Remote sensing peat erosion in the southern Pennines

Cutler, M. E. J.; McMorrow, J.; Evans, M.

Published in:
North West Geography

Publication date:
2002

Document Version
Publisher's PDF, also known as Version of record

ISSN 1476-1580

North West Geography

Volume 2, Number 1, 2002

Remote sensing of upland peat erosion in the southern Pennines

M. E. J. Cutler[1], J. McMorrow[2] and M. Evans[2]

[1] School of Civil Engineering and Geosciences, University of Newcastle
Email: m.e.j.cutler@newcastle.ac.uk
[2] School of Geography, University of Manchester
Email: julia.mcmorrow@man.ac.uk; martin.evans@man.ac.uk

Abstract

The severe erosion of upland peat bog in the southern Pennines is a major environmental problem that requires mapping and monitoring at regular intervals. This paper presents preliminary results from an investigation of the use of hyperspectral remotely sensed data to provide quick and accurate information on peat extent and type. Both image classification and correlation analysis between reflectance and peat characteristics were investigated; promising images of both peat type and degree of humification were produced. The results from this ongoing study suggest that hyperspectral remote sensing offers an efficient and valuable tool in mapping and monitoring upland habitats.

Keywords

Remote sensing, hyperspectral data, HyMap, peat erosion, humification, Pennines, blanket bog, uplands

Introduction

Upland areas of the United Kingdom (UK) are coming under increasing pressure from a wide range of activities and influences. Of particular concern is the loss and accelerated erosion of blanket peat in areas such as the Southern Pennines. Blanket peat covers almost 9% of the land surface of the UK, a significant proportion of the scarce total world resource and the bulk of the British soil carbon (Latter *et al*, 1998).

While an important resource, peatlands are also important for carbon storage (Garnett *et al*, 2000). Undisturbed accumulating peatlands in Britain sequester some 0.4 – 0.7 t C ha^{-1} $year^{-1}$ (Gorham, 1991), while eroding bogs are a carbon source. The spatial extent of exposed peat, intact, vegetated bog surface and pools are thus an important component in modelling the carbon budget of peatlands and global climate change.

Upland blanket peat forms in response to excess rainfall and water logging (ombotrophic mire) (Moore, 1995). Peat formation in the English uplands began about 8000 years ago, and dates for peat initiation in the southern Pennines cluster around 5-6000 ka BP. Peat built upward during a series of wet phases, with humification and erosion occurring as a result of natural and/or anthro-pogenic drying of the bog surface (Tallis, 1985b). Much of the upland peat in the UK is heavily eroded, and in the southern Pennines the main erosion began between 400 and 1000 years ago (Tallis, 1985b).

Eroding environments, such as those in the southern Pennines, are of major geomorphological influence and have value both ecologically, supporting a wide range of plant and animal communities, and archaeologically in the preservation of records. Much of this ombotrophic peat is actively eroding or under threat of erosion but the causes of the erosional processes and resulting patterns are unclear. Theories include fluvial (headwater extension), biotic (burning, grazing, air pollution), karstic (subterranean drainage) and catastrophic (bog bursting, drought) processes (Tallis 1973, 1985b and 1994; Mackay and Tallis, 1996; Anderson *et al*, 1997). Of particular concern is the speed at which erosion is taking place with peat exposure and erosion occurring at a much faster rate than the slow rate of natural accumulation (Bower 1961; Tallis 1973). There is, therefore, an urgent need to improve our understanding of patterns and processes of blanket peat degradation. In addition, the severity of erosion and distribution of degradation is non-uniform across the southern Pennine region. Reasons for such spatial variations are not clear, although topographic and drainage characteristics, land management practices, climatic differences and land cover have all been suggested (Tallis 1985a).

Methods for monitoring and mapping the extent and pattern of existing upland habitats (including exposed and eroding peat) range from ground survey to the interpretation of aerial photography. However, these are often expensive, time consuming and only moderately accurate (Mehner *et al*, 2001). For example, an exercise to map habitats in Northumberland National Park according to the Nature Conservancy Council's (NCC) Phase I habitat classification took 717 workdays to complete (Walton, 1993), with only moderately accurate results at the end. New methods for mapping and monitoring these diminishing but important areas are thus required.

Remote sensing techniques have often been seen as potentially less subjective and cheaper alternatives. Until recently though, the coarse spatial resolution of sensors, such as the Landsat Thematic Mapper (TM) with a spatial resolution of 30m, have proved inadequate for providing high quality habitat maps at appropriate scales (McMorrow and Hume, 1986). Recent advances in sensor design, however, mean that satellite sensors such as IKONOS can provide multispectral data at a spatial resolution of 4m, which should prove more useful in monitoring both vegetation and exposed peat dynamics.

While the spatial resolution of satellite borne instruments has improved, such sensors still have relatively poor spectral coverage, with typically four broad wavebands in the visible and near infrared (NIR) parts of the electromagnetic spectrum. This coarse spectral coverage limits the use of such data when trying to discriminate between spectrally similar land cover types, such as different peat types. This is compounded by the lack of spectral coverage in the short-wave infrared (SWIR), which has been shown to be useful in monitoring the decomposition process of organic material (BenDor *et al*, 1997) and relative degree of humification (Stoner and Baumgardner, 1980). The limited spectral sampling also prohibits the detection of subtle absorption features associated with other biochemical and biophysical properties of both vegetation and peat.

Plate 1: Exposed bare peat at Sykes Moor.

Developments in sensor technology, however, have led to the development of hyperspectral resolution sensors, such as AVIRIS (Airborne Visible and Infrared Imaging Spectrometer) and HyMap™. The new sensors collect data in many narrow discrete bands, often across extended wavelength ranges (including the SWIR), allowing subtle absorption features to be resolved. Such sensors provide a new tool for environmental monitoring and have been used to estimate a number of critical ecosystem variables, such as foliar biochemistry (Wessman, 1994; Wülder, 1998) and vegetation stress (Jago *et al*, 1998). In addition, these systems are test-bed sensors for next-generation satellite based hyperspectral missions such as ENVISAT (Curran, 2001). This paper reports preliminary results from an investigation into the use of hyperspectral remote sensing as a potential means to monitor peat erosion, type and patterns.

Data Acquisition and Study Area

Hyperspectral data for this study were provided as part of the SAR and Hyperspectral Airborne Campaign (SHAC), a campaign supported by the Natural Environment Research Council (NERC) and the British National Space Centre (BNSC) (BNSC online). The campaign lasted for several weeks during the summer of 2000 and included the collection of hyperspectral data from the HyMap instrument for a 12km transect across the southern Pennines. The transect approximately followed the line of the Pennine Way from Doctor's Gate at the top of Snake Pass, near Glossop, through to the Longdendale Valley (Figure 1). The area includes large expanses of severely eroding blanket peat moorland around Bleaklow Head, with a number of peat erosion types present, from Bower's (1961) anastomising type 1 to linear type 2 gullies.

Two HyMap images were acquired on 18th June 2000. HyMap is an airborne hyperspectral scanner that acquires data in 128 contiguous narrow bands, each of 13–17nm, over a wavelength range from visible to short wave infrared (450 to 2480nm). The images were acquired at two different spatial resolutions (3.2m and 4.5m). For the sake of brevity, only the processing and results from analysis of the 3m image will be discussed in this paper (Figure 2).

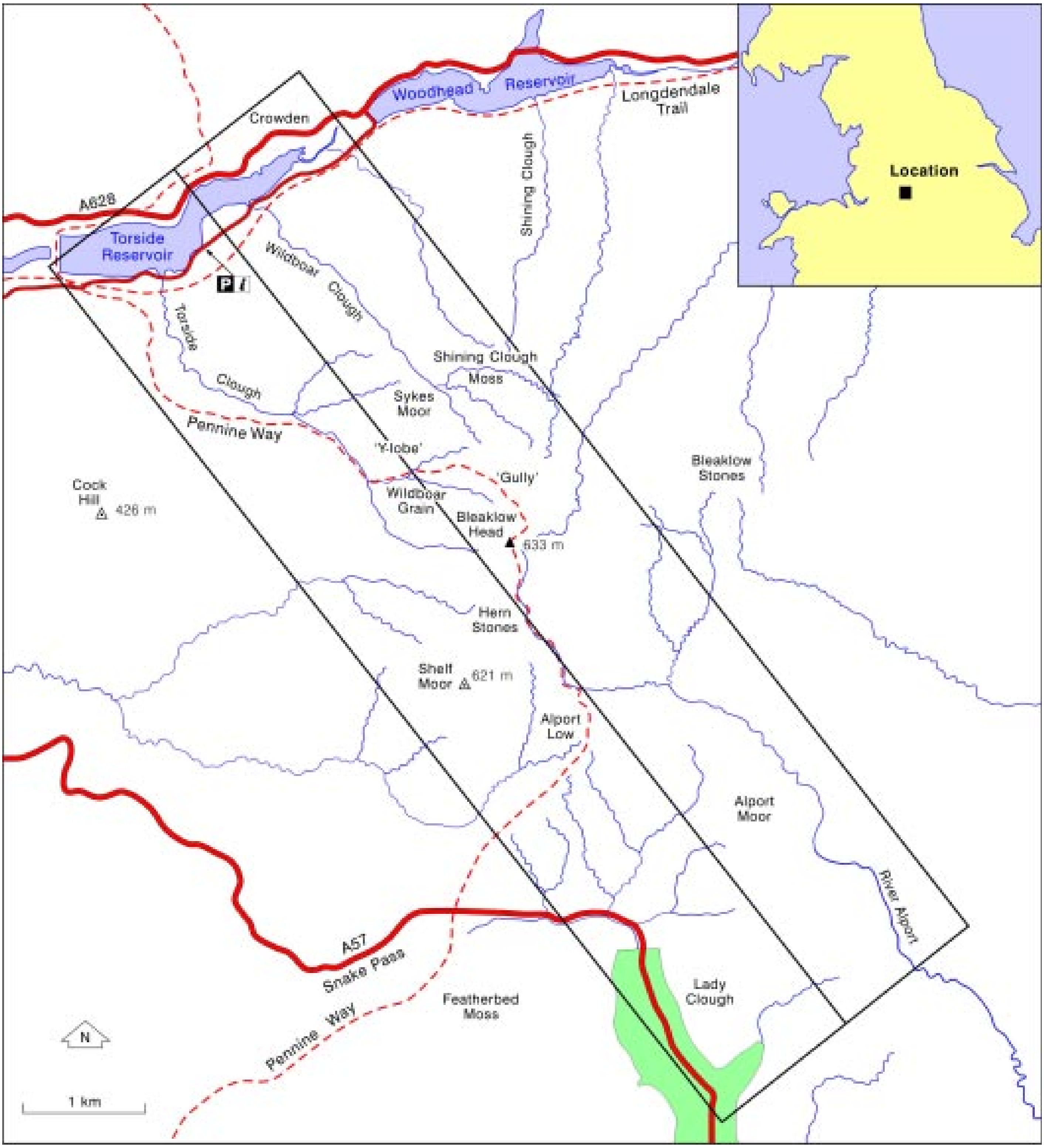

Figure 1. Location of study area HyMap and transect.

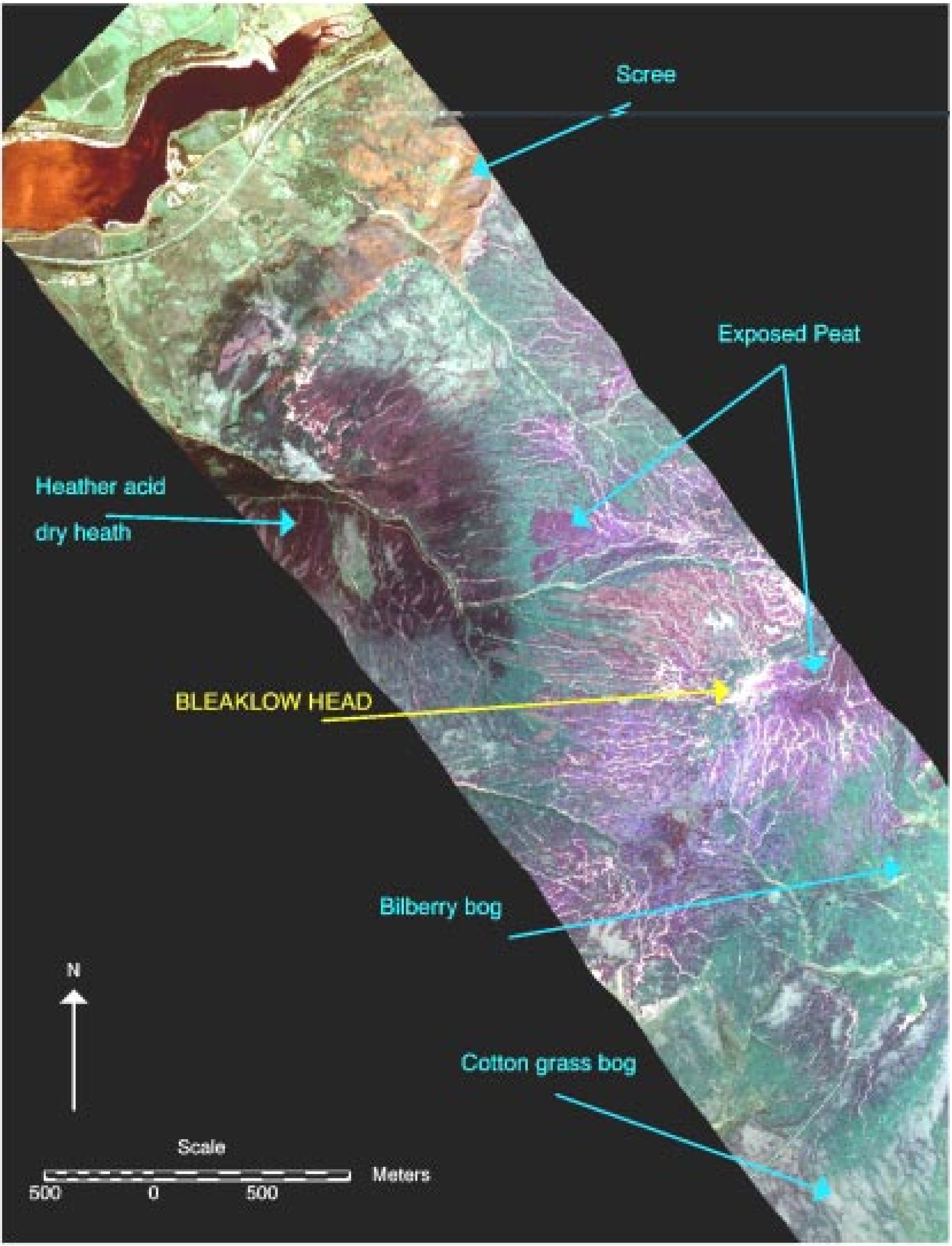

Figure 2. SHAC HyMap 3m transect, flown 18 June 2000; false colour composite of bands 18, 10, 4 (NIR, red, green light) to red, green and blue colour guns, respectively.

The geometric correction of the image was based upon the aircraft's GPS ephemeris data and had a random alongtrack displacement of up to two pixels. This in itself was less than adequate for the purposes of this study as many patches of peat and vegetation were less than 8m in size and the image required further correction. Initial errors in locating sites were minimised with the aid of enlarged aerial photographs, which are now being used to provide a fully orthorectified product.

The radiometric properties of the data were assessed, with 12 bands excluded from the analysis due to excessively poor signal to noise ratio values, leaving 114 'non-noise' bands. The data were also corrected for the effects of atmospheric absorption and scattering using the ATREM atmospheric correction procedure (Goetz *et al*, 1997; CIRES, online).

Concurrent with the acquisition of airborne remotely sensed data, ground-based data were collected using an Analytical Spectral Devices (ASD) portable field spectro-radiometer, FieldSpec Pro. Over 300 ASD spectra were collected on the day of the flight, with further spectra acquired at other times from a number of sites representing different peat and vegetation types. There were three reasons for collecting these data: first, as 'pure' spectra for inputs into linear unmixing models to obtain fractional peat and mineral soil images, second to develop regression models between spectra and peat composition, and third, to calibrate ground to airborne spectra for the day of the flight. Sites were chosen for their within-site homogeneity and between site variability in peat and vegetation type.

In addition to the collection of remotely sensed data, peat samples were also collected from 22 sites where ASD spectra were recorded. A 14cm sampling ring was used to sample peat to a depth of 2cm in an attempt to maintain a constant volume. The samples were subsequently analysed with four measures adopted:

(i) *Moisture content* was measured because of the well-known absorbance with water content (e.g. Nagler *et al*, 2000). It was assessed gravimetrically on the 2cm depth disc of peat removed from the peat surface.

(ii) *Transmission*: the degree of peat humification was assessed colorimetrically after a wash in 5% NaOH following the method of Blackford and Chambers (1993). Values are of relative humification, expressed as percentage transmission, where high transmission relates to low humification.

(iii) *Particle size distribution* was measured as a possible proxy for woodiness of the peat, and perhaps lignin content, and because particle size affects soil reflectance (Bowers and Hanks, 1965). Particle size distributions were measured by wet sieving of the material at one Phi intervals from 2mm to 63mm. Samples were dispersed in sodium hexameta-phosphate and then wet sieved with a large quantity of water. Sieved fractions were recovered by settling and decantation.

(iv) *Organic content* was determined by loss on ignition at 550^{o}C for one hour. Values ranged from 82 to 98%.

Plate 2: Collecting peat spectra with an ASD Fieldspec Pro spectroradiometer.

Data Processing and Results

The physical measures of peat, described above, were used to identify peat classes while both the HyMap and ASD spectra were used to determine whether these peat classes could be discriminated. Two approaches were adopted, including image classification and correlation analysis between reflectance and peat classes.

Peat Types

Fieldwork identified four broad peat types; well humified, poorly humified, burned and washed peat. Washed peat refers to re-deposited peat derived from hags by creep and surface wash. As an alternative to fieldwork, five empirical peat types, referred to here as peat lab classes, were defined from hierarchical cluster analysis of physical properties measured in the laboratory for the 35 sites (transmission, percent organic and four particle size variables) (Table 1). Moisture content was excluded because it was not valid to compare samples collected on different dates. The relationship between the two sets of classes is discussed below.

Table 1: Results of hierarchical clustering on laboratory variables (humification is expressed as % transmission, where high transmission indicates low humification. Particle size expressed as % material under 125mm and over 250μm)

Lab Class	Description
1	Well humified (23%). Very fine, (90, 5%). Lowest organic content (89%).
2	Poorly humified (61%). Quite coarse (38, 48%). High organic content (96%)
3	Intermediate humification (32%). The most coarse and woody (23, 65%). Highest organic content (96%)
4	Well humified (22%). Quite fine (68,18%). Relatively low organic content (90%)
5	Well humified (24%). Quite coarse (36, 46%). Intermediate organic content (93%)

Variation in peat physical properties between sites can be explained by their stage of erosion and fire history. For instance, the site known as 'Bleaklow' (Figure 1) is the highest elevated and most eroded site. Rounded hags of peat and re-vegetated patches are surrounded by the mineral soil of 'Bleaklow beach' where the peat has been stripped away. The topmost layer is absent, exposing well humified fine to quite coarse peats (peat lab classes 1, 4 and 5). Poorly humified peats at the 'Hern Stones' site (class 2) occur in a pool and hummock topography, possibly representing less advanced erosion.

The dominant cover at the 'Gully' site is burned peat with dead bilberry roots, giving intermediate transmission values (peat lab class 3). Fire history appears to be at least as important as stratigraphic or topographic position in determining peat characteristics.

Washed peats all have a smooth surface but very mixed physical characteristics (peat lab classes 1, 2, 5), related to those of the adjacent hags from which they are derived. Spectral uniformity should not be expected for washed peats unless surface texture proves to be the dominant control, a variable that will be investigated in forthcoming fieldwork.

Both HyMap image data and ASD spectra were used to determine whether peat classes, determined from their physical properties, could be discriminated spectrally. Several approaches were adopted, including traditional image classification techniques, canonical analysis and correlation of spectral features with peat physical properties.

Image classification

After geometric correction the image was classified into peat, non-peat, and mineral soil classes using a supervised maximum likelihood approach (Mather, 1999). Both peat and mineral soil were distinctly separable from the surrounding vegetation and visual comparison with aerial photography suggested the classification to be realistic, although no formal accuracy assessment has yet been produced. The classified image was then used to mask non-peat classes from the image to reduce the size of data set and avoid further mis-classification errors.

An unsupervised, five class classification was applied to the masked image as an initial investigation as to whether the five peat lab classes could be discriminated. Sites of known peat lab class were then compared to the unsupervised classification. Both poorly humified (peat lab class 2) and well-humified peat (classes 1 and 4) appeared to occur in exclusive clusters within the image, although there was significant confusion for classes where the peat was coarse in texture.

Training sites, for a supervised classification, were located within the image at sites where peat characteristics had been determined in the laboratory. Due to the small number of training sites and high-dimensionality of the data, a supervised maximum likelihood classification was unsuitable and an artificial neural network approach adopted (Benediktsson, *et al*, 1993). Neural networks have been widely applied to the fuzzy classification of remotely sensed data at a wide variety of spatial scales (e.g., Atkinson *et al*, 1997; Benediktsson, *et al*, 1990). They are attractive in that they make no assumptions regarding the data in terms of statistical distribution and independence, but do, however, require a significant amount of training data.

By far the most widely used neural networks are multi-layered feed forward networks. In particular, the multi-layer perceptron (MLP) has been shown to perform significantly better than other unmixing techniques, such as linear mixture modelling and fuzzy *c*-means (Atkinson *et al,* 1997). A number of MLP networks were tested with varying architectures. The networks were trained using all 114 'non-noise' spectral bands (coded as continuous valued representations, suitable for high-dimensional data sets (Benediktson, *et al*, 1993)) and 'hard' class inputs from each of the 35 sites. Half of the data were used to train the network while the other half used as a testing data set. It was not possible to adopt a fully fuzzy approach (Foody, 1996) as information on mixing within pixels was unavailable and the accuracy of geometric correction of the image uncertain.

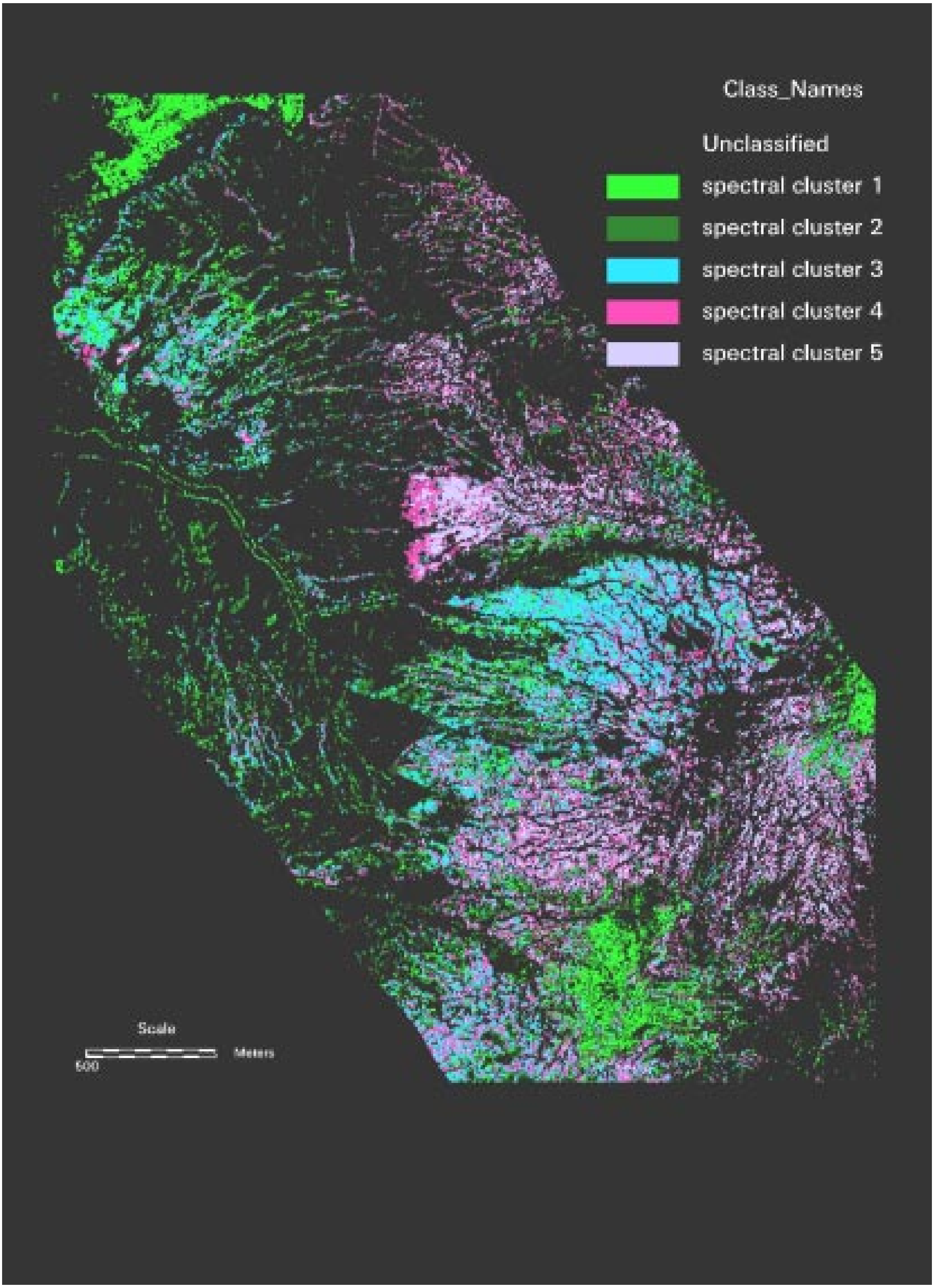

Figure 3: Unsupervised classification of HyMap 'non-noise' bands.

A fuzzy classification output was produced and initial results suggest that realistic peat classes can be determined from the HyMap image. However, there is evidence that a stratified approach is required, with some networks being able to generalise between levels of humification but performing poorly when discriminating sites of different particle sizes (and surface texture), while other networks separated particle size with only limited discrimination of humification. The reasons for this are unclear, but as this work is at a very early stage this pattern will be investigated further. Rigorous testing of the outputs from the fuzzy classification will be conducted in the spring/ summer of 2002.

Although at an initial stage, the image analysis results as a whole appear promising and future work will include modification and development of the classification process, as well as applying a topographic correction to the image to account for anisotropic reflectance effects of the peat and surrounding vegetation (Mather, 1999).

Reflectance spectra

HyMap reflectance spectra were extracted for the 35 sample sites and imported into a statistical software package (Figure 4). They were compared visually and statistically with laboratory variables defining peat physical characteristics.

Despite having an organic content of over 80%, the peat spectra were not concave between 500 and 1300 nm (bands 5 and 60), as expected for organic rich soils (Huerte and Escadafal, 1991). They were sigmoidal with a steep red edge from band 17 to 25 (677-799nm) and a linear near-infrared (NIR) slope to band 46 (1108nm) and were much more similar to plant litter curves in Nagler *et al*, (2000). Peats were much better separated at longer wavelengths. The SWIR is critical for peat differentiation. Most separation is seen on the right shoulders of water absorption features at bands 63 and 95 (1406 and 1952 nm) (Figure 4).

HyMap washed peat spectra were more variable than those initially collected with the ASD, covering a wider variety of sites and parent peat types. They show reduced reflectance across wavelengths, probably due to the presence of water, but retain the same shape as those for adjacent hags, from which they derived. This suggests that their signature is a spectral mixture of peat parent material and water (Clark, 1999), and that composition may be a more important control than surface texture, but further sampling is required. For smaller patches of washed peat, signatures may also be a linear mixture of peat hag and pool so that linear mixture modelling may be an appropriate technique to map them.

Canonical discriminant function analysis

Canonical discriminant function analysis of the extracted HyMap spectra confirmed the importance of the SWIR in discriminating between peat lab classes. There was a statistically significant difference among the means of the five peat classes for visible band 3 (461nm) and SWIR bands 61 to 119 (1324–2376nm), with p 0.01 and Wilk's lambda values of below 0.655. Two samples not included in the

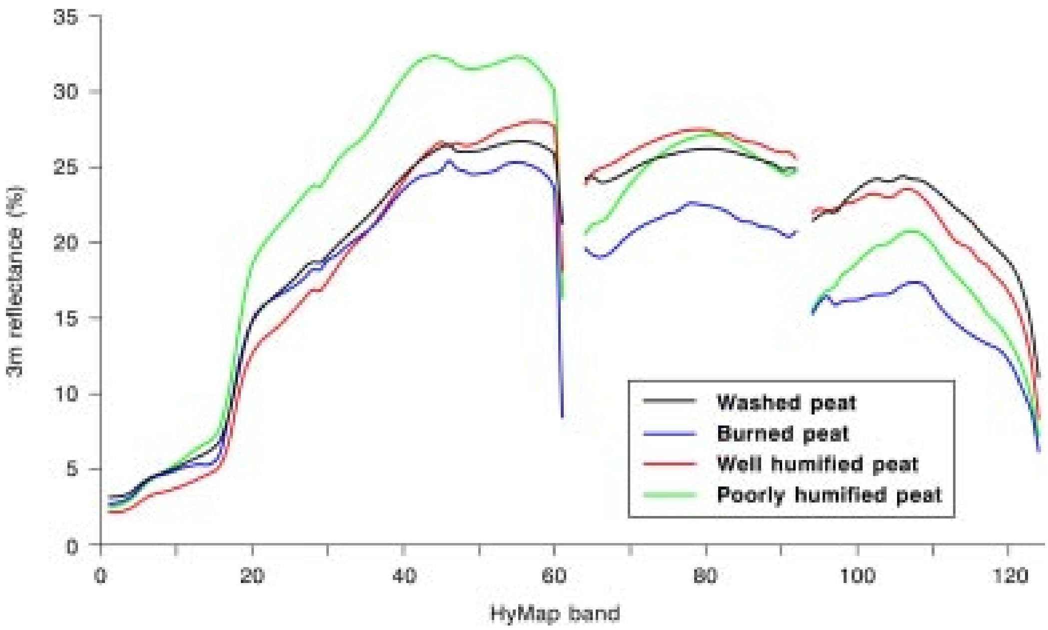

Figure 4. HyMap 3m spectra for washed, burned, well and poorly humified peats.

analysis were correctly allocated to their lab class. The stepwise process selected bands 97, 87 and 71 (1990, 1747 and 1517 nm, respectively) as the discriminating variables for the three discriminant functions. Band 97 is near a major water, cellulose and lignin absorption at 1940 nm, which was also selected first in single band stepwise regression.

Bivariate correlation of reflectance and laboratory variables

Moisture content showed a negative but not statistically significant correlation with reflectance at major water absorption features; for instance, band 65 (r -0.41), band 94 (r -0.32) and band 119 (r –0.42) (1434, 1806 and 2376 nm, respectively). The relationship for visible bands was not consistently negative or significant as expected (Nagler *et al,* 2000). For instance, r values for bands 3, 8, 17 (461, 539 and 677 nm, respectively) were –0.18, 0.08 and 0.32. The small sample size probably explains the lack of significant relationships, as only moisture data concurrent with the flight were used.

Particle size and percentage organic matter were not significantly correlated with reflectance. Transmission, however, showed many significant correlations in the SWIR. For instance, band 96 (1971nm) had an r of -0.75 ($p < 0.01$). All further statistical analysis was conducted using this variable. Relationships with transmission were not significant for visible and NIR bands, partly due to fewer samples at high transmission and very few in the middle range, which is a common problem for peats recognised by McTiernan *et al*, (1998).

Figure 4 suggests that well humified peat (low transmission) has a lower albedo, but negative correlations were found between visible reflectance and transmission. In the NIR, well-humified peats were darker than less decomposed ones (r positive with transmission) and brighter in the SWIR (r negative). This agrees with the findings of McTiernan *et al.* (1998) for amorphous well humified peat at the base of a core, but is contrary to those for decomposting plant and animal waste (BenDor *et al,* 1997) and soils (Krishnan *et al,* 1980; Nagler *et al,* 2000). The former showed that the relationship in the NIR varies with broad peat type. Less decomposed *Sphagnum* peats at the top of their core absorbed less NIR as they became more humified (r negative with transmission). This suggests that separate transmission regression models should be developed for broad peat classes such as *Sphagnum* peat and amorphous peat. However, samples for all peat types were aggregated in McTiernan's regression models, and the same approach has been adopted here due to the small sample size for poorly humified peats.

The strong relationship between the remotely sensed data and peat transmission provides a basis for estimating peat humification across extended areas. Further work is required to investigate this relationship further, including regression modelling using artificial neural networks, to account for noise within both the laboratory and remotely sensed data (Foody *et al*, 2001). This is currently being tested and the results will be presented at a later date.

Conclusions

This paper has outlined the results from a study to assess the potential of hyperspectral remotely sensed data to map the extent of different peat types across an area of the southern Pennines. In general, the results appear promising with realistic maps of peat extent and type being produced from statistical and fuzzy classification approaches. The data were also significantly correlated with peat transmission, an indicator of humification, which suggest that estimates of peat humification may be made across extended areas with the use of hyperspectral remotely sensed data.

Current work is focusing on the analysis of absorption spectra for peat (derived from the HyMap and ASD spectra) to determine if there are any relationships with humification, lignin and other biochemical content. Work also continues on validating images of predicted transmission.

Future work will assess the pattern of peat erosion and vegetation types across the area using landscape ecology metrics to aid in the interpretation and understanding of this highly dynamic and threatened landscape. Eventually we hope to combine remotely sensed peat composition data with topographic variables in an attempt to identify controls on peat erosion pattern.

Acknowledgements

The authors wish to thank the following: BNSC/NERC for the HyMap data; NERC EPFS for the loan of the spectroradiometer; Manchester Geographical Society, the School of Geography in the University of Manchester and the School of Civil Engineering and Geosciences in the University of Newcastle for financial aid toward the cost of fieldwork; National Trust and United Utilities for field access; Tristan Quaife for help with data import; and Dr Jo Cheesman, Amer Al-Roichdi and postgraduates from Manchester and Salford University for fieldwork assistance.

References

Anderson P A Tallis J H and Yalden D W 1997 *Restoring moorlands: the moorland management project, phase 3 report* Bakewell: Peak Park Joint Planning Board

Atkinson P M Cutler M E J and Lewis H 1997 Mapping sub-pixel proportional land cover with AVHRR imagery *International Journal of Remote Sensing* 18 917-935

BenDor E Inbar Y and Chen Y 1997 The reflectance spectra of organic matter in the visible near-infrared and short wave infrared region (400-2500 nm) during a controlled decomposition process *Remote Sensing of Environment* 61 1-15

Benediktsson J A Swain P H and Ersoy O K 1990 Neural network approaches versus statistical methods in classification of multisource remote sensing data *IEEE Transactions on Geoscience and Remote Sensing* 28 540-552

Benediktsson J A Swain P H and Ersoy O K 1993 Conjugate-gradient neural networks in classification of multisource and very high dimensional remote sensing data *International Journal of Remote Sensing* 14 2883-2903

Blackford J J and Chambers F M 1993 Determining the degree of peat decomposition for peat-based palaeoclimatic studies *International Peat Journal* 5 7-24

Bower M 1961 The distribution of erosion in blanket peat bogs in the Pennines. *Transactions of the Institute of British Geographers* 29 17-30

Bowers S A and Hanks R J 1965 Reflection of radiant energy from soils *Soil Science* 100 130-138

BNSC British National Space Centre *Earth observation news, announcement of SAR & hyperspectral airborne campaign (SHAC) data availability* (http://www.bnsc.gov.uk/) [Accessed 13 May '02]

Clark R N 1999 *Spectroscopy of rocks and minerals, and principles of spectroscopy* (http://speclab.cr.usgs.gov/PAPERS.refl-mrs/refl4.html)

CIRES University of Colorado, Boulder *Atmospheric removal program* (ATREM) (http://cires.colorado.edu/cses/atrem.html)

Curran P J 2001 Imaging spectrometry for ecological applications *International Journal of Applied Earth Observation and Geoinformation (JAG)* 3 305-312

Foody G M 1996 Approaches for the production and evaluation of fuzzy land-cover classification from remotely sensed data *International Journal of Remote Sensing* 17 1317-1340

Foody G M Cutler M E J McMorrow J M Pelz D Tangki H Boyd D S and Douglas I 2001 Mapping the biomass of Bornean rain forest from remotely sensed data *Global Ecology and Biogeography* 10 379-388

Garnett M H Ineson P and Stevenson A C 2000 Effects of burning and grazing on carbon sequestration in a Pennine blanket bog, UK *The Holocene* 10 729-736

Goetz A F H Boardman J W Kindel B and Heidebrecht K B 1997 Atmospheric corrections: on deriving surface reflectance from hypespectral imagers *Proceedings SPIE Annual Meeting* 3118 14-22

Gorham E 1991 Northern peatlands: role in the carbon cycle and probable responses to climatic warming *Ecological Applications* 1 182-195

Huerte A R. and Escadafal R 1991 Assessment of biophysical soil properties through spectral decomposition techniques *Remote Sensing of Environment* 35 149-159

Jago R A Cutler M E J Curran P J 1999 Estimating canopy chlorophyll concentration from field and airborne spectra. *Remote Sensing of Environment* 68 217-224

Krishnan P Alexander J D Butler BJ and Hummel J W 1980 Reflectance technique for predicting soil organic matter *Soil Science Society of America Journal* 44 1282-1285

Latter P M Howson G Howard DM and Scott W A 1998 Long-term study of litter decomposition on a Pennine peat bog: which regression *Oecologia* 113 94-103

Mackay A W and Tallis J H 1996 Summit-type blanket mire erosion in the Forest of Bowland, Lancashire, UK: predisposing factors and implications for conservation *Biological Conservation* 76 31-44

Mather P 1999 *Computer processing of remotely sensed images: an introduction* Wiley, Chichester

McMorrow J M and E Hume 1986 Problems of applying multispectral classification to upland vegetation *International Archives Photogrammetry & Remote Sensing* 26 610-620

McTiernan K B Garnett M H Mauquoy D Ineson P and Couteaux M M 1998 Use of near-infrared reflectance spectroscopy (NIRS) in palaeoecological studies of peat *The Holocene* 8 729-740

Mehner H Fairbairn D and Cutler M E J 2001 Habitat monitoring in the Northumberland National Park using high resolution IKONOS satellite data *Proceedings of the 1st Annual Conference of the Remote Sensing and Photogramnmetric Society* The Remote Sensing and Photogrammetric Society, Nottingham 594-601

Moore P D 1995 Biological processes controlling the development of modern peat-forming systems *International Journal of Coal Geology* 28 99-110

Nagler P L Daughtry C S T and Goward S N 2000 Plant litter and soil reflectance *Remote Sensing of Environment* 71 207-215

Stoner E R and Baumgardner M F 1980 Physiochemical, site and bi-directional reflectance factor characteristics of uniformly moist soils *LARS Technical. Report 111679*, West Lafayette, Indiana, Laboratory for Applications of Remote Sensing, Purdue University.

Tallis J H 1973 Studies on Southern Pennine peats: V. direct observation on peat erosion and peat hydrology at Featherbed Moss, Derbyshire *Journal of Ecology* 61 1-22

Tallis J H 1985a Erosion of blanket peat in the southern Pennines: new light on an old problem in Johnson R H (ed) *The geomorphology of North-West England* Manchester University Press 313-336

Tallis J H 1985b Mass movement and erosion of a southern Pennine blanket peat *Journal of Ecology* 73 283-315

Tallis J H 1994 Pool-and-hummock patterning in a southern Pennine blanket mire II. the formation and erosion of the pool system *Journal of Ecology* 82 789-803

Wessman C A 1994 Remote sensing and the estimation of ecosystem parameters and functions in J Hill and J Mégier (eds) *Imaging Spectrometry – a Tool for Environmental Observations* Kluwer Academic Publications, Dordrecht 39-56

Wülder M 1998 Optical remote sensing techniques for the assessment of forest inventory and biophysical parameters *Progress in Physical Geography* 22 449-476