# The Discrimination of Irrigated Orchard and Vine Crops Using Remotely Sensed Data

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ABSTRACT: Multispectral data recorded by a SPOT HRV sensor and an airborne Daedalus 1268 ATM sensor were analyzed for use in the monitoring of irrigated orchard and vine crops in the Riverland of South Australia. The spectral data were essentially two dimensional and the additional bands and increased spatial resolution of the Daedalus 1268 ATM sensor over the SPOT HRV sensor did not provide useful additional information. An accuracy of 85 to 93 percent at the 95 percent confidence level was obtained for the classification of four orchard and vine crops using bands 2 and 3 of the SPOT HRV data. It is suggested that temporal data are required if the classification is to be extended successfully to include other crops and dryland farming areas.

## INTRODUCTION

THE CULTIVATION of irrigated crops depends on a reliable supply of water. When the supply is limited, it is necessary to monitor the volume and distribution of water use. This may be undertaken by controlling the establishment of irrigated crops and by regulating irrigation scheduling. Remote sensing techniques can contribute to this through the monitoring of crop types grown and the spatial distribution of these crops.

Considerable research has been undertaken to determine the most suitable wavebands and spatial resolutions for the classification of different crop types (Townshend, 1984; Csillag, 1986; Huete, 1986). It has been suggested that data from a waveband in each of the visible (0.5 to 0.7 μm), near infrared (0.7 to 1.1 μm), and middle infrared (1.5 to 2.4 μm) regions of the electromagnetic spectrum produce the most accurate results while reducing the amount of data to be processed (Toll, 1984; Townshend, 1984). The most suitable spatial resolution has been shown to be related to the spectral variability of the scene and field size (Gervin *et al.*, 1985; Curran and Williamson, 1986).

Little research has been published describing the spectral characteristics of orchard crops and vines or the dimensionality of multispectral data recorded from these crops. Algorithms have been developed to distinguish between orchard trees and forest (Gordon and Philipson, 1986; Gordon *et al.*, 1986) while Morse and Card (1983) classified orchard crops in the San Joaquin valley of California using multitemporal data.

The aims of this research are to analyze SPOT HRV and airborne Daedalus 1268 multispectral data for the classification of irrigated crops (citrus, stonefruit, vines, vegetables) in the Riverland of South Australia where there is a limited supply of good quality water for irrigation. Analyses were undertaken to select (1) wavebands containing the greatest amount of spectral information about the crops, which includes an examination of the dimensionality of the data, (2) a spatial resolution which is related to the spectral variability of the crops and the fruit block size in the study area, and (3) the most suitable season for the discrimination of these crops.

## STUDY AREA

The study area is based in the Riverland of South Australia (Figure 1). The initial study was undertaken using data from the irrigated land in the Loxton area and the later study included the entire study area. The area covers 1000 km², of which 255 km² is irrigated by water from the River Murray. It is a flat, lowland area of grey clay with poor drainage (Laut *et al.*, 1977). The average irrigated block size is 36 ha, and cultivation of vines and citrus dominates the area with scattered cultivation of stonefruit and vegetables. Beyond the irrigated area dryland cereal cropping is practiced except on the floodplains of the River Murray which support native vegetation.

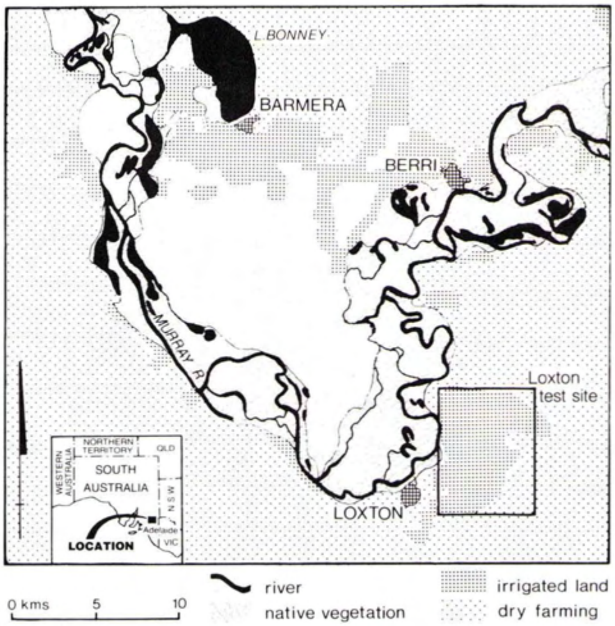


FIG. 1. The study area.

## DATA COLLECTION

Three sets of remotely sensed data were used in the research: (1) SPOT HRV multispectral data recorded in three wavebands at a 20-m spatial resolution (Chevrel *et al.*, 1981) on 21 October 1986; (2) airborne Daedalus ATM 1268 multispectral data recorded in eleven wavebands at a 10-m spatial resolution on 27 March 1985 (Table 1); and (3) color aerial photographs at a scale of 1:20,000. The SPOT HRV data were radiometrically corrected using information supplied by SPOT Image, but calibration data were not available for the Daedalus MSS data.

The color aerial photographs were used to identify and locate crop types and areas of new plantings. The mature orchard trees had an almost complete canopy cover while the vines were planted in rows 2 to 3 m apart. The interpretation was confirmed by ground checking. The collection of multispectral data in spring (SPOT HRV) and summer (Daedalus MSS) did not per-



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TABLE 1. SENSORS AND WAVEBANDS USED IN THIS STUDY

| Sensor | Waveband Number | Band edges (μm) |
|---|---|---|
| SPOT HRV | 1 | 0.50 - 0.59 |
| | 2 | 0.61 - 0.68 |
| | 3 | 0.79 - 0.89 |
| Daedalus ATM | 1 | 0.42 - 0.45 |
| | 2 | 0.45 - 0.52 |
| | 3 | 0.52 - 0.605 |
| | 4 | 0.605 - 0.625 |
| | 5 | 0.63 - 0.69 |
| | 6 | 0.695 - 0.75 |
| | 7 | 0.76 - 0.90 |
| | 8 | 0.91 - 1.05 |
| | 9 | 1.55 - 1.75 |
| | 10 | 2.08 - 2.35 |
| | 11* | 8.5 - 13.0 |

* Data in this band were saturated and not used in this work.

mit the comparison of spectral characteristics between sensors, but did allow an analysis of the seasonal effect on crop separability to be made.

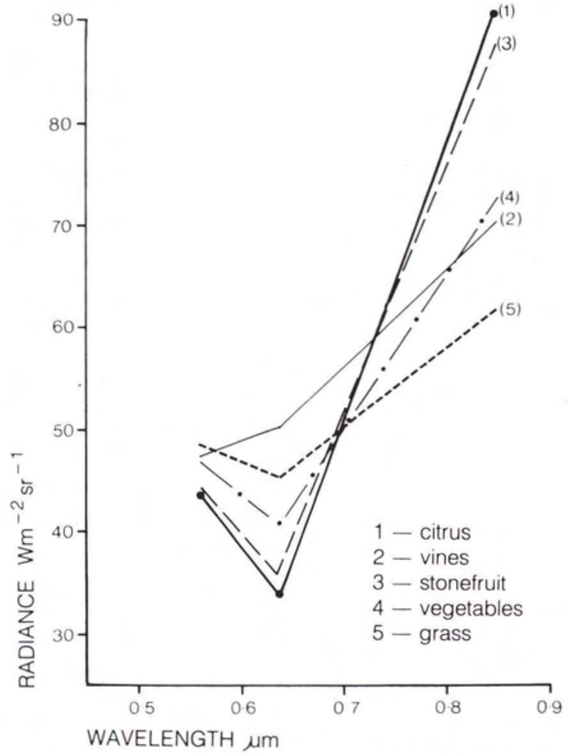


FIG. 2. The spectral response of citrus, vines, stonefruit, vegetables, and grass as recorded by a SPOT HRV sensor.

## DATA ANALYSIS

The data analysis was undertaken using multispecral data recorded by the SPOT HRV sensor and the Daedalus 1268 ATM in the Loxton irrigation area. The nature and dimensionality of the data were analyzed by employing standard statistical techniques and were tested in a trial classification. The information obtained from these analyses was used to classify irrigated and subsequently dryland crops over the entire study area.

### STATISTICAL ANALYSIS OF THE DATA

The mean radiance and standard deviation of 35 blocks were calculated from both data sets in all wavebands. This included blocks of mature citrus and stonefruit, vines, grass, and vegetables.

*Data Description.* The spectral response of the crops was plotted for each sensor (Figures 2 and 3). The responses as recorded by SPOT HRV in October were typical of vegetation at varying stages of growth. The stonefruit and citrus had low radiance values in the red waveband (Band 2) and high radiance values in the near infrared waveband (Band 3) as was expected from a green vegetation canopy. The vines and grass scrub had higher red radiance and lower near infrared radiance values than the orchard crops because of their relative lack of greenness in October.

Due to the lack of calibration of the Daedalus MSS data, it was not possible to compare radiance variations between wavebands. The radiance from vines is higher than from citrus in the visible (Bands 1 to 5) and middle infrared (Bands 9 and 10) wavebands, but lower in the near infrared (Bands 7 and 8) wavebands (Figure 3).

Interpretation of the aerial photographs showed differences in within-block variability between crops as the citrus had a full canopy while the vines were planted in rows with bare soil showing between the rows. This was measured in the multispectral data on a per-block basis using the coefficient of variation (CV): i.e.,

$$CV = \frac{SD}{\bar{x}} \times 100 \quad (1)$$

where

CV is coefficient of variation,
$\bar{x}$ is mean radiance of a block, and
SD is standard deviation of radiance in a block.

There was a significant difference at the 95 percent confidence level, using a students t test, between the CV of vine and citrus in the green and near infrared wavebands of the SPOT HRV data, and in wavebands 2 and 6 of the Daedalus MSS data (Table 2).

It should be noted that the radiance and standard deviation values of the two data sets cannot be compared as the bandwidths differ and no atmospheric corrections were applied, but the CV data should be comparable.

*Correlation Analysis.* The correlation coefficients between wavebands were calculated for each crop and the data set as a whole. Only the results of the latter are discussed in detail here.

SPOT HRV data. The visible wavebands were positively correlated at the 95 percent confidence level and the red and near infrared wavebands were negatively correlated at the 95 percent confidence level (Table 3). In contrast to the overall results, the radiance values from the vines were all significantly positively correlated. This is probably caused by the large amount of woody vegetation and soil within the vine blocks in October.

DAEDALUS MSS data. There were significant positive correlations between the wavebands at which radiance is primarily absorbed by green vegetation (Bands 2, 3, 4, 5, 6, 9, 10) and between the two wavebands at which radiance is primarily reflected by green vegetation (Bands 7 and 8) (Table 4). The correlations between these two groups of wavebands were not significant at the 95 percent confidence level. This suggests that the data are two dimensional. Results from the individual crop types were similar to the overall results.

*Principal Component Analysis.* The correlation analysis undertaken showed significant positive correlations between several of the wavebands. A principal component analysis (PCA) was employed to examine this further and to identify groups of related data (Johnston, 1980; Townshend *et al.*, 1983).

The PCA was undertaken using multispectral data from each of the 35 blocks described previously for each sensor. The first two components calculated with the SPOT HRV data explained

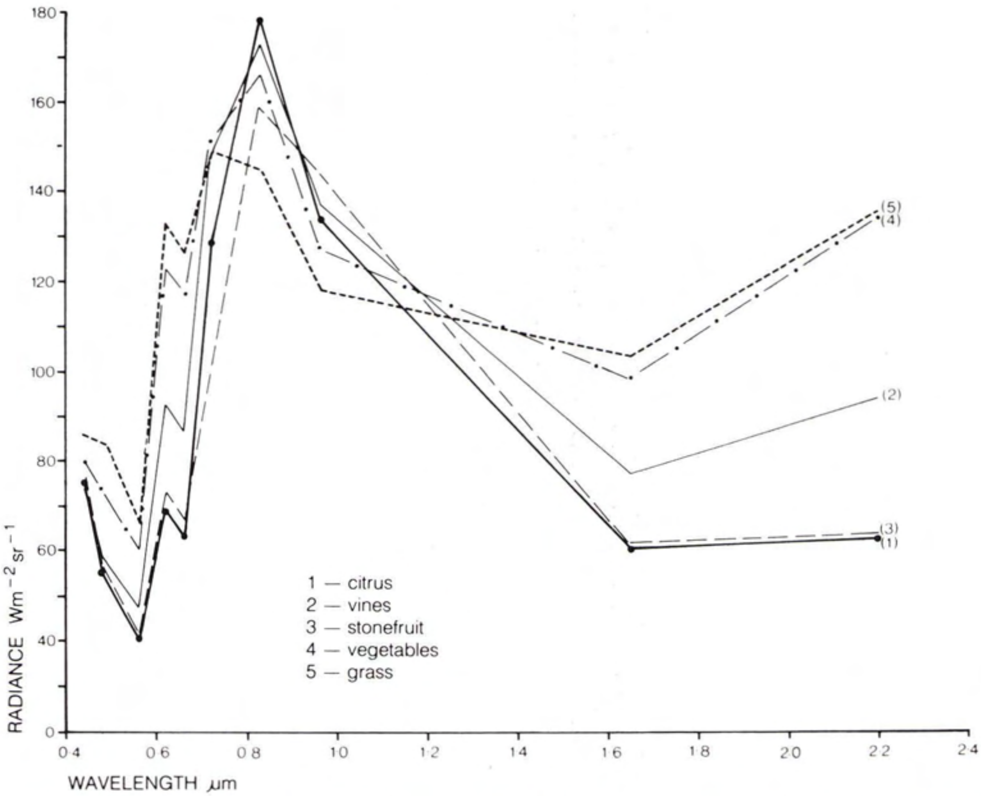


FIG. 3. The spectral response of citrus, vines, stonefruit, vegetables, and grass as recorded by a Daedalus 1268 ATM sensor.

TABLE 2. MEAN COEFFICIENT OF VARIATION (%) FOR FIVE CROPS AS RECORDED BY A SPOT HRV AND A DAEDALUS 1268 ATM SENSOR

| | SENSOR | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SPOT HRV CV (%) | | | Daedalus MSS CV (%) | | | | | | | | | |
| CROP | 1 | 2 | 3 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Vine | 2.4 | 3.0 | 1.1 | 1.8 | 4.2 | 5.6 | 7.9 | 8.6 | 5.1 | 5.1 | 4.8 | 7.8 | 11.7 |
| Citrus | 3.8 | 3.6 | 2.5 | 1.5 | 2.9 | 3.8 | 5.5 | 5.9 | 3.0 | 5.3 | 3.3 | 6.2 | 10.3 |
| Stonefruit | 3.5 | 7.3 | 2.7 | 1.6 | 3.8 | 5.2 | 7.2 | 7.5 | 2.8 | 3.9 | 3.2 | 7.0 | 10.5 |
| Grass | 3.7 | 4.8 | 3.2 | 1.7 | 4.1 | 4.5 | 9.8 | 5.4 | 5.1 | 4.5 | 4.0 | 4.2 | 7.2 |
| Vegetables | 3.9 | 7.4 | 3.7 | 1.9 | 2.9 | 3.2 | 3.3 | 3.6 | 4.2 | 4.1 | 3.5 | 4.4 | 10.0 |
| All | 3.3 | 5.8 | 3.5 | 1.7 | 3.5 | 4.4 | 6.6 | 6.7 | 3.8 | 4.8 | 3.8 | 6.5 | 10.3 |

TABLE 3. CORRELATION MATRIX FOR SPOT HRV BANDS FOR THIRTY FIVE IRRIGATED BLOCKS

| | | Waveband | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| Waveband | 1 | | 0.82* | 0.17 |
| | 2 | | | −0.45* |
| | 3 | | | |

*Significant at 95% confidence level.

TABLE 4. CORRELATION MATRIX FOR DAEDALUS 1268 ATM BANDS FOR 35 IRRIGATED BLOCKS

| | | Waveband | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Waveband | 1 | | 0.46 | 0.36 | 0.36 | 0.36 | 0.18 | −0.14 | −0.20 | 0.34 | 0.36 |
| | 2 | | | 0.94* | 0.91* | 0.89* | 0.64* | −0.14 | −0.14 | 0.83* | 0.81* |
| | 3 | | | | 0.98 | 0.97* | 0.79* | −0.12 | −0.01 | 0.92* | 0.89* |
| | 4 | | | | | 0.99* | 0.77* | −0.19 | −0.09 | 0.96* | 0.95* |
| | 5 | | | | | | 0.75* | −0.21 | −0.12 | 6.97* | 0.96* |
| | 6 | | | | | | | 0.09 | 0.50* | 0.70* | 0.64* |
| | 7 | | | | | | | | 0.41* | −0.19 | −0.20 |
| | 8 | | | | | | | | | −0.15 | −0.23* |
| | 9 | | | | | | | | | | 0.99* |
| | 10 | | | | | | | | | | |

* Significant at 95% confidence level.

TABLE 5. PRINCIPAL COMPONENT ANALYSIS FOR SPOT HRV AND DAEDALUS 1268 ATM DATA

| | Cumulative percentage | | |
|---|---|---|---|
| Sensor | 1st component | 2nd component | 3rd component |
| SPOT HRV | 64.1 | 97.9 | 100.0 |
| Daedalus MSS | 64.4 | 81.7 | 98.3 |

97.9 percent of the variance of the data set (Table 5). The first component contained high loadings from the visible wavebands, and the second component contained a high loading from the near infrared waveband. These are similar groupings to those displayed by the correlation analysis. When the individual crops were analyzed, over 90 percent of the variance from the vines was explained by the first component with high loadings in all wavebands. The results from the other crops were similar to the overall results.

Using the Daedalus MSS data, 98.3 percent of the variance was explained by the first three components (Table 5). The first component had high loadings in all wavebands except wavebands 1, 7, and 8. The second component had high loadings in wavebands 7 and 8. The third component was dominated by waveband 1, which was affected by haze. The individual crops varied little from this.

The PCA and correlation analysis suggest that the data are essentially two dimensional. The brown or dry vegetation (vines in October, grass throughout spring and summer) has been shown to be one dimensional, which concurs with other research (e.g., Quarmby and Townshend, 1986) and shows the value of collecting data at a season when differences in greenness between crops are maximized.

*Discriminant Analysis.* The two dimensionality of the data suggested in the previous analyses was tested using Wilks Lambda discriminant analysis (Johnston, 1980) to classify the data. The classification used the radiance data which were free from edge effects and contained data solely from the crops under study in the 35 blocks. Due to the limited number of samples, the discriminant function was calculated using all the samples, and the classification used the same data. This back-classification approach is not considered a legitimate statistical measure of accuracy but does provide insight into the relative effectiveness of the spectral variables to discriminate between classes (Yool *et al.*, 1985). Classifications were undertaken using all wavebands and also using a combination of wavebands as suggested by the earlier analyses, by stepwise discriminant analysis, and by other researchers (e.g., Nelson *et al.*, 1984; Townshend, 1984; Everitt *et al.*, 1986).

Accuracies achieved using the red and near infrared wavebands were similar to the results obtained using all wavebands of the SPOT HRV data. Accuracies decreased when using only a red and a near infrared waveband of the Daedalus MSS data as compared to using all the Daedalus wavebands. The addition of a middle infrared waveband to the red and near infrared did not increase significantly the accuracy of the classification (Table 6).

## Classification of Data

Maximum–likelihood classifications were undertaken using a Dipix digital image processor. The supervised classifications were undertaken on a per-pixel basis rather than using the mean radiance of a block as previously. These classifications therefore included a larger range of radiance and boundary pixels. Several classifications were computed using the information decribed above. The accuracies of the classifications were calculated for 200 fruit blocks using the aerial photographs as ground data. The percent confidence level was calculated by means of bionomial expansion (Hay, 1979).

The classification using SPOT HRV red and near infrared wavebands had an accuracy of 85 to 93 percent at the 95 percent confidence level (Table 7). The discrimination between the citrus and stonefruit was poor, but they were successfully separated from other crops. It would be possible to separate citrus and stonefruit using data recorded during winter months as stonefruits are a deciduous tree and citrus are evergreen. There was also some overlap between the vegetables and vines.

Table 6. Classification Accuracy Using Discriminant Analysis for Five Crops

| Sensor | Waveband | Accuracy % (95% confidence level) |
|---|---|---|
| SPOT HRV | All bands | 56-88 |
| | 2,3 | 57-87 |
| | 2,3,CV3 | 64-90 |
| Daedalus MSS | All bands | 70-96 |
| | 3,4,6,10 | 53-84 |
| | 3,4,8,10 | 46-80 |
| | 3,4,6,9 | 60-90 |
| | 3,4,7,10 | 41-75 |
| | 4,7 | 53-84 |
| | 3,4,6,9,CV6 | 56-86 |

CV3 is the coefficient of variation for band 3
CV6 is the coefficient of variation for band 6

Table 7. Classification Accuracy of Irrigated Crops

| Sensor | Waveband | Accuracy % (95% confidence level) |
|---|---|---|
| SPOT HRV | All bands | 71-82 |
| | 2,3 | 85-93 |
| Daedalus MSS | All bands | 58-73 |
| | 3,4,6,10 | 55-68 |
| | 4,7 | 68-81 |

The accuracy of the classification using the red and near infrared wavebands of the Daedalus MSS was slightly lower than when using the corresponding wavebands of the SPOT HRV sensor (Table 7). There was some variability in classification within blocks; consequently, the classification was considered correct if the majority of the pixels fell in the correct class. The main source of error was a confusion between the vines and vegetables, and in some blocks new citrus plantings were classified as vines. This was probably because radiance from the canopy, bark, soil, and grass contributed to the mean radiance of these blocks while most of the citrus and stonefruit blocks have an almost complete canopy cover. The vines and vegetables are planted in distinct rows at all angles in relation to the multispectral data. No pattern of misclassification was found which was related to the row direction. As the number of wavebands used in the classification increased, a larger proportion of the scene remained unclassified. Between 34 and 45 percent of the vines were unclassified while only 11 to 23 percent of the citrus blocks remained unclassified.

# DISCUSSION

The statistical analyses showed that many of the wavebands were significantly positively correlated, and the red and near infrared wavebands explained much of the variance in the data. Data from additional wavebands only restricts the spectral domain of the classifier, resulting in large areas unclassified, especially boundary pixels and areas of high variability.

The spatial resolution of the SPOT HRV data (20 m) was sufficiently high to prevent edge effects affecting the radiance of a large proportion of the pixels. The 20–m spatial resolution smoothed out the variability within blocks containing row crops. Although the Daedalus MSS with a 10–m spatial resolution provided more spectral information about each block, this led to confusion during classification. The 20–m spatial resolution gave an adequate number of pixels within each block, retained the most consistant percentage of canopy and background within a pixel, and required less processing time than the 10–m Daedalus MSS data. Landsat Thematic Mapper data with a 30–m spatial resolution may also prove to be useful for this type of work but was not tested in this study. A second series of classifications were undertaken to test the accuracy over the larger study area of the South Australian Riverland using SPOT HRV data in the red and near infrared waveband. The training statistics computed in the Loxton study were used, and the accuracy of the classification was tested on 150 fruit blocks using color aerial photographs taken near Barmera as ground data. An accuracy of 77 to 90 percent at the 95 percent confidence level was obtained using only sites within the irrigated areas. The main source of error was vines which were classified as vegetables or grass. The area of citrus was much smaller than in the Loxton area, but there was little misclassification between vines and citrus.

The work has concentrated on the discrimination of crops within the irrigated areas. If remotely sensed data are to be used in monitoring the extent or area of irrigated crops, it is necessary to separate them from other land uses such as dryland agriculture and native vegetation. The spectral responses of these classes are shown in Figure 4.

Training sites of dryland cereal crops and native vegetation [floodplain (*Eucalyptus* spp.) and shrublands (*Chenopodium* spp.)] were defined. A maximum-likelihood classification was undertaken for the larger study area using these classes in addition to vines and citrus. The area of vegetables was small and was excluded from the classification and, as the spectral response from the grass (which was dead) was similar to that of the dryland agriculture, the former was also excluded.

The accuracy of the classification was calculated using color aerial photographs from the Loxton and Barmera areas. Accuracies of 51 to 59 percent at the 95 percent confidence level and 50 to 67 percent at the 95 percent confidence level were calculated for the Barmera and Loxton areas, respectively. The accuracy of the classification was above 90 percent for the citrus, but there was considerable misclassification between the vines and the dryland cereal cropping. At the time of data collection (October) there was little green vegetation on the vines and the soil background effect was dominant. There was also some misclassification between the floodplain and the shrubland due to the similar spectral responses of the different types of native vegetation. Remotely sensed data recorded in summer would increase the accuracy of a classification separating dry and irrigated areas, although at this time of year it would be increasingly difficult to discriminate between the irrigated crops.

## CONCLUSIONS

- The radiance data recorded in the irrigated areas of orchard and vine crops were two dimensional. Data from a red waveband and a near infrared waveband explained most of the spectral variance.
- The accuracy of the classification was higher using data with a 20-m spatial resolution than using data with a 10-m spatial resolution for the crops and block size occuring in this study.

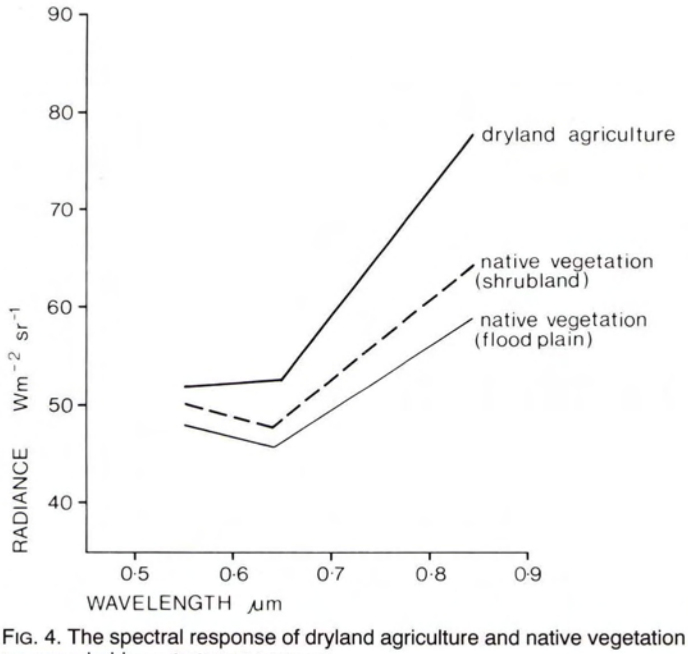


FIG. 4. The spectral response of dryland agriculture and native vegetation as recorded by a SPOT HRV sensor.

- SPOT HRV data were used to classify irrigated orchard and vine crops with an accuracy of 85 to 93 percent at the 95 percent confidence level. The accuracy was reduced to 51 to 59 percent when the study was extended to include dryland cropping classes.
- Discrimination between crops is greatest when the difference in the greenness between crops is at a maximum. Multispectral data recorded in different seasons would assist in separating citrus and stonefruit, orchard and vine crops, and irrigated and non-irrigated crops.

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Three families of workstations, the Sun-3™, Sun-4™, and Sun386i™ product lines, provide a range of performance from 1.5 to 10 MIPS, and include standalone and networked systems, diskless workstations and large fileservers, color, grayscale, and high-resolution monochrome models. Sun's large server systems are used as fileservers for diskless workstations, as terminal servers (replacing traditional minicomputers), and as shared-resource compute engines.

Two new workstations have enhanced Sun's product line: The Sun386i™ family of workstations is the first true workstation based on the Intel 80386 microprocessor to fully merge the power of UNIX system performance with DOS applications while accommodating AT bus add-on boards; the newest Sun workstation is the Sun-4/110TC, a low-cost, high-resolution 24-bit color system based on Sun's SPARC™ (Scalable Processor Architecture) microprocessor. The system's virtually limitless "true color" graphics capabilities lets GIS and mapping users accurately display the full range of their data with 16.7 million color possibilities.

A dramatic addition to Sun's product line is the high-performance, 32-bit TAAC-1™ Application Accelerator. The TAAC-1 increases productivity for compute-intensive applications such as image processing, surface modeling, and GIS. While the TAAC accelerator board includes a variety of highly interactive functions (image filtering, transforms, 3D perspective, etc.), it offers a wealth of tools to the users, and is programmable in C. All of these systems provide the backdrop for Sun's growing commitment to the GIS market.

Sun gives customers more than 1,500 software applications and add-on hardware products from third-party vendors — the largest number of UNIX system-based application solutions in the industry. Sun offers a full selection of the top vendors over a wide range of application software, peripherals and add-on hardware, and connectivity products. With a full range of hardware and software, Sun gives OEMs and end-users a complete workstation platform.