Fuzzy Supervised Classification of Remote Sensing Images

FANGJU WANG, MEMBER, IEEE

Abstract—In the conventional remote sensing supervised classification, training information and classification results are represented in a one-pixel-one-class method. Class mixture cannot be taken into consideration in training a classifier and in determining pixels' membership. The expressive limitation has reduced the classification accuracy level and led to the poor extraction of information.

This paper describes a fuzzy supervised classification method in which geographical information is represented as fuzzy sets. The algorithm consists of two major steps: The estimate of fuzzy parameters from fuzzy training data, and a fuzzy partition of spectral space. Partial membership of pixels allows component cover classes of mixed pixels to be identified and more accurate statistical parameters to be generated, and, in turn, a higher classification accuracy to be achieved. Results of classifying a Landsat MSS image are presented and their accuracy is analyzed.

Keywords—Remote sensing, fuzzy set theory, image classification, information representation.

I. INTRODUCTION

The current remote sensing image analysis methods are unable to extract the majority of information dormant within digital remotely sensed data [1] and accuracy levels of image classification are quite often unsatisfactory [2]. To improve the analysis, it was suggested that studies are required on resolutions of sensor systems, physical principles of remote sensing, and data processing algorithms [1]. However, so far the effects of information representation has not yet been given its deserved attention in remote sensing data analysis.

This research reveals that an important factor which reduces the analysis quality lies in the loss of spectral information in the process of image classification. The information loss is caused by the current methods for representing geographical information.

Geographical information (including remote sensing-derived information) is imprecise in nature. Many relevant concepts do not have precisely defined intension and extension. "Grassland" and "soil" are such concepts. In talking about land cover, a piece of land with sparse grass can be classified into either grassland or soil. There is not a well-specified criterion for distinguishing between the two cover-types. The impreciseness also results from natural variations or arises through original measurements, as well as data processing.

Information representation is central to computer information processing. To be processed, information must be represented into structures which can be manipulated by computers. A representation method should be well suited with natures of the information it represents. Expressive inadequacy may lead to loss of valuable information. However, the currently used methods for representing geographical information cannot deal with the impreciseness properly. The essence of the limitation is that imprecise geographical information is represented by the methods which are intended for precise information.

The expressive inadequacy is largely due to the underlying membership concept of classical set theory, according to which a set has precisely defined boundaries, and an element has either full or none membership in a given set. In the current representation, a pixel can be assigned a single attribute with respect to a given theme; e.g., a cover class. Clearly, such a representation scheme has difficulty in dealing with the situations which cannot be precisely described by a single attribute. To improve the information representation, an alternative membership concept is needed.

Fuzzy set theory [3] provides useful concepts and tools to deal with imprecise information. Partial membership allows that the information about more complex situations, such as cover mixture or intermediate conditions, can be better represented and utilized. However, works in remote sensing image analysis using fuzzy sets are rather scarce. Jeansoulin et al. [4] proposed to measure properties of image entities in terms of several criteria and use the tools of fuzzy set theory to combine the criteria for automating multitemporal segmentation. Cannon er al. [5] developed a fuzzy c-means clustering algorithm to perform unsupervised classification on a TM image. In their algorithm, fuzzy sets are mainly used to represent intermediate results. Zenzo et al. [6] developed a fuzzy relaxation algorithm for contextual classification. In their work, cover classes were regarded as fuzzy sets and set-theoretic operations were used to adjust membership grades of pixels to classes. Kent and Mardia [7] used fuzzy membership models to perform classification on Landsat data. However, their statistical parameters were generated from ground truth recorded as a hard membership process.

The existing approaches can improve analysis to different extents. However, they do not fully bring out the potential of fuzzy sets for remote sensing image analysis. The major limitation is that the techniques of fuzzy set theory were mainly employed in limited, usually intermediate, phases of the works. This limitation still in-
itably leads to loss of valuable information which could otherwise be used to obtain better results.

A fuzzy supervised classification method has been developed in this research. Compared with the conventional methods, this method improves remote sensing image classification in the aspects of: 1) Representation of geographical information, 2) partitioning of spectral space, and 3) the estimate of classification parameters. Unlike the previous works, this method uses fuzzy sets for information representation throughout the entire process of image classification. Very encouraging results have been obtained: Identification of cover class components of mixed pixels and higher overall classification accuracy.

II. FUZZY SETS AND FUZZY REPRESENTATION OF GEOGRAPHICAL INFORMATION

Let $X$ be a universe of discourse, whose generic elements are denoted $x$. Thus, $X = \{x\}$. Membership in a classical set $A$ of $X$ is often viewed as a characteristic function $x_A$ from $X$ to $\{0, 1\}$ such that $x_A(x) = 1$ if and only if $x \in A$. A fuzzy set $\{A\}$ in $X$ is characterized by a membership function $f_A$, which associates with each $x$ a real number in $[0, 1]$. $f_A(x)$ represents the "grade of membership" of $x$ in $A$. The closer the value of $f_A(x)$ is to 1, the more $x$ belongs to $A$. A fuzzy set does not have sharply defined boundaries, and a set element may have partial membership.

Geographical information is conventionally represented in thematic maps. A thematic map is a set of points, lines, and areas that are defined both by their location in space and by their nonspatial attributes about a single theme. Currently, the linkages between the spatial entities and their nonspatial attributes are based on the membership concept of classical set theory—an entity either has an attribute, or not at all. No third situation is allowed.

Information representation in remote sensing image analysis basically follows the conventional method. Each pixel can only be associated with a single cover class. Such a method cannot properly represent class mixture and intermediate conditions that occur in most remote sensing images.

A pixel corresponds to a cell on the ground. Quite often such a cell contains a mixture of surface-cover classes; for example, grass and underlying soil. Mixture may also take place when the size of the cell is larger than the size of the features about which information is desired. Since, currently, only one cover class can be assigned to a pixel, information about the other component classes and the deviation of the assignment cannot be represented.

Different conditions may exist within a cover class. For example, vegetation may be in different conditions that are caused by such factors as plant health, age, and water content. However, these conditions currently cannot be differentiated unless more classes are defined. It is clearly inaccurate to assign the same class to fresh grass and half-dry grass without specifying their differences. Introducing more classes will lead to higher analysis costs and, no matter how finely the classes are defined, within-class variability may exist.

Fuzzy set theory can provide a better representation for geographical information, much of which cannot be described well by a single class. In a fuzzy representation for remote sensing image analysis, land-cover classes can be defined as fuzzy sets, and pixels as set elements. Each pixel is attached with a group of membership grades to indicate the extent to which the pixel belongs to certain classes. Pixels with class mixture or in intermediate conditions can be described by membership grades. For example, if a ground cell contains two cover-types, "soil" and "vegetation." it may have two membership grades indicating the extents to which it is associated with the two classes.

III. FUZZY PARTITION OF SPECTRAL SPACE

In remote sensing, pixel measurement vectors are often considered as points in a spectral space. Pixels with similar spectral characteristics form groups which correspond to various ground-cover classes that the analyst defines. The groups of pixels are referred to as spectral classes, while the cover classes are information classes. To classify pixels into groups, the spectral space should be partitioned into regions, each of which corresponds to one of the information classes defined. Traditionally, the information classes are implicitly represented as classical sets. Thus, a partition of spectral space is based on the principles of classical set theory. Decision surfaces are defined precisely by some decision rules (for example, the decision rule of conventional maximum likelihood classifier) to separate the regions. Pixels inside a region are classified into the corresponding information class. Such a partition is usually called a hard partition. Fig. 1 illustrates a hard partition of spectral space and decision surfaces. A serious drawback of the hard partition is that a great quantity of spectral information is lost in determining the pixel membership.

A ground-cover class has its spectral characteristics which depend upon the interaction of electromagnetic waves with that type of ground cover. In a given radiometric band, a pixel value of a remote sensing image is a measure of spectral characteristics of the corresponding ground cell. When the cell contains a single cover class, the pixel records spectral characteristics of that class. When the cell contains a mixture of cover classes, the pixel value is a function of the reflectance from the mixture of component classes [8], [11], [9]. Generally, the more a pixel contains a cover class, the more spectral characteristics of that class it has. As the mixture proportions change from pixel to pixel, the spectral characteristics change. Thus, a mixed or heterogeneous pixel has spectral characteristics that differ from those of a homogeneous pixel. Similarly, changes in condition within a given cover class also cause variation in spectral characteristics.

Spectral characteristics of a pixel measurement vector determine its position in a spectral space. Assuming that in each spectral class there is a prototype (representative pixel vector) which represents the spectral characteristics
In a hard partition, as long as a pixel vector resides within a spectral region, it is assigned a single cover class which corresponds to the spectral class. The assignment implies full membership in that class and no membership in the other classes. The possibility that a pixel may partially belong to a class and simultaneously belong to more than one class is excluded. A great deal of valuable spectral information contained in pixel vector positions is discarded when the membership is determined. Final output of the classification is represented in a one-pixel-one-class image. No information about the cover mixture or intermediate condition is available. This is an important reason for the current poor extraction of spectral information.

Fuzzy representation of geographical information enables a new method for spectral space partition. When information classes are represented as fuzzy sets, so can the corresponding spectral classes. Thus, a spectral space is not partitioned by sharp surfaces. A pixel may belong to a class to some extent and meanwhile belong to another class to another extent. Membership grades are attached to indicate the extents. Such a partition is referred to as a fuzzy partition of spectral space. Fig. 2 illustrates membership grades of a pixel in a fuzzy partition of spectral space.

Formally, a fuzzy partition of spectral space is a family of fuzzy sets \( F_1, F_2, \ldots, F_m \) on universe \( X \) such that

\[
\forall x \in X
\begin{align*}
0 & \leq f_i(x) \leq 1 \\
\sum_{x \in X} f_i(x) & > 0 \\
\sum_{i=1}^{m} f_i(x) & = 1
\end{align*}
\]

where \( F_1, F_2, \ldots, F_m \) represent the spectral classes, \( X \) is the whole pixels, \( m \) is number of predefined classes, \( x \) is a pixel measurement vector, and \( f_i \) is the membership function of the fuzzy set \( F_i \) (\( 1 \leq i \leq m \)).

The fuzzy partition can be recorded in a fuzzy partition matrix:

\[
\begin{bmatrix}
    f_{F_1}(x_1) & f_{F_1}(x_2) & \cdots & f_{F_1}(x_n) \\
    f_{F_2}(x_1) & f_{F_2}(x_2) & \cdots & f_{F_2}(x_n) \\
    \cdots & \cdots & \cdots & \cdots \\
    f_{F_m}(x_1) & f_{F_m}(x_2) & \cdots & f_{F_m}(x_n)
\end{bmatrix}
\]

where \( n \) is the number of pixels, and \( x_i \)'s are pixels (\( 1 \leq i \leq n \)). A hard partition matrix can be derived from the fuzzy partition matrix by changing the maximum value in each column into "1," and others into "0." A "hardened" classification image can be generated by assigning the label of the row with the value "1" of each column to the corresponding pixel.

A fuzzy partition of spectral space can represent a real situation better than a hard partition and allows more spectral information to be utilized in subsequent analysis. Membership grades can be used to describe cover class mixture and intermediate cases. Another advantage of the fuzzy partition in cluster analysis is that stray pixels and pixels isolated between classes may be classified as such.

IV. FUZZY PARAMETERS FOR IMAGE CLASSIFICATION

A key step in supervised classification is the classifier training in which parameters of the classification algorithm are generated by applying statistical methods to training data. The parameters play a critical part in determining the pixels’ membership to predefined classes. Low classification accuracy is largely due to the variations between statistically generated parameters and the “real” ones.

Among the factors giving rise to the variations, an important, however, a so far not fully realized, factor relates with the information representation methods. Currently, training information is represented on a basis of one-pixel-one-class. Once a pixel is associated with a class, it makes
a full contribution in generating statistical parameters of the class. Class mixture and intermediate conditions cannot be taken into consideration. This may reduce the estimate accuracy. Fuzzy representation of geographical information makes it possible to calculate statistical parameters that are closer to the "real" ones. This can be achieved by means of the probability measures of fuzzy events [10].

In probability theory, an event $A$ is a member of a $\sigma$-field $\mathcal{F}$ of subsets of a sample space $\Omega$. When $A$ is a precisely defined set of points in $\Omega$, $P(A)$, a probability measure of $A$ can be expressed in the Lebesgue-Stieltjes integral as

$$P(A) = \int_A d\mu$$

or equivalently,

$$P(A) = \int_{\Omega} \chi_A(x) d\mu$$

where $x$ denotes a point in $\Omega$ and $\chi_A$ is the characteristic function of $A$ ($\chi_A(x) = 0$ or 1).

When $A$ is a fuzzy event, i.e., a fuzzy set of points in $\Omega$, a probability measure of $A$ can be defined as

$$P(A) = \int_{\Omega} f_A(x) d\mu$$

where $f_A$ is the membership function of $A$ ($0 \leq f_A(x) \leq 1$). This definition is a generalization of (4). Partial membership of a point $x$ in $A$ can be taken into consideration in calculating $P(A)$.

Similarly, the mean and variance of fuzzy event $A$ relative to a probability measure $P$ can be expressed as

$$\mu_A^* = \frac{1}{P(A)} \int_{A} x f_A(x) d\mu$$

and

$$\sigma_A^2 = \frac{1}{P(A)} \int_{\Omega} (x - \mu_A^*)^2 f_A(x) d\mu.$$  

The basic idea for (6) and (7) is that by however much a point belongs to an event, however much it contributes to the mean and variance of that event. The mean and variance calculated in this way are called a fuzzy mean and fuzzy variance. From (6) and (7), the discrete type of sample mean and sample covariance matrix, the multivariate analog of variance, can be obtained for a land-cover class $c$, which is represented as a fuzzy set. The fuzzy mean can be expressed as

$$\mu_c^* = \frac{\sum_{i=1}^{n} f_c(x_i) x_i}{\sum_{i=1}^{n} f_c(x_i)}$$

where $n$ is the total number of sample pixel measurement vectors, $f_c$ is the membership function of class $c$, and $x_i$ is a sample pixel measurement vector ($1 \leq i \leq n$).

The fuzzy covariance matrix can be expressed as

$$\Sigma_c^* = \frac{\sum_{i=1}^{n} f_c(x_i) (x_i - \mu_c^*) (x_i - \mu_c^*)^T}{\sum_{i=1}^{n} f_c(x_i)}.$$  

In calculating a fuzzy mean for class $c$, a sample pixel measurement vector $x$ is multiplied by its membership grade in $c$, $f_c(x)$ before being added to the sum. Similarly, in calculating a fuzzy covariance matrix for class $c$, $(x - \mu_c^*) (x - \mu_c^*)^T$ is multiplied by $f_c(x)$ before being added. The fuzzy mean and fuzzy covariance matrix can be considered as extensions of the conventional mean and covariance matrix. When $f_c(x) = 0$ or 1, (8) and (9) become definitions of the conventional mean and covariance matrix.

V. TRAINING AND MEMBERSHIP FUNCTION

Training in fuzzy supervised classification differs from the conventional training in training-site selection. Conventionally, training sites are selected for each training class and the sites must be sufficiently homogeneous. For fuzzy classification, the requirement for being homogeneous is less important, and a training site can be used to generate statistical parameters for more than one class. In this work, training is based on a previously determined land cover which is in a fuzzy representation, and training sites are selected in the areas where no land-cover change took place since the previous determination of the land cover. The areas of nonchange can be effectively detected by using a change mask [11]. Training data are represented in a fuzzy partition matrix. Equations (8) and (9) are applied to each row of the matrix to generate a fuzzy mean and fuzzy covariance matrix for each class.

A fuzzy set is characterized by its membership function. To perform a fuzzy partition on a spectral space, a membership function must be defined for each class. In this work, the membership functions are defined based on the maximum likelihood classification algorithm with fuzzy mean $\mu^*$ and fuzzy covariance matrix $\Sigma^*$ replacing the conventional mean and covariance matrix. The following is the definition of the membership function for cover class $c$:

$$f_c(x) = \frac{P_c^*(x)}{\sum_{i=1}^{m} P_i^*(x)}$$

where

$$P_c^*(x) = \frac{1}{(2\pi)^{n/2}|\Sigma|^1/2} \cdot \exp \left[ -\frac{1}{2} (x - \mu_c^*)^T \Sigma_c^{-1} (x - \mu_c^*) \right].$$

11
and \( N \) is the dimension of the pixel vectors, \( m \) is the number of predefined classes, and \( 1 \leq i \leq m \).

The membership grades of a pixel vector \( x \) depend on \( x \)'s position in the spectral space. \( f_i(x) \) increases exponentially with the decrease of \( (x - \mu_i^c)' \Sigma_i^{-1} (x - \mu_i^c) \); i.e., the Mahalanobis distance between \( x \) and class \( c \). \( \Sigma_i^{-1} P_i^c(x) \) serves as a normalizing factor.

VI. RESULTS AND ACCURACY ANALYSIS

Encouraging results have been obtained in applying the fuzzy supervised classification algorithm to Landsat MSS and TM data. The major achievements include the identification of types and proportions of component land covers in mixed pixels, and improvement in overall classification accuracy. In this section, results of classifying a MSS image are presented.

The study area is southwest of Hamilton City, Ontario, Canada. Fig. 3 is a raw MSS image of this area, taken on July 12, 1978. The image size is \( 256 \times 256 \) pixels and the subimage in the rectangle is Fig. 4. Seven cover classes are defined for the classification. They are water body, industrial or commercial area, residential or other paved area, forests or woods, grass or farm land, bare soil, and pasture or other vegetation. (In the following discussion, water, industrial, residential, forests, grass, bare soil, and pasture are short for the seven classes.) Results of the classification are recorded in a \( 256 \times 256 \times 7 \) fuzzy partition matrix. Seven membership grades are assigned to each pixel to indicate the extents to which the pixel belongs to the seven predefined cover classes.

A. Identification of Mixed Pixels and Component Classes

The fuzzy classification provides more information about land cover. Tests have verified that a membership grade calculated from (10) is proportional to the percentage to which the pixel contains a given type of land cover. Fig. 4 shows a subimage of Fig. 3, in which seven pixels are selected to illustrate this fact. Fig. 5 shows an aerial photograph of the area in which locations of the pixels selected are indicated by labeled arrows. The aerial photograph was taken on August 2, 1978, twenty days after the satellite image was taken. Membership grades of the seven pixels are recorded in the fuzzy partition matrix in Table I. (Because of decimal rounding, some column sums are not exactly equal to 1.)

Mixed pixels can be well identified by analyzing the combination of the membership grades. From Table I, \( B \), \( C \), \( F \), and \( G \) can be identified as mixed pixels, since each of them contains more than one cover class and each of the component classes is not negligible, while \( A \), \( D \), and \( E \) can be identified as relatively homogeneous pixels.

Proportions of component cover classes in a pixel can be estimated from the membership grades. For instance, it can be estimated that \( E \) contains almost 100 percent residential area, \( F \) contains about four-fifths residential area and one-fifth vegetation, and \( B \) contains about one-third residential area, one-third bare soil, and one-third vegetation. This estimation conforms well with the real situation. The major cover-type of the above three pixels is residential area. However, the three pixels are in different situations: \( E \) is in a completed residential area and has no other cover-type; \( B \) is under construction and thus contains bare soil and other cover-types; and \( F \) is at a fringe of a residential area, thus containing some vegetation. Their land covers can be well-understood by analyzing the membership grades.

Fig. 6 illustrates the positions of the pixel vectors of \( B \), \( E \), and \( F \), as well as the class means of residential area, bare soil, grassland, and pasture in a spectral space of band 5 and 7. (Relative positions of the pixel vectors and means in the two-dimensional space might be somewhat different from those in a four-dimensional space in which
The fuzzy classification is performed. It can be observed that the percentage of a cover-type in a pixel is roughly inversely proportional to the distance between the pixel vector and the mean of that class. The fuzzy classification allows the information contained in the positions to be extracted and utilized in the subsequent analysis, whereas a conventional classification simply classifies the three pixels into the same class of residential area without specifying their differences.

The identification of a pixel component cover class has been successfully applied in a land-cover change detection expert system [12] to facilitate automated image analysis. When determining a change-type, if only one cover class is available for each date, it is sometimes difficult for an expert system to identify the change-type. However, more cover classes may provide useful information. For example, when an area changes from vegetation to bare soil, if only a cover-class “bare soil” is available for the second date, it is difficult to determine that this change is a crop rotation, an urban development, or something else. However, if a component cover class, say, residential area, can also be identified in the area, even in a small percentage, the decision-making becomes much easier.

In addition, if a hard partition (conventional classification output) is required from the fuzzy partition, the membership grades enable the assessing of the classification accuracy for individual pixels. For example, if class “residential area” is assigned to pixel E, F, and B when the fuzzy position is hardened, it can be inferred from their membership grades of 0.99, 0.79, and 0.35 in that class that the deviation with the assignment to pixel E is very small, the deviation with pixel F is bigger, and the deviation with pixel B is even bigger. This estimate is quite consistent with the real situation.

Accuracy assessment for individual pixels may contribute to the integration of remote-sensing image analysis systems and geographical information systems. The current accuracy assessment methods used in remote sensing cannot provide the local accuracy levels of a data set which are usually required by the error models of geographical information systems. The incompatibility between the accuracy assessment methods has been considered to be one of the major hindrances in incorporating remote-sensing inputs into geographical information systems. The fuzzy techniques may help bridge this gap [13].

**B. Improvement in Overall Classification Accuracy**

Improvement in overall classification accuracy has been achieved using the fuzzy mean and fuzzy covariance matrix. For comparison, the conventional maximum likelihood classification was also performed on the same data sets. The fuzzy training data were “hardened” for training the conventional classification algorithm. The statistical parameters generated by the fuzzy and conventional algorithms are somewhat different. Table II shows the conventional and fuzzy means of the seven classes, and the following are the fuzzy and conventional covariance matrices for the class of industrial or commercial areas:

\[
\text{fuzzy covariance matrix} = \begin{bmatrix}
57.05 & 78.18 & 78.89 & 76.13 \\
78.18 & 120.22 & 109.97 & 101.67 \\
78.89 & 109.97 & 210.24 & 246.91 \\
76.13 & 101.67 & 246.91 & 317.11 
\end{bmatrix}
\]
Fig. 7. Image "hardened" from the fuzzy partition of the image in Fig. 3. (Refer to the front cover of this issue and the color explanation below the Table of Contents.)

TABLE II

FUZZY AND CONVENTIONAL MEANS

<table>
<thead>
<tr>
<th>band</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td>32.16</td>
<td>29.84</td>
<td>24.12</td>
<td>11.12</td>
</tr>
<tr>
<td>conventional</td>
<td>31.11</td>
<td>29.58</td>
<td>23.78</td>
<td>10.76</td>
</tr>
<tr>
<td>industrial</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td>51.37</td>
<td>60.89</td>
<td>67.87</td>
<td>59.41</td>
</tr>
<tr>
<td>conventional</td>
<td>51.14</td>
<td>60.55</td>
<td>67.08</td>
<td>58.43</td>
</tr>
<tr>
<td>residential</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td>49.86</td>
<td>56.85</td>
<td>89.27</td>
<td>94.38</td>
</tr>
<tr>
<td>conventional</td>
<td>49.73</td>
<td>57.08</td>
<td>88.05</td>
<td>93.99</td>
</tr>
<tr>
<td>forests</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td>37.08</td>
<td>36.97</td>
<td>108.21</td>
<td>126.01</td>
</tr>
<tr>
<td>conventional</td>
<td>33.79</td>
<td>34.87</td>
<td>108.76</td>
<td>128.35</td>
</tr>
<tr>
<td>grass</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td>43.19</td>
<td>47.39</td>
<td>104.51</td>
<td>123.17</td>
</tr>
<tr>
<td>conventional</td>
<td>43.03</td>
<td>47.31</td>
<td>104.73</td>
<td>123.67</td>
</tr>
<tr>
<td>bare soil</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td>57.82</td>
<td>72.28</td>
<td>103.23</td>
<td>107.27</td>
</tr>
<tr>
<td>conventional</td>
<td>61.22</td>
<td>74.25</td>
<td>106.59</td>
<td>109.61</td>
</tr>
<tr>
<td>pasture</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td>47.61</td>
<td>53.34</td>
<td>98.03</td>
<td>108.75</td>
</tr>
<tr>
<td>conventional</td>
<td>47.93</td>
<td>53.99</td>
<td>98.31</td>
<td>108.74</td>
</tr>
</tbody>
</table>

Table II

<table>
<thead>
<tr>
<th></th>
<th>water</th>
<th>residential</th>
<th>forests</th>
<th>grass</th>
<th>bare soil</th>
<th>pasture</th>
</tr>
</thead>
<tbody>
<tr>
<td>variance</td>
<td>58.50</td>
<td>80.60</td>
<td>83.32</td>
<td>81.36</td>
<td>80.60</td>
<td>83.32</td>
</tr>
<tr>
<td>covariance</td>
<td>80.60</td>
<td>123.99</td>
<td>117.82</td>
<td>111.28</td>
<td>83.32</td>
<td>117.82</td>
</tr>
<tr>
<td></td>
<td>83.32</td>
<td>211.72</td>
<td>244.83</td>
<td>308.81</td>
<td>81.36</td>
<td>244.83</td>
</tr>
</tbody>
</table>

VII. CONCLUSION

These studies on fuzzy supervised classification explore a new method for remote-sensing image interpretation. A pixel is no longer considered as an indecomposable unit in image analysis. Information about pixel component cover classes becomes available, and a pixel's partial membership enables more accurate statistical parameters.

Computer information processing is composed of nothing more than knowledge (or information) representations and algorithms. Good processing depends upon a good representation method which is well-suited with the nature of the information to be processed. However, this point is not always given deserved attention in developing new processing techniques and improving the processing quality and efficiency. Quite often, efforts are mainly made on algorithms. If knowledge representation is poor, even sophisticated algorithms can produce inferior outputs. On the contrary, improvement in representation might achieve twice the benefit with half the effort. Improving remote-sensing image analysis will yet require a great deal of work on information representation methods.

ACKNOWLEDGMENT

This work was made possible by the financial support from the International Development and Research Center (IDRC) Canada, which enabled the author to undertake graduate studies in Canada. The author wishes to thank Dr. P. Howarth for providing the raw images.

REFERENCES


*Fangju Wang (S’86–M’89) received the B.Eng. degree in computer science from the Central-South Institute of Mining and Metallurgy, Changsha, China, in 1981, the M.Sc. degree in computer science from Peking University, Beijing, China, in 1985, and the Ph.D. degree in the field of digital image analysis and spatial databases from the University of Waterloo, Waterloo, Canada, in 1989. He is currently a Postdoctoral Research Fellow in the Department of Computer Science, University of Waterloo. His research interests are in automated remote sensing image analysis, geographic information system design and development, knowledge representation for computer vision systems and spatial databases, approximate reasoning, and database query optimization.*