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The development of remote sensing techniques for marine SAC monitoring

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The development of remote sensing techniques for marine SAC monitoring

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Contents

Appendices

List of Figures

List of Tables

Definitions and acronyms

Activation levels:	The output from a neural network (Appendix C.2.2)
Azimuth angle:	The direction of the sun.
Bi-directional effects:	The effect seen over some surfaces where the amount of light being reflected depends on the direction of the light source and the viewing direction (Appendix C.1.3)
CASI:	Compact Airborne Spectrographic Imager (Appendix B.1)
Classification:	The process by which remotely sensed data are converted to a land cover map (Appendix C.2)
DEM:	Digital Elevation Model
Edge matching:	A method of radiometric normalisation
Geocorrect:	The process of transforming data so that it may be used in a GIS. Making a data layer 'map ready'.
Georeference:	The process of transforming data so that it may be used in a GIS. Making a data layer 'map ready'.
GIS:	Geographic Information System
GPS:	Global Positioning System
LIDAR:	Light detection and Ranging. A laser terrain mapper (Appendix B.1)
Maximum likelihood classifier:	A statistical classification method (Appendix C.2.1)
ML:	Maximum likelihood classifier
MLP:	Multi layer perceptron
Mosaic:	The process of joining adjacent remotely sensed images
Multi layer perceptron:	A neural network classifier (Appendix C.2.2)
Multispectral:	A sensor that can record light at several separate wavelengths
Neural network:	An artificial intelligence classifier
NN:	Neural network
Overall accuracy:	A measure of the proportion of pixels for a classification that are correctly classified (Appendix C.2.5)
Photogrammetry:	Use of aerial photography to derive physical measures of the environment. In the context of this report refers to creating a DEM from aerial photography.
Producer's accuracy:	A measure of the accuracy of a particular class from a classification (Appendix C.2.5).
Radiometric normalisation:	The process of minimising the effect of different lighting conditions on remotely sensed data from the same site (Appendix C.1.3).
Resolution:	The size of a pixel on the ground
RMS/RMSE:	Root Mean Square Error. A measure of error. 66% of data will fall within +/-1 RMSE.
SAC:	Special Area of Conservation
Supervised classification:	A classification approach in which pixels are identified as belonging to a given class. An algorithm then estimates the spectral characteristics of the class and then uses those characteristics to determine which class each pixel in an image belongs to.
Tau:	An overall accuracy measurement (Appendix C.2)
Uncertainty:	The probability that a given parameter is correct. Eg the probability that a pixel has been correctly classified.
Unsupervised classification:	A classification approach that does not require ground data. A computer algorithm places pixels into classes according to spectral patterns within the data.
User's accuracy:	A measure of the accuracy of a particular class from a classification (Appendix C.2.5)

1. Executive summary

In March 2000 a three year project entitled *Collaborative Agreement for developing remote sensing techniques for marine SAC monitoring* was initiated between English Nature and the Environment Agency's National Centre for Environmental Data and Surveillance (NCEDS). After discussion with English Nature, a range of proposed habitats were considered to be of interest to both parties. These were saline lagoons, inter-tidal mudflats, vegetated coastal shingle, saltmarsh and sand dunes. Factors affecting the status and extent of these habitats and an explanation of how remote sensing techniques could be employed to measure such attributes over time were included within the initial proposal discussed with English Nature on 4 August 2000; *Proposal to develop remote sensing techniques for the measurement of environmental change in coastal habitats*.

Three main areas of study were identified that are critical for the use of remote sensing in habitat monitoring:

- Data preparation and accuracy
- Image classification and habitat mapping
- Morphological change

One of the main factors in accurately converting remotely sensed data into habitat maps is ensuring that differences in the lighting conditions between images are minimised. Methods of normalising imagery were examined and two methods were identified that could be used in terrestrial and intertidal habitats. A traditional approach known as edge matching was most suitable for terrestrial habitats. In this method the relationship between the spectral characteristic radiance values in the overlapping areas between images are used to compensate for differences in lighting. For intertidal habitats a novel method known as band ratioing was successfully used to compensate for differences in illumination.

Innovative methods of improving the accuracy of habitat mapping were developed. Data merging was used to increase the accuracy of intertidal vegetation and sand dune mapping by adding contextual data such as slope and elevation into the classification process. The use of artificial intelligence based classification methods was examined and these techniques were also found to increase the accuracy of habitat mapping.

Methods of monitoring morphological change in the coastal environment were studied and techniques were developed for quantifying the volume of erosion and accretion at regular intervals along the coast and for identifying the areas where those changes are taking place.

Methods of visualising habitats were examined, particularly with reference to showing morphological changes in three dimensions.

Using remotely sensed data for monitoring vegetation change was examined, but there were issues that remained unresolved. This area was identified as one that requires further study.

The operational use of remote sensing for habitats monitoring is discussed and areas are identified, particularly monitoring coastal vegetation changes, where this work may be taken forward.

2. Introduction

In March 2000 a three year project entitled *Collaborative Agreement for developing remote sensing techniques for marine SAC monitoring* was initiated between English Nature and the Environment Agency's National Centre for Environmental Data and Surveillance (NCEDS).

The National Centre for Environmental Data and Surveillance had demonstrated the use of remotely sensed data for mapping several habitats in the coastal environment, particularly in the inter-tidal zone. These techniques are capable of distinguishing saltmarsh, algae and bare mud, in addition to water and terrestrial vegetation. Investigations of the requirements for monitoring of coastal habitats, particularly those within Special Areas of Conservation, have suggested a much wider use for the remote sensing methodologies. NCEDS identified a number of habitats based primarily on their inclusion within the UK Biodiversity Action Pan (UK BAP) that would lend themselves to remote sensing techniques.

Maritime habitats are important for conservation, agriculture, flood defence and recreation, and are often protected by European legislation. They are under intense pressure from a combination of sea level rise and anthropogenic factors, and through increased protection and regulation, regular monitoring is essential to inform more strict management of the environment. Through the implementation of the Habitats Directive, there is a need to monitor and report on the status of such habitats, and new assessment methodologies are required to develop more efficient ways of monitoring changes in these difficult and dynamic habitats.

For this study, a range of maritime habitats were considered and sites were chosen to assess the use of remote sensing methods on saline lagoons, intertidal mudflats, vegetated coastal shingle, saltmarsh and sand dunes. A series of sites were chosen, which have been designated as candidate Special Areas of Conservation (SACs) for the relevant habitats for study. Location of these sites are given in Figure 2.1.

The operational use of the methodologies developed is discussed and the advantages of such techniques over traditional methods is considered. Recommendations are developed for the optimum use of remote sensing for each of the habitats studied

This report contains a description of the work carried out over the three years.

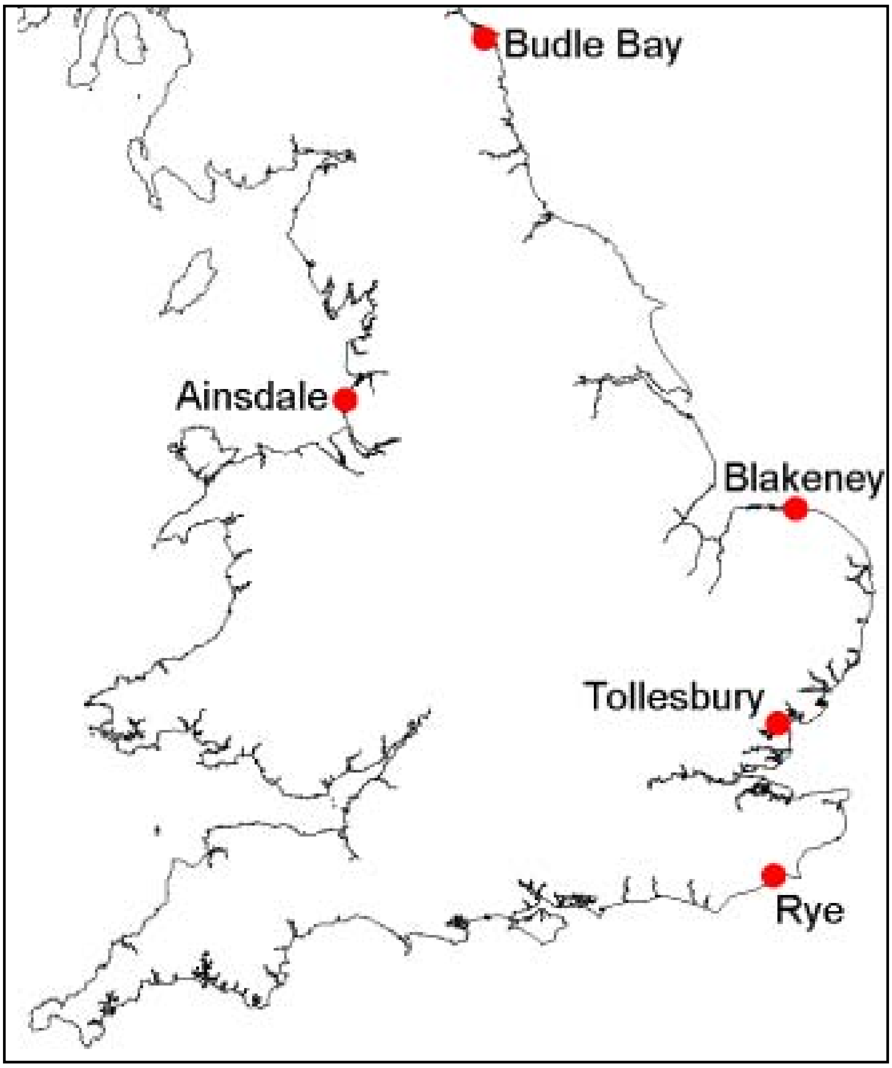


Figure 2.1 Project test sites

3. Data gathered

The remotely sensed data collected are summarised in Table 3.1. The 2000 Ainsdale data were reflown, because the LIDAR data failed the Environment Agency quality assurance.

Table 3.1 Remotely sensed data gathered

Site	Date	Time (GMT)	CASI	LIDAR	Notes
Blakeney (WP 1)	08/06/00	1630-1700	Cloud shadow + gaps between lines	Good	CASI okay for visual interpretation, but gaps between lines
Ainsdale (WP 5)	10/06/00	1155-1255	Poor, cloud shadow	Failed quality control	CASI okay for visual interpretation
Rye (WP 3)	16/06/00	1811-1910	Good	Good	
Blakeney	09/09/00	1430-	No LIDAR attitude data	No	Manual geocorrection required

Site	Date	Time (GMT)	CASI	LIDAR	Notes
(WP 1)		1500	or GPS, geocorrection poor		for CASI
Rye (WP 3)	11/09/00	1440-1230	Good	Good	
Blakeney (WP 1)	23/09/00	0920-0955	Cloud shadow	No	
Tollesbury (WP 4)	23/09/00	1055-1140	Good	Good	Hyperspectral data gathered for section of marsh
Ainsdale (WP 5)	17/10/00	1127-1240	Okay, some cloud shadow and low solar angle	Failed quality control	
Tollesbury (WP 4)	25/06/01	0900-1040	Okay	Good	Good lighting but strong bi-directional effects
Ainsdale (WP 5)	28/08/01	1330-1400	Good	Good	
Blakeney (WP 1)	26/07/02	1020-1110	Good	Good	
Rye (WP 3)	27/07/02	1320-1355	Good	Good	
Ainsdale (WP 5)	11/09/02	0940-1010	Good but solar angle low	Good	
Budle (WP 2)	11/09/02	1105-1140	Good	Good	
Tollesbury (WP 4)	01/10/02	1050-1220	Okay-poor Variable lighting conditions	Good	

4. Data analysis

The purpose of this study was to provide remote sensing methods of monitoring coastal Special Area of Conservation (SAC). Three major areas within remote sensing were identified that were relevant to achieving this objective:

- Data preparation and accuracy
- Image classification
- Morphological change

Descriptions of the data analysis techniques used in this study are given in Appendix C.

4.1 Habitat classification

4.1.1 Saltmarsh

A number of studies have shown that remote sensing techniques can make a valuable contribution to monitoring of saltmarshes. Remote sensing has been used to non-destructively estimate the biomass and productivity for a number of intertidal species. These studies include the following species; *Zostera marina* Linnaeus (Budd and Milton, 1982), *Halimione portulacoides* (Jensen, 1980) and a variety of *Spartina* species including *S. alterniflora* (Gross *et al.*, 1987), *S. anglica* (Gross *et al.*, 1986) and *S. foliosa* (Zhang *et al.*, 1997). Donoghue and Shennan (1987) and Thomson *et al.* (1998) used Landsat TM and CASI imagery respectively to discriminate between intertidal vegetation types. Donoghue *et al.*

(1994) classified Landsat Thematic Mapper (TM) images to derive thematic maps of intertidal vegetation and determine temporal change.

The studies above used multispectral imagery to classify saltmarsh vegetation. However, the ecology of saltmarsh vegetation provides an opportunity to use other data layers in addition to multispectral data, in order to increase classification accuracy.

All saltmarsh species are tolerant of saline inundation but the level of tolerance varies between species (Adam, 1990; Zedler *et al.*, 1999). The position within the tidal cycle and elevation will determine the length of time that inundation occurs and this will in turn influence intertidal species distribution (Adam, 1988, 1990; Gray *et al.*, 1990, Zedler *et al.*, 1999). Saltmarsh elevation data would therefore have the potential to increase class discrimination.

Though the mechanisms are not understood (Sanderson *et al.*, 2001), species composition within and close to intertidal creeks tends to be different from other areas of saltmarsh (Adam, 1990; Zedler *et al.*, 1999; Sanderson *et al.*, 2000, 2001). This spatial pattern provides a mechanism by which remote sensing classification accuracy may be increased. Use of a fine resolution digital elevation model (DEM) and slope derived from it would enable creek areas to be identified.

From this it may be seen that elevation and slope data have the potential to improve the discrimination of multispectral classification of the intertidal zone by enabling position within the tidal cycle and the presence of creeks to be taken into consideration.

4.1.2 Sand dunes

There are very few studies that have used remote sensing for sand dune community classification. These studies have generally classified to a general community type rather than specific species level (Hobma, 1995; Seeliger *et al.*, 2000). The main reason is likely to be the diversity of species present in most dune systems. Classification requires reasonably large areas to be identified for each class used. If the classification is to be to genus or species level then the number of classes and therefore the amount of ground data required could be very high and may result in low classification accuracies. 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. However, though species compositions of slack areas are different, there will be areas that contain species with similar structures to those in fixed dunes and so slope could be used in addition to spectral characteristics to increase accuracy of the final classification.

4.1.3 Saline lagoons

Little or no work using remote sensing has been carried out on these habitats. However, there is the potential to use techniques developed in other areas for increasing understanding of lagoon habitats. As well as classifying the lagoon area to identify important species, possible methods include using multispectral data to determine water depth and lagoon area.

4.1.4 Mudflats

Studies have been carried out that used remote sensing to provide data on mudflats (Meulstee *et al.*, 1988; Bajjouk *et al.*, 1998; Guichard *et al.*, 2000). These studies have mainly been interested in estimating algal biomass using aerial photography (Meulstee *et al.*, 1988; Guichard *et al.*, 2000). Identification of algae and mudflat sediments has also been carried out using CASI data (Bajjouk *et al.*, 1998).

4.1.5 Vegetated shingle

Little previous work has been carried out on these habitats using remote sensing.

4.2 Morphological change

Monitoring coastal morphological change using remote sensing involves the derivation of a DEM from some sensor such as a LIDAR and then the use of the DEM to monitor the change of a morphological variable such as elevation.

Using remote sensing for morphological change detection has become more common, particularly with the advent of cheaper, quicker methods of collecting and processing data in recent years. Simplistic approaches, such as monitoring the position of shoreline position using LIDAR have been used (Stockdon *el al.*, 2002). Deriving volume changes or indicating where change has taken place, provides more information about the whole system. This more complex form of morphological study has been carried out using LIDAR to monitor beach movement (Revell *et al.*, 2002) and cliff erosion (Sallenger *et al.*, 2002). LIDAR and photogrammetry have been used to monitor short term change of soft cliffs (Adams and Chandler, 2002). Monitoring and measurement of fluvial bank erosion has been carried out using photogrammetry (Barker *et al.*, 1997).

4.3 Ridge characteristics of percolation lagoons

The characteristics of the ridge between open water and percolation lagoons are important factors in the determining whether the system is changing over time. In a percolation lagoon system, such as that present at Blakeney, the width of the ridge has an impact on the rate of saline replenishment. LIDAR data have been used to estimate the width of the shingle ridge at Blakeney at regular intervals. The ridge height can give indications of whether overtopping will occur, which also influences the dynamics of a saline lagoons.

5. Methods and results

5.1 Classification and radiometric correction

5.1.1 Saltmarsh

Of the habitats being classified in this project, the greatest amount of previous work has been carried out on saltmarsh. Remote sensing is an ideal approach for mapping this habitat, as the intertidal zone may be difficult to access due to tides, soft sediments and island areas of habitat.

However, the limitations due to tidal restrictions mean that flying high quality data is difficult due to the requirement to wait for the correct stage of the tide and good lighting conditions. The regular inundation of the habitat also makes it more likely to display bi-directional effects, further restricting the times when data may be flown. In this context it may be seen that expanding survey opportunities and minimising the effects of adverse lighting are crucial for this method to become operational for regular monitoring.

Figure 5.1 CASI imagery of Tollesbury test site, Essex

Maximising saltmarsh classification accuracy

Possible techniques for maximising classification accuracy were tested using data from the Tollesbury marsh area of the test site for the 2000 data (Figure 5.1).

A 1m resolution CASI image using 5 flightlines was mosaiced using edge matching. A ratio image was also generated using the same 5 flightlines. A slope layer was generated from the 2m LIDAR DEM. Both the LIDAR data layers were resampled using nearest neighbour to a 1m grid. The CASI image and ratio image were combined with the resampled LIDAR data. The ML statistical classifier and MLP neural network classifier were tested with CASI data and CASI, LIDAR elevation and slope data. The MLP classifier was also tested with the

12 band ratios that were suitable (Appendix D) and with the 12 band ratios and LIDAR elevation and slope data.

The classifiers were tested using two sets of ground data based on slightly different class sets, Original and SAC (Table 5.1). In the SAC set of classes the *Halimione portulacoides*, *Puccinellia maritime* and *Limonium vulgare* were merged to form the Atlantic 1 (Atlantic Salt Meadow) class.

Table 5.1 Classes used in saltmarsh classification

Cover/ Species	Original Class Set	SAC Class Set
Water	Water	Water
Mud	Mud	Mud
Green and Brown Algae	Algae	Algae
Ann. *Salicornia* spp. *Suaeda maritime* *Aster tripolium*	Pioneer	Pioneer
Halimione portulacoides	Halimione	Atlantic 1 (Atlantic Salt Meadow)
Puccinellia maritime	Puccinellia	Atlantic 1 (Atlantic Salt Meadow)
Limonium vulgare	Limonium	Atlantic 1 (Atlantic Salt Meadow)
Elymus pycnanthus	Elymus	Atlantic 2 (Driftline Atlantic Salt Meadow)
Terrestrial Vegetation	Terrestrial	Terrestrial

From the accuracy assessment results (Table 5.2) it may be seen that the ML classifier has much lower accuracy than the MLP neural network for all input combinations. The difference was statistically significant for all combinations of input apart from the CASI only classification for the SAC classes (Tables 5.3 and 5.4).

Table 5.2 Accuracy assessment results from saltmarsh classification testing using tau accuracy

Inputs	Original			SAC		
	ML	**CASI MLP**	**Ratio MLP**	**ML**	**CASI MLP**	**Ratio MLP**
CASI	0.663	0.764	0.775	0.772	0.811	0.826
CASI+DEM+Slope	0.705	0.810	0.789	0.804	0.896	0.865

As described in Appendix C there are a number of reasons why the ML classifier may be less accurate than the MLP neural network. These include the relatively low number of training data used and the difficulty in identifying areas for the classification that are only made up of one class. The low classification accuracy was particularly noticeable when the LIDAR data were added to the classifier, especially for the SAC classification (Table 5.2). This relatively low increase in classification accuracy is likely to be due to the ML classifier's limitations when data from different sources are used in a classification. The consistent lower classification accuracy shows that the ML classifier is less suitable for saltmarsh classifications than the MLP neural network.

Table 5.3 Changes in accuracy for saltmarsh original class set (bottom left) and levels of significance (top right)

	CASI ML	CASI+ DEM+ Slope ML	CASI MLP	CASI+ DEM+ Slope MLP	Ratio MLP	Ratio+ DEM+ Slope MLP
CASI ML		NS	**$p<0.05$**	**$p<0.01$**	**$p<0.001$**	**$p<0.005$**
CASI+ DEM+ Slope ML	0.038		NS	**$p<0.01$**	NS	**$P<0.05$**
CASI MLP	**0.090**	0.052		NS	NS	NS
CASI+ DEM+ Slope MLP	**0.130**	**0.093**	0.041		NS	NS
Ratio MLP	**0.100**	0.062	0.010	-0.031		NS
Ratio+ DEM+ Slope MLP	**0.112**	**0.075**	0.023	-0.018	0.013	

Table 5.4 Changes in accuracy for saltmarsh SAC class set (bottom left) and levels of significance (top right)

	CASI ML	CASI+ DEM+ Slope ML	CASI MLP	CASI+ DEM+ Slope MLP	Ratio MLP	Ratio+ DEM+ Slope MLP
CASI ML		NS	NS	**$p<0.001$**	NS	**$p<0.005$**
CASI+ DEM+ Slope ML	0.032		NS	**$p<0.05$**	NS	**$P<0.05$**
CASI MLP	0.065	0.033		**$p<0.05$**	NS	**$P<0.05$**
CASI+ DEM+ Slope MLP	**0.118**	**0.086**	**0.052**		NS	NS
Ratio MLP	0.079	0.047	0.014	-0.039		NS
Ratio+ DEM+ Slope MLP	**0.112**	**0.080**	**0.047**	-0.006	0.033	

The input of LIDAR elevation and slope data increases classification accuracy for both classifiers. However, this increase is only statistically significant when the SAC classes were classified for the neural network (Tables 5.3 and 5.4).

The per-class accuracy of the MLP classifications for the CASI only and the CASI, DEM and slope classifications were compared (Tables 5.5 and 5.6). The greatest increases in user's accuracy are in the algae and pioneer classes. These classes have the potential to be mixed, as the pioneer class may contain a high proportion of mud or algae resulting in confusion in the classification. The LIDAR DEM and slope appear to reduce this confusion between classes. The increase in the accuracy of pioneer class is important for Habitats Directive monitoring, as this class was so inaccurately classified using CASI multispectral data alone (Table 5.5).

As may be seen in Table 5.5, though the overall accuracy of the saltmarsh classification using the original class set was high (*tau* = 0.76 (Table 5.2)), individual classes had accuracies in the low 60%. The main reason for this is likely to be that for each of the Halimione, Limonium and Puccinellia classes there is likely to be a significant amount of one of the other classes present, confusing the classifier. By combining these in the Atlantic 1 class, this reduces the errors overall and increases the minimum class accuracy of the vegetation classes (Tables 5.5 and 5.6)

Table 5.5 Saltmarsh class accuracy using original class set

Class	CASI	CASI LIDAR	Ratio	Ratio LIDAR
Water	96	100	100	100
Mud	100	100	100	100
Algae	64	81	65	64
Pioneer	69	83	85	89
Halimione	63	62	61	71
Puccinellia	66	67	85	67
Limonium	100	95	94	90
Elymus	89	88	73	89
Terrestrial	84	88	96	91

Table 5.6 Saltmarsh class accuracy using SAC class set

Class	CASI	CASI LIDAR	Ratio	Ratio LIDAR
Water	96	100	96	100
Mud	100	95	93	100
Algae	60	73	66	64
Pioneer Marsh	79	89	77	82
Atlantic 1	100	96	93	92
Atlantic 2	75	77	83	98
Terrestrial	85	97	93	96

The effect of using the band ratio, as opposed to the image matched data, may be seen in Tables 5.2 to 5.6. There is no significant decrease in classification accuracy when the band ratio data are used in the classification (Tables 5.3 and 5.4). The class accuracy values are consistent using the ratio and the CASI data (Tables 5.5 and 5.6).

The activation values obtained from the MLP neural network classifier were tested to determine what relationship if any there was between the outputs and the proportion of correctly classified pixels. Trial results indicated that there was a linear relationship between the outputs and the proportion of correctly classified pixels (Figure 5.3). The hypothesis was tested that normalised activation was the equivalent to the probability of correct classification. This assumption was tested for all MLP classifications. The results showed that there was a significant relationship between the activation and probability of correct classification ($p<0.001$ for all classifications (Table 5.7)).

This relationship allows an additional data set to be generated with the classification. The additional layer provides a per-pixel indication of whether the classification was correct (Figure 5.3) and can be used to determine the most likely alternative classes.

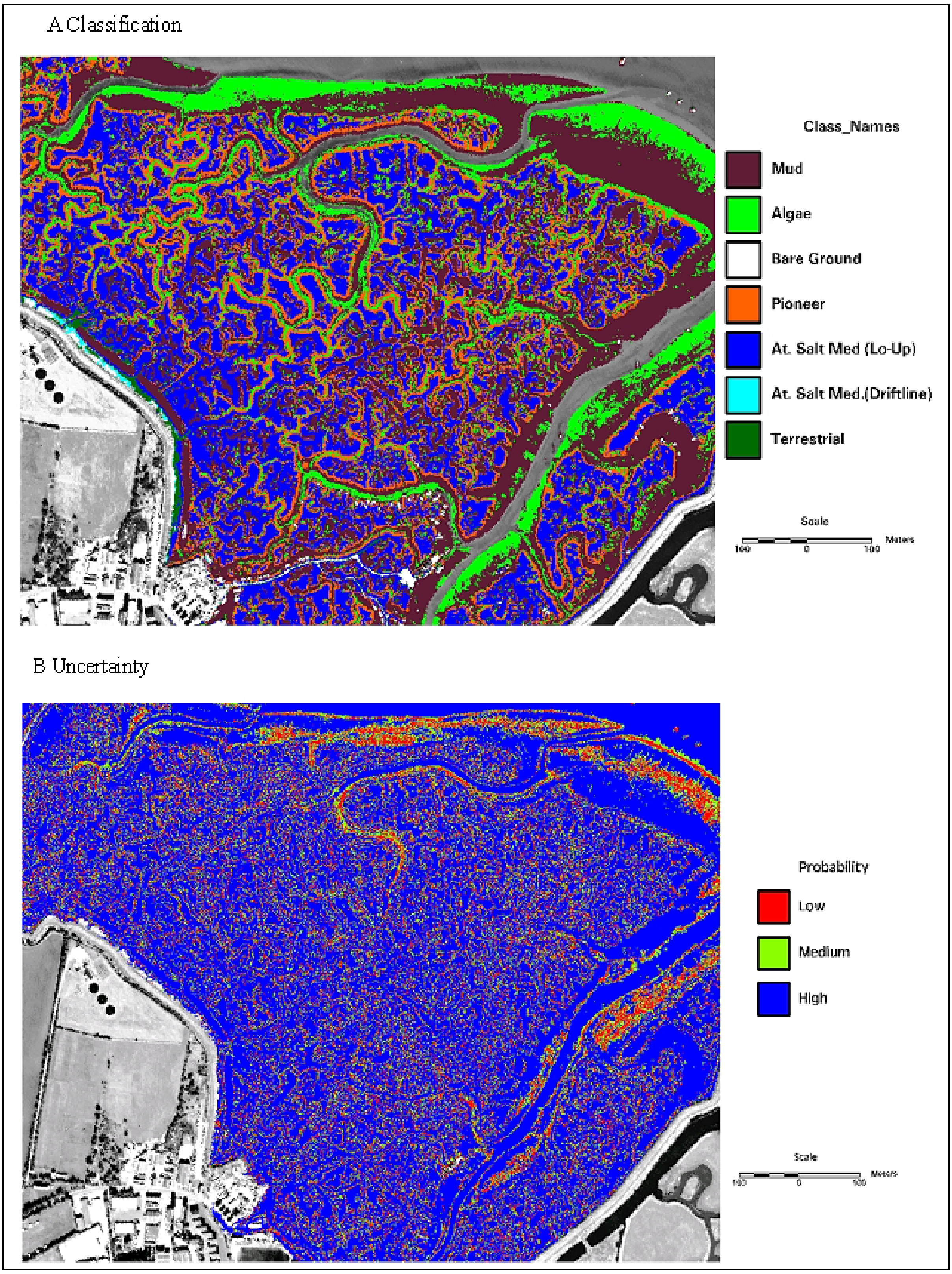


Figure 5.2 MLP neural network classification and uncertainty map of 2000 Tollesbury data

Table 5.7 Comparison of activation levels with proportion of correct pixels from MLP classifier

	Original Class Set				SAC Class Set			
	CASI	CASI LIDAR	Ratio	Ratio LIDAR	CASI	CASI LIDAR	Ratio	Ratio LIDAR
Significance	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
RMSE	0.0526	0.0317	0.0425	0.0331	0.0536	0.0331	0.0349	0.0416

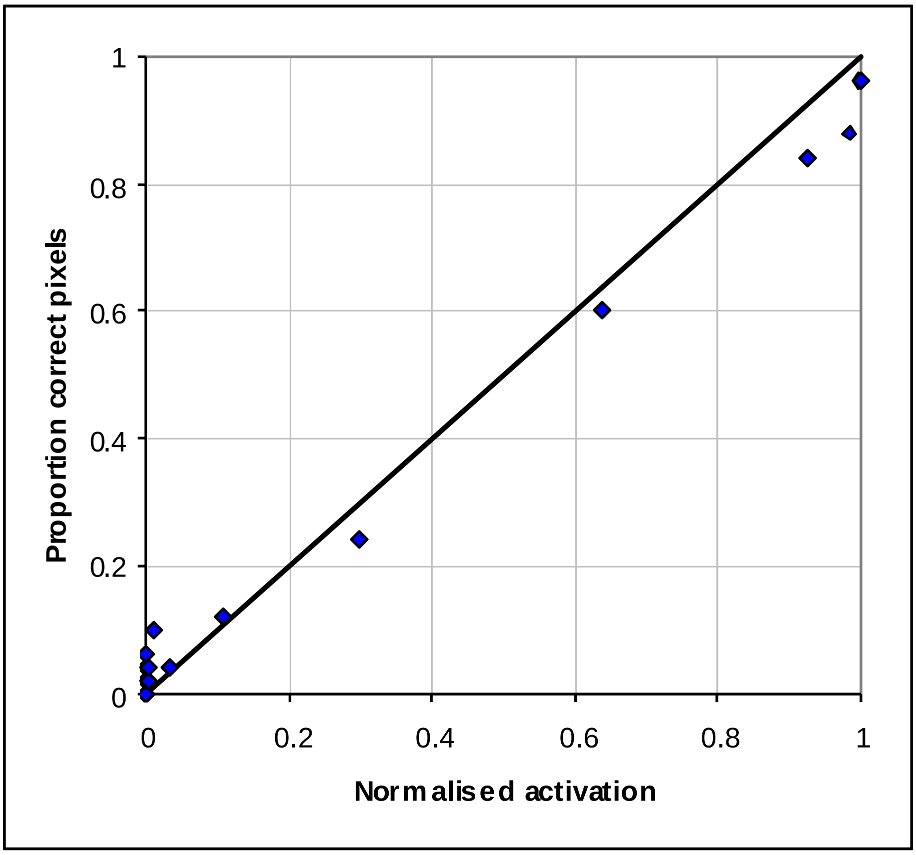


Figure 5.3 Proportion of correct pixels as a function of MLP normalised activation levels for original class set using Tollesbury ratioed CASI and LIDAR data

Final Tollesbury classifications

The final classifications of the Tollesbury data were carried out using a MLP neural network classifier with 20 nodes and trained for 2000 iterations. Input data consisted of 500 pixels per-class of image ratioed CASI data (Appendix D) and LIDAR derived elevation and slope. Classifications were carried out of the data gathered in September 2000 and June 2001. The remotely sensed data gathered in November 2002 was not classified, as the ground data collection was incomplete. The ground data collection was carried out for Old Hall and Abbot's Hall, but access to the Tollesbury Marsh was not permitted. Two local wildfowling groups who own the land would not allow access for Health and Safety reasons, as the shooting season had started. The Tollesbury Marsh area made up the major part of the study site and contained large areas of each of the classes used in the classification. The other areas did not contain enough of the variation present for certain classes, particularly the Pioneer, *Halimione* and *Limonium* classes and so it was decided to omit this classification.

Table 5.8 Final Tollesbury classifications overall accuracy (Tau accuracy)

Year	Original classes	SAC classes
2000	0.788	0.892
2001	N/A	0.752

September 2000 Tollesbury classification

The 2000 classification of the Tollesbury data was carried out using both the original and SAC class sets (Tables 5.8 - 5.10).

Table 5.9Confusion matrix for 2000 Tollesbury classification (Original class set)

		Ground Data									
		Water	Mud	Algae	Pioneer	Halimione	Puccinellia	Limonium	Elymus	Terrestrial	**User's Accuracy**
Classified Data	Water	25	0	0	0	0	0	0	0	0	1.00
	Mud	0	20	0	0	0	0	0	0	0	1.00
	Algae	0	6	24	2	0	0	0	0	0	0.75
	Pioneer	0	0	1	22	3	1	0	0	0	0.81
	Halimione	0	0	0	0	17	7	2	0	0	0.65
	Puccinellia	0	0	0	1	5	15	5	0	0	0.58
	Limonium	0	0	0	1	0	0	15	0	0	0.94
	Elymus	0	0	0	0	0	0	0	22	3	0.88
	Terrestrial	0	0	0	0	0	2	0	3	21	0.81
	Producer's accuracy	1.00	0.77	0.96	0.85	0.68	0.60	0.68	0.88	0.88	

Table 5.10 Confusion matrix for 2000 Tollesbury classification (SAC class set)

		Ground Data							
		Water	Mud	Algae	Pioneer	Atlantic 1	Atlantic 2	Terrestrial	**User's Accuracy**
Classified Data	Water	50	0	0	0	0	0	0	1.00
	Mud	1	39	0	0	0	0	0	0.98
	Algae	0	11	49	3	0	0	0	0.78
	Pioneer	0	0	2	43	3	0	0	0.90
	Atlantic 1	0	0	0	2	50	0	0	0.96
	Atlantic 2	0	0	0	0	0	40	2	0.95
	Terrestrial	0	0	0	0	2	6	42	0.84
	Producer's Accuracy	0.98	0.78	0.96	0.90	0.91	0.87	0.95	

June 2001 Tollesbury classification

Test classifications of the June 2001 data were carried out using the original class set. However, the accuracy of the *Halimione*, *Puccinellia* and *Limonium* classes was less than 50%. The errors were mainly due to the classes being misclassified as one another and so it was decided to carry out the classification of this data set using the SAC class set. The inability of the classifier to discriminate between these classes is most likely to be due to the time of year that the data were collected, as previous classifications have been successful. The *Limonium* class is likely to be easier to discriminate when in flower.

The SAC classification for June 2001 was less accurate than that carried out on the September 2000 data (Table 5.8). The lowest class accuracy values were for the Pioneer, Atlantic 2 and Terrestrial classes (Table 5.11).

Table 5.11 Confusion matrix for 2001 Tollesbury classification (SAC class set)

		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	45	7	1	0	0	0	0.85
	Algae	0	3	33	2	0	0	4	0.79
	Pioneer	0	5	14	35	5	0	0	0.59
	Atlantic 1	0	0	0	1	41	0	2	0.93
	Atlantic 2	0	0	0	0	2	50	30	0.61
	Terrestrial	0	0	0	0	0	1	20	0.95
	Producer's Accuracy	1.00	0.85	0.61	0.90	0.85	0.98	0.36	

It is likely that one of the reasons for the relatively poor classification of the Pioneer class in June 2001 is due to the data being gathered early in the intertidal vegetation growing season. Annual pioneer species such as *Salicornia europea* and *Sueada maritima* are still small compared to their final size generally achieved by August or September. This means that the areas where the Pioneer species would be considered dominant are mainly mud from a percentage cover point of view. In the case of the classifier tested, most of the errors resulted from mud, algae and the Atlantic 1 class being misclassified as Pioneer (Table 5.11). More than 60% of the Terrestrial class has been misclassified as Atlantic 2 (Table 5.11).

The large class errors within the June 2001 classification suggest that classification of intertidal vegetation early in the growing season is not appropriate and that data gathered later in the year should be more accurate. By comparing the June 2001 and September 2000 classifications it may be seen that data gathered later in the growing season appears to give more accurate classification results.

Tollesbury habitat change

Meaningful land cover change analysis for the Tollesbury site was not possible, as the quality of the 2001 classification was so poor. The large class errors, particularly Pioneer and Atlantic 2 (Table 5.11), are likely to result in large errors when the classifications were compared and this will be reflected in large percentage change values (Table 5.12B). It is highly unlikely that the Pioneer class will increase by 70% over one year and the Atlantic 2 will increase by almost 300%. These values almost certainly reflect errors in one or both classifications.

Table 5.12 Class areas for Tollesbury classification

A 2000 Original classes

Class	Area (Ha)
Water	223.54
Mud	235.19
Algae	137.14
Pioneer	68.70
Halimione	40.02
Puccinellia	47.10
Limonium	12.74
Elymus	2.63
Terrestrial	15.52

B 2000 and 2001 SAC classes

Class	Area (Ha)		% difference
	2000	2001	
Water	223.54	120.71	-46
Mud	235.19	370.34	57
Algae	137.14	86.00	-37
Pioneer	68.70	117.10	70
Atlantic 1	99.87	83.68	-16
Atlantic 2	2.63	10.50	299
Terrestrial	15.52	7.27	-53

Saltmarsh habitat mapping

Remote sensing is able to generate high accuracy maps of intertidal vegetation, and techniques developed here have the potential to increase that accuracy. The image ratioing method of radiometric normalisation appears to solve many of the lighting problems associated with remote sensing in the intertidal zone, including internal lighting differences. However, further testing of image ratioing in other types of saltmarsh, particularly those dominated by *Spartina* should be carried out before this method is considered robust.

The timing of remotely the data gathering is critical for the success of the final classification accuracy. It was shown here that data gathered too early in the season has the potential to result in a greatly reduced classification accuracy particularly of particular classes such as the annual Pioneer class.

The use of remote sensing for monitoring change in intertidal vegetation needs further study using two accurate classifications, generated using data from a suitable time of year.

5.1.2 Sand dunes

The classification of the sand dune site was more complicated than the saltmarsh work. The main SAC habitats present at the Ainsdale test site contain vegetation types that are similar. For example the fixed dune areas will have some of the same species present as the dune slack areas, but in different proportions. For this reason the classification was carried out in three stages.

The first part was a classification to determine the vegetation cover type. The classes chosen were determined by trial and error. The original classes for which data had been collected were merged to the class set in Table 5.13. This class set extracted some of the SAC areas, but some of the land cover types contained mixed SAC type.

The second stage was the use of an expert system to remove errors within the initial classification.

The third stage in the sand dune classification was to use the LIDAR data to extract dune slack areas using the topographic characteristics of these areas.

To provide an overall SAC habitat classification, the vegetation classification was merged with the LIDAR based dune slack classification areas.

Vegetation classification testing

Classifications of the 2002 Ainsdale sand dune site were carried out using a similar method to the Tollesbury site. A 1m resolution CASI image using 5 flightlines was generated by mosaicing the imagery using edge matching. A ratio image was also generated using the same 5 flightlines. A slope layer was generated from the 2m LIDAR DEM. The LIDAR slope data layer was resampled using nearest neighbour to a 1m grid. The CASI image and ratio image were combined with the resampled LIDAR data. The ML statistical classifier and MLP neural network classifier were tested with CASI data and CASI and LIDAR slope data. The MLP classifier was also tested with band ratioed data (Appendix D) and band ratioed and LIDAR slope data.

Table 5.13 Classes used in sand dune classification

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

Table 5.14 Accuracy assessment results from sand dune classification testing (tau accuracy)

Inputs	ML	CASI MLP	Ratio MLP
CASI	0.749	0.795	0.756
CASI+ Slope	0.772	0.826	0.788

Table 5.15 Changes in accuracy for sand dune classification (bottom left) and levels of significance (top right)

	CASI ML	CASI+ Slope ML	CASI MLP	CASI+ Slope MLP	Ratio MLP	Ratio+ Slope MLP
CASI ML		NS	**P<0.05**	**p<0.001**	NS	**p<0.05**
CASI+ Slope ML	0.023		NS	**p<0.005**	NS	NS
CASI MLP	**0.046**	0.023		NS	**P<0.05**	NS
CASI+ Slope MLP	**0.077**	**0.053**	0.031		**P<0.001**	**p<0.05**
Ratio MLP	0.007	-0.017	**-0.039**	**-0.070**		NS
Ratio+ Slope MLP	**0.039**	0.015	-0.008	**-0.038**	0.032	

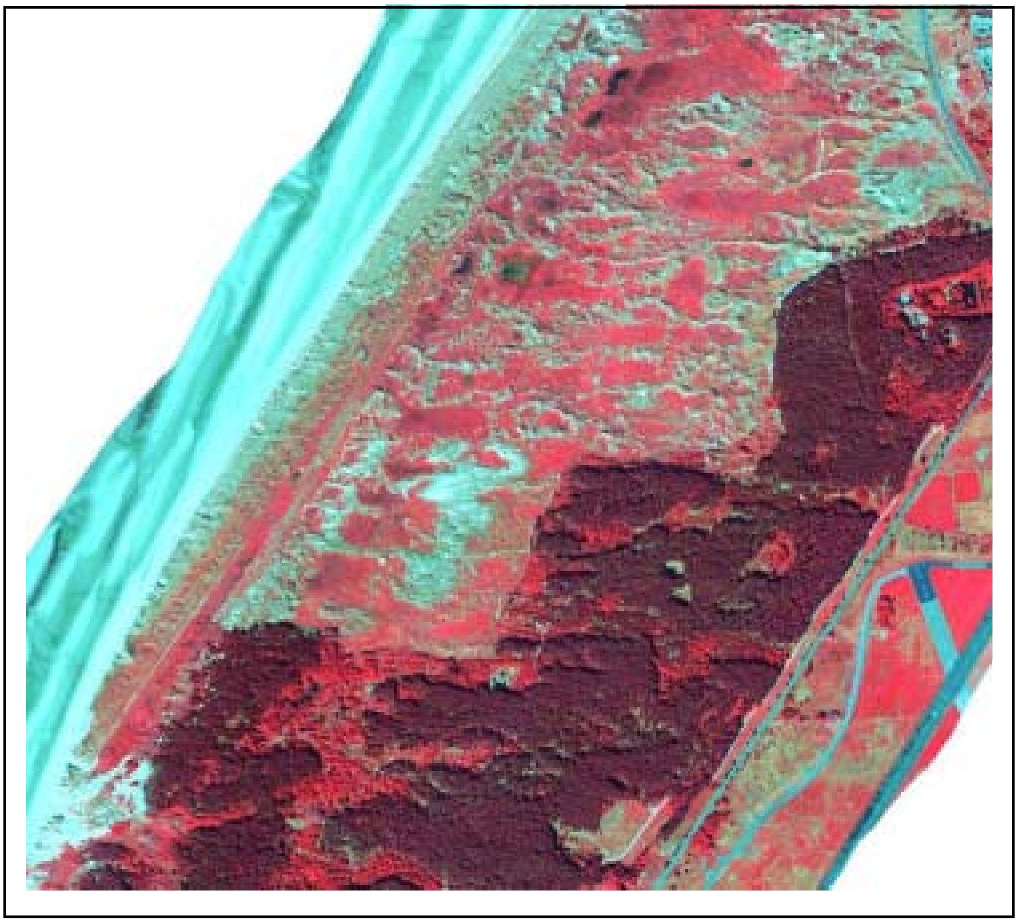


Figure 5.4 False colour CASI Imagery of Ainsdale test site, Merseyside

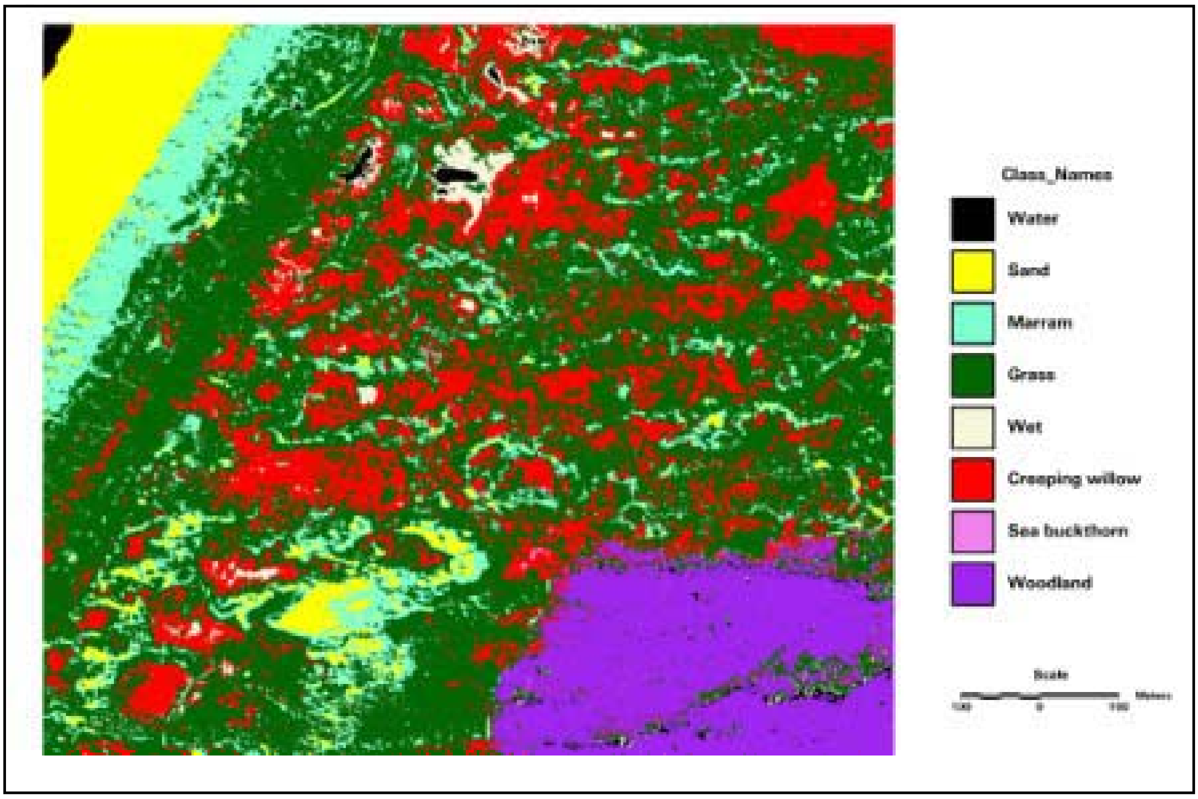


Figure 5.5 MLP Neural Network Classification of 2001 Ainsdale data

The classification accuracy of the ML statistical classifier was significantly less than the MLP neural classifier for both the CASI only classification and the CASI and LIDAR slope classification (Tables 5.14 and 5.15). The consistent lower classification accuracy shows that the ML classifier is less suitable for sand dune classifications than the MLP neural network.

The ratioing method of radiometric normalisation was not as successful as the edge matching technique and was significantly less accurate with and without the LIDAR data (Tables 5.14 and 5.15).

Expert system classification

An expert system is the use of expert observations combined with a classified data layer in a geographic information system (GIS). The purpose of the expert system was to remove errors in the first classification mainly caused by shadowing within the imagery. Shadowing within the CASI data resulted in two main types of error. Areas of the grass and herbaceous vegetation in shadow were misclassified as woodland. These were removed by simply reclassifying these areas as the Grass/Moss/Herb class. There were also problems with shadowing on the seaward side of the frontal dunes, resulting in misclassification. This was particularly a problem with the 2002 data, which were gathered when the sun angle was relatively low (Figure 5.6). As the shadowed area would be difficult to classify using spectral CASI data, an alternative LIDAR based approach was used. The seaward boundary of the mobile dune system was determined using the LIDAR slope. A slope value of greater than 15 degrees was used as the boundary for both years. This value was determined by detailed study of the dune system, using CASI and LIDAR data.

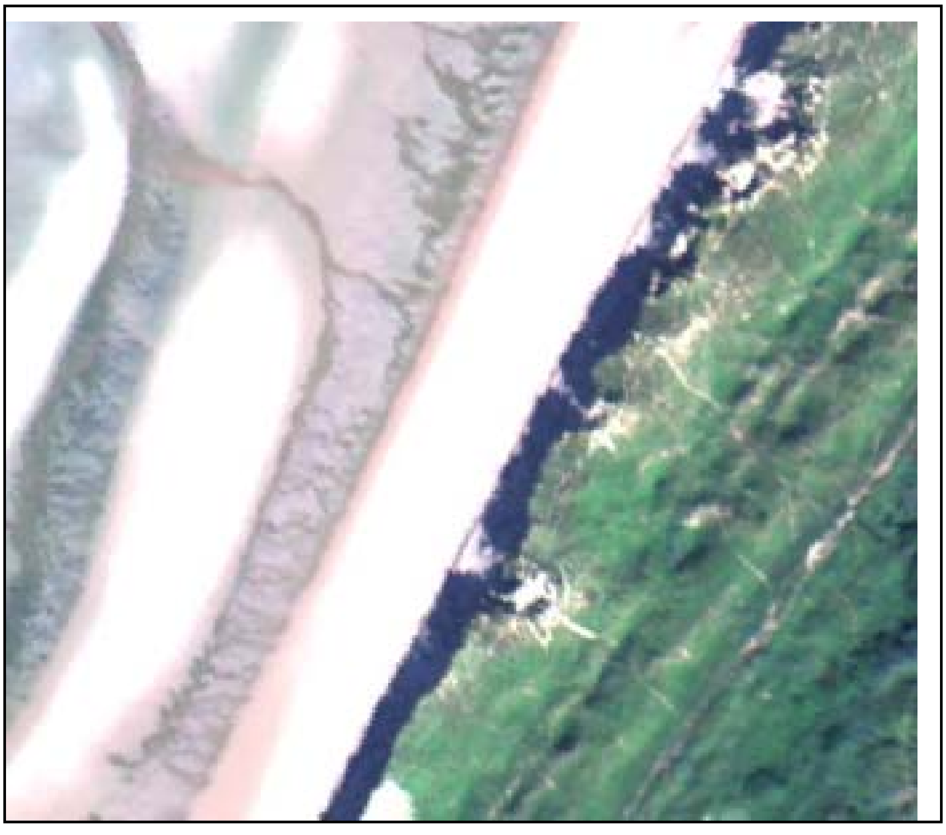


Figure 5.6 Shadowing of Ainsdale frontal dunes in 2002 CASI data

Dune slack extraction

The classes used in the initial classification were unsuitable for extracting dune slack areas and so an alternative method had to be developed. The most promising method was to use the slope characteristics of slack areas as a method of identification. Using a slack map supplied by English Nature, the slope characteristics of the slack areas of the Ainsdale site were determined and these were used to optimise a method of extracting dune slack areas using LIDAR. The main physical characteristic of slacks is an area of consistently low slope. It must be noted that the variables used apply to the Ainsdale site and may not be applicable to other sites, though the general methods should be applicable.

The LIDAR slope data was used to identify areas with slope of less than 3 degrees. As may be seen from Figure 5.8b this resulted in a data layer with a great deal of noise. In order to remove the noise and identify areas that were most likely to be dune slack areas, a two part merging algorithm was used. The first algorithm known as 'clumping' identifies contiguous groups of pixels in one thematic class. The clumped data are then passed through an 'elimination' algorithm (Figure 5.8c). A clump smaller than a user-specified number is eliminated and replaced by values the same as nearby larger clumps. Large numbers of pixels will have a low slope value, but are not in slack areas. For example the tops of ridges will have a low slope, but the areas of low slope are unlikely to be large or contiguous. The clump and elimination process remove these scattered pixels.

The resultant layer overestimated slack area and so further analysis had to be carried out in order to improve the discrimination of dune slack areas. It was found that it was possible to improve the classification of slack areas by carrying out additional analysis using areas with a slope of less than 2 degrees. Pixels with a slope of less than 2 degrees were identified. The clump and elimination algorithms were carried out using an elimination value of 40 pixels. The areas identified using the less than 3 degree slope were polygonised and polygons were rejected as areas of dune slack if they did not contain areas identified in the analysis with a slope value of less than 2 degrees (Figures 5.7 and 5.8). The accuracy of the final LIDAR only dune slack classification may be seen in Table 5.16.

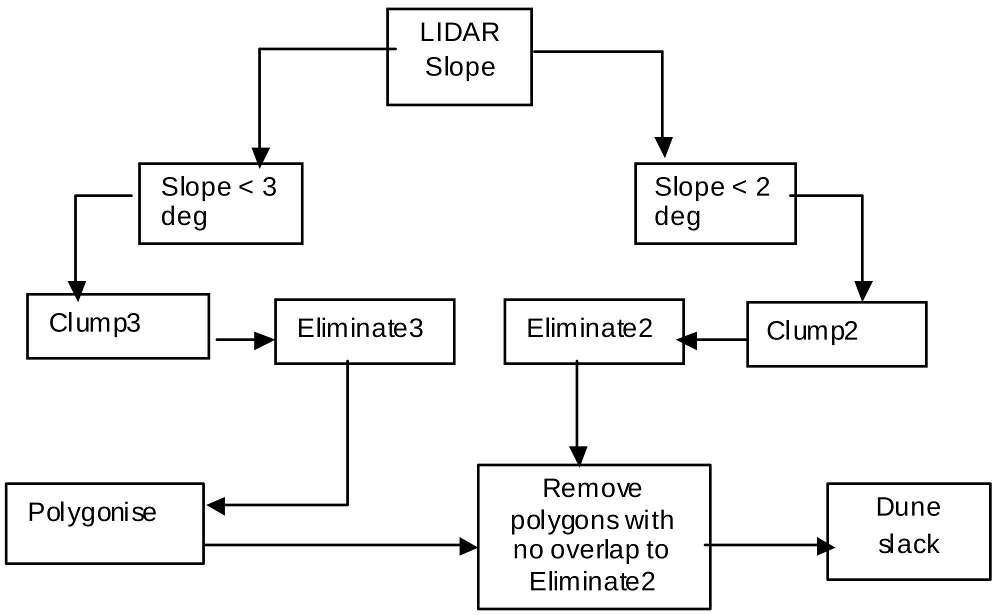


Figure 5.7 Dune slack extraction model

Table 5.16 Dune slack classification using LIDAR data

	Fixed dune	Slack	User's Accuracy
Fixed dune	248	23	0.92
Slack	16	50	0.76
Producer's accuracy	0.94	0.68	

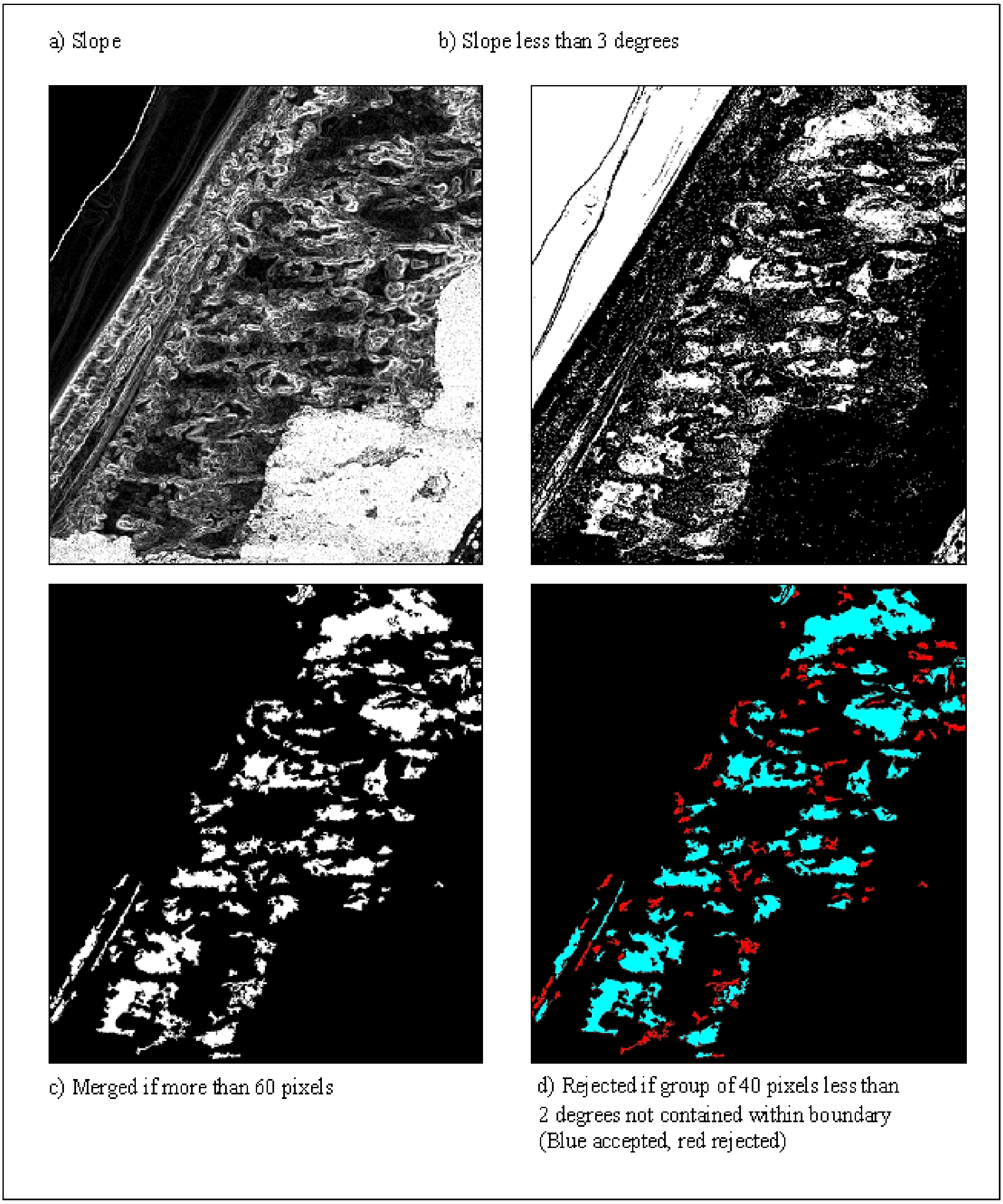


Figure 5.8 Dune slack extraction from 2001 LIDAR data

Uncertainty and probabilities of correct classification

The probability measures derived using the saltmarsh classifier are also applicable to the sand dune classification. These were tested using the output of the MLP neural network classifier and a statistically significant relationship was found between the output and probability of correct classification ($p<0.001$, RMSE = 0.0352).

However, as a variety of classification methods were used, it is not possible to derive probability measures for the final output. In order to derive probabilities from an expert system further work would need to be carried out

Final Ainsdale classifications

The final vegetation classifications of the Ainsdale data were carried out using a MLP neural network classifier with 20 nodes and trained for 800 iterations. Input data consisted of 1000 pixels per-class of CASI data and LIDAR derived slope. Classifications were carried out of the data gathered in August 2001 and September 2002. The overall accuracy of these classifications was high (Table 5.17), but the 2001 classification was 6.1% more accurate than the 2002 classification.

From the confusion matrices of the classification (Tables 5.18 and 5.19) it may be seen that there were considerable differences in the accuracy of the different classes between the classifications.

The 2001 MLP classification had user's accuracy values of greater than 80% for all classes except the Wet/Reeds class and the *Hippophae* (Sea Buckthorn) classes (Table 5.18). The *Hippophae* was exclusively misclassified as woodland and so these classes were merged in the final analysis.

Table 5.17 Final Ainsdale classifications overall accuracy (tau accuracy)

Year	Original classes	SAC classes
2001	0.879	0.881
2002	0.818	0.907

Table 5.18 Confusion matrix for 2001 MLP Ainsdale classification

		Ground Data								
		Water	Sand/ shingle	*Ammophila arenaria*	Grass/ moss/ herb	Wet/ reeds	Salix repens	Hippophae rhamnoides	Woodland/ scrub	**User's Accuracy**
Classified Data	Water	4	0	0	0	0	0	0	0	1.00
	Sand/shingle	0	18	0	0	0	0	0	0	1.00
	Ammophila arenaria	0	1	12	2	0	0	0	0	0.80
	Grass/moss/herb	0	0	1	48	0	0	0	0	0.98
	Wet/reeds	0	0	0	1	3	1	0	1	0.50
	Salix repens	0	0	0	4	0	17	0	0	0.81
	Hippophae rhamnoides	0	0	0	0	0	0	2	3	0.40
	Woodland/scrub	0	0	0	2	0	1	0	39	0.93
	Producer's accuracy	1.00	0.95	0.92	0.84	1.00	0.89	1.00	0.91	

Table 5.19 Confusion matrix for 2002 MLP Ainsdale classification

		Ground Data								
		Water	Sand/ shingle	*Ammophila arenaria*	Grass/ moss/ herb	Wet/ reeds	Salix repens	Hippophae rhamnoides	Woodland/ scrub	**User's Accuracy**
Classified Data	Water	57	7	0	2	0	0	0	1	0.85
	Sand/shingle	0	55	3	5	0	0	0	0	0.87
	Ammophila arenaria	0	0	26	15	0	1	0	0	0.62
	Grass/moss/herb	0	2	1	220	1	22	0	1	0.89
	Wet/reeds	0	0	0	4	11	4	0	1	0.55
	Salix repens	0	0	0	33	4	54	0	0	0.59
	Hippophae rhamnoides	0	0	0	0	0	0	7	0	1.00
	Woodland/scrub	0	0	0	17	0	1	0	231	0.93
	Producer's accuracy	1.00	0.86	0.87	0.74	0.69	0.66	1.00	0.99	

The 2002 MLP classification had a number of classes that were poorly classified, particularly the *Ammophila*, Wet/Reeds and *Salix* (Creeping willow) classes (Table 5.19). Visual inspection of the *Ammophila* class identified that the shadowed area to the seaward side of the frontal dunes (Figure 5.6) was the main area of error. As this was to be reclassified using the expert system this error was not considered important to the final classification. The errors in the *Salix* class were more problematic. These resulted from shadowing, particularly in areas of herbaceous vegetation on the fixed dune system. Experimentation was carried out to see if these errors could be removed from the classification using LIDAR derived slope and aspect. Initial results have suggested that this would be possible, but time constraints meant that a robust method could not be developed to remove these errors

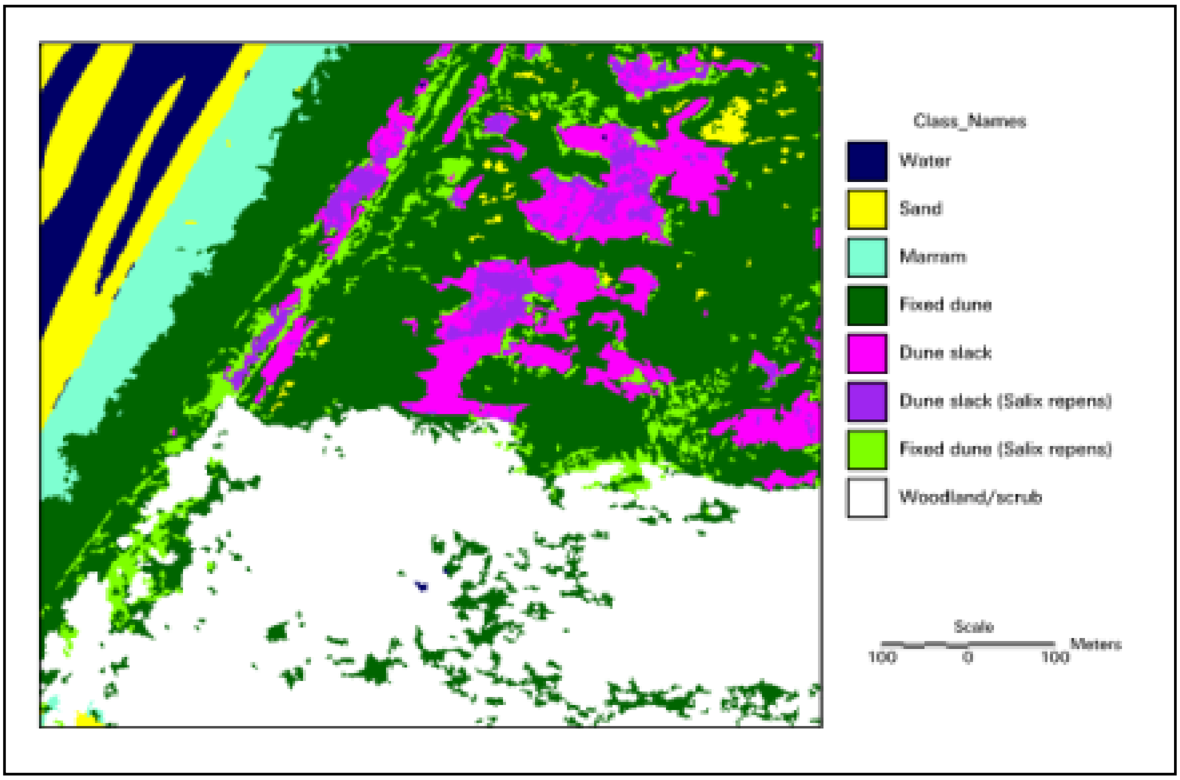


Figure 5.9 Ainsdale 2002 SAC classification

However, once the three stage classification had been carried out, the overall accuracy values were very similar (Table 5.17; SAC classes). The effect of the expert classification was to remove many of the errors present in the 2002 MLP classification due to shadowing.

The final classifications resulted in very similar class accuracy values (Tables 5.20 and 5.21). Most of the classes for both years have User's accuracy values of greater than 80% (with the exception of the Dune slack class) indicating a good final classification (Tables 5.20 and 5.21).

Table 5.20 Confusion matrix for 2001 Ainsdale SAC classification

		Ground Data						
		Water	**Sand**	**Mobile dune**	**Fixed dune**	**Dune slack**	**Woodland/ scrub**	**User's Accuracy**
Classified Data	**Water**	18	1	0	0	0	0	0.95
	Sand	0	36	1	0	0	0	0.97
	Mobile dune	0	0	7	1	0	0	0.88
	Fixed dune	0	0	1	51	6	1	0.86
	Dune slack	0	0	0	7	20	0	0.74
	Woodland/ scrub	0	0	0	1	0	40	0.98
	Producer's accuracy	1.00	0.97	0.78	0.85	0.77	0.98	

Table 5.21 Confusion matrix for 2002 Ainsdale SAC classification

		Ground Data						
		Water	**Sand**	**Mobile dune**	**Fixed dune**	**Dune slack**	**Woodland/ scrub**	**User's Accuracy**
Classified Data	**Water**	36	0	0	0	0	0	1.00
	Sand	4	40	0	2	0	0	0.87
	Mobile dune	0	1	12	0	0	0	0.92
	Fixed dune	0	2	3	221	16	0	0.91
	Dune slack	0	0	0	18	52	0	0.74
	Woodland/ scrub	0	0	1	3	0	237	0.98
	Producer's accuracy	0.90	0.93	0.75	0.91	0.76	1.00	

Ainsdale habitat change

When the area values for the Ainsdale SAC classes are compared, it may be seen that for the vegetation classes there is less than 5% difference between years (Table 5.22A). Parts of some of these differences are likely to be due to errors within the remotely sensed data. However, for long term monitoring it would be possible to carry out a trend analysis to determine whether change was actually taking place.

When the *Salix repens* class was combined with the SAC classes, considerably greater differences occurred (Table 5.22B). These are likely to be due to the large errors within this class seen in the 2002 classification (Table 5.19). These errors were thought to be the result of shadowing and could possibly be removed with further study.

The changes in the water and sand classes are mainly due to the different tidal states between the 2001 and 2002 data collection (Table 5.22).

Table 5.22 Areas for Ainsdale NNR classifications

A SAC classes

Class	Area (Ha)		% difference
	2001	2002	
Water	21.6	32.4	50.2
Sand	36.4	22.8	-37.5
Mobile dune	10.7	10.2	-4.2
Fixed dune	127.1	124.5	-2.0
Dune slack	26.5	27.6	4.4
Woodland/scrub	169.3	173.0	2.2

B SAC classes using *Salix repens*

Class	Area (Ha)		% difference
	2001	2002	
Water	21.6	32.4	50.2
Sand	36.4	22.8	-37.5
Mobile dune	10.7	10.2	-4.2
Fixed dune	105.8	101.7	-3.9
Dune slack	12.7	16.2	27.3
Dune slack (Salix repens)	13.7	11.4	-16.8
Fixed dune (Salix repens)	21.3	22.9	7.4
Woodland/scrub	169.3	173.0	2.2

Sand dune habitat mapping

High accuracy maps of sand dune habitat have been generated using a combination of remote sensing techniques. Problems were encountered due to shadowing on dunes, resulting in misclassification errors. This was a problem that was partially resolved using an expert classification, but further techniques need to be examined in order to derive methodologies that are more robust.

A simple change analysis using class areas appears to be possible, but care needs to be taken to ensure that differences seen are the result of genuine change rather than artefacts of errors within the data layers used.

5.1.3 Saline lagoons

A classification of general habitat types was carried out for the 2000 Blakeney data using NVC ground data. The ground data supplied appeared to be poor quality, as areas on the NVC map did not match the Ordnance Survey 1:10 000 data or the CASI imagery. As the ground data appeared unreliable it was decided to carry out an unsupervised classification. Generally unsupervised classifications are less accurate than a supervised approach and the resulting classification was not suitable for this study. Classifications were also attempted on the 2002 Blakeney data but again accuracies were low. The site is spatially complex containing vegetated shingle, saltmarsh, terrestrial and freshwater habitats. The ground data gathered did not encompass all this variation and so classification accuracies were low. It was therefore decided to concentrate on information that could be extracted using image interpretation.

Figure 5.10 2002 CASI imagery of Blakeney study site

Lagoon area is one of the indicators of saline lagoon health and is required for Habitats Directive reporting. Manual digitising of CASI imagery has been used to generate this variable.

Table 5.23 Flight dates of aerial photography and CASI imagery

Sensor	Date	Ground resolution (m)
CASI	23rd September 2000	1
Digital camera	09th September 2000	0.25
CASI	26th July 2002	1
Digital camera	26th July 2002	0.15

The areas of the lagoons were estimated using CASI and digital photography in 2000 and 2002 (Table 5.23). The 2000 digital photography data were not complete as the camera used was a test model and did not supply complete coverage. It should also be noted that in 2000 the photography was flown on a different date from the CASI data.

Table 5.24 Area of Blakeney saline lagoons as determined from airborne remote sensing

	2000 Areas (ha)		2002 Areas (ha)	
Lagoon	**CASI**	**Digital photography**	**CASI**	**Digital photography**
Half Moon Pond	0.11	/	0.07	0.07
New Moon Pond	0.10	/	0.14	0.15
Seahorse Pond	1.24	1.13	1.32	1.20
Arnold's Marsh Lagoon	5.17	/	4.72	4.65
Salthouse Broad	3.31	/	1.54	1.62
Little Eye	0.05	0.03	0.12	0.12
W. Gramborough Hill	0.13	0.13	0.07	0.06
E. Gramborough Hill	0.10	0.11	0.11	0.11

Table 5.25 Difference between estimated areas of Blakeney saline lagoons between digital photography and CASI data for 2002

Lagoon	Area difference (ha)	% Difference
Half Moon Pond	0.002	3
New Moon Pond	-0.007	-4
Seahorse Pond	0.123	10
Arnold's Marsh Lagoon	0.067	1
Salthouse Broad	-0.080	-5
Little Eye	0.005	4
W. Gramborough Hill	0.009	15
E. Gramborough Hill	-0.005	-4

Generally there was good agreement between the areas determined by CASI and digital photography, especially in 2002 (Table 5.24). There are greater differences in the estimated lagoon areas from each of the two sensors from the 2000 data than the 2002 data. This is likely to be due to data collection being on different dates and the lagoon area changing due to tide, rainfall or evaporation.

Using the different methods of determining the lagoon area for the 2002 data (where no change will have occurred between image collections), it may be seen that the greatest absolute difference between the methods is 0.123ha and the largest percentage difference was 15% (Table 5.25). The largest percentage difference occurred for a lagoon that was small and so relatively small changes in the boundaries could result in a large percentage difference.

Problems arose trying to distinguish algal plant matter lying on the surface of the water, which should be included in lagoon area and land based plant matter, which shouldn't. Other problems were encountered trying to distinguish between shallow waters and mud. LIDAR data were used to compare heights in order to determine if a tone or hue was likely to be part of the water body. This was achieved by comparing the height of pixels known to be water with pixels that were unknown.

One method used to determine the colour boundaries of the water bodies was to pick 25 random LIDAR pixels from the known water body part of the image and 25 random LIDAR pixels from the part where there was some doubt (in the same lagoon). Students' T-tests were then performed on the two resulting data sets to see if there was a significant difference in height between the two sample sets. Figure 5.11 shows an area where such a test was performed. Section "A" is known to be water, but "B" may be shallow water or mud. Note the differing hue in "B" compared with "A".

In this case, there was shown to be a significant difference in heights between the random height pixels pulled out of A and B (Figures 5.11 and 5.12)

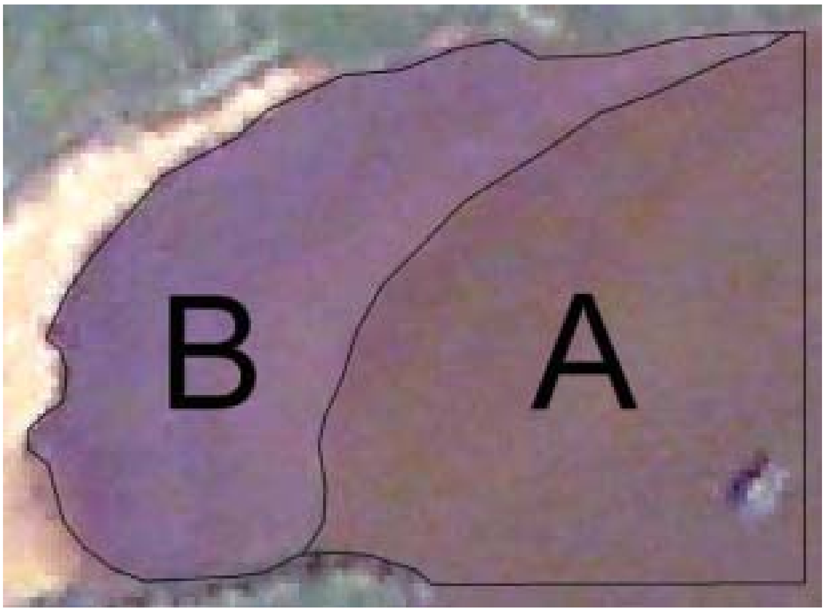


Figure 5.11 Example of uncertainty in whether area is water

Water has a relatively low reflectance in near infrared compared with bare ground and vegetation. These characteristics enable visualisation of the water/land boundary using CASI imagery. Air photos with a spatial resolution of 0.25m and 0.15m (CASI is 1m) were also used to estimate the extent of lagoons. The finer spatial resolution enabled easier interpretation of the lagoon extent in most cases. However, shallow lagoons, with light sediment proved difficult to interpret and in those cases CASI imagery was easier to interpret or LIDAR was used as an additional data source.

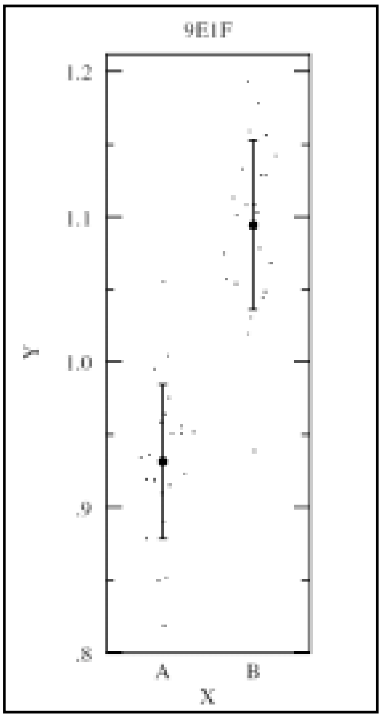


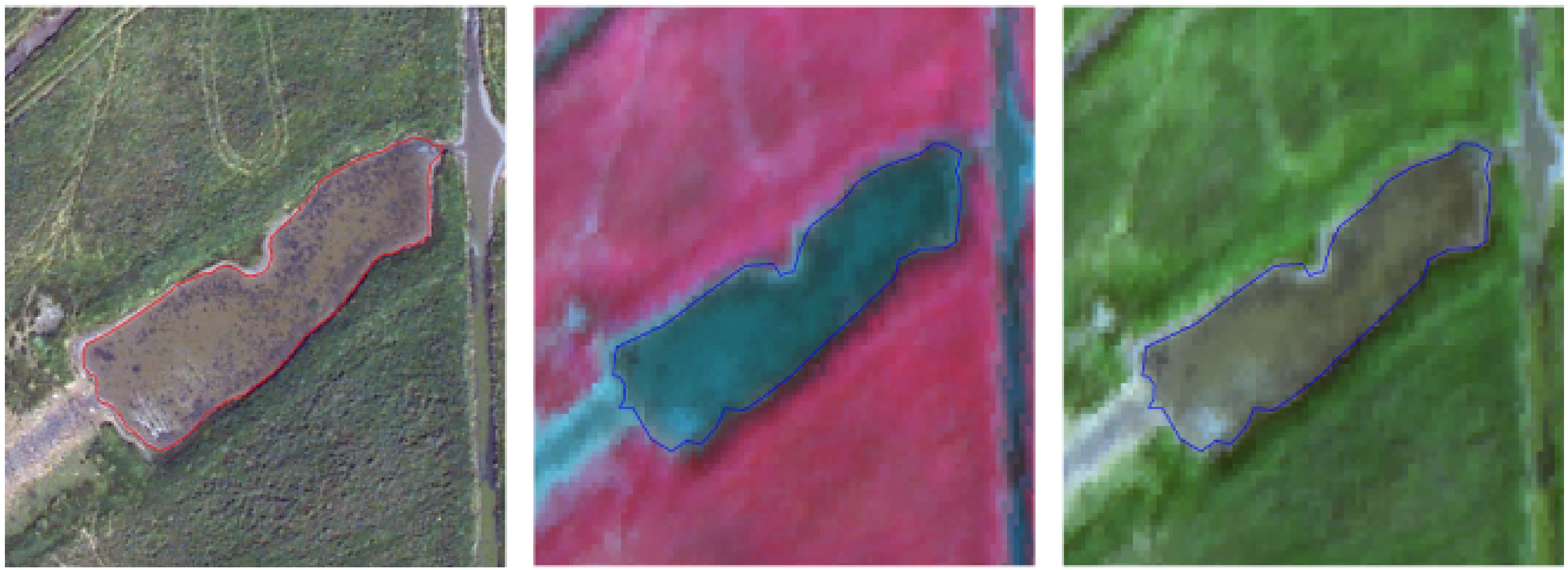
Figure 5.12 Plot of the t-test, showing the difference in mean heights between the sample areas A and B (Figure 5.11)

Figure 5.13 Derived lagoon polygons for East Gramborough Hill, Blakeney

A Digital photography

B False colour CASI

C True colour CASI



5.1.4 Mudflats

The Budle Bay data were scheduled for collection during low water spring tides of the first year of the project. However, these coincided with poor weather in both 2000 and 2001. The CASI, LIDAR and aerial photography data were finally gathered in September 2002.

The data were collected in good lighting conditions close to solar midday. However, there were problems radiometrically normalising the CASI using the edge matching technique and so image ratioing was used (Figure 5.15). Ground data were collected in the same week as the remotely sensed data, but a visual inspection of the data revealed that there were problems with the suitability of the ground data for image classification.

The ground data appeared to give a synoptic overview of the cover, but did not seem to identify the full spatial complexity of the classes used. This was a particular problem for the *Mytilus edulis* class, as may be seen from Figure 5.16. On the basis that the ground data were synoptic, rather than a specific identification of land cover boundaries, an unsupervised classification was carried out. The ground data supplied were used to determine the general positioning of the classes used. The unsupervised classification was carried out using the ISODATA algorithm (Campbell, 1996) and 20 classes. Classes that belonged to more than one land cover type were reclassified and split further until they could be discriminated.

Figure 5.14 2002 CASI imagery of Budle Bay

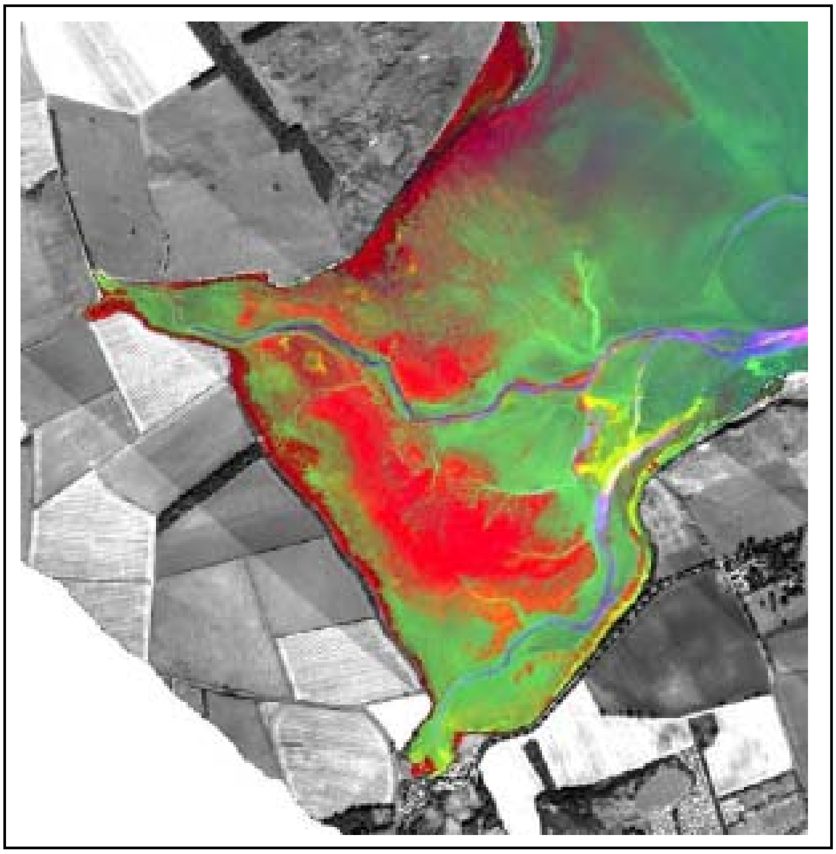


Figure 5.15 2002 ratioed CASI imagery of Budle Bay overlaid on grayscale image

Figure 5.16 Example of *Mytilus edulis* ground data (blue outline) not matching remotely sensed data

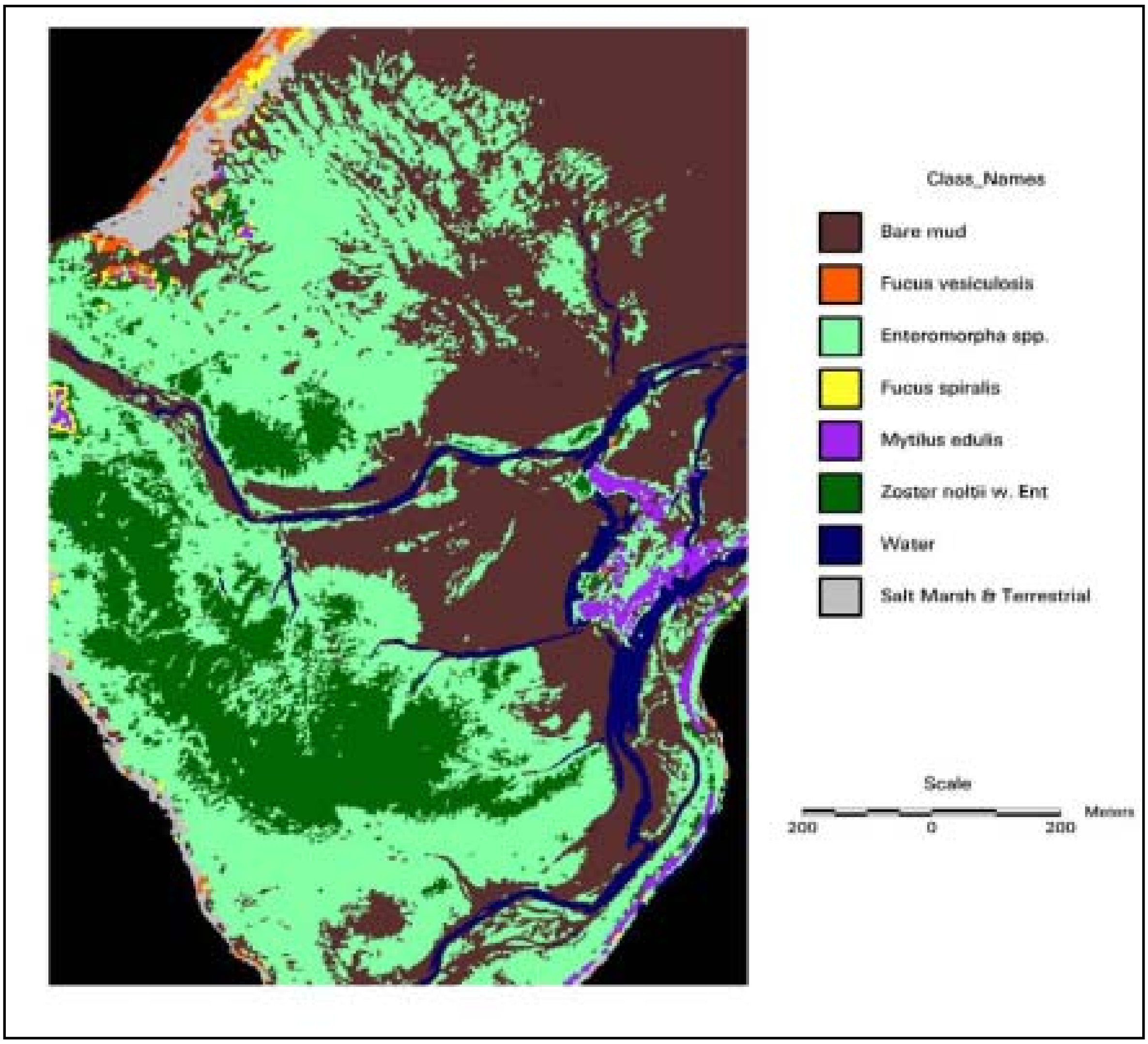


Figure 5.17 Unsupervised classification of Budle Bay ratioed CASI data

The unsupervised approach to image classification is likely to result in a classification accuracy well below that obtained using a supervised approach. This approach was only carried out as the ground data did not match the remotely sensed data. Synoptic ground data are not suitable for use as training data in a supervised classification. Ground data used in a classification should clearly identify the boundaries between land cover types.

The problems encountered with the ground data also meant that an accuracy assessment could not be carried out. Therefore no conclusions can be made about the suitability of remotely sensed data for mapping intertidal habitats from this study. Other studies have used remote sensing to map cover and biomass of mudflats (Meulstee *et al.*, 1988; Bajjouk *et al.*, 1998; Guichard *et al.*, 2000) and so remote sensing is likely to be able to make a contribution to monitoring this habitat.

5.1.5 Vegetated shingle

Figure 5.18 2002 CASI data of Rye site

Vegetated shingle is a difficult habitat for CASI to provide a comprehensive vegetation map, as many of the species present occur in very low densities surrounded by shingle. The remotely sensed signal from the shingle can mask out the smaller signal from the vegetation and the resulting pixel is likely to be classified as shingle. This meant that species such as *Crambe maritima* (Sea-kale) are unlikely to be discriminated at 1m resolution.

A study was carried out using 2000 Rye data to determine which classes could be detected using the CASI sensor. The classes chosen for the CASI classification are listed in Table 5.26 and were based on those classes that could be discriminated using the CASI sensor. The non-shingle sediment class included mud, tarmac and concrete. These cover types were merged, as the classifiers had difficulty in discriminating between them. It should be noted that the use of digital photography has the potential to provide information that the CASI sensor can not due the large improvement in spatial resolution (Figure 5.19)

Table 5.26 Classes used in Rye classification

Water
Non-shingle sediment
Shingle
Saltmarsh
Grasses/moss/herb
Arrhenatherum elatius low density
Arrhenatherum elatius high density
Reeds/rushes
Centranthus ruber (Red valerian)
Scrub

A CASI B Photography

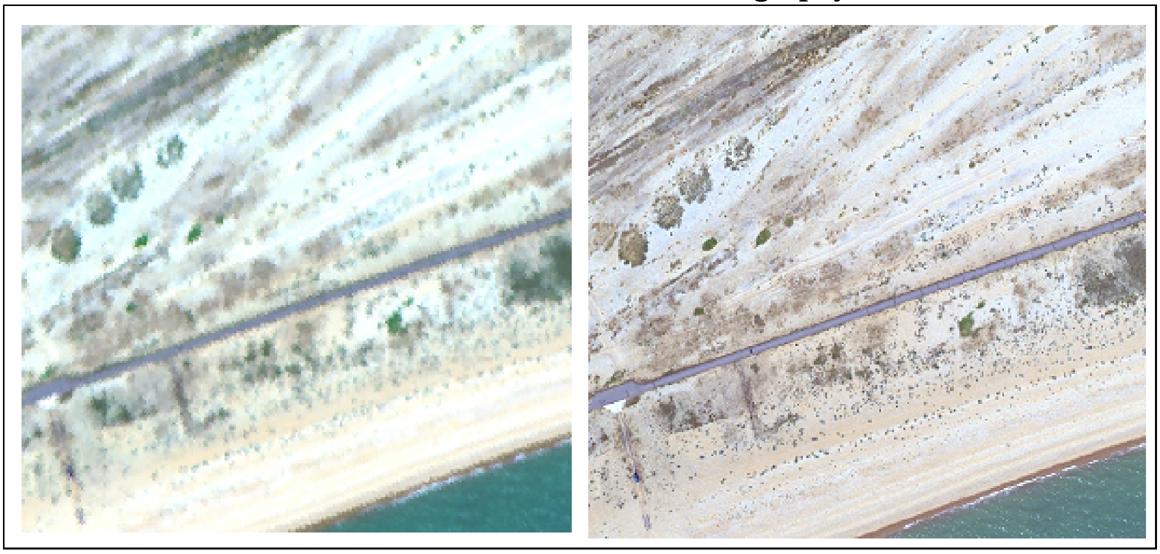


Figure 5.19 Example of CASI and photography of Rye site showing detail visible in photography

The ML classifier was compared with the MLP neural network for the 2000 Rye classifications (Table 5.27). The MLP classifier was more accurate than the ML classifier data and so was used for the 2002 data.

Table 5.27 Overall accuracy for Rye classifications

Year	**2000**	**2000**	**2002**
Classifier	**ML**	**MLP**	**MLP**
Accuracy	0.761	0.809	0.856

Table 5.28 2000 Rye classification

		Ground data										
		Water	Non-shingle Sediment	Shingle	Saltmarsh	Grasses/ moss/ herb	Arrhenatherum Low density	Arrhenatherum High density	Reeds/ rushes	Centranthus	Scrub	**User's accuracy**
Classified Data	Water	22	1	0	0	0	0	0	0	0	0	0.96
	Non-shingle sediment	1	25	2	0	0	0	0	0	0	0	0.89
	Shingle	0	4	35	0	0	1	0	0	0	0	0.88
	Saltmarsh	0	1	0	34	2	0	0	0	0	0	0.92
	Grasses/ moss/ herb	0	0	0	2	28	2	3	0	0	0	0.80
	Arrhenatherum low density	1	1	1	0	2	31	4	0	3	0	0.72
	Arrhenatherum high density	0	0	0	0	1	6	12	1	0	0	0.60
	Reeds	1	0	0	0	0	1	0	30	0	4	0.83
	Centranthus	1	3	0	0	1	3	0	0	31	0	0.79
	Scrub	0	0	0	0	0	0	0	5	0	32	0.86
	Producer's accuracy	0.85	0.71	0.92	0.94	0.82	0.70	0.63	0.83	0.91	0.89	

Generally the class accuracy values of the classifications for both years were high, but the classifier had difficulty discriminating between low and high density *Arrhenatherum* (Table 5.28 and 5.29). Visual inspection of these errors indicated that these errors generally occurred in medium density *Arrhenatherum* and so are not indicative of a major problem with the classification

Table 5.29 2002 Rye classification

		Ground data										
		Water	Non-shingle sediment	Shingle	Saltmarsh	Grasses/ moss/ herb	Arrhenatherum		Reeds/ rushes	Centranthus	Scrub	**User's accuracy**
							Low density	High density				
Classified Data	Water	30	0	0	0	0	0	0	0	0	0	1.00
	Non-shingle sediment	0	21	2	0	0	0	0	0	0	0	0.91
	Shingle	0	0	37	0	0	1	0	0	0	0	0.97
	Saltmarsh	0	2	0	35	2	0	0	0	0	0	0.90
	Grasses/ moss/ herb	0	0	0	1	42	1	3	0	0	0	0.89
	Arrhenatherum low density	0	0	2	0	2	30	5	0	3	0	0.71
	Arrhenatherum high density	0	0	0	0	3	6	14	0	1	0	0.58
	Reeds	0	0	0	0	0	0	0	34	0	1	0.97
	Centranthus	0	0	0	0	7	0	0	0	32	0	0.82
	Scrub	0	0	0	0	0	0	0	2	0	20	0.91
	Producer's accuracy	1.00	0.91	0.90	0.97	0.75	0.79	0.64	0.94	0.89	0.95	

The Rye classifications indicate that multispectral remote sensing has the potential to discriminate between some of the general habitat types present on vegetated shingle. However, it has difficulty in discriminating between some species, particularly those that cover small proportions of the shingle.

Digital photography does provide a higher resolution solution to mapping vegetated shingle, but would probably require manual interpretation, which would require specialists with experience of both the habitat, and mapping it using photography.

5.2 Morphological changes

Morphological changes are an important indicator of the status of a habitat, particularly if there are erosion or accretion changes. Some of these changes are pertinent at local levels and indications of where change is taking place may be used to improve management of a site. The main advantage that a remote sensing approach has over a ground based study is that it provides continuous data. The ground-based transect approach used previously cannot provide information along a whole coastline and may miss important areas of change. These ground-based approaches are also unsuitable for surveillance. If change suddenly takes place in an area without prior warning it may not be possible to establish a baseline. Remote sensing data may be gathered that provide general indicators of the changes taking place

Research was carried out on multiple LIDAR data sets from the Rye shingle and Ainsdale dune sites in order to examine methods of detecting and quantifying morphological change.

5.2.1 LIDAR data preparation

Systematic differences between LIDAR surfaces can occur due to a variety of reasons and are likely to result in errors in morphological change detection. Removal of these offsets is crucial if morphological analysis is to be as sensitive as possible to change. The easiest method of calculating these offsets is to identify areas within the LIDAR data that are flat, unlikely to have changed between the times of data collection and are unvegetated. Elevation data are extracted from both LIDAR surfaces and compared (Figure 5.20). The offset between the data may be calculated and applied to one of the surfaces (Table 5.30; Figure 5.21). The data are then ready for change analysis.

Table 5.30 Offsets between LIDAR surfaces

Site	$LIDAR_{t1}$	$LIDAR_{t2}$	Offset (m) ($LIDAR_{t2} - LIDAR_{t1}$)
Ainsdale	August 2001	September 2002	0.05
Rye	September 2000	July 2002	0.185
Blakeney	June 2000	July 2002	0.105

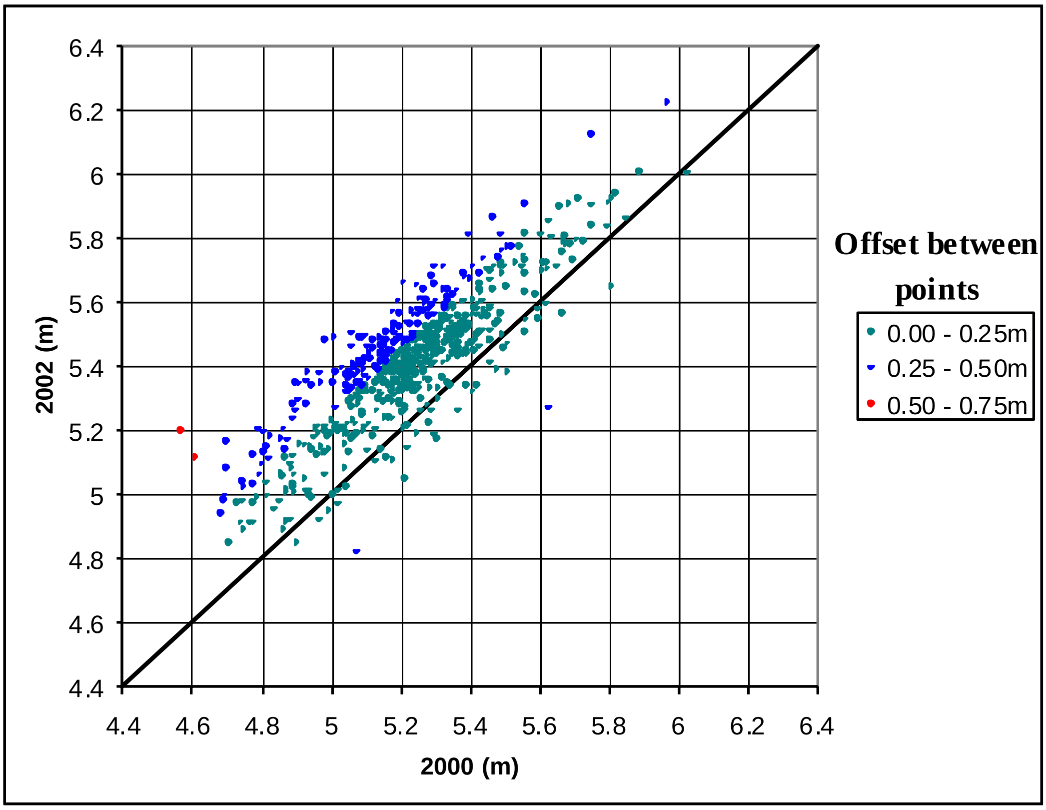


Figure 5.20 Rye harbour LIDAR data from 2000 and 2002 over a flat, unchanged area

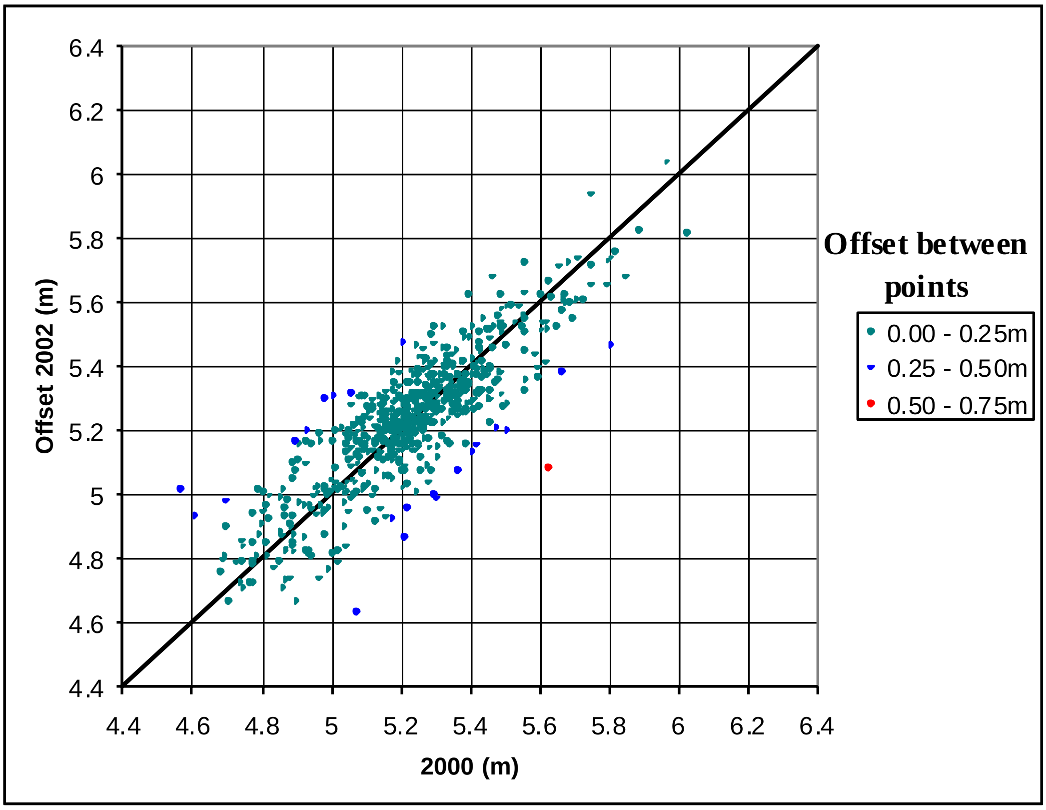


Figure 5.21 Rye harbour LIDAR data from 2000 and offset 2002 over a flat, unchanged area (offset calculated from Figure MC1; 0.185m)

5.2.2 Volume changes

Volume change estimates were made for the Ainsdale, Rye and Blakeney sites. In all of these sites the following procedure was followed:

1. A mask was created that removed areas that were not to be included in the analysis. This included areas with trees and scrub vegetation.

2. A lower limit of analysis was determined. For example: for Ainsdale site this was approximately the high water mark, as calculated from local tide estimates.

3. An upper limit of analysis was determined. The more pixels that are included in the analysis that have little or no change occurring, the lower the sensitivity of the analysis.

4. The masks were applied to remove areas that should not be analysed.

5. The volume changes were determined for approximately rectangular contiguous quadrats (Figure 5.22).

6 A 95% confidence interval for volume change was determined using the following method. Areas were identified that were unlikely to have undergone change. The difference between the datasets for the two times was calculated for every pixel and the value for each pixel was extracted. Pixels were randomly grouped together and the

average difference calculated for each group. The groups were then placed in order of absolute difference and the value of the group at the 95 percentile was found. It may be seen from Figure 5.23 that as the number of pixels grouped together is increased the 95% confidence interval decreases and reaches an asymptote. It is the confidence value at the asymptote that was used in the volume analysis.

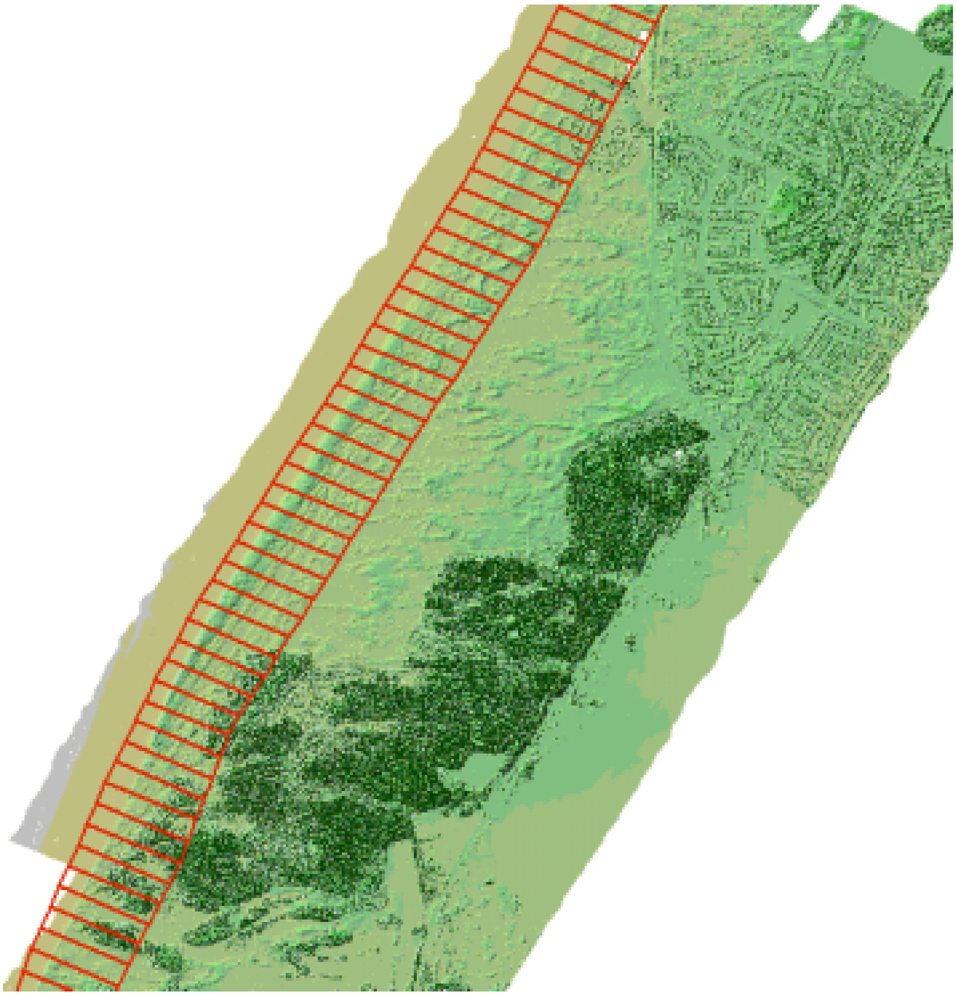


Figure 5.22 Quadrats used for Ainsdale volume change analysis

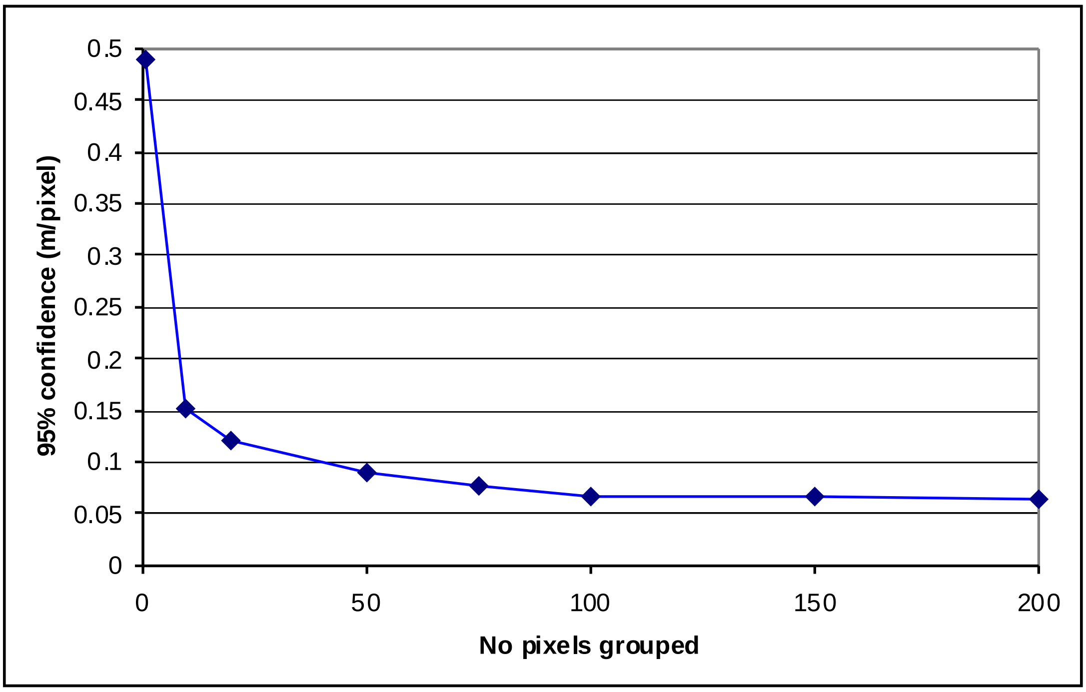


Figure 5.23 Effect of increasing group size on 95% confidence interval of volume change (Ainsdale 2001 to 2002 volume change)

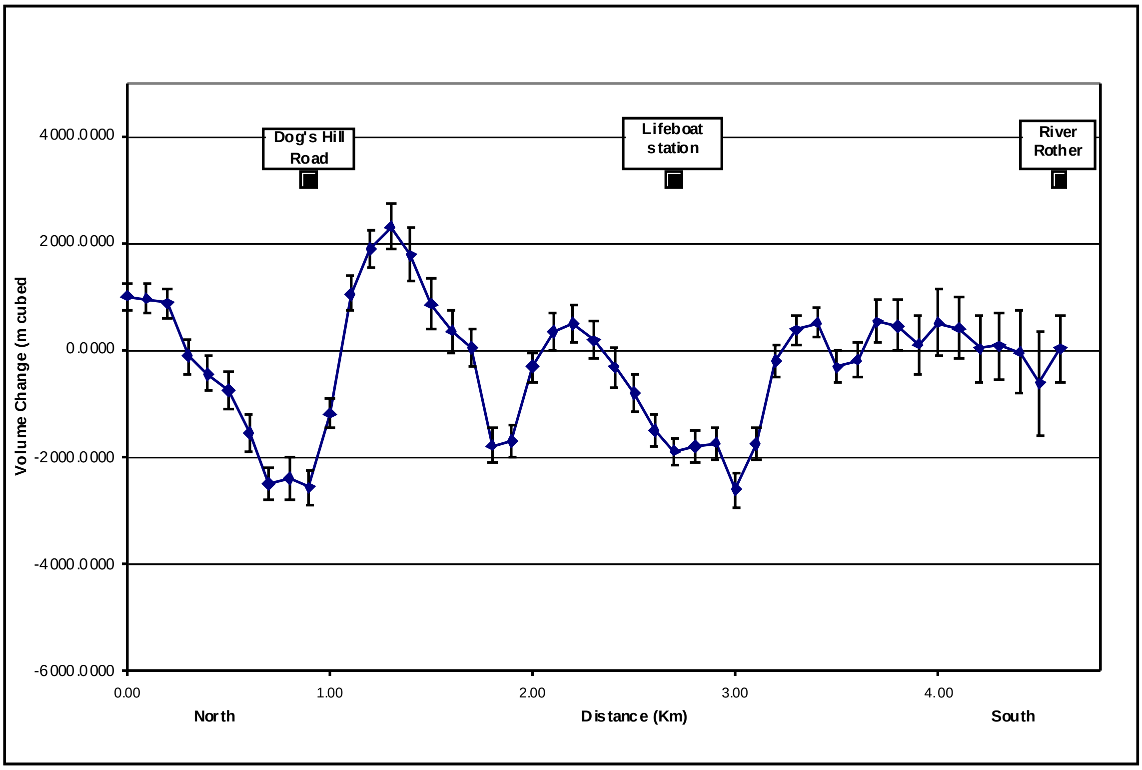


Figure 5.24 Volume change along Rye coastline 2000-2002

(Volume per 100m of coast; 95% confidence intervals)

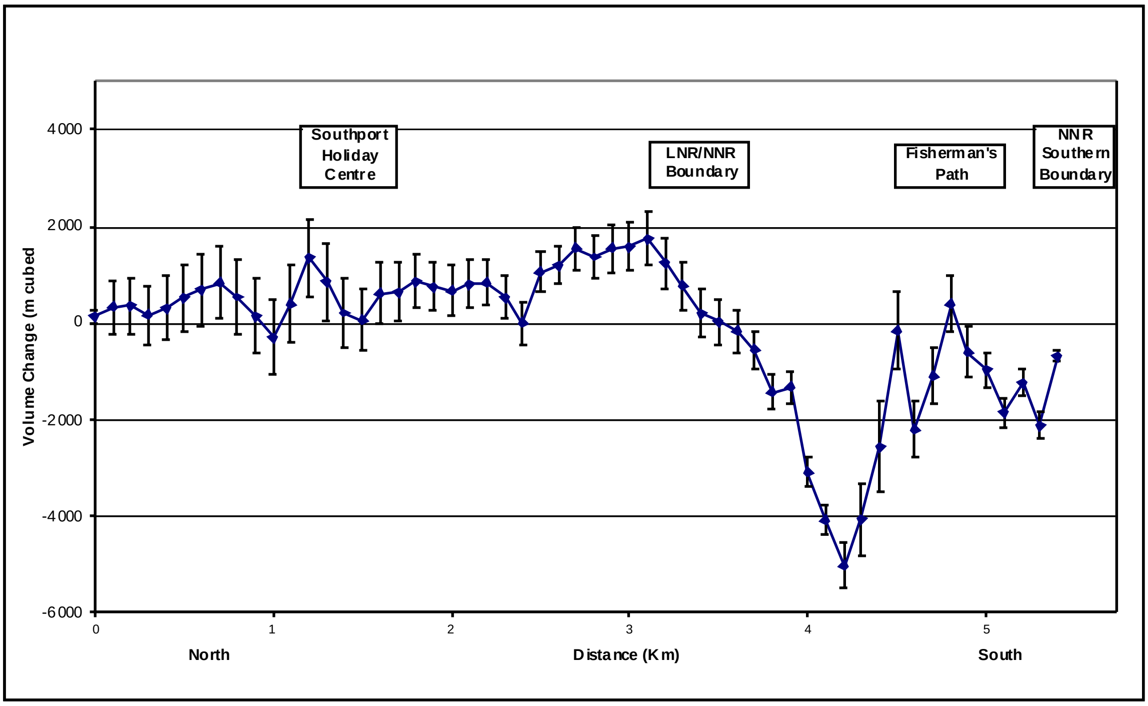


Figure 5.25 Volume change along Ainsdale coastline 2001-2002

(Volume per 100m of coast; 95% confidence intervals)

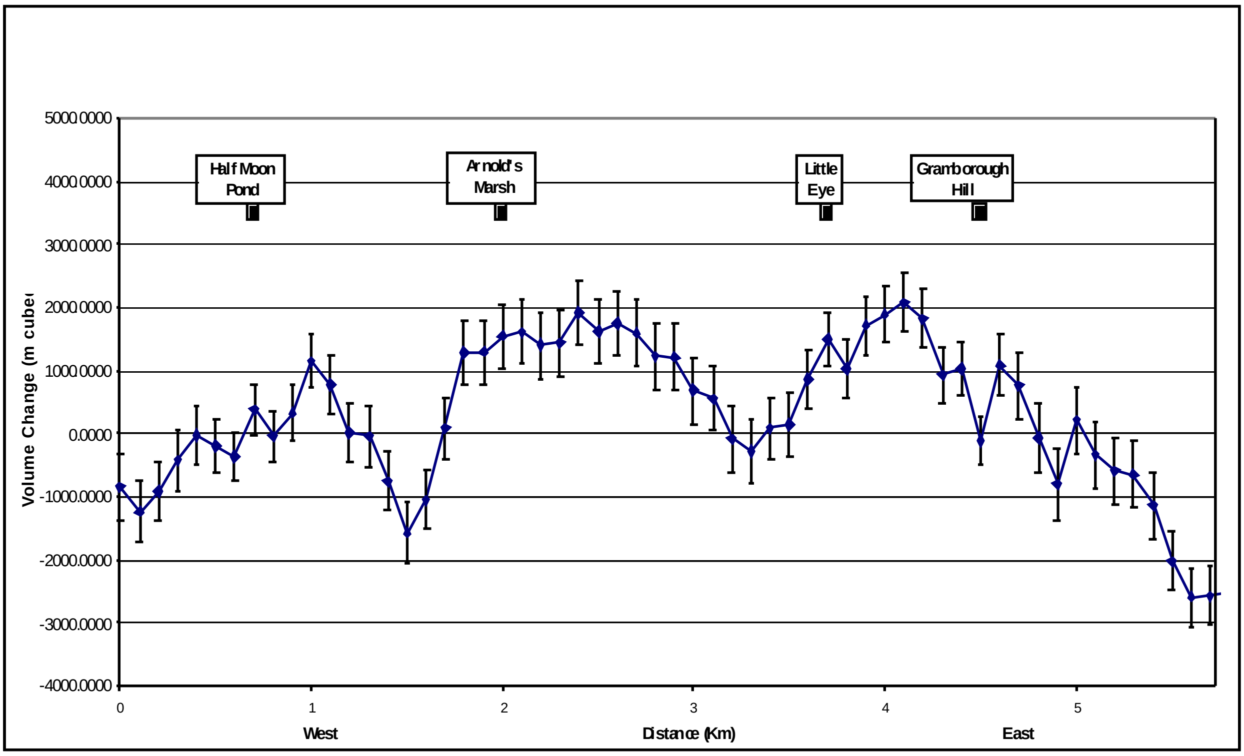


Figure 5.26 Volume change along Blakeney coastline 2000-2002

(Volume per 100m of coast; 95% confidence intervals)

5.2.3 Area of change

In order to identify areas in which morphological change is taking place it is important to consider the errors and imprecision within the data sets being used. Though the vertical error within LIDAR is understood, its impacts when change detection is being carried out have not previously been documented. The effects of horizontal errors are also crucial in determining changes that have actually taken place and those that are artefacts of the data sets being used.

The horizontal errors within LIDAR and the way that the data are processed can result in complex errors within the final change layer that are partially functions of the surface being studied. As slope increases, the effect of horizontal errors will increase (Figure 5.27). This is borne out by Figure 5.28, which shows the standard deviation of the error between two surfaces in an area where no change has taken place increasing with slope.

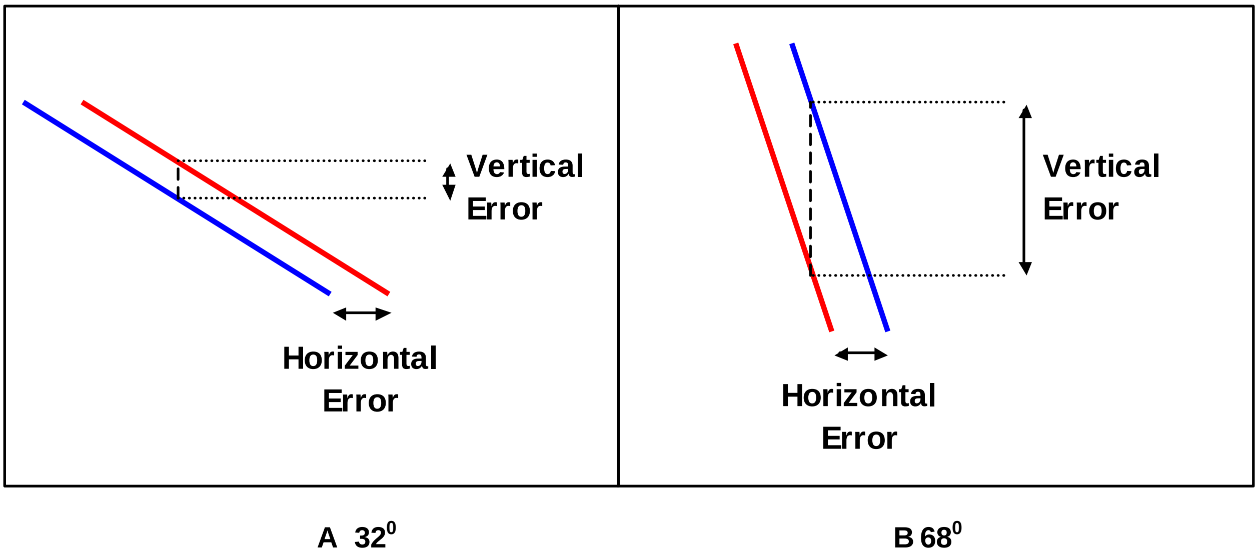


Figure 5.27 Effects of varying slope on vertical error of change detection

A system was devised that accounts for the horizontal errors that occur due to the LIDAR system error and the resampling carried out on the raw data (Figure 5.29).

The system uses a filter with varying size to generate minimum and maximum values within a specified distance of a given point for two LIDAR data sets. The filtering reduces the combined effects of slope and horizontal error when LIDAR change detection is carried out, as can be seen in Figure 5.30. In flat areas the minimum and maximum filter have very similar values to the original LIDAR (Figure 5.30). In areas with high slope the minimum and maximum values account for the potential variation in vertical values due to horizontal errors (Figure 5.30).

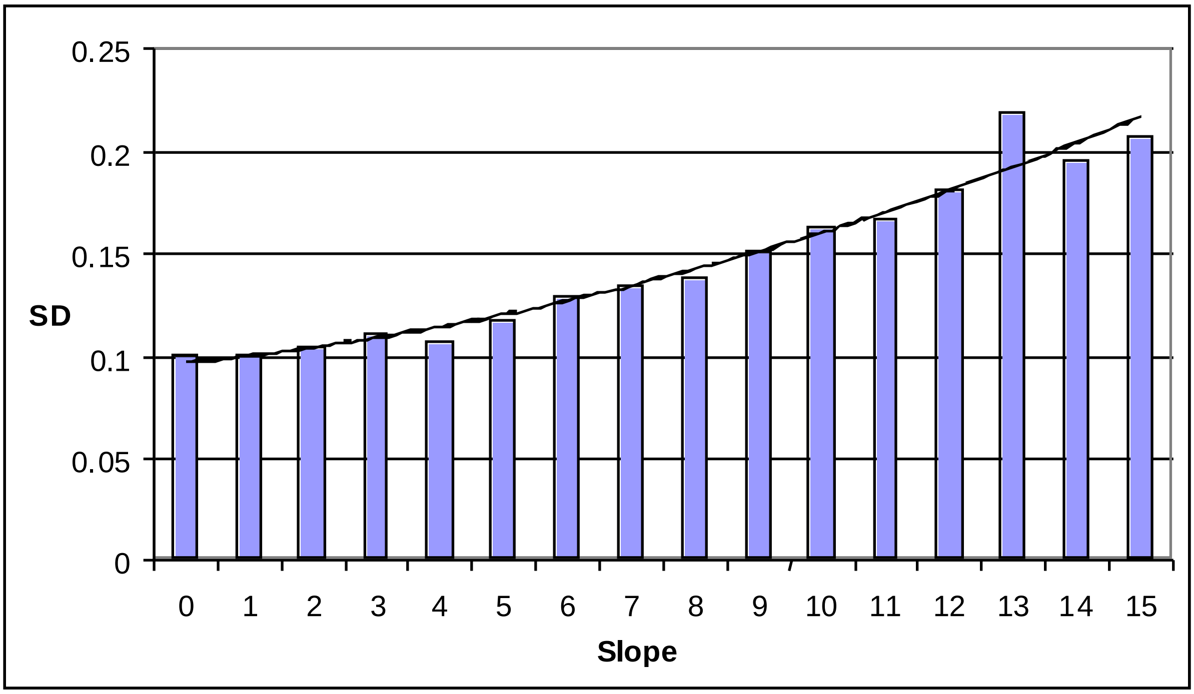


Figure 5.28 SD of differences between two LIDAR DEMs in an area of no change

Rye Harbour Nature Reserve June and September 2000

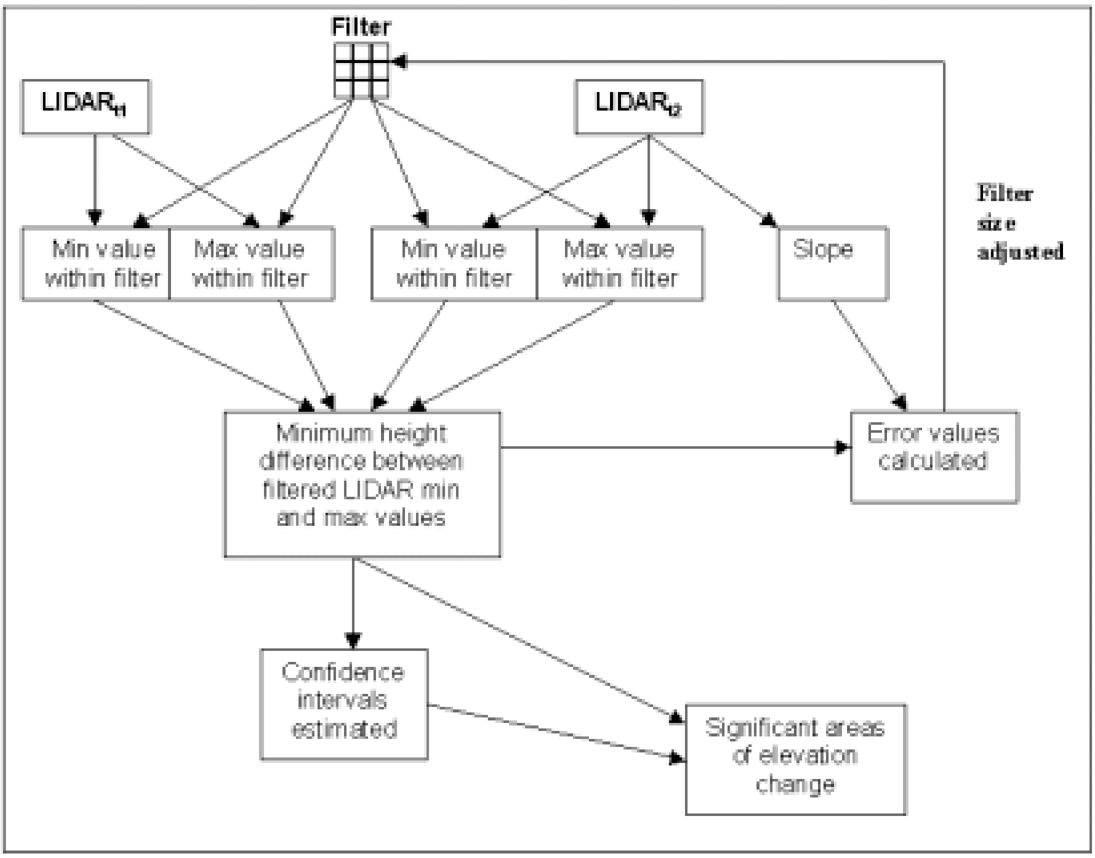


Figure 5.29 LIDAR filtering system for identifying areas of significant change

The filtered minimum and maximum values of the two LIDAR datasets are then overlaid and the minimum difference between them is estimated (Figure 5.31). If there is overlap between the filtered data (Figure 5.31A) then it is assumed that there is no difference between them. If there is no overlap then the difference is the minimum elevation between them (Figure 5.31B and C)

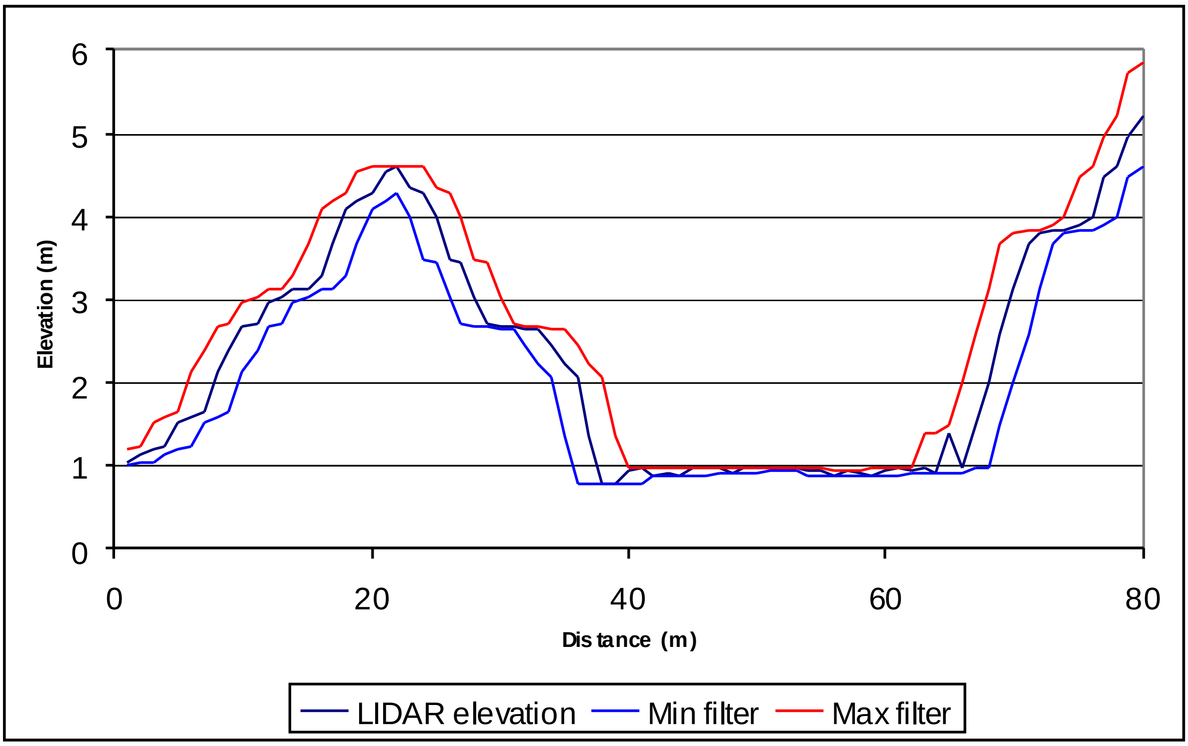


Figure 5.30 Effect of minimum and maximum filter on simulated LIDAR transect

The 99% confidence interval is estimated empirically using a separate area where no change has taken place. To do this, the absolute pixel values are ordered and the value at the 99 percentile is assumed to be the confidence interval. This is applied to the filtered image to provide areas where the difference is greater than the 99% confidence interval. This could be carried out for any confidence interval.

Using the difference surface, error statistics are generated for an area where no change has taken place. Difference surface and slope surface values are extracted for an area of no change. A regression is applied to the data with slope as the independent variable and standard deviation of the difference values as the dependent variable (Figure 5.32). If the number of pixels with a given slope is less than 50 these values are removed from the regression stage to reduce the possibility of noise. The correct filter size is assumed to occur when the slope of the regression line is approximately zero. The filtering and regression stages are repeated until the correct filter size is found. Once the correct filter size is found, the filter is applied to the whole of the area of interest.

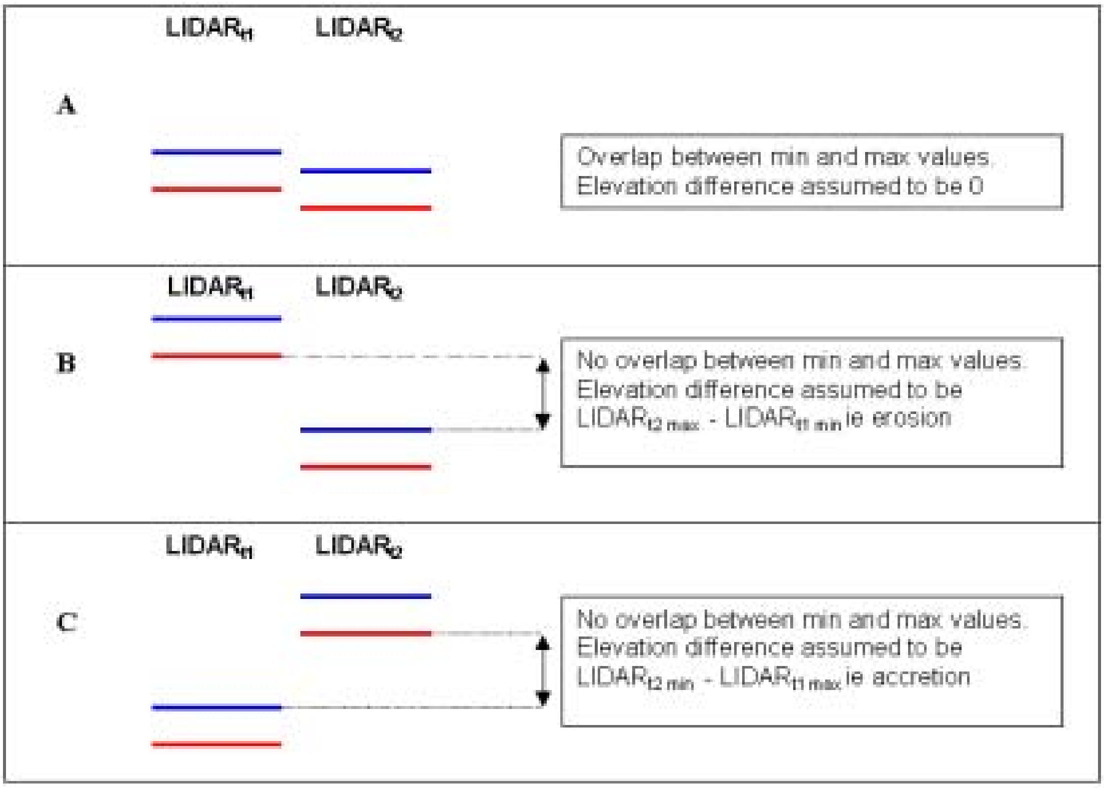


Figure 5.31 Calculating differences between filtered LIDAR data
(Red minimum filter, blue maximum filter)

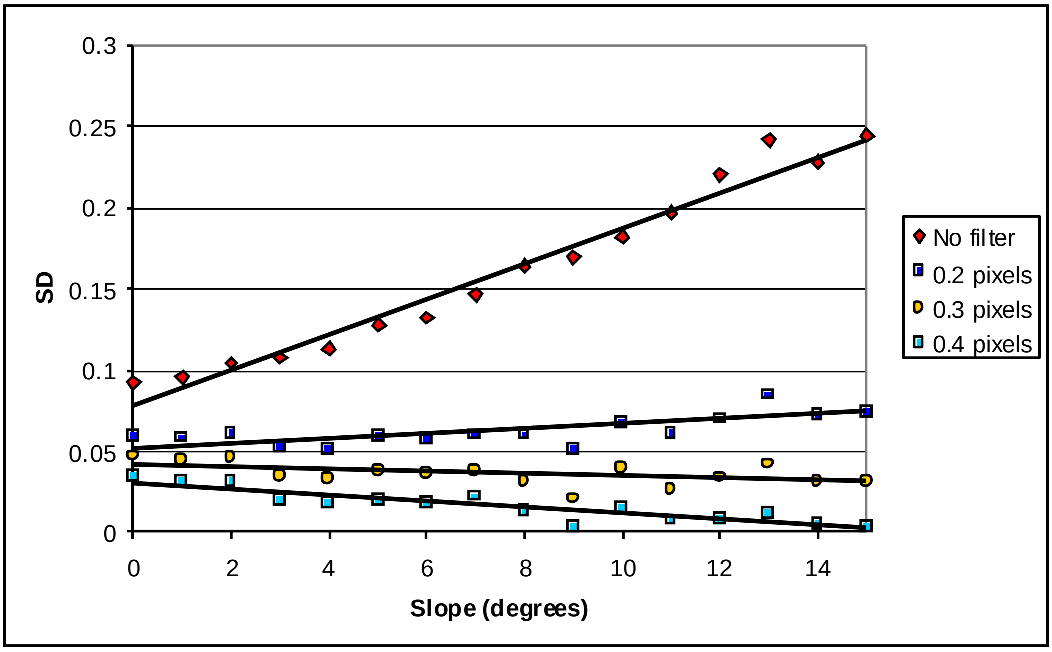


Figure 5.32 Error statistics generated from filtered difference layer in area of no change
(Rye Harbour; September 2000 to July 2002)

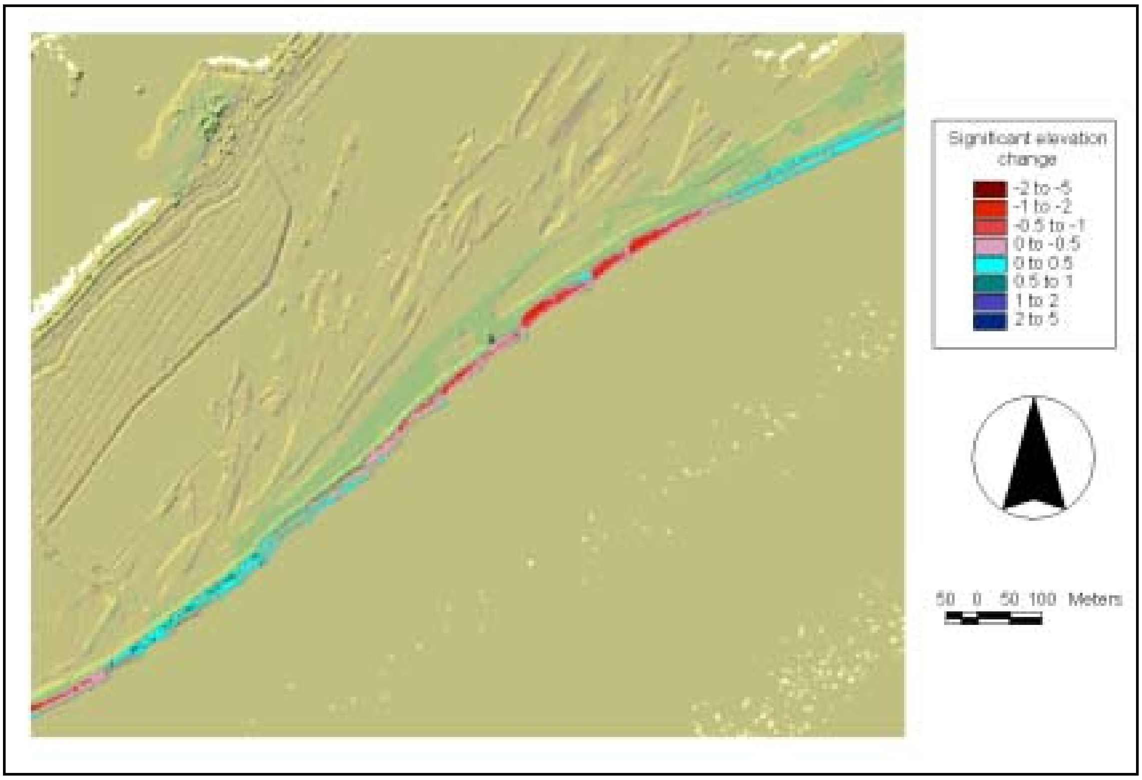


Figure 5.33 Areas of significant elevation change (Rye Harbour; September 2000 to July 2002; 95% confidence interval)

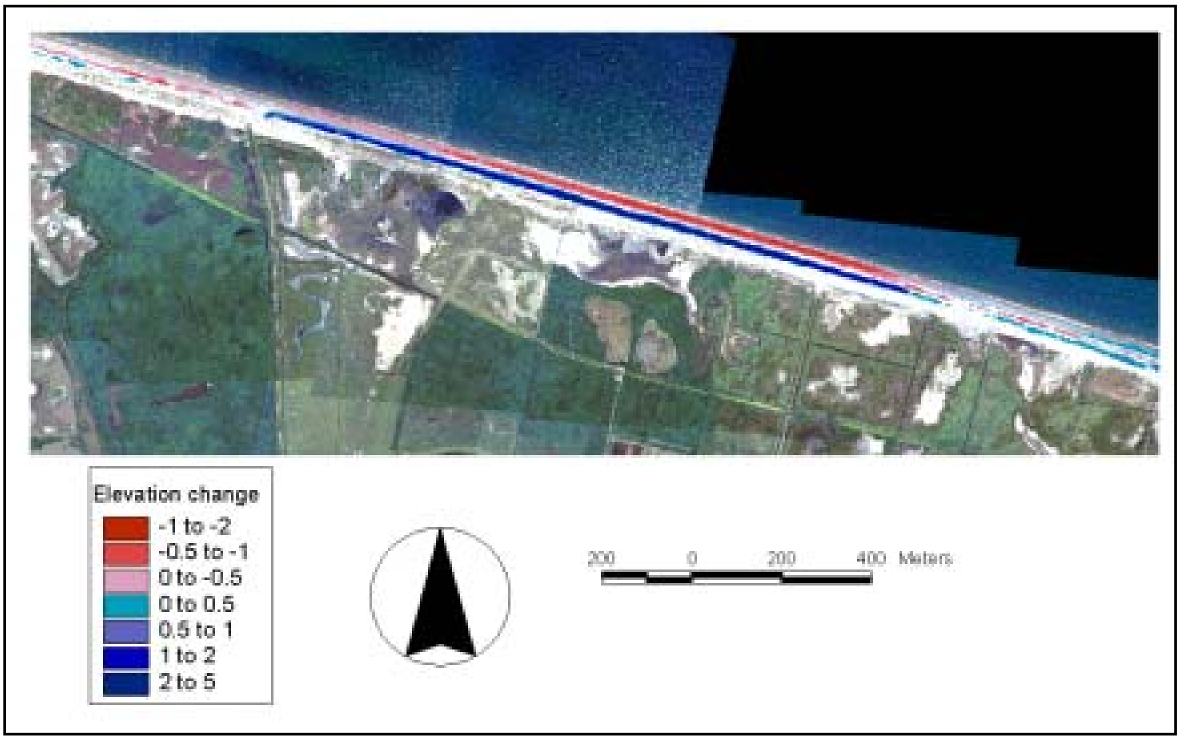


Figure 5.34 Areas of significant elevation change (Blakeney; June 2000 to July 2002; 95% confidence interval)

5.2.4 Combining elevation datasets for long term morphological change

Though LIDAR is useful for determining morphological change it is a relatively new technique. However, there is the potential to use other datasets combined with LIDAR to detect change over longer timescales.

Sefton Council provided a 1982 DEM generated using photogrammetry, enabling long term change monitoring of the Sefton coast to be carried out. The DEM was supplied as a series of points representing 2m vertical intervals. Additional points were present for areas where the topography was flat. In order to compare the dataset with the LIDAR data, a raster grid had to be constructed. This was carried out by interpolating the point dataset to a 2m horizontal spacing raster using a method known as kriging (Swales, 2002).

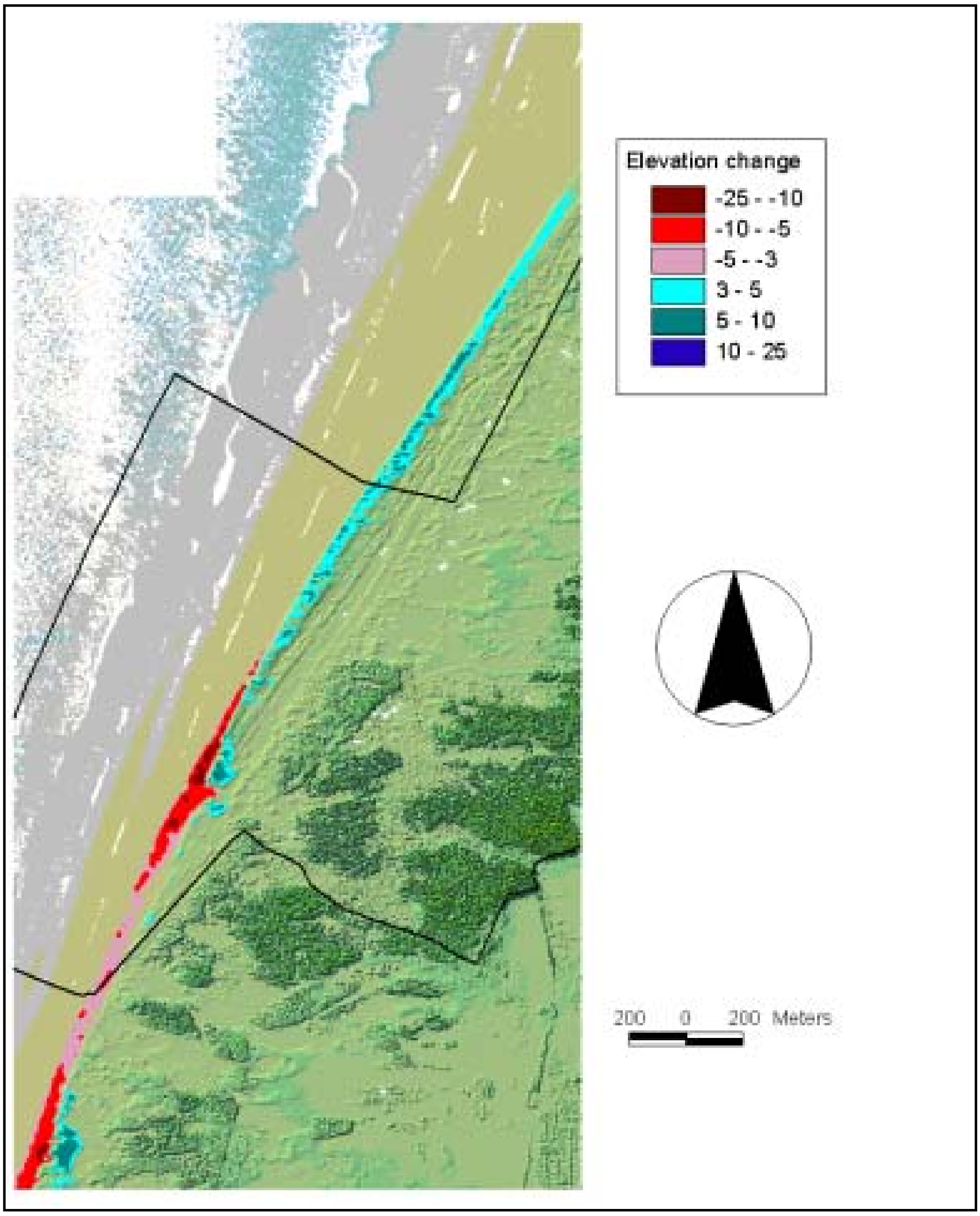


Figure 5.35 Elevation changes between 1982 and 1999 for Ainsdale Sand Dunes NNR

(NNR boundary marked in black)

This allowed a comparison of elevations to be made between 1982 and more recent data sets. It was decided that using 1999 LIDAR would allow a comparison to be made along much of the Sefton coast, as a more extensive survey was carried out in this year. As the 1982 photogrammetry data is not as precise as the LIDAR data, the final comparison cannot be as precise and so the changes are assumed to occur when the differences between the LIDAR and the photogrammetry are greater than 2m, the spacing of the contours of the photogrammetry data. This resulted in a data layer that is insensitive to change (ie underestimates change). Despite this the resulting elevation change layer shows clearly the gross long term change that is occurring along the Sefton coast (Figure 5.35).

5.2.5 Profiles

LIDAR data allow multi date profiles to be generated for change detection (Figure 5.36). These may be targeted at areas where change has been identified as taking place using the methods above, or at regular intervals. The main advantage of using LIDAR to gather these transects is that they may be revisited if the transect position is unsuitable. This is one considerable advantage of using LIDAR data for generating profiles rather than ground based approaches.

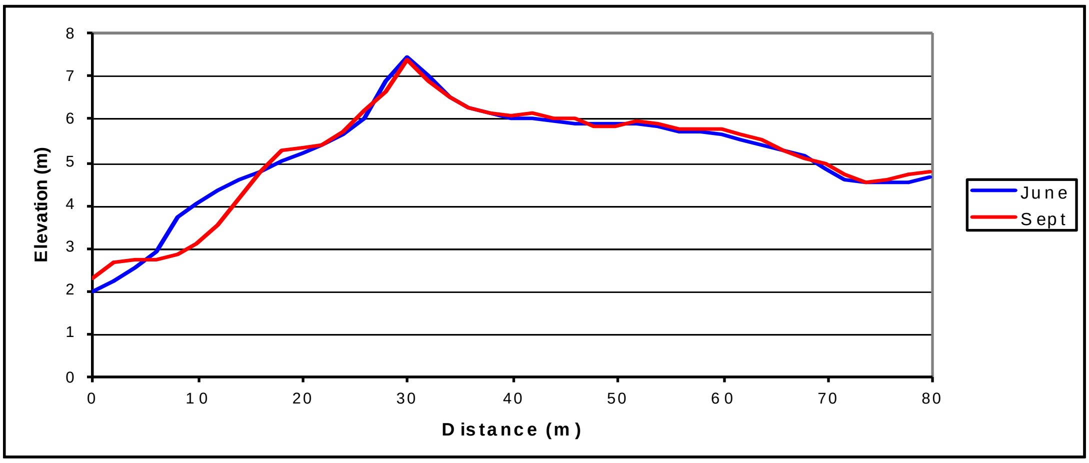


Figure 5.36 2000 LIDAR Profiles, Rye Harbour, East Sussex

5.2.6 Ridge characteristics

The characteristics of the ridge between open water and percolation lagoons are important factors in the determining whether the system is changing over time.

Ridge width

In order to plot the width of Blakeney ridge as a function of distance along coast, a reference line was set up from which to create transects of the landward extent of the dune. The intersection of these transects and the landward extent line would form the basis for measuring the minimum distance to the line of the mid water mark

A baseline for the ridge width was required. On the seaward side the baseline was mean water height (MWH). For each year this was determined by the following technique:

1. Twenty-five sample LIDAR heights were taken over the sea.

2. The height difference between MWH and the tide at the time of data gathering over the sea was then estimated.

3. The MHW was estimated using the value calculated in (2) and the mean LIDAR sea value.

4. Large differences in the position of the MWH between 2000 and 2002 were examined using the raw LIDAR imagery.

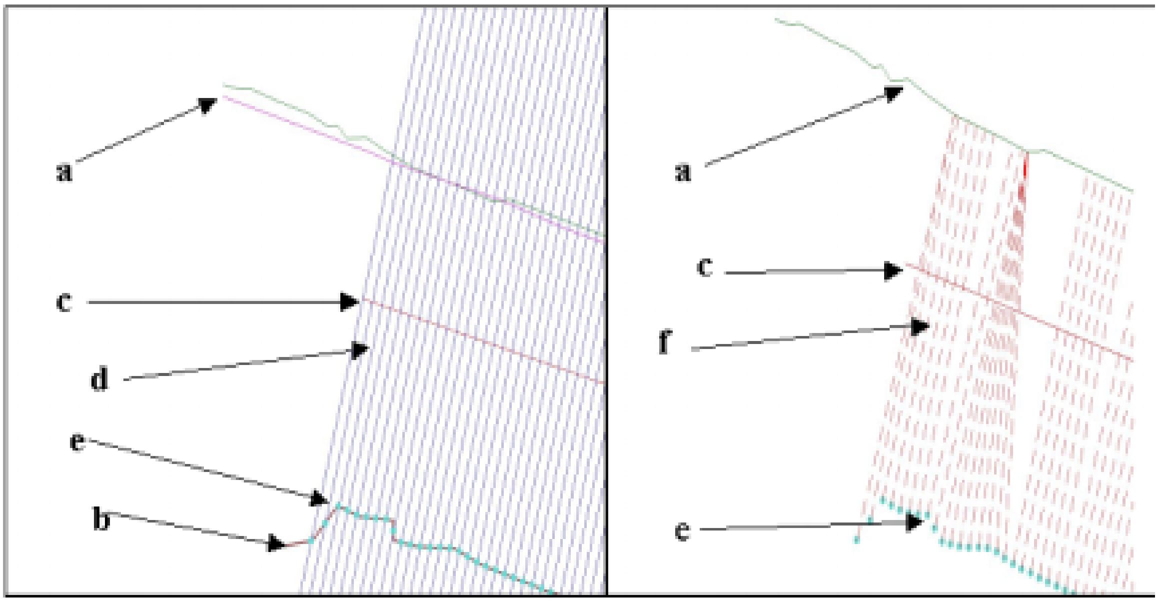


Figure 5.37 Technique for determining ridge width

The ridge width was determined using the following method (Letters refer to Figure 5.37):

a. The MWH line was estimated from the LIDAR. 2000 (green) and 2002 (red)

b. Line of landward side of ridge extent as determined from 2000 LIDAR data.

c. Straight distance reference line, parallel to ridge direction.

d. Transect lines perpendicular to distance reference line (c).

e. Points at intersection of perpendicular transect lines(c) and ridge extent line (b)

f. The lines of shortest distance from points (e) to MWH line (a) were calculated.

Ridge height

The LIDAR elevation data had a maximum value filter customised to the direction of the shingle ridge (Appendix E). The filter consisted of a kernel, organised perpendicular to the direction of the ridge. This enabled the maximum value across the ridge to be estimated.

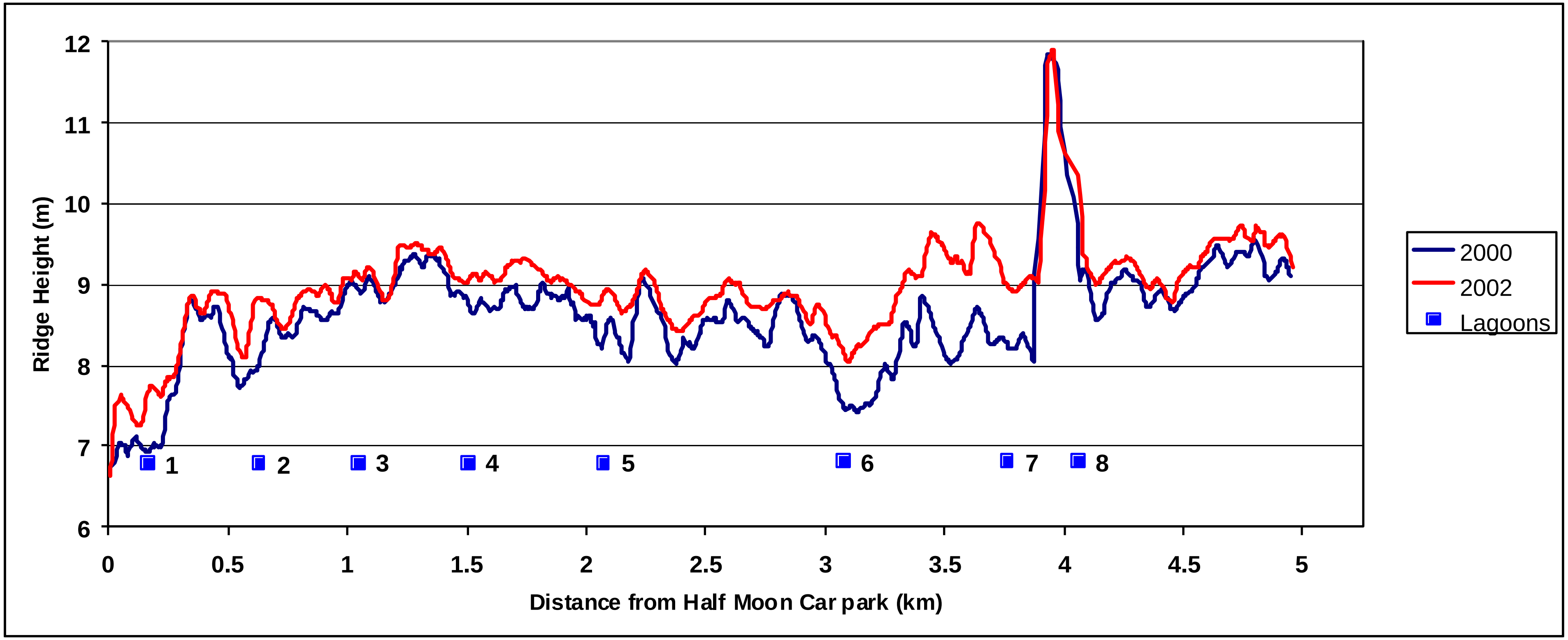


Figure 5.38 Ridge width for Blakeney Saline lagoons (lagoon positions marked on)

1 Half Moon Pond; 2 New Moon Pond; 3 Seahorse Pond; 4 Arnold's Marsh Lagoon;
5 Salthouse Broad; 6 Little Eye; 7 W. Gramborough Hill Lagoon; 8 E. Gramborough Hill Lagoon

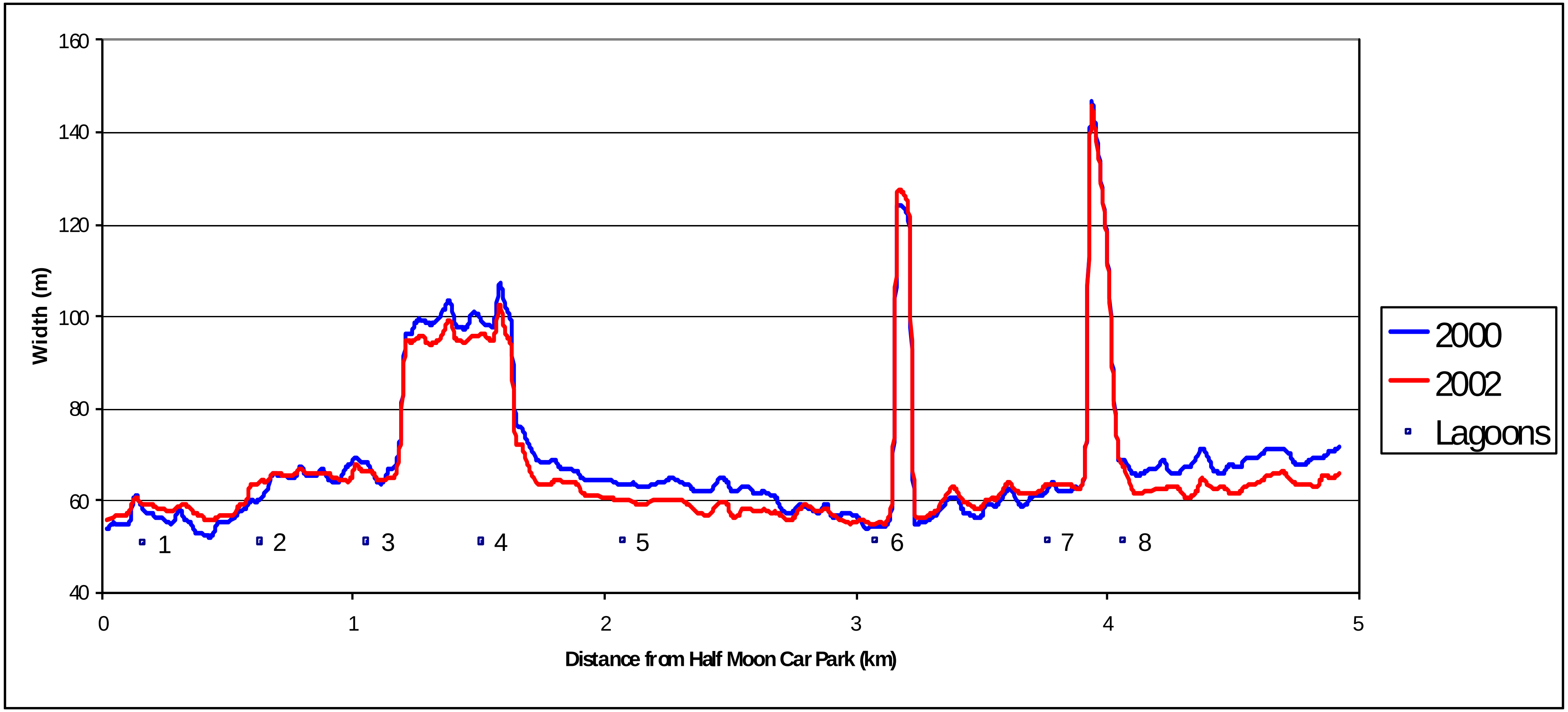


Figure 5.39 Ridge width for Blakeney Saline lagoons (lagoon positions marked on)

1 Half Moon Pond; 2 New Moon Pond; 3 Seahorse Pond; 4 Arnold's Marsh Lagoon;
5 Salthouse Broad; 6 Little Eye; 7 W. Gramborough Hill Lagoon; 8 E. Gramborough Hill Lagoon

6. 3D visualisations

In order to educate people of the effects of coastal change or to provide an alternative perspective of an area it is possible to provide three dimensional (3D) visualisations using CASI, digital photography and LIDAR data. The visualisations may be generated in specialist software that uses the elevation data to generate a 3D model. The digital photography or CASI data may then be draped over the elevation model to provide a real world 3D view (Figure 6.1).

The 3D visualisation techniques may be used to provide an alternative aerial perspective of a habitat. These perspectives may be generated using a camera in an aircraft. However, as the original digital elevation and multispectral data are available, the perspective may be changed and emphasis placed on alternative areas depending on requirements.

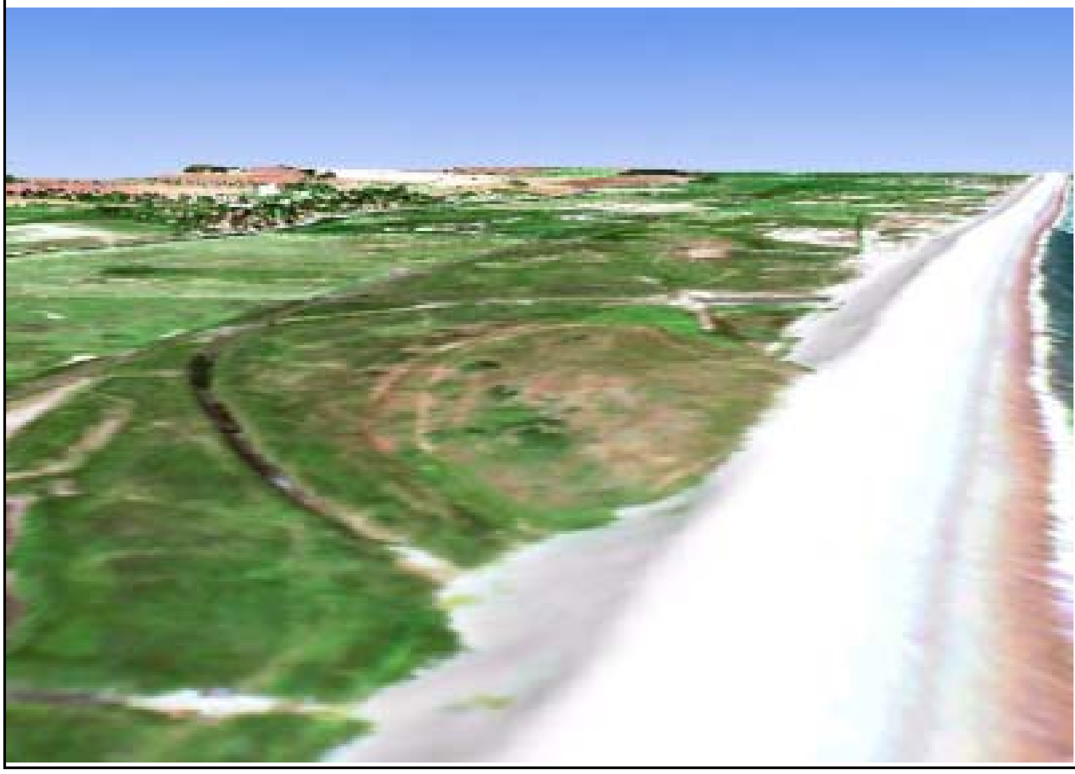


Figure 6.1 3D LIDAR and CASI visualisation of Blakeney saline lagoons

Additional data may be added to the 3D world in order to visualise morphological changes. It is possible to highlight areas of change by adding data derived from multi temporal LIDAR data (Figures 6.2 and 6.3). The LIDAR data may be used by itself to provide visualisations of the morphological changes taking place (Figure 6.4). These methods can be very successful in conveying an impression of the dynamics occurring at these sites.

Any form of similar resolution DEM may be used in a visualisation. Using 1982 photogrammetry data with 2002 LIDAR data it is possible to see the large changes in the Ainsdale dune system (Figure 6.5). All of the visualisations described can be presented as static images or as flythroughs. These simulate a bird eye or plane eye view of the habitat and may be used to provide a particularly dynamic view of the area of interest.

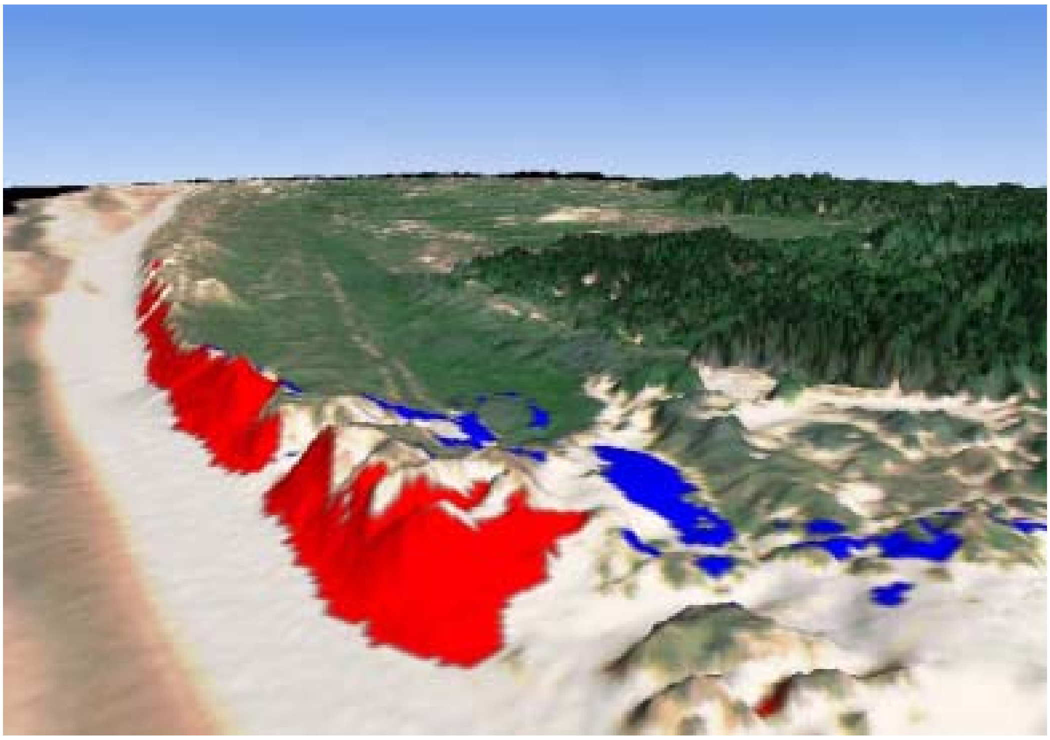


Figure 6.2 3D LIDAR and CASI visualisation with significant change between 1999 and 2001 overlaid, Ainsdale Sands

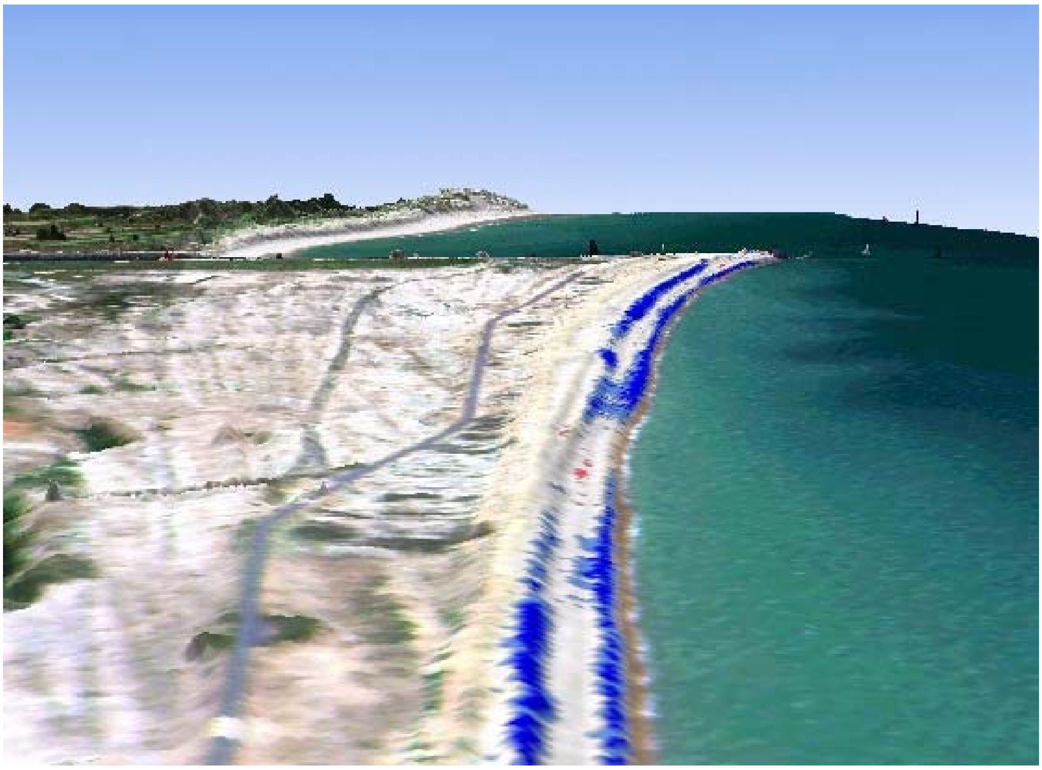


Figure 6.3 3D LIDAR and CASI visualisation with significant change 2000-2002 overlaid, Rye Harbour

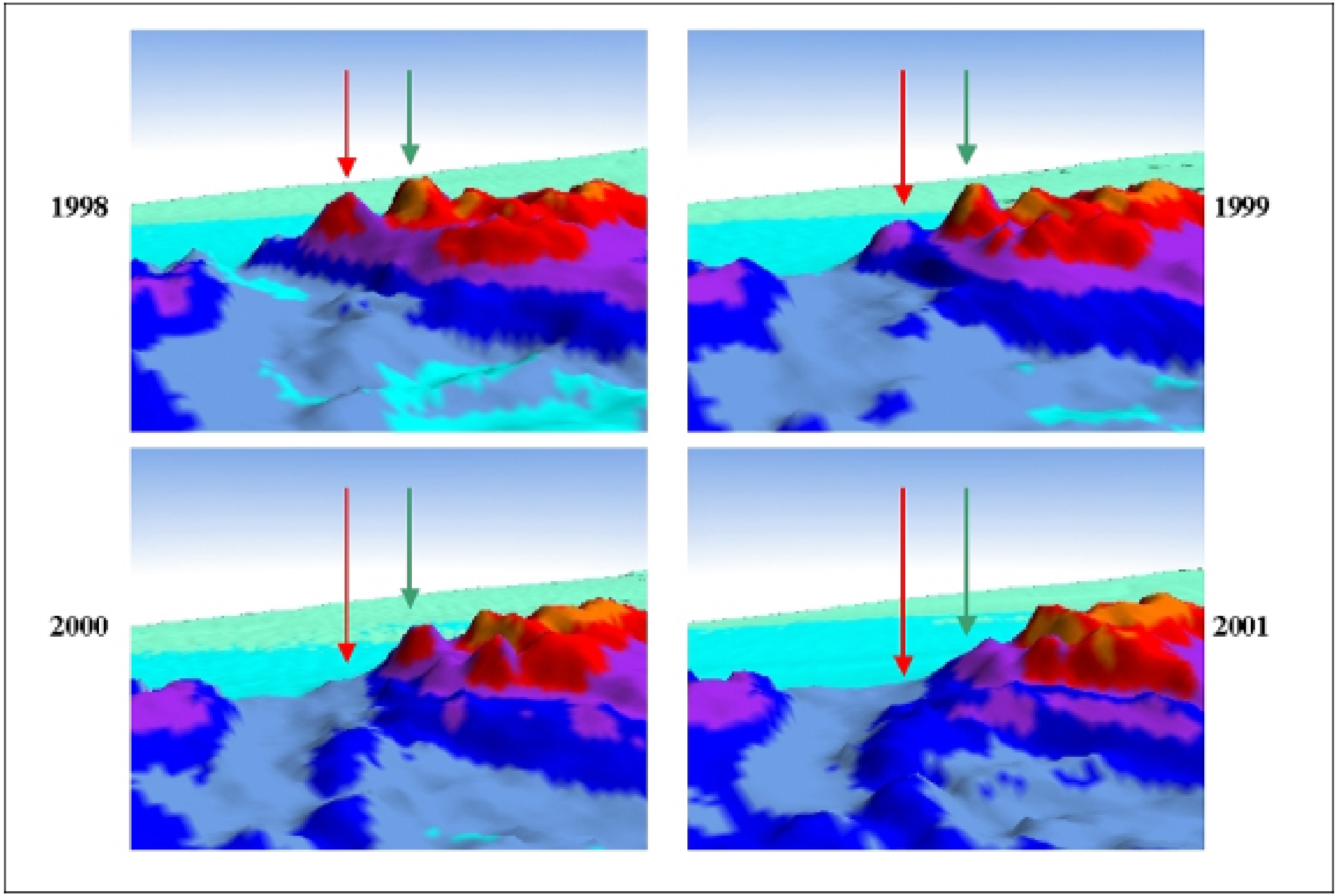
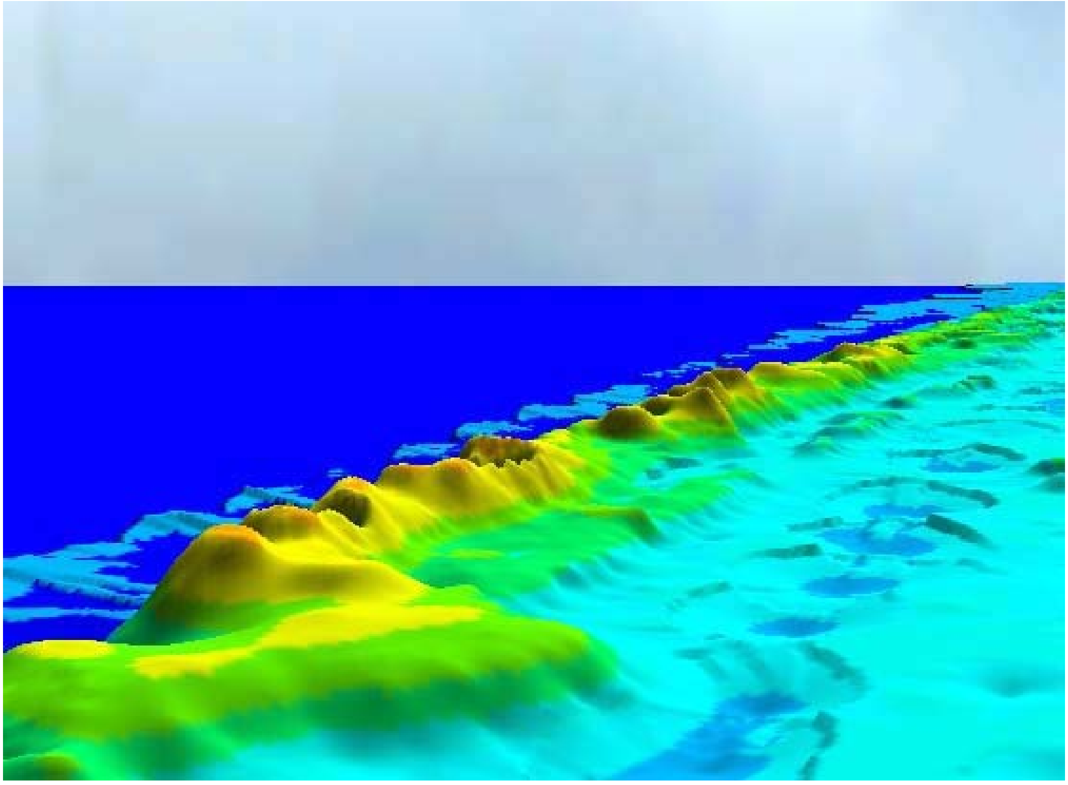


Figure 6.4 LIDAR 3D Visualisation of Erosion at Ainsdale Sands, Merseyside between 1998-2001

(Red and green arrows point to same part of the coast. Similar area to Figure 6.2)

A **1982 photogrammetry data**



B **2002 LIDAR data**

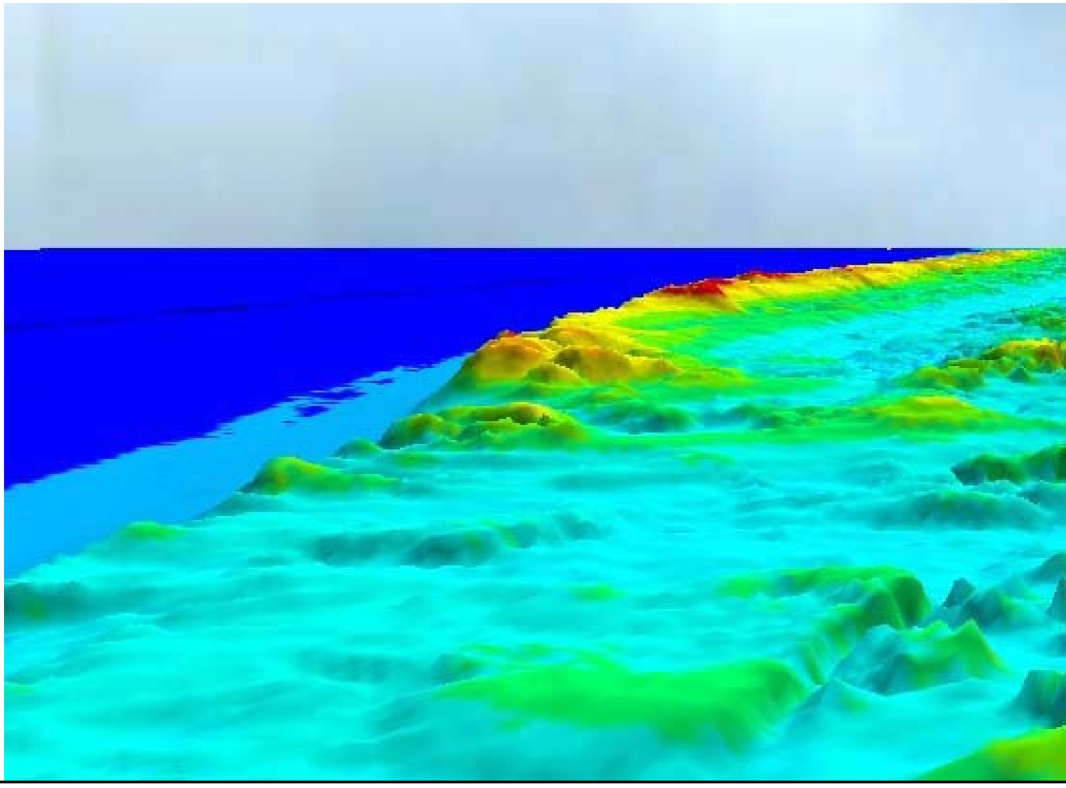


Figure 6.5 3D Visualisation of change at Ainsdale Sands, Merseyside 1982-2002

(View from end of Fisherman's path facing approximately north)

7. Conclusions and recommendations

7.1 Image normalisation

Preparing the imagery for classification is one of the most important stages in a successful, accurate classification. Using edge matching is generally appropriate when terrestrial habitats are being classified, as long as care is taken when selecting the areas that can be matched.

The use of image ratioing is an interesting development for intertidal sites and can be used to increase classification accuracy when there are variations in lighting due to bi-directional effects or variations in overall lighting levels.

The technique may also be used to expand the window of opportunity for collection of data over intertidal sites, by collecting data when bi-directional effects are high such as early morning. By expanding the time that data can be collected by 1 hour either side of low water the number of monitoring opportunities per month can be increased by between 3 and 4 days per month. This equates to a 25%-35% percentage increase in the number of days that data can potentially be collected.

This is an area that will continue to be developed by the Environment Agency, as the success or otherwise of a monitoring program can be dependent on the quality of the image normalisation.

7.2 Classification

7.2.1 Alternative classifiers

This study has conclusively shown that the use of traditional statistical based approaches for classification can be less accurate than more modern techniques. Remote sensing is a relatively new science and hardware and software are improving rapidly. The development of alternative classification methods will continue both for commercial and academic use, and as methods are developed, it is essential that they be considered in the context of habitat monitoring.

7.2.2 Use of additional datasets in classification

The use of additional datasets in classification has been shown to be successful, particularly in the case of saltmarsh and sand dune systems. The data used in the classifications in this study were LIDAR derived, but there is no reason why other datasets could not be used, including those derived from non-remote sensing sources, such as soil type.

7.2.3 Probability and uncertainty

The derivation of per pixel probabilities enables two main types of change detection to be carried out more accurately, estimates of class area and identification of the areas where change is occurring.

Estimates of the area of each class may be improved by accounting for probability of correct allocation and deriving confidence intervals to these areas. This is particularly useful for the reporting of the status of habitats, as it may be determined whether the level of change is significant.

When classifications from different years are compared, the probability of correct classification for each pixel may be used to determine the probability of change for each pixel. This will enable the areas of change to be identified, combined with a probability that the change is occurring, enabling management decisions to be made on the basis of where change is occurring and what the change is.

7.3 Morphological monitoring

This study has examined methods of monitoring the morphology of coastal habitats. This is an area of remote sensing that has advanced a great deal in recent years. LIDAR systems have improved to stage where high precision DEM generation over large areas has become routine. Using the high quality DEMs available offers a method of monitoring habitats that was previously unavailable. Data may be used for targeted monitoring of specific areas, or surveillance of whole habitats. This approach is a vast improvement on the one or at best two dimensional ground based methods that had the potential to miss large areas of change in a dynamic environment such as the UK coast.

7.4 Obtaining remote sensing ground data

Remote sensing offers a broad-brush approach to land cover mapping and is able to map the main species present and may be used to detect general trends in species composition. It is not possible to detect single plants of a rare or infrequent species.

The accuracy of maps derived from remotely sensed data has in the past been compromised by ground data that do not meet the requirements of image analysis. This is largely due to lack of communication between image analysts and ground survey teams. In order to improve the accuracy of data derived from remotely sensed imagery it is essential that collaboration occur between the personnel carrying out ecological ground data collection and those carrying out image analysis. In remote sensing terms, it is better to gather large quantities of what may be considered broad-brush data than attempting to map each individual plant on the ground. Difficulties were found during this study where ecologists were interested in individual rare or unusual species, increasing the time taken for data gathering and reducing the amount of usable data gathered.

Problems may also occur when synoptic data are collected as in the Budle Bay section of this study. Areas of a given class must be clearly identified, so that any pixel within a given polygon will belong to that class.

This report recommends that a consistent method of obtaining ground data for classifications is derived and used to provide standard operating procedures for future work.

7.4.1 Image resolution/ground resolution

The spatial resolution (the pixel size) of a CASI image is generally somewhere between 1-10m. To maximise classification accuracy, the training sites need to be as pure as possible. This has two implications from the point of view of image analysts. This means that there should only be one class of vegetation present. In an area such as saltmarsh this may be difficult or impossible. Some areas of saltmarsh are intermediate communities that are made up of a number of species, such as *Puccinellia* lawns, that contain *Aster, Limonium*, etc.

Where it is not possible to identify pure areas, then the approximate amount of coverage by each species should be recorded. This should include the amount of bare ground and what surface this is e.g. mud, shingle or sand. Remote sensing is not able to distinguish coverage at a very small level and so unless specifically required cover of less than 10% should be ignored.

7.4.2 Classes

It is essential that the classes present in a habitat be known prior to ground data collection. A classifier cannot know whether an area belongs to a class other than the ones that data have been collected for and will misclassify any areas that belong to classes that ground data have not been collected for. Knowledge of the land cover types present in a study area prior to ground data collection will enable surveyors to ensure that sufficient data are collected for all classes.

7.4.3 Training sites

Areas should be identified of each of the classes used in the classification. It is essential that enough pixels be identified for use in the classification. Selecting point samples is not an option unless large numbers of points are sampled (See 7.4.4 below).

Sites should be as large as possible. The classification is most accurate when the range of variation in the class is represented in the training data. This means that low and high productivity areas should be represented, as well as the variation in the dominance of the species making up the class.

The effects of mixing at boundaries can severely reduce the quality of training data and therefore the accuracy of the subsequent classification if a statistical classifier is used (Foody, 1999). However, for non-parametric classifiers such as neural networks this is less importance.

During processing the training sites have to be identified on the image. This creates problems between data obtained and requirements for image processing. GPS or other accurate position data from the field may be of less use than mapping straight to an image. When an image is obtained it is distorted. The process of fitting the image to a map is not perfect and so there will be positional errors in the final map. Even though the ground data may be perfect, the image data may not be.

This means that areas of vegetation marked on an image are easier to identify. If the imagery is not available a sketch map may be of use to the image analyst. This may show positions relative to roads, streams or creeks. A map is particularly useful when the areas identified are small patches of vegetation. The position of a point will be of use as well, but a sketch map will tie down geographic position with more accuracy than many commercially available GPS systems.

Even with a differential GPS there may be problems associated with post processing and fieldwork may be of little use unless simple maps are obtained. Photographs of the general position may also help.

Data should be gathered for all of the classes being used. A particular problem with classification of intertidal vegetation is algae, but a lot of ground surveys do not include this class. It is then up to the image analyst to identify areas of algae from the imagery, a task many are not qualified for. It is therefore essential that all classes are included in the ground data collection.

7.4.4 Number of pixels gathered

The number of pixels gathered per class is an essential factor in the accuracy of final classification. It is critical that enough pixels are gathered per class and that the areas gathered cover the variation within the class. For example, for a mixed woodland class, it would not be acceptable to gather ground data that does not include deciduous woodland. There are rules for the number of pixels used, but these generally apply to statistical classifiers. Work was not carried out to identify the correct number of pixels per class. However, for the habitats classified here, between 500 to 1000 pixels per class were adequate to provide a high accuracy classification.

7.4.5 Ground survey teams

Throughout this study it was found that having an image analyst involved in data gathering was very useful. It aided the classification process for two main reasons:

- Ensuring the correct data were gathered.
- An understanding of the site was helpful during the QA of the classification stage and reduced errors in the final product.

7.5 Remote sensing for monitoring coastal SACs

The use of remote sensing will not remove the need for ground based studies, but can provide additional information that may not be obtained using ground studies. There are a number of differences to a remote sensing approach to monitoring the environment that may be used positively to provide additional information that may be difficult or impossible to gather using a ground based approach.

Remote sensing provides a continuous coverage. This is a particular advantage with elevation data. Ground surveys are generally points or transects and cannot represent the three dimensional complexity of the landscapes being examined.

A ground based approach to mapping habitats cannot completely cover the entire area being mapped unless it is small. For this reason the boundaries between habitats may be incorrectly mapped, particularly when the area may be difficult to reach, such as intertidal vegetation

This may be a particular problem if large areas are to be monitored, as the distance between survey points may be increased due to time constraints. As coastal habitats are spatially heterogeneous, much of the variation within these habitats is not accounted for. Boundaries are drawn by eye between sampling points. This approach is necessarily limited due to the discontinuous nature of these sampling strategies.

When ground based mapping is carried out the map layers used to record on may not be up to date. This is a particular problem in dynamic habitats such as the intertidal zone where mapping occurs less frequently than in terrestrial environments (Collier *et al.*, 1995).

Access to intertidal habitats can be very difficult or dangerous. On saltmarsh and mudflats deep mud can create access problems, as well as being dangerous for surveyors. The foot and mouth outbreak in 2001 also highlighted the access problems with ground-based surveys.

As a tool for monitoring coastal habitats, especially the intertidal zone, 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 or offshore areas inaccessible without specialist equipment. Comprehensive surveys may be difficult, especially at areas low in the tidal range.

7.5.1 Operational use of remote sensing in SAC monitoring

This project has developed a series of operational methodologies for the application of remote sensing techniques to the monitoring of marine Special Areas of Conservation (mSACs). These tools may now be implemented by qualified remote sensing staff either within the Environment Agency or within English nature.

Further developments are still to be made to these tools, making use for example of the new generation of satellite sensors. Similarly, it may be appropriate to transfer the technologies used to other environments, for example terrestrials SACs. All the methodologies suggested are completely transferable, but their success will depend on the spectral characteristics of the habitat being surveyed.

A number of key points are valid for each of the habitat types:

- Remote sensing methods offer the ability to conduct large scale surveys with limited ground data thus reducing the impact on the environment being monitored and improving the monitoring of areas which have poor access
- The digital nature of the data mean that analysis of change between years and seasons is a real possibility
- The use of terrain information derived from LIDAR data results in a three-dimensional view of the site, which has huge benefits in planning, education and demonstration of monitoring to the wider public

7.5.2 Saltmarsh

This study in conjunction with previous studies (ABP 2000) has shown that it is possible to derive accurate vegetation maps using CASI or CASI and LIDAR data. The use of alternative neural network classifiers was extensively tested and found to be an improvement on previously used classification methods. The study did not successfully use the saltmarsh classification for monitoring change due to the inaccuracy within the 2001 classification. This was due to the data being collected too early within the growing season. A classification of the 2002 data was not carried out due to incomplete ground data.

Remote sensing methods offer the following capabilities:

- Classification of main SAC habitats
- Classification of dominant species (although with greater uncertainty)
- Hydrological modelling of creeks (using LIDAR)

A combination of CASI and LIDAR data is recommended, with a ground resolution of 1m to 2m.

7.5.3 Sand dunes

This habitat type has been monitored over each of the three years leading to some clear findings.

Remote sensing data from this habitat have been found to be suitable for:

- Identification of main SAC habitats
- Monitoring of dune development and erosion
- Production of a 3D visualisation

A combination of CASI and LIDAR data is recommended, with a ground resolution of 1m to 2m.

7.5.4 Saline lagoons

The area considered for this habitat was complex, with a mix of fresh water, salt water and terrestrial vegetation.

The remote sensing deliverables from this habitat are:

- Lagoon area at one instant (remembering that it is highly temporal variability)
- Ridge width
- Ridge height

In terms of monitoring of status, the remote sensing methods offer no clear advantages over traditional methods.

However, the remote sensing methods can offer a three-dimensional view of the environmental system. This type of visualisation is becoming increasingly important in the education of the public in environmental matters, in addition to demonstrating monitoring in action and enabling clear planning to be carried out.

Moreover, DEM data will aid in the monitoring of percolation barrier width.

7.5.5 Mudflats

No conclusions could be drawn for this habitat type due to problems with ground data capture.

However previous studies and qualitative results indicate that remote sensing methods can:

- Monitor the extent of algae
- Monitor the extent of mussel beds
- Distinguish different surface types

The environment is typically difficult to monitor due to access problems and the wide areas requiring coverage. This means that remote sensing techniques are ideally suited. The use of satellite data would probably be precluded by problems associated with cloud cover, but should be further investigated as current sensors offer the required spatial resolution and may offer sufficient spectral information for this habitat type.

If using airborne data, CASI data collection is recommended with full spectral classification. A spatial resolution of 4m would offer the required differentiation and would allow higher altitude flying and a reduced survey cost. Although data collection has proved difficult for the Budle Bay site, the techniques being developed, including band ratio methods, will most probably extend the weather window of opportunity.

Further investigations are also being conducted under contract to the EC Life Ythan Project to measure the biomass of algal in estuarine and mudflat environments. This would offer a substantial increase in the value of the CASI data collected.

7.5.6 Vegetated shingle

Whilst the multispectral CASI methods are able to classify the presence of coarse vegetation they are unable to detect the presence of some of the most important species in this habitat due to the small areas over which they grow. Assuming that species cannot be differentiated, it is recommended that digital photography data be gathered. The increased spatial resolution of these data would allow a better identification of the presence of vegetation.

The collection of LIDAR data has proven of high value in the monitoring of erosion and accretion at the front of the shingle system. Examples of this have been seen at both the Rye Harbour site and at the shingle ridge offshore of Blakeney.

Thus although the remote sensing methods cannot replace the traditional sampling for the monitoring of key species the data can offer added value in terms of the wider environmental management of a shingle ridge system.

7.5.7 Costs of remote sensing

If use is to be made of remote sensing for monitoring marine SACs some decisions need to be made on the data collection and processing model to be adopted.

Table 7.1 Recommended sensors for coastal monitoring

Habitat	LIDAR	CASI	Digital Photos
Saltmarsh	✔	✔	
Sand dune	✔	✔	
Mudflats		✔	
Vegetated shingle	✔		✔
Saline lagoon	✔		✔

To date the work has been carried out by the Environment Agency National Centre for Environmental Data and Surveillance. This has involved the development of methodologies that could in theory now be applied either by Environment Agency staff or by staff within English Nature. For the work to be carried out within EN, the following would be required:

- Hardware set up costs equivalent to £3000 per staff member
- Software set up costs equivalent to £5000 per staff member
- Suitably qualified remote sensing staff

If the work were to continue with NCEDS, then a charge would be made to cover staff time, which in the Table 7.2 has been worked out on a per square kilometre basis.

Table 7.2 Costs of coastal SAC monitoring using remote sensing

	Data collection			Ground data *	Classification *
	CASI	LIDAR	Digital Photos		
Saltmarsh	£200	£200	N/A	£50	£200
Sand Dunes	£200	£200	N/A	£50	£200
Mudflats	£150	N/A	N/A	£30	£150
Vegetated shingle		£300	£50	£50	N/A
Saline lagoons	N/A	£200	£50	£30	N/A

Alternatively, the work could be carried out within the NCEDS by one or a number of staff funded directly by English Nature, which may allow for some cost savings.

7.6 Future areas of study

Though this study took operational remote sensing of the coastal zone forward in terms of image preparation, classification and morphological change detection, there are still areas that require further study.

7.6.1 Satellite data

This study only examined the use of airborne remote sensing for monitoring coastal SACs. However, satellites are now capable of producing fine spatial resolution multispectral data (Table 7.3). There are three main factors to be considered when selecting a multispectral sensor to monitor vegetation; ground resolution, waveband availability (wavelength and width) and monitoring opportunities. Much of the variation within UK coastal habitats particularly saltmarshes, occurs at scales of a few metres and so coarse spatial resolution data would be inappropriate for monitoring the diversity of species within the intertidal zone, even if sub pixel classifications are carried out. Of the satellite data readily available, SPOT HRV and Landsat TM are therefore inappropriate as they have multispectral spatial resolution of

20m and 30m respectively (Table 7.3). In the last 4 years, three high spatial resolution satellites have been launched that provide the spatial resolution that is suitable for coastal monitoring in the UK and two more are due in the next two years.

Table 7.3 High spatial resolution imaging satellites

Satellite	Resolution (m) (panchromatic or black and white)	Resolution (m) (multispectral)	Operational
Landsat Enhanced TM (ETM+)	15	30	Yes
SPOT HRV	10	20	Yes
IKONOS	1	4	Yes
EROS-A1	1.8	N/A	Yes
QuickBird-2	0.6	2.5	Yes
Orbview-3	1	4	Late 2003
EROS-B	0.9	4	Late 2004

The classification and erosion monitoring techniques developed in this study could be directly applicable to satellite remote sensing. Radar data may be of use to provide DEMs for monitoring coastal morphological changes.

Satellite data are cheaper and provide greater coverage than airborne data, but there are other limitations. The satellites only overpass at certain times of the day and in most cases do not overpass every day and so are more weather dependent than airborne systems.

7.6.2 Habitat change detection

Change detection is an area of remote sensing that needs to be examined further. Any further work should study overall habitat area estimates and identifying areas of change. Though these areas were examined during this study, there was insufficient time to carry out a full study.

7.6.3 Other habitats

The use of remote sensing is applicable to monitoring other habitats. All of the techniques developed here have the potential to be transferable. Other habitats in which remote sensing may be of considerable use include:

- Grazing marsh: habitat monitoring
- Maritime cliffs and slopes: erosion monitoring
- Reed beds: habitat monitoring
- Moorland areas: habitat monitoring

7.7 Logistical changes

One of the limitations with the project plan for this study was the short time between the final flights and project delivery (approximately 6 months). This meant that a large amount of work, including ground data collection and collation, classifications, morphological change detection and report writing had to be carried out over a relatively short time frame. This resulted in certain areas not being studied as fully as was required, particularly the crucial area of habitat change detection.

Ideally, more time would have been allocated for each classification. However, this time was not available and so classification accuracy may be reduced from the optimum achievable. In future studies it is essential that enough time be given for technique development.

There were also problems with the ground data collection for the Tollesbury site in 2002. This was because certain areas belong to local wildfowling groups who were unwilling to let a survey team onto their land during the wildfowling season. This resulted in incomplete ground data collection for the site. Ideally the sites chosen for developing techniques should be accessible for as long a period as possible for ground data collection, so that these problems do not arise again.

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Appendices

Appendix A. Original work packages

A1 Work Package 1: Saline lagoons

Over the proposed three year period, combined LIDAR and CASI data will be collected on two occasions at a two-year or greater separation. The use of CASI data in addition to LIDAR is justified on the need to identify the vegetation of the surrounding areas in order to establish the likelihood of lagoon creation.

The study site will be confined to a small area, approximately 2km by 5km to allow intensive study of the ground cover types. Data will be collected at 2m resolution to allow operational use of techniques developed.

Initial research will investigate the spectral signatures associated with each of the ground cover types surrounding the lagoon sites to establish whether they will or will not be spectrally distinguishable. The results of these investigations, to include discussion of the relevant literature, will be presented in the final report for this habitat type.

The CASI and LIDAR imagery will then be processed and an unsupervised classification carried out on the CASI data. This classification will be provided to ground staff from English Nature who will be asked to verify the composition of spectrally differentiated classes within the study site. This information will be used to fine tune the classification. The results of this classification will be included in the final report including pictorial representation of the study site.

The LIDAR data will be used to derive a three-dimensional digital elevation model of the study site. Investigations will then be carried out into the potential for flooding using specialist techniques developed within the National Centre in association with expert information from English Nature scientists. Various techniques for three-dimensional change detection analysis will also need to be explored. All the techniques developed within this study will be included within the final report.

A2 Work Package 2: Inter-tidal mudflats

The scientific requirements for this habitat type do not ask for any assessment of change. Data will therefore be collected on only one occasion, which will be in September. This period coincides with the peak in growth of the mussel beds, one of the sub-habitats which is being investigated, and will precede the die off of macro-algae.

Both CASI and LIDAR data will be collected. The CASI data will be used in association with detailed ground truth data, to classify the various ground cover types within the inter-tidal mudflat. Attempts have been made previously to distinguish between sediment types within mudflats, including the differentiation of sand, silt and mud. These have had limited success due to the similarity in spectral signature between the sediment types. The different sediment types have clearly distinguished particle size which will result in the establishment of differing slopes on the beach profile. It is proposed that this study will investigate the use of LIDAR derived slope as a further information source to improve the quality of the classification.

The study site will again be confined to a small area to enable the groundcover types to be surveyed in detail. Currently the preferred study site is Lindisfarne, although the area within this would need to be discussed in detail to allow each of the ground cover types to be encompassed.

Initial research will investigate the spectral signatures associated with each of the ground cover types to establish whether they will or will not be spectrally distinguishable. The expected variation in sediment type and consequent variation in anticipated beach profile will also require investigation. The results of these investigations, to include discussion of the relevant literature, will be presented in the final report for this habitat type.

The CASI and LIDAR imagery will then be processed and an unsupervised classification carried out on the data. This classification will be provided to ground staff from English Nature who will be asked to verify the composition of spectrally differentiated classes within the study site. This information will be used to fine tune the classification. The results of this classification will be included in the final report including pictorial representation of the study site.

A3 Work Package 3: Coastal shingle

Rye Harbour has been chosen for this study, as it comprises areas in which shingle is both eroding and accreting. Both CASI and LIDAR data will be collected as two surveys separated by at least one year to allow the detection of changes in the morphology. Data will be collected at 2m resolution to allow an assessment of the operational use of these techniques to be made.

The CASI data will be used to establish the ability to classify vegetation on the shingle ridges. It is anticipated that the narrow nature of this habitat type may make this difficult, with problems of mixed pixels. Initially the spectral signatures of the vegetation types will be investigated, through review of current literature as well as investigation of new data. An unsupervised classification will then be carried out, and the ground cover types identified will be verified by English Nature ground staff to allow fine tuning of the classification. The results of this analysis will be included in the final report for this habitat type.

The LIDAR data will be used to derive a digital elevation model. The models derived from the two surveys will be compared using three dimensional change detection analysis which will be developed by the National Centre as part of this project. The results of this analysis will be included in the final report including pictorial representation of the study site.

A4 Work Package 4: Saltmarsh

Recent investigations have shown that the ability to distinguish saltmarsh species may depend on a combination of the amount of time that the vegetation is submerged and the elevation of the site. In order to establish the ability of remote sensing to aid in the investigation of individual species it will be necessary to collect a combination of CASI and LIDAR data from four different seasons.

The CASI data will be used to derive a classification of vegetation with information from the LIDAR being used as an extra classification tool. This work is experimental and has not been attempted previously, but it is anticipated that a combination of the two techniques will greatly enhance the classification of saltmarsh vegetation.

The LIDAR data will also be used to investigate the development of creeks within the saltmarsh. In order to allow a reasonable time scale over which to monitor creek development, an area with historic data should be used. The Blackwater estuary has therefore been selected as both historic CASI and LIDAR data exist for this site.

A site will be selected within the Tollesbury Marsh (Blackwater Estuary) approximately 2km by 5km. Data will be collected at 2m spatial resolution to allow testing of the operational use of the techniques developed. The study area will be overflown with both CASI and LIDAR data.

The CASI data will initially be used to derive an unsupervised classification of the vegetation types within the marsh. This will be provided to English Nature ground staff who will check the composition of the spectral classes derived from the classification. This information will then be combined with the data on elevation from the LIDAR data to improve the quality of the classification. It is anticipated that the addition of the LIDAR data will enable the differentiation of more spectral classes at certain seasons which may necessitate further ground data collection. Comparison of the data collected at differing seasons will enable decisions to be made on the optimum time of year for future data collection exercises. It is possible that differing seasons will be recommended depending upon the final information required, for example whether the extent of annual species is required. The results of this analysis and recommendations for future monitoring will be included within the final report.

A5 Work Package 5: Sand dune morphology and vegetation change

This section of the project will investigate the use of LIDAR to monitor erosion and accretion of sand dunes and to measure volumetric changes. In addition, the use of CASI to monitor changes in the vegetation types found within dune systems will also be examined.

The site chosen is Ainsdale, which forms part of the Sefton coast mentioned above. A small area approximately 2km by 5km will be selected within this dune system. The main requirement for this habitat type is the measurement of change. Data will therefore be collected twice, once early in the three year project plan and once within the third year to allow for maximum change to take place.

The first data set will be used to produce a three-dimensional digital elevation model of the dune system within the study area. Techniques will then be developed to allow accurate measurement of change in three dimensions. This work will obviously be carried out in parallel with the work carried out on shingle ridges. When the second data set is gathered change analysis will be carried out and the results of this, including the techniques used, will be included within the final report for this habitat type.

The CASI data will also be used to produce an unsupervised classification of vegetation types within the dune area. This classification will be provided to English Nature ground staff to identify the classes within the classification. The data from this ground survey will be used to fine-tune the classification. The results of this classification will be included in the final report for this habitat type.

Appendix B. Instrumentation

B1 LIDAR overview

LIDAR (Light Detection and Ranging) is an airborne mapping technique which uses a laser to measure the distance between the aircraft and the ground. This technique results in the production of a cost-effective terrain map suitable for assessing flood risk.

The aircraft is positioned and navigated using global positioning (GPS) corrected to known ground reference points.

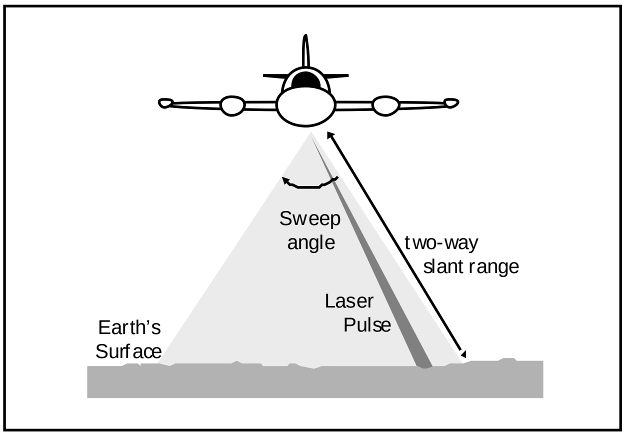

Figure B.1 Principle of operation of the LIDAR

The aircraft flies at a height of about 800 metres above ground level and a scanning mirror allows a swathe width of about 600 metres to be surveyed during a flight (Figure B.1), with individual measurements made at 2 metre intervals. Highly accurate attitude data and post-processed differential GPS enable the direction of the laser pulse and the position of the laser head to be accurately determined, allowing a highly resolved model of the terrain to be generated.

The Agency's Flood Defence function has a requirement under the Water Resources Act 1991 to monitor the flood plain. LIDAR is being used to measure land topography and assess coastal erosion and geomorphology. The Conservation function requires information on land being set aside for managed retreat of sea defences. There is also a need to obtain data for a model linking land use, soil type and the potential for erosion prediction.

The National Centre has generated routines to allow for the removal of surface features from the data sets including vegetation and buildings. Products that can be generated from the LIDAR data include colour coded elevation models, height contour plots and three-dimensional perspective views allowing easy visualisation of surveyed areas.

B2 CASI overview

The CASI (Compact Airborne Spectrographic Imager) is a passive sensor, which generates imagery by detecting visible and near infrared electromagnetic energy that is reflected from the earth's surface. CASI is designed to provide a flexible system which is easy to transport and straightforward to install and operate in small aircraft. The system operates in a ‘pushbroom’ configuration, mapping out a swath that lies directly below the aircraft (Figure B.2). By instantaneously imaging the full swath width at repetitive intervals, a full image is built up line by line.

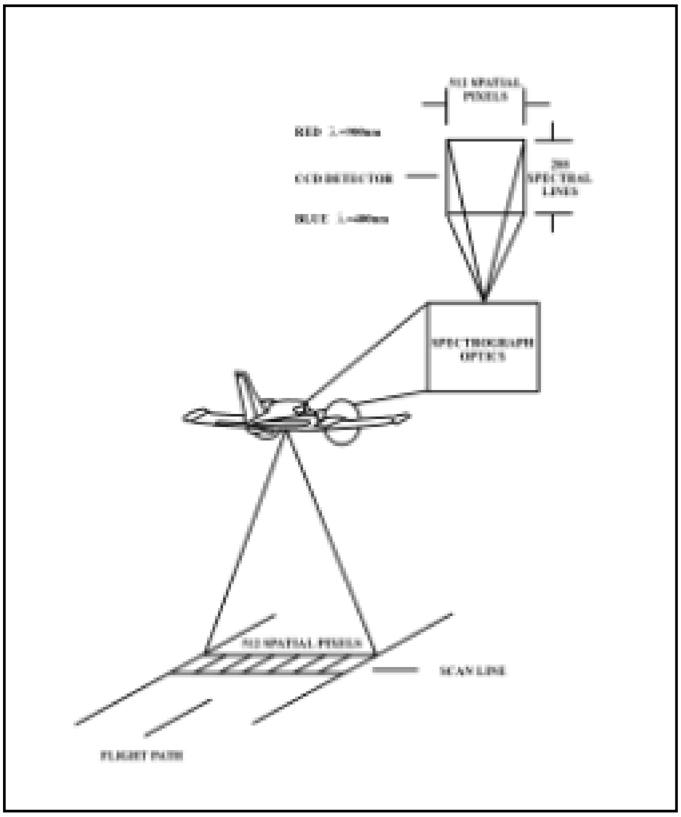

Figure B.2 Principle of operation of the CASI

Imagery produced by the CASI consists of up to 512 pixels across the swath and the spatial resolution (area represented by one pixel) can be varied from ten metres down to less than a metre by adjusting the altitude of the aircraft and the CASI imaging lens. The maximum operational altitude of the aircraft is 10,000 feet, restricting the maximum swath width to approximately 5.2 km. If the area to be imaged is larger than the swath width available at the desired resolution, it is possible to obtain a number of adjacent flight lines and join these in order to generate a single large image, or mosaic.

The CASI uses a Charge Coupled Device (CCD) detector to produce hyperspectral imagery which can comprise of up to 288 spectral bands (wavelengths), covering the electromagnetic spectrum from 430 nm (visible blue light) to 900 nm (near infra-red). The number and width of wavelength channels recorded is flexible with more channels providing more detailed spectral profiles of the different ground cover types.

The CASI has three operational modes, which are suited to different applications and should be selected according to the spatial and spectral resolution required of the data. The operational modes are:

Spatial mode: All 512 swath pixels are recorded in up to 19 wavebands. The wavelengths covered by all the bands and the width of the bands are configurable.

Spectral mode: Data from all 288 bands are recorded from 39 pixels across the swath.

Enhanced spectral mode: This flexible mode allows a compromise between spatial and spectral modes to be achieved. The exact combination of pixels and bands that is achievable is determined by the amount of ambient light at the time of imaging.

B3 Data analysis

B3.1 Data preparation and accuracy

In order for accurate reproducible information to be obtained from remote sensing data there has to be an understanding of the inaccuracies within the data. These inaccuracies then need to be reduced. The inaccuracies of the sensors used in this study are inherently different and the implications of these errors are therefore different. The inaccuracies in the LIDAR system are in the x, y z planes. The CASI system has inaccuracies in the x and y planes and caused by changes in the relative levels of lighting or the radiometric effects.

B3.1.1 LIDAR accuracy

The accuracy of the Environment Agency LIDAR system and the errors incurred when converting the LIDAR data to OSGB co-ordinates has been independently assessed (Ashkenazi, 1999). Errors are calculated using Root Mean Square addition and are not strictly additive. The quoted error is ± one standard deviation which means that 66% of the values lie within the defined error bands. This complies with the standard practice for error calculation in surveying.

Height accuracy of point measurements (z).

The LIDAR system accuracy for a WGS84 product (including instrument errors, calibration errors and GPS errors) may be stated as **± 9 – 15 cm**.

The accuracy after transformation to OSGB36 (inclusive of LIDAR system errors) may be stated as **± 11 – 25 cm**.

Plan accuracy of point measurements (x,y)

The LIDAR system accuracy for a WGS84 product (including instrument errors, calibration errors and GPS errors) may be stated as **± 40 cm.**

The accuracy after transformation to OSGB36 (inclusive of LIDAR system errors) may be stated as **± 45 cm**.

B3.1.2 CASI Geometric accuracy

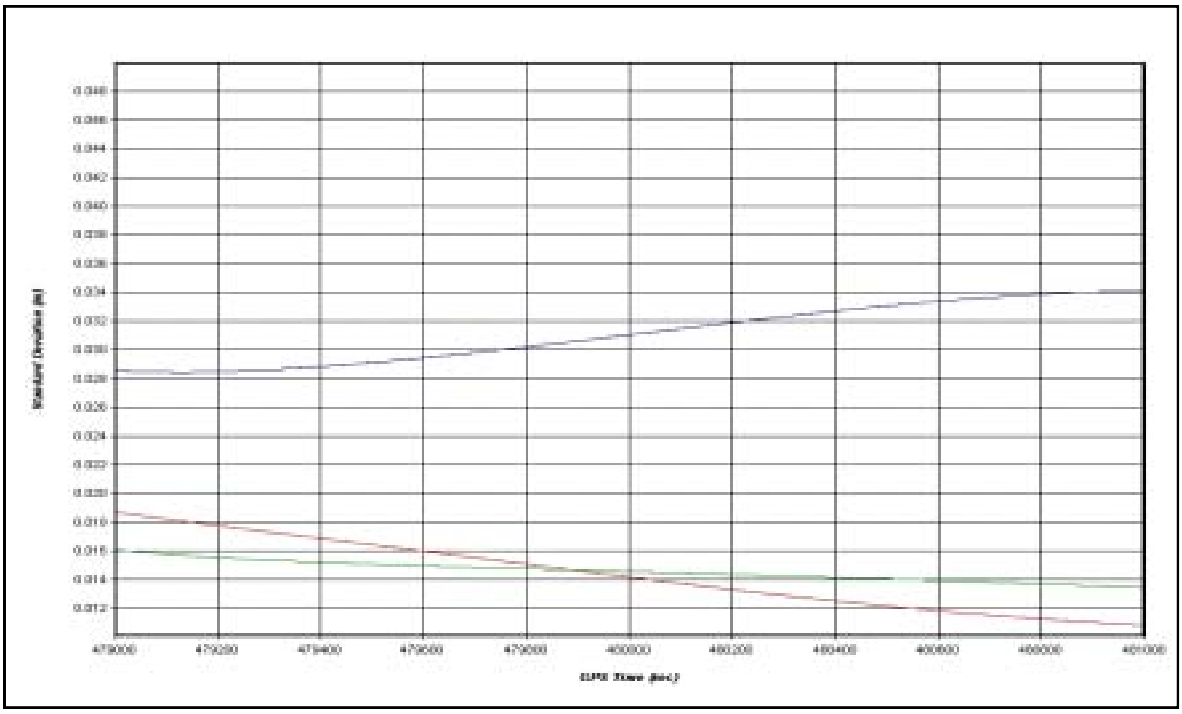

Figure C.1 Estimated Positional Standard Deviation
(Estimates from GPS processing software)
(Red: X, Green: Y, Blue: Z)

The current CASI system uses high accuracy, high precision positional and attitude data to georeference imagery. Each time the CASI is inserted into the plane a calibration is carried out, to estimate positional and angular offsets between the CASI system and the navigation data. This is then applied at the georeferencing stage.

The system uses differential GPS to provide the increased accuracy positional data. The positional accuracy of the GPS system is better than 5cm at 1 standard deviation (ie 66% of the data are within 5cm or better). This means that the positional errors caused by the GPS are less than 10 % of 1 pixel at 1m resolution. The GPS processing provides an indication of this error (Figure C.1).

Tests have been made of the CASI system positional accuracy using a test site at Coventry airport. The results indicate that the RMSE (66% of the data are within 1 RMSE) is better than 1.6m if the base station GPS is within 120km of the survey site and if topographic errors are ignored. As the positional data are so precise, it is likely that the GPS causes a small proportion of the error. The main errors are therefore likely to be in the calibration stage and the inertial measurement unit (IMU) that provides the attitude data. The calibration stage is only accurate to the nearest pixel and so errors of 50cm (in 1m resolution data) can result from this stage.

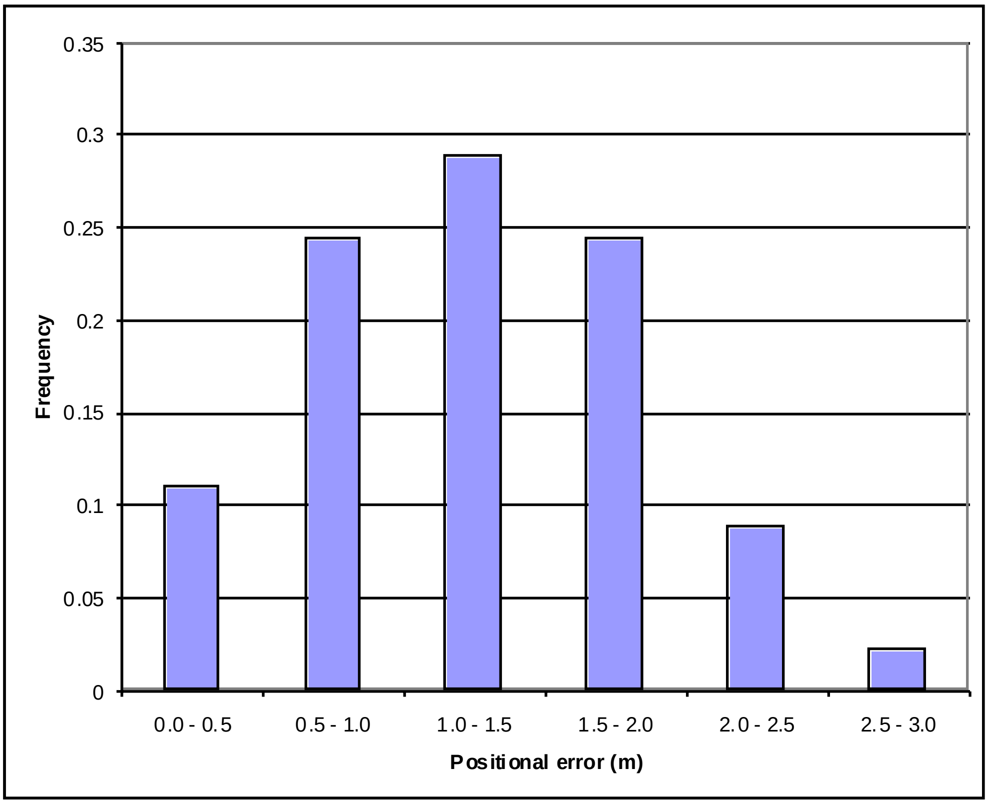

Figure C.2 **Frequency of CASI positional errors for long baseline (120km)**

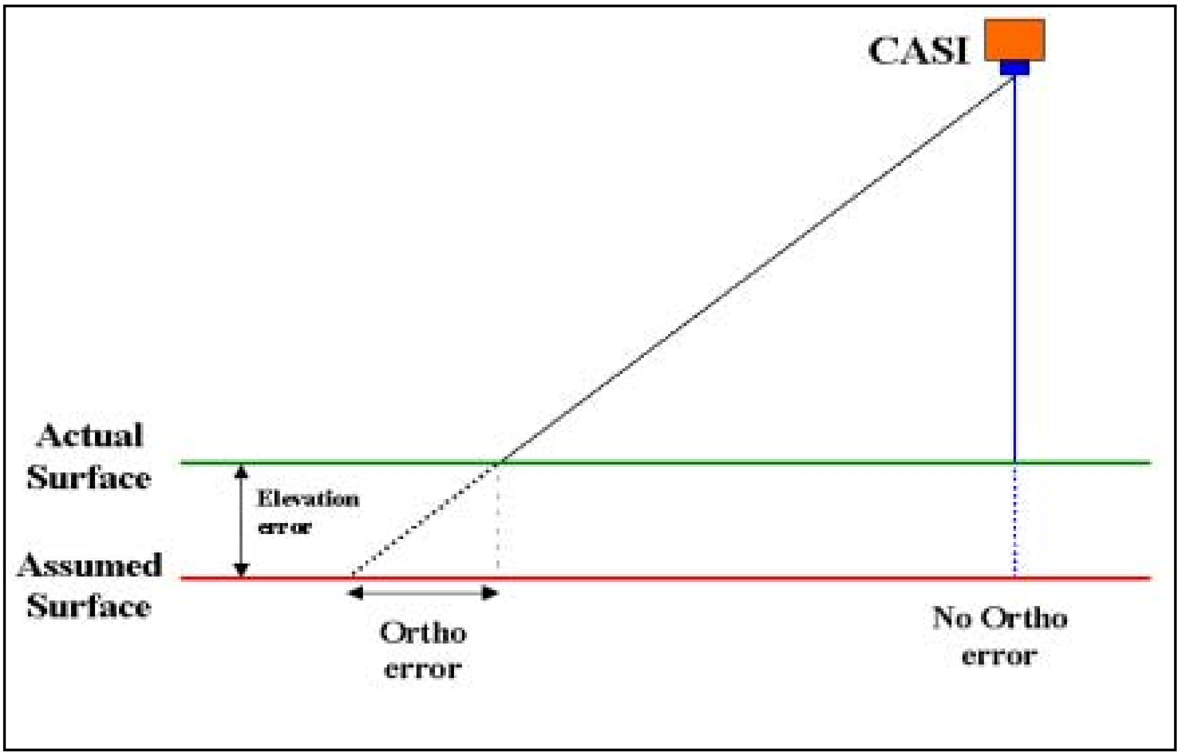

Figure C.3 **Effect of topographic errors on CASI horizontal accuracy**

However topographic errors need to be incorporated in any consideration of the CASI errors (Figure C.3). Topographic errors will be dependant on the accuracy of the digital elevation model (DEM) used and the terrain being surveyed. In areas in which the slopes are high the topographic errors will tend to be greater. Using the CASI system currently in operation at the Environment Agency, an error in the DEM of 1m will produce an x, y error of approximately 26cm, at the edge of the imagery. In the sites being studied for this project, topographic errors will generally be relatively low, as most of the study sites are flat and even in the sand dune site a high accuracy LIDAR DEM was used in the geocorrection process.

Radiometric normalisation

The CASI data collected for this project consist of multiple flightlines gathered over time periods of up to 2 hours. Within this time period it is possible for the lighting and atmospheric conditions to change considerably, resulting in large variations in light levels on the ground. Even in relatively stable atmospheric and lighting conditions, the effects of lighting changes may severely reduce the accuracy of any land cover output (Figure C.4).

There may also be variations due to the surfaces being viewed. For example wet mud will exhibit what is known as bi-directional reflectance. The amount of light reflected from the surface is dependant on the angle of the sun and the viewing angle (Figures C.5 and 4.6). Bi-directional reflectance can have effects within a single image, resulting in changes within the imagery due to the angle that a surface is viewed from. These variations can result in a very large decrease in the accuracy of the classification.

These will result in variations within any given image and are very difficult to remove using conventional techniques. Therefore two types of variations within lighting need to be considered:

- Between image differences due to changes in lighting levels or atmospheric conditions
- Within image differences due to changes in lighting levels or bi-directional effects

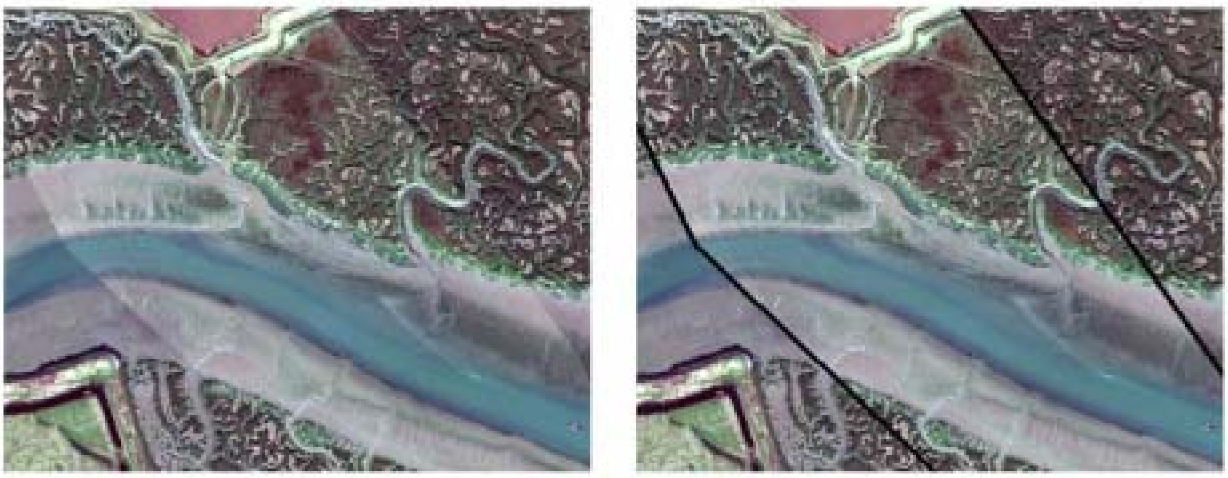

Figure C.4 Example mosaic showing differences in lighting between images

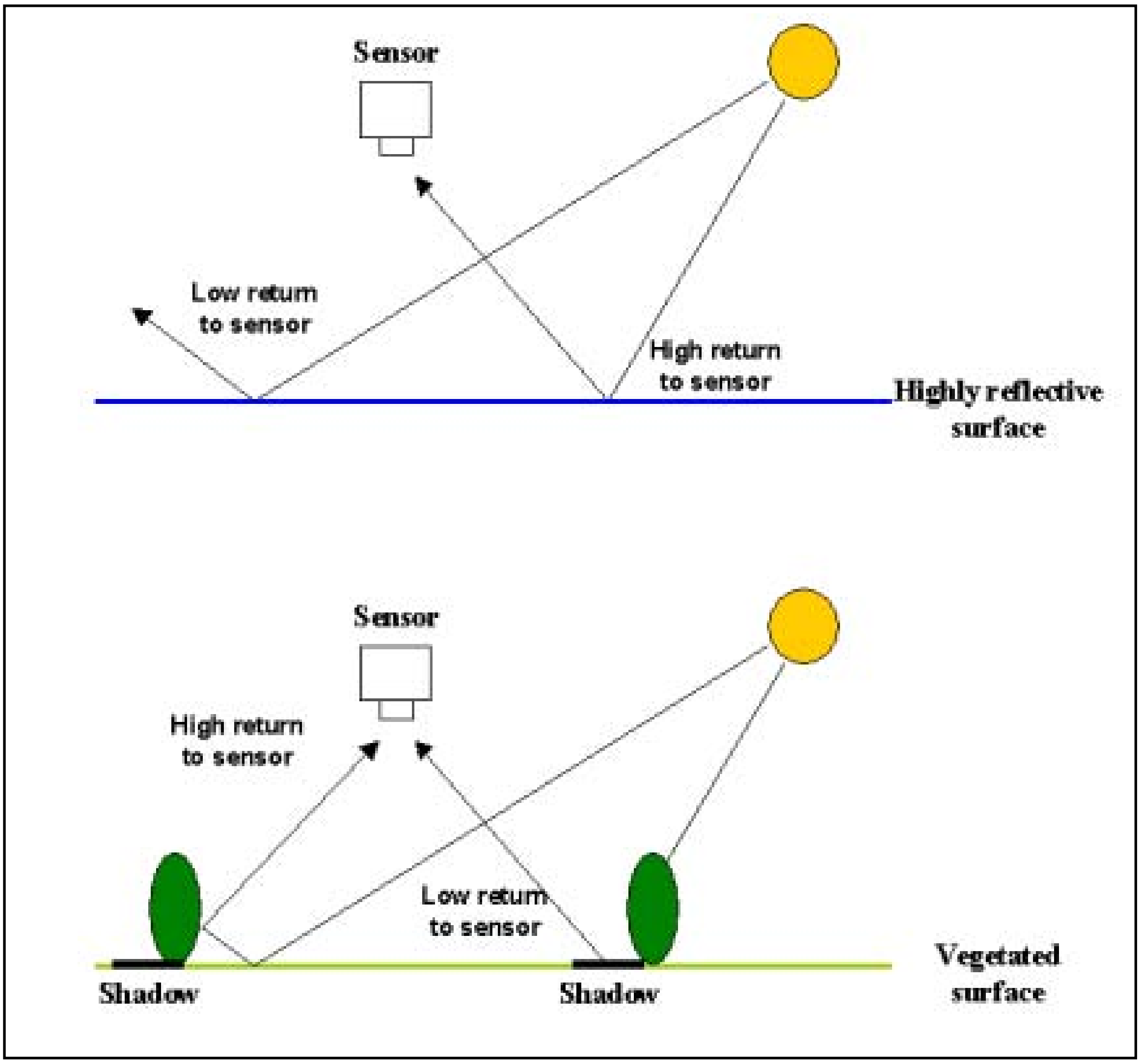

Figure C.5 Bi-directional effects in remote sensing imagery

In order to reduce the effects of changes in lighting and atmospheric conditions and minimise bi-directional effects, radiometric correction has to be carried out. The simplest form of radiometric correction normalises the imagery in order to reduce lighting differences. Errors in classification due to radiometric changes are minimised and the possibility of having to classify CASI flightlines individually, rather than as a mosaic, is avoided.

There are numerous radiometric normalisation methods that are used in remote sensing. However, many are not practical for this form of study, as they require specialised equipment, fieldwork simultaneous to flights or sophisticated modelling. Three approaches were identified that are applicable to the imagery gathered in this study and have potential for operational use in airborne remote sensing studies:

- Edge matching
- Image ratioing
- On-board irradiance measurements

Figure C.6 Bi-directional effects in CASI imagery
(Left hand edge of image: vegetation- high radiance, mud-low radiance
Right hand edge of image: vegetation- low radiance, mud-high radiance)

Edge matching

Edge matching is a relatively common approach when overlapping images are to be merged (ABP, 2000). In this method the relationship between the radiance values in the overlapping areas between images are used to compensate for differences in lighting.

The technique can use specifically selected calibration areas where bi-directional effects are minimal (ie there is little directional reflection), or match the whole of the area of overlap. The use of calibration sites in a scene to calibrate imagery to reflectance or normalise images has been relatively common in remote sensing studies. Studies identify that care must be taken to select surfaces with wide ranges of reflectance, or the relationship obtained is liable to be skewed. Specifically selecting areas is time consuming and difficult especially where there are few areas that have the required surface characteristics, such as concrete and tarmac. This was the case in this study.

The second approach where the whole of the overlap area is used is much easier, and the approach may be modified slightly to remove obvious problem areas. Areas that should be omitted include; mudflats, water with glint and woodland. This approach can work well when there is very little variation within the images due to bi-directional effects or clouds.

However, when the imagery has been flown over a wet surface or the flightlines are across the sun azimuth angle this approach may be unsuccessful. One major limitation is that small bi-directional effects may result in a systematic error being introduced into the imagery (Figure C.7).

The most common reasons for a directional component to imagery are when images are flown at an offset to the solar azimuth angle, particularly when the surface being surveyed is wet. This limits the approach for intertidal habitat monitoring. Directional imagery is also common when the sun angle is low.

Figure C.7 Effect of bi-directional lighting on edge matching techniques (using same imagery as Figure C.6)

Image ratios

The principle behind image ratios is that though there may be differences in the level of lighting, the relative light levels in different wavelengths remain relatively constant. This will not apply over long time periods as atmospheric conditions change, but the approach is a possible method of compensating lighting variations. This method also has the potential to reduce within image differences due to bi-directional effects.

There are limitations with this approach, as the assumption that the relative lighting levels remain constant may not be met, especially if atmospheric changes occur. Another limitation of this approach is that information may be lost by the ratioing process, reducing the separability of classes and therefore reducing classification accuracy. The effectiveness of ratioing as a method of radiometrically correcting imagery is likely to be dependant on the habitats being examined.

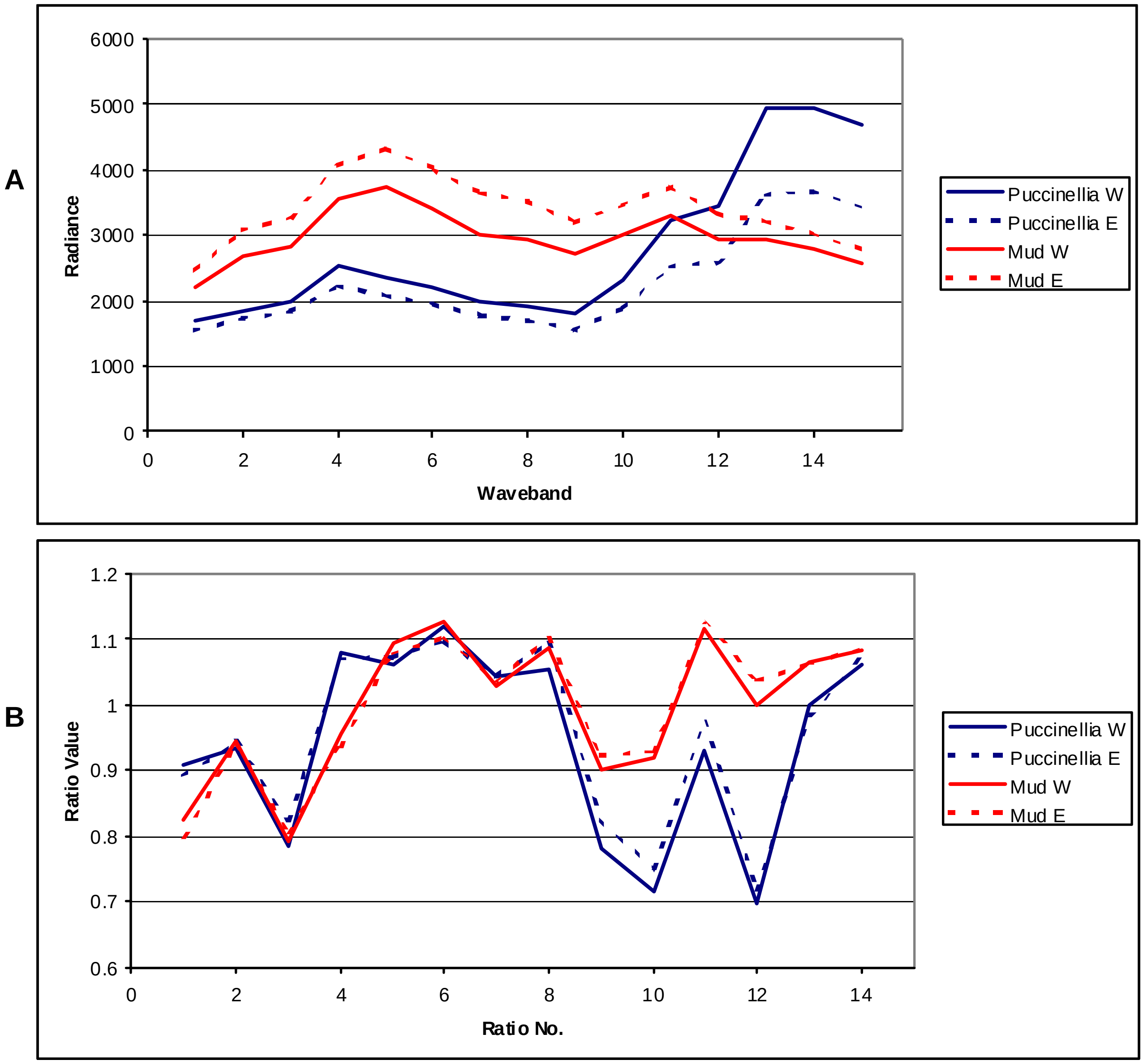

Figure C.8 **Radiance (a) and ratios (b) for intertidal classes showing bi-directional effects (W and E of Figure C.6)**

The ratioing method was tested by creating consecutive ratios (eg band 3 and band 4) for all the CASI bands. This results in a number of ratio layers equal to one minus the total number of bands (eg 14 data layers from the 15 band coastal bandset). Ratios were also generated using all combinations of blue, green, red and NIR, providing up to 6 more data layers depending on the bandset (Table C.1).

Table C1 Additional ratios based on colour combinations

Colour combinations	Coastal Bandset (15 bands)		Vegetation Bandset (14 bands)	
	Ratio No.	CASI Band Combinations	Ratio No.	CASI Band Combinations
Blue/Green	15	2/4	14	2/4
Blue/Red	16	2/7	15	2/5
Blue/Near Infrared	17	2/15	16	2/14
Green/Red	18	4/7	17	4/5 (all ready generated)
Green/Near Infrared	19	4/15	18	4/14
Red/Near Infrared	20	7/15	19	5/14

Table C2 Grades and descriptions for ratioing

Grade	Description
1	Mostly noise/little land cover information
2	Noise greatly reducing usefulness of land cover information
3	Noise reducing usefulness of land cover information
4	Some noise
5	Little or no noise

The ratios were all inspected visually to ascertain whether they contained artefacts from lighting differences or noise. Each ratio was graded from 1 to 5 using a descriptive scale (Table C.2 and Figures C.9 and 4.10). Any ratios with a grade of less than 4 were not used in the classification.

Figure C.9 Example of grade 2 ratio
(Tollesbury 2001 data)

Figure C10 **Example of grade 5 ratio**
(Tollesbury 2001 data)

On board irradiance measurements

The CASI system includes an incident light sensor (ILS) that provides a measure of irradiance at the level of the aircraft in the same wavebands as those viewing the ground. This has the potential to provide estimates of changes in light on the ground and therefore may be used to normalise imagery. The Geodata Institute at Southampton University has examined this method previously in 1999 and 2000 in a joint project between the Agency, Geodata and ABP for the English Nature Hampshire and Isle of Wight office in 1999-2000 (ABP, 2000). However, at the time the approach did not work, as it was not possible to accurately estimate the look direction of the ILS. Since that time the CASI has been integrated with the LIDAR allowing accurate attribute data to be obtained. This has enabled a robust method of estimating a sky radiance model from ILS data to be developed (Choi and Milton, 2001). The Agency commissioned Geodata to produce a software package that would normalise CASI imagery using ILS data. This software was delivered in 2002. The software has shown promise, but issues with calibrating the system have meant that the software has not been properly commissioned.

Testing radiometric normalisation

The most effective method of testing the various approaches to operational radiometric normalisation is to compare classification accuracy values. The results of these tests are in the classification section.

B4 Classification

Classification is the process by which remotely sensed data are converted to thematic data layers generally representing land cover or land use. This process may be carried out by manual digitisation of the boundaries or using automated computer based methods.

The manual approach has advantages in that it may be carried out on data where the lighting conditions vary and requires less specialist software than automated classification. The limitation with this approach is that it is time consuming and requires specialist knowledge of the habitats being classified. It is also not suited to habitats that are continuums (ie where the boundaries are not sharp), as drawing lines between land cover types will always be arbitrary.

The automated approach to classification has limitations in that the remote sensed data need to be well radiometrically normalised and ground data are required for each classification. However, no specialist knowledge of the habitat is required by the person processing the data, automated approaches can be relatively quick and therefore cheaper than manual methods. This approach is also suitable for continuums.

The supervised approach to classification involves three stages:

1. Training
2. Allocation
3. Assessment

The training process involves identifying pixels within the image that belong to the classes to be used in classification. The spectral characteristics of the pixel are then determined by the classification algorithm used.

In the allocation stage the characteristics of each class as determined in the training process are used to allocate the most likely class to each pixel.

The assessment stage determines the accuracy and therefore usefulness of the classification. The accuracy of each classification can be derived using the *tau* coefficient, also known as the modified *kappa* (Foody 1992, Ma and Redmond 1995). *Tau* variance was used to estimate *Z* scores and test for a significant increase in classification accuracy when testing for the most appropriate method of classification (Ma and Redmond 1995).

This study will consider two main approaches to classification:

- Traditional statistical methods
- Neural networks.

B4.1 Traditional classification

The most common of the traditional parametric approaches to classification is maximum likelihood (ML) classifier (Campbell, 1996). The ML classifier provides an approach for classifying remotely sensed data that is relatively easy to understand and to carry out.

In the ML approach, mean vectors are generated for each class and the variances about these means are generated from training data. Probability density functions for all classes are then derived from these statistics. The 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.

If the data are normally distributed, this approach can produce high classification accuracies. The analyst does not have to set any parameters for the classification to run, just select suitable training data and classes. To an analyst who has a minimal amount of statistical knowledge, the ML classifier is relatively simple to understand and most image processing packages (e.g. ERDAS Imagine, ENVI, IDRISI) have an easy to use ML classifier.

However, in the last ten to fifteen years, studies have shown that there are other non-parametric classifiers that classify more accurately than the ML under certain conditions (Kanellopoulos *et al.*, 1992; Peddle *et al.*, 1994; Yool, 1998).

The ML classifier assumes normal distribution of the spectral data (Campbell, 1981; Benediktsson *et al.*, 1990). This is often not the case, especially when a class contains a number of different surfaces. For example, a woodland class may contain a variety of species, with mixtures of coniferous and deciduous species, resulting in multi-modal distributions.

The ML classifier is also very sensitive to the form and quality of ground data. There should be enough sampling points to represent the full variety within each class. According to Swain (1978) the amount of training data required for the ML classifier is linked to the dimensionality of the data set being classified. The greater the number of dimensions, the larger the sample size of training points needs to be. Therefore, if the training set is too small ML classification accuracy may be reduced as the number of data layers is increased (Lee and Langrebe, 1993). According to the study by Swain (1978), the sample size for each class should be at least 30 times and preferably 100 times the number of dimensions. Carrying out a ML intertidal classification using the 15-band bandset recommended by Thomson *et al.* (1998) and additional LIDAR data, it may be impractical to gather the required amount of training data for each class.

If the training data do not incorporate the variation within the classes used, the accuracy of the classification may be reduced, even if the required numbers of pixels are used for each class (Campbell, 1981). In many cases, training data are sampled in blocks of contiguous pixels. As these pixels may exhibit autocorrelation, the class statistics (means, variances and covariances), may inadequately represent the classes, leading to a reduced classification accuracy (Campbell, 1981). A requirement for statistical classification approaches is that the training data need to be pure (Paola and Schowengerdt, 1995). However, in the case of intertidal vegetation this is very difficult, as certain species rarely exist in pure stands. This is particularly true of the mid and upper marsh species

The use of data from multiple sources has the potential to reduce ML classification accuracy (Peddle *et al.*, 1994). 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 (Benediktsson *et al.*, 1990). Thematic data, such as soil class, may have the potential to increase class discrimination, but as they are non-parametric, they should not be used in ML classification. If thematic data are used, they may result in reduced classification accuracy.

Though the ML classifier may be of use under certain conditions, in this study there are a number of factors that may make its use inappropriate. These include the use of relatively high dimensionality multisource data and small training data sets.

B4.2 Neural networks

Neural networks (NN) are the computing equivalent of a very simple biological brain. They provide a possible solution to a variety of problems in remote sensing including classification and biophysical property extraction.

Neural network and statistical methods of classification are fundamentally different in approach. The non-parametric properties of neural networks mean 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.

As well as being distribution free, neural networks are importance free (Zhou, 1999), meaning that the network will model the relative importance of the input data surfaces during the training process without requiring operator input. This characteristic is particularly critical when considering multisource data, as prior knowledge of the level of importance of data layers is not required. A neural network will set weightings to account for a data layer's importance during the training process (Zhou, 1999).

The most commonly used neural network in remote sensing is the multi-layer perception (MLP). The following sections offer a brief description of its characteristics.

Structure of the Multi Layer Perceptron (MLP)

The basic unit of the MLP is the node, which mimics a biological neurone. The node sums the inputs and performs a function on the summed input. The MLP consists of three types of layers; input, hidden and output (Figure C.11). The input layer has as many nodes as there are input data layers. There may be one or more hidden layers with the number of layers and nodes specified by the user. The output layer contains as many nodes as there are output classes. 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, being modified by the weights associated with the connection between nodes and the functions of each node. The movement of input signals and their modification through the network from input to output is the 'feed-forward' stage of the MLP. The outputs of the MLP are activation levels at each output node. These activation levels may be linked to a biophysical property or land cover class.

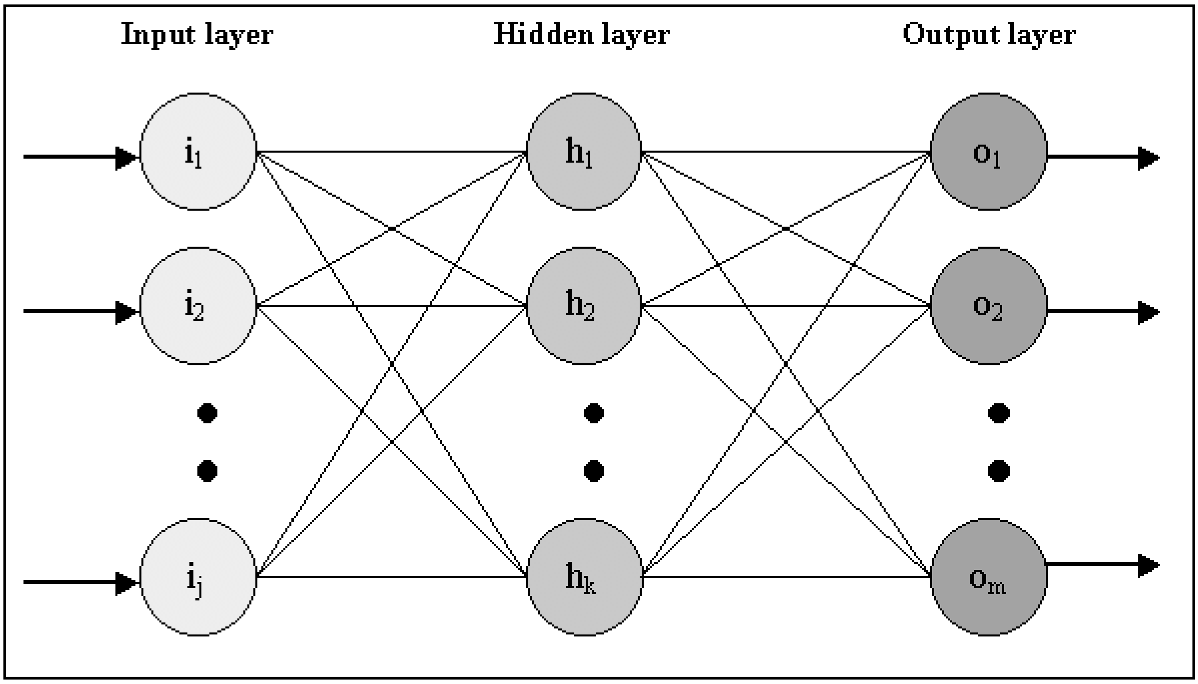

Figure C11 Multi Layer Perceptron Neural Network

Training the MLP

Training data are entered into the NN and the activation level of each of the output nodes is compared with the validation values, generally ground data, and an error function is calculated. A learning algorithm is applied that alters the weightings within the network to minimise the error. The whole process is then repeated until a specified number of iterations have taken place, or the error is minimised or reduced below a predetermined level.

This process allows the network to ‘learn’ the characteristics of the training data set.

The number of iterations used in training can strongly influence the accuracy of the final classification. If too few iterations are carried out, the network will not be able to model the full complexity of the data set. If too many iterations are carried out, the network may become very good at classifying the training data, but may be much poorer at classifying the main data set. This effect is known as over-training and results in a loss of the network’s ability to classify data it has not seen before.

Network architecture

The ability of a neural network to accurately classify data that are not used in the training process is known as generalisation. This is an important consideration when constructing and training the network. There are a number of factors that affect the ability of a network to generalise and therefore optimise classification accuracy. These include the architecture of the network, the training set and training time.

The structure of a network can be crucial to its success as a classifier. Generally the larger the network the more accurate it is at classifying the training data (Kavzoglu and Mather, 1999), but it may be less able to generalise. Subjectivity has been identified as an issue when setting up the structure, specifying the training parameters and the starting conditions of a neural network (Peddle *et al.*, 1994). However, a study by Paola and Schowengerdt (1997) found that the number of nodes in a single hidden layer could be varied a great deal with only minimal effects on classification accuracy. This would suggest that though there may be subjectivity in the determination of network architecture, this may have little effect on the final classification. However, this is likely to be data dependant and should be tested with each new habitat classified.

There have been a variety of approaches for empirically determining MLP architecture (Hirose *et al.*, 1991; Kavzoglu and Mather, 1999; Foody *et al.*, 1995; Paola and Schowengerdt, 1997). Trials to determine the optimum network are a useful operational approach for determining network architecture. However, exactly the same training and accuracy assessment datasets should not be used as for the main study, as this may bias the final results creating the optimum network to classify the accuracy assessment dataset, rather than one that will classify general data well.

Training data

As with most classifiers, one critical factor in selecting training data is that they are representative of classes (Gong *et al.*, 1996). Classification accuracy may be reduced if training data do not represent the variation within classes. Neural networks are more likely to misclassify pixels that are not similar to those in the training samples (Benediktsson *et al.*, 1990). Unlike statistical approaches, neural networks are able to cope with mixed pixels in training data (Paola and Schowengerdt, 1995). Indeed when training pixels from border regions are used, neural network classification accuracy may be increased compared with training using pure pixels (Foody, 1999).

A study by Arora and Foody (1997) found that classification accuracy using a neural network related to training set size and waveband combination.

MLP outputs

The MLP provides an activation level for every output class of each pixel. In a hard classification the pixel is allocated the class with the highest activation level. However, the activation levels for all classes may be used to provide additional information for each pixel. Output activation levels have been used to provide estimates of the probability that a given pixel is correctly classified.

B4.3 Classifier summary

Statistical approaches have traditionally been used in remote sensing and are well documented. Most commercially available image processing packages offer this form of classifier. In many cases these approaches work well. However, there are a number of limitations to this approach and so other techniques are being assessed, in order to maximise the potential for accurate classification of coastal habitats.

The MLP neural network is a non-parametric classification method that complements the aims of this study as it can provide high accuracy classifications using high dimensionality, multisource data with complex distributions. As well as providing classifications, additional data may be derived from neural networks that may be used to provide indications of correct classification on a per-pixel basis. Neural networks are simple artificial intelligence systems and have been shown by a number of studies to provide accurate classifications of a variety of habitats. In recent years neural network systems suitable for classifying remotely sensed data have become commercially available, making this more than just an academic approach to classification. The operational use of neural networks for classification is being examined within this project.

B4.4 Classification uncertainty and probability of error

As use of remote sensing increases, there has been an increase in the realisation that estimations of error are an important part of remote sensing studies, both for a whole study area and at the pixel or local level. A global measure may provide estimations of the overall classification error, but it does not indicate where those errors are occurring. The error at the pixel level, or the uncertainty associated with correct categorical allocation has recently generated considerable academic interest (Ediriwickrema and Khorram, 1997; de Bruin and Gorte, 2000; McIver and Friedl, 2001).

One aim of this study is to provide a method of classification that is appropriate for monitoring change in coastal habitats. If pixel level categorical uncertainty is not accounted for, classification errors have the potential to be magnified in the change detection process. Per-pixel thematic uncertainty measures would allow probabilities of change to be derived, increasing informational content of the change surface and its usefulness for reporting and management purposes. They may also be used to increase the accuracy of estimates of habitat area. Normalised MLP activation levels have been used as indicators of membership on a per-pixel basis, where a pixel with a high normalised activation is assumed to have a high probability of correct class allocation (Gong *et al.* 1996).

B4.5 Testing classification accuracy

In order to compare classifications, accuracy measures were required. Comparisons of classifiers are generally carried out using a global accuracy measure. Of the two global accuracy measures most commonly used in remote sensing, the overall accuracy (P_o; proportion of correctly classified pixels) fails to take into account the correct allocation of pixels by chance and *kappa* overestimates chance agreement and therefore underestimates accuracy (Foody 1992, Ma and Redmond 1995). 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 (Foody 1992, Ma and Redmond 1995).

Tau variance (Ma and Redmond 1995) was used to estimate *Z* scores and test for significant differences in classification accuracy.

Table C1 Example confusion matrix

Ground Data

	Classes	**A**	**B**	**C**	**D**	**Correct**	**Total**	**User's Accuracy**
	A	54	3	3	3	54	63	0.86
Classified Data	**B**	5	20	2	1	20	28	0.71
	C	2	1	65	2	65	70	0.93
	D	0	0	5	11	11	16	0.69
	Correct	54	20	65	11			
	Total	61	24	75	17			
	Producer's Accuracy	0.89	0.83	0.87	0.65			

Other methods of providing measures of accuracy may be used that further describe the classification. The confusion matrix may be used to provide indications of what misclassifications occur within the data (Table 5.1). The confusion matrix may be used to show how classes are misclassified and provide overall indications of the class accuracy. The matrix may be used to determine the suitability of the final classification for the purpose for which it is required.

Appendix C. Band ratios used in study

Table D1 Ratioing for Tollesbury Data

CASI Band		Central wavelength (nm)		Information content relative to noise content of ratio (1 = low, 5=high)	
A	**B**	**A**	**B**	**2000**	**2001**
1	2	443	490	2	2
2	3	490	512	1	3
3	4	512	555	1	2
4	5	555	600	5	5
5	6	600	626	5	4
6	7	626	663	5	5
7	8	663	673	3	1
8	9	673	684	2	5
9	10	684	692	5	5
10	11	692	703	5	5
11	12	703	712	5	5
12	13	712	751	5	5
13	14	751	857	1	1
14	15	857	881	1	1
2	4	490	555	1	2
2	7	490	663	5	2
2	15	490	881	5	3
4	7	555	663	5	4
4	15	555	881	5	2
7	15	663	881	5	3

Table D2 Original ratioing for Ainsdale Data

CASI Band		Central wavelength (nm)		Information content relative to noise content of ratio (1 = low, 5=high)
A	B	A	B	
1	2	445	471	2
2	3	471	490	2
3	4	490	550	5
4	5	550	671	5
5	6	671	682	1
6	7	682	701	5
7	8	701	710	4
8	9	710	720	4
9	10	720	750	3
10	11	750	762	1
11	12	762	780	1
12	13	780	860	1
13	14	860	880	1
2	4	471	550	3
2	7	471	701	3
2	14	471	880	3
4	7	550	701	2
4	14	550	880	3
7	14	701	880	4

Table D3 Final ratioing for Ainsdale data

CASI Band		Central wavelength (nm)		Information content relative to noise content of ratio (1 = low, 5=high)
A	**B**	**A**	**B**	**2001**
4	5	550	671	5
5	6	671	682	4
6	7	682	701	5
8	9	710	720	5
9	10	720	750	5
10	11	750	762	5
11	12	762	780	5
12	13	780	860	5
4	7	550	701	4
4	9	550	720	4
9	11	720	762	5
9	14	720	880	5

Table D4 Ratioing for Budle Bay Data

CASI Band		Central wavelength (nm)		Information content relative to noise content of ratio (1 = low, 5=high)
A	B	A	B	
1	2	443	490	2
2	3	490	512	3
3	4	512	555	5
4	5	555	600	5
5	6	600	626	4
6	7	626	663	4
7	8	663	673	3
8	9	673	684	1
9	10	684	692	5
10	11	692	703	5
11	12	703	712	5
12	13	712	751	5
13	14	751	857	3
14	15	857	881	3
2	4	490	555	5
2	7	490	663	3
2	15	490	881	5
4	7	555	663	3
4	15	555	881	5
7	15	663	881	5

Appendix D. Kernel for determining shingle ridge height

Kernel used in determining maximum height of Blakeney shingle ridge along it's length. Actual kernel used was 35 (x) by 135 (y). Red line indicates approximate bearing of ridge.

0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0

Appendix E. Data layers supplied with this project

	Ainsdale	Blakeney	Budle Bay	Rye	Tollesbury
CASI JPEGs	Y	Y	Y	Y	Y
Digital photography	Y	Y	Y	Y	Y
LIDAR JPEGs	Y	Y	Y	Y	Y
LIDAR ASCII	Y	Y	Y	Y	Y
Classifications	Y	N	Y	Y	Y
Lagoon areas	N	Y	N	N	N
Morphological change polygons	Y	Y	N	Y	N
Morphological change spreadsheets	Y	Y	N	Y	N

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