

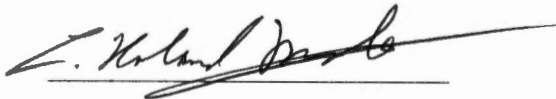
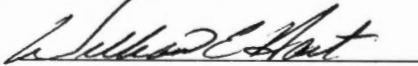
To the Graduate Council:

I am submitting herewith a dissertation writing by Ruixiu Sui entitled "A Ground-Based Real-Time Remote Sensing System for Diagnosing Nitrogen Status in Cotton Plants." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Biosystems Engineering.



Luther R. Wilhelm, Major Professor

We have read this dissertation
and recommend its acceptance:



Accepted for the Council:



Associate Vice Chancellor and
Dean of The Graduate School

**A GROUND-BASED REAL-TIME REMOTE SENSING SYSTEM
FOR DIAGNOSING NITROGEN STATUS IN COTTON PLANTS**

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Ruixiu Sui
May 1999

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Thesis

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DEDICATION

This dissertation is dedicated to
my wife, Weihua Jiang and our daughter, Yu Kathleen Sui
for their love and support.

题献

谨将此博士文献给
我的妻子姜卫华和我们的女儿隋玉，
她们的爱和支持是我完成学业的保证。

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ABSTRACT

A ground-based real-time remote sensing system has been developed for diagnosing nitrogen status in cotton plants. Study on spectral reflectance characteristics of cotton leaves was conducted at The University of Tennessee Milan Agricultural Experiment Station for three consecutive years (1996, 1997, and 1998). Spectral reflectance from cotton canopies with different nitrogen treatments was measured using a fiber optic spectrometer. It was found that useful spectral features could be extracted from the spectral reflectance spectra in the blue, green, red, and near infrared wavebands. A mathematical model was developed to calculate the spectral index of the measured plants. The spectral index showed strong correlation with nitrogen application rate, petiole nitrate content, and yield at pinhead square. Based on the relationship between the spectral reflectance characteristics and the nitrogen status in the cotton plants, a multispectral plant health sensor was developed and field tested. The sensor has four wavebands (blue, green, red, and near infrared). Each output of the sensor represents the intensity measurement of spectral reflectance in that waveband. To avoid measurement error that may be induced by variations in spectral characteristic under natural illumination of the plant canopy; a modulated light source was used to illuminate the canopy. A demodulating electronic system was employed in the sensor to measure the spectral reflectance of the canopy resulting from the modulated light. Field test results demonstrated that the plant health index, calculated using the data from the plant health sensor, strongly correlated with the nitrogen application rate and the yield ($R^2 = 0.99$ and 0.81 , respectively). An artificial neural network (ANN) was trained using the spectral

reflectance data. The ANN models had three layers, five inputs, and two outputs. Inputs were spectral reflectance measurements in blue, green, red, and near infrared wavebands and the stage of plant development (days after planting). Nitrogen-deficiency and non-nitrogen-deficiency were the two outputs. ANN models were tested and results showed that the trained ANNs could diagnose the nitrogen status in cotton plants with an accuracy rate greater than 95%. The ground-based remote sensing system with ANNs has shown great potential for real-time variable-rate control of nitrogen in cotton.

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CHAPTER I

INTRODUCTION

Background

It is well known that nitrogen (N) fertilizer is an essential nutrient element required by crops. A proper N application must be provided to maximize yields. Both under-fertilization and over-fertilization of N can affect the normal growth of plants and further reduce their yield. Additionally, over-fertilization of N will increase production cost while having a potentially negative environmental impact. Although soil and plant tissue testing can be used to predict N requirements of plants, soil and plant N analysis often require considerable time and can be expensive (Tracy et al., 1992). Extensive research has been conducted to find a quick and reliable method to diagnose N status of plants.

Precision farming technology provides a way to adjust production inputs based on the needs of individual areas within a field rather than applying uniform applications across the entire field. Two types of data, historical and real-time, are used in precision farming. With the use of a Global Positioning System (GPS), precisely determined inputs can be applied at precise field locations based on pre-determined site-specific historical data within the field. However, it would be more desirable if inputs could be varied by using a real-time *in-situ* ground-based remote sensing and control system.

Leaf color is usually the most sensitive indicator of deficient nutrient levels (Blinn

et al., 1988). The main pigment responsible for leaf color is chlorophyll. Because N is a major component of the chlorophyll molecule (Tracy et. al., 1992), chlorophyll and leaf N are usually correlated.

Leaf color can be evaluated by using simple tools or instruments. These include various kinds of leaf color scales such as the Munsell Color Chart for plants (Shiga et al. 1983). Using these color scales, the operator simply compares the color of measured leaves with the standard colors and finds the difference (Furuya, 1987). Those simple tools are inexpensive and easy to use, but the results obtained between operators may vary considerably.

Instruments commonly used in the field are spectrometers, radiometers, and imaging systems. These instruments measure the reflectance spectra of plant leaves non-intrusively. By analyzing the reflectance spectra, relationships between the characteristics of the reflectance spectra and N concentration of the plant leaves can be obtained. Two major problems have been encountered using these instruments to measure the reflectance spectra of a crop canopy. One is that they are generally expensive and not designed for an agricultural environment. Secondly, the time-of-day and atmospheric conditions affect the sunlight spectra reaching the plant canopy (Pinter, 1993).

Cotton is one of the most important crops in the world, and it is also grown in West Tennessee. Like other crops, N application is critical to cotton as well. Maintaining a proper N status in cotton plants is very important for optimizing yields. If a system could be developed to apply the optimum amount of N based on the N status in cotton plants in real-time, cotton yields could be increased and N use would likely be reduced in

certain areas of a field. Further a system like this would make a great contribution toward the protection of our environment by reducing the amount of N in areas of a field where the plants can not fully utilize this nutrient.

Objectives

The goal to which this study contributed is to develop a multispectral plant health sensor and ground-based associated control systems that can apply crop inputs based on real-time sensing of crop needs. Specific objectives for this study were to

1. Document the relationship between N status of cotton plants and spectral reflectance characteristics of the cotton canopy;
2. Design and fabricate an optical sensor to measure spectral reflectance indices of cotton plants based on the relationship found in objective 1; and to
3. Develop and test an artificial neural network (ANN) for diagnosing the N status based on spectral characteristics of cotton canopy.

Dissertation Organization

To achieve the specific objectives noted above, spectral reflectance characteristics of cotton canopies were measured. Based on these spectral characteristics, a multispectral plant health sensor has been developed and field tested. ANNs for diagnosing N status in cotton plants were trained and tested using the spectral reflectance data.

Chapter III of this dissertation presents the experiments conducted for determining the spectral reflectance characteristics. Chapter IV describes the development of plant

health sensors. The ANN training and testing is showed in Chapter V. Each chapter includes its own procedure and result sections.

CHAPTER II

REVIEW OF LITERATURE

Spectral Reflectance Measurements from Crop Canopies

Grain Crops

Ma et al. (1996) conducted a field experiment with six maize hybrids for three years to evaluate whether canopy reflectance, and "greenness" can be used to measure changes in maize yield response to N fertility. Canopy reflectance, leaf area and greenness, and grain yield were measured. Results demonstrated that direct radiometer readings at the 600 and 800 nm wavelengths best differentiated N and hybrid treatments at most sampling dates. Canopy reflectance was strongly correlated with field greenness at almost all growth stages. Both canopy light reflectance and field greenness measured preanthesis were correlated with yield at harvest. Light reflectance measured after anthesis differentiated hybrid differences in leaf senescence. Light reflectance measurements prior to anthesis may predict grain yield response and provide in-season indication of N deficiency.

Sembiring et al. (1998) detected N and phosphorus nutrient status in winter wheat using spectral radiance. The spectral radiance was measured using a PSD 1000 Ocean Optics fiber optic spectrometer and an integrated sensor that has photodiode detectors and interference filters for red and near infrared (NIR). A normalized difference vegetation index (NDVI) was calculated using $NDVI = (NIR - RED) / (NIR + RED)$. NIR is the spectral radiance at NIR waveband and RED represents the spectral radiance at the red waveband.

Results demonstrated that NDVI was a good index to predict biomass, and N and phosphorus uptake for winter wheat.

Stone et al. (1998) developed optical based sensors for detection of N availability in winter wheat. In the sensor, an optoelectronic circuit was used for green, red, and NIR bands and the interference filters were chosen at wavelengths of 550 ± 6 nm (green), 671 ± 6 nm (red), and 780 ± 6 nm (NIR). They found that there is a good correlation between vegetative N mass per unit area and the spectral index, and the NIR reflectance rises in the NIR band and falls in the red band for increasing N availability. They pointed out that the affect of solar angle on the sensor must be evaluated.

Penuelas et al. (1997) studied the effects of a soil salinity gradient on spectral reflectance of 10 genotypes of barley. NDVI was calculated using the equation $NDVI = (R_{900\text{ nm}} - R_{680\text{ nm}}) / (R_{900\text{ nm}} + R_{680\text{ nm}})$, where R = reflectance. It showed that NIR reflectance decreased and visible reflectance increased as the salinity gradient increased, thereby lowering NDVI, decreasing biomass and yield. They concluded that NDVI was a good indicator of biomass and yield, and useful for measuring agronomic response of barley to salinity.

Furuya (1987) used a Standard Rice Leaf Color Scale to conduct a series of studies on rice growth diagnosis by leaf color. It was found that the rice leaf color value was significantly correlated with average N concentration in all the living leaves. And it was noticed that small differences in leaf color corresponded to large differences in leaf N concentration at the tillering stage, but that relation was reversed at the spikelet differentiation stage and the heading stage. Takebe et al. (1990) obtained a highly significant correlation between the ratios of the reflectance at 550 nm and 800 nm and the

chlorophyll contents of rice leaf sections. Based on this principle, a remote sensing instrument called a Canopy Green Meter was developed by Minolta Co., Ltd. Takebe et al. (1990) used the Canopy Green Meter for estimating rice N status. Takebe et al. (1990) pointed out that the measurements were affected by spectral reflectance characteristics of sunlight from the leaf surface. With such limitation being taken into account, rice canopy green color intensity could be evaluated with this meter.

Shibayama (1993) studied spectral reflectance of rice canopies in visible, near and mid-IR ranges. Spectra sampled at 5 nm intervals in the 400-900 nm range and 10 nm intervals in the 900-1900 nm range and their first derivatives were statistically analyzed. Results indicated that high spectral resolution reflectance measurements and their first derivatives in near and mid-IR ranges offer a promising method for early detection of water stress in rice canopies.

Cotton

Gausman (1982) compared the spectrophotometrically measured light reflectance and transmittance over the 450 to 700 nm wavebands of four differently pigmented cotton leaves. Results demonstrated that green and yellow-green leaves (chlorophylls and carotenoid) had about the same reflectance and transmittance peaks at the 550 nm wavelength, although yellow-green leaves had much higher reflectance and transmittance than the green leaves. Anthocyanin pigment manifestation in common red, blue, and yellow-green leaves occurred at about the 600 nm wavelength. Spectral responses of cotton leaves were very sensitive to either their masked or predominant pigmentation over the 450 to 700 nm wavebands.

A chlorophyll meter can instantaneously determine the amount of chlorophyll present in plant leaves. Chlorophyll values are calculated based on the amount of light transmitted through the leaf in two wavelength regions, a red region and an infrared region. Spectral absorbency of chlorophyll is high in red region and extremely low in infrared region. The ability of a chlorophyll meter (SPAD-502 Chlorophyll Meter, Minolta Camera Co., Ltd., Japan) to predict cotton N status was tested in Alabama and Missouri (Wood et al., 1992). Meter readings on the leaf were compared to leaf N concentration at different growth stages. Results showed that the chlorophyll meters were as reliable as leaf N concentration for predicting supplemental N fertilization requirements of cotton.

Illumination

Beck and Vyse (1995) patented an apparatus and a method that can be used to selectively eliminate weeds in agriculture operations. To provide selective elimination, two light emitters are modulated at very high frequencies. Light beams with different wavelength and phase, provided by the emitters, are reflected off plant or soil and intercepted by a photodetector. The spectral reflectance characteristics of plants and soil were used to differentiate between plant and soil.

The collection of accurate spectra in the field requires an awareness of the influences of the various sources of illumination, atmospheric characteristics and stability, winds, instrument field of view, target viewing and illumination geometry, instrument scanning time, and the spatial and temporal variability of the target characteristics (Curtiss and Goetz, 1994). Spectral measurements are typically made in

the field using ambient solar illumination. In the field, the target material is mainly illuminated by direct solar illumination, diffuse illumination and scatter from surroundings. Parameters such as solar elevation angle and atmospheric conditions will effect the overall intensity and spectral characteristics of direct solar illumination.

Pinter et al. (1987) found that variable cloud cover affected individual reflectance in NIR and red bands for alfalfa, but the affects on those two bands were similar. So cloud cover in this study did not have a significant affect on NDVI measurements. Pinter (1993) later studied the affects of solar angle on NDVI for alfalfa and reported that solar angle had a strong affect. The NDVI for alfalfa changed from 0.42 to 0.70 over a solar angle change from 27⁰ to 72⁰.

Remote Sensing

Remote sensing is the science of deriving information about an object from measurements made at a distance from the object. The quantity most frequently measured in remote sensing systems is the electromagnetic energy emanating from the object of interest (Swain and Davis, 1978). This technology has been used in many industries including agriculture. To evaluate the advantages and limitations of using remote sensing to map and monitor within-field crop growth and yield variations for grain sorghum, Yang, C. H. et al. (1998) used an aerial multispectral digital video imaging system to acquire field data on different dates during two growing seasons. Images in the green (555-565 nm), red (625-635 nm), and NIR (845-857 nm) portions of the electromagnetic spectrum were captured at altitudes ranging from 1,300 to 1,400 meters under sunny conditions. Their study showed that aerial digital videography in conjunction with ground

sampling, GPS, GIS, and image processing technologies could be a useful tool for monitoring within-field plant growth variation and establishing management zones for precision farming.

Smith et al. (1995) reported the relationship between the spatial variation in mean wheat yield of 50 Local Government Areas in Western Australia and satellite measures of the NDVI. The significant correlation of NDVI with final yield by the middle of the growing season indicated the feasibility of making useful yield forecasts from that time forward.

Thenkabail et al. (1992) evaluated Landsat satellite thematic data indices to quantify field differences in corn and soybean crop parameters, and determine if the ground truth and satellite data could be used to identify and quantify soil type and influences of agricultural management practices on crop development. They found that the correlation of individual indices with crop variables was generally poor but combinations of bands and indices could be used to describe between 50 and 70% of the between field variability in leaf area index, plant biomass, and crop yield. Generally, thematic vegetation indices can be used to identify significant differences in crop responses to different management systems. These differences were mainly a function of plant density, management problems associated with drought conditions, and tillage.

In 1989-91 Franklin et al. (1993) examined the reflectance of the shaded and unshaded components of Chihuahuan desert plant communities using a hand-held radiometer. Shrub canopy and shaded components had similar reflectance in the visible wavebands. However, in the near-IR band, which was strongly scattered by green plant

canopies, the shaded canopy and shaded background components were similar to each other and lower than either sunlit background or sunlit canopy.

Multispectral Image Processing

Multispectral images can be obtained using an instrument which record the emittance or reflectance of an object by scanning with discrete spectral resolution over a wide spectral band, or recording many discrete spectral bands simultaneously (Photonics, 1999). Information about the object can be extracted from the image. Multispectral image processing technologies have been used in airborne, satellite-borne, and ground-based remote sensing in agriculture. Gopalapillai et al. (1998) used high-resolution color infrared aerial images for detecting in-field spatial patterns, especially due to N stress in corn. The color infrared images indicated soil type in the earlier stages of crop growth and N stress during the later stages of crop growth. Canopy reflectance was well correlated to N application and the yield after 75 days from planting. The yield could be predicted fairly accurately from the canopy reflectance of red light. They suggested that aerial remote sensing could be a promising tool for obtaining spatial and temporal in-field data on crop variability that can be used for site-specific crop management and yield prediction.

To help assess the impact of soil salinity on crop production, Wiegand et al. (1994) developed procedures from soil salinity, plant height and boll counts, and digitized color infrared aerial photography and videography acquired during mid-boll set development stage for four salt-affected cotton fields. Unsupervised classification

procedures were used to produce seven category spectral maps by field. Results showed that the spectral classification maps and the estimated salinity maps corresponded well.

Thai et al. (1998) studied spectral video images of bush bean plants in the visible range (500-600 nm) and in NIR range (695-795 nm) under natural sunlight and inside a greenhouse. Their results showed that either visible or NIR band could be used for detecting chlorophyll content differences of bush bean plants, that result from different N treatments.

A Compact Airborne Spectroscopic Imager was flown over an intensively used agricultural area and over a location that had suffered from a forest fire (Furrer et al., 1994). Many surface feature details could be identified either from synthesized near true color images, from the NDVI, from a principal component analysis, or by treating data with an unsupervised neural network.

Artificial Neural Network

An artificial neural network is a data processing system consisting of a large number of simple highly interconnected processing elements (artificial neurons) in architecture inspired by the structure of the cerebral cortex of the brain. The network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections between elements (The Math Works, Inc., 1995). Today neural networks have been used in a wide variety of data processing applications where real-time data analysis and information extraction is required.

One advantage of the neural network approach is that most of the intense computation takes place during the training process. Once the ANN is trained for a particular task, operation is relatively fast and unknown objects can be rapidly identified in the field (Keller, 1994).

Stone (1994) used ANNs to process information from an optical sensor for weed detection. After selection of a best performing network for training conditions, the unit was able to detect 92% of the cases where weeds were presented to it and rejected 80% of the cases where weeds were not presented to it. He found low sensitivity of the unit for situations where the conditions were beyond the training set of data.

Lee and Slaughter (1998) developed a real-time intelligent robotic weed control system for tomatoes and tested for selective spraying of in-row weeds using a machine vision system and precision chemical application. A real-time neural network implemented in hardware was used to recognize tomato plants and weeds. Test results indicated that 38.9% of tomato cotyledons, 37.5% of tomato true leaves, and 85.7% of weeds were correctly identified by the system.

Yang, C. C. (1998) reported an application of ANNs to image recognition for precision farming. The ANN model was trained to distinguish between corn plants and weeds by using the color index from each pixel in an image. The accuracy rate of image recognition was 90 to 100% for corn and 60 to 70% for weeds.

After completing the remote sensing image classification for a LANDSAT image for the NASA Kennedy Space Center, Singh et al. (1998) described that the ANN classifier provided better accuracy than a statistical classifier method. The ANN method was superior to the statistical approach in terms of classification accuracy of training data

and testing data. Having the advantage of being distribution-free, the ANN approach did not require any information describing the statistical distribution of the data.

CHAPTER III

SPECTRAL REFLECTANCE CHARACTERISTICS OF COTTON CANOPY

Experimental Plot Layout

Experimental plots were established at The University of Tennessee Milan Agricultural Experiment Station for three successive years (1996, 97, and 98). Cotton varieties D&PL 20, D&PL 5409 and Stoneville 474 were planted with a row spacing of 40 inches. Plots were established to generate varying levels of plant tissue N concentrations and yields. A randomized block design (RBD) with five replications was used for establishing experimental plots in 1996 and 1997. A RBD split plot with N treatments in whole plot was used in 1998. Ammonia nitrate fertilizer was applied at planting at rates of 0, 30, 60, 90 and 120 lbs/ac. Plots in 1996 and 1997 were managed as a no-tillage cotton production system and as a conventional tillage system in 1998.

Spectral Data Collection

Reflectance spectra of cotton leaves were obtained using a SD-1000 Fiber Optic Spectrometer manufactured by Ocean Optics, Inc. Its optical bench accepts light from a single optical fiber and disperses it across a linear array of 1024 CCD detectors. It can measure the spectrum with wavelengths ranging from 237 to 816 nm. The spectrometer was interfaced with a laptop computer through a PCMCIA analog-to-digital interface (Figure 1).

Reflectance spectra of cotton canopy were measured at the growth stages of early-pinhead square (6-9 nodes), mid-pinhead square (7-10 nodes), late-pinhead square (8-11

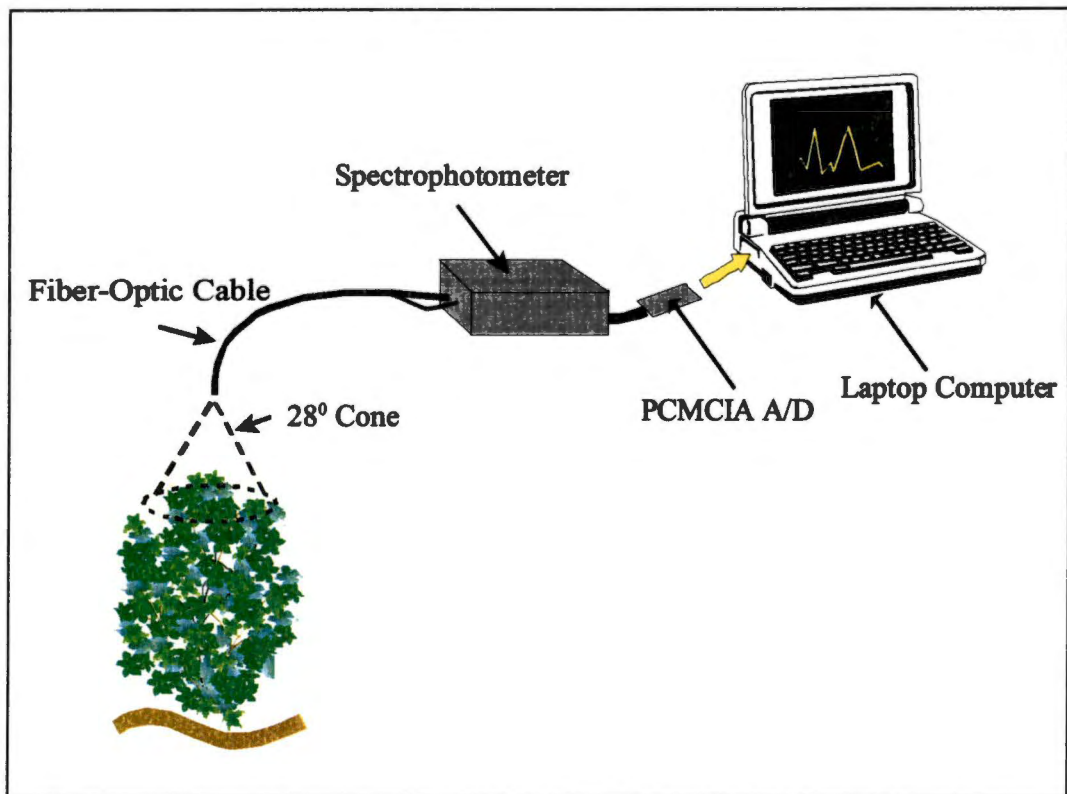


Figure 1. Illustration of the field-based spectral reflectance measurement instrumentation.

nodes), first bloom, and mid-bloom. Spectral measurements were made by positioning the fiber optic sensor perpendicular to the cotton plant canopy. Distance between the top of the crop canopy and the input to the fiber optic cable was approximately 6 inches. The spectrometer scanned the cotton canopy and the spectral data were recorded by the data acquisition system. Ten spectral scans were made at various locations within each plot at the growth stages noted above. A total of 2500 spectral reflectance scans were made and analyzed. There were 1100 data points in each scan (Appendix A). Wavelengths of the reflectance spectrum ranged from 237 nm to 816 nm. The spectrum was normalized using its total intensity (summation of intensity counts at each wavelength) as a reference (Figure 2).

Figure 2 illustrates that the plants receiving different N application rates had different spectral responses at each wave band. With increases in N application rates, spectral response magnitude increased in the NIR band. The 60 lbs/ac treatment had the strongest spectral reflectance in the blue band. At the green band, with the increases in N application rates the spectral response decreased in 0, 30, and 60 lbs/ac treatments, but it increased in 90 and 120 lbs/ac rates. At the red band, the spectral response of 60 lbs/ac treatment was almost the same as 90 and 120 lbs/ac rates. The reflectance spectra indicated that the N status was not linearly related with the spectral reflectance intensity at each band. Cotton plant canopies with different N status had their own spectral patterns or signatures. Therefore, diagnosing N status is a process of spectral signature analysis.

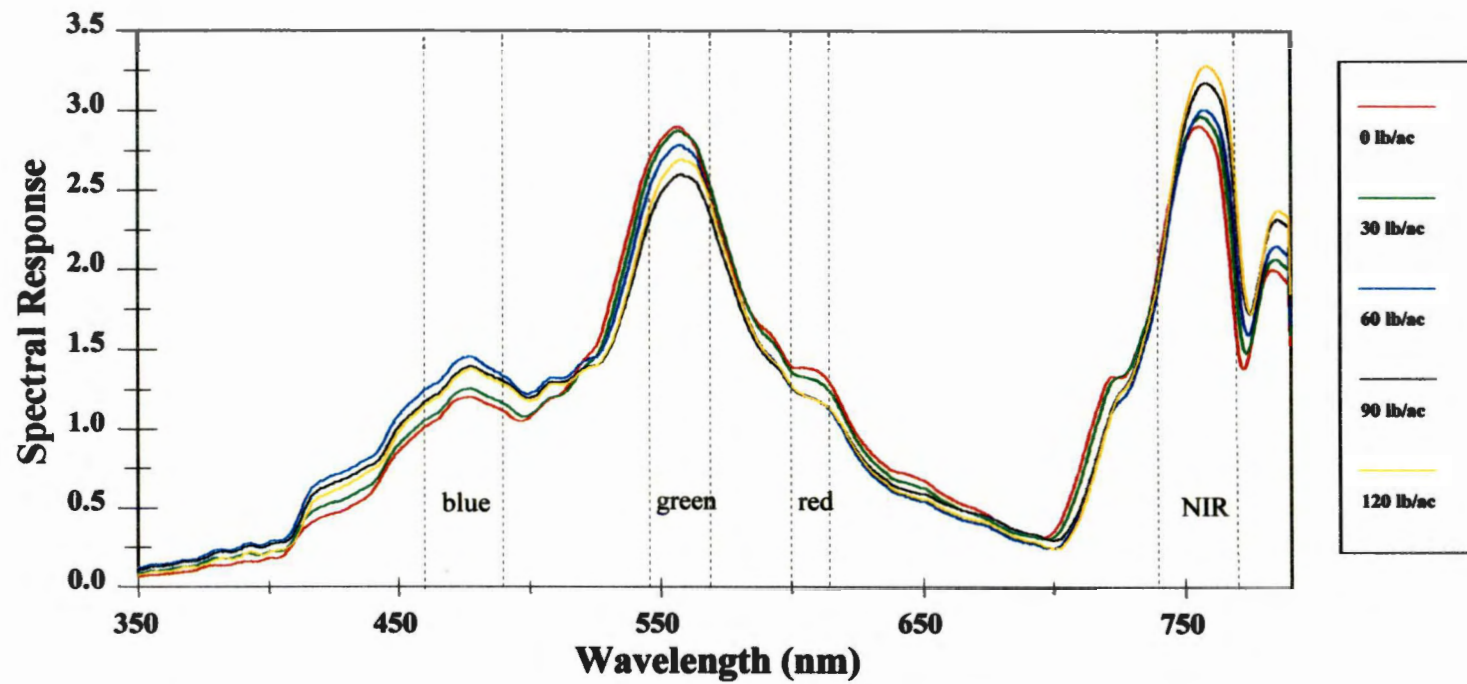


Figure 2. Spectral reflectance of cotton leaves.

Plant Nitrogen Measurements

Petioles on the uppermost fully expanded leaves were randomly collected from 10 plants within each plot concurrently with the spectral reflectance measurements. Petiole samples were analyzed as a composite for each plot. A total of 250 petiole samples were collected and analyzed.

N content analysis of petiole samples for the 1996 growing season was conducted using the procedure established by Laced Instruments. The method used was titled "Total N in Soil and Plant Digests" (13-107-06-2-D). Petioles were dried at 83 °C for 48 hours, and then ground for digesting.

Nitrate content of the petiole samples in 1997 and 1998 were analyzed using a laboratory procedure documented by the soil-testing laboratory at the University of Arkansas (1991). Petiole samples were dried at 83 °C for 48 hours and ground to pass a 20 mesh screen. An extracting solution composed of aluminum sulfate and deionized water was used. Dry ground petiole samples were added to the solution and the nitrate content was measured using a nitrate electrode (ORION, 1990) with a Model 290A pH meter (ORION, 1991).

Spectral Index Model

When there are many independent variables and a known relationship is not available, variable selection techniques provided in SAS® (1989) may be used to explore the data and choose the best independent variables to explain differences in the dependent variable. Five techniques in SAS® can be used for selecting independent variables: FORWARD, BACKWARD, STEPWISE, RSQUARE, and CP. The FORWARD

technique adds variables to the equation one at a time, including the variable with the most significant partial regression coefficient at each step. BACKWARD starts with all variables in the model, then removes the least significant variables one at a time. STEPWISE adds the most significant variables one at a time, but at each step, also checks if any variables are no longer significant, and if so removes them from the model. RSQUARE examines all possible linear models, and ranks them by R-square. This guarantees that the highest R-squared model with a given number of independent variables will be found. CP operates like RSQUARE but uses adjusted R-square or Mallows' CP statistic to decide on the best model. CP is a measure of total performance of the model. If there are n variables in the model, the CP value should not be much more than $n+1$.

Through experimentation over three years, four wavelength bands were identified within the full-scale range of wavelength available on the spectrometer (Figure 2). These four bands were defined as the blue band from 460 to 490 nm, green band from 545 to 565 nm, red band from 600 to 610 nm and near infrared band from 740 to 770 nm.

N status in the plants as a function of spectral characteristics of plant canopy was explored based on selected features extracted from a normalized spectral reflectance curve in the visible and NIR wavelength band. The relative reflectance values from the cotton canopy in different wavelength bands were used as independent variables to predict dependent variable, plant N levels. Statistic variable selection techniques FORWARD, BACKWARD, STEPWISE, RSQUARE, and CP were employed for selecting the most significant variables to the N level. Results of variable selecting are presented in Table 1. It was found that the dependent variable (N application rate) could

Table 1. Results of variable selection using different methods provided in SAS®. Six hundred sixty two spectral scans taken from variety D&PL 20 in 1996 were used in computation.

Methods	Dependent Variable	Independent Variables in Model	Results		
			R-square	Cp	p
FORWARD	N-Rate	Red	0.2130	232.4343	0.0001
	N-Rate	Green Red	0.3388	92.0985	0.0001
	N-Rate	Blue Green Red	0.4163	6.3929	0.0001
	N-Rate	Blue Green Red NIR	0.4193	5.0000	0.0001
BACKWARD	N-Rate	Blue Green Red NIR	0.4193	5.0000	0.0001
STEPWISE	N-Rate	Red	0.2130	232.4343	0.0001
	N-Rate	Green Red	0.3388	92.0985	0.0001
	N-Rate	Blue Green Red	0.4163	6.3929	0.0001
	N-Rate	Blue Green Red NIR	0.4193	5.0000	0.0001
RSQUARE	N-Rate	Red	0.2130	Not reported by SAS®	
	N-Rate	Green	0.1628		
	N-Rate	Blue	0.1445		
	N-Rate	NIR	0.0893		
	N-Rate	Blue NIR	0.3710		
	N-Rate	Green Red	0.3388		
	N-Rate	Blue Red	0.3175		
	N-Rate	Blue Green	0.2685		
	N-Rate	Red NIR	0.2160		
	N-Rate	Green NIR	0.1651		
	N-Rate	Blue Green Red	0.4163		
	N-Rate	Green Red NIR	0.4139		
	N-Rate	Blue Red NIR	0.3915		
	N-Rate	Blue Green NIR	0.3715		
	N-Rate	Blue Green Red NIR	0.4193		
CP	N-Rate	Blue Green Red NIR	0.4193	5.0000	Not reported by SAS®
	N-Rate	Blue Green Red	0.4163	6.3929	
	N-Rate	Green Red NIR	0.4139	9.1396	
	N-Rate	Blue Red NIR	0.3915	34.4895	
	N-Rate	Blue NIR	0.3710	55.6497	
	N-Rate	Blue Green NIR	0.3715	57.1280	
	N-Rate	Green Red	0.3388	92.0985	
	N-Rate	Blue Red	0.3175	116.2537	
	N-Rate	Blue Green	0.2685	171.6289	
	N-Rate	Red NIR	0.2163	230.7107	
	N-Rate	Red	0.2130	232.4343	
	N-Rate	Green NIR	0.1651	288.6198	
	N-Rate	Green	0.1628	289.2026	
	N-Rate	Blue	0.1447	309.7264	
	N-Rate	NIR	0.0893	372.4175	

be explained with the greatest R-square and smallest CP values when four independent variables (blue, green, red, and NIR) were used in the model.

Based on the results of variable selecting, the following model was used to calculate a spectral index for each spectral scan.

$$\text{Spectral Index} = (NIR + Blue) / (Green + Red)$$

Where

Blue: Normalized spectral reflectance from 460 to 490 nm;

Green: Normalized spectral reflectance from 545 to 565 nm;

Red: Normalized spectral reflectance from 600 to 610 nm;

NIR: Normalized spectral reflectance from 740 to 770 nm.

Spectral index calculated using this model showed the highest correlation with petiole nitrate content, yield, and N application rate.

Results of Spectral Analysis

Spectral index data, petiole N content, yield and N application rate was analyzed for correlations between measured variables. Results of correlation analysis are summarized in Table 2 for three different years and different growth stages within each year. Figure 3 illustrates the relationship between spectral index and N application rate for one variety, season, and growth stage. Spectral index was measured at the growth stage of mid-pinhead square during the 1998 growing season. Cotton variety is Stoneville 474. Figure 4 illustrates the relationship between the spectral index and petiole nitrate content at late-pinhead square in 1997 for variety D&PL 20. It indicated that spectral index increase linearly with the increase of petiole nitrate content with a $R^2=0.74$. Figure

Table 2. Correlation coefficients among parameters in Field N29, Milan Experiment Station in 1996, 1997 and 1998.

	Spectral Index	Nitrogen Rate	Petiole Nitrate/N	Cotton Yield	Cotton Variety	Growth Stage**
1996						
Spectral Index	1	0.85*	0.72	0.85	DP&L 20	B
	1	0.95*	0.56	0.89	DP&L 20	D
	1	0.89*	0.28	0.89	DP&L 20	E
Nitrogen Rate	0.85*	1	0.69	0.85	DP&L 20	B
	0.95*	1	0.86	0.85	DP&L 20	D
	0.89*	1	0.4	0.85	DP&L 20	E
Petiole N	0.72	0.69	1	0.85	DP&L 20	B
	0.56	0.68	1	0.72	DP&L 20	D
	0.28	0.40	1	0.54	DP&L 20	E
Cotton Yield	0.85	0.85	0.85	1	DP&L 20	B
	0.89	0.85	0.72	1	DP&L 20	D
	0.89	0.85	0.54	1	DP&L 20	E
1997						
Spectral Index	1	0.90*	0.77	0.88	DP&L 20	B
	1	0.92*	0.86	0.92	DP&L 20	C
	1	0.90*	0.83	0.88	DP&L 20	D
Nitrogen Rate	0.90*	1	0.95*	0.95*	DP&L 20	B
	0.92*	1	0.90	0.95*	DP&L 20	C
	0.90*	1	0.89	0.95*	DP&L 20	D
Petiole Nitrate	0.77	0.95*	1	0.92	DP&L 20	B
	0.86	0.90	1	0.89	DP&L 20	C
	0.83	0.89	1	0.87	DP&L 20	D
Cotton Yield	0.88	0.95*	0.92	1	DP&L 20	B
	0.92	0.95*	0.89	1	DP&L 20	C
	0.88	0.95*	0.87	1	DP&L 20	D
1998						
Spectral Index	1	0.83	0.79	0.87*	DP&L 5409	A
	1	0.69*	0.60*	0.79	STVL 474	
	1	0.93*	0.75*	0.93	DP&L 5409	B
	1	0.95*	0.91*	0.82	STVL 474	
Nitrogen Rate	0.83	1	0.75*	0.90*	DP&L 5409	A
	0.69*	1	0.77*	0.79*	STVL 474	
	0.93*	1	0.74	0.90*	DP&L 5409	B
	0.95*	1	0.81	0.79*	STVL 474	
Petiole Nitrate	0.79	0.75*	1	0.72	DP&L 5409	A
	0.60*	0.77*	1	0.62	STVL 474	
	0.75*	0.74	1	0.69*	DP&L 5409	B
	0.91*	0.81	1	0.79*	STVL 474	
Cotton Yield	0.87*	0.90*	0.72	1	DP&L 5409	A
	0.79	0.79*	0.62	1	STVL 474	
	0.93	0.90*	0.69*	1	DP&L 5409	B
	0.82	0.79*	0.79*	1	STVL 474	

* Second order polynomial; Others: Linear

** A = Early-Pinhead Square; B = Mid-Pinhead Square; C = Late-Pinhead Square; D = First Bloom; and E = Mid-Bloom.

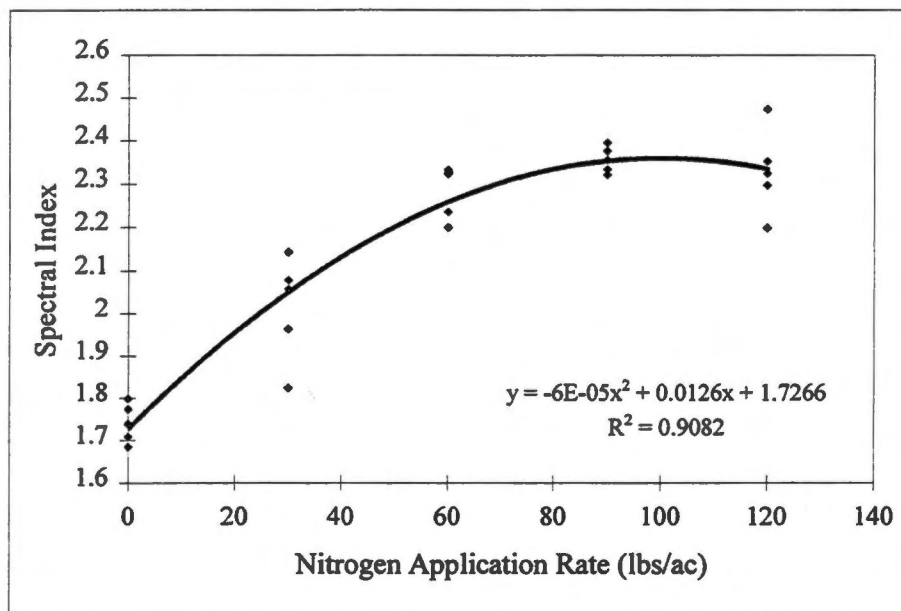


Figure 3. Spectral index measured at mid-pinhead square in 1998 as a function of soil applied nitrogen for variety Stoneville 474.

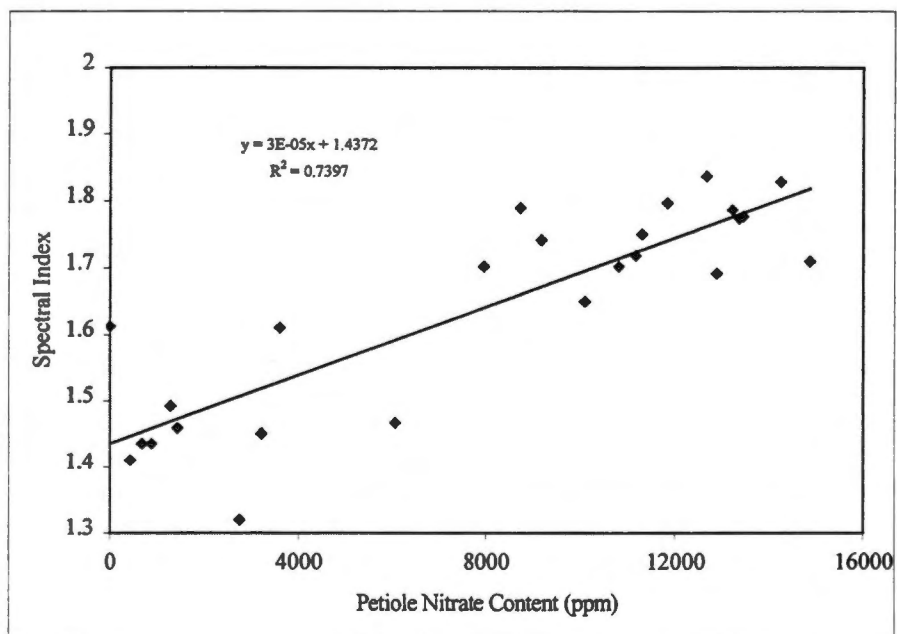


Figure 4. Spectral index measured at late-pinhead square in 1997 as a function of petiole nitrate content for variety D&PL 20.

5 illustrates a good linear relationship between spectral index and cotton yield ($R^2=0.86$). The spectral index shown in Figure 5 was measured at mid-pinhead square during the 1998 growing season for the variety D&PL 5409. Spectral index proved to be a better predictor of yield than petiole N levels (Table 2). Figure 6 indicates that cotton yield increases with N up to an application rate equal to or less than 60 lbs/ac. And the yield does not increase with increased N application rates beyond 60 lbs/ac. The best N application rate in this specific situation was about 60 lbs/ac.

Table 2 shows that the correlations between spectral index and other measured variables changed with growth stages. Using 1997's data for the same variety as an example, at the growth stage of late-pinhead square the correlation value between spectral index and petiole nitrate content was 0.86, but at the growth stage of mid-pinhead square it was 0.77. The correlation coefficient between spectral index and N application rate using a second order polynomial function ranged from 0.69 to 0.95 with a three year average of 0.88. The spectral index showed a more linear relation with yield. The correlation coefficient between spectral index and yield ranged from 0.79 to 0.93 with an average of 0.87.

Figure 7 illustrates the spectral index variation introduced by plant variety. Spectral data for both varieties were taken on the same day at mid-pinhead square during the 1998 growing season. These plants were grown under the same conditions. However, Figure 7 shows that Stoneville 474 had a higher spectral index than D&PL 5409 with the same petiole nitrate content. This indicates that spectral reflectance characteristics of cotton leaves may vary among varieties.

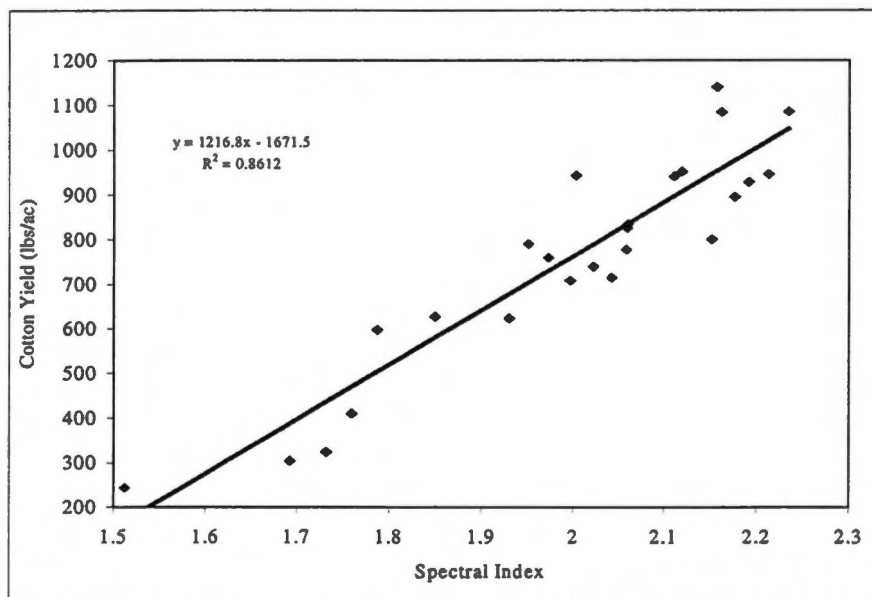


Figure 5. Cotton yield as a function of spectral index measured at mid-pinhead square in 1998 for variety D&PL 5409.

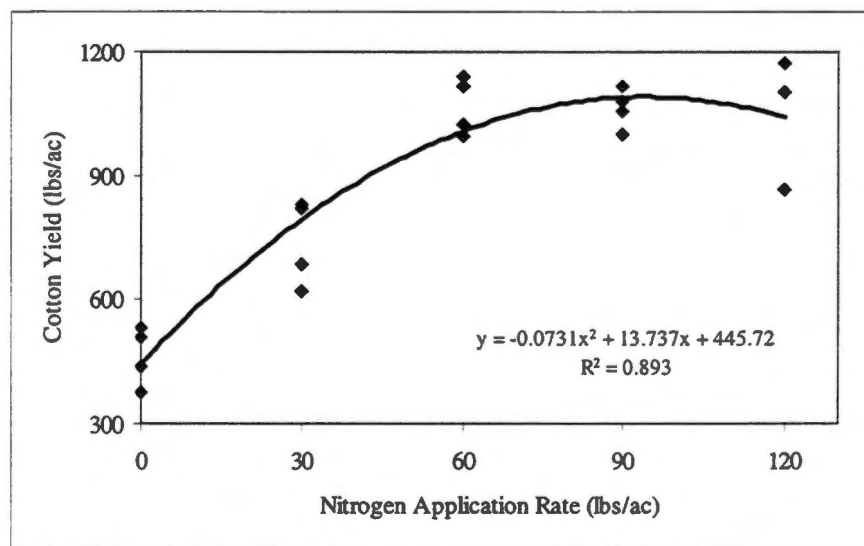


Figure 6. Cotton yield versus soil applied nitrogen in 1996 for variety D&PL 20.

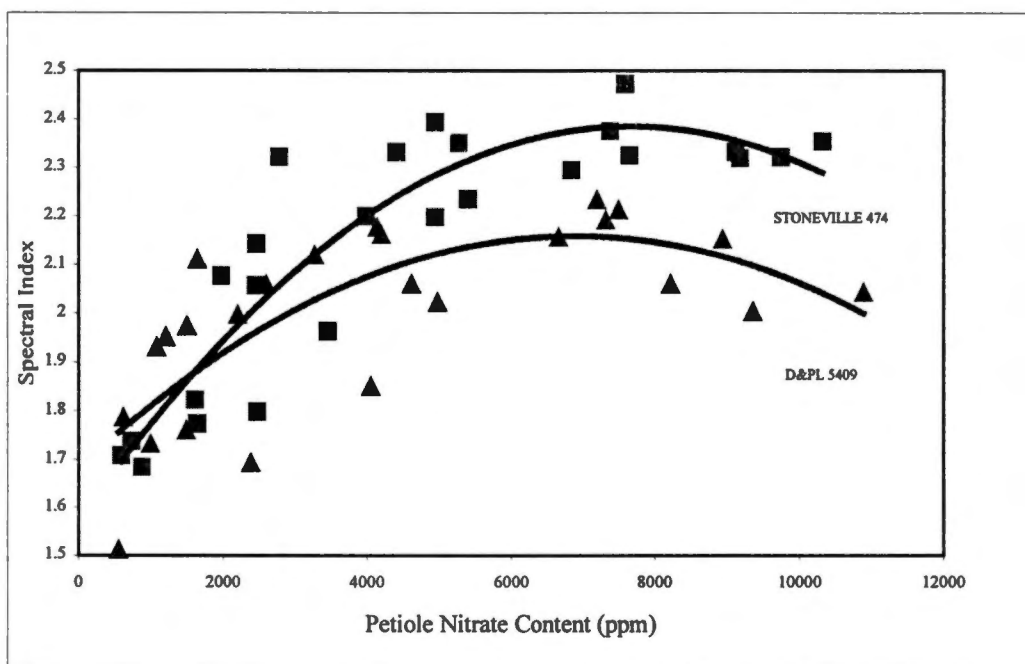


Figure 7. Illustration of spectral index variation induced by variety at the growth stage of mid-pinhead square in 1998.

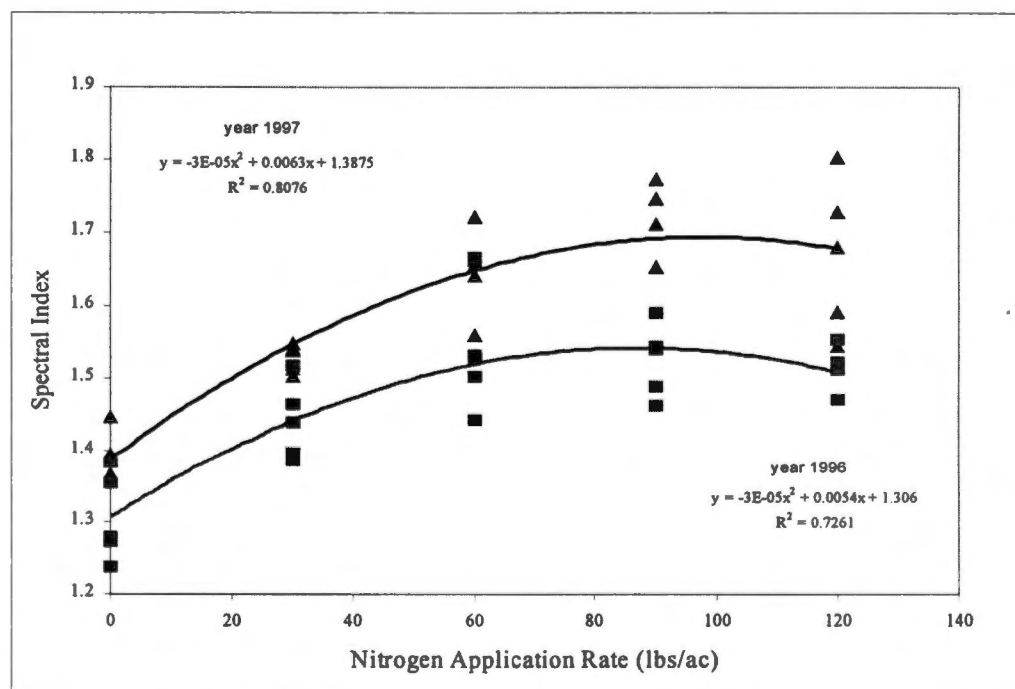


Figure 8. Illustration of spectral index variation induced by growing year at the growth stage of mid-pinhead square.

Spectral index variation with growth year was demonstrated in Figure 8. The spectral index shown in the figure were measured at mid-pinhead square in 1996 and 1997 with the same variety (D&PL 20) in the same field (N29, Milan). The plants grown in 1997 had a higher spectral index than in 1996 under the same N application rate. Weather conditions during growing season for each year may have affected the canopy reflectance characteristics.

In general, spectral index had a good correlation with the N status and yield. Mid-pinhead square, the right time period to apply supplemental N to the cotton plants that are N deficient, was the growth stage where spectral index shows the best correlation with petiole N content and the yield. Beyond the growth stage of first bloom, petiole N content was not closely related with spectral index, N application rate, or yield. Cotton variety and growth year also affected the spectral index. This suggests that the growth stage, variety, and even weather conditions in the growing year may need to be taken into consideration if the spectral index is used in a continuous function for predicting N status in cotton plants.

Comparison of Spectral Index with NDVI

NDVI (Normalized Difference Vegetation Index) has been used for evaluating plant conditions for many years (Printer et al., 1987). It is calculated using following equation.

$$NDVI = (NIR - Red) / (NIR + Red)$$

For comparison with the spectral index calculated in this study, NDVI was computed using 1997 spectral data. The relationship between the NDVI and N

application rate, petiole nitrate content, and yield was analyzed. Results are shown in Table 3.

Table 3 indicates that the spectral index derived specifically for cotton had a better correlation with N application rate, petiole nitrate content, and yield at any growth stage than NDVI did. Results suggest that the spectral index model developed for cotton performed better than the generalized NDVI model.

Table 3. Comparison of correlation coefficient between spectral index and nitrogen application rate with that between NDVI and nitrogen application rate. Spectral data were measured from variety D&PL 20 in 1997.

	Spectral Index	NDVI	Growth Stage
Nitrogen Rate	0.90	0.75	Mid-Pinhead Square
Nitrogen Rate	0.92	0.86	Late-Pinhead Square
Nitrogen Rate	0.90	0.77	First Bloom
Petiole Nitrate	0.77	0.56	Mid-Pinhead Square
Petiole Nitrate	0.86	0.79	Late-Pinhead Square
Petiole Nitrate	0.83	0.69	First Bloom
Yield	0.88	0.64	Mid-Pinhead Square
Yield	0.92	0.88	Late-Pinhead Square
Yield	0.88	0.73	First Bloom

CHAPTER IV

GROUND-BASED REMOTE SENSING SYSTEM

A ground-based remote sensing system was designed for diagnosing N status in cotton plants based on the results realized in the previous chapter. The system consists of two basic components: an optical sensing unit and associated analog electronics, and a computer-based artificial neural network for processing inputs from the sensing unit. Figure 9 illustrates the fundamental operating components of the sensing system. The sensing unit non-intrusively measures the spectral light energy reflected from the cotton canopy in the blue, green, red, and near infrared wavebands, respectively. Specific wavebands were chosen based on statistical results reported in Chapter III. A neural network classifies the N status in cotton by analyzing spectral data from the sensor unit along with the stage of plant growth. Outputs of the neural network have the potential to control a variable-rate N application unit based on site-specific N needs within a field. This chapter focuses on the design and fabrication of the sensor. Training and testing of artificial neural networks for the system will be presented in the next chapter.

Sensor Structure

Based on the spectral reflectance characteristics of the cotton canopy obtained from tests in 1996-97, it was determined that four wavelength bands could be used to adequately classify N status in the cotton plants. All previous work with spectral reflectance measurements of plant canopy was based on natural illumination (sunlight). However, solar elevation angle and atmospheric conditions can effect the spectral

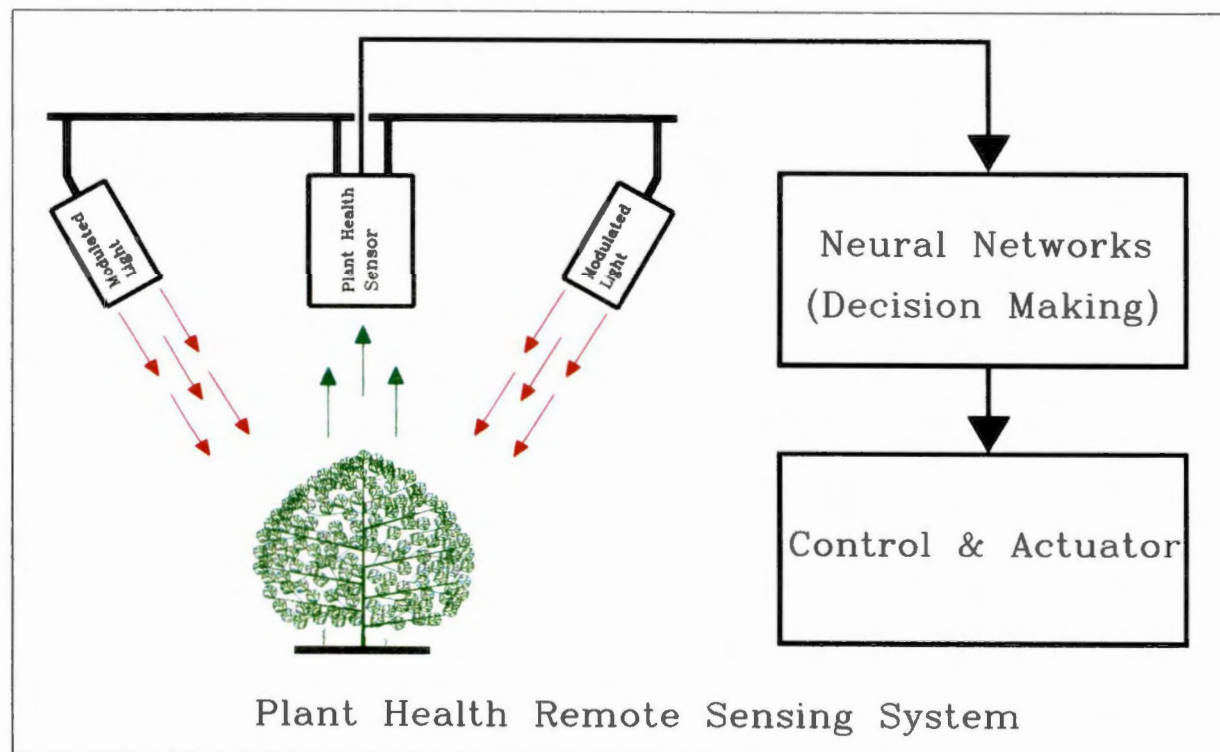


Figure 9. Illustration of a ground-based real-time plant health remote sensing system.

characteristics of the solar illumination reaching the plant canopy. Previous research documented this effect and its significance on NDVI measurements (Stone et al., 1998 and Pinter et al., 1987). For these reasons, two physically similar sensor models were designed and fabricated, one with an artificial illumination source, and one that relies solely on natural illumination. The unit that relies solely on sunlight as the illumination source is identified to as Model SL98. The other unit, Model AL98, relies on a modulated artificial light source for canopy illumination. Figure 10 is a photograph of the plant health sensor. A cross section view of the sensor is shown in Figure 11. The sensor has four channels representing spectral bands of blue, green, red, and near infrared light, respectively. Each channel includes both optical and electronic components.

Optical Component of the Sensor

Both sensing units (models SL98 and AL98) share the same optical features. The optical component consists of an optical window, focusing lens, optical filters, hot and cold mirrors, and a photodiode. Light portion reflected by the cotton canopy travels through the optical window where it is focused by the lens onto the optical filters (Figure 11). Each filter only allows light within a selected waveband to pass. Figure 12 illustrates the spectral responses of the optical filters and the photodiode that is used for detecting the reflected light from the cotton canopy. The blue filter has a light transmission rate of 93% within the wavelength range of 350 - 500 nm. The pass band of the green filter is from 520 - 580 nm. The red filter attenuates the light with a wavelength less than 600 nm. The hot mirror only allows visible light to pass while the cold mirror reflects visible light and transmits infrared light. Spectral response of the photodiode covers the visible band

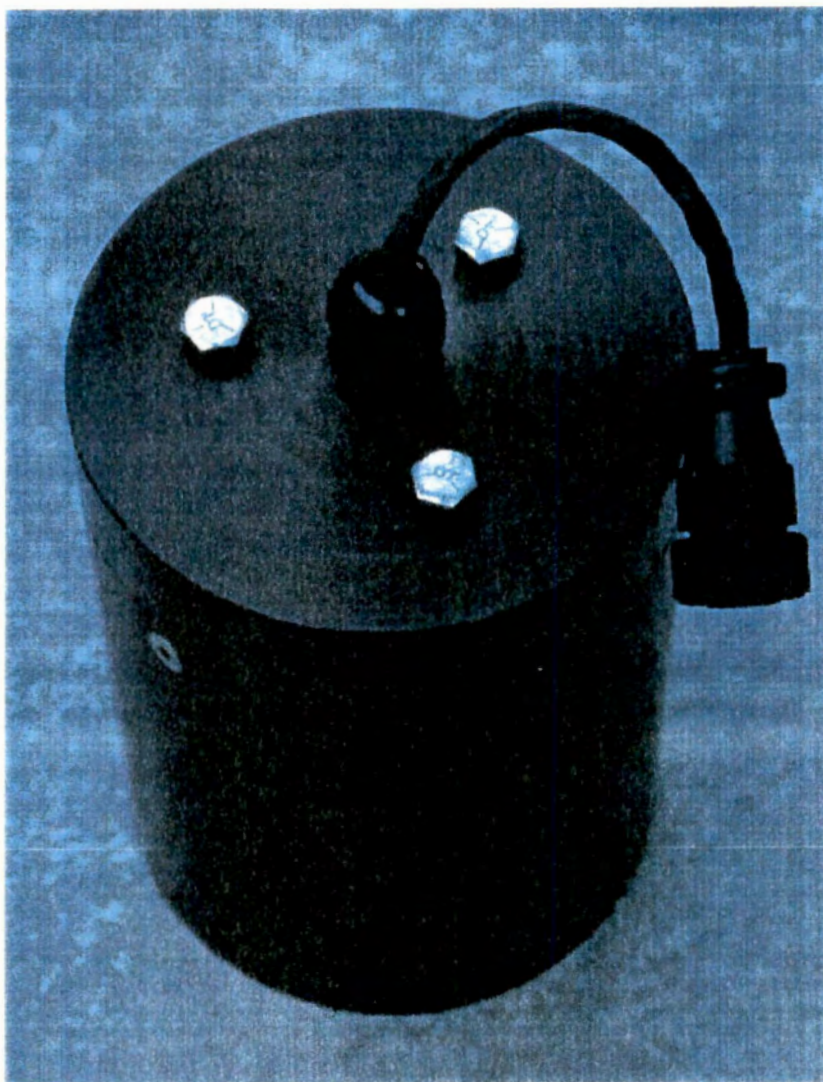
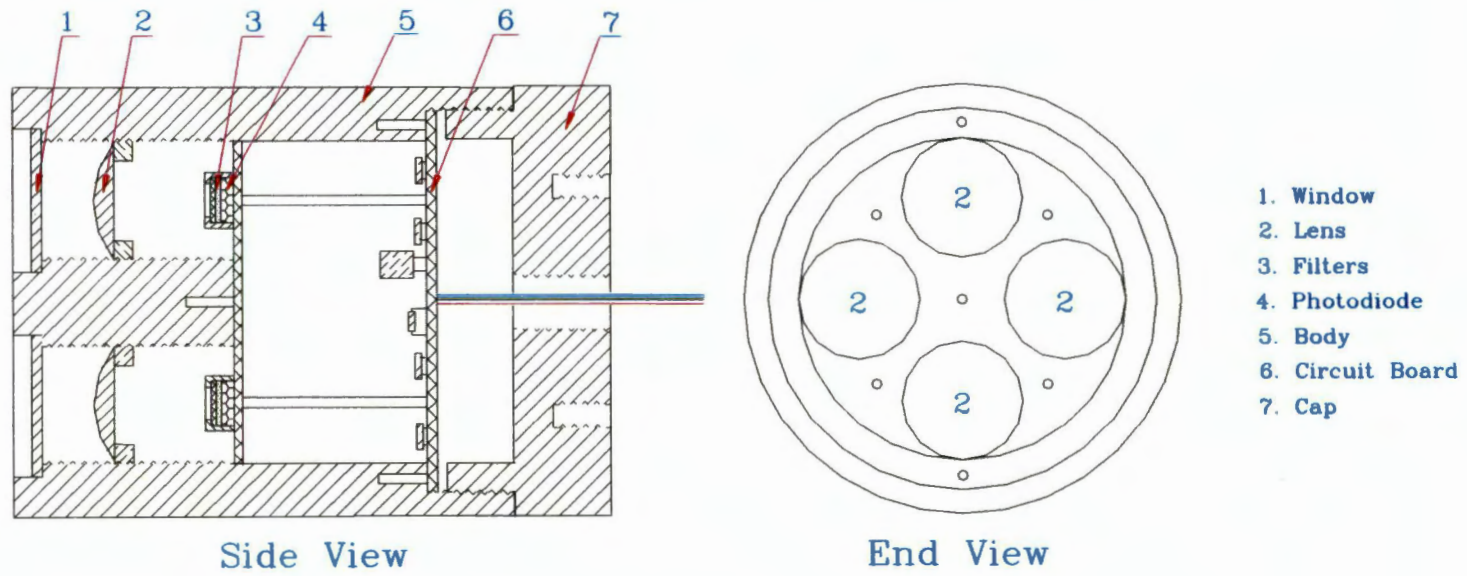


Figure 10. Plant health sensor.



Schematic Diagram of Plant Health Sensor

Figure 11. Schematic diagram of plant health sensor.

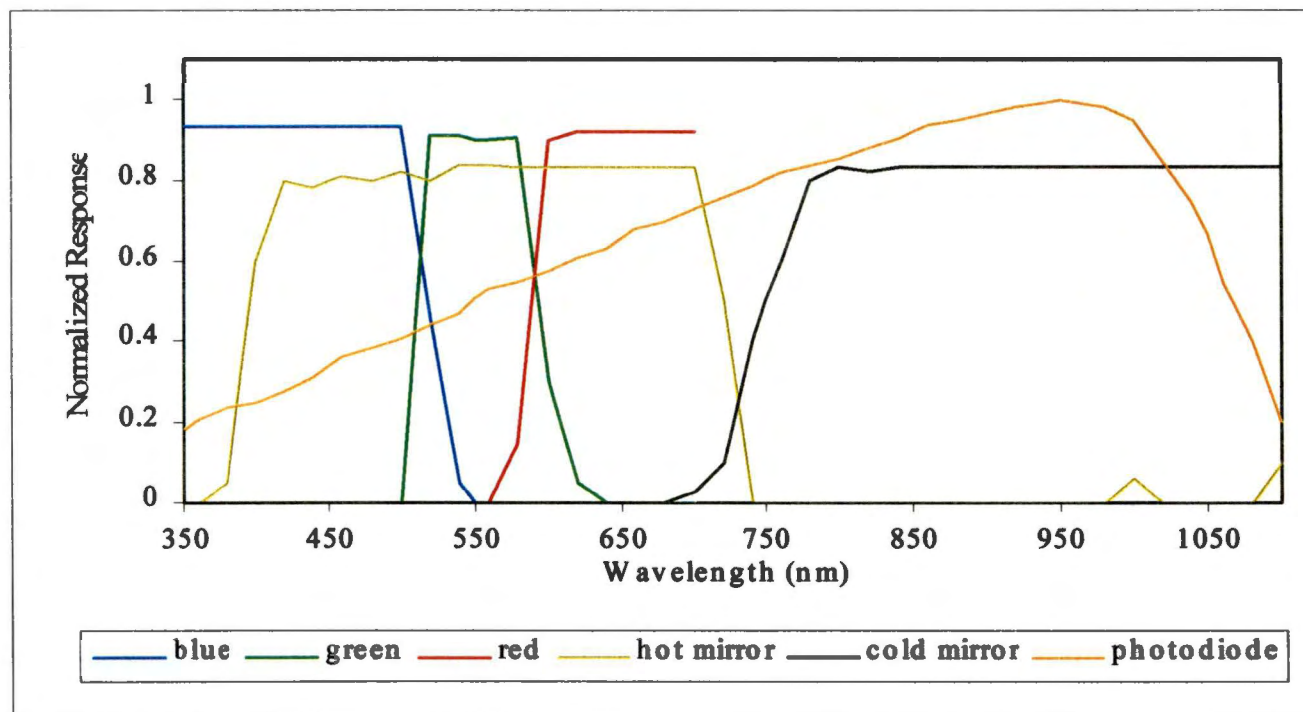


Figure 12. Spectral responses of optical filters and the photodiode.

and near infrared band. The blue filter in combination with the hot mirror forms the blue channel. Combination of the green filter with the hot mirror forms the green channel. A red filter in conjunction with hot mirror forms the red channel. The NIR channel only uses the cold mirror. Spectral bandwidth for the blue channel is 350-500 nm, 520-580 nm for the green channel, 600-740 nm for the red channel, and 750-1100 nm for the NIR channel.

Blue, green, and red filters are precision dichroic color separation filters with a diameter of 25 mm and a thickness of 2.0 mm. The hot and cold mirrors are multilayer dielectric mirrors with a thickness of 3.0 mm. The photodiode is a silicon photodiode with a light active area of 5.8x5.8 mm and a spectral response range from 320 to 1100 nm. The lenses used to focus the light onto the photodiode are plano-convex condenser lenses with a focal length of 25.4 mm and a diameter of 25.4 mm. Lenses are glued on a metal ring with fine threads for focus adjustment. Windows are 30 mm in diameter with a thickness of 1 mm and are fabricated from a fine annealed glass (BK 7 grade A). The filter combination for each channel is placed in front of the photodiode and all components are sealed in a dark gray plastic case. Figure 13 shows the optical module for all four channels.

Electronic Component of the Sensor

The Model SL98 and Model AL98 differ in the design of their electronic components. The electronic component of the sensor includes a photodiode, an electronic filter and an amplification circuit. Each channel of the sensor has a single analog output. Figures 14 and 15 are schematic diagrams of the analog electronic circuits for sensor

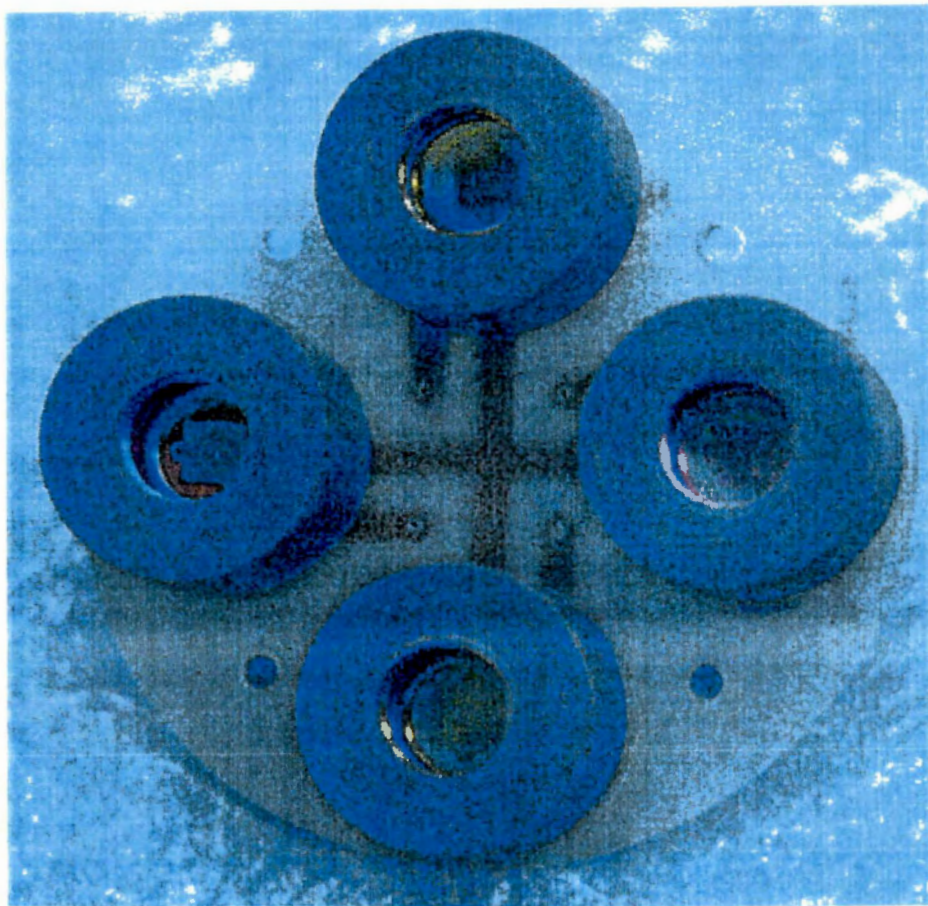


Figure 13. Optical module of plant health sensor.

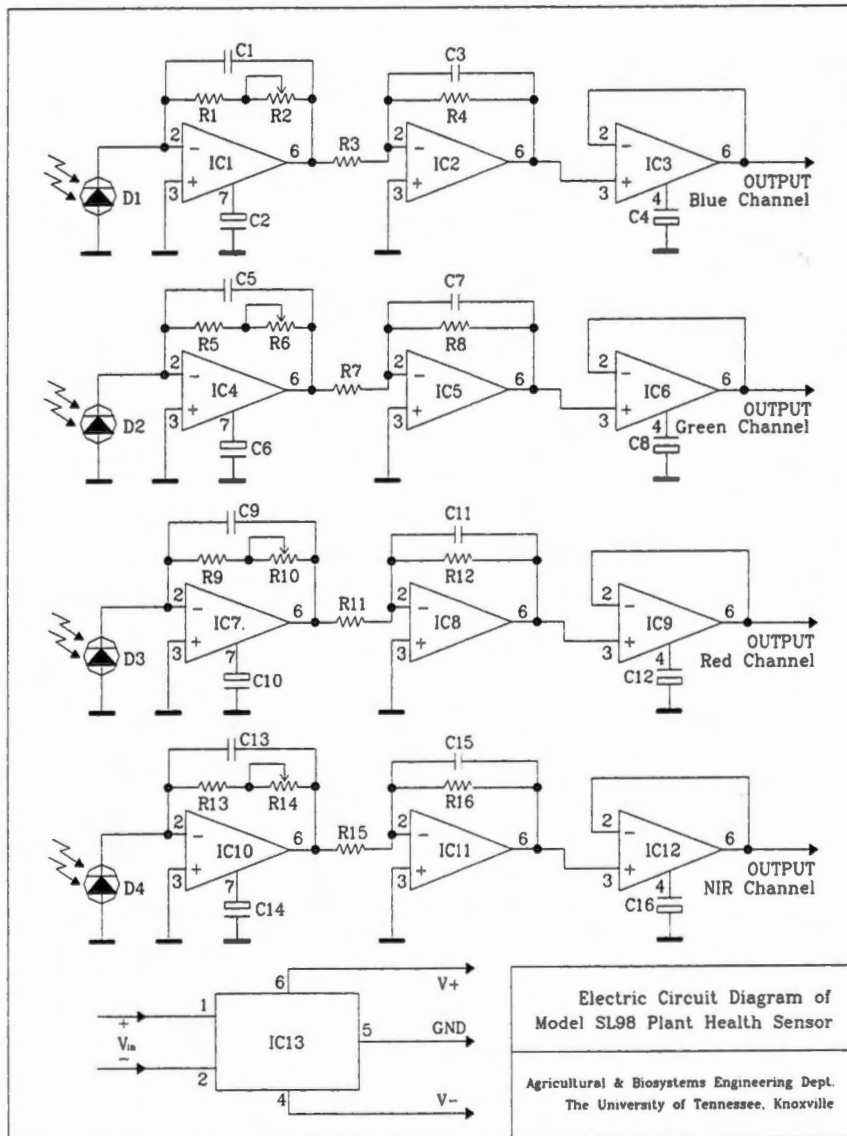


Figure 14. Electronic circuit of model SL98 plant health sensor.

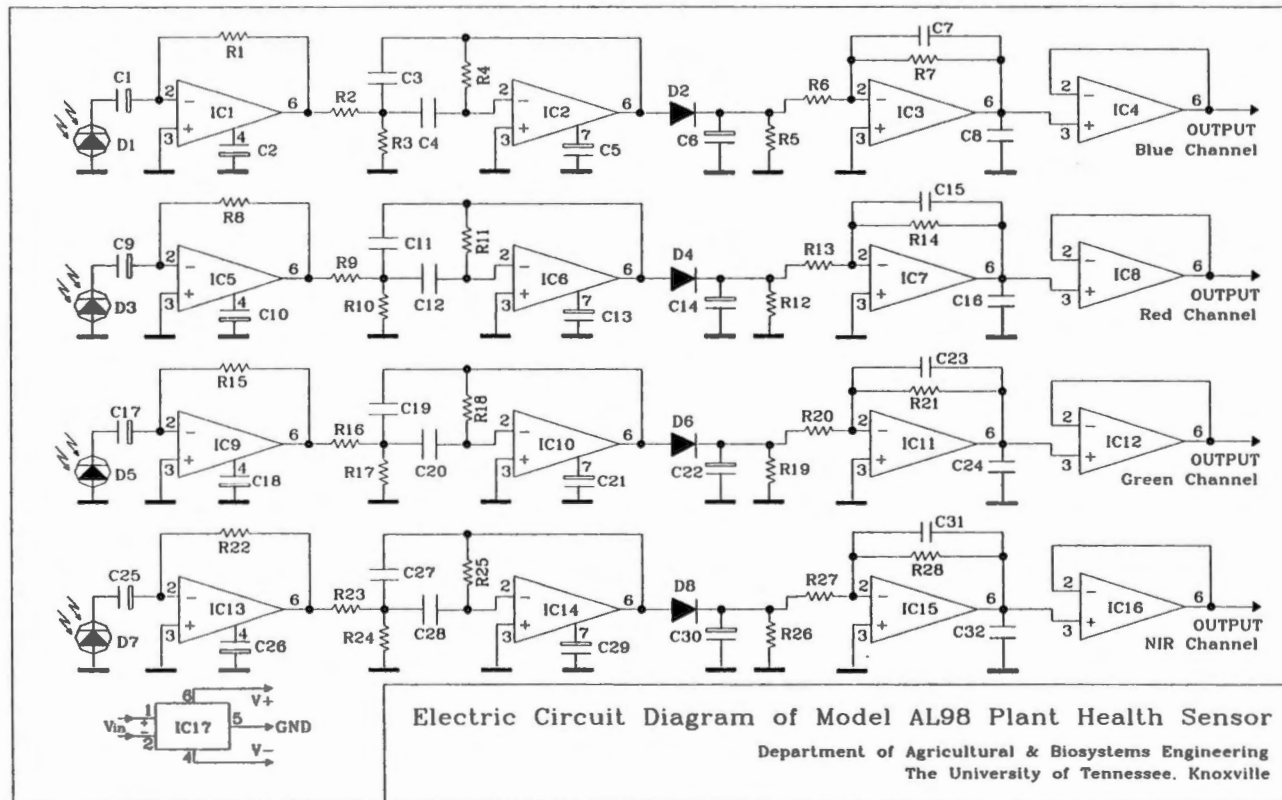


Figure 15. Electronic circuit of model AL98 plant health sensor.

models SL98 and AL98, respectively. For illustration purposes, electronics for the blue channel will be discussed for both sensor designs. For Model SL98, the photodiode (D1) transforms the light that passes through the optical filter into an electric current. Current, proportional to light intensity, is converted into an electrical voltage using a typical current-to-voltage amplifier (IC1) circuit. Output from the current-to-voltage circuit is amplified using the second operational amplifier (IC2). The third amplifier (IC3) is used to form a voltage follower to provide stable current drive capacity with relative low output impedance.

To avoid the effect of the spectral characteristic change of solar illumination on the spectral reflectance measurements, a modulated artificial illumination source was used in the design of the Model AL98 sensor. Figure 16 shows the electric circuit for powering the illumination source. A diode was used to rectify the input voltage to reduce the effect of natural light source on the sensor. The artificial light source consisted of two 75 W halogen bulbs modulated at 60 Hz. Each light was focused on the plant canopy such that the sensing unit could detect the reflected modulated light from the plant canopy.

The circuitry design that differentiates the AL98 from the SL98 is an added electronic filter and a demodulation circuit. These added components work in conjunction with a modulated light source. For the Model AL98, an AC current component is generated as a result of the modulated light striking the photodiode D1 (Figure 15). Capacitor C1 only allows AC current generated by the modulated light to be converted into a voltage signal through IC1. Thus the output signal of IC1 has no significant component that is attributed to natural illumination (sunlight). To further minimize other

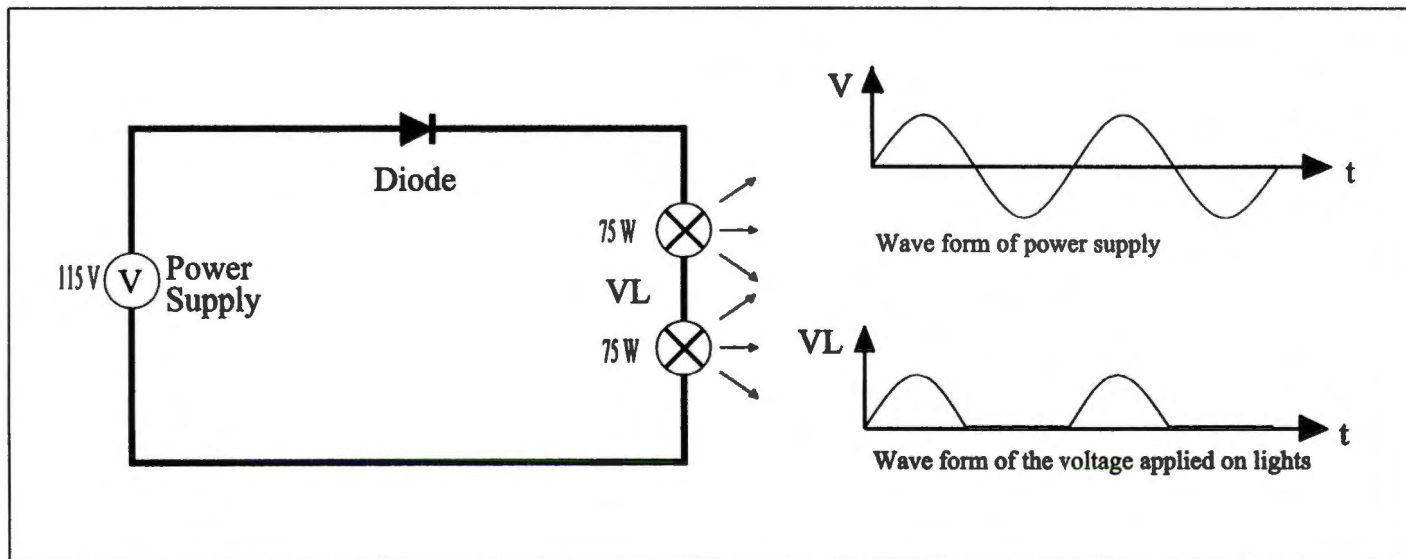


Figure 16. Electric circuit for light modulation

dynamic light changes not directly attributed to the modulated light, a band-pass filter with cut-off frequencies of 35 and 90 Hz is added to attenuate the output signal for frequencies outside the 60 Hz range. Figure 17 illustrates the frequency response of the active band-pass filter. A demodulation circuit followed the band-pass filter. It consists of a diode (D2) for rectification followed by a RC network for signal integration “smoothing”. After the signal is demodulated, IC3 and IC4 then amplify the DC signal.

IC 17 in Figure 15 is used to convert an uni-polar supply voltage (+12 V) to a bi-polar supply (± 12 V). This bi-polar power supply is required by the amplifiers.

Electronic modules for Model SL98 and AL98 sensors are shown in Figures 18 and 19 respectively. A single ribbon connector is used to connect the electronic module with the optical module. Specifications for the electronic components used to implement both plant health sensors Model SL98 and AL98 are listed in Appendix C.

All optical parts and electronic components are housed in a machined cylindrical aluminum enclosure (Figure 20). The machined enclosure has an overall length of 6 inches with a diameter of 4.5 inches.

Results of the Sensor Test

The experimental field design for evaluating the plant health sensor was a RBD. The treatment was N application rate. The cotton variety used in the experiment was D&PL 5409. Five treatments were used (0, 30, 60, 90, and 120 lbs/ac). Each treatment was replicated five times.

Plant health sensor Model AL98 was tested at mid-pinhead square during the 1998 cotton growing season at The University of Tennessee Milan Agricultural

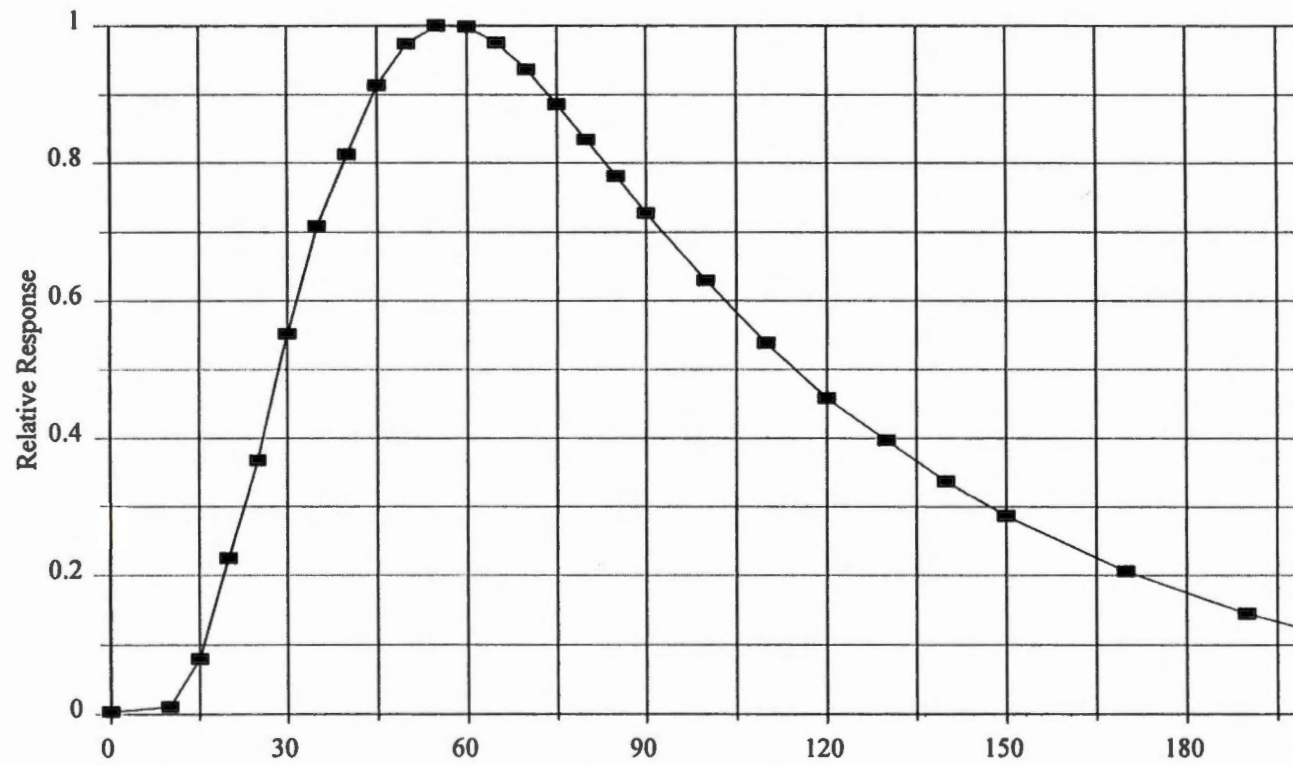


Figure 17. Frequency response of active band pass filter.

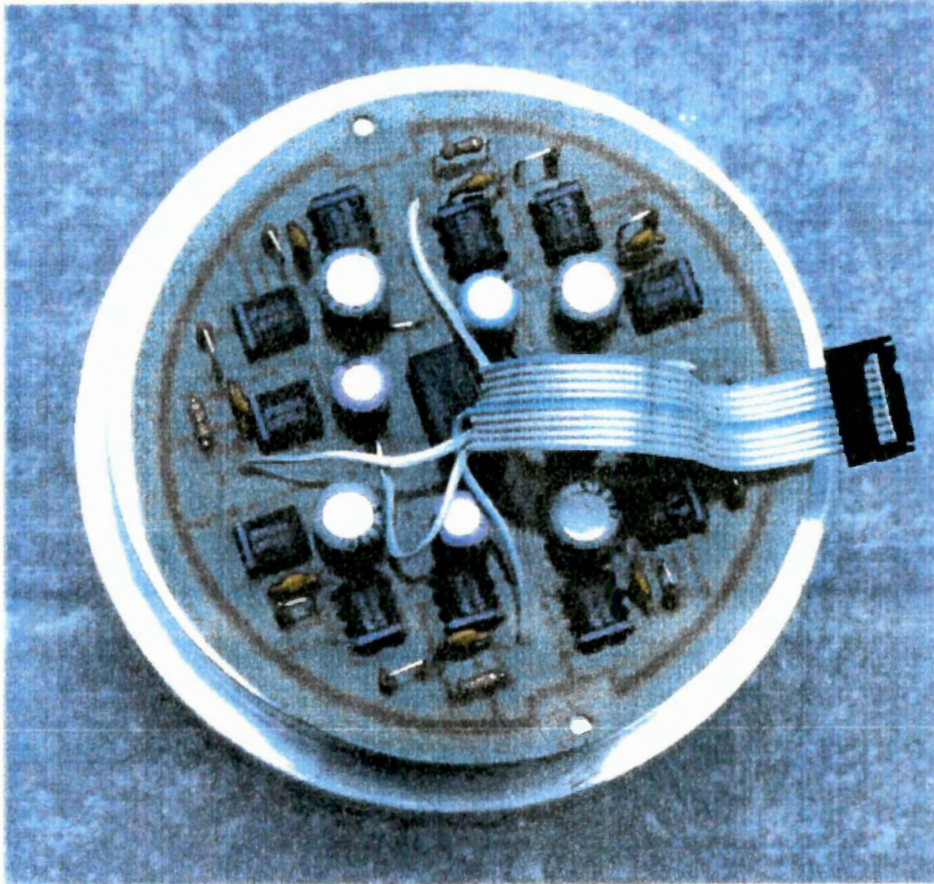


Figure 18. Electronic module of model SL98 plant health sensor.

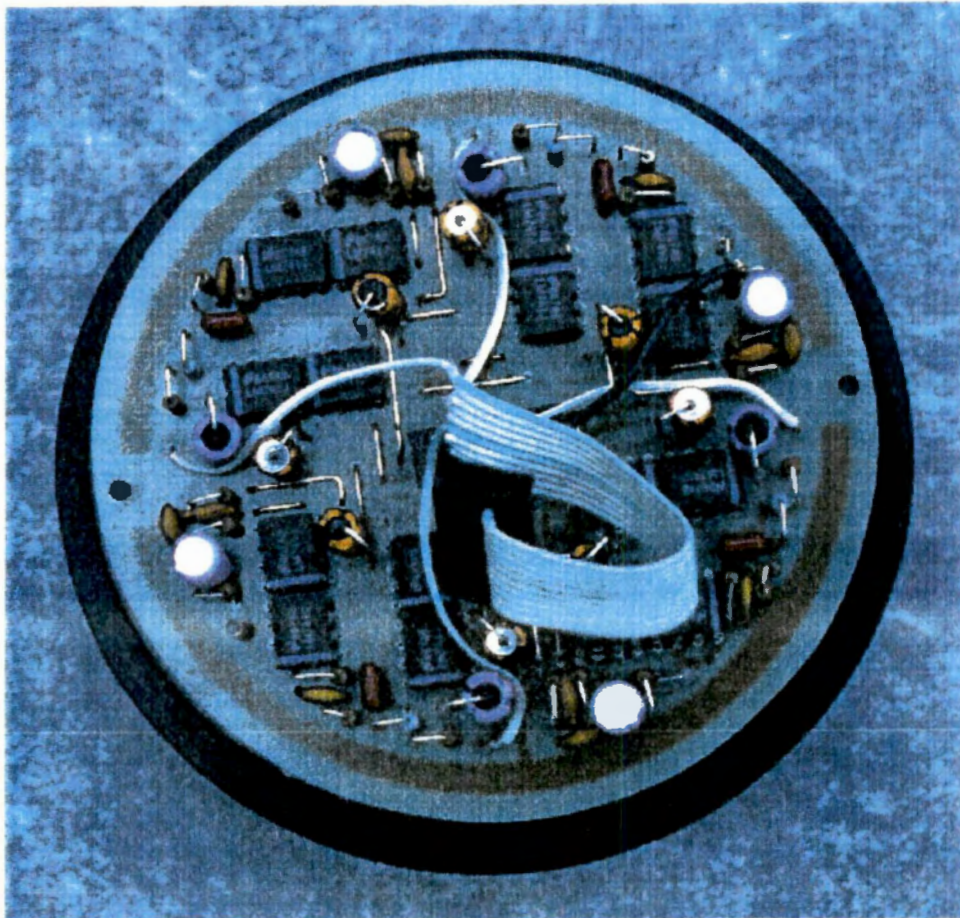


Figure 19. Electronic module of model AL98 plant health sensor.

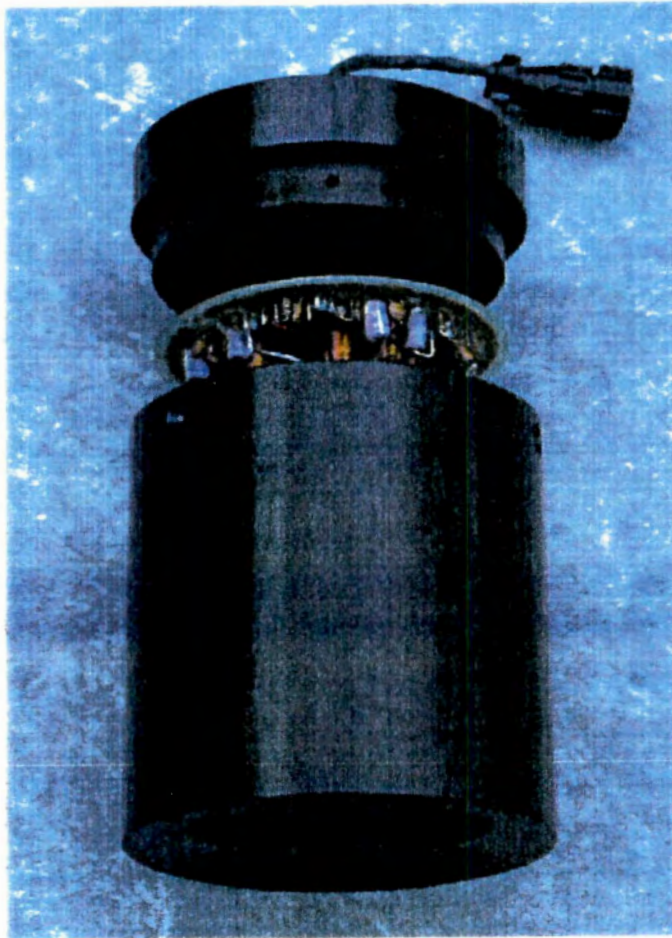


Figure 20. Module connection of plant health sensor.

Experiment Station. Hereafter in this chapter, plant health sensor only refers to the Model AL98 plant health sensor. Equipment used in the testing is shown in Figure 21. The plant health sensor was installed on the front of a hand-push cart and facing toward the cotton plant canopy. Two halogen lights powered by a small AC generator provided modulated illumination for the plant canopy. The incident angle of modulated illumination was adjusted based on plant height and sensor position to maximize reflectance of the incident modulated illumination. The distance between the sensor and the canopy was maintained at approximately 18 inches. Analog outputs of the sensor were collected using a data logger (Campbell 21X) and stored in a laptop computer. The sensor was evaluated under both static and dynamic conditions. For static measurements, the cart was static while collecting data. Five scans were taken at random locations in one row of each plot. For dynamic measurements, the sensor continuously scanned the cotton canopy and the data acquisition system collected and stored data in one-second intervals as the cart was pushed along the row at approximately two miles per hour.

After analyzing the spectral data from the plant health sensor, the following mathematical model was developed for calculating plant health index (PHI).

$$\text{Plant Health Index} = (B + G) / NIR$$

Where

B: Output of blue channel

G: Output of green channel

NIR: Output of near infrared channel

The red channel here was not used in calculating plant health index because it contributed little to explaining plant N content. This could be attributed to the weak



Figure 21. Field evaluation of plant health sensor.

reflectance from the canopy in the red waveband (600-740 nm). The red channel was significant in the spectral index model discussed in Chapter III because the waveband used for that channel was very narrow (600-610 nm) and plant N levels showed up in that narrow wavelength region.

The plant health index model was different from the spectral index model mentioned in Chapter III. The spectral wavelength range for these four channels changed and the spectral response of the photodiode used in the plant health sensor differs from that of the spectrometer. Thus the spectral response of plant health sensor is different from the spectral response of the spectrometer. The spectral index model was developed using the spectral data from the spectrometer. Whereas, data from the plant health sensor were used to develop the plant health index model.

Figure 22 shows the relationship between the PHI and N application rate. Data were taken at mid-pinhead square using the Model AL98 plant health sensor. In this figure each point of PHI is an average of 25 observations (5 replicates per treatment, 5 measurements per replicate). The relationship between PHI and cotton yield is illustrated in Figure 23 (each point represents one replicate). The PHI had a very strong correlation with N application rate ($R^2=0.9975$) and yield ($R^2=0.8153$). Preliminary results suggest that the plant health sensor can be implemented for determining supplemental N needs for cotton.

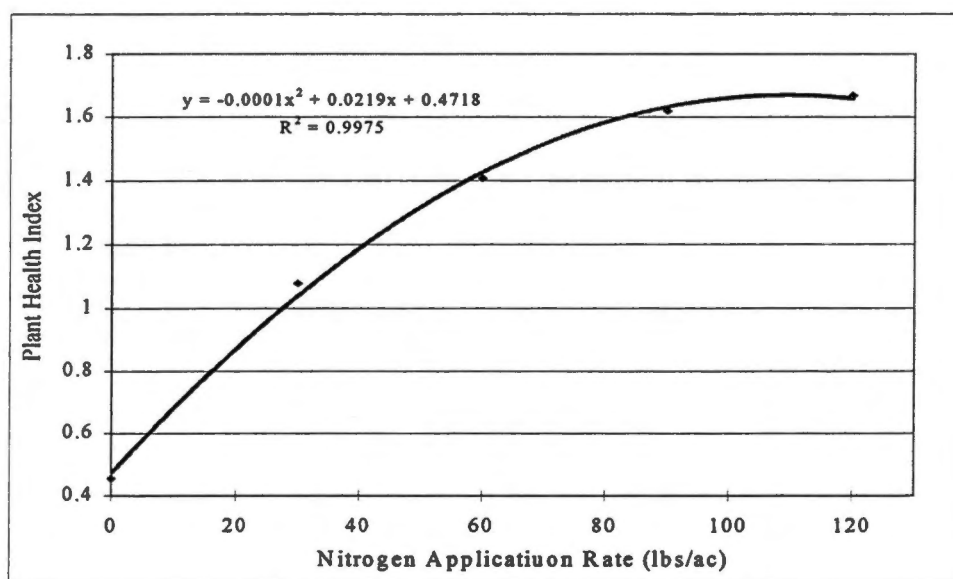


Figure 22. Plant health index measured using Model AL98 plant health sensor as a function of nitrogen application rate at mid-pinhead square in 1998 for variety D&PL 5409.

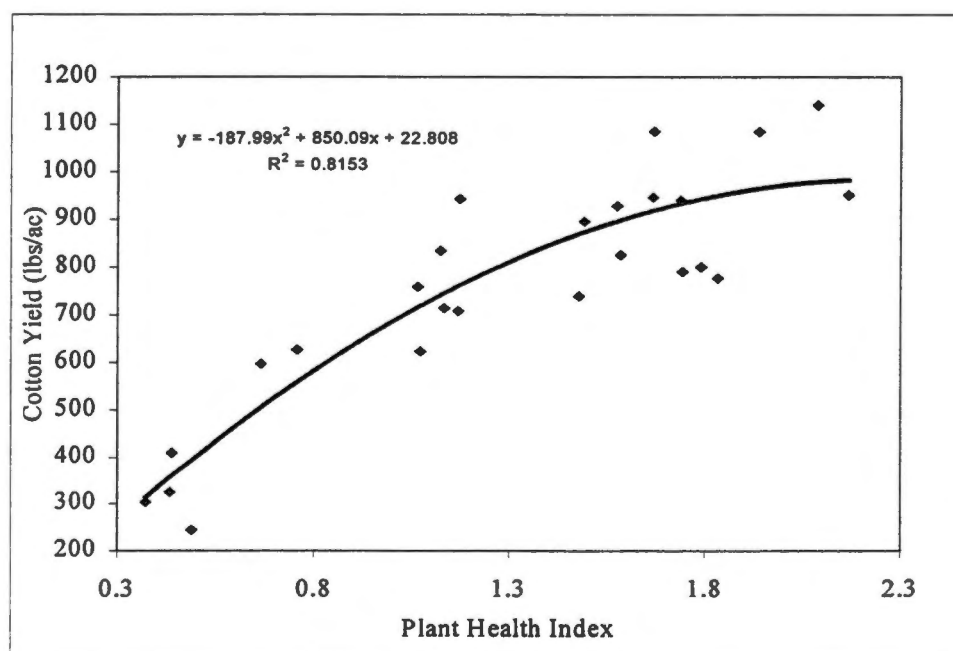


Figure 23. Relationship between cotton yield and plant health index measured using Model AL98 plant health sensor at mid-pinhead square in 1998 for variety D&PL 5409.

CHAPTER V

ARTIFICIAL NEURAL NETWORKS

Neural Network Architecture

Artificial neural networks (ANNs) have become powerful tools for analyzing nonlinear systems using classification and pattern recognition techniques. Even though spectral index was found to have a close relationship with N status in cotton plants, parameters such as cotton varieties and growth stages strongly affected the relationships. Therefore, an ANN method was chosen for determining N status in cotton plants. The ANNs were trained and tested using spectral data collected from the spectrometer discussed in Chapter III.

Architecture and learning algorithms of an ANN are the most important factors in its performance. The architecture of the ANN used in this study is as followings:

- Number of layers: three (input layer, hidden layer, and output layer).
- Number of neurons in the hidden layer: three.
- Type of activation functions: Sigmoid for both hidden layer and output layer.
- Number of inputs: five.
- Number of outputs: two.

The Architecture of the ANN is graphically illustrated in Figure 24. The ANN has five inputs, one for each of the four spectral bands (*blue, green, red, NIR*) plus one input (*time*) to indicate the stage of plant maturity. There are two outputs *nitrogen-deficiency (ND)* and *non-nitrogen-deficiency (NND)*. Plants with a spectral index equal or less than the average spectral index of plants with N application rates of 30 and 60 lbs/ac was

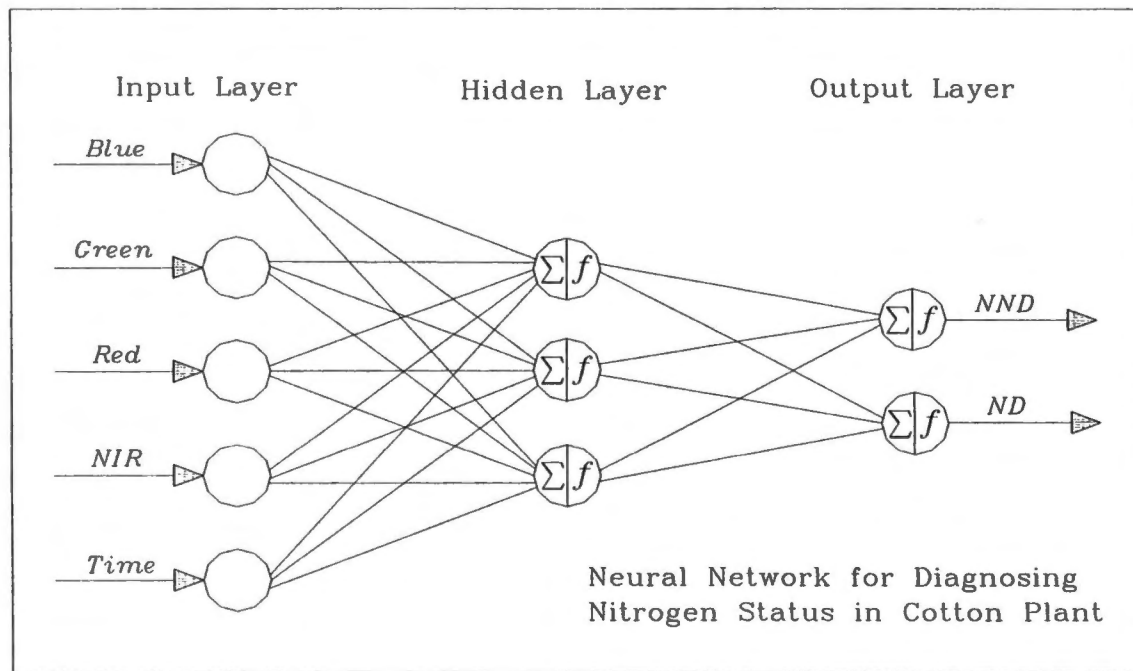


Figure 24. Architecture of artificial neural networks.

considered as *ND*. And plants with a spectral index greater than the average spectral index of the plants with *N* application rates of 30 and 60 lbs/ac were considered as *NND*.

One hidden layer was employed in the ANN. Bounded activation functions such as the logistic function are particularly useful when the target has a bounded range (Sarle, 1997). The target value of the ANN in this study had a known bounded value range from 0 to 1. A logistic sigmoid function $f(x) = 1/(1 + \exp(-\beta x))$ was selected as an activation function for both the hidden layer and output layer of the network, where x is the input to the neuron and $\beta = 1$.

The number of neurons for the network were calculated using the equation

$$\text{Number of Neuron} = \sqrt{\text{Number of Input} * \text{Number of Output}}$$

Based on this formula, three neurons were employed to train the network

$$(\text{Number of Neuron} = \sqrt{5*2} = 3.16).$$

Neural Network Training

MATLAB[®] with the Neural Network Toolbox was used to implement the ANN. This ANN was built as a supervised multilayer feedforward network and trained with a backpropagation algorithm.

The backpropagation algorithm is a training method that uses backpropagation to compute the error gradient for a feedforward network. First, it randomly initializes the weights to small values. It then applies the pattern to the input and calculates the network output. The output is compared with the desired output and the error (difference) is computed. Finally, the error is backpropagated through the network and the weights are adjusted to minimize the error. This learning process is repeated by applying the patterns

to the input and calculating next output of the network until a desired error goal is reached.

The training error goal was calculated using the following formula with an assumption that 90% of the answer given by the network is correct:

$$\begin{aligned} \text{Error_Goal} &= \text{Output} * \text{Pattern} * (10\% * (0.9)^2 + 90\% * (0.1)^2) \\ &= 2 * 471 * (0.1 * 0.81 + 0.9 * 0.01) = 84.8 \end{aligned}$$

Where

Output: number of outputs

Pattern: number of input/output patterns

A training data set and a test data set are required for training and testing ANNs. A training data set is a set of examples used for ANN learning, that is to fit the weights of the ANN model. A test data set is a set of examples used only to assess the performance of a trained ANN model. In this project, the total number of patterns for evaluating the ANNs consisted of 951 field observations. Of the total number of patterns, either 50%, 75%, or 25% of the observations were used for training. The remaining observations were used for testing the ANN. Training data were randomly selected from different plant varieties and growth stages in 1998. The training data, test data, and MATLAB® codes for making the training data set and test data set are presented in Appendix D.

To determine how the growth stage of cotton plants affects the ANN training and performance in N status recognition, the ANNs were also trained and tested only using four spectral inputs without the input parameter of time.

To begin the ANN training process, the training program requires a file name for the training data set, number of neurons used in hidden layer, activation functions for

hidden layer and output layer, error goal, and maximum training epochs. Then, the program starts the training. When the error goal or maximum training epochs is met, the training process stops and a trained ANN model is saved in a file with a user-defined file name.

The ANN training process was repeated until the desired error goal was reached. After each training process, the performance of the trained network was tested using the test data set. The script program for training and testing the ANNs is included in Appendix D.

One example of the trained ANN models for diagnosing the N status is presented below. Matrix W1 is the weights for connections between the input layer and hidden layer. Its five columns represent five neurons in the input layer and three rows represent three neurons in the hidden layer. Matrix W2 is the weights for connections between the hidden layer and output layer. Its three columns stand for the three neurons in the hidden layer and two rows for the two neurons in output layer. Matrix B1 is the biases for the three neurons in the hidden layer and B2 for the two neurons in the output layer.

$$W1 = \begin{bmatrix} -4.5209 & 0.4223 & -0.0636 & -5.1443 & 2.4204 \\ 2.2384 & -6.5817 & -0.7550 & 17.7924 & -10.7728 \\ -47.0288 & -3.6650 & -0.2489 & -4.1771 & -39.9425 \end{bmatrix}$$

$$W2 = \begin{bmatrix} -454.5523 & 424.5411 & 196.5073 \\ 454.5523 & -424.5411 & -196.5073 \end{bmatrix}$$

$$B1 = \begin{bmatrix} 2.9432 \\ 0.3497 \\ -4.2489 \end{bmatrix}$$

$$B2 = \begin{bmatrix} -5.2897 \\ 5.2897 \end{bmatrix}$$

Results of ANN Testing

Generalization of the trained ANNs was evaluated using the test data sets. Test results are summarized in Table 4. ANNs were trained and tested under varying conditions. Under the conditions of 50% data for training and the other 50% for testing, the average diagnosing accuracy rate ranged from 95 to 99% with an average of 96.8%. Even though the training and testing used the data collected in two different growth stages and from two varieties, the diagnosing accuracy was 95%. In general, the more data used for training, the better the ANN model may perform. When only 25% of the total patterns were used for training and 75% for testing, the diagnosing accuracy rate still reached 87% to 92%.

If the ANN-based system did not involve growth stage of the plant, it would be greatly simplified for manufacturing and the end users. The training result shows the ANNs could still perform very well without using the growth stage as one of the ANN's inputs. Under varying training and testing conditions, the diagnosing accuracy rates of the ANNs with only four inputs ranged from 87% to 98% with an average of 93%. Using four spectral inputs, the diagnosing accuracy rate was 94% with 50% data for training and the other 50% for testing. This also included data from two varieties and two growth stages. The diagnosing accuracy rate was 91% using only 25% of total patterns for training with data from different growth stages.

Table 4. Test results of trained artificial neural networks

Cotton Variety	Growth Stage	ANN training and Test Conditions	Diagnosing Accuracy Rate (%)
D&PL 5409	EPS*	50% data for training 50% for test 5 inputs (blue, green, red, NIR , and time)	99
	MPS**	50% data for training 50% for test 5 inputs (blue, green, red, NIR , and time)	96
	EPS & MPS	50% data for training 50% for test 5 inputs (blue, green, red, NIR , and time)	97
Stoneville 474	EPS	50% data for training 50% for test 5 inputs (blue, green, red, NIR , and time)	98
	MPS	50% data for training 50% for test 5 inputs (blue, green, red, NIR , and time)	96
	EPS & MPS	50% data for training 50% for test 5 inputs (blue, green, red, NIR , and time)	97
D&PL 5409 & Stoneville 474	EPS & MPS	50% data for training 50% for test 5 inputs (blue, green, red, NIR , and time)	95
D&PL 5409 & Stoneville 474	EPS & MPS	50% data for training 50% for test 4 inputs (blue, green, red, and NIR)	94
D&PL 5409	EPS	75% data for training 25% for test 4 inputs (blue, green, red, and NIR)	97
	MPS	75% data for training 25% for test 4 inputs (blue, green, red, and NIR)	98
	EPS & MPS	75% data for training 25% for test 4 inputs (blue, green, red, and NIR)	97
Stoneville 474	EPS	75% data for training 25% for test 4 inputs (blue, green, red, and NIR)	95
	MPS	75% data for training 25% for test 4 inputs (blue, green, red, and NIR)	95
	EPS & MPS	75% data for training 25% for test 4 inputs (blue, green, red, and NIR)	95
D&PL 5409 & Stoneville 474	EPS & MPS	75% data for training 25% for test 4 inputs (blue, green, red, and NIR)	94
D&PL 5409	EPS	25% data for training 75% for test 4 inputs (blue, green, red, and NIR)	91
	MPS	25% data for training 75% for test 4 inputs (blue, green, red, and NIR)	91
	EPS & MPS	25% data for training 75% for test 4 inputs (blue, green, red, and NIR)	89
Stoneville 474	EPS	25% data for training 75% for test 4 inputs (blue, green, red, and NIR)	92
	MPS	25% data for training 75% for test 4 inputs (blue, green, red, and NIR)	90
	EPS & MPS	25% data for training 75% for test 4 inputs (blue, green, red, and NIR)	91
D&PL 5409 & Stoneville 474	EPS & MPS	25% data for training 75% for test 4 inputs (blue, green, red, and NIR)	87

* Early-Pinhead Square; ** Mid-Pinhead Square.

CHAPTER VI

SUMMARY AND CONCLUSIONS

Summary

Specific objectives for this study were to identify the relationship between N status in cotton plants and spectral reflectance characteristics of cotton leaves, design and fabricate an optical sensor to detect spectral reflectance of cotton plants, and diagnose the N status using artificial neural networks based upon spectral characteristics of a cotton canopy.

Field experiments were conducted successively for three years (1996, 1997 and 1998) at The University of Tennessee Milan Agricultural Experiment Station. N fertilizer was applied at rates of 0, 30, 60, 90 and 120 lbs per acre in the experimental plot area to generate a range of plant N concentrations and cotton yields.

Reflectance spectra from cotton leaf canopies were measured at growth stages of pinhead square and early bloom. A fiber optic spectrometer was used to make these measurements. The spectrometer was interfaced with a laptop computer to form a data acquisition system. Earliest matured cotton leaves of scanned cotton canopies were randomly collected. Petiole N content of those leaves was chemically analyzed. It was found that useful spectral features of cotton canopies could be extracted in the following spectral wavebands: blue band (460-490 nm), green band (545-565 nm), red band (600-610 nm), and NIR band (740-770 nm). A mathematical model [$spectral\ index = (blue + NIR)/(green + red)$] was developed to calculate a spectral index of the cotton canopy. Results showed that in general spectral index had a good correlation with N status and

yield. Mid-pinhead square, the correct time period to apply supplemental N to the cotton plants that are N deficient, was a growth stage when spectral index showed the best correlation with petiole N content and the yield. Cotton variety and growth stage affected spectral index.

Based on the spectral characteristics of a cotton canopy, two plant health sensors were developed. The first sensor (Model SL98) measured sunlight reflectance from the plant canopy. However, the sunlight spectrum varies with solar angle, atmospheric conditions, etc., thus inducing errors in the remote sensing system. Hence, a second sensor (Model AL98) was designed to measure reflectance of modulated artificial light from the canopy. Both sensors were able to detect the spectral reflectance of a cotton canopy at four wave bands (blue, green, red, and NIR). Spectral bandwidth for each band was 350-500 nm for blue, 520-580 nm for green, 600-740 nm for red, and 750-1100 nm for NIR. Two 75 W halogen lights were employed to provide modulated illumination for the cotton canopy when the spectral reflectance was measured using the Model AL98 plant health sensor.

The Model AL98 plant health sensor was field tested in 1998. Spectral reflectance data from the cotton canopy were measured and analyzed. The plant health index calculated using spectral data from this sensor had a strong correlation with N application rate and cotton yield ($R^2=0.9975$ and 0.8135).

MATLAB[®] with the Neural Network Toolbox was used to implement a neural network. The network was built with three layers. Three neurons were used in the hidden layer. There were five inputs and two outputs in the neural network architecture. Five inputs were spectral reflectances from blue, green, red, and NIR wavebands, and the

growth stage of the plants. Two outputs were N-deficiency and non-N-deficiency. A backpropagation algorithm was selected for ANN training. Logistic sigmoid activation functions were used for both hidden and output layers. Artificial neural networks were trained and tested using 951 spectral data scans. Performance of trained ANN models was tested. Results showed that trained ANNs can diagnose the N status in cotton plants with accuracy greater than 95% when 50% of samples were used for training. An accuracy of 87% was obtained when 25% of total observations were used for training the ANN and 75% for testing, and the parameter growth stage was removed from the inputs.

Conclusions

Based on the results obtained in this study, the following conclusions can be made.

- Cotton leaves with different N concentration levels have different spectral reflectance characteristics.
- The plant health sensor developed in this study can measure the spectral reflectance characteristics of cotton plant canopy from a modulated light source in the presence of sunlight.
- A well-trained artificial neural network model can accurately diagnose the N status in cotton plants for varying growth stages and varieties.
- Application of the plant health sensor with an artificial neural network shows great potential for variable-rate application of N in cotton and possibly for other crop inputs as well.

Suggestions for Future Work

Sensor-based ground remote sensing technology has been an important part of precision agriculture research and is becoming even more important. Results obtained in

this project have proven that a plant health sensor in conjunction with artificial neural networks could be used to realize variable rate application of inputs for crops. However, the sensors and system developed in this study were prototypes. More research work is required before this technique can be put into field use. I hope The University of Tennessee will secure the necessary funding so this project can be continued. When the second generation of the plant health sensor and system is developed, I suggest

- Use modulated LEDs with a frequency around 1 kHz for illuminating plant canopies. Compared with halogen light, LEDs have advantages of low power consumption, small size, and easy modulation at high frequencies.
- Make all channels view the same area of the canopy by adding a field-of-view selector in front of each optical channel.
- Investigate narrowing the spectral band used in each optical channel by using an interference filter in the optical module. This will increase the signal-to-noise ratio by only measuring the light energy at the waveband where the spectral response varies with a parameter interested.
- Establish an ANN-based control system using C/C++. The system should be able to take the outputs from the plant health sensor as its inputs, make a decision based on the inputs through a trained ANN, and output a control signal for variable rate control.

Disclaimer

Mention of a commercial product is solely for the purpose of providing specific information and should not be construed as a product endorsement by the author or The University of Tennessee.

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APPENDICES

Appendix A
Spectral Data of One Canopy Scan Using the Spectrometer
(Ocean Optics, Inc. SD 1000)

Spectral Data of One Canopy Scan
Using the Spectrometer (Ocean Optics, Inc. SD 1000)

<u>Point No.</u>	<u>WL (nm)</u>	<u>Count</u>	<u>Norm. Count</u>	<u>Point No.</u>	<u>WL (nm)</u>	<u>Count</u>	<u>Norm. Count</u>
1	237.14	35.95	0.0820	414	472.41	515.21	1.1750
2	237.74	5.40	0.0123	415	472.95	516.60	1.1782
3	238.33	-2.43	-0.0055	416	473.50	517.77	1.1808
4	238.93	-1.48	-0.0034	417	474.04	520.12	1.1862
5	239.52	1.45	0.0033	418	474.59	521.74	1.1899
6	240.12	-1.48	-0.0034	419	475.13	522.97	1.1927
.	.	.	.	420	475.67	521.60	1.1896
.	.	.	.	421	476.22	521.95	1.1904
.	.	.	.	422	476.76	523.36	1.1936
380	453.84	404.36	0.9222	423	477.30	523.30	1.1934
381	454.39	407.92	0.9303	424	477.84	523.64	1.1942
382	454.94	411.78	0.9391	425	478.39	521.88	1.1902
383	455.48	414.34	0.9449	426	478.93	521.11	1.1884
384	456.03	418.67	0.9548	427	479.47	519.88	1.1856
385	456.58	421.08	0.9603	428	480.01	518.52	1.1825
386	457.13	423.40	0.9656	429	480.56	516.49	1.1779
387	457.68	426.08	0.9717	430	481.10	514.00	1.1722
388	458.22	430.28	0.9813	431	481.64	511.66	1.1669
389	458.77	433.84	0.9894	432	482.18	511.50	1.1665
390	459.32	436.85	0.9963	433	482.72	507.95	1.1584
391	459.86	440.88	1.0055	434	483.27	506.40	1.1549
392	460.41	444.13	1.0129	435	483.81	504.13	1.1497
393	460.96	445.70	1.0165	436	484.35	502.61	1.1463
394	461.50	447.36	1.0203	437	484.89	501.16	1.1429
395	462.05	450.70	1.0279	438	485.43	499.93	1.1401
396	462.60	452.06	1.0310	439	485.97	497.51	1.1346
397	463.14	454.73	1.0371	440	486.51	494.13	1.1269
398	463.69	458.00	1.0445	441	487.05	491.59	1.1211
399	464.24	459.97	1.0490	442	487.59	490.06	1.1176
400	464.78	460.89	1.0511	443	488.14	489.45	1.1162
401	465.33	461.31	1.0521	444	488.68	488.07	1.1131
402	465.87	464.93	1.0603	445	489.22	485.49	1.1072
403	466.42	468.59	1.0687	446	489.76	482.08	1.0994
404	466.96	473.02	1.0788	447	490.30	480.28	1.0953
405	467.51	477.67	1.0894	448	490.84	478.06	1.0903
406	468.05	482.03	1.0993	449	491.38	476.55	1.0868
407	468.60	486.35	1.1092	450	491.92	473.67	1.0802
408	469.14	490.39	1.1184	451	492.45	471.67	1.0757
409	469.69	493.92	1.1264	452	492.99	466.92	1.0649
410	470.23	500.24	1.1408	453	493.53	463.44	1.0569
411	470.78	506.40	1.1549	454	494.07	461.25	1.0519
412	471.32	511.96	1.1676	455	494.61	457.97	1.0444
413	471.87	513.67	1.1715	456	495.15	455.06	1.0378

Spectral Data of One Canopy Scan
Using the Spectrometer (Ocean Optics, Inc. SD 1000)(continued)

<u>Point No.</u>	<u>WL (nm)</u>	<u>Count</u>	<u>Norm. Count</u>	<u>Point No.</u>	<u>WL (nm)</u>	<u>Count</u>	<u>Norm. Count</u>
457	495.69	453.02	1.0332	589	565.72	1164.92	2.6567
.	.	.	.	590	566.24	1153.18	2.6299
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
550	545.25	1126.52	2.5691	.	.	.	.
551	545.78	1135.44	2.5895	655	599.92	547.63	1.2489
552	546.31	1145.49	2.6124	656	600.44	543.02	1.2384
553	546.83	1155.26	2.6347	657	600.95	540.26	1.2321
554	547.36	1164.24	2.6552	658	601.47	538.35	1.2278
555	547.89	1171.17	2.6710	659	601.98	536.80	1.2242
556	548.41	1177.88	2.6863	660	602.49	535.03	1.2202
557	548.94	1185.51	2.7037	661	603.01	533.28	1.2162
558	549.47	1193.86	2.7227	662	603.52	532.47	1.2144
559	549.99	1197.26	2.7305	663	604.03	533.20	1.2160
560	550.52	1206.17	2.7508	664	604.55	531.60	1.2124
561	551.05	1209.72	2.7589	665	605.06	531.26	1.2116
562	551.57	1215.70	2.7725	666	605.57	529.54	1.2077
563	552.10	1219.38	2.7809	667	606.09	527.98	1.2041
564	552.62	1222.68	2.7885	668	606.60	527.74	1.2036
565	553.15	1228.56	2.8019	669	607.11	526.51	1.2008
566	553.67	1234.15	2.8146	670	607.62	525.32	1.1980
567	554.20	1235.81	2.8184	671	608.14	524.83	1.1969
568	554.72	1241.20	2.8307	672	608.65	522.36	1.1913
569	555.25	1244.97	2.8393	673	609.16	522.58	1.1918
570	555.77	1248.06	2.8463	674	609.67	520.97	1.1881
571	556.30	1245.48	2.8404	675	610.18	518.88	1.1834
572	556.82	1249.04	2.8486	676	610.70	517.45	1.1801
573	557.35	1250.06	2.8509	677	611.21	513.56	1.1712
574	557.87	1247.39	2.8448	678	611.72	509.79	1.1626
575	558.39	1246.48	2.8427	.	.	.	.
576	558.92	1243.95	2.8369	.	.	.	.
577	559.44	1237.56	2.8224	.	.	.	.
578	559.97	1233.74	2.8137	937	739.99	971.44	2.2155
579	560.49	1231.97	2.8096	938	740.47	996.40	2.2724
580	561.01	1231.00	2.8074	939	740.95	1019.81	2.3258
581	561.54	1226.09	2.7962	940	741.43	1045.11	2.3835
582	562.06	1221.75	2.7863	941	741.91	1072.23	2.4453
583	562.58	1216.84	2.7751	942	742.38	1100.36	2.5095
584	563.11	1210.71	2.7611	943	742.86	1126.63	2.5694
585	563.63	1205.12	2.7484	944	743.34	1153.56	2.6308
586	564.15	1199.00	2.7344	945	743.82	1180.73	2.6928
587	564.67	1188.97	2.7116	946	744.30	1203.77	2.7453
588	565.20	1175.68	2.6813	947	744.78	1228.62	2.8020

Spectral Data of One Canopy Scan
Using the Spectrometer (Ocean Optics, Inc. SD 1000)(continued)

<u>Point No.</u>	<u>WL (nm)</u>	<u>Count</u>	<u>Norm. Count</u>	<u>Point No.</u>	<u>WL (nm)</u>	<u>Count</u>	<u>Norm. Count</u>
948	745.25	1253.75	2.8593	979	760.01	1510.74	3.4454
949	745.73	1277.69	2.9139	980	760.48	1506.04	3.4347
950	746.21	1297.04	2.9580	981	760.95	1500.33	3.4216
951	746.69	1316.67	3.0028	982	761.43	1495.27	3.4101
952	747.16	1336.36	3.0477	983	761.90	1486.16	3.3893
953	747.64	1352.83	3.0853	984	762.37	1475.36	3.3647
954	748.12	1367.89	3.1196	985	762.85	1462.53	3.3355
955	748.59	1384.02	3.1564	986	763.32	1448.39	3.3032
956	749.07	1400.27	3.1934	987	763.79	1429.05	3.2591
957	749.55	1416.10	3.2296	988	764.27	1404.47	3.2030
958	750.03	1430.82	3.2631	989	764.74	1375.95	3.1380
959	750.50	1445.17	3.2959	990	765.21	1344.68	3.0667
960	750.98	1457.96	3.3250	991	765.69	1305.88	2.9782
961	751.45	1465.02	3.3411	992	766.16	1267.07	2.8897
962	751.93	1476.45	3.3672	993	766.63	1221.31	2.7853
963	752.41	1487.35	3.3921	994	767.10	1175.78	2.6815
964	752.88	1499.29	3.4193	995	767.57	1127.08	2.5704
965	753.36	1507.58	3.4382	996	768.05	1078.89	2.4605
966	753.83	1513.65	3.4520	997	768.52	1030.97	2.3512
967	754.31	1517.20	3.4601	998	768.99	981.52	2.2384
968	754.78	1522.35	3.4719	999	769.46	932.51	2.1267
969	755.26	1525.49	3.4790	1000	769.93	887.61	2.0243
970	755.74	1529.02	3.4871	1001	770.40	846.69	1.9310
971	756.21	1530.66	3.4908	.	.	.	.
972	756.69	1531.00	3.4916	.	.	.	.
973	757.16	1528.83	3.4866	.	.	.	.
974	757.63	1526.89	3.4822	1096	814.61	-145.23	-0.3312
975	758.11	1526.03	3.4803	1097	815.07	-150.80	-0.3439
976	758.58	1523.88	3.4754	1098	815.53	-145.60	-0.3321
977	759.06	1518.78	3.4637	1099	815.99	-148.05	-0.3377
978	759.53	1513.43	3.4515	1100	816.45	-146.10	-0.3332

Appendix B
Computer Codes for Spectral Data Analysis

QuickBASIC codes for making data file for SAS®

```
ON ERROR GOTO 1000
CLS
5 INPUT "ENTER OUTPUT FILE NAME FOR SAS"; F2$
10 FOR A = 1 TO 4
15 FOR L = 5 TO 7
20 FOR T = 1 TO 5
25 FOR R = 1 TO 5
30 FOR S = 2 TO 11
35 F$ = "D:\SUISUI-97-" + LTRIM$(STR$(A)) + "\" +
      LTRIM$(STR$(A)) + LTRIM$(STR$(L)) + "ND" + LTRIM$(STR$(T)) +
      LTRIM$(STR$(R)) + LTRIM$(STR$(S))
40 OPEN F$ + ".SSM" FOR INPUT AS #2
   IF A = 1 THEN D$ = "07/01/97"
   IF A = 2 THEN D$ = "07/08/97"
   IF A = 3 THEN D$ = "07/15/97"
   IF A = 4 THEN D$ = "07/22/97"
45 LOC$ = MID$(F$, 18, 1)
50 IF LOC$ = "1" THEN
   LOC$ = "N29"
   V$ = "DPL20"
   END IF
55 IF LOC$ = "5" THEN
   LOC$ = "N10A"
   V$ = "DPL50"
   END IF
60 IF LOC$ = "6" THEN
   LOC$ = "N10B"
   V$ = "STVL132"
   END IF
65 IF LOC$ = "7" THEN
   LOC$ = "N10C"
   V$ = "S.G.125"
   END IF
70 IF LOC$ = "N29" THEN
75   TREAT$ = MID$(F$, 21, 1)
80 IF TREAT$ = "1" THEN TREAT$ = "0 "
   IF TREAT$ = "2" THEN TREAT$ = "30 "
   IF TREAT$ = "3" THEN TREAT$ = "60 "
   IF TREAT$ = "4" THEN TREAT$ = "90 "
   IF TREAT$ = "5" THEN TREAT$ = "120"
   END IF
85 IF (LOC$="N10A")OR(LOC$="N10B")OR(LOC$="N10C")THEN
   TREAT$ = MID$(F$, 21, 1)
90 IF TREAT$ = "1" THEN TREAT$ = "0"
   IF TREAT$ = "2" THEN TREAT$ = "15"
   IF TREAT$ = "3" THEN TREAT$ = "30"
   IF TREAT$ = "4" THEN TREAT$ = "60"
   IF TREAT$ = "5" THEN TREAT$ = "90"
   END IF
```

QuickBASIC codes for making data file for SAS®(continued)

```
95  REP$ = MID$(F$, 22, 1)
100 SAMPLE$ = MID$(F$, 23, 2)
105 OPEN F2$ + ".SAS" FOR APPEND AS #1
    PRINT F$, D$, V$, LOC$, TREAT$;
    PRINT #1, F$, " "; D$, " "; V$, " "; LOC$, " ";
    TREAT$, " ";
110 DO UNTIL EOF(2)
115 INPUT #2, L1, C1, L2, C2
    PRINT USING "#####.##"; C1;
120 PRINT #1, USING "#####.##"; C1;
125 LOOP
130 PRINT #1, ""
    PRINT ""
    CLOSE
    NEXT
    NEXT
    NEXT
    NEXT
    NEXT
135 INPUT "PRESS 'C' TO CONTINUE"; X$
140 IF X$ = "C" OR X$ = "c" THEN GOTO 25
150 END

1000  CLS
1005  PRINT "FILE DOES NOT EXIST"
1010  GOTO 25
```

SAS® codes for developing spectral index model

/* This code is used to find which parameters have significant relationship with the K application rate in this case. It can help in developing a model to calculate the spectral index.

*/

```
data all; infile 'd:\sui\dataames.sas' lrecl=8000;
  input file$24. time mmddyy8. variety$ location$
        Krate spec1 - spec1040;
```

```
  fgroup=substr(file,1,21);
  rep=substr(file,22,2);
  format time mmddyy8. ;
run;
```

```
data one; set all;
  total = sum(of spec1 - spec1040);
  array sss spec1 - spec1040;
  array nnn norm1 - norm1040;
  do over sss;
    nnn = (sss / (total/10000));
end;
```

```
  drop spec1-spec1040;
  if variety='DPL20';
  blue = sum(of norm391-norm447);
  green = sum(of norm550-norm588);
  red= sum(of norm655-norm675);
  nir = sum(of norm937-norm1001);
  index = (blue+nir)/(green+red);
run;
```

```
proc sort; by variety time;
  proc corr; by variety time;
    var blue green red nir index Krate;
run;
```

```
proc reg;
  model Krate = blue green red nir/selection=forward;
  model Krate = blue green red nir/selection=backward;
  model Krate = blue green red nir/selection=stepwise;
  model Krate = blue green red nir/selection=rsquare;
  model Krate = blue green red nir/selection=cp;
run;
```

SAS® codes for calculating spectral index

/* this code is used to analyze the spectral data from the Field N29, Milan Experimental Station in 1998. The cotton variety is D&PL 5409.

*/

```
data all; infile 'd:\users\sui\data98.sas' lrecl=8000;
  input file$28. time mmddyy8.
        variety$ location$
        nrate spec1 - spec1040;
  fgroup=substr(file,1,25);
  rep=substr(file,26,2);
  format time mmddyy8. ;
run;
```

```
data one; set all;
  total = sum(of spec1 - spec1040);
  array sss spec1 - spec1040;
  array nnn norm1 - norm1040;
  do over sss;
    nnn = (sss / (total/10000));
  end;
```

```
drop spec1-spec1040;
```

```
if variety='DPL5409';
blue = sum(of norm391-norm447);
green = sum(of norm550-norm588);
red = sum(of norm655-norm675);
nir = sum(of norm937-norm1001);
index = (blue + nir)/(green + red);
run;
```

```
proc print data = one;
  var file time variety location nrate blue green red nir index;
run;
```

```
proc sort; by variety time;
proc corr; by variety time;
  var blue green red nir index nrate;
run;
```

```
proc reg;
  model blue = nrate;
  model green = nrate;
  model red = nrate;
```

SAS® codes for calculating spectral index (continued)

```
model nir = nrate;  
model index = nrate;  
run;  
  
proc plot;  
plot index*nrate = "*";  
run;  
  
proc sort; by fgroup;  
proc means noprint; by fgroup;  
var index blue green red nir;  
output out=mmm mean=index blue green red nir;  
run;  
  
proc print;  
run;
```

SAS® Codes for calculating NDVI

```
/* this code is used to analyze the spectral data  
and calculate NDVI (normalized difference vegetation index)  
*/
```

```
data all; infile 'd:\users\sui\ruixiu1\data97b.sas' lrecl=8000;  
input file$25. time mmddyy8 variety$ location$  
       nrate spec1 - spec1040;  
fgroup=substr(file,1,22);  
rep=substr(file,23,2);  
format time mmddyy8. ;  
run;
```

```
data one; set all;  
total = sum(of spec1 - spec1040);  
array sss spec1 - spec1040;  
array nnn norm1 - norm1040;  
do over sss;  
    nnn = (sss / (total/10000));  
end;
```

```
drop spec1-spec1040;
```

```
if variety='DPL20';
```

```
red = sum(of norm655-norm675);  
nir = sum(of norm937-norm1001);  
NDVI = (nir - red)/(nir + red);  
run;
```

```
proc print data = one;  
var file time variety location nrate red nir NDVI;  
run;
```

```
proc sort; by variety time;  
proc corr; by variety time;  
var red nir nrate NDVI;  
run;
```

```
proc reg;  
model red = nrate;  
model nir = nrate;  
model NDVI = nrate;  
run;
```

SAS® Codes for calculating NDVI (continued)

```
proc plot;  
plot NDVI*nrate = "*";  
run;
```

```
proc sort; by fgroup;  
proc means noprint; by fgroup;  
var NDVI;  
output out=mmm mean=MNDVI;  
run;
```

```
proc print;  
run;
```

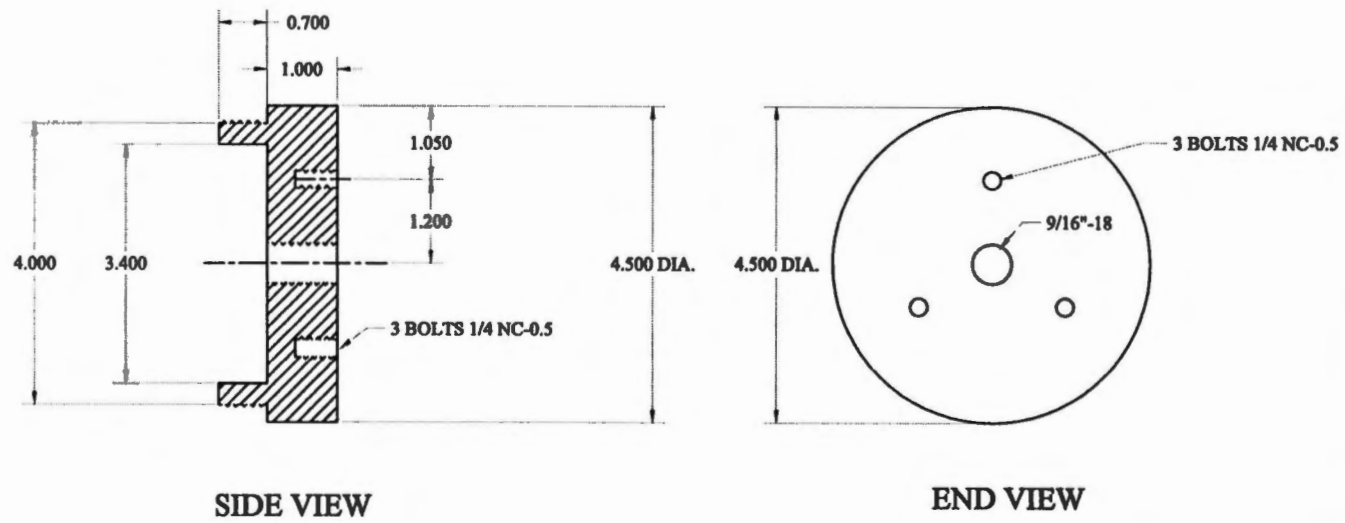
Appendix C
Sensor Drawings and Electronic Component Tables

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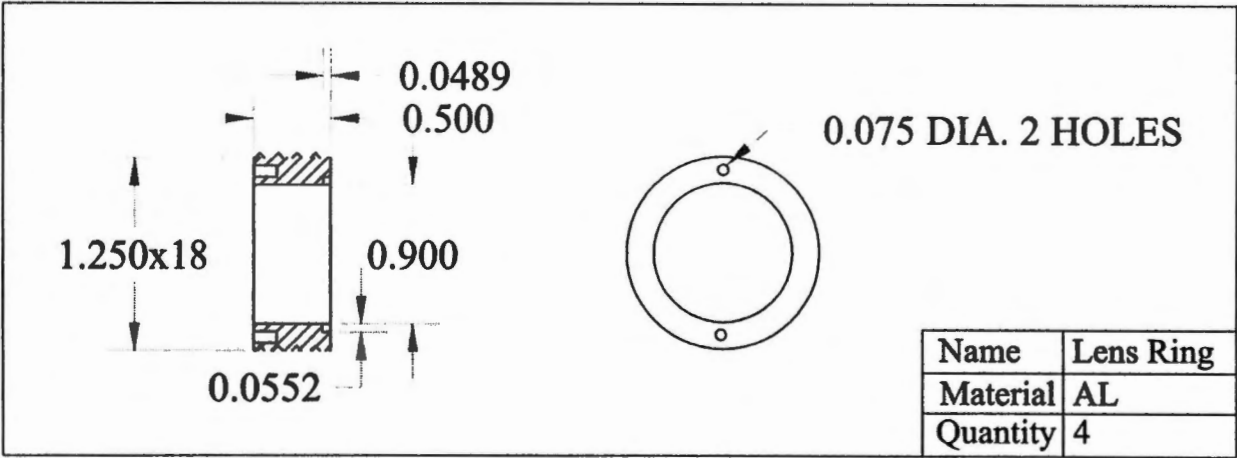
Name	Sensor Body
Material	AL
Quantity	4

Drawing of sensor housing cap

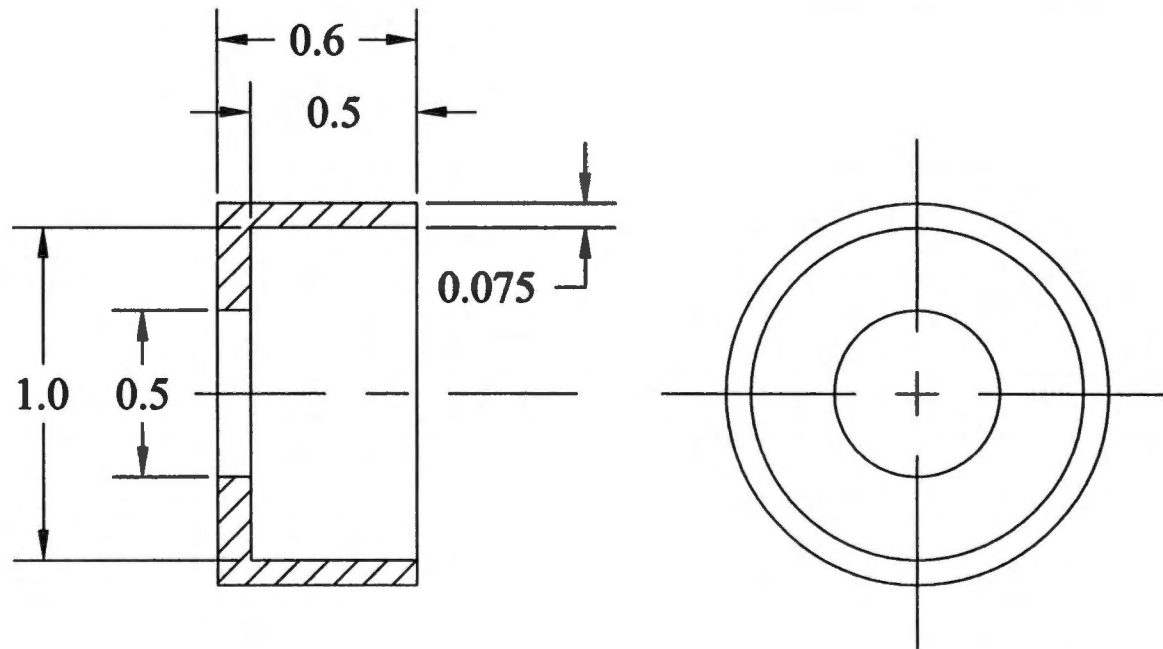


Name	Sensor Housing Cap
Material	AL
Quantity	1

Drawing of lens ring

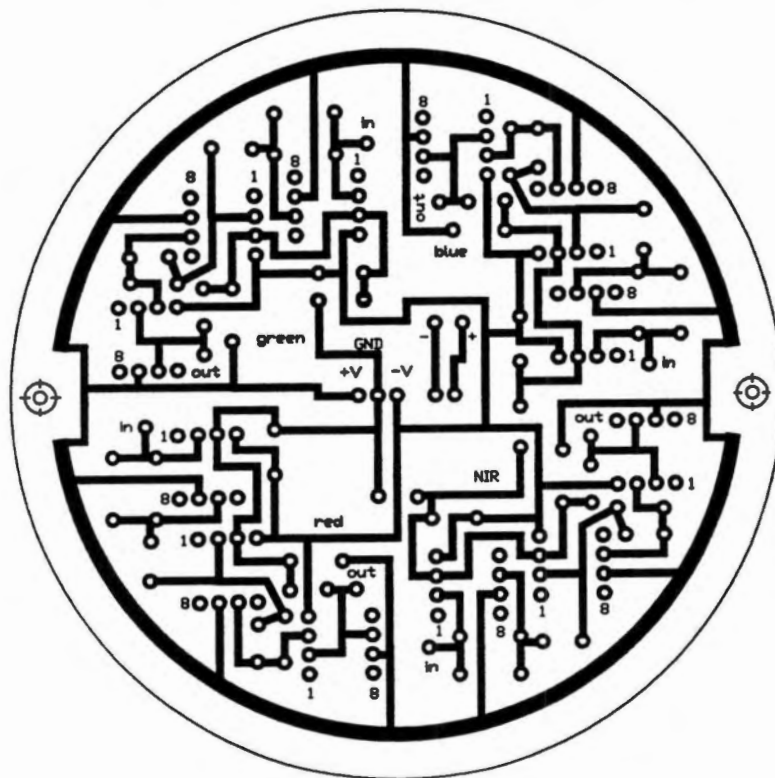


Drawing of the optical case

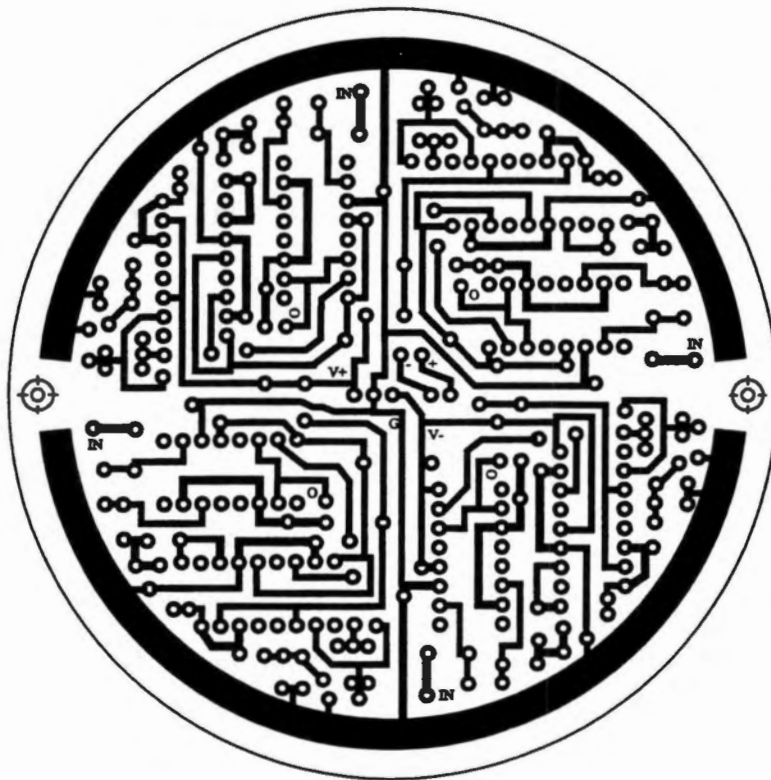


Name	Optical Case
Material	Grey Plastic
Quantity	4

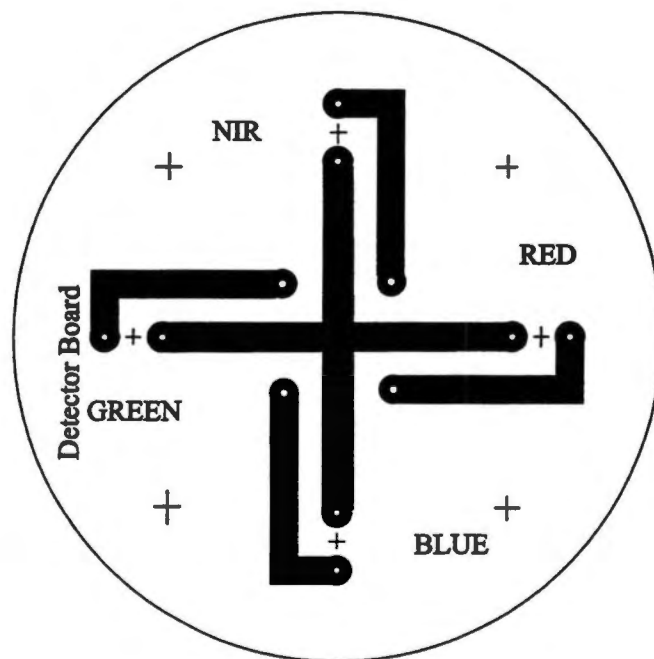
Circuit board for model SL98 plant health sensor



Circuit board of model AL98 plant health sensor



Circuit board for optical module



Electronic component table for model SL98 plant health sensor

Name	Symbol	Parameter	Name	Symbol	Parameter
photodiode	D1	S2386-8k (HAMAMATSU)	photodiode	D3	S2386-8k (HAMAMATSU)
photodiode	D2	S2386-8k (HAMAMATSU)	photodiode	D4	S2386-8k (HAMAMATSU)
resistor	R1	18k	resistor	R9	5.6k
resistor	R2	adjustable(3.3k)	resistor	R10	adjustable(1k)
capacitor	C1	100p	capacitor	C9	100p
capacitor	C2	33 μ F	capacitor	C10	33 μ F
Op-amplifier	IC1	LM741J	Op-amplifier	IC7	LM741J
resistor	R3	3k	resistor	R11	3k
resistor	R4	30k	resistor	R12	30k
capacitor	C3	100p	capacitor	C11	100p
Op-amplifier	IC2	LM741J	Op-amplifier	IC8	LM741J
capacitor	C4	33 μ F	capacitor	C12	33 μ F
Op-amplifier	IC3	LM741J	Op-amplifier	IC9	LM741J
resistor	R5	13k	resistor	R13	1.3k
resistor	R6	adjustable(3.3k)	resistor	R14	adjustable(1k)
capacitor	C5	100p	capacitor	C13	100p
capacitor	C6	33 μ F	capacitor	C14	33 μ F
Op-amplifier	IC4	LM741J	Op-amplifier	IC10	LM741J
resistor	R7	3k	resistor	R15	3k
resistor	R8	27k	resistor	R16	27k
capacitor	C7	100p	capacitor	C15	100p
Op-amplifier	IC5	LM741J	Op-amplifier	IC11	LM741J
capacitor	C8	33 μ F	capacitor	C16	33 μ F
Op-amplifier	IC6	LM741J	Op-amplifier	IC12	LM741J
DC-DC converter	IC13	NMH1212S 12V to $\pm$ 12V	Note: Tolerance for Resistors < 5%; Tolerance for Capacitors < 5%.		

Electronic component table for model AL98 plant health sensor

Name	Symbol	Parameter	Name	Symbol	Parameter
photodiode	D1	S2386-8k (HAMAMATSU)	photodiode	D5	S2386-8k (HAMAMATSU)
photodiode	D3	S2386-8k (HAMAMATSU)	photodiode	D7	S2386-8k (HAMAMATSU)
resistor	R1	560k	resistor	R15	560k
capacitor	C1	33 μ F	capacitor	C17	33 μ F
capacitor	C2	47 μ F	capacitor	C18	47 μ F
Op-amplifier	IC1	LM741	Op-amplifier	IC9	LM741
resistor	R2*	100k	resistor	R16*	100k
resistor	R3*	110k	resistor	R17*	110k
resistor	R4*	110k	resistor	R18*	110k
capacitor	C3**	0.022 μ F	capacitor	C19**	0.022 μ F
capacitor	C4**	0.068 μ F	capacitor	C20**	0.068 μ F
capacitor	C5	47 μ F	capacitor	C21	47 μ F
Op-amplifier	IC2	LM741	Op-amplifier	IC10	LM741
diode	D2	Ge diode (SK3088)	diode	D6	Ge diode (SK3088)
capacitor	C6	100 μ F	capacitor	C22	100 μ F
resistor	R5	200k	resistor	R19	200k
resistor	R6	10k	resistor	R20	10k
resistor	R7	230k	resistor	R21	62k
capacitor	C7	100p	capacitor	C23	100p
capacitor	C8	4700p	capacitor	C24	4700p
Op-amplifier	IC3	LM741	Op-amplifier	IC11	LM741
Op-amplifier	IC4	LM741	Op-amplifier	IC12	LM741
resistor	R8	560k	resistor	R22	560k
capacitor	C9	33 μ F	capacitor	C25	33 μ F
capacitor	C10	47 μ F	capacitor	C26	47 μ F
Op-amplifier	IC5	LM741	Op-amplifier	IC13	LM741
resistor	R9*	100k	resistor	R23*	100k
resistor	R10*	110k	resistor	R24*	110k
resistor	R11*	110k	resistor	R25*	110k
capacitor	C11**	0.022 μ F	capacitor	C27**	0.022 μ F
capacitor	C12**	0.068 μ F	capacitor	C28**	0.068 μ F
capacitor	C13	47 μ F	capacitor	C29	47 μ F
Op-amplifier	IC6	LM741	Op-amplifier	IC14	LM741
diode	D4	Ge diode (SK3088)	diode	D8	Ge diode (SK3088)
capacitor	C14	100 μ F	capacitor	C30	100 μ F
resistor	R12	200k	resistor	R26	200k
resistor	R13	10k	resistor	R27	10k
resistor	R14	230k	resistor	R28	9.1k
capacitor	C15	100p	capacitor	C31	100p
capacitor	C16	4700p	capacitor	C32	4700p
Op-amplifier	IC7	LM741	Op-amplifier	IC15	LM741
Op-amplifier	IC8	LM741	Op-amplifier	IC16	LM741
DC-DC converter	IC17	NMH1212S 12V to $\pm$ 12V	Note: * Accuracy: 1% ** Accuracy: <2%		

Appendix D
Computer Codes for ANN Training and Test
and
ANN Training and Test Data

MATLAB® codes for making training data set

```

%%%%%%%%%%
%
%                               TRAINING DATA
%                               (December 18, 1998)
%
% This code is used for creating a data file to train an ANN
% The data were from varieties D&PL 5409 and STONEVILLE 474, Milan,1998.
%
% x: input patterns. Each row is one pattern. Each column is one parameter
% The 1st column of x: Light Reflectance Intensity in 460--490 nm (BLUE)
% The 2nd column of x: Light Reflectance Intensity in 545--565 nm (GREEN)
% The 3rd column of x: Light Reflectance Intensity in 600--610 nm (RED)
% The 4th column of x: Light Reflectance Intensity in 740--770 nm (NIR)
% The 5th column of x: Days after planting
%
% y: Outputs. Each row is one pattern corresponding to the input pattern x
%       with the same row number.
%
% There are two outputs:
% 0 1: Nitrogen status is low (spectral index is equal or less than the average
%       spectral index of the plants with N application rates of 30 and 60 lbs/ac ).
% 1 0: Nitrogen status is normal (spectral index is greater than the average
%       spectral index of the plants with N application rates of 30 and 60 lbs/ac ).
%
%%%%%%%%%%

% input patterns

x=[
633    955    341    1220    56
627    1043   310    1464    56
617    1033   323    1371    56
606    961    317    1450    56
666    936    337    1214    56
668    851    364    1052    56
564    1016   315    1580    56
634    941    341    1290    56
669    893    360    1126    56
667    936    348    1193    56
587    986    320    1507    56
618    903    340    1313    56
620    1049   303    1525    56
574    1033   300    1673    56

```

```

664    955    347    1197  56
596    971    329    1465  56
675    999    298    1496  56
.      .      .      .      .
.      .      .      .      .
.      .      .      .      .
];

```

% desired outputs

```
y=[  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
0      1  
1      0  
0      1  
0      1  
0      1  
.      .  
.      .  
.      .  
];
```

```
% save the training data in a file named trdata98.
```

```
save trdata98 x y;
```

end

MATLAB® codes for making test data set

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%                               Test Data Set
%                               December, 18, 1998
% This code is used for creating a data file for testing an ANN model.
% Data are from varieties D&PL5409 and STONEVILLE 474, Milan, N29, 1998
%
% x: input patterns. Each row is one pattern. Each column is one parameter.
% The 1st column of x: Light Reflectance Intensity in 460--490 nm (BLUE).
% The 2nd column of x: Light Reflectance Intensity in 545--565 nm (GREEN).
% The 3rd column of x: Light Reflectance Intensity in 600--610 nm (red).
% The 4th column of x: Light Reflectance Intensity in 740--770 nm (NIR).
% The 5th column of x: Number of Days after Planting the Cotton.
%
% y: Outputs
% Each row is one pattern corresponding to the input pattern x with the same row
% number.
%
% There are two outputs:
% 0 1: Nitrogen status is low (spectral index is equal or less than the average spectral
%     index of the plants with N application rates of 30 and 60 lbs/ac).
% 1 0: Nitrogen status is normal (spectral index is greater than the average spectral
%     index of the plants with N application rates of 30 and 60 lbs/ac).
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

% Input patterns

```

x=[
656   937   321  1361   56
677   903   340  1184   56
630   949   323  1360   56
624   943   340  1236   56
555  1077   317  1538   56
598  1039   307  1529   56
620  1009   341  1300   56
607   954   321  1445   56
645   961   326  1399   56
664   935   338  1243   56
627  1080   303  1517   56
588  1031   316  1525   56
558   992   315  1636   56

```

MATLAB® codes for making test data set (continued)

```
656    1012    321    1379    56
552    982    328    1556    56
.      .      .      .      .
.      .      .      .      .
.      .      .      .      .
]
```

% Desired outputs

```
y=[
0      1
0      1
0      1
0      1
0      1
0      1
0      1
0      1
0      1
0      1
0      1
0      1
0      1
0      1
1      0
0      1
0      1
.      .
.      .
.      .
]
```

% save the test data in a file name 'tedata98'.

save tedata98 x y;

end

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>
1	632.64	954.70	340.76	1220.44	56	0 1
2	627.46	1043.01	310.28	1463.67	56	0 1
3	616.66	1033.34	323.16	1371.17	56	0 1
4	606.17	960.91	316.96	1450.04	56	0 1
5	665.60	935.62	337.12	1213.76	56	0 1
6	668.39	851.13	364.15	1052.28	56	0 1
7	564.41	1015.59	315.27	1580.35	56	0 1
8	633.97	941.36	341.47	1289.50	56	0 1
9	668.99	892.59	359.85	1125.98	56	0 1
10	666.71	935.61	347.51	1193.07	56	0 1
11	587.35	985.53	319.98	1506.61	56	0 1
12	618.38	902.52	339.82	1312.96	56	0 1
13	620.18	1049.10	303.43	1525.33	56	0 1
14	573.51	1033.37	300.17	1673.04	56	1 0
15	664.24	954.71	346.81	1197.48	56	0 1
16	596.34	970.78	329.39	1465.03	56	0 1
17	674.71	998.88	298.24	1496.24	56	0 1
18	628.59	969.78	320.14	1439.90	56	0 1
19	642.78	933.45	361.63	1154.50	56	0 1
20	648.19	1003.23	306.63	1463.08	56	0 1
21	625.47	1069.89	327.63	1365.49	56	0 1
22	608.16	948.71	328.42	1442.04	56	0 1
23	637.61	970.15	333.22	1329.55	56	0 1
24	657.78	1040.48	297.42	1496.56	56	0 1
25	701.89	1004.74	295.08	1419.00	56	0 1
26	666.32	953.65	339.47	1207.86	56	0 1
27	631.25	979.84	318.90	1351.38	56	0 1
28	573.45	1019.90	294.66	1669.23	56	1 0
29	660.22	1051.55	303.34	1458.82	56	0 1
30	558.36	956.73	301.20	1719.60	56	1 0
31	636.14	971.32	267.57	1696.20	56	1 0
32	767.15	1017.99	293.06	1268.25	56	0 1
33	611.58	1004.13	303.12	1578.93	56	1 0
34	622.53	980.32	284.51	1706.19	56	1 0
35	651.15	1047.17	306.97	1435.54	56	0 1
36	673.59	1008.06	290.69	1519.18	56	1 0
37	659.31	1027.38	305.92	1459.19	56	0 1
38	609.79	1037.85	296.79	1661.00	56	1 0
39	536.31	979.42	287.62	1863.71	56	1 0
40	646.09	1010.14	283.88	1630.98	56	1 0
41	565.98	1025.51	297.09	1702.22	56	1 0
42	660.44	985.31	287.22	1628.58	56	1 0
43	657.49	1035.96	305.98	1489.81	56	0 1
44	747.36	996.49	313.35	1283.22	56	0 1
45	687.38	1023.49	301.60	1428.01	56	0 1

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
46	666.50	1023.80	308.42	1462.01	56	0	1
47	650.31	1039.51	309.03	1490.18	56	0	1
48	518.17	971.55	298.63	1755.92	56	1	0
49	575.15	1088.21	296.73	1624.16	56	0	1
50	676.31	1013.63	295.99	1460.08	56	0	1
51	619.72	1012.85	323.89	1367.02	56	0	1
52	728.18	981.72	291.18	1404.21	56	1	0
53	586.43	1000.55	309.76	1589.51	56	0	1
54	533.74	971.75	303.20	1744.70	56	1	0
55	602.20	1065.66	302.61	1535.78	56	0	1
56	687.69	1014.89	284.16	1503.12	56	1	0
57	642.32	1030.72	279.51	1656.18	56	1	0
58	738.89	995.36	290.05	1374.59	56	0	1
59	610.65	1058.92	301.01	1532.21	56	0	1
60	582.72	1005.39	295.25	1733.58	56	1	0
61	630.17	886.26	330.55	1405.98	56	1	0
62	549.93	972.70	292.12	1771.84	56	1	0
63	634.89	1018.36	293.07	1661.98	56	1	0
64	621.62	1019.18	296.56	1653.07	56	1	0
65	579.01	1011.52	303.77	1627.51	56	1	0
66	668.14	1050.03	301.46	1462.68	56	0	1
67	714.54	982.24	291.52	1472.29	56	1	0
68	611.08	970.03	314.67	1531.60	56	1	0
69	629.12	1036.26	310.51	1518.44	56	0	1
70	568.30	937.80	276.80	1752.64	56	1	0
71	702.46	1012.90	277.83	1495.25	56	1	0
72	629.07	1009.12	285.53	1627.33	56	1	0
73	508.08	955.97	282.82	1919.32	56	1	0
74	615.57	1000.67	303.44	1537.65	56	0	1
75	609.25	1041.81	282.04	1681.18	56	1	0
76	729.20	980.01	286.36	1420.72	56	1	0
77	544.16	1052.98	280.49	1794.99	56	1	0
78	690.45	1034.30	292.82	1451.17	56	0	1
79	570.58	1002.13	302.65	1667.57	56	1	0
80	599.77	952.03	324.93	1484.94	56	0	1
81	565.31	970.05	295.36	1756.95	56	1	0
82	454.73	967.40	279.69	2057.41	56	1	0
83	727.00	986.00	285.95	1437.67	56	1	0
84	519.76	898.54	279.92	1977.11	56	1	0
85	659.34	998.98	297.87	1517.17	56	1	0
86	647.06	911.02	337.42	1289.07	56	0	1
87	662.58	1043.53	309.28	1464.50	56	0	1
88	598.75	1068.86	300.48	1611.92	56	0	1
89	636.34	1045.12	298.49	1545.90	56	0	1
90	689.39	1022.88	301.76	1424.71	56	0	1

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
91	683.23	1027.85	296.06	1527.89	56	1	0
92	706.47	978.21	297.90	1434.45	56	1	0
93	635.67	936.88	277.70	1696.63	56	1	0
94	597.21	1031.11	281.17	1662.95	56	1	0
95	582.45	1006.48	291.48	1629.50	56	1	0
96	655.55	974.25	291.77	1566.06	56	1	0
97	636.54	1040.07	304.17	1476.68	56	0	1
98	671.48	991.08	286.03	1571.90	56	1	0
99	520.03	962.07	264.02	2043.07	56	1	0
100	559.03	1072.72	290.93	1694.77	56	0	1
101	510.62	1039.90	274.23	1941.16	56	1	0
102	621.08	1061.16	300.15	1560.40	56	0	1
103	623.51	1001.56	281.58	1715.81	56	1	0
104	602.80	1062.66	310.67	1554.84	56	0	1
105	557.92	963.33	281.00	1866.96	56	1	0
106	659.89	1046.20	295.77	1512.52	56	0	1
107	645.90	973.65	307.14	1547.17	56	1	0
108	689.09	1025.17	313.36	1390.40	56	1	0
109	594.77	1011.20	284.07	1781.41	56	1	0
110	503.20	979.86	266.95	2101.26	56	1	0
111	562.36	968.71	309.76	1664.95	56	1	0
112	728.33	1001.85	288.41	1488.93	56	1	0
113	749.73	998.19	299.68	1446.68	56	1	0
114	598.24	1046.53	296.98	1657.08	56	1	0
115	612.18	1087.94	304.38	1543.23	56	0	1
116	722.46	988.89	293.37	1442.39	56	1	0
117	653.29	1128.31	277.96	1816.33	70	0	1
118	663.70	1120.96	299.52	1685.59	70	0	1
119	657.57	1098.92	300.75	1745.12	70	0	1
120	651.96	1119.67	294.52	1748.53	70	0	1
121	702.81	1109.59	304.59	1566.61	70	0	1
122	641.90	1105.82	300.09	1735.58	70	0	1
123	653.29	1096.26	288.08	1811.04	70	0	1
124	616.97	1063.39	295.11	1935.04	70	0	1
125	645.41	1086.93	295.71	1836.29	70	0	1
126	652.02	1094.69	297.79	1778.65	70	0	1
127	695.61	1019.03	324.30	1561.78	70	0	1
128	688.24	1072.74	302.85	1691.45	70	0	1
129	693.06	1085.93	287.33	1807.78	70	0	1
130	712.54	1075.02	287.51	1755.62	70	0	1
131	702.48	1077.24	291.59	1755.66	70	0	1
132	631.50	1059.07	341.68	1554.66	70	0	1
133	659.58	986.07	377.53	1260.01	70	0	1
134	662.52	988.52	363.60	1374.22	70	0	1
135	660.70	1008.99	350.45	1493.37	70	0	1

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
136	652.72	1088.01	320.94	1782.03	70	0	1
137	706.08	1084.54	327.41	1601.41	70	0	1
138	694.75	1091.47	310.48	1722.56	70	0	1
139	666.46	1102.07	311.26	1791.41	70	0	1
140	665.39	1117.07	319.73	1768.67	70	0	1
141	718.07	1044.56	265.25	1810.60	70	0	1
142	673.86	1118.20	276.72	1854.71	70	0	1
143	701.16	1072.10	271.96	1796.55	70	0	1
144	681.40	1087.80	277.23	1795.76	70	0	1
145	680.62	1087.66	269.15	1872.98	70	0	1
146	710.35	1030.92	270.96	1878.89	70	0	1
147	683.21	1064.52	285.68	1816.92	70	0	1
148	694.61	1001.97	273.00	1928.09	70	1	0
149	628.27	1060.01	282.63	1993.78	70	0	1
150	588.83	1096.75	266.91	2280.11	70	1	0
151	676.23	1063.67	274.05	2060.58	70	1	0
152	643.94	1042.68	285.13	2098.47	70	1	0
153	701.21	1100.13	300.81	1707.74	70	0	1
154	678.33	1046.84	263.23	2175.75	70	1	0
155	586.56	1056.57	279.48	2191.41	70	1	0
156	629.77	1116.76	309.93	2002.95	70	0	1
157	726.56	1075.80	298.48	1762.01	70	0	1
158	670.43	1092.58	304.11	1903.46	70	0	1
159	705.83	1074.75	288.97	1869.73	70	0	1
160	654.44	1060.79	306.99	1969.81	70	0	1
161	704.68	1113.64	293.90	1972.64	70	0	1
162	693.93	1077.42	302.42	2017.78	70	0	1
163	674.03	1074.66	314.31	1886.87	70	0	1
164	712.78	1030.03	303.33	1861.57	70	0	1
165	778.39	1086.65	235.24	2128.88	70	1	0
166	716.55	1057.34	259.13	1873.90	70	1	0
167	726.46	1051.63	274.39	1806.39	70	0	1
168	650.05	1064.35	268.69	2037.36	70	1	0
169	655.35	1048.57	263.15	2079.33	70	1	0
170	779.80	998.18	249.90	1908.03	70	1	0
171	723.63	959.07	253.72	2035.88	70	1	0
172	749.31	995.64	262.87	1885.96	70	1	0
173	633.68	1081.39	272.55	1990.61	70	0	1
174	730.07	985.74	271.40	1897.32	70	1	0
175	707.60	1065.73	261.90	1976.19	70	1	0
176	754.95	1029.39	271.76	1826.60	70	0	1
177	722.19	1053.92	272.02	1956.48	70	1	0
178	716.73	1039.68	272.07	1938.76	70	1	0
179	701.19	1017.83	255.89	2110.84	70	1	0
180	715.87	995.93	275.18	1943.28	70	1	0

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
181	699.02	1006.18	295.08	1940.69	70	1	0
182	683.12	1034.32	274.39	2074.82	70	1	0
183	648.30	1066.10	284.01	2087.37	70	1	0
184	675.43	1067.59	270.31	2076.09	70	1	0
185	762.17	995.64	273.18	1983.41	70	1	0
186	760.61	1017.58	291.25	1814.39	70	0	1
187	695.62	1011.60	296.86	1964.88	70	1	0
188	693.40	1038.68	319.08	1732.37	70	0	1
189	660.37	1064.78	294.74	2018.63	70	0	1
190	707.89	1004.16	246.52	2040.49	70	1	0
191	712.50	1007.83	244.92	2044.80	70	1	0
192	755.71	1002.12	256.70	1882.24	70	1	0
193	691.36	933.43	238.09	2228.54	70	1	0
194	642.38	1007.39	253.59	2138.02	70	1	0
195	802.97	1016.48	244.10	2018.64	70	1	0
196	800.27	987.49	263.69	1794.80	70	1	0
197	765.51	998.43	264.73	1899.66	70	1	0
198	697.20	982.47	251.01	2194.09	70	1	0
199	656.57	995.16	247.47	2166.37	70	1	0
200	807.33	1045.86	285.73	1581.11	70	0	1
201	667.76	1027.99	266.51	2122.85	70	1	0
202	689.18	1056.60	266.78	2135.26	70	1	0
203	739.95	1004.31	265.95	1919.19	70	1	0
204	727.61	971.91	291.84	1742.90	70	0	1
205	704.39	1002.05	261.95	2106.75	70	1	0
206	749.71	1043.94	277.37	1814.45	70	0	1
207	704.16	1059.09	236.07	2598.47	70	1	0
208	750.26	1034.77	273.02	1839.03	70	0	1
209	739.51	1016.32	261.54	2084.16	70	1	0
210	853.83	977.20	276.45	1625.78	70	0	1
211	695.91	1065.86	276.95	2224.56	70	1	0
212	785.60	1040.74	275.73	1872.61	70	1	0
213	823.14	1005.22	275.68	1803.08	70	1	0
214	770.27	1016.75	239.81	1876.03	70	1	0
215	746.60	1051.88	237.86	1937.02	70	1	0
216	747.06	1036.28	248.75	1869.82	70	1	0
217	693.13	1040.27	240.95	2137.93	70	1	0
218	727.82	1011.63	244.56	1994.36	70	1	0
219	751.50	1030.62	270.14	1746.46	70	0	1
220	789.70	990.64	266.07	1749.71	70	1	0
221	752.46	986.38	263.10	1829.98	70	1	0
222	744.56	1038.95	270.77	1799.04	70	0	1
223	712.68	1059.60	278.25	1772.68	70	0	1
224	777.56	998.76	261.79	1879.60	70	1	0
225	757.76	1034.25	264.59	1968.59	70	1	0

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
226	803.21	993.94	272.08	1744.25	70	1	0
227	773.48	967.99	264.80	1869.85	70	1	0
228	751.81	1030.63	264.73	2021.17	70	1	0
229	752.64	1042.45	265.77	2006.43	70	1	0
230	763.44	994.37	267.90	1982.86	70	1	0
231	748.51	1048.66	269.28	2081.50	70	1	0
232	781.11	1006.95	272.28	1880.18	70	1	0
233	785.99	1006.22	267.23	1939.26	70	1	0
234	701.06	1042.46	285.23	2035.49	70	1	0
235	758.63	1044.95	278.38	1941.78	70	1	0
236	660.34	799.38	295.64	1111.64	56	0	1
237	654.98	751.54	313.33	945.08	56	0	1
238	643.04	747.86	288.35	1132.37	56	0	1
239	669.69	735.37	318.97	928.57	56	0	1
240	609.60	733.37	279.97	1173.97	56	1	0
241	657.74	740.31	320.45	939.69	56	0	1
242	685.20	777.10	306.59	1074.91	56	0	1
243	616.46	798.36	283.95	1243.90	56	0	1
244	643.85	721.56	297.77	1034.71	56	0	1
245	647.31	801.30	301.20	1085.30	56	0	1
246	633.33	773.22	313.76	1097.16	56	0	1
247	623.90	813.05	291.60	1193.60	56	0	1
248	645.13	858.05	278.39	1306.95	56	0	1
249	635.07	852.05	288.17	1269.29	56	0	1
250	547.74	745.09	265.15	1388.21	56	1	0
251	613.20	820.25	276.30	1319.85	56	1	0
252	608.67	791.80	285.36	1256.50	56	0	1
253	595.79	744.39	280.41	1272.86	56	1	0
254	619.88	719.42	289.76	1156.22	56	1	0
255	642.72	763.64	287.49	1147.54	56	0	1
256	691.59	939.45	324.12	1347.95	56	0	1
257	630.23	960.30	306.42	1494.37	56	0	1
258	672.35	917.98	346.47	1193.32	56	0	1
259	599.95	773.20	280.31	1219.24	56	0	1
260	640.62	832.60	274.29	1259.61	56	0	1
261	657.28	823.53	277.10	1251.29	56	0	1
262	646.14	854.06	279.96	1250.52	56	0	1
263	636.60	833.65	279.38	1249.98	56	0	1
264	623.74	772.98	271.70	1304.53	56	1	0
265	578.40	799.03	262.36	1439.63	56	1	0
266	685.99	771.43	317.73	954.56	56	0	1
267	659.79	739.31	306.20	1020.08	56	0	1
268	604.09	703.99	287.88	1146.24	56	1	0
269	681.40	862.75	290.53	1196.69	56	0	1
270	583.58	795.44	268.35	1315.69	56	1	0

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
271	573.63	742.30	265.34	1412.65	56	1	0
272	655.26	853.93	283.39	1244.00	56	0	1
273	651.51	849.14	285.32	1235.27	56	0	1
274	586.87	748.73	268.36	1337.79	56	1	0
275	680.13	858.34	289.31	1186.22	56	0	1
276	634.01	850.39	275.36	1349.43	56	1	0
277	649.92	797.24	283.51	1244.62	56	0	1
278	565.60	757.52	259.63	1409.38	56	1	0
279	643.26	861.89	362.66	1174.19	56	0	1
280	629.84	933.97	298.89	1609.99	56	1	0
281	616.21	913.97	331.45	1432.27	56	0	1
282	636.31	890.98	327.58	1427.70	56	0	1
283	695.27	991.45	311.24	1370.08	56	0	1
284	614.10	804.65	267.25	1353.94	56	0	1
285	693.39	808.41	283.19	1151.87	56	0	1
286	707.59	861.68	292.07	1156.07	56	0	1
287	617.25	779.10	262.35	1319.78	56	1	0
288	705.22	822.79	283.10	1157.82	56	0	1
289	662.78	827.84	276.57	1295.41	56	1	0
290	667.09	842.20	265.99	1299.17	56	1	0
291	669.65	841.06	260.59	1333.55	56	1	0
292	651.35	864.86	282.93	1297.40	56	0	1
293	659.75	867.05	276.29	1358.13	56	1	0
294	684.01	853.40	287.73	1218.49	56	0	1
295	707.35	839.03	288.46	1159.71	56	0	1
296	628.70	742.00	298.20	1121.40	56	0	1
297	674.02	817.34	279.23	1244.94	56	1	0
298	634.76	745.80	312.77	1054.25	56	0	1
299	636.17	847.52	280.74	1292.75	56	0	1
300	598.51	839.02	281.03	1318.78	56	0	1
301	638.01	793.66	269.44	1352.32	56	1	0
302	605.62	847.48	279.30	1361.95	56	1	0
303	680.36	819.40	285.92	1177.38	56	0	1
304	601.27	988.46	264.91	1827.57	56	1	0
305	671.75	1042.28	303.29	1497.43	56	0	1
306	719.64	983.45	297.42	1423.27	56	0	1
307	660.36	994.71	291.12	1645.30	56	1	0
308	688.07	817.66	277.95	1191.73	56	0	1
309	685.25	810.34	286.37	1168.40	56	0	1
310	637.49	804.53	274.95	1263.96	56	1	0
311	664.28	838.59	286.20	1191.51	56	0	1
312	605.55	748.98	259.27	1306.87	56	1	0
313	651.03	789.96	263.17	1318.65	56	1	0
314	634.55	805.87	270.07	1254.37	56	1	0
315	665.79	831.37	278.74	1245.62	56	0	1

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
316	685.78	834.35	280.81	1239.06	56	0	1
317	654.85	814.20	268.30	1280.32	56	1	0
318	641.12	788.80	261.26	1383.70	56	1	0
319	642.79	787.16	271.48	1282.29	56	1	0
320	652.73	822.38	274.64	1212.86	56	0	1
321	672.60	861.25	285.79	1216.71	56	0	1
322	724.07	812.69	291.40	1125.73	56	0	1
323	634.20	862.03	274.12	1350.48	56	1	0
324	689.76	801.07	258.87	1277.10	56	1	0
325	640.14	822.49	279.17	1281.86	56	1	0
326	613.32	841.77	274.82	1341.00	56	1	0
327	669.82	1006.49	298.56	1541.35	56	0	1
328	730.76	1009.02	303.14	1356.30	56	0	1
329	658.82	1017.94	297.19	1527.24	56	0	1
330	715.58	967.54	290.02	1593.71	56	1	0
331	682.18	837.10	294.88	1144.25	56	0	1
332	637.50	762.71	265.06	1214.37	56	1	0
333	684.38	831.70	285.90	1206.48	56	0	1
334	638.12	809.89	281.60	1232.07	56	0	1
335	634.80	789.32	272.68	1240.46	56	1	0
336	623.83	751.00	290.07	1152.70	56	0	1
337	657.41	823.37	286.79	1165.40	56	0	1
338	599.64	807.29	275.12	1284.96	56	1	0
339	629.15	796.22	273.34	1316.06	56	1	0
340	672.73	841.06	276.74	1231.10	56	0	1
341	608.03	755.62	263.79	1326.40	56	1	0
342	682.97	841.66	285.46	1254.77	56	0	1
343	682.82	868.66	285.10	1239.85	56	0	1
344	631.19	811.43	267.77	1384.83	56	1	0
345	653.61	832.88	279.28	1325.98	56	1	0
346	621.55	783.24	267.11	1335.27	56	1	0
347	680.32	829.88	301.89	1127.77	56	0	1
348	623.29	856.18	281.53	1311.42	56	0	1
349	697.98	846.44	278.43	1273.29	56	1	0
350	678.82	874.33	287.56	1222.29	56	0	1
351	633.37	845.12	281.59	1280.46	56	0	1
352	564.20	830.85	263.88	1461.83	56	1	0
353	661.45	845.42	286.12	1244.73	56	0	1
354	649.39	1097.29	290.47	1762.65	70	0	1
355	666.16	1073.81	307.23	1645.21	70	0	1
356	685.32	1090.59	307.87	1564.89	70	0	1
357	650.69	1074.95	287.24	1854.82	70	0	1
358	663.79	1076.64	279.02	1847.06	70	0	1
359	656.48	1071.76	306.75	1691.83	70	0	1
360	682.10	1025.20	332.54	1449.14	70	0	1

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
361	622.05	1070.67	290.47	1924.00	70	0	1
362	611.59	1085.74	289.48	1988.70	70	0	1
363	677.41	1058.67	306.25	1724.84	70	0	1
364	683.27	1052.79	295.46	1801.60	70	0	1
365	591.56	1091.35	307.94	1964.57	70	0	1
366	612.70	997.86	346.94	1653.73	70	0	1
367	673.90	998.02	332.05	1557.62	70	0	1
368	649.63	1075.90	317.48	1664.25	70	0	1
369	639.31	1059.99	325.46	1662.32	70	0	1
370	632.61	1089.32	297.45	1842.53	70	0	1
371	651.95	1080.48	304.89	1798.50	70	0	1
372	681.26	1018.86	339.95	1517.00	70	0	1
373	642.03	1046.86	327.80	1777.97	70	0	1
374	633.40	1091.64	316.06	1858.38	70	0	1
375	609.30	1125.69	313.98	1955.68	70	0	1
376	597.15	1153.35	295.05	2127.02	70	0	1
377	590.34	1113.67	296.79	2152.31	70	0	1
378	668.68	1034.70	249.44	2119.44	70	1	0
379	631.80	1103.22	259.88	2075.79	70	0	1
380	610.81	1066.98	256.19	2122.60	70	0	1
381	629.24	1091.15	271.02	1989.09	70	0	1
382	615.09	1047.92	251.39	2240.73	70	1	0
383	644.15	1000.99	261.36	2119.10	70	1	0
384	666.75	1035.09	261.63	2069.71	70	0	1
385	631.27	1029.30	270.30	2121.71	70	0	1
386	682.69	1024.83	268.91	1977.31	70	0	1
387	647.92	1047.69	265.92	2041.72	70	0	1
388	642.41	1081.07	269.86	1983.06	70	0	1
389	646.99	1016.39	264.28	2121.38	70	1	0
390	604.05	1079.71	267.33	2118.74	70	0	1
391	642.54	1091.22	288.51	1918.54	70	0	1
392	691.93	1044.09	300.00	1749.14	70	0	1
393	633.52	1061.69	283.55	2060.62	70	0	1
394	626.89	1042.72	285.97	2099.73	70	0	1
395	616.53	1033.68	286.87	2051.73	70	0	1
396	640.96	1086.40	283.20	2110.77	70	0	1
397	629.68	998.57	329.44	1777.19	70	0	1
398	617.38	1041.57	303.99	2126.49	70	0	1
399	635.09	984.06	350.30	1666.57	70	0	1
400	635.80	1008.14	336.87	1775.09	70	0	1
401	588.60	1119.02	259.17	2222.17	70	1	0
402	600.01	1013.59	251.62	2356.09	70	1	0
403	693.23	1009.91	258.86	2026.73	70	1	0
404	671.89	972.75	258.85	2084.69	70	1	0
405	588.64	1029.03	246.54	2528.28	70	1	0

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
406	676.85	1027.47	269.30	1975.87	70	0	1
407	620.92	1033.23	243.29	2401.21	70	1	0
408	613.20	1061.26	258.65	2177.24	70	0	1
409	615.47	1022.80	252.74	2312.45	70	1	0
410	640.12	968.86	242.89	2349.52	70	1	0
411	682.72	1005.84	252.62	2240.38	70	1	0
412	621.39	1016.68	264.45	2246.75	70	1	0
413	722.59	1040.30	287.68	1829.80	70	0	1
414	674.11	1054.02	279.19	2021.89	70	0	1
415	677.39	1037.04	263.68	2116.41	70	1	0
416	679.50	979.92	251.35	2213.25	70	1	0
417	708.20	997.58	282.22	1952.36	70	0	1
418	590.26	1011.76	236.49	2753.38	70	1	0
419	687.89	981.20	264.25	2232.75	70	1	0
420	661.15	1042.95	265.17	2280.82	70	1	0
421	752.13	998.17	270.92	1977.98	70	1	0
422	661.62	1021.26	249.16	2416.23	70	1	0
423	681.26	989.77	262.15	2457.59	70	1	0
424	717.89	1039.33	269.28	2174.70	70	1	0
425	673.19	1018.36	249.27	2089.45	70	1	0
426	679.73	1006.62	241.31	2130.48	70	1	0
427	713.06	983.65	235.13	2108.67	70	1	0
428	689.08	980.29	235.65	2238.79	70	1	0
429	682.50	992.17	244.68	2133.13	70	1	0
430	648.00	1048.72	270.80	1954.98	70	0	1
431	662.27	979.40	257.66	2101.81	70	1	0
432	695.79	949.44	239.08	2291.57	70	1	0
433	681.73	978.49	247.00	2163.80	70	1	0
434	678.57	948.05	250.08	2266.17	70	1	0
435	670.86	977.86	244.91	2342.25	70	1	0
436	664.82	987.08	251.69	2313.94	70	1	0
437	710.15	975.86	250.84	2069.83	70	1	0
438	699.72	1012.80	260.69	2040.13	70	1	0
439	687.36	985.01	253.30	2121.14	70	1	0
440	624.54	1007.00	266.66	2498.32	70	1	0
441	588.91	988.92	239.11	2738.44	70	1	0
442	644.24	1028.42	252.34	2538.36	70	1	0
443	636.86	1063.77	264.26	2414.61	70	1	0
444	682.08	1001.35	238.96	2728.44	70	1	0
445	650.30	999.07	235.79	2930.05	70	1	0
446	705.21	1007.69	274.88	2133.92	70	1	0
447	733.60	980.19	286.64	1988.76	70	1	0
448	688.64	977.36	260.67	2340.03	70	1	0
449	694.65	1057.61	266.11	1911.94	70	1	0
450	649.74	1014.43	221.82	2488.10	70	1	0

Neural network training data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>BOS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
451	711.87	1011.81	236.33	2138.27	70	1	0
452	714.29	1010.14	244.67	2056.90	70	1	0
453	688.83	986.69	259.67	2004.79	70	1	0
454	641.26	1016.72	252.21	2130.59	70	1	0
455	705.52	967.66	259.73	2037.34	70	1	0
456	712.74	1014.33	259.02	1971.04	70	0	1
457	691.76	993.19	256.09	2059.28	70	1	0
458	625.45	1000.23	269.93	2227.40	70	1	0
459	622.69	960.45	237.24	2486.95	70	1	0
460	685.97	964.24	255.63	2114.46	70	1	0
461	631.24	954.46	239.12	2497.70	70	1	0
462	690.65	978.10	266.44	2092.95	70	1	0
463	725.85	1004.39	264.50	2048.36	70	1	0
464	675.08	970.41	254.05	2212.63	70	1	0
465	708.52	982.10	256.97	2196.35	70	1	0
466	716.01	990.15	249.46	2182.68	70	1	0
467	729.37	982.82	259.16	2124.90	70	1	0
468	638.91	989.75	240.95	2606.66	70	1	0
469	652.31	960.64	223.77	2761.87	70	1	0
470	621.64	1025.38	251.53	2460.37	70	1	0
471	687.08	1073.31	261.95	2535.01	70	1	0

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
1	655.69	937.38	321.44	1361.27	56	0	1
2	677.14	902.54	339.72	1184.21	56	0	1
3	630.23	948.76	323.41	1359.80	56	0	1
4	624.17	943.06	340.20	1236.37	56	0	1
5	554.56	1076.75	316.97	1538.34	56	0	1
6	597.89	1039.07	306.86	1529.48	56	0	1
7	620.02	1009.26	340.59	1300.30	56	0	1
8	606.79	954.25	320.67	1445.19	56	0	1
9	644.79	960.60	326.21	1398.57	56	0	1
10	664.31	934.90	338.27	1242.72	56	0	1
11	627.25	1079.75	303.12	1516.98	56	0	1
12	587.64	1030.77	316.26	1524.64	56	0	1
13	558.03	991.53	314.64	1635.93	56	1	0
14	655.71	1011.82	321.39	1379.34	56	0	1
15	552.13	981.53	327.53	1556.38	56	0	1
16	618.12	922.71	359.73	1223.17	56	0	1
17	646.49	931.27	363.44	1140.10	56	0	1
18	599.89	1020.71	342.78	1346.83	56	0	1
19	602.43	1110.32	320.90	1468.52	56	0	1
20	673.02	967.52	321.18	1377.96	56	0	1
21	662.36	963.01	337.54	1287.48	56	0	1
22	678.37	871.02	368.05	1032.60	56	0	1
23	641.45	1046.38	334.04	1306.74	56	0	1
24	706.45	977.73	331.75	1233.58	56	0	1
25	674.61	935.90	285.17	1497.48	56	1	0
26	666.52	1045.91	313.58	1401.37	56	0	1
27	574.23	1048.56	301.35	1604.20	56	0	1
28	555.24	1047.39	309.53	1572.21	56	0	1
29	553.67	1072.77	287.70	1678.82	56	0	1
30	627.28	1042.73	279.98	1669.67	56	1	0
31	625.12	1027.19	294.60	1587.61	56	0	1
32	599.84	1070.28	299.02	1595.57	56	0	1
33	691.07	995.69	287.95	1496.59	56	1	0
34	634.28	1047.94	300.32	1448.87	56	0	1
35	548.16	1018.03	294.83	1765.10	56	1	0
36	653.50	1015.49	302.54	1493.55	56	0	1
37	635.73	886.97	343.70	1283.14	56	0	1
38	582.42	947.74	333.74	1475.44	56	0	1
39	733.63	1017.83	286.71	1460.57	56	1	0
40	538.77	995.55	298.20	1821.98	56	1	0
41	639.01	1070.88	309.72	1434.43	56	0	1
42	607.29	1032.54	305.09	1605.69	56	0	1
43	639.60	1027.02	287.07	1609.09	56	1	0
44	631.57	1059.42	314.92	1476.64	56	0	1
45	647.54	1032.82	304.52	1485.52	56	0	1

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
46	625.98	995.65	310.03	1547.97	56	0	1
47	654.25	956.20	334.41	1282.50	56	0	1
48	663.59	1018.76	314.09	1401.56	56	0	1
49	534.53	944.66	302.74	1693.45	56	1	0
50	554.71	1004.38	293.63	1731.32	56	1	0
51	572.02	989.16	297.40	1663.53	56	1	0
52	522.64	995.98	295.26	1763.70	56	1	0
53	627.82	795.72	326.23	1373.24	56	1	0
54	597.48	1073.41	306.69	1537.74	56	0	1
55	677.56	1053.53	305.91	1410.84	56	0	1
56	669.37	1039.72	292.13	1513.43	56	0	1
57	730.83	993.05	296.65	1359.21	56	0	1
58	607.47	962.72	292.38	1639.02	56	1	0
59	688.55	1005.44	290.90	1500.62	56	1	0
60	581.50	960.77	302.57	1670.73	56	1	0
61	517.14	977.50	290.53	1886.45	56	1	0
62	677.80	957.66	311.90	1456.62	56	1	0
63	594.58	1030.05	304.13	1565.54	56	0	1
64	613.40	923.26	307.24	1610.75	56	1	0
65	594.38	910.89	316.02	1549.59	56	1	0
66	710.99	996.53	324.95	1299.18	56	0	1
67	659.53	1033.16	307.70	1450.44	56	0	1
68	527.22	1002.17	302.34	1778.40	56	1	0
69	618.70	1041.46	303.68	1593.32	56	0	1
70	677.42	1024.62	308.34	1449.60	56	0	1
71	691.13	1031.28	305.60	1432.26	56	0	1
72	666.21	1037.10	306.54	1469.20	56	0	1
73	659.01	1055.32	308.17	1456.28	56	0	1
74	697.87	978.60	286.49	1507.54	56	1	0
75	655.69	1011.89	288.09	1518.67	56	1	0
76	638.00	1041.76	281.79	1641.59	56	1	0
77	614.77	1012.63	292.97	1623.52	56	1	0
78	661.33	1055.85	290.93	1522.45	56	0	1
79	684.96	1026.80	304.24	1354.91	56	0	1
80	492.11	1047.08	272.47	1979.23	56	1	0
81	650.90	1023.42	281.42	1551.65	56	1	0
82	705.75	1000.67	287.49	1463.78	56	1	0
83	542.62	1067.44	288.96	1736.87	56	1	0
84	687.48	1034.72	306.77	1432.13	56	0	1
85	622.11	983.45	278.46	1757.84	56	1	0
86	657.42	958.42	293.94	1540.04	56	1	0
87	510.14	970.61	291.93	1906.54	56	1	0
88	662.79	980.45	289.86	1559.67	56	1	0
89	520.65	1026.49	277.46	1924.66	56	1	0
90	669.15	1033.09	302.97	1432.76	56	0	1

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
91	631.25	1006.19	321.71	1454.40	56	0	1
92	646.17	938.09	277.15	1698.47	56	1	0
93	649.97	939.77	307.50	1511.48	56	1	0
94	652.16	1035.04	295.67	1556.46	56	0	1
95	610.61	849.51	352.28	1281.56	56	0	1
96	702.33	1025.44	301.25	1432.38	56	0	1
97	640.79	1071.86	318.10	1450.70	56	0	1
98	691.34	1015.05	304.55	1399.11	56	0	1
99	567.74	956.72	266.67	1845.54	56	1	0
100	710.52	1028.72	286.68	1439.42	56	0	1
101	629.21	1056.18	305.00	1474.84	56	0	1
102	461.87	1018.47	290.72	1911.43	56	1	0
103	572.95	1064.08	297.69	1588.70	56	0	1
104	547.65	962.56	306.89	1719.92	56	1	0
105	656.84	961.31	270.26	1675.59	56	1	0
106	574.11	973.77	303.20	1698.70	56	1	0
107	557.20	989.96	274.97	1825.28	56	1	0
108	575.39	1044.99	287.22	1725.36	56	1	0
109	596.11	1065.34	302.57	1601.50	56	0	1
110	503.38	965.28	273.05	2025.26	56	1	0
111	551.89	966.27	306.70	1719.82	56	1	0
112	609.75	961.20	262.64	1890.29	56	1	0
113	697.63	1036.17	312.97	1368.68	56	0	1
114	646.88	1035.31	291.06	1590.23	56	1	0
115	619.47	937.80	272.53	1801.34	56	1	0
116	614.51	878.80	272.96	1774.23	56	1	0
117	692.73	1002.76	302.61	1476.02	56	0	1
118	565.30	976.67	292.06	1770.71	56	1	0
119	535.51	1034.74	279.23	1889.79	56	1	0
120	660.74	974.97	271.69	1640.91	56	1	0
121	714.19	1002.39	304.28	1438.96	56	1	0
122	665.54	1120.03	299.57	1655.15	70	0	1
123	666.66	1121.30	289.23	1732.09	70	0	1
124	649.68	1152.75	289.14	1789.91	70	0	1
125	669.64	1113.87	280.38	1838.30	70	0	1
126	681.66	1116.63	293.98	1672.50	70	0	1
127	618.91	1112.81	294.88	1852.12	70	0	1
128	692.19	1090.70	305.78	1609.21	70	0	1
129	618.51	1104.11	294.97	1896.04	70	0	1
130	629.67	1071.86	309.41	1776.86	70	0	1
131	702.21	1070.66	294.29	1710.58	70	0	1
132	732.34	1028.09	315.55	1526.38	70	0	1
133	636.13	1125.58	296.53	1934.06	70	0	1
134	723.36	1053.50	275.53	1862.57	70	0	1
135	676.99	1093.63	288.86	1808.90	70	0	1

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
136	690.76	1080.04	293.15	1782.61	70	0	1
137	679.94	996.59	352.80	1373.72	70	0	1
138	673.14	1026.40	346.77	1481.33	70	0	1
139	651.24	999.48	343.76	1580.77	70	0	1
140	652.26	1101.48	302.10	1908.39	70	0	1
141	643.31	1107.70	314.29	2020.02	70	0	1
142	659.89	1071.08	318.86	1759.89	70	0	1
143	650.50	1104.80	335.73	1654.78	70	0	1
144	637.94	1124.44	318.36	1908.90	70	0	1
145	721.93	1004.56	302.16	1562.59	70	0	1
146	647.23	1094.41	265.53	1992.93	70	0	1
147	674.19	1101.18	278.09	1826.40	70	0	1
148	651.48	1114.53	272.15	1917.77	70	0	1
149	706.73	1070.83	283.65	1804.06	70	0	1
150	716.86	1021.30	271.26	1954.86	70	1	0
151	727.00	1031.47	268.78	1874.31	70	0	1
152	754.39	1049.14	286.21	1679.71	70	0	1
153	630.50	1072.12	298.34	1899.60	70	0	1
154	572.05	1091.98	272.40	2217.48	70	1	0
155	748.60	1049.17	289.72	1739.91	70	0	1
156	641.14	1064.33	288.72	2060.55	70	0	1
157	668.66	1089.28	282.73	2013.88	70	0	1
158	666.54	1051.40	266.37	2201.36	70	1	0
159	738.63	1028.45	288.94	1755.13	70	0	1
160	684.30	1085.37	305.68	1774.06	70	0	1
161	676.02	1071.43	285.64	2178.56	70	1	0
162	755.44	1069.21	296.89	1714.21	70	0	1
163	606.69	1152.77	292.64	2028.63	70	0	1
164	677.91	1041.03	315.37	1871.49	70	0	1
165	624.88	1087.57	292.35	2258.17	70	1	0
166	660.40	1095.70	305.34	1994.28	70	0	1
167	693.64	1056.47	305.15	1893.32	70	0	1
168	687.84	1043.38	290.42	1960.25	70	0	1
169	730.80	1067.89	258.39	1861.18	70	0	1
170	702.18	1036.48	257.44	1977.94	70	1	0
171	639.10	1073.08	275.35	2035.40	70	0	1
172	626.20	1077.43	267.52	2053.22	70	0	1
173	681.62	1033.73	247.79	2194.29	70	1	0
174	774.94	970.67	248.53	1855.80	70	1	0
175	812.73	975.14	263.19	1764.46	70	1	0
176	682.98	985.31	247.09	2145.19	70	1	0
177	757.40	1006.26	260.55	1870.22	70	1	0
178	722.40	1036.98	272.35	1828.81	70	0	1
179	651.60	1043.85	260.72	2138.02	70	1	0
180	650.87	1099.18	276.50	2072.52	70	0	1

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
181	664.00	1060.34	259.69	2208.31	70	1	0
182	750.55	1016.65	266.87	1891.29	70	1	0
183	778.47	1025.78	266.21	1793.91	70	0	1
184	770.74	973.88	277.00	1829.82	70	1	0
185	695.11	1005.06	286.35	1983.85	70	1	0
186	707.13	1040.15	273.52	1999.50	70	1	0
187	746.48	1000.12	271.11	1928.32	70	1	0
188	734.63	1004.89	294.58	1825.46	70	0	1
189	746.68	1023.53	272.65	2049.05	70	1	0
190	696.89	1013.96	299.19	1894.34	70	0	1
191	700.53	1051.28	292.77	1939.98	70	0	1
192	762.85	1002.96	277.07	2095.09	70	1	0
193	668.09	1023.61	246.88	2070.75	70	1	0
194	712.63	968.46	251.52	2098.61	70	1	0
195	737.76	1018.83	258.30	1928.84	70	1	0
196	724.00	1063.96	261.15	1902.72	70	0	1
197	820.40	1004.45	271.63	1736.98	70	1	0
198	746.00	1003.28	266.01	1916.84	70	1	0
199	785.33	993.09	270.12	1778.90	70	1	0
200	660.93	1012.09	246.35	2270.47	70	1	0
201	792.99	981.33	262.71	1842.67	70	1	0
202	715.02	1052.03	270.60	1882.14	70	0	1
203	766.10	984.39	295.27	1616.37	70	0	1
204	710.10	1036.60	272.76	1982.36	70	1	0
205	709.31	1015.62	259.21	1927.98	70	1	0
206	704.92	1011.55	295.64	1838.23	70	0	1
207	679.33	1084.25	264.23	2023.53	70	1	0
208	749.66	982.30	263.38	1923.88	70	1	0
209	731.28	1022.84	267.60	1983.29	70	1	0
210	672.40	1030.75	254.32	2394.43	70	1	0
211	766.55	1050.23	269.46	1910.60	70	1	0
212	691.16	1048.55	256.71	2398.33	70	1	0
213	756.54	1038.59	273.76	1918.00	70	1	0
214	734.79	1039.47	286.38	1839.28	70	0	1
215	733.81	1038.11	276.95	1898.72	70	1	0
216	723.68	1008.43	258.64	2329.59	70	1	0
217	676.30	1053.94	251.72	2093.47	70	1	0
218	699.13	1006.61	231.66	2265.39	70	1	0
219	708.56	1008.23	221.96	2328.89	70	1	0
220	740.34	1022.80	256.40	1963.31	70	1	0
221	727.49	1043.09	248.59	1939.55	70	1	0
222	738.67	1012.92	259.84	1888.35	70	1	0
223	720.11	981.55	261.26	1957.73	70	1	0
224	739.56	1014.35	251.86	1998.27	70	1	0
225	620.69	1002.62	241.36	2297.13	70	1	0

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
226	660.90	1040.87	262.80	2027.54	70	1	0
227	778.97	993.93	264.93	1865.61	70	1	0
228	729.77	988.30	257.20	2029.06	70	1	0
229	741.16	997.66	263.44	1912.12	70	1	0
230	664.01	1017.83	278.13	2054.77	70	1	0
231	740.74	948.34	239.17	2247.09	70	1	0
232	773.37	1001.18	261.32	1903.29	70	1	0
233	738.01	990.24	259.99	2048.67	70	1	0
234	743.71	996.66	287.61	1872.89	70	1	0
235	653.59	1045.88	253.59	2448.46	70	1	0
236	758.67	1000.39	273.67	1904.38	70	1	0
237	812.43	997.57	273.27	1791.79	70	1	0
238	678.54	1029.88	292.56	2046.21	70	1	0
239	758.80	1004.42	267.67	1945.23	70	1	0
240	724.20	1053.46	274.83	2093.91	70	1	0
241	671.01	991.31	263.02	2238.78	70	1	0
242	628.88	754.62	279.50	1179.08	56	1	0
243	670.14	739.98	282.15	1106.77	56	0	1
244	623.67	755.13	282.94	1166.50	56	0	1
245	631.62	747.43	303.58	1039.84	56	0	1
246	599.63	730.10	271.32	1215.69	56	1	0
247	676.76	792.19	305.69	1076.30	56	0	1
248	651.41	834.75	286.36	1239.78	56	0	1
249	677.16	760.06	324.94	907.30	56	0	1
250	615.59	773.61	282.25	1220.35	56	0	1
251	646.68	726.62	321.36	923.94	56	0	1
252	689.81	855.98	289.01	1184.16	56	0	1
253	608.98	823.86	297.44	1194.57	56	0	1
254	646.15	846.09	284.22	1226.29	56	0	1
255	600.61	758.11	269.68	1330.63	56	1	0
256	646.73	880.25	286.23	1295.80	56	0	1
257	599.36	746.20	281.35	1291.09	56	1	0
258	587.05	774.69	287.09	1281.66	56	1	0
259	629.09	799.82	277.10	1260.42	56	1	0
260	715.85	741.10	342.67	776.93	56	0	1
261	690.37	811.00	308.41	1060.72	56	0	1
262	736.18	927.75	350.62	1033.47	56	0	1
263	618.22	1036.37	312.96	1492.26	56	0	1
264	693.92	1036.36	323.95	1298.71	56	0	1
265	611.20	946.07	319.59	1482.37	56	0	1
266	738.49	924.57	316.96	1327.22	56	0	1
267	615.58	763.82	273.34	1228.69	56	1	0
268	664.76	812.75	277.58	1220.47	56	0	1
269	591.85	753.54	259.06	1307.23	56	1	0
270	592.62	752.56	270.64	1309.82	56	1	0

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
271	647.36	743.23	285.65	1102.63	56	0	1
272	659.96	752.96	308.90	1018.75	56	0	1
273	699.56	833.47	291.24	1150.34	56	0	1
274	646.35	757.12	276.24	1212.30	56	1	0
275	676.69	848.33	286.87	1186.01	56	0	1
276	613.30	817.51	268.93	1320.93	56	1	0
277	618.18	848.86	279.92	1315.58	56	0	1
278	626.35	871.28	288.23	1270.19	56	0	1
279	676.77	867.12	286.56	1225.23	56	0	1
280	686.59	865.31	288.76	1193.17	56	0	1
281	631.85	719.21	294.88	1087.86	56	0	1
282	648.34	840.57	285.25	1221.82	56	0	1
283	664.91	782.35	281.71	1256.81	56	1	0
284	608.63	807.14	275.75	1307.98	56	1	0
285	649.67	798.46	276.97	1272.14	56	1	0
286	691.15	906.61	356.30	1103.72	56	0	1
287	639.30	930.45	327.63	1401.55	56	0	1
288	632.92	922.37	329.59	1395.55	56	0	1
289	642.18	976.90	320.80	1441.24	56	0	1
290	626.97	975.81	315.08	1494.56	56	0	1
291	655.82	833.79	277.74	1288.57	56	1	0
292	666.61	823.97	273.10	1281.17	56	1	0
293	633.16	806.46	271.39	1313.74	56	1	0
294	644.55	867.07	281.40	1281.12	56	0	1
295	595.90	747.61	255.98	1361.74	56	1	0
296	675.20	869.73	279.48	1295.47	56	0	1
297	608.75	860.98	273.63	1417.58	56	1	0
298	601.88	823.68	267.84	1441.39	56	1	0
299	579.86	793.12	265.69	1442.74	56	1	0
300	653.47	843.62	279.45	1299.87	56	1	0
301	658.87	795.73	277.36	1230.64	56	1	0
302	670.12	799.53	269.81	1316.64	56	1	0
303	704.75	850.70	285.26	1230.62	56	0	1
304	559.97	715.12	250.60	1460.02	56	1	0
305	586.71	757.50	252.54	1503.21	56	1	0
306	689.92	851.75	289.04	1217.92	56	0	1
307	642.63	819.81	276.83	1310.83	56	1	0
308	617.81	727.11	255.65	1344.30	56	1	0
309	649.18	865.15	286.17	1248.70	56	0	1
310	726.24	970.63	298.43	1444.85	56	0	1
311	662.14	990.30	285.36	1598.13	56	1	0
312	600.51	1012.64	287.06	1714.35	56	1	0
313	702.73	839.29	284.59	1169.63	56	0	1
314	555.29	743.09	251.77	1462.09	56	1	0
315	648.18	823.99	274.75	1258.48	56	1	0

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
316	657.33	802.60	279.31	1232.99	56	1	0
317	677.28	843.86	285.94	1187.09	56	0	1
318	667.86	875.49	285.73	1233.54	56	0	1
319	655.76	848.90	282.10	1235.36	56	0	1
320	599.02	739.56	256.45	1342.76	56	1	0
321	719.34	824.85	281.91	1171.29	56	0	1
322	654.69	821.54	281.00	1233.63	56	0	1
323	653.10	822.18	288.12	1196.52	56	0	1
324	641.53	732.08	266.73	1216.48	56	1	0
325	669.56	847.69	285.48	1186.94	56	0	1
326	683.46	787.75	301.62	1065.01	56	0	1
327	600.61	732.88	264.21	1321.29	56	1	0
328	599.94	827.34	270.54	1370.77	56	1	0
329	607.41	894.07	284.69	1354.08	56	0	1
330	705.84	838.24	282.74	1187.98	56	0	1
331	603.76	837.10	270.42	1382.45	56	1	0
332	652.50	806.27	274.24	1264.13	56	1	0
333	693.81	992.47	300.91	1442.10	56	0	1
334	692.23	829.99	278.98	1620.67	56	1	0
335	731.04	998.74	306.99	1342.77	56	0	1
336	653.26	1001.28	297.52	1519.76	56	0	1
337	568.28	719.87	252.65	1367.78	56	0	1
338	608.04	784.31	266.97	1330.08	56	1	0
339	573.74	784.16	254.48	1446.40	56	1	0
340	640.94	804.50	281.76	1233.55	56	0	1
341	642.22	854.36	284.66	1267.02	56	0	1
342	656.64	844.32	284.05	1208.54	56	0	1
343	651.90	794.19	278.08	1206.07	56	0	1
344	657.26	796.16	270.89	1302.24	56	1	0
345	652.23	822.44	279.54	1284.73	56	1	0
346	621.50	857.51	281.84	1281.78	56	0	1
347	592.62	808.38	261.26	1418.36	56	1	0
348	741.53	865.13	287.12	1150.25	56	0	1
349	676.91	834.83	280.05	1210.55	56	0	1
350	614.53	814.40	262.24	1378.27	56	1	0
351	696.98	858.41	287.54	1147.72	56	0	1
352	617.60	791.34	267.26	1353.67	56	1	0
353	642.14	814.97	275.56	1318.08	56	1	0
354	613.61	869.77	291.00	1325.79	56	0	1
355	642.74	826.97	277.69	1272.57	56	0	1
356	686.18	842.12	289.76	1191.69	56	0	1
357	619.09	819.46	276.48	1302.28	56	1	0
358	638.14	644.16	275.54	1056.19	56	1	0
359	572.50	792.08	257.66	1477.10	56	1	0
360	682.37	821.71	282.94	1197.56	56	0	1

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
361	666.71	822.88	290.47	1166.78	56	0	1
362	701.23	1020.09	333.31	1337.52	70	0	1
363	622.70	1092.38	281.13	1933.78	70	0	1
364	650.80	1075.49	287.89	1872.00	70	0	1
365	690.55	1044.75	298.98	1642.19	70	0	1
366	649.27	1108.67	293.56	1756.87	70	0	1
367	677.51	1069.61	291.77	1732.20	70	0	1
368	623.20	1081.72	293.58	1906.60	70	0	1
369	629.11	1081.82	301.14	1844.17	70	0	1
370	613.21	1035.34	286.99	2020.67	70	0	1
371	611.73	1071.75	282.30	1976.32	70	0	1
372	650.46	1021.76	344.45	1514.84	70	0	1
373	676.25	1060.33	320.98	1625.99	70	0	1
374	581.62	1109.98	305.47	2042.24	70	0	1
375	648.35	1018.30	319.30	1737.44	70	0	1
376	670.08	1008.99	341.83	1434.18	70	0	1
377	612.79	1106.06	310.15	1813.28	70	0	1
378	632.87	1084.93	317.25	1854.46	70	0	1
379	691.59	1026.93	340.61	1414.37	70	0	1
380	672.56	1075.41	305.86	1770.38	70	0	1
381	651.82	1029.70	353.63	1515.49	70	0	1
382	645.29	1071.75	327.30	1737.06	70	0	1
383	607.42	1135.49	309.31	2107.84	70	0	1
384	548.34	1123.93	311.39	2179.39	70	0	1
385	635.16	1081.62	270.98	1998.14	70	0	1
386	634.77	1083.45	256.48	2098.76	70	0	1
387	607.04	1067.42	245.08	2298.99	70	1	0
388	645.79	1077.21	249.66	2170.69	70	0	1
389	674.63	1021.45	262.45	2024.25	70	0	1
390	618.39	1033.10	264.51	2135.07	70	0	1
391	651.09	1020.66	256.43	2161.26	70	1	0
392	651.90	1021.81	265.31	2059.09	70	0	1
393	707.19	992.70	248.69	2110.55	70	1	0
394	688.43	988.59	258.36	2059.48	70	1	0
395	658.93	1054.71	279.21	1945.29	70	0	1
396	633.58	1068.61	274.69	2073.74	70	0	1
397	609.18	1040.49	270.90	2203.63	70	1	0
398	662.67	1057.24	288.52	1849.96	70	0	1
399	629.98	1037.79	294.65	1951.62	70	0	1
400	650.77	1042.14	303.53	1887.69	70	0	1
401	613.64	1044.62	277.66	2157.39	70	0	1
402	665.56	1010.31	300.26	1881.31	70	0	1
403	631.03	1095.01	278.10	2147.30	70	0	1
404	640.35	1026.59	323.76	1854.71	70	0	1
405	621.24	1034.49	309.75	2040.91	70	0	1

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
406	618.05	1010.36	346.51	1719.44	70	0	1
407	652.13	1028.67	329.31	1848.56	70	0	1
408	636.43	1115.67	269.98	2038.65	70	0	1
409	576.84	1044.45	247.41	2366.95	70	1	0
410	672.24	1001.30	261.65	2072.71	70	1	0
411	590.49	985.17	234.15	2595.60	70	1	0
412	602.42	1052.42	250.99	2202.65	70	1	0
413	603.18	1004.39	244.19	2378.10	70	1	0
414	654.74	1030.40	261.25	2060.18	70	0	1
415	630.86	982.64	217.85	2681.74	70	1	0
416	615.37	995.83	250.95	2287.63	70	1	0
417	624.99	1055.30	281.55	2132.41	70	0	1
418	705.02	1012.86	275.54	1902.31	70	1	0
419	753.67	984.20	276.53	1904.00	70	0	1
420	606.07	1070.37	256.49	2402.91	70	1	0
421	666.98	1065.27	259.80	2369.17	70	1	0
422	618.30	1033.61	254.73	2385.55	70	1	0
423	712.01	1010.28	270.05	2116.02	70	1	0
424	674.25	1021.72	264.06	2271.17	70	1	0
425	721.03	1009.15	254.47	2212.30	70	1	0
426	704.27	1047.13	280.25	2073.23	70	0	1
427	654.34	1046.28	240.26	2724.49	70	1	0
428	737.43	987.90	255.77	2170.53	70	1	0
429	739.39	1026.34	258.53	2193.93	70	1	0
430	702.84	1039.64	265.53	2251.76	70	1	0
431	607.37	1083.04	264.93	2453.47	70	1	0
432	734.65	973.64	239.77	2062.15	70	1	0
433	624.42	946.26	218.56	2427.11	70	1	0
434	750.04	953.80	245.56	1975.52	70	1	0
435	679.04	980.80	237.07	2210.04	70	1	0
436	676.71	1008.53	248.21	2089.65	70	1	0
437	684.31	975.18	247.56	2106.87	70	1	0
438	656.55	947.02	236.17	2360.31	70	1	0
439	695.43	951.49	248.82	2122.57	70	1	0
440	671.77	1017.28	253.89	2077.42	70	1	0
441	667.06	956.32	245.66	2327.01	70	1	0
442	662.47	1031.05	258.28	2273.76	70	1	0
443	660.17	994.12	246.46	2293.09	70	1	0
444	717.26	1000.27	261.37	2033.24	70	1	0
445	759.71	960.54	260.78	1926.80	70	1	0
446	645.61	1060.14	267.35	2368.33	70	1	0
447	732.21	987.52	268.76	2028.05	70	1	0
448	674.21	1051.60	250.81	2496.58	70	1	0
449	716.03	1010.11	285.37	2020.91	70	0	1
450	732.36	1020.25	281.22	1873.06	70	0	1

Neural network test data
(50% of total observations, D&PL 20 and Stoneville 474, 1998)(continued)

<u>OBS</u>	<u>BLUE</u>	<u>GREEN</u>	<u>RED</u>	<u>NIR</u>	<u>TIME</u>	<u>OUTPUT</u>	
451	703.19	1013.69	254.91	2396.34	70	1	0
452	781.44	962.45	263.15	2081.08	70	1	0
453	683.05	976.45	297.80	2077.58	70	1	0
454	754.71	982.78	281.96	1971.22	70	1	0
455	723.38	956.14	283.07	2006.95	70	1	0
456	679.16	1011.08	249.60	2112.50	70	1	0
457	730.66	929.51	228.02	2170.26	70	1	0
458	705.92	945.64	241.54	2197.34	70	1	0
459	696.30	974.89	250.16	2091.94	70	1	0
460	621.00	1036.86	240.74	2272.07	70	1	0
461	625.17	1002.69	250.86	2141.41	70	1	0
462	706.91	986.32	265.22	1922.95	70	0	1
463	651.38	985.07	246.18	2299.06	70	1	0
464	670.48	998.03	245.52	2172.69	70	1	0
465	690.79	1005.23	264.41	1973.55	70	0	1
466	685.54	960.55	274.13	1986.78	70	1	0
467	671.64	985.88	264.41	2102.54	70	1	0
468	665.61	981.82	260.37	2098.15	70	1	0
469	715.78	1006.72	263.92	1983.98	70	0	1
470	708.83	975.99	263.20	2055.37	70	1	0
471	712.06	967.28	254.78	2178.04	70	1	0
472	724.39	996.23	281.71	1840.19	70	0	1
473	662.47	955.31	244.67	2345.03	70	1	0
474	715.67	967.63	270.89	2061.43	70	1	0
475	616.62	1032.56	242.75	2678.21	70	1	0
476	662.63	1006.90	243.21	2292.68	70	1	0
477	653.78	1046.87	255.97	2451.03	70	1	0
478	716.97	1036.72	270.38	2023.83	70	0	1
479	738.42	1042.22	288.91	1855.87	70	0	1
480	630.30	1041.57	245.75	2862.78	70	1	0

MATLAB® codes for training neural networks

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%      SCRIPT PROGRAM FOR TRAINING A NEURAL NETWORK
%
%      RUIXIU SUI
%
%      Department of Agricultural and Biosystems Engineering
%      The University of Tennessee, Knoxville
%      December 7, 1998
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%      Input the training data
%      &
%      Design the neural network structure
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

vecfile = input('Enter filename of training data: ','s');
numhid = input('How many neurons in the hidden layer? ');

sel1 = input('Sigmoid, Tansigmoid, or Linear for hidden layer? [s,t,l]: ','s');
sel2 = input('Sigmoid, Tansigmoid, or Linear for output layer? [s,t,l]: ','s');

sc=input('Input/Output Scaling Type MCVU=m,linear=l,none=n?[m,l,n]:','s');

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%      Set up default parameters
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

fprintf('\n\n The default variables are:\n\n');
fprintf('Output error tolerance (sse) = 1\n');      tolerance = 1;
fprintf('Errors plotted in progress every 5 epochs.\n');  epoch_disp = 5;
                                plotflag = 1;
fprintf('Maximum number of training epochs = 50.\n');    maxepochs = 50;

```

MATLAB® codes for training neural networks (continued)

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%           Allow user to change default parameters
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```
choice = input('Are you satisfied with these selections? [y,n]:' , 's');
```

```

if choice == 'n'
epoch_disp = input('How often to display error(# of epoches): ');
tolerance = input('Output error tolerance (sse): ');
maxepochs = input('Maximum number of epoches to train: ');
end

```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%           Load training data
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```

eval(['load ',vecfile])
[nov1,numin] = size(x);
[nov2,numout] = size(y);

```

```

if nov1~=nov2
error('The number of input vectors and target vectors has to be the same.')
end
fprintf('\nThis network has:\n\n');
fprintf('%0.f input neurons\n',numin);
fprintf('%0.f neurons in the hidden layer\n',numhid);
fprintf('%0.f output neurons\n\n',numout);
fprintf('There are %0.f input/output pairs in this training set.\n\n',nov1);

```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%           Scale inputs
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```

if sc=='m'
[xn,xm,xs]=makenice(x);
elseif sc=='l'
[xn,xm,xs]=scale(x);
else

```

MATLAB® codes for training neural networks (continued)

```

    xn=x;
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%           Initialize weight vectors to small values
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[R,Q]=size(xn');
S1=numhid;
[S2,Q]=size(y');

[W1,B1]=rands(S1,R);
[W2,B2]=rands(S2,S1);
W2=W2*.5;
W1=W1*.5;
B2=B2*.5;
B1=B1*.5;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%           Set training parameters for Levenberg-Marquardt
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

TP=[epoch_disp,maxepochs,tolerance,.0001,.001,10,0.1,1e10];

if sel1 == 'l'           % First layer selection
    F1 = 'purelin';
elseif sel1 == 't'
    F1 = 'tansig';
else
    F1 = 'logsig';
end

if sel2=='t'           % Second layer selection
    F2 = 'tansig';
elseif sel2=='l'
    F2 = 'purelin';
else
    F2 = 'logsig';
end

```

MATLAB® codes for training neural networks (continued)

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%                               Train the network using LM
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[W1,B1,W2,B2,epochs,TRLM] = trainlm(W1,B1,F1,W2,B2,F2,xn',y',TP);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%                               LM tolerance criteria not met
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

if epochs==maxepochs
    fprintf('\n***LM training complete, no answer found!')
    fprintf('\n*** SSE=%e \n\n',min(TRLM))
else

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%                               LM tolerance criteria met
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

    fprintf('\n*** LM training complete after %0.f epochs! ***', epochs)
    fprintf('\n*** SSE = %e \n\n',min(TRLM))
end

save WEIGHT98 W1 B1 W2 B2 xm xs F1 F2 sc

%END

```

MATLAB® codes for testing the trained neural networks

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%                               Test Program
%                               by
%                               Ruixiu Sui
%       Department of Agricultural & Biosystem Engineering
%       University of Tennessee,Knoxville
%       December 18,1998
%
% This program tests the performance of the trained neural network.
% The file name of test data and the file name of the weight vectors
% are asked to input. The output is the diagnosing accuracy rate.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% load the test data
testdat = input('Enter filename of test data: ','s');
eval(['load ',testdat]);

[nov1,numin] = size(x);

% load trained neural network
weights = input('Enter filename of weight vectors: ','s');
eval(['load ',weights]);

% scaling input data
if sc=='m'
    [x]=makenice(x,xm,xs);
elseif sc=='l'
    [x]=scale(x,xm,xs);
else
    x=x;
end

y=y';
x=x';

% recognize the input pattern using the network
ysim=simuff(x,W1,B1,F1,W2,B2,F2);

% display the generalization
n=0; %clear n
for i=1:nov1

```

MATLAB® codes for testing the trained neural networks (continued)

```
%find the row in which the desired output is
desire_max=find(y(:,i)==max(y(:,i)));

%find the row in which the maximum output is
output_max=find(ysim(:,i)==max(ysim(:,i)));

pattern_num=i

% maximum desired ouput is in the first column.
if desire_max==1
    disp('desired nitrogen status is normal')

% maximum desired ouput is in the second column.
elseif desire_max==2
    disp('desired nitrogen status is low')
end

% maximum ouput is in the first column.
if output_max==1
    disp('PREDICTED NITROGEN STATUS IS NORMAL')

% maximum ouput is in the second column.
elseif output_max==2
    disp('PREDICTED NITROGEN STATUS IS LOW')
end

if desire_max~=output_max
    n=n+1;
end
end

diagnosing accuracy rate = (nov1-n)/nov1

%END
```

VITA

Ruixiu Sui was born in Qiansuilou, Xiayi County, Henan Province, China on 28 November 1956. He attended Jiguolou Elementary School, and graduated from Huiting High School, Xiayi, Henan, China in February 1974.

In August of 1976, he entered Lanzhou University, Lanzhou, China, and graduated in August of 1979 with a major in Radio-Physics. Then he worked with Chinese Academy of Agricultural Sciences in Beijing, China. As a visiting scholar, he was sent by the Chinese Government to the United States for furthering his study in March of 1986. In January of 1987, He entered the Graduate School of The University of Tennessee at Knoxville. He received a Master of Science degree with a major in Agricultural Engineering in December of 1987. After the graduation he went back to China and resumed his research work at the Chinese Academy of Agricultural Sciences until he returned to The University of Tennessee again in January of 1996 to pursue a Ph.D. degree. He accepted a graduate research assistantship in the Agricultural and Biosystems Engineering Department. He completed his Ph.D. program in May of 1999 and received a Doctor of Philosophy degree with a major in Biosystems Engineering.

He is a member of Gamma Sigma Delta, the honor Society of Agriculture, a member of American Society of Agricultural Engineering, and a member of China Society of Instrumentation.

