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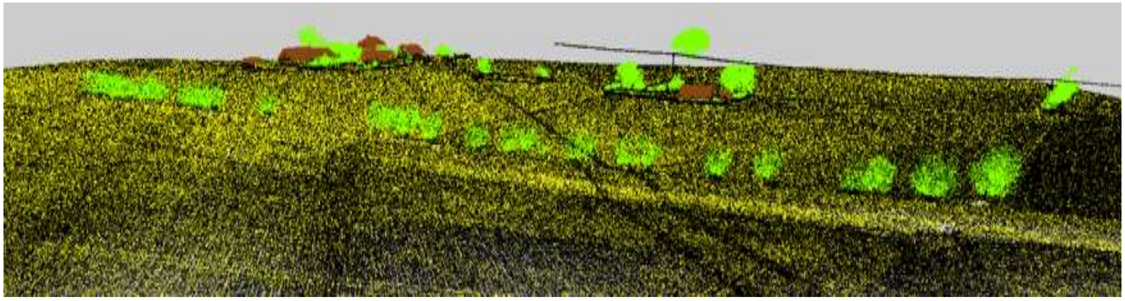
Investigating the potential of object-based image analysis to identify tree avenues in high resolution aerial imagery and lidar data

A literature review



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Greta Moreen Wistrand (2016)
Investigating the potential of object-based image analysis to identify tree avenues in high resolution aerial imagery and lidar data
En undersökning av potentialen hos objektbaserad bildanalys för att identifiera alléer i högupplösta flygbilder och lidardata
Bachelor degree thesis, 15 credits in *Physical Geography and Ecosystem Analysis*
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Greta Moreen Wistrand

Bachelor thesis, 15 credits, in *Physical Geography and Ecosystem Analysis*

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Abstract

The aim of this study was to investigate the potential of geographic object-based image analysis (GEOBIA) for the identification and monitoring of tree avenues with the help of aerial imagery and lidar data. For this, a literature review into three topics was conducted: First, scientific literature in form of journal articles, text books, and reports were used to highlight key features of GEOBIA. Second, eCognition, a widely used GEOBIA software, was introduced by referring to user manuals, and web-tutorials. Third, a detailed overview of tree avenues and their characteristics was derived from reports and text books. The main finding of the study is that, although there have been no earlier attempts to identify tree avenues using GEOBIA, there is considerable potential for doing so. This is motivated mainly due to the characteristics of tree avenues and their similarity with landscape objects that have been successfully identified with eCognition. As a progressive result of this literature review, an action plan for practitioners interested in mapping tree avenues is designed and discussed.

Keywords: (geographic) object-based image analysis, (GE)OBIA, remote sensing, eCognition, lidar, tree avenues, landscape elements, monitoring

Sammanfattning

Syftet med den här studien var att undersöka potentialen hos geografisk objektbaserad bildanalys (GEOBIA) för att identifiera och övervaka alléer med hjälp av fjärranalysbilder och lidardata. För detta genomfördes en trefaldig litteraturstudie: först användes artiklar, böcker och rapporter för att skapa en bild av de viktigaste funktionerna inom GEOBIA. Sedan introducerades eCognition, ett välkänt GEOBIA-program genom att referera till användarmanualer och webbaserade tutorials. Och slutligen togs en detaljerad beskrivning av alléer fram med hjälp av rapporter och böcker. Den huvudsakliga upptäckten med studien var att, trots att inga tidigare studier gjorts med syftet att identifiera alléer med hjälp av GEOBIA så finns det stora möjligheter med den här metoden. Detta motiveras framförallt genom alléers attribut och likheter med andra landskapsobjekt som framgångsrikt kunnat identifieras i eCognition. Som ett framåtsträvande resultat av litteraturstudien föreslås och diskuteras ett tillvägagångssätt riktat till användare intresserade av att kartlägga alléer.

Nyckelord: (geografisk) objekt-baserad bildanalys, (GE)OBIA, fjärranalys, eCognition, lidar, alléer, landskapselement, övervakning

Abbreviations

CHM – canopy height model

CWM – crown width model

DCM – digital canopy model

DEM – digital elevation model

DSM – digital surface model

DTM – digital terrain model

GEOBIA – geographic object-based image analysis

GIS – geographical information systems

GLCM – gray level co-occurrence matrix

HVS – human visual system

Lidar – light detection and ranging

MRIS – multi-resolution image segmentation

MSS – multispectral scanner system

nDSM – normalized digital surface model

NDWI – normalized difference water index

NIR – near infrared

OBIA – object-based image analysis

REVI – red edge vegetation index

RGB – red green blue

RVI – ratio vegetation index

VHR – very high resolution

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1. Introduction

Since the first Landsat satellite in 1972, remotely sensed imagery has provided vast amounts of geographic information. The technology has evolved drastically from panchromatic sensors to hyper spectral and multi spectral data, lidar and radar data of increasing spatial and temporal resolution. These amounts of high quality geographical data has opened the door to many new applications within e.g. nature conservation, landscape ecology, urban planning and safety management at the same time as the role of spatial patterns has received increasing focus within these fields.

The basic methods for data extraction have remained fairly unchanged since the first Landsat satellite; they rely on measurements of reflection of the Earth's surface wherein the smallest entity is the pixel. In most of these techniques, each pixel is treated independently based exclusively on spectral properties (Blaschke and Strobl 2001). Since the acceleration of high quality, high resolution geographical data, however, the demand has grown for efficient, automated techniques for information extraction and targeted provision of relevant information (Lang 2008). Pixel-based image analysis approaches have shown insufficient in cases of 1) objects being considerably larger than the size of pixels 2) several objects of interest having similar spectral properties and 3) differences in illumination or shadows causing spectral differences within or between images. Additionally, these difficulties have proven to make pixel-based approaches scene-specific and unable to change between scales (Blaschke and Strobl 2001).

In the late 1990s, object-based image analysis (OBIA) approaches grew as a field within geoscience. OBIA approaches takes advantage of spatial information such as image texture, contextual information and geometric attributes of features (Blaschke 2010). They classify images in a hierarchical manner that allows the change in scale. The techniques origin in segmentation techniques developed during the 1970s within the field of industrial vision to analyse material texture and in the beginning of the 21st century the approach was adapted within geosciences and eventually renamed to geographic object-based image analysis (GEOBIA) to account for the geographic orientation (Haralick et al. 1973; Hay and Castilla 2008; Blaschke 2010). For simplicity this term will be used throughout this report. In 2000 the first commercially available GEOBIA software called eCognition was released and since then a majority of research on GEOBIA has circulated around this program (Blaschke 2010).

Small and linear landscape elements are increasingly important as landscapes become fragmented and homogenised (Hou and Walz 2014). Tree avenues specifically have gained more attention in Sweden during the last two decades as a result of the environmental support introduced in 1996, growing focus on green spaces and green infrastructure and their role in supporting biodiversity and providing important ecosystem services (Höjer and Hultengren 2004; Naturvårdsverket 2012; Forssblad 2015). Tree avenues provide important natural habitats and dispersal corridors for a number of species. The protection of biodiversity is formulated in many of Sweden's environmental quality objectives as well as in a paragraph on biotope protection added to the environmental code in 1998. Tree avenues are one of seven biotopes covered by this law, independent of their status. Furthermore, the Swedish Environmental Protection Agency has compiled an action plan towards the protection of especially valuable trees that comprises five groups of which one is tree avenues (Höjer and Hultengren 2004). In an international context, small landscape elements are included in the UN convention on biodiversity and in the European biodiversity monitoring system (EEA). Consequently, the demand for a method to efficiently and regularly extract such elements is substantial, and due to their characteristics they are difficult targets for pixel-based image analysis approaches (Hou and Walz 2014).

The use of geographical information allows change detection surveys and the identification of biodiversity risk areas. As of today, only a small portion of Sweden's tree avenues along the public road network are documented (Sjölund 2015). In 2014, The Swedish National Heritage Board and the Swedish Transport Agency signed an agreement with Regionmuséet Kristianstad, located in Southern Sweden, to forward the task of developing a knowledge base for future monitoring and protection of tree avenues in Sweden. The aim is to collect data on the distribution of and historical development of tree avenues.

This study is conducted as part of the project managed by Regionmuséet Kristianstad. They have mapped the tree avenues in the county of Scania based on old maps from the years 1812-1820, 1860-1869, 1910-1934 and 1935-1986 and now request an updated version (Olsson and Jakobsson 2005). The aim of this study is however not to provide this updated map but to propose a new, efficient methodology applicable for the purpose.

1.1. Aim & research questions

The aim of this study is to investigate the potential of geographic object-based image analysis for the identification of tree avenues and similar landscape elements in high resolution remote sensing imagery and lidar data.

Following are the research questions of the study:

- How are tree avenues defined and why is monitoring important?
- How can geographic object-based image analysis contribute to the detection of and monitoring of tree avenues or similar landscape elements?
- What practical considerations in terms of data and analysis have to be taken?

1.2. Target group

The goal of the author is to provide a helpful overview and advice for GIS and remote sensing specialists interested in advancing image analyses or making classification processes more efficient and transferable. Furthermore the study targets people interested in the efficient monitoring of tree avenues and similar landscape elements. Among them, Regionmuséet in Kristianstad is the primary target group. Finally, as it is the impression of the author that GEOBIA at the conductance of the study is a fairly undiscovered concept in Sweden, it is believed that everyone interested in GIS, remote sensing and new methods to analyse images will benefit from the report.

2. Methodology

The aim of this study was reached through an extensive review of available literature, and as a tangible outcome, a table of tree avenue characteristics, implementation within GEOBIA and a proposed step-by-step action plan were presented.

A background to GEOBIA including its historical development, important concepts, advantages and challenges was retrieved from scientific articles, books and reports. Due to the eCognition software being the most common GEOBIA software and the fact that most GEOBIA research circulates around it, special focus was put on GEOBIA solutions available in this software. The majority of this information was retrieved from literature, user guides and web-tutorials.

Furthermore, special focus was put on GEOBIA and the eCognition software in the context of vegetation analysis and tree detection especially. Examples of key words used in the literature search process were “OBIA”, “GEOBIA”, “object-based”, “tree avenue”, “landscape element”, “biotope”, “tree”, “tree crown”, “lidar”, “monitoring” as well as relevant concepts found during the process such as “local maxima”, “crown width model”, “normalized digital surface model” etc. Owing to the fast, recent development within the field of research, most studies conducted before year 2000 were disregarded with the exception of research on pixel-based methods and various basic, still applied concepts such as segmentation and fuzzy set theory.

A background to tree avenues, various definitions, values and present monitoring in Sweden was based primarily on scientific articles, reports from the Swedish Environmental Protection Agency and the book by Olsson and Jakobsson (2005). A table of tree avenue characteristics and solutions to be implemented within GEOBIA approaches was constructed based on the found definitions and previous studies. In cases where identified, specific parameter values were included for references. Finally the proposal for the identification of tree avenues using a combination of aerial imagery and lidar data was developed based on the combined knowledge gained from the literature review, user guides and experimentation in the software. Shortcomings and alternative steps depending on data availability were discussed.

2.1. Limitations

The review on GEOBIA was limited to its main functions and solutions as well as those related to the identification of small landscape elements. Owing to the vast amount of functions and research and to the focus of the study, no complete review was executed. Furthermore, the evaluation of the eCognition software was not based on the underlying algorithms but was limited to its predefined tools. Due to time limitations, other possibly relevant software were brought up but not thoroughly evaluated.

The analysis was focused on the characteristics of location, shape and size of tree avenues and due to limitations in time other characteristics such as tree species, vitality, height and trunk size were only briefly examined. Also accuracy assessment approaches were only briefly presented and excluded from the action plan at the end of the report.

3. Literature review

3.1. What is wrong with pixel-based image analysis?

Digital analysis methods of remotely sensed data evolved from manual image interpretation. Initially, features were interpreted visually and delineated by hand. With the digitalization, automated pixel-based approaches evolved. These algorithms classified imagery based on spectral properties, treating every pixel independently of the others. Before the development of very high resolution (VHR, < 5m pixel size) remote sensing images, pixels commonly covered several objects of interest or were of similar size and were therefore appropriate for their representation (Blaschke 2010). As the pixels decreased in size, image analysis techniques failed to detect these objects. Eventually they were adapted to take into account neighbourhood information through different texture measurements, neural network classifiers or moving windows, also called kernel methods. The most common kernel method is the gray level co-occurrence matrix method (GLCM) which measures homogeneity, contrast, angular second moment and entropy (Haralick and Dinstein 1975; Blaschke and Strobl 2001; Blaschke 2010). Today, a vast range of pixel-based methods exist, such as linear mixing models, fuzzy set and neural net classifiers. However, in an extensive review by Blaschke and Strobl (2001) to compare pixel-based and object-based approaches to image analysis, the authors argue that, despite incorporating various texture measurement most pixel-based techniques do not make use of spatial information. For a review of pixel-based methods for image analysis, see Blaschke et al. (2000).

The performance of pixel-based image analysis depends on the type of application and conditions. The most common challenges are cases where several objects have the same spectral properties or where differences in data collection time across an image causes differences in reflectance or shadows. One example is the differentiating of cut blocks and seismic lines of interest within forestry research. These real-world objects are rather defined by their relation to neighbouring objects or by the shape of their outline than by spectral reflectance (Flanders et al. 2003).

The focus on spectral characteristics has further implications for the transferability of pixel based methods, as it tends to make them scene-dependent (Lyon et al. 1998; Rogan et al. 2003). Furthermore, an important cause of error in pixel approaches origins in the often overlooked issue that the reflectance from a specific pixel in fact is largely composed of reflectance from its neighbouring pixels (Blaschke and Strobl 2001). This error logically increases as the pixel size decreases. Pixel based approaches also result in pixelated objects and consequently speckled images (Desclée et al. 2006). This so called “salt and pepper effect” makes results difficult to interpret and visually unappealing (Blaschke et al. 2000). It can to some extent be solved by applying different smoothing filters (Marpu 2009). The use of pre-defined boundaries within pixel-based approaches (“per-parcel” or “per-field classification”) is another way to avoid pixelated objects. However these approaches fail when boundaries are missing or when it is in fact the boundaries that need to be updated (Blaschke and Strobl 2001).

The limitations of pixel-based approaches have received increasing focus since the acceleration of high resolution remote sensing data. With improved resolution, the number of applications of remote sensing data increase and today the demand for regularly updated remote sensing data is growing within fields such as environmental assessment and monitoring, global change detection and monitoring, agriculture and military surveillance (Schowengerdt 2006). A common application is change detection analyses, which usually require tedious work when manual image interpretation is applied.

A strong motivation for a different approach to image analysis was the issue of scale. When the spatial resolution is finer than the size of objects one usually ends up with several scales in the same image–and depending on the application, various scales might be requested. In pixel-based approaches, the scale is dependent on the size of pixels and hence there is not much possibility for adaptation (Blaschke and Strobl 2001).

3.2. Geographical object-based image analysis (GEOBIA)

Since the release of the Landsat Multispectral Scanner System (MSS) in 1972, the field of Earth Observation has developed substantially towards higher spectral, spatial and temporal resolution data. The first Landsat images had a spatial resolution of 80 m and four spectral bands (Marpu 2009). Today more than 50 optical satellites orbit the globe on a regular basis. An increasing number of satellites produce VHR data, multispectral and hyper spectral sensors provide increasing spectral detail. Radar and lidar sensors allow for 3D imaging of the earth's surface. Multi sensor data collection such as applied on the TERRA satellite station help overcome errors caused by temporal differences in illumination or atmospheric conditions between datasets (Blaschke and Strobl 2001).

3.2.1. Turning geo-spatial data into geo information

Owing to the fast qualitative and quantitative development of remote sensing imagery, recent satellite data can be used for applications previously requiring aerial imagery. The fundamental idea of GEOBIA is to take advantage of all available spatial information in this data. This includes image texture, context, pixel proximity and geometric attributes of features (Blaschke 2010) where image texture is defined as a regularity in spectral contrast and its resulting spatial arrangement, also called "structural diversity". One case that exemplifies the importance of texture is the classification of a forest patch, or other "rough" surfaces. With high-resolution imagery, the spectral heterogeneity of pixels due to shadows and shade increases, and all pixels are consequently not representative of the patch (see Figure 1 for example). Several studies show that object-based approaches to image analysis can overcome this problem by allowing a certain degree of "within-patch heterogeneity".

Figure 1 Forest patch demonstrating high "within-patch heterogeneity". Retrieved from https://pixabay.com/sv/flygfoto-skog-tr%C3%A4d-perspektiv-gata-1031028/.

3.2.2. Incorporating semantics in the classification process

The key aim of OBIA is to mimic the human visual system (HVS) and this approach is closely related to the topic of semantics. The HVS tends to generalize areas into homogenous sections, followed by a closer investigation. It does not think in pixels but rather in objects (Blaschke and Strobl 2001). GEOBIA workflows allow for the inclusion of human semantics and hierarchical networks. Multi-resolution segmentation resembles hierarchy theory in the way it models and decomposes complexity but, opposed to hierarchy theory which deals with increasing size of organisation, hierarchical segmentation produces regions of increasing average size (Bian 2007).

3.2.3. The slow evolution of GEOBIA

Although image segmentation techniques developed within the field of computer vision and material sciences already in the1970s and within biomedical imaging in the 1990s, it was not until the end of the 1990s that the field gained increased attention within the GIS community (Kartikeyan et al. 1998; Blaschke and Strobl 2001; Hay and Castilla 2008). Notable exceptions are the Machineseg program, a region-growing image-analysis technique that used the shapes, sizes, and spectral data of regions to classify aerial imagery, and the program "A road finder" used for road detection, which were developed in the 1980s (McKeown 1988).

Part of the reason for the delay, Flanders et al. (2003) argue was due to obstacles of the models in "fusing information from multilevel analysis, validating classifications, reconciling conflicting results, attaining reasonable efficiency in processing (time and effort), and automating the analysis". Furthermore, Flanders et al. (2003) argue, capability was limited by hardware, software, poor resolution of images, and interpretation theories. This led to the majority of research instead focusing on improving existing pixel-based analysis methods. They produced satisfactory results and were much more efficient than the early object-based approaches (Flanders et al. 2003).

Another reason for the delayed adoption of OBIA within the field of geoscience was the limitations to panchromatic imagery. Today, GEOBIA can be applied also to multispectral images and to various kinds of data such as lidar and radar data. Additionally, geographical applications required a detection of objects with an unlimited variation of shapes and fuzzy boundaries and the multi-scale nature of the images complicated segmentation tasks (Schiewe et al. 2001).

3.2.4. The methodological pillars

GEOBIA is based on two main methodological steps; the first step being the segmentation when pixels are merged into clusters and the second step being the rule-based classification (Baatz et al. 2008). Usually, an initial large number of small segments are merged into fewer, larger segments with the purpose of minimizing the within-object variability compared to the between-object variability. The classification process allows for the incorporation of required spectral and geometrical properties as well as spatial relationships (Lang 2008).

There are four main types of segmentation algorithms; the point-based, edge-based, region-based and combined (Schiewe 2002). Region-based segmentation algorithms, the most common type, produce regions according to a certain criterion of homogeneity (spectral similarity, compactness etc.). Due to their bottom-up nature, they are limited in providing delineations of aggregates that consist of high contrast, but regularly appearing sub objects (Lang 2008). One commonly mentioned example is the orchard–it is usually an area of grassland with trees distributed in a pattern (Lang and Langanke 2006; Castilla and Hay 2008).

One commonly mentioned advantage of object-oriented classification is the fact that rule sets are recorded and can easily be rerun in another location or at another time. It is hypothesized that object-based image analysis approaches are equally or more universal than pixel-based methods as they account for shape and context which are not affected by imaging conditions (Flanders et al. 2003). Furthermore, Bian (2007) argues that GEOBIA allows the inclusion of the “emergent property” concept in real world representation–an important concept within environmental modelling stating that an aggregate might have properties irrelevant to its aggregate objects; such as a forest having a certain species diversity, which is irrelevant to a single tree.

3.2.5. Accuracy assessment approaches

Many studies still apply only visual interpretation for assessing accuracy of GEOBIA results (Tiede et al. 2005; Tiede and Hoffmann 2006). Biging et al. (1999) argue that for a polygon-based mapping output, any pixel-based accuracy assessment would tend to underestimate the map accuracy. Newton et al. (2009) further states that a validation of a remote sensing analysis at all times should include an overall percentage of number of correctly mapped objects. For different examples of accuracy assessment approaches within GEOBIA, please see Schöpfer and Lang (2006); Möller et al. (2007); Lang (2008).

3.2.6. Difficulties and risks of representing reality as objects

Closely related to section 3.2.2., Lang (2008) argues that the regions formed through a segmentation do not become image objects until they are considered "meaningful". The definition of "meaningful objects" is a common issue within GEOBIA. If more than one scale, or level of abstraction, is required, conventional GIS database models face a problem. According to Blaschke and Strobl (2001), one purpose of the multi-resolution image segmentation approach in GEOBIA is to work around this issue through an "iterative refinement of objects and some experimentation".

Object-based image analysis does not originate in geography and Bian (2007) discusses the relevance of representing reality as sets of objects. The discrete representation of real-world objects is an inevitable effect of the discrete computing environment and Bian (2007) argues that the unlimited number of definitions of an object means a risk of misclassifications. He distinguishes between three head groups within environmental modelling, namely "spatial objects" (which covers "sedentary individuals" which in turn among others includes individual plants), "spatial regions" and "fields" and evaluates, by relating the principles and models within GEOBIA to the conceptual models of these object groups, the compatibility of GEOBIA. Bian (2007) concludes that the object-based approach is suitable for the representation of "spatial objects", fairly suitable for "spatial regions" and unsuitable for "fields". The reason for the latter, Bian (2007) explains, is the incapability of GEOBIA to mimic continuous features. Fuzzy set theory, introduced by Zadeh (1965), allows a continuum of grades of membership, meaning classes are rather continuous than having crisp boundaries such as between "field" and "forest". To be able to describe the natural vagueness of objects, certain fuzzy rules need to be applied and this has been implemented in pixel-based image analyses but rarely in GEOBIA analyses (Hofmann et al. 2011).

One common criticism of GEOBIA is related to the requirements of the user to have a significant knowledge of the objects of interest in order to choose appropriate hierarchies, weights and scales. The number of possible solutions is large (Flanders et al. 2003) and much recent research is focused on this issue; how to identify the most appropriate segmentation levels and scales. At present, the incorporation of semantics and extraction of meaningful, or "conditioned information" as Lang (2008) refers to it, poses a larger challenge than the accessing of high quality data (Blaschke 2010).

Despite challenges and uncertainties, several review articles point to the fast increase in literature, articles and conferences on the topic of object-based classification. Blaschke et al. (2014) showed that the number of articles including GEOBIA as much as quadrupled between April 2009 and September 2013. The book entitled *Object-based image analysis: spatial concepts for knowledge-driven remote sensing applications* by Blaschke et al. (2008) provides a thorough review on GEOBIA, methodological implications, solutions and challenges.

When the software eCognition (Baatz and Schäpe 2000) was released in 2000 it was the first commercially available object-based processing software, and its objective was to be "user-friendly, multi scaled and fully functional" (Blaschke and Strobl 2001; Flanders et al. 2003). Since then, a majority of the research linked to GEOBIA originate around this software (Blaschke 2010).

3.3. eCognition

The eCognition software was developed and released by the German company Definiens Imaging GmbH in 2000. It is based on the cognition network technology, a context-based technology developed by the same company for image analysis within earth, medical and life sciences. Within medical and life science it is used for tasks such as identifying cell types in tissue slide scans, which is useful for the detection of tumours (Definiens AG 2009a). The cognition network technology uses a script called cognition network language (Baatz et al. 2008). Basically, it is aimed to mimic the human cognitive processes which means a semantic approach to identify meaningful objects in an image; an understanding of their mutual relationships and properties. Hence in the image analysis process, all subobjects building up the desired objects and scale are stored as well as their semantic relationships–the approach is termed "multi-scaled" (Definiens AG 2009b). This allows the user to draw information from various scales simultaneously. The process is iterative and cyclic rather than linear; the identification of high-level objects is also used to identify lower-level objects.

The eCognition software was developed solely for remote sensing and other geospatial applications. Today a number of alternative programs exist such as Envi Lidar, Quick Terrain Modeller (QTM) and ArcObjects in ArcGIS and according to Neubert et al. (2008) the number of both free and commercially available GEOBIA software is increasing steadily. eCognition however remains the most common application (Blaschke 2010) although the use in Sweden is still limited. At the Swedish National Land Survey, the use of object-based image analysis techniques is still limited while Metria uses eCognition for some tasks.

3.3.1. Main features

Within image processing, segmentation is not consistently a process of dividing entities into smaller portions but it can also mean a merging or reshaping of entities. Essentially, the program builds on the definition of objects as a given number of delineated areas that hold maximized between-object variability and minimized within-object variability (Flanders et al. 2003; Trimble 2015).

The eCognition software provides two main segmentation approaches; the top-down strategy which starts with larger objects that are sequentially divided into smaller and the bottom-up strategy which conceptually means a merge of smaller objects into larger (Trimble 2015). Top-down strategies such as the chessboard (Figure 2) and quadtree-based segmentation (Figure 3) are ultimately limited in their ability to divide objects into subobjects that have a different shape than a square. Additionally, while the chessboard technique only allows a division of objects into equal, optional sized squares, the quad tree based segmentation divides objects into squares of differing sizes based on an optional scale parameter that defines the spectral variability within each square. The chessboard technique is usually used for tasks such as tilling and stitching images that are too large to be handled as one piece, refinement of already specified objects for further analysis and to divide objects into object primitives, enabling subsequent multi-resolution segmentation. The quadtree-based segmentation, however, is considered a reasonable alternative to multi-resolution segmentation when time and memory storage is limited, especially for images where contrasts are high between the objects of interest and their background (Trimble 2015). More information about top-down segmentation techniques can be found in the eCognition Developer user guide (Trimble 2015).

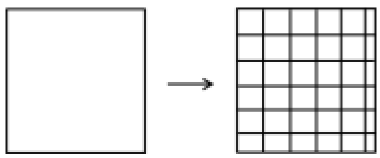

Figure 2 Chessboard segmentation. Modified from Trimble (2015).

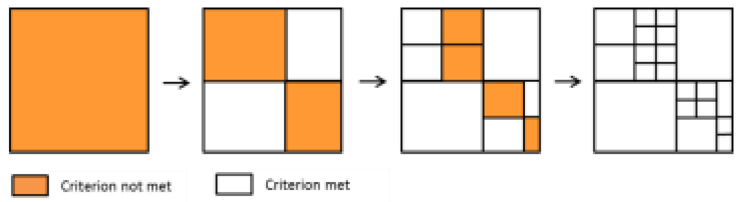

Figure 3 Quadtree-based segmentation. Modified from Trimble (2015).

In bottom-up segmentations, a merge is performed with respect to local conditions and the specified rule set. Basically, it is a pairwise merge where three image object types are distinguished as illustrated in Figure 4. The seed is the active image object specified by the object domain. The object domain, in turn, can be described as the link between segmentation and classification (Baatz et al. 2008). It defines for what subset of objects every algorithm should be applied and thus enables localized functions. In an hierarchical network it is also possible to set subdomains, which specify on what neighbour objects, sub objects or super objects at a defined distance, with a specific classification, or with specific attributes, the algorithm should operate. The neighbouring image objects (the potential merging partners) are named candidates. The target is the imagined new image object resulting from merging the seed with its candidates. For all different candidates, the potentially resulting targets are compared in detail with the input structure (seed and candidates) and the option that best corresponds with the set parameters is chosen (Trimble 2015).

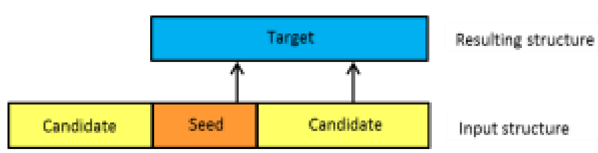

Figure 4 Image object types of local pairwise merging procedures. Modified from Definiens AG (2009b).

The most common bottom-up segmentation technique is the multi-resolution image segmentation (MRIS). The first step in the segmentation process is the creation of object primitives–polygons of similar size with minimized within-object variance. These are created through a pairwise merging, where size and homogeneity criteria are selectable for the user. The average object size is decided by setting the scale parameter, a unit less parameter that most commonly is decided upon through an informed trial and error process (Flanders et al. 2003; Jia 2015). The scale parameter aims to solve the scale issue–depending on whether the study of focus aims at detecting forest patches or individual trees, the user can adapt the scale parameter to best fit the desired level of scale. Hence the scale parameter should not be thought of as related to the pixel number but rather to the maximum allowed heterogeneity within an object (Trimble 2015).

The homogeneity parameter in turn specifies the relative weights of spectral versus shape information; a ratio where both figures add up to 1 defines the relative importance of each. Similarly, the ratio of smoothness to compactness weights expresses their relative importance for the object (Flanders et al. 2003). Here, compactness is identical to discreteness and smoothness refers to the spectral variability between objects. A high compactness weight is useful when objects are similar in colour but distinguishable primarily by shape–one example is the separation of clear cuts and bare patches in a forest (Flanders et al. 2003).

The ability to store objects in a hierarchal system is one characteristic property of the eCognition software. The image object hierarchy levels can be thought of as representing different scales of the image–in higher levels, superobjects are found and in lower levels, subobjects are stored. Figure 5 demonstrates one example of an image object hierarchy, where the entire image is broken down into forest, tree types and individual trees–different scales which are potentially interesting for different purposes. All objects are networked in a way that information about neighbouring objects, superobjects and subobjects is stored in each object (Trimble 2015).

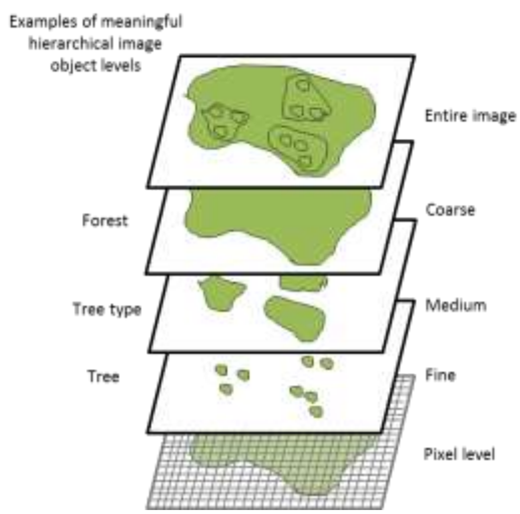

Figure 5 The hierarchy of image objects. Modified from Trimble (2015).

For the complete user guide of eCognition Developer 9.1, see Trimble (2015). Readers interested in the algorithms are also advised to read the article by Baatz and Schäpe (2000).

3.3.2. Flexibility and transferability

One often highlighted advantage of eCognition is the fact that it is universal–while other algorithms are tailored for a specific location, eCognition allows for customized parameter inputs (Desclée et al. 2006) and instead of creating a whole new protocol, parts can easily be modified to suit a specific task. Furthermore, eCognition supports various data types and sensors; airborne and satellite imagery, lidar, radar, hyperspectral and multispectral data and thanks to its GIS-like functionality it allows an integration of these data in complex analyses. The results can then be converted to different data types such as shape files which can be exported to GIS programs for further analysis (Baatz and Schäpe 2000). On the other hand, Flanders et al. (2003) states that within eCognition, in line with most software, not all algorithms are entirely transparent to the user. This complicates the adaptation to specific situations.

3.4. Previous studies aimed at detecting small landscape elements in aerial imagery and lidar data

Several previous studies have attempted to detect different landscape elements in a combination of aerial imagery and lidar data (Pitkänen et al. 2004; Tiede et al. 2005; Tiede and Hoffmann 2006; Hou and Walz 2014; Sjölund 2015). While Sjölund (2015) uses a combination of ArcGIS functions and a visual interpretation, most studies apply GEOBIA and the majority use the eCognition software (Pitkänen et al. 2004; Tiede and Hoffmann 2006; Hou and Walz 2014). Another study uses a combination of GIS software and TopoSys GmbH, a software specialized for the analysis and reprocessing of lidar and RGB/NIR data (Tiede et al. 2005). Common for many studies aimed at detecting different landscape elements is the use of lidar data.

Flanders et al. (2003) demonstrated a significant accuracy improvement when identifying cut blocks in forested areas using eCognition over the pixel-based maximum likelihood classification (MLC) approach. Furthermore, Flanders et al. (2003) argues for the likelihood that eCognition performs even better in more complex tasks due to its "highly refined and specialized membership functions".

3.4.1. Advantages of lidar data for the detection of landscape elements

The availability and use of lidar data for geospatial purposes has accelerated during the last decades (Charaniya et al. 2004). Few recent studies apply GEOBIA solely on an orthographic photo but the majority use a combination of aerial imagery and lidar data (Jia 2015). A few studies use lidar data exclusively (Tiede et al. 2005; Tiede and Hoffmann 2006). Many researchers highlight the improved accuracy of results when using a combination of aerial imagery and lidar data for different analyses; Bork and Su (2007) points at the benefit of integrating multispectral images and lidar data for the purpose of rangeland vegetation classification, Gamba and Houshmand (2002) found that a combined analysis improved the extraction of land cover classes, digital terrain models (DTM) and buildings in 3D. Jia (2015) however, applied GEOBIA to produce a land cover map and achieved fairly similar results when using a combination of data types as opposed to using them separately; the combination resulted in a classification accuracy of 95.2 % while the orthographic photo produced a result of 89.2 % and the use of lidar data resulted in an accuracy of 88.6 %.

Lidar (light detection and ranging) is an active remote sensing technique which involves a transmission of laser pulses towards the ground and measurements of the time of pulse return. Modern systems can record five or more returns per pulse. These result in a surface of points, which explains why lidar data sets are often referred to as “point clouds” (Lillesand et al. 2014). The point clouds are often calibrated to classify collected data automatically based on surface roughness. Data is commonly classified into the four classes of ground, water, vegetation and buildings but recent methods allow more detailed classifications of e.g. low, medium and high vegetation (Charaniya et al. 2004). Other characteristics that are assigned to the data are point elevation and intensity. The intensity of lidar data is a relative measure of the strength of the return pulse. It depends on the reflectivity of the surface (at the lidar wavelength), of its texture and orientation relative to the sensor. Surfaces typically producing high intensity values are bright building roofs while dark or rough surfaces absorb or scatter some of the pulse and hence produce low intensity values (Lillesand et al. 2014).

The ability of lidar techniques to record several returns in the same location allows a derivation of 3D models in which real-world objects can be distinguished and represented. If lidar data is combined with aerial imagery or terrestrial photos, object texture and colour can be superimposed onto the 3D objects, resulting in models closely resembling reality. The number of returns has been used in several studies to detect objects such as trees and buildings. Due to the rough structure of tree crowns, they commonly produce multiple returns while fields or buildings produce single returns (Definiens AG 2009b; Lillesand et al. 2014). Hence, by filtering lidar data, i.e. extracting a portion based on certain attributes, one can quickly extract information that requires many processing steps if only aerial imagery is available. Such attributes commonly include the number of returns, first return points, last return points, elevation and intensity. In the eCognition Developer user guide (Definiens AG 2009b) a return number of 1.1 is advocated as threshold value to detect trees in a vegetation mask. When non-evergreen trees are targeted, the accuracy of results is dependent on the time of data collection. For these kinds of purposes, lidar data collected during so called leaf-on conditions is recommended (Hoberg and Müller 2011).

Common for previous studies applying GEOBIA to lidar data is an initial derivation of a digital elevation model (DEM), alternatively a digital terrain model (DTM), and a digital surface model (DSM). The DSM is a standard lidar-derived product which can be derived from the first return lidar data–and hence includes vegetation and other vertical ground features. The DTM is derived by applying the so called active contour algorithm onto the lowest points in the DSM (Cohen 1991). This works as a net that is pushed upward from underneath the surface, interpolating the point cloud.

The height of the vertical features, in turn, can be derived by subtracting the DEM (or DTM) from the DSM. This is termed a normalized DSM (nDSM, Figure 5) or within forestry applications a raster canopy height model (CHM) (Zhao and Popescu 2007; Hou and Walz 2014) or digital canopy model (DCM) (Holmgren and Persson 2004).

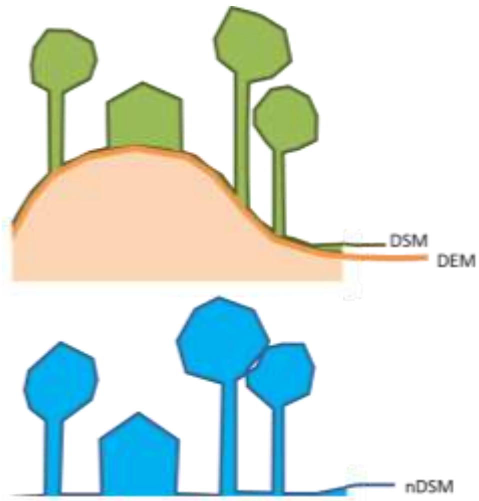

Figure 5 The digital surface model (DSM), digital elevation model (DEM) and normalized digital surface model (nDSM).

One often discussed general disadvantage of lidar data is the size of its data sets. Resolutions range from 0.5-50 points per m^2, which translates into 500 000-50 million points per km^2. These files require huge storage space. A few different lidar formats exist of which *.las is the most common and *.laz is the compressed version (Lillesand et al. 2014). Many previous studies applying GEOBIA on lidar data use small study areas of the magnitude of several hundred m^2 (Tiede and Hoffmann 2006) to a few km^2 (Tiede et al. 2005; Tiede et al. 2010; Hou and Walz 2014) which leaves the potential of GEOBIA to handle large lidar datasets relatively undiscovered. Tiede et al. (2005) however argue that the large files can be handled in a GIS environment under the condition that some point filtering is applied.

3.4.2. Detecting individual trees in lidar data and aerial imagery

Many previous studies have been conducted with the aim of identifying individual trees (Tiede et al. 2005; Tiede and Hoffmann 2006; Tiede et al. 2010) or landscape elements consisting of a few trees (Hou and Walz 2014). A common approach is the so called local maxima method which essentially means an identification of peaks in the DSM, using a specified search radius (Pitkänen et al. 2004; Tiede et al. 2005). This corresponds to the focal statistics tool in ArcGIS.

Tiede et al. (2005) used the dynamic algorithm called the crown width model (CWM, Equation 1) to improve results from local maxima searches to detect single tree tops. Based on a regression model, the CWM is applied to unprocessed lidar point data to adapt the search radius based on tree height, assuming that the crown width increases with tree height. The model (parameters *a* and *b*) has to be calibrated to local conditions, and logically the accuracy will be dependent on the homogeneity of the area. In the study by Tiede et al. (2005) conducted in a Bavarian mixed forest, values of 1.54 and 0.123 were chosen for *a* and *b* respectively.

$$CD = a + b*TH \qquad \text{Equation 1}$$

Where *CD* = maximum diameter of a tree crown (in m) and *TH* = tree height (in m)

Furthermore, Tiede et al. (2005) applied a region-growing algorithm that uses the resulting local maxima as seed points for the delineation of individual trees. It uses a nearest neighbour moving-window approach applied on the centroids derived from the tree top detection and a maximum radius limit of 10 m, and results show an accuracy of 72.2 % for large trees and an overall accuracy of 51 %. When Pitkänen et al. (2004) applied the same model over a forest dominated by spruce and pine in Southern Finland, values of *a* and *b* were instead chosen to 1.20 and 0.16 respectively. Accuracies reached similar figures; 60-70 % of large trees and 40 % of all trees were detected. Both studies discover limitations of the CWM in detecting juvenile trees in dense forests.

Another group of approaches identify tree crowns in an initial step followed by a detection of peaks. Holmgren and Persson (2004) applied the watershed segmentation on a DSM to detect tree crows followed by the extended maxima transformation to detect the peaks within each crown. The watershed segmentation can be applied to aerial photographs or DSMs to delineate single trees by the identification of the edges (valleys) of each crown. In aerial images, it detects the difference in reflectance value between the tree top (usually brighter) and its edges (usually darker) but due to low resolution of some imagery or differences in illumination, these contrasts are not always present (Kwak et al. 2007). Kwak et al. (2007) achieved accuracies between 67.4-86.7 % in a study to delineate individual trees using the watershed segmentation approach on lidar data in coniferous and deciduous South Korean forests.

A study by Hou and Walz (2014) focuses on the identification of “small biotopes” wherein hedges, copses, tree rows and single trees are included, and achieve a producer’s accuracy of 67 % and a user’s accuracy of 76 %. The approach used to detect tree rows specifically builds on two steps where the first involves a creation of a land-cover map through an MRIS followed by a classification based on several vegetation indices (the normalized difference vegetation index, NDVI and the red edge vegetation index, REVI) as well as the normalized difference water index, NDWI. In the second step, the resulting “field” class is used as a mask (this is one of the criteria used for tree rows) onto an nDSM and another MRIS is executed on the pixel level using a height threshold of 2 m. The resulting individual trees are connected by applying a pixel-based object resizing algorithm, available in eCognition (Definiens AG 2009b). This creates buffers which can be customized according to the maximum allowed tree interval distance and merges them. Alternatively, the function termed “relational features” in eCognition can be used to set a specified “distance to neighbour” (Trimble 2015). A subsequent length and length/width criteria is finally applied to differentiate tree rows (Hou and Walz 2014).

3.4.3. Different approaches to detect vegetation

Depending on the type of available data, different indices can be used to distinguish vegetation in aerial images. Hou and Walz (2014) uses NDVI threshold values of 0.3 respectively 0.4 to create vegetation masks from aerial images collected in August and May, respectively, in an area in southeastern Germany. The threshold needs to be adapted according to the location, time of data collection and phenology (Hou and Walz 2014). The use of NDVI implies that only photosynthesising vegetation is detected–if also dead and old trees are targeted, this index does not suffice. The red edge vegetation index (REVI) can be used for tree species differentiation (Hou and Walz 2014) and the ratio vegetation index (RVI) for forest identification (Jia 2015). One way to improve the capacity of standard colour images is to use spectral rationing i.e. band ratios. They can improve results of e.g. multi-temporal analyses as they tend to normalize differences caused by lighting and terrain. Such images are called ratio images and due to their universality they can be transferred between locations (Lillesand et al. 2014).

Another often available strategy for vegetation detection is to take advantage of the already defined classes of the lidar dataset. Attention then needs to be paid regarding the accuracy of the classification. Furthermore, a common approach is to set a threshold of 1 or 1.1. for the number of returns and in that way extract vegetation. The performance of these methods, however, is affected by the time of lidar data capture–while some trees are easily identified during leaf-on period, they might be difficult to detect under leaf-off conditions. Finally, because of seasonal differences in plant phenology, approaches that integrate multi-temporal images can improve vegetation classifications (Hoberg and Müller 2011).

3.4.4. Alternative methods to GEOBIA

Sjölund (2015) developed a methodology for the identification of tree avenues in ArcGIS using lidar data. The survey aimed to cover information on tree location, species, age group, number of large trees, geographical orientation and crown width and the results were used as input in different connectivity models to identify appropriate locations for new tree avenues. Tree avenues were identified through a number of steps. The lidar ground data was converted to a DEM and the "unspecified" (pre classified) lidar data was converted to a DSM where areas of 3-30 m in height were extracted to sort out bushes, cars and tall buildings. Roads were buffered by 20 m on each side and this layer was then used as a mask on the DSM. Five different criteria were used to remove further distracting features; buildings, small and large power lines, vegetation >50 000 m^2 and power lines above rail roads. Individual tree crowns were allocated by identifying focal maxima using "focal statistics" and finally trees belonging to tree avenues were identified through a visual interpretation and merged one at the time. The process includes several in-between steps – many that are linked to the inability of ArcGIS to handle point clouds directly. Sjölund (2015) advocates the development of a fully automated approach and encourages the combination of lidar data and an orthographic photo. However the difficulties of identifying tree avenues of mixed trees and structures and those that "hide" in other vegetation is emphasized. Additionally Sjölund (2015) believes that lidar data from the summer months would generate improved results.

The example of Sjölund (2015) demonstrates that although tedious and complex, the task of identifying trees alongside roads is possible also in ArcGIS. The final step, however; to extract only those trees that are part of tree avenues proves impossible and must be conducted manually. Due to the limited GEOBIA features in the program, ArcGIS is not able to identify trees as objects and set internal relationship criteria accordingly.

3.5. Biological and cultural values of tree avenues

The Swedish landscape becomes increasingly fragmented, with extended urbanization, infrastructure and intensified agriculture. Natural habitats of many animal and plant species are lost and replaced by agricultural land, urban areas or industries. Road networks are extended and straightened. In this landscape, small biotopes such as solitary trees, hedges and tree avenues compose important refugees and migration corridors for a vast variety of species (Hou and Walz 2014). It is primarily the older trees that hold important biological values and in many areas in Sweden today, old trees do only exist as part of tree avenues (Olsson and Jakobsson 2005). These trees and their surrounding environment are great potential hosts for different lichens, mosses, insects, fungi, birds and small mammals–many of which are threatened due to decreasing habitat areas (Höjer and Hultengren 2004). Furthermore tree avenues compose important dispersal corridors for birds, insects and bats on the move as they provide important camouflage.

The concept of “green infrastructure”, first established by Sandström (2002), refers to urban green space systems as a coherent planning entity equally important as other physical urban structures. The growing attention to green spaces is likely a result of recent urbanization which puts great pressure on both ecosystems and human health. In 1995 this called forth a modification of the Swedish legislation on urban planning which should from then on “promote a good state of living environment, biodiversity, efficient use of energy and other resources” and in 1996 this was implemented also in the Swedish environmental code.

Green infrastructure improves the function of ecosystems and hence contributes to the protection of biodiversity and ecosystem services. The Swedish Environmental Protection Agency recently adapted the concept and called for action plans to be submitted by all county administrative boards by 2017. In this context, green infrastructure applies to environmental planning also outside cities. It is intertwined with a few of Sweden’s environmental quality objectives, foremost “A rich diversity of plant and animal life”, “Sustainable forests”, “A varied agricultural landscape”, “Flourishing lakes and streams” and “A balanced marine environment, flourishing coastal areas and archipelagos”. Additionally, in 1998 a paragraph on biotope protection was added to the environmental code, where biotopes are defined as “small terrestrial or aquatic areas that host threatened animal or plant species, or that for other reasons are worth of protection” (Naturvårdsverket 2012). Seven biotopes are protected nationwide, regardless of their status, and one group is tree avenues.

Olsson and Jakobsson (2005) further highlight the cultural and recreational values of tree avenues. Many of the remaining tree avenues in Sweden were planted in the 17th or 18th century, and inspired by the trends and societal structures of past times, they remind us about our history. Additionally, they have an esthetical impact on the landscape, break up homogeneity and provide a sense of direction, shelter and protection.

3.5.1. The present protection and monitoring of tree avenues in Sweden

In 2004, the Swedish Environmental Protection Agency constructed an action program in collaboration with the Swedish Species Information Centre and the county administrative boards towards the conservation and treatment of biologically or culturally valuable trees (Höjer and Hultengren 2004). The program is focused on deciduous trees in Southern Sweden and one of the strategy is to collect all available information on location and status of the trees in a database named “the Tree Portal” (http://www.tradportalen.se/). The portal invites county administrative boards, organisations and citizens to register their findings from field inventories. This can but does not necessarily include information on tree species and vitality, diameter, surrounding–such as whether the tree is part of a tree avenue, species of plants growing on the tree and photographs. The Tree Portal is most likely the most comprehensive database containing information about tree avenues in Sweden today. The accuracy of data is however only sporadically verified (ArtDatabanken).

Between 1996 and 2013, environmental support was available for landowners of agricultural land containing certain landscape elements of high cultural or biological value. The support would be handed to landowners under the condition that they would take care of and protect these elements, and this was seen as an action that would promote the environmental objective “A varied agricultural landscape”. Three types of trees were included in the support; trees in tree avenues, solitary trees and pollard trees. Forssblad (2015) investigated the impact of the support on the status of the trees, and discovered a positive effect especially on species commonly appearing in tree avenues.

The Swedish National Heritage Board and the Swedish Transport Agency signed an agreement with Regionmuséet Kristianstad, located in Southern Sweden, to forward the task of developing a knowledge base for future monitoring and protection of tree avenues in Sweden. The aim is to collect data on the distribution of and historical development of tree avenues with the purpose of providing practitioners and interest groups such as county administrative boards, municipalities and nature protection agencies with useful information for the protection and monitoring of tree avenues. As part of the project, Olsson and Jakobsson (2005) present four historical maps of Scania’s tree avenues that have been digitized from four analogue maps of which the most recent is from 1986 (“Skånska rekognoseringskartan, 1812-1820”, “Generalstabskartan, 1860-1869”, Häradskartan före detta Malmöhus län, 1910-1915, före detta Kristianstads län, 1926-1934” and ”Ekonomisk karta 1935-1986” respectively).

3.5.2. Various definitions of tree avenues

There exists no universal definition of a tree avenue, but depending on the location and purpose, definitions differ to be more or less specific and exclusive. In Sweden, a definition of tree avenues has been developed and implemented in the environmental code with the primary purpose of protecting their biological values. The project managed by Regionmuséet Kristianstad however applies a slightly different definition that is more general and leaves a lot of space for interpretation. Due to the focus on public tree avenues, this definition is limited to tree avenues along public roads outside of cities and private land. Below is the description.

- A planted or managed landscape element of trees along a (possibly abandoned) road
- Short or long
- One or two-sided
- Deciduous or coniferous trees, young or old
- Randomly occurring trees along ditches or farmlands are not included even if managed
- Tree avenues in cities, parks and gardens are excluded

The definition of tree avenues implemented in the Swedish environmental code is summarized in the list below (Naturvårdsverket 2014). It is important to keep in mind that any modifications of this definition will produce results that cannot be implemented in legally binding decisions.

- A minimum of five deciduous trees, alive or dead, in one or two "fairly straight" rows (usually indicating that the tree avenue is planted and not natural)
- No maximum or minimum limit for the length of the tree avenue
- No maximum or minimum limit for the distance between trees
- Located along a (possibly abandoned) road in an open landscape
- A majority of old trees. Trees defined as old in this case have a trunk diameter of >20 cm at chest height or are 30 years of age.
- Rows of fruit trees planted in connection to a fruit tree plantation are excluded
- Tree lines in urban areas are included if not located in immediate proximity to buildings or legally protected
- Tree lines along a road in forested areas are included
- *A road, in this context, is defined as a road, street, square or other path or place used for motor traffic, a bike path, walkway or horse track alongside a road or bike path and in some cases a separate walkway*

4. Discussion

In the following sections, a table of tree avenue characteristics, implementation within GEOBIA and references is presented. Then, the proposed action plan is presented followed by comments about limitations and alternative approaches. Finally, a discussion on advantages and challenges of GEOBIA in the context of tree avenue identification and monitoring is outlined.

4.1. Implementation of tree avenue attributes within GEOBIA

Table 1 presents the various tree avenue attributes identified in the existing definitions, implementation within GEOBIA and references. Only those attributes compatible with the conceptual and practical limitations of GEOBIA and the software are included. The separation of attributes into intrinsic respectively contextual is conformable with the hierarchical object system in eCognition and relevant when applying different strategies or scales.

The implementation strategies are the synthesis from the literature review and references are included for guidance. When choosing appropriate parameter values and thresholds, attention needs to be paid to the location, vegetation type and purpose of the specific study. For practitioners that lack any data required for the proposed action plan, alternative strategies can be found in these tables. Some of these alternative approaches are discussed in section 5.

Table 1 Implementation strategies with references on different attributes of tree avenues.

	Intrinsic attributes	Implementation/comments	References	Contextual attributes	Implementation/comments	References
Tree level	Tree species, phenology, age, vitality	A local maxima search alternatively a watershed segmentation can be used to identify tree tops. Spectral information can be used to separate deciduous and coniferous trees. Some species differentiation however requires lidar data. Tree age can be estimated from stem size, which can be modelled from lidar data. If also dead trees are targeted, a method exclusively based on lidar data has to be applied.	Holmgren and Persson (2004) developed an approach to discriminate between Norway spruce and Scots pine using structure and tree crown shape information derived from lidar data.	Located along a (possibly abandoned) road or in an open landscape.	If located along roads, a buffer can be used as mask. If this criteria is not applied, a mask of open areas should instead be used.	Sjölund (2015) applies a buffer of 20 m from the centre of roads.
	Crown diameter	The tree crown diameter is logically dependent on the species. For a dynamic approach, the CWM can be implemented in a local maxima search.	Tiede et al. (2005) applied the CWM on a mixed forest in Bavaria, Germany and used parameter values of 1.54 and 0.123 for *a* and *b* respectively. Pitkänen et al. (2004) used corresponding values of 1.20 and 0.16 in a study in southern Finland.	Trees in cities, parks and gardens are excluded.	Buffer thematic layers or use only public road layer, if applicable.	Sjölund (2015) applies a buffer of 2 m around buildings to avoid reflectance of balconies and noise caused by roofs.
	Tree height	The tree height is logically dependent on the species. A height threshold can be applied to a nDSM.	Sjölund (2015) specifies threshold values of 3-30 m for mixed trees in Sollentuna municipality, Sweden.	Tree interval distance	A buffer can be applied by the pixel-based "object rezising algorithm" or by setting a specific distance to neighbour in the "relational features" function in eCognition.	Hou and Walz (2014) used the object rezising algorithm with a distance of < 10 m to detect tree rows in line with the defintion by the German official survey guide. Olsson and Jakobsson (2005) found that avenues in the county of Scania, Sweden have a tree interval distance of 4-15 m.
				Minimum number of trees	Appears difficult to implement on a tree level. It is possible that a minimum number of 1 neighbour, using the specified tree interval distance, can be set as criteria after a local maxima detection. No automated approaches found.	No references found.
Tree avenue level	Tree species, phenology, age, vitality	Spectral information can be used to separate deciduous and coniferous trees. Some species differentiation however requires lidar data. Tree age can be estimated from stem size, which can be modelled from lidar data. If also dead trees are targeted, a method exclusively based on lidar data has to be applied.	Holmgren and Persson (2004) developed an approach to discriminate between Norway spruce and Scots pine using structure and tree crown shape information derived from lidar data.	One or two-sided.	For simplicity, the two tree rows forming a two-sided avenue should be handled separately. No automated approaches to differentiate between one and two-sided avenues found.	No references found.
	Minimum number of trees	If tree avenues are identified through a top-down segmentation, it is possible that a criteria of minimum number of local maxima can be set. No automated approaches found.	No references found.	Located along a (possibly abandoned) road or in an open landscape.	If located along roads, a buffer can be used as mask. If this criteria is not applied, a mask of open areas should instead be used.	Sjölund (2015) applies a buffer of 20 m from the centre of roads.
	Tree avenue shape	A length/width ratio is potentially useful to separate avenues from forest patches.	Hou and Walz (2014) use a length/width ratio threshold of 3 to distinguish tree rows from forest areas.	Avenues in cities, parks and gardens are excluded.	Buffer thematic layers or use only public road layer, if applicable.	Sjölund (2015) applies a buffer of 2 m around buildings to avoid reflectance of balconies and noise caused by roofs.
	Tree avenue height	The tree height is logically dependent on the species. A height threshold can be applied to a nDSM.	Sjölund (2015) specifies threshold values of 3-30 m for mixed trees in Sollentuna municipality, Sweden.			

4.2. The action plan

The suggested approach is inspired by the approach developed by Hou and Walz (2014) for the identification of tree rows. It is simplified owing to the fact that this study targets exclusively tree avenues and is not species-specific. Hou and Walz (2014) define small biotopes, including tree rows, as patches having an area of 0.5-1 ha, minimum width of 5 m, and being located in an open landscape outside of a forest. Tree rows, specifically, have a minimum height of 2 m, a length/width ratio > 3 and a maximum tree interval distance of 20 m. These exact values do not necessarily need to be implemented in the proposed action plan but can be adapted according to local conditions and applications.
The next section presents the list of required data, developed based on findings from the literature review and considerations regarding applicability.

4.2.1. Data requirements

- High resolution lidar data collected under “leaf-on” conditions and with a point density > 10 points/m^2
- High resolution RGB aerial imagery with a spatial resolution < 25 cm
- Road layer with road width attributes
- Urban areas layer

4.2.2. Step by step action plan

Detect vegetation

1. Import the aerial image into eCognition.
2. Apply the MRIS to all bands of the aerial image (Hou and Walz (2014) uses a scale parameter of 22, compactness of 0.5 and shape of 0.1). Merge objects.
3. Calculate NDVI across the whole image.
4. Classify the objects into vegetation/non-vegetation by NDVI.

Detect individual trees

5. Import the lidar file into eCognition.
6. Create a DTM using the "lidar file converter" with "Elevation", "Average" and "First" as converter parameters and a linear interpolation method.
7. Create a DSM using the "lidar file converter" with "Elevation", "Average" and "Last" as converter parameters and a linear interpolation method.
8. Create an nDSM by subtracting the DTM from the DSM.
9. Classify the nDSM into vegetation/non-vegetation using the mask from step 4.
10. Apply the multi-threshold segmentation on the pixel-level using height attributes as threshold values (see Figure 6 a).

Connect trees

11. Apply the "pixel-based object resizing" algorithm with maximum tree interval distance as threshold value.
12. Merge all candidates and buffers (see Figure 6 b).
13. Extract objects that exceed the length and length/width thresholds (see Figure 6 c).

14. Smooth the borders of identified objects and shrink to original size using the "pixel-based object resizing" function (see Figure 6 d).
15. If required, import a road layer ("thematic layer") into eCognition, buffer and use as mask. Important: do not apply this mask before steps 13 and 14 since that might lead to an incorrect identification of trees belonging to a forest.

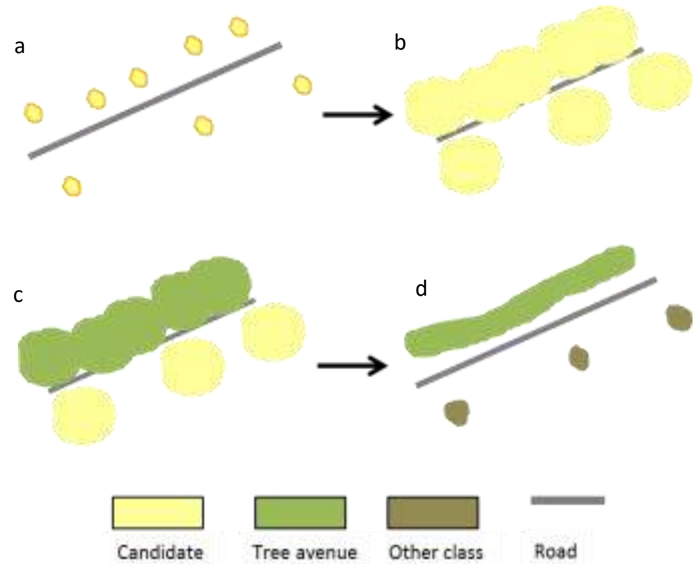

Figure 6 a-d Process of tree avenue identification applied in the action plan; a) step 10, b) step 12 c) step 13 and d) step 14. Modified from Hou and Walz (2014).

Limitations

- No restriction for minimum number of trees, rather than that automatically implemented through the setting of a length/width ratio.
- No differentiation between tree species, age or vitality.
- Dead trees are ignored due to the implementation of an NDVI mask.

4.3. Advantages and challenges of applying GEOBIA to identify tree avenues

Although no earlier studies applying GEOBIA for the identification of tree avenues were detected, many similar studies that aim at identifying different vegetation classes, individual trees or tree rows were assessed. A range of methods exist, some using lidar data exclusively but the majority using a combination of aerial imagery and lidar data. Drawing on these findings, it is the belief of the author that the case of tree avenue identification can be considered a highly appropriate task for GEOBIA techniques and the eCognition software. There are a few especially convincing findings:

- Tree avenues cannot be separated from forest areas based exclusively on spectral properties.

- The hierarchical object system in GEOBIA is conceptually appealing to fit the hierarchy of tree avenues–where the avenues can be considered superobjects to their trees.
- Tree avenues can be considered discrete objects.

Future research on the potential of top-down segmentation techniques for the identification of tree avenues is encouraged. If tree avenues are defined as superobjects to trees in a GEOBIA environment, it is possible to use both tree avenue-level and tree-level attributes in the identification process. Top-down segmentation strategies for the identification of tree avenues were not thoroughly investigated but could possibly be applied and thereby make use of the hierarchical object relationship in other ways. For example, it would be interesting to investigate the possibilities of calculating number of local maxima within predefined tree rows.

Furthermore, this study has its limitations as it only briefly examines characteristics important to landscape elements and applied in present definitions of tree avenues including e.g. tree species, stem size, age and vitality. It is likely that tree species and vitality can be distinguished by detailed investigations of species-specific spectral characteristics. Furthermore, lidar data allows for modelling of tree stem size. The implementation of these more detailed characteristics of tree avenues in segmentation approaches is highly encouraged for future studies.

As outlined in the literature review, GEOBIA faces some problems regarding the implementation of fuzzy objects. Drawing on the review by Bian (2007) and the case of tree avenues, however, single trees can be regarded fairly discrete objects and hence it seems logical to define tree avenues the same way. Should the same approaches be applied to more fuzzy objects, it is the belief of the author that the likelihood of misinterpretation increases.

Furthermore, limitations of software in handling the amounts of data was both reviewed and experienced from experiments in eCognition. As mentioned, the majority of case studies use small plots and most studies do not contemplate over the ways to upscale analyses. In regard to one of the main aims with GEOBIA which is to facilitate large scale and regular land surface monitoring, it seems that this issue has to be taken seriously. It might very well be that the possibilities exist but are not published or summarized in an intuitive way. Anyhow, this is highly encouraged for future research.

5. Conclusions

This thesis set out to investigate the potential of GEOBIA to identify and monitor tree avenues. For this, an extensive literature study on GEOBIA, eCognition, and tree avenues was conducted. The main findings of this literature study were that a) there have not been any earlier attempts using GEOBIA to identify tree avenues, and b) due to their specific characteristics, tree avenues appear to be a suitable research object for GEOBIA based approaches.

The findings of the literature study were then combined into a set of guidelines, an action plan, for practitioners that want to use GEOBIA, and specifically eCognition, to identify or monitor tree avenues.

Whereas the author is confident of the general applicability of GEOBIA approaches towards the detection of tree avenues, the main drawback of this thesis is its limitation to practically show or exemplify this applicability. The use of the eCognition software, as well as handling the required volumes of data have within this study shown to be considerable hindrances, not only to the author, but even to the possible application by other practitioners. However, this thesis and its action plan can serve as and should be seen as an initial help to overcome these hindrances. Herein lies the overarching accomplishment of this thesis.

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