MAPPING OLIVE VARIETIES AND WITHIN-FIELD SPATIAL VARIABILITY USING HIGH RESOLUTION QUICKBIRD IMAGERY

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Abstract

The growth of the Australian olive (*Olea europaea L.*) industry requires support from research to ensure its profitability and sustainability. To contribute to this goal, our project tested the ability of remote sensing imagery to map olive groves and their attributes. Specifically, this study aimed to: (a) discriminate olives varieties; and to (b) detect and interpret within-field spatial variability. Using high spatial resolution (2.8m) QuickBird multispectral imagery acquired over Yallamundi (southeast Queensland) on 24 December 2003, both visual interpretation and statistical (divergence) measures were employed to discriminate olive varieties. Similarly, the detection and interpretation of within-field spatial variability was conducted on enhanced false colour composite imagery, and confirmed by the use of statistical methods.

Results showed that the two olive varieties (i.e. *Kalamata* and *Frantoio*) can be visually differentiated and mapped on the enhanced image based on texture. The spectral signature plots showed little difference in the mean spectral reflectance values, indicating that the two varieties have a very low spectral separability. In terms of within-field spatial variability, the presence or absence of Rhodes grass (*Chloris gayana*) was detected using visual interpretation, corroborated by the

results of quantitative statistical measures. Spatial variability in soil properties, caused by the presence of a patch of sandy soil, was also detected visually. Finally, the “imprint” of former cover-type or land-use prior to olive plantation

establishment in 1998 was identified. More work is being done to develop image classification techniques for mapping within-field spatial variability in olive varieties, biomass and condition using hyperspectral image data, as well as interpreting the cause of observed variability.

1. Introduction

The olive (*Olea europaea L.*) industry in Australia is growing, with an estimated 4.7 million olive trees planted across Australia in 2000 and then over 7.5 million olive trees planted in 2002 (RIRDC, 2002). This growth is a direct response to the large and growing markets for olives and olive oil in Australia and overseas. For example, as of 1998, Australia imported approximately 16,000 tonnes per year of olive oil and 7,000 tonnes per year of olive fruit, valued at approximately $90 million and $20 million, respectively (Sweeney and Davies, 1998).

To build and maintain a competitive advantage for the Australian olive industry, research programs should be conducted on priority areas to enhance productivity. RIRDC (2002) has recently developed the industry’s research and development program, and identified “sustainable production” as one of its key result areas. Under this theme the industry aims for “*commercially viable best-practice production systems that are profitable, efficient and ecologically sustainable*” (RIRDC, 2002, p.8). To realise this, the development of tools or techniques applicable to horticulture and crop management is essential.

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Remote sensing technology, combined with geographic information systems (GIS), global positioning systems (GPS) and simulation models, has already demonstrated its usefulness and benefits for crop management (e.g. Pinter et al., 2003). Imagery from space-borne and airborne sensors can provide information to support water management, nutrient management, pest and disease management, and yield prediction. In addition, recently launched imaging sensors, equipped with improved spatial, spectral and radiometric resolutions, offer enhanced capabilities over the moderate spatial resolution and multispectral “Landsat or SPOT” like systems that have dominated remote sensing for the past thirty years.

While the application of remote sensing to orchard and plantation management is not new, very few applications have used remote sensing for olive plantation management. Moreover, the use of high spatial resolution multispectral image data from satellite sensors to map olive grove attributes, has yet done in Australia. This study aimed to test the ability of high resolution remote sensing imagery to: (a) discriminate olives varieties in olive groves; and (b) to discriminate and interpret within-field (or within-block) spatial variability based on the biophysical attributes of olive trees.

2. Background

There are only few studies found in the literature that have employed remote sensing imagery for orchard management. In north-eastern New South Wales, Australia, Landsat 5 Thematic Mapper (TM) imagery was successfully used to map the distribution of macadamia nut orchards and support yield forecasting (Whelan, 2002). In relation to olives, a study that used conventional-colour and colour-infrared aerial photographs and vegetation indices was conducted in Spain to determine variations in cover crop, bare soil and tree areas in olive groves as affected by the season (Peña-Barragán et al., 2004). They found that early summer was the most suitable time to distinguish between cover crops and olive trees. In addition, the study found that indices based on blue and red band reflectance values were suitable for cover crop and olive tree discrimination.

Zarco-Tejada, et al. (2004) used high-spatial resolution hyperspectral image data to estimate leaf biochemistry in open olive canopies. Indices related to leaf chlorophyll content were used to test different radiative transfer modelling assumptions in open canopies where tree crown, soil and shadow components were separately targeted. Predictive equations built on a Modified Chlorophyll Absorption in Reflectance Index (MCARI) and Optimized Soil-Adjusted Vegetation Index (OSAVI) index combination minimized soil background variations, demonstrating superior performance compared to other single-ratio indices previously shown as good indicators of chlorophyll concentration in closed canopies.

The availability of high spatial resolution (< 5m) multispectral image from commercial satellite sensors (e.g. IKONOS, QuickBird and EROS) offers potential for orchard management. Acquiring imagery from sub-meter to 2.0m spatial resolution may allow the capture of individual mature tree crown, thereby improving the detection of crop attributes relevant to monitoring and management. These data may also be integrated with crop models to assess productivity and yield. High spatial resolution imagery could also improve the mapping of orchard infrastructure and facilities (e.g. roads, sheds, irrigation facilities, dams, etc.) needed in asset management.

3. Research Methods

3.1. Study Area

The 3,220-hectare study area covers the irrigated olive groves established by the *Australian Olives Ltd.,* located in Yandilla, south-east Queensland (Figure 1). The olive groves are in plantation blocks of different areal extent, e.g. “B” block (34 ha), “H” block (38 ha), “C” block (42 ha), and “E” block (39 ha). The earliest plantings

were started in 1998, with olive varieties *Manzanillo*, *Frantoio* (Paragon), *Kalamata*, *Hardy’s Mammoth* and *Sevillano*, with at a spacing of 8m x 5m. Now, these six-year old olive trees have an average height of 3.84m, and an average canopy diameter of about 3.38m, based from samples obtained from the “B” block on 2 June 2004. These olive trees were the focus of this current study (Figure 2).

Figure 1. QuickBird multispectral image of the Yandilla, south-east Queensland study area, acquired on 24 December 2003. The image is displayed with red, near-infrared and

blue bands in the red, green and blue colour guns.

Figure 2. Olive trees in “B” Block (20 January 2004).

3.2. Imagery Data and Field Work

The study used a QuickBird multispectral image product supplied by DigitalGlobe™. The image has a spatial resolution of 2.8m, covering four spectral bands: Blue (450-520nm), Green (520-600nm), Red (630-690nm) and Near Infrared (760-900nm). Acquired over the study area on 24 December 2003 (summer), the image was delivered as a radiometrically calibrated image product, corrected for sensor and platform-induced distortion.

A field reconnaissance survey of the olive orchards were conducted on 20 January 2004 to assess the structure and condition of the study area, as well as to conduct informal interviews with the plantation manager and the agronomist. A more intensive field data collection was conducted on 2 June 2004 to measure tree height, diameter at breast height, crown canopy diameter, and leaf chlorophyll content, and to describe other tree attributes.

3.3. Image Processing and Analysis

The image processing for this study focused on two major approaches:

- qualitative visual interpretation; and
- statistical (quantitative) analysis of sample pixels.

The visual interpretation of imagery was done to examine whether the (i) within-field spatial variability of spectral response could be due to green biomass differences; and (ii) if varieties of olives, could be visually identified and delineated

using QuickBird data. The visual interpretation of these images was conducted after image enhancement techniques, including contrast enhancements using linear and non-linear (histogram equalisation) stretching were applied. The basic interpretation criteria used included color, texture, pattern, and association of the olive groves.

Statistical analysis of sample pixels was conducted to determine if statistically significant differences in radiance values could be associated with differences in olive variety types, biomass and condition. To achieve this, two major techniques were used: (i) visual assessment of spectral signature plots of group/class means and levels of variance; and (ii) assessment of spectral signature values using statistical divergence measures.

The image processing steps used in this study were implemented using the ENVI 4.0 software (RSI, 2004), and are briefly described below:

1. **Mosaic images** – assemble four separate non-overlapping images supplied by the data provider.
2. **Reproject to MGA94** – converted the geographic coordinates (latitude-longitude) into the Map Grid of Australia (MGA94), Zone 56.
3. **Clipped to the study area** – subset the image into the areal extent of the olive groves and vicinities, producing a a 5.2 km x 5.9 km subset image.
4. **Radiance calibration** – converted the image pixel values of relative radiance

into absolute at-sensor radiance in units of *µ W / cm2 . nm . str*. The calibration is performed using the calibration factors supplied in the QuickBird metadata file.

5. **Image enhancement** – optimised image contrast for visual interpretation using histogram equalisation method.

6. **Preliminary interpretation and hypothesis generation** – visually interpreted within-block spatial variability of spectral signature response, and offered hypothesis on the underlying cause(s) of variability.

7. **Selection of sample pixels** – sample pixels collected for two different olive varieties (35 pixels for *Kalamata* and 37 pixels for *Frantoio*), and three different cover types (35 pixels for olive, 44 pixels for native vegetation, and 48 pixels for grass). *(The number of collected pixels was relatively small due to the constraint on the 2.8m spatial resolution of the image and the average crown canopy diameter of 3.38m. Under these circumstances, the selection of sample pixels (aided by GPS and association with tree shadow) was carefully done, hence the reduced number of pixels.)*

8. **Assessment of spectral plots –** plots of mean and variance in spectral radiance values for training sites was assessed visually, focusing on the separability of values on the different spectral bands.

9. **Assessment of spectral radiance values using divergence measures –** assessed the separability of the spectral values using the *Jeffries-Matusita* and *Transformed Divergence* separability measures.

10. **Synthesis and interpretation –** synthesised results and re-stated hypothesis about causes of spatial variability of spectral signatures.

4. Results and Discussion

During the initial stage of project implementation, we attempted to identify, as much as possible, the probable causes of within-field spatial variability in the spectral response. These are preliminary assessments and will be assessed from a quantitative basis in later studies. Thus, an initial list of possible factors was produced based from field data, preliminary visual interpretation, and/or interviews from plantation personnel:

- the presence or absence of grasses/weeds;
- soil properties;
- variety of olive trees;
- past management practices (prior to olive plantation establishment); and
- crop stresses due to pests and diseases, lack or uneven supply of water, nutrition, etc.

For crop stresses, note that these were only speculations at this initial stage in an attempt to seek explanation, and do not indicate the actual condition of the olive groves. Later, however, we decided not to pursue this aspect of investigation for this QuickBird study, in favour of separate research that we were concurrently conducting using Hymap hyperspectral data.

4.1. The Presence or Absence of Grasses/Weeds

We identified the major cause of within-field spatial variability of spectral radiance response in most olive blocks as the presence or absence of “Rhodes grass” (*Chloris gayana*) in between and within rows of olive trees (Figure 3). Rhodes grass is a good cattle feed and has potential for hay making. Jensen and Neale (*personal communication*) suggested that this would be a good grass to have between rows of any horticultural / tree crop, as it has erosion control properties due to its stoloniferous habit. On the ground, these grasses were distributed in big patches, and appeared healthy and green in colour during the image capture. Their

presence or absence may be due to differing irrigation/water regimes, soil fertility or they simply appeared in random. For instance, a patch of Rhodes grass in one of the blocks was a former sheep yard where soil condition may be different from its surroundings.

Figure 3. Rhodes grass in between rows of olive trees at "B" Block (20 January 2004).

Figure 4. Areas with Rhodes grass ("A") in bright green colour *vs.* without / very minimal Rhodes grass ("B"), displayed in R, NIR, B in RGB image, respectively, with histogram equalisation contrast stretching.

The results of the quantitative analysis of the spectral signatures agreed with the visual interpretation — there is a significant separability between Rhodes grass, olive and native vegetation in terms of differences in their mean spectral radiance values in each band. Olive pixels have a lower mean NIR values than grass and native vegetation, and conversely, they have higher mean spectral values in the red, green, and blue bands (Figure 5). The highest difference was observed at the red (630-690nm) band, indicating differences in chlorophyll absorption properties.

MEAN and +/-STD SPECTRAL VALUES OF OLIVE, GRASS & NATIVE VEGETATION
30004000500060007000800090000BlueGreenRedNIR**BANDSRADIANCE (X 1000)**-STD(STD(STD(nat-veg)+STD(nat-STD(STD(grass)

Figure 5. Spectral values (mean and standard deviation) of olive, grass and native vegetation.

The results of the *Jeffries-Matusita* separability measure showed that olive tree canopies and Rhodes grass have a very good spectral separability (1.94 out of 2.0). Similarly, olive tree canopies and native vegetation produced very good separability (1.93), indicating that they can be differentiated using the QuickBird imagery.

OliveNative VegGrass
olive)+
olive)-
veg)-
grass)+

4.2. Soil Properties

While we did not conduct intensive soil sampling and analysis of the area to make detailed comparison, there was a site where differences in soil type became visually apparent on the enhanced image. In Figure 6, a patch identified as "A" shows colour difference from the rest of the block as in patch "B". Field verification revealed that the "A" patch has more sandy soil, possibly deposited on that patch during road construction or site preparation.

Figure 6. Patch “A” in magenta (purple) colour distinctly different from the rest of the block (e.g. patch “B”), due to soil texture difference.

4.3. Variety of Olive Trees

The two olive varieties (i.e. *Kalamata* and *Frantoio*) on “H” block (Figure 7) can be visually differentiated and mapped on the enhanced image. However, the basis of segregation is more focused on the texture of the image (e.g. the density of shadows and green foliage) rather than on individual pixel values (Figure 8). This observation was supported by the spectral plots which showed little difference on the mean spectral values between the two olive varieties (Figure 8). Furthermore,

the *Jeffries-Matusita* separability measure gave a value of 0.55 (out of 2.0), indicating that the two varieties have a very poor spectral separability.

Figure 7. The two olive varieties, *Kalamata* (left) and *Frantoio* (right) assessed in this study.

Figure 8. The two olive varieties, *Kalamata* (“A”) and *Frantoio* (“B”) showing colour and textural differences on the image.

MEAN and +/-STD SPECTRAL VALUES OF OLIVE VARIETIES
40005000600070008000BlueGreenRedNIR**BANDSRADIANCE (X 1000)**KalamataFrantoio-STD(Kal)+STD(STD(STD(Fran)

Figure 9. Spectral values (mean and standard deviation) of the two olive varieties.

4.4. Past Management Practices

Some olive blocks show distinct patterns that can be attributed to past management regime. For instance, in block “H”, there is a semi-squared pattern that made the land cover features (olive, soil, plant residue, etc.) noticeably lighter than their surroundings (see patch “A” in Figure 10). Looking at the pre-plantation 1997 Landsat 5 TM image, it indicated the patch was formerly a paddock, although its actual use is still unknown (Figure 11). Nevertheless, the Landsat 5 TM image showed that the patch had small amount of green vegetation compared to its surroundings, with its edges containing dry grass or plant residue.

Kal)-
Fran)+

Figure 10. Patch “A” with spectral response different from its surroundings, attributed to past management regime.

Figure 11. Pre-olives Landsat 5 TM image (12 August 1997), showing patch “A” of different cover types from its surroundings.

5. Conclusions

High-spatial resolution QuickBird imagery was able to quantify within-field spatial variability of olive groves. Several compositional and structural features were identified as possible controls on the observed variations. At the time of image capture, the presence or absence of Rhodes grass (*Chloris gayana*) was adequately detected using visual interpretation method, corroborated by the results of quantitative statistical measures. Spatial variability in soil properties, caused by the presence of a patch of sandy soil, was also detected visually on the enhanced false colour imagery. Likewise, the "imprint" of former cover type or land use prior to olive plantation establishment in 1998 was identified on the image by visual interpretation. Furthermore, two olive varieties (i.e. *Kalamata* and *Frantoio*) were visually differentiated and able to be mapped on the enhanced image mainly based on image texture, i.e. differences in the density and patterns of shadows and green foliage. More work is being done to develop image classification techniques for mapping within-field spatial variability in olive varieties, biomass and condition using hyperspectral image data.

Acknowledgments

We thank the staff of the *Australian Olives Ltd.*, particularly Phil Ward and Keith McIntosh, for their assistance during the field data collection, and for providing us some information. Tek Maraseni and Shawn Darr (USQ students) provided help during the field work. Troy Jensen and Tim Neale helped in the identification of Rhode grass.

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