Approaches for the production and evaluation of fuzzy land cover classifications from remotely sensed data

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Abstract

Remote sensing is an attractive source of data for land cover mapping applications. Mapping is generally achieved through the application of a conventional statistical classification, which allocates each image pixel to a land cover class. Such approaches are inappropriate for mixed pixels, which contain two or more land cover classes, and a fuzzy classification approach is required. When pixels may have multiple and partial class membership measures of the strength of class membership may be output and, if strongly related to the land cover composition, mapped to represent such fuzzy land cover. This type of representation can be derived by softening the output of a conventional 'hard' classification or using a fuzzy classification. The accuracy of the representation provided by a fuzzy classification is, however, difficult to evaluate. Conventional measures of classification accuracy cannot be used as they are appropriate only for 'hard' classifications. The accuracy of a classification may, however, be indicated by the way in which the strength of class membership is partitioned between the classes and how closely this represents the partitioning of class membership on the ground. In this paper two measures of the closeness of the land cover representation derived from a classification to that on the ground were used to evaluate a set of fuzzy classifications. The latter were based on measures of the strength of class membership output from classifications by a discriminant analysis, artificial neural network and fuzzy *c*-means classifiers. The results show the importance of recognising and accommodating for the fuzziness of the land cover on the ground. The accuracy assessment methods used were applicable to pure and mixed pixels and enabled the identification of the most accurate land cover representation derived. The results showed that the fuzzy representations were more accurate than the 'hard' classifications. Moreover, the outputs derived from the artificial neural network and the

fuzzy *c*-means algorithm in particular were strongly related to the land cover on the ground and provided the most accurate land cover representations. The ability to appropriately represent fuzzy land cover and evaluate the accuracy of the representation should facilitate the use of remote sensing as a source of land cover data.

1. Introduction

Land cover is one of the most fundamental geographical variables. It plays a role in a broad spectrum of geographical inquiry including, *inter alia*, control of the Earth's albedo, erosion rates, species dispersion routes, resource planning and utilization. Although the importance of land cover is a recognised, data on land cover are often out-of-date, of poor quality or inappropriate for a particular application (Townshend *et al.*, 1991; DeFries and Townshend, 1994; Estes and Mooneyhan, 1994). Furthermore, land cover data are not, contrary to popular belief in some quarters, easy to acquire (Rhind and Hudson, 1980; Estes and Mooneyhan, 1994). This is particularly the case if data are required for large areas or if frequent up-dating is required. Often the only feasible approach to map land cover is through the use of remotely sensed data, especially for mapping at regional to global scales. Relative to traditional mapping methods remotely sensed data are an attractive source of land cover data. This is mainly a result of their map-like format combined with favourable coverage, consistency, availability and cost. As a result land cover mapping has become one of the most common applications of remote sensing. This application has, however, not yet reached operational status (Townshend, 1992). A number of reasons may be cited for the failure to realise the full potential of remote sensing as a source of land cover data. One set of factors relate to the methods used to map land cover from the remotely sensed data.

Typically a supervised digital image classification is used in the mapping of land cover from remotely sensed data. This type of classification is generally applied on a per-pixel basis and has three distinct stages. First, the training stage, in which pixels of known class membership in the remotely sensed data are characterised and class 'signatures' derived. In the second stage, these training statistics are used to allocate pixels of unknown class membership to a class in accordance to some decision rule. Third, the quality of the classification is evaluated. This is generally based on the accuracy of the classification which is assessed by comparing the actual and predicted class of membership for a set of pixels not used in training the classification.

Of the many classification techniques available the most widely used are conventional statistical algorithms such as discriminant analysis and the maximum likelihood classification. These aim to allocate each pixel in the image to the class with which it has the highest probability of membership (Mather, 1987; Thomas *et al.*, 1987). Problems with this type of classification, particularly in relation to distribution assumptions and the integration of ancillary data, particularly if incomplete or acquired at a low level of measurement precision (Moon, 1993; Peddle, 1993), prompted the development of alternative classification approaches. Thus, for instance, attention has turned recently to approaches such as those based on evidential reasoning (Srinivasan and Richards, 1990; Peddle, 1993) and artificial neural networks (Benediktsson *et al.*, 1990; Foody *et al.*, 1995). Although there are many instances when the conventional and alternative classification techniques have been used successfully in the accurate mapping of land cover, they are not always appropriate for land cover mapping applications. One important limitation of the classification approaches to land cover mapping is that the output derived consists only of the code of the allocated class. This type of output is often referred to as being 'hard' or 'crisp' and is wasteful of information on the strength of class membership generated in the classification (Wang, 1990a). This information on the strength of class membership may, for instance, be used to indicate the confidence that may be associated with an allocation on a per-pixel basis, indicating classification reliability (Foody *et al.*, 1992; Maselli *et al.*, 1994; Corves and Place, 1994), or be used in post-classification processing (Harris, 1985; Wang and Civco, 1992) and enable more appropriate and informed analysis by later users, particularly within a geographical information system (Hall *et al.*, 1992). Perhaps a more important limitation of 'hard' classifications is that they were developed for the classification of classes that may be considered to be discrete and mutually exclusive, and assume each pixel to be pure, that is comprised of a single class. Often this is not the situation. Frequently, for example, pixels of mixed land cover class composition may be abundant in an image. Thus, for instance, the classes may be continuous and inter-grade gradually with many areas of mixed class composition, particularly near imprecise or fuzzy class boundaries (McBratney and Moore, 1985; Wood and Foody, 1989). Alternatively, a pixel may represent an area on the ground which comprises more than one discrete land cover class. This may occur when the area represented by the pixel straddles the boundaries of two or more classes and is common in coarse spatial resolution data sets (Townshend and Justice, 1981; Crapper, 1984; Campbell, 1987). Despite having a mixed land cover composition a conventional classification will force the allocation of a mixed pixel to one class, and this class need not even be one of the component classes (Campbell, 1987). Conventional classification approaches therefore may not provide a realistic or accurate representation of land cover.

A 'hard' classification output can therefore fail to appropriately represent land cover. An alternative to the 'hard' classification representation of land cover is therefore often required and should allow for partial and multiple class membership (Wang, 1990a). This could be achieved by 'softening' the output of a 'hard' classification. For instance, measures of the strength of class membership, rather than just the code of the most likely class of membership, may be output. Thus, for example, with a probability based classification a probability vector containing the probability of membership a pixel has to each defined class could be output. In this probability distribution the partitioning of the class membership probabilities between the classes would, ideally, reflect to some extent the land cover composition of a mixed pixel (Wang, 1990b; Foody *et al.*, 1992). This type of output may be considered to be fuzzy, as an imprecise allocation may be made and a pixel can display membership to all classes. The data must still, however, satisfy the assumptions and requirements of the classification technique used, which is often unlikely with the widely used probability based classifiers. The lack of distribution assumptions is one major attraction of alternative classifiers such as artificial neural networks. Although generally used to produce a hard classification (Kanellopoulos *et al.*, 1992) the output may be softened to provide measures of the strength of class membership (Foody *et al.*, 1995) which may better model fuzzy land cover than a 'hard' classification.

Since the concept of multiple and partial class membership is fundamental to fuzzy sets techniques (Bosserman and Ragade, 1982; Hisdal, 1994) these may, however, be more appropriate for land cover representation than softened classifications. One technique which has been used widely in the classification of remotely sensed data is the fuzzy *c*-means algorithm. This is a clustering algorithm which may be used for either unsupervised (e.g. Cannon *et al.*, 1986) or supervised classification (e.g. Key *et al.*, 1989). In the course of the classification fuzzy membership functions are calculated from which membership values which indicate the relative strength of class membership a pixel has to each class may be derived. These fuzzy memberships may be used to derive information on the land cover composition of mixed pixels (Fisher and Pathirana, 1990; Foody and Cox, 1994). One significant problem in the use of such a technique is the lack of methods for the evaluation of the accuracy of the fuzzy classification output and this is a major barrier to the adoption of fuzzy classifications (Goodchild, 1994). An accuracy statement is required not only to describe the accuracy of the land cover representation derived but also to aid the selection of the most accurate land cover representation as the degree of fuzziness is variable in the fuzzy *c*-means classification.

Although fuzzy classifications have been used to provide a more appropriate representation of land cover that may be considered to be fuzzy, the fuzziness of the land cover being represented has often been overlooked in the assessment of the accuracy of the representation derived. This problem stems largely from the use of the pixel as the basic spatial unit. In terms of factors such as size, shape and location on the ground, the pixel is largely an arbitrary spatial unit (Rhind and Hudson, 1980; Fisher, 1995). Often the area represented by a pixel crosses the boundaries of classes resulting in a pixel of mixed land cover composition. It is important, however, to recognise that this problem is not restricted to just the remotely sensed data set but applies also to the ground data as these are related to the classification output at the scale of the pixel. Since a pixel may represent an area containing more than one land cover class it is desirable that this should be reflected in the classification output and, if the classification is to be appropriately evaluated, it should also be included in the assessment of classification accuracy. Thus the fuzziness of both the classification output and the land cover on the ground at the scale of the pixel both need to be recognised.

Ground data on class membership are required to both train the classification and evaluate its accuracy (Campbell, 1987; Mather, 1987). Since the pixel size of data from many remote sensing systems is relatively large (e.g. around 1.2km^2 for NOAA AVHRR data used in regional/global scale mapping) many pixels are of mixed composition; most image pixels may be mixed but the exact proportion of mixed pixels in an image is a function of the sensor's spatial resolution and the fabric of the landscape (Crapper, 1984; Campbell, 1987). Since it is impractical to collect ground data at a scale directly comparable to the remotely sensed data analysts often sample from large homogeneous regions of each class where it can be assumed that pixels are pure in order to minimise the problem of training site contamination by other classes. Care is, however, required to ensure that the training data are representative of the class (Campbell, 1987); the problems of relating ground and remotely sensed data sets acquired at differently sized supports is a major problem in the use of remotely sensed data for the scaling-up of information and is currently the focus of considerable effort (Atkinson, 1995).

In evaluating the accuracy of a classification the ground data must again relate to the same spatial unit as the remotely sensed data for a meaningful comparison. As in training the classification 'pure' pixels only are often used to reduce the mixed pixel problem. However, since a large proportion of pixels in an image may be mixed an accuracy statement based on pure pixels only will not provide a full or adequate description of the overall classification performance. It is therefore important that mixed pixels be included in an accuracy assessment. While the assessment of classification accuracy for pixels that are pure in the remotely sensed and ground data sets has been the subject of considerable research and a range of methods exist (e.g. Rosenfield and Fitzpatrick-Lins, 1986; Congalton, 1991) relatively little attention has addressed the problems of assessing the accuracy of classifications which include mixed pixels. However, if a fuzzy classification is used to map land cover that may be considered to be fuzzy the assessment of the accuracy of the representation derived must accommodate for the fuzziness of both the land cover classification derived and the actual land cover on the ground.

The aim of this paper was to illustrate the fuzzy classification of land cover from remotely sensed data. It was based on three algorithms used widely for the classification of remotely sensed data. These were a discriminant analysis, an artificial neural network and the fuzzy *c*-means algorithm. It should be noted that the first two techniques have been widely used for the 'hard' classification of remotely sensed data. Although the softening of probabilistic classifications has been reported in the literature (e.g. Foody *et al.*, 1992) little attention has focused on artificial neural network classifications. A secondary aim of the paper was therefore to illustrate an approach for the derivation of a fuzzy classification from an artificial neural network. In contrast to the two other classification techniques, the fuzzy *c*-means algorithm has been used extensively for fuzzy classification and is particularly interesting as the degree of fuzziness is controlled by the analyst. Here attention was also focused on the assessment of the accuracy of the land cover representation derived as this is an essential part of any land cover mapping programme. Methods for evaluating the accuracy of fuzzy classifications would help fill the gap in this part of the classification procedure which currently inhibits the wider adoption of fuzzy classifications (Goodchild, 1994). Furthermore, an ability to assess the accuracy of a fuzzy land cover classification will assist in the selection of most appropriate degree of fuzziness for use in the fuzzy *c*-means algorithm.

2. Approaches for fuzzy land cover mapping

A range of approaches may be used to derive a fuzzy classification of remotely sensed data. In addition to the use of fuzzy classifiers it is possible to soften the output of conventional 'hard' classifiers to derive a fuzzy land cover representation. In general, fuzzy land cover may be represented by mapping measures of the strength of class membership, which may be output from conventional 'hard' classifications or from fuzzy classification techniques. These measures of the strength of class membership derived for a pixel are taken to reflect the relative proportion of the classes in the area represented by the pixel. Here three classification approaches were used to map land cover that may be considered to be fuzzy. Two of these approaches, a discriminant analysis and an artificial neural network, are normally used for 'hard' classifications while the other, the fuzzy *c*-means algorithm, is a fuzzy classifier. The salient features of each of these classifications and the measures of the strength of class membership which may be derived from them are briefly outlined in this section.

Discriminant analysis is widely used in the classification of remotely sensed data (Tom and Miller, 1984; Lark, 1994). It is a conventional statistical classifier which allocates each case to the class with which it displays the highest *a posteriori* probability of membership. The latter may be derived from,

$$L(i|X) = P_i p(X|i) / \sum_{j=1}^{c} P_j p(X|j) \tag{1}$$

where $L(i|X)$ is the posterior probability of case X belonging to class i, $p(X|i)$ is the typicality probability (the probability that case X would be a member of class i given the distance it is from the centroid of class i), P_i the *a priori* probability for class i, and c the total number of classes. These posterior probabilities lie on a 0-1 scale and sum to 1.0 for each pixel. Further details on the algorithm used are given in Klecka (1980).

Problems, especially in relation to distribution assumptions, with statistical classifiers such as discriminant analysis have led to increased use of alternative approaches. One particularly attractive alternative for the supervised classification of remotely sensed data is the use of artificial neural networks. An artificial neural network is constructed from a set of simple processing units interconnected by weighted channels according to some architecture (Aleksander and Morton, 1990; Fischer and Gopal, 1993). Typically a layered architecture is used for classification (Figure 1). In this type of network each unit in a layer is connected to every unit in the next layer. The data are entered at the input layer, pass through one or more hidden layers to the output layer. The latter comprises one unit for each class in the classification and is where class allocation may be determined.

Each unit in the network consists of a number of input channels, an activation function and an output channel. Signals impinging on a unit's inputs are multiplied by the inter-connecting channel's weight and are summed to derive the unit's net input. Thus for the unit s the net input may be determined from,

$$net_s = \sum_r a_r w_r \tag{2}$$

where a_r is the magnitude of the r^{th} input and w_r the weight of the interconnection channel. This net input (net_s) is then transformed by the activation function to produce an output for the unit (Schalkoff, 1992). Typically a sigmoid activation function such as,

$$o_s = \frac{1}{1 + \exp^{-\lambda net_s}} \tag{3}$$

where λ is a gain parameter is used. The output of a network unit is sometimes referred to as its activation level. The magnitude of the activation level of a unit in the output layer is a measure of the strength of membership to the class associated with the unit. A 'hard' classification is achieved by allocating each pixel to the class associated with the unit in the output layer with the highest activation level.

Classification with an artificial neural network usually begins with the network weights connecting the units set at random. Generally a backpropagation learning algorithm (Rumelhart *et al.*, 1986) is used to train the network to correctly characterise the classes. Network training begins with the input of the training data from which an output may be computed. Since the desired output is known for the training data the error in the computed output may be determined. This is then fed backward through the network to the input layer with the weights connecting units changed in proportion to the calculated error (Aleksander and Morton, 1990; Schalkoff, 1992). The training data are then entered again and the process repeated. Thus with backpropagation learning the aim is to iteratively minimize an error function over the network outputs and a set of target outputs, taken from a training data set. The process continues until the error value converges to a (possibly local) minima. Conventionally the error function is given as,

$$E = 0.5\sum_i (T_i - O_i)^2 \tag{4}$$

where T_i is the target output vector for the training set $(T_1,\ldots,\ T_c)$ and O_i is the output vector from the network for the given training set. On each iteration backpropagation recursively computes the gradient or change in error with respect to each weight ($\mathrm{d}E/\mathrm{d}w$) in the network and these values are used to modify the weights between network units. The weight change on the t^{th} iteration is achieved by,

$$\Delta w_t = -\eta(\mathrm{d}E/\mathrm{d}w)_t + \alpha\Delta w_{t-1} \tag{5}$$

where η and α are parameters which define the learning rate and momentum which facilitate network learning (Schalkoff, 1992). Once trained the network may be used for the classification of cases of unknown class membership.

The fuzzy *c*-means clustering algorithm may be used to subdivide a data set into *c* clusters or classes. It is a non-hierarchical clustering technique. It begins by randomly assigning cases (pixels) to classes and then, iteratively, moves cases to other classes with the aim of minimizing the generalised least-squared error,

$$J_m(U,v) = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m \, \|y_k - v_i\|_A^2 \tag{6}$$

where U is a fuzzy *c*-partition of the data set Y containing n cases $(y_1, y_2,.., y_n)$, c is the number of classes, $\| \; \|_A$ is an inner product norm, v is a vector of cluster centres, v_i is the centre of cluster i, and m is a weighting component that lies within the range $1 \leq m \leq \infty$ which determines the degree of fuzziness. The squared distance between y_k and v_i is derived from,

$$\|y_k - v_i\|_A^2 = (y_k - v_i)^{\mathrm{T}} A (y_k - v_i) \tag{7}$$

A number of norms may be selected. Here the Mahalanobis norm, $A = C_y^{-1}$, was used, where C_y is the covariance matrix of the data set Y. The elements of U, u_{ik}, represent the grade of membership of a case to a class. These membership values satisfy the constraints,

$$u_{ik} \in [0,1] \tag{8a}$$

$$\sum_{k=1}^{n} u_{ik} > 0, \quad i=1...c \tag{8b}$$

$$\sum_{i=1}^{c} u_{ik} = 1, \quad k=1...n \tag{8c}$$

In a fuzzy *c*-partition of a data set membership functions characterise the membership of each case in all classes. These memberships lie on a 0-1 scale and the memberships for each case sum to unity. These membership values indicate the degree of similarity between a case and a class. Memberships close to unity indicate a high degree of similarity between a case and a class whereas memberships close to zero indicate little similarity between a case and a class. Further details and examples of the use of this algorithm may be found in the literature such as Cannon *et al.* (1986), Fisher and Pathirana (1990) and Key *et al.* (1989) and a listing of the fuzzy *c*-means clustering (unsupervised) algorithm may be found in Bezdek *et al.* (1984). Since the classes are known *a priori* in a supervised classification the fuzzy *c*-means clustering algorithm may be modified so that the classification is based on class centres provided by the analyst from training samples (Key *et al.*, 1989).

In performing a classification with the fuzzy *c*-means algorithm the analyst must select the value of the weighting component m. When $m=1$ a 'hard' or conventional classification may be obtained in which each pixel is associated unequivocally with just one class. There is no optimal value of m and most studies have used a value in the range $1.5 < m < 3.0$ (Bezdek *et al.*, 1984; M^{c}Bratney and Moore, 1985). To aid the selection an appropriate value of m and describe the quality of the land cover representation derived from an analysis a measure of classification accuracy is required.

The posterior probabilities, output unit activation levels and fuzzy membership values derived from the discriminant analysis, artificial neural network and fuzzy *c*-means classifications respectively are all measures of the strength of class membership that may be mapped to represent fuzzy land cover. The use of each measure for the representation of fuzzy land cover is outlined below in section 6. First the procedures for the evaluation of the accuracy of the land cover representation provided by a classification will be discussed.

3. Evaluation of classification accuracy

A statement of classification accuracy is an essential accompaniment to a land cover map derived from remotely sensed data. Many methods for assessing classification accuracy have been proposed (e.g. Hay, 1979; Aronoff, 1985; Congalton, 1991; Foody, 1992). Ideally classification accuracy should be expressed in the form of a single index which is readily interpretable and which allows the relative performance of different classifications to be evaluated. The most widely used measures are derived from a classification confusion or error matrix. This matrix shows the predicted and actual class of membership for a set of pixels sampled from the classification. In this matrix the main diagonal illustrates those pixels which have been allocated correctly whilst the off-diagonal elements represent incorrect allocations. A range of measures of classification accuracy may be derived from the matrix. For instance, the percentage correct allocation may be derived as an index of the overall accuracy of the classification. If desired this could be calculated for individual classes from the producer's and users's perspectives (Story and Congalton, 1986). To make more use of the information contained in the confusion matrix a statistic such as the kappa coefficient of agreement may be used for the assessment of the accuracy of the classification as a whole and for individual classes after making some compensation for chance agreement (Cohen, 1960; Congalton, 1991).

One fundamental problem with the use of accuracy measures derived from the classification confusion matrix is that they are only appropriate for use with a 'hard' classification. Thus these measures of classification accuracy may be derived when each pixel is associated with only one class in the classification and only one class in the ground data (Congalton *et al.*, 1983; Gong and Howarth, 1990). Consequently, an allocation is either correct or incorrect. Although account may be made for factors such as varying degrees of severity of error (Cohen, 1968), the measures of classification accuracy derived from the confusion matrix are inappropriate for the evaluation of fuzzy classifications. In some investigations a fuzzy classification has been produced but in order to evaluate the accuracy of the classification it has been necessary to 'harden' the classification output and/or focus only on pure pixels in the data set to enable a conventional measure of classification accuracy to be calculated (e.g. Foody and Trodd, 1993). The resulting accuracy statement is not, however, a good measure of the accuracy of a fuzzy classification. Furthermore, as the pixel is generally the spatial unit used in accuracy assessment and as the majority of image pixels may be mixed (Crapper, 1984), multiple and partial class membership may therefore be considered to be a function of both the remotely sensed and ground data sets. The ground data used also are often not error-free (Curran and Williamson, 1985; Curran and Hay, 1986; Bauer *et al.*, 1994) and may be based on subjective assessments which can be a source of ambiguity and confusion within them. There may therefore also be occasions when the ground data are fuzzy or where there is ambiguity in the ground data (Gopal and Woodcock, 1994). Again it may be possible to 'harden' these data to enable the accuracy to be assessed by a conventional measure derived from a confusion matrix but the end result is not an evaluation of the fuzzy classification.

There is therefore a need to derive measures of classification accuracy which go beyond the confusion matrix (Congalton, 1994). A number of approaches have been suggested with emphasis on fuzzy measures. Gopal and Woodcock (1994), for instance, show how a number of fuzzy sets techniques may be used to derive a range of indicators of classification performance. The methods used, however, are only appropriate for the situation in which there is ambiguity in the ground data but not the classification output (i.e., the ground data are fuzzy and the classification is 'hard'). Furthermore, the methods do not allow the comparison of classifications, which is relatively easy with conventional measures such as the kappa coefficient (Cohen, 1960). Other approaches that have been used are based on measures of entropy (e.g. Finn, 1993; Maselli *et al.*, 1994; Foody, 1995a). Entropy is a measure of uncertainty and information formulated in terms of probability theory, which expresses the relative support associated with mutually exclusive alternative classes (Klir and Folger, 1988). When two or more alternative classes have non-zero probabilities associated with them then each probability is in conflict with the others. When there is a finite set of alternative classes the expected value of conflict is given by the Shannon entropy (Klir, 1994). This may be used to describe the variations in class membership probabilities associated with each pixel. Entropy is therefore particularly attractive as an indicator of classification quality in situations where ambiguity exists as it indicates the degree to which the class membership probabilities are partitioned between the defined classes. The entropy, H, of a probability distribution, $\mathbf{p}$, may be calculated from the class membership probabilities, $p(x)$, contained through,

$$H(\mathbf{p}) = -\sum_{x} p(x) \log_2 p(x) \qquad (9)$$

The choice of logarithm base is arbitrary but the logarithm base 2 is widely used. With this base the uncertainty is measured in bits (Klir and Folger, 1988).

Entropy is maximised in the situation when the probability of class membership is partitioned evenly between all defined classes in the classification and minimized when it is associated entirely with one class. Entropy and related measures are becoming popular in a range of applications in remote sensing (Conese and Maselli, 1993; Finn, 1993; Maselli *et al.*, 1994). For instance, the relative entropy (ratio of observed to maximum entropy) has been used to indicate the confidence that may be associated with a classification output - with pixels showing a low relative entropy assumed to be well classified and those with a high relative entropy poorly classified (Maselli *et al.*, 1994). Its value as an indicator of classification accuracy is therefore based implicitly on the assumption that in an accurate classification each pixel will have a high probability of membership with only one class. This is, however, only appropriate for situations in which the output of the classification is fuzzy (i.e., the probabilities of membership to all defined classes are output for each pixel) and the ground data are 'hard' (i.e., the code of the single class of membership). When the land cover may be considered to be fuzzy at the scale of the pixel, as may exist for a classification of continuous classes or an image with a high proportion of mixed pixels, then the direct use of entropy is no longer appropriate as an accurate classification output for a pixel could involve the total probability of class membership being partitioned among several classes (Foody, 1995a). In such a situation a more appropriate index of accuracy may be a measure of the closeness of the classification output to the ground data.

4. Measures of closeness

One approach which could be used in the evaluation of classification accuracy is to measure the distance between land cover on the ground the fuzzy land cover representation derived from the classification (Kent and Mardia, 1988). This distance may be determined in a number of ways (Klir and Folger, 1988; Altman, 1994). One simple approach would be to use the Euclidean distance between the representation of the land cover from the classification and ground data. This would measure the separation of the two data sets and could be based on the relative extent or proportion of each class in the pixel. This measure could be derived for each pixel from,

$$S = \sum_{i=1}^{c}({}^{1}e_i - {}^{2}e_i)^2/c \tag{10}$$

where ${}^{1}e_i$ is the proportion of class i in a pixel from the ground data and ${}^{2}e_i$ is the measure of the strength of membership to class i taken to represent the proportion of the class in the pixel from the fuzzy classification.

Since the classification problem is essentially one of uncertainty in the class allocation, measures of closeness based on information uncertainty may, however, be the most appropriate to use in classification evaluation. Two broad categories of uncertainty may be identified. These are vagueness and ambiguity (Klir and Folger, 1988). Vagueness is associated with the difficulties of making precise distinctions. In mapping it may be associated therefore with the problem of locating a sharp dividing line between two continuous classes which, rather than lying as two distinct classes adjacent to each other, gradually inter-grade. Ambiguity is associated with one-to-many situations and conflicts of evidence (Klir and Folger, 1988). The concept of a fuzzy set and fuzzy measure provide the framework for dealing with vagueness and ambiguity respectively.

In mapping land cover from remotely sensed data uncertainty issues often arise.

Uncertainty may be quantified in a number of ways (Klir and Folger, 1988; Pal and Bezdek, 1994). In probabilistic systems entropy has been used successfully to illustrate the accuracy of a classification (Maselli *et al.*, 1994; Foody, 1995a). However, it was noted above that entropy may not be a good indicator of classification quality if multiple and partial class membership is a feature of both the classification output and ground data. However, since there is ambiguity in both the fuzzy classification and ground data the entropy of each may be calculated. It is then possible to assess the closeness of the two probability distributions for each pixel, derived from the fuzzy classification output and the fuzzy ground data. One approach could be to assess the similarity of the land cover representation provided by the classification output to the ground data through an evaluation of their mutual information content (Conese and Maselli, 1993; Finn, 1993). Alternatively the distance between the two data sets could be assessed. Essentially the aim is to express the information closeness of a pair of probability distributions, ${}^1\mathbf{p}$ and ${}^2\mathbf{p}$. In the evaluation of the accuracy of a fuzzy land cover map the probability distribution of the ground data (${}^1\mathbf{p}$) and that of the fuzzy classification output (${}^2\mathbf{p}$) for a pixel would be used. An approach which may be used is to calculate the directed divergence or cross-entropy. Directed divergence may be derived from,

$$d({}^1\mathbf{p},\, {}^2\mathbf{p}) = -\sum_x {}^1p(x)\log_2 {}^2p(x) + \sum_x {}^1p(x)\log_2 {}^1p(x) \tag{11}$$

This provides a measure of the closeness of the classification to the ground data. A small difference would, for instance, indicate that the classification was an accurate representation of the land cover (Foody, 1995a). This measure may be used as a criterion to evaluate the degree of similarity between two data sets (Chang *et al.*, 1994). Directed divergence, however, may only be derived when the supports of the probability distributions to be compared are compatible. Specifically the support ${}^1\mathbf{p} \subseteq$ support ${}^2\mathbf{p}$. Higashi and Klir (1983), however, present a measure of information closeness which is applicable to any pair of probability distributions. This generalised measure of information closeness, D, may be derived from,

$$D({}^1\mathbf{p}, {}^2\mathbf{p}) = d({}^1\mathbf{p}, \frac{{}^1\mathbf{p} + {}^2\mathbf{p}}{2}) + d({}^2\mathbf{p}, \frac{{}^1\mathbf{p} + {}^2\mathbf{p}}{2})$$

$$= \sum_x {}^1p(x)\log_2 {}^1p(x) - \sum_x {}^1p(x)\log_2 \frac{{}^1p(x) + {}^2p(x)}{2}$$

$$+ \sum_x {}^2p(x)\log_2 {}^2p(x) - \sum_x {}^2p(x)\log_2 \frac{{}^1p(x) + {}^2p(x)}{2} \tag{12}$$

and used to assess the closeness of pairs of probability distributions.

The measures S and D should enable the closeness of the fuzzy land cover representation, derived from the three classification techniques, to the fuzzy ground data to be assessed. Both S and D are used here to evaluate the accuracy of a set of fuzzy classifications derived from remotely sensed data, although D was developed for use with probability distributions.

5. Test sites and data

The test site was a 0.5 km^2 area located adjacent to the University campus on the fringe of the City of Swansea, UK. Airborne thematic mapper (ATM) data in eleven spectral wavebands were acquired for the site with a Daedalus 1268 sensor with a spatial resolution of approximately 1.5m in 1990. The advantage of using fine spatial resolution data for a small test site was that the composition of image pixels could be evaluated accurately.

This test-site was comprised of mainly three land cover classes, trees, grass and asphalt (car park), and these could be readily identified from the imagery. For the purpose of this investigation each pixel in this fine spatial resolution image was assumed to be pure and classified visually into the three classes. This classification was verified in the field and used as ground/reference data on the distribution of the three land cover classes. To simplify the analysis of this data set, only the data from three wavebands, which account for much of the dimensionality and information content of ATM data (Townshend, 1984), were used. These were the data in the 605-625nm, 695-750nm and 1550-1750nm wavebands. The ATM data were then spatially degraded with an 11x11 low pass (mean) filter to simulate an image with a relatively coarse spatial resolution; further details on these data and the test site may be found in Foody and Cox (1994). For each pixel in this simulated coarse spatial resolution image the proportion of three land cover classes contained within it could be derived from the classification of the spatially undegraded image. Using 5 pure pixels of each class as training sites the simulated coarse spatial resolution image was then classified into the three classes by the discriminant analysis, artificial neural network and fuzzy *c*-means algorithm. To vary the degree of fuzziness in the land cover representations derived from the fuzzy *c*-means algorithm the analysis was repeated with different values for the weighting parameter m. In addition to the conventional 'hard' classification outputs the posterior probabilities of class membership from the discriminant analysis, output unit activation levels from the artificial neural network and fuzzy memberships generated from the analyses with the fuzzy *c*-means algorithm were output for each pixel. The accuracy of the classification outputs derived were assessed relative to ground data on class membership for a sample of 35 pixels. Although this is a relatively small sample it is large enough to illustrate the methods. The ground data for each pixel comprised the proportion of each land cover class in the 35 pixels sampled from the simulated coarse spatial resolution image. These lie on a 0-1 scale and sum to unity for each pixel. Although not strictly probabilities they may reasonably be considered as such and forming a probability distribution for each pixel.

Thus the data for each pixel used to evaluate the accuracy of the land cover representations derived from the fuzzy classifications comprised the strength of membership to all classes derived from the three classification techniques together with ground data in the form of the proportion of each class in the area represented by the pixel. The closeness of each fuzzy land cover representation derived to the ground data was assessed by correlation analysis as well as with measures *S* and *D*.

6. Results and discussion

The discriminant analysis was used to produce a conventional statistical classification of the data. The mean entropy of the 35 testing pixels was 0.095 with a corresponding mean relative entropy of 0.059. These values could be interpreted as indicating a fairly good classification. However, as the entropy value was greater than the minimum value this indicated the posterior probability of class membership for all pixels was not associated solely with a single class. This is desirable for a fuzzy classification. However, the posterior probabilities of class membership output from the analysis were generally either high or low with little variation between these extremes. Thus although the magnitude of probabilities did to some extent reflect the composition of the pixels the relationships were not strong (Figure 2). Relative to the 'hard' classification output, however, the land cover representation portrayed by the probabilities was closer, as measured by both *S* and *D*, to the ground data (Table 1). These results show two main features. Firstly, they reinforce the danger of using entropy as a measure of classification accuracy when mixed pixels are present and secondly, that a conventional 'hard' statistical classification may be softened to provide a more appropriate representation of fuzzy land cover than the 'hard' classification.

Although both *S* and *D* may be derived for the probabilities output from the discriminant analysis the use of *D* at first seems inappropriate for the evaluation of the accuracy of the non-probabilistic fuzzy land cover representations based on fuzzy memberships and the activation level of artificial neural network output units. Although similar in some ways to posterior probabilities of class membership, fuzzy membership values and artificial neural network output unit activation levels are not probabilities and should not be treated as such (Bezdek, 1993). One obvious difference is that fuzzy memberships, in general, and the activation level of artificial neural network output units need not sum to 1.0 for each pixel. However, because of the constraints (8) in the fuzzy *c*-means algorithm the vector of fuzzy memberships for each pixel is mathematically identical to a probability vector enabling a complete formal analogy to Shannon's entropy for a fuzzy *c*-partition (Bezdek, 1981). With the artificial neural network, the output unit activation levels were on a scale 0-1 but need not sum to 1.0 for a pixel. Moreover, the sigmoid transfer function of the output units imposed a bias toward high or low values which results in a non-linear relationship between the activation level of a class and the proportion of the pixel composed of that class. Since the nature of the transfer function was known (equation 3) its effect was removed, which resulted in activation levels which should be more linearly related to the proportion cover of a class (Foody, 1995b). These transfer-function corrected activation levels were then rescaled and normalised so that they lay on a 0-1 scale sum to 1.0 for each pixel and only these rescaled activation levels were used in the research. Although neither these rescaled activation levels or fuzzy memberships are probabilities both are mathematically similar and, for comparative purposes, were used in the calculation of the distance measure D. The closeness of all the classification outputs to the ground data were also assessed with the generally applicable distance measure S.

As with the discriminant analysis the artificial neural network was used to derive a 'hard' classification of the data. The artificial neural network used was a four-layered feedforward network with three input units, twelve hidden units arranged in two equally sized hidden layers and three output units (Figure 1); the number of input and output units was determined by the number of discriminating variables and classes respectively. The number of hidden units is generally determined subjectively. Here the number of hidden units was selected after a series of trial runs and with the aim of ensuring both a high learning and generalisation capacity. Each unit had a sigmoid activation function and an external bias unit. A stochastic backpropagation learning algorithm was used with $\lambda = 1.0$ and the parameters η and α were set at 0.1 and 0.9 respectively. Training the artificial neural network involved 2000 iterations, by the end of which the average root sum squared error was 0.000521.

The rescaled activation level of the units in the output layer were derived for each of the 35 testing pixels. As with the probabilities of class membership derived from the discriminant analysis these were then related to the ground data (Figure 3). The activation level of an output unit was found to be strongly related to the proportion of the pixel area covered by the class associated with that unit. This indicated that although artificial neural networks have generally been used to drive a 'hard' classification the activation levels of the output units may, as measures of the strength of class membership, be mapped to provide a softened representation of land cover. The closeness of this representation to the ground data was assessed with both S and D. The results showed that the softened network classification output provided a more accurate representation of the fuzzy land cover than the 'hard' classification. Moreover, the softened artificial neural network classification was more accurate than the softened classification from the discriminant analysis (Table 1) with a strong relationship between the output unit activation level and the proportion of the pixel area covered by the class associated with the unit (Figure 3).

Four fuzzy classifications with the fuzzy *c*-means algorithm were performed with different values for the weighting parameter m. These were a fairly 'hard' analysis with $m=1.2$ and three fuzzier classifications with $m=1.5$, 2.0 and 2.5. From each classification the fuzzy membership values for each pixel to each class were output. For completeness the end points of the continuum of fuzzy classifications were also simulated and their closeness to the ground data assessed. The 'hard' classification, equivalent to $m=1.0$, had been derived by allocating each pixel to the class with which it had highest membership value in the analysis with $m=1.2$. The fuzziest classification output would be derived with $m=\infty$ in which class membership would be partitioned evenly between the classes. This was therefore simulated by dividing the total membership for each pixel equally between the classes. Combined with the reference data on the land cover composition of each pixel this enabled an assessment of the accuracy of the fuzzy land cover representations derived from the fuzzy *c*-means classifications.

With the weighting parameter $m=1.2$ the fuzzy membership values derived tended towards 1.0 and 0.0, characteristic of a fairly 'hard' classification (Figure 4). These fuzzy memberships were relatively poorly related to the land cover class composition of the pixels, with the relationship between the membership values and coverage of a class having some similarity to the results from the discriminant analysis (Figure 2). The membership values derived with $m > 1.2$ were, as expected, less constrained to relatively high or low values. As expected the degree of fuzziness increased positively with m with the values showing the general trend towards class membership being partitioned equally between the classes with increasing m; ultimately the membership values will tend to $1/c$ as $m \rightarrow \infty$ (Bezdek *et al.*, 1984). More importantly, the fuzzy memberships derived from the three fuzzier classifications were more strongly correlated with the composition of the pixels (Figures 5-7). The problem now faced by the analyst is that of selecting the classification which most closely models the actual land cover distribution. The relationships between fuzzy membership values and land cover composition (Figures 4-7) indicated that the memberships from the classification with $m = 2.0$ were most strongly related to the ground conditions and so that this was the most accurate representation of the land cover. Although correlations could be used as an index of classification quality a set of correlation coefficients are required when ideally a single index of classification quality is desired and the data may not always be appropriate for correlation analysis (e.g. Figure 4).

On the basis of the membership values from each fuzzy classification the closeness of the fuzzy land cover representations to the ground data were assessed by correlation analysis and with measures S and D. The results are summarised in Figures 4-7 and Table 1. It is worth noting that although the sample size was small the correlations coefficients derived (Figures 4-7) were all significant at the 99% level of confidence. From the results it was apparent that, overall, the classification closest to the ground data, and so indicating the most accurate representation of the land cover, was derived with $m = 2.0$ and the conventional 'hard' classification provided the least accurate representation. These results concur with the interpretation of the correlations between the fuzzy memberships and class cover above. They also show that the fuzzy representation is more accurate than a 'hard' one and allow the selection of the most appropriate representation.

Interpretation of the measures S and D, however, requires information on the sample used in its definition. Although the fuzzy classification derived from the fuzzy c-means algorithm with $m=2.0$ appeared to be the closest of all the classifications produced to the ground data the results were more variable on a per-pixel basis. This is illustrated in Table 2 which summarises the results for a pure pixel and one of mixed land cover composition. Note how the 'hard' classifications generally provided the most accurate representation of the pure pixel and the closeness of the fuzzy representations derived from the classifications based on the fuzzy c-means algorithm to the ground data declined as m increased. Conversely, for the mixed pixel the 'hard' representations were generally furthest from ground data and, for this pixel, the closest representation derived with the fuzzy c-means algorithm was derived with $m=\infty$, a consequence of its area being split fairly evenly between the three classes. Therefore if S and D are to be used as indicators of overall classification accuracy the testing sample of pixels acquired to assess classification accuracy should be drawn from a random sample. Information on the sampling design used in the acquisition of testing cases should therefore be included in accuracy statements (Janssen and van der Wel, 1994) to help their correct interpretation.

7. Summary and conclusions

Land cover is generally mapped from remotely sensed data through the application of a conventional 'hard' classification technique. In the output of this type of classification each pixel is associated unambiguously with a single class. Recognition that pixels in an image may have multiple and partial class membership, however, severely limits the appropriateness of such approaches to land cover mapping. Since the majority of pixels in an image may have a mixed land cover composition there is therefore a need for conceptual and methodological change in mapping land cover from remotely sensed data.

Fuzzy classification approaches may, however, enable a more accurate and realistic representation of land cover than conventional 'hard' classification techniques. A fuzzy classification output may be derived by softening the output of a 'hard' classifier or through the use of a fuzzy classifier. Although fuzzy classifications appear to provide a more appropriate representation of land cover a major limitation to their use and interpretation is the evaluation of the accuracy of the land cover representation derived (Goodchild, 1994). The measures of accuracy usually used in the evaluation of a classification were derived for application to 'hard' classification outputs in which cases are associated unambiguously with one class. Such measures are inappropriate for the evaluation of a classification in which multiple and partial class membership is a feature. Measures which show how the strength of class membership in the classification output is partitioned between the classes, such as entropy, are also inappropriate as the fuzziness of the land cover on the ground is overlooked. An approach is therefore required which accommodates for the fuzziness in both the classification output and the ground data against which the accuracy of the representation is assessed. This may be achieved by measuring the closeness of the land cover composition in the fuzzy classification, as reflected by the strengths of class membership, to the composition measured on the ground. This may be achieved with the use of a simple measures of distance such as the euclidean distance (measure *S*) or through the use of a measure of information closeness for probability distributions (measure *D*). These two measures were used to assess the accuracy of fuzzy classifications derived from three classification approaches. Two of these, a discriminant analysis and an artificial neural network, are usually used to derive 'hard' classifications. Fuzzy classifications were derived from these classifiers by outputting measures of the strength of class membership generated in the conventional 'hard' classification. The third classification approach was based on the fuzzy *c*-means algorithm with measures of the strength of class membership again output to illustrate land cover composition. The fuzzy *c*-mean algorithm was used to derive a series of fuzzy classifications of differing degrees of fuzziness.

The measures of the strength of class membership derived from all three classification approaches were related to data on the land cover composition on the ground and the closeness of each classification to the ground data measured by both S and D. Three main points may be noted from the results. First, the results reinforce the danger of using entropy as a measure of classification accuracy if multiple and partial class membership is a feature of both the classification output and ground data. Second, conventional 'hard' classifications may be softened to derive more accurate and appropriate representations of land cover. The softened outputs of the discriminant analysis and, in particular, the artificial neural network were more accurate than the 'hard' classifications from which they were derived. This further supports the view that conventional classification techniques are wasteful of information on class membership generated in the analysis. Third, the measures of closeness, S and D, provided similar results and enabled the identification of the most accurate land cover representation. The use and interpretation of S and D, however, does require information on the sampling design used in the acquisition of testing cases.

Since S and D may be used to measure the closeness of the land cover representation to the ground data for pure and mixed pixels they may in some situations be more general and appropriate indices of classification accuracy than conventional measures based on classification confusion matrices. Before they could be adopted, research on their properties, especially in terms of identifying significant differences between classification outputs would be required. None-the-less these measures do enable the assessment of the accuracy of fuzzy classifications and this should help further develop the use of fuzzy land cover mapping approaches. Given the significance of the mixed pixel problem the recognition and accommodation of fuzziness in the classification output and assessment of accuracy should provide later users of the land cover classification derived with more appropriate and useful information. Further advances may be made when fuzziness is accommodated in the training stage in addition to the class allocation and testing stages of the supervised classification.

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Table 1. Overall closeness of the land cover representations derived from all three classification algorithms. The mean and median values are given since the distributions were generally positively skewed

Classifier (measure of strength of class membership)		Measure of closeness *S* Mean	Median	*D* Mean	Median
Discriminant analysis (posterior probabilities)	Hard	0.0997	0.0633	0.4508	0.4112
	Softened	0.0834	0.0602	0.3848	0.3384
Neural network (output unit activation level)	Hard	0.0904	0.0612	0.3779	0.3135
	Softened	0.0303	0.0141	0.1710	0.1269
Fuzzy *c*-means (fuzzy membership)	$m=1.0$	0.1223	0.0689	0.5181	0.4175
	$m=1.2$	0.0632	0.0450	0.2818	0.2673
	$m=1.5$	0.0368	0.0294	0.1667	0.1410
	$m=2.0$	0.0253	0.0138	0.1376	0.1032
	$m=2.5$	0.0294	0.0166	0.1672	0.1347
	$m=\infty$	0.0910	0.0651	0.3757	0.3614

Table 2. Variations in the closeness of the land cover representations derived from the use of all three algorithms for a pure pixel and one of mixed land cover composition.

Ground data (% cover)			Measure of closeness	Classification							
				Discriminant analysis	Neural network	Fuzzy *c*-means algorithm					
Trees	Grass	Asphalt				$m=1.0$	$m=1.2$	$m=1.5$	$m=2.0$	$m=2.5$	$m=\infty$
0	0	100	S	0.0000	0.0356	0.0000	0.0000	0.0000	0.0059	0.0281	0.2222
			D	0.0000	0.2954	0.0000	0.0000	0.0075	0.1140	0.2606	0.9183
31	42	27	S	0.1312	0.0316	0.2418	0.2047	0.0691	0.0215	0.0119	0.0040
			D	0.5161	0.1269	0.9658	0.7066	0.1996	0.0626	0.0354	0.0126

Figure captions

Figure 1. An overview of the classification of remotely sensed data by a feedfoward artificial neural network. The network architecture comprises one unit in the input layer for each discriminating variable and one unit in the output layer for each class. The number of hidden layers and units is subjectively determined, often on the basis of a set of trial runs. Each unit in the network is connected to every unit in adjacent layers by a weighted channel. Together the network units and weighted channel act to classify the remotely sensed data, with each case allocated to the class associated with the unit in the output layer with the highest activation level. The network used in the research had three input units (one for each waveband), two hidden layers each containing six units, and three output units (one for each class).

Figure 2. Results from the discriminant analysis. (a) the relationship between the probability of membership to trees with the proportion of the pixel area covered by trees (r=0.774); (b) the relationship between the probability of membership to grass with the proportion of the pixel area covered by grass (r=0.838); (c) the relationship between the probability of membership to asphalt with the proportion of the pixel area covered by asphalt (r=806); (d) histogram showing the closeness of the two representations measured by S; and (e) histogram showing the closeness of the two representations measured by D.

Figure 3. Results from the artificial neural network. (a) the relationship between the activation level of the output unit associated with trees with the proportion of the pixel area covered by trees (r=0.873); (b) the relationship between the activation level of the output unit associated with grass with the proportion of the pixel area covered by grass (r=0.866); (c) the relationship between the activation level of the output unit associated with asphalt with

the proportion of the pixel area covered by asphalt ($r=0.809$); (d) histogram showing the closeness of the two representations measured by S; and (e) histogram showing the closeness of the two representations measured by D.

Figure 4. Results from the fuzzy c-means classification with $m=1.2$. (a) the relationship between the fuzzy membership to trees with the proportion of the pixel area covered by trees ($r=0.828$); (b) the relationship between the fuzzy membership to grass with the proportion of the pixel area covered by grass ($r=0.851$); (c) the relationship between the fuzzy membership to asphalt with the proportion of the pixel area covered by asphalt ($r=0.785$); (d) histogram showing the closeness of the two representations measured by S; and (e) histogram showing the closeness of the two representations measured by D.

Figure 5. Results from the fuzzy c-means classification with $m=1.5$. The correlations coefficients (r) for the relationships between the fuzzy membership and proportion of pixel area covered by a class were 0.877, 0.867 and 0.822 for trees, grass and asphalt respectively (see Figure 4 for further details).

Figure 6. Results from the fuzzy c-means classification with $m=2.0$. The correlations coefficients (r) for the relationships between the fuzzy membership and proportion of pixel area covered by a class were 0.881, 0.875 and 0.834 for trees, grass and asphalt respectively (see Figure 4 for further details).

Figure 7. Results from the fuzzy c-means classification with $m=2.5$. The correlations coefficients (r) for the relationships between the fuzzy membership and proportion of pixel area covered by a class were 0.877, 0.874 and 0.832 for trees, grass and asphalt respectively (see Figure 4 for further details).

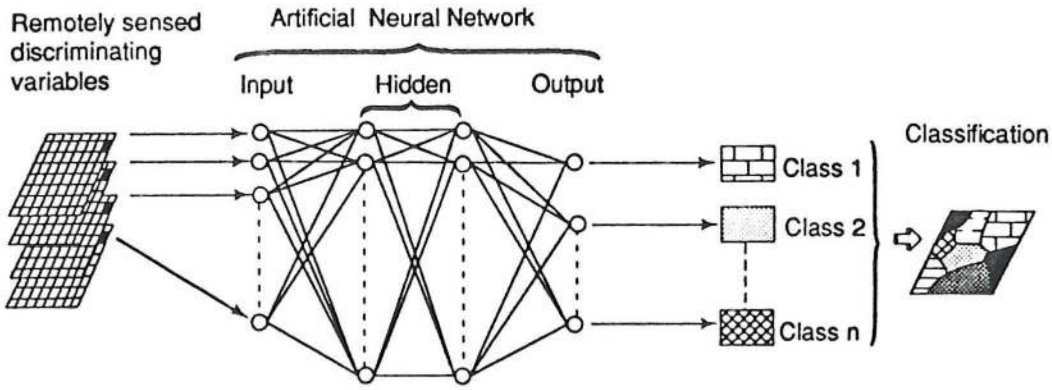
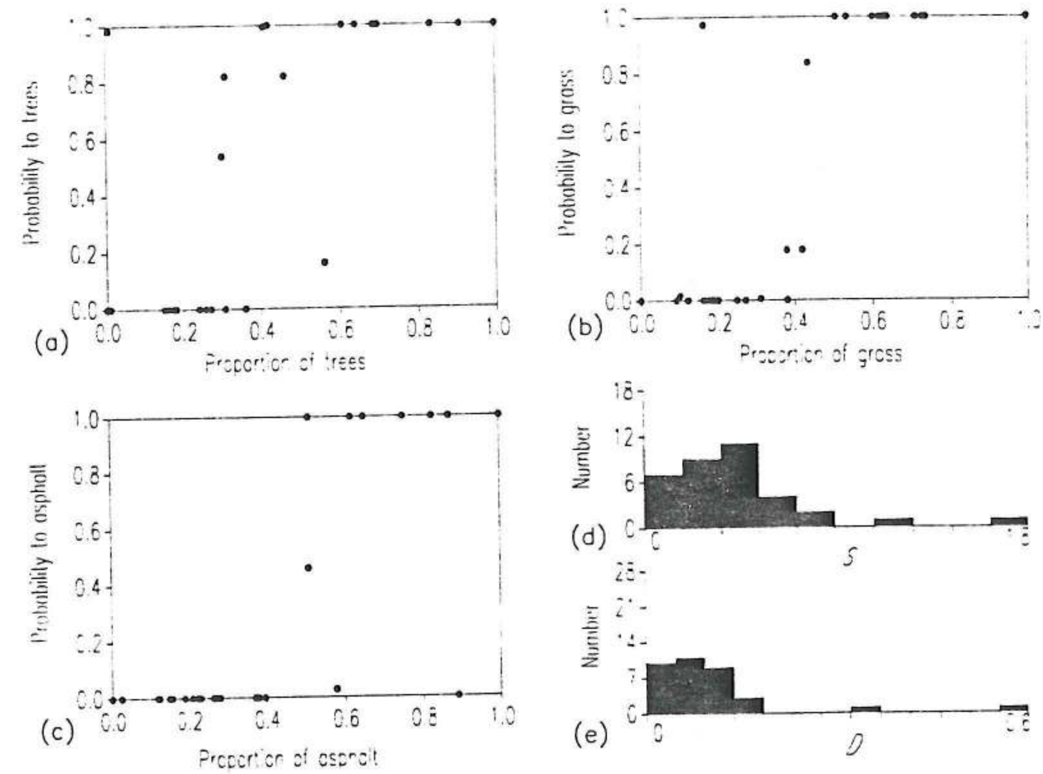
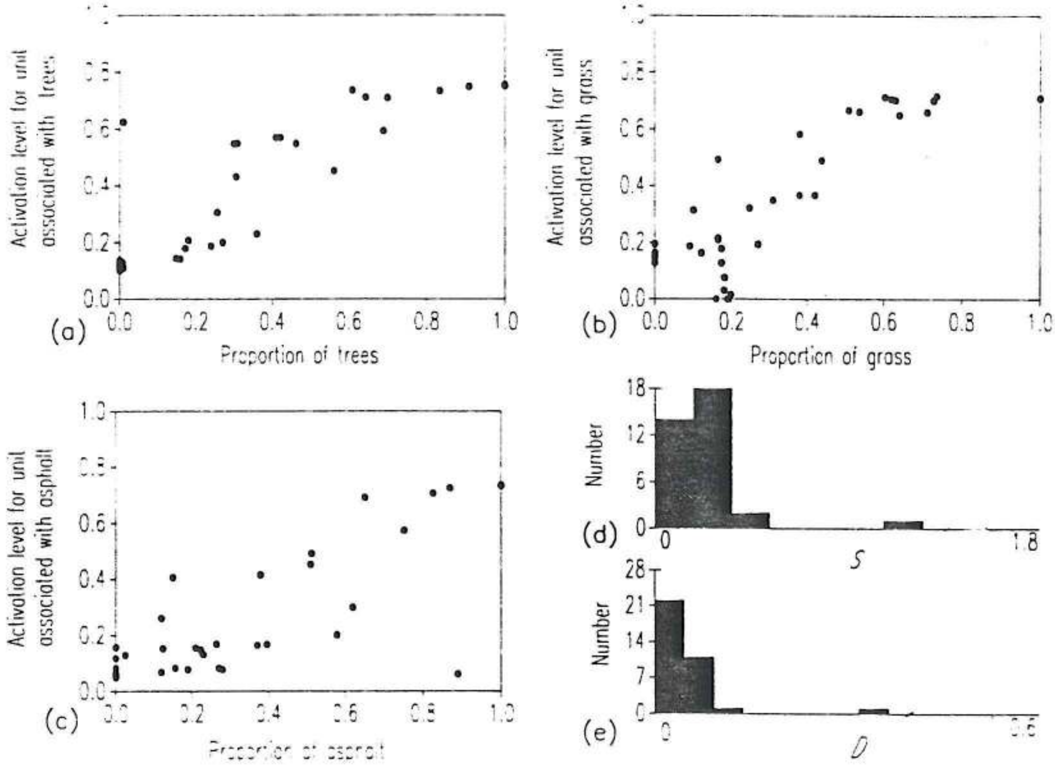

Remotely sensed
discriminating
variables
Artificial Neural Network
Input
Hidden
Output
Classification
Class 1
Class 2
Class n

Figure 1



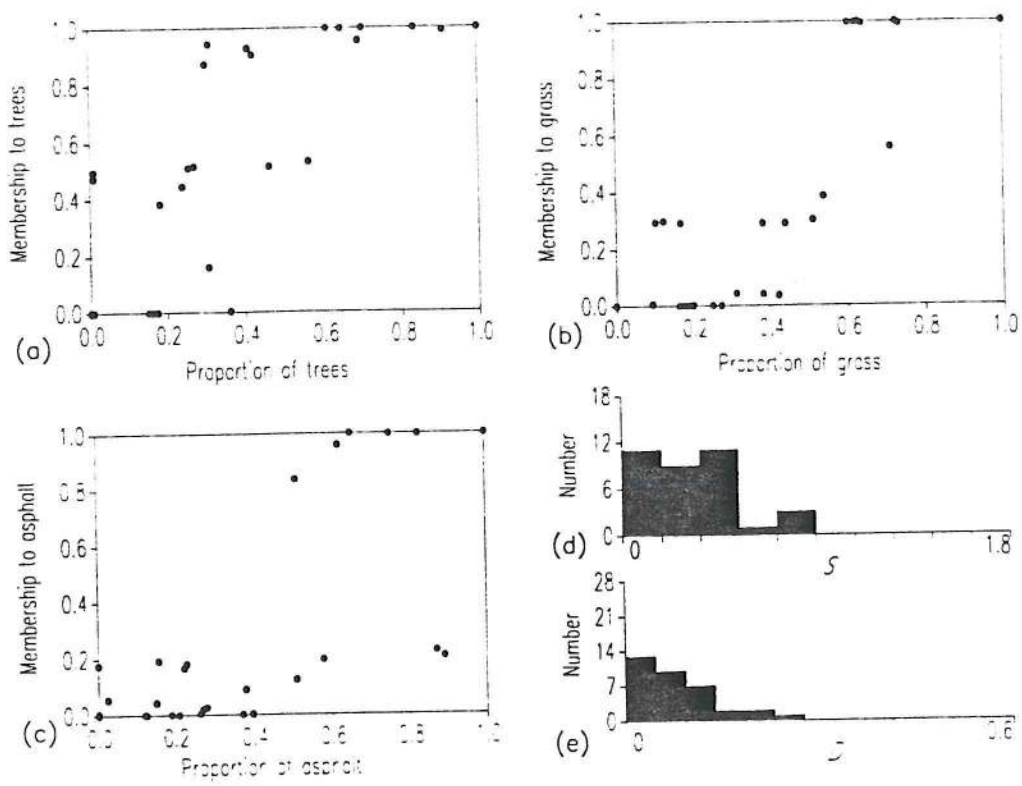
Probability to trees
Proportion of trees
(a)
Probability to grass
Proportion of grass
(b)
Probability to asphalt
Proportion of asphalt
(c)
Number
S
(d)
Number
D
(e)

Figure 2



Activation level for unit associated with trees
Proportion of trees
(a)
Activation level for unit associated with grass
Proportion of grass
(b)
Activation level for unit associated with asphalt
Proportion of asphalt
(c)
Number
S
(d)
Number
D
(e)

Figure 3



Membership to trees
Proportion of trees
(a)
Membership to grass
Proportion of grass
(b)
Membership to asphalt
Proportion of asphalt
(c)
Number
(d)
Number
(e)

Figure 4

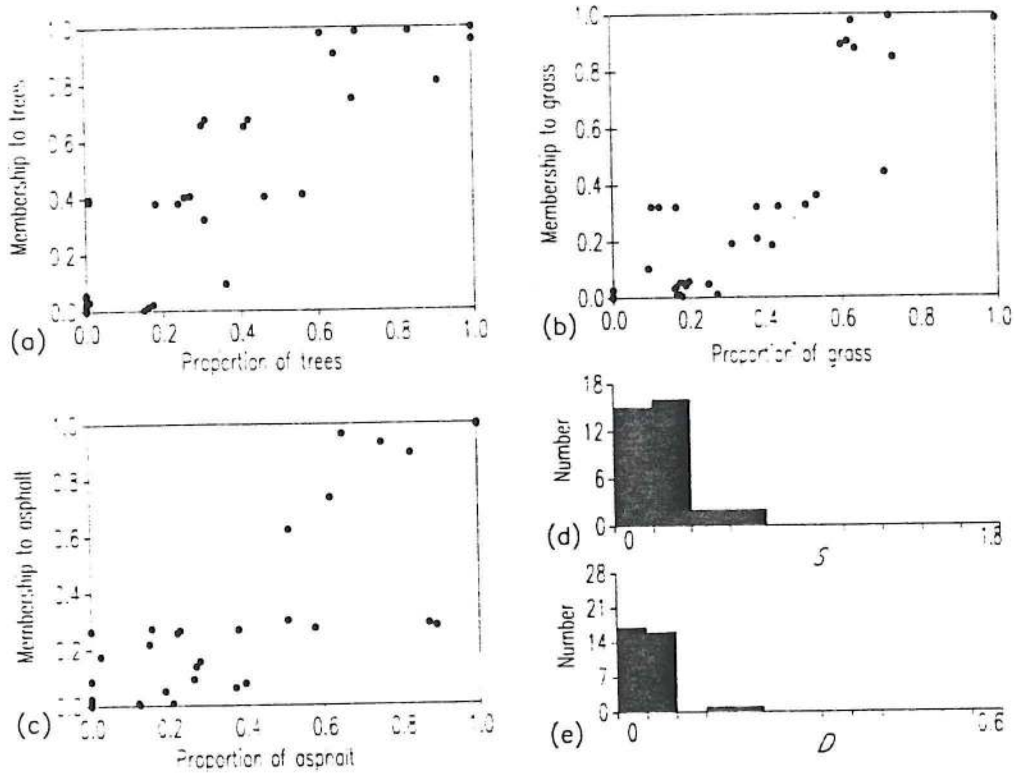

Membership to trees
Proportion of trees
(a)
Membership to grass
Proportion of grass
(b)
Membership to asphalt
Proportion of asphalt
(c)
Number
S
(d)
Number
D
(e)

Figure 5

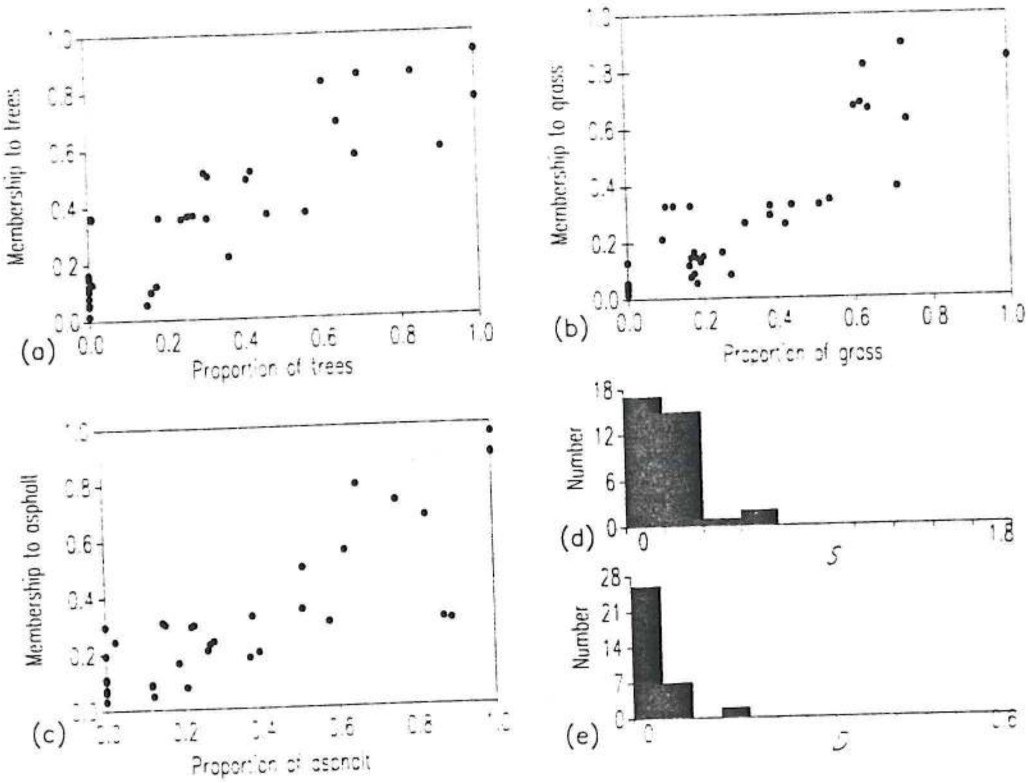

Membership to trees
Proportion of trees
(a)
Membership to grass
Proportion of grass
(b)
Membership to asphalt
(c)
Number
(d)
Number
(e)

Figure 6

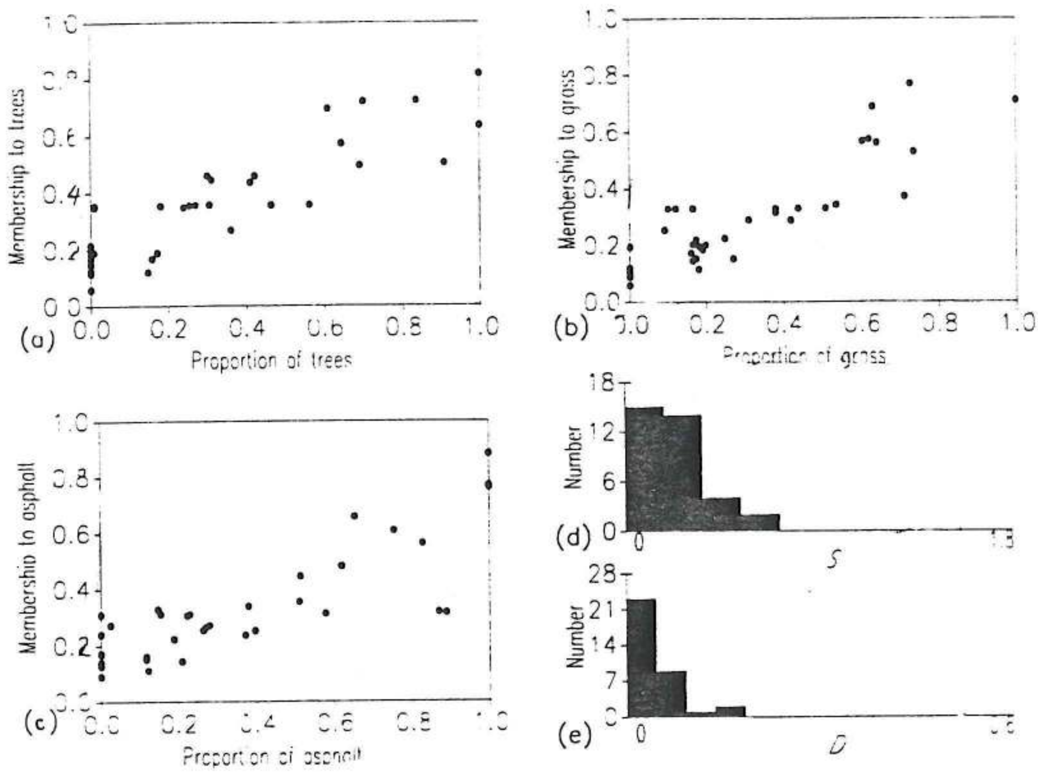

(a)
Membership to trees
Proportion of trees
(b)
Membership to grass
Proportion of grass
(c)
Membership to asphalt
Proportion of asphalt
(d)
Number
S
(e)
Number
D

Figure 7