Techniques for Yield Prediction from Corn Aerial Images – A Neural Network Approach –

Q. Zhang, S. Panigrahi, S. S. Panda, Md. S. Borhan

Abstract: Neural network based models were developed and evaluated for predicting corn yield from aerial images based on 1998 and 1994 image data. The model used images in multi-spectral bands such as R, G, B, and IR (Red, Green, Blue and Infrared). The inputs to the neural network consisted of mean and standard deviation of multispectral bands of the aerial images. Performances of several neural network architectures using back-propagation with momentum were compared. The maximum yield prediction accuracy obtained was 97.81%. The BPNN model prediction accuracy could be enhanced by using more number of observations to the model, other data transformation techniques, or by performing optical calibration of the aerial image.

Keywords: Aerial image, Yield prediction, Neural network, Image processing, Precision farming

Introduction

To achieve maximum crop yield with minimum inputs is one of the final desirable goal of agricultural production. Traditionally, crop yield is known after it is harvested. However with the help of new remote sensing technology, crop yield could be predicted in earlier stages of crop growth. Remotely sensed imaging technology including satellite and aerial imagery could predict crop yield on a large-scale basis. Although aerial images cannot produce a great synoptic view as satellite imaging, the former has been proven reliable in detecting changes in crop condition on farm as well as a site-specific level. Main advantages of aerial imaging over satellite imaging in the field of agriculture are reliability, timeliness of acquisition, and fine resolution. Moreover, aerial image is relatively economical and is independent of cloud cover.

Neural network, commonly known as artificial neural network, is a artificial intelligent technique that has the ability of computing, processing, predicting and classifying data. Neural network models are algorithms for cognitive tasks such as learning and optimization. A neural network can also be defined as an information-processing paradigm that is nonalogrithmic, nondigital and intensely paralleled. It is totally different from traditional computing. It has the advantages of nonlinearity, input-output mapping, adaptivity, generalization, and fault tolerance (Haykin, 1994).

Backpropagation neural network architecture (BPNN) is used for majority of the applications (Caudill and Butler, 1992). It is usually the first choice of neural network users because it is simple to implement and is mature compared to other neural network models. Backpropagation networks were developed on the basis of adaline (adaptive linear element).

However, neural network is still an art than a science (Haykin. 1994). Therefore, there is no definite standard procedure to identify the best neural network architecture and it varies from application to application. Therefore, many times, it is time consuming in finding an optimum neural network model for a specific problem.

Zhuang and Engel (1990a) discussed the application of backpropagation neural network for two agricultural applications. Zhuang and Engel (1990b) used a backpropagation neural network (BPNN) algorithm to classify multispectral remotely sensed data. They compared statistical classification methods including minimum distance and maximum likelihood with BPNN, and concluded that neural network method provided better results than statistical methods did.

Molto and Harrell (1992) used neural network for classification of sweet potato embryos. A back-propagation neural network algorithm was used, and

The authors are **Q. Zhang**, Graduate Research Assistant. **S. Panigrahi**. Associate Professor, **S. S. Panda,** Graduate Research Assistant, **Md. S. Borhan**, Graduate Research Assistant. Dept. of Agricultural & Biosystems Engineering, North Dakota state University, North Dakota, USA.
Corresponding author : S. Panigrahi, Associate Professor, Dept. of Agricultural & Biosystems Engineering, North Dakota State University, North Dakota, USA; e-mail: Suranjan-panigrahi@ndsu.nodak.edu

the inputs of the neural network were the geometric features of sweet potato embryos. The performance of neural network was similar with that of the linear discriminant analysis method. Park et al. (1994) used a backpropagation neural network for modeling beef sensory evaluation. Different learning schedules were used for evaluating the performance of the neural network. Neural network prediction model performed better than the statistical models for predicting all sensory attributes of beef. The root mean square values of predicted flavor intensity were 0.1350 and 0.6523 respectively, for neural network and statistical methods.

Elizondo et al. (1994) used backpropagation neural network model for predicting flowering and physiological maturity of soybean. The model used different parameters as its input and was: daily maximum and minimum air temperature, photoperiod, and days after planting (or days after flowering). The obtained results showed that the average relative error of the test data sets for date of flowering was +0.143 days and for date of physiological maturity was +2.19 days.

Hahn (1996) applied a simple backpropagation neural network to discriminate crop/weed/soil by optical reflectance. Almost 100% discrimination accuracy was achieved with the neural network model. Bodur (1996) used neural network to predict corn yield and compared neural network models with fuzzy logic model. In Bodur's neural network model, the inputs were organic matter, drought and pounding potential, monthly rainfall, and temperature. The output was the yield. He compared three different networks, i.e., backpropagation, radial basis function network and modular network. The backpropagation model predicted yield with 84% and 69% accuracies using training and test data respectively.

Uhrig et al. (1992) also used neural network with weather data, soil moisture data and a trend variable as input to predict corn yield. The performance was satisfactory in predicting corn yield. Simpson (1994) investigated the use of a fast Cerebellar Model Articulation Controller (CMAC) neural network for crop yield prediction. First, prediction performance was evaluated using only monthly agricultural and meteorological data (soil moisture, temperature, and sunshine). Then, the improvement in yield prediction performance was evaluated after adding remote sensing data (Landsat TM). The standard error of prediction was 5%, with the inclusion of TM data and the error was 6% without the TM data.

Aerial images, both color (RGB) and color infrared (CIR) were used to predict nitrogen uptake and yield (Blackmer et al., 1995; Tomer et al., 1997) as well as for field map interpolation. Sreekala et al. (1998) used high-resolution color infrared aerial images for detecting spatial pattern, due to nitrogen stress in corn. It was observed that canopy reflectance was well correlated to the applied nitrogen and the yield (from 75 days after sowing). They concluded that yield could be predicted fairly accurately (r^2=0.96) from the canopy reflectance of red light.

At present, the techniques of processing remote sensed images are still being developed, and they are not mature. Using aerial images to predict crop yield is still a challenging research topic because of the complexity of crop production environment.

Objective

Thus, the objective of this study is to investigate the capability of neural network models for predicting corn yield from aerial images.

Materials and Methods

1. Aerial image acquisition

In this study, aerial images of corn, their yield data/map, and nitrogen data were collected from the research site. The research site NW29 quarter (65 ha) was the Oakes Irrigation Test area (OITA), North Dakota located at 46.051974 N and −98.111879 W. There were a total of 90 test plots in the study quarter and each plot was of 9.14 m × 18.26 m. The imaging system was a SLM 35mm camera loaded with either 100 or 200 ASA Ektachome slide file. The slides were scanned with a Nikon Scanner at 2800 dpi resolution (dots per inch). The corn aerial images were acquired in 1994, 1997, and 1998. The images were saved as 8-bit TIFF format. Each pixel represented actual area of 0.67 m 0.67 m in the field. An aerial image of research site with corn crop on July 28, 1994 is provided in Fig. 1 along with its geographical coordinates. Ninety test plots are also indicated in the figure.

2. Image processing

A software package, IDRISI 2.0 (Clark Labs, Clark University, Worcester, MA) was used for converting acquired composite color images into separate R, G, B,

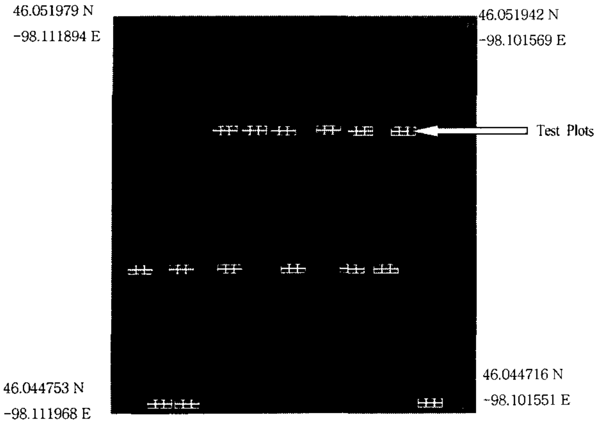

Fig. 1 Aerial image (July 28, 1994) of corn in NW29 quarter with test plots.

for RGB band images. IR band images (TIFF) were acquired and processed separately. Yield data were also converted to yield map (gray scale image) using IDRISI. For each band of the image, mean and standard deviations were determined using IDRISI. Thus, there were 90 means and standard deviations for each band image. The data were then imported to Microsoft Excel' 97 (Microsoft Corporation, Washington D.C.) to create training and testing patterns file for a neural network simulator, SNNS (Stuttgart Neural Network Simulator).

3. Neural Network model development

A typical neural network model consists of an input layer, hidden layer(s), and an output layer (Fig. 2). Various models were initially attempted to optimize neural network architecture for predicting yield from multispectral image bands.

Backpropagation architecture was selected for developing neural network model for this application. SNNS (version 4.1) on a PC (Linux operating system) was used for the development and evaluation of neural networks. The inputs of the NN were the means and standard deviations of different bands of the aerial image. For example, for an aerial image with 3 bands (Red, Green and Blue); the number of inputs were 6. For the neural network that only used one band image (i.e. Red); the number of inputs were 2. Thus, several NN models were developed with different inputs, ranging from 2 to 8. For all the neural network models, the number of output node was 1 and it represented yield.

During the development and optimization of the NN model, different numbers of hidden nodes were evaluated. Other architectural parameters such as learning rate, learning coefficient, momentum, and number of epochs were also varied. The optimum combination of different architectural parameter that provided a lowest RMSE (Root Mean Square Error) was selected as the optimum model. The equation for RMSE is

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\text{SSE}/n\text{-}p} \qquad (1)$$

Where, n = Number of observation

p = Number of parameter to be estimated

SSE = Sum of squared error

A total of 90 observations were obtained from 90 randomized plots. 60 observations were randomly selected and used for the training. The rest 30 observations were used as test data. Separate validation dataset of 89 data points (observations) relating to the same research site in 1998 were used to validate the model. All the input and output data were scaled to a range between 0 and 1. The scaling was performed using equation 2.

$$Scaledvalue = \frac{X - Min}{Max - Min} \qquad (2)$$

Where,

X = Value of an individual observation corresponding to a given parameter

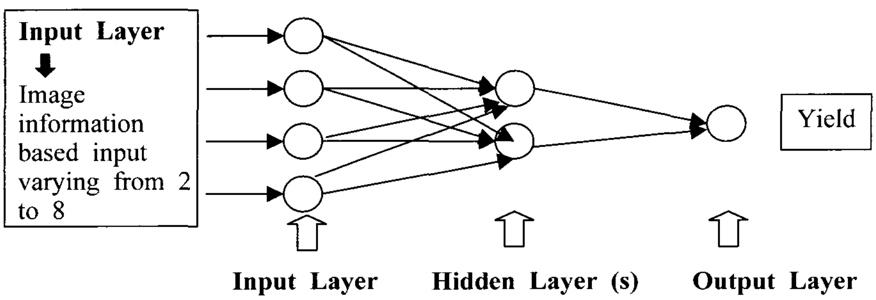

Fig. 2 Typical neural network architecture used in the study.

Min = Minimum of all the observation corresponding to the same parameter

Max = Maximum of all the observation corresponding to the same parameter

The NN were trained on the training data set until an optimum architecture is attained. Fig. 3 depicts the procedure used for optimizing neural network architecture. The optimized architecture is tested on the test data set to validate the performance of the developed NN.

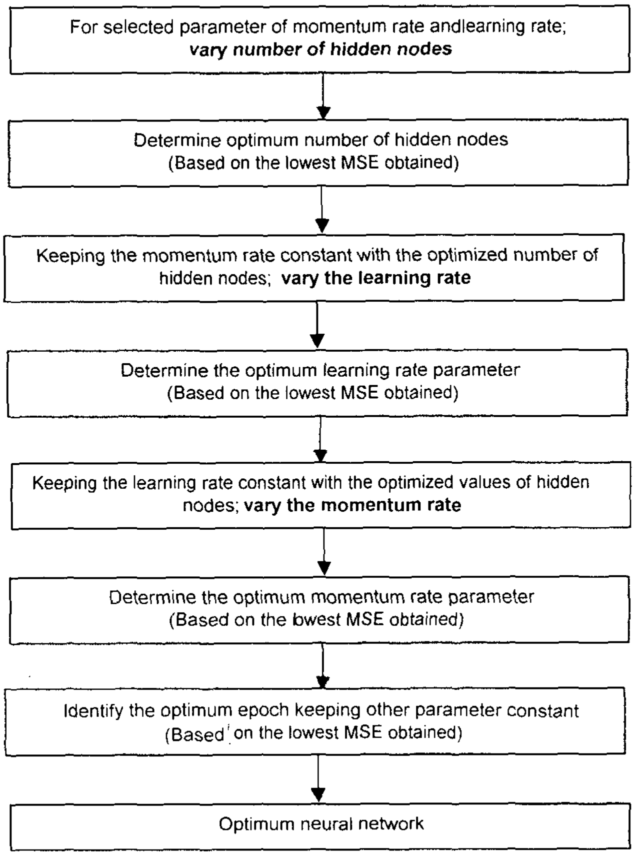

Fig. 3 Flow chart for determining the optimum neural network architecture.

Predicted output (yield) is scaled back to obtain predicted yield in conventional unit. This allows user to compare predicted yield with that of original for determining prediction accuracy and associated error of the NN model. The average prediction accuracy of the NN model was calculated using the following equation.

Average Prediction Accuracy (%)

$$= (1 - \frac{1}{N}\sum_{i=1}^{N}\frac{|Actual\_output - Predicted\_output|}{Actual\_output}) \times 100 \quad (3)$$

Where, N is total number of observations.

NN models were developed separately based on 1994 (July 28th), 1997 (September 23rd), 1998 (July 30th) data. Additional tests were also conducted to validate 1998 NN model (developed/trained on 1998) on 1994 data. This cross validation allowed to investigate how a model developed using 1994 data will perform using 1998 data.

Results and Discussion

1. Optimum configuration of different NN models

Using 1998 RGBIR neural network model as an example, the followings describe the selection of optimum configuration of a neural network model.

RGBIR 98 model has 8 input nodes representing the means and standard deviations of 4 bands (R, G, B, IR) of aerial image. Yield was the single output node of the model. Initially the momentum (m) and learning rate (η) were selected as 0.5 and 0.3 respectively. Keeping these parameters constant, different neural network models were evaluated with the number of hidden nodes varying from 2 to 6. Fig. 4 shows the lowest mean square error (MSE) with 5 hidden nodes. Thus the optimum number of hidden nodes was identified to be 5. The mean square error (MSE) of the neural network model with 5 hidden nodes was also the lowest for the testing data set.

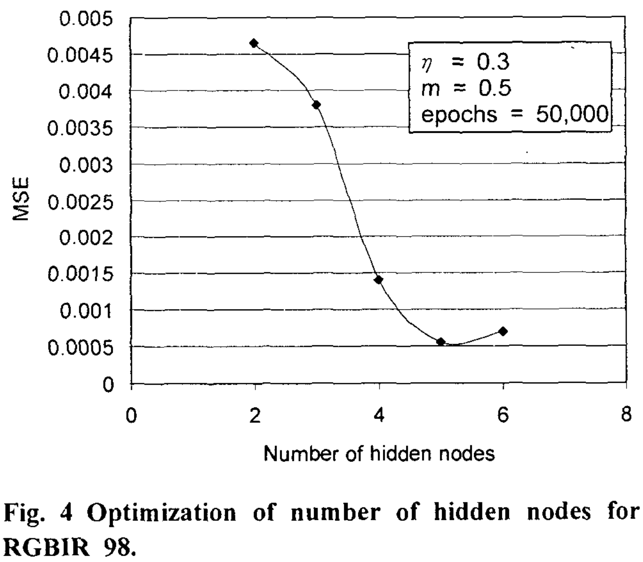

Fig. 4 Optimization of number of hidden nodes for RGBIR 98.

Then the learning rate for the selected neural network (8-5-1) was varied from 0.01 to 1.0 and the momentum was kept as 0.5. Figs. 5 and 6 depict the variations of mean square error (MSE) with different

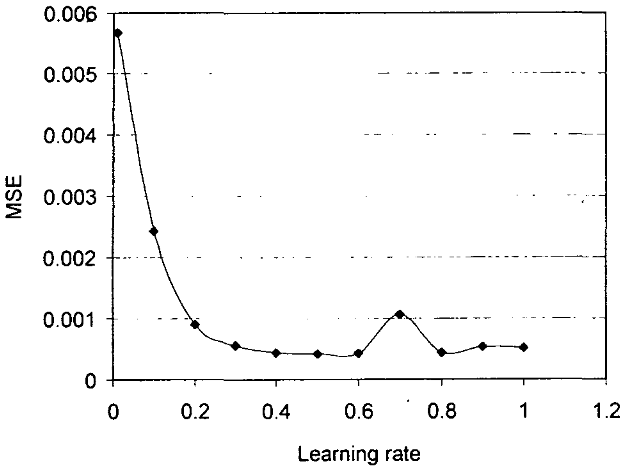

Fig. 5 Optimization of learning rate parameter for training data set for RGBIR 98.

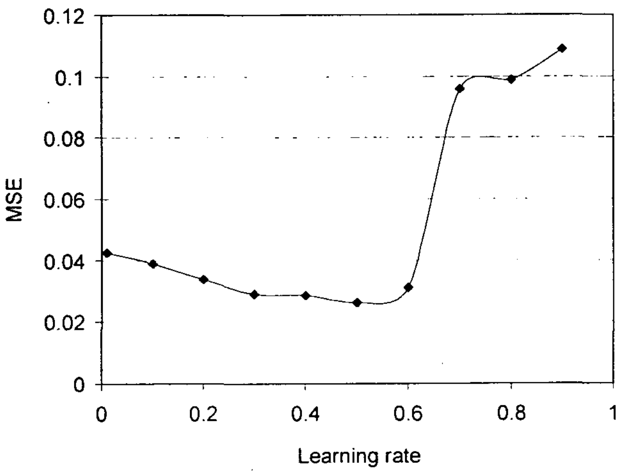

Fig. 6 Optimization of learning rate parameter for testing data set for RGBIR 98.

learning rates for both training and testing data. Their analysis implied the selection of 0.5 as the optimum learning rate.

Further to identify the optimum moment, the learning rate was kept at 0.5 and the momentum was varied from 0.001 to 1.0. Analysis of Figs. 7 and 8 suggest the lowest MSE with the momentum at 0.5.

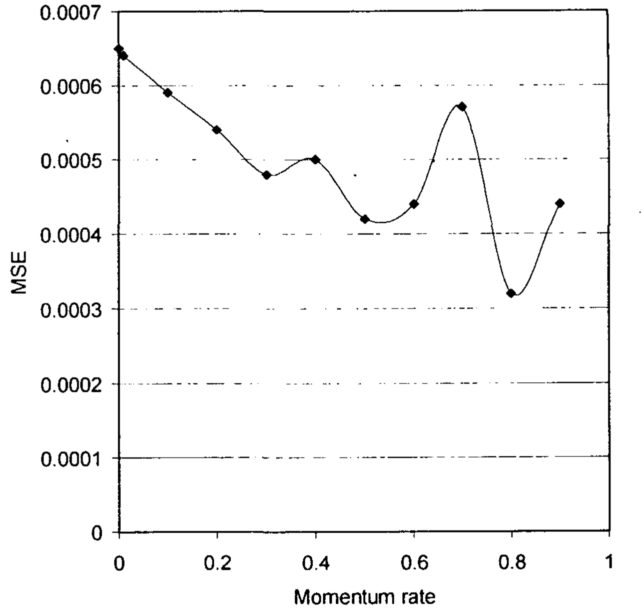

Fig. 7 Optimization of momentum for training data set for RGBIR 98.

Thus 0.5 was selected as the optimum value for momentum with all other optimum parameters (described above). This 8-5-1 neural network model (RGBIR 98) was further evaluated for different epochs and the number of epochs at 70,000 showed lowest MSE (Figs 9 and 10).

Similar procedure was used for determining the optimum parameters for other neural network models. Table 1 lists the corresponding values of these parameters.

2. Prediction performance of optimized network models

The RGBIR 98 model showed highest training accuracy of 97.81% with a corresponding testing accuracy of 89.67% (Table 2). For the same data set, another model RGBIR 98A was evaluated. Although it provided a bit lower (2%) training accuracy compared to that provided by RGBIR 98 model, an average

Table 1 Optimized models for different year data sets

Data Sets	Model with Optimum Hidden Nodes	Optimum Learning Rates	Optimum Momentums	Optimum Epochs
RGBIR 98	8-5-1	0.5	0.5	70,000
RGB 98	6-4-1	0.6	0.9	50,000
RGBIR 94	8-6-1	0.1	0.9	70,000
RGB 94	6-4-1	0.3	0.9	50,000

Table 2 Performance of neural network models

Network model	Training results				Testing results			
	Max. Absolute error (t/ha)	Min. absolute error (t/ha)	Average absolute error (t/ha)	Average accuracy (%)	Max. Absolute error (t/ha)	Min. absolute error (t/ha)	Average absolute error (t/ha)	Average accuracy (%)
RGBIR 98 (8-5-1)	0.7056	0.00441	0.2079	97.81	4.21155	0.00063	0.89838	89.67
RGBIR 98A (8-3-1)	3.73464	0.00088	0.38115	95.58	2.66175	0.02394	0.61803	92.91
RGB 98 (6-4-1)	1.70793	0.00756	0.29169	96.72	2.03805	0.0378	0.69615	91.17
RGBIR 94 (8-6-1)	3.06495	0.01701	0.89901	86.59	3.47571	0.0378	1.17936	86.49
RGB 94 (6-4-1)	2.00718	0.01323	0.67095	89.57	5.34618	0.04032	1.67202	78.7

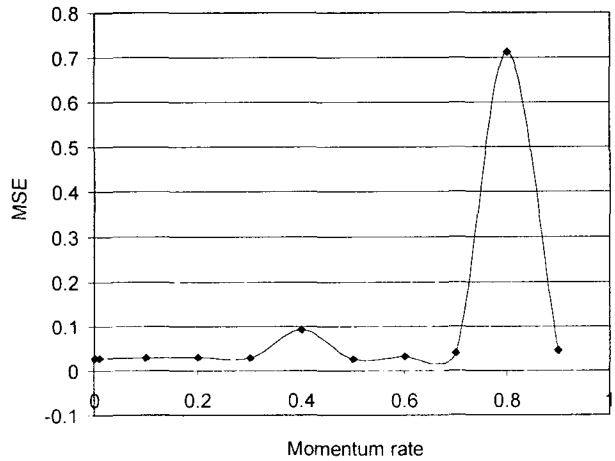

Fig. 8 Optimization of momentum for testing data set for RGBIR 98.

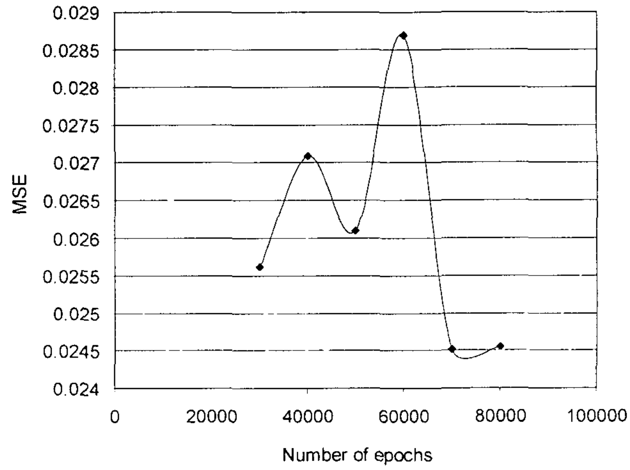

Fig. 10 Optimization of epochs for testing data set for RGBIR 98.

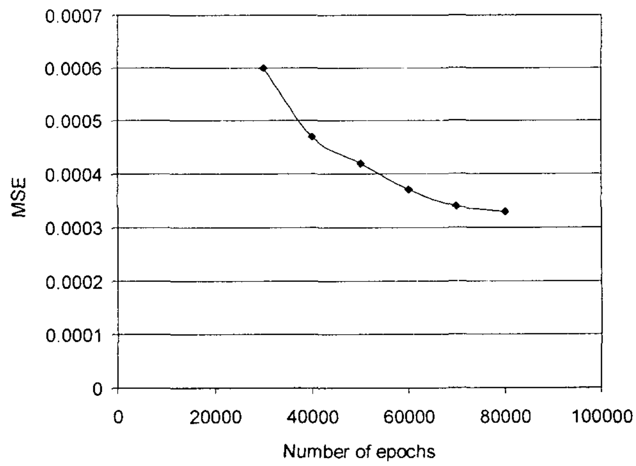

Fig. 9 Optimization of epochs for training data set for RGBIR 98.

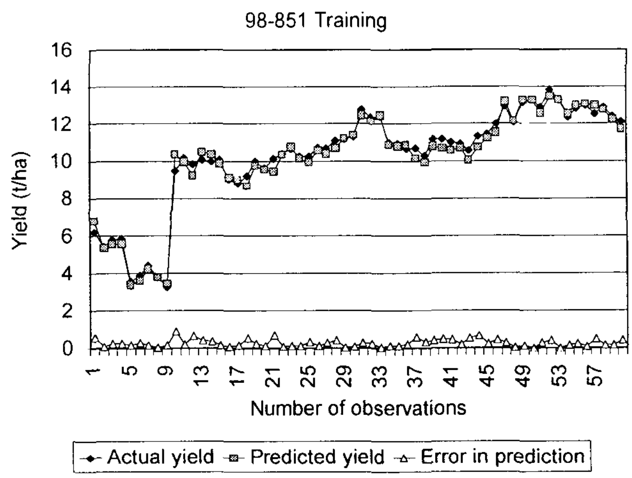

Fig. 11 Comparison of predicted versus desired yield of training data for RGBIR 98.

testing accuracy of 92.91% was obtained. This testing accuracy was approximately 3.5% higher than that obtained by the RGBIR 98 model. Comparing the average absolute errors on the basis of the yield output, the RGBIR 98A model provided higher error (0.189 t/ha) than that of the RGBIR 98 model for the training data set. At the same time, it predicted the yield with an average absolute error of 0.618 t/ha (9.81 Bu/ac). The average yield prediction error of 0.315 t/ha is considered reasonably acceptable from a practical viewpoint. Although an average yield prediction error of less than 0.2-0.3 t/ha will be more desirable. Figs 11 and 13 show that the prediction patterns on the training data set by both the models are very much similar. However the prediction patterns of two models on test data (Figs 12 and 14) showed some variations. Especially, the errors (deviation of original from predicted) were higher for yields between 3.15-9.45 t/ha. For higher yield (>9.45 t/ha) range, the desired and predicted output were almost same for both cases. Based on the observations, it could be postulated that for a larger data set both the models could be equally useful in predicting the yield.

The RGB 98 model showed an average training accuracy of 96.72% and a corresponding testing accuracy of 91.17% (Table 2). Its comparison with RGBIR 98 model shows that their prediction accuracies (Figs 15 and 17) were almost similar. For training data; the average differences (absolute error) in prediction by both models (RGB 98 and RGBIR 98) differed approximately by 0.063 t/ha. The same for the test data turned out to be only 0.189 t/ha (Table 2). It was observed that the deviations/errors is higher in the range of 3.15-9.45 t/ha for both models (Figs 12 and 16). However on testing data for yields between 3.15-6.30 t/ha, it was underestimated by RGB 98 model and overestimated by RGBIR model (Figs 12 and 16). At the same time, the similarity in accuracies of prediction implied that both the models of 1998 could be equally useful in predicting the corn yield. It is always useful to consider a model with less input parameters to avoid complexity. In the case of RGB model, it does not require the input of additional Infrared band information.

The RGB 94 and RGBIR 94 (Figs 17 through 20) models behaved similarly as RGB 98 and RGBIR 98 models. But the difference was that the training and testing accuracies of 94 models were lower than those

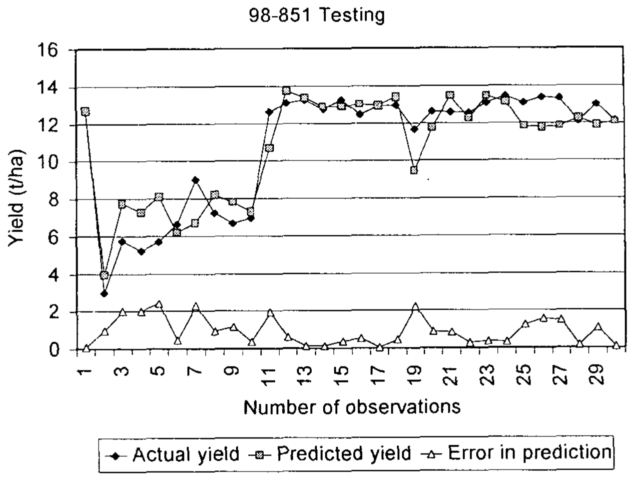

Fig. 12 Comparison of predicted versus desired yield of testing data for RGBIR 98.

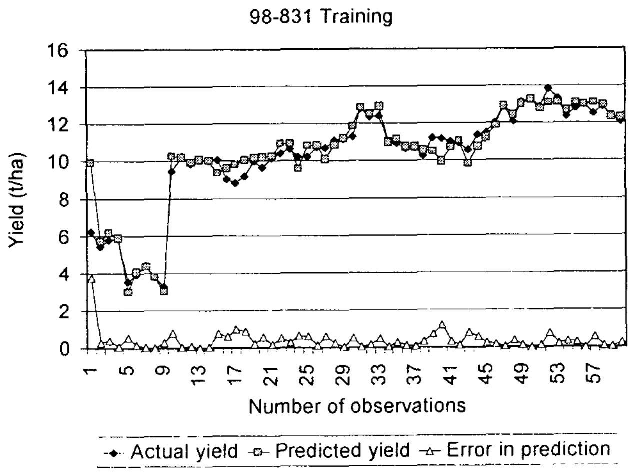

Fig. 13 Comparison of predicted versus desired yield of training data for RGBIR 98A.

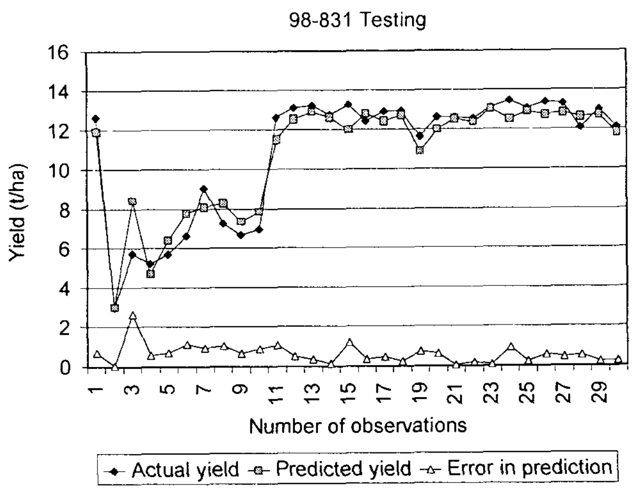

Fig. 14 Comparison of predicted versus desired yield of testing data for RGBIR 98A.

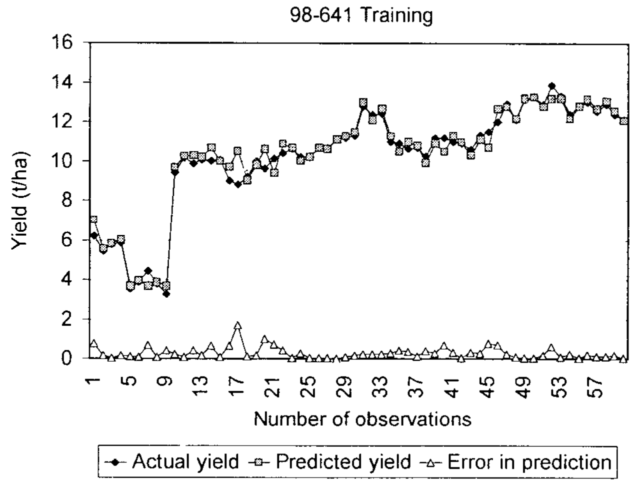

Fig. 15 Comparison of predicted versus desired yield of training data for RGB 98.

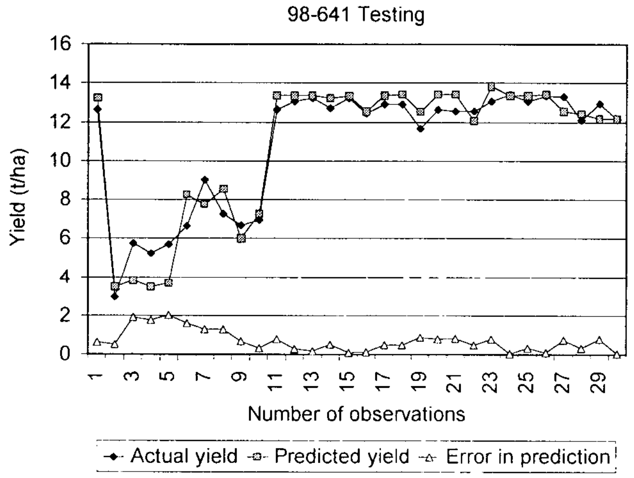

Fig. 16 Comparison of predicted versus desired yield of testing data for RGB 98.

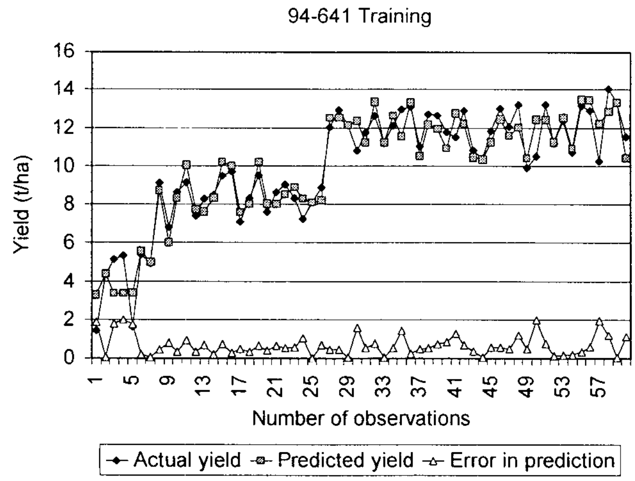

Fig. 17 Comparison of predicted versus desired yield of training data for RGB 94.

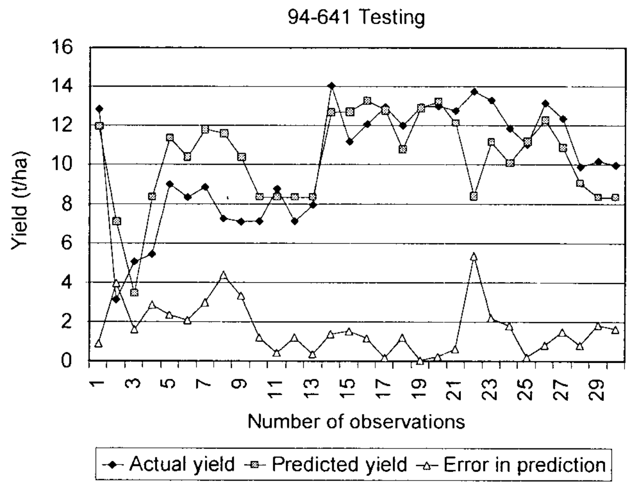

Fig. 18 Comparison of predicted versus desired yield of testing data for RGB 94.

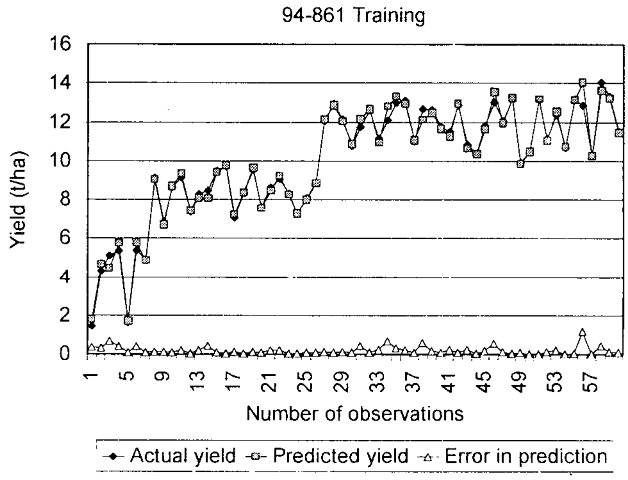

Fig. 19 Comparison of predicted versus desired yield of training data for RGBIR 94.

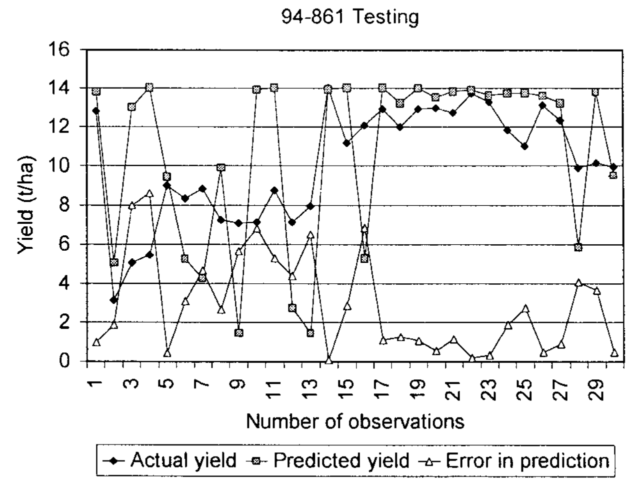

Fig. 20 Comparison of predicted v/s desired output of testing data for RGBIR 94.

of the 1998 models. Thus it implied that the 1998 models performed better. The RGB 94 model provided a training accuracy of 89.57% with a testing accuracies of 78.70%, whereas the RGBIR 94 model had training and testing accuracy of 86.59% and 86.49% respectively. The RGBIR 94 model provided an 8% higher accuracy than the RGB 94 model, which resulted in a difference of 0.504 t/ha of difference in yield. The error in prediction, which is a difference between the actual yield and the predicted yield, is provided for each model in respective graphs (Figs 11-20).

3. Cross-validation

In addition to develop separate yield models based on same year data, study was extended to validate the performance of a model using another year data. In this study, 1994 data were used to validate three yield models (RGBIR 98, RGBIR 98A, RGB 98) developed on 1998 data. The average prediction accuracy (testing) of both RGBIR 98 and RGBIR 98A models on 1994 data were 76% and 68% respectively (Table 3). It should be noted that training accuracy of these models (Table 3) are performance indicators of these models on 1998 data and thus are not relevant for this cross-validation analysis. Minimum average error in predicting yield was around 2.205 t/ha. Figs 21 and 22 show the comparisons of actual (desired) and predicted yield using both the models and their respective errors in prediction. Similarly, the prediction accuracy of RGB 98 model on 1994 data was only 68.5% with an average absolute error of 2.778 t/ha. Fig. 23 shows the comparison between actual and predicted yield along with the error in prediction. The findings imply that the reduction of prediction accuracy could be contributed to the fact that the crop production practice and other associated information were not the same for both 1994 and 1998. The image information used in the model might not have contained all the parameters affecting the yield in these two years. This finding warrants additional studies to verify these effects.

4. Summary and Conclusions

The multi-temporal aerial images were used to extract features relating to different crop yield factors. For this study, aerial images at different crop growth stages including bare land condition were used for the years 1994 and 1998. The supervised backpropagation momentum-learning algorithm was used for the development of neural network yield models.

Neural network yield models using multispectral bands Red, Green, Blue, and Infrared (RGBIR) and Red, Green, and blue (RGB) were developed for both the years. Both the models performed well while they were tested for the same year. The prediction accuracy of RGB and RGBIR models were very much similar for the same year. The accuracies for training and testing dataset for RGBIR model using 1998 data (RGBIR 98) were 97.81% and 89.67% respectively as compared to 96.72% and 91.17% respectively for the RGB (RGB 98) model. The prediction accuracies for training and testing dataset for RGBIR model using 1994 data (RGBIR 94) were 86.59% and 86.49% respectively. Similarly, the RGB model using 1994 data (RGB 94) provided accuracies of 89.57% and 78.70% respectively for training and testing data set. Neural network yield models developed using 1998 data performed better than those using 1994 data.

RGB and RGBIR models developed using 1998 data

Table 3 Cross validation of model across different years

Architecture	Training		Testing	
	Average Absolute error (t/ha) (min.-max.)	Average accuracy (%)	Average Absolute error (t/ha) (min.-max.)	Average accuracy (%)
1994 data tested on RGBIR 98A model	0.38115 (0.000882-3.73464)	95.58	2.22327 (0.01512-6.90795)	75.94
1994 data tested on RGBIR 98 model	0.2079 (0.00441-0.7056)	97.81	2.74995 (0.04032-8.39286)	67.62
1994 data tested on RGB 98 model.	0.29169 (0.00756-1.70793)	96.72	2.78082 (0.00882-7.57638)	68.54

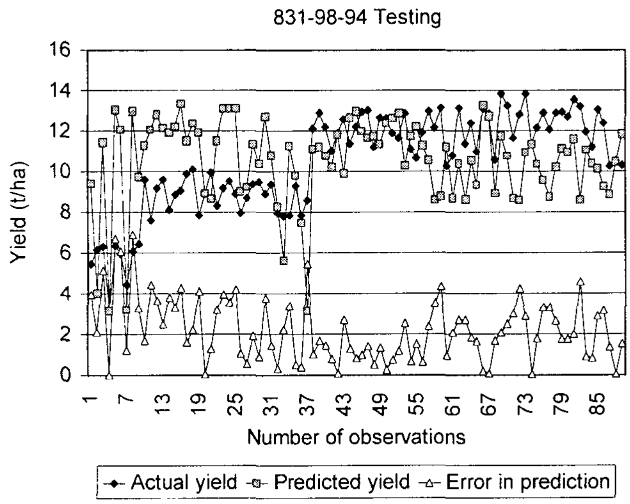

Fig. 21 1994 Data tested on RGBIR 98A.

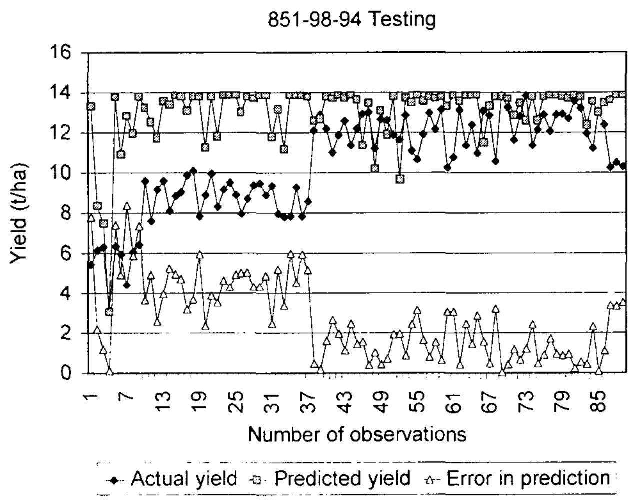

Fig. 22 1994 Data tested on RGBIR 98.

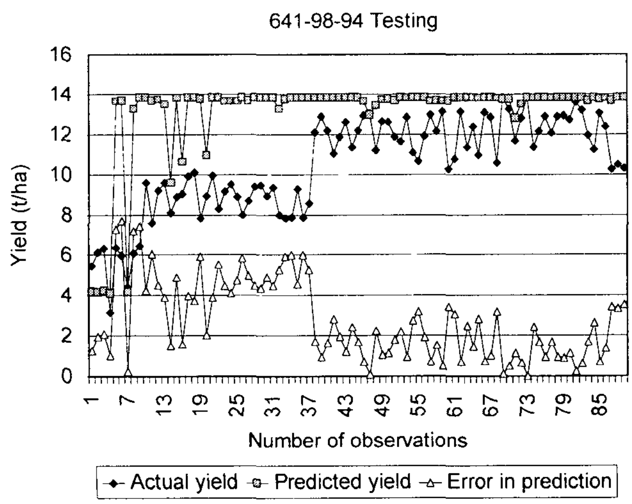

Fig. 23 1994 data tested on RGB 98.

were also used for cross validation using similar 1994 data sets. A maximum accuracy of 75.94% was provided by RGBIR 98A model. Although the models provided higher accuracy for the same year data, the accuracy levels were reduced, when they were tested on another year's data. This implies that more study is needed to identify the involvements of different crop production practices and associated factors in different years. Future work is also recommended to incorporate a suitable color calibration of aerial images.

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