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Review article

Object based image analysis for remote sensing

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ABSTRACT

Remote sensing imagery needs to be converted into tangible information which can be utilised in conjunction with other data sets, often within widely used Geographic Information Systems (GIS). As long as pixel sizes remained typically coarser than, or at the best, similar in size to the objects of interest, emphasis was placed on per-pixel analysis, or even sub-pixel analysis for this conversion, but with increasing spatial resolutions alternative paths have been followed, aimed at deriving objects that are made up of several pixels. This paper gives an overview of the development of object based methods, which aim to delineate readily usable objects from imagery while at the same time combining image processing and GIS functionalities in order to utilize spectral and contextual information in an integrative way. The most common approach used for building objects is image segmentation, which dates back to the 1970s. Around the year 2000 GIS and image processing started to grow together rapidly through object based image analysis (OBIA - or GEOBIA for geospatial object based image analysis). In contrast to typical Landsat resolutions, high resolution images support several scales within their images. Through a comprehensive literature review several thousand abstracts have been screened, and more than 820 OBIA-related articles comprising 145 journal papers, 84 book chapters and nearly 600 conference papers, are analysed in detail. It becomes evident that the first years of the OBIA/GEOBIA developments were characterised by the dominance of 'grey' literature, but that the number of peer-reviewed journal articles has increased sharply over the last four to five years. The pixel paradigm is beginning to show cracks and the OBIA methods are making considerable progress towards a spatially explicit information extraction workflow, such as is required for spatial planning as well as for many monitoring programmes.

1. Introduction

Environmental monitoring requirements, conservation goals, spatial planning enforcement, or ecosystem-oriented natural resources management, to name just a few drivers, lend considerable urgency to the development of operational solutions that can extract tangible information from remote sensing data. The 'work horses' of satellite data generation, such as the Landsat and SPOT satellites or the ASTER and MODIS instruments, have become important in global and regional studies of biodiversity, nature conservation, food security, deforestation impact, desertification monitoring, and other application fields. With the increasing spatial resolution of the '1-m generation' of IKONOS (launched in 1999), QuickBird (2001) or OrbView (2003) sensors, new application fields which had previously been the domain of airborne remote sensing could be tackled by satellite remote sensing. In the late 2007, the first commercial satellite with a resolution of less than half a metre (Worldview-1; 0.44 m panchromatic) became operational, and at present we see security applications, vehicle detection, and many urban applications developing rapidly, in terms of both number and sophistication. By simplification and generalisation we can distinguish two major trends: (a) an increasing amount of data being produced in an ever broader range of spatial, spectral, radiometric and temporal resolutions, including the high spatial resolutions mentioned above, and (b) orchestrated supranational programmes and systems for regular or on-demand surveys of the earth's surface (e.g. GEOSS, GMES).

This article assesses recent developments in object based image analysis or OBIA – the acronyms OBIA and GEOBIA, which stands for geospatial object based image analysis, are both herein used interchangeably – based on a thorough analysis of over 820 articles dealing with the concept of OBIA. It reflects only very briefly on the tradition of image segmentation, which is much older than the advent of popularised commercial software. The concatenation of two trends has made this new area of research possible: the advent of high resolution imagery, and the availability of powerful, off-the-shelf software that bridges image processing and GIS functionalities in an object based environment (Blaschke et al., 2000). The subject of OBIA is related to concepts of object-oriented software and to object handling in the GIS world; the reader is referred

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to a recent review paper on object-oriented presentation in GIS by Bian (2007).

It is generally agreed (Blaschke et al., 2000; Blaschke and Strobl, 2001; Schiewe, 2002; Hay et al., 2003; Burnett and Blaschke, 2003; Koch et al., 2003; Flanders et al., 2003; Benz et al., 2004; Blaschke et al., 2004; Zhang et al., 2005a; Liu et al., 2006; Navulur, 2007; Lang, 2008; Hay and Castilla, 2008) that OBIA builds on older segmentation, edge-detection, feature extraction and classification concepts that have been used in remote sensing image analysis for decades (Kettig and Landgrebe, 1976; Haralick, 1983; Haralick and Shapiro, 1985; Levine and Nazif, 1985; Strahler et al., 1986; McKeown et al., 1989; Pal and Pal, 1993; Câmara et al., 1996; Hay et al., 1996; Lobo et al., 1996; Ryherd and Woodcock, 1996; Wulder, 1998; Aplin et al., 1999; Baltsavias, 2004). Its emergence has nevertheless provided a new, critical bridge between the spatial concepts applied in multiscale landscape analysis (Wu, 1999; Hay et al., 2001; Wu and David, 2002; Burnett and Blaschke, 2003), Geographic Information Systems (GIS, (Câmara et al., 1996; Yu et al., 2006)), Geographic Information Science (abbreviated to GIScience, see (Goodchild, 1992, 2004)), and the synergy between image-objects and their radiometric characteristics and analyses in Earth Observation data (Benz et al., 2004; Blaschke et al., 2004; Langanke et al., 2007; Laliberte et al., 2007; Navulur, 2007; Möller et al., 2007; Jobin et al., 2008; Stow et al., 2008; Tiede et al., 2008; Trias-Sanz et al., 2008; Aubrecht et al., 2008; van der Werff and van der Meer, 2008; Weinke et al., 2008).

In recent years, a critical online discussion has arisen within an evolving multidisciplinary community concerning whether or not geographic space should be included in the name of this concept (see Hay and Castilla (2008); Castilla et al. (2008); Lang (2008)). Hay and Castilla (2008) argue that it should be called "Geographic Object Based Image Analysis" (GEOBIA), as only then will it be clear that it represents a sub-discipline of GIScience. Indeed, the term OBIA may be too broad, for it goes without saying for remote sensing scientists, GIS specialists and many 'environmental' based disciplines that 'their' image data represents portions of the Earth's surface. However, such an association may not be taken for granted by scientists in disciplines such as Computer Vision, Material Sciences or Biomedical Imaging who also conduct OBIA. Since this debate of naming remains ongoing, the author has chosen to acknowledge both terms equally but to conform with the usage in the title of the definitive book in this field (Blaschke et al., 2008) as well as in two previous books (Blaschke, 2002; Blaschke and Kux, 2005), and for the sake of simplicity use the term OBIA in the remainder of this article.

2. Object based image analysis in remote sensing

2.1. What's wrong with pixels?

Blaschke and Strobl (2001) have raised the provocative question "What's wrong with pixels?", having identified an increasing dissatisfaction with pixel-by-pixel image analysis. Although this critique was not new (Cracknell, 1998; see also Blaschke and Strobl (2001), Burnett and Blaschke (2003) and Blaschke et al. (2004) for a more thorough discussion) they observed something like a hype in applications 'beyond pixels'. A common denominator of these applications was, and still is, that they are built on image segmentation (see also Burnett and Blaschke (2003), Hay et al. (2003), Benz et al. (2004), Liu et al. (2006), Blaschke et al. (2004), Hay et al. (2005), Blaschke and Lang (2006), Lang and Blaschke (2006), Lang (2008), Hay and Castilla (2008) and Blaschke et al. (2008)). Image segmentation is not at all new (Haralick, 1983; Haralick and Shapiro, 1985; Pal and Pal, 1993; Kartikeyan et al., 1998), but has its roots in industrial image processing and was not

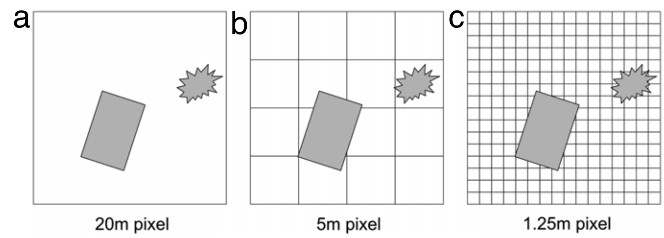

Fig. 1. Relationship between objects under consideration and spatial resolution: (a) low resolution: pixels significantly larger than objects, sub-pixel techniques needed. (b) medium resolution: pixel and objects sizes are of the same order, pixel-by-pixel techniques are appropriate. (c) high resolution: pixels are significantly smaller than object, regionalisation of pixels into groups of pixels and finally objects is needed.

used extensively in Geospatial applications throughout the 1980s and 1990s (Blaschke et al., 2004).

Uses for segmentation methods outside remote sensing – including industrial or medical image processing – are legion (Pal and Pal, 1993). Within remote sensing applications, algorithms are numerous and have been rapidly increasing over the past few years (Kartikeyan et al., 1998; Baatz and Schäpe, 2000; Blaschke et al., 2004; Neubert et al., 2008). Image segmentation, from an algorithmic perspective, is generally divided into four categories: (a) point-based, (b) edge-based, (c) region-based and (d) combined (Schiewe, 2002) — for technical details of segmentation techniques, readers can refer to Pal and Pal (1993). No matter which of the methods is applied, segmentation provides the building blocks of object based image analysis (Hay and Castilla, 2008; Lang, 2008), at least for now, since the user may ultimately wish to deal with spatially fuzzy objects (Gorte, 1998) or with fields (Cova and Goodchild, 2002). Segments are regions which are generated by one or more criteria of homogeneity in one or more dimensions (of a feature space) respectively. Thus segments have additional spectral information compared to single pixels (e.g. mean values per band, and also median values, minimum and maximum values, mean ratios, variance etc.), but of even greater advantage than the diversification of spectral value descriptions of objects is the additional spatial information for objects (Blaschke and Strobl, 2001; Darwish et al., 2003; Flanders et al., 2003; Benz et al., 2004; van der Werff and van der Meer, 2008; Hay and Castilla, 2008). It has been frequently claimed that this spatial dimension (distances, neighbourhood, topologies, etc.) is crucial to OBIA methods, and that this is a major reason for the marked increase in the usage of segmentation-based methods in recent times, compared to the usage of image segmentation in remote sensing during the 1980s and 1990s (Hay et al., 2003; Koch et al., 2003; Benz et al., 2004; Blaschke et al., 2004; Liu et al., 2006; Navulur, 2007; Conchedda et al., 2008; Wuest and Zhang, 2009; Gamanya et al., 2009).

Fig. 1 lays out schematically the relationship between the spatial resolution and the object under consideration. Although we have difficulties in defining generically applicable thresholds we can differentiate semantically between these three situations. For simplicity, we can regard the pixel in a similar way to the spatial resolution. Furthermore, when considering the Shannon sampling theorem (sometimes called Nyquist–Shannon sampling theorem), we can conclude that an object should be of the order of one tenth of the dimension of the sampling scheme – the pixel – in order to ensure that it will be completely independent of its random position and its orientation relative to the sampling scheme. The three situations outlined graphically in Fig. 1 require completely different techniques to unravel information from the data sets. It can be assumed that the situations (a) and (b) do not leave much choice when the task is to identify, classify and characterise a given object as illustrated. The situation (c), however, may be considered a 'high resolution situation', and only here can the specific advantages of the OBIA approach be deployed, although regionalisation approaches have also been applied to other situations, for example to Landsat images, and recent studies have also utilised OBIA methods for medium or coarse resolution data (Dorren et al., 2003; Geneletti and Gorte, 2003; Duveiller et al., 2008; Myint et al., 2008; Jobin et al., 2008).

Before OBIA, the main task of image segmentation was to produce a set of non-overlapping segments (polygons), and this step was quite separate from the classification. The problem, though, is scale: scale is a 'window of perception' (Marceau, 1999) and we typically end up with several scales in imagery – if the spatial resolution is finer than the size of the objects of interest. A segmentation algorithm is used in the expectation that it will divide the image into (a) relatively homogeneous and (b) semantically significant groups of pixels. Burnett and Blaschke (2003) called these groups 'objects candidates' which are to be recognised by further processing steps and to be transferred into meaningful objects. It is well known that semantically significant regions are found in an image at different scales of analysis (Hay et al., 2001, 2003), and OBIA is inextricably linked to multiscale analysis concepts (Burnett and Blaschke, 2003; Benz et al., 2004; Lang, 2008; Hay and Castilla, 2008), even if single levels are targeted for specific applications (Lang and Langanke, 2006; Lang, 2008; Weinke et al., 2008). Burnett and Blaschke (2003) called this OBIA concept "multiscale segmentation/object relationship modelling" (MSS/ORM). Lang and Langanke (2006) developed an iterative One Level Representation (OLR), and Tiede et al. (2008) applied the OLR concept convincingly to airborne LiDAR data for tree crown segmentation (as did many other research groups, e.g. Brennan and Webster (2006) and Bunting and Lucas (2006)). Weinke et al. (2008) empirically applied and evaluated both OBIA concepts, and found pros and cons for each approach. For a high resolution aerial image, for example, at coarse scales we can discriminate fields or forest stands, while at finer scales we can discriminate individual trees or plants: parameters and thresholds in a typical single-scale segmentation algorithm must therefore be tuned to the correct scale for analysis. It is, however, often not possible to determine the correct scale of analysis in advance because different kinds of images require different scales of analysis, and furthermore, in many cases significant objects appear at different scales of analysis of the same image (Arbiol et al., 2006).

It should be clearly stated that much of the work referred to as OBIA originated around the software known as "eCognition" (Baatz and Schäpe, 2000; Flanders et al., 2003; Benz et al., 2004), which was later renamed "Definiens" (Lang and Tiede, 2007). Furthermore, very few of these 'early' OBIA developers used the term 'object based'. Some authors used 'object oriented' (Blaschke et al., 2000; Blaschke and Hay, 2001; Benz et al., 2004) and some of these later switched to 'object-based' (with or without a hyphen), whilst some authors still use 'object-oriented' (e.g. Navulur (2007)). It has so far been assumed that most authors prefer to use the term 'based' since 'oriented' may be too closely related to the object-oriented programming paradigm (see Hay and Castilla (2008) for discussion). The idea of incorporating contextual information in the classification of remote sensing images can be traced back to the 1970s (Kettig and Landgrebe, 1976), even though the importance of incorporating texture increases with increasing resolution (see Fig. 1 and explanations). One of the aims of grouping pixels into image objects is to overcome the so called 'salt and pepper effect' (Blaschke et al., 2000). Many researchers have claimed that OBIA methods are suitable for overcoming this situation, e.g. "*Thanks to the recent improvements in image segmentation, object-based approaches can be used to delineate and classify land cover efficiently*" (Duveiller et al., 2008, p. 1971). In recent articles it has even been claimed that "*Object-oriented processing techniques are becoming more popular compared to traditional pixel-based image analysis*" (Gamanya et al., 2009, p. 571).

2.2. OBIA studies

Even a first, brief literature search reveals that publications in the early period of OBIA (2000 to 2003/04) were dominated by conference proceedings and 'grey' literature', but increasing numbers of empirical studies published in peer-reviewed journals have subsequently provided sufficient proof of the improvements that OBIA offers over per-pixel analyses. For instance, Yu et al. (2006) created a comprehensive vegetation inventory for a study area in Northern California and could empirically demonstrate that the OBIA approach overcame the problem of salt-and-pepper effects found in classification results from traditional per pixel approaches. (Xie et al., 2008) used an object based geographic image retrieval approach for detecting invasive, exotic Australian Pine in South Florida, USA. Dorren et al. (2003) as well as Heyman et al. (2003) favoured an OBIA approach to discriminate broad-scale forest cover types, and in a subsequent study Maier et al. (2008) incorporated very detailed information from LiDAR-derived canopy surface models. Chubey et al. (2006) used OBIA to derive forest inventory parameters. Herrera et al. (2004) classified trees outside forests using an OBIA approach in Costa Rica. Radoux and Defourny (2007) used high resolution satellite images and OBIA methods to produce large scale maps and quantitative information about the accuracy and precision of delineated boundaries for forest management. For a highly fragmented forest landscape in Southern Vancouver Island, Canada, Hay et al. (2005) proved how segments corresponded cognitively to individual tree crowns, ranging up to forest stands, using segmentation, object-specific analysis and object-specific up-scaling. Gergel et al. (2007) distinguished forest structural classes in riparian forests in British Columbia for riparian restoration planning. Shiba and Itaya (2006) used high-resolution satellite imagery (IKONOS, Quick Bird) to evaluate forest land use structure and to assess environmental change in Central Japan. Weiers et al. (2004), Bock et al. (2005), Lathrop et al. (2006), Diaz-Varela et al. (2008) and Jobin et al. (2008) all demonstrated the usefulness of OBIA methods for habitat mapping tasks. Wiseman et al. (2009) successfully identified and quantified 93 out of 97 shelterbelts across the Canadian Prairie Provinces using multi-spectral reflectance, shape, texture and other relational properties, in comparison with 1:40,000 scale orthophoto interpretation; spectral reflectance, variance and shape parameters were combined to differentiate between species compositions for six shelterbelts. Bunting and Lucas (2006) delineated tree crowns within mixed-species forests of complex structure in central east Queensland, Australia, based on 1 m airborne CASI hyperspectral data.

Pascual et al. (2008) presented a two-stage approach for characterising the structure of *Pinus sylvestris* stands in forests of central Spain: building on the delineation of forest stands and a digital canopy height model derived from LiDAR data they investigated forest structure types. Addink et al. (2007) demonstrated, in a very detailed study with 243 field plots, that the accuracy of parameter estimation for vegetation parameters, aboveground biomass and leaf area index (LAI) in Southern France was higher for object-oriented analysis than for per-pixel analysis. Chen et al. (2007) demonstrated the potential of OBIA to map urban land cover for the city of Beijing from ASTER data with a relatively high accuracy. Similarly, Lackner and Conway (2008) used IKONOS images to automatically delineate and classify land-use polygons in Ontario, Canada, within a diverse urban setting; they obtained high overall accuracies for six- and ten-class maps, with 90% and 86% accuracy respectively. Zhang et al. (2005c) used OBIA methods for the automatic extraction of land cover objects in the Three Gorges Reservoir, China. Kong et al. (2006) also employed an OBIA approach to extract urban land-use information from a high-resolution image. In a study of apparently similar design, Mo et al. (2007) carried out land cover classification experiments in the Zhuzhou area, China, using a QuickBird multi-spectral image. The authors found it consistent with the visual interpretation results and superior to the per-pixel method. In another Chinese urban dynamic monitoring study in Beijing, An et al. (2007) found the overall accuracy and the Kappa Index of Agreement (KIA) to be significantly higher when using OBIA methods compared with traditional approaches. Coincidentally, Im et al. (2008) compared three different change detection techniques, based on object/neighbourhood correlation, image analysis and image segmentation, with two different per-pixel approaches, and found that object based change classifications were superior (KIA up to 90%) compared to the other change detection results (KIA 80 to 85%).

Stow et al. (2008) could differentiate changes in "true shrubs" and "sub-shrubs" within coastal sage scrub vegetation communities in California: they proved that patterns of shrub distribution were more related to anthropogenic disturbance than to a long drought. Mallinis et al. (2008) performed a multi-scale, object based analysis of a QuickBird satellite image to delineate forest vegetation polygons in a natural forest in Northern Greece. Johansen et al. (2007) mapped vegetation structure in Vancouver Island, Canada, and discriminated structural stages in vegetation for riparian and adjacent forested ecosystems, using various texture parameters for a QuickBird image including co-occurrence contrast, dissimilarity, and homogeneity texture measures: an OBIA-classification resulted in a very detailed map of vegetation structural classes, with an overall accuracy of 79%. Corbane et al. (2008) developed an approach based on remotely sensed radiometric and spatial information for the mapping of hydrological soil surface characteristics classes according to a predefined typology based on infiltration rates.

Krause et al. (2004) integrated remote sensing data, aerial photographs and point data obtained by fieldwork. They assessed temporal–spatial changes on a mangrove peninsula in Northern Brazil and the adjacent rural socioeconomic impact area, as well as of the nature of the mangrove structure. A land-use cover analysis was also undertaken, and the authors were able to differentiate between strong and weak patterns in the mangrove ecosystem, suggesting different management measures and monitoring at hierarchical scales. Yu et al. (2006) carried out a comprehensive vegetation inventory for protected seashore areas in Northern California. For mangroves on the Caribbean coast of Panama, Wang et al. (2004) were able to enhance spectral separability among mangrove species by taking the object as the basic spatial unit, as opposed to the pixel. Möller et al. (2007) assessed segmentation results and inaccuracies in an agricultural area in Saxony-Anhalt, Germany. They developed the methodology for a 'Comparison Index', which allowed a comparison of different segmentation results.

Su et al. (2008) used OBIA methods to improve texture analysis based on both segmented image objects and moving windows across the whole image, and co-occurrence matrix (GLCM) textural features (homogeneity, contrast, angular second moment, and entropy) were calculated. Single additional features such as Moran's I were able to improve the classification accuracy by up to 7%. A comparison of results between spectral and textural/spatial information indicated that textural and spatial information can be used to improve the object-oriented classification of urban areas using high resolution imagery. As one of the earlier attempts to compare per-pixel and object based methods (see also Neubert, 2001; Meinel et al., 2001; Flanders et al., 2003; Koch et al., 2003; Ehlers et al., 2006), Shackelford and Davis (2003) presented a fuzzy logic methodology to improve classification accuracy of high-resolution multispectral satellite imagery for the classification of urban and suburban areas. For urban IKONOS images they achieved Maximum Likelihood Classification accuracies of 79% to 87%, with significant misclassification errors between the spectrally similar 'Road' and 'Building' urban land cover types. After incorporating texture measures and a length-width contextual measure, the discrimination between spectrally similar classes could be enhanced by between 8% and 11% compared to the Maximum Likelihood approach.

Zhou and Troy (2008) presented an object-oriented approach for analysing and characterising the urban landscape structure at the parcel level, using high-resolution digital aerial imagery and LIDAR data for the Baltimore area. They incorporated a three-level hierarchy in which objects were classified differently at each level. The overall accuracy of the classification was 92.3%, and the overall Kappa statistic was 0.89. Luscier et al. (2006) evaluated precisely an OBIA method based on digital photographs of vegetation, to objectively quantify the percentage ground cover of grasses, forbs, shrubs, litter, and bare ground within 90 plots of 2 by 2 m: the observed differences between true cover and OBIA results ranged from 1% to 4% for each category.

Desclée et al. (2006) proved the effectiveness of OBIA-based change detection capability in detecting forest changes in temperate regions, while Duveiller et al. (2008) investigated land cover change by combining a systematic regional sampling scheme based on high spatial resolution imagery with object based, unsupervised, classification techniques for a multi-date segmentation, to obtain objects with similar land cover change trajectories, which were then classified by unsupervised procedures. This approach was applied to the Congo River basin to accurately estimate deforestation at regional, national and landscape levels. Ivits and Koch (2002) and Ivits et al. (2005) analysed landscape patterns for 96 sampling plots in Switzerland, based on OBIA-derived patch indices for land-use intensities ranging from old-growth forests to intensive agricultural landscapes: landscape patterns could be quantified on the basis of merged Landsat ETM–IRS, QuickBird and aerial photographic data. Yan et al. (2006) compared per-pixel and OBIA classifications for land-cover mapping in a coal fire area in Inner Mongolia, and found the differences in accuracy, expressed in terms of proportions of correctly allocated pixels, to be statistically significant. They concluded that the thematic mapping result using an object-oriented image analysis approach gave a much higher accuracy than that obtained using the per-pixel approach. Gitas et al. (2003) mapped recently burned areas on the Spanish Mediterranean coast.

Marignani et al. (2008) developed a standardised method to develop restoration practices capable of increasing the efficacy of landscape management. They claimed that object-oriented approaches could assist in the development of methods for selecting areas to be prioritised for restoration purposes, since they act on images using a predefined, and thus repeatable, algorithm. In many landscape ecological applications, in landscape planning and in nature conservation, OBIA methods are used to link the objects obtained to the "patches" in landscape ecology (Burnett and Blaschke, 2003; Devereux et al., 2004; Laliberte et al., 2004; Schiewe and Ehlers, 2005; Lang and Langanke, 2006; Langanke et al., 2007).

CART (classification and regression trees) models are increasingly being used in conjunction with object-oriented methods in urban mapping (Thomas et al., 2003), rangeland mapping (Laliberte et al., 2007) and coastal zone applications (Yu et al., 2006), or for the extraction of forest inventory parameters (Chubey et al., 2006). Mathieu et al. (2007) successfully mapped private gardens in urban areas using object-oriented techniques and very high-resolution satellite imagery. Stow et al. (2007) delineated residential land use polygons and identified low and high socio-economic status neighbourhoods within Accra, Ghana, on the basis of QuickBird multispectral satellite data.

Platt and Rapoza (2008) compared results from a Maximum Likelihood classification with results from OBIA for a mixed urban-suburban-agricultural landscape surrounding Gettysburg, Pennsylvania. They noted that OBIA has at least four components not typically used in per-pixel classification: (1) the segmentation procedure, (2) the nearest neighbour classifier, (3) the integration of expert knowledge, and (4) feature space optimisation. They evaluated each of these components individually and found that the combination of segmentation into image objects, use of the nearest neighbour classifier, and the integration of expert knowledge yielded substantially improved classification accuracy for the scene, compared to a per-pixel method.

OBIA applications focussing on the identification and classification of urban features are too numerous to be listed here. Most notably, Thomas et al. (2003) assessed the accuracy of three different methods for extracting urban land-cover/land-use information from high-resolution imagery for the city of Scottsdale, Arizona, for storm-water runoff estimation. They demonstrated that the increased amount of spatial information in one meter or less resolution imagery strains the resources of image classification using traditional supervised and unsupervised spectral classification algorithms. Similarly, Carleer et al. (2005) compared four segmentation algorithms from the two main groups of segmentation algorithms (boundary-based and region-based), applied on very high spatial resolution images for different landscapes, and differentiated urban areas into residential, urban administrative zones and urban dwelling zones. In recent applications, research has been expanded into the characterisation of urban structures, the incorporation of ancillary geospatial information and socio-economic data (Lemp and Weidner, 2005; Liu et al., 2005; Nobrega et al., 2008; Kux and Araujo, 2008; Hofmann et al., 2008; Aubrecht et al., 2008; Kressler and Steinnocher, 2008), and into subsequently tackling dynamic aspects of urban change, especially urban sprawl (An et al., 2007; Jacquin et al., 2008; Durieux et al., 2008). Based on Airborne Laser Scanning and optical imagery, Aubrecht et al. (2008) analysed land cover and urban function types on the basis of their relative heights and integrated socioeconomic data. Durieux et al. (2008) successfully applied OBIA methods in urban environments and for mapping urban sprawl. Jacquin et al. (2008) proved OBIA capacities and revealed an improved capacity to delineate urban extent at regional scales and to quantify urban objects at local scales through a comparison with an urban database realised using a computer assisted photo interpretation. Lang et al. (2006) applied OBIA methods to the classification of refugee camps and the quantification of houses and tents while Ebert et al. (2009) applied OBIA methods for the definition and estimation of variables from optical and LiDAR data in combination with elevation information and existing hazard information, aiming to estimate social vulnerability indicators through the use of physical characteristics.

Zhou et al. (2008) showed that OBIA methods to model lawn characteristics, such as parcel lawn area and parcel lawn greenness, combined with household characteristics, could be used to predict household lawn fertilisation practices on private residential lands in the Baltimore area, Maryland. Walker and Briggs (2007) developed an object based classification approach for high resolution, true-colour aerial photography for the Phoenix Metropolitan area, and isolated vegetation patches ranging from shrubs to large trees for further analysis, while Walker and Blaschke (2008) adapted this classification method into transferable rule-sets. Schöpfer and Möller (2006) demonstrated the transferability of OBIA methods for several metropolitan areas. Berberoglu and Akin (2009) used detection techniques including image differencing, image rationing, image regression and change vector analysis, to assess their effectiveness for detecting land use/cover change in a Mediterranean environment.

A brief look at damage analysis, disaster management and risk management (excluding the wide range of security or geointelligence applications) is also warranted. Myint et al. (2008) identified tornado damaged areas, comparing supervised, unsupervised, and object-oriented classification approaches: accuracy assessment (KIA) revealed that the OBIA approach showed the highest degree of accuracy in tornado damage detection. Reiche et al. (2007) classified oil spills in Western Siberia using OBIA methods. For the group of risk analysis and management applications the reader is referred to Van de Sande et al. (2003) who applied OBIA to land cover mapping for flood risk and flood damage assessment, and to Park and Chi (2008), who investigated potential landslide occurrences in Korea and adapted unsupervised change detection analysis based on multi-temporal object based segmentation of high-resolution remote sensing data, and thresholding, to detect landslide-prone areas. The OBIA method predicted landslide susceptibility on the basis of detected landslide areas and GIS-based spatial databases, and 83% of actual landslide areas were detected. Turker and Sumer (2008) detected damaged buildings from an earthquake in Golcuk, Turkey, one of the urban areas most strongly affected by the 1999 Izmit earthquake. A watershed segmentation of post-event aerial images utilised the relationship between the buildings and their shadows and labelled 80.6% of buildings correctly as either damaged or undamaged.

Gusella et al. (2005) quantified the number of buildings that collapsed following the Bam earthquake, commencing with the inventory of buildings as objects in QuickBird satellite imagery captured before the event. From 18,872 structures identified for Bam, the results suggested that 34% had collapsed, a total of 6,473, leading to an overall accuracy of 70% for the damage classification. To elucidate the communalities of OBIA methods for earthquake or otherwise demolished houses, and subsequently for all kinds of man-made structures, al Khudairy et al. (2005) analysed structural damage caused by war-like conflicts using pre-conflict IKONOS images of Jenin (2 m resolution), in the Palestinian territories, and Brest (1 m resolution) in FYROM. They examined the feasibility of using mathematical morphological operators to automatically identify zones of likely structural damage in dense urban settings. The overall results showed that object-oriented segmentation and classification systems facilitate the interpretation of change detection results derived from very high-resolution (1 m and 2 m) commercial satellite data. They concluded (al Khudairy et al., 2005, p. 825): "*The results show that object-oriented classification techniques enhance quantitative analysis of traditional pixel-based change detection applied to very high-resolution satellite data and facilitate the interpretation of changes in urban features*".

2.3. Remaining problems

The investigations cited above and many other studies not listed here for reasons of space, demonstrate the potential of OBIA but also reveal that other problems more specific to high resolution situations can arise. In high-resolution images, for example, each pixel is not closely related to vegetation physiognomy as a whole, and vegetation always shows heterogeneity as a result of irregular shadow or shade (Ehlers et al., 2003). However, many studies are able to demonstrate that the advantage (one may say the luxury) of being able to aggregate pixels to segments to objects and to address objects characteristics through sub-objects allow one to explicitly treat various kinds of 'within-patch heterogeneity' (Blaschke, 1995), which enables applications in studying forest gaps, vegetation patchiness or landscape complexity.

It is widely acknowledged that advances in sensor technologies, particularly those relating to sensor spatial resolution, are helping to make remote sensing more appropriate to detailed studies of the earth's surface. The resulting huge amounts of data pose a challenge, and object based methods are far from the only way to deal with this problem. Developments in image classification techniques—notably, artificial neural networks (ANNs), fuzzy set methods, genetic algorithms, and support vector machines, just to name a few, may offer the prospect of improved representation of complex environments. This article does not adequately nor comprehensively address those developments but concentrates on regionalisation approaches to fine scaled information, which aim to address real world objects.

Without venturing into any epistemological analysis of the pixel paradigm it can be stated that it has been, and still is, the basis for thousands of successful applications in remote sensing. It does, however, have its limitations in regard to relative scale, context, and fuzzy or smooth transitions. Clearly, it was the launch of the 'new generation' of very high spatial resolution satellite sensors and the wide dissemination of a variety of digital data sources that provided the incentive to augment detailed satellite data.

Fig. 2 is just one example of many applications which deals with fuzzy patterns or chess-board patterns, where single pixel information may be misleading when classified individually.

In conclusion, starting from around the year 2000 we can document a sharp increase in the usage of image segmentation techniques and an increasing use of the terms "object based image analysis" and "object oriented image analysis". This increase in usage has been frequently reported in literature but has not previously been proven quantitatively, and hence the next section will document a comprehensive content analysis for OBIA publications, considering peer-reviewed and non-peer-reviewed publications separately.

3. Content analysis

3.1. Rationale

Early stages of new developments are characterised by a relatively high number of conference articles and 'grey' literature, since it is more difficult to publish new methodologies in established journals, while specific journals on, for example, OBIA, do not exist. It can also be assumed that, in almost all fields of science, there are de facto communities of specialists and scientists who care about the issues related to the formalisation, analysis and use of concepts and data. In GIScience, for example, there is the University Consortium for Geographic Information Science (UCGIS), or the Association of Geographic Information Laboratories for Europe (AGILE). In remote sensing too, there is the International Society of Photogrammetry and Remote Sensing (ISPRS) and relevant national organisations such as the American Society of Photogrammetry and Remote Sensing (ASPRS), and the German Society for Photogrammetry and Remote Sensing (DGPF), some of them with a history of up to 100 years. The GIScience community has been developing for nearly two decades (Goodchild, 1992, 2004) and is described as an increasingly specialised field. OBIA is somehow the link between the remote sensing world and GIScience; Hay and Castilla (2008) even call OBIA a sub-discipline of GIScience, linking the pixel world and the vector world. In recent years a significant number of authors has claimed the use of OBIA to be advantageous (Blaschke et al., 2000; Baatz and Schäpe, 2000; Blaschke and Strobl, 2001; Burnett and Blaschke, 2003; Flanders et al., 2003; Benz et al., 2004; Carleer et al., 2005), and the author has found it necessary to complement this belief with a quantitative analysis of publications in this field, and the type of media that they appear in. The rationale for adopting this method was two-fold: the appropriateness of comparing amounts of 'grey' literature and journal articles in a still young and developing field, and the absence of a quantitative foundation for the hypothesis that the use of OBIA is an important trend or a new paradigm in remote sensing and GIScience.

3.2. Method

The importance of a major trend – to avoid a discussion on the more complex term "paradigm" and associated discussion (Kuhn, 1962) – is in most scientific fields closely linked to the amount of relevant publishing activity. The 'productivity' of researchers is evaluated partially through the quantity of their published works (for instance, the number of papers published), but also on their quality (based, for example, on awards for the best papers, personal invitations to publish, etc.), (Caron et al., 2008), as well as on the way these publications impact on their area of expertise (particularly the frequency with which articles are cited) (Dubois and Reeb, 2000).

It is assumed that, whenever possible, researchers tend to publish in well established journals (Caron et al., 2008). Although the ranking of academic journals is common practice in many fields of research, the activity is not without contention or criticism. Whilst recognising this situation, the author agrees with Harzing and van der Wal (2008) in considering this to be just part of academic life; it is nevertheless important to ensure that such rankings are as comprehensive and objective as possible. The "impact factor" is one of the standardised measures created by the Institute of Scientific Information (ISI), which can be used to measure variations over time in the number of citations received for articles in a journal (Amin and Mabe, 2000). The ISI citation databases are designed to cover the highest impact scientific research journals. Google Scholar also contains citation information, but includes less quality control over the collection of publications from different types of web documents. van Kousha and Thelwall (2008) found that those citations unique to Google Scholar, which were not in the ISI database, were mainly from full-text sources, and that the large disciplinary differences between different types of citing document suggested that a wide range of non-ISI citing sources, especially those from non-journal documents, were accessible through Google Scholar. The authors considered this to be an advantage of Google Scholar, especially for open access scholarly documents providing a broader type of citation impact (van Kousha and Thelwall, 2008). Harzing and van der Wal (2008) investigated 536 journals from the Harzing Journal Quality List that had both an ISI factor and a Google Scholar h-index or g-index for 2003–2006. The correlation was shown to be strong and very significant, even though they measure in different ways, and as a consequence, both ISI Web of Knowledge and Google Scholar were used in the following analysis.

3.3. Non peer-reviewed literature

The main sources for this search were the Internet, some CD-ROMs and books from relevant conferences and workshops, and also edited books. Following a first, rough Internet search carried out with the help of some PhD students in the third quarter of 2008, twelve conferences with at least five relevant papers or extended abstracts were identified (Table 1). From these sources 1320 abstracts were screened to identify papers relevant to OBIA and 349 abstracts were identified as being related to OBIA in a broad sense.

Other conferences and other documents available as CD-ROMs or over the Internet were pre-screened and another 242 not fully peer-reviewed articles were identified as relevant to OBIA. For these sources, error of omission – missing the occasional conference paper – is not critical to obtaining a valid result, since this is not an absolute measurement.

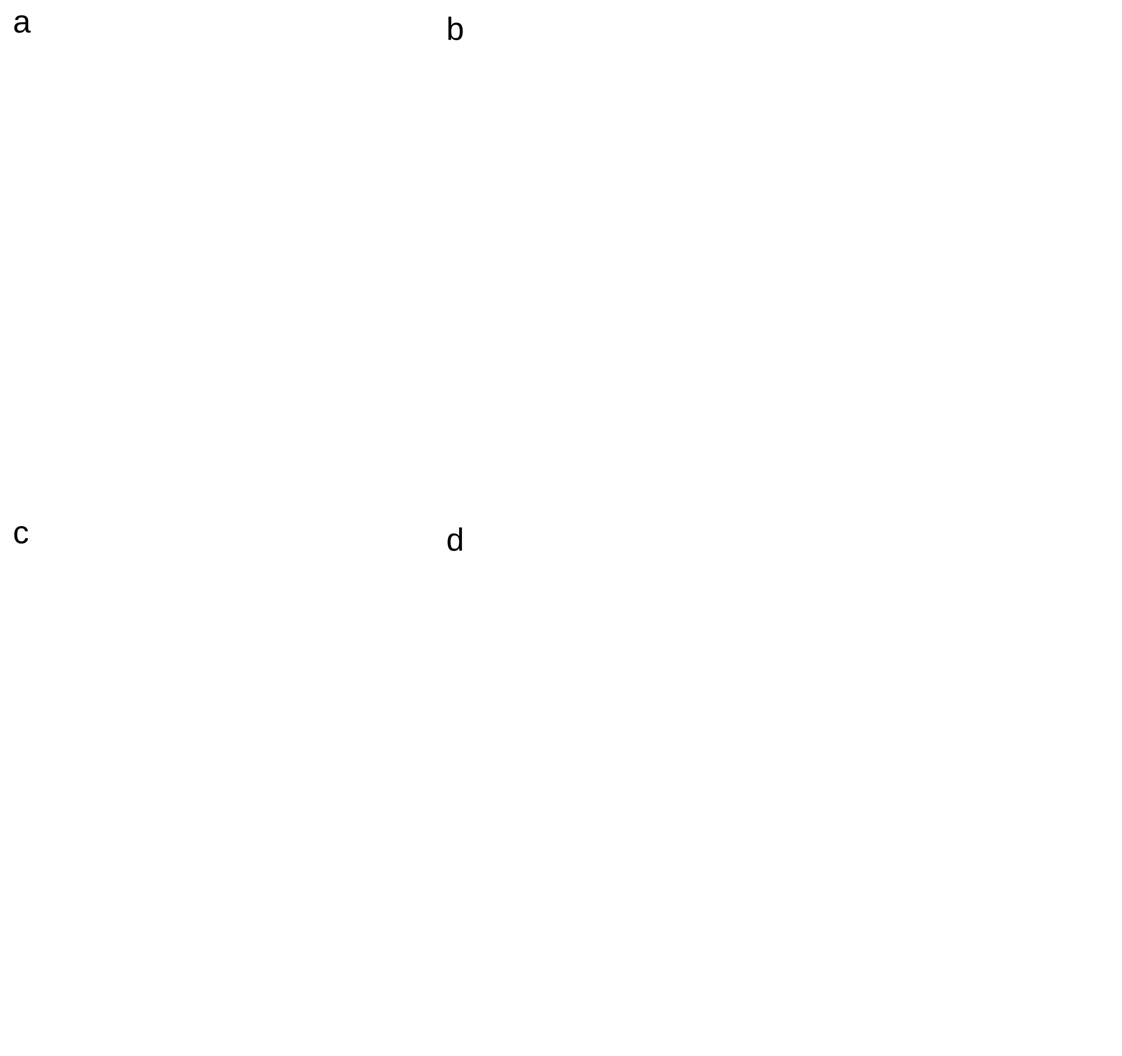

Fig. 2. (a) Aerial photograph of heterogeneous landscape (b) fine scale segmentation (c) coarse scale segmentation (d) object based classification of woody cover, resulting in 97% accuracy (from: Levick and Rogers, 2008, with permission).

Table 1
Conferences identified as relevant, and number of relevant papers (not overall papers).

Title of conference/workshop	Relevant papers
IEEE 2003 workshop on advances in techniques for analysis of remotely Sensed Data, Washington DC	9
ISPRS 2003 workshop on challenges in geospatial analysis, integration and visualisation, Athens, USA	9
ISPRS 2004 international workshop on processing and visualisation using high-resolution imagery, Pitsanulok, Thailand	5
ISPRS 2004 world congress, Istanbul	29
ISPRS 2005WG VII/1 human settlements and impact analysis. Tempe/Phoenix USA	32
ASPRS 2006: ASPRS annual conference, Boston, USA	32
MAPPS/ ASPRS 2006: Specialty conference measuring earth II: Latest developments with digital surface modelling and automated feature extraction, San Antonio, USA	24
OBIA 2006 international conference on object-based image analysis, Salzburg, Austria	84
ASPRS 2007 annual conference — Identifying geospatial solutions, Tampa, USA	34
ARCS 2007 28th Asian conference on remote sensing, Kuala Lumpur, Malaysia	17
ARCS 2008 29th Asian conference on remote sensing, Colombo, Sri Lanka	19
GEOBIA 2008, 2nd international conference, Calgary, Canada	55

3.4. Peer-reviewed literature

For the second group, comprising peer-reviewed edited book chapters and journal papers, it is important to identify most of the relevant articles and to reduce the error of omission as much as possible. Although such an attempt can never lead to a 'complete' result it is believed that the vast majority of relevant articles accessible in February 2009 have been identified. The task was accomplished through a two-fold search using the ISI Web of Knowledge and Google Scholar during the fourth Quarter of 2008. The papers identified were re-visited in February 2009 and analysed for how often they were cited. Only titles, abstracts and keywords were searched but not the full text, the hypothesis being that the object based methodology should be so important in the respective papers that one of the search combinations ("object based", "object-based", "object-oriented", "object-driven"....) should be mentioned in the abstract. Only then could a paper be called an OBIA-relevant paper. This search