Mapping vegetation community types in a highly disturbed landscape: integrating hierarchical object-based image analysis with lidar-derived canopy height data

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ABSTRACT

Focusing on the semi-arid and highly disturbed landscape of San Clemente Island (SCI), California, we test the effectiveness of incorporating a hierarchical object-based image analysis (OBIA) approach with high-spatial resolution imagery and canopy height surfaces derived from light detection and ranging (lidar) data for mapping vegetation communities. The hierarchical approach entailed segmentation and classification of fine-scale patches of vegetation growth forms and bare ground, with shrub species identified, and a coarser-scale segmentation and classification to generate vegetation community maps. Such maps were generated for two areas of interest on SCI, with and without vegetation canopy height data as input, primarily to determine the effectiveness of such structural data on mapping accuracy. Overall accuracy is highest for the vegetation community map derived by integrating airborne visible and near-infrared imagery having very high spatial resolution with the lidar-derived canopy height data. The results demonstrate the utility of the hierarchical OBIA approach for mapping vegetation with very high spatial resolution imagery, and emphasizes the advantage of both multi-scale analysis and digital surface data for accurately mapping vegetation communities within highly disturbed landscapes.

1. Introduction

Mapping vegetation communities in the field or by visual image interpretation can be challenging, inefficient, and subjective (Xie, Sha and Yu 2018; Ullerud et al. 2018). Advances in object-based image analysis (OBIA) technology have the potential to facilitate novel remote sensing methods to address the challenge of accurately and efficiently mapping vegetation community types. Previous studies have demonstrated that OBIA has the potential to quantify and map fine-scale land cover and biophysical attributes with high-resolution imagery (Mallinis et al. 2008; Chen et al. 2009; Yu et al. 2006; Mathieu and Aryal 2007; Stow et al. 2008). While closed-canopy shrublands have been successfully mapped using OBIA methods at the lifeform level (Uyeda et al. 2016),
mapping open-canopy shrublands at the vegetation community level has been shown to be problematic (Clark and Kilham 2016). Spectral signatures of open-canopy shrublands in very high spatial resolution image are highly varying, reflecting the spatially heterogenous land cover associated with this ecosystem type.

A potential solution to this challenging mapping situation is to first map patches of vegetation growth forms and selected species types and then use these patches as the bases for delineating and classifying vegetation community units. This approach of integrating hierarchical object-based image analysis for vegetation community mapping has been used only in a limited number of studies. Laliberte et al. (2010) developed a hierarchical-based approach to classify very-high spatial resolution (VHSR) imagery to map and assess arid rangelands and found that OBIA was a viable approach for quantifying vegetation cover, although it resulted in a classification that is less detailed than one would achieve when relying on field-based mapping and measurements. Similarly, Mishra and Crews (2014) assessed the integration of hierarchical OBIA methods with a Random Forest classification algorithm to map vegetation morphology types, and found the hierarchical OBIA approach to be a reliable mapping technique.

While the few previous studies cited above have demonstrated that both traditional and hierarchical OBIA approaches are effective tools for mapping vegetation with VHSR imagery, this study appears to be the first of its type to investigate the integration of hierarchical object-based classification, aerial multispectral orthoimagery, and canopy height information generated from light detection and ranging (lidar) point clouds to map vegetation communities. We assess whether incorporating lidar with high-resolution aerial imagery, through a multi-scale object-based analysis, provides a reliable means for identifying and delineating grassland and shrubland vegetation community types.

The following research question is addressed in this study: How does incorporating a lidar-derived normalized digital surface model (nDSM) data affect the accuracy of vegetation classification products compared to products derived exclusively from VHSR visible/near-infrared orthoimagery?

2. Study area and classification system

San Clemente Island is the southernmost of the eight Channel Islands that lie off the coast of Southern California (Figure 1). The centre of the island is approximately 98 km southwest of Long Beach and 129 km west-northwest of San Diego. The island’s area is 148 km², and it is composed almost entirely of volcanic rocks of Miocene age that are overlain in places by sedimentary rocks of marine origin (Olmstead 1958). Topographically the island rises gradually from its western shore to a peak elevation of 599 m then plunges dramatically on its east side. Precipitation timing on the island follows a typical Mediterranean-climate pattern with approximately 94% of the precipitation falling from October through April with high inter-annual variability. Average annual precipitation ranges from 14.2 cm near sea level on the western shore increasing to 23.1 cm at intermediate elevations and is doubtless greater on the island’s highest areas (Tierra Data Inc 2011). San Clemente Island as well as the other Channel Islands, coastal southern California, and northern Baja California are strongly influenced by persistent stratus and fog, especially during May and June (Clemesha et al. 2016). This maritime influence substantially moderates temperatures on the island which range from an average of
Figure 1. Study area maps and images. (a) Map of San Clemente Island California, the southern-most of the channel Island complex (www.wikipedia.org). (b) Locations of the two areas of interest (AOI) on San Clemente Island for which vegetation map procedures were tested. Each AOI is approximately 3.5 km² in area.
18°C during summer months to 13°C during winter months (Schoenherr, Feldmeth, and Emerson 2003).

The vegetation of San Clemente Island has withstood a prolonged history of heavy grazing pressure by exotic herbivores and was particularly impacted by feral goats. Sheep ranching likely commenced on the island in 1848 (Schoenherr, Feldmeth, and Emerson 2003), and by 1883 10,000 sheep were reported to occur on the island (Johnson 1975). It is uncertain whether goats were also introduced to the island in 1848 but they were undoubtedly present by 1875 (Johnson 1975). Ranchers also introduced pigs to the island most likely for food and sport hunting (Schoenherr, Feldmeth, and Emerson 2003). Sheep and cattle ranching continued until 1934 when the island was acquired by the U.S. Navy. In the absence of natural predators, the goat population increased to an estimated size of 10,000–20,000 in 1972 when systematic removal of the goats and pigs was initiated by the U.S Fish and Wildlife Service with cooperation of the U.S. Navy (Resnick 1986). Complete eradication of both species occurred in the early 1990s (U.S. Fish and Wildlife Service 2002).

The current vegetation of the island is dominated by two vegetation types, maritime succulent scrub and non-native grassland. Maritime succulent scrub occurs very largely on drier, lower elevation areas on the west side of the island, and is dominated by succulent subshrubs such as _Lycium californicum_, _Bergerocactus emoryi_, and _Euphorbia misera_. Non-native grassland is most prevalent at intermediate-to-higher elevations on the island and is dominated by _Avena barbata_, _Vulpia myuros_, and _Bromus hordeaceus_. Two cacti species, _Opuntia littoralis_ and _Cylindropuntia prolifera_, as well as native grass species, are admixed in varying amounts throughout the non-native grassland. Chaparral shrubs, such as _Rhus integrifolia_, are sparsely scattered throughout SCI. The recovery of these and other shrubs after the removal of exotic herbivores is of particular interest for SCI, as these shrubs provide important habitat for endemic endangered birds (Tierra Data Inc 2013).

Two study sites or areas of interest (AOI) used for this analysis were selected based on the relative diversity and representativeness vegetation types for most of SCI, and their accessibility when planning and performing ground-based accuracy assessments. The AOI cover approximately 7 km² (3.5 km² per study site), and have been subjected to a variety of anthropogenic disturbances.

The classification system (Table 1) used for this study was specifically designed as part of the broader research effort to develop an updated vegetation community map for San Clemente Island. It follows the alliance-based classification system for California (Sawyer, Keeler-Wolf, and Evens 2009) and is based on the vegetation sampling, classification, and

<table>
<thead>
<tr>
<th>Stratum</th>
<th>Community</th>
<th>Minimum Mapping Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shrub</td>
<td><em>Artemisia californica</em> Shrubland Alliance</td>
<td>0.25 ha</td>
</tr>
<tr>
<td></td>
<td><em>Baccharis pilularis</em> Shrubland Alliance</td>
<td>0.25 ha</td>
</tr>
<tr>
<td></td>
<td><em>Lycium californicum</em> Provisional Shrubland Alliance</td>
<td>0.25 ha</td>
</tr>
<tr>
<td></td>
<td><em>Opuntia littoralis</em> Shrubland Alliance</td>
<td>0.25 ha</td>
</tr>
<tr>
<td></td>
<td><em>Rhus integrifolia</em> Shrubland Alliance</td>
<td>Individual shrub</td>
</tr>
<tr>
<td>Herbaceous</td>
<td><em>Ambrosia chamissonis</em> – <em>Abronia maritima</em> Alliance</td>
<td>0.25 ha</td>
</tr>
<tr>
<td></td>
<td>Annual and Perennial Grasslands</td>
<td>0.25 ha</td>
</tr>
<tr>
<td></td>
<td><em>Mesembryanthemum</em> spp. – <em>Carposbrotus</em> spp. Semi-natural Stands</td>
<td>0.25 ha</td>
</tr>
<tr>
<td>Non-vegetated</td>
<td>Developed</td>
<td>0.25 ha</td>
</tr>
</tbody>
</table>
mapping protocol recommended by the California Native Plant Society (http://cnps.org/cnps/vegetation/sampling.php). An associated vegetation mapping key based on the membership rules published for the alliances of interest (Sawyer, Keeler-Wolf, and Evens 2009; Sproule et al. 2011) was also used. Due to the special management significance of *R. integrifolia*, this alliance was mapped at the resolution of the individual shrub. Every other alliance was mapped using a minimum mapping unit (MMU) of 0.25 ha.

3. Data and methods

3.1. Aerial imagery and lidar data

Four-waveband, digital VHSR image data with a nominal ground sampling distance of 15 cm were acquired in November 2015 from a commercial provider. The imaging system consists of two (visible and near-infrared sensitive) Canon Mark II 5D Digital SLR cameras (21 megapixel) mounted on a Cessna 182 fixed wing aircraft. VHSR image frames were collected with 80% forward and 70% sideways overlap to enable generation of high-precision DSMs, which in turn enabled the generation of georeferenced, orthorectified, and mosaicked imagery of the island using Agisoft Photoscan software. The VHSR orthomosaic datasets were the primary input data for OBIA vegetation mapping.

Orthoimagery from the National Agriculture Imagery Program (NAIP) for three image dates, 28 April 2012, 6 July 2014, 22 July 2016, were also utilized for vegetation mapping. This imagery was captured at a spatial resolution of 1 m for 2012 and 2014 imagery, and 0.6 m for 2016, and with four visible and near-infrared bands. Differences in the season of imagery collection and recent rainfall history in the three NAIP images were leveraged to help discriminate species in problematic areas of the 2015 imagery. Three normalized difference vegetation index (NDVI) image layers were created from the NAIP imagery, and used as input during the image classification phase. NDVI is derived by subtracting the red waveband digital number values from the near-infrared band and dividing by the sum of DNs for those two bands (Jensen 2007).

The U.S. Navy Pacific Fleet provided lidar data captured for San Clemente Island in Fall 2014 with 10 cm vertical accuracy that we used to generate canopy height data sets. The point cloud data were converted to a 0.5 m raster with ESRI’s ArcMap 10.4.1 software. This LAS format dataset was then manually classified and edited to remove extraneous noise and features (flying birds, electrical poles and wires, etc.). Digital surface models (DSM) and digital elevation models (DEM) were produced for the AOI using a triangulation interpolation method that derives cell values using a triangular irregular network. The resultant lidar derivatives were used to produce a normalized digital surface model (nDSM), or canopy height model by image differencing (O’Neil-Dunne et al. 2013). An example nDSM is shown in Figure 2. This plant structural information aided in the classification of and discrimination between various plant species and communities (Levick and Rogers 2006).

3.2. Hierarchical object-based image analysis strategy

To effectively account for the complex and non-linear relationships that are encountered in spatially heterogeneous and dynamic natural systems, a hierarchical segmentation and classification model was developed with eCognition software tools to perform
a multi-scale mapping of plant community types into two levels: Level 1 – shrub and patch-sized objects and Level 2 – plant community sub-objects. We differentiate image segments, as groupings of pixels based on image brightness homogeneity characteristics, from image objects that are segments that have been assigned a class label. With this multi-scale approach, orthoimage, NDVI, and nDSM data were first segmented at a finer level (Level 1), and parameters were set to delineate individual shrubs and very small patches of heterogeneous land cover types.

A second, coarser-scale segmentation (Level 2) was then performed, where new image objects were delineated around the already existing Level 1 objects. This resulted in an image of multi-scale image objects, where Level 1 segments are nested within Level 2 segments. After segmentation, image segments produced at Level 1 were classified as growth form types, with shrub species identifications for shrub forms.

A total of 13 Level 1 classes were identified. The non-vegetative land cover classes are: developed, soil, sand dunes, and bare/rock. The class bare/rock consists of bright areas, devoid of vegetation and with no litter, or large rocks and boulders. The soil class represents patches of exposed soil, the developed class denotes areas that are comprised of man-made features such as roads and large-scapings due to construction, while the sand dune class pertains to areas that have active sand dunes, on which no vegetation is present. The nine vegetated classes include the shrubs *A. californica*, *Baccharis pilularis*, *L. californicum*, *Opuntia littoralis*, and *R. integrifolia*, the herb *Calystegia macrostegia*, and

Figure 2. Sample subset depicting spatial data used for vegetation mapping. (a) VHSR orthoimage displayed in true colour; (b) digital surface model (DSM) derived from lidar data set; (c) digital elevation model (DEM) from the same lidar data set; (d) threshold-classified normalized digital surface model (nDSM) generated by differencing (subtracting the DEM from the DSM) – shrub objects (white) within a black matrix of low stature herbaceous cover.
the general classes of grasses, forbs, and ice plants. Grasses in the study area include the non-native species *Avena barbata*, *Bromus diandrus*, *Bromus hordeaceus*, and *Bromus madritensis*, with the native perennial grass *Stipa pulchra* sometimes present. The forb and iceplant categories are specific to AOI 2 and are predominately comprised of a combination of *Ambrosia chamissonis* and *Abronia umbellata* and a combination of *Mesembryanthemum crystallinum* and *Mesembryanthemum nodiflorum*, respectively.

The classification product was used to inform the Level 2 product that provides the primary basis for generating the vegetation community map. The rules for the Level 2 classification were primarily based on the individual per cent cover rules that were developed as part of the classification system and key. Generalization and aggregation algorithms were applied to fill-in gaps and dissolve boundaries between neighbouring objects of the same class. By using this multi-scale approach and incorporating cover per cent rules, we were able to incorporate insight from ecological relationships, while overcoming the limitations that are faced when trying to accurately classify heterogeneous vegetation stands (Zhang et al. 2016; Yu et al. 2006).

### 3.3. Image segmentation

The multi-resolution image segmentation algorithm within eCognition software was performed on a raster stack composed of four wavebands from the VHSR imagery (blue, green, red and NIR), 2012, 2014, and 2016 NDVI images, and the nDSM layer. Parameters for the standard hierarchical MRIS routine were as follows: Level 1 – scale parameter = 10, shape = 0.2, and compactness = 0.7, and Level 2 – scale parameter = 50, shape = 0.2, and compactness = 0.7.

### 3.4. Feature selection

To identify the ideal data inputs and parameters for image classification, a data mining tool called Feature Space Optimization (FSO) was implemented in eCognition, which is based on a Euclidean distance in feature space to measure separability of samples between all classes (Laliberte, Browning, and Rango 2012). ‘Features’ in this context refers to spectral (image bands, band ratios), geometric (area, compactness, etc.), contextual (difference to neighbour) and textural properties of images input to OBIA routines. After object statistics of the optimized feature space were calculated, the features providing the greatest discriminant power were incorporated into rule-based algorithms for image classification. FSO was conducted after segmenting the VHSR imagery into fine-scale land-cover objects, and choosing test objects for the 13 Level 1 land cover classes. Twenty training samples for each class were identified based on interpretation of geotagged ground-based images. Thirty image-based features emphasizing the spectral, shape, and texture components of objects within the test areas where chosen, and separability metrics were calculated.

### 3.5. Image classification

Classification of image segments was achieved by exploiting numerous feature inputs, contextual relationships and classification decision rules (reported in Results). Image
segments were classified using a rule-based threshold algorithm to assign Level 1 image objects to growth form, shrub species and land cover types, and at Level 2 to vegetation community classes. Process Trees (instructional sequence of segmentation and classification routines and parameters) in eCognition enabled processing of multiple images across the AOI, and parameters and rule sets were conveniently modified. A preliminary Process Tree was developed to classify vegetation communities within a subset of each AOI, and after refinement to the entire AOI. This was done to take advantage of similarities in vegetation and land cover types within the study areas, and to minimize processing time.

3.6. Map generalization

The ruleset developed for classification also implemented algorithms and parameters to generalize the vegetation polygons. Individual rules for each mapping category contained built-in functions to fill in any holes, filter out map objects that were smaller than the MMU, and dissolve boundaries between like-classified image objects. Additionally, image objects that were filtered out or remained unclassified were assigned to a class with a neighbour-based algorithm that calculated the per cent of a border it shared with a neighbouring image object. If it shared a majority border, or at least 51%, it was assigned to the class of that bordering object. A post-classification smoothing routine was applied, and the final classification map was output as ‘smoothed’ polygons in vector format.

3.7. Accuracy assessment and comparison of products

Accuracy of mapped vegetation community type polygons was estimated based on field assessment of 198 sample units (100 in AOI 1, 98 in AOI 2), conducted from July–December 2017. Sampling points were randomly selected within each AOI using the ‘Create Random Points’ tool in ArcMap software, with a minimum distance of 60 m between points. Circular sample units were created around each of the randomly generated points. To ensure that each of these circular units would be completely contained inside a vegetation community polygon, an inverse buffer was performed on the final vegetation polygon maps using ArcMap software. Survey areas were delineated around each point, and sizes were refined by trial-and-error until the maximum sized circle could be drawn within the smallest-sized polygon. This resulted in circular survey units with a 30-m radius and approximate area of 0.28 ha.

A modified rapid assessment procedure to assess vegetation composition was conducted on the ground within each of the circular units. The five species with the greatest per cent cover at within the sample unit were recorded. A vegetation community was assigned using associated cover per cent rules and the vegetation key. The vegetation community class from the rapid assessment of the sampling units and OBIA-derived polygons containing such units were compared to generate accuracy matrices.

An additional accuracy assessment was implemented to assess the accuracy of the *R. integrifolia* vegetation class, which has an MMU as small as an individual plant or small patch. Reference data were generated through visual analysis of color infrared VHHSR orthoimagery and when available, field-based survey data. The locations of identified
R. integrifolia plants were overlain on the OBIA vegetation community product. If an image object that was classified as R. integrifolia intersected with one of the R. integrifolia points, that object was considered to be correctly identified (i.e. accurate). This visual-based accuracy assessment was conducted for a total of 109 image-derived R. integrifolia objects between the two AOI.

4. Results

4.1. Image feature selection for classification

The FSO data mining tool selected a variety of image features as most suitable for separating classes during the Level 1 classification stage, as shown and described in Table 2. Of the 30 spectral, geometric, and texture-based features assessed, spectral-radiometric (i.e. waveband digital number) features are found to be the most useful for separating the land cover classes. A combination of segment mean and standard deviation spectral-radiometric and spectral transform features was used to develop the rulesets for individual land cover and vegetation classes.

4.2. Object-based classification

Image classification consisted of developing the rule-based process tree and applying customized process trees for the two AOI. The initial development of process trees was time-consuming, partly due to the number of classes and complexity of the image being analyzed. Most of the work effort and analyst interaction pertained to determining and refining classification threshold levels for each feature type.

The classification of vegetation communities (Level 2 objects) within the two AOI is based on a scheme with nine classes: one non-vegetative and eight vegetation community types. Three classes found in the Level 1 classification (Calystegia macrostegia, soil, and bare/rock) are excluded from the community level classification because they do not meet the MMU requirements. Vegetation community map products generated from the object-based image analyses are portrayed in Figures 3 and 4.

4.3. Accuracy assessment

Accuracy matrices for vegetation community maps generated with high spatial resolution inputs, with and without a canopy height model produced from the lidar point

<table>
<thead>
<tr>
<th>Features</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean layer value</td>
<td>Mean brightness of an image object within a single band; selected features: mean brightness, mean red, mean blue, mean NIR, mean NDVI, mean nDSM.</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>Standard deviation of all pixels which form an image object within a band; selected features: standard deviation red, standard deviation blue, standard deviation green, standard deviation NIR.</td>
</tr>
<tr>
<td>Hue, saturation, and intensity transformations</td>
<td>Transforms RGB bands in an image to hue-saturation-intensity (HSI) values; selected features: hue (H).</td>
</tr>
</tbody>
</table>
cloud, for the two AOI individually and combined are presented in Tables 3 and 4. Using only image inputs to the OBIA classifier yielded maps averaging 62% overall accuracy, while the inclusion of the canopy height information yields maps averaging a 75% overall accuracy. All individual vegetation community and land cover classes were

**Figure 3.** Vegetation community classification products for AOI 1. (a) Product from image inputs only, (b) Product from the integrated image and lidar-derived canopy height model data.
mapped as or more accurately when the lidar-derived canopy height layer was included. Inclusion of the layer was particularly useful for discriminating between shrub alliances, and between grassland and non-vegetation classes.

When analysing individual AOI, however, certain mapping classes appeared to have fairly high omission and commission error, suggesting that the inclusion of the canopy height model has less of an impact on classification accuracy on these classes. This is particularly noticeable in certain areas of AOI 2, where large and very dense stands of the drought-deciduous shrub *L. californicum* are present. A probable reason for this difference in accuracies between AOI is the variable senescence between the plant species in the two AOI and the responsiveness of shrubs with a dense canopy, such as *L. californicum*, to lidar detection. Rather than detecting multiple returns, top of canopy returns were exclusively captured (i.e. none from the ground surface). Thus, in the lower terraces of AOI 2 where most *L. californicum* cover was present, the canopy height model represented those areas as having a height of 0 m (i.e. ground level), although field-assessment shows that is not the case. The inability to correctly capture the height of these shrubs made it more difficult to separate them from other vegetation classes in the study area during the automated classification process.

Some confusion in the vegetation communities was due to the difficulty in fitting the field data within the categories used for the mapping. Several plots were found to be dominated by forbs such as *C. macrostegia*, *Salsola sp.*, or *Atriplex semibaccata*. We grouped these plots into the category of 'Other forbs', and used this category only for the reference data.

*Figure 4.* Vegetation community classification products for AOI 2. (a) Product from image inputs only, (b) the product from the integrated image and lidar-derived canopy height model data.
Table 3. Accuracy table and statistics for object-based classification for combined AOI, without a lidar-derived canopy height model.

<table>
<thead>
<tr>
<th>Class</th>
<th>Ambrosia-Abronia</th>
<th>Artemisia californica</th>
<th>Baccharis pilularis</th>
<th>Grassland</th>
<th>Lycium californicum</th>
<th>Mesembryanthemum-Carpobrotus</th>
<th>Opuntia littoralis</th>
<th>Other Forbs</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ambrosia-Abronia</td>
<td>8</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td>Artemisia californica</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Baccharis pilularis</td>
<td>0</td>
<td>3</td>
<td>9</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td>Grassland</td>
<td>0</td>
<td>3</td>
<td>3</td>
<td>55</td>
<td>2</td>
<td>3</td>
<td>6</td>
<td>2</td>
<td>74</td>
</tr>
<tr>
<td>Lycium californicum</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>28</td>
<td>0</td>
<td>24</td>
<td>2</td>
<td>59</td>
</tr>
<tr>
<td>Mesembryanthemum-Carpobrotus</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Opuntia littoralis</td>
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<td>0</td>
<td>11</td>
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<tr>
<td>Other Forbs</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sum</td>
<td>10</td>
<td>9</td>
<td>13</td>
<td>75</td>
<td>31</td>
<td>4</td>
<td>51</td>
<td>6</td>
<td>198</td>
</tr>
<tr>
<td>Producer's accuracy (%)</td>
<td>80.0</td>
<td>22.2</td>
<td>69.2</td>
<td>73.3</td>
<td>90.3</td>
<td>25.0</td>
<td>38.0</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>User's accuracy (%)</td>
<td>72.0</td>
<td>66.7</td>
<td>60.0</td>
<td>74.3</td>
<td>47.5</td>
<td>33.3</td>
<td>57.6</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td>62.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4. Accuracy table and statistics for object-based classification for combined AOI, integrating a lidar-derived canopy height model.

<table>
<thead>
<tr>
<th>Class</th>
<th>Ambrosia-Abronia</th>
<th>Artemisia californica</th>
<th>Baccharis pilularis</th>
<th>Grassland</th>
<th>Lycium californicum</th>
<th>Mesembryanthemum-Carpobrotus</th>
<th>Opuntia littoralis</th>
<th>Other Forbs</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ambrosia-Abronia</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Artemisia californica</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6</td>
</tr>
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Producer’s accuracy (%)  
User’s accuracy (%)  
Overall accuracy (%)
Results for the separate accuracy assessment for *R. integrifolia* are shown in Table 5. Because *R. integrifolia* was assessed at a separate scale and with different survey methods, its mapping accuracy was not included previous tables. The classification method integrating the canopy height model yielded a substantially higher mapping accuracy of *R. integrifolia*. Although both classification techniques had some confusion between *R. integrifolia* and grassland and forb classes, in the absence of the nDSM data maps exhibited a particularly high amount of commission error.

### 5. Discussion and conclusions

With the aim to improve the mapping of vegetation communities in disturbed landscapes using high-spatial resolution imagery, the objective of this study was to assess the effectiveness of integrating hierarchical object-based image analysis with a digital canopy model. In this approach, objects are first classified at the scale of individual shrubs or small patches of land cover type using spectral and canopy height information. Coarser objects are then classified based on coverage of these finer objects to produce a map that meets the requirements of the specified minimum mapping unit.

Similar to previous studies (Mishra et al. 2014; Laliberte, Fredrickson, and Rango 2007; Chen et al. 2009; Zhang et al. 2016), the results of this study also indicate that a hierarchical object-based approach is effective for delineating and classifying vegetation community units. Results from this study also indicate that the integration of lidar-derived canopy height data into the semi-automated classification routine results in a product with a 13% increase in accuracy than when using image-derived features only. While an improvement in accuracy with the inclusion of canopy height is to be expected in closed-canopy systems (Su et al. 2016; Zhang, Xie, and Selch 2013), it has not been well documented in open-canopy systems, particularly when implementing the hierarchical object-based approach. Amongst individual classes, most notably *R. integrifolia*, the incorporation of the canopy height model resulted in a classification with an accuracy upwards of 56% higher. An improvement in *R. integrifolia* classification accuracy is particularly important due to the conservation management interest in this species.

This study is one of the first to utilize a hierarchical OBIA approach with UHSR image and lidar-derived canopy height data for mapping vegetation communities. The semi-automated vegetation community mapping procedures developed in the study combine the strengths of object-based image analysis, contextual hierarchies that naturally occur
throughout the environment, and structural vegetation data derived from digital surface models. Although the products derived from this study could be improved with refinement of the canopy height model, the mapping products that were generated provide a sound foundation for automated mapping of vegetation communities using high spatial resolution imagery. This approach is particularly valuable for the disturbed, open-canopy shrublands present throughout SCI, although it also shows potential for other open-canopy ecosystems or any ecosystem where vegetation community membership is defined by per cent cover thresholds. As the shrubland communities on SCI continue to recover from grazing pressure, accurately tracking the change in shrub cover over time will remain an important aspect of understanding the health of the ecosystem. The vegetation community products generated through the study will support biological monitoring of San Clemente Island and the conservation and management efforts of the United States Navy and natural resource personnel on the island.

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