# Mapping Banana Plantations from Object-oriented Classification of SPOT-5 Imagery

Kasper Johansen, Stuart Phinn, Christian Witte, Seonaid Philip, and Lisa Newton

## Abstract

*The objectives of this research were to develop and evaluate an approach for object-oriented mapping of banana plantations from SPOT-5 imagery, and to compare these results to banana plantations manually delineated from high spatial resolution airborne imagery. Cultivated areas were first identified through large spatial scale mapping using spectral and elevation data. Within the cultivated areas, separation of banana plantations and other land-cover classes increased when including image co-occurrence texture measures and context relationships in addition to spectral information. The results showed that a pixel size of ≤2.5 m was required to accurately identify the row structure within banana plantations, which enabled object-based separation from other crops based on texture information. The user's and producer's accuracies for mapping banana plantations increased from 73 percent and 77 percent, respectively, to 94 percent and 93 percent after post-classification visual editing. The results indicate that the data and processing techniques used offer a reliable approach for mapping banana plants and other plantation crops.*

## Introduction

Remote sensing has been used extensively for crop yield estimation (Horie *et al.*, 1992; Lobell *et al.*, 2003; Singh *et al.*, 2002; Sun, 2000), crop management (Pinter *et al.*, 2003; Yang and Anderson, 1996), and precision farming (Basso *et al.*, 2001; Robert, 1997). Other approaches have focused on a combination of crop models and the use of remote sensing (Basso *et al.*, 2001; Doraiswamy *et al.*, 2003; Moulin *et al.*, 1998). Many of these approaches have used empirical models and spectral vegetation indices to predict crop variability, biomass, and yield (Tucker *et al.*, 1980; Wiegand *et al.*, 1991). Remote sensing has been used for mapping the extent of grain crops and to a limited extent, horticulture. However, there has been limited application of high spatial resolution image data because of the heterogeneity of the fields to be mapped in traditional per-pixel image classification (Navalgund *et al.*, 1991; Shrivastava and Gebelein, 2007; Tennakoon *et al.*, 1992; Yadav *et al.*, 2002).

The segmentation of image pixels into homogenous objects has been explored in several studies through clustering routines and region-growing algorithms (e.g., Haralick and Shapiro, 1985; Ryherd and Woodcock, 1996). The concept of segmentation is based on the theory of spatial scale in remote sensing described by Woodcock and Strahler (1987) who showed that the local variance of digital image data in relation to the spatial resolution can be used for selecting the appropriate image scale for mapping individual land-cover features. Image data of the Earth's surface can be divided into homogenous objects at a number of different spatial scales, which are interrelated in a hierarchy, where large objects consist of several smaller objects (Burnett and Blaschke, 2003; Muller, 1997). Wu (1999) and Hay *et al.* (2003) explored different multi-scale image segmentation methods and found image objects to be hierarchically structured, scale dependent, and with interactions between image components.

Object-oriented image classification typically consists of three main steps: (a) image segmentation, (b) development of an image object hierarchy based on training objects, and (c) classification (Benz *et al.*, 2004; Blaschke and Hay, 2001; Flanders *et al.*, 2003). Object-oriented image classification is based on the assumption that image objects provide a more appropriate scale to map environmental features at multiple spatial scales and more relevant information than individual pixels (Gamanya *et al.*, 2007). The advantage of using object-oriented image analysis is the capability to define criteria for image objects at set scales using spectral reflectance characteristics, as well as within and between object texture, shapes of features, context relationships, and ancillary spatial data of different spatial resolution consisting of both thematic and continuous data values (Bock *et al.*, 2005). Recently, object-oriented image classification has been used more extensively due to improvements of object-oriented segmentation and classification routines such as Definiens Professional 5 and Definiens Developer 7 (Benz *et al.*, 2004; Definiens,

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2006). Definiens object-oriented segmentation and classification routines have been used for forest mapping (Johansen et al., 2007; Lennartz and Congalton, 2004; Dorren *et al.*, 2003), mapping of mangrove species composition (Wang *et al.*, 2004), mapping of fractional cover of green and senescent vegetation (Laliberte *et al.*, 2007), mapping of agricultural fields (Mueller *et al.*, 2004), urban mapping (Herold *et al.*, 2003; Thomas *et al.*, 2003), mapping of shrub encroachment in arid and semi-arid grasslands (Laliberte *et al.*, 2004), as well as more general land-cover classifications (Bock *et al.*, 2005; Gamanya *et al.*, 2007). The main conclusions of these papers were that object-oriented classification: (a) reduces misclassification caused by spectral variability within land-cover classes, (b) enables analysis and classification of landscape features at multiple spatial scales, and (c) increases classification accuracies because of the ability to include contextual information (such as object shape and relative location of objects) in addition to spectral and textual information. One of the main issues encountered were the selection of an appropriate spatial scale for image segmentation to ensure multiple land-cover classes did not occur within the same object. The majority of these studies also recognized the suitability of using high spatial resolution image data for object-oriented segmentation and classification. Based on these findings, object-oriented image classification may therefore be suitable for banana plantation mapping.

Banana production provides a significant export income for many tropical countries, and management of banana plantations requires spatial information for a number of reasons (UNCTAD, 2007). For example, bio-security is a focus area in Australia, especially in the wake of recent cyclone destruction and disease outbreaks in banana plantations. Also, state and national land-use mapping programs in Australia are mostly based on manual visual interpretation to adjust the output from land-cover classifications (Witte *et al.*, 2006). Automated image processing routines have the potential to be used for updating specific land-uses more effectively in a timely manner.

Currently, no set approach for mapping the extent and condition of banana plantations exists. High spatial resolution multi-spectral and panchromatic SPOT-5 image data provide a potential means for mapping the presence of banana plantations. Image-based mapping can operate on spectral reflectance and spatial (pattern) features in an environment (Laliberte *et al.*, 2004). Hence, the aim of this work was to develop a new mapping approach that will capture both the spatial and spectral reflectance properties of banana plantations to separate them from other land-cover features. Reference data for this work, i.e., maps showing the extent and age of banana plantations in north Queensland, Australia, were derived from manual delineation and visual interpretation of banana plantations from very high spatial resolution airborne digital image data. A semi-automated mapping approach was then developed using SPOT-5 image data and compared with the reference map produced from manual delineation. The objectives of this research were (a) to develop and evaluate an approach for mapping banana plantations from SPOT-5 image data using object-oriented segmentation and classification, and (b) to compare the semi-automated object-oriented mapping results with the extent of banana plantations derived from visual interpretation of airborne image data.

## Data and Methods

### Study Area

The study area was located in the Innisfail-Tully area of north Queensland, Australia covering the full extent of a SPOT-5 scene (60 km × 60 km) (Figure 1). The study area receives a mean annual rainfall of 2,800 mm with the majority of rain falling between December and May. The major land-cover classes found within the study area consisted of rainforest (conservation areas), rangelands (grazing of natural vegetation), water bodies, and cultivated areas (covering approximately 350 km$^2$). Within the cultivated areas of the study area, the most dominant practices identified within the land-use mapping (QLUMP) data described below included production of irrigated and dryland agriculture and plantations mainly consisting of banana plantations and sugar cane fields.

### Data Sets

Multi-spectral and panchromatic SPOT-5 images of the Tully region were acquired on 04 June 2006 (Figure 1). The images were radiometrically corrected using the SPOT-5 absolute calibration gains and subsequently georeferenced in ERDAS Imagine® 9.0 using 150 reference points (Root Mean Square Error = 3.78 m; maximum error = 7.02 m) derived from the airborne digital image data set presented below. These data were then orthorectified using a 30 m Digital Elevation Model (DEM) where possible and a 90 m DEM for the remaining areas. The SPOT-5 image data consisted of multispectral bands located in the green, red, near infrared (NIR), and mid infrared (MIR) part of the spectrum at 10 m pixels. In addition, a panchromatic band of 2.5 m pixels was provided. The SPOT-5 image data were captured at 30.1° off-nadir due to the urgent need for assessing the destruction in this area caused by a category five tropical cyclone (Cyclone Larry) on 20 March 2006 (Falco-Mammone, 2006). The March to June period in this area experiences extensive cloud cover, hence no cloud-free image data were captured until 04 June. The SPOT-5 image was not atmospherically corrected as time series analysis was not required in this research, nor were the land-cover features to be mapped highly similar in terms of their reflectance values.

Airborne digital images of the Innisfail-Tully region covering the full extent of the SPOT-5 scene were captured on 04, 05, 06, 23, and 26 August 2006 at a scale of 1:5 000 using a Vexcel UltraCam$_D$ digital aerial camera (AEROmetrex, 2006). The airborne images, consisting of blue, green, and red bands of 0.45 m × 0.45 m pixels captured at 12 bits per pixel, were geometrically calibrated prior to delivery using the methods outlined by Honkavaara *et al.* (2006).

A land-use map of Queensland from 1999 outlining the presence of irrigated crops was also used to assist with identification of banana plantations. The data set is a product of the Queensland Land Use Mapping Program (QLUMP) and comprises a digital vector based map at nominal scales of 1:50 000 and 1:100 000, depending on the intensity of land-use in individual catchments. The land-use map was based on Landsat TM and ETM+ image data from 1999 to 2001 with a positional accuracy higher than 50 m, a digital cadastral database, as well as a number of other database sources. Verification of the land-use map was conducted through field data and image interpretation.

A DEM of 90 m × 90 m pixels derived from the Shuttle Radar Topography Mapping (SRTM) Mission was used to identify elevation and terrain characteristics of the banana plantations. The elevation data represent the reflective surface illuminated by the Synthetic Aperture Radar, which may be vegetation, man-made features, or bare earth. The SRTM data used met the absolute horizontal and vertical accuracies of 20 m (circular error at 90 percent confidence) and 16 m (linear error at 90 percent confidence), respectively, as specified for the mission (Rodriguez *et al.*, 2006; Slater *et al.*, 2006).

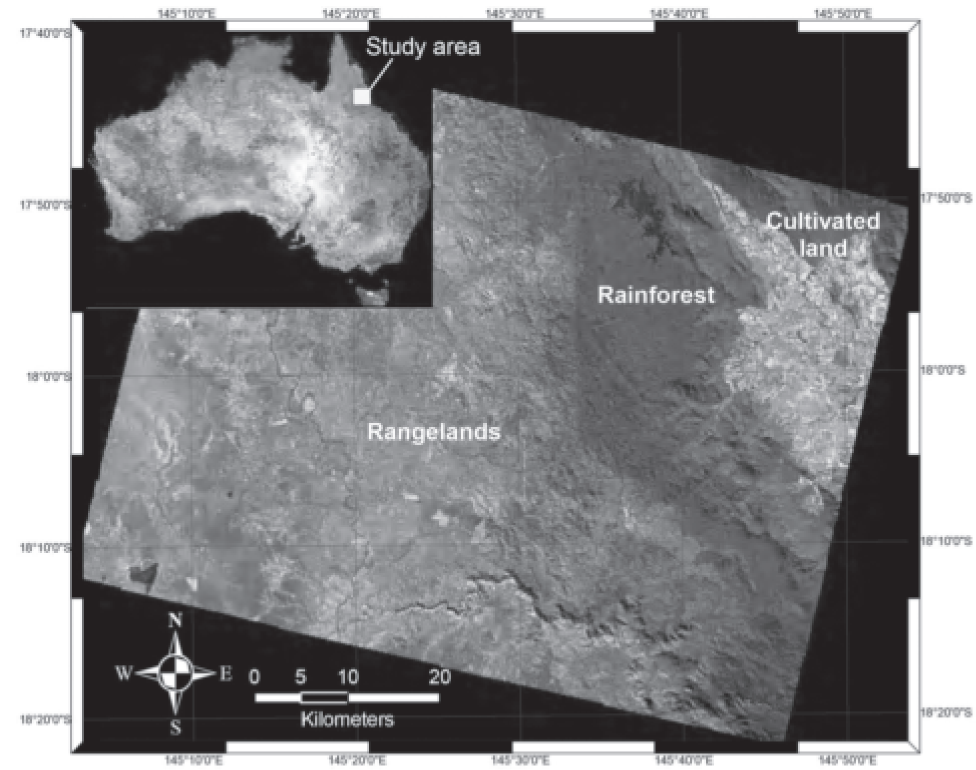


Figure 1. Study area showing the full extent of the SPOT-5 scene located in the Tully region of north Queensland, Australia. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

#### Manual Delineation of Banana Plantations from Airborne Images

The very high spatial resolution airborne image data and the QLUMP data set were used to manually delineate boundaries of banana plantations and visually interpret the plant age. The delineated boundaries used in this research represented banana plantations directly associated with any stage of banana production, from fallow to mature plants, on the same property at the time of airborne digital image capture (August 2006). This process allowed fallow and cultivated land to be recorded in the data set. Field assessment was carried out to confirm the reliability of banana plantation identification and verify mapped boundaries and plant age. Plant age was divided into the following groups: mature, variably aged, young, damaged (caused by Cyclone Larry), and fallow. The map products from the manual delineation were used to calibrate and validate the image classification based on the SPOT-5 image data and for comparison purposes.

#### Image Processing and Object-oriented Mapping

Initially, an image mask for the SPOT-5 image data was produced in Definiens Professional 5 using object-oriented segmentation and image classification to identify cultivated areas. The separability of banana plantations and other land-cover classes were then assessed within the cultivated areas at the object level, i.e., clusters of spectrally homogenous pixels, using both spectral, textural, and spatial pattern information. Based on the separability assessment, image object features (attribute representing certain information concerning an object, e.g., describing spectral, form, or hierarchical properties of an object such as "object area"), membership functions (relationship between feature values and the degree of membership to a class defined by a minimum and maximum value in combination with the function slope), and associated thresholds and intervals were set to map the location of banana plantations in Definiens Professional 5. The map products derived from the SPOT-5 image data were accuracy assessed against stratified randomly selected points derived from the very high spatial resolution airborne image data. Finally, the areal extent of banana plantations mapped from the object-oriented classification using SPOT-5 image data was compared to that of the manual delineation of banana plantations using the airborne image data.

##### *Image Masking*

To reduce data storage and image processing time, an image mask was initially developed to mask out large proportions of the image consisting of rainforest, rangelands, and water bodies. Prior to the segmentation, the pixel size of the SPOT-5 image was resampled to 30 m in ENVI 4.3 (Research Systems, Inc., 2005) using the pixel aggregate function (Bian and Butler, 1999) to decrease the total number of pixels, which significantly reduced the processing time. This produced larger objects more suitable for image masking of broad land-cover classes. The Process Tree in Definiens Professional 5 was used for producing the image mask. The Process Tree in Definiens is used to produce a sequence of processes consisting of algorithms and image objects domains (indicating which objects are included in the process). This enables the user to structure the workflow from the initial segmentation to the final output map (Definiens, 2006). Multi-resolution segmentation with the composition of the homogeneity criterion (which measures how homogeneous or heterogeneous an image object is within itself and is defined by a combination of spectral homogeneity and shape homogeneity) set to 0.9 for color, and 0.1 for shape with compactness and smoothness of 0.5 was used as a parent process to segment the image into spectrally homogenous objects based on the red, NIR, and NDVI bands. The size of the objects produced by the multi-resolution segmentation is determined by the user-defined scale parameter, which is an abstract term that defines the maximum allowed heterogeneity of each object. Using the QLUMP land-use data for training, the segmentation of rainforest, rangelands, and water bodies in the study area required the scale parameter to be set to produce very large objects due to the large spatial extent of these land-cover classes. Spectral difference segmentation merges neighboring objects according to their main layer intensity values. Prior to classification, the spectral difference segmentation process was used to combine adjacent objects with similar spectral properties to maximize spectral homogeneity and create larger objects easier to classify.

A second parent process in the Process Tree was added to perform the classification. A parent process does nothing except executing child processes. Using parent and child processes allows the user to group processes that may be running the same algorithm on different image objects. Creating different parent processes (e.g., for segmentation and classification) makes it easier to structure the processing flow in the Process Tree. Individual child processes were produced for each land-cover class. The first child process was used to map “water bodies” and ‘”not water bodies.” Those areas classified as “not water bodies” were used in a second child process to classify “rainforest” and “not rainforest.” The “not rainforest” areas were then further subdivided by additional child processes into rangelands and then cultivated land. The red, NIR, and NDVI bands and the 90 m SRTM DEM were used to classify the image. Subsequent minor visual editing (approximately 10 minutes) was performed based on visual assessment of the multispectral SPOT-5 image data. The final classification was used to produce an image mask for subsetting the image data to include only cultivated areas, where banana plantations occur.

### *Texture Analysis*

Image based mapping can operate on spectral reflectance and spatial features in an environment. Due to the spatial scale of the SPOT-5 image pixels (10 m), multispectral pixels are larger than individual banana plants, but significantly smaller than the size of an individual banana plantation. As a result, it is not possible to map individual trees, but criteria may be defined based on characteristic spatial patterns or texture found in banana plantations. Individual banana plants were not visible at the 2.5 m pixel size of the SPOT-5 panchromatic band, but identification of the row structure of the banana plantations was possible at this spatial scale

To select a feasible window size for co-occurrence texture analysis, spatial profiles of image pixel digital numbers were produced perpendicular to the row structure of the banana plantations to identify the level of spatial information extractable from different spectral bands. The six spatial profiles based on the green, red, NIR, MIR, NDVI, and panchromatic bands showed that the multi-spectral bands (10 m pixels) had peaks and troughs every 20 to 50 m, while the panchromatic band (2.5 m pixels) had peaks and troughs every 7.5 to 12.5 m (Figure 2). As the red and panchromatic bands provided the most information on spatial changes, these were used for texture analysis. The peaks in digital numbers corresponded to the ground reflectance between each row within the banana plantations, which occurred approximately every 7.5 m. Based on Figure 2 and a semi-variogram analysis of spectral variability within the banana plantations, a window size of $5 \times 5$ pixels for the red and panchromatic bands were used to derive the texture measures. The five pixels in the red (50 m) and panchromatic (12.5 m) bands indicated the distance at which pixels were no longer correlated and hence were related to the size of the largest and most dominant elements within the banana plantations, i.e., several rows of banana plants clustered together (Franklin *et al.*, 1996). To reduce processing time in Definiens Professional 5, the following co-occurrence texture measures were calculated in ENVI 4.3 and subsequently imported into Definiens: variance; homogeneity, dissimilarity, entropy, contrast, second moment, and correlation (Haralick *et al.*, 1973; Research Systems, Inc., 2005).

### *Separability Assessment*

A critical component of object-oriented classification is the examination of separability of individual land-cover classes.

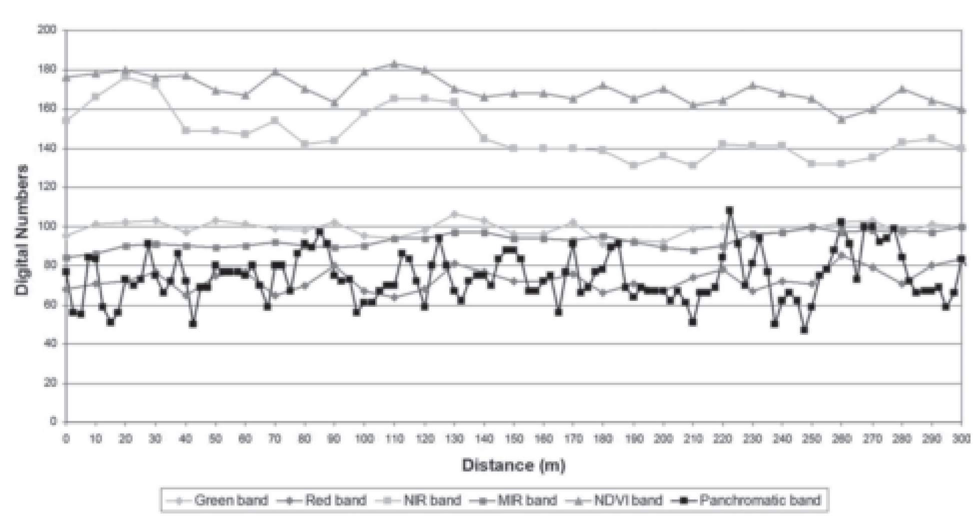


Figure 2. Spatial profiles located perpendicular to the banana plant rows showing the spatial variation in reflectance of six spectral bands.

Definiens provides several tools for both visual and quantitative assessment of the difference in spectral, spatial, and contextual characteristics of individual objects (Feature Viewer, Image Object Information, Feature Space Optimizer, Feature Space Plots, and the Sample Editor). The most suitable of these functions for the separability assessment of banana plantations and non-banana plantations was the Sample Editor, as it can display the histogram and range of multiple samples of each land-cover class and membership function. In addition, the samples for two land-cover classes can be displayed simultaneously for comparison.

To develop a land-cover class hierarchy, the separability of banana plantations in terms of image spectral reflectance and texture for each of the following land-cover classes was first assessed: sugar cane fields, remnant patches of rainforest/riparian vegetation, grasslands, rangelands, cleared areas, fallow land, and water bodies. The separability was assessed at the object level (e.g., banana plantations) by selecting 50 to 60 test training objects for each land-cover class. The bands included in the separability assessment of each land-cover class were the green, red, NIR, MIR, NDVI, and panchromatic bands and the variance, homogeneity, dissimilarity; entropy, contrast, second moment, and correlation texture co-occurrence measures derived from the red and panchromatic bands using a window size of $5 \times 5$ pixels. For each individual land-cover class, all spectral bands were used in the Sample Editor in Definiens to identify the most suitable of the following membership functions: layer mean values per object, standard deviation per object, mean difference to scene per object, ratio to scene per object, minimum pixel values per object, area per object, shape index per object (the border length of the image objects divided by four times the square root of the image objects' area), border index, and rectangular fit. Subsequently, box-and-whisker plots were produced for those bands, land-cover classes, and membership functions that provided the best discrimination between banana plantations and other land-cover classes to depict the median, range, and the 5 and 95 percentiles to determine the level of overlap between land-cover classes (StatSoft, Inc., 2007). The *box-and-whisker* plots were used, as they provided useful information on the level of separation based on the percentiles and identification of outliers, which cannot be derived from the Sample Editor in Definiens. Based on the box-and-whisker plots, the final image bands, membership functions, and their associated thresholds and intervals were selected for optimizing the differentiation between banana plantations and other image objects representing non-banana plantation land-cover classes.

### *Segmentation, Class Hierarchy, and Classification*

Using the masked SPOT-5 image consisting of cultivated land, only one scale parameter was required for mapping individual banana plantations due to their similar size, homogenous internal row structure, and the distinct separation between individual fields (Figure 3). Multi-resolution segmentation with the composition of the homogeneity criterion set to 0.9 for color and 0.1 for shape with compactness and smoothness of 0.5 was used to segment the image based on the NIR (weight = 1), NDVI (weight = 1), and panchromatic (weight = 3) bands (Benz *et al*., 2004). As the panchromatic band provided more distinct separation of banana plantations due to the narrow tracks between each plantation, the panchromatic band was given a weight of three in the segmentation process. The scale parameter analysis function in Definiens Professional 5 was

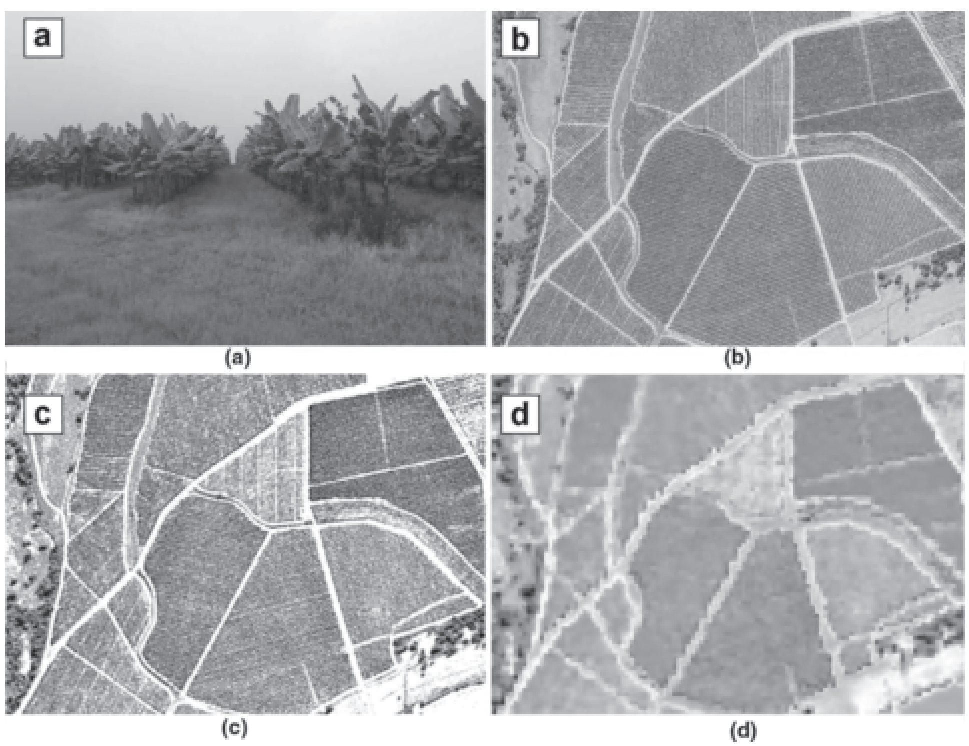


Figure 3. (a) Field photo, (b) airborne image (45 cm pixels), (c) SPOT-5 panchromatic image (2.5 m pixels), and (d) SPOT-5 multi-spectral image (10 m pixels) of banana plantations in the Tully region, Queensland, Australia. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

used to optimize the segmentation so that each banana plantation represented a single object (Definiens, 2006). Membership functions and associated thresholds and intervals derived from the separability assessment were used to classify the SPOT-5 image subset consisting of cultivated areas. In case the box-and-whisker plots of banana plantations and non-banana plantation classes were overlapping based on the training data, thresholds were set to optimize both user's and producer's accuracies of the banana plantation land-cover class. The classified image was further improved by visual editing performed purely on the basis of the panchromatic SPOT-5 band. This was done in Definiens by manually recoding objects that were visually identified as incorrectly classified. Approximately 40 minutes were spent on visual editing.

*Accuracy Assessment*

The accuracy of the classified images both with and without post-classification visual editing was assessed against stratified randomly selected points on the airborne images. The randomly selected points were derived from banana plantations that were confidently identified on the airborne images or verified through in-situ identification. To ensure geometric compatibility between the two image data sets, ground control points used for the accuracy assessment were located at least 10 m from the edge of banana plantations identified in the airborne image data and classified from the SPOT-5 image data set.

### Comparison of Banana Plantations Mapped from Object-oriented Classification of SPOT Imagery and Manual Delineation of Airborne Imagery

The results of the object-oriented classification approach based on the SPOT-5 image data were compared to those results derived from the manual delineation of banana plantations based on the airborne digital image data set. This comparison was conducted in terms of areal extent and location of mapping boundaries of banana plantations. The object-oriented image classifications of banana plantations with and without post-classification visual editing were first exported from Definiens as vector files. The area of intersection between the classified banana plantations and the manually delineated plantations derived from the airborne image data was then calculated to determine errors of omission and commission.

## Results

### Image Mask

An image mask was developed at moderate spatial resolution (30 m × 30 m pixels) to mask out non-cultivated areas within the SPOT-5 image (Figure 4). Based on the QLUMP data set and visual interpretation, the mapping result was effective at separating cultivated areas from rainforest, rangelands, and water bodies. Using the resampled SPOT-5 image significantly reduced the segmentation time in Definiens and improved the separation in the segmentation process between cultivated land and adjacent rainforest. The number of membership functions and their corresponding thresholds required for separating the four land-cover classes (cultivated land, rainforest, rangelands, and water bodies) was significantly reduced compared to that required at a pixel size of 10 m × 10 m due to reduced within-class variability. Figure 5 shows that either one or two image object features were required in Definiens Process Tree to progressively classify each land-cover class when excluding pixels already classified. The SRTM DEM data were useful in identifying the location of rangelands and cultivated areas within the study area, as these areas were located at different elevations within the SPOT-5 image scene.


Figure 4. Map based on multi-spectral SPOT-5 image data resampled to a pixel size of 30 m × 30 m and used for masking out non-cultivated areas. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

### Separability Assessment

The separability of land-cover classes was assessed at the object level by comparing the median, 5 and 95 percentiles, and the range of samples for each land-cover class (banana plantations, other cropped fields, bare ground, water bodies, fallow fields, grasslands, rainforest/riparian zones, and rangelands). Although the image mask was used to isolate cultivated areas, the spatial scale of mapping was too coarse to mask out small remnant patches of rainforest, water in creeks, and small areas of rangelands. The box-and-whisker plots showed that banana plantations and other land-cover classes with significantly different spectral characteristics (bare ground, water bodies, fallow land, and grasslands) could be discriminated using the image object feature based on the mean NDVI difference of individual objects and the scene (Figure 6a). Other crops, the majority being sugar cane, could not be spectrally separated from banana plantations. However,

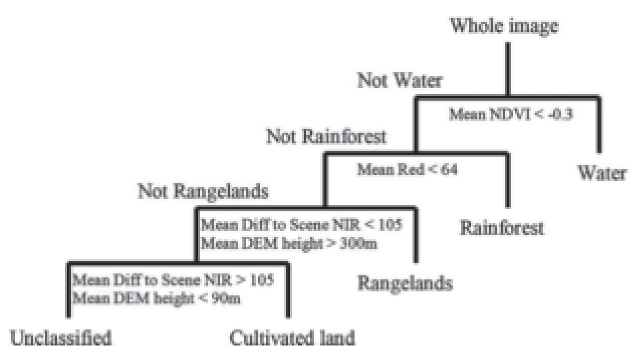


Figure 5. Domains, land-cover classes, image object features, membership functions and thresholds used for development of the image mask in Definiens Process Tree. Land-cover classes on the right hand side of the decision trees obey the membership function thresholds.

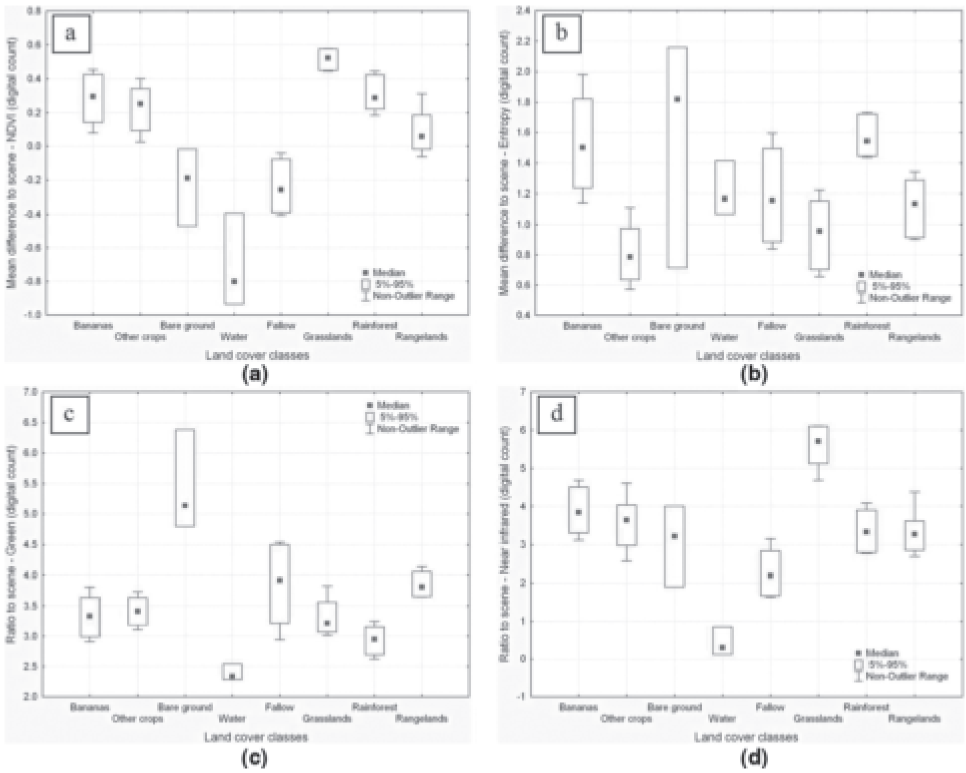


Figure 6. Box-and-whisker plots showing the median, 5 and 95 percentiles, and the range for land-cover classes present within the area classified as cultivated land using the following image object features: (a) NDVI mean difference to scene; (b) entropy man difference to scene; (c) green ratio to scene; and (d) near infrared ratio to scene.

image co-occurrence texture measures such as entropy calculated from windows of 5 $\times$ 5 pixels in the panchromatic band were found effective for separation due to the distinct row structure of the banana plantations (Figure 6b). In the majority of cases (54 out of 58), image objects consisting of rangelands could be discriminated from banana plantations using the green band when calculating the ratio of the object to the scene (Figure 6c). Grasslands could be discriminated from banana plantations using the NIR ratio to scene (Figure 6d). Remnant patches of rainforest and riparian zones were found to have very similar spectral and spatial characteristics to mature banana plantations, while those plantations with young or damaged banana plants had different green and NDVI reflectance values. Contextual features, such as area, shape index, and rectangular fit, and their corresponding membership functions provided additional separation between banana plantations and the other land-cover classes. The image object features and membership functions used in the final classification were determined based on the separability analysis (Table 1). It was found that all the image object features and associated membership functions and thresholds were required for mapping the banana plantations within the cultivated area. However, only a subset of these features was required for individual areas covering smaller spatial extents. Both spectrally and spatially, fallow banana plantations could not be automatically separated at the object level from fallow areas of other crops (mainly sugarcane).

Table 1. Image Object Features, Membership Functions and Thresholds and Range Values used in the Final Classification

| Image object features | Membership function | Value |
|---|---|---|
| Object area | Threshold | $<$11,000m$^2$ |
| Minimum value of object, NIR | Interval | 12 - 159 |
| Shape index | Interval | 1.225 - 2.729 |
| Rectangular fit | Interval | 0.4217 - 0.9803 |
| Mean value of object, Green | Interval | 87.6 - 117.35 |
| Mean value of object, MIR | Interval | 70.82 - 122.13 |
| Mean value of object, NDVI | Interval | 0.1 - 0.573 |
| Mean value of object, Second moment | Interval | 0.0862 - 0.2492 |
| Mean difference to scene, NDVI | Interval | 0.05 - 0.498 |
| Mean difference to scene, Entropy | Interval | 1.05 - 2.142 |
| Ratio to scene, Green | Interval | 2.903 - 4.021 |
| Ratio to scene, NIR | Interval | 3.15 - 5.183 |

### Classification and Accuracy Results With and Without Visual Editing

Banana plantations were classified based on the separability assessment (Table 1) of the land-cover classes present within the area initially classified as cultivated land (Figure 7). The enlarged area in Figures 7 and 8 shows some fallow banana plantations as well as some plantations with young re-growing banana plants. Most of the banana plantations consisting of

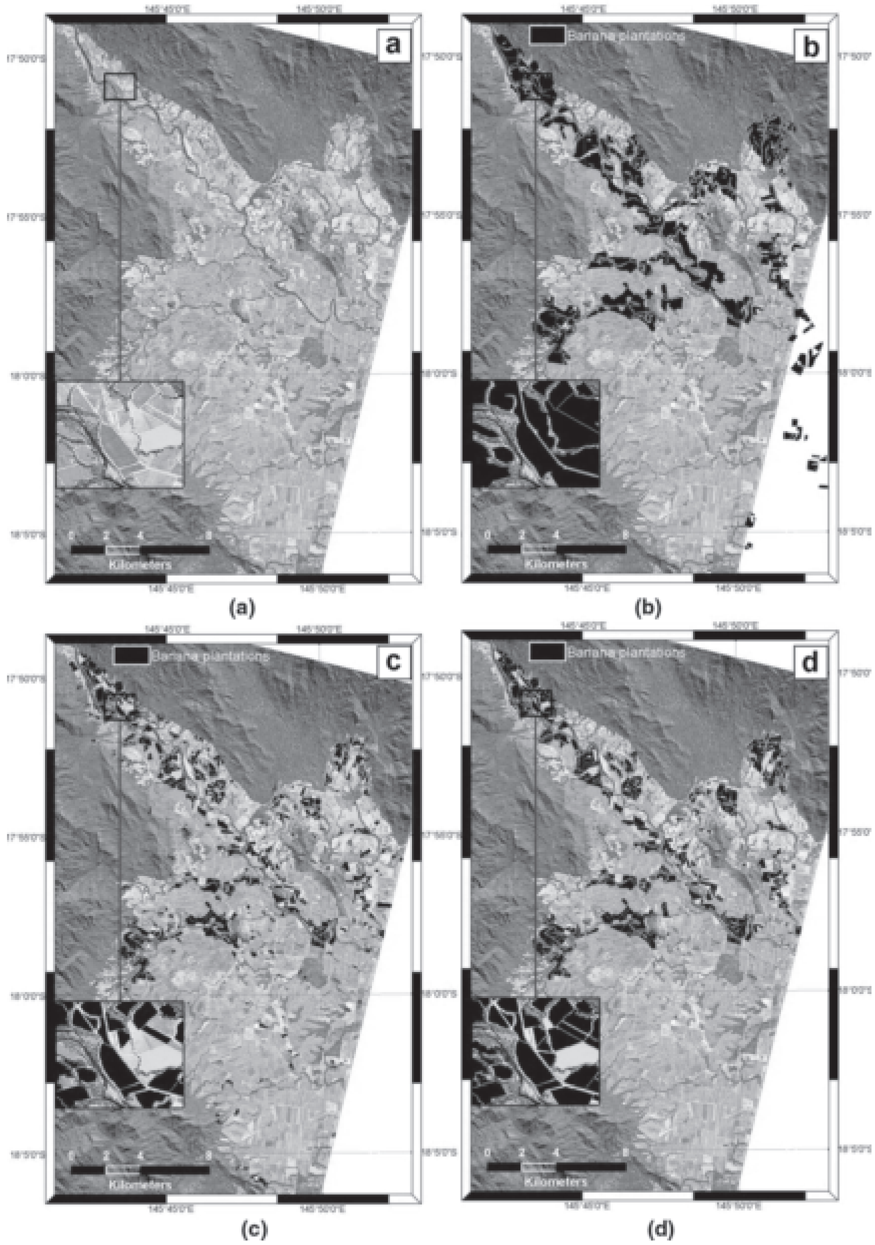


Figure 7. Maps showing (a) cultivated land within the study area, (b) areas delineated as banana plantations using manual airborne image interpretation, (c) areas classified as banana plantations using the object-oriented approach in Definiens, and (d) areas classified as banana plantations using the object-oriented approach in Definiens with subsequent visual editing. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

mature banana plants could be classified using the object-oriented classification. However, those banana plantations with young regrowth banana plants or damaged plants (from Cyclone Larry in March 2006) were not automatically mapped. Subsequently, visual editing enabled identification of most of these plantations in the panchromatic SPOT-5 image (Figure 8). The fallow banana plantations could not be discriminated from other fallow agricultural fields using either the panchromatic or the multi-spectral SPOT-5 image data. Some smaller banana plantations or parts of plantations located next to riparian zones were not classified as banana plantations as these were found within image objects consisting of a combination of riparian vegetation and banana plantations because of the similarity in spectral and textural characteristics of these two land-cover classes (Figure 8b; the dotted polygon).

The accuracy of the object-oriented SPOT-5 image classification with and without visual editing was assessed against randomly selected points from the reference map derived from the airborne image data. As the fallow banana plantations could not be identified in the SPOT-5 image data, these were not included in the accuracy assessment. Using the object-oriented classification approach in Definiens

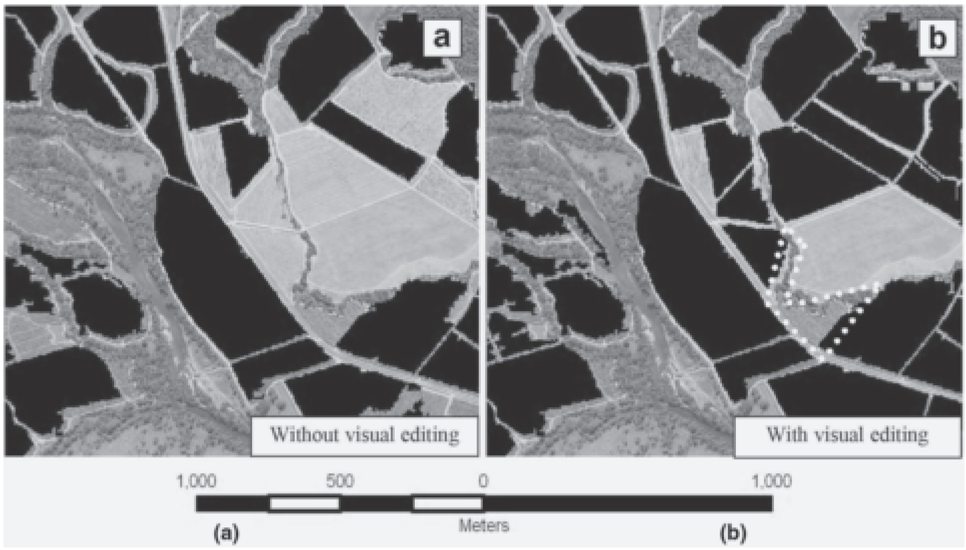


Figure 8. Subsets of the object-oriented image classification (a) without visual editing, and (b) with visual editing overlayed on the airborne image data. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

TABLE 2. PRODUCER'S ACCURACIES AND ERRORS OF OMISSION OF THE OBJECT-ORIENTED CLASSIFICATION OF BANANA PLANTATIONS

| | | Reference data | |
|---|---|---|---|
| | | No visual editing Banana plantations | Visual editing Banana plantations |
| Classified data | Banana plantations | 323 | 390 |
| | Non-banana plantations | 98 | 31 |
| | Total | 421 | 421 |
| | Producer's accuracy | 76.72% | 92.64% |
| | Error of omission | 23.28% | 7.36% |

TABLE 3. USER'S ACCURACIES AND ERRORS OF COMMISSION OF THE OBJECT-ORIENTED CLASSIFICATION OF BANANA PLANTATIONS

| | | Classified data | |
|---|---|---|---|
| | | No visual editing Banana plantations | Visual editing Banana plantations |
| Reference data | Banana plantations | 489 | 545 |
| | Non-banana plantations | 182 | 32 |
| | Total | 671 | 577 |
| | User's accuracy | 72.88% | 94.45% |
| | Error of commission | 27.12% | 5.55% |

produced producer's accuracies of 92.64 percent and 76.72 percent with and without post-classification visual editing, respectively (Table 2). The user's accuracies were 94.45 percent and 72.88 percent, respectively, for the image classification with and without visual editing (Table 3).

### Comparison of Manual Delineation from Aerial Images and Image Segmentation/Classification of Banana Plantations

The results of the comparison of areas mapped as banana plantations in the SPOT-5 and airborne image data showed that 86.19 percent (25.59 km$^2$ / 29.69 km$^2$) of banana plantation areas classified and visually edited based on the SPOT-5 image data overlapped the manually delineated banana plantations based on the airborne image data. A total of 80.54 percent (25.59 km$^2$ / 31.78 km$^2$) of the manually delineated area overlapped the banana plantations classified and manually edited from the SPOT-5 image data (Table 4). These levels of overlap were only achieved when including the panchromatic SPOT-5 image data (2.5 m pixels), as textural information from the plantation row structure were lost using the multi-spectral bands (10 m pixels).

Generally, the fallow plantations could not be identified from the SPOT-5 image data. Table 4 and Figure 9 show the effects that the inclusion of fallow areas in banana plantations had on the overall area mapped and the effect of the visual editing of the object-oriented classification of the SPOT-5 image data. Including fallow areas such as uncropped plantations and surrounding tracks and other features in close proximity to the banana plantations significantly increased the area mapped as banana plantations (31.78 km$^2$ to 41.04 km$^2$). Gaps between plantations were not classified as banana plantations using the object-oriented classification approach, but were included in the manual delineation of the airborne image data (Figure 10a). This resulted in overestimation of the area of banana plantations manually delineated from the airborne image data, which would not need to be included for a plant area application, as this would lead to overestimates of plant related features, e.g., canopy cover and biomass.

Visual editing of the banana plantations mapped from the SPOT-5 image data made a significant difference to the area estimate derived, irrespective of whether or not fallow areas were included in the definition of banana plantations (Table 4 and Figure 9). The visual editing mainly involved

TABLE 4. OVERLAPPING AREAS OF BANANA PLANTATIONS CLASSIFIED FROM THE SPOT-5 IMAGE DATA AND MANUALLY DELINEATED FROM THE AIRBORNE IMAGE DATA

| | | SPOT-5 image data | |
|---|---|---|---|
| | | Area classified as banana plantations with visual editing = 29.69km$^2$ | Area classified as banana plantations with no visual editing = 29.95km$^2$ |
| Airborne image data | Area of manually delineated banana plantations excluding fallow land = 31.78km$^2$ | 25.59km$^2$ | 20.72km$^2$ |
| | Area of manually delineated banana plantations including fallow land = 41.04km$^2$ | 27.21km$^2$ | 21.91km$^2$ |

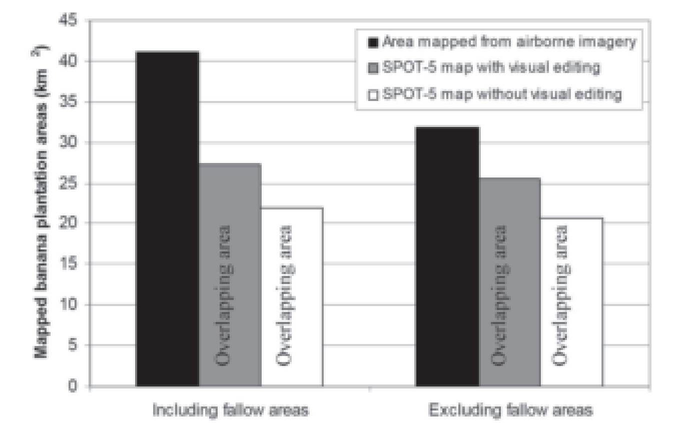


Figure 9. Areas of banana plantations mapped from manual delineation of the airborne images (both including and excluding mapping of fallow areas) and the overlapping plantation areas derived from object-oriented processing of SPOT-5 image data. Plantation area estimates from the SPOT-5 imagery are presented both with and without post-classification visual editing.

adding plantation areas in the image that were missed by the object-oriented mapping approach. The areas of omission included plantations mainly with young and damaged banana plants. Areas of commission only occurred in few instances, where banana plantations were located next to riparian areas. Small temporal changes had occurred in the time gap between the SPOT-5 image capture (04 June 2006) and the acquisition of the airborne image data (August 2006). For example some damaged banana plantations had been cleared between June and August (Figure 10b). However, the identified amount of changes in the time gap between the image captures (<0.4 km$^2$) did not affect the results significantly.

## Discussion

### Mapping of Banana Plantations from SPOT-5 Image Data

The assessment of land-cover class separability at the object level showed that there is a trade-off between user's and producer's classification accuracies, i.e., a choice between mapping all banana plantations at a medium accuracy and mapping only some plantations at a highly accurate level. In this study, user's and producer's accuracies were balanced to obtain approximately equal levels of accuracy by adjusting the thresholds and intervals of the membership functions. Some plantations with banana plants of variable age, or consisting of damaged or young banana plants were not identified, as these caused confusion between other crops and fallow land. Differences between the areal extent of banana plantations mapped by the object-oriented classification approach and the manual delineation method were identified. Geometric mis-registration between the two image data sets was smaller than 7.02 m with an average displacement of 3.78 m, but could have contributed to differences in the comparison of the two data sets. Banana plantations were in some cases merged with riparian zones in the segmentation process when located next to each other, as both land-cover classes had spectrally and texturally low contrast relative to each other. Mueller *et al.* (2004) also found that low brightness contrast between neighboring objects can cause under-segmentation. Conversely, variation within banana plantations larger than the homogeneity threshold set by Definiens' scale parameter caused over-segmentation (segmenting areas with the same land-cover classes into multiple objects) in some cases, where parts of plantations consisted of damaged banana plants.

The off-nadir angle of 30.1° of the SPOT-5 image data caused an increase in the effective pixel size and hence reduced the ability to identify a clear row structure within some mature banana plantations. The off-nadir angle may also have reduced the spectral variation in the multi-spectral bands. The regular structure of the plantations could be seen in the panchromatic band, but the spatial resolution of the multi-spectral bands was too low to discriminate the 7.5 m structure. This was evident in the spatial profile in Figure 4, where reflectance peaks did not appear every 7.5 m, which was the approximate distance between rows measured from the airborne image data. The classification results may be improved if the image data are captured close to nadir. Addition of clues such as distance to water bodies or riparian vegetation indicating a source of water for irrigation may also improve mapping accuracies, as objects mapped as banana plantations in areas with no drainage network are likely to be incorrectly classified.

The developed approach worked in terms of mapping banana plantations, as the segmentation in Definiens allowed characteristic scales of features to be mapped, e.g., the plant-row structure in banana plantations is highly characteristic and evident in panchromatic SPOT-5 data and higher spatial resolution data. At the pixel level, each plantation contained a multitude of spectrally different pixels, but averaged at the object level, unique information on the banana plantations was derived and used for mapping. Similar instances of this type of combined feature mapping are found in Bock *et al.* (2005), Gamanya *et al.* (2007), and Mueller *et al.* (2004). The approach did not work when trying to assess more detail than the broad cover types, e.g. individual tree characteristics and detection of earlier growth stages of banana plants. Higher spatial resolution multi-spectral sensors such as QuickBird and Ikonos should provide more suitable data for

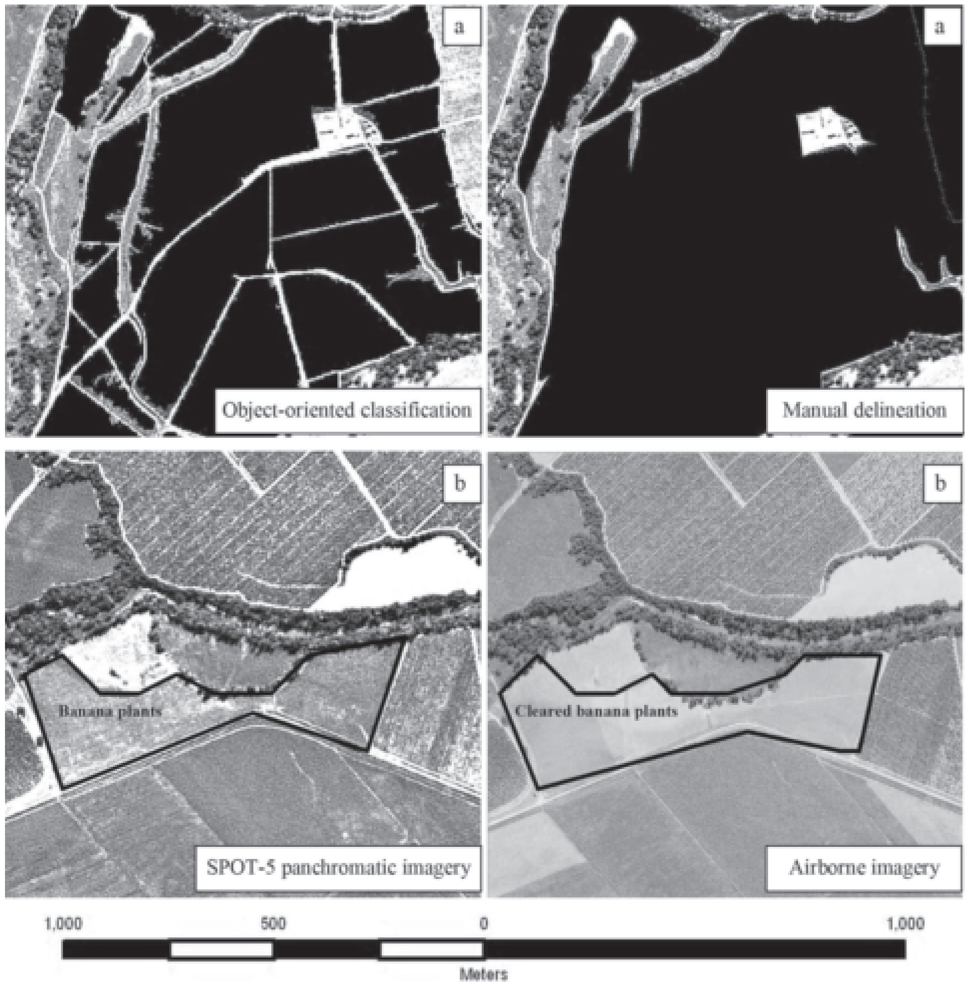


Figure 10. (a) Difference between the object-oriented classification based on SPOT-5 image data and manual delineation from airborne image data; (b) Presence of banana plants on the SPOT-5 image data (04 June 2006) and clearing of banana plants on the airborne image data (August 2006). A color version of this figure is available at the ASPRS website: **www.asprs.org**.

this scale of application and enable individual tree canopies and inter-row spacing to be assessed in more detail.

This increased level of detail from higher spatial resolution image data is also likely to improve the detection of variably aged and damaged banana plantations, as plantations with banana plants of different ages, e.g., young versus mature banana plants, would be both spatially and spectrally different. Therefore, banana plantations with different characteristics would have to be treated as separate land-cover classes to avoid a large interval range of membership functions. Generally, the larger the interval range is, the more likely it is that the interval range will overlap those of other land-cover classes, and hence, prevent discrimination of individual land-cover classes (Brandtberg, 2002). The mapping of (a) mature, (b) young, (c) variably aged, and (d) damaged banana plants at the object level with high spatial resolution image data would most likely require these growth stages to be mapped as separate land-cover classes using different features, membership functions, and certainly different thresholds and intervals to find unique spectral, spatial, and contextual characteristics of each land-cover class. However, this theory is still to be tested with object-oriented image classification of banana plantations. Furthermore, the level of discrimination of different stages of banana plant growth will depend on the characteristics of other land-cover classes present in the area to be mapped. If this knowledge gap is addressed, it is likely to have application not just for mapping banana plantations, but many other types of plantation and horticultural productions exhibiting distinct spectral, textural, or contextual characteristics at the object level.

#### Future Opportunities for Banana Plantation Mapping

The manual delineation mapping based on airborne digital image data of 0.45 m pixels created the foundation for establishing a database including information on banana plantations, location, area, and plant age. This research shows the importance of using high spatial resolution image data for object-oriented image classification to achieve mapping accuracies feasible for the banana industry. The SPOT-5 panchromatic band was essential for mapping banana plantations. Both airborne hyperspectral and light detection and ranging (lidar) data sets may be used for mapping banana plantations with high accuracies, but are less likely to gain widespread application because of the limited availability of hyperspectral image data and the acquisition costs of lidar data. Higher accuracies are also likely to be achieved using high spatial resolution QuickBird and Ikonos image data, as these image data enable clear identification of the row structure of banana plantations. Some of the commonly-used airborne digital cameras such as the Zeiss/Intergraph DMC, Vexcel Ultracam$_D$ and Ultracam$_X$, and Leica Geosystems ADS40 cameras (Johansen *et al.*, 2008) may also be important data sources for banana plantation mapping applications. These multispectral sensors could be used for regularly updating a database on banana plantations, but also expand the application of remotely sensed image data towards crop management, disease control, production yield, and related income prediction for banana growers. The method presented in this research is considered transferable to other high spatial resolution image data sets allowing analysis of the image texture of banana plantations. Some banana plantations within the SPOT-5 image used for this research had suffered cyclone damage prior to image capture. This produced several growth stages of banana plants, which lowered the mapping accuracy. Hence, other high spatial resolution image data sets captured of areas consisting mainly of mature, and hence homogenous, banana plantations are likely to produce similar or better results than those presented in this research. A database including ancillary information such as management practices, yield, plant age, soil type, monthly precipitation, and level of irrigation could potentially be used to develop algorithms for prediction of yield and for crop management optimization. Similar approaches have been proposed for citrus plantations in Florida, USA (Shrivastava and Gebelein, 2007).

## Conclusions and Futur e Work

The mapping of banana plantations worked well as spectral, textural, and contextual characteristics provided distinct information at the object level, i.e., homogenously segmented clusters of pixels the size of the individual plantations. Separation of banana plantations and other land-cover features with spectrally similar characteristics at the object level (e.g., sugarcane fields) required textural information derived from the SPOT-5 panchromatic band to enable differentiation. The row structure of the banana plantations produced distinct textural information at the object level. Context relationships, such as object area and shape, added further information to the object-oriented classification, while elevation data were useful for separation of large spatial scale land-cover classes. However, to increase the user's and producer's accuracies to >90 percent, post-classification minor visual editing (approximately 40 minutes) based on the panchromatic band (2.5 m pixels) was required.

The comparison of the manually delineated banana plantations based on the airborne image data and those classified from the SPOT-5 image data using object-oriented classification and post-classification visual editing showed that plantations with damaged, young or variably aged banana plants were difficult to identify at the object level. This was because of the "limited" spatial resolution of the SPOT-5 image data, which did not provide the required level of detail necessary for mapping of different growth stages of banana plants. Fallow banana plantations could not be reliably separated from fallow sugarcane fields.

This study showed a high potential for partial automation of the banana plantation mapping process from remotely sensed image data. However, a requirement is the use of high spatial resolution image data with pixels ≤2.5 m captured close to nadir for inclusion of additional textural information. Both hyperspectral and light detection and ranging (lidar) data sets may be used for mapping banana plantations with high accuracies, but are less likely to be used because of the limited availability of hyper-spectral image data and the acquisition costs of lidar data. Future work should focus on (a) testing high spatial resolution satellite image data such as QuickBird and Ikonos data, and (b) mapping different characteristics of banana plantations as individual land-cover classes, i.e., different growth stages, to avoid confusion between other land-cover classes.

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