Applications of multivariate statistical analysis in remote sensing of agriculture

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Applications of satellite remote sensing to agriculture involve two main objectives, the identification and mapping of crops, including estimation of acreages, and monitoring of plant growth or production factors, aiming at estimation/prediction of yields.

Deterministic models of the interaction of electromagnetic radiation and plant canopies are used to relate the measured reflected or emitted radiation to crop type and agronomically relevant parameters. The great natural variation of reflectance properties of crops does, however, call for use of a statistical approach. The high dimensionality of the data-sets involved, very often more than ten, requires the use of multivariate techniques.

This paper will deal with the use of multivariate statistical techniques for both crop identification and crop monitoring based on high-resolution satellite remote sensing data, such as those produced by Landsat MSS and -TM and SPOT. Emphasis will be placed upon use of statistical methods in classification and on removal of redundancy in multi-dimensional data-sets. The relative merits of deterministic and statistical methods will be discussed as will the possibilities of incorporating spatial information into statistical methods.

Keywords: *Remote sensing, Digital image processing, Multivariate statistics, Agriculture.*

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One of the driving forces behind the development of the non-military use of the remote sensing technology has been the need for timely and precise data on agricultural production. Since 1972 multispectral scanners onboard satellites have produced digital images from which a great number of experiments and a few operational services have drawn information of relevance for estimation of agricultural production. The assessment of agricultural production involves determination of two components, the area planted and the yield. Both these components may be assessed with the use of remote sensing, and in both cases statistical techniques may play a part. A considerable volume of litterature on the application of statistical techniques to agricultural remote sensing has been published. Alternatively, deterministic models for extracting agricultural information from remotely sensed data can be applied.

As well-known to most readers the scanners onboard remote sensing satellites produce "multispectral" images containing information from a number of spectral bands in the visible and infrared parts of the electromagnetic spectrum (microwave sensors will not be considered here). Thus the nature of remotely sensed data makes the use of multivariate analysis necessary. If data from several dates, f.i. representing different stages of crop development, are merged in a so-called multitemporal data-set, the number of variables may become quite high, yet the "intrinsic" dimensionality of such data-sets may be relatively low because of high correlations between the spectral bands.

Analysis of images may be considered as parallel to analysis of any other set of data, since the individual picture elements ("pixels") can be perceived as observations independent of each other. By doing so any particular spatial arrangement of the pixels, such as the existence of "fields" consisting of several spectrally similar pixels, is disregarded. In contrast to this methods are available that take "spatial context" into consideration. Some of these methods are based on statistical theory, some are not.

This paper will exemplify and discuss the use of statistical methods, and in particular multivariate analysis, for the extraction of agricultural information from multispectral scanner data, their relative merits as compared to deterministic methods and their ability to take spatial context into consideration.

DETERMINISTIC AND STATISTICAL MODELS

Basically two approaches to the extraction of agriculturally relevant information from remotely sensed images are possible. Either the grey level measured by the sensor is explained on the basis of an elaborate deterministic model of the interaction between the electromagnetic radiation and the plant canopy, or it is seen as the outcome of a stochastic process, which implies that a statistical approach will be needed to sort out the relevant information.

In the deterministic approach the measured grey levels are considered as outcomes of physical measurements, for which a proper model must be established. This implies that sensor calibration effects and atmospheric influence must be adequately accounted for. Such corrections will make it possible to translate the raw grey levels into values of the relevant physical parameter describing the reflectance properties of the surface, i.e. the "bidirectional reflectance factor", $BRF(\lambda, \theta, \varphi, \theta', \varphi')$, where λ is the wavelength of the radiation, θ and φ determine the angle of illumination, θ' and φ' the angle of viewing. By the use of a model relating the physical characteristics of the plant canopy, i.e. leaf area and spatial arrangement, leaf angle distribution and leaf colour to BRF, the calculated BRF-

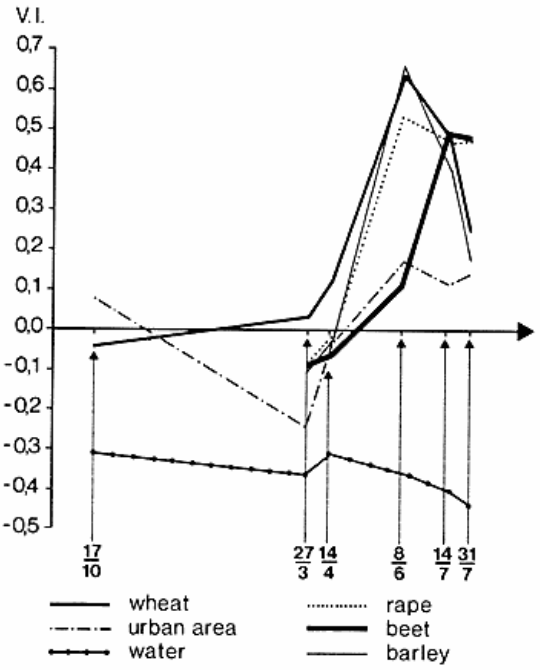

Fig. 1. The variation over the year of the vegetation index for certain crops/land-use classes. (From Niels-Christiansen & Rasmussen 1984)

values are then translated into values of parameters describing the plant canopy.

In spite of the methodological attractions of the deterministic approach it is not without problems. Firstly, the calculation of BRF-values at ground level presumes, as mentioned, a good model of sensor characteristics and atmospheric influence, which is not always available. Secondly, it is presumed that a model relating physical characteristics, of which quite a few are needed to give a good description of the plant, to BRF for given illumination and viewing angles and a given set of spectral bands can be inverted so that the physical parameters can be determined uniquely from the remotely sensed data. An adequate description of the radiation/plant canopy interaction may be so complex that the model can not be inverted, because there are many more plant parameters to be determined than spectral measurements to determine them from. Thirdly, real crops vary a lot from place to place and year to year, making them difficult to describe by such deterministic models. Well-known examples of this approach can be found in Suits (1972) and Bunnik (1978).

Simpler, but still largely deterministic, models relate crop species and condition to certain "features" calculated from remotely sensed data, typically linear combinations or ratios of spectral bands. F.i. Danish crops can largely be identified on the basis of the variation through the growing season of a so-called vegetation index, as shown in fig.1. These "models" are generally based on empirical evidence rather than genuine physical/biological understanding of the processes involved.

The deterministic models are based on the assumption that BRF-values for different crops are not overlapping in the spectral bands available. However, in many cases they are, among other things because of the spread of the measured BRF-values caused by sensor-imperfections, atmospheric influence and the natural variations of the crop. In the case of overlap between "spectral signatures", as BRF-values for a crop are sometimes called, between two crops, it is evident that statistical methods are necessary to identify the optimal decision boundaries. It is clear, therefore, that deterministic approaches must be supplemented by the use of statistical techniques in order to cope with real-life problems. It is therefore not surprising that many hybrids of deterministic and statistical methods exist.

In a great many studies use of deterministic models has not been attempted at all. On the basis of ground data a statistical characterization of the spectral signature of the crops or land use classes studied has been established, and this is subsequently used as a basis for identification of similar pixels or areas in the rest of the satellite image. In the case of yield prediction empirical relationships between yield-indicators and spectral properties are established, often using simple or multiple regression models. The obvious attraction of this approach is that the statistical methods used are quite general, which means that computer software is often readily available, and relatively little knowledge of the physical/biological characteristics of the plant will be needed.

PREPROCESSING OF MULTIDIMENSIONAL DATA-SETS

Rationale

As mentioned previously remotely sensed images often contain several spectral bands, and for many applications multitemporal data-sets are required. Thus the dimensionality of data-sets may become quite high, making it difficult for the analysts to overview the information content of and interrelationships between the various bands. Also the full information content can not be expressed in a colour-representation, which is limited to displaying only 3-band information. Since bands in multispectral scanner images are often highly correlated – see sect. "Principal components analysis (pca)" – there is a potential for "compressing" the information content. This may be done using one of the available methods of orthogonal transformation, the Karhunen-Loeve or Hotelling transform or principal components analysis (pca), or by means of some "intelligent" method, which involves calculation of "features" expressing the relevant information in an "economic" and easily interpretable form. Both the statistical and the "intelligent" approach are widely used and will be discussed in the following.

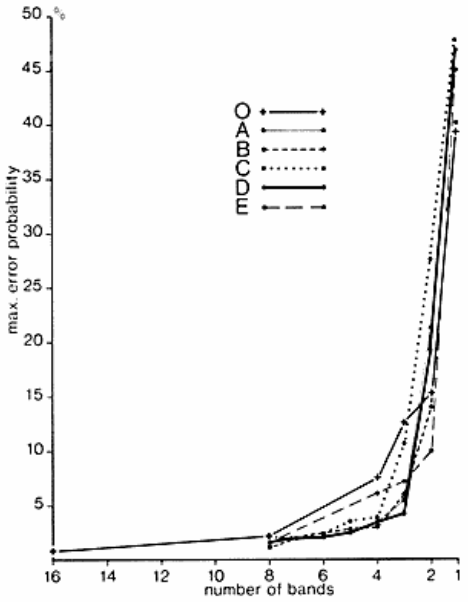

Fig. 2. The mean maximum error probability for seven pairs of (spectrally overlapping) crops as a function of the number of principal components used as a basis for the calculation. It appears that the dimensionality of the data-set can be reduced from the original 16 to 3 with only minor effects on the separability of classes. (From Niels-Christiansen et al., 1983)

In both cases the transformations involved are purely "spectral", in the sense that the spatial arrangement of the pixels does not have any influence on the outcome of the operation. The actual existence of spatial entities, such as fields, forests etc. does, however, call for methods capable of enhancing them. Such methods are becoming available but are beyond the scope of the present paper.

Display of multidimensional satellite images

Efficient analysis of satellite images requires that they are displayed in a way ensuring that the full capacity of human vision is utilized. The colour perception of the eye is an extremely complicated process, yet "tri-stimulus theory" explains some of the characteristics of colour vision satisfactorily. According to this, colour is perceived through stimulation of three "sensor-types" in the retina, and this has the consequense that any perceived colour can be described as a mixture of three basic colours that may be red, green and blue. This is of course the rationale of the use of display devices such as RGB-monitors. It should be noted that since a perceived colour can be approximately described as a point in a three-dimensional RGB-colour-space, an infinite number of alternative 3-dimensional colour-spaces can be constructed by simple coordinate transformations. For instance, one may choose a spherical coordinate representation instead. The so-called "intensity-hue-saturation" (IHS) colour-space is one such representation that has certain advantages. Since physical display units are almost always RGB-devices, any alternative representation, f.i. the IHS, must be transformed into the RGB-representation before actual display.

If all perceivable colours can be considered as filling out, approximately, a RGB-colour-cube, it is important that the information content in a satellite image is mapped into this cube in a way that ensures that large parts of this cube are not left unused. If two highly correlated bands in a satellite image are used in a straightforward linear way to determine intensities in two of the three colour-components, the displayed colours will lie close to a plane within the colour cube. Likewise, if all three bands are highly correlated, the displayed colours will lie along a line in RGB-space. Thus only a small fraction of all possible colours is used, and the resulting display will appear greyish. This is a simple reflection of the fact that the two or three components, used to display the correlated bands, contain approximately the same information. To avoid this "waste" or redundance, it must be ensured that the bands or features used to determine the intensities in the R-, G- and B-components, are not highly correlated, or, to be more specific, that a sphere-like or cubus-like distribution of RGB-values is obtained.

Several methods have been suggested to obtain this, one of them being "colour decorrelation", described in Niblack (1985). This involves principal component transformation of the RGB-data, "stretching" of the principal components to ensure that the entire colour-space is utilized, and transformation back into RGB-space. The latter step ensures that the interpretation of the "new" display of the image is similar to that of the original. Alternatively the principal components can be considered as the I-, H- and S-components of an IHS-representation, which can then be transformed back into RGB-space for the actual display process. Since colour perception is very subjective, there is no definitive answer to the question of which method is preferable.

In addition to the capability of a display method to enhance information content, in a statistical sense, the ease of interpretation is likewise of great importance for the practical applicability of the method. The above mentioned method, in which principal components are used to determine I, H and S, has the advantage that the physical meaning of the first principal component, calculated from any three satellite bands, will usually be a weighted mean of reflectance in all bands, i.e. the approximate albedo of the surface, and intuitively it makes sense to display this as intensity in an IHS-representation. The "physical" interpretation of the second principal component will vary, depending of course on the bands used as a basis for its calculation, but it will in many cases be logical to let it determine hue, H, whereas the use of the third principal component to determine colour-saturation, S, seldom has meaning. Instead S may simply be set to a

A. SPOT, 3 spectral bands, 22-06-86

Wavelength

Band 1	0.50-0.59 µm	green
" 2	0.61-0.68 "	red
" 3	0.79-0.89 "	near-infrared

	Band 1	2	3	Sum
Mean-value	39.7	25.4	102.7	
Variance	32.7	52.0	648.2	733

Correlation matrix

	Band 1	2	3
Band 1	1.00	0.92	-0.05
" 2		1.00	-0.33
" 3			1.00

	Principal component 1	2	3	Sum
Eigenvalue	654.6	76.8	1.5	733
% of variance	89.3	10.5	0.2	100

B. LANDSAT MSS, 4 spectral bands, 07-06-82

Wavelength

Band 1 (4)	0.5-0.6 µm	green
" 2 (5)	0.6-0.7 "	red
" 3 (6)	0.7-0.8 "	(red)/near-infrared
" 4 (7)	0.8-1.1 "	near-infrared

	Band 1	2	3	4	Sum
Mean-value	51.1	37.4	114.7	119.3	
Variance	39.9	84.2	486.6	736.2	1347

Correlation matrix

	Band 1	2	3	4
Band 1	1.00	0.85	0.32	0.15
" 2	0.85	1.00	0.03	-0.16
" 3	0.32	0.03	1.00	0.95
" 4	0.15	-0.16	0.95	1.00

	Principal component 1	2	3	4	Sum
Eigenvalue	1199.0	128.5	14.1	5.5	1347
% of variance	89.0	9.5	1.0	0.4	100

C. LANDSAT TM, 6 spectral bands, 01-05-86

Wavelength

Band 1	0.45-0.52 µm	blue/green
" 2	0.52-0.60 "	green
" 3	0.63-0.69 "	red
" 4	0.76-0.90 "	near-infrared
" 5	1.55-1.75 "	middle-infrared
" 7	2.08-2.35 "	" "

	Band 1	2	3	4	5	7	Sum
Mean-value	83.5	35.1	38.8	50.9	88.6	52.6	
Variance	61.3	24.9	67.9	98.3	540.9	353.4	1147

Correlation matrix

	Band 1	2	3	4	5	7
Band 1	1.00	0.94	0.93	0.41	0.83	0.81
" 2	0.94	1.00	0.96	0.56	0.83	0.78
" 3	0.93	0.96	1.00	0.42	0.87	0.86
" 4	0.41	0.56	0.42	1.00	0.48	0.22
" 5	0.83	0.83	0.87	0.48	1.00	0.92
" 7	0.81	0.78	0.86	0.22	0.92	1.00

	Principal component 1	2	3	4	5	7	Sum
Eigenvalue	995.4	103.0	31.1	12.2	4.2	0.7	1147
% of variance	86.8	9.0	2.7	1.1	0.4	0.1	100

Table 1. Examples of correlation matrices and principal-component eigenvalues based on data covering Danish agricultural areas from 3 different satellites: SPOT, Landsat MSS and Landsat TM. The high correlations between spectral bands are evident, and the effective dimensionality of the data is less than the nominal in all cases.

certain fixed value (f.ex. maximum) or determined in some other way. Such "logical" display methods, that may not be statistically optimal but which ease interpretation, are widely used together with spectral transformations, replacing the original bands of a satellite image by "features" having physical/biological meaning.

Principal components analysis (pca)

Pca has already been mentioned several times as a method of orthogonal transformation of multiband satellite data. No treatment of the theory behind will be given here, many excellent descriptions with or without reference to image processing are available. As described in the preceeding section, pca may be used on 3D data-sets, such as sets of RGB-values, but in general pca provides a means of reducing the dimensionality of data-sets with minimum information loss, and therefore its relevance increases with the dimensionality of the original data-sets and with increasing correlations between the original bands.

In table 1 some examples of correlation matrices between bands in Landsat MSS-, TM- and SPOT-images from agricultural areas in Denmark are given, and the results of pca on these data-sets are summarized as well. The pca was based on the correlation (rather than the alternative variance/covariance) matrices. It is obvious from table 1 that the "intrinsic dimensionality" (see Landgrebe, 1978) of MSS-and SPOT-data is not much more than two, due to the high correlations between the two visible, and in the case of MSS also the two near-infrared, bands. In the case of TM and not taking the thermal band into account the dimensionality is close to three. Reduction from an original dimensionality of six to three gives meaning, since the three first principal components, which represent 98 % of the variance, can be displayed, using either a RGB- or an IHS-representation.

When working on multitemporal data-sets pca may be even more helpful, since the high dimensionality of such data-sets make them very difficult to handle, both mentally and computer-wise, and impossible to display in raw form without a great loss of information. Niels-Christiansen et al. (1983) investigate the use of pca to compress a 16-dimensional data-set, including MSS-data from four dates during a growing season. It is concluded that the separability (see below) of certain critical land use classes is not seriously affected by reducing the dimensionality from 16 to 3, as illustrated in fig. 2, which means that practically all critical information (i.e. information needed for crop- and land use classification) can be displayed on a RGB-device. The main problem remaining is that the colours of the resulting displayed image may be quite difficult to interprete. It is also concluded that a pca must be "tuned" in order to obtain the required result by carefully selecting the basis for calculation of the correlation or covariance matrix, which serves as a basis for calculation of the principal components.

CROP IDENTIFICATION BASED ON MULTISPECTRAL/MULTITEMPORAL SATELLITE DATA

The use of statistical measures of separability

As mentioned above, the rationale of choosing a statistical approach to crop or land cover identification is that the spectral signatures of naturally occuring classes are overlapping in n-dimensional space.

In order to assess the "overlaps" in multidimensional feature space between spectral signatures of a set of class-

es, measures of separability are needed. If the classes are assumed to have n-dimensional Gaussian distributions, the Jeffries-Matusita distance (or the more or less equivalent "transformed divergence") is applicable (Swain, 1978).

Once a statistical description, including mean-values, variances and co-variances of/between bands, of all classes has been established through a "training" process utilizing ground truth data, a "separability matrix", containing separability values of all combinations of classes, can be calculated and used as a basis for evaluation of whether the statistical descriptions of the classes are adequate. Very often the spectral bands are highly correlated, meaning that exclusion of certain bands will have negligible effect on the separability of classes. This can be checked by recalculating the separability matrix on the basis of the reduced set of bands. In this way the dimensionality of the data-set can typically be reduced with only a small loss of classification accuracy. A similar use of the J-M-distance was made in a study of principal components analysis of a multitemporal data-set (Niels-Christiansen et al., 1983).

Maximum likelihood classification

When a clear-cut boundary in multidimensional feature-space between any two crops does not exist, the aim of the classification process must be to minimize the "error" or "loss", resulting from the unavoidable misclassifications.

The classical statistical solution to this problem is the maximum likelihood classification technique, probably one of the most widely used image processing procedures. No detailed treatment of this well-known method will be given here, the reader is referred to standard texts on the issue, f.ex. Swain (1978) and Niblack (1985).

In the standard version, available in most comprehensive image processing software packages, it is assumed that all classes have Gaussian n-dimensional distributions of grey levels. Furthermore it is assumed that all misclassifications are equally "bad", resulting in a simple loss-function (Niblack, 1985), yet for certain purposes, where identification of some seldomly occuring class is more important than overall classification accuracy, more complicated loss-functions may be relevant. As for a priori probabilities of the involved classes, some simple versions assume that all classes have similar values, whereas the more comprehensive variants allow user-specified values for each class. The maximum likelihood algorithm can also be used in an iterative way, allowing the first iteration to determine a priori probabilities in the second a.s.o. In the more advanced versions the a priori probabilities of each class are made location dependent, thereby moving the method away from the limitations of "per-pixel" image processing procedures.

One particularly interesting way of making a priori probabilities location dependent is to let a priori values depend on the classification of the neighbouring pixels. This will, of course, require that the algorithm is run in an iterative mode, so that a priori values for a pixel is dependent on classification results from the preceeding iteration. One variant of this context-dependent maximum likelihood classifier is described by Niblack (1985).

Thus still more flexible maximum likelihood classifiers are being developed, some even taking spatial context into consideration. The practical limit to the utilization of these developments has hitherto been presented by the excessive processing requirements involved, but this may be overcome with the development of "smart" versions of such algorithms, making it possible to utilize dedicated hardware based on parallel processing and ultra-fast data-busses. Practical experience with use of maximum likelihood classification algorithms tends to show that the main problem is not whether one or another variant of maximum likelihood classification is best suited, nor is it a matter of adjustment of a priori probabilities, it is rather that proper performance presumes that

1. all classes have Gaussian distributions, and
2. every class is adequately described statistically.

The latter presumption may be very difficult to fulfill, if the number of classes and bands is high. The number of statistical parameters to be determined is given as

$$P = N \times (b \times (b + 1)/2 + b)$$

where N is the number of classes and b the number of bands. In a practical experiment (Rasmussen & Niels-Christiansen, 1985) a four-temporal MSS dataset was used as a basis for crop identification, and in this case N was approximately 30 and b = 16, which means that 4560 statistical parameters had to be determined from training data. It is evident that it is extremely difficult to make sure that all these parameters have reasonable values, and the classification result may be quite sensitive to any error in these values.

Multitemporal data-sets represent other problems as well. If some bands are totally irrelevant for the discrimination of two crops, f.i. because the bands contain information from dates when the crops are not visible at all, the inclusion of these bands in the data-set, which may be necessary for discriminating between other crops, will create problems. Classes will tend to split up into irrelevant sub-classes, f.ex. representing different soil types, increasing problems of getting adequate statistics even further, and reducing the obtained classification accuracy. Thus, multitemporal data-sets call for methods that utilize specific subsets of the bands for separation of any pair of classes. This means that standard maximum likelihood algorithms can not be utilized in a straightforward fashion, and the methods to be applied will depend upon the data-set in question.

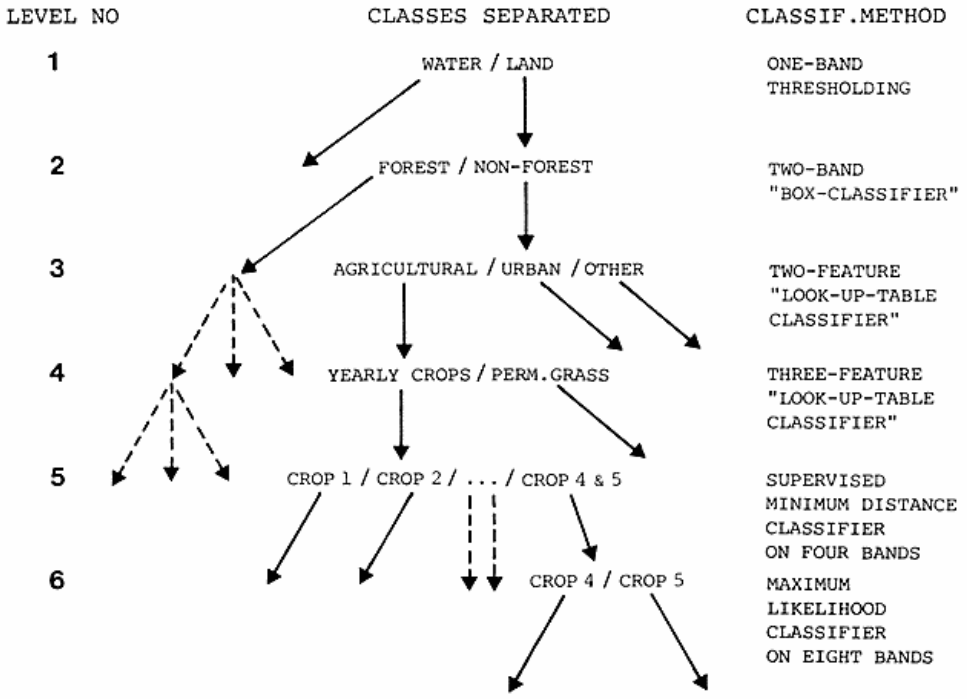

Fig. 3. Diagram of the structure of a "decision tree" classification algorithm using simple "deterministic" decision rules in the upper branches, and progressively more complicated statistical rules in the lower branches, which contain only a small fraction of the total amount of data.

The segmentation-classification approach

In the preceeding section an example of how spatial context can be included in a maximum likelihood classification was outlined. In this method, where the neighbours of the pixel to be classified are allowed to influence the a priori probabilities in that pixel, does not fully utilize the fact that most pixels are organized in spatially homogeneous units, fields. In contrast to this, the human vision-/brain system is very efficient in the identification of such spatial entities. Much emphasis within the field of image processing and "computer vision" is presently devoted to finding ways of making computers equally efficient.

Numerous attempts have been made to perform segmentation of remotely sensed images as a preprocessing step before classification. Generally two approaches have been tried, one involving edge detection, followed by linking of the found edges to form closed polygons, one based on merging of similar pixels to create regions, the so-called "region-growing" method. Probably some combination of the two approaches will be the most satisfactory. Having created the segments, they can be classified using methods similar to those applied to classification of single pixels. Within-field texture may, however, be included in addition to the spectral bands, which may be of interest in some cases, even though fields are not generally characterized by texture to any great extent.

Hierarchical algorithms, expert systems

The use of relatively complex multivariate classification methods, such as the maximum likelihood method, on all pixels (or segments) of an image may in many cases be a considerable "over-kill", since many objects, such as water and forests can be easily classified using much simpler methods. Water is f.ex. characterized by an extremely low reflectance in the near-infrared part of the spectrum and can therefore be classified using a simple "density-slicing" method in a near-infrared band. In general it is advantageous to reduce the dimensionality of the feature space in which the classification methods operate to a minimum in order to make it possible for the analyst to overwiev what he is doing.

Often overlap in n-dimensional feature-space of spectral signatures, requiring the use of maximum likelihood classification to minimize the misclassification frequency, can be removed by clever feature enhancement techniques, by including extra spectral bands, f.ex. the middle-infrared bands of Landsat TM, or by extra data acquisitions from properly chosen dates. The latter is exemplified in fig. 3, which illustrates how the temporal development of spectral signatures of crops/land use classes can be used to characterize them unambiguously. In this way the need for statistically based methods is diminished, and simpler, deterministic algorithms can replace them. In particular in the case of multitemporal

data-sets such simpler methods are easier to handle and tend to improve classification results. There is, nevertheless, considerable scope in combining the simple deterministic and the statistical methods in hierarchical algorithms, as sketched in fig. 4.

Fig. 4 indicates that the more demanding methods, both in terms of processing load and, not the least, of "training" requirements, are only used on a small minority of the pixels. The majority of the pixels can be classified using only one- or two-dimensional "look-up-table" classifiers, which run very fast even on microcomputers.

This type of approach to crop identification/mapping is flexible enough to facilitate the use of decision rules involving non-spectral data. This leads in the direction of so-called "expert systems", in which all the various common-sense or expert decision rules, utilized more or less consciously by a trained photo-interpreter, are modelled or mimicked. It is believed that the long-term trend in the evolution of crop identification methods will be towards such hierarchical systems, integrating deterministic, statistical and "logical" elements.

YIELD PREDICTION

As known to most readers, agricultural yields are often predicted on the basis of either relatively simple regression-type agrometeorological models or more complicated simulation-type models that aim at "mimicking" actual biological processes to some extent.

With the advent of satellite remote sensing it has been suggested by many that remotely sensed data should serve as an input to modified versions of models of the two above mentioned types. Very substantial research effort has been invested in such exercises, f.i. within the LACIE and AGRISTARS programmes. Generally the results are not too encouraging, so while remotely sensed images are used in an operational manner to estimate areas sown with certain crops in certain parts of the world, there is little or no operational use for yield forecasting at present. Discussions on whether and how remote sensing can contribute to improved yield forecasting are continuing, however, f.i. in an EEC context.

In certain parts of the world, among other places in drought-striken areas in Africa, the non remote sensing based estimates of yields are poor due to great local variations and few agrometeorological observations. Early warning of crop failures would be of importance in such areas, and recently FAO has included a remote sensing component in their national centers, which are presently being established for purposes of early warning of food shortages.

Use of high resolution satellite images is precluded for financial reasons in such crop monitoring exercises, and the long time-intervals between observations and the slow distribution of data makes them even less atttractive.

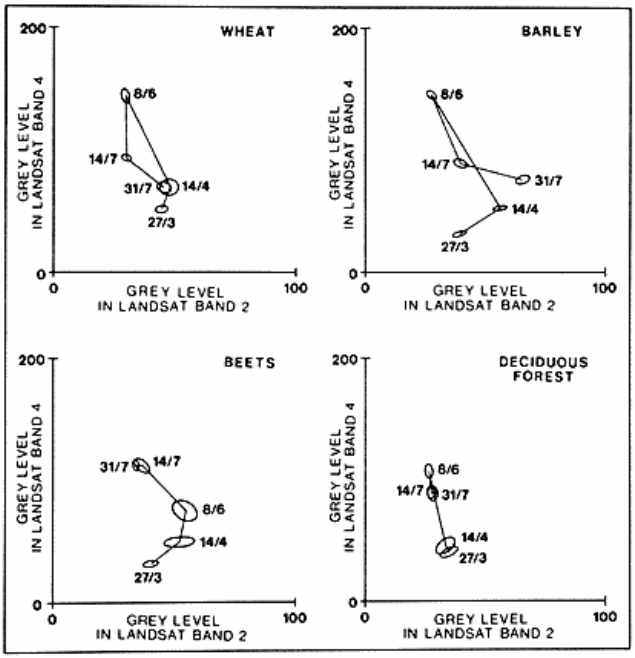

Fig. 4. The variation through the growing season of spectral signatures of 4 crops/land-use classes. The spectral signatures are illustrated by the 1-standard deviation covariance ellipses. The time path for each class can be used as basis for classifications. (From Rasmussen, 1986)

Only low resolution meteorological satellite data are of relevance, and in particular NOAA AVHRR-data are important, because of the choice of spectral bands, in particular the existence of a near-infrared band.

Two main approaches to yield forecasting based on satellite data can be pointed at. Either the satellite data are used alone, for example by comparing the crop development, observed from satellite, with the expected "standard" development and interpreting deviations in terms of stress induced reductions of predicted yields. Or the satellite data are used as one input among many to a regression- or simulation-type model. In spite of the theoretical advantages of the latter approach few well-developed examples of its application are known. Perhaps the most widely used method is based on variants of the vegetation index. No comprehensive treatment of this extremely active area of study can be given here, the reader is referred to classical papers on the issue, f.i. Rouse et al. (1973), Richardson & Wiegand (1977), Jackson (1983). Many variants of the vegetation index have been proposed, the common purpose being to construct a measure of crop/vegetation greenness (preferably related to green biomass or leaf area index), which is independent of the soil background. This is, in most cases, done by contrasting near-infrared and red reflectance. The most widely used variant, the "normalized difference vegetation index" (NDVI) is thus given as

$$NDVI = (NIR-RED)/(NIR+RED)$$

where NIR is the reflectance in the near-infrared and RED in the red part of the spectrum of the surface in question. By monitoring this parameter during critical phases of crop development crop yield may be predicted, often using a simple regression model. This method is presently being tested for use in the Sahel. In Denmark a similar technique has been suggested for assessing frost damage on winter-crops (Olesen et al., 1986).

Whether this technique will prove useful and competitive, in comparison to standard methods using only ground-based agrometeorological measurements as input, is difficult to say, yet in many African countries the cost of alternative methods of data acquisitions are very high due to poorly developed infrastructure and the great local variations in crop condition.

DISCUSSION

The extremely widespread use of mathematical/statistical methods in remote sensing applied to agriculture is caused partly by the fact that there are stochastic elements in remote sensing data and partly by the generality of the methods in question. Better modelling of the physical processes involved and addition of more measurements (new spectral bands, multiple data acquisitions) will gradually move the balance towards a deterministic approach, however. The need for integrating statistical, deterministic and "logical" elements in crop identification is obvious, and in particular methods, that take into account the existence of spatial entities such as fields, will become ever more necessary as the spatial resolution of satellite images is improved. Whether contextual classification methods, segmentation techniques or some other geostatistical method will prove to be the most efficient way of treating spatial context is difficult to say, since none of these techniques have been developed to their full potential. The practical use of yield prediction based on satellite data is usually assumed to be less realistic than estimation of areas. High resolution data can at the most be used in a sampling framework, both because of the cost, the long intervals between data acquisitions and because of cloud cover. Low resolution data, such as NOAA AVHRR images can not be used on a per-field basis, yet they provide the most relevant input into predictive models. The best results must be expected to be obtainable from models integrating satellite data into "traditional" models using also in-situ measurements.

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$$NDVI = (NIR-RED)/(NIR+RED)$$

where NIR is the reflectance in the near-infrared and RED in the red part of the spectrum of the surface in question. By monitoring this parameter during critical phases of crop development crop yield may be predicted, often using a simple regression model. This method is presently being tested for use in the Sahel. In Denmark a similar technique has been suggested for assessing frost damage on winter-crops (Olesen et al., 1986).

Whether this technique will prove useful and competitive, in comparison to standard methods using only ground-based agrometeorological measurements as input, is difficult to say, yet in many African countries the cost of alternative methods of data acquisitions are very high due to poorly developed infrastructure and the great local variations in crop condition.

DISCUSSION

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