Reprinted from

# Symposium on Machine Processing of Remotely Sensed Data

**June 27 - 29, 1979**

The Laboratory for Applications of
Remote Sensing

Purdue University
West Lafayette
Indiana 47907 USA

IEEE Catalog No.
79CH1430-8 MPRSD

# AN INTERACTIVE COLOR DISPLAY SYSTEM FOR LABELLING CROPS

TOYOHISA KANEKO, LINDA K. MOORE, AND
ROBERT T. SMART

IBM - Federal Systems Division

ABSTRACT

To perform classification on remotely sensed imagery data, a small number of pixels or fields need to be labelled. It has been found that this labelling task requires many auxiliary materials such as crop calendar, soil data, cropping practice and a weather summary. This task is at the present time manually performed by photo-interpreters. It is time-consuming and liable to human error. The paper describes a computer based interactive color display system for assisting photo-interpreters. Its objective is to reduce contact time and to increase labelling accuracy. This system has been designed to extract features from a temporal series of MSS data and to display these features using color graphic techniques. Special attention was paid to convert crop calendar information to quantitative information consistent with observed data. More specifically, descriptive crop phenology on a crop calendar was converted into quantitative growth index curves, to which observed features derived from MSS data are directly comparable. This system has been designed for feasibility demonstration only and although it is still in the evolutionary stage, it has already demonstrated that the method to be presented offers an effective solution to alleviating many problems associated with the current manual labelling process.

## I. INTRODUCTION

Recently, considerable effort has been expended to forecast the production of crops such as wheat, soybeans, and corn based upon remote sensing technology.[1,2] The Large Area Crop Inventory Experiment (LACIE)[1,2] undertaken jointly by NASA, USDA, and NOAA, the CITARS experiment[3] by NASA, and the Illinois Crop-Acreage Experiment[4] by USDA are examples of such efforts. Since production of food and fiber crops is subject to large year to year fluctuations, the reliable and timely global production estimates will reduce the economic and social impacts of such fluctuations by allowing informed planting and marketing decisions.

The acreage estimate is one of two essential tasks for deriving total production (the other is yield estimate and is not addressed by this paper). In order to compute the acreage of a crop, for example wheat, from remotely sensed data, each pixel in the scene needs to be classified to determine whether it belongs to the crop.[6] The current crop classification technology[1,2,5,6] requires a small number of pixels or fields (generally called training set) in the scene to be labelled prior to the machine classification of the entire scene.

Both NASA's CITARS experiment and USDA's Illinois experiment used ground truth information which was obtained either through personnel visiting the sites or high resolution infrared aircraft photography. However, collection of ground truth information is costly and not always available particularly in foreign regions. In LACIE, photo-interpreters who were called analyst-interpreters because of the high degree of analysis functions involved were employed to label fields as pixels. The latter environment will be assumed in this paper.

In order to perform labelling, photo-interpreters must be provided with such materials as historical and adjusted crop calendars, soil data, cropping practice, a weekly meterological summary in addition to false color infrared films generated from MSS imagery data. These materials usually come in various forms (maps, tabulation, reports, etc.) and are often difficult for photo-interpreters to relate to one another, particularly in a quantitative manner. This labelling process is time consuming and moreover is found to be the largest error source in classification. This paper describes a solution that employs a computer controlled interactive color display system. This system is designed to integrate all the materials; more specifically, to display relevant data with proper display formats, to establish a labelling procedure, to perform machine classification, and to verify the results. If this entire process could be executed within a few minutes, for example, several iterations could be performed, increasing the overall classification accuracy from the learning procedure.

Toward the above goal, an interactive display system called the Analyst-Interpreter Interactive Display System (AIIDS) was constructed on an IBM 370/135, RAMTEK GX-100B, and CONRAC displays (a color display and a black and white display). The color display with the RAMTEK GX-100B has the capability of displaying 512 scan lines by 640 pixels each with 256 different colors (8 levels for red and blue, and 4 levels for green).

## II. MATERIALS FOR LABELLING

This section describes in detail the materials used in the labelling process.

The following materials[7] have been provided to analyst-interpreters:

1. Nominal crop calendar for the Crop Reporting District (CDR).

2. The Robertson Biometerological Time Scale (BMTS) growth stage[8].

3. Soil data for the CRD.

4. Cropping practices for the CRD.

5. Historical crop percentage for the political subdivision (usually country in the United States) for the previous 4 to 5 years.

6. Topographic maps (1 = 24,000 and 1 = 250,000).

7. False color infrared films generated on a production film converter (PFC) from LANDSAT MSS data.

8. A weekly meterological summary containing:

   a. A narrative summary for crop and weather assessment on a statewide basis.

   b. Episodic events such as rainfalls, hails, snowfalls, floods, winter kills, etc.

   c. Soil moisture index maps.

All the above materials except the topographic maps are readily generated in digital formats without an image scanner, and therefore can be stored in data bases. With respect to labelling, the initial two items (i.e. nominal and variable crop calendars) together with false color infrared films are by far the most important for analyst-interpreters to perform their function. The other materials become generally relevant either when exceptional conditions become dominant or when classification results are verified.

A nominal crop calendar is usually presented to analyst-interpreters on a graphic format as is shown in Figure 1. Based upon this information photo-interpreters estimate the degree of vegetation vigor for each crop for a given date, and then test qualitatively a hypothesis that a given pixel is a certain crop. For a series of acquisitions the above procedure is repeated, increasing the probability of accepting or rejecting the hypothesis. This process is qualitative and erroneous decisions are liable to occur.

## III. CROP CALENDAR AND FEATURE SELECTION METHODS

This section discusses underlying concepts which founded the basis of designing the AIIDS in the present form. Special attention will be focused on the presentation of crop calendar information in a manner consistent with the feature space domain.

The raw LANDSAT MSS provides four channel data. The entirety of temporal LANDSAT MSS data from a given imagery is a temporal series of four channel data with the dates of acquisitions specified. In a mathematical representation the entire data set for a given pixel in the imagery is written as:

$$D = \left\{C_i(j), T_i\right\}, \ j = 1,2,3,4, \text{ and } i = 1,2,\ldots,n,$$

where $C_i(j)$ is the j-th channel MSS data at the i-th acquisition, $T_i$ is the date of the i-th acquisition, and n is the total number of acquisitions.

The problem to be concerned with is to search for a method of extracting interpretable or useful information from D, and presenting the extracted information with external data, particularly crop calendar information, to analyst-interpreters so as to assist them with labelling decisions.

The following three feature selection methods were investigated:

1. The temporal trajectory method[9].

2. The dates of significant event method, or the time event method[10], and

3. The signature surface map method[11].

The temporal trajectory method considers trajectories on the two-dimensional domain of data variability as crop signatures. Angles between successive acquisitions on the two dimensional domain were used as features for classification.

The dates of significant event method uses temporal curves of growth index (e.g. Kauth greenness numbers[12] and Kanemasu leaf area index[13]), and characterizes crops by dates of events such as the peak and a half of the peak of the growth index curve. A method to employ growth index curves plotted against time for classification will be referred to as the time event method.

The signature surface map method exploits visual patterns of iso-count contour lines derived from three dimensional data of (x, y, z) where x, y, and z represent, respectively, time, wavelength, and the MSS data value (i.e. count). At the present time no quantitive forms for features are provided with this method.

Details of each of the above feature selection methods are described in Appendices A, B, and C.

Features extracted from LANDSAT data alone are insufficient for AI's to make labelling decisions. Extracted features need to be correlated with information on crop growth, primarily crop calendar information. A normal crop calendar is constructed from statistical tabulations of dates of visually observed phenomena such as emergence, soft dough, yellowing, and tasselling. Generally a crop calendar is available for each crop reporting district (CRD). An example of a crop calendar is shown in Figure 1.

The immediate difficulty in comparing extracted features and the crop calendar is that extracted features and data on the crop calendar differ in physical dimensions so that comparison cannot be made directly. To solve this problem there are two approaches. The first approach is to convert extracted features to the values in the domain of a crop calendar, i.e. dates. The dates of significant event method[10] used this approach.

The second approach is to convert a crop calendar to the values comparable in the feature domain. With the trajectory method[9] a trajectory has to be generated for each crop. The time event and signature surface methods require the generation of crop growth index and signature surface map. Labelling would be performed by visually inspecting the magnitude of differences between the observed pattern from LANDSAT data and the predicted pattern from the crop calendar.

Let us investigate the second approach in detail. Since LANDSAT MSS data can be reasonably well approximated by two numbers, called brightness and greenness numbers, the task is to generate these two numbers for a given crop stage of a given crop. One of the simplest methods is to employ LANDSAT data with ground truth and ground observation of crop growth stages. However, this is difficult because both the brightness and greenness numbers for a crop vary significantly from field to field particularly in the early and post harvest stage. This is probably due to the fact that reflection of light from a field containing bare soil varies with the surface condition of soil. The magnitude of the MSS output reflected from bare soil can easily vary by a factor of two, for instance, depending upon whether it is dry (high output) or wet (low output). Generally, additional data such as soil type, soil moisture, and field conditions (tilting, plowing, etc.) are needed to predict brightness numbers.

The situation for greenness numbers is different. It has been noticed that temporal greenness curves of a crop species show similar temporal trends in spite of the fact that their magnitude might differ significantly from field to field. This is probably due to the fact that LANDSAT data from soil, regardless of its surface condition, has a greenness number of approximately zero by definition.[9] With the present knowledge it seems that temporal growth index can be generated based upon dates on a crop calendar alone. For instance, in the Robertson variable crop calendar the peak occurs approximately at Robertson growth stage 3.5, and half the peak occurs at 2.6 and 4.6. Figure 2 shows an empirical relationship between Kauth greenness and Robertson growth stage.

Based upon the above empirical relationship, an average crop calendar can be converted to temporal curves of greenness numbers in the following manner. First the following three dates are identified for the i-th crop: (1) $t_{2i}$ = the expected date of the peak in the greenness, (2) $t_{1i}$ = the expected date of half the peak value before the peak date, and (3) $t_{3i}$ = the same date as (2) except after the peak date. These dates are reasonable well known for wheat but empirical studies would be needed to obtain these values for other crops. Then the greenness curve for the i-th crop is calculated as:

$$g_i(t) = \begin{cases} \dfrac{g_{oi}}{\sqrt{2\pi}\,\sigma_{1i}} \operatorname{Exp}\left\{- \dfrac{(t - t_{2i})^2}{2\sigma_{1i}^2}\right\} & t \le t_{2i} \\[2ex] \dfrac{g_{oi}}{\sqrt{2\pi}\,\sigma_{2i}} \operatorname{Exp}\left\{- \dfrac{(t - t_{2i})^2}{2\sigma_{2i}^2}\right\} & t > t_{2i} \end{cases}$$

where $g_{oi}$ is the expected peak greenness value, and $\sigma_{1i} = (t_{2i} - t_{1i})/a$, and $\sigma_{2i} = (t_{3i} - t_{2i})/a$, and $a = \sqrt{2 \log_e 2}$. These curves could be superimposed on the observed growth index curves using different colors.

At the present time, it is difficult to extend the above approach to the other two feature selection methods (i.e. temporal trajectory and signature surface map methods), because they require brightness information. Prediction of brightness is difficult and little work has been done on this subject.

## IV. DESCRIPTION OF THE ANALYST-INTERPRETER INTERACTIVE DISPLAY SYSTEM (AIIDS)

This section describes in detail a software system called the Analyst-Interpreter Interactive Display System (AIIDS).

The entire software system was developed on the IBM's MTMT (Multiple Terminal Monitor Task) System. The basic hardware components of AIIDS are an IBM 370/135, a RAMTEK GX-100B, CONRAC Display Terminals (one color and one black and white), a keyboard, and a curser.

FORTRAN IV was used whenever applicable. Since AIIDS is an experimental system, the reduction in development time realized by using a high level language for outweighted any probable decrease in execution time. Inputs to the RAMTEK GX-100B are byte streams of commands, instructions, and data. Since FORTRAN cannot OPEN and CLOSE the RAMTEK, Assembly Language had to be used.

The AIIDS has three distinct hierarchical levels in the software architecture. The first level written solely in Assembly Language deals with the interface with the RAMTEK, such as OPEN, CLOSE, and transmission of commands, instructions, and data. The modules in the second level perform functions related with terminals such as display, keyboard, and curser. The third level contains application programs.

The following describes functional steps of AIIDS in the order of execution:

1. Start
This step initializes the RAMTEK GX-100B and also reads crop calendar dates from a file.

2. Image Read
Image data can be read from either a disk or a tape. Also a simulated image can be generated, which has been used to debug the system. Images are 117 scan lines by 196 pixels covering an area of 9 km by 11 km on the ground.

3. Header Modification
Although acquisition date, location identification number, and sun elevation angles are found in the header, they are occasionally erroneous and this step allows a modification of these data.

4. Image Display
False color images can be shown: channel 1, 2, and 4 data modulate, respectively, the blue, green, and red guns. Two methods for selecting bias and scale factors are available. One method maximizes contrast and the other maintains color chromatic fidelity although the resulting contrast is lower.

5. Pixel Sampling
Pixels can be sampled using one of the following three procedures:

a. A preset grid mesh - 28 locations on the grid points at 10, 40, 70, and 100 scan lines and 10, 40, 70, 100, 130, 160, and 190 pixels.

b. Any locations selected by manipulating the curser.

c. Any locations determined by typing the scan line and pixel numbers.

6. Field Definition
Either a single pixel or 3 scan lines by 3 pixels area around the sampled pixel can be selected.

7. Sun Angle Adjustment
The following sinusoidal sun angle adjustment factor has been employed: $a = \sin(59^\circ/\sin\theta_j$, where $\theta_j$ is the sun elevation angle at the j-th acquisition.

8. Principal Axis Transformation
Either of the following two principal axis transformation can be selected. The first is due to Kauth and Thomas[12].

$$b = .330\,X_1 + .603\,X_2 + .676\,X_3 + .263\,X_4$$

$$g = -.283\,X_1 - .661\,X_2 + .577\,X_3 + .389\,X_4.$$

The second is due to Wheeler, Misra, and Holmes[13].

$$b = .406\,X_1 + .600\,X_2 + .645\,X_3 + .243\,X_4$$

$$g = -.386\,X_1 - .530\,X_2 + .535\,X_3 + .532\,X_4,$$

where b and g denote the first and second components, usually referred to as the brightness and greenness components, respectively, and $X_i$ denotes the i-th channel component of LANDSAT II MSS data.

9. Feature Display
One of the following options may be chosen to display features computed for sampled pixels.

a. Trajectory Plot
Trajectory plots on the brightness and greenness domain can be shown. Different color lines allow superimposition of two or more trajectories on a display.

b. Temporal Plot
The y axis representing the greenness component is plotted against the x axis representing the Julian date. Superimposition of many curves is possible using different colors.

c. Signature Surface Maps
A signature surface map can be shown for each sampled pixel. Eight different colors were employed for drawing iso-count contour-lines in the signature surface domain. Color assignment from the highest to the lowest is in the order of white, blue, red, magenta, purple, green, yellow, and reddish

d. Scatter Plot And A Histogram
A scatter plot on the brightness and the greenness domain is shown for each selected imagery data. Furthermore, a histogram created from all pixels can be superimposed on the scatter plot so that the adequacy of the sampled data for representing all pixels may be visualized.

e. Neighboring Pixels
The five scan line by five pixel neighboring area surrounding a sampled pixel is displayed using eight time magnification. There neighboring areas are shown for all the acquisitions by juxtaposing. This display allows analyst-interpreters (1) to determine whether the sampled pixel is on the boundary and (2) to recognize temporal color transitions.

f. Crop Calendar
Three predicted curves are shown for each crop: early, average, and late growth. The maximum number of crops to be able to be shown on a display is four. Then an observed greenness curve is superimposed on each of the predicted curves. Analyst-interpreters can perform labelling by visually comparing the resulting curves.

10. Classification
At the time of writing, the only available classifier is that on a scatter diagram. A decision boundary may be drawn directly on a scatter diagram. The classification for a four channel image can be executed usually within 30 seconds on the IBM 370/135. Other classification algorithms such as a linear classifier will be implemented in a near future.

## V. EXPERIMENTS

This section describes the performance of the AIIDS using color photographs taken from the CONRAC color terminal. AIIDS was tested using a 9 km by 11 km area located in North Dakota. It has six acquisitions: 77120 (April 30), 77138 (May 18), 77156 (June 5), 77174 (June 23), 77211 (July 30), and 77229 (August 17). Twenty-four pixels were sampled to which ground truth information was available. Samples 1-4, 5-8, 9-12, 13-16, 17-20, and 21-24 are, respectively, soybean, corn, spring wheat, barley, sunflower, and suger beets.

Figure 3 shows six images of the area using the maximum contrast method. Overview of the entire acquisitions will enable one to delete acquisitions with clouds or haze if any, and to select an acquisition which is best suited to select sampling pixels.

Figure 4 shows the third image with two by two magnification using the method which maintains chromatic fidelity. Twenty-four symbols (9 numerals from 1 to 9 and 15 alphabets from A to O) were superimposed.

Figure 5 shows trajectories on the brightness and greenness domain for four sampling pixels.

Figure 6 shows a scatter diagram of these samples on the third acquisition, namely date 77156 (June 5). Purple dots on the background show the scatter diagram constructed from the entire pixels from the same image. It is evident that at this date spring crops are much greener than summer crops and that these two groups of crops are reasonably well separated. With this superposition it may be possible to determine whether the selected samples are representative or not.

Figure 7 shows temporal greenness curves for the above four samples. Similarity of samples 9 (spring wheat) and 13 (barley) are apparent.

Figure 8 shows the signature surface maps of samples from 1 to 20 listed on Table 1. Each row from the bottom to the top shows soybeans, corn, spring wheat, barley, and sunflower, respectively. Confusions between spring wheat and barley are common.

Figure 9 shows the results from the three feature selection methods for sampling pixel No. 9. The signature surface map, six acquisitions of the 5 scan line by 5 pixel neighbors surrounding the sampled pixel, the trajectory on the brightness and greenness domain, and the time event curves are shown, respectively, on the left upper, right upper, right bottom, and left bottom quadrants. On the left bottom quadrant, brightness and greenness curves are indicated by white and green curves, respectively. Three bell shape curves show temporal greenness curves (earlier, normal, and later growth) for spring wheat. The excellent matching between the observed greenness curve and the predicted curve (normal growth) indicates that the sampling pixel No. 9 is probably spring wheat.

## VI. FUTURE SYSTEM DEVELOPMENT

The system described is still in an evolutionary stage. Other materials to be needed for further increasing labelling accuracy need to be incorporated. Figure 10 depicts a conceptual design for the future system. Input data are divided into two types: observed and predicting data. Observed data are typically LANDSAT MSS data. Data to contribute predicted crop growth are crop calendar (nominal and variable), episodal events (rainfalls, storms, floods, etc.), temperature and precipitation, soil moisture indices, and yield data. Labelling may be performed by observing similarities between observed and predicted patterns on such quantitative values as greenness and leaf area index. Two types of spatial information, global and local, are also very important.

The global information, for instance, image display of a 9 km by 11 km area, will allow analyst-interpreters to interpret the pixel of interest in relation to the entire scene. The local information such as display of neighboring pixels is useful for determining whether the pixel of interest is on the boundary. Immediately after labelling is performed, classification should be executed. Execution time is an important criterion to select classification algorithms. The last step is the verification, where the result is compared with anticipated results. Other verification techniques are statistical indicators such as goodness of classification. Although design of verification procedure is still in an embryonic stage, this is recognized as the critical step with respect to labelling efficiency improvement.

## VII. CONCLUSION

Although the work has not yet been completed at the present time, it has been demonstrated that the presented approach offers an effective solution to alleviating many problems associated with the current manual labelling process. In particular, it appears that the experience and skill level required to perform labelling can be significantly reduced and that technology training/transfer difficulties can be minimized through the application of the aforementioned techniques.

## APPENDIX

A. Trajectory Plots

As was shown by Kauth and Thomas[12] and Wheeler, Misra, and Holmes[13], LANDSAT imagery data are essentially two-dimensional. In other words, two variables suffice: one variable is called a brightness number (b) and the other a greenness number (g). They are defined for LANDSAT II data as follows:

$$\begin{aligned} b &= .330\chi_1 + .603\chi_2 + .676\chi_3 + .263\chi_4 \\ g &= .283\chi_1 - .661\chi_2 + .577\chi_3 + .389\chi_4 \end{aligned} \qquad (1)$$

where $\chi_i$ represents the i-th channel response of LANDSAT Multispectral Scanner (MSS).

LANDSATs cover the same area in a period of 18 days. Therefore, several imagery data sets over the same area can be acquired during the growing season of a crop of interest. Assume that there are n acquisitions over a location. The above transform (called the Kauth Transform) maps the MSS response $(x_1^i, x_2^i, x_3^i, x_4^i)$ from the j-th acquisition to $(b^j, g^j)$ on the brightness and greenness domain. A temporal trajectory on the brightness and greenness domain is obtained by connecting the points $(b^1, g^1), (b^2, g^2), \ldots, (b^n, g^n)$ in the order of acquisitions.

B. Dates Of Significant Events

Crop specifics may be characterized by dates of events such as planting, emergence, jointing, yellowing, and harvesting. (These events are applicable to winter wheat.) The Robertson BMTS growth stages[8] (also called the Robertson variable crop calendar) identify these events by numbers from 1.0 (planting) to 7.0 (harvesting).

If a crop stage is identified from the MSS response at each acquisition of LANDSAT, correlation of a set of observed crop stages with another set of expected growth stages from the crop calendar (either historical or variable) will identify crop species or subspecies. However, LANDSAT four channel data from a single acquisition do not seem to permit reliable calculation of growth stages.

A more straight forward method of calculating growth stages is to use a growth index function calculated from a temporal series of LANDSAT data. A growth index function is defined to be a scalar function which is indicative of growth stages. Kauth greenness number, and the leaf area index defined by Kanemasu[14] are examples.

An experimental observation between the Robertson growth stage and Kauth greenness number is shown in Figure 2. The peak of Kauth greenness occurs approximately at Robertson growth stage of 3.5 (half way between jointing and heading). Also the event that the Kauth greenness number is half of the peak value, occurs at growth stages of approximately 2.6 and 4.3.

The above observation leads to the following feature selection and classification scheme. First, the Kauth greenness number is calculated using Eq. (1) for each acquisition for a pixel or a field. Then the date, $D_2$, that provides the peak Kauth greenness number is identified. Then the dates, $D_1$ and $D_3$, corresponding to a half of the peak value before and after, respectively, reaching the peak are calculated. Classification or labelling could be performed by comparing these three selected dates $(D_1, D_2, D_3)$ with the expected dates corresponding to the Robertson growth stages of 2.6, 3.5, and 4.6, respectively. The peak value devoted by $g_{max}$ could be used auxiliarily for classification.

C. Signature Surface Maps

A complete set of LANDSAT MSS responses is represented by a set,

$$R = (x_1^j, x_2^j, x_3^j, x_4^j), t_j \qquad j = 1, 2, \ldots, n,$$

where n is the total number of acquisitions, $x_i^j$ is the i-th channel response at the j-th acquisition and $t_j$ is the Julian date of the j-th acquisition. R can be displayed in the following manner. Consider a three dimensional space (X,Y,Z), where the X, Y, and Z axis represent, respectively, the sensor wave length, the Julian date, and count value. Since LANDSAT channel 1, 2, 3, and 4, respectively, have wave lengths from .5 th .6, .6 to .7, .7 to .8 and .8 to 1.1, the MSS response $(x_1^j, x_2^j, x_3^j, x_4^j)$ is located at (.55, 165, .75, .95) along the X axis and at $t_j$ along the Y axis. Their heights along the Z axis are $(x_1^j, x_2^j, x_3^j, x_4^j)$. Finally, the signature surface is obtained by interpolating all the points linearly.

The signature surface of R can be displayed in terms of contour lines of equal counts. Two dimensional pattern of these contour lines constitutes a feature. The explicit algorithmic expression for the feature has not been identified at the present time.

## REFERENCES


1. R. B. MacDonald and F. G. Hall, "LACIE: A Look to the Future", Proc. of the Eleventh International Symposium on Remote Sensing of Environment, 25-29 April, 1977, Environmental Research Institute of Michigan, Ann Arbor, Michigan, p.p. 429 to 465.

2. Earth Observation Division, Johnson Space Center, NASA, "Briefing Materials for Technical Presentation Volume A and B", the LACIE Symposium, Johnson Space Center, NASA, Houston

Texas, October 1978.

3. F. G. Hall and R. M. Bizzel, "Crop Identification Technology Assessment for Remote Sensing (CITARS)", Volume I, Task Design Plan, NASA Johnson Space Center, JSC-093484, February 1975.

4. C. Gleason, R. R. Stanbuck, R. S. Sigman et al, "The Auxiliary Use of LANDSAT Data in Estimating Crop Acreages: Results of the 1975 Illinois Crop-Acreage Experiment", Statistical Reporting Service, U.S. Department of Agriculture, Washington, D.C., October 1977.

5. K. S. Fu, D. A. Landgrebe, and T. L. Phillips, "Information Processing of Remotely Sensed Agricultural Data", Proc. of IEEE, Volume 57, No. 4, April 1969, p.p. 639-653.

6. G. Nagy and J. Tolaba, "Nonsupervised Crop Classification Through Airborne Multispectral Observations", IBM Journal of Research and Development, March 1972, p.p. 138-153.

7. W. W. Austin, "Detailed Description of the Wheat Acreage Estimation Procedure Used in the Large Area Crop Inventory Experiment", LEC Technical Memorandum, LEC-11497, February 1978.

8. G. W. Robertson, "A Biometerological Time Scale for Cereal Crop Involving Day and Night Temperatures and Photoperiod", International Journal of Biometerology, 1968, Volume 12, No. 3, p.p. 191-223.

9. P. N. Misra and S. G. Wheeler, "Crop Classification with LANDSAT Multi-Spectral Scanner Data", Pattern Recognition Volume 1D, 1978, p.p. 1-13.

10. T. Kaneko, "Crop Classification Using Time Features Computed from Multi-Temporal Multispectral Data", to appear in the Proc. of the Fourth International Joint Conference on Pattern Recognition, Nov. 7-10, Kyoto, Japan.

11. R. T. Smart, "Three Dimensional Presentation Of Multispectral LANDSAT Data", IBM Memorandum, RES 23-31, June 7, 1977.

12. R. J. Kauth and G. S. Thomas, "The Tasselled Cap - A Graphic Description of the Spectral-Temporal Development of Agricultural Crops As Seen by LANDSAT", Machine Processing of Remotely Sensed Data, June 29 - July 1, 1976, LARS, Purdue University, West Lafayette, Indiana, p.p. 4B-41 to 4B-51.

13. S. G. Wheeler, P. N. Misra, and Q. A. Holmes, "Linear Dimensionality of LANDSAT Agricultural Data with Implications for Classification", i.b.i.d. p.p. 2A-1 to 2A-9.

14. E. T. Kanemasu, "Estimated Winter Wheat Yield from Crop Growth Predicted by LANDSAT", Final Report to NASA/JSC, NAS 9-14899, May 1977.

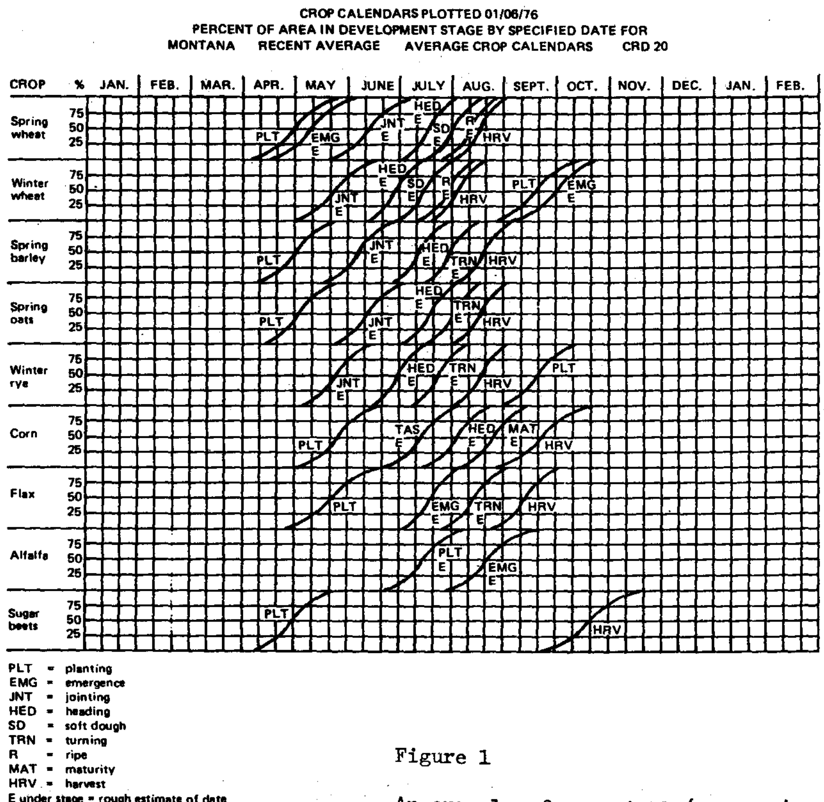


Figure 1

An example of a nominal (average) crop calendar.

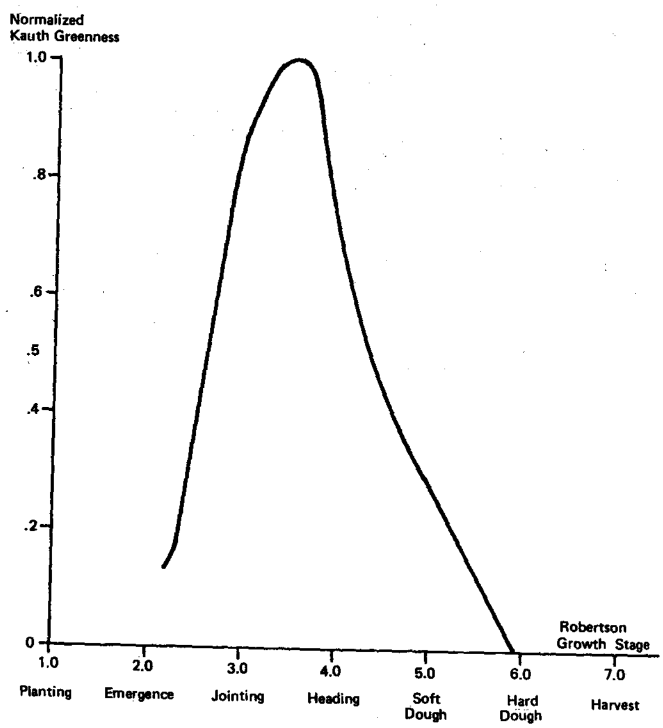


Figure 2

An empirical relationship between normalized greenness numbers and Robertson numbers.

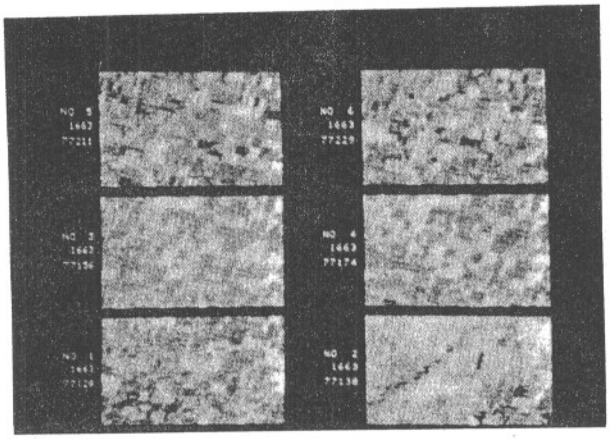


Figure 3

Six Images of Sample Segment 1663
(The Maximum Contrast Method)

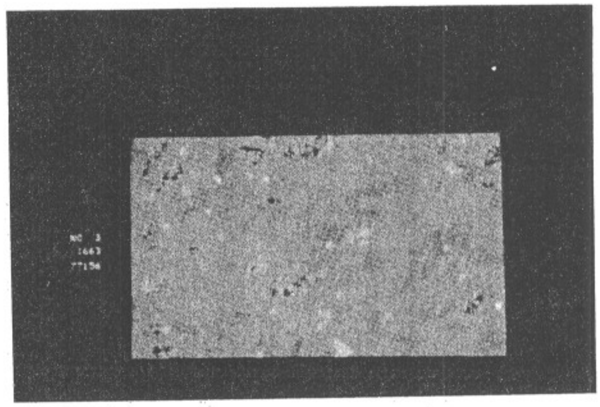

Figure 4

Sample Segment 1663 date 77156 (June 5) with 2 by 2 magnification using the color chromatic fidelity method. Alphanumeric symbols (1 to 9, and A-Z) indicate the locations of sampling pixels.

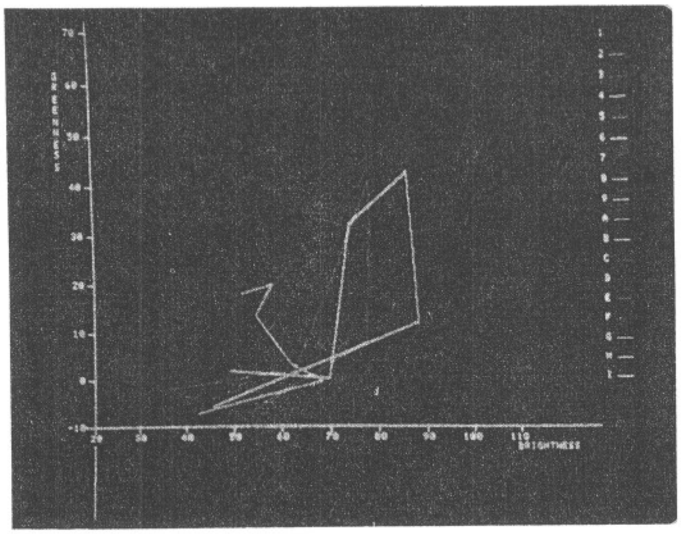


Figure 5

Trajectories of four sampling pixels where red, green, blue, and yellow represent pixel No. 1, 5, 9, and 13.

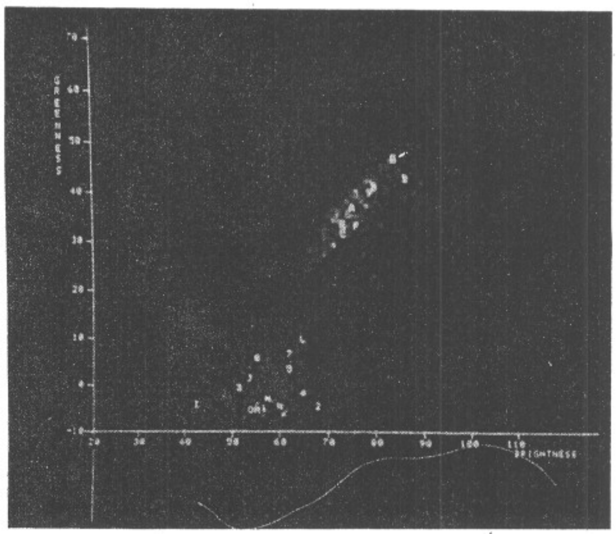


Figure 6

A scatter diagram of the third acquisition. Alphanumeric symbols represent sampling pixels and purple squares show the scatter diagram generated from the entire pixels.

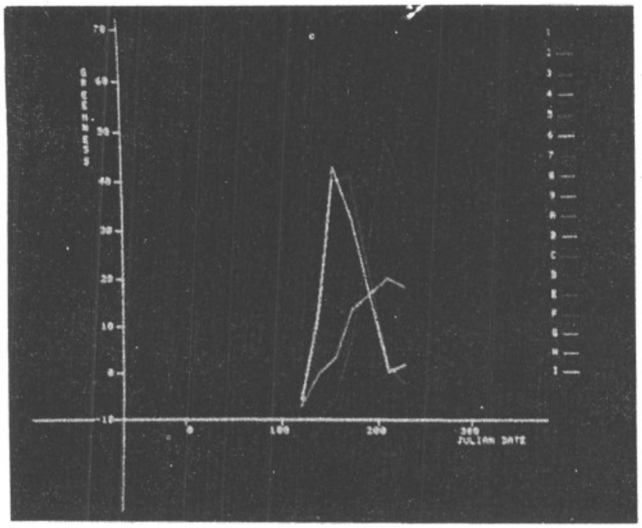


Figure 7

Temporal greenness curves of the four sampling pixels where red, green, blue, and yellow represent pixel No. 1, 5, 9, and 13.

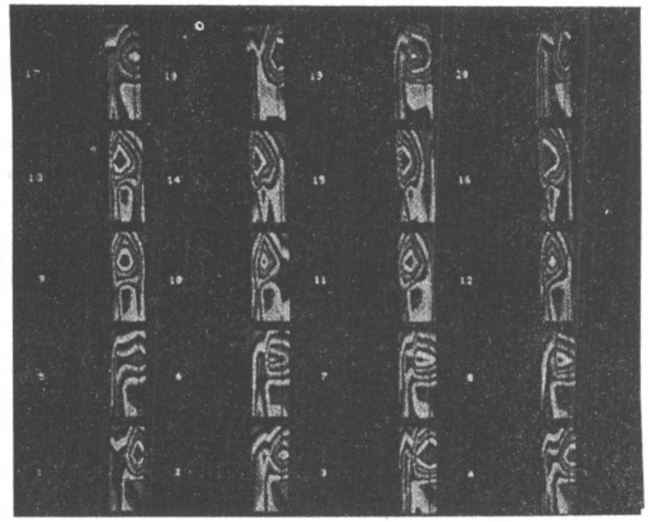

Figure 8

The signature surface maps of sampling pixels No. 1 to No. 20.

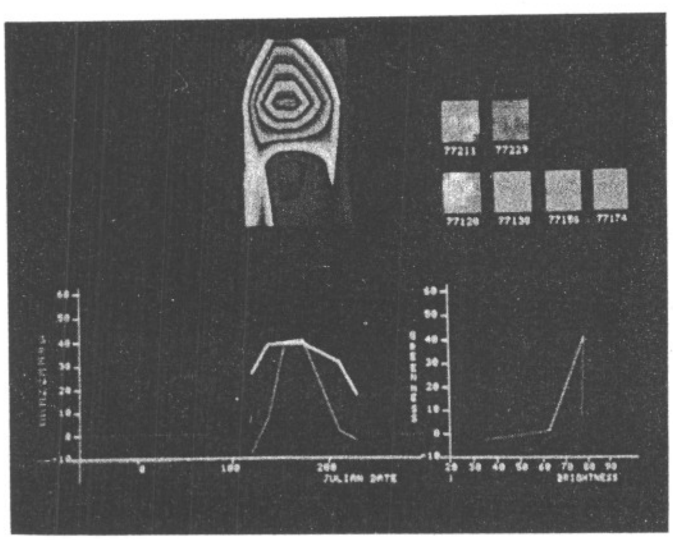


Figure 9

Collection of the outputs of the three feature selection methods. The trajectory plot, time event curve, and signature surface map of sampling pixel No. 9 (spring wheat) are shown on the right bottom, left bottom, and the left top quadrants, respectively. Six square boxes at the right top quadrant show six acquisitions of the 5 by 5 neighbors of sampling No. 9 with product 3 color reproduction. Three bell shaped red curves superimposed on the time event curves represent greenness curves of spring wheat with early, normal, and late growth. The observed greenness and brightness curves are shown in green and white, respectively.

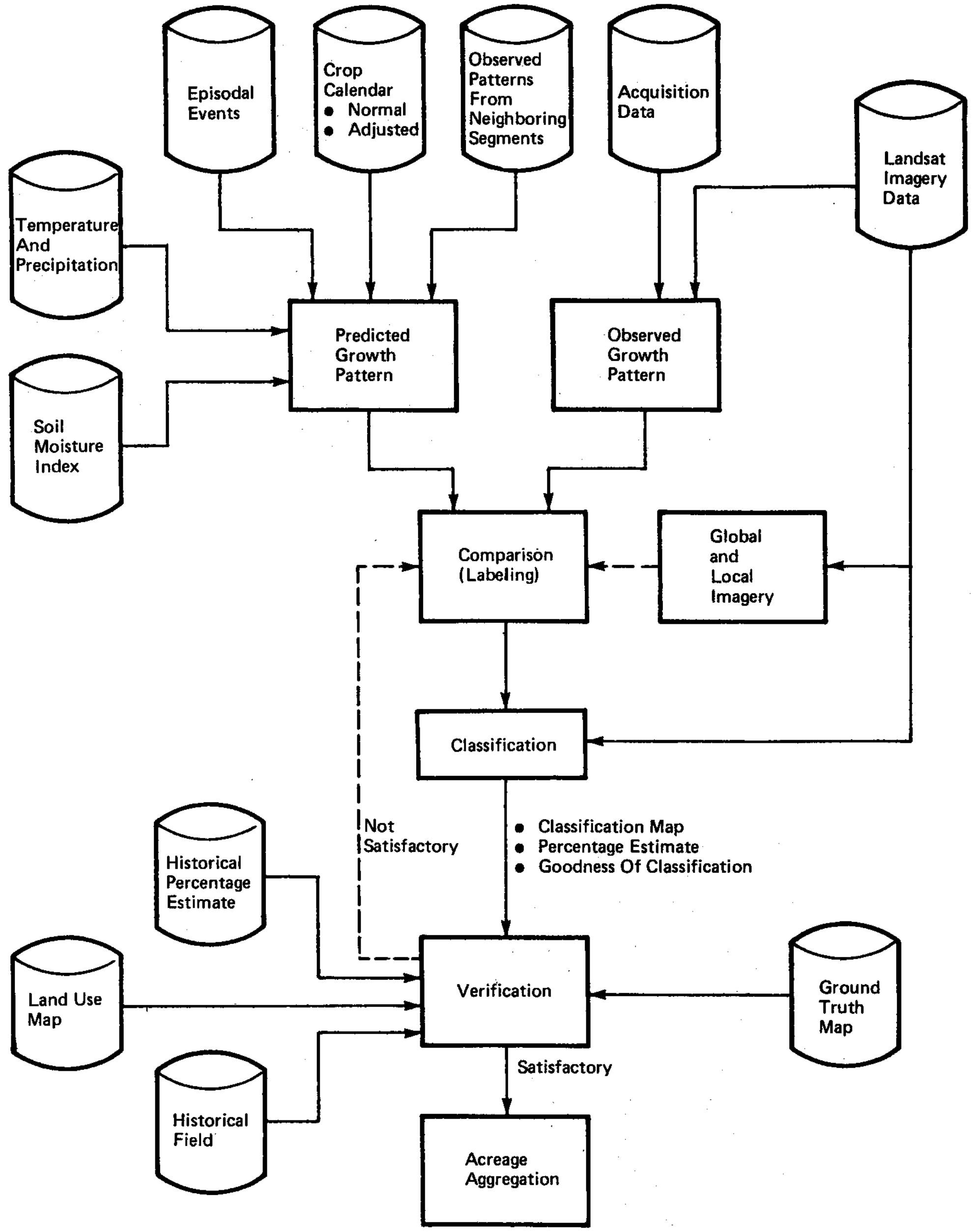


Figure 10

A schematic diagram of future AIIDS.

Toyohisa Kaneko

Received the B.E. and M.E. degrees in electrical engineering from the University of Tokyo, in 1962 and 1964 and the Ph.D. degree in electrical engineering from Princeton University in 1970.

From 1970 to 1974 he was with IBM T. J. Watson Research Center, Yorktown Heights, N.Y., working on image processing, digital processing, and storage hierarchy.

Since 1974 he has been in the IBM Federal Systems Division, Houston, Texas, being involved with computer processing of remotely sensed data in such areas as automatic image quality assessment, color file generation, and multicrop classification.

Linda K. Moore

Ms. Linda K. Moore is completing her M.S. degree from the University of Florida, Gainsville, Florida, in electrical engineering. Her B.S. degree is in mathematics. Ms. Moore joined the Federal Systems Division of IBM in Houston, Texas in June, 1978. She is currently involved in graphics display terminal applications for the study of earth resources.

Robert T. Smart

Holds a B.S. degree in Physics from Louisiana State University (1960) and joined IBM in 1965. He is currently assigned to the Earth Resources Systems department at the Federal Systems Division facility at Houston, Texas. He has been involved with remote sensing applications since 1974.