NUTRIENT STRESS DETECTION IN CORN, USING NEURAL NETWORKS AND AVIRIS HYPERSPECTRAL IMAGERY

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1. INTRODUCTION AND BACKGROUND

The U.S. Department of Agriculture (USDA) Agricultural Research Service (ARS) Variable Rate (VRAT) Nitrogen Application site in Shelton, Nebraska, represents a well-documented, corn-growing quarter section. The USDA VRAT site is used to systematically study nutrient stress in corn by varying sub-plot application of fertilizer. The field has four replicates of five blocks that vary by nitrogen treatment from 0-kg/ha to 200-kg/ha in 50-kg/ha increments. The treatment blocks are set out in a randomized, complete block design.

Typically, the VRAT is planted in a ridge till, monoculture corn and is watered by a central pivot irrigation system on a three-day period. Since water stress can increase spectral reflectance from corn leaves (Wooley, 1971), it is important that the N-application plots be adequately watered so that only nutrient-related stress will predominate. Figure 1 shows imagery of the USDA VRAT site with the fertilizer amounts for each block shown.

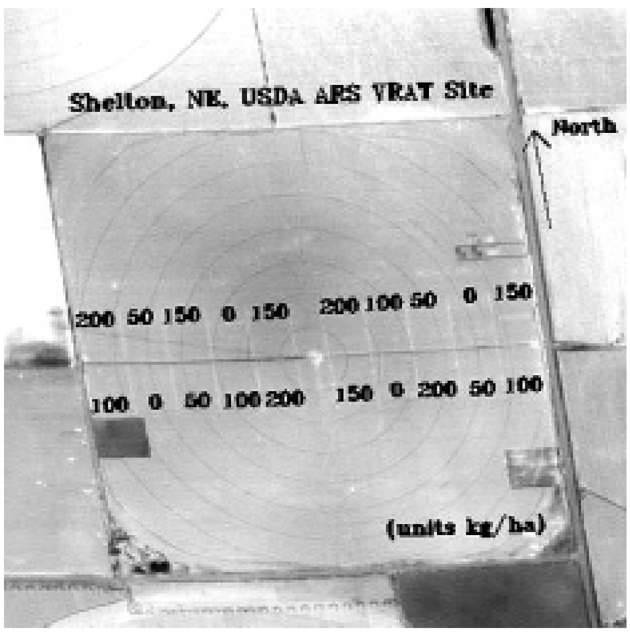

Figure 1. ATLAS NIR Image of USDA VRAT Study Site

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Low-altitude AVIRIS hyperspectral imagery was acquired over the Shelton, Nebraska, VRAT site on July 22, 1999. The overflight produced 3-meter pixels with 224 spectral bands. Ground personnel supported the mission with measurements at the time of the overflight. The image data was pre-processed at JPL before being sent out to an investigator. The data arrived radiometrically corrected, allowing ready application of an atmospheric correction procedure. The Atmosphere Removal Program (ATREM) (Gao et al., 1993) was used to perform an atmospheric correction. The AVIRIS imagery after ATREM correction was output as relative reflectance. This relative reflectance file was scaled by an empirical line procedure to provide reflectances that matched closely those measured in the field.

2. APPROACH

The objective of this study was to compare the results of Artificial Neural Network (ANN) processing of hyperspectral image data for stress detection to the results of standard processing techniques and algorithms that have been exercised in the literature for the detection of crop, or plant, stress. A stress detection method or technique was evaluated by whether the imagery associated with the method or technique was capable of separating the different N-treatment blocks in the VRAT field from a set of controls – with the best nourished, 200-kg/ha plots as the controls.

The ANN program used in this study applies a standard back propagation method (Rumelhart and McClelland, 1986) to adjust the nodal weights and biases using an iterative, gradient descent technique so that the network “learns,” or trains, given input data and output target values (Haykin, 1994). The neural network program used in this study was implemented in the following manner. First, reflectance values associated with regions of interest (ROI's) were extracted from each of the five plots, within the two replicates on the western side of the VRAT field. The pixel data were collated row-wise for each type treatment block and the amount of fertilizer provided to the plot (e.g., 50-kg/ha, 100-kg/ha) was appended to the end of the row of pixel spectral data. Once completed for each treatment plot, the merged data set for all the test blocks formed the input file used by the back-propagation, neural network for training.

When training was completed, the resulting weights and biases for the relevant network topology were saved and used to compute, on a pixel-by-pixel basis, an apparent fertilizer application over the two replicates on the eastern side of the VRAT field. The apparent fertilizer amounts for this region were then displayed as an image, which, in turn, could be interpreted as a nutrient stress index over the VRAT field.

3. DISCUSSION

Relevant algorithm results that were compared included the following:
1) Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974)
2) Rededge (Horler et al., 1983)
3) Weighted Difference Vegetation Index (WDVI) (Clevers, 1988)
4) Transformed Soil Adjusted Vegetation Index (TSAVI) (Baret and Guyot, 1991)
5) Three Channel Vegetation Index (TCHVI) (Efremenko et al., 2000)
6) Gitelson and Merzlyak (1996)
7) Red-edge Stress Vegetation Index (RSVI) (Merton, 1998)
8) Estep (2000)

The ANN results were also compared to results generated by two supervised classification procedures. Comparative imagery between the above algorithms and trained neural network imagery are displayed for the venerable NDVI algorithm only. Refer to Table 1 for a complete comparison summary of results.

3.1 Comparison of NDVI Neural Network and Plant Stress Algorithm Results

AVIRIS Bands 36 and 52 provide the requisite red and near-infrared (NIR) bands required for the NDVI computation. Figure 2 shows the NDVI results over the VRAT site. Note that the untreated blocks (0-kg/ha) are readily distinguishable. To a lesser extent, the 50-kg/ha treatment blocks exhibit some stress as well. Moreover, the 100-kg/ha block on the eastern margin of the field visually shows stress. This stress, however, can be somewhat ascribed to a misapplication of the fertilizer – but not all.

The AVIRIS NDVI image also picks up a stressed area of vegetation, seen as a darker-toned band on the north-central periphery of the field. The irrigator is turned off over this area to create water stress effects in the corn. This deliberately stressed region is used in this study to assess whether a given algorithm, or neural network result, can distinguish nutrient stress from water stress effects in corn.

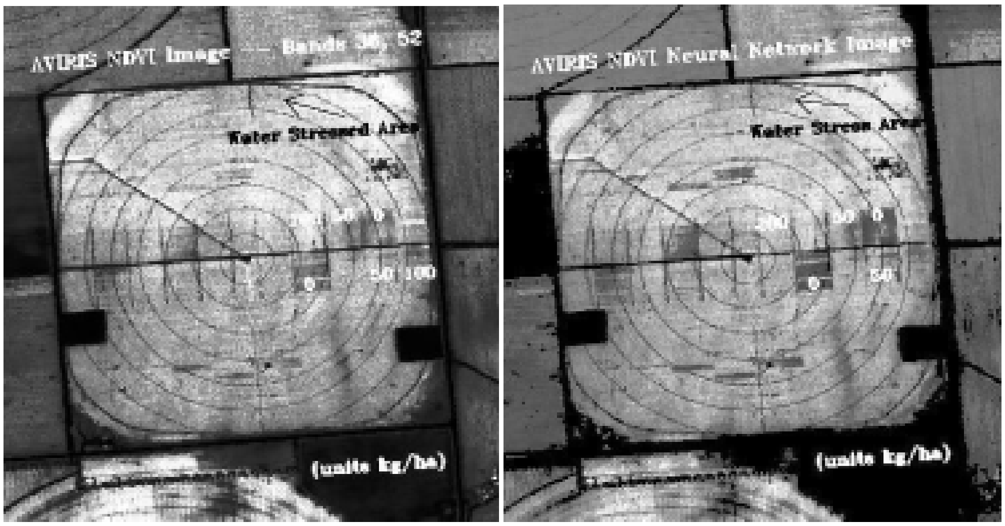

Figure 2. NDVI Comparison Images, Bands 37 and 51 (both images similarly stretched)

In comparison, Figure 2 also provides the neural network equivalent of the NDVI. Both images were stretched by the same default values. Here, “equivalent” means that the same bands that are used to compute the NDVI are used as input data to train the neural network. In this way, one can assess whether a neural network that has learned to distinguish the different levels of nutrient stress present over the VRAT can perform as well as the standard NDVI algorithm at displaying extant crop stress, given the selected spectral data input. As seen, the neural network version of a hyperspectral NDVI provides comparable nutrient stress information for the relevant treatment blocks. Note that both the neural network result and the NDVI algorithm detect the water stress area.

It is interesting to compare these two single-band images by plotting their average NDVI value side by side as a function of nitrogen treatment. Using ROI's, plot data were extracted from the images in Figure 2 and compiled. Figure 3 shows curves of the respective plot data.

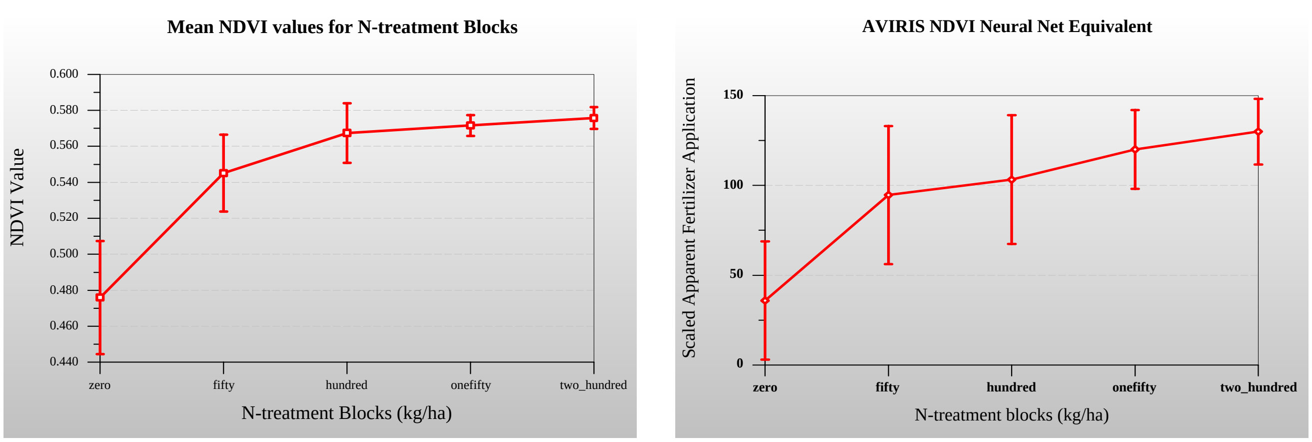

Figure 3. NDVI Algorithm and ANN Data Plot

The graph on the left in Figure 3 shows the mean NDVI values plotted against the N-treatment blocks from which the NDVI values were extracted. Error bars are also plotted and represent an excursion of one standard deviation above and below the mean value. In image terms, a given mean NDVI value is really a mean brightness associated with an N-treatment plot. The error bars, then, express the dominant range of brightness values that is associated with an N-treatment plot.

In both plots shown in Figure 3, a falling off of the NDVI-type values is seen at the higher levels of fertilizer application. This appears to be something of a saturation effect. This roll-off signals a loss of sensitivity in the detection of the N-treatment plots at the higher nitrogen applications. This loss can make it difficult to distinguish the higher N-treatment applications from the controls. Note that the roll-off seen in the ANN graph in Figure 3 is somewhat mitigated. The general trend of the plot stays the same – moving from lower to higher values of effective N-application.

Given the data used to construct Figure 3, an ANOVA was run. The results for both data sets provided for the rejection of the null hypothesis at the $p < 0.0001$ level. The follow-on Dunnett multiple comparison tests (Siegel, 1956), which compare the mean 0-, 50-, 100-, and 150-kg/ha plots to the controls, determined that the standard NDVI algorithm could separate all N-treatment plots from the controls. The mean 0-, 50-, and 100-kg/ha plots were separable from the controls at a $p < 0.01$ level. The mean 150-kg/ha plot was separable from the controls at the $p < 0.05$ level.

The Tukey-Kramer multiple comparison tests (Siegel, 1956), which intercompare all plots with one another, showed that the standard NDVI algorithm could not separate statistically the 100-kg/ha mean plot from the 150-kg/ha mean plot. This result is not surprising, given the fact that the NDVI saturates somewhat at higher fertilizer applications. In contradistinction, the neural network NDVI equivalent results allowed complete separation between all mean N-treatment plots and the controls at a $p < 0.01$ level of significance. Moreover, the Tukey-Kramer multiple comparison tests for the neural network results showed all mean blocks separable from one another at the $p < 0.01$ level.

3.2 Compilation of Comparison Results

Table 1 provides a head-to-head comparison between ANN outcomes and the associated standard algorithm results. Column 1 names the algorithm used. Columns 2 and 4 provide the mean N-treatment blocks that can be separated from the controls by the standard algorithm and the neural network, respectively. SAM and MLC refer to Spectral Angle Mapper and Maximum Likelihood Classifier respectively. The last column states whether the band of deliberately water-stressed corn was visible in either the imagery associated with the standard algorithms or the imagery associated with the neural network outcome, respectively. As can be seen, the neural network results are consistently better at statistically separating the N-treatment blocks from the controls.

Table 1. Comparison Summary of Standard Algorithms and Neural Network Results

Standard Algorithm Name/Clevers' Bandset	Block/Control Separation – Algorithm	Neural Network Bands Used	Block/Control Separation – Neural Net	Sensitive to Water Stress – Algorithm/ Neural Net (y/n)
NDVI	0,50,100,150	Bands 36,52	0,50,100,150	Y/Y
Red Edge	0,50,100,150	Bands 36-40	0,50,100,150	Y/Y
Gitelson-Merzlyak	0,50,100	Bands 19,43	0,50,100,150	N/Y
RVSI (Merton)	0,50,100	Bands 39,41,43	0,50,100	Y/Y
WDVI	0,50,100,150	Bands 36,53	0,50,100,150	Y/Y
TSAVI	0,50,150	Bands 36,53	0,50,100,150	Y/Y
TCHVI	0,50,100	Bands 20,36,53	0,50,100,150	Y/N
Estep	0,50,100,150	Bands 12,20	0,50,100,150	N/Y
Clevers VIS SAM/Nnet	0,50,100	Bands 15-38	0,50,100	Y/Y
Clevers NIR SAM/Nnet	0,50	Bands 41-107	0,50,100,150	Y/Y
Clevers SWIR SAM/Nnet	0	Bands 122-206	0,50,100	Y/Y
Clevers VIS MLC/Nnet	0,50	Bands 15-38	0,50,100	Y/Y
Clevers NIR MLC/Nnet	0,50,100	Bands 41-107	0,50,100	Y/Y
Clevers SWIR MLC/Nnet	0	Bands 122-206	0,50,100	Y/Y

4. SUMMARY

AVIRIS image cube data were processed for the detection of pre-visual stress in corn by both standard algorithmic forms and by trained artificial neural networks. The ANN results, compared to analogous forms of known stress algorithms, appear to provide a better overall capability to separate stressed crops from in-field controls.

The stress present over the VRAT arose from two predominant sources: nutrient stress and water stress. The deliberately water-stressed area on the northern boundary of the VRAT provided an important reference region. This water-stressed region allowed an assessment of the sensitivity of the tested stress detection techniques – both algorithmic and ANN – to discriminate between these two important types of crop stress. As shown in Table 1, in only three cases were the two sources of stress separated. However, this finding could possibly provide a benefit to the grower community, if further corroborated, by yielding a technique to distinguish between these important crop stressors.

5. REFERENCES

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