SALTMARSH HABITAT CLASSIFICATION FROM SATELLITE IMAGERY

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ABSTRACT

Saltmarsh habitats provide a good indicator of the condition of the coastal margin environment with respect to changing sea levels, saltwater inundation, air and water temperature, and land management practices. Fragmented saltmarsh vegetation is often mapped by field techniques, however these are both labour and time intensive and not amenable to the objective monitoring of continuous change. Airborne remote sensing requires extensive logistical preparation, and commissioning of overflights for small areas is expensive. Satellite imagery however is relatively easy to acquire, and once the processing chain has been established can be repeated on a regular basis and at varied sites allowing interannual variations in extent and dynamics to be identified. This research seeks to identify the optimum spatial, temporal and spectral resolutions required to discriminate key indicator habitats from satellite imagery, at sites in northern England and Wales. Pixel-based and object-based methods of distinguishing vegetation classes are compared for imagery products from a range of sensors and platforms. The potential benefits of integrating LiDAR data with the multispectral imagery are investigated, as are results obtained through both hard and fuzzy classification methods. These investigations are used to frame guidelines and recommendations for the analysis of saltmarsh habitats from space.

INTRODUCTION

Saltmarshes are intertidal ecosystems located between the open sea and the managed inland environment, thus embodying the characteristics of both marine and terrestrial communities. These coastal regions are very dynamic, responding to interactions and feedbacks between water, sediment and vegetation. Coastal saltmarshes are unusual amongst wetland ecosystems in that their surfaces are regularly inundated with saltwater, and all vegetation is submerged periodically, although to varying extents and to varying durations depending on location within the assemblage (1). As a result, an important feature of saltmarshes is the variation in species composition of vascular plants with elevation (2). Intertidal vegetation is typically taxonomically and physiologically varied including algae with a wide range of plant pigments, whereas habitats near the highwater mark resemble terrestrial vegetation in being predominantly composed of higher plants with chlorophyll as the dominant plant pigment (3). A key element in intertidal system dynamics is halophytic vegetation (plants that have evolved to develop and reproduce in highly saline environments) that is able to colonise saltmarshes and is largely responsible for the stability of these areas. The roots serve to stabilise the soil while the above-ground biomass reduces water flow velocity and dampens waves, impeding the resuspension and erosion of sediment (4).

The transitional nature of saltmarsh environments therefore allows them to perform an essential function in maintaining the health and ecology of the coastal and estuarine zone (5). In recent years the environmental importance of conserving these coastal habitats has been recognised, and the 1992 European Habitats Directive (92/43/EEC) requires reporting of their status on a six year cycle. Meeting the demands of this reporting schedule may be problematic using ground-based techniques due to the difficulty of accessing and surveying large areas dominated by saturated sediment and water, and remote sensing may offer a cheaper, more objective alternative for providing spatially continuous data at temporally regular intervals.

Remote sensing of saltmarshes

There have been a number of studies undertaken over the years to determine the most effective methods by which an inventory of extent and distribution of plant communities within saltmarsh environments can be derived using remotely sensed data. Imagery from a variety of air and space borne platforms has been utilised, with the objectives of these studies ranging from quantifying the total area of saltmarsh, to describing the biogeographical variation of the main habitats with respect to environmental factors, to testing of hypotheses relating to the predominance of plant distribution in different saltmarsh zones.

Research since the 1980s has demonstrated the potential for deriving information on intertidal vegetation from remotely sensed imagery (e.g.6, 7, 8,9). Many of these examples used broad band spectral data from instruments such as Landsat Thematic Mapper, although the more recent work explores the potential of higher spectral and spatial resolution instruments such as the Compact Airborne Spectrographic Imager (CASI) (e.g.10). Airborne remote sensing has been used extensively in preference to satellite borne imagery for monitoring the coastal environment (e.g.ix, x,11) as it offers advantages of higher spatial resolution and the ability to acquire data at specific times (under suitable weather and tide conditions).

Field observations and measurements are of fundamental importance in studying any natural habitat, and particularly saltmarshes where there are close relationships between geomorphic, pedologic and vegetative regimes. However the greater spatial scale that can be studied by remotely sensed means has proved advantageous in many studies. Sensors used for wetland and marsh mapping include AVHRR, Landsat MSS and TM, IRS-LISS, SPOT and ASTER. The spatial heterogeneity and narrow ecotones of some marsh environments limits the use of multispectral instruments to mapping of broad cover patterns (e.g.12), but nevertheless a lot of success has been achieved using sensors such as Landsat Thematic Mapper and IRS LISS (e.g.13, 14,15). These authors found that data at a 30m spatial resolution was of sufficiently high quality to map a good range of intertidal habitats, providing it is acquired under good atmospheric conditions and at a time of year when vegetation is at its most mature. These studies typically classified saltmarsh vegetation into between 3 and 6 generic classes defined by the dominant species or ground cover with a reasonable degree of success.

One of the objectives of this current study is to assess whether a series of satellite-based images (visible and infra-red) of Morecambe Bay in Northwest England, at low water can cost-effectively provide a view of the extent and temporal dynamics of saltmarshes, as well as detect and quantify changes in the extent and species diversity of saltmarsh habitats in a dynamically varying intertidal environment.

METHODS

The study site

Morecambe Bay is the second largest embayment in the United Kingdom (Figure 1), with 310km^2 of intertidal sandflats and mudflats making it the largest continuous intertidal area in the whole of Britain, with over 5% of the UK's total saltmarsh habitat.

Two types of pioneer saltmarsh are represented at Morecambe Bay (www.jncc.gov.uk). Pioneer glasswort (*Salicornia* spp.) occurs intermittently along the coastline forming a transition from the extensive intertidal sand and mudlfats to the distinctive saltmeadows. Other species within the pioneer community include common saltmarsh-grass (*Puccinellia maritime*), common cord-grass (*Spartina angelica*) and sea aster (*Aster tripolium*). These pioneer communities are an important precursor to the development of more stable saltmarsh vegetation, with the density of plants varying and typically lower on sites with sandier substrate. Morecambe Bay is characteristic of saltmarshes in north-west England, with large areas of closely grazed upper marsh. The mid-upper marsh vegetation is strongly dominated by the saltmarsh-grass/fescue (*Puccinellia/Festuca)* communities, and by smaller areas of saltmarsh rush (*Juncus gerardii)* community. The *Juncus maritimus* community is also more strongly represented here than elsewhere in England. Grazing by domestic livestock is particularly significant in controlling the structure and species composition of the habitat type, and in determining its relative value for plants.

Morecambe Bay is a designated Special Area of Conservation according to the EC Habitats Directive, primarily because of the presence of a series of Annex I habitats that include Glasswort (*Salicornia)* and other annuals colonising mud, sand and Atlantic salt meadows (16). Three study sites were selected within the Bay environment (Tummer Hill on Walney Island, Grange and Carnforth, see Figure 1), chosen on the basis of their very different assemblages of saltmarsh vegetation.

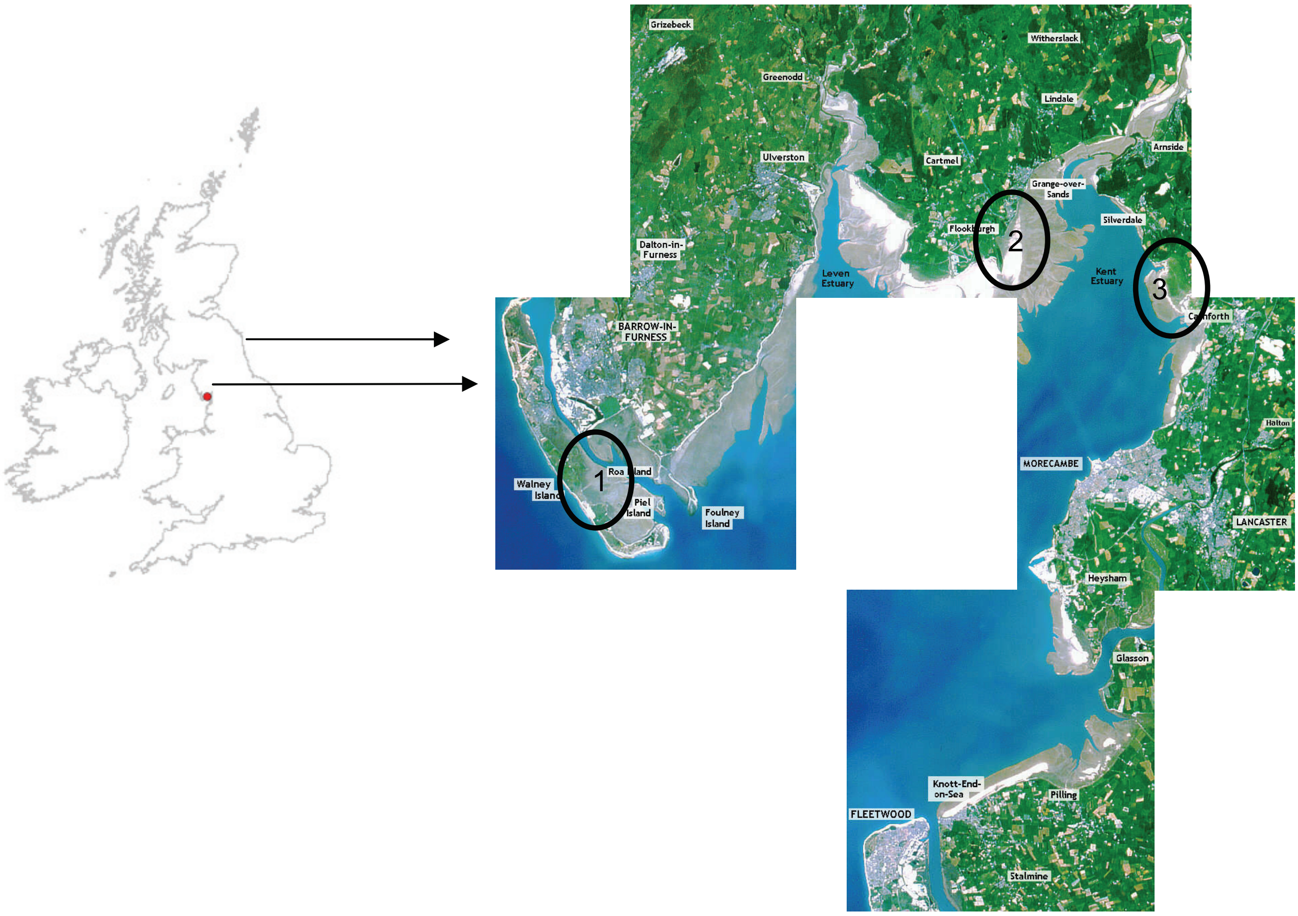


Figure 1: Map showing the location of Morecambe Bay saltmarshes (from www.morecambebay.com) and the test areas used in this study ((1) Tummer Hill, Walney Isalnd, (2) Grange and (3) Carnforth marshes).

Satellite Data and Pre-processing

Five multi-temporal, multi-spectral images from the SPOT and IRS satellites for 2006 and 2007 were used in the study. A SPOT panchromatic image was also acquired. Details are given in Table 1.

ERDAS Imagine 9.1 was used to carry out the image pre-processing. Firstly, all the images were georeferenced to 2 m aerial photography of the area from 2002. Over 30 ground control points per image were taken, and the average displacement error for each rectified image was less than 10m. The accuracy of the photography was assessed through ground based GPS measurements and also proved to be of the order of 10m.

Table 1: Specifications of the images used in the study.

Sensor	Bands	Spatial Resolution	Date
SPOT-2	G,R,NIR	20m	24/04/06
SPOT-4	G,R,NIR,MIR	20m	02/06/06
SPOT-5	G,R,NIR,MIR	10m	03/10/06
IRS-P6 LISS-3	G,R,NIR,MIR	20m	18/07/06
SPOT-5	G,R,NIR,MIR	10m	03/05/07
SPOT-5	PAN	5m	03/05/07

The 20 m multi-spectral SPOT images from April and June 2006 were sharpened to 10m with the NIR band of the October 2006 image using fusion techniques. The High Pass Filter (HPF), Wavelet and Ehler's methods of image fusion were applied, with the former proving to be the best at retaining the radiometric characteristics of the original multi-spectral images. The May 2007 image was pan-sharpened to 5m using the HPF method, which again was shown to be the most robust at retaining the radiometric fidelity of the multi-spectral bands.

The three SPOT images from 2006 were radiometrically normalised against the June 2006 image using a simple linear regression. Bright and dark spectrally invariant areas were selected in order to calculate the slope and intersect values for the regression equation.

***In situ* data**

Field work was carried out during the third week of April 2007. Late April falls at the start of the period considered to be the most appropriate for the discrimination of perennial and some pioneer species. At each of the three sites highlighted in figure 1, approximately 100 quadrats measuring 10m x10m were sampled. The corner co-ordinates of the quadrats were defined on a stratified random basis to ensure a significant number of samples were taken across the whole site and in a range of vegetative zones. For training areas, points were taken in homogenous zones of vegetation to represent all the major species present at each site. To validate classifications, points were chosen in the transition zones between vegetation types and in areas with a mosaic of different vegetation types. In each quadrat the dominant species cover was estimated to the nearest 10%. A Garmin GPS 60 was used to determine the positions of each quadrat.

Image classification

To facilitate efficient image processing, an area of interest around each site was defined using the designated Site of Special Scientific Interest boundary on the landward side of the saltmarsh and continuous deep water on the seaward side.

A number of different image classification methodologies and techniques were explored. Hard classifiers, fuzzy classifiers and object oriented techniques were tested.

The maximum likelihood classifier (MLC) is the most widely used hard classification method. It estimates the probability of a pixel belonging to a particular class based on information provided in the training data. It uses the Euclidian distance algorithm to calculate the distance of the pixel to the centroid of the training data for each class. The algorithm ensures that the pixel will be assigned to the nearest class centroid by modeling the probability distribution for each class. The benefit of the MLC technique is that the maximum likelihood of a pixel belonging to a class is controlled by a critical value set by the analyst. It not only considers the mean and variance of values in each class but also the range of brightness values so that extreme values are assigned to the most likely class.

Fuzzy clustering differs from hard classification in that there is no discrete, pixel-to-class association. Fuzzy logic does not assume that each pixel is homogenous in its spectral content, but permits partial membership of a class which relates closely to the problem of mixed pixels. The fuzzy *c*-means classifier within Parbat (www.parbat.net) was used here and is akin to a traditional unsupervised classification in that it uses an iterative procedure to refine the initial random allocation of pixels to a pre-defined number of clusters. With each iteration pixels are reallocated among the classes as a function of the relative similarity between the pixel and cluster centres. The degree of membership to each class is determined by the degree of affinity with the centroid of that class (17). The fuzziness, or overlap parameter, can be controlled by the user, and when set close to 1 class allocation is crisp with no overlap allowed. For large values there is total overlap and all the clusters are identical. Ideally, the fuzziness parameter should be selected to match the total amount of overlap, however this is generally unknown.

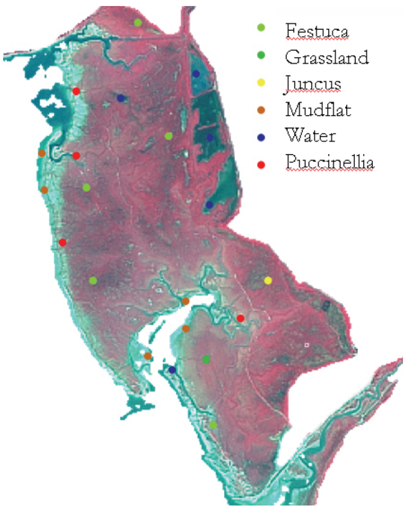
In many cases, image analysis leads to meaningful classes only when the image is segmented into 'homogeneous' areas (18). The goal of image segmentation is to associate pixels with similar values into objects with minimal heterogeneity. These 'object-primitives' can subsequently be grouped into meaningful objects by classification techniques. Segmentation is an interesting technique to explore in this case because of the nature of saltmarshes. Typically saltmarshes are occupied by only a single species or a characteristic association of a few species, which are often found to be growing in 'patches' or areas which retain their homogeneity from a radiometric point of view. Within each patch one species usually prevails, occupying the greater part of the area but with other species present in smaller proportions. The patch size can vary from a few square metres to tens of square metres in which there can be considerable variation in vegetation density.

The eCognition software was used to segment images using a homogeneity measure based on both pixel value and on object shape. The resulting segmented images were then classified using a process tree which allowed the application of different classification algorithms.

RESULTS

Classification of 2007 SPOT image

The number of training sites for classification purposes was determined by the homogeneity and proportion of each land cover class, with more sites for those sites with a more varied spectral response and those covering a larger ground area. A maximum likelihood (ML) classification of the Carnforth test site (Figure 1, No. 3) was carried out. The training areas and the habitat type are shown overlaid on a false colour composite in Figure 2 (a). Figure 2 (b) shows that the spectral response of grassland, festuca and juncus is quite similar



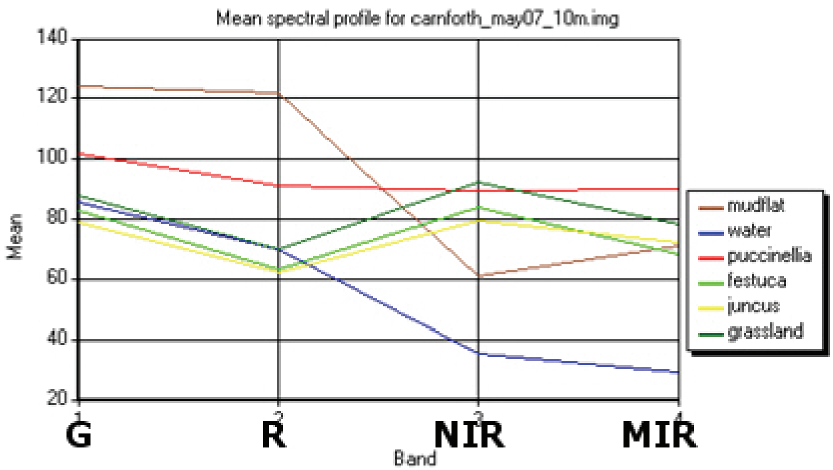


Figure 2: (a) A false colour composite (green-red-NIR) of the SPOT 2007 image showing the location of the training areas. (b) The spectral response of the habitat types in the four bands.

A separability analysis using the transformed divergence shows good separability between the classes, although the *puccinellia* is confused, to some extent, with the *festuca*, mudflats and water.

The maximum likelihood classification of the green-red-NIR bands of the original 10m image is shown in figure 3. The zonation shown matches well with observations in the field. An accuracy assessment, carried out using a standard confusion matrix, based on approximately 100 validation sites gives an average accuracy of 70%. As expected there is significant confusion between the *festuca* and the *puccinellia*, with an error of commission for *festuca* of 6%, but of 50% for *puccinellia*, due almost entirely to confusion between these two species.

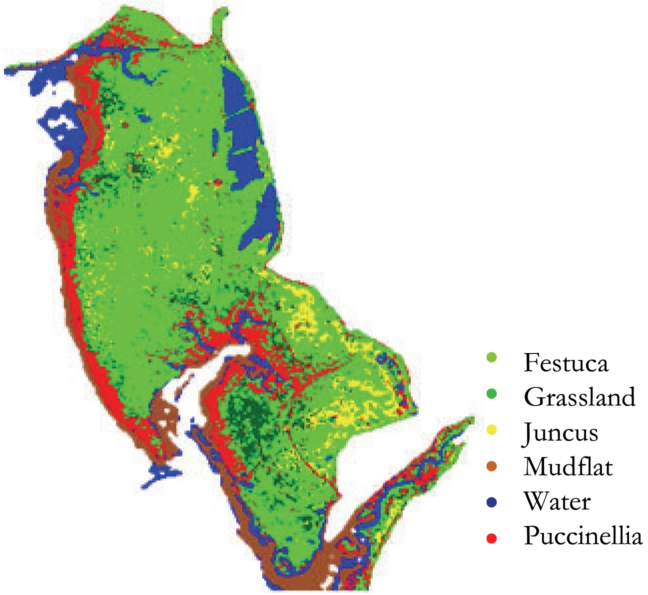


Figure 3: A Maximum Likelihood Classification of the 2007 10m SPOT image.

An unsupervised ISODATA classification carried out using six classes failed to distinguish the small areas of *juncus* and grassland, however did suggest the existence of an additional class which would appear to indicate a “mixed” zone essentially composed of *festuca* and other grasses including puccinellia. A number of training areas were defined for this new class. Examination of the Transformed Divergence separability measure indicated good discrimination between the *puccinellia* and this mixed class, while some spectral overlap was introduced between *festuca* and this new class. A qualitative analysis of a ML classification confirmed this, as many of the areas previous classified as *festuca* now became mixed, while the majority of the *puccinellia* zone remained the same.

Investigation of 2006 temporal series

It would be expected that the vegetation status in April 2006 image would be not dissimilar to that of May 2007, and a ML classification was undertaken using the same training sites. Surprisingly, classification of the three bands of this image has an average accuracy of only 54%, and although the error of commission for *festuca* is still low at 9%, that of *puccinellia* is very high at 76% with a number of misclassifications as bare mud.

Spectral analysis of the 2006 temporal series would indicate that discrimination between classes can be improved by using imagery from more than one date. Figure 4 shows how the spectral response for *festuca* and *puccinellia* varies for the three SPOT images in April, June and October respectively. This figure indicates that while in April, the responses are quite similar, there is a significant difference in both June and October. Training areas from the 2007 field campaign were used, under the assumption that there was no change in the actual landcover types between 2006 and 2007.

A separability analysis carried out using different band and month combinations indicated that maximum separability between all classes was achieved by including all three months but by removing the green channel for all three dates, therefore leaving a total of eight channels. The results of a maximum likelihood classification using these bands produced an image that qualitatively appeared to overestimate the extent of puccinellia, which inspection of the individual images revealed to be driven by the October data. A ML classification was thus carried out using only the April and June imagery, as shown in figure 5, with an overall accuracy of 68%, comparable with that of May 2007. Again, confusion between *festuca* and *puccinellia* appears to be the main cause for misclassification. There is also misclassification of an area covered by thin cloud present in April 2006 as mudflat in the southern part of the image.

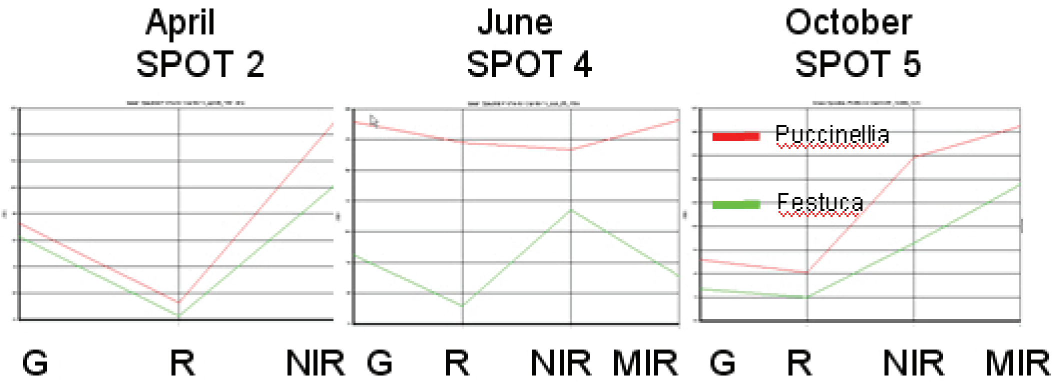


Figure 4: Spectral response of two habitat types for the 3 SPOT 2006 images.

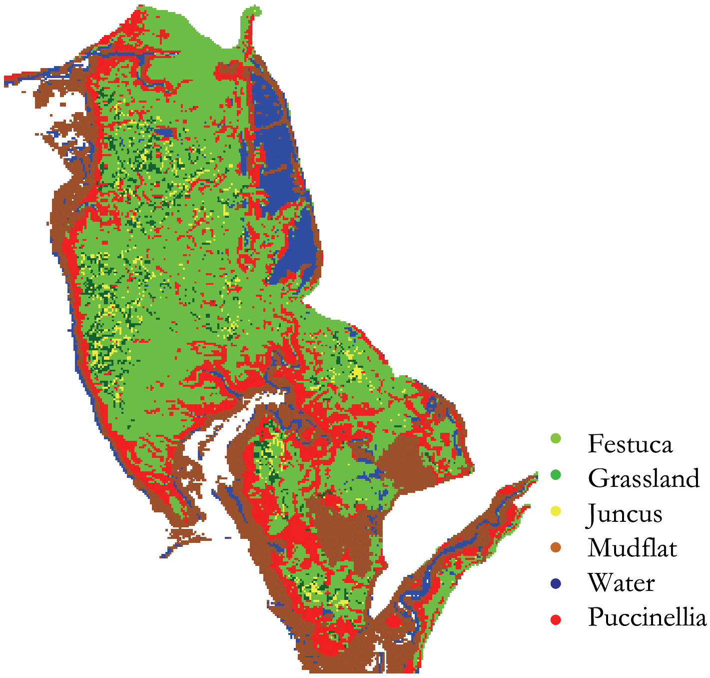
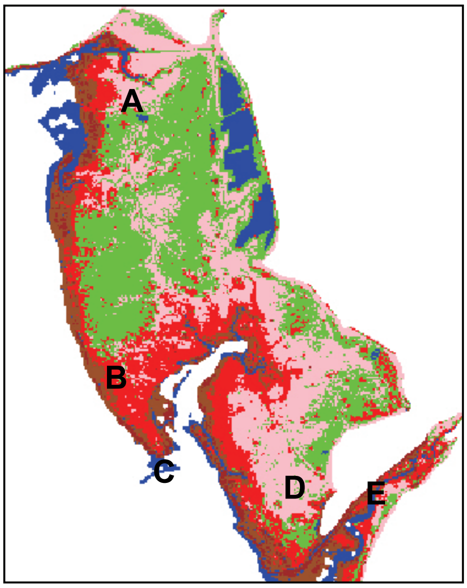


Figure 5: A Maximum Likelihood classification of the SPOT 2006 April and June temporal series without the green bands.

Fuzzy Classification Approaches

In acknowledgment of the mixed nature, of not just areas of *festuca* and *puccinellia*, but also many other land covers, an unsupervised fuzzy approach to classification was undertaken. With 6 classes the Carnforth result also identified the mixed zone between homogeneous *festuca* and *puccinellia* habitats in 2007 (Figure 6a). Examination of the confusion image that is associated with this classification confirms the high level of multiple classes found in this mixed zone (Figure 6b). For each pixel in the fuzzy classification the proportion of each vegetation class present at that location can be determined as shown by selected pixels in table 2. Repeating this classification for the April 2006 and April-June 2006 combinations as above is qualitatively in agreement with the

2007 result. Conducting traditional accuracy assessments on fuzzy classified images somewhat negates the principle of constraining each pixel to a single habitat class, One method of determining the accuracy of fuzzy classified images is through fitting a chi-squared distribution to the distribution of the confusion values with the pixels that are most likely to be misclassified being those with the higher values at the tail of the histogram. A threshold can be defined as the point where the plot flattens out, and on this basis 73% of the pixels were correctly classified in May 2007, 74% in April 2006 and 73% in April-June 2006.



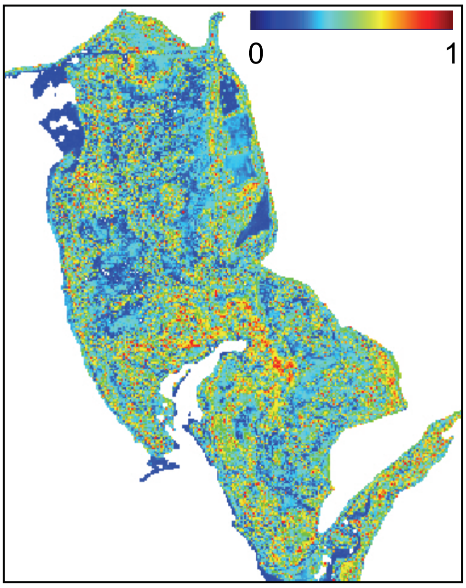


Figure 6: (a) Unsupervised fuzzy classification using 6 classes (letters refer to selected pixels with the fraction of land cover class at each shown in table 2) and (b) the associated confusion image where a value of 0 represents single class membership and increasing values show multiple class membership.

Table 2: Fractions of land cover classes of selected pixels in the fuzzy classified image

	A	B	C	D	E
Deep water	0.003	0.002	0.001	0.011	0.052
festuca	0.034	0.961	0.017	0.091	0.429
mudflat	0.008	0.002	0.005	0.029	0.060
shallow water	0.002	0.001	0.001	0.011	0.014
mixed vegetation	0.885	0.016	0.043	0.702	0.158
puccinellia	0.067	0.017	0.933	0.152	0.277

DISCUSSION

Maximum likelihood classification of the 2007 SPOT image, which was acquired very shortly after the field work, indicates that the saltmarsh extent can be mapped and that the key habitat types can be identified. However, there is confusion between some of the vegetation classes. Fieldwork indicated that although there was a certain zonation of vegetation types with distance from saltmarsh edge the existence of pure vegetation stands, where only one habitat type was present in a 10 x 10 m quadrat were very rare, with mosaics of vegetation types being most common. This would appear to be reflected in the classifications.

In terms of spectral bands, both the near and mid-infrared seem to be vital in maximizing discrimination. The April 2006 image from SPOT 2 does not have a mid infrared band and initial results would indicate that discrimination between vegetation types is reduced in this image. This image also has a higher proportion of bare mud classified, possibly arising from the cooler spring weather experienced in April 2006, and thus the danger of using imagery from too early in the growing season in environments where annual pioneer growth is significant.

Imagery from 5m to 20m spatial resolution has been investigated in the course of this project. The higher spatial resolution imagery, in particular that at 10m and better, provides a much more realistic interpretation of the vegetation distribution with elements of connectivity between like classes. Fusion, in particular the high-pass filter technique, has been shown to be useful in improving the spatial resolution of the imagery while retaining the radiometric characteristics. Ideally a panchromatic image acquired at the same time and on the same platform as the multi-spectral imagery should be used. However, fusion using one multi-spectral band can also be carried out in the absence of a panchromatic band, with successful results. Nevertheless, fusion should always be used with care, when spectral based classification is to follow on the fused images.

The use of a number of images acquired at different times in the growing season is also being investigated as part of this project. Initial analysis would indicate that the variability in the spectral response from the different habitat types over time can be used to improve discrimination between the habitat classes. Analysis of the SPOT image sequence shows that removal of the green spectral band and inclusion of all three images improves separability between the classes. However, seasonal changes in vegetation cover suggest that October may be too late in the year for reliable discrimination of higher order grasses. Use of two images from the start and middle of the growing season gives results that are comparable with those of an image acquired concurrently with field sampling. At around 70%, these classification results are somewhat lower than is achieved for some other vegetation habitats, which is likely to be a function of the complex mosaic of vegetation found in natural saltmarsh environments. This requires further investigation of the value of using single-species dominated vegetation classes. Ongoing work is examining the potential for defining mixed vegetation classes, as well as the effects of using different image combinations including the July IRS image.

Discrimination based on fuzzy methods appears to offer a lot of promise for mapping the vegetation of the saltmarsh environments as it does not constrain the vegetation classes to artificially delineated boundaries that have no true surface manifestation. Being able to analyse each class individually allows a much greater understanding of the spatial distribution of species and habitats, with the confusion image providing a helpful spatial distribution of the areas of greatest uncertainty. Further investigation to be conducted includes supervised fuzzy classification, based on the data collected in the field, with the potential for mixed classes of greater variability in this context.

Object oriented approaches to image segmentation and classification were also tested. These did not give improved results compared to pixel based approaches. The segmentation process is both subjective and laborious, requiring expert knowledge of the area in order to select the correct scaling parameters reliably in order to arrive at an optimum number of segments. Although the field training data, based on quadrats, can be used to carry out the classification, individual segments should be used to train the classifier. A rule based classifier may be constructed, but this again requires significant user intervention.

CONCLUSIONS

Multi-spectral satellite images with a spatial resolution of 10m or better have been shown to be useful in the mapping of saltmarsh habitats in England. A High Pass Filter Fusion technique has been applied to improve the spatial resolution of the imagery without loss of radiometric information. The presence of a mid-infrared band would appear to improve the spectral separability of saltmarsh vegetation classes, while the green band is of limited value in discrimination.

Both an image contemporaneous with the collection of ground data in 2007 and a temporal series of SPOT images from 2006 were analysed. Supervised Maximum Likelihood, unsupervised fuzzy and object oriented classifiers were used as a means of discriminating vegetation habitats. The ML classifier provides a realistic classification of the area, however, there is confusion between some of the similar grass-based classes. The use of multiple images collected in different parts of the growing season would appear to improve vegetation discrimination, however, initial analysis suggests that some of the natural fragmentation of the vegetation may be reduced with loss of areas of sparse coverage for some classes. Fuzzy classification allows the spatial confusion between vegetation types to be visualized and represents more truly the variability in vegetation cover, and the lack of crisp boundaries.

Object oriented approaches would appear appropriate to represent the complex mosaic of a saltmarsh. However, both the segmentation and classification steps are quite subjective and time consuming, demanding very high levels of user intervention and an in-depth knowledge of the area being analysed. In this case the results were not superior to pixel-based classification methods and the methodology would be difficult to transfer into an operational environment.

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REFERENCES

1 Armstrong W, E J Wright, S Lythe & T J Gaynar, 1985. Plant zonation and the effects of the spring-neap tidal cycle on soil aeration in a Humber saltmarsh. Journal of Ecology, 73: 323-339.

2 Adam P, 1990. Saltmarsh Ecology (Cambridge University Press, Cambridge, UK) 461pp.

3 Thomson A G, R M Fuller, T H Sparks, M G Yates, & J A Eastwood, 1998. Ground and airborne radiometry over intertidal surfaces: waveband selection for cover classification. International Journal of Remote Sensing, 19(6): 1189-1205.

4 Belluco E, M Camuffo, S Ferrari, L Modenese, S Silvestri, A Marani & M Marani, 2006. Mapping saltmarsh vegetation by multispectral and hyperspectral remote sensing. Remote Sensing of Environment, 105: 54-67.

5 Kreeger D A & M P Weinstein, 2000. Preface - Special issue on saltmarshes: concepts and controversies. Wetlands Ecology and Management, 8, p. 7

6 Bartlett D & V Klemas, 1982. In situ spectral reflectance studies of tidal wetland grasses. Photogrammetric Engineering and Remote Sensing, 47: 1695-1703.

7 Gross M F, V Klemas & J E Levasseur, 1988. Remote sensing of biomass of saltmarsh vegetation in France. International Journal of Remote Sensing, 9: 397-408.

8 Donoghue D N M, D C R Thomas, & Y Zong, 1994. Mapping and monitoring the intertidal zone of the East coast of England using remote-sensing techniques and a coastal monitoring GIS. Marine Technology Society Journal, 28: 19-29.

9 Hunter E L & C H Power, 2002. An assessment of two classification methods for mapping Thames Estuary intertidal habitats using CASI data. International Journal of Remote Sensing, 23(15): 2989-3008.

10 Thomson A G, A Huiskes , R Cox, R A Wadsworth & L A Boorman, 2004. Short-term vegetation succession and erosion identified by airborne remote sensing of Westerschelde saltmarshes, The Netherlands. International Journal of Remote Sensing, 25(20): 4151-4176.

11 Brown K, 2004. Increasing classification accuracy of coastal habitats using integrated airborne remote sensing. EARSeL eProceedings, 3: 34-42.

12 Phinn S R, C Menges, G J E Hill & M Stanford, 2000. Optimising remotely sensed solutions for monitoring, modeling and managing coastal environments. Remote Sensing of Environment, 73: 117-132.

13 Donoghue D N M & I Shennan, 1987. A preliminary assessment of Landsat TM imagery for mapping vegetation and sediment distribution in the Wash estuary. International Journal of Remote Sensing, 8: 1101-1108.

14 Donoghue D N M & N Mironnet, 2002. Development of an integrated geographical information system prototype for coastal habitat monitoring. Computers and Geosciences, 28: 129-141.

15 Isacch J P, C S B Costa, L Rodriguez-Gallego, D Conde, M Escapa, D A Gagliardini & O O Iribarne, 2006. Distribution of saltmarsh plant communities associated with environmental factors along a latitudinal gradient on the south-west Atlantic coast. Journal of Biogeography, 33: 888-900.

16 ERC, 2003. Saltmarsh condition survey of Morecambe Bay and Duddon Estuary European Marine Sites (Draft Final Report); Environmental Research and Consultancy, University of Liverpool (ref: ERC/J2730/Draft Final v2/09-03)

17 Lucieer A & M-J Kraak, 2004. Interactive and visual fuzzy classification of remotely sensed imagery for exploration of uncertainty. International Journal of Geographical Information Science, 18(5): 491-512.

18 Blaschke T, S Lang, E Lorup, J Strobl & P Zeil, 2002. Object-oriented image processing in an integrated GIS/Remote Sensing environment and perspectives for environmental applications; 555-570