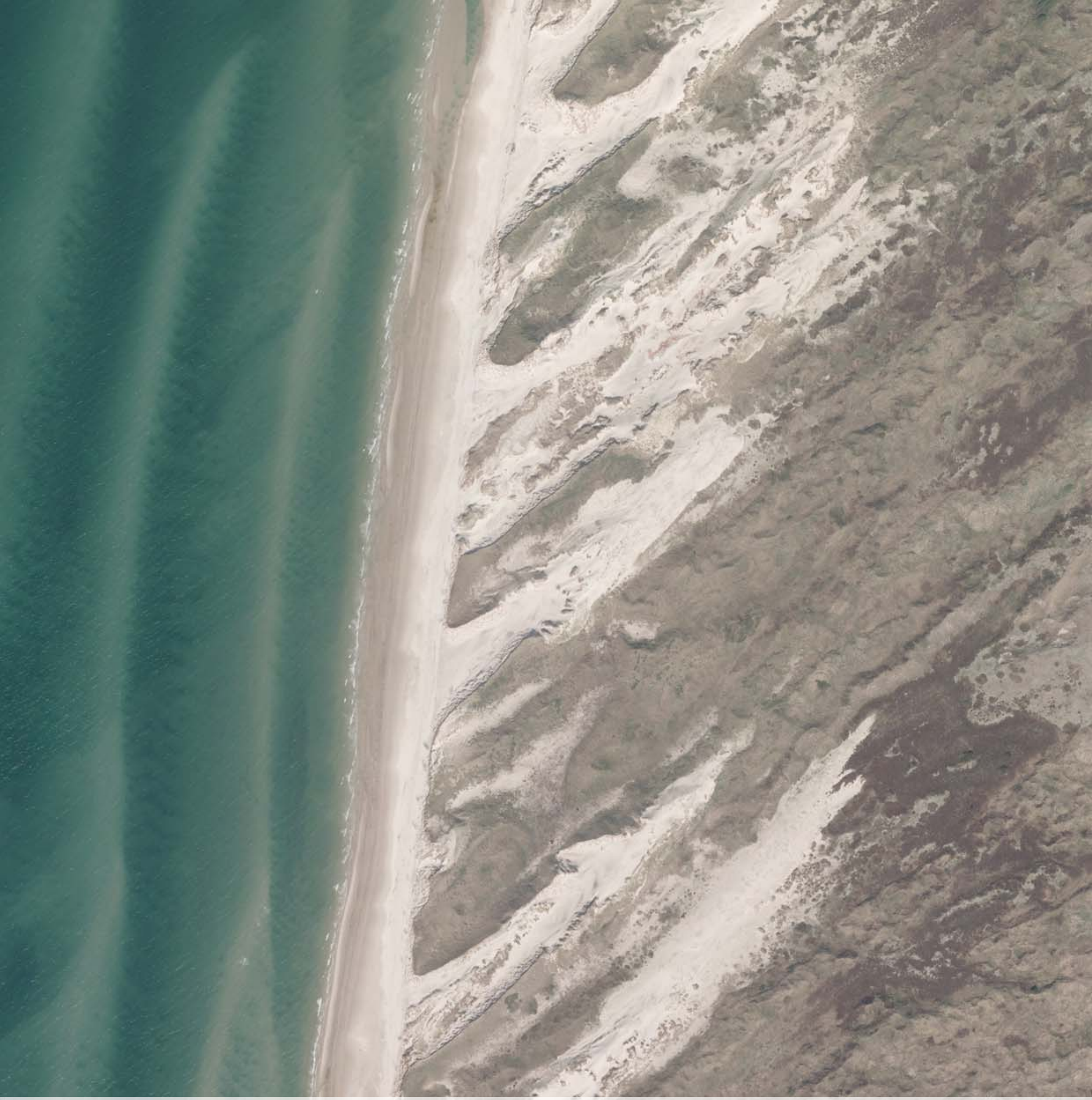

REMOTE SENSING BASED CLASSIFICATION OF STRUCTURAL ELEMENTS OF COASTAL HABITATS

(Telemålingsbaseret klassifikation af strukturelle enheder i kyst-habitatnaturtyperne)

Scientific Report from DCE – Danish Centre for Environment and Energy No. 144 2015

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Abstract: Denne videnskabelige rapport beskriver mulighederne for automatiseret klassifikation af strukturelle indikatorer i danske kyst-habitatnaturtyper, vha. orthofotos og højdemodeller, til udvikling af en forbedret overvågning og kortlægning af disse habitatnaturtyper i ift. hvad der er muligt med traditionelle feltbaserede metoder. Vurderingen koncentrerer sig om brugen af telemålingsbaserede data tilgængelige omkring år 2010 og en klassifikation af strukturer observeret i dette år. Rapporten inkluderer en vurdering af klassifikationsmuligheder, klassifikationssikkerheder og opstillingen af adskillelsesparametre baseret på indrapporterede feltreferencedata fra 2012.

Keywords: Habitats Directive, Natura 2000, coastal habitats, remote sensing, aerial orthophotos, object based image analysis, GEOBIA, Random Forest

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Contents

1 Summary

Inclusion of additional habitat types in the NOVANA nature monitoring places new demands on the work. For several of these habitat types it is not so much the vegetation species composition and chemical parameters that are central to assessment of the conservation status and trend, but more structural factors, such as the land distribution, geomorphology, coverage of woody plants, dwarf shrubs, etc., which are essential. The project that this report describes the work of covers 14 coastal habitat types, for which remote sensing data in the form of aerial orthophotos has been used as a supplement to field-based monitoring.

The six-year EU-reporting cycle of habitat conservation status includes reporting of habitat extents and the structure and function of habitats. With remote sensing (aerial photographs and/or satellite), it will be possible to monitor the entire Danish coastal zone, while traditional field-based methods only cover Natura 2000 sites or a random sample of the coastal zone.

The project has shown that the method is useful to identify and map structural elements. A final implementation of the method in NOVANA monitoring requires further development based on the data already collected, but even now there is good reason to be optimistic for the future applications.

This scientific report describes the possibilities for automated classification of structural element types in Danish coastal habitat types using aerial orthophotos and elevation models, towards development of a remote sensing based method for monitoring and mapping of these habitats that is better suited than the currently used field based methods. The assessment focuses on the use of remote sensing based data available around 2010 and a classification of structures present in this year. The report includes assessment of classification options, classification accuracy, and the use of the classification parameters based on field reference data from 2012.

2 Sammenfatning

Inddragelse af flere habitatnaturtyper i NOVANAs naturtypeovervågning stiller nye krav til overvågningen. For flere af disse naturtyper er det i mindre grad vegetationens artssammensætning og de kemiske parametre, der er centrale for at vurdere tilstand og udvikling, men i højere grad strukturelle forhold, såsom arealets udbredelse, geomorfologi, dækning af vedplanter, dværgbuske m.m., der er afgørende. Projektet omfatter 14 kystnære naturtyper, herunder stenstrande og klittyper, hvor telemålingsdata i form af flyfotos (orthofotos) er benyttet som supplement til den feltbaserede kontrolovervågning.

I den seksårige EU-rapportering af bevaringsstatus for habitatnaturtyperne indgår areal, udbredelse og naturtypernes struktur og funktion. Med telemåling (flyfotos og/eller satellitbilleder) vil det være muligt at overvåge hele den danske kystzone, mens traditionelle feltbaserede metoder kun dækker habitatområderne eller et stikprøvebaseret udsnit af kystzonen.

Projektet har vist at metoden er brugbar til at identificere og kortlægge strukturelle elementer. En endelig implementering af metoden i NOVANA overvågningen kræver yderligere udvikling baseret på de allerede indsamlede data, men allerede nu er der god grund til at være optimistisk for de fremtidige anvendelsesmuligheder.

Denne videnskabelige rapport beskriver mulighederne for automatiseret klassifikation af strukturelle indikatorer i danske kyst-habitatnaturtyper, vha. orthofotos og højdemodeller, til udvikling af en forbedret overvågning og kortlægning af disse habitatnaturtyper i ift. hvad der er muligt med traditionelle feltbaserede metoder. Vurderingen koncentrerer sig om brugen af telemålingsbaserede data tilgængelige omkring år 2010 og en klassifikation af strukturer observeret i dette år. Rapporten inkluderer en vurdering af klassifikationsmuligheder, klassifikationssikkerheder og opstillingen af adskillelsesparametre baseret på indrapporterede feltreferencedata fra 2012.

3 Introduction

The current biodiversity crisis invokes increasing demands for cost-effective mapping and monitoring of natural resources. The mapping and monitoring should be sufficiently informative as to guide the effective management of species, habitats and landscapes. On the other hand it also needs to be of utility at large geographical extents. In Europe the EU Habitats Directive demands of its member states, to carry out a surveillance of Annex I habitat types at a national level, in order to assess status and trends in distribution, area, structure and function.

Field-based monitoring provides the best available data for many ecosystems, by supplying detailed spatial information and species records. Some habitats, though, are difficult to monitor effectively in the field due to spatially discontinuous and unpredictable processes such as flooding, encroachment, erosion and succession, while coverage of large extents is very costly. Further, even with strict rules for field mapping methods, inter-observer errors remain an issue (Stevens et al., 2004). There is therefore a need to develop monitoring methods, which can assess status and trends of habitat cover, structure and function, occurring at greater spatial and temporal scale.

With advances in spatial resolution and quality of remote sensing (RS) data, and the possibilities offered by advanced object-based image analysis (OBIA) software, examples of RS-based habitat type mappings have appeared, even at a national scale (Lucas et al., 2011). These examples offer a cost-effective alternative to field-based habitat mapping.

We can divide primary RS data into satellite-based and aerial-based data, with the most commonly used being satellite data. The strengths of satellite data include high radiometric resolution, with consistent values through regions, the inclusion of both near infrared (NIR) and shortwave infrared (SWIR) bands useful for vegetation indices, and the possibilities of acquiring multi-seasonal images of regions recorded over a short time-span. Yet, for the purpose of identifying and delimiting detailed features within habitat types, most satellite imagery remains either too coarse in spatial resolution (e.g. from Landsat TM or SPOT) or too expensive (e.g. from IKONOS or Quickbird) for large and even medium sized areas (Klemas, 2008, 2011a).

Aerial-based imagery has some advantages too, the major ones being higher spatial resolution, the exclusion of atmospheric distortion, and in some cases, better availability and lower cost. The higher spatial resolution opens possibilities for mappings closer to field-derived mapping scales, making them intuitively understandable and possible to verify in the field. The use of aerial-based imagery has so far been limited by low radiometric resolution of bands, low range in the spectral domain and variation in illumination depending on time of day, weather or variation in look angle (Lucas et al., 2007). The low sensor coverage implies that nationally covering data will usually be acquired over a long time scale, limiting the possibilities of acquiring multi-seasonal images (Lucas et al., 2007).

The properties of aerial-based imagery, precludes analyses requiring a high level of spectral data fidelity (Groom et al., 2011) such as many forms of pixel-based image analysis. However, much of the semantic information necessary to interpret images is not represented by single pixels (Brodsky et al., 2008), while the definitions of habitat types often rely on spatial context. A project using aerial-based imagery should therefore have the abilities of analyzing pixels in spatial context, as well as have the ability of relating information from different spatial levels. For this purpose OBIA is well suited by abilities of incorporating ecological relations and semantics into rulesets (i.e. stepwise OBIA analysis algorithms) and having the possibilities of multi-scale analysis. OBIA also has parallels to manual image interpretation with its cognitive abilities and separation into image primitives. OBIA is especially suitable where the pixel size is far smaller than the feature to be mapped, e.g. patches of vegetation or substrate, as is the case when using aerial based imagery (Groom et al., 2011). The advantage of an object-based approach, when using aerial imagery for habitat structure identification, is therefore evident.

The application of RS-based monitoring is especially needed in coastal habitat types (Klemas, 2008, 2011b) with considerable spatial complexity and temporal variability. The natural dynamics in coastal habitat types are a prerequisite for the maintenance of their structure and biodiversity, but are regarded as threatened due to eutrophication (Remke et al., 2009a, 2009b), coastal engineering, climate change (Miller et al., 2010), the introduction of invasive species (Damgaard et al., 2011) and land use changes. Indicators of lost dynamics may be increasing area of closed vegetation cover, reed swamps, closed bush vegetation and the beginning of forest formation. Yet very little research on the implications of decreased habitat dynamics exists, and coastal zone management is usually done without thought to negate such effects (Baily and Nowell, 1996; Carboni et al., 2009). The coastal habitat types are further assessed to be particularly suited for remote sensing monitoring, since the coastal zone is largely held free from anthropogenic influences, with vegetation responding to variation in topography, hydrology and natural disturbances, as opposed to inland habitat types, where vegetation is often unpredictable without detailed knowledge of land use history (Dyer, 2010; Gilliam and Dick, 2010).

With its 7,300 km of coastline, Denmark contains major areas of coastal habitats, including a significant part of the European area of coastal dunes and salt marshes. Danish coasts are a challenging case as they span a gradient from extremely exposed to highly sheltered habitats, and therefore exhibit large variation in geomorphological processes involving erosion and sedimentation.

The Danish National surveying program (NOVANA) provides field based habitat type mappings in Natura-2000 sites (Fredshavn et al., 2011) and means to assess changes in species composition by detailed sampling in stationary, circular 5-m plots (Fredshavn et al., 2009). However, the Natura 2000 sites cover a minor and biased fraction of the habitats at national level, and when the work reported here began in 2011 no surveillance had yet been undertaken in the most dynamic habitats, including: embryonic dunes, white dunes, coastal lagoons, saltmarshes (habitat types 1310 and 1320) and beaches.

In the work that is reported here, a strategy is outlined which integrates the characteristics of the habitat information, acquired from field survey, with the characteristics of habitat information that can be interpreted from sub-meter aerial orthophoto imagery and digital elevation model data (Juel et al. 2013). When the established relationships are applied to image data they provide a basis for monitoring of habitat structure and dynamics in previously unmapped areas. The methodology is the subject of further development, but early results from test localities are shown and discussed in this report.

This report focuses on the development of the overall approach and methods of one-time classification and mapping of the structure elements of coastal habitat types. The associated “Briefing” (Groom et al. 2015) discusses the potential for incorporating the results reported here, and remote sensing methods more generally, in the national monitoring programme (NOVANA).

4 Data and method

The long term goal of the work that this report is a part of is to use remote sensing methods in nature monitoring by quantifying spatio-temporal changes in the structures and areas of coastal habitat types. A key assumption of the approach that is reported here is that habitat types in the coastal zone can be distinguished by firstly understanding the relationship of structural components within the habitat types, and key landscape components of the coastal zone. This understanding is obtained through an integrative approach, where samples of the image data of coastal zone sites are segmented into object primitives. A subset of the object primitives are labeled in the field into structural categories, as well as, on larger scale, to their habitat type contexts. These reference data are applied to a range of variables derived from the image data to enable accurate classification of object primitives to structure element classes. The derived classification model can then also be used on object primitives away from the areas of field reference data collection. Spatial and temporal patterns of the structure element classes are seen as representing the driving processes and thereby a basis for monitoring that has ecological meaning, the required coverage and is cost effective. Understanding of the contextual relationships of the structural elements is seen as a basis for mapping the extents of habitat types (Figure 4.1).

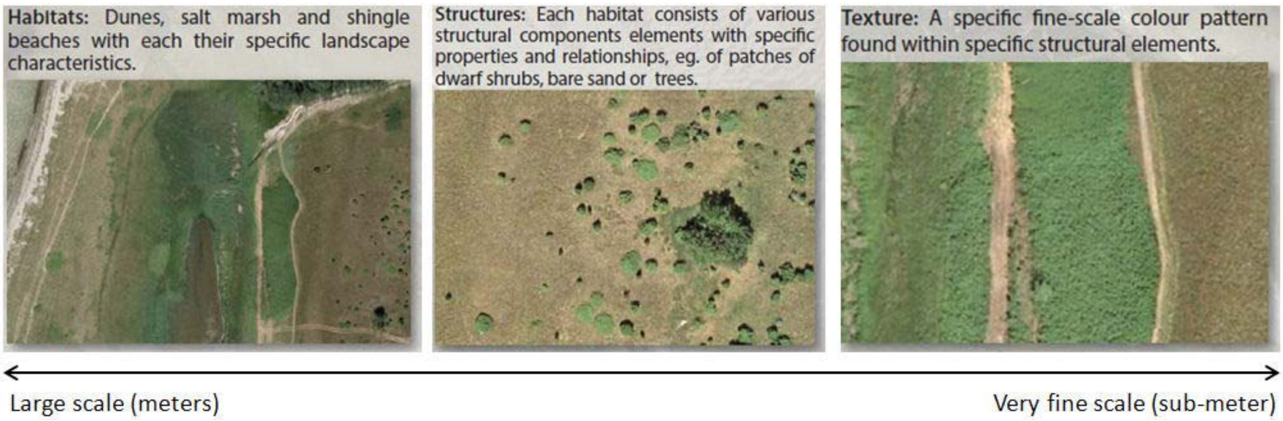


Figure 4.1. A method with analysis on different levels of spatial scale

4.1 Scope and overall strategy

Thematically, the work is scoped with respect to 14 terrestrial EU habitat types in Denmark that are always found in association with the coastal zone (Table 4.1; Miljø- og Energiministeriet 2000, European Commission 2013). These comprise of dune systems (types 2110–2190, together with coastal dunes with *Juniperus spp*., type 2250), the salt marshes and salt meadows (types 1310–1330) and the vegetation on shingle or stony beaches (types 1210 and 1220). Of the coastal terrestrial EU habitat types present in Denmark only coastal cliffs have been excluded from the work.

Table 4.1. The 14 coastal habitat types, focused upon in this work.

Code	Habitat type name
1210	Annual vegetation of stony banks
1220	Perennial vegetation of stony banks
1310	Salicornia and other annuals colonizing mud and sand
1320	Spartina swards
1330	Atlantic salt meadows
2110	Embryonic shifting dunes
2120	Shifting dunes along the shoreline with Ammophila arenaria
2130	Fixed dunes with herbaceous vegetation
2140	Decalcified fined dunes with Empetrum nigrum
2160	Dunes with Hippophaë rhamnoides
2170	Dunes with Salix repens spp. argentea
2180	Wooded dunes of the Atlantic, Continental and Boreal region
2190	Humid dune slacks
2250	Coastal dunes with Juniperus spp.

Geographically, the work is scoped for nationwide application to the coastal zone, i.e. land adjacent to the sea with a marked influence of its proximity to the sea upon its ecology.

The development phase work that is reported here has been scoped in terms of a geographic sample of coastal habitat occurrences, comprising shore-inland 80 m wide areal reference transects (Figure 4.2).

Figure 4.2. An example of a reference transect. (Backdrop image is 2010 summer aerial orthophoto RGB image data; source: GST.)

Eighty-nine reference transects were used. The locations for these 89 transects (Figure 4.3) were selected with consideration of:

- replication of the 14 habitat types, with a minimum of 7 replicates per habitat type
- representation of the main environmental gradients associated with the Danish coast: exposed / sheltered, saline / brackish, calcareous / silaceous substrate.

Location selection of the 89 transects in terms of the occurrences of habitat types was based on (a) the habitat occurrence mappings and registrations made for EU Habitat Directive sites and associated areas (Miljø- og Energiministeriet 2000) and (b) the Danish Nature Protection Law (1991) §3 protected nature areas (Miljøministeriet 2009). Data of source (a) were the basis for location selection for approximately two-thirds of the transects, and data of source (b) for the remainder (mainly being for salt marshes, salt meadows and coastal heathlands). The average size of the 89 transects is ca. 0.5 ha i.e. a length of ca. 600 m, but with the shortest and longest being 50 m and 2900 m long respectively there is also considerable variation in transect extent (Table 4.2).

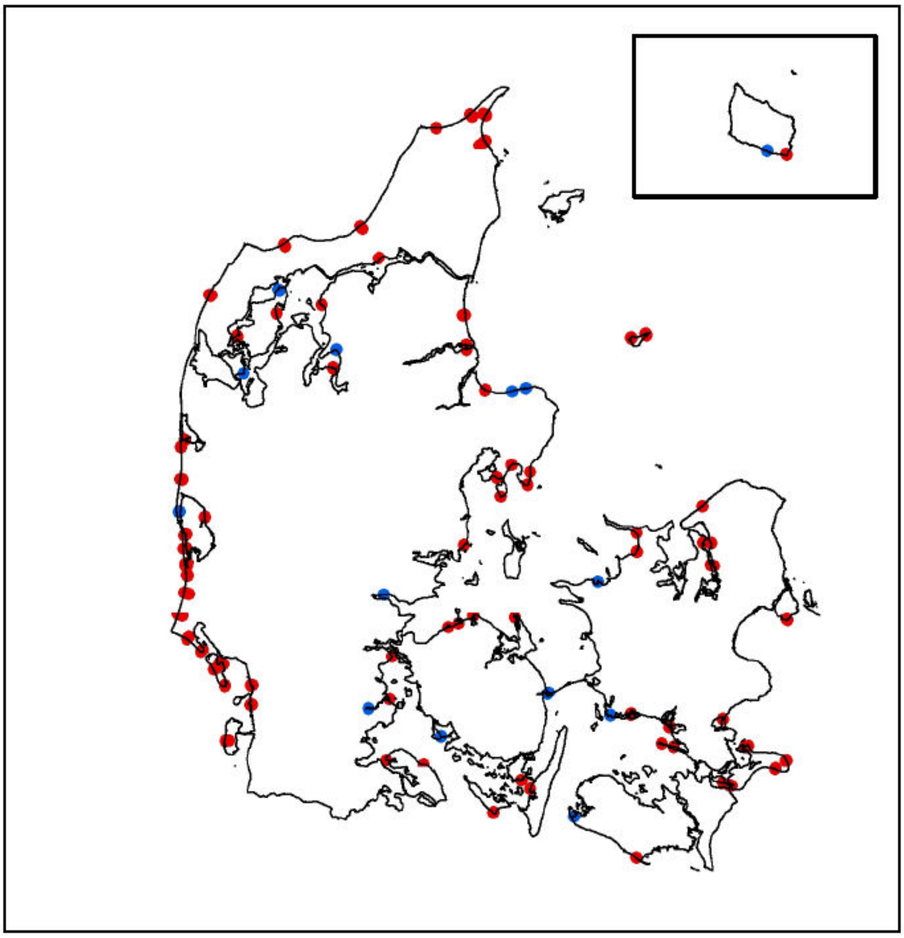


Figure 4.3. Overview of the set of 89 reference transects used as a basis set, of which 67 were used for actual field verification data collection. Red: Reference locality containing habitat type mapped areas. Blue: Reference locality containing § 3 saltmarsh or § 3 heathland within 200 m of the shoreline

The purpose of the reference transects in this work is to develop and test the methods for classification of the structure elements of the habitat types using field reference data, i.e. field observations from reference transects (Section 5).

Table 4.2. Summary description of the set of 89 reference transects in terms of their length and area. (See also Table 4.3 for more detail of each transects area.)

Length (m)	Area (approx. ha)	Number of transects
0 – 100	0.04 – 0.08	8
101 - 200	0.09 – 0.15	11
201 – 300	0.16 – 0.23	17
301 – 400	0.24 – 0.29	7
401 – 500	0.30 – 0.40	8
501 – 600	0.41 – 0.47	9
601 – 700	0.48 – 0.55	3
701 – 800	0.56 – 0.64	4
801 – 900	0.65 – 0.72	2
901 – 1000	0.73 – 0.80	2
1001 – 1500	0.81 – 1.20	10
1501 – 2000	1.21 – 1.60	5
2001 – 2500	1.61 – 2.00	2
2501 – 3000	2.01 – 2.40	1

4.2 Data, indices and processing description

4.2.1 Data

The use of image data for coastal habitat monitoring is at the core of this work.

In Denmark there has been a tradition for nationwide aerial orthophoto image acquisition since the beginning of the 1990s, and since 2002 the data acquisitions have been repeated on a biennial basis. Data have been captured with a ground sampling distance (GSD) of 0.8 m in 1995 gradually reducing to 0.2 m or less since 2008. Acquisition time has been post-spring, i.e. late May till early July, and these data are generally referred to as the "summer orthophotos". Summer orthophoto image data of 2010 have been applied in this work. The 2010 image data, acquired with a GSD of 0.16 m were the first set of summer orthophotos acquired with four spectral channels: blue, green, red and near-infrared (B-G-R-NIR).

In addition to the summer orthophoto image data, spring (April/May) aerial orthophoto image data are imaged as a rolling nationwide coverage programme for the purpose of topographic map update by the Danish Geodata Agency (Geodatastyrelsen, formerly Kort- og Matrikelstyrelsen). Spring image data from the acquisitions made in 2010, 2011 and 2012 have been applied in this work, and these have all also been acquired with four (B-G-R-NIR) spectral bands.

The national coverage of summer 2010 aerial surveying used several, similar large format metric cameras, operated by two air survey contractors. These survey systems image as a combination of high spatial resolution panchromatic image data and lower spatial resolution B-G-R-NIR image data. The key design criterion of surveys with metric camera systems is to acquire image data with high spatial detail, which is achieved via lens quality and the sensitivity of the CCD elements and the associated electronics to differences in reflected light levels. However, lacking sophisticated radiometric calibration data acquisition, the fidelity of the image data in terms of scene reflectances, which is the basis for many remote sensing application image data analysis methods, is foregone. Furthermore, post-survey but pre-delivery to users, the acquired raw image data are subject to:

- Orthorectification, georegistration, resampling and mosaicking.
- Pan-sharpening, whereby the spatial resolution of the lower spatial resolution B-G-R-NIR image data is enhanced to that of the panchromatic image data by integration with the latter.
- Colour balancing to reduce the effect of differences in survey illumination conditions (e.g. between survey days).
- Data compression to reduce the size of delivered data files: a lossy ECW compression was applied.

Even taken individually, these processing procedures further reduce the possibilities for applying many standard remote sensing application data analysis methods that require that the image data values describe consistent relationships to surface reflectances. Thus, the spectral and radiometric patterns in these image data have had to be applied more cautiously than is the case with applications involving many other forms of remote sensing data.

Greater spectral resolution, significant for vegetation related study, with better radiometric resolution would have been possible through use of one or other forms of satellite image data. Few of those however, would have provided at all adequate levels of spatial detail to discern sub-meter structure elements of the coastal habitats, such as water pools and channels, and patches of bare ground; mapping in terms of such structure elements is seen as key to the possibility for developing a structure element approach to the monitoring and mapping of coastal habitats. Multi-spectral satellite image data with even the highest spatial resolutions (e.g. WorldView-2) are nearly one order of magnitude coarser in that respect than the aerial orthophoto image data used in this work. Furthermore, possibilities for actual acquisition of such image data for large and widely distributed locations is limited by the current satellite coverage and cost factors. With scene size dimensions of just a few tens of kilometers coverage of all the coastal habitat locations in Denmark would be likely to have required imaging over a long period of time, even several years, which would have consequences for monitoring and mapping in terms of its temporal fidelity.

The spring aerial orthophoto image data have been acquired with similar imaging systems and processing as the summer aerial orthophoto image data, other than that they are delivered with different spatial resolutions than the summer orthophotos, with a pixel size of either 0.1 m or 0.2 m.

Besides aerial orthophoto imagery, the nationwide airborne lidar scanner (ALS) derived digital terrain model (DTM) data of 2006 have been applied to the work. These data have a pixel size of 1.6 m and a vertical accuracy between 0.1 and 0.15 m. The DTM is used in the work as an indication of the terrain and slope, aspect and curvature indices of the terrain, while the Digital Object Model (DOM) derivative (Digital Surface Model minus DTM) data are used as an expression of the height of vegetation and built-structures. Terrain data are seen as relevant for this work on account of the role of elevation, such as in relation to erosion and deposition processes, humidity patterns and the influence of sea-related factors (e.g. saltwater).

4.2.2 Image data acquisition and pre-processing

For the preparation of data, image, DEM and vector, the spatial reference ETRS_1989_UTM_Zone_32N was used throughout.

2010 summer aerial orthophotos

The national coverage of these image data was made available via the participation of Aarhus University in the common agreement made by Danish state organisations for acquisition of summer 2010 aerial orthophotos (KMS Fællesindkøb af sommerortofoto 2010). Under that agreement, the summer 2010 aerial orthophoto image data were supplied as two colour composition of the spectral image data : one being a "natural colour" rendition of the Red-Green-Blue (RGB) spectral components, and one (the so-called "colour infrared" CIR) utilising the near-infrared (NIR) spectral image data for the red rendition in the colour composition (Figure 4.4). These image data were accessed as an ESRI ArcMap File Geodatabase raster mosaic dataset of the supplied .ecw compressed 8-bit unsigned integer data files. However, the applied software for the object-based image analysis does not support .ecw format files or ESRI File Geodatabase for raster data. Therefore, seamless clipping of the 2010 summer aerial orthophoto image data for the required locations for was made via the File Geodatabase raster mosaic dataset, based on polygon shape representations of the required extents.

Figure 4.4. Example of the "natural colour" (upper) and "CIR" (lower) renditions of the summer 2010 aerial orthophoto image data.

In addition to the 2010 summer aerial orthophoto image data, the associated national mosaic seamline vector line and PPC data were acquired. These data were required in order to control for spatial aspects of the aerial survey and data mosaicking in the analysis of image data patterns associated with structure elements. The seamline and PPC data were processed to provide vector polygon representations of extents of the national coverage associated with imaging on different days and/or by different imaging equipment.

Spring aerial orthophotos

The 2010, 2011 and 2012 spring aerial orthophoto image data were acquired by special arrangement with the Danish Geodata Agency (GST). These data were supplied as 3-band (RGB) .tif format data files, i.e. without having been subject to lossy data compression. ESRI File Geodatabase raster mosaic datasets were made and clippings made for image data files of the required extents.

DEM data

The national coverage Digital Terrain Model (DTM) and Digital Object Model (DOM), representing the height of up-standing features such as buildings and trees) data, with 1.6 m raster cells have been acquired by Aarhus University from the Danish Geodata Agency as .img files. In addition, aggregated (mean) versions of the DTM with pixel sizes of 9.6 m and 24.0 m, generated by the Center for Massive Data Algorithms (MADALGO) of Aarhus University, were acquired, and slope, aspect and curvature derivatives of the 1.6, 9.6. and 24.0 m DTM data were generated for this work. Required clippings of these data were prepared for the analyses.

4.2.3 Data processing, segmentation and indices

The ability to classify image data to structure elements of the coastal habitats lies at the heart of the methods being developed. In their simplest form the image data can be considered as the 3 or 4 channel sets of pixels values of the different image data sets, i.e. in a rather crude sense "spectrally". The use of both summer and spring aerial orthophoto image data adds a second, seasonal, dimension to the analytical possibilities, and the use of DTM and DOM data represents an additional form of habitat structure element information, i.e. an expression of the 3D form of the ground and the vegetation. The image data can also be considered beyond their simple bandwise representations, in terms of derived indices that can exploit both spectral and spatial domains:

- spectral indices that express the relative level of image greenness (i.e. green vegetation albedo) or redness (i.e. bare surface albedo) or surrogates of photosynthetic activity (e.g. the Normalised Difference Vegetation Index)
- spatial indices that express aspects of the spatial arrangements of pixels with respect to their image data values, i.e. expression of image texture.

Analytically, these raw and derived expressions of the image and DEM data can be evaluated and operated with either pixel-wise or object-wise. Pixel-wise evaluation and operation, the traditional way of making analyses in remote sensing, means that derived values (e.g. greenness, NDVI) are calculated pixel-by-pixel, and that classification (i.e. "labeling") is made independently for each individual raster cell (i.e. pixel). The object-wise way of working means that the data are understood first and foremost as a set of subsets of the individual raster cells, which, most normally, implies spatially contiguous cell subsets. The object-wise mode is both flexible (e.g. indices may be derived pixel-wise, but used in classification object-wise), and increases analytical depth via modeling of spatial and hierarchical relationships between objects. Moreover, an object-wise approach is highly meaningful in the context of habitat structural element classification with fine spatial resolution image data, since the applied model of the coastal habitats that is proposed for their monitoring and mapping analyses is itself, irrespective of data and methods used, understood as being essentially object-based, i.e. that biological processes, and thereby nature, are spatially organised (Lidicker, 2008).

Segmentation

Thus, the applied processing and analysis of the image and DEM data used in the work reported here is strongly object-based. Object-wise analysis implies a segmentation of the spatial domain into its raster cell subsets. This segmentation in this work has been made by using together the three channels of the RGB composite and the first (NIR) channel of the CIR composite of the summer aerial orthophoto image data, as a two-stage operation:

- Stage-1: so-called multi-resolution segmentation that divides the spatial domain into a set of objects based on the single raster cell data values; this operation is parameterised through parameters relating to spatial scale and the relative importance of spectra-vs-shape and compact-vs-convoluted aspects of the resulting objects;
- Stage-2: so-called spectral-difference segmentation, which merges objects from Stage-1 that are contiguous and have a difference between the image data means of their sets of pixels that is below a set threshold.

The applied success criteria for the segmentation have been two-fold. Firstly, it has been one of visual satisfaction, i.e. that as far as can be ascertained, the resulting segmentation expresses the main "objects" that are discernible by human perception of the same image data. In particular, this criterion was implied in terms of controlling that resulting objects did not comprise major contiguous sub-portions with highly contrasting summer aerial orthophoto image data visual characteristics. Secondly, it has been one of field checking for optimization that was undertaken for 11 transects. On the basis of assessments made using these success criteria segmentation parameter settings (Table 4.2) were selected and applied for the segmentation of the image data of all transects.

Table 4.3. Parameter settings used in the image data segmentation.

Stage	Parameter	Value used
1. Multi-resolution segmentation	Scale	40
	Influence of shape	0.8
	Influence of compactness	0.2
2. Spectral difference segmentation	Difference threshold	5

The spring orthophoto image data was acquired too late to be used in this segmentation, as that had to be completed in time for field reference data collection starting in summer 2012.

The segmentation (e.g. Figure 4.5) has the key role in the work of being the spatial support for the multivariate analyses of habitat structure element classification possibilities, as:

- the basis for the collection of field reference data (Section 5)
- the basis for evaluation of image, DEM data and metadata (see below) features for compilation of the core the analysis database (Section 6).

Figure 4.5. An example of the image data segmentation result within one of the 11 test transects.

In general across the set of 89 reference transects, larger segmentation objects cover over half of each transect (Table 4.4), but also with some marked variations in object size densities, such as between transects characterized by a relatively small number of relatively large objects (e.g. RT 360034863, Figure 4.6(a)) and ones characterized by many relatively small objects (e.g. RT 1433097, Figure 4.6(b)).

Table 4.4. Summary data of the number and areal extents of the segmentation objects of the 89 reference transects. Reference transects are here ordered by their total area.

Reference transect		All segmentation objects	% by area of segmentation objects in seven size (m^2) categories						
Ref.Trans. #	**Total area (m^2)**	**Number**	**0 – 10**	**11 – 20**	**21 - 30**	**31- 40**	**41 - 50**	**50 – 100**	**>100**
1494992	4118	124	7.4	13.0	7.4	5.2	3.3	13.4	50.4
71834	4551	181	8.4	15.0	15.8	9.2	7.6	16.4	27.6
360037401	5126	141	5.2	10.8	9.8	7.4	7.7	16.5	42.6
360027680	5765	238	8.6	22.5	12.4	7.5	5.5	24.4	19.2
68072	7274	253	6.7	15.1	14.5	5.2	8.0	13.4	37.0
66404	7376	116	3.1	6.6	6.9	2.5	3.0	3.8	74.1
71764	7596	381	12.5	25.0	13.5	7.1	5.9	10.7	25.3
360033945	7813	369	11.0	23.6	12.1	9.3	6.6	16.5	21.0
200129429	9027	380	7.8	21.0	15.5	6.7	7.2	12.8	28.9
66808	9033	227	3.8	11.4	6.7	4.5	3.8	22.4	47.4
72116	9770	381	6.5	20.0	11.2	9.0	4.9	27.0	21.3
360038519	10093	355	5.7	17.0	11.6	9.4	7.9	20.1	28.3
360034262	11423	380	8.2	13.3	8.5	7.8	3.6	11.5	47.1
360034683	11598	282	5.6	13.1	5.5	3.8	1.2	5.5	65.2
72982	13138	458	6.4	15.7	13.4	11.7	8.1	13.0	31.7
69614	13567	391	6.7	12.1	5.6	6.6	4.7	12.5	51.9
360036880	14965	322	3.6	9.0	7.3	7.5	5.7	10.5	56.4
200059730	15415	367	4.3	10.0	7.5	4.6	5.3	15.0	53.3
360034047	15624	322	3.2	8.0	6.8	6.0	2.9	19.0	54.0
360037640	16094	486	7.1	11.9	8.1	6.3	5.5	9.8	51.3
1433097	16641	756	10.3	20.2	14.2	11.0	5.1	14.9	24.3
360033686	16833	507	5.5	12.2	10.7	6.5	4.3	11.9	48.9
71032	16969	502	6.0	13.2	10.1	6.8	4.0	16.2	43.8
64906	17049	432	4.5	10.5	8.3	6.1	6.3	13.7	50.6
65770	17066	636	7.4	17.6	13.1	5.9	4.7	15.5	35.8
66800	18326	555	5.5	12.4	13.5	7.2	3.4	15.5	42.5
360034631	18527	385	2.9	9.3	7.6	5.0	6.5	15.3	53.4
73494	18690	507	5.2	11.3	11.2	5.7	4.7	10.2	51.7
360034619	19084	273	1.9	6.1	5.6	4.3	2.6	10.1	69.3
360038601	19388	249	1.9	5.3	4.2	4.4	1.4	8.7	74.0
66344	19465	373	3.4	9.1	5.3	5.0	3.0	11.7	62.6
954141	20362	433	3.8	9.8	7.9	5.5	3.1	8.3	61.6
200075543	20708	683	5.3	16.0	13.5	9.8	8.2	14.8	32.3
791417	20943	422	4.2	8.1	5.4	4.1	2.8	9.5	65.9
360037875	21205	326	2.1	5.5	6.2	4.9	3.2	7.3	70.9
67546	22808	691	5.8	13.8	11.8	8.3	4.5	11.1	44.7
360037735	24462	402	2.5	7.4	5.9	4.3	3.1	9.1	67.7
360037143	25170	579	3.8	11.0	6.6	6.7	5.0	12.5	54.5
360034486	25175	495	3.0	8.3	7.4	5.1	4.7	12.0	59.5
70742	26458	583	3.4	8.4	9.2	4.7	3.2	18.0	52.9
360032222	26543	629	4.5	9.2	8.4	6.0	4.0	9.0	58.8
73580	28359	731	6.2	10.1	7.2	6.3	3.3	10.5	56.3
1495790	28724	444	2.1	6.9	5.2	4.5	2.4	10.2	68.8
65202	33717	993	5.4	14.5	10.8	7.5	4.2	11.1	46.5
72142	34011	910	5.0	12.6	9.0	7.0	4.7	11.6	50.0
200201128	34353	594	3.1	7.7	5.6	4.9	4.1	7.9	66.7

770233	34948	1977	13.4	29.6	20.3	8.9	4.6	8.8	14.4
71802	37205	1068	5.0	13.0	10.5	7.8	4.6	13.5	45.5
73616	38176	1620	10.1	19.1	11.2	8.0	4.4	14.3	32.8
200031724	38253	1021	4.6	12.5	8.9	6.3	5.5	15.1	47.0
360033119	39462	1163	5.8	14.9	9.9	6.5	4.3	11.8	46.9
360028602	40838	716	2.5	7.5	6.2	5.9	4.0	9.9	63.9
69842	40918	956	3.8	10.3	7.2	5.8	4.4	14.0	54.4
63814	41076	588	1.8	5.2	5.5	4.2	2.5	11.5	69.3
360037989	41643	736	3.0	7.7	7.1	4.3	2.7	7.9	67.3
360039730	42846	1867	10.0	20.3	13.2	8.7	6.3	15.8	25.7
71148	42957	992	3.7	11.0	9.1	4.9	4.6	11.4	55.4
360037445	43888	1212	4.8	12.4	10.1	8.2	5.7	11.5	47.2
72462	44361	913	3.4	8.3	6.1	5.3	3.9	12.8	60.3
72828	44750	1464	7.0	16.9	11.7	5.2	3.6	7.3	48.3
200158388	50073	1428	4.8	13.6	10.7	7.7	6.1	13.7	43.5
360037363	51241	1076	3.6	8.6	7.4	5.1	4.0	12.7	58.6
360037675	52518	1063	4.3	7.9	5.7	3.7	2.4	12.0	64.0
360035928	60224	1627	4.7	12.5	11.1	6.7	4.6	12.0	48.3
64890	60237	1422	4.6	11.1	8.2	5.9	3.5	8.2	58.6
72824	61603	2479	8.6	18.5	13.5	8.1	5.5	14.2	31.6
360035796	62380	1395	4.2	10.2	7.6	5.7	3.5	11.0	57.7
200065865	68479	1040	2.5	5.7	4.8	3.2	3.1	9.2	71.5
360035917	70794	618	1.0	3.3	3.5	2.7	1.4	4.6	83.5
360037646	73201	1823	4.9	12.4	7.9	5.2	3.2	10.2	56.2
200164373	79279	906	2.1	4.8	3.4	2.1	1.8	5.4	80.4
360027411	82681	4040	11.9	24.9	14.3	7.6	5.0	7.7	28.6
360035248	93086	1854	3.0	8.6	8.4	5.7	4.0	11.6	58.7
65044	95628	1660	2.6	6.4	6.9	4.6	3.9	12.7	62.8
70998	96313	2163	4.3	11.7	8.5	4.7	3.4	8.9	58.5
360032282	99173	2210	4.0	9.4	7.4	6.2	3.9	13.7	55.4
64884	100146	2478	4.6	10.9	8.4	5.0	4.0	13.1	54.0
65024	103061	2842	5.0	12.9	9.4	6.6	5.2	14.3	46.6
360035349	107755	1921	2.5	7.4	6.4	5.1	3.5	11.6	63.5
69892	111351	3913	7.2	16.7	11.1	8.4	5.1	14.8	36.7
360036107	117185	3292	5.7	11.9	8.9	6.2	4.3	13.2	49.8
70612	123357	3184	3.7	11.5	10.4	7.6	6.1	16.0	44.6
360036228	135777	3199	4.1	10.3	8.0	5.6	4.7	13.6	53.7
360027860	138227	6609	10.2	25.3	16.1	9.4	6.7	14.5	17.8
360035031	143562	4435	6.0	15.1	10.2	6.6	6.2	13.2	42.7
360034541	146197	1891	1.9	5.2	4.8	3.3	3.0	10.0	71.9
360029054	164518	4522	4.6	12.2	11.0	7.6	5.1	14.9	44.5
360035850	190694	6528	7.5	13.9	10.0	7.5	5.5	14.0	41.6
360030496	234546	6058	5.4	12.5	7.8	5.7	3.4	9.9	55.3

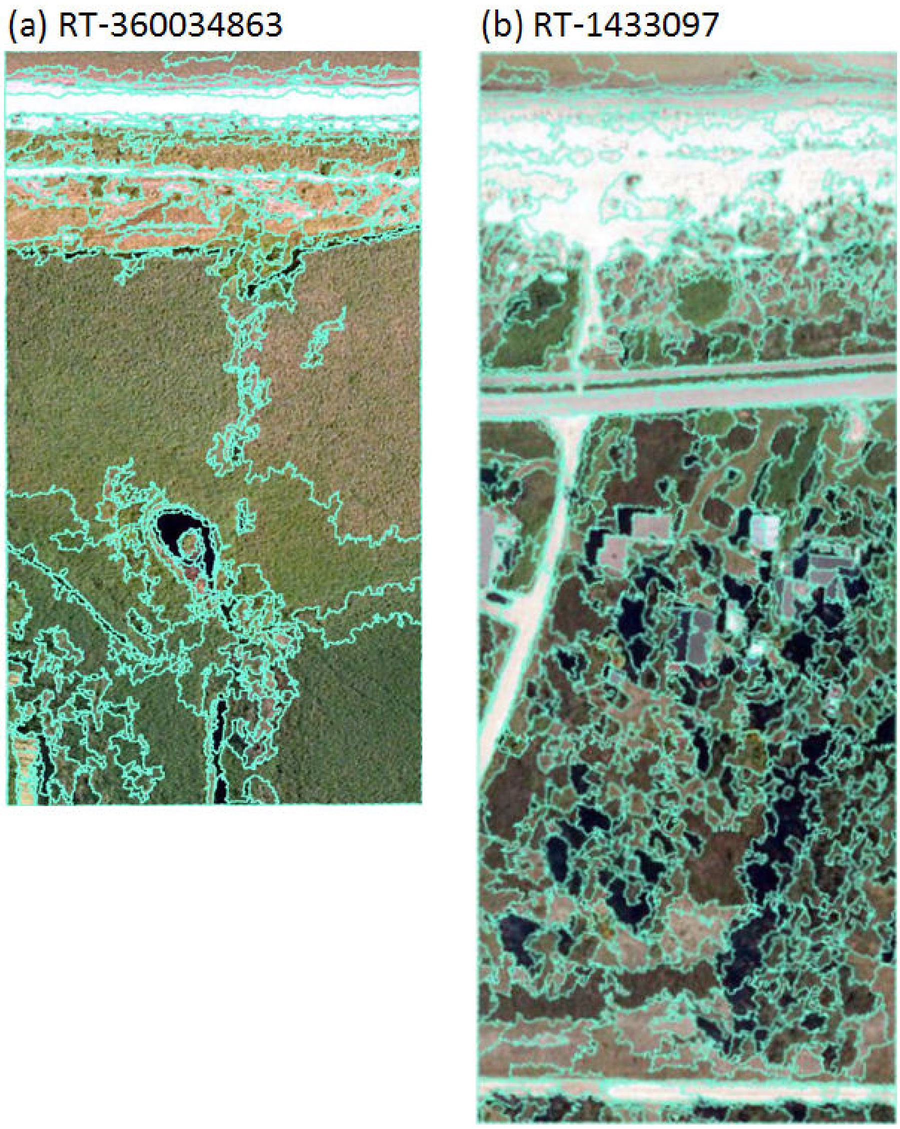


Figure 4.6. Examples of reference polygons with different spatial segmentation object patterns : refer also to Table 4.3. Backdrop image is the natural colour composite rendition of the summer 2010 aerial orthophoto image data. Scale guide : width of RT is 80 m. (N.B. As they are shown here, these transects have been rotated away from their true orientation.)

Object indices

All segmentation objects were associated with a unique identifier value, and the required object-wise indices values presented (i.e. segmentation software export operation) as csv table columns.

In all, per-object evaluation and export was made for 407 indices. Table 4.5 summarises key aspects of the set of image, DEM and meta- data indices used in this work. The set of indices comprises mostly ones that were evaluated from image data segmentation described above. However, the resulting objects can have within-object texture variations that are not fully expressed by simple texture indices such as the standard deviation of the image data within the object. Therefore texture indices were also derived based on sub-objects of each of the initial objects, i.e. a hierarchically nested finer-scale set of objects. These were made using segmentation parameter settings of scale parameter = 8, shape parameter = 0.05 and compactness parameter = 0.05. Two sets of sub-objects were made, one based on the summer aerial orthophoto RGB ch-1, ch-2, ch-3 plus CIR ch-1 image data, and a second based on the spring aerial orthophoto RGB image data. Figure 4.7 explains the basis of the sub-object associated indices, which are included in Table 4.5 as the last two rows. An example of the spatial variation patterns that occur in indices value is given in Figure 4.8.

Table 4.5. Classification with examples of the 407 object indices.

Indices type	Number of	Examples of indices of this type
Mean of data of 1 primary channel	19	Mean of summer image RGB ch-1 pixel values Mean of spring image ch-2 pixel values Mean of 9.6 m DEM data pixel values
Mean of functions of > 1 primary channels	46	Mean of (summer RGB ch-2 / summer CIR ch-3) pixel values Mean of spring RGB (ch-2 / (ch-1 + ch-2 + ch-3) pixel values Mean of difference between summer RGB ch-3 and spring RGB ch-3 pixel values
Standard deviation of data of 1 primary channel	12	SD of summer RGB image ch-3 pixel values SD of spring RGB image ch-2 pixel values SD of 1.6 m DEM data pixel values
Standard deviation of functions of > 1 primary channels	44	SD of summer RGB (ch-1 / ch-2) pixel values SD of spring RGB (ch-2 / (ch-1 + ch-2 + ch-3) pixel values SD of difference between summer RGB ch-1 and spring RGB ch-1 pixel values
10%, 25%, 75%, 90% Quantiles of data of 1 primary channel	37	10% Q of summer CIR ch-3 pixel values 75% Q of spring RGB ch-2 pixel values 90% Q of 1.6 m DOM pixel values
10%, 25%, 75%, 90% Quantiles of functions of > 1 primary channels	151	25% Q of spring RGB (ch-2 / ch-3) pixel values 75% Q of (summer RGB ch-2 / (summer RGB ch-1 + ch-2 + ch-3 + summer CIR ch-1)) pixel values 90% Q of difference between summer RGB ch-3 and spring RGB ch-3 pixel values
Geometric properties of objects	11	Area Asymmetry Roundness
Associated metadata	9	Date summer orthophoto was acquired ID of camera used to acquire summer orthophoto Year that the spring image data were acquired
Texture indices involving "Haralick" analysis (Haralick, 1973)	18	GLCM_homogeneity (all directions) of the summer RGB ((ch-1 + ch-2 + ch3)/3) pixel values GLCM_entropy (all directions) of the summer CIR ch-1 pixel values GLVD contrast (all directions) of the spring RGB ((ch-1 + ch-2 + ch3)/3) pixel values
Texture indices involving the layer values of sub-objects:	44	Average over all sub-objects of an object of the mean summer RGB ch-1 difference of a sub-object to its neighbor sub-objects. Average over all sub-objects of an object of the mean summer RGB (ch-2/(ch-1 + ch-2 + ch-3)) difference of a sub-object to its neighbor sub-objects. SD of the spring RGB ch-3 means of the sub-objects of an object.
Texture indices involving the shape of sub-objects:	16	Mean of the areas of sub-objects derived with the spring RGB image data Mean asymmetry of sub-objects derived with the summer RGB-ch-1,ch-2,ch3 & CIR-ch-1 image data SD of the directions of sub-objects derived with the spring RGB image data

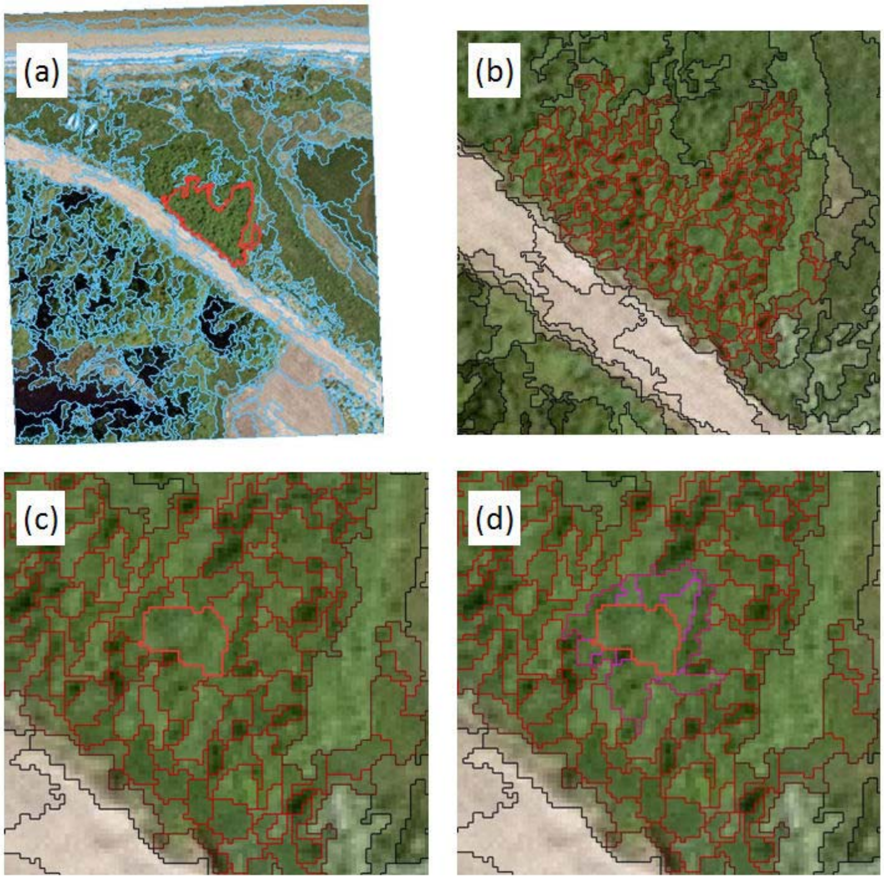
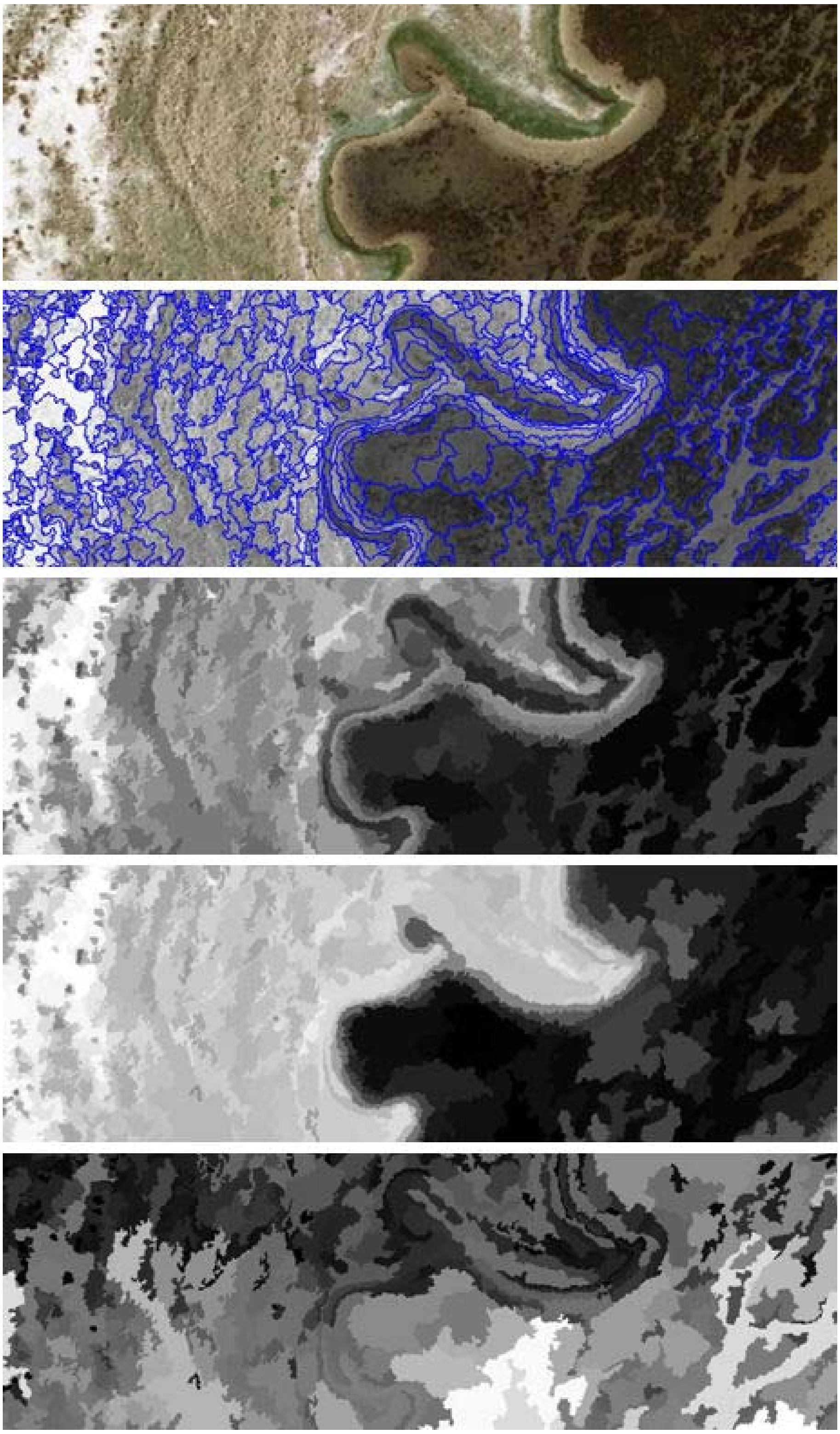


Figure 4.7. Explanatory example of sub-object indices: (a) the primary structure element segmentation (blue) of Reference Transect 71764, with one object selected (red), (b) sub-object segmentation (brown) of the selected primary segmentation object, (c) one sub-object selected (red), (d) sub-object neighbours of the selected sub-object (purple). For example, for the selected sub-object, the mean will be calculated of the difference of its image layer mean to the image layer mean of each of its neighbours. This will be repeated for each sub-object of the selected primary object, to give a mean (or SD) sub-object texture indices value for that selected primary object.

Figure 4.8. Example for a part of Reference Transect 71802 showing summer 2010 natural colour image data, primary segmentation and spatial patterns of three indices: top-to-bottom: Summer aerial orthophoto image data natural colour composite; Primary structure element segmentation; Object mean summer RGB ch-2; Object mean summer CIR ch-1; 75% quantile value of the ((Summer CIR ch-1 – Summer RGB ch-1) / (Summer CIR ch-1 + Summer RGB ch-1)).



5 The field derived reference dataset collected in 2012

5.1 Introduction

The purpose in this work of undertaking field data collection was to acquire a set of reference data of habitat structural element characteristics to use in analyses with spatially comparable expressions of the image and DEM data and metadata, in order to develop remote sensing-based structural mappings and evaluate the possibilities for coastal habitat type classification.

A second purpose, by involving NST personnel in the field data collection, was to introduce a wider set of relevant specialists to the ideas and methods that are being developed and evaluated in this work, and get inputs and feedback from them.

Field data collection was undertaken in November 2012 and April 2013 by 19 NST open-nature specialists at 67 of the 89 reference transects.

The spatial support of the field data collection was the sets of 2010 summer aerial orthophoto image data segmentation objects, derived as described in Section 4.2.3. The image data of the field data collection reference transects were presented for field data collection as the paper colour prints of the natural colour composites at a scale of 1:800, with the outlines of the segmentation objects visible. Field data collection was then undertaken by the NST teams, following the protocol described in Juel et al. 2012.

5.2 The field data collection protocol – in summary

The applied field data collection protocol is based on the assumption that the coastal habitats can be considered as comprising a repeated, relatively small set of key structural elements; this model for field data collection also relates directly to that applied in this work as a whole. Thus, the protocol was designed to enable efficient and effective collection of field data that was coherent with that key tenet of the habitat classification model.

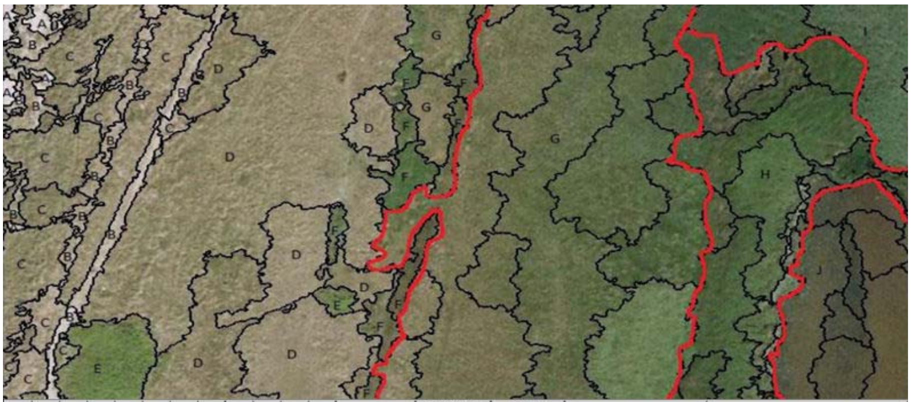
The surveyors were required and instructed to describe the image data segmentation objects via a simple schema relating to percentile (25-49, 50-74, 75-89, 90-100%) composition of objects in terms of a set of 14 structural element type categories (Table 5.1). In addition, the surveyors were instructed to record, as appropriate, dominating (> 50% coverage) plant species and supplementary context related information (Table 5.2). The protocol required alphabetic coding of each segmentation object field signature pattern (e.g. "90-100% dwarf bush", "25-49% short grass, 50-74% bare sand") to enable rapid recording of other objects with the same characteristic (Figure 5.1). Special instructions were detailed for recording of non-conformities between the spatial arrangements of segmentation objects and in-field conditions, such as could be due to habitat change since 2010.

Table 5.1. The 14 structural element type categories specified for use in field reference data collection.

Type (English translation)	As specified in Juel et al 2011. (Danish)
Bare ground, stone / gravel	Mineraljord, Sten/grus. Område dækket af større sten eller grus (over 2 mm i kornstørrelse).
Bare ground, sand	Mineraljord, Sand. Område dækket af sand (under 2 mm i kornstørrelse). Gælder både vådt og tørt sand
Bare ground, clay / mud	Mineraljord, Ler/Mudder. Område dækket af ler eller mudder som sediment. Typisk nyligt deponeret.
Organic soil	Organisk jord: Bar jord/tørv. Flade af blottet muldjord eller tørvejord.
Open water	Åbent vand. Område med synlig vandflade.
Lichen	Lav. Område dækket af jordboende laver. Omfatter ikke laver på grene og stammer.
Moss	Mos. Område dækket af jordboende mosser. Omfatter ikke mosser på grene og stammer
Herbs	Urter. Område dækket af urter (omfatter også græsser). Adskilles i lav (0-25cm) og høj (>25cm) urtevegetation.
Dwarf bush	Dværgbuske. Område dækket af diverse dværgbuske. Adskilles i lav (0-15cm) og høj (>15cm)
Woody vegetation	Vedplanter. Område med buske eller træer. Adskilles i lave (0-200cm) eller høje (>200cm) buske og træer
Mosaic	Mosaik. Et område med en fint opdelt struktur hvor de enkelte strukturelementer er på under 2 m2
Shadow	Skygge. Anvendes såfremt en strukturpolygon er opstået pga. en kastet skygge
Doubt	Tvivl. Strukturpolygoner, der ikke længere kan identificeres eller karakteriseres, f.eks. pga. rydninger, brand, erosion eller lignende henføres til denne kategori
Failure	Fejl. Anvendes i de tilfælde, hvor segmenteringen ikke har adskilt de angivne strukturkategorier korrekt fra hinanden. Ved meget fine strukturmosaikker anvendes i stedet kategorien 'mosaik'

Table 5.2. Examples of specific context related aspects of structure elements to be recorded, as appropriate, in addition to structure element type composition.

Type (English translation)	As specified in Juel et al 2011. (Danish)
Specific plant communities (e.g. reeds, dwarf-shrub, etc.)	Specifikke plantesamfund (rør-sump, dværgbuske, mm.)
Metalled / concrete road	Asfaltvej
Garden	Have
Burnt area	Brandflade
Building	Bygning
Path / track	Sti
Agricultural field (including improved grassland)	Mark
Car parking area	P-plads
Ant-nest	Myretuer
Beach drift line	Tanglinie
Lagoon	Lagune
Stream	Å
Sea	Hav
Dead vegetation	Død vegetation
Tidal creeks (e.g. associated with salt marshes)	Lo
Salt water pans and pools (e.g. assoiciated with salt marshes)	Strandsø



Pol.	Sten/ grus	Sand	Ler/ mudder	Bar jord/ tørv	Åbent vand	Lav	Mos	Mosaik	Tvivl	Skygge	fejl i segment	Urter (højde) 0-15 cm	Urter (højde) >15 cm	Dværgbusk (højde) 0-15 cm	Dværgbusk (højde) >15 cm	busk/træ (højde) 0-2 m	busk/træ (højde) >2 m	Angiv dominerende art (>50 % dækning)	Bemærkninger/anden strukturtype og dens dækningsgrad(1-4)
A.		3																	
B.		1						4				2						sand-hjælme	
C.																		sand-hjælme	
D.							1					3							
E.																4		rynket rose	
F.			1									2							
G.												4						rød svingel	
H.													3					strand-kogleaks	
I.													4					tagrør	
J.					4														lagune 4

Figure 5.1. Illustrative example of the field recording's use of alphabetically coded information for repeated structure element characteristics.

The field surveyors were also required to record, as simple polygons on a second set of the image map prints, parts of a reference transect that, in their judgment, represented good examples of any of the 14 coastal EU habitat types (Figure 5.2).

Typefelt nr.	Naturtype	Undertype/kommentar
1	2110	
2	2130	
3	1330	
4	1330	strandrørsump
5	2130	
6	2250	

Figure 5.2. Illustrative example of the field recording of simple polygons for parts of reference transects that represent good examples of any of the 14 coastal EU habitat types.

The NST field workers collected field reference data for 67 of the 89 reference transects. Collected field data were provided to DCE by NST as attributed vector polygon data for 55 reference transects during spring 2013, and for the remaining 12 transects during summer 2013. In all, the spring 2013 delivered field data comprised 52,965 structure element objects and 162 "good habitat examples" records.

5.3 Field data processing

The collected field reference data were simplified for analytical purposes in terms of four hierarchical levels of classes (Table 5.3), with Level-4 comprising 16 classes. Level-4 is referred to the "field class" level. 14 of the 16 field classes relate directly to the structure element types of the field reference protocol. The other two classes "built-up" and "non built-up" relate to recordings by the field surveyors of the context related aspects of structure elements; structure objects were assigned to one or other of these two classes wherever the structure polygons could not be assigned to any of the other structure types.

Table 5.3. Four-level field class classification system for structure element labelling

Level-1	Level-2	Level-3	Level-4
Terrestrial non-vegetated	Inorganic	Inorganic	Stone/gravel
			Sand
			Clay/mud
			Built-up
			Non built-up
	Organic	Organic	Bare soil
Aquatic	Aquatic	Aquatic	Open water
Terrestrial vegetated	Non-woody	Low non-woody	Lichen
			Moss
			Herbs 0 – 0.15 m
		High non-woody	Herbs > 0.15 m
	Woody	Low woody	Dwarf bushes 0 – 0.15 m
			Dwarf bushes > 0.15 m
		High woody	Bush/tree 0 - 2 m
			Bush/tree > 2 m
Shadow	Shadow	shadow	Shadow

6 Dataset Analysis and Structure Element Object Classification

6.1 Introduction

Via the unique identification value given to each segmentation object the image, DEM data and metadata tables were integrated with the field reference data tables for the subset of 55 reference transects, forming a dataset of 52,965 elements, each described in terms of the 16 dependent (field class, Table 5.3) variables and 407 independent (image and DEM data and metadata) variables. The key objective of the data analyses made to date has been to derive a model that could, for all objects, use an object's independent variable data to correctly classify (i.e. label) it to its dependent class. The ability to make that classification is a core objective of the remote sensing method development, i.e. that as well as enabling the delineation of ecologically meaningful structure elements (i.e. make the segmentation), remote sensing methods can also be used to identify the primary characteristic of each element.

The data set of the 52,965 structure polygons were first filtered to remove data of polygons:

- with reference data detailing transient or unusable characteristics, e.g. "sheep", "garbage"
- with an area of less than 15 m^2 and having > 25% of their border shared with the border of the reference transect (such cases being problematic to analyse).

Thereby the analysis data set was reduced to one relating to 45,341 polygons.

6.2 Description of Random Forest

All classifications work was carried out in R version. 3.0.2. with the Random Forest (RF) package (Liaw, 2002). Random Forest can be described as a machine learning, ensemble approach which can be used both for classification and regression. The method is efficient at handling a dataset as the one available with a high number of variables, variables with a lot of noise and is also effective when variables are highly correlated. Random Forest has previously been successfully applied in ecological studies with remote sensing data similar to the current work (e.g. Bradter, et. al. 2011).

In essence, a multitude of classification trees are constructed in Random Forest with each tree trained on a different subset of observations and with a different subset of variables available at each split in the trees. The final predicted class of an observation is then chosen by majority vote of the trees. The randomization in the method gives a higher expression of weaker predictor variables and the possibilities of complex interactions between variables, leading to an increased performance in complex classification tasks.

6.3 Classification

Due to memory constraints, the large classes "bush/tree > 2 m" and "herbs> 0.15 m" (with 9,540 and 10,116 observations respectively) were down sampled to 4,000 observations each before model training. This was done based on the assumption that a random subset of the observations could cover the within class variation. Missing variable values in the data set (typically due to lack of DTM cover over water) were imputed based on weighted distance to other observations (Liaw, 2002).

For the classifications to field reference class levels 1, 2 and 3 RF models were trained based on the non-mixed (i.e. single structure element type) observations for the respective level. For the classification to the field class level (level 4) one RF model was trained on observations recorded by the field surveyors as having >89% structure element type purity and a second RF model was trained on observations recorded by the field surveyors as having >74% structure element type purity.

Initially, exploratory RF models on the four thematic levels were trained, using all 407 available explanatory variables, to calculate variable importance and detect outlier observations. The final models were then constructed based on the 55 - 103 variables with the highest model importance rated by the highest mean decrease in overall model accuracy if each variable was excluded from the model. The models were optimized by varying the number of variables available at each split and varying the number of variables included overall by setting different importance thresholds for inclusion of each variable.

When applying an unbalanced dataset to RF, the bootstrap sample for each tree will contain a higher number of observations of larger classes than from smaller classes. Since each RF tree maximizes the overall classification accuracy without regard to per class accuracy, the classification accuracy of each class will depend highly on the number of observations per class. To counteract this, the bootstrap sampling was stratified per class with training sample sizes being a maximum of 2/3 of class observations in the smallest classes and with much smaller sample percentages per tree in larger classes. Since different class sample sizes are necessary to obtain balanced class accuracies, due to differing class difficulties, the final sample size of each larger class was adjusted based on iteration of the model. This balancing of per class error, however, decreases the overall classification accuracy by 1-2%. (The classification accuracies on level-4 of the small and ecological unimportant structure types, "built-up" and "non built-up", were not balanced since that would have had a highly detrimental effect on the classification accuracies of the remaining classes.) The final predictions on the four thematic levels were performed on the full dataset giving class member probabilities as outputs.

6.4 Results

The results of the initial classification are here presented in terms of (a) the error rates associated with the structure element field classes and (b) the correspondence between the classifications's labelling of objects to the field classes and the field recorded habitat types. These are initial results as analysis and classification has not yet included all reference transects and, as discussed in Section 6, final analysis and classification methods are still to be refined. The defined RF classification labelled 44,286 of the 45,341 structure polygons to one or other of the 14 field classes.

6.4.1 Error rates of the field class classifications

Taking the set of classes corresponding to level-4 in the structure element class hierarchy (Table 5.2) the classification process described above was associated with error rates of 11 - 14% for 11 of the 12 structure element type related field classes (Table 6.1). One field class, low dwarf bushes, is associated with a higher error rate, of nearly 32%. For the two field classes, "bare soil" and "moss", only 6 and 5 structure objects respectively had been recorded by the field surveyors as having a structure element purity >74%. Since these structure types are naturally so rarely occurring in the coastal zone, and the numbers of reference cases too few to build reliable classification models, these classes were omitted from the rest of the work. The two non structure element type related classes, "built-up" and "non built-up" are associated with higher error rates (34.6% and 18.8% respectively), but as described above, in order to not affect the classification of the other classes the RF model was not optimized for lower error rates in its classification of these classes. Since these two structure types are so rarely occurring relative to most other structure types, the number of false-negatives of "built-up" and "non built-up" has only a minor effect on the classification accuracies of the ecologically important structure types.

Table 6.1. Random Forest based classification error rates associated with field class for the structure objects recorded by the field surveyors as having >74% structure element type purity.

Field class	Error rate (%)
Stone/gravel	12.1
Sand	12.1
Clay/mud	13.3
Built-up	34.6
Non built-up	18.8
Open water	11.4
Lichen	11.1
Herbs 0-15 cm	11.8
Herbs > 15 cm	11.8
Dwarf bushes 0-15 cm	31.9
Dwarf bushes > 15 cm	11.8
Bush/tree 0-2 m	13.3
Bush/tree > 2 m	11.3
Shadow	11.3

6.4.2 Correspondence of structure element field class labels to habitat types

The spatial and geographic arrangements of the structure elements represent the basis for their interpretation as required target classes, such as habitat types. This stage of the method has yet to be developed. The work undertaken to date has assessed the possibility for using a remote sensing based method for identifying structural elements within reference transects. Initial results (Table 6.2) indicate, for the reference transects, a strong pattern of association between the structure element mapping results and habitat type mappings. Comparison of the distributions of the field class classified polygons has been assessed in terms of the distributions of target habitat types also by visual assessment (Figure 6.1), which indicates that the derived maps of the field classes (a) display high levels of spatial organization and (b) relate well to visual interpretation of the image data in terms of discernible habitat types.

Table 6.2. The correspondence between habitat types (rows) and structure elements type classification of structure polygons (columns). Polygons of pure habitat type as registered in reference transects by NST in the 2012 reference data fieldwork are presented in terms of their structure elements composition as was recorded by NST in the 2012 reference data fieldwork. Values represent pooled data with respect to 55 reference transects. The table also records the structure element composition of six habitat types (1150, 4010, 6XXX, 7230) other than 13 out of the set of 14 coastal habitat type, which were also recorded by NST as present within the reference transects.

	Clay mud	**High dwarf**	**High herb**	**High tree**	**Lichen**	**Low dwarf**	**Low herb**	**Low tree**	**Sand**	**Sha-dow**	**Stone/ gravel**	**Water**
1150			.27				.02					.71
1220			.51	.03			.12	.01	.13		.19	
1230	.70		.08							.23		
1310							.43					.57
1320			.73									.27
1330	.01		.56				.32	.01				.09
2110			.27						.73			
2120			.58			.01	.04	.06	.28	.01	.01	
2130		.19	.35	.04	.06		.21	.11	.02			.02
2140		.76	.15	.04		.03	.01			.01		
2160			.10					.87	.03			
2180				.96	.02				.01	.01		
2190		.37	.47				.05	.09				.02
2250				.30				.19		.51		
4010			.78	.02						.10		.10
6210			.44	.03			.51			.02		
6230			.07	.09			.64	.15	.01	.03		
6410			.89	.04								.07
7230	.01		.94	.03								.02

Figure 6.1. Examples of the Random Forest field class classification of reference transect (RT) structure element polygons.(a) Field class legend. Image order in (b) – (g) : spring natural colour, summer natural colour, summer CIR.

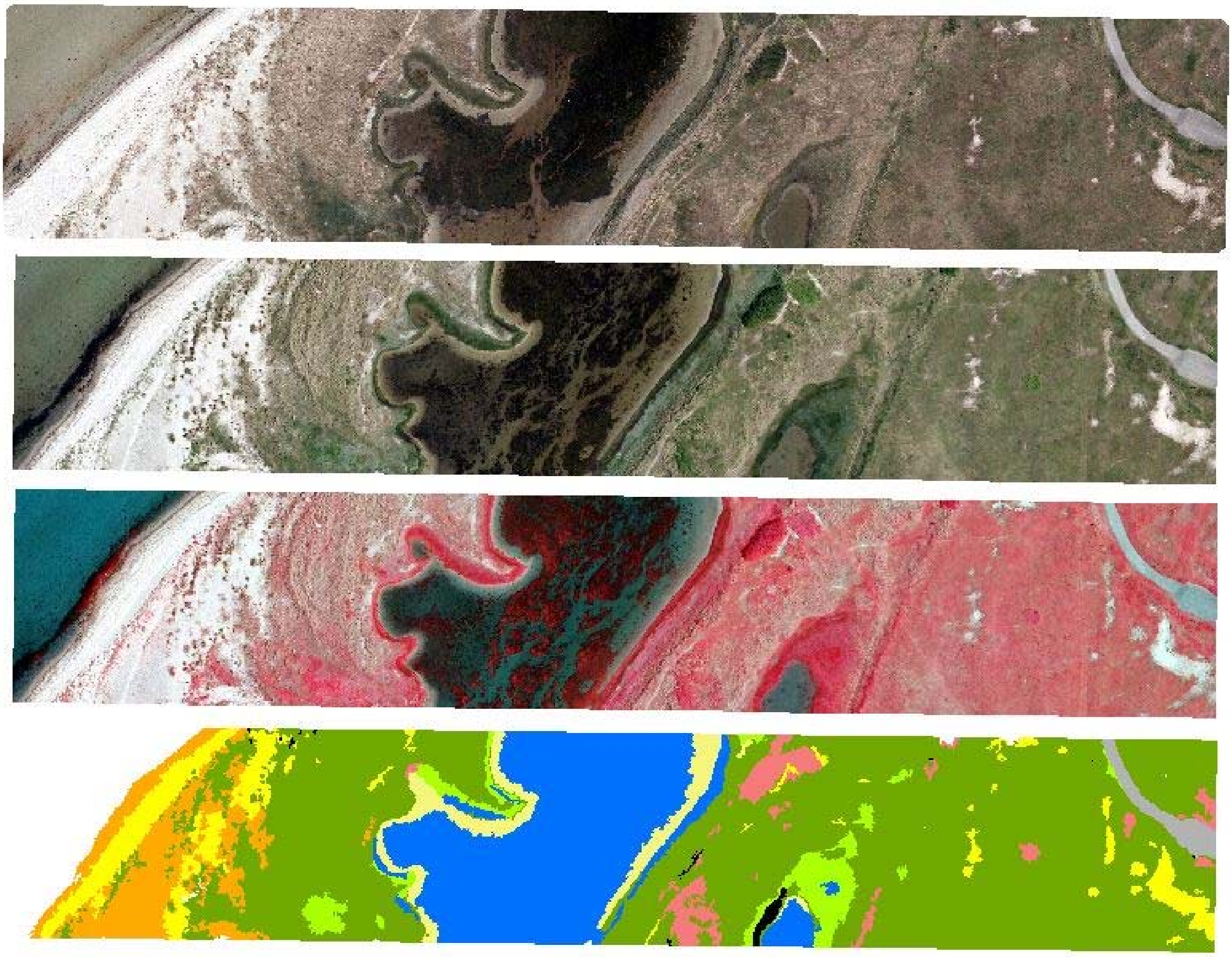


Figure 6.1(b). RT # 71802 (Image order and legend as described above).

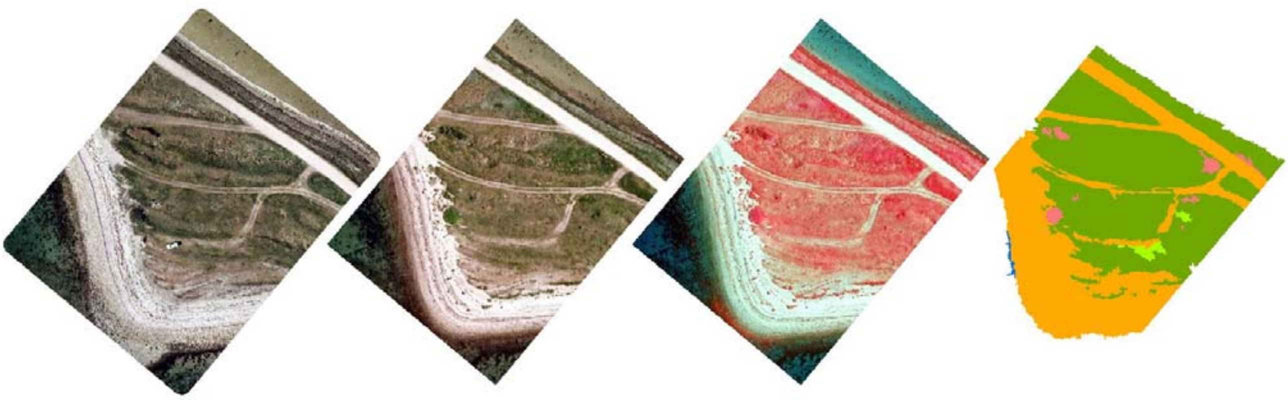


Figure 6.1(c). RT # 72116 (Image order and legend as in (a)).

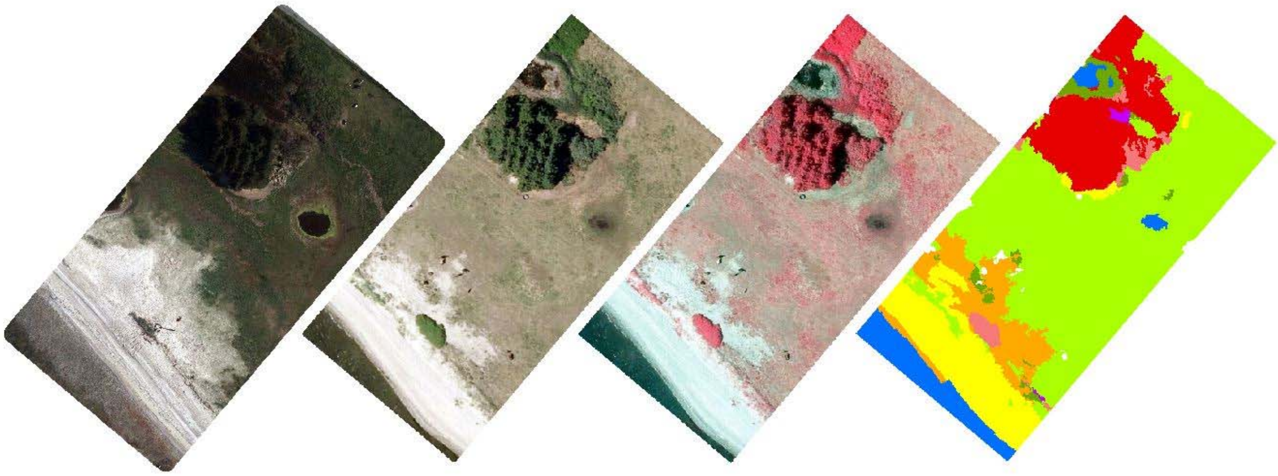


Figure 6.1(d). RT # 69614 (Image order and legend as in (a)).

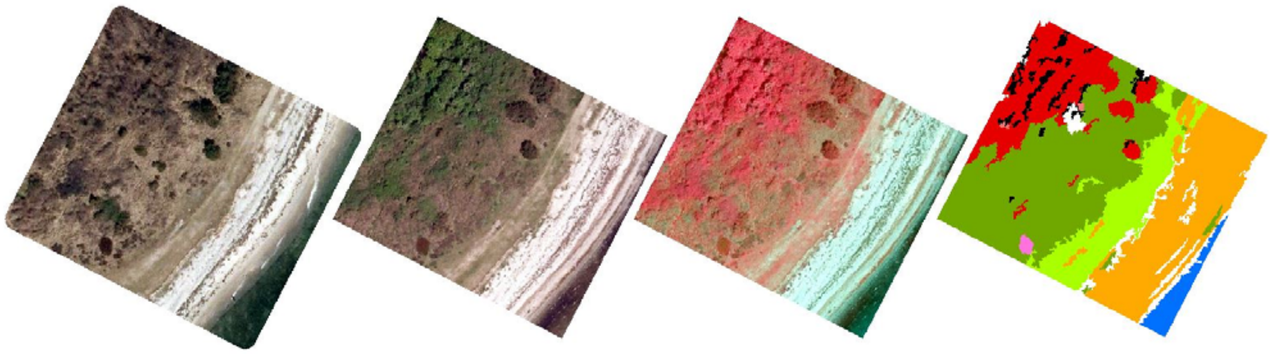


Figure 6.1(e). RT # 68072 (Image order and legend as in (a)).

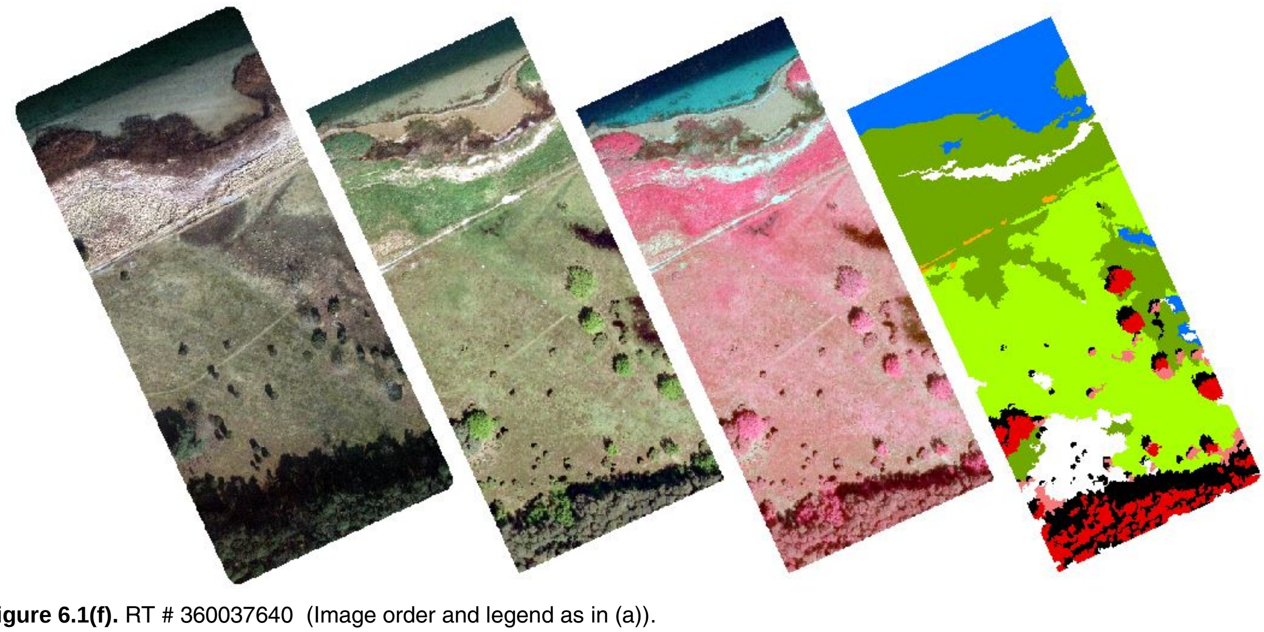


Figure 6.1(f). RT # 360037640 (Image order and legend as in (a)).

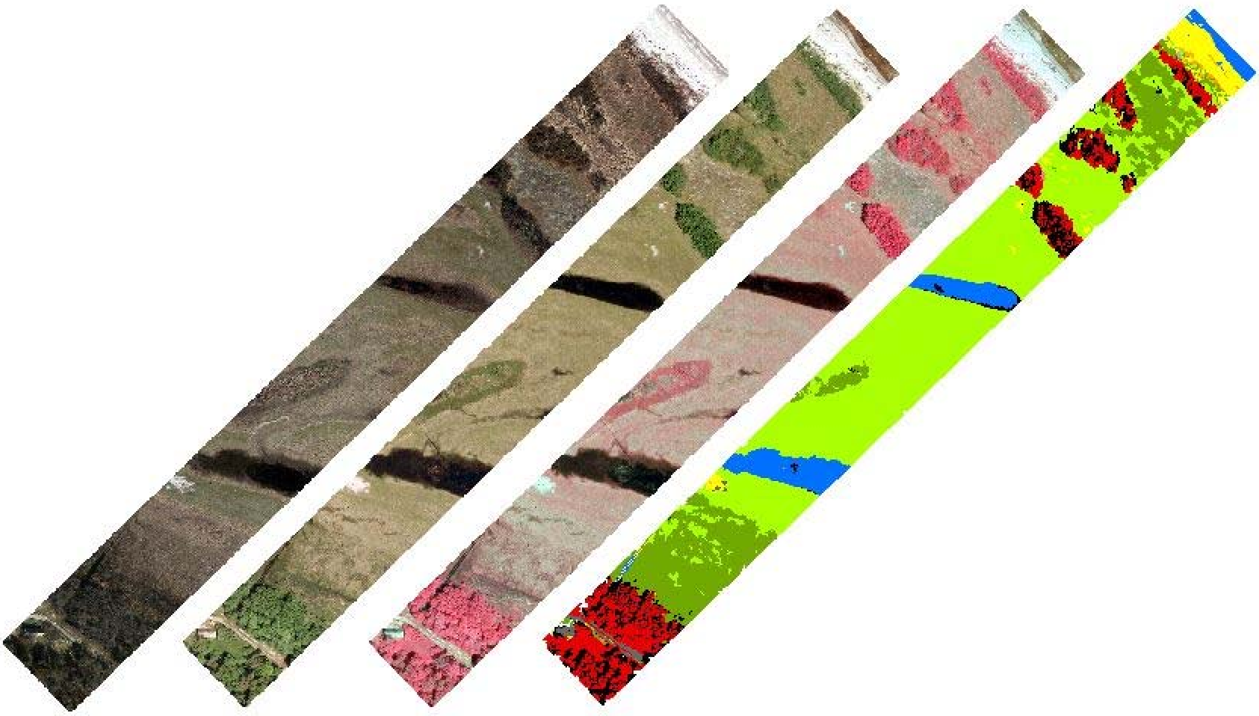


Figure 6.1(g). RT # 360037646 (Image order and legend as in (a)).

7 Discussion

7.1 Discussion introduction

The development of a remote sensing based method undertaken to date should be seen as a success, on several fronts. It has been a considerable and successful achievement to acquire and assemble for a unified analysis of a mass of image, DEM and meta data, representing a widely distributed set of locations. Secondly, the ability to successfully reduce the complexity of the image data to sets of objects, which relate closely to the spatial patterns of habitat structures observed in the field, is a significant achievement and key step in development of the overall remote sensing method. The development and application of a field data collection protocol that is effective for the needs of development and use of a remote sensing based method and ecological aspects of habitats, and is efficient to implement is a major step in the linkage of field and image data is another aspect of the success of this work. Creation of the database of over 400 independent layer, ratio, texture and geometry variables from the image, DEM and meta data demonstrates the considerable power of synthesis and integration of the applied object-based image analysis software. Finally, the ability to define a model that can in nearly 90% of cases successfully classify structure objects across 12 ecologically significant field classes demonstrates the possibilities and the sophistication, of modern automated classification routines, such as Random Forest, and represents great promise for the further development of remote sensing methods in this work.

The results achieved to date, and what they represent as possibilities for further development of the remote sensing method, have to be seen in the context of the alternatives. In Section 1 it has been noted that the current field based methods for monitoring and mapping of Danish coastal habitats is costly and is ineffective in several key aspects, such as detailed habitat type mapping, meaningful recording of structural and biological indicators, and change detection. For the coastal habitats, and certain non-coastal habitat types, the remote sensing method represents an alternative to field based monitoring and mapping that is more cost effective in terms of its ability to be applied for vast areas, and ecologically meaningful in that it can address the relevant biophysical factors of these habitats.

Moreover, the developed methods represent the basis for monitoring and mapping with high levels of transparency, objectivity and synopsis: Transparency, in that it is possible to review and examine the entire process by which every item in the structural element identification has been made, and following the further development of the method, the delineation and labelling to a habitat type of each mapping unit. Objectivity, in that the same method has been applied to all parts of Denmark, without any systematic processes that represent subjectivity, such as the skills of different field survey teams. The application of equivalent data and the same analysis method for all Danish coastal areas gives the remote sensing method its synoptic meaning and value, making possible the analysis of structural indicator related patterns upon different spatial scales.

7.2 Use of the spring image data

The primary segmentation in the work to date has been made from the 2010 summer aerial orthophoto image data. Summer and spring image data have then been used to derive image data indices used for the structure element classification. Since the acquisition, in spring 2013, of the spring image data a second segmentation has been made that utilizes both summer and spring image data, and validation field data have, in summer-autumn 2013, been collected by NST for the resulting sets of objects for the 67 previously surveyed reference transects, following the protocol described in Juel et al. (2013). It is thus possible, in future analyses, to compare the properties of the two (summer, summer+spring) segmentations, and the performance of structure element classifications based on the two segmentations.

7.3 Use of the spring image metadata

The summer aerial orthophoto image data used in the work have been image data acquired in 2010 for all areas. In the case of the spring image data, the national coverage of coastal areas is made from image data acquired in 2010, 2011 and 2012. Metadata relating to the different dates and instrumentation used in the 2010 summer aerial survey have been included as variables in the structure element analysis; these metadata variables were associated with error rate reduction by 4%. For future improvement of the classification results, metadata describing the years of the spring image acquisition could be expected to have at least as significant a role in the classification results as the summer image metadata. Dynamic habitats such as the dunes, are expected to correlate with year-to-year differences in structure element distribution and form. Analysis is now needed that incorporates the spring image metadata as a variable in the RF classification.

7.4 Image data processing to express texture patterns

So far, the image indices have all been acquired for the analysis dataset from image data with 0.16 m pixels. In some situations the applied indices of local texture, acquired with the 0.16 m pixel size image data, do not fully distinguish between different types of structure elements that have different texture patterns; this can happen where there are several, nested, texture patterns present in one or other element type. Degrading the image data to a larger pixel size can help suppress a finer texture pattern, enabling expression as indices of the coarser, element type discriminant texture pattern. Full implementation of this approach will be built into the further development of the structure element classification, based on the new summer-autumn 2013 field reference data.

7.5 Structure elements with mixed reference data properties

In principle, the image segmentation should provide structure element objects that have a high degree of structure element type purity. However, in dynamic coastal habitats, changes between the time of data acquisition and the field reference data collection by NST could result in structure elements that could not be recorded as just a single structure element type. In addition, in some situations different structure element types naturally occur as a fine spatial mixture pattern, resulting in "mixed" structure elements. This possibility was accommodated in the field reference data collection protocols (Juel et al. 2012, Juel et al. 2013) via the recording of the proportions of a structure element object with each of two or more structure element types.

59% of the 45,341 objects analysed from the 2012 field work were ones recorded as being at least 90% pure with respect to structure type, and just 20.3% were recorded as being less than 75% comprised of a single structure element type (Table 7.1).

The classification analyses made to date, reported here, have been made for those structure elements that were field recorded as being at least 75% pure, i.e. 36,135 polygons out of 45,341. The effectiveness of the method for less pure structure objects needs to be analysed. It may be that a method is needed to initially identify less pure objects and either label them with a different model, or divide them into sub-objects.

Table 7.1. Analysis of the 45,341 classified structure elements in terms of their structure type purity as recorded in the field reference data.

Structure objects recorded as	number	%
being > 89% comprised of just 1 structure type	26,732	58.9
being >74% comprised of just 1 structure type	36,135	79.7

7.6 Structure element types with multi-modal image data signatures

Many of the supervised (i.e. training based) analytical methods applied for classification based on image data have required that each class is represented by training data that have approximately normal (Gaussian) data distributions, i.e. a training data for a class should not be multi-modal. For certain of the structure element types being classified in this work, with training data labelling based on field reference recordings, data normality cannot be assumed, e.g. for the bare ground field class depending on the geology of the substrate and the moisture condition, or the built-upon field class with different materials used. In contrast to classifiers such as Maximum Likelihood, the Random Forest classifier is robust to multi-modal training data classes.

7.7 Use of the method for monitoring and mapping

The method that has been developed in this work is seen as a basis for monitoring and not merely mapping of coastal habitat types. It has therefore been built-up with that purpose in mind. For many of the coastal habitat types, there is an ongoing process of local level changes that relates to the natural dynamics of the abiotic factors and processes that play key roles in coastal habitats. Therefore relatively frequent and widespread localized natural changes are often observed, such as in dune habitats. Evolutions between habitat types on relatively short time frames are also part of the natural dynamics of coastal habitat areas. The developed remote sensing method, with its basis in the structural elements of the coastal habitats, which represent responses to the abiotic factors and processes, will provide data on these natural change patterns as part of its monitoring role. Changes in the sets of structure elements associated with habitat types will serve to indicate situations in which habitat type is changing, or where non-abiotic, more anthropogenic factors and processes are also involved in habitat change.

The developed remote sensing methods can make contributions to the process of updating the mappings for each successive reporting period in a number of ways, which will be developed and assessed more fully in the subsequent work. Given the established method, assessment of habitat type changes can be made in the following ways:

- changes in the mapped extents of the habitat types
- changes in the mapped extents of structure elements
- changes in the image data characteristics of structure elements.

Integration of field based species data with the remote sensing methods is also merited for the development of the monitoring. There is a wealth of species composition field data of the coastal habitats that is available through NOVANA and other activities for such investigation and method development work.

7.8 Extension to all coastal areas

The work with the reference transects has established a classifier model to use with object-based image, DEM and metadata data variables for labelling of segmentation objects to structure element types. In principle, that classifier model can be applied to the labelling of structure elements objects away from the reference transects, to form a basis for the monitoring and mapping of coastal habitats over the whole of Denmark. Development of the possibilities for that step should proceed first in terms of use of a Leaving-One-Out evaluation across the set of reference transects, i.e. for each reference transect in turn, to check the ability of a model based on the data of the other reference transects to correctly label its structure objects. Based on this evaluation there may be a need to adjust the parameters of the classifier model to improve its spatial applicability.

The applied classification method is based on classifier training, i.e. that classification is only possible for structure element type classes that have been observed and recorded in the field as properties associated with the structure objects. Structure objects elsewhere that have structure element type characteristics unlike any of the field reference data, such as distinct combinations of structure element types, will not be classified correctly.

7.9 Future analysis

The work reported here represents just the development of a basis for using remote sensing methods in NOVANA, undertaken with ca. 2½ years of research effort. The focus in the work undertaken to date has been to establish the possibility for the mapping of coastal habitat structure elements for all coastal areas of Denmark, with a structure element based approach seen as a sound basis for monitoring and mapping of the associated habitat types. As such, there are several aspects of the work yet to work with, in terms of both the "next stages" and further development of the stages worked with so far.

Moving from a field survey based set of methods for coastal habitat monitoring and mapping to one based on use of remote sensing methods is a considerable undertaking. Thus, the current situation in Denmark of this work compared to that found in several other European countries (e.g. The Netherlands, Wales, Sweden) is relatively modest. Similar works have elsewhere been undertaken by teams of researchers engaged on the activities for many years. It is important to recognize therefore that the work undertaken in Denmark to date is only a first step in establishing remote sensing methods for coastal habitat monitoring and mapping in NOVANA. Moreover, as the first such activities in NOVANA in this direction, considerable time has been used in acquiring and preparing the necessary data for use in the analysis work. In addition, the key field reference data were delivered to DCE only relatively late (winter – summer 2013) in the work period, and the analysis has been made with the data for just those 55 reference transects for which field reference data was delivered in winter 2013.

The currently achieved error rates are at least as low as those commonly reported from applications of remote sensing methods for classification of habitats or related vegetation and land cover classes (e.g Bradter et. al. 2011, Mücher et al, 2013, Hellesen and Matikainen, 2013). Furthermore, the general consistency of the error rates for most classes is noteworthy. The applied classification method is based on classifier training, i.e. that classification is only possible for structure element type classes that have been observed and recorded in the field as properties associated with the structure objects. Structure objects with characteristics unlike any of the field reference data, such as distinct combinations of structure element types, will not be classified correctly.

8 Conclusions

1. The work to date indicates that some remote sensing based monitoring and mapping of coastal habitat types for NOVANA reporting requirements is possible.

2. The developed remote sensing approach represents a complementary approach to the existing methods for the NOVANA monitoring and mapping of coastal habitat types. With a similar or perhaps reduced level of resources, some parts of the coastal habitats can be surveyed by the RS method, supplemented by field mapping to collect reference data and to monitor the more complex structures. As the RS method relates more closely to the overall spatial and temporal patterns of the driving processes, the RS approach can enable targeting of field survey to a limited number of relevant areas.

3. Practical methods have been developed for use of national coverages of image data in this work, and the integration of field collected reference data with remote sensing data.

4. The basis for the remote sensing method has been demonstrated, but its full implementation requires further development work.

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REMOTE SENSING BASED CLASSIFICATION OF STRUCTURAL ELEMENTS OF COASTAL HABITATS

(Telemålingsbaseret klassifikation af strukturelle enheder i kyst-habitatnaturtyperne)

Denne videnskabelige rapport beskriver mulighederne for automatiseret klassifikation af strukturelle indikatorer i danske kyst-habitatnaturtyper, vha. orthofotos og højdemodeller, til udvikling af en forbedret overvågning og kortlægning af disse habitatnaturtyper i ift. hvad der er muligt med traditionelle feltbaserede metoder.

Vurderingen koncentrerer sig om brugen af telemålingsbaserede data tilgængelige omkring år 2010 og en klassifikation af strukturer observeret i dette år. Rapporten inkluderer en vurdering af klassifikationsmuligheder, klassifikationssikkerheder og opstillingen af adskillelsesparametre baseret på indrapporterede feltreferencedata fra 2012.

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