MAPPING VEGETATION STRUCTURE ON AMELAND USING MACHINE BASED LEARNING TECHNIQUE TO SUPPORT RISK MANAGEMENT OF VECTOR-BORNE DISEASES

Masih Rajaei Najafabadi

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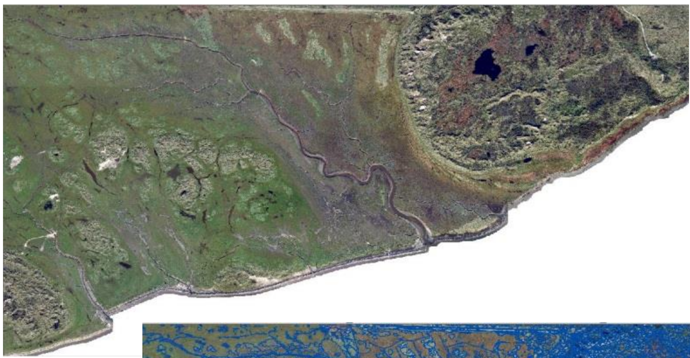

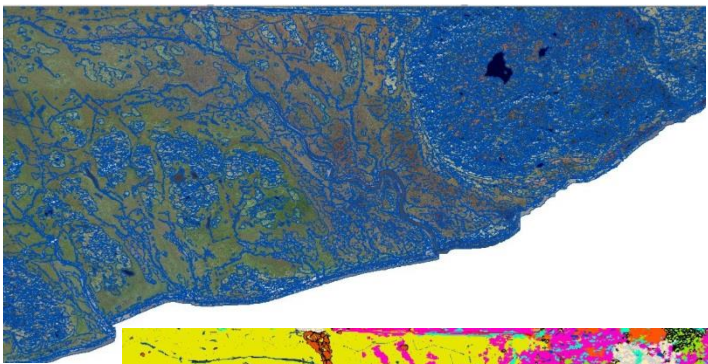

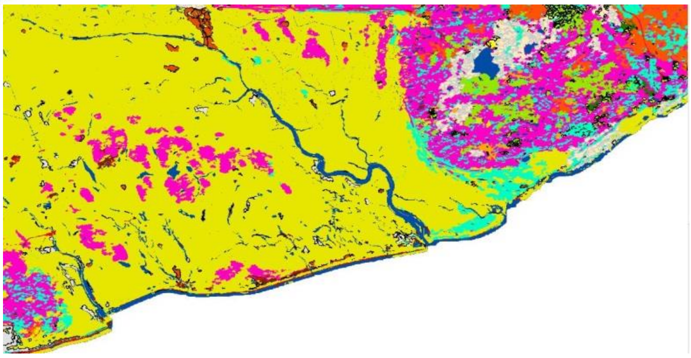

Date September 2014

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Mapping Vegetation Structure on Ameland

Using Machine Based Learning Technique to Support Risk Management of Vector-borne Diseases

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CERTIFICATE

This is to certify that the project work entitled, “Mapping Vegetation Structure on Ameland Using Machine Based Learning Technique to Support Risk Management of Vector-borne Diseases" submitted to Laboratory of Geo-Information Science and Remote Sensing, Wageningen University during the year 2014, has been carried by **Mr. Masih Rajaei Najafabadi** under the supervision of Lammert Kooistra from Laboratory of Geo-Information Science and Remote Sensing), Henk Kramer, Sander Mücher and Pieter Slim from Altera, Wageningen University, the Netherland for the partial fulfilment of the degree of Master of Geoinformation Science.

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DECLARATION

I, Mr. Masih Rajaei Najafabadi declare that the dissertation “Mapping Vegetation Structure on Ameland Using Machine Based Learning Technique to Support Risk Management of Vector-borne Diseases" is submitted to Laboratory of Geo-Information Science and Remote Sensing, Wageningen University. In the partial fulfilment of the requirements for the award of the degree of Master of Geoinformation Science, is original work carried out by me and has not been previously submitted for the obtaining degree of any other university.

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ABSTRACT

Vector-borne diseases in particular Ixodes ricinus, are a vector to several diseases such as Lyme borreliosis that affect human's health. It is the most spread tick-borne infection of humans in the Netherlands. Prediction of ticks requires many factors such as temperature, humidity, vegetation structure, host and litter. Vegetation structure data is one of the most important factors for tick prediction. Very high resolution aerial images and LiDAR (AHN2) datasets with a national coverage provide opportunities to produce vegetation maps automatically.

In this study, the novel datasets are used to map the Ameland Island in the North part of the Netherlands into 25 vegetation structure classes. The method follows object-based image analysis principles. Objects are defined in FNEA segmentation and classified using the ensemble-tree classifier random forest. Four scenarios (Scenario 1 was created by RF classifier using VHR image and LiDAR data, scenario 2 was created by the Altera's rule-based approach (Wageningen University, the Netherlands), scenario 3 was created by RF classifier and Altera's segmentation and finally scenario 4 was created by RF classifier using only VHR image) were created. The mapping scale is checked by selecting segmentation parameters from comparison between reference polygons and segmented objects.

The results show that it is important to be able to select the right segmentation parameters to control the mapping scale. Therefore, scale 50, shape 0.1 and compactness 0.9 were selected as optimal parameters. The application of random forest on the objects resulted in an estimated classification accuracy of 70.53% without LiDAR data and with LiDAR data classification accuracy improved y 6.28% and reached to 70.53%.Variable importance measures of random forest showed that the ahn2 LiDAR dataset is a valuable addition to the spectral information contained in the aerial images in the classification. The tick suitability map showed woodland and forested area are count as tick rich area with total tick number of 1348.

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Acronyms

AHN2	Actual Dutch digital elevation model
DCM	Digital Canopy Model
DEM	Digital Elevation Model
DSM	Digital Surface Model
FNEA	Fractal Net Evolution Approach
GLCM	Gray Level Co-occurrence Matrix
GLDV	Gray Level Difference Vector
GREN	Green Red red-Edge and Near-infrared
IHS	Intensity Hue and Saturation
LiDAR	Light Detection and Ranging
OBIA	Object Based Image Analysis
RGB	Red Green and Blue
RF	Random Forest

CHAPTER 1

INTRODUCTION

1.1. Vector-Borne diseases

Vector-borne diseases or diseases carried by vectors such as ticks or mosquitoes have been the scourge of man and animals since the beginning of time (Gubler 2009). These diseases transmitted to human and animal hosts through biting or physical contact are of increasing concern to public health bodies in many European countries (Kruijff et al., 2011). At the turn of the 20th century, vector-borne diseases were among the most serious public and animal health problems in the world. Global trends, combined with changes in animal husbandry, urbanization, modern transportation and globalization, have resulted in a global re-emergence of epidemic vector-borne diseases affecting both humans and animals over the past 30 years (Gubler 2009).

Ticks, in particular *Ixodes ricinus*, are a vector to several diseases that affect human's health. Lyme disease, or Lyme borreliosis, is the most spread tick-borne infection of humans in the Netherlands and it has alarmingly increased since the 1980s (Randolph 2001, Tack, Madder et al. 2013). The two main factors determining tick-borne Lyme disease infection are abundance of infected ticks and human exposure to tick bites (Guglielmone, Beati et al. 2006, Sprong, Tijsse-Klasen et al. 2012).

The distribution and abundance of ticks is affected by various abiotic and biotic factors such as the microclimate (temperature and humidity), habitat (vegetation) and vertebrate host community (Lindgren, Tälleklint et al. 2000, Gassner and Hartemink 2013). Several scientific studies have shown that the spatial and temporal variation in tick abundance is strongly associated with specific types of micro-climates (Estrada-Peña, Gray et al. 2013, Medlock, Hansford et al. 2013) such as temperature, relative humidity, and vegetation type (Hancock, Brackley et al. 2011, Ruiz-Fons, Fernández-de-Mera et al. 2012). *Ixodes ricinus* requires a relative humidity of at least 80 % to maintain its water balance (Kahl and Knülle 1988). Thus the species can be found mostly in habitats with a moist litter layer that allows ticks to rehydrate periodically during the driest periods of the year (Tack, Madder et al. 2013). Each life stage (larva, nymph, adult) must seek a vertebrate host for its blood meal and, at each life stage ticks are present on different area of vegetation (adults on top and nymph and larva on lower part) (Guglielmone, Beati et al. 2006, Tack 2013, Tack, Madder et al. 2013). In order to find one, has to climb onto low vegetation to await a passing host, the so-called questing behaviour. It is very important to have accurate vegetation structure map for prediction, monitoring and risk management of ticks.

Although *I. ricinus* feeds on a wide variety of hosts, larvae typically parasitize birds and small mammals whereas adult females prefer larger mammals, such as ungulates (e.g., deer) (Gray 1998).Ticks may acquire pathogens during feeding on infected hosts that act as competent reservoirs of pathogenic microorganisms and may then pass the infection on to humans (Tack et al., 2013; Vorou, Papavassiliou, & Tsiodras, 2007). The litter layer and host type, availability, and size (Hofmeester, 2014) are affecting the number of ticks. The chances of getting high number of ticks in broad leaf forest are higher than in coniferous forest because amount of litter present in broad leaf forest is higher (Tack 2013). Therefore, the risk of human infection is increases in the forest area(Tack, Madder et al. 2013, Michelchen 2014). There are 1.2 million tick bites per year in the Netherlands and around 17,000 reports of warning symptoms of Lyme borreliosis. A survey of general practitioners showed an increase of both tick bites and Lyme cases in the last decade (Hofhuis, Harms et al. 2010, Roest, Tilburg et al. 2011, Schimmer, Notermans et al. 2012). Therefore, characterization of vegetation complexity is one of the requirements for improvement of vector-borne diseases.

1.2. Detailed Vegetation Structure Mapping

Human and natural forces are rapidly modifying the vegetation structure which all of life depends, affecting our climate now and for the foreseeable future, causing steep reductions in species diversity (Hall, Bergen et al. 2011). Accurate representation of the vegetation classification of the earth system is a continuing challenge. The range of climates, geomorphic substrates, natural disturbance and human encroachments has produced an incredible diversity of terrestrial vegetation.

Vegetation structure mapping and monitoring are critical for many applications, including biodiversity studies (Wood, Pidgeon et al. 2012) nature management, impact studies (e.g., extraction of natural gas in Ameland, Netherlands) (Wessels, Mathieu et al. 2011, WaddenZee 2014), risk management (Daniel, Kolar et al. 2004, Kaya, Sokol et al. 2004) and wildlife management (Bunce, Bogers et al. 2013).

Environmental monitoring requirements, conservation goals, spatial planning enforcement, or ecosystem-oriented natural resources management, demand considerable urgency to the development of operational solutions that can extract tangible information from remote sensing data. On the other hand, by increasing in availability of VHR images and LiDAR and their processing methods, it's still remaining a challenge for scientist to create detailed mapping (e.g., species-level vegetation) (Harvey and Hill 2001).

1.3. Object-based Image Analysis (OBIA) vs. Pixel-based

Pixel-based analysis

Remote sensing imagery is composed of rows and columns of pixels; and in many studies land cover mapping analysis has been pixel-oriented (Casals-Carrasco, Kubo et al. 2000, Bhaskaran, Paramananda et al. 2010, Auquilla 2013). A pixel-based analysis is a pixel by pixel process based on spectral similarity which classifies all pixels in an image into land cover classes. In pixel-based analysis, the input features represent the numerical values of the spectral pattern (spectral bands of the image) (Bhaskaran, Paramananda et al. 2010, Auquilla 2013).

Minimum distance, Nearest Neighbour (NN), parallelepiped, Iterative Self-Organizing Data Analysis Technique (ISODATA) and Maximum Likelihood Classifier (MLC) are pixel-based classifiers (Casals-Carrasco, Kubo et al. 2000, Gao and Mas 2008, Auquilla 2013). These methods have been used for producing coarse-scale classifications from moderate resolution satellite imagery such as Landsat TM (Alberti, Weeks et al. 2004, Hollister, Gonzalez et al. 2004, Zhang and Xie 2013).

While high spatial resolution remote sensing provides more information than coarse resolution imagery for detailed mapping, increasingly finer spatial resolution produces challenges for pixel-based techniques. These techniques are treated individual pixels in the classification algorithm without considering any spatial association with neighbouring pixels. With high spatial resolution imagery, single pixels no longer capture the characteristics of classification targets (Yu, Gong et al. 2006, Guo, Kelly et al. 2007, Cleve, Kelly et al. 2008).

Object-based Image Analysis (OBIA)

OBIA is a process of grouping pixels into meaningful objects and analyses the objects for classification which gives more suitable results (Aguado, Montiel et al. 1998, Yan, Mas et al. 2006, Whiteside, Boggs et al. 2011, Kuilder 2012, Auquilla 2013). On top of the information contained in the individual pixels, objects contain information about the relevant context of a pixel and alternative to OBIA is to use a moving window to incorporate contextual information of pixel's direct neighbourhoods (Auquilla 2013). It has mentioned in many studies, the overall accuracy of OBIA is higher than pixel-based analysis(Yan, Mas et al. 2006, Cleve, Kelly et al. 2008, Gao and Mas 2008), however, some studies have found no difference in their accuracies (Duro, Franklin et al. 2012).

An OBIA approach is consisting of segmentation and classification. The aim of the segmentation process is to create homogeneous objects that will be used as input for the classification process (Yan, Mas et al. 2006). One important characteristic of segmentation is that, it eliminates the salt and pepper effect produced by a pixel-based analysis; since, the objects, created by the segmentation process, represent land cover types contained in homogeneous regions which may be spectrally variable at the pixel level (Whiteside, Boggs et al. 2011, Kuilder 2012, Auquilla 2013). The segmentation parameters (see Section 2.1) must be set according to the resolution and scale of the real world objects (Blaschke 2003, Thomas Blaschke 2004, Kuilder 2012, Auquilla 2013).

(Dorren, Maier et al. 2003) as well as (Heyman, Gaston et al. 2003) favoured an OBIA approach to discriminate broad scale forest cover types. (Herrera, Kleinn et al. 2004) classified trees outside forests using an OBIA approach in Costa Rica. (Chubey, Franklin et al. 2006) used OBIA to derive forest inventory parameters. (Radoux and Defourny 2007) used high resolution satellite images and OBIA methods to produce large scale maps quantitative information about the accuracy and precision of delineated boundaries for forest management.

A multi-scale, object-based analysis has been carried out to delineate forest vegetation polygons in a natural forest in Northern Greece which the accuracy of the final map did not exceed 80% (Mallinis, Koutsias et al. 2008). (Xie, Roberts et al. 2008) used an object based geographic image retrieval approach for detecting exotic Australian Pine in South Florida, USA. Such an approach has downside which 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 (Stuckens, Coppin et al. 2000, Blaschke and Strobl 2001, Ehlers, Gähler et al. 2003, Blaschke 2010, Liu and Xia 2010, Auquilla 2013).

The quality of the segmentation process is directly affecting the classification process; segments that do not reflect the reality, will led to an incorrect classification (Yan, Mas et al. 2006, Auquilla 2013). By adding to the analysis information of different sources, such as topological and contextual, OBIA can result in objects that represent very well the real world ones (Whiteside, Boggs et al. 2011). OBIA gives the user control over the mapping scale and can handle the implicit variability that comes with very-high resolution imagery (Jyothi, Babu et al. 2008, Liu and Xia 2010, Auquilla 2013) and also the user has more control over the final mapping result since it has choices in both steps (segmentation and classification), but being in control does not necessarily give better results. OBIA separates the identification from the classification which is in line with the manual approach of delineation of boundaries and the assignment of labels in the field. Thus, this means that there should be objective mechanisms to identify objects of the right scale, and consistently assign the correct labels.

One of the drawbacks of an OBIA is the need to have a prior knowledge about the area of study and the complexity of the computations needed to perform the segmentation and retrieve the information related to the objects (Yan, Mas et al. 2006, Blaschke 2010, Whiteside, Boggs et al. 2011, Auquilla 2013). Other drawbacks of OBIA are transferability of parameter settings between areas, datasets and scales, and dependency on vegetation typology or typologies in general.

1.4. Problem of Scale and Assigning Labels

Every aerial image contains different objects. The larger an object, the better the contextual information of pixels and thus the more accurate the classification result, but its good until the objects include too many pixels and lose their physical meaning (Blaschke 2010, Liu and Xia 2010, Auquilla 2013). The same data may give different segmentation results depending on the parameters are used (scale, shape, compactness and spectral difference value). This is known as the issue of scale (Lam and Quattrochi 1992, Marceau 1999) and was first recognized by (Gehlke and Biehl 1934). Therefore, a common problem in OBIA is identifying objects of the right scale in the image segmentation step (Auquilla 2013).

In OBIA, the problem is shifted from data to the segmentation. The higher the resolution of the image the smaller the objects of interest may be simultaneously, the higher the resolution, the more heterogeneous objects of similar scale will be. (Hall, Hay et al. 2004) showed that landscapes are complex and scale dependent. Research has primarily been focused on finding an optimum scale for the data in respect to segmentation accuracy: maximizing intra-segment homogeneity and inter-segment heterogeneity(Ronfard 1994, Espindola, Câmara et al. 2006, Gao, Mas et al. 2011, Johnson and Xie 2011, Kuilder 2012) . (Möller, Lymburner et al. 2007) developed a promising tool for comparing manually digitized areas with generated objects to asses segmentation accuracy. Whereas previous research defined the right scale as the scale where the map accuracy is maximized; Kuilder (2012) has achieved a segmentation scale which is relevant for the mapper and can be kept consistent in following years, independent of the data.

This research focuses on objectively finding an automated object based classification method to segment and classify images and compares it with other automated method (see section 3.5).

Traditional labels assigning to the identified segments are relying heavily on human interpretation. This dependence makes the process intensive and increasing errors, resulting in a map with low accuracy and high uncertainty (Koutsias, Karteris et al. 2000, Burnett and Blaschke 2003, Kuilder 2012).This dependence also makes the process labour intensive and prone to human error, resulting in a map with low accuracy and high uncertainty (Knotters, Brus et al. 2008). An automated classification method lowers the dependence on expert knowledge (but still the right features need to be selected in relation to the selected vegetation typology by expert knowledge) about the mapped objects, potentially lowers the subjectivity and may include information about the uncertainty of the assigned label. Many researches have shown variables such as textural features and colour-space transformation affecting the accuracy of classification. To keep the mapping procedure robust to changes in data, there is a need to understand the importance of the data layers and variables for classification.

1.5. Machine Learning Techniques

Traditional methods for vegetation mapping and monitoring (e.g. field surveys, literature reviews, map interpretation and collateral and ancillary data analysis) can be highly accurate(Hyde, Dubayah et al. 2006) but are not effective to acquire vegetation covers because they are time consuming, date lagged, often too expensive and normally limited to small areas(Zhang and Xie 2013).

Therefore, high resolution images (Hyyppa, Hyppa et al. 1998), hyperspectral (Hyde, Dubayah et al. 2006, Mücher, Kooistra et al. 2013) and LiDAR data (Kempeneers, Deronde et al. 2009, Lee, Ni-Meister et al. 2011, Hantson, Kooistra et al.

2012, Hellesen and Matikainen 2013, Ficetola, Bonardi et al. 2014) have been used to classify and map vegetation structure at high resolution and broad scales.

Combining information from multiple sensors, or data fusion, has yielded promising results for vegetation structural characteristics (Wulder, Hall et al. 2004).VHR images are capable more of characterising the bio-chemical aspects of the vegetation while LiDAR data are characterizing the structural aspects of the vegetation (Weishampel, Blair et al. 2000). Hudak et al. (2002) combined LiDAR and multispectral data; the results were more accurate than either data set alone. The highest classification accuracy (Kappa=91.6%) was acquired when using both spectral- and LIDAR-derived metrics based on objects segmented from both spectral and LIDAR layers (Ke, Quackenbush et al. 2010).

However, there is a demand for tangible classification at different scales and by increasing the availability of Very-High-Resolution (VHR) images and LiDAR data, it led to applying classification to the automated process.

Machine learning is a type of artificial intelligence (AI) that has the ability to learn from data (Chen 1995, Wang and Li 2014). Numerous methods, algorithms and also machine learning approaches have been developed towards the automation of the vegetation classification process (Gamanya, De Maeyer et al. 2007).Most traditional classification approaches are based on statistical analysis of individual pixels. These approaches are well-suited to images with relatively coarse spatial resolution. Machine learning techniques have been used in land cover and vegetation mappings problems (Atkinson, 1997; Heumann, 2011; Kuilder, 2012).

Machine Learning techniques were compared to inferential statistics classifiers for land cover classification, which minimize the prior assumptions of the datasets are preferable for geographical data(Gahegan 2003) . Several ML techniques have been used such as Multi-layer Perceptrons (MLP) which is widely used for land cover types classification in remote sensing (Huang, Davis et al. 2002, Atkinson and Tatnall 2010, Auquilla 2013, Zare, Pourghasemi et al. 2013, Shiraishi, Motohka et al. 2014) . Kanellopoulos & Wilkinson, 2010 provided a list of best practices for classification of multispectral imagery using MLP in terms of architecture, optimization algorithms, scaling input data, avoidance of chaos effect and use of enhanced feature sets(Auquilla 2013).

Support Vector Machine (SVM) is another ML technique that is widely used for classification of land cover types using multispectral imagery(Cristianini and Shawe-Taylor 2000, Schölkopf, Smola et al. 2000, Melgani and Bruzzone 2002, Melgani and Bruzzone 2004, Zhang, Marszałek et al. 2007, Tzotsos and Argialas 2008, Heumann 2011, Auquilla 2013). A remarkable result is that, SVM is a good alternative to conventional patter recognition classifiers like K-Nearest Neighbour (Melgani and Bruzzone 2002, Melgani and Bruzzone 2004, Auquilla 2013). In 2011, Heumann and in 2006, Tzotsos were used SVM in combination with an Object-based Image Analysis and 94% accuracy was obtained.

Random Forest (RF) is another ML technique .The random forest is an ensemble approach which is a divide-and-conquer approach used to improve stability and performance. The main principle behind ensemble methods is that a group of "weak learners" can come together to form a "strong learner". In training, the Random Forest algorithm creates multiple CART-like trees (Breiman, Friedman et al. 1984, Gislason, Benediktsson et al. 2006), each trained on a sample of the original training data, and searches only across a randomly selected subset of the input variables to determine a split. For classification, each tree in the Random Forest casts a unit vote for the most popular class at input x. The output of the classifier is determined by a majority vote of the trees.

Many researchers have used RF for classification (Díaz-Uriarte and De Andres 2006, Bosch, Zisserman et al. 2007, Prinzie and Van den Poel 2008, Kuilder 2012) and the majority of papers employs it, have proofed it's high accuracy (Lunetta, Hayward et al. 2004, Buckinx and Van den Poel 2005, Prinzie and Van den Poel 2008, Kuilder 2012, Auquilla 2013). RF makes no assumptions on the distributional characteristics of neither the independent variables nor the response variables and may handle situations where v greatly exceeds n (Cutler et al., 2007; Kuilder, 2012)

The leaf nodes of each tree are labelled by estimates of the posterior distribution over the image classes. Each internal node contains a test that best splits the space of data to be classified. An image is classified by sending it down every tree and aggregating the reached leaf distributions. Randomness can be injected at two points during training: in subsampling the training data so that each tree is grown using a different subset; and in selecting the node tests (Breiman 2001, Bosch, Zisserman et al. 2007, Cutler, Edwards Jr et al. 2007, Genuer, Poggi et al. 2010).

1.6. Research Objectives and Questions

This research aims to develop and test an automated method for mapping of vegetation structure with increased accuracy and detail compared to Altera's method as basis for an improved risk management of vector borne diseases.

To implement random forest approach for complex vegetation systems in dune ecosystems including woody patches.

- ✓ Is random forest approach applicable for vegetation structure classification?
- ✓ Does the availability of LiDAR data changes the result of segmentation?

To develop an extensive validation scheme for random forest approach and rule-based approach.

- ✓ What validation scheme is the most suitable for this approach and vegetation ecosystem?
- ✓ How accurate is the outcome of classification of random forest in compare with other approaches (e.g. rule-based approach developed by Alterra, 2014(Altera, Wageningen University))

To determine the relationship between vegetation distribution and tick Ixodes ricinus for risk assessment.

- ✓ How to evaluate the accuracy of tick habitat suitability map?

1.7. Outline of the thesis

This thesis is organized in six chapters. Following the introduction in this chapter, *Chapter 2* contains a literature review; this chapter provides the background information in segmentation and classification issues of OBIA; it also mentions the advantages, disadvantages, and the state of the art of the referred techniques.

Chapter 3, the materials and methods, used in this work, are presented. The materials subsection describes the boundary conditions of this thesis by describing the study area, the datasets used in the experiments. Since this study performs an OBIA, the methodology is divided in two well defined parts: segmentation and classification. Furthermore, the process of creating suitability map of ticks is explained.

✓ The segmentation methodology illustrates the first step in an OBIA paradigm. First, four scenarios, which represents sets of segmentation parameter configurations, and their characteristics are described; these so-called scenarios are specific configurations used to select the optimal parameters to perform the segmentation process. The input data (VHR aerial image and LIDAR dataset). Finally, a visual quality assessment is held using the different scenarios; as a result, the optimal parameters settings are found. Additionally, the result of segmentation process is compared with the segmentation result of Henk Kramer (Altera's study), 2014 (Altera, Wageningen University).

✓ The classification methodology is the second step in the OBIA paradigm described. Random forest technique is used as classification method. Furthermore, Variables and classes are listed and briefly explained. Finally, the process of selecting training data set for the classifiers and the classification process and validation data set is described.

Chapter 4 presents the results of the segmentation and classification process performed in this study and suitability map of ticks.

✓ Segmentation results present the different segmentation scenarios and visual quality assessment outputs for each of the segmentation scenarios; according to these results, a set of optimal segmentation parameters is selected. Furthermore, a visual comparison is done to find the effect of LIDAR in segmentation step.

✓ Classification results show the overall accuracy of the RF classifier and its confusion matric. A comparison is done between classification result of RF result and rule-based (Altera's study, 2014(Altera, Wageningen University)). The results are presented according to the six classification scenarios analysed.

✓ Suitability map of ticks shows the risk level of ticks in study area and the validation process of this result is explained.

Chapter 5 contains the discussion. This chapter discusses the results and their implications by interpreting obtained results and comparing them to other similar studies. The chapter focuses on the added value of including LIDAR information to RF process, training example selection and the effects of merging segmented objects based on a difference colour threshold. Lastly, *Chapter 6* presents the conclusions and recommendations. In this chapter, an overview of the results found in this thesis is presented.

CHAPTER 2

LITERATURE REVIEW

2.1. Image Segmentation

Segmentation algorithms

Image segmentation has its roots in machine vision of the 1980's (Fu and Mui 1981, Haralick and Shapiro 1985, Pal and Pal 1993, Kuilder 2012). Segmentation is defined as the process of partitioning a scene, such as a remote sensing image, into regions that are not overlapping each other. Segmentation algorithms commonly used for earth observation are divided in point-based, region-based, and edge- based (Fu and Mui 1981, Haralick and Shapiro 1985, Pal and Pal 1993, Schiewe 2002, Kuilder 2012, Auquilla 2013).

Point-based approaches perform threshold operations on the image to find homogeneous elements. These operations are aimed first, to group pixels according to their position and feature values and second, combining the members of a group based on their spatial connectivity. The choice of the threshold parameters can be achieved by statistics by the histogram information (Schiewe 2002, Kuilder 2012, Auquilla 2013).

Edge-based approaches use a filter follow by a contour generating algorithm to create objects in the scene (Schiewe 2002). Edge-based approaches are not suggested to use when noise is present, but more useful for the mapping of discrete features which contain clear boundaries such as urban areas (Schiewe 2002, Auquilla 2013).

Region-based approaches start with region growing step which select a group of seed pixels and detect similarities between the pixels. The process ends with by region merging and splitting when all the pixels have been assigned to one object(Schiewe 2002, Auquilla 2013) or until some criterion is met, such as certain value of homogeneity in the segment (Thomas Blaschke 2004, Möller, Lymburner et al. 2007, Auquilla 2013).

Fractal net evolution approach and effect of parameters

The Fractal Net Evolution Approach (FNEA) is a segmentation algorithm that is based on a region-based approach (Baatz and Schäpe 2000, Benz, Hofmann et al. 2004, Blaschke 2010, Drăguţ, Tiede et al. 2010, Martha, Kerle et al. 2011). FNEA uses a bottom-up region growing approach where smaller objects are merged to create larger ones (Liu and Xia 2010, Auquilla 2013). It may either start with existing objects, functioning as ’seeds ‘or it starts with individual pixels, objects consisting of 1 pixel. FNEA algorithm is used in this thesis for segmentation step. The software eCognition is one of the commercially available software packages that FNEA algorithm can be implemented in.

FNEA has been widely used researches (Möller, Lymburner et al. 2007, Heumann 2011, Kuilder 2012, Auquilla 2013, Auquilla, Heremans et al. 2014, Räsänen 2014) Parameters that FNEA uses in segmentation process are scale (also known as the homogeneity criteria(Möller, Lymburner et al. 2007)), colour and shape (it is a combination of compactness and smoothness). The value of the scale parameter affects image segmentation by determining the size of image objects. If the scale value is high, the variability allowed within each object is high and image objects are relatively large. Conversely, small scale values allow less variability within each segment, creating relatively smaller segments. The scale parameter affects the homogeneity of the segmented objects. The degree of fit between two objects is defined according to the increase in heterogeneity as a result of a merge of two objects.

Colour and shape parameters control the homogeneity. The merging of two adjacent objects is conditioned by the threshold defined by the scale parameter (Baatz and Schäpe 2000, Benz, Hofmann et al. 2004, Auquilla 2013). This segmentation algorithm is optimized when the heterogeneity measure of the resulting objects is minimized (Benz, Hofmann et al. 2004, Liu and Xia 2010, Auquilla 2013). Researches have been done on finding a right segmentation scale independent of the data (Martha, Kerle et al. 2011, Kuilder 2012).

Colour parameter (spectral properties) and shape parameters (smoothness and compactness) affect how objects are created during segmentation. The higher the value for colour or shape criteria the more the resulting objects would be optimized for spectral or spatial homogeneity. Within the shape criterion, the user also can alter the degree of smoothness (of object border) and compactness of the objects. The composition of homogeneity was controlled by both spectral and shape percentages as well as by a weight for the relative contribution of each input band(Im, Jensen et al. 2008).

Over and under segmentation

The amount of information contained in an object is subject to the amount of pixels and thus a result of the segmentation scale and the resolution of the data (Kuilder 2012). Two types of errors often exist in image segmentation including over-segmentation (creates too many and too small objects) and under-segmentation(creates too few and too big objects) (Jouda, Perret et al. 2004, Möller, Lymburner et al. 2007, Kampouraki, Wood et al. 2008, Liu and Xia 2010).

From a classification perspective, over-segmentation and under-segmentation have different impacts on the potential accuracy of object-based classification(Liu and Xia 2010). These segmentation errors could affect the subsequent classification process in two ways: (1) under-segmentation results in image objects that cover more than one class and thus introduce classification errors because all pixels in each mixed image object have to be assigned to the same class and (2) features extracted from mis-segmented image objects with over-segmentation or under-segmentation errors do not represent the properties of real objects on the Earth surface (e.g. shape and area), so they may not be useful and could even reduce the classification accuracy if not chosen appropriately (Song et al. 2005).

Liu & Xia (2010) has shown that the highest classification accuracy is found at the scale where the errors due to the inclusion of the wrong pixels in an object, equalizes to the increase in information from inclusion of the right pixels(Kuilder 2012). Some studies shown that their results were more biased towards under-segmentation (Zhang, Fritts et al. 2008) and slight over- or under-segmentation did not significantly affect the classification accuracies (Kampouraki, Wood et al. 2008, Ke, Quackenbush et al. 2010). According to Gao et al. (2011) the loss of accuracy is higher with under-segmentation than with over-segmentation. In other words, it is more harmful to the classification accuracy to make objects too big, than to make objects too small.

2.2. Classification

Random forest classifier

Random forests (RF) is a popular and very efficient algorithm, based on model aggregation ideas, for both classification and regression problems (Gislason, Benediktsson et al. 2006) and compared to other classifiers it is a modern machine learning classifier. Ensemble decision trees are among a couple of modern popular alternatives to the traditional maximum likelihood classification (Kuilder 2012). RF is a classifier consisting of a collection of tree-structured classifiers {h(x, Θk), k = 1,…} where the {Θk} are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x (Breiman, 2001).

RF is able to perform an object-based classification with low number of training data and a high amount of object-features that is why RF is become more and more popular. Additionally, Random Forest is not computationally intensive because its algorithm is considerably lighter than conventional bagging with a comparable tree-type classifier (Gislason, Benediktsson et al. 2006).

Random Forests have already provided promising results in fields such as genomics (Díaz-Uriarte and De Andres 2006, Diaz-Uriarte 2007, Saeys, Inza et al. 2007, Statnikov, Wang et al. 2008), ecology (Cutler, Edwards Jr et al. 2007, Peters, Baets et al. 2007, Evans and Cushman 2009, Marmion, Parviainen et al. 2009) and remote sensing (Liaw and Wiener 2002, Svetnik, Liaw et al. 2003, Schroff, Criminisi et al. 2008, Strobl, Boulesteix et al. 2008, Stumpf and Kerle 2011, Kuilder 2012).

According to Gislason et al., (2006), RF classifier performed well and in terms of accuracies it was comparable to the accuracies obtained by other ensemble methods. It also was much faster in training when compared to the ensemble methods, especially boosting. The results of RF for object- based mapping of landslides, show accuracies between 73% and 87% for the affected areas and other studies were shown same results (Breiman 2001, Gislason, Benediktsson et al. 2006, Bosch, Zisserman et al. 2007, Genuer, Poggi et al. 2010, Ghimire, Rogan et al. 2010). All authors agree that RF generally ranks high concerning classification accuracy and that RF is relative insensitive to its parameters.

For a comparison based on several datasets of the practically available alternatives including RF and the popular support vector machines, please refer to Meyer et al. (2003).A comparison between RF and other ensemble tree methods using bagging and boosting, tested on land cover datasets which the results shown improvement with RF in compare with other methods (Chan and Paelinckx 2008, Waske, van der Linden et al. 2012). Another study shows that RF classifier has poor performance with high class-imbalance (Lusa 2010, Kuilder 2012, Lin and Chen 2012).

Variables

Besides the colour and elevation means, over a hundred other features can be included: variance of spectral bands, a vegetation index, colour space transformations, texture measures, and geometric features use in OBIA. Similar features have been used by (Yu, Gong et al. 2006, Kuilder 2012). Yu et al. (2006) found that for classification of vegetation, three texture features are in the top other features. Colour is often presented as RGB, consisting of the reflection in the red, green and blue parts of the spectrum. There are several studies (Alata and Quintard 2009, Qazi, Alata et al. 2011) that have been tested on several models of light in the visible spectrum to estimate their accuracies (colour space, RGB or YC1C2).

Intensity, Hue and Saturation (IHS) are spatial characteristics of composite images are separated to the intensity and the spectral information is kept with the saturation and hue. Several studies have been successfully used IHS in their mapping (Koutsias, Karteris et al. 2000, Chen, Hepner et al. 2003, Tapiador and Casanova 2003, Tu, Huang et al. 2004, Kuilder 2012). Texture is one of the main components beside colour and shape. Texture in this study is quantified using Gray Level Co-occurrence Matrix (GLCM) and Gray Level Difference Vector (GLDV) (Haralick, Shanmugam et al. 1973, Ojala, Pietikäinen et al. 1996, Kuilder 2012). GLCM is a matrix of frequency of band values at a specified distance in an object and GLDV is the sum of the diagonals of the matrices (Jyothi, Babu et al. 2008, Kuilder 2012). Different metrics may be deduced from the matrices and vectors; common are mean; variance; homogeneity; contrast; dissimilarity; and entropy. Texture calculated of different bands (Foody, Campbell et al. 1992, Johansen and Phinn 2006, Yu, Gong et al. 2006, Jyothi, Babu et al. 2008, Kuilder 2012). These texture metrics provided valuable information in predicting the class of objects. Geometry refers to the extent and shape information related to the segmented object.

CHAPTER 3

METHODOLOGY

3.1. Study area

Figure 1 show the boundaries of the study area. This research carried out for the eastern part of the Wadden-Island Ameland. It is the third major island of the West Frisians Islands off the north coast of the Netherlands. A total of 27 vegetation structure classes are identified within the study area by Pieter Slim (Plant Ecology, Altera, Wageningen University) and used as reference (Appendix A). However, the area is represented by 11 major classes of vegetation structure (Table 6).

In 1871 and 1872, a dike was built between Ameland and the mainland by a society for the reclamation of Frisian land from the sea. The dike ran from Holwerd to Bueren and was 8.7 km long. In the end, it was unsuccessful; the dike did not prove to be durable and in 1882, after heavy storms in the winter, repair and maintenance of the dam were stopped. The dike can still be partially seen at low tide. As early as 1975 suggestions were brought again for the stabilization of the Frisian Islands, both saving the ecological systems of these islands and protecting them from some of the brunt of North Sea storm surges. It consists mostly of sand dunes. Initial construction began after 17 years from its suggestion in 1992 and in mid-May 2006 final stage of construction was completed.

Natural gas has been extracted from a depth of about 3.5 km below the east part of the Dutch Wadden Sea island of Ameland since 1986. Due to gas extraction a subsidence has been formed with a diameter of 10km and the maximum subsidence of center is around 32cm (WaddenZee 2014). In ecological terms, subsidence has the same consequences as sea level rise. Therefore, since 1994 different monitoring plans were executed. The recent monitoring plan has been started from 2006 with a group of researchers under supervision of an independent committee which have been study and measure this area. Investigation is carried out to discover whether or not the subsidence has any consequence for nature. This is the longest integrated ecological research project on the impact of subsidence worldwide. The monitoring will be continued till the end of gas production according the long-term Monitoring Plan 2006-2020.

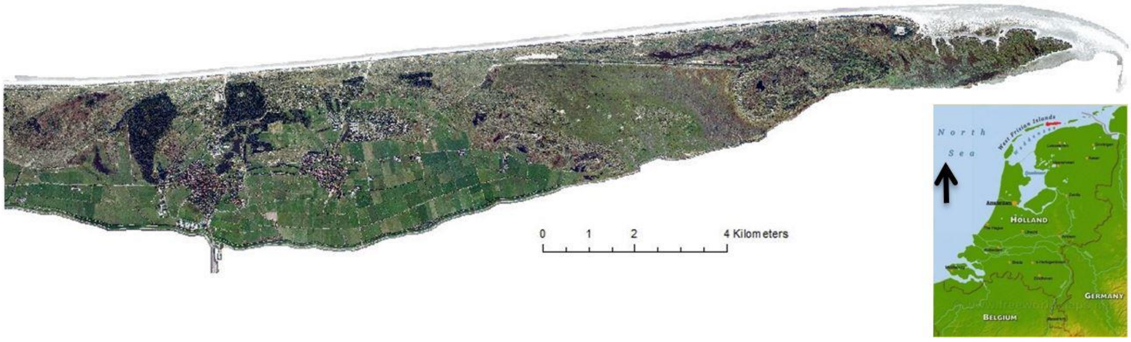


Figure 1: True-color aerial image of 2008 of the study area

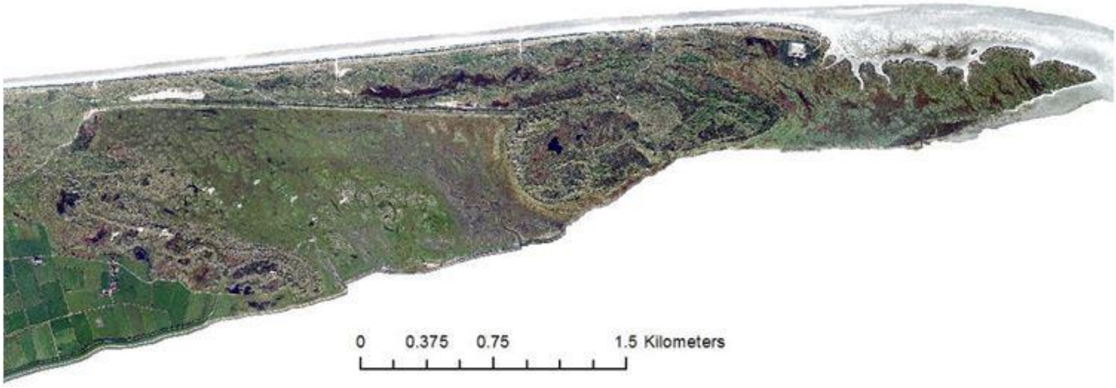


Figure 2: True-color aerial image of 2008 of the Altera's study area

3.2. General explanation on methodology

Figure 3 is showing the methodology of this research which is divided in three sections: segmentation, classification and tick suitability map. All the analysis is done in eCognition developer 9 (Trimble, 2014).

3.3. Data sets

VHR Aerial Imagery and LiDAR Data

Two data sets are used to perform OBIA and creation of vegetation structure map. VHR aerial imagery has been acquired by Eurosense BV Company in 2008. The sensor includes four bands blue, green, red, and NIR which is an ideal setting for the mapping of vegetation. The spatial resolution of 25 cm is detailed enough to perform an OBIA for this complex situation. LiDAR data from the AHN_2 database (Algemeen Hoogtebestand Nederland) has been acquired in 2008. The Object Height Model (OHM) was created by subtracting the pixel values of the Digital Elevation Model

(DEM) of the Digital Surface Model (DSM) (Figure 4). This dataset is used to examine the effects of using height information in segmentation and classification.

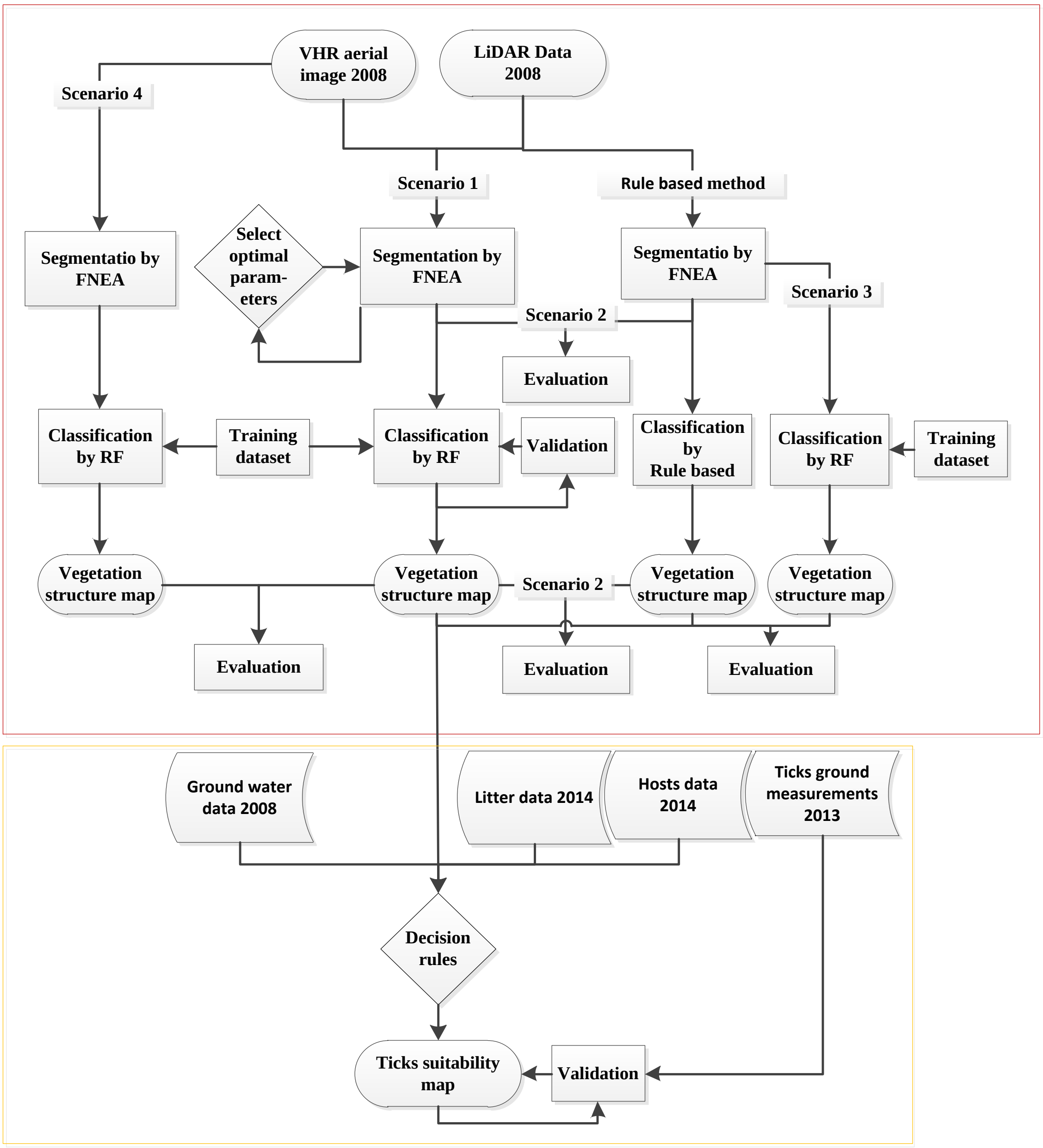


Figure 3: Methodology flow chart

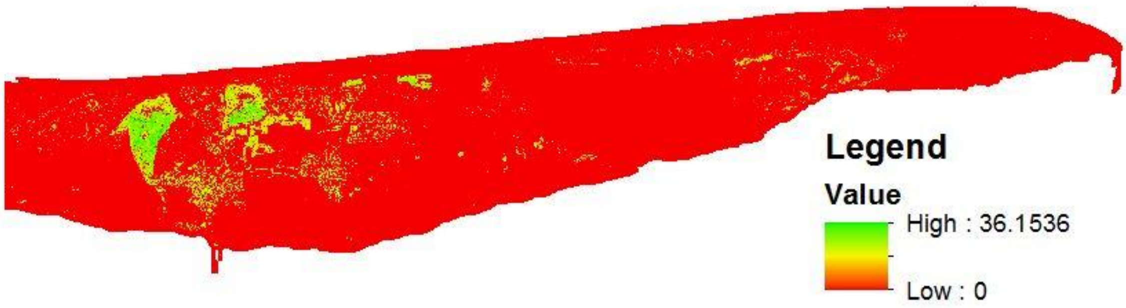


Figure 4: Object Height Model (OHM)

Other data sets

There are nine external datasets are used in this study. Table 1 shows the main characteristic of these nine datasets. Four of these datasets (soil, ground water, host and litter) and vegetation structure map were used to create tick suitability map. The training datasets were used to train the RF classifier and validation dataset was used to create confusion matrix for acquire accuracy of all classification results. For more information refer to section 3.5.

Tick ground measurements contain points with number of ticks (larva, nymph, male, and female) present in the location of measurements.

Training dataset III and validation dataset were collected during two weeks of fieldwork on the Ameland Island from 10th to 24th of June, 2014. In the field, each location was measured by a hand held GPS (Garmin etrex 30) and also at least one photo was taken at each location. At each location the dominant species was selected as vegetation structure type. The decision was made for some areas in the east part of the island to do not measure points, due to presence of bird's colonies. Many of training and validation points were confirmed and evaluated by expert knowledge of Pieter Slim for increasing the accuracy of these two datasets.

3.4. Segmentation by FNEA

The most suitable segmentation result has been selected out of 4 segmentation results. The four segmentations have four unique scale settings (Table 3). Shape and compactness values were used according to Altera's study (Shape 0.1 and compactness 0.9). These parameters influencing the identification of objects are kept constant. To select the optimal segmentation, four plots were selected. These plots were segmented manually and used as reference segmentation (Möller, Lymburner et al. 2007, Kuilder 2012, Auquilla 2013).

Table 1: Information on datasets

No.	Data sets	Resolution	Data type	Production date	Production by
1	Ground water	50*50	Raster	2008	GeoDesk-Wageningen University
2	Litter		Vector	2014	Pieter Slim (Masih Rajae)
3	Host		Vector	2014	Fris Oud (It Fryske Gea, Ameland) and Johan Krol (Nature Center Ameland)
4	Tick ground measurements		Vector (Points)	2013	Sophia Michelchen University of Antwerp
5	Training I		Vector (Points)	2013	Henk Kramer and Sander Mücher
6	Training II		Vector (Points)	2012-2013	Pieter Slim
7	Training III		Vector (Points)	2014	Masih Rajaei
8	Validation		Vector (Points)	2014	Masih Rajaei

However, after the optimal scale parameter was selected; shape and compactness parameters were changed (0, 0.5, and 0.9 for both parameters) just to observe the changes occurred in segmentation. The effects of these parameters have not been analyzed in this study.

Segmentation process is involves two parts: a Multi-Resolution Segmentation (MRS) and a spectral difference merge. Segmentation process is performed in eCognition developer 9 (Johansen and Phinn 2006, Jyothi, Babu et al. 2008, Mücher, Roupioz et al. 2010, Kuilder 2012, Auquilla 2013, Mücher, Kooistra et al. 2013, Zhang, Selch et al. 2013, Zhang and Xie 2013, Zhang and Xie 2013, Zhang 2014).

The data layers and their corresponding weights that are used for segmentation are shown in table 2. The multispectral layers have been assigned with equal weights because they the same influence to the increased heterogeneity of a merge of two objects, but the OHM layer has been assigned with weight 2, which its structural information has, double effect in the segmentation process. Altering these weights might have a positive effect on the segmentation but this has not been pursued in this study.

MRS is the first step of segmentation process which creates the initial objects. Table 3 shows all the parameter settings used for this step are scale. Shape and compactness are left constant. The second step of segmentation process is a spectral difference segmentation which usually performed on the output of the multi-resolution segmentation (Andrés Auquilla, 2013; Hantson et al., 2012; Heumann, 2011; Kuilder, 2012; Tzotsos & Argialas, 2008; Yan et al., 2006)

Table 2: Data layers and associating weights used in segmentation

Data type	Image layer	Weight
Aerial image	Blue	1
	Green	1
	Red	1
	Near-Infrared (NIR)	1
AHN_2	OHM	2

Since multi-resolution segmentation creates objects by creating seed points (Yan, Mas et al. 2006, Möller, Lymburner et al. 2007), homogeneous areas such as water become multiple objects. Hence, spectral difference segmentation is merged objects on the basis of color heterogeneity only. Color here stands for the digital numbers in all of the data layers and therefore the weights of Table 1 are used here as well. After visual inspection, the allowed spectral heterogeneity has been set at 4. The final segmentation result is used as input in RF classifier in classification step.

Table 3: Segmentation settings for scenario 1 Parameter settings of the segmentation

Parameter name	Value	Data set
Scale	25-100 incremented with 25	VHR aerial image and AHN_2(OHM) (combined datasets)
Shape	0.2	
Compactness	0.9	

In the first analysis scenario, the most suitable segmentation (Figure 3: scenario 1) is selected by comparison of all 4 results of segmentation process with reference segmentation. The final segmentation is used as input for RF classifier (for more information refers to section 3.5).

The second scenario is to evaluate the segmentation (Table 4) and classification (appendix B) results prepared in a study by Alterra (Altera, Wageningen University)). This study area covers more than half of the study area of this study. The segmentation and classification of this scenario were evaluated by the result of scenario 1. The Altera's segmentation process has two MRSs. This method is used to segments all small objects as much as possible. The final result is used as input for rule-based classification. The classification step gives 8 major classes (Appendix B).

Table 4: add settings scenario 2 Multi-resolution segmentations, parameters setting and Image layer weight.* the thematic layer contained 5 stratification levels which identified based on DTM

MRS	Dataset	Image layer	Thematic layer*	Weight	Parameters		
					Scale	Shape	Compactness
1	VHR aerial image	blue, green, red	Yes	1 for each layer	50	0.1	0.9
2	AHN2	OHM	Yes	1	10	0.1	0.5

In scenario 3, the segmentation result of Altera's study is used as input for RF classifier. The result of this scenario is compared with the result of scenario 1 and 2, to investigate whether or not better classification result have been achieved.

Scenario 4 is used parameters setting of segmentation of scenario 1; to create segmentation with only VHR aerial image (only blue, green, red and NIR layers) and RF classifier used for classification. Its result was compared with the results of scenario 1 over two selected areas to investigate the effect of LiDAR dataset.

3.5. Classification by Random Forest

Random forest classifier on the basis of 46 variables (Kuilder 2012, Auquilla 2013) and 934 training points has been classified objects in to 25 vegetation structure classes Appendix C.

Variables

Three groups of information have been computed for each segmented object: layer values, geometry and texture. Table 5 shows all the 46 variables are used in RF classification. Some of these features are selected from (Chubey, Franklin et al. 2006, Kuilder 2012, Auquilla 2013).

Classes

The full list of defined classes is available in Appendix A. The final vegetation structure map contains eleven major classes (Table 6). This result is made by merging classes with similar type and structure. The decisions have been made by an expert, Pieter Slim.

Training Data

The third data set consisting of training data has been collected during the fieldwork in Ameland Island. All the three datasets are merged and created a single training dataset with 1843 observation points. Labelling of all collected points was done during data collection. A visual interpretation has been done to check whether the training points are located correctly or not. The distribution of the different classes within the training dataset is given in Table 7. The abundance of some classes was low in the study area which made it impossible to get an even amount of training points for every class.

Table 5: Object features used as variables in the classification

Category	Group	Feature
Spectral	Mean	Blue, Green, Red and NIR
	Standard deviation	Blue, Green, Red and NIR
	Pixel based	Min and Max value for all four layers
	Hue, Saturation and Intensity	Blue, Green, and Red
Geometry	Extent	Area
		Border length
		Length
		Length/width
		Width
	Shape	Compactness
		Density
		Elliptic fit
		Rectangular fit
		Roundness
		Shape index
Texture		GLCM Homogeneity
		GLCM Contrast
		GLCM Dissimilarity
		GLCM Entropy
		GLCM Standard deviation
		GLCM Correlation
		GLDV Angular Second Moment
		GLDV Entropy
		GLDV Contrast
		GLDV Mean

Validation Data

Before fieldwork, minimum two points for each class were selected manually in center of vegetation class (appendix). These points were selected in segments which have area more than five meters, due to GPS accuracy. However, the number of selected points increases for classes with larger area. This selection was performed after the classification result was achieved. Total 232 points were selected, but during the fieldwork this number increases to 624. The distribution of the different classes within the validation dataset is given in Table 7. Five confusion matrixes were created to calculate classification overall accuracy of scenarios 1, 3, 4, and rule-based method. Two of them were covered the whole study area and other three were covered according to Altera's study area (Figure 2).

Table 6: Vegetation structure classes grouped according to 27 vegetation structure types (Appendix A)

No.	Class name	Structure type
I.	Low height vegetation	Vegetation of Sea Club-rush
		Salt marsh vegetation
		Sea Wormwood
		Dune valley vegetation
		Vegetation of dry dunes
II.	Medium height vegetation	Marram vegetation
		Dune fresh valley
		Sea Rush
III.	Small shrubs	Sea-buckthorn shrub
		Bramble thicket
		Creeping Willow shrub
IV.	Tall shrubs	High willow shrub
		Elder shrub
		Hawthorn shrub
		Rose shrub

V.	Tall forbs	Vegetation of Sea Club-rush Vegetation of Rosebay Willowherb Vegetation of Common Nettle Creeping Thistle Ferns
VI.	Tall grasses	Wood Small-reed vegetation Sea Couch vegetation Common Reed vegetation
VII.	Agricultural land	Agricultural field (grazed, mowed, hayed)
VIII.	Planted forest	Coniferous forest (Pine, Spruce) with broadleaved trees in understory (Maple, Oak)
IX.	Woodland	Spontaneous Aspen Shrub of planted broadleaved & coniferous wooden species
X.	Water body	Water - fresh Water - salt/brackish
XI.	Soil (no vegetation)	Sand Artificial, e.g. stone, buildings, road-surfacing (shells, asphalt, brick), boulders

Table 7: Training points and validation point distribution

No.	Structure type	Training points	Validation Points
1	High willow shrub	70	41
2	Elder shrub	38	34
3	Hawthorn shrub	30	12
4	Sea-buckthorn shrub	71	56
5	Rose shrub	12	5
6	Bramble thicket	5	7
7	Creeping Willow shrub	75	40
8	Marram vegetation	102	32
9	Wood Small-reed vegetation	12	9

10	Sea Couch vegetation	13	14
11	Common Reed vegetation	102	47
12	Vegetation of Sea Club-rush	10	7
13	Vegetation of Rosebay Willow herb	2	5
14	Vegetation of Common Nettle	3	2
15a	Salt marsh vegetation	91	52
15b	Marram	0	
15c	Sea Wormwood		
15d		0	
15e	Sea Rush		
15f			
15g	Creeping Thistle		
16	Dune valley vegetation	11	10
16a	Dune valley (fresh) with tussocks of Soft-rush (as a result of grazing with husbandry	5	6
17	Vegetation of dry dunes	101	52
18	Ferns	7	3
19	Sand	15	20
20	Water - fresh	9	24
21	Water - salt/brackish	16	23
22	Agricultural field	36	39
23	Artificial, e.g. stone, buildings, road-surfacing (shells, asphalt, brick), boulders	67	22
24	Drift line vegetation	0	0
25	Shrub of planted broadleaved & coniferous wooden species	22	8
26	Spontaneous Aspen	7	2
27	Coniferous forest (Pine, Spruce) with broadleaved trees in understory (Maple, Oak)	44	50

3.6. Suitability map of tick

To create tick suitability map, five datasets were used. Figure 5 show the decision tree that is used to create tick suitability map (Haverkort 2013). Each datasets have a weight which shows it influence on the decisions (host: 4, litter: 3, vegetation structure type: 2, and ground water: 1).

The final suitability map was created by combining different levels of tick availability of datasets. The final map contains four levels: tick no, tick poor, tick average, and tick rich. The final result was evaluated by the ground measurements data provided by Sophia Michelchen. The presence and number of tick were in to account for the evaluation.

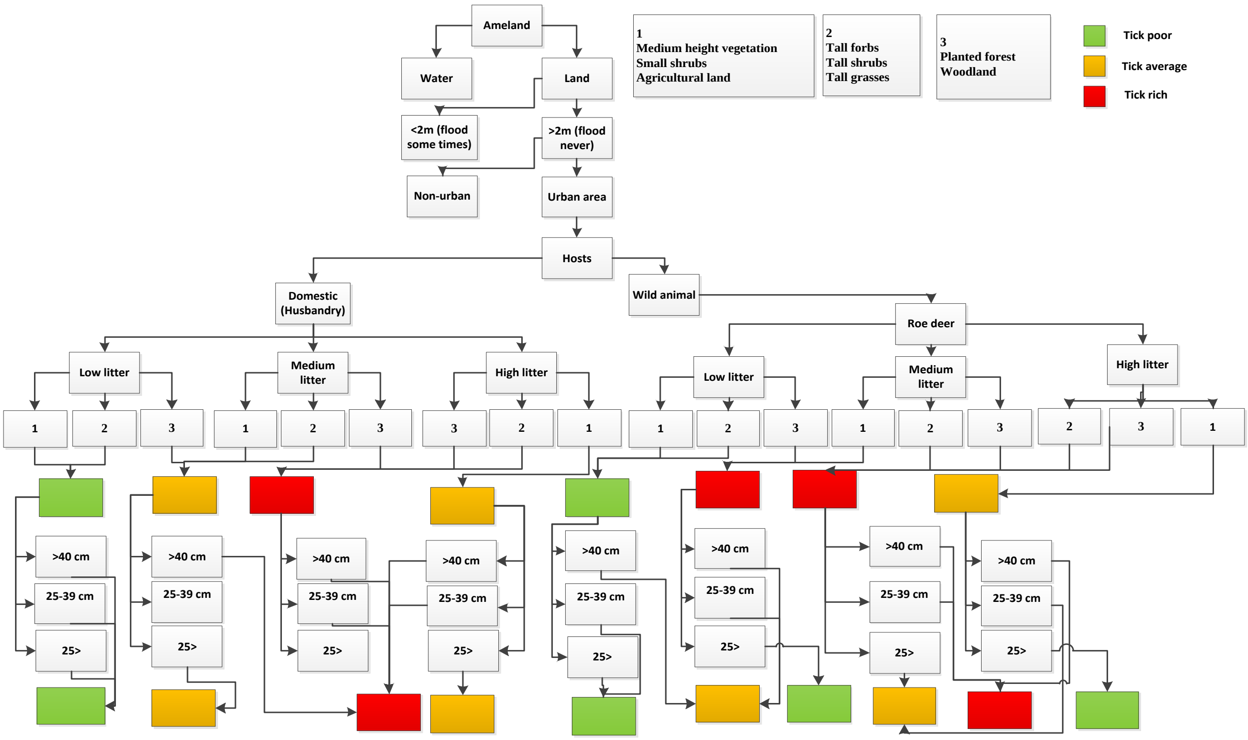


Figure 5: decision tree for tick's suitability map (Modified after Haverkort, 2013)

CHAPTER 4

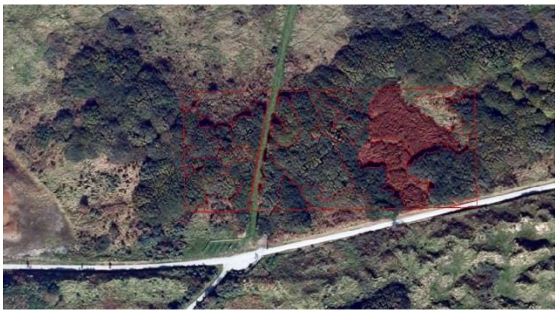
RESULT

4.1 Segmentation

To select the optimum segmentation parameters, four segmentations (Table 3) with different scale parameter were visually compared with identified reference objects identified through manual segmentation. For such a complex situation present in this study area, it is important to have all objects segmented. Therefore, to evaluate the quality of the segmentation, four plots were chosen for which manually identified objects were compared to the automated segmentation (Figure 6) (appendix H).

Scale25 Scale50

Scale 75 Scale 100



Reference segmentation

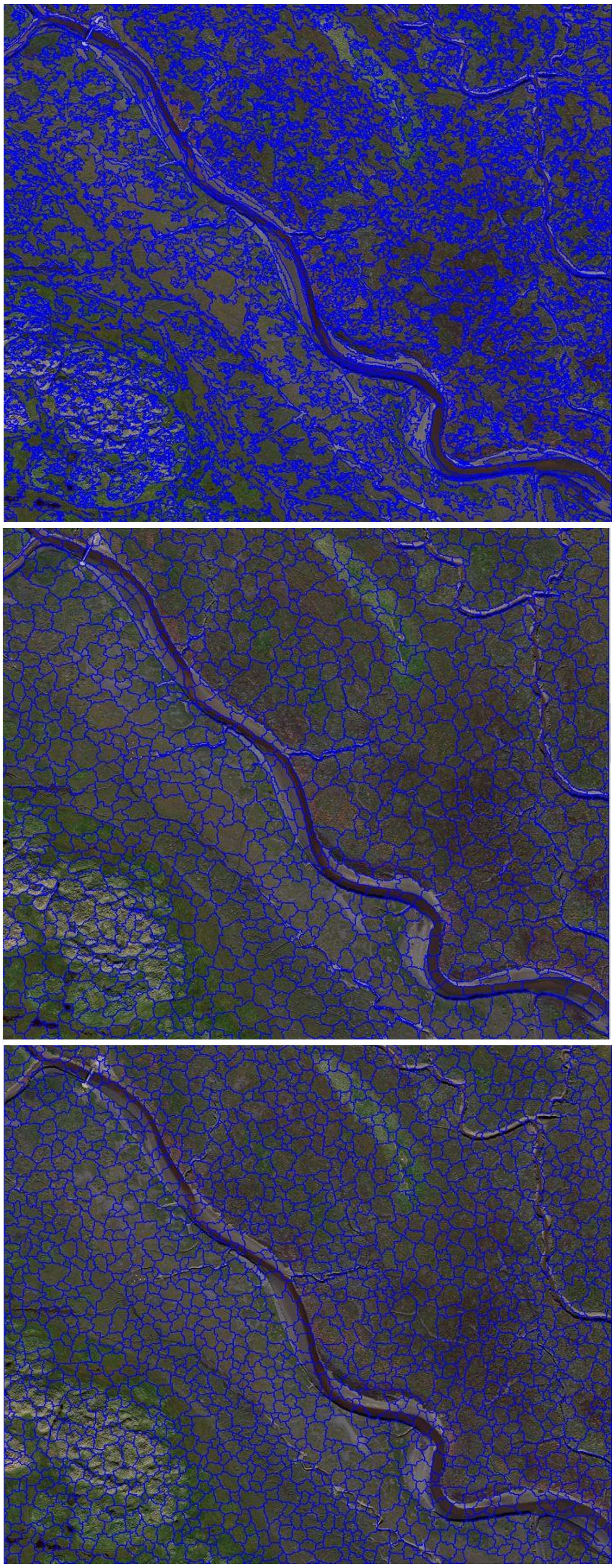
Figure 6: Four plots of segmentation with shape of 0.1 and compactness of 0.9 and scale parameter of 25, 50, 75 and 100

The parameters of a plot which have the segmented objects as similar as possible to the reference plot, was consider as the one that contains the optimal segmentation parameters for this problem.

The result of the visual comparison between the reference segmentation and others shows that segmentation with scale parameter of 50 has successfully segmented all objects (Figure 6). For example; the red patch in the scale 50 segmentation gives segments large enough which is suitable overall to avoid confusion in segmentation step. The red patch in segmentation with scale 25 was segmented to very small segments in comparison with the reference segmentation. It is not suitable for this study if it applies to the whole study area. Because very small segments are causing confusion in the classification step (over-segmentation).

In case of scale 100, the red patch was segmented in two segments. Part of it was segmented as other segments. These segments are too large which cause under segmentation and may be causing confusion in the classification step. Segmentation with a scale parameter of 75 was able to segmented objects in some area better than scales 25 and 100 (Figure 6), but not overall. Both segmentation (scale 75 and 100) settings also have included other objects in those segments. Thus, the segmentations with scale 50, was consider as the one that contains the optimal segmentation parameters.

Figures 7 and 8 show the changes in the result of segmentation by altering the shape and compactness parameters. Figure 7 shows the effects of no recognition of the shape of natural objects by segmentation with a weight of 0.0 assigned to weight in Figure 7a. Figure 7b and 7c shows the opposite with objects which are almost circular. Colour is the only source of information for the segmentation and is thus also the most important, but there is a need to keep the shape of objects resembling those of the real world to keep the result representative. The higher is the value of shape; the lower is the influence of colour on segmentation.

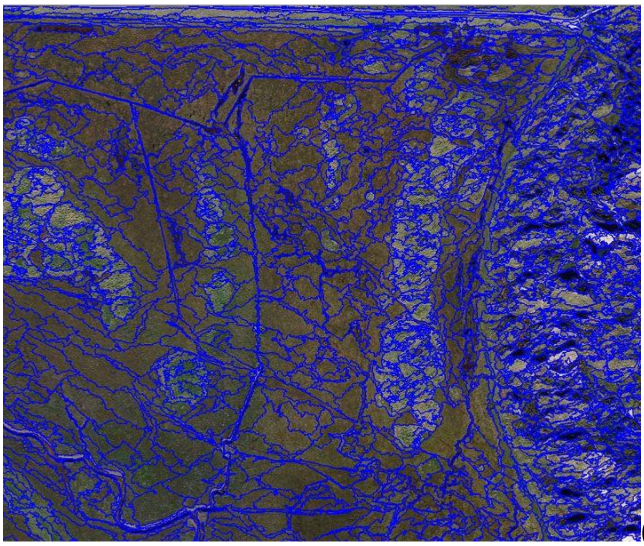


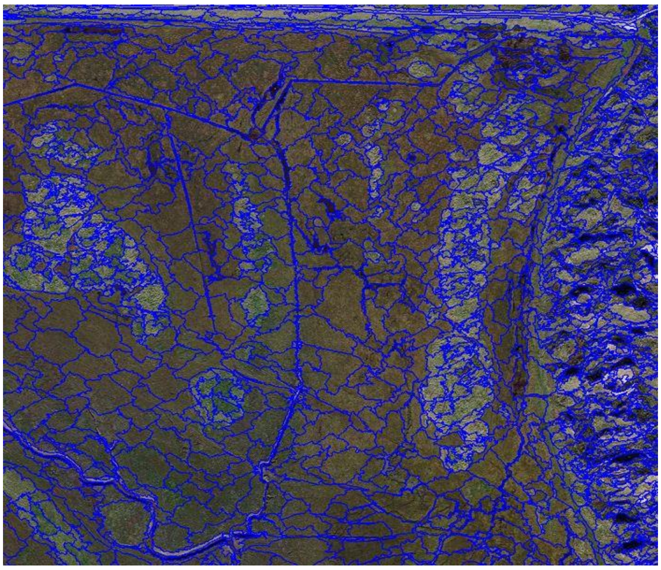
(a)

(b)

(c)

Figure7: Shape parameter with values of 0.0, 0.5 and 0.9 (scale 50 and compactness 0.9)


(a)


(b)

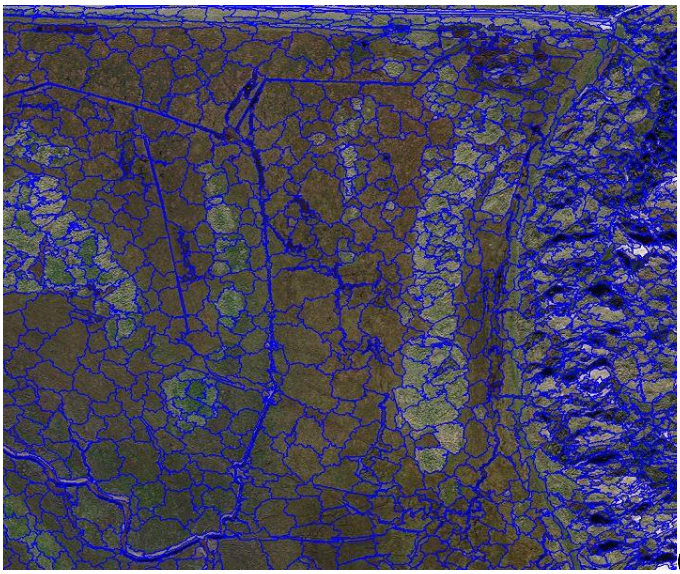

(c)

Figure 8: Compactness parameter with values of 0.0, 0.5 and 0.9 (scale 50 and shape 0.1)

The effects of compactness are illustrated by Figure 8. A low compactness setting gives smooth, more rectangular objects (Figure 8a). With the same scale and shape, a high compactness setting gives compact, square or circular objects (Figure 8b and c). Therefore, scale of 50, shape of 0.1 and compactness of 0.9 were used for final segmentation of Ameland's complex vegetation ecosystem.

Comparison of segmentations of Alterra's method (scenario 2) and scenario 1

To compare the segmentation of Alterra's method (Table 4) and the segmentation according to scenario 1 (scale: 50; shape: 0.1; and compactness: 0.9), four plots were selected (appendix M) of which one of these plots has been represented in Figure 9.

a b

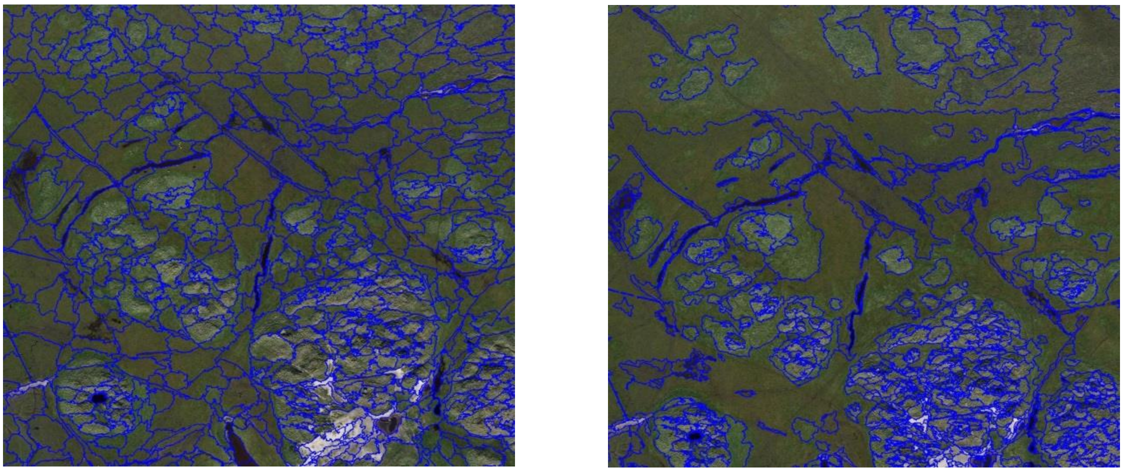


Figure 9: Results of Alterra's method (scenario 2) (left) and scenario 1 (right)

The left image of figure 9a is the segmentation result of Altera's method and the right image is the result of scenario 1. From the comparison it can be observed that the left image contains more appropriate segments, specially objects with specific boundaries (near to real objects). On the other hand, the right image contains less number of segments and many objects, even those which have specific boundaries were merged in one segment. We have to keep in mind; segments which contain different objects, in RF classifier are causing miss training and leading to miss classification (Figure 10). Therefore, the accuracy of such classification decreases.

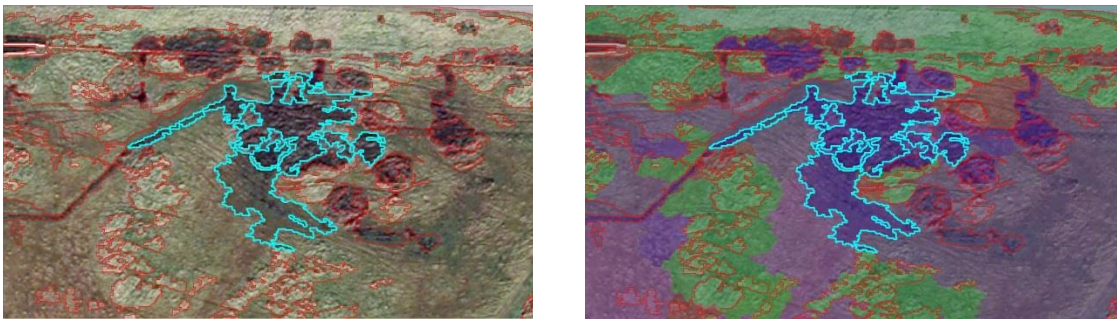


Figure 10 : Miss segmentation and miss classification of scenario 1(class 15(Salt marsh(dark purple)) was classified as 15e (Sea Rush))

Effect of using LiDAR information

A lot of studies have mentioned the effects of LiDAR data in segmentation and classification (Guo, Kelly et al. 2007, Ke, Quackenbush et al. 2010). Therefore, figures 11a and 12a are represented two plots of segmentation result of scenario 4 (not including LiDAR data) in comparison to segmentation result of scenario 1(including LiDAR data) (Figures11b and 12b). Figures 11a and 12a show larger segments in comparison to segments of other image and many objects are merged in one segment. On the other hand, figures 11b and 12b show appropriate segments where objects with specific boundaries are segmented and even small objects are segmented properly too. Thus, segmentation results of scenario 4 have partly failed to do so. Scenario 1 including with LiDAR data gives more suitable results.

a b

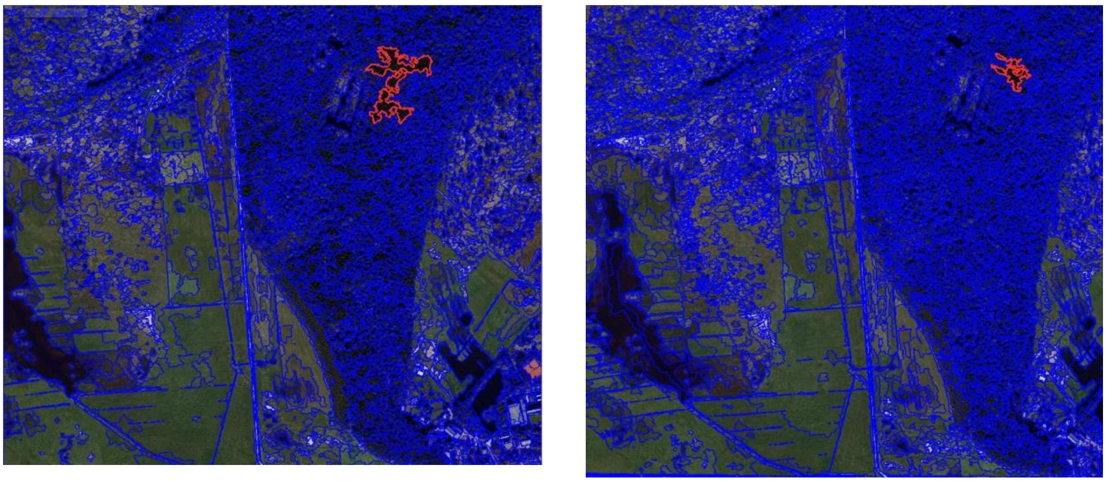


Figure 11: Segmentation result of scenario 4 and scenario 1

The red segment in both images are represented the size of segmentations (both have same parameters settings (scale:50, shape:0.1and compactness: 0.9)) a b

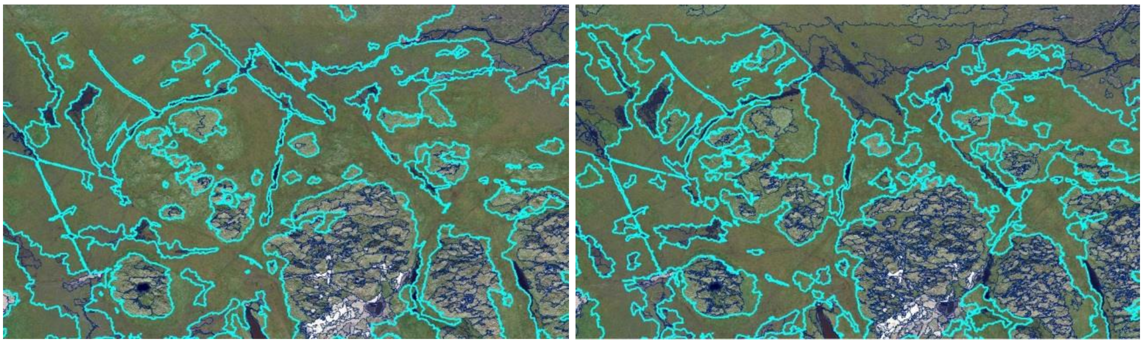


Figure12: Segmentation result of scenario 4 and scenario 1

The selected segment in both images are represented the size of segmentations(both have same parameters settings(scale:50, shape:0.1and compactness: 0.9))

4.2. Classification

The next step of the OBIA approach is classification of the objects into specific vegetation types according to the determined typology (Appendix A). In this research, three segmentations of three scenarios (1, 3, and 4) were used as input for the RF classifier. Before using RF on the whole study area with the final training points; three plots with different training points were tested (Figure 13-15).

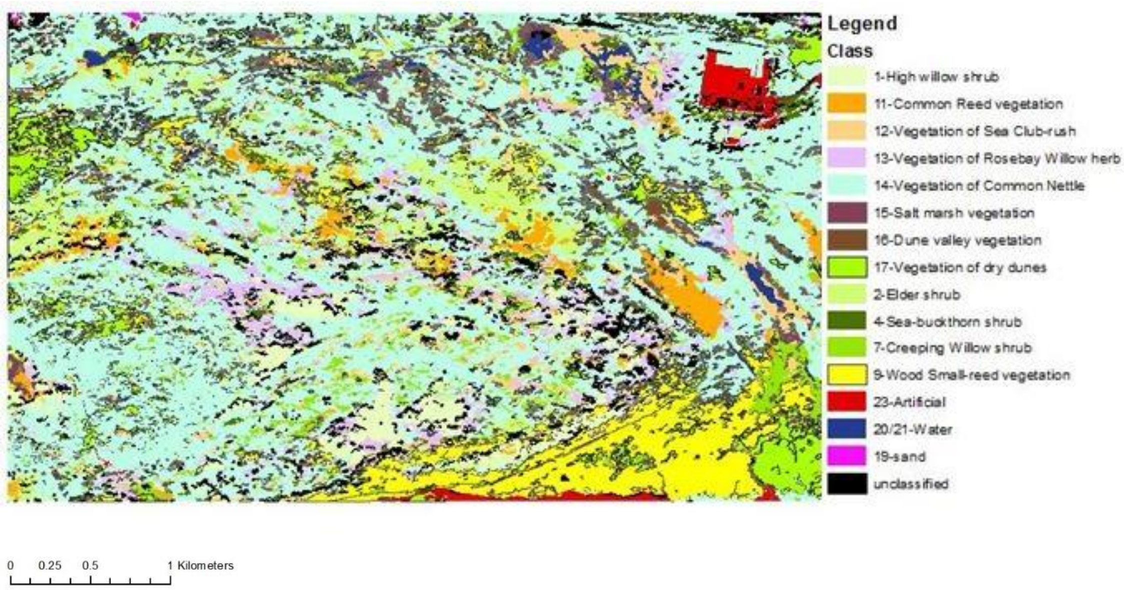


Figure 13: First test area with training points I (Table 1)

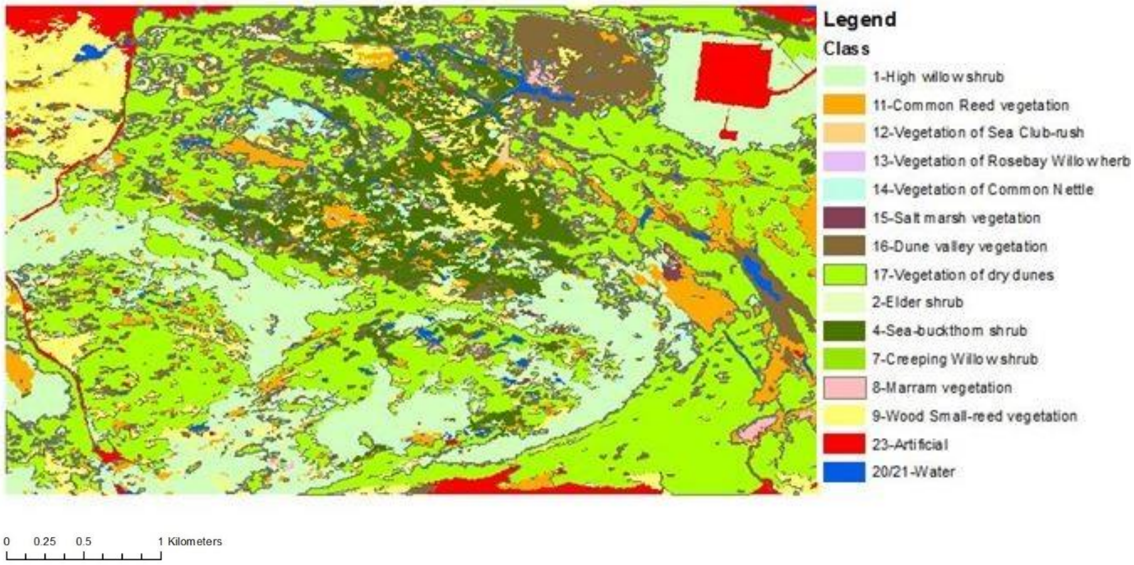


Figure 14: Second test area with training points II (Table 1)

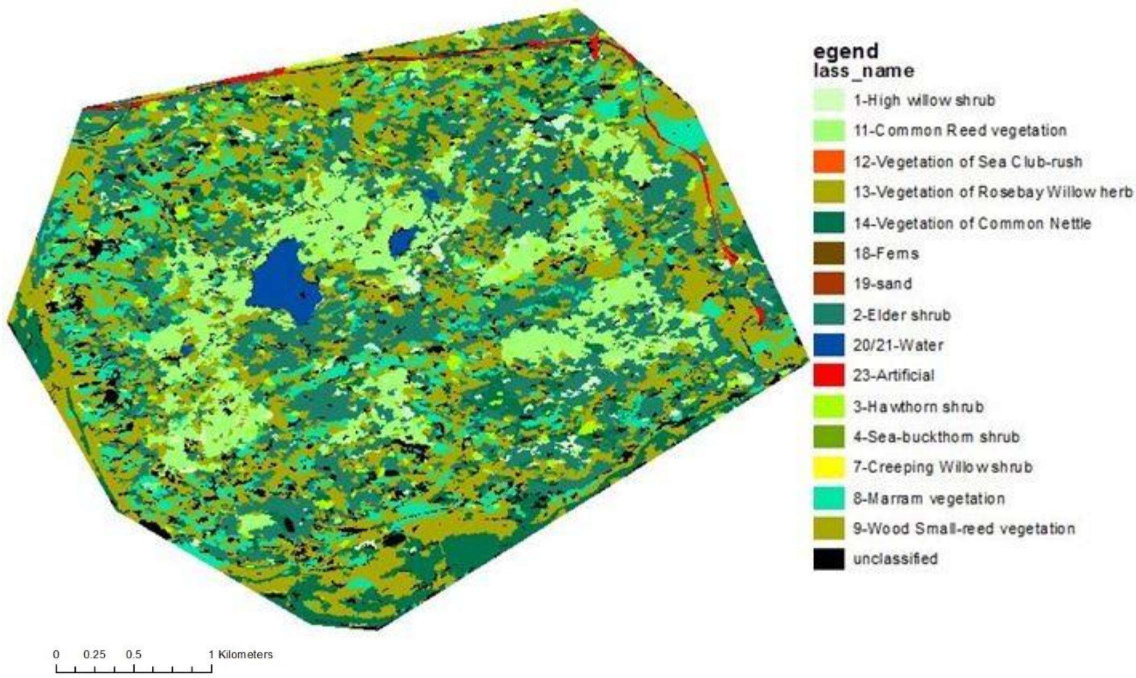


Figure 15: Third test area with training points III(Table 1)

The first two plots (Figure 13 and 14) shown appropriate results for some classes such as Artificial, common reed vegetation, water and High Willow shrub. However, these results may be suitable for small area, but they are not suitable to apply for whole study area. Because the training points (I and II) which were used for these plots (Figure 13 and 14) are not sufficient for the whole study area. Therefore, training points III was used in the third test area which it shows very suitable results. The assessment of all three test areas was done visually. Their results were compared with the original image with known vegetation structure types. Finally, the training points III and features (Table 5) of this result were applied to the whole area.

The classification results of scenario 1, 2, 3 and 4 for the same location are shown in figures 16, 17 and 18. Figure 19 is also shown the classification result of Altera's method. The study area wide classification results are presented in Appendix D.

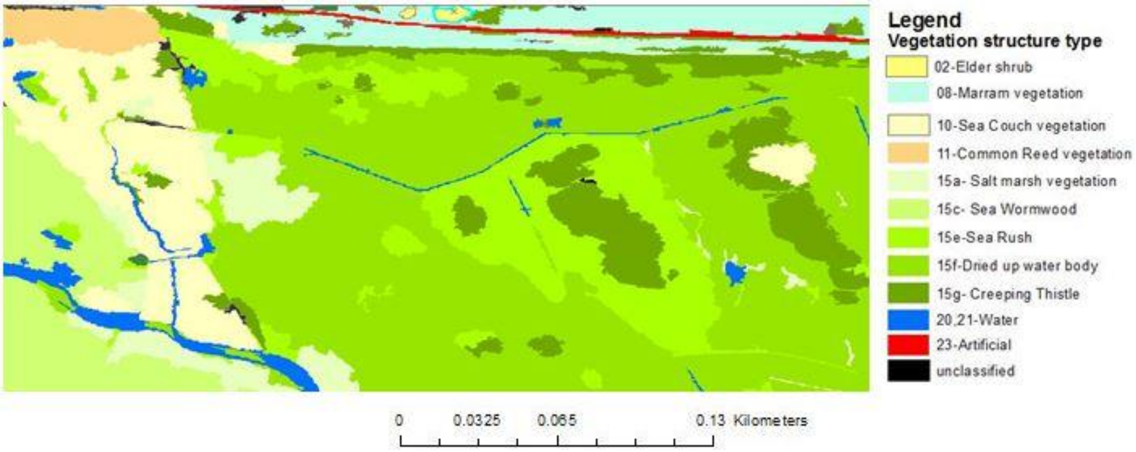


Figure16: Classification result of scenario 1.

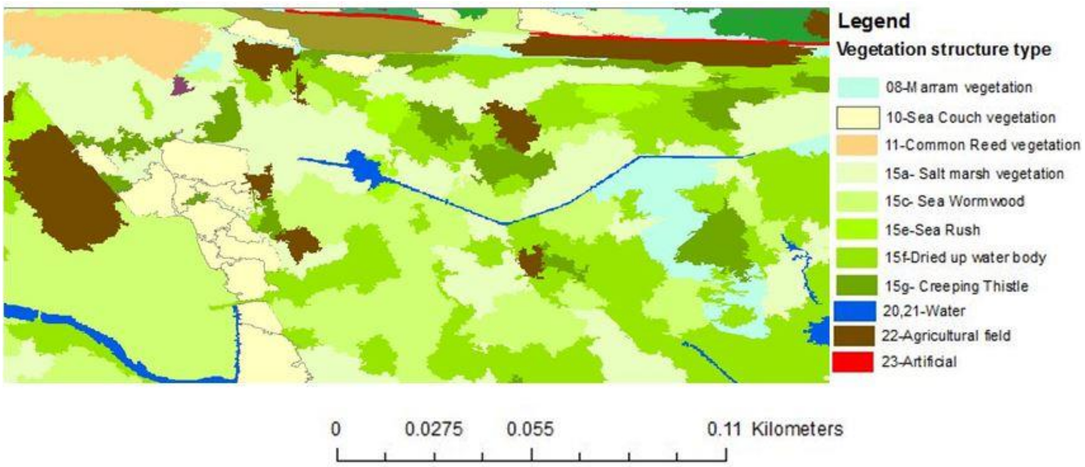


Figure 17: Classification result of scenario 3

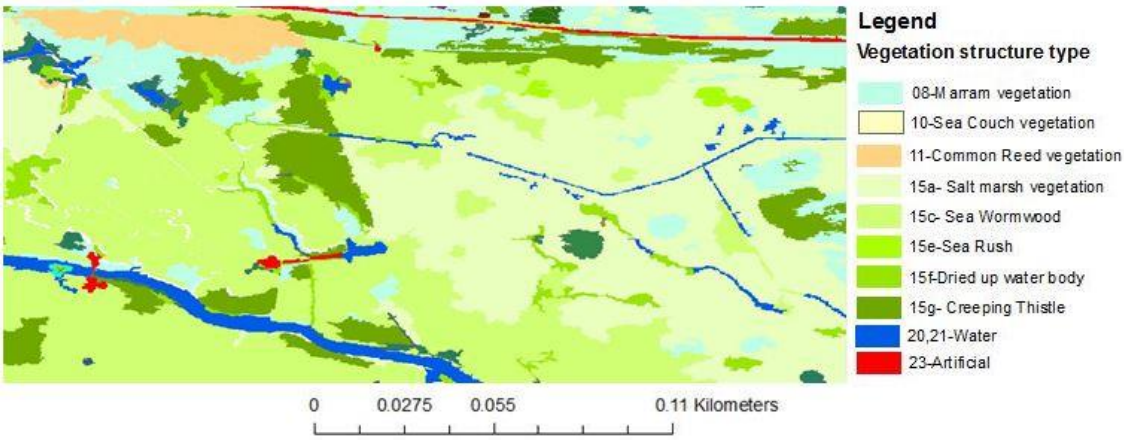


Figure18: Classification result of scenario 4

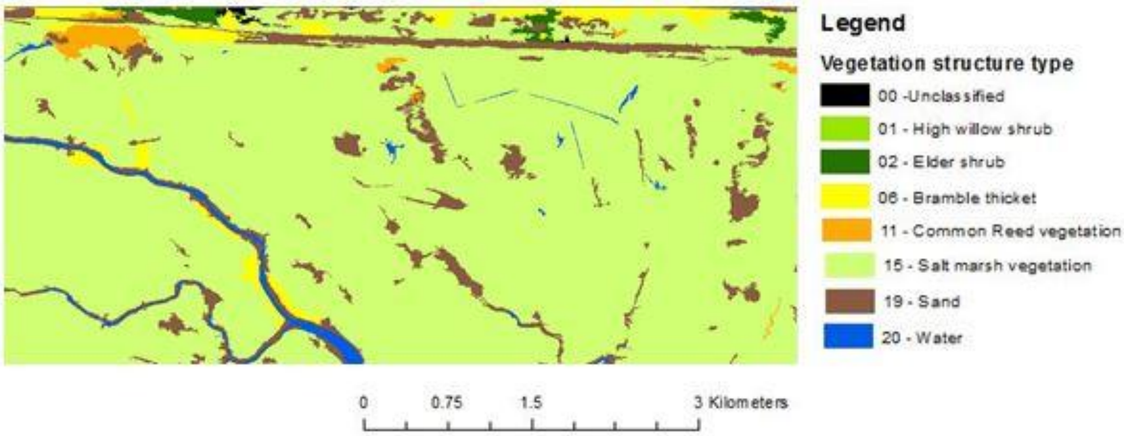


Figure19: Classification result of scenario 2

Scenario 1, 3 and 4 in comparison to scenario 2 are showing different vegetation structure types of Salt marsh (15). Scenario 2 does not show any vegetation structure types of Marram vegetation (8), Sea Couch vegetation (10) and Artificial (23). Most of the Artificial (23) vegetation structure type in scenario 2 was classified as Sand (19). The only vegetation structure type which classified right in all 4 scenarios is Water (20-21). Scenario 3 (Figure 14) shows Agricultural field (22) vegetation structure type which any of other scenarios are showing such results.

Table 8 and 9 shows the accuracy assessment of each vegetation structure type for scenario 1, scenario 2 and 4 for the study area of Altera's method (Figure 2). Some classes do not have any data available for calculating accuracy. Therefore, they are assigned with NA in table 8. The result of scenario 2 was based on less class.

Scenario 4 has given higher accuracy in vegetation structure types of 1.High willow shrub, Hawthorn shrub, 5.Rose shrub, 8.Marram vegetation, Common Reed vegetation, Vegetation of dry dunes, Ferns, Sand, Agricultural field, and Spontaneous

Aspen in compare with scenario 1 and 2. For vegetation structure type of Elder shrub, Scenario 2 has given higher accuracy in in compare to other two scenarios. On the other hand, scenario 1 has given higher accuracy for vegetation structure types of 15a-g.Salt marsh vegetation, Dune valley vegetation, Water – fresh and salt/brackish, and Shrub of planted broadleaved & coniferous wooden species. Five vegetation structure types (4.Sea-buckthorn shrub, Creeping Willow shrub, Sea Couch vegetation, Vegetation of Sea Club-rush, Artificial, e.g. stone, buildings, road-surfacing (shells, asphalt, brick), boulders) have 100% accuracy in scenario 1 and 4. In the same scenarios, Wood Small-reed vegetation and Coniferous forest have 0% accuracy.

The overall accuracy of Scenario 2 (Appendix B), Scenario 1 and Scenario 4 are 65%, 74.15% and 75.17% respectively. Scenario 4 gave higher accuracy than other scenarios.

Table 8: The accuracy table of two scenarios in the Alterra study area (excluding forest).

Vegetation structure type	Class accuracy %	
	Scenario 1	Scenario 4
1.High willow shrub	68.42	73.91
2.Elder shrub	64.7	45.83
3.Hawthorn shrub	66.7	100
4.Sea-buckthorn shrub	100	100
5.Rose shrub	0	100
6.Bramble thicket	NA	0
7.Creeping Willow shrub	100	100
8.Marram vegetation	50	57.14
9.Wood Small-reed vegetation	0	0
10. Sea Couch vegetation	100	100
11. Common Reed vegetation	84	86.95
12. Vegetation of Sea Club-rush	100	100
13. Rosebay Willow herb	NA	NA
14. Vegetation of Common Nettle	NA	NA
15a-g. Salt marsh vegetation	78.6	75.75
16-16a. Dune valley vegetation	100	0
17. Vegetation of dry dunes	59.4	62
18. Ferns	66.7	100
19. Sand	63.7	77.8

20-21. Water – fresh and salt/brackish	83.4	81.25
22. Agricultural field	57.9	100
23. Artificial	100	100
24. Drift line vegetation	NA	NA
25.Shrub of planted broadleaved	100	0
26.Spontaneous Aspen	42.9	100
27. Coniferous forest	0	0

Table 9: The accuracy table of scenario 2 (Altera's study)

Simplified legend classes	Accuracy (%)
Shrubs>2m (1,2,3,4,5,25, and 26)	80
Shrubs 0.5- 2m (6,7,8,9,12, and18)	19
Reed (11)	48
Salt marsh(10 and 15)	94
Dune vegetation (16 and 17)	55
Sand (19)	71
Water fresh (20)	80
Water salt (21)	64

Table 10 shows the accuracy of the whole study area included and not included with LiDAR data. The total accuracy of scenario 1 and scenario 4 are 70.53% and 64.25% respectively. The overall accuracy of scenario 1 gave higher accuracy than scenario 4 (LiDAR not included). The overall accuracy of scenario 1 decreases when forest area is added (form 74.15% to 70.53%).

Scenario 1 gave higher accuracy for vegetation structure types of High willow shrub, Sea-buckthorn shrub, Elder shrub, Sea Couch vegetation ,Common Reed vegetation, Coniferous forest, Vegetation of Common Nettle, Salt marsh vegetation, Dune valley vegetation, Sand, Water – fresh and salt/brackish, Agricultural field, Spontaneous Aspen, Vegetation of Sea Club-rush in comparison to scenario 4.

On the other hand, vegetation structure types of Hawthorn shrub, Rose shrub , Creeping Willow shrub , Marram vegetation , Vegetation of dry dunes , Ferns , Artificial, e.g. stone, buildings, road-surfacing (shells, asphalt, brick), boulders , Shrub of planted broadleaved & coniferous wooden species gave higher accuracy in scenario

Bramble thicket has 0% accuracy and Wood Small-reed vegetation has 100% accuracy in both scenarios. The lowest accuracy in scenario 1 is belonging to Spontaneous Aspen with 40% accuracy and in scenario 4 are belonging to Bramble thicket, Vegetation of Rosebay Willow herb, and Vegetation of Common Nettle with 0% accuracy.

Table 10: The accuracy table of scenario 1 and 4 of the whole study area (including forest)

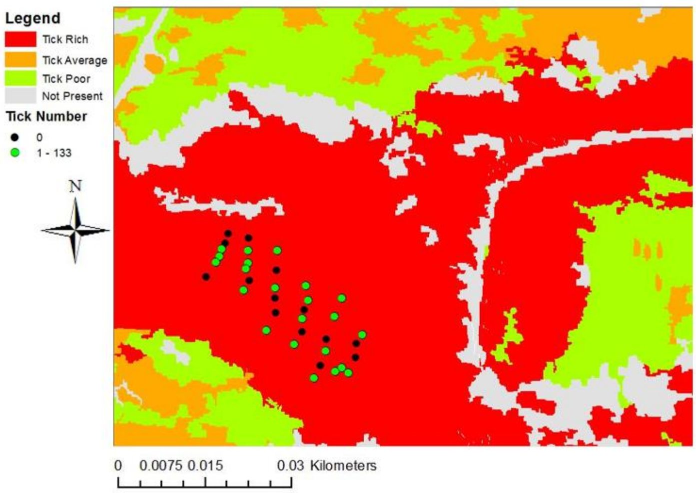
Vegetation structure type	Class accuracy %	
	Scenario 1	Scenario 4
1.High willow shrub	57.78	55
2.Elder shrub	70.6	50
3.Hawthorn shrub	62.5	100
4.Sea-buckthorn shrub	92.5	77.8
5.Rose shrub	0	100
6.Bramble thicket	0	0
7.Creeping Willow shrub	77.5	88.3
8.Marram vegetation	47.9	51.1
9.Wood Small-reed vegetation	100	100
10. Sea Couch vegetation	100	81.25
11. Common Reed vegetation	92.5	91.2
12. Vegetation of Sea Club-rush	44.5	36.4
13. Vegetation of Rosebay Willow herb	NA	0
14. Vegetation of Common Nettle	100	0
15a-g. Salt marsh vegetation	64.93	56.4
16-16a. Dune valley vegetation	66.8	66.5
17. Vegetation of dry dunes	52.5	57.6
18. Ferns	50	66.2
19. Sand	53.9	53.3
20-21. Water – fresh and salt/brackish	83.4	81.25
22. Agricultural field	93.75	76.5
23. Artificial	68.2	69.2
24. Drift line vegetation	NA	NA
25.Shrub of planted broadleaved	44.5	50
26.Spontaneous Aspen	40	10
27. Coniferous forest	83.4	63

4.3. Tick suitability map

The full map is shown in appendix N. Figure 20 shows a plot of the study area with its tick suitability map. It shows tick rich areas are in the Woodland (IX) and planted forest (VIII). The data from the study of Michelchen (2013) also show high number of ticks (with total of 43 ticks) present in this area. Tick average areas are in tall shrubs (IV) and Medium height vegetation (II). Tick poor areas are in Low height vegetation (I) and small shrubs (III). Finally, soil (XI) and water body (X) have no tick.

Table 11: Tick abundance number in suitability map

Tick mapping unit	Average number of ticks	Min	Max	St. dev.
Not present	0	0	0	1003.6
Poor	53	0	4	
Average	125	0	31	
Rich	2064	0	56	



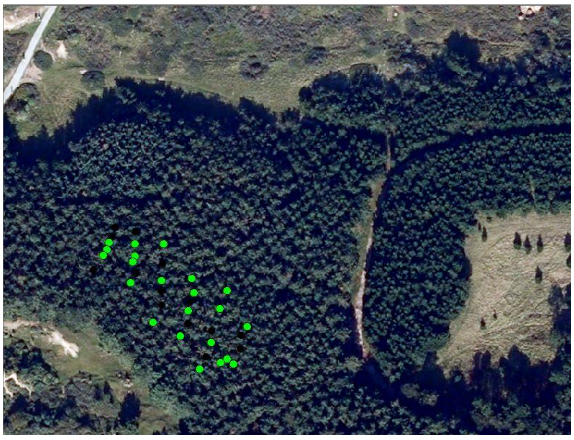


Figure 20 : Tick suitability map for forested area with high number of tick

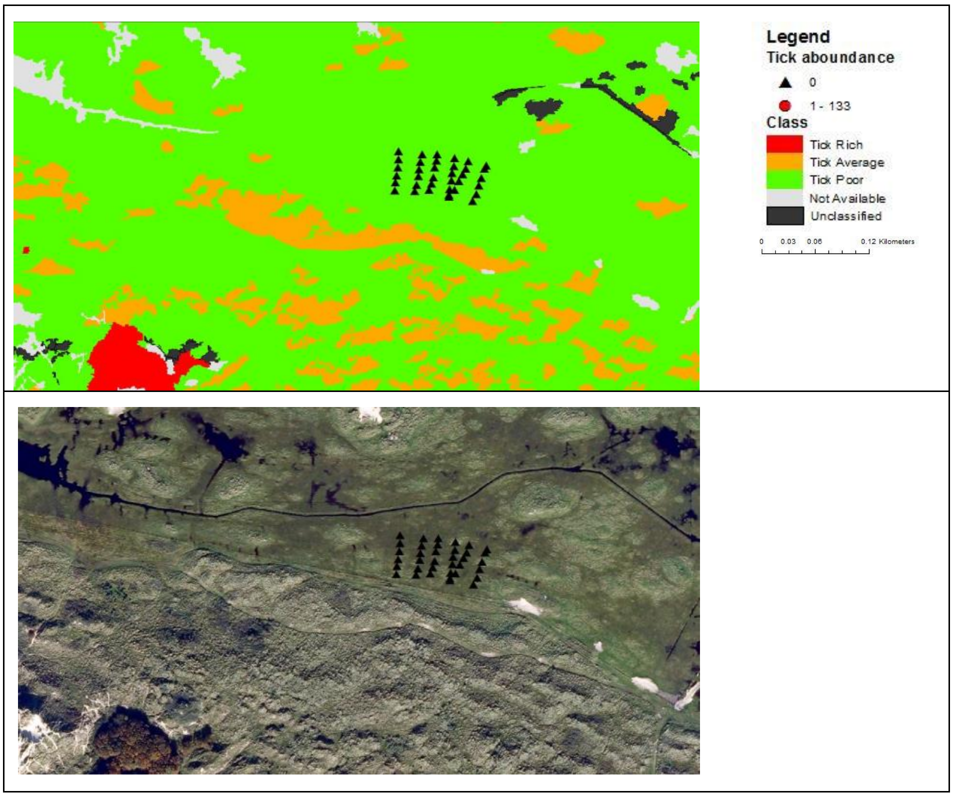


Figure 21 : Tick suitability map for Salt marsh area

CHAPTER 5

Discussion

The result in the segmentation process showed that finding the suitable scale parameter was complex and that it must be performed with care; since, human interpretation is needed in some steps in segmentation process. Hence, this process is prone to subjectivity and requires experience to differentiate, by visual interpretation, the different classes involved in the land cover classification problem.

The results in the classification process showed that RF is well able to distinguish the 23 out of 27 vegetation structure classes used in this study. The addition of LIDAR information influenced positively in the improvement of the classification result.

Segmentation parameters

Scale

The optimal scale parameter found, by the process of visual assessment seems to be acceptable because of the good classification performance by the RF classifier.

The scale settings found in this study are more or less similar in comparison to FNEA scale settings found in other studies. Möller et al. (2007) found a scale setting of 56 with a similar method on a different dataset. Liu et al. (2012) found optimum scales in the range of 50-200 with different methods based on reference polygon and Kuilder (2012) found scales in the range of 100-400 with the similar method based on reference polygon. Johnson (2011) found an optimum of 70 based on a global intra- and intersegment empirical goodness measure. Auquilla (2013) found a scale setting of 19 with similar method which was quite low in comparison to scale setting of this study.

The Altera's segmentation (Table 4) was shown compact, square and circular segments in comparison with segmentation of scenario 1 (Figure 9), but the overall accuracy of scenario 2 was very low (36.4%). On the other hand, the overall accuracy of scenario 4 (Altera's segmentation with RF classification approach) was shown very high improvement (64.25%).

Over and under segmentation are very important issue in the segmentation process (Möller, Lymburner et al. 2007, Liu and Xia 2010, Johnson and Xie 2011). From a classification perspective, over-segmentation and under-segmentation have different impacts on the potential accuracy of object-based classification (Liu and Xia 2010). When under-segmentation arises, it is not possible, no matter the classifier used, to perform a correct classification (Liu and Xia 2010). This analysis suggest that, the scale parameter obtained for this study is correct; since, larger scale values led to a correct match of objects such as water and bare soil, but an incorrect match of objects like Creeping Willow shrub, Vegetation of Sea Club-rush, Rose shrub, Elder shrub and Hawthorn shrub.

However, the trade-off of small objects is that, they represent partially larger objects; for instance, a set of neighbour objects can represent a larger one. Having more small objects represents extra computation time; besides, there is a chance that certain smaller objects that represent a larger one to be classified incorrectly; this is the reason why a spectral difference operation must be performed after segmentation to merge small objects into larger ones that represents real objects.

Reference polygons

Liu et al. (2012), Möller et al. (2007), Kuilder (2012), and Auquilla (2013) used individual reference polygons and compared these with the corresponding segmented object. The creation of manual segments is a challenging task; since, there is no literature about how to proceed. Besides, the information of the bands is not fully used. Therefore, only an expert could interpret correctly the colours shown on the screen.

The aim of the manual segmentation is to create segments that match, as perfect as possible, the shape of the objects. Since the manual segmentation is a subjective task, errors are very likely to arise during this process. The only way to avoid these errors is to define segmentation according to ground truth data. Another possibility is that an expert is to perform this task. In this study, the manual segmentation was done by visual interpretation; and, was performed by the author of this thesis.

Shape and colour parameters

The colour and shape parameters balance each other, i.e., if colour has a high value (high influence on segmentation), shape must have a low value, with less influence. If colour and shape parameters are equal, then each will have roughly equal amounts of influence on the segmentation outcome (Benz, Hofmann et al. 2004, Möller, Lymburner et al. 2007, Auquilla 2013).

In this study, shape parameter was tested with three values (Figure 7) and a value of 0.1 (same value was selected by Altera's method (Table 4)) was selected due to high importance of colour for this study.

Classification

For complex vegetation system RF gave result with accuracy 70.53% which is more applicable for vegetation structure classification. The result of this study shows higher accuracy in compare with Kuilder's result in 2012 (overall accuracy of 43% with 10 classes) and Guo, 2011 (overall accuracy of 50% with 5 classes), but shows lower accuracy in comparison with (Stumpf and Kerle 2011) (overall accuracy of 73%), and Zhou, 2008 (overall accuracy of 90.0% with 11 classes).

The classification result including with LiDAR data shows higher accuracy (Table 8). Therefore, it indicates that LiDAR data with VHR data give much better result (Figure 15). Ke, 2010 achieved classification accuracy of 91.6% when using both spectral and LiDAR data. Hellesen (2013) also shows a significant increase in accuracy with the use of LiDAR data compared to the use of spectral data only (respectively, 89.7% and 52.9%).

The number of training points is an important point to take in to account. Because high number of training point might increase the process time. The locations of the points in segments are important. To avoid confusion in the classification step, it's recommended to checking location of training points.

The random forest approach in comparison with scenario 2 (Altera's study) showed a more accurate result (Table 7). The very important issue discovered in the classification step by RF is that what features must be used for classification? In this study 46 features were used in RF classifier (Table 6). Some of these features such as brightness caused huge miss classification in RF classification step and showed one class took over of all other classes (result not shown). Because the LiDAR data contain zero as minimum value. Therefore, it is necessary to have prior information about the importance of features that must be used. Kuilder (2012) investigated the most important features according to the source data layer.

The acquisition time of data sources are another issue that can be one cause for low overall accuracy. There are six years difference between aerial image and LiDAR data acquisition and training III and validation data. This time gap could influence Common Reed vegetation (11), Sea Couch vegetation (10), Vegetation of Sea Club-rush (12), and Vegetation of Rosebay Willow herb (13). This can cause confusion for RF in classification step and validation step. For example; in some area on the image it shows water, but training and validation data show other vegetation structure types or dried up area. According to Kuilder (2012), the gaps between acquisitions of different data sets are especially influential in the estimate of classes which generally change rapidly, such as agricultural fields and pioneer vegetation.

Data acquisition was in early spring; leaf off, while training and classification was done on samples acquired in summer. This could influence the classification because some feature in RF classifier use spectral information. Change in data acquisition can influence the result. The classes with similar spectral information are difficult to distinguish and classify from other classes such as: Common Reed vegetation from Vegetation of Sea Club-rush and Salt marsh vegetation form agricultural field.

Tick suitability map

There were some dificult challenges during the design of the decision tree. The decision tree for tick abundance on local scale (island of Ameland in this study) is based on literature and information obtained from experts. The decision tree is not tested in the field yet and should be verified by further tick abundance researchs in the Netherlands. There are four outcomes: tick rich, tick average, tick poor and not present. It has to be kept in mind that tick poor do not mean that there is no presence of tick in a certain area. Michelchen (2014) showed that forests had greater tick abundance than other vegetation structure types. Because forested area provided more favourable condition for tick survival (Lindström and Jaenson 2003).

Only a few studies exist that deal with ticks on Ameland (e.g., Tijsse-Klasen et al. 2011; Rijpkema and Bruinink 1996; Rijpkema et al. 1994), all rather focussing on infection prevalence than addressing tick abundance, so there are no data available from the island that the tick abundance recorded in this study could be compared with.

The vegetation structure map improves the characterisation of tick abundance. Form vegetation structure map, litter map also was derived which is very important for tick prediction. It is important to keep in mind, any misclassification in vegetation structure can affect the result of tick suitability map.

CHAPTER 6

Conclusion and Recommendations

6.1. Conclusion

This study was set up to contribute the knowledge about the integration of LIDAR information and multispectral imagery in classification of vegetation structure mapping on Ameland using object-based classification techniques. Specifically, RF classifier was compare with a rule-based approach (Altera's method) determine their accuracies in terms of classification. Also an optimal parameter selection phase was performed in the segmentation step.

The study included four scenarios (Figure 2). All four scenarios divided in two main stages: segmentation and classification. In segmentation step of scenario 1, optimal parameter selection phase was performed. Scenarios 1 and 4 were analysed to gain insights about the effects of using LIDAR information. Classification was performed using RF classifier with 46 feature inputs for scenarios 1, 4 and 3.

The optimal scale parameter 50 was selected after comparison of four scale parameters with the reference polygon (figure 6) and also other parameters such as shape and compactness were checked. Thus, 0.1 and 0.9 were used for shape and compactness, respectively. The Altera's segmentation was shown compact, square and circular segments in comparison with segmentation of scenario 1.

The highest classification accuracy in the study area excluding forest was obtained by scenario 4 with 75.17% (with 25 classes) and the lowest accuracy was obtained by Altera's method (65% with 8 classes) (scenario 2). On the other hand, scenario 1 showed higher accuracy in comparison with scenario 4 in the whole study area (including forest).

There is not any improvement in the classification accuracy of scenario 2 when the RF classifier was used instead of rule-based approach. The accuracy was changed from 65% to 64.25%.

In OBIA approach, most influencing factors for classification accuracy are segmentation parameters, training points and used features.

The tick suitability map showed that tick rich areas are in vegetation structure types with high litter and high moisture such as type Woodland, Planted forest, and Tall shrub. The vegetation structure types such as Soil, Water body, Low height vegetation and Medium height vegetation.

Tick field observations are taken in the study, are not cover the whole area, but the high number of ticks are in woodland and forest area (Appendex L).

6.2. Recommendations

It is recommended to include a segmentation quality assessment and adding other parameters such as shape, compactness and the degree of spectral difference merging which could improve finding the optimal segmentation parameters. A post processing step also could improve the over and under segmentation issue.

It is recommended to use recent aerial images and LiDAR data and also include other data sets such as NDVI for segmentation and classification step.

When using reference polygons it is recommended to use individual non-touching polygons as done by Liu and Xia (2010). This makes it possible to directly compare reference to corresponding segments, without having to intersect both.

It is recommended to use more accurate and additional data sets for creation of tick suitability map. For such large study area; there should be more tick observation points. It is also recommended in the future studies to check whether landscape variables affect tick abundance or not.

Appendix

Appendix A: 27 vegetation structure classes identified in study area by Pieter Slim

No.	Structure type	Dominant type (s)	Image	Height in m
1	High willow shrub	*Salix* spp. (mainly *cinerea*) Neighbourhood Nes also *Amelanchier*		2-6
2	Elder shrub	*Sambucus nigra*		2-5
3	Hawthorn shrub	*Crataegus monogyna*		2-5
4	Sea-buckthorn shrub	*Hippophae rhamnoides*		1.2-4.5
5	Rose shrub	*Rosa rugosa* (flower white, red), photo *R. pimpinellifolia* *R. canina* (flower pink)		*rugosa* 1-2 *pimpinellifolia* 0.1-0.9 *canina* 1-3
6	Bramble thicket	*Rubus fruticosus* *R. corylifolius* *R. caesius*		*fruticosus* 0.5-3 *corylifolius* 0.3-1 *caesius* 0.2-0.5
7	Creeping Willow shrub	*Salix repens*		0.2-1.0
8	Marram vegetation	*Ammophila arenaria*		0.2-0.8
9	Wood Small-reed vegetation	*Calamagrostis epigejos*		0.2-1.5
10	Sea Couch vegetation	*Elytrigia atherica*		0.3-1.2

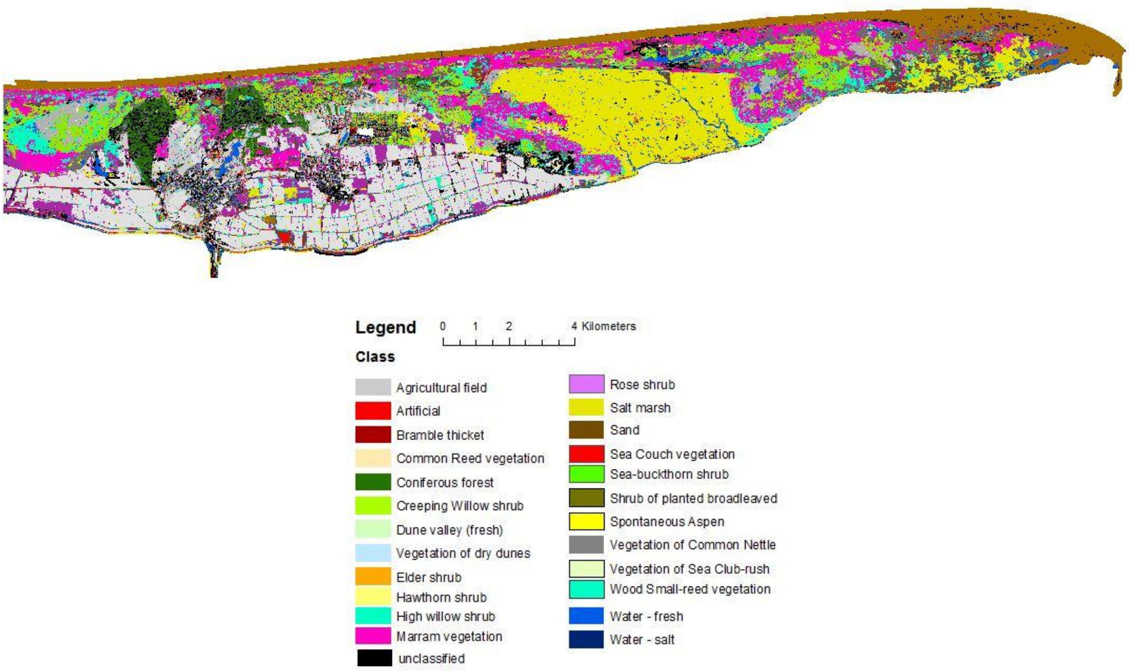
11	Common Reed vegetation	*Phragmites australis*		1-2.5
12	Vegetation of Sea Club-rush	*Bolboschoenus maritimus* (syn. *Scirpus maritimus*)		0.15-1.5
13	Vegetation of Rosebay Willowherb	*Chamerion angustifolium*		0.3-1.5
14	Vegetation of Common Nettle	*Urtica dioica*		0.3-1
15a	Salt marsh vegetation	*Festuca rubra*, *Puccinellia maritima*, *Juncus gerardii* *Spartina anglica* *Salicornia europaea*		*F. rubra*, *P. maritima*, *J. gerardii* 0.0-0.4 *S. anglica* 0.2-0.5 *S. europaea* 0.0-0.3
15b>8	Marram	*Ammophila arenaria*		0.2-0.8
15c	Sea Wormwood	*Artemisia maritima*		0.3-0.6
15d		see also 10 *Elytrigia atherica* & 11 *Phragmites*		
15e	Sea Rush	*Juncus maritimus*		0.3-1.2
15f		sometimes dried up water body: *Spergularia salina*, *Puccinellia distans* bare		0.0-0.3
15g	Creeping Thistle	*Cirsium arvense*		0.6-1.2
16	Dune valley vegetation			
16a	Dune valley (fresh) with tussocks of Soft-rush (as a result of grazing with husbandry	*Juncus effusus*		*Juncus effusus* 0.2-1.0

17	Vegetation of dry dunes	for example with lichens		
18	Ferns	*Athyrium filix-femina* *Dryopteris filix-mas* *Dryopteris dilatata* *Pteridium aquilinum* *Polypodium vulgare*		*A. filix-femina* 0.3-0.5 *D. filix-mas* 0.3-1 *D. dilatata* 0.3 *P. aquilinum* 0.8 *P. vulgare* 0.1-0.4
19	Sand			
20	Water - fresh			
21	Water - salt/brackish			creek water creek mud (can be merged)
22	Agricultural field	grazed, mowed, hayed		
23	Artificial, e.g. stone, buildings, road-surfacing (shells, asphalt, brick), boulders			
24	Drift line vegetation			
25	Shrub of planted broadleaved & coniferous wooden species	*Acer*, *Populus alba*, *Amelanchier*, *Picea*		
26	Spontaneous Aspen	*Populus tremula* (clones)		
27	Coniferous forest (Pine, Spruce) with broadleaved trees in understory (Maple, Oak)	*Pinus*, *Picea*, *Acer*, *Quercus*		

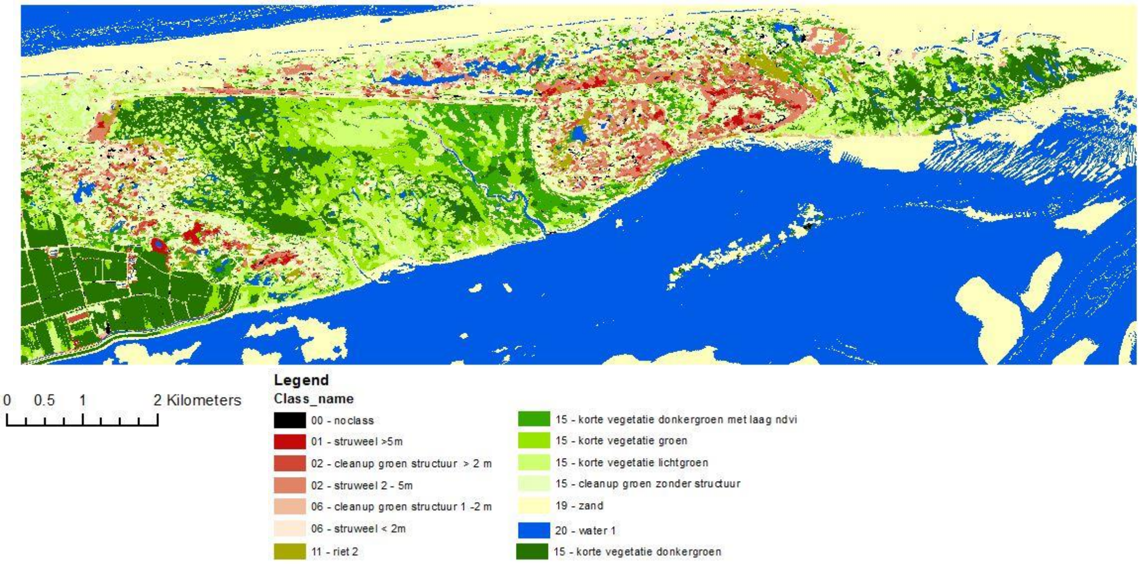
Appendix B: The classification process with used object features with rule values (Altera's study (scenario 2))

Classname	Feature					
	ohn max ohn	index ndvi	spectral Brightness	blue	GLCM Homogenity ohn	ratio red
First classification round						
01 - shrub > 5m	> 5	> 0.16			< 0.45	
02 - shrub 2 - 5m	2 - 5	> 0.16			< 0.45	< 0.31
06 - shrub < 2m	0.5 - 2	> 0.16			< 0.65	< 0.31
11 - reed	< 3.5	0.05 - 0.31	< 110		< 0.65	> 0.31
11 - reed	< 3.5	0.05 - 0.31	< 110		0.65 - 0.95	> 0.31
15 - short vegetation lightgreen		> 0.25	86 -110		> 0.95	
15 - short vegetation green		> 0.25	79 - 86		> 0.95	
15 - short vegetation darkgreen		> 0.25	55 - 79		> 0.95	
15 - short vegetation darkgreen with low ndvi		0.14 - 0.25	65 - 110		> 0.95	
19 - wet sand		-0.25 - -0.13	> 100			
19 - sand		-0.13 - 0.1	> 100			
20 - water 1		< 0	< 110		> 0.95	
20 - water 2		< 0.3	< 50		> 0.95	
20 - water 3 met ndvi		< 0.45	< 60		> 0.98	
20 - water 4		< -0.1	< 110			
When not classified in first classification round, then classiffy with these classes:						
01 cleanup shrub > 5 m	> 5	> 0.16			> 0.45	
02 cleanup shrub 2 - 5 m	2 - 5 m					
06 cleanup shrub < 2 m	0.5 - 2	> 0.16			> 0.45	
11 cleanup reed	< 3.5	< 0.31	< 110		< 0.45	
15 cleanup short vegetation	< 0.5	> 0.16				
19 cleanup bare		< 0.16				

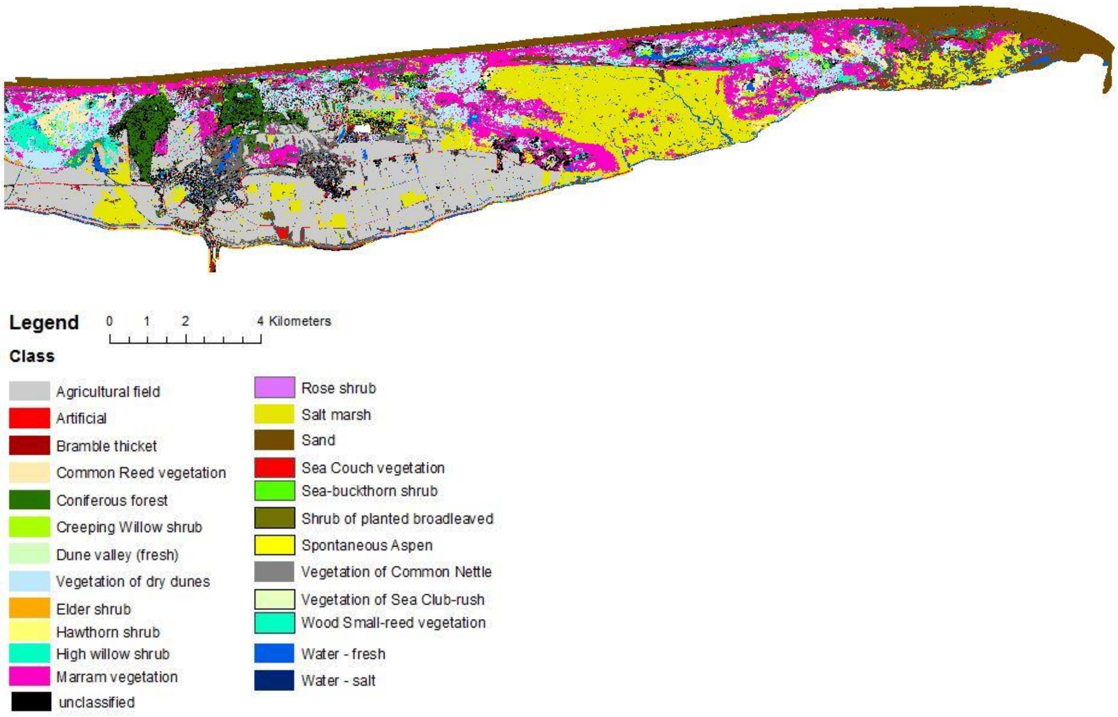
Appendix C: The full result of scenario 1



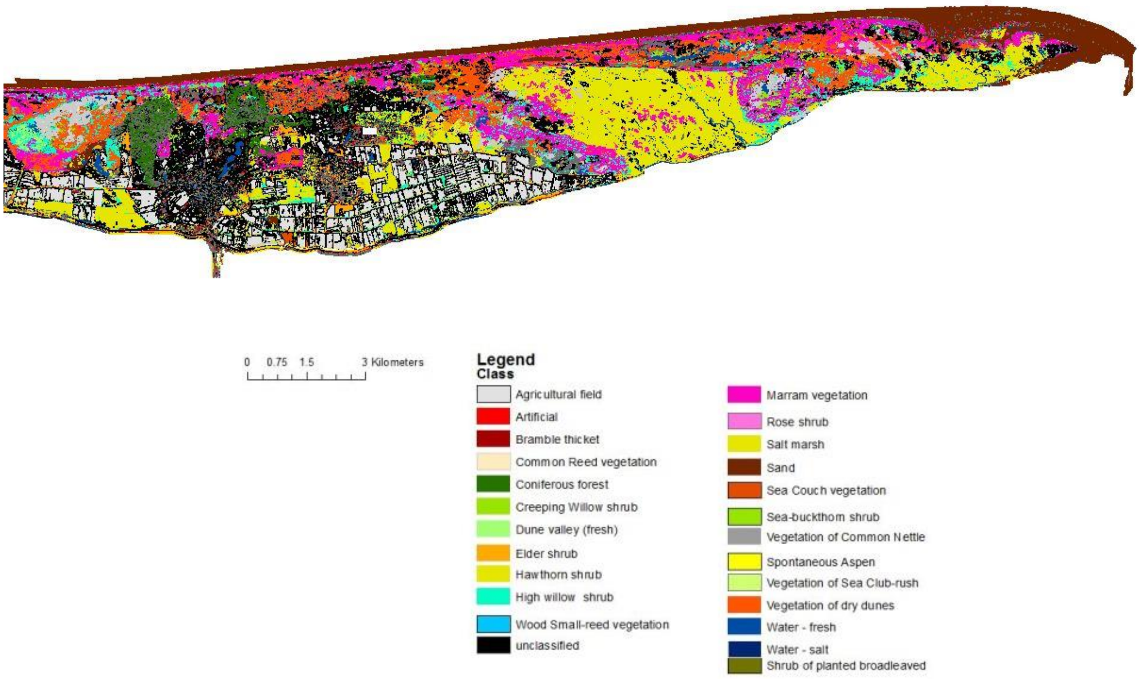
Appendix D: The full result of scenario 2



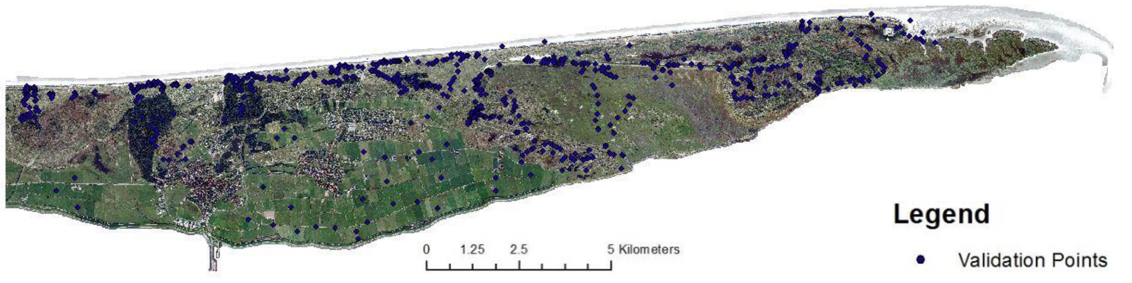
Appendix E: The full result of scenario 3



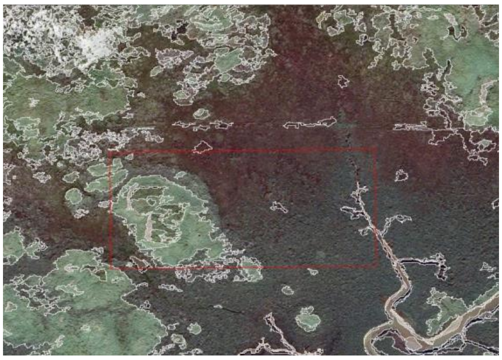
Appendix F: The full result of scenario 4



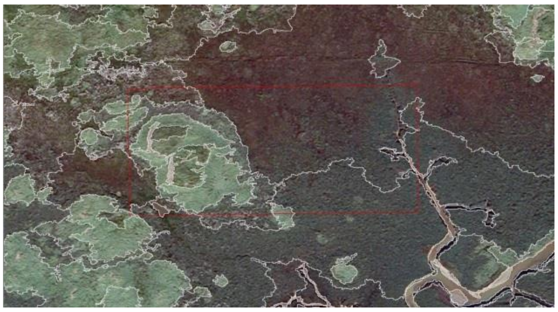
Appendix G: Validation points



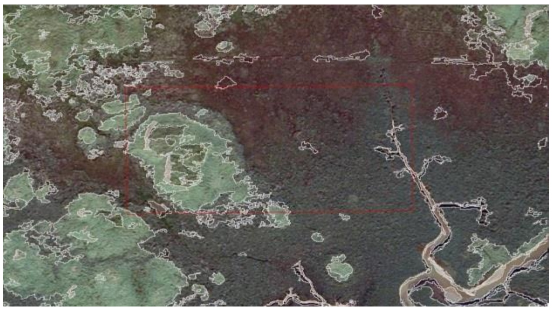
Appendix H: Segmentation plots with shape of 0.1 and compactness of 0.9 and scale parameter of 25, 50, 75 and 100



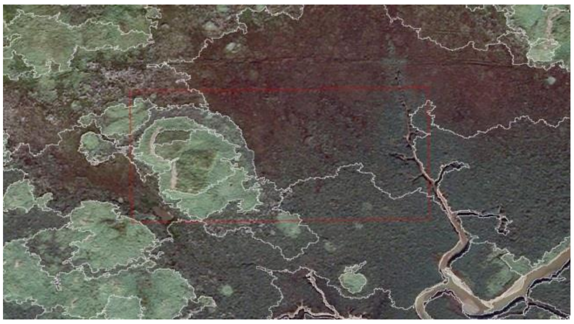
Scale 25



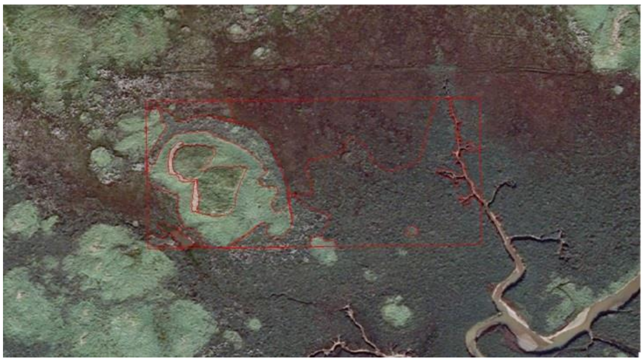
Scale 50



Scale 75

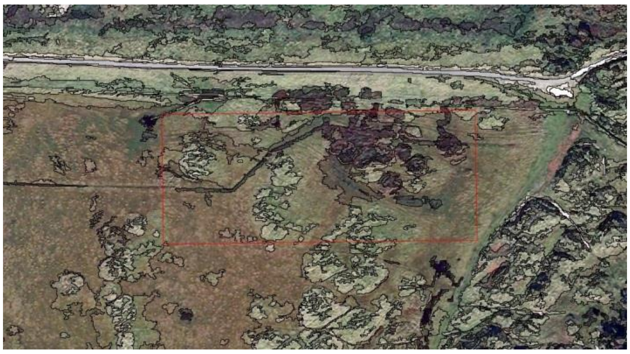


Scale 100



Reference Image

Scale 25



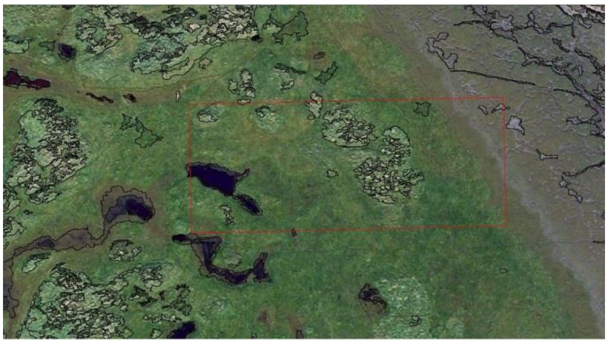
Scale 50

Scale 75

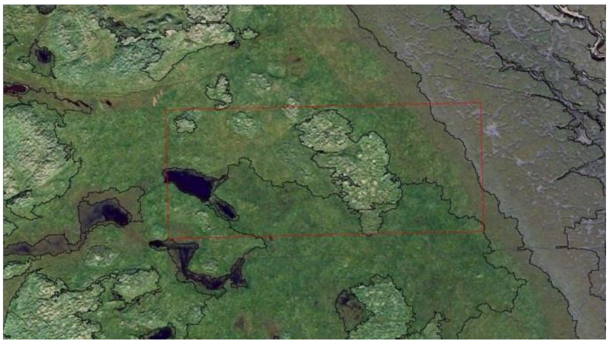
Scale 100

Reference image

Scale 25

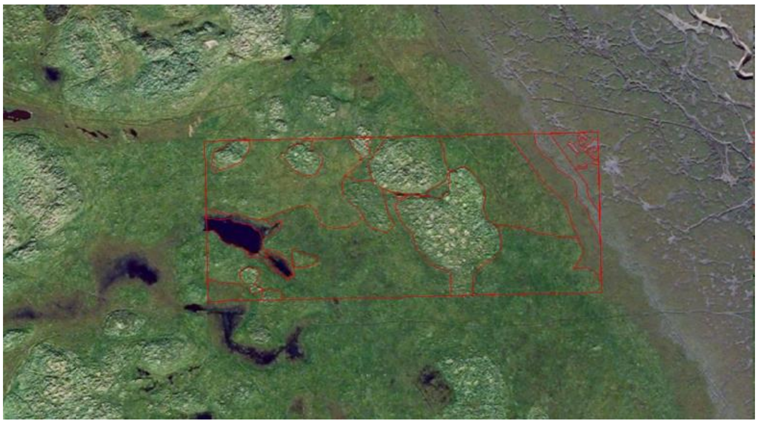


Scale 50



Scale 75

Scale 100



Reference image

Appendix I: accuracy assessment of of Alterra's method (scenario 2)

vegetation structure classification Ameland

results from rule based object classification in ecognition

	Simplified legend classes	reference (Juli/August 2014 fieldwork) 1 - 5 + 25 + 26	6-9 + 12 + 18	11	10 + 15	16 + 17	19	20	21	total	reliability
classification	shrubs > 2 m (1,2,3,4,5 + 25 + 26)	56	11	2	1					70	80%
(October 2008 image)	shrubs 0.5 - 2 m (6,7,8,9 + 12 + 18)	8	9	5	1	7				30	30%
(march 2008 ObjectHeights)	reed (11)	2	2	12		1				17	71%
	salt marsch vegetation (10,15)	1	7		62		1		1	72	86%
	dune vegetation (16 + 17)	2	9	1		16				28	57%
	sand (19)	1	9	4		1	5		5	25	20%
	water - fresh (20)			1		4	1	4	2	12	33%
	water - salt/brackish (21)		1		2			1	14	18	78%
	total	70	48	25	66	29	7	5	22	274	
	accuracy	80%	19%	48%	94%	55%	71%	80%	64%		
	overall accuracy	65%									

remarks

when interpreting the table, please keep the following in mind:

there is a six year difference between image/height information and fieldwork

-> this has an effect on:

sand <-> water

vegetation height

sand <-> vegetation

difference between the two shrub classes and the salt marsch or dunes vegetation classes is based on the maximum object height that occurs within the objec

difference between salt marsch / dunes / sea (salt water) is based on a stratification map

differrence between vegetated and non-vegetated is based on NDVI

for the classification of reed (11) a sepcific spectral signature is used (reddish color)

Appendix J: Three tables of confusion matrix in Altera's study area

1. Confusion matrix of scenario 2

Vegetation structure type	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15a-g	16	17	18	19	20-21	22	23	25	26	27	Total
1	7	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	14
2	12	11	4	11	2	0	8	0	0	1	2	2	0	0	0	0	1	1	0	0	0	0	0	2	0	57
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	1	0	8	0	0	7	0	0	1	4	0	0	0	0	1	1	0	0	0	0	0	0	0	0	23
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	12	2	0	0	0	0	1	1	0	0	0	0	0	0	0	16
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15a-g	0	0	1	2	0	0	1	8	6	12	2	1	0	0	49	1	19	0	1	1	15	1	0	0	0	120
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	2	0	0	0	0	0	7	1	0	3	1	0	0	0	0	1	0	6	5	0	6	0	0	0	32
20-21	0	0	0	0	0	0	0	0	0	0	2	0	0	0	2	4	0	0	0	22	0	0	0	0	0	30
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0
Unclassified	1	0	1	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	5
total	20	15	8	21	2	0	16	16	7	14	25	7	0	0	52	6	23	2	7	28	12	7	3	3	0	294

2. Confusion matrix of scenario 3

Vegetation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15a-g	16	17	18	19	20-21	22	23	25	26	27	total
1	17	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23
2	3	11	3	4	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24
3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
4	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
6	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
7	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11
8	0	0	0	0	0	0	2	12	0	0	2	0	0	0	0	0	5	0	0	0	0	0	0	0	0	21
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10
11	0	0	0	0	0	0	0	0	0	0	20	3	0	0	0	0	0	0	0	0	0	0	0	0	0	23
12	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	4
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15a-g	0	0	0	0	0	0	1	4	0	4	0	0	0	0	52	2	0	0	0	1	2	0	0	0	0	66
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	2	1	0	0	0	7	0	1	0	0	0	0	0	18	0	0	0	0	0	0	0	0	29
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	2	0	0	0	9
20-21	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	4	0	0	0	26	0	0	0	0	0	32
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	10
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	4
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2
27	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	6
Unclassified	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
total	20	15	8	21	2	0	16	16	7	14	25	7	0	0	52	6	23	2	7	28	12	7	3	3	0	294

3. Confusion matrix of scenario 1

Vegetation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15a-g	16	17	18	19	20-21	22	23	25	26	27	total
1	13	4	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19
2	2	11	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17
3	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
4	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13
8	0	0	0	0	0	0	3	10	0	0	3	0	0	0	0	0	4	0	0	0	0	0	0	0	0	20
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12
11	0	0	0	0	0	0	0	0	0	1	21	2	0	0	0	0	0	1	0	0	0	0	0	0	0	25
12	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	4
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15a-g	0	0	1	0	0	0	0	6	0	1	0	0	0	0	44	2	0	0	0	1	1	0	0	0	0	56
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
17	0	0	2	2	2	0	0	0	7	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	32
18	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	3
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	2	0	2	0	0	0	11
20-21	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	4	0	0	0	25	0	0	0	0	0	30
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	11	0	0	0	0	19
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	4
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
26	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	3	0	7
27	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
Unclassified	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
total	20	15	8	21	2	0	16	16	7	14	25	7			52	6	23	2	7	28	12	7	3	3	0	294

Appendix K: Two tables of confusion matrix in full study area

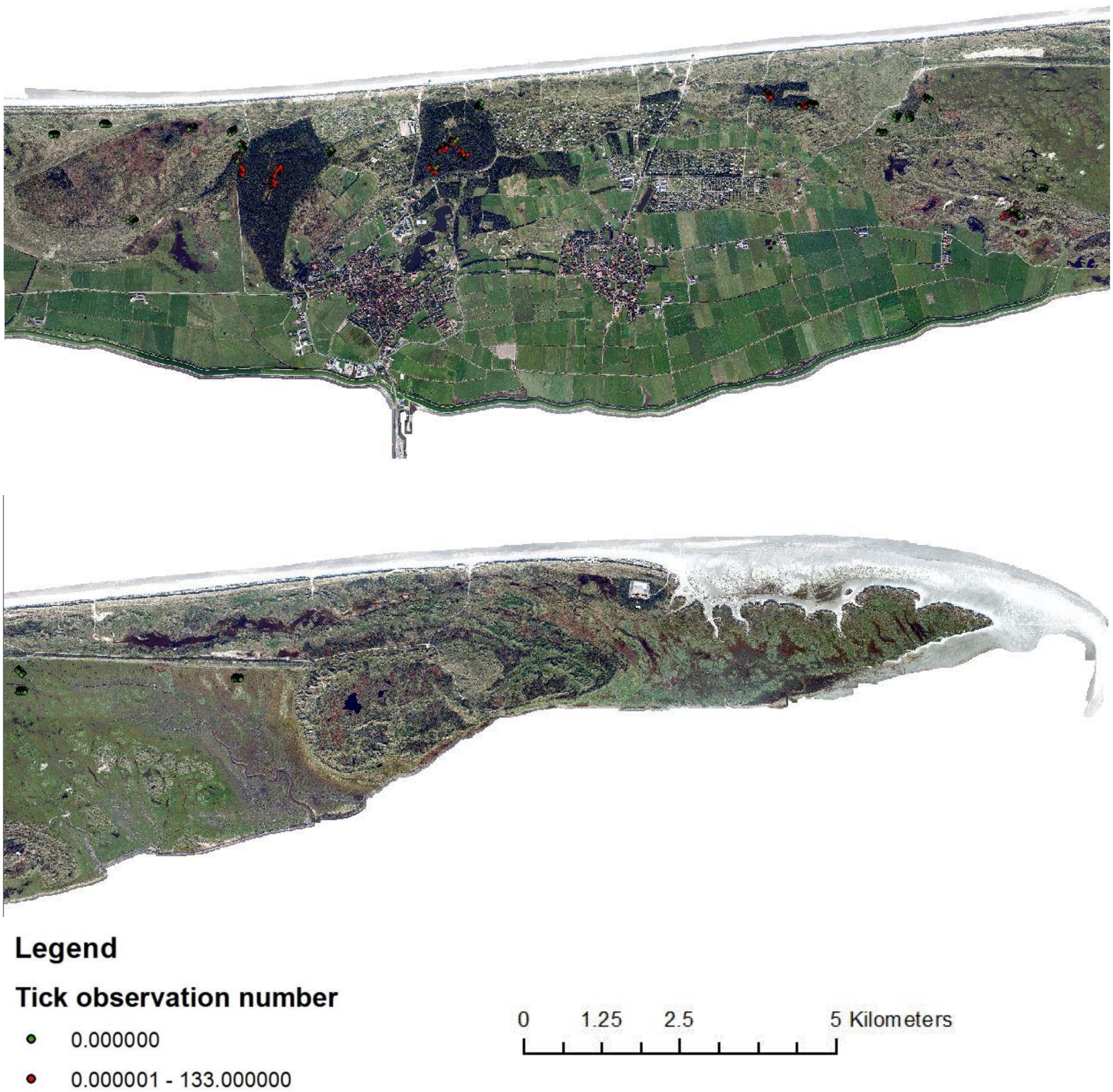
1. Confusion matrix of scenario 1

Vegetation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15a-g	16-16a	17	18	19	20-21	22	23	25	26	27	Total
1	26	4	3	3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	6	45
2	3	24	0	5	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	34
3	0	3	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8
4	0	3	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	6	3	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40
8	0	0	0	3	0	0	5	23	1	0	3	0	1	0	0	0	12	0	0	0	0	0	0	0	0	48
9	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
10	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13
11	0	0	0	0	0	0	0	0	0	1	37	2	0	0	0	0	0	0	0	0	0	0	0	0	0	40
12	0	0	0	0	0	0	0	0	0	0	4	4	0	0	0	0	0	1	0	0	0	0	0	0	0	9
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
15a-g	0	0	2	0	0	0	0	7	0	0	0	0	0	0	50	3	5	0	0	1	9	0	0	0	0	77
16-16a	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	3	0	0	0	0	0	0	0	0	9
17	0	0	2	2	2	7	2	2	6	0	0	0	4	0	0	2	32	0	0	0	0	0	0	0	0	61
18	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	2	0	0	0	0	0	0	0	4
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	5	0	7	0	0	0	26
20-21	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	5	0	0	0	40	0	0	0	0	0	48
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	30	0	0	0	0	32
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	15	0	0	1	22
25	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	2	9
26	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	5
27	7	0											0	0									1	0	40	48
Unclassifie	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
total	41	34	12	56	5	7	40	32	9	14	47	7	5	2	52	16	52	2	20	47	39	22	8	2	50	624

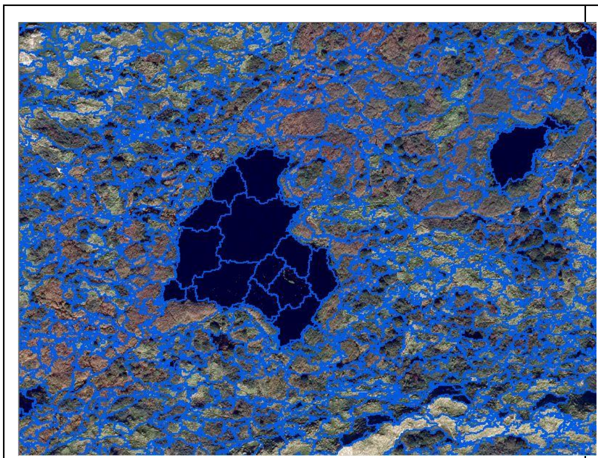
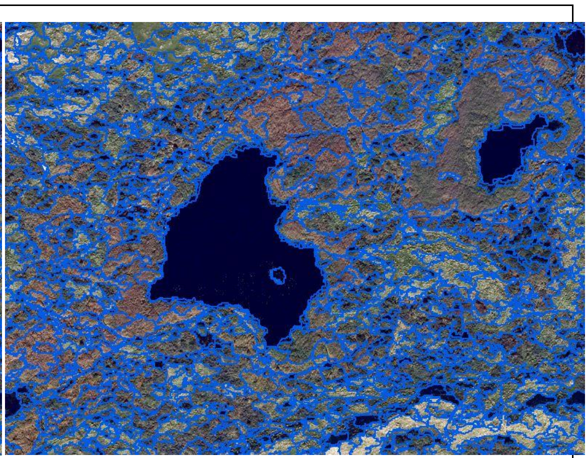
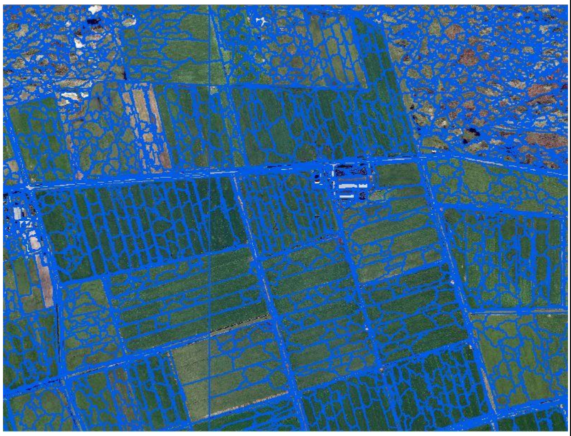
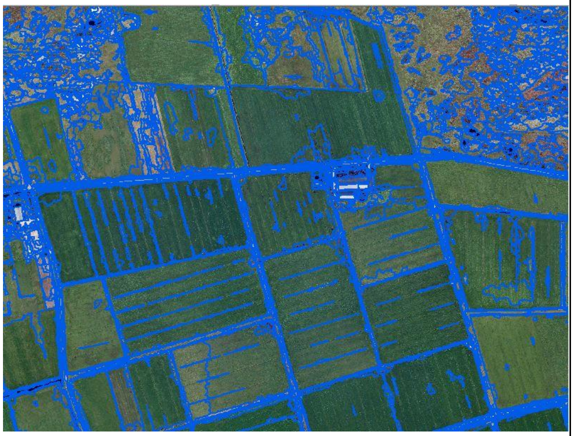
2. Confusion matrix of scenario 4

Vegetation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15a-g	16-16a	17	18	19	20-21	22	23	25	26	27	Total
1	22	4	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	9	40
2	3	22	2	8	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	44
3	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
4	0	3	0	35	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	45
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	1	0	3	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34
8	0	0	0	4	0	3	1	24	1	0	4	0	0	0	0	1	5	0	0	0	4	0	0	0	0	47
9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
10	0	0	0	0	0	0	2	0	0	13		0	0	0	0	0	1	0	0	0	0	0	0	0	0	16
11	0	0	0	0	0	0	0	0	0	1	31	2	0	0	0	0	0	0	0	0	0	0	0	0	0	34
12	0	0	0	0	0	0	0	0	0	0	7	4	0	0	0	0	0	0	0	0	0	0	0	0	0	11
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15a-g	0	1	1	1	0	0	1	3	0	0	3	0	0	0	44	2	8	0	0	3	9	2	0	0	0	78
16-16a	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	6
17	0	0	2	2	4	3	0	2	5	0	0	0	5	2	0	3	38	0	0	0	0	0	0	0	0	66
18	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	3
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	3	0	11	0	0	0	30
20-21	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	6	0	0	0	39	0	0	0	0	0	48
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	26	0	0	0	0	34
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	9	0	0	0	13
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	6
26	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	2	10
27	11	3	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	46
Unclassifie	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	2
total	41	34	12	56	5	7	40	32	9	14	47	7	5	2	52	16	52	2	20	47	39	22	8	2	50	624

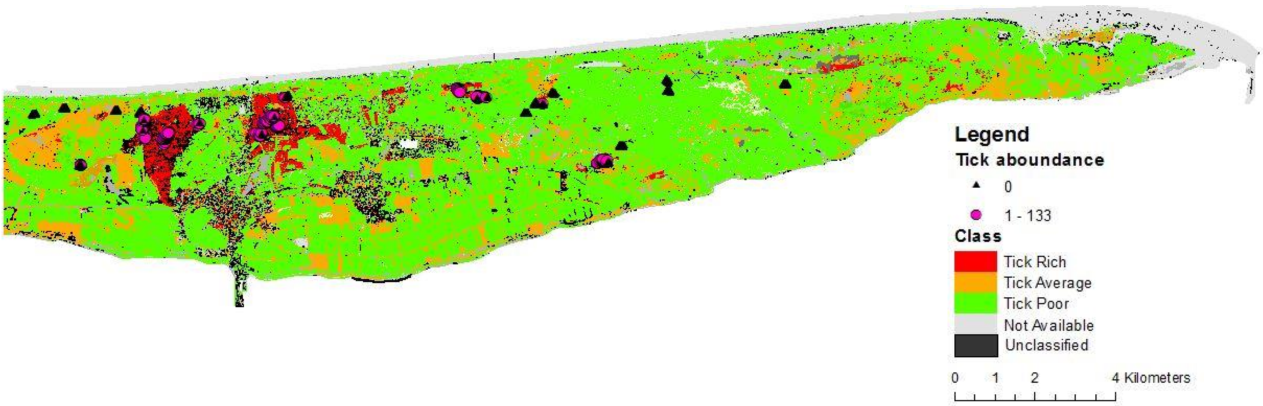
Appendix L: Tick observation point



Appendix M: Segmentations of Alterra's method (scenario 2) and scenario 1

	
	
	
Segmentation of scenario 2	Segmentation of scenario1

Appendix N: Tick suitability map



BIBLIOGRAPHY

Aguado, A., E. Montiel and M. Nixon (1998). Fuzzy image segmentation via texture density histograms, EU project Nr, ENV4-CT96-0305—Fuzzy Land Information from Environmental Remote Sensing (FLIERS) Final Report.

Alata, O. and L. Quintard (2009). "Is there a best color space for color image characterization or representation based on Multivariate Gaussian Mixture Model?" Computer Vision and Image Understanding 113(8): 867-877.

Alberti, M., R. Weeks and S. Coe (2004). "Urban land-cover change analysis in central Puget Sound." Photogrammetric Engineering & Remote Sensing 70(9): 1043-1052.

Atkinson, P. M. and A. Tatnall (2010). "Introduction neural networks in remote sensing." International Journal of remote sensing 18(4): 37–41.

Auquilla, A. (2013). Comparison of Machine Learning methods for object-based classification of multispectral satellite imagery in terms of land cover types. Master of Science in Artificial Intelligence.

Auquilla, A., S. Heremans, P. Vanegas and J. Van Orshoven (2014). A Procedure for Semi-automatic Segmentation in OBIA Based on the Maximization of a Comparison Index. Computational Science and Its Applications–ICCSA 2014, Springer: 360-375.

Baatz, M. and A. Schäpe (2000). "Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation." Angewandte Geographische Informationsverarbeitung XII: 12-23.

Benz, U. C., P. Hofmann, G. Willhauck, I. Lingenfelder and M. Heynen (2004). "Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information." ISPRS Journal of photogrammetry and remote sensing 58(3): 239-258.

Bhaskaran, S., S. Paramananda and M. Ramnarayan (2010). "Per-pixel and object-oriented classification methods for mapping urban features using Ikonos satellite data." Applied Geography 30(4): 650-665.

Blaschke, T. (2003). Object-based contextual image classification built on image segmentation. Advances in Techniques for Analysis of Remotely Sensed Data, 2003 IEEE Workshop on, IEEE.

Blaschke, T. (2010). "Object based image analysis for remote sensing." ISPRS journal of photogrammetry and remote sensing 65(1): 2-16.

Blaschke, T. and J. Strobl (2001). "What’s wrong with pixels? Some recent developments interfacing remote sensing and GIS." GeoBIT/GIS 6(01): 12-17.

Bosch, A., A. Zisserman and X. Munoz (2007). "Image classification using random forests and ferns."

Breiman, L. (2001). "Random forests." Machine learning 45(1): 5-32.

Breiman, L., J. Friedman and R. Olshen (1984). " Classification and Regression Trees." Wadsworth, Belmont, California.

Buckinx, W. and D. Van den Poel (2005). "Customer base analysis: partial defection of behaviourally loyal clients in a non-contractual FMCG retail setting." European Journal of Operational Research 164(1): 252-268.

Bunce, R., M. Bogers, D. Evans, L. Halada, R. Jongman, C. Mucher, B. Bauch, G. de Blust, T. Parr and L. Olsvig-Whittaker (2013). "The significance of habitats as indicators of biodiversity and their links to species." Ecological Indicators 33: 19-25.

Burnett, C. and T. Blaschke (2003). "A multi-scale segmentation/object relationship modelling methodology for landscape analysis." Ecological modelling 168(3): 233-249.

Casals-Carrasco, P., S. Kubo and B. B. Madhavan (2000). "Application of spectral mixture analysis for terrain evaluation studies." International Journal of Remote Sensing 21(16): 3039-3055.

Chan, J. C.-W. and D. Paelinckx (2008). "Evaluation of Random Forest and Adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery." Remote Sensing of Environment 112(6): 2999-3011.

Chen, C.-M., G. Hepner and R. Forster (2003). "Fusion of hyperspectral and radar data using the IHS transformation to enhance urban surface features." ISPRS Journal of photogrammetry and Remote Sensing 58(1): 19-30.

Chen, H. (1995). "Machine learning for information retrieval: neural networks, symbolic learning, and genetic algorithms." Journal of the American Society for Information Science 46(3): 194-216.

Chubey, M. S., S. E. Franklin and M. A. Wulder (2006). "Object-based analysis of Ikonos-2 imagery for extraction of forest inventory parameters." Photogrammetric Engineering & Remote Sensing 72(4): 383-394.

Cleve, C., M. Kelly, F. R. Kearns and M. Moritz (2008). "Classification of the wildland–urban interface: A comparison of pixel-and object-based classifications using high-resolution aerial photography." Computers, Environment and Urban Systems 32(4): 317-326.

Cristianini, N. and J. Shawe-Taylor (2000). An introduction to support vector machines and other kernel-based learning methods, Cambridge university press.

Cutler, D. R., T. C. Edwards Jr, K. H. Beard, A. Cutler, K. T. Hess, J. Gibson and J. J. Lawler (2007). "Random forests for classification in ecology." Ecology 88(11): 2783-2792.

Daniel, M., J. Kolar and P. Zeman (2004). "GIS tools for tick and tick-borne disease occurrence." Parasitology 129(S1): S329-S352.

Diaz-Uriarte, R. (2007). "GeneSrF and varSelRF: a web-based tool and R package for gene selection and classification using random forest." BMC bioinformatics 8(1): 328.

Díaz-Uriarte, R. and S. A. De Andres (2006). "Gene selection and classification of microarray data using random forest." BMC bioinformatics 7(1): 3.

Dorren, L. K., B. Maier and A. C. Seijmonsbergen (2003). "Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification." Forest Ecology and Management 183(1): 31-46.

Drăguţ, L., D. Tiede and S. R. Levick (2010). "ESP: a tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data." International Journal of Geographical Information Science 24(6): 859-871.

Duro, D. C., S. E. Franklin and M. G. Dubé (2012). "A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery." Remote Sensing of Environment 118: 259-272.

Ehlers, M., M. Gähler and R. Janowsky (2003). "Automated analysis of ultra high resolution remote sensing data for biotope type mapping: new possibilities and challenges." ISPRS Journal of Photogrammetry and Remote Sensing 57(5): 315-326.

Espindola, G., G. Câmara, I. Reis, L. Bins and A. Monteiro (2006). "Parameter selection for region-growing image segmentation algorithms using spatial autocorrelation." International Journal of Remote Sensing 27(14): 3035-3040.

Estrada-Peña, A., J. S. Gray, O. Kahl, R. S. Lane and A. M. Nijhof (2013). "Research on the ecology of ticks and tick-borne pathogens—methodological principles and caveats." Frontiers in cellular and infection microbiology 3.

Evans, J. S. and S. A. Cushman (2009). "Gradient modeling of conifer species using random forests." Landscape Ecology 24(5): 673-683.

Ficetola, G. F., A. Bonardi, C. A. Mücher, N. L. Gilissen and E. Padoa-Schioppa (2014). "How many predictors in species distribution models at the landscape scale? Land use versus LiDAR-derived canopy height." International Journal of Geographical Information Science 28(8): 1723-1739.

Foody, G. M., N. Campbell, N. Trodd and T. Wood (1992). "Derivation and applications of probabilistic measures of class membership from the maximum-likelihood classification." Photogrammetric Engineering and Remote Sensing 58(9): 1335-1341.

Fu, K.-S. and J. Mui (1981). "A survey on image segmentation." Pattern recognition 13(1): 3-16.

Gahegan, M. (2003). "Is inductive machine learning just another wild goose (or might it lay the golden egg)?" International Journal of Geographical Information Science 17(1): 69-92.

Gamanya, R., P. De Maeyer and M. De Dapper (2007). "An automated satellite image classification design using object-oriented segmentation algorithms: A move towards standardization." Expert Systems with Applications 32(2): 616-624.

Gao, Y. and J. F. Mas (2008). "A comparison of the performance of pixel based and object based classifications over images with various spatial resolutions." Online journal of earth sciences 2(1): 27-35.

Gao, Y., J. F. Mas, N. Kerle and J. A. Navarrete Pacheco (2011). "Optimal region growing segmentation and its effect on classification accuracy." International Journal of Remote Sensing 32(13): 3747-3763.

Gassner, F. and N. Hartemink (2013). Tick–Borrelia interactions: burden or benefit? Ecology of parasite-vector interactions, Springer: 141-154.

Gehlke, C. and K. Biehl (1934). "Certain effects of grouping upon the size of the correlation coefficient in census tract material." Journal of the American Statistical Association 29(185A): 169-170.

Genuer, R., J.-M. Poggi and C. Tuleau-Malot (2010). "Variable selection using random forests." Pattern Recognition Letters 31(14): 2225-2236.

Ghimire, B., J. Rogan and J. Miller (2010). "Contextual land-cover classification: incorporating spatial dependence in land-cover classification models using random forests and the Getis statistic." Remote Sensing Letters 1(1): 45-54.

Gislason, P. O., J. A. Benediktsson and J. R. Sveinsson (2006). "Random forests for land cover classification." Pattern Recognition Letters 27(4): 294-300.

Gubler, D. (2009). "Vector-borne diseases." Revue scientifique et technique (International Office of Epizootics) 28(2): 583-588.

Guglielmone, A., L. Beati, D. Barros-Battesti, M. Labruna, S. Nava, J. Venzal, A. Mangold, M. Szabó, J. Martins and D. González-Acuña (2006). "Ticks (Ixodidae) on humans in South America." Experimental & applied acarology 40(2): 83-100.

Guo, Q., M. Kelly, P. Gong and D. Liu (2007). "An object-based classification approach in mapping tree mortality using high spatial resolution imagery." GIScience & Remote Sensing 44(1): 24-47.

Hall, F. G., K. Bergen, J. B. Blair, R. Dubayah, R. Houghton, G. Hurtt, J. Kellndorfer, M. Lefsky, J. Ranson and S. Saatchi (2011). "Characterizing 3D vegetation structure from space: Mission requirements." Remote Sensing of Environment 115(11): 2753-2775.

Hall, O., G. J. Hay, A. Bouchard and D. J. Marceau (2004). "Detecting dominant landscape objects through multiple scales: an integration of object-specific methods and watershed segmentation." Landscape Ecology 19(1): 59-76.

Hancock, P. A., R. Brackley and S. C. Palmer (2011). "Modelling the effect of temperature variation on the seasonal dynamics of< i> Ixodes ricinus</i> tick populations." International journal for parasitology 41(5): 513-522.

Hantson, W., L. Kooistra and P. A. Slim (2012). "Mapping invasive woody species in coastal dunes in the Netherlands: a remote sensing approach using LIDAR and high-resolution aerial photographs." Applied Vegetation Science 15(4): 536-547.

Haralick, R. M., K. Shanmugam and I. H. Dinstein (1973). "Textural features for image classification." Systems, Man and Cybernetics, IEEE Transactions on(6): 610-621.

Haralick, R. M. and L. G. Shapiro (1985). Image segmentation techniques. 1985 Technical Symposium East, International Society for Optics and Photonics.

Harvey, K. and G. Hill (2001). "Vegetation mapping of a tropical freshwater swamp in the Northern Territory, Australia: a comparison of aerial photography, Landsat TM and SPOT satellite imagery." International Journal of Remote Sensing 22(15): 2911-2925.

Haverkort, F. (2013). Integrated Tick Management.

Hellesen, T. and L. Matikainen (2013). "An object-based approach for mapping shrub and tree cover on grassland habitats by use of LiDAR and CIR orthoimages." Remote Sensing 5(2): 558-583.

Herrera, B., C. Kleinn, B. Koch and M. Dees (2004). "Automatic classification of trees outside forest using an object-driven approach: An application in a Costa Rican landscape." PHOTOGRAMMETRIE FERNERKUNDUNG GEOINFORMATION(2): 111-120.

Heumann, B. W. (2011). "An object-based classification of mangroves using a hybrid decision tree—Support vector machine approach." Remote Sensing 3(11): 2440-2460.

Heyman, O., G. G. Gaston, A. J. Kimerling and J. T. Campbell (2003). "A per-segment approach to improving aspen mapping from high-resolution remote sensing imagery." Journal of forestry 101(4): 29-33.

Hofhuis, A., M. Harms, J. Van der Giessen, H. Sprong, D. Notermans and W. Van Pelt (2010). "Ziekte van Lyme in Nederland 1994-2009." Aantal huisartsenconsulten blijft toenemen. Is voorlichting en curatief beleid genoeg: 84-87.

Hollister, J. W., M. L. Gonzalez, J. F. Paul, P. V. August and J. L. Copeland (2004). "Assessing the accuracy of National Land Cover Dataset area estimates at multiple spatial extents." Photogrammetric Engineering & Remote Sensing 70(4): 405-414.

Huang, C., L. Davis and J. Townshend (2002). "An assessment of support vector machines for land cover classification." International Journal of Remote Sensing 23(4): 725-749.

Hyde, P., R. Dubayah, W. Walker, J. B. Blair, M. Hofton and C. Hunsaker (2006). "Mapping forest structure for wildlife habitat analysis using multi-sensor (LiDAR, SAR/InSAR, ETM+, Quickbird) synergy." Remote Sensing of Environment 102(1): 63-73.

Hyyppa, J., H. Hyppa, M. Inkinen and M. Engdahl (1998). Verification of the potential of various remote sensing data sources for forest inventory. Geoscience and Remote Sensing Symposium Proceedings, 1998. IGARSS'98. 1998 IEEE International, IEEE.

Im, J., J. Jensen and J. Tullis (2008). "Object-based change detection using correlation image analysis and image segmentation." International Journal of Remote Sensing 29(2): 399-423.

Johansen, K. and S. Phinn (2006). "Mapping structural parameters and species composition of riparian vegetation using IKONOS and Landsat ETM+ data in Australian tropical savannahs." Photogrammetric Engineering & Remote Sensing 72(1): 71-80.

Johnson, B. and Z. Xie (2011). "Unsupervised image segmentation evaluation and refinement using a multi-scale approach." ISPRS Journal of Photogrammetry and Remote Sensing 66(4): 473-483.

Jouda, F., J.-L. Perret and L. Gern (2004). "Density of questing Ixodes ricinus nymphs and adults infected by Borrelia burgdorferi sensu lato in Switzerland: spatio-temporal pattern at a regional scale." Vector-Borne and Zoonotic Diseases 4(1): 23-32.

Jyothi, B. N., G. Babu and M. Krishna IV (2008). "Object Oriented and Multi-Scale Image Analysis: Strengths, Weaknesses, Opportunities and Threats-A Review." Journal of Computer Science 4(9).

Kahl, O. and W. Knülle (1988). "Water vapour uptake from subsaturated atmospheres by engorged immature ixodid ticks." Experimental & applied acarology 4(1): 73-83.

Kampouraki, M., G. Wood and T. Brewer (2008). Opportunities and limitations of object based image analysis for detecting urban impervious and vegetated surfaces using true-colour aerial photography. Object-Based Image Analysis, Springer: 555-569.

Kaya, S., J. Sokol and T. Pultz (2004). "Monitoring environmental indicators of vector-borne disease from space: a new opportunity for RADARSAT-2." Canadian journal of remote sensing 30(3): 560-565.

Ke, Y., L. J. Quackenbush and J. Im (2010). "Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification." Remote Sensing of Environment 114(6): 1141-1154.

Kempeneers, P., B. Deronde, S. Provoost and R. Houthuys (2009). "Synergy of airborne digital camera and lidar data to map coastal dune vegetation." Journal of Coastal Research: 73-82.

Knotters, M., D. Brus and A. Heidema (2008). Validatie van ecotopenkaarten van de rijkswateren, Alterra.

Koutsias, N., M. Karteris and E. Chuvico (2000). "The use of intensity-hue-saturation transformation of Landsat-5 Thematic Mapper data for burned land mapping." Photogrammetric Engineering and Remote Sensing 66(7): 829-840.

Kuilder, E. (2012). Mapping river flood plain vegetation structure with a consistent mapping scale by color-infrared aerial images and LiDAR data in object-based random forest classification. Master, Wageningen University and Research.

Lam, N. S. N. and D. A. Quattrochi (1992). "On the Issues of Scale, Resolution, and Fractal Analysis in the Mapping Sciences*." The Professional Geographer 44(1): 88-98.

Lee, S., W. Ni-Meister, W. Yang and Q. Chen (2011). "Physically based vertical vegetation structure retrieval from ICESat data: Validation using LVIS in White Mountain National Forest, New Hampshire, USA." Remote Sensing of Environment 115(11): 2776-2785.

Liaw, A. and M. Wiener (2002). "Classification and Regression by randomForest." R news 2(3): 18-22.

Lin, W.-J. and J. J. Chen (2012). "Class-imbalanced classifiers for high-dimensional data." Briefings in bioinformatics: bbs006.

Lindgren, E., L. Tälleklint and T. Polfeldt (2000). "Impact of climatic change on the northern latitude limit and population density of the disease-transmitting European tick Ixodes ricinus." Environmental health perspectives 108(2): 119.

Liu, D. and F. Xia (2010). "Assessing object-based classification: advantages and limitations." Remote Sensing Letters 1(4): 187-194.

Lunetta, K. L., L. B. Hayward, J. Segal and P. Van Eerdewegh (2004). "Screening large-scale association study data: exploiting interactions using random forests." BMC genetics 5(1): 32.

Lusa, L. (2010). "Class prediction for high-dimensional class-imbalanced data." BMC bioinformatics 11(1): 523.

Mallinis, G., N. Koutsias, M. Tsakiri-Strati and M. Karteris (2008). "Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a

Mediterranean test site." ISPRS Journal of Photogrammetry and Remote Sensing 63(2): 237-250.

Marceau, D. J. (1999). "The scale issue in social and natural sciences." Canadian Journal of Remote Sensing 25(4): 347-356.

Marmion, M., M. Parviainen, M. Luoto, R. K. Heikkinen and W. Thuiller (2009). "Evaluation of consensus methods in predictive species distribution modelling." Diversity and distributions 15(1): 59-69.

Martha, T. R., N. Kerle, C. J. van Westen, V. Jetten and K. V. Kumar (2011). "Segment optimization and data-driven thresholding for knowledge-based landslide detection by object-based image analysis." Geoscience and Remote Sensing, IEEE Transactions on 49(12): 4928-4943.

Medlock, J. M., K. M. Hansford, A. Bormane, M. Derdakova, A. Estrada-Peña, J.-C. George, I. Golovljova, T. Jaenson, J.-K. Jensen and P. M. Jensen (2013). "Driving forces for changes in geographical distribution of Ixodes ricinus ticks in Europe." Parasites & vectors 6(1): 1-11.

Melgani, F. and L. Bruzzone (2002). Support vector machines for classification of hyperspectral remote-sensing images. Geoscience and Remote Sensing Symposium, 2002. IGARSS'02. 2002 IEEE International, IEEE.

Melgani, F. and L. Bruzzone (2004). "Classification of hyperspectral remote sensing images with support vector machines." Geoscience and Remote Sensing, IEEE Transactions on 42(8): 1778-1790.

Michelchen, S. (2014). Effect of habitat and landscape characteristics on ticks and Borrelia infections at Ameland, the Netherlands. Master, University of Antwerpen.

Möller, M., L. Lymburner and M. Volk (2007). "The comparison index: A tool for assessing the accuracy of image segmentation." International Journal of Applied Earth Observation and Geoinformation 9(3): 311-321.

Mücher, L. Kooistra, M. Vermeulen, J. V. Borre, B. Haest and R. Haveman (2013). "Quantifying structure of Natura 2000 heathland habitats using spectral mixture analysis and segmentation techniques on hyperspectral imagery." Ecological Indicators 33: 71-81.

Mücher, C., L. Roupioz, H. Kramer and B. Bunce (2010). Use of LiDAR to map and monitor habitats. European LiDAR Mapping Forum, The Hague.

Ojala, T., M. Pietikäinen and D. Harwood (1996). "A comparative study of texture measures with classification based on featured distributions." Pattern recognition 29(1): 51-59.

Pal, N. R. and S. K. Pal (1993). "A review on image segmentation techniques." Pattern recognition 26(9): 1277-1294.

Peters, J., B. D. Baets, N. E. Verhoest, R. Samson, S. Degroeve, P. D. Becker and W. Huybrechts (2007). "Random forests as a tool for ecohydrological distribution modelling." Ecological Modelling 207(2): 304-318.

Prinzie, A. and D. Van den Poel (2008). "Random forests for multiclass classification: Random multinomial logit." Expert systems with Applications 34(3): 1721-1732.

Qazi, I.-U.-H., O. Alata, J.-C. Burie, A. Moussa and C. Fernandez-Maloigne (2011). "Choice of a pertinent color space for color texture characterization using parametric spectral analysis." Pattern Recognition 44(1): 16-31.

Radoux, J. and P. Defourny (2007). "A quantitative assessment of boundaries in automated forest stand delineation using very high resolution imagery." Remote Sensing of Environment 110(4): 468-475.

Randolph, S. E. (2001). "The shifting landscape of tick-borne zoonoses: tick-borne encephalitis and Lyme borreliosis in Europe." Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences 356(1411): 1045-1056.

Räsänen, A. (2014). "Developing and comparing methods for mapping habitat types and conservation values using remote sensing data and GIS methods."

Roest, H., J. Tilburg, W. Van der Hoek, P. Vellema, F. Van Zijderveld, C. Klaassen and D. Raoult (2011). "The Q fever epidemic in The Netherlands: history, onset, response and reflection." Epidemiology and infection 139(01): 1-12.

Ronfard, R. (1994). "Region-based strategies for active contour models." International Journal of Computer Vision 13(2): 229-251.

Ruiz-Fons, F., I. G. Fernández-de-Mera, P. Acevedo, C. Gortázar and J. de la Fuente (2012). "Factors driving the abundance of Ixodes ricinus ticks and the prevalence of zoonotic I. ricinus-borne pathogens in natural foci." Applied and environmental microbiology 78(8): 2669-2676.

Saeys, Y., I. Inza and P. Larrañaga (2007). "A review of feature selection techniques in bioinformatics." bioinformatics 23(19): 2507-2517.

Schiewe, J. (2002). "Segmentation of high-resolution remotely sensed data-concepts, applications and problems." International Archives of Photogrammetry Remote Sensing And Spatial Information Sciences 34(4): 380-385.

Schimmer, B., D. Notermans, M. Harms, J. Reimerink, J. Bakker, P. Schneeberger, L. Mollema, P. Teunis, W. Van Pelt and Y. Van Duynhoven (2012). "Low seroprevalence of Q fever in The Netherlands prior to a series of large outbreaks." Epidemiology and infection 140(01): 27-35.

Schölkopf, B., A. J. Smola, R. C. Williamson and P. L. Bartlett (2000). "New support vector algorithms." Neural computation 12(5): 1207-1245.

Schroff, F., A. Criminisi and A. Zisserman (2008). "Object class segmentation using random forests."

Shiraishi, T., T. Motohka, R. B. Thapa, M. Watanabe and M. Shimada (2014). "Comparative Assessment of Supervised Classifiers for Land Use–Land Cover Classification in a Tropical Region Using Time-Series PALSAR Mosaic Data." Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of 7(4): 1186-1199.

Sprong, H., E. Tijsse-Klasen, M. Langelaar, A. De Bruin, M. Fonville, F. Gassner, W. Takken, S. Van Wieren, A. Nijhof and F. Jongejan (2012). "Prevalence of Coxiella burnetii in ticks after a large outbreak of Q fever." Zoonoses and public health 59(1): 69-75.

Statnikov, A., L. Wang and C. F. Aliferis (2008). "A comprehensive comparison of random forests and support vector machines for microarray-based cancer classification." BMC bioinformatics 9(1): 319.

Strobl, C., A.-L. Boulesteix, T. Kneib, T. Augustin and A. Zeileis (2008). "Conditional variable importance for random forests." BMC bioinformatics 9(1): 307.

Stuckens, J., P. Coppin and M. Bauer (2000). "Integrating contextual information with per-pixel classification for improved land cover classification." Remote Sensing of Environment 71(3): 282-296.

Stumpf, A. and N. Kerle (2011). "Object-oriented mapping of landslides using Random Forests." Remote Sensing of Environment 115(10): 2564-2577.

Svetnik, V., A. Liaw, C. Tong, J. C. Culberson, R. P. Sheridan and B. P. Feuston (2003). "Random forest: a classification and regression tool for compound classification and QSAR modeling." Journal of chemical information and computer sciences 43(6): 1947-1958.

Tack, W. (2013). Impact of forest conversion on the abundance of Ixodes ricinus ticks. Phd, Gent.

Tack, W., M. Madder, L. Baeten, M. Vanhellemont and K. Verheyen (2013). "Shrub clearing adversely affects the abundance of Ixodes ricinus ticks." Experimental and Applied Acarology 60(3): 411-420.

Tapiador, F. J. and J. L. Casanova (2003). "Land use mapping methodology using remote sensing for the regional planning directives in Segovia, Spain." Landscape and urban planning 62(2): 103-115.

Thomas Blaschke, C. B., Anssi Pekkarinen (2004). "Image Segmentation Methods for Object-based Analysis and Classification in Remote Sensing Image Analysis: Including The Spatial Domain." 5: 211-236.

Tu, T.-M., P. S. Huang, C.-L. Hung and C.-P. Chang (2004). "A fast intensity-hue-saturation fusion technique with spectral adjustment for IKONOS imagery." Geoscience and Remote Sensing Letters, IEEE 1(4): 309-312.

Tzotsos, A. and D. Argialas (2008). Support vector machine classification for object-based image analysis. Object-Based Image Analysis, Springer: 663-677.

WaddenZee. (2014). "Subsidence Ameland." Retrieved May 12,2014, from http://www.waddenzee.nl/index.php?id=2181&L=2.

Wang, Y. and Q. Li (2014). "Review on the Studies and Advances of Machine Learning Approaches." TELKOMNIKA Indonesian Journal of Electrical Engineering 12(2): 1487-1494.

Waske, B., S. van der Linden, C. Oldenburg, B. Jakimow, A. Rabe and P. Hostert (2012). "A user-oriented implementation for remote sensing image analysis with Random Forests." Environmental Modelling & Software 35: 192-193.

Weishampel, J. F., J. B. Blair, R. Knox, R. Dubayah and D. Clark (2000). "Volumetric lidar return patterns from an old-growth tropical rainforest canopy." International Journal of Remote Sensing 21(2): 409-415.

Wessels, K., R. Mathieu, B. Erasmus, G. Asner, I. Smit, J. Van Aardt, R. Main, J. Fisher, W. Marais and T. Kennedy-Bowdoin (2011). "Impact of communal land use and conservation on woody vegetation structure in the Lowveld savannas of South Africa." Forest Ecology and Management 261(1): 19-29.

Whiteside, T. G., G. S. Boggs and S. W. Maier (2011). "Comparing object-based and pixel-based classifications for mapping savannas." International Journal of Applied Earth Observation and Geoinformation 13(6): 884-893.

Wood, E. M., A. M. Pidgeon, V. C. Radeloff and N. S. Keuler (2012). "Image texture as a remotely sensed measure of vegetation structure." Remote Sensing of Environment 121: 516-526.

Wulder, M. A., R. J. Hall, N. C. Coops and S. E. Franklin (2004). "High spatial resolution remotely sensed data for ecosystem characterization." BioScience 54(6): 511-521.

Xie, Z., C. Roberts and B. Johnson (2008). "Object-based target search using remotely sensed data: A case study in detecting invasive exotic Australian Pine in south Florida." ISPRS Journal of Photogrammetry and Remote Sensing 63(6): 647-660.

Yan, G., J. F. Mas, B. Maathuis, Z. Xiangmin and P. Van Dijk (2006). "Comparison of pixel-based and object-oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China." International Journal of Remote Sensing 27(18): 4039-4055.

Yu, Q., P. Gong, N. Clinton, G. Biging, M. Kelly and D. Schirokauer (2006). "Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery." Photogrammetric Engineering & Remote Sensing 72(7): 799-811.

Zare, M., H. R. Pourghasemi, M. Vafakhah and B. Pradhan (2013). "Landslide susceptibility mapping at Vaz Watershed (Iran) using an artificial neural network model: a comparison between multilayer perceptron (MLP) and radial basic function (RBF) algorithms." Arabian Journal of Geosciences 6(8): 2873-2888.

Zhang, C. (2014). "Applying data fusion techniques for benthic habitat mapping and monitoring in a coral reef ecosystem." ISPRS Journal of Photogrammetry and Remote Sensing.

Zhang, C., D. Selch, Z. Xie, C. Roberts, H. Cooper and G. Chen (2013). "Object-based benthic habitat mapping in the Florida Keys from hyperspectral imagery." Estuarine, Coastal and Shelf Science 134: 88-97.

Zhang, C. and Z. Xie (2013). "Data fusion and classifier ensemble techniques for vegetation mapping in the coastal Everglades." Geocarto International(ahead-of-print): 1-16.

Zhang, C. and Z. Xie (2013). "Object-based vegetation mapping in the Kissimmee River watershed using HyMap data and machine learning techniques." Wetlands 33(2): 233-244.

Zhang, H., J. E. Fritts and S. A. Goldman (2008). "Image segmentation evaluation: A survey of unsupervised methods." computer vision and image understanding 110(2): 260-280.

Zhang, J., M. Marszałek, S. Lazebnik and C. Schmid (2007). "Local features and kernels for classification of texture and object categories: A comprehensive study." International journal of computer vision 73(2): 213-238.