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LANDSAT DATA FROM AGRICULTURAL SITES: CROP SIGNATURE ANALYSIS*

P. N. Misra and S. G. Wheeler
International Business Machines Corporation
Federal Systems Division
Houston, Texas 77058

ABSTRACT

The LANDSAT multispectral scanner (MSS) data have been analyzed with a view toward classification to identify wheat. The notion of spectral signature of a crop, a commonly used basis for classification, has been found to be inadequate. Data analysis has revealed that the MSS data from agricultural sites are essentially two dimensional, and that the data from different sites and different acquisitions lie on parallel planes in the four-dimensional feature space. These results have been exploited to gain new insight into the data and to develop alternate models for classification. In particular, it has been found that the temporal pattern of change in the spectral response of a crop constitutes its signature and provides a basis for crop classification.

1. INTRODUCTION

The classification of multispectral observations from agricultural sites is commonly based on the notion of spectral similarity of like ground covers in a scene. With this model, the data are characterized on the basis of a sample of training fields from each crop class of interest. The data from each class are usually assumed to be Gaussian, and, then, the characterization consists of computation of sample mean and dispersion matrix. These parameters are said to constitute the 'spectral signature' of the class and are used as a basis for classification of the test data [1-3].

Experience with LANDSAT multispectral scanner (MSS) data, however, has shown this model generally to be inadequate for crop classification. While the within-field variability of data is small, the field-to-field variability is usually so large as to make the notion of representative fields of a crop class untenable. This difficulty is compounded by the lack of wide separability in the data from different crop classes. Both these factors depend upon the relative biological phases of the different crops in the scene at the time of the data acquisition. In wheat identification problem, for example, it has been found that in most instances the data from any single acquisition at any time during the wheat crop calendar cannot be classified satisfactorily on the basis of the spectral similarity model. Actually, even with multitemporal data (i.e. merged data from multiple acquisitions at different times in the crop calendar of wheat), the different sets of training fields produce substantially differend classification results [4].

The difficulty with basing classification on spectral signatures described above is illustrated in Figures 1a and 1b. These figures provide typical plots of the mean vectors for several randomly selected wheat and nonwheat fields in a LANDSAT subframe covering a 5x6 nautical miles area in Kansas. The plots correspond to four acquisitions over the site during different biological phases (viz., crop establishment, green, heading, and mature) of the wheat crop. The sizes of the fields range from 50-100 ground resolution elements (pixels). The standard deviations in the four channels range from 0.9 to 3.5. Figure 1a suggests that the data from the wheat fields cannot reasonably be modeled as having been drawn from the same probability distribution. Actually, hypothesis tests for equality of mean vectors across wheat fields invariably fail at each stage of the crop. In a generalization of the model described

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above, the data from each crop class are regarded to constitute a Gaussian mixture distribution [5] This model, though more realistic, is still not entirely adequate for a situation where training is based on data from sample of fields. Quite often the mixture distribution is found to have as many constituents as there are fields! The basic difficulty, of course, still is with the notion of distinct spectral crop classes and their representation in a sample of training fields.

With this background, an extensive analysis of the LANDSAT MSS data was undertaken with the objective of discovering features of spectral response that constitute a signature of wheat. The data available for this study consisted of mean vectors and dispersion matrices for a number of known wheat and nonwheat fields from each of several sites with multiple acquisitions. The results of data analysis are given in the next section.

2. SIGNATURE ANALYSIS

The following findings on the LANDSAT MSS data from agricultural sites were reported by the authors in an earlier paper [6]. (1) The data from any acquisition are essentially two dimensional, and (2) the data from different acquisitions/sites essentially lie on parallel two-dimensional planes in the four-dimensional feature space. See also the related, independent work of Kauth and Thomas [7], who give an interesting phenomenological identification to the spectral measurements and report roughly similar conclusions on the dimensionality of the data.

The above finding on dimensionality offers a significant benefit in terms of graphical display of the four-dimensional data. This can be done by finding representation of the data in a rotated coordinate frame with, say, the first two axes on the plane of the data and the remaining two orthogonal to it. In this representation, the first two (in-plane) components, giving the location of the data on the plane, essentially distill the 'information' from the four-channel MSS data; the last two (off-plane) components, measuring the deviation of the data from the plane, have only a very small range of values and are regarded as noise. The relative positions of the data in the original four dimensional feature space are very nearly preserved in a data display based only on the first two components of the transformed data. Note that having identified the plane, for our purpose, the orientation of the two orthogonal axes on it is entirely arbitrary [6] The coordinate frame, i.e., orthonormal transformation (see Appendix), used in the graphical representation of data in this paper was chosen solely for clean displays. In plots of in-plane (off-plane) components, the first (third) component of the transformed data is plotted along the abscissa.

Figures 2a and 2b give scatter plots of data from the Kansas site (acquisition 2) mentioned earlier, These data correspond to 22,932 ground resolution elements in the scene. The plots use characters ·,1,2,..,9,A,B,..., Z to represent 36 increasing levels of concentrations in a cell. The character assignment is on a uniform scale in the range 1 through KMAX, specified on the plots. The plot in Figure 2a is typical; the data are densely packed in a roughly triangular region with no apparent cluster structure. The spectral similarity model, however, is predicated on the existence of cluster structure in the data. The scatter plot of the off-plane components is also typical; it demonstrates the two-dimensionality of the data.

For each of the available acquisitions over several sites, the transformed mean vectors of a set of wheat and nonwheat fields were plotted on the plane of the data. Two such scatter plots are presented in Figures 3a and 4a. The former corresponds to a site in Kansas with registered data available from six acquisitions over the crop calendar of wheat. Figure 4a corresponds to a site in Oklahoma with eight acquisitions. The acquisition dates are given below each plot as five-digit numbers. The first two digits identify the year, and the last three the day of that year. These two sites were chosen for availability of good-quality data from several acquisitions over each. In view of the small within-field variability, the data from all pixels of a field can be thought of as densely scattered about the mean. The wheat grown at both sites is of winter wheat variety. It is planted early in the fall, is dormant during winter, greens and matures during spring, and is harvested in early summer.

Figures 3a and 4a illustrate the difficulty with the spectral signature model for wheat identification. The large field-to-field variability, as noted earlier, is generally compounded by the lack of strong separability in wheat-nonwheat data. For example, in Figure 4a, in one-half of the acquisitions the decision boundaries are not apparent to separate the wheat and nonwheat data from the training fields. Even in cases where such decision boundaries can be drawn, what can be said of classification of the test data?

Experience with maximum likelihood classification with Gaussian (-mixture) model for data from the various crop classes has shown that the decision boundaries determined by the different sets of training fields are substantially different. The more training fields there are of wheat, the greater is the amount of wheat discovered in the scene by classification of data [4]. The reason for this is apparent from Figures 3a and 4a. The difficulty is that the data from a sample of fields of a crop class is not representative of the population. A better characterization of the data would be obtained by taking a pixel, rather than a field, as a unit for training. For example, a 5% sample of pixels from the wheat fields in a scene would provide a better basis for characterization of the distribution of the wheat data than a set of pixels of the same size belonging to a sample of wheat fields. Such training process, however, is not deemed cost effective in large-scale utilization of the LANDSAT data.

This basic difficulty in characterization of the data from different crop classes is resolved by examining the pattern of temporal changes in the spectral response. Again, the results on the data dimensionality have been crucial to this work: The temporal pattern can be plotted as a trajectory on the plane of the data by joining together the points representing the locations of the field means in successive acquisitions. Figures 3b, 3c, 4b, and 4c present these temporal trajectories for some of the training fields from the Kansas and Oklahoma sites. An asterisk marks the starting point of each trajectory. The scale of each plot, unless otherwise specified, is the same as that of the plot above it.

These trajectories constitute a complete graphical description of the spectral-temporal response of the field. Note that for each of the two sites, the trajectories associated with wheat fields are similar, and are sufficiently distinct from the corresponding trajectories of nonwheat. Even for acquisitions where the wheat and nonwheat data had appeared confused, the corresponding patterns of spectral changes bear unique information for classification. Examination of multitemporal data from a number of sites has revealed that in each case the pattern of temporal changes characterizes the crop and constitutes a valid signature. Supervised classification of the data can be based on features extracted from the temporal trajectories of the training fields [8].

Simple interpretations based on crop phenology can be associated with this pattern. It has been proposed, [7], for example, that in our coordinate frame on the plane of the data, the abscissa and ordinate give measures of brightness and greenness, respectively, of the ground cover. Interpretation of the temporal trajectories of winter wheat in terms of the anticipated phenomenological changes generally supports this view, though this issue appears far from resolved.

Note that the trajectories associated with wheat fields at the two sites have certain qualitative similarity. Both sets are sampled versions of a continuous trajectory which appears to resemble an ℓ (lower case script E). The sampling times at the Oklahoma site (Figure 4b), however, are such as to miss the distinguishing feature of the 'loop'. Distortion in trajectories can be introduced by atmospheric conditions, such as haze. The nature of this distortion, however, being common to data from all classes, would generally not mask the class-specific features. Such identification of the features of the temporal trajectory with the crop phenology and the atmospheric conditions would permit development of unsupervised crop-calendar tracking classification schemes.

3. CONCLUSIONS

Graphical representation of the LANDSAT MSS data acquired during the different phases of the wheat crop has shown that wheat can be identified on the basis of its characteristic pattern of temporal changes in the spectral response. This pattern can be interpreted in terms of the crop calendar and the crop vigor. Features of this temporal pattern provide a basis for both supervised and unsupervised classification of the data. These results, presented here in the context of wheat identification, are applicable to the general crop classification problem.

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APPENDIX

Orthonormal Transformation for the MSS Data

The following orthonormal transformation was used for the graphical representation of data in Figures 2-4.

$$T = \begin{bmatrix} 0.406 & 0.600 & 0.645 & 0.243 \\ -0.386 & -0.530 & 0.535 & 0.532 \\ 0.723 & -0.597 & 0.206 & -0.278 \\ 0.404 & -0.039 & -0.505 & 0.762 \end{bmatrix}$$

The rows of T define the bases vectors of the new coordinate frame. The first two rows span a subspace parallel to the plane of the data.

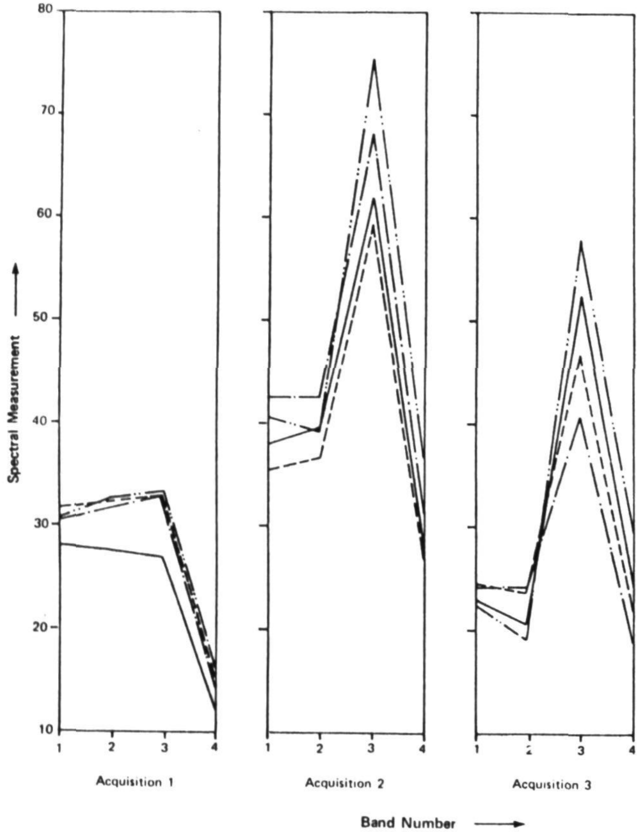

Figure 1a. Plots of Mean Vectors for Four Wheat Fields

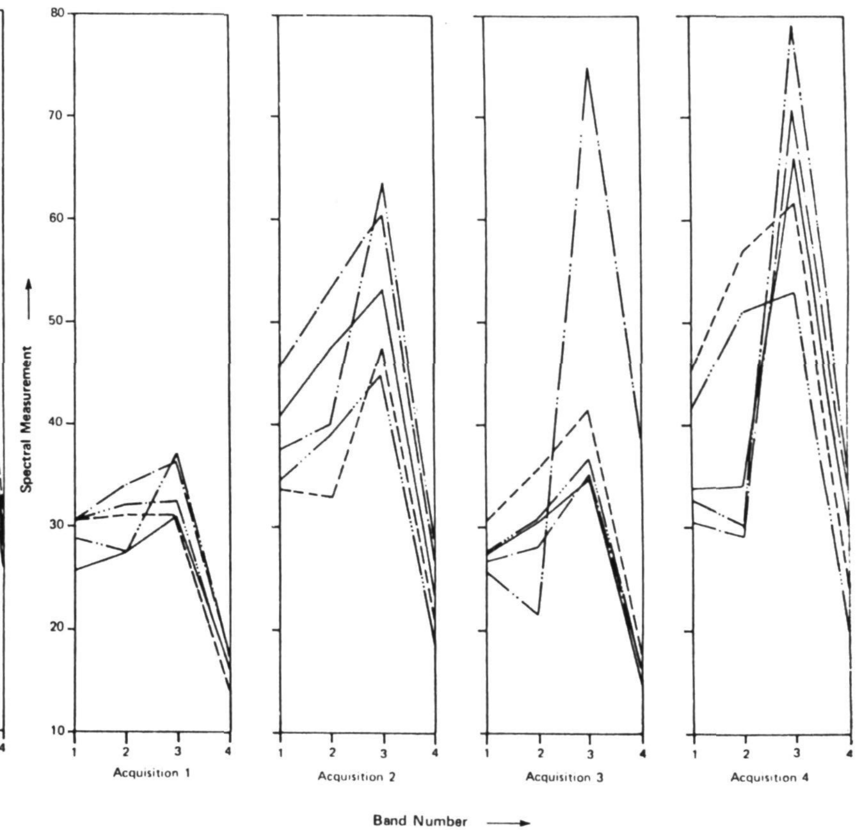

Figure 1b. Plots of Mean Vectors for Five Nonwheat Fields

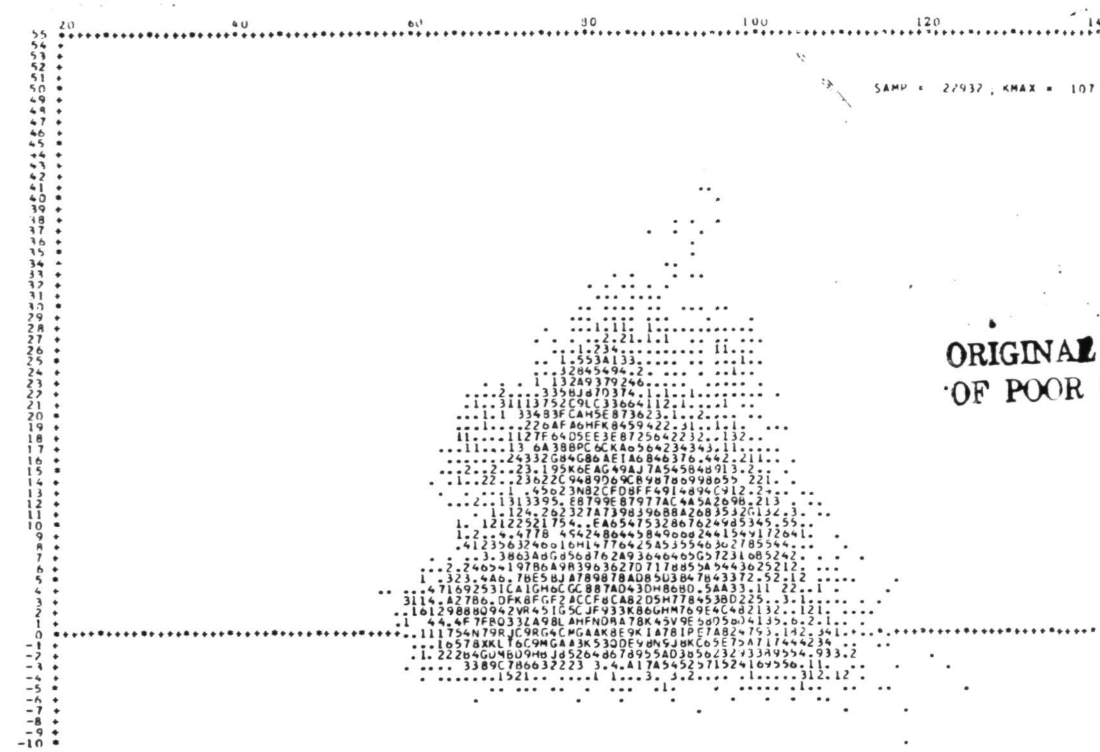

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Figure 2a. Scatter Plot of the In-plane Components of Data

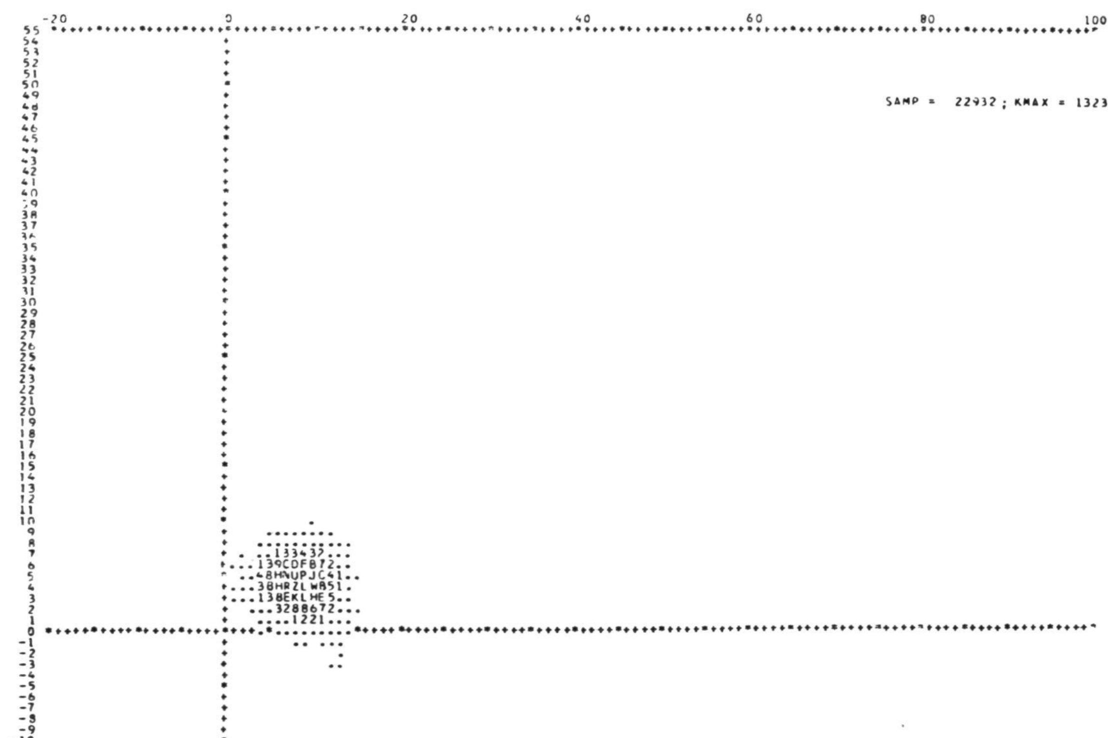

Figure 2b. Scatter Plot of the Off-plane Components of Data

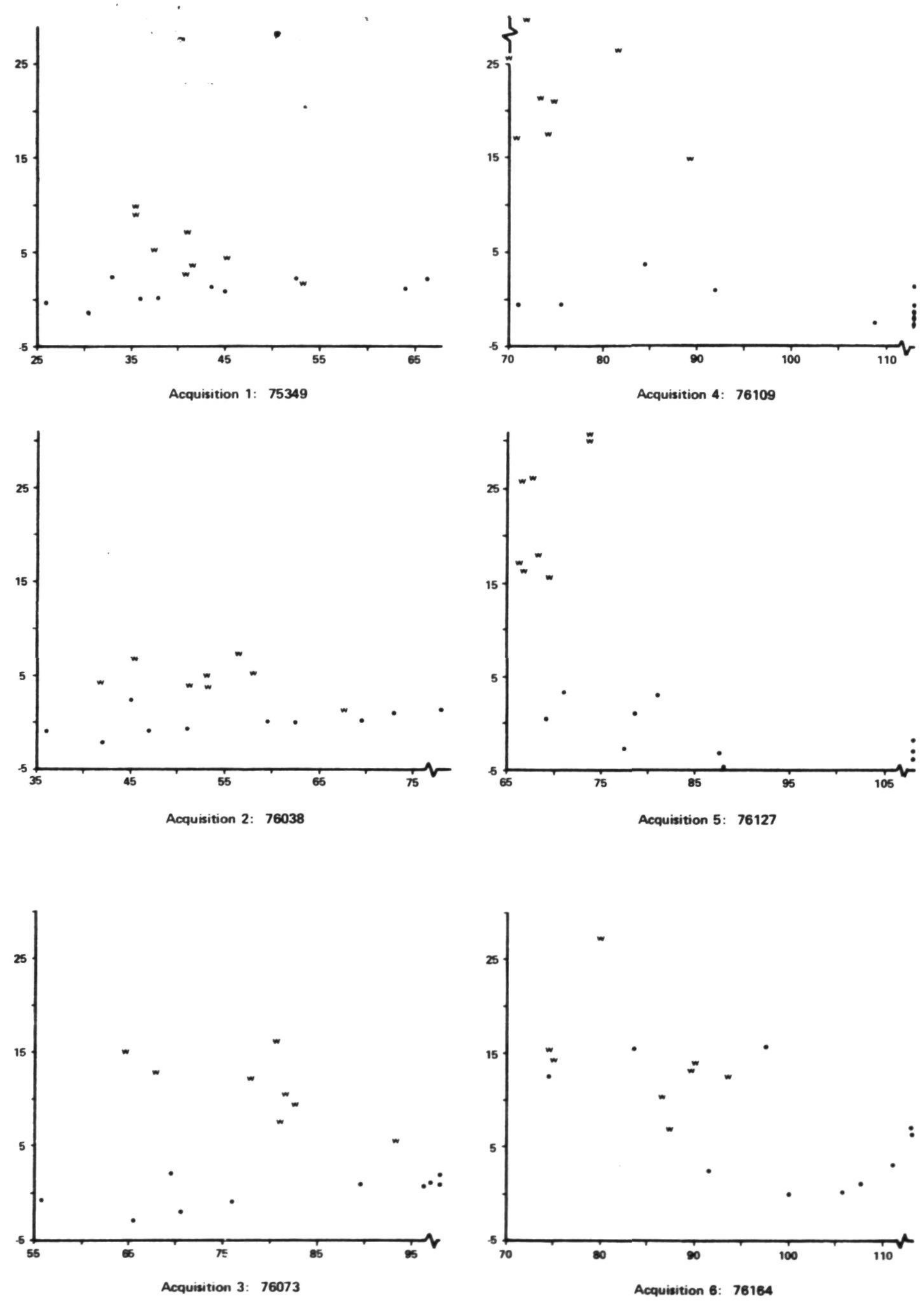

Figure 3A. Scatter Plot Of Field Means (Kansas)

w = Wheat; • = Nonwheat

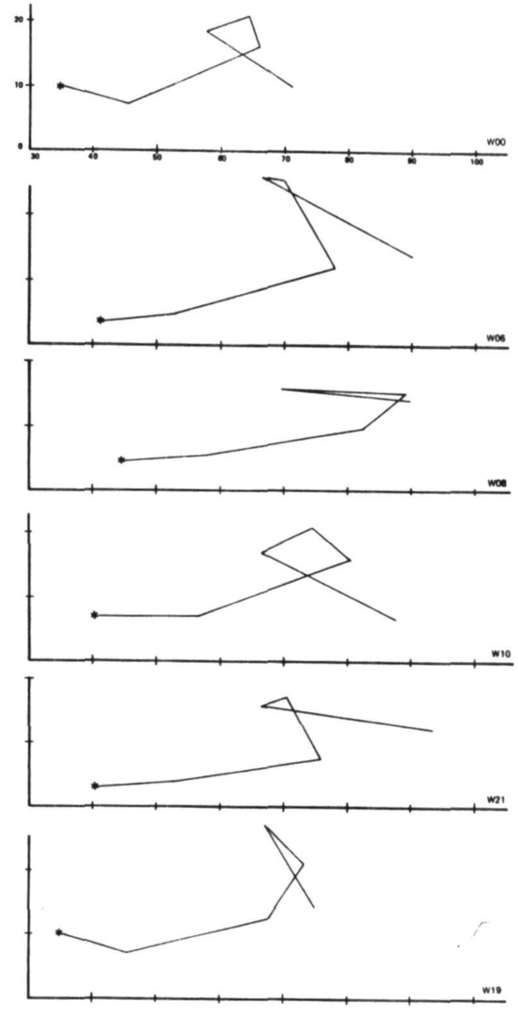

Figure 3B. Temporal Trajectories Of Wheat Fields

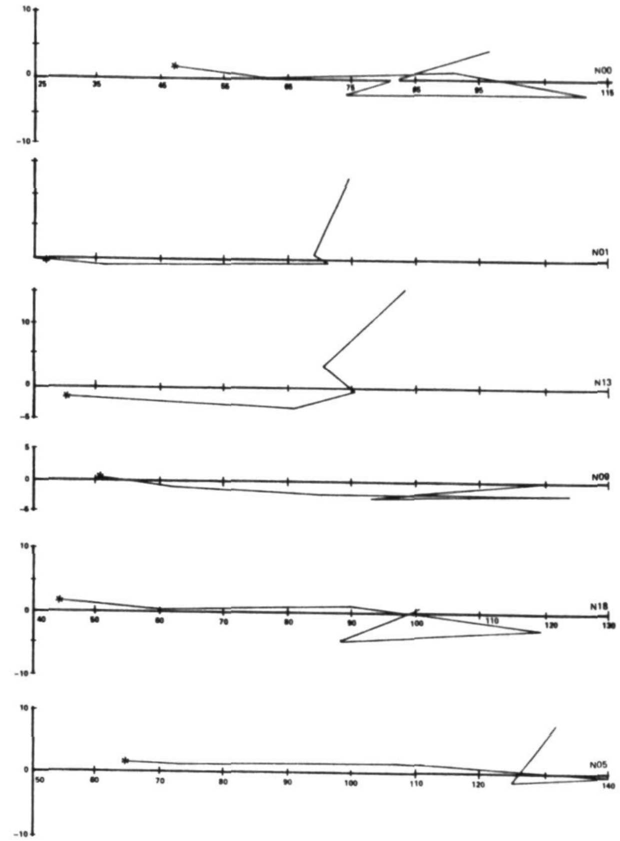

Figure 3C. Temporal Trajectories Of Non Wheat Fields

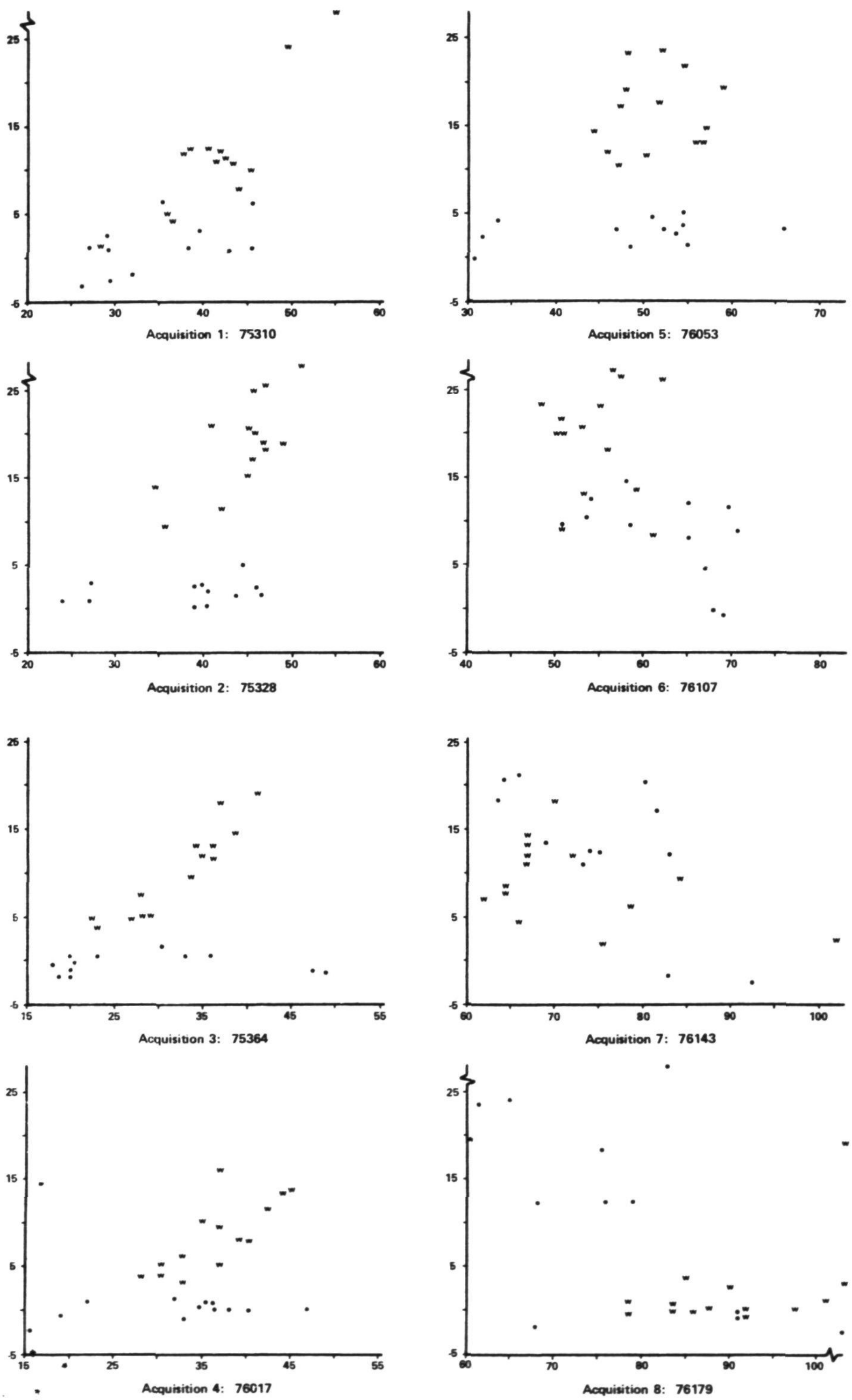

Figure 4A. Scatter Plot Of Field Means (Oklahoma)

w = Wheat; • = Nonwheat

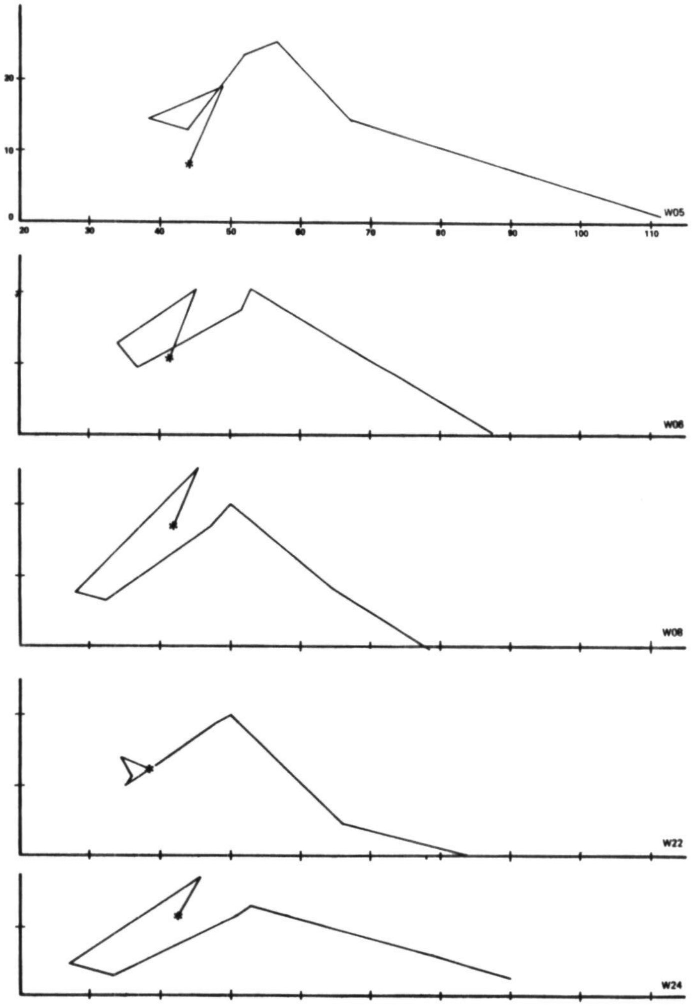

Figure 4B. Temporal Trajectories Of Wheat Fields

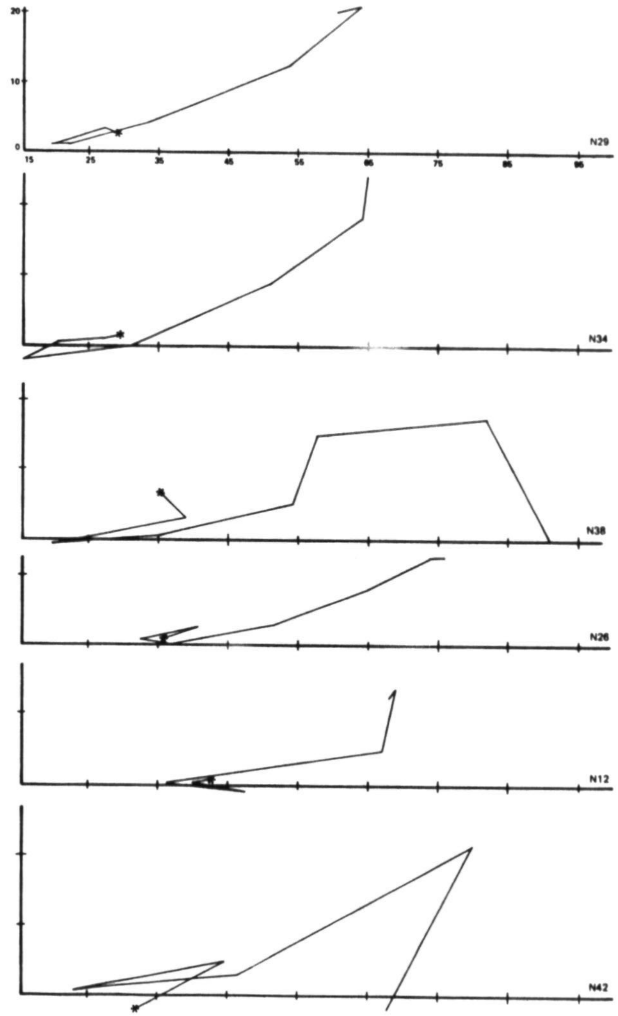

Figure 4C. Temporal Trajectories Of Non-Wheat Fields