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An object-oriented approach to assessing changes in tree cover in the Colorado Front Range 1938–1999

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ABSTRACT

In the wake of numerous catastrophic wildfires, forest management policies have been implemented in recent years in the United States with the goals of reducing fire risk, including the National Fire Plan and the Healthy Forest Restoration Act. A key premise underlying these policies is that fire suppression has resulted in denser forests than were present historically that now have higher fire risk. To evaluate this premise for the northern Front Range, Colorado, we used object-oriented image analysis to compare change in tree cover delineated from historical and modern imagery. Historical photographs from 1938 and 1940 were scanned, orthorectified, and overlaid on Digital Orthoimagry Quarter Quadrangles (DOQQs) from 1999. Using an object-oriented image analysis technique, the photos were then finely segmented and classified into two classes: tree and non-tree. Trees are heterogeneous in appearance in black and white aerial photography, so we employed separate membership functions to identify four visually distinct types: 'interior forest', 'isolated trees', 'dark forest', and 'edge forest'. Our classification strategy employed spatial relationships between objects in addition to spectral information, so that our classification is fairly robust to variations in illumination. Based on the classification of fine objects, we then calculated the percent tree cover within a larger set of objects for the two time periods. We estimate that average tree density across the study area increased minimally (4%) during the 60-year period, with considerable spatial variation across the landscape. The results of the analysis illustrate that, consistent with independent tree-ring evidence, the highest increase in tree density is in areas characterized by low initial density, south-facing slopes, low elevations, and ponderosa pine dominance. In contrast, the highest elevation areas dominated by mixed conifer and lodgepole pine forests revealed no significant change in tree cover. Furthermore, there is no significant difference between objects dominated by low, medium, and high departure from historical conditions, as classified in the Landfire Fire Regime Condition Class (FRCC) data product. The results of the study can help managers prioritize forest treatments aimed at restoring pre-suppression forest structure.

1. Introduction

Wildfires have imposed increasing economic and environmental costs in recent years. Annual appropriations to federal agencies to prepare and respond to wildland fires approached $3 billion during the years 2001–2005 (US GAO, 2007). A small but increasing fraction of federal money goes toward forest treatments that aim to reduce the intensity and spread of wildfires. In 2007, the final year of the Healthy Forests Restoration Act, 13 million dollars were spent on such treatments (DOI and USDA, 2007).

A key premise of fuel-reduction treatments – such as mechanical thinning and controlled burns – is that forest fuels have increased as a result of fire suppression activities as well as drought, insect infestations, and disease. Illustrating this is the rationale for the Healthy Forests Initiative, which aims to reduce wildfire risk: "America's public lands have undergone radical changes during the last century due to the suppression of fires and a lack of active forest and rangeland management. Our forests and rangelands have become unnaturally dense, and these unhealthy forests are vulnerable to unnaturally severe wildfires." (White House, 2003).

But to what degree have canopy fuel loads – and in particular tree cover – increased and where have such increases occurred since the advent of fire suppression? Such information is valuable in prioritizing forest management at local scales aimed at restoring pre-suppression forest structure and fuels. Numerous studies in

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the ponderosa pine forests of the southwestern United States indicate that fire suppression has indeed resulted in fuel accumulation and uncharacteristic susceptibility to crown fires (Covington and Moore, 1994; Fule et al., 1997). However, it is unclear how these results apply to other ponderosa pine-dominated forests outside the region. For example, in the Colorado Front Range tree-ring reconstruction of historic forest structures and fire history records indicates that ponderosa pine ecosystems were spatially heterogeneous, containing patches of dense stands even before fire suppression (Kaufmann et al., 2000; Ehle and Baker, 2003; Sherriff and Veblen, 2008). Unfortunately, tree-ring reconstructions of past forest structure are extremely labor-intensive and not typically spatially contiguous. The main alternative to tree-ring reconstructions for evaluating departure from historic conditions is the continent-wide Fire Regime Condition Class (FRCC) data layer of the Landfire project. However, the FRCC layer is based on simulated reference conditions (Hann et al., 2004) and is usually not validated locally.

To complement existing research, we compared orthorectified historic aerial photography (from 1938 and 1940) to modern digital orthoimagery quarter quadrangles (DOQQs) from 1999 in the northern Front Range of Colorado. The northern Front Range is dominated by ponderosa pine, but also includes mixed conifer and lodgepole pine forests at higher elevations. Our research questions are: (1) To what degree has tree cover increased from 1938 to 1999 and (2) How has tree cover changed with respect to elevation, aspect, slope, dominant vegetation type, historic tree cover, and fire regime condition class?

To make these comparisons, we applied an object-oriented technique that segmented the images into homogeneous objects and then quantified the percent cover of trees within those objects. Object-oriented image analysis holds two primary advantages over traditional pixel-based methods. First, while pixels are classified solely on spectral and sometimes textural information, objects can also be classified on size, shape, pattern and spatial relationships. This is especially important in this case, as black and white aerial photographs have limited spectral data on which to base a classification. Secondly, while pixels are fixed in size and shape, objects are able to represent ecologically meaningful areas at multiple scales (e.g. groups of trees, or landscape patches) (Laliberte et al., 2004).

In a variety of recent studies, object-oriented analyses have yielded higher classification accuracies compared to pixel-based methods. For example, the integration of image segmentation, expert knowledge, and nearest neighbor classifier led to substantially improved land use classifications along an urban-to-agricultural gradient in Pennsylvania (Platt and Rapoza, 2008). In California, an object-oriented approach was better able to delineate the wildland-urban interface because it is able to more accurately classify built area in a highly vegetated landscape (Cleve et al., 2008). Object-oriented strategies that use object-correlation images were also found to be better than pixel-based strategies for change detection in Las Vegas (Im et al., 2007).

Object-oriented image analyses have been successfully applied to myriad studies on vegetation and fuels. For example, object-oriented approaches have been used to classify fuel types in Spain, as proper fuel classification requires the consideration of spatial context (Arroyo et al., 2006). Other studies applied object-oriented methods to mapping shrub encroachment in the Southwest US (Laliberte et al., 2004), extracting forest inventory parameters (Chobey et al., 2006), measuring woodland expansion (Pillai et al., 2005), documenting change in fractional forest cover in Switzerland (Waser et al., 2008), and estimating tree size diversity (Ozdemir et al., 2008) and stem volume (Ozdemir, 2008) in Mediterranean forests, and delineating forest vegetation using classification trees (Mallinis et al., 2008). While a few studies employ panchromatic aerial photos (e.g. Laliberte et al., 2004; Pillai et al., 2005; Browning et al., 2009), most studies use various high resolution multi-spectral imagery in their object-oriented image analysis.

2. Methods

2.1. Study area and data

Our study area is the montane zone of the northern Front Range of Colorado, which contains parts of Gilpin, Jefferson, Boulder, and Larimer Counties (Fig. 1). The montane zone is located approximately between 1830 and 2740 m. At the lowest elevations, the montane zone is dominated by a mixture of ponderosa pine (*Pinus ponderosa*), Douglas-fir (*Pseudotsuga menziesii*), and grasses. Prior to fire suppression, these areas were characterized by frequent fires at an interval of 10–40 years (Veblen et al., 2000; Sherriff and Veblen, 2007). At the higher elevations ponderosa pine and Douglas-fir still dominate on south-facing slopes, but other species such as lodgepole pine (*Pinus contorta)* and aspen (*Populus tremuloides)* can also be important on north-facing slopes. Historic fire intervals at the higher elevations were 30–100 years prior to fire suppression and included high severity crown fires (Veblen and Lorenz, 1986; Sherriff and Veblen, 2008). We expected increased tree density at the lowest elevations of the montane zone since these areas were historically kept open by frequent fires, but less of an increase in tree density at the highest elevations where fires were less frequent and of mixed-severity and as a consequence stands were often historically dense.

We started with 52 historic aerial photographs (approximate scale 1:20,000) commissioned by the USDA Soil Conservation Service and the USDA Forest Service and scanned at 600 ppi with 24-bit color (~1m pixels). We orthorectified each 1938/1940

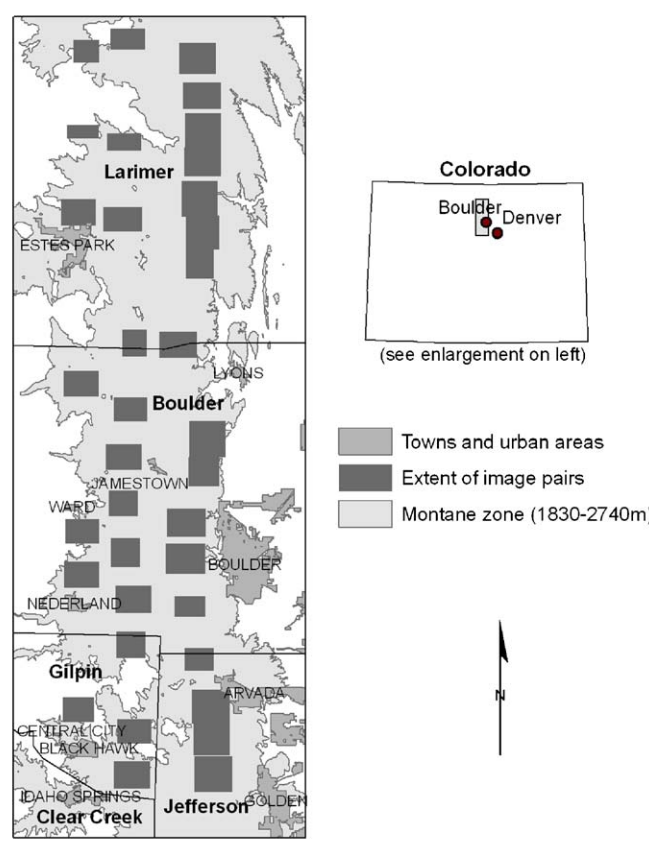

Fig. 1. Study area in the northern Colorado Front Range.

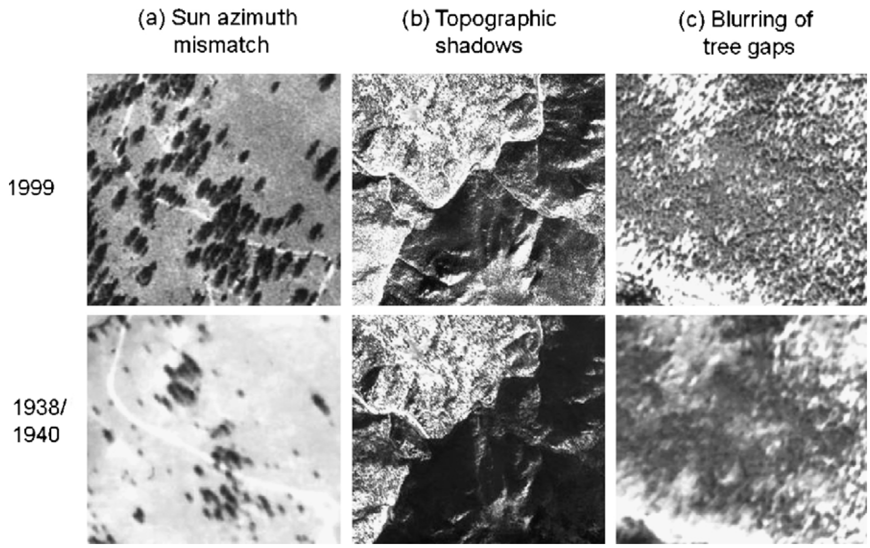

Fig. 2. Image issues.

image to 1999 1m DOQQs using 7–10 ground control points (GCPs) and a 10m DEM. The average root mean square (RMS) error for the control points was 16 m. We assessed the average displacement between the orthorectified 1938/1940 images and 1999 DOQQs by measuring displacement at 10 non-GCP locations within each image pair. The average displacement between the two sets of images was 11 m. Due to the displacement, individual trees often do not align perfectly between the two time periods but the displacement was not large enough to materially affect the coarse segmentation procedure described below.

Some image pairs had limitations, including poor overlay, poor match of sun azimuth/elevation (Fig. 2a), and blurriness in the 1938/1940 image (Fig. 2c). A total of 13 image pairs were rejected due to image limitations. The remaining 39 image pairs comprise a modern orthophoto taken October 10th, 1999 paired with a historic image taken on October 25–26, 1938 (26 images) or October 9th, 1940 (13 images) (Fig. 1). The selected image pairs are of relatively high quality, though in some cases the images have deep topographic shadows in parts of the image (Fig. 2b). As described below, our analyses attempted to address the potential effects of topographic shadows.

The elevation, aspect, and vegetation cover of the overall montane zone were compared to that of the 39 image pairs to ensure that the images were representative.

2.2. Object-oriented image analysis

2.2.1. Segmentation of image objects

We used Definiens Developer software (formerly eCognition) to segment and later classify image objects. The goal of segmentation was to create a single set of coarse objects that roughly approximated the size and shape of the Common Vegetation Units used by the USDA Forest Service (2003). The Common Vegetation Units within the study area delineated major forest patches and average 17 ha in size. Nested within the coarse objects, we aimed to create fine objects that delineate individual trees and groups of trees in the 1938/1940 images and in the 1999 images, which we used to estimate percent tree cover classes within the coarse objects.

The size and shape of image objects created by segmentation are controlled by a set of parameters: scale, color, shape, smoothness and compactness (Benz et al., 2004). The average size of image objects is a function of the scale parameter, a unitless number which sets the maximum allowable heterogeneity within objects. Heterogeneity has a spectral component (the sum of standard deviations of each image band) and a shape component. The contribution of color and shape to heterogeneity is determined by the color and shape parameters, which must add up to 1. In turn, the shape parameter comprises compactness (the ratio of the border length and the square root of the number of object pixels) and smoothness (the ratio of the border length and the shortest possible border length) (Baatz et al., 2004). The contribution of smoothness and compactness to shape is determined by the compactness and smoothness parameters, which must add up to 1.

To derive the coarse objects (Fig. 3), we selected the parameters iteratively, giving greatest weight to spectral (brightness) information, while attempting to delineate objects that were relatively compact and smooth like the Common Vegetation Units. We used the following criteria: scale parameter of 1000, a color parameter of 0.8, a shape parameter of 0.2, a smoothness parameter of 0.5, and a compactness parameter of 0.5. Prior to segmentation, we applied a 3×3 Median filter to the 1938/1940 images to minimize the effects of image grain on the segmentation procedure. We segmented the 1938/1940 and 1999 imagery together as if they were two bands of a single image, weighing the 1999 image by 1 and the 1938/1940 image by 1.5 to compensate for the lower variation in brightness levels in the 1938/1940 images. Thus, individual objects should delineate areas of stability and areas of change, but should not include a mixture of stability and change within a single object. The resulting objects were an average of 24 ha in size.

To derive the two sets of fine objects (one for the 1938/1940 imagery, and one for the 1999 imagery), we used the same parameters as for the coarse segmentation process, but a scale parameter of 5. We then merged adjacent objects with similar brightness values (spectral difference < 16 for objects of brightness ≥ 75, and spectral difference < 100 for objects of brightness < 75). The resulting objects were an average of 15 m^2 in size.

2.2.2. Object classification

In order to estimate percent tree cover in the coarse objects, we classified the fine objects into two categories: tree and non-tree

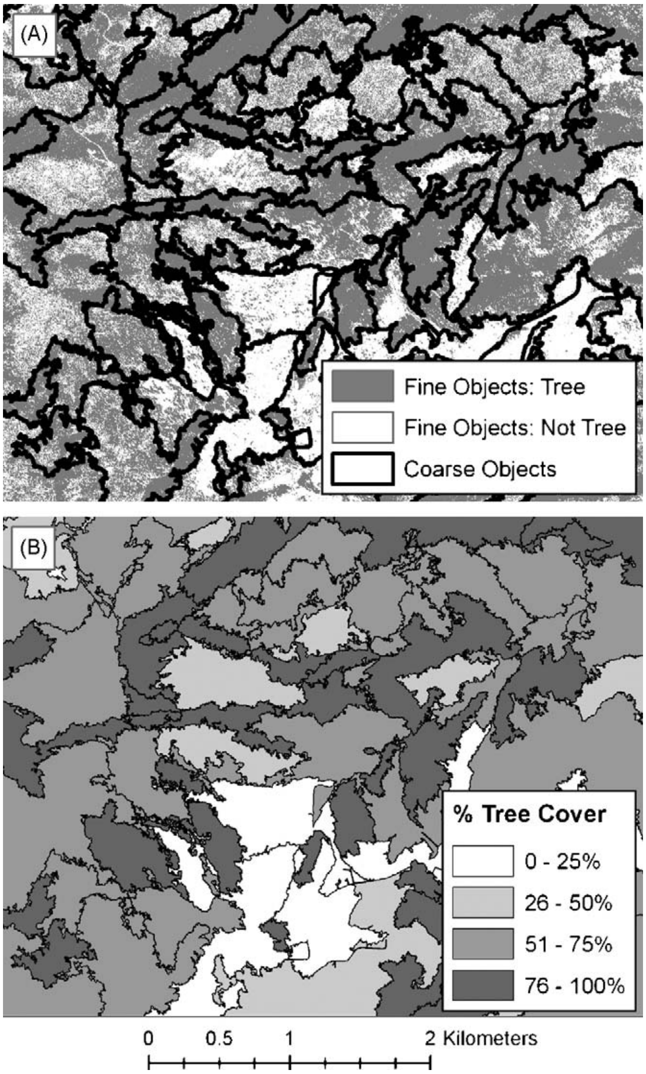

Fig. 3. (a) Segmentation and (b) classification.

(Fig. 3a). A particular challenge was making the classification robust to variations in illumination across the scene. The brightness level of trees varies depending on the level of illumination, but trees appear dark compared to the surrounding soil, rock, and grass. Thus, in addition to the "mean brightness" of each object, we calculated "mean difference to brighter neighbors" and "relative border to brighter objects" (the percentage of the border of an object that touches a brighter neighbor-object) to identify objects that were dark relative to their surroundings. Water and topographic shadows also appear dark in the image, and were initially classified as "tree" in this classification of fine objects. Iteratively, we developed membership functions to identify four visually distinct forest types:

1. Dark forest
   - Objects must be dark (mean brightness < 65 for 1999, <75 for 1938/1940).
2. Edge forest
   - Objects must be dark (mean brightness < 135 for 1999, <195 for 1938/1940).
   - Objects must contrast brighter neighbors (mean difference to brighter neighbors > 10).
   - Within objects that met these hard criteria, a fuzzy membership function was applied. Fuzzy membership functions assign a degree of membership (between 0 and 1) to an object. In this case, an object has a higher degree of membership to the "tree" class if it is characterized by high mean difference to brighter neighbors (Fig. 4a), high relative border to brighter objects (Fig. 4b), and low mean brightness (Fig. 4c). If the average degree of membership for the three functions was 0.5 or above, the object was classified as "tree".
3. Interior forest
   - Objects must be dark (mean brightness < 100 for 1999, <115 for 1938/1940).
   - Objects must be primarily surrounded by darker neighbor objects (relative border to brighter neighbors < 50).
4. Isolated trees
   - Objects must not be too large (<300 m^2).
   - Objects must not be too light (brightness threshold <175 for 1999, <205 for 1938/1940).
   - Objects must contrast brighter neighbors (mean difference to brighter neighbors > 25 for 1999, >20 for 1938/1940).
   - Objects must be primarily surrounded by brighter neighbor objects (relative border to brighter neighbors > 0.5).

Because the average brightness of the images varied, we iteratively adjusted the thresholds slightly upward or downward for many images (17 of 39 1938/1940 images, and 7 of 39 1999 images), to create a classification that visually corresponded to the distribution of trees.

Within coarse objects, we then calculated the percent area covered by fine objects classified as "tree" in each time period (Fig. 3b). We also coded coarse objects in to the following environmental classes: elevation class (quartile), majority aspect (north, east, south, west), slope (above or below 10%), majority

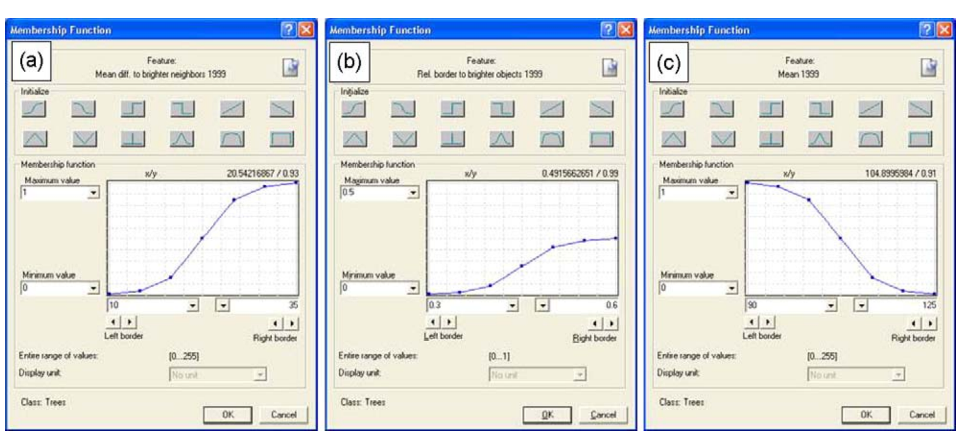

Fig. 4. Fuzzy membership functions used to classify 'edge forest" (a) high mean difference to brighter neighbors, (b) high relative border to brighter objects, and (c) low mean brightness.

vegetation type from Landfire existing vegetation type layer (shrub, ponderosa pine, lodgepole pine, mixed conifer; The National Map LANDFIRE, 2006), 1938/1940 percent tree cover (quartile), and the majority fire regime condition class (FRCC) from the Landfire FRCC layer (low, medium, or high departure from historical conditions).

Before running the analysis, we identified 7 coarse objects that were dominated by water (contained lakes or ponds delineated by the USGS) and 278 objects that were dominated by topographic shadows in either time period (henceforth called shadow objects). Shadow objects were identified by (1) creating a hillshade model based on the time and date of the photography acquisition and (2) identifying coarse objects that were below a threshold of predicted illumination (mean hillshade value < 60) and were dark in the image (mean brightness < 40 for 1999 and <80 for 1938/1940). Water and shadow objects comprised 9% of the study area.

We used a *t*-test to evaluate whether change in percent tree cover was significantly different from zero. Since we have limited or no information on the tree cover of "shadow objects", we evaluated change in two ways: (1) Best estimate: shadow objects are assumed to be randomly distributed, so they are removed. (2) Conservative estimate: shadow objects are disproportionally located on north facing slopes where we would expect to find stable, dense tree cover (Sherriff and Veblen, 2007). Therefore, percent tree cover is assumed not to change in shadow objects.

We then conducted a series of ANOVAs and multi-comparison Tamhane tests to evaluate whether the mean difference in percent tree cover (shadow objects removed) was significantly different from zero and significantly different within environmental classes.

2.3. Validation

To evaluate the quality of our 1938/1940 and 1999 percent tree cover calculations, we compared them to two other sources: a manual classification of tree cover and a Forest Service classification of tree cover (Fig. 5). An image interpreter manually classified

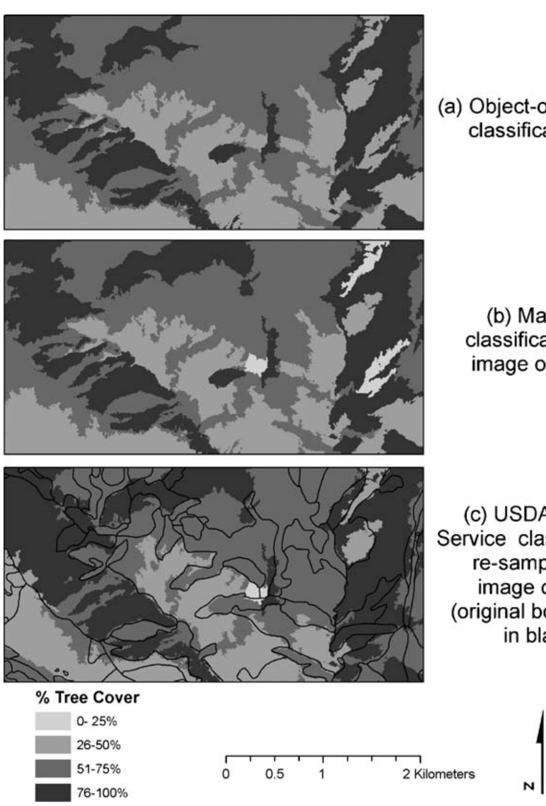

Fig. 5. Classification of image objects.

300 randomly selected objects into four classes: 0–25%, 25–50%, 50–75%, and 75–100% by comparing imagery to a visual key. The image interpreter used the 1938/1940 imagery to classify the historic tree density and 1999 orthophotos to classify the modern tree density. In difficult cases where the 1999 vegetation fell between two classes, the interpreter used Google Earth Imagery (ca. 2003) as a "tie breaker". The Forest Service classification was derived from the Common Vegetation Units of the Forest Service's Integrated Resource Inventory (IRI) database (USDA Forest Service, 2003). The IRI dataset covers 367 km^2, or 70% of the area of the image tiles within the study area. The IRI dataset was created primarily through photointerpretation of 1994 orthophotos, supplemented with field inventory and interpretation of Landsat Imagery. While our image objects were designed to approximate the size and shape of the manually digitized forest stands in the IRI data, they usually did not directly correspond (Fig. 5c). Therefore we calculated percent tree cover within image objects by finding an area-weighted average of the IRI polygons that intersect the image objects. We then classified the percent tree cover estimate into the four classes. We used Spearman's rank correlations (Spearman's rho) to evaluate the correspondence between the percent tree cover estimates. Though we lack the historical field measurements to validate the detection limits for 1938/1940 imagery, one study found that the detection limits for shrubs in 1936 panchromatic imagery is comparable to those reported for contemporary imagery (Browning et al., 2009).

3. Results

3.1. Comparability to montane zone and validation

Overall, the study area is representative of the broader montane zone (Table 1). The study area has a similar elevation mean and range to the overall montane zone. However, south-facing slopes and present-day ponderosa pine are slightly overrepresented in the study area, while north facing slopes and present-day mixed conifer are slightly underrepresented. This difference is more pronounced when shadows objects are removed from the study area. Interpretations of the overall change in tree cover should take this bias into account.

Our validation procedures suggest that the object-oriented classification performs well. There is a high Spearman's rho correlation between the object-oriented and manual classification of the orthophotos (0.88 for both years, Table 2), which indicates that the object-oriented methodology successfully mimics visual

Table 1
Comparison of montane zone in the northern Colorado Front Range to study area and the study area with shadow objects removed.

	Montane zone	Study area	Shadows removed
Elevation (m)			
Mean	2368	2354	2356
Min	1780	1706	1706
Max	2795	3165	3165
Aspect			
North	26%	23%	19%
East	32%	32%	34%
South	26%	29%	32%
West	16%	16%	15%
Vegetation type			
Ponderosa	29%	34%	35%
Mixed	30%	29%	26%
Lodgepole	13%	13%	13%
Shrubland/grassland	10%	9%	9%
Aspen	8%	7%	7%
Other	10%	8%	9%

Table 2
Spearman's Rho correlation: object-oriented classification versus manual and IRI classifications.

Year	Object-oriented classification compared to...	Correlation	Asymp. std. error[a]	Approx t[b]	Approx sig.[c]
1999	Manual classification of 1999 orthophotos supplemented with ca. 2004 Google Earth Imagery	0.88	0.015	8.62	0.0000
1999	IRI classification of 1994 orthophotos	0.61	0.018	29.24	0.0000
1938/1940	Manual classification of 1938/1940 orthophotos	0.88	0.015	31.46	0.0000

[a] Not assuming the null hypothesis.
[b] Using the asymptotic std error assuming the null hypothesis.
[c] Based on normal approximation.

image interpretation. However, the correlation is an imperfect measure of classification accuracy, as the same images were used for both classifications. We found a moderate Spearman's rho correlation between the object-oriented classification and the Forest Service IRI data (0.61 for 1999, Table 2). Though the IRI data uses different data sources than the object-oriented classification, the comparison is still imperfect due to unknown accuracy of the IRI data, the date discrepancy, and the area-weighted re-sampling.

3.2. Change in tree cover between time periods

The overall mean change in tree cover across the study area between 1938 and 1999 was significantly greater than zero, but minimal (~4%). Whether shadow objects are excluded or assumed not to change, the overall mean difference in percent tree cover was similar (Table 3).

Percent tree cover at higher elevations (2432–3125 m) did not differ significantly between the two time periods (Table 4), however intermediate elevations (2432–2778 m) changed by an average of 5%. Objects at the lowest elevations (1737–2084 m) increased percent tree cover by 13% on average.

In terms of aspect, percent tree cover increased by an average of 6% in objects dominated by south-facing slopes, while north-facing slopes did not change significantly between the two time periods. These results are consistent with tree-ring evidence (Sherriff and Veblen, 2008) and photographic evidence (Veblen and Lorenz, 1986) suggesting that tree cover has increased the most at the lowest elevations and on south-facing slopes.

Table 3
t-Test of overall mean of difference in percent tree cover 1938–1999.

	t	df	Mean	95th lower	95th upper	Std. dev.	N
Overall mean, excluding shadow objects	9.464	2111	4.0%	3%	5%	19%	2112
Overall mean, assuming no change in shadow objects	9.438	2425	3.5%	3%	4%	18%	2426

Table 4
Mean change in percent tree cover within environmental classes. Mean change was not considered significant if the upper and lower bounds of the mean estimate (95th percentile) straddled zero. Significant change is highlighted in bold.

Elevation	Percentage of study area	Mean	95th lower	95th upper	Std. dev.	N	Sig. different from[a]
1737–2084 m	11%	**13%**	10%	15%	20%	259	All
2085–2431 m	47%	**5%**	4%	6%	19%	1011	All except 2779–3125 m
2432–2778 m	38%	0%	−1%	1%	18%	763	All except 2779–3125 m
2779–3125 m	5%	2%	−2%	6%	18%	79	1737–2084 m
Aspect							
North	24%	1%	−1%	3%	18%	414	South
East	32%	**4%**	2%	5%	20%	751	–
South	32%	**6%**	5%	8%	19%	677	North
West	12%	**4%**	1%	6%	22%	270	–
Slope							
$\leq 10^\circ$	14%	2%	0%	4%	17%	333	$>10^\circ$
$>10^\circ$	86%	**4%**	3%	5%	20%	1779	$\leq 10^\circ$
Dominant vegetation							
Lodgepole pine	17%	−1%	−3%	1%	17%	283	All except mixed conifer
Mixed conifer	30%	0%	−1%	2%	20%	598	All except lodgepole pine
Ponderosa pine	45%	**8%**	7%	9%	19%	967	All
Shrub	5%	**5%**	2%	8%	13%	111	All
1938/1940 cover							
0–25%	21%	**17%**	15%	18%	15%	534	All except 25–50%
25–50%	19%	**15%**	13%	16%	16%	440	All except 0–25%
50–75%	22%	0%	−2%	1%	18%	464	All
75–100%	38%	**−10%**	−11%	−9%	14%	674	All
Departure from historical vegetation conditions (FRCC)							
Low	4%	1%	−1%	3%	20%	112	–
Moderate	73%	**5%**	5%	6%	20%	1497	–
High	22%	0%	−1%	1%	21%	486	–

[a] Significantly different at the 0.05 level according to a multiple comparison Tamhane test.

In terms of slope, we found that areas of steep slope ($>10^{\circ}$) have a slightly higher difference in percent tree cover than relatively flat areas ($\leq 10^{\circ}$) which did not change significantly. This result was marginally significant and low in magnitude.

Objects dominated by ponderosa pine or shrub today have increased the most in tree cover (8% and 5% respectively), whereas objects dominated by lodgepole pine and mixed conifer today did not change significantly between the two time periods.

The highest mean change in percent tree cover (17%) was observed in objects characterized by low 1938/1940 cover (0–25%), while objects characterized by high 1938/1940 cover (75–100%) actually decreased by 10% between the two time periods. The apparent large decrease in the densest cover class may be partially an artifact of the 1938/1940 imagery; it is sometimes difficult to resolve gaps between trees in areas where trees are closely spaced (Fig. 2c). In addition, closed-canopy forests may experience self-thinning, insect outbreaks or stand-replacing fires that would decrease tree cover.

Finally, we found that objects dominated by low, medium, and high departure from historical conditions (according to the Landfire FRCC layer) were not significantly different from each other in terms of change in percent tree cover according to the Tamhane test. This discrepancy may be due to limitations of the simulations used to generate reference conditions for the FRCC data layer and the challenge of developing locally accurate estimates.

Overall, we estimate that tree cover increased by an average of 4% across the entire study area (Table 3) which is consistent with tree-ring reconstructions of fire regimes in Boulder County where only a small proportion primarily at lowest elevations (less than 20% of the ponderosa pine zone) was predicted to have frequent fire regimes where fire suppression would have promoted increased tree cover (Sherriff and Veblen, 2007). Our results are also consistent with a study of aerial photo analysis of tree invasion into the lower ecotone of ponderosa pine, where an increase in woodland was observed in areas of former grasslands (Mast et al., 1997).

4. Conclusions

In this analysis we used a novel approach to evaluate to what degree percent tree cover has changed between 1938/1940 and 1999 imagery taken along the Northern Front Range of Colorado. Object-oriented image classification allowed us to analyze objects representing forest stands, allowing meaningful characterization of changes in percent tree cover within stands over time. It also enabled us to develop a classification strategy that employs spatial relationships between objects in addition to spectral information, so that our classification is fairly robust to variations in illumination. A limitation of this analysis is that we do not take into account natural or anthropogenic disturbances such as fire, insect outbreaks, logging, mining, or clearing for housing developments. Historical data for such disturbances is unavailable or of poor quality.

Overall increase in tree cover was $\sim$4% across the study area, and $\sim$16% in areas that were historically "open canopy" (e.g. $<$50% cover in 1938/1940). Mean tree cover did not increase between 1938/1940 and 1999 in objects above 2432 m in elevation, and dominated by mixed conifer and lodgepole pine. This finding contradicts the assumption that "mixed conifer" with its substantial proportion of ponderosa pine, has become denser during this period of fire suppression. We found percent tree cover increased primarily at the lowest elevations, on south-facing aspects, in areas currently dominated by ponderosa pine and shrubs, and where 1938/1940 cover was $<$50%. Our results are consistent with tree-ring and photographic evidence that suggest that the major increase in tree density has taken place primarily at the lowest elevations and south-facing slopes, which also tend to be dominated by the ponderosa pine vegetation type. Our results cast doubt on the utility of the FRCC data for prioritization of forest fuel-reduction projects locally, as the areas predicted to have the greatest departure from historical vegetation conditions demonstrated no change in tree density since 1938. Overall, results from this comparison of changes in tree cover since 1938/1940 suggest that fuel-reduction treatments would only restore pre-fire suppression tree cover or densities in very limited areas in the study area.

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