Reprinted from

Seventh International Symposium

Machine Processing of

Remotely Sensed Data

with special emphasis on

Range, Forest and Wetlands Assessment

June 23 - 26, 1981

Proceedings

Purdue University
The Laboratory for Applications of Remote Sensing
West Lafayette, Indiana 47907 USA

A TECHNIQUE TO DETERMINE WHICH CROP DEVELOPMENT STAGES CAN BE ESTIMATED FROM SPECTRAL DATA

V.J. POLLARA, V.C. VANDERBILT, C.S.T. DAUGHTRY

Purdue University/LARS
West Lafayette, Indiana

ABSTRACT

Estimates of crop development stage by remote sensing techniques are potentially more cost effective for large areas than present labor intensive estimates. Here, discriminant analysis for identifying crop development stage using multispectral data is discussed. The data analyzed were Exotech 100 measurements in four wavelength bands (.5-.6, .6-.7, .7-.8, .8-1.1 um) over field plots of soybeans and corn in West Lafayette, Indiana. Different row spacings, soils, plant populations, planting dates, soybean cultivars and crop years (1978, 1979, 1980) increased the generality of the data set.

Results show that development stage classes at the beginning and end of the growing season have relatively high classification accuracy. Midseason classes have moderate to low classification accuracies. Overall accuracy increases as development stages are pooled to form fewer classes per growing season. Applying discriminant analysis to a subset of development stages in a season increases classification accuracy.

I. INTRODUCTION

Crop simulation models are becoming increasingly important for forecasting yields of several economically important crops. For prediction purposes, yield models require information about crop development stage because weather and stresses affect crops differently at different parts of the crop life cycle.

Crop development, indicated by reflectance change, has been examined by Collins (1) who looked at the shift in the red region of wheat and sorghum reflectance curves as those crops grew. Gausman et. al. (2) noted species specific patterns of reflectance changes for corn and cotton leaves in several bands between 0.55 and 2.2 um as the season progressed. Blair and Baumgardner (3) used ratio transformations of Landsat data to monitor springtime greening and autumn browning of hardwood forests. Kauth and Thomas (4) presented the tasselled cap as a way of looking at changes in reflectance from planting to harvest. Their approach demonstrates a distinct pattern of reflectance change during the course of a season. This pattern is described by brightness, greenness, yellowness and nonsuch, transformations of the four Landsat MSS bands.

These previous researchers compared some measure of crop age such as LAI, biomass, or development stage to the reflectance in some selected spectral bands or transformations of spectral bands. Their goal was to determine if changes in crop status could be detected with spectral measurements. Our objective was to test whether the clusters of data points representing specific development stages are statistically separable in spectral space.

II. MATERIALS AND METHODS

A. DATA

Data from field experiments were collected on the Purdue Agronomy Farm 10 km northwest of West Lafayette, Indiana.

Radiometric measurements were made with an Exotech 100 with four wavelength bands (.5-.6, .6-.7, .7-.8, .8-1.1um) over field plots of soybeans (Glycine max (L.) Merr.) and corn (Zea mays L.).

The treatments of the soybean and corn field experiments are outlined in Table 1. The 1978 soybean experiment also included three levels of potassium and phosphorus treatments. Development stages of soybeans were recorded with the Fehr and Caviness (5) scale and later converted to the Kalton and Weber (6) numerical scale to facilitate analysis. Corn development stages were recorded with the Hanway (7) maturity index. There were a total of 25 different development stages recorded for corn and 18 development stages recorded for soybeans throughout the entire growing season.

B. ANALYSIS

The data were analyzed two ways. For the first part of the analysis the 25 possible corn development stages were grouped eight different ways into 25, 16, 12, 11, 10, 10, 9, and 6 classes (representing the whole season) for eight separate discriminant analyses using SAS PROC DISCRIM (8). The 18 possible soybean development stages were grouped five different ways into 18, 12, 9, 9, and 5 classes for five separate discriminant analyses. Prior probabilities of all classes were set equal.

For the second analyses, discriminant analysis was performed on three subsets of the development stage classes in a growing season to give a separate analysis on development stage classes from the three major portions of the crop life cycle (vegetative, reproductive and grain fill). For each analysis, the development stages under consideration were assigned equal prior probabilities and the stages not considered were assigned a prior probability close to zero.

Of the eight development stage class schemes for corn used in the first part analyses, four (25, 16, 10, 6) were selected for further analysis. Three separate analyses were done on subsets of the classes from each of the four schemes for a total of 12 analyses. Of the five development stage class schemes used in the first soybean analyses, three were selected (18, 9, 5) and three analyses were done on subsets of the classes from each scheme for a total of nine analyses.

III. RESULTS

Classification results for nine training classes of corn, Table 2, and soybeans, Table 3, show the proportions of the training data that are correctly and incorrectly classified. The main diagonal contains the percentage of correctly reclassified data vectors for each class. Off diagonal elements represent incorrectly classified data vectors. For example, 46.2% of the corn data points from class 8.0 were correctly reclassified into class 8.0. But 8.5% of those corn data were incorrectly classified as the class 2.75-3.5, which included the development stages from 2.75 to 3.5, 3.8% as class 3.75-6.0, 34.0% as class 7.0 and 7.6% as 9.0. Soybean class 10.0-11.0 was 90.3% correctly reclassified with 3.2% and 2.0% of the data vectors misclassified into classes 0-0.25 and 0.5-0.75 respectively.

Figure 1 contains results for eight separate discriminant analyses for corn where each column represents one analysis with development stages grouped in classes as shown. The number in each class box is the percent of data vectors correctly reclassified. The column for nine classes in Figure 1 corresponds to the diagonal of Table 2. For example, in the analysis for 25 classes, 91.7 % of data vectors from class 0.0 were correctly classified as 0.0. Likewise, 1.7% of data vectors from class 2.75 were correctly classed as 2.75. When all development stages were grouped into six classes, the first class containing stages 0.0 to 1.5 had a 92.9% reclassification accuracy. The class containing development stages 1.75 to 2.5 had a reclassification accuracy of 43.8%.

Results of five separate discriminant analyses for soybeans appear in Figure 2. With 18 classes, 80.8% of the data vectors from stage 0.0 were correctly reclassified. For five classes, 89.1% of the data vectors from the stages 0.0 to 1.5 were correctly reclassified as class 0.0-1.5.

The results show that development stage classes at the beginning and end of the season have relatively high classification accuracies, indicating good separability between classes. Midseason classes have moderate to low classification accuracies indicating these classes are less separable.

Overall accuracy increases as development stages are pooled to form fewer classes. In some cases such as class 9-11 for the five class analysis of soybeans (Figure 2), reclassification accuracy decreased when three classes were pooled.

The results in Figure 3 are from analyses on subsets of the classes of four class schemes (25, 16, 10 and 6 classes) for corn data. The trend of increased accuracy with class pooling remains and accuracy increases or remains the same. Figure 4 shows results for discriminant analysis for growing season subsets of development stage classes for three class schemes (18, 9 and 5 classes) for soybeans.

IV. DISCUSSION

The results indicate classification accuracies for the ideal condition; the data set used to test the classifier is the same as the training data set. The results provide an upper bound on the accuracy of determining crop development stage from spectral data with the SAS classifier. The percent of points correctly reclassified is high at both ends of the season and low in the middle of the season (Figures 1 and 2). Since all classes were considered equally probable, bare soil and yellowing or brown crops occupy regions of spectral space with little overlap of other classes. The low midseason classification accuracies indicate that reflectance of crops at development stages near midseason occupy overlapping regions of spectral space.

Grouping several neighboring classes usually provides increased reclassification accuracy. When classification accuracy decreases with pooling it is most likely because the new class occupies too large a region of spectral space and it overlaps with other classes. Such a class would include reflectance measurements over a crop that has changed its scene characteristics substantially by growing.

The results in Tables 2 and 3 show that misclassified data vectors are not restricted only to neighboring development stage classes. The set of confusion classes often includes classes at the opposite end of the growing season.

Classification accuracy of some classes increased dramatically when the most viable confusion classes were eliminated (Figures 3 and 4). The greatest increases in classification accuracy are for the classes near the cut-off of the season segment under consideration. Prior probabilities of the classes immediately neighboring the cut-off classes were set to zero preventing misclassification into them.

In reality prior probabilities of some development stages are higher than others. The probability of a development stage class being present in a scene depends on the time of the growing season. Knowledge of an average crop calendar would allow a researcher to assign different prior probabilities to each development stage class on a real time basis. Prior probabilities of zero would be assigned to improbable classes. The result would be an increase in accuracy of real time development stage assessment with spectral data.

V. REFERENCES

1. Collins, W. 1978. Remote Sensing of Crop Type and Maturity. Photogrammetric Engineering and Remote Sensing 44:43-55.

2. Gausman, H. W., W. A. Allen, R. Cardenas, and A. J. Richardson. 1973. Reflectance Discrimination of Cotton and Corn at Four Growth Stages. Agronomy Journal 65:194-198.

3. Blair, B.O., M.F. Baumgardner. 1977. Detection of the Green and Brown Wave in Hardwood Canopy Covers Using Multidate, Multispectral Data from Landsat-1. Agronomy Jounral 69:808-811.

4. Kauth, R.J., G.S. Thomas. 1976. The Tasselled Cap - A Graphic Description of the Spectra-Temporal Development of Agricultural Crops as Seen by Landsat. Symposium on Machine Processing of Remotely Sensed Data. Purdue University, W. Lafayette, IN 47906.

5. Fehr, W.R., C.E. Caviness, D.T. Burmood and J.S. Pennington. 1971. Stage of Development Descriptions for Soybeans, <u>Glycine max</u> (L.) Merrill. Crop Sci. 11:929-931.

6. Kalton, R.R., C.R. Weber, and J.C. Ethredge. 1949. The Effect of Injury Simulating Hail Damage to Soybeans. Iowa Agr. and Home Econ. Exp. Sta. Res. Bull. 359. 60 p.

7. Hanway, J.J. 1966. How a Corn Plant Develops. Iowa State University. Special Report No. 48. Cooperative Extension Service. Ames, Iowa.

8. Helwig, J.T. and K.A. Council. 1979. SAS User's Guide, 1979 Edition. SAS Institute, Inc. Cary, North Carolina. pp. 183-190.

V. Pollara is a graduate student pursuing a M.S. degree at Purdue University in Agronomy. He received a B.S. in Biology (1979) from Coole College, Rutgers University.

Dr. V. C. Vanderbilt is with the Laboratory for Applications of Remote Sensing as a research engineer developing physically based analyses and mathematical models of remotely sensed biological systems. He has the usual degrees from Purdue University in electrical engineering.

Craig Daughtry is a research agronomist with the Laboratory for Applications of Remote Sensing at Purdue University. He has B.S. and M.S. degrees in agronomy from the University of Georgia and a Ph.D. in crop physiology from Purdue University. Dr. Daughtry has actively participated in design, implementation, and analysis of crop inventory research at LARS. He is a member of the American Society of Agronomy, Crop Science Society of America, American Society of Photogrammetry and several honorary societies.

Table 1. Treatments of the field experiments over which the data was collected.

	SOYBEANS			CORN	
	1978	1979	1980	1979	1980
SOIL	Raub†	Russell‡ Chalmers§	Toronto¶ Chalmers	Fincastle# Chalmers	Fincastle Chalmers
PLANTS/ha	288,000	266,000	266,000	25,000 50,000 75,000	25,000 50,000 75,000
ROW SPACING	15 cm	25cm 75cm	25cm 75cm	76cm	76cm
PLANTING DATES	1	3	7	3	7
CULTIVAR	Amsoy 71	Amsoy 71 Williams	Amsoy 71 Williams	Beck 65X	Beck 65X

†silt loam-mesic Aquic Argiudoll
§silty clay loam-typic Haplaquoll
#fine silt-mesic Aeric Ochraqualf
‡silt loam-typic Hapludalf
¶fine silt-Udollic Ochraquolf

TABLE 2. ERROR MATRIX FOR 9 DEVELOPMENT STAGE CLASSES OF CORN FOR A WHOLE SEASON.

TRUE CLASS	PERCENTS CLASSIFIED INTO CLASS 0-0.5	0.75-1.5	1.75-2.5	2.75-3.5	3.75-6.0	7.0	8.0	9.0	10.0	NUMBER OF OBSERVATIONS
0-0.5	95.2	4.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	208
0.75-1.5	40.2	48.0	8.7	0.9	0.2	0.0	0.0	1.8	0.2	550
1.75-2.5	2.0	23.2	42.3	21.4	2.5	1.3	4.6	2.6	0.0	392
2.75-3.5	0.0	0.0	11.5	58.3	4.8	10.7	11.1	3.6	0.0	252
3.75-6.0	0.0	0.7	4.7	34.6	11.4	30.5	17.8	0.3	0.0	298
7.0	0.0	0.0	1.3	10.1	2.0	63.8	22.8	0.0	0.0	149
8.0	0.0	0.0	0.0	8.5	3.8	34.0	46.2	7.6	0.0	106
9.0	0.0	1.1	2.2	4.9	0.6	1.6	9.9	56.6	23.1	182
10.0	0.0	2.4	0.0	0.0	1.2	0.0	0.0	8.9	87.5	168
TOTAL										2305
PRIOR PROBABILITY	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	

TABLE 3. ERROR MATRIX FOR 9 DEVELOPMENT STAGE CLASSES OF SOYBEANS FOR A WHOLE SEASON.

TRUE CLASS	PERCENTS CLASSIFIED INTO CLASS 0-0.25	0.5-0.75	1.0-1.5	2.0-2.5	3.0-3.5	4.0-5.0	6.0-7.0	8.0-9.0	10.0-11.0	NUMBER OF OBSERVATIONS
0-0.25	89.2	8.8	1.6	0.0	0.5	0.0	0.0	0.0	0.0	194
0.5-0.75	44.9	26.7	21.7	4.2	1.0	0.0	0.0	0.0	1.4	285
1.0-1.5	10.5	10.5	61.3	12.1	3.2	0.8	0.0	0.0	1.6	124
2.0-2.5	1.6	10.6	19.7	39.9	19.7	6.9	0.5	0.0	1.1	188
3.0-3.5	1.2	0.6	16.9	19.3	41.6	20.5	0.0	0.0	0.0	166
4.0-5.0	0.0	0.0	7.4	8.4	16.8	45.5	13.9	7.9	0.0	202
6.0-7.0	0.0	0.0	0.5	1.4	4.7	3.7	74.8	15.0	0.0	214
8.0-9.0	0.0	0.1	1.0	0.7	2.0	11.8	32.7	50.2	1.4	697
10.0-11.0	3.2	2.0	0.8	0.0	0.4	1.6	0.0	1.6	90.3	248
TOTAL										2318
PRIOR PROBABILITY	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	

<table>
<tr><th rowspan="2">Hanway Maturity Index</th><th colspan="8">NUMBER OF CLASSES IN THE CLASSIFICATION</th></tr>
<tr><th>25</th><th>16</th><th>12</th><th>11</th><th>10</th><th>10</th><th>9</th><th>6</th></tr>
<tr><td>0.0</td><td>91.7</td><td>97.2</td><td rowspan="2">89.6</td><td rowspan="3">95.1</td><td rowspan="3">95.1</td><td rowspan="3">95.1</td><td rowspan="3">95.1</td><td rowspan="7">92.9</td></tr>
<tr><td>0.25</td><td>15.2</td><td rowspan="2">37.5</td></tr>
<tr><td>0.5</td><td>90.9</td><td></td></tr>
<tr><td>0.75</td><td>5.3</td><td rowspan="2">41.6</td><td rowspan="3">54.2</td><td rowspan="4">54.2</td><td rowspan="4">48.0</td><td rowspan="4">48.0</td><td rowspan="4">48.0</td></tr>
<tr><td>1.0</td><td>51.6</td></tr>
<tr><td>1.25</td><td>25.6</td><td rowspan="2">35.1</td></tr>
<tr><td>1.5</td><td>0.6</td><td></td></tr>
<tr><td>1.75</td><td>31.9</td><td rowspan="2">36.9</td><td rowspan="3">54.1</td><td rowspan="4">42.3</td><td rowspan="4">42.3</td><td rowspan="4">42.3</td><td rowspan="4">42.3</td><td rowspan="8">43.8</td></tr>
<tr><td>2.0</td><td>30.1</td></tr>
<tr><td>2.25</td><td>33.3</td><td rowspan="2">25.0</td></tr>
<tr><td>2.5</td><td>16.6</td><td></td></tr>
<tr><td>2.75</td><td>1.7</td><td rowspan="2">18.5</td><td rowspan="3">39.1</td><td rowspan="4">30.9</td><td rowspan="4">40.8</td><td rowspan="4">43.2</td><td rowspan="4">58.3</td></tr>
<tr><td>3.0</td><td>10.6</td></tr>
<tr><td>3.25</td><td>45.8</td><td rowspan="2">28.9</td></tr>
<tr><td>3.5</td><td>18.2</td><td></td></tr>
<tr><td>3.75</td><td>17.8</td><td rowspan="2">25.0</td><td rowspan="3">18.5</td><td rowspan="3">1.0</td><td rowspan="5">8.8</td><td rowspan="3">1.0</td><td rowspan="6">11.4</td><td rowspan="6">44.3</td></tr>
<tr><td>4.0</td><td>30.5</td></tr>
<tr><td>4.25</td><td>2.9</td><td rowspan="2">2.3</td></tr>
<tr><td>4.5</td><td>50.0</td><td>61.5</td><td rowspan="2">33.0</td><td rowspan="3">54.0</td></tr>
<tr><td>5.0</td><td>11.1</td><td>14.8</td><td>12.9</td></tr>
<tr><td>6.0</td><td>19.1</td><td>52.9</td><td>26.4</td><td>60.2</td><td>64.7</td></tr>
<tr><td>7.0</td><td>18.7</td><td>24.1</td><td>24.8</td><td>28.1</td><td>29.5</td><td>53.6</td><td>63.7</td><td rowspan="2">67.5</td></tr>
<tr><td>8.0</td><td>39.6</td><td>41.5</td><td>42.4</td><td>43.4</td><td>45.2</td><td>43.4</td><td>46.2</td></tr>
<tr><td>9.0</td><td>54.4</td><td>55.4</td><td>55.4</td><td>56.0</td><td>56.0</td><td>56.5</td><td>56.5</td><td>59.3</td></tr>
<tr><td>10.0</td><td>85.1</td><td>86.9</td><td>88.6</td><td>86.3</td><td>86.9</td><td>86.3</td><td>87.5</td><td>87.5</td></tr>
<tr><td>Overall</td><td>32.5</td><td>39.8</td><td>52.5</td><td>49.0</td><td>49.7</td><td>52.9</td><td>52.1</td><td>67.0</td></tr>
</table>

Figure 1. Percent correct classification for eight analyses of corn.

<table>
<tr><th rowspan="2">Kalton & Weber Index</th><th colspan="5">NUMBER OF CLASSES IN THE CLASSIFICATION</th></tr>
<tr><th>18</th><th>12</th><th>9</th><th>9</th><th>5</th></tr>
<tr><td>0.0</td><td>80.8</td><td rowspan="3">85.2</td><td rowspan="3">85.2</td><td rowspan="2">89.1</td><td rowspan="6">89.1</td></tr>
<tr><td>0.25</td><td>73.4</td></tr>
<tr><td>0.50</td><td>16.3</td><td rowspan="2">26.6</td></tr>
<tr><td>0.75</td><td>26.5</td><td rowspan="2">47.9</td><td rowspan="2">47.9</td></tr>
<tr><td>1.0</td><td>50.0</td><td rowspan="2">61.2</td></tr>
<tr><td>1.5</td><td>20.5</td><td rowspan="2">39.5</td><td rowspan="2">40.3</td></tr>
<tr><td>2.0</td><td>33.3</td><td rowspan="2">39.8</td><td rowspan="4">61.3</td></tr>
<tr><td>2.5</td><td>28.5</td><td rowspan="2">27.7</td><td rowspan="2">27.7</td></tr>
<tr><td>3.0</td><td>20.0</td><td rowspan="2">41.5</td></tr>
<tr><td>3.5</td><td>50.0</td><td rowspan="2">62.6</td><td rowspan="2">63.4</td></tr>
<tr><td>4.0</td><td>29.4</td><td rowspan="2">45.5</td><td rowspan="2">62.3</td></tr>
<tr><td>5.0</td><td>58.2</td><td>58.9</td><td rowspan="2">56.5</td></tr>
<tr><td>6.0</td><td>53.3</td><td>52.3</td><td rowspan="2">74.7</td><td rowspan="3">87.3</td></tr>
<tr><td>7.0</td><td>40.4</td><td>40.4</td><td rowspan="2">79.3</td></tr>
<tr><td>8.0</td><td>54.8</td><td>54.8</td><td rowspan="2">50.2</td></tr>
<tr><td>9.0</td><td>11.8</td><td>11.8</td><td rowspan="2">12.3</td><td rowspan="3">32.6</td></tr>
<tr><td>10.0</td><td>75.0</td><td>77.7</td><td rowspan="2">90.3</td></tr>
<tr><td>11.0</td><td>70.7</td><td>71.7</td><td>89.6</td></tr>
<tr><td>Overall</td><td>39.5</td><td>47.1</td><td>50.5</td><td>55.8</td><td>63.0</td></tr>
</table>

Figure 2. Percent correct classification for five analyses for soybeans.

NUMBER OF CLASSES IN THE CLASSIFICATION

Hanway Maturity Index	25			16			10			6		
	Subset of Development Stages											
	Veg.	Repro.	G.F.	Veg	Repro.	G.F.	Veg.	Repro.	G.F.	Veg.	Repro.	G.F.
0	91.7 0.0			97.2 0.0			95.2 0.0			93.9 + 1.1		
.25	15.2 0.0			37.5 0.0								
.5	90.9 0.0											
.75	5.4 0.0			42.1 + 0.4			49.1 + 1.1					
1.0	51.6 - 0.1											
1.25	26.2 + 0.6			36.1 + 1.0								
1.5	0.7 0.0											
1.75	32.6 + 0.7			38.8 + 1.9			45.9 + 3.6			82.8 +39.0		
2.0	31.0 + 0.9											
2.25	37.0 + 3.7			33.3 + 8.3								
2.5	52.6 +35.9	30.8 +14.1										
2.75	20.7 +19.0	3.4 + 1.7		66.9 +48.4	43.6 +25.0		83.3 +40.1	68.6 +25.4				
3.0	43.9 +33.3	10.6 0.0										
3.25		50.0 + 4.2			37.5 + 8.6							
3.5		20.2 + 1.9										
3.75		17.9 0.0			37.5 +12.5			3.1 + 2.0			52.2 + 7.9	
4.0		38.9 + 8.3										
4.25		2.9 0.0			2.3 0.0							
4.5		50.0 0.0						78.2 +24.2	64.9 +10.9			
5.0		14.8 + 3.7			16.7 + 1.9							
6.0		25.0 + 5.9	70.6 +51.7		67.6 +14.7	70.6 +51.7						
7.0		25.5 + 6.7	32.9 +14.1			32.9 +14.1			55.7 + 2.0		78.8 11.3	86.3 +18.8
8.0			48.1 + 8.5			48.1 + 8.5			44.3 + 0.9			
9.0			60.4 + 6.0			60.4 + 6.0			61.0 + 4.4			63.7 + 4.4
10.0			91.9 + 6.0			91.1 + 5.9			91.1 + 4.8			90.5 + 3.0

Figure 3. Twelve discriminant analyses for subsets of corn development stage classes. Upper values are the percentage of correctly classified data and lower values indicate the improvement over whole season analyses.

NUMBER OF CLASSES IN THE CLASSIFICATION

<table>
<tr><th rowspan="3">Kalton & Weber Index</th><th colspan="3">18</th><th colspan="3">9</th><th colspan="3">5</th></tr>
<tr><th colspan="9">Subset of Development Stages</th></tr>
<tr><th>Veg.</th><th>Repro</th><th>G.F.</th><th>Veg.</th><th>Repro</th><th>G.F.</th><th>Veg.</th><th>Repro</th><th>G.F.</th></tr>
<tr><td>0</td><td>96.8
+16.0</td><td></td><td></td><td rowspan="2">85.7
+ 3.5</td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="6">89.2
+ 0.1</td><td rowspan="10"></td><td rowspan="6"></td></tr>
<tr><td>.25</td><td>78.1
+ 4.7</td><td></td><td></td></tr>
<tr><td>.50</td><td>41.3
+25.0</td><td></td><td></td><td rowspan="2">29.5
+ 2.8</td><td rowspan="2"></td><td rowspan="2"></td></tr>
<tr><td>.75</td><td>32.6
+ 6.1</td><td></td><td></td></tr>
<tr><td>1.0</td><td>50.0
0.0</td><td></td><td></td><td rowspan="2">58.1
- 3.2</td><td rowspan="2"></td><td rowspan="2"></td></tr>
<tr><td>1.5</td><td>20.6
0.0</td><td></td><td></td></tr>
<tr><td>2.0</td><td>33.3
0.0</td><td></td><td></td><td rowspan="2">38.1
- 1.8</td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="4">80.7
+19.4</td><td rowspan="4"></td></tr>
<tr><td>2.5</td><td>26.7
- 1.9</td><td></td><td></td></tr>
<tr><td>3.0</td><td>25.0
+ 5.0</td><td></td><td></td><td rowspan="2">64.0
+22.4</td><td rowspan="2">80.8
+39.3</td><td rowspan="2"></td></tr>
<tr><td>3.5</td><td>59.6
+ 9.6</td><td></td><td></td></tr>
<tr><td>4.0</td><td></td><td>91.1
+61.7</td><td></td><td rowspan="2"></td><td rowspan="2">39.9
- 5.7</td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="2">88.9
+26.5</td><td rowspan="2"></td></tr>
<tr><td>5.0</td><td></td><td>60.8
+ 2.6</td><td></td></tr>
<tr><td>6.0</td><td></td><td>52.9
- 0.4</td><td></td><td rowspan="6"></td><td rowspan="2">88.3
+13.6</td><td rowspan="2">80.8
+ 6.1</td><td rowspan="3"></td><td rowspan="3">89.3
+ 2.0</td><td rowspan="3">94.1
+ 6.7</td></tr>
<tr><td>7.0</td><td></td><td>33.3
- 7.2</td><td></td></tr>
<tr><td>8.0</td><td></td><td>62.0
+ 7.2</td><td>86.1
+31.2</td><td rowspan="4"></td><td rowspan="2">63.7
+13.5</td></tr>
<tr><td>9.0</td><td></td><td></td><td>51.9
+40.0</td><td rowspan="3"></td><td rowspan="3"></td><td rowspan="3">48.0
+15.3</td></tr>
<tr><td>10.0</td><td></td><td></td><td>77.8
+ 2.8</td><td rowspan="2">96.8
+ 6.5</td></tr>
<tr><td>11.0</td><td></td><td></td><td>77.8
+ 7.1</td></tr>
</table>

Figure 4. Nine discriminant analyses for subsets of soybean development stage classes. Upper values are the percentage of correctly classified data and lower values indicate the improvement over whole season analyses.