A Fuzzy Sets Approach to the Representation of Vegetation Continua from Remotely Sensed Data: An Example from Lowland Heath

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ABSTRACT: Conventional image classification routines are often inappropriate for the mapping of continuous phenomena such as heathland vegetation. To allow for the natural fuzziness of such an environment, a fuzzy sets algorithm may be used to model the heathland vegetation more appropriately than a classification. The results of this study show that the fuzzy c-means algorithm can be used to discriminate accurately between the end points of a set of continua, and that class membership functions derived from the analysis are sensitive to the botanical composition of the vegetation canopy. Mapping the fuzzy membership functions will therefore enable a more realistic portrayal of the heathland vegetation than a conventional classification.

INTRODUCTION

THEMATIC MAPPING FROM REMOTELY SENSED DATA has typically been achieved through the process of a supervised digital image classification. These techniques are designed to allocate cases of unknown class membership to a class on the basis of their spectral properties in relation to a pre-defined decision rule. Thus, for instance, in the maximum-likelihood classification each pixel is allocated to the class with which it displays the highest likelihood of membership. Many factors influence the accuracy with which such a technique may be employed. These include the number, size, and location of training sites (Swain and Davis, 1978; Schneider, 1980; Campbell, 1981; Foody, 1988), the type of classifier, and the available ancillary data (Mather, 1987). One feature which is often overlooked is the nature of the themes to be classified.

Image classification techniques were designed for application on phenomena which can be considered to exist in discrete classes. Each pixel is allocated simply to the class with which it displays the greatest level of similarity. Because only one class is associated with each pixel in the output and no indication of the relative strength of class membership is provided, full membership of the allocated class is implied. However, full membership of the allocated class is often not the case. For instance, mixed pixels may, dependent on the characteristics of the classes on the ground and the spatial resolution of the imagery, be common. Furthermore, many geographical phenomena do not exist in discrete classes but instead lie along continua, and the classes inter-grade (Greig-Smith, 1980; Leung, 1987; Wang, 1990). For instance, in a heathland environment one does not observe a sudden change in land cover from dry heath to bog but instead views usually a gradual change along a moisture gradient from dry through wet heath to bog. Along the continuum the composition of the canopy will contain variable proportions of the different classes. At the "end points" of the continuum cases may be "pure" and comprise only species associated with one class. In the zones where classes inter-grade, cases will exhibit the characteristics of two or more classes. Conventional classification routines will therefore be inappropriate for the representation of such phenomena. This problem with classification techniques has been acknowledged widely in the ecological community (Whittaker, 1973; Greig-Smith, 1980; Goldsmith *et al.*, 1986) where the "hardness" of classification routines implies a discrete environment which is the antithesis of the continuum concept in ecology (Greig-Smith, 1980). Furthermore, the sharpness of the boundaries and the apparent objectivity of classification routines (Johnston, 1968) compound the problem and may degrade the quality of later analyses, especially if within a geographical information system (Burrough, 1986). To provide a more valuable representation of continuous classes, an alternative approach to classification which models the gradients between class centroids is required. One way to achieve this is to indicate the relative strength of class membership that a case has relative to all defined classes, similar to spectral mixture modeling (Campbell 1984a), and thus indicate its composition and position along the continua.

Mapping the probabilities of class membership is one approach which has been used to represent continua (Wood and Foody, 1989; Foody and Trodd, 1990). In essence, the approach consists of outputting the probabilities of membership each case has to each class. Thus, instead of outputting a conventional classification in which one class code is associated with each pixel, the probability of membership that the pixel has for each class can be output. Thus, the output could be conceived as a series of probability surfaces where each surface represents the probability of membership to a specified class, and for each measure of probability there is one surface per class. This technique has the advantage that the probabilistic measures may be derived as a by-product of the widely available maximum-likelihood classification (Trodd *et al.*, 1989), although care must be taken in selecting the appropriate probabilistic measure. One important limitation to this approach, however, is that the maximum-likelihood classification is not a particularly robust technique (Tom and Miller, 1984). The technique is only reliable when its assumptions are satisfied, and only small deviations from the assumed conditions may cause instability (Swain and Davies, 1978). One critical assumption made is that the digital numbers (DN) of each class are distributed normally. Because the statistical distribution of DN can vary considerably between classes, and as class membership is unknown before the classification, it is impossible to adequately test, let alone correct, for non-normality in the data. If it can be assumed that the data display only minor deviations from normality, an alternative is to utilize linear discriminant analysis. This technique has been used widely to classify remotely sensed data and, while similar to the maximum-likelihood classification, it is a more robust technique (Tom and Miller, 1984). Unfortunately, however, the probabilities derived in the discriminant analysis are assessed relative to the discriminant functions and can therefore be difficult to interpret and compare reliably and may differ markedly from those derived from a maximum-likelihood classification

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(Campbell, 1984b). To overcome the potential problem of non-normality, a fuzzy sets approach which makes no assumptions about the statistical distribution of the data and which indicates the strength of membership a case has to each class may be used. One approach is based on the fuzzy c-means algorithm (Bezdek, 1981; Bezdek *et al.*, 1984; McBratney and Moore, 1985). This paper illustrates the applicability of this technique for the representation of continuous classes, in this example heathland vegetation, from remotely sensed data.

THE ALGORITHM

Conventional classification routines allocate each pixel to one of several classes assumed to be discrete and mutually exclusive. Because these assumptions are often untenable, the use of the fuzzy c-means algorithm may appear appropriate. The algorithm used was that described by Bezdek *et al.* (1984). Briefly, the fuzzy c-partion space is

$$M=\left\{\mathbf{U}: u_{ik} \in [0,1]; \sum_{k=1}^{n} u_{ik} > 0, i=1 \ldots c; \sum_{i=1}^{c} u_{ik} = 1, k=1 \ldots n\right\}$$

where $\mathbf{U}$ is a fuzzy c-partion of n observations and c classes (strictly, fuzzy groups), and u_{ik} is an element of $\mathbf{U}$ and represents the membership of an observation, $\mathbf{x}_k$, to the i^{th} class where $\mathbf{x}_k$ is a vector the length of which is the number of attributes, p (e.g., wavebands), used. The fuzzy membership function values, u_{ik}, lie on a scale between 0 and 1 and sum to 1 for each case. They may therefore to some extent be likened to probabilities of class membership. The optimal fuzzy c-partion is identified through the minimization of the generalized least-squared errors functional J_m:

$$J_m(\mathbf{U}, \mathbf{V}) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^m (d_{ik})^2$$

where $\mathbf{V}$ is a c by p matrix, the elements, v_{ik}, of which represent the mean of the k^{th} of p attributes in the i^{th} class, m is a weighting component, $1 < m < \infty$, and d_{ik} is a measure of dissimilarity based on the distance between an observation and a class centroid which can be determined from

$$(d_{ik})^2 = (\mathbf{x}_k - \mathbf{v}_i)^T \mathbf{A} (\mathbf{x}_k - \mathbf{v}_i)$$

in which $\mathbf{A}$ is weight matrix which determines the norm (e.g., Euclidean, Mahalanobis) to be used (Bezdek, 1981; Bezdek *et al.*, 1984).

In this investigation the algorithm was used in a supervised mode (Key *et al.*, 1989), requiring direct input of class centroids into the program. In all the analyses the Mahalanobis norm was used and values for the parameter m are indicated with the results because the degree of fuzziness obtained is positively related to m; a "hard" or conventional classification may be obtained from $m = 1$.

TEST SITE AND DATA

Lowland heaths in northwest Europe, while recognized as being of considerable ecological value, are undergoing relatively rapid change (Foody and Wood, 1991). Some of the finest examples of these heaths are located in the United Kingdom where total heathland coverage has been reduced by approximately 75 percent in the last two centuries. In some regions changes have been much greater. The Surrey Heaths, one of the most important heathland resources in the UK, have been reduced in extent by about 90 percent in this period and are under considerable threat from a variety of agencies, including woodland and urban encroachment (Foody and Wood, 1991). Information on these heaths, especially in terms of their areal extent and composition, is essential for their effective management and conservation. Remotely sensed imagery is an attractive source of data for this application but, as discussed above, conventional classification routines are inappropriate here because they do not model the continuous environment satisfactorily. The latter is an important limitation because knowledge of the gradients between classes is important environmental information, especially with the current resurgence in the importance of ectones and environmental change (di Castri *et al.*, 1988; Johnston and Bonde, 1989) and provides valuable information for geographical information systems. In this type of environment the desire to indicate the inherent imprecision or fuzziness of the classes is paramount and one where the fuzzy sets approach is valuable.

To evaluate the applicability of the fuzzy c-means technique to the representation of the heathland vegetation, a small study area in the Surrey Heaths at Pirbright Common was selected as the test site (Figure 1). This site is owned by the Ministry of Defence and so, to some extent, is a protected environment. This heath supports communities of wet and dry heathland vegetation, which differ considerably in composition but also exhibit a high level of intra-class variability. Typically, dry heaths, however, were dominated by *Calluna vulgaris* and *Ulex minor* whereas wet heaths comprised significant amounts of *Erica tetralix* and *Molina* species. Lower lying areas tended to support bog dominated by species of *Sphagnum* and *Carex*. In areas which have been neglected *Pteridium, Betula,* and *Pinus* species have invaded and the potential for scrub woodland development is

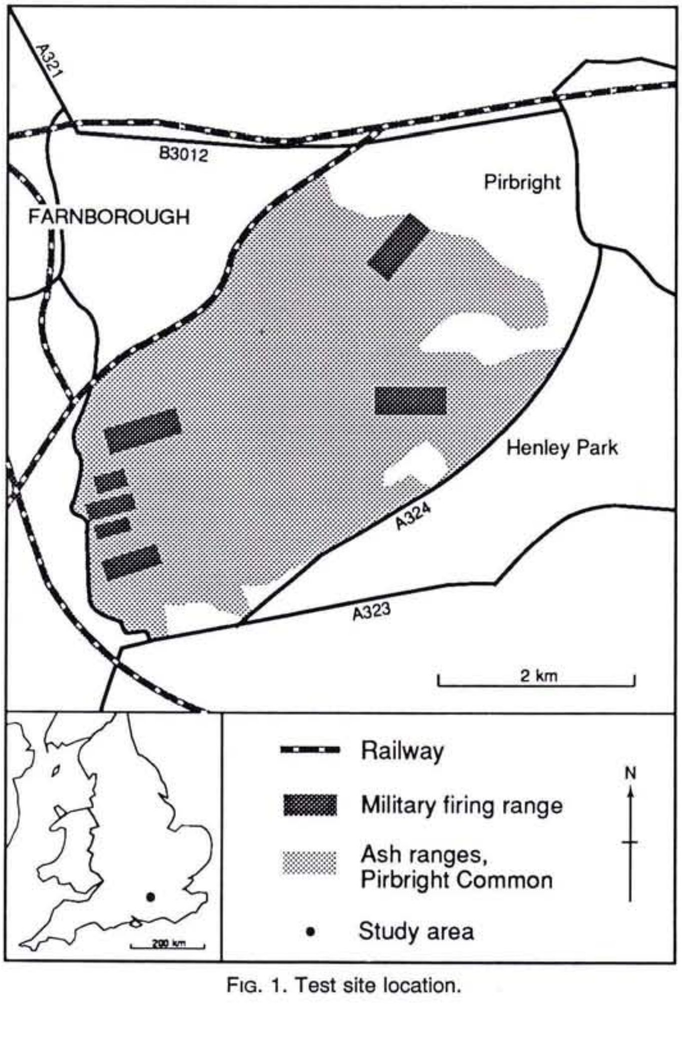

FIG. 1. Test site location.

considerable. The investigation focused on the ability of the fuzzy c-means technique to identify the class end points accurately and then on its sensitivity to the continua that exist between them; both are necessary for accurate modeling of the heathland environment.

The analyses were all performed with airborne thematic mapper data acquired by a Daedalus 1268 sensor for the test site on 31 March 1989. The data were acquired within two hours of solar noon along a flight line that ensured that the relative solar azimuth angle (angle between the Sun's principal plane and sensor scanning direction) was approximately 90°. After smoothing with a 3 by 3 low pass mean filter to reduce potential mislocation errors, the data had a spatial resolution of approximately 15m. Unfortunately, one of the 11 wavebands recorded by the sensor, the 1.55 to 1.75 μm waveband, exhibited significant radiometric distortion due to striping and could not be used. All the remaining wavebands were used to classify the end points by applying the fuzzy c-means technique in a fairly hard, near classificatory, mode ($m = 1.25$) and allocating each case to the class with which it displayed the largest membership value. To achieve this the DN in the ten remaining wavebands for 92 pixels associated with the four main vegetation classes (31 dry heath, 17 wet heath and bog, 20 coniferous woodland, and 24 mixed woodland pixels) were extracted from the data. These samples were then used to both train and test the analysis. While this approach will provide a guide to the level of separability between class end points, it must be noted that the accuracy of the classification may be overestimated (Swain and Davis, 1978).

The sensitivity of the technique to the composition of the vegetation communities along a continuum was investigated with a transect that graded from dry heath to wet heath and bog. Because the continuum under investigation was therefore essentially a reflection of a moisture gradient, only the 2.08 to 2.35 μm moisture sensitive middle infrared waveband was analyzed; the more sensitive 1.55 to 1.75 μm waveband could not be used because of the afore-mentioned poor data quality. At 15 sample sites along the 1020-m transect (Figure 2), detailed ground data on the canopy composition were acquired from 16m² quadrats. For each of the pixels corresponding to these sites, the DN in the 2.08 to 2.35 μm waveband was extracted. These data were then used to determine the relationship between community composition and the fuzzy membership function, u_{ik}, derived from the fuzzy c-means algorithm. The algorithm was used in a supervised form (Key *et al.*, 1989), and the data on the spectral characteristics of class centroids were derived from a total of 48 samples acquired from the end points of the continuum which were used in the classification; 31 dry heath and 17 wet heath and bog.

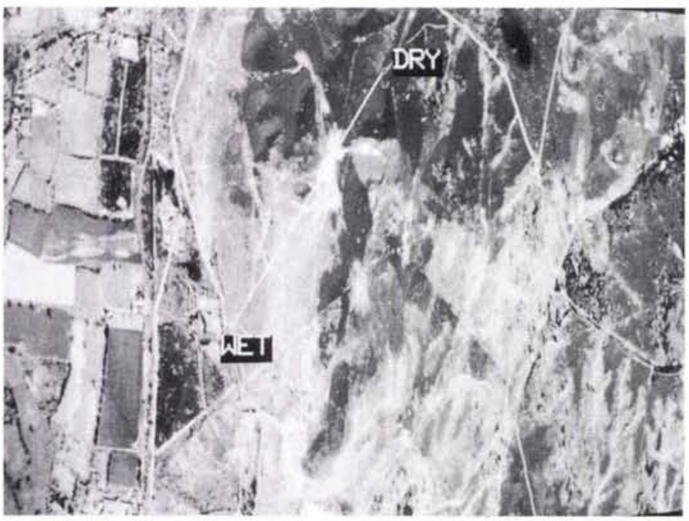

FIG. 2. Location of the transect on the dry to wet heath and bog continuum displayed on the 2.08- to 2.35-μm waveband image.

RESULTS AND DISCUSSION

With the parameter $m = 1.25$ (fairly hard), the samples of the four classes were classified. The result, 100 percent accurate classification, shows that the end points of the continua are separable. This is, however, no more than would be obtained from a conventional classification algorithm. A discriminant analysis of the same data set also gave a 100 percent accurate classification and showed the class end points to be separable spectrally. The main concern here, however, was once having established the separability of the end points, to determine the sensitivity of the fuzzy membership function, u_{ik}, to the canopy composition. This was investigated with reference to the wet heath and bog and dry heath classes with respect to the middle infrared image only (Figure 2). The relevant class end point data used in the classification were used to determine the fuzzy membership functions for the 15 sample sites along the transect. The analyses were repeated several times with different values for the parameter m; the degree of fuzziness is positively related to m. The fuzzy membership functions associated with dry heath were then compared with the percentage of dry heath species present at each sample site. The results showed that the fuzzy membership functions do display a systematic relationship with the canopy composition (Figure 3). In general, the fuzzy membership function associated with dry heath, for example, was positively related to the percentage dry heath vegetation in the samples and the relationship appeared to become increasingly linear as m increased. Although the data set is rather limited, a linear regression of the fuzziest state, the one with the most linear trend, was significant (at the 95 percent level of confidence) and had an $R^2 = 0.81$. The analyses have therefore shown that the end points may be discriminated to a high level of accuracy and the fuzzy membership functions can be used to model the variations in composition between class end points. While further study is required, especially in terms of the description of the ground data, these results do indicate the potential of the technique for mapping heathland vegetation in a manner similar to probability mapping.

SUMMARY AND CONCLUSIONS

Image classification routines are inappropriate for the representation of continuous environments. Of the alternative techniques available (e.g., Trodd *et al.* 1989; Wang, 1990), those based on fuzzy sets approaches are particularly attractive because they do not make rigid assumptions about the characteristics of the data and they allow for the natural fuzziness or imprecision of the scene to be mapped. The results of this study have shown that (i) the fuzzy c-means algorithm can be used to classify accurately the end points of continua and, (ii) the fuzzy membership functions, u_{ik}, derived from the analysis are related to the canopy composition; correlations between u_{ik} as-

TABLE 1. CONFUSION MATRIX DERIVED FROM THE DATA AFTER THE APPLICATION OF THE FUZZY C-MEANS ALGORITHM IN A FAIRLY HARD MODE ($M = 1.25$).

	DH	WHB	CW	MW
Dry Heath	31	0	0	0
Wet Heath and Bog	0	17	0	0
Coniferous Woodland	0	0	20	0
Mixed Woodland	0	0	0	24

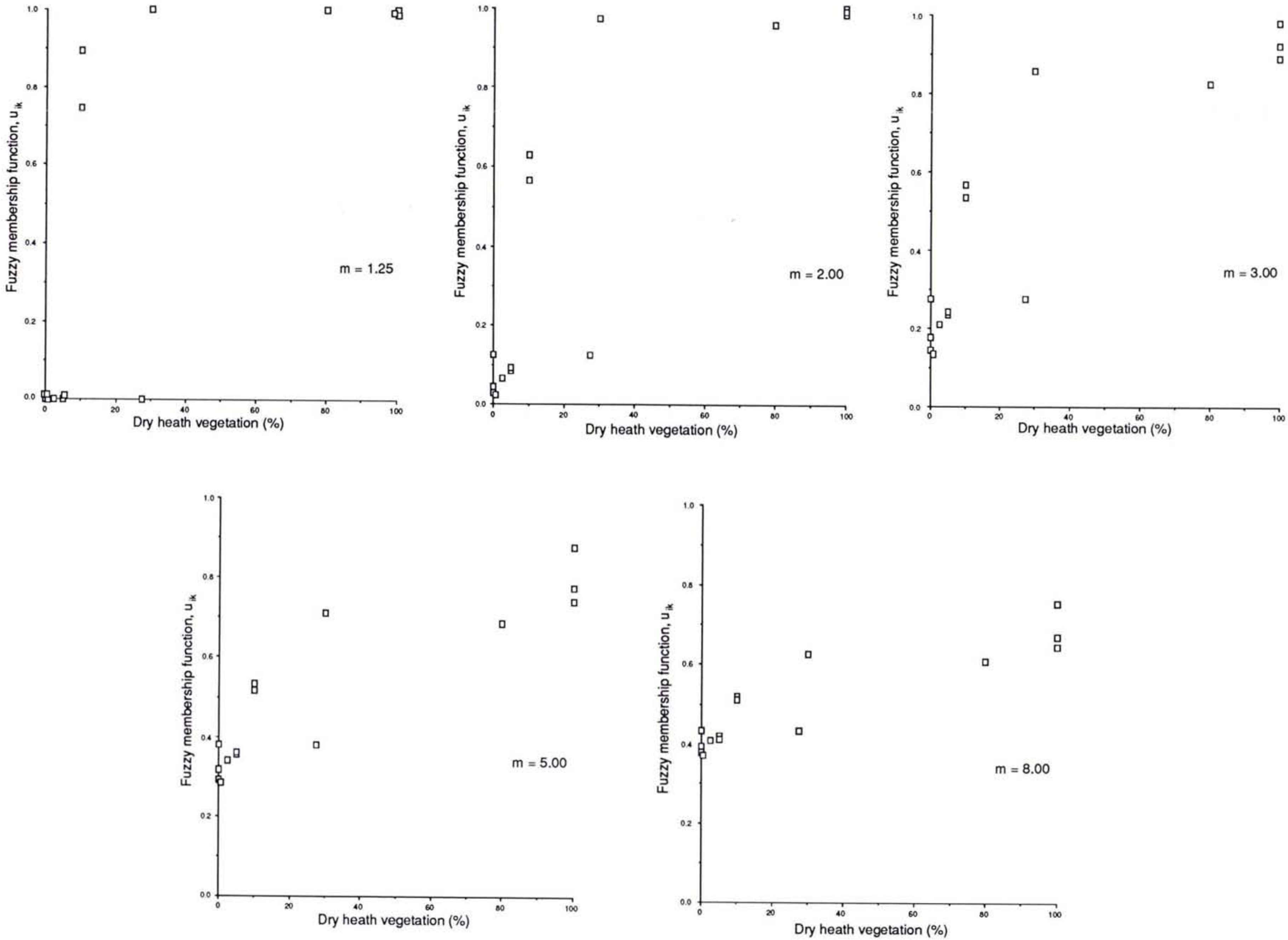

FIG. 3. Relationship between the fuzzy membership functions for dry heath vegetation and the percentage of dry heath vegetation at sample sites along the transect for different values of the parameter *m*.

sociated with dry heath vegetation and the percentage cover of these vegetation types at a heathland test site were high, typically >0.9 and significant at the 95 percent level of confidence. By mapping these membership functions, it should therefore be possible to model more appropriately the distribution of vegetation types than can be achieved with a conventional image classification. This output may also be of more value than that from a conventional classification. It would, for instance, represent a more useful input to a geographical information system because it reveals the gradual transitions between classes and not the sharp artificial boundaries characteristic of most classified scenes and thematic maps.

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