

Urban green structure

Validation of automatic classification



Note no

Authors

Date

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Abstract

The purpose of this study was to evaluate the appropriateness of using Quickbird 0.6 m – 2.4 m resolution satellite images for the automatic mapping of green structures in urban and suburban areas. A Quickbird image of Oslo, Lørenskog and Oppegård from 2 June 2008 was classified by an automatic algorithm. The algorithm was written in Definiens Developer. The algorithm was trained on a subset of the image, and tested on 6 randomly selected subsets of 1000 x 1000 pixels. The validation was performed by manual editing of the classification result. The main focus of the editing process was to detect misclassifications between grey areas (such as roads and buildings) and green areas (trees, grass, and sparse vegetation). The most striking problem with the automatic method was that the object borders were very rugged. However, these segmentation problems were to some extent ignored in the evaluation process, concentrating on correcting major parts of objects being misclassified rather than correcting all minor segmentation inaccuracies. The result was that the classification step had approximately 9% misclassification rate in the two-class problem grey area versus green area. This is a very good basis for further improvement. The obvious segmentation problems are clearly the first things to address when further improving the method. Another problem is to what extent the automatic method can be used on another image with different light conditions, e.g., with the presence of clouds or light haze. Will a simple retraining of the classification rules be sufficient or will the rules have to be redesigned? It could even happen that redesigning the rules is not sufficient, so that other methods have to be developed.

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1 Introduction

This project was initiated to meet the need of municipalities in Norway to develop a green structure plan. Traditional mapping has its limitation, since the land use is in focus and not the actual land cover. Therefore, other sources of information about urban and suburban green structure are being sought. A municipality is interested in a green structure plan for several reasons:

1. To map current status of green areas and their changes over time. For example, what happens with the vegetation in public parks over time, even if the mapped land use does not change?
2. To maintain biological diversity. Different species or groups of species use different varieties of green structure as corridors. For example, small birds would avoid open areas, and need a corridor of trees to move safely. In open areas, they would expose themselves to predators.
3. Green structures are being used for recreation.
4. Vegetation converts carbon dioxide to oxygen, reduces noise, and has aesthetical value. Vegetation also binds water, reducing the prospect of floods after heavy rainfall.
5. If accurate, the green structure map can be used in overlays

The green structure includes private gardens. Although not accessible to the public, private gardens containing trees contributes to items 2 and 4 above.

Forest and farmland are not in the focus of this study, since they are well mapped, and the land cover aligns well with the land use classification of traditional mapping.

The purpose of this study was to evaluate the appropriateness of using Quickbird 0.6 m – 2.4 m resolution satellite images for the automatic mapping of green structures in urban and suburban areas. The rest of the report is organized as follows: Section 2 presents the available Quickbird image data, followed by a detailed description of the segmentation, training, classification and postprocessing steps of the automatic algorithm in Section 3. In section 4, the validation methodology is described. The validation results are presented in Section 5 and discussed in Section 6. An appendix contains all the validation images, and for each, the pansharpened original image, the classification result and the validated image are reproduced.

2 Data description

The project has acquired parts of a Quickbird scene of parts of Oslo and surrounding area (Figure 1).

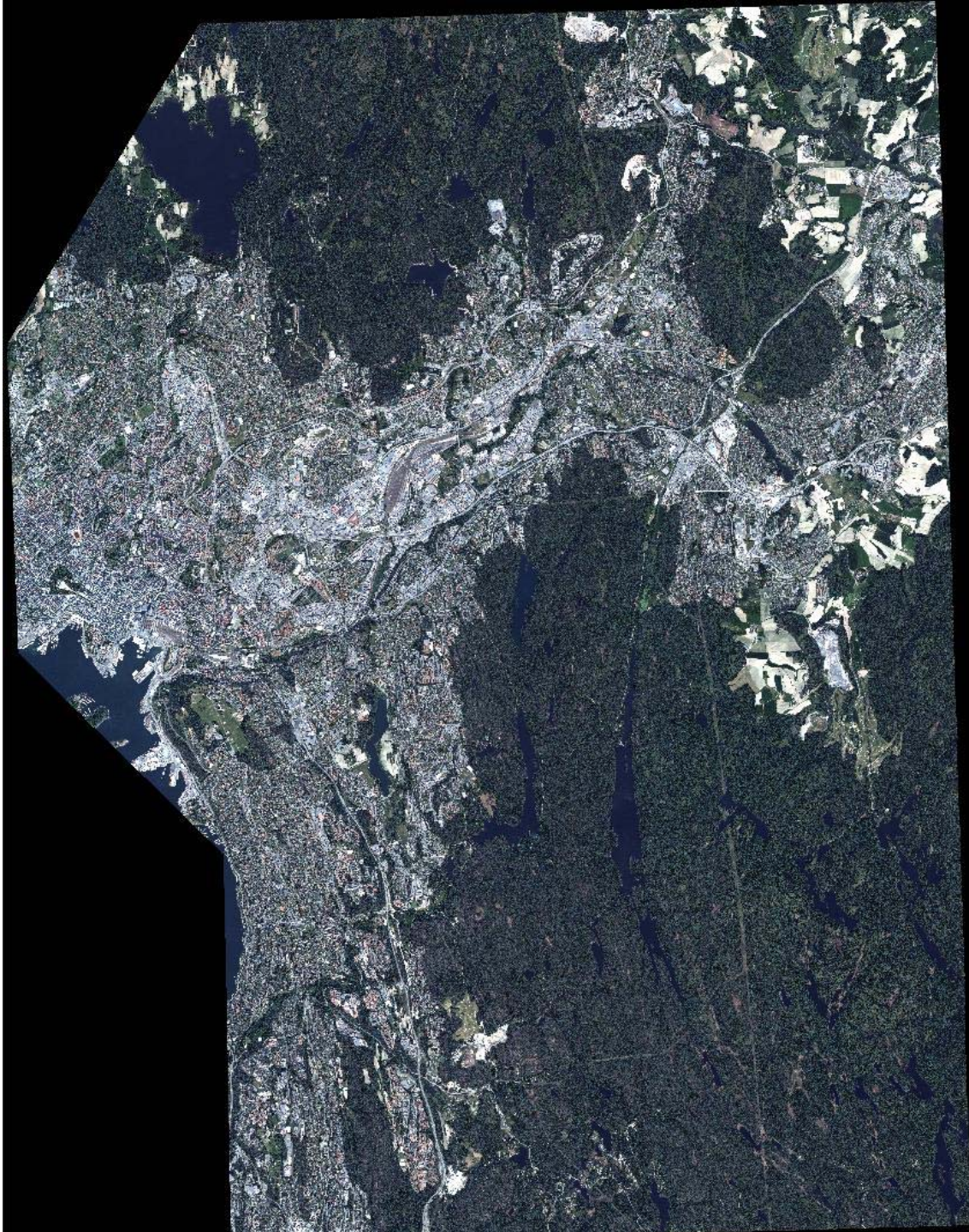


Figure 1. Quickbird image of Oslo, Lørenskog and Oppegård, acquired on 2 June 2008.

3 Classification procedure

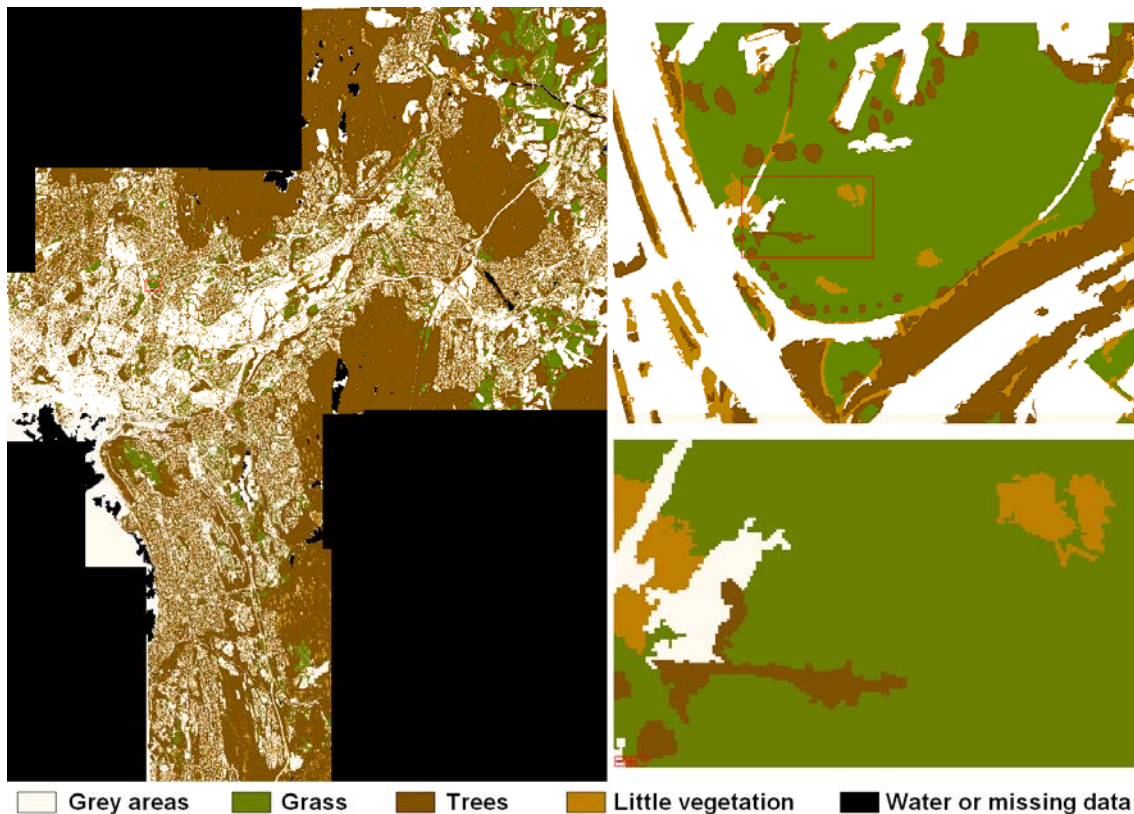


Figure 2. Classified image. Legend:

This section has been written in cooperation with Einar Lieng, Geodatasenteret, who was responsible for developing the classification procedure.

Definiens Developer (Definiens, 2007) was used to segment the image, based on pixel colors and parameters describing the segment shapes. Then the user defined a set of rules to classify the segments based on texture, neighborhood, color and other attributes. The final classification result consist of five classes (Figure 2):

1. grey areas,
2. grass,
3. trees,
4. little vegetation, and
5. water/missing data.

3.1 Segmentation

The segmentation was done in two levels in a bottom-up fashion.

The segmentation has to be a compromise between conflicting needs. On one hand, one would like to obtain large building blocks. At the same time, one would like to keep narrow corridors of green structure. Multiresolution segmentation was used, with two levels. The level 1 segmentation was based on the panchromatic image alone, whereas the level 2 segmentation also used the multispectral image bands (Table 1). The level 2 segmentation is based on the level 1 segmentation, which means it is locked to the segment boundaries that were created in level 1. The level 2 segmentation essentially aggregates segments from level 1.

Table 1. Segmentation parameters.

Level settings	level name	
	level1	level2
Level Usage		Create above
Image layer weights		
QB_PAN	1	1
QB_NIR	0	1
QB_Red	0	1
QB_Green	0	1
QB_Blue	0	1
Thematic layer usage	(not used)	(not used)
Scale parameter	20	50
Composition of homogeneity criterion		
Shape	0.1	0.1
Compactness	0.5	0.5

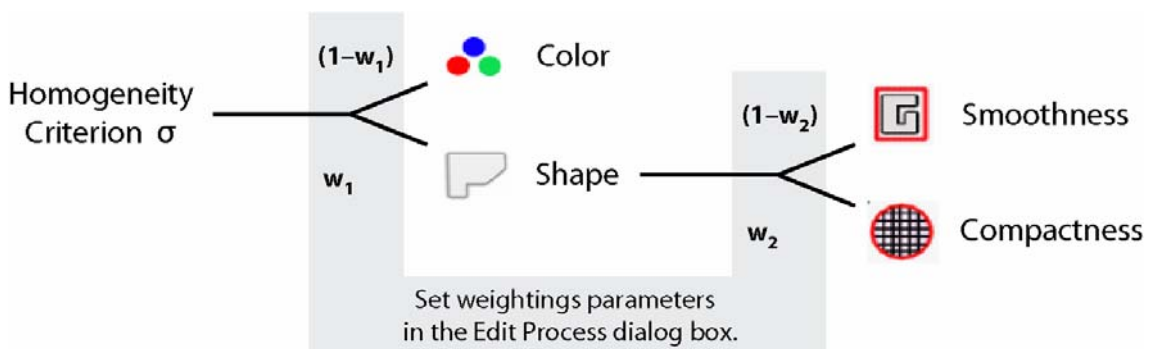


Figure 3. Homogeneity criteria in Definiens Developer. The figure is from (Definiens 2007), page 160.

On each level, the segmentation process iterates several times. In the first iteration in level one, all segments are one pixel each. The mutually best pairs according to a homogeneity criterion are found, and each identified segment pair is merged into a new segment. This continues as long as segments can be merged without breaking the scale parameter constraint. The scale parameter is a threshold on the homogeneity value of a segment, and the homogeneity value is computed as the standard deviation from the ideal situation. The following criteria can be used, in combination

- Color: homogeneity is computed as standard deviation of the spectral colors.
- Shape: divided into smoothness and compactness
 - Compactness: homogeneity is computed as the deviation from a compact object

- Smoothness: homogeneity is computed as the deviation from a smooth object boundary.

The color and shape weights sum to 1. Within the shape criterion, the compactness and smoothness weights sum to 1 (Figure 3). So, the shape value of 0.1 in Table 1 denotes that the shape criterion has weight 10% and the color criterion 90%. By increasing the shape weight, the segmentation will be more eager to find objects which are compact and/or smooth, and less eager to find objects with low color variation.

As an example, if the color homogeneity is 12, the smoothness homogeneity is 48 and the compactness homogeneity is 60 for a segment, then the weighted homogeneity, as defined in Table 1, is

$$0.9 \times 12 + 0.1 \times 0.5 \times 48 + 0.1 \times 0.5 \times 60 = 9.2 + 2.4 + 3.0 = 14.6$$

which is below the scale threshold for level 1, so this segment is accepted. However, if the shape homogeneity had been set to 0.5, then the weighted homogeneity had been

$$0.9 \times 12 + 0.5 \times 0.5 \times 48 + 0.5 \times 0.5 \times 60 = 6 + 12 + 15 = 33$$

which is above the scale threshold for level 1.

In level 2, equal weight is placed on the four multispectral bands (blue, green, red and near infrared (NIR)) (Table 1). One could place a higher weight on NIR for vegetation mapping, and also reduce the weight of blue if there is haze in the image.

The scale parameter indicates how large objects one is interested in. To find individual trees, a low value should be used. To segment parts of a forest, a large value is used. We are interested in private gardens, where trees are present but the pattern is less homogeneous than in a forest. So we are interested in single trees and groups of trees, and a value of 50 seemed to work well.

3.2 Classification

The classification was done in a hierarchical fashion. At each level, there are competing rules, and the rule that gives the highest score is selected. (In the documentation, the rules are called membership functions (Definiens 2007).) There is also a threshold for setting an object to be unclassified. This was set to 0.1. One can set this to, say, 0.9 during training.

The rules used on the 2008 Quickbird image are outlined in Figure 4, and the actual values for the thresholds should be adjusted for a new image. However, one may also want to use different rules for another image, due to different colors, phenological cycle, date, haze, etc.

Both the panchromatic 0.6 m resolution and the four bands multispectral 2.4 m resolution information was used in the classification procedure.

The classification rules are organized in a hierarchical fashion (Figure 4). Note that so-called soft thresholds are being used. This means that instead of using a simple if-test on a threshold value, essentially producing a sharp transition from 0 to 1, there is a smooth transition zone where the response goes gradually from 0 to 1 (Figure 5). Then the rule with the highest score wins.

Water:

GLCM Homogeneity (quick 8/11) all directions
QB_PAN high value, above soft threshold 0.75 .. 0.85
Mean QB_NIR low, below soft threshold 100 .. 110
NDVI low, below soft threshold 0.15 .. 0.18

Comment. If there is a lot of wind, solar reflections, or algae blooms, the homogeneity of water may be low, and the rule could probably not be used.

Ground:

NOT Water

Vegetation:

Mean QB_Green low value, below soft threshold 330 .. 400
NDVI high value, above soft threshold 0.26 .. 0.34

Grey area

NOT Vegetation

Shadows and water

Mean QB_Blue low value, below soft threshold 180 .. 210

Impervious

NOT shadows and water

Comment: Could have used a band ratio. Band ratios are more important in low resolution images, when shadows are mixed with non shadow. But in Quickbird images, the shadows are quite sharp, and one wanted to have simple rules.

Water edge:

Mean QB_NIR low value, below soft threshold 90 .. 100
Relative border to Water high value, above soft threshold 0.1 .. 0.3

Shadow 2

NOT Water edge

Comment: Shadows and water are difficult to distinguish between based on image colors alone. Height information would be useful to predict shadow locations and shapes. Also, water is well mapped in Norway and the boundaries may be obtained from a GIS.

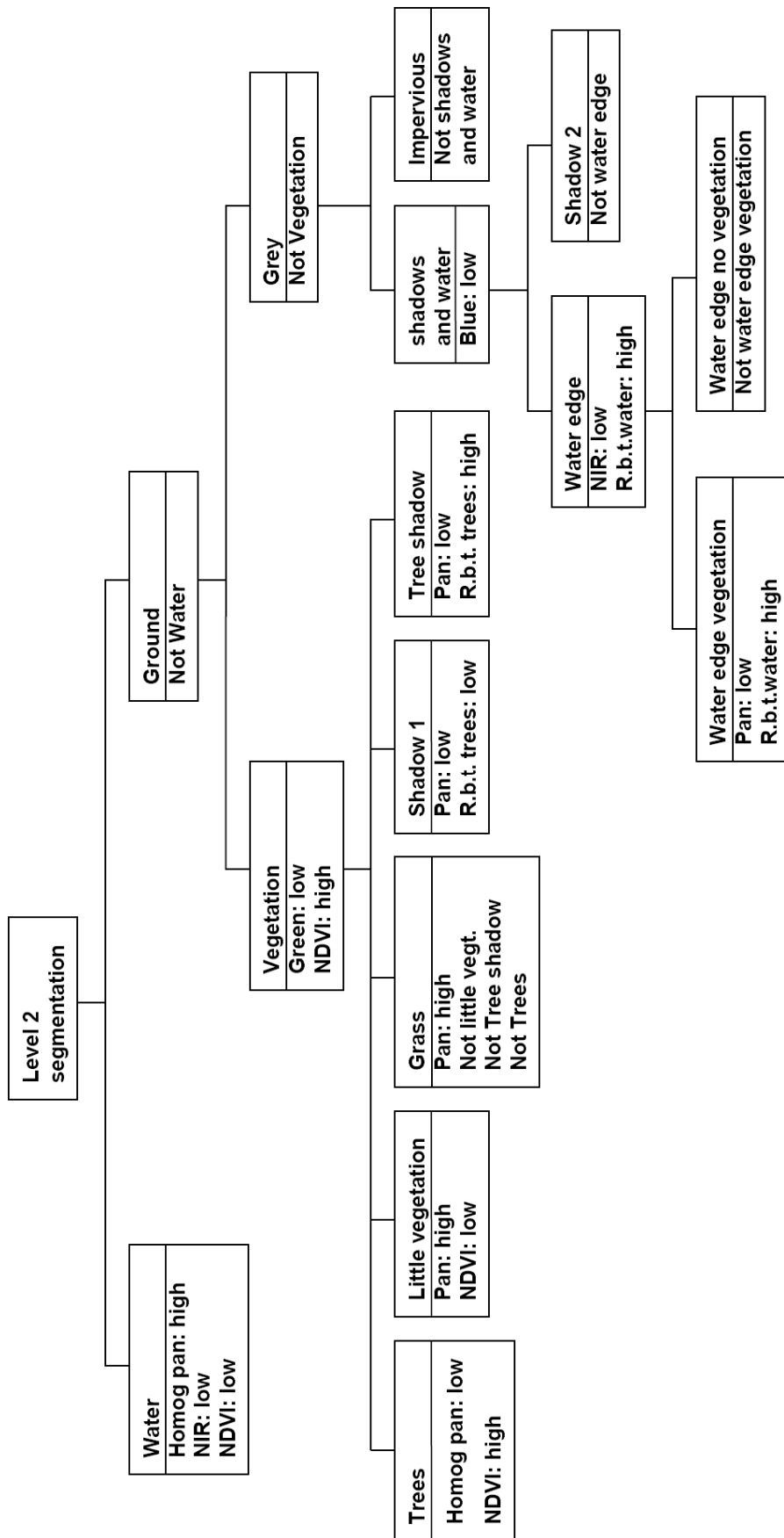


Figure 4. Hierarchy of classification rules.

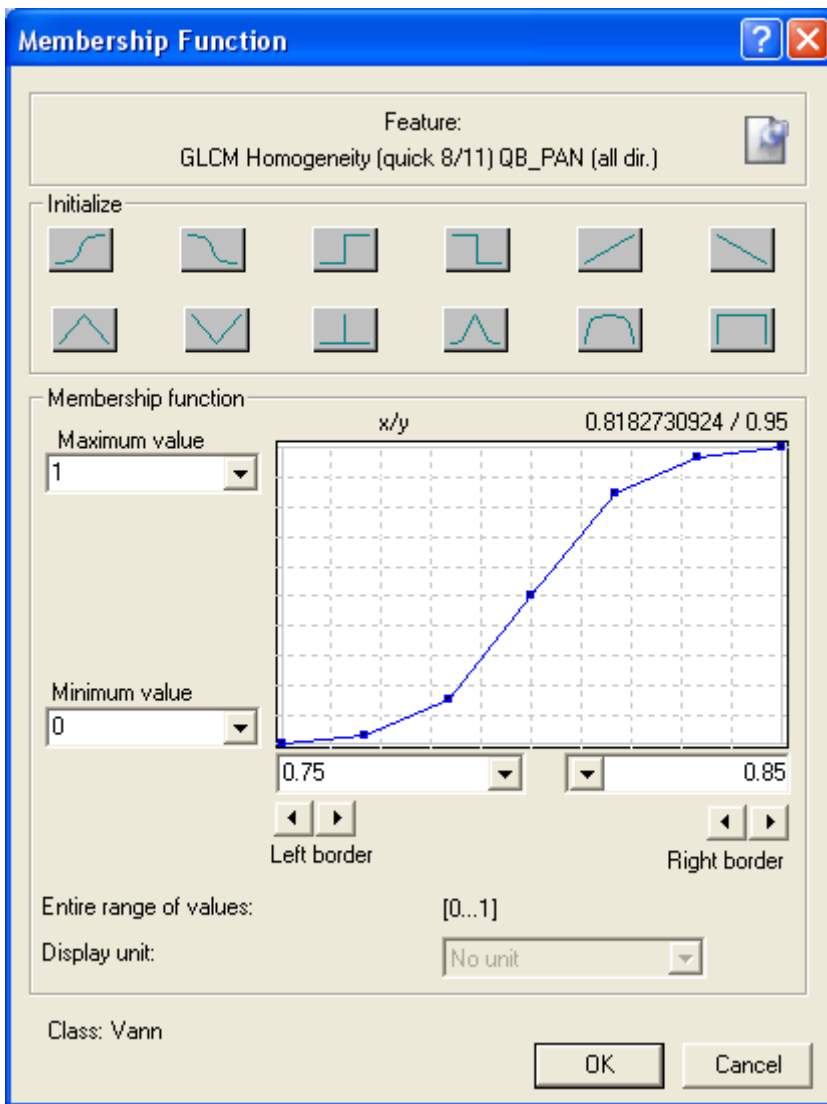


Figure 5. Soft threshold for a rule, here, a test on the Haralick's grey level co-occurrence matrix homogeneity measure, measured in eight directions in the panchromatic input image. Instead of a sharp threshold on 8.8, a transition from 0.75 to 0.85 is used.

Grass

- Mean QB_Pan high value, above soft threshold 250 .. 300
- NOT little vegetation
- NOT tree shadow
- NOT trees

Little vegetation

- Mean QB_Pan, above soft threshold 180 .. 220
- NDVI below soft threshold 0.4 .. 0.55
- NOT water edge
- NOT vegetation

Shadow

- Mean QB_PAN below soft threshold 150 .. 220
- Relative border to trees below soft threshold 0 .. 0.1

Trees

GLCM Homogeneity (quick 8/11) QB_PAN all dir low value, below 0.26 .. 0.4
NDVI high value, above soft threshold 0.45 .. 0.5

Tree shadow

Mean QB_Pan below soft threshold 180 .. 200
Relative border to trees above soft threshold 0 .. 0.2

Comment: There should be a tree south of the tree shadow. However, there might be misclassifications, so there is not always a correctly classified tree object directly to the south of the tree shadow. So, an adjacent tree in another direction is accepted. This will be common in forests, with many trees.

Water edge vegetation

Mean QB_PAN below soft threshold 140 .. 190
Relative border to water, above soft threshold 0.2 .. 0.4

Water edge no vegetation

NOT water edge vegetation

When working with the rules, one might add new rules or tune the thresholds. At the end, one has a handful of misclassified and unclassified objects. One may then want to add “cleanup rules”. The following cleanup rules are used:

Assign class

IF Class = Unclassified
AND Relative border to trees > 0.5
THEN Use class tree shadow

Assign class

IF Class = grass
AND GLCM Homogeneity QB_Pan <= 0.21
THEN Use class trees

Assign class

IF Class = trees
AND GLCM Homogeneity QB_Pan >= 0.45
THEN Use class grass

Assign class

IF Class = shadow
AND Relative border to trees > 0.3
THEN Use class tree shadow

Assign class

IF Class = shadow
AND Relative border to tree shadow > 0.3
THEN Use class tree shadow

Assign class

```
IF Class = impervious
AND NDVI > 0.55
THEN Use class grass
```

3.3 Comments

The segmentation and classification modules in Definiens developer provided a means to quickly obtain a fairly good classification result. Some time was spent on optimizing the parameters, but it was felt that it was not a good idea to spend too much time on this, as this would have to be repeated for a new model.

Agricultural land, rivers and lakes are not considered important in this project, as it is well mapped, and can be obtained from GIS. However, the positional accuracy is often lower than for buildings and roads.

The result of the classification procedure was a 0.6 m resolution image with the following classes (Figure 2):

- Green (■ R: 96, G: 128, B: 0): Open grass land and lawns.
- Dark brown (■ R: 128, G: 96, B: 0): Bushes, trees, forest. (Parts of) private gardens are expected to fall into this class.
- Light brown (■ R: 192, G: 128, B: 0): Little vegetation: Paths, grass areas with substantial wear and tear.
- White (□ R: 255, G: 251, B: 240): "grey" areas, that is, covered by buildings, roads, parking lots, etc; thus with no vegetation.
- Black (■ R: 0, G: 0, B: 0): Not classified or missing data, also used for water.

The three first classes are regarded as "green" areas, and can be seen as subclasses of green areas.

3.4 Postprocessing of classification result

The classified image can be combined with GIS data of buildings and roads. Trees overlapping buildings and roads are kept, based on the NDVI value, but other parts of the buildings and roads are subtracted from the vegetation classes.

Enhanced versions of the Oppegård and Lørenskog areas were created by using GIS data for buildings and roads. The houses and roads were subtracted from the green areas if the NDVI was low. In cases where the NDVI was high, for example, caused by a tree overlapping a house or a road, the tree was kept.

4 Validation methodology

The Classification may be validated manually or automatically. In order to perform an automatic validation, a ground truth must be established. For Oppegård and Lørenskog municipalities, we have obtained digital maps, free of charge, of roads and buildings, for use within the project. These maps can be used to validate grey versus green area classification, but can not be used to validate which of the three green area classes that has been assigned.

One major shortcoming of the digital map we had access to is that not all grey areas are included. Large parking lots are missing, as well as private driveways. So, the digital map could be used to find houses and public roads that were partially or fully missing in the automatic classification. However, areas that had been misclassified as grey areas could not be flagged, since many grey areas are missing in the digital map.

Thus, manual validation of the automatic classification was needed. The intention was also that the manual classification be used to validate the subclasses of green areas. However, this turned out to be too difficult to do in a quantitative manner. Only some general observations could be made. Where available, the digital map was used to guide the manual validation

Finally, a comparison between the manual and the automatic validations will be done..

4.1 Manual validation method

4.1.1 Selection of validation areas

Given the size of the image, and the available resources for the project, a complete inspection of the classification result of the entire image was considered infeasible. Instead, a selection had to be made. Manual selection of areas that could be considered “representative” would lead to a biased result. On the other hand, some of the selected areas should cover the areas of which we had map coverage. These considerations led to the following selection procedure of validation areas.

1. Set the image counters $N_{Oppegård}$, $N_{Lørenskog}$ and N_{Oslo} all to zero.
2. Pick an x,y coordinate within the image at random. The range of possible values are $1 .. x_{max}-x_{size}$ for the x coordinate, and $1 .. y_{max}-y_{size}$ for the y coordinate, with x_{max} , y_{max} being the Quickbird image size and x_{size} , y_{size} being the validation area size.
3. If the validation area only contains missing or no data, discard the area and jump back to step 2 above.
4. If the new validation area partially overlaps an existing validation area, then replace the overlap with missing data in the new validation area
5. Compute the fraction of the area within the Oppegård map coverage ($f_{Oppegård}$), within the Lørenskog map coverage ($f_{Lørenskog}$), outside map coverage (f_{Oslo}), and with no or missing data (f_{Nodata}). These four fractions should sum to 1.
6. Add the map fractions to the counters, for example, $N_{Oppegård}(i+1) = N_{Oppegård}(i) + f_{Oppegård}(i+1)$, where i and $i+1$ denote iterations i and $i+1$, respectively.

7. Continue, by jumping back to step 2 above, until all three counters are above predefined thresholds $M_{Oppegård}$, $M_{Lørenskog}$ and M_{Oslo} .

The Quickbird image size, $(x_{max}, y_{max}) = (28090, 36602)$, and the validation area size $(x_{size}, y_{size}) = (1000, 1000)$. The validation thresholds are $M_{Oslo} = M_{Oppegård} = M_{Lørenskog} = 2$. Initially, we intended to have M_{Oslo} much higher, but the manual editing was so time-consuming that we ended up with $M_{Oslo} = 2$.

4.1.2 Validation of automatic classification

For each validation area, make a copy which is then edited, as described below. The difference between the validation area and the edited version is then used to compute a confusion matrix, counting the number and type of misclassification (Table 2). Although the editing is object-based, see below, the counts in the confusion matrix are pixel-based.

Table 2. Confusion matrix of classified versus edited image.

		Edited				Sum
		Grassland	Trees/bushes	Little vegetation	Grey areas	
Classified	Grassland					
	Trees/bushes					
	Little vegetation					
	Grey areas					
	Sum					1000000

For each validation area, the classified image is compared with the original image and an aerial orthophoto from (date) with 0.5 m resolution (Figure 6) or 0.1 m resolution (Oppegård). All obvious misclassifications are corrected. The editing is mainly object-based, that is, individual pixels are not edited. The classified image has quite rugged object boundaries, many which could have been cleaned by using road and building outlines as a guide in the segmentation process. Noting this, we have, to some extent, avoided editing these rugged boundaries.

On some occasions, however, what should have been two or more objects have by mistake been segmented into one object only. In such cases, the object has been split and parts of it reclassified in the editing process.

On some occasions, parts of water bodies have been mistaken as grey areas, probably due to wind patterns. Since water bodies can be easily removed by using GIS data, we have not counted these as misclassifications, but regarded them as missing/no data.

Although originally intended, a validation of the three subclasses of green areas is not performed. Only a few occasional substitutions of one subclass of green with another are done.

During the manual verification, the need for a gravel subclass emerged. This class has been used in some instances to denote grey areas that are not sealed, and thus may be recovered as green areas. This is indeed the case for construction sites. Typically, when a new house is being built, the entire garden looks like a grey area in the Quickbird image, but is planted shortly after. In practice it is difficult to see the difference between gravel, asphalt and concrete, so the gravel class is only used in very obvious occasions. It is in practice a subclass of grey areas.



Figure 6. Assessment of classification result. Upper left: classification result. Upper center: edited classification result. Upper right: Pansharpened Quickbird image. Bottom: Aerial orthophotography.

5 Validation results

The manual validation procedure, as described in section 4, was applied, resulting in 6 validation areas. Of these, two were from Oppegård, two from Lørenskog, and two from Oslo. The overall classification performance is about 89% correct classification rate (Table 3). This figure hides the fact that the object boundaries from the segmentation step are far from ideal. Further, in the manual validation procedure, almost no objects from one of the three green structure classes were reclassified as another green structure class. In this respect, it is more meaningful to look at the two-class problem: green versus grey areas. In this case, the recognition performance was slightly better, about 91% (Table 4).

Table 3. Classification performance when using six classes.

correct classification	89.13%
misclassification	10.87%
total	100.00%

Table 4. Classification performance when using two classes.

correct classification	91.38%
misclassification	8.62%
total	100.00%

The most common misclassification is to confuse little vegetation and grey areas. This resulted in about 300,000 pixels being reclassified (Table 5). This is about 5% of the 6,000,000 image pixels. Of the 683,141 pixels that were regarded as little vegetation after the manual validation step, 178,704, or 26%, were originally classified as grey area (Table 5 – Table 6).

All the validation areas, their edited versions, as well as the original image data and corresponding aerial orthophoto are reproduced in appendix A. The combined confusion matrixes (Table 5 – Table 6) and classification results (Table 3– Table 4) appears here, whereas the confusion matrixes for individual validation areas appear in appendix A (Table 7 – Table 18).

Table 5. Combined confusion matrix for all six verification areas, in number of pixels.

Area 1-6		Edited						Sum classified
		Grass	Forest	Little vege.	Grey area	Gravel	No data	
Classified	Grass	535353	0	1	4479	110	1	539944
	Forest	931	2737263	4568	110921	2013	8650	2855696
	Little vege.	59	3164	499868	135870	3387	432	642348
	Grey area	3029	65620	178704	1575587	126162	3256	1949102
	Gravel	0	0	0	0	0	0	0
	No data	0	558	0	13	0	1	571
Sum edited		539372	2806605	683141	1826870	131672	12340	6000000

Table 6. Combined confusion matrix, in percentages.

		Edited					
		Grass	Forest	Little vege.	Grey area	Gravel	No data
Classified	Grass	99.25%	0.00%	0.00%	0.25%	0.08%	0.01%
	Forest	0.17%	97.53%	0.67%	6.07%	1.53%	70.10%
	Little vege.	0.01%	0.11%	73.17%	7.44%	2.57%	3.50%
	Grey area	0.56%	2.34%	26.16%	86.25%	95.82%	26.39%
	Gravel	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	No data	0.00%	0.02%	0.00%	0.00%	0.00%	0.01%
Sum edited		100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

6 Discussion

The classification results show that the classification part of the automatic algorithm is able to classify between green and grey areas, with approximately 10% misclassification. This is clearly a good starting point for improvements. However, the ruggedness of objects suggests that the segmentation step of the automatic algorithm has a great potential for improvement.

Another issue is to what extent the automatic algorithm can be used on another Quickbird image or not. The classification rules in the automatic classification method have been trained on a subset of the image, and then evaluated on random portions of 1000 by 1000 pixels. The illumination conditions were very close to ideal and uniform over the entire scene, whereas many other Quickbird images of Oslo have clouds. It is possible that the classification rules will have to be adjusted for every image to be processed. Also, it is not known what problems the presence of clouds will result in. All in all, it could happen that redesigning the rules is not sufficient, so that other methods have to be developed.

One minor issue was dealt with wrongly in the manual evaluation procedure. Whenever a house or road was partly obscured by a tree, the tree was ignored and the house or road was edited to show its extent. However, in the context of green structure, one is more interested in the trees than in the houses and roads. So, some correct classifications have been marked as misclassifications. However, the total number of pixels that have wrongly been edited in this manner, is small, so the main findings of the evaluation are still valid.

The smallest mapped area is approximately 100 m². If for example there is a piece of grass land in a private garden of 10 by 10 meters, then it will be mapped. However, if a medium to large tree appears in the middle, then the homogeneity criterion may flag the entire area as forest.

Private gardens appear as a mixture of the three green structure classes in addition to the houses and driveways. Gardens also contain a mix of different materials in addition to vegetation, including furniture, trampolines, etc. In the classification rules, there are additional classes. Many of these are merged into the grey area class. In addition, there are two shadow classes, one for tree shadows, which are regarded as part of green vegetation, and one for other shadows.

The manual editing resulted in an additional class: gravel, which is considered as grey area. This class was added mainly to meet a potential need to indicate temporary grey areas, and was used on construction sites. Gravel also indicates an area that is not sealed, permitting water drainage. However, it turned out that gravel was not a focus area in this project. Also, gravel and sand is very difficult to discriminate spectrally from concrete.

6.1 Segmentation

The results of the segmentation step are not directly available to us in the classified image, since neighboring segments in many cases have been assigned the same class in the classification step. From the classification result, it is obvious that the object boundaries of classified grey areas deviate substantially from the true outlines of houses and roads. This is especially true in suburban areas (**Error! Reference source not found.**), where there are a lot of small roads and buildings.



Figure 7. Segmentation problems in suburban areas. Top: a 330 m x 250 m part inside validation area 1 of the Pansharpned Quickbird image. Middle: the automatic classification result for this subimage, with houses and roads from a digital map superimposed in grey. Bottom: Aerial orthophoto of the same area, captured with 10 cm ground resolution



Figure 8. Close-up of the upper left corner of the aerial image in **Error! Reference source not found.**

However, the segmentation results can be examined in Definience. This was done for a few selected areas. Level 1 segmentation often creates border segments one pixel wide and very long. These pixels are often a spectral mixing of the two neighboring regions, for example, building and vegetation, or at the edge of shadows. Many roads are also segmented into many parallel narrow and long segments. In other instances, the gradual transitions between different objects allowed segments to be merged across the true object boundaries.

Many of the segmentation problems are due to shadows from buildings (Figure 9) and trees (Figure 10). Building shadows are often classified as grey areas. It could be possible to predict these shadows from the building height and the sun's position. The building height might be available from a digital map, and the sun's position can be computed from the acquisition time and date for the satellite image.

Tree shadows are sometimes classified as grey areas, other times they block grey areas (Figure 10). In both cases, the shadows need to be detected and removed. The tree height is not readily available, but one can make a few guesses and see if one of the heights matches the shadow length fairly well.

For both tree shadows and building shadows, the shadow outline must be extracted, and the intensity values inside the shadow increased to the level outside the shadow.

Shadows aside, there are many more segmentation issues to solve. The most important shortcoming of the current segmentation approach is that no prior information is used. By including outlines of buildings, roads, rivers and lakes from a digital map, the outlines could be used to guide the segmentation step so that the outlines from the map were preferred to some extent. In some cases, there might be coregistration errors in the order of 1-2 m between the GIS and the Quickbird image. Ideally, the segmentation algorithm should be aware of this uncertainty and allow that a, say, house be moved 1-3 pixels.



Figure 9. House shadows are sometimes misclassified as grey areas. All these examples are from validation area 1.



Figure 10. Tree shadows are sometimes mistaken as grey areas (far and middle left), and other times they block grey areas (far and middle right).

6.2 Time series of chlorophyll or NDVI

An entirely different approach than the current could be to use time series of medium or low resolution satellite images to directly measure the variation from year to year in chlorophyll, which is often estimated from the so-called *normalized difference vegetation index*, NDVI. The NDVI for a pixel (x, y) is computed from the *near infrared* (NIR) spectral band and the red (R) spectral band as

$$NDVI(x, y) = \frac{NIR(x, y) - R(x, y)}{NIR(x, y) + R(x, y)}$$

By using 250 meter resolution images from MODIS, or even 1 km resolution images from AVHRR, one obtains average values, in which a decrease in chlorophyll in one small area may

be cancelled by an increase in another small area within the same pixel. However, the general trend can be monitored, since these images are captured very often.

NR has developed time series analysis algorithms for vegetation monitoring in other projects. These algorithms could be modified for use on monitoring of green structure in urban and suburban areas. The time series analysis algorithm models change on three scales:

1. Daily variations due to imaging conditions
2. Phenological variation during one year
3. Changes from year to year.

During one year, the green vegetation goes through one cycle, which has nearly the same shape from one year to another, but with variations in the start and end dates of the summer season, as well as the strength of the peak of the cycle. By eliminating the modeled changes on the daily, seasonal and yearly scale, one can detect statistically significant changes in individual pixels, and detect areas in which the green structure has been reduced or improved.

6.3 Further work

In this year's project, Definiens Developer was used for segmentation and classification of a Quickbird scene from 2008. The result is validated in the present report, and the conclusion is that this is a good starting point for further improvements of the method. The most striking problems are related to the segmentation. Object contours are often ragged, and do not follow the true boundaries of houses and roads very well. Another difficulty is shadows from buildings and trees, resulting in frequent misclassifications of whatever happens to be in the shadow areas.

By combining the Quickbird images with laser height measurements from airplane, the height and shape of buildings and trees may be determined. From the satellite image metadata, we know the solar incidence and aspect angles, which can then be used to compute the shadow extents in the image. The shadows may then be eliminated by increasing the intensities to agree with the rest of the image. One could also compensate for reduced reflection of sunlight from tilted surfaces.

The lidar data will stay valid for many years. Trees don't grow that fast, and few buildings change over time. It is possible to develop algorithms that can detect changes from the satellite images combined with a single lidar acquisition. However, this requires a substantial effort, and should be weighted against the slightly higher misclassification rate. If the change detection is only used to improve shadow computation, then it might not be worth the extra effort. However, if the change detection becomes a part of the processing chain for other reasons, then it can be used to improve shadow computation as well.

In the current segmentation method, GIS data was not used directly. In an improved segmentation method, one could use the outlines of buildings, roads, private driveways, rivers and lakes as preferred segmentation boundaries. In addition, the segmentation method should include additional segmentation boundaries, which it finds in the image.

The Quickbird scene from 2008 contained no clouds, but the other few acquisitions of Oslo that we have seen do contain clouds. The Norwegian Computing Center has automatic cloud

detection algorithms, which have been applied successfully in other projects, and which can be adapted to the monitoring of green structure. When the cloud shapes have been extracted, one could look for the cloud shadows on the ground, with cloud shadow shapes corresponding to the cloud shapes. To restore the shadow areas, similar techniques for intensity adjustment as for shadows from buildings and trees may be used.

In the 2009 project, there was very limited time for experimenting with and fine tuning of the segmentation and classification methods. By spending more time on this in the next phase, it could be possible to improve the results. A drawback with the current method is the need to manually set threshold values for the various classification rules, based on a subset of the image. In the next phase, one could try to develop automatic calibration methods to determine these thresholds, or, alternatively, to use a statistical method to train the segmentation and classification methods. By starting with the GIS data's road and building outlines, one could use these areas for automatic training and calibration of the methods. In addition, one could define some representative areas of forest, private gardens, grass areas and single trees.

In order to use the method on areas without lidar height data coverage, one could try if it is possible to detect shadows without using any height measurements, except from what happens to be contained in the GIS data. It might be possible to estimate the building heights and the tree heights from the Quickbird images. The shape and color of a roof may indicate whether it is an apartment complex, a semi-detached house or a villa. One may then try with two or three hypotheses on the building height, and see if any match with what might be shadow. One may also investigate if it is possible to do shadow detection without knowing the building or tree heights.

In the automatic classification method, three subclasses of green structure were used in the final classified image: grass, trees, and little vegetation. The validation indicated that the most common misclassifications between green area and grey area involved the subclass 'little vegetation'. On the other hand, private gardens were a confusing mixture of the three green structure classes. One could analyze the data in order to determine what are the spectral classes within green areas. This could, for example, be done using cluster analysis or unsupervised learning. For the analysis of green corridors and biodiversity, private gardens with trees are essential to small birds, which avoid crossing large open spaces, since they would then expose themselves to predator birds. Therefore, it is important to detect the macrostructure that is created by private gardens with trees, and to be able to extract contiguous areas of this type.

The main problem with the prototype that is developed using Definiens, is that segmentation errors introduced early in the process are never corrected. Definiens uses a bottom-up approach, in which small objects are found first, then merged into larger objects. Merging is done both at level 2 in the segmentation step, as well as a result of classification, by assigning neighboring segments to the same class. This problem may be solved in two ways. Either one could construct a better segmentation method, which is able to follow the correct object borders more closely. Or, one could use a top-down approach, in which one first tries to find large continuous areas of the same type, e.g., continuous areas of private gardens with trees. It might be necessary to use different top-down strategies or variations for areas with different shapes. For example, roads are long and narrow, whereas residential areas have no particular shape but are in general more compact than roads.

Some possible top down strategies are image pyramid and texture, possibly in a combination. By generating copies of the image in gradually coarser resolution, for example, by merging 2×2

pixels to a new pixel, an image pyramid results. By running image analysis methods on different resolution, one may, for example, find segments at a low resolution, which may provide a subdivision of the image into different kinds of vegetation. The segments may be further subdivided at a finer resolution.

Texture is used when one is interested in finding continuous areas having a pattern which repeats itself, with some natural variation, small or large. One is not necessarily interested in classifying the individual elements of the texture at this stage. A texture-based approach could be well suited to extract residential areas, with a mixture of houses, grass, trees, garden furniture, etc. In this case, one will probably have to use a texture measure which allows some degree of variation of the relative arrangement of the various texture elements. When the residential areas have been identified, the next step could be to further subdivide them into individual objects, like single trees, houses, grass patches, etc. The knowledge that one is inside a residential area provides useful context for the classification of the individual segments.

In very high resolution images, like Quickbird images, the individual pixels' spectral properties may be somewhat difficult to use for segmentation, since there will be smooth transitions between the individual objects. In the level-1 segmentation in Definiens, there were many such transition segments, e.g., between houses and shadows. However, at a coarser resolution, the individual pixels' spectral properties may be more meaningful as they represent mean values for larger areas. They may therefore work well in a top-down approach, in which segment borders are refined as one goes from a coarser resolution to a finer.

The segmentation methods that are being developed should utilize all available information, like GIS data and lidar. However, they should also produce a result when such additional information is missing, as not all areas can be expected to have lidar coverage, and GIS data may be out of date or not available. In a top down approach, one may use the GIS data quite late in the process to refine the segment borders that were identified, or one may use the GIS data early to quickly identify the "correct" segments. In any case, one needs to consider whether the GIS data should always be obeyed or if they can be deviated from. For example, a tree may obscure a patch of a house or road. In the present project, we are more interested in the tree than the house, so the house boundary should be moved. On the other hand, if a shadow obscures a house or road patch, the shadow should be removed, highlighting the house or road.

7 References

Definiens Developer 7, User Guide, 2007. Definiens AG, Munich, Germany.

Appendix A: All validation areas

Validation area 1



Figure 11. Validation area 1: pansharpener Quickbird image

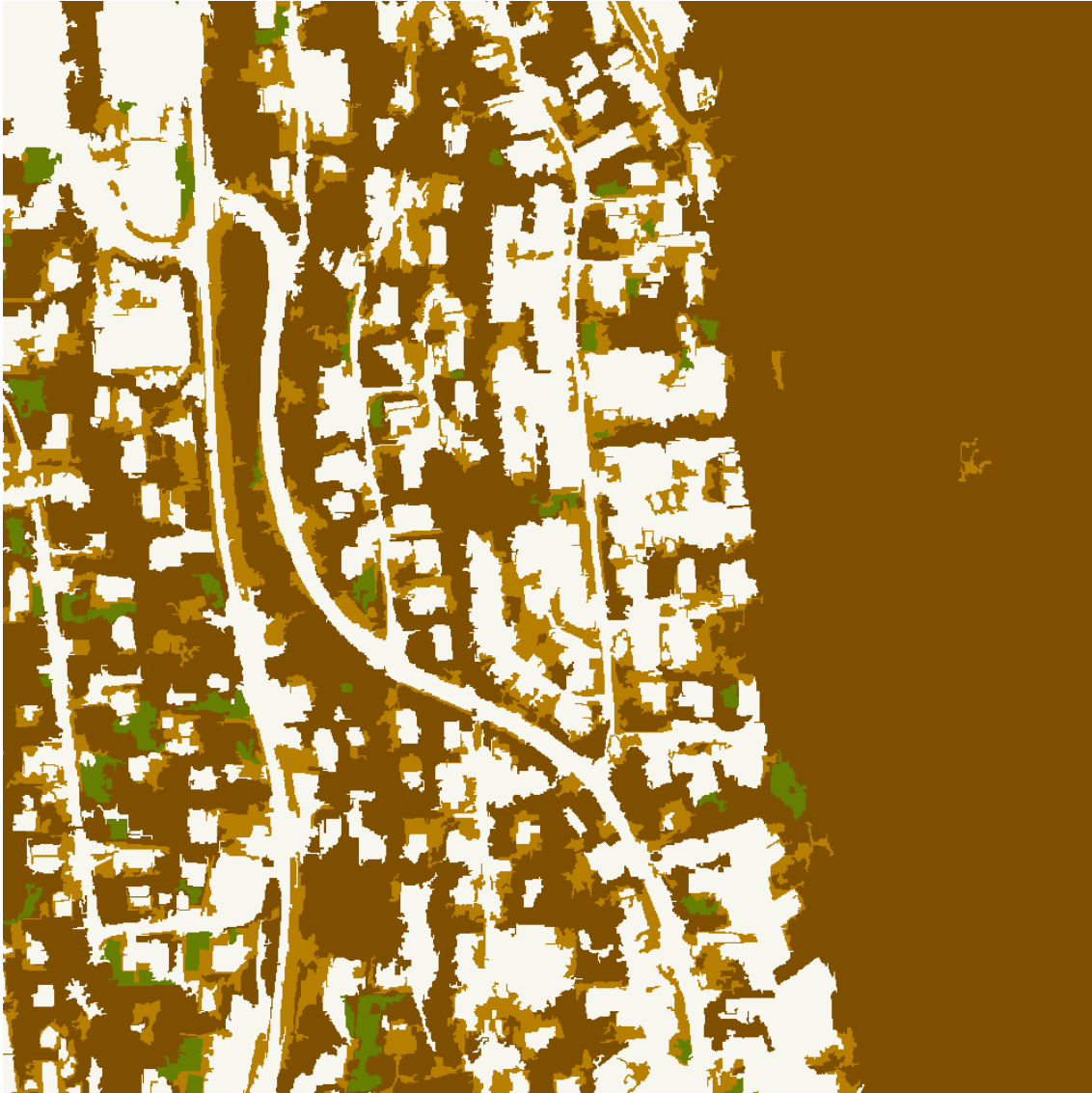


Figure 12. Validation area 1: classified image

The legend for the classified images are

- Green (R: 96, G: 128, B:0): Open grass land and lawns.
- Dark brown (R: 128, G: 96, B: 0): Bushes, trees, forest. Private gardens are expected to fall into this class.
- Light brown (R: 192, G: 128, B: 0): Little vegetation: Paths, grass areas with substantial wear and tear.
- White (R: 255, G: 251, B: 240): “grey” areas, that is, covered by buildings, roads, parking lots, etc; thus with no vegetation.
- Black (R: 0, G: 0, B: 0): Not classified or missing data, also used for water.

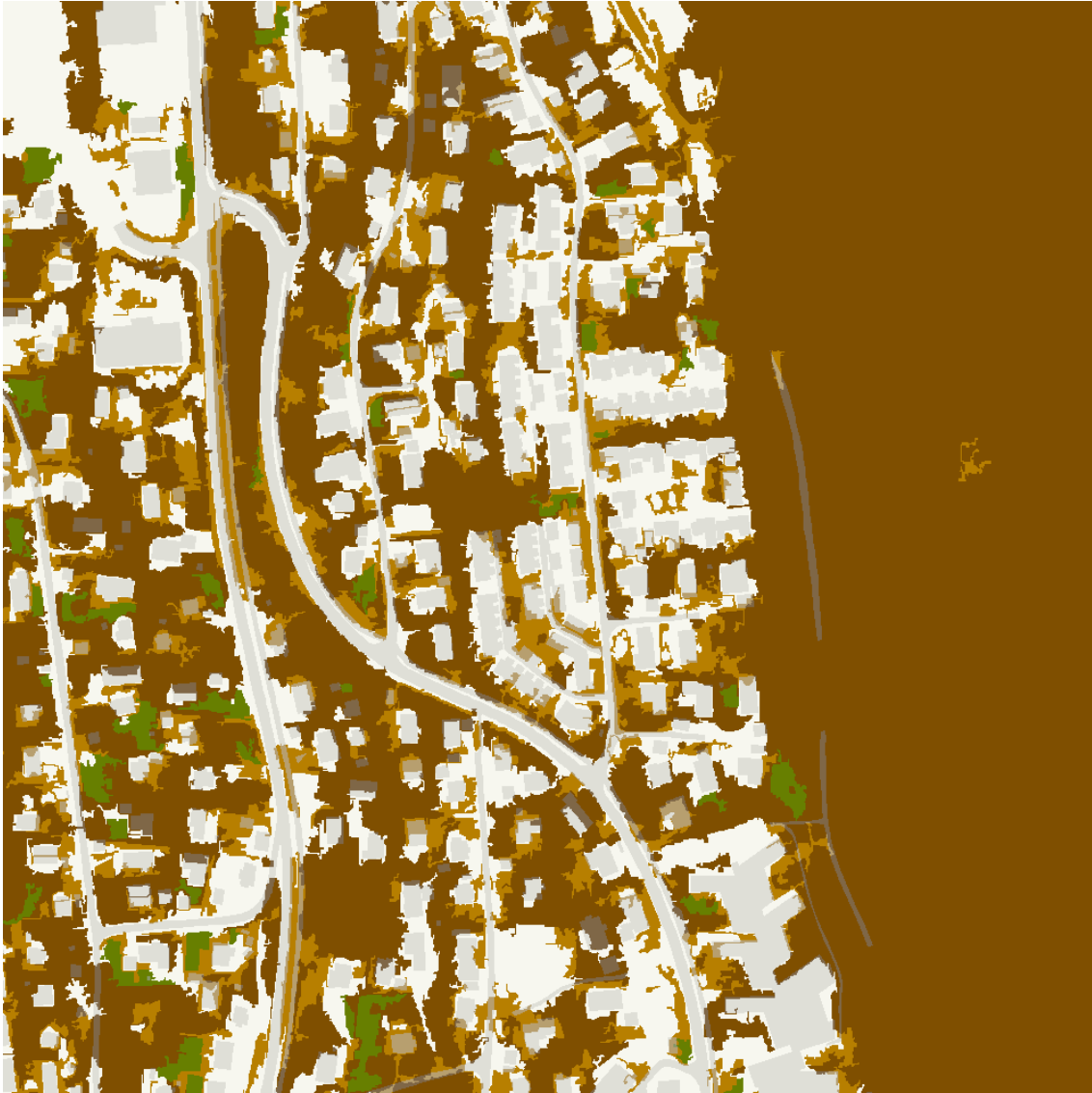


Figure 13. Validation area 1: Classified image with superimposed roads and buildings

To show the building and road outlines, these are superimposed in grey on top of the other colors.

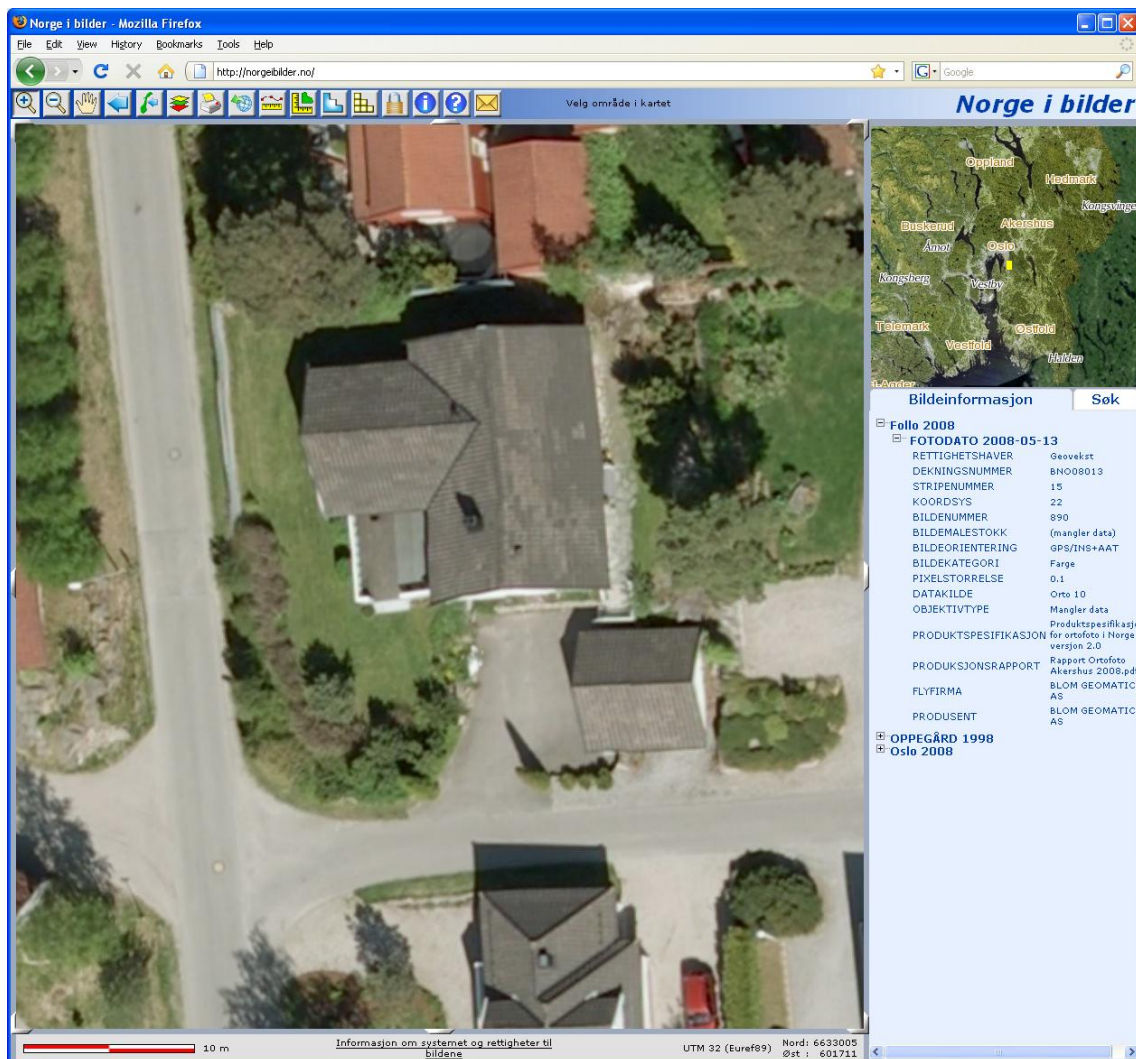


Figure 14. Aerial image with 10 cm resolution, used for verification. The image was acquired on 13 May 2008.

Table 7. Validation area 1: Confusion matrix in number of pixels.

		Edited				Sum classified
		Grass	Forest	Little vegt.	Grey area	
Classified	Grass	18878	0	0	159	19037
	Forest	0	562700	3487	17413	583600
	Little vegt.	0	1360	83978	24026	109364
	Grey area	15	5269	11272	271443	287999
Sum edited		18893	569329	98737	313041	1000000

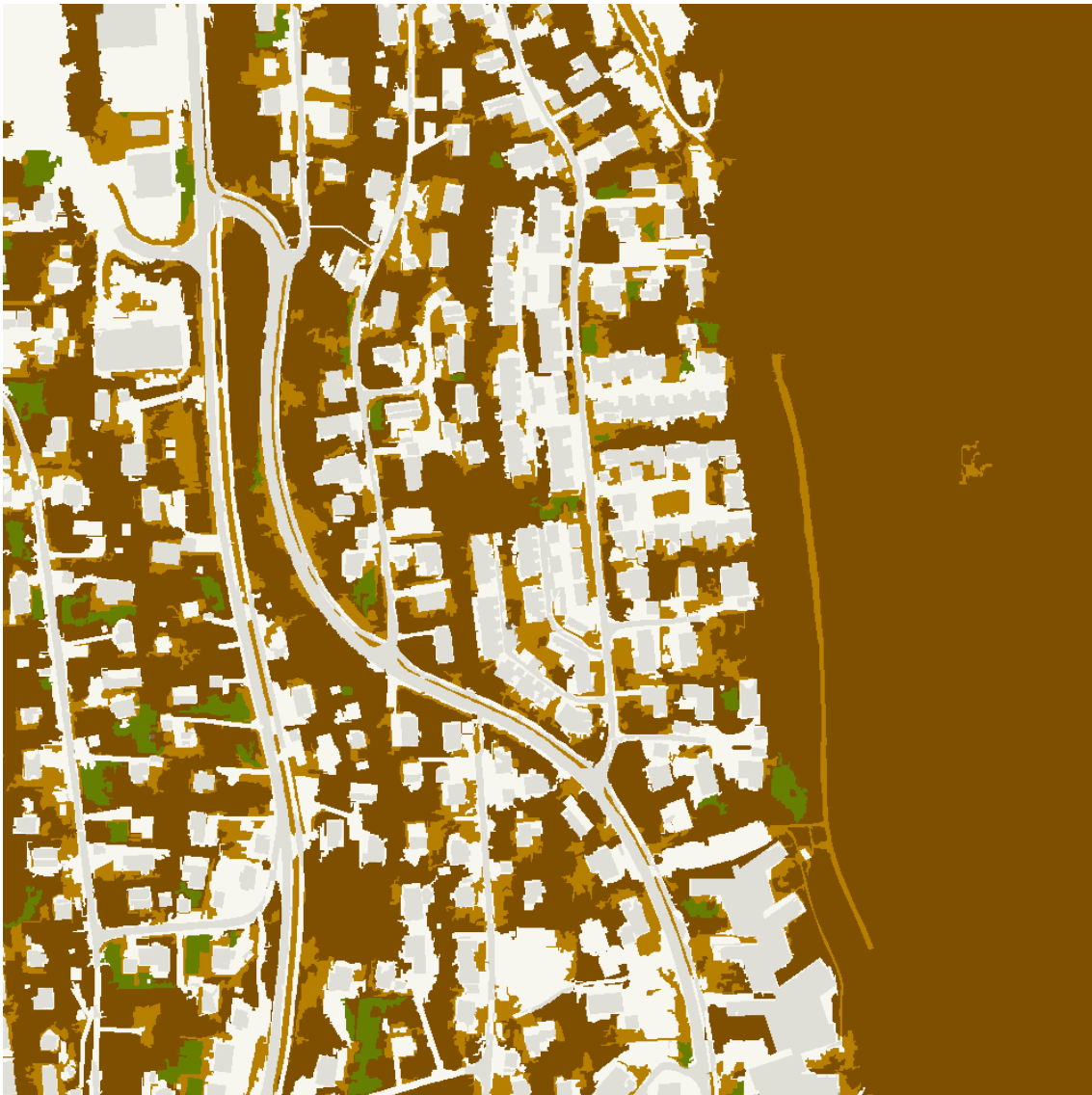


Figure 15. Validation area 1: edited classification result.

Table 8. Validation area 1: Confusion matrix in percentages.

		Edited			
		Grass	Forest	Little veqt.	Grey area
Classified	Grass	99.92 %	0.00 %	0.00 %	0.05 %
	Forest	0.00 %	98.84 %	3.53 %	5.56 %
	Little veqt.	0.00 %	0.24 %	85.05 %	7.68 %
	Grey area	0.08 %	0.93 %	11.42 %	86.71 %
Sum edited		100.00 %	100.00 %	100.00 %	100.00 %

Validation area 2



Figure 16. Validation area 2: pansharpned Quickbird image.

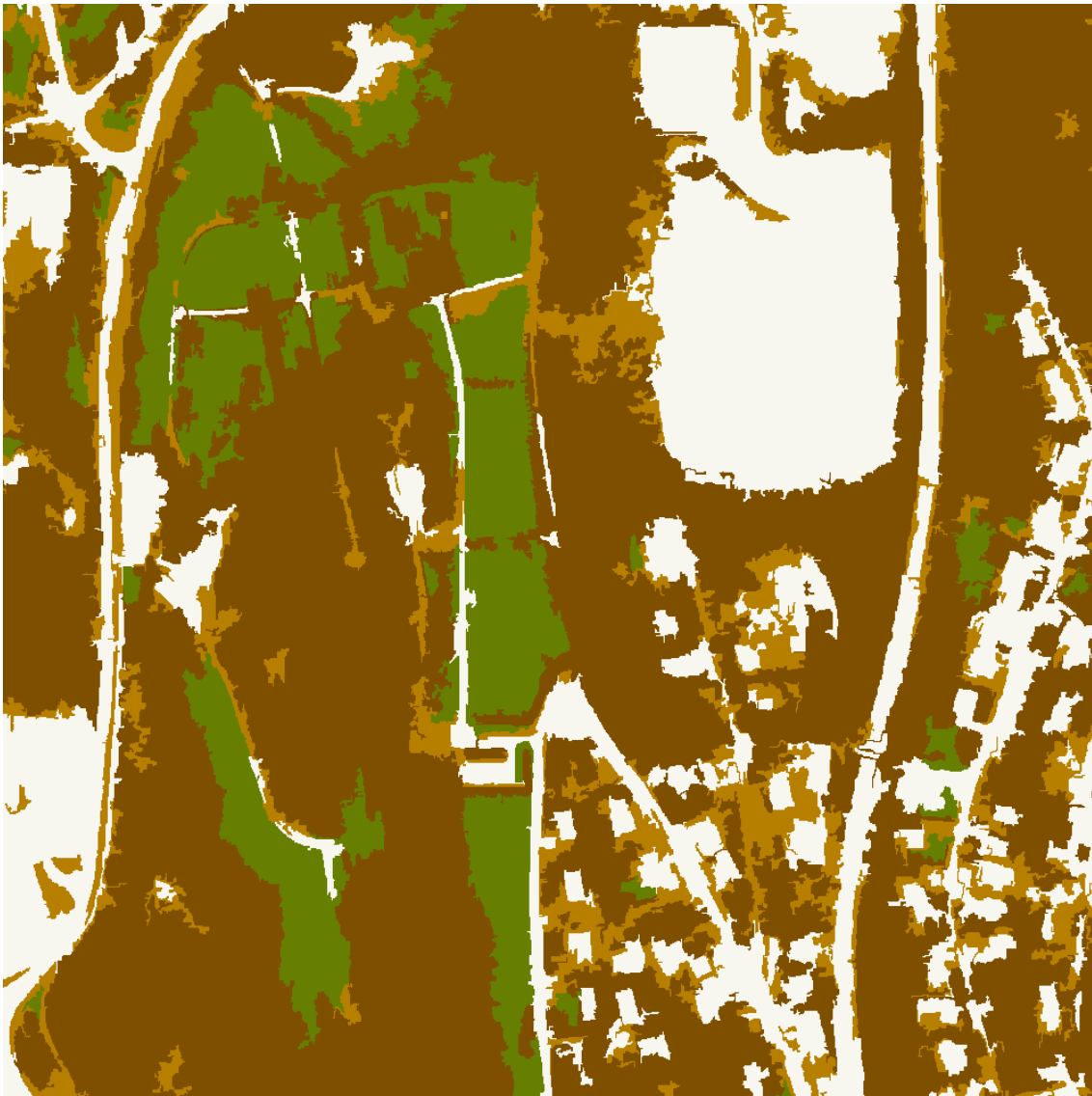


Figure 17. Validation area 2: classified image.

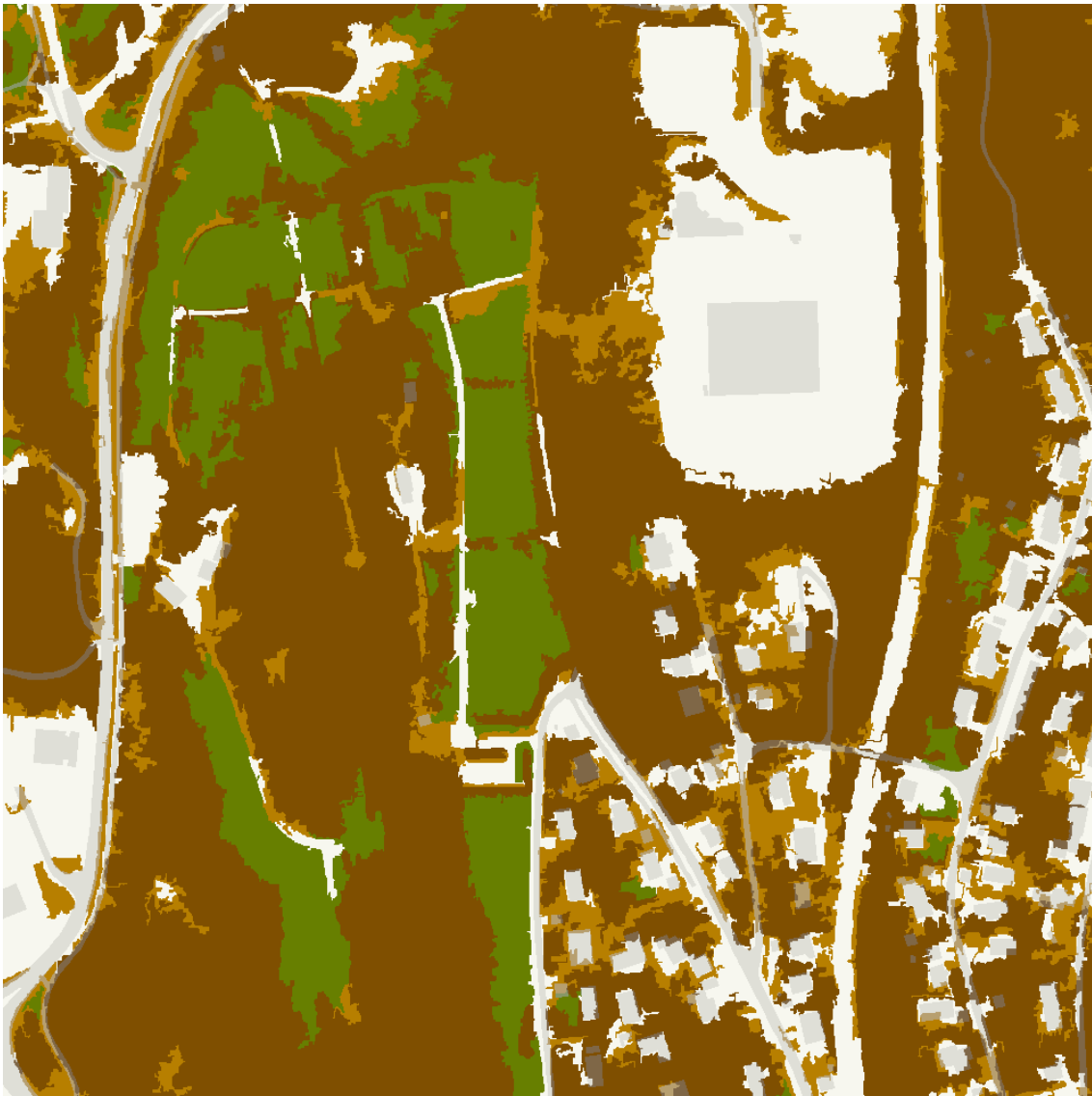


Figure 18. Validation area 2: Classified image with road and building areas superimposed in grey.

Table 9. Validation area 2: Confusion matrix in number of pixels.

		Edited					Sum classified
		Grass	Forest	Little veqt.	Grey area	Gravel	
Classified	Grass	116976	0	0	2024	0	119000
	Forest	17	525086	390	23861	53	549407
	Little veqt.	52	137	80711	21243	173	102316
	Grey area	971	5193	13232	198673	11208	229277
	Gravel	0	0	0	0	0	0
Sum edited		118016	530416	94333	245801	11434	1000000



Figure 19. Validation area 2: Edited classification result.

In some of the edited classification results, yellow areas appear (Figure 19). These are sand or gravel areas that may be reversed into green areas, but at the moment they are regarded as grey areas. They were marked yellow, since they are something between grey area and little vegetation.

Table 10. Validation area 2: Confusion matrix in percentages.

		Edited				
		Grass	Forest	Little veqt.	Grey area	Gravel
Classified	Grass	99.12 %	0.00 %	0.00 %	0.82 %	0.00 %
	Forest	0.01 %	99.00 %	0.41 %	9.71 %	0.46 %
	Little veqt.	0.04 %	0.03 %	85.56 %	8.64 %	1.51 %
	Grey area	0.82 %	0.98 %	14.03 %	80.83 %	98.02 %
	Gravel	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
Sum edited		100.00 %	100.00 %	100.00 %	100.00 %	100.00 %

Validation area 3



Figure 20. Validation area 3: pansharpned Quickbird image.

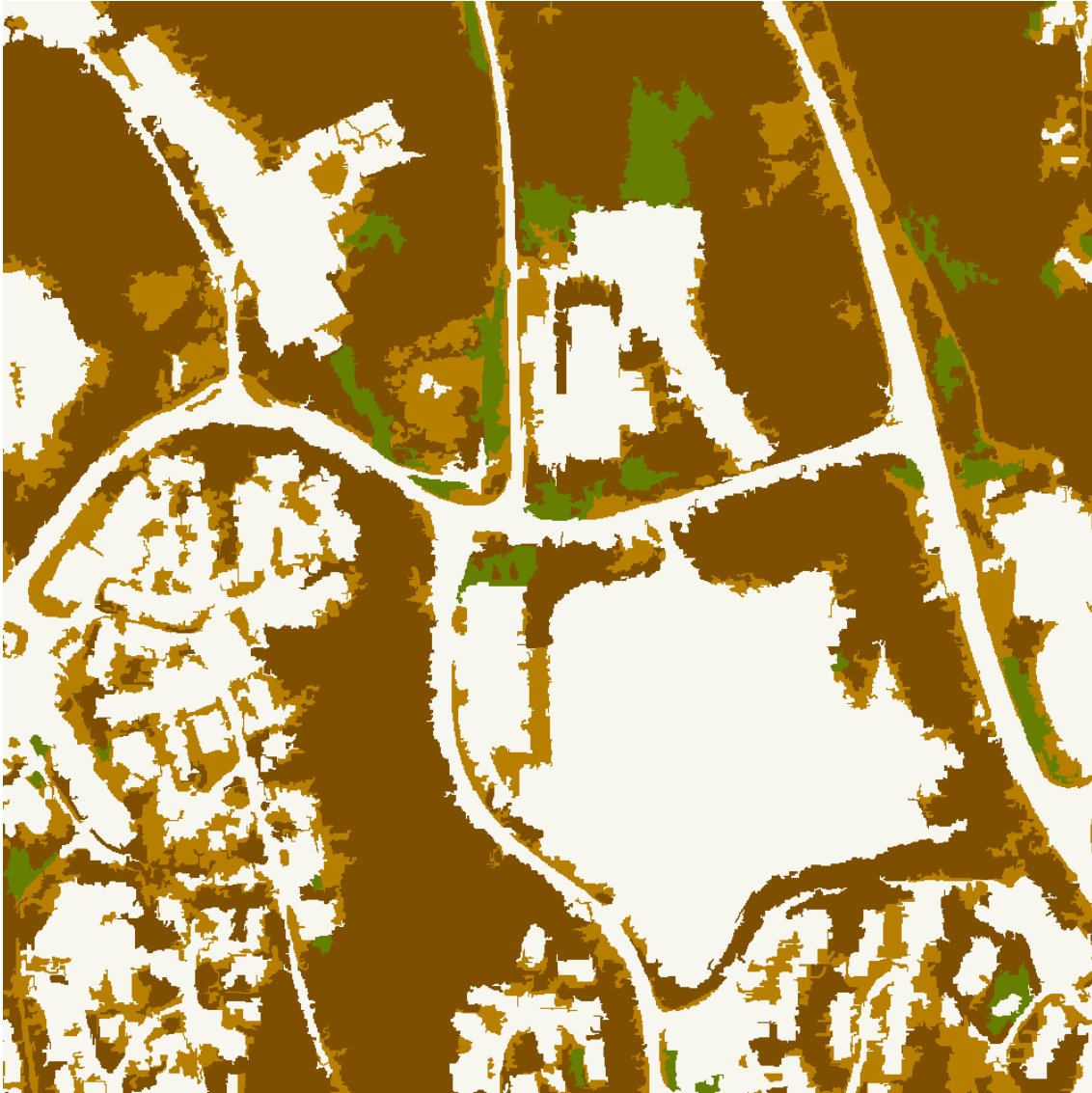


Figure 21. Validatin area 3: classified image.



Figure 22. Validation area 3: Classified image with building and house areas superimposed in grey.

Table 11. Validation area 3: Confusion matrix in number of pixels.

		Edited					Sum classified
		Grass	Forest	Little vege.	Grey area	Gravel	
Classified	Grass	29384	0	0	900	0	30284
	Forest	0	439735	67	10633	110	450545
	Little vege.	0	1038	113634	21500	387	136559
	Grey area	435	9808	41413	260750	70206	382612
	Gravel	0	0	0	0	0	0
Sum edited		29819	450581	155114	293783	70703	1000000

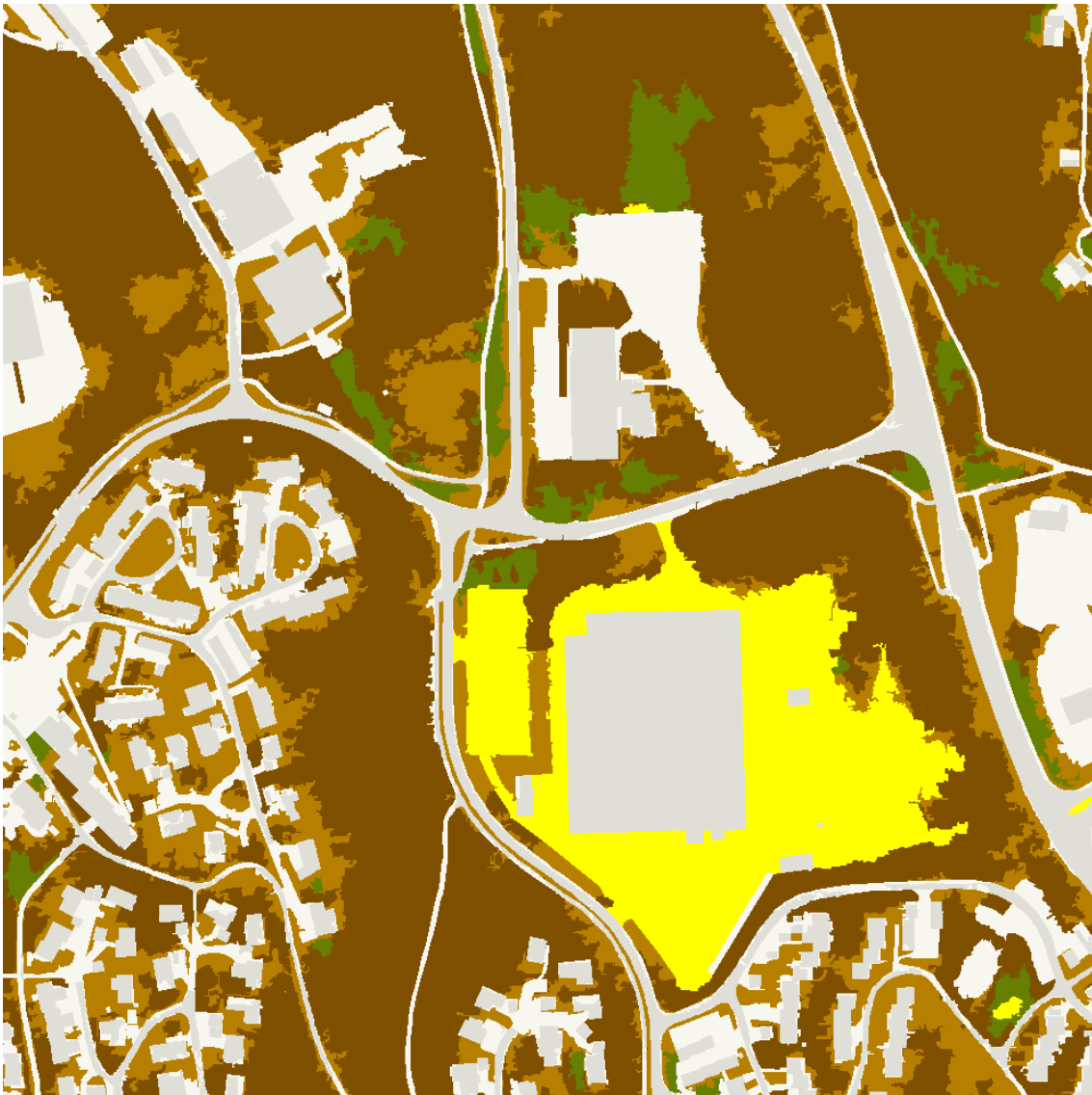


Figure 23. Validation area 3: Edited classification result.

Table 12. Validation area 3: Confusion matrix in percentages.

		Edited				
		Grass	Forest	Little vezt.	Grey area	Gravel
Classified	Grass	98.54 %	0.00 %	0.00 %	0.31 %	0.00 %
	Forest	0.00 %	97.59 %	0.04 %	3.62 %	0.16 %
	Little vezt.	0.00 %	0.23 %	73.26 %	7.32 %	0.55 %
	Grey area	1.46 %	2.18 %	26.70 %	88.76 %	99.30 %
	Gravel	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
Sum edited		100.00 %	100.00 %	100.00 %	100.00 %	100.00 %

Validation area 4



Figure 24. Validation area 4: pansharpned Quickbird image.

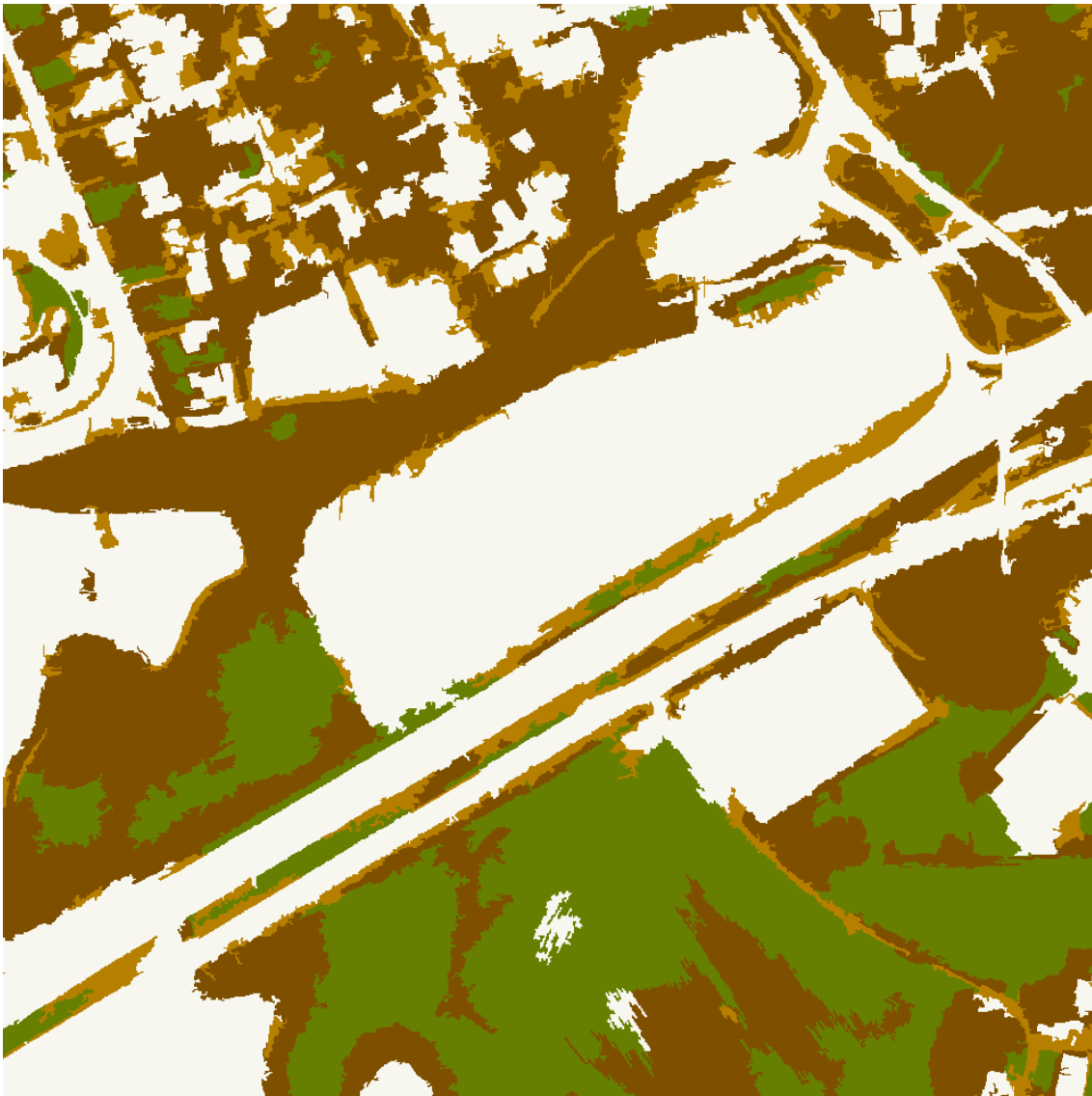


Figure 25. Validation area 4: classification result.

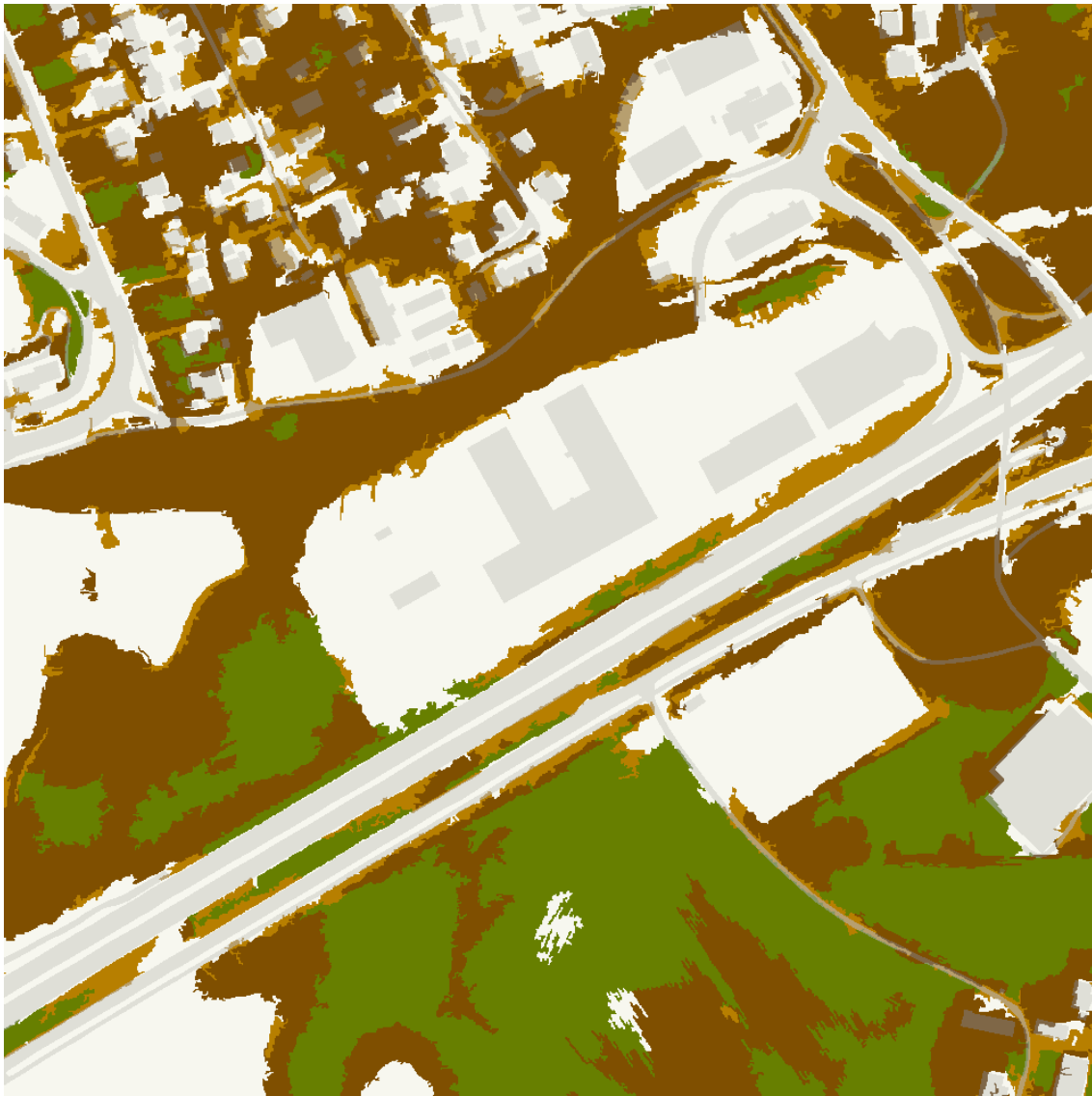


Figure 26. Validation area 4: Classified image with building and road areas superimposed.

Table 13. Validation area 4: Confusion matrix in number of pixels.

		Edited						Sum classified
		Grass	Forest	Little vege.	Grey area	Gravel	No data	
Classified	Grass	177955	0	1	758	0	0	178714
	Forest	914	310541	397	12385	74	8650	332961
	Little vege.	0	486	57397	17373	202	432	75890
	Grey area	1363	7807	70907	295974	33128	3256	412435
	Gravel	0	0	0	0	0	0	0
	No data	0	0	0	0	0	0	0
Sum edited		180232	318834	128702	326490	33404	12338	1000000



Figure 27. Validation area 4: Edited classification result

Table 14. Validation area 4: Confusion matrix in percentages.

		Edited					
		Grass	Forest	Little vegt.	Grey area	Gravel	No data
Classified	Grass	98.74 %	0.00 %	0.00 %	0.23 %	0.00 %	0.00 %
	Forest	0.51 %	97.40 %	0.31 %	3.79 %	0.22 %	70.11 %
	Little vegt.	0.00 %	0.15 %	44.60 %	5.32 %	0.60 %	3.50 %
	Grey area	0.76 %	2.45 %	55.09 %	90.65 %	99.17 %	26.39 %
	Gravel	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
	No data	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
Sum edited		100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %

Validation area 5



Figure 28. Validation area 5: pansharpened Quickbird image.

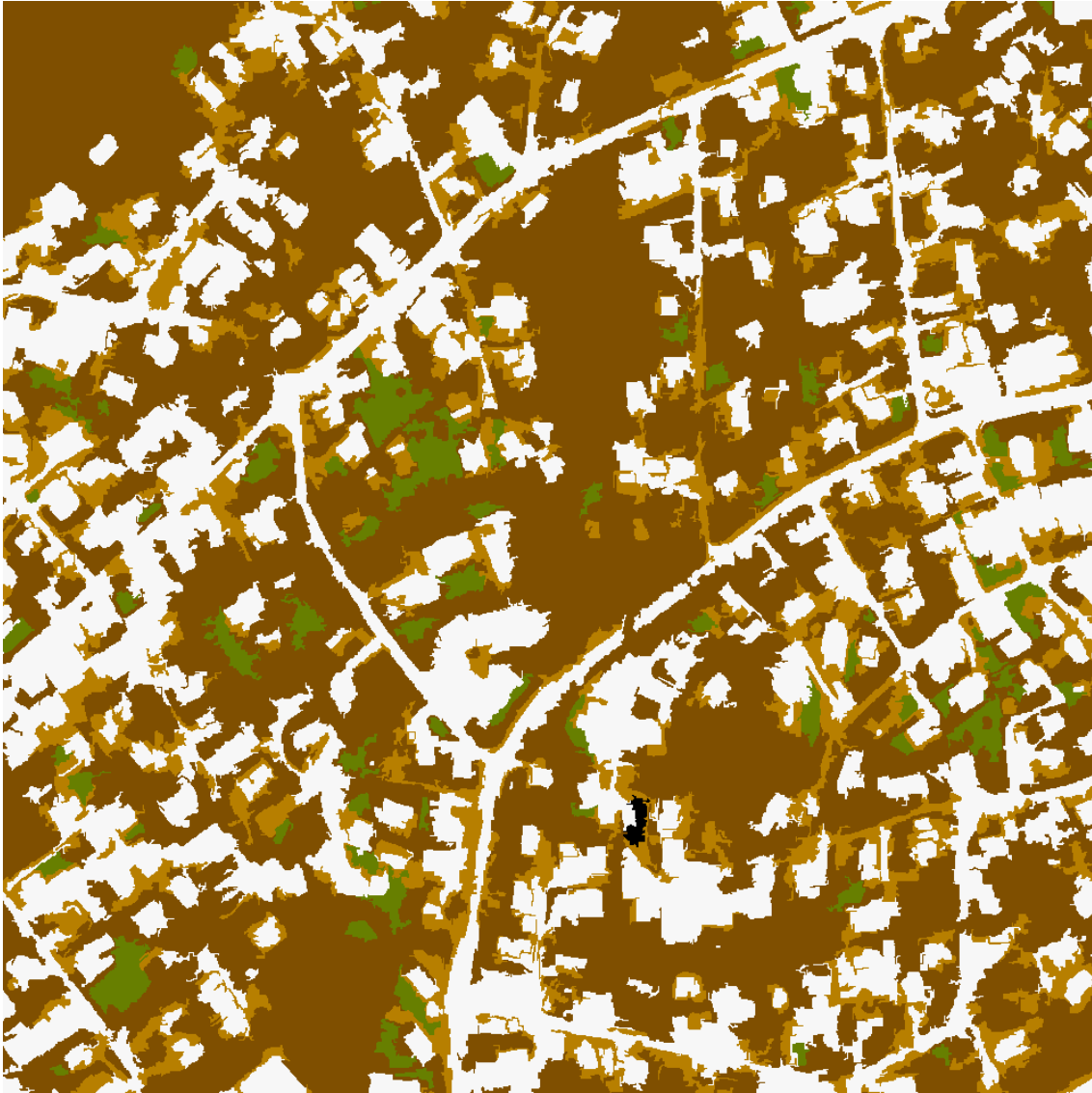


Figure 29. Validation area 5: classified image.

After classification, validation area 5 has a remaining unclassified object (Figure 29). Special rules are designed to get rid of most of these. However, an occasional unclassified object slips through from time to time.

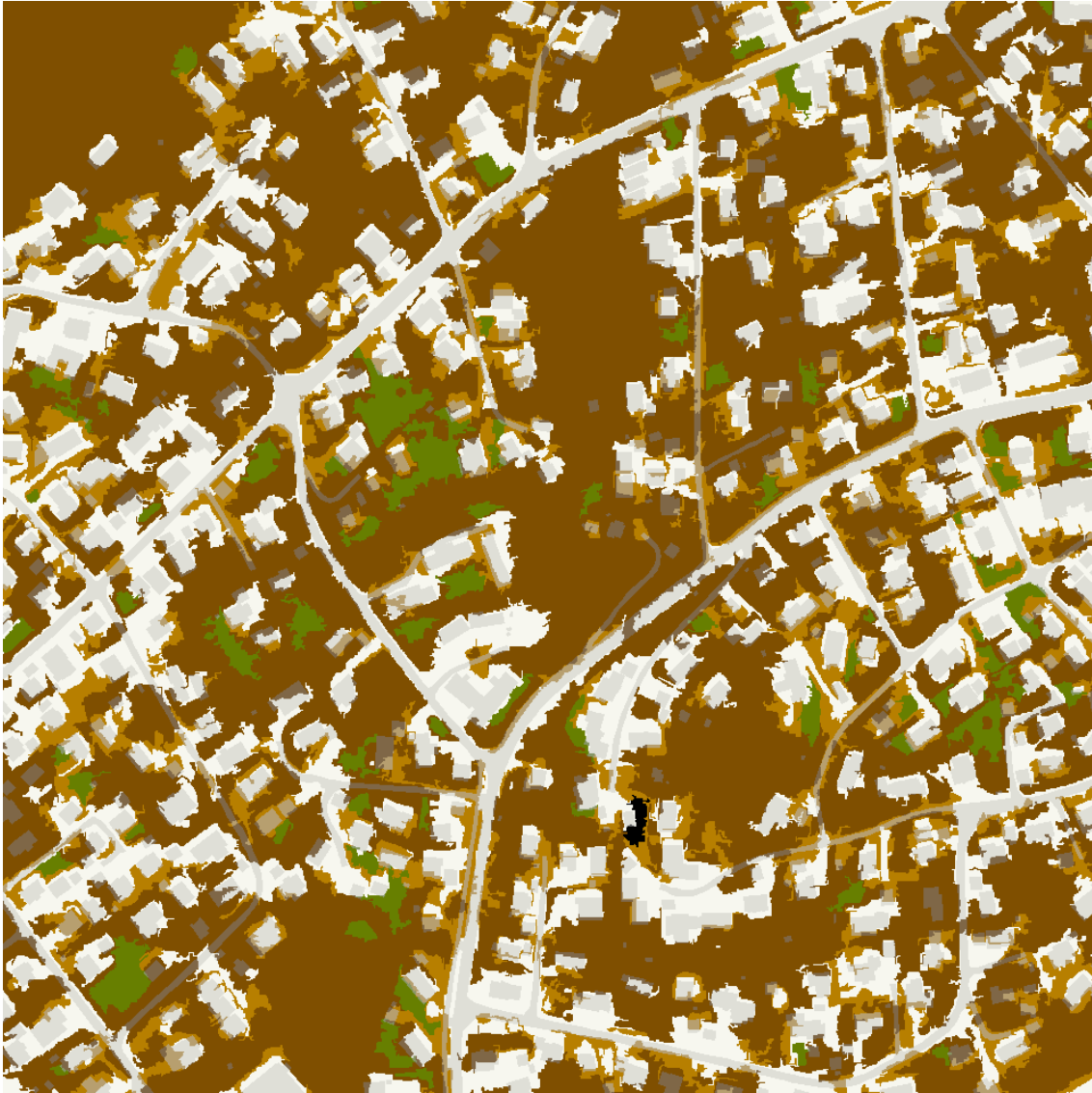


Figure 30. Validation area 5: classified image, with buildings and roads superimposed in grey.

Table 15. Validation area 5: Confusion matrix in pixels.

		Edited						Sum classified
		Grass	Forest	Little veqt.	Grey area	Gravel	No data	
Classified	Grass	35120	0	0	578	84	0	35782
	Forest	0	479591	210	38141	1664	0	519606
	Little veqt.	0	123	84171	39767	1501	0	125562
	Grey area	221	28225	24389	255459	10184	0	318478
	Gravel	0	0	0	0	0	0	0
	No data	0	558	0	13	0	1	572
Sum edited		35341	508497	108770	333958	13433	1	1000000

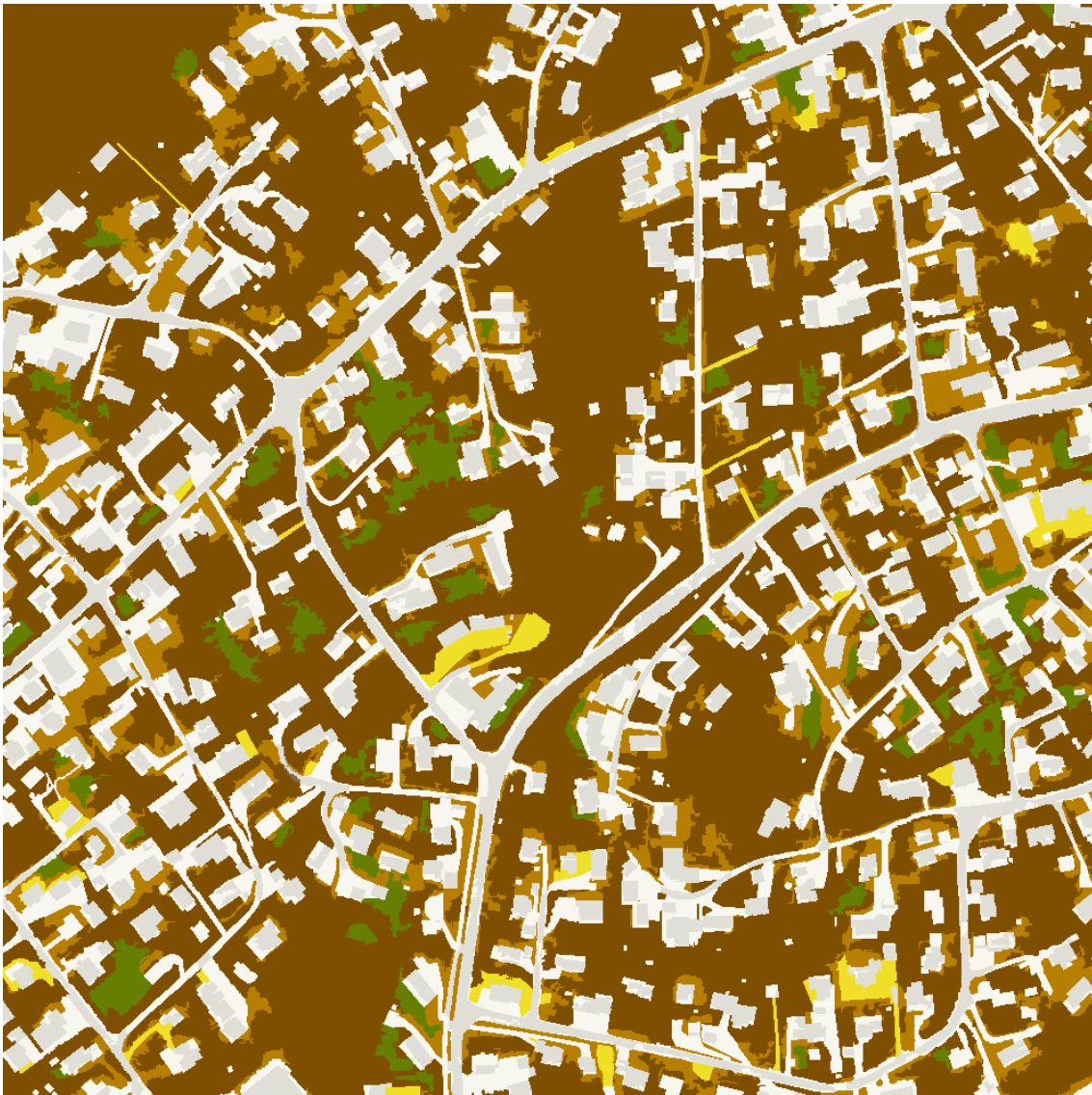


Figure 31. Validation area 5: edited classification result.

Table 16. Validation area 5: Confusion matrix in percentages.

		Edited					
		Grass	Forest	Little vezt.	Grey area	Gravel	No data
Classified	Grass	99.37 %	0.00 %	0.00 %	0.17 %	0.63 %	0.00 %
	Forest	0.00 %	94.32 %	0.19 %	11.42 %	12.39 %	0.00 %
	Little vezt.	0.00 %	0.02 %	77.38 %	11.91 %	11.17 %	0.00 %
	Grey area	0.63 %	5.55 %	22.42 %	76.49 %	75.81 %	0.00 %
	Gravel	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
	No data	0.00 %	0.11 %	0.00 %	0.00 %	0.00 %	100.00 %
Sum edited		100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %

Validation area 6



Figure 32. Validation area 6: pansharpened Quickbird image.



Figure 33. Validation area 6: classified image.

Table 17. Validation area 6: Confusion matrix in pixels.

		Edited						Sum classified
		Grass	Forest	Little veqt.	Grey area	Gravel	No data	
Classified	Grass	157040	0	0	60	26	1	157127
	Forest	0	419610	17	8488	112	0	428227
	Little veqt.	7	20	79977	11961	1124	0	93089
	Grey area	24	9318	17491	293288	1436	0	321557
	Gravel	0	0	0	0	0	0	0
	No data	0	0	0	0	0	0	0
Sum edited		157071	428948	97485	313797	2698	1	1000000



Figure 34. Validation area 6: edited classification result.

Table 18. Validation area 6: Confusion matrix in percentages.

		Edited					
		Grass	Forest	Little vezt.	Grey area	Gravel	No data
Classified	Grass	99.98 %	0.00 %	0.00 %	0.02 %	0.96 %	100.00 %
	Forest	0.00 %	97.82 %	0.02 %	2.70 %	4.15 %	0.00 %
	Little vezt.	0.00 %	0.00 %	82.04 %	3.81 %	41.66 %	0.00 %
	Grey area	0.02 %	2.17 %	17.94 %	93.46 %	53.22 %	0.00 %
	Gravel	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
	No data	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
Sum edited		100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %