. Segmentations, plus the resultant characteristics of object primitives and final image objects, are based on size, shape, color, and pixel topology which are controlled through set parameters made by the user. The parameter values define the extent of influence of spectral and spatial characteristics of image layers will have on defining the shape and size of the image objects. The user can modify the settings depending on the objective, as well as bands available, image quality and image resolution.

The general rule is, 'good' image objects should be as huge as possible, but still small enough to show the contours of interest and serve as the building blocks for objects of interest not yet identified. If the objective was to classify large shrubs, then each object should contain only one (or one group of) shrub. If a single shrub is made up of multiple small objects, the objects are too small.

The "best" settings for segmentation parameters vary widely, and are usually determined through a combination of trial and error, and experience. Settings that work well for one image may not work at all for another, even if the images are similar.

The image objects can then be described and classified by an extensive variety of features that include color, texture, form, and context properties in several forms. This is usually done with a standard nearest neighbor classifier or fuzzy membership functions, or a combination of both. The variety of object features can be used either to describe fuzzy membership functions, or to determine the feature space for NN (Baatz and Schape, 1999).

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