Spectral and Spatial Characterisation of Orchards In New York State Using Thematic Mapper Imagery *

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ABSTRACT

The variability of orchards ensures that their identification and classification is difficult. Examination, therefore, of the variation within and between individual orchards, and between different types and varieties should enable the possibilities and limitations of classification to be better defined. Using principal components analysis to describe the main axes of variation this study investigated basic orchard pixel distribution in Landsat thematic mapper spectral space.

The major cause of variation, as indicated by the first principal component, was the increasing contribution to the reflectance from the soil as tree cover was reduced. This component, basically an axis of brightness with a positive weighting in all reflectance bands except band 4, distributed pixels on the proportion of low valued vegetation to high valued soil. The second component, a band 4 and band 5 combination, was related to the proportion of tree cover to vegetation and of tree cover to soil based on vegetation differences.

The first component was mainly affected by orchards with a soil background, whereas orchards with a vegetation background were mainly distributed along the second component axis. A further principal component analysis was carried out on each of these subgroups. Strong correlations between orchard crown cover and one of the main principal components from each of the two subgroups enabled a transformed space to be tentatively defined indicating the relative contributions from tree cover, vegetation background, and soil exposure.

The approach to spatial characterisation is through the use of Fourier transform analysis. There are, however, problems to this appproach; the small size and varying orientation of the orchards mean that few orchards can be sampled into a regular array on which a standard FFT can be performed. The training site needs to be extended, obeying the laws of periodicity, to fill a rectangular array. This paper outlines an approach to this problem.

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Introduction

With Landsat thematic mapper (TM) imagery, separation of orchards from woodland and classification of orchard type based solely on spectral characteristics are difficult. Orchards are diverse, ranging from those which are intensively managed, with dwarf trees and exposed soil backgounds, to those virtually abandoned, with large old trees and unmanaged undergrowth. Tree type, variety, height and spacing, planting pattern, and row orientation, together with imposed environmental conditions, ensure that virtually every orchard is unique in some manner. The complex interaction of these attributes ensure great spectral and spatial variability in the reflectance sensed by the satellite.

Gordon et al. (1986b) were not able to separate orchards by type but, using the more uniform spatial characteristics of orchards, were able to separate them from woodland. This gave good classification accuracies but a high rate of omission. Where Gordon et al.(1986b) addressed the variation between orchard and non-orchard vegetation, this study is concentrating on the variation within, and between, individual orchards; both within the same type (e.g. apples) and between types (e,g. apple versus pears, peaches and cherries). Examining the data structure, identifying major axes of variation, and isolating relationships between orchard attributes and their spectral, and spectral-spatial, response will enable the limits and possibilities of classification to be better defined with TM as well as other high resolution satellite data.

This paper presents preliminary findings of an analysis of the basic orchard pixel distribution in TM spectral space. From relationships between spectral structure and orchard crown cover, a transform space, describing the interactions between crown cover and the soil-vegetation components of the understory, is suggested. An approach to spatial characterisation is also outlined.

Background

The study area is in Orleans County, N.Y., on the south shore of Lake Ontario. In all, 120 orchard training sites were chosen throughout the county based on aerial photographic interpretation, advice of extension agents, and field checking. Typical of New York orchards, the training sites were mostly 2.5 to 4 ha., but some stands reached 25 ha. in size. The sites were located and outlined on an August TM scene. The image date, being post-harvest, was chosen to reduce confusion with field crops in subsequent classifications.

The analysis is being carried out on a microcomputer (IBM AT) using custom-written image processing software. In order to define a spatial analysis methodology some of the research will be carried out on Cornell University's supercomputer (IBM 3090 with attached processors).

Spectral Characterisation

The initial approach to describing orchard spectral variation has been through principal components (PC) analysis. Interpretation of the PC axes is primarily a reasoned analysis relating vector loadings with an interpretation of plant and soil spectral response. Emphasis has been on using orchard pixels, though some analyses have examined the distribution of orchard means and standard deviations in PC space. A PC analysis was also carried out on two subgroups of the orchard data set; those orchards with a soil background and those with an entire vegetation background. The correlation between orchard crown cover and each of the subgroup's major PC axes was found in order to assess whether crown cover was a major factor in orchard variation and also whether any of the axes could be used to approximate crown cover. An estimate of crown cover was obtained by digitising low altitude aerial photographs with subsequent thresholding. A cover estimate (percentage) is then just based on pixel proportions.

Spectral Distribution Using All Training Sites:

The PC loadings obtained using the whole orchard data set are shown in Table 1. The first three PCs account for 98% of the total variation. The first axis, accounting for 82% of the variation, is dominated by orchards with soil background which stream away from the main cluster (Fig. 1). This axis is similar to the tasseled cap's brightness axis, defined by Crist and Cicone (1984), in that there is an almost equal contribution from all reflectance bands. One difference is that the weighting from band 4 is negative, indicating that any vegetation component in a pixel will lower the value of that pixel. The amount that the value is lowered is primarily dependant upon the type of vegetation, its leaf area index (LAI), and its proportion to the soil. Differing soil reflectance would also be expected to modify the pixel value, however, the orchards in this scene were on similar soils.

The second PC axis, accounting for 12% of the variation, consists of a band 4 and band 5 combination, bearing little relation to any tasseled cap features. It would be expected that different plants reflect differently in band 4 because of leaf structure and varying leaf densities. It has been shown that reflectance for leaves varies asymptotically until a LAI of about eight is reached (Wiegand et al., 1979). This is the basis of vegetation classication and biomass estimation in the near-infrared. Any soil component, though, will change the overall radiance according to its dominance in the pixel field of view. If the soil-vegetation contrast is reasonably high, then the reflectance is strongly related to plant cover, and variations in leaf density are only a secondary factor (Satterwhite and Henley, 1982). Furthermore Franklin (1986) found a nonlinear relationship between band 4 and biomass in coniferous forests; as the canopy closes, shadowing reduces the band 4 reflectance. In orchards the effect of shadowing should also vary with row orientation.

Studies on leaves in the mid-IR region relate reflectance to leaf water content (Everitt and Nixon 1986). Absorption by water increases as the water content of the leaf increases (Allen et al. 1970). There are some leaf structure effects, however. The response to leaf density in this region is normally saturated at a LAI of about two (Wiegand et al. 1979). It has been found that a ratio of band 4 to 5 could monitor leaf water content (Rock, 1982). Nevertheless, using TM data on a forest canopy, Horler and Ahern (1986) found that mid IR was a measure of vegetation density, whilst studies on rangeland by Ahern et al. (1981) concluded that the sensitivity to biomass, as opposed to leaf water content per se, was due to this region being particularly sensitive to shadowing. Other workers have found significant information for separating cover types in the mid-IR region (e.g., Nelson et al., 1984).

Soil reflectance in the near-IR usually has a lower reflectance than vegetation and vice versa in the mid-IR. (Leamer et al., 1978). Therefore, since soils in the study area are similar their reflectance is going to be constant in both bands and sum to a constant. Assuming a high soil-vegetation contrast, the effects of variations in the tree vegetation itself are likely to be secondary to the soil-vegetation proportion. Leamer et al. (1978) used the reflectance differences at 0.9, 1.65, and 2.2 um to separate wheat from soil.

In the orchards with a vegetation background, the band 4-band 5 combination is more complicated. If there is a significant tree-understory contrast, then the response, as with the soil, is going to be related to cover area. The weaker the contrast, the more the amount of biomass and leaf water content are going to affect, and dominate, the reflectance. The effect of fluctuations in biomass, within a vegetation group, is somewhat moderated by the opposite responses of these two bands (Horler and Ahern, 1986). The relative band 4 and 5 weightings are going to affect the separability. Any soil component in the understory will move the reflectance towards the soil "constant" depending upon its exposure in the understory.

Despite the high correlation of band 7 with band 5 there is virtually no contribution from band 7. This indicates significant differences, in this context, between the two spectral regions.

The third PC axis has certain similarities to the wetness band (Crist and Cicone, 1984), except that the contribution from band 7 is negligible and greater emphasis is given to the visible region. Horler and Ahern (1986) note that "wetness" is a misleading term as the mid-IR response is not always strongly related to leaf moisture content. Variation with band 6 is being introduced at this stage, indicating a possible role for thermal properties in "wetness" mapping. Owing to the different spatial resolution of this band, 120m, it is uncertain what emphasis it should have.

Means and standard deviations of orchards are illustrated in Figure 2. Here, the cross indicates the position of the mean in the three component space; the length and direction of the axes from the means represent one standard deviation in each axis direction. As expected the distribution of the means follows the distribution of all orchard pixels, especially in the less dense regions. This indicates that, in the overall pixel distribution, it is variation between, rather than within, orchards that is dispersing the data. Orchards toward the edges of the distribution, however, tend to have larger within-orchard variation, particularly the soil-background orchards as they disperse from the main orchard group. This is most likely due to the contrast between soils and trees being greater than that between vegetation and trees so that the within-orchard range is larger and hence has a larger standard deviation. Variation in soil characteristics throughout the orchard, without the disguising effect of a vegetation cover, will also add variability.

The alignment of the two orchard subgroups, soil and vegetation background, along the PC axes enables their individual variation and relationship to the complete group to be investigated.

<u>Orchards with Soil Background</u>

Results of the PC analysis using only orchards with exposed soil backgrounds are given in Table 2. As with the first PC from the complete orchard set, the first component here bears certain similarities to tasseled cap brightness. The main differences are the complete absence of a band 4 weighting, and an increased contribution from band 7. Dropping band 4 removes a major source of vegetation variation. As a result, separation is almost entirely due to the relative brightness of the soil as opposed to vegetation. A reasonably high band 5 and band 7 correlation with the visible bands ensures that they emulate each other as a measure of scene brightness (Guyot 1984). That the response in this component is the proportion of "dark" vegetation to "light" soil is also indicated by the high correlation, -0.89, of this vector with orchard crown cover (Fig. 3). On this graph, the location of the orchard means in the first PC relative to the entire orchard tree crown cover is indicated.

The second PC becomes virtually a band 4 component. The response is dictated by vegetation type (on the basis of leaf structure), vegetation density (on the basis of leaf density), and plant structural characteristics modified to a greater or lesser extent by the soil response. There is poor correlation, -0.24, of this vector with orchard crown cover.

Except for the low contribution from band 4, the third component is similar to the "wetness" vector (Crist and Cicone, 1984). Unlike the third vector in the full orchard group, however, band 6 is not a component in this vector. Correlation of this vector with crown cover is also relatively low (-0.44).

Orchards with Vegetation Background

The nucleus in the full orchard distribution of Figures 1 and 2 are orchards with a vegetation background. Although orchards with the most complete understory were chosen for this part of the analysis, it is difficult to find orchards that have no disruption of the understory.

The vector matrix (Table 3) shows, by the low first vector contribution of 55%, that there is much less directionality than occurs in both the full and soil background orchards, likely because of the reduced soil influence. As expected, the first PC bears a strong resemblance to the tasseled cap greenness, having a moderate negative weighting in all bands except band 4 which has a strong positive weighting. Differences occur in that the visible region is de-emphasized and a much greater contribution comes from the mid IR region. This latter difference can be attributed to the small range of vegetation types, different canopy stuctures, and rigid distributions. Being a measure of vegetation differences, and pixels being a mix of vegetation types, there is only a poor correlation, 0.04, between orchard crown cover and this principal component.

The second PC, which accounts for 27% of the variation, is similar to the second PC defined by the full orchard set, primarily a band 4 - 5 combination. The other reflectance bands do have a modest contribution in this vector though. The arguments about the tree-vegetation understory interaction with the full orchard second vector also apply here. This vector's strong negative correlation, -0.86, with orchard crown cover is seen in Figure 4, lending validity to the conclusion that this combination, with this weighting, is measuring the proportion of tree cover to background vegetation. The high intercorrelation of many biological parameters does not imply that tree cover is the only highly correlated variable. More research is neccesary to define other parameters.

The third PC bears a resemblance to the third PC from the soil background orchards, except that, in this case, a large weighting is given to the thermal band. There is a low correlation, -0.18, between this vector and orchard crown cover.

Definition of Crown Cover Space

The high correlations between orchard tree crown cover and both the first soil background PC, and the second vegetation background PC, suggest the possibility of defining a spectral space to map the relative contributions from the soil, vegetation, and tree crown. Figure 5 presents the first stage in this process by plotting the first soil-background PC against the second vegetation-background PC. The soil-background orchards are the squares around the top line; the crosses around the bottom line are orchards with vegetation background. The distance along either line, away from the first PC axis, represents decreasing crown cover, although not necessarily at the same rate on each line. The top axis goes to a point of soil and no vegetation; the bottom line goes to a point of complete background vegetation. Orchards in the intervening space consist, in theory, of a predictable combination of tree cover, soil background, and vegetation cover.

A high correlation, 0.98, between the two PCs for the soil background orchards, and a comparatively low correlation, 0.72, for the vegetation background orchards, adds validity to these conclusions. With increasing background vegetation the response in the 2nd PC direction increases towards a level defined by complete background vegetation (ignoring variation in this vegetation) as the proportion of tree vegetation to background vegetation is reduced. If no vegetation background is present, however, the vegetation response depends entirely on the proportion of tree in the pixel. If the relative band weightings are correct, then the response proceeds to a constant point defined by the soil alone. With the soil PC, however, all vegetation appears dark compared with the soil so that varying proportions of tree to vegetation understory have a reduced effect. Any increased reflectance in this PC is caused mainly by an increased contribution from the brighter soil.

Obviously, the tree-soil-understory vegetation space could be transfomed and calibrated to the x and y axis. The space also needs to be tested more rigorously.

Conclusions

Orchard data distribution in TM spectral space is basically three dimensional; the first three components account for 98% of the variation.

Whilst there are certain similarities between the first PC and "brightness" (Crist and Cicone, 1984), there is significant dissimlarity; primarily from a negative band 4 weighting ensuring that any vegetation will have a low value in this component. This suggests that the first PC is providing a measure of vegetation to soil cover, based on the vegetation-soil contrast.

The major axis of variation is primarily driven by the differences in the soil background orchards. The similarity between the first soil background PC and that from the full orchard set emphasises this. As the soil background PC is mainly dealing with a single vegetation group, fruit trees, the vegetation "normalising" carried out by a negative band 4 in the full orchard PC, is no longer apparent. A strong negative correlation between the soil background orchards' first PC and orchard tree crown cover summarises the tree-soil relationship.

The effect of varying soil type is uncertain as the exposed soils were similar.

The second PC for the overall data set is a complete departure from others reported. This vector, a band 4 and 5 combination, is providing information on the proportions of tree cover to soil exposure, and tree to vegetation cover, being driven by tree-soil, tree-vegetation, and vegetation-soil contrasts. A strong correlation between the vegetation-background second PC, and the similarity of this vector to the full orchard second PC supports this conclusion.

The ability to define axes related to crown cover, and their close relationship to the major variation axes in the full set, suggests the mapping of a vector space which can define major orchard variation in terms of the relative proportions of tree, background vegetation, and soil influence.

Work is ongoing to test these conclusions and assumptions, and to consider the effect of soil type, shadowing caused by tree size, planting pattern and row orientation, and tree type and other variables.

Spatial Characterisation

There is significant textural information with TM data and automatic recognition of orchards should be possible. Although there are many approaches to describing textures, patterns, and spatial distributions. (e.g. Fu, 1982, Haralick, 1979, Vilnrotter et al., 1986), there is no single technique that is sufficiently robust and easily used. Since the Fourier transform provides the most complete specification of the spatial characteristics related to texture, it is reasonable to expect that texture can be most effectively described, if not defined, in terms of spatial frequency distributions. The concept of using Fourier transforms would seem to provide a bridge between the qualitative description of texture and a quantitative, numerical description required for pattern recognition. Fourier transform techniques would be considerably more powerful than the filtering techniques that were used by Gordon et al. (1986a).

Approaches to using the Fourier transform have been varied; (e.g. D'Astous and Jernigan, 1984 Gramenopoulos, 1973, Hornung and Smith,1973, Kirvida,1976, Jernigan and D'Astous, 1984, Lendaris and Stanley,1970, Maurer, 1974, Weszka et al., 1976,). There are, however, several difficulties associated with using the Fourier transform in this type of study. The small orchard size, with varying orientation, and the 30 m spatial resolution of the imagery, ensure that there are few orchards large enough to create even an 8 x 8 training set needed for the smallest, standard, fast Fourier transform. In order to fill a rectangular training sample, the sample must be synthesised from a full orchard training site. Yaroslavsky (1985) documents various periodic extension procedures applied to picture processing. These methods , though, distort the signal structure unnaturally by forcing a predefined relationship between the often discontinuous wraparound edges of the actual signal sequences.

In order to retain the integrity of the data, the approach adopted here has been to use the sampling theory. Sampling theory suggests that an image, consisting entirely of a particular texture, when multiplied by a mask with size and shape of the training area but with unity inside the area and zero outside, will result in the training site image. Therefore a site is the product of a texture and a mask. In order to recreate the texture it would be necessary to divide the training site by the mask, which obviously cannot be done. However it would seem possible that, using the periodic properties of the Fourier transform, the division becomes a deconvolution of the transform of the mask with the transform of the training site. In effect this becomes a series of linear simultaneous equations. Solving the resulting large system of linear equations is not easy; the fact that often the system is nearly collinear, and often with less than full rank, means that, even with singular value decomposition and least squares approximation an acceptable solution is difficult to achieve.

Current investigation is underway to resolve this situation.

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Table 1. Eigenvector (principal component) matrix for the complete orchard set.

Eigenvector Matrix.

Component	Eigenvector 1	2	3	4	5	6	7
1	0.3333	0.0405	-0.4160	0.2221	0.3636	0.7132	0.0012
2	0.2300	0.0520	-0.2677	0.1083	0.1468	0.3139	0.8319
3	0.4286	-0.0296	-0.4594	0.1115	-0.0675	0.5425	-0.5413
4	-0.3529	0.8429	-0.3575	0.0159	0.1878	-0.0021	-0.0400
5	0.4934	0.5259	0.5625	-0.1680	-0.3602	-0.0513	-0.0537
6	0.0536	0.0782	0.3131	0.9051	0.2649	-0.0575	-0.0165
7	0.5305	0.0395	-0.0441	-0.2326	0.7792	0.2089	0.1008
Eigenvalues and percent contribution.							
Value	582.1085	84.1564	26.3689	8.0354	5.8909	1.8188	1.0084
Trace %	82.0579	11.8633	3.7171	1.1327	0.8304	0.2564	0.1421
Cum. %	82.0579	93.9212	97.6383	98.7710	99.6015	99.8579	100.0000

Table 2. Eigenvector (principal component) matrix for the soil background orchard set

Eigenvector Matrix.

Component	Eigenvector 1	2	3	4	5	6	7
1	0.3419	-0.0446	0.5574	-0.2417	0.0270	0.7146	-0.0254
2	0.2351	0.0321	0.3190	-0.0122	0.0076	0.3327	0.0550
3	0.3970	-0.0785	0.5055	0.2172	0.0180	-0.5328	-0.4993
4	0.0164	0.9616	0.0745	0.2366	0.0858	0.0696	-0.0370
5	0.6363	0.1827	-0.4474	-0.5534	-0.1837	-0.1269	-0.0743
6	0.0609	-0.0299	-0.0542	-0.1946	0.9724	-0.0921	-0.0232
7	0.5112	-0.1787	-0.3512	0.7030	0.1104	0.2557	0.1080
Eigenvalues and percent contribution.							
Value	615.3646	48.0414	26.5759	6.7874	4.9115	2.2003	1.4401
Trace %	87.2460	6.8113	3.7679	0.9623	0.6963	0.3120	0.2042
Cum. %	87.2460	94.0573	97.8252	98.7875	99.4839	99.7958	100.0000

Table 3. Eigenvector (principal component) matrix for the vegetation background orchard set.

Eigenvector Matrix.

Component	Eigenvector 1	2	3	4	5	6	7
1	-0.1015	0.1793	-0.5821	0.4064	-0.2672	-0.6181	-0.0108
2	-0.0790	0.1581	-0.2897	0.2051	0.0086	0.4039	-0.7801
3	-0.1670	0.1584	-0.3768	0.2877	0.0707	0.5759	0.6210
4	0.8133	0.5608	0.0329	0.0694	0.0839	0.0090	0.0436
5	-0.4456	0.7153	0.2262	-0.3314	0.3581	0.0041	0.0254
6	-0.0924	0.0258	0.6171	0.7658	0.1528	0.0111	-0.0046
7	0.2949	0.2862	0.0470	0.0944	0.8796	0.2278	0.0558
Eigenvalues and percent contribution.							
Value	61.9330	31.0865	8.5139	7.2817	2.2144	1.3366	0.5864
Trace %	54.8310	27.5218	7.5376	6.4467	1.9605	1.1834	0.5191
Cum. %	54.8310	82.3528	89.8904	96.3371	98.2975	99.4809	100.0000

Table 4. Correlation between sub group orchard crown cover and its eigenvectors.
The sub groups are soil background, and vegetation background, orchards.

Tree cover in orchards with :	Eigenvectors: Soil background orchards 1	2	3	Vegetation background orchards 1	2	3
soil background	-0.1928	0.2398	-0.4352			
vegetation background				0.0401	0.8609	0.1215

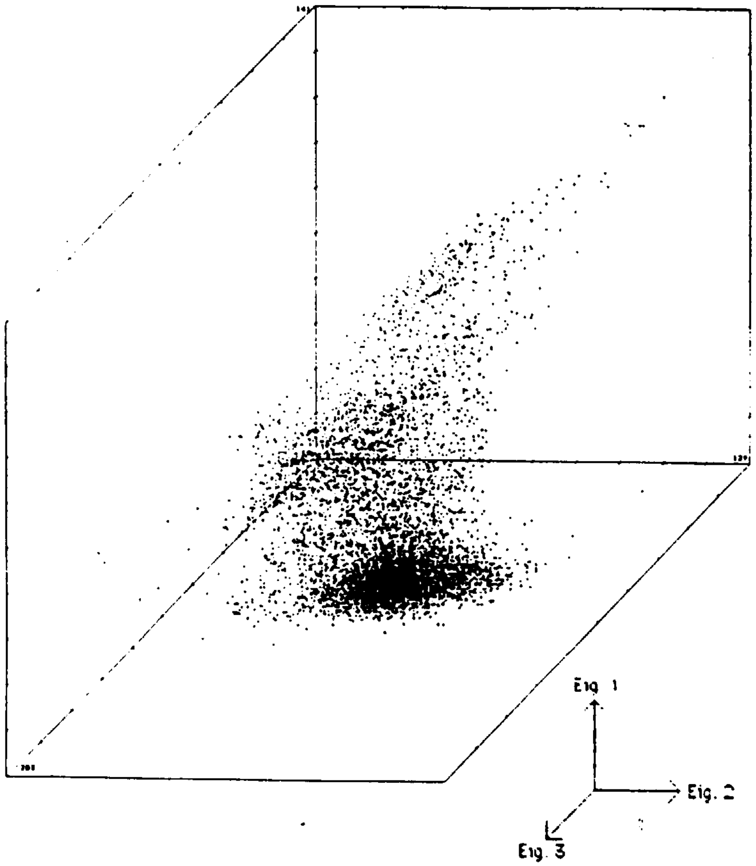

Fig. 1. Orchard pixel distribution in the full orchard principal component spectral space (first three components). The corresponding two dimensional histograms are the dots on the rear, side, and base

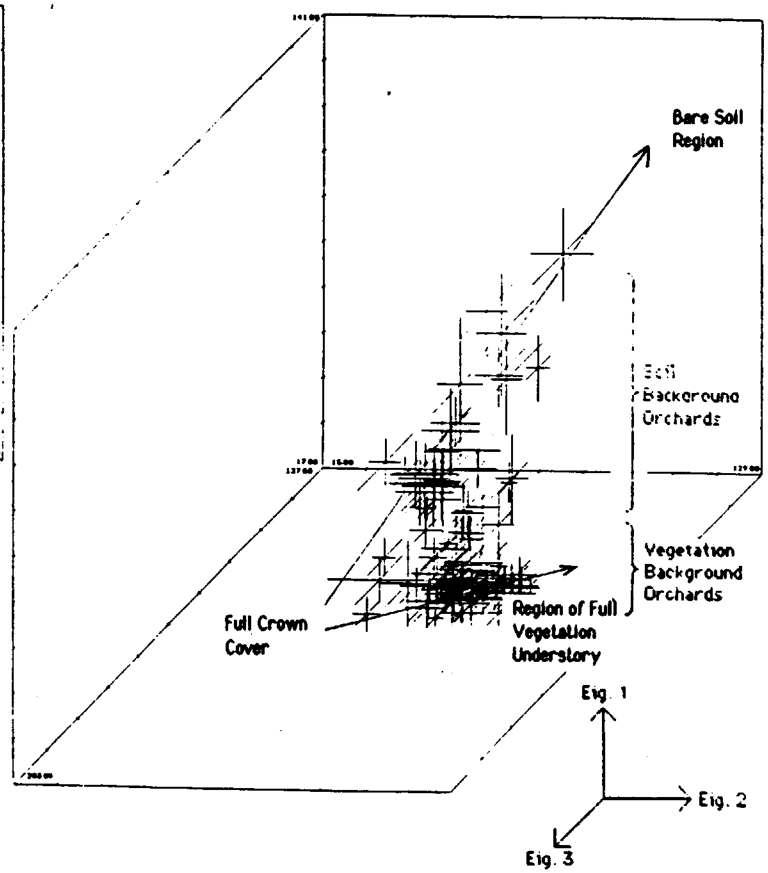

Fig. 2. Orchard means (intersections) and standard deviations (line length and direction) in the full orchard principal component spectral space (first three components)

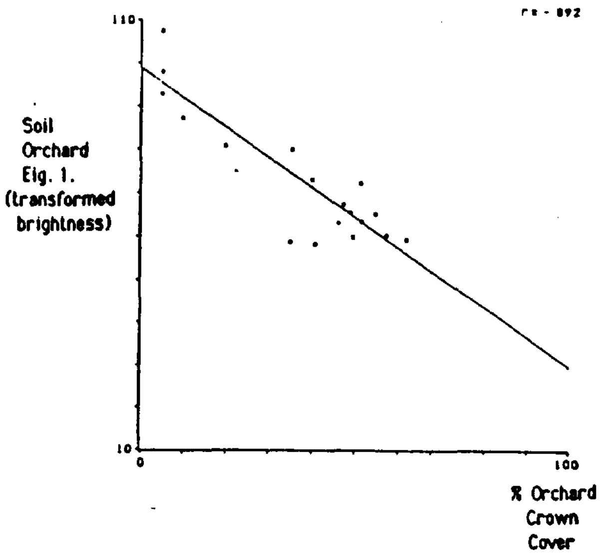

Fig. 3. Soil background orchard crown cover plotted against first, soil-orchard, eigenvector (orchard means).

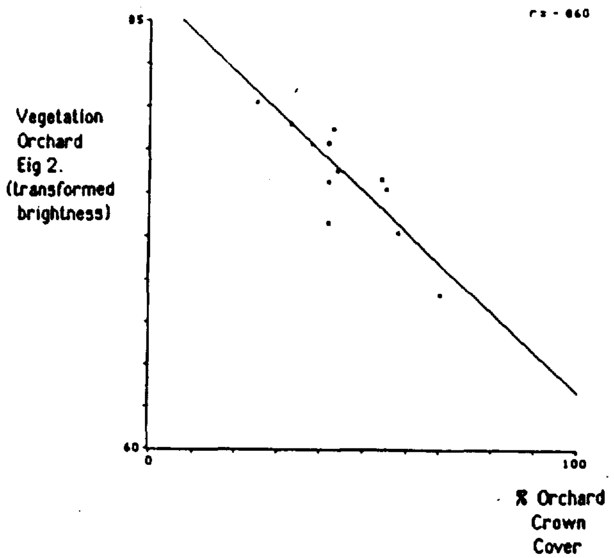

Fig. 4. Vegetation background orchard means in crown cover plotted against the second, vegetation-orchard eigenvector (orchard means).

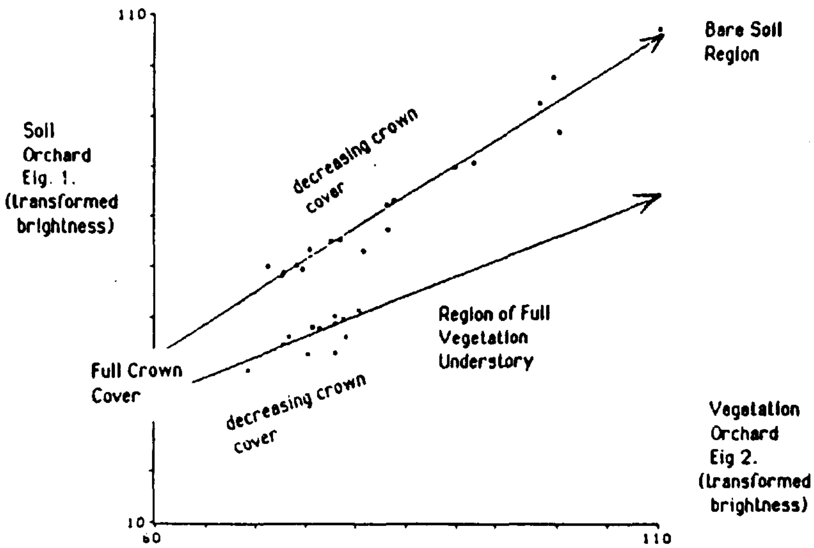

Fig. 5. 2-D histogram of soil (squares along top line) and vegetation background orchard means(crossses along bottom line) plotted in soil-orchard first, and vegetation-orchard second, eigenvector space.