

# OBJECT-ORIENTED CHANGE DETECTION OF RIPARIAN ENVIRONMENTS FROM HIGH SPATIAL RESOLUTION MULTI-SPECTRAL IMAGES

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## ABSTRACT:

The objectives of this research were to: (1) develop rule sets in Definiens Developer 7® for mapping and monitoring riparian zone land-cover classes within two QuickBird images; and (2) compare the results of four object-oriented and pixel-based change detection approaches. Two QuickBird images, atmospherically corrected to at-surface reflectance, were captured in May and August 2007 for a savanna woodlands area along Mimosa Creek in Central Queensland, Australia. In-situ vegetation structural measurements and LiDAR data, obtained on 28 May - 5 June and 15 July 2007 respectively, were used for calibration and validation. A sequential segmentation routine was applied to enable segmentation of large image datasets. An Isodata unsupervised classification was used for pixel-based classification and rule sets were developed for object-oriented classification of the following land-cover classes: streambed; riparian vegetation; bare ground; rangelands; and woodlands. Four object-oriented and pixel-based change detection routines were applied to the image data: post-classification comparison; image differencing; image regression; and the tasselled cap transformation. The object-oriented classification results showed that object- and class-related features and membership functions could be standardized in the rule sets for classifying the two QuickBird images. Results from the different change detection approaches indicated that post-classification comparison and image differencing produced more accurate results, especially when used together. All four change detection approaches were suited to object-oriented analysis. Advantages of the object-oriented change detection routines included: (1) no need for post-change detection filtering and smoothing; (2) less impact of slight geometric offsets between image datasets; and (3) the ability to include context relationships to improve change detection results.

## 1. INTRODUCTION

The increased use of high spatial resolution image data (pixels < 5m x 5m) has produced a need for more research using object-oriented approaches, as traditional per-pixel analysis is not suited to high spatial resolution image data because of the high level of variance of spectral reflectance signatures within individual features and land-cover classes. Image data of the Earth's surface can be divided into homogenous objects at a number of different spatial scales. Object-oriented image segmentation and classification use this concept to divide image data into a hierarchy, where large objects consist of several smaller objects. This matches up with the widely accepted notion of hierarchy theory and spatial scales of ecological features from plants to global scales (Wiens, 1989). 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. Object-oriented image classification typically consists of three main steps: (1) image segmentation; (2) development of an image object hierarchy based on training objects; and (3) classification (Benz et al., 2004). 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). The inclusion of context relationships and shape of objects are important sources of additional information because most high spatial resolution image datasets consists of only four multi-spectral bands and a panchromatic band.

Change detection techniques identify differences in the landscape occurring over time from two or more image datasets (Coppin et al., 2004). There have been limited attempts to compare object-oriented and pixel-based change detection approaches. Im et al. (2008) presented a comparison of object-oriented and pixel-based change classification incorporating neighbourhood correlation images and found that the object-oriented change classification produced higher accuracies than per-pixel classification when all other conditions were held constant. Desclee et al. (2006) investigated the utility of object-oriented methods for forest change detection and found that the change detection accuracies achieved by the object-oriented method were higher than pixel-based methods regardless of the validation data source. Im et al. (2008) pointed out that future research should investigate the application of multi-resolution image segmentation in object-oriented change detection.

The aim of this research was to compare the results of object-oriented and pixel-based mapping approaches with focus on four different change detection techniques. The change detection approaches included post-classification comparison, image differencing, image regression and the tasselled cap transformation. Classified images were first produced using both object-oriented and pixel-based techniques and then applied to the post-classification comparison routine. The object-oriented and pixel-based techniques were embedded in the change analysis for the remaining three change detection approaches. The objectives of this research were to: (1) develop rule sets in Definiens Developer 7 for mapping and monitoring riparian zone land-cover classes within two QuickBird images;

and (2) compare the results of object-oriented and pixel-based change detection approaches. As the two images used were captured less than three months apart, no land-cover change in the imaged area was expected. Hence, the focus of this work was to compare the results of object-oriented and pixel-based change detection approaches rather than mapping actual change. The results of the work are considered applicable to other land-cover classes and will therefore provide information that can be used to determine the advantages, disadvantages and the suitability of object-oriented and pixel-based analysis using different change detection techniques.

## 2. STUDY AREA

The study area was located within the Fitzroy Catchment, Queensland, Australia and covered a 19km stretch of Mimosa Creek and associated riparian vegetation 10km upstream of the junction with the Dawson River (24°31'S; 149°46'E). Extensive clearing of surrounding woody vegetation has occurred in the past and transformed large areas into open woodland, here referred to as rangeland. However, patches of remnant woodland vegetation remain and regrowth is common. The major land use is grazing with some agriculture also occurring. The area receives on average 600-700mm of rain with the majority of rain between October and March. The stream and riparian zone widths of Mimosa Creek were in most cases between 10-30m and 15-80m, respectively.

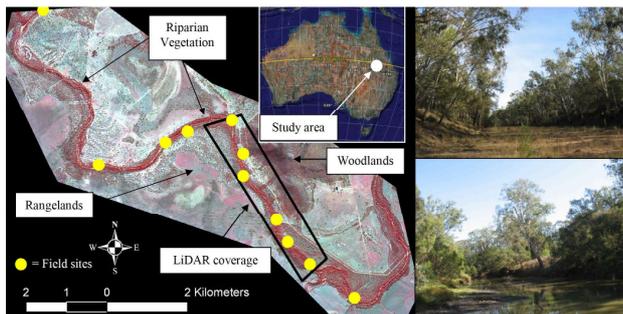


Figure 1. Location of study area, LiDAR coverage, and field sites. Photos show the riparian zone along Mimosa Creek.

## 3. DATA AND METHODS

### 3.1 Image and Field Data

Two multi-spectral QuickBird images were captured of the study area on 18 May 2007 and 11 August 2007 with off-nadir angles of 20.0° and 14.6° respectively. The images were radiometrically corrected to at-sensor spectral radiance based on pre-launch calibration coefficients provided by DigitalGlobe. The FLAASH module in ENVI 4.3 was then used to atmospherically correct the August image to at-surface reflectance, with atmospheric parameters derived from the MODIS sensor and the Australian Bureau of Meteorology. Four pseudo-invariant features, with dark, moderate, and high reflectance, were used to produce a linear regression function to normalise the May image to at-surface reflectance (Jensen, 2005). A total of 18 ground control points (GCPs) derived in the field were used to geometrically correct the August image (root mean square error (RMSE) = 0.59 pixels). The AutoSync function in Erdas Imagine 9.1 was used to automatically select 300 GCPs to geo-reference the two QuickBird images. GCPs with a RMSE > 0.8 pixels were omitted from the rectification.

Light Detection and Ranging (LiDAR) data were captured by the Leica ALS50-II on 15 July 2007 for a 5km stretch along Mimosa Creek (Figure 1). The LiDAR data were captured with an average point spacing of 0.5m and consisted of four returns with an average point density of 3.98 points/m<sup>2</sup>.

In-situ vegetation structural measurements were obtained from 28 May – 5 June 2007 within the riparian zone and the areas where riparian vegetation was merging into woodland vegetation or rangelands (Figure 1). Quantitative field measurements of ground cover, plant projective cover, trunk diameter, vegetation overhang, bank stability, creek width, and riparian zone width were obtained.

### 3.2 Image Processing Methodology

The two QuickBird images were first segmented and classified into major land-cover classes. The developed rule sets used for the classification were then compared to assess their general applicability for classifying different image datasets. The next stage focussed on comparing differences in the results of four object-oriented and pixel-based change detection techniques. Comparisons were then made between the per-pixel and object-oriented results for each change detection approach, and then between the different change detection approaches.

**3.2.1 Image Segmentation and Classification:** The QuickBird images were segmented in Definiens Developer 7 using a sequential segmentation to avoid exceeding the maximum allowable number of objects in the first multi-resolution segmentation cycle. The green, red, and NIR bands from both QuickBird images were used together in the segmentation process to avoid misalignments of objects between images in areas without change to reduce erroneous detection of change along boundaries of land-cover classes (Johansen et al., in press). The sequential segmentation approach involved a number of individual steps (Figure 2a-h). First the image was segmented into large squares consisting of 1000 pixels x 1000 pixels (Figure 2a-b). Each of these squares were then segmented one at a time using multi-resolution segmentation with a scale parameter of 30 (Figure 2c-d). Objects in contact with the separating line of the large squares (Figure 2e) were re-segmented using a scale parameter of 60 to eliminate effects from the line on the objects (Figure 2f). Those objects that did not touch the line of the large squares were also re-segmented using a scale parameter of 60 to ensure a consistent spatial scale of objects (Figure 2g-h). The segmentation divided the multi-spectral image pixels (6,800,000) into a total of 51,003 objects.

A rule set was then developed independently for each of the two QuickBird images to classify the following land-cover classes: (1) riparian vegetation; (2) streambed; (3) woodlands; (4) rangelands; and (5) bare ground. The field and LiDAR data were used for training. Both object- and class-related features were used together with different membership functions and associated thresholds. The features, membership functions and thresholds required for classifying the two images were compared to assess the general applicability of the rule sets for object-oriented image classification.

Pixel-based image classification of the two QuickBird image were all carried out based on Isodata unsupervised image classification of the same land-cover classes. To avoid any bias in the comparison of the object-oriented and pixel-based comparison, the pixel-based classification was based on the same bands as the object-oriented classifications, i.e. blue, green, red, NIR, NDVI, and standard deviation of the NIR band.

However, the standard deviation band was excluded as it prevented accurate mapping of bare ground. The field and LiDAR data were used for labelling the 50 Isodata classes. A majority filter of 7x7 pixels was used for each image classification to reduce the salt-and-pepper effect prior to post-classification comparison.

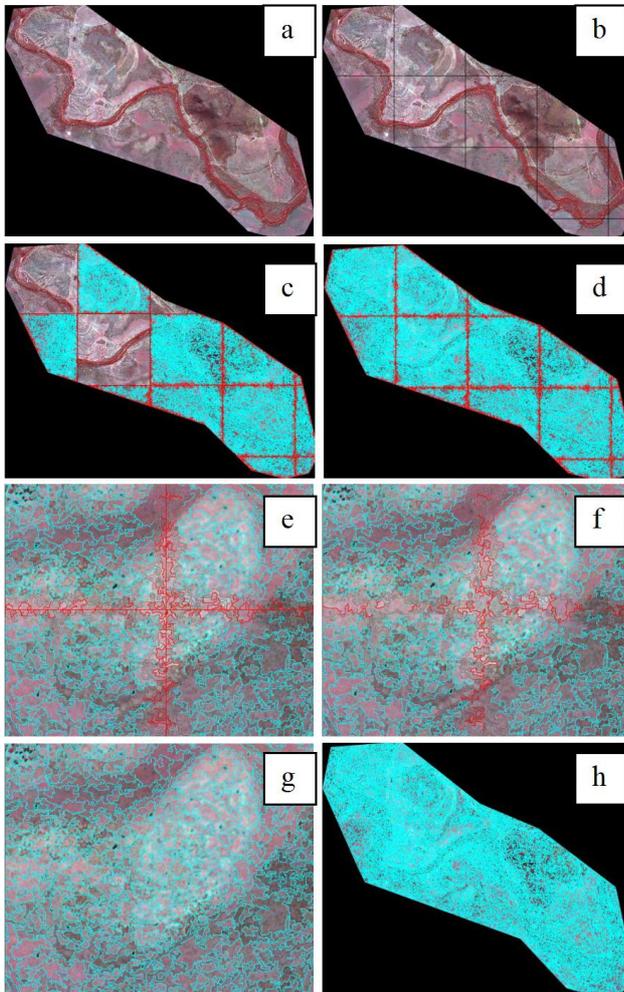


Figure 2. Sequential segmentation routine showing the individual stages of dividing the original image into objects.

**3.2.2 Post-Classification Comparison:** The object-oriented image classifications of the two QuickBird images were used for post-classification comparison. Riparian vegetation changes occurring in the object-oriented post-classification comparison were compared to the corresponding pixel-based post-classification comparison. As no change in land-cover classes was expected between the two images, the field data and the LiDAR data were considered suitable for validation. The labelled unsupervised per-pixel classifications were used as input into the pixel-based post-classification comparison.

**3.2.3. Image Differencing:** Image differencing was used to subtract the blue, green, red, NIR, and NDVI bands of the May image from those of the August image. The pixel-based image differencing subtracted all image pixel values in the May image from the pixel values at the corresponding location in the August image for each band. The same approach was used for the object-oriented image differencing, where the mean value of each object (average value of all pixels within each object) in the May image was subtracted from the corresponding objects

in the August image. Thresholds for different levels of change were set based on trial and error.

**3.2.4 Image Regression:** Image regression describes the fit between two images captured at different times of the same area. The approach assumes that pixels/objects in one image are linearly related to the corresponding pixels/objects in the other image, i.e. the majority of pixel/object values have not changed between the time of the two image captures. The spectral reflectance of the August image was estimated using the May image and the best-fit regression equation between the two image datasets for each band. In the object-oriented approach, all 51,003 mean object values were included in the image regression of the blue, green, red, NIR, and NDVI bands. For the pixel-based approach a representative subset of 315,000 pixels was used in the image regression. The dimension of the residuals was then used as an indicator of the level of change. The standard deviation of the residuals was used to set a threshold for change.

**3.2.5 Tasseled Cap Transformation:** The multi-temporal generalisation of the tasseled cap transformation by Collins and Woodcock (1994) was used for both the object-oriented and pixel-based change detection. The reflectance values of twenty of the darkest objects/pixels (mainly areas with deep shadow or water) that had not changed between May and August were averaged and used as the origin of a new coordinate system. Twenty of the brightest unchanged objects/pixels and 20 of the unchanged objects/pixels with the highest NDVI values were used to produce an unchanged brightness axis and greenness axis. Ten objects/pixels showing the highest increase in NDVI values between May and August were then used to create a NDVI change vector through the origin perpendicular to the plane of the unchanged brightness and greenness axes. These were visually inspected to ensure that changes were not occurring due to image mis-registration. The tasseled cap transformation coefficients were applied in Definiens by defining three new arithmetic features: unchanged brightness, unchanged greenness, and vegetation changes. The pixel-based algorithms were calculated in the Modeler in Erdas Imagine 9.1. This produced images consisting of three bands, where the third band represented vegetation change. A threshold to identify change was set at 200 based on visual assessment.

**3.2.6 Comparison of Change Detection Results:** Based on the results of the four change detection routines, advantages and disadvantages were identified in relation to using object-oriented and pixel-based techniques. The combined utility of the post-classification comparison and the image differencing was also assessed using areas of land-cover change to develop a mask to examine the variation between the two images in NDVI values in areas classified as change in the post-classification comparison. Finally, the change detection results of the four different techniques used were compared.

## 4. RESULTS AND DISCUSSION

### 4.1 Object-Oriented Image Classification

The results of the object-oriented classification of the two QuickBird images revealed that similar features and membership functions could be used for both dates, but different thresholds for the membership functions were required for object-related features (Table 1). However, the standard deviation of the NIR band was required in the August image but not the May image for mapping rangelands. This was because

of spectral overlap in NDVI values between rangelands and woodlands in August. Very little rain fell in the three months prior to the first image capture, while the study area received over 100mm in June, which affected the greenness of groundcover in August. However, it did not appear sufficient to create any water bodies within the creek. An obvious reduction in NDVI and NIR reflectance of the riparian canopy could be observed in the August image. As indicated in Table 1, the same membership functions and thresholds could be used for the class-related contextual features for both images, which show capacity for rule set standardization. Streambeds could not be spectrally classified in the pixel-based classification. Assessing the relative area of riparian vegetation within a local area (10 pixel radius) enabled reclassification of bare ground to streambed, when more than 55% of the local area with bare ground consisted of riparian vegetation. Other context relationships such as assessment of the relative border of classified image objects were useful in improving the object-oriented image classification.

#### 4.2 Change Detection Results

Because of the small time gap (< 3 months) between the two image acquisition dates, no change in land-cover was expected between the two images. A total of 713,481 pixels were classified by the object-oriented approach as riparian vegetation in either the May or August image. The corresponding pixels were evaluated for the pixel-based post-classification comparison. Only 34.69% of pixels were classified as no change in the pixel-based change detection, while 81.44% showed no change in the object-oriented change detection. A total of 418,019 pixels were classified by the pixel-based approach as riparian vegetation in either the May or August image. Out of these 51.44% of pixels were classified as no change in the pixel-based change detection, while 92.49% showed no change in the object-oriented change detection (Table 2). This clearly emphasizes the higher accuracy of the object-oriented change detection, as no pixels were expected to change land-cover.

A large part of the objects/pixels showing change between riparian vegetation and woodlands occurred in close proximity (within 30m) to the riparian zone. This issue was caused by woodland vegetation next to the riparian zone being denser and

greener in May than in August. Hence, riparian zone width was overestimated in the May image and more accurately mapped in the August image. This is a common issue of mapping riparian zone width in the wet-dry tropics (Johansen et al. in press). Mapped changes from rangelands to riparian vegetation in the object-oriented change detection were in most cases rangelands in both May and August, but with greener patches in August resulting in misclassification as riparian vegetation. Slight mis-registration between the two image datasets resulted in some small objects along the edges of riparian vegetation and rangelands being classified as rangelands in May and riparian vegetation in August. The object-oriented classification of change from riparian vegetation to bare ground (mainly from dry streambed to riparian vegetation) was correct in 95% of assessed cases (19 out of 20) because of thinning in the riparian canopy and the smaller off-nadir sensor angle in August, which increased the visible area of dry streambed.

Table 2. Comparison of the percentage of pixels classified as change in the object-oriented and pixel-based post-classification comparison in areas classified as riparian vegetation in either the May or August image.

Change classes	Pixels related to riparian change in object-oriented post-classification comparison		Pixels related to riparian change in pixel-based post-classification comparison	
	Object-oriented approach	Pixel-based approach	Object-oriented approach	Pixel-based approach
No change	81.44	34.69	92.49	51.44
Non-riparian change	0.00	44.86	1.32	0.00
Bare ground – riparian	0.00	0.05	0.00	0.58
Rangelands – riparian	0.38	0.11	0.25	1.08
Woodlands – riparian	6.64	14.73	2.72	33.93
Riparian – bare ground	0.41	0.07	0.19	0.23
Riparian – rangelands	0.20	1.05	0.03	4.02
Riparian – woodlands	10.93	4.43	3.00	8.73
<b>Total pixels</b>	<b>713,481</b>	<b>713,481</b>	<b>418,019</b>	<b>418,119</b>

Table 1. Parameters for the rule sets used to classify bare ground, rangelands, riparian vegetation, woodlands, and streambeds.

Domain	Class name	Object and Class-Related Features	Membership function	Value (May)	Value (August)	Purpose
Unclassified	Bare ground	Mean Red	Larger than	1585-1595	1490 - 1495	To classify bare ground
Unclassified	Rangelands	Mean NDVI / Standard deviation NIR	Smaller than / Smaller than	0.39-0.395 / 222-224	0.51-0.52 / 222-224	To classify rangelands
Unclassified	Riparian Vegetation	Mean NDVI	Larger than	0.645-0.65	0.54-0.55	To classify riparian vegetation
Unclassified	Woodlands	Mean NDVI	About range	0.2-0.66	0.22-0.57	To classify woodlands
Riparian Vegetation	Woodlands	Number of riparian vegetation	<=	4 (within a 15 pixel perimeter)	4 (within a 15 pixel perimeter)	To eliminate objects incorrectly classified as riparian vegetation
Woodlands	Riparian Vegetation	Relative border to riparian vegetation	>	0.4	0.3	To eliminate objects within the riparian zone classified as woodlands
Bare ground	Streambed	Relative area of riparian vegetation	>	0.55 (within a 10 pixel perimeter)	0.55 (within a 10 pixel perimeter)	To convert areas classified as bare ground within the riparian zone to streambed.
Woodlands and Rangelands	Riparian Vegetation	Relative area of riparian vegetation	> (find enclosed by class algorithm)	0.60 (within a 10 pixel perimeter)	0.60 (within a 10 pixel perimeter)	To eliminate incorrectly classified woodlands and rangelands objects surrounded by riparian vegetation
Woodlands	Rangelands	Relative border to woodlands	<	0.5	0.5	To eliminate objects incorrectly classified as woodlands within rangelands areas
Rangelands	Woodlands	Relative border to rangelands	<	0.4	0.4	To eliminate objects incorrectly classified as rangelands within woodlands areas

The results of the NDVI image differencing showed that the pixel-based change detection had more pixels indicating large decreases and increases in NDVI values compared to the object-oriented NDVI image differencing. That is a result of the extreme NDVI values being averaged out within the individual objects, which on average included 133 pixels. The pixel-based image differencing was more sensitive to slight geometric offsets between the two image datasets, while the object-oriented approach was not affected (Figure 3). The characteristics were similar for the blue, green, red, and NIR bands.

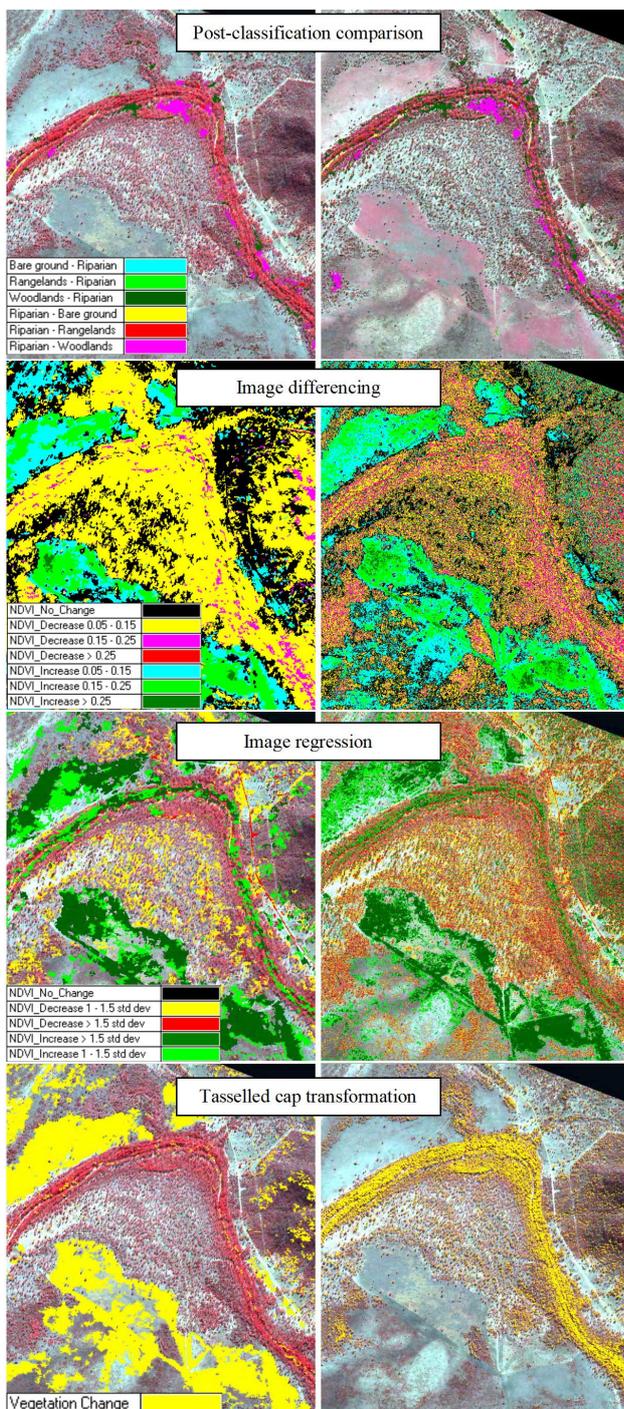


Figure 3. Differences between object-oriented (left hand side) and pixel-based (right hand side) change detection of four different change detection techniques.

The best-fit equations and the coefficient of determination ( $R^2$ ) were calculated for both the object-oriented and pixel-based image regression of the two images (Table 3). The change maps derived using the object-oriented and pixel-based image regression were similar (Figure 3). However, many individual pixels were identified as change in the pixel-based approach possibly because of small changes caused by the sensor viewing geometry and the occurrence of slight image mis-registration.

Table 3. Regression equations and  $R^2$  values for estimating spectral band values for August.

Bands	Object-oriented analysis		Pixel-based analysis	
	Equations	$R^2$	Equations	$R^2$
Blue	0.82B+116.1	0.76	0.75B+106.7	0.75
Green	0.85G+142.2	0.79	0.73G+163.6	0.74
Red	0.80R+219.8	0.77	0.65R+270.8	0.74
NIR	0.70NI+557.8	0.62	0.51NI+917.7	0.31
NDVI	0.58ND+0.15	0.69	0.61ND+0.15	0.70

Note: B = blue band, G = green band, R = red band, NI = NIR band, and ND = NDVI band.

The tasseled cap transformation worked well using the object-oriented approach, where rangelands with increased grass cover in August were clearly identified. However, the pixel-based transformation provided very poor results (Figure 3). The transformation coefficients derived from the object-oriented approach were tested for the pixel-based transformation, which significantly improved the result. This indicates that the 10 pixels selected for producing the axis representing change in vegetation were not representative. The 10 objects selected represented > 1000 pixels, which most likely makes the object-oriented approach more robust. Slight image mis-registration (<2 pixels) as well as effects from the differences in image off-nadir viewing resulted in the boundaries of tree crowns and their associated shadows appearing as change in the pixel-based transformation. The object-oriented transformation was not affected by slight image mis-registrations and off-nadir viewing differences (dependent on object size), as these were averaged out at the object level.

### 4.3 Comparison of Change Detection Approaches

The post-classification comparison provided useful information on changes from one land-cover class to the other. The results implied that phenological changes were not misclassified as land-cover change. This approach relies on high image classification accuracies of the two images. Mis-classification and mis-registration errors often result in unsatisfactory results (Coppin et al., 2004). The use of object-oriented post-classification comparison significantly reduced effects of small mis-registration errors. In addition, the ability to include context information is a powerful tool that can improve the image classification accuracy. Also, the ease of manual editing of selected image objects, as opposed to thousands of pixels, further improves the ability of obtain accurately classified images. To enable comparison of two classified images of the same area, it is essential that the same segmentation (outline of individual objects) is used for both images to avoid misalignments of objects between images in areas without change to reduce erroneous detection of change along boundaries of land-cover classes.

Image differencing was found useful and easy to interpret because of the simplicity of the approach. The critical part of the approach is the definition of thresholds indicating change. It was found important to include more than just one band to identify all changes. The combined utility of the post-classification comparison and the image differencing approach

was assessed by evaluating the amount of change in NDVI values for those areas that changed from one land-cover class to another. Assuming that an NDVI increase or decrease of at least 0.15 represented change, the amount of change within the riparian zone was reduced from 203,058 pixels to 69,777 pixels in the pixel-based approach and from 132,404 pixels to 36,668 pixels in the object-oriented approach. That enabled not only elimination of areas incorrectly detected as change in the post-classification comparison, but also assessment of the level of change in e.g. NDVI values within areas classified as the same land-cover class in both images.

Image regression was fairly easy to apply and analyse. In this case, the values of the regression standard error were useful for the establishment of a threshold to detect change. One of the assumptions of this approach is that the majority of objects/pixels have not changed between the two times of image capture. This makes the pixel-based image regression very sensitive to small geometric offsets between the two images when using high spatial resolution image data. The object-oriented approach on the other hand fulfils these requirements because of the larger objects ensuring a high degree of overlap even when slight mis-registrations occur. This would have been one of the reasons why the  $R^2$  values for the NIR band was lower for the pixel-based regression (Table 3).

The tasselled cap transformation is relatively easy to interpret with a new layer representing change. However, this method only detects changes in a particular direction based on the selected change objects. The approach can be used to identify changes along the constructed axis of change, but other changes will not be reflected in the change component. For example, if examining vegetation change based on NDVI, changes between water and streambed along rivers and creeks may not be detected. The pixel-based tasselled cap transformation yielded poor results most likely because the selected vegetation change pixels were not representative. This is especially a problem when working with high spatial resolution image data, where pixels cover very small areas. For high spatial resolution image data the object-oriented tasselled cap transformation was superior in this image dataset. In addition, a disadvantage of the tasselled cap transformation approach is that the construction of the new coordinate system is laborious and requires previous knowledge of the study area and accurate definition of the changes to be identified.

## 5. CONCLUSIONS

This work focussed on the development and comparison of rule sets for object-oriented image classification and the comparison of results from four object-oriented and pixel-based change detection techniques using high spatial resolution QuickBird image data. The development of rule sets for classifying the two images showed that the setup of the rule sets can be standardized but that different thresholds for the membership functions are required for object-related features.

In general, the object-oriented change detection approaches provided better results than the pixel-based routines because of the ability of the object-oriented approach to: (1) reduce effects of slight mis-registration between the two images; (2) reduce the 'salt and pepper' noise; (3) include context relationships and object shape information; (4) reduce effects of shadows from trees; and (5) reduce effects of differences in sensor viewing geometry. A combination of object-oriented post-classification comparison and NDVI image differencing produced the best

results as this provided information on both land-cover change and the level of change. The image regression routine produced similar results for the object-oriented and pixel-based change detection, but the pixel-based approach is less likely to fulfil the associated assumptions. The tasselled cap transformation provided poor results for the pixel-based change detection because of the small size of the sample used for the calculation of change coefficients. This research shows the improved capabilities of using object-oriented change detection approaches for analysis of high spatial resolution image data.

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