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Can digital image classification be used as a standardised method for surveying peatland vegetation cover?

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ABSTRACT

The ability to carry out systematic, accurate and repeatable vegetation surveys is an essential part of long-term scientific studies into ecosystem biodiversity and functioning. However, current widely used traditional survey techniques such as destructive harvests, pin frame quadrats and visual cover estimates can be very time consuming and are prone to subjective variations. We investigated the use of digital image techniques as an alternative way of recording vegetation cover to plant functional type level on a peatland ecosystem. Using an established plant manipulation experimental site at Moor House NNR (an Environmental Change Network site), we compared visual cover estimates of peatland vegetation with cover estimates using digital image classification methods, from 0.5 m × 0.5 m field plots. Our results show that digital image classification of photographs taken with a standard digital camera can be used successfully to estimate dwarf-shrub and graminoid vegetation cover at a comparable level to field visual cover estimates, although the methods were less effective for lower plants such as mosses and lichens. Our study illustrates the novel application of digital image techniques to provide a new way of measuring and monitoring peatland vegetation to the plant functional group level, which is less vulnerable to surveyor bias than are visual field surveys. Furthermore, as such digital techniques are highly repeatable, we suggest that they have potential for use in long-term monitoring studies, at both plot and landscape scales.

1. Introduction

The ability to carry out systematic, accurate and repeatable vegetation surveys is an essential part of scientific studies into ecosystem biodiversity and functioning. Such surveys, for example the Countryside Survey of Great Britain (Carey et al., 2008) and Environmental Change Network vegetation recording (Rose et al., this issue), can provide invaluable information about long-term vegetation change, biodiversity and indicators of environmental change. In addition, given the growing recognition that vegetation composition plays a vital role in driving important ecosystem functions, vegetation surveys can help to inform on the ecosystem service value of land. For example, vegetation composition is important in controlling ecosystem carbon cycling processes (De Deyn et al., 2008). This is particularly relevant to carbon-rich ecosystems such as peatlands (Gorham, 1991), where different plant functional types (PFTs) have been shown to influence both short- and long-term rates of carbon cycling (Dorrepaal et al., 2007; McNamara et al., 2008; Trinder et al., 2008). Indeed, the influence of vegetation composition on greenhouse gas fluxes and rates of decomposition has recently been shown to be stronger than the effects of moderate climate warming (Ward et al., 2013, 2015). These influences of vegetation on ecosystem function (Hooper and Vitousek, 1997; Tilman et al., 1997), may be the result of changes in different aspects of vegetation including: community species richness (Naeem et al., 1994; Tilman et al., 1996); effects of specific individual species (Chapin et al., 1995) or changes in the composition of plant functional traits (Lavorel and Garnier, 2002; Garnier et al., 2004; Diaz et al., 2007; Grigulis et al., 2013). Thus, the development of cost and time effective ways to repeatedly monitor vegetation composition accurately to PFT level, is of great relevance to ecosystem function studies, particularly for long-term monitoring sites such as those operated by the Environmental Change Network (ECN) and other networks in the International Long Term Ecological Research Network (ILTER).

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To assess vegetation change over time, repeatable and reliable survey and monitoring techniques are needed to allow comparisons between data sets (Howard et al., 2003). However, current widespread traditional methods such as destructive harvests (Nordh and Verwijst, 2004), are damaging to the environment and therefore cannot be used in most long-term investigations where conservation is paramount and repeated sampling of other parameters is required (Gilbert and Butt, 2009). Although other survey methods such as visual cover estimates (Howard et al., 2003; Vittoz and Guisan, 2007) and recording presence/absence of species (Scott and Hallam, 2003) are non-destructive, they tend to be subjective and can be affected by errors and surveyor biases, and therefore can be difficult to repeat accurately. Techniques such as pin-frame point counts, although more accurate, can be time consuming.

Digital image analysis (DIA) offers a non-destructive method which is a potentially faster and less biased alternative to these commonly used techniques (Richardson et al., 2001; Rasmussen et al., 2007; Booth et al., 2008). Several DIA techniques show great potential for use in long-term monitoring projects to build up large scale temporal datasets (Laliberte et al., 2007), particularly for those that require survey data to PFT level rather than to detailed species level, which would require specialist botanical knowledge. Given the importance of PFTs as key drivers of ecosystem functions, the development of DIA techniques in monitoring to this scale could provide a standardised technique for monitoring vegetation change and hence the impact of change on ecosystem functions.

The aim of this study was to develop a practical, accurate and repeatable technique to distinguish between PFTs, using an established plant removal experiment on the peatland ECN site at Moor House National Nature Reserve (NNR). To do this, we used a standard compact digital camera (Nikon 5.1 Megapixel) and two methods of image classification. The first method was an unsupervised classification method, referred to as a histogram peak classification method, which classifies images on the basis of peaks in histograms of red, green and blue (RGB) values. The second method was a supervised classification method, which classifies images on the basis of training areas (manually defined pixels). These methods can be carried out using a variety of Geographical Information Systems software, including freeware such as QGIS and others, meaning that they are practical and affordable techniques for use in future studies by a range of projects and users. In our study, we used ArcGIS (version 9.3, ESRI UK. Ltd., Aylesbury, UK) for method 1, hereafter named as "histogram peak classification". For method 2, hereafter named as "supervised classification", we used ERDAS (version 9.1, ERDAS Inc., Norcross, GA, USA).

2. Materials and methods

2.1. Study site

Our study site was located on an area of blanket bog within Moor House NNR in the North Pennines of England (54°65′ N, 2°45′ W; altitude 590 m). Moor House NNR has been studied in ecological research since the 1930s (Crowle, 2008), and is currently the largest of the terrestrial ECN sites, making it an important long-term monitoring site with a wealth of historic and present day scientific information. The vegetation present on the blanket bog is typical of UK National Vegetation Classification M19b, *Calluna vulgaris-Eriophorum vaginatum* blanket mire, *Empetrum nigrum* ssp. *nigrum* sub-community (Rodwell, 1991). Species present can be divided into three broad functional types: ericoid dwarf-shrubs (dominated by *Calluna vulgaris* and *Empetrum nigrum*), graminoids (dominated by *Eriophorum vaginatum*) and lower plants (comprising a diverse community of mosses, liverworts and lichens, including *Sphagnum*, *Hypnum*, *Plagiothecium*, *Rhytidiadelphus*, *Aulacomnium*, *Polytrichum*, *Pleurozium*, *Dicranum*, *Campylopus* and *Cladonia* spp.).

More specifically, our study was based on an established plant removal manipulation experiment (Ward et al., 2013). This consisted of 1.5 m × 1.5 m plots where above-ground vegetation had been selectively removed to create areas with one, two or all of the 3 PFTs (dwarf-shrubs, graminoids and lower plants) in all combinations, giving a total of seven manipulation treatments, each replicated four times ($n = 28$).

2.2. Field techniques

For each field treatment plot, visual field surveys of vegetation cover were carried out and a digital photograph taken at two dates during the growing season. A white plastic quadrat measuring 0.5 m × 0.5 m was placed in each treatment plot, and the corner positions of the quadrat marked with fixed wooden canes, to ensure accurate repeat measurements. Digital photographs were taken using a Nikon Coolpix L3 5.1 Megapixel digital compact camera, mounted on a tripod with a horizontal boom and spirit level to ensure that the images were taken 1–1.2 m directly above the plot. A light metre (Skye Pyranometer Sensor, Skye Instruments, UK) was used to record light conditions and, wherever possible, images were taken whilst there was cloud cover and the light metre readings were less than 400 W m^{-2} in order to avoid shadows.

For the visual surveys, the percentage cover for each of the three PFTs was estimated by eye to the nearest 5%, a technique widely used in surveys such as the Countryside Survey (Maskell et al., 2008). Cover estimates were made on a two dimensional 'birds eye' view to total 100% cover, so that direct comparison could be made with the photographs. To investigate the effects of surveyor bias on the accuracy of visual field surveys, we compared percentage cover estimates of 9 plots from 5 different surveyors.

2.3. Visual estimate technique using a Fishnet grid

A schematic overview of all digital image techniques is given in Fig. 1. To provide a baseline estimate of PFT percentage cover upon which the results from the visual field surveys and DIA analysis could be compared, we first analysed each digital photograph using a fishnet grid technique. This visual estimate technique involved dividing each photograph into a 'fishnet grid' of 100 squares, with each square representing 1% of the total area. This grid provided a framework within which vegetation in each 1% square could then be allocated visually to one of the 3 PFTs, with the standard rule that any square that was more than half occupied by a functional group was recorded as 1% cover for that group. As with the visual field surveys, we tested the effect of surveyor bias on the accuracy of this technique by comparing cover estimates of 9 plots from 5 different surveyors.

2.4. Digital image analysis techniques

All images were initially standardised using Corel Paint Shop Pro (version X1, Corel Corporation, Maidenhead, Berks, UK), a commonly available digital photograph editing software package. Firstly, images were straightened and cropped to the plot boundary to remove any vegetation from outside the quadrat (final average image resolution was 3.1 mm). Secondly, the brightness and contrast of the digital photographs were altered in order to examine whether they affected the accuracy of DIA techniques in estimating PFT cover. We then analysed the images using two techniques, both of which classified images based on values of the red, green and blue (RGB) spectrum. One method used the histogram of RGB

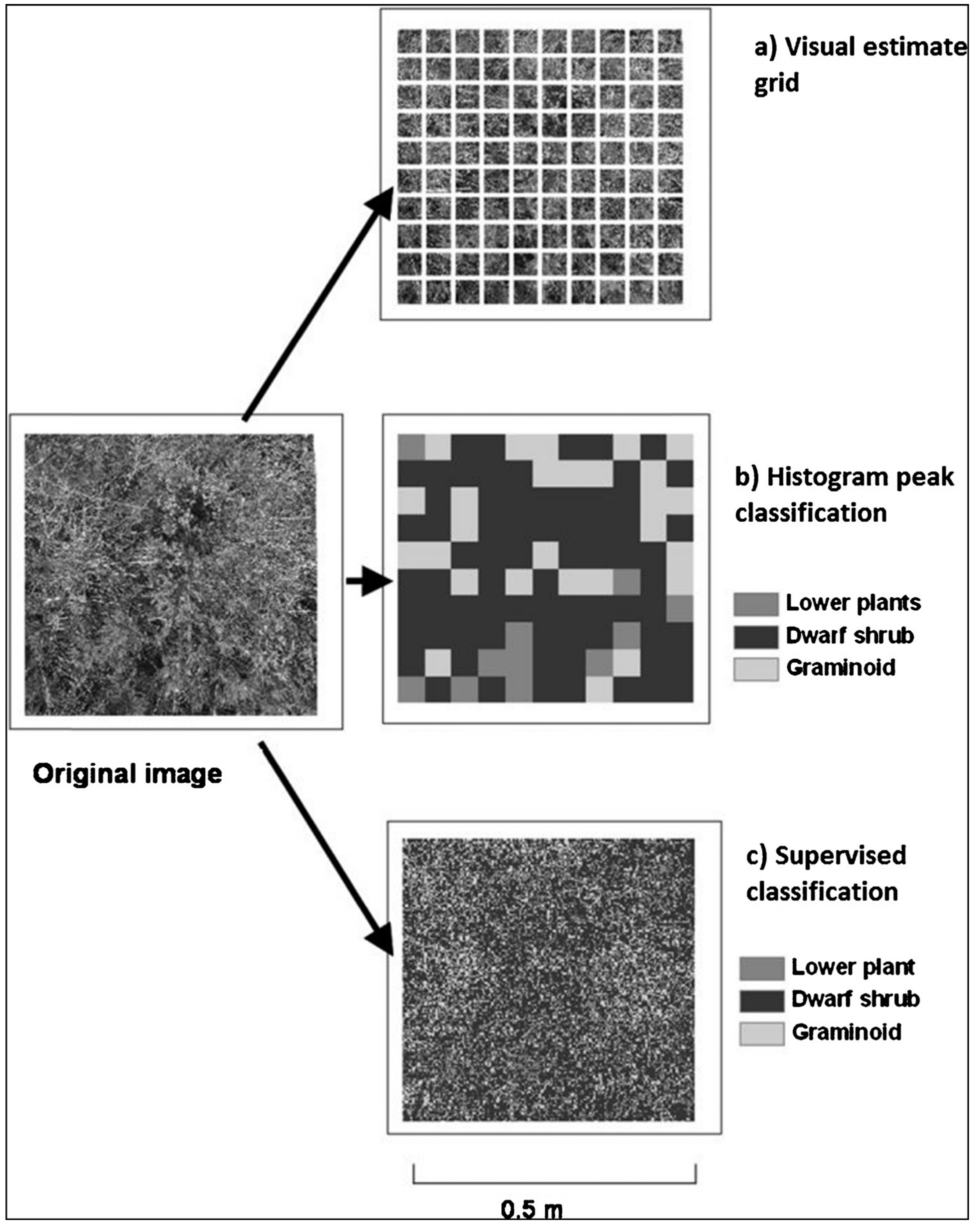

Fig. 1. Original digital image and analyses used: (a) visual estimate grid; (b) histogram peak classification and (c) supervised classification.

values within the image to identify peaks representing different PFTs; the other used a supervised classification method.

2.4.1. DIA technique 1 – histogram peak classification method

The first DIA technique applied was an unsupervised classification method, involving the classification of images based on clusters of RGB values ('peaks') identified in histograms of RGB values. We used ArcGIS, a widely used geographical information software package, capable of carrying out digital analysis on raster images in a number of ways. The resolution of the image was reduced to pixels of 5 cm, thus matching the resolution of the fishnet grid, with 100 squares representing 5 cm × 5 cm on the ground. Reducing the resolution of the images helped to minimise the 'salt and pepper' effect (Laliberte et al., 2007), where small amounts of bare ground in between the vegetation were detected.

We then classified the cells into between 3 and 5 classes representing the different PFTs and also bare ground and white quadrat where applicable. Within the software, a histogram was automatically generated from all the RGB colour values within the image. Each peak in the histogram represented a distinct colour range found in the image. For example, an image containing pixels of only 2 colours had 2 distinct histogram peaks. The assumption was that each PFT had a distinct homogenous colour signal that could be identified as a separate peak in the RGB histogram. The peaks were separated into classes (or ranges of RGB values), by setting the range boundaries manually on the histogram. The software then allowed classification of the image by allocating the individual pixels, based on their RGB value, to each defined class (or RGB range) i.e.: bare ground, each of the 3 PFTs and the white plastic quadrat around the edge of the image. Once classified, the pixel counts for each class enabled the percentage cover per PFT for each image to be calculated. The histogram peaks for each class (RGB ranges) obtained from the single vegetation type images were then applied in the classification of plots containing mixed vegetation

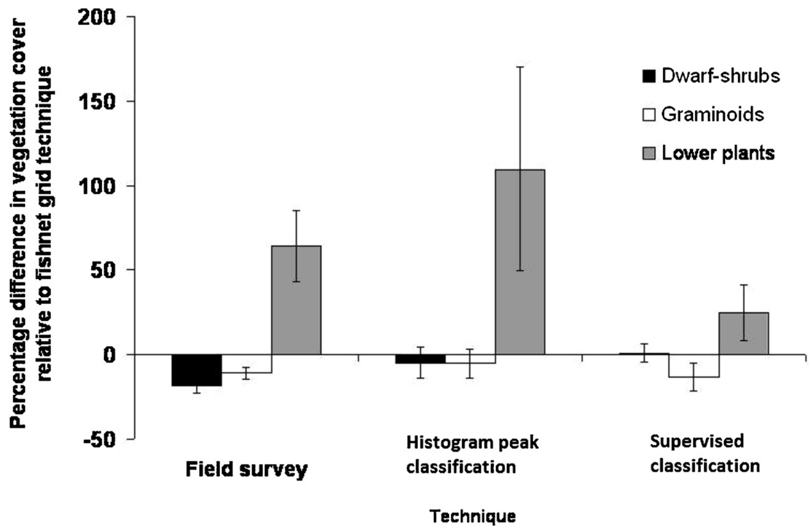

Fig. 2. Comparisons of vegetation cover estimated using the visual field survey, histogram peak classification and supervised classification techniques for each of the three plant functional groups, shown as percentage difference compared with vegetation cover estimated by the baseline fishnet grid technique. Data shown are taken from analysis of all plots using all techniques. Values are means ± standard error.

types. This technique allowed PFTs to be easily defined at a coarse scale.

2.4.2. DIA technique 2 – supervised classification method

The second DIA technique used a supervised classification method. This was carried out in ERDAS Imagine, which is typically used in large-scale remote sensing, such as land cover mapping, using satellite imagery. The method classified images using several signature areas for each of the five classes, manually defined by the analyser by selecting pixels representing each class and saving them as signatures within the software. Images were classified through the allocation of pixels to classes according to the identified signatures, using a maximum likelihood classifier, to show the three PFTs. Percent cover of each PFT was then calculated using the pixel counts per class.

2.5. Statistical analysis

Statistical analysis was carried out using SAS, Enterprise Guide 4 (version 9.1, SAS Institute Inc., Cary, NC, US) to compare vegetation cover estimates of PFTs from the different techniques using general linear models (GLMs). Pairwise *t*-tests (Tukey–Kramer) were used to identify significant differences between PFT treatment plots (one PFT, two PFT or all three PFT) and techniques. Residuals of all data were plotted to check for normality.

3. Results

The estimated percentage cover of all PFTs did not differ between survey dates (dwarf-shrubs ($F = 0.39$, $P = 0.53$), graminoids ($F = 0.02$, $P = 0.88$) or lower plants ($F = 2.87$, $P = 0.09$)), or with alteration of image brightness ($P = 1$). Survey data from all dates were therefore combined into one data set.

Comparison of PFT percentage cover estimated visually in the field by 5 different surveyors showed that the estimated percentage cover of lower plants differed significantly between surveyors ($F = 4.95$, $P = 0.002$). In contrast, visual percentage cover estimates under office conditions using the fishnet grid technique did not differ significantly between surveyors for any of the 3 PFTs. This supports our assumption that visual percentage cover estimates under non-field conditions using a photo and grid reduces variation between surveyors relative to estimates carried out in the field.

When comparing percentage cover estimates of all PFT from each technique from all plots, the ability of traditional and digital survey techniques to accurately estimate percentage cover of PFTs (when compared to the fishnet grid), was dependent on the PFT in question (Fig. 2). For dwarf-shrubs, visual field surveys significantly underestimated cover ($F = 3.69$, $P = 0.015$ respectively), whereas both DIA techniques gave percentage cover that did not differ significantly from fishnet estimates. For graminoids, visual field surveys and both DIA techniques gave percentage cover estimates that did not differ significantly from the fishnet technique ($F = 2.32$, $P = 0.081$). For lower plants, visual field surveys and both DIA techniques gave significantly greater percentage cover estimates than the fishnet technique in single PFT plots ($F = 4.3$, $P = 0.007$), with large variations between techniques (64% for visual surveys, 110% for histogram peak classification and 25% for supervised classification). The ability of all techniques to accurately estimate the percentage cover of a single PFT was influenced by the presence or absence of other PFTs in the surveyed plot (Fig. 3). For dwarf-shrubs, absence of other PFTs resulted in underestimation of this shrub cover in visual field surveys ($F = 3.4$, $P = 0.032$). Graminoid percentage cover was not influenced by the presence or absence of other PFTs, whereas lower plant percentage cover was overestimated in the absence of the other PFT when measured using the histogram peak classification ($F = 4.47$, $P = 0.0113$).

4. Discussion

Evidence that vegetation composition impacts on ecosystem processes highlights the vital need to monitor vegetation change over time, and therefore, the need for standardised accurate monitoring techniques. Our aim was to develop repeatable and accurate methods of quantifying vegetation cover to PFT level on a 0.5 m × 0.5 m scale on a peatland ecosystem using DIA techniques. We found that the DIA techniques tested (histogram peak classification and supervised classification) were both effective ways of estimating percent cover for the three peatland PFTs. Both techniques worked best for dwarf-shrubs and graminoids, but were less effective for lower plants.

Traditional field survey techniques tend to be time consuming and may be biased by surveyor efficiency or fatigue, and adverse weather conditions (van Hees and Mead, 2000). However, in

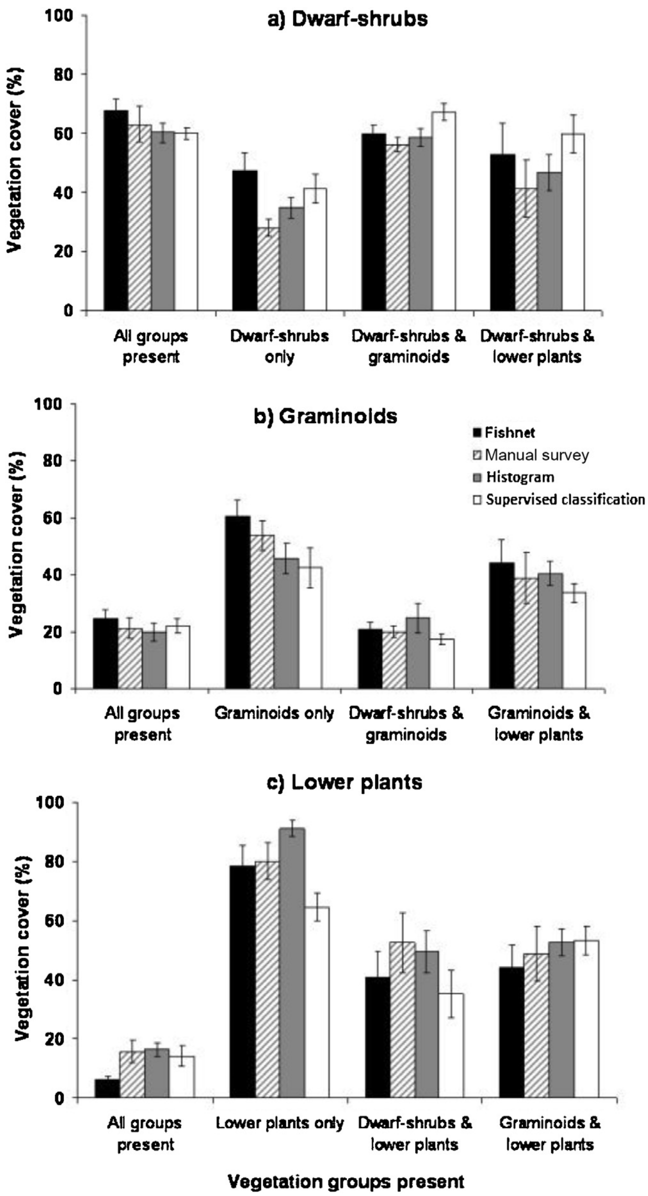

Fig. 3. Vegetation percent cover estimated by all four techniques, split between field plant manipulation treatments. (a) Dwarf-shrubs, (b) graminoids, (c) lower plants (figures are means ± standard error).

studies that only require recording to the level of plant functional types, there is potential to use coarser scale digital image analysis, which does not require the same level of botanical expertise and is easily repeatable and accurate. Plant removal experiments, such as the one used in this study, are not only ecologically valuable in providing information on the role of diversity and individual PFTs on ecosystem processes (Diaz et al., 2003); they are also ideal for testing the practicality of using digital imaging techniques for estimating vegetation cover to PFT scale. For example, the three PFT studied here have distinct and homogenous RGB signatures, thus making the classifications used in this study easier to define.

The fishnet grid technique used in this study uses visual estimation in the same way as the traditional field surveys, but in a controlled environment and using a calibration grid, thus removing some of the factors that can cause bias (such as weather conditions and surveyor fatigue). For these reasons, the assumption was made that this technique was the most accurate technique for vegetation surveys in this study; and therefore taken as the baseline against which other techniques were measured. Our data support this assumption by showing that observations from five different surveyors were more variable in the field than those carried out with the fishnet grid.

The accuracy of the DIA techniques tested did not differ between survey dates and light conditions, but was dependent on the PFTs present. The consistency in accuracy of the DIA techniques between survey dates and light conditions suggests that these techniques are repeatable at this site, hence fulfilling one of our main aims. However, it should be noted that both DIA techniques required classification criteria to be defined for each survey date and as stated previously, photographs for DIA analysis should be captured in stable light conditions (Rasmussen et al., 2007) and where possible below 400 W m^{-2} to prevent shadows. In situations where it is not possible to capture all photographs in stable light conditions, use of a flash (Laliberte et al., 2007) or manual shading using an umbrella may reduce shadowing. In contrast to date and light conditions, the accuracy of DIA techniques was influenced by the individual PFT in question as well as the presence/absence of other PFTs in the surveyed plot. There was no difference in the accuracy of PFT cover estimates using DIA techniques on the complex survey plots containing two or three PFT. However, it was more difficult to carry out the histogram peak classification in plots containing 2 or all 3 PFTs as there was some overlap in the colours of the plant tissues between PFTs and it was thus more difficult to determine the boundaries between the different RGB value peaks in the histogram. Contrary to expectation, differences in the percentage cover of shrubs and lower plants were detected in the simple single PFT plots. Traditional visual field surveys were less accurate than DIA techniques in estimating dwarf-shrub cover in the absence of other PFTs, highlighting a limitation of this technique. The underestimation of dwarf-shrubs cover in these single PFT plots by the visual survey technique was probably due to observer bias, i.e. surveyors may have perceived these plots as simple to survey, therefore taking less time to survey them accurately, or alternatively may have found the long cover of stemmed shrub vegetation difficult to estimate due to its scattered nature (Dethier et al., 1993; Torell and Glimskar, 2009). DIA techniques showed large variation in cover estimates of lower plants, suggesting that the techniques differ in ability to distinguish mosses from bare ground, and thus highlighting the difficulty of quantifying cover of this PFT. There are several possible reasons for the large variation between techniques in estimating moss cover. Firstly, lower plants are the most diverse PFT in peatlands (Lang et al., 2009), with high interspecific variation in growth forms and tissue colouration. A greater amount of moss, lichen and liverwort were visible in the single PFT plots relative to the mixed PFT plots. Variations in colour and textures were, therefore, more pronounced in these single PFT plots. Secondly, lower plants were the most variable in cover between surveyed plots, and had the smallest contribution to total vegetation when all three groups were present. Lastly, this PFT occupied a large area underneath the canopy of the other PFT, which was not captured by the 2D digital images, resulting in possible underestimation of this PFT from DIA techniques.

The DIA techniques studied here revealed a trade-off between accuracy (supervised classification) and speed (histogram peak classification). Once the time consuming process of selecting colour bands for each PFT has been carried out, histogram peak classification is repeatable for a large number of images captured on the same day and containing the same PFT in a short period of time (approx. 4–5 min per photograph). In contrast, supervised classification is only easily repeatable if the training signatures used are identical between images. This is rarely possible and therefore training signatures have to be selected for each image, making this technique slow, taking approx. 20–30 min per photograph.

Whilst the supervised classification method provides more accurate estimations due to finer resolution classification based on the original photograph pixels, and signature areas allowing variability in colour per class can be included in this method, this method is more time intensive. The greater time required for the supervised classification technique compared with the histogram peak classification is disadvantageous, particularly when analysing complex vegetation plots such as those with a large number of mixed PFT and lower plants. In addition, the process of selecting signature areas for each PFT in this software requires prior knowledge and observer involvement, therefore introducing possible observer bias and subjectivity. Due to the sensitivity of the supervised classification, extra detail such as twigs and other debris that histogram peak classification or other less sensitive techniques would broadly classify as bare ground are detected, therefore signature areas are required for these additional details, adding to the time required for this technique.

The plots surveyed in this investigation showed a large amount of variation over a small scale for the more sensitive method of supervised classification, making it impractical for large-scale surveys such as ECN and ILTER studies. However, the histogram peak classification method provides a quick and easy to use technique, which could be used in these large-scale studies. Both the histogram peak classification and the supervised classification methods could be used in long term surveys, such as Countryside Survey, which are repeated on a 7–10 year timescale, because they both use methods that require repeat selection of classification criteria (i.e. histogram peaks and training areas) for repeat surveying. Indeed, current repeated surveys such as the land cover map use a classification method very similar to the supervised classification technique described here, albeit on a larger scale (Morton et al., 2011). There would be limitations related to the complexity of vegetation community composition, since neither technique would be suitable for species-rich swards such as high diversity grasslands, where there is less variation in the colour spectrum of PFTs. However, we suggest that this novel use of digital imaging analysis offers a valid alternative to manual surveying of less species-rich systems with distinct PFTs.

5. Conclusion

Our study illustrates a novel application of digital methods for measuring and monitoring peatland vegetation to PFT level, which can be both more accurate and more time efficient than visual field surveys, and, in the case of one of the techniques, highly repeatable. Of the two DIA techniques tested, the supervised classification showed a higher degree of accuracy when compared with visual estimates. However, in view of the greater amount of time required to operate this system, we conclude that the histogram peak classification would be the most suitable technique to develop and automate for widespread use in monitoring vegetation change. We suggest that the high degree of repeatability, and the lack of specialist equipment required, make DIA techniques a useful tool for use on long-term monitoring sites where broad-scale vegetation surveys are required.

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