Proceedings of KFIS 2001 Fall Conference, 2001. 12. 1

신경망 기반의 오염부하량 산정을 위한 위성영상 토지피복 분류기법

Neural Network Based Land Cover Classification Technique of Satellite Image for Pollutant Load Estimation

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ABSTRACT

The classification performance of Artificial Neural Network (ANN) and RBF-NN was compared for Landsat TM image. The RBF-NN was validated for three unique landuse types (e.g. Mixed landuse area, Cultivated area, Urban area), different input band combinations and classification class. The bootstrap resampling technique was employed to estimate the confidence intervals and distribution for unit load. The pollutant generation was varied significantly according to the classification accuracy and percentile unit load applied. Especially in urban area, where mixed landuse is dominant, the difference of estimated pollutant load is largely varied.

Keywords: RBF-NN, ANN, Landcover Classification, Landsat TM, Pollutant unit load

요 지

Landsat TM 위성영상을 대상으로 인공신경망 모형과 RBF 신경망 모형의 토지피복분류 정확도를 평가하였다. 토지피복의 특성에 따라 세 개의 연구지역(복합토지이용, 농경지, 도시지역)을 대상으로 RBF 신경망 모형의 입력밴드 조합 및 분류 항목의 변화에 따른 민감도 분석이 수행되었다. 오염부하 원단위의 신뢰구간 및 분포를 추정하기 위하여 붓스트랩기법이 적용되었다. 발생 오염량은 모형의 분류정확도 및 오염부하량의 확률 규모에 비례하여 크게 변화하였으며, 특히 토지이용이 다양한 도시지역에서 가장 큰 변화폭을 보였다.

핵심용어 : RBF-NN, ANN, 토지피복분류, Landsat TM, 오염부하

I. Introduction

Information on water body such as pollutant generation, loading and influent is of great importance in water quality management field. Conventional pollutant estimation methods are based on administrative district and pollutant unit load, so it is difficult to obtain precise estimation especially in Korea where mixed landuse is predominant. Using remotely sensed data has capability in understanding the dynamic of pollutant transition by providing vast range of timely information. The quality, quantity and timing of watershed runoff are strongly dependent on landuse & landcover classes. Trolier and Philipson (1986) identified various landuse & landcover classes in New York State using Landsat TM data. Classification of landuse and landcover information has been the widest application of remote sensing data in hydrology. For example, the quality, quantity and timing of watershed runoff are strongly dependent on landuse & landcover classes relevant to runoff studies. Since the end of the 1980"s, when the first work on the use of neural networks for classification of remote sensing data were published (key *et al.*, 1989; Ersoy *et al.*, 1990), several papers have appeared that stress the capability of neural networks for analyzing remotely sensed data. In particular, different models of neural networks have been proposed, among which, the multilayer perceptron (MLP) trained with the error backpropagation learning algorithm is the most widely used. The popularity of the MLP stems from the ability of the model to generate arbitrary decision boundaries in the feature space, provided that the network architecture relies on two or more hidden layers. However, MLP has a serious drawback and limitations such as the slow convergence and the local minimum. RBF neural networks (1988; Moody *et al.*, 1989; Bishop *et al.*, 1995) overcome some of these problems by relying on a rapid training phase, and presenting systematic low responses to input patterns that have fallen into regions of the input space where there are no training samples. The goal of this study is to propose a classification technique of remotely sensed data for pollutant load estimation and to validate the proposed classification methods.

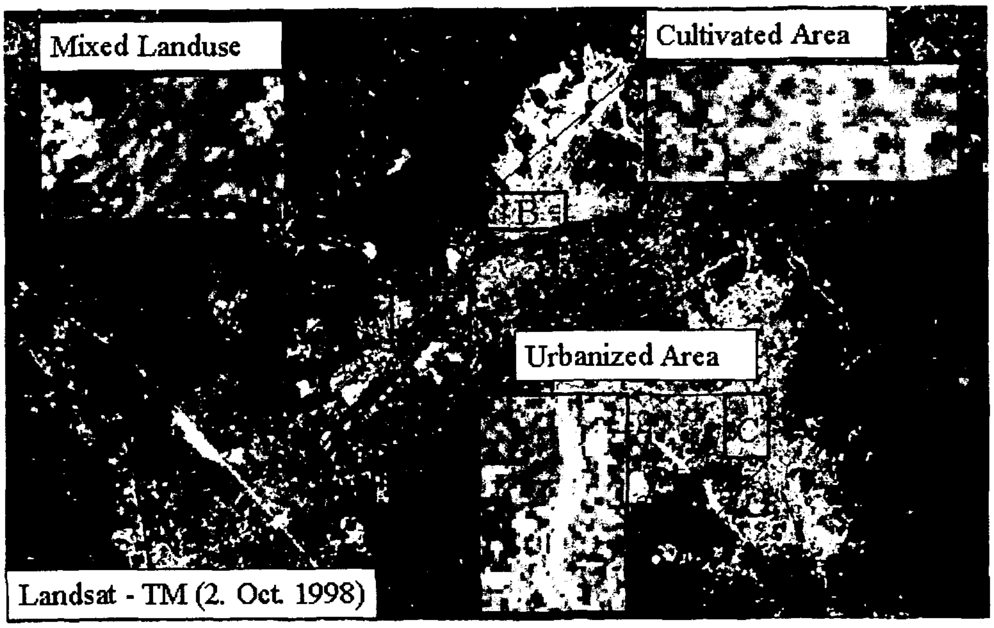

Fig. 1. Landsat TM image for study area acquired on 2 Oct. 1998. (A) Mixed landuse, (B) Cultivated area, (C) Urbanized area.

II. Experiment

606(pixelclass) data were used in calibration and 4006 pixels were used in verification process. Multi layer perceptron with sigmoid activation function was employed. ANN model parameters set to double number (2n) of hidden layer node of input data (n) and 1, 000 epochs with adaptive and momentum BP algorithm, which showed good results at preliminary experiment.(Ha *et al.,* 1999) RBF-NN model was simulated for its SC(spread constant) value, which determines the spread with of radial function, ranging from 0.1 to 1.0. The digital map and aerial photograph were used to prepare a reference map to assess the classification error. We considered 6 land use classes such as urban, bare soil, stream, paddy, orchard and forest. After verification, the fixed model parameter was validated for three unique landuse areas: 1) Mixed landuse area 2) Cultivated area 3) Urban area. Multi-band (7 bands) image acquired by Landsat TM on 2 October 1998 was selected. The selected data refers to the section of the scene acquired in Miho stream area near Cheongju city, Korea (Fig 1). The classification accuracy is evaluated by overall accuracy. (eq. 1).

$$O = \frac{\sum_{i,j=n}^{n} x_{ij}}{N} \qquad (1)$$

Where, O : overall accuracy, N : number of checking pixel, X_{ij} : diagonal elements of confusion matrix, n : number of class

III. Results and Discussion

3.1. Dependence on input band combination

Multiple training runs were made for ANN on input band combination ranging from 3 to 6 bands. Multi-training runs were done for each configuration. Classification by the input bands combination for ANN resulted the best result using Bands 1, 3, 4, and 5 (overall accuracy: 91.75), which is better than those of MLE(overall accuracy: 90.16). SC value of RBF-NN was set to 0.3 and trained to 200 iterations. At the preliminary experiments, RBF-NN reached error goal (SSE=0.001) within 200 iterations. RBF-NN, the best results were obtained with the band combination of 2, 3, 4, and 5 (overall accuracy: 95.79) RBF-NN showed better overall classification results for training area.

3.2. Landcover classification by RBF-NN

The proposed RBF-NN was validated for three unique landuse types (e.g. Mixed landuse area, Cultivated area, Urban area), different input band combinations from 3 to 6 input bands and classification class from 3 to 5. Overall classification accuracy showed the better results when the fewer classification class applied. The maximum accuracy showed at 3-classification class and Urban area, which can be explained by the relatively rough resolution of TM(30*30 m) and the complexity of landuse. However, the classification results of Urban area, which is dominated by building and commercial area, varied largely by input band combinations. The validation results of input band combinations showed better classification accuracy by increasing the number of input band combination for Cultivated and Mixed landuse area. While, for Urban area, 3-bands combination showed best result.

3.3. Pollutant load estimation with bootstrap

Estimation of pollutant load is generally performed by multiplying unit load and target area. There are, however, not many reliable unit load data available. The unit load from various literatures is different from researchers and institutes. Hence, the bootstrap resampling technique (Efron and Tibshirani, 1993) was employed to estimate the confidence intervals and distribution for unit load with S-PLUS software package. 1000 replication was made and the empirical percentile of unit load for each landuse was estimated. The estimated unit load was multiplied by the classified pixel of each category. The pollutant generation was varied significantly according to the classification accuracy and percentile unit load applied (Fig. 2). Especially in urban area, where mixed landuse is dominant, the difference of estimated pollutant load is largely varied.

Ⅳ. Conclusions

RBF-NN reached error goal (SSE=0.001) at SC value of 0.3 and 200 iterations. The best classification result of RBF-NN was obtained with the band combination of 2, 3, 4, and 5 (overall accuracy: 95.79). Overall classification accuracy showed the better results when the fewer classification class applied. The maximum accuracy obtained at 3-classification class and Urban area, which can be explained by the relatively rough resolution of TM(30*30 m) and the complexity of landuse. The validation results of input band combinations showed better classification accuracy by increasing the number of input band combination for Cultivated and Mixed landuse area, while 3-bands input combination showed best result at Urban area. The pollutant generation was varied significantly according to the classification accuracy and percentile unit load applied. From the application results as above, it was suggested that the landuse classification by satellite be conducted separately on account of its dominant landuse types in the process of pollutant estimation.

ACKNOWLEDGEMENT

This work was partly supported by the Korea Science and Engineering Foundation (KOSEF) through the Advanced Environmental Monitoring Research Center at Kwangju Institute of Science and Technology.

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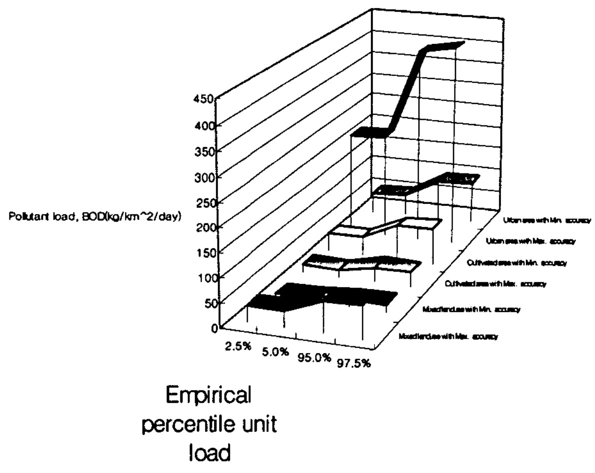

Fig. 2. Estimated pollutant load depend on classification accuracy and empirical percentile of unit load