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Land Cover Classification of Image Data Using Artificial Neural Networks

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인공신경망 모형을 이용한 영상자료의 토지피복분류

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ABSTRACT : 본 연구에서는 최대우도법과 인공신경망 모형에 의해 카테고리 분류를 수행하고 각각의 분류 성능을 비교 평가하였다. 인공신경망 모형은 오류역전파 알고리즘을 이용한 것으로서 학습을 통한 은닉층의 최적노드수를 결정하여 카테고리 분류를 수행하도록 하였다. 인공신경망 최적 모형은 입력층의 노드수가 7개, 은닉층의 최적노드수가 18개, 그리고 출력층의 노드수가 5개인 것으로 구성하였다. 위성영상은 1996년에 촬영된 Landsat TM-5 영상을 사용하였고, 최대우도법과 인공신경망 모형에 의한 카테고리 분류를 위하여 각각의 카테고리에 대한 분광특성을 대표하는 지역을 절취하였다. 분류 정확도는 인공신경망 모형에 의한 방법이 90%, 최대우도법이 83%로서, 인공신경망 모형의 분류 성능이 뛰어난 것으로 나타났다. 카테고리 분류 항목인 토지 피복 상태에 따른 분류는 두 가지 방법에서 밭과 주거지의 분류오차가 큰 것으로 나타났다. 특히, 최대우도법에 의한 밭에서의 태만오차는 62.6%로서 매우 큰 값을 보였다. 이는 밭이나 주거지의 특성이 위성영상 촬영시기에 따라 나지의 형태로 분류되거나 산림, 또는 논으로도 분류되는 경향이 있기 때문인 것으로 보인다. 차후에 카테고리 분류를 위한 각각의 클래스의 보조적인 정보를 추가한다면, 카테고리 분류 향상이 이루어질 것으로 기대된다.

Key words : Artificial neural networks, Maximum likelihood classifiers, Land cover, Remote sensing

I. Introduction

In recent decades, remote sensing has proved to be a powerful technology for monitoring the earth's surface and atmosphere at a global, regional, and even local scale. This has been made possible by the large amount of data acquired by different types of sensors. Digital processing of remotely sensed imagery, such as Landsat, offers many advantages over traditional photo-interpretation mapping (Mas, 2004). The Landsat data have clear practical advantages over the spectrally comparable SPOT imagery, including lower costs (Hyyppa et al., 2000). In comparison to hyperspectral or hyperspatial resolution sensors, Landsat data are less expensive, have lower storage requirements, higher spatial coverage and are relatively easy to process due to the substantial body of published literature concerning Landsat image processing methods (Ingram et al, 2005).

The constitution of the optimum data space is a common problem in connection with classification. In order to construct realistic classifiers, features that are sufficiently representative of the physical process must be included in the search (Kurnaz et al., 2005). Different classification algorithms produce different results, even using the same training sets (Liu et al., 2002). For some application fields, neural network classifiers (NNC) yield better results, while for other applications a statistical classifier, such as the maximum likelihood classifier (MLC), performs better (Kanellopoulos et al., 1993, Liu et al., 2002).

It has been shown that no image classifier is perfect. However, classifiers may also be assumed to have complementary capabilities (Matsuyama, 1987, Liu et al., 2002).

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Therefore, a useful and practical approach for classification performance is required in order to increase classification accuracy.

The statistical analyses used for understanding the relationships among spectral data and land cover attributes should allow for the possibility that these relationships may be non-linear and complex. Regression and correlation analyses have commonly been used within remote sensing studies. However, these approaches typically assume linear relationships among variables of interest, while plant biophysical characteristics often do not conform to these criteria (Jensen et al., 1999). For this reason, nonparametric statistical methods may be more useful for describing the relationship between remotely sensed imagery and environmental variables, since these tests make no priori assumptions about the data. The MLC is a well-known parametric method. It is base on the assumption that the data may be modeled by a set of multivariate normal distributions (Gaussian). Typically artificial neural networks (ANN) can be used in estimating various fields without making assumptions about the data. Many authors have reported better accuracy when classifying spectral images using an ANN approach than with statistical methods such as MLC (Paola and Showengerdt, 1995, Atkinson and Tatnall, 1997, Mas, 2004). However, a more important contribution of the ANN is their ability to incorporate additional data into the classification process.

Artificial neural networks (ANN) are widely used for the classification of remote sensing images (Berberoglu et al., 2000, Jozwik et al., 1998, Bruzzone and Fernandez, 1999, Giacinto et al., 2000, Serpico et al., 1996, Chen et al., 1999, Villmann et al., 2003). Artificial neural networks (ANN) are computational models that attempt to emulate the capabilities of the human brain by mimicking its simplest and most obvious mechanisms. They are known as black-box methods, since it is not known exactly how ANN learns particular problems and apply the extracted rules to new cases, or how conclusions can be drawn from the trained networks (Gomez, 2002, Knag and Park, 2003, Gomez and Kavzoglu, 2005, Kang et al., 2006a, Kang et al., 2006b). ANN is capable of handling non-normality, non-linearity and collinearity in a system (Haykin, 1994). This ability is a major advantage of ANN for assessing the relationship between land cover attributes and spectral reflectance values, which are frequently non-linear and complex and in turn, may vary across different wave bands.

The remote sensing literature on back propagation neural network applications to multispectral image classification is relatively new, dating back only about ten years. These studies have examined the classifier in more detail and compared it to standard techniques, such as maximum likelihood method. Few studies, however, have looked at the finer details of the class decision regions and classifier-produced probability estimation in order to fully understand how and why the two algorithms perform differently on a particular image. Although in early studies ANN was mostly used to classify data, the method has also shown great potential for predicting continuous variables (Uno et al., 2005). ANN has recently been shown to provide useful alternatives to traditional statistical analyses in various remote sensing research. Successful applications have already been reported for land cover classification (Jensen et al., 1999, Foody et al., 2003, Ingram et al., 2005), surface water quality assessment (Keiner and Yan, 1998; Gross et al., 1999, Zhang et al., 2002), soil moisture estimation (Chang and Islam, 2000, Del Frate et al., 2003), and yield prediction (Simpson, 1994; Liu et al., 2001, Drummond et al., 2003). However, a more thorough investigation on the use of ANN in remote sensing data analysis is necessary (Uno et al., 2005).

This paper describes the operation of one type of neural network technique, back propagation, under the conditions encountered in processing remote sensing data for the study area. To allow for a comprehensive evaluation of the neural network technique, it is compared to the maximum likelihood classifier method and the results of an experimental application are discussed.

II. Theoretical Description

1. Maximum Likelihood Classifier

The maximum likelihood classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. To do this, an assumption is made that the distribution of the cloud of points forming the category training data is Gaussian (Lillesand and Kiefer, 1994). This assumption of normality is generally reasonable for common spectral response distributions. Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and the covariance matrix.

In essence, the maximum likelihood classifier delineates ellipsoidal "equiprobability contours" in the scatter diagram. These decision regions are shown in Fig. 1. The shape of the equiprobability contours expresses the sensitivity of the likelihood classifier to covariance.

The principal drawback of maximum likelihood classification is the large number of computations required to classify each pixel. This is particularly true when either a large number of spectral channels are involved or a large number of spectral classes must be differentiated. In such cases, the maximum likelihood classifier is much slower computationally than other classification techniques.

The maximum-likelihood classifier is a parametric classifier that relies on the second-order statistics of a Gaussian probability density function (pdf) for each class. It is often used as a reference for classifier comparison because if the class pdf's are indeed Gaussian, it is the optimal classifier.

2. Artificial Neural Netwoks

Neural networks stem from research in artificial intelligence as an attempt to mimic the workings of the brain using a simplified model of nodes connected by neurons. Artificial neural networks have been investigated by scientists in a diverse range of disciplines, including computer science, psychology, biology, organic chemistry and hydrology. Although the motivation for these studies varies, the main idea, computing using methods inspired by biological systems, remains the same.

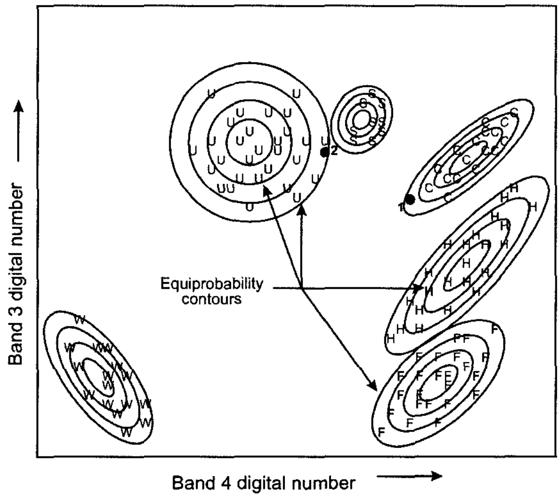


Fig. 1. Equiprobability contours defined by a maximum likelihood classifier (Lillesand and Kiefer, 1994).

Error back propagation, which is also known as the Generalized Delta Rule, is one of the most popular and widely investigated methods for training neural networks. The most common network topology is made up of multiple layers with connections only between nodes in neighboring layers. Many variants of neural network algorithms are derived from a three layer back propagation neural network. For multispectral image classification, the most widely used input/output configuration is one input node for each input channel and one output node for each desired class label. The hidden layer is not determinate and few guidelines exist to help the user. Every input and output node is connected to all of the hidden layer nodes. Each interconnection has an associated weight and as a whole contain the distributed, learned information about the classes.

The network consists of layers of parallel processing elements, called neurons, with each layer being fully connected to the preceeding layer by interconnection strengths, or weights, W. The network consists of layers i, j, and k, with the corresponding interconnection weights being W_{ij} and W_{jk} between layers of neurons. Initially, estimated weight values are progressively corrected during a training process that compares predicted outputs to known outputs, and back-propagates any errors to determine the appropriate weight adjustments necessary to minimize the errors.

The total error TE, based on the squared difference between predicted and actual outputs for pattern p, is computed as

$$TE = \frac{1}{2}\sum_{p=1}^{n}\sum_{k=1}^{m}(y_{pk} - p_{pk})^2 \tag{1}$$

where n is the number of input-output patterns, m is the number of output variables, y_{pk} is the target value of output node k of pattern p, and p_{pk} is the output value of output node k of pattern p.

The pattern errors can be assumed to be a function of the multidimensional weight space, visualized as a surface of peaks and valleys. The valleys are the minima in pattern errors that are located by a process called the gradient descent method. At the beginning of the training process, the location of the error surface will be near the peaks, with movement to the minima being achieved by progressively correcting the interconnection weights by the amount:

$$\Delta W_{kj} = -\eta \frac{\partial E}{\partial W_{kj}} \quad (2)$$

where ΔW_{kj} is the change in the interconnection weight between the arbitrary layers k and j of pattern p, η is a proportionality constant (or a learning constant), and $\partial E/\partial W_{kj}$ is the slope of the error surface.

The present study adopted a method whereby the weights are adjusted by the learning rate and the momentum term as follows:

$$\Delta W_{kj}(t+1) = \eta\delta_{pk}h_{pj} + \alpha\Delta W_{kj}(t) \quad (3)$$

where ΔW_{kj} $(t+1)$ is the interconnection weight between layers k and j, η is the learning rate, δ_{pk} is the error of layer k on pattern p, h_{pj} is the output of the hidden layer on pattern p, and α is the momentum constant.

The larger value of η correspond to larger changes in the weight, allowing the desired weight to be found more rapidly. However, if η is too large it may cause oscillations (Phien and Sureerattanan, 2000). The momentum α is added to the weight adjustment to avoid the formation of local minima.

III. Methodology

1. ANN classifier

First, all the digital numbers describing seven bands in the image data were normalized into the theoretical range of [0, 1]. As the sigmoid function is involved, all the data were actually transformed into the range of [0.05, 0.095] using the following equation (Kang et al., 2006a & 2006b):

$$X' = \left[\frac{1}{(X_{\max} - X_{\min})}\right] \times (X - X_{\min}) \quad (4)$$

$$X' = 0.05 + 0.90 \times \left[\frac{1}{(X_{\max} - X_{\min})}\right] \times (X - X_{\min}) \quad (5)$$

where X' is the transformed variable, and $X_{\max}$ and $X_{\min}$ are its maximum and minimum digital numbers, respectively.

Using the trial and error method, the best combination model was found to be:

$$Classifier: \quad O(i) = function\ [B(j)] \quad for\ i = 1\ to\ 5\ and\ j = 1\ to\ 7 \quad (6)$$

where $O(i)$ is the digital number in the output layer (class) i, and $B(j)$ is the digital number in the input layer (band) j.

As a direct consequence of Equation 4, the network used in this study has seven input nodes. The number of nodes in the hidden layer is the only factor that must be determined, as the numbers of input and output nodes were determined using neural network classifier model. The optimal number of nodes in the hidden layer was found to be eighteen nodes. The image data used for training ANN and testing the classification accuracy was selected from a section (500×1000 pixels) of the Landsat-TM scene (Path116/Row34) showing an area of the republic of Korea. The five categories of landuse classified by ANN were forest, paddy, upland, urban, and water bodies for use as input data for hydrology and water quality models.

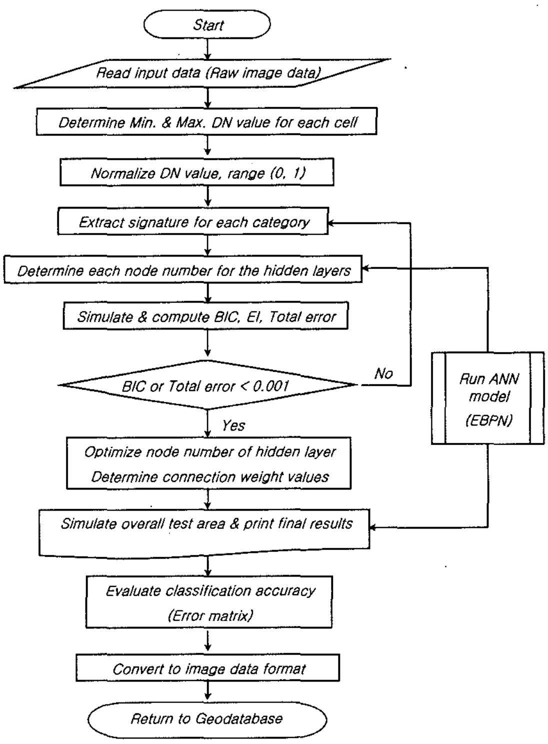


Fig. 2. Flow chart of the ANN classifier for image data analysis.

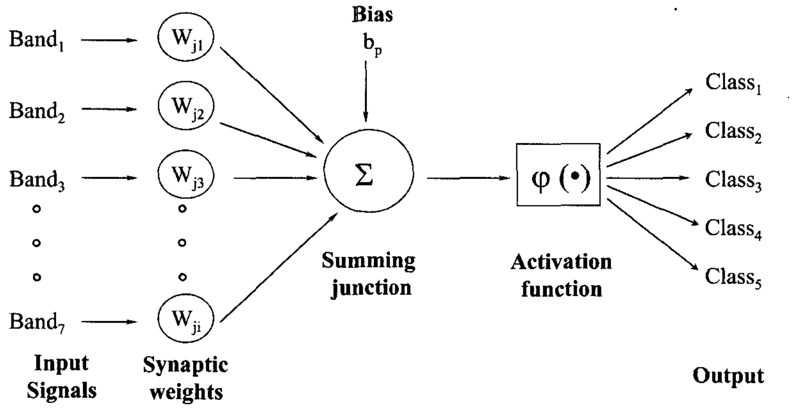


Fig. 3. Architecture of the three-layer ANN classifier.

Fig. 2 shows the flow chart for the ANN classifier for Landsat-TM image data analysis. The architecture of the ANN model for land cover classification is shown in Figure 3.

In this study, a more relaxed stopping rule for determining the efficient number of nodes in the hidden layer was adopted for the Bayesian information criterion (BIC) (Hsu et al., 1995, Phien and Sureerattanan, 2000, Kang et al., 2006a) as follows:

$$BIC = M\ln(MSE) + P\ln M \tag{7}$$

$$\left|\frac{BIC(k+1) - BIC(k)}{BIC(k)}\right| \le 0.001 \tag{8}$$

where *BIC* describes the Bayesian information criterion, *M* is the number of data points, *MSE* is the mean squared error, *P* is the number of parameters, and *k* is the number of nodes in the hidden layer.

IV. Results and Discussion

1. Data and Training

The image data used for training and testing the classification accuracy of the neural network were selected from a section (500×1000 pixels) of Landsat-TM scene (Path116/Row34) of an area in South Korea.

Table 1 and Table 2 indicate the resampling results and characteristics for this area obtained from the Landsat-TM data, respectively.

Table 1. Resampling results from the Landsat-TM data.

Scene	Date	Time	GCP Selected No. of GCP	GCP X residual	GCP Y residual	GCP RMSE
Landsat-TM (Path116/Row34)	09/01/96	01:27:59	34	0.1097	0.1099	0.1553

Table 2. Characteristics of the resampling area from the Landsat-TM data.

Coordinate	Min.	Max.		
X	185,000	200,000	Column: 500 Row: 1,000 Resolution: 30 m	Ref. system : TM Korea (Mid ref.)
Y	400,000	430,000		

The use of the Bayesian Information Criterion (BIC) suggested by Rissanen (1978) was proposed to determine the best architecture for a back propagation neural network with one hidden layer when the number of input nodes and output nodes was determined based on "physical" criteria. Fig. 4 illustrates the change in the total error with the number of nodes in the hidden layer, and shows that the least error occurred when the network had eighteen nodes. It should be noted that the best structure obtained for the total error also corresponds to the highest value of the efficiency index. In other words, the best structure also gives the best performance. Fig. 5 shows the training results for different numbers of nodes in the hidden layer.

2. Classification

The aim of this classification using a neural network was to distinguish more accurately and effectively between the five land cover categories for applying hydrologic and water quality models: forest, paddy, upland, urban, and

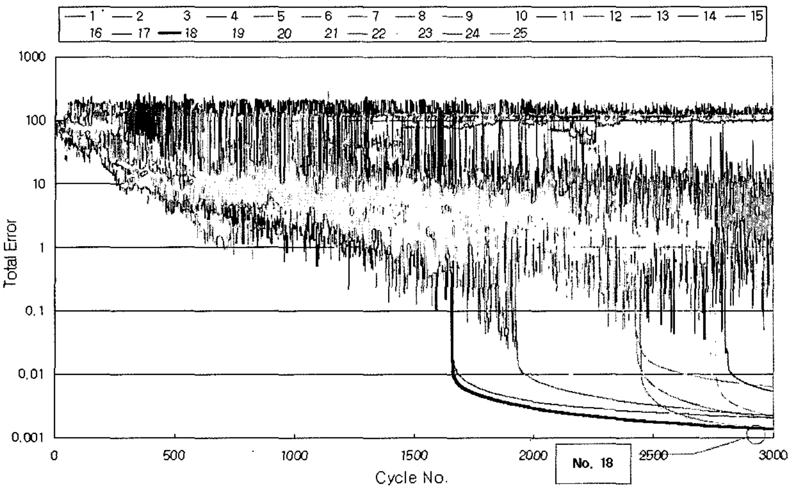


Fig. 4. Change of total error with the number of nodes in the hidden layer.

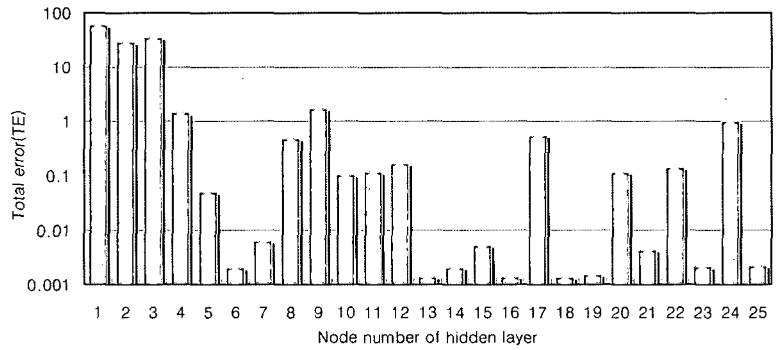
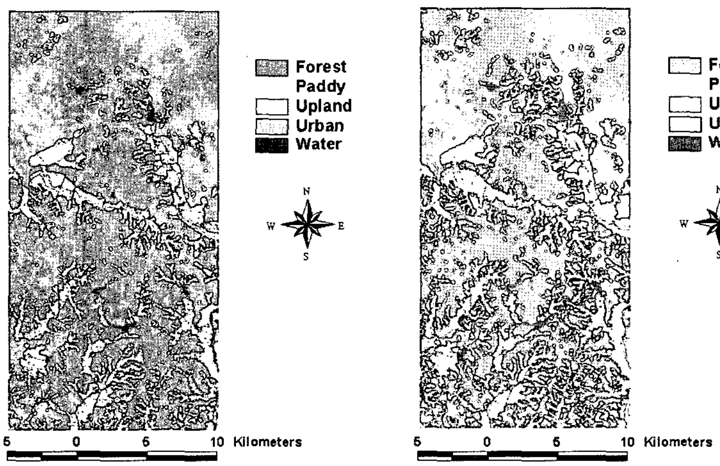


Fig. 5. Training results for different numbers of nodes in the hidden layer.

water. The resulting thematic map was compared with the Gausian maximum likelihood classification.

The Gausian maximum likelihood classifier assumes a normal distribution of the data (six bands). Fig. 6 illustrates the results of category classification using MLC and ANN classifier. As the figure shows, the ANN classifier was more successful for land cover classification compared to the MLC method.



(MLC) (ANN)

Fig. 6. Results of category classification using MLC and ANN classifier.

Table 3. Error matrix for MLC results.

Item		Training data set (known cover types)							
		Forest	Paddy	Upland	Urban	Water	Total	User's accuracy (%)	Commission error (%)
Classification data	Forest	380	3	0	0	128	511	74.4	25.6
	Paddy	4	555	0	12	3	574	96.7	3.3
	Upland	34	47	80	53	0	214	37.4	62.6
	Urban	0	1	0	148	0	149	99.3	0.7
	Water	0	0	0	0	199	199	100.0	0.0
	Total	418	606	80	213	330	1,647	-	-
Producer's accuracy (%)		90.9	91.6	100.0	69.5	60.3	-	-	-
Omission error (%)		9.1	8.4	0.0	30.5	39.7	-	-	-
Overall accuracy		82.7%							

Table 4. Error matrix for ANN classifier results.

Item		Training data set (known cover types)							
		Forest	Paddy	Upland	Urban	Water	Total	User's accuracy (%)	Commission error (%)
Classification Data	Forest	428	49	17	1	16	511	83.8	16.2
	Paddy	2	554	1	16	1	574	96.5	3.5
	Upland	13	4	156	41	0	214	72.9	27.1
	Urban	0	0	4	145	0	149	97.3	2.7
	Water	0	0	0	0	199	199	100.0	0.0
	Total	443	607	178	203	216	1,647	-	-
Producer's accuracy (%)		96.6	91.3	87.6	71.4	92.1	-	-	-
Omission error (%)		3.4	8.7	12.4	28.6	7.9	-	-	-
Overall accuracy		90.0%							

Table 3 and Table 4 are the error matrices prepared by an image analyst to determine how well a classification has categorized a representative subset of pixels used in the training process for the MLC and ANN classifier, respectively. These matrices stem from classifying the sampled training set pixels and listing the known cover types used for training (columns) versus the pixels actually classified into each land cover category by the two classifiers.

Note that in Table 3 and Table 4, the training set pixels that are classified into the proper land cover categories are located along the major diagonal of the error matrix (running from upper left to lower right). All nondiagonal elements of the matrix represent errors of omission or commission. Omission errors correspond to nondiagonal column elements. Commission errors are represented by nondiagonal row elements.

The error matrix indicates an overall accuracy of 83% in Table 3 and 90% in Table 4, showing that the ANN classifier produced more realistic and noise-free results obtained using the maximum likelihood classifier method.

These tables show that paddy areas tended to be classified as forest areas because the image shooting date was the harvesting period. The reason that urban areas were classified as upland areas is because some parts of urban areas share a reflection characteristic with upland areas. As a result, there were larger commission errors for upland and urban areas in both the applied classifiers. In particular, the commission error of 62.6% for upland areas in the MLC method was the highest error value of all (Table 3). The characteristics of upland and urban areas can thus easily be mis-classified as forest or paddy areas, respectively, depending on the image shooting date.

V. Conclusions

In an effort to more accurately and effectively classify land cover in remote sensing data, a new artificial neural networks (ANN) model for land cover classification was developed. The proposed ANN classifier model is comprised of neural network techniques, specifically back propagation, are in applied under conditions normally encountered in processing remote sensing data. The image data used for training and testing of the classification accuracy of ANN classifier and MLC were selected from a section (500× 1000 pixels) of Landsat-TM scene (Path116/Row34) of an area in South Korea. This paper shows that the use of neural networks for multispectral image classification gives results comparable to those obtained using maximum likelihood classifiers, with the error matrix indicating an overall accuracy of 83% for MLC and 90% for the ANN classifier. The ANN classifier thus produces more realistic and noise-free results than those possible using the maximum likelihood classifier method. ANN offers a promising new way to improve the classification accuracy for remotely sensed images. In this study, ancillary data were not used, but additional improvement may be expected by incorporating information such as the texture or the shape and the size of objects in the case of an object-oriented classification procedure. Based on the results obtained from this study, the ANN classifier shows promise as a feasible classifier for large multispectral images.

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