Application of Neural Network-based Classification for Watershed Land Cover Mapping

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Abstract -- Watersheds are of great ecological significance not only because they are important components of virtually all ecosystems but also because they are closely related to water quality, estuarine productivity, and wildlife habitat. In recent years, to enhance intensive watershed restorations, many watershed land cover characterization studies have been conducted using remotely sensed data. In a local scale watershed application, high spatial resolution is often necessary for feature extraction with an acceptable degree of accuracy. Neural network-based classifiers have been found to be robust and well suited for a wide variety of remotely sensed data. The advantages of neural network approaches include no need for a *priori* knowledge of the statistical distribution of data, high adaptability, and great error tolerance.

In this study, an innovative application was developed to use high-resolution digital color infrared (CIR) Digital Orthophoto Quarter Quad (DOQQ) data and a neural network classifier to produce detailed and highly improved watershed mapping. The one-meter digital CIR DOQQ data for the study area was generated by digitizing CIR photographs and registering them to the corresponding black and white (B&W) DOQQs. Using the derived high resolution CIR DOQQ data, classification was carried out by training a multi-layer neural network classifier. The training process was implemented by a supervised backpropagation learning algorithm. First, an adaptive error function was chosen to measure the quality of the network's approximation to the input-output relation in the training set. Second, an iterative approach was applied to find the optimal network parameters by minimizing the selected error function. Finally, the well-trained network with minimal error was then able to classify other image data efficiently and accurately. Experimental results from the application were analyzed in terms of generalization capability, stability of results, and computational efficiency. Classification accuracy obtained from the neural network classifier was evaluated. The results from this application could provide us an insight into what spatial resolution is most beneficial for water quality restoration at different scales. This procedure is applicable for a variety of Land-Use/Land-Cover classification applications at local and global scales. Based on the experimental results from this study, the potential advantages and disadvantages will be discussed and recommendations will be given for future applications in this area.

1. Introduction

Watersheds are of great ecological significance not only because they are important components of virtually all ecosystems but also because they are closely related to water quality, estuarine productivity, and wildlife habitat. In recent years, to enhance intensive watershed restorations, many watershed land cover mapping studies have been conducted using remotely sensed data [1] [2] [3]. In a watershed application at local scale, multispectral data with high spatial resolution is often necessary for a detailed land cover mapping with an acceptable degree of accuracy.

However, to date, commercial high-resolution (less than 5 meters) multispectral satellite data is not widely available and is very expensive. Alternatives are lower spatial resolution data sources such as the 20 meter French Systeme pour L'Observation de la Terre (SPOT), NASA's 30 meter Landsat Thematic Mapper satellite data and USGS Digital Orthorectified Quarter Quads (DOQQ). Multispectral IKONOS data provides 4 meter spatial resolution, but its cost is often prohibitive. None of these alternatives is acceptable for use in a high detail land cover classification. Given the lack of appropriate satellite datasets, color infra-red (CIR) Digital Orthophoto Quarter Quad (DOQQ) could be the ideal dataset to provide both high spatial resolution and multispectral information.

Classification approaches based on neural networks have been applied successfully in land cover and land use mapping during the last decade and have been proven to be robust and well suited for a wide variety of remotely sensed data [4] [5] [6] [7]. Neural network approaches are independent of statistical distribution of the input data and have a high adaptability to estimate the non-linear relationship between the input data and desired outputs by repeatedly presenting training data through an interconnected multi-layer neural network system. Furthermore, once a well-trained network, which proves to generalize well, is found, it can process other large data sets very quickly. For such reasons, neural networks would be more attractive for the classification of large and multi-source data sets [8].

In this study, one-meter digital CIR DOQQ data for a small watershed study area was generated by digitizing CIR photographs and registering them to the corresponding black and white (B&W) DOQQs. Using the derived CIR DOQQ data, classification was carried out by training a multi-layer neural network-based classifier. The training process was implemented by a supervised backpropagation learning algorithm. With this supervised algorithm, our goal is to minimize an adaptive error function, which is chosen to measure the quality of the network's approximation to the input-output relation in the training set. The main purposes of this study are to: first, evaluate the effectiveness of high spatial resolution image data in the small watershed area using one-meter CIR DOQQ data; and second, demonstrate the applicability of the supervised neural network-based classifier in a land cover mapping application.

2. Neural Network-based Classifier

The multi-layer neural network (MNN) is the most commonly used network model for image classification in remote sensing. MNN is usually implemented using the Backpropagation (BP) learning algorithm [9]. The learning process requires a training data set, i.e., a set of training patterns with inputs and corresponding desired outputs. The essence of learning in MNNs is to find a suitable set of parameters that approximate an unknown input-output relation. Learning in the network is achieved by minimizing the least square differences between the desired and the computed outputs to create an optimal network to best approximate the input-output relation on the restricted domain covered by the training set.

A typical MNN consists of one input layer, one or more hidden layers and one output layer. Figure 1. shows a typical three-layer neural network system with four input nodes in the input layer, 10 hidden nodes in the hidden layer, and 5 output nodes in the output layer often noted as 4 -10 - 5. All nodes in different layers are connected by associated weights. For each input pattern presented to the network, the current network output of the input pattern is computed using the current weights. At the next step, the error or difference between the network output and desired output will be backprogated to adjust the weights between layers so as to move the network output closer to the desired output. The goal of the network training is to reduce the total error produced by the patterns in the training set. The mean square error *J* (MSE) is used as a classification performance criterion given by

$$J = \frac{1}{2N}\sum_{i=1}^{N}\varepsilon_i^2$$

Where N is the number of training patterns. ε_i^2 is the Euclidean distance between the network output of the pattern and the desired output. This MSE minimization procedure via weigh adjusting is called learning or training. Once this learning or training process is completed, the MNN will be used to classify new patterns. Further implementation details of MNNs are addressed by Principe *et al.* [10].

MNNs are known to be sensitive to many factors, such as the size and quality of training data set, network architecture, learning rate, overfitting problems, etc. To date, there are no explicit methods to determine most of these factors. Fortunately, based on many previous researches, there are many practical suggestions to help choose these factors.

The size and quality of the training data set have a considerable influence on the generalization capability of the resulted network classifier and the final classification accuracy. The selection of the training data set is often related to how many classes would be expected to derive. First of all, these classes must be determined carefully so that they would have enough spectral separability so that the classifier is able to discriminate them. Second, the training

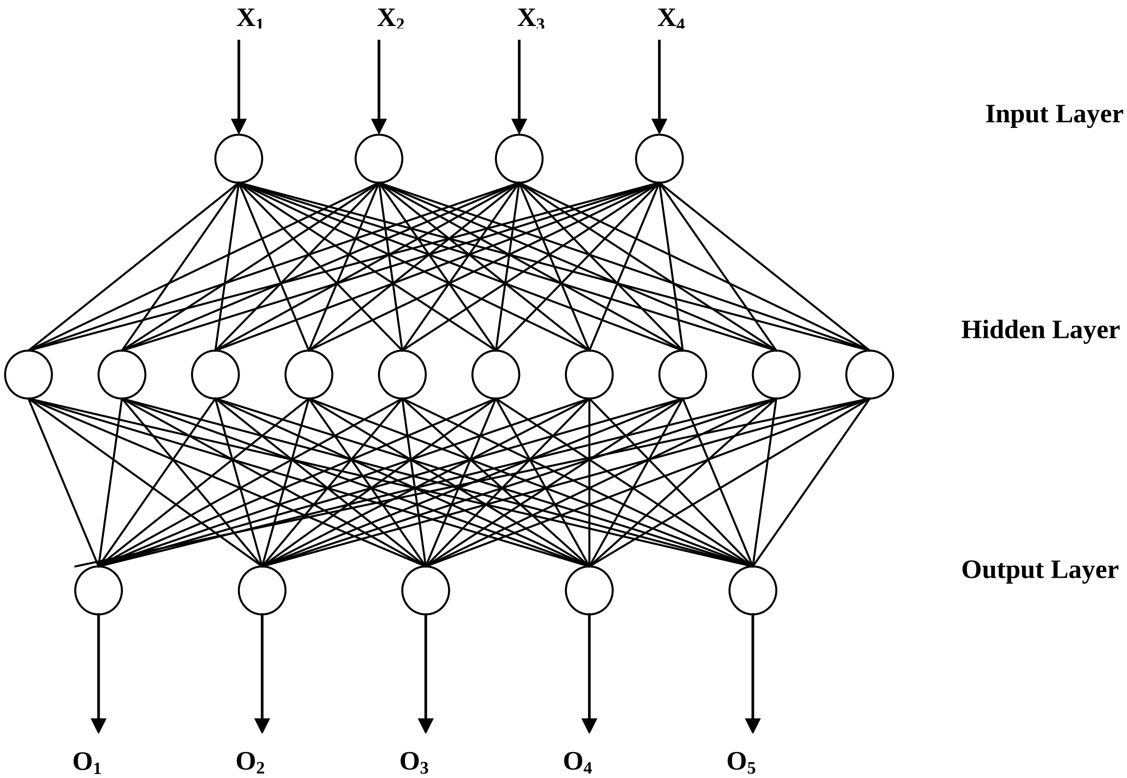

Figure 1. The Structure of Three-layer Neural Network (4–10–5) that has four input nodes at input layer, 10 nodes at hidden layer, and 5 output nodes at output layer.

data set must contain sufficient representatives of each class. Third, the size of training set is related to the number of associated weights and the desired classification accuracy [10].

The neural network architecture that gives the best results for a particular problem can only be determined experimentally. In neural network architecture, the number of input nodes equals the input dimension and the number of output nodes equals to the number of expected classes. For example, each input node in the input layer represents one optical spectral band, and each output node in the output layer is often encoded to represent one of the output classes. However, Kanellopoulos and Wilkinson (1997) have shown that the number of hidden layer and hidden nodes, which could give the best classification results, must be determined experimentally for a particular problem. They suggested that single hidden layer networks are sufficient for most classification problems and the number of hidden nodes should be at least four times the number of input nodes or twice the number of the output nodes [11].

In the implementation of the BP learning algorithm, the weight adjustment is controlled by a parameter called learning rate. The learning rate usually starts with a small number. However, very small learning rates will make the training very slow, which is not realistic for practical implementation. Learning rates are also application-related and have to be determined experimentally.

In practical implementations of MNNs, it often happens that a well-trained network with a very low training error fails to classify unseen patterns or produces a low generalization accuracy when applied to a new data set. This phenomenon is called overfitting. This is partly because the over-training process makes the network learning focus on specifics of this particular training data which are not the typical characteristics of the whole data set. Thus, it is important to use a cross-validation approach to stop the training at an appropriate time. Basically, we collect two data sets: training data set and testing data set. During training only the training data set is used to train the network. However, the classification performances with both testing and training data are computed and checked. The training will stop while the training error keeps decreasing and the testing performance starts to deteriorate. This parallel cross-validation approach can ensure that the trained network be an effective classifier to generalize well to new/unseen data and can avoid wasting time to apply an ineffective network to classify other data.

3. Implementation and Results

The objective of this study was to generate a customized high spatial detail land cover mapping for the Hominy Creek Watershed near Wilson, NC. The resulted CIR DOQQ data has high spatial resolution of one meter. To address the classification problem with such a large image data set, a neural network classifier was trained using BP learning algorithm. Then the well-trained network was applied to accomplish the land cover mapping for the whole study area. All of the digital image preprocessing of remotely sensed were performed using ERDAS 8.4 Imagine tools. The neural network classification was conducted by a new-developed classification system with C++ and ERDAS Imagine 8.4 Toolkit.

The image processing steps included: generation of the CIR DOQQ data for the study area from the CIR aerial photographs, visual analysis of the image and determination of a proper classification scheme, neural network-based classification, classification accuracy evaluation and result analysis.

Study Area

The study area for this study is the Hominy Creek watershed near Wilson, NC. The Hominy Creek watershed is in Sub-basin 07 of the Neuse River Basin. The study area is estimated to be 11 by 11 miles. Figure 2. is the derived CIR DOQQ image for the study area.

Data Preprocessing

Because the Digital CIR DOQQ data were still in the development stage and not available when this study was taken, six CIR National Aerial Photography Program (NAPP) aerial photographs with a scale 1:40,000 covering the whole study area were scanned to generate create a CIR DOQQ for the area of interest. The scanning processing is an analog-to-digital (A/D) conversion and, like all quantization procedures, will introduce errors. To minimize these errors, the scan settings were consistent from photo to photo.

After scanning, the images were just pictures without any coordinate system. Furthermore, geometric distortions on these images due to aircraft tilt, feature geometry, and lens distortion were still present. To make the images useable, they had to be orthorectified and georeferenced. Orthorectification is a process to correct geometric distortions of the images. a Digital Elevation Model (DEM) and the calibration information such as the camera and lens parameters were used to create six orthoimages (digital orthophoto). Georeferencing is the process of assigning a coordinate system to an image. In this study, we used the Ground Control Points (GCPs) selected from the corresponding Black/White (B/W) DOQQs to georeference the five CIR DOQQ images. Following orthorectification and georeferencing, the five images were mosaicked to form one large CIR DOQQ for the study area. The resulting image is a CIR DOQQ for the Hominy Creek watershed.

Figure 2. The Hominy Creek watershed. The red line around the edge is the boundary of the watershed.

Neural Network-based Classification and Experimental Results

In this study, to simplify the computation complexity, we chose a three-layer neural architecture as the basic architecture. To perform a neural network-based classification, the first task is to determine the number of input bands and the number of the classes to be derived from the image. There are three spectral bands in the CIR DOQQ image. All these three bands are used to classify the image. Thus, the input layer in the network had three input nodes with each input node for one band.

Water flows through the landscape. The character of the land surface affects the way water flows through it. The condition of the land surface affects the flow and quality of water. A barely vegetated land surface with thin soils and steep slopes will produce a different runoff response to a given rainfall than will a lushly vegetated surface overlying deep soils on shallow slopes. Landscape characterization is the process of summarizing the properties of the landscape that influence the hydrologic behavior. The watershed land cover mapping information is essential for the hydrologic landscape characterization. Our basic goal is to use the CIR DOQQ data to generate a land cover map for the study area which would be feasibly incorporated into a hydrologic model to evaluate the water activities and serve for the water quality restoration in the area. Based on these reasons, the classification scheme was determined as follows:

1. Urban – Commercial area, residential, roads, and highways.
2. Grassland – Lawns and golf courses
3. Forest – Coniferous, Deciduous, and Mixed forest
4. Agriculture – Row crops and pasture
5. Bare Soil – Construction sites and bare agricultural land
6. Water – Ponds and lakes
7. Shadow/Unknown – Areas that were in shadow on the photos. The shadow problem. Which is very typical for aerial photos. Because of the time and budget limitations, we did not develop any procedure to remove the shadow on the image. To reduce the effect of

the shadow on the classification accuracy, we used the shadow/unknown as an additional class.

By visually analyzing the original CIR DOQQ image, 2200 training pixels (300 to 350 pixels per class) and 660 testing pixels (90 to 95 pixels per class) were selected from the original CIR DOQQ image. The testing data set was used to check the generalizing performance of the trained network. Both data sets were input into the network training system but only training patterns are used to adjust the weights of the trained network. The MSE behaviors of these two data sets during training process were monitored for several purposes: verification of the classification performance; generalization improvement; assisting selecting optimal network parameters like the number of hidden nodes, learning rate, etc. If the MSE of the testing data set increases while the MSE of training data set decreases, the training process should be stopped so as to avoid overfitting. Overfitting will cause the trained network to fail to generalize well for other unseen data beyond the training data set.

Via preliminary experiments, the network architecture with 3–22–7 proved to be optimal and was used as the network architecture for this particular application. The epoch training method was used to train the network. In epoch training, the weight update for each input training sample is computed and stored (without changing the weights) during one pass through the training set, which is called an epoch. At the end of the epoch, all the weight updates are added together, and only then will the weights be updated with the average weight value. The mean square error of neural network epoch training and testing is plotted as a function of the number of the training epochs for the 3-22-7 network, as shown in Figure 3.

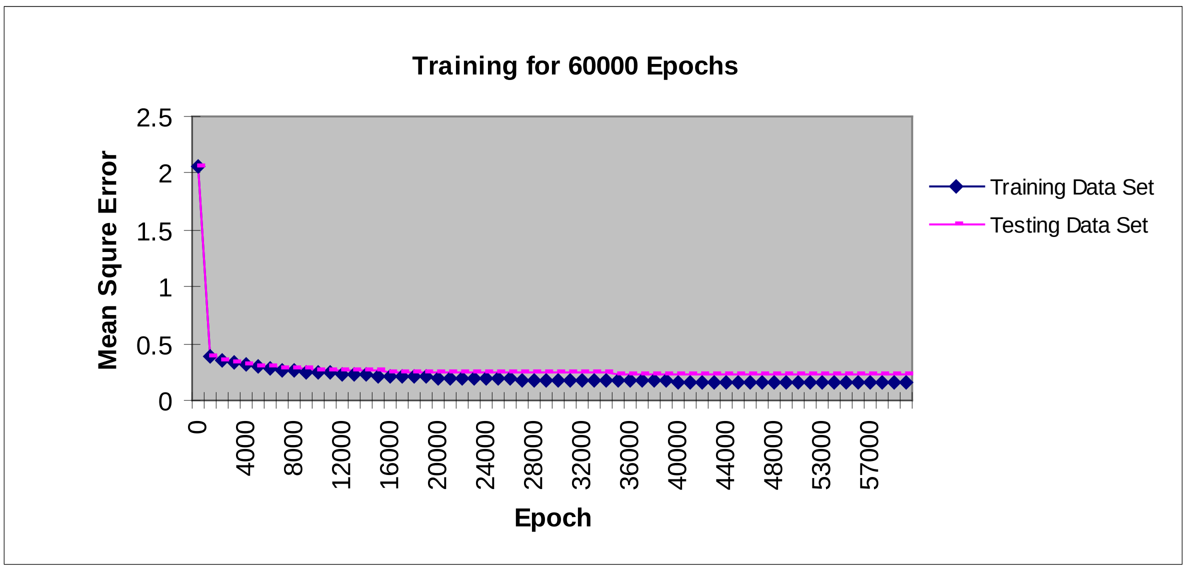

Figure 3. Mean square error of Neural Network training and training epochs

This well-trained network was then used as a feed-forward network to classify the whole image. The resulting land cover map is shown in Figure 4. The classification results were assessed using 535 points interpreted from aerial photos. Table 1 shows the error matrix of the land cover map classified by the neural network-based system. The overall accuracy is 64.30%.

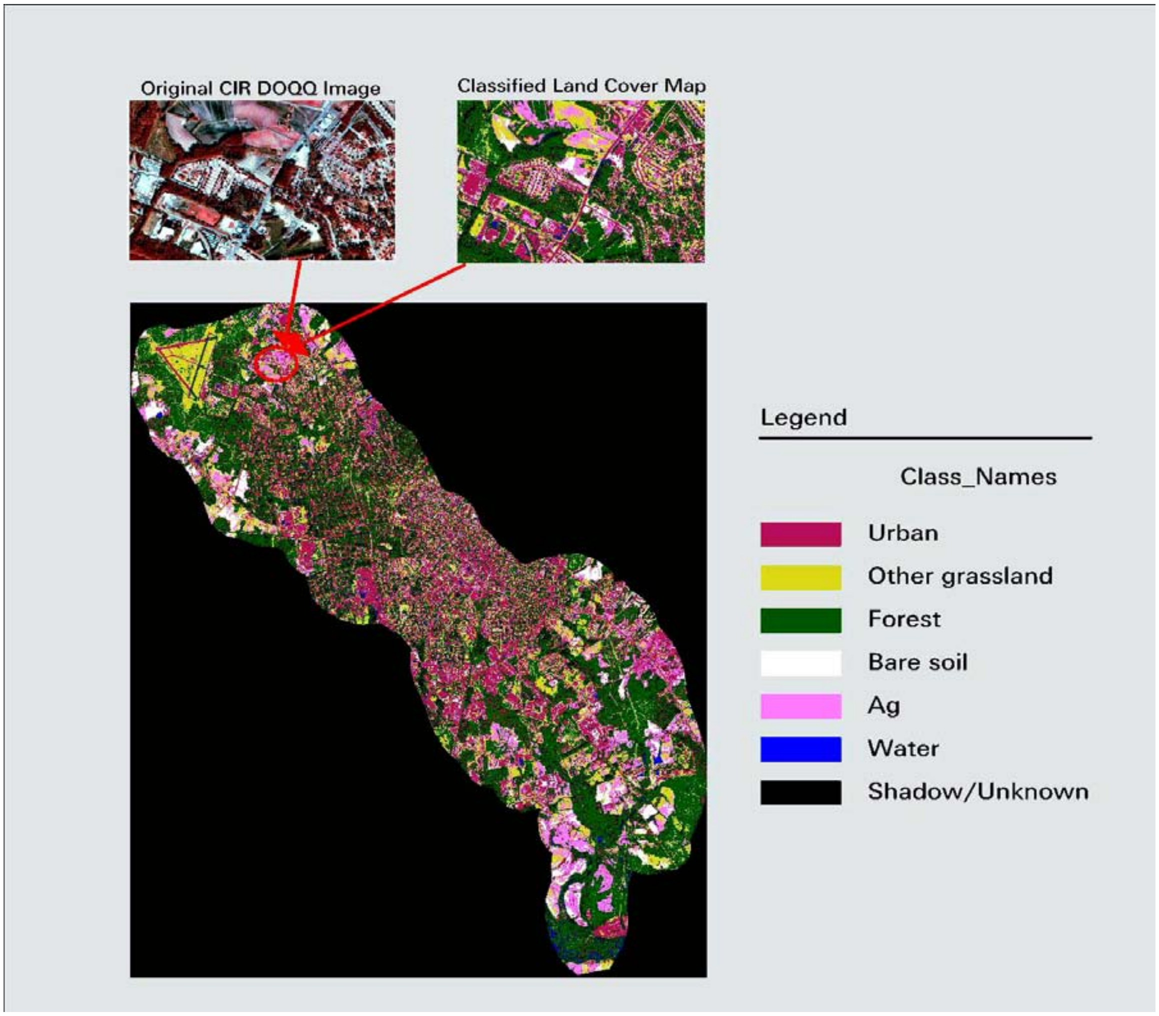

Figure 4. Classified Map of the Hominy Creek Watershed from the MLP module

Table 1. Error Matrix of the Hominy Creek Watershed Characterization

	Reference Data									
		Urban	Grassland	Forest	Bare Soil	Agriculture	Water	Shadow	Total	User's Error
Classified Results	Urban	61	17	17	2	4	0	5	106	57.55%
	Grassland	3	24	5	1	17	0	0	50	48.00%
	Forest	12	14	124	0	11	1	8	170	72.94%
	Bare soil	4	5	0	42	7	0	0	58	72.41%
	Agriculture	5	5	0	1	19	0	0	30	63.33%
	Water	18	0	0	0	0	20	20	58	34.48%
	Shadow	0	0	6	0	2	1	54	63	85.71%
	Total	103	65	152	46	60	22	87	535	
	Producers' error	59.22%	36.92%	81.58%	91.30%	31.67%	90.91 %	62.07%		344
Overall Classification Accuracy = 64.30%										

4. Discussion and Conclusions

In this study, we developed an automated neural network classification system and applied it to classify the high-resolution CIR DOQQ data into seven land cover classes which provides important spatial information for water quality modeling and assessment in this area. The CIR DOQQ data were generated using an analog-digital (A/D) conversion.

By analyzing the experimental results, we can see that during the training procedure, the MSEs of training and testing went down together shown in Figure 3, which meant that the trained network generalized well for the unseen data set. The MNN system seemed to proceeded well in terms of reducing the training and testing error together. But the process stalled. This training process was far from enough because the expected MSEs at convergence should be at least below 0.01 for an acceptable classification accuracy. The high MSEs at convergence suggested that the resulting low classification accuracy was caused by the imprecision of the original image data and its incapability of providing enough information needed for such an accurate and detailed land cover mapping.

First, the CIR DOQQ data generation process is a quantization procedure, which introduced errors. Second, the CIR DOQQ data only have three spectral bands (Red band, Green Band, Infrared Band), which is not sufficient for this classification application demanding higher level classification details. For these reasons, the spectral signatures of several classes are not well differentiated, and so reduce the classification accuracy. In this application, high and low density residential areas were combined into one urban class. This class had a great deal of spectral confusion with other grassland and forest areas. Because the original aerial photos were taken in winter, the reflectance characteristics of other grassland and agricultural pasture were therefore very similar. Also, the shadow problem which is typical for aerial photos also greatly reduce the classification accuracy. The shadow problem had a significant influence on the water class. Generally we can find there are high spectral diversity within classes and high similarity between classes by analyzing the original image data visually. All these problems made the selection of appropriate training data sets for some classes very difficult or impossible.

The MNN system is a supervised classification method. Its accuracy highly depends on the quality of the selected training data. The training data for each class must be able to provide sufficient information about the class with which it is associated. In addition, these classes must have some separability in the feature space for the classifier to be able to discriminate them. This is the main reason why the implementation of the MNN classification system failed in this particular application. To improve the classification accuracy, for future research we recommend the incorporation of other image data source with high spectral resolution, such as SPOT, IKONOS, or Landsat TM data, into the neural network-based system. One of the typical advantages of neural network approaches is their independence of statistical distribution of the input data, which would make the developed MNN system to able to merge additional source image for more accurate land cover mapping.

Results from this application also demonstrated that high spatial resolution image data is necessary if a detailed land cover mapping is desired. CIR DOQQ data with one-meter spatial resolution is a good choice when a particular application requires high spatial resolution and is cost limited. Since the CIR DOQQ data have currently been developed by USGS and are available to order, we suggest that the future applications would be able to save time to produce the data and avoid the errors possibly occurred in the generation process.

Based on the detailed analysis above, we conclude that, although the resulting classification accuracy is low in this particular watershed mapping application, the developed neural network-based classification system itself proves to be an effective and efficient classification system while applied to such a large image with very high spatial resolution. Once a well-trained network is resulted from this system, it could be used to classify other large data sets with the same spectral characteristics quickly. However, the classification accuracy of this supervised classification system highly depends on the quality of training data. In the case of sufficient and reliable training data sets provided, more accurate classification would be expected from the neural network-based system. The developed neural network-based classification system not only can be applied to classify single data source but also be used to fuse complimentary information from multiple source image data to create a more accurate recognition of land cover patterns, in which the associated uncertainty is decreased and the classification accuracy is improved. To improve the classification accuracy for this watershed land cover mapping application, more research efforts will be focused on adapting the neural network-based system for a data fusion system to fuse the CIR DOQQ data with other image data like SPOT or Landsat TM so as to improve the classification accuracy as compared to using single CIR DOQQ data.

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