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Monitoring shrubland habitat changes through object-based change identification with airborne multispectral imagery

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Abstract

An object-based approach to generating shrub cover change maps of potential use for monitoring shrubland habitat reserves was developed and tested. A high fidelity, bi-temporal airborne image data set was generated through frame-based image acquisition, precise image-to-image registration, radiometric normalization, and selection of near-anniversary image acquisition dates with similar precipitation conditions prior to both image acquisitions. Image segmentation and classification processes were applied to the bi-temporal layer stack of very high spatial resolution visible and near infrared (V/NIR) image data, such that shrub change objects were delineated and identified directly.

Image segments derived from the bi-temporal V/NIR image data set having 1 m spatial resolution delineated most shrub change features in a qualitatively realistic manner. A Standard Nearest Neighbor classifier with segment mean and standard deviation measures of Red, NIR, and normalized difference vegetation index (NDVI) image features yielded the shrub change map that agreed more closely with reference data than the classifier based on fuzzy membership functions. The overall accuracy and kappa statistics for the optimal shrub change map were 0.83 and 0.64, respectively, with the predominant error being associated with "over-classification" of no-change objects as some type of shrub change. No statistical difference in accuracies of three- and five-class maps was found, suggesting that changes in true shrubs and sub-shrubs within coastal sage scrub vegetation communities can be differentiated reliably. A net 5% loss of shrub cover was determined for the 1998–2005 period from the shrub change map of the study area. The greatest decrease and net loss of shrub cover occurred within the urban edge zone and within flat-lying areas. Patterns of shrub loss appear to be more related to anthropogenic disturbance than effects of the severe seven-year drought that occurred between image acquisition dates.

Keywords: Vegetation change; Object-based classification; Image segmentation; Airborne multi-spectral camera

1. Introduction and background

Extinction of animal and plant species is one of the most serious problems facing humankind. When species are eliminated, the biological diversity of ecosystems is reduced, potentially to the point where such ecosystems may no longer be viable. Reduction of animal and plant populations to the point of extinction often results from direct and indirect habitat disturbance effects from human activities. This means that successfully preserving species determined by wildlife agencies to be rare, threatened, or endangered requires management of both species and their habitats. Critical to effective management is access to information on species populations and the amount, distribution, and condition of their associated habitats over time. Such information is obtained through biological monitoring. Field-based monitoring methods are generally required for observing and recording plant and animal species occurrences, but are limited in their effectiveness and comprehensiveness of spatial coverage.

Remote sensing can play an important role in biological monitoring by providing spatially explicit, continuous, and extensive data on the composition and condition of wildlife habitats. Managers of habitat preserves can use time sequential remote sensing imagery to map baseline characteristics of habitats and then monitor changes over time. The primary information content of remotely sensed data with respect to wildlife habitat pertains to vegetation composition (e.g., life form or community

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types) and condition (e.g., percent cover, height, or stress), though data on the amount of exposed soil and rock cover may also be derived. Since the extent of home ranges or territories of animal species is primarily a function of their size and mobility, the requisite spatial extent characteristics of remotely sensed data depend on the type(s) of animals under consideration for habitat management, and/or the size of habitat preserves being monitored. The appropriate spatial resolution depends on the size and spacing of habitat and disturbance features to be monitored. The appropriate temporal resolution, the interval between successive capture of remotely sensed data, depends on the nature of landscape dynamics associated with natural and anthropogenic disturbances and the recovery from such disturbances.

In southern California, shrublands have a high degree of biological diversity and endemism and provide habitat for a large number of rare, endangered and threatened animal and plant species. The most endangered shrubland habitat type is the coastal sage scrub (also known as soft chaparral) community. Extensive urban development in southern California has occurred at the expense of coastal sage scrub habitat. This has resulted in wildlife agencies and non-government organizations establishing connected systems of habitat preserves that contain coastal sage scrub and chaparral shrublands. Wildlife agencies are responsible for ensuring that the populations of rare, endangered and threatened species do not decline any further and managers of individual habitat preserves are responsible for maintaining populations and the habitats that support these critical species. To date, monitoring efforts have been limited to periodic population enumerations of a few species, with very little emphasis on habitat monitoring. While cost and lack of personnel are the primary reasons for why little monitoring of coastal sage scrub habitats has occurred, another reason is lack of knowledge and understanding of which habitat characteristics of critical species are most important to monitor. One of the few conclusive studies of coastal sage scrub habitat requirements is that of Hunsaker et al. (2000) for the endangered bird species, *Polioptila californica* (commonly called the California gnatcatcher). The authors determined that viable gnatcatcher habitat must be composed of at least 50% cover of native shrubs and sub-shrubs (having lower stature and more open canopies than true shrubs). This suggests that change in shrub/subshrub cover may be a useful indicator of change in habitat condition, and such an indicator has a high potential for being successfully mapped and monitored with remote sensing.

The potential of remote sensing-based monitoring of coastal sage scrub habitat preserves and preserve systems has been explored in several previous studies (Longmire & Stow, 2001; Stow et al., 2004; Witztum & Stow, 2004). These studies have been based on very fine spatial resolution, visible and near infrared (V/NIR) image data sets acquired with airborne digital camera and commercial satellite sensor systems. Pixel-based change detection techniques have been emphasized in an effort to resolve fine-scale changes associated with human-induced disturbances. Critical to the success of these pixel-based monitoring approaches is high precision of image (date-to-date) registration (Coulter et al., 2003; Stow et al., 2003). While manual interpretation approaches enable identification of relatively specific land cover changes, semi-automated change identification approaches are limited to general land cover change classes (e.g., increase or decrease in green vegetation cover) (Stow et al., 2004). The results of these previous studies have been inconclusive because of the relatively short time interval between image acquisition dates (one to three years), such that important habitat changes are rarely manifested in such a short time interval. This is compounded by the high year-to-year variability of vegetation greenness that results from highly variable winter precipitation amounts for the Mediterranean-type climate of southern California.

Object-based approaches to change detection may be more appropriate for shrubland habitat monitoring than per-pixel approaches when applied to multitemporal image data sets having very fine spatial resolution characteristics. This follows the H-resolution scene model concept of Strahler et al. (1985), such that habitat disturbance effects are most likely to be manifested as multi-pixel objects. Land cover change objects within coastal sage scrub habitats that could be monitored are: death, removal, regrowth and expansion of shrubs; changes in size and shapes of sub-shrub patches; formation, expansion and compression of recreational trails; and invasion and spreading of non-native vegetation.

While references to object-based image analysis approaches such as segmentation and linear feature extraction are evident in the remote sensing research literature for the past three decades (Haralick & Shapiro, 1985; Kettig & Landgrebe, 1976; Woodcock & Harward, 1992), such approaches are more accessible today to researchers and practitioners through commercially available software products. This and the greater availability of fine spatial resolution image data have resulted in a rapid increase in research articles on object-based image processing, particularly for classification of land use and land cover and recognition of urban features such as roads (Song & Civco, 2004) and buildings (Zhang et al., 2005), and for vegetation mapping (Koch et al., 2006; Lathrop et al., 2006). A few object-oriented approaches to land cover change analysis have been reported (Blaschke, 2005; Desclée et al., 2006; Hall & Hay, 2003; Walter, 2004), but apparently, only Desclée et al. (2006) have attempted to directly segment and classify land cover change objects and none have dealt with changes in habitat condition or vegetation dynamics.

The objective of this study was to assess the utility of an object-based, image-derived approach to monitoring changes within a shrubland habitat preserve in southern California. Besides the unique technical and application aspects of this study, the creation of a precisely controlled bi-temporal data set consisting of very fine spatial resolution visible/near infrared imagery captured seven years apart provides an excellent opportunity to determine if important habitat changes can be identified. During the seven-year period between image acquisition dates southern California experienced one of the more severe droughts on record, such that shrublands may have experienced a reduction in habitat quality.

The following research questions were addressed with this objective and application context in mind:

- Which object-based classification approach is most effective: (1) Membership Function with analyst-selected feature inputs and function type, or (2) Standard Nearest Neighbor with features selected through separability analysis (called Feature Space Optimization)?

- Which types of input features provide the greatest discrimination when classifying image segments into shrub change classes: spectral bands, spectral vegetation indices, frequency distribution characteristics of objects, etc.?
- What level of classification accuracy can be achieved for delineating and quantifying shrub change (increase and decrease) from no change?
- Do the spatial patterns and magnitude of shrub change depicted on object-based maps appear to be realistic and do they indicate effects of anthropogenic and drought-related disturbances?

2. Study area and period

The study area, shown in Fig. 1, covers approximately 1 km^2 of the Mission Trail Regional Park (MTRP) that is subject to a variety of anthropogenic disturbances and contains a range of coastal sage scrub habitat conditions. Located within San Diego, California, the MTRP is an open space preserve adjacent to suburban residential areas. The park serves a dual purpose as a habitat preserve and outdoor recreational area. As a preserve, it is an important land holding within the system of preserves established by the Multiple Species Conservation Plan of southern San Diego County. As a recreational area, the MTRP is used for hiking, running, climbing, horseback riding, and bicycling. These recreational uses are sources of disturbance that can affect habitat quality of the shrubland vegetation communities that cover most of the preserve. Other sources of disturbance are associated with urban development and edge effects, fire, exotic plant invasion, and drought. The specific study area corresponds to a subset of two larger image mosaics that were used for the multitemporal analyses, and was delineated by encompassing a variety of terrain and disturbance types in a manageable size area for data processing and field observation purposes.

The climate of MTRP is typical of Mediterranean ecosystems, with an average annual precipitation of 280 mm, most of which occurs in winter. The terrain within the specific study area ranges from 25 to 485 m in elevation with many steep slopes. Coastal sage scrub, the predominant vegetation community type of the study area, is composed of a mixture of drought deciduous sub-shrubs, evergreen shrubs, and perennial grasses and forbs. Heavily disturbed or degraded forms of coastal sage scrub contain a large fraction of non-native grasses. Riparian corridors traverse sinuously through the shrublands along drainages and consist primarily of deciduous trees.

The seven-year period of study starts 27 June 1998, when the first airborne imagery was captured and extends through 21 June 2005 when a second image acquisition occurred, nearly on the seven-year anniversary of the original acquisition. The total precipitation for both of the water years (October through September) preceding each acquisition date was within a few millimeters of 635 mm. These water years were two of the wettest on record for an area having an average annual

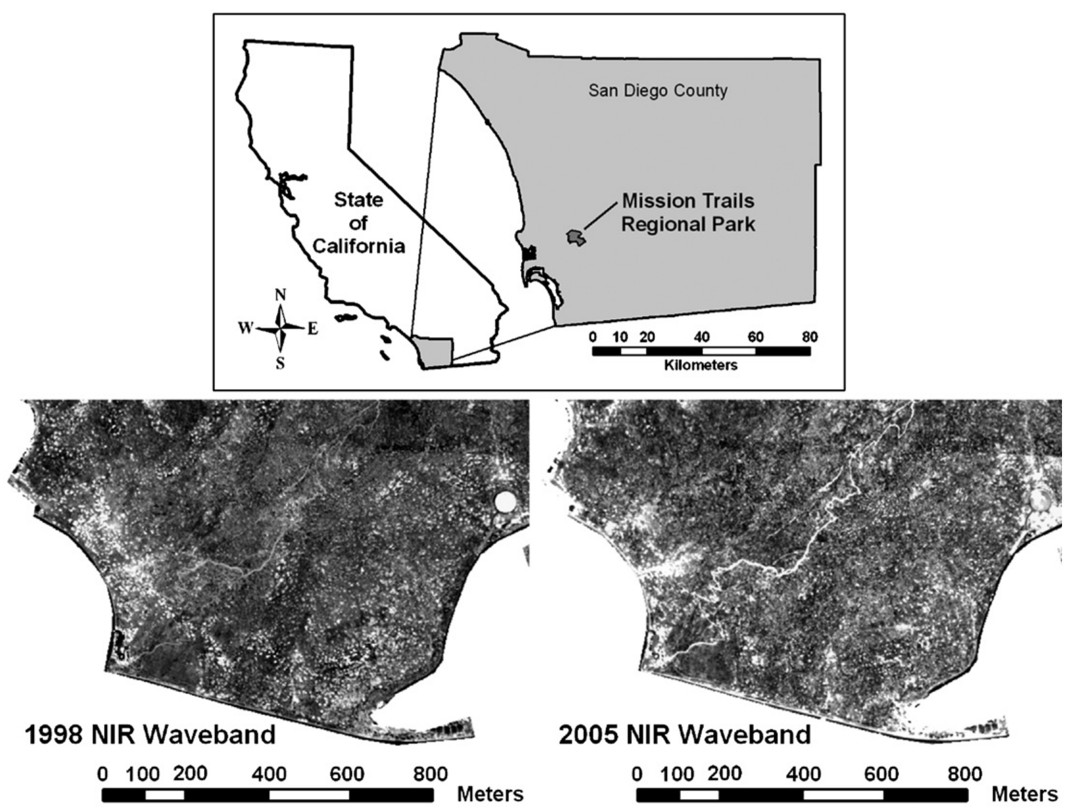

Fig. 1. Map of the Mission Trails Regional Park study area within San Diego County and the State of California, USA. Mission Trails Regional Park locator map shown above and near-infrared (NIR) images from 1998 and 2005 shown below. Adjacent urban areas have been masked out (shown as white) of the images.

precipitation of 280 mm. Negligible precipitation was recorded for a month prior to both acquisition dates. Thus, the surface moisture and phenological conditions were very similar at the time of both image acquisitions. As stated above, a severe drought occurred in the intervening years between acquisition dates, with the 2002 and 2004 water years being two of the driest on record.

3. Data

Digital multispectral image data with a nominal ground sampling distance (GSD) of 1 m were acquired for both imaging campaigns with an Airborne Data Acquisition and Registration (ADAR) System 5500 mounted on a fixed-wing aircraft flying at 2300 m above ground level. Characteristics of the imagery collection are listed in Table 1. Fig. 2 portrays the entire image data capture and processing flow. Four separate digital cameras acquired image frames in blue, green, red, and near infrared wavebands. Band-to-band registration and an anti-vignetting filter were applied to each frame, as a component of standard ADAR 5500 post-acquisition processing (Stow et al., 1996).

The primary goal for the image acquisition plan was to replicate image geometric and radiometric characteristics of the first date of imagery when capturing the second, which greatly simplifies subsequent geometric and radiometric processing and minimizes associated errors. This was achieved with frame center matching (Coulter et al., 2003; Stow et al., 2003) and anniversary date approaches to multitemporal image acquisition. The goal of the original (27 June 1998) imaging campaign was to cover the entire MTRP, with flightlines being oriented in a north–south direction and camera stations spaced 0.4 km apart to achieve 60% overlap. The frame center matching approach was implemented during the 21 June 2005 acquisition of ADAR image frames to enable precise spatial registration between the two dates of imagery. The frame center matching approach is based upon matching camera stations in terms of horizontal position and altitude between multitemporal image acquisitions (Coulter et al., 2003; Stow et al., 2003).

When image frames are captured from the same camera stations, parallax between frame center matched images is substantially reduced and the images exhibit similar terrain-related geometric distortions (Coulter et al., 2003). Further, precise spatial registration between multitemporal image frames may be achieved using standard image-to-image registration procedures based on simple (low-order) warping transformations.

The 2005 ADAR image frames were matched to those captured in 1998 by: (1) retrieving camera station coordinates of 1998 image frame, (2) flying the same flightlines in 2005 as in 1998 with the aid of a GPS-assisted pilot navigation display, and (3) capturing 2005 images at 1998 frame center locations using a GPS-assisted camera triggering mechanism. Selective availability degraded GPS positions to an uncertainty of +/− 100 m during the 1998 ADAR acquisition. To solve this problem, camera stations were determined through block triangulation of the 1998 ADAR imagery to provide more accurate and reliable positions of the camera stations.

Field data were collected in the summer of 2006, to provide training and test data for calibrating and validating (respectively) change analysis products. Large-scale CIR hardcopy images of the 1998 and 2005 ADAR data facilitated, delineation and identification of objects corresponding to shrub decrease or increase. Observations were limited to areas along the urban edge or within 100 m of trails, which were more accessible and contained more disturbance-related change features. While these field-based observations were conducted one year after the second date of imagery and no extant field data were available near the time period of the first image date (1998), in most cases change objects within the urban edge could be verified by cross-validating the fine spatial resolution imagery with direct field observations.

Table 1
Date, time, and sun angles for each ADAR 5500 image acquisition

Year	Month/day	Time of acquisition	Solar zenith angle (degrees)	Solar azimuth angle (degrees)
1998	June 26	1:26–1:41	12–14	221–232
2005	June 21	1:25–1:43	12–15	222–235

Times of acquisition are post meridian (PM) Pacific Daylight Time (PDT).

4. Image pre-processing

ADAR image frames were corrected for anisotropic reflectance effects (i.e., within-frame radiometric normalization), and radiometrically normalized and spatially registered between image dates. These pre-processing steps were applied to minimize spatial and temporal variability in the relationship between image brightness and surface reflectance, as well as noise sources that may influence the success of identifying changes in habitat condition over time.

Anisotropic reflectance effects include across-frame brightness variations and hot spots associated with the backscatter of solar illumination from soil and vegetated surfaces. The approach used to suppress anisotropic reflectance variability, a manifestation of differing bidirectional reflectance distribution functions for different land cover types was based on methods by Royer et al. (1985) and Pickup et al. (1995). Royer et al. (1985) developed a method for reducing variations in sun/scene/sensor geometry into a single variable called a “scattering angle” for each pixel in an image. Scattering angles were calculated for each pixel in each image, based on the sun/scene/sensor geometry, such that patterns in the resulting scattering angle image mimicked patterns of brightness variation associated with anisotropic reflectance. The relationship between mean brightness values within zones of similar scattering angles was used to de-trend the image. We applied this correction approach to ADAR frames acquired along each flight line. The solar illumination and view geometry conditions of the 2005 ADAR imagery were matched to those of the 1998 flight, as the times of acquisition in 1998 and 2005 varied by less than 2 min.

A method referred to as mean-standard deviation (MS) normalization by Yuan and Elvidge (1996) was applied to normalize like-band brightness values between image dates.

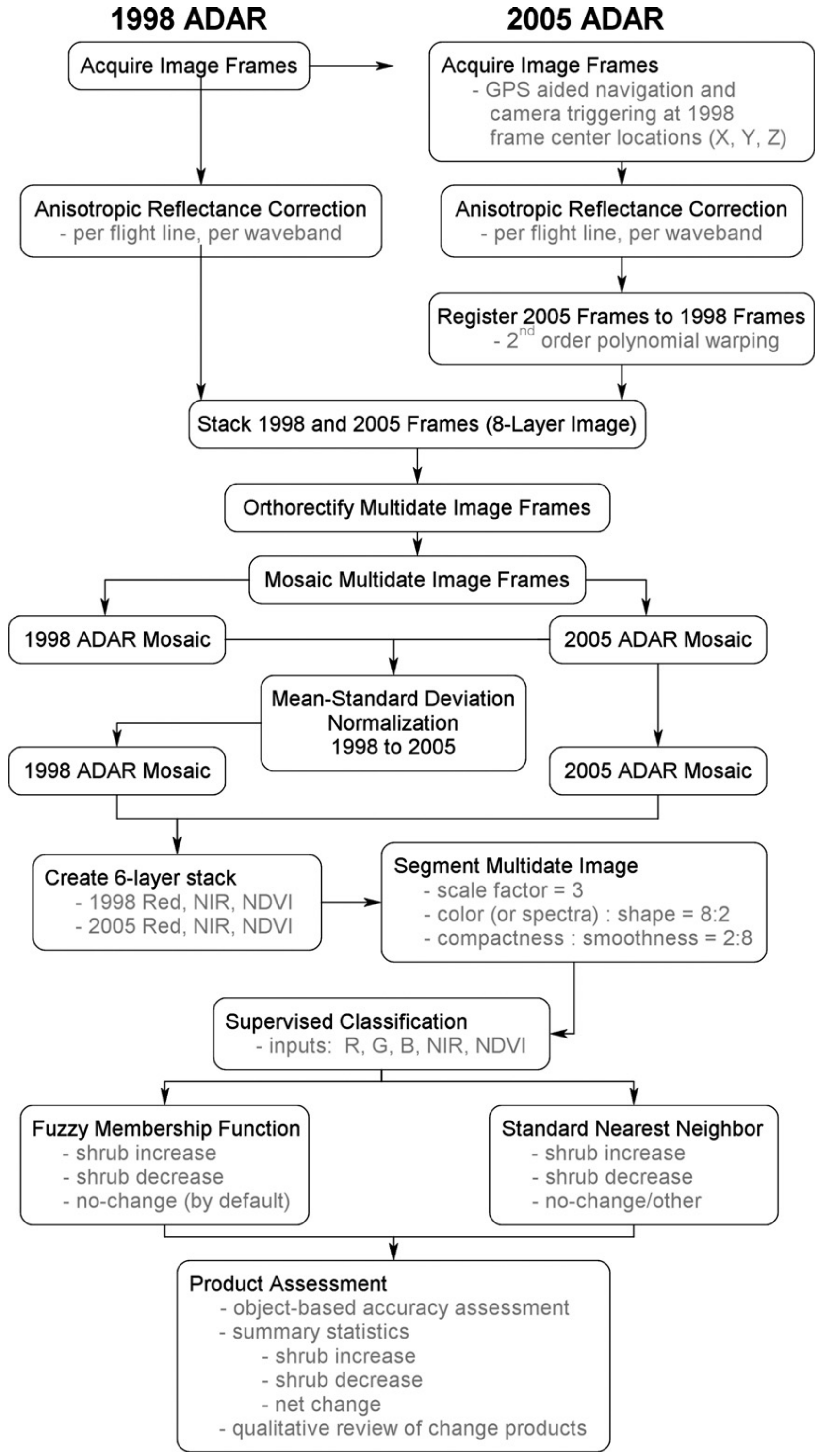

Fig. 2. Image data capture and processing flow.

The 2005 ADAR image had the higher dynamic range and provided the reference to which the 1998 image was adjusted. Since the MS method can be affected by statistical outliers (i.e., areas of change with real brightness differences between dates), special care was taken to ensure that no large areas of change were incorporated when generating the empirical normalization relationship. Urban areas surrounding the MTRP and areas of non-overlap between bi-temporal mosaics were masked out.

ADAR imagery acquired in June 1998 had been orthorectified using ERDAS Orthobase (now called Leica Photogrammetry Suite) software and digital elevation model (DEM) data. Horizontal ground control was extracted from a United States Geological Survey (USGS) color infrared Digital Orthophotographic Quarter Quadrangle (DOQQ) having 1 m spatial resolution and based on photography captured in 1997. Vertical ground control was extracted from a USGS 10 m spatial resolution DEM. Tie points were automatically generated between ADAR image frames and a block triangulation solution was achieved. Individual orthorectified image frames were output and subsequently mosaicked.

Image-to-image registration and orthorectification of 2005 image frames to 1998 imagery was accomplished using two procedures: (1) individual 2005 image frames were registered to corresponding non-georeferenced 1998 image frames using approximately 30 ground control points (GCPs) and a second-order polynomial warping transformation, and (2) the registered 1998 and 2005 image frames were orthorectified using the same block triangulation solution originally developed and applied to the 1998 image frames. Following orthorectification, the areas of non-overlap between the individual date image frames were set to zero (background values) and the eight layer image frames were mosaicked. Using these procedures, precise spatial registration was maintained and mosaic cutline locations were identical between the bi-temporal mosaics.

The accuracy of spatial registration between the 1998 and 2005 image mosaics was assessed using 620 independent check points distributed throughout the image mosaics. The root mean square error (RMSE) of check points, a measure of overall positional difference between two image data sets, is 0.64 m.

5. Object-based change mapping approach

5.1. Segmentation

Definiens (formerly known as eCognition) software was used to perform object-based image change analyses. The object classification process of Definiens involves two steps, segmentation and classification. Image inputs (referred to as "features" by Definiens) to segmentation included two multispectral wavebands, NIR and red, and NDVI (in order of input), for both 1998 and 2005 dates (in order of input).

The segmentation routine in Definiens is based on a multiresolution segmentation strategy, which utilizes a type of region growing approach, and is generally implemented in an interactive, trial-and-error fashion (Baatz & Schape, 2000; Yu et al., 2006). Resultant segmentations are controlled by both scale and shape parameters. These parameters were modified to achieve a realistic segmentation of shrub cover change objects, such that the smallest of shrub change features were delineated. The final segmentation parameters were as follows: Scale Factor = 3, Color (or Spectra): Shape = 8: 2, Compactness: Smoothness = 2:8. Segmentation was run for only one level, based on the assumption that changes in shrub cover would be manifested as small objects (e.g., canopy expansion or removal of individual shrubs) relative to the 1 m spatial resolution of the imagery.

5.2. Object classification

For the classification phase within Definiens software, an analyst has a myriad of options available for feature inputs and classification approaches. Specific features, statistical moments for summarizing features for each segment/object, and classification parameters were determined through histogram analysis and separability measures incorporated in the Feature Space Optimization function. These were based on training data that were extracted for field-verified objects of shrub change and for objects determined to represent no land cover change based on visual interpretation of the ADAR imagery.

Image features used as potential input in the classification phase included all four multispectral wavebands (NIR, red, green, blue) and a normalized difference vegetation (NDVI) image for both 1998 and 2005 dates. Jensen (2005) refers to this as a multitemporal composite classification approach, which is commonly implemented for pixel-based change identification (Collins & Woodcock, 1996; Coppin et al., 2004). It differs from the change vector analysis (CVA) approaches, where temporal difference (second date minus first date) images are utilized. An advantage of the multitemporal composite approach is that information on both the beginning and ending states of surface cover is retained, limiting the potential for ambiguous land cover transition signatures that can occur when only temporal differences in image brightness are utilized.

Two supervised, object-based image classification routines, fuzzy membership function and standard nearest neighbor were tested with the objective of identifying changes (increase and decrease) in shrub cover and no change categories associated with image-derived segments. For the fuzzy membership function (called Membership Function) classifier, the shape and thresholds of the membership function were selected interactively, based on expert knowledge, training data, and/or trial and error. Optimization of the membership function shape and thresholds was based on an inclusiveness of training objects criterion, meaning that classification parameters were considered optimal when all training segments were classified correctly. With the Membership Function classifier, only Shrub Increase or Shrub Decrease segments were classified, with all other segments being considered as No Change by default.

We also tested the Standard Nearest Neighbor classifier in Definiens, which is based on a feature space distance to training data measure (Yu et al., 2006). For the Standard Nearest Neighbor classifier, all segments were classified, meaning that training samples were required for other- and no-change subcategories of the No Change class, in addition to Shrub Increase and Shrub Decrease classes.

The accuracy and reliability of the shrub change products were examined using an object-based accuracy assessment approach, summary statistics for zones delineated by terrain and distance to urban edge characteristics, and qualitative visual analysis. Object-based accuracy was assessed by first selecting test objects, defined as image-derived segments that corresponded to field-observed objects of shrub change or image interpreted shrub change or no change objects. None of these test objects were utilized for training the classifiers. This approach was taken because of the difficulty in deriving reference data for land cover change objects in general (Khorram et al., 1999), and particularly for such fine spatial resolution maps (Stow et al., 1997). However, such an approach can only account for the accuracy of the class labels assigned to the image-derived segments and not how well the spatial characteristics of change objects are represented. Summary statistics for the amount of shrub increase, decrease, and net change were derived to determine sensitivity of change estimates to differences in feature input and classification approach, and to assess whether image-derived estimates of shrub cover changes are reasonable based on expected spatial variations resulting from disturbance effects. Qualitative analysis by visual interpretation of change products also served this purpose.

6. Results

Image-derived segments ranged in size from 1 to 90 pixels, with the largest segments corresponding to built features (e.g., roads). Since the entire image was segmented, not only were objects of interest (i.e., shrub increase and decrease) delineated, but so too were objects corresponding to no change or other types of land cover change. Field-based assessment of shrub change objects revealed that the image-derived segments depicted reasonably the shape and extent of most of the distinct change features. However, these visual-based observations must be qualified for two reasons: (1) many of the features were not much larger than the 1 m image GSD, such that shape representation is approximate, and (2) it is difficult to determine the size and shape of change objects because of the uncertainty in validating the morphology of detailed land cover change objects before and after changes have occurred.

Between eight and 11 image features were selected for inclusion to image classifiers based on the quantitative separability analysis and qualitative analysis of histograms portraying frequency distribution of image features for training segments. The mean Red, NIR, and NDVI values of image segments (i.e., mean of all pixels in a segment) for both dates (1998 and 2005) were selected as input features for both Membership Function and Standard Nearest Neighbor classifiers. For the Standard Nearest Neighbor classifier, the per-segment standard deviation values of Red, NIR, and NDVI for both dates (except NDVI for 1998) were also selected as input features, based on the separability analysis. For the Membership Function classifier, an optimal product was generated with the Approximate Gaussian function centered on the mean of the training data, with end and inflection points selected interactively.

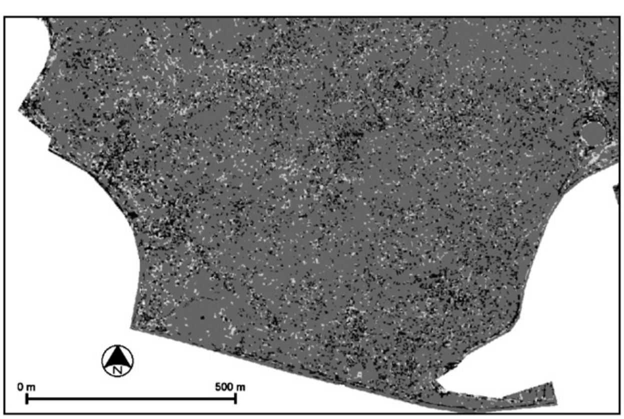

Fig. 3. Object-based shrub change map for Mission Trails Regional Park study area derived with image segmentation and Standard Nearest Neighbor classification of a bi-temporal image composite. Three-class shrub change map: black = Shrub Decrease, mid-grey = No Change, light-grey = Shrub Increase.

Of the two general approaches to classifying segments that are supported by Definiens, the Standard Nearest Neighbor classifier yielded superior shrub change results (see accuracy assessment results below). While the Standard Nearest Neighbor classifier requires all image segments to be classified, meaning that training data are required for classes other than the shrub change classes of interest (e.g., no change or other change), the resultant change map more accurately and realistically depicted shrub changes. The Membership Function classifier enabled only shrub change segments to be classified, but was limited by a tendency to "over-classify" no change or other change segments as shrub change (i.e., contained high commission errors).

The Standard Nearest Neighbor classifier with 11 input features was used to generate the final shrub change maps, one based on a three-class scheme (Shrub Increase, Shrub Decrease, and No Change) and another based on a five-class scheme (True Shrub Increase, Sub-shrub Increase, True Shrub Decrease, Sub-shrub Decrease, and No Change). Examples of the three-class shrub change map are shown in Fig. 3 for the entire study area and in Fig. 4 (along with the ADAR image data) for an enlarged subset. Shrub increase objects are located throughout the study area, but are more concentrated away from high disturbance areas, whereas segments classified as Shrub Decrease tended to be located near urban edges and trails. However, in several areas, such as the western slope of Cowles Mountain near an urban edge, Shrub Increase and Decrease objects were intermixed. A majority of the segments mapped as Shrub Increase on the three-class map were classified as Sub-shrub Increase on the five-class map, whereas a majority of the Shrub Decrease objects were classified as True Shrub decrease on the map with the greater categorical detail.

The object-based accuracy assessment of the three- and five-class shrub change maps generated with the Standard Nearest Neighbor classifier and 11 input features yielded an overall accuracy of 0.833 and 0.829, and a kappa of 0.637 and 0.639, respectively, based on 257 test segments, as shown in Tables 2 and 3. That the two maps had similar overall accuracies suggests that changes in true shrub are generally separable from changes in sub-shrubs. The dominant error trend is an "over-classification" of shrub changes, such that the user's accuracy of Shrub Increase and Decrease classes for the three-class map were 0.586 and 0.587, respectively. A similar trend is seen for the five-class map, which reveals that most of the commission errors occurred for True Shrub Increase and Decrease classes, which have user's accuracy estimates of around 50%. Most of the errors associated with the True Shrub change classes seem to be related to a difficulty in discriminating fine-scale changes in the size of large evergreen shrubs from differences in leaf conditions. This is a common source of noise and confusion when conducting image-based land cover change analyses for semi-arid shrublands.

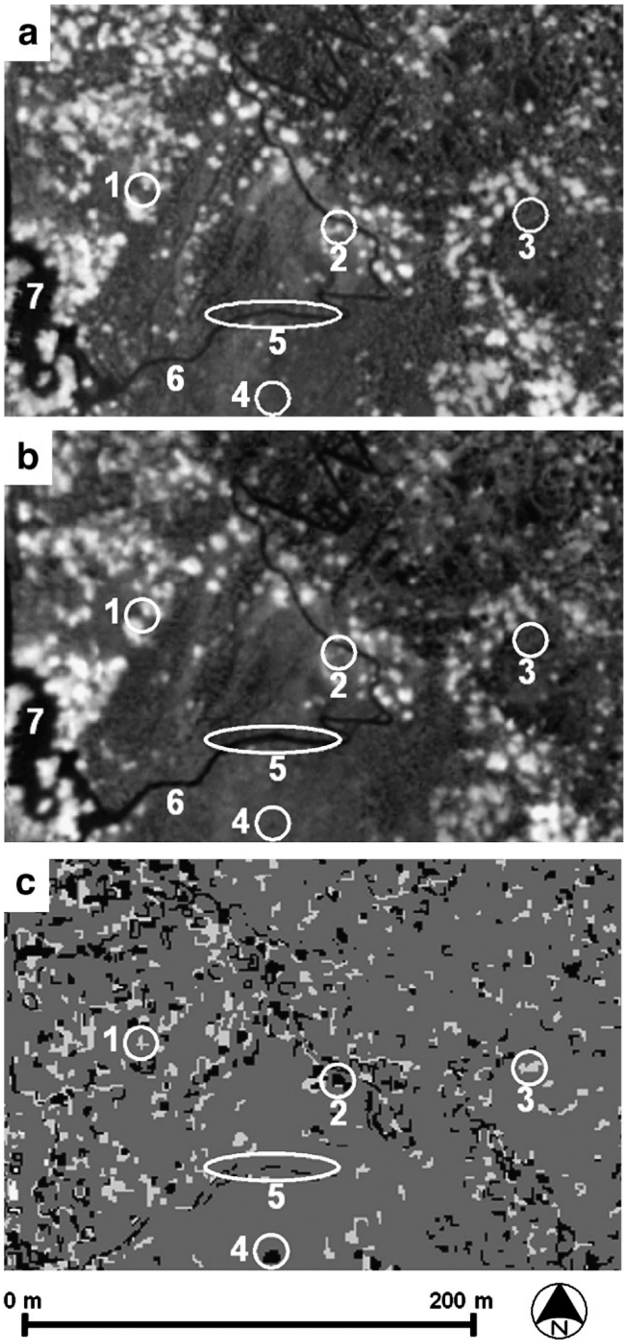

Fig. 4. Enlarged subsets of ADAR NDVI images and corresponding shrub change map for the Mission Trails Regional Park study area. Shrub increase and decrease features are indicated. a. 1999 image subset; b. 2005 image subset; c. three-class map subset derived using object-based approach with Standard Nearest Neighbor classifier: black=Shrub Decrease, mid-grey=No Change, light-grey=Shrub Increase. Features marked with ellipses demonstrate: 1=shrub expansion, 2=shrub mortality, 3=sub-shrub expansion, 4=sub-shrub removal, 5=trail widening, 6=main trail to top of Cowles Mountain, 7=parking lot for hikers.

The overall accuracy and kappa statistics for the three- and five-class shrub change maps generated with the Membership Function classifier and eight input features were essentially identical at 0.829 and 0.829, and 0.594 and 0.606, respectively, as indicated in Tables 4 and 5. While these accuracy statistics are similar to those for the maps derived with the Standard Nearest Neighbor classifier, the "over-classification" of shrub changes is much more visually pronounced in the map from the Membership Function classifier and is indicated by the low user's accuracy. In spite of the very high image registration accuracy, it is reasonable to assume that some of the shrub change objects are artifacts from localized misregistration. Though it may be more efficient and convenient to identify only shrub change objects vis-à-vis the Membership Function classification approach, it appears that using training data for and classifying other-change and no-change objects is required to minimize false detection of shrub changes.

The net change in shrub cover between 1998 and 2005 determined from the three-class shrub change map of the study area was a decrease of 5%, as shown in Table 5. The proportions of Shrub Increase and Shrub Decrease for the study area were 6%, and 11%, respectively, based on the three-class map. According to the five-class map, most of the Shrub Increase objects occurred as expansion of sub-shrubs, which are more drought tolerant and most of the shrub decrease as reduction in true shrubs, which require more mesic conditions. This apparent net reduction in shrub cover may have resulted from the affects of the prolonged drought and/or anthropogenic disturbances from urban edge effects and recreational activities.

Table 2
Accuracy table and statistics for three-class, object-based classification of shrub cover changes based on ADAR multispectral data and Standard Nearest Neighbor classifier

User class\sample	Shrub increase	Shrub decrease	No change	Sum
Shrub increase	17	0	12	29
Shrub decrease	1	37	25	63
No change	1	4	160	165
Sum	19	41	197	257
Accuracy				
Producer	0.8947	0.9024	0.8122	
User	0.5862	0.5873	0.9697	
Overall	0.8327			
Kappa	0.6366			

Table 3
Accuracy table and statistics for five-class, object-based classification of shrub cover changes based on ADAR multispectral data and Standard Nearest Neighbor classifier

User class\ sample	True shrub increase	True shrub decrease	Subshrub increase	Subshrub decrease	No change	Sum
True shrub increase	11	0	0	0	11	22
True shrub decrease	1	29	0	1	25	56
Subshrub increase	0	0	6	0	1	7
Subshrub decrease	0	0	0	7	0	7
No change	1	3	0	1	160	165
Sum	13	32	6	9	197	257
Accuracy						
Producer	0.8462	0.9063	1.0000	0.7778	0.8122	
User	0.5000	0.5179	0.8571	1.0000	0.9697	
Overall	0.8288					
Kappa	0.6394					

Table 4
Accuracy table and statistics for three-class, object-based classification of shrub cover changes based on ADAR multispectral data and Membership Function classifier

User class\sample	Shrub increase	Shrub decrease	No change	Sum
Shrub increase	15	0	11	26
Shrub decrease	2	30	18	50
No change	2	11	168	181
Sum	19	41	197	257
Accuracy				
Producer	0.7895	0.7317	0.8528	
User	0.5769	0.6000	0.9282	
Overall	0.8288			
Kappa	0.5939			

To see if shrub changes, particularly loss of shrub cover, were more prevalent in areas where anthropogenic disturbance effects are more likely to have occurred, we stratified the three-class shrub change map into zones representing two types of likely disturbances. An urban edge zone was defined as all land area within 150 m of an urban edge (residential subdivisions) and a trail zone was delineated as a 15 m buffer on either side of the major hiking trail that is utilized by hundreds of hikers a day to climb up and down Cowles Mountain. As shown in Table 6, net shrub losses of 7% and 6% were determined for the Urban Edge and Trail zones, respectively, while only a 2% net loss was found for "Other" areas located outside of these more disturbed zones. This suggests that mechanical disturbances from people recreating, clearing vegetation for fire protection, etc. may have had a greater influence on reducing shrub cover than drought conditions.

We also stratified the shrub change map by slope aspect classes to determine if shrub changes may be controlled by terrain-related exposure to solar illumination. South and southwest facing slopes receive greater solar illumination loadings and tend be more xeric (warmer afternoon temperatures in concert with direct illumination) than north and east facing slopes, such that effects of soil moisture on shrubs may vary with differing aspects. A digital elevation model generated from interferometric synthetic aperture radar data and having 5 m grid cells was used to generate a map with five aspect classes: Northeast (0–90° azimuth), Southeast (91–180° azimuth), Southwest (181–270° azimuth), Northwest (271–360° azimuth), and Flat (0–2° slope). Shrub cover changes were only slightly higher (net loss of 5%) for southwest facing slopes than for other sloping terrain areas (between 2 to 4% net loss), as seen in Table 6. However, net shrub loss was much greater (11%) for Flat areas, according to the shrub change map. While these areas may be expected to receive and/or hold greater amounts of runoff, most of the urban edge and some of the recreated areas tend to correspond to flat-lying terrain.

Finally, we explored the relationship of shrub change with fire history. Most of the study area has not burned since 1986 or 1988, with a small portion having not been burned since 1944. No substantial difference in shrub cover change (general net loss) was observed when stratifying by fire history (i.e., age since last burn), as shown in Table 6.

Table 5
Accuracy table and statistics for five-class, object-based classification of shrub cover changes based on ADAR multispectral data and Membership Function classifier

User class \sample	True shrub increase	True shrub decrease	Subshrub increase	Subshrub decrease	No change	Sum
True shrub increase	10	0	0	0	5	15
True shrub decrease	2	24	0	0	17	43
Subshrub increase	0	0	5	0	6	11
Subshrub decrease	0	0	0	6	1	7
No change	1	8	1	3	168	181
Sum	13	32	6	9	197	257
Accuracy						
Producer	0.7692	0.7500	0.8333	0.6667	0.8528	
User	0.6667	0.5581	0.4545	0.8571	0.9282	
Overall	0.8288					
Kappa	0.6059					

Table 6
Shrub change percentages (%) of study area and environmental strata for object-based change identification approach

	Shrub increase	Shrub decrease	Net shrub change
Study area	6	11	−5
Aspect			
Northeast	4	6	−2
Southeast	5	9	−4
Southwest	7	12	−5
Northwest	6	10	−4
Flat (slope=0–2°)	4	15	−11
Disturbance			
Urban edge (150 m)	7	14	−7
Trail (±15 m)	7	13	−6
Less disturbed	6	8	−2
Last burned			
1944	7	11	−4
1986	6	11	−5
1988	8	10	−2

7. Discussion and conclusions

The major contribution of the research presented in this paper is the development and testing of an object-based approach to generating shrub cover change maps of potential use for monitoring shrubland habitat reserves. Image segmentation and classification processes were applied to a bi-temporal composite of very fine spatial resolution V/NIR image data, such that shrub change objects were delineated and identified directly, rather than through bi-temporal map comparison. The results are promising, partly because of the high-fidelity bi-temporal image data set that was generated through careful image acquisition and pre-processing. High precision in image-to-image registration, near-anniversary dates and same time of day for image acquisitions, and similar precipitation conditions in the week, month, and year prior to both image acquisitions ensured that most changes in image brightness corresponded to actual land cover changes.

The major strengths and weaknesses of the shrub change mapping approach pertain to both the bi-temporal composite and object-based aspects of the approach. The strength of the bi-temporal composite aspect is that resultant shrub change objects represent land units where shrub was either the "from" or "to" state (but not both) of a land cover transition sequence. Image difference or change vector approaches only exploit the magnitude of spectral-radiometric change, such that ambiguities can result with land cover transitions other than shrub changes. Post-classification approaches require multiple image classifications and can be limited by the cumulative errors generated by each classification. A disadvantage of the bi-temporal composite approach is the requirement for selecting training sample objects that represent shrub loss and shrub increase, creating a need for *a priori* knowledge of the location of shrub changes.

The strength of the object-based aspect of our approach to mapping shrub changes within coastal sage scrub landscapes is the ability to capture expansion and decline of individual shrub canopies and sub-shrub patches, and to distinguish actual shrub changes from other land cover changes (e.g., tree and herbaceous vegetation changes) and artifacts (e.g., misregistration). While we have not rigorously tested and compared object- and per-pixel based approaches, our attempt at per-pixel classification based on the same training samples and input features yielded a shrub change map that "over-classified" shrub changes and did not realistically characterize the shape of canopy changes. The primary weaknesses of the object-based aspect of the approach are the requirement to segment and then classify the image composite, the potential to omit or overly generalize small shrub change objects, and the difficulty in objectively assessing map accuracy. These weaknesses will likely be overcome as the emerging sub-field of object-based image analysis (OBIA) advances.

The specific research findings from this study are as follows:

1. Image segments derived from a bi-temporal V/NIR image data set having 1 m spatial resolution delineated most shrub change features in a qualitatively realistic manner, though many apparent objects were small relative to the ground resolution element and.
2. The Standard Nearest Neighbor classifier with segment mean and standard deviation measures of Red, NIR, and NDVI image features yielded the shrub change map that agreed more closely with reference data.
3. The Membership Function classifier was more difficult to implement for the bi-temporal composite classification approach and yielded a map that excessively classified no-change objects as shrub changes.
4. The overall accuracy and kappa statistics for the optimal shrub change map were 0.83 and 0.64, respectively, with the predominant error being associated with "over-classification" of no-change objects as some type of shrub change.
5. No statistical difference in accuracies of three- and five-class maps was found, suggesting that changes in true shrubs and sub-shrubs within coastal sage scrub vegetation communities can be differentiated reliably.
6. A net 5% loss of shrub cover was determined from the shrub change map of the study area; since the User's and Producer's accuracies were essentially the same for both Shrub Increase and Decrease classes, this map-based estimate of net shrub loss seems to be reliable.
7. The greatest decrease and biggest net loss of shrub cover occurred within the urban edge zone and within flat-lying areas; patterns of shrub loss appear to be more related to anthropogenic disturbance than drought effects.

While the object-based approach to shrub change delineation and identification developed through this study is promising, several follow-on research tasks are recommended, with the goal of developing an operational monitoring system for shrubland habitat reserves. If reliable information on changes of individual shrubs or sub-shrub patches is essential, then image data with spatial resolutions finer than 1 m will likely be required (Ehlers et al., 2006; Laliberte et al., 2007). This should be tested, along with refinements in the selection of image segmentation parameters, in relation to the size and shape of shrub change objects. A comparison of the approach utilized here, where a bi-temporal composite is directly segmented and classified, with change vector and post-classification approaches is warranted. A new classification strategy in the Definiens software called Process Trees, an integration of expert systems and object-based classification, may be more successful at mapping shrub habitat changes. Approaches to characterizing and classifying misregistration objects relative to actual shrub changes should be developed. Finally, new schemes for calibrating/training and validating/testing object-based classifications of shrub changes that rely on coordinated field observations and/or even higher spatial resolution image data need to be developed. A possible solution is the capturing of ultra-fine spatial resolution (0.1 to 0.3 m) images in a nested sampling framework, and using such images to generate training and test data sets.

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