Estimating Crop Yield from Multi-temporal Satellite Data Using Multivariate Regression and Neural Network Techniques

Ainong Li, Shunlin Liang, Angsheng Wang, and Jun Qin

Abstract

Accurate, objective, reliable, and timely predictions of crop yield over large areas are critical to helping ensure the adequacy of a nation's food supply and aiding policy makers on import/export plans and prices. Development of objective mathematical models of crop yield prediction using remote sensing is highly desirable. In this study, we develop a new methodology using an artificial neural network (ANN) to estimate and predict corn and soybean yields on a county-by-county basis, in the "corn belt" area in the Midwestern and Great Plains regions of the United States. The historical yield data and long time-series NDVI derived from AVHRR and MODIS are used to develop the models. A new procedure is developed to train the ANN model using the SCE-UA optimization algorithm. The performance of ANN models is compared with multivariate linear regression (MLR) models and validation is made on the model's stability and forecasting ability. The new algorithms can effectively train ANN models, and the prediction accuracy can be as high as 85 percent.

Introduction

Crop yield is a key element for rural development and an indicator for national food security. Accurate, objective, reliable, and timely predictions of crop yield over large areas are critical for national food security through policy making on import/export plans and prices. In recent years, a variety of mathematical models relating to crop yield have been proposed (Dan, 1998; Landan *et al.*, 2000; Wheeler *et al.*, 2000; Hansen *et al.*, 2004). Remote sensing techniques have the potential to provide quantitative and timely information on agricultural crops over large areas, and many different methods have been developed to estimate crop yields (Guérif and Duke, 2000; Liang *et al.*, 2004; Walthall *et al.*, 2004; Doraiswamy *et al.*, 2004; Wu, 2004; Xiao *et al.*, 2005; Tao *et al.*, 2005).

One practical approach using satellite data is the development of empirical relationships between the integrated Normalized Difference Vegetation Index (NDVI) and crop yield. NDVI responds to changes in the amount of green biomass, chlorophyll content, and canopy water stress. It is simple and easy to implement, and can be effective in predicting surface properties when the vegetation canopy is not too dense or too sparse (Liang, 2004). The relationship between NDVI and production has been confirmed by various field experiments (Prince and Justice, 1991). Rasmussen (1992) showed that yield could be estimated directly from the regression with NDVI. However, the general drawback of most methods using statistical relationships between NDVI and crop yield is that they have a strong empirical character and that the correlation coefficients are moderate to low (e.g., Groten, 1993; Sharma *et al.*, 1993). Therefore, although many studies have been conducted to estimate and predict crop yield using remote sensing data, the operational systems are mainly based on the anomalies of vegetation indices in a subjective fashion. Development of objective mathematical models using remote sensing is still highly desirable.

In this study, we develop a methodology using Artificial Neural Networks (ANN) to simulate and predict corn and soybean yields on a county-by-county basis. NDVI values derived from multi-temporal remote sensing image (such as AVHRR and MODIS) within the crop growth season are used to characterize the whole growing process instead of simply extracting some specified values or using the integrated value. The performance of the ANN model is compared with the multivariate linear regression (MLR) model, and validation is made on the model's stability. The model's predictive power for yield as well as its management and update on time and space are discussed in the context of evaluating the feasibility of developing a yield forecasting system. Crop production estimation and forecasts have two components: acres to be harvested and expected yield per acre. We mainly focus on estimating the crop yield per area in this paper.

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Material and Methods

Study Area

The study area is the "corn belt," a major agricultural region in the American Midwest and Great Plains that include the states of North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Michigan, Wisconsin, Illinois, Indiana, and Ohio with 1,059 counties, as shown in Figure 1. Large-scale commercial and mechanized farming prevails in this region of deep, fertile, well-drained soils and long, hot, humid summers. This region produces much of the American corn crop, but agriculture is diversified, and soybeans are an important crop as well. Planting dates for corn and soybeans are available at state level from reports published by the U.S. Department of Agriculture (USDA), National Agricultural Statistical Service (NASS). In general, crop planting in the region is completed by mid-May, with corn planted about two weeks earlier than soybeans. Crop maturity occurs by late-September.

Data and Processing

Data are organized and focused on the county as a unit. The remote sensing data contain a 16-day NDVI composite from Moderate-Resolution Imagine Spectroradiometer (MODIS) data with a five-year span (2000 to 2004) and a resolution of 1 km, downloaded from **http://redhook.gsfc.nasa.gov/**, and half-of-a-month composite NDVI from Advanced Very High Resolution Radiometer (AVHRR) data during a 22-year span (1982 to 2003) with a resolution of 8 km, downloaded from **ftp://ftp.glcf.umiacs.umd.edu/**. This dataset is improved with more accurate radiometric calibration and correction of view geometry, volcanic aerosols, and other effects not related to actual vegetation change. The cropland classification data (30 m × 30 m) derived from Thematic Mapper (TM) data are gained from Research and Development Division of USDA-NASS, with a resolution of 30 m. The crop yield data also come from USDA-NASS. According to crop growing season, 12 MODIS scenes taken Day 129 to 305, and 12 AVHRR scenes taken Day 135 to 300 were chosen as remote sensing data, because the original data are composite data, which can be applied directly to compute average NDVI values on a county basis. Meanwhile, to eliminate the effect of non-vegetation canopy surface (e.g., bare soil and water) and atmospheric contamination, only data with NDVI > 0.1 were computed. Illinois State was selected to explore the relationship between yield and NDVI. To eliminate the influence of non-crop pixels, a cropland classification map was used to compute a percent crop map with a resolution of 1 km (Figure 2). It can be assumed that, when 75 percent of a pixel is covered with a crop, the radiation value of this pixel is considered to represent the crop's canopy radiation value. Thus, those pixels with a value more than 0.75 on the percent crop map and NDVI > 0.1 on the NDVI map were selected as the masking condition, by which the NDVI mean value of each county at each period was computed.

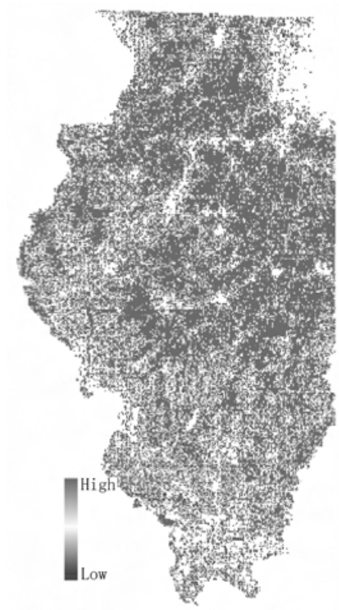

Figure 2. Crop percentage map (1 km) calculated from crop classification map (30 m × 30 m) from USDA data.

Figure 1. A sketch of study area: Midwestern and Great Plains States showing the sample states and the sample counties.

Model Development

Multivariate Linear Regression (MLR) Model

In this study, the MLR model and the ANN model are used to simulate yield using NDVI. The difference of simulating precision using AVHRR and MODIS datasets is explored by MLR analysis. Before developing the model, the input and target value of the model should be fixed first. Based on the growing season of corn and soybean crops in the area, we chose 12 NDVI scene's values within a year to act as input variables and the corresponding yield of corn and soybeans as the target variable. Initially, in the sample state (Illinois), the method of MLR was adopted to explore the relation between NDVI and yield, and to study the precision difference presented between AVHRR and MODIS data.

MLR is one of the most commonly used methods to develop empirical models for large datasets, as has been done for a number of canopy-level crop condition parameters (Shibayama and Akiyama, 1991). However, in some cases, the model tends to over-fit data thus reducing its applicability to unseen data. The model was described by the basic linear relationship

$$Y_i = \beta_i + \sum_{j=1}^{N} \alpha_{ij} X_{ij} + \varepsilon_i \qquad (1)$$

where Y_i, $i = 1, \ldots n$ denotes the i^{th} year yield observation, X_{ij} is the respective value of the j^{th} explanatory variable X_j as selected NDVI value and β_i, α_{ij}, $j = 1 \ldots 12$ denote the linear parameters, the error term ε_i reflects factors not accounted for in the model, for example management factors or mere random (intrinsic) variability.

A New Artificial Neural Networks (ANN) Model

Simulating yield using NDVI should represent non-linear relationships between input variables and desired variables. The ability of ANN models to associate complicated spectral information with target attributes without any constraints of sample distribution (Mather, 2000) makes them ideal for describing the complex non-linear relationships between canopy-level spectral signatures and various crop conditions (Kimes *et al.*, 1998). Successful applications already have been reported for yield prediction (Liu *et al.*, 2001; Drummond *et al.*, 2003; Uno *et al.*, 2005). Taking a county as unit and applying the long time-series NDVI value derived from AVHRR, yield was simulated and predicted by the ANN model.

In this study, all the models were developed using Matlab 6.5 software (The MathWorks, Inc.), except for the regression analysis, which was done with Microsoft® Excel. The feed-forward multi-layer perceptron (MLP) neural network (NN) is built for learning. This NN can be abstracted as:

$$Y = f(X, W) \qquad (2)$$

where Y denotes the output of NN, X the input, and W the synaptic weights. In standard training processes, both input X vector and output vector Y are known and prepared. The synaptic weights in W are adjusted in order to obtain appropriate functional mapping from input X to output Y. The adjustment process can be performed by minimizing the network error function:

$$J(Y, f(X,W)) : (X^{D1}, Y^{D2}, W^{D3}, f) \rightarrow R \qquad (3)$$

where D_1, D_2, and D_3 represent the dimensions of input vector, output vector, and weight vector, respectively.

The entire training process is an optimization process to determine the optimal weights W for minimization of error function J. Thus, many optimization algorithms are applied to NN training, including both deterministic and stochastic methods. However, these methods all have their own shortcomings. Deterministic ones, such as Quasi-Newton (QN) and Levenberg-Marquadt (LM), are easy to be trapped into local optima. Stochastic ones such as Differential-Evolution (DE) may require more times than deterministic ones and may have lower efficiency, although they can find the global optima. If there is an optimization algorithm, which has deterministic and stochastic properties at the same time, and it is used to train NN, the two shortcomings mentioned above will be effectively overcome.

Recently, a global optimization approach, shuffled complex evolution algorithm (SCE), has been developed and successfully applied to the calibration of hydrological models (Duan *et al.*, 1994). The use of deterministic strategies permits SCE to make effective use of response surface information to guide the search and the simultaneous inclusion of stochastic elements helps make SCE both flexible and robust. The implementation of an implicit clustering strategy helps to concentrate the search in the most promising of the regions identified by the initial complex. The use of a systematic complex evolution strategy helps ensure that the search is relatively robust and is guided by the structure of the cost function. The use of a competitive evolution scheme is useful for improving global convergence efficiency. Based on advantages mentioned above, SCE-UA (shuffled complex evolution method developed at The University of Arizona) is used to train NN in this study; the flowchart is shown in Figure 3.

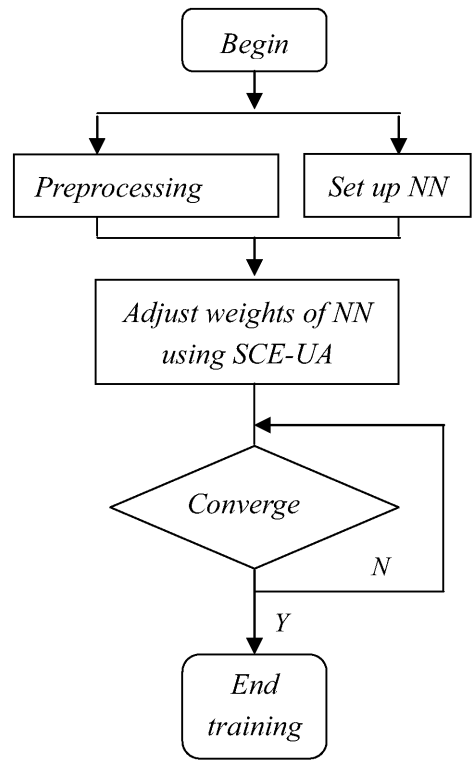

Figure 3. Flowchart of using SCE-UA for training NN.

One of the problems that occur during neural network training is called over-fitting. The risk of over-fitting arises when large numbers of independent variables are handled with a small number of samples. One of the solutions is testing the reliability or robustness of the developed models by using a validation data set. This study selected the regularization method for preventing over-fitting, which was desirable to determine the optimal regularization parameters in an automated fashion. It is possible to improve generalization if we modify the performance function by adding a term that consists of the mean of the sum of squares of the network weights and biases (Foresee and Hagan, 1997). Using this performance function will cause the network to have smaller weights and biases, and this will force the network response to be smoother and less likely to over-fit. In addition, a seven-fold cross-validation procedure was carried out to evaluate the generalization ability of the ANN model with 12 input variables. In this procedure, the original data set of 22 samples was first randomly divided into seven subgroups, and six out of seven subgroups were used for model development, while the remaining subgroup was used for model testing. This process was repeated seven times with different combinations. It should be noted that different data sets were used for model development and model validation for a given run was done with unseen data.

Performance Analysis
Three statistical parameters were used for performance analysis: correlation coefficient (*r*), root mean square error (RMSE), and average difference (AVDIF). RMSE is one of the most commonly used statistical parameters, which represents the average difference between estimated and observed value. The RMSE was calculated as a better evaluation method for yield prediction at the farm level but can also explain whether the model under- or over-predicted. The values were evaluated by plotting the simulated value against the measured value and by testing the statistical significance of regression parameters.

Results and Analysis

Changes of NDVI

According to the above data processing method, the average NDVI value of each county in each composite period during 22 years can be obtained. Figure 4 shows that NDVI changed regularly over time in Illinois. The crop slowly turned green on Day 129. On Day 209, NDVI reached the highest value and remained there until Day 225, when it begins to fall rapidly. By Day 289, the crop had already grown yellow, represented by the low NDVI value. Figure 5 shows that corn in zone 1, soybeans in zone 2, and trees in zone 3 accounted for a large proportion. Differences in the phonological cycles of each target were observed (Figure 5). Corn turned green two weeks earlier than soybeans, yet matured later; other crops (cotton, oats, sorghum, potato, etc) had a later growing season; trees had the longest growth season and always had high NDVI values. Therefore, although there were differences in planting date for different crops, the growth season generally was covered from Day 129 to 305.

From the profile of Figure 6a, the growing cycle of crop can be observed in a county with apparent differences in different years. Meanwhile, the difference forward of Day 209 is more remarkable than after that day. Figure 6b shows the difference in profiles of the five sample counties in Illinois State because of their different geographical position.

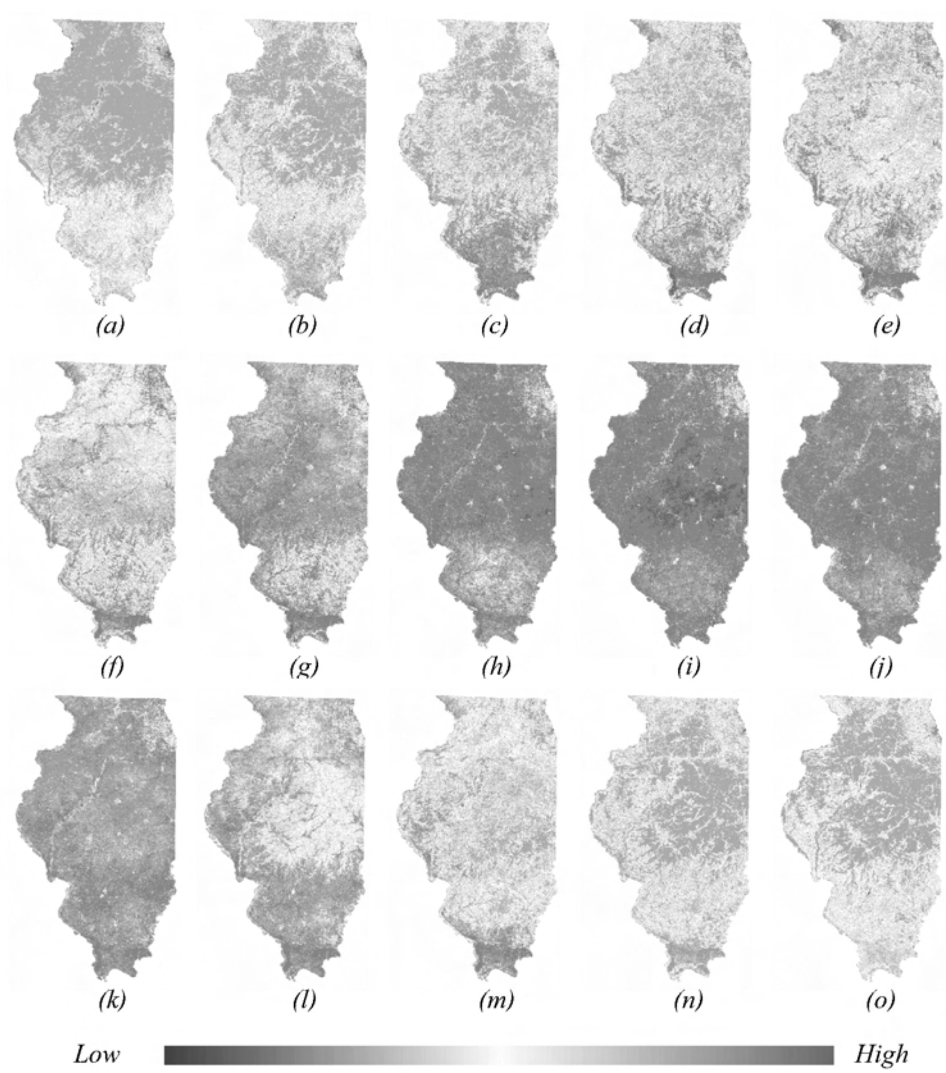

Figure 4. NDVI change derived from MODIS data during crop growing season in Illinois State in 2003 by number of days: (a) 81, (b) 97, (c) 113, (d) 129, (e) 145, (f) 161, (g) 177, (h) 193, (i) 209, (j) 225, (k) 241, (l) 257, (m) 273, (n) 289, and (o) 305. A color version of this figure is available on the ASPRS website: **www.asprs.org**.

Figure 5. The classification of cropland deriving from USDA-NASA with a resolution of 30 m × 30 m. A color version of this figure is available on the ASPRS website: **www.asprs.org**.

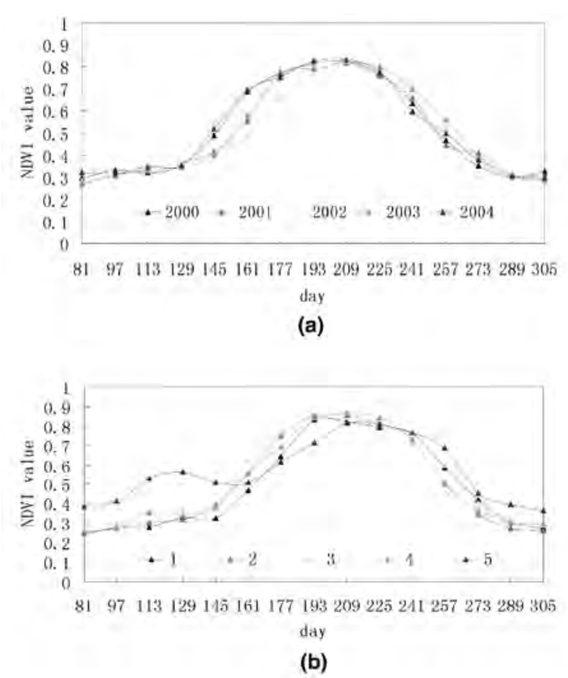

Figure 6. (a) NDVI profile in Sample 4 from 2000 to 2004, and (b) NDVI profile in 2003 for Samples 1 through 5.

It indicates that the NDVI values ahead of Day 209 contribute much more for final crop yield; both the different geographical position and environmental changes in crop growth season can cause the difference in the NDVI profile. This study held the hypothesis that such differences denoted a crop's growing process and was finally reflected in crop yield.

The Linear Simulation Precision for Yield Using avhrr and modis Data

MLR analysis was made using AVHRR and MODIS data, respectively. There was only five-year MODIS data which was not sufficient to make such analysis on a county scale. This study made use of statistics from USDA-NASS to divide Illinois into nine districts according to such conditions as agricultural meteorology and soil, labeled 10, 20, 30, 40, 50, 60, 70, 80, and 90, thus assuring enough samples for MLR analysis using MODIS data. Yet, there were 22-years of AVHRR data, which is enough for MLR analysis on a county scale. This study randomly selected a county in each district as a sample, correspondingly labeled a, b, c, d, e, f, g, h, and i shown in Figure 7. It should be mentioned that although the scale of two datasets is different, the result of analysis is still comparable since the background of crop growing is similar. Moreover, such a sampling approach can ensure that the sample numbers are approximately equal.

A MLR analysis was performed between the measured and simulated yield for both training and validation data sets. The MLR performance parameters are given in Table 1. The results are as follows:

1. The simulation precision of MODIS data is commonly better than that of AVHRR, and the simulation of MODIS for corn and soybeans both can achieve a comparatively ideal precision of about 10 percent;
2. In Illinois, the simulation precision for the north crop plain is higher than the south areas, which are more heavily forested;
3. The simulation precision of AVHRR data for yield can also achieve reasonably good accuracy of about 15 percent;
4. The simulation ability of NDVI for corn is better than for soybeans, represented by comparatively stable simulation precision for corn while fluctuating for soybeans, shown in Figure 8.

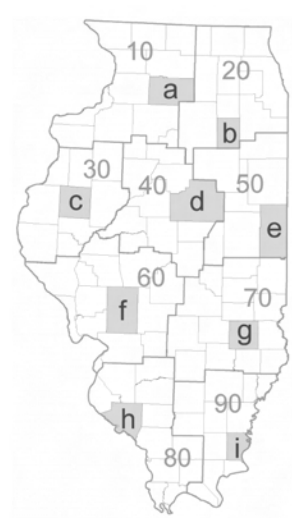

Figure 7. Samples for simulating precision difference analysis using MODIS and AVHRR, respectively.

Table 1. Performance Parameters of MLR Model for Observed and Simulated Yield Data, Respectively, Using MODIS and AVHRR NDVI ($P \leq 0.05$)

	MODIS							AVHRR					
	Corn			Soybeans				Corn			Soybeans		
ID	*r*	RMSE	AVDIF	*r*	RMSE	AVDIF	ID	*r*	RMSE	AVDIF	*r*	RMSE	AVDIF
10	0.95	6.04	3.74%	0.96	2.62	5.80%	a	0.91	14.97	11.06%	0.80	5.41	12.54%
20	0.95	8.36	5.86%	0.71	6.08	15.26%	b	0.95	14.97	11.59%	0.96	2.78	6.95%
30	0.94	6.45	3.85%	0.87	2.73	5.86%	c	0.90	18.66	13.34%	0.88	4.73	10.59%
40	0.84	11.98	7.31%	0.56	6.16	13.51%	d	0.86	21.69	15.65%	0.76	5.53	12.72%
50	0.93	7.57	4.79%	0.92	3.34	7.32%	e	0.87	18.48	13.90%	0.88	4.37	10.57%
60	0.94	8.57	5.38%	0.67	4.61	10.25%	f	0.87	19.47	14.46%	0.93	3.58	9.12%
70	0.95	8.71	6.01%	0.80	4.07	9.36%	g	0.77	27.04	23.63%	0.81	5.49	15.44%
80	0.90	15.47	12.17%	0.85	4.23	11.34%	h	0.95	10.17	10.64%	0.89	2.99	9.62%
90	0.92	13.54	11.30%	0.91	3.44	9.66%	i	0.94	10.80	8.96%	0.86	4.26	12.30%

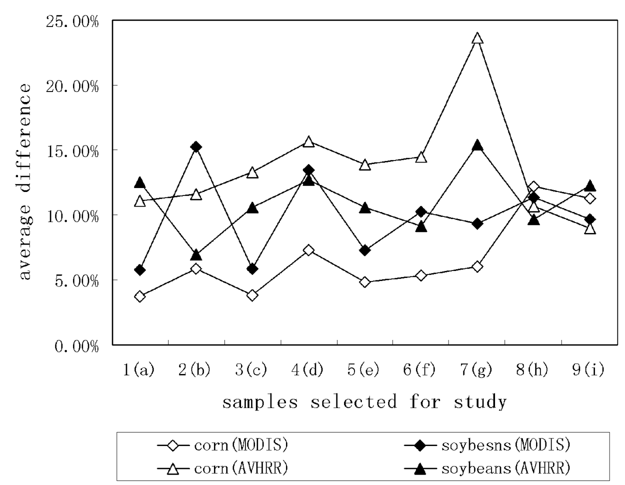

Figure 8. Simulating precision for corn and soybean yield using MODIS and AVHRR, respectively, by MLR models.

As is proven by the results, there exists an apparent link between NDVI and yield, with *r* commonly more than 0.85. Meanwhile, simulated precision also show considerable errors, partly due to the data precision itself as it is easy to introduce errors when using mixed pixel values to replace pure crop pixel values. This can also explain why NDVI has a stable simulation precision for corn since it has a much bigger planting proportion than soybeans. The other reason is that the relationship between NDVI and yield is not strongly linear, and applying a linear method to simulate yield can also lead to more errors.

Evaluation on the ANN Model

The simulating result of the ANN model was evaluated by MLR analysis. According to the above ANN method, corn yield was chosen as desired data to practice the simulated computation on all samples (shown in Figure 1), and ran regularization method to prevent over-fitting. Meanwhile, the MLR model was conducted using the same samples as the ANN model. The results are presented in Table 2. The analysis shows:

Table 2. Performance Parameters for Observed and Simulated Corn Yield Data, Respectively, for MLR Models and ANN Models ($P \leq 0.05$), and Average Value of Validation Data set for Seven-fold Cross Validation of the ANN Model (Unit of RMSE: Bushal/Acre)

		Multivariable Regression Analysis			Artificial Neural Network Analysis			Cross Validation for ANN	
State Name	Sample	*r*	RMSE	AVDIF	*r*	RMSE	AVDIF	RMSE	AVDIF
	1	0.86	14.94	10.70%	0.89	13.51	9.67%	14.60	10.86%
	2	0.90	18.66	13.34%	0.90	18.49	13.23%	16.42	12.33%
Illinois	3	0.86	21.69	15.65%	0.92	18.32	13.22%	20.17	15.58%
	4	0.87	18.48	13.90%	0.90	15.89	11.95%	17.12	13.81%
	5	0.86	21.09	19.45%	0.97	10.58	9.76%	12.54	11.06%
Indiana	6	0.93	14.91	12.09%	0.93	14.60	11.83%	14.72	12.24%
Iowa	7	0.85	16.33	12.98%	0.85	14.74	11.71%	16.82	13.21%
Kansas	8	0.70	24.99	25.40%	0.83	16.20	16.47%	18.41	17.62%
Michigan	9	0.74	18.07	17.80%	0.84	14.88	14.66%	17.83	17.01%
Minnesota	10	0.90	19.03	14.39%	0.90	19.06	14.41%	19.10	14.44%
Missouri	11	0.86	22.45	23.44%	0.92	17.23	17.99%	18.36	18.22%
Nebraska	12	0.58	17.85	12.45%	0.74	17.23	12.02%	17.66	12.21%
Ohio	13	0.58	21.03	20.28%	0.73	17.11	16.50%	18.91	18.01%
South Dakota	14	0.88	12.90	19.94%	0.89	7.71	11.92%	9.37	14.78%
Wisconsin	15	0.75	18.96	17.15%	0.83	14.28	12.92%	15.11	13.04%

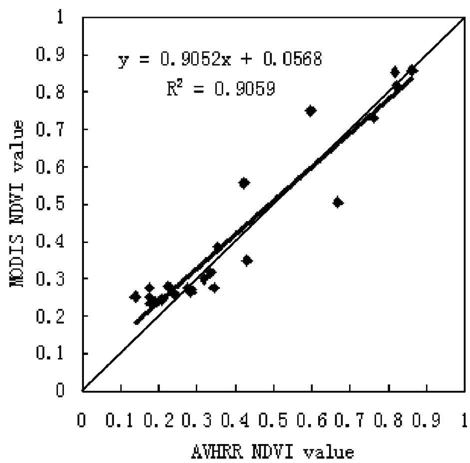

Figure 9. NDVI relationship between MODIS and AVHRR for Sample 4 in 2003.

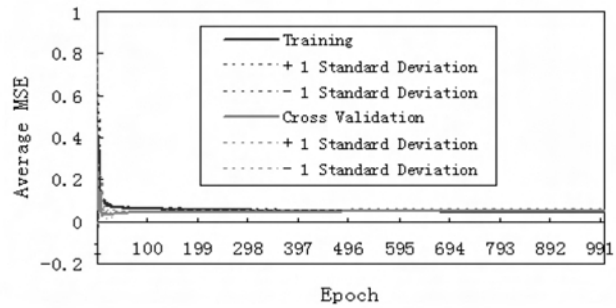

Figure 10. Average RMSE with standard deviation for cross validation boundaries.

1. When using MLR model to simulate corn yield, simulation accuracy in the whole study area is not very stable, with the AVDIF of several samples above 20 percent such as sample 8, 11, and 13. In contrast, when using the ANN method, accuracy is improved with errors smaller than 20 percent;
2. The ANN method has a different effect on each sample. For those samples, such as 8, 9, 12, 13, and 15, when MLR models do not perform well, the result is improved very obviously after using ANN models. Otherwise, the improvement is not significant. In general, our ANN model is superior to the MLR model developed using NDVI.

Cross-validation is one of the methods that test performance supervised learning from samples. The summary of the seven-fold cross-validation results for the validation data is also given in Table 2. The mean RMSE for samples from the seven-fold cross-validation for the ANN model was not more than 20 bushels/acre. Meanwhile, the AVDIF also was not more than 20 percent, and most of them were around 15 percent. It indicated a good model performance. The range of RMSE for all samples was from 9.37 to 20.17, and the span of AVDIF was from 10.86 percent to 18.22 percent, which indicated a consistent performance by the model. The average RMSE with standard deviation for cross-validation boundaries is presented in Figure 9. These results indicated that the ANN model in which we developed a new training algorithm did a good job, without any over- or under-predictions, and a markedly improved capability of the model for yield prediction.

Discussion

We have developed a new ANN model for estimating and predicting corn and soybean yield respectively using NDVI derived from satellite data. In general, NDVI can more accurately represent the yield when using higher spatial and temporal resolution satellite data. However, a dataset with a high spatial resolution, such as Landsat Thematic Mapper (TM), is often characterized by a low temporal resolution. This means that NDVI cannot capture the crop growth accurately. MODIS and AVHRR data are selected to develop the model in this study. The spatial resolution of MODIS is better than that of AVHRR, and both have comparatively good temporal resolution so that they can eliminate cloud influence and acquire time-series generalized NDVI over many years, in which technologies such as cloud identification and composite multi-temporal data are used, e.g., NDVI from MODIS is a 16-day composite data and NDVI from AVHRR is half-a-month composite data. As a result, the MODIS data presentation of crop growth condition is superior to AVHRR data. And in theory, if MODIS data is applied to simulate and predict crop yield, its precision should be better. But, the time series of MODIS data was not long enough (just a five-year span); it presents limitations when reflecting the factors affecting crop yield such as meteorological condition, technology and management. Even if the model possesses a strong simulated ability, it still lacks the learning ability on prediction for unseen data outside the time series. That makes the model unstable and its predicted results unreliable. Moreover, a previous study (Michael *et al.*, 2003) showed there was an apparent link between MODIS and AVHRR data, which the data of this study also illustrate as shown in Figure 10. So, in a large-scale area, this study adopted a longer time-series AVHRR data (22-year span) to develop the model.

From the results mentioned above, the utilization of the model developed in this study can predict corn and soybean yields on a county basis with a precision of around 85 percent. It should be pointed out that input values used by the model were all NDVI values within the crop growth season, that is, yield is predicted only after the crop was harvested. However, yield prediction in fact needs to be made some time ahead of the harvesting date. Therefore, whether the method in this study can make such prediction depends on the relation between NDVI and yield. Using NDVI and yield to make stepwise multivariate linear regression analysis and r and RMSE were computed (Figure 11). From the figure, it can be seen that the correlation coefficient reached was comparatively stable between NDVI and corn yield for almost all samples some time before maturity, i.e., before this date NDVI value functions decisively on final yield. Yet this date for each sample was different, which quite explained the differences on a crop's growing season between samples because of different agricultural meteorological and soil conditions. Prediction of corn and soybean yields can be made before its maturity by applying real-time monitoring satellite data. For monitoring the growing cycle, the method applied on a county scale results in a large number of models featured by extending time and spatial distribution, which will cause a certain difficulty for model's updating and management. Yet the integrating of GIS technology and ANN models can easily solve these problems (Tappeiner *et al.*, 2001; Ermini *et al.*, 2005). The remote sensing prediction model in the county level is characterized of high accuracy as well as easy implementation. Such information can be used directly in decision support systems and provide an effective prediction within the growing season to assist farm managers to make better-informed decisions.

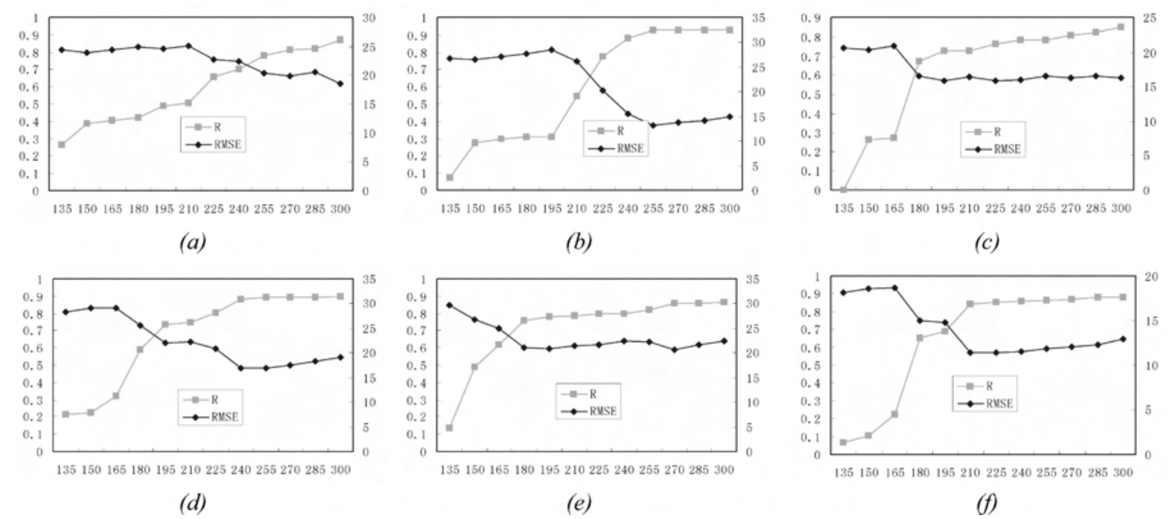

Figure 11. The *r* and RMSE changes by stepwise regression during growing season for some samples: (a) Sample 4, (b) Sample 6, (c) Sample 7, (d) Sample 10, (e) Sample 11, and (f) Sample 14.

Conclusions

This study explored the potentials of the ANN model for developing the corn and soybean yield prediction systems using multi-temporal satellite data at the county level. The results showed that the ANN models were quite efficient in capturing the complex relationship between crop yield and spectral reflectance values, and the application of the ANN model can efficiently improve the prediction for crop yield. The developed SCE-UA algorithms can effectively train ANN models to be more flexible and robust. The expected prediction errors of approximately 15 percent (EMSE for validation) appear to be high for creation of yield maps for precision agriculture, which would also be suitable on crop yield prediction. At the same time, the ability of the model to reasonably forecast the final crop yield some time ahead of the harvesting date provide some opportunities for a farm manager to make decisions before harvest. Although the analysis focuses on some samples, the approach taken is generally applicable. A large number of models in the county scale can be updated and managed by a combination of GIS and ANN technologies.

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