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An assessment of Hawaiian dry forest condition with fine resolution remote sensing

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Abstract

Remote sensing offers the potential to spatially map forest cover quickly and reliably for inventory purposes. We developed a new image analysis approach using an integrated methodology of "object-based" image classification techniques and field-based measurements to quantify forest cover in a degraded dry forest ecosystem on the leeward side of the Island of Hawaii. This new approach explicitly recognized the transitional areas between tree crowns and tree shades (tree shadows) as a unique class and fully utilized them for the quantification of canopy cover. Object-oriented classification of Ikonos-2 satellite images allowed delineation of tree shades and crowns and the transitional areas between them from objects with similar reflectance and size that were surrounding the trees. These included patches of fountain (*Pennisetum setaceum*) and kikuyu (*Pennisetum clandestinum*) grass, lava outcrops and lava–grass mixtures. Crown-shade transitions were clearly differentiated in spite of their wide range of spectral values and reflectance similarities with areas of lava–grass mixture. Segments representing tree shades and dark lava outcrops were also classified into their respective classes even if they were contiguous. The image estimates of canopy cover using the tree shade plus transition classes were linearly related with field estimates of canopy cover ($R^2 = 0.86$ and slope = 0.976). Based on this relationship, dry forest cover throughout the 2627-ha area was estimated at 7.7 ± 1.9%. An immediate application of this new approach is to select and delineate areas with higher canopy cover in order to concentrate ecological restoration and conservation efforts.
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Keywords: Dry forest; Hawaii; Transitional area; Object-based classification; Ikonos-2

1. Introduction

Tropical dry forests are among the most endangered and degraded ecosystems in the world (Bullock et al., 1995; Janzen, 1986, 1988; Murphy and Lugo, 1986). Over 90% of the original Hawaiian dry forests have been destroyed (Bruegmann, 1996; Mehrhoff, 1993), and about 25% of the officially listed endangered Hawaiian plant taxa are from dry forest and/or dry scrub ecosystems (Sakai et al., 2002). The North Kona region of the Island of Hawaii represents one of the largest areas of remaining dry forest habitats in the Hawaiian archipelago. However, forest cover has dramatically declined in the region, and native vegetation is now represented by small and highly fragmented patches with few, often declining trees of the most common species (Blackmore and Vitousek, 2000; Bruegmann, 1996). Among the causes of degradation are land conversion, fire, alien plant invasions, long-term use as grazing land and low dry forest regeneration rates due to browsing of seedlings and saplings by cattle and feral ungulates (Cuddihy and Stone, 1990; Scowcroft, 1983; Stemmermann and Ihsle, 1993). Extensive invasions of an escaped ornamental grass, *Pennisetum setaceum* (fountain grass), and an introduced pasture grass, *Pennisetum clandestinum* (kikuyu grass), limit seedling survival. They also promote fires during the dry season that kill seedlings and saplings and force mature trees into premature senescence or even death (Cabin et al., 2002a,b; Mueller-Dombois and Fosberg, 1998). Therefore, there is a great concern that Hawaii's remaining dry forest ecosystems could vanish without intensive, aggressive management and restoration efforts (Cabin et al., 2000).

Several studies have been made to improve our understanding of degradation processes and ecosystem function of remaining dry forests in Hawaii. Blackmore and Vitousek (2000) estimated long-term loss of dry forest cover at Puu Waa

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Waa Ranch in the North Kona region using classified aerial photographs from 1954 to 1994. They calculated a dry forest cover decline of 62% and a grassland area increase of 237% during that time. They also found that continued grazing could potentially increase forest decline due to low regeneration by browsing; however, grazing removal could increase fire incidence due to fuel build-up of dried kikuyu and fountain grass litter. Elmore and Asner (2006) found that soil organic carbon (SOC) pools were smaller in converted pastures when compared to native dry forests. They also found relationships between field SOC measurements and surface litter estimations from hyperspectral remote sensing data, which may be useful in the analysis of pasture and C storage conditions at a regional scale. Cabin et al. (2000, 2002a,b) have shown that dry forest species can regenerate after grazing removal, alien species control and introduction of native species. Cordell et al. (2002) developed cost-effective techniques for the control of fountain grass invasion at smaller spatial scales (<1 ha). Detailed botanical records of native and non-native species and vegetation classification studies also exist for this region, including a list of endangered plant and animal species (Giffin, 2003).

The majority of these studies have focused on determining dry forest biodiversity and understanding its ecosystem function. A more accurate assessment of dry forest cover, including native and non-native tree species, is needed in order to complement the existing knowledge and to support forest ecosystem management and restoration. Fine resolution satellite imagery provides new opportunities to develop detailed forest inventories by exploiting the large amount of spatial information and analyzing multispectral bands in the visible and near-infrared wavelength regions (Dial et al., 2003). Several studies have used such data to map tree-top crowns or the shadows case by tree crowns (tree shade) in order to estimate tree cover in dense forested areas (Carleer and Wolff, 2004; Carleer et al., 2005; Chubey et al., 2006; Herold et al., 2003; Hu et al., 2005; Wang et al., 2004; Warner and Steinmaus, 2005; Xu et al., 2003). Carleer and Wolff (2004) derived principal components (PCs), normalized difference vegetation index (NDVI), and texture images from Ikonos satellite data and used them in the identification of tree species in a forested area in Belgium. Seven tree species, including two different ages, were successfully identified with 86% overall classification accuracy.

Object-based analysis and image segmentation techniques have been increasingly applied in fine resolution, multispectral imagery as an alternative to overcome the difficulties of conventional procedures of spectral and texture image analysis for various forestry applications (Chubey et al., 2006; Herold et al., 2003; Hu et al., 2005). Instead of analyzing a single pixel spectral response, a wide range of spectral values in a group of pixels representing a forest stand is interpreted as a homogeneous object which can be further segmented into even more homogeneous subgroups. Pixel grouping can be controlled by the user through the definition of parameters such as size, homogeneity and shape in order to reduce heterogeneity in the resulting objects (Chubey et al., 2006). Wang et al. (2004) utilized a combination of spectral classification techniques and segmentation methods for tree-top detection and tree classification in a forested area in British Columbia, Canada. They calculated the first principal component from a set of spectral images from the Compact Airborne Spectrographic Imager and applied a Laplacian edge detection method for tree-crown delimitation. They further applied a segmentation technique and tree-top markers in order to differentiate final individual tree crowns. They estimated a tree density of 1211 trees per hectare with accuracy of 85% when compared to a manual tree counting method by visual image interpretations. For the same study region in Belgium, Carleer et al. (2005) reduced the edge effects and improved classification accuracy with the use of segmentation techniques using region-based algorithms that enabled the analysis of specific spatial attributes of vegetation in each region without taking into account nearby regions.

Although these authors showed that object-based methods were more effective than spectral methods in the classification of homogeneous forest surfaces, there still existed confusions in the transition zones between contrasting objects in highly heterogeneous areas (Carleer et al., 2005). Likewise, most of previous studies have been carried out in temperate climate areas. Dry forest ecosystems in the tropics constitute a greater variety of tree species and more heterogeneous canopy background due to a larger number of shrub and grass species. Green grass areas and bare surfaces in volcanic regions such as volcanic ash, lava outcrops or ash from burned vegetation can be misclassified as tree crowns and shades. Consequently, there is a need to develop an image classification approach to differentiate transitional areas in order to elaborate more accurate and reliable forest resource inventories.

We used Ikonos-2 satellite images from 2005 with a spatial resolution of 1 m^2 per pixel to quantify current dry forest cover in Hawaii. The objective of this study was to investigate the performance of spectral and object-based classification algorithms in delineating tree canopy cover in a highly heterogeneous dry forest environment. We hypothesized that the object-based approach would allow for the differentiation of tree crowns, tree shades, and their transitional areas from other objects of similar size, shape, or spectral range (e.g. green grass and lava outcrops) and that some combination of these parameters would improve the accuracy and strengthen the relationship with standard field-based measurements. We also applied conventional spectral classification algorithms and compared their results to those from the object-based classification. Canopy cover estimates were then compared to field-based measurements to evaluate their accuracy and precision.

2. Site description

Our study site, the land division of Puu Waa Waa, is located on the western and leeward side of the Island of Hawaii in the North Kona District (Fig. 1). It lies on the northern flank of Hualalai Volcano, extending from sea level to 2000 m near the mountain summit. There are two types of lava surfaces in Hawaii: pahoehoe (smooth lava flows) and aa (clinker type lava

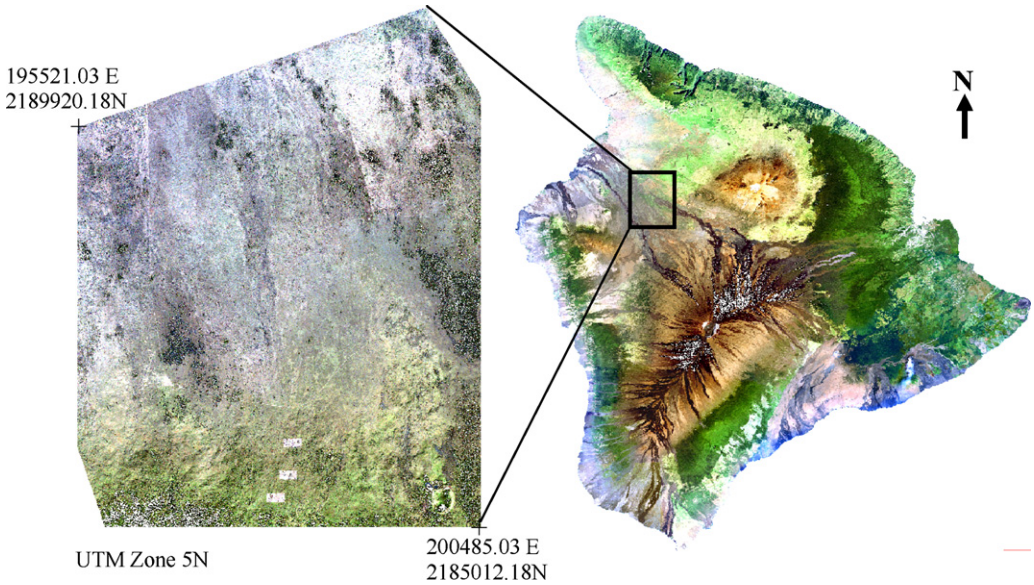

Fig. 1. Landsat satellite image of the Island of Hawaii (right) and Ikonos-2 satellite image depicting Puu Waa Waa Ranch.

flows). The Puu Waa Waa Ranch soil substrate is primarily a 1500–3000 yr-old aa lava flow covered mainly by fountain and kikuyu grasses with extensive lava outcrops throughout the landscape. Several wildlife conservation units have been created, such as the Puu Waa Waa Forest Bird Sanctuary (PWWFBS), classified as a subtropical lower montane dry forest, and the Waihou Forest, classified as a subtropical dry forest (Mueller-Dombois and Fosberg, 1998; Wagner et al., 1999). The PWWFBS (1540 ha) contains a diversity of threatened or endangered native flora and fauna and one of the best remaining habitats for these species. The Waihou Forest, once dominated by ohia lehua (*Metrosideros polymorpha*), koa (*Acacia koa*), mamane (*Sophora chrysophylla*), and naio (*Myoporum sandwicense*), among other native tree species, was created to control fine fuels, to prevent wildfire spread, and to encourage native vegetation regeneration (DLNR, 2003). Several endangered species have been planted within a fenced area (82 ha) in the Waihou Forest, including *Hibiscadelphus hualalaiensis* (hua kuahiwi), *Kokia drynarioides* (kokio), and *Pleomele hawaiiensis* (hala pepe) among others, and the habitat in this area is suitable for several other rare plant species (DLNR, 2003).

3. Materials and methods

3.1. Ikonos-2 fine resolution imagery

A set of Ikonos-2 images, covering the northern part of Puu Waa Waa, were obtained with a near-nadir view at a solar zenith angle of 46° on December 20, 2005 during the wet season in the study area. Ikonos-2 is a satellite-borne sensor that simultaneously collects 1-m panchromatic and 4-m multispectral images (Dial et al., 2003). The multispectral image consists of four separate spectral bands: blue, green, red, and near-infrared (NIR), whereas the panchromatic band covers the entire wavelength region covered by the four multispectral bands (Fig. 2) (Pagnutti et al., 2003). The images were radiometrically calibrated and orthorectified with nearest neighbor resampling to a horizontal accuracy of 10.2 m, equivalent to the U.S. National Map Accuracy Standards of 1:12,000 (Space Imaging, 2003). Due to the gently sloping topography of the study area, the images did not show any geometric artifacts that were typically found in orthorectified Ikonos-2 images over rugged terrain. Preliminary visual inspections of the images showed the advantage of the panchromatic band at capturing very fine spatial details of individual dry forest trees which were not resolved well on the 4 m spatial resolution images. Thus, the panchromatic image was fused to the multispectral image to derive a 1-m multispectral image using the spectral-sharpening technique of Vrabel (2000) and Vrabel et al. (2002), who demonstrated that a pan-sharpened multispectral image maintained the radiometric accuracy of the original bands.

We also attempted to distinguish individual trees using 30-m pixel Landsat Enhanced Thematic Mapper Plus (ETM+) satellite images, but the spatial resolution only allowed detection of large patches of trees. Tree-crown areas of about 50 m^2 were common in this site, and only the 1-m spatial resolution could provide enough details to characterize individual trees.

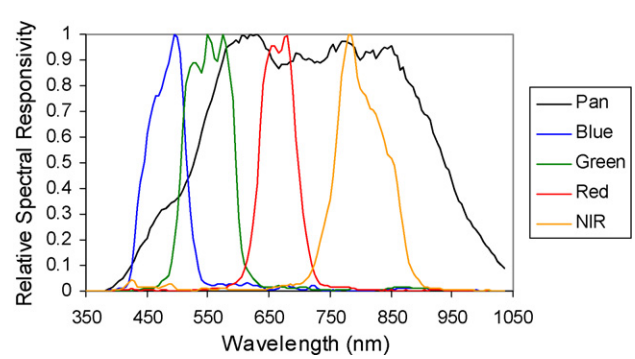

Fig. 2. Relative spectral response for Ikonos-2 satellite in the visible and near-infrared (NIR) spectral regions.

3.2. Image classification

A characterization of current spatial patterns of dry forest cover was obtained by advanced spectral and object-based image classification techniques. ENVI (ITT Visual Information Solutions, Boulder, CO, USA) and eCognition (Definiens AG, München, Germany) software packages were used for the spectral and object-based image classification techniques, respectively.

Spectral classification assigns every individual pixel to a class based on reflectance variations across the spectral bands, or spectral signatures (Jensen, 2000). Pixels with similar spectral signatures are assigned to the same class. Our advanced spectral classification method derived co-occurrence measures of texture (mean, variance, contrast, homogeneity and dissimilarity), PCs and NDVI from the original spectral bands and used them as additional bands in classification. The texture analysis applied to the four original spectral bands produced an output of 20 additional bands. These texture bands, along with the first PC and NDVI, were integrated into the three out of the four original spectral bands (i.e., the green, red and NIR bands), totaling 25 bands. Individual pixels were classified into one of seven classes according to the ''pseudo''-spectral signatures observed across these 25 bands using the Isodata unsupervised classification algorithm. The classes were intended to represent the tree crown, the shadow cast by the tree crown (named ''tree shade''), the crown-shade transition zone, dry grass, green grass, grass-lava mixture, and bare lava.

The object-based technique takes groups of pixels, or ''objects,'' instead of individual pixels as the unit of classification and assigns every object in an image to a class (Chubey et al., 2006). In our analysis, the image was first segmented into groups of pixels. This one-step segmentation process was applied to the four original spectral bands. We used the following settings for scale (12), shape (0.2), smoothness (0.7) and compactness (0.3), selected after testing several combinations of these parameters due to better pixel aggregation into segments representing individual tree-crowns, tree-shades and crown-shade transitions. Visual inspections and interactive comparisons of segments to a true color composite image helped to determine if segment boundaries clearly represented the shape of objects as depicted in the spectral data.

The segmented image was then classified into seven classes using the same class description applied in the spectral classification method. Classification was achieved through selections of multiple representative segments for each of the seven classes throughout the image which were utilized as training sites. A supervised method using the nearest neighbor algorithm included in eCognition was applied to obtain a classified image that contained groups of segments representing each of the seven classes. This procedure was repeated several times in order to increase classification accuracy as the number of training sites for each class increased from 20 to about 200.

3.3. Field measurements of canopy cover

Forest stand characteristics were collected in 15 plots located throughout the ranch. Locations of these plots were determined by a stratified random sampling procedure performed on the Ikonos-2 images.

Five 50 m × 50 m plots were inventoried before the image processing (March, 2006). The measurements included tree species composition, stand density, tree height, stem diameter at breast height (dbh), and percent canopy cover. Tree height was measured using a clinometer. Stem dbh of all trees > 5 cm dbh was measured at 1.3 m above the ground. Percent canopy cover was measured using a hemispherical densitometer at 5 points in each plot (at the center and 5 m from the corners). These data were used to obtain the training dataset for the object-based classification described above.

Ten 25 m × 25 m plots were measured for tree cover after the image classifications (March, 2007). Percent canopy cover was measured using a vertical densitometer at 100 locations within each plot. We first created a grid of coordinates along the two axes of the plot at every meter, so that the plot contained 25 × 25 grid points. Next, we generated a random list of 100 numbers from 0 to 25 (www.random.org) and assigned them to the first axis and then repeated this process to generate another 100 random points from 0 to 25 along the second axis. Densitometer readings were taken at each of the 100 pairs of grid points. The measured tree cover at these plots ranged from 0 to 70%. Two of the plots had no trees, providing a ''zero'' canopy cover baseline.

3.4. Image estimation of canopy cover

Percent tree canopy cover was computed for the ten 25 m × 25 m plots from the classified images using four parameters: tree crown, tree shade, tree-crown plus transition, and tree-shade plus transition. Pixels located in transitional areas between tree crown and tree shade were difficult to assign to either crown or shade classes due to the high to low gradient of reflectance values. Therefore, the transition areas were classified as a single class that can represent both tree crown and tree shade classes. We tested the addition of transitional areas to either tree crown or tree shade areas to calculate percent canopy cover in order to determine which parameter was in better agreement with field estimates.

The field-measured canopy cover values were then regressed against the image estimates. The regression lines were forced through the origin. This was reasonable because both image and field estimates of tree canopy cover should be equal to zero in completely open areas. We used Sigma Plot software (Systat Software Inc.) to calculate the regression coefficients, coefficients of determination (R^2), standard errors, and 95% confidence intervals using the procedures described in Eisenhauer (2003).

We calculated the total area of forest canopy cover from the classified image over the 2627 ha of Puu Waa Waa Ranch using the regression coefficient for each of the classified image parameters. Since the regression coefficients were calculated based on 25 m × 25 m field plots, we first reclassified single pixels into binary numbers of 0 and 1 and then aggregated by summing them into groups containing 625 pixels. Percent cover estimates from aggregated pixels were multiplied by the

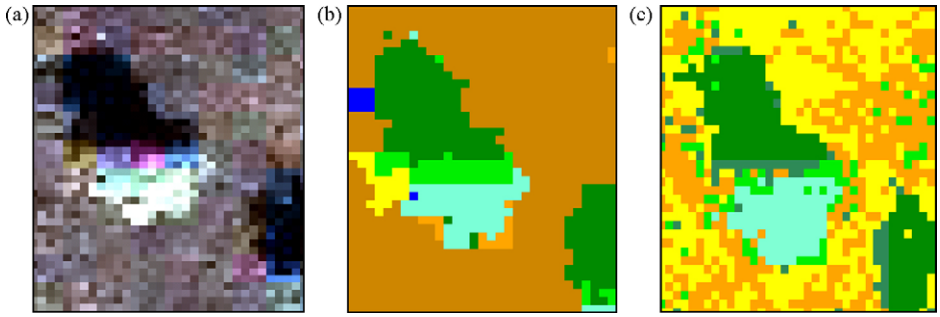

Fig. 3. Comparison between classification techniques. (a) True color composite representing a tree crown (white), shade (black) and transition (color mixture); (b) object-based classification of tree crown (cyan), shade (dark green) and transition (light green); (c) spectral classification of the same tree. Note the misclassification of transitional areas in the spectral classification.

corresponding regression coefficient, summed for the complete image, and multiplied by a conversion factor of 0.000625 to obtain canopy cover in hectares for the whole ranch. The confidence interval of the regression coefficient was likewise used to calculate the upper and lower 95% confidence intervals of canopy cover. Percent canopy cover for each image parameter was calculated in relation to the total number of pixels in the image. This information was useful to derive an overall percentage of forest cover for the whole ranch, which can be used to assess the degree of forest degradation in the entire region or in selected areas.

4. Results

A visual comparison of the classified images from the spectral and object-based methods at the individual tree scale showed that both methods were able to differentiate tree crowns and tree shades from other image classes. The object-based classification clearly distinguished tree crowns and crown-shade transitions, while the spectral method did not (Fig. 3). The object-based method performed well in differentiating between lava areas and tree-shaded areas, which tended to have similar reflectance characteristics. It was not possible to differentiate these two objects with the spectral method (Fig. 4).

At the landscape level, tree crowns and dry and green grasses surrounding trees had similar reflectance properties, which the object-based method was able to differentiate accurately (Fig. 5a). The spectral method was unable to clearly distinguish among tree crowns, dry and green grass and lava–grass mixture surfaces due to their similar heterogeneity of reflectance values. As a result, large areas were classified as crown-shade transition without corresponding tree crowns or shade (Fig. 5b).

Percent canopy cover calculated from the spectral and object-based classification methods were all significant ($P < 0.01$); however, the accuracy and precision varied among the different approaches (Table 1). The object-based estimate of canopy cover using tree shade plus transition had the highest correlation with field measurements ($R^2 = 0.86$) and a coefficient that was close to unity (0.976). The tree shade and tree-crown plus transition estimates also had high correlations, but the coefficients deviated further from unity and had wider confidence intervals. The estimation of tree canopy cover using shade by the spectral method had a lower correlation with field measurements ($R^2 = 0.69$) but a correlation coefficient (1.462) that was within the range of the object-based estimates. The object-based estimate using only the tree-crown class had the lowest correlation with field measurements ($R^2 = 0.56$) and a regression coefficient that was far from unity (3.149).

A comparison of the cross-plots substantiated these results (Fig. 6). For both the spectral and object-based methods, the image estimates of canopy cover in the completely open plots were all zero percent, as expected. The canopy cover estimates using tree shade plus transition were scattered about the 1:1 line over the entire range of measurements (Fig. 6a). For the other approaches, there was a tendency to underestimate canopy

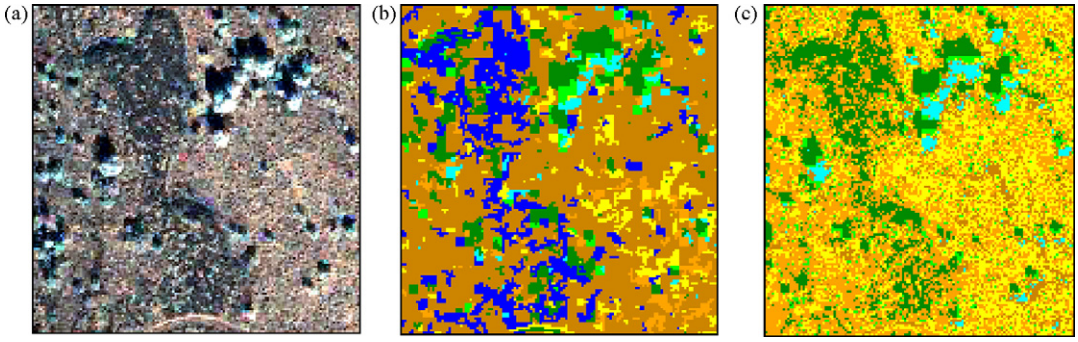

Fig. 4. Classification comparison of tree shades and lava outcrops. (a) True color composite representing tree shade (black) and lava outcrop (dark gray); (b) object-based classification of tree shade (dark green) and lava outcrop (blue); (c) spectral classification of the same area, with extensive misclassification of lava outcrop as tree shade.

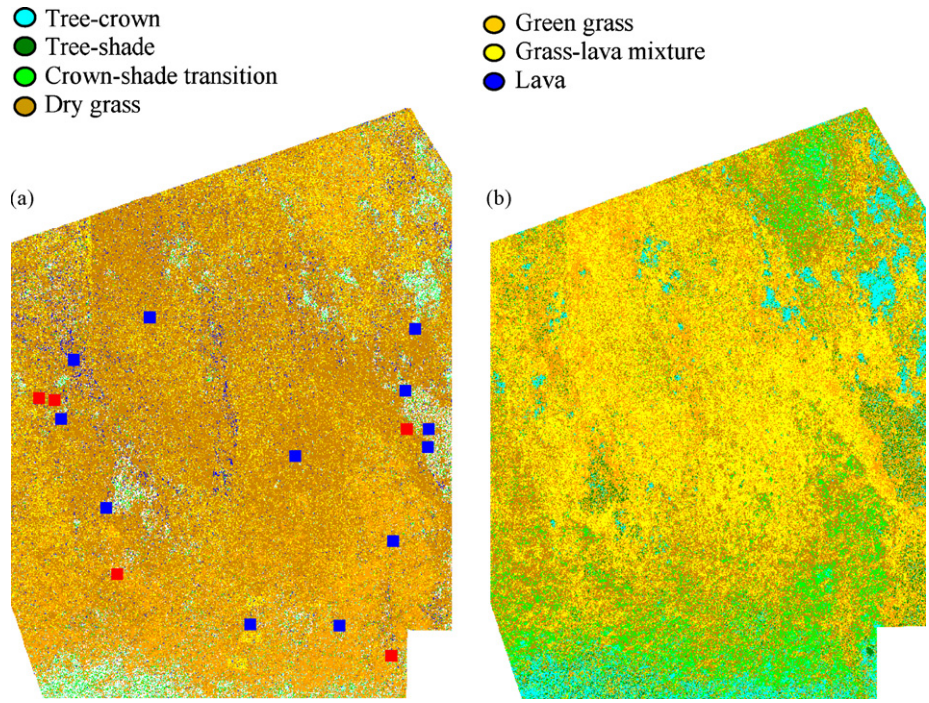

Fig. 5. Series of classified images for Puu Waa Waa Ranch. (a) Object-based classification (red and blue squares represent plots for image training and classification validation, respectively); (b) spectral classification.

Table 1
Statistical parameters from linear regression analysis between different image analysis techniques and field measurements of canopy cover

Image parameter	R^2	Coefficient	95% confidence interval	P value
Object-based Shade + Transition	0.86	0.976	0.689–1.240	<0.01
Object-based Shade	0.82	1.249	0.872–1.667	<0.01
Object-based Crown + Transition	0.80	1.995	1.248–2.741	<0.01
Spectral Shade	0.69	1.462	0.755–2.169	<0.01
Object-based Crown	0.56	3.149	1.129–5.159	<0.01

cover as it increased. For example, all of the estimates of canopy cover using the tree-crown parameter were <25%, and two plots with field estimates of >60% had image estimates of <10% (Fig. 6e).

At the landscape scale, we obtained the lowest estimate of percent canopy cover from the spectral analysis using the shade parameter (Table 2). The object-based shade and shade plus transition parameters provided similar estimates of percent cover with less uncertainty in the latter. Crown and crown plus transition provided the highest estimates with the largest uncertainty (Table 2).

5. Discussion

The use of fine resolution, multispectral satellite imagery processed with the object-based image classification technique showed promise as an accurate and relatively precise tool for estimating and mapping forest tree cover at the landscape scale in a dry forest environment in Hawaii. Our results indicated that the application of a segmentation technique was effective in differentiating tree crowns from objects of similar reflectance and size as surrounding trees, such as patches of fountain and kikuyu grass. This indicated that dissimilarities in shape rather than reflectance characteristics were more important to differentiate these objects. Tree crowns generally had compacted circular shapes; whereas, grass patches were highly spread and irregular. Crown-shade transitions were also clearly differentiated in spite of their wide range of spectral values (from highly reflective tree crowns to very low reflective shades). The lava–grass mixture had a similar range of spectral values, but the pattern was different. Crown-shade transitions had patterns of gradually decreasing reflectance, while lava–grass mixture patches had irregular reflectance changes. This indicates that texture was an important parameter in their classification.

The differentiation between tree shades and dark lava outcrops characteristic of volcanic regions was another aspect overcome by the object-based classification method. Segments of similar size and reflectance representing lava and shade were clearly grouped into their respective classes even when they were contiguous. This indicates that differences in shape and texture between tree shades and lava outcrops were the most

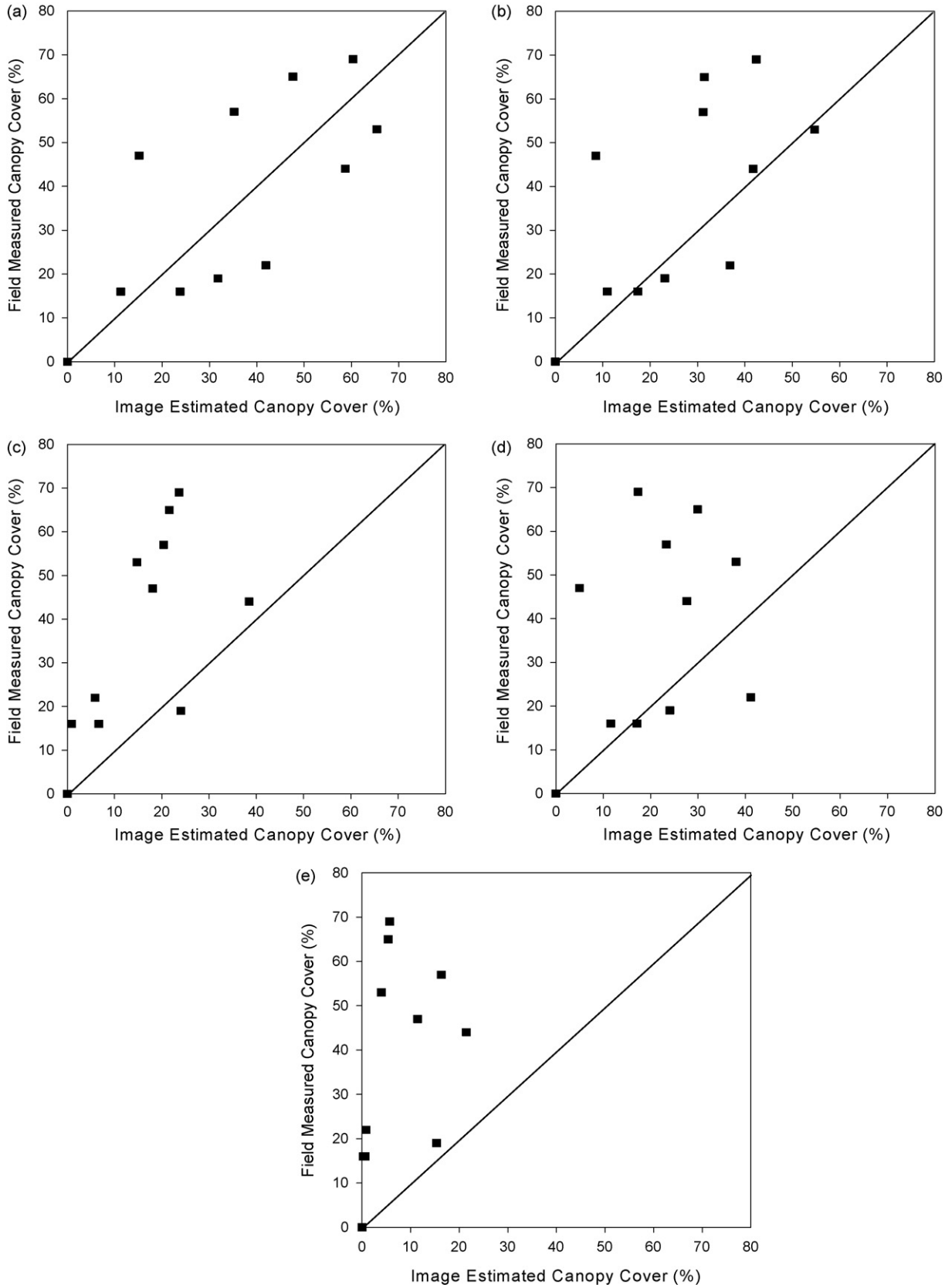

Fig. 6. Relationship between percent canopy cover measured in the field using a vertical densitometer and calculated from an Ikonos-2 image using different image analysis techniques. Lines represent a 1:1 relationship between image estimates and field measurements of canopy cover. (a) Object-based Shade + Transition; (b) Object-based Shade; (c) Object-based Crown + Transition; (d) Spectral Shade; (e) Object-based Crown.

Table 2
Tree canopy cover estimates over a 2627-ha area in a Hawaiian dry forest using object-based and spectral image classification approaches

Image parameters	Canopy cover (ha)	Canopy cover (%)
Object-based Shade + Transition	190 (±51)	7.2 (±1.9)
Object-based Shade	177 (±59)	6.7 (±2.2)
Object-based Crown + Transition	263 (±98)	10 (±3.7)
Spectral Shade	151 (±73)	5.7 (±2.8)
Object-based Crown	246 (±156)	9.3 (±5.9)

Ninety-five percent confidence intervals in parentheses.

important parameters to classify these objects rather than their size and reflectance properties. While tree shades were smooth and compacted cone-shaped areas for individual trees or broader circular-shaped areas for groups of trees, lava outcrops had rough surfaces with very irregular and spread shapes. Lava–grass mixtures were also differentiated from lava outcrops due to their contrasting shape and texture.

The poor accuracy and precision of the object-based estimate of canopy cover using the crown parameter might be explained by the shadow overcast of smaller and shorter trees, especially in plots with higher tree density and canopy cover. The typical higher tree-crown reflectance may be suppressed by the shadow effect on smaller trees, which would lead to misclassification of these crown areas. The overall tree density, however, may have been low enough to reduce the overlap of individual tree shade and transition areas. This would account for the better accuracy and precision of estimates using these parameters as well as their tendency to underestimate canopy cover at higher levels.

At the landscape scale, the canopy cover estimates from the object-based shade and shade plus transition parameters were similar. However, the shade parameter was less precise since there was systematic underestimation of canopy cover above ~20% cover. This indicates that the classification of transitional areas that can be added to shaded areas could increase the accuracy of canopy cover estimates from satellite imagery.

The Ikonos-2 satellite image used in this study was acquired in December at the solar zenith angle of 46° when tree shadows were relatively large. Although we found that a combination of the shade plus transition classes was the most accurate and precise estimator of canopy cover, images taken at a different time of day or season of the year (i.e., lower or higher solar zenith angles) may affect the strength of these relationships. We were unable to examine the effect of this factor in the present study since another Ikonos-2 image acquired at a different solar zenith angle was not available from the Hawaii Ikonos Consortium.

Prioritization of restoration areas could be accomplished through the analysis of the object-based classified images due to clear differentiation of tree distribution patterns. Therefore, regions with the greatest restoration potential could be selected and delineated near the boundaries of denser native dry forest fragments. Conversely, the spectral classification does not allow for an accurate or precise visual interpretation of dry forest distribution due to extensive misclassification and systematic underestimation of canopy cover.

Another potential application of the object-based classified image is the estimation and mapping of individual tree heights. Nagler et al. (2005) visually estimated tree heights in a semi-arid riparian zone using the length of tree shadow on an image. Since our classification approach delineated tree shadows precisely and accurately, a tree height map could be derived from the classified image. This requires the use of an algorithm that would automatically recognize the locations of tree shadow tips and of crown centers throughout the image. In our study area, we expect it will be difficulty to precisely determine the locations of crown centers due to the predominance of clusters of trees. Additional research is needed to thoroughly address this potential.

6. Conclusions

The object-based image classification techniques available in commercial software facilitated developing practical and more reliable methodologies for the estimation of dry forest canopy cover in highly fragmented and degraded dry forest ecosystems. The application of conventional spectral/texture classification techniques was limited for accurate dry forest inventory due to the high variability within individual land cover types and similarity of reflectance properties among them. Object-oriented methodologies are more appropriate to use in these types of landscapes because the analysis is primarily based on spatial relationships inherent to each land cover type, such as size, shape, texture and distribution. An analogy to human reasoning interpretation mechanisms is then provided by these algorithms. Adding a tree canopy transition class to the tree shade parameter improved the accuracy and precision of the canopy cover estimate.

A useful application of these technologies for tropical dry forests could be in the selection and prioritization of areas for restoration of critical habitat for endangered plant and animal species. More successful management and conservation programs could be implemented by integrating areas with higher potential for restoration with surrounding intact dry forest ecosystems.

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