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MULTI-TEMPORAL CLASSIFICATION OF WINTER WHEAT USING A GROWTH STATE MODEL

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ABSTRACT

In this paper we describe a multi-temporal classification procedure for crops in LANDSAT scenes. The method involves the creation of crop signatures which characterize multi-spectral observations as functions of phenological growth states. The phenological signature models spectral reflectance explicitly as a function of crop maturity rather than a function of observation date. This means that instead of stacking spectral vectors of one observation on another, as is usually done for multi-temporal data, we establish for each possible crop category a correspondence of time to growth state which minimizes the smallest difference between the given multi-spectral multi-temporal vector and the category mean vector indexed by growth state. The results of applying this procedure to winter wheat show that the method is capable of discrimination with about the same degree of accuracy as more traditional multi-temporal classifiers. It shows some potential to label degree of maturity of the crop without crop condition information in the training set.

I. PHENOLOGICAL DISCRIMINATION MOTIVATIONS

Degree of maturity of the crop, or phenological stage can vary even within a small area at a given time. For example, Nalepka[15] has observed significant differences in phenological stage of winter wheat between fields in Kansas LACIE Intensive Test Sites and even between areas within the same field. Furthermore, it is possible for one field to be at the same stage of maturity as a neighboring field was 18 days earlier. Differences in growth stage are particularly significant in the later parts of the growing season of winter wheat due to the rapid changes in appearance that occur with maturation, cutting, and in some cases, tilling of the fields.

We have experimented with a crop discrimination method that takes account of and utilizes this grown stage factor. Multi-temporal classification is usually carried out by simply appending the spectral reflectance vectors observed at one time with the spectral reflectance vectors observed at another time. Then one processes the new data set as if it consisted of vectors like a single observation data set. The usual crop signature is a mean of these multi-temporal and multi-spectral vectors associated with the crop type.

We use a crop signature which consists of sets of multi-spectral vectors and associated crop type-growth states. Associated with each crop is an "M-th order signature" which is a set of M-tuples $(g;(\alpha_1,b_1),\ldots,(\alpha_M,b_M))$ where g is a growth state for the crop and (α_i,b_i) is an ordered pair designating that α_i is possible for band b_i when the crop is in growth state g. We say that a pixel is of a given crop if: (1) each set of observed gray levels on a particular date is consistent with some growth stage g described in the signature of that area, and (2) these g's are consistent with what we know about vegetation phenology: growth states at later dates must be more mature than growth states at earlier dates. Classification is done by eliminating categories which do not satisfy conditions (1) and (2). If more than one category is left after the process of elimination, then the pixel is unclassified.

To illustrate the meaning of this, consider a 2-band example. Suppose observations (α_1,α_2) and (α_1',α_2') of a small patch of ground are taken at times t_1 and

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t_2 using the bands b_1, b_2. This can be classified by determining, for each category c, the first growth stage g_1 such that (g_1, α_1, b_1) and (g_1, α_2, b_2) is in the signature for c. If there is no such growth state, then the category c is not consistent with the observed spectral reflectance and c is not a possible classification for the pixel. If there is not a later growth stage g_2 of category c such that (g_2, α_1', b_1) and (g_2, α_2', b_2) is in the signature for c, then c is not a possible classification for the pixel. Also note that we may impose restrictions on the growth states because only certain growth states may be possible at a particular observation time. In that case, category c will not be a possible choice if the only growth states consistent with the observed spectral reflectances are not possible for the observation times.

The effect of associated crop reflectance with growth state, rather than observation time, is to reduce the variance of crop signature. For example, in one typical experiment, the average standard deviation by band-date was 2.88, yet by band-growth state was 1.42.

The implementation of this discrimination method requires two basic steps: (1) signature creation using a training set and (2) classification of the multitemporal image using the derived signatures and crop calendar information.

A. GROWTH STATE SIGNATURES

Growth state signatures can be derived from training sets with an iterative procedure consisting of a step of dynamic programming minimization followed by averaging very much in the spirit of the ISODATA clustering technique[33]. Let us restrict our attention to one category for the moment. Let $x(b_i,j,t)$ be the observed spectral reflectance in the i-th band, j-th sample (pixel or average over a field) of one crop type, taken at the t-th observation time. The set $\{x(b_i,j,t) \mid i = 1,\ldots,I;\ j = 1,\ldots,J;\ t = 1,\ldots,T\}$ is the training set for this crop category.

A category signature will be a function which gives for each band and growth state, the mean spectral reflectance for the category. Let u be a category signature. Then $u(g,b_i)$ is the mean i-th band reflectance of a small area ground patch of that category in the g-th growth state. The iterative procedure begins with a spectral signature for the category and successively improves it.

We take for the initial mean signature the average of the training vectors whose time components have been simply interpolated over time to describe intermediate growth states. For example, say we have 5 observations, 13 growth states, and $\bar{\alpha}_1(1)$ and $\bar{\alpha}_1(2)$ are the average reflectances in the first band at the first and second observation times. Then $(1;\alpha_1(1))$, $(2;\alpha_1(1) + \frac{1}{3}(\alpha_1(2) - \alpha_1(1)))$, $(3;\alpha_1 + \frac{2}{3}(\alpha_1(2) - \alpha_1(1)))$ and $(4;\alpha_1(2))$ are in the initial signature u for the crop. Figure 3 shows an example of an initial signature of Morton County wheat with 20 growth states. On each iteration we find a monotonic mapping called m, $(j,t) \to g$, which minimizes $\sum_{t=1}^{T} \max_i |x(b_i,j,t) - u(m,j,t);b_i)|$ for every sample j using a dynamic programming procedure. Note that this allows samples at different observation times to map into the same growth state.

At the end of each iteration the mean signature is updated. Define a set A_g as the set of all sample observation time pairs which are mapped to growth state g. The updated mean signature u' is defined as:

$$u'(g,b_i) = \sum_{(j,t)\ \varepsilon\ A_g} \frac{x(b_i,j,t)}{\#A_g} \qquad (1)$$

The procedure iterates until it reaches a fixed point. Figures 1 and 2 show the final mean signature created by this procedure and the final growth state mapping in a five date observation of a Kansas LACIE site.

After iterating, we broaden the signature. In the broadening process, (g,α,b_i) is included in the signature if $|\alpha - u(g,b_i)| < w$. We chose the "signature width" w to be about twice the magnitude of the average standard deviation of pixel reflectance within the growth stage. Then for each band b_i and growth state g, there is an interval of length 2w centered on $u(g,b_i)$ of gray levels in the signature, as shown in Figure 3. We note that, given the degree of variation

in sample standard deviation for the grow growth state bands, a single width for all bands and growth states is probably not best, but is chosen for simplicity.

B. DISCRIMINATION WITH GROWTH STATE SIGNATURES

In the discrimination process, one chooses which bands in the signature to use. Observed gray levels for a pixel in these bands must fall within these intervals in order for the pixel to be identified as in growth stage g. In the case where more than one growth state identification is possible, the earliest growth state is identified. In order for a pixel to be identified as crop c, each observation must be identified as being in a growth stage for crop c and the growth stages must be chronologically ordered, as mentioned before. One also has the option of using crop calendar information. This limits the growth stages to a specified range for each observation time.

C. BAYESIAN PERSPECTIVE

The phenological discrimination procedure is a Bayes classification. In Bayes classification a multi-spectral observation $(x_1,\ldots,x_N)$ for N dates is assigned to the class c for which the conditional probability of c given $(x_1,\ldots,x_N)$ is highest. Suppose we narrow the range of values for which $P(c|x_1,\ldots,x_N)$ is non-zero. This means that if $P(c|x_1,\ldots,x_N)$ is non-zero, then for any other crop type c', $P(c'|x_1,\ldots,x_N)$ is zero in most cases. Therefore, $(x_1,\ldots,x_N)$ is labeled c by the Bayes rule. In the phenological discrimination of c (wheat), the range of values for which $P(c|x_1,\ldots,x_N) > 0$ is narrowed by use of training sets, crop calendar information and chronology restrictions. This range of values is stored in tabular form.

D. EXAMPLE

An example easily illustrates the table look-up idea graphically. Figure 4 shows graphs for the tables $R(b_1,\alpha,c)$ that store the growth state signature for category c. A square blacked in for coordinates (g,α) means that for the corresponding spectral value α, the phenological growth stage g belongs to the table R. Suppose that there are two spectral wavelengths band 1 and band 2, two categories, and two times at which observations are taken. Let the spectral observation for time 1 be (9,10) and the spectral observation for time 2 be (3,6). Examining the tables for category 1, we have:

$$R(1,9,1) = \{3,5,6,7\}$$
$$R(2,10,1) = \{0,1,2,3,17,18,19\}$$
$$R(1,9,1) \cap R(2,10,1) = \{3\}$$

This means that the only time the observation (9,10) could occur from category 1 is during phenological growth stage 3. Examining the tables for category 2, we have:

$$R(1,9,2) = \{5,6,7,13,14\}$$
$$R(2,10,2) = \{0,1,7,8,18,19\}$$
$$R(1,9,2) \cap R(2,10,7) = \{7\}$$

This means that the only time the observation (9,10) could occur from category 2 is during phenological growth stage 7. So after the first spectral observation, both categories are still possible.

Now consider the second observation (3,6). By the tables:

$$R(1,3,1) = \{13,14\}$$
$$R(2,6,1) = \{6,7,8,9,13,14\}$$
$$R(1,3,1) \cap R(2,6,1) = \{13,14\}$$

This means that spectral observation (3,6) is possible for category 1 only during phenological growth stages 13 and 14.

By the tables:

$$R(1,3,2) = \{0,1\}$$
$$R(2,6,2) = \{11,12\}$$
$$R(1,3,2) \cap R(2,6,2) = \emptyset$$

This means that there is no phenological growth stage for category 2 which yields the spectral observation (3,6). The conclusion, therefore, is that the small area ground patch having early spectral return of (9,10) and later spectral return of (3,6) must be an area of vegetation category 1 observed during its 3 and 13 or 14 phenological growth stages.

If instead of the intersection $R(1,3,2) \cap R(2,6,2) = \emptyset$, we had $R(1,3,2) \cap R(2,6,2) = \{4,6\}$, category 2 would be eliminated because the spectral reflectance it has at a late calendar time match possible a spectral reflectance for category 2 only at early phenological growth states 4 or 6. Later calendar times must correspond to later phenological growth states.

II. IDENTIFICATION OF WHEAT IN MORTON COUNTY USING PHENOLOGICAL DISCRIMINATION METHODS

An extensive investigation of the use of phenological discrimination was carried out using the Morton County image. The phenological discrimination procedure involves a number of choices for the user. The procedure involves two steps: (1) creation of the signature mean and (2) identification using the mean signature created in step (1). The effects of the choices on the quality of classification will be discussed. The validity of use of our dynamic programming method for creation of mean signature is also investigated.

A. A DISCUSSION OF RESULTS

Consider the two steps in the discrimination procedure. In the first step the user chooses an input sample to train the signature and the number of growth states to be characterized in the signature. In the identification step the user chooses the "signature width" and which MSS band/observation date combinations to use. The choice of "signature width" is critical, especially when one is identifying only one crop class. The larger the "signature width" the more pixels will be identified as in the crop class. The percent correct identification will increase with "width" but at the cost of increased false identification. In the identification step the user also has the option of specifying a range of allowed growth states for each observation time. A good choice of these growth state restrictions effectively cuts down on the number of false classifications, without much reduction in the rate of correct classification.

Sample adequacy was investigated by comparing the discrimination results with no growth state restrictions using a sample of 35 wheat field averages and several random samples of individual pixels. It seems that a sample of around 100 pixels (about 2.5 percent of the ground truth wheat) is of adequate size as discrimination was not significantly better with a sample of twice that size or with the field average samples.

We have performed 4 identifications of wheat with signatures having 5, 10, 20, and 36 growth states. This is a range of one to seven growth states per observation time, since we have five observations of the Morton County test site. The general shape of the mean signatures with differing numbers of growth states is the same. Our best discrimination was with a 36 growth state signature with a width of 3.25. Using this signature and all observation dates, the results were 83 percent correct identification of ground truth wheat and 4 percent false identification. With a 5 growth state signature with a width of 6.0, the corresponding figures were 79 percent and 13 percent. The improved discrimination shows the usefulness of modeling several growth states per observation time.

The number of MSS bands needed for accurate identification was investigated. Most of our testing of the discrimination procedure has been done using MSS bands 4, 5, and 6. However, it has been found that MSS bands 4 and 5 are sufficient for good wheat identification. Adding MSS band 7 reduced correct classification significantly. It was thought that perhaps MSS bands 5 and 7 were more useful for phenological discrimination of wheat, because they have often been most useful in other discrimination procedures in classifying an agricultural scene. The identification of wheat with MSS bands 5 and 7 turned out not to be as good as with MSS bands 4 and 5.

The possibility of accurate wheat identification with a single channel of information per observation time was investigated. The phenological method of discrimination is a process of identifying growth stages. It seemed likely, then, that a single measure, indicating greenness of the pixel at the observation times, would be sufficient for identification of the crop. The four MSS band values for each observation date were transformed into Kauth greenness[17], a linear combination of the band values scaled to fit in the 0-31 integer value range.

$$KG = .514(-.290\ MSS4 - .562\ MSS\ 5 + .600\ MSS6 + .491\ MSS7) + 13.6 \qquad (2)$$

Wheat identification with this measure was not as good as identification with two or three MSS bands.

Good wheat identification depends on the proper choice of growth state restrictions, especially if a subset of observation times are used. A description of a run using only two observation times will illustrate this. The growth state identifications with a 36 growth state signature allowed were states 1-5 for observation time 1 and states 10-12 for observation time 2. The narrow choice of growth states allowed for the second observation time, May 9, is important because winter wheat is mainly distinguished from other crop types because it is green on the May 9 date. The growth states 19-12 in the

signature had low gray tone values in MSS band 5, which shows that they correspond to green states. Eighty-one percent of the ground truth wheat was identified and 5 percent of the non-wheat cells were falsely labeled wheat.

The best choice of observation times was October 23 and May 9 for first-order discrimination of wheat. The best single observation time turned out to be May 9, as expected. The October 23 observation turned out to be the best addition to the May 9 observation. A third observation improved results significantly only when wheat was broken into two categories--quickly maturing wheat and slowly maturing wheat. The same 36 growth state signature was used to identify both subcategories of wheat, but with two sets of growth state restrictions. This discrimination resulted in a total of 83 percent of the wheat being identified, with only 4 percent false classification.

B. TESTING THE VALIDITY OF DYNAMIC PROGRAMMING IN MEAN SIGNATURE GENERATION

Recall that different observation times map into the same growth state in the construction of the mean signature. In order to test whether it is good to allow observations from different times to be used in the construction of growth state, an alternate procedure was tested. Let us say we have G_0 as the number of growth states per observation time. In each iteration we define a mapping m:

$(j,t) \rightarrow G$ which minimizes $\sum_{t=1}^{T} \max_i |x(b_i,j,t) - u(m(j,t);b_i)|$ for each sample j with the additional restriction that the pair (j,t) must map into one of the growth states in the set $\{(t-1)G_0 + 1, (t-1)G_0 + 2, \ldots, G_0 t\}$. Because these sets are not overlapping, the method for finding the mapping turns out to be a simple minimization.

A few phenological discrimination runs using five observation dates were made using mean signatures generated by simple minimization. Discrimination was not quite as good as with similar runs using dynamic programming. The average standard deviation by band and growth state for the samples mapped into 20 growth states was higher with simple minimization. This demonstrates the validity of combining observations with different dates in characterizing a signature growth state.

C. AN EXPERIMENT WITH USE OF TWO SIGNATURES FOR WHEAT

Discrimination with a fairly small signature width results in about half the wheat being identified with a very small amount of false identification, when aproiate growth state restrictions are used. It was thought that perhaps wheat is better characterized by two or three signatures with small widths. Our experimentation did not lead to improved classification, but provides insight into the properties of the growth states in the signature.

A sequential procedure was used. Areas of wheat which were poorly identified by phenological discrimination were examined. It seemed that there were two types of wheat not being identified. One type was wheat with reflectances generally higher than average for all MSS bands on all observations. The other type was wheat with generally lower than average reflectances, especially for MSS bands 4 and 5 on the May 9 observation. In order to try to identify these problem areas of "high" and "low" wheat, signatures were created from samples of wheat not yet identified. A "high" signature was created from pixels in this sample whose quantized values in MSS bands 4 and 5 on the May 9 observation was below a threshold of 6. A "low" signature was created from pixels whose values in MSS bands 4 and 5 on the May 9 observation was above 8. "High" and "low" wheat was classified with these signatures. Areas identified as "high" and "low" wheat were quite distinct.

The areas of "high" and "low" wheat were examined on the aerial photographs of Morton County. It was noted that small "low" wheat areas within fields were often near field borders, and are probably weedy areas. High areas within fields were often in areas that appeared to be high ground or light-colored, poor soil.

We also investigated the "high" and "low" wheat by looking at field mean of Kauth greenness and Kauth soil brightness, Kauth is a linear combination of the MSS band which we rescaled to fit in the 0-31 value range:

$$KSB = .522(.433\ MSS4 + .632\ MSS5 + .586\ MSS6 + .264\ MSS7) \quad (3)$$

Fields identified as primarily "high" wheat were areas of high KSB and about as much as KG as field with predominantly "low" wheat, except on the May 9 date when they were "greener".

We investigated further by examining the samples for the "high" and "low" signature. We looked at a 36 growth stage signature created from a random sample of ground-truth wheat and found which growth states each observation of the sample mapped to. "Low" samples are mapped into relatively earlier growth states compared to the high reflectance samples, except for the October 23 observation.

The explanation which seems most consistent in explaining the "high" and "low" areas is that "high" areas are poor quality stands of wheat, high are adversely effected by the dry weather in Morton County in 1974 or by poor soil. The "low" areas are vigorous stands of wheat, or areas with a lot of weeds. Vigorous stands of wheat mature more slowly than stands maturing in less than optimal conditions. The dryer fields will be the first to head, and therefore, look less green on May 9.

D. COMPARISON OF PHENOLOGICAL DISCRIMINATION WITH OTHER PROCEDURES

We identified wheat using Bayes table look-up and unsupervised clustering procedures developed at the University of Kansas Remote Sensing Laboratory and linear discrimination as implemented in the BMDP package[30]. In our best phenological discrimination runs, we achieved about 80 percent correct identification of wheat with about 5 percent false identification, with 83 percent and 4 percent when all observation dates were used. This is about as good as wheat identification by the linear discrimination method, which resulted in 84 percent wheat identification and 4 percent false identification of wheat. Wheat identification was much better than with a Bayes table look-up method[26]. In the case of these methods, however, multiple discrimination of several crops was carried out. The phenological method identified the wheat fields much better than unsupervised clustering. This method had trouble identifying wheat fields that were clustered with summer fallow, probably because wheat fields were abandoned.

The growth state identification made in the discrimination process are the earliest growth states consistent with the multi-spectral observations, allowed growth states for observation date, and the requirement that growth states by chronologically ordered. In order to use the growth state identification for information on crop maturity, it might be better to identify "best" consistent rather than earliest consistent growth states. Our identification may also be improved if our signature width varies with band and growth state. This idea led to limited testing of the use of "second-order" growth state signatures. These signatures account for covariance of spectral bands, as well as allowing signature width to vary with band and growth state. It is too early to tell if the second-order signatures will lead to improved classification or give better information about crop maturity.

III. CONCLUSION

The phenological growth state procedure seems to be able to discriminate wheat about as well as some more standard procedures and label degree of maturity as well. Discrimination is comparable to discriminant analysis on Kansas wheat. The phenological method also identified corn well on a small site in Iowa.

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GROWTH STATE 1 WITH 41 SAMPLES				GROWTH STATE 11 WITH 48 SAMPLES			
19.07	21.66	11.88	20.41	9.71	10.90	17.69	16.02
1.97	1.39	2.45	1.74	1.12	1.10	0.85	1.27
GROWTH STATE 2 WITH 31 SAMPLES				GROWTH STATE 12 WITH 24 SAMPLES			
15.68	18.45	11.65	22.48	12.04	13.33	18.04	17.75
1.53	1.13	0.48	1.34	1.34	1.46	1.24	1.33
GROWTH STATE 3 WITH 33 SAMPLES				GROWTH STATE 13 WITH 21 SAMPLES			
15.21	18.61	10.76	17.82	9.38	10.62	13.38	15.76
1.79	1.32	0.49	1.40	1.13	1.46	1.17	1.11
GROWTH STATE 4 WITH 16 SAMPLES				GROWTH STATE 14 WITH 29 SAMPLES			
11.75	16.50	9.00	10.37	11.41	12.83	15.24	18.14
2.30	2.60	0.94	2.64	1.25	1.56	1.16	1.63
GROWTH STATE 5 WITH 52 SAMPLES				GROWTH STATE 15 WITH 21 SAMPLES			
6.85	8.02	9.37	12.46	17.29	17.24	19.71	19.76
0.86	0.89	0.90	0.99	1.93	1.77	2.07	1.41
GROWTH STATE 6 WITH 37 SAMPLES				GROWTH STATE 16 WITH 46 SAMPLES			
4.49	4.43	7.95	12.54	14.83	15.46	16.59	17.74
1.39	1.64	1.21	0.95	1.77	1.47	1.57	1.99
GROWTH STATE 7 WITH 19 SAMPLES				GROWTH STATE 17 WITH 18 SAMPLES			
3.84	3.84	13.74	13.68	11.33	12.94	9.00	9.06
1.39	1.72	1.21	1.89	1.80	1.78	1.94	2.25
GROWTH STATE 8 WITH 10 SAMPLES				GROWTH STATE 18 WITH 20 SAMPLES			
6.90	7.20	11.90	17.50	14.50	15.40	18.85	20.85
1.51	0.98	2.02	1.63	1.12	1.07	1.06	0.85
GROWTH STATE 9 WITH 31 SAMPLES				GROWTH STATE 19 WITH 26 SAMPLES			
8.87	10.32	10.58	12.55	17.88	17.58	20.69	21.58
1.13	1.03	1.16	0.94	1.55	0.84	1.41	1.69
GROWTH STATE 10 WITH 30 SAMPLES				GROWTH STATE 20 WITH 47 SAMPLES			
7.77	9.10	15.87	14.70	21.02	19.70	22.91	22.91
0.99	0.91	0.62	1.29	1.67	1.61	1.51	2.14

Table 1. The averages (which constitute mean signature) and standard deviations by growth state and MSS band of subsamples of a 120 wheat pixel sample of the Morton County Intensive Test site. The first row of numbers are band means and the second row of numbers are band standard deviations.

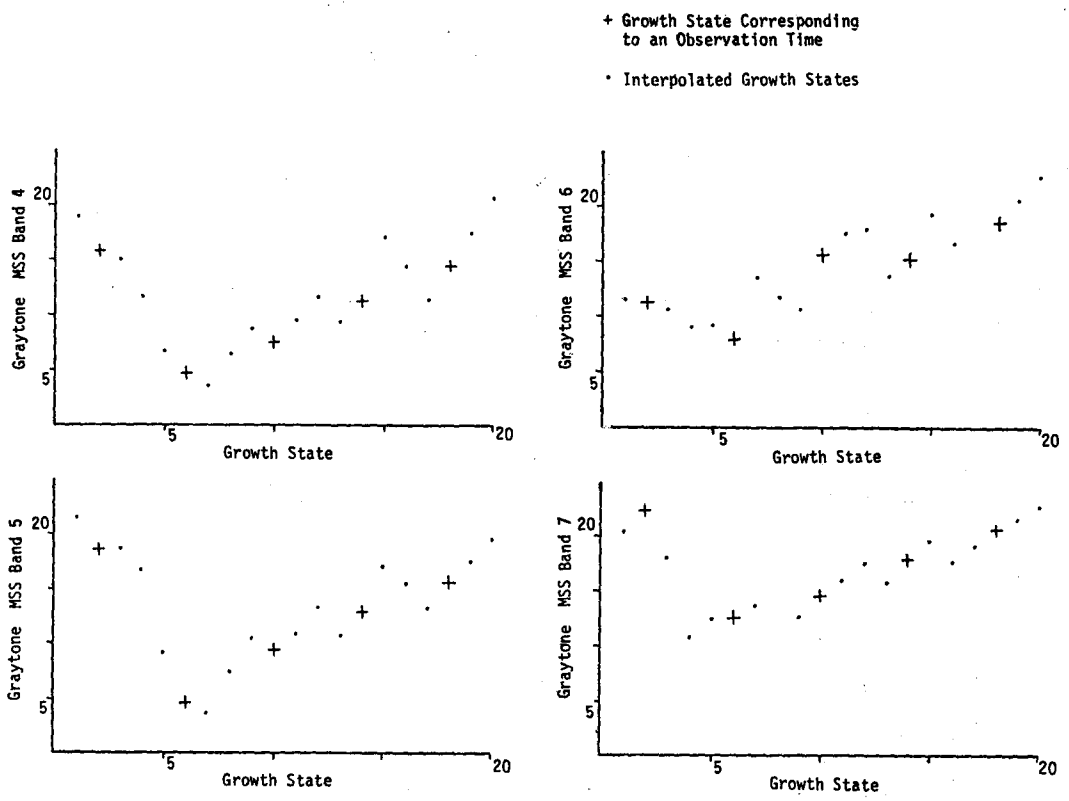

Figure 1. Final mean wheat signature for Morton County test site.

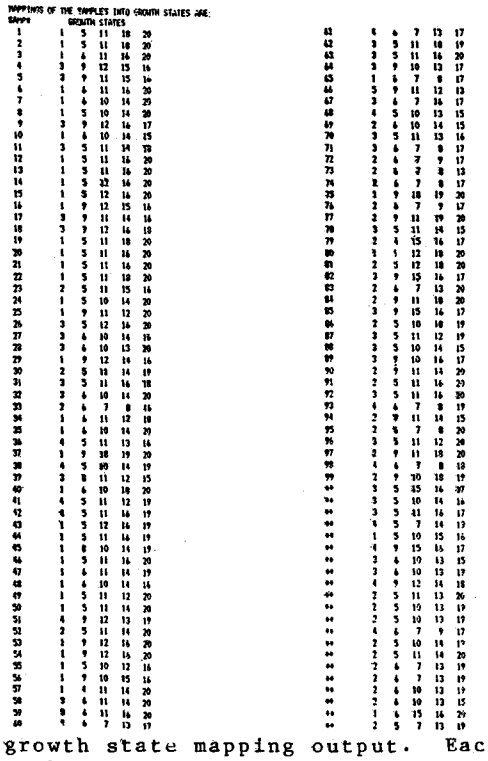

Figure 2. Final growth state mapping output. Each row is a sample of pixel number and the growth state mappings for each of the five observation dates.

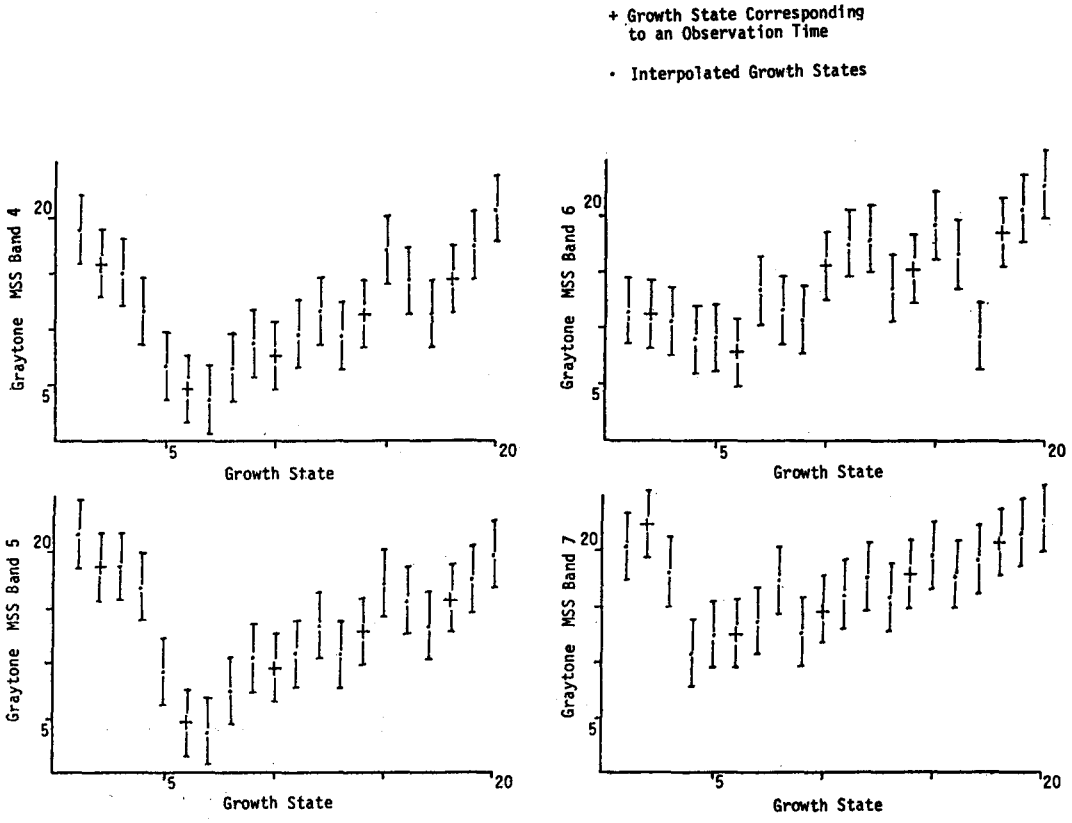

Figure 3. Final mean wheat signature for Morton County test site with tolerance interval set.

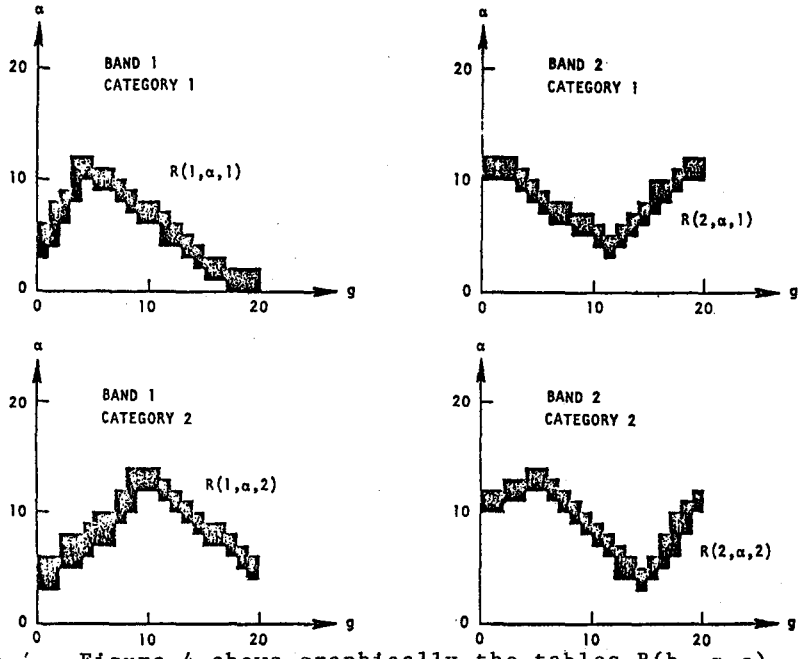

Figure 4. Figure 4 shows graphically the tables $R(b_i,\alpha,c)$. A square blocked in for coordinates (g,α) means that for the corresponding α, the phenological growth stage g belongs to the table R. A growth stage $g \in R(b_i,\alpha,c)$ if and only if $P_b(\alpha|g,c) > \varepsilon \geq 0$ for some specified value of ε.

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