Alien and invasive woody species in the dunes of the Wadden Sea Island of Vlieland

A remote sensing approach

W. Hantson, L. Kooistra and P.A. Slim

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A remote sensing approach

Wouter Hantson¹, Lammert Kooistra¹ and Pieter A. Slim²

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Abstract


In this study we mapped (alien) invasive shrubs for management and conservation purposes. On the study site, the Wadden Sea Island of Vlieland, they are a serious treat for the quality of the grey dune habitat. We developed a remote sensing approach that delivers detailed and standardized maps of (alien) shrub cover. Three classification methods are used: maximum likelihood (ML) classification of aerial photographs, maximum likelihood classification of aerial photographs combined with vegetation heights derived from LiDAR data (ML+), and object-based shrub classification.

Keywords: Alien species, Classification, Dunes, Hippophae rhamnoides, Invasive species, Maximum Likelihood, Object based, Prunus serotina, Remote sensing, Rosa rugosa, Shrub mapping, Vlieland, Wadden Sea Island

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Summary

Shrub encroachment due to a lack of appropriate grazing and the atmospheric deposition of nitrogen is a major threat to the Natura 2000 area the 'Vlieland Dunes' in Northern Europe. A key management objective for conservation of this area is to increase the quality and area of 'grey dunes', which are characterized by sandy slopes rich in lichens and open, species-rich vegetation. Dense shrub cover reduces species richness and changes the composition of the dunes.

This study develops a remote sensing approach to deliver detailed and standardized maps of (alien) shrub cover. Three classification methods are used: maximum likelihood (ML) classification, maximum likelihood classification combined with vegetation heights derived from LIDAR data (ML+), and object-based shrub classification.

The ML classification was carried out using multispectral aerial photographs. For the ML+ classification, LIDAR-derived vegetation height data was added as an extra layer. Although the derived vegetation height information turned out to be of low quality (as it was obtained during winter), it nonetheless increased the classification accuracy by more than 10%. Classification accuracy was particularly improved for the taller shrubs and small trees. The object-based shrub detection also performed well, with 82% accuracy of shrub detection.

The object-based classification (59.7% overall accuracy) performed better than the ML+ classification (50.4% overall accuracy) and produces results comparable to human visual analysis while offering guaranteed reproducibility and the process can be automated.

Overall, the object-based classification delivers reproducible shrub maps that are useful for management and evaluation of alien and invasive species in dune ecosystems. Use of LIDAR data obtained during summer could increase the accuracy of the mapping. Not only would the obtained vegetation heights be more precise, but also structural analyses like skewness and standard deviation of the measured heights could be used for the (object-based) classification.
1 Introduction

1.1 Grey dunes on the Wadden Sea Islands

1.1.1 Conservation value

The Wadden Sea Islands are located in Northern Europe and stretch from the coast of the Netherlands via Germany to Denmark in the south-eastern intertidal zone of the North Sea. The German and Dutch part of the Wadden Sea is a UNESCO World Heritage Site thanks to the unique habitats it offers.

‘Grey dunes’ represent a widely distributed vegetation type in the dune systems of the Wadden Sea Islands in North-west Europe (Fig. 1) (De Vries, 1950; Van Wingerden et al., 2002; Janssen and Schaminée, 2003; Isermann et al., 2007; Houston, 2008). In coastal dune systems, ‘grey dunes’ occupy the zone between the mobile dunes and dune shrub and are characterized by sandy slopes of lichens and open, species-rich vegetation (Fig. 2). The open nature of the habitat was maintained by extensive grazing of native herbivores, rabbits and domestic livestock.

Conservation of the grey dunes is an important task, because of their limited coastal occurrence, the semi-natural conditions, and the unique variation displayed in plant species (Isermann et al., 2007). The EU Habitats Directive (92/43/EEC) lists grey dunes as a priority habitat type, and categorizes them as ‘fixed and semi-fixed
coastal dunes with herbaceous vegetation (grey dunes)' (Natura 2000 Code 2130). Threats to the habitat come from over-stabilization, inappropriate grazing, growth of native and non-native shrub (Fig. 3), afforestation and alien species (Houston, 2008). Atmospheric deposition of nitrogen compounds is speeding up vegetation succession while also leading to bush encroachment and loss of the grey dunes habitat type.

1.1.2 Grazing, shrubs and exotic species

As with many semi-natural habitats, the loss of traditional management practices in the grey dunes has played a key role in its evolution from a dynamic state to a stable state (Houston, 2008). Historically, management of the grey dunes was characterized by extensive grazing together with a significant rabbit population.

After the introduction of the rabbit 800 years ago (Mühl, 1999), their activities like grazing, browsing, dunging (defecating), trampling and excavating holes became an important factor in maintaining habitat heterogeneity. However, the rabbits were almost eradicated by various virus infections in the late 1950s and late 1980s. Grazing with husbandry (goats) ended in the early 1920s. Cattle grazing as a management tool was locally introduced in the 1990s (Aptroot et al., 2007). The lack of grazing in recent decades speeded up the succession of the open dunes by shrubs and low trees.

Mortimer et al. (2000) called the expansion of shrubs in the grey dunes highly problematic from a conservation perspective. Isermann et al. (2007) pointed to shrub expansion as one of the most serious threats to the grey dune vegetation of the Frisian Islands (German Wadden Sea Islands). Indeed, expansion of native and exotic shrub in the coastal dune grasslands has had a considerable effect on species richness and diversity (Fuller and Boorman, 1977; Isermann et al., 2007; Isermann, 2008). It has caused the area of open grassland to decline (Isermann and Cordes, 1992) and altered environmental conditions. By forming dense, impenetrable layers, shrub reduces light availability, giving soils higher organic matter content, higher water storage capacity, and a different chemical composition than soils with open dune grassland vegetation (Hodgkin, 1984). This is a positive feedback mechanism by which 'more vegetation leads to more vegetation', and a driving force for vegetation succession resulting in shrub- and woodland.
Figure 2
Close up of the ‘grey dunes’ of Vlieland with the typical lichen vegetation including Cladina portentosa and Cladina arbuscula. The lower picture shows Prunus serotina sprouting, Cladonia coccifera, which is the lichen with the red apothecia, Cladonia ramulosa, the lichen with the brown apothecia and the neophytic invasive moss Campylopus introflexus.


1.2 Invasive shrubs

The increase of (exotic) shrubs is seen in a number of dune habitats, with a corresponding impact on the original vegetation. Rejmánek and Rosén (1988) found that a moderate level of shrub encroachment could increase species richness. Thiele et al. (2010) found an unimodal relationship between Rosa rugosa cover and dune species, but negative correlations with small species and annuals in grey and white dunes. A dense Rosa rugosa cover (Fig. 3) showed only a negative trend. Pearson and Rogers (1962) and Isermann et al. (2007) found a positive relationship between (tall, nitrogen-demanding) herbaceous species and Hippophae rhamnoides, but a negative relation with many typical (annual) dune species. Binggeli et al. (1992) found a 50% decrease in species richness in H. rhamnoides shrubland in the North Irish Dunes.

Figure 3
Invasive shrubs Hippophae rhamnoides (grey) and Rosa rugosa (green) in the dunes of Vlieland

Presence of the exotic Prunus serotina from North-America in the dunes is also increasing (Quist and Weeda, 2009), reducing species richness in the infected regions (Ehrenburg et al., 2008). Rosa rugosa (see Fig. 3) is an ‘invasive exotic’ from the Pacific coast of China, Japan and Korea. Its fast-growing rhizomes colonize various habitats in the Netherlands, Germany, Norway, Sweden and Lithuania (Bruun, 2005). These form dense shrubs, allowing virtually no native vegetation of high conservation value (Jensen, 1994; Weidema, 2000; Bruun, 2005). Rosa pimpinellifolia is a comparable species native to the grey dunes, but is eaten by rabbits and grows in a more open shrub that allows establishment of other species (Leentvaar, 2010). Isermann (2008) showed a greater decline in species richness, Shannon Index and evenness associated with an increase of the exotic Rosa rugosa than for the native Hippophae rhamnoides in the same grey dune environment. Quist and Weeda (2009) forecast that exotic species will become more prominent in the Netherlands in the future.

1.3 Shrub management

The primary management goal required by the EU Habitats Directive for the grey dunes is preservation of the species-rich short grasslands, by which some bare soil is maintained by the activities of animals such as rabbits (Houston, 2008). Management of shrubs and removal of invasive species, together with the introduction of extensive, year-round grazing, may be successful in restoring and maintaining fixed dune habitats.

Three species in particular pose specific problems and management issues in the grey dunes: Hippophae rhamnoides, Rosa rugosa and Prunus serotina.
1.3.1 Hippophae rhamnoides

*Hippophae rhamnoides* is native to North-west Europe, but became highly invasive after the reduction of grazing pressure in the grey dunes. Young slacks and open dunes are especially prone to invasion. Specific management projects to counter *H. rhamnoides* expansion have been developed in the United Kingdom, the Netherlands, France and Belgium (Houston, 2008).

1.3.2 Rosa rugosa

Establishment of the exotic *Rosa rugosa* is seed-limited in coastal dune habitats, but once arrived the species is able to populate all dune habitats (Kollmann et al., 2007). In coastal dunes of Denmark, *R. rugosa* has shown a relative annual area increment of 16.4% and an establishment rate of 0.02 patches per hectare per year (Kollmann et al., 2009). Kollmann et al. (2009) suggest that the aim of dune management should be to reduce seed production and dispersal of *R. rugosa* near natural sites.

1.3.3 Prunus serotina

*Prunus serotina* can reside in an area for many years, but suddenly increase in number and cover (Ehrenburg et al., 2008). Early detection of *P. serotina*, which is difficult in dunes, combined with direct management is necessary to protect the grey dunes from expansion of this species.

1.4 Habitats Directive

Article 17 of the Habitats Directive of the European Commission requires member states to report the condition and progress of their Natura 2000 sites once every six years (EC, 2002). Guidelines for compiling these reports are published by the Joint Nature Conservation Committee (www.jncc.gov.uk). With regard to shrubs and non-native species in dune grasslands, several targets are set:

- non-native species should be no more than rare
- shrubs/trees should be no more than occasional, or less than 5%
- tree invasion from adjacent plantations should be rare

Proper mapping of shrub cover and exotic species is a useful tool for obtaining the information necessary to compile the reports. Up-to-date and accurate maps, furthermore, allow for easier, cheaper, and more efficient management of exotic/invasive plant species, and can provide information on invasive species at an early succession stage, before they become problematic (Ehrenburg et al., 2008).

Remote sensing techniques could provide useful estimates of shrub and exotic species occurrence. Non-native species occurrence could also be used as a measure of the disturbance of an area, as this is reflected in the number of exotic and invasive species present (Callaway and Maron, 2006).

1.5 State of the art in remote sensing

Remote sensing has often been applied together with hyperspectral imagery to detect exotic species (Andrew and Ustin, 2008; Hestir et al., 2008). Imaging instruments are able to distinguish vegetation, but they cannot deliver physical information on vegetation structure. LIDAR (Light Detection and Ranging) is an active remote sensing technique that seems promising for vegetation structure mapping. Rango et al. (2000) used LIDAR data to map the characteristics of shrubs in coppice dunes. Johansen et al. (2010) successfully combined LIDAR data with an object-based image analysis to map streambed vegetation and its structural attributes.
Various other authors too have used image data together with LIDAR: Hudak et al. (2002) combined Landsat Enhanced Thematic Mapper (ETM) imagery with LIDAR data; Lee and Shan (2003) combined IKONOS imagery and LIDAR data; Mundt et al. (2006) combined hyperspectral imagery and LIDAR; and Erdody and Moskal (2010) combined LIDAR with multispectral images for the estimation of forest canopy fuels. Kempeneers et al. (2009) and Baptist (2009) combined airborne digital camera and LIDAR data to map costal dune vegetation. These studies demonstrate the ample potential for using remote sensing to map coastal shrub.

1.5.1 LIDAR

Airborne LIDAR systems derive information on elevation and reflectance of a terrain and its vegetation from a pulse (or continuous wave) laser emitted by an airborne transmitter fitted with an accurate positioning system. The time the pulse requires to travel from the laser to the earth’s surface and back provides an accurate measure of distance. Figure 4 shows a schematic illustration of an airborne LIDAR system.

![Airborne laser scanning system](image)

**Figure 4**

An airborne laser scanning system (McGaughey, 2010)

LIDAR data can provide information on the height of both the vegetative canopy and the ground surface to an accuracy within 0.10 m (Mallett and Bretar, 2009). The reflection of the airborne laser pulse is used to calculate the canopy height and the vegetation structure.

1.5.1.1 Canopy height

LIDAR data points are classified as ‘ground’ and ‘non-ground’. The ground data deliver information about the topography and are separated from the non-ground data, which are reflections of vegetation or artificial objects. The difference between the vegetation (maximum height) and topography (minimum height) is used to build a raster dataset of the vegetation height (Antonarakis et al., 2008; Stojanova et al., 2010; Streutker and Glen, 2006).

1.5.1.2 Vegetation structure

The vegetation height measure can be supplemented with information about the LIDAR point distribution. Figure 5 shows such a point distribution for a natural forest and a planted forest. Differences such as those observed in the figure can be used to classify the vegetation.
Antonarakis et al. (2008) used the point distribution of the LIDAR data to construct six models with which to classify land types: a canopy surface model, a terrain model, a vegetation height model, an intensity difference model, a kurtosis model and a percentage canopy model. These enable a highly accurate classification.

Lee and Lucas (2007) built a canopy density model that provides a quantitative measure of the relative penetration of LIDAR pulses into the canopy. These authors’ primary focus was to determine forest properties, but their index is also of interest for detection and classification of different shrub types.

### 1.5.2 Pixel-based classification

The maximum likelihood (ML) classifier is a supervised pixel-based classification algorithm. For each spectral category a probability density function is calculated. The probability of an unknown pixel value belonging to each category is calculated and the pixel is assigned to the class with the highest probability (Lillesand et al., 2008). The ML classifier is commonly used for image classification.

Kempeneers et al. (2009) used the ML classifier to map coastal vegetation, but they included vegetation height as extra information by adding an additional band to the aerial photography data and treating this as a normal spectral band.

The combination of spectral information from aerial photographs together with the vegetation height delivered by the LIDAR data should enable us to produce a map of (exotic) shrubs at the species level with the maximum likelihood classifier.

### 1.5.3 Object-based classification

Pixel-by-pixel analysis of remote sensing data is typical as long as the pixel size is smaller than or similar to the size of the object of interest, but in light of the increased availability of high-resolution images there is a trend to derive objects made up of several pixels (Blaschke, 2010). Object-based classifiers use both spectral and spatial patterns for image classification. This two-step process involves segmentation of the image into discrete objects followed by the classification of these objects (Lillesand et al., 2008).

Image segmentation was used in combination with LIDAR by Johansen et al. (2010), Antonarakis et al. (2008) and Baptist (2009). This approach, which combines an object-based classifier, spectral data and information on vegetation structure should enable us to create a map of the dune shrubs.
1.6 Objectives

Taking into account the need to conserve and manage the grey dune habitats and the results of previous research, remote sensing techniques appear promising for detecting and mapping (exotic) shrub species - especially with a combination of airborne LIDAR data (vegetation height), airborne digital camera images and an object-based classification.

The current study investigates a remote sensing approach to mapping dune shrubs, both native and exotic. It uses aerial images, once accompanied with LIDAR data, combined with a ML classification algorithm for the island of Vlieland. The ability to deliver species-specific shrub information useful for the management of exotic and invasive species is studied for a traditional pixel-based classification, and the opportunities for an object-based classification are explored.
2 Methodology

2.1 Study site: Vlieland

Vlieland is one of the West Frisian barrier islands, situated in the North of the Netherlands and surrounded by the North Sea in the north and the Wadden Sea in the south (Fig. 6). Most of the island is covered by dunes, except areas in the north and east, which are sandy beach. The ‘Vliehors’, situated in the south-west, is a sand bank in the first stages of dune succession. In the south the island is protected against the Wadden Sea by a dike.

The dry dunes are poor in chalk and iron, creating the specific conditions required for lichens, dune grasslands and heathland vegetation. Parabolic bare sand dunes are a typical phenomenon. Some of the dunes, especially those close to the town Vlieland-Oost, have been fixed by forest species which have stabilized the sand. ‘Kroon’s polders’ are dune valleys close to the groundwater level with chalk-rich vegetation.

Figure 6

*Vlieland, the Netherlands. The protected Natura 2000 area ‘Vlieland Dunes’ is outlined in yellow (as per the Habitats Directive and Birds Directive)*

The ‘Vlieland Dunes’ Natura 2000 area (Fig. 6) covers 1,533 ha protected by the EU Habitats and Birds directives (EC, 2002). The forest zone in the north-east is protected only by the Habitats Directive. Table 1 presents the Natura 2000 habitat types found on Vlieland and management objectives set for each. Grey
dunes are a key habitat type on the island, and their management is aimed at increasing both their quality and area.

Table 1

<table>
<thead>
<tr>
<th>Natura 2000 habitat types on Vlieland and the management objectives for each in terms of area and quality (objectives are reached: = or the objectives are an increase of the specific habitat type: &gt;)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natura 2000 habitat types on Vlieland</td>
</tr>
<tr>
<td>----------------------------------------</td>
</tr>
<tr>
<td>H1.310 Salicornia and other annuals colonizing mud and sand</td>
</tr>
<tr>
<td>H1.330 Atlantic salt meadows</td>
</tr>
<tr>
<td>H2110 Embryonic shifting dunes</td>
</tr>
<tr>
<td>H2120 Shifting dunes along the shoreline with Ammophila arenaria ('white dunes')</td>
</tr>
<tr>
<td>H2130 Fixed coastal dunes with herbaceous vegetation ('grey dunes')</td>
</tr>
<tr>
<td>H2140 Decalcified fixed dunes with Empetrum nigrum</td>
</tr>
<tr>
<td>H2160 Dunes with Hippophae rhamnoides</td>
</tr>
<tr>
<td>H2170 Dunes with Salix repens ssp. argentea</td>
</tr>
<tr>
<td>H2180 Wooded dunes</td>
</tr>
<tr>
<td>H2190 Humid dune slacks</td>
</tr>
</tbody>
</table>

The small West Frisian barrier island of Vlieland was selected for this study due to its quasi-undisturbed dunes, although groundwater extraction has influenced its biodiversity. The grey dunes have been invaded by various shrub species. To preserve this habitat type, the Dutch Forestry Service (Staatsbosbeheer) introduced light grazing by Scottish highland cattle in 1993 in an attempt to make up for the diminished rabbit grazing. Studying 10 years of monitoring data, Aptroot et al. (2007) found that herbivores are able to retard vegetation succession to species-poor shrub.

2.2 Key species

Of the shrubs and trees present, this study selected six species of interest (Table 2) based on their invasive character, their non-native origin and their occurrence in the grey dunes.

Table 2

<table>
<thead>
<tr>
<th>Shrub and tree species of Vlieland</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common name</td>
</tr>
<tr>
<td>-------------</td>
</tr>
<tr>
<td>Sea buckthorn</td>
</tr>
<tr>
<td>Black pine</td>
</tr>
<tr>
<td>Black cherry</td>
</tr>
<tr>
<td>Japanese rose</td>
</tr>
<tr>
<td>Creeping willow</td>
</tr>
<tr>
<td>Common elder</td>
</tr>
</tbody>
</table>

2.3 Materials

To set up a proper shrub monitoring system based on remote sensing, availability of frequently updated data is crucial. Almost every year there is an aerial photograph campaign in the Netherlands, but these do not always include the near-infrared band. Previous years Alterra obtained aerial images for every three years. Acquisition of LIDAR data is less frequent. With a time span of ten years in between Actual Height of the
Netherlands (AHN-1 and AHN-2). Table 3 presents the data employed. Most was obtained from Alterra’s GeoDesk (in 2010) and Albert Prakken, Ministry of Transport, Public Works and Water Management (in 2009 and 2010).

**Table 3**

*Data employed*

<table>
<thead>
<tr>
<th>Data</th>
<th>Source</th>
<th>Type</th>
<th>Resolution</th>
<th>Projection</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerial photograph – red, green and blue (RGB)</td>
<td>GeoDesk</td>
<td>Raster</td>
<td>0.25m</td>
<td>RD</td>
<td>2008</td>
</tr>
<tr>
<td>Aerial photograph – colour infrared (CIR)</td>
<td>GeoDesk</td>
<td>Raster</td>
<td>0.25m</td>
<td>RD</td>
<td>2008</td>
</tr>
<tr>
<td>LIDAR</td>
<td>Rijkswaterstaat</td>
<td>Points</td>
<td></td>
<td>RD</td>
<td>winter - 2008</td>
</tr>
<tr>
<td>Fieldwork</td>
<td>Alterra</td>
<td>Polygons</td>
<td></td>
<td>RD</td>
<td>July - 2010</td>
</tr>
</tbody>
</table>

2.3.1 **Aerial photographs**

The aerial photographs obtained from the GeoDesk are high resolution (25 cm) and fully cover the island of Vlieland. They were taken during the summer of 2008, and both RGB and CIR are available.

2.3.2 **LIDAR**

The available LIDAR data has a point distribution of 0.18 m and was flown in the winter of 2008 to derive the AHN2 map. Because the shrubs of interest in this study lose their leaves in winter, the LIDAR laser must be reflected by the plant stems and branches, meaning that the measurements will be influenced more by stem and branch density than by the maximum height of the green vegetation. It will be challenging to derive vegetation height from this data, and special attention will therefore be spent validating and determining the accuracy of the LIDAR-derived vegetation height. The LIDAR data covers only the North Sea side of Vlieland (Fig. 7), so the analysis will be performed only for that part of the island.

![Figure 7](Image)

*Figure 7*

*Area of Vlieland covered by the LIDAR data*
2.3.3 Field data

Classification of the (exotic) shrub vegetation requires calibration and validation data. The calibration and validation data were collected during a field campaign on Vlieland from 29 June through 6 July 2010. Shrub data was collected on the three transects shown in Figure 8. Along these transects, single-species patches with homogeneous vegetation were identified and measurements were taken of the mean height. The vegetation was described and the patch was drawn on the aerial photograph.

![Figure 8](image)

Figure 8
Transects for the 2010 field campaign. From left to right: 1. Lange Paal, 2. Kooipleksld-Vuurboetsduin, 3. Noordoosthoek

In total, 145 patches were selected, localized on the map and stored in ArcGIS. Figure 9 shows the number of single-species patches per shrub species.

![Figure 9](image)

Figure 9
Single species plots per species of interest
2.4 Methods

The creation of a shrubs map of Vlieland was based on the 2008 LIDAR and aerial photograph data combined with the fieldwork data from 2010. Figure 10 shows the workflow, starting from the 2008 datasets. The data obtained during the fieldwork campaign were used to calibrate and validate the classification algorithms and to validate the vegetation height model.

Figure 10
Workflow from raw data to the classification

2.4.1 LIDAR processing

Analyses of the LIDAR data started with the creation of a bare earth model. The raw data includes both reflectance from the soil and that from vegetation. In order to derive the vegetation height, the point data was rasterized. The lowest point in each cell was assumed to represent the ground surface while the highest was taken to represent the canopy surface height. The difference between the canopy surface height and the ground surface was calculated as the vegetation height. The spatial resolution of the raster was set at 1.5 m so as to obtain all of the representative information from the LIDAR dataset (Kempeneers et al. 2009).

Canopy height model
LIDAR point extraction and calculations were done with the freely available Fusion software (www.fs.fed.us/eng/rsac/fusion/). The Groundfilter algorithm was used to identify the bare earth points. This
output was used in Grid Surface Create to produce a surface model. The Canopy Model algorithm creates a canopy surface model by assigning the highest return within each grid cell to the grid centre. The canopy height is calculated by extracting the surface model from the canopy surface model.

**Random vertical error**
The relative error was determined by performing a statistical analysis of a collection of points returned from a flat surface (Streutker and Glen, 2006). These LIDAR points are expected to lie on a flat plane. The error so measured is random error (ASPRS, 2004) and represents the upper bound for the absolute and relative vertical accuracy of the vegetation height dataset (Kempeneers et al., 2009).

**Systematic vertical error**
Systematic error occurs in estimating vegetation heights due the limited ability of the laser to penetrate vegetation (ASPRS, 2004; Hodgson and Bresnahan, 2004; Kempeneers et al., 2009). The penetration coefficient is species-specific and in this case high because the LIDAR data was obtained in the winter. Determination of the systematic error was done for Hippophae rhamnoides, Prunus serotina, Rosa rugosa and Salix repens. Pinus nigra and Sambucus nigra were not included because their average height is greater than 2 m, making them difficult to measure in the field.

Streutker and Glen (2006) found that LIDAR measurements underestimate vegetation height. In their study, linear regression showed LIDAR-derived heights to be less than half the heights measured in the field. They also found a lack of correlation below 20 cm.

In the current study, a species-specific linear regression was included to determine the systematic vertical error in the dataset. The heights measured during the fieldwork were compared with the LIDAR-derived vegetation heights for different patches. Both average and maximum heights (see Fig. 16) were compared. Furthermore, a linear relationship was investigated both with and without a fixed intercept at (0,0). The goodness of fit was observed using R².

**Vegetation structure**
The standard deviation of the vegetation heights represents the variability of the vegetation height (Streutker and Glen, 2006). Mundt et al. (2006) described an even better method to capture the variability of the canopy than by the mean height or skewness. Their calculation is done by comparing the number of points reflected by the top canopy with the total number of points in a specified area. In Fusion, the CloudMetric algorithm is used to estimate of the canopy cover by calculating the percentage of LIDAR returns above a specific height.

**2.4.2 Classification**

**Pixel-based classification**
ML classification was carried out for the CIR aerial photographs and for the dataset including the extra height information. The validation and calibration dataset was kept separate, but the same dataset was used as for the two classifications so as to make the results comparable.

The validation dataset is made up of polygons identified in the field which are covered with almost 100% of a single shrub species. Classification accuracy was measured as the percentage of correctly classified pixels within these polygons.

The ML classifier was integrated using the ENVI 4.5 software, and the data fusion was done in ArcGIS 9.3.
Object-based classification

The purpose of object-based mapping is to derive ‘objects’ that are made up of several pixels but have similar (shrub) characteristics. The object-based classification started with segmentation of the image data into ‘objects’ based on three parameters: scale, shape and spectral information. The parameter settings were determined by trial and error.

The object-based shrub detection used the segmented aerial photographs, the canopy height, the Normalized Difference Vegetation Index (NDVI) and canopy cover as inputs. Based on validation data, thresholds were set to classify the objects. Levick and Rogers (2008) classified woody vegetation cover to up to 95% accuracy using an object-based classification system.

The objects classified as shrubs can be used in another classification step in which extra data is added to classify the shrubs to the species level. This study conducts this classification step via two paths:

- Object based classification with species probability maps
- Object based classification combined with the ML+ classification

Regarding the first, species probability maps were created using the characteristics of the different shrub species (Table 4). The data used is similar to that employed in shrub detection, but the ML+ classification is added. For every species a rule dataset was produced to reclassify the layers in order to obtain a probability layer for each shrub species. The mean probabilities for each layer were compared at the patch level. Each shrub patch was classified as the species with the highest probability. The second path, maximum likelihood classification, uses only the ML+ classification results of the different shrub species as layers, and patches are classified as the species with the highest occurrence.

The software used for image segmentation was eCognition Developer 8.0.1. Segmentation of the CIR aerial images was performed with shape = 0.5 and compactness = 0.8. The scale parameter was set at 40. An NDVI > 0.21 and canopy cover > 11% (between 0.1 and 2 m) was used to determine shrubs. These parameters were determined by trial and error.

Table 4
Parameters used in calculating the probability maps

<table>
<thead>
<tr>
<th></th>
<th>NDVI</th>
<th>CHM</th>
<th>CC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Sd</td>
<td>Min</td>
</tr>
<tr>
<td>Hippophae rhamnoides</td>
<td>0.30</td>
<td>0.08</td>
<td>0.21</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>0.39</td>
<td>0.09</td>
<td>0.30</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>0.36</td>
<td>0.07</td>
<td>0.29</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>0.50</td>
<td>0.09</td>
<td>0.41</td>
</tr>
<tr>
<td>Salix repens</td>
<td>0.36</td>
<td>0.09</td>
<td>0.27</td>
</tr>
</tbody>
</table>
2.4.3 Validation

The accuracy of the different classification methods is expressed using the familiar error matrix in which the obtained classification result is compared to the validation dataset. The overall accuracy is calculated for all classifications and for the different shrub species the producer's accuracy is reported together with the user's accuracy. As the focus of the current study is to compare the different species, values are presented as percentages. The producer's accuracy is obtained by dividing the number of correct classified pixels in each category by the total number of pixels in each category (here the different shrub species). The user's accuracy is calculated by dividing the number of correct classified pixels for each category by the total number of classified pixels as that category. The overall accuracy is computed by dividing the correct classified pixels of each category by the total number of reference pixels.

The detection limit of the ML+ classification is determined by comparing the classification accuracy with the number of pixels of the validation dataset. A graph will shown the classification accuracy in relation to the patch size, which makes it possible to determine the detection limit for the different alien and/or invasive shrub species.
3 Results

3.1 LIDAR calculations

To derive the vegetation height from the raw LIDAR data, a canopy surface model (CSM, Fig. 11), a terrain model (TM, Fig. 12) and a canopy height model (CHM, Fig. 13) were created. Using the vegetation height, the canopy cover was calculated for vegetation less than 2 m (shrubs and smaller species) and for vegetation greater than 2 m (large shrubs and trees) (Fig. 14). The height data obtained was validated and the random and systematic species-dependent error was determined. In order to use the height distribution for the classification, height characteristics were investigated for the different shrub species.

3.1.1 Vegetation height

The canopy surface model (Fig. 11) shows the surface height together with the vegetation height. The continuous row of dunes is clearly visible on the North Sea side of the island (in the north-west), and considerable height is recorded for the planted forest surrounding the town of Vlieland in the north-east. Some dune slacks and the Kroon’s polders are almost at sea level, so they are bluish in colour. It is not yet clear whether the attributes that appear to be high (red) are dunes or vegetation.

Figure 12, the terrain model, shows the topography of the terrain under the vegetation. Some dune slacks become visible below the forest layer. By subtracting the canopy surface model from the terrain model, the vegetation height (Fig. 13) becomes visible, and the location of the forests and shrubs are clearly revealed. Figure 14 shows the canopy cover, making a distinction between shrub (<2m) and forest (>2m).
Figure 11
LIDAR-derived canopy surface model (CSM) of Vlieland

Figure 12
LIDAR-derived terrain model (TM) of Vlieland
Figure 13
LIDAR-derived canopy height model (CHM) of Vlieland

Figure 14
LIDAR-derived canopy cover of Vlieland
3.1.2 Validation of the height obtained using LIDAR

The vegetation height obtained using LIDAR was possibly affected by different types of error. Two types of error are especially relevant: (i) the random vertical error or measurement error and (ii) the systematic species-dependent vertical error.

Random vertical error
Vertical accuracy was determined by performing a statistical analysis on several flat surfaces: bare sand, a parking lot and a road. Figure 15 shows the height distribution of these flat surface measurements. All of the points should indicate a zero height difference without the occurrence of any error. The mean of the sample was 0.025 m with a standard deviation of 0.029 m. The height of 0.054 m represents the upper bound of the absolute and relative vertical accuracy of the vegetation height dataset (Kempeneers et al., 2009).

Systematic vertical error
The results of the plotted dataset with a fixed intercept (Fig. 16 and Table 5) show an almost one to one relationship with the maximum height, while the mean height is only 40% of the measured mean height. The low $R^2$ values indicate high variability for all species. The $R^2$ values for the linear relationship without a fixed intercept are better but still low.
**Figure 16**
Relationship between the maximum obtained LIDAR-derived height within a grid cell of 1.5 m and the reference height measured in the field with a fixed intercept at (0,0) (Analysed in excel 2003)

**Table 5**
Linear relationship from the plot dataset between the maximum and mean LIDAR-derived height and the field-measured reference height with and without a fixed intercept at (0,0)

<table>
<thead>
<tr>
<th>Plot data</th>
<th>Max height</th>
<th>Mean height</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intercept = 0</td>
<td>R²</td>
</tr>
<tr>
<td>Hippophae rhamnoides</td>
<td>0.43</td>
<td>0.86</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>0.34</td>
<td>0.73</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>0.24</td>
<td>1.22</td>
</tr>
<tr>
<td>Salix repens</td>
<td>0.25</td>
<td>0.80</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Plot data</th>
<th>Max height</th>
<th>Mean height</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intercept &gt;0</td>
<td>R²</td>
</tr>
<tr>
<td>Hippophae rhamnoides</td>
<td>0.43</td>
<td>-</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>0.35</td>
<td>-</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>0.30</td>
<td>-</td>
</tr>
<tr>
<td>Salix repens</td>
<td>0.29</td>
<td>-</td>
</tr>
</tbody>
</table>

### 3.1.3 Shrub height distribution

Figure 17 shows the distribution of the LIDAR height measurements per shrub species. All of them show highly dense height measurements below half a meter. Only for *Pinus nigra* are 50% of the height measurements
greater than 3 m, and *Prunus serotina* and *Sambucus nigra* have a more uniform distribution. Most of the differences in height distribution are found in the heights 0-0.1 m and 0.1-0.2 m.

<table>
<thead>
<tr>
<th>Species</th>
<th>LIDAR Mean Height (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prunus serotina</td>
<td>0.0 10.0 20.0 30.0 40.0</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>0.0 10.0 20.0 30.0 40.0</td>
</tr>
<tr>
<td>Salix repens</td>
<td>0.0 10.0 20.0 30.0 40.0</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>0.0 10.0 20.0 30.0 40.0</td>
</tr>
<tr>
<td>Hippophae rhamnoides</td>
<td>0.0 10.0 20.0 30.0 40.0</td>
</tr>
<tr>
<td>Sambucus nigra</td>
<td>0.0 10.0 20.0 30.0 40.0</td>
</tr>
</tbody>
</table>

**Figure 17**
Histograms of the LIDAR-derived height distribution per species

The derivation of extra height parameters, like skewness and standard deviation, was not useful due to the poor vegetation reflectance in the winter season. Comparing the histograms of Figure 17, little difference is observed between the species in height distribution. The extra parameters will not be used in the further mapping and classification.
3.2 Pixel-based classification

3.2.1 Maximum likelihood classification

Figure 18 displays the maximum likelihood (ML) classification of the CIR aerial photograph of Vlieland and the location of a close up where the shrub classification is shown in detail (Fig. 20). Figure 19 presents the results of the ML+ classification of Vlieland (the CIR aerial photograph with the extra vegetation height layer), with the same close-up area indicated to provide a comparable shrub classification detail (Fig. 21). The maps show the classification of only the species of interest.

Figure 18
Maximum likelihood (ML) classification. The boxed location is the area of detail shown in Figure 20

Figure 19
Maximum likelihood classification with extra vegetation height information (ML+). The boxed location is the area of detail shown in Figure 21
Differences in the registered occurrence of the various shrub species are clearly visible on the two detailed classification maps (Figs. 20 and 21). *Rosa rugosa, Salix repens* and *Sambucus nigra* form patches while *Hippophae rhamnoides* has a more spread occurrence. Tables 6 and 7 present classification accuracies, with the producer’s accuracy on the diagonal and the user’s accuracy in the far-right column.
Table 6
Accuracy of the ML classification of the CIR image, per cent correctly classified pixels in the validation polygons. The diagonal represents the producer’s accuracy.

<table>
<thead>
<tr>
<th>Field</th>
<th>Hippophae rhamnoides</th>
<th>Pinus nigra</th>
<th>Prunus serotina</th>
<th>Rosa rugosa</th>
<th>Salix repens</th>
<th>Sambucus nigra</th>
<th>Row Total</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hippophae rhamnoides</td>
<td>32</td>
<td>15</td>
<td>29</td>
<td>4</td>
<td>31</td>
<td>1</td>
<td>112</td>
<td>29</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>6</td>
<td>34</td>
<td>6</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>50</td>
<td>68</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>9</td>
<td>14</td>
<td>29</td>
<td>6</td>
<td>2</td>
<td>2</td>
<td>66</td>
<td>44</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>54</td>
<td>1</td>
<td>15</td>
<td>73</td>
<td>74</td>
</tr>
<tr>
<td>Salix repens</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>10</td>
<td>22</td>
<td>3</td>
<td>42</td>
<td>52</td>
</tr>
<tr>
<td>Sambucus nigra</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>65</td>
<td>71</td>
<td>92</td>
</tr>
</tbody>
</table>

Table 7
Accuracy of the ML+ classification of the CIR image with the added height information, per cent correctly classified pixels in the validation polygons. The diagonal represents the producer’s accuracy.

<table>
<thead>
<tr>
<th>Field</th>
<th>Hippophae rhamnoides</th>
<th>Pinus nigra</th>
<th>Prunus serotina</th>
<th>Rosa rugosa</th>
<th>Salix repens</th>
<th>Sambucus nigra</th>
<th>Row Total</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hippophae rhamnoides</td>
<td>46</td>
<td>7</td>
<td>41</td>
<td>6</td>
<td>33</td>
<td>2</td>
<td>135</td>
<td>34</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>3</td>
<td>76</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>84</td>
<td>90</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>17</td>
<td>6</td>
<td>42</td>
<td>11</td>
<td>16</td>
<td>9</td>
<td>101</td>
<td>42</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>60</td>
<td>2</td>
<td>9</td>
<td>72</td>
<td>83</td>
</tr>
<tr>
<td>Salix repens</td>
<td>2</td>
<td>0</td>
<td>4</td>
<td>14</td>
<td>30</td>
<td>1</td>
<td>51</td>
<td>58</td>
</tr>
<tr>
<td>Sambucus nigra</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>75</td>
<td>79</td>
<td>95</td>
</tr>
</tbody>
</table>

The overall accuracy of the ML classification is 38.7%, but the user’s and producer’s accuracies shown that the classification accuracy is very species-dependent. The producer’s accuracy is ranging from 22% to 65% and the user’s accuracy varying from 29% to 92% (Table 6). The ML+ classification have an overall accuracy of 50.4% and is also species-dependent with the user’s accuracy ranging between 34% and 95% and the producer’s accuracy between 30% and 76% (Table 7). Visually comparing the detail maps (Figs. 21 and 22),
they appear similar. Nonetheless, looking at the overall classification accuracy we find that the extra vegetation height information improved classification success, raising it from 38.7% up to 50.4%. Table 8 shows the change in producer’s and user’s accuracy per species, showing that the extra height information especially improved the taller shrub species.

Table 8
Change in accuracy of ML classification with additional height information as an extra layer

<table>
<thead>
<tr>
<th>Species</th>
<th>Producer’s accuracy</th>
<th>User’s accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hippophae rhamnoides</td>
<td>+14%</td>
<td>+5%</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>+42%</td>
<td>+22%</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>+13%</td>
<td>-2%</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>+6%</td>
<td>+9%</td>
</tr>
<tr>
<td>Salix repens</td>
<td>+8%</td>
<td>+6%</td>
</tr>
<tr>
<td>Sambucus nigra</td>
<td>+10%</td>
<td>+3%</td>
</tr>
<tr>
<td>Overall accuracy</td>
<td>+11%</td>
<td></td>
</tr>
</tbody>
</table>

3.2.2 Detection limit of pixel-based classification

The correctly classified pixels (expressed as percentages) were compared to the total area of the validation polygon (pixel = 0.0625 m²). Figures 22, 23 and 25 show that the curves follow a species-dependent logarithmic function. The general trend is a rapid increase of correctly classified pixels as patch size increases. Exceptions are Hippophae rhamnoides, which shows a fast decrease before levelling out, and Sambucus nigra, which has an almost constant classification accuracy of 70%.

![Graph showing detection limit based on the ML+ classification, part 1](image)

*Figure 22* Detection limit based on the ML+ classification, part 1
Figure 23
Detection limit based on the ML+ classification, part 2
3.3 Object-based classification

3.3.1 Shrub detection

Segmentation of the CIR aerial images was performed first, with parameters determined by trial and error. Extra layers, such as percentage cover and the Normalized Difference Vegetation Index (NDVI), were used for shrub detection (Figs. 25 and 26).

The shrub map of Vlieland (Fig. 25) is dominated by the central forest, but looking at the detail map (Fig. 26) we see that lower vegetation is correctly classified as shrub.
The object-based shrub detection performed well, with a minimum of 82% of all validation patches classified correctly (Table 9). This layer is the basis of the shrub species classification, so a good classification at this stage is encouraging for further analysis.

### 3.3.2 Species classification

After shrub detection, two species probability maps were created for further shrub classification to the species level. This was done by constructing a probability map for each species (Fig. 27) based on the NDVI, canopy cover, and vegetation height and by using the ML+ classification. The probability maps (Fig. 28) used only the per-species results of the ML+ classification.
Figure 27
Per species probability maps. Red represents a high probability for that species to occur. (A) Salix repens, (B) Pinus nigra, (C) Prunus serotina, (D) Sambucus nigra, (E) Hippophae rhamnoides and (F) Rosa rugosa
Figure 28
Per species results of the ML + classifier. (A) Salix repens, (B) Pinus nigra, (C) Prunus serotina, (D) Sambucus nigra, (E) Hippophae rhamnoides, and (F) Rosa rugosa
**Figure 29**
Object-based shrub classification based on the probability maps. Figure 31 shows the detailed map of the pointed area and the legend.

**Figure 30**
Object-based shrub classification based on the per species results of the ML+ classifier. Figure 32 shows the detailed map of the pointed area and the legend.
Figure 31
Detail of the object-based shrub species classification based on the probability maps

Figure 32
Detail of the object-based shrub species classification based on the per species results of the ML+ classifier
Table 10
Classification accuracy of the object-based shrub species classification based on the probability maps. The diagonal represents the producer’s accuracy

<table>
<thead>
<tr>
<th>Classification data</th>
<th>Reference data</th>
<th>User's accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hippophae rhamnoides</td>
<td>Pinus nigra</td>
</tr>
<tr>
<td>Hippophae rhamnoides</td>
<td>55</td>
<td>0</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Salix repens</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sambucus nigra</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Not classified</td>
<td>30</td>
<td>90</td>
</tr>
</tbody>
</table>

Table 11
Classification accuracy of the object-based shrub species classification based on the per species results of the ML+ classifier. The diagonal represents the producer’s accuracy

<table>
<thead>
<tr>
<th>Classification data</th>
<th>Reference data</th>
<th>User's accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hippophae rhamnoides</td>
<td>Pinus nigra</td>
</tr>
<tr>
<td>Hippophae rhamnoides</td>
<td>66</td>
<td>7</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>0</td>
<td>73</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>16</td>
<td>3</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Salix repens</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Sambucus nigra</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Not classified</td>
<td>17</td>
<td>17</td>
</tr>
</tbody>
</table>

The overall accuracy of the shrubs species, classified using the per species results of the ML+ classifier (Figs. 30 and 32), delivered with 59.7% accuracy a better classification results than the classification using the probability maps (Figs. 29 and 31) which have an overall accuracy of 49.0%. In general Salix repens and Prunus serotina are difficult to classify using an object based approach. The classification results the object-based shrub species classification based on the per species results of the ML+ classifier (Tables 10 and 11) are better for Hippophae rhamnoides, Rosa rugosa and Sambucus nigra, while Pinus nigra and Salix repens performed equal in comparison to the ML+ classification.
Table 12
Overview of the classification results obtained by the different classification methods. (PA: producer’s accuracy, UA: user’s accuracy)

<table>
<thead>
<tr>
<th>Species</th>
<th>ML</th>
<th></th>
<th>ML+</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PA (%)</td>
<td>UA (%)</td>
<td>PA (%)</td>
<td>UA (%)</td>
</tr>
<tr>
<td>Hippophae rhamnoides</td>
<td>32</td>
<td>29</td>
<td>46</td>
<td>34</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>34</td>
<td>68</td>
<td>76</td>
<td>90</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>29</td>
<td>44</td>
<td>42</td>
<td>42</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>54</td>
<td>74</td>
<td>60</td>
<td>83</td>
</tr>
<tr>
<td>Salix repens</td>
<td>22</td>
<td>52</td>
<td>30</td>
<td>58</td>
</tr>
<tr>
<td>Sambucus nigra</td>
<td>65</td>
<td>92</td>
<td>75</td>
<td>95</td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td>39</td>
<td></td>
<td>50</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Species</th>
<th>OB (prob.)</th>
<th></th>
<th>OB (ML+)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PA (%)</td>
<td>UA (%)</td>
<td>PA (%)</td>
<td>UA (%)</td>
</tr>
<tr>
<td>Hippophae rhamnoides</td>
<td>55</td>
<td>60</td>
<td>66</td>
<td>32</td>
</tr>
<tr>
<td>Pinus nigra</td>
<td>10</td>
<td>96</td>
<td>73</td>
<td>99</td>
</tr>
<tr>
<td>Prunus serotina</td>
<td>0</td>
<td>0</td>
<td>15</td>
<td>21</td>
</tr>
<tr>
<td>Rosa rugosa</td>
<td>67</td>
<td>100</td>
<td>69</td>
<td>100</td>
</tr>
<tr>
<td>Salix repens</td>
<td>28</td>
<td>80</td>
<td>28</td>
<td>75</td>
</tr>
<tr>
<td>Sambucus nigra</td>
<td>77</td>
<td>99</td>
<td>82</td>
<td>98</td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td>49</td>
<td></td>
<td>60</td>
<td></td>
</tr>
</tbody>
</table>

Comparing the results of the different classification methods, the object based species classification (based on the per species results of the ML+ classifier) delivered the best overall accuracy (Table 12).

The object based approach delivered a vegetation map with clear patches of the different shrub species and a better overall classification result than the ML+ classification (+10%). The combined effect of extra height information and the object based approach resulted in an increase of 21% in comparison to the classical pixel based maximum likelihood classification.

3.3.3 Effect of grazing analysed using object-based classification

The object-based shrub classification was used to conduct a follow-up analysis of the effect of grazing on shrub encroachment on Vlieland. Shrub occurrence on five plots with and without grazing pressure was compared with field results from 2000 by Van Wingerden et al. (2001). The earlier data was gathered to evaluate the impact of seven years of cattle grazing in the dune valleys of Vlieland. The plots are indicated by the dashed lines in the figures below, though these locations are not exact, due to the inaccuracy of the GPS used.
Plots 14, 15 and 16 are quite dry and dominated by sedges. Comparing the data from 2008 (Fig. 33) with that from 2000 (Fig. 34), the effects of grazing are clearly visible. Plots 14 and 15 were grazed (begraasd) and had no shrub vegetation in 2008. Plot 16 is an enclosure without grazing pressure (onbegraasd) and there shrubs were present. Plots 14 and 15 were dominated by *Salix repens*, though this shrub was not detected in the 2008 data. The *Prunus serotina* and *Rubus fruticosus* on the east of plot 16 were still present in 2008, but classified as *Hippophae rhamnoides* or as a non-specified shrub (*Rubus fruticosus* was not included in the 2008 classification). The *Prunus serotina* shrubs on plot 15 and on the east side of plot 16 have disappeared, or went undetected in 2008.

**Figure 34**
Shrub encroachment on plots 14, 15 and 16 based on field observations in 2000. The left column represents the occurrence of *Prunus serotina* (black) and *Rubus fruticosus* (cube). The right column represents the occurrence of *Salix repens* (Van Wingerden et al., 2001).
Plots 19 and 20

Plots 19 and 20 are located in a humid dune valley. Both plots had grazing pressure and a comparable cover of *Salix repens* in 2000 (Fig. 36). The shrub cover in 2008 is quite different (Fig. 35). The shrubs on plot 20 are not classified at the species level, but in view of the 2000 data, it is probably *Salix repens*.

There is a general decrease in shrub area from 2000 to 2008, except for the enclosed plot 16 and for plot 20. Analyses of these five plots show the potential value of remote sensing imagery for vegetation mapping. While this exercise focused narrowly on classification of shrubs on Vlieland, it demonstrates that remote sensing is useful on a small scale (40 m by 40 m) if the constraints of the method are known and accommodated. Here the constraints are basically the scale and the detection limit of single species of shrubs.
4 Discussion

4.1 Vegetation height

The LIDAR data is highly accurate, with a random error of just 0.025 m +/- 0.029 m. The derived vegetation heights are therefore quite precise. Despite this degree of accuracy, the current study’s validation of the LIDAR-derived vegetation heights for the different shrub species produced low R² values, between 0.01 and 0.48. This substantial error is attributable to the fact that the LIDAR data was acquired in winter. The shrub species observed have no leaves in winter, meaning that the height measurements were dependent on the shrub stems reflecting the laser pulse. This produced less accurate measures than those previously found using LIDAR data. For example, Kempeneers et al. (2009) found a linear relation between LIDAR-derived shrub heights and reference values, with an R² of 0.98 (Fig. 37). In contrast, our best result was 0.48. This poor correlation between the heights calculated using the vegetation-reflected LIDAR signal and reference values was a limiting factor in this study’s use of LIDAR-derived vegetation structure parameters.

![Figure 37](image)

*Figure 37*  
Scatterplot showing vegetation heights of shrubs vs. reference heights from Kempeneers et al. (2009), p.78

The poor estimation of vegetation height meant that a larger raster size was needed. The raster size used was 1.5 m², large enough to catch the LIDAR reflection from some vegetation, but small enough for the calculated vegetation height to be representative for the complete grid cell. A larger grid cell might have led to a better estimation of height for the larger patches, but would have overlooked some small patches of specific shrub species. A similar issue arises for measurements in dense vegetation, but there the problem is to obtain sufficient non-vegetated pulses to be able to create a proper terrain model. In fact, that was the main reason for conducting the 2008 LIDAR flight.

Use of LIDAR data obtained in late spring or summer would increase classification accuracy to the high level obtained by Kempeneers et al. (2009). This would also enable the use of smaller pixels and LIDAR-derived vegetation structure parameters.
4.2 Pixel-based classification

The maximum likelihood (ML) classification based on the CIR aerial images performed relatively well, though the overall classification accuracy was low (38.7%). Because the validation dataset was set up specifically to determine the detection limit of single-shrub patches, it was made up mostly of small, hard-to-classify patches. Moreover, species-level classification of shrubs is difficult. For mixes of shrub species, Baptist (2009) similarly reports low classification accuracy for Salix repens (0%) and Hippophae rhamnoides (56%). Kempeneers et al. (2009) obtained, respectively, 21% and 49%, comparable with the results of the current study.

The use of LIDAR-derived vegetation height as an additional classification layer substantially improved the classification result. Up to 50.4% for the overall accuracy, but especially for the taller species Pinus nigra, for which accuracy rose from 34% to 76%. This supports the conclusion by Kempeneers et al. (2009) that tall vegetation types benefit most from fusion of the data. Overall, our species classification results improved by 6-42%, comparable to previous studies, which have obtained increases of 16% (Kempeneers et al., 2009) and 16-20% (Bork and Sue, 2007).

Unfortunately the accuracy of the Salix repens classification, which was 22%, increased only to 30% with the additional classification layer, because the smallest patches were still classified as Hippophae rhamnoides. With a more accurate vegetation height measurement (flown during summer), classification accuracy for the shorter vegetation should improve as well.

In this study, larger patch size improved classification results for all shrubs except Hippophae rhamnoides, and the observed trend is log linear. H. rhamnoides is the only species for which classification accuracy declined with an increase in patch size. This is probably because larger, and thus older, shrubs tend to be less dense and more mixed with other vegetation. The patch size required to obtain acceptable classification accuracy is too large to be useful for early detection of non-native (invasive) shrub species. However, with more accurate measurement of vegetation height, this method could be useful for early detection purposes. Despite the low accuracy with which small patches were classified, the maps produced are highly valuable for studying, monitoring and evaluating shrub encroachments in the dunes.

4.3 Object-based classification

The object-based shrub detection performed well, with a minimum accuracy of 82%. This is comparable to the 87% accuracy obtained for patch detection (larger than 2 m²) by Laliberte et al. (2004). The extra classification at the species level, with the use of the per species results of the ML+ classifier, did improve the accuracy of most species compared to the ML+ classification. Also the overall accuracy increased to 60%. The object based classification produced useful maps that are not as speckled as the maps produced with the ML+ classification results. The object-based classification is comparable to human visual analysis, while offering guaranteed reproducibility. The approach therefore appears to be very useful for monitoring applications. The addition of high-quality vegetation height measures and structural analyses like skewness or standard deviation would increase the classification success.
5 Conclusion

The main objective of this research was to investigate a remote sensing approach to mapping dune shrubs, both native and exotic, on the island of Vlieland, using LIDAR data and high-resolution aerial photographs. Beside the traditional pixel-based classification methods, like maximum likelihood (ML) classification, opportunities for an object-based classification were also explored. Two main research questions were answered:

1. What combination of imaging and LIDAR data combined with a classification algorithm can deliver information on specific shrub species that is useful for the management of exotic and invasive species?
2. What object-based classifier can deliver a dune shrub classification based on vegetation structure?

The maximum likelihood classification using the combination of multispectral aerial photographs and vegetation height derived from LIDAR data performed obviously better than the classification using the multispectral aerial photographs alone (minimum improvement of 11%). This classification result was used, together with the NDVI, canopy cover and vegetation height, to produce a probability map for each dune shrub species of interest.

The multispectral aerial photographs were segmented, shrub segments were selected, and these shrub patches were classified with an overall accuracy of 60%. This object-based classification delivered a shrub map comparable to one produced by human visual analysis, but with a guaranteed reproducibility that makes it more valuable for management and evaluation of alien and invasive woody species. A test case investigating the effect of grazing on shrub occurrence shows a practical application of the derived shrub maps.

Use of LIDAR data obtained in late spring or summer could easily increase the accuracy of the obtained vegetation heights and enable extra structural parameters to be derived. This would also allow the use of smaller pixels, delivering a better classification and higher accuracy.
References


Alien and invasive woody species in the dunes of the Wadden Sea Island of Vlieland

A remote sensing approach

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