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Time Dimension for Crop Surveys from Space

With operational earth resources satellites likely being in orbit in the near future, time dimension can be used to exploit automatically the potential of the surveying platform.

(Abstract on next page)

INTRODUCTION

SINCE 1950 a number of investigations in various parts of the world have been concerned with the detailed identification of agricultural crops on black-and-white aerial photographs (Goodman, 1954, in Illinois; Hunting Survey Corporation, 1960, in Alberta; Hunting Technical Services, Ltd., 1960, in Ghana; Steiner, 1961, in Switzerland). They have shown some of the possibilities, but above all the limitations of conventional means and methods. It was recognized that the interpretability of land use depends highly on season and that no single season permits the identification of individual crops with absolute certainty. In some instances it was suggested that a combination of photographic coverages of the same area taken at different times during the growing season might solve the problem. The costs involved with this approach, however, would be prohibitive.

In Germany, Meinberg (1966) obtained a remarkable accuracy in the conventional interpretation of detailed land use on color aerial photographs. But even if it would be possible to use classical photo interpretation with success for practical crop surveys, the speed with which such surveys could be carried out would depend primarily on the availability of trained, high qualified photo interpreters, who are in short supply. Moreover, conventional photo interpretation remains subjective and therefore suffers from the uncertainties inherent in subjective judgment. Two photo interpreters working on the same area will always obtain different results.

More recently, efforts have been made to development objective, semi-automatic or automatic methods of crop surveying from the air. In Switzerland, the author of this paper and his collaborators have been concerned with the use of a digital computer for the analysis and the classification of densitometric and stereometric measurements made at sample points on a combination of multitype photography, including panchromatic, infrared, true color and false color (Steiner and Maurer, 1967; Steiner, 1968; Steiner and Maurer, 1968; Baumberger, 1969; Steiner and Maurer, 1969). At the Universities of Michigan and Purdue, respectively, complex data-handling techniques are being researched to

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determine the suitability of utilizing a rather sophisticated instrument, namely a multichannel airborne spectrometer, for purposes of automated surveys of agricultural areas (Lowe and Braithwaite, 1966; Cardillo and Landgrebe, 1968; Laboratory for Agricultural Remote Sensing 1968; Lowe, 1968). With this method, the pictorial stage (photography or imagery) may be skipped and the signals received from the various channels processed directly by an analog or digital computer. The final product is a computer printout in map form, or simply a table summarizing the area identified as the various crop species present.

In both instances, the approach used is based on the concept that the combination of a larger number of crop parameters (photographic densities and height information in the first case, spectral returns in the second) is more likely to produce a correct identification of crops than the use of a single parameter. Also, in both experiments, the classification arrived at is produced by a maximum-likelihood principle commonly known as a discriminant analysis.

Instead of combining parameters which describe crop aspects at one given time, it would be desirable to perform an integration of observations taken at a number of different times throughout the growing season. The logic of the method remains the same. For example, Steiner and Maurer (1968), in combining June and July true color photos, were able to raise the accuracy of crop classification to 75 percent as compared with 40 percent (June) and 29 percent accuracy (July) on single photo sets. However, the involvement of aircraft of a surveying platform seriously limits the feasibility of repetitive observations for economical reasons.

With operational earth resources satellites likely being in orbit in the near future, the use of the time dimension becomes possible, if not mandatory, to exploit fully the potential of a surveying platform circling the earth continuously. This, on the other hand, could mean that the demand on the spectral dimension would be much less and that the use of a few spectral bands, or even one only, may supply sufficient information for a reliable crop classification. The following example shows some of the power of the application of discriminant analysis to time-sequence data.

Example of a Crop Classification with Time-Sequence Data

To demonstrate the methodology we made use of data collected by the author some years ago on 11 major crop types in various mixed farming areas of Switzerland (Steiner, 1961). The crops considered are natural hay, sown hay, winter wheat, spring wheat, winter rye, winter barley, spring barley, oats, potatoes, beets and rape. Densitometric measurements were performed on a large number of panchromatic photographs taken at various times during the growing seasons of several years. To eliminate the influence of differences in exposure and processing from film to film and also of variations in crop phenology from area to area and from year to year, the data were standardized.* The result consisted of sea-

Abstract: *A number of research projects have been concerned with the development of the technology and/or methodology for automated crop surveys from air- or spacecraft. Crop parameters are obtained either from measurements on imagery or by scanning the terrain directly. Signals are processed in analog or digital computers on the basis of statistical decision-making procedures. A multitude of parameters (variables) is usually needed for a crop classification with a reasonable degree of accuracy. The two basic dimensions which provide multi-variate information are the spectral dimension and the time dimension. So far, one has experimented almost exclusively with the spectral dimension (use of multiband imagery or of multi-channel spectrometers). The present paper demonstrates the possible use of the time dimension. Tonal changes in a given spectral interval are analyzed throughout the growing season and information obtained at a number of seasonal intervals is combined. This approach is of special interest in the case of an orbiting survey satellite.*

* The method used for standardization was, briefly, the following: The characteristic curve of individual films was determined either from the photographic appearance of special panels with known reflectances or, where not available, from other objects with know reflectance (for example, road surfaces), and all density values were corrected for a film gamma of 1.0. Furthermore, the seasonal densitometric data were checked against

sonal densitometric profiles for all 11 crops. These served as a basis for the present study.

Average densities were read off the graphs at 10-day intervals from April 10 to August 8 (compare with Figures 1 and 2). To simplify matters, it was assumed that the variation of density values would be the same for all crops and all dates, and based on the original observations, an estimated average value of 0.04 for the standard deviation was adopted. A normal distribution was simulated, i.e., for each crop and each date 9 observations were drawn from this distribution at random. The data matrix considered here therefore consists of 99 subjects (9 for each crop type), for which we have observations on 13 variables (densitometric values at 10-day intervals).

This matrix was subjected to a linear discriminant analysis. Discriminant analysis is a multi-variate statistical method that calculates functions which discriminate between groups in an optimum manner. *Optimum* means the following: The individual observations belonging to one group can be visualized as a cluster of points in a multi-dimensional space defined by the variables in question. The discriminant functions calculated by the analysis determine boundaries which produce a set of subspaces, one subspace for each group. The location of the boundaries is such that a minimum number of misclassifications (i.e., individual points lying in the incorrect subspace) occur. Functions are linear equations of the form

$$y = a + b_1x_1 + b_2x_2 + \cdots + b_mx_m,$$

where y is the discriminant score, x_i is the score on i-th original variable $(i=1, m)$, b_i is the weight (coefficient) attached to the i-th variable, and a is a constant (for a more detailed discussion of mathematics involved see Kendall, 1961).

New observations not contained in the original data set can be allocated in exactly the same way, by making use of the previously determined discriminant functions. It should be noted, therefore, that automated aerial or space surveys do not differ from the basic principles of conventional photo interpretation, i.e., the selection of a sample of subjects of known identity, the establishment of a key based on this sample, and the application of the key information to classify all other subjects in the study area whose identity is not known as yet. For the mathematical solution the discriminant functions represent the key, and the comparison of the classification of sample subjects as produced by the analysis with the true identity of these subjects provides a statistical estimate for the overall accuracy of the survey.

The application of discriminant analysis to the present example with 99 subjects (11 groups with 9 members each) and 13 variables resulted in a crop classification with 100 percent accuracy. This outcome seems to indicate that accurate crop surveys could be conducted using remote sensing techniques within the visible spectral band, provided that observations were repeated a fair number of times during the growing season. We are aware of the difficulties produced by the presence of frequent cloud cover over certain areas, of course. However, data gathering at more irregular intervals might produce satisfactory results, or else the use of another spectral band less or not affected by clouds might be the solution. Another question not dealt with here is the problem of spatial resolution from satellite altitudes.

After having demonstrated the possibility of arriving at 100 percent correct crop classifications by combining observations taken on 13 different days, we can ask whether the same, or at least a sufficient accuracy, could not be obtained with a smaller number of variables. This is a matter of economy; in fact, we would have to expect a resources satellite to be a multi-purpose sensing platform and, consequently, the smaller the number of days required for gathering data on crops, the more frequently the orbiting spacecraft could perform other functions.

To answer the above question, we have to sort out the variables according to their discriminating power in descending order. This can be done by calculating a F-ratio (ratio of between-group variance to within-group variance) for each of them. The higher the F-value, the better the discrimination provided by the variable in question. These F-values are listed in Table 1.

This is the old question asked in land use photo interpretation, namely, what is the best single season for separating crops on the basis of tonal differences, reformulated and answered in numerical terms. Table 1 indicates that June 9 is the best date among the 13. We have to assume that the variable associated with that day will, if subjected to a discriminant analysis, also produce the

seasonal reflectance measurements taken within the visible part of the spectrum.

Phenological observations taken by the Swiss Meteorological Service in the years concerned formed the basis for adjusting all dates of photography to a standard phenological time table valid for the Zurich area and an average year.

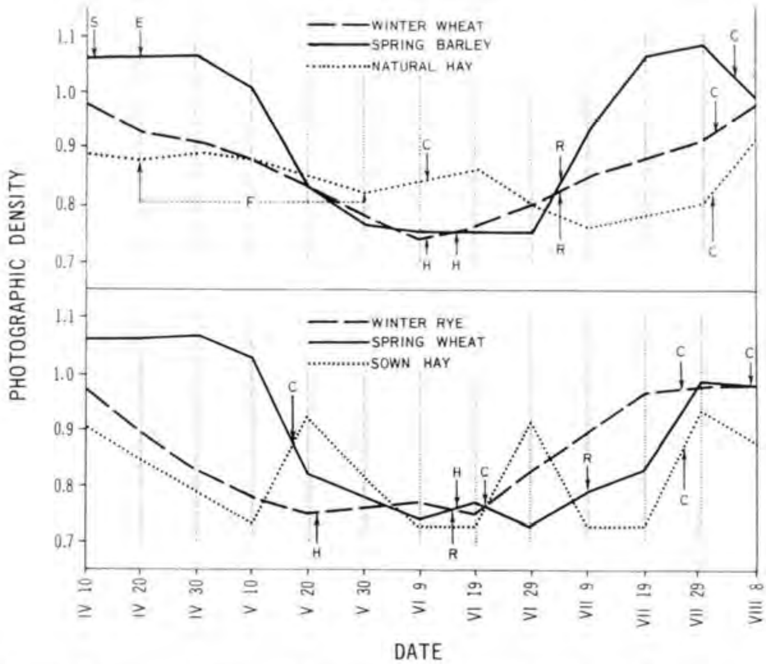

FIG. 1. Seasonal changes of average photographic densities of winter wheat, spring barley, natural hay, winter rye, spring wheat and sown hay, measured on low-altitude panchromatic aerial photographs: Valid for the Zurich area, Switzerland. The letters indicate the average dates or time periods for the following phenological aspects or farming activities: *C*, cutting (harvesting); *E*, emerging; *F*, flowering; *H*, heading; *P*, planting; *R*, beginning of ripening; *S*, sowing.

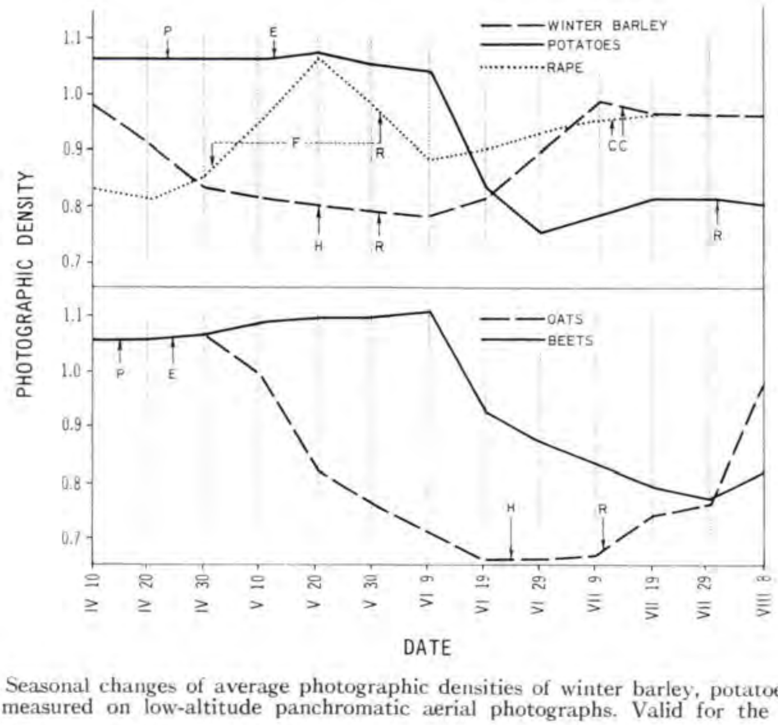

FIG. 2. Seasonal changes of average photographic densities of winter barley, potatoes, rape, oats and beets, measured on low-altitude panchromatic aerial photographs. Valid for the Zurich area, Switzerland.

TABLE 1. F-VALUES (BETWEEN-GROUP (VARIANCE/WITHIN-GROUP VARIANCE), FOR ALL 13 VARIABLES IN DESCENDING ORDER

Variable no.	*Corresponding date*	*F-value*
7	June 9	141.3
5	May 20	140.9
6	May 30	123.7
3	April 30	117.0
4	May 10	103.0
11	July 19	84.6
10	July 9	81.4
2	April 20	69.0
12	July 29	64.6
9	June 29	62.7
13	Aug. 8	55.9
8	June 19	42.3
1	April 10	36.2

best crop classification. We therefore take variable No. 7 as our first variable to enter the analysis. The results of the classification are given in Table 2.

The overall accuracy, although it is remarkably high for a detailed crop classification by means of only one variable, is certainly not sufficient for practical purposes. We might now be inclined to select the variable with the second highest *F*-ratio (this would be variable No. 5, corresponding to May 20; see Table 1) and then repeat the analysis for a combination of variables 7 and 5. This combination, however, will not necessarily result in a significant increase in classification accuracy. Variables 7 and 5 represent observations taken only 20 days apart, and crops may exhibit some similarity in appearance at the beginning and at the end of this period. In other words, the two variables may be correlated with each other to some degree, and thereby little information will be added. Consequently, one should be aware of this problem and not select variables which are close to each other in time.

A non-subjective and entirely straightforward solution to this problem of correlation between variables is provided by multiple discriminant analysis. This is a type of multivariate statistical technique which is similar to factor analysis, and since the term *multiple discriminant analysis* is sometimes used for the analysis explained earlier as well, we suggest that the method outlined below be called *discriminant factor analysis*. Simple factor analysis is a numerical technique developed primarily by psychologists and it has been introduced to other sciences within the last decade or so. The purpose of factor analysis is to break down and simplify the complexity of a highly intercorrelated multivariate data set by determining a minimum number of new independent (uncorrelated) variables (factors) which explain a maximum amount of the original data variation satisfactorily. The basis from which factors are extracted is the matrix of simple correlation coefficients between original variables (see Harman, 1967). Similarly, discriminant factor analysis produces from a large set of variables

TABLE 2. CLASSIFICATION MATRIX PRODUCED BY A DISCRIMINANT ANALYSIS WITH VARIABLE NO. 7

	NH	*SH*	*WW*	*SW*	*WR*	*WB*	*SB*	*OA*	*PO*	*BE*	*RA*
NH	56				11						33
SH		33	11		11		11	33			
WW			33		22		33	11			
SW				11	55		22	11			
WR		11	11	11	67						
WB	11			33	44	0		11			
SB		22	11	22	11		22	11			
OA		11	22	11				56			
PO									88	11	
BE									11	88	
RA	56										44

Overall accuracy: 55% (54 out of 99 sample points classified correctly).

Explanations to Table 2: NH—natural hay, SH—sown hay, WW=winter wheat, SW=spring wheat, WR=winter rye, WB=winter barley, SB=spring barley, OA=oats, PO=potatoes, BE=beets, RA=rape. Figures indicate percentages. Correct classifications occur in the diagonal (underlined) cells, incorrect allocations in the off-diagonal cells. Thus, in the case of natural hay, 5 out of 9 sample points (or 56%) were classified correctly as natural hay, whereas 3 sample points (33%) were misclassified as rape and 1 (11%) as winter rye.

a reduced number of new independent variables (discriminant factors) which, in this application, account for as much of the discriminating power of the old variables as possible. To this end a $W^{-1}B$ matrix is factored instead of the correlation matrix, where matrix B contains the between-group cross products of deviations of group from grand means weighted by group sizes, and matrix W the pooled within-group cross products of deviations of individual scores from group means, as explained by Cooley and Lohnes (1962) and Veldman (1967).

One of the products of discriminant factor analysis is a matrix of correlations between old variables and factors. Table 3 lists the correlations obtained from a discriminant factor analysis of our 13-dimensional data set for the first 3 factors. These three factors together account for 88 percent of the discriminating power of the original variables. As the factors themselves are uncorrelated, we can expect to get a classification with a high degree of accuracy if we select the three original variables that best represent these factors, i.e., for each factor the variable that correlates highest with it (underlined in Table 3). Consequently, we select variables 7, 9, and 11 and perform with them a discriminant analysis as before. The results of the classification are provided by Table 4.

Thus it is possible to obtain a very high classification accuracy with only three variables. Should one decide that it is still not sufficient, one could, of course, include more variables. We can also look at the accuracy in another way. In a practical survey we may be interested solely in the total acreage devoted to various crops within a given area and not in the spatial distribution of these crops. In this case we can compare the total number of sample points allocated to each group by the computer with the actual total number of sample points within each group. This comparison, together with percentage deviations, is given in Table 5.

Winter wheat and spring wheat show the largest deviations in the above Table, and one might reject the solution based on three variables only if these two grain types are important for the area in question. This leads us to point out that the analysis could, of course, be modified by attaching weights to individual crops. The importance of crops could be expressed by simple frequency

TABLE 3. CORRELATIONS BETWEEN ORIGINAL VARIABLES AND DISCRIMINANT FACTORS

Variable no.	*Date*	*Factor no.* I	II	III
1	April 10	0.33	−0.68	0.27
2	April 20	0.53	−0.72	0.21
3	April 30	0.62	−0.65	0.33
4	May 10	0.80	−0.32	0.36
5	May 20	0.81	0.50	−0.10
6	May 30	0.82	0.52	0.02
7	June 9	0.87	0.30	0.12
8	June 19	0.47	0.57	0.28
9	June 29	−0.06	0.88	−0.04
10	July 9	−0.26	0.47	0.80
11	July 19	−0.33	0.22	0.86
12	July 29	−0.59	0.11	0.52
13	Aug. 8	−0.72	−0.18	0.37

TABLE 4. CLASSIFICATION MATRIX PRODUCED BY A DISCRIMINANT ANALYSIS WITH VARIABLES 7, 9 AND 11

	NH	*SH*	*WW*	*SW*	*WR*	*WB*	*SB*	*OA*	*PO*	*BE*	*RA*
NH	89			11							
SH		100									
WW	11		78		11						
SW				100							
WR				11	67	22					
WB					22	67					11
SB							100				
OA				11				89			
PO									100		
BE										100	
RA											100

Overall accuracy: 90% (89 out of 99 sample points classified correctly)
For explanations see Table 2.

TABLE 5. COMPARISON OF COMPUTER-GENERATED GROUP FREQUENCIES WITH ACTUAL FREQUENCIES

Type of crop	*Computer-generated frequency* (*C*)	*Actual frequency* (*A*)	*Percent deviation* ((*C-A*)/*A*.100)
NH	9	9	0
SH	9	9	0
WW	7	9	−22
SW	12	9	+33
WR	9	9	0
WB	8	9	−11
SB	9	9	0
OA	8	9	−11
PO	9	9	0
BE	9	9	0
RA	10	9	+11

For explanation of crop abbreviations see Table 2.

coefficients, or else by some economical coefficients. It has been demonstrated in another paper (Steiner and Maurer, 1969) that the modification of group membership probabilities as produced by discriminant analysis by relative frequencies favours the predominant crops, i.e., their classification accuracy increases, whereas infrequent crops may disappear from the results of the analysis completely.

Let us conclude the analysis of our example by stating that the above findings may be somewhat too optimistic for at least three reasons:

1. The assumed average standard deviation of densitometric values around means (0.04) may be too small;
2. For simplicity, we made the assumption that all fields belonging to a particular crop group are harvested on the same day;
3. Because of atmospheric interference, contrasts between crops as seen from space will be smaller than the ones used here, which are based on low altitude photography.

SOME SUGGESTIONS FOR OPERATIONAL AUTOMATED CROP SURVEYS FROM SPACE

Suppose an orbiting spacecraft senses the earth's surface and transmits signals to ground stations where they are processed. The following is a broad outline of the procedure which possibly may be followed in the preparation and execution of automated crop surveys:

- Perform a regionalization of the survey area, for example, of the United States of America, or of the entire North American Continent, in terms of land use and climate, i.e., subdivide the survey area into a set of regions which are in both respects as highly homogeneous as possible. This could be accomplished by using such multivariate techniques as distance grouping (see Veldman, 1967) and discriminant analysis (explained above);
- Select for all the regions representative sample areas and map land use within these areas;
- Let the orbiting resources satellite make observations in promising spectral bands during one growing season as continuously as feasible. This step is needed to determine for each region the most efficient key information, i.e., the minimum amount of information which produces a required degree of accuracy. It would involve high costs initially, but would certainly pay off in the long run. Provide also locational key information so that perfect spatial registration is possible between sequential coverages.
- Start operational survey the following year and have the satellite sensing each region on the most suitable days. Of course, it will not be possible to express a *suitable day* simply as a calendar day; instead it should be related to the phenological development of crops. In an advanced stage, it should be possible to automate fully the decision as to when to collect the information as well. Observations on meteorological variables highly correlated with the phenology of crops may be provided by automatic weather stations and/or by weather satellites and fed into a computer which in turn controls the functions of the satellite.
- Store signals received from satellite until information set is complete, then process and introduce crop weights to modify classification if necessary.

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Book Review

OVERVIEW, A Lifelong Adventure in Aerial Photography, by Brig. Gen. George W. Goddard, USAF (ret.), with DeWitt S. Copp: Doubleday & Co., Garden City, N. Y.; xiii+415 pp., 32 pp. b&w photos (not numbered); $8.95.

If this is not the most fascinating book ever written by a member of ASP—an Honorary Member since 1952 to be precise—then I am abysmally ignorant of the literature. Many members of the Society have written or contributed to books. All such books known to me are technical and usually didactic in intent and hence ineligible for filing on the shelf labeled "Books I Read Because I Want To."

General Goddard presents his memoirs of half a century in aerial photographic reconnaissance with the aid of a ghost writer, DeWitt S. Copp, who can be classed as a journeyman but not an expert. I am surprised that the publisher didn't supply a good editor to scour the text and remove the unnecessary and annoying little flaws that remain. Here I speak as an editor myself, I admit. The flaws I note will not be visible to the vast majority of readers, but they annoy me when I see them in a book that should be read by every member of ASP.

No doubt the book was compiled by the modern technique of taped interviews. More than 175 people are listed by name as having contributed information. I do hope that the tapes have not been destroyed, as most of them would be even more interesting than the text at hand.

Most of the text is cast in the first person, which is as it should be, because this is the story as General Goddard lived it and saw it. The younger members of ASP will be amazed to learn that Goddard spent no less than 14 years as a First Lieutenant, from 1920 to 1934, all the while performing at a level that can hardly be called routine. He had other offers, notably from Sherman Fairchild (another Honorary Member of ASP, and by far its richest), but he stuck with the Army Air Corps. My explanation is that Goddard had two professional loves—photography and aviation—and the Air Corps offered virtually unlimited opportunity for flying, and apparently it didn't matter if you washed out a