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Remote sensing of coastal vegetation in the Netherlands and Belgium

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Abstract

Vegetation maps are frequently used in conservation planning and evaluation. Monitoring commitments, a.o. in relation to the European Habitat Directive, increase the need for efficient mapping tools. This paper explores methods of vegetation mapping with particular attention to automated classification of remotely sensed images. Characteristics of two main types of imagery are discussed, very high spatial resolution false colour images on the one hand and hyperspectral images on the other. The first type has proved its qualities for mapping of – mainly – vegetation structure in dunes and salt marshes. Hyperspectral imagery enables thematic detail but encounters more technical problems.

Keywords: Vegetation; Mapping; Remote sensing; GIS.

Introduction

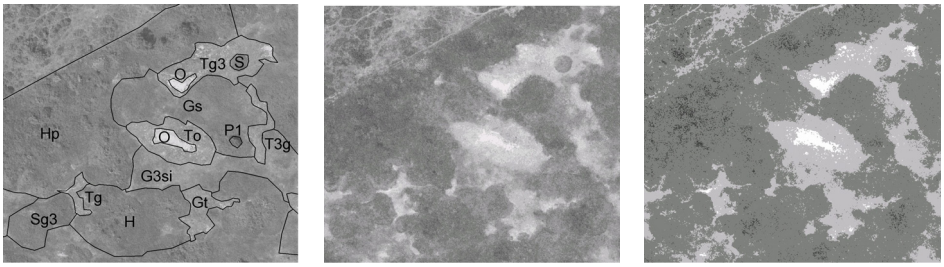
Vegetation maps are essential tools for planning and evaluation in nature conservation. To a large extent, management objectives can be defined in terms of vegetation attributes, either because of their intrinsic value or because of their significance in habitat characterisation. Moreover, there is an increasing demand for biodiversity indicators, for a large part due to the European Habitat Directive but also on national or regional administrative levels. The reporting frequency seems to increase simultaneously. These tendencies underline the need for efficient tools for detailed and recurrent vegetation mapping.
From a purely scientific point of view, spatially detailed vegetation maps provide basic information for research on for instance vegetation dynamics or habitat characteristics.
This paper explores the past, present and future of vegetation mapping in coastal dunes and salt marshes along the Dutch and Belgian coast. Therefore the first chapter is spent

on vegetation mapping in general. As remote sensing is always involved in one or another stage of the mapping process an overview of the techniques is given in the second part of the text. Only airborne remote sensing is mentioned since spaceborne images (so far) do not meet the characteristics required for detailed vegetation studies. The last chapter summarizes actual experience with remote sensing in coastal areas in the Netherlands.

Vegetation classification and mapping

Vegetation can be looked at in various ways, which will be reflected in its classification and mapping. We consider three major approaches:

- Vegetation is an essential **functional element** in ecosystems' carbon, water and nutrient cycling and in this respect, vegetation properties will mostly depend on features such as biomass, leaf area index (LAI) or physiological characteristics. Classification based on 'ecological behaviour' of species is a similar approach.
- Physiognomic classification is based on the outward appearance of vegetation and relates to **structure and life forms** of the dominant species. Basic physiognomic units or 'formations' are defined top down and they are generally used within a broad geographical context (Whittaker, 1962). However, vegetation structure can also be relevant on a more detailed scale, for instance as a determinant of species' habitats.
- Phytosociological classifications define plant communities in a bottom up way, starting from records of **species composition** (Westhof and van der Maarel, 1973). The system closely relates to botanical evaluation and is well established in habitat typologies for conservation in the Netherlands.



A B C

Fig. 1. Different types of vegetation maps: a) tagged vector feature map on aerial photo, b) continuous raster representing NDVI values; c) discrete raster containing five NDVI classes (NDVI=Normalised Difference Vegetation Index; see text).

An ideal classification should integrate a top down landscape ecological approach with an elaborate set of vegetation relevés into an ecotope typology (Klijn, 1997). Such typologies have only been elaborated for local applications so far. The chosen classification type will strongly determine the map properties. Conventional vegetation maps - in GIS terminology – would be characterised as single-layered vector maps, consisting of polygons (or possibly line and point features), with arbitrary shape, surface

area and attributes (Fig. 1). Vector maps can easily cope with several attributes, such as for example a hierarchical typology would demand, by linking them to a database.
Quantified vegetation characteristics, such as height, LAI, biomass or vegetation indices will preferably be mapped in a continuous raster. Raster maps or grids consist of equally shaped cells (mostly squares) to which a continuous or discrete value is attributed (Fig. 1). They are advantageous for GIS calculation purposes and are compatible with georeferenced images, which are also stored as grid files.
Another potential of grids is the use of 'fuzzy' boundaries, whereas vector features are always separated by a sharp boundary ('crisp'). Raster maps are therefore beneficial for representation of ecological gradients such as elevation or a range in grazing intensity.

Remote sensing in a nutshell

General concepts

In general, remote sensing is based on the detection of electromagnetic radiation by sensors mounted on airplanes or satellites. Active techniques measure return signals from artificial illumination sources while in passive remote sensing, no external source is involved. LIDAR (laser) and RADAR are the most common active remote sensing systems. LIDAR is frequently used for the acquisition of detailed digital elevation models. Most applications however, can be categorised as passive remote sensing.
Incident electromagnetic waves can be absorbed, transmitted or reflected, either in the atmosphere or at the earth's surface. The signals detected by remote sensors are therefore influenced by both atmospheric conditions and landscape characteristics. Obtaining pure spectral signatures, the so-called 'endmembers', representing the chemical and physical properties of sudden features, requires measurements at ground level with field spectrometers. Such devices commonly register wavelengths between 350 and 2500nm, including the part of the spectrum visible by the human eye (about 400 to 700nm), near infrared (NIR, from about 700 to 1300nm) and short wave infrared (SWIR, situated between 1300 and 2500nm, Lillesand and Kiefer, 2000).
Spectral measurements are commonly presented as reflectance values, defined as the ratio of reflected to incident radiation. It is a characteristic property of materials, independent of the intensity of incident radiation. Reflectance is a function of wavelength, which in turn is related to the energy level of the radiation.

Spectral characteristics of vegetation

Fig. 2 shows examples of reflectance curves of some basic (coastal) landscape elements measured by a field spectroscope (FieldSpec Pro Fr, Analytical Spectral Devices, Inc.). Distinct patterns can be distinguished, indicating the ability to discern several land cover classes. The interpretation of spectral properties of vegetation in this paragraph is largely based on the clarifying review by Kumar *et al*. (2001).

Green plants show a strong absorption of ultraviolet and visible light due to leaf pigmentation. The predominant absorption of red and blue light causes their green appearance. About 70% of the absorbed radiation is converted into heat, while most of the remaining energy is used for photosynthesis. The dominance of chlorophyll pigments

in healthy leafs explains absorption peaks at 420, 490 and 660nm. This phenomenon is apparent in the scrub reflectance curve in Fig. 2. In senescent leafs, carotenes and xanthophylls tend to dominate, which changes the absorption pattern and through that the colour. The red absorption peak (690nm) in the mud reflection curve seems strange but is actually caused by photosynthetic pigments in the epibenthic algae (*cf.* Paterson *et al*., 1998). Reflectance of dry (beach) sand is high in the visible wavelengths, making it easy to discriminate it from vegetated areas. At time of measurement, the moss dune plot (*Tortula ruralis* ssp. *ruraliformis*) was dried out, which explains the vegetation unlike reflectance curve in Fig. 2.

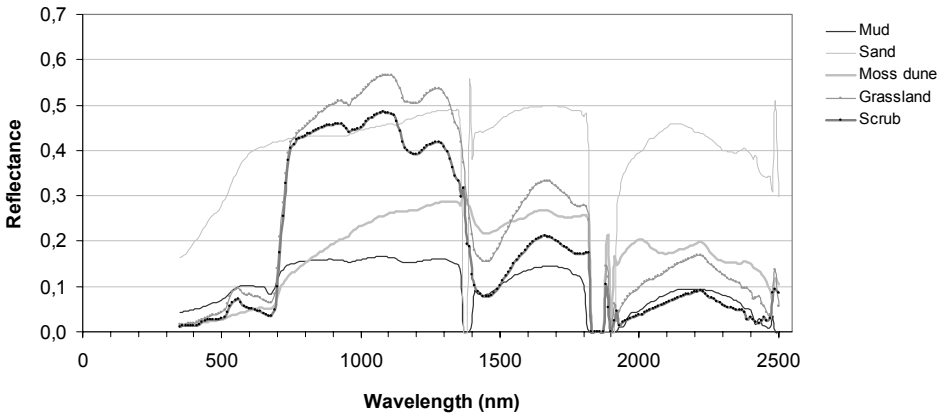


Fig. 2. Reflectance curves of some characteristic coastal habitat elements along the western part of the Belgian coast (July 2004, ASD measurements VITO).

Near infrared is hardly absorbed by green plants. More than 95% of the incident radiation is either transmitted or reflected. The characteristics of the upper epidermis and the refractive index of the cuticula determine the reflectance from the leaf surface but also the anatomical structure of the leafs contributes significantly to NIR reflectance. In multi-layered canopies, transmitted radiation is partly reflected by lower leafs, causing an increase in NIR reflection.
The contrast between red absorption and NIR reflection, known as the 'red edge', is an apparent spectral characteristic of healthy vegetation. It is used to calculate vegetation indices among which the Normalised Difference Vegetation Index (NDVI = [NIR – RED] / [NIR + RED]) is most commonly used.
The SWIR reflectance is related to the features' water content. This part of the spectrum is characterised by distinct water absorption bands at about 1400 and 1850nm (Fig. 2).

A large number of studies deals with the spectral properties of leafs, plants or canopies (Kumar *et al*., 2001) in which vegetation is considered from a functional ecological point of view (nutrient cycling, vegetation stress, phytomass production,…). Indeed, spectral properties relate to biochemical and physical properties rather than species as such. Within a single species, plants show a variety of phenological, morphological and

physiological conditions, complicating the spectral separability of vegetation types based on species composition.
In spite of this, Schmidt (2003) found characteristic spectral signatures with statistically significant differences for the majority of 27 salt marsh vegetation types. A classification of 19 vegetation types based on canonical variance analysis of field spectra (579 bands) resulted in an overall accuracy of 91%.
Van Til *et al.* (2004) studied spectral characteristics in dry dunes on the Dutch mainland. Field spectra of 10 vegetation types were recorded in May and June and converted to 29 bands to simulate the EPS-A hyperspectral scanner (Fig. 3). Non parametric statistical tests on the May data revealed separability for 42 out of 45 pairs of types. In the June records, only 37 out of 45 pairs could be separated. It seemed difficult to spectrally discern a number of important vegetation types, such as vegetations dominated by *Calamagrostis epigejos* and *Ammophila arenaria* respectively.

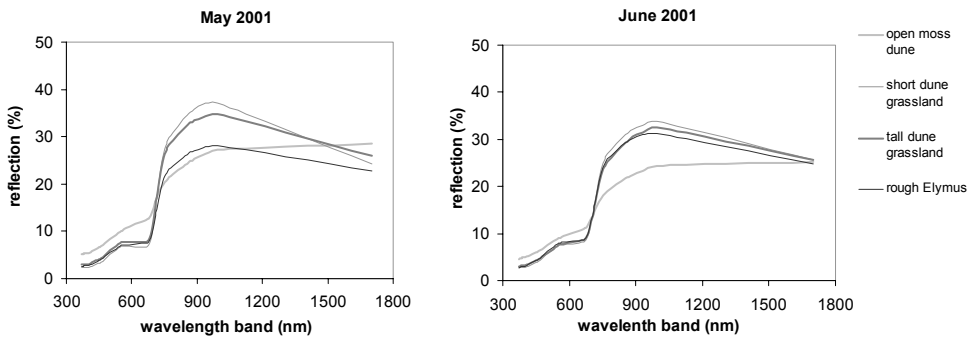


Fig. 3. Reflectance of four vegetation types of calcareous dry dunes in the Amsterdam waterworks dunes in May and June 2001 (Van Til et al., 2004).

Aerial photographs

Analogue aerial photographs are the most basic remotely sensed images. The oldest black and white photos known from the Belgian coast date from WW 1. After WW 2, aerial photographs were taken quite regularly in function of cartography or coastal defence.
Panchromatic ('black and white') images integrate reflectance along a large part of the spectrum into one information 'band'. Interpretation is based on grey scale, texture, size and shape of features, patterns and contextual elements. Though seemingly trivial, context is a very important element in image interpretation. Due to its complexity, context is very difficult to translate into computer algorithms, which makes manual photo interpretation to some extent irreplaceable.
True colour images consist of three broad bands representing the red, green and blue (RGB) part of the spectrum. Due to correlation of the visual bands, the extra information content of colour images is limited. Near infrared sensitive film however, offers a considerable extra value for vegetation research (as mentioned above). In standard

infrared photos, the blue, green and red layers represent green, red and near infrared reflection respectively, making them appear as 'false colour' images.

Thorough interpretation requires use of stereo photo pares which allow 3D viewing of landscape and vegetation. Several vegetation maps were produced using this technique, mostly for specific and local applications such as management planning and evaluation. Examples of merely scientific use of manual aerial photograph interpretations are rare (*e.g.* van Dorp *et al*., 1985; Shanmugan and Barnsley, 2002).
Recurrent mapping of salt marshes in the Netherlands is carried out by the Survey Department of the Ministry of Public Works since the early seventies (Janssen, 2001). The same authority started vegetation mapping of the (fore)dunes in the 1980s. A similar program for the Belgian coast was started in the same period by the coastal defence administration of the Ministry of the Flemish Community.

Digital imagery

Digital imagery is acquired through scanning of photographs (prints or preferably films) or directly by digital remote sensors. The image quality includes four elements (Lillesand and Kiefer, 2000): the **spatial resolution,** denoting the size of one image pixel measured on the ground; the **number of bands**; the band width or **spectral resolution** and the storage precision of the information or **radiometric resolution**. The value of an 8 bit image pixel, for example can range from 1 up to 256.
The number of bands can range from one (panchromatic image) to over one hundred (hyperspectral imagery or imaging spectroscopy). Multispectral images consist of several bands.

An ideal image would have a high spatial resolution and many spectral bands but optimizing both qualities is a technical challenge. Spatial resolution of scanned film is limited by the size of the light sensitive grains, which is about 7µm. A current scanning resolution would be 15µm. Application of a semi-automated classification system for three band false colour NIR images, developed for Dutch coastal dunes, requires a pixel size of - order of magnitude - 20 cm (Droesen, 1999). This resolution could be achieved with aerial photos on scale 1:15 000 (Van der Hagen and van Til, 2001). The use of such a scale for high resolution orthophoto production is very cost-effective in comparison to larger scale images but the advantage of the latter is the far better applicability for manual stereo interpretation. Digital cameras obtain equal resolutions and have the advantage of skipping the - quality reducing – scanning and the ability of recording three visual bands in addition to NIR.

Line scanners, in contrast to frame cameras, consist of an array of spatial sensor elements per spectral band and images are gradually built up as the aircraft advances. Most hyperspectral scanners or imaging spectrometers belong to this group of sensors. Commercial hyperspectral sensors have about 100 to 300 bands and spectral resolutions up to 2.2nm. But a high number of bands can only be achieved at the expense of spatial resolution due to the integration time required by the sensitive elements (Charge Coupled Device) to attain an acceptable signal to noise ratio. At sub meter spatial

resolution, hyperspectral scanners can only be used in multispectral mode, thereby losing their strongest potency.
Images obtained by line scanners or frame cameras also imply a different georeferencing procedure. Camera images, in which a large surface is recorded simultaneously, are geometrically consistent and can be georeferenced and rectified quite accurately (depending on the topography). Scanned images are much more sensitive to movements of the aircraft and georeferencing requires detailed GPS and INS data (Inertial Navigation System). In practice, the best geometric accuracy attainable seems to be about two pixels or several meters (Aspinall *et al*., 2002).

Image classification

The success of automated image classification will firstly depend on the spectral homogeneity. Images show variation in colour or reflection value due to local atmospheric conditions, angle of incident radiation, light fall-off towards the image margins, etc... and therefore need to be radiometrically corrected (see Droesen, 1999 for false colour images). Calibration to true reflectance values requires information on camera or scanner characteristics and field measurements. This processing step is useful for hyperspectral data but is often skipped in case of for instance false colour images.

Automated classification can be either supervised or unsupervised. Supervised classification is based on spectral similarities between image and training pixels (with known ground cover type). Its performance is favoured by a high spectral resolution as provided by hyperspectral images, as well as a high spatial resolution, which reduces the occurrence of mixed pixels. Unsupervised classifications do not use test pixels and carry out a clustering of pixels based on their spectral properties. This may be interesting in order to explore the spectral variability of an image although it can be hard to define the obtained classes. Another distinction can be made between pixel and object oriented classification methods. The first consider the image pixels as basic classification elements while the latter group pixels into objects prior to classification (image segmentation). Both pixel and object oriented methods can be either supervised or unsupervised (de Jong and van der Meer, 2004).

In the Netherlands, the first steps towards digital image interpretation were taken in the 1990s. False colour aerial photographs were used for semi-automatic classification of the vegetation in dry coastal sand dunes (Assendorp and Van der Meulen, 1994; Droesen *et al.,* 1995). A fuzzy classification algorithm was developed in order to discriminate five herbaceous vegetation types, based on structural characteristics. Validation with ground truth data yielded correlation coefficients of 0.8 up to 0.9 (Droesen, 1999). Janssen (2001) used multispectral CAESAR images with spatial resolution of 0.5m for classification of seven salt marsh vegetation classes and achieved an overall accuracy of 75%.
Hyperspectral GER EPS-A images with 5 m pixel size were used in dune vegetation classification by De Lange *et al.* (2004). In this study 22 vegetation classes were mapped with overall accuracies of 60 to 70%. An expert system with ancillary ecological information was used to obtain the highest accuracies.

Schmidt *et al*. (2004) used HYMAP data with 3.5m spatial resolution for salt marsh vegetation mapping. An overall accuracy of 40% was obtained for 19 vegetation types. Integration with additional laser altimetry data increased the accuracy to 66%.
Several images are available for the Belgian coast but classification is still in an early stage. During the summer of 2004, the dunes and salt marshes along the Belgian coast have been surveyed with the hyperspectral AISA-Eagle sensor. The images are presently being classified (*cf.* Bertels *et al.*, 2005).

Conclusion: towards desktop vegetation monitoring?

Mapping of coastal vegetation through automated image processing has not yet reached a fully operational stage in conservation practice although present expertise and knowledge show that certain techniques are well suited for that purpose. Table I. summarizes the properties of and classification possibilities with the main image types which are relevant for detailed vegetation mapping. But as explained below, the choice for a particular image demands a subtle assessment of different qualities.
Very high spatial resolution, false colour images certainly enable accurate classifications of a limited number of vegetation types in dry herbaceous dunes and salt marshes. Due to their potential for high geometric accuracy, these images are appropriate for the monitoring of vegetation dynamics, for instance in relation to grazing management evaluation. A cost estimate for the Amsterdam waterworks dunes (3500 ha) revealed that the manual production of a vegetation map would be about 75% more expensive. In the Netherlands an ArcView module has been developed in order to enable a wider use of this technique. Until now, mainly scanned film has been used but in the (near) future, digital camera images will probably play an important role due to their superior radiometric quality.

Table I. Main image types and their properties (* = depending on the number of bands)

	Scanned FCIR film	Digital frame camera FCIR image	Hyperspectral image
Radiometric quality	moderate	good	good
Number of bands	3	3 or 4	up to hundreds
Spectral discrimination	low	low	high*
Spatial resolution	dm	dm	m*
Geometric quality	good	good	moderate
Cost	moderate	moderate	high

In spite of their merits, false colour images only represent three (broad) spectral bands, which limits their potential for further improvement of image classifications. The spectral information is mainly comprised in the red and NIR bands, which only vaguely represent the red edge. Therefore vegetation classes delimited so far mainly represent vegetation structure. In species poor systems such as salt marshes, this leads to quite satisfactory results but in complex dune vegetations only a very rough picture of the vegetation can be obtained.

Hyperspectral data contain more detailed information on different aspects of vegetation. The work of Schmidt (2003) showed that most salt marsh vegetation types can be distinguished spectrally, at least with field spectroscopic measurements. The dataset with field spectra of dune vegetation is not large yet and first results indicate spectral overlap between important vegetation types. This is quite logical if we compare the species sets of both systems. Salt marsh vegetation can be characterised fairly well using about 15 species, while dry dunes alone would require at least 50 species. An elaborate campaign for ground reflection measurements of dune vegetation is desirable and will reveal some possibilities and limitations of hyperspectral remote sensing. But due to lower spectral and spatial resolution and atmospheric distortions in the aerial image, field measurements will always be of superior quality, representing the maximum attainable spectral separability.
At present, the use of hyperspectral images for remote sensing of coastal vegetation is still not obvious because of the constrained spatial resolution, difficulties with georeferencing and the relatively high cost. Georeferencing accuracy is of paramount importance for relating images to GPS referenced ground truth data and appears to be a key bottleneck in recent hyperspectral remote research projects (*cf.* de Lange *et al.,* 2004; Schmidt, 2003; Jacobson *et al.,* 2000).

Each application needs a fundamental assessment whether spectral or spatial resolution is most important, reflecting a trade off in respectively classification and geometric accuracy. Another end user's choice is related to the trade off between classification accuracy and detail of class-definitions. It is up to map producers to indicate the possibilities and up to the users to decide whether uncertainty is accepted in the map itself or in the classes it represents. In this respect, Jacobson *et al*. (2000) refer to different levels in the EUNIS classification.

In future research a variety of techniques need to be tested or refined. On the one hand these are related to image processing and classification. Techniques taking into account the spatial domain (*e.g.* image segmentation), feature selection techniques (*e.g.* wavelet analysis) and sub-pixel methods are only a few examples. On the other hand, many studies pointed out the importance of ancillary data. Classification of salt marshes in particular seems to improve significantly with the aid of Digital Terrain Models obtained by laser altimetry (Brown, 2004; Schmidt, 2003). In dunes, elevation data should be used more cautiously and preferably in relation with hydrology (Thackrah *et al.*, 2002; De Lange *et al*., 2004). Finally, canopy height derived from laser scans (Ritchie *et al.*, 2001) can provide very useful additional information for vegetation mapping.

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