INCREASING CLASSIFICATION ACCURACY OF COASTAL HABITATS USING INTEGRATED AIRBORNE REMOTE SENSING

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ABSTRACT

The 1992 European Habitats Directive (92/43/EEC) requires reporting of the status of a variety of habitats on a six-year cycle. One potential method of carrying out this monitoring is to use remote sensing. Improvements in remote sensing techniques would allow more accurate monitoring to be carried out, thereby providing more accurate indications of the extent and status of these habitats. This paper describes a study carried out to increase the potential of remote sensing for monitoring saltmarsh and sand dune Special Areas of Conservation (SACs). Methods of increasing coastal habitat classification accuracy by adding elevation derived data to multispectral data are examined.

Data were gathered using the ITRES Compact Airborne Spectrographic Imager (CASI) to provide multispectral data and the Optech Airborne Laser Terrain Mapper (ALTM) to provide digital surface models (DSMs) of two UK test sites. Multispectral remote sensing has previously been used for mapping the extent of coastal vegetation classes. However, there are ecological basis for including additional data in classifications, particularly slope and in the case of intertidal vegetation, elevation. This study used data derived from the ALTM DSMs to provide additional data layers in classifications. Statistical and neural network classifiers were used to assess increases in saltmarsh and sand dune vegetation classification accuracy when ALTM data were used in addition to multispectral data. Results are presented that show an increase in discrimination between intertidal land cover types when ALTM data are used in conjunction with fine spatial resolution multispectral imagery and that neural network classifiers can be more accurate for classifying coastal habitats particularly when multisource data are used.

Keywords: saltmarsh, sand dune, classification, elevation

INTRODUCTION

Despite the risks of flooding and erosion, the coastal region of the UK is under intense pressure due to requirements for agricultural, housing, commercial and recreational land. Anthropogenic and natural forcings cause a variety of negative environmental impacts to the coastal zone including erosion, pollution, eutrophication, and the drainage and reclamation of intertidal areas. In recent years the environmental importance of conserving coastal habitats has been recognised and certain of these habitats are now protected under the 1992 European Habitats Directive (92/43/EEC). This directive requires reporting of the status of a variety of habitats on a six-year cycle.

As a tool for regularly monitoring coastal habitats, remote sensing can provide information that may be difficult or impossible to gather using ground-based studies. Thick layers of saturated sediments and water can make intertidal areas inaccessible without specialist equipment. Ground surveys may be difficult to carry out, especially at areas low in the tidal range and the large areas covered by saltmarsh can make comprehensive ground-based surveys difficult and expensive. Remote sensing offers a relatively cheap alternative survey method and can provide spatially continuous data at temporally regular intervals.

This study will examine increasing the accuracy of classifications for vegetation studies by using digital surface model (DSM) data in addition to multispectral data in saltmarsh and sand dune habitat. The two UK test sites used in this study were part of a joint Environment Agency and English Nature project examining the use of remote sensing for coastal zone mapping and had been selected for their national importance (1). The saltmarsh site is Tollesbury Marsh in Essex. The sand dune site is at Ainsdale, Merseyside and is part of the Sefton sand dune system (Figure 1).

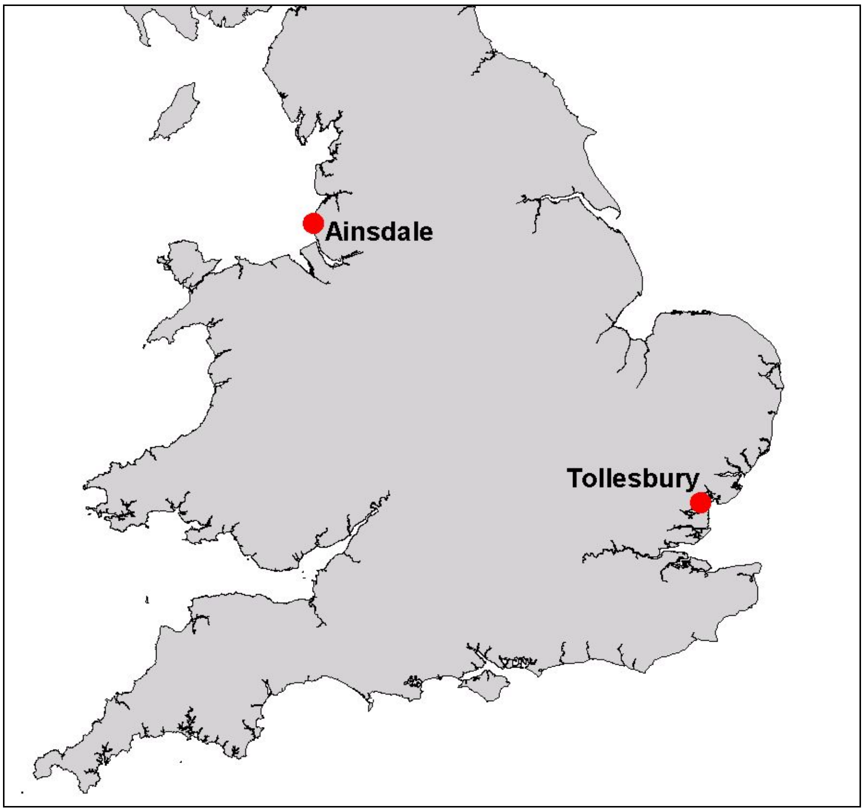

Figure 1 Position of two test sites

There are a number of studies that have used multispectral remotely sensed data for saltmarsh vegetation classification (2,3,4). However, increasing the accuracy of intertidal classification would enable more accurate estimation of the extent of vegetation types for Habitats Directive reporting. This in turn has the potential to increase the accuracy of any estimates of land cover change, an important consideration for the management of sites as well as reporting for legislation such as the Habitats Directive.

Saltmarsh species have varying tolerances to inundation and their distribution is partially determined by position within the tidal cycle and therefore elevation (4, 5). Intertidal species distribution is also influenced by creeks, with certain species more tolerant of the dynamic nature of these areas (5,6,7).

Elevation data therefore has the potential to increase discrimination of intertidal species by providing surrogate data for position within the tidal cycle. Use of slope data in addition to elevation will aid identification of creek edges, potentially increasing discrimination of the pioneer species that are dominant in these areas.

There are fewer studies that have used remote sensing for sand dune community rather than saltmarsh classification using multispectral data (8,9). Dune systems have a variety of characteristics that could be used in order to improve classification accuracy using additional data. Mobile dune systems tend to occur at the seaward edge of frontal dunes, and so contextual information may be used to reduce misclassification errors, particularly as the main species of mobile dunes in the UK, *Ammophila arenaria*, occurs throughout dune systems. Dune slacks are characteristically flat areas containing different species from the surrounding fixed dunes. Though species compositions of slack areas are different, there will be areas that contain species with similar structures to those in fixed dunes. Use of slope has the potential to increase the discrimination of classes compared with using spectral characteristics alone.

Two standard remote sensing approaches to classification were taken in this study, maximum likelihood (ML) (10) and neural network (11) in order to compare these methods and their suitability for classifying merged multispectral and elevation data.

The following hypothesis were tested for both habitats:

1) Use of fine resolution elevation and slope data can increase classification accuracy compared to using only multispectral data.
2) Neural network classifiers can classify data more accurately than statistical methods.

METHODS

The data for the Tollesbury saltmarsh and Ainsdale sand dune test sites were gathered by the Environment Agency (EA) using an Optech lidar (Light Detection and Ranging) and ITRES Compact Airborne Spectrographic Imager (CASI) (Table 1).

Table 1 Data gathered at test sites

Site	Date	Data	
		lidar	Multispectral
Tollesbury	23rd September 2000	ALTM 1020	CASI 1
Ainsdale	11th September 2002	ALTM 2033	CASI 2

For each site five CASI images were collected. The CASI data were geocorrected to a 1 m grid using lidar attitude and post-processed GPS data referenced to a local Ordnance Survey station and then radiometrically normalised by histogram matching the overlap areas. A lidar DSM was used to derive the surface slope in degrees. Ground data for both sites were gathered within 3 weeks of the remotely sensed data by field study for the classes in Table 2 and 3. The ground data consisted of training and accuracy assessment data. Between five and fifteen areas consisting of one class were identified per class and these data used for training the classifiers. Independent land cover class point data were gathered for use in the accuracy assessment stage.

In the ML approach, class mean vectors in feature space and variance-covariance matrix for each class are generated from training data. From these statistics probability density functions for all classes are derived. The posterior probabilities of class membership are estimated for each pixel and the pixel is then allocated membership to the class that it has the greatest probability of membership to.

The ML classifier has the potential to accurately classify spectrally separable data if certain assumptions, such as normal distribution of input data, are met (12). However, the use of high dimensionality or multisource data has the potential to decrease ML classification accuracy (12,13). This is because data sources are not equally reliable or useful in discriminating between classes and the ML classifier does not have a mechanism for weighting data according to importance (12). Studies in the last ten years have shown that other non-parametric classifiers can classify data more accurately than the ML under certain conditions (13,15,16).

The neural network and ML approach to classification are fundamentally different in that the ML approaches depend on assumed model, while neural networks depend on data (11,16,17). This means that the underlying assumptions made for statistical classification, such as the data are normally distributed and data layers are not correlated do not need to be met for neural networks.

Table 2 Classes used in saltmarsh classification

Class	Cover/ Dominant Species	Saltmarsh Zone
Water	Water	Non-vegetated
Mud	Mud	Non-vegetated
Algae	Green and Brown Algae	Algae
Pioneer Marsh	Ann. *Salicornia* spp./ *Suaeda maritime*/ *Aster tripolium*	Lower Lower Lower
Atlantic 1 Marsh (Atlantic Salt Meadow)	*Halimione portulacoides*/ *Puccinellia maritime*/ *Limonium vulgare*	Mid Mid Mid
Atlantic 2 Marsh (Driftline Atlantic Salt Meadow)	*Elymus pycnanthus*	Upper
Terrestrial	Terrestrial Grass	Terrestrial

Table 3 Classes used in sand dune classification

Class	Cover/ Species	Dune Type
Water	Water	Water
Sand	Sand	Sand
Marram	*Ammophila arenaria* (Marram grass)	Mobile dune Fixed Dune
Grass	Grasses Moss Herbaceous vegetation	Fixed dune Dune slack
Reeds	Reeds Wet vegetation	Dune slack
Creep	*Salix repens* (Creeping willow)	Fixed dune Dune slack
Scrub	*Hippophae rhamnoides* (Sea buckthorn)	Dune woodland
Woodland	Woodland	Dune woodland

As well as being distribution free, neural networks are importance free (12,17), meaning that a network will model the relative importance of the input data surfaces during the training process without requiring operator input. The neural network will increase the weighting given to layers that are most useful in discriminating between classes during training. This characteristic is particularly critical when considering multisource data, as *a priori* knowledge of the level of importance of different data is not required.

The neural network used in this study is the multi layer perceptron (MLP), described in (11). The basic unit of the MLP is the node, which sums its inputs and performs a function on the summed input. The MLP consists of three types of layer: input, hidden and output. The number of nodes in the input layer generally corresponds to the number of dimensions of the input data. When used for classification, the number of classes required determines the number of output nodes. Every node in the hidden and output layers is connected to all nodes in the previous layer. As the signal passes between nodes it is modified by weights specific to each node-node connection. Input signals are passed through the MLP and are modified by the weights associated with the connection between nodes and the functions of each node. The outputs of the MLP are activation levels at each output node. In the case of classification, the activation levels are linked to membership of a land cover class and in a hard classification each pixel is allocated the class with the largest activation.

During the training process the training data are entered into the network and the errors of the output calculated. An error function is propagated back through the network and the weights are changed in order to optimise the error. This process is repeated iteratively until the error is minimised or the required number of iterations has occurred.

In this study ML classifications were carried out using ERDAS Imagine 8.4. Trajan 6.0 was used to generate MLP networks. For the saltmarsh site classifications were carried out using four combinations of input data: CASI only, CASI + DSM, CASI + slope, CASI + DSM + slope. The sand dune data were classified using two different combinations of input data: CASI only, CASI + DSM.

Previous studies that describe the optimum MLP architecture and training conditions for classifying data are inconsistent (17) and so a study was carried out to assess the optimum MLP network to classify the data used in this study. Networks with between five and thirty nodes in the hidden layer were tested using a subset of the training data. Between 250 and 2500 training iterations were carried out on each network. The most accurate network for the saltmarsh classification consisted of 20 nodes in the hidden layer and 2000 iterations. For the sand dune classifications the network had 20 nodes and 800 iterations were carried out.

In order to compare classifications, accuracy measures were required. Of the two classification accuracy measures most commonly used in remote sensing, the overall accuracy fails to take into account the correct allocation of pixels by chance and kappa overestimates chance agreement and therefore underestimates accuracy (19,20). The accuracy of each classification was therefore derived using the modified kappa or tau coefficient, which considers correct allocation of pixels by chance, but does not overestimate chance agreement (19,20):

$$T = \frac{P_o - P_r}{1 - P_r} \qquad (1)$$

where P_o is overall accuracy

P_r the random agreement function is:

$$P_r = \frac{1}{M} \qquad (2)$$

where M is the number of classes

Tau (T) variance (20) was used to estimate Z scores and test for a significant increase in classification accuracy when lidar and CASI data were used compared with CASI only classification.

RESULTS

There were small but statistically insignificant increases in classification accuracy when the additional lidar data layers were added to the saltmarsh ML classifier (Table 4). There were small, statistically insignificant increases in classification accuracy when the DSM or slope layers were added individually to CASI for the saltmarsh classification (Table 5). However, when the DSM and the slope layers were both added to the CASI, a significant increase in the classification accuracy occurred (Table 5).

Part of the increase in overall accuracy in the MLP classification when the DSM and slope layers were added appears to be due to an increase in discrimination between the Algae and Pioneer classes (Table 6 and 7). The Atlantic 2 class user's accuracy is increased with fewer areas being misclassified as Terrestrial. The Terrestrial class has an increase in accuracy due to a reduction in the areas of algae misclassified as Terrestrial and a decrease in the misclassification of Terrestrial as Atlantic 2.

Table 4 Overall accuracy for ML saltmarsh classifications

Input	T	Estimated variance	ΔT CASI only classification	Z	Significance
CASI	0.772	0.000576	-	-	-
CASI + DSM	0.797	0.000527	0.025	0.75	NS
CASI + Slope	0.788	0.000545	0.016	0.48	NS
CASI + DSM + Slope	0.804	0.000513	0.032	0.97	NS

Table 5 Overall accuracy for MLP neural network saltmarsh classifications

Input	T	Estimated variance	ΔT CASI only classification	Z	Significance
CASI	0.811	0.000498	-	-	-
CASI + DSM	0.840	0.000434	0.029	0.95	NS
CASI + Slope	0.823	0.000472	0.012	0.39	NS
CASI + DSM + Slope	0.896	0.000298	0.085	3.01	NS

Table 6 Confusion matrix for CASI only MLP classification

		Ground Data							
		Water	Mud	Algae	Pioneer	Atlantic 1	Atlantic 2	Terrestrial	User's Accuracy
Classified Data	Water	49	2	0	0	0	0	0	0.96
	Mud	0	38	0	0	0	0	0	1.00
	Algae	2	10	32	9	0	0	0	0.60
	Pioneer	0	1	10	44	1	0	0	0.79
	Atlantic 1	0	0	0	0	49	0	0	1.00
	Atlantic 2	0	0	2	0	3	50	12	0.75
	Terrestrial	0	0	6	0	0	1	41	0.85
	Producer's Accuracy	0.96	0.75	0.64	0.83	0.92	0.98	0.77	

Table 7 Confusion matrix for CASI and lidar MLP classification

		Ground Data							
		Water	Mud	Algae	Pioneer	Atlantic 1	Atlantic 2	Terrestrial	User's Accuracy
Classified Data	Water	48	0	0	0	0	0	0	1.00
	Mud	0	38	0	0	0	0	0	1.00
	Algae	3	13	42	0	0	0	8	0.64
	Pioneer	0	0	5	51	6	0	0	0.82
	Atlantic 1	0	0	2	2	47	0	0	0.92
	Atlantic 2	0	0	1	0	0	49	0	0.98
	Terrestrial	0	0	0	0	0	2	45	0.96
	Producer's Accuracy	0.94	0.75	0.84	0.96	0.89	0.96	0.85	

The ML classifier had lower tau than the MLP for all combinations of inputs, but it was only when the CASI, DSM and slope inputs were combined that a significant difference was observed (Table 8).

In the sand dune classification, the addition of lidar slope data to the CASI data resulted in an increase in the classification accuracy for both the ML and MLP classifiers, but the increase was not significant (Table 9 and 10).

The performance of the classifiers was compared for the two combinations of inputs there was found to be a significant increase in classification accuracy when the MLP was used rather than the ML classifier (Table 11).

Table 8 Comparison of ML and MLP saltmarsh classifications

Input	ML	MLP	ΔT	Significance
CASI	0.772	0.811	0.039	NS
CASI + DSM	0.797	0.840	0.043	NS
CASI + Slope	0.788	0.823	0.035	NS
CASI + DSM + Slope	0.804	0.896	0.092	$P<0.05$

Table 9 Overall accuracy for ML sand dune classifications

Input	T	Estimated variance	ΔT CASI only classification	Z	Significance
CASI	0.749	0.000285	-	-	-
CASI + Slope	0.772	0.000265	0.023	0.98	NS

Table 10 Overall accuracy for MLP neural network sand dune classifications

Input	T	Estimated variance	ΔT CASI only classification	Z	Significance
CASI	0.795	0.000245	-	-	-
CASI + Slope	0.826	0.000214	0.031	1.45	NS

Table 11 Comparison of ML and MLP sand dune classifications

Input	ML	MLP	ΔT	Significance
CASI	0.749	0.795	0.046	$p<0.05$
CASI + Slope	0.772	0.826	0.054	$p<0.05$

DISCUSSION AND CONCLUSIONS

When DSM and slope were used in addition to CASI data the saltmarsh classification accuracy was significantly increased (8.5%; Table 5) disproving the null hypothesis that use of lidar derived data does not increase classification accuracy for saltmarsh habitat. From this it may be concluded that lidar data can significantly increase, at 95% confidence, the accuracy of saltmarsh vegetation classification when added to multispectral remotely sensed data. The increase in classification accuracy due to the combined DSM and slope (8.5%) was greater than the sum of the increases due to DSM (2.9%) and the slope (1.2%) individually (Table 5). There appears to be a synergistic effect between the layers in increasing classification accuracy. It may be that the combination of data layers allows greater information to be derived about a critical discriminatory variable, such as creek position (6,7).

When both lidar data layers are used in addition to CASI data, the increase in classification accuracy compared to CASI only classification was greater for the MLP (8.5%) than the ML (3.2%). The MLP was significantly more accurate than the ML classifier only when both lidar data layers were used. The null hypothesis that use of the MLP does not significantly increase classification accuracy compared to ML cannot be rejected for the CASI only, CASI + slope and CASI + DSM inputs. The null hypothesis may only be rejected when the DSM and slope layers are used. This is likely to be due to the increased ability of neural networks, compared to statistical classifiers, to use multisource, high dimensionality data (13,16).

The use of lidar data has been shown to increase saltmarsh vegetation classification accuracy for this test site. However, at other saltmarsh sites, elevation and slope may be of less use in discriminating between classes, due to greater overlap in the distribution of species or different species being present. Further studies are therefore required at other saltmarsh sites, especially those that have different community types. In areas where the tidal range is different from the Tollesbury test site, there will be differences in elevation ranges and overlap between community types. These differences could alter the suitability of elevation data for classification. For example the differences in elevation between communities will be magnified in areas where tidal range is greater, increasing the effect of lidar on classification accuracy.

The use of slope in the sand dune classification did not result in a significant increase in classification accuracy and so the null hypothesis could not be disproved. However, a single extra data layer did not result in a significant increase in saltmarsh classification accuracy. Additional lidar derived data may be required before significant increases occur. One possible option is to use the difference in height between the first return pulse of the laser and the last return pulse, which may provide an indication of canopy height.

The MLPs were significantly more accurate than the ML classiers for all of the sand dune classifications (Table 11) disproving the null hypothesis that use of the MLP does not significantly increase classification accuracy compared to ML. This indicates that the neural network approach to classification of sand dunes may more suitable than the ML approach, especially when classifying data from sensors such as the CASI that are high dimensionality.

It may be concluded that the use of data derived from lidar can be of use for increasing classification accuracy. However, further work needs to be carried out to determine the mechanisms that result in the increased ability to discriminate between land cover classes. This is particularly true in the case of the saltmarsh, where there appear to be synergistic effects between the lidar data layers. Further work should also be carried out to determine whether the effects of high-resolution elevation data on classification accuracy are dependent on the saltmarsh or sand dune examined, or are sensor dependent.

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