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Mapping invasive woody species in coastal dunes in the Netherlands: a remote sensing approach using LIDAR and high-resolution aerial photographs

Wouter Hantson, Lammert Kooistra & Pieter A. Slim

Keywords

Vegetation mapping; alien species; digital elevation model; pixel-based classification; object-based classification; *Rosa rugosa*; *Prunus serotina*; *Hippophae rhamnoides*; grey dunes

Abbreviations

AHN-2 = Second actual height model of the Netherlands; BRI_{NDVI} = band ratio index, according to the definition of the normalized difference vegetation index; LIDAR = Light detection and ranging; ML = Maximum likelihood classification from aerial images; ML+ = Maximum likelihood classification from aerial images extended with LIDAR-derived vegetation height; OB = Object-based classification; PA = Producer accuracy; CSM = Canopy surface model; TM = Terrain model; UA = User accuracy.

Nomenclature

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Introduction

'Grey dunes' are a widely distributed habitat type in the dune systems of northwest Europe, including the Wadden Sea Islands in the Netherlands (Vries 1950; Van Wingerden et al. 2002; Janssen & Schaminée 2003; Isermann et al. 2007; Houston 2008), occupying the zone between the mobile dunes and dune shrub. These are characterized by

sandy slopes of lichens and open, species-rich vegetation. The open nature of the habitat was maintained by extensive grazing of native herbivores, rabbits and domestic livestock. As with many semi-natural habitats, the loss of traditional management practices in the 'grey dunes' has played a key role in its ecological and geomorphological evolution from a dynamic state to a stable state (Houston 2008). The lack of grazing in recent decades and

Abstract

Questions: Does remote sensing improve classification of invasive woody species in dunes, useful for shrub management? Does additional height information and an object-based classifier increase woody species classification accuracy?

Location: The dunes of Vlieland, one of the Wadden Sea Islands, the Netherlands.

Methods: Extensive monitoring using optical remote sensing and LIDAR deliver large amounts of high-quality data to observe and manage coastal dunes as a defence against the sea in the Netherlands. Using these additional data could increase the accuracy of vegetation mapping and monitoring in coastal areas. In this study, a remote sensing approach has been developed to deliver detailed and standardized maps of (invasive) woody species in the dunes of Vlieland using multispectral aerial photographs and vegetation height derived from LIDAR. Three classification methods were used: maximum likelihood (ML) classification using aerial photographs, ML classification combined with vegetation heights derived from LIDAR (ML+) and object-based (OB) classification.

Results: The use of vegetation height from the LIDAR data increased the overall classification accuracy from 39% to 50%, but particularly improved classification of the taller woody species. The object-based classification increased the overall accuracy of the ML+ from 50% to 60%. The object-based results are comparable to human visual analysis while offering automated analysis.

Conclusions: Overall, the object-based classification delivers detailed maps of the woody species that are useful for management and evaluation of alien and invasive species in dune ecosystems.

atmospheric deposition of nitrogen compounds has speeded up the succession of the open dunes by shrubs and low trees (Aptroot et al. 2007).

The threats to the 'grey dunes' habitat come from disturbance reduction, inappropriate grazing, afforestation, growth of shrubs and invasion of alien species (Houston 2008). Mortimer et al. (2000) called the expansion of woody species in the 'grey dunes' highly problematic from a conservation perspective and Isermann et al. (2007) pointed to shrub expansion as one of the most serious threats to the 'grey dune' vegetation of the Wadden Sea Islands. Indeed, expansion of native and exotic woody species in the original coastal dune vegetation has had a considerable effect on species richness and diversity (Peardson & Rogers 1962; Fuller & Boorman 1977; Rejmánek & Rosén 1988; Binggeli et al. 1992; Isermann et al. 2007; Isermann 2008), decreasing the extent of open grassland (Isermann & Cordes 1992) and altering environmental conditions. By forming dense impenetrable layers, the shrub layer reduces light availability, increases soil organic matter content and water storage capacity and leads to a different chemical composition to soils with open dune grassland vegetation (Hodgkin 1984). This altering of the environmental conditions is a positive feedback mechanism: an increase in woody vegetation leads to even more woody vegetation.

The presence of invasive exotic shrub species in the dunes has recently increased in the Wadden Sea Islands, making the natural scrubland encroachment even more problematic. The most problematic species are *Prunus serotina* from North America (Ehrenburg et al. 2008; Quist & Weeda 2009) and *Rosa rugosa* from the Pacific coast of China, Japan and Korea. The fast-growing rhizomes of *R. rugosa* have colonized various habitats in the Netherlands, Germany, Norway, Sweden and Lithuania (Bruun 2005) and formed dense shrubs (Leentvaar 2010). This has led to the local extinction of the native vegetation types of high conservation value (Bruun 2005; Isermann 2008; Thiele et al. 2010). Furthermore, forecasts indicate that exotic species will become more prominent in the Netherlands (Quist & Weeda 2009).

Conservation of the 'grey dunes' is important 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. The primary management goal required by the EU Habitats Directive for the 'grey dunes' is preservation of the species-rich short grasslands, through which some bare soil is maintained by the activities of animals such as rabbits (Houston 2008). Management of woody species and removal of invasive species, together with the introduction of extensive, year-round grazing, may be

successful in restoring and maintaining fixed dune habitats. Current and accurate maps of woody species, furthermore, allow for targeted and more efficient management of exotic/invasive plant species, and can provide information on woody invasive species at an early succession stage, before they become problematic (Ehrenburg et al. 2008). Remote sensing techniques could provide useful information on the spatial distribution of woody and exotic species occurrence.

Optical remote sensing has often been applied to detect exotic, invasive and woody species (Andrew & Ustin 2008; Hestir et al. 2008) but is limited in the capacity to deliver information on vegetation structure. LIDAR (light detection and ranging) is an active remote sensing technique that delivers information directly related to the vertical structure of the canopy (Lefsky et al. 2002). Airborne LIDAR systems derive information on elevation and reflectance of a terrain and its vegetation from a pulse laser emitted by an airborne transmitter fitted with an accurate positioning system. The time the pulse requires to travel from the laser to a surface and back provides an accurate measure of distance. The reflection of the airborne laser pulse is used to create a digital elevation model and to calculate canopy height and cover.

This LIDAR technique was used to set up a second high-resolution actual height model (AHN-2) of the Netherlands by 2008, which would be updated every 5 years. The sea side has been measured annually from 1996 for coastal management purposes by LIDAR at a lower spatial resolution. The availability of these high-resolution data with the intention to refresh on a regular basis has made this data source useful for mapping the actual situation and for future monitoring. Asner et al. (2008) used LIDAR to map invasive plants by showing that they transform the three-dimensional structure of forests. Brock & Purkis (2009) showed the value of LIDAR for coastal research, and different studies have demonstrated the ample potential for (coastal) mapping of (invasive) woody species using LIDAR combined with remote sensing imagery. Lee & Shan (2003) merged imagery with LIDAR-derived elevation data and showed the benefits for coastal classification mapping. Bork & Su (2007) supported the benefits of integrating LIDAR and multispectral imagery for vegetation classification (eight classes), but LIDAR-derived vegetation height underestimated the shrub vegetation height (Su & Bork 2007). Previous studies have shown that the underestimation of vegetation height occurs due the low probability of the small-footprint laser being reflected by shrub vegetation (Weltz et al. 1994; Gaveau & Hill 2003), but the integration of LIDAR and imagery made it possible to distinguish shrub vegetation types with similar LIDAR heights (Bork & Su 2007). Kempeneers et al. (2009) mapped coastal dune vegetation types and shrub species

by merging aerial photographs with LIDAR data (14 classes). Data merging of imagery with LIDAR has generally improved the classification results.

Pixel-by-pixel analysis of remote sensing data is feasible as long as the pixel size is smaller than or similar to the size of the object of interest, but in light of the increasing 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). Object-based image analysis of high-resolution imagery has been successfully used for vegetation (structure) mapping in many papers (Laliberte et al. 2004; Chubey et al. 2006; Yu et al. 2006; Cleve et al. 2008; Smith et al. 2008). Such methods have obtained better classification results than with a traditional pixel-based classification. Laliberte et al. (2004) used this method specifically for shrub encroachment mapping over time, and Smith et al. (2008) studied the process of juniper encroachment over a period of 59 years.

The use of an object-based classification method combined with high-resolution imagery merged with vegetation height data should increase the classification accuracy. Further research on the applicability of remote sensing techniques for managing and preserving 'grey dune' habitats is desirable, as previous studies suggest that these methods appear to be capable of detecting exotic woody dune species, and remote sensing data will be increasingly available in the future. The combination of spectral information from aerial photographs with vegetation height delivered from LIDAR data should enable mapping of (exotic) woody species. In our study, we determine the effect of additional height information on the classification result and the added value of using an object-based classification compared to a pixel-based classification. As a result, the following research questions were investigated in this study: (1) what is the effect of additional height information obtained from the LIDAR data on the classification result; (2) can the use of an object-based classifier increase the accuracy of the woody species classification; and (3) do remote sensing-based methods deliver information on specific invasive woody species that is useful for shrub management?

Methods

Study area and field data

Vlieland is one of the West Wadden Sea barrier islands, situated in the north of the Netherlands (53°17'N, 5°01'E). Most of the island is covered by dunes, 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 in this ecosystem. The 'Vlieland Dunes' Natura 2000 area covers ca. 1500 ha protected by the EU Habitats and Birds Directives (92/43/EEC and 79/409/EEC). 'Grey dunes' are a key habitat type on the island, and their management is aimed at increasing both their quality and area. The small island of Vlieland was selected for this study due to its quasi-undisturbed dunes, although groundwater extraction has influenced its biodiversity.

During a field campaign on Vlieland in June and July 2010, data for woody species occurrences were collected on three transects. These calibration and validation data will be used for the different classification methods. Along the transects, single-species patches with homogeneous vegetation were identified and the mean height was measured by hand. The woody species were described and the clearly determined patches were drawn on the detailed aerial photographs. In total, 145 spatial independent patches were selected, localized and stored as polygon in ArcGIS. Table 1 shows the number of observed patches for the six shrub species taken into account in this study.

Remotely sensed data

The aerial photographs were obtained from the laboratory of Geo-Information Science and Remote Sensing (GeoDesk) at Wageningen University. They were acquired during the summer of 2008 with a Vexcel UltraCam-X camera (Vexcel Imaging GmbH, Graz, Austria) at 3600 m above ground and have a spatial resolution of 25 cm. Vlieland falls entirely within the field of view of the camera and CIR images (near-infrared: 700–805 nm, red: 635–675 nm, green: 455–580 nm) were available (Clevers et al. 2005). The imagery was not calibrated to reflectance. The LIDAR data were acquired with a FLI-MAP LIDAR system from Fugro (www.flimap.com; Fugro, Leidschendam, The Netherlands) at 375 m above ground and have a point distribution of 0.18 m. The data were acquired in the winter of 2008 to derive the AHN-2 height map

Table 1. Number of observed spatial independent plots per shrub species.

	Number of plots
<i>Hippophae rhamnoides</i>	32
<i>Pinus nigra</i>	17
<i>Prunus serotina</i>	24
<i>Rosa rugosa</i>	23
<i>Salix repens</i>	13
<i>Sambucus nigra</i>	12

(www.ahn.nl; Het Waterschapshuis, Amersfoort, The Netherlands). Both data sets are cloud-free and geometrical corrected. The co-reference of both aerial photographs and LIDAR was assessed by visual inspection (e.g. buildings) and the existing geometric correction appeared to be accurate. The LIDAR data cover only the North Sea side of Vlieland, so the analysis was performed on that part of the island.

Data analysis

Extraction and validation of vegetation height from LIDAR

Analyses of the LIDAR data started with the creation of a terrain model (TM) (Fig. 1) by filtering the cloud of LIDAR returns to identify the returns that lie on the probable ground surface (ground filter algorithm – based on Kraus & Pfeifer 1998). In order to derive the vegetation height, the point data were rasterized and the highest point in each cell was assumed to represent the canopy surface height [canopy surface model (CSM)]. The spatial resolution of the raster was based on Kempeneers et al. (2009). They performed a sensitivity analysis to determine the best pixel size for dune vegetation LIDAR height measurements, with an optimal grid size of 1.5 m. The same raster size was used for the creation of the CSM, to minimize errors of different raster sizes. The difference between the canopy surface height and the ground surface was calculated as the vegetation height (canopy height model). The vegetation height was used as an additional information layer in the classification by adding an extra band to the aerial photography data and treating this as a normal spec-

tral band (Lee & Shan 2003). The LIDAR point extraction and calculations (CSM and ground filter) were done with the freely available Fusion software (<http://www.fs.fed.us/eng/rsac/fusion/>).

Pixel-based classification

The maximum likelihood (ML) classifier is a supervised pixel-based classification algorithm included in ENVI, a family of software products for processing and analysing geospatial imagery data. 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). For training of the ML classifier, special selected patches with single species occurrence were used. The ML classifier is commonly used for image classification and was used to classify the colour infrared (CIR)_image with three spectral bands (method ML). This was compared with the ML classification method based on the CIR image with the additional height information added (method ML+). The detection limit of the ML+ classification is determined by comparing the classification accuracy with the number of pixels of the validation dataset.

Object-based classification

The purpose of object-based mapping or classification 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 in order to obtain the segmentation result on the same scale of the vegetation patches. The object-based shrub detection used the segmented aerial photographs, canopy height, canopy cover and a band ratio index (BRI) according to the definition of the normalized difference vegetation index (BRI_{NDVI}) as inputs. Here the BRI_{NDVI} was calculated as $(DN_{NIR} - DN_{RED}) / (DN_{NIR} + DN_{RED})$, where DN is the digital number as measured by the Vexcel UltraCam camera in the red (RED) and near-infrared (NIR) bands. The objects classified as shrubs were used in another classification step to species level. This study conducts this classification step *via* object-based classification combined with the ML+ classification. The mean probabilities of the ML+ classification for each layer were compared at the patch level. Each shrub patch was classified as the species with the highest probability. The software used for image segmentation was eCognition Developer 8.0.1 (Trimble GeoSpatial, Munich, Germany). Segmentation of the CIR aerial images was performed with the following

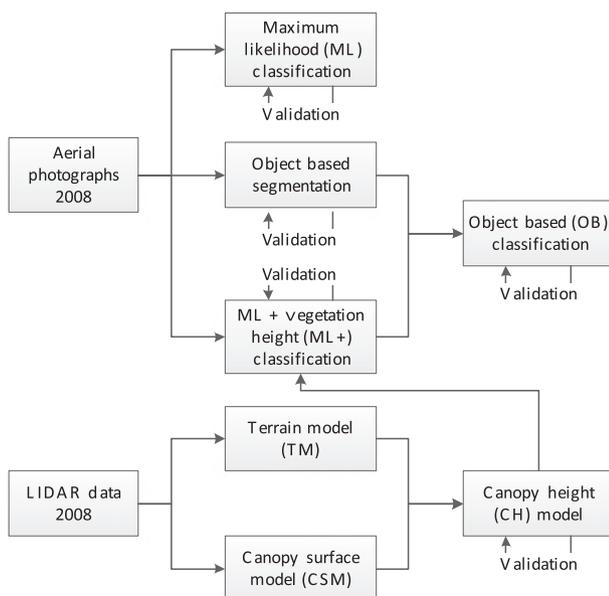


Fig. 1. Workflow from raw data to the object-based classification of shrub species.

eCognition segmentation parameters: shape = 0.5, compactness = 0.8, and scale = 40. The scale parameter relates to the relative size of the output polygons, it determines the maximum allowed heterogeneity for the image objects. The shape ratio determines to what degree shape influences the segmentation in relation to spectral colour, and the compactness is defined as the ratio of the area of a polygon to the area of a circle with the same perimeter. A canopy cover of more than 11% (between 0.1 m and 2.0 m) and a $BRI_{NDVI} > 0.21$ was used to determine shrub cover in the segments. The CIR imagery was not calibrated to reflectance, implying that the calculated BRI_{NDVI} could not be used quantitatively but should be seen as a ratio for differentiating between shrub vegetation and bare soil.

Validation

The random vertical error of the LIDAR data set was determined by performing a statistical analysis of a collection of points returned from a well-known flat surface in the study area (Streutker & Glenn 2006). These LIDAR points are expected to lie on a flat plane. This means that the error measured is assumed random (ASPRS 2004) and represents the upper bound for the absolute and relative vertical accuracy of the vegetation height data set. Systematic vertical errors occur in estimating vegetation heights due to the limited ability of the laser to penetrate vegetation (ASPRS 2004; Hodgson & Bresnahan 2004; Kempeneers et al. 2009). The vegetation penetration is species-specific and in this case high, because the LIDAR data were obtained in the winter in leaf-off conditions. Determination of the systematic error was done for *Rosa rugosa*, *Prunus serotina*, *Hippophae rhamnoides* and *Salix repens*. *Pinus nigra* and *Sambucus nigra* were not included because we focused our research on shorter woody species. In the current study, a species-specific linear regression was included to determine the systematic vertical error in the data set. The height of the vegetation measured during the fieldwork was compared with both the LIDAR-derived maximum vegetation height corrected for the systematic error and the non-corrected vegetation height. The strength of this correlation was tested using Pearson's r coefficient.

The accuracy of the different classification methods is expressed using an error matrix (Congalton 1991) in which the obtained classification result is compared to the validation data set obtained during the fieldwork. The overall accuracy is calculated for all three classifications and for the different woody species the producer accuracy is reported together with the user accuracy. As the focus of the current study is to compare the different species, values are presented as percentages. The producer accuracy is obtained by dividing the number of

correctly classified pixels in each category by the total number of pixels in each category (here the different woody species). The user accuracy is calculated by dividing the number of correctly classified pixels for each category by the total number of classified pixels of that category. The overall accuracy is computed by dividing the correctly classified pixels of each category by the total number of reference pixels.

Results

First, we processed the LIDAR data set in order to derive the vegetation height. The canopy surface model (CSM) (Fig. 2a) shows a map of the LIDAR signal, while the terrain modelTM shows only the reflectance of the surface (Fig. 2b). The TM shows the topography of Vlieland, with the dune row in the northwest (see arrow in Figs 4 and 5). If we subtract the TM from the CSM we obtain the canopy height (CH) (Fig. 2c). The two forested areas appear dark in Fig. 2c.

The vegetation height is validated because two relevant error types affect LIDAR vegetation height estimation: (1) the random vertical error or measurement error and (2) the systematic species-dependent vertical error. If the random vertical error should be zero, all of the points without vegetation should indicate a zero height difference. The mean of our sample was 0.025 ± 0.029 m SD. The height of 0.054 m represents the upper bound of the absolute and relative vertical accuracy of the vegetation height data set. The systematic vertical error is shown *via* the linear regression between reference height and LIDAR estimated height (Fig. 3) for each species separately. The R^2 of the linear regression range from 0.29 (*S. repens*) to 0.43 (*H. rhamnoides*) and they all have a P -value below 0.1 (Table 2). There is one outlier from *R. rugosa*, with a LIDAR estimated vegetation height above 5 m, while the measured height was only 1.8 m. The LIDAR estimated height could be corrected for this systematic error but Table 3 shows a lower correlation for the corrected than for the non-corrected data. Based on the low R^2 and Pearson's correlation no systematic error correction was applied to the data. This implies an underestimation of the shrub height show in Fig. 3.

The second step was the classification of the aerial photographs. A detail of the ML classification (Fig. 4a) shows a central patch *R. rugosa* and the occurrence of *H. rhamnoides* behind the first dune row. The overall accuracy of the ML classification is 38.7%, but the user and producer accuracies show that the classification accuracy is very species-dependent. The producer accuracy ranges from 22% (*S. repens*) to 65% (*Sambucus nigra*) and the user accuracy varies from 29% (*H. rhamnoides*) to 92% (*S. nigra*) (Table 4).

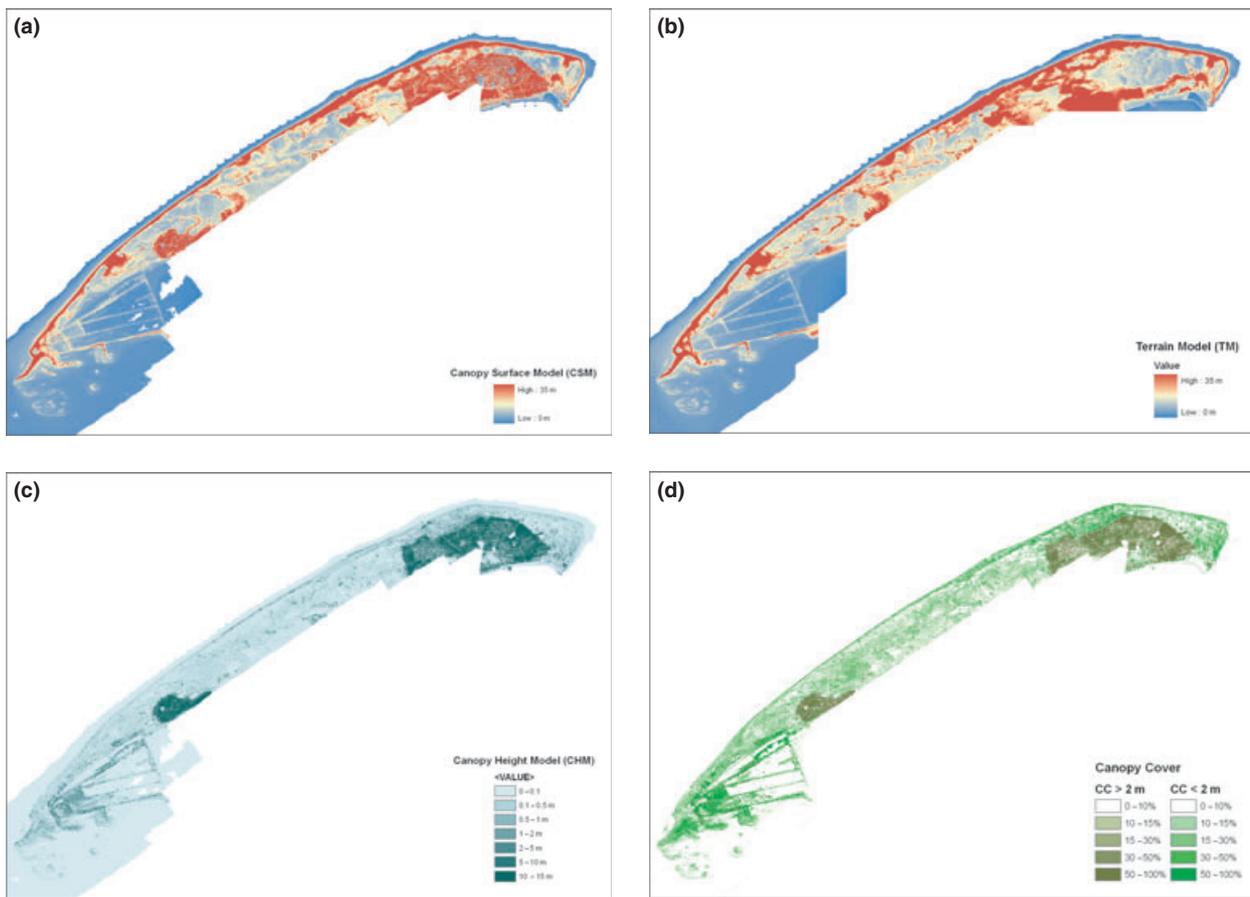


Fig. 2. LIDAR-derived measurements of Vlieland (a, canopy surface model; b, terrain model; c, canopy height model; and d, canopy cover).

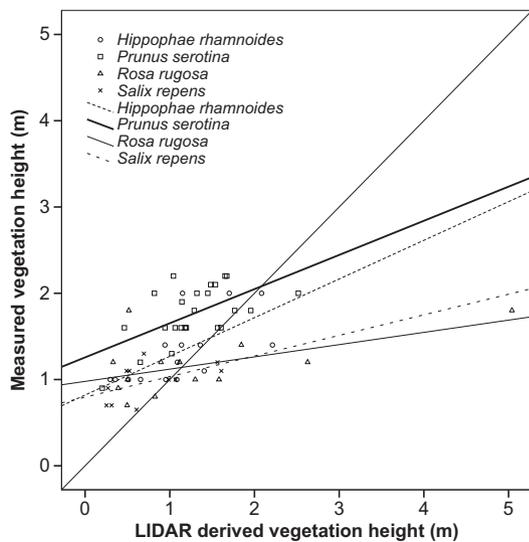


Fig. 3. Species-specific systematic vertical error shown via the linear relationship between the LIDAR-derived vegetation height and the field-measured vegetation height.

Table 2. Species-specific systematic vertical error shown via the linear regression between reference height and LIDAR estimated height.

	R^2	P
<i>Hippophae rhamnoides</i>	0.433	0.008*
<i>Prunus serotina</i>	0.347	0.002*
<i>Rosa rugosa</i>	0.298	0.054
<i>Salix repens</i>	0.286	0.090

*Significant linear relationship, $p < 0.05$.

Table 3. Correlation between the field measured vegetation height and both corrected and raw LIDAR-derived vegetation height.

	r (raw)	r (corrected)
<i>Hippophae rhamnoides</i>	0.659	0.294
<i>Prunus serotina</i>	0.589	-0.300
<i>Rosa rugosa</i>	0.546	-0.222
<i>Salix repens</i>	0.537	-0.384

r , Pearson's correlation coefficient.

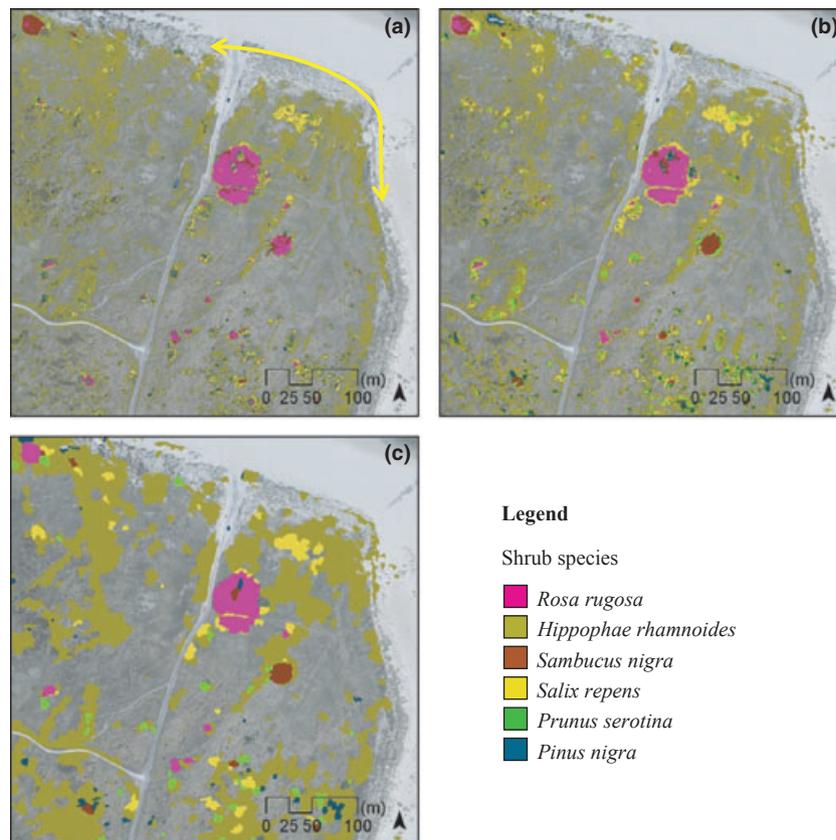


Fig. 4. Detail of the different classification results (**a**, maximum likelihood; **b**, maximum likelihood plus vegetation height; and **c**, object-based classification). The yellow arrow shows the first dune row in the northeast of Vlieland.

The ML+ classification, with the additional height information (Fig. 4b), shows in addition to the ML classification the correct classified patch *S. nigra* under the *R. rugosa* and a patch of *S. repens* in the dune valley behind the *H. rhamnoides*. The ML+ classification has an overall accuracy of 50.4% and is also species-dependent, with the user accuracy ranging between 34% (*H. rhamnoides*) and 95% (*S. nigra*) and the producer accuracy between 30% (*S. repens*) and 76% (*Pinus nigra*) (Table 4).

Both the ML and ML+ classifications show high variability over short distances resulting in a ‘pepper and salt’ effect for the pixel-based classification and having classification problems with the same species. Nonetheless, looking at the overall classification accuracy, we find that the additional vegetation height information improved classification success, raising it from 38.7% up to 50.4%. Table 3 shows the change in producer and user accuracy for all the species.

The object-based species classification (Figs 4c, 5) delivered a vegetation map with clear patches of the different woody species. The overall classification result (60%) improved compared to the pixel-based methods used in this study. The classification accuracy (Table 4) is better or

equal in comparison to the ML+ classification for all the species, except for *P. serotina*. The combined effect of additional height information and the object-based approach resulted in an increase of 21% in comparison to the classical pixel-based maximum likelihood classification.

Finally we compared the results of the ML+ classification in relation to patch size (Fig. 6) in order to determine the detection limit for the different woody (invasive) species. All the species show a logarithmic increase of classification accuracy with a larger patch size; only *H. rhamnoides* shows a logarithmic decrease of classification accuracy. *Sambucus nigra*, *P. nigra* and *P. serotina* have a very small detection limit and reach almost direct high classification accuracy. The classification of *R. rugosa* increased slowly to a classification result higher than 50%, and the classification of *S. repens* was generally low.

Discussion

LIDAR-derived vegetation height

The LIDAR data are highly accurate, with a random error of just 0.025 ± 0.029 m for homogeneous flat surfaces. The derived height measurements are therefore quite

Table 4. Overview of the classification results obtained with the different classification methods: maximum likelihood (ML), ML with extra height information (ML+), and object-based (OB).

	ML		ML+		OB	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
<i>Hippophae rhamnoides</i>	32	29	46	34	66	32
<i>Pinus nigra</i> *	34	68	76	90	73	99
<i>Prunus serotina</i> *	29	44	42	42	15	21
<i>Rosa rugosa</i> *	54	74	60	83	69	100
<i>Salix repens</i>	22	52	30	58	28	75
<i>Sambucus nigra</i>	65	92	75	95	82	98
Overall accuracy	39		50		60	

PA, producer accuracy; UA, user accuracy.

*Exotic species.



Legend

Shrub species

- *Rosa rugosa*
- *Hippophae rhamnoides*
- *Sambucus nigra*
- *Salix repens*
- *Prunus serotina*
- *Pinus nigra*

Fig. 5. Object-based map of the woody species in Vlieland. The yellow arrow indicates the location of the area in Fig. 4.

precise. They support the findings of Mallet & Bretar (2009) that LIDAR data can provide information on the ground surface to an accuracy within 0.10 m. Despite this degree of accuracy, the current study's validation of the LIDAR-derived vegetation heights shows an underestimation for the different woody species but a good regression between measured and LIDAR predicted vegetation height, with Pearson's r values between 0.43 and 0.66 (Table 3). This is for a large part attributable to the fact that the LIDAR data were acquired in winter. The observed woody species lose their leaves in winter (except *Pinus*) and the reflection of the LIDAR laser will be through their stems and branches. The stem density will thus influence the reflectance more than by the maximum height of the green vegetation. This produced less accurate measures than those previously found using LIDAR data. For exam-

ple, Kempeneers et al. (2009) found a linear relation between LIDAR-derived shrub heights and reference values, with an R^2 of 0.98. In contrast, our best result was 0.43. This relatively low correlation between the heights calculated using the vegetation-reflected LIDAR signal and reference values is a limiting factor to use of LIDAR-derived vegetation structure parameters. The estimation of vegetation height suggests that a larger raster size is needed. Although the raster size used was 1.5 m, which is 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 small patches of specific woody 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 an accurate terrain model. In fact, that was the main reason for conducting the 2008 LIDAR flight in winter, in order to support coastal management planning. It is foreseen that use of LIDAR data obtained in late spring or summer would raise classification accuracy to a higher level. This would also enable the use of smaller pixels and LIDAR-derived vegetation structure parameters.

The primary purpose of the LIDAR data was to derive the digital elevation model for AHN-2. However, coastal management agencies also deliver LIDAR and imaging data to observe geomorphological development of the coastline and to support management of coastal dunes as a defence against the sea in The Netherlands. The combined use of these two sources of remote sensing data could increase the spatial and temporal accuracy of vegetation monitoring in coastal areas.

Pixel-based classification

The maximum likelihood (ML) classification based on the CIR aerial images performed visually relatively well (Fig. 4a), although the overall classification accuracy was 38.7% (Table 4). Because the validation data set was set up specifically to determine the detection limit of single-shrub patches, it consists of a large portion of small, hard-to-classify patches. Moreover, species-level classification of woody species is difficult. For mixtures of shrub species, Baptist (2009) similarly reported low classification accuracy for *S. repens* (0%) and *H. 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 (Table 4). The overall accuracy of ML+ increased up to 50.4%, with the tallest species such as *P. nigra* registering maximum increases from 34% to 76%.

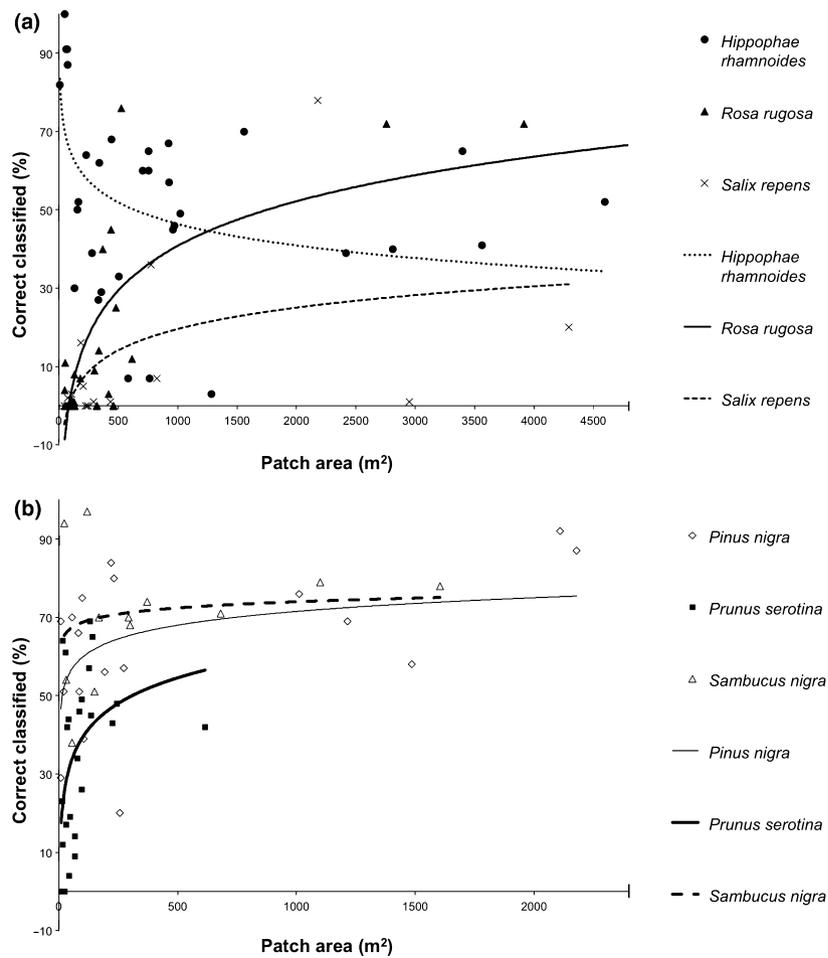


Fig. 6. Relationship between patch area and classification accuracy for the different woody species. The results are separated between **a**, smaller woody species; and **b**, larger woody species.

This supports the conclusion of Kempeneers et al. (2009) that tall vegetation types benefit most from fusion of the data. Overall, our species classification results improved by 6% to 42%, comparable to previous studies, which have obtained increases of 16% (Kempeneers et al. 2009) and 16% to 20% (Bork & Su 2007). Unfortunately, the accuracy of the *S. repens* classification, which was 22%, increased only to 30% with the additional classification layer. This could be explained by the combination of a low ML classification result (Table 4) and the low height prediction of *S. repens* (Table 2). In comparison, *R. rugosa* also has a low height prediction, but combined with a good ML classification it resulted in an increase of classification accuracy from 54% to 60%. In general, low species have a lower LIDAR height prediction accuracy, so with more accurate vegetation height measurement the classification accuracy for the lower vegetation could also improve. The accuracy of the vegetation height estimation could be increased by a LIDAR flight during summer, although this could reduce the accuracy of the ground surface estima-

tion, but also by the use of an object-based, instead of a pixel-based, vegetation height derivation.

Object-based classification

The object-based classification (Fig. 5) 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 and 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. Smith et al. (2008) also described a high accuracy for an eCognition, segmentation and classification of juniper encroachment, but noted that the parameter setting of eCognition requires optimization for the local situation.

Patch size

In this study, larger patch size improved classification results for all woody species except *H. rhamnoides*, and the observed trend was log linear (Fig. 6a,b). *H. rhamnoides* is the only species for which classification accuracy declined with an increase in patch size (Fig. 6a). This is probably because larger, and thus older, *H. rhamnoides* shrubs tend to be less dense and more mixed with other vegetation, where the other species create a dense, single species cover and thus a more detectable patch. The shown trend was not statistically significant and further research will be necessary to define this relationship between plant physiognomy and classification success. The patch size required to obtain acceptable classification accuracy is too large to be useful for early detection of non-native (invasive) woody 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 useful for studying, future monitoring and evaluating woody encroachments in the dunes.

Conclusion

The main objective of this research was to investigate a remote sensing approach for woody species, both exotic and native, in coastal 'grey dunes' on the island of Vlieland, using LIDAR data and high-resolution aerial photographs. As well as the traditional pixel-based classification methods, e.g. maximum likelihood (ML) classification, opportunities for an object-based classification approach were explored.

The ML classification using a combination of multi-spectral aerial photographs and vegetation height derived from LIDAR data performed better than the classification using the multispectral aerial photographs alone (minimum improvement of 11%). The multispectral aerial photographs were segmented, woody species segments were selected, and these patches were classified at species level with an overall accuracy of 60%. This object-based classification delivered an automated woody species map comparable to that produced by human visual analysis, which makes it a valuable tool for management and evaluation of alien and invasive woody species. Use of LIDAR data obtained in late spring or summer could easily increase the accuracy of the estimated vegetation heights and enable additional structural parameters to be derived. This would also allow the use of smaller pixel sizes, delivering a better classification and higher accuracy.

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