Cranfield University

Maria Kampouraki

The application of Remote Sensing to identify and measure Sealed Soil and Vegetated Surfaces in Urban Environments

PhD Thesis

Cranfield University

School of Applied Sciences

Department of Natural Resources

PhD

2010

Maria Kampouraki

The application of Remote Sensing to identify and measure Sealed Soil and Vegetated Surfaces in Urban Environments

Supervisors: Dr. Gavin A. Wood and Mr Tim R. Brewer

December 2010

This thesis is submitted in partial fulfilment of the requirements for the Degree of Doctor of Philosophy.

Abstract

Soil is an important non-renewable source. Its protection and allocation is critical to sustainable development goals. Urban development presents an important drive of soil loss due to sealing over by buildings, pavements and transport infrastructure. Monitoring sealed soil surfaces in urban environments is gaining increasing interest not only for scientific research studies but also for local planning and national authorities.

The aim of this research was to investigate the extent to which automated classification methods can detect soil sealing in UK urban environments, by remote sensing. The objectives include development of object-based classification methods, using two types of earth observation data, and evaluation by comparison with manual aerial photo interpretation techniques.

Four sample areas within the city of Cambridge were used for the development of an object-based classification model. The acquired data was a true-colour aerial photography (0.125 m resolution) and a QuickBird satellite imagery (2.8 multi-spectral resolution). The classification scheme included the following land cover classes: sealed surfaces, vegetated surfaces, trees, bare soil and rail tracks. Shadowed areas were also identified as an initial class and attempts were made to reclassify them into the actual land cover type. The accuracy of the thematic maps was determined by comparison with polygons derived from manual air-photo interpretation; the average overall accuracy was 84%. The creation of simple binary maps of sealed vs. vegetated surfaces resulted in a statistically significant accuracy increase to 92%. The integration of ancillary data (OS MasterMap) into the object-based model did not improve the performance of the model (overall accuracy of 91%). The use of satellite data in the object-based model gave an overall accuracy of 80%, a 7% decrease compared to the aerial photography.

Future investigation will explore whether the integration of elevation data will aid to discriminate features such as trees from other vegetation types. The use of colour infrared aerial photography should also be tested. Finally, the application of the object-based classification model into a different study area would test its transferability.

Acknowledgements

I would like to thank my supervisors, Dr Gavin Good and Tim Brewer, for their help and support during my PhD. Gavin, I also thank you for being supportive in my good and bad times. Tim, an extra thank you for your indispensable advice and comments since my Master's time until now.

Many thanks to Mark Stephens. Mark, you have done so many things for me since we were sharing the same office in Silsoe until now...Thank you for accommodating me until I submit my PhD thesis! Thanks for the cooking, the delicious cheese scones and the emergency bread. ☺

I would also like to acknowledge all the friends I've made while I was living in England, among them, my beloved Liz Farmer, Dan Simms, Simon, Pericles, Sarah, Runi, Kristell, Irene and Alan; it was an unforgettable life experience. But also a big thank you goes to Alexia and Mary. Their friendship during the last one and a half years that I was back to Greece was a priceless gift. Αλεξία και Μαίρη, η φιλία σας είναι το πολυτιμότερο δώρο, σας ευχαριστώ που ήρθατε στην ζωή μου!

Last but not least, a heartfelt "*thank you*" goes to my family for their love and never ending support. And of course, a thank you to Pantelis for being my partner all these years. Thank you for the moments we shared together, for been there when I needed you and that you still are, even though you are far away. Thank you for everything! Χωρίς εσένα δεν ξέρω αν θα ήμουν εδώ τώρα. Σ'αγαπάω τιγράκο. Σλουρπ, σλουρπ.

Dedicated to my parents

Αφιερωμένο στους αγαπημένους μου γονείς,
Ευαγγελία και Γεώργιο Καμπουράκη

Table of Contents

Chapter 9: Conclusions

References

Appendices

List of Figures

Chapter 1

Chapter 2

Chapter 3

Chapter 4

Chapter 5

Chapter 6

Chapter 7

Chapter 8

List of Tables

Chapter 2

Chapter 3

Chapter 4

Chapter 5

Chapter 6

Chapter 7

Chapter 8

`

Chapter 1

Introduction

This chapter provides an introduction to soil as a natural resource and describes how soil sealing and urban growth are a threat to soil. Then the interest in monitoring soil sealing at European as well as at local levels is indicated. In addition, the aim and objectives of this research study are specified. Finally, a thesis structure and an explanation of the context of each chapter follow.

1.1 Introduction

Soil resources

Soil is a fundamental natural resource that provides essential support to our ecosystems. Soil performs a number of functions which are environmentally, economically and socially important (Scalenge and Marsan, 2009). The National Soil Resource Institute, in UK, highlighted the importance of soil by identifying the following soil functions (NSRI, 2001):

- environmental interaction
- food and fibre production
- provision of a platform for development and human activities
- support for ecological habitat and biodiversity
- provision of raw materials and
- protection of cultural and natural heritage

Soil apart from being the interface between earth, air and water, also transforms many substances including water, nitrogen and carbon; it is actually the most important carbon store in the world (EC, 2006). However, as the European Committee describes, "soil is a largely non renewable natural resource as it takes hundreds of years to produce a few centimetres of soil".

In 2002, the sixth Environmental Action Programme (6EAP) structured the soil Thematic Strategy group aiming at the protection and sustainable development of soil at European level. The European Union (EU) has further developed environmental policies targeting soil protection such as the Soil Framework Directive (SFD) and the Directorate-General Environment (DG ENV). These policies aimed to "identify and control/reduce the threats to soil and to preserve soil functions in Europe" (Mayr and Cooke, 2004). Soil today is threatened by eight hazards: erosion, organic matter loss, soil contamination, soil compaction, floods and landslides, decline in soil biodiversity, salinisation and soil sealing (ENVASSO, 2007).

In relation to the soil sealing threat, EU developed the "Thematic Strategy on the Urban Environment" targeting a "sustainable urban design" in order to reduce soil sealing and the loss of natural biodiversity and habitats (EC, 2008). Urban development whether it is in the form of increasing built structures by reducing the inner-city green zones or of land consumption of rural and agricultural land at the urban fringe, presents the most important drive of soil loss due to sealing over buildings, pavements and transport infrastructures (Huber et al., 2007). According to the authors, "sealing affects natural processes including water cycle (infiltration, filtering of rainwater, groundwater renewal and evapotranspiration), geochemical cycles and energy transfers but also the climate at micro- and mesoscales by altering albedo, evaporation and local air temperatures and increases surface water runoff, the latter leading to additional flood risks". Soil sealing is probably the most serious threat to European soils (Kibbelwhite, 2007). According to the EU, urban and industrial sprawl and transport networks have sealed a significant proportion of fertile soils; between 1990 and 2000, the sealed area in EU increased by 6% while "the demand for both new construction and transport infrastructures due to increased urban sprawl continues to rise" (EC, 2006).

Soil sealing monitoring

The recent interest of monitoring soil sealing and urban growth at European level is clearly apparent with the, increasing in number, development of various GMES (Global Monitoring for Environment and Security) projects as well as the FTS soil sealing layer production, in 2006. Monitoring the urban land cover for sustainable development is also of interest to local urban planning authorities, decision makers and insurance companies who require land cover information at regional scales.

According to the Department for Environment, Food and Rural Affairs (DEFRA), in UK, urban monitoring is important not only for identifying the percentage of soil sealing but also for the management of green areas. As DEFRA reports, “soils are present in the built environment at large scales, in the form of gardens and allotments, open spaces and parks, derelict and brownfield land, road verges, school playing fields and cemeteries. A careful planning of green spaces can mitigate the loss of soil functions in developed areas” (DEFRA web-site, 2006). Additionally, while soil is the habitat for below-ground biodiversity, the urban green is important for above-ground biodiversity and habitats. Recent literature has indicated the importance to monitor vegetation and trees within the cities (Tzoulas et al., 2007; Raflee et al., 2009; Yang et al., 2009).

In the UK, the urban environment has been investigated at large mapping scales during the Biodiversity in Urban Gardens in Sheffield (BUGS) project in which plant habitats and biodiversity were surveyed using 61 domestic back gardens across the city of Sheffield, Yorkshire, for biological diversity monitoring (Smith et al., 2005). In addition, DEFRA and the British National Space Centre (BNSC) were interested in finding a methodology for producing land cover maps at large scales, showing not only the percentage of urban soil sealing but to also add values in terms of biodiversity importance, drainage impact and aesthetic impacts of sealing (Wood et al., 2006). As another example, London’s Borough was interested to identify how the sealing of the front gardens of the houses, mainly for providing off-street parking, affects flooding (DEFRA web-site, 2006).

In order to monitor the percentage of sealed-unsealed soil, the urban land cover shall be mapped. Surveying and mapping land cover has evolved the last 50 years from a period of using transects and tape measures into ground survey using theodolites and then into aerial photogrammetry until the recent development of computers, digital aerial photogrammetry and satellite systems (Wolf, 2002). Theodolites have been mainly used by the army for land cover mapping as well as for engineering surveying. Later, the detection of land cover types and their changes was implemented by aerial photo interpretation (API) and ground survey. The API classification is a widely accepted method as it is commonly accepted that the map produced by a human interpreter is correct; as Congalton and Green (1999) argued "the quantitative assessment of the photo interpretation has never become a requirement of any project". However, API is also a subjective, time consuming and expensive method, requiring skilled operators. Further to manual techniques researchers have managed to develop various semi-automated and automated methods for land cover mapping. Since remote sensing is the primary source of data for the spatial analysis of the landscape, EO data have been commonly used to monitor the land cover for many decades.

Recent advances in image processing

Pixel-based approaches, developed approximately 30 years ago, were solely used until recently due to limitations in computer capabilities for advance algorithm development as well limitations in data availability and accessibility. Over the last decade with the rapid progress of hardware, software and data improvement in terms of spatial resolution, availability and accessibility, there has been a noticeable shift in the analysis from the predominantly used pixel, sub-pixel methods towards the development of new classification techniques. Recent research has highlighted that the classification accuracy for land cover mapping is improved by incorporating spatial texture information and/or levels of hierarchy in the classification method (Peijun and Yingduan, 2005; Berberoglou et al., 2007, Cots-Folch et al., 2007; Ouma et al., 2008). In addition, the use of hybrid approaches of spectral classification and rule-based clustering of ancillary data produce better results than the classification itself (Latifovic et al., 2004, Yan et al., 2005; Cots-Folch et al., 2007). Furthermore, the growing amount of high and very high resolution of satellite and airborne data has stimulated the rapid development of more efficient image analysis techniques such as the object-based. Object based methodologies have been approximately used the last decade and, according to the literature review, there is a constant increase in land cover mapping applications. Object-based image analysis (OBIA) can be implemented in two iterative steps:

- the image is first segmented into homogeneous regions using spectral, textural and contextual information; these regions are called segments or image objects (Baatz and Schape, 2000; Benz et al., 2004)

- the image objects are then classified using various methods such as manual labelling, use of statistical algorithms or use of expert knowledge to develop fuzzy rules for discriminating the classes

Other attempts to classify land cover by introducing polygons instead of individual pixels have been done during the so called "per-parcel" classification (Dean and Smith, 2003; Raclot et al., 2005; Fuller et al., 2005; Smith et al., 2007, Smith and Wyatt, 2007).

The production of thematic land cover maps still remains a challenge as there is a continuously demand from regional and national organizations for highly accurate, rapidly and regularly updated, timeless and low in cost geo-spatial information.

1.2 Aim & Objectives

The aim of this research was to identify a transferable methodology to classify sealed soil and vegetated surfaces in UK urban environments at large mapping scale, with the use of remotely sensed data. The specific objectives were:

1. to investigate the performance of an automated object delineation for urban land cover mapping using aerial photography
2. to develop and evaluate the performance of an object-based classification model, using fuzzy rules and expert knowledge with the use of aerial data
3. to test the performance of the object-based classification model by integrating existing national data sets i.e. the Ordnance Survey (OS) MasterMap
4. to examine the transferability of the object-based classification model when applied on very high resolution (VHR) satellite imagery

1.3 Thesis structure

Chapter 2: Literature review

This chapter reviews pixel-based and object-based classification methods for monitoring soil sealing in urban environments. The review was based on both scientific research and operational studies.

Chapter 3: The study area and data description

This chapter describes the study area and the development of a classification scheme according to its specific urban structure characteristics. The data used for the implementation of this research are also listed.

Chapter 4: Preliminary research

This chapter describes the method undertaken for monitoring soil sealing using pixel-based classification techniques of satellite data. It also describes the production of reference data by applying the pre-defined parcels of the Ordnance Survey MasterMap onto the aerial photography.

Chapter 5: Comparison of object extraction methods using aerial photography

This chapter compares a manual and a semi-automated method for boundary delineation, i.e. manual digitising against automated segmentation using the eCognition software

Chapter 6: Object-based image analysis of the aerial photography using rules and expert knowledge

This chapter describes the development of the object-based rule set classification model for mapping soil sealed and vegetated surfaces. Also the comparison of the automated method against the manual and semi-automatic methods, developed in chapter 5, is illustrated.

Chapter 7: Integration of ancillary data in the object-based classification model

This chapter examines whether the performance of the automated rule-based classification is improved by integrating the OS MasterMap into the classification model.

Chapter 8: Object-based rule set classification using VHR satellite data

This chapter initially describes the application of the rule-based model, developed using the aerial data (chapter 6), on the VHR satellite imagery. Then, the re-development of a new classification model when satellite data were used is analysed. Comparisons between the object-based models developed using different data sets were analysed. Also the comparison of pixel against object based classification techniques is discussed.

Chapter 9: Overall discussion, conclusions and recommendations

This final chapter draws together a summary discussion of the classification methods taken for mapping soil sealing and vegetated surfaces. Issues on the development and application of each approach are discussed. Final conclusions, future work and recommendations are also illustrated.

The interconnection of the thesis structure and the objectives of this research is outlined in Figure 1-1.

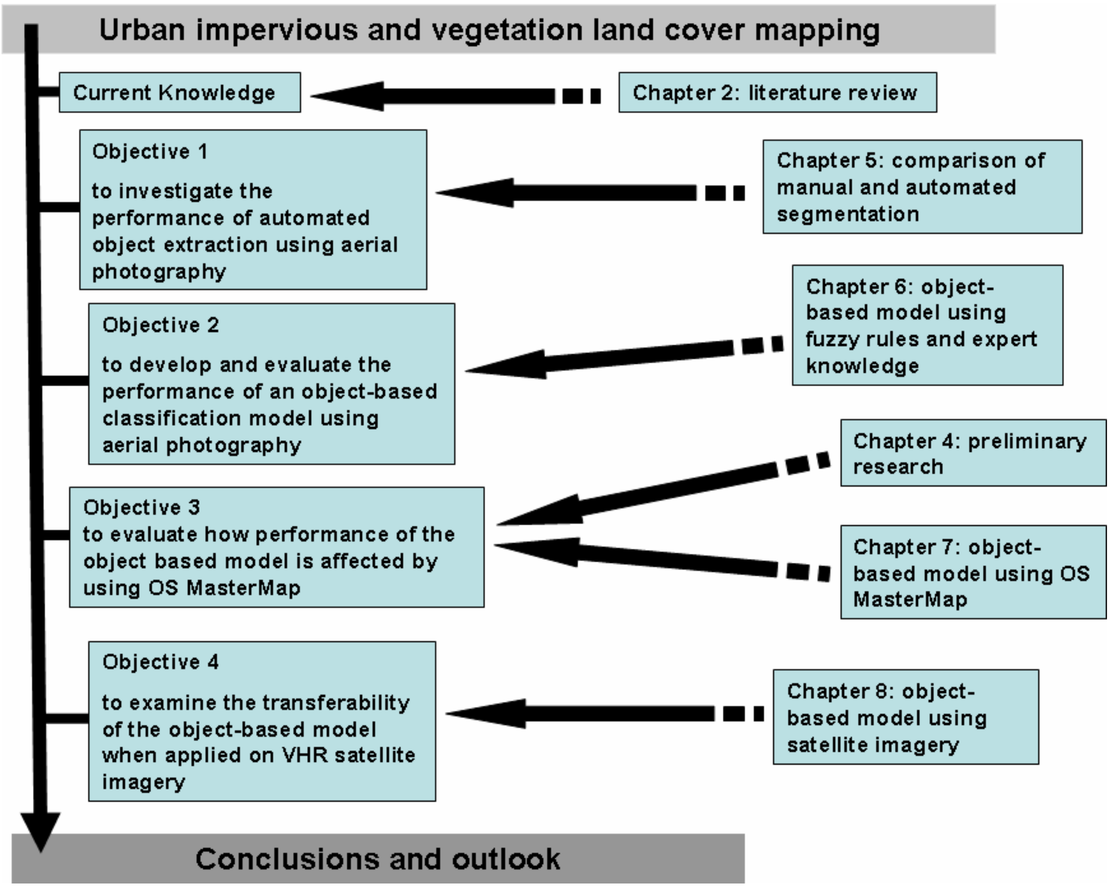


Figure 1-1 The thesis structure as a flow chart

Chapter 2

Literature review

This chapter firstly provides an introduction to soil sealing. The variety of methods used to monitor soil sealing in operational European projects follows. Then the scientific studies that used pixel and sub-pixel approaches to map soil sealing in urban environments are analysed. The review of object-based methodologies follows as well as the comparison between pixel and object based approaches. A summary of the key findings of the literature review is finally illustrated.

2.1 Definition of soil sealing

The characterisation of the environmental quality of urban landscapes, such as the density and growth of the built environment, the climate quality, the proportion of green spaces and impervious surfaces, are key indicators for sustainable development. Impervious surfaces are generally understood to be any material, natural or man-made, that prevents the infiltration of surface water to the underlying strata. As a result, impervious surfaces not only indicate urbanization but are also major contributors to the environmental impacts of urbanization. A suitable qualification of whether a soil is sealed or not is to assess whether it is permeable. The European Union (EU) accepts that "soil sealing refers to changing the nature of the soil such that it behaves as an impermeable medium and describes the covering or sealing of the soil surface by impervious materials by, for example, concrete, metal, glass, tarmac and plastic" (EEA glossary, 2006). In addition to the EU definition, Burghardt et al. (2004) describe soil sealing by three different means: (i) following a systems approach: "Soil sealing is the separation of soils by layers and other bodies from totally or partly impermeable material from other compartments of the ecosystem, such as biosphere, atmosphere, hydrosphere, anthroposphere and other parts of the pedosphere", (ii) according to a purpose related approach: "Soil sealing is the covering of the soil surface with an impervious material or the changing of its nature so that the soil becomes impermeable, such that soil is no longer able to perform the range of functions associated with it" and (iii) by including natural characteristics: "Changing the nature of the soil such that it behaves as an impermeable medium. This definition includes compaction of soils or sub-soils which may affect larger areas than the sealing as defined in definition (ii)". Grenzdörffer (2005) considered a soil to be sealed when it is covered by an impervious material and categorised sealed areas as either built-up or non-built-up areas. He also defined partially sealed surfaces as partly permeable surfaces such as open celled pavers that allow a reduced growth of plants. DEFRA argues that soil sealing is (i) the covering of the soil surface with an impervious material or the changing of its nature so that the soil becomes impermeable; the soil is no longer able to perform the range of functions associated with it, and (ii) the separation of soils from other compartments of the ecosystem by layers and other bodies of completely or partly impermeable material (Defra, 2005). The implications of soil sealing in the environment as well as in human health were identified by Burghardt et al. (2004) as follows:

Negative effects:

- Decrease of soil functions
- Inhibition of storm water infiltration
- Inhibition of storm water storage
- Floods by inhibition of water infiltration
- Reduction of ground water renewal in some cases
- Health hazards by ground water contamination caused by break through of polluted water to ground water at the edges
- Destruction of soil fertility
- Reduction of urban green and biodiversity
- Dissection of habitats and water catchment areas
- Unfavourable climatic effects
- Health problems by urban overheating
- Contamination effects on adjacent areas
- Stimulating and preventing wind and water erosion and land slides
- Change of organic matter production, conservation and decay

Positive effects

- Protection of soils against emissions
- Increase acid neutralization capacity underneath sealing cover
- Drainage function of the soil under streets
- Reducing evaporation, improved water supply to street trees

Putting all these definitions together it can be summarised that soil sealing results in changing the nature and quality of soil and has an effect on the soil functionality. Soil sealing is generally produced by covering the soil with an impervious material. In this project soil sealed areas were identified by monitoring the built up vs. non-built up areas in the urban environment.

2.2 Monitoring soil sealing in Europe

The need to understand the impact of soil loss on European and global socio-economic and environmental systems demands the monitoring of rates, types and geo-spatial distribution of soil sealing. A variety of projects have been undertaken in the last few years in Europe to detect soil sealing at European, national or regional scales. Some EU projects are:

I. The SAGE project

The SAGE project is one of the ten European Space Agency (ESA) "Global Monitoring for Environment and Security" (GMES) Service Element (GSE) projects ongoing in Europe and lead by Infoterra GmbH. The GMES project was an initiative set up jointly by the European Commission (EC) and ESA to establish a European Capacity of GMES by 2008. SAGE was concentrated on water pollution, water abstraction, agro-environmental indicators and soil sealing indicators, at European scale. Thus, the focus was on "supporting services for reporting and management obligations arising from the implementation of the European Water Framework Directive (WFD) and the Thematic Strategy for Soil Protection (STS)" (SAGE service prospectus, 2003). The project comprised of two product lines, the AquaSAGE and the SoilSAGE, and intended to bridge the gap between the policy demand and the technology offered today. The SoilSAGE was developed in Austria, where GeoVille

GmbH evaluated three pilot provinces with respect to administrative land consumption, the ecological impact of soil sealing and also the geophysical impact connected to the sealing degree. The aim was to allow use of the information as a basis for regional and spatial planning decisions. The SoilSAGE products were maps and statistics related to land consumption and soil sealing and its change during the nineties. The products were based on spaceborne EO data, aerial photography, maps, demographic and zoning data. The EO component was used to derive land cover and soil sealing data, where the land cover component applied the CORINE LC nomenclature (level 1 and partly levels 2/3). The basic SAGE service (general and specific urban land cover with a minimum mapping unit of 1ha at scale 1:100,000 and 0.25 ha at scale 1:25,000 respectively) delivered a thematic accuracy of at least 95% for artificial (i.e. sealed) areas (SAGE Service Prospectus, 2004). Finally, the amount of land consumption was described and quantified in relation to demographic data, and parameters for ecological and geophysical impact assessment of soil sealing were provided. The EO methodology was composed of a sequence of methods for extracting information using satellite data (SPOT, ERS, Landsat) such as automated image classification techniques, visual treatment of the classification results for correction and class refinement, and vegetation index based derivation of the degree of soil sealing. An intrinsic component of the methodology was the verification of the thematic results via aerial photography. The land cover products served to generate secondary products via GIS analysis and models along with demographic and geo-spatial data, such as land use zoning data. They concluded that Landsat ETM+ and Spot satellite data are reliable enough to use even until 2013 with expected improved performances such as better spatial resolution, wider swaths and hyper spectral channels. Additionally, they argued that very high spatial resolution in panchromatic mode (e.g. IKONOS) is a useful complement to moderate resolutions with multi-spectral (or hyperspectral) channels.

SAGE project aimed to monitor soil sealing at European level with a minimum mapping unit of 1ha; this scale is too broad for this PhD study and the exact methodology could not be used. However, this project gave insights about the types of data shall be used such as aerial photography or VHR satellite data and ancillary data if available.

II. The GMES Urban Services (GUS) project

One of the thematic areas being addressed by ESA in the framework of GMES is the monitoring of urban areas in Europe, covering issues related to urban sprawl, urban planning modelling and forecast, changes in urban land use, environmental monitoring and urban planning discipline enforcement. The GUS project (2003-2004) aimed to demonstrate a portfolio of products derived from satellite data and other sources in close cooperation with a selection of users (cities and regional authorities) as a starting point for the full implementation of GMES by 2008. The project was developed by a consortium of 11 European partners lead by Indra Systems, Inc. The products and services of GUS project were clustered into four parts: (i) urban land use, including change detection and modelling tools, (ii) urban development control such as short term hot spot monitoring for urban planning discipline enforcement, (iii) environmental quality (noise, sealing, thermography and risk) and (iv) regional products offering basic land use and sealing maps for monitoring of soil consumption (GUS web-site). In relation to soil sealing, GUS produced two related outputs:

(a) The first product was part of the "Environmental quality" project and has a particular value in relation to increasing urbanization, increases in surface run off and increasing concerns with the unpredictability of weather patterns in the context of global warming. The basic data for developing the Sealing Map product was supplied by Spot 5 sensor. For current or future land use products, the emphasis was put on Spot 5 with 10 m colour mode and 5 m panchromatic data. By the same time, QuickBird 2 and OrbView 3 could be considered as alternative systems in case of unavailability or failure of Spot 5. After the end of the Spot 5 planned mission, it was proposed to consider the Pleiades constellation as the basic source of data for this product. Table 2.1 shows the considered data sources for the development of sealing map products within an overall time frame of 10 years. It should be mentioned that Pleiades satellite hasn't been launched but data derived from the other mentioned satellites are available in the current market.

Table 2.1 Sealing map-assessment of EO data sources (Rabaute, 2005)

Period	0-2 years		2-5 years			5-10 years				
Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Proposed Sensors	Spot 5									
					Pleiades					
Alternative Sensors	QuickBird 2									
	OrbView 3									
Coverage	Worldwide									
Quality and reliability	High									

(b) The second product is part of the “Regional” project which is actually complementary with the Regional Land Use project. For current or future Regional Sealing products the emphasis was on Envisat ASAR data. TerraSAR (ScanSAR mode) and Cosmo Skymed (wide region mode) were considered as alternative systems in case of failure or unavailability of Envisat. At the end, the project delivered a very simple land use map where only two classes were identified: sealed and not-sealed surfaces (identification of man-made landscape – non rural). The idea of this project is to repeat it every 2 or 3 years. To map sealed surfaces, apart from EO data, ancillary data were also needed such as Digital Eleveation Models (DEMs), topographic Maps (at scale < 1:10000) and Thematic Maps (at scale <1:10000).

III. *The GMES Service Element (GSE) Land monitoring project*

The GSE land monitoring project started in autumn 2005 for a 3 years period and was based on the results according to land issues of the three GMES projects (GUS, SAGE and CoastWatch). The GSE project aimed to deliver core land cover data and geo-information services based on space-borne and in-situ monitoring. The GSE Land monitoring services portfolio included (Steenmans, 2005):

(i) at European scale:

- European Urban Atlas, mapping land use and land cover of European functional areas with more than 100,000 inhabitants, with a minimum mapping unit of 0.1 ha
- Detailed land cover mapping compatible with Corine land cover, but with minimum mapping unit of 1 ha instead of 25 ha, updated every 3-5 years
- Low cost yearly updated land cover change mapping service

- Mapping of land cover changes within and surrounding NATURE 2000 sites

(ii) at regional to local scale:

- Impervious areas and soil sealing levels
- Inland water quality/contamination
- Irrigation/agricultural water consumption
- High resolution inventory, assessment and monitoring of protected areas
- High resolution information service for environmental management, development control and spatial planning in urban areas
- Monitoring impact of agri-environmental measures on rural landscape

The data used for the implementation of the GMES project were satellite images with very high to high resolution, 1 to 5 m, (provided by national projects such as Pleiades, TerraSAR, Cosmo-Skymed and the Spanish National Earth Observation System). Additionally, priority was given to the future development of the following (GMES report, 2004):

- A radar satellite providing high resolution imagery for continuity with ERS and Envisat-class radars, with an interferometric capability for small surface motion monitoring.
- Multi-spectral optical imaging satellites at two spatial resolutions: (a) high resolution for local and regional operational monitoring applications (continuity of SPOT and Landsat classes) and (b) medium resolution for global applications (continuity of ENVISAT-global imaging and SPOT-Vegetation classes), with multi-spectral capabilities and optimised for vegetation, cloud & aerosol and ocean colour
- Atmospheric dynamics and chemistry monitoring, including instruments providing continuity to ERS and ENVISAT-class data streams

Similarly to SAGE project, the main interest of all GMES products was the land cover classification at European level. For this purpose, soil sealing was monitored based on the level 2 of CORINE’s land cover hierarchy, i.e. identification of the cities and villages as artificial surfaces and not classification of soil sealing within the urban cities as this project aims.

IV. The Technical Working Groups (TWG) of the EU Soil Thematic Strategy

Within the soil sealing theme, the TWG recognized various aspects including: (i) methods to survey sealing according to the quality and the quantity of an area, (ii) investigations of the indirect effects of sealing on the fragmentation of habitats, (iii) evaluation of the existing methods of examination of the degree of sealing and developing a standard "sealing degree" assessment procedure, (iv) development of standard sealing quality assessment methods with the inclusion of regional demands and specifications such as natural differences, (v) application of rules concerning the determination of minimum surface and spatial distribution pattern, and the quality of soils in areas which have a high degree of sealing and (vi) analysis of the sealing impact on local, landscape and global level (Kleeschulte, 2004). More specifically, the TG5 soil team worked on soil consumption by sealing, urban soils, land use and land use planning. The aims and the questions that had to be answered by this research project were (Burghardt, et al., 2004):

- Define sealing thresholds according to regions. Identify the landscape types that have a similar sealing dynamic and develop methods for managing these landscape types
- Identify the role of soil consumption to socio-economic development and the de-sealing effect into the quality parameters of sealing, changes of underlying soils and the functions of sealing cover
- How the excavation and construction of new soil covers affects soil erosion, ground water renewal, soil heat storage, climate, health, biodiversity, pollution and the socio-economic cost of the direct and indirect effects of soil sealing
- Data collection, analysis and specification of data on a regional level
- Effects and relation of the new soil urban properties with the present land use and the potential to avoid them
- The response of the environment to land use planning. What affects the environment and which are the main driving factors?

The gravity of this project was on the socio-economic effect of soil sealing which is beyond the scope of this research study.

V. The Monitoring Urban dynamics (MURBANDY) project

The overall aim of MURBANDY was to enhance remotely sensed data and provide earth observation based procedures in order to estimate changes of Land Cover and/or Land Use in urban and peri-urban areas for a number of European cities. MURBANDY had three major objectives that were worked out in three linked components (i) *change detection* (CHANGE): to measure the changes in the spatial extent and in urban structure for the past 40 years in 13 European cities, (ii) *understanding* (UNDERSTAND): to compute static and dynamic urban and environmental indicators to help understand urban and peri-urban landscapes and to estimate their level of sustainability and (iii) *development scenarios* (FORECAST): to develop scenarios for sustainable urban and regional development using a combination of earth observation and non-space data. To this end, urban growth scenarios are developed using state of the art dynamic urban models. For the implementation of the three parts a recent extension of the CORINE land use/land cover database was used which has considerably contributed to a more detailed study of urban areas (White et al., 2000).

Referring to the CHANGE project, the methodology used for the production of the four land use databases for urban and peri-urban areas of the studied cities is based on satellite images and aerial photography processing. More specifically, they used IRS-1C Pan satellite images at 5.8 m spatial resolution for the creation of the reference land use database, aerial photographs and satellite images for the creation of the three historical land use databases, thematic and topographic maps and tourist maps and guides. The minimum mapping unit was 1ha for Artificial Surfaces and 3 ha for non-Artificial Surfaces. The reference land use database was produced by aerial photo interpretation of the IRS-1C imagery, analogous to a 1:25,000 scale map and was provided in Arc/Info compatible format. Linear features such as transportation (road and rail) and river networks were digitised as linear features. Only those linear features that are also displayed on a topographic sheet at scale of 1:25,000 were taken into account. MURBANDY used the CORINE Land Cover nomenclature. Additional historical land use databases were produced through interpretation and were compared with the reference image and reference database. The final products of MURBANDY Project are vector databases presenting the land uses of urban and peri-urban areas for the selected cities for the four periods (mid-1950s, end of 1960s, year 1997 and mid-1980s). The resulting maps have a scale of 1:25,000.

MURBANDY project's methodology goes beyond the soil sealing identification/categorisation as the focus was on monitoring urban land cover change and forecasting urban growth.

VI. The Monitoring Land use/ cover Change Dynamics (MOLAND) project

The MOLAND project is an expansion of the MURBANDY project and it aims to define a precise methodology for monitoring the dynamics of human settlements and provide information for different existing EU cities and others being developed (Lavalle *et al.*, 2001). The methodology is based on the same processed as the Murbandy project (Change, Understand and Forecast). In the first part, which detected changes in urban growth, panchromatic Indian Remote Sensing satellite (IRS Pan) and IKONOS data were used together with aerial photographs from the mid-1950s till the late 1980s. The second part (UNDERSTAND) aimed to analyse urban land-use changes and derive indicators focused on urban and regional sustainability. The MOLAND indicators were divided into (a) spatially referenced indicators providing information on different land uses and changes in them; and (b) cross-sectoral spatially referenced indicators to evaluate more complex processes for landscape changes (e.g. fragmentation). The indicators showed changes, over a 50 year period, of three main land use classes: artificial surfaces, agriculture and natural. The structural changes (i.e. fragmentation) of the urban landscapes were calculated with the Spatial Pattern Analysis Program for Categorical Maps (FRAGSTATS) software; "The trends over time of the various fragmentation metrics (e.g. edge metrics, core area metrics, nearest neighbour metrics, diversity metrics) computed by FRAGSTATS were being interpreted in the light of known environmental and demographic factors for the different urban areas" (Lavalle et al., 2001). The final creation of that part of the project was a document with guidelines on how to report urban sustainability. During the forecast part, scenarios of territorial evolution of urban areas were developed by using EO and non-space data and also a regional spatial dynamics model consisting of a “cellular automata” land-use model linked with a GIS and regional economic demographic models.

VII. The Environmental Assessment of Soil for Monitoring (ENVASSO) project

The ENVASSO European project started in 2006 and completed at the end of 2007. The driver for this project was soil protection with the aim of identifying and monitoring threats to soil. Eight threats to soil were identified: erosion, declining organic matter, contamination, compaction, salinisation, loss in biodiversity, landslides and soil sealing. The project used existing methodologies and data sets in order to develop a system that could be commonly used by the EU countries for assessing the soil status and ensure sustainable use (ENVASSO, 2007).

The aim of all European projects was to monitor soil sealing at European level. Consequently the data used had a spatial resolution of 20 m and the minimum mapping unit (MMU) was either 1 or 0.5 ha; these specifications and the identified methodologies were too broad to be used in this PhD study. However, all the aforementioned projects identified the interest of monitoring soil sealing as well as they provided insights about the types of data shall be used for similar studies such as aerial photography, VHR satellite data and ancillary data if available. In addition, the traditional air photo interpretation (API) method proved to be commonly used for the statistical analysis of the classification results. In this PhD study, the literature review continued based on scientific studies in order to identify methodologies for monitoring soil sealing at local or regional levels.

2.3 Urban land cover mapping using pixel and sub-pixel classification methods

The history of identifying surface impermeability goes back further than the European projects described above. The oldest and most traditional way of detecting urban land cover types and the percentage of impermeable surfaces is by aerial photo interpretation (API) and ground survey. Although API considered to be the most accurate procedure, it is also very subjective, time consuming, expensive and labour intensive. Also skilled operators are required. Further to manual techniques, researchers have managed to develop various automated methods for land cover identification, like multi-spectral remote sensing which lends itself to automatic or semi-automated classification techniques.

Deguchi and Sugio (1994) evaluated the applicability of satellite images to estimate the percentage of impervious areas in the urban environment for a runoff discharge model. The study area was a small urbanised watershed, covering 3.54 km^2, within the city of Miyazaki in Japan. They used three types of satellite imagery of medium resolution, LANDSAT-MSS (multi-spectral scanner), 80 m ground resolution, MOS-MESSR (multi-spectral electronic self-scanning radiometer), 50 m resolution and SPOT-HRV (high resolution visible), 20 m ground resolution. The automated classification was implemented with the Nearest Neighbour Method and the images were classified into water, forest, open land and urbanized areas. For reference data production, the imperviousness was estimated by visual interpretation of buildings, roads and parking lots, using digital black and white maps (B&W-maps). On the maps, the black pixels corresponded to the impervious surfaces. The percentage of imperviousness was calculated by dividing the number of black pixels by all pixels within a zone. The results showed that the estimation error of the percentage of impervious surfaces derived from the satellite images is less than 10%; similar error obtained by the visual interpretation of the B&W maps. Finally, the study concluded that the satellite imagery can be used for the simulation of runoff discharge and indicated the opportunity of also using high resolution data.

Dousset (1995) analysed a set of SAR images of Los Angeles to assess their potential to derive soil moisture. The analysis of the SAR images was done by using a multi-spectral SPOT image, classified with the joint distribution of the visible (HRV-1) and infrared channels (HRV-3). The image was subdivided to four classes: water, vegetation/parks, residential buildings and devoid of vegetation areas, comprising commercial buildings, industrial/metallic buildings and smooth paved areas. SAR images seemed not to be suitable for land cover classification as large variations of backscatter were observed for the different features. They concluded that land cover information could be derived from SPOT or LANDSAT images.

Ridd (1995) developed a conceptual model for analysing urban land cover types within urban areas. The vegetation-impervious-soil (V-I-S) model was presented as a possible aid for urban ecological investigations through remote sensing technology by offering new inputs to morphology, ecology, energy, moisture, vegetation and human responses. The central idea lies around the triangular V-I-S diagram where each axis represents one component. Values along the axis indicate the percentage of that corresponding component. Just like the sand-silt-clay illustration in the soil texture diagram, which was used to quantify the textural components of soil in the Earth Sciences, the spatial composition of a segment of the urban landscape can be described in terms of proportion of vegetation, impervious surface and soil. The V-I-S model also provides a way of measuring and mapping the environmental change of urbanization in response to three factors: (i) nature of the original condition, (ii) nature of urban conversion, and (iii) time.

The V-I-S model was later used by Ward et al., (2000) for monitoring urban growth. Based on that model they produced a hierarchical image classification scheme for delimiting urban land cover types and their intervals in terms of urban, rural, natural and land use mixes. The classification results of a Normalised Difference Vegetation Index (NDVI) derived from Landsat 5 Thematic Mapper (TM) Image data, 25 m resolution, showed overall accuracy of 83%. Later, Phinn et al., (2002) built on the previous research work and used Ridd's model to monitor the composition of urban environments. They argued that maps of the V-I-S composition of a city could address questions of urban morphology, condition, function and to assess encroachment on non-built areas. Furthermore, the V-I-S model was used by Hung and Ridd (2001) to develop a new supervised classifier for subpixel remote sensing. Instead of using only the three basic ground components (vegetation, impervious surfaces, soil) as described by Ridd (1995), six ground components were selected as basic ground cover types in urban areas; two for vegetation, three for impervious surfaces and one for soil. The supervised classification was implemented by the ERDAS Imagine software and the accuracy assessment was compared with predicted component percentages from visual interpretation of aerial photographs. They concluded that the image classification method used could be useful in urban studies such as population, runoff modelling, air pollution, urban growth and urban change modelling.

Ji and Jensen (1999) estimated impervious surface fraction based on a hybrid approach of a multi-signature subpixel analysis (the Subpixel Classifier) coupled with a layered classification using Landsat Thematic Mapper (TM) imagery. The study area was Charleston, South Carolina. The imperviousness indicated the degree of urbanization associated with the amount of urban imperviousness detected from the pixel. The study showed that the hybrid approach may provide a better solution to modelling urban imperviousness than the traditional "hard" classification of land use types. Similarly, Smith (2000) used subpixel analysis to estimate impervious surface cover using Landsat TM imagery for Montgomery County, Maryland. The classification algorithms derived from various combinations of Landsat TM data using a decision tree classifier and a GIS planimetric data proved capable of estimating the amount of impervious coverage at the subpixel level.

Rashed et al. (2001) argued that the "hard" classification approach limits the potential of remote sensing as a research tool for urban analysis and examined the feasibility of Spectral Mixture Analysis (SMA) to derive comparable physical measurements of urban land cover. For that reason they compared two conventional per-pixel classifiers, Maximum Likelihood (ML) and Minimum Distance to Means (MDM), with the SMA model where the resulting fractions were used to classify the urban environment through a decision tree (DT) classifier. SMA was applied to an Indian Remote Sensing multi-spectral image (IRS-1C) of the Greater Cairo region, Egypt, using four image endmembers; vegetation, impervious surfaces, soil and shade. The selection procedure of the endmembers was inspired by Ridd's V-I-S model (1995). The results showed that SMA-derived measures are superior to other traditional per-pixel classification techniques with an overall accuracy of 88%.

Small (2001) has also introduced the problem of mixed pixels, in the context of urban land cover by defining the linear unmixing problem. He examined the applicability of linear spectral mixture models to estimate the urban vegetation abundance using Landsat TM data of New York City. He assumed that urban reflectance measurements could be described by the linear mixing of high albedo, low albedo and vegetative endmembers. His analysis was compared with the Normalised Difference Vegetation Index (NDVI) and proved that spectral unmixing provided a better estimate of vegetation abundance than NDVI. The SMA model has also been used by Phinn et al., (2002); they used the V-I-S method for monitoring the composition of urban environments, as mentioned in previous paragraphs. Wu and Murray (2003) estimated the distribution of impervious surfaces, together with vegetation and soil cover, using a linear spectral mixture model and the V-I-S model. The data was a Landsat Enhanced Thematic Mapper Plus (ETM+) image of the metropolitan area of Columbus, USA. The urban land cover was demonstrated by four endmembers; low albedo, high albedo, vegetation and soil while only high and low albedo were used to estimate imperviousness. The results of this research indicated that impervious surfaces can be derived from remotely sensed imagery with promising accuracy. The V-I-S model and SMA analysis seems to be a useful indicator to simply categorise the urban environment into sealed and vegetated surfaces.

Davis and Wang (2002) examined the effectiveness of IKONOS imagery for urban land cover classification. They combined one panchromatic (PAN) image, 1 m resolution, with a multi-spectral (MS) image, 4 m resolution, to produce two pan-sharpened MS images, 1 m resolution, of the City of Columbia, Missouri. The images were subdivided into seven urban land cover classes; water, grass, woods, bare soil, buildings, impervious surfaces (comprising streets, parking lots and small/residential buildings) and shadow. The classification process was done by a parallelepiped supervised algorithm for the three images separately. The fusion of PAN and MS images gave an overall classification accuracy of 83%. Moreover, the classification scheme used seemed to be suitable for this PhD study and it was taken into account when the research methodology was built.

Bauer et al. (2004) examined whether Landsat TM imagery can be used to map the percentage of impervious surfaces and quantify the changes over time across the Twin Cities Metropolitan Area (TCMA) in Minnesota. For this, an Impervious-Greenness Model was introduced to relate the impervious surface areas with the “tasselled cap” greenness (an orthological transformation of the reflective bands of TM data). The results showed a strong relationship between the Landsat tasselled cap greenness and the percent of impervious surface area.

Yang et al. (2004) developed an alternative approach to spatially quantify urban land cover and land use changes using Landsat TM and ETM+ imagery; named the “Sub-pixel Imperviousness Change Detection” (SICD) method. They first used a regression tree algorithm (the Cubist algorithm) to model sub-pixel percent of imperviousness and then digital orthophoto quarter quadrangles images which were classified to five broad land cover classes; trees, grass, water, barren and shadow. The results verified that the method gave sub-pixel level information that recognises non-heterogeneity over large geographic areas.

The use of satellite and airborne imagery in remote sensing has also been an interesting area of research in the United Kingdom. The National Remote Sensing Centre (1997), in Farnborough, explored a number of applications of Synthetic Aperture Radar (SAR) systems, with a particular focus on mapping and monitoring land features in the areas of (i) Agriculture, (ii) Forestry, (iii) Urban mapping and development and (iv) Oil and Gas exploration. Two years later, the UK in collaboration with Germany and Italy was involved in the "Prototype Landscape Assessment Information System" (PLAINS) European Union project. The aim of PLAINS was to identify the benefits of introducing satellite Earth Observation (EO) data into the landscape assessment process and to develop a decision support system that would provide a basis for landscape and urban classification (Cudlip et al., 1999). The project involved three different business sectors who have inherently similar requirements in landscape assessment; the (i) Regional planning authorities, (ii) Estate agents and (iii) tourism. PLAINS project methodology was off interest in this particular research study but it has identified that the contribution of satellite EO data is valuable in the decision process of regional planning authorities and should be widely appreciated and adopted with more conventional data for urban/landscape classification.

University College London (UCL) compared the Digital Chart of the World dataset (DCW) with the Defence Meteorological Satellite Programme Operational Linescan (DMSP-OLS) city lights dataset to evaluate global urban growth. The aim of the study was to investigate the extent of urban growth in recent times and to identify the classes had been misclassified in recently produced global maps (Doll and Muller, 1999). The city-lights images were converted into polygons that were overlaid with the DCW polygons to identify any differences. The conclusion was that the DMSP-OLS data offers a unique view of urbanization from satellite that makes it a suitable tool for urban mapping and monitoring. The same university (UCL) in collaboration with Boston University, USA, used the Moderate Resolution Imagining Spectroradiometer

(MODIS) sensor, onboard the Terra spacecraft, for evaluating the use of Bidirectional Reflectance Distribution Function (BRDF)/ Albedo product for global urban mapping (Doll et al., 2001).

The University of Southampton examined the potential usage of the Hopfield neural network technique, to map the location of urban class components at the sub-pixel scale, from IKONOS images (4 m spatial resolution) of the city of Bath (Tatem et al., 2001). The Hopfield neural network was compared with the traditional “hard” classification. The classification typology was building, road, tree and grass. The results showed increased classification accuracy assessment by using the Hopfield neural network technique; building: 90%, road: 95%, tree: 93%, and grass: 76%.

The University of Manchester described four simple ecological performance indicators which could quantify the effects of urbanization on surface temperature, hydrology, carbon storage and sequestration, and biodiversity (Whitford et al., 2001). These were the (i) climate indicator, (ii) hydrology indicator, (iii) carbon storage and sequestration indicators and (iv) biodiversity indicators. The indicators were tested by using them in four UK cities on Merseyside. They additionally used aerial photography to interpret the percentage of the land covered by buildings, different types of vegetation and bare soil. The results showed that the greatest influence on ecological performance was the percentage of green space (trees) and suggested that the indicators could be a useful planning tool by helping predict the ecological impact of new developments.

Furthermore, the Aston University at Birmingham showed the prospective usefulness of airborne data by mapping the impervious areas in the Industrial Black Country of the West Midlands (Elgy, 2001). The data used in this study were daytime Airborne Thematic Mapper (ATM) data and aerial photography on scale of 1:5,000. The classification was done by using the Marr-Hidreth edge detector (Marr and Hidreth, 1980) which is based on the zero-crossings of a Laplacian convolution mask. The image was first segmented into homogeneous polygons and then was classified into roofs, paved areas and permeable land. It was concluded that airborne remote sensing improved the classification of land cover for urban drainage studies. The author refers to dawn thermal ATM imagery as an excellent way of discriminating between roads, houses and vegetation in urban imagery.

Finally, the Kingston University in Surrey, in association with USA and Germany, used high resolution IKONOS data to derive the spatial distributions of landscape ecological metrics within suburban areas onthe south-west edge of London. These indicators were the Weighted Mean Patch Size (WMPS) and the Lacunarity index. They aimed to show how data from the latest generation of remote sensing satellites can be used to guide planning decisions and policy, particularly in the green belt and urban areas, with the aim of maximizing sustainability (Greenhill et al., 2003). The IKONOS data were combined with Ordnance Survey data for better classification accuracy while land use was classified into vegetated and non-vegetated patches with the use of the Normalised Difference Vegetative Index (NDVI). The results showed that the metrics are a new insight to land use planning.

2.4 Pixels or Objects?

The picture element (pixel) is the smallest element of an electronic image and has been used originally as the unit of digital image analysis. Typical pixel-based approaches of image classification for land use mapping target to assign a land use label to each single pixel of the image. The main information used is the spectral information of each pixel itself and/or texture attributes in certain defined vicinity around the pixel (Blaschke and Strobl, 2001). A significant problem with pixel-based classification is that the reflectance of the pixel does not correspond always to the field-of-view, e.g. it may come only from the central part of the pixel, or partially from the surrounding pixels depending on the specific sensor (Townshend et al., 2000). The authors introduce as an alternative the use of contextual procedures in which observations from surrounding pixels are used to assist the characterisation. The spatial context in pixel-based methods can be implemented by using, certain in size, moving window filters (e.g. 5*5 pixel kernel) but thus not allowing a free-shape organisation of pixels. Object-based methods introduce the spatial context of an object as a relation of neighbouring objects (Blaschke, 2004). In high and very high resolution imagery each pixel is not a direct match to the object or area as a whole but to the components within an object and therefore simple pixel classification techniques might be invalid (Yuan and Bauer, 2006). Caprioli and Tarantino (2003) argued that "when we apply standard procedures of per pixel multispectral classification to VHR data, the increase of spatial resolution leads to augmentation in ambiguity in the statistical definition of land cover classes and a decrease of accuracy in automatic identification". Moreover, according to the authors, the increase in spatial resolution results in an increase in variability within land parcels ("noise" in the image), generating a decrease in accuracy in the classification with pixel-based techniques. Similarly, Zhou and Troy (2008) argued that "a single building may have a wide range of reflectance values in its constituent pixels based on differences in materials and shading".

When visually interpreting features in natural or urban environments, humans neither observe nor think in pixels (Blaschke et al., 2005). The interpreter spontaneously uses the concepts of texture, shape, distance, relationship to neighbour objects in order to identify complicated features, information that pixels are not able to give. Always the identification is at multi-scales as there is a constant switch between scales, focusing either in the detail of a scenery or in a larger context. Moreover, complex systems are inherently multi-scale systems and to model, monitor and manage such systems, appropriate approaches are required to assess their multiscale dynamics (Blaschke et al., 2005). To overcome these limitations, found in pixel-based methods, new techniques are required. One solution is image segmentation into objects rather than pixels. As Walker and Blaschke (2008) argued, "in a very high resolution situation, where the pixel size is significantly smaller than the average size of the object of interest, segmentation is an efficient means of aggregating the high level of detail and producing usable objects". Image analysis in many cases leads to meaningful objects when the image is segmented into "homogeneous" areas (Baatz and Schape, 2000). The segmentation process is not new (Haralick et al., 1973) but was seldom used in processing remote sensing data (Blaschke and Strobl, 2001). Many segmentation algorithms have been developed such as texture segmentation, watershed information and mean shift, found in Woodcock and Harward (1992); Li et al. (1999); Comanicu and Meer (2002); Blaschke et al. (2004); Meinel and Neubert (2004); Zhou and Wang (2006) (source: Zhou and Wang, 2006). Other segmentation techniques developed in the past are (i) the region based (i.e. region growing and texture based segmentation) found in Aguado et al., (1998); Bezdek, (1981); Liu and Yang (1994); Ronfard (1994), (ii) the edge based (i.e. snakes, dynamic programming) found in Canny (1986); Pal and

Pal (1994) and (iii) the active shape models, active appearance models found in Cootes et al., (1995); Cootes et al., (1998) (source: Gamanya et al., 2007). These approaches have yet proved to be a robust and operational approach. Abeyta and Franklin (1998) believed that "it would have been naïve to expect an image segmentation algorithm based solely on spectral and textural pattern recognition to delineate image objects of interest as human-interpreted polygons would do".

The algorithm called "fractal net revolution approach" proved to be an advance in image processing (Baatz and Schape, 2000). In 2000, Definiens Imaging GmbH introduced a new software in which segmentation and classification processes were combined into one working package; the eCognition software. eCognition divides the image process into two parts: segmentation and classification. During the segmentation process, homogeneous image object extraction at any resolution is allowed. This entails the representation of image information on different scales which are connected with hierarchy-levels simultaneously. In contrast to the pixel approach, the object-based approach contains not only spectral information but also shape and texture information as well as a network operation of relationships between image objects, allowing contextual information. The objects extracted during the segmentation process, are later classified. The classification is based on fuzzy rules which use a continuous range of all numbers between 0 and 1 in order to describe a certain state of the class membership (Baatz et al., 2000). The big advantage of eCognition is that it can produce image objects at different resolutions and connect the different object levels hierarchically. The resulting image objects carry a full complement of attributes which can be integrated into GIS for further analysis (Baatz et al., 2000).

Recently, more commercial packages became available on the market offering object-based image classification techniques. In 2008, the ITT Visual Information Solutions (ITT VIS) has also produced the ENVI Fx © (Feature extraction) software which enables the extraction of objects using high resolution image data. ENVI Fx fist segments the image into objects which can either be extracted as vector files or be classified with supervised and rule based techniques (ITT website, 2009). At the end of 2008, ERDAS IMAGINE introduced a new product, the IMAGINE Objective ©, in which geospatial data layers can be created and maintained. Expert knowledge in an object-based feature extraction environment is also possible. IMAGINE Objective allows creating, and being able to update, geospatial information with automated feature extraction (ERDAS website, 2009). Additionally, the extracted features or the classification can be saved and re-used on other images. In January 2009, Clark Labs released a new version of the Idrisi software, the IDRISI Taiga, an integrated GIS and image processing software offering among others, segmentation and classification tools. In IDRISI Taiga, image segments can be classified either by using training sites and signatures or by utilising rules (Clark Labs website, 2009). Due to the very recent availability of these software packages, the majority of the published research has been implemented by using the eCognition software.

2.5 Object-based urban land cover mapping- scientific research studies

Recently, many research studies attempted to extract urban features and classify urban land use and land cover with the use of eCognition software, e.g. Hoffman (2001a); Hoffman (2001b); Herold et al. (2003); Corr et al. (2003); Darwish et al. (2003); Wang et al. (2004); Guindon et al. (2004); Frauman and Wolf (2005); Greiwe and Ehlers (2005); Mori et al., (2004); Harayama and Jaquet (2005); Blaschke et al. (2005), Jacquin et al. (2008).

Caprioli and Tarantino (2003) tried to classify urban land cover using VHR satellite data (QuickBird, 2.8 m resolution) and object-based approaches. The study area is a part of the peripheral district of Bari, Italy. They subdivided the area into seven classes: asphalt road, country road, buildings, meadows, uncultivated land, arable land and olive-grove. The nearest neighbour classification implemented with eCognition was compared with land use survey maps of the area and the overall accuracy proved to be 96.2%. Confusion was mainly between roofs with asphalt roads and arable land with country roads. Although the nearest neighbour object based classification approach proved able to analyse VHR image data, membership rules of all object types need to be developed and assigned into more complex scenes for a better evaluation.

Coe et al. (2005) developed a hybrid method of an object-oriented and a pixel-based classification approach to detect impervious surfaces at multi-scales. They used

Landsat and IKONOS satellite data but also elevation (Lidar) data for helping them to separate buildings from other urban objects such as parking lots and roads. For the image classification eCognition was applied. Accuracy assessments for Landsat and IKONOS data were not published, but they argued that the object-based classification using additional Lidar information has the potential to be very effective for urban land classes.

Grenzdorffer (2005) used a combination of satellite (Landsat TM and SPOT) images with high resolution aerial photographs to identify land use change in the city of Rostock, East Germany. He tried to identify sealed surfaces and the degree of sealing with the help of eCognition software. Initially, both aerial and satellite images were visually classified at 1:5,000 scale and the produced baseline map was used as an additional input layer to eCognition. The image was classified into three classes, i.e. sealed, partially sealed and not sealed. The NDVI index was also used to discriminate vegetated and non-vegetated surfaces. Based on visual accuracy assessment, sealed areas could be identified with an average accuracy of 85-90%.

The Senate Department of Urban Development in Berlin, Germany, estimated the degree of sealing at the level of housing blocks by using Landsat-TM satellite imagery for west Berlin and Colour Infrared (CIR) aerial photographs for east Berlin (Department of Urban Development web-site, 2005). According to the information found in the web-site, in west Berlin a degree of sealing was given for each the land use category; forest 1%, agriculture 2%, rural areas 7% and parks 10%. The degree of sealing was initially estimated by visual interpretation of Landsat images in 1985 and 1988 which were classified into a ten point scale of sealing. Then, the digital land cover map was then overlaid the degree of sealing was re-calculated as percentage for each block segment. The data were updated in 1991 by comparison with aerial photographs taken in 1990. In east Berlin, the degree of sealing was determined by the "degree of built-up development" and "other sealing" (non-built-up sealing) which included roads, parking places, loading and storage areas. As mentioned in the web-site, “great difficulty was encountered in estimating the degree of sealing (and the non-built-up sealed surfaces themselves) in the dense interior courtyards dating from the late 19th century as a result of the shadow-effect of buildings and trees in the 1:6.000 scale aerial photographs”. This is why average values of the degree of sealing was given to these areas by adding to the already determined degree of built-up surfaces. Other vegetation-free areas, bare soil or gravel surfaces on railroad land, were initially classified as sealed. However, according to their arguments, it should have been classified as 40% sealed areas and not as 100% sealed. Four surface sealing classes were produced according to their effect on the ecosystem (Table 2.2).

Table 2.2. The surface sealed classes (source: The Senate Department of Urban Development in Berlin, 2005)

Sealing class	Estimated effects on ecosystem	Sealing type
1	extreme	Asphalt, concrete, paving stones with joint sealer or concrete substructure, plastic materials
2	high	Artificial stone and plates (edge length > 8 cm), concrete-stone composites, clinker, medium and large-sized paving stones
3	medium	Small and mosaic paving stones (edge length < 8 cm)
4	low	Grass trellis stones, water-bound cover (i.e. ash, pebbles, tamped ground), crushed rock, gravel

The Office for Urban Drainage System in Dresden, Germany, sanctioned the mapping of sealed areas by aerial image mapping. Ortho-rectified aerial photography (1:50,000 scale) was digitized stereoscopically and interpreted with an overlay of the Authoritative Topographic Cartographic Information System (ATKIS) to include soil sealing values for the whole city. The classification typology was created according to soil sealing value (Table 2.3). The mapping was carried out with a positional accuracy of <0.2 m. The degree of sealing was estimated at the level of housing blocks (Figure 2-1)

Table 2.3 Classification key of soil sealing data (Meinel and Hering, 2005)

Feature type	Definition/feature	Soil sealing value
roofs	all shapes of roofs except green roofs	100%
green roofs	flat roof; clearly identified as green roof	50%
impermeable areas	concrete, asphalt, flagging	100%
semi-permeable areas	paving stone, flagging with seep able joints (semi-permeable)	70%
low flow off areas	water-absorbing areas like gravel and crushed stones (semi-permeable)	50%
residual areas	non-fixed areas like grass, garden, meadow, etc.	0%

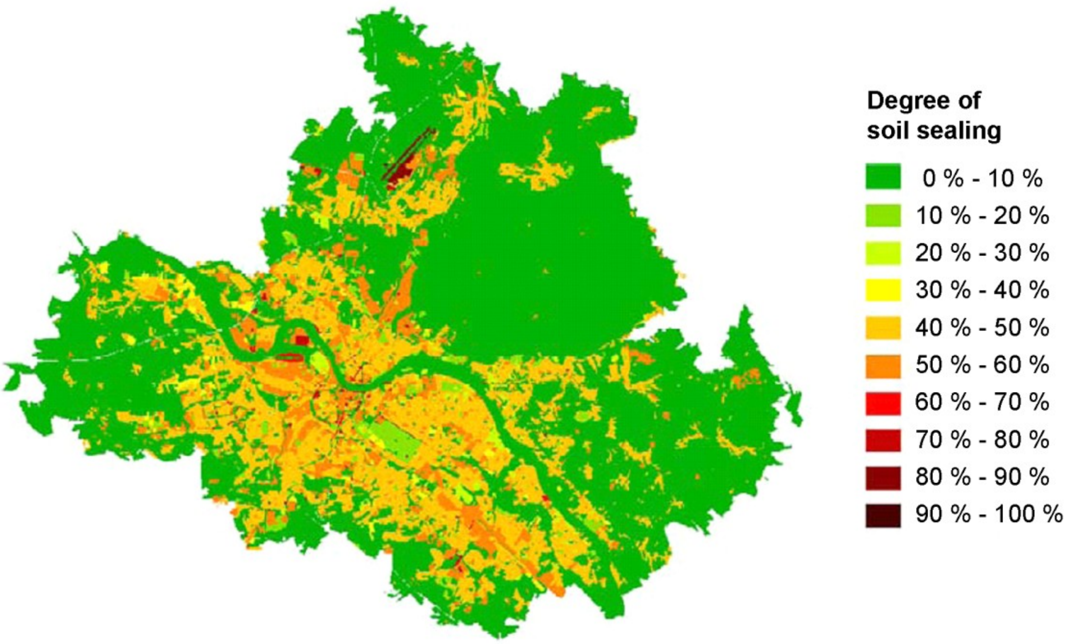


Figure 2-1 Soil sealing in Dresden, Germany (source: Meinel & Hernig, 2005)

Yuan and Bauer (2006) investigated digital classification techniques (both pixel and object based) for mapping urban impervious surfaces of an area 2.1 km by 1.7 km by using satellite QuickBird images (2.4 m multispectral resolution and 0.6 m panchromatic). The classification results were compared with the visual interpretation of ortho-rectified aerial photography (1 m resolution). The study area was classified into five classes: impervious surface, forest, non-forested rural, water and shadow. The classifications were made by using the multispectral bands both with and then without the panchromatic band. The results showed that the fusion with the panchromatic band did not help and in fact slightly decreased the overall accuracy. Moreover, the object-based classification, using the nearest neighbour approach, had better overall accuracy and produced more homogeneous land cover classes with a higher individual accuracy between the classes.

Stow et al. (2007) used object-based methods in conjunction with the V-I-S model, explained earlier, to classify urban land use and identify the socio economic status of Accra in Ghana. QuickBird satellite image, 2.4 m and 0.6 m multispectral and panchromatic resolution respectively, was initially segmented in two scale levels and then was classified using the fuzzy membership function, in eCognition. At level 1 three land cover classes were introduced: vegetation, impervious, soil (VIS) which were further subdivided into low residential, high-residential and no-residential. The results were compared with an on-screen visual interpretation of the panchromatic band of the QuickBird image, resulting in an overall accuracy of 75%.

Mathieu et al. (2007) used object-based techniques and very-high resolution satellite IKONOS imagery (4 m multispectral) to identify the density and distribution of the residential gardens in Dunedin, New Zealand. The image was segmented into two hierarchical levels and the created objects were classified using the Nearest Neighbour method (eCognition software) according to the following classes; <u>three at broad level</u>: "*industrial/commercial* (no or small vegetation patches), residential (mixed patches of vegetation, houses, and roads), *vegetation* (vegetation dominated), and *water*" and <u>six at fine level</u>: "(a) *three private garden classes*: mature and dense gardens with more than 70% of the area comprising trees and shrubs (garden 1), open gardens with a mixture of vegetation structure elements (tree group, shrub, hedge, and lawn), more than 30% and less than 70% of the area comprising trees and shrubs (garden 2) and gardens dominated by lawn and less than 30% of the area comprising trees and shrubs (garden 3), (b) *one amenity pasture class* which included public playgrounds and sport grounds larger than 500m^2, and (c) *two built up classes* (road and house)" (Mathieu et al., 2007). The classification results were compared with the interpretation of aerial photographs and the overall accuracy was 77.5% that was increased to 90.7% when the three different garden classes were grouped together in one class. The methodology described is quite similar to the methodology followed during this PhD study. However, apart from being published later, the main difference is that the authors used the NN object-based classification approach while the rule-based classification was applied on this PhD research.

Zhou et al. (2008) applied object-based classification techniques for land cover mapping of the Gwynns Falls watershed, an area of 17,150 ha in Baltimore metropolitan area, USA. Colour infrared (CIR) digital aerial photographs with 0.6 m resolution of two different dates (1999 and 2004) were classified with the aid of Light Detecting and Ranging (LIDAR) data, 1 m resolution, and the use of ancillary topographic data for identifying building footprints. The images were classified according to five land cover classes: buildings, pavement, coarse texture vegetation (trees and shrubs), fine texture vegetation (herbaceous vegetation and grass) and bare soil (Zhou et al., 2008). The exact methodology of the object-based image analysis (OBIA) is not described in this publication but according to the authors, the overall accuracies achieved were 92.3% and 93.7% for the 1999 and 2004 year respectively.

Walker and Blaschke (2008) applied two different object-based methods to classify the urban land cover of Phoenix metropolitan area (64000 Km^2) in USA. True colour aerial photography, 0.6 m resolution was initially segmented into two levels and was classified into 5 classes: sealed surfaces (roads, sidewalks and parking lots), buildings, soil, woody vegetation and herbaceous vegetation. Two classification techniques, developed in eCognition software, the standard nearest-neighbour (SNN) classifier and the fuzzy rules classification were compared with 500 ground-truthing random points and the overall accuracies were 84% and 79% respectively. They concluded that although the SNN classification had higher accuracy they would recommend the fuzzy rule approach, for land cover mapping, due to the following disadvantages of the first: (i) significant number of samples for each class is required (ii) time consuming method (iii) lack of transferability in additional areas or in different times (iv) uncertainty of accuracy of different scenes (Walker and Blaschke, 2008).

Lizarazo and Barros (2010) developed a fuzzy image analysis approach for urban land cover classification in Bogota, Colombia. The method, called Fuzzy Image-Regions

Method (FIRME), was consisted of three stages; fuzzy image segmentation, feature analysis of the extracted fuzzy regions and classification of the regions using defuzzification techniques. Fuzzy segmentation starts by a fuzzy classification that allows the pixels of each object produced to belong to one or more regions (Lizarazo and Barros, 2010). That's difference with the hard segmentation in which the pixels of each object have a value of either zero (when the don't belong to an object) or one (when they fully belong to certain object). QuickBird satellite imagery at 2.5 m MS resolution was used for the implementation of the study. The area was classified into the following land cover classes: roads, roofs (two types), trees, water and soil. The classification was implemented using an open source software and was tested by comparing the results with a land cover classification using hard segmentation as well as with a traditional pixel-based maximum likelihood classification. According to the results of this study, the highest accuracy achieved with the fuzzy classification approach (83%) while the other two classification methods had an accuracy of 75% (OBIA) and 66% (pixel). The method proposed in this research study was applied in a very small urban region (842 m * 825 m). More applications should be employed in order to prove the reliability of the method. In addition, as the fuzzy classification is based on the selection of training image samples can hardly be operational /transferable.

Tiede et al. (2010) developed an algorithm for semi-automated object-based classification modelling of biotope complexes in Stuttgart region, Germany. The biotope complexes, apart from rural, forest, natural vegetation and other land cover classes, included the identification of urban land cover features such as buildings, industrial and commercial units, vehicular and pedestrian networks as well as green spaces and domestic gardens. On the whole, a generic land use/ land cover multi-scale classification approach was implemented. The modelling was based on the development of object-based rule sets using the eCognition software (Definiens Developer version). The challenge of this study was that the final maps of the biotope complexes had to have the same object boundaries with the cadastral information available. In order to meet the users requirements, a combination of GIS tools and boundary generalisation algorithms were applied. The Object Fate Analysis (OFA) was implemented in order to assess the differences between the boundary objects. OFA initially identified all the objects that have a good boundary match and then highlighted the overlapping polygons. These polygons were further analysed using a buffer analysis approach; the buffering distance was periodically increased until the extinction of the overlapping polygons. The classification method was validated by a random selection of sample points and ground truthing. The authors consider the method to be of high potential for operational studies as it showed transferability capabilities with an average of 86% accuracy when applied to a total of 30,000 biotope complexes in the region.

Object Fate Analysis (OFA) was also applied by Albrecht et al. (2010) for analysing boundary differences of an object-based land cover classification. The automated classification was implemented with the use of RG aerial data at 0.5 m resolution. The study area was a small part of Plainfield, Austria. The area was classified automatically into buildings, roads, garden, farmland, forest and shadow. The classification results were compared with the results of an API of the same area by applying OFA, i.e. boundary evaluation between OBIA and API by applying buffers, around the image objects, with increasing width. The conclusion of this study was that OFA is a potential method to measure the variation between different object delineation methods. OFA needs to be tested further in order to validate the prospective of the method.

2.6 Object-based classification methods in operational land cover mapping projects

OBIA has already been applied for the development of operational land cover mapping products at national levels throughout Europe such as in Spain, UK, Sweden, Norway and German. More specifically, the products of each country are:

- the National Land Cover Map 2000 (LCM2000) and 2007 (LCM2007) of the UK (Smith et al., 2007)
- the Spanish Information System of Land Occupation (SIOSE) project (Arozarena et al., 2006)

- the Digital Landscape Model (DLM-DE) in Germany (Arnold, 2006)
- the Swedish land cover data (SMD)- (Lantmäteriet, 2005b; Halling, 2008)

In UK specifically, the object-based segmentation technique was used for the production of the national Land Cover Map of UK (LCM2000). With the use of multi-seasonal Landsat images (25 m resolution), the land was firstly segmented by a region growing algorithm and later classified using a maximum likelihood classifier (Robinson et al., 2005; Fuller et al., 2005). The classification result was manually enhanced by knowledge-based information derived from ancillary data, such as elevation and soil density (Smith and Wyatt, 2007). The product was later upgraded by producing the Land Cover Map 2007 (LCM2007) in which parcel-based segmentation, using the polygons of the Ordnance Survey MasterMap (OS MM), and rule-based classification methods were applied (Smith et al., 2007).

A general review of these national products revealed that the input data used were mainly Landsat TM and ETM images in conjunction with SPOT, IRS and IKONOS imageries. A wide range of ancillary data such as aerial photography, elevation information and the CORINE Land Cover (LC) has also been employed. In most cases, multi-scale methodologies were applied (most commonly in 3 levels) with a range of minimum mapping unit (MMU) of 0.5-1 ha. The object extraction is either based on segmentation techniques (such as the LCM 2000 in UK and the Harmonise Object Oriented Data Model (OODM) in Spain), or on the use of ancillary data for parcel-based classification (LCM 2007 in UK and DLM-DE in Germany). In the LCM2007 the object extraction was based on polygons derived from cadastral information such as the Ordnance Survey (OS) MasterMap, while the Authoritative Topographic-Cartographic Information System (ATKIS) was used in Germany. For the validation and verification of the products, field surveys and visual interpretation of VHR data were applied. The review also identified that in all products a lot of manual aerial photo interpretation was still required, mainly for the validation of the data but also for the production of certain classes. The technical features and specifications of each national product are summarised in Table 2-4.

Table 2-4. Summary of object and parcel based land cover mapping operational applications

National Land Cover Mapping	Input data		Methodology			Production
	Image data	*Ancillary data*	*Minimum Mapping Unit*	*Hierarchy*	*Validation*	
UK	Landsat-5 TM, ETM (25m)	OS MasterMap	0.5 ha	Multi-scale levels	filed survey	National Land Cover Map (LCM) 2007
	IRS (25m)	DEM			visual intepretation	
		Soil types				
		Socio-economic data				
Spain (application also in Norway)	Landsat ETM (25 m)	Orthophoto	0.5-1 ha	Multi-scale levels	sample points-visual interpretation	Harmonised Object Oriented Data Model (OODM)
	Landsat (30m)	Corine land cover				
	IRS (25m)	Cadastral info				
	SPOT (2.5m)	National crop maps				
	IKONOS (1m)					
Sweden	Lansdat-7 (25m)	CIR aerial photos	1:50.000	Multi-scale levels	sample points-visual interpretation	Swedish land cover data (SMD)
		DEM				
		Vegetation maps				
		Forest maps				
Germany	Landsat TM, ETM (25m)	ATKIS data	0.5 ha	Multi-scale levels	filed survey	Digital Landscape Model (DLM-DE)
	IRS (25m)	DEM				
		Soil types				

2.7 Comparison of pixel vs. object based classification methods for urban land cover mapping

Object based image analysis (OBIA) is promising great potential to improve classification accuracies of land cover and land use mapping. Although OBIA is increasingly being used there are few studies that have specifically tested object based results in comparison with pixel based approaches.

Mittelberg (2002) attempted to analyse the urban environment of a typical suburban residential area outside Toronto (1 x 1 km), by using aerial photography and very high resolution IKONOS data. The classes contained in the class hierarchy were: water, woods, greenland, streets, bank promenade, remnants, residential areas and shadow. Both aerial and satellite imagery were classified using an object-based approach and then compared with a per-pixel maximum likelihood classification, for the aerial image and the neural network classifier approach, for the satellite image. Comparing pixel and object based classification techniques, the results showed better accuracy when object-based classifiers were used to analyse both satellite and aerial images. The classification of the panchromatic aerial photography was of medium accuracy while the satellite imagery had better accuracy due to the additional spectral information (i.e. the near infrared channel). The overall accuracy of the object-based classification was 74.4% compared with 67.4% with the neural networks pixel classification.

Hodgson et al. (2003) used aerial photography and elevation data (LIDAR), of South Carolina, to identify urban imperviousness with three different approaches: maximum likelihood classification, ISODATA clustering classification and “rule-based per-segment” classification using the See-5 algorithm. The data were compared with the visual interpretation of the aerial photography that was segmented with the use of eCognition software. The land cover of each segment was identified and labelled manually. The results showed that the additional use of LIDAR data improved all of the classification techniques. In addition, the most suitable methods for mapping surface imperviousness proved to be the maximum-likelihood pixel classification and the “rule-based per-segment” classification. Slightly better results were achieved by classifying the image with the “rule-based per-segment” classification; R^2= 0.78 with standard error 5.85 for the object classification compared with R^2= 0.71 with standard error 6.62 for the pixel classification.

Blaschke (2004), from a theoretical point of view, discussed about the advantages of using image segmentation as a pre-classification step, mainly due to the ability to use context and texture information and group pixels into meaningful image objects. The way that object-based methods can improve image analysis in comparison to pixel-based methods was also reviewed.

Cothren and Gorham (2005) analysed QuickBird satellite images, 2-feet ground sample distance (GSD), to detect impervious and permeable surfaces. The classification accuracy was nearly 90% with object-based classifiers and 78-80% when pixel-based classifiers were used. More details about both classification methods applied and the accuracy assessment used were not provided within this publication. That was a general phenomenon with the OBIA publications at the recent years (2000-2006 approximately). As the object-based classification method was a new approach in remote sensing, scientific papers were easier accepted for publication in comparison to the current situation.

Platt and Rapoza (2008) evaluated the object-based image analysis by comparing nearest neighbour algorithms, using the eCognition software version 4, with the traditional pixel based maximum likelihood classification for land cover/ land use mapping of Gettysburg, Pennsylvania. Their study area was a rural region of 148 Km^2, northwest of Baltimore and Washington DC and the data used was IKONOS satellite imagery, 4 m resolution. The conclusion of their study was that OBIA improved the classification accuracy, mainly due to the opportunity of using expert knowledge during segmentation and classification processes. However, specific methods of the accuracy assessment and final accuracy results were not included on the paper.

Zhou et al. (2008) assessed pixel-based with object-based post classification comparisons for land cover change detection of the Gwynns Falls watershed, USA. The overall accuracies of the pixel and object based approaches were 81.3% and 90% respectively. As it was argued, the object-based post classification method was superior due to the fact that the user's and producer's accuracies for certain classes, of the pixel-based change detection method, were too low (i.e. ranging from 43.6% to 48.3%) while both user's and producer's accuracies of the object-based change detection method were constantly high, ranging from 81.8% to 96.3%.

Cleve et al. (2008) investigated the accuracy of pixel-based and object-based classification techniques for mapping the wild land-urban interface (WUI) within a Deer park in Napa County, California. For this purpose aerial photography, 0.15 m resolution, was classified into four categories: (i) built-up areas (structures and transportation), (ii) surface vegetation (grassland, irrigated lawns, urban landscaping, and agriculture), (iii) trees/shrubs and (iv) shadow. An unsupervised pixel-based classification (ISODATA) and a combination of fuzzy and nearest neighbour supervised object-based classification were compared with 256 visually interpreted random points and the overall accuracy was increased from 62% (pixel) to 80% (object). They concluded that object-based classification performed specifically well in identifying the built-up areas.

2.8 Summary

Given the background for mapping urban land cover environments by remote sensing the literature review points towards the following conclusions:

A variety of operational projects have been developed aiming to monitor soil sealing in Europe such as a range of GMES projects (GSE Land, GUS, MURBANDY) or the MOLAND and ENVASSO projects. Due to the mapping requirements at national or European levels, the data used for the implementation of these operational studies were mainly low resolution satellite images at 20-25 m resolution (Landsat, SPOT, IRS). As this PhD study aimed to map urban soil sealing at very large scales (within the cities) such data and methods provided were not appropriate due to their limited information about soil sealing at such scales.

The use of very high resolution (VHR) satellite data such as QuickBird, IKONOS provide potential capability for mapping urban complex features in detail. In nowadays, the full potential of new VHR satellite image data, the decreasing cost and the increasing availability leads to gradually more successful use of digital satellite data for mapping urban land cover and impervious surfaces worldwide.

Standard true-colour (RGB bands) aerial photography is also a potential data source. The advantage of using aerial data is the spatial resolution which is much higher than the satellite data providing more detail at a local level. However, it might produce limitations due to lack of the infrared wavelength which is important when separating vegetation from non-vegetation classes. This needs to be investigated. Nevertheless, new aerial photographic data with additional use of the Near Infrared (NIR) band are increasingly available; for example, the Leica ADS40 Airborne Digital Sensor with 5 centimetre spatial resolution.

A variety of research for mapping urban soil sealing has been conducted using pixel and sub-pixel classification techniques. However, the literature review has indicated that there are a number of limitations in pixel-based classification methods, especially when VHR data are used:

- the reflectance of the pixel does not correspond always to the field-of-view, e.g. it may come only from the central part of the pixel, or partially from the surrounding pixels depending on the specific sensor (Townshend et al., 2000).

- in high and very high resolution (VHR) imagery, the increase in spatial resolution results in an increase in variability within land parcels ("noise" in the image), generating a decrease in classification accuracy (Caprioli and Tarantino, 2003; Yuan & Bauer, 2006)
- typical pixel-based approaches use only the spectral information of each pixel itself and do not take into account context and spatial information (Burnett and Blaschke 2003; Benz et al., 2004)
- pixel-based approaches are in contrast with the human perception in visual image interpretation. When visually interpreting features in natural or urban environments, "humans neither observe nor think in pixels" (Blaschke et al., 2005)
- pixel-based approaches work at single scales while complex systems, such as the land cover, are inherently hierarchical multi-scale systems (Benz et al., 2004; Blaschke, 2004).

New approaches in image classification (i.e. object-based methods) seem to produce better results and to increase the overall accuracy compared to pixel-based approaches. This is mainly due to the ability given to the user to employ spectral, spatial, contextual information and expert knowledge for the classification of the objects of interest. The "trend" of moving from pixel-based classification methods towards object-based methods for land cover mapping can be implied by the increased in number scientific publications (year 2005 and onwards as well as from the recent applications of OBIA in national operational projects. However, in order to have a robust argument of OBIA's superiority, comparisons between pixel and object based approaches for mapping urban land cover at very large scales should be explored.

The classification of urban environments and the identification of surface impermeability have been explored in the past. But most of the research has either been conducted using broader scales than the project aims to; for example, the attempt to classify amalgamated blocks of the built environment to map urban growth, in Germany. There are few very recently published examples that studied soil sealing at large scale but the test site is either very small or have different land cover structure compared to the urban environment in the UK (USA or New Zealand).

Furthermore, the method of visual interpretation of aerial photographic data has been broadly used in order to either:
(i) produce the reference data for comparison with digital classification techniques or (ii) for enhancing automated classification results for mapping certain classes, by manual editing. Manual classification by visual interpretation is time consuming and laborious. The need is still to find an automated method for urban land cover classification, at very large scales, without the necessity of performing API in order to achieve the thematic accuracy that is required.

Chapter 3

The study area and data description

This chapter firstly provides an introduction to the study area in relation to location, land cover characteristics, population and urban growth during the last decades. The data used for the implementation of this research study are also described. Finally, an analysis of the development of the land cover typology scheme regarding the data availability and the features types of the study area follows.

3.1 The study area

The area used for the implementation of this research is the city of Cambridge, Cambridgeshire, UK, which is located in East Anglia, (Figure 3-1). The particular site was chosen due to the data availability of the specific region but also due to its characteristic urban formation. Cambridge has a residential type area that is particularly common to the south-east part of England. The industrial areas of Cambridge vary from the old traditional to newly developed industrial types. Cambridge in general, consists of a variety of land cover features which form the urban structure for most cities within UK.

According to Cambridge City Cancel, during the last 50years the population of Cambridge increased from 81,500 to 108,863 while the city has expanded by 2,800 hectares. Clearly, Cambridge has not grown a lot during the last half of the century (Figure 3-2) and it has been well preserved as the traditional university city.

The town centre of the city is predominantly sealed with densely spaced, large commercial buildings and very few vegetated areas, like in most cities across the country. The big difference in Cambridge is the existence of the university colleges within the centre which cover a big area with open green space, consisted of lawn covered parks and trees. Around the city centre, the typical Victorian and Edwardian terraced houses exist. This residential part of the city is densely built with narrow gardens, giving a medium area of vegetated surfaces. At the outskirts, particularly in the north side where the main expansion of the city has occurred, the residential type changes to the low in density, 1960's semi-detached houses with broad large gardens. Due to the age of the city and to its low expansion, the residential gardens of Cambridge are mostly mature with large trees giving a high percentage of urban green. The industrial area, which is mainly on the east side of the city along the rail track lines, comprises large industrial buildings and it is predominately sealed with very little vegetation.

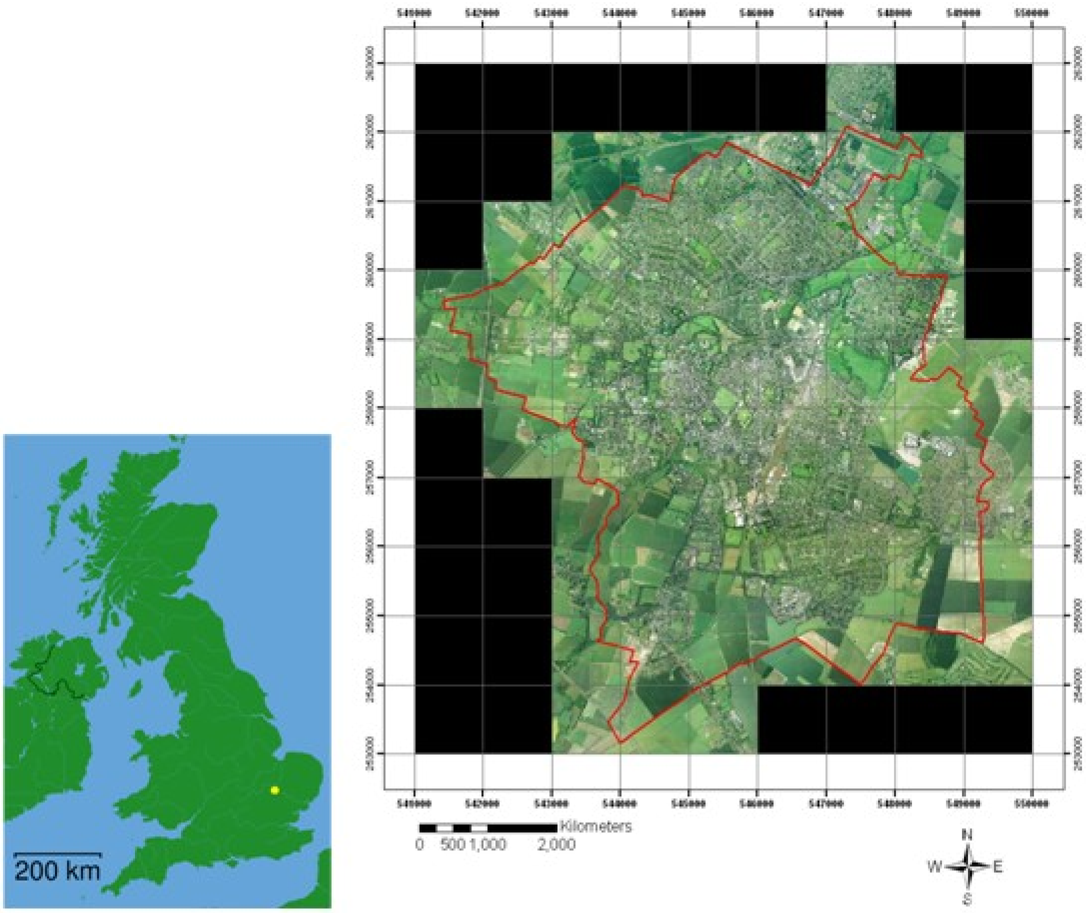


Figure 3-1 The location of the city of Cambridge in UK and the Cambridge district as shown from mosaic of ortho-corrected aerial photography

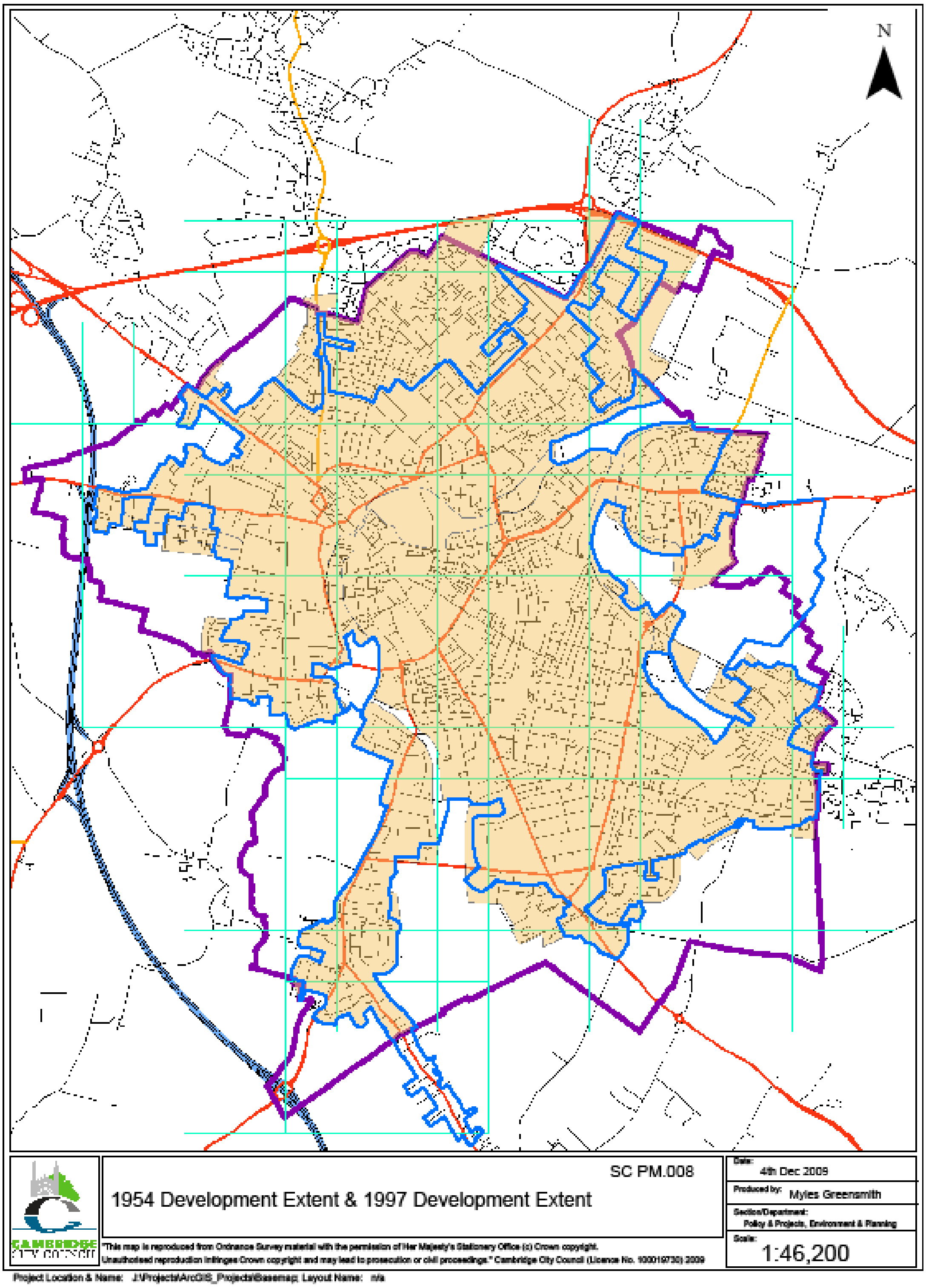


Figure 3-2 The urban growth of Cambridge during the last 50 years. The blue lined boundary indicates the size of the city in 1954 while the orange shaded area indicates the city boundaries in 1997. The purple line represents the Cambridge district

3.2 Data acquisition

The available data sources acquired for the analysis of this research study were:

1. Aerial photography taken in June 2003, consisted of 63 tiles of 1 km squared each and ortho-corrected with a simple rubber sheet transformation. The resulting image is a true colour aerial photograph, with red, green and blue (RGB) bands, at 0.125 m spatial resolution, 8 bit radiometric resolution and georeferenced in D_OSGB 1936.
2. QuickBird satellite imagery taken in October 2003, covering an area 8 x 8 Km. The image is at spatial resolution of 2.8 m multispectral (MS) and 0.7 m panchromatic (PAN) with spectral properties of 0.45-0.52, 0.52-0.6, 0.63-0.69, 0.76-0.9 μm and 16 bit radiometric resolution.
3. Ordnance Survey (OS) MasterMap at 1:1250 scale. The OS MasterMap contains baseline polygons delineating transport network infrastructure as well as residential and commercial buildings. Additionally, each polygon has a unique Topographic Object Identifier (TOID) 16-digit number for easy identification. Each polygon feature is grouped onto one of the following theme names: “buildings”, “roads, track and paths”, “land”, “structures”, “rail” and “water”.

3.3 The urban land cover typology of Cambridge at large scales

According to Anderson (2001), a land cover classification system should meet the following criteria:

- The classification system should be suitable for use with remote sensing data obtained at different times of the year
- The minimum level of interpretation accuracy in the identification of land cover categories from remote sensing data should be at least 85 percent
- The accuracy of interpretation for the different land cover categories should be about equal

- Repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another
- The classification system should be applicable over extensive areas
- Effective use of subcategories that can be obtained from ground surveys or from the use of larger scale or enhanced remote sensing data should be possible
- Aggregation of the land cover categories must be possible
- Comparison with future land cover data should be possible

The development of the classification scheme is depended on the requirements of the project and the resolution of the remote sensing data used. The minimum mapping unit is also in close relation to the spatial resolution of the remotely sensed data used. Regardless the desirable mapping scale, the urban land cover objects are defined as fairly complex and indistinct due to the heterogeneity of the urban environment (Ridd, 1995). The available data for the classification scheme development of this PhD study was a true colour aerial photography at 0.125 m resolution. The aim was to monitor urban sealed soil and vegetated surfaces at the larger possible scale that the available data would allow according to their spatial resolution. The land cover classification system was based on the identification of every different land cover feature type that could be observed at such resolution, by the visual interpretation of the aerial data. The first and most important step in visual interpretation is the definition of the mapping scale and the development of the interpretation key that is adapted according to the aim of the interpretation and the data used (Grenzdorffer, 2006). The recognition of a certain scale and a minimum mapping unit has great significance because the interpreter needs to follow a certain pattern during the identification of the objects of interest. The visualisation of the aerial photography of the city of Cambridge recognised a big variety in size of the urban land cover types in the built environment of Cambridge (Figure 3-3). Examining the typical range of cover, given in Figure 3-3, a minimum mapping unit (MMU) of 2 m (i.e. area coverage of 4 m^2) was determined. Other parameters that influenced the decision of choosing a scale of 1:200 were: (i) a larger scale than 1:200 revealed a higher degree of pixelation which was difficult to interpret (ii) mapping features smaller than 2 m would produce “noise” in the final map due to the very small size of the delineated objects and (iii) the larger the mapping scale the larger the data size for image processing.

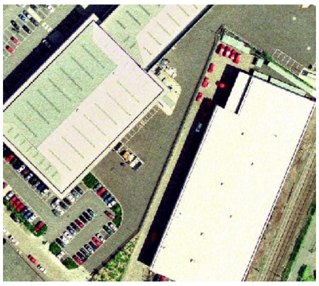
Large scale land cover features	**Small scale land cover features**	**Typical range of area cover**
Roof 	***Roof*** 	***Roof*** 5 – 4600 m^2
Lawn/ grass 	***Lawn/ grass*** 	***Lawn/ grass*** 5 – 2700 m^2
Tree 	***Tree*** 	***Tree*** 5 – 450 m^2
Road 	***Road*** 	***Road*** 100 – 2800 m^2

Figure 3-3 Indication of the large variability of urban land cover features in relation to size and area coverage

The visual photo interpretation, which can be defined as the automated extraction of semantic information from the imagery, is considered to be a difficult issue (Durand et al., 2007). In object based image analysis (OBIA) specifically, the semantic information that is used to interpret and classify an image is not only linked to pixels but also to meaningful objects and their mutual relations, which include spectral and additional spatial and contextual information. In order to give the objects a semantic meaning a matching process between the object and the ontology must be developed (Durand et al., 2007). There is a close resemblance between the real world objects and the feature objects in an ontology model. In computer science, ontology is a model for describing the world that consists of a set of types, properties, and relationship types (Wikipedia, 2010). In a land cover classification system, the ontology model describes a set of features (the land cover classes), their characteristics and their relations to each other. Fonseca et al. (2002) described a five-universes example for a better understanding of the role of ontologies in computer modelling: i) the physical universe, which consist of the real world objects that will be modelled in the computer, ii) the logical universe, which includes the definition of these objects, iii) the representation universe, in which the mathematical description of the objects is applied, iv) the implementation universe, which is used to map the representation universe in a computer language and v) the cognitive universe, which captures the human understanding about the physical universe, i.e. the real world, the earth's land cover such as the lakes, the rivers, the cities, the woodlands etc. In geographical information and remote sensing the physical, cognitive and logical universes are used for image interpretation and the development of a classification scheme. Initially, the physical universe has to be captured with the use of earth observation data. An understanding of the existed real world objects, identified in the remotely sensed data, is then required. The feature extraction and the definitions of these real worlds objects follow. As already aforementioned, in this PhD study the physical universe of Cambridge was captured by aerial photography at 0.125m resolution. The urban land cover types that were identified within the city of Cambridge (feature extraction), at different scales, and their relation to soil sealing are shown in Table 3.1. These land cover types, which were disaggregated to form the image classification typology, comprised the interpretation key. The classification scheme developed was the tool kit for the future manual classification via air photo interpretation as well as for creating the desirable class hierarchy for the development of the semi-automated and automated object-based classification methods.

The development of the classification scheme focused on the aim for monitoring soil sealing. Soil sealing mapping can contain information about the type of the building development as well as about the ground cover type such as asphalt, concrete or cracked pavement, which allows a reduced soil functionality and vegetation growth. Based on the fact that remote sensors can only see the physical layout of the land cover features the degree of surface permeability was beyond the scope of this research study. This type of analysis could have been implemented if thermal data were available. Thermal data are capable of measuring the underlying surface temperature giving an estimate of whether the surface is permeable or not (Warner and Chen, 2001). Sealed soil surfaces were considered to be caused only by infrastructural sealing and not by crusting, capping or compaction (e.g. compacted soil in public green spaces). As soil sealed areas were identified to be all the built up areas, the discrimination of sealed vs. unsealed areas was equated as sealed vs. vegetated areas. An exception was the “bare soil” urban feature which is a non built-up as well as a non-vegetated feature but undoubtedly unsealed. Similarly, open water features were identified as “water”.

Furthermore, since the classification methods were based on the use of earth observation data, shadow was an issue. In automated classification methods the software cannot recognise the actual land cover types in shadow. Specifically in urban environments, the identification and classification of the shaded areas is a particular significant problem with the use of VHR data because the elevation varies dramatically. In order to deal with this problem, a typical procedure in object-based automated classification is to firstly identify the polygons in shadow and then “replace” these polygons with an existing land cover class. This is the reason why also shadow exists as a class in the image classification scheme. Shadow must initially be treated as a class for potential further analysis.

Table 3.1 The land cover classes used for image classification and their relation to soil sealing and the features type

Image classification	Sealed/ Unsealed	Land cover type
Built- up areas	Sealed surface	• Roof (grey, red, white, green) • Road (dark, light) • Roadside (dark, light) • Path (dark, light) • Yard/drive • Cark park • Shed • Patio • Artificial sport surface
Vegetated surfaces	Unsealed surface	• Grass/ lawn • Shrubs/bushes • Playing field • Allotment
Trees	Unsealed surface	• Individual or band of trees (green, red, yellow)
Rail tracks	Unsealed surface	• Rail tracks
Bare soil	Unsealed surface	• Bare soil • Construction site
Water	Water	• River • Lake • Pond • Outdoor swimming pool
Temporary feature	N/A	• e.g. trampoline
Arable field	Unsealed surface	• Arable field (green or soil)
Shadow	N/A	N/A

3.3.1 The National Land Use Database (NLUD) of UK

A classification system should be as compatible as possible with other classification systems that are broadly in use (James et al., 2001). In UK, a widely used classification system is the National Land Use Database (NLUD). The NLUD classification scheme originally aimed at the development of baseline data for land use change evaluation. A newer version of the NLUD targeted on clear separation between land use and land cover classes. “The NLUD baseline methodology assigns a land use and land cover attribute to each topographic feature within OS MasterMap by deriving information either directly from the ‘internal’ OS MasterMap feature descriptions or indirectly from ‘external’ data sources with national coverage” (Harrison, 2006). The NLUD consist of a two-tier hierarchical classification schemes which were separately developed for land use or land cover classification. The nomenclature developed for a land cover classification is presented in Figure 3-4.

The NLUD has been designed to provide a general purpose land cover classification system at national level. The land cover features identified in the NLUD system could have been grouped according to sealed vs. unsealed surfaces in order to meet the objectives of this research study. One reason that this did not happened is the mapping scale. The NLUD typology was based on national land cover mapping while the aim of this research was a localised sealed vs. unsealed mapping at “domestic garden level” scale. Consequently, the typology used in this PhD study is a simplified classification desired for the specific purpose of this research. The main difference between the two classification schemes is that at this research study, the image classification typology was developed for the use in semi-automated/automated image classification techniques; therefore classes such as shadow were included.

ORDER		GROUP	
C010	CROPPED LAND	C011	Field crops
		C012	Fallow land
		C013	Horticulture
		C014	Orchards
C020	GRASS	C021	Improved grass
		C022	Unimproved grass
		C023	Recreational and amenity grass
C030	WOODLAND AND SHRUB	C031	Conifer woodland
		C032	Mixed woodland
		C033	Broad-leaved woodland
		C034	Shrub
C040	HEATHLAND AND BOG	C041	Heathland
		C042	Bracken
		C043	Bog
		C044	Montane
C050	INLAND ROCK	C051	Inland rock
C060	WATER AND WETLAND	C061	Standing water
		C062	Running water
		C063	Freshwater marsh
C070	COASTAL FEATURES	C071	Sea and coastal waters
		C072	Inter-tidal sand and mud
		C073	Salt marsh
		C074	Dunes
		C075	Coastal rock and cliffs
C080	BUILDINGS AND STRUCTURES	C081	Building
		C082	Other built structure
C090	PERMANENT MADE SURFACES	C091	Metalled roadway
		C092	Railway
		C093	Pathway
		C094	Other made surface
C100	GENERAL LAND SURFACES	C101	Multiple surface
		C102	Bare surface

Figure 3-4 The British land cover classification scheme at national level

Chapter 4

Preliminary work

This chapter analyses the classification of satellite data using pixel-based techniques and its comparison with reference data produced by overlaying the Ordnance Survey MasterMap onto the aerial photography of Cambridge. The following methodology identified in a funded research project by the Department for Environment Food and Rural Affairs (DEFRA) and the British National Space Centre (BNSC), was carried out by Cranfield University. This project formed the basis of a pilot study for this present PhD research.

The material presented on this chapter is extracted from the final report of the GIFTSS project (Wood et al., 2006) and it is either exclusively written by the author or it is a contribution of the author to the writing of the report. Part of this work has also been presented at the 1st International OBIA conference in Salzburg, Austria in 2006.

4.1 Production of reference data

The study area is the city of Cambridge, UK. The data sources acquired for the analysis are listed in the section paragraph 3.2. Due to the size of the data, sample segments of the area (250 m x 250 m) were used for the development of the digital methodology. From a total of 650 possible segments, 18 samples were randomly drawn (c.2.5%). These sample segments were used for the development of the validation (reference) data by aerial photo interpretation (API).

The OS MasterMap was overlaid onto the true colour aerial photography for the visual interpretation process and the baseline map production (Figure 4-1). Baseline maps of sealed soil were produced by developing and implementing a key interpretation to selected ortho-corrected aerial photography. The key interpretation included: (i) visual aerial photo interpretation, (ii) image segmentation according to the developed typology, analysed in chapter 3, and (iii) ground survey for the refinement of both interpretation and typology.

Figure 4-1 Orthophoto mosaic of the aerial photography of Cambridge with the 250 x 250 m 18 sample areas within the city of Cambridge. The example square illustrates the detail of the 1:1250 scale Ordnance Survey Master Map.

4.1.1 Aerial photo interpretation

The production of the API data was based on the specific classification scheme developed in the previous paragraph chapter 3. 3 (Table 3.1). Six land cover classes were introduced for the classification process: (i) sealed surfaces, (ii) vegetation surfaces, (iii) trees, (iv) bare soil and (v) water.

The segmentation of the sample areas was based on the pre-identified polygons of the OS MasterMap, by overlaying the OS MasterMap onto the aerial photography of Cambridge. The classification achieved by visual interpretation and manual labelling of the extracted polygons. The proportions of each land cover class, within each polygon, were estimated visually and limited to a precision of 25% intervals, i.e. 0, 25, 50, 75 or 100%. The percentage ranges were calculated by mentally dividing each OS

MasterMap polygon into four parts and calculating the proportion of each existing land cover feature.

Sealed soil surfaces were considered to be caused by infrastructural sealing and not by crusting, capping or compaction in public green spaces. Vegetated surfaces were equated to unsealed soil, and non-vegetated surfaces were equated to sealed soils. Bare soil was visually classified as unsealed. But due to the expected infrequency of bare soil within urban environments, this class was considered negligible for the statistical analysis and accuracy assessment of the research.

The fact that there were many examples where sealed surfaces, vegetation, trees and bare soil had an area percentage per MasterMap parcel smaller than 25% lead to the creation of three more classes: (i) less than 25% sealed, (ii) less than 25% grass and (iii) less than 25% bare soil. Whenever one of these classes were a part of a polygon's classification a value of 1 was noted in the database to indicate a presence. Furthermore, these classes were not calculated into the total percent of each class. They just point out the characteristics of each polygon with every possible detail that a human eye can catch. Additionally, one further class was created named as "notes" and any comment that may have an effect on the interpretation of the data was added. In few examples the description in the MasterMap attributes of a polygon didn't match with what could be seen in the photograph and this mismatch was noted in that class (Figure 4-2). The classes were added to the attribute table of the Master Map in the ArcGIS programme where the classification occurred (Figure 4-3). Finally, the total percentage (%) of each class, for each sample segment, was calculated (Table 4.1).

Figure 4-2 The highlighted polygons according to OS Master Map data are buildings. In the photo on the left it is clear that only grass is now there while in the photo on the right it is impossible to say whether there is a building or not due to overlying trees – the same problem will be encountered using satellite imagery.

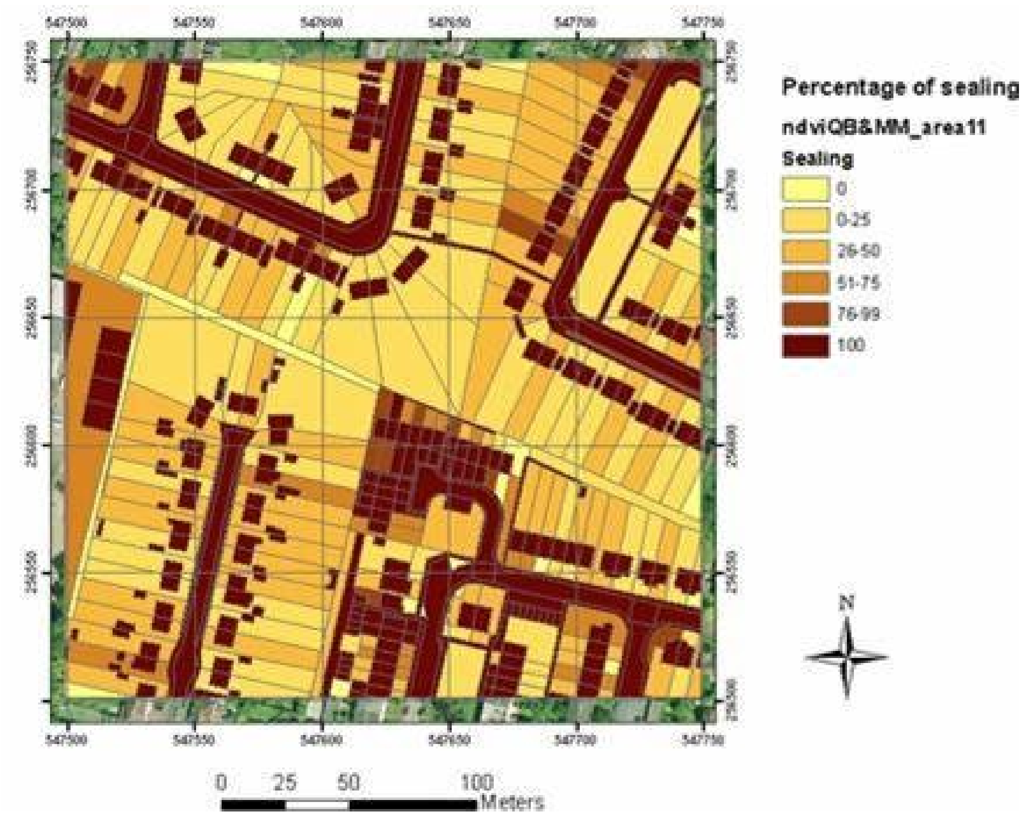


Figure 4-3 The classification of sample area 11 according to sealing by visual interpretation of the aerial photograph

Table 4.1 The total percentage (%) of each class for all the sample areas

Sample areas	**Area Sealed**	**Area Surface vegetation**	**Area Trees**	**Area Bare soil**	**Area Water**	**Area Unclassified**
Area 1	53.22	17.30	12.35	6.58	10.31	0.02
Area 2	19.78	67.03	13.19	0.00	0.00	0.00
Area 5	57.27	20.58	14.67	6.49	0.00	0.98
Area 6	65.61	7.85	24.08	1.87	0.00	0.57
Area 10	18.82	45.25	31.16	4.06	0.00	0.71
Area 11	50.41	33.63	15.57	0.32	0.00	0.07
Area 12	21.60	72.41	5.16	0.69	0.00	0.13
Area 13	39.90	44.95	13.75	0.03	0.00	1.39
Area 16	18.78	62.12	18.39	0.62	0.00	0.08
Area 17	21.72	65.45	12.65	0.11	0.00	0.08
Area 19	34.46	41.15	16.37	5.25	0.00	2.76
Area 20	92.29	3.17	4.49	0.01	0.00	0.03
Area 21	19.15	53.88	23.39	3.32	0.00	0.27
Area 22	33.30	43.82	21.87	0.55	0.00	0.45
Area 24	73.84	11.65	14.45	0.00	0.00	0.05
Area 25	41.07	45.46	2.15	11.32	0.00	0.00
Area 26	46.31	34.03	19.62	0.04	0.00	0.00
Area 28	58.90	4.64	36.43	0.00	0.00	0.05

4.1.2 Field work

After the completion of the visual classification of the photography, a visit to Cambridge took place. The scope was to walk in various areas that had been identified as difficult to interpret in the aerial photography and to become familiar with the land cover characteristics of the area.

The ground verification is a supporting tool that also helped to understand errors and misclassifications occurred when compared different data sets. For example, during the visit new developments had been found that did not exist in the aerial photographs, but had been built (at least commenced) by the time the satellite images had been acquired and the time of the visit (Figure 4-4). Note was made of the time passed between image date (2003) and the field trip (2006).

Figure 4-4 Sample area 25 as it looks in the aerial photograph and on the day of visiting Cambridge. Part of the new development has been also detected on the satellite image.

4.1.3 Problems met

I. Ordnance Survey MasterMap

A time consuming problem was the duplication and the overlapping of polygons found in the original OS MasterMap. The result of this was the incorrect over-estimation of the total area of each sample and class. Working in the ArcGIS environment, the problem was solved by exporting the “shapefile” of each sample area to a “geodatabase” and by creating a new topology with the rule “polygons must not overlap” (Figure 4-5). The new topology showed where the errors were and resolved by deleting the duplicated polygons. In cases where one polygon also belonged to another and could not be deleted the “shapefile” was exported to “coverage” and then the “union” overlay process was followed to join the attribute table from the original feature class with the topology errors to the imported feature class. Finally, all the problematic areas were recalculated.

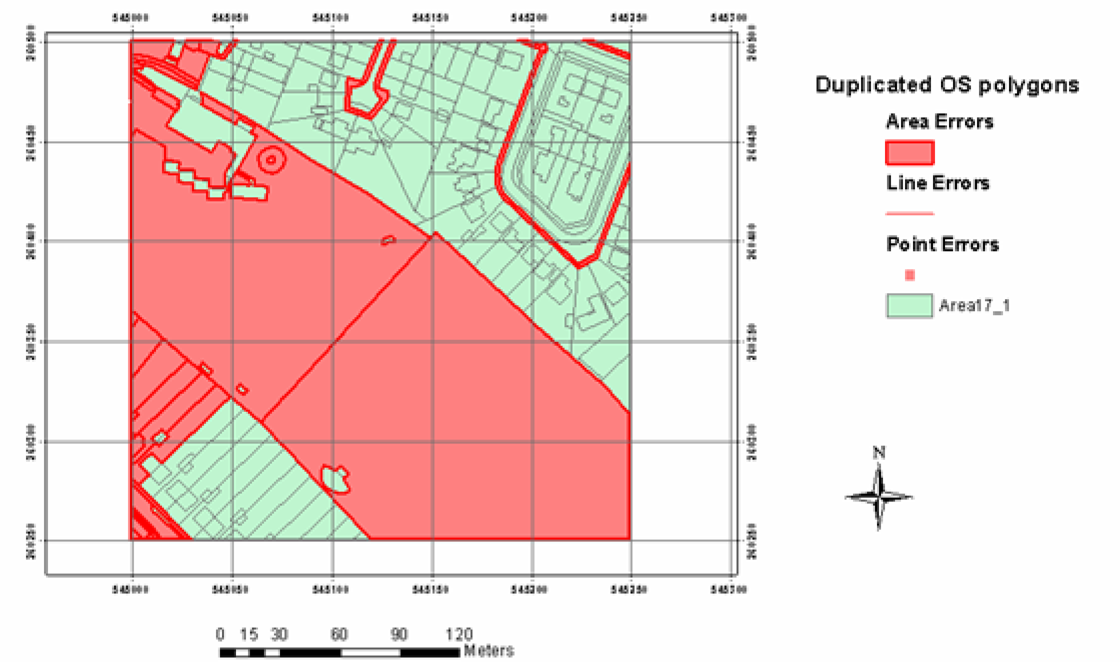


Figure 4-5 The production of typology for area 17 shows where exactly the problem of the duplicated polygons occurred.

The duplicated polygons are a result of the way in which Ordnance Survey (OS) includes information in the MasterMap. Basically, apart from the underlying polygons which represent what is on the ground there is also a polygon that sits on top representing slope, named “landforms” polygons. There are also a few instances of what the OS term "broken" polygons which create some of the feature stacks. These features are an artefact of the OS editing environment and are being removed as the OS transition to their new editing environment. Normally there is an attribute flagging these but in this case it was not present which made it more demanding to detect and remove. It also appeared that some of the features are duplicates which are related to the way that the OS delivers data as "hairy" tiles; meaning that you get the same feature repeated if it sits on a boundary between two tiles. These can be separated by removing data that shares the same TOID (unique Topographic Identifier in MasterMap).

Whether the problem of duplicated polygons will always occur or not, regardless of the source of the data, depends on the type of the duplicated polygons. The OS only ever ships exact duplicates on tile boundaries in the supplied GML files where the duplication will have to be handled regardless of the data source. However, most

MasterMap translators suppose to handle this so it would not really be a big issue. That "problem" was not met in the current OS MasterMap data which was supplied in single file and not in tile format. The other cases of duplicates or overlaps would be with the "landforms" or the "broken" polygons and these can be processed out when the data are translated or as a post processing option. Both of these are simple to identify through the data's attribution and the choice to leave them or process them depends on the intended application; for example, "Landform" polygons are important if the data are being used as a cartographic output but they should be removed for the purpose of extracted area estimations. Landforms and broken polygons were the only case of duplication, in the work presented here, which will always occur independently of the data source. So, it is necessary to check the data by creating the topology and deleting the duplications before continuing with any other processing.

II. Visual interpretation

The most frequent difficulties in aerial photo classification were due to shadow and roof leaning (relief displacement). The taller the buildings are the greater mismatch between the air photos and the MasterMap will be introduced (Figure 4-6i). Furthermore, tree and building shadow is a common problem in the aerial interpretation and is the reason behind most unclassified polygons (Figure 4-6ii). Apart from their shadow, trees can cause problems with their canopy. There were situations where trees covered the whole or a part of a building, paths, roads and road side verges (Figure 4-6iii). These areas were classified according to what can be seen (i.e. tree canopy) but notes were kept to indicate what, intuitively, was there (i.e. if a path reaches a tree and then continues after the tree, it would seem reasonable to assume the path still exists under the tree canopy). Another difficulty was in front gardens which were often very small in size and were very difficult to determine the percentage sealed; such small patches would not be spatially resolved in the satellite images (Figure 4-6iv).

i)

ii)

iii)

iv)

Figure 4-6 i) Building leaning, ii) two examples of the shadow effect, iii) tree canopy covering road & roadside and iv) small front gardens

4.2 Pixel based classification using VHR satellite data

The data used for the development of the pixel based classification method was a QuickBird imagery with red, green, blue and near infrared bands, at 0.7 m PAN and 2.8 m MS spatial resolution.

4.2.1 Maximum likelihood classification

The maximum likelihood algorithm (Richards and Jia, 2005) was used for the classification of the VHR satellite data. Due to the fact that sealed vs. unsealed surfaces were equated with non-vegetated vs. vegetated surfaces, respectively, the classification method aimed at identifying vegetation.

The use of image band combinations from the red and near infrared wavelengths provides the greatest opportunity for discriminating vegetation (Jensen, 2000). Such band combinations are typically referred to as vegetation indices; the most popular is the normalised difference vegetation index (NDVI) which is calculated as:

$$NDVI = \frac{\rho_{IR} - \rho_R}{\rho_{IR} + \rho_R}$$

where ρ = the pixel reflectance value

ρ_{IR} = the pixel reflectance value in the near infrared (IR) waveband

ρ_R = the pixel reflectance value in the red (R) waveband

An NDVI imagery, extracted from the QuickBird multi-spectral satellite image, was used for further analysis. The NDVI image classification consisted of two stages: i) "training"– the production of signatures by extraction of sample satellite image pixels from locations of known land-cover, ii) image classification based on the maximum likelihood.

For the selection of the sample areas, a similar procedure as described for the API data sampling was followed. From the total of 650 possible segments of the city of Cambridge, 18 samples were randomly drawn (Figure 4-7).

The aerial photography of Cambridge was used to select training pixels in QuickBird imagery (i.e. the seed points forming a cross shaped pattern of five pixels) and to create the signature classes for the supervised classification by using the ERDAS Imagine software (Figure 4-8). The land cover typology, in which the signature classes were based, was derived by the land cover types (i.e. roofs, roads, lawn, trees etc) observed in the high resolution aerial photography. At the end, a simple two class grouping of sealed vs. unsealed land was provided.

Finally, the NDVI image was classified with a maximum likelihood supervised classification. The image was reclassified according to the binary format of sealed vs. unsealed classes and was exported into ArcGIS to be spatially joined with the OS MasterMap data. The attributes of the Master Map were used to mask the entire "manmade" infrastructure (i.e. roads, roadsides and buildings). The remaining polygons were identified with a 0-100% percentage of sealing.

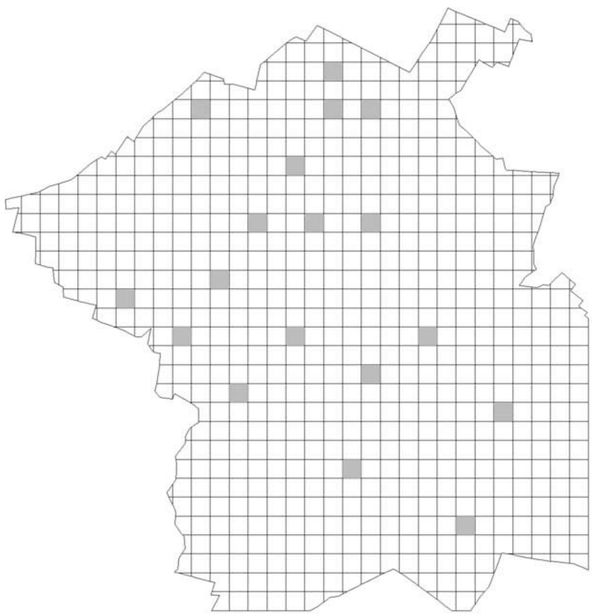


Figure 4-7 A 250 x 250 m area-frame overlaid over the district of Cambridge. The filled squares represent the random samples

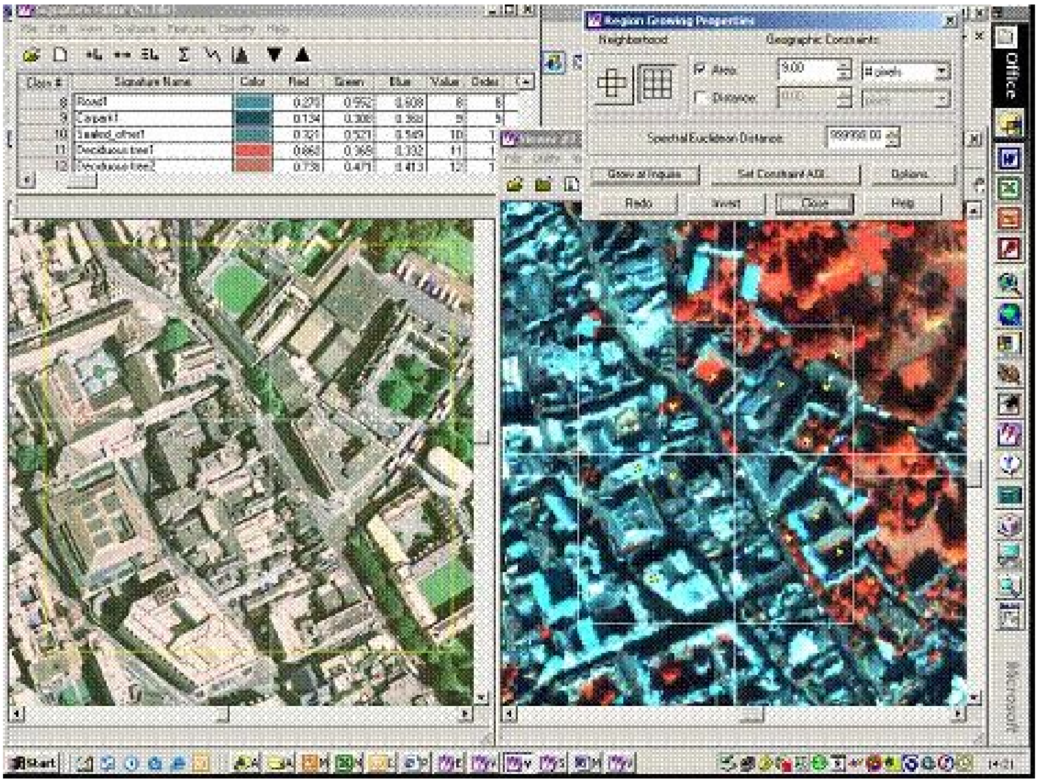


Figure 4-8 The aerial photograph (right) was used to locate the seed points onto the QuickBird imagery (left) in ERDAS imagine software

4.3 Results – Discussion

The accuracy of the pixel-based classification was assessed by comparison with the baseline maps produced by API. The eighteen sample areas were used for the statistical analysis. An example of one of the classified map segments is presented in Figure 4-9. This particular segment has 561 individual polygons. Given all 18 segments, 8086 polygons were available to test the correspondence between the classification and the API.

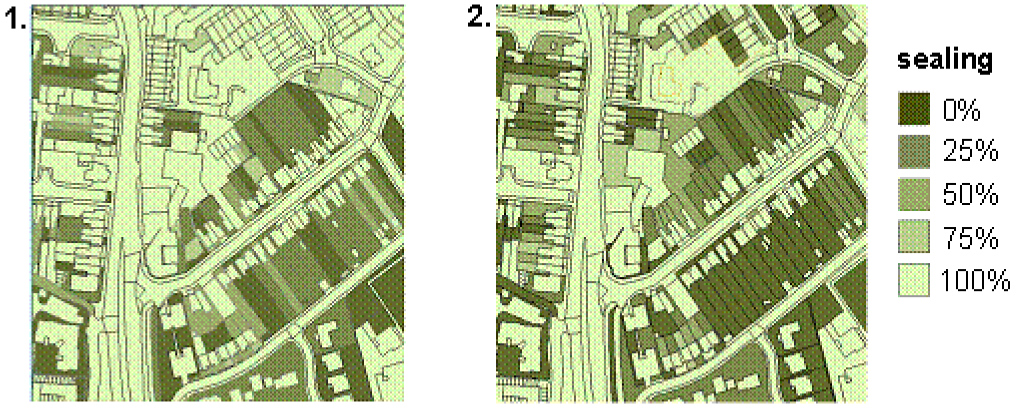


Figure 4-9 Comparison of (1) the API classification, and (2) the maximum likelihood classification

The results of the two classification methods were analysed with the confusion matrix approach. A confusion matrix (Table 4.2) cross-tabulates the frequency of class combinations, 0%, 25%, 50%, 75% and 100% sealed, in the digital classification with the equivalent sample survey from the API classification. This process is analogous to overlaying the two maps in Figure 4-9, and comparing classes, but for all 18 segments. The diagonal axis represents agreement between the two observations. Off-diagonal values represent misclassification errors. Of importance to users of the classified maps is an idea of the overall mapping accuracy and the accuracy for the individual classes.

In Table 4.2, the overall accuracy is 69%. The numbers in brackets represent a weighted accuracy estimate that takes into account the probability that the API observations may contain some level of uncertainty. The digital classification provides maps of sealing on a continuous scale from 0 – 100%. The API classes, however, are discrete classes within that scale (i.e. 0%, 25%, 50%, 75% and 100%). To take into account the level of human interpretation error, ‘fuzzy’ boundaries were applied to the confusion matrix interpretation. The dashed box outlines represent a tolerance of one class either side of the expected class. According to the assumptions given, a 50% weight is given to the values either side of the diagonal, and 100% to the diagonal. The effect is to increase the estimated accuracy. For example, the overall accuracy increases from 69% to 75%. The adjusted accuracies are indicated in brackets and have been applied to the overall estimate and the user accuracy.

Table 4.2 The confusion matrix indicates correspondence between the digital classification and the API classification of sealing

		CLASSIFICATION (Satellite + topo graphic)						
		0	25	50	75	100	Total	Producer
API	0	475	134	50	36	140	835	57%
	25	288	267	94	53	66	768	35%
	50	149	124	88	53	107	521	17%
	75	111	47	28	50	150	386	13%
	100	523	143	120	123	4683	5592	84%
	Total	1546	715	380	315	5146	8102	
	User	31%(40%)	37%(55%)	23%(39%)	16%(44%)	91%(92%)		69%(75%)

4.3.1 The effect of parcel size in accuracy

Due to low overall accuracy the next stage was to test whether the estimate of the accuracies would improve if only larger land parcel sizes were considered. For that purpose, the same process was repeated using only areas greater than 32 m^2, 100 m^2 and 300 m^2; areas smaller than 32 m^2 (equivalent area to 4 pixels) were excluded since such small polygons are very likely to be misclassified. The confusion matrices (Tables 4.3- 4.5) shows that the overall accuracy is not affected, but the individual classes are improved.

Table 4.3 Digital classification vs. API for areas >32 m^2. Figures in brackets indicate adjusted accuracies, to allow for a degree of uncertainty in the API.

	CLASSIFICATION (Satellite + topographic)						
	0	25	50	75	100	*Total*	*Producer*
0	346	123	37	25	30	561	**62%**
25	261	267	92	48	50	718	**37%**
50	130	115	82	49	78	454	**18%**
75	88	41	24	49	127	329	**15%**
100	83	58	31	40	2298	2510	**92%**
Total	908	604	266	211	2583	4572	
User	**38%**(52%)	**44%**(64%)	**31%**(53%)	**23%**(44%)	89%(91%)		**66%**(76%)

Table 4.4 Digital classification vs. API for areas >100 m^2. Figures in brackets indicate adjusted accuracies, to allow for a degree of uncertainty in the API.

	CLASSIFICATION (Satellite + topographic)						
	0	25	50	75	100	*Total*	*Producer*
0	220	55	11	6	3	295	**74%**
25	146	194	67	24	12	443	**43%**
50	47	70	53	23	35	228	**23%**
75	22	17	10	22	59	130	**17%**
100	26	18	11	18	535	608	88%
Total	461	354	152	93	644	1704	
User	**47%** (64%)	**54%**(72%)	**34%**(60%)	**24%**(46%)	83%(88%)		**60%**(73%)

Table 4.5 Digital classification vs. API for areas >300 m^2. Figures in brackets indicate adjusted accuracies, to allow for a degree of uncertainty in the API.

	CLASSIFICATION (Satellite + topographic)						
	0	25	50	75	100	*Total*	*Producer*
0	124	14	1	0	2	141	88%
25	68	91	24	8	6	197	**46%**
50	12	16	19	13	14	74	**26%**
75	8	1	4	7	32	52	**13%**
100	11	7	3	5	195	221	88%
Total	223	129	51	33	249	685	
User	**56%**(70%)	**70%**(82%)	**37%**(65%)	**21%**(48%)	78%(85%)		**64%**(76%)

The next step was to aggregate small adjacent polygons (i.e. individual houses and gardens) into larger blocks that share a common 'block' of land (Figure 4-10). From the total 18 sample areas, 20 "house-garden blocks" were derived. The average area of sealing for each of these 20 examples from the digital classification was compared by regression analysis against the API survey (Figure 4-11). The average standard percentage error estimate of the area sealed is 7.3% (i.e. an average accuracy of 92%).

The accuracy of individual blocks (the prediction accuracy) is 81%. This result indicates that if the maps were presented as summarised blocks, the maps should be much more reliable but less spatially precise.

Figure 4-10 An example block of associated gardens and houses used to assess the improvement in accuracy using parcel aggregation.

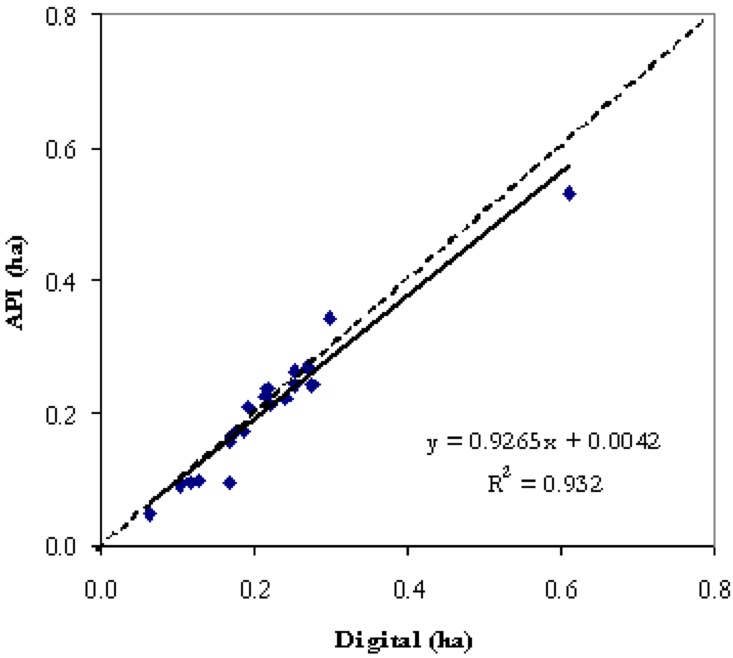


Figure 4-11 Correlation between estimates of sealing from digital and visual classification, respectively, for amalgamated blocks of houses and gardens. The dashed one shows the optimal correlation between the two methods.

4.4 Conclusions

In this chapter the results of a pixel-based classification for mapping the percentage of sealed soil surfaces in urban environments, was presented. The data used was a VHR QuickBird imagery. The results of the automated classification were compared with reference data produced by API and the overall accuracy calculated to be 69%. During the visual aerial photo classification, ancillary data such as the Ordnance Survey (OS) MasterMap was used to provide an initial segmentation of the image and to identify areas of soil known to be sealed over (e.g. building footprints and roads). But the method of overlaying the MasterMap onto the aerial photography led to coarse visual identification; classification of each land parcel into the 25% intervals. Consequently, the satellite digital classification had to be reclassified according to 25% intervals resulting in overall low accuracy when manual and automated methods were statistically compared with the confusion matrix approach (Table 4.2). For that reason, a new approach for the visual segmentation and classification of the aerial photographic data is needed. The next stage will explore whether the use of object-based classifiers (eCognition software) could produce an objective and more efficient visual interpretation method and increase the overall accuracy.

In addition, the use of the pixel-based classification method (maximum likelihood) identified accuracy limitations for mapping soil sealing at garden level scale. Following the specific approach, it was proved that higher accuracy can be achieved when working with amalgamated blocks of houses and gardens. Object-based classification techniques will be tested in the future in order to evaluate whether the percentage of sealing could be classified in greater detail (i.e. domestic garden level) in urban environments.

Chapter 5

Comparison of object extraction methods using aerial photography

The aerial photo interpretation (API) has been commonly used as a standard method to verify the accuracy of digital classification techniques with the use of earth observation (EO) data. This chapter aims to compare manual classification using API with automated object-based methods. The focus is on the image segmentation process by investigating the extent to which object-based image analysis (OBIA) could replace the traditional method of manual digitising for the detection of sealed soil and vegetated surfaces at the residential garden plot level.

Part of the work described in this chapter has been published as a chapter in the book entitled: "Object-Based Image Analysis: Spatial Concepts for Knowledge - Driven Remote Sensing Applications", Springer, as well as a conference paper at the annual conference of the Remote Sensing and Photogrammetry Society (RSPSoc) in Newcastle, September 2007.

5.1 Traditional aerial photo interpretation (API)

As described in the previous chapters, the data source acquired for the analysis was a true colour aerial photography, taken in June 2003, at 0.125 m spatial resolution. The study area initially consisted of 18 sample segments used for the production of the API, with the use of ancillary data, and the pixel-based classification method (see chapter 4). At this stage of the research, which was mainly the evaluation of OBIA methods and the assessment of its transferability, it was concluded that fewer sample segments could be sufficiently representative of Cambridge's urban land cover. Thorough visual examination of the Cambridge district identified four different urban and sub-urban types. Consequently, four sample segments demonstrating the commercial, the industrial and two types of residential area in Cambridge were selected as study areas. Three of the four sample areas were part of the preliminary 18 segments (areas 5, 20 and 26) while "area 0" was added to be the representative industrial sample segment of the city (Figures 5-1 and 5-2).

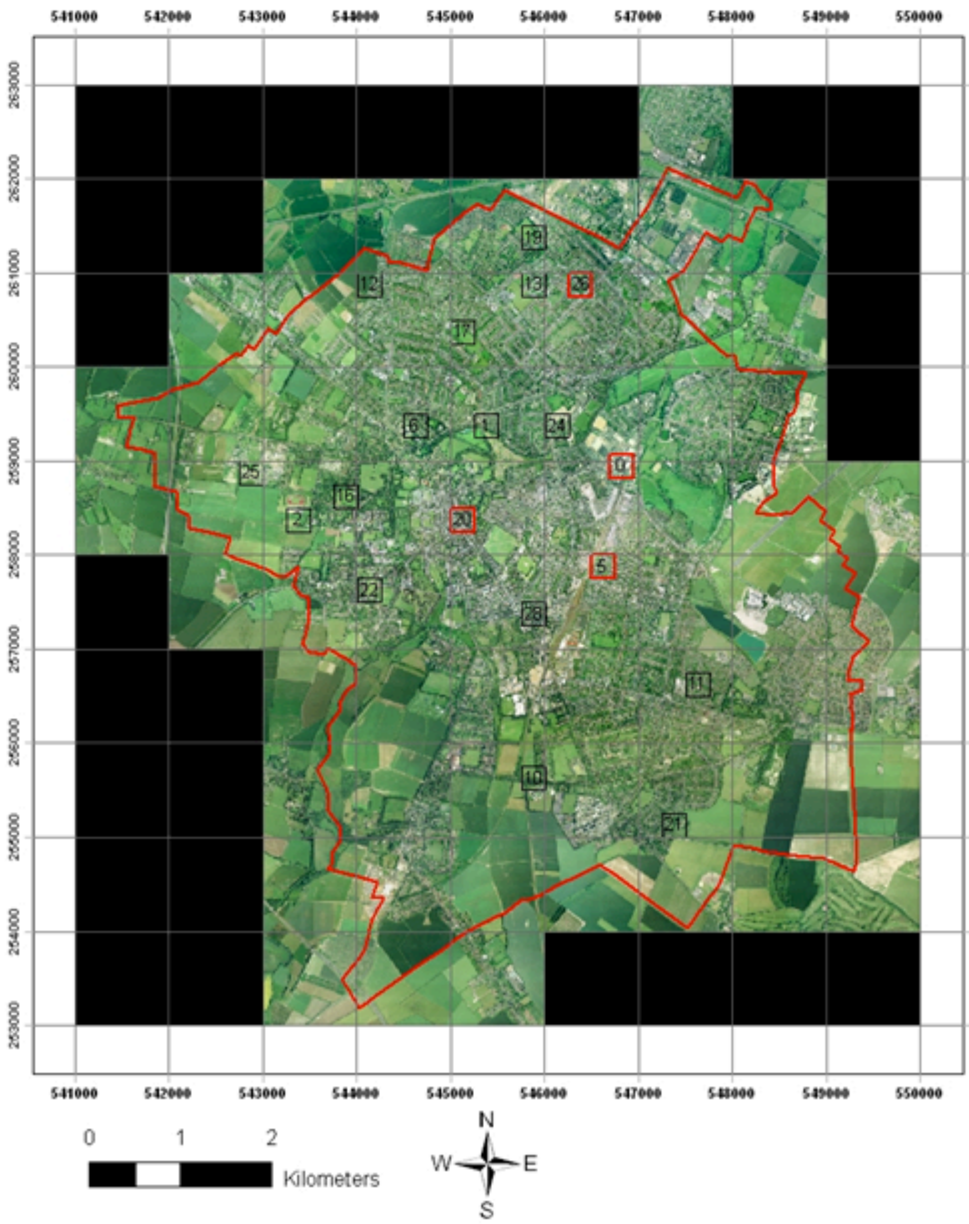


Figure 5-1 Cambridge district sample segments; No's 0, 5, 20 and 26 are the representative samples for the whole city and outlined in red

	**Reference sample site 1 ('area26')** Low density residential area of 1960's semi-detached houses with broad large gardens, giving a large area of vegetated surfaces
	**Reference sample site 2 ('area 5')** Densely built residential area of 1930's Victorian terraced houses with narrow small gardens, giving a medium area of vegetated surfaces
	**Reference sample site 3 ('area20')** Part of the commercial area in the city centre; predominantly sealed area with large buildings, densely spaced with few vegetated surfaces
	**Reference sample site 4 ('area0')** Part of an industrial area; predominantly sealed area with industrial buildings and very few vegetated surfaces

Figure 5-2 The representative sample areas of the urban land cover of Cambridge

The four study areas were manually segmented by on-screen digitising using ArcGIS® software (Figure 5-3). The API classification was based on the typology developed in chapter 3. The MMU was determined to be at 1:200 scale for the following reasons:

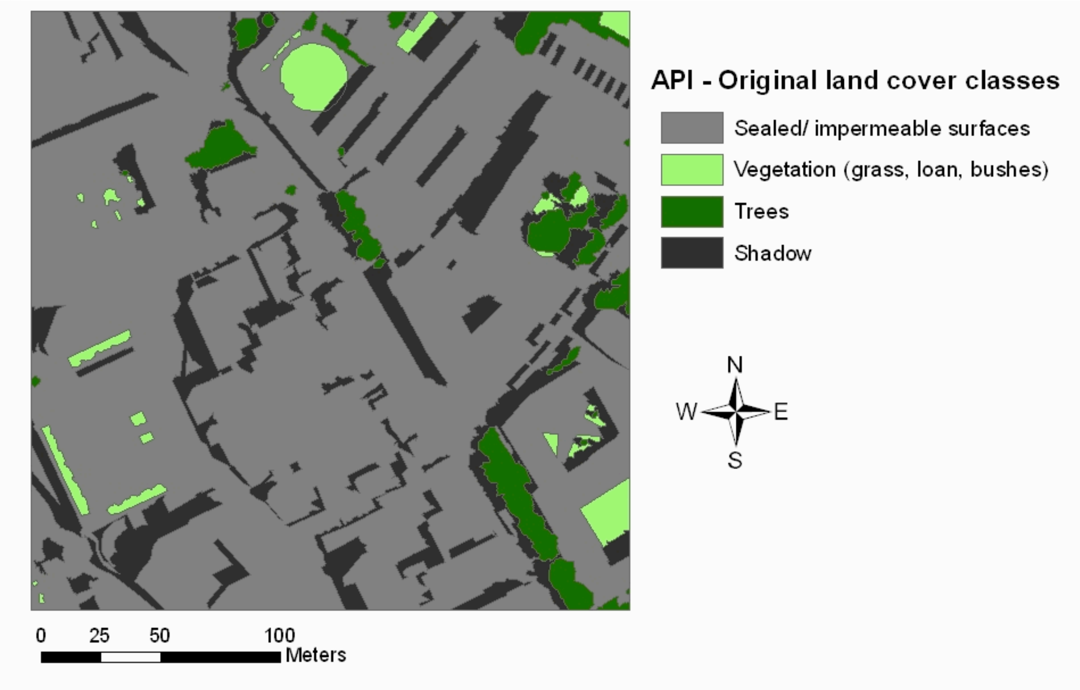
- due to the resolution of the data used for the API (aerial photography at 12.5 cm scale)
- based on the range area each land cover feature, in the built environment of Cambridge, cover (Table 3.1)
- mapping features smaller than 2 m would produce “noise” in the final map due to the very small size of the delineated objects
- a larger scale than 1:200 revealed a higher degree of pixelation which was difficult to interpret
- the larger the mapping scale the larger the data size for image processing.

Figure 5-3 On-screen manual digitising of the four study areas

During the manual labelling of the sample segments, vegetated surfaces were equated to unsealed soil, and non-vegetated surfaces were equated to sealed soils. Only shadow cast on ground surfaces was identified as 'shadow' while the sides of buildings in shadow, visible due to relief displacement, were interpreted as 'sealed'. Given these broad guidelines and the land cover typology of Cambridge presented in table 3.1 seven land cover classes were used: sealed surfaces, vegetation, trees, shadow, rail tracks, bare soil and temporary features (Figures 5-4 (i) and 5-5 (i)). As shadow is not considered to be an actual land cover class of the urban environment, the shadow class was further classified as 'sealed surface in shadow', 'grass in shadow', 'tree in shadow', and 'mixed or unclassified shadow' when it was impossible to identify the land cover type covered by shadow or more than one type was recognised in a single polygon (Figures 5-4 (ii) and 5-5 (ii)).

Occasionally, in order to aid the manual classification process, oblique "pictometry" style data, available on-line, of the sample areas were also used (Figure 5-6). Information about the date that the photos were taken was not given but from visualisation the same season seemed to be the same with the acquired aerial data (June). So, there were no implications of using these data. The oblique view was specifically useful when the "rotation" tool was used to view a location from the south, west, north and easterly direction which aided the separation of trees from shrubs (green fences) or to clarify whether there were sealed patio areas in the back gardens. These types of feature were very difficult to identify from the ortho-photo due to relief displacement and shadow.

(i)



(ii)

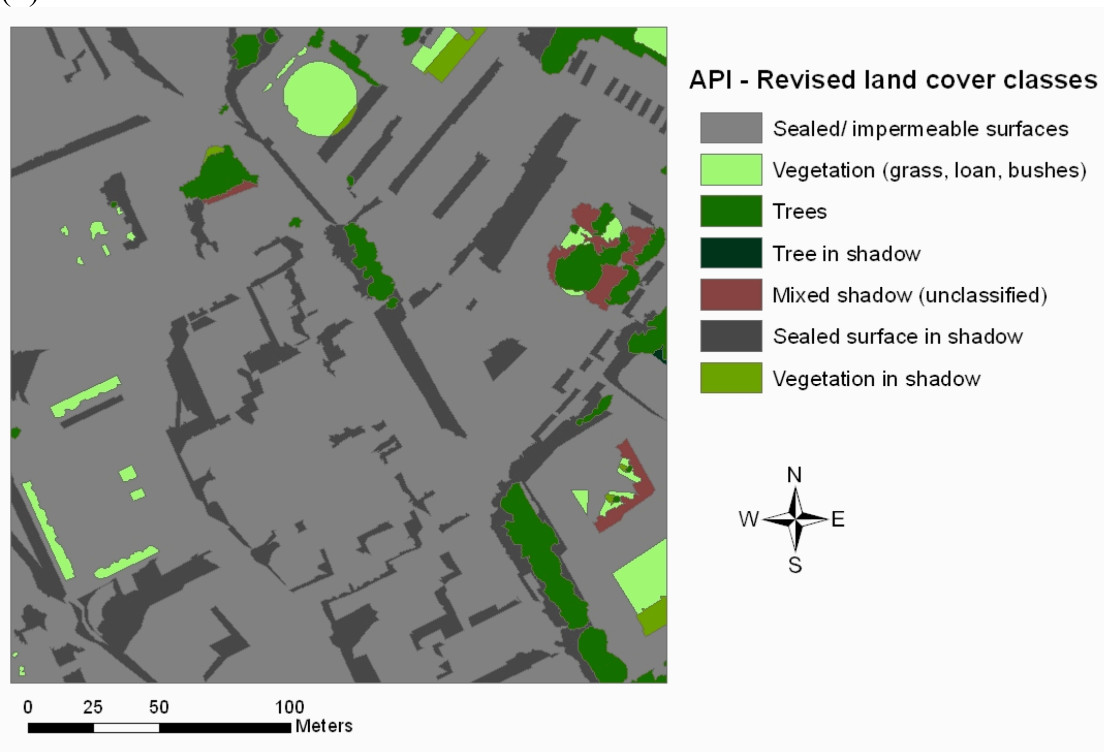
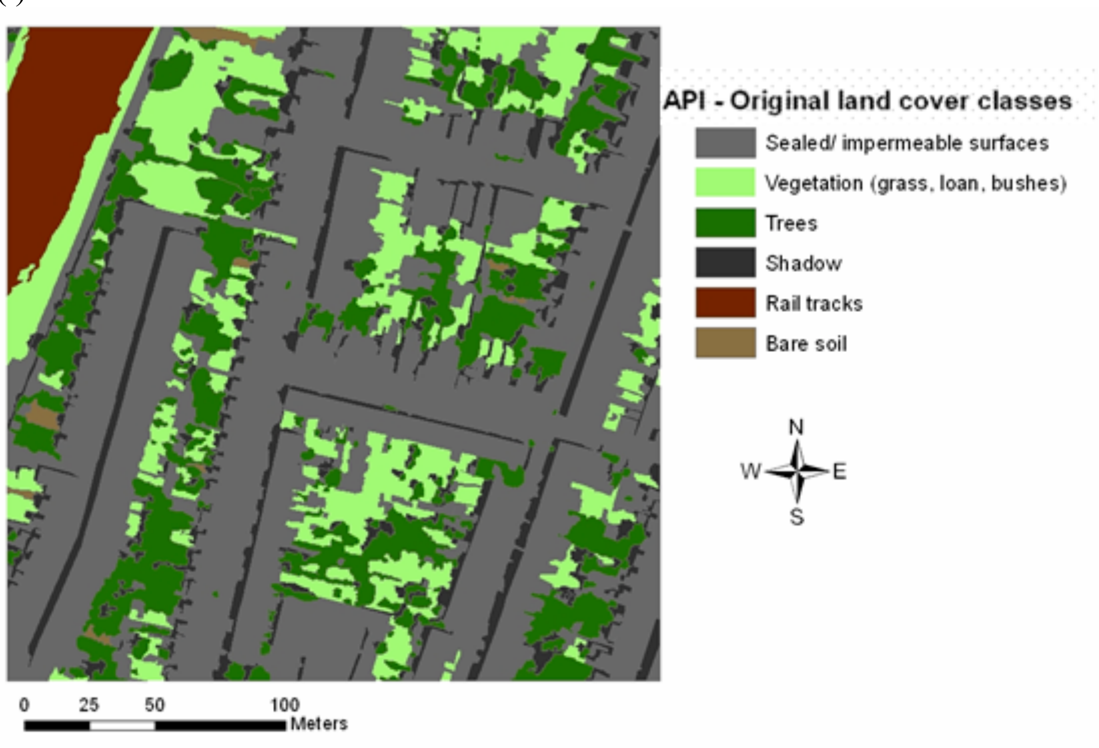


Figure 5-4 (i) Manual land cover classification of the commercial area; (ii) Reclassified shadow of the same sample area

(i)



(ii)

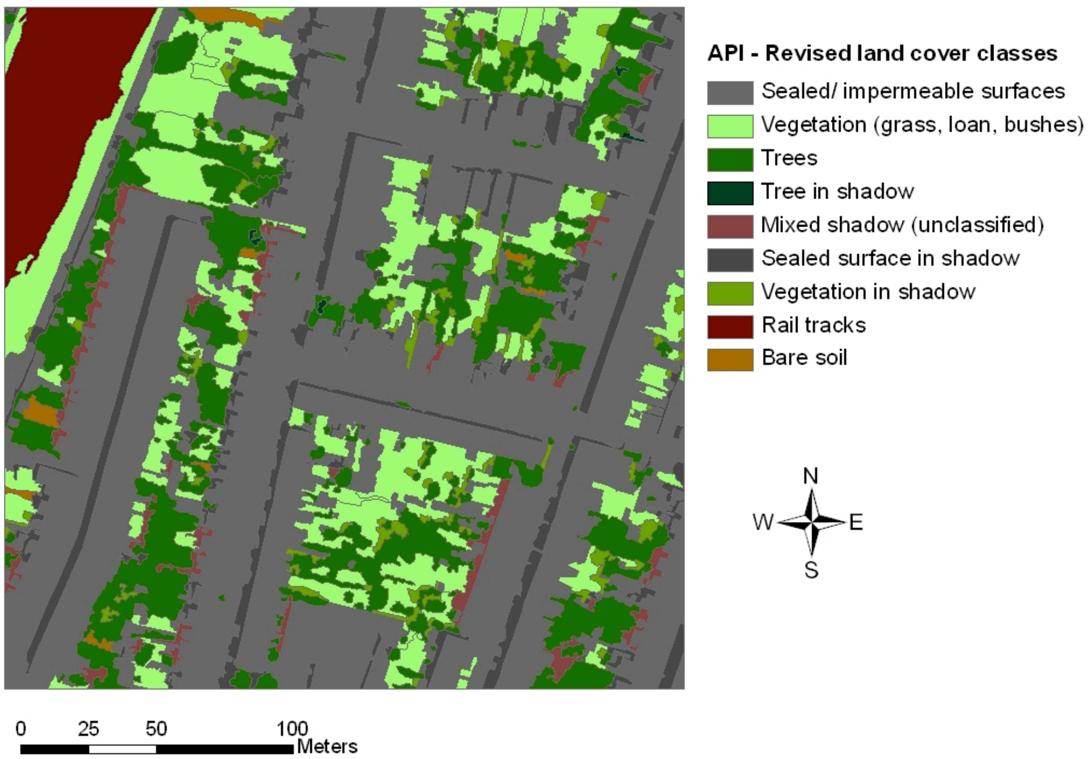


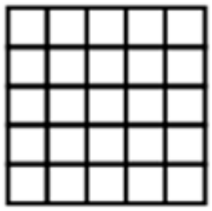
Figure 5-5 (i) Manual classification land cover of the densely built residential area; (ii) Reclassified shadow of the same sample area

Figure 5-6 Part of the residential area ("area 26") as shown in the oblique image (Source: http://local.live.com/)

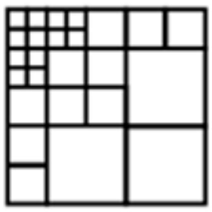
5.2 Object-based image analysis and the eCognition software-an introduction

The eCognition software (former Definiens) offers an object-based approach to image analysis that is separated into two processes; segmentation and classification. During the segmentation process, neighbouring pixels are merged into homogeneous image objects on the basis of their spectral, shape, texture and positional information (Definiens Professional, 2006). There are three segmentation algorithms available in the software: Chessboard, Quadtree and Multiresolution segmentation (Figure 5-7). As the urban land cover consisted of various multi-sized and multi-shaped polygons, the multiresolution segmentation seemed to be the most appropriate for use (Burnett and Blaschke, 2003). The extracted objects are later classified using pre-defined classes. Class descriptions can be defined either by using a fuzzy nearest neighbour (NN) algorithm or by a fuzzy rule set of object features identified using membership functions (Baatz et al., 2000). The NN classifier is a simple and quick classification which is based on sample selection of each class; each image object is assigned to the class of the nearest sample object (Definiens Professional, 2006). The fuzzy rule classifier is based on a whole network of membership functions derived for each parameter and combined to produce the classification of each object. A simple workflow of the segmentation-classification process using the eCognition software is shown in Figure 5-8.

Multiresolution segmentation
Segments the image using a heuristically optimised user defined resolution defined by colour, shape, smoothness and compactness



Chessboard segmentation
Splits the image into square objects. The smallest object can be the size of one pixel



Quadtree segmentation
The quad tree based segmentation algorithm creates squares of differing sizes by cutting. Thus it is a top-down segmentation algorithm. Each square is cut into four smaller squares if the homogeneity criterion is not met.

Figure 5-7 The different segmentation algorithms available within the eCognition software (source: Definiens Professional 5 User Guide)

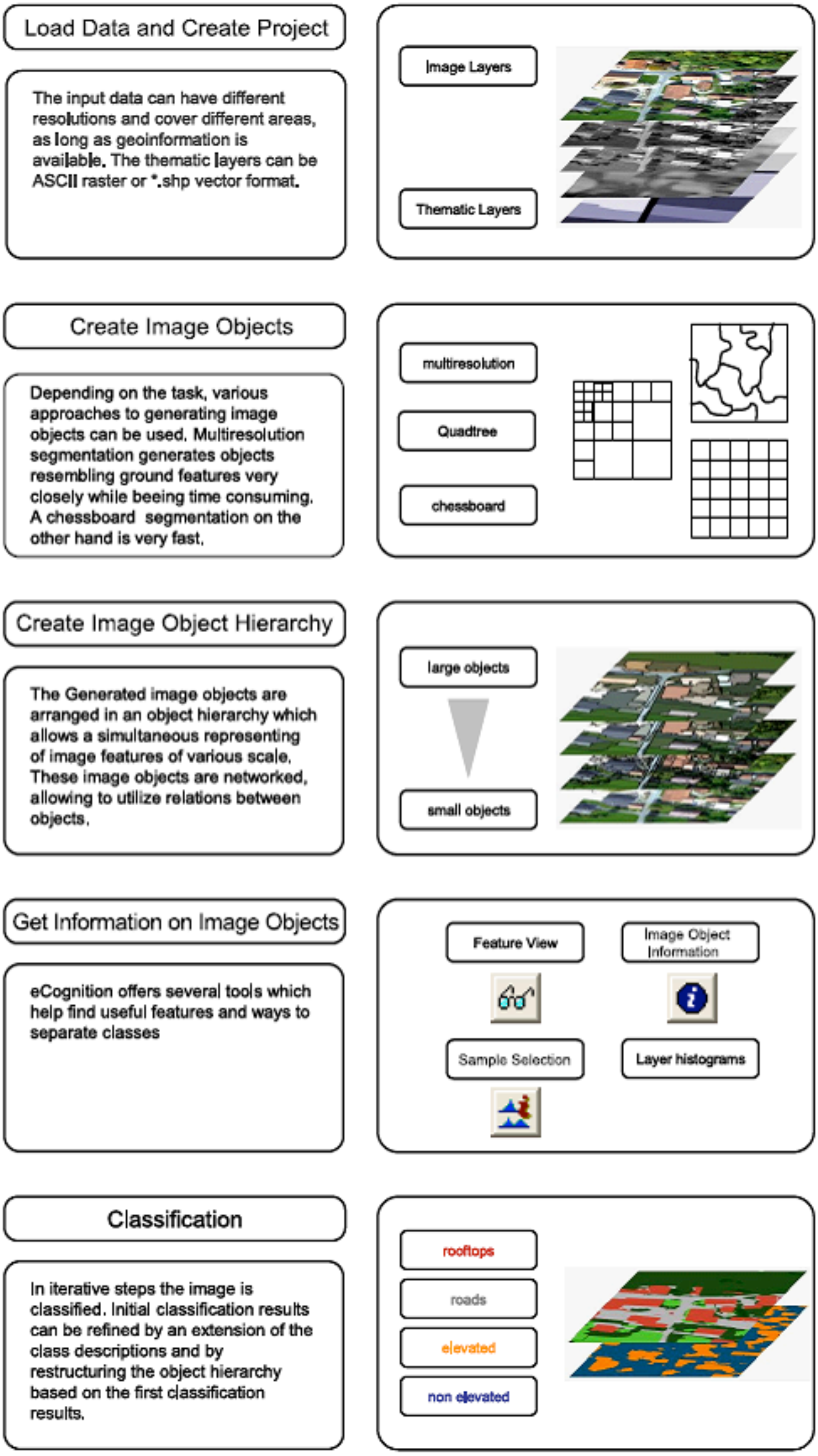


Figure 5-8 The classification workflow in the eCognition software
(source: Definiens Professional 5 User Guide)

In the latest versions of the eCognition software (Definiens Professional 5, Definiens Developer and eCognition 8) the image analysis can be implemented using the process tool. Every individual operation can be described by a single process which has to be edited to define the algorithm which is executed on a specific image object domain (Definiens Professional, 2006). The image object domain describes the area of interest and can either be the raw data at the pixel level, the entire image objects in a specific level of the hierarchy, or a specific object class from any level. The process editor provides the ability to apply rules in a specific class domain of the class hierarchy that suits local conditions in an image. The concept of using processes in order to build a complete rule set for image analysis is described in Figure 5-9.

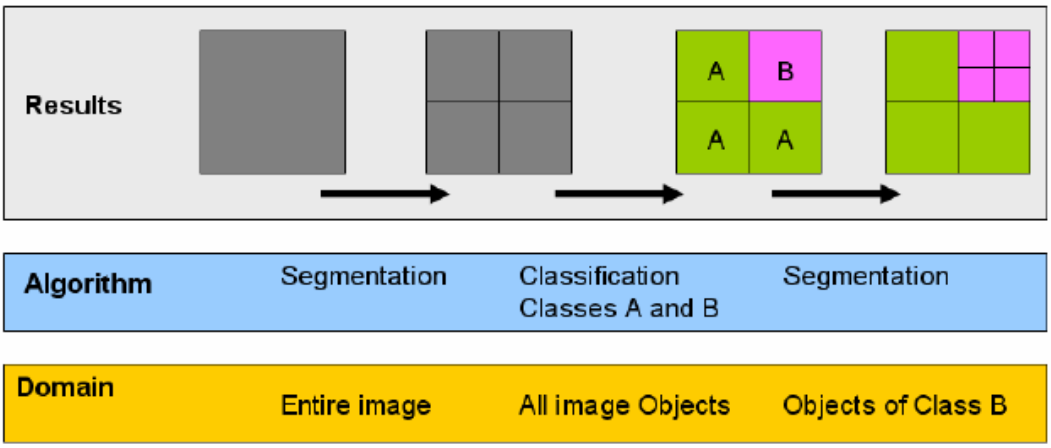


Figure 5-9 The workflow of a process sequence (source: Definiens Professional 5 User Guide)

5.2.1 Multi-resolution segmentation

Multiresolution segmentation is based on the fractal net evolution approach (FNEA), a region-growing algorithm that minimizes the average heterogeneity of the image objects. Initially single pixels are merged together to produce image objects by extracting homogeneous areas. The outcome of the segmentation is dependent on various parameters such as scale, colour, shape, compactness and image layer weights. The scale parameter is an abstract term that determines the maximum allowable heterogeneity for the resulting image objects and also the size of image objects. The

object homogeneity to which the scale parameter refers is defined in the composition of homogeneity criterion field. In this circumstance, homogeneity is used as a synonym for minimized heterogeneity.
Internally three criteria are computed: colour, smoothness, and compactness. For most cases the colour criterion is the most important for creating meaningful objects. However, a certain degree of shape homogeneity often improves the quality of object extraction. This is due to the fact that the compactness of spatial objects is associated with the concept of image shape (Definiens Professional, 2006).

The heterogeneity criterion is defined by the following equations (Benz et al. 2004): The increase of heterogeneity, *f*, has to be less than a certain threshold.

$$f = w_{color} \cdot h_{color} + (1\text{-}w_{shape}) \cdot h_{shape} \qquad (1)$$

$$w_{color} + w_{shape} = 1$$

The weight parameters (w_{color}, w_{shape}) allow adaptation of the heterogeneity definition to the application. The spectral heterogeneity allows multi-variant segmentation by adding a weight w_c to the image channels c. A difference in spectral heterogeneity, $\Delta h_{color,}$ is defined as:

$$h_{color} = \sum w_c \left(m_{erge} \cdot \sigma_{c,\, merge} \text{ - } (n_{obj\_1} \cdot \sigma_{c,\, obj\_1} + n_{ob\_2} \cdot \sigma_{c,\, obj\_2})\right) \qquad (2)$$

Where:
n_{merge} = number of pixels within a merged object
n_{obj_1} = number of pixels in object 1
n_{obj_2} = number of pixels in object 2
σ_c = standard deviation within an object of channel c

The shape heterogeneity, $h_{shape,}$ is a value that describes the improvement of the shape with regard to smoothness and compactness of an object's shape.

$$h_{shape} = w_{compt} \cdot h_{compt} + (1\text{-}w_{ompt}) \cdot h_{smooth} \qquad (3)$$

with

$$h_{smooth} = (n_1 + n_2)\frac{l_{(1+2)}}{b_{(1+2)}} - \left(n_1 \frac{l_1}{b_1} + n_2 \frac{l_2}{b_2} \right) \tag{4}$$

$$h_{compact} = (n_1 + n_2)\frac{l_{(1+2)}}{\sqrt{n_1 + n_2}} - \left(n_1 \frac{l_1}{\sqrt{n_1}} + n_2 \frac{l_2}{\sqrt{n_2}} \right) \tag{5}$$

Where;

l = perimeter of object

b = perimeter of object's bounding box

n = number of pixels of each object

The smoothness heterogeneity equals the ratio of the de facto perimeter length, l, and the border length, b, given by the bounding box of an image object parallel to the raster orientation. The compactness heterogeneity equals the ratio of the de facto perimeter length, l, and the square root of the number of pixels forming this image object. The weights w_c, w_{color}, w_{shape}, w_{smooth}, w_{compt} are parameters, which can be selected in order to obtain suitable segmentation results for a certain image data stack and the application under consideration.

The scale parameter is the stop criterion for the optimization process. Prior to the fusion of two adjacent objects, the resulting increase of heterogeneity *f* is calculated. If this resulting increase exceeds a threshold, t, determined by the scale parameter, t =W (scale parameter), then no further fusion takes place and the segmentation stops. The larger the scale parameter, the more objects can be fused and the larger the objects grow. The multiresolution concept is shown in figure 5-10.

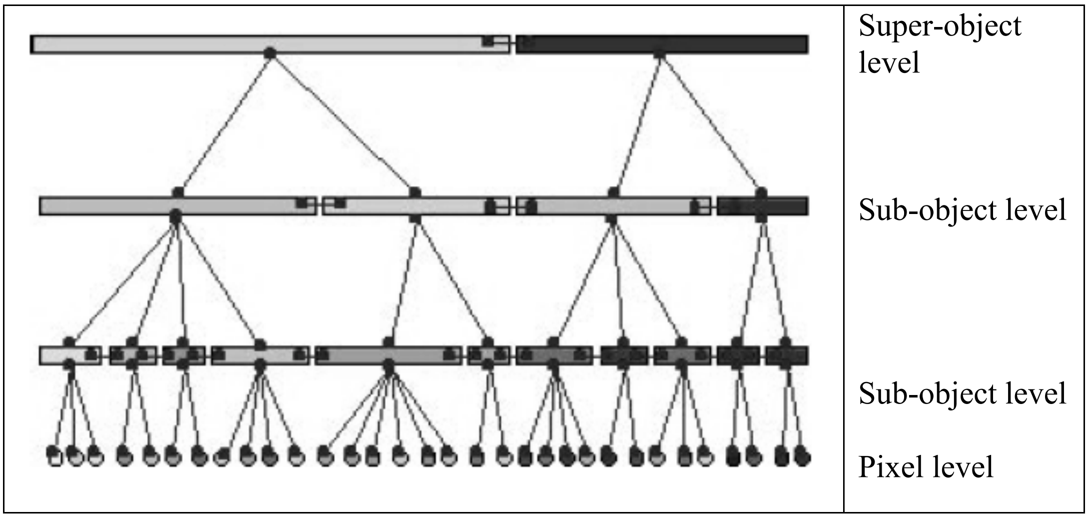


Figure 5-10 Multiresolution concept flow diagram (source: Definiens Professional 5 User Guide)

5.3 Semi-automated classification of the aerial photography

This paragraph describes the classification of the aerial photography by using the eCognition software for image segmentation and the manual editing tool for manually labelling the extracted image objects. For this reason, it is called semi-automated classification method.

5.3.1 Automated segmentation-object extraction

The four study areas were automatically segmented with the use of the eCognition software, Definiens Professional version 5. The multiresolution segmentation, which generates objects very closely resembling ground features (Definiens Professional, 2006), was used for this study.

A general rule of thumb for a meaningful segmentation is to create image objects as large as possible and as small as necessary (Definiens Professional, 2006). At the same time, the image should also be segmented at such a scale in order to identify the smallest feature of interest. It is apparent that it is not always possible to extract all the image objects of interest by performing one segmentation. An example is given at the user guide explaining why mulitresoltution segmentation is needed “when working on high resolution imagery with the task of classifying rooftops and forested areas at the same time”. Consequently, it is important to use as many object levels, at different scales, as necessary until all image objects explicitly represent the classes to be assigned for the classification procedure.

From the four sample areas (Figure 5-3) the industrial area (“area0”) was selected to be used for the initial analysis. The sample site was selected due to the simplicity of the area’s land cover, giving the opportunity to the user to become familiar with the software and be able to provide a competent image analysis. According to the user guide, “a convenient approach for the segmentation of new projects is to run different segmentations with different parameters until the result is satisfying”. The assessment of the segmentation method is based on trial-error and visual inspection methods. Consequently, several different values of each segmentation parameter were run until a satisfactory, in the eye, result achieved. The image was finally segmented into two levels. At the fist level, small scale features such as big roof tops and rail tracks were extracted while level 2 aimed to extract the smallest features such as individual trees (Figure 5-11). As Benz et al. (2004) argues, “it is important to note that there is no such thing as optimal parameters for image segmentation. For object level models, the normal procedure is simply to iteratively try different parameters until the resulting objects are appropriately sized and shaped for the particular task”.

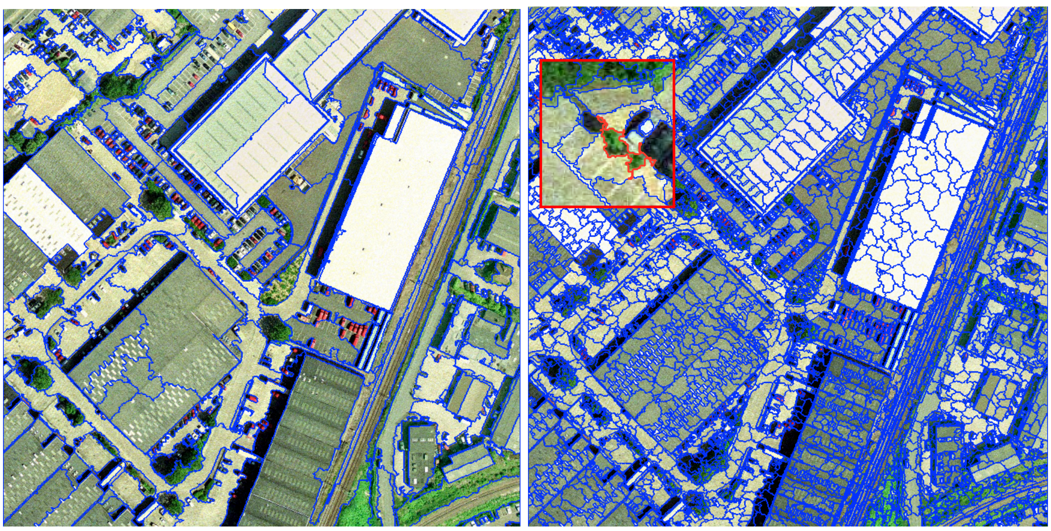


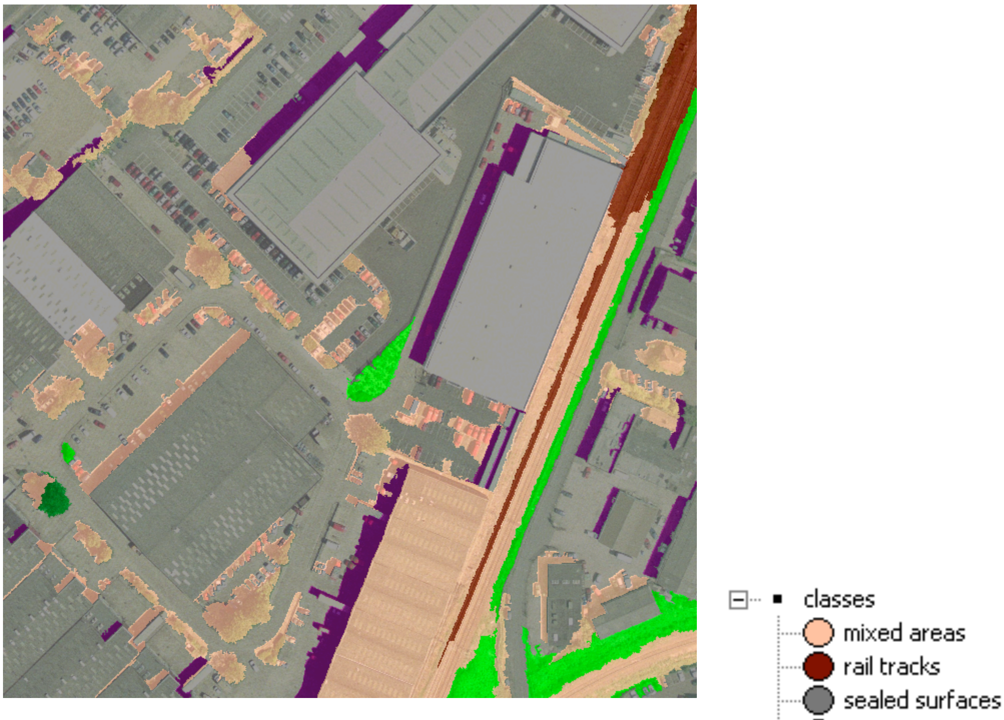
Figure 5-11 The multi-resolution segmentation of the sample image

At the upper level, the best values for each parameter were found to be: scale=225, shape= 0.3, compactness= 0.7, weight of red band (layer 1) = 2, weight of green band (layer 2) = 4 and weight of blue band (layer 3) = 1. Using these parameters, the image sample was segmented into the coarse classes of sealed, unsealed and shadowed areas. Features that were not extracted at that scale were identified later when a new level with a smaller scale value was applied. High values of compactness along with larger weights in the red and green wave bands resulted in a better discrimination between trees (highly compacted objects) and other vegetated surfaces.

5.3.2 Manual classification of the image objects

The segmented image was manually classified with the manual editing tool available in the eCognition software. The manual classification followed the same pattern and criteria used with the API. The classes identified were: sealed surfaces, vegetation, trees, shadow, rail tracks and mixed areas. The 'mixed areas' class represented the regions of the image that were not satisfactorily segmented and required a lower scale parameter in order to create meaningful objects. After visual examination and using the trial and error procedure, the 'mixed areas' class was re-segmented with a scale parameter value equal to 40 as at that scale all the objects of interest were extracted; all other parameters remained the same (Figure 5-12). Every individual neighbouring polygon assigned to the same class was merged at both segmentation levels. The whole process rule set was saved and used for the image analysis of the remaining study areas. The same methodology and identical parameter values (rules) were used in the other three test areas in order to determine the transferability of the rules to areas where the urban land cover is different.

(i)



(ii)

Figure 5-12 (i) Manual classification of the industrial area at scale 225; the pink areas are the mixed areas which were later re-segmented at scale 40 (ii) and re-classified according to the predefined land cover classes

Segmenting the residential study areas at scale= 225 resulted in the production of too many "mixed areas" that needed to be re-segmented and re-classified. This was due to the fact that the urban land cover of the residential areas was much more complex than the industrial and commercial sites. The re-segmentation at scale 40 had satisfactory results as all the objects of interest were again extracted (Figure 5-13).

(i)

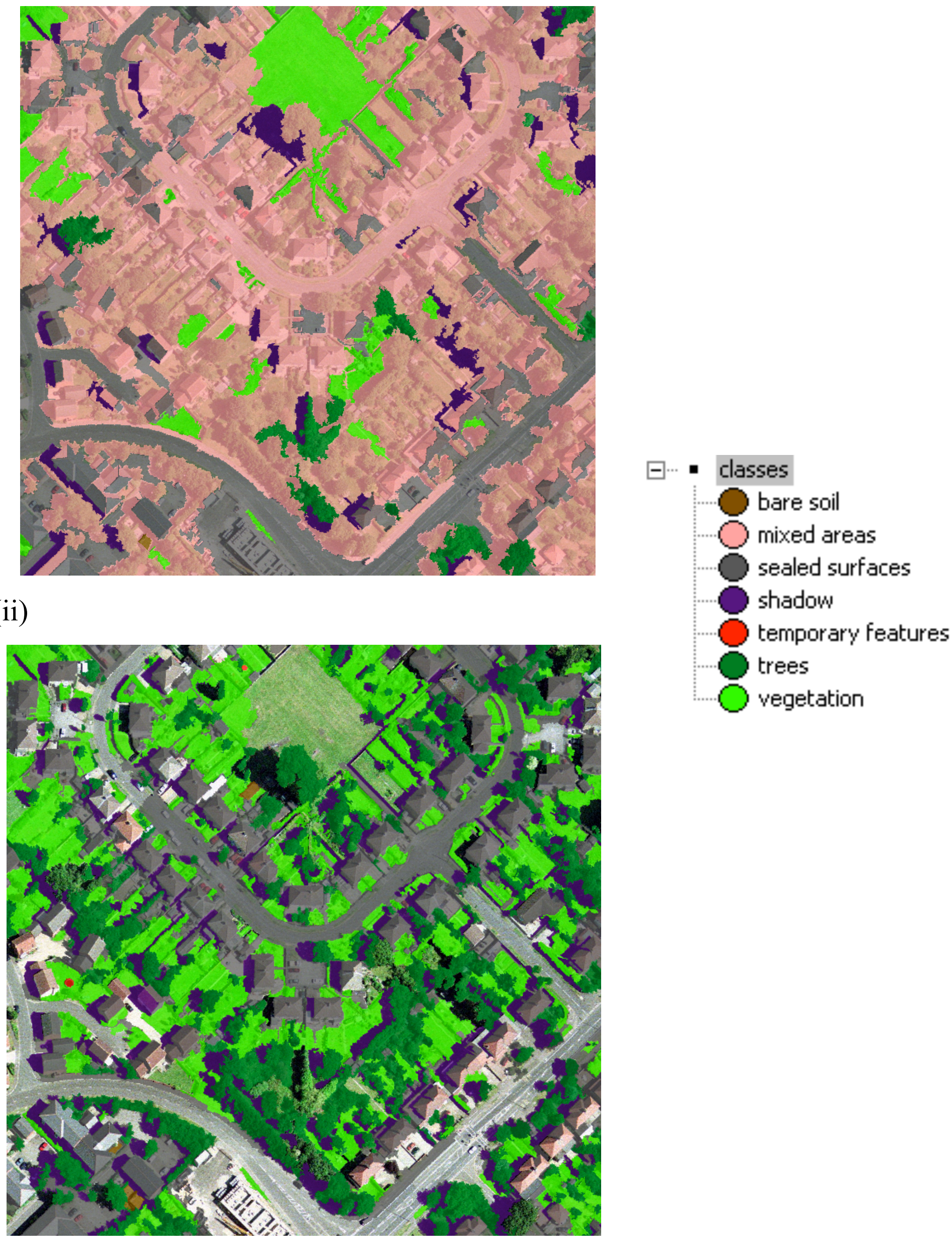


Figure 5- 13 (i) Manual classification of the residential area, "area26", at scale 225 and (ii) the reclassification of the pink "mixed areas" at scale 40

5.4 Comparison of API and semi-automated classification method: results- discussion

The results from the eCognition processing were exported to ArcGIS as smoothed polygons in vector format. The accuracy of the results was quantitatively assessed by cross-tabulation with the visual interpretation of the ortho-rectified aerial photography. The maps were also qualitatively analysed in order to explain any differences between the two approaches

5.4.1 Quantitative analysis

The most common and widely accepted approach to statistically quantify the thematic accuracy is the production of a confusion matrix, also called error matrix. A confusion matrix compares two different classification techniques for a number of classes. The classification that is assumed to be the correct one is called the "reference data" while the one to be tested is called "classified data". According to Congalton and Green (1999) a confusion matrix is "a square array of numbers set out in rows and columns that express the labels of samples assigned to a particular category in one classification relative to the labels of samples assigned to a particular category in another classification" (Figure 5-14). The overall accuracy between the two classification methods can be simply calculated by dividing the sum of the major diagonal from the total number of samples in the error matrix. The producer and user accuracies are used to assess accuracies of the individual classes.

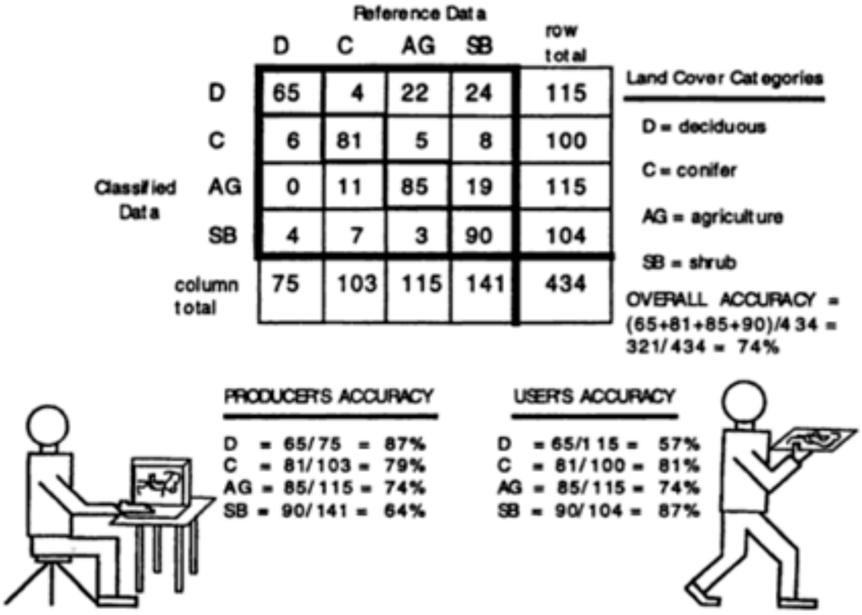


Figure 5-14 Example of a confusion matrix (source: Congalton and Green 1999)

For the production of the confusion matrices for each sample area, the exported data produced by manual and semi-automated methods were merged together by a union function, in ArcGIS environment, and the attributes of the new map were exported to an Excel spreadsheet. Initially, the results showed very low agreement between the two methods as for all the four sample areas the classification accuracies were between 28-29%. The results can be explained by the fact that although the two segmentations look very similar at the small scale, the boundaries of each polygon do not perfectly match; many insignificant 'sliver' polygons were produced when the maps were combined (Figure 5-15ii). The reason of the sliver polygons production is that eCognition follows a pixel pattern while the interpreter digitizes with smoother lines. The very small sliver polygons carry the same weight in the cross-tabulation as the larger polygons of interest, which introduces bias and leads to an artificial underestimate of the overall mapping accuracy.

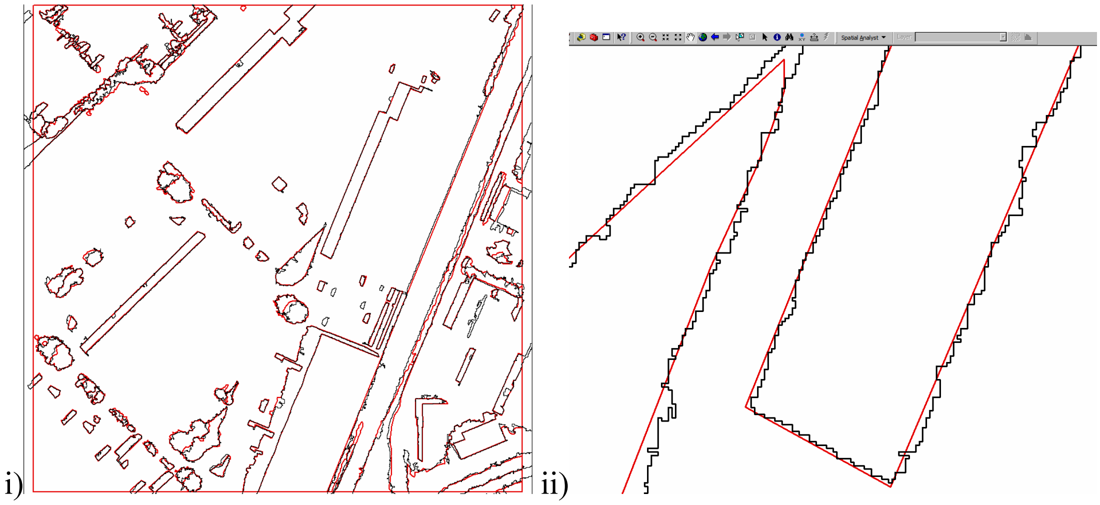


Figure 5-15 (i) The two maps produced by API (red line) and eCognition (black line) overlaid for comparison – the differences are negligible at this scale. (ii) The enlargement reveals the minor discrepancies of the boundary delineation between the two methods

To solve the boundary problem and to eliminate the majority of sliver polygons, the vector files were converted to a raster format with a cell size of 0.125 m which is equivalent to the pixel resolution of the aerial photography. The production of the error matrices was repeated. The overall accuracies obtained for each study area were (Table 5.1):

- industrial area (area0) = 96%
- commercial area (area20) = 94%
- residential area (semi-detached houses - area26) = 89% and
- residential area (dense terrace houses - area5) = 90%

Examining the confusion matrices, it was revealed that the software produced very high accuracies at the "sealed" class with average producer accuracy of 96%. It is also worth to say that these producer accuracies were higher than the user accuracies for all the four test sites. Analogous results occurred with the "trees" class of which the producer accuracies were higher than the user accuracies in the three of the four test sites, with average accuracy of 88.2%. The average producer accuracy for the "vegetation" class was 87.5% while the average user accuracy was 88.5%; fact that also indicates general high performance of the software.

In order to further examine eCognition's performance for the different classes individually, apart from the user and producer accuracies, the geometric mean (or g-mean) of each class in each confusion matrix was also calculated. The g-mean index is a combination of the user and producer indices and its value varies from zero to one. The nearer the g-mean value is to unity the more successful eCognition is at predicting the correct land cover class. The geometric mean is defined in equation 6 (Kubat et al., 1998):

$$g - mean = \sqrt{TP * P} \tag{6}$$

Where: TP= the true positive rate also called the producer accuracy

P= the index of precision also called the user accuracy

The g-mean values for all classes of each test site are indicated in Table 5.2. The best prediction was within the 'sealed' class with an average g-mean= 0.95 followed by the 'vegetation' class with an average g-mean= 0.88. The lowest values of the geometric mean of each study area were in the classes 'shadow' and trees' with an average of 0.85 and 0.84, respectively. Although the lowest, these values are still close to unity (which would have meant total agreement between the two methods) showing very good success of the eCognition software at predicting the correct land cover class. However, these two classes were visually examined using the Map Comparison Kit (MCK) software for the qualitative analysis and a better understanding of the differences seen. The qualitative analysis is comprehensively analysed in the next section.

Table 5.1 Confusion matrices for each reference site between the manual API (reference data) and the semi-automated object-based classification.

Commercial area "area20"							
API \ semi_eCg	sealed	vegetation	trees	shadow	Sum Map 1	User	
sealed	2906249	5081	4979	127630	3043939	0.955	
vegetation	7526	109230	1821	1070	119647	0.913	
trees	10921	1097	151990	25386	189394	0.803	
shadow	52110	1332	4811	588767	647020	0.910	
Sum Map 2	2976806	116740	163601	742853	4000000		
Producer	0.976	0.936	0.929	0.793			
							0.939
							94%

Industrial area "area0"								
API \ semi_eCg	sealed	vegetation	trees	shadow	rail tracks	Sum Map 1	User	
sealed	3125165	9750	9061	17812	21263	3183051	0.982	
vegetation	9746	138197	371	771	8096	157181	0.879	
trees	17029	2397	104397	6495	0	130318	0.801	
shadow	23614	150	6864	282540	0	313168	0.902	
rail tracks	3649	12185	0	0	200448	216282	0.927	
Sum Map 2	3179203	162679	120693	307618	229807	4000000		
Producer	0.983	0.850	0.865	0.918	0.872			
								0.963
								96.3%

Residential area (Victorian houses) "area5"									
API \ semi_eCg	sealed	vegetation	trees	shadow	rail tracks	bare soil	Sum Map 1	User	
sealed	1931337	26684	27516	55849	0	0	2041386	0.946	
vegetation	41587	544090	35711	7020	5675	991	635074	0.857	
trees	30575	57438	543010	21728	0	1617	654368	0.830	
shadow	32102	10551	19735	388719	0	6	451113	0.862	
rail tracks	156	1781	0	0	193500	0	195437	0.990	
bare soil	1282	3108	3306	230	0	14696	22622	0.650	
Sum Map 2	2037039	643652	629278	473546	199175	17310	4000000		
Producer	0.948	0.845	0.863	0.821	0.972	0.849			
									0.904
									90%

Residential area (semi-detached houses) "area26"									
API \ semi_eCg	sealed	vegetation	trees	shadow	b.soil	temp.features	Sum Map 1	User	
sealed	1590282	49022	25650	41228	0	0	1706182	0.932	
vegetation	46940	845611	42653	15253	166	119	950742	0.889	
trees	25271	63576	674979	52927	327	0	817080	0.826	
shadow	34009	16946	31127	433752	349	0	516183	0.840	
b.soil	1257	140	60	46	6295	0	7798	0.807	
temp.features	0	93	237	0	0	997	1327	0.751	
Sum Map 2	1697759	975388	774706	543206	7137	1116	3999312		
Producer	0.937	0.867	0.871	0.799	0.882	0.893			
									0.888
									89%

Table 5.2 The g-mean values indicate the eCognition's performance

Land cover classes	***g-mean values***			
	Area 0	**Area 20**	**Area 5**	**Area 26**
Sealed	0.98	0.96	0.95	0.93
Vegetation	0.86	0.92	0.85	0.88
Trees	0.83	0.86	0.84	0.85
Shadow	0.91	0.85	0.84	0.82
Rails Tracks	0.89	N/A	0.98	N/A
Bare soil	N/A	N/A	0.74	0.84
Temporary features	N/A	N/A	N/A	0.82

5.4.2 Qualitative analysis using the Map Comparison Kit software

In the previous paragraph, the two classification methods were qualitatively analysed with the use of the error matrix where the emphasis on the overall, user and producer accuracies was given. However, significant interesting is to also investigate what causes the differences in the error matrix and understand why the two classification methods differ. According to Congalton and Green (2009) the differences in an error matrix, which is indicated by the off- diagonal values, can be the result of four possible sources:

- errors in the reference data
- sensitivity of the classification scheme to observe variability
- use of inappropriate remote sensed data for mapping specific land cover classed
- mapping error

For a better understanding of the differences between the two classification methods, the results were qualitatively analysed with the use of the Map Comparison Kit (MCK). The MCK is a software tool developed in 2004 by the Research Institute for Knowledge Systems (RIKS) in Netherlands. The MCK was originally developed for the analysis of the land use maps of Netherlands but it became employable for many

GIS applications providing general methods for pattern recognition. The software was designed to compare pairs of categorical maps, in raster format, in order to evaluate the differences related to the overall extent, the spatial distribution as well as to understand the nature of the differences (Visser, 2004). There are a range of algorithms within the software for the comparison of categorical maps including the automated production of the classic kappa statistics and the percentage of agreement between classes. The software also offers tools for visualising, organising and exporting raster maps. According to Visser and de Nijs (2006), the comparison between the two maps, using MCK, can also be based on a) fuzzy set calculation rules, b) hierarchical fuzzy pattern matching and c) single map statistics. The software is free of charge and can be downloaded from the http://www.riks.nl/mck. A user's manual is also provided.

The MCK software was generally employed in this PhD study for the automated production of the confusion matrices and the kappa statistics for each pair of maps. The procedure was part of the statistical analysis of the comparison results between each classification method. At this stage of the research, additional comparison tools, available within the software, were used in order to identify similarities and dissimilarities between the two techniques of the manual API and the semi-automated object based classification. The aim was to quantify as well as understand the differences between the objects/classes of each map produced by the different classification methods. For that purpose the "per category" tool (Figure 5-16) was used. The "per category" algorithm performs a cell-by cell comparison of one categorical class at a time (defined by the user) and gives information about the occurrence of the selected class in both maps. The result provides an equal-unequal map in which the green colour shows the cells that belong to identical categories/classes of both maps while the red and blue colours show the unequal categories/classes (Figure 5-17). The resultant map was exported as an ASCII file, imported into the ArcGIS environment where it was converted into a raster format for further examination.

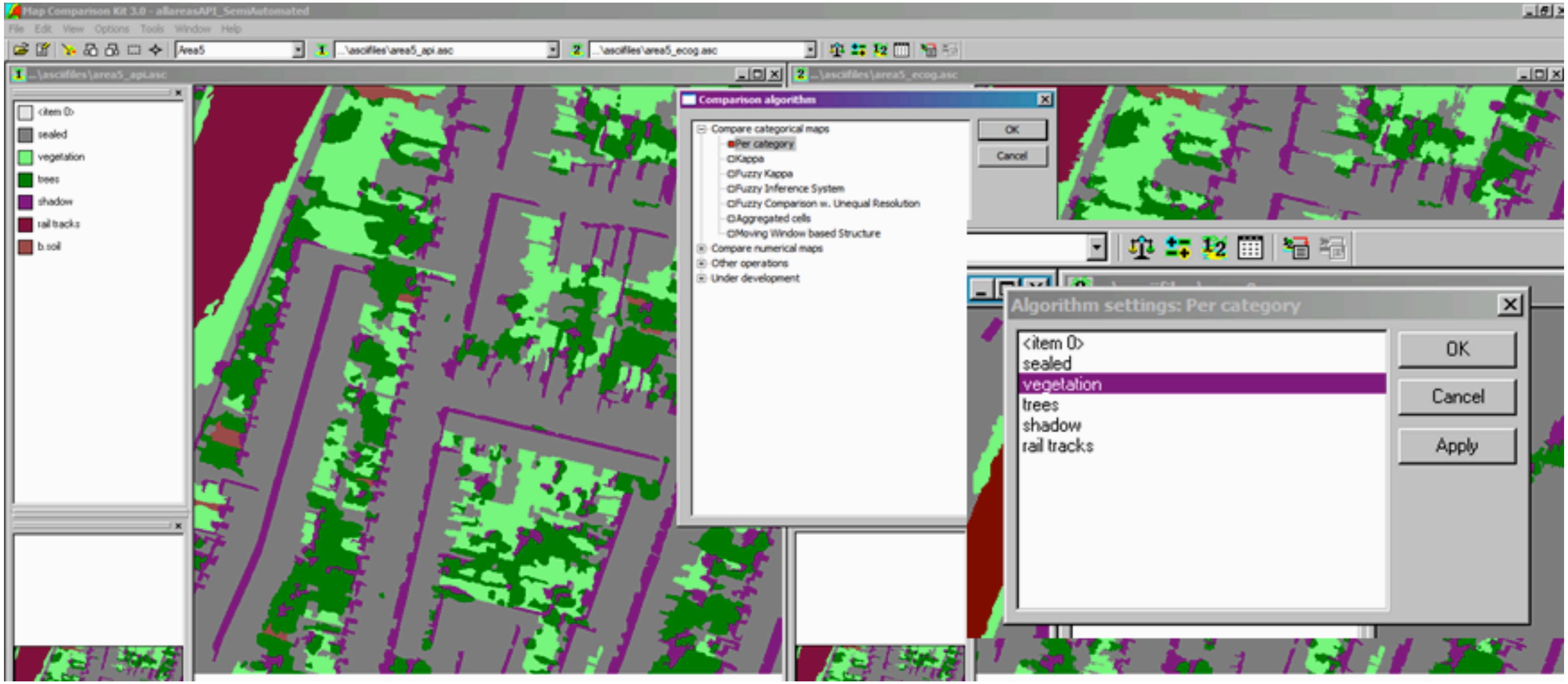


Figure 5-16 Implementation of the residential with Victorian houses test site within the MCK software. The two maps were compared "per category" by selecting each class individually.

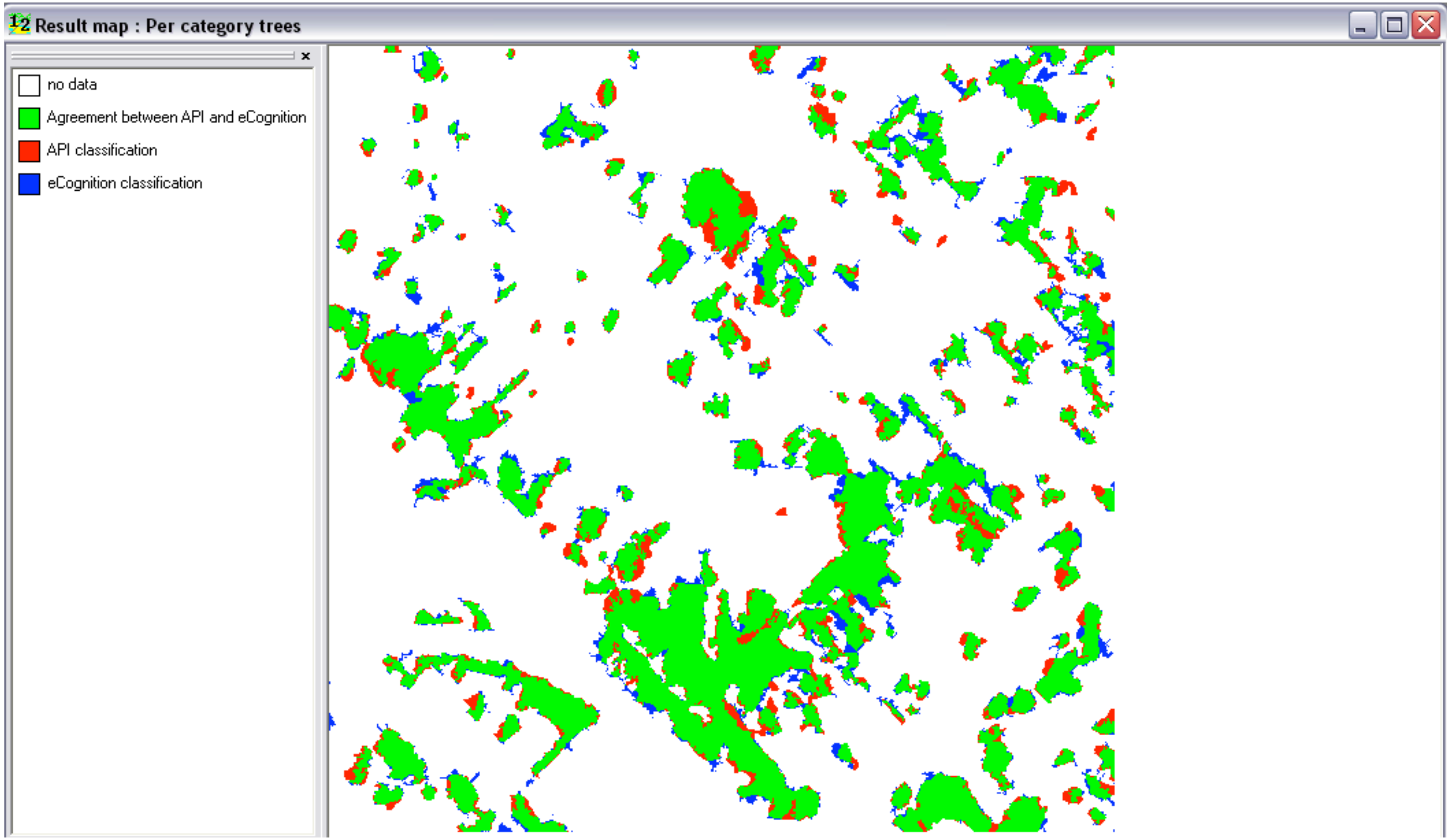


Figure 5-17 Per category comparison between the two methods (API and semi-automatic eCognition) for the “trees” class (Reference site 1, “area26”: residential area with semi-detached houses).

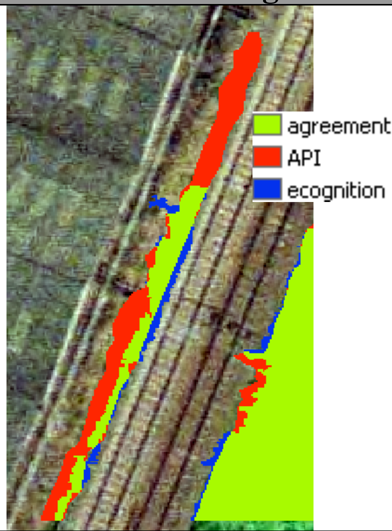
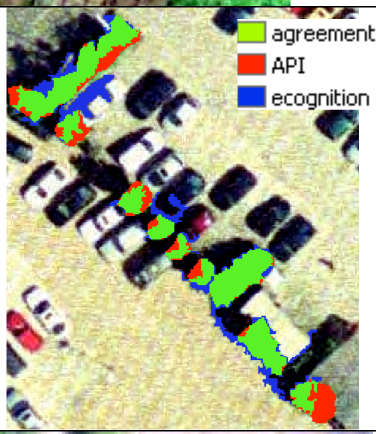
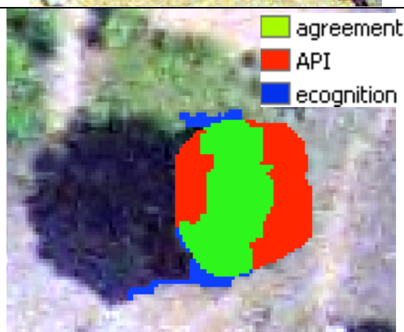
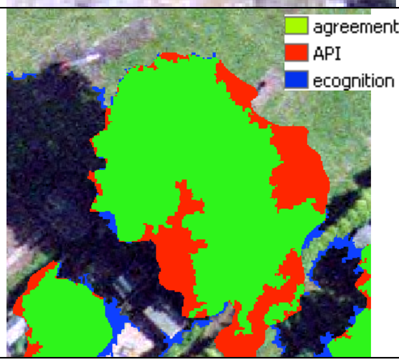
The “per category” comparison analysis was repeated for each land cover class (sealed, vegetation, trees and shadow) individually and for all the four test areas. The tool proved to be helpful for visually comparing and analysing the disagreement between the two maps especially when imported into the ArcGIS environment.

The main benefits of using the MCK software for the visual analysis of the different classification methods were (i) the less time and human effort needed for identifying the differences and (ii) the objectivity and explicitnesses of where the actual differences are. The software gave a complementary insight of combining visual and automated comparisons.

Analysing the results of the “per category” comparison analysis (such as in Figure 5-17), the main reasons of why there were differences between the manual digitising and the automated object based image segmentation can be categorised below:

- the software follows a pixelised pattern during the boundary delineation on the contrary with the interpreter who creates smooth lines around the features of identification
- the eCognition’s segmentation is based on the reflectance spectral value of the image and not to the physical structure of the landscape. Consequently, there is no recognition of real objects during segmentation as the human eye does
- due to spectral confusion during automated segmentation, differences in boundary delineation have been identified in examples such as: i) canopy boundaries; the edge of the canopy was usually included into the class that surface underneath the tree belong to, which was mainly either a sealed or vegetated surface, ii) the part of the trees that was in shadow was identified as different object from the rest of the tree (classified to the shadow class at this stage). Similar results were identified with the vegetated surfaces in shadow and the sealed areas in shadow. Examples of differences between the two segmentation methods can be seen in the Table 5-3 while an analytical discussion is following in the next paragraph 5.5.

Table 5-3. Differences between manual boundary delineation and automated object-based segmentation for extracting urban land cover features

Examples of different object extraction between API and eCognition		
Areas with low reflectance value of vegetation: The interpreter identified the whole vegetated area (red and green objects together) while eCognition picked up only the polygon with high reflectance value of green		
Features in shadow Confusion in boundaries between trees and shadow		
Mixed pixels Canopy boundaries- tree in shadow and a sealed surface underneath		
Mixed pixels Canopy boundaries- confusion between trees and lawn		

5.5 Discussion

5.5.1 Summary discussion of the manual and automated object delineation

Close scrutiny of the disagreement between the classes of each study area has identified the main reasons causing the differences between manual delineation and eCognition's segmentation. These are:

- <u>thematic discrepancy:</u>

Some examples of misclassification were due to human error. In few cases even though a land cover feature was successfully segmented (digitised) it was then manually labelled with an incorrect land cover class, in the attribute table of the vector data. In addition, some surface objects greater than the proposed 4 m^2 were faulty omitted (the minimum mapping unit was set to 2 m while on-screen digitising). These same objects were successfully recognized in eCognition. The omitted features were predominantly shadow or individual trees, either in back gardens or along streets. Sometimes, especially for trees, the reason they were not digitised was because they had low contrast with neighbouring objects and were not distinct enough to be visually identified.

- <u>eCognition's more detailed boundary delineation:</u>

On a 1:200 scale, it is sometimes difficult for the human eye to distinguish a tree when it is next to grass, with the use of a single view aerial photography. This depends on the type of tree and the condition of the grass, as they affect the intrinsic contrast between object tones. It also depends on the levels of illumination and quality of the photograph or the scan. A larger scale can help to overcome this, but the delineation of the boundary is less precise and difficult to digitise. Consequently, there is a high probability that such features will be missed by API. eCognition automatically recognised these cases due to subtly different textures (internal object tonal variability) in the tree canopies; trees are very compact with a 'rough' texture, while grass is more monotone. Again, this may vary depending on image quality. Furthermore, a big advantage of using eCognition is that the image can be segmented at scales larger than

1:200. In many examples, eCognition has extracted features that were lost in the API due to this threshold. If automated segmentation is used for boundary delineation, a fixed scale is not necessary and the image can be analysed in greater detail compared to API.

- mixed pixels/ spectral confusion between classes :

There are cases where eCognition has not satisfactorily identified or separated features, for example, the fusion of individual trees with the shadow next to them and also the misidentification of smooth textured trees with bushes or grass. But this discrimination was also difficult during the API and therefore these mis-segmentations can also occur in manual digitising. Examples of these mis-segmentations are infrequent (approximately 10 objects out of 10.000) and mainly occurred with red trees next to shadow as both features are dark. These examples could also be considered less important for mapping sealing, since both these classes are indicators of unsealed soil.

- a human being's intelligence to identify real objects and not image objects.:

A significant difference between the API and the image segmentation is that eCognition identifies image objects, which are not always real world objects. A representative example is shown in Figure 5-18. The interpreter ignores the fact that part of the tree is in shadow and digitises a polygon as a rounded shape following the canopy shape. eCognition segments the same feature according to spectral difference. So, most of the tree is correctly identified but the part in shade is merged with the 'shadow' polygon. Neither methods of segmenting the image are wrong.

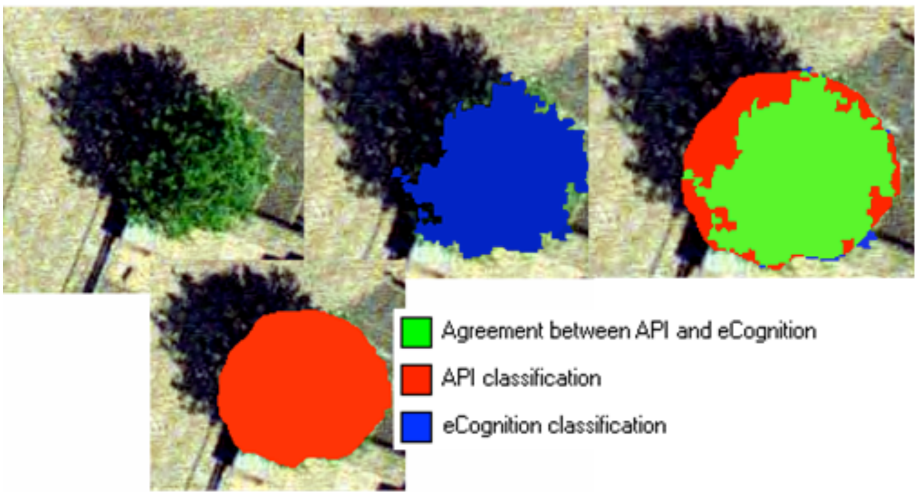


Figure 5.18 The difference between the interpreter and the eCognition software in the boundary delineation

Another example is the discrimination between shadow cast on the ground surfaces and shadow either wholly or partially covering buildings. The interpreter has the intelligence to identify the two different types of shadow by interpreting the dark sides of the buildings as sealed surfaces. eCognition cannot distinguish dark, shaded areas from shadow and identifies them as one feature. A similar example regarding shadow produced by buildings and by chimneys. The interpreter has the intelligence to identify the two different types of shadow ignoring the "chimney shadow" by digitising the shadow polygon along the roof edge. But eCognition has created one polygon with both shadow types included in it (Figure 5-19). However, these segmentation differences are insignificant as the shadow class is reclassified according to the land cover features that are in it.

The advantages and disadvantages of each method are summarised in Table 5.4.

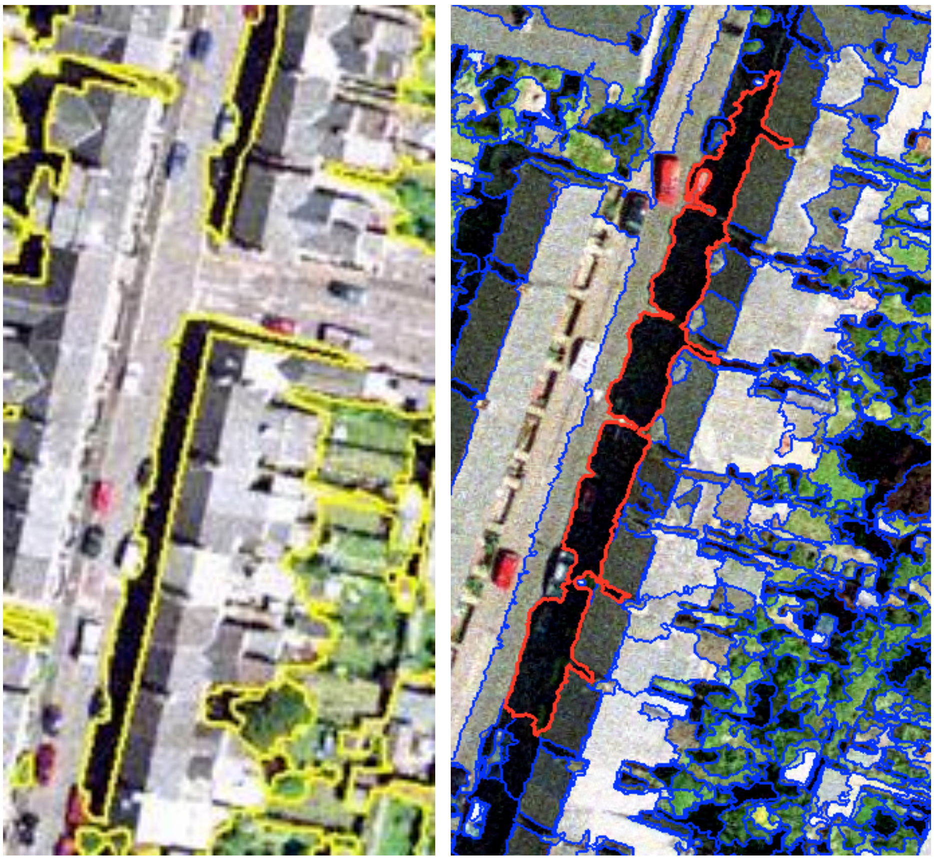


Figure 5-19 Difference between API and eCognition's delineation of shadowed areas

Table 5.4 The advantages and disadvantages of using either API or eCognition to delineate real-world objects from remotely sensed imagery (Kampouraki et al., 2008)

	Advantages	Disadvantages
API	♦ Interpretation of real objects ♦ Identification of complex patterns and complex situations ♦ Ability to include or ignore features intelligently ♦ Multi-scale representation ♦ Use of shape, context, neighbourhood relationships	♦ Subjective ♦ Time consuming ♦ A fixed scale is necessary ♦ Inconsistency in the use of a steady scale to the whole image ♦ Human error ♦ Imprecise boundary delineation ♦ Expensive
eCognition	♦ Objective (the rules and chosen parameters are subjective but the rules are applied to the whole image objectively) ♦ Multi-scale representation ♦ Hierarchical connection between multi-scales ♦ Use of shape, context, neighbourhood relationships ♦ Transferable rules: boundaries reproduced automatically across different data sets ♦ Quick method	♦ Identification of image objects, not real objects ♦ Inability to include or ignore features intelligently ♦ Fusion of real objects due to spectral confusion

In general, API is considered an expensive method for mapping land cover as a lot of laborious and time consuming work is required. This is why there is a general interest in finding new methods that could replace manual digitising and, if possible, manual labelling. The automated segmentation has the advantage of being much quicker, especially if rule sets can be universally applied. In this research study, the manual digitising and manual labelling of the four study areas lasted for 40 days. The examination of the industrial study area, in order to find the appropriate parameters for the segmentation, in eCognition, took ten days including the time required for the manual classification of the 'mixed areas' of the upper segmentation level. These parameters were instantly transported to the remaining study areas. A further day was required to segment and classify the commercial area and three days to segment and classify each residential area.

5.5.2 General considerations of the accuracy assessment of object-based image segmentation

The main advantage of using the eCognition software is the multi-resolution segmentation and the hierarchical connection between the levels. The approach is similar to interpreter's ability to hierarchically segment the image into various scales and simultaneously label the image objects using semantic knowledge. Although, a critical issue in using automated approaches for repeating the same process is the selection of the appropriate segmentation "scale" which determines the size of the objects and the classification accuracy. The assessment of segmentation methods is mainly based on trial-error and visual inspection methods, a time consuming process. The real challenge still exists in finding an automated, objective ways for defining the appropriate segmentation parameters. Consequently, there is a need to develop object validation techniques in order to assess uncertainties in segmentation-based object extraction (Shi et al., 2005; Hay et al., 2005; Hajek, 2008).

Very recent literature shows the tendency for developing statistical approaches for selecting the appropriate feature for image segmentation without requiring feature selection defined by the user (Lizarazo and Elsner, 2009; Pekkarinen et al., 2009; Kawakubo et al., 2009).

Recent attempts have also been made for segmentation accuracy assessment. Moller et al. (2007) used Landsat images (30m resolution) and the eCognition software to calculate two object metrics; the 'relative area in super-object' (RA_{SO}) and the 'relative position to super-object' (RP_{SO}) in order to assess over and under segmentation in two levels. According to the authors, the metrics were grouped together using a K-means clustering algorithm showing which "objects represent the best geometrical (high cluster means of $RA_{SO)}$ and topological (low cluster means of RP_{SO}) match of super and sub objects". The extracted polygons were compared with randomly selected reference polygons (400 were manually digitised) by using circular buffers of 1000 m.

In order to quantify the semantic object accuracy, the "comparison index" CI was used (7). The authors concluded that the CI method can be used for evaluating segmentation results and that the process is suitable for the accuracy assessment of different thematic data sets and change detection analysis.

$$Ci = \frac{\sum_{i=1}^{n} (\mathrm{Ci \ x \ ACi})}{n} \qquad (7)$$

Ci= the comparison class which represents clustered and ranked object metrics; Ci= (0, 100)
ACi= ACi is equivalent to the proportion of Ci within the reference space.
n= the segmentation levels

It must be made clear that Moller et al. (2007) referred to "super objects" while they were meaning the reference objects and the "sub objects" in their study are the objects that were extracted during eCognition's segmentation. According to the literature, reference to super and sub objects indicates a multi-resolution segmentation and not a comparison between two different methods.
The work of Moller et al. (2007) was used by Clinton et al. (2008) who tried to develop another approach for segmentation accuracy assessment. Various segmentation results, implemented in eCognition and ASTRO software, were compared with a set of training objects that were manually digitised using digital RGB aerial photographs. The objects of interest were vehicles, trees and buildings. The data used was digital aerial RGB photography at 0.175 m resolution. The work presented was a preliminary research of the study published later on by Clinton et al. (2010). A clustering approach was used in order to evaluate the segmentation results. The cluster with the most number of segmentations assigned to was identified and its parameter combination was used as the optimal one. The results showed that more than one cluster can identify the "optimal" parameter combination. The methodology described can be applied only when predefined objects are extracted from the image of interest.
Stein and De Beurs (2009) applied various complexity metrics such as aggregation index, fragmentation index, contagion and patch size in order to identify objects and understand how segmentation can influence the map complexity. They observed that

the final segmentation outcome is dependent on the data quality, experience of a human interpreter and the complexity of the patterns on a map. According to the authors, the complexity metrics could be used to find the most feasible segmentation result. However, the method used in this study has not been validated and as they argued the method still needs to be evaluated by comparing it with actual field data.

Dragut et al. (2010) proposed a new tool, available in Definiens Developer software, for the evaluation of image segmentation. The Estimation of Scale Parameter (ESP) tool generates image objects at multi-scales by an iterative process and calculates the local variance of the objects on each scale. The local variance of each object is plotted against the scale value in order to indicate the most appropriate scale parameters that should be used for objects segmentation. According to the authors, the ESP tool provides a great potential for the development of an automated assessment of the most appropriate scale parameters for image segmentation.

Smith and Morton (2010) discussed the potential of using existing maps to extract initial object information instead of considering segmentation as the starting point of OBIA. Implementation of this approach took over for the update of the national land cover map of UK (known as the LCM 2007). The LCM 2007 production was based on the use of existing digital cartography, i.e. the Ordnance Survey (OS) MasterMap (MM), in order to extract the object's structure. The OS MM information had to be generalised in order to provide object information according to the requirements of the LCM 2007 (20 m MMU), which was a time consuming process. In addition, according to the authors, the generalised map was lacking of boundaries at agricultural and semi-natural areas while urban and rural areas were well defined. The main conclusion of this study was that one data source or one approach was not enough to generate the required object information. Various sources as well as API had to be combined in order to maximise the quality of the final result.

These techniques were developed later than the implementation of this PhD study and could only be considered as future investigation.

5.6 Conclusions

Two approaches for mapping the urban land cover (for the purposes of identifying sealed soils), using a true colour ortho-rectified aerial photography, have been presented. The traditional technique of the aerial photo interpretation (API) has been compared against object-based automated methods for boundary delineation, with the use of eCognition software. A quantitative analysis showed a very high agreement between the two methods (92%) across the four, different in structure, reference sites of Cambridge. A qualitative analysis identified the advantages and disadvantages of each method (Table 5.4). The main advantages of the eCognition's segmentation are:

- the ability to work flexibly on specific parts of the image, allowing the user to analyse the image in a way that replicates API.
- the ability to save the segmentation result and apply it to another sample area having an automated boundary reproduction. That makes the method much faster than the time consuming manual digitising. In this research study, the semi-automated object based classification of the four sample areas decreased the processing time by 25% in comparison to manual API.

The main disadvantage of the automated segmentation is that it cannot adjust the boundary delineation based on recognition of what the object is in the "real world'", as the human would do. The automated segmentation is based on the spectral reflection of pixel values and this is why it cannot replicate human interpretation which is based on the structural characteristics of the landscape shown on the image. A complete OBIA, i.e. an iterative process of segmentations and classifications, is needed in order to introduce spatial relationships (shape, texture, geometry etc) of the extracted objects. However, automated segmentation can assist API by using the automated object-based delineation instead of the time consuming and labour intensive digitising process.

If the semi-automated segmentation was to be repeated again, the most complicated sample area should be used first in order to find the appropriate values for the segmentation's parameters. In this way, fewer 'mixed areas' will need to be manually classified in order to run the segmentation again at a smaller level by using object domains (example in Figure 5-13).

Finally, as the aim of this PhD study was to identify an automated classification method to monitor soil sealing in urban environments, the next step is to test the performance of the object-based classification technique.

Chapter 6

Object-based image analysis (OBIA) of the aerial photography using rules and expert knowledge

This chapter aims to evaluate automated object-based classification methods to map soil sealing. The theory of the OBIA when using fuzzy rules and expert knowledge is firstly described. Then a statistical approach is analysed; the approach was employed in order to automatically select the best image object features combination for discriminating each urban land cover class.

The development of the object-based classification model with the use of a true colour aerial photography follows. The model was built up in the eCognition software by employing automated multi-resolution segmentation and hierarchical rule-based classification. The results were compared with the other two classification methods that were described in chapter 5, i.e. traditional API and automated image segmentation with manual labelling. The effect in overall classification accuracy when using different levels of thematic detail is also analysed.

Part of the work described in this chapter has been presented at the Object based landscape analysis (OBLA) conference, (Nottingham, April 2009), organised by the Remote Sensing and Photogrammetry Society (RSPSoc).

6.1 Rule-based automated classification using processes in the eCognition software–the theory

As already aforementioned, in OBIA the image is first segmented into homogeneous regions extracting the image objects and then the image objects are classified using either statistical algorithms, expert knowledge to develop rules or a combination of the two methods. Image segmentation can be implemented in multi levels in order to extract objects at different scales. The image objects are then classified in order to give them “both a meaning and a label” (Definiens, 2006). During classification, the user firstly needs to define the desired classes and then identify the specific characteristics of each class using spectral and/or contextual information. In the eCognition software the classification can be implemented using the Nearest Neighbour (NN) classifier or a set of fuzzy rules and membership functions. In NN classification, image object samples for each defined class need to be collected first. For classifying an object, the NN algorithm calculates the distances between the object means and the samples means using a distance function with a range between 0-1 (Figure 6-1a). The rule based classification in eCognition is based on fuzzy rules which replace the strict class definitions of “yes” or “no” with a continuous range between 0 and 1 (Baatz et al., 2000). The value of 0 means “exactly no”, the value of 1 means “exactly yes” while the range in between describe a certain state of yes and no (Definiens, 2007). The class in which an image object belongs to, is defined with the use of membership functions (Figure 6-1b).

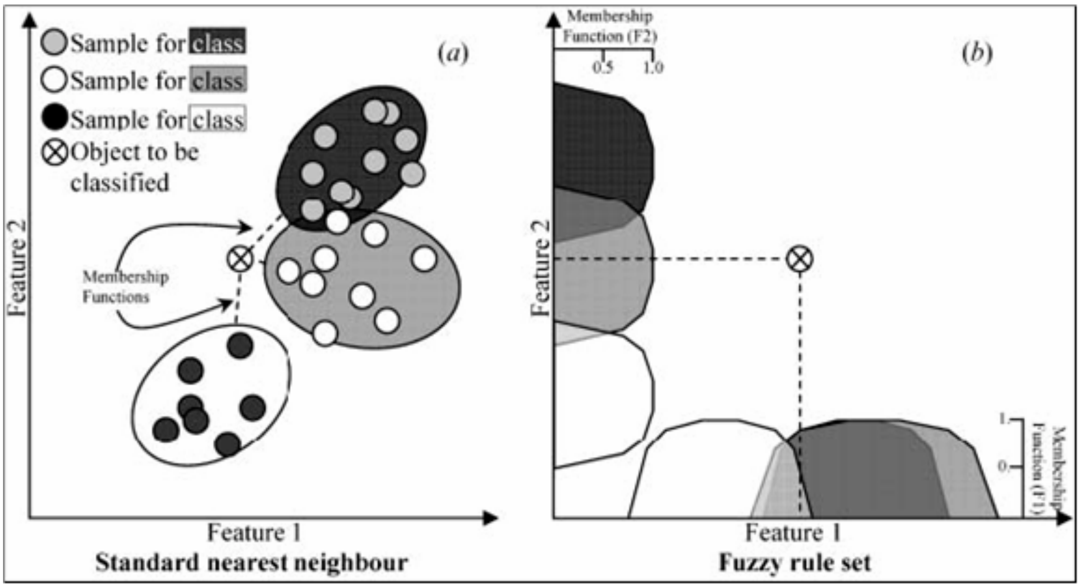


Figure 6-1 Illustration of the (a) NN classifier and (b) the fuzzy rule sets classification (source: Walker and Blaschke, 2008)

The NN classification is a fast and easy method based on a ‘click and classify’ strategy (Baatz et al., 2000; Benz et al., 2004; Moller and Blaschke, 2005). However, it is not a transferable to other scenes method as the same sample selection could not be used in different areas or with different data sets (Walker and Blaschke, 2008). On the other hand, in the rule-based classification, the development of the rule-set classification can be saved and applied into different image scenes or data types. Based on the review of the literature, the advantages and disadvantages of using nearest neighbour (NN) versus rule-based classification techniques can be summarised in Table 6.1.

Table 6.1 Summary of the advantages and disadvantages of NN and rule-based classification methods in OBIA

	Advantages	Disadvantages
Nearest Neighbor classification	simple method (similar procedure to pixel-based supervised classification methods)	Walker and Blaschke (2008): ▪ Significant number of samples for each class is required ▪ Time consuming method ▪ Lack of transferability in additional areas or in different times ▪ Uncertainty of accuracy of different scenes
Rule-based classification	Gamanya et al. (2007): ▪ Possibility to modify the rules ▪ Iterative process until a satisfactory classification result is achieved ▪ Transferability (leading to a potential operational approach) ▪ Local application of the rules in specific classes	▪ Expert knowledge of the study area is required ▪ The selection of the rules is subjective

As, the aim of this research was to identify an automated transferable methodology, and only object-based models build up using rules and expert knowledge got the potential to be transferable, the focus of this chapter is on the fuzzy logic classification. The development of the object-based rule set classification model is comprehensively analysed in chapter 6.3.

In the latest versions of the eCognition software (Definiens Professional 5, Definiens Developer, Definiens Architecture and eCognition 8) the image analysis can be implemented using the process tool. Processes-based classification allows you to combine several classification steps of into one process while different types of classification algorithms can be used in each classification step (Definiens, 2007). Rules can also be applied in a specific class domain of the class hierarchy in order to work with local conditions during image analysis.

The first step in the classification process is the assignment of the classes. Then attributes are given to each class (by classification) using either the "assign class" algorithm or the "classification algorithm", both available in the process tool. The first one is the most simple classification algorithm in which a single condition (rule) is given to an object or a class. The "classification algorithm" allow you to develop a combination of conditions that can be simultaneously applied in one class. The condition is based on various image features which can either be "object features" or "class related features" (Figure 6-2).

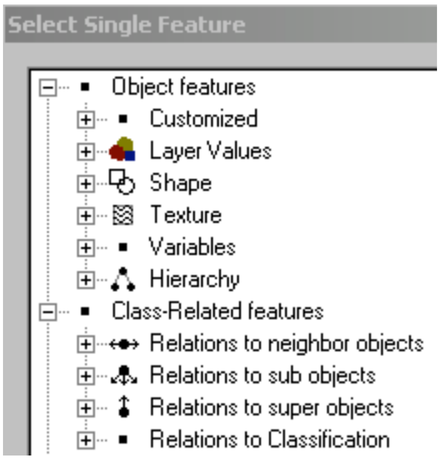


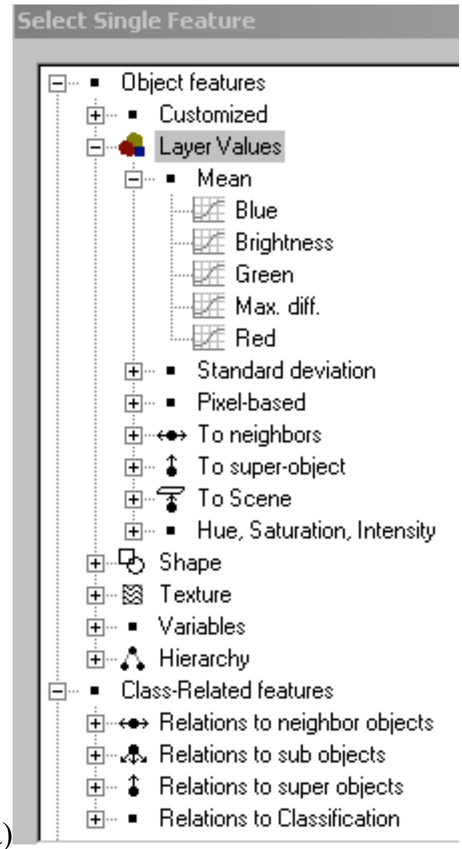
Figure 6-2 The feature types that can be selected for creating the rules in classification

The "object features" types describe spectral, structural, hierarchical, or other properties of an image object (Definiens, 2006). The most important ones can be grouped as follows:

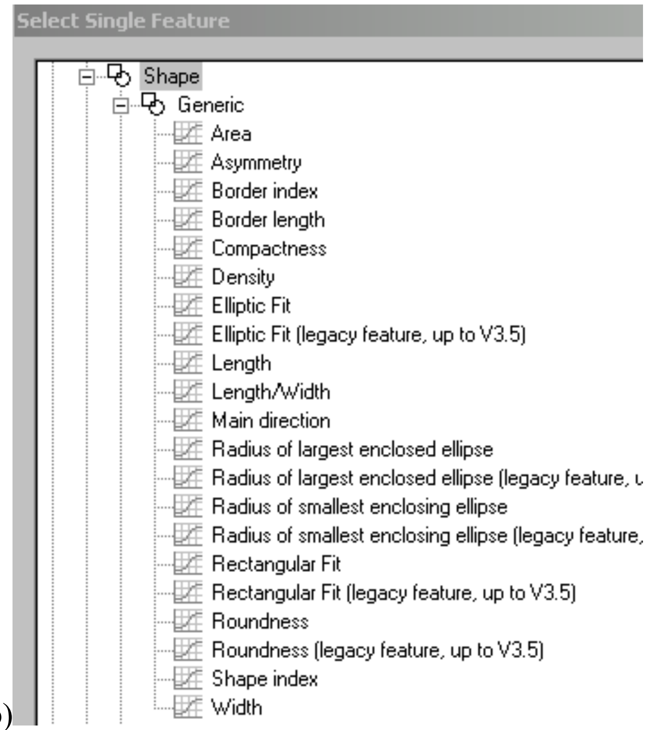
- Layer Values: these values usually comprise the fist classification step and are used in order to discriminate the image objects in relation to their spectral properties (Figure 6-3a)
- Shape: can be used to describe the shape of an image object using a variety of variables (Figure 6-3b). "The basic shape features are calculated based on the object's pixels" (Definiens, 2007)
- Customized: These features can be created in the "Edit Customized Feature" window and are mainly arithmetic features (calculated using an equation) such as the Normalised Difference Vegetation Index (NDVI) or any other index, mean ratios of the image's bands, the Principal Component (PC) etc
- Texture: The texture of the image objects can be defined using different texture features which the majority of them are based upon the "texture after Haralick" co occurrence matrix (Definiens, 2007)

The "class-related features" are used for indicating the location of a class in the image object hierarchy. This position can be defined either by a vertical distance (relation to super-objects and sub-objects) or by a horizontal distance (relation to neighbour objects). The class-related features can be categorised as follows:

- Relations to sub-objects: Are used in order to describe the relations of an image object with other image objects that belong to a class which exist in a lower level of the classification hierarchy.
- Relations to super-objects: Are used in order to describe the relations of an image object with other image objects that belong to a class which exist in a higher level of the classification hierarchy.
- Relations to classification: Are used in order to identify the current or potential classification of an image object.
- Relations to neighbour objects: Are used in order to describe the relationship of an image to other image objects of a certain class on the same level.



- a)



b)

Figure 6-3 Object feature based on (a) spectral or (b) shape information

When more than one rule needs to be applied in order to define a class, the "classification algorithm" shall be used. This method is based on class descriptions in which you can use fuzzy logic rules with object and class related features or a combination of various other expressions, for describing the characteristics of a class. For example, in Figure 6-4, the impermeable class was defined using the following class descriptions/expressions:

- Use of fuzzy logic with a class-related feature in order to indicate the relationship of the class with the "built-up" class which is in a vertical distance 1 (i.e. one level difference in the class hierarchy)
- Use of fuzzy logic with an object-related feature (use spectral information) in order to define the range of the mean value of the blue band that the objects must have in order to belong to the "impermeable" class
- The expression "similarity to classes" was used in order to indicate that image objects can be classified as "impermeable" only if they do not belong in the "green" class (i.e. the masking out technique: class A is not class B)

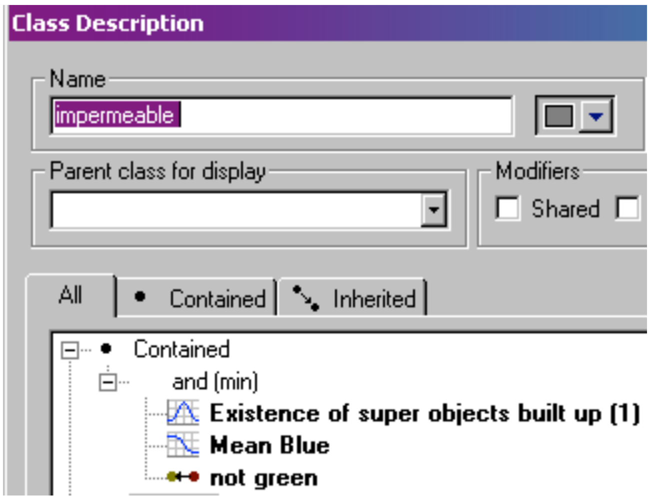
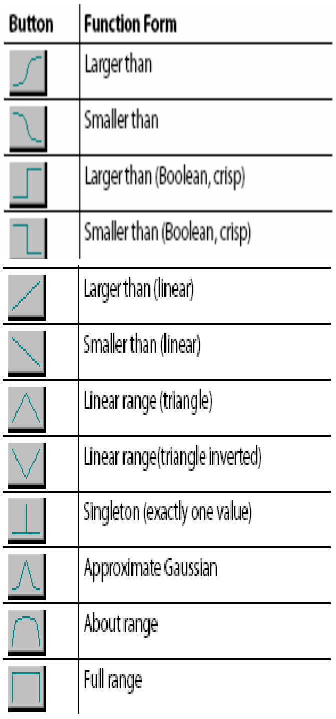


Figure 6-4 The "impermeable" class was defined with a combination of various expressions, using spectral and context information

Fuzzy logic is applied with the use of membership functions by which the degree of the membership is defined with a value between 0 and 1. The highest membership value defines the class to which the image object is assigned while image objects with lower than the pre-defined minimum membership value remain unclassified

(Definiens, 2006). The membership functions that can be used in the fuzzy rule classification are shown in Figure 6-5



Button	Function Form
	Larger than
	Smaller than
	Larger than (Boolean, crisp)
	Smaller than (Boolean, crisp)
	Larger than (linear)
	Smaller than (linear)
	Linear range (triangle)
	Linear range(triangle inverted)
	Singleton (exactly one value)
	Approximate Gaussian
	About range
	Full range

Figure 6-5 List of the pre-defined membership function types available in the eCognition software

In order to combine two or more expressions, in the class description, logical operators are used. Two common operators are the "or (max)" and the "and (min)" which are used in the following way (Definiens, 2007):

- or (max):

When a number of conditions are combined by the maximum operator, the output equals the maximum fulfilment of the single statements (Figure 6-6a)

- and (min):

When a number of conditions are combined by the minimum operator, the output equals the minimum fulfilment of the single statements (Figure 6-6b)

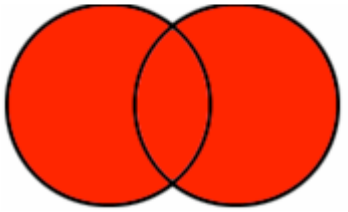
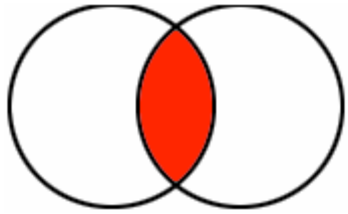
a)  b) 

Figure 6-6 (a) the "or (max)" operator combines conditions while the (b) "and (min)" operator uses the intersection of conditions (source: Definiens, 2007)

All these rules (such as assign expressions, conditions, and fuzzy logic membership values in the predefined classes) are defined by the user using the "trial - error" method along with repetitive visual inspection until the desirable classification results are met. The tool that is used during this procedure is the "Feature view" window which allows the user to perform the following (Definiens, 2007):

- get a visual view of a selected image object feature
- investigate threshold values of a feature in order to decide the value limits a membership function should have. Each image object is displayed in a grey value or a defined range from blue (low values) and green (high values).

6.2 Feature extraction information using the STATISTICA software

The image objects extracted during the segmentation process contain spectral and contextual information. In chapter 5, the segmented images were manually classified according to the land cover classes of the area. Consequently, a "database" for each object had been created knowing what values every feature that belongs to a class has. The best feature combination for maximising land cover class discrimination was attempted to be statistically evaluated. These features could then be used into the eCognition software for the automated object-based classification.

The two levels of the semi-automated classification, of the most complicated sample area ("area5"), implemented in the eCognition software, were exported including information of the following image object features:

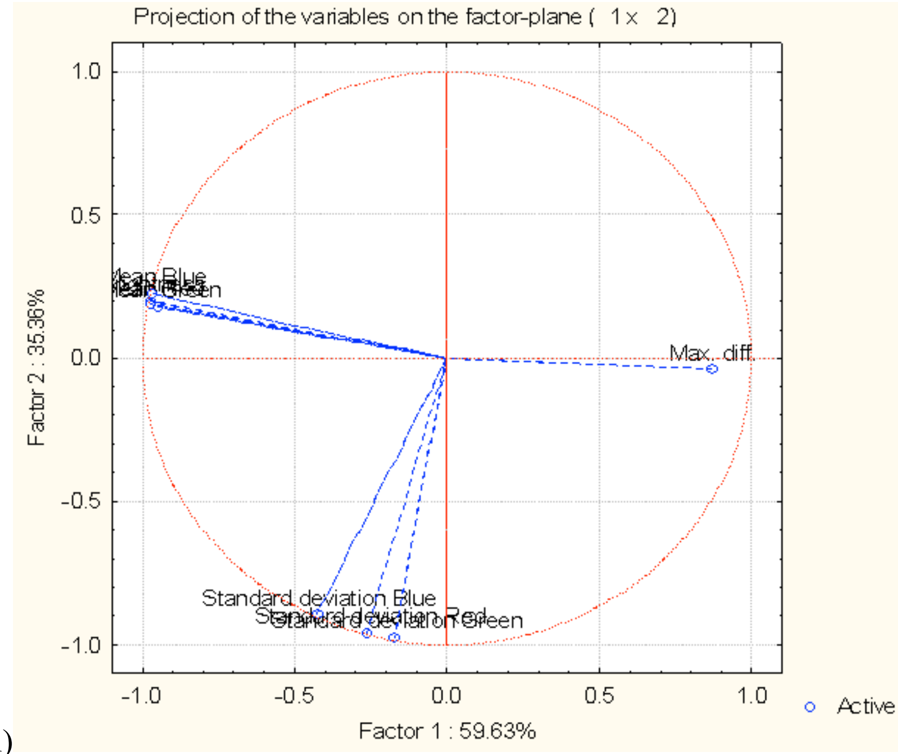
- features that contained spectral information such as: mean values and mean values of the standard deviations (sttdv) of blue, red and green bands, max difference and brightness. In eCognition, brightness is calculated as the sum of the mean value of each band divided by their quantity computed for an image object while the max difference is the mean value of all bands belonging to an object divided by brightness (Definiens, 2006).
- features that contained contextual information such as: area, shape index, compactness, length/width, roundness

The exported polygons attributed to a land cover class were imported into the Statistica software. The aim was to identify the optimum object feature combination in order to discriminate the land cover classes from each other. For that purpose, the Principal Component Analysis (PCA) was implemented. The PCA "is a multivariate method which can identify redundancy or correlation among a set of measurements or variables for the purpose of data reduction" (creascience, 2009). In this study, the PCA was used as a tool for evaluating the object features and graphically represent the key features/ variables that could be used for the automated classification. The land cover classes and the image object features used for the analysis are represented in Table 6.2.

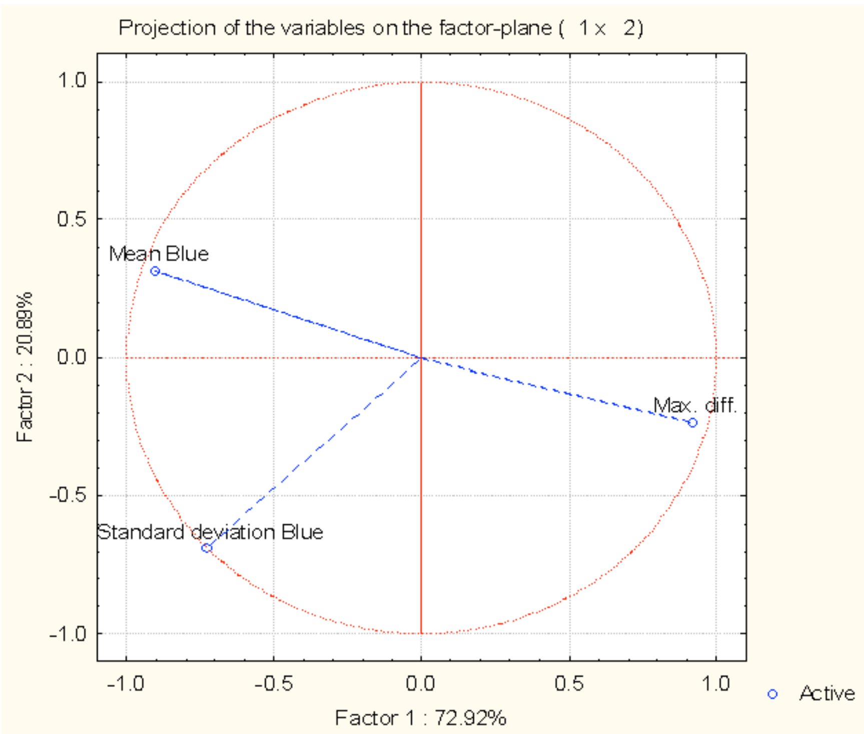
Table 6.2 Object features of each land cover class, available in the eCognition software, that were tested using STATISTICA software

Land cover classes of the sample "area5"– use of all objects extracted in both classification levels, a total of 944 polygons	**Variables that were tested in Statistica software using the PCA**
Sealed surfaces	Mean value of the red band
Vegetated surfaces	Mean value of the blue band
Trees	Mean value of the green band
Shadow	Brightness
Rail tracks	Max.diff
Mixed areas	Sttdv of the red band
	Sttdv of the blue band
	Sttdv of the green band
	Area index
	Shape index
	Length
	Compactness

Initial trials with the PCA identified that among all image object features the contextual features (area, shape, length etc) did not give any information that could be used to separate the land cover classes at this stage. According to the graphical results of the PCA, every combination of the contextual features, including or not spectral information, could not separate the classes more than 30%. Consequently, the trials continued with the rest of the image object features that basically contained only spectral information. Representing the rest of the variables into a graphical plot, the PCA clearly demonstrated that the max. difference is one of the object features that should be used for the discrimination of each land cover class (Figure 6-7i). The same plot analysis also identified that brightness and the mean values of the red, green, blue (RGB) bands are equally important for the discrimination; so any of those parameters should be used. Similarly, the use of one of the sttdv values of the RGB band was sufficient. Consequently, it was concluded that a combination of brightness or the mean values with the sttdv values of any of the RGB bands, in conjunction with "max.diff", should be sufficient for the discrimination of the classes. Further trials among these variables showed that the use of the mean value of the blue band, the sttdv of the blue band and the max.diff gave the highest percentage of 73% separation of the land cover classes (Figure 6-7ii). For that reason these three image object features were used for the analysis and calculation of the principal component (PC_1).



i)



ii)

Figure 6-7 i) the image object features that could be used for the class discrimination, ii) the image object feature combination that was identified to separate the land cover classes with the higher percentage

The PC_1 can be calculated by using the following equation (1), available in the Statistica software:

PC_1= [((([max.diff.] – mean)/ stddv) * eigenvector) – ((([mean blue] – mean)/ stddv) * eigenvector) – ((([stddv blue] – mean)/ stddv) * eigenvector)] (1)

The [max.diff], [mean blue] and [stddv blue] variables are the image object features extracted from the land cover classes, after the semi-automated classification with eCognition software. The mean, stddv, and eigenvector values were calculated within the Statistica software. The first two values were indicated by using the "descriptive analysis" and the "brakedown table" option while the eigenvector value by clicking at the "variable" tab at the PCA tool bar. The descriptive analysis standardises the PC_1 values into a normal distribution. There is a number of variables that can be used for the breakdown table production such as the mean value, minima and maxima of each value, standard deviations, confidence meanings of the mean values, etc (Table 6.3).

Table 6.3 The values of mean and stddv as calculated using the Breakdown Table of the Descriptive analysis

Breakdown Table of Descriptive Statistics (RangePC1_Area5L3_unmerged)
N=434 (No missing data in dep. var. list)

class	Factor1 Means	Confidence -95.000%	Confidence +95.000%	Factor1 N	Factor1 Std.Dev.	Factor1 Minimum	Factor1 Maximum	Percentile 15.00000	Percentile 85.00000
sealed surfaces	-1.31637	-1.47065	-1.16210	136	0.909700	-2.54928	0.773734	-2.22033	-0.113260
vegetation	0.89880	0.64036	1.15724	11	0.384696	0.14111	1.414846	0.49083	1.348349
trees	1.34391	0.13996	2.54785	8	1.440095	-2.08475	2.474698	1.19118	2.104797
shadow	1.78620	1.54006	2.03234	24	0.582902	0.67089	2.858215	1.34363	2.664999
mixed areas	0.47873	0.34779	0.60967	249	1.049035	-1.91523	2.804893	-0.62542	1.641676
rail tracks	-0.61397	-1.12270	-0.10524	6	0.484766	-1.27294	-0.010837	-1.27294	-0.010837
All Grps	-0.00000	-0.12860	0.12860	434	1.363095	-2.54928	2.858215	-1.72529	1.533625

For each of these variables a graph was created showing the PC_1 results for the land cover classes. When the whole range of the PC_1 values was used (minimum, maximum) the graph indicated that all the classes are overlapping and separation is not possible (Figure 6-8). However, by using the 95% confidence limits of the mean values the most land cover classes are separable (Figure 6-9). According to the graph, there is an overlap between the bare soil and the rail tracks as well as these classes with the sealed class but this was expected as it is commonly know that there is a spectral confusion between these land cover features. The importance of the graph was the demonstration that the sealed areas could be separated and from the vegetated areas, trees and the areas in shadow.

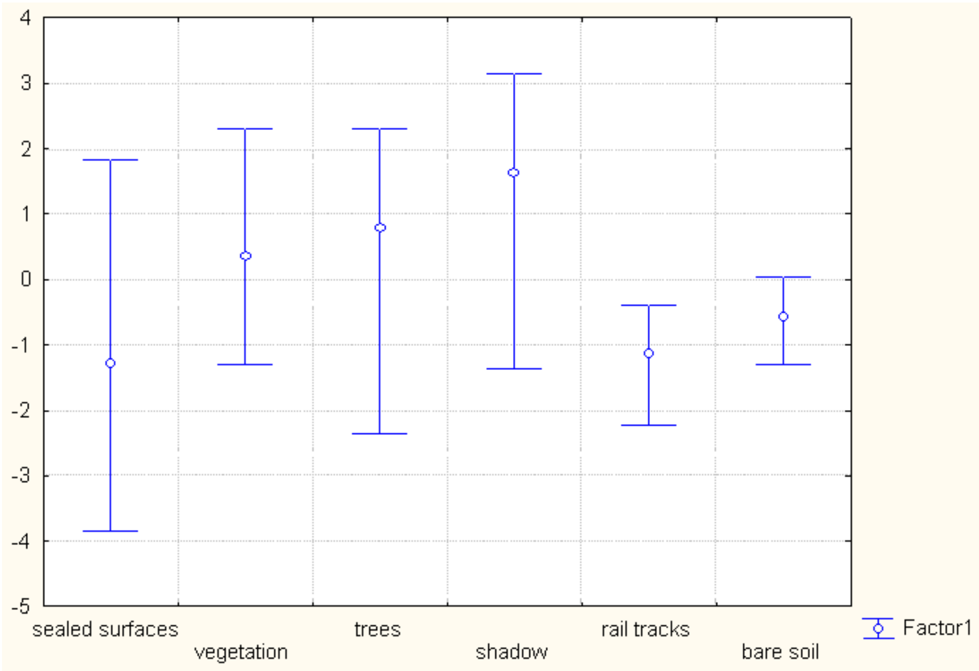


Figure 6-8 PC_1 graph of the mean values for each land cover class

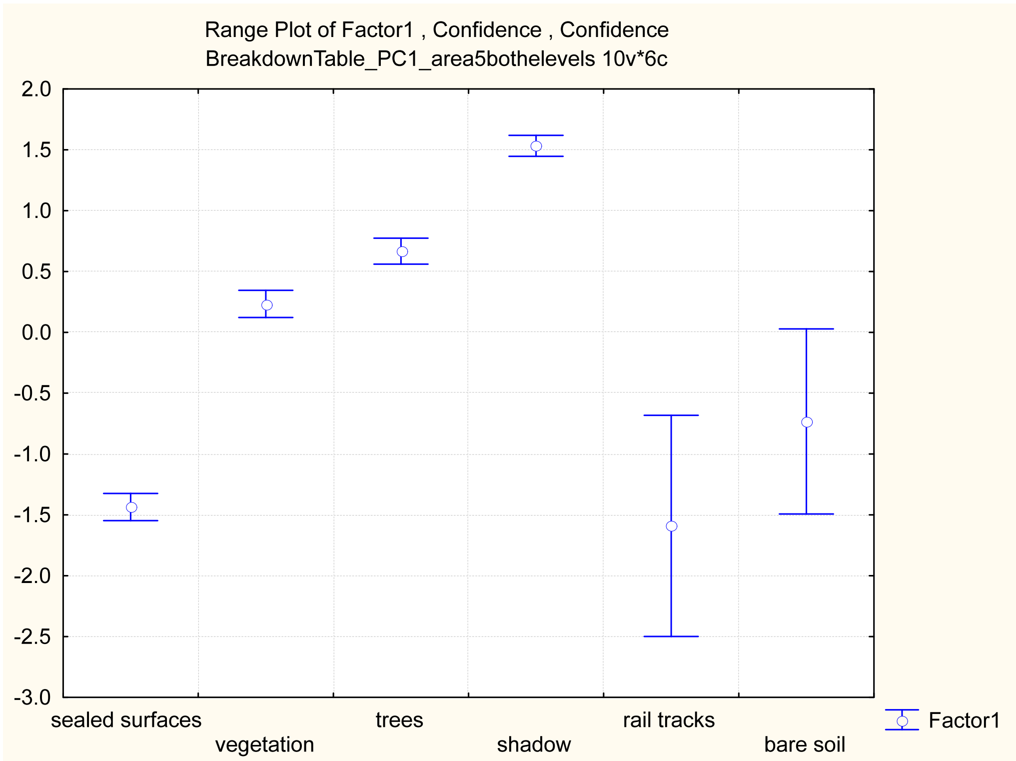


Figure 6-9 PC_1 graph of the mean value for each land cover class at 95% confidence limits

The next step was to apply the PC_1 for the automated classification of these land cover classes with the use of the eCognition software. First of all, the PC_1 was calculated in eCognition as an arithmetic feature by building the same equation (1) and using the values of Table 6.2 (Figure 6-10). Then, for each land cover class, a fuzzy rule using the membership function of the “approximate Gaussian” distribution and the PC1 values was implemented (Table 6.4). The idea was that by using this membership function type the software should be able to identify/classify the polygons in the appropriate classes using the highest values (peaks of the Gaussian distribution). The classification result was unsatisfactory. Only some polygons were classified into the given land cover classes while misclassifications between the classified polygons were also included (Figure 6.11). The main reason was that the normal distribution of the mean value the 95% confidence limits used a certain range of values. As a result, eCognition classified only the polygons that have matched the defined by the user criteria leaving the rest of the image objects unclassified.

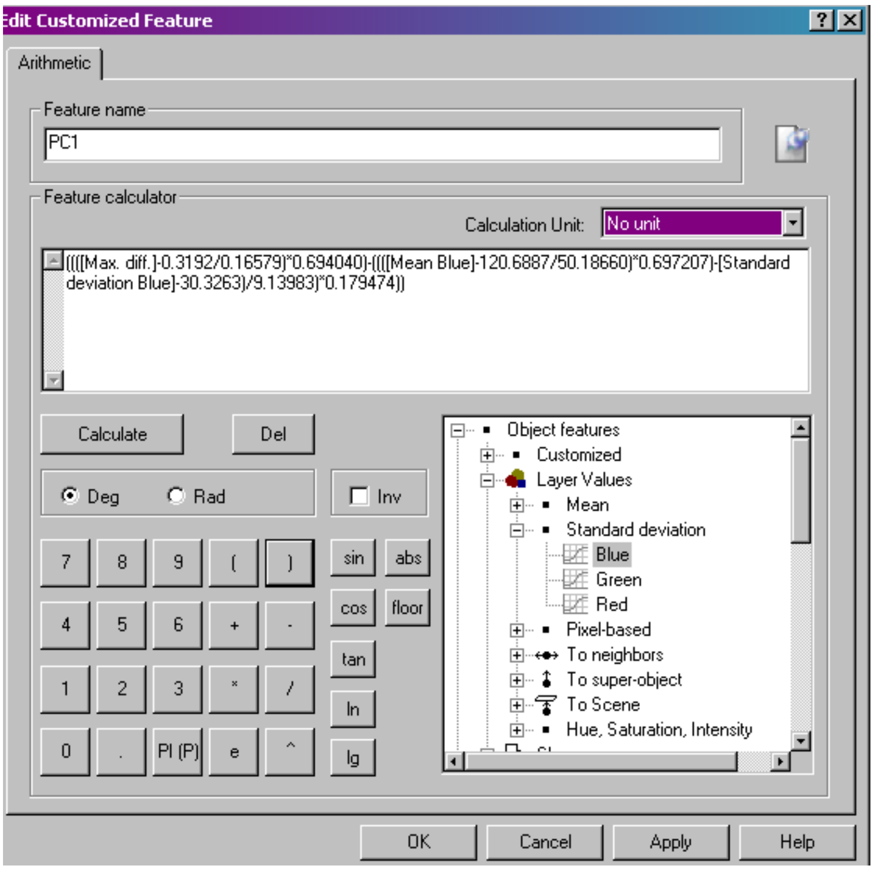


Figure 6-10. Creating an arithmetic feature, based on the PC analysis, in the eCognition software

Table 6.4 The membership function and the range of the mean values of PC_1, at 95% confidence limits, used in order to built-up the classification rules for each land cover class

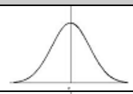
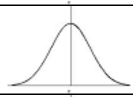
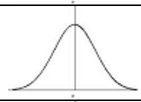
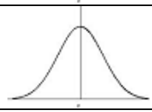
Land cover class	Membership function	Range values of PC_1
Sealed areas		-3.4, 0.6
Vegetated areas		-1, 1.5
Trees		-0.6, 1.9
Shadow		0.2, 2.8

Figure 6-11. The land cover classification result, in eCognition, using of the mean values of the PC_1 at 95% confidence limits

A new trial was implemented including the “mixed areas” class into the PCA. The aim was to copy the classification method applied during the semi-automated classification (chapter 5) i.e. classification in two hierarchical levels. At the broad level the PC_1 was used in order to separate the sealed areas from the rest (mixed areas). Then the mixed areas class was re-segmented and reclassified according to the remaining land cover classes; ideally the PC_1 could identify the range that those classes are separable. Various tests of the PC_1, using different value ranges, were applied until it was found that by using the 70% of the whole value range of each land cover class, the classes were almost separated from each other (Figure 6-12).

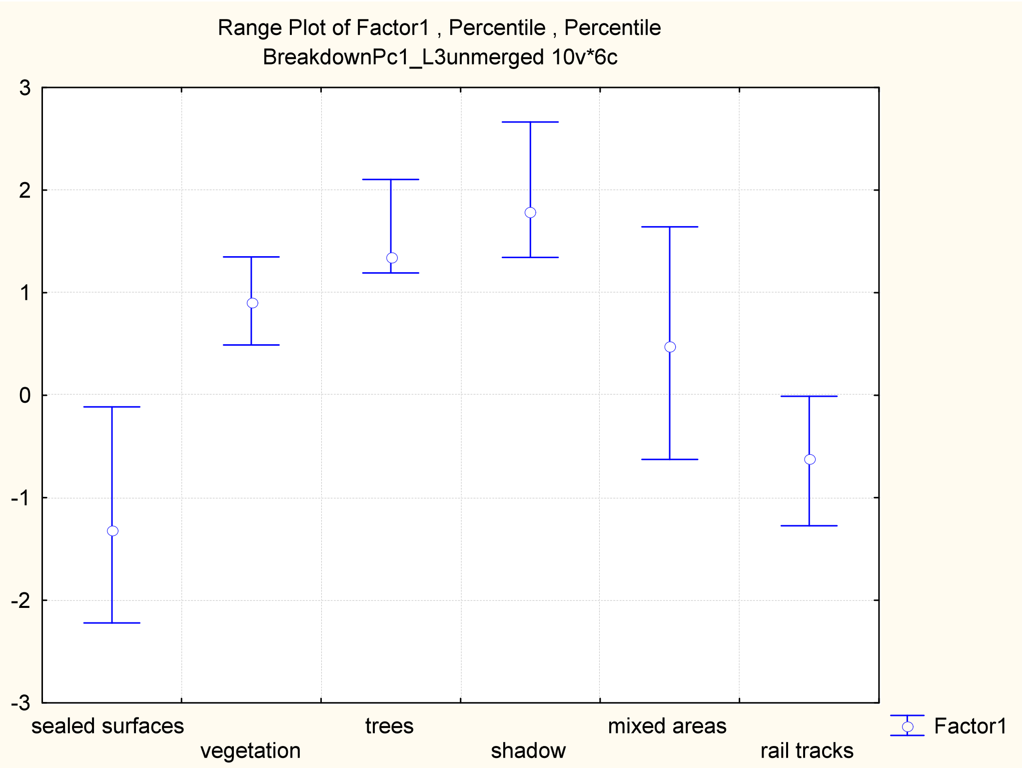


Figure 6-12 PC_1 graph of the mean value for each land cover class using the 70% of the whole range of the data value

The same procedure like previously described was followed. A new PC_1 was again developed in the eCognition software as an arithmetic feature. The classification results at the coarse mixed vs. sealed level are shown in Figure 6.13i while Figure 6.13ii illustrates the classification results at the lower level by including or not the rail tracks class. The results were again unsatisfactory and similar to the ones when the 95% confidence limits of the mean PC_1 value were used.

i)

ii)

Figure 6-13. The land cover classification result, in eCognition, using of the 70% percentile of the PC_1 value i) at the broad scale of 225, identifying sealed vs. mixed areas and ii) at scale 40 where the mixed areas class s re-classified into the remaining land cover classes

Another trial was based on the whole range (min and max values) of the PC_1. For every land cover class the whole range values are indicated in Table 6.5 below.

Table 6.5 The whole range values of PC_1 for each land cover class

Land cover class	Range values of PC_1
Sealed	-2.55, 0.77
Vegetation	0.14, 1.41
Trees	-2.8, 2.47
Shadow	0.67, 2.86
Mixed areas	1.91, 2.8

During this analysis an exact value range and not a normal Gaussian distribution was aimed to be used. The PC_1 values with a combination of different percentiles were tested until the optimal values, for discriminating the sealed class from the mixed areas one, were identified (Figure 6-14).

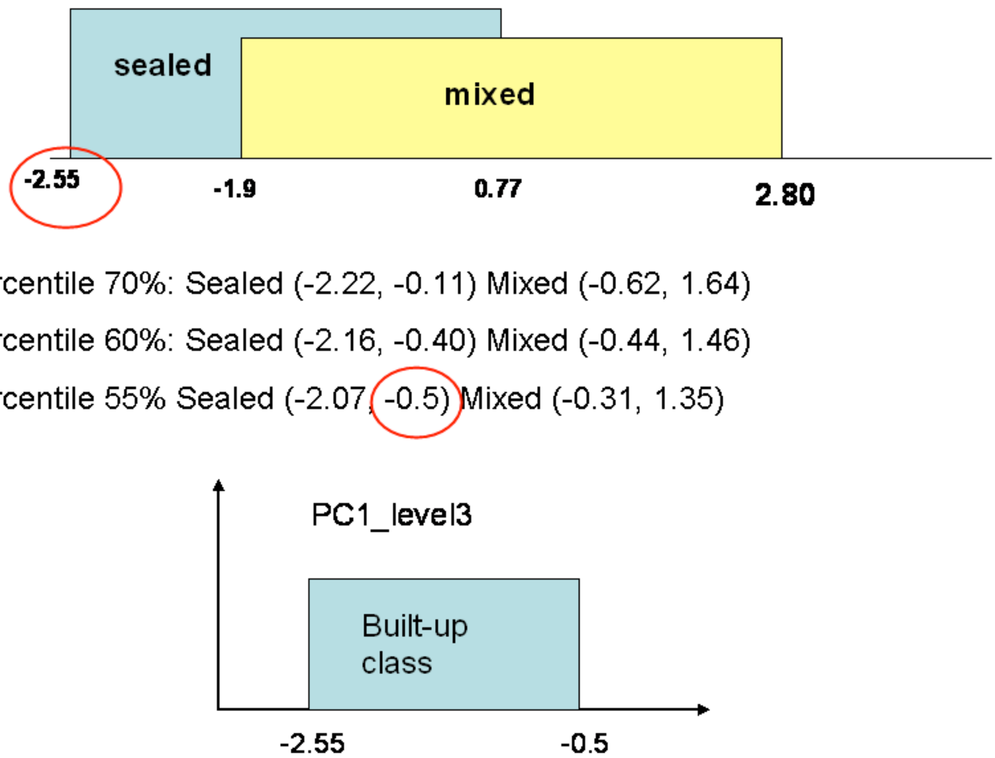


Figure 6-14 Representation of how the final PC_1values were identified in order to discriminate "built up" class vs. "mixed areas" class

The same procedure as before was followed in the eCognition software. The new specific value range of the PC_1 was used to classify the “sealed” class vs. “mixed areas” class, at the coarse level (Figure 6-15). This time the result was satisfactory as the majority of the sealed areas were successfully classified.

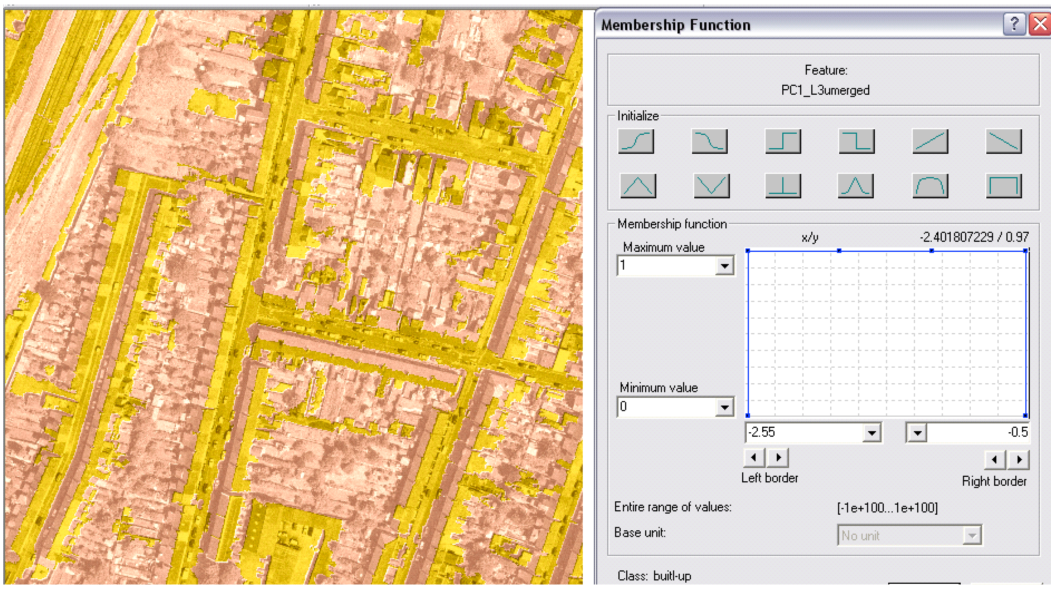


Figure 6-15 The classification result at the broad scale level in which most of the sealed surfaces were extracted using the PCA

The “mixed areas” class was re-segmented at scale 40. Looking at the whole range of al the land cover classes (Table 6.5) it was obvious that an exact range of PC_1 values could not separate the “trees” class form the “vegetated areas” class. For this reason, the two classes were merged together creating the “green” class. A similar procedure of the PCA with a combination of different percentiles were again tested in order to find the optimal values for the following classes: “sealed”; the remaining sealed surfaces not classified at the broad level, “green” and “shadow” (Figure 6-16). The classification result was unsatisfactory as there were major misclassifications between the sealed and green class (Figure 6-17).

Sealed percentile 60%: (-2.34, -0.61)

Sealed membership value: (-4.06, -0.61)

Green class (trees+vegetation)= (-2.54, 2.20)

Shadow: (2.21- 3.06)

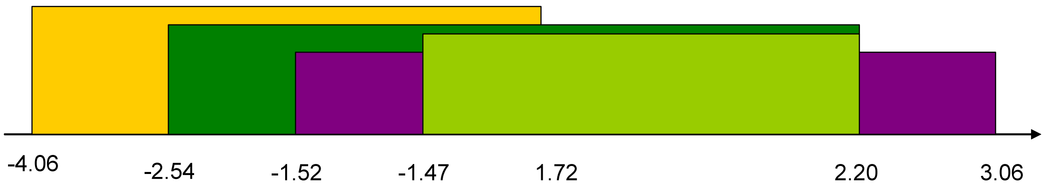


Figure 6-16 Representation of how the final PC_1 values were identified in order to discriminate the remaining land cover classes

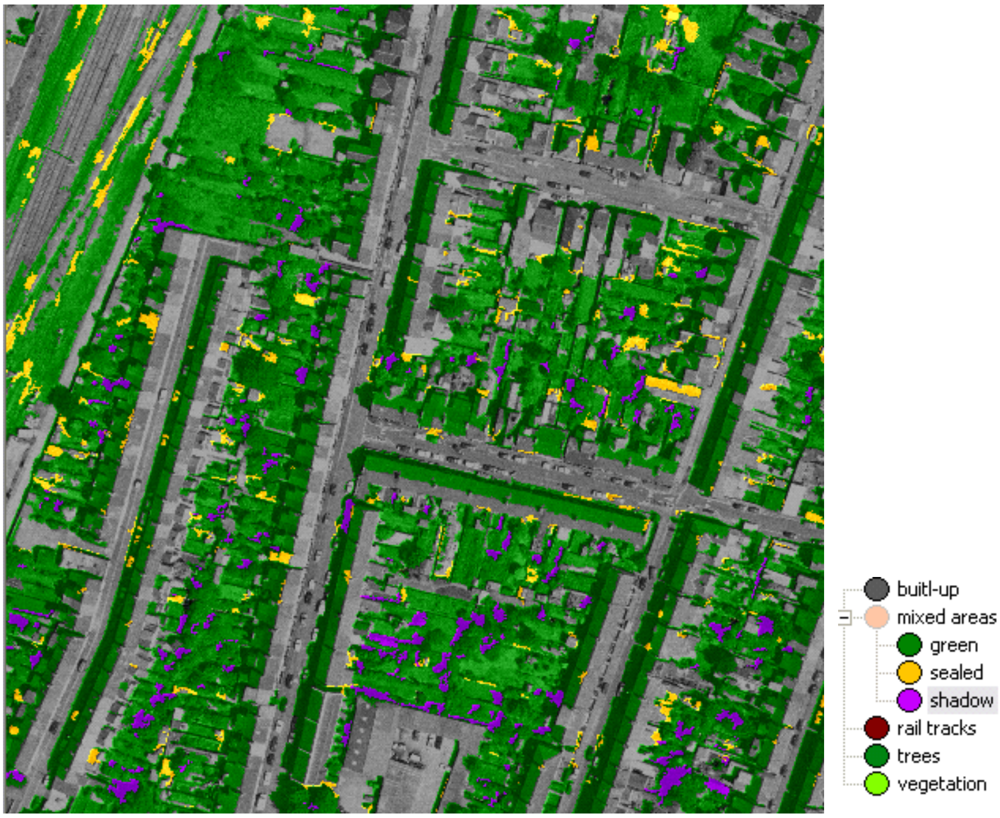


Figure 6-17 Final rule-based automated classification using the PC_1 values identified in the Statistica software

A general conclusion, based on the results of the different trials implemented, was that the PCA could not solely be used in order to accurately classify the sample area. The feature selection using the PCA was based only on the spectral information of specific image object features (i.e. max. difference, mean value of the blue band and the stddv of the blue band). The approach could successfully discriminate the majority of the sealed surfaces from the rest of the urban land cover classes but proved to be inappropriate for distinguishing all the classes at the once, at the hierarchical same level (Figures 6-11, 6-13, 6-17). However, the whole method proved to be a good exercise in order to get familiar with the image object features and the visual evaluation of the classification results in eCognition software. The main conclusions drawn from the PCA approach were:

- a new approach for automated classification is needed
- due to the successful discrimination of the majority of the sealed surfaces from the rest land cover classes, the PC_1 object feature that was developed in eCognition, will be tested further
- the automated classification approach must be based on the main principles of OBIA which are:
    - o detailed and precise segmentation at as many levels as necessary in order to detect all features of interest
    - o hierarchical classification based not only on spectral information of the image features but also on structure, context, morphology and relations between the detected features

6.3 Development of the rule-based classification model using the eCognition software

6.3.1 Multiresolution Segmentation

Although image analysis can be performed at single image object level, the advantage of the eCognition software is the ability of using multiple segmentation levels. The multi-levels are hierarchically connected. As described in the user guide (Definiens,

2007) in this image object hierarchy, each image object simultaneously provides access to information about its neighbours, sub- and super-objects (Figure 6-18).

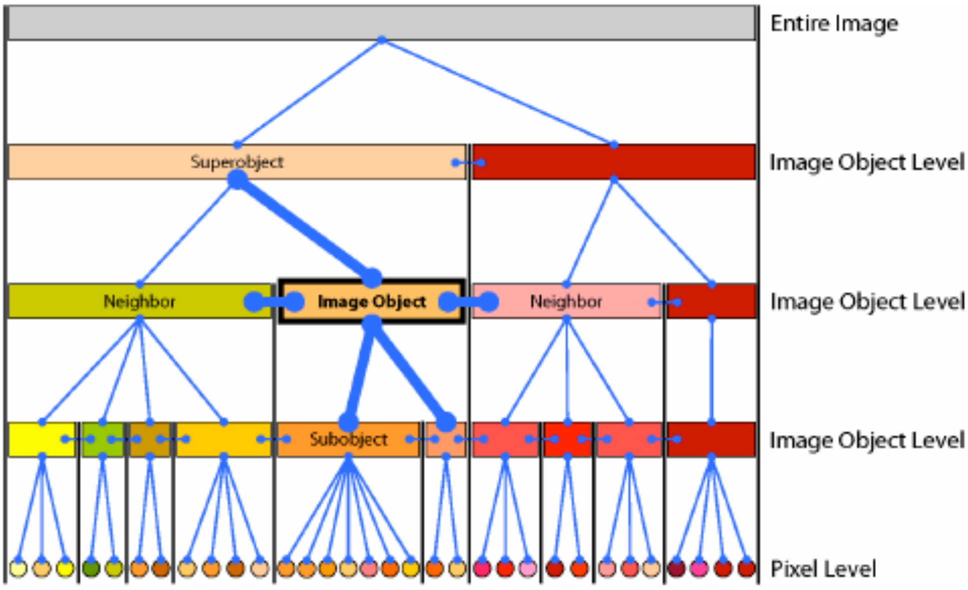


Figure 6-18 The concept of the image objects hierarchy. Each object is linked to super-objects, sub-objects and neighbour objects (source: Definiens, 2007)

A comprehensive analysis of the multiresolution segmentation has been implemented in the previous chapter 5, paragraph 5.2.1. One of the conclusions-recommendations of previous research, analysed in chapter 5, was that the automated segmentation should have initial be employed to the most complicated sample area in order to find the appropriate values for the segmentation's parameters. For this reason, from the four sample areas used in this research study (Figure 6-19), the reference sample site 2 ('area 5') was chosen for the continuation of this research. Consequently, the fist step was to examine whether the segmentation developed in the chapter 5.3.1, constituted the appropriate bases for the construction of the automated object-based model. At that time, the values for each parameter of the upper segmentation level were: scale = 225, shape = 0.3, compactness = 0.7, weight of red band (layer 1) = 2, weight of green band (layer 2) = 4 and weight of blue band (layer 3) = 1. The segmentation results of the 'area 5', using these parameters are shown in Figure 6-20.

	**Reference sample site 1 ('area26')** Low density residential area of 1960's semi-detached houses with broad large gardens, giving a large area of vegetated surfaces
	**Reference sample site 2 ('area 5')** Densely built residential area of 1930's Victorian terraced houses with narrow small gardens, giving a medium area of vegetated surfaces
	**Reference sample site 3 ('area20')** Part of the commercial area in the city centre; predominantly sealed area with large buildings, densely spaced with few vegetated surfaces
	**Reference sample site 4 ('area0')** Part of an industrial area; predominantly sealed area with industrial buildings and very few vegetated surfaces

Figure 6-19 The representative sample areas of the urban land cover of Cambridge

Figure 6-20 The segmentation results of the sample area

According to Gamanya et al. (2007) the qualitative criterion for the evaluation of the segmentation is that "any segmentation results have to satisfy the human eye". In addition, as described in the eCognition user guide (Definiens, 2006), for successful processing the image objects should explicitly represent the classes to be assigned during the classification procedure. A visual inspection of the segmentation results, of the sample area "area5", identified that the scale value of 225 was too big to meet the above criteria. A smaller scale value should have been assigned. A trial and error procedure of testing various scales below 225 finally identified that the appropriate scale value for the upper segmentation level was 90. Comparisons between scale=225 and scale=90 are shown in Figure 6-21. The scale of 90 constituted the upper segmentation level. More segmentation levels were employed using an iterative process between segmentations and classifications resulting in a hierarchical, multilevel classification with three main image segmentation levels (Figure 6-22). The iterative process is comprehensively analysed in the rule-based classification section that follows (paragraph 6.3.2).

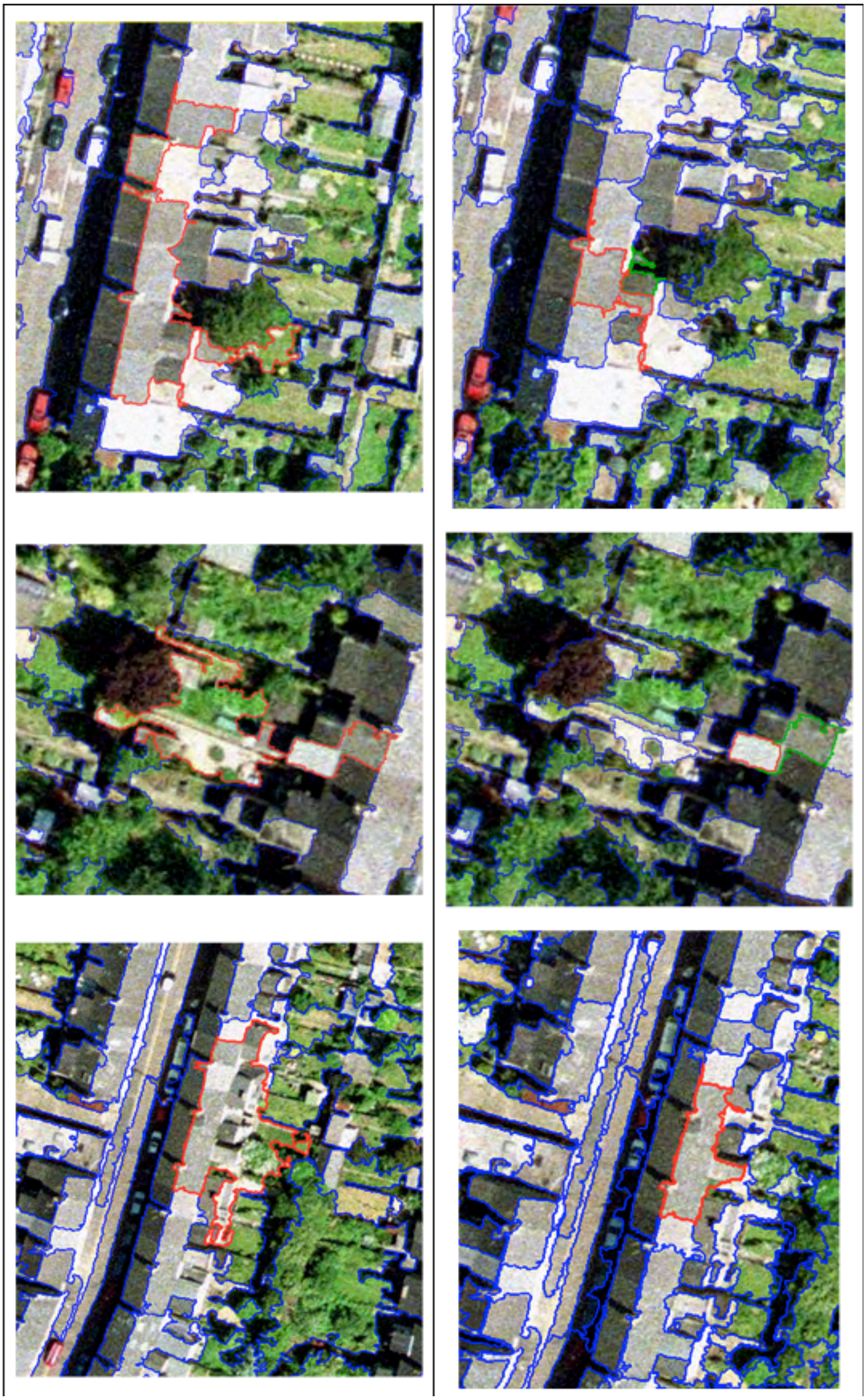


Figure 6-21 Examples of the segmentation results when using scale-225 (left column) and scale 90 (right column)

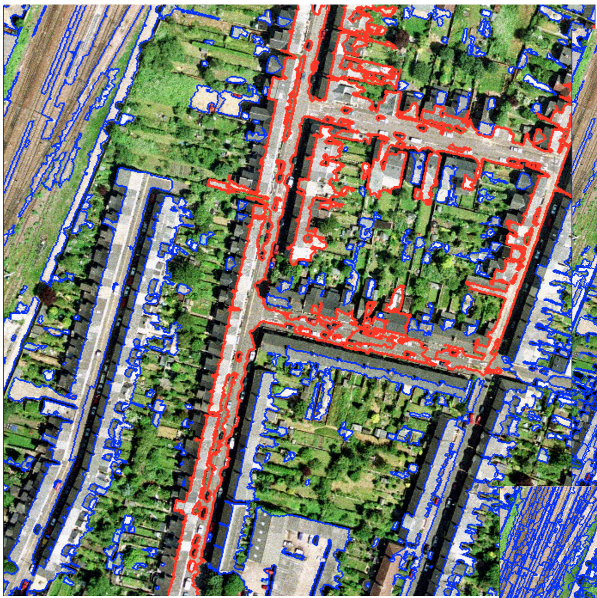


Figure 6-22 The three segmentation levels

6.3.2 Rule-based classification

For a successful object-based classification, once the initial segmentation is implemented, the image analysis should follow a general pattern that is consisted of iterations between segmentations and classifications of defined image objects until the desirable result it is achieved. Baatz et al. (2008) nicely represented this iteration between segmentation and classification used in OBIA (Figure 6-23).

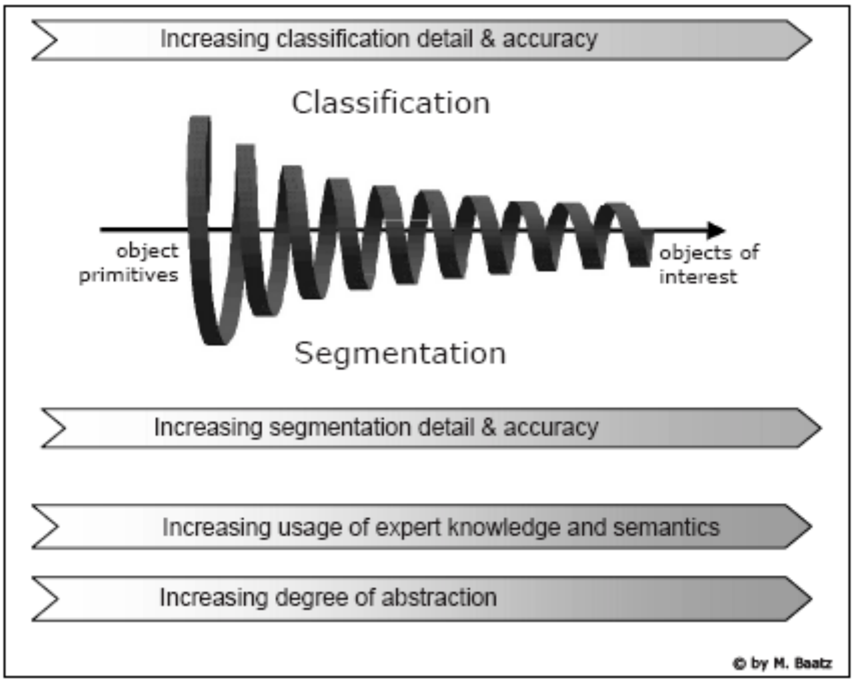


Figure 6-23 Object-oriented image analysis: the generic procedure (source: Baatz et al., 2008)

The rule-based classification is a complicated method which needs a lot of experience, accompanied by many cycles of "trial and error" (Definiens, 2007). According to the user guide, the image analysis should be done according to the following steps/ advices:

- start the classification with a simple class description, for example, a single threshold, classify and review the results.
- if the result is inadequate, adapt your settings, classify again and review again until the result is good. Only then start adding additional thresholds, membership functions or similarity expressions to the class description which you combine with logical operators.
- class descriptions are necessary in order to use fuzzy logic to classify the image object and when multiple conditions must be assigned to distinguish each class.
- test and review repeatedly until you are visually satisfied (trial and error method).
- “in this way, you can build up complex classification scenarios with many – hierarchically ordered - classes and complex class descriptions”.

In this research study, the development of the classification model was based on fuzzy rules and expert knowledge, following the previous advices. The trial and error method and a lot of visual inspection of each trial were repeated until the best features for each land cover class were identified. Following that approach, all rules were employed. The development of the rules was based on the use of individual processes. In the end, the whole rule-set classification was comprised by a series of processes that were executed in a defined order.

A single process executes an algorithm on an image object domain and provides solution to a specific image analysis problem. The algorithms were applied by selecting a number of features that can either be object features, class-related features or scene related features. The object features are generally based on the spectral information of the data and were used for measuring colour, shape, and texture of the extracted polygons. The image analysis was extended further by taking the whole classification network structure into account. Such analysis can be achieved by using the "class-related features" algorithms. The class-related features depend on image object features and refer to the class assigned to image objects situated at any location in the image object hierarchy. This location can be defined by a vertical distance in the image object hierarchy, refereeing to super-objects and sub-objects, or by a horizontal distance, refereeing to neighbour objects.

The image object features that were mainly used for the image analysis of the aerial photography and the development of the rule-based classification model are listed in the Table 6-6. Apart from the object features that solely use the spectral information of the image objects, spatial relationship object features were as well applied. The class-related features used for the development of the classification rule-set were the following:

1. Relations to Neighbour Objects: used to describe an image object by its relationships to other image objects of a given class on the same image object level. Individual relations-to-neighbour-objects algorithms used were:

a) **Border To:** It is referring to the absolute border of an image object shared with neighbouring objects. For geo-referenced data, the feature value is the real border to image objects of a defined class.

b) **Rel. Border To:** determines the relative border length that an object shares with a neighbouring image object assigned to a defined class. If, for example, the relative border of an image object to image objects of a certain class is 1, the image object is totally embedded in them.

c) **Rel. Area Of:** determines the area covered by image objects of a selected class, (found within a user-defined circular area around the selected image object) divided by the total area of image objects inside this area.

d) **X position to:** describes the position/ distance (in pixels) of the image object's centre concerned to the closest image object's centre assigned to a defined class.

2. Relations to super-objects: used to identify image objects by theirs relations to other image objects of a given class on a higher image object level in the image object hierarchy.

a) **Existence Of:** Checks if the super-object is assigned to a defined class. If this is true, the feature value is 1. The existence of an image object assigned to a defined class in a certain perimeter around the image object is concerned. If an image object of the defined classification is found within the perimeter, the feature value is 1 (= true); otherwise it would be 0 (= false).

The ability to use class related features is the main advantage of OBIA as the opportunity to apply contextual information and expert knowledge is given. Class related features are particularly useful to solve issues such as the classification of shaded areas or misclassifications due to the spectral confusion among land cover features and produce an enhance classification result. Due to elevation variability in urban environments, the identification and classification of the shaded areas becomes a particular significant problem when VHR data are used. In order to deal with the problem of shadow, a typical procedure in object-based automated classification is to initially identify the polygons in shadow and then "replace" these polygons with an existing land cover class. With the application of spatial relationship rules, the objects in shadow can be reclassified according to their relation to existing neighbour land cover classes.

Class related features such as the "Border to" can be applied to identify the land cover classes in shade by association with the adjacent polygon using a probability function.

For example in this study, the probability function was used to identify sealed surfaces in shade by creating the rule “if the shadow polygon shares a border with the sealed class more than 80% then reclassify as sealed”. Other useful class related features are the “Rel. Border to” or “Rel. Area of” which was used to identify the polygons in shade that were surrounded by a land cover class. If the relative border or relative area is unity then the object in shadow is completely surrounded by a land cover class. This function was used to reclassify shaded polygons when they were 100% surrounded by either sealed, vegetated surface or trees. The spatial relationship features are also capable to identify the shadow according to the position of the sun. Depending on the time of the year and the date the imagery was taken the shadow will either be on the left or right of high objects. The “X position to” feature can be used to identify if an object (i.e. shadow in this case) is on the left or right side of a land cover feature by indicating a negative or positive value respectively.

Table 6.6 The main feature algorithms applied for the object-based image analysis using fuzzy rules

Features for the image analysis		Fuzzy membership functions	Thresholds	Classification
Object features				
Customised - arithmetic feature	PC_1		(-2.61, -0.8)	Used to identify image objects that belonged to the built-up class on the coarser level
Layer Values	Mean value of brightness		(77, 79)	Used to identify image objects that belonged to the shadow class
	Mean value of "Max. diff."		(0.35, 0.37)	Used to identify image objects that belonged to the sealed class in lower levels
	Mean value of red band		(109, 111)	Used to identify image objects that belonged to the tress class
Shape	Length	" = "	(124.9)	Used to extract image objects that belonged to the rail-tracks class with a specific length
Class-Related features				
Relation to super-objects	"Existence of"	" = "	multiple	Used to bring image objects, classified to a certain class, from broader levels to lower hierarchical level
Relation to neighbour objects	"Existence of" "x position to" "Rel. border of" "Border to"	" = "	multiple	Several functions that used to identify the spatial relationship between image objects that belong to a certain class at the same hierarchical level
Scene-related				
Class-related	"Invert expression"	" = "	multiple	Used for the masking our technique, i.e., "class A is not class B"

The image analysis undertaken and the development of the object-based model, which was based on a whole rule-set of processes (Figure 6-24), can be described as follows:

- The image was initially segmented at a coarse level in which large sealed surfaces were extracted (i.e. roofs, roads). At that level the image was classified according to the "built up" class. The trial and error method showed that the best results were achieved by developing an arithmetic feature, in eCognition, which was based on the principal component analysis, described in the previous section 6.2. The image object features that used in order to construct the PC_1 for the "built up" class were the maximum difference, the mean value and the standard deviation of the blue band (equation 1, paragraph 6.2). The unclassified image objects were labelled as "mixed areas". The "mixed areas" class was identified using the masking out technique (i.e. class B is not class A). The technical specifications are described in Table 6.7, level 1
- The "mixed areas" class was re-segmented into a smaller scale in order to extract the polygons in shadow. The "shadow" class was identified using the mean value of brightness while the rest of the mixed areas were classified as "non shadow" using the masking out technique (Table 6.7, level 2)
- At the same segmentation level 2 (no re-segmentation into a smaller level occurred; just a copy of the level was used) the "non-shadow" class was further classified into the "sealed" and "green" classes. The "sealed" class consisted of all the small built-up objects that were not classified at the initial coarse level. The feature used in order to classify the sealed objects was the mean value of the maximum difference. The green class was classified using the masking out technique. The technical specifications are described in Table 6.7, level 3
- Another copy of the same segmentation level 3 was used in order to unite "built up" and "sealed" class into one; the label of "impermeable" was given. In addition, the rail tracks were also extracted using the "shape" information of the image object features and more specifically the "length" of the objects. Additional "class-related features" i.e. relations to the neighbour objects were used in order to fully extract the rail tracks (Table 6.7, level 4). The "Existence

of" feature indicates the existence of the "rail tracks" class as neighbour object and the "x position to" indicates the position of the object with regard to its neighbour "rail tracks" class. The "green" class was also copied from the previous hierarchical level using relations to the super-objects

- The image was further re-segmented into a lower scale in order to separate the "green" class into vegetation and trees. The "trees" class was identified using the mean value of the red band while the rest of the green areas were classified as "grass" using the masking out technique (Table 6.7, level 5)
- The level was copied in order to bring together all the classes that were individually classified in the various hierarchical levels. At that stage the image was completely classified into the following classes: impermeable surfaces, vegetation, trees, shadow, and rail tracks (Table 6.7, level 6). The classification results for each sample area are showed in Figures 6-25i, 6-26i, 6-27i and 6-28i
- The shadow class was reclassified into shadow sealed, shadow grass and shadow trees using various rules based on the relationship of neighbour objects (Table 6.7, level 7). Relations to neighbour objects such as "Rel. border of" and "Border to" were used. The first feature indicates "proportion" i.e. the percentage of an object to the surrounded class while the second indicates the exact number of pixels that the object shares with the neighbour object (Definiens, 2006). All classes were brought together. In order to re-classify individual red cars, misclassified as tress, or single trees with sealed surface underneath, the "Rel. border to" feature was used. The final classification results of each sample area is showed in Figures 6-25ii, 6-26ii, 6-27ii and 6-28ii

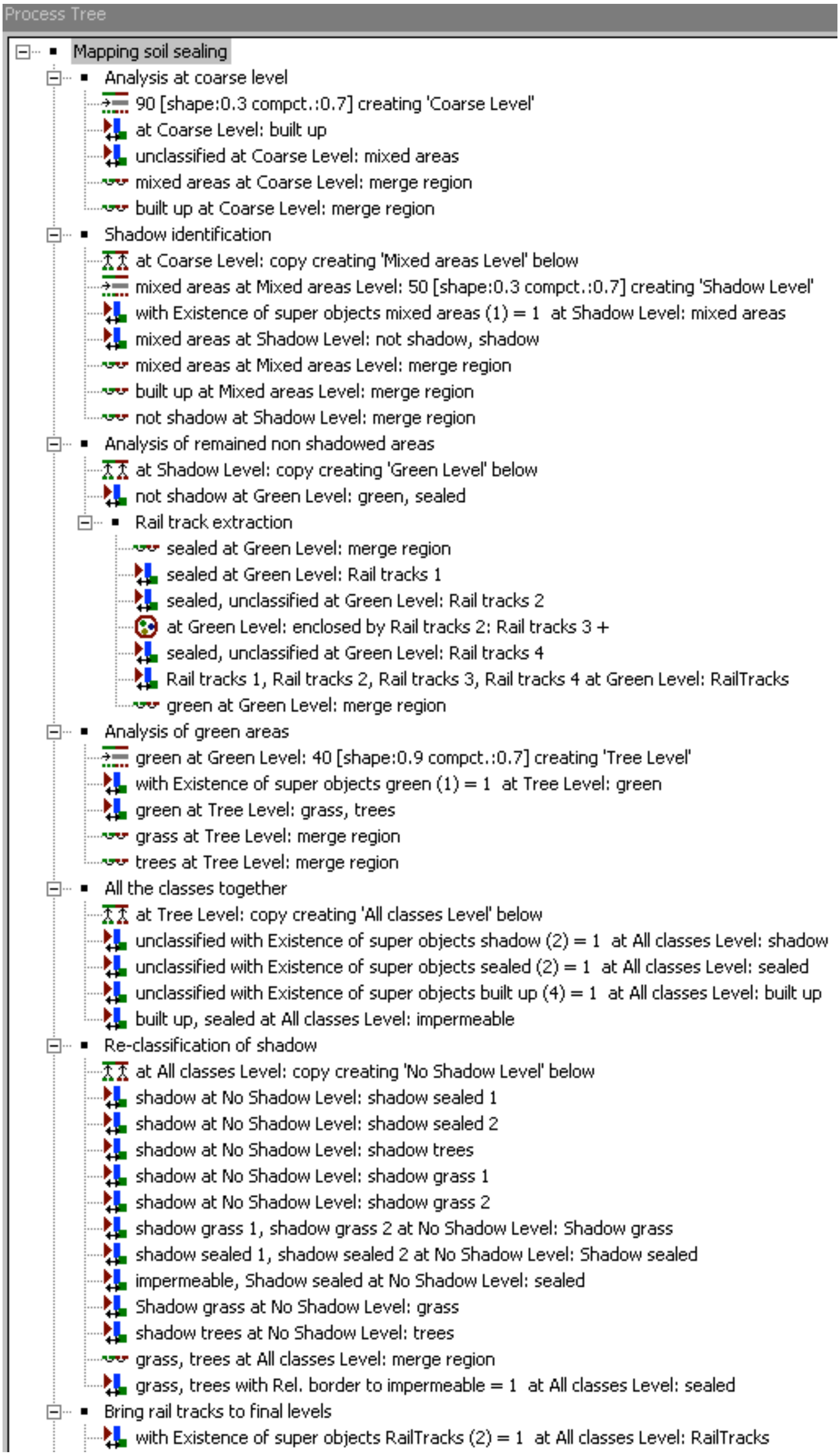
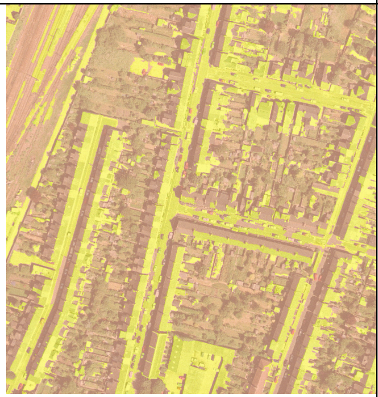
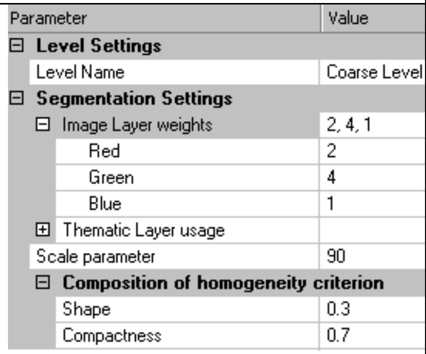
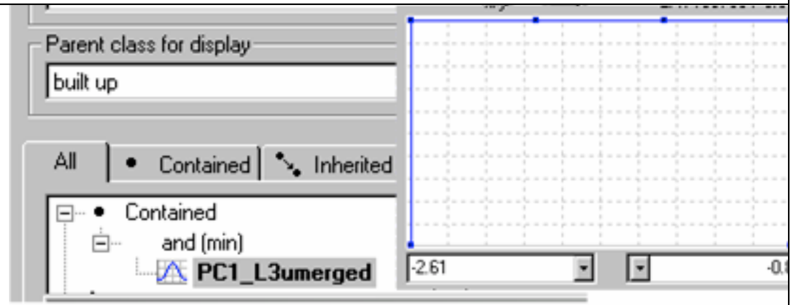


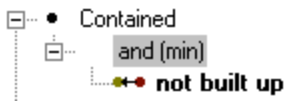
Figure 6-18 The complete rule-set, using processes in eCognition, for the development of the object-based model

Table 6.4 The main steps and parameters used for the development of the object-based model using fuzzy rules

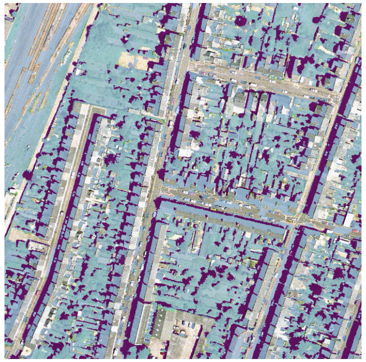
<table>
<tr><th>Working levels</th><th>Extracted classes</th><th>Segmentation parameters</th><th>Critical features of the fuzzy-rule classification</th></tr>
<tr><td>Level 1: built-up vs. mixed</td><td></td><td>

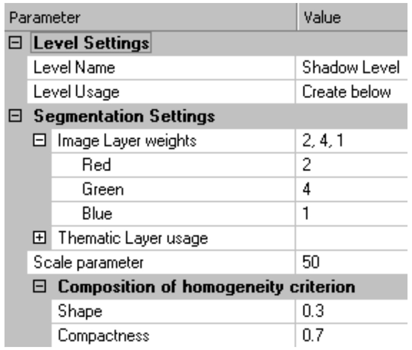
Parameter	Value
Level Settings	
Level Name	Coarse Level
Segmentation Settings	
Image Layer weights	2, 4, 1
Red	2
Green	4
Blue	1
Thematic Layer usage	
Scale parameter	90
Composition of homogeneity criterion	
Shape	0.3
Compactness	0.7

</td><td>

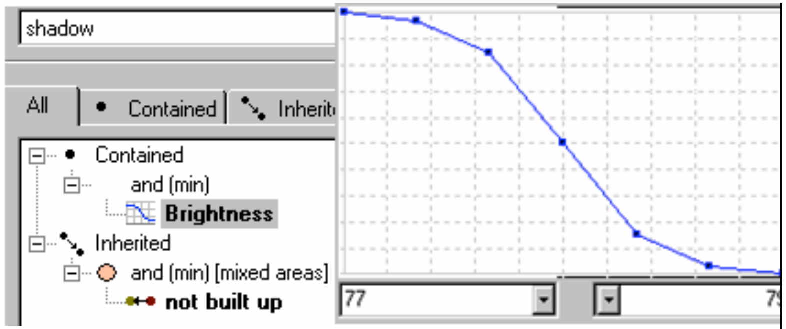
“mixed areas” class = 
</td></tr>
</table>

Level 2: shadow vs. non shadow



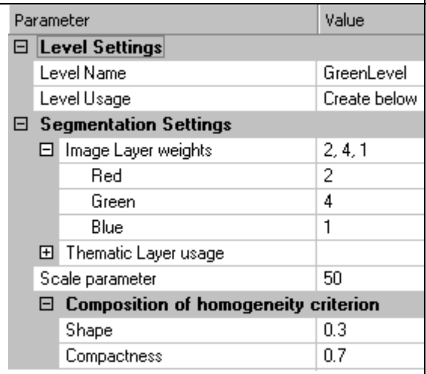


Parameter	Value
Level Settings	
Level Name	Shadow Level
Level Usage	Create below
Segmentation Settings	
Image Layer weights	2, 4, 1
Red	2
Green	4
Blue	1
Thematic Layer usage	
Scale parameter	50
Composition of homogeneity criterion	
Shape	0.3
Compactness	0.7

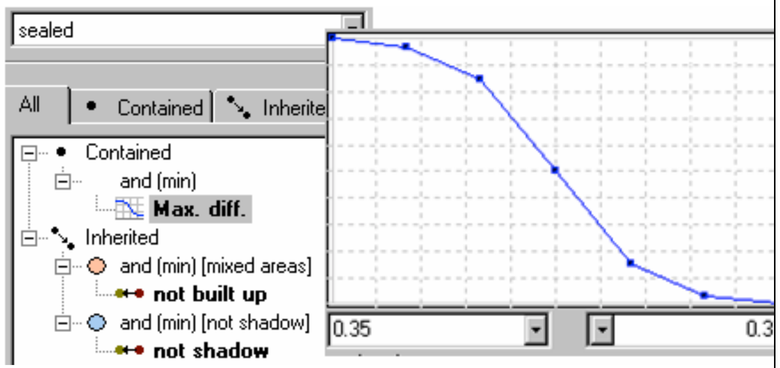


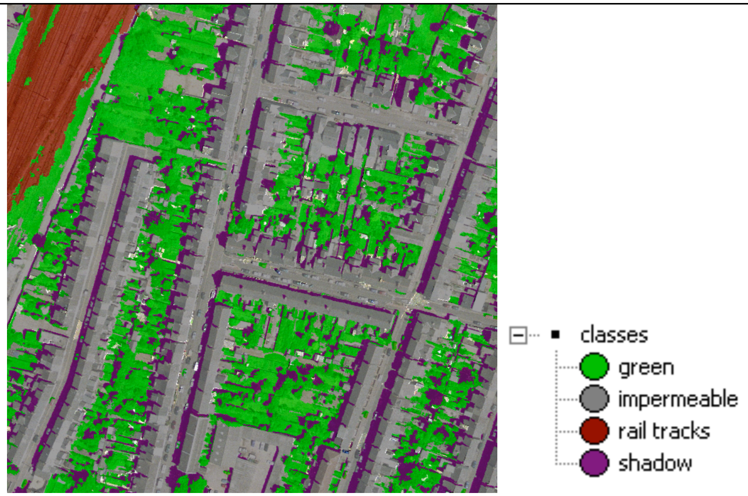
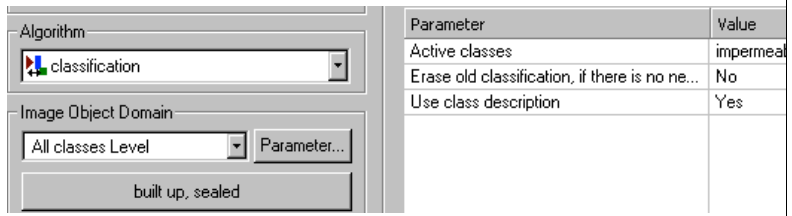
“non shadow” class=

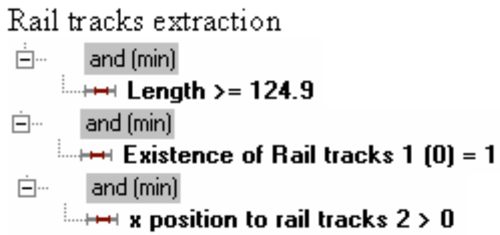
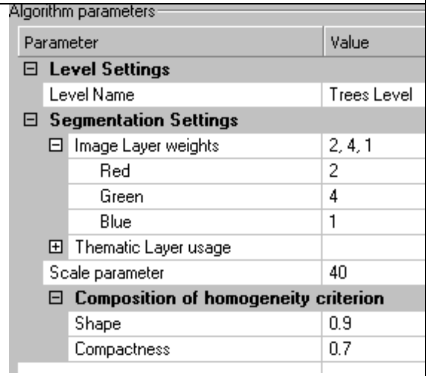
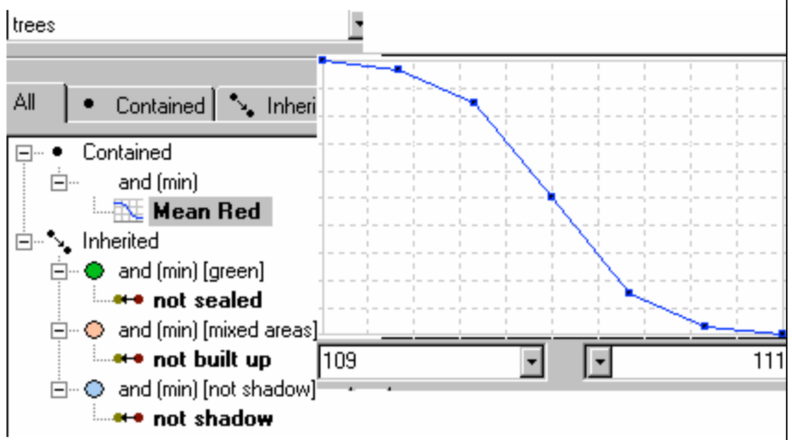
Level 3: sealed vs. green

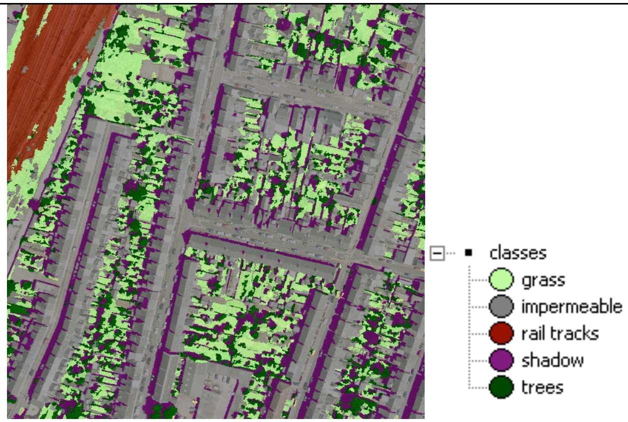
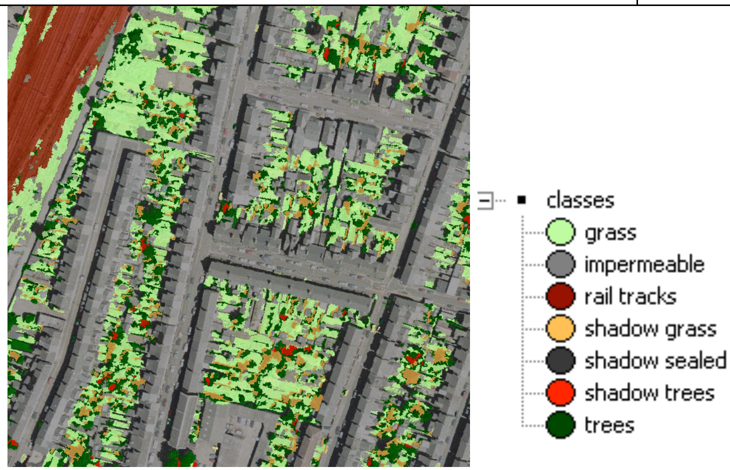


Parameter	Value
Level Settings	
Level Name	GreenLevel
Level Usage	Create below
Segmentation Settings	
Image Layer weights	2, 4, 1
Red	2
Green	4
Blue	1
Thematic Layer usage	
Scale parameter	50
Composition of homogeneity criterion	
Shape	0.3
Compactness	0.7



<table>
<tr>
<td>Level 4:
rails
extraction</td>
<td>
</td>
<td>


</td>
</tr>
<tr>
<td>Level 5:
trees vs.
vegetation</td>
<td></td>
<td>
</td>
<td>
</td>
</tr>
</table>

Level 6 All classes at the same level		All the classes together at Tree Level: copy creating 'All classes Level' below green, unclassified at All classes Level: built up, sealed, shadow built up, sealed at All classes Level: impermeable grass, trees with Rel. border to impermeable = 1 at All classes Level: impermeable < 1 ms impermeable with Existence of super objects RailTracks (2) = 1 at All classes Level: RailTra
Level 7: shadow reclassific ation		Shadow sealed and (min) **Border to impermeable >= 10** or (max) **Rel. border to impermeable >= 0.2** **Rel. border to shadow sealed 1 >= 0.2** Shadow grass or (max) **Rel. area of grass (0) >= 0.2** **Rel. border to grass = 1** Shadow trees or (max) **Rel. area of trees (0) >= 0.8** **Rel. border to trees = 1**

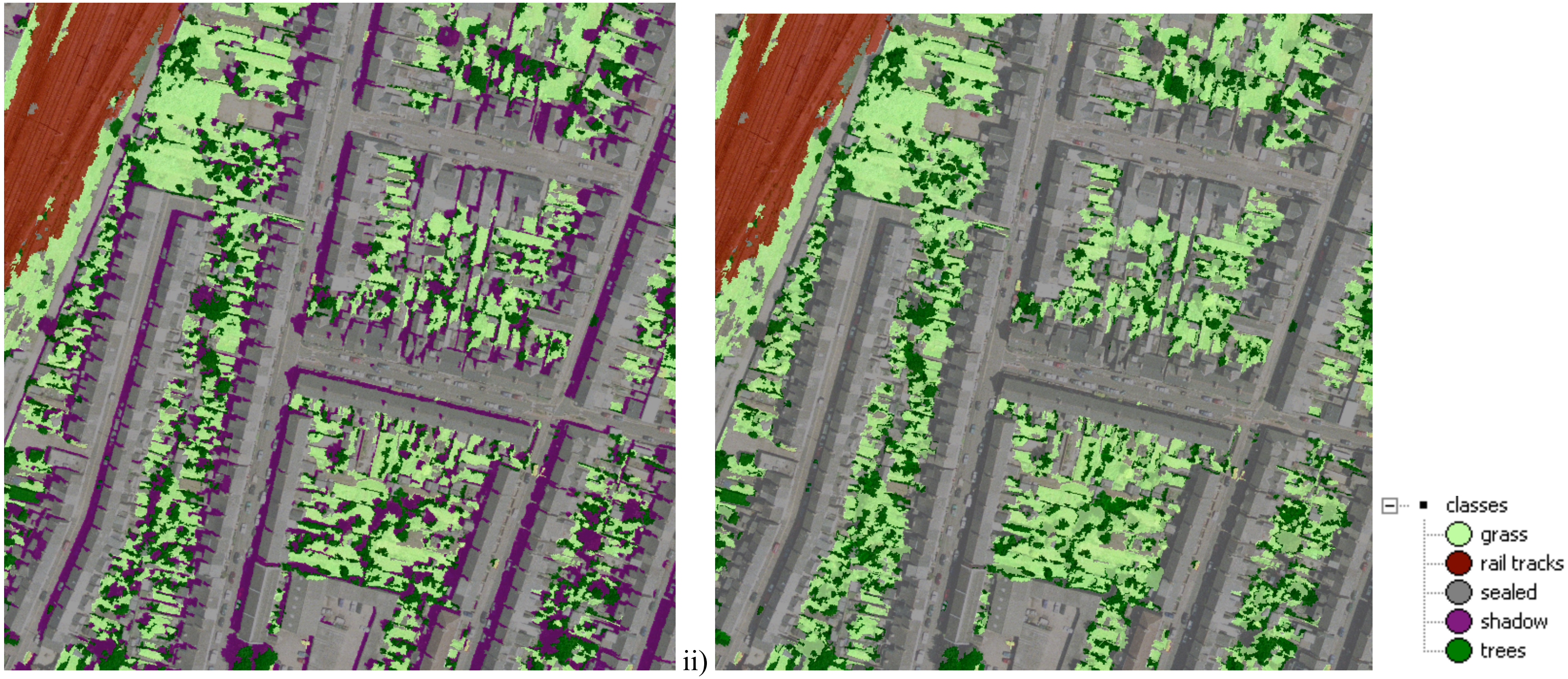
i) ii)


Figure 6-25 Final rule-based classification of the test site (“area5”) (i) with or (ii) without the shadow class

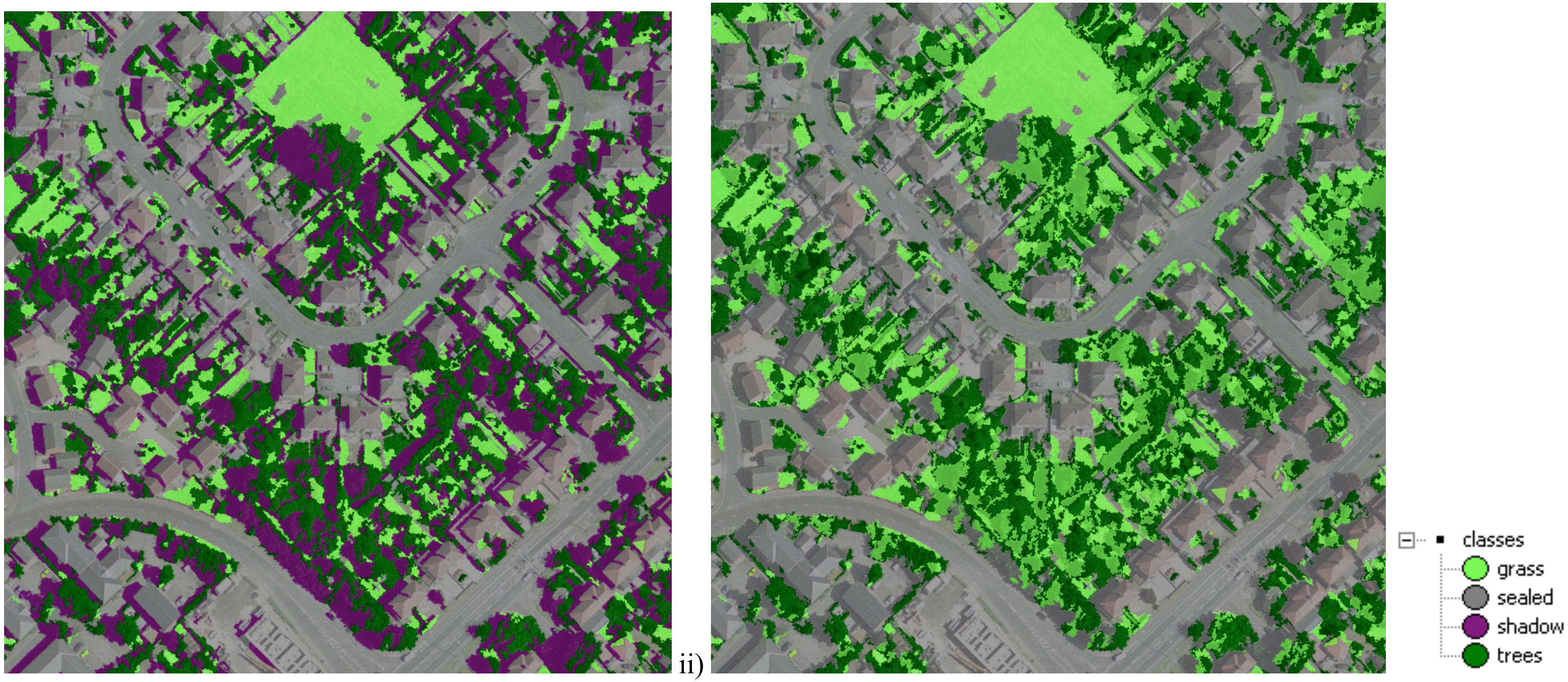


Figure 6-26 Final rule-based classification of the test site (“area26”) (i) with or (ii) without the shadow class

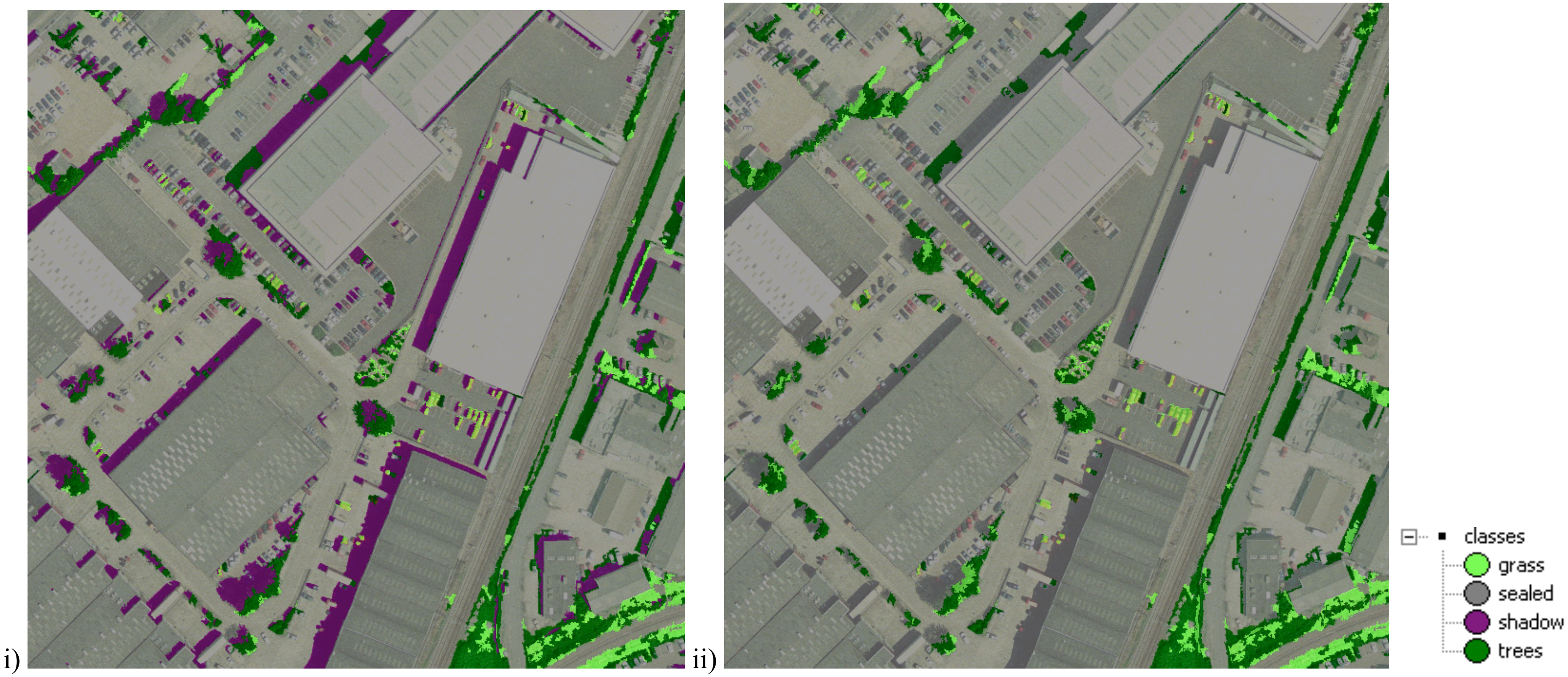


Figure 6-27 Final rule-based classification of the test site (“area0”) (i) with or (ii) without the shadow class

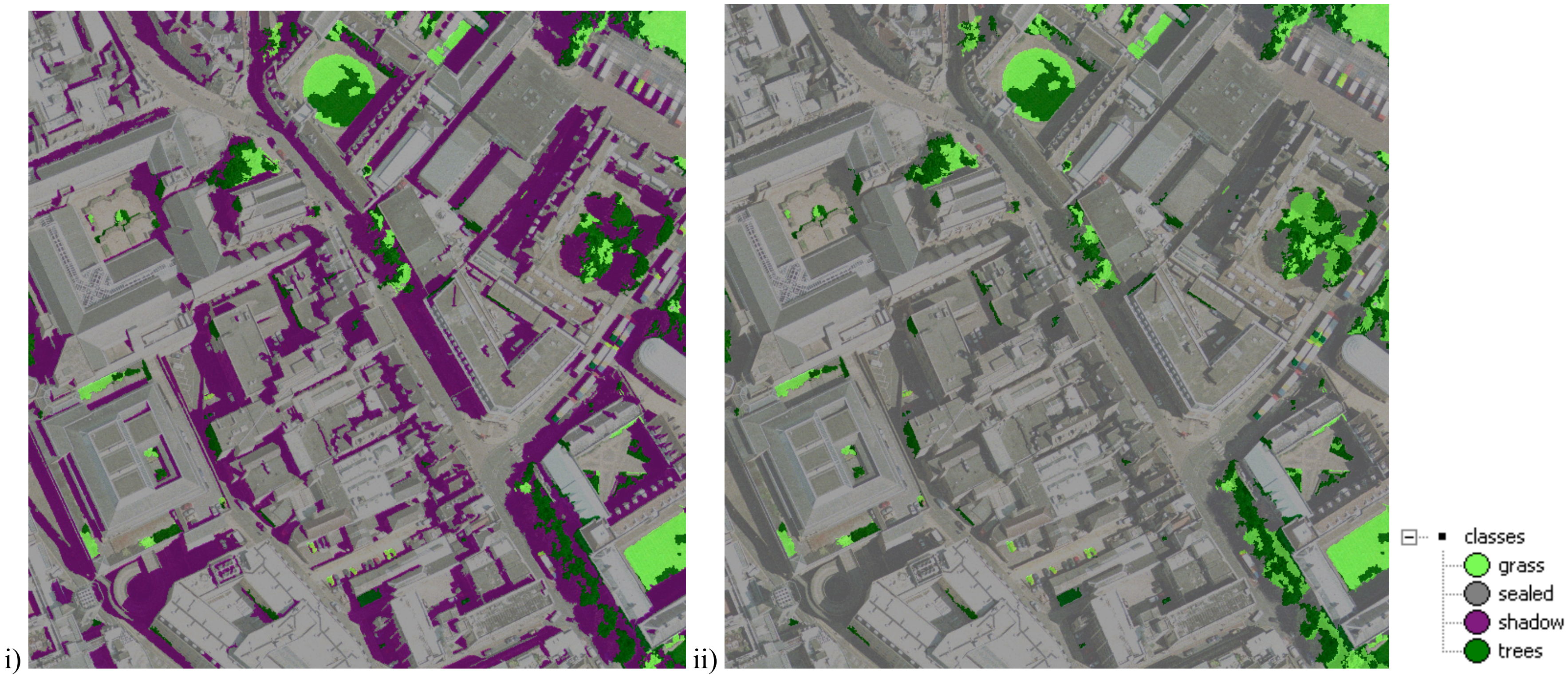


Figure 6-28 Final rule-based classification of the test site ("area20") (i) with or (ii) without the shadow class

6.4 Comparisons of the automated, semi-automated and manual methods

The automated object-based rule set classification, of each test site, was quantitatively assessed by cross-tabulation with the manual API as well as with the semi-automated classification in eCognition, both developed in chapter 5. The thematic maps were also qualitatively analysed in order to understand the differences between the three approaches. Happiness

6.4.1 Quantitative analysis

The rule-based model was built using the test site entitled “area5” which is the densely built residential area of 1930’s Victorian terraced houses with narrow small gardens and medium area of vegetated surfaces. The result of the automated classification was exported from eCognition to ArcGIS as smoothed polygons in vector format. The data were then converted into raster format with cell size= 0.125 (equal to the resolution of the aerial photography) in order to avoid the production of ‘sliver’ polygons (analysis in previous chapter 5.4.1). The overall accuracy of the automated classification was statistically evaluated with the error matrix production. The error matrix compares two different classification techniques for a number of classes. The rule-based automated classification was compared with two both the API and the semi-automated classification developed in eCognition.

During API (manual classification), the “area5” was finally classified according to the following land cover features: ‘sealed surfaces’, ‘vegetation’, ‘trees’, ‘rail tracks’ and ‘bare soil’ while the polygons belonged in the ‘shadow’ class were re-classified as ‘sealed surface in shadow’, ‘grass in shadow’, ‘tree in shadow’, and ‘mixed/unclassified shadow’ (Figure 6-29a). During the semi-automated classification, the “area5” was classified according to the same land cover features apart from the ‘shadow’ class which was not further re-classified (Figure 6-29c). For that reason, the results of the rule-based classification were exported in two different levels; one with the shadow class reclassified to the analogous land cover features (Figure 6-29b), for the comparison with the API, and one with shadow class (Figure 6-29d) in order to be compared with the semi-automated classification.

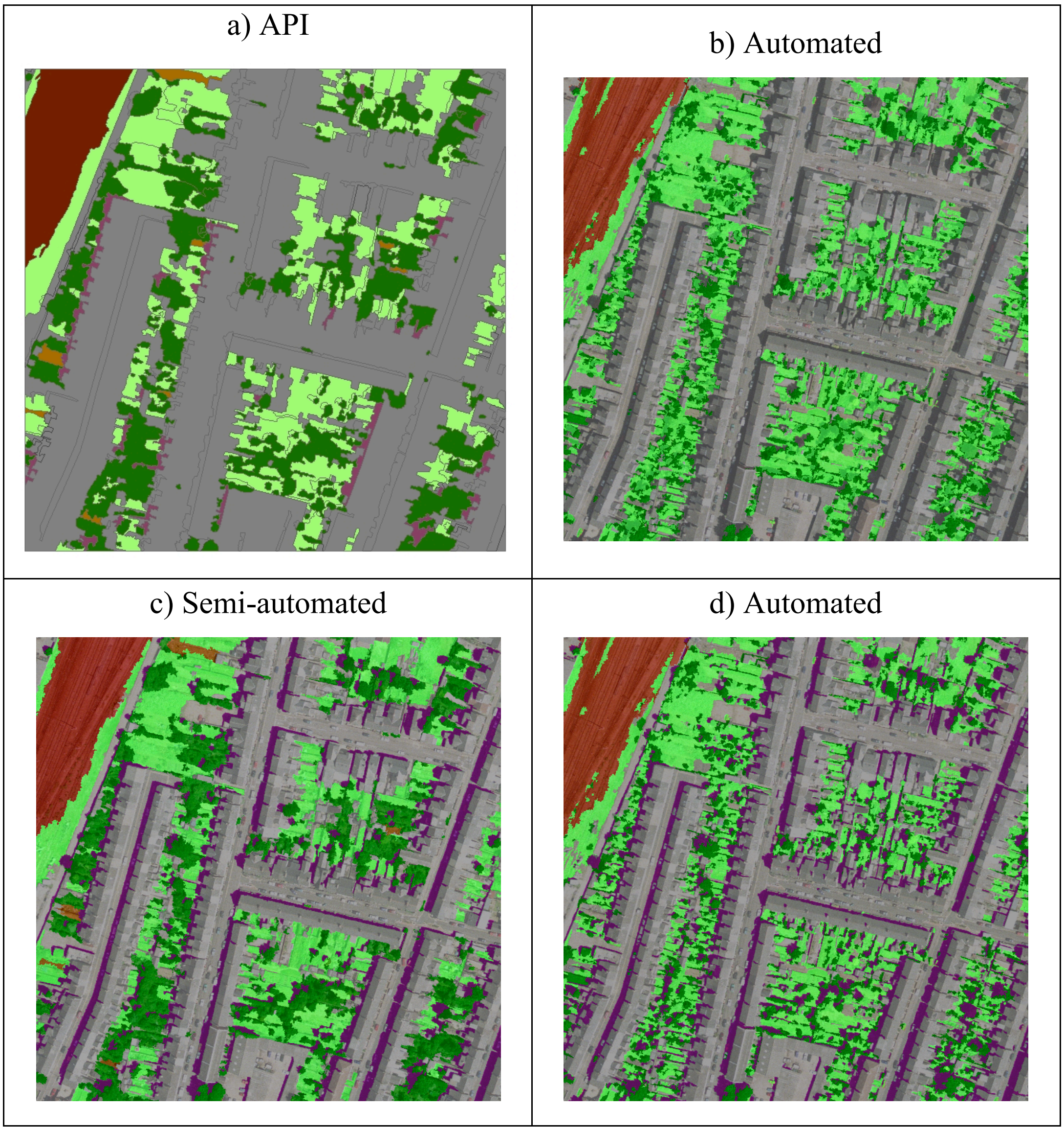


Figure 6-29 The results of each classification method for the “area5”

The error matrix production between the automated classification and the manual API revealed an overall accuracy of 79% (Table 6.8).

Table 6.8. Error matrix between the manual API and the automated classification.

Residential area - "area5"									
API/ auto_eCg	sealed	vegetation	trees	rails	b.soil	unclassified	Sum Map 1	User accuracy	
sealed	2229972	50843	41366	3850	0	0	2326031	0,959	
vegetation	134404	482186	91298	7625	0	0	715513	0,674	
trees	74299	318721	264372	48	0	0	657440	0,402	
rails	174	8004	630	186629	0	0	195437	0,955	
b.soil	17438	3375	1809	0	0	0	22622	0,000	
unclassified	62667	13697	6593	0	0	0	82957	0,000	
Sum Map 2	2518954	876826	406068	198152	0	0	4000000		
Producer accuracy	0,885	0,550	0,651	0,942	N/A	N/A			0,791
									79%

The ‘bare soil’ class as well as the ‘unclassified’ class exist only at the manual API. Bare soils were classified as sealed surfaces in the rule-based classification due to the spectral confusion between the two classes. However, bare soils were also difficult to interpret during API and were only recognised when oblique images were used. In addition, the existence of bare soils in urban environments found to be infrequent. Visual inspection of the “area5” identified only 5 out of 5.775 polygons (extracted during the segmentation process) that could have been classified as bare soil. For these reasons, the “b. soil” class was considered insignificant and was excluded from the statistical analysis.

The ‘unclassified’ class contained polygons in shadow which remained unclassified during the API because it was not possible to identify the land cover types covered by shadow or more than one type was recognised in a single polygon. The majority of these shadowed polygons were in the back gardens next to the residential houses (Figure 6-30).

Figure 6-30 The study area “area5” and the unclassified shadowed areas during API

In automated object-based classification all shadowed polygons (the ‘shadow’ class) were reclassifying to the specific land cover types using rules. Specifically, the shadowed polygons in the back gardens, next to the residential houses, were reclassified as ‘sealed surfaces’. This was based on the visual inspection of Cambridge and a general knowledge of the residential typology in UK that it is very common in the back gardens to have a patio next to the building before the lawn starts (Figure 6-31). These ‘unclassified’ polygons were as well excluded from the statistical analysis as the interest was to evaluate the performance of the automated classification model but no API data existed in that case. So, by not including the bare soil and the unclassified polygons the overall accuracy of the automated rule-based classification in comparison with the API was increased to 81% (Table 6.9).

Figure 6-31. Examples of the sealed surfaces that are in shadow in a true colour aerial photo (left column) and their identification with the use of an oblique image (right column)

Table 6.9 Error matrix between the manual API and the automated classification.

Residential area - "area5"							
API/ auto_eCg	sealed	vegetation	trees	rails	Sum Map 1	User accuracy	
sealed	2229972	50843	41366	3850	2326031	0,959	
vegetation	134404	482186	91298	7625	715513	0,674	
trees	74299	318721	264372	48	657440	0,402	
rails	174	8004	630	186629	195437	0,955	
Sum Map 2	2438849	859754	397666	198152	3894421		
Producer accuracy	0,914	0,561	0,665	0,942			0,812
							81%

The error matrix also showed that the automated classification produced very high accuracies at the 'sealed' and the 'rail tracks' classes. The producer accuracies of the 'trees' and the 'vegetation' class are low. However relatively low are also the user accuracies of these two classes indicating the difficulty in discriminating them.
As already aforementioned, during the semi-automated classification, developed in eCognition, the 'shadow' class was not reclassified. Consequently, in order to compare similar land cover types, the comparison of the automated with the semi-automated classification included the 'shadow' class. The overall accuracy between these two methods was 82% (Table 6.10).

Table 6.10 Error matrix between the semi-automated and the automated classification.

Residential area- "area5"								
Semi_eCg/AutoeCg	sealed	vegetation	trees	shadow	rails	Sum Map 1	User accuracy	
sealed	1907621	36701	32078	55539	5100	2037039	0,936	
vegetation	75805	457004	76181	31662	3000	643652	0,710	
trees	32023	240128	279680	77447	0	629278	0,444	
shadow	22700	296	12697	437853	0	473546	0,925	
rails	0	8493	630	0	190052	199175	0,954	
Sum Map 2	2038149	742622	401266	602501	198152	3982690		
Producer accuracy	0,936	0,615	0,697	0,727	0,959			0,822
								82%

In order to test whether the comparisons between the three methods are significant different, again the 'shadow' class had to be included. So, the error matrices that were finally compared are shown in Table 6.11. To statistically test whether two independent error matrices are significantly different the Z was calculated (Congalton and Green, 1999). When the Z value is greater than 1.96 the two classification results are significantly different. The calculation of the Z parameter is defined in equation (2).

$$Z = \frac{/ \hat{K}_1 - \hat{K}_2 /}{\sqrt{\hat{\mathrm{v}}\mathrm{ar}(\hat{K}_1) + \hat{\mathrm{v}}\mathrm{ar}(\hat{K}_2)}} \quad (2)$$

The K_1, K_2 are calculated from the following equation:

$$\hat{K} = \frac{p_o - p_c}{1 - p_c} \quad (3)$$

Where,

P_o is the actual agreement ($p_0 = \sum_{i=1}^{k} P_{ii}$) and

P_c is the chance agreement ($p_c = \sum_{i=1}^{k} P_{i+} P_{+j}$)

Table 6.11 Error matrices between the three classification methods and the Z analysis.

Residential area - "area5"								
API/ auto_eCg	sealed	vegetation	trees	shadow	rails	Sum Map 1	User accuracy	
sealed	1863496	41836	34531	97723	3800	2041386	0,913	
vegetation	88976	423631	78634	36208	7625	635074	0,667	
trees	45485	261718	262561	84556	48	654368	0,401	
shadow	38660	5420	23446	383537	50	451113	0,850	
rails	174	8004	630	0	186629	195437	0,955	
Sum Map 2	2036791	740609	399802	602024	198152	3977378		
Producer accuracy	0,915	0,572	0,657	0,637	0,942			
								0,784
								78%
	θ1=	0,7844				Kappa 1=	0,678824	
	θ2=	0,328717						
	θ3=	0,564909				Var(k1)=	3,02E-07	
	θ4=	0,564966						
Semi_eCg/AutoeCg	sealed	vegetation	trees	shadow	rails	Sum Map 1	User accuracy	
sealed	1907621	36701	32078	55539	5100	2037039	0,936	
vegetation	75805	457004	76181	31662	3000	643652	0,710	
trees	32023	240128	279680	77447	0	629278	0,444	
shadow	22700	296	12697	437853	0	473546	0,925	
rails	0	8493	630	0	190052	199175	0,954	
Sum Map 2	2038149	742622	401266	602501	198152	3982690		
Producer accuracy	0,936	0,615	0,697	0,727	0,959			
								0,822
								82%
	θ1=	0,821608				Kappa 1=	0,734426	
	θ2=	0,328277						
	θ3=	0,582678				Var(k1)=	2,62E-07	
	θ4=	0,565676						
			z=	**74,06899**				

Exactly the same process was followed for the other three test sites. The thematic classification results, of each classification method, for the “area26” are shown in Figure 6-32. “area26” represents the low density residential area of 1960’s semi-detached houses with broad large gardens, giving a large area of vegetated surfaces.

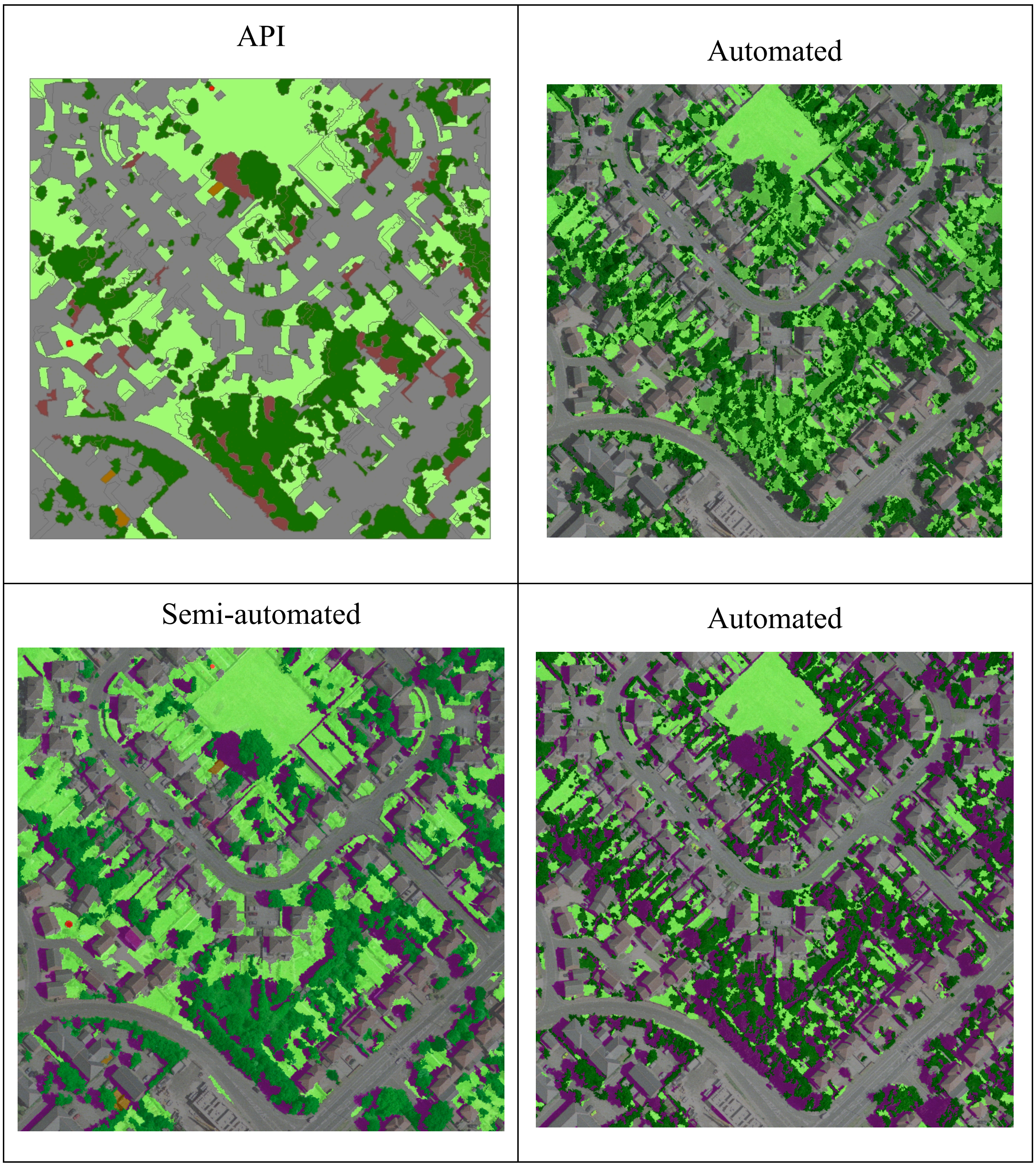


Figure 6-32 The results of each classification method for the “area26”

The error matrices and the overall accuracies when comparing the three different classification methods, including or not the ‘shadow’ class are represented in Tables 6.12, 6.13 and 6.14.

Table 6.12 Error matrix between the manual API and the automated classification.

Residential area- "area26"						
API/ auto_eCg	sealed	vegetation	trees	Sum Map 1	User accuracy	
sealed	1781064	50336	62994	1894394	0,940	
vegetation	274555	511866	324425	1110846	0,461	
trees	135703	233558	488654	857915	0,570	
Sum Map 2	2191322	795760	876073	3863155		
Producer accuracy	0,813	0,643	0,558			0,720
						72%

Table 6.13 Error matrix between the semi-automated and the automated classification.

Residential area- "area26"							
semi_eCg/auto_eCog	sealed	vegetation	trees	shadow	Sum Map 1	User accuracy	
sealed	1563773	28942	38586	66458	1697759	0,921	
vegetation	143497	404173	333642	94076	975388	0,414	
trees	20900	46170	480882	226754	774706	0,621	
shadow	21389	150	11511	510156	543206	0,939	
Sum Map 2	1749559	479435	864621	897444	3991059		
Producer accuracy	0,894	0,843	0,556	0,568			
							0,741
							74%

Table 6.14 Error matrices between the three classification methods and the Z analysis.

Residential area- "area26"							
API/ auto_eCg	sealed	vegetation	trees	shadow	Sum Map 1	User accuracy	
sealed	1528440	33188	52228	92326	1706182	0,896	
vegetation	151646	387226	307995	103875	950742	0,407	
trees	30506	56773	475659	254142	817080	0,582	
shadow	38421	2516	28021	447225	516183	0,866	
Sum Map 2	1749013	479703	863903	897568	3990187		
Producer accuracy	0,874	0,807	0,551	0,498			
							0,711
							71%
	θ1=	0,711383			kappa 1=	0,593779	
	θ2=	0,289506					
	θ3=	0,456412			Var(k1)=	2,71E-07	
	θ4=	0,392041					
semi_eCg/auto_eCog	sealed	vegetation	trees	shadow	Sum Map 1	User accuracy	
sealed	1563773	28942	38586	66458	1697759	0,921	
vegetation	143497	404173	333642	94076	975388	0,414	
trees	20900	46170	480882	226754	774706	0,621	
shadow	21389	150	11511	510156	543206	0,939	
Sum Map 2	1749559	479435	864621	897444	3991059		
Producer accuracy	0,894	0,843	0,556	0,568			
							0,741
							74%
	θ1=	0,741403			kappa 1=	0,63655	
	θ2=	0,288494					
	θ3=	0,470985			Var(k1)=	2,52E-07	
	θ4=	0,390482					
			z=	**59,16631**			

Similarly, the thematic classification results, of each classification method, for the “area0” are shown in Figure 6-33. “area0” is part of the industrial area of Cambridge which is predominantly sealed with industrial buildings and very few vegetated surfaces.

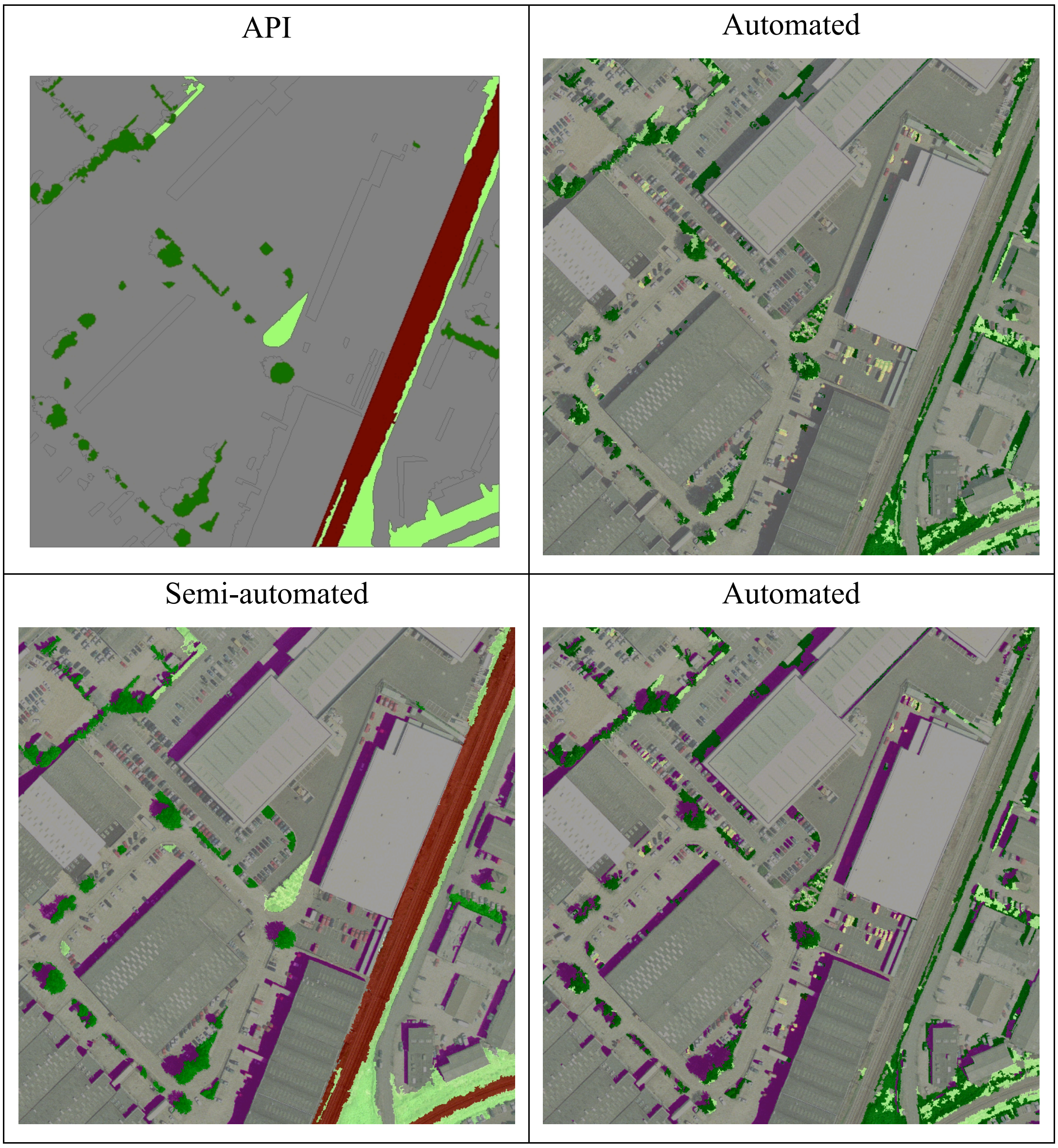


Figure 6-33 The results of each classification method for the “area0”

The error matrices and the overall accuracies when comparing the three different classification methods, including or not the ‘shadow’ class are represented in Tables 6.15, 6.16 and 6.17.

Table 6.15 Error matrix between the manual API and the automated classification.

Industrial area "area0"							
API \ auto_eCg	sealed	vegetation	trees	rails	Sum Map 1	User Accuracy	
sealed	3388160	31709	76350	0	3496219	0,969	
vegetation	35141	35228	86812	0	157181	0,224	
trees	28481	21904	79933	0	130318	0,613	
rails	207693	569	8020	0	216282	0,000	
Sum Map 2	3659475	89410	251115	0	4000000		
Producer accuracy	0,926	0,394	0,318	N/A			0,876
							88%

Table 6.16 Error matrix between the semi-automated and the automated classification.

Industrial area "area0"								
Semi_eCg/AutoeCg	sealed	grass	trees	shadow	rails	Sum Map 1	User accuracy	
sealed	3082358	23560	25803	47482	0	3179203	0,970	
grass	26660	33770	97873	4376	0	162679	0,208	
trees	7846	9253	81817	21777	0	120693	0,678	
shadow	23997	526	44757	238338	0	307618	0,775	
rails	229184	380	79	164	0	229807	0,000	
Sum Map 2	3370045	67489	250329	312137	0	4000000		
Producer accuracy	0,915	0,500	0,327	0,764				0,859
								86%

Table 6.17 Error matrices between the three classification methods and the Z analysis.

Industrial area "area0"								
API \ auto_eCg	sealed	vegetation	trees	shadow	rails	Sum Map 1	User Accuracy	
sealed	3079232	22405	29362	52052	0	3183051	0,967	
grass	34117	31719	86812	4533	0	157181	0,202	
trees	15301	11152	79634	24231	0	130318	0,611	
shadow	33866	1644	46501	231157	0	313168	0,738	
rails	207529	569	8020	164	0	216282	0,000	
Sum Map 2	3370045	67489	250329	312137	0	4000000		
Producer accuracy	0,914	0,470	0,318	0,741	N/A			
								0,855
								85,5%
	θ1=	0,855436				Kappa 1=	0,549292	
	θ2=	0,67925						
	θ3=	1,27253				Var(k1)=	9,01E-06	
	θ4=	2,136879						
Semi_eCg/AutoeCg	sealed	vegetation	trees	shadow	rails	Sum Map 1	User Accuracy	
sealed	3082358	23560	25803	47482	0	3179203	0,970	
grass	26660	33770	97873	4376	0	162679	0,208	
trees	7846	9253	81817	21777	0	120693	0,678	
shadow	23997	526	44757	238338	0	307618	0,775	
rails	229184	380	79	164	0	229807	0,000	
Sum Map 2	3370045	67489	250329	312137	0	4000000		
Producer accuracy	0,915	0,500	0,327	0,764	N/A			
								0,859
								86%
	θ1=	0,859071				Kappa 1=	0,562054	
	θ2=	0,678204						
	θ3=	1,27331				Var(k1)=	8,68E-06	
	θ4=	2,13389						
				z=	**3,034483**			

Finally, the thematic classification results, of each classification method, for the "area20" are shown in Figure 6-34. This sample area is part of the commercial area located in the city centre of Cambridge. "area20" is a predominantly sealed area with large buildings, densely spaced with few vegetated surfaces.

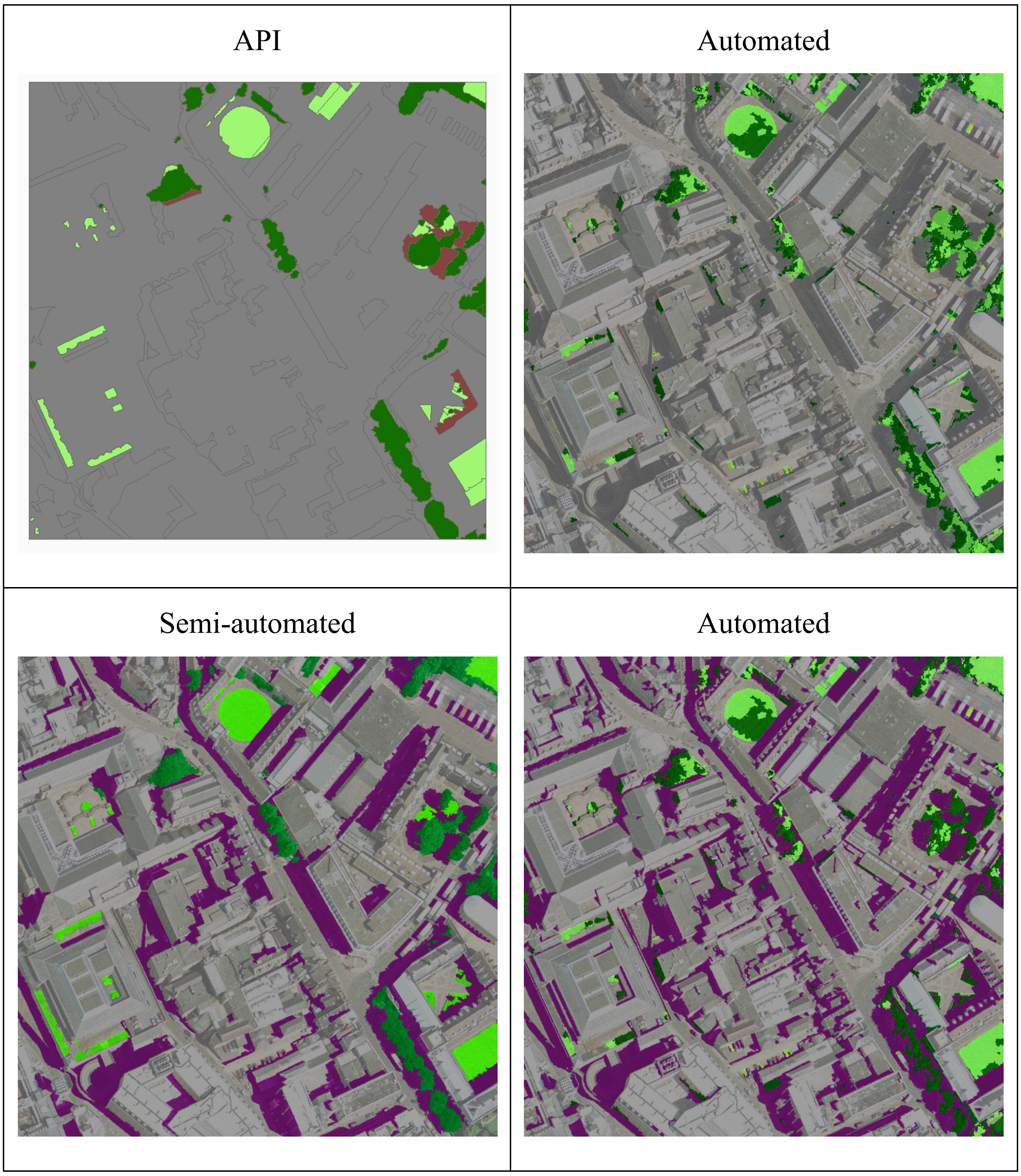


Figure 6-24. The results of each classification method for the "area20"

The error matrices and the overall accuracies when comparing the three different classification methods, including or not the 'shadow' class are represented in Tables 6.18, 6.19 and 6.20.

Table 6.18 Error matrix between the manual API and the automated classification.

Commercial area - "area20"						
API/auto_eCg	sealed	vegetation	trees	Sum Map 1	User accuracy	
sealed	3567122	21265	37469	3625856	0,984	
vegetation	40125	63721	37163	141009	0,452	
trees	57732	42756	89923	190411	0,472	
Sum Map 2	3664979	127742	164555	3957276		
Producer accuracy	0,973	0,499	0,546			0,940
						94%

Table 6.19 Error matrix between the semi-automated and the automated classification.

Commercial area "area20"							
Semi_eCg/AutoeCog	sealed	vegetation	trees	shadow	Sum Map 1	User accuracy	
sealed	2716817	10603	25098	224288	2976806	0,913	
vegetation	15839	61922	37700	1279	116740	0,530	
trees	5837	23430	89220	45114	163601	0,545	
shadow	57054	573	13663	671563	742853	0,904	
Sum Map 2	2795547	96528	165681	942244	4000000		
Producer accuracy	0,972	0,641	0,539	0,713			0,885
							88.5%

Table 6.20 Error matrices between the three classification methods and the Z analysis.

Commercial area - "area20"							
API/auto_eCg	sealed	vegetation	trees	shadow	Sum Map 1	User accuracy	
sealed	2707080	10127	31472	295260	3043939	0,889	
vegetation	18211	61894	36805	2737	119647	0,517	
trees	6848	23488	89073	69985	189394	0,470	
shadow	63408	1019	8331	574262	647020	0,888	
Sum Map 2	2795547	96528	165681	942244	4000000		
Producer accuracy	0,968	0,641	0,538	0,609			
							0,858
							86%
	θ1=	0,858077			kappa 1=	0,667917	
	θ2=	0,572628					
	θ3=	1,047851			Var(k1)=	2,11E-06	
	θ4=	1,546293					
Semi_eCg/Auto_eCg	sealed	vegetation	trees	shadow	Sum Map 1	User accuracy	
sealed	2716817	10603	25098	224288	2976806	0,913	
vegetation	15839	61922	37700	1279	116740	0,530	
trees	5837	23430	89220	45114	163601	0,545	
shadow	57054	573	13663	671563	742853	0,904	
Sum Map 2	2795547	96528	165681	942244	4000000		
Producer accuracy	0,972	0,641	0,539	0,713			
							0,885
							88%
	θ1=	0,884881			kappa 1=	0,73459	
	θ2=	0,566258					
	θ3=	1,053541			Var(k1)=	1,64E-06	
	θ4=	1,511019					
			z=	**34,40369**			

The results of the overall thematic accuracies of each classification method, for each test site individually, and their significance when the three methods were compared, are summarised in Table 6.21 that follows.

Table 6.21 Summary of the overall accuracies and their significance when the three classification methods were compared

Classification methods		Overall accuracy		K_1	K_2	Z statistics	Significance
Residential area "area5"			**Shadow class**				
API	Rule-based (eCognition)	81%	78%	0,68		74	Yes
semi-automated (eCognition)	Rule-based (eCognition)		82%		0,73		
Residential area "area26"							
API	Rule-based (eCognition)	72%	71%	0,59		59	Yes
semi-automated (eCognition)	Rule-based (eCognition)		74%		0,64		
Commercial area "area20"							
API	Rule-based (eCognition)	94%	86%	0,67		34	Yes
semi-automated (eCognition)	Rule-based (eCognition)		88,5%		0,73		
Industrial area "area0"							
API	Rule-based (eCognition)	88%	88,5%	0,55		3	Yes
semi-automated (eCognition)	Rule-based (eCognition)		86%		0,56		

Table 6.21 clearly indicated that the overall accuracy of the automated rule-based classification method decreased when shadow is treated as a class. But shadow is not an actual land cover class as it is not steady and it depends on the time of the day that the aerial photograph was taken. So, it cannot be compared with other data types or classification methods. The shadowed polygons should have been reclassified during the semi-automated method. Only then, the comparisons between the three methods could give a true estimate of whether the results are significant different. Consequently, the evaluation of the performance of the automated rule-based model can only be indicated when using the manual API as reference data.

Examining the Table 6.21, the very good performance of the rule-based classification in identifying sealed surfaces is also revealed by the very high overall accuracy (94%) of the “area20” which is a predominantly sealed area. The same would have probably occurred with “area0” if the rail tracks were not misclassified as sealed surfaces.

In order to further examine the performance of the object-based model for each class individually, in comparison with the traditional API, the geometric mean (or g-mean) was calculated (Table 6.22). The g-mean index is a combination of the user and producer indices and its value varies from zero to one. The g-mean index was calculated by using the equation 6 of chapter 5.4.1.

Table 6.22 Evaluation of the object-based model when comparing it with the traditional API

Land cover classes	***g-mean values***			
	Area 0	**Area 20**	**Area 5**	**Area 26**
Sealed	0.95	0.98	0.94	0.87
Vegetation	0.30	0.47	0.73	0.54
Trees	0.44	0.51	0.51	0.55
Rails Tracks	0	N/A	0.95	N/A

The g-mean value showed very good performance of the automated rule-based classification in the identification of the sealed surfaces. Also the rail tracks were identified successfully, in “area5”. The rail tracks were classified based solely on contextual rules that were used in the object-based model. But these rules are not transferable, as it was proved with the application of the model in “area0”, unless there is a modification according to the local conditions of the area. In general, rail tracks are misclassified as sealed surfaces due to the similar spectral information between the two classes.

The model showed bad performance in discriminating trees from vegetation. This was expected as the two classes are very similar spectrally and ancillary data i.e. elevation information is needed in order to successfully separate low vegetation from high vegetation. The next step was to examine whether the agglomeration of the classes into a binary format of sealed vs. unsealed (vegetation and trees as one “green” class) would increase the classification accuracy. This approach is analysed in chapter paragagh 6.4.3, after the qualitative analysis that follows.

6.4.2 Qualitative analysis

The qualitative analysis, between the manual API and the automated rule-based classification, was implemented with the use of the Map Comparison Kit (MCK) software using the “per category” algorithm. As already mentioned in the previous chapter 5, this algorithm performs a cell-by cell comparison of one categorical class at a time and gives information about the occurrence of the selected class in both maps. The results were exported in the ArcGIS environment for a visual understanding of the differences between the two classification methods. There are two main reasons of having different results; thematic inconsistency and spectral confusion between the classes.

The thematic discrepancy occurs due to the following reasons:

- The eCognition software draws more specific boundaries around the land cover features, following a pixelised the pattern
- Manual classification was done at scale 1:200. eCognition picked up smaller land cover features (covering areas less than $4m^2$) during segmentation resulting a classification at scale larger than 1:200

The thematic difference between manual API and object-based automated classification, due to spectral confusions among the various land cover features, is summarised in Table 6.23.

Table 6.23 Spectral confusion among the urban land cover features during the automated object-based classification

Spectral confusion between the classes							
Area 5		**Area 0**		**Area20**		**Area 26**	
Sealed	• Bare soil • Low reflectance value of vegetation • White trees • Red trees	**Sealed**	• Canopy boundaries-sealed surface underneath • Trees	**Sealed**	• Grass in dark shadow • Red tree • Trees in shadow with sealed surface underneath	**Sealed**	• Bare soil • Trees • Red trees • Vegetation in shadow
Vegetation	• Trees • Bright trees • Red cars	**Vegetation**	• Trees • Red cars	**Vegetation**	• Trees • Red cars	**Vegetation**	• Trees • Red cars Red trees
Trees	• Vegetation • Sealed in shadow	**Trees**	• Vegetation • Red cars	**Trees**	• Vegetation • Sealed in shadow	**Trees**	• Vegetation • Sealed in shadow (shadow of a tree)
Rails Tracks	• Sealed (successful extraction with rules)	**Rails Tracks**	• Sealed	**N/A**		**N/A**	

6.4.3 Results when different thematic detail is employed

The results from the quantitative and qualitative analysis showed low performance of the rule-based classification model between the ‘vegetation’ and ‘trees’ classes. So, the next step was to examine the performance of the rule-based model when simple binary thematic maps of ‘sealed’ vs. ‘green’ land cover classes were compared (Figure 6-35).

Figure 6-35 The results of the rule-based classification is a two level thematic detail

The results of each automated classification were statistically evaluated with the error matrix production, using as reference data the manual API (Table 6.24).

Table 6.24 Error matrices for each sample site between the manual API and the automated rule-based classification

Residential area - "area5"						
API/ auto_eCg	sealed	green	rails	Sum Map 1	User	
sealed	2229972	92209	3850	2326031	0,959	
green	208703	1156577	7673	1372953	0,842	
rails	174	8634	186629	195437	0,955	
Sum Map 2	2438849	1257420	198152	3894421		
Producer	0,914	0,920	0,942			0,918
						92%

Industrial area "area0"						
API \ auto_eCg	sealed	green	rails	Sum Map 1	User Accuracy	
sealed	3388160	108059	0	3496219	0,969	
green	63622	223877	0	287499	0,779	
rails	207693	8589	0	216282	0,000	
Sum Map 2	3659475	340525	0	4000000		
Producer accuracy	0,926	0,657	N/A			0,903
						90%

Commercial area - "area20"					
API/auto_eCg	sealed	green	Sum Map 1	User accuracy	
sealed	3567122	58734	3625856	0,984	
green	97857	233563	331420	0,705	
Sum Map 2	3664979	292297	3957276		
Producer accuracy	0,973	0,799			0,960
					96%

Residential area- "area26"					
API/ auto_eCg	sealed	green	Sum Map 1	User accuracy	
sealed	1781064	113330	1894394	0,940	
green	410258	1558503	1968761	0,792	
Sum Map 2	2191322	1671833	3863155		
Producer accuracy	0,813	0,932			0,864
					86%

The producer accuracies of each test site revealed high performance of the rule-based model in identifying both sealed and green areas supporting the previous results found during the quantitative and qualitative analysis. In addition, the overall accuracies were all higher in comparison with the classification results when the 'green' class was divided into 'trees' and 'vegetation'. To statistically test whether the two classifications are significantly different the Z was also calculated. The results of the overall thematic accuracies of each classification method, for each test site individually, and their significance when the two methods were compared, are summarised in Table 6.25 that follows.

Table 6.25 Summary of the overall classification accuracies and their significance when the classifications with different thematic detail were compared

Classification methods		Overall accuracy		K_1	K_2	Z statistics	Significance
Residential area "area5"		**Trees vs. Vegetation**	**Green class**				
API	Rule-based (eCognition)	81%		0,68		154	Yes
API	Rule-based (eCognition)		92%		0,8		
Residential area "area26"							
API	Rule-based (eCognition)	72%		0,54		151	Yes
API	Rule-based (eCognition)		86%		0,7		
Commercial area "area20"							
API	Rule-based (eCognition)	94%		0,6		7	Yes
API	Rule-based (eCognition)		96%		0,7		
Industrial area "area0"							
API	Rule-based (eCognition)	88%		0,37		10	Yes
API	Rule-based (eCognition)		90%		0,5		

6.5 Discussion

6.5.1 Summary discussion of the rule-based classification model

During the development of the rule-based classification model the PCA was used for discriminating sealed surfaces, at the broad level scale, from the rest urban land cover features. Principal Components (PCs) were also applied by Nobrega et al. (2008) for detecting sealed surfaces (road infrastructures) among other urban features, using IKONOS satellite data. Other methods for discriminating sealed surfaces from the rest were the ratio of the blue band (Yan and Bauer, 2006). The latter method was tested in this research study but the PC_1 created in Statistica software gave the most satisfactory results. Cleve et al. (2008) also used aerial data and the PC_1 for identifying sealed surfaces and trees in combination with other image object features.

The use of rule sets for integrating contextual information and expert knowledge in the automated classification had the following advantages in comparison with other classification methods based only on the spectral information of the image:

- Using only spectral information the sealed surfaces covered by tree canopy (trees alongside a pavement for example) were initially identified as permeable surfaces (trees). Using expert knowledge all single trees surrounded by sealed surface were reclassified as 'sealed'. This rule also solved the problem of the spectral confusion of the red cars with trees or vegetation. Similarly, all red cars surrounded by sealed surface were reclassified as 'sealed'.
- All polygons in shadow were re-classified according to the identified urban land cover features using rules. Even when dark, thick shadow covered the polygons, cases that no spectral information can be used, the re-classification was based on the neighbour objects.
- The rail tracks that were initially spectrally confused with sealed surfaces were very successfully identified using rules and expert knowledge. These rules proved not to be transferable to other areas as they are based on very specific

local conditions, such as specific polygon length. However they can be used as framework and easily modified in order to suit the new conditions

Misclassification of bare soil with sealed surfaces due to spectral confusion cannot be solved using the specific rule based model. However, the appearance of bare soil surfaces in urban environments are infrequent (for example, only 4 polygons out of 1,059 for the "area26" and 5 out of 5,775 for the "area5" were identified).

The discrimination of vegetation and trees was also difficult with the use of a true coloured (RGB) aerial photography. The literature has indicated that elevation information (such as LIDAR data) is important to discriminate low from high vegetation (Huang et al., 2008; Zhou and Troy, 2008; Chen Y. et al., 2009).

6.5.2 General considerations of the accuracy assessment for object-based classification

Recent advances in remote sensing data in terms of spatial resolution and data availability urges to develop new methods for fast and automated image information extraction. OBIA methodologies have shown the potential of meeting the now days demands. However, there are still issues that need to be explored. Dealing with objects and not with pixels has raised the need in finding new methods to evaluate:

- The object extraction method and the overall segmentation accuracy (analysed in chapter 5.5.2)
- The thematic and spatial accuracy of the classification method

The advantages and disadvantages of the object-based methodologies have been summarised in Figure 6-36.

	Advantages	Disadvantages
OBIA	multi-scale segmentation	segmentation and classification feature selection are based on "trial and error" methods
	hierarchical classification	segmentation accuracy cannot be statistically tested
	builds relations to sub and super objects with coarser or finer scale	the assessment of classification accuracy is an unsolved issue
	feature analysis (spectral, shape, relation to neighbour objects	
	re- usable classification scheme	
	process rules, repeatable-transferable	
	compatible with GIS environment	

Figure 6-36 The advantages and disadvantages of OBIA (modified from Moeller and Blaschke, 2005)

The main drawback in automated object extraction is that segmentation evaluation is based on trial error procedure. The desirable segmentation is based on the visual inspection of the user instead of any kind of statistical evaluation. A comprehensive discussion related to image segmentation has been done in chapter 5 (section 5.5.2).

In relation to object-based classification, the evaluation of thematic classification accuracies was estimated by using confusion/ error matrices and specific assessment values such as the errors of omission and commission, kappa and KHA statistics (see in: Congalton and Green, 1999). The accuracy assessment was based on the comparison between digital classifications with reference data. The error-matrix comprised the most common/standard procedure for pixel-based classification assessment. However, the literature review indicated that this method has also been broadly used and still comprise the predominant method for evaluating object-based classification results. Although, object-based image analysis is facing a challenge as these techniques only compare thematic differences and do not introduce the context of spatial difference between data sets. As Zhan et al. (2005) argued, "current per-pixel-based measures are considered inadequate for assessing the quality of objects extracted from images. This is because our spatial unit has been changed from an individual pixel to an individual object whereas in image classifications the error matrix and related measures are usually location based (per-pixel)". Lang (2008) identified a problem in using the Congalton and Green (1999) method: “a 100% geometrical fit between reference and evaluation data is usually not given due to the issue of scale and the difference ways of delineation”. The result is the sliver polygons production which has a great affect in the overall accuracy estimation. In this PhD study the problem of the sliver polygons production was overcame by exporting the thematic maps into a raster format and statistically analysing them as a cell-by-cell comparison. However, in OBIA there is a needed to assess the quality of the extracted objects according to position, size, and shape and solve the problem of object matching.

Lang et al. (2009) has recently tried to use the landscape interpretation support tool (LIST), an extension tool in ArcView3, in order to evaluate spatial relationships between image objects. The tool enables the comparison of two vector data derived either manually or digitally (segmentation or classification) by integrating external boundaries around the objects and allowing inner object statistics. The process is similar to buffer analysis. The LIST tool was applied for: i) a comparison between pixel classification and a vector type segment boundaries, ii) a comparison between two digital segmentations and iii) a comparison between digital segmentation and manual delineation. According to the authors, the LIST GIS tool extension seems to be working more efficiently with VHR data instead of HR data such as Landsat ETM+ (30 m). The same tool was used in the past by Weinke et al. (2008) for habitat mapping and monitoring the spatial changes of the habitat’s areas in an Alpine region, as well as by Schopfer and Lang (2006) and Schopfer et al. (2008) for land cover change detection.

These techniques were developed later than the implementation of this research study and could only be considered as future investigation.

6.5.3 Object-based classification in operational applications

The object-based classification methods used in operational studies across Europe were analysed in the literature review (chapter 2). The rule-based classification methods have been already applied by Spain, UK, Sweden, Norway and Germany for the development of operational products for land use/ land cover mapping. More specifically, the products of each country are:

- the Spanish Information System of Land Occupation (SIOSE) project
- the National Land Cover Map 2007 (LCM2007) of the UK
- the Digital Landscape Model (DLM-DE) in Germany (Arnold, 2006). The models update has already started in June 2009 (DLM-DE 2009 production)
- the Swedish land cover data (SMD) project

6.6 Conclusions

The object-based classification using rule sets is a complicated method that needs a lot of experience, accompanied by many cycles of the "trial and error" procedures (Definiens, 2007). Additional knowledge of the area is as well needed. The more expert the user is the better classification results can be achieved. But it will still be unknown whether the object features, used during segmentation and classification, are the optimal ones or not (Platt and Rapoza, 2008) since there is no statistical method for the best feature selection. In addition, the solution in choosing the parameters can be more than one (Feitosa, 2006). However, recent literature shows the tendency for developing statistical approaches for selecting the appropriate feature for image segmentation without requiring feature selection defined by the user (Lizarazo and Elsner, 2009; Pekkarinen et al., 2009; Kawakubo et al., 2009, Stein and De Beurs, 2009; Clinton et al., 2010; Dragut et al., 2010).
Once the object-based model is developed, it can be easily and rapidly applied in different study areas using the same data set. The rule-based model seems to be transferable as its application in four different reference sites that represented different structures of urban land cover types, showed high overall accuracies. The application occurred without changing the threshold values of the individually defined rules in the whole rule set. However, a future investigation shall examine whether by changing

these thresholds according to the local conditions of the area's characteristics, higher overall accuracies are achieved.

The application of the classification model in more than four reference sites, in whole Cambridge for example or in another city, is necessary in order to conclude its transferability with certainty.

The use of additional elevation information for separating low from high vegetation should be examined. Recent studies have shown a good potential for identifying different vegetation types (Chen et al., 2009; Meng et al., 2009). LIDAR information in object-based models was also applied for the building detection (Huang et al., 2008; Zhou and Troy, 2008).

Colour infrared (CIR) aerial photographs also show a good potential due to the extra spectral information in the Near Infrared (NIR) band. The benefit of using such data is the predominant reflectance signature of vegetation in the NIR band compared to the visible bands. CIR aerial photographs and object-based methods have been successfully applied for urban land cover and vegetation mapping (Blaschke et al., 2005; Zhou and Troy, 2008; Walker and Blaschke, 2008; Tansey et al., 2009).

Implications on the transferability of the model when using different data sets should also be examined. A future investigation should test the effects when the day of the image taken differs or the image type is changing. In this PhD study the rule-based classification model, built with the use of the aerial photography, was also applied on VHR QuickBird satellite data. The automated rule-based classification of the VHR data is analysed in chapter 8.

The next chapter 7 investigates the performance of the object-based classification model, based on the aerial photography, by integrating additional ancillary data information.

Chapter 7

Integration of ancillary data in the object-based classification model

This chapter aims to evaluate whether the performance of the rule-based classification model, developed in chapter 6, will increase by integrating additional ancillary data information. The classification of the aerial photography with the integration of Ordnance Survey (OS) MasterMap into the object-based classification model is described. The (OS) MasterMap gives cadastral information. A model was built up in the eCognition software using the same hierarchical rule-set classification, developed in the previous chapter. The results were compared with two data sets: i) the API described in chapter 5 and ii) the API based on the division, in 25% intervals, of the OS MasterMap polygons (developed in chapter 4). The implication of using ancillary data in the object-based model is discussed.

7.1 The object-based rule set classification model using the OS MasterMap

The OS MasterMap contains baseline polygons that delineate transport network infrastructure as well as residential and commercial buildings. In each OS MasterMap polygon several attributes are enclosed such as the land cover type and an indication whether it is manmade or not. Each land cover type has a unique code (the "feature code") giving the ability to identify each land cover feature by a number. For example all polygons that define roads have the feature code of 10172 while every building has the feature code of 10021.

The OS MasterMap polygons were integrated in the eCognition software as a "thematic layer". Thematic layers can be either vector (polygons, lines, points) or raster files which have an associated attribute table (Definiens, 2007). During the segmentation process, a thematic layer can be used in order to generate polygons/

image objects. The boundaries of the extracted polygons remain unchanged during sub-segmentation, i.e. the image objects are only re-segmented within these borders, at lower scales. In this study, the OS MasterMap was employed as a thematic layer in order to initially segment the aerial data according to its discrete polygons.

The automated classification of the aerial data, by integrating the OS MasterMap in the object-based model, was implemented with the development of a whole rule-set of processes (Figure 7-1). The whole methodology can be described, in simplicity, as follows:

- The image was initially segmented using the thematic layer, i.e. the baseline polygons of the OS MasterMap. In order to produce image objects based exclusively on the information of the thematic layer, the weights of all image layers were switched to 0 (Table 7.1, level 1). The scale parameter was set to 1000, an arbitrary large number in order to make sure that the extraction of the objects were solely based on the baseline polygons. Default values were used for the shape and compaction parameters as they don't influence the segmentation process when the image layers (spectral information) are not used.
- The extracted polygons that indicated the sealed soil surfaces were masked out based on the attributes of the OS MasterMap. As explained above, each land cover feature has a unique feature code.
    - o Buildings were classified using the feature code of 10021 (Table 7.1, level 2).
    - o Roads and roadsides were also classified using the analogous feature codes (Table 7.1, level 3).
    - o Similarly, the baseline polygon that indicated the rail tracks was classified using the representative feature code (Table 7.1, level 4).
- The classification of the remaining image objects was based on the rule sets of the object-based model, developed in the previous chapter 6. Therefore, all the unclassified image objects were initially labelled as "mixed areas".
- The "mixed areas" class was re-segmented into a smaller scale in order to extract the polygons in shadow. The "shadow" class was identified using the mean value of brightness while the rest of the mixed areas were classified as

"non shadow" using the masking out technique, i.e. class B is not class A (Table 7.1, level 5)

- At the same segmentation level (a copy of the previous level was used) the "non-shadow" class was further classified into the "sealed" and "green" classes. The "sealed" class consisted of all the remaining soil sealed objects that were not extracted using the OS MasterMap attribute table, such as paths and sealed surfaces in the back gardens. The feature used in order to classify the sealed objects was the mean value of the maximum difference. The green class was classified using the masking out technique. The technical specifications are described in Table 7.1, level 6.
- Because the rail tracks polygon, extracted based on the OS MasterMap, contained more land cover features than the rail tracks (the polygons is bigger then the actual rail tracks) it was decided to further re-segmented and classified. The analysis was relied on the parameters used in the original object-based model. The technical specifications and the reclassification result are shown Table 7.1, level 7. By this way, it was demonstrated that even when using ancillary data, the OBIA can still continue locally until the desirable classification result is achieved.
- Finally, the level was copied in order to bring together all the classes that were individually classified in the various hierarchical levels. The shadow class was reclassified into shadow sealed and shadow green using the original rules which were based on the relationship of neighbour objects (Table 7.1, level 8). The figure at level 8, in table 7.1, shows the final classification result of the sample area "area5".

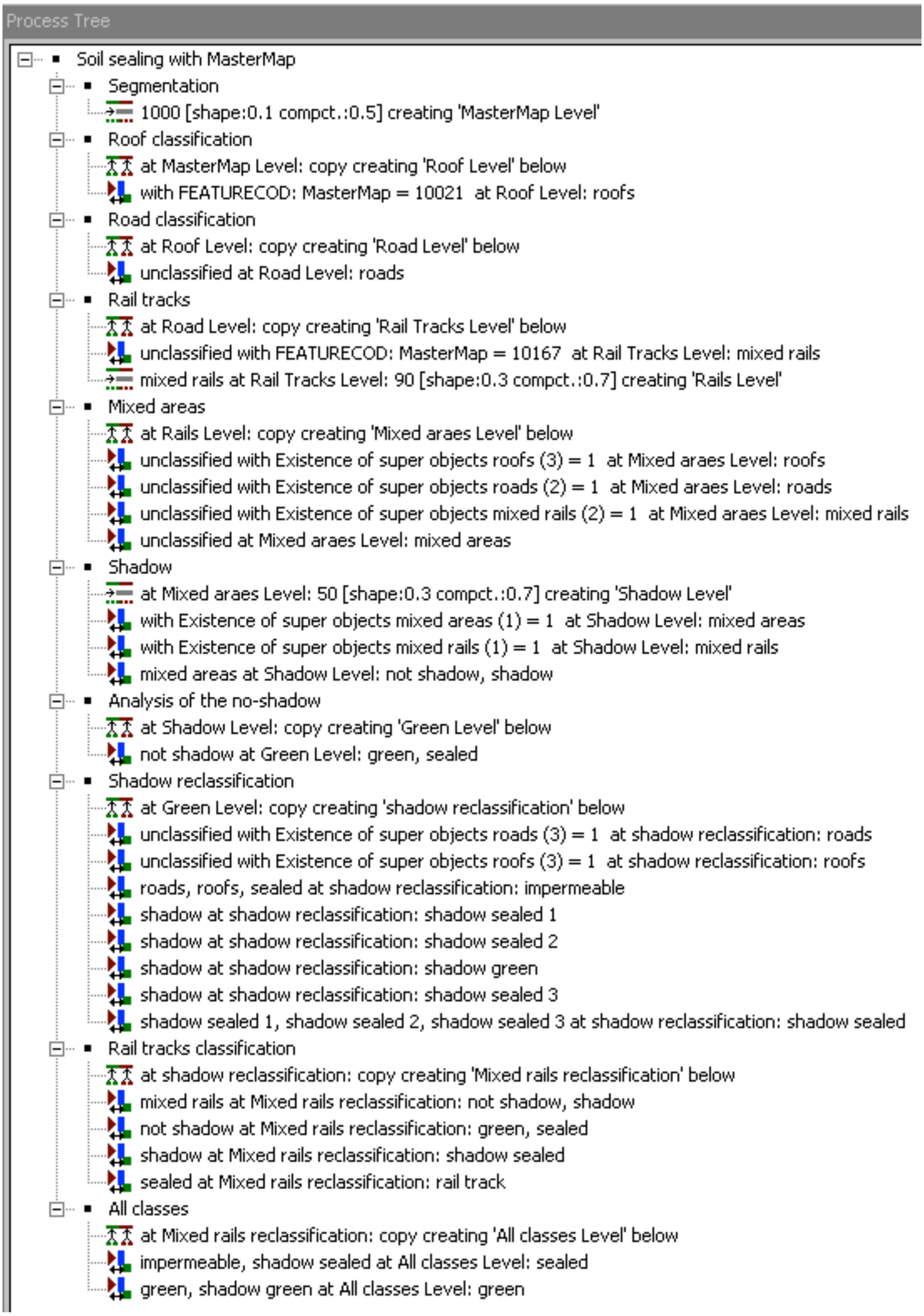
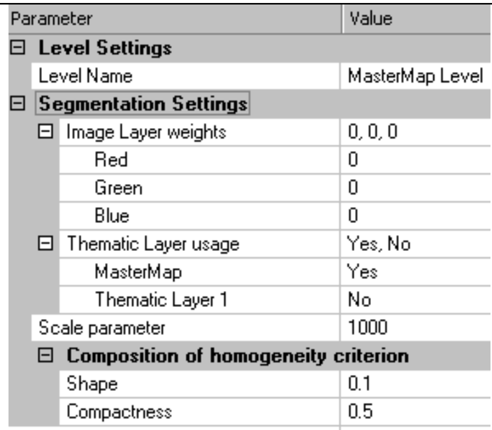


Figure 7-1 The complete rule-set, using processes in eCognition, for the development of the object-based model

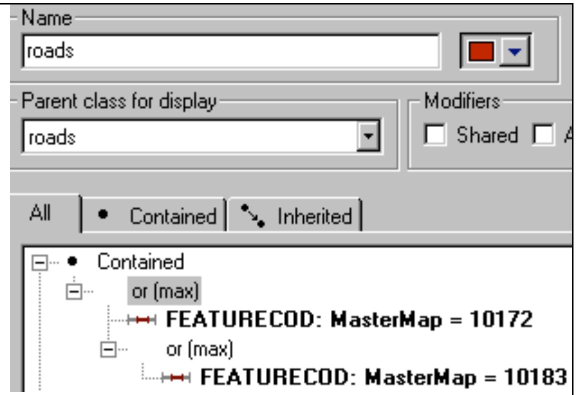
Table 7.1 The main steps and parameters used for the development of the object-based model using ancillary data

Working level	**Extracted classes**	**Segmentation parameters**	**Critical features of the fuzzy-rule classification**
Level 1: Initial segmentation based on the OS MasterMap polygons		Parameter / Value Level Settings Level Name: MasterMap Level Segmentation Settings Image Layer weights: 0, 0, 0 Red: 0 Green: 0 Blue: 0 Thematic Layer usage: Yes, No MasterMap: Yes Thematic Layer 1: No Scale parameter: 1000 Composition of homogeneity criterion Shape: 0.1 Compactness: 0.5	N/A
Level 2: Building extraction from OS MasterMap		Parameter / Value Level Settings Level Name: MasterMap Level Segmentation Settings Image Layer weights: 0, 0, 0 Red: 0 Green: 0 Blue: 0 Thematic Layer usage: Yes, No MasterMap: Yes Thematic Layer 1: No Scale parameter: 1000 Composition of homogeneity criterion Shape: 0.1 Compactness: 0.5	Parameter / Value Use class: roofs dit threshold condition Feature FEATURECOD: MasterMap Threshold settings < <= = <> >= 10021 No unit

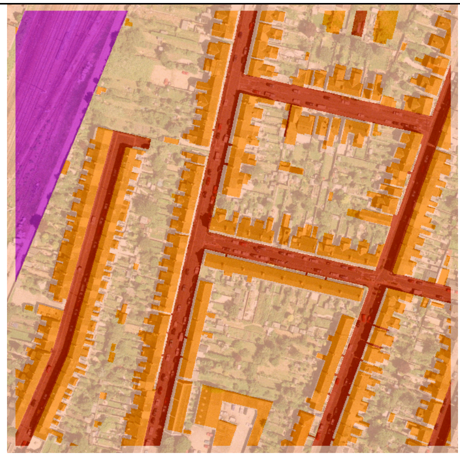
Level 3: road extraction from OS MasterMap

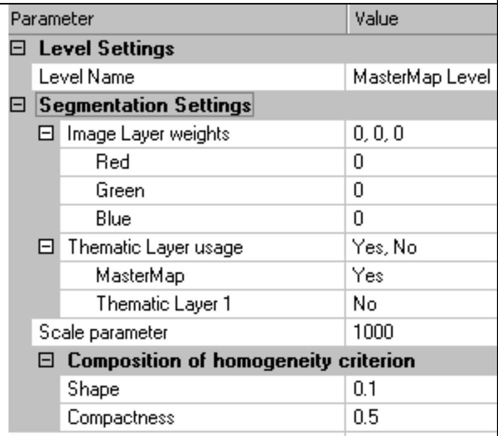


Parameter	Value
⊟ **Level Settings**	
Level Name	MasterMap Level
⊟ **Segmentation Settings**	
⊟ Image Layer weights	0, 0, 0
Red	0
Green	0
Blue	0
⊟ Thematic Layer usage	Yes, No
MasterMap	Yes
Thematic Layer 1	No
Scale parameter	1000
⊟ **Composition of homogeneity criterion**	
Shape	0.1
Compactness	0.5

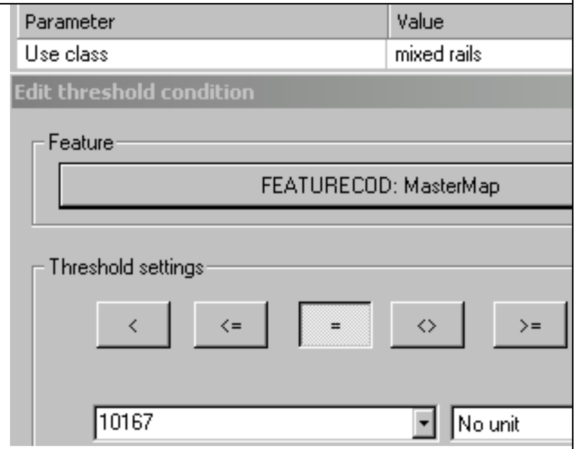


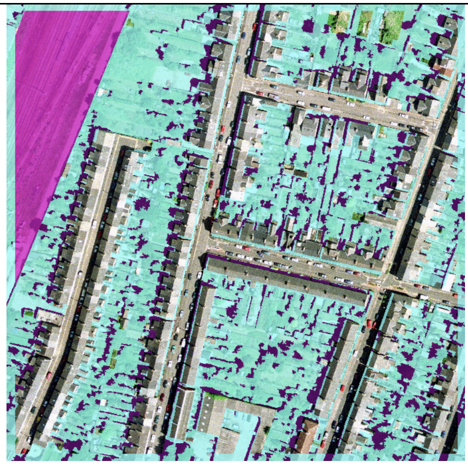
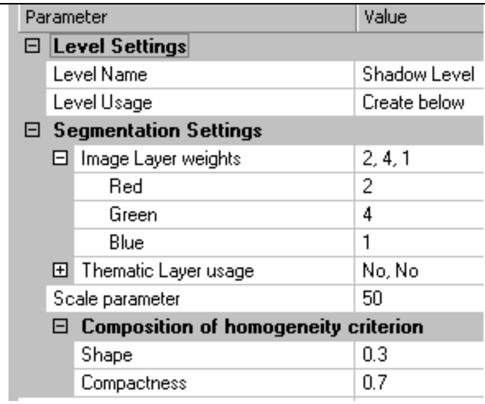
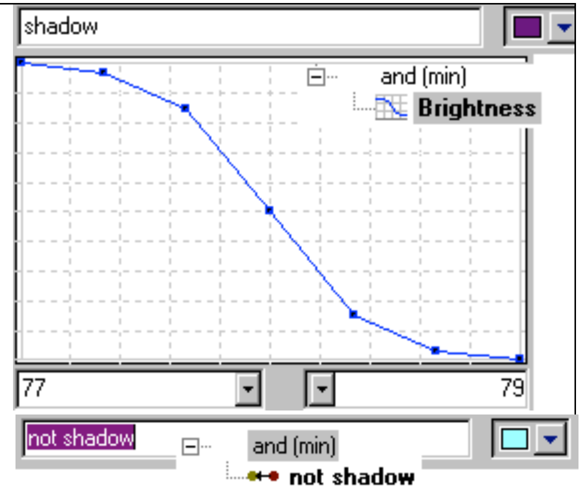
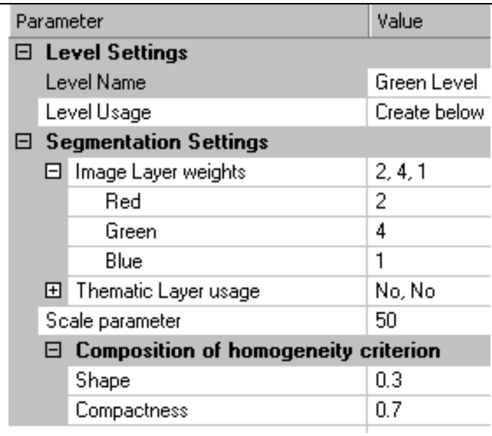
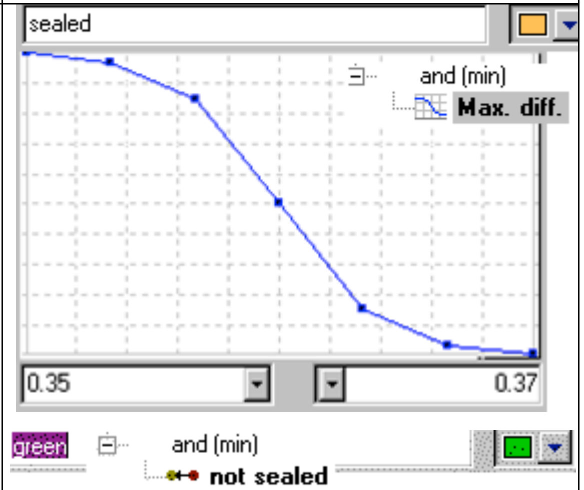
Level 4: Rail tracks extraction from OS MasterMap

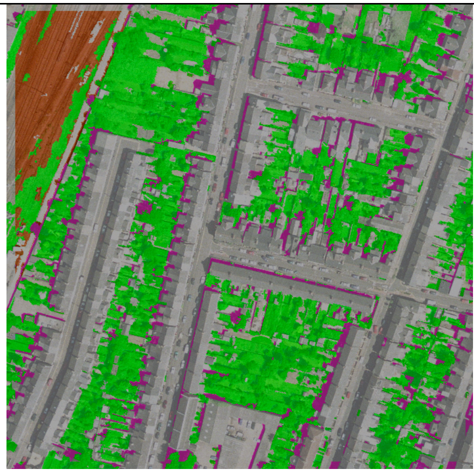
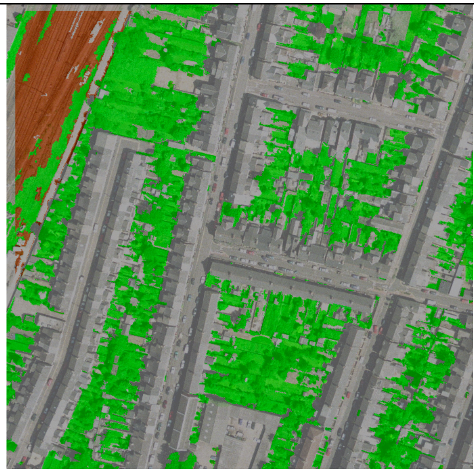




Parameter	Value
⊟ **Level Settings**	
Level Name	MasterMap Level
⊟ **Segmentation Settings**	
⊟ Image Layer weights	0, 0, 0
Red	0
Green	0
Blue	0
⊟ Thematic Layer usage	Yes, No
MasterMap	Yes
Thematic Layer 1	No
Scale parameter	1000
⊟ **Composition of homogeneity criterion**	
Shape	0.1
Compactness	0.5



<table>
<tr>
<td>Level 5:
shadow vs.
non shadow</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 6:
remaining
sealed vs.
green</td>
<td></td>
<td></td>
<td></td>
</tr>
</table>

Level 7: Rail track re-classification		Parameter | Value Level Settings Level Name | Rails Level Level Usage | Create below Segmentation Settings Image Layer weights | 2, 4, 1 Red | 2 Green | 4 Blue | 1 Thematic Layer usage | No, No Scale parameter | 90 Composition of homogeneity criterion Shape | 0.3 Compactness | 0.7	Name: rail track Parent class for display: rail track Modifiers: Shared, Abs All | Contained | Inherited Contained and (min) **Brightness < 218** **Existence of super objects mixed rails (2) =**
Level 8: Shadow re-classification and final classification		Parameter | Value Level Settings Level Name | shadow reclassification Level Usage | Create below Segmentation Settings Image Layer weights | 2, 4, 1 Red | 2 Green | 4 Blue | 1 Thematic Layer usage | No, No Scale parameter | 50 Composition of homogeneity criterion Shape | 0.3 Compactness | 0.7	Shadow green and (min) **Border to green >= 5.5** Shadow sealed and (min) **Border to impermeable >= 5.5** and (min) **Border to impermeable >= 0.2** **Border to shadow sealed 1 >= 0.2**

Exactly the same procedure was employed to the other two sample areas; the classification results, for each sample area, are shown in Figure 7-2.

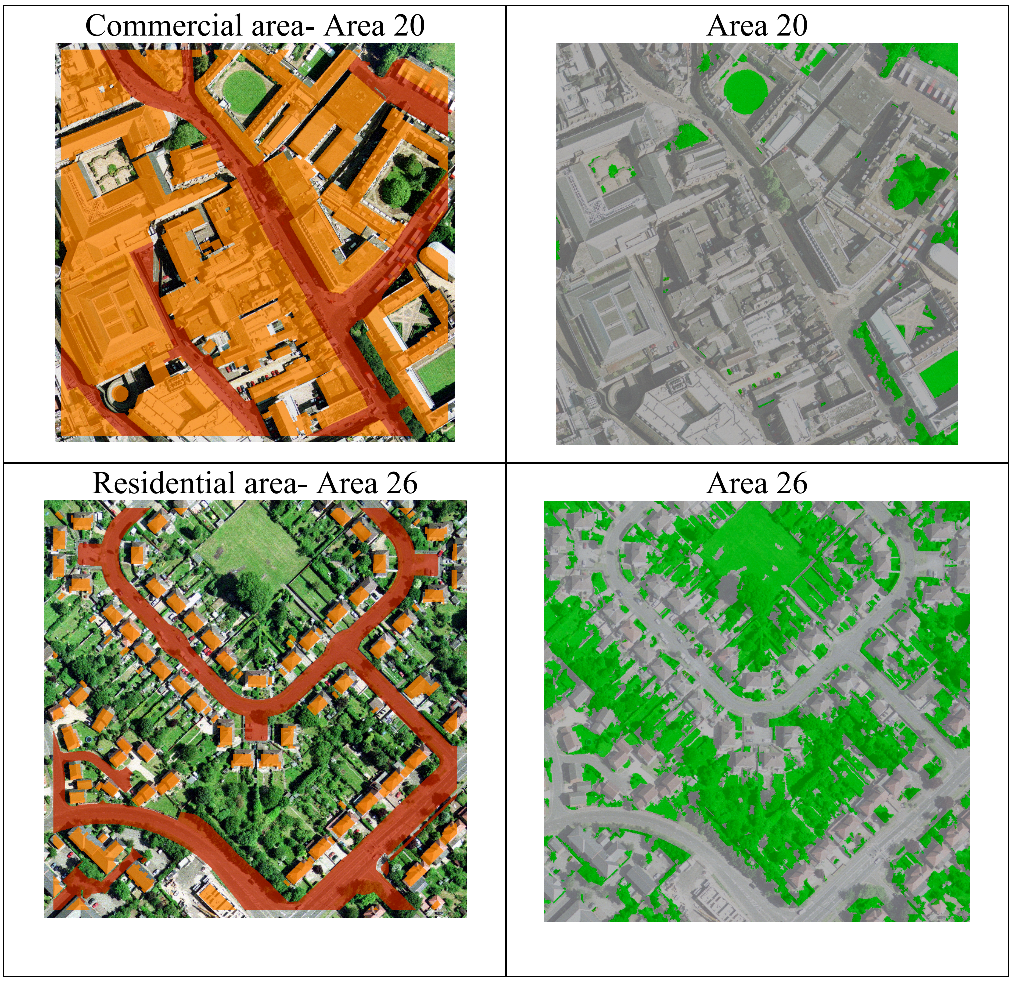


Figure 7-2 The columns on the left show the initial classification results based on the OS MasterMap attributes while on the right hand side is the final classification results

The classification of the industrial area “area0” could not be implemented as the OS MasterMap polygons were not updated according to the land cover changes of the specific sample site. If the masking out technique had been used in order to extract buildings and roads, based on the attributes of the ancillary data, the classification result would have not represented the actual land cover types of the area (Figure 7-3).

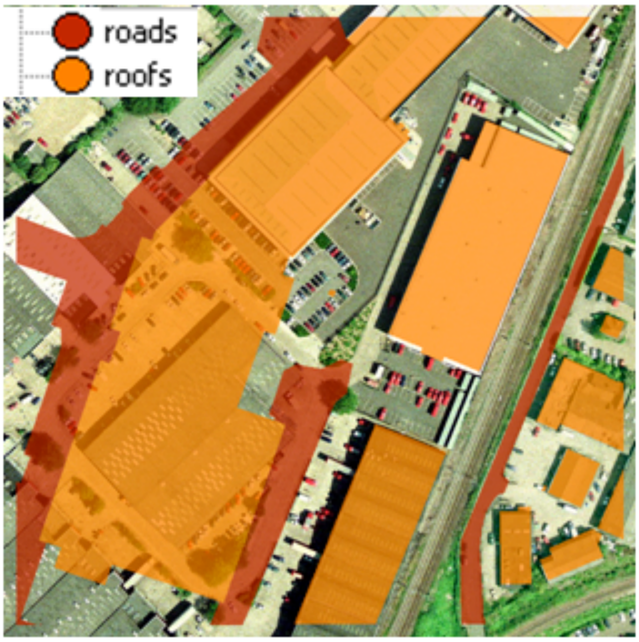


Figure 7-3 The classification of the sealed surfaces if the MasterMap would have been used

7.2 Accuracy assessment and discussion

The automated object-based classification was compared with API reference data that were produced in two different ways. The first was the traditional API, developed in Chapter 5. The second was the API based on the OS MasterMap baseline polygons, by classifying each polygon according to 25% intervals (developed in Chapter 4).

7.2.1 Comparison of the object-based classification model with the traditional API

The results of each automated object-based rule set classification were exported from eCognition to ArcGIS as smoothed polygons in vector format. The data were then converted into raster format with the cell size of 0.125. The overall thematic accuracy of each classification was statistically evaluated with the error matrix production (Table 7.2). The average overall accuracy for the three sample areas was 90%.

The error matrices indicated that the automated classification produced very high accuracies at the 'sealed' and the 'rail tracks' classes. Of course, this was expected as these classes were classified based on the attributes of the ancillary data (OS MasterMap). The producer accuracies of each test site also revealed high performance in identifying green areas, supporting the previous results of chapter 6 indicating a generally good performance of the rule-based model.

Table 7.2 Error matrices between the traditional API and the automated object-based classification for each sample

Residential area "area 5"						
API/ eCg_MM	sealed	green	rail tracks	Sum Map 1	User Accuracy	
sealed	2225207	89628	11196	2326031	0,957	
green	234147	1122028	16778	1372953	0,817	
rails tracks	6352	8815	180270	195437	0,922	
Sum Map 2	2465706	1220471	208244	3894421		
Producer Accuracy	0,902	0,919	0,866			
						0,906
						91%

Commercial area "area 20"					
API/ eCg_MM	sealed	green	Sum Map 1	User Accuracy	
sealed	3612826	13030	3625856	0,996	
green	142826	188594	331420	0,569	
Sum Map 2	3755652	201624	3957276		
Producer Accuracy	0,962	0,935			0,961
					96%

Residential area "area 26"					
API/ eCg_MM	sealed	green	Sum Map 1	User Accuracy	
sealed	1820569	73822	1894394	0,961	
green	529863	1438898	1968761	0,731	
Sum Map 2	2350432	1512720	3863155		
Producer Accuracy	0,775	0,951			
					0,844
					84%

In order to understand whether the integration of ancillary data in the object-based model aid the classification results a comparison with the automated classification, which was solely based on rules and expert knowledge (chapter 6), was also made. The comparison showed that the integration of the OS MasterMap produced lower overall accuracies (Table 7.3). To test whether the two independent error matrices are statistically significant different the Z value was calculated. The Z test revealed that the difference between the two classification methods is significant apart from the commercial area ("area20") sample site. This can be explained due to the proportion of sealed soil surfaces in the area as it is explained below. The object-based model has shown very good performance in the identification of the sealed surfaces. The ancillary data were used to mask out the sealed surfaces. Since the area is predominantly sealed, it is normal to have the similar results using the two different methods to extract the sealed surfaces. However, the Kappa coefficient showed that the performance of the object-based model without the integration of the OS MasterMap is higher. According to Congalton and Green (1991), the Kappa coefficient is another way to measure the overall agreement in an error matrix. In contrast to the overall accuracy, which is the summary of the diagonal values to the total number in the error matrix, the Kappa coefficient also takes the non-diagonal values into account (Banko, 1998).

Table 7.3 Summary of the overall accuracies and their significance when the three classification methods were compared

Classification methods		Overall accuracy		K_1	K_2	Z statistics	Significance
Residential area "area5"							
API	Rule-based (eCognition)	92%		0,84		21,2	Yes
API	Rule-based & OS MasterMap (eCognition)		91%		0,81		
Residential area "area26"							
API	Rule-based (eCognition)	86%		0,73		28,8	Yes
API	Rule-based & OS MasterMap (eCognition)		84%		0,67		
Commercial area "area20"							
API	Rule-based (eCognition)	96%		0,73		1,88	No
API	Rule-based & OS MasterMap (eCognition)		96%		0,67		

7.2.2 Comparison of the object-based classification model with the API based on OS MasterMap

For the production of the API based on the OS MasterMap polygons, 18 randomly selected sample segments (250 x 250 m) were visually interpreted using the aerial photography. Each polygon was attributed according to the percentage of sealed soils with a limited precision of 25%, e.g. 0, 25, 50, 75 and 100% of sealing. The methodology has been analytically described in chapter 4. The API method was used as the reference data for the comparison with the automated object based classification when the OS MasterMap was integrated within the model.

The results of the automated object-based classification were exported from eCognition to ArcGIS as smoothed polygons in vector format. All the polygons that were classified according to the attributes of the OS MasterMap (i.e. buildings, roads, roadsides and rail tracks) were masked out (Figure 7-4).

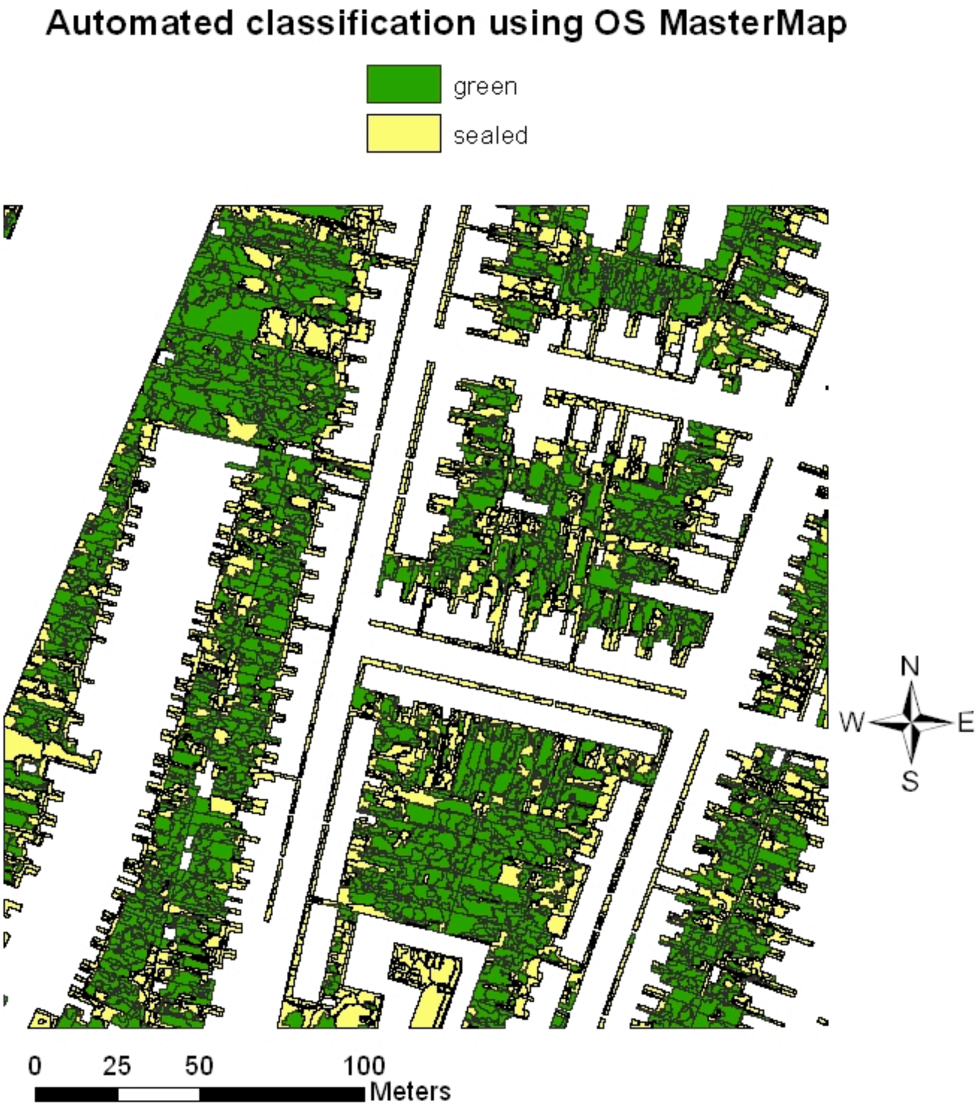


Figure 7-4 The automated rule-based classification results after masking out the OS Mastermap polygons

The same polygons were also masked out form the original API using the OS MasterMap. The remaining polygons from both classification methods were combined together using the “Zonal Statistics” tool, available in the ArcGIS software. The united attribute table was exported to an Excel spreadsheet for the production of the error matrices using the class combinations, 0%, 25%, 50%, 75% and 100% sealed (Table 7.4). The error matrices identified very low overall classification accuracies as well as producer and user accuracies, indicating that the method used in chapter 4, for the production of API data is not appropriate. The reason for such low accuracies is the (visual) coarse division of every “back garden” OS MasterMap polygon into four parts following by the 25% interval calculation of sealed area. On the contrary, as the previous statistical analysis results indicated (Table 7.2), the sub-segmentation of the OS MasterMap polygons produced very high accuracies.

Table 7.4 Error matrices between the API and the automated classification in 25% intervals of the soil sealing class

Residential area "area 5"								
	eCg_MM SEALED							
API_MMSealed	*0*	*25*	*50*	*75*	*100*	Grand Total	User Accuracy	
0	18	39	34	23	58	172	0,105	
25	12	23	14	15	37	101	0,228	
50	8	10	15	3	29	65	0,231	
75		8	5	3	23	39	0,077	
100	22	51	39	24	135	271	0,498	
Grand Total	60	131	107	68	282	648		
Producer Accuracy	0,300	0,176	0,140	0,044	0,479			
								0,299
								30%

Residential area "area 26"								
	eCg_MM SEALED							
API_MMSealed	*0*	*25*	*50*	*75*	*100*	Grand Total	User Accuracy	
0	8	24	18	4	3	57	0,140	
25		12	29	5		46	0,261	
50		1	14	5	1	21	0,667	
75			3	4	1	8	0,500	
100			1	14	21	36	0,583	
Grand Total	8	37	65	32	26	168		
Producer Accuracy	1,000	0,324	0,215	0,125	0,808			
								0,351
								35%

Commercial area "area 20"								
	eCg_MM SEALED							
API_MMSealed	*0*	*25*	*50*	*75*	*100*	Grand Total	User Accuracy	
0	9	4	7	3	17	40	0,225	
25			1	1	1	3	0,000	
50		1	1	1		3	0,333	
75				1		1	1,000	
100	1	1		3	102	107	0,953	
Grand Total	10	6	9	9	120	154		
Producer Accuracy	0,900	0,000	0,111	0,111	0,850			
								0,734
								73%

To evaluate whether the low classification accuracy was random or not, the same procedure was implemented for all the 18 sample areas. First the sample areas were automatically classified using the object-based rule set model with the MasterMap integrated (proving the transferability of the model). Then, the results of the automated object-based classification were converted into 25% intervals of the soil sealing class. Once again, the overall accuracies were very low; average of 49.6% for the 18 sample areas.

To test the results further and to understand if the low precision was due to the use of the ancillary data or to the 25%, intervals the traditional API classification was also converted into 25% intervals of the sealing class. The results once again showed very low overall accuracies and Kappa coefficient values (Table 7.4). In addition, the Z test showed that the two classification methods for producing the reference data were not statistically different. That result indicates that the "fault" in the whole procedure is the conversion of the classification into 25% interval proportions of sealing and not the integration or not of the ancillary data into the classification model.

Table 7.5 Summary of the overall accuracies and their significance when all the classification results were converted into 25%

Classification methods		Overall accuracy		K_1	K_2	Z statistics	Significance
Residential area "area5"							
API -25% intervals	Rule-based & OS MasterMap (eCognition) -25% intervals	31%		0,04		0,26	No
API & OS MasterMap (eCognition) - 25% intervals	Rule-based & OS MasterMap (eCognition) -25% intervals		30%		0,05		
Residential area "area26"							
API -25% intervals	Rule-based & OS MasterMap (eCognition) -25% intervals	51%		0,36		1,63	No
API & OS MasterMap (eCognition) - 25% intervals	Rule-based & OS MasterMap (eCognition) -25% intervals		35%		0,22		
Commercial area "area20"							
API -25% intervals	Rule-based & OS MasterMap (eCognition) -25% intervals	81%		0,53		0,32	No
API & OS MasterMap (eCognition) - 25% intervals	Rule-based & OS MasterMap (eCognition) -25% intervals		73%		0,39		

7.3 Conclusions

In the GIFTSS project (chapter 4) the reference data production was based on the OS MasterMap polygons; the polygons were visually interpreted using the aerial photography. Each polygon was attributed a percentage of sealing. In large polygons which included more than one land cover feature, such as in the residential gardens, the percentage of sealed soils was identified with a limited precision of 25%, e.g. 0, 25, 50, 75 and 100% of sealing (by visually dividing each polygon in four). In order to compare this reference data with the automated classification (using the OS

MasterMap), the results of the latter were also summarised in 25% intervals of the sealing class. The statistical evaluation showed very low accuracies (average 49.7%). Similar results were found when both the traditional API and the automated classification were also summarised in 25% intervals of the sealing class (Table 7.4). The results indicate that the conversion of detailed thematic maps in percentage of soil sealing with 25% intervals is not appropriate. This was also proved when the comparison of the traditional API and the automated rule-based classification, without concerting the data in percentages, revealed an average overall accuracy of 90%.

The integration of the OS MasterMap in the object-based model was successful achieving very high accuracies (90% average). However, the comparison with the results of the original automated object-based classification model identified that the integration did not increase the overall accuracy of the produced maps; instead it was decreased (91% overall accuracy without using the OS MasterMap). The results of the two methods proved statistically different.

The integration of ancillary data in the OBIA model also identified some disadvantages:

- The OS MasterMap is not always updated regarding the land cover changes of an area and consequently cannot be used in the object- based classification model. For instance, no classification could be implemented for the industrial area sample site using this method.
- Some polygons include more than one land cover classes however they are identified according to one, like the “rail tracks” polygon. The polygon is bigger than the actual rail tracks including neighbour land cover features such as vegetation and soil sealed surfaces.
- Problems also occur due to the displacement between the ancillary data and the aerial data resulting on misclassifications. The problem is very clear looking when at buildings (Figure 7-5). The data used for this study was a mosaic of true colour ortho-corrected aerial photographs. If ortho-rectified photographs were used the problem of the relief displacement would probably been solved due to the better quality of the data. However, regardless of the type of EO data that was used, the use of OS MasterMap in identifying buildings resulted to misclassifications due to the lack of updated thematic information; some

polygons identified as sealed surfaces (probably garages or sheds) did not exist any more (Figure 7-5).

Figure 7-5 Misclassification results due to relief displacement between EO and ancillary data as well as not updated thematic information ancillary data (in red circles)

In the previous chapter 6, the rule-based classification model showed very high performance in identifying soil sealed surfaces. It can be concluded there is no need to use the OS MasterMap for masking out the sealed areas. The identified problems in using the ancillary data would also have been avoided. However, the results are based four sample areas, covering an area of 250 x 250 m each. The conclusion would have been more robust if more sample areas where tested.

The OS MasterMap has been used in UK for the production of the national Land Cover Map 2007 (LCM2007) based on the so called parcel-based classification. The EO data used was satellite images at 25 m. The LCM2007 represents the land cover and the broad habitats mapping of whole UK with 0.5 ha MMU. Because the OS MasterMap signifies a very detailed digital cartography a generalised version was used "by removing unnecessary lines and objects and making more manageable and appropriate to land cover mapping at national scale" (Countryside Survey, 2008). However, generalisation methods tend to be time-consuming and expensive requiring specialist hardware and software (Smith et al., 2007). For the completion of the LCM2007 a sub-segmentation of the land parcels was required.

The main question that still exists is: do you really need the OS MasterMap for the initial identification of land parcels or an automated segmentation method could be used from the beginning? The use of OS MasterMap in the initial segmentation of the EO data produces very fast results. However, various problems were also identified which might be more expensive and time consuming in order to be solved. In addition, this research study identified that the OS MasterMap didn't help in the production of more accurate land cover maps.

Chapter 8

Object-based rule set classification using VHR satellite data

In the previous chapters OBIA has been evaluated with the use of a true colour aerial photography (RGB bands). This chapter initially describes the application of the rule-based model, developed using aerial data (chapter 6), on the very high resolution (VHR) QuickBird satellite imagery. Then, the development of a new object-based classification model using the satellite data and its additional spectral information is analysed. The comparison between the two object-based classification models developed using different data sets follows. The object-based classification was also tested against the pixel-based classification of the same VHR satellite data (developed in chapter 4). The API method comprised the reference data for the implementation of the statistical analysis during the comparisons of the three object-based models.

8.1 Application of the rule-based classification model developed using true colour aerial photography

In chapter 6, the development of a rule-based classification model with the use of true colour aerial photography (RGB bands) was analysed. In this paragraph, the same model was applied on the satellite imagery in order to test its transferability and examine the accuracy results that can be achieved when only the true colour band combination is used. The values of each parameter and object features were identically applied. In the next paragraphs, this rule-based model is described for simplicity as the RGB classification model.

8.1.1 Testing and modifications of the RGB clasisfication model

In the RGB model and during the image segmentation of the aerial data the emphasis was given on the green band (image weights of the RGB= 241 in eCognition) in order to extract vegetation. As the aim at this stage of the research was to duplicate the process, the first image segmentation of the VHR satellite data was solely based on the multispectral (MS) imagery. In the eCognition software, the segmentation of the satellite MS data was implemented using exactly the same image weights and values for each parameter as used at the RGB model (Figure 8-1). As Figure 8-1 shows, the segmentation result was one big polygon around the data without extracting any image object. For this reason another test was implemented using the same parameter values but also the spectral information/ spatial resolution of the panchromatic (PAN) band of the satellite imagery.

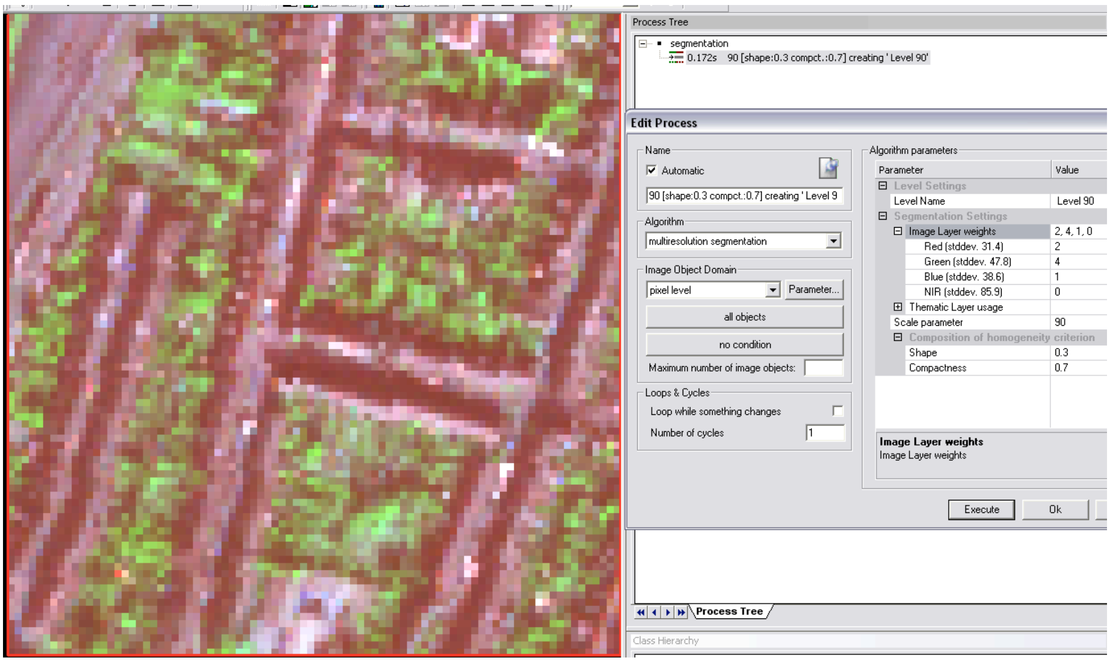


Figure 8-1 Segmentation results using solely the MS satellite data and the same rules of the RGB model. The result of the segmentation is one big polygon (red line around the imagery)

The additional use of the PAN band (image weight value of 1) on the RGB model, during the image segmentation at scale 90, gave satisfactory results by broadly extracting the three main land cover features; sealed surfaces, green areas and areas in shadow (Figure 8.2). That result constituted the upper segmentation level. More segmentation levels were employed using an iterative process between segmentations and classifications resulting in a hierarchical, multilevel classification.

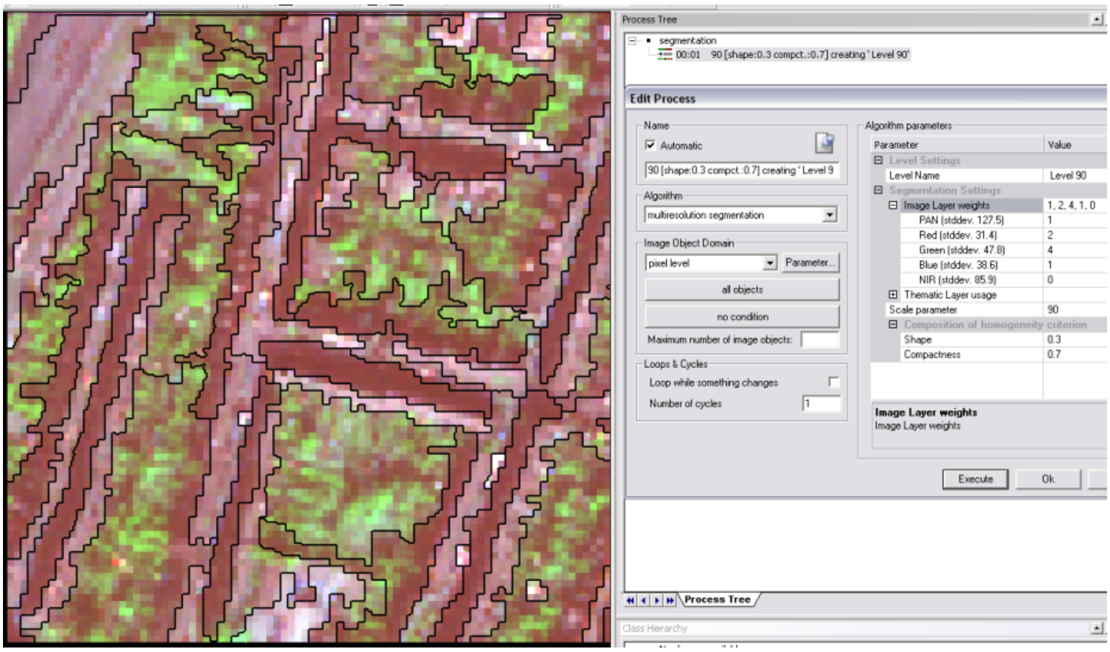


Figure 8.2 Segmentation results using both PAN and MS data with the 241 RGB rule

The next step was to classify the image according to the "built up" class by developing in eCognition the same arithmetic feature, as in the RGB model, which was based on the principal component analysis. The image object features that used in order to construct the PC_1 arithmetic feature for the "built up" class were the maximum difference, the mean value and the standard deviation of the blue band (equation 1, paragraph 6.2). The classification result was completely unsatisfactory when the same range of the PC_1 values, as the one used in the RGB model (-2.61, -0.8), was applied (Figure 8.3). However, with the 'trial and error' method and the use of the "feature view" tool a new range of the PC_1 that could successfully classify the built-up areas was identified. The image objects with PC_1 range value of (-0.31, 2.8) were classified as "built-up" areas while the rest of the unclassified objects as "mixed areas" by using the masking out technique (Figure 8-4).

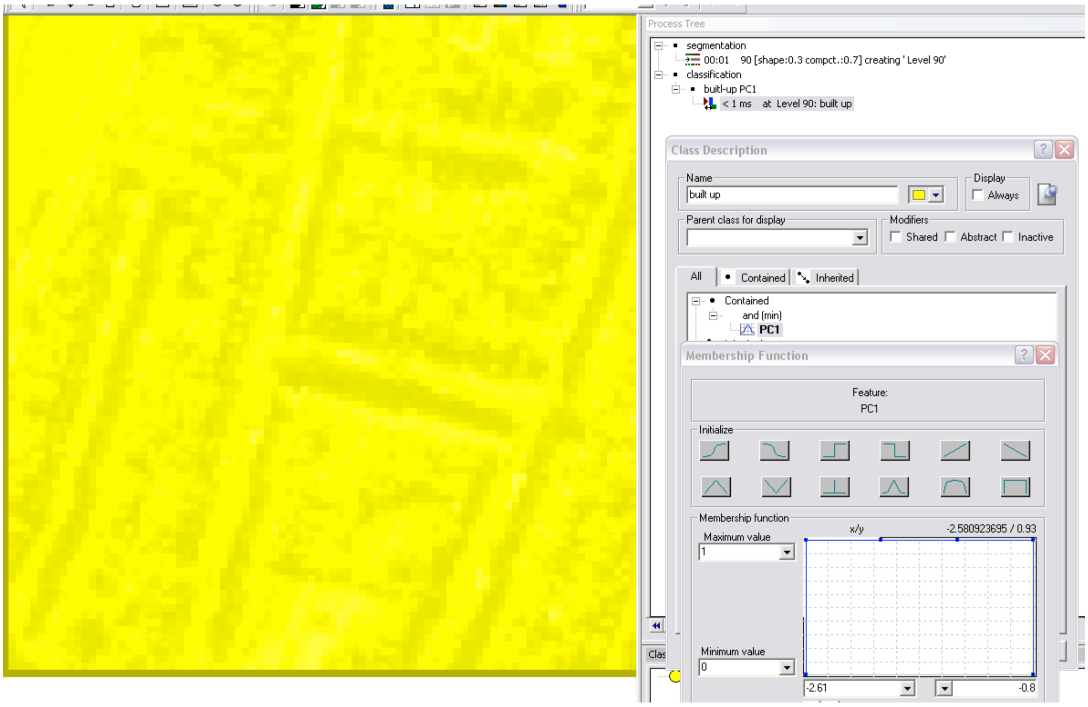


Figure 8-3 The use of the same PC_1 range value of the RGB model could not successfully classify the extracted image objects

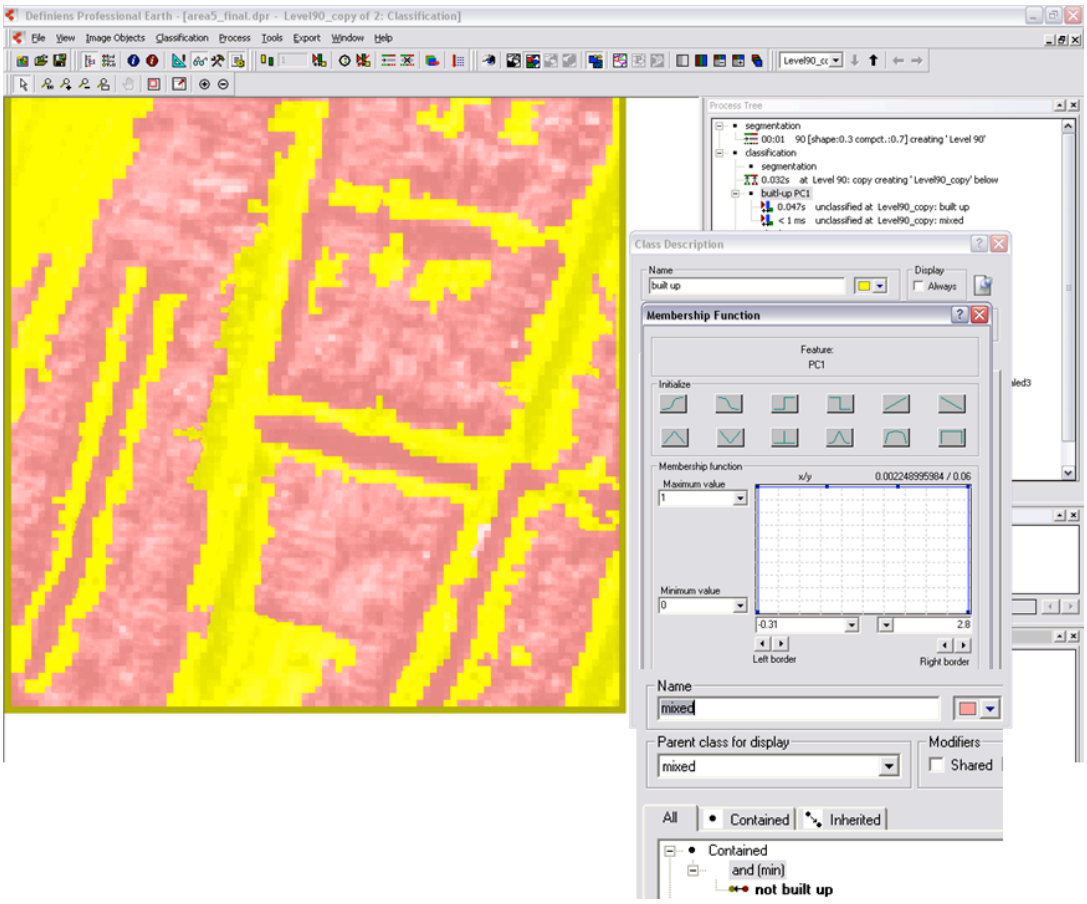


Figure 8-4 Classification result of the built-up (yellow) and mixed areas (pink) classes

The “mixed areas” class was re-segmented into a smaller scale, with a scale value of 50, in order to extract the polygons in shadow (Figure 8-5). During the development of the RGB model, the “shadow” class was identified using the mean value of brightness. As with the built-up class, the initial test was to use the same range value of brightness but the “feature view” tool identified that no satisfactory results could be achieved within such range (Figure 8-6i). The thresholds of the brightness feature value had to change. The image objects with a range of brightness value between (122, 124) were classified as “shadow” while the rest of the mixed areas were re-classified as “non shadow” by using the masking out technique (Figure 8-6ii).

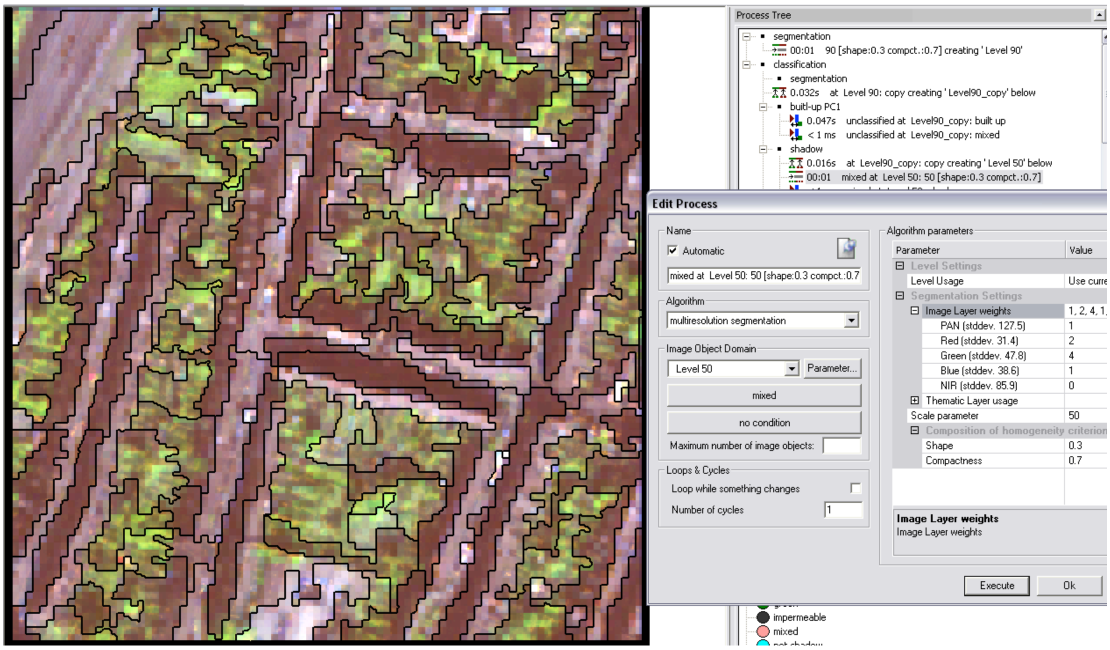
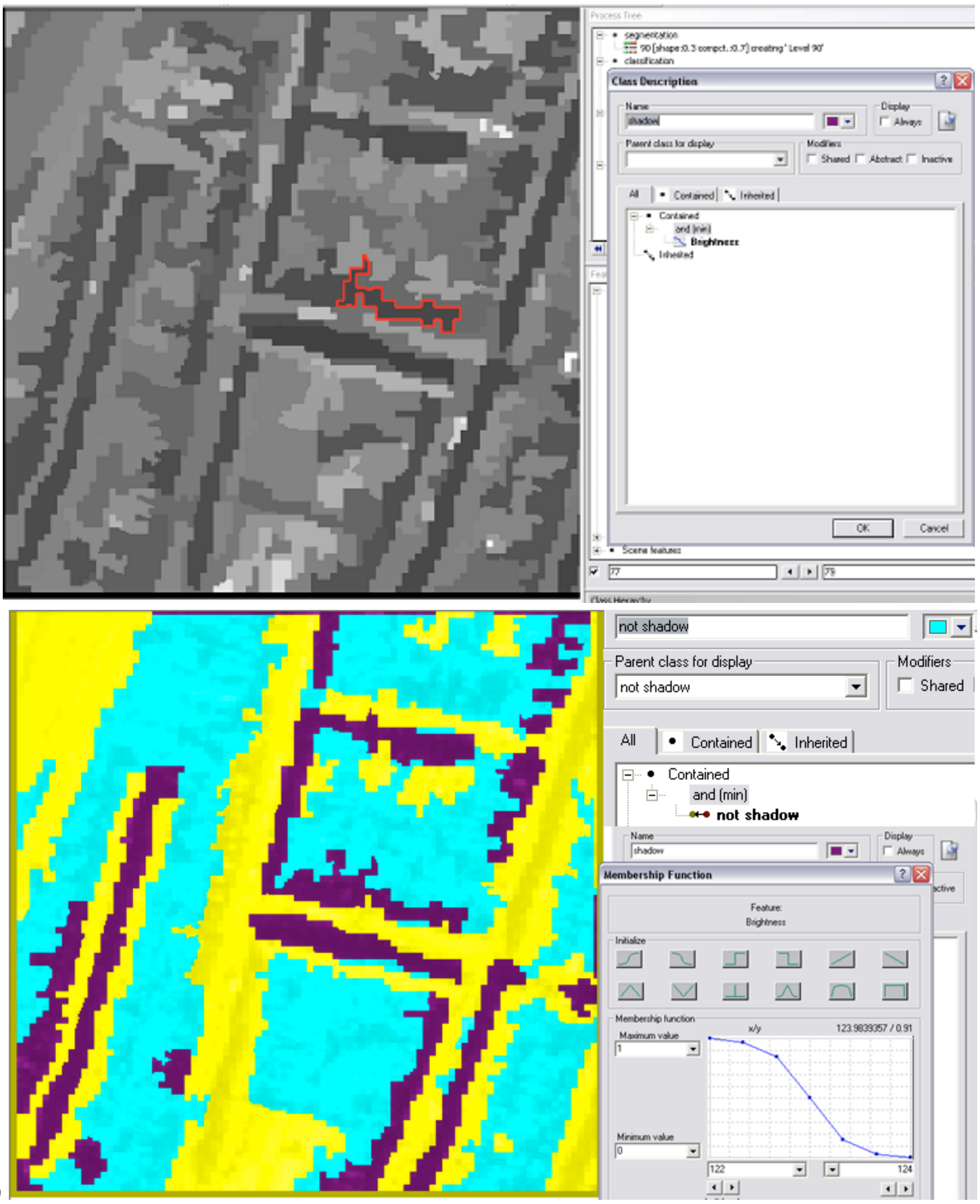


Figure 8-5 Re-segmentation of the mixed areas only at scale 50 in order to extract the areas in shadow



i)
ii)

Figure 8-6 i) The use of the 'feature view' tool and the grey colour indicated that the specific range values of brightness does not extract any image objects and ii) classification results of the shadowed (purple) – not shadowed areas (tirquaz)

At the same segmentation level of scale 50, the "non-shadow" class was further classified into the "sealed" and "green" classes. The "sealed" class consisted of all the small built-up objects that were not classified at the initial coarse segmentation level. The object feature used in order to classify the sealed objects was the mean value of the maximum difference (Max. diff). A similarly process as described for the previous classed followed, in order to identify a new 'Max. diff' range value. The "sealed" class was finally classified using a range between (0.9, 1) while the green class by using the masking out technique (Figure 8.7).

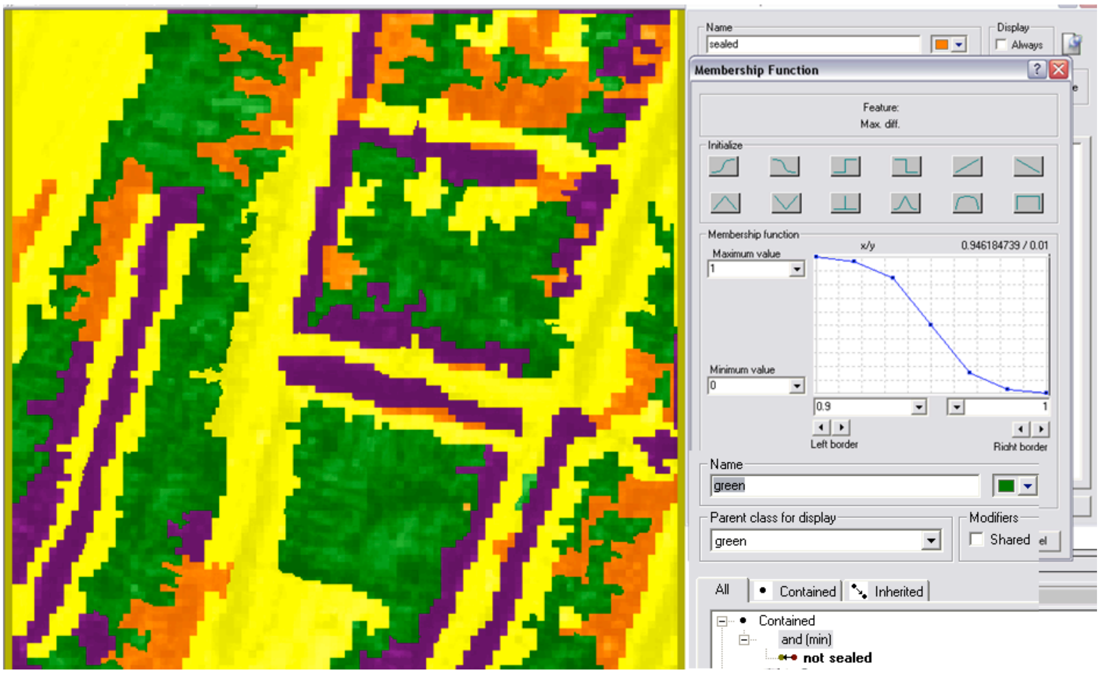


Figure 8-7 Classification results of the non-shadowed areas into green and the rest sealed areas

According to the RGB model, the next step was to re-classify the "green" class into "vegetated surfaces" and "trees" classes by discriminating the trees with the use of the mean value of the red band. However, the 'feature view' tool showed that there is no range of the mean value of the red band that could separate trees from the rest of the vegetated surfaces (Figure 8-8). For this reason the "green" class was neither re-segmented nor re-classified further. The "built up" and "sealed" classes were united into one "impermeable" class. At the same level, the shadow class was reclassified as sealed or green surfaces using rules based on the spatial relationship of the neighbour objects such as the "border to" feature. The results are shown in Figure 8-9.

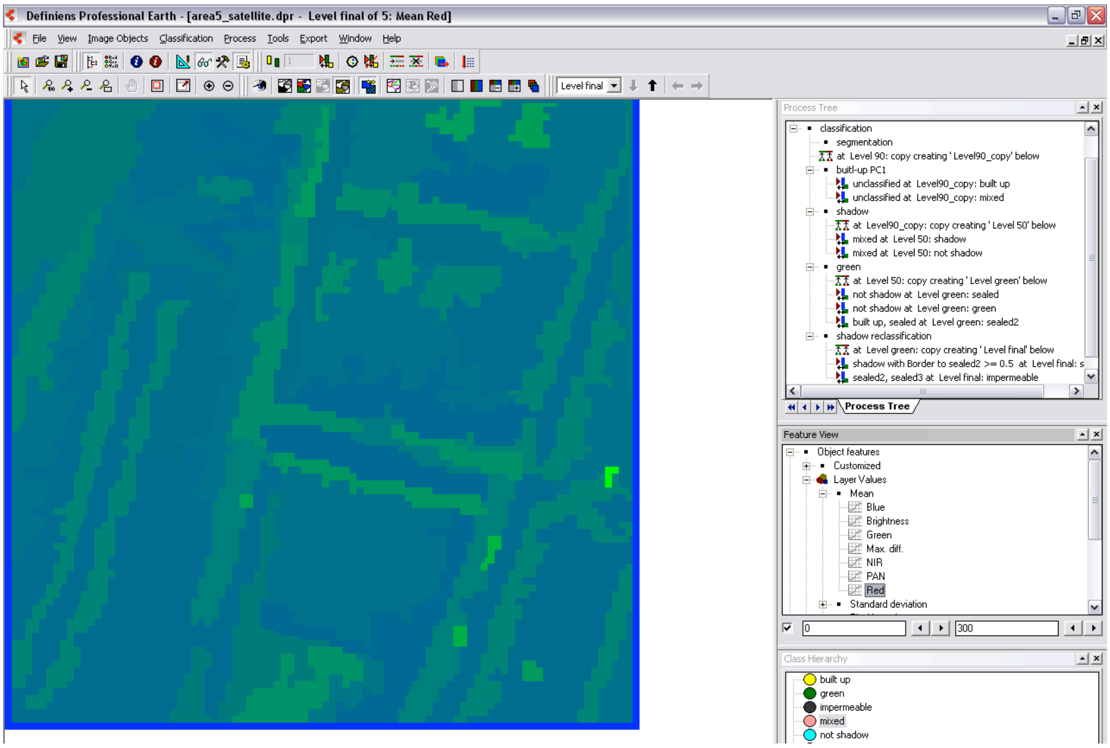


Figure 8-8 The use of the "feature view" tool identified that no range of the mean value of red can give a discrimination of trees from rest of vegetation. Both features have low values in the red band (blue colour)

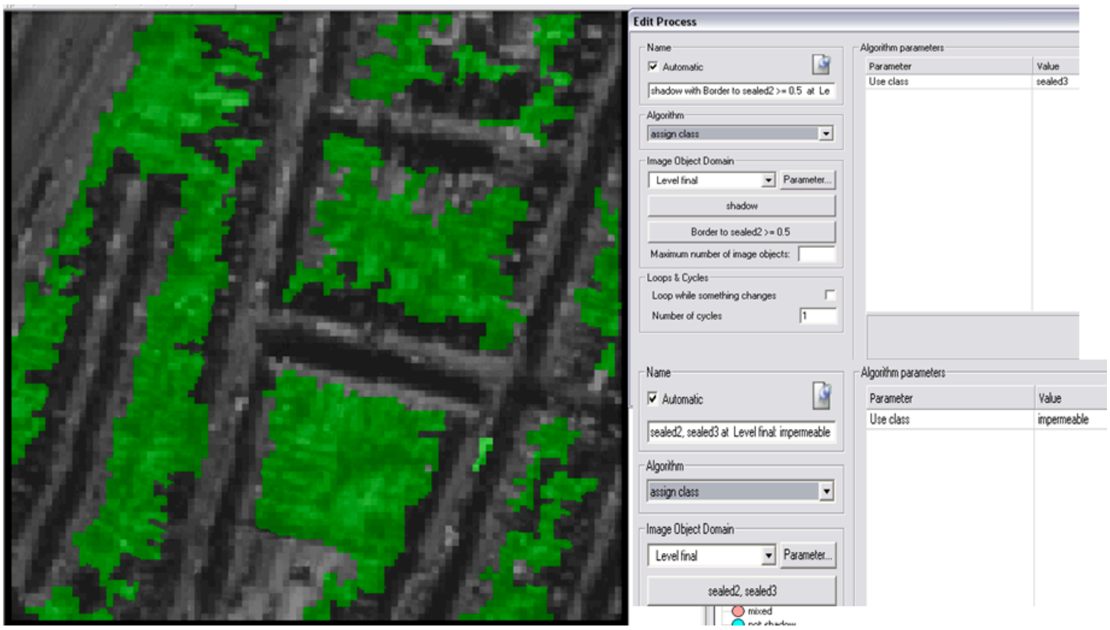
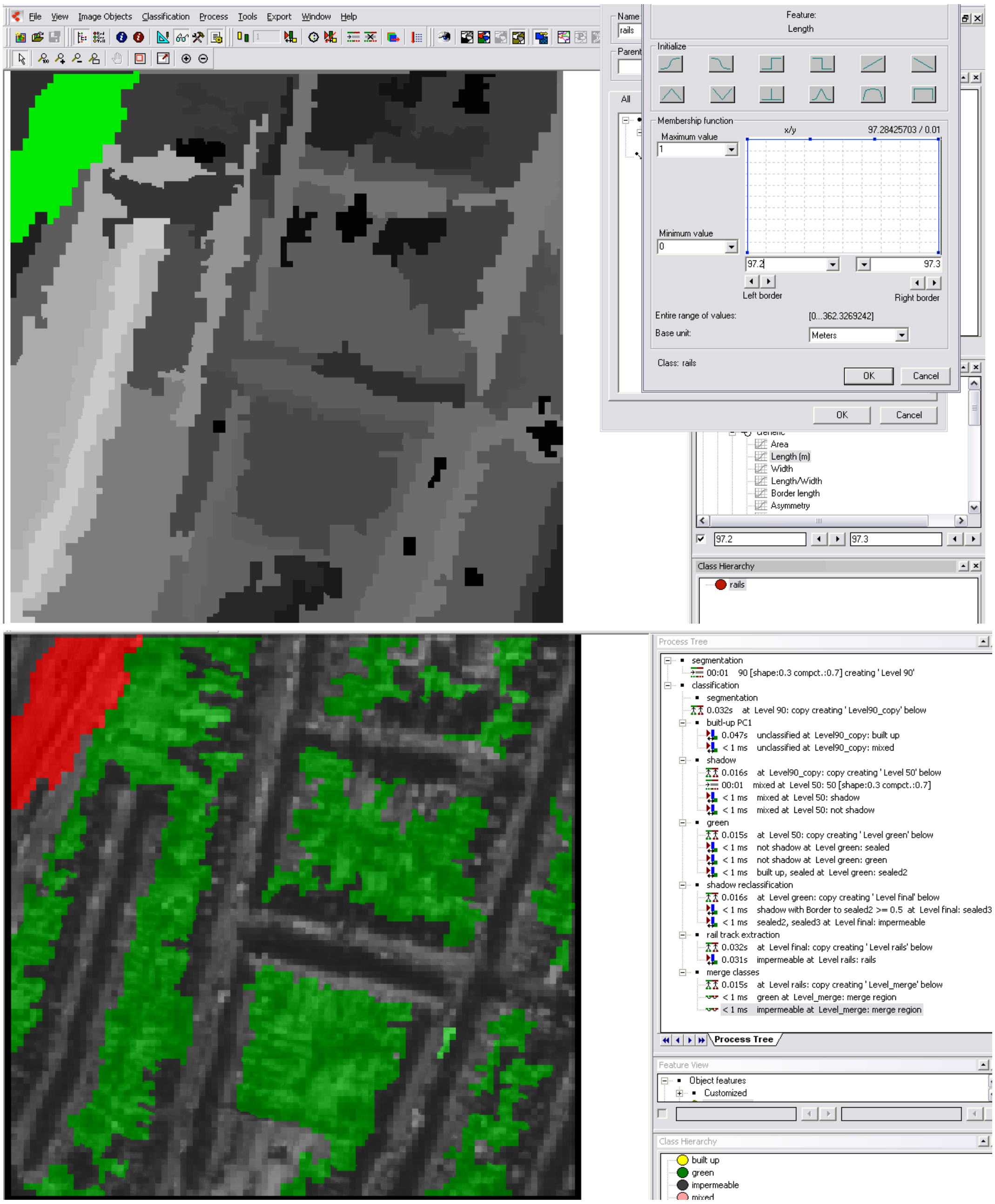


Figure 8-9 Classification results after the reclassification of the shadow class and the group of all the sealed classed together by renaming them "impermeable",

Looking at the classification result it is obvious that the rail tracks had not been classified. The “rail tracks” class could not be identified by solely using spectral information because of the spectral confusion of sealed soil and the misclassification with the “impermeable” class. However, the rails tracks were extracted using the “shape” information of the image object features and more specifically the “length” of the objects. The ‘feature view’ tool identified that the rail tracks objects had a length value between 97.2 and 97.3 (Figure 8-10i). All classes were brought together and the final classification results can be seen in Figures 8-10ii.

The same modified RGB classification model was applied to the other two test sites; the“area26” (low density residential area of 1960’s semi-detached houses with a large area of vegetated surfaces) and the “area20” (part of the commercial area in the city centre with large buildings and few vegetated surfaces). The classification results are shown in Figure 8-11.



i)

ii)

Figure 8-10 i) use of the ‘feature view’ tool in order to find the value range of length for extracting the rail tracks and ii) final classification result of the residential “area5”

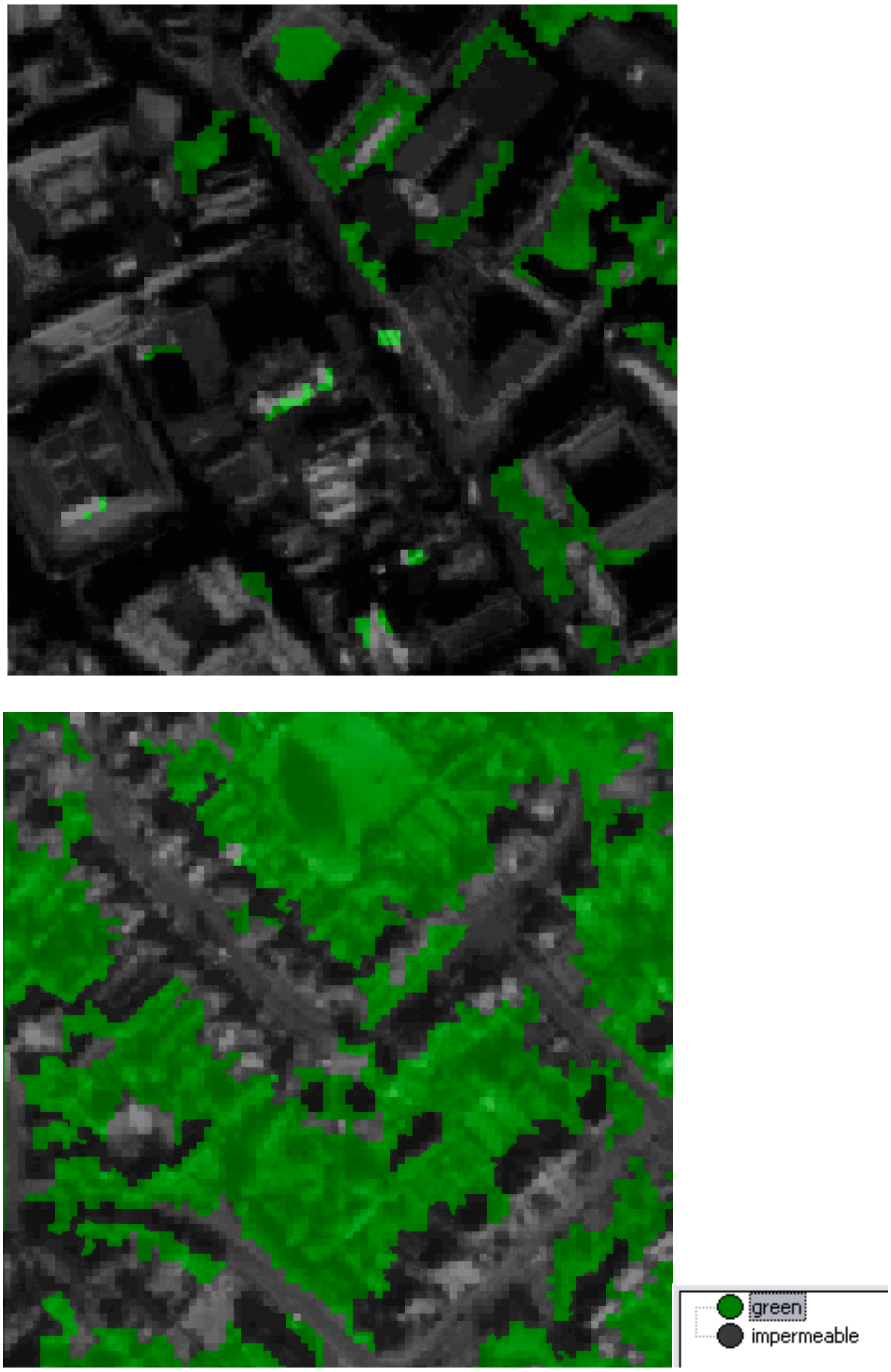


Figure 8-11. Final classification results of the VHR satellite data based on the application of the RGB classification model of “area20” and “area26” respectively

8.1.2 Results - discussion

The results of each automated object-based rule set classification, using VHR satellite data, were exported from eCognition to ArcGIS in vector format. To test the accuracy of the classification model, the results were compared with the traditional API. In order to avoid the sliver polygons production when comparing vectors, the data of both classification methods were converted into raster format with cell size of 0.7m (equal to the PAN resolution of the QuickBird imagery). By this way the resolution of the aerial data (0.125 m) was "degraded" in an equal resolution with the satellite data for a more reasonable comparison.

The overall accuracy of the automated satellite classification, based on the RGB model, was statistically evaluated with the error matrix production. The error matrices production between the two classification methods revealed an overall accuracy of (Table 8-1):

- 74% for the test area "area5"
- 88.6% for the test area "area20" and
- 73% for the test area "area 26"

The overall thematic accuracy of the classification results is relatively low apart form the "area 20". The much higher thematic accuracy of this area can be explained due to the simplicity of the test site. "area20" is a predominately sealed area with very little vegetation. Consequently, the comparison of the two classification methods, using a simply binary map of sealed and not sealed (equals green), was expected to show high accuracy for this test site. The sample area "area20" is not a representative example. In addition, the user and producer accuracies of the "area20" revealed that although a high agreement was achieved with the sealed class the identification of the green areas is very poor (Table 8.1).

The user and producer accuracies of the other two study areas identified a moderate agreement between the two classification methods, which is in agreement with the low thematic accuracy results. Furthermore, the Kappa coefficient, which is another way to measure of the overall agreement of an error matrix, was calculated (equation 3, chapter 6). The nearer the Kappa coefficient value is to unity the more similar the object-based model is to the traditional API. The Kappa coefficient of each test site showed very poor performance of the RGB object-based model (mean Kappa value of 0.47 for 'area5', 0.26 for 'area20' and 0.43 for 'area26').

Table 8.1 Error matrices of the automated object-based satellite classification when the RGB rule-set model was applied

Residential area "area5"						
API \ eCg_RGBmodel	sealed	green	rails	Sum Map 1	User accuracy	
sealed	59086	14994	20	74100	0.797	
green	15244	28313	205	43762	0.647	
rails	1515	35	4667	6217	0.244	
Sum Map 2	75845	43342	4892	124079		
Producer accuracy	0.779	0.653	0.954			
					0.742	
						74%

Commercial area "area20"					
API/eCg_RGBmodel	sealed	green	Sum Map 1	User accuracy	
sealed	108161	7401	115572	0.936	
green	6913	3603	10516	0.343	
Sum Map 2	115074	11004	126088		
Producer accuracy	0.940	0.327			
				0.886	
					88.6%

Residential area "area26"					
API \ eCg	sealed	green	Sum Map 1	User accuracy	
sealed	43428	16917	60345	0.720	
green	16511	46202	62713	0.737	
Sum Map 2	59939	63119	123058		
Producer accuracy	0.725	0.732			
				0.728	
					73%

8.1.3 Conclusions

The rule-based classification model, developed with the use of the aerial photography, was applied on the QuickBird satellite imagery in order to test its transferability and examine the thematic accuracy results that can be achieved when only the true colour band combination is used. The transferability of the model was indicated as it has been successfully applied on different data sets but more sample areas should be tested in the future to statistically validate it. However, the classification results did not give a satisfactory overall thematic accuracy (average of 73.5%). The low accuracies can be explained by the fact that the RGB model did not make any use of the NIR band available in the satellite data. The NIR band is useful to enhance sensitivity for detecting vegetation.

Generally in satellite data, vegetation is usually extracted by using the rule of thumb that vegetation highly absorbs the visible light while highly reflects the NIR energy. This is why the most common way to identify vegetation in satellite data is to compare the levels of reflection between the red band and NIR band. The comparison is usually implemented with the calculation of the NDVI that is the subtraction of the red visible light from the infrared light, divided by the total amount of the reflected light.

The next step of this PhD study was to develop a new rule-based classification model using the QuickBird satellite data and all the spectral information available as well as the NDVI as an extra layer.

8.2 New object-based classification model developed using VHR satellite data

The satellite data used for the development of the classification model was QuickBird images at 0.7 m PAN and 2.8 m MS spatial resolution. The multi-spectral imagery contains four spectral bands: the red, green and blue (RGB) bands of visible light and near-infrared (NIR) band.

8.2.1 Multiresolution Segmentation

The segmentation of the satellite data was again based on the “trial and error” method and visual inspection. Various segmentations with different parameters were tested until the result was satisfactory. As a statistical way for the best parameters selection, for implementing segmentation, has not yet identified, the only evaluation criterion is the human eye (Definiens, 2006; Gamanya et al., 2007).

Initial trials focused on choosing the appropriate satellite data (the mage layers in the eCognition language) to implement segmentation. There were three types of satellite data that could be used as image layers; the PAN and MS bands of the QuickBird imagery as well as the NDVI imagery derived from the MS image at a previous stage of the research. In order to take advantage of the highest possible resolution the PAN imagery was initially tested for image segmentation. However, visual inspections of the segmentation results did not identified any robust satisfactory result. In addition, it was quite difficult to visually discriminate all the features of interest at grey scale. Solely use of the NDVI imagery proved unsatisfactory due to the coarse resolution which resulted in pixelised boundaries of the image objects (Figures 8-12iii, 8-12iv). For these reasons, a combination of using both the PAN and the NDVI imagery was also tested. A trial and error procedure that followed identified that using both images in the initial segmentation produced better results than using either the PAN or the NDVI themselves. Some examples were given at Figure 8-12: At the upper segmentation level (scale parameter value of 90) the rail tracks were clearly extracted as one object when both image layers were used (Figure 8-12iv). Similarly, at a lower segmentation level (scale=50), the polygons in shadow were more smoothly extracted by using a combination of both layers (Figure 8-12vi). After a visual inspection of the whole study area it was concluded that using both PAN and NDVI image layers is more appropriate due to the benefit of combining high resolution (PAN band) and spectral information for extracting vegetation (NDVI).

It must be made clear that the image data fusion did not occur. By referring to a “combination of the PAN and NDVI imagery” means putting equal weights in both image layers, during the segmentation process. The theory about weighting image layers in the eCognition software has been presented in chapter 5.

The values of each segmentation parameter (scale, shape and compactness) were determined using the systematic “trial and error” approach. More than two segmentation levels were employed using an iterative process between segmentations and classifications resulting in the development of a hierarchical, multilevel classification model. The iterative process is comprehensively analysed in the following section which describes the rule-based classification.

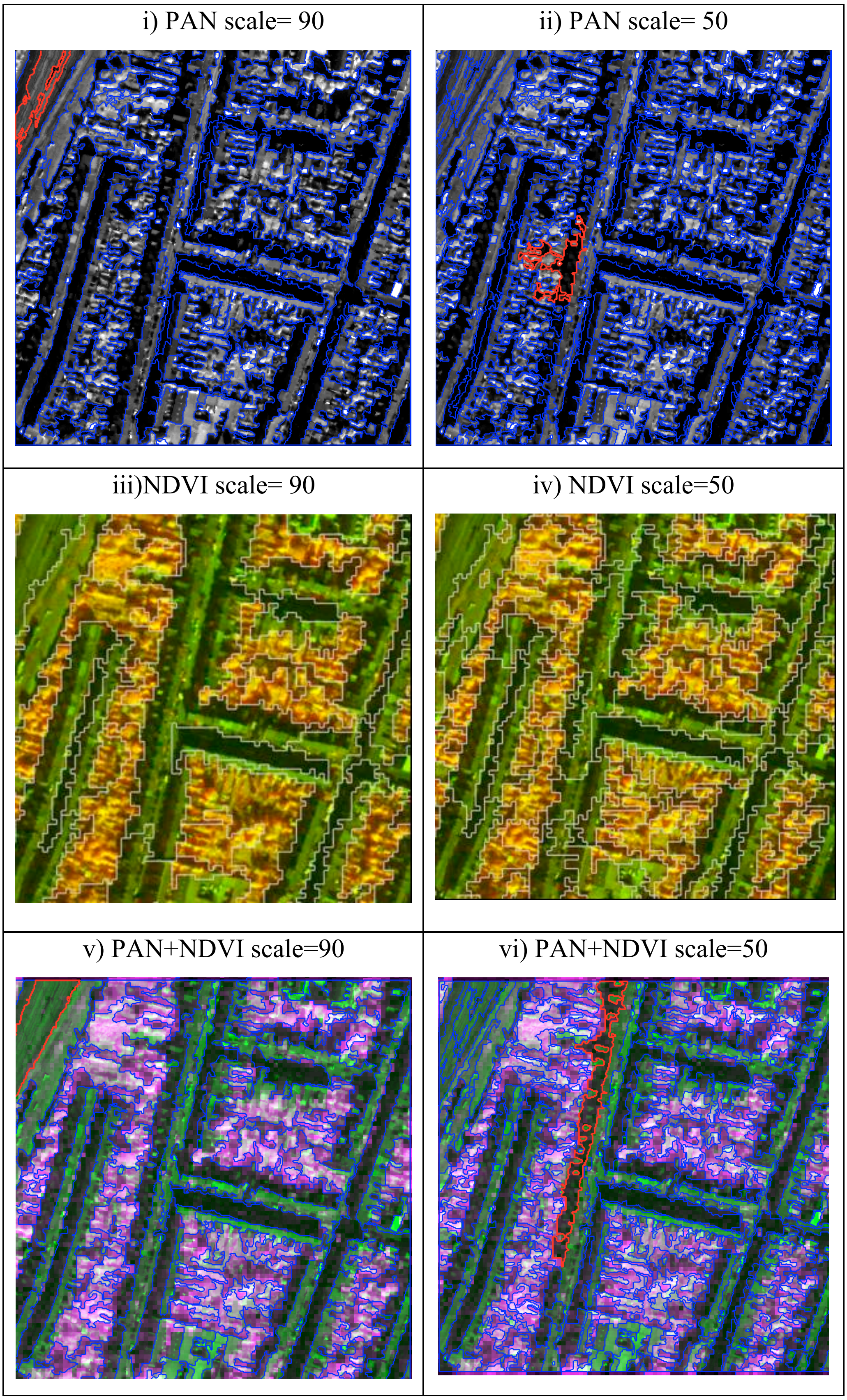


Figure 8-12 Comparisons of segmentation results using solely either the PAN or the NDVI images or a combination of those

8.2.2 Fuzzy rule classification

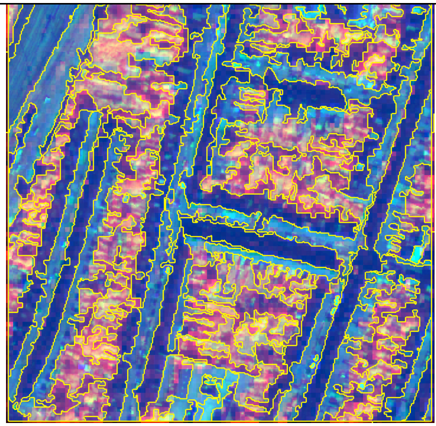
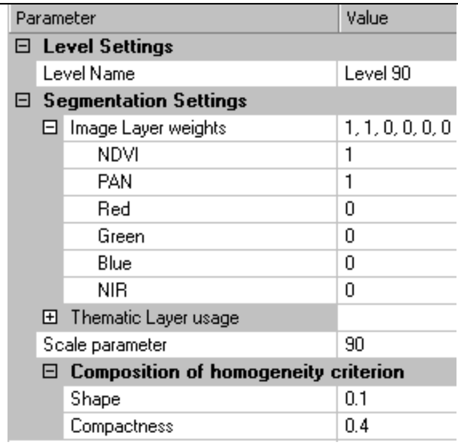
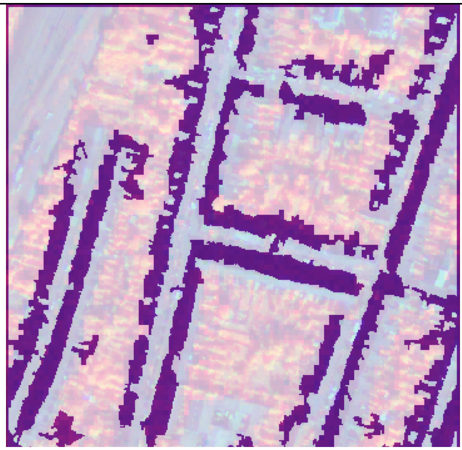
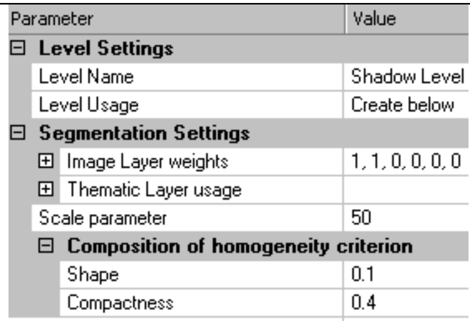
The development of the classification model was based on fuzzy rules and expert knowledge. The object-based model that was based on the development of a whole rule-set of processes (Figure 8-13) can be described, in simplicity, as follows:

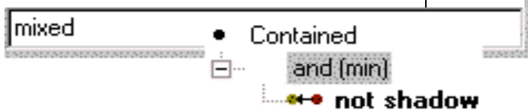
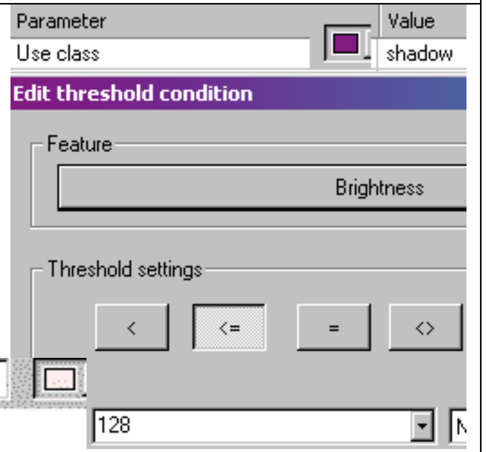
- After testing several scale values, the image was initially segmented with the scale parameter value of 90, in which the rail track polygon was extracted. A trial and error procedure identified that the shape and compactness values of 0.1 and 0.4, respectively, gave satisfactory results. These shape and compactness values were also recommended during the personal training course given by the Definiens company, in 2005. However, as previously aforementioned, more than one solution can exist as there are no optimal parameters for image segmentation (Benz et al., 2004; Feitosa et al., 2006; Platt and Rapoza, 2008). The technical specifications of the initial segmentation are given in Table 8.2, level 1
- The image was re-segmented into a smaller scale in order to attempt to extract the polygons in shadow. The "shadow" class was identified using the mean value of brightness while the rest of the mixed areas were classified as "non shadow" using the masking out technique, i.e. class B is not class A (Table 8.2, level 2)
- Using a copy of the same segmentation level, the "non-shadow" class was further classified into the "sealed" and "vegetation" classes. The "sealed" class was identified using the mean value of the NDVI while the rest of the image was classified as "vegetation" using the masking out technique (Table 8.2, level 3)
- The "vegetation" class was further re-segmented into a lower scale in an attempt to separate the trees from the remaining vegetation. During this segmentation, only the panchromatic imagery was used in order to get the advantages of the highest possible resolution (the PAN band covers the same part of the spectrum but only at one fourth of the pixel size, in comparison with the MS band). The "trees" class was separated from vegetation by using a specific range of the mean value of the NIR band (Table 8.2, level 4)

- The level was copied in order to bring together all the classes that were individually classified in previous hierarchical levels. At that stage, the image was classified into the following classes: sealed surfaces, vegetation, trees and shadow. The shadow class was reclassified into shadow sealed, shadow grass and shadow trees using various rules based on the relationship of neighbour objects (Table 8.2, level 5). The "Border to" rule was mainly used which indicates the exact number of pixels that the object shares with the neighbour object (Definiens, 2006)
- Another copy of the same segmentation level was used in order to classify the rail tracks which were initially extracted at scale= 90. In order to implement that step, the "Existence of super objects" feature was used. The rails tracks were identified by using the "shape" information of the image object features and more specifically the "length" of the objects. The technical specifications of the rail tracks classification are given in Table 8.2, level 6
- The final classification results of each sample area are first represented with the attempt to discriminate trees form the remaining vegetation (Figures 8-14i, 8-15i, 8-16i, and 8-17i). However, a visual examination of the results identified misclassifications between the two classes; the main ones are highlighted on the figures in red circles
- Due to the fact that the extraction of trees was not successful (similarly to the previous object-based classification model when aerial data was used), the classification results were reproduced in the binary form of sealed vs. green - and rail tracks where applicable (Figures 8-14ii, 8-15ii, 8-16ii, and 8-17ii)

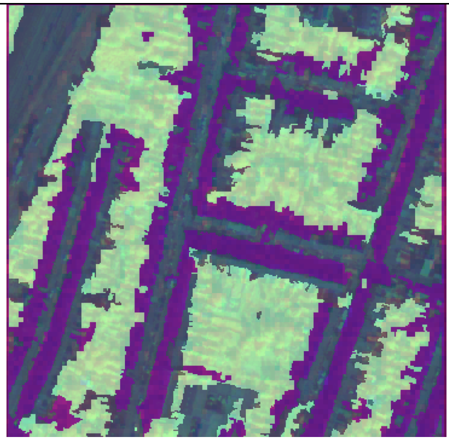
Figure 8-13 The complete rule-set, using processes in eCognition, for the development of the object-based model

Table 8-2 The main steps and parameters used for the development of the object-based model using fuzzy rules

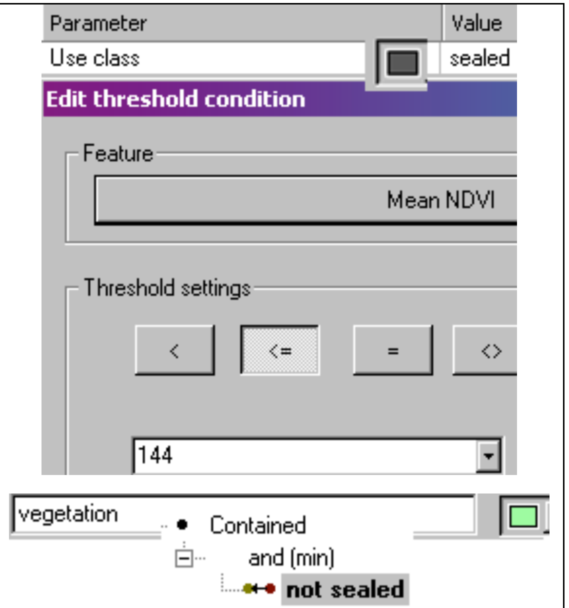
<table>
<tr><th>Working level</th><th>Extracted classes</th><th>Segmentation parameters</th><th>Critical features of the fuzzy-rule classification</th></tr>
<tr>
<td>Level 1: Upper segmentation level. Rail tracks extraction</td>
<td></td>
<td>
</td>
<td>N/A</td>
</tr>
<tr>
<td>Level 2: Shadow vs. mixed areas</td>
<td></td>
<td>


</td>
<td>
</td>
</tr>
</table>

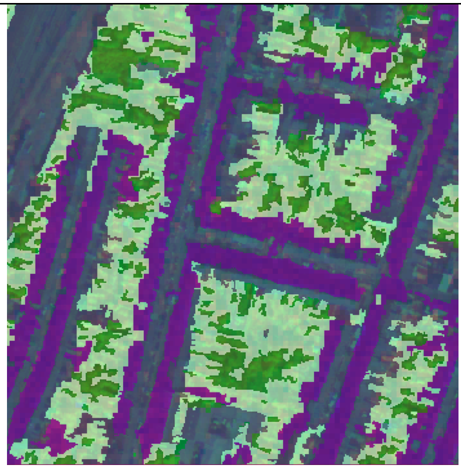
Level 3: Sealed vs. vegetation



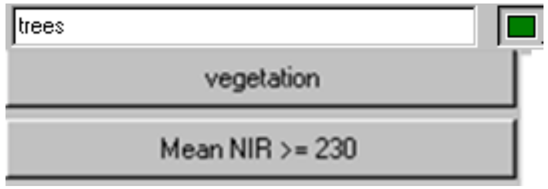
Parameter	Value
Level Settings	
Level Name	Level sealed
Level Usage	Create below
Segmentation Settings	
Image Layer weights	1, 1, 0, 0, 0, 0
NDVI	1
PAN	1
Red	0
Green	0
Blue	0
NIR	0
Thematic Layer usage	
Scale parameter	50
Composition of homogeneity criterion	
Shape	0.1
Compactness	0.4

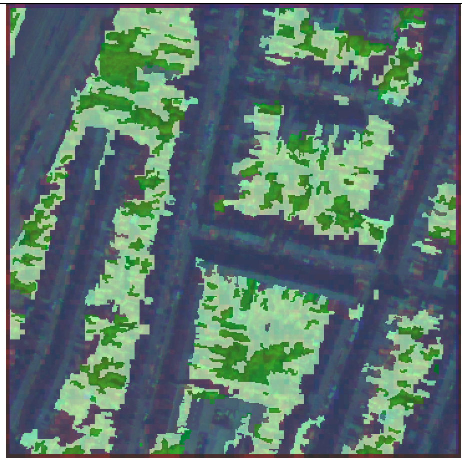
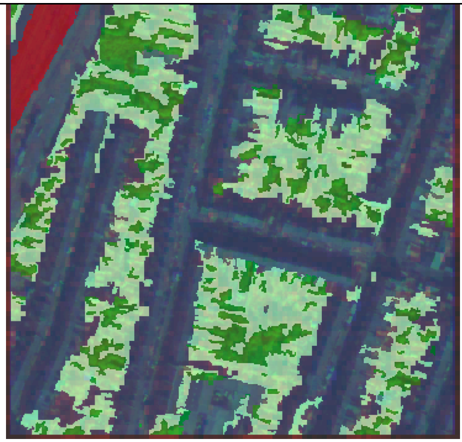


Level 4: Trees extraction



Parameter	Value
Level Settings	
Level Name	Trees Level
Level Usage	Create below
Segmentation Settings	
Image Layer weights	0, 1, 0, 0, 0, 0
NDVI	0
PAN	1
Red	0
Green	0
Blue	0
NIR	0
Thematic Layer usage	
Scale parameter	30
Composition of homogeneity criterion	
Shape	0.1
Compactness	0.4



Level 5: Shadow reclassification		shadow sealed Border to sealed >= 2.5 Border to shadow sealed 1 >= 2.5 shadow grass Border to vegetation >= 2 shadow trees **Rel. border to trees = 1** shadow sealed 1, shadow sealed 2 at All classes level: shadow sealed sealed, shadow sealed at All classes level: sealed shadow grass, vegetation at All classes level: vegetation shadow trees , trees at All classes level: trees	
Level 6: Rail track classification		Parameter — Value **Level Settings** Level Name — Rails Level **Segmentation Settings** Image Layer weights — 1, 1, 0, 0, 0, 0 Thematic Layer usage Scale parameter — 90 **Composition of homogeneity criterion** Shape — 0.1 Compactness — 0.4 sealed with Existence of super objects rail tracks (6) = 1 at rails track level: rail tracks	rail tracks and (min) and (*) **Length/Width <= 3.5** **Length/Width >= 3.3**

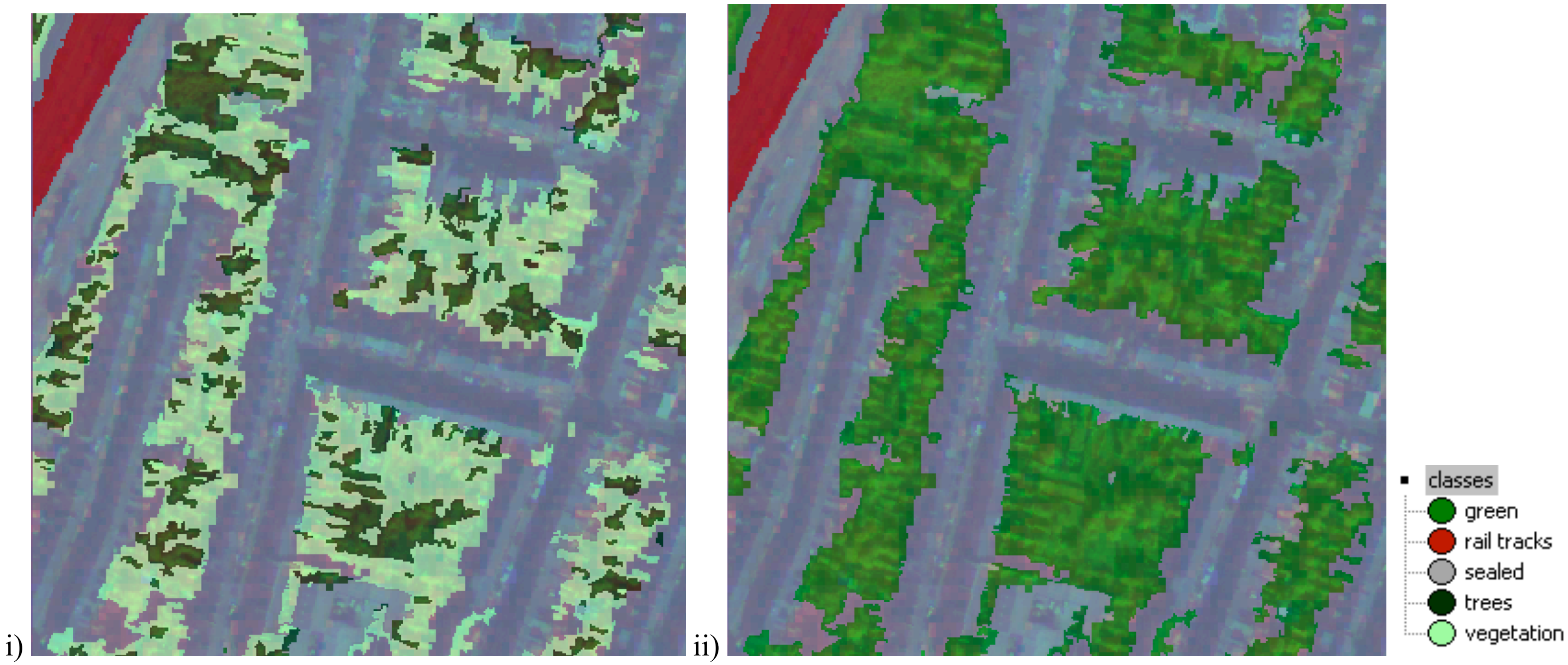


Figure 8-14 Final rule-based classification of the residential area (“area5”) i) with or ii) without extracting the trees

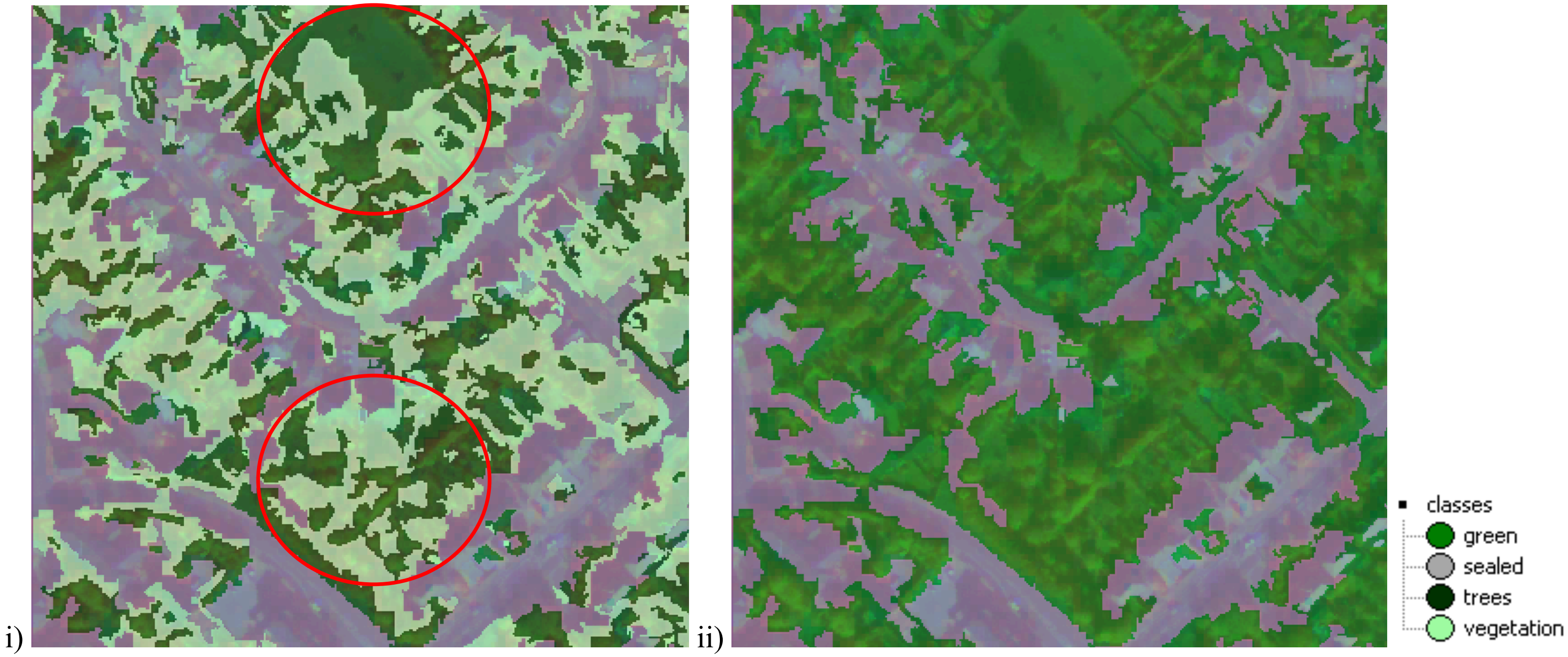


Figure 8-15 Final rule-based classification of the other type of residential area (“area26”) i) with or ii) without extracting the trees

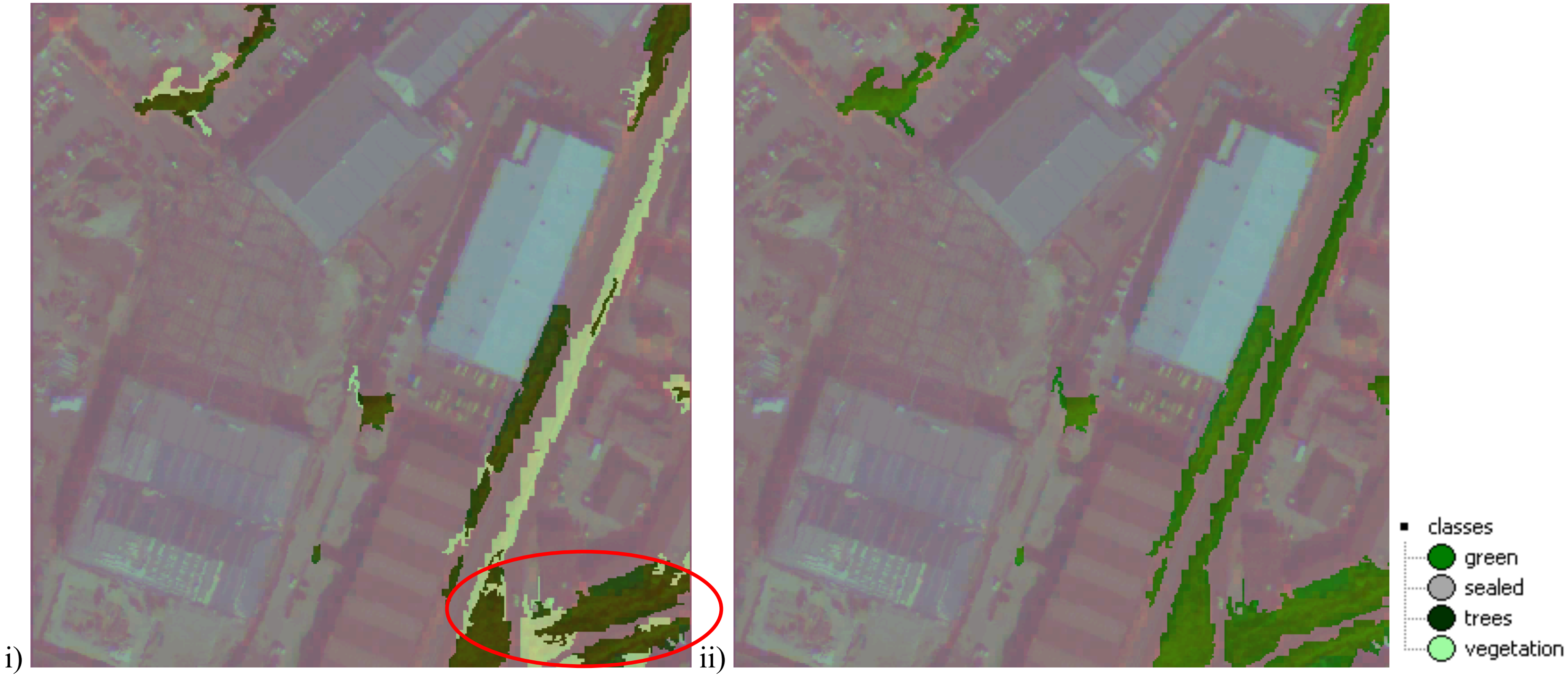


Figure 8-16 Final rule-based classification of the industrial area (“area0”) i) with or ii) without extracting the trees

i) ii)

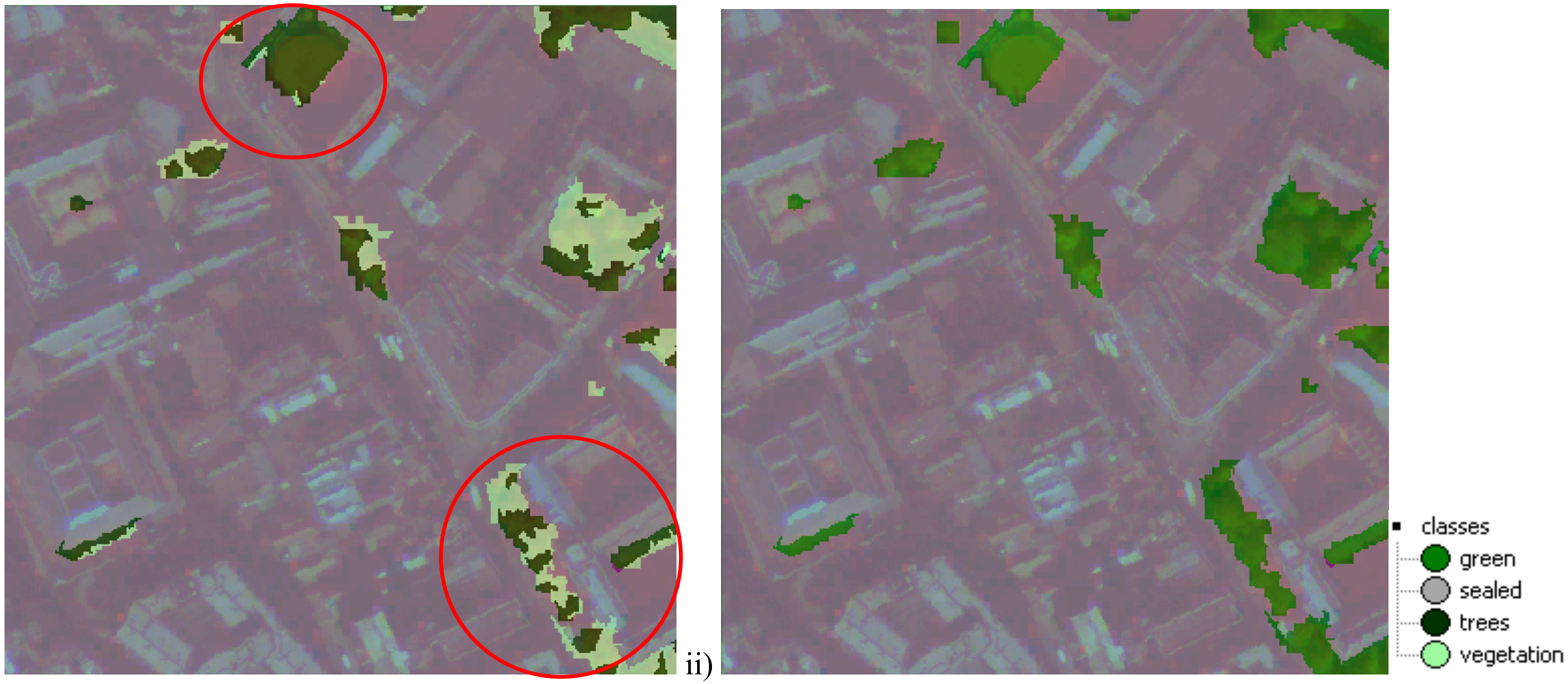


Figure 8-17 Final rule-based classification of the commercial area ("area20") with or without extracting the trees

8.2.3 Results - discussion

The results of each automated object-based rule set classification, using VHR satellite data, were exported from eCognition to ArcGIS in vector format. To test the accuracy of the classification model, the results were compared with the traditional API. In order to avoid the sliver polygons production when comparing vectors, the data of both classification methods were converted into raster format with cell size of 0.7m (equal to the PAN resolution of the Quickbird data). By this way the resolution of the aerial data (0.125 m) was “degraded” in an equal resolution with the satellite data for a more reasonable comparison.

The overall thematic accuracy of each classification result was statistically evaluated with the use of error matrices. Due to the bad results of extracting trees (Figures 8-15, 8-16, 8-17), the statistical analysis was done using the binary maps of sealed vs. green (and rail tracks where applicable). The statistical analysis of the industrial area, “area 0”, between the satellite and aerial data was not implemented as the site was under construction at the time that the satellite imagery was taken. (Figure 8-18).

Figure 8-18 The industrial sample area as taken from the aerial and satellite image data

The statistical analysis of the remaining three study areas revealed an average overall accuracy of 80% (Table 8.3). In addition, the producer accuracies of each test site identified very high performance of the rule-based model in classifying sealed areas. The overall producer accuracy in extracting vegetation was not high even though the NIR band and the calculation of the NDVI to extract vegetation were used; the average mean value was 0.64. The low value can be attributed to the date of the satellite imagery which was taken in October 2003. At this time of the year the vegetation is not as green as it is in July (aerial photography taken) resulting a relative low reflectance in the NIR band.

Table 8.3 Error matrices between the traditional API and the automated object-based satellite classification for each sample area

Residential area "area5"						
API/eCg_satellite	sealed	green	rails	Sum Map 1	User accuracy	
sealed	59114	14986	0	74100	0,798	
green	10755	33007	0	43762	0,754	
rails	3362	21	2834	6217	0,456	
Sum Map 2	73231	48014	2834	124079		
Producer accuracy	0,807	0,687	1,000			0,765
						76,5%

Residential area- "area26"					
API/eCg_satellite	sealed	green	Sum Map 1	User accuracy	
sealed	37184	23161	60345	0,616	
green	10137	52576	62713	0,838	
Sum Map 2	47321	75737	123058		
Producer accuracy	0,786	0,694			0,729
					73%

Commercial area - "area20"					
API/eCgsatellite	sealed	green	Sum Map 1	User accuracy	
sealed	110083	5479	115562	0,953	
green	5887	4629	10516	0,440	
Sum Map 2	115970	10108	126078		
Producer accuracy	0,949	0,542			0,910
					91%

Furthermore, examining the error matrix of the residential area, “area 5” (Table 8.3) a 100% producer accuracy for the “rail tracks” class was achieved while the user accuracy was much lower. The reason is that the area that was identified as rail tracks in the automated method, although it was smaller than it should be, was 100% correctly classified because it totally fitted within the rail tracks area that was digitised and classified via API (Figure 8-19). However, the automated classification failed to pick up the remaining area that was labelled as rail tracks in API. In addition, in the aerial photography a patch of vegetated area along the rail tracks is clearly recognised (Figure 8-19i). This vegetated surface has not been identified in the satellite imagery and during segmentation of the NDVI imagery resulting the misclassification of the area as sealed (Figure 8-19ii). This again can be explained due to the time of the season that the satellite imagery was taken; in October this vegetated area shall be yellowish with very low reflectance of green.

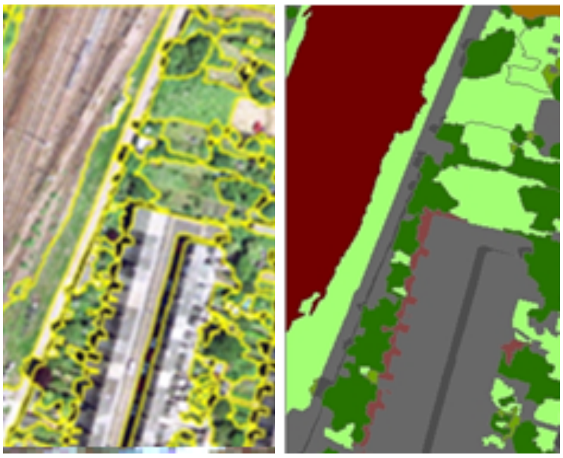
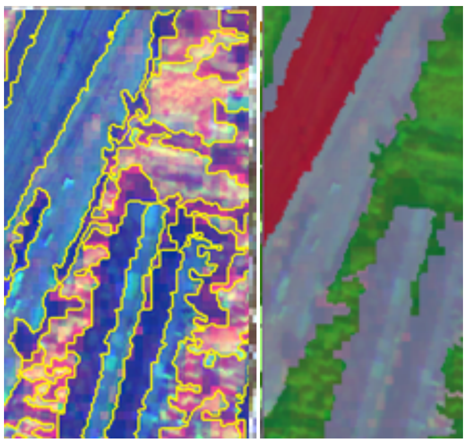
i)  ii) 

Figure 8-19 Differences in delineation and classification of the same land cover features, such as rail tracks, by i) manual API and ii) object-based automated classification

8.3 Multiple comparisons: accuracy assessment and discussion

This paragraph analyses the comparison between the three classification models developed with different rules and data sets (in chapters 6 and 8) as well as the object-based classification method against the pixel-based classification method when satellite data were used.

8.3.1 Comparison of the two object-based models applied on the sattelite imagery

The object-based classification model, developed in chapter 6 with the use of aerial photography (entitled as the RGB model), was applied on the QuickBird satellite imagery. During application, all rules and parameter values (such as scale, layer's weights, object features etc) remain identical but the thresholds of each object feature value had to be changed in order to achieve acceptable classification results. The classification results provided a relative low mean thematic accuracy of 79.2% between the three sample areas.

Another rule-based model was developed using the additional spectral information of the satellite data i.e. the NIR band and the NDVI layer. The performance of this object-based model was slightly better than the RGB model achieving an average thematic accuracy of 80%.

Looking at the overall accuracies of both methods and for each sample area (Table 8.4), it is indicated that the object-based classification model performed better when the NIR and the NDVI information were used. To further test whether the two independent object-based models are statistically significant different, the Z value was calculated. The Z test revealed that it was not possible to statistically evaluate the difference between the two models due to the limited amount of data (only three study areas).

Table 8.4 Summary of the overall accuracies and their significance when two different object-based classification models were applied on the satellite imagery

Classification methods		Overall accuracy		K_1	K_2	Z statistics	Significance
Residential area "area5"							
API	RGB model (Satellite data)	74.0%		0.54		4.9	Yes
API	object-based (Satellite data)		77%		0.49		
Residential area "area26"							
API	RGB model (Satellite data)	73%		0.46		0.0	No
API	object-based (Satellite data)		73%		0.46		
Commercial area "area20"							
API	RGB model (Satellite data)	88.6%		0.27		0.19	No
API	object-based (Satellite data)		91%		0.40		

Both models did not achieve high classification accuracies apart from the “area 20” which is a predominately sealed area. The two object-based models were examined further in order to identify the differences and similarities between the rule-sets applied on each model (Table 8.5).

Table 8.5 Similarities and differences between the two object-based models applied on the VHR satellite data

RGB model	Satellite model
Rule-set	Rule-set
Segmentation	**Segmentation**
layers= PAN and MS	layers= PAN and NDVI
scale= 90	scale= 50
shape= 0.3	shape= 0.1
compactness= 0.7	compactness= 0.4
Classification	**Classification**
built-up vs. mixed areas: Use of PC1	built-up vs. mixed areas: N/A
shadow vs. not shadow: use of brightness	shadow vs. not shadow: use of brightness
sealed vs. green: use of 'max. diff'	sealed vs. green: use of NDVI

In both models a completely different rule set was developed based on the use of different parameters and object features. This research study recommends, as future work, the combination of the two models in order to investigate whether more accurate classification results could be achieved. For example, as also indicated in Figure 8-12, the use of the NDVI layer during the object extraction improved the segmentation results. In addition, the shape and compactness values used during the satellite model seem to be more suitable as these parameters were chosen based on the visual assessment of the satellite data. The same parameters of the RGB model were based on the visual assessment of the aerial photography. The PC_1 arithmetic feature proved competent to extract built-up surfaces but it was not used on the satellite model as a different class hierarchy was applied. The combination of NDVI and the "Max.diif" object features might improve the extraction of the sealed areas and vegetation at the lower classification level. Consequently, a new model developed by a combination of different the parameters and object features used could be better than the use of each model individually.

8.3.2 Comparison of the object-based models developed using different data sets

The object based classification model, using satellite data, was tested against the classification model that used the aerial photography. The aim was to evaluate which data type is more suitable for identifying soil-sealed and vegetated surfaces at very large mapping scales. Both classification results were statistically assessed using the manual API as reference data.

Looking at the overall accuracies of both methods (Table 8.6), it was clear that the object-based classification model performed better when the aerial photography was used. To test whether the two independent object-based models are statistically significant different, the Z value was calculated. The Z test revealed that the difference between the two classification methods is significant for all test sites (Table 8.6). In addition, the Kappa coefficient showed that the performance of the object-based model using aerial data is much higher (mean Kappa value of 0.47 with the satellite data but 0.77 with the aerial data). According to Congalton and Green (1999), the Kappa coefficient is another way to measure of the overall agreement of an error matrix. The nearer the Kappa coefficient value is to unity the more similar the object-based model is to the traditional API.

Table 8.6 Summary of the overall accuracies and their significance when the two classification methods were compared

Classification methods		Overall accuracy		K_1	K_2	Z statistics	Significance
Residential area "area5"							
API	Rule-based (Satellite data)	76,5%		0,54		45,75	Yes
API	Rule-based (aerial data)		81%		0,84		
Residential area "area26"							
API	Rule-based (Satellite data)	73%		0,46		37,5	Yes
API	Rule-based (aerial data)		86%		0,73		
Commercial area "area20"							
API	Rule-based (Satellite data)	91,0%		0,4		3,5	Yes
API	Rule-based (aerial data)		96%		0,73		

The statistical analysis between the two object-based models using either aerial or satellite data identified that the performance is better when the aerial data was used. The availability of the NIR band and the capability of extracting vegetation with the use of the NDVI, using the satellite data, didn't improve the classification accuracy. Much higher classification accuracies were achieved with the aerial photography (mean overall accuracy 87% vs. 80% with the satellite data). The difference in the overall accuracy between the two classification models can be attributed to the much higher resolution of the aerial data (0.125 m) which seems to be more appropriate for identifying urban land cover features at very large scales i.e. back garden level scale. However, the results of these two models would have been more comparable if the acquisition dates between the satellite and aerial imagery were at the least during the same seasonal period. The statistical analysis was based on the reference API data. The comparison between the object-based classification model using aerial data and the API is done with the use of the same aerial photography. As a result there are no classification differences due to data differentiations. On the contrary, the classification model based on the satellite imagery, compared with the API result, leads to differences in the classification results due to the dissimilarity of the data such as the date that were taken.

8.3.3 Comparison of object-based and pixel-based methods using satellite data

The object-based classification model, using satellite data, was further tested against the pixel-based classification in order to evaluate which method is more suitable for mapping soil sealed and vegetated surfaces at “garden level” mapping scale. Both classification results were again statistically evaluated using the manual API as reference data.

The comparison of the different classification methods showed that the object-based approach has a higher overall accuracy in study areas “area5” and “area20” while the pixel based approach has a higher accuracy in “area26” (Table 8.7). In “area26” it seems to be an overestimation of green areas (Figure 8-15ii) highlighting the potential that the object-based model might need modifications when it is transferred to other study areas. As a reminder, the values of each parameter, used for developing the classification rules, were not modified during the application of the model in the different study areas. However, the results of this research highlight that the rules can remain the same but the values should change according to the local conditions. In addition, the Z test revealed that the results of the two classification methods are not always significantly different such as in of the commercial study area “area 20”. Examining the results, in table 8-5, for the “area20”, both methods have very similar overall accuracies as well as Kappa coefficient values. So, it is not surprising that the Z value has indicated that the two methods produced similar results.

Table 8.7 Summary of the overall accuracies and their significance when the three classification methods were compared

Classification methods		Overall accuracy		K_1	K_2	Z statistics	Significance
Residential area "area5"							
API	object-based (Satellite data)	76,5%		0,54		8,5	Yes
API	pixel-based (Satellite data)		73%		0,46		
Residential area "area26"							
API	object-based (Satellite data)	73%		0,46		4,9	Yes
API	pixel-based (Satellite data)		75%		0,5		
Commercial area "area20"							
API	object-based (Satellite data)	91,0%		0,4		0,19	No
API	pixel-based (Satellite data)		90%		0,42		

A solid conclusion of whether the object-based approach is better than the pixel-based approach, when satellite data were used, could not be drawn. More sample areas must be tested in order to have a valid statistical evaluation. This was not feasible at this stage of this research due to the lack of reference data. The manual API classification was only produced for the four sample areas. However, due to the numerous advantages of the OBIA in comparison with pixel approaches, identified in the literature review, it is suggested that the object-based classification seems to be a more appropriate method for mapping urban land cover using VHR data. The main advantages that have been identified can be summarised below:

- Pixel-based classification methods cannot function successfully with VHR data while object-based methods seems to overcome these difficulties (Caprioli and Tarantino, 2003; Blaschke et al., 2005; Yan and Bauer, 2006; Im et al., 2007; Chen et al., 2009)
- OBIA takes into account spectral, context and spatial information which have proved necessary for identifying urban land cover features (Burnett and

Blaschke 2003; Benz et al., 2004; Im et al., 2007). Typical pixel-based approaches use only the spectral information

- In OBIA the user can perform hierarchical classification at multi-levels (Benz et al., 2004; Blaschke, 2004; Jacquin et al., 2008). The hierarchical classification of the urban land cover has also proved an advance due to the existence of the urban features in different scales (i.e. the scale for classifying a single tress is much larger than identifying the top of a building). The advantages of the multiscale hierarchical classification have also been identified by Lucas et al., (2007)
- OBIA is closer to the human perception in visual image interpretation. (Blaschke et al., 2005) as both methods employ a multiscale representation of the land cover features and they use shape, context and neighbourhood relationships for the classification of the objects of interest. The big difference between API and OBIA is that the human performs these techniques simultaneously and sometimes subconsciously while a whole set of rules and processes with iterations between segmentation - classification must be built up in the object-based models
- The object-based rule set classification is a transferable method (Bock et al., 2005; Walker and Blaschke, 2008)
- An advanced benefit of the object-based classification, using the eCognition software, is the ability to integrate additional earth observation and/or ancillary data for more complex classification concepts. For example, the use of multi-temporal images could have been very useful for urban land cover classification due to the distinctive seasonal characteristics of vegetation
- Very recent comparative studies between pixel-based and object-based methods for land cover and land use mapping illustrated better performance of the object-based classification methods (Cleve et al., 2008; Platt and Rapoza, 2008; Fung et al., 2008; Chen M. et al., 2009)
- OBIA “is quickly gaining acceptance among remote sensors” and has shown great potential for the classification of heterogeneous urban environments using VHR satellite data (Zhou et al., 2008)

The main disadvantage of the building object-based models using rules is that it can become computational intensive and an advanced knowledge of the expert is required. Yet it is always uncertain whether the optimal rules were used for the development the classification scheme. There is no unique solution in a rule-set object based classification; it is depended on the developer. Probably this is the reason why the pixel-based approaches, according to Lu and Weng (2007), are still most commonly used although the thematic accuracy does not meet the operational requirements for land cover mapping.

8.4 Conclusions – recommendations

The object-based classification model, developed in chapter 6 with the use of aerial photography, was applied on the QuickBird satellite imagery (entitled as the RGB model). The model showed the potentiality of being transferable, as it has been successfully applied on different data sets. However, additional testing in more than 3 test sites should configure its validity. The classification results provided a relative low mean thematic accuracy of 79.2% between the three sample areas. Another rule-based model was developed using the additional spectral information of the satellite data i.e. the NIR band and the NDVI layer. The performance of this object- based model was slightly better than the RGB model achieving an average thematic accuracy of 80%. This could be an acceptable result as most operation studies usually require thematic accuracies of 80% and above. The comparisons of the two models to statistically evaluate which model had better performance could not give robust results. This research study suggests that in the future the combination of the two models should be examined in order to investigate whether more accurate classification results could be achieved.

The comparison of the object-based models developed using the two different data sets identified that the aerial photography seems more appropriate to use for the classification of sealed and vegetated surfaces at very large scales. The main advantage of the aerial photography is the spatial resolution which permits a highly accurate delineation of urban land cover features at such scale. However, a stronger conclusion would have been drawn if the aerial and satellite data used in this research study were at the same time of the year. Also more sample areas are needed for the statistical validation of the results.

In all classification models, the extraction of trees from other types of vegetation, with the solely use of spectral information, was not successful. As aforementioned in previous chapters, elevation information seems necessary for discriminating low from high vegetation (Huang et al., 2008; Chen Y. et al., 2009).

Based on the statistical analysis, a solid conclusion of whether the object-based classification using satellite is better than the pixel-based approach could not be drawn. However, the aim of this research was to identify an automated transferable methodology and only the object-based models have the potential of transferability in other study areas or when different data sets are used. In addition, due to the numerous advantages of OBIA analysed in the discussion, especially when VHR data are used, this research study recommends the use of object-based methodologies for mapping soil sealed and vegetated surfaces at large scales.

Chapter 9

Conclusions

This final chapter draws together the key findings and conclusions of the current research for mapping soil sealing and vegetated surfaces in urban environments, at large mapping scales. The structure that follows is based on the aim of this research study and the specific objectives that have been identified.

The key findings of each methodology, developed for the identification of the most appropriate classification method, are discussed. The applicability and transferability of the developed object-based classification models into different study areas or with the use of different data sets are examined. Opportunities and limitations when using different types of earth observation data are also considered. Finally, the future investigations and recommendations are highlighted.

9.1 Discussion of the key findings

Soil sealing is one of the major threats to soil. Soil is an important non-renewable resource taking hundreds of years to form. According to the literature review, the interest in the protection of soil by monitoring soil sealing is clearly apparent through the increasing amount of scientific research and operational European projects. The majority of these studies have investigated soil sealing at small mapping scales due to their interest in land cover mapping at national or European level. However, the production of soil sealing maps at large mapping scales is also of great interest to local planning authorities and DEFRA for urban planning control, urban habitat biodiversity mapping as well as for other research studies related to the aesthetic value of urban green spaces and its importance to the environment. Until now, the majority of the local or operational studies have used manual interpretation methods, traditional pixel-based classification methods or hybrid approaches of the two. The disadvantages and limitations of these techniques have been identified and broadly discussed by others

(Caprioli and Tarantino, 2003; Burnett and Blaschke 2003; Benz et al., 2004; Blaschke et al., 2005; Yuan & Bauer, 2006; Huang et al., 2008 etc).

A relatively new classification method, object based image analysis (OBIA), shows promise in overcoming the limitations found in manual and pixel-based methods. Some research has been already conducted using OBIA for mapping soil sealing at either regional or local scales (Coe et al., 2005; Yan and Bauer, 2006; Mathieu et al., 2007; Zhou et al., 2008; Walker and Blaschke, 2008) but the production of a transferable and potentially operational object-based methodology for mapping soil sealing at large scales has not yet been identified.

This PhD study aimed to identify an automated transferable methodology to classify sealed soil and vegetated surfaces in UK urban environments at large mapping scales. For this purpose various techniques and data were compared: true colour aerial photography (0.125 m RGB) against satellite images (QuickBird, 0.7 PAN and 2.8 m MS), traditional manual and pixel-based classification methods against object-based classification techniques. The key findings and conclusions of each method are discussed below with reference to the specific objectives of this study.

Assessment of the performance of an automated object-based boundary delineation for soil sealing mapping with the use of RGB aerial photography

In order to investigate the automated boundary delineation a comparison of an object extraction method and manual digitising using aerial photography was implemented. The traditional technique of aerial photo interpretation (API) comprises manual delineation (digitising) of an area or object corresponding to land cover features of interest; this is followed by manual labelling of each land cover feature (classification or attribution). API was compared against object-based image analysis (OBIA) techniques for boundary delineation. Four sample areas of the city of Cambridge were classified by API. Then the same study areas were classified using a semi-automated classification method i.e. automated segmentation in eCognition and manual labelling. Both classification techniques were implemented by the author giving the advantage of familiarity with the study areas during the semi-automated approach. The statistical analysis showed a very high agreement between the two classification methods across a variety of urban structures of Cambridge (mean overall agreement of 92%, Table 5.1). A qualitative analysis of the two classification methods identified the following similarities and advantages of the automated delineation in comparison with manual digitising:

- In automated, object-based segmentation the land cover features can be represented at multi-scale levels which are hierarchically connected to each other. Between these levels, an iterative process of segmenting and labelling the objects can be implemented until a satisfactory classification result is achieved. Additional information about the shape, context and neighbourhood relationships of the image object can also be used. All these functions bring object-based image analysis (OBIA) closer to the way a human carries out API. However, the big difference between API and OBIA is that the human performs these techniques simultaneously and sometimes subconsciously when manually interpreting and digitising boundaries. Further classification of the boundary delineation is required within the software in order to achieve similar results
- One advantage of the automated segmentation is that the method is systematic; the rules and the chosen parameters are subjective and depend on the user, but they are applied to the whole image objectively and consistently. In addition, the segmentation result can be saved and easily applied to other sample areas of the same image data for automated boundary reproduction. Due to this possibility, the boundary delineation using the object-based segmentation method is much quicker in comparison to time consuming manual digitising. In this research study, the semi-automated object based classification of the four sample areas decreased the processing time by 25% in comparison to manual API (section 5.5).

However, the main difference between the two approaches is that the software cannot identify real objects and it is not able to include or ignore land cover features with the same intelligence as a human. The segmentation is based on a region merging algorithm which groups similar image pixel values (homogeneous areas) together; it cannot adjust the boundary delineation based on precognitive knowledge and recognition of what the object is in the “real world”. For example, if a feature is partly obscured by shadow, the software is likely to create two segments separating the bright and dark side of the same object. This is why the iteration process of classification and re-segmentation is necessary; the two segments can only be united into one and form the object of interest by using expert knowledge. The object-based approach cannot replace API as it cannot replicate the way a human would interpret an image. However, it can assist API by using the automated object-based delineation instead of the time consuming and labour intensive digitising process.

Development and evaluation of an automated rule-based classification model using aerial photography

The object-based classification of the aerial data was implemented in the eCognition software by developing a rule-based model with the use of fuzzy rules and expert knowledge. The development of the model is a complicated method that needs a lot of experience. The more expert the user is the better classification results can be achieved. The main difficulty in the development of the model is that the object features selection is based on visual interpretation accompanied by many cycles of the "trial and error" method. An automated statistical approach for selecting the optimal image object features and parameter values for image segmentation and classification is not yet available in the market.

The object-based model developed was easily applied as-is to the remaining sample study areas, i.e. without changing the values of each feature used for the development. The procedure indicated the transferability of the model to different study areas as its identical application in the four different urban areas showed very high overall accuracies. The performance of the model in the four sample areas was tested against the API with the production of error matrices. The statistical analysis showed a mean overall thematic accuracy of 84% when the following land cover classes were identified: sealed surfaces, vegetation, trees and rail tracks.

A future investigation should examine whether by changing the threshold values, according to the local conditions of each sample area, higher overall accuracies could be achieved. This method avoids visual interpretation of the classification results for each sample area and extra time to define the new threshold values for each object feature. Furthermore, the application of the classification model in more than four sample areas, in the whole Cambridge for example or in another city, is necessary in order to conclude its transferability with certainty.

The classification accuracy increased by approximately 7% with the production of a simple binary classification of sealed vs. unsealed (i.e. sealed vs. vegetation) areas and rail tracks where applicable (Table 6.24). That was due to the fact that the attempt to differentiate trees from other types of vegetation with the use of the RGB aerial data was not successful. The spectral similarity between vegetation and trees is very similar that makes their discrimination very difficult without the use of extra information such as ancillary data.

The classification of urban green spaces and especially the separation of trees from other vegetation is gaining interest in scientific studies due to their important role in the aesthetic value of urban green infrastructure and human health (Tzoulas et al., 2007; Raflee et al., 2009; Yang et al., 2009). However, their extraction requires additional information during the development of the object-based model such as elevation information. This type of information could be derived from Light Detection and Ranging (LIDAR) data. LIDAR has been recently used in land cover mapping studies to discriminate low from high vegetation (Chen et al., 2009; Meng et al., 2009) and according to their findings the results look promising. For example, when Chen et al. (2009) used LIDAR data for the discrimination of bushes and trees the overall classification accuracy was increased from 84% to 95%.

Testing the performance of the object-based classification model with the integration of the Ordnance Survey MasterMap

The Ordnance Survey (OS) MasterMap contains baseline polygons that delineate transport network infrastructure as well as residential and commercial buildings. The OS MasterMap polygons were integrated into the object-based classification model in order to initially mask out sealed surfaces such as buildings and roads. The classification of the remaining land cover features was based on the rule sets of the object-based model that was developed using the aerial data (chapter 6). The integration of the OS MasterMap in the object-based classification model with the use of the aerial photography produced very high accuracies (90% on average, Table 7.2). However, the comparison with the original automated object-based classification model, using aerial data, identified that the integration of the ancillary data did not improve the classification accuracy but actually decreased it by 1% (Table 7.3). The results of the two classification methods proved statistically different. Additionally, the qualitative analysis of the results identified a variety of problems while using OS MasterMap such as displacement between the ancillary and image data or lack of updating in the MasterMap product in relation to land cover changes that occurred in an area (section 7.3).

The OS MasterMap has already been used operationally for the production of the national Land Cover Map 2007 (LCM2007) in the UK (Smith et al., 2007; Smith and Wyatt, 2007). The initial segmentation was based on the OS MasterMap polygons; those polygons were then subdivided by segmentation using a scale factor deemed, by iteration, to lead to satisfactory delineation of objects of interest. However, as Alpin and Smith (2008) argued, the integration of OS MasterMap or any other vector data is not always a straightforward method as “the scale of the mapping and its original purpose may not match well with the land cover mapping task”. In this study, the scale is not an obstacle as both aerial and OS MasterMap data were at the same scale of 1:1250 which were also suitable for identifying land cover features at a “domestic garden” mapping level.

According to the results of this research study, the use of OS MasterMap in the specific object-based classification model did not improve the classification accuracy. Chapter 6 demonstrated that the rule-based classification model showed very high performance in identifying sealed soil surfaces without any additional ancillary data information. However, the results of this study are based only on four sample areas covering an area of 250 x 250m. A more valid conclusion can be drawn when, more scattered sample areas or a bigger area, like the whole Cambridge is examined.

Transferability assessment of the object-based classification model when applied to different data sets i.e. VHR satellite imagery

The satellite data available was a QuickBird image (0.7 m PAN and 2.8 m MS). The initial aim was to apply the object-based model, built up based on the use of the aerial photography (developed in chapter 6), on the satellite data. The threshold values of each image object feature, used during the development, had to be changed but the whole rule-set remained identical. The model showed the potential of being transferable, as it has been successfully applied on the different data sets. The classification results were compared with the API reference data and indicated a relative low mean overall thematic accuracy of 79.2% (Table 8.1).

A new object-based model was developed by using the satellite data and the additional spectra information provided such as the NIR band and the NDVI. The performance of the new set of object-based classification rules, unrelated to those developed by using aerial photography, was statistically evaluated with the error matrix approach, using the API as the reference data, revealing an average overall thematic accuracy of 80% (Table 8.3).

The statistical analysis of the two models, performed in order to evaluate which model had the better performance, could not give robust results due to the limited data available (only three sample areas). However, this research study suggests that instead of examining the performance of each model individually, the combination of the two rule-sets should be examined in order to investigate whether more accurate classification results could be achieved.

To further test the performance of the new object-based classification model, built up with VHR satellite data, a comparison with the model developed by using aerial photography (in chapter 6), was implemented. The aim was to evaluate which data set could achieve better classification results for mapping soil sealing and vegetated surfaces at large scales. The comparison identified a decrease in the overall accuracy of 7% (Table 8.6) when the satellite data was used. However, a more valid conclusion might be drawn if the aerial and satellite data were taken at the same time of the year. The satellite imagery was taken in October when some vegetation types are senescing, limiting the advantage of using the NIR band in which the reflectance of vegetation is high. On the contrary, the aerial photography was taken in June when the reflectance of vegetation in the green waveband is high.

In all the classification models, the extraction of trees from other types of vegetation, with the sole use of spectral information, was not successful. As already mentioned, elevation information seems necessary for discriminating low from high vegetation.

9.2 Concluding statements and recommendations

Sustainable management of natural resources require constant and detailed monitoring of various aspects of the environment. Land cover mapping, and soil sealing mapping in particular, is considered a key element for planning protection, management and monitoring of semi-natural areas in urban environments. Remote sensing is a major source of data to acquire the necessary information needed for monitoring the urban environment. The methods commonly used to map urban environments, apply either pixel-based or object-based classification techniques.

This research study recommends object-based classification techniques for mapping sealed soils and vegetated surfaces at large scales. Although pixel-based methods are probably still more commonly used (Lu and Weng, 2008), the advantages of OBIA over pixel approaches were thoroughly identified in chapters 2, 6 and 8. The main advantage of OBIA is the ability to combine spectral and spatial information as well as expert knowledge to enhance classification results (Burnett and Blaschke 2003; Benz et al., 2004; Blaschke et al., 2005; Im et al., 2007; Blaschke, 2009; Liazaro and Barros, 2010). In addition as Smith and Morton (2010) argued, the majority of geo-information activity in commercial and operational studies uses vector-based products, which link to conventional mapping and their spatial perceptions, and the users feel comfortable with this as they are used to seeing vector maps.

In OBIA, the rule-set classification is considered to be the only method with potential of transferability to other areas of the same data set or to different data sets. Some research has been conducted by Bock et al. (2005); Schopfer and Moller (2006) and Walker and Blaschke (2008) in this area. This research study has partially demonstrated the transferability of the rule-based classification by applying exactly the same model in different sample areas of the aerial photography (chapters 5, 6 and 7) as well as in different data sets (chapter 8). The application of the model in more than four sample areas would statistically validate or otherwise the transferability of the rule-based classification method.

In general, the classification method presented in this study demonstrated a good potential for a soil sealing monitoring programme. However, the classification model outlined must be extended beyond the example of Cambridge to other urban areas in different regions of UK. This will provide a more robust indication of the accuracy and the transferability of the developed methodology. A suggestion as to whether the proposed object-based classification models are suitable for an operational application can then be made. However, object-based classification methods have already been applied operationally for land cover mapping applications, at national levels, in Germany (Arnold, 2006), in Spain (Arozarena et al., 2006), in Sweden (Lantmäteriet, 2005b; Halling, 2008) and the UK (Smith et al., 2007; Smith and Morton, 2010).

The main disadvantage of OBIA is the “trial and “error” technique which provides uncertainty as to whether the optimal image object features have been selected. This is due to the fact that a standard statistical methodology for evaluating the segmentation as well as the classification steps has not been identified yet. The evaluation of the results is still based on visual interpretation of the "trial and error" method. As a result, it is unknown whether the object features, used during segmentation, are the most appropriate or not (Platt and Rapoza, 2008). In addition, there can be more than one solution to choosing the parameters (Feitosa, 2006). As a result, image segmentation becomes a time consuming method that requires significant iterative processing (Lizarazo and Barros, 2010).

There is a need to develop validation techniques in order to assess uncertainties in segmentation-based object extraction (Shi et al., 2005; Hay et al., 2005; Hajek, 2008). Segmentation is considered to be the most important step of OBIA due to the fact that the classification accuracy is dependent on the shape accuracy of the objects extracted during segmentation. However, Tiede et al. (2010) argue that the initial segmentation results are not especially crucial due to the inevitable changes of the object boundaries that occur by the iteration of segmentations/classifications when expert knowledge is applied. Recent literature shows the tendency for developing statistical approaches for selecting the appropriate object features for image segmentation without requiring feature selection defined by the user (Lizarazo and Elsner, 2009; Pekkarinen et al., 2009; Kawakubo et al., 2009, Stein and De Beurs, 2009; Clinton et al., 2010; Albercht et al., 2010; Dragut et al., 2010). Smith and Morton (2010) have suggested the potential of using existing ancillary data information such as the Ordnance Survey (OS) MasterMap, instead of image segmentation, for the initial object extraction and boundary delineation. An argument as to whether these recently published techniques could contribute to the evaluation of object-based segmentation or not cannot be justified without testing them.

In this research study, the additional use of ancillary data to extract thematic information, such as the OS MasterMap, did not improve the classification accuracy. However, the object-based model has been evaluated by using only four small test sites. Ancillary data have been broadly used for object-based land cover mapping, in operational studies such as in Germany (Arnold, 2006), in Spain (Arozarena et al., 2006), in Sweden (Lantmäteriet, 2005b; Halling, 2008) and the UK (Smith et al., 2007; Smith and Morton, 2010).

The validation of the object-based classification results also remains an issue that needs additional work (Zhan et al. 2005; Schopfer and Lang, 2006; Grenier et al., 2008). The majority of the studies use the production of an error matrix for the accuracy assessment, which is a method produced by Congalton in the eighties, particularly developed for pixel-based approaches (Congalton and Green, 1999 and 2009). Attempts to develop new methods for object-based classification evaluation have been recently made by Schopfer et al. (2008); Weinke et al. (2008); Land (2009) and Chmiel and Fijalkowska (2010).

The choice of using either aerial or satellite data depends on the requirements of the project and the data availability for having a cost effective method. This research study recommends the use of aerial photography for monitoring soil sealing and vegetated surfaces at large scales due to the spatial resolution that is required. The main advantage of aerial photography is the spatial resolution permitting an accurate delineation of urban land cover features at larger mapping scales. However, the choice of using either aerial or satellite data is dependent on the requirements of the user. For example, local authorities (or DEFRA) would be interested in mapping soil sealing and vegetated surfaces at garden level scales as they use this information for urban planning and garden re-development control as well as for habitat surveys to identify broad changes in urban environments. In addition, such authorities are more familiar with aerial data as they usually buy aerial photographs because the resolution of satellite data is too low for their investigation. Even though the spatial resolution of satellite data is increasing with time e.g. the WorldView satellite sensor at 0.5 m multispectral resolution, for a back garden level scale survey aerial photography is still the most appropriate due to their availability at only a few centimetres spatial resolution. On the contrary, for mapping soil sealing and vegetation surfaces at national scale the use of satellite data is wise due to spatial coverage of the project.

In future investigations, colour aerial photography with NIR information should be used (CIR photos such as ADS40 images) in order to test the performance of the object-based model in identifying vegetation. Colour infrared (CIR) aerial photographs also have a great potential due to the additional spectral information in the Near Infrared (NIR) band. CIR photos and object based methods have been recently applied for urban land cover and vegetation mapping (Zhou and Troy, 2008; Walker and Blaschke, 2008; Tansey et al., 2009).

In addition, elevation information data could be integrated into the model to test the performance of discriminating low from high vegetation and for minimising the problems caused by shadow. The elevation information can be either extracted by using stereo pairs of aerial photographs or ancillary data such as LIDAR data. Due to the 3D vision, stereo aerial photographs have a big advantage in interpreting land cover features and overcoming difficulties also met with shadow. The integration of LIDAR data or any other type of elevation information in this object-based model is a very interesting future investigation.

The potential of also using multi-temporal image data should not be neglected. Multi-temporal data would have been useful to identify vegetation through its seasonal cycles as well as to determine the land cover features under tree canopies when the trees have no leaves. Finally, Wood et al. (2006) during their investigation of monitoring soil sealing proposed the use of radar data, such as TerraSAR, as another potential data source. SAR data (available at 1m resolution) could also been useful to determine the underlying surface types below tree canopies. Radar has the benefit that it is largely unaffected by cloud cover.

References

Alpin, P. and Smith, G.M. (2008). Advances in object-based image classification. *The international Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences symposium*. Beijing 2008. http://www.isprs.org/congresses/beijing2008/proceedings/7_pdf/4_WG-VII-4/45.pdf (accessed: 13 November 2009)

Albrecht, F., Lang, S. and Holbling, D. (2010). Spatial accuracy assessment of object boundaries for object-based image analysis. *The international Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII-4/C7

Anderson, J.M., Hardy, E.E., Roach, J.T. and Witmer, R.E. (2001). A Land Use And Land Cover Classification System For Use With Remote Sensor Data. http://landcover.usgs.gov/pdf/anderson.pdf (accessed: 15 September 2009)

Arnold, S. (2006). DIGITAL LANDSCAPE MODEL DLM-DE – DERIVING LAND COVER INFORMATION BY INTEGRATION OF TOPOGRAPHIC REFERENCE DATA WITH REMOTE SENSING DATA, *ISPRS workshop, 2-5 June 2009, Hannover, Germany*. www.isprs.org/proceedings/XXXVIII-1-4-7_W5/paper/Arnold-167.pdf (accessed 10 September 2009)

Arozarena, A., Villa, G., Valcárcel, N., Peces, J.J, Domenech, .E., and Porcuna, A. (2006). New concept on land cover / land use information system in Spain design and production. Center for Remote Sensing of Land Surfaces. Bonn.

Baatz, M., Hoffmann, C., and Willhauck, G. (2008). Progressing from object-based to object-oriented image analysis. In In: Object-based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications. *Springer-Verlag*, p.29-42.

Baatz, M. and Schape A. (2000). Multiresolution Segmentation – an optimization approach for high quality multi-scale image segmentation. *AGIT-Symposium Salzburg 2000*, p. 12–23. http://www.definiens.com/documents/publications_earth2000.php (accessed: 03 March 2005)

Baatz, M., Heynen, M., Hofmann, P., Lingenfelder, I., Mimler, M., Schäpe, A., Weber, M. and Willhauck, G. (2000). eCognition User Guide. *Definiens AG*. Munich.

Bauer, M.E., Heinert, N.J., Dyle, J.K. and Yuan, F. (2004). Impervious Surface Mapping and Change Monitoring Using Landsat Remote Sensing. *American Society of Photogrammetry and Remote Sensing (ASPRS), Annual Conference,* May 2004, Denver, Colorado, p. 24-28. http://rsl.gis.umn.edu/Documents/ASPRS%202004I_Bauer_Impervious%20mapping.pdf (accessed: 17 March. 2006)

Benz, U.C, Hoffman. P., Willhauck, G., Lingenfelder, I. and Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for gis-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing,* 58, p. 239-258.

Berberoglu, S. and Akin, A. (2009). Assessing different remote sensing techniques to detect land use/cover changes in the eastern Mediterranean. *International Journal of Applied Earth Observation and Geoinformation,* 11, p. 46–53.

Blaschke, T. (2009). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing,* 65(1), p. 2-16.

Blaschke, T. (2004). Object-based contextual image classification built on image segmentation. *IEEE,* p. 113-119.

Blaschke, T. and Strobl, J. (2001). What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *GeoBIT/GIS,* 6, p. 12-17. http://www.definiens.com/documents/publications_earth2001.ph (accessed: 11 March 2006)

Blaschke, T., Lang, S. and Moeller, M. S. (2005). Object-based analysis of remote sensing data for landscape monitoring. Recent developments. *Anais XII Simpósio Brasileiro de Sensoriamento Remoto,* April 2005, Goiânia, Brasil, 16-21, p. 2879-2885. http://www.definiens.com/documents/publications_earth2005.php (accessed 13 July 2006)

Bock, M., Xofis, P., Mitchley, J., Rossner, G. and Wissen, M. (2005). Object-oriented methods for habitat mapping at multiple scales - Case studies from Northern Germany and Wye Downs, UK. *Journal for Nature Conservation,* 13(2-3), p. 75-89.

Burghardt, W. and the Working Group Urban Soils of the German Soil Science Society. (2004a). Soil Monitoring Instruction on Sealed Areas in the European Union, Contribution to the EU Soil Thematic Strategy. http://www.uni-essen.de/bodenkunde/links/eusoil/sealingmonitoring2703.pdf (accessed: 10 October 2005)

Burghardt, W., Banko, G., Hoeke, S., Hursthouse, A., de L' Escaille, T., Ledin, S., Marsan, F. A., Sauer, D. and Stahr, K. (2004b). TG 5 –SOIL SEALING, SOILS in URBAN AREAS, LAND USE and LAND USE PLANNING. http://www.uni-essen.de/bodenkunde/links/eusoil/EUUrbansoilsapr04.pdf (accessed: 10 October. 2005)

Burnett, C. and Blaschke T. (2003). A multi-scale segmentation/object relationship modelling methodology for landscape analysis. *Ecological Modelling*, 168, p. 233-249.

Caprioli, M. and Tarantino, E. (2003). Urban features recognition form VHR satellite data with an object-oriented approach. *International Symposium of Remote Sensing (ISPRS) Commission IV Joint Workshop "Challenges in Geospatial Analysis, Integration and Visualization II"*. http://www.igf.uni-osnabrueck.de/mitarbeiter/schiewe/papers/24.pdf (accessed 12 July 2006)

Chen, M., Su, W., Li, L., Zhang, C., Yue, A. and Li, H. (2009). Comparison of pixel-based and object-oriented knowledge-based classification using SPOT5 imagery. *Information Science and Applications***,** 6(3), p. 477-489.

Chen, Y., Su, W., Li, J. and Sun, Z. (2009). Hierarchical object oriented classification using very high resolution imagery and LIDAR data over urban areas. *Advances in Space Research*, 43(7), p. 1101-1110.

Chmiel, J. and Fijalkowska, A. (2010). Thematic accuracy assessment for object based classification in agricultural areas: comparative analysis of selected approaches. http://geobia.ugent.be/proceedings/papers%20proceedings/chmiel_fijalkowska_thematic_accuracy_assessment_geobia2010.pdf (accessed: 20 October 2010)

Cleve, C., Kelly, M., Kearns, F.R. and Moritz, M. (2008). Classification of the wildland–urban interface: A comparison of pixel- and object-based classifications using high-resolution aerial photography. *Computers, Environment and Urban Systems*, 32, p. 317-326.

Clinton, N., Ashley, H., Li, Y. and Gong, P. (2008). An accuracy assessment measure for object based image segmentation. *The international Archives of the Photogrammetry, Remote Sensing and Spatial information sciences*, XXXVII, p. 1189-1194.

Clinton, N., Ashley, H., Scarborough, J. Li, Y. and Gong, P. (2010). Accuracy assessment measures for object-based image segmentation goodness. *Photogrammetric Engineering and Remote sensing*, 76(3), p. 289-299.

Coe, S.E., Alberti, M., Hepinstall, J.A. and Coburn, R. (2005). A hybrid approach to detecting impervious surface at multiple scales. *ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005),* March 2005, Tempe, AZ, USA, p. 14-16. http://www.definiens.com/documents/publications_earth2005.php (accessed: 12 July 2006)

Congalton, R.G. and Green, K. (1999). Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. *CRC press*.

Congalton, R.G. and Green, K. (2009). Second edition: Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. *CRC press*.

Corr, D.G., Walker, A., Benz, U., Lingenfelder, I. and Rodgigues, A. (2003). Classification of urban SAR imagery using object oriented techniques. *IEEE,* p. 188-190.

Cothren, J. and Gorham, B. (2005). Automated Feature-Extraction: Software Advances Extract Impervious Surfaces from Satellite Imagery. *Earth Imaging Journal,* 2, p. 32-34.

Cots-Folch, R., Aitkenhead, M.J. and Martínez-Casasnovas, J.A.(2007). Mapping land cover from detailed aerial photography data using textural and neural network analysis, *International Journal of Remote Sensing,*28(7), p. 1625 — 1642.

Countryside Survey (2008). Land Cover Map 2007: A world-leading product in the making. http://www.countrysidesurvey.org.uk/pdf/CS_News_Issue02_July2008.pdf (accessed: 17 July 2009)

Cudlip, W., Lysons, C., Ley, R., Deane, G., Stroink, H. and Roli, F. (1999). A new information system in support of landscape assessment: PLAINS. *Computers, Environment and Urban Systems,* 23, p. 459-467.

Darwish, A., Leukert, K. and Reinhardt, W. (2003). Urban Land -Cover Classification: An object based Perspective. *IEEE: 2nd GRSS/ISPRS Joint Workshop on "Data Fusion and Remote Sensing over Urban Areas",* p. 278-282.

Davis, C.H. and Wang, X. (2002). Urban Land Cover Classification from High Resolution Multi-Spectral IKONOS Imagery. *IEEE,* p. 1205-1206.

Dean, A.M. and Smith, G.M. (2003) An evaluation of per-parcel land cover mapping using fuzzy classification methods. *International Journal of Remote Sensing*, 24, p. 905-2920.

Definiens Professional user guide (2006). Definiens AG.

Definiens Developer user guide (2007). Definiens AG.

Deguchi, C. and Sugio, S. (1994). Estimations for percentage if impervious area by the use of Satellite Remote Sensing imagery. *Water Science Technology,* 29, p. 135-144.

Department for Environment, Food and Rural Affairs (DEFRA) web-site (2006): unsealed soil and green space. http://www.defra.gov.uk/environment/quality/land/soil/built-environ/planning.htm#pressure (accessed: 7 October 2009)

Department for Environment, Food and Rural Affairs (DEFRA) web-site (2005). soil sealing. http://www.defra.gov.uk/environment/land/soil/background/threats/index.htm (accessed: 17 March 2006)

Doll, C.N.H. and Muller, J.P. (1999). An Evaluation of Global Urban Growth via Comparison of DCW and DMSP-OLS Satellite Data. *IEEE*, p. 1135-1136.

Doll, C.N.H., Muller, J.P., Schaaf, C., Strahler, A.H. and Gao, F. (2001). Mapping Urban Landcover using the Bidirectional Reflectance Distribution Function BRDF/Albedo Product from the Moderate Resolution Imagining Spectroradiometer (MODIS). *IEEE,* p. 2680-2682.

Dragut, L., Tiede, D. and Levick, S. (2010). ESP: a tool to estimate scale parameter for multiresolution segmentation of remotely sensed data. *International Journal of Geographic Information Science.* 24(6), p. 859-871.

Durand, N., Boussaid, O. and Puissant, A. (2007). Ontology-based Object Recognition for Remote Sensing Image Interpretation. http://lsiit.u-strasbg.fr/Publications/2007/DDFWGBP07/ictai2007.pdf (accessed 11 October 2009)

Dousset, B. (1995). Synthetic Aperture Radar imaging of urban surfaces: a case study. *IEEE,* p. 2092-2096.

EC, Europa website (2008). Thematic Strategy on the Urban Environment. http://ec.europa.eu/environment/urban/towards_com.htm (accessed: 09 September 2009)

EC, Europa website (2006). Soil sealing in Europe. http://europa.eu/rapid/pressReleasesAction.do?reference=MEMO/06/341&format=HTML&aged=1&language=EN&guiLanguage=en (accessed: 09 September 2009)

Elgy, J. (2001). Airborne remote sensing for urban drainage. *Urban Water*, p. 287-297.

ENVASSO website (2007). Environmental Assessment of Soil for monitoring: Soil threats.
http://www.envasso.com/home.htm (accessed: 07 July 2008)

European Environment Agency (EEA) glossary web-site (2006). http://glossary.eea.europa.eu/EEAGlossary/S/soil_sealing (accessed: 15 March 2006)

Feitosa, R.Q., Costa, G.A.O.P., Cazes, T.B. and Feijo, B. (2006). A GENETIC APPROACH FOR THE AUTOMATIC ADAPTATION OF SEGMENTATION PARAMETERS. *1st International Conference on Object-based Image Analysis (OBIA)*, July 2006, Salzburg, Austria.

Fischer, P. (1997). The pixel: a snare and a dilution. *International Journal of Remote Sensing*, 18(3), p. 679-685.

Fonseca, F.T, Egenhofer, M.J. and Agouris, P. (2002). Using ontologies for Integration Geographic Information Systems. *Transactions in GIS*. 6(3), p.231-257.

Frauman, E. and Wolf, E. (2005). Segmentation of very high spatial resolution satellite images in urban areas for segments-based classification. *In*: Anon., *ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005)*, March 2005, Tempe, AZ, USA, p. 14-16.
http://www.definiens-imaging.com/documents/reference.htm (accessed: 13 March 2006)

Fuller, R.M., Cox, R., Clarke, R.T., Rothery, P., Hill, R.A., Smith, G.M., Thomson, A.G., Brown., N.J., Howard, D.C. and Stott, A.P. (2005). The UK Land Cover Map 2000: planning, construction and calibration of a remotely sensed, user-oriented map of broad habitats. *International Journal of Applied Earth Observation and Geoinformation*, 7, p. 202-216.

Fung, T., So, L.L.H., Chen, Y., Shi, P. and Wang, J. (2008). Analysis of green space in Chongqing and Nanjing, cities of China with ASTER images using object-oriented image classification and landscape metric analysis. *International Journal of Remote Sensing*, 29(24), p. 7159-7180.

Gamanya, R., De Maeyer, P. and De Dapper, M. (2007). An automated satellite image classification design using object-oriented segmentation algorithms: A move towards standardization. *Expert Systems with Applications*, 32, p. 616-624.

GMES project (2004). Global Monitoring for Environment and Security; Final Report for the GMES Initial Period (2001-2003). http://www.gmes.info/library/files/Events%20documents/IP_Report_100204_final.pdf (accessed: 09 October 2005)

Greenhill, D.R., Ripke, L.T., Hitchman, A.P., Jones, G.A. and Wilkinson, G.G. (2003). Use of Lacunarity index to characterize sub-urban areas for land use planning using IKONOS-2 Multispectral imagery. *IEEE: 2nd GRSS/ISPRS Joint Workshop on "Data Fusion and Remote Sensing over Urban Areas"*, p. 294-298.

Greiwe, A. and Ehlers, M. (2005). Combined analysis of hyperspectral and high resolution image data in an object oriented classification approach. *ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005),* March 2005, Tempe, AZ, USA, p. 14-16. http://www.definiens-imaging.com/documents/reference.htm: (accessed: 14 March 2006)

Grenier, M., Labrecque, S., Benoit, M. and Allard, M. (2008). Accuracy assessment method for wetland object-based classification. http://www.isprs.org/proceedings/XXXVIII/4-C1/Sessions/Session1/6739_Grenier_Proc_pos.pdf (accessed: 11 October 2009)

Grenzdorffer, G.J. (2005). Land use change in Rostock, Germany since the reunification - a combined approach with satellite data and high resolution aerial images. *In*: Anon., *ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005),* March 2005, Tempe, AZ, USA, p. 14-16. http://www.definiens-imaging.com/documents/reference.htm: (accessed: 13 March 2006)

Guindon, B., Zhang, Y. and Dillabaugh, C. (2004). Landsat urban mapping based on a combined spectral-spatial methodology. *Remote Sensing and Environment*, 92, p. 218-232.

Hájek, J. (2008). Process-based approach to automated classiWcation of forest structures using medium format digital aerial photos and ancillary GIS information. *Eur J Forest Res*, 127, p. 115-124.

Halling, M. (2008). Swedish national land cover programs http://etc-lusi.eionet.europa.eu/activities/announcements/ann1212050983/4_GMES_maj08 (accessed: 03 July 2009)

Haralick, R., Shanmungam, M.,K. and Distein, I. (1973). Texture features for image segmentation. *IEEE Transactions on Systems, Man and Cybernetics*, 3, p. 610-621.

Harayama, A. and Jaquet, J.M. (2004). Multi-source object-oriented classification of landcover using very high resolution imagery and digital elevation model. *Enviroinfo Conference 2004*, 21-23 October 2004, Geneva. http://www.definiens-imaging.com/documents/reference2004.htm (accessed: 10 October 2005)

Hay, G.J, Castilla, G., Wulder M.A and Ruiz J.R. (2005). An automated object-based approach for the multiscale image segmentation of forest scenes. *International Journal of Applied Earth Observation and Geoinformation* 7, p. 339–359.

Herold, M., Guenther, K. and Clarke, C. (2003). *Mapping urban areas in the Santa Barbara South Coast using IKONOS data and eCognition*. Available at: http://www.definiens-imaging.com/documents/an/sb.pdf. (accessed: 25 March 2005)

Hodgson, M.E., Jensen, J.R., Tullis, J.A., Riordan, K.D. and Archer, C.M. (2003). Synergistic use of Lidar and color aerial photography for mapping urban parcel imperviousness. *Photogrammetric Engineering and Remote Sensing*, 69, p. 973-980.

Hoffman, P. (2001). Detecting urban features from IKONOS data using an object-oriented approach. *Fist Annual Conference of the Remote Sensing & Photogrammetry Society*, 12-14 September 2001, 28-33. http://www.definiens.com/documents/publications_earth2001.php (accessed 10 October 2005)

Huang, M.J., Shyue, S.W., Lee, L.H. and Kao, C.C. (2008). A Knowledge-based Approach to Urban Feature Classification Using Aerial Imagery with Lidar Data. *Photogrammetric Engineering & Remote Sensing*, 74(12), p. 1473–1485.

Huber, S., Prokop, G., Arrouays, D., Banko, G., Bispo, A., Jones, R., Kibblewhite, M., Lexer, W., Möller, A., Rickson, J., Shishkov, T., Stephens, M., Van den Akker, J., Varallyay, G., Verheijen, F.(2007). Indicators and Criteria report. ENVASSO Project (Contract 022713) coordinated by Cranfield University, UK, for Scientific Support to Policy, European Commission 6th Framework Research Programme, p. 77-102.

Hung, M.C. and Ridd, M.K. (2001). Development of a Supervised Classifier for Subpixel Remote Sensing. *IEEE*, p. 1892-1894.

Im, J., Jensen, J.R. and Tullis, J.A. (2007). Object-based change detection using correlation image analysis and image segmentation. *International Journal of Remote Sensing*, 29(2), p. 399-423.

Jacquin, A., Misakova, L., and Gay, M. (2008). A hybrid object-based classification approach for mapping urban sprawl in periurban environment. *Landscape and Urban Planning*, 84, p.152–165.

Jensen, O.C., Azofeifa, G. and Arturo, S. (2006). Satellite-derived ecosystems classification: image segmentation by ecological region for improved classification accuracy, a boreal case study. International Journal of Remote Sensing, 27(2), p.233-251.

Jensen, R. (2001). Remote sensing of the environment: an earth resource perspective. Prentice Hall series in geographic information science, p. 544.

Ji, M. and Jensen, J.R. (1999). Effectiveness of Subpixel Analysis in Detecting and Quantifying Urban Imperviousness form Landsat Thematic Mapper Imagery. *Geocarto International* , 14, p. 33-41.

Kampouraki M., Wood G.A, Brewer T.R. (2008). Opportunities and limitations of object based image analysis for detecting urban impervious and vegetated surfaces using true-colour aerial photography. In: Object-based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications. *Springer-Verlag*, p.555-570.

Kampouraki M., Wood G.A, Brewer T.R. (2007). "The suitability of object-based image segmentation to replace manual aerial photo interpretation for mapping impermeable land cover". *Annual Conference 2007 Remote Sensing and Photogrammetry Society* (RSPSoc), September 2007, Newcastle.

Kampouraki M., Wood G., Brewer T.R. (2006). "The application of remote sensing to identify and measure sealed areas in urban environments". *1st International Conference on Object-based Image Analysis (OBIA)*, July 2006, Salzburg, Austria.

Kawakubo, F.S., Morato, R.G., Midaglia, C.L., Gomide, M.L.C. and Luchiari, A. (2009). Land-use and vegetation-cover mapping of an indigenous land area in the state of Mato Grosso (Brazil) based on spectral linear mixing model, segmentation and region classification. *Geocarto International*, 24(2), p.165-175.

Kibblewhite M. (2007). Towards a European soil directive - the rationale and some reflections. *ENVIRONMENTAL LAW AND MANAGEMENT*, 19(5), p. 227-231.

Kleeschulte, S. (2004). Soil Sealing Workshop; a summary report. http://terrestrial.eionet.europa.eu/gmes/minutes#search=%22%22soil%20sealing%20workshop%22%2C%20kleeschulte%22 (accessed: 10 October 2005)

Kubat M., Holte, R. and Matwin, S. (1998). Machine Learning for the detection of oil spills in satellite radar images. *Machine Learning*, 2(30), p. 195-215.

Lang, S. (2008). Object-based image analysis for remote sensing applications: modeling reality-dealing with complexity. *Object-Based Image Analysis: Spatial Concepts for Knowledge- Driven Remote Sensing Applications,* Springer, p. 3-27.

Lang, S., Schöpfer, E. and Langanke, T. (2009). Combined object-based classification and manual interpretation-synergies for a quantitative assessment of parcels and biotopes. *Geocarto International,* 24(2), p. 99-114.

Lantmäteriet (2005b). Thematic accuracy of the Swedish Land Cover Data. Report document number SCMD-0020. p.34.

Latifovic, R., Zhu, Z.L., Cihlar, J., Giri, C. and Olthof, I. (2004). Land cover mapping of North and Central America- Global Land Cover 2000. *Remote Sensing of Environment*, 89(4), p. 116-127.

Lavalle C., Demicheli L., Turchini M., Casals Carrasco P., Niederhuber M. (2001). Monitoring mega-cities: the MURBANDY/MOLAND approach. *Development in Practice,* 11(2-3), p. 350-357.
http://moland.jrc.it/publications.htm (accessed: 10 October 2005)

Leica Geosystems Geospatial Imaging web-site (2006). ADS40 digital sensor.
http://gi.leica-geosystems.com/LGISub1x2x0.aspx (accessed: 20 October 2006)

Lizarazo, I. and Elsner, P. (2009). Fuzzy segmentation for object-based image classification. *International Journal of Remote Sensing*, 30(6), p.1643-1649.

Lizarazo, I. and Baros, J. (2010). Fuzzy image segmentation for urban and-cover classfication. *Photogrammetric Engineering and Remote sensing*, 76(2), p. 151-162

Lu, D. and Weng, Q. (2007). 'A survey of image classification methods and techniques for improving classification performance', *International Journal of Remote Sensing*, 28(5), p.823-870.

Lucas, R., Rowlands, A., Brown, A., Keyworth, S., and Bunting, P. (2007). Rule-based classification of multi-temporal satellite imagery for habitat and agricultural land cover mapping. *ISPRS Journal of Photogrammetry & Remote Sensing,* 62(7), p. 165–185.

Lucieer, V.L. (2008). Object-oriented classification of sidescan sonar data for mapping benthic marine habitats. *International Journal of Remote Sensing,* 29(3), p. 905-921.

Marr, D. and Hildreth, E. (1980). A theory of edge detection. *Proceedings of the Royal Society of London B*, 207, p. 187 - 217.

Mathieu, R., Freeman C. and Aryal, J. (2007). Mapping private gardens in urban areas using object-oriented techniques and very high-resolution satellite imagery. *Landscape and Urban Planning,* 81 (2007), p.179–192.

Mayr T. and Cooke H. (2004). State of the art report on digital soil mapping in Europe and Feasibility study for digital soil data improvement. http://eusoils.jrc.ec.europa.eu/siwg/forum/DSM/DSM4%20SubGroup%20Report_policyrelevance.doc (accessed: 17 September 2008).

Meinel, G. and Hernig, A. (2005). Survey of soil sealing on the basis of the ATKIS basic DLM − feasibilities and limits. *10th International Conference on Information & Communication Technologies (ICT) in Urban Planning and Spatial Development and Impacts of ICT on Physical Space*, 22-25 February 2005. http://www.schrenk.at/corp/archiv/papers/2005/CORP2005_MEINEL_HERNIG.pdf (accessed: 11 October 2005)

Meng, X., Wang, L. and Currit, N. (2009). Morphology-based Building Detection from Airborne Lidar Data. *Photogrammetric Engineering and Remote Sensing,* 75(4), p. 437-442.

Miller, J.E., Nelson, Stacy A.C. and Hess, G.R. (2009). An Object Extraction Approach for Impervious Surface Classification with Very-High-Resolution Imagery. *The Professional Geographer*, 61(2), p.250-264.

Mittelbeg, B. (2002). PIXEL VERSUS OBJECT: A method comparison for analysing urban areas with VHR data. http://www.definiens-imagining.com (accessed: 12 September 2005)

Moeller M. and Blaschke T. (2005). Monitoring LULC Dynamics in the Urban - Rural Fringe. Simpósio Brasileiro de Sensoriamento Remoto (SBSR), December 2005, São José dos Campos: INPE, 2005.

Moller, M., Lymburner, L. and Volk, M. (2007). The comparison index: A tool for assessing the accuracy of image segmentation. *International Journal of Applied Earth Observation and Geoinformation,* 9, p. 311-321.

Mori, M., Hirose, Y., Akamatsu, Y. and Li, Y. (2004). Object-based classification of IKONOS data for rural land use mapping. *International Symposium of Remote Sensing (ISPRS),* Istanbul 2004. http://www.google.co.uk/search?hl=en&q=object based+classification%2C+Mori&btnG=Google+Search&meta (accessed: 10 October 2005)

Nobrega, R.A.A., Hara, C.G.O. and Quintanilha, J.A. (2008). An object-based approach to detect road features for informal settlements near Sao Paulo, Brazil *Object-Based Image Analysis: Spatial Concepts for Knowledge- Driven Remote Sensing Applications*, Springer, p. 589-607.

NSRI, 2001 NSRI (National Soil Resources Institute), 2001. Identification and development of a set of national indicators for soil quality. In: Loveland, P.J., Thompson, T.R.E. (Eds.), R&D Technical report p5-053/2/TR. National Soil Resource Institute, Environment Agency, Bristol

Oumaa, O.Y., Josaphatb, S.S, and Tateishi, R. (2008). Multiscale remote sensing data segmentation and post-segmentation change detection based on logical modeling: Theoretical exposition and experimental results for forestland cover change analysis. *Computers & Geosciences*, 34(8), p.715–737.

Peijun L. and Yingduan H. (2005). Land Cover Classification of Remotely Sensed Image with Hierarchical Iterative Method. *Progress in Natural Science*. 15(5), p. 442-447.

Pekkarinen A., Reithmaier, L. and Strobl, P. (2009). Pan-European forest/non-forest mapping with Landsat ETM+ and CORINE Land Cover 2000 data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 64, p. 171-183.

Phinn, S., Stanford, M., Scarth, P. and Murray, A.T. (2002). Monitoring the composition of urban environments based on vegetation-impervious surface-soil (VIS) model by subpixel analysis techniques. *International Journal of Remote Sensing*, 23, p. 4131-4153.

Platt, R.V. and Rapoza, L. (2008). An Evaluation of an Object-Oriented Paradigm for Land Use/Land Cover Classification. *The Professional Geographer*, 60(1), p. 87-100.

Rabaute, T. (2005). GUS project; C12 Data needs & availability prospectus report. http://esamultimedia.esa.int/docs/GMES/GUS_C12_Ph2_V2%5B1%5D.1_01_03_05_Final.pdf#search=%22%22C12%20%E2%80%93%20Data%20Needs%20%26%20Availability%22%22 (accessed: 10 October 2005)

Raclot, D., Colin, F. and Puech, C. (2005). Updating land cover classification using a rule-based decision system. *International Journal of Remote Sensing*, 26(7), p. 1309-1321.

Rafiee, R., Salman Mahiny, B., Khorasan, N. (2009). Assessment of changes in urban green spaces of Mashad city using satellite data. *International Journal of Applied Earth Observation and Geoinformation*, 11, p. 431–438

Rashed, T., Weeks, J.R., Gadalla, M.S. and Hill, A.G. (2001). Revealing the Anatomy of Cities through Spectral Mixture Analysis of Multispectral Satellite Imagery: *A Case Study of the Greater Cairo Region, Egypt*. http://geosciences.ou.edu/~rashed/publications/Revealing%20the%20Anatomy%20of%20Cities.pdf (accessed: 5 August 2005).

Richards, J.A. and Jia, X. (2005). Remote sensing digital image analysis. *Springer*

Ridd, M.K. (1995). Exploring a V-I-S (vegetation-impervious surface -soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities. *International Journal of Remote Sensing*, 16, p. 2165-2185.

Riedel, T., Thiel, C. and Schmullius C. (2008). Fusion of multispectral optical and SAR images towards operational land cover mapping in Europe. In: Object-Based Image Analysis: Spatial Concepts for Knowledge- Driven Remote Sensing Applications, *Springer*, p. 493-511.

Robinson, P., Fisher, P. and Smith, G. (2005). Evaluating Object-Based Data Quality Attributes in the Land Cover Map 2000 of the United Kingdom. *Photogrammetric Engineering and Remote Sensing*, 71, p. 269-276.

SAGE service prospectus (2004). Service for the Provision of Advanced Geo-Information on Environmental Pressure and State. http://www.gmes-sage.info/download/SAGE-PolicyFoundationReview-I1.01.PDF (accessed: 10 October 2005)

Scalenghe, R. and Marsan, F.A. (2009). The anthropogenic sealing of soils in urban areas. *Landscape and Urban Planning*, 90(1-2), p. 1-10.

Schopfer, E.and Lang, S. (2006). Object fate analsyis- A virtual overlay method for the categorization of object transition and object-based accuracy assessment. *1st International Conference on Object-based Image Analysis (OBIA)*, July 2006, Salzburg, Austria.

Schopfer, E.and Moller, M.S. (2006). Comparing metropolitan areas- Tranferable object-based image analys approach. *Photogrammetrie, Fernerkundung, Geoinfromation*, 10(4), p. 277-286.

Schopfer, E., Lang, S. and Albrecht, F. (2008). Object-fate analysis: Spatial relationships for the assessment of object transition and correspondence. *Object-Based Image Analysis: Spatial Concepts for Knowledge- Driven Remote Sensing Applications*, Springer, p. 785-801.

Senate department of urban development of Berlin web-site (2005). http://www.stadtentwicklung.berlin.de/umwelt/umweltatlas/eda102_03.htm#top (accessed: 10 October 2005)

Shi, W.Z., Ehlers, M. and Molenaar, M. (2005). Uncertainties in integrated remote sensing and GIS. *International Journal of Remote Sensing*, 26, p. 2911-2915.

Small, C. (2001). Estimation of urban vegetation abundance by spectral mixture analysis. *International Journal of Remote Sensing* , 22, 1305-1334.

Sims, F.M. and Mesev, V. (2007). Use of Ancillary Data in Object Based Classification of High Resolution Satellite Data. *IEEE*, 11(13), p. 1-10.

Sims, F.M. (2007). Use of Ancillary Data in Object Based Classification of High Resolution Satellite Data. *IEEE- Urban Remote Sensing Joint Event*.

Smith, A.J. (2000). Subpixel Estimates of Impervious Surface Cover Using Landsat TM imagery. http://www.geog.umd.edu/academic/occasional/wp2000/ajsmith_sp.pdf (accessed: 5 August 2005).

Smith, R.M., Gaston, K.J., Warren, P.H. and Thompson, K. (2005). Urban domestic gardens (V): relationships between land cover composition, housing and landscape. *Landscape Ecology*, 20, p. 235-253.

Smith, G., Beare, M., Boyd, M., Downs, T., Gregory, M., Morton, D., Brown, N. and Thomson, A. (2007). UK Land Cover Map Production Through the Generalisation of OS MasterMap. *The Cartographic Journal*, 44(3), 276-283.

Smith, G., Beare, M., Boyd, M., Downs, T., Gregory, M., Morton, D., Brown, N. and Thomson, A. (2007). UK Land Cover Map Production Through the Generalisation of OS MasterMap. *Cartographic Journal*, 44(3), p. 276-283.

Smith G.M. and Wyatt B.K. (2007). Multi-scale survey by sample-based field methods and remote sensing: A comparison of UK experience with European environmental assessments. *Landscape and Urban Planning*, 79, p. 170-176

Smith G.M. and Morton D.R. (2010). Real World Objects in GEOBIA through the Exploitation of Existing Digital cartography and Image Segmentation. *Photogrammetric Engineering and Remote sensing*, 76(2), p. 163-171.

Song, M., Civco, D.L. and Hurd, J.D. (2005). A competitive pixel-object approach for land cover classification. *International Journal of Remote Sensing*, 26(22), p. 4981-4997.

Steenmans C. (2005). GMES Service Element Land Monitoring (GSE Land). European Environmental Protection Agencies , Prague, 28-30 September 2005. http://terrestrial.eionet.europa.eu/gmes/GSELand#search=%22%22GMES%20Service%20Element%20Land%20Monitoring%20(GSE%20Land)%22%20Chris%20Steenmans%20-%20EEA%22 (accessed: 08 October 2005)

Stein, A. and De Beurs, K. (2005). Complexity metrics to quantify semantic accuracy in segmented Landsat images. *International Journal of Remote Sensing*, 26(14), p. 2937-2951.

Stow, D., Lopez, A., Lippitt, C., Hinton, S. and Weeks, J. (2007). Object-based classification of residential land use within Accra, Ghana based on QuickBird satellite data. *International Journal of Remote Sensing*, 28(22), p. 5167-5173.

Tansey. K., Chambers, I., Anstee, A., Denniss, A. and Lamb, A. (2009). Object-oriented classification of very high resolution airborne imagery for the extraction of hedgerows and field margin cover in agricultural areas. *Applied Geography*, 29, p.145–157.

Tatem, A.J., Lewis, H.G., Atkinson, .P.M. and Nixon, M.S. (2001). Super-Resolution mapping of Urban Scenes from IKONOS Imagery Using a Hopfield Neural Network. *IEEE*, p. 3203-3205.

Tiede, D., Lang, S., Florian, A. and Daniel, H. (2010). Object-based class modelling for Cadastre-constrained Delineation of Geo-objects. *Photogrammetric Engineering and Remote sensing*, 76(2), p. 193-1202

Townshend, J.R.G., Huang, C., Kalluri, S.N.V., Defries, R.S., Liang, S. and Yang, K. (2000). Beware of per-pixel characterization of land cover. *International Journal of Remote Sensing*, 21(4), p. 839 - 843.

Tzoulas, K., Korpela, K., Venn, S., Yli-Pelkonen, V., Kazmierczak, A., Niemela, J. and James, P. (2007). Promoting ecosystem and human health in urban areas using Green Infrastructure: A literature review. *Landscape and Urban Planning*, 81, p.167-178.

Visser, H. (2004). The Map Comparison Kit: methods, software and applications. RIVM report 550002005. http://www.rivm.nl/milieu/modellen. (accessed: 11 September 2006)

Visser, H. and de Nijs (2006). The Map Comparison Kit. *Environmental Modelling & Software*, 21(6), p. 346-358.

Walker, J.S. and Blaschke T. (2008). Object-based land-cover classification for the Phoenix metropolitan area: optimization vs. transportability. *International Journal of Remote Sensing*, 29(7), p. 2021 - 2040.

Wang, Z., Wei, W., Zhao, S. and Chen, X. (2004). Object-oriented Classification and Application in Land Use Classification Using SPOT-5 PAN imagery. *IEEE*, p. 3158-3160.

Warner, T. and Chen, X. (2001). Normalization of Landsat thermal imagery for the effects of solar heating and topography. International Journal of Remote Sensing, 22, p. 773-788.

Ward, D., Phinn, S.R. and Murray, A.T. (2000). Monitoring Growth in Rapidly Urbanizing Areas Using Remotely Sensed Data. *Professional Geographer*, 52, p. 371-386.

Weinke, E., Lang, S. and Preiner M. (2008). Strategies for semi-automated habitat delineation and spatial change assessment in an Alpine environment. *Object-Based Image Analysis: Spatial Concepts for Knowledge- Driven Remote Sensing Applications*, Springer, p. 711-732.

White, R., Engelen, G., Uljee, I., Lavalle, C. and Ehrlich, D. (2000). Developing an Urban Land Use Simulator for European Cities. *Proceedings of the 5th EC GIS Workshop: GIS of Tomorrow*, European Commission Joint Research Centre, p. 179-190.

Whitford, V., Ennos, A.R. and Handley, J.F. (2001). "City form natural process"-indicators for the ecological performance of urban areas and their application to Merseyside, UK. *Landscape and Urban Planning*, p. 91-103.

Wikipedia (2010). Ontology (information science). http://en.wikipedia.org/wiki/Ontology_%28information_science%29 (accessed: 15 October 2010)

Wolf, P.R. (2002). Surveying and Mapping: History, Current Status, and Future Projections. Journal of *American Society of Civil Engineers*, 128(3), p. 79-107.

Wood, G.A., Braganza, S., Brewer, T.R., Kampouraki, M., Harris, J., Hannam, J., Burton, R., Deane, G. (2006). "Monitoring urban sealing from space-The Application of Remote sensing to Identify and Measure Changes in the area of Soil Prevented from Carrying Out Functions by Sealing". Technical report of GIFFTS project BNSC/ITT/54 - DEFRA-SP0541.

Wu, C. and Murray, A.T. (2003). Estimating impervious surface distribution by spectral mixture analysis. *Remote Sensing and Environment,* 84, p. 493-505.

Jun Yang J., Zhaob, L., Mcbridec, J., and Peng Gong, P. (2009). Can you see green? Assessing the visibility of urban forests in cities. *Landscape and Urban Planning,* 91(2009), p. 97–104.

Yan, F. and Bauer, M. (2006). Mapping impervious surface are using high resolution imagery: a comparison of object-based and pixel classification. *American Society of Photogrammetry and Remote Sensing (ASPRS) Annual Conference*, Reno, Nevada, 1-5 May 2006. http://www.definiens.com/documents/publications_earth.php (accessed: 13 July 2006)

Yuan, F., Bauer, M., Heinert E., Nathan J. and Holden, G.R.(2005). Multi-level Land Cover Mapping of the Twin Cities (Minnesota) Metropolitan Area with Multi-seasonal Landsat TM/ETM+ Data. *Geocarto International*, 20(2), p. 5-13.

Yang, L., Xian, G., Klaver, J.M. and Deal, B. (2004). Urban land cover detection through sub-pixel imperviousness mapping using remotely sensed data. http://dodesp.er.usgs.gov/reports/urbanaspr_2003.pdf. (accessed: 10 May 2005)

Zhan, Q., Molenaar, M., Tempfli, K. and Shi, W. (2005). Quality assessment for geo-spatial objects derived from remotely sensed data. *International Journal of Remote Sensing*, 26(14), p. 2953-2974.

Zhou, W. Troy, A. and Grove M. (2008). Object-based Land Cover Classification and Change Analysis in the Baltimore Metropolitan Area Using Multitemporal High Resolution Remote Sensing Data. *Sensors*, 8, p. 1613-1636.

Zhou, W. and Troy, A. (2008). Extraction of Impervious Surface Areas from High Spatial Resolution Imagery by Multiple Agent Segmentation and Classification. *Photogrammetric Engineering & Remote Sensing*, 74(7), p. 857-868.

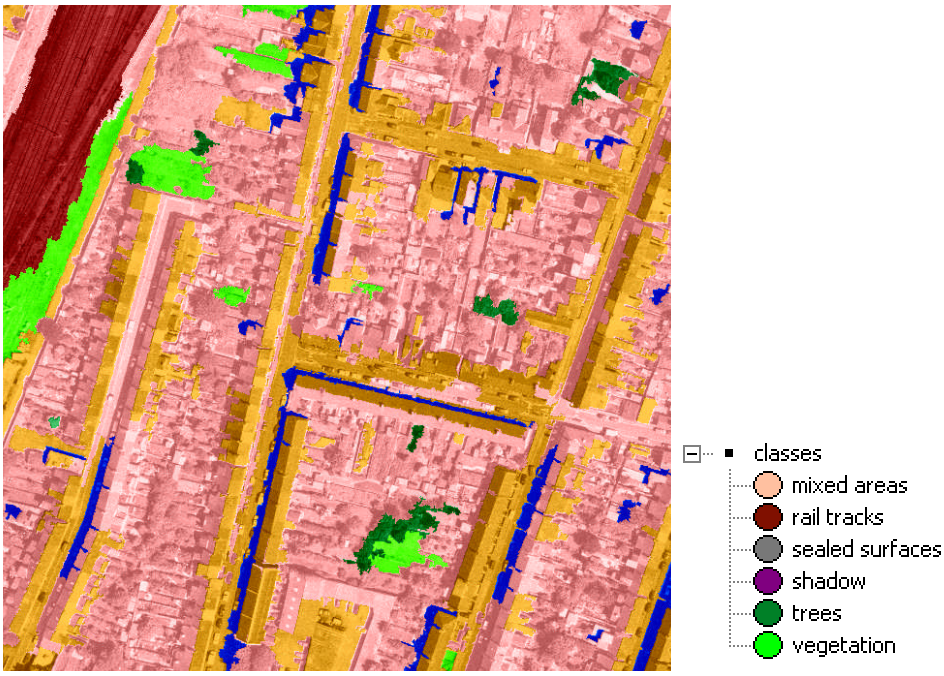
Zhou, Y. and Wang, Y.Q. (2006). Extraction of impervious surface area using orthophotos in Rhode island. *American Society of Photogrammetry and Remote Sensing (ASPRS) Annual Conference*, Reno, Nevada, 1-5 May 2006. http://www.definiens-imaging.com/documents/reference.htm: (accessed: 13 March 2006)

Zhou, W., Huang, G., Troy, A. and Cadenasso, M.L. (2009). Object-based land cover classification of shaded areas in high spatial resolution imagery of urban areas: A comparison study. *Remote Sensing of Environment*. 113 (8), p. 1769-1777.

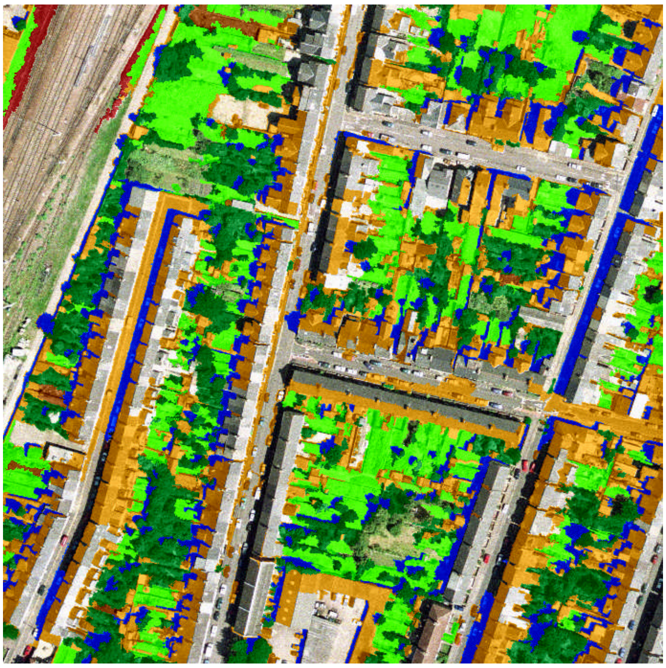
Appendix A

Semi-automated classification of the aerial photography using eCognition software

Residential area - area5

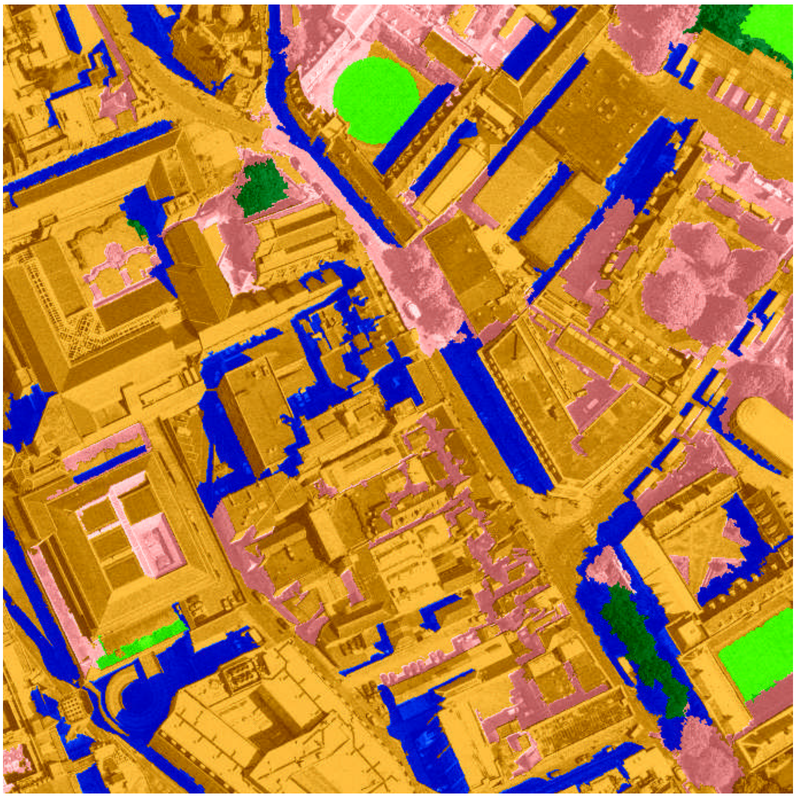


i)

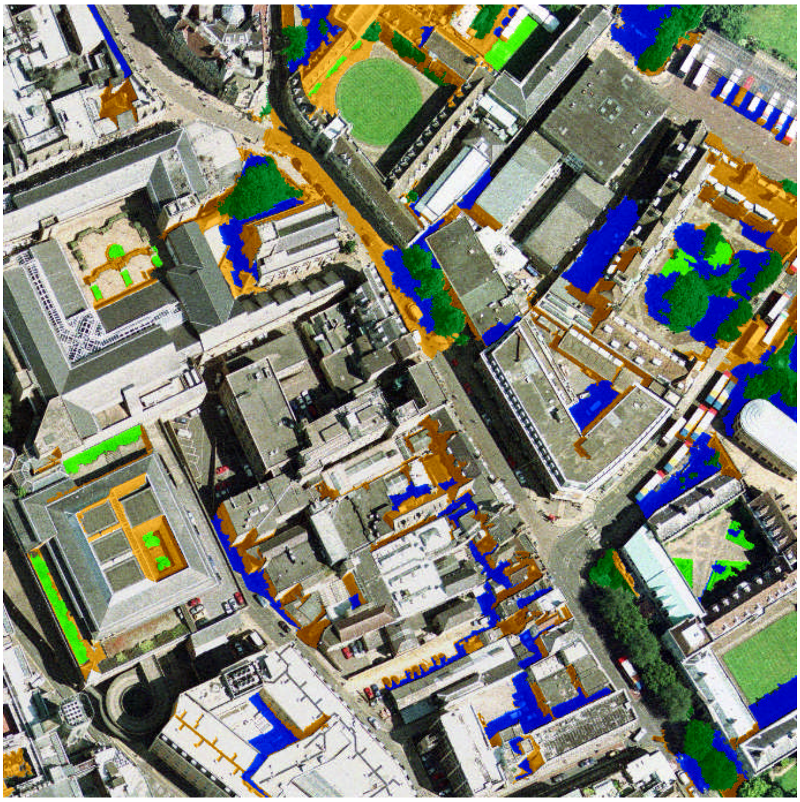


ii)

Commercial area – area20



i)



ii)

Results from the multiple comparison tests between API and semi-automated object-based classification

Error matrices - comparisons of vector data

Residential area - area5

Sum of FREQUENCY							
API/semi_auto_eCg	bare soil	rail tracks	sealed surfaces	shadow	trees	vegetation	Grand Total
bare soil	6		9	7	10	6	38
rail tracks		1	2			3	6
sealed surfaces			124	227	185	156	692
shadow	2		221	250	198	141	812
trees	7		175	232	171	170	755
vegetation	6	2	149	142	164	130	593
Grand Total	21	3	680	858	728	606	2896
							23.50%

Industrial area - area0

Sum of FREQUENCY						
API/semi_auto_eCg	rail tracks	sealed surfaces	shadow	trees	vegetation	Grand Total
rail tracks	1	2			3	6
sealed surfaces	2	30	84	44	16	176
shadow		87	79	40	5	211
trees		56	50	49	4	159
vegetation	6	17	9	3	14	49
Grand Total	9	192	222	136	42	601
						29%

Commercial area – area20

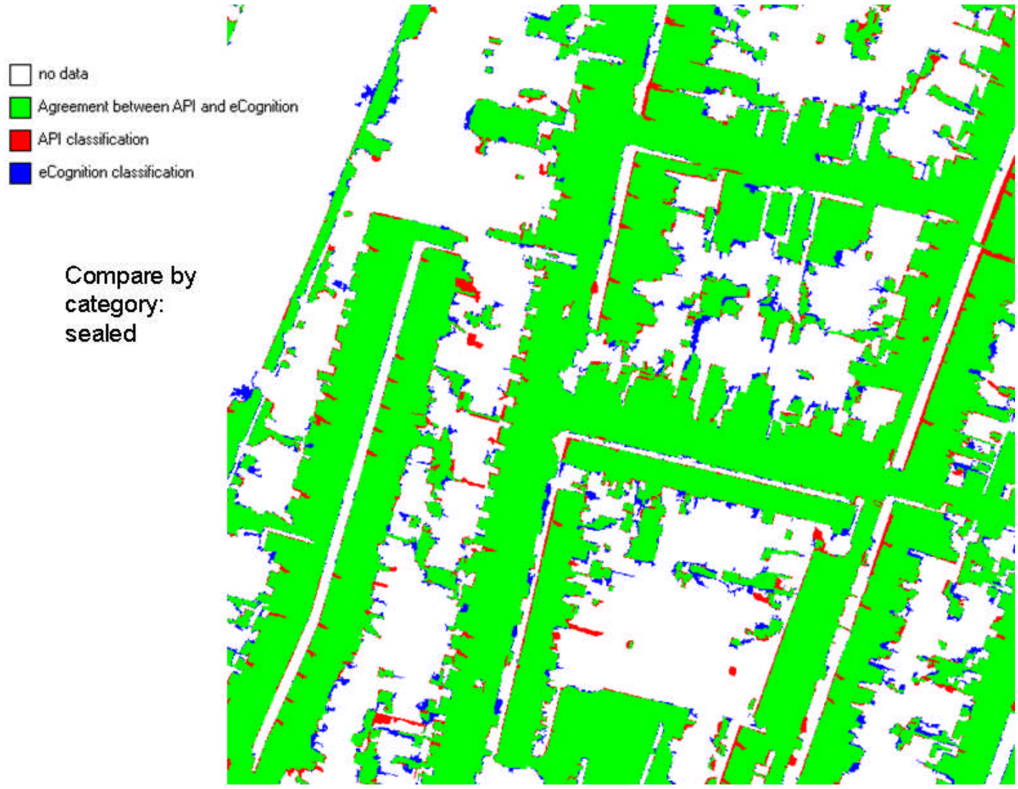
Sum of FREQUENCY					
API/semi_auto_eCg	sealed surfaces	shadow	trees	vegetation	Grand Total
sealed surfaces	18	83	21	21	143
shadow	97	92	30	16	235
trees	32	35	28	8	103
vegetation	27	16	6	26	75
Grand Total	174	226	85	71	556
					29.50%

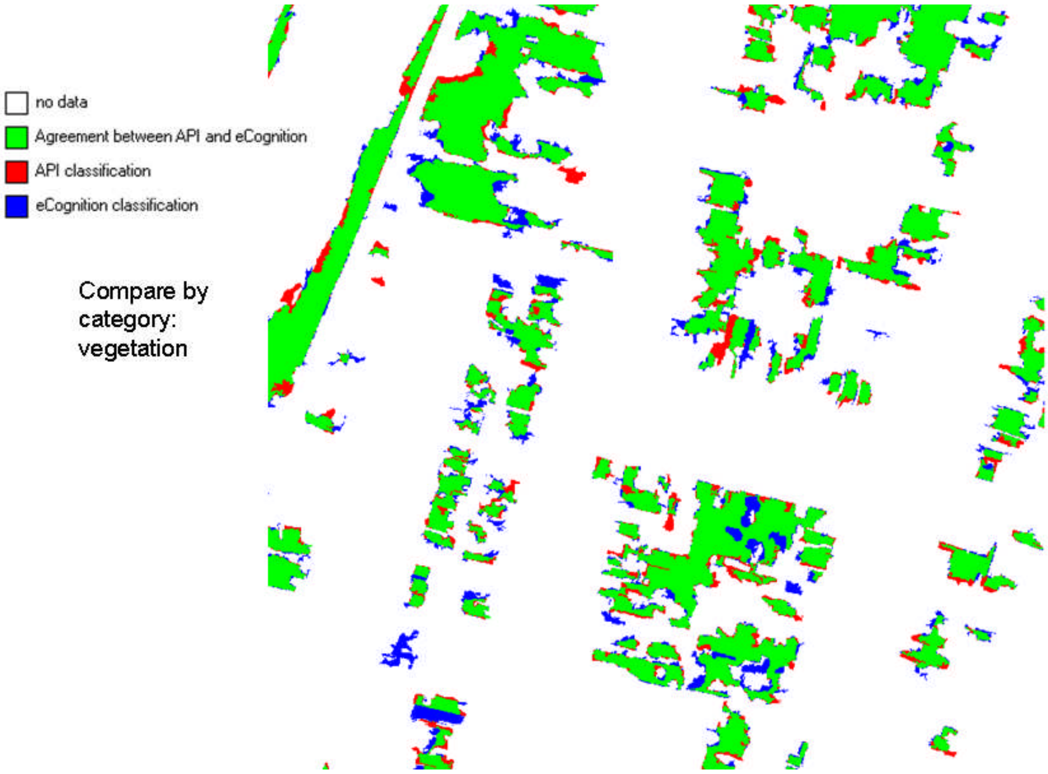
Residential area – area26

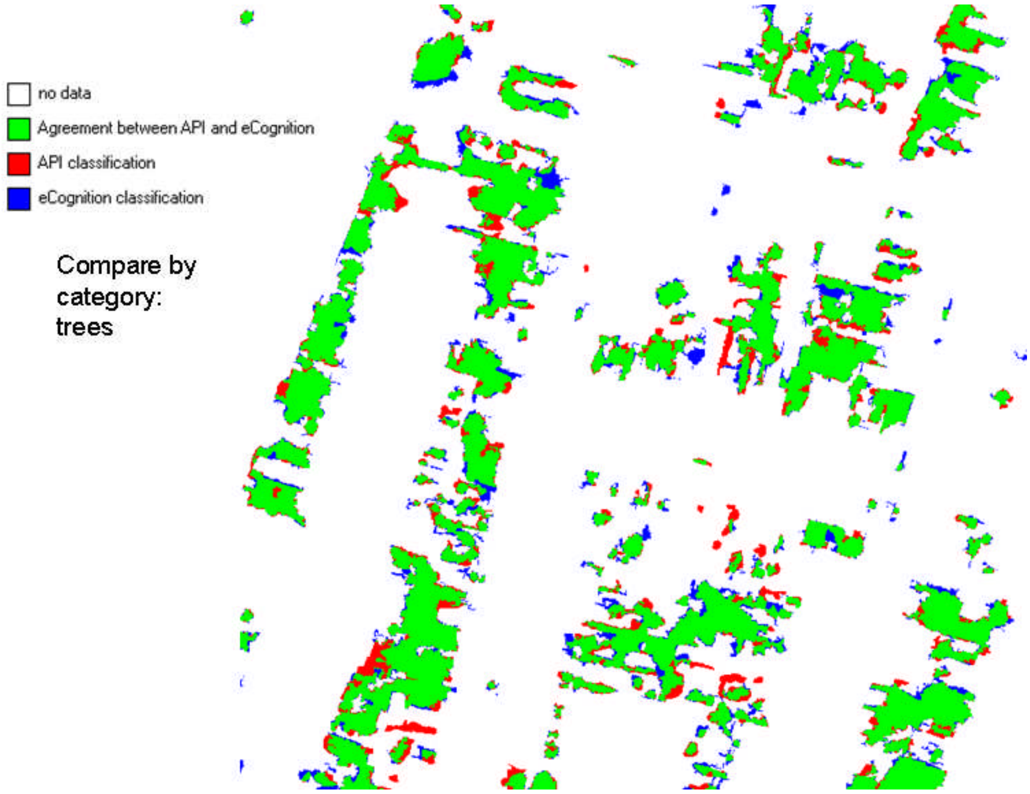
Sum of FREQUENCY							
API/semi_auto_eCg	bare soil	sealed surfaces	shadow	temp. features	trees	vegetation	Grand Total
bare soil	4	3	2		3	2	14
sealed surfaces	1	416	414		322	324	1477
shadow	3	356	410		309	262	1340
temporary features				2	2	3	7
trees	1	249	305	1	267	199	1022
vegetation	3	249	216	2	199	250	919
Grand Total	12	1273	1347	5	1102	1040	4779
							28%

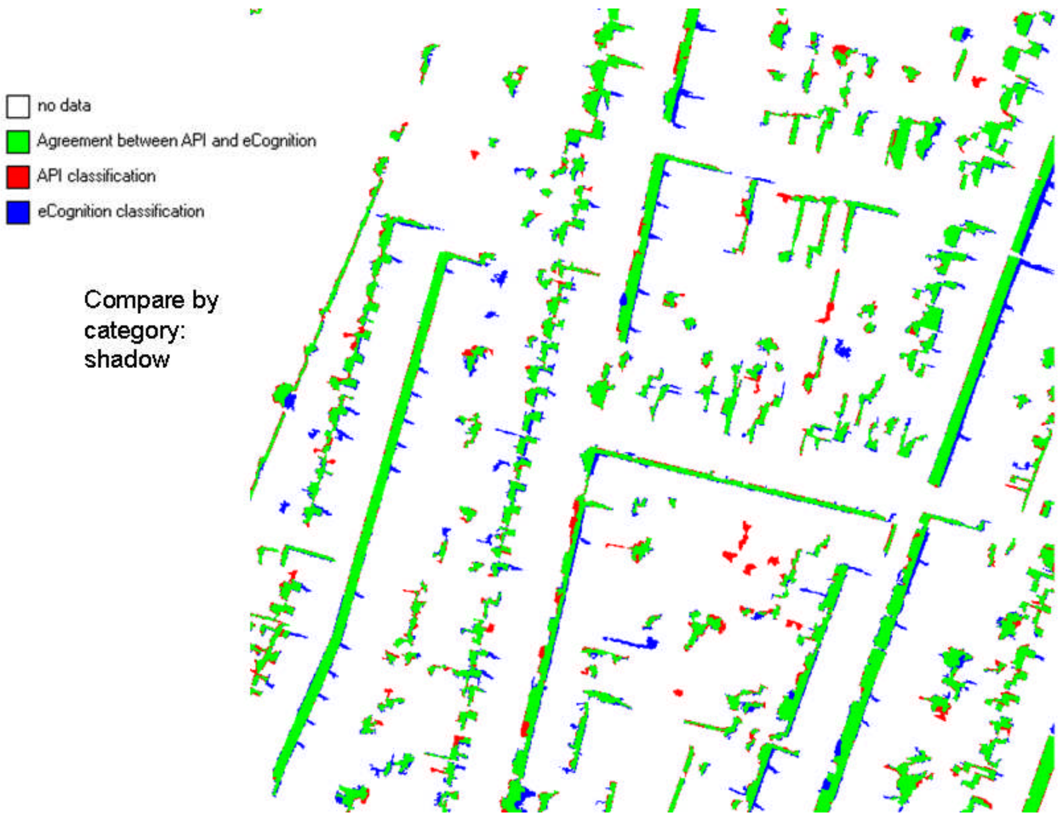
Qualitative analysis between API and semi-automated OBIA using the Map Comparison Kit

i) Residential area - area 5

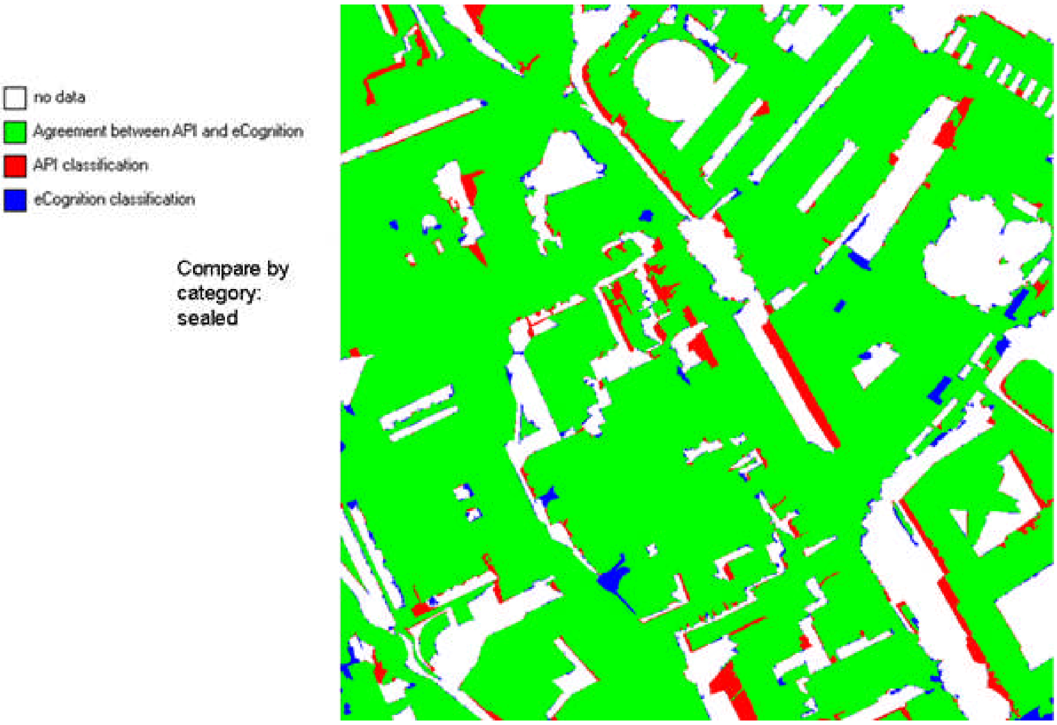


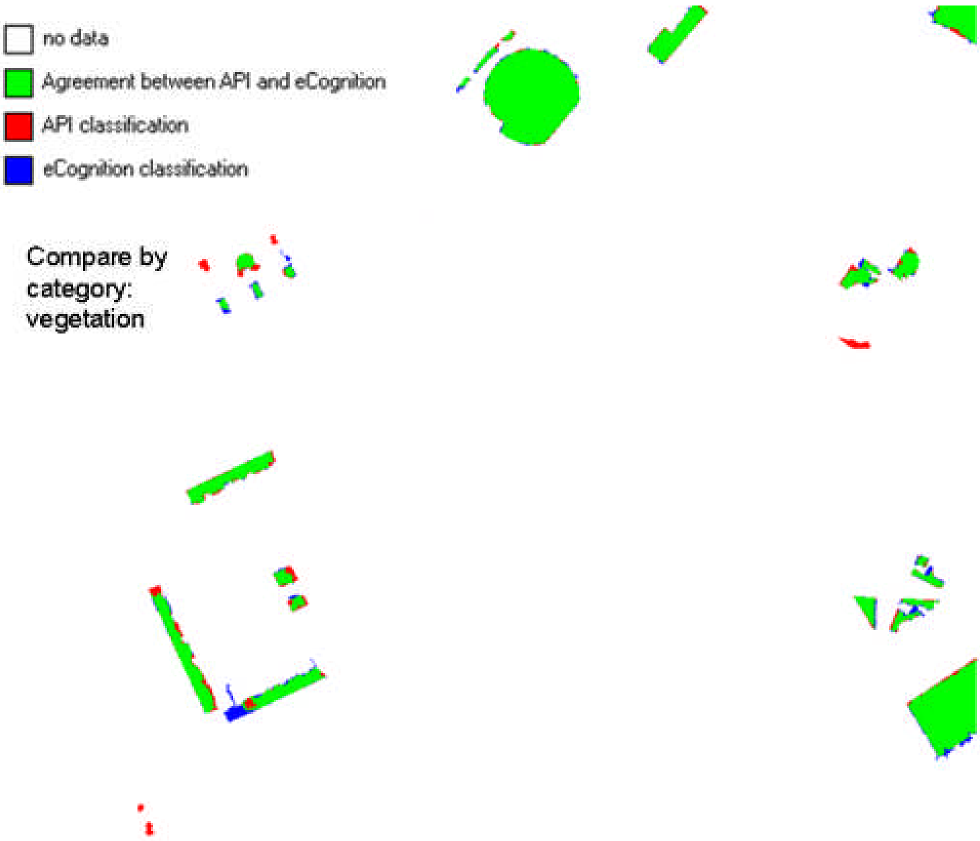


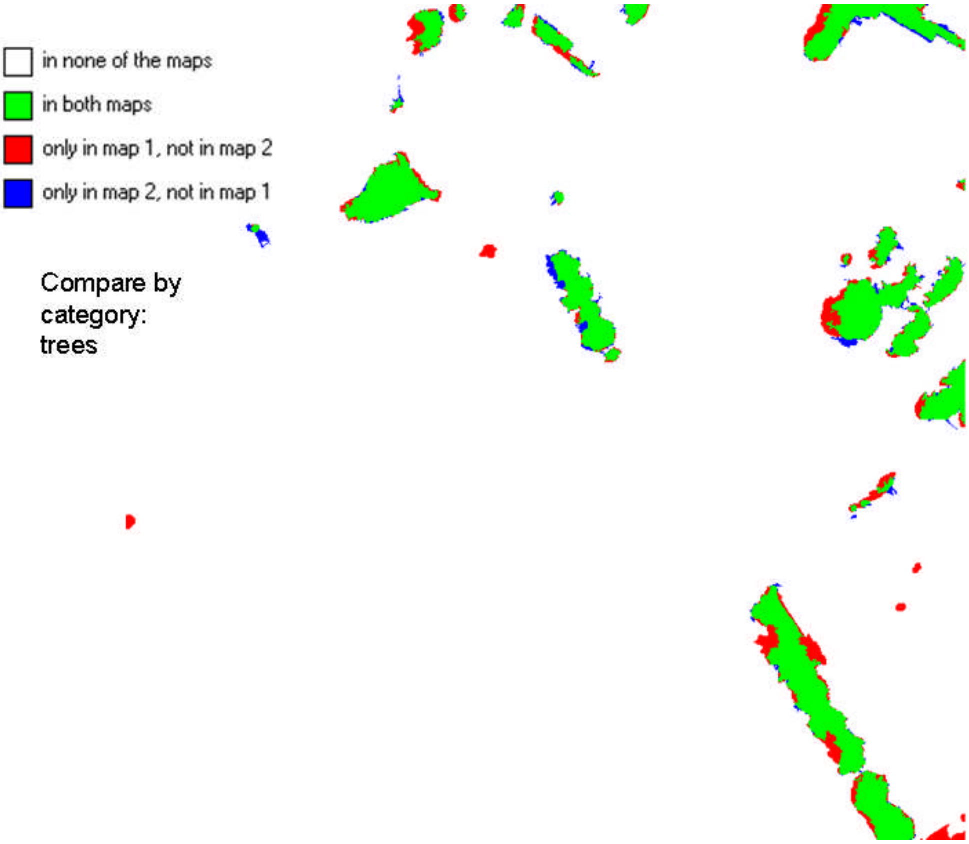

no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: trees

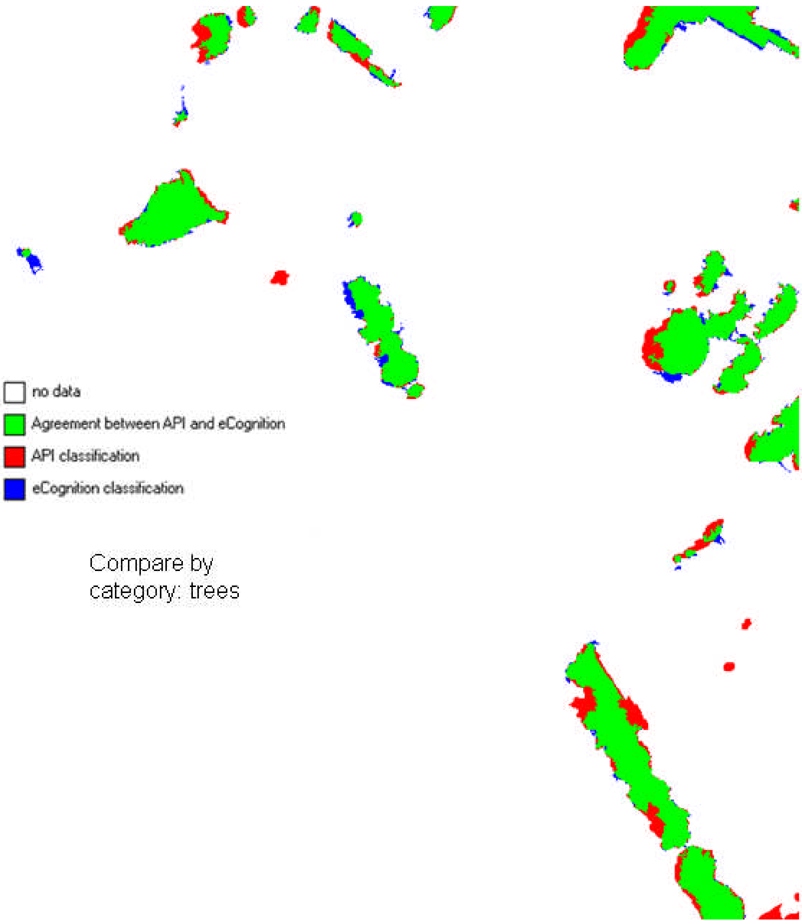

no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: shadow

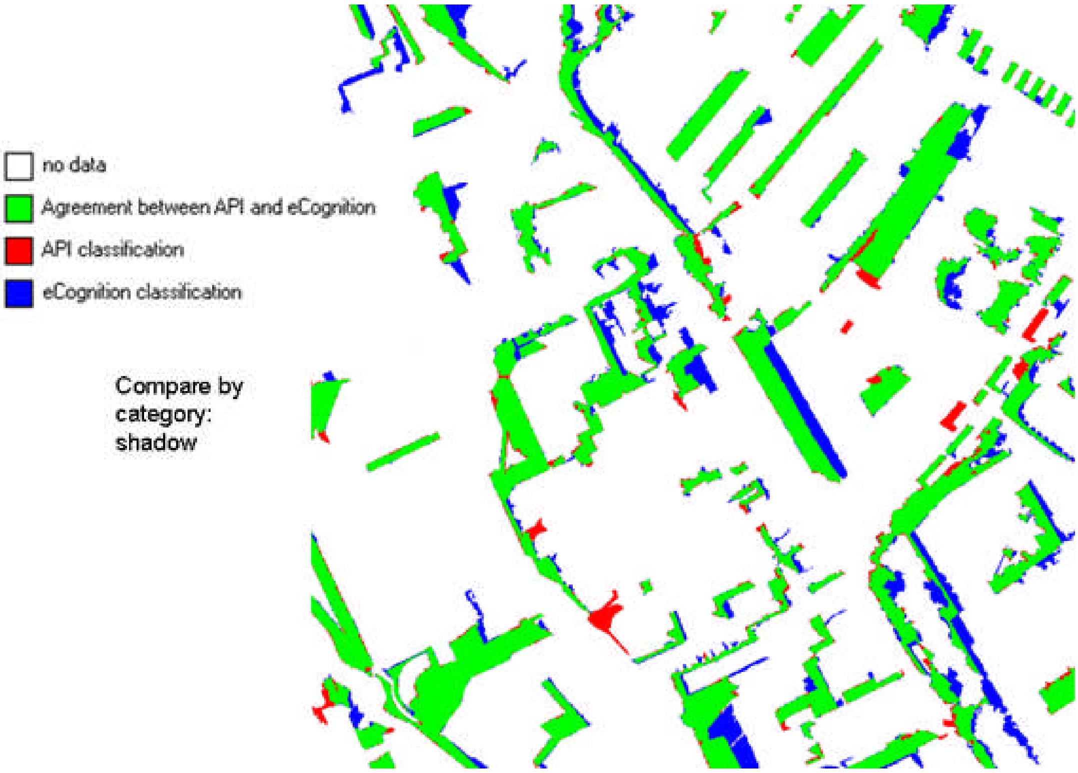
ii) Commercial area - area 20






in none of the maps
in both maps
only in map 1, not in map 2
only in map 2, not in map 1
Compare by category: trees


no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: trees


no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: shadow

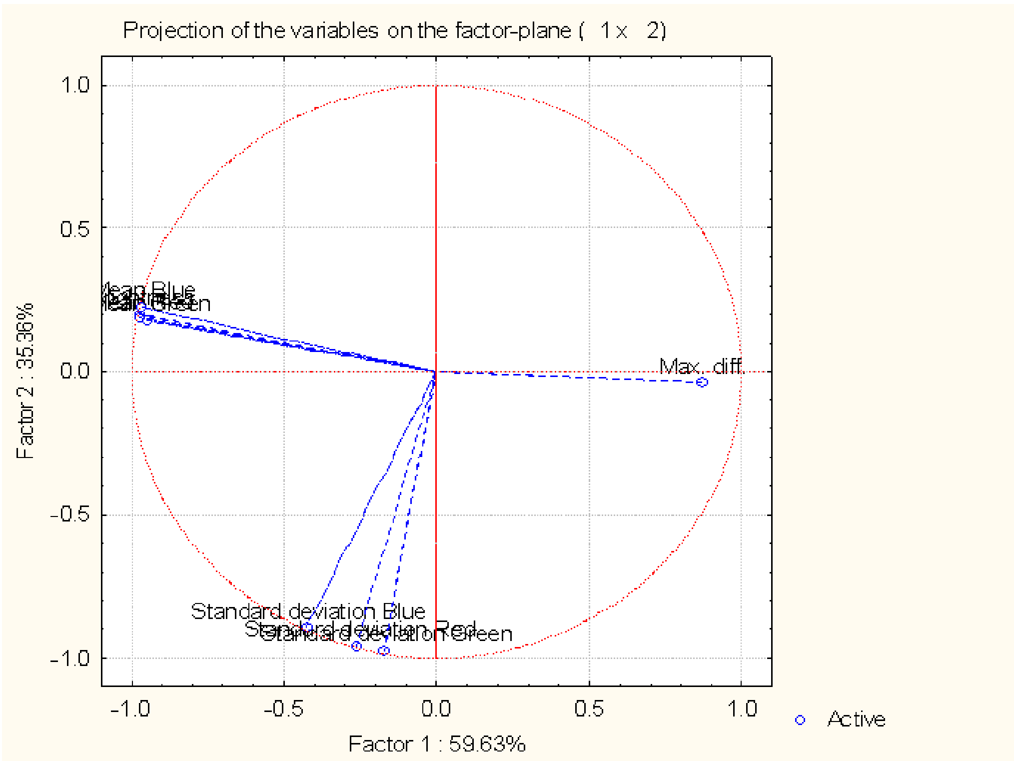
Trials using STATISTICA software

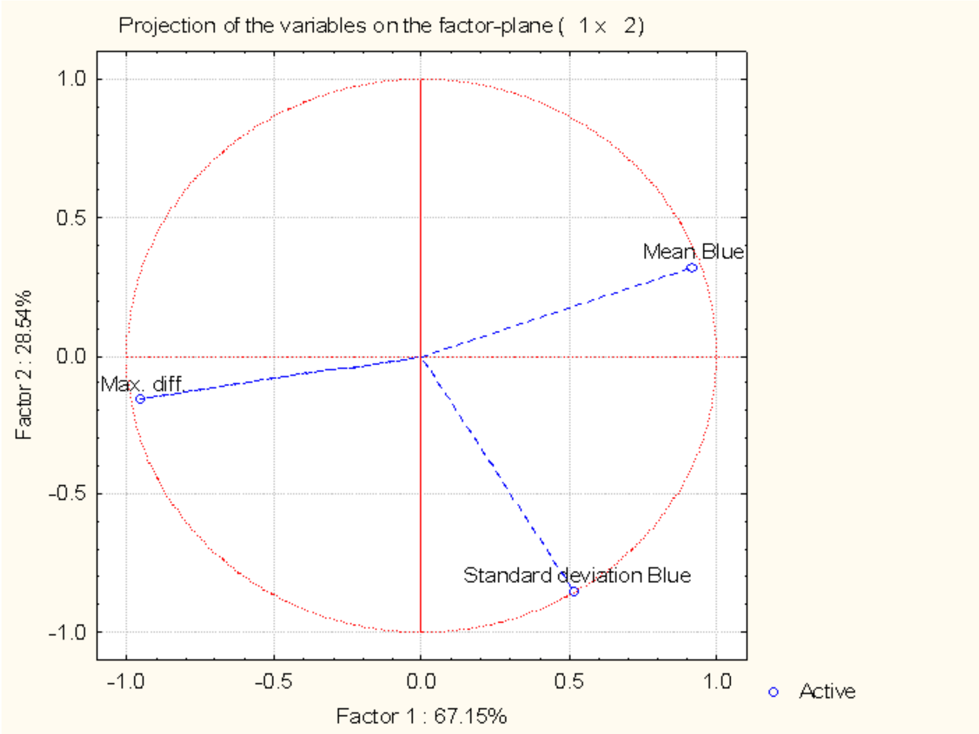
1st trial- Area 5

Coarse level (scale 225)
Urban classes:

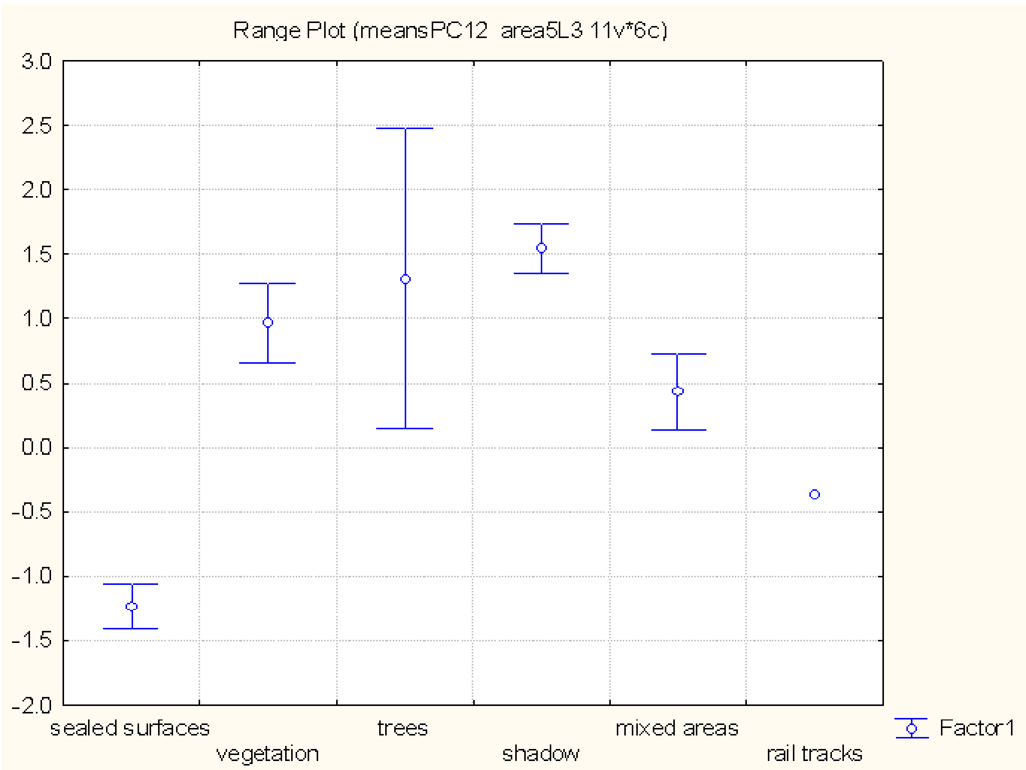
Sealed surfaces
Vegetated surfaces
Trees
Mixed areas
Shadow
Rail tracks

STATISTICA variables
Mean red
Mean green
Mean blue
Brigthness
Max Diff
Sttdv red
Sttdv green
Sttdv blue

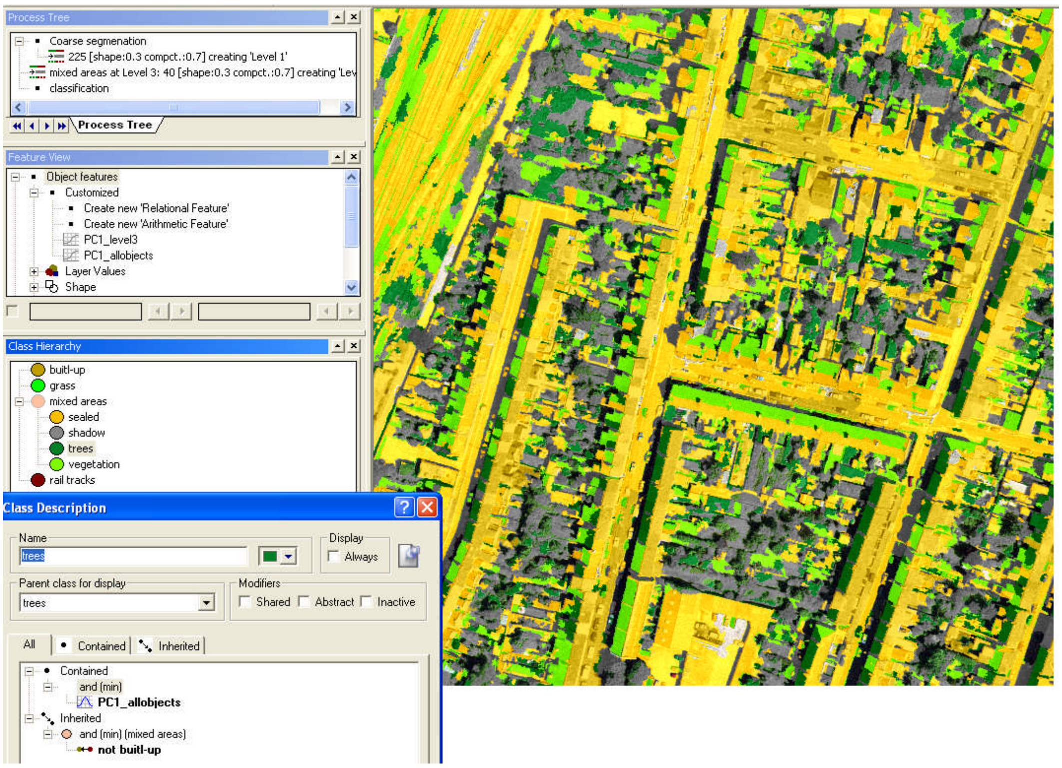




Projection of the variables on the factor-plane (1 x 2)
Mean Blue
Max. diff.
Standard deviation Blue
Factor 2 : 28.54%
Factor 1 : 67.15%
Active
1.0
0.5
0.0
-0.5
-1.0



Range Plot (meansPC12 area5L3 11v*6c)
3.0
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
sealed surfaces
vegetation
trees
shadow
mixed areas
rail tracks
Factor1

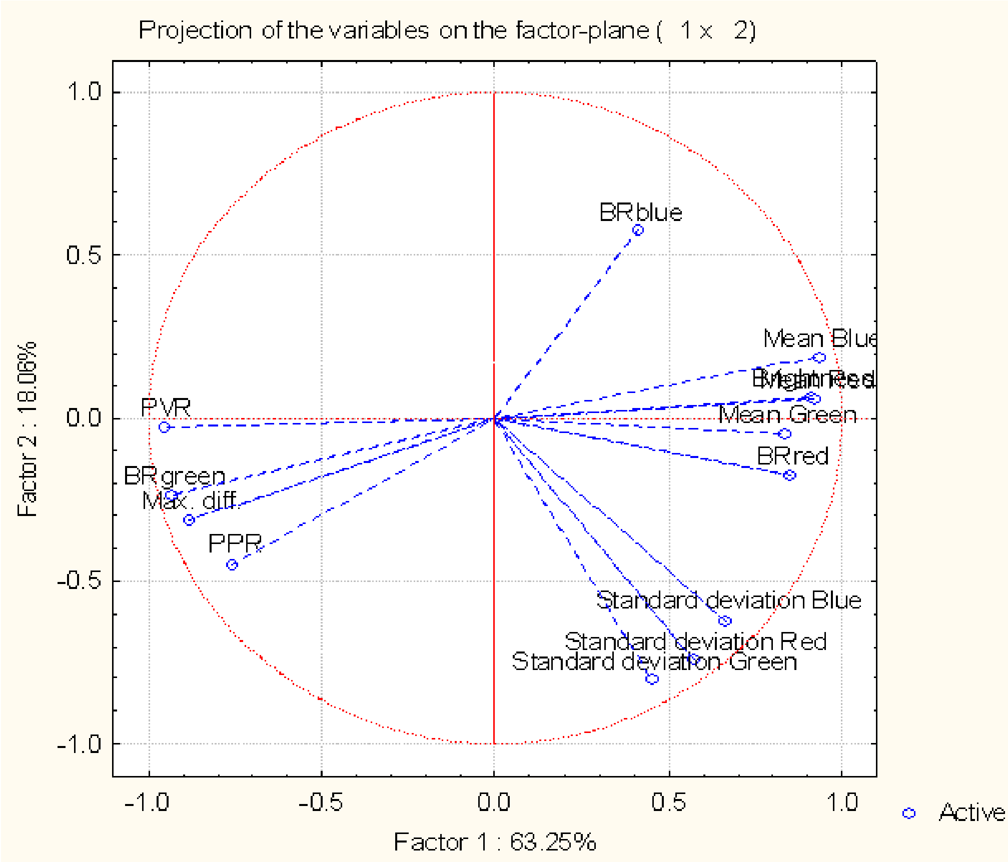


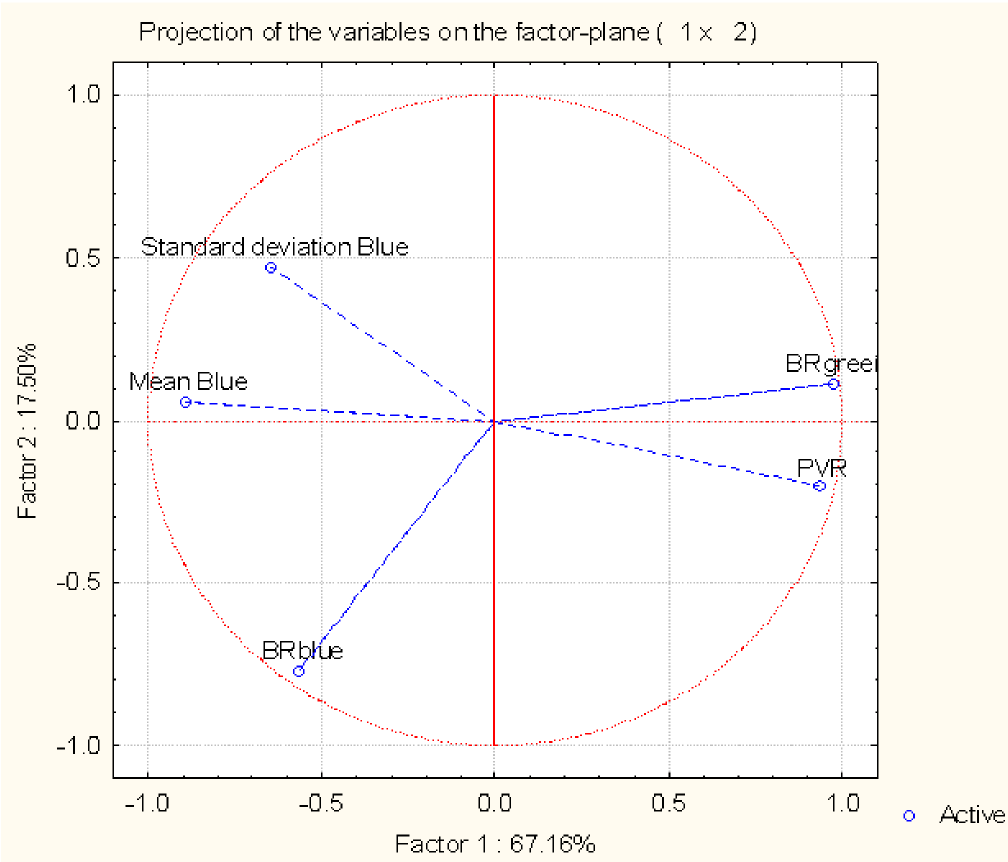
2nd trial- Area 5

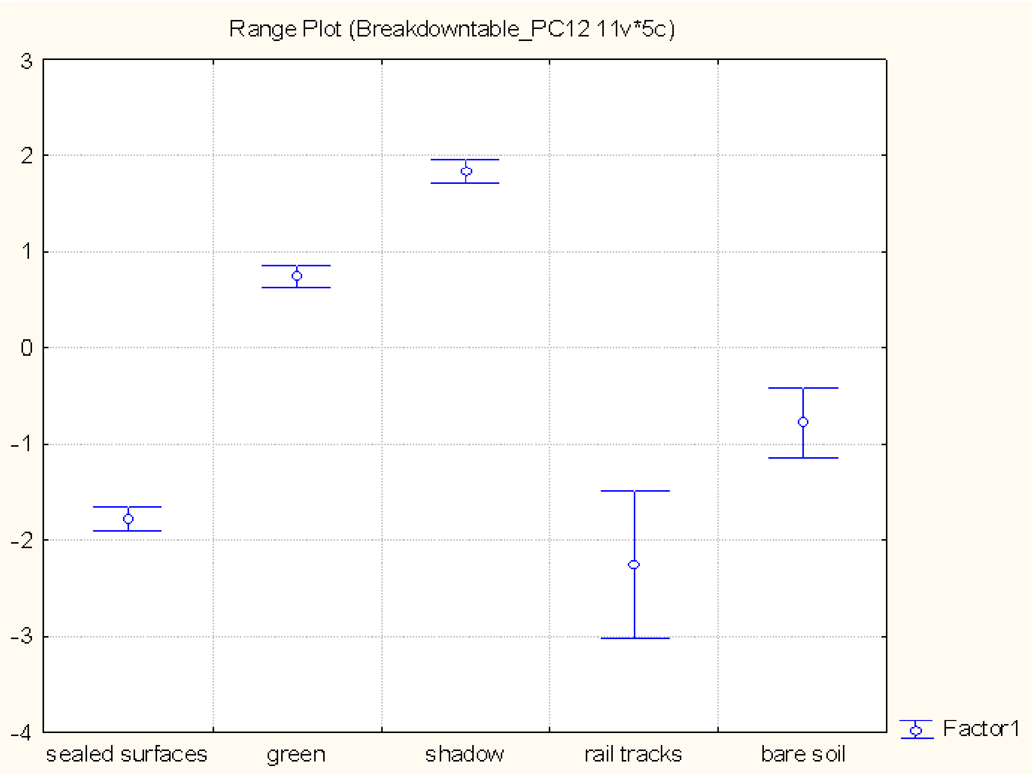
Urban classes:

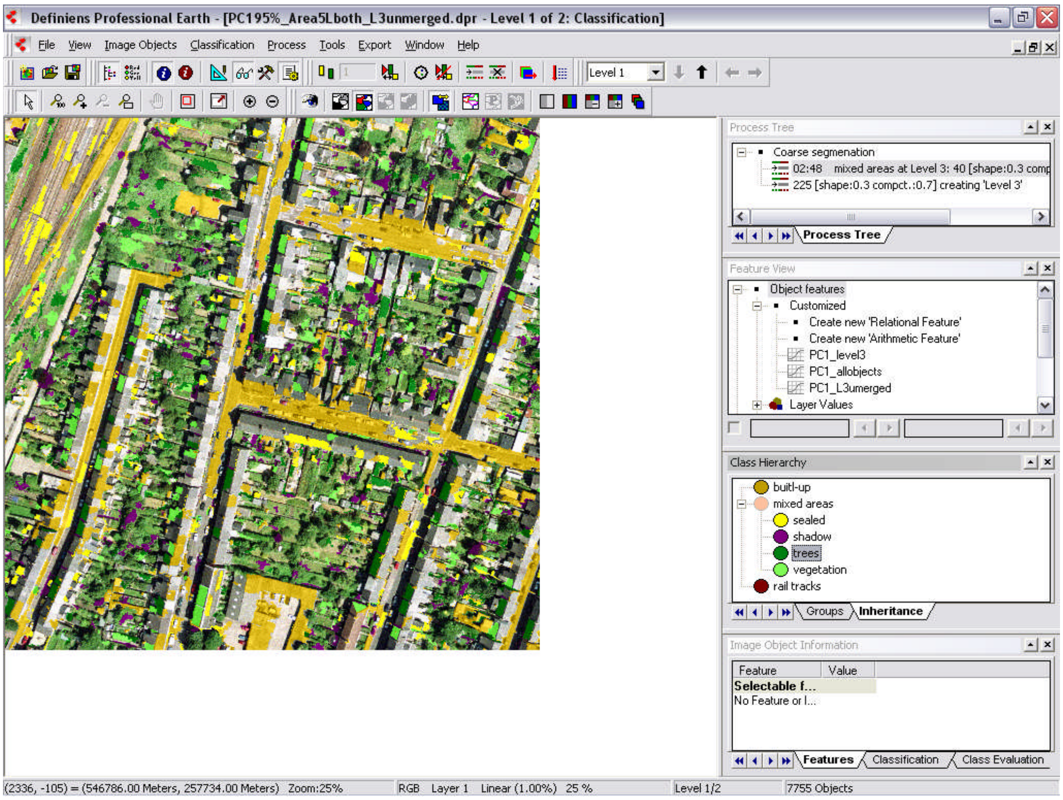
Sealed surfaces
Green surfaces
Shadow
Bare soil
Rail tracks

STATISTICA variables
Mean red
Mean green
Mean blue
Brigthness
Max Diff
Sttdv red
Sttdv green
Sttdv blue
BRred= mean red/mean(RGB)
BRgreen= mean green/mean(RGB)
BRblue=mean blue/mean(RGB)
PPR= (mean green-mean blue)/(mean green+ mean blue)
PVR= (mean green-mean red)/(mean green+ mean red)

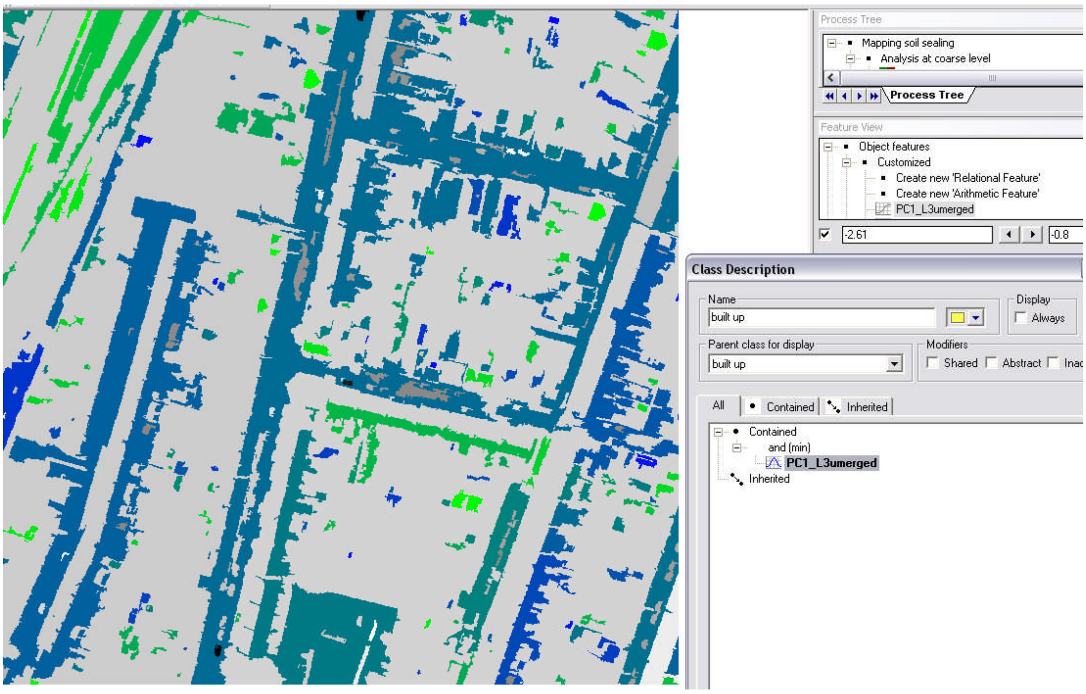

Projection of the variables on the factor-plane (1 x 2)
BRblue
Mean Blue
BrightRed
Mean Red
Mean Green
BRred
PVR
BRgreen
Max. diff.
PPR
Standard deviation Blue
Standard deviation Red
Standard deviation Green
Factor 2 : 18.08%
Factor 1 : 63.25%
Active


Projection of the variables on the factor-plane (1 x 2)
Standard deviation Blue
Mean Blue
BRgreen
PVR
BRblue
Factor 2 : 17.50%
Factor 1 : 67.16%
Active

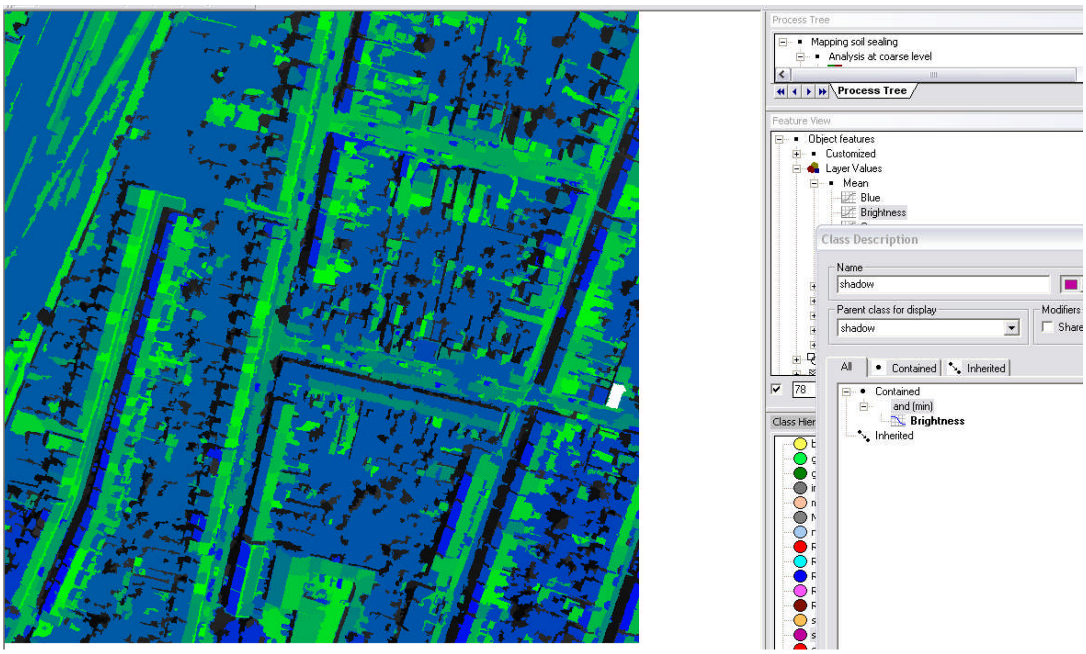

Range Plot (Breakdowntable_PC12 11v*5c)
3
2
1
0
-1
-2
-3
-4
sealed surfaces
green
shadow
rail tracks
bare soil
Factor1


Definiens Professional Earth - [PC195%_Area5Lboth_L3unmerged.dpr - Level 1 of 2: Classification]
File View Image Objects Classification Process Tools Export Window Help
Level 1
Process Tree
Coarse segmenation
02:48 mixed areas at Level 3: 40 [shape:0.3 comp
225 [shape:0.3 compct.:0.7] creating 'Level 3'
Process Tree
Feature View
Object features
Customized
Create new 'Relational Feature'
Create new 'Arithmetic Feature'
PC1_level3
PC1_allobjects
PC1_L3umerged
Layer Values
Class Hierarchy
built-up
mixed areas
sealed
shadow
trees
vegetation
rail tracks
Groups
Inheritance
Image Object Information
Feature
Value
Selectable f...
No Feature or I...
Features
Classification
Class Evaluation
(2336, -105) = (546786.00 Meters, 257734.00 Meters) Zoom:25%
RGB Layer 1 Linear (1.00%) 25 %
Level 1/2
7755 Objects

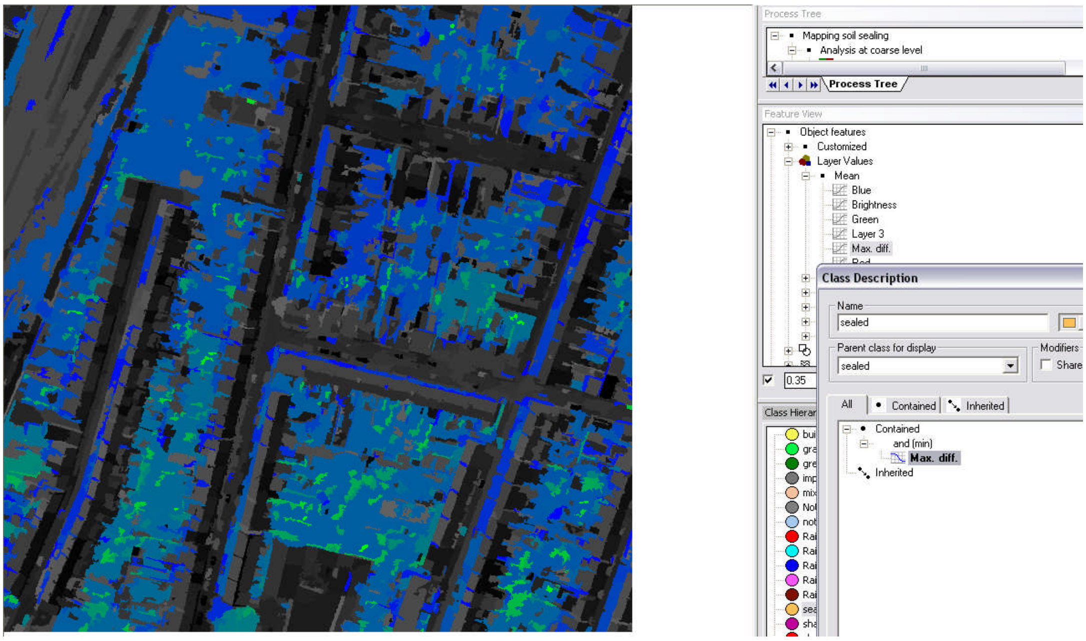
The fuzzy rules of the object-based classification model using aerial photography



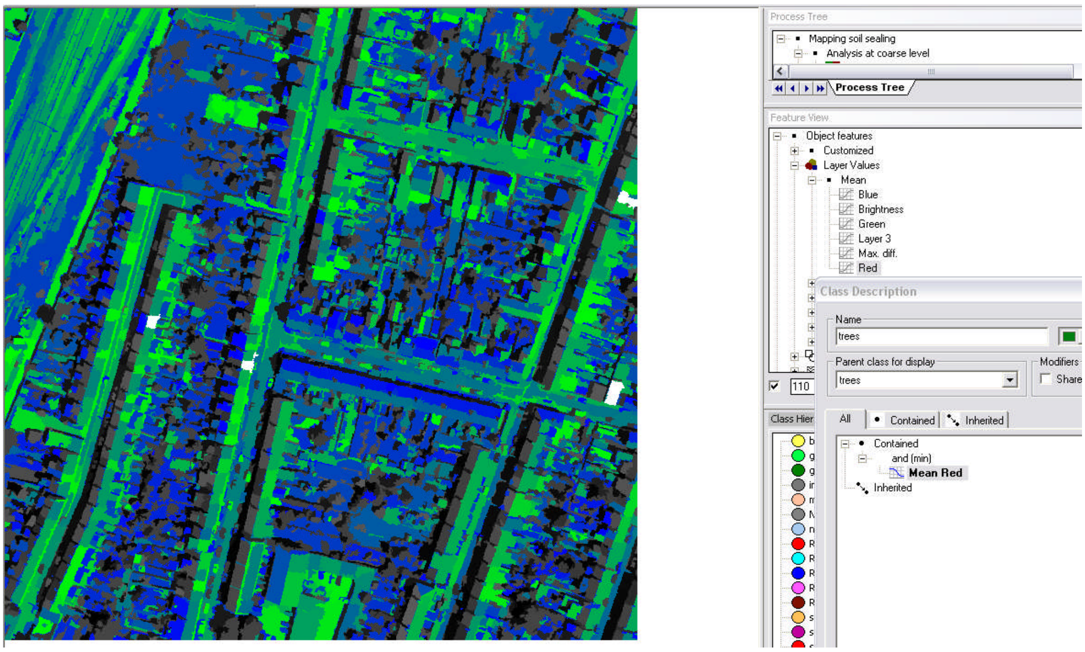
The PC_1 range for the built-up class as identified using the Feature view tool (blue shades)



The brightness range for the shadow class as identified using the Feature view tool (black shade)



The ‘max.diff.’ range for the sealed class as identified using the Feature view tool (black shade)



The red band range for the trees class as identified using the Feature view tool (black shade)

Results from the multiple comparison tests between API and rule-based based classification

Error matrices when different thematic information is used

Industrial area - area0

API \ auto_eCg	sealed	grass	trees	shadow	rails	Sum Map 1	
sealed	3079232	22405	29362	52052	0	3183051	
grass	34117	31719	86812	4533	0	157181	
trees	15301	11152	79634	24231	0	130318	
shadow	33866	1644	46501	231157	0	313168	
rails	207529	569	8020	164	0	216282	
Sum Map 2	3370045	67489	250329	312137	0	4000000	
							85.50%

API \ auto_eCg	sealed	grass	trees	rails	Sum Map 1	
sealed	3388160	31709	76350	0	3496219	
grass	35141	35228	86812	0	157181	
trees	28481	21904	79933	0	130318	
rails	207693	569	8020	0	216282	
Sum Map 2	3659475	89410	251115	0	4000000	
						88%

API \ auto_eCg	sealed	green	rails	Sum Map 1	
sealed	3388160	108059	0	3496219	
green	63622	223877	0	287499	
rails	207693	8589	0	216282	
Sum Map 2	3659475	340525	0	4000000	
					90%

API \ auto_eCg	sealed	grass	trees	rails	Sum Map 1	User
sealed	3388160	31709	76350	0	3496219	0.96909
grass	35141	35228	86812	0	157181	0.22412
trees	28481	21904	79933	0	130318	0.61337
rails	207693	569	8020	0	216282	0.00000
Sum Map 2	3659475	89410	251115	0	4000000	
Producer	0.92586	0.39401	0.31831	#DIV/0!		0.87583025
	θ1=	0.87583			kappa 1=	0.371072602
	θ2=	0.802569				
	θ3=	1.517738			Var(k1)=	9.02705E-05
	θ4=	2.788405				
API \ auto_eCg	sealed	green	rails	Sum Map 1	User	
sealed	3388160	108059	0	3496219	0.96909	
green	63622	223877	0	287499	0.77871	
rails	207693	8589	0	216282	0.00000	
Sum Map 2	3659475	340525	0	4000000		
Producer	0.92586	0.65745	#DIV/0!		0.90300925	
	θ1=	0.903009			kappa 1=	0.50065471
	θ2=	0.805764				
	θ3=	1.524077			Var(k1)=	7.9066E-05
	θ4=	2.792733				
		z=	**9.9579447**			

Residential area - area5

API/ auto_eCg	sealed	grass	trees	shadow	rails	b.soil	Sum Map 1	
sealed	1863496	41836	34531	97723	3800	0	2041386	
grass	88976	423631	78634	36208	7625	0	635074	
trees	45485	261718	262561	84556	48	0	654368	
shadow	38660	5420	23446	383537	50	0	451113	
rails	174	8004	630	0	186629	0	195437	
b.soil	17020	2807	1809	986	0	0	22622	
Sum Map 2	2053811	743416	401611	603010	198152	0	4000000	
								78%

API/ auto_	sealed	grass	trees	shadow	rails	Sum Map 1	
sealed	1863496	41836	34531	97723	3800	2041386	
grass	88976	423631	78634	36208	7625	635074	
trees	45485	261718	262561	84556	48	654368	
shadow	38660	5420	23446	383537	50	451113	
rails	174	8004	630	0	186629	195437	
Sum Map 1	2036791	740609	399802	602024	198152	3977378	
							78%

API/ auto_eCg	sealed	grass	trees	rails	Sum Map 1	
sealed	2229972	50843	41366	3850	2326031	
grass	134404	482186	91298	7625	715513	
trees	74299	318721	264372	48	657440	
rails	174	8004	630	186629	195437	
Sum Map 2	2438849	859754	397666	198152	3894421	
						81%

API/ auto_eCg	sealed	green	rails	Sum Map 1	
sealed	2229972	92209	3850	2326031	
green	208703	1156577	7673	1372953	
rails	174	8634	186629	195437	
Sum Map 2	2438849	1257420	198152	3894421	
					92%

API/ auto_eCg	sealed	grass	trees	rails	Sum Map 1	User
sealed	2229972	50843	41366	3850	2326031	0.95870
grass	134404	482186	91298	7625	715513	0.67390
trees	74299	318721	264372	48	657440	0.40212
rails	174	8004	630	186629	195437	0.95493
Sum Map 2	2438849	859754	397666	198152	3894421	
Producer	0.91435	0.56084	0.66481	0.94185		0.812228
	θ1=	0.812228			kappa 1=	0.66802
	θ2=	0.434389				
	θ3=	0.77391			Var(k1)=	6.57E-07
	θ4=	0.941602				

API/ auto_eCg	sealed	green	rails	Sum Map 1	User	
sealed	2229972	92209	3850	2326031	0.95870	
green	208703	1156577	7673	1372953	0.84240	
rails	174	8634	186629	195437	0.95493	
Sum Map 2	2438849	1257420	198152	3894421		
Producer	0.91435	0.91980	0.94185		0.917512	
	θ1=	0.917512			kappa 2=	0.838126
	θ2=	0.490419				
	θ3=	0.906024			Var(k2)=	5.66E-07
	θ4=	1.062319				
			z=	**153.82513**		

Commercial area – area20

API/auto_eCg	sealed	grasss	trees	shadow	Sum Map 1	
sealed	2707080	10127	31472	295260	3043939	
grasss	18211	61894	36805	2737	119647	
trees	6848	23488	89073	69985	189394	
shadow	63408	1019	8331	574262	647020	
Sum Map 2	2795547	96528	165681	942244	4000000	
						86%

API/auto_eCg	sealed	grasss	trees	unclassified shadow	Sum Map 1	
sealed	3567122	21265	37469	0	3625856	
grasss	40125	63721	37163	0	141009	
trees	57732	42756	89923	0	190411	
unclassified	29912	10926	1886	0	42724	
Sum Map 2	3694891	138668	166441	0	4000000	
						93%

API/auto_eCg	sealed	grasss	trees	Sum Map 1	
sealed	3567122	21265	37469	3625856	
grasss	40125	63721	37163	141009	
trees	57732	42756	89923	190411	
Sum Map 2	3664979	127742	164555	3957276	
					94%

API/auto_eCg	sealed	green	Sum Map	User	
sealed	3567122	58734	3625856	0.98380	
green	97857	233563	331420	0.70473	
Sum Map 2	3664979	292297	3957276		
Producer	0.97330	0.79906			96%

API/auto_eCg	sealed	grasss	trees	Sum Map 1	User	
sealed	3567122	21265	37469	3625856	0.98380	
grasss	40125	63721	37163	141009	0.45189	
trees	57732	42756	89923	190411	0.47226	
Sum Map 2	3664979	127742	164555	3957276		
Producer	0.97330	0.49883	0.54646		0.940234	
	θ1=	0.940234			kappa 1=	0.596927
	θ2=	0.851724				
	θ3=	1.663875			Var(k1)=	0.000198
	θ4=	3.09658				
API/auto_eCg	sealed	green	Sum Map 1	User		
sealed	3567122	58734	3625856	0.98380		
green	97857	233563	331420	0.70473		
Sum Map 2	3664979	292297	3957276			
Producer	0.97330	0.79906		0.960429599		
	θ1=	0.96043			Kappa 2=	0.727553
	θ2=	0.854759				
	θ3=	1.670046			Var(k2)=	0.000149
	θ4=	3.100578				
			z=	**7.017594401**		

Residential area – area26

API/ auto_eCg	sealed	grass	trees	shadow	b.soil	temporary	Sum Map 1	
sealed	1528440	33188	52228	92326	0	0	1706182	
grass	151646	387226	307995	103875	0	0	950742	
trees	30506	56773	475659	254142	0	0	817080	
shadow	38421	2516	28021	447225	0	0	516183	
b.soil	6344	114	483	857	0	0	7798	
temporary features	334	231	733	29	0	0	1327	
Sum Map 2	1755864	480082	865191	898863	0	0	4000000	
								71%

API/ auto_eCg	sealed	grass	trees	shadow	Sum Map 1	
sealed	1528440	33188	52228	92326	1706182	
grass	151646	387226	307995	103875	950742	
trees	30506	56773	475659	254142	817080	
shadow	38421	2516	28021	447225	516183	
Sum Map 2	1749013	479703	863903	897568	3990187	
						71%

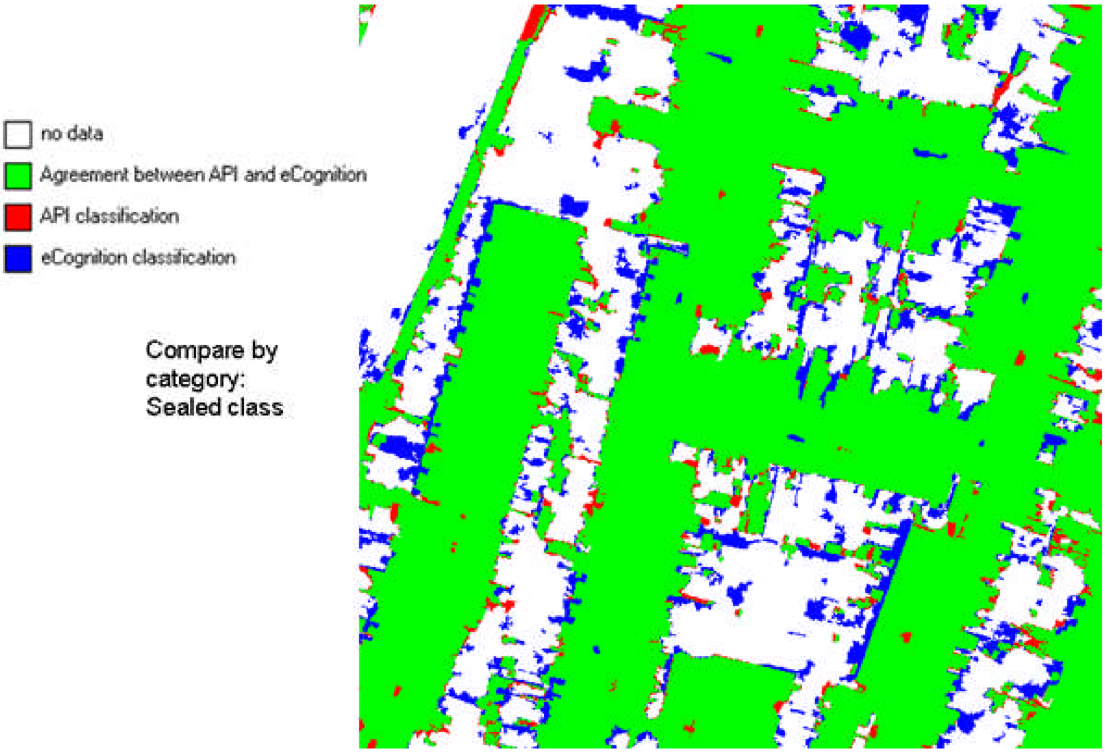
API/ auto_eCg	sealed	grass	trees	Sum Map 1	
sealed	1781064	50336	62994	1894394	
grass	274555	511866	324425	1110846	
trees	135703	233558	488654	857915	
Sum Map 2	2191322	795760	876073	3863155	
					72%

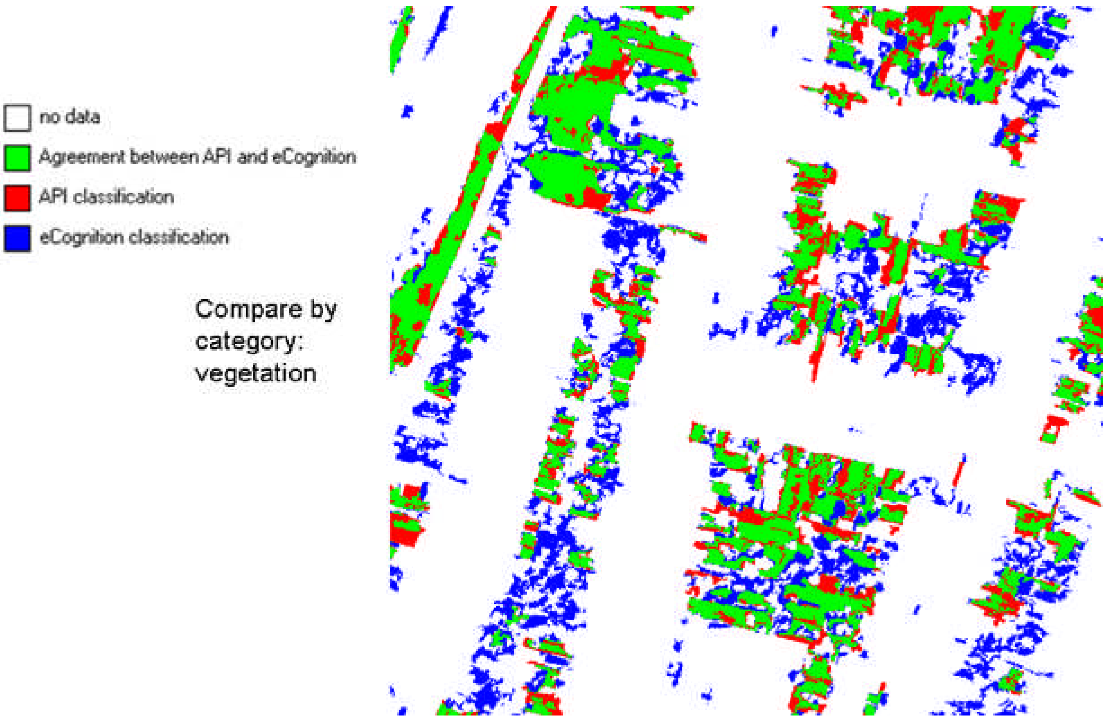
API/ auto_eCg	sealed	green	Sum Map 1	
sealed	1781064	113330	1894394	
green	410258	1558503	1968761	
Sum Map 2	2191322	1671833	3863155	
				86.50%

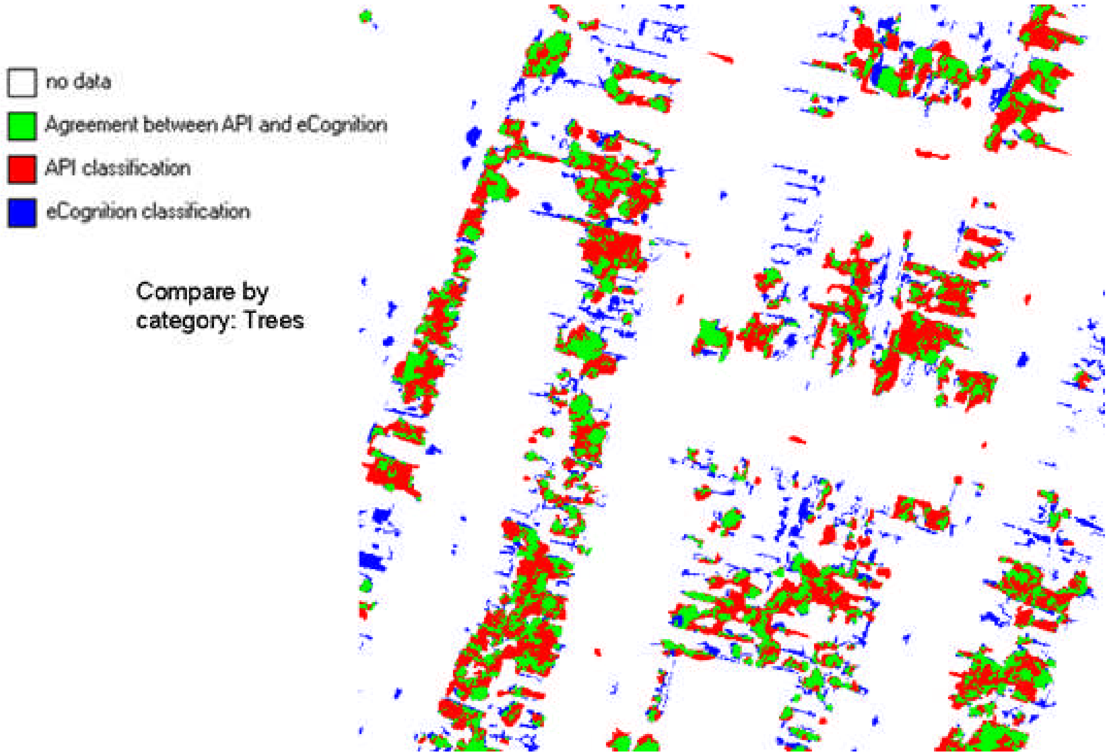
API/ auto_eCg	sealed	grass	trees	Sum Map 1	User	
sealed	1781064	50336	62994	1894394	0.94018	
grass	274555	511866	324425	1110846	0.46079	
trees	135703	233558	488654	857915	0.56958	
Sum Map 2	2191322	795760	876073	3863155		
Producer	0.81278	0.64324	0.55778		0.720029	
θ1=	0.720029095				kappa 1=	0.542716889
θ2=	0.387751487					
θ3=	0.609768764				Var(k1)=	5.85041E-07
θ4=	0.677039001					
API/ auto_eCg	sealed	green	Sum Map 1	User		
sealed	1781064	113330	1894394	0.94018		
green	410258	1558503	1968761	0.79162		
Sum Map 2	2191322	1671833	3863155			
Producer	0.81278	0.93221		0.8644662		
θ1=	0.86446622				kappa 2=	0.729632326
θ2=	0.498705678					
θ3=	0.86778527				Var(k2)=	9.55234E-07
θ4=	0.998492611					
		Z=	**150.60732**			

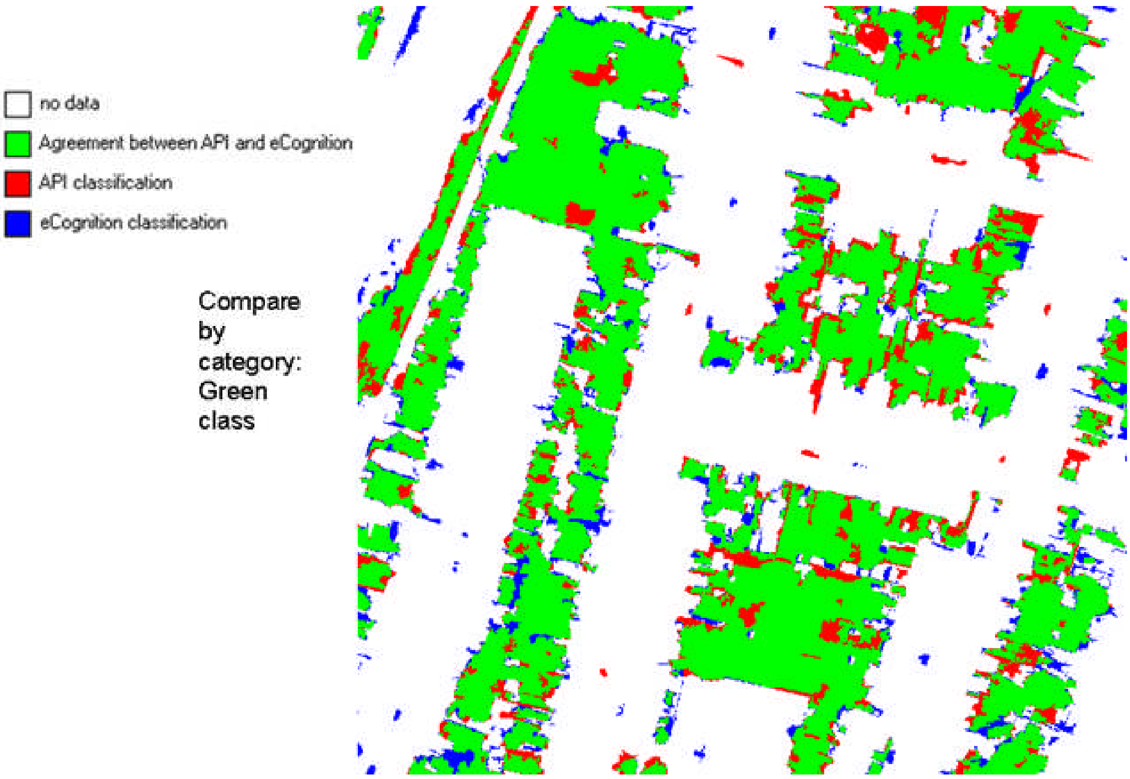
<u>Qualitative analysis between API and automated OBIA using the MCK</u>

i) Residential area - area5

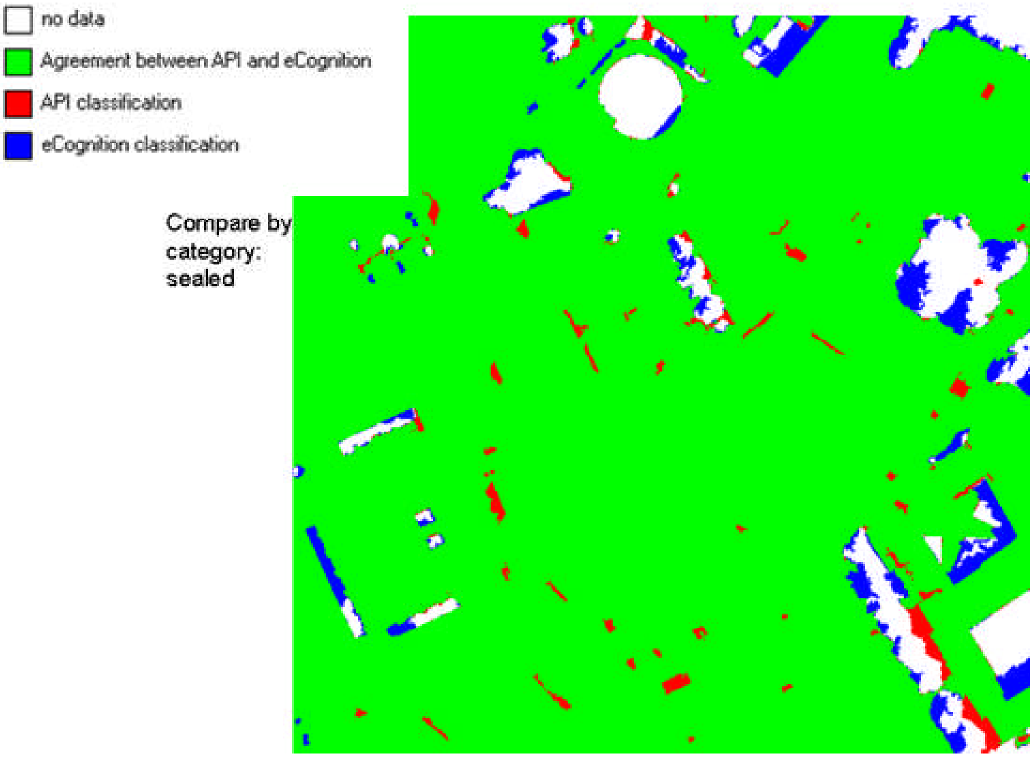


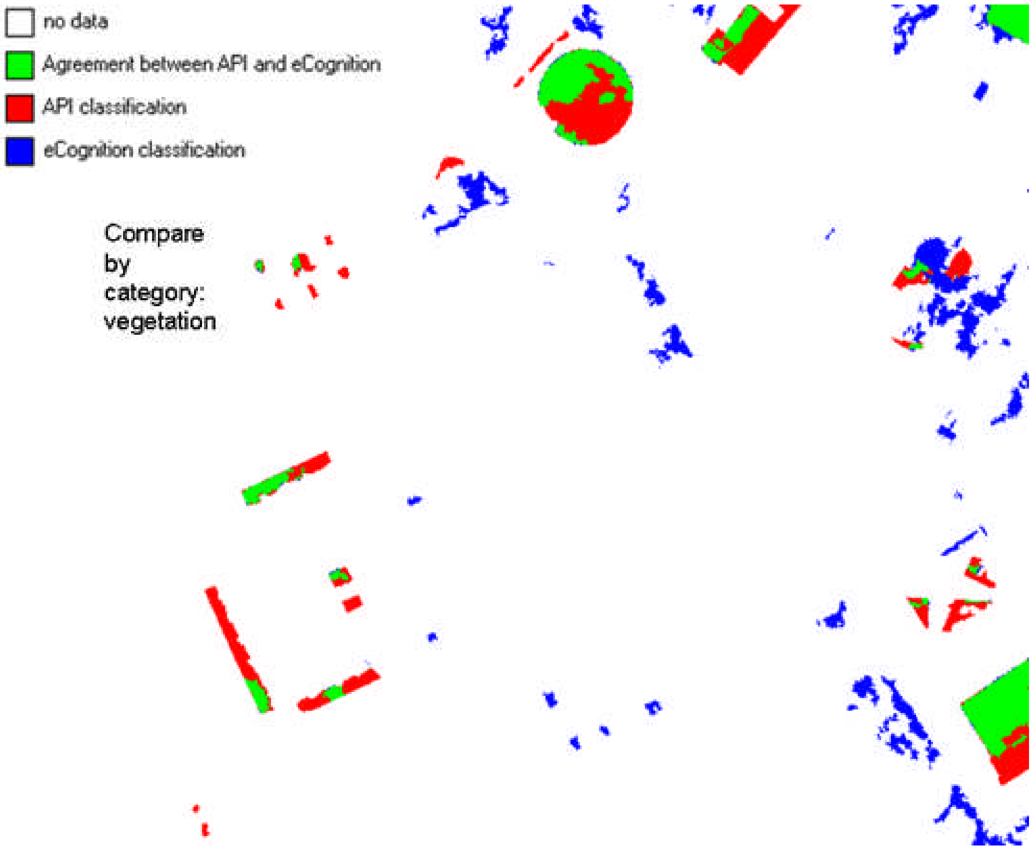


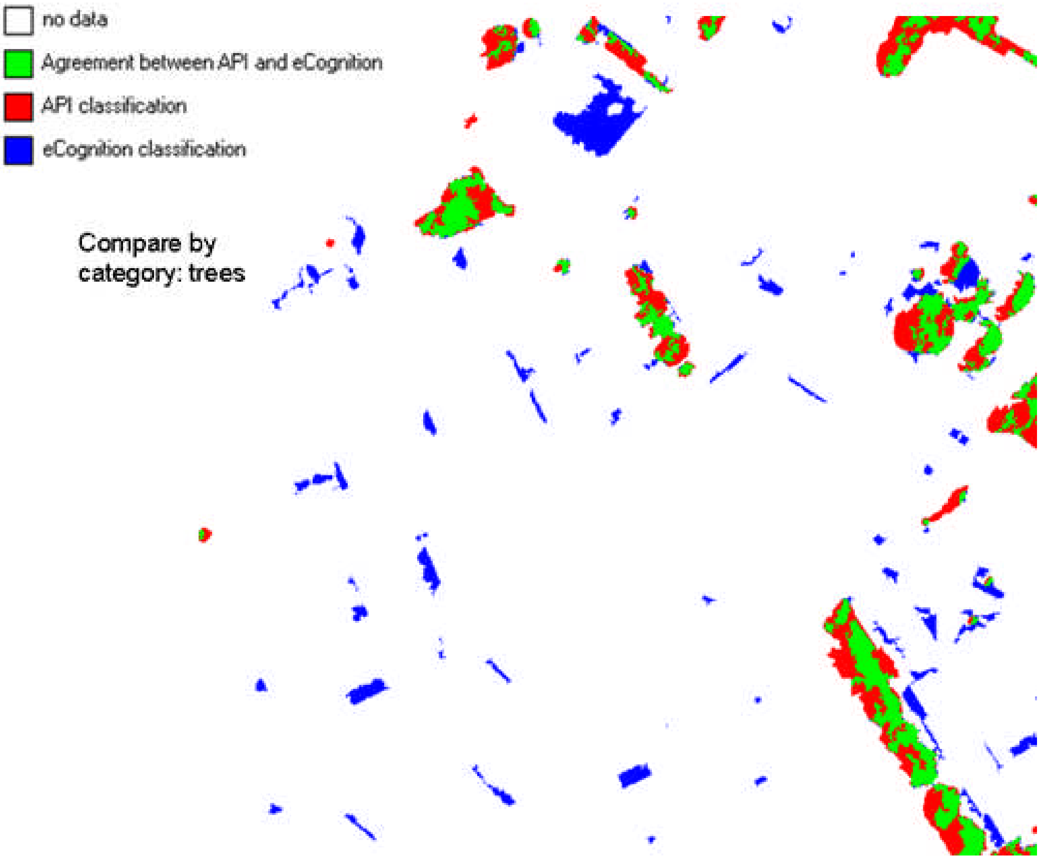

no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: Trees

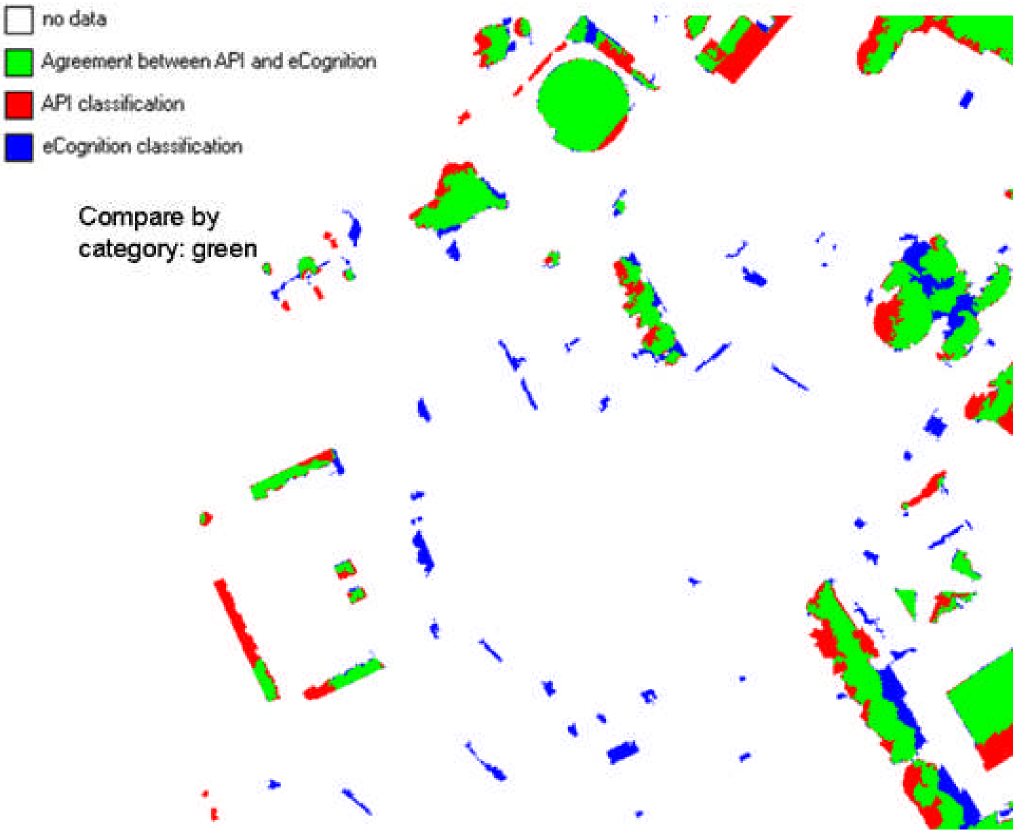

no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: Green class

ii) Commercial area – area20

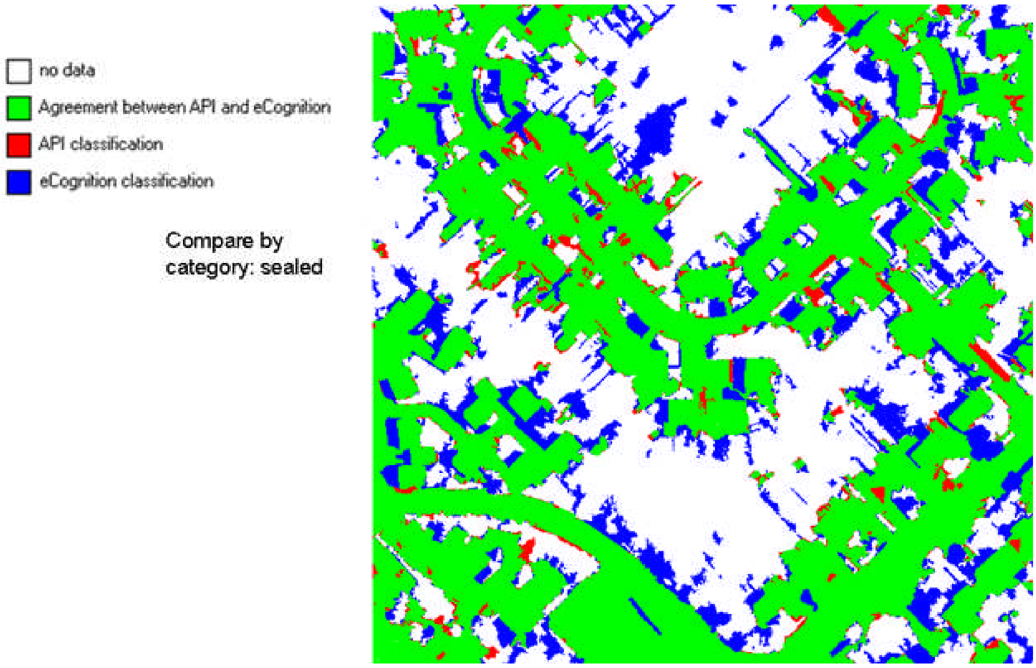


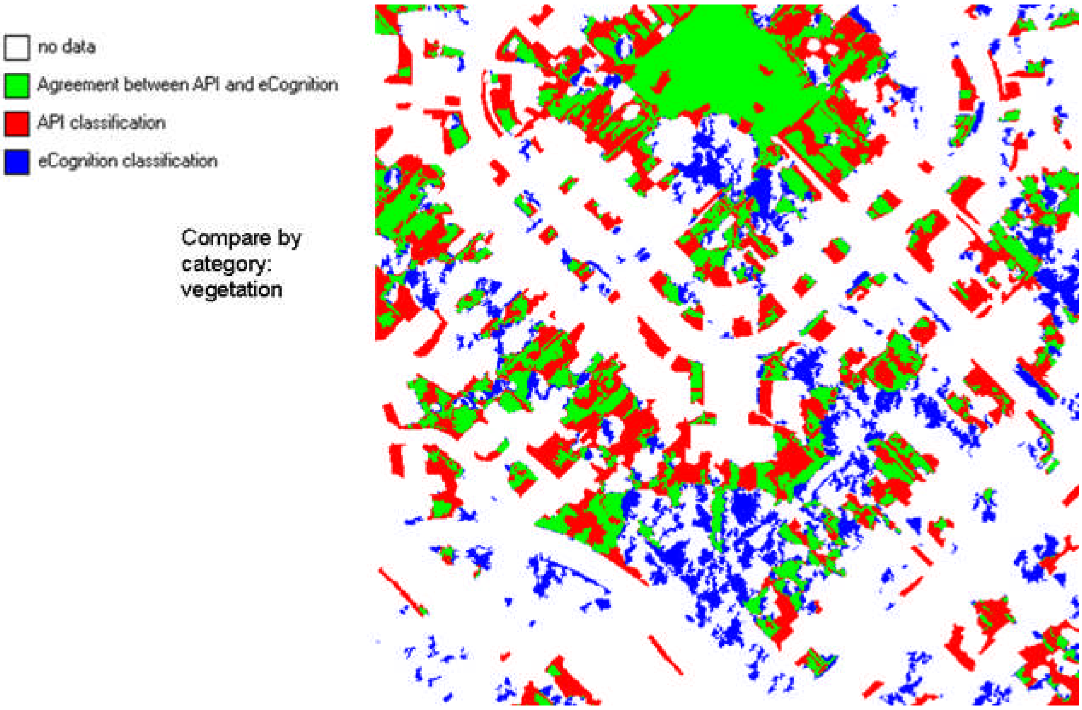


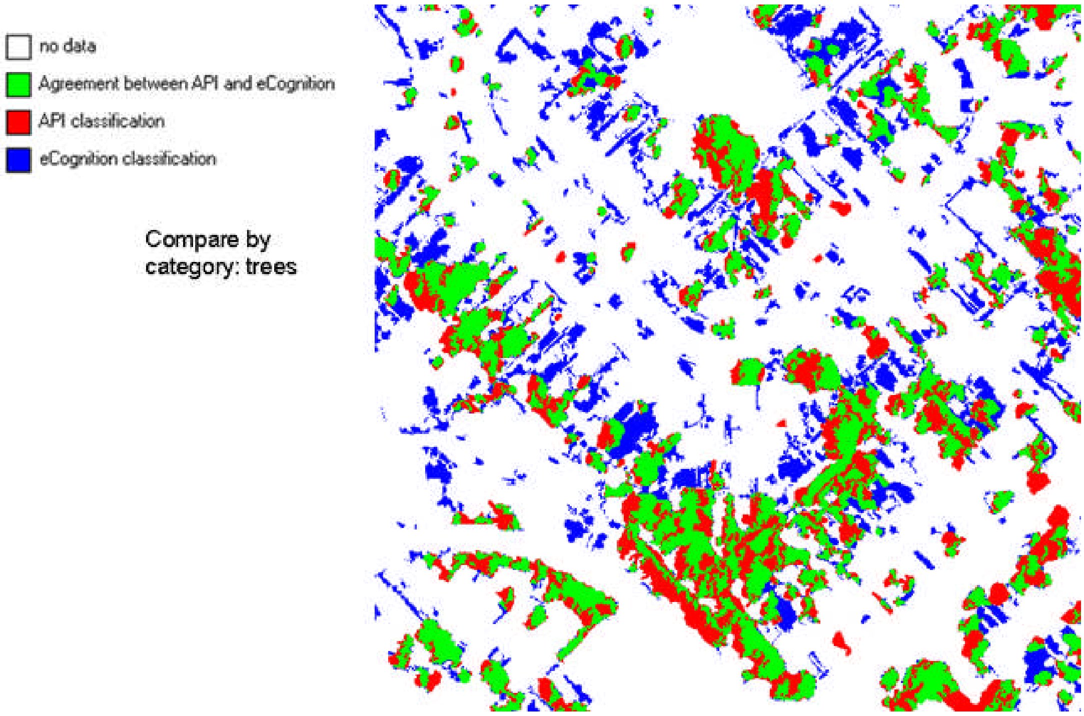

no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by
category: trees

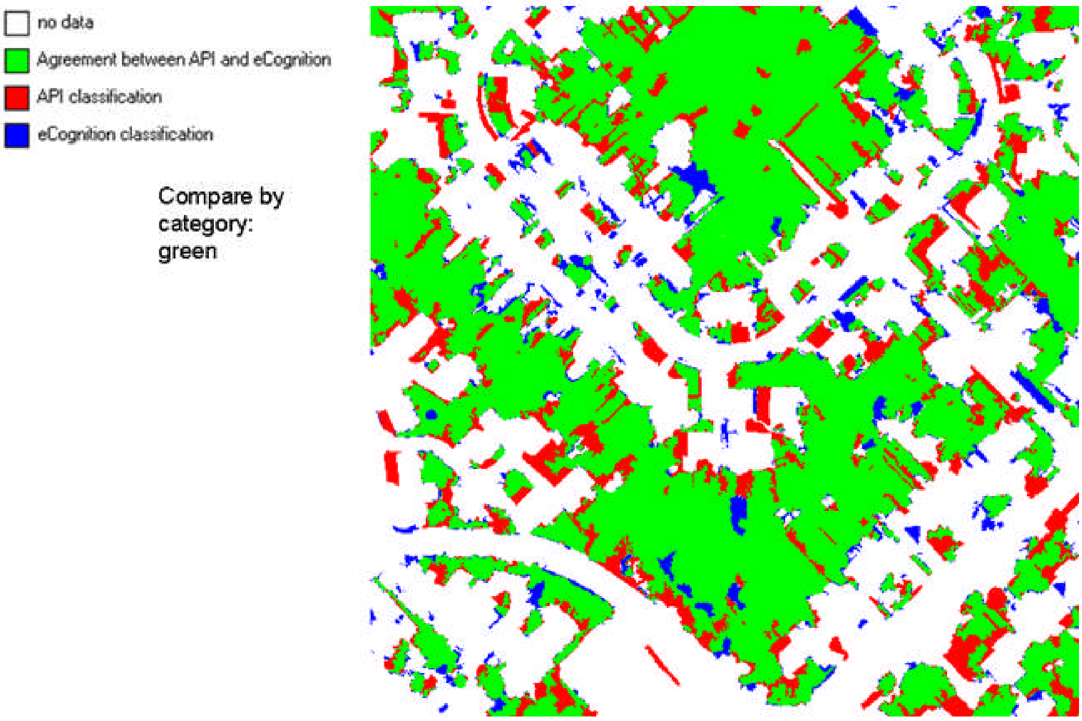

no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by
category: green

iii) Residential area – area26

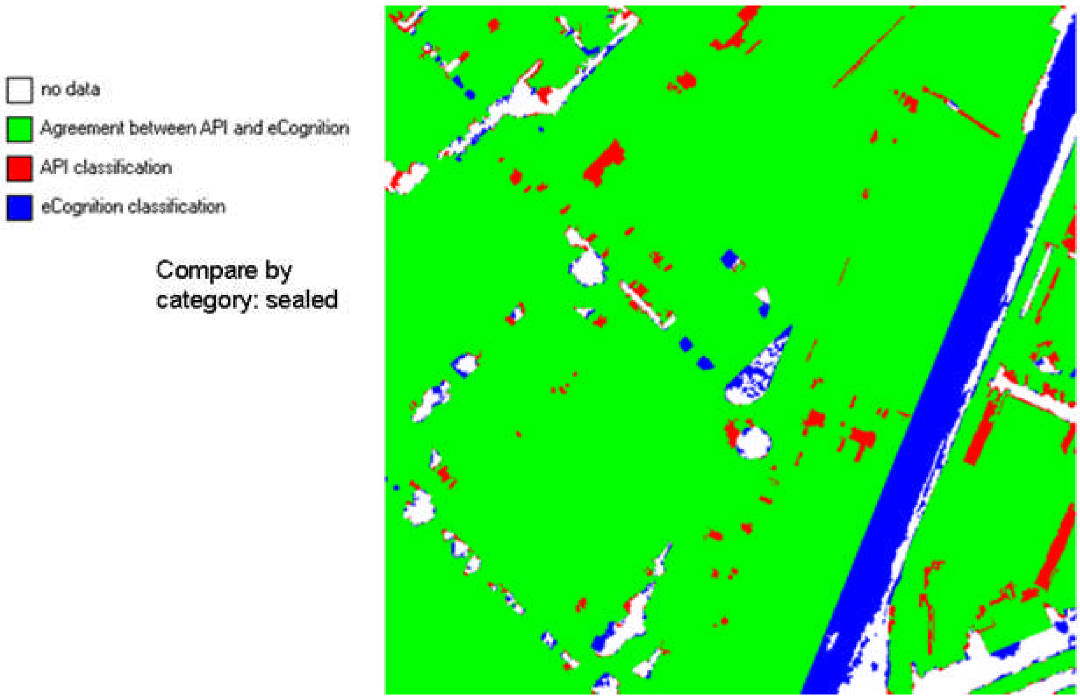


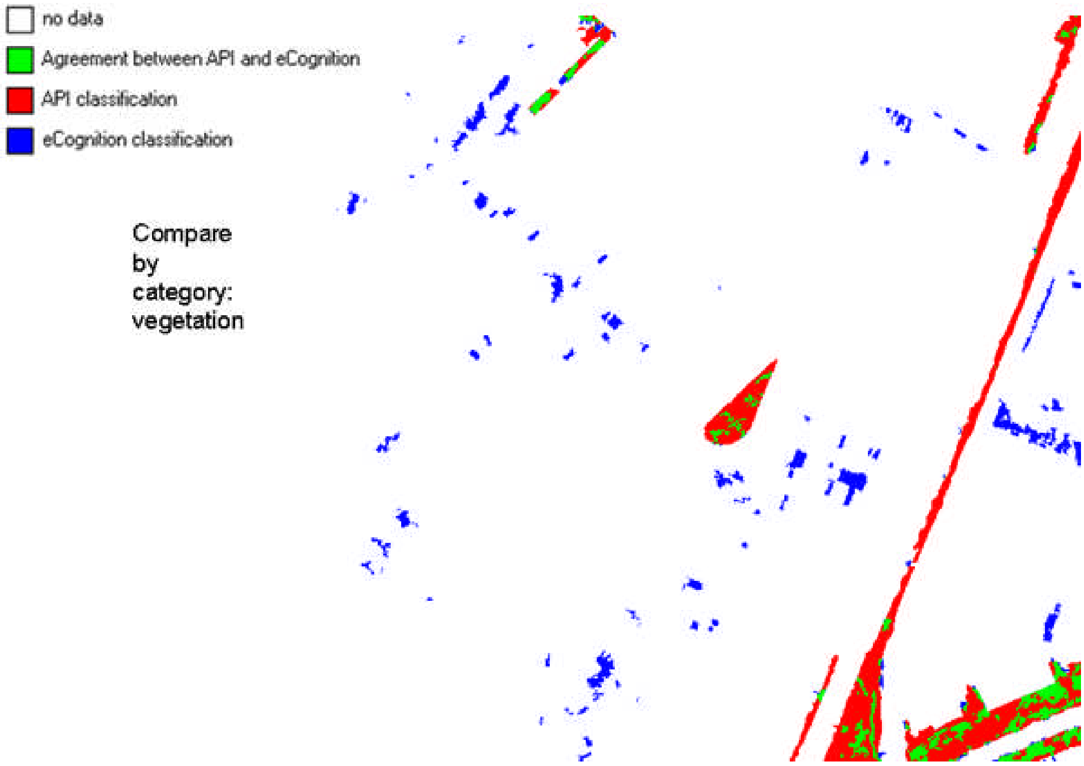


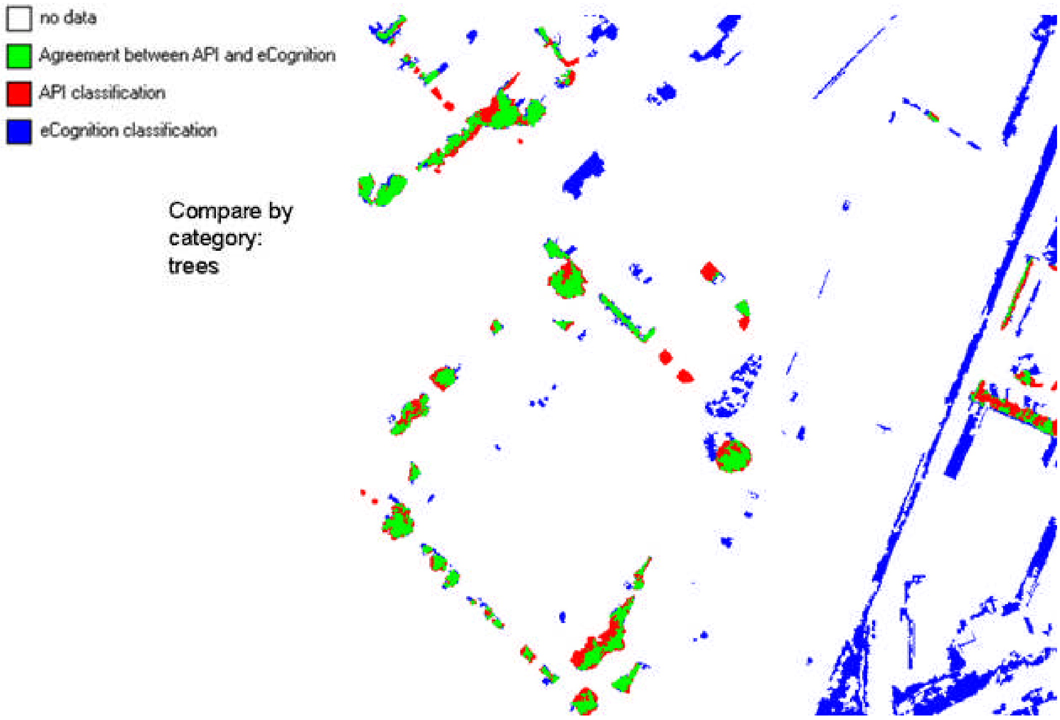

no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: trees

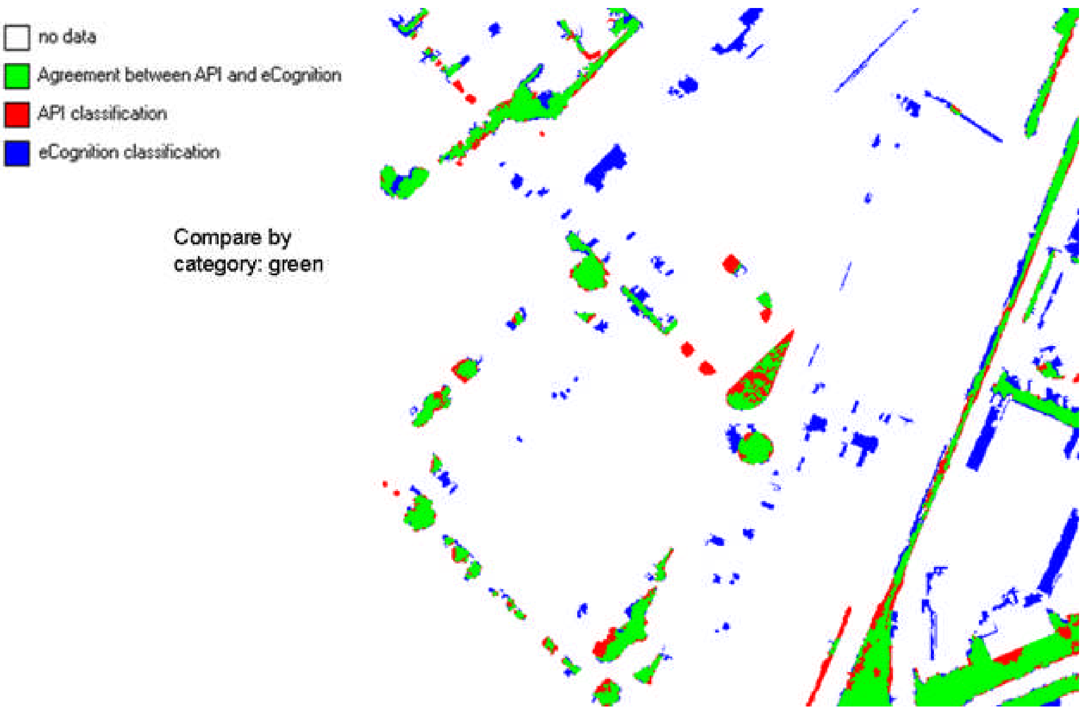

no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: green

iv) Industrial area – area0






no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: trees


no data
Agreement between API and eCognition
API classification
eCognition classification
Compare by category: green

Conversion of API in 25% intervals and comparison with API based on MasterMap polygons; automated OBIA with the use of MasterMap

Residential area - area5

Count of TOID	eCgMMSEALED							
APIMMSealed	0	25	50	75	100	Grand Total	User	
0	18	39	34	23	58	172	0.104651	
25	12	23	14	15	37	101	0.227723	
50	8	10	15	3	29	65	0.230769	
75		8	5	3	23	39	0.076923	
100	22	51	39	24	135	271	0.498155	
Grand Total	60	131	107	68	282	648		
Producer	0.3	0.175573	0.140187	0.044118	0.478723			
						30%	0.299383	
	θ1=	0.299383				Kappa 1=	0.051984	
	θ2=	0.260964						
	θ3=	0.207352				Var(k1)=	0.00132	
	θ4=	0.321764						
Count of TOID	eCgMMSEALED							
ManualAPISEALED	0	25	50	75	100	Grand Total	User	
0	10	16	12	11	38	87	0.114943	
25	13	30	29	17	53	142	0.211268	
50	7	19	15	10	24	75	0.2	
75	6	12	7	2	24	51	0.039216	
100	24	54	44	28	142	292	0.486301	
Grand Total	60	131	107	68	281	647		
Producer	0.166667	0.229008	0.140187	0.029412	0.505338			
						31%	0.307573	
	θ1=	0.307573				Kappa 1=	0.037797	
	θ2=	0.280374						
	θ3=	0.224539				Var(k1)=	0.00154	
	θ4=	0.362664						
				z=	**0.265306**			

Residential area – area26

Count of TOID	MMeCgSEALED						
MM_APISealed	0	25	50	75	100	Grand Total	User
0	8	24	18	4	3	57	0.140351
25		12	29	5		46	0.26087
50		1	14	5	1	21	0.666667
75			3	4	1	8	0.5
100			1	14	21	36	0.583333
Grand Total	8	37	65	32	26	168	
Producer	1	0.324324	0.215385	0.125	0.807692		
						35%	0.35119
	θ_1=	0.35119				Kappa 1=	0.221064
	θ_2=	0.167056					
	θ_3=	0.148172				Var(k1)=	0.003034
	θ_4=	0.123878					

Count of TOID	MMeCgSEALED						
ManualAPISEAL	0	25	50	75	100	Grand Total	User
0	5	13	3	1	1	23	0.217391
25	1	23	36	6		66	0.348485
50		1	25	8	1	35	0.714286
75	1		1	13	5	20	0.65
100	1			4	19	24	0.791667
Grand Total	8	37	65	32	26	168	
Producer	0.625	0.621622	0.384615	0.40625	0.730769		
						51%	0.505952
	θ_1=	0.505952				Kappa 1=	0.367877
	θ_2=	0.218431					
	θ_3=	0.235615				Var(k1)=	0.004989
	θ_4=	0.208086					
				z=	**1.638985**		

Commercial area – area20

Count of TOID	MMeCgSEALED						
APIMMSealed	0	25	50	75	100	Grand Total	User
0	9	4	7	3	17	40	0.225
25			1	1	1	3	0
50		1	1	1		3	0.333333
75				1		1	1
100	1	1		3	102	107	0.953271
Grand Total	10	6	9	9	120	154	
Producer	0.9	0	0.111111	0.111111	0.85		
						73%	0.733766
	θ_1=	0.733766				Kappa 1=	0.394166
	θ_2=	0.56055					
	θ_3=	0.996205				Var(k1)=	0.07378
	θ_4=	1.536426					

Count of TOID	MMeCgSEALED						
ManualAPISEALED	0	25	50	75	100	Grand Total	User
0	8	4	1	2	2	17	0.470588
25		2	4	2		8	0.25
50			2	2		4	0.5
75	1		2	1	7	11	0.090909
100	1			2	111	114	0.973684
Grand Total	10	6	9	9	120	154	
Producer	0.8	0.333333	0.222222	0.111111	0.925		
						80.50%	0.805195
	θ_1=	0.805195				Kappa 1=	0.522875
	θ_2=	0.59171					
	θ_3=	1.107438				Var(k1)=	0.086855
	θ_4=	1.719424					
				z=	**0.321136**		

Statistical analysis between satellite data in automated OBIA using two different rule-sets

Comparison between the satellite and the RGB model

Area 5

API/eCgsatellite	sealed	green	rails	Sum Map 1		
sealed	59114	14986	0	74100		
green	10755	33007	0	43762		
rails	3362	21	2834	6217		
Sum Map 2	73231	48014	2834	124079		0.765279
θ1=	0.765279			kappa 1=	0.539681	
θ2=	0.49009					
θ3=	0.764129			Var(k1)=	4.2E-05	
θ4=	1.019143					
API \ eCg_APImodel	sealed	green	rails	Sum Map 1		
sealed	59086	14994	20	74100		
green	15244	28313	205	43762		
rails	1515	35	4667	6217		
Sum Map 2	75845	43342	4892	124079		
						0.741995
θ1=	0.741995			kappa 2=	0.493888	
θ2=	0.490222					
θ3=	0.739021			Var(k2)=	4.5E-05	
θ4=	1.035864					
			z test=	4.908859		

Commercial area "area20"					
API/eCg_RGB	sealed	green	Sum Map 1	User accuracy	
sealed	108161	7401	115572	0.935875	
green	6913	3603	10516	0.342621	
Sum Map 2	115074	11004	126088		
Producer accurac	0.939926	0.327426			
				0.886397	
					88.6%
θ1=	0.886397		kappa 1=	0.272659	
θ2=	0.84381				
θ3=	1.574044		Var(k1)=	0.008578	
θ4=	2.984711				
API/eCgsatellite	sealed	green	Sum Map 1		
sealed	110083	5479	115562		
green	5887	4629	10516		
Sum Map 2	115970	10108	126078		
				0.909849	
					91%
	θ1=	0.909849		Kappa 2=	0.399825
	θ2=	0.849793			
	θ3=	1.609446		Var(k2)=	0.0085
	θ4=	3.0357			
		Z=	**0.9730687**		

Residential area "area26"					
API \eCg_RGBmodel	sealed	green	Sum Map 1	User accuracy	
sealed	43428	16917	60345	0.719662	
green	16511	46202	62713	0.736721	
Sum Map 2	59939	63119	123058		
Producer accuracy	0.724537	0.731982		0.728356	
					73%
θ1=	0.728356		kappa 1=	0.456441	
θ2=	0.500249				
θ3=	0.728864		Var(k1)=	5.16E-05	
θ4=	1.001368				
API/eCg_satellite	sealed	green	Sum Map 1	User	
sealed	37184	23161	60345	0.61619	
green	10137	52576	62713	0.83836	
Sum Map 2	47321	75737	123058		
Producer	0.78578	0.69419			
				0.729412	73%
θ1=	0.729412		kappa 2=	0.456409	
θ2=	0.502222				
θ3=	0.745057		Var(k2)=	5.22E-05	
θ4=	1.023329				
		Z=	**-0.0031737**		

Statistical analysis between aerial and satellite data in automated OBIA

Residential area - area5

API/eCgsatellite	sealed	green	rails	Sum Map 1	User		
sealed	59114	14986	0	74100	0.79776		
green	10755	33007	0	43762	0.75424		
rails	3362	21	2834	6217	0.45585		
Sum Map 2	73231	48014	2834	124079			
Producer	0.80723	0.68745	1.00000				
					76.5%	0.765279	
θ1=	0.765279					kappa 1=	0.539681
θ2=	0.49009						
θ3=	0.764129					Var(k1)=	4.2E-05
θ4=	1.019143						
API/ auto_eCg	sealed	green	rails	Sum Map 1	User		
sealed	2229972	92209	3850	2326031	0.95870		
green	208703	1156577	7673	1372953	0.84240		
rails	174	8634	186629	195437	0.95493		
Sum Map 2	2438849	1257420	198152	3894421			
Producer	0.91435	0.91980	0.94185				
					92%	0.917512	
	θ1=	0.917512			kappa 2=	0.838126	
	θ2=	0.490419					
	θ3=	0.906024			Var(k2)=	5.66E-07	
	θ4=	1.062319					
		Z=	45.75493				

Residential area – area26

API/eCg_satellite	sealed	green	Sum Map 1	User	
sealed	37184	23161	60345	0.61619	
green	10137	52576	62713	0.83836	
Sum Map 2	47321	75737	123058		
Producer	0.78578	0.69419			
				73%	0.729412
θ1=	0.729412		kappa 1=	0.456409	
θ2=	0.502222				
θ3=	0.745057		Var(k1)=	5.22E-05	
θ4=	1.023329				
API/ auto_eCg	sealed	green	Sum Map 1	User	
sealed	1781064	113330	1894394	0.94018	
green	410258	1558503	1968761	0.79162	
Sum Map 2	2191322	1671833	3863155		
Producer	0.81278	0.93221			
				86%	0.864466
θ1=	0.864466		kappa 2=	0.729632	
θ2=	0.498706				
θ3=	0.867785		Var(k2)=	9.55E-07	
θ4=	0.998493				
		Z=	**37.483303**		

Commercial area – area20

API/eCgsatellite	sealed	green	Sum Map 1		
sealed	110083	5479	115562		
green	5887	4629	10516		
Sum Map 2	115970	10108	126078		
				91%	0.909849
θ1=	0.909849		kappa 1=	0.399825	
θ2=	0.849793				
θ3=	1.609446		Var(k1)=	0.0085	
θ4=	3.0357				
API/auto_eCg	sealed	green	Sum Map 1	User	
sealed	3567122	58734	3625856	0.98380	
green	97857	233563	331420	0.70473	
Sum Map 2	3664979	292297	3957276		
Producer	0.97330	0.79906			
				96%	0.96043
	θ1=	0.96043		Kappa 2=	0.727553
	θ2=	0.854759			
	θ3=	1.670046		Var(k2)=	0.000149
	θ4=	3.100578			
		Z=	**3.5239669**		

Residential area - area5

API/eCgsatellite	sealed	green	rails	Sum Map 1		
sealed	59114	14986	0	74100		
green	10755	33007	0	43762		
rails	3362	21	2834	6217		
Sum Map 2	73231	48014	2834	124079		
					76.5%	0.765279
θ1=	0.765279			kappa 1=	0.539681	
θ2=	0.49009					
θ3=	0.764129			Var(k1)=	4.2E-05	
θ4=	1.019143					
API/ pixel	sealed	green	rails	Sum Map 1		
sealed	57442	16658	0	74100		
green	10843	32919	0	43762		
rails	5647	570	0	6217		
Sum Map 2	73932	50147	0	124079		
					73%	0.728254
θ1=	0.728254			kappa 2=	0.45826	
θ2=	0.498382					
θ3=	0.753114			Var(k2)=	4.97E-05	
θ4=	1.036132					
			z test=	8.50461		

Residential area – area26

API/eCg	sealed	green	Sum Map 1	User	
sealed	37184	23161	60345	0.61619	
green	10137	52576	62713	0.838359	
Sum Map 2	47321	75737	123058		
Producer	0.785782	0.694192			
				73%	0.729412
θ1=	0.729412			kappa 1=	0.456409
θ2=	0.502222				
θ3=	0.745057			Var(k1)=	5.22E-05
θ4=	1.023329				
API/pixel	sealed	green	Sum Map 1	User	
sealed	38875	21470	60345	0.644212	
green	8792	53921	62713	0.859806	
Sum Map 2	47667	75391	123058		
Producer	0.815554	0.715218			
				75%	0.754083
θ1=	0.754083			kappa 1=	0.506025
θ2=	0.502168				
θ3=	0.769033			Var(k1)=	4.9E-05
θ4=	1.022554				
		Z=	**4.9323635**		

Commercial area – area20

API/eCg	sealed	green	Sum Map 1		
sealed	110083	5479	115562		
green	5887	4629	10516		
Sum Map 2	115970	10108	126078		
				91%	0.909849
θ1=	0.909849			kappa 1=	0.399825
θ2=	0.849793				
θ3=	1.609446			Var(k1)=	0.0085
θ4=	3.0357				
API/pixel	sealed	green	Sum Map 1		
sealed	108021	7551	115572		
green	4876	5640	10516		
Sum Map 2	112897	13191	126088		
				90%	0.901442
θ1=	0.901442			kappa 1=	0.42218
θ2=	0.829431				
θ3=	1.560754			Var(k1)=	0.004874
θ4=	2.912101				
		z=	**0.1932971**		

Appendix B

Published material

Paper 1

This paper is published as book chapter in the book entitled: "Object-Based Image Analysis: Spatial Concepts for Knowledge - Driven Remote Sensing Applications", Springer, p.555-570.

Opportunities and limitations of object based image analysis for detecting urban impervious and vegetated surfaces using true-colour aerial photography

M. Kampouraki, G. A. Wood, T. R. Brewer

School of Applied Sciences, Department of Natural Resources,
Cranfield University, Bedfordshire, MK43 0AL, UK
(m.kampouraki.s04, g.a.wood, t.brewer)@cranfield.ac.uk

Abstract

Monitoring soil sealing in urban environments is of great interest as a key indicator of sustainable land use. Many studies have attempted to automatically classify surface impermeability by using satellite or aerial imagery. Air photo interpretation (API) has been used as a method to verify their accuracy. However, independent accuracy assessments of API have not been widely reported. The aims of this research are, firstly, to investigate independent accuracy assessments of API. Secondly, to determine whether object-based image analysis could replace manual interpretation for the detection of sealed soil and vegetated surfaces at the residential garden plot level. Four study areas, representing the industrial, commercial and residential parts of Cambridge, UK were manually digitised and classified by API. The same areas were automatically segmented and manually classified with the use of eCognition. The two methods were compared and the average overall mapping agreement was estimated to be 92%. The disagreement wais qualitatively analysed and the advantages and disadvantages of each method were discussed. The very high agreement between the two methods in conjunction with the benefits of the automated method led to the conclusion that automated segmentation using eCognition could replace the manual boundary delineation when true-colour aerial photography is used. Future work will examine automated image classification methods, using eCognition, as a replacement for normal image interpretation methods.

1. INTRODUCTION

Urban development presents the greatest driver of soil loss due to sealing-over by buildings, pavement and transport infrastructure. Soil sealing is recognised as one of the major threats to soil. The ability to monitor the rates, types and geo-spatial distribution of soil sealing is crucial to understanding the severity of pressure on soils and their impact on European and global socio-economic and environmental systems (Wood et al., 2006).

1.1 Monitoring soil sealing by remote sensing

There are few internationally recognised definitions of soil sealing (Burghardt et al. 2004). The European Union accepts that "soil sealing refers to changing the nature of a soil such that it behaves as an impermeable medium and describes the covering or sealing of the soil surface by impervious materials" (EEA glossary 2006). Remotely sensed data cannot directly measure whether a surface is permeable but it can monitor cover types (e.g. concrete or tarmac) and infer permeability. Grenzdörffer (2005) categorised sealed areas simply as either built-up or non-built-up areas.

Arguably, the most detailed mapping of soil sealing was carried by the Office for Urban Drainage Systems in Dresden, Germany. They used orthorectified aerial photography (1:50,000 scale) and digitized soil sealing values for the whole city by air photo interpretation (API). The degree of sealing was estimated for each housing plot and given a soil sealing value, e.g. roofs were 100% sealed; green roofs, 50%; concrete-asphalt 100%; semi-permeable areas (paving stone) 70%; water-absorbing areas like gravel, 50% and residual areas, 0% (Meinel and Hering 2005).

Recently, a variety of projects have been undertaken in Europe to develop more automated methods for detecting soil sealing at European, national or regional scales such as the SoilSAGE project, the GMES Urban Services (GUS) project, the GMES Service Element (GSE) Land monitoring project, the Monitoring Urban Dynamics (MURBANDY) project and the Monitoring Land Use/Cover Change Dynamics (MOLAND) project. Soil sealing has also been investigated by the Technical Working Groups (TWG) of the Soil Thematic Strategy described by Burghardt et al. (2004) in two reports. Most of these projects have used remote sensing image classification techniques based on pixel procedures.

The argument for using object based image analysis over pixel-based methods will not be repeated here (see Blaschke and Strobl 2001; Caprioli and Tarantino 2003; Yuan and Bauer 2006). Suffice it to say that real-world objects are not characterized by single, square pixels. In the case of high and very high resolution imagery, groups of individual pixels are more likely to represent what would normally be interpreted as recognisable land cover features. Object-based image analysis is based on sensible pixel groupings and is, therefore, more representative of the systematic process carried out in API. Delineating image objects by 'segmentation' in the digital domain is analogous to API boundary delineation.

Automatic segmentation is not new (Blaschke and Strobl 2001). Existing algorithms include texture segmentation, watershed information and mean shift, but none of them have proved to be a robust, operational approach (Zhou and Wang, 2006). More recently, with the introduction of eCognition software, from Definiens Imaging GmbH, homogeneous image object extraction, over a range of image object sizes, is now possible. In contrast to pixel approaches, image objects produced using eCognition contain spectral, shape and texture information but also a whole network of relations which connects image objects and incorporates contextual information. The objects extracted during the segmentation process are then later classified.

Many studies have attempted to extract urban features and classify urban land cover and land use by using eCognition, e.g. Hoffman (2001); Herold et al. (2003); Wang et al. (2004); Frauman and Wolf (2005); Blaschke et al. (2005). Mittelberg (2002) attempted to analyse the urban environment by using aerial photography and very high resolution IKONOS data. Hodgson et al. (2003) used aerial photography along with elevation data (Lidar) to identify urban imperviousness. The data were compared with visual interpretation of aerial photography which was segmented using eCognition. Cothren and Gorham (2005) analysed QuickBird images to detect impervious and permeable surfaces. Grenzdorffer (2005) used a combination of satellite (Landsat TM and SPOT) images with high resolution aerial photographs to identify urban land use change. Yuan and Bauer (2006) investigated digital classification techniques (both pixel and object based) for mapping urban impervious surfaces using QuickBird images. In most cases, the classification results were compared with an air photo interpretation of ortho-rectified aerial photography.

API is considered *de facto* as the most accurate procedure for mapping land cover and none of the studies cited determines the appropriateness of using API methods to assess the accuracy of boundary delineation for landcover mapping. API is also subjective, time consuming, expensive, labour intensive, and requires skilled operators.

This paper aims to evaluate manual classification of aerial photography by comparing it with results produced using eCognition. The work specifically focuses on the segmentation stage of the process, where API will be compared with semi-automated object-based procedures. The scope is to investigate whether object-based image analysis could replace the traditional way of manual digitising and visual labelling for the detection of sealed soil and vegetated surfaces at the residential garden plot level.

2. DATA and METHODS

The study area is the city of Cambridge, UK. The data source acquired for the analysis is ortho-rectified aerial photography, taken in June-July 2003 at 0.125 m spatial resolution and scanned to an 8 bit RGB format. Four study areas of 250 by 250 m were selected as representative land covers of the built environment: two types of residential, one commercial and an industrial part of Cambridge (Fig. 1).

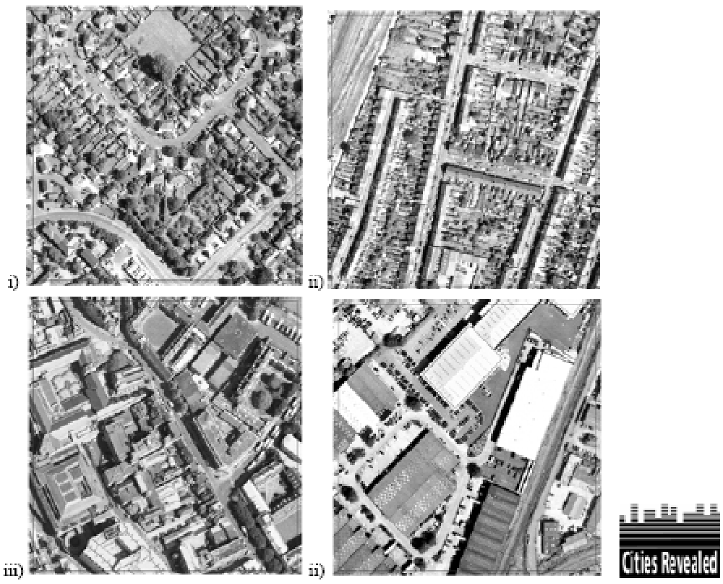


Fig. 1. *(**i**) 1960's semi-detached residential area with large gardens, (**ii**) Densely built Victorian terrace house residential area with small, narrow gardens (**iii**) City centre commercial area with tall buildings, densely built, predominantly sealed, (**iv**) Industrial area mainly sealed with little green space. Cities Revealed® copyright by The GeoInformation® Group, 1996 and Crown Copyright© All rights reserved*

2.1 Aerial Photo Interpretation (API)

The four study areas were manually segmented by on-screen digitising using ArcGIS® software (Figs. 2i, 2ii) at 1:200 scale for two main reasons: (a) a 2 m minimum mapping unit ($4m^2$ area) was deemed to provide a good threshold for extracting urban features found in the built environment of Cambridge, and (b) a larger scale than 1:200 revealed a higher degree of pixelation which was difficult to interpret. Features smaller than 4 m^2 on the ground were ignored even though they could be seen (i.e. small individual trees, narrow footpaths in back gardens, or small areas of shadow). Vegetated surfaces were equated to unsealed soil, and non-vegetated surfaces were equated to sealed soils. Only shadow cast on ground surfaces were digitised as 'shadow'; sides of buildings in shadow, visible due to relief displacement, were interpreted as 'sealed'. Seven land cover classes were used (Fig. 2iii): sealed surfaces, vegetation, trees, shadow, rail tracks, bare soil and temporary features. Shadow was further classified as 'sealed surface in shadow', 'grass in shadow', 'tree in shadow', and 'mixed or unclassified shadow' when it was impossible to identify the kind of objects in the shadow.

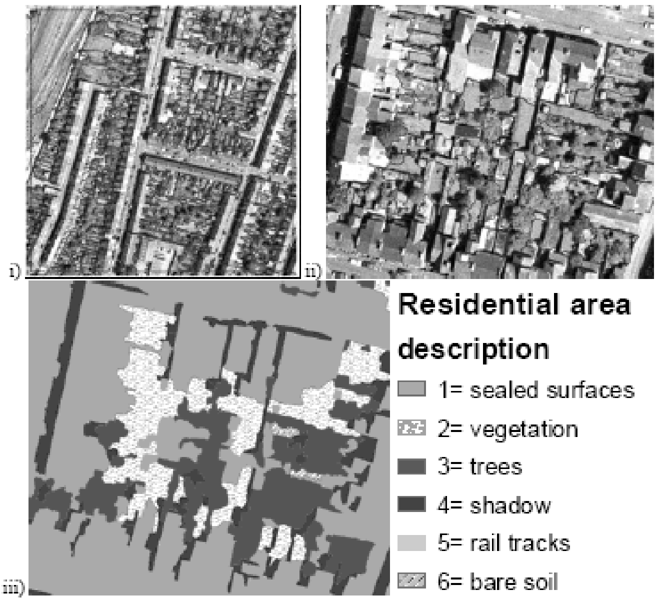


Fig. 2. ***(i)*** *On-screen manual digitising of the densely built residential study area* ***(ii)*** *Delineation of feature detail,* ***(iii)*** *Manual classification. No temporary features were identified in this example*

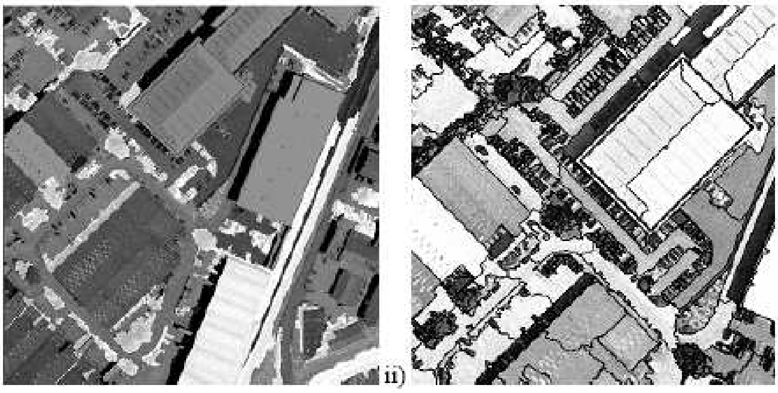
2.2 Semi-automated object based classification approach

The four study areas were automatically segmented with the use of eCognition software, Definiens Professional version 5. The multi-resolution segmentation, which generates objects resembling ground features very closely (Definiens User Guide 2006), was used for this study. As a first step, eCognition links pixels to produce image objects by extracting homogeneous areas. The outcome of the segmentation is dependent on several parameters, such as, scale, colour, shape, compactness and image layer weights. These parameters are defined manually by the user. The scale parameter determines the maximum allowable heterogeneity for the resulting image objects and, consequently, their size.

A new feature of eCognition v.5 is the process editor. A single process represents an individual operation of an image analysis routine and defines an algorithm which is executed on a specific image object domain. The image object domain describes the area of interest where the algorithm will be executed in the image hierarchy (Definiens User Guide 2006) and can either be the raw data at the pixel level, all of the image objects in a specific level of the hierarchy, or a specific object class from any level. The flexibility of the new version gives the ability to apply rules in a specific class domain of the class hierarchy that suits local conditions in an image. This affords similar flexibility that an interpreter has during manual API.

A general rule of thumb for a meaningful segmentation is to create image objects as large as possible and as small as necessary (Definiens User Guide 2006). The image must be segmented at such a scale so as to identify the smallest feature of interest. It is very important to use as many object levels, at different scales, as necessary until all image objects explicitly represent the classes to be assigned for the classification procedure. For a detailed description of image segmentation using eCognition and how the parameters affect the image analysis, see Baatz and Schape (2000), Benz et al (2003) and Definiens User Guide (2006).

The first study area examined was the industrial area. After several empirical trials the image was segmented into two levels. At the upper level, the best values for each parameter were found to be: scale=225, shape= 0.3, compactness= 0.7, weight of red band (layer 1) = 2, weight of green band (layer 2) = 4 and weight of blue band (layer 3) = 1. Using these parameters, the image sample was segmented into the coarse classes of sealed, unsealed and shadowed areas. Features that were not extracted at that scale were identified later when a new level with a smaller scale value was applied. High values of compactness along with larger weights in the red and green wave bands resulted in a better discrimination between trees (highly compacted objects) and other vegetated surfaces. The image was then manually classified with the manual editing tool. The manual classification followed the same pattern and criteria used with the API. The classes identified were: sealed surfaces, vegetation, trees, shadow, rail tracks and mixed areas. The 'mixed areas' class represents the regions of the image which are not satisfactorily segmented and require a lower scale parameter in order to create meaningful objects. Consequently, the 'mixed areas' class was re-segmented with a scale parameter value equal to 40; all other parameters remained the same (Fig. 3). Every individual neighbour polygon assigned to the same class was merged at both segmentation levels. The whole process rule set was saved and used for the image analysis of the remaining study areas. The same methodology and identical parameter values (rules) were used in the three other urban areas, in order to determine the transportability of the rules to areas where the urban land cover is different.



i) ii)

Fig. 3. ***(i)*** *Industrial area segmentation at scale 225 and manually classified.* ***(ii)*** *The bright areas are the mixed areas which were later re-segmented at scale 40*

2.4 Accuracy assessment

The results from eCognition were exported to ArcGIS® as smoothed polygons in vector format. The accuracy of the results was quantitatively assessed by comparison with the visual interpretation of the ortho-rectified aerial photography by cross-tabulation. The maps were also qualitatively analysed in order to understand any differences between the two approaches.

3. RESULTS AND DISCUSSION

3.1 Quantitative analysis

Initially, all the maps produced by the two methods were in vector format. The data from each method in a study area were merged together by a union function and the attributes of the new map were exported to a spreadsheet for the production of confusion matrices. The results showed very low agreement between the two methods. All four areas had accuracies between 28-29% which can be explained by the fact that although the two segmentations look very similar at the small scale, the boundaries of each polygon do not match perfectly (Fig. 4). Many insignificant 'sliver' polygons were produced when the maps were combined. This is due to the fact that eCognition follows a pixel pattern while the interpreter digitizes with smoother lines. The very small sliver polygons carry the same weight in the cross-tabulation as the larger polygons of interest, which introduces bias and leads to an artificial underestimate of the overall mapping accuracy.

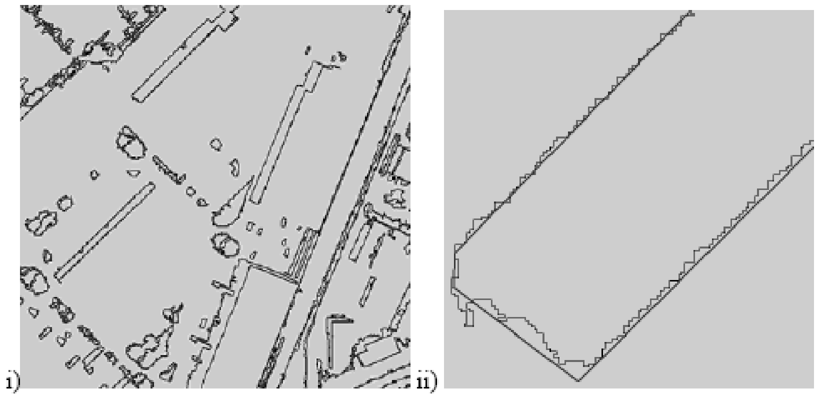


Fig. 4. ***(i)*** *The two maps produced by API and eCognition overlaid for comparison – the differences are negligible at this scale.* ***(ii)*** *Enlargement of a polygon reveals the minor discrepancies*

To solve the boundary problem and to eliminate the majority of sliver polygons, the vector files were converted to a raster format with a cell size of 0.125 m (equivalent to the pixel resolution of the aerial photography). The cross-tabulation was repeated. The accuracies obtained for each study area were: industrial area 96.3%, commercial area 94%, residential area (semi-detached houses) 89% and residential area (dense terrace houses) 90%. Because the polygons were attributed manually in both methods, the high agreement was expected (92% on average). Perhaps of greater interest is the 7-8% disagreement. Although this is not significant in the example of Cambridge, the causal factors may have greater predominance in other urban areas or at different times, and so must be understood.

3.2 Qualitative analysis

Close scrutiny of the factors causing the differences between manual delineation and eCognition's segmentation identified many examples of misclassification that were due to human error during digitisation. When the manual digitising was compared with the automated segmentation, some surface objects greater than the proposed 4 m^2 were found to have been omitted. These same objects were successfully recognized in eCognition.

The omitted features were predominantly shadow or individual trees, either in back gardens or along streets. Sometimes, especially for trees, the reason they were not digitised was because they had low contrast with neighbouring objects and were not distinct enough to be easily identified. At 1:200 scale, it is sometimes difficult for the human eye to distinguish a tree when it is next to grass. This depends on the type of tree and the condition of the grass, as they affect the intrinsic contrast between object tones. It also depends on the levels of illumination and quality of the photograph or scan. A smaller scale can help to overcome this, but the delineation of the boundary is less precise and difficult to digitise. Consequently, there is a high probability that such features will be missed by API. eCognition automatically recognised these cased due to subtly different textures (internal object tonal variability) in the tree canopies; trees are very compact with a 'rough' texture, while grass is more monotone. Again, this may vary depending on image quality.

A big advantage of using eCognition is that the image can be segmented at scales larger than 1:200. In many examples, eCognition has extracted features that were lost in the API due to this threshold. If automated segmentation is used for boundary delineation, a fixed scale is not necessary and the image can be analysed in greater detail compared to API.

Conversely, there are cases where eCognition has not satisfactorily identified or separated features, for example, the fusion of individual trees with the shadow next to them and also the misidentification of smooth textured trees with bushes or grass. But this discrimination was also difficult during the API and therefore this misclassification can occur in the manual digitising. Examples of these misclassifications are infrequent and can be considered less important for mapping sealing, since both these classes are indicators of unsealed soil.

A significant difference between the API and the image segmentation is that eCognition identifies image objects, which are not always real world objects. A very good example is shown in Figure 5. The interpreter has the intelligence to identify the two different types of shadow, one produced by the building and one by the chimneys, and can ignore the latter by digitising the shadow polygon along the roof edge. But eCognition has created one polygon with both shadow types included in it. This may cause problems during automated classification if different features are classified with this type of shadow polygon.

The automated segmentation has the advantage of being much less time consuming, especially if rule sets can be universally applied. The manual digitising of the four study areas lasted a month and one more month was needed for the visual classification. Using eCognition, ten days were needed to find the appropriate parameters for the segmentation of the industrial area, which also included the time required for the manual classification and re-classification of the 'mixed areas' at the lower segmentation level. These parameters were applied 'as-is' to the remaining study areas. A further day was required to classify the commercial area and three days to segment and classify each residential area. The advantages and disadvantages of each method are summarised in Table 1.

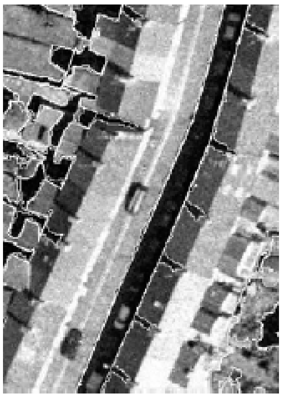


Fig. 5. *eCognition's segmentation of shadows cast by buildings and chimneys*

Table 1. The advantages and disadvantages of using either API or eCognition to delineate real-world objects from remotely sensed imagery

	Advantages	Disadvantages
API	♦ Interpretation of real objects ♦ Identification of complex patterns and complex situations ♦ Ability to include or ignore features intelligently ♦ Multi-scale representation ♦ Use of shape, context, neighbourhood relationships	♦ Subjective ♦ Time consuming ♦ A fixed scale is necessary ♦ Inconsistency in the use of a steady scale to the whole image ♦ Human error ♦ Imprecise boundary delineation
eCognition	♦ Objective (the rules and chosen parameters are subjective but the rules are applied to the whole image objectively) ♦ Multi-scale representation ♦ Hierarchical connection between multi-scales ♦ Use of shape, context, neighbourhood relationships ♦ Transferable rules: boundaries reproduced automatically across different data sets ♦ Quick method	♦ Identification of image objects, not real objects ♦ Inability to include or ignore features intelligently ♦ Fusion of real objects due to spectral confusion

4. CONCLUSIONS

In this paper, two approaches for mapping urban land cover (for the purposes of identifying sealed soils) using true colour ortho-rectified aerial photography have been presented. The traditional technique of aerial photo interpretation (API) has been used to compare against new automated methods for boundary delineation, with the use of eCognition software. A quantitative analysis showed a very high agreement between the two methods across a range of different UK urban land use types: 1960s residential, Victorian residential, commercial, and industrial.

Both methods identify features at multi-scales and use shape, context and proximity information. The great benefit of eCognition is that once the user finds the appropriate parameters for a satisfactory segmentation and classification then these can instantly be applied in other areas with similar land cover. Consequently, the automated analysis is objective and quick in contrary to the subjective and very time consuming API.

eCognition's main disadvantage is that it cannot interpret an image as intelligently as a manual interpreter would, mainly because it does not recognise real objects, but identifies image objects, which can be spectrally confused. This can be overcome to an extent by applying fuzzy rules during the classification stage.

The ability to work flexibly on specific parts of the image, allows the user to analyse the image in a way that replicates API. The benefits of the automated approach in conjunction with the high agreement that the quantitative analysis showed, led to the conclusion that eCognition can replace the manual method of on-screen digitisation of aerial photography.

This research study will continue by exploring eCognition's automated classification using the 'membership function' approach. This will prove whether API can be replaced by a completely automated method. In the future automated classification, shadow will be reclassified and assigned to a specific land cover class. This procedure has already been done manually during API but has not been used as only segmentation (and not classification) was compared in this paper. If the work was to be repeated again, the most complicated sample area should be used first in order to find the appropriate values of the segmentation's parameters. In this way, fewer 'mixed areas' will need to be manually classified in order to run the segmentation again in a smaller level by using object domains (applicable in eCognition Professional v5).

5. REFERENCES

Baatz M, Schape A (2000) Multiresolution Segmentation – an optimization approach for high quality multi-scale image segmentation. AGIT-Symposium Salzburg 2000, 12–23. http://www.definiens.com/documents/publications_earth2000.php

Benz UC, Hofmann P, Willhauk G, Lingenfelder I, Heyen M (2004) Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry & Remote Sensing, 58, 239-258.

Blaschke T, Strobl J (2001) What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GeoBIT/GIS, 6, 12-17. http://www.definiens.com/documents/publications_earth2001.ph

Blaschke T, Lang S, Moller M (2005) Object-based analysis of remote sensing data for landscape monitoring: Recent developments. Anais XII Simpósio Brasileiro de Sensoriamento Remoto, Goiania, Brasil, 16-21 April 2005, http://www.definiens-imaging.com/documents/reference.htm:2879-2885.

Burghardt W, the Working Group Urban Soils of the German Soil Science Society (2004) Soil Monitoring Instruction on Sealed Areas in the European Union, Contribution to the EU Soil Thematic Strategy. http://www.uni-essen.de/bodenkunde/links/eusoil/sealingmonitoring2703.pdf

Burghardt W, Banko G, Hoeke S, Hursthouse A, de L' Escaille T, Ledin S, Marsan FA, Sauer D, Stahr K (2004) TG 5 –SOIL SEALING, SOILS in URBAN AREAS, LAND USE and LAND USE PLANNING. http://www.uni-essen.de/bodenkunde/links/eusoil/EUUrbansoilsapr04.pdf

Caprioli M, Tarantino E (2003) Urban features recognition form VHR satellite data with an object-oriented approach. International Symposium of Remote Sensing (ISPRS) Commission IV Joint Workshop "Challenges in Geospatial Analysis, Integration and Visualization II" http://www.igf.uni-osnabrueck.de/mitarbeiter/schiewe/papers/24.pdf

Cothren J, Gorham B (2005) Automated Feature-Extraction: Software Advances Extract Impervious Surfaces from Satellite Imagery. Earth Imaging Journal, 2, 32-34.

Definiens Professional 5 User Guide (2006) Definiens AG

European Environment Agency (EEA) glossary web-site (2006) http://glossary.eea.europa.eu/EEAGlossary/S/soil_sealing

Frauman E, Wolf E (2005) Segmentation of very high spatial resolution satellite images in urban areas for segments-based classification. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March 2005, http://www.definiens-imaging.com/documents/reference.htm:

Paper 2.

The following conference paper has been submitted at the annual conference of the Remote Sensing and Photogrammetry Society (RSPSoc) in Newcastle, September 2007, in which the author gave an oral presentation. The paper is available on line in the following web page:

http://www.ceg.ncl.ac.uk/rspsoc2007/papers/238.pdf

THE SUITABILITY OF OBJECT-BASED IMAGE SEGMENTATION TO REPLACE MANUAL AERIAL PHOTO INTERPRETATION FOR MAPPING IMPERMEABLE LAND COVER

M. Kampouraki [a]* G. A. Wood [a], T. R. Brewer [a]

[a] School of Applied Sciences, Dept of Natural Resources, Cranfield University, Bedfordshire, MK43 0AL, UK-(m.kampouraki.s04, g.a.wood, t.brewer)@cranfield.ac.uk

KEY WORDS: Object, Segmentation, Classification, Urban, Mapping, Remote Sensing, Semi-automation

ABSTRACT:

Monitoring the sealing-over of the soil surface by impermeable material in urban environments is of great interest as a key indicator of sustainable land use. Many studies have attempted to automatically classify surface impermeability by using satellite or aerial imagery. Air photo interpretation (API) has been used as a method to verify their accuracy. However, independent accuracy assessments of API have not been widely reported. The aims of this research are, firstly, to investigate independent accuracy assessments of API. Secondly, to determine whether object-based image analysis could replace manual interpretation for the detection of sealed soil and vegetated surfaces at the residential garden plot level. Four study areas, representing the industrial, commercial and residential parts of Cambridge, UK, were manually digitised and classified by API. The same areas were automatically segmented and manually classified with the use of eCognition software, Definiens Professional 5. The two methods were compared and the average overall mapping agreement was estimated to be 92%. The disagreement was qualitatively analysed and the advantages and disadvantages of each method were discussed. The very high agreement between the two methods in conjunction with the benefits of the automated method led to the conclusion that automated segmentation using eCognition has a considerable potential to replace the manual boundary delineation when true-colour aerial photography is used.

1. INTRODUCTION

Soil is an important natural resource that is threatened by many ways, including by soil sealing. A suitable qualification of whether a soil is sealed or not is to assess whether it is permeable. There are few internationally recognised definitions of soil sealing (Burghardt et al. 2004). The European Union (EU) accepts that "soil sealing refers to changing the nature of the soil such that it behaves as an impermeable medium and describes the covering or sealing of the soil surface by impervious materials by, for example, concrete, metal, glass, tarmac and plastic" (EEA glossary 2006). Grenzdörffer (2005) considered a soil to be sealed when it is covered by an impervious material and categorised sealed areas as either built-up or non-built-up areas.

1.1 Monitoring soil sealing

The most detail mapping of soil sealing was carried by the Office for Urban Drainage Systems in Dresden, Germany. They used aerial photography, at 1:50,000 scale, and digitized soil sealing values for the whole city by air photo interpretation (API). The degree of sealing was estimated for each housing plot (Meinel and Hernig 2005).

Additionally, a variety of projects have been undertaken in Europe to develop automated methods for detecting soil sealing at European, national or regional scales by using remote sensing image classification techniques based on pixel procedures.

The argument for using object based image analysis over pixel-based methods will not be repeated here (see Blaschke and Strobl 2001; Caprioli and Tarantino 2003; Yuan and Bauer 2006). Object-based image analysis is based on sensible pixel groupings and is, therefore, more representative of the systematic process carried out in API. Delineating image objects by 'segmentation' in the digital domain is analogous to API boundary delineation. Automatic segmentation is not new (Blaschke and Strobl 2001). Existing algorithms include texture segmentation, watershed information and mean shift, but none of them have proved to be a robust, operational approach (Zhou and Wang, 2006). More recently, with the introduction of eCognition software, from Definiens Imaging GmbH, homogeneous image object extraction, over a range of image object sizes, is now possible. The objects extracted during the segmentation process are then later classified.

Many research studies attempted to identify surface impermeability and the degree of soil sealing in urban environments by using object- based digital techniques (Hodgson et al. 2003, Cothern and Gorham 2005, Grenzdorffer 2005, Yan and Bauer 2006). In most cases, the classification results were compared with an air photo interpretation of ortho-rectified aerial photography.

API is considered *de facto* as the most accurate procedure for mapping land cover and none of the studies cited determines the appropriateness of using API methods to assess the accuracy of boundary delineation for landcover mapping. API is also subjective, time consuming, expensive, labour intensive, and requires skilled operators.

This paper aims to evaluate manual classification of aerial photography by comparing it with results produced using eCognition. The work specifically focuses on the segmentation stage of the process, where API will be compared with semi-automated object-based procedures. The scope is to investigate whether object-based image analysis could replace the traditional way of manual digitising and visual labelling for the detection of sealed soil and vegetated surfaces at the residential garden plot level.

2. MATERIALS AND METHODS

2.1 The study area

The study area is the city of Cambridge, UK. The data source acquired for the analysis is ortho-rectified aerial photography, taken in June-July 2003 at 0.125 m spatial resolution and scanned to an 8 bit RGB format. Four study areas of 250 by 250 m were selected as representative land covers of the built environment: two types of residential, one commercial and an industrial part of Cambridge (Fig. 1).

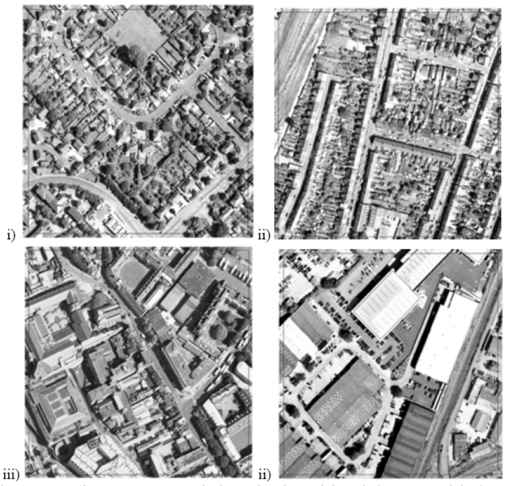


Figure 1. (i) 1960's semi-detached residential area with large gardens, (ii) Densely built Victorian terrace house residential area with small, narrow gardens (iii) City centre commercial area with tall buildings, densely built, predominantly sealed, (iv) Industrial area mainly sealed with little green space. Cities Revealed® copyright by The GeoInformation® Group, 1996 and Crown Copyright© All rights reserved

2.2 Manual classification

The four study areas were manually segmented by on-screen digitising using ArcGIS® software at 1:200 scale for two main reasons: (a) a 2 m minimum mapping unit ($4m^2$ area) was deemed to provide a good threshold for extracting urban features found in the built environment of Cambridge, and (b) a larger scale than 1:200 revealed a higher degree of pixelation which was difficult to interpret. Features smaller than 4 m^2 on the ground, were ignored even though they could be seen (i.e. small individual trees, narrow footpaths in back gardens, or small areas of shadow). The manual digitisation followed manual labelling of the produced polygons by aerial photo interpretation. Vegetated surfaces were equated to unsealed soil, and non-vegetated surfaces were equated to sealed soils. Only shadow cast on ground surfaces were classified as 'shadow'; sides of buildings in shadow, visible due to relief displacement, were interpreted as 'sealed'. Seven land cover classes were used: sealed surfaces, vegetation, trees, shadow, rail tracks, bare soil and temporary features. Shadow was further classified as 'sealed surface in shadow', 'grass in shadow', 'tree in shadow', and 'mixed or unclassified shadow' when it was impossible to identify the kind of objects in the shadow.

2.3 Semi-automated classification

The four study areas were automatically segmented with the use of eCognition software, Definiens Professional version 5. A new feature of eCognition v.5 is the process editor. A single process represents an individual operation of an image analysis routine and defines an algorithm which is executed on a specific image object domain. The image object domain describes the area of interest where the algorithm will be executed in the image hierarchy (Definiens User Guide 2006) and can either be the raw data at the pixel level, all of the image objects or a specific class in a specific level of the hierarchy. The flexibility of the new version gives the ability to apply rules in a specific class domain of the class hierarchy that suits local conditions in an image. The first study area examined was the industrial area. After several empirical trials the image was segmented into two levels. At the upper level, the best values for each parameter were found to be: scale=225, shape= 0.3, compactness= 0.7, weight of red band= 2, weight of green band = 4 and weight of blue band= 1. Using these parameters, the image sample was segmented into the coarse classes of sealed, unsealed and shadowed areas. High values of compactness along with larger weights in the red and green wave bands resulted in a better discrimination between trees (highly compacted objects) and other vegetated surfaces. The image was then manually classified with the manual editing tool. The manual classification followed the same pattern and criteria used with the API. The classes identified were: sealed surfaces, vegetation, trees, shadow, rail tracks and mixed areas. The 'mixed areas' class represents the regions of the image which are not satisfactorily segmented and require a lower scale parameter in order to create meaningful objects. Consequently, the 'mixed areas' class was re-segmented with a scale parameter value equal to 40; all other parameters remained the same (Fig. 2). Every individual neighbour polygon assigned to the same class was merged at both segmentation levels. The whole process rule set was saved and used for the image analysis of the remaining study areas. The same methodology and identical parameter values (rules) were used in the three other urban areas, in order to determine the transportability of the rules to areas where the urban land cover is different.

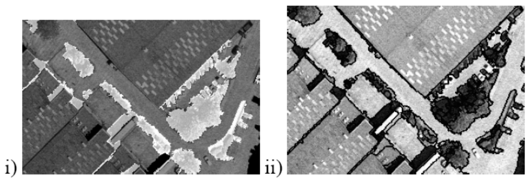


Figure 2. (i) Part of the industrial area: segmentation at scale 225 and manual classification, (ii) The bright areas are the mixed areas which were later re-segmented at scale 40 and manually re-classified

2.4 Accuracy assessment

The results from eCognition were exported to ArcGIS® as smoothed polygons in vector format. The accuracy of the results was quantitatively assessed by comparison with the visual interpretation of the ortho-rectified aerial photography by cross-tabulation. The maps were also qualitatively analysed in order to understand any differences between the two approaches.

3. RESULTS –DISCUSSION

3.1 Quantitative Analysis

When the produced maps were compared in vector format the accuracy assessment showed very low agreement between the two methods, average 28-29%. This can be explained by the fact that although the two segmentations look very similar the boundaries of each polygon do not match perfectly. This is mainly due to the way digital classification follows a pixel pattern while the interpreter digitizes with smoother lines. The result is the production of many insignificant 'sliver' polygons and, hence, the artificial underestimation of the overall mapping accuracy. To solve this boundary problem and to eliminate the sliver polygons, the vector files were converted to a raster format with cell size= 0.125 m (equivalent to the pixel resolution of the aerial photography). The two raster formats, of each sample area, were combined and the attribute table was exported to Excel for the production of the contingency tables, also known as confusion matrices. The accuracy for each study area was: industrial area 96.3%, commercial area 94% (Table 1), residential area (semi-detached houses) 89% and residential area (dense terrace houses) 90%. The Kappa statistics showed a very good overall agreement between the two methods with values between 0.841-0.895 for each study area. Because the polygons were attributed manually in both methods, the high agreement was expected (92% on average). Perhaps of greater interest is the 7-8% disagreement.

		Classification of the 'Commercial' study area **eCognition**					
API		1	2	3	4	Total	Producer
	1	2906249	5081	4979	127630	3043939	95%
	2	7526	109230	1821	1070	119647	91%
	3	10921	1097	151990	25386	189394	80%
	4	52110	1332	4811	588767	647020	91%
Total		2976806	116740	163601	742853	4000000	
User		98%	94%	93%	79%		94%

Table 1. The confusion matrix indicates correspondence between the semi-automated classification and the API classification of sealing

In order to examine the eCognition's performance at the different classes individually, the geometric mean (or g-mean) of every class in each confusion matrix was calculated. The nearer the g-mean is to unity the more successful eCognition is at predicting the correct land cover class. The geometric mean is defined in equation 1 (Kubat et al., 1998):

$$g - mean \ = \sqrt{TP * P} \qquad (1)$$

where TP= the true positive rate also called the producer accuracy

P= the index of precision also called the user accuracy

The best prediction was within the 'sealed' class with an average g-mean of 0.95 followed by the 'vegetation' class with an average g-mean=0.88. The lowest values of the geometric mean of each study area was in the classes 'shadow' and trees' with an average of 0.85 and 0.84 respectively. These two classes were visually examined in the ArcGIS® for a qualitative analysis and a better understanding of the differences between the two methods.

3.2 Qualitative analysis

Close scrutiny of the 'trees' and 'shadow' classes of each study has identified the main reasons causing the differences between manual delineation and eCognition's segmentation. These are: (i) thematic discrepancy, (ii) mixed pixels/ spectral confusion between classes, (iii) eCognition's more detail boundary delineation; follows a pixel pattern and (iv) human's intelligence to identify real objects and not image objects.

Many examples of misclassification were due to human error. First of all, in few cases a land cover feature was successfully segmented it was manually labelled in a wrong land cover class. Secondly, when the manual digitising was compared with the automated segmentation, some surface objects greater than the proposed 4 m^2 were found to have been omitted. These same objects were successfully recognized in eCognition. The omitted features were predominantly shadow or individual trees, either in back gardens or along streets. Sometimes, especially for trees, the reason they were not digitised was because they had low contrast with neighbouring objects and were not distinct enough to be easily identified. At 1:200 scale, it is sometimes difficult for the human eye to distinguish a tree when it is next to grass. This depends on the type of tree and the condition of the grass, as they affect the intrinsic contrast between object tones. It also depends on the levels of illumination and quality of the photograph or scan. A larger scale can help to overcome this, but the delineation of the boundary is less precise and difficult to digitise. Consequently, there is a high probability that such features will be missed by API. eCognition automatically recognised these cases due to subtly different textures (internal object tonal variability) in the tree canopies; trees are very compact with a 'rough' texture, while grass is more monotone. Again, this may vary depending on image quality.

A big advantage of using eCognition is that the image can be segmented at scales larger than 1:200. In many examples, eCognition has extracted features that were lost in the API due to this threshold. If automated segmentation is used for boundary delineation, a fixed scale is not necessary and the image can be analysed in greater detail compared to API.

Conversely, there are cases where eCognition has not satisfactorily identified or separated features, for example, the fusion of individual trees with the shadow next to them and also the misidentification of smooth textured trees with bushes or grass. But this discrimination was also difficult during the API and therefore this misclassification can occur in the manual digitising. Examples of these misclassifications are infrequent and can be considered less important for mapping sealing, since both these classes are indicators of unsealed soil.

A significant difference between the API and the image segmentation is that eCognition identifies image objects, which are not always real world objects. A very good example is shown in Figure 3. The interpreter ignores the fact that part of the tree is in shadow and digitises a polygon in a rounded shape following the canopy shape. eCognition segments the same feature according to spectral difference. So, most of the tree is correctly identified but the part of it being in shade is being merged with the 'shadow' polygon. None of both ways to segment the image is wrong.

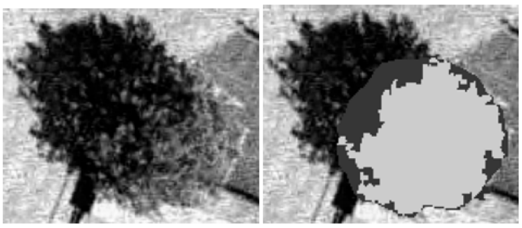


Figure 3. In light grey is the agreement between the two methods (same as eCognition's segmentation in this example). In dark grey is the rest of the API segmentation; human identifies a tree in a rounded shape

Another good example is the discrimination between shadow cast on the ground surfaces and shadow due to relief displacement. The interpreter has the intelligence to identify the two different types of shadow and the dark sides of the buildings have been identified as sealed surfaces. eCognition cannot distinguish dark areas from the shadow and identifies them as one feature. Furthermore, regarding shadow produced by buildings and by chimneys. The interpreter can ignore the latter by digitising the shadow polygon along the roof edge. But eCognition has created one polygon with both shadow types included in it. Both differences will be eliminated when shadow will be reclassified according to the land cover types during automated classification. Problems will occur if different features are classified with this type of shadow polygon.
The automated segmentation has the advantage of being much less time consuming, especially if rule sets can be universally applied. The advantages and disadvantages of each method are summarised in Table 2.

4. CONCLUSIONS

In this paper, two approaches for mapping urban land cover (for the purposes of identifying sealed soils) using true colour ortho-rectified aerial photography have been presented. The traditional technique of aerial photo interpretation (API) has been used to compare against new automated methods for boundary delineation, with the use of eCognition software. A quantitative analysis showed a very high agreement between the two methods across a range of different UK urban land use types: 1960s residential, Victorian residential, commercial, and industrial.
Both methods identify features at multi-scales and use shape, context and proximity information. The great benefit of eCognition is that once the user finds the appropriate parameters for a satisfactory segmentation and classification then these can instantly be applied in other areas with similar land cover. Consequently, the automated analysis is objective and quick in contrary to the subjective and very time consuming API.
eCognition's main disadvantage is that it cannot interpret an image as intelligently as a manual interpreter would, mainly because it does not recognise real objects, but identifies image objects, which can be spectrally confused. This can be overcome to an extent by applying fuzzy rules during the classification stage.

The ability to work flexibly on specific parts of the image, allows the user to analyse the image in a way that replicates API. The benefits of the automated approach in conjunction with the high agreement that the quantitative analysis showed, led to the conclusion that eCognition can replace the manual method of on-screen digitisation of aerial photography.
This research study will continue by exploring eCognition's automated classification using the 'membership function' approach. This will prove whether API can be replaced by a completely automated method. In the future automated classification, shadow will be reclassified and assigned to a specific land cover class. This procedure has already been done manually during API but has not been used as only segmentation (and not classification) was compared in this paper. If the work was to be repeated again, the most complicated sample area should be used first in order to find the appropriate values of the segmentation's parameters. In this way, fewer 'mixed areas' will need to be manually classified in order to run the segmentation again in a smaller level by using object domains (applicable in eCognition Professional v5).

	Advantages	**Disadvantages**
API	♦ Interpretation of real objects ♦ Identification of complex patterns and complex situations ♦ Ability to include or ignore features intelligently ♦ Multi-scale representation ♦ Use of shape, context, neighbourhood relationships	♦ Subjective ♦ Time consuming ♦ A fixed scale is necessary ♦ Inconsistency in the use of a steady scale to the whole image ♦ Human error ♦ Imprecise boundary delineation
eCognition	♦ Objective (the rules and chosen parameters are subjective but the rules are applied to the whole image objectively) ♦ Multi-scale representation ♦ Hierarchical connection between multi-scales ♦ Use of shape, context, neighbourhood relationships ♦ Transferable rules: boundaries reproduced automatically across different data sets ♦ Quick method	♦ Identification of image objects, not real objects ♦ Inability to include or ignore features intelligently ♦ Fusion of real objects due to spectral confusion

Table 2. The advantages and disadvantages of using either API or eCognition to delineate real-world objects from remotely sensed imagery

5. REFERENCES

Blaschke, T., Strobl, J., 2001. "What's wrong with pixels? Some recent developments interfacing remote sensing and GIS". GeoBIT/GIS, 6, 12-17. http://www.definiens.com/documents/publications_earth2001.ph (accessed 11 June 2006)

Burghardt, W., the Working Group Urban Soils of the German Soil Science Society, 2004. "Soil Monitoring Instruction on Sealed Areas in the European Union, Contribution to the EU Soil Thematic Strategy". http://www.uni-essen.de/bodenkunde/links/eusoil/sealingmonitoring2703.pdf (accessed 17 Sep. 2005)

Caprioli, M., Tarantino, E., 2003. "Urban features recognition form VHR satellite data with an object-oriented approach". International Symposium of Remote Sensing (ISPRS) Commission IV Joint Workshop "Challenges in Geospatial Analysis, Integration and Visualization II" http://www.igf.uni-osnabrueck.de/mitarbeiter/schiewe/papers/24.pdf (accessed 11 June 2006)

Cothren, J., Gorham, B., 2005. Automated Feature-Extraction: Software Advances Extract Impervious Surfaces from Satellite Imagery. Earth Imaging Journal, 2, 32-34.

European Environment Agency (EEA) glossary web-site, 2006. http://glossary.eea.europa.eu/EEAGlossary/S/soil_sealing (accessed 18 Sep. 2005)

Grenzdorffer, GJ., 2005. "Land use change in Rostock, Germany since the reunification - a combined approach with satellite data and high resolution aerial images". In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March 2005, http://www.definiens-imaging.com/documents/reference.htm (accessed 13 Sep 2005)

Hodgson, ME., Jensen, JR., Tullis, JA., Riordan, KD., Archer, CM., 2003. Synergistic use of Lidar and color aerial photography for mapping urban parcel imperviousness. *Photogrammetric Engineering and Remote Sensing*, 69, 973-980.

Kubat, M., Holte, R., Matwin, S., 1998. Machine learning for the detection of oil spills in satellite radar images, *Machine Learning* 2(30): 195--215.

Meinel, G., Hernig, A., 2005. "Survey of soil sealing on the basis of the ATKIS basic DLM − feasibilities and limits". 10th International Conference on Information & Communication Technologies (ICT) in Urban Planning and Spatial Development and Impacts of ICT on Physical Space, 22-25 February 2005. http://www.schrenk.at/corp/archiv/papers/2005/CORP2005_MEINEL_HERNIG.pdf (accessed 10 June 2006)

Yan, F., Bauer, M., 2006. "Mapping impervious surface are using high resolution imagery: a comparison of object-based and pixel classification". American Society of Photogrammetry and Remote Sensing (ASPRS) Annual Conference, Reno, Nevada, 1-5 May 2006. http://www.definiens.com/documents/publications_earth.php (accessed 07 Nov. 2006)

Zhou, Y., Wang, YQ., 2006. "Extraction of impervious surface area using orthophotos in Rhode island". American Society of Photogrammetry and Remote Sensing (ASPRS) Annual Conference, Reno, Nevada, 1-5 May 2006. http://www.definiens-imaging.com/documents/reference.htm (accessed 07 Nov. 2006)

Paper 3

The following conference paper has been submitted at the 1st International Conference on Object-based Image Analysis (OBIA 2006), in Salzburg, Austria, July 4-5, 2006. The paper is available one line at the official ISPRS web-site at the following page:

http://www.commission4.isprs.org/obia06/Papers/16_Automated%20classification%20IC%20II%20-%20Settlements%20&%20Infrastructure/OBIA2006_Kampouraki_Wood_Brewer.pdf

THE APPLICATION OF REMOTE SENSING TO IDENTIFY AND MEASURE SEALED AREAS IN URBAN ENVIRONMENTS

M. Kampouraki [a, *], G. A. Wood [a], T. Brewer [a]

[a] Dept of Natural Resources, National Soil Resources Institute, Cranfield University, Bedfordshire, UK, MK45 4DT-
(m.kampouraki.s04, g.a.wood, t.brewer)@cranfield.ac.uk

KEY WORDS: Soil, Urban, Sealing, Object, classification, segmentation, mapping, QuickBird

ABSTRACT:

Numerous studies have used satellite images for mapping urban land cover and land use along with modelling green spaces and surface impermeability. Recently, monitoring the percentage of sealed soils in urban environments is of great interest as a key indicator of sustainable landuse. The aim of this research is to identify an appropriate methodology to classify sealed soil and green space surfaces in urban environments with the use of satellite remotely sensed data. The study area is the city of Cambridge, UK. The percentage of sealed soils, within 18 randomly selected sample segments (250 x 250 m), was interpreted visually from the aerial photography and the Ordnance Survey (OS) MasterMap polygons attributed accordingly; the percentage was limited to a precision of 25%, i.e. 0, 25, 50, 75 and 100%. The results were compared with a maximum likelihood classification of Normalised Difference Vegetation Index (NDVI) images derived from QuickBird data integrated with the OS MasterMap and summarised using confusion matrices. The overall mapping accuracy was estimated to be approximately 75%. The low map accuracy is due to coarse precision of the aerial photo interpretation (API) and the use of pixel based classification procedures. The described methodology are the preliminary results of an on going research study. In the future, object-based classifiers (eCognition) will be investigated to provide an objective approach of the visual interpretation and improve efficiency and accuracy. eCognition is also anticipated to be used as the main classifier of the satellite image analysis.

1. INTRODUCTION

1.1 Soil sealing

The characterisation of the environmental quality of urban landscapes, such as the density and growth of the built environment, the climate quality, the proportion of green spaces and impervious surfaces, are key indicators for sustainable development. Impervious surfaces are generally understood to be any material, natural or man-made, that prevents the infiltration of surface water to the underlying strata. As a result, impervious surfaces not only indicate urbanization but are also major contributors to the environmental impacts of urbanization. A suitable qualification of whether a soil is sealed or not is to assess whether it is permeable. There are hardly any internationally recognised definitions of soil sealing (Burghardt *et al.*, 2004). The European Union (EU) accepts that "soil sealing refers to changing the nature of the soil such that it behaves as an impermeable medium and describes the covering or sealing of the soil surface by impervious materials by, for example, concrete, metal, glass, tarmac and plastic" (EEA glossary, 2006). In addition to the EU definition, Burghardt et al. (2004) describe soil sealing by three different means: (i) following a systems approach: "Soil sealing is the separation of soils by layers and other bodies from totally or partly impermeable material from other compartments of the ecosystem, such as biosphere, atmosphere, hydrosphere, anthroposphere and other parts of pedosphere", (ii) according to a purpose related approach: "Soil sealing is the covering of the soil surface with an impervious material or the changing of its nature so that the soil becomes impermeable, such that soil is no longer able to perform the range of functions associated with it" and (iii) by including natural characteristics: "Changing the nature of the soil such that it behaves as an impermeable medium. This definition includes compaction of soils or sub-soils which may affect larger areas than the sealing as defined in definition (ii)". Grenzdörffer (2005) considered a soil to be sealed when it is covered by an impervious material and categorised sealed areas as either built-up or non-built-up areas. He also defined partially sealed surfaces as partly permeable surfaces such as open celled pavers that allow a reduced growth of plants.

1.2 Monitoring soil sealing

During the last few years, a variety of projects have been undertaken in Europe to detect soil sealing at European, national or regional scales such as the *Soil*SAGE project, the GMES Urban Services (GUS) project, the GMES Service Element (GSE) Land monitoring project, the Monitoring Urban Dynamics (MURBANDY) project and the Monitoring Land use/cover Change Dynamics (MOLAND) project. Soil sealing has also been investigated by the Technical Working Groups (TWG) of the Soil Thematic Strategy described by Burghardt *et al.* (2004) and Burghardt, Banko *et al.* (2004).

Furthermore, Deguchi and Sugio (1994) evaluated the use of medium resolution satellite images (20-80 m) to estimate the percentage of impervious areas in urban environment by mapping urban growth. Dousset (1995) analysed a set of SAR images to derive soil moisture. The analysis of the SAR images was done by using a multi-spectral SPOT image, classified with the joint distribution of the visible and infrared channels.

He concluded that in areas devoid of construction there is a limit on estimating roughness or soil moisture. Ridd (1995) developed a conceptual model for analysing urban land cover types within urban areas. The vegetation-impervious-soil (V-I-

* Corresponding author

S) model was presented as a possible aid for urban ecological investigations through remote sensing technology by offering new inputs to morphology, ecology, energy, moisture, vegetation and human responses. The V-I-S model was later used by Ward *et al.* (2000) for monitoring urban growth and Phinn *et al.* (2002) to monitor the composition of urban environments. Herold, *et al.* (2003) simulate and compare Landsat data (30m resolution) and IKONOS data (4m resolution) using hyperspectral airborne data (AVIRIS) to identify the optimum waveband positions for classifying the built environment. In an unpublished manuscript, Herold, *et al.* (2003) used near-infrared (NIR) waveband combinations and vegetation indices (i.e. NDVI) for monitoring useful indicators of unsealed soil. Coe *et al.* (2005) developed a hybrid method of an object-oriented and a pixel-based classification approach to detect impervious surfaces at multi-scales by using Landsat, IKONOS satellite data and Lidar ancillary data to discriminate buildings from other urban objects like parking lots and roads. Accuracy assessments for Landsat and IKONOS data have not been published but they argued that object-based classification and the addition of Lidar has the potential to be very effective to identify urban classes. Grenzdorffer (2005) used a combination of Landsat TM and SPOT images with high resolution aerial photographs to identify sealed surfaces and the degree of sealing with the help of eCognition software. The NVDI index was also used to discriminate vegetated and non-vegetated surfaces. He argued that based on visual accuracy assessment sealed areas could be identified with an average accuracy of 85-90%. It is worthy of note that some attempts have been made to classify urban land cover with the use of object-based classification techniques. Examples include Darwish, *et al.* (2003); Wang, *et al.* (2004); Guindon *et al.* (2004); Frauman & Wolf (2005); Greiwe & Ehlers (2005); Harayama & Jaquet (2005); Blaschke, *et al.* (2005). These either attempt to classify amalgamated blocks of the built environment to map urban growth or they use airborne sensors with spatial resolutions better than that possible from space. Similarly, the Senate Department of Urban Development in Berlin, Germany, used Landsat-TM satellite imagery and Colour Infrared (CIR) aerial photographs to estimate the degree of sealing at the level of housing blocks (Department of Urban Development web-site). Lastly, the Office for Urban Drainage System in Dresden, Germany, sanctioned the mapping of sealed areas by aerial image mapping. Ortho-rectified aerial photography (1:50,000 scale) were digitized stereoscopically and interpreted with an overlay of the Authoritative Topographic Cartographic Information System (ATKIS) to include soil sealing values for the whole city. The mapping was carried out with a positional accuracy of <0.2 m. The work of Meinel & Hernig (2005) was an inspiration to this research study.

The aim of this research is to identify an appropriate methodology to classify sealed soil and green space surfaces in urban environments with the use of satellite remotely sensed data. The scope is to evaluate the possibility of mapping soil sealing within UK cities in detail (i.e. back gardens of each house) and not in residential blocks.

For that purpose, sealed soil surfaces were considered to be caused by infrastructural sealing and not by crusting capping or compaction in public green spaces. In addition, the discrimination between vegetated and non-vegetated urban surfaces seems to provide a good surrogate for making initial assessments of the degree to which an area is either sealed or unsealed. Consequently, vegetated surfaces were equated to unsealed soil, and non-vegetated surfaces were equated to sealed soils. Bare soil was accepted to be a non-vegetated surface and, therefore, was visually classified as unsealed. But due to the infrequency of the "bare soil" class within the urban environments, this class was considered negligible for the statistical analysis and accuracy assessment of the research.

2. DATA AND METHODS

The study area is the city of Cambridge, UK. Eighteen sample segments (250 x 250 m) were randomly drawn from the region to provide a basis for the air photo interpretation (API). The data sources acquired for the analysis consisted of: (i) QuickBird satellite imagery (2.8 m MS and 0.7 m PAN spatial resolution), (ii) ortho-rectified aerial photography, 0.125 m resolution, and (iii) Ordnance Survey (OS) MasterMap ancillary data at a scale of 1:1250.

2.1 Baseline map production

A baseline map was produced by developing and implementing a key interpretation of the selected aerial photography which comprised a visual segmentation and classification of the eighteen sample segments. For that purpose, the OS MasterMap, which contains baseline polygons that delineate transport network infrastructure and residential and commercial buildings, was overlaid onto the aerial photography of Cambridge. Each land parcel in the topographic data was allocated a proportion of the following land cover types: (i) sealed surfaces, (ii) vegetation surfaces, (iii) trees, (iv) bare soil and (v) water. The proportions were estimated visually and limited to a precision of 25%, i.e. 0, 25, 50, 75 or 100%. As mentioned before, sealed surfaces were considered to be caused by infrastructural building and not by soil crusting, capping or compaction. Figure 1 shows an example of the map production displaying the percentage of sealing using the API information for one of the eighteen sample areas. This procedure was repeated for all the eighteen segments.

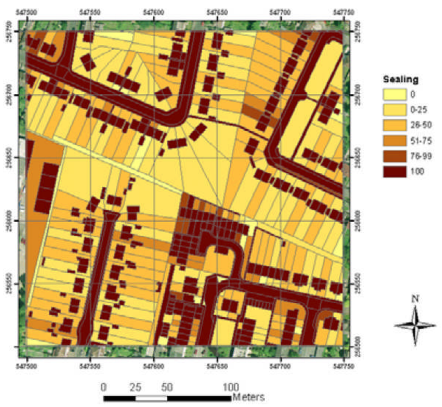


Figure 1. The visual classification of one of the sample areas according to sealing

2.2 Satellite Image classification

The satellite imagery was classified as either vegetated or non-vegetated as this was considered an acceptable surrogate for unsealed and sealed soils, respectively. The use of image band combinations from the red and near infrared wavelengths

		CLASSIFICATION (Satellite + topographic)						
		0	25	50	75	100	*Total*	*Producer*
API	0	475	134	50	36	140	835	57%
	25	288	267	94	53	66	768	35%
	50	149	124	88	53	107	521	17%
	75	111	47	28	50	150	386	13%
	100	523	143	120	123	4683	5592	84%
	Total	1546	715	380	315	5146	8102	
	User	**31%**(40%)	**37%**(55%)	**23%**(39%)	**16%**(44%)	**91%**(92%)		**69%**(75%)

Table 1. The confusion matrix indicates correspondence between the digital classification and the API classification of sealing

4. CONCLUSIONS AND OUTLOOK

In this paper we have presented an approach for the automated mapping of sealed soils in urban environments using QuickBird images. The automated classification was compared with the air photo interpretation approach and the overall accuracy calculated to be 75%. The accuracy estimate could be an 'under'-estimate, due to the nature of the visual interpretation which classified sealing into 25% intervals. The low mapping accuracy also comprises the use of pixel based classifiers which are well known for their mapping accuracy limitations. A better assessment could be achieved by using more refined intervals. Future work will explore the potential of using object-based classifiers (i.e. eCognition software) to produce an objective and more efficient visual interpretation for increasing the overall accuracy. The methodology will be validated against three additional urban areas which will be (i) 'less green' than the city of Cambridge, (ii) of different sizes and (iii) located in different parts of England. Furthermore, eCognition will be used to classify the QuickBird imagery and the results will be compared with the pixel based approach. Finally, an operational approach for routine soil-related monitoring in the built environment will be recommended.

"REFERENCES"

Blaschke, T., Lang, S. & Moller, M., 2005. Object-based analysis of remote sensing data for landscape monitoring: Recent developments. In: Anon., Anais XII Simpósio Brasileiro de Sensoriamento Remoto, Goiania, Brasil, 16-21 April 2005, http://www.definiens-imaging.com/documents/reference.htm:2879-2885. (accessed: 26 Febr. 2006)

Burghardt, W. and the Working Group Urban Soils of the German Soil Science Society, 2004. Soil Monitoring Instruction on Sealed Areas in the European Union, Contribution to the EU Soil Thematic Strategy, http://www.uni-essen.de/bodenkunde/links/eusoil/sealingmonitoring2703.pdf (accessed: 11 Octobr.2005)

Burghardt, W., Banko, G., Hoeke, S., Hursthouse, A., de L' Escaille, T., Ledin, S., Marsan, F. A., Sauer, D. and Stahr, K., 2004. TG 5 –SOIL SEALING, SOILS in URBAN AREAS, LAND USE and LAND USE PLANNING. http://www.uni-essen.de/bodenkunde/links/eusoil/EUUrbansoilsapr04.pdf (accessed: 10 Octobr. 2005)

Coe, S.E., Alberti, M., Hepinstall, J.A. & Coburn, R., 2005. A hybrid approach to detecting impervious surface at multiple scales. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March 2005, http://www.definiens-imaging.com/documents/reference.htm (accessed: 10 Octob. 2005)

Darwish, A., Leukert, K. and Reinhardt, W., 2003. Urban Land -Cover Classification: An object based Perspective. IEEE: 2nd GRSS/ISPRS Joint Workshop on "Data Fusion and Remote Sensing over Urban Areas", pp. 278-282.

Deguchi, C. and Sugio, S., 1994. Estimations for percentage if impervious area by the use of Satellite Remote Sensing imagery. Water Science Technology, 29, pp. 135-144.

Dousset, B., 1995. Synthetic Aperture Radar imaging of urban surfaces: a case study. IEEE, pp. 2092-2096.

EEA glossary web-site, 2006. http://glossary.eea.europa.eu/EEAGlossary/S/soil_sealing (accessed: 15 June 2006)

Frauman, E. & Wolf, E., 2005. Segmentation of very high spatial resolution satellite images in urban areas for segments-based classification. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March 2005, http://www.definiens-imaging.com/documents/reference.htm (accessed: 27 Febr. 2006)

Greiwe, A. & Ehlers, M., 2005. Combined analysis of hyperspectral and high resolution image data in an object oriented classification approach. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March 2005, http://www.definiens-imaging.com/documents/reference.htm (accessed: 26 Febr.2006)

Grenzdorffer, G.J., 2005. Land use change in Rostock, Germany since the reunification - a combined approach with satellite data and high resolution aerial images. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March

Guindon, B., Zhang, Y. and Dillabaugh, C., 2004. Landsat urban mapping based on a combined spectral-spatial methodology. Remote Sensing and Environment, 92, pp. 218-232.

Harayama, A. & Jaquet, J.M., 2004. Multi-source object-oriented classification of landcover using very high resolution imagery and digital elevation model. In: Anon., Enviroinfo Conference 2004, Geneva, 21-23 October 2004. http://www.definiens-imaging.com/documents/reference2004.htm (accessed: 10 Octobr. 2005)

provides the greatest opportunity for discriminating vegetation (Jensen, 2000). Such band combinations are typically referred to as vegetation indices, the most popular being the normalised difference vegetation index, or NDVI, and is calculated as:

$$NDVI = \frac{\rho_{IR} - \rho_R}{\rho_{IR} + \rho_R} \quad (1)$$

where p = the pixel reflectance value
p_{IR} = the pixel reflectance value in the near infrared (IR) waveband
p_R = the pixel reflectance value in the red (R) waveband

The NDVI image classification comprises three stages: (i) definition of a land cover typology, (ii) "training"–the production of signatures by extraction of sample satellite image pixels from locations of known land-cover and the actual image classification, and (iii) accuracy assessment

2.2.1 Land cover typology: The land cover typology was derived by the land cover types (i.e. roofs, roads, car parks, gardens, trees etc) observed in the high resolution aerial photography, and their membership was assigned to either the sealed or unsealed classes. At the end, a simple two class grouping of sealed vs. unsealed land was provided.

2.2.2 Training the classifier: The district of the city of Cambridge was sub-divided into a number of 250 m x 250 m segments; from a total of 650 possible segments, 15 (*c*.2.5%) were randomly drawn. The ortho-rectified aerial photography of Cambridge was used to select training pixels in QuickBird imagery (i.e. the seed points forming a cross shaped pattern of five pixels) and to create the signature classes for the supervised classification by using the ERDAS Imagine software (Figure 2).

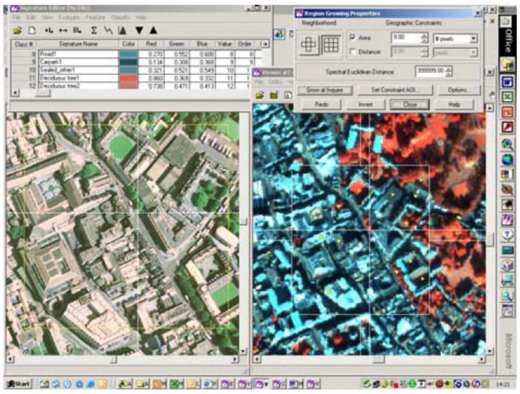


Figure 2. The aerial photograph (right) was used to locate the seed points onto the QuickBird imagery (left)

Finally, the NDVI image was classified with a maximum likelihood supervised classification. The image was reclassified according to the binary format sealed-unsealed and was exported into GIS to be joined with the OS MasterMap data. The topographic data were used to mask all the "Manmade" infrastructure (i.e. roads, roadsides and buildings) with a percentage of 100% sealing.

2.2.3 Accuracy assessment

The accuracy of the classification was assessed by comparison with the baseline maps that were produced by visually interpreting the ortho-rectified aerial photographs, for the 18 sample segments, as described in section 2.1.

3. RESULTS-DUSCUSSION

Eighteen segments, 250 x 250 m, have been visually classified from 0.125 m resolution ortho-corrected aerial photography. An example of one of the classified map segments is presented in Figure 3. This particular segment has 561 individual polygons. Given all 18 segments, 8086 polygons were available to test the correspondence between the classification and the API

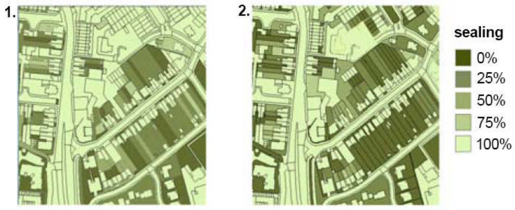


Figure 3. Comparison of (1) the aerial photograph classification, and(2)the supervised image classification

The results of the two classification methods were analysed with the confusion matrix approach. A confusion matrix (Table 1) cross-tabulates the frequency of class combinations, 0%, 25%, 50%, 75% and 100% sealed, in the digital classification with the equivalent sample survey from the API classification. This process is analogous to overlaying the two maps in Figure 3, and comparing classes, but for all 18 segments. The diagonal axis represents agreement between the two observations. Off-diagonal values represent mis-classification errors. Of importance to users of the classified maps is an idea of the overall mapping accuracy and the accuracy for the individual classes.

In Table 1, the overall accuracy is 69%. The numbers in brackets represent a weighted accuracy estimate that takes into account the probability that the API observations may contain some level of uncertainty. The digital classification provides maps of sealing on a continuous scale from 0 – 100%. The API classes, however, are discrete classes within that scale (*i.e.* 0%, 25%, 50%, 75% and 100%). To take into account the level of human interpretation error, 'fuzzy' boundaries were applied to the confusion matrix interpretation. The dashed box outlines represent a tolerance of one class either side of the expected class. According to the assumptions given, a 25% weight is given to the values either side of the diagonal, and 50% to the diagonal. The effect is to increase the estimated accuracy. For example, the overall accuracy increases from 69% to 75%. The adjusted accuracies are indicated in brackets and have been applied to the overall estimate and the user accuracy.

		CLASSIFICATION (Satellite + topographic)						
		0	25	50	75	100	*Total*	*Producer*
API	0	475	134	50	36	140	835	57%
	25	288	267	94	53	66	768	35%
	50	149	124	88	53	107	521	17%
	75	111	47	28	50	150	386	13%
	100	523	143	120	123	4683	5592	84%
	Total	1546	715	380	315	5146	8102	
	User	**31%**(40%)	**37%**(55%)	**23%**(39%)	**16%**(44%)	**91%**(92%)		**69%**(75%)

Table 1. The confusion matrix indicates correspondence between the digital classification and the API classification of sealing

4. CONCLUSIONS AND OUTLOOK

In this paper we have presented an approach for the automated mapping of sealed soils in urban environments using QuickBird images. The automated classification was compared with the air photo interpretation approach and the overall accuracy calculated to be 75%. The accuracy estimate could be an 'under'-estimate, due to the nature of the visual interpretation which classified sealing into 25% intervals. The low mapping accuracy also comprises the use of pixel based classifiers which are well known for their mapping accuracy limitations. A better assessment could be achieved by using more refined intervals. Future work will explore the potential of using object-based classifiers (i.e. eCognition software) to produce an objective and more efficient visual interpretation for increasing the overall accuracy. The methodology will be validated against three additional urban areas which will be (i) 'less green' than the city of Cambridge, (ii) of different sizes and (iii) located in different parts of England. Furthermore, eCognition will be used to classify the QuickBird imagery and the results will be compared with the pixel based approach. Finally, an operational approach for routine soil-related monitoring in the built environment will be recommended.

"REFERENCES"

Blaschke, T., Lang, S. & Moller, M., 2005. Object-based analysis of remote sensing data for landscape monitoring: Recent developments. In: Anon., Anais XII Simpósio Brasileiro de Sensoriamento Remoto, Goiania, Brasil, 16-21 April 2005, http://www.definiens-imaging.com/documents/reference.htm:2879-2885. (accessed: 26 Febr. 2006)

Burghardt, W. and the Working Group Urban Soils of the German Soil Science Society, 2004. Soil Monitoring Instruction on Sealed Areas in the European Union, Contribution to the EU Soil Thematic Strategy, http://www.uni-essen.de/bodenkunde/links/eusoil/sealingmonitoring2703.pdf (accessed: 11 Octobr.2005)

Burghardt, W., Banko, G., Hoeke, S., Hursthouse, A., de L' Escaille, T., Ledin, S., Marsan, F. A., Sauer, D. and Stahr, K., 2004. TG 5 –SOIL SEALING, SOILS in URBAN AREAS, LAND USE and LAND USE PLANNING. http://www.uni-essen.de/bodenkunde/links/eusoil/EUUrbansoilsapr04.pdf (accessed: 10 Octobr. 2005)

Coe, S.E., Alberti, M., Hepinstall, J.A. & Coburn, R., 2005. A hybrid approach to detecting impervious surface at multiple scales. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March 2005, http://www.definiens-imaging.com/documents/reference.htm (accessed: 10 Octob. 2005)

Darwish, A., Leukert, K. and Reinhardt, W., 2003. Urban Land -Cover Classification: An object based Perspective. IEEE: 2nd GRSS/ISPRS Joint Workshop on "Data Fusion and Remote Sensing over Urban Areas", pp. 278-282.

Deguchi, C. and Sugio, S., 1994. Estimations for percentage if impervious area by the use of Satellite Remote Sensing imagery. Water Science Technology, 29, pp. 135-144.

Dousset, B., 1995. Synthetic Aperture Radar imaging of urban surfaces: a case study. IEEE, pp. 2092-2096.

EEA glossary web-site, 2006. http://glossary.eea.europa.eu/EEAGlossary/S/soil_sealing (accessed: 15 June 2006)

Frauman, E. & Wolf, E., 2005. Segmentation of very high spatial resolution satellite images in urban areas for segments-based classification. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March 2005, http://www.definiens-imaging.com/documents/reference.htm (accessed: 27 Febr. 2006)

Greiwe, A. & Ehlers, M., 2005. Combined analysis of hyperspectral and high resolution image data in an object oriented classification approach. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March 2005, http://www.definiens-imaging.com/documents/reference.htm (accessed: 26 Febr.2006)

Grenzdorffer, G.J., 2005. Land use change in Rostock, Germany since the reunification - a combined approach with satellite data and high resolution aerial images. In: Anon., ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, 14-16 March

Guindon, B., Zhang, Y. and Dillabaugh, C., 2004. Landsat urban mapping based on a combined spectral-spatial methodology. Remote Sensing and Environment, 92, pp. 218-232.

Harayama, A. & Jaquet, J.M., 2004. Multi-source object-oriented classification of landcover using very high resolution imagery and digital elevation model. In: Anon., Enviroinfo Conference 2004, Geneva, 21-23 October 2004. http://www.definiens-imaging.com/documents/reference2004.htm (accessed: 10 Octobr. 2005)

Herold, M, Gardner, M.E., Noronha, V. and Roberts, D.A., 2003. Spectrometry and hyperspectral remote sensing of urban road infrastructure, unpublished manuscript provided by the authors to the GIFTSS project, pp. 29.

Herold, M., Gardner, M.E. and Roberts, D.A., 2003. Spectral resolution requirements for mapping urban areas. IEEE Transactions on Geoscience and Remote Sensing, 41 (0), pp. 1907-1919.

Jensen, R., 2001. *Remote sensing of the environment: an earth resource perspective.* Prentice Hall series in geographic information science, pp. 544.

Meinel, G and Hernig, A., 2005. Survey of soil sealing on the basis of the ATKIS basic DLM – feasibilities and limits, proceedings ISBN 3-901673-12-1, pp. 359-363.

Phinn, S., Stanford, M., Scarth, P. and Murray, A.T., 2002. Monitoring the composition of urban environments based on vegetation-imprvious surface-soil (VIS) model by subpixel analysis techniques. International Journal of Remote Sensing, 23, pp. 4131-4153.

Ridd, M.K., 1995. Exploring a V-I-S (vegetation-impervious surface -soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities. International Journal of Remote Sensing , 16, pp. 2165-2185.

Senate Department of Urban Development in Berlin web-site, 2004.
http://www.stadtentwicklung.berlin.de/umwelt/umweltatlas/eia102.htm (accessed 11 Octobr. 2005)

Wang, Z., Wei, W., Zhao, S. and Chen, X., 2004. Object-oriented Classification and Application in Land Use Classification Using SPOT-5 PAN imagery. IEEE, pp. 3158-3160.

Ward, D., Phinn, S.R. and Murray, A.T., 2000. Monitoring Growth in Rapidly Urbanizing Areas Using Remotely Sensed Data. Professional Geographer, 52, pp. 371-386.

"ACKNOWLEDGEMENTS"

This research has been funded by the Department for Environment, Food and Rural Affairs (DEFRA) and the British National Space Centre (BNSC)