Improving Classification of Crop Residues Using Digital Land Ownership Data and Landsat TM Imagery

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ABSTRACT: Knowledge about the amount and effects of plant residue on the surface of cultivated soils is important in the design and implementation of a conservation program for most agricultural soils. Landsat Thematic Mapper (TM) data were utilized to determine the type and amount of crop residue on the surface of cultivated soils in Miami County, Indiana. Land ownership data were incorporated into a geographic information system (GIS) to enhance the Landsat TM data in an attempt to improve classification. The data were classified using maximum-likelihood, minimum-distance, and neural network classifiers. With the maximum-likelihood classifier it was not possible to classify the GIS-enhanced data because second-order statistics of the land-ownership data were not meaningful. The classification result using the neural network on the enhanced data was better than those obtained by applying the maximum-likelihood and minimum-distance classifiers to the original Landsat TM data.

INTRODUCTION

CROP RESIDUE IS THE PORTION OF A CROP that remains in the field after harvest. It is an important natural resource – not a waste as some have termed it (Oschwald, 1978). The residue left in the field increases surface roughness and then reduces soil erosion by minimizing surface crusting and slowing runoff velocities. It also improves water quality because the rough surface can prevent chemicals such as phosphorus from entering drainageways through surface runoff. Traditional methods to determine amount and kinds of crop residues depend on field measurements, require a significant amount of time and labor, and are costly to apply on a large scale. Determining crop residues using remote sensing data can overcome limitations of range coverage and topographic conditions and is suitable for ensuring compliance with USDA requirements in conservation and other programs.

Traditionally, the link between remote sensing and geographic information systems (GIS) has been perceived as unidirectional, with remote sensing data being used as an input into the GIS (Walsh *et al.*, 1990). Classified remotely sensed data can provide timely ground information such as vegetation and crop residue coverage and land-cover change that are necessary for GIS and simulation models. Theoretically, the information from a spatial database should be of assistance for classification of remote sensing data. Based on this hypothesis, a digital spatial data set – *land ownership* – was employed in an attempt to improve classification of Landsat Thematic Mapper (TM) data.

The objectives of this study were to develop techniques to improve the classification of Landsat TM data for measurement of crop residue with the aid of GIS data and to make comparisons of classification results by applying minimum-distance, maximum-likelihood, and neural networks to the original and the GIS-enhanced Landsat TM data sets.

BACKGROUND

Integration of GIS information with remote sensing is becoming increasingly important. Janssen *et al.* (1990) spatially integrated a topographic map with remote sensing data for land-cover classification. A false color photograph and land-cover maps were digitized as the object boundaries used in an object classification. They defined an object as an area in which only one land-cover type is expected. The pixel classification results were relabeled in an object-base. The authors concluded that the object classification improved the overall accuracy of the two study regions by 12 percent and 20 percent, respectively.

Landsat TM data and topographic information were integrated for evaluation of hydrological characteristics in Glacier National Park, Montana (Walsh *et al.*, 1990). The integration proved valuable in understanding the hydrological processes in complex and rugged topography. Goodenough (1988) reported that the integration of GIS and remotely sensed data could be used to update the spatial database and to guide the selection of training data for image classification.

Neural networks have been applied to several types of classification of multispectral remotely sensed data. The following examples are representative. Neuro-classification, when applied to Landsat Multispectral Scanner (MSS) data merged with geographic data including elevation, slope, and aspect, was better than conventional methods in terms of classification accuracy of training data (Benediktsson *et al.*, 1990a), but was worse when used with very high dimensional data – more than 20 channels (Benediktsson *et al.*, 1990b). A four-band (bands 1, 2, 3, and 4) Landsat TM image (459 by 368 pixels) with four land-cover classes (water, urban, forest, and grass) was classified by Hepner *et al.* (1990). It was concluded that the neural classifier, which used a minimal training set compared with the maximum-likelihood classifier, performed well for all areas including those for which the conventional approach did not. In a classification of synthetic aperture radar (SAR) data (896 by 1024 pixels) with three classes (urban, park, and ocean), Decatur (1989) concluded that the neuro-classifier presented better results than the Bayesian classifier when accurate assumptions about probability density functions could not be made and *a priori* probability could not be given. However, it should be

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pointed out that in this study only three distinctive land-cover types were used and that SAR data generally do not have a Gaussian distribution. A merged image of the Advanced Very High Resolution Radiometer (AVHRR) and the Scanning Multispectral Microwave Radiometer (SMMR) data for an Arctic area was classified by Key *et al.* (1989) using traditional and neural classifiers. They found that the neural classifier had greater flexibility than the maximum-likelihood classifier for classifying indistinct classes, such as those containing pixels with spectral values significantly different from the pixels in the training areas.

MATERIALS AND METHODS

SITE DESCRIPTION

A study area of approximately 10.36 km² was comprised of sections 3, 4, 9, and 10 located in T28N, R5E of Richland township, Miami County, Indiana. Land cover for these sections included corn residues, soybean residues, grasslands, forests, roads, an abandoned railroad, farm-steads, and the Eel River. Portions of the area are owned by 58 farmers (Figure 1). This area represents much of northern Indiana and other states of the midwestern U.S.

DATA

A Landsat TM scene acquired 26 April 1988 was used in this project, along with accompanying ground observation data for section 9. Aerial photographs from 1987 for this study area were available. The U.S. Geological Survey 1:24,000-scale topographic map of the Roann, Indiana Quadrangle was used as a reference. The corresponding ownership map was digitized using ERDAS (ERDAS, 1988), and an ownership boundary data layer registered to the 30-meter TM data was generated.

GIS-ENHANCED DATA

The GIS data layer used in this study was the ownership map associated with the four sections studied. The map was added as an eighth band to the original Landsat TM image data, as illustrated in Figure 2. The eight-band merged data were called *Landsat TM Plus*.

The reasons for choosing the ownership layer were (a) the boundaries representing different owners matched field boundaries, (b) land-use and thus crop residues change at field and ownership boundaries, (c) an enclosed region represented one owner, (d) each area was coded with a digital number (i.e., each was numerically uniform), and (e) the classification results may be improved because of the unique digital number inside each polygon.

NEURAL NETWORKS

The neural network (NN) used in this study, as shown in Figure 3, was configured as a three-layer back-propagation network, including input, hidden, and output layers, with full interconnections between adjacent layers. The input layer was composed of an N by 8 array of units corresponding to N bands (N = 7 or 8 in this study) of the 8-bit Landsat TM data. Thirty-five units were assigned to the hidden layer, and seven units in the output layer referred to seven land-cover classes. For the training, the TM data were fed to the input layer and propagated through the hidden layer to the output layer, and then the differences between the computed outputs and the desired outputs were calculated and fed backward. This process continued until the training arrived at the desired error. Additional details of the network are given in Zhuang (1990).

The neural network simulator used was NASA NETS (Baffes, 1989), which runs on a variety of machines including workstations and PCs. The simulator provides a flexible system for manipulating a variety of neural network configurations using the *generalized delta back propagation* learning algorithm. The NETS software used for image classification was run on SUN SPARC

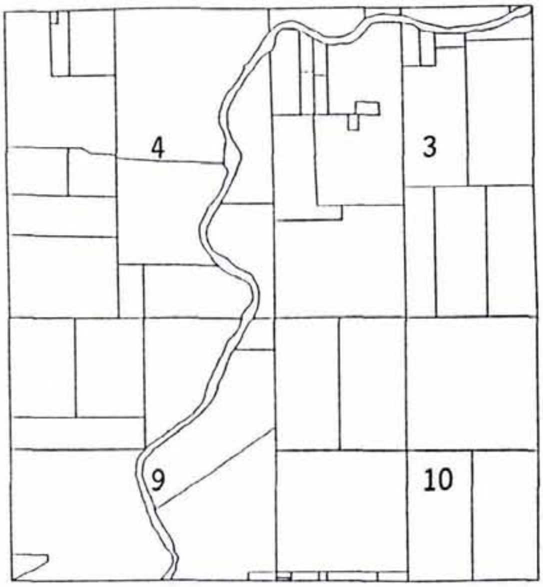

FIG. 1. Ownership boundaries for sections 3, 4, 9, and 10.

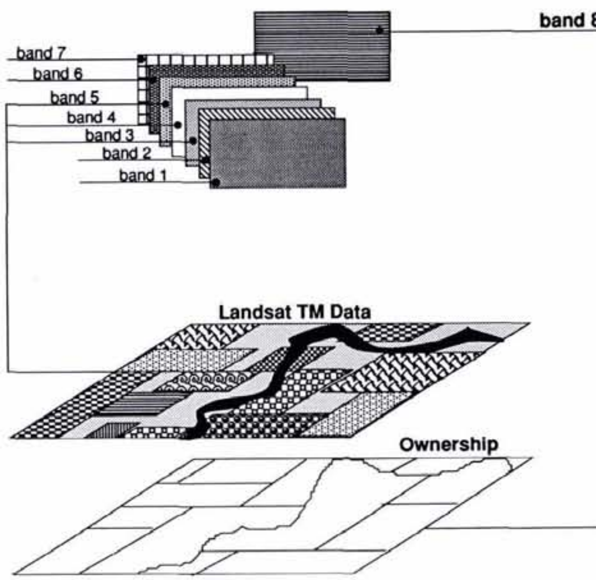

FIG. 2. Creation of Landsat TM Plus data.?

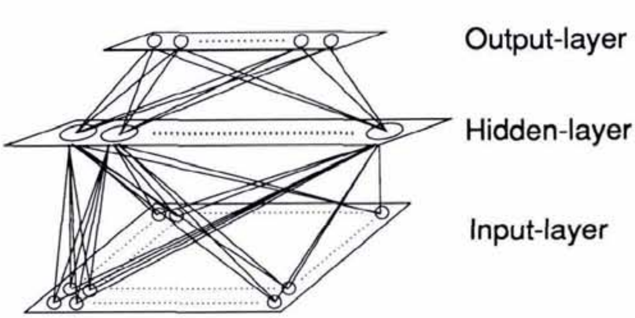

FIG. 3. The back-propagation neural-network structure.

workstations. Interface routines were developed to make NETS suitable for image classification (Zhuang, 1990).

CLASSIFICATION

The minimum-distance (L1) and maximum-likelihood (ML) classifiers (Richards, 1986) were applied to the original Landsat TM data. The minimum-distance classifer used in this study classified an unknown pixel by computing the L1 distance (Richards, 1986) between the value of the unknown pixel and each of the information class means, and then assigned the unknown pixel to the "closest" information class. Under the assumption of normality, the maximum-likelihood classifier categorized a given pixel by computing the statistical probability of the pixel being a member of a particular information class. The neural network (NN) classified an unknown pixel by applying the knowledge learned from a training data set to the pixel. For the study area, training fields were selected for seven different land-cover classes based on the corresponding ground observation data and the spectral features. The classes were: *corn*/51 percent (corn residue, 51 perent coverage), *forest, pasture/grass, river, soybeans*/74 percent (soybean residue, 74 percent coverage), *bare soil*, and *corn/unknown* (unknown coverage of corn residue). The training data for class *river* were obtained by unsupervised classification (clustering) of the portion of the image containing the river.

For the GIS-enhanced data, it was not possible to complete the maximum-likelihood classification because the second-order statistics of the land ownership band were not meaningful. The neural-network classifier was utilized because it need not address the second-order statistic, *covariance*. Because the minimum-distance classifier considers only the first-order statistic, *mean*, it was possible to use this classifier for classification of the GIS-enhanced data set.

RESULTS

Figure 4 illustrates the classification results obtained by using L1 and ML for the training and testing data. As shown in the figure, L1 achieved 59 percent and 49 percent accuracies, whereas ML obtained 89 percent and 85 percent accuracies, for the entire training and tesing data set. Confusion matrices were also generated for the testing data set and are shown in Tables 1 and 2

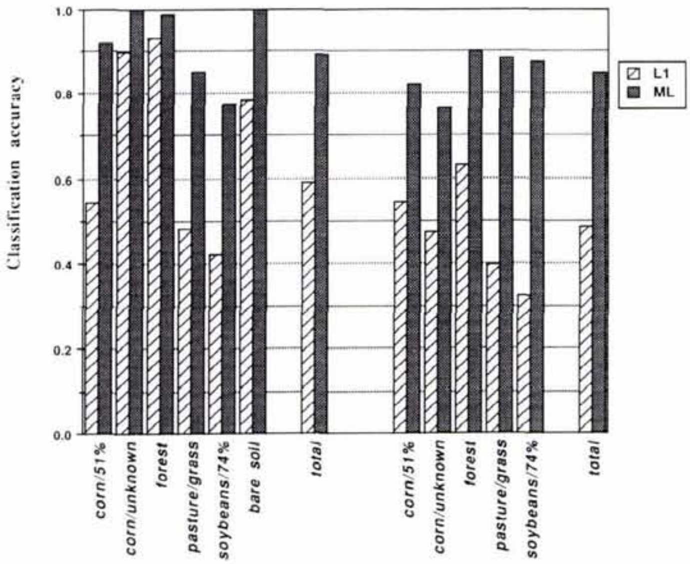

FIG. 4. Performance of the training and testing data sets for the original Landsat TM data.

TABLE 1. CONFUSION MATRIX FOR THE LANDSAT TM TESTING DATA CLASSIFIED USING MINIMUM-DISTANCE (L1) ALGORITHM.

TM classes	Percent correct	Ground observation classes					Total
		corn/51%	corn/unknown	forest	pasture	soybeans/74%	
corn/51%	54%	337	17	0	13	70	437
corn/unknown	47%	203	50	0	60	12	325
forest	63%	0	0	101	110	0	211
pasture	40%	0	3	0	172	2	177
river	---	0	0	59	3	0	62
soybeans/74%	32%	66	34	0	72	41	213
bare soil	---	14	2	0	1	2	19
Number of ground observation pixels		620	106	160	431	127	1444

TABLE 2. CONFUSION MATRIX FOR THE LANDSAT TM TESTING DATA CLASSIFIED USING MAXIMUM-LIKELIHOOD (ML) ALGORITHM.

TM classes	Percent correct	Ground observation classes					Total
		corn/51%	corn/unknown	forest	pasture	soybeans/74%	
corn/51%	82%	508	0	0	1	14	523
corn/unknown	76%	5	81	0	42	0	128
forest	90%	0	0	144	7	0	151
pasture	88%	1	25	0	381	1	408
river	---	0	0	16	0	0	16
soybeans/74%	87%	79	0	0	0	111	190
bare soil	---	27	0	0	0	1	28
Number of ground observation pixels		620	106	160	431	127	1444

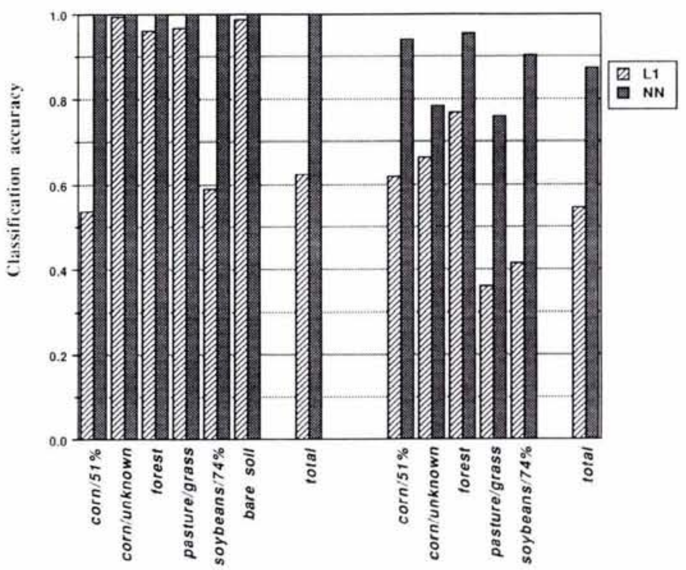

FIG. 5. Performance of the training and testing data sets for the Landsat TM Plus data.

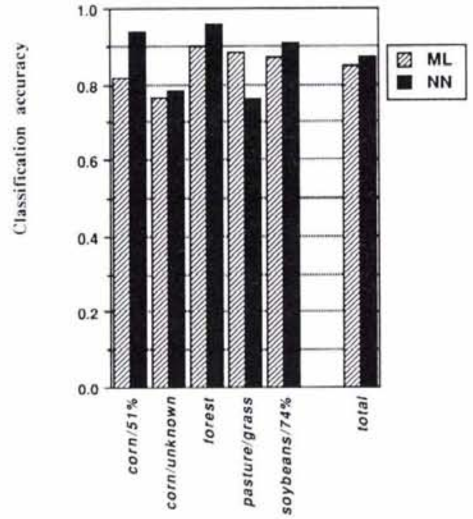

FIG. 6. Comparison of the testing results from two data sets.

corresponding to classifiers L1 and ML. The percentages listed in the tables represent the proportion of ground observation pixels correctly labeled by the classifier. From the tables, the greatest confusion among crop residue classes is 55 percent (class *soybeans/74* percent) for L1 and 13 percent (class *corn/51* percent) ML. The confusion between each of the crop residue classes and the bare soil class is 2 percent from each of the crop residue classes for L1, and 4 percent from class *corn/51* percent, zero from class *corn/unknown*, and 1 percent from class *soybeans/74* percent for ML.

The classification results obtained by applying L1 and NN to the GIS-enhanced training and testing data set (Landsat TM Plus) are shown in Figure 5. L1 achieved 62 percent and 54 percent accuracies, whereas NN obtained 100 percent and 87 percent accuracies for the entire training and testing data set. As noted above, it was not possible to use ML. As seen in Tables 3 and 4, a certain amount of confusion exists between the crop residue classes and the bare soil class for L1 but not for NN.

DISCUSSION

As seen in Figure 4, the L1 results are unsatisfactory, while the ML results are much improved for the training and testing

TABLE 3. CONFUSION MATRIX FOR THE LANDSAT TM PLUS TESTING DATA CLASSIFIED USING MINIMUM-DISTANCE (L1) ALGORITHM.

TM classes	Percent correct	Ground observation classes					Total
		corn/51%	corn/unknown	forest	pasture	soybeans/74%	
corn/51%	62%	383	0	0	4	68	455
corn/unknown	66%	92	70	0	85	3	250
forest	77%	0	0	123	133	0	256
pasture	36%	0	3	0	156	2	161
river	---	0	0	37	0	0	37
soybeans/74%	42%	142	0	0	10	53	205
bare soil	---	3	33	0	43	1	80
Number of ground observation pixels		620	106	160	431	127	1444

TABLE 4. CONFUSION MATRIX FOR THE LANDSAT TM PLUS TESTING DATA CLASSIFIED USING NEURAL-NETWORK (NN) APPROACH.

TM classes	Proportion correct	Ground observation classes					Total
		corn/51%	corn/unknown	forest	pasture	soybeans/74%	
corn/51%	94%	582	12	0	34	4	632
corn/unknown	78%	24	83	0	34	3	144
forest	96%	10	1	153	35	2	201
pasture	76%	3	10	7	328	2	350
river	---	0	0	0	0	1	1
soybeans/74%	91%	1	0	0	0	115	116
bare soil	---	0	0	0	0	0	0
Number of ground observation pixels		620	106	160	431	127	1444

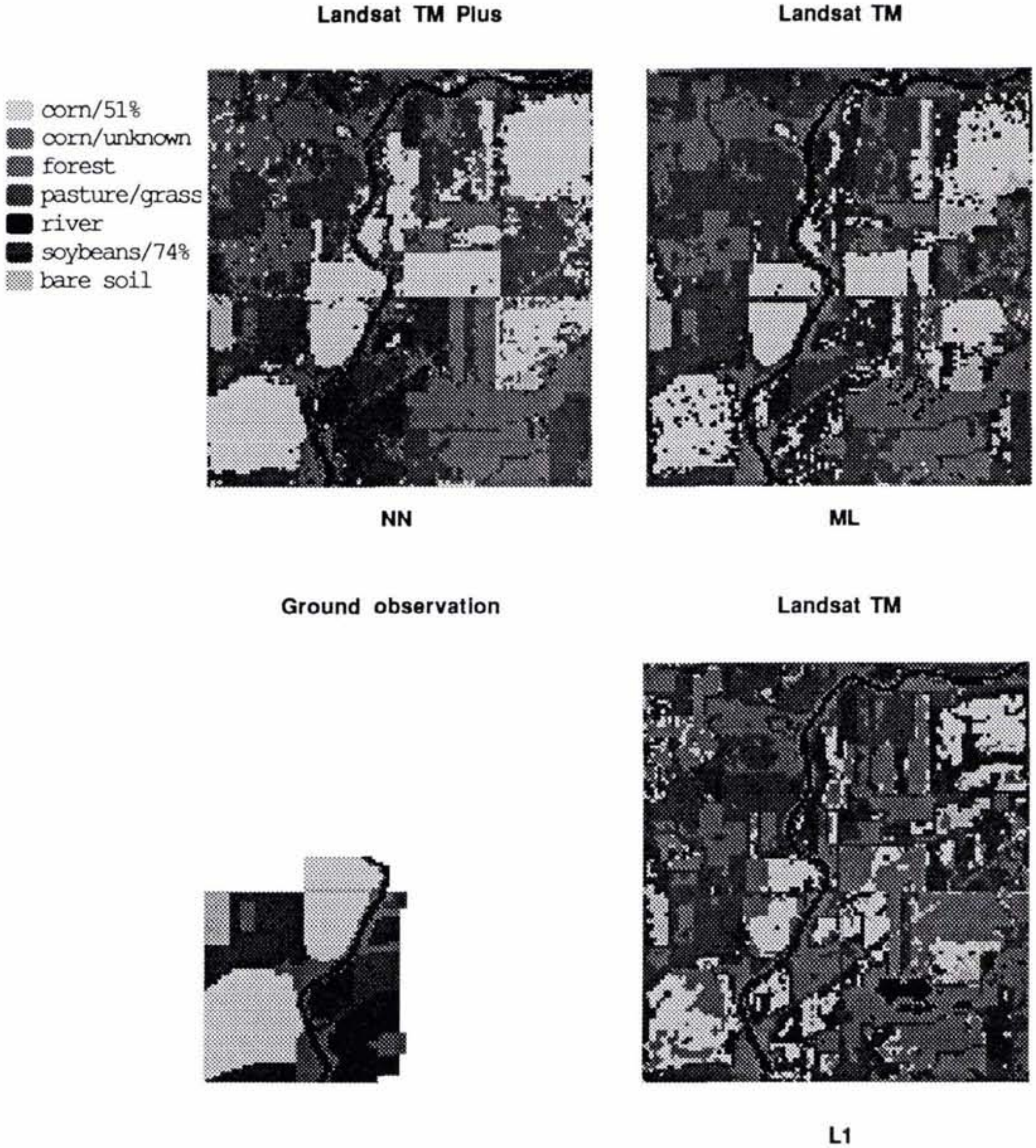

FIG. 7. Classification results for two data sets.

data sets. This is because ML utilizes second-order statistics. For the GIS-enhanced data, L1 still performed poorly for both the training and the testing data sets. However, NN improved the classification accuracies. The reason that NN achieved perfect classification accuracies for each of the training classes and the entire training data set is that NN was able to distinguish the features of the training data and thereby to classify the data correctly.

Figure 7 shows the classification results obtained by applying L1 and ML to the original Landsat TM data set and NN to the GIS-enhanced Landsat TM Plus data set. It can be seen that the L1 result has a large amount of misclassification because of its consideration of only the first order statistic, *mean*. The NN result shows some confusion as indicated in the corresponding confusion matrices, whereas the ML result has much more confusion among the crop residue classes, especially between class *corn*/51 percent and class *soybeans*/74 percent, which were shown earlier in the confusion matrices. Moreover, for NN there was no confusion between each of the crop residue classes and the bare soil class, as shown in Table 4. Therefore, it can be concluded that the classification of the GIS-enhanced Landsat TM data set for crop residue classes was improved by using the neural network, *i.e.*, integrating GIS information, the neural network outperformed the other classifiers. The improved NN classification results for the testing data set are also reflected in the comparison shown in Figure 6, the map results shown in Figure 7, and its accuracies for the testing data depicted in Figure 5.

A major advantage of the neural-network classifier is that an assumption about distribution of data is not needed. The neural-network classifier is able to extract automatically the features of data used in training and to apply them to the classification of data for the entire image. In other words, the neural-network classifier is distribution-free. Moreover, it does not explicitly consider the second-order statistic, *covariance*, which inhibited the maximum-likelihood classifier for the GIS-enhanced data set.

CONCLUSIONS

Landsat TM data were used to determine crop residue type and class for a large area. There was much misclassification of

Landsat TM data for the crop residue classes when utilizing the maximum-likelihood and minimum-distance classifiers on the original Landsat TM data, though the maximum-likelihood classifier achieved higher accuracies than the minimum-distance classifier.

A digital spatial layer, *ownership*, was added to the original Landsat TM image as the eighth band of data in an attempt to improve the classification results. Unfortunately, maximum-likelihood classification could not be used for the eight-band data because the covariance matrices corresponding to the eight-band image are meaningless. Therefore, the back-propagation neural-network classifier was used to substitute for the maximum-likelihood classifier. The classification results obtained using the neural classifier showed less confusion among the crop residue classes, no confusion between the crop residue classes and the bare soil class, clearer fields for the crop residue classes, and clear boundaries for these fields, compared to the results obtained by applying the maximum-likelihood classifier to the original seven-band Landsat TM data. The minimum-distance classifier did not obtain satisfactory classification accuracies for either the original Landsat TM data or the Landsat TM Plus data because it could not consider the second-order statistics, the covariances between image bands.

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