THE USE OF HYPERSPECTRAL DATA IN COASTAL ZONE VEGETATION MONITORING

Remko de Lange[1], Mark van Til [2] and Stephen Dury[1]*

1. Ministry of Transport, Public Works and Water Management, Survey Department, Delft, The Netherlands; s.j.dury(at)agi.rws.minvenw.nl
2. Amsterdam Water Supply, Vogelenzang, The Netherlands; m.vtil(at)wlb.amsterdam.nl

ABSTRACT

Vegetation monitoring is an important tool in the evaluation of nature management in the coastal zone of The Netherlands. Remote sensing images are valuable in order to investigate spatio-temporal changes in the vegetation. A classification method has been developed based on airborne hyperspectral data, which were acquired using the GER EPS-A scanner. A supervised classification method has been used applying the Spectral Angle Mapper, in combination with an expert system. The SAM algorithm determines the similarity between spectra of different vegetation types. The expert system adds extra information about environmental conditions to the classification in order to improve the discrimination of vegetation types, which are otherwise spectrally difficult to identify. In our case, this method gives the opportunity for rapid classification with an overall accuracy of 60-70%.

Keywords: Hyperspectral remote sensing, expert system, dune vegetation, monitoring

INTRODUCTION

The Dutch coastal dunes belong to the most extensive protected nature areas of The Netherlands. For several decades many dune areas have been subject to decreasing biodiversity in flora and fauna due to acidification, eutrophication and prolonged desiccation which are primarily caused by water abstraction, atmospheric deposition of nitrogen, and reduced pasture (1,2). These changes lead to acceleration of the vegetation succession, and domination of species-poor roughs and scrub over species-rich pioneer vegetation and dune grasslands (3). In order to maintain biodiversity and restore threatened vegetation, nature managers have applied a number of management measures. These require accurate monitoring systems to investigate autonomous vegetation development and to evaluate the effect of nature management.

The use of remote sensing images is not new in dune vegetation research (4,5). Currently, the monitoring of vegetation development is based on sequential manual mapping of vegetation structures seen from aerial false colour photos and fieldwork (6,7). This method is both cost- and labour-intensive. Furthermore, manual aerial photo interpretation and digitising both incur errors in the geometric and thematic accuracy. With regard to dry dune areas a (semi)automatic processing method has been developed for the classification of vegetation structures from false colour photos (8). This method is used for deriving vegetation maps with the purpose of monitoring the effects of cattle grazing (9).

The Survey Department of the Ministry of Transport, Public Works and Water Management conducts research in applying innovative measurement methods with the aim of obtaining a more detailed, objective and efficient vegetation monitoring system (10,11).

[*] Present address: University of Leeds, School of Geography, Leeds, England; r.de-lange(at)geog.leeds.ac.uk

DATA

For this research hyperspectral data has been collected from the Amsterdam Water Supply Dunes (AWD), one of the ecologically most complex dune areas of The Netherlands. It is situated along the central part of the Dutch coastal shoreline, south of Zandvoort (Figure 1). The selected area within the AWD includes the full range of dune landscapes (12), i.e. the transition from Old dune systems (3000 – 500 years BC) to Young dune systems (1000 years AD – present) ending at the beach coastline. The hyperspectral scan describes an area of approximately 5 km × 2 km, which is more or less 30% of the total area of the AWD. Field data has been collected for classification purposes and for validation of the classification. In the following subsections the two datasets, that is hyperspectral scanning data and field data, will be described.

Figure 1. Location of the Amsterdam Water Supply Dunes in The Netherlands.

Hyperspectral scanning data

An airborne GER EPS-A scanner was used to record an image of the AWD area on 23 May 2001. The EPS-A scanner recorded data in 33 wavelength bands, 28 of which are in the wavelength range of 363 nm to 1061 nm. Two bands were sampled in the SWIR range of the spectrum, at 1691 nm and 2173 nm, and one band in the thermal at 10260 nm. The band spectral resolution is approximately 9 nm. Two other bands are reserved for flight information. Table 1 gives information about flight details during the scan.

Table 1. Flight details of the GER EPS-A scanner at 23 May 2001.

Height	6000 feet
Ground speed	120 m/s
Scan speed	12 scan lines/s
Pixel size	5 m x 5 m

The hyperspectral image is geometrically corrected with use of a digital false colour ortho-photo from the area of the same year (2001). More than 200 reference points made it possible to correct the image with the rubber sheeting method (13). The accuracy of the geometric correction model expressed in root mean square error is set on 1.2 pixels (6 meters) and is based on 40 dGPS measurements in the field. Reduction of the RMS errors was not possible due to considerable flight manoeuvres.

Radiometric corrections were also applied based on the radiative transfer model Modtran (v.4). The correction for atmospheric influence could only be applied on 25 of the 33 bands, ranging from 380 nm to 950 nm, due to limitations in the wavelength range of the radiative transfer model used. The radiation model was not able to remove the effect of sun glitter so eventually an area of 4.75 km × 1.0 km was used for classification.

Field data

During the growing season (May and June) of 2001 an extensive field campaign took place for collecting field data. 216 homogeneous field plots of 5 m × 5 m were delineated, from which the following data were collected: vegetation type, vegetation structure, spectra measured with a field spectrometer and location of each plot using a dGPS (11,14). Eight different vegetation structures (11,15) were discriminated, and 23 vegetation types (Table 2), following the typology of the Amsterdam Water Supply (11,16). Each plot was accordingly classified (i.e. one vegetation structure and one vegetation type per plot).

Table 2: Vegetation types, structures and plant communities (17,18,19) discriminated within the AWD area whereupon further classification is based.

Vegetation type	Vegetation structure	Plant community
Sand	Sand	--
P2	Pioneer vegetation	Phleo-Tortuletum typicum
M4	Open moss vegetation	Violo-Corynephoretum koelerietosum
M5	Dense moss vegetation	Violo-Corynephoretum typicum Frame community of Campylopus introflexus-[Koelerio-Corynephoretea]
G13	Short dune grassland	Festuco-Galietum veri
G13+	Tall dune grassland	Festuco-Galietum veri
R6	Rough	Frame community of Calamagrostis epigejos-[Koelerio-Corynephoretea]
D4/D5	Scrub	Hippophao-Sambucetum Hippophao-Ligustretum Frame community of Hippophae rhamnoides-[Koelerio-Corynephoretea]
K5	Scrub	Frame community of Salix repens-[Polygalo-Koelerion]
M2	Open moss vegetation	Phleo-Tortuletum cladonietosum
G5	Short dune grassland	Taraxaco-Galietum veri
G5+	Tall dune grassland	Taraxaco-Galietum veri
R2	Rough	Frame community of Ammophila arenaria-Carex arenaria-[Ammophiletea/Koelerio-Corynephoretea]
R5	Rough	Derivate community of Elymus spec-[Koelerio-Corynephoretea]
K4	Scrub	Frame community of Ligustrum vulgare-[Berberidion vulgaris]
V1	Dune slack vegetation	Festuco-Galietum veri → Botrychio-Polygaletum
V2	Dune slack vegetation	Taraxaco-Galietum veri → Botrychio-Polygaletum
V4	Dune slack vegetation	Frame community of Holcus lanatus-[Molinio-Arrhenateretea], Derivate community Calamagrostis epigejos-[Convolvulo-Filipenduletea]

Table 2 cont.

V5	Dune slack vegetation	Pallavicinio-Sphagnetum
V6	Dune slack vegetation	Junco baltici-Schoenetum
V8	Dune slack vegetation	Derivate community of Phragmites australis-[Convolvulo-Filipenduletea]
V9	Dune slack vegetation	Derivate community of Typha latifolia-[Phragmitetea]
K6	Scrub	Taraxaco-Galietum veri (with Salix repens)

CLASSIFICATION

A supervised classification of the image was undertaken based on the field observations. The field study provided the training data for the presence of the vegetation types and vegetation structures and their locations. The spectra of these locations are extracted from the geometrically and radiometrically corrected hyperspectral image. A subsequent study (14), based on field spectrometer data, has shown that most combinations of spectra of vegetation types are spectrally distinctive at the beginning of the growing season (May). Figure 2 gives examples of spectra of vegetation structures extracted from the EPS-A image.

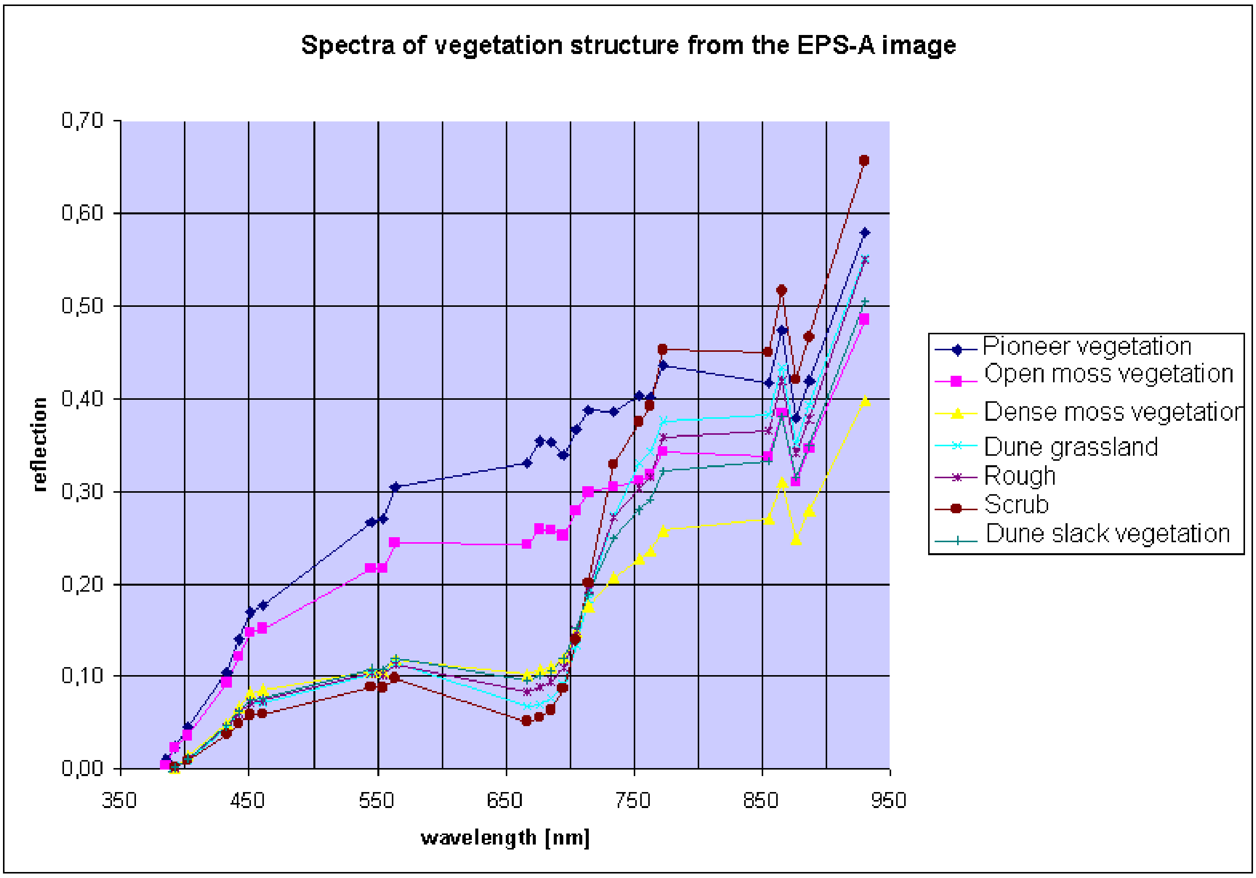

Figure 2: Spectra of different vegetation structures derived from individual pixels of the EPS-A hyperspectral image.

Spectral characterisation

To spectrally classify an image (using supervised methods) a set of reference spectra is required. A canopy reflectance signal is the integrated outcome of a complex interaction of tissue chemical, canopy structural, and landscape organisational factors (20). Furthermore, as vegetation reflection characteristics change in time (14), standardising of vegetation spectra (i.e. using spectral libraries as used in geological applications) is mostly not desired (21). Therefore, spectra extracted from the image itself are preferred as a basis for vegetation classification. This research illustrates two methods for spectrally characterising the local vegetation, where both methods make use of the EPS-A spectra of the field plots.

'Mean vector determination'

Image spectra corresponding with the locations of the field plots were collected. Half of the 216 field plots have been used for determining spectral 'endmembers'. Within the 'mean vector determination' the spectra belonging to the same vegetation type or vegetation structure are averaged per band. The mean reflectance forms the prototype spectrum for the given vegetation type. The set of prototype spectra forms the spectral 'library', which will be used for classification.

'Individual vector determination'

The 'individual vector determination' regards each spectrum, derived from the image at the location of the field plots, as unique. In this method all 108 (out of 216) field plots are used for the classification with no prior averaging. After classification the classes corresponding to the same vegetation type or vegetation structure are combined to form unique vegetation classes.

Spectral Angle Mapper

A common classification method for hyperspectral data is the Spectral Angle Mapper (SAM) (22). This is one of the leading classification methods because it evaluates the spectral similarity in order to repress the influence of shading to accentuate the target reflectance characteristics (23). The spectra are treated here as vectors in n-dimensions, where n is the amount of bands measured in the spectra. The SAM algorithm determines the similarity between two spectra (e.g. known vegetation type spectrum versus image pixel spectrum) by calculating the angle between the two vectors. The SAM classification results in an image with angles to the classes; a derivative product of this image is a classified map based on the smallest angles to the known vegetation type spectra.

Expert system

The reliability of a classification can be improved by making use of knowledge of environmental conditions (10,22). Since vegetation structures and/or vegetation types can be directly related to environmental conditions, it is possible to use a-priori ecological expert knowledge to estimate the occurrence of vegetation structures/types based on environmental conditions at a given site. The result of the SAM classification can also serve as an input to the expert system.

Rules provide the link between the GIS database layers and the knowledge of experienced vegetation scientists. The expert rule links together ecologists' knowledge concerning individual species with the geographic data available for the study area. Expert tables are constructed containing the probabilities of occurrence for vegetation structures and vegetation types under different environmental conditions. The expert tables, the environmental condition maps and the fuzzy classification result of the SAM classification enables us to reclassify the hyperspectral data (see Figure 3). The SAM classification results in per pixel estimations of probability of occurrence for each vegetation structure or vegetation type by means of the spectral angles. These probabilities are multiplied with the probabilities of occurrence (expert tables) in the given environmental conditions (thematic maps). Each pixel is thus classified according to the vegetation type/structure with the highest probability of occurrence.

The choice of which environmental conditions to use to refine the classification, is strongly dependent on the rate of influence of the conditions on vegetation species composition and the distribution of vegetation types in the AWD. A number of different datasets from vegetation studies in the AWD have been analysed and have given insight into the importance of several environmental variables in coastal sand dunes, i.e. soil decalcification (gradient decalcified – calcareous), moisture content of the soil (gradient dry – wet) and nature management (12,16,24).

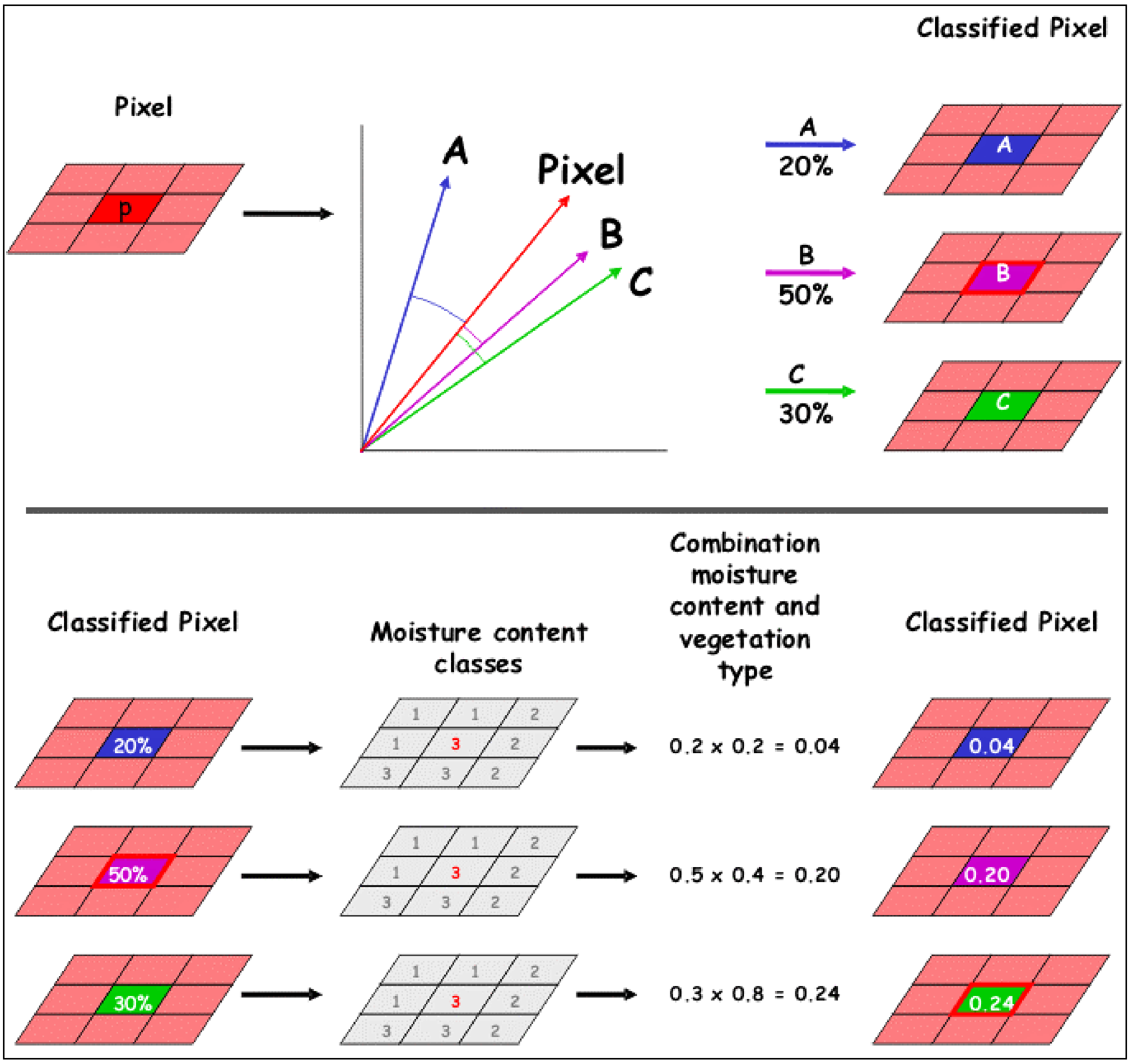

Figure 3: Operating mode of the expert system. A pixel has been classified in a fuzzy manner (above), for example with the SAM classifier. Probabilities for the pixel are given for three different vegetation types (map layers). The addition of a thematic map (below), in this example the soil moisture content, together with probabilities for the different vegetation types belonging to the soil moisture content conditions at the position of this specific pixel, give a reclassified map. The obtained fuzzy classification can be converted into a final classification by assigning the vegetation type with the highest probability to each pixel.

Soil decalcification

The decalcification depth of the soil is strongly dependent on lime content and the age of the soil. The soil decalcification depth has been derived from a detailed landscape ecological map and vegetation map of the AWD (16,25). Both maps are based on false colour aerial photos (1:5000) and fieldwork. For the vegetation map a typology has been developed, based on 1100 vegetation observations for which the vegetation species composition was described and the decalcification depth was measured. With this information a detailed soil decalcification map was produced.

For every landscape type, and thus for every decalcification class, the relative area of the different vegetation types from the test site was determined by making an overlay with a recent map showing the distribution of the chosen vegetation types and vegetation structures. The expert table for soil decalcification has been constructed using these relative areas, which can be considered a reliable measure for the probability of each vegetation type and vegetation structure per decalcification class.

Moisture content

The moisture content of the soil is mainly determined by the groundwater level. In the AWD the groundwater level is monitored by soundings four times a year and by measurements once every two weeks. The time sequence of soundings has been interpolated and converted into a map of the mean spring groundwater level (26), using a digital elevation model.

For each vegetation type and vegetation structure in the expert table a probability of occurrence has been assigned, depending on the moisture content, by means of overlaying the map of the mean spring groundwater level with a recent vegetation map and incorporating expert judgement (16).

Nature management

For restoration and preservation of the biodiversity, several nature management measures are applied in specific parts of the AWD. Large parts of the dune slack vegetation are mown and other areas are grazed by sheep or cattle. The relative area of the vegetation types, which was determined by overlaying a map of the managed areas with the recent vegetation map, has been used for estimating the probabilities of the vegetation types per management measure and composing the expert tables.

Model calibration

The expert system needs to be calibrated as it is likely that not all environmental conditions are equally important. The conditions can be weighted based on their importance so that an optimal classification result can be reached. The order of importance has been investigated by means of a SAM classification in combination with each environmental variable separately. Four test areas were chosen representing different landscape zones in the AWD. The areas measure about 350 m $\times$ 150 m and do not overlap with the field plots; therefore they do not interfere with the accuracy assessment, which is based on the field plots. Based on the classifications of the test areas, i.e. the separate environmental variables combined with the SAM classification, and the inspection of an experienced vegetation ecologist who knows the AWD well, an order of importance of the environmental conditions was set.

After evaluation of the relative importance of each of the environmental conditions, the next step was to evaluate the appropriate weighting between the SAM classification and the combined environmental conditions. This was determined by an expert (i.e. vegetation ecologist) by inspecting the results of the combined classification of the four test areas with different weighting factors.

RESULTS

Model calibration has given insight into the importance of the environmental conditions. After some trial and error the weightings for soil decalcification, moisture content and nature management were set at 0.5, 0.3 and 0.2 respectively. The ratio for the SAM classification versus the expert system was set to 3:1. With this ratio a balance was found between the over 'noisy' result of the SAM and the over 'smoothened' result due to the expert system classification. This behaviour of both methods is well illustrated by figure 4, where the SAM classification results are compared with those of SAM with combination with the expert knowledge (with ratio 1:1) for one of the test areas. The best results were obtained for the four test areas with the 'individual vector determination' SAM classifier combined with the expert system.

An accuracy assessment was made based on the remaining half of the field observations (108), not used in the classification procedure (validation data set). The results can be seen in table 3 and support the conclusions based on the visual interpretation of the four sample areas. Both methods show a better result for the 'individual vector determination' SAM classifier than for the 'mean vector determination' SAM classifier. In general the addition of the expert system gives better results although one exception is given, namely the vegetation type classification combined with the SAM classification (64% versus 60% correctly classified). The best result was obtained for the vegetation structure with the 'individual vector determination' SAM classifier combined with the expert system, for which 69% is correctly classified.

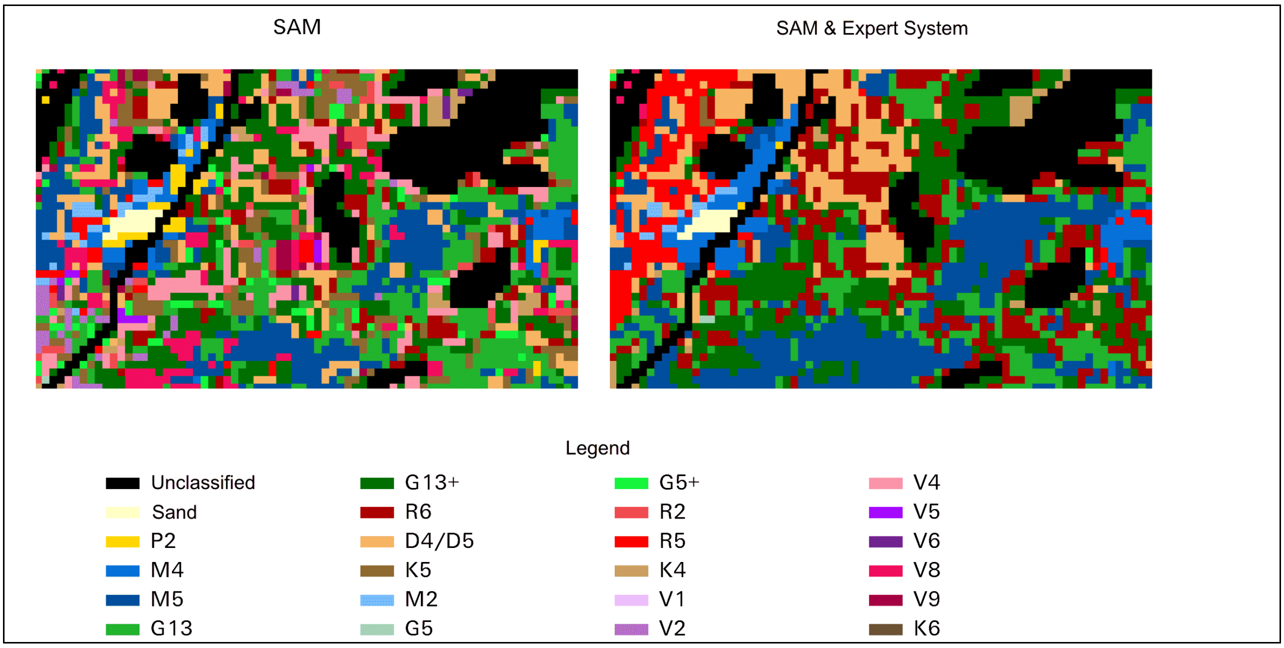

Figure 4: The results of a SAM classification and a classification with additional expert knowledge of one of the test areas (ratio of 1:1). The pixel size is 5 m x 5 m. The legend codes stand for different vegetation types that are explained in Table 2.

Table 3: Results of the accuracy assessment for different classification methods which are based on 108 field observations, expressed in percentage correct classified.

	SAM classification		**SAM & expert system classification**	
	'Mean vector determination'	'Individual vector determination'	'Mean vector determination'	'Individual vector determination'
Vegetation structure	48	61	67	69
Vegetation type	42	64	52	60

Cross tables of the reference data (i.e. the field observations) against the image classifications were used to give insight into which vegetation types were mainly responsible for the 30-40% misclassification. Where no discrimination could be achieved with the SAM classification method between the dry dune vegetation and the moist dune valleys, the addition of the expert system gave opportunities to partly discriminate these vegetation types.

Misclassification with the expert system was found to occur regularly within vegetation types which are ecological neighbours of each other, i.e. closely related in vegetation succession. These vegetation types are often spatial neighbours in the gradient rich dune landscape of the AWD. Therefore, the misclassification might also be ascribed to errors in the geometric correction of the EPS-A image. Due to this inaccuracy, field plots which are situated in gradient rich parts of the dunes could be misclassified into their neighbours.

Furthermore, misclassifications with the SAM- and the expert system classification were frequently observed among vegetation types with only 2 or 3 vegetation observations for the classification and 2 or 3 observations for the validation. Obviously two observations are not enough for a correct classification or validation.

DISCUSSION & CONCLUSIONS

This study shows that airborne hyperspectral data can be used for the classification of coastal dune vegetation, while expert knowledge can enhance the results. For the gradient rich area of the AWD an accuracy of 60-70% was obtained. Schmidt et al. (22) obtained the same kind of results with airborne hyperspectral data combined with an expert system for the classification of a saltmarsh in The Netherlands, obtaining an accuracy of 66%. This was an improvement of 23% compared to aerial photo interpretation classification of that area (22).

In this study two different methods for the SAM were compared. The so-called 'mean vector determination' method is commonly used for hyperspectral analysis. Spectra for each material are averaged so that the spectral variability within the obtained prototype spectrum is not taken into account. Although common in geological studies, the use of prototype spectra is difficult to apply in vegetation classification as spectra vary in time (14). This research shows that averaging spectra from vegetation types will not yield accurate results within a SAM classification as the spatial variability within vegetation types is too great. To overcome this we used the so called 'individual spectral determination' which treats each obtained spectra as unique. The spectral variability within each vegetation type is better represented and better results are obtained when combining vegetation classes after classification. The consequence of this method is the loss of the possibility to obtain a multi applicable spectral library. However, this is not a serious loss as the goal of a universal spectral library is difficult to achieve for vegetation.

The combination of the SAM with an expert system can improve the classification when vegetation is spectrally difficult to discriminate. The expert system we used increased the accuracy, averaged for the two classifications (that is, vegetation type and -structure) and the two vector derivations, by 8%. Misclassifications occurred mostly among vegetation structures and -types which are ecological and spatial neighbours. As the abiotic gradients in the coastal dunes of the AWD change within the same dimension of one image pixel (i.e. 5 m x 5 m), the derived spectra from the image need to exactly correspond with the field plots. When this is not the case, the derived image spectra of these field plots might represent a different, neighbouring vegetation type or a mixed pixel. This will result in misclassifications among spatially close vegetation types and therefore ecological neighbours. The geometric correction of the GER EPS-A scan has a RMS error of 1.2 pixels (6 m) and can therefore have direct influence on the classification. The accuracy of the classification can therefore be improved when the geometry of the image is enhanced. One way to accomplish this is to install a GPS/INS instrument on board of the airplane carrying the hyperspectral scanner, so that significant flight manoeuvres are correctly recorded. In that case, another, more accurate correction algorithm can be used. Misclassification of neighbouring vegetation types can also be reduced with an increased image resolution, as long as the RMS error is reduced to the normal accepted level of less than 0.5 pixels. In that case, the error introduced by geo-correction, will not reach to the spatial dimensions of the vegetation gradients.

The SAM classification can be considered as a fuzzy classification (27) which is the most suitable for ecological transition areas such as encountered here. Such classification algorithms are more sensitive to the imprecise (fuzzy) nature of the real world, and offer potential for extracting information on the makeup of the biophysical materials within a mixed pixel. However users require hardened classification maps with each pixel representing a single vegetation type, which produces errors as a result of the mixed pixels encountered.

The expert system can potentially be used for reducing the misclassification of neighbouring vegetation types as the abiotic environmental conditions are used as inputs for the classification. In this research the expert knowledge together with the spectral information is used for the whole study area at once. As mixing still occurs between vegetation types with different abiotic conditions, an expert system with stricter rules might further reduce mixing. This can be obtained with a classification method based on hierarchical stratification, for example one with sub-areas so that spectral mixing between vegetations on different abiotic conditions is excluded.

It is still not clear whether hyperspectral data, in combination with an expert system, can be used as a monitoring tool for vegetation changes as no other hyperspectral images have yet been recorded for this area. However, the methodology employed here gives an overall accuracy of classification of 60-70%, which is still low for monitoring purposes. This methodology may therefore be more appropriate for use in monitoring areas with lower frequency abiotic gradients, where there will be fewer mixed pixels and where a 'hard' classification is therefore more appropriate.

ACKNOWLEDGEMENT

Many thanks go to K. Schmidt and A. K. Skidmore of the International Institute for Aerospace Survey and Earth Sciences (ITC) for their support with the expert system.

REFERENCES

1 Meulen F van der, A M Kooijman, M A C Veer & J H van Boxel, 1996. Effectgerichte maatregelen tegen verzuring en eutrofiëring in open droge duinen. Eindrapport fase 1: 1991-1995. (University of Amsterdam) (in Dutch)

2 Dijk H W J van, & A P Grootjans, 1993. Wet dune slacks, decline and new opportunities. In: Netherlands – Wetlands, edited by E H P Best & J P Bakker, 281-304

3 Kooijman A M, J C R Dopheide, J Sevink, I Takken & J M Verstraten, 1998. Nutrient limitations and their implications on the effects of atmospheric deposition in coastal dunes; lime-poor and lime-rich sites in the Netherlands. Journal of Ecology, 86: 511-526

4 Dorp D van, R G A Boot & E van der Maarel, 1985. Vegetation succession in the dunes near Oostvoorne, The Netherlands, since 1934, interpreted from air photographs and vegetation maps. Vegetatio, 58:123-136

5 Til M van, P Ketner, S F Boersma & L H W T Geelen, 1999. De duinen in dynamisch perspectief. Landschap, 16: 237-249 (in Dutch, with English summary)

6 Janssen J, 2001. Monitoring of salt-marsh vegetation by sequential mapping. (University of Amsterdam)

7 Ehrenburg A M van Til & J Mourik, 1995. Vegetatieontwikkeling en begrazingsbeheer van het zeedorpenlandschap bij Zandvoort. De Levende Natuur, 96: 202-211 (in Dutch, with English summary)

8 Droesen W J, 1999. Modelling of natural landscapes, with cases in the Amsterdam Waterworks Dunes. (Landbouwuniversiteit Wageningen)

9 Grontmij Geogroep, 1996. Interpretatie en analyse van digitale kleur-infrarode orthofoto's van de gebieden Helmduinen en Kijfhoek/Bierlap. (in Dutch)

10 Skidmore A K, K Schmidt, H Kloosterman, L Kumar & H van Oosten, 2001. Hyperspectral imagery for coastal wetland vegetation mapping. NRSP-2 rapport nr. 01-31. (Beleidscommissie voor Remote Sensing, Delft)

11 Til M van, R de Lange & A M Bijlmer, 2003. Hyperspectrale beeldverwerking voor de kartering van duinvegetatie. (Rijkswaterstaat, Meetkundige Dienst & Gemeentewaterleidingen Amsterdam) (in Dutch, with English summary)

12 Ehrenburg A & G Baeyens, 1992. Landscape-ecological mapping as basis for management of the Amsterdam Waterwork Dunes. In: Coastal Dunes: Geomorphology, Ecology and Management for Conservation, edited by R W G Carter et al. (Balkema, Rotterdam/Brookfield)

13 ERDAS, 1997. ERDAS Field Guide. (ERDAS Inc., Atlanta, Georgia, USA)

14 Til M van, A M Bijlmer & R de Lange, 2003. Seasonal variability in spectral reflectance of coastal dune vegetation. EARSeL eProceedings, 3(2): 154-165

15 Assendorp D & F van der Meulen, 1994. Habitat classification of dry coastal ecosystems, the integration of image and field sample. In: EARSeL Workshop on Remote Sensing and GIS for Coastal Zone Management, edited by Janssen L L F & R Allewijn (EARSeL, Delft), 16-26

16 Til M van & J Mourik, 1999. Hiëroglyfen van het zand. Vegetatie en landschap van de Amsterdamse Waterleidingduinen. (Gemeentewaterleidingen Amsterdam) (in Dutch)

17 Schaminée J H J , A H F Stortelder & E J Weeda, 1996. De Vegetatie van Nederland 3. Plantengemeenschappen van graslanden, zomen en droge heiden. (Opulus Press, Uppsala) (In Dutch)

18 Schaminée J H J, E J Weeda & V Westhoff, 1995. De Vegetatie van Nederland 2. Plantengemeenschappen van wateren, moerassen, natte heiden. (Opulus Press, Uppsala) (in Dutch)

19 Stortelder A H F, J H J Schaminée & P W F M Hommel, 1999. De Vegetatie van Nederland 5. Plantengemeenschappen van struwelen en bossen. (Opulus Press, Uppsala) (in Dutch)

20 Asner G P, 1998. Biophysical and biochemical sources of variability in canopy reflectance. Remote Sensing of Environment, 64: 234-253

21 Peterson D L & G S Hubbard, 1992. Scientific issues and potential remote sensing requirements for plant biochemical content. Journal of Imaging Science and Technology, 36(5): 446-456

22 Schmidt K S, A K Skidmore, E H Kloosterman, H van Oosten, L Kumar & J Janssen, 2004. Mapping coastal vegetation using an expert system and hyperspectral imagery. Photogrammetric Engineering & Remote Sensing, (in press)

23 Kruse F A, A B Lefkoff, J W Boardman, K B Heiedbrecht, A T Shapiro, P J Barloon & A F H Goetz, 1993. The Spectral Image Processing System (SIPS) – Interactive Visualization and Analysis of Imaging Spectrometer Data. Remote Sensing of Environment, 44: 145-163

24 Kooijman A M & M Besse, 2000. Bodemontwikkeling in duinvalleien in de Amsterdamse Waterleidingduinen. Het belang voor vegetatie en beheer. (Universiteit van Amsterdam & Geementewaterleidingen Amsterdam) (in Dutch)

25 Ehrenburg A, 1994. Landschapskartering van de Amsterdamse Waterleidingduinen 1988-1989. (Gemeentewaterleidingen Amsterdam) (in Dutch)

26 Stevers R A M, J Runhaar, H A Udo de Haes & C L G Groen, 1987. Het CML-ecotopensysteem, een landelijke ecosysteemtypologie toegespitst op de vegetatie. Landschap, 4: 135-150

27 Wang F, 1990. Improving Remote Sensing Image Analysis through Fuzzy Information Representation. Photogrammetric Engineering & Remote Sensing, 56(8): 1163-1169