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Vegetation change during 40 years of repeated managed wildfires in the Sierra Nevada, California

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ABSTRACT

Fire suppression has been reported to homogenize landscapes in regions that historically experienced frequent wildfire. The Illilouette Creek Basin in Yosemite National Park experienced nearly 100 years of fire suppression, but after a change in management strategy it is now one of the few areas in the United States that has experienced a frequent fire regime for the past half-century. This study quantifies changing landscape properties in the Basin from its fire-suppressed state to the present. These landscape properties range from the relative dominance of different vegetation types to the spatial distribution of vegetation patches. This is the first detailed study of watershed-scale changes in overstory vegetation within a landscape transitioning from a fire suppressed condition to frequent, mixed severity wildfires.

We mapped major vegetation types over time within Illilouette Creek Basin using high resolution aerial images from four different decades, starting with the final years of a fire-suppressed period and capturing multiple snapshots during forty years of repeated fires. We quantify landscape heterogeneity and vegetation patch shape properties using landscape metrics. From 1969 to 2012, conifer cover decreased by 24% while shrub area increased by 35%, sparse meadow area increased by 199% and dense meadows by 155%. The Shannon's Evenness Index based on these four vegetation types increased from 0.4 to 0.7, indicating increased landscape heterogeneity. This study demonstrates that wildfires can return diversity to a fire-suppressed landscape, even after protracted fire suppression. Management of forests to restore fire regimes has the potential to maintain healthy, resilient landscapes in frequent fire-adapted ecosystems.

1. Introduction

Landscape structure, as defined by the types and spatial organization of vegetation communities, is shaped by the interactions between disturbance events and succession following disturbance (Miller and Urban, 2000a). Succession trajectories vary depending on disturbance history, local site characteristics, and temporally varying conditions as young vegetation establishes in disturbed sites (Johnson and Miyanishi, 2010). Disturbance processes are also affected by the landscape structure, which can influence disturbance frequency, spatial extent, and severity (Turner, 1989; Turner et al., 1989). These two-way interactions allow landscape composition to be thought of as a non-equilibrium complex system, in which punctuated inputs of energy (in the form of disturbance) prevent the landscapes from achieving steady state conditions (Mori, 2011; Sousa, 1984). Removing these energy inputs, by suppressing disturbance events, would be expected to move landscapes towards a successional "steady state", which, for spatially uniform soil and climate conditions, could produce uniform vegetation cover (D'Odorico et al., 2006).

Homogenization of the landscape has been observed in response to the prevalence of fire suppression as a fire-management strategy in the Western USA during most of the 20th Century. In the Sierra Nevada, the homogeneity of both the landscape and individual forest stands has increased compared to pre-1900 baseline conditions (Scholl and Taylor, 2010; Stephens et al., 2015; Perry et al., 2011; Hessburg et al., 2005), and fire-suppressed forest stands have more than doubled in density since the early 1900s (Collins et al., 2011). In contrast, there are few opportunities to directly observe the response of landscape structure to increases in disturbance frequency due to fire. Simulations suggest that forest density and spatial autocorrelation of forest patches should decrease as fire disturbance rates increase (Miller and Urban, 2000b), with concomitant increases in the abundance of species that prefer open

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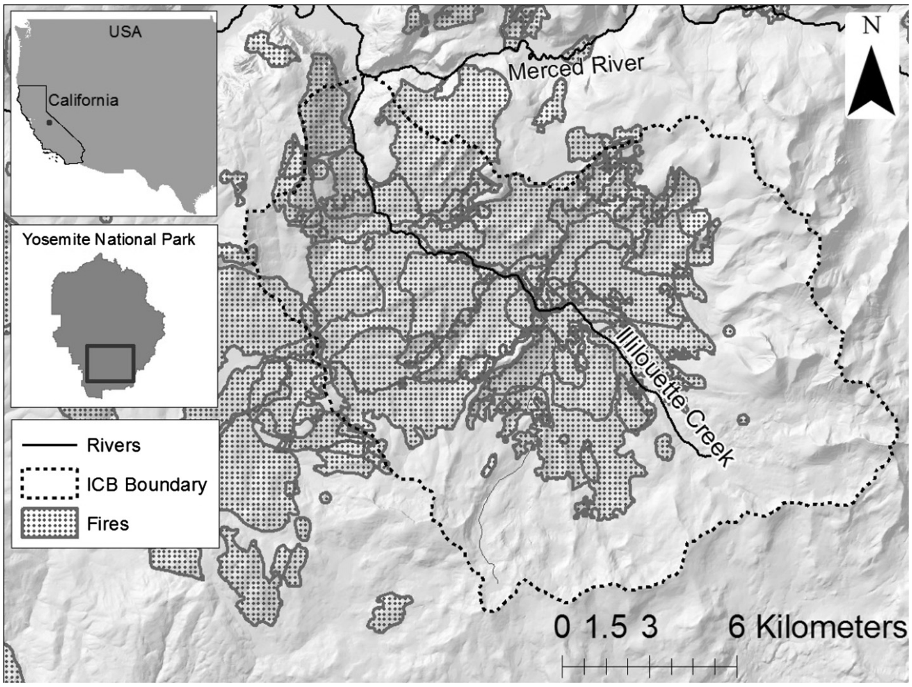

Fig. 1. Map of Yosemite National Park and ICB extent with all known fire perimeters from 1972 to 2012 (fire perimeter maps provided by the California Department of Forestry and Fire Protection).

habitat such as shade-intolerant flowering plants (Pausas, 2006), and in fire- or disturbance-adapted shrub species (Pausas and Lloret, 2007).

Opportunities to empirically evaluate such predictions have generally been limited to considering the immediate effects of isolated disturbance events such as individual stand-replacing fires, yet the conclusions to be drawn are not always clear. Large, stand-replacing fires can increase or decrease species richness, and can reduce beta diversity (the ratio of regional to local species diversity, measuring differentiation between habitats), particularly if the fire results in colonization by a small number of disturbance-tolerant species (Burkle et al., 2015). In contrast, mixed severity fires may increase beta diversity (Burkle et al., 2015; Perry et al., 2011). Such increases are theoretically consistent with increases in landscape heterogeneity in more frequently disturbed systems, since heterogeneity in natural landscapes is generally positively correlated with biodiversity (Seiferling et al., 2014).

However, drawing conclusions about landscape-scale effects of changing disturbance regimes from modeling or individual disturbance events alone is problematic. For example, fire return intervals can affect post-fire recruitment, even amongst fires with the same severity (Donato et al., 2009). Empirically evaluating the effects of increasing fire frequency on previously fire-suppressed landscapes is increasingly important. Forest and land management agencies are striving to find techniques to manage forested landscapes for resilience against the likely increases in fire and drought stress predicted to occur as consequences of climate change (Westerling et al., 2006; Westerling and Bryant, 2008; Stephens et al., 2016). The dense, homogeneous forests generated by decades of fire suppression are likely to exacerbate fire risks due to elevated fuel loads (Stephens et al., 2009; Collins and Skinner, 2014; Taylor et al., 2014) and drought risks due to increased water demand from dense forest stands and uniformly forested landscapes (Goulden and Bales, 2014; Grant et al., 2013). Indeed, high intensity wildfire and large-scale insect outbreaks are altering the Sierra Nevada landscapes faster than they did before fire suppression and logging (Hessburg et al., 2015), and drought-related tree mortality has been increasing throughout the Western US (Moore, 2015; Hicke et al., 2016).

In the Sierra Nevada, vegetation communities are adapted to a frequent, lightning-induced fire regime and Native American ignitions (Stephens et al., 2007; Hessburg et al., 2015). Consequently, "managed wildfire", a land management strategy in which such naturally ignited fires are allowed to burn without intervention (subject to an approved fire management plan) is attracting increased interest. Since 2016, three Californian National Forests (Inyo, Sequoia and Sierra National Forests) have been evaluating if more than 50% of their total area should support the use of managed wildfire (http://www.fs.usda.gov/detail/r5/landmanagement/planning/?cid = STELPRD3802842). Managed wildfire is anticipated to benefit landscapes by restoring a "natural" structure (Hessburg et al., 2015). Natural landscape structure is hypothesized to benefit local ecology (e.g. species abundance and dispersal responding to changes in patch size and shape; Turner, 1989), and hydrology (e.g. canopy interception; Andreadis et al., 2009, evaporative demand; Brown et al., 2005, and timing of snowmelt; Lundquist et al., 2013). Despite the increasing interest in managed wildfire and its effects on landscape structure, empirical evaluations of how landscape structure changes in response to such a management regime are rare, largely due to the paucity of landscapes managed under a natural fire regime.

Here we address this gap by providing a detailed description of how forty years of managed wildfire has altered a previously fire-suppressed landscape in the Illilouette Creek Basin (ICB) of Yosemite National Park in the Sierra Nevada, California. ICB has operated under a managed wildfire policy since 1972, one of only two such long-running managed wildfire regimes in forested areas of California (Van Wagtendonk, 2007). We evaluate changes in the ICB using historical aerial imagery spanning the final years of the fire-suppressed period through 2012. We present the results in terms of overall land cover compositional change, along with a range of metrics describing landscape patterns and vegetation patch structure (Turner, 1989). Results not only provide insight into possible trajectories of landscape structural change upon initiation of a natural wildfire regime, but also form a basis for managers to evaluate the effects of fire-induced landscape compositional changes on basin-scale ecosystem functions, such as water cycling and carbon storage.

2. Methods

2.1. Study area

The ICB is a 150 km^2 watershed spanning elevations of 1800 m to ≈3000 m in the Central Sierra Nevada region, located within Yosemite National Park, California, USA (119.50 °W, 37.66 °N; Fig. 1). The climate is mediterranean with approximately 100 cm average annual precipitation, dominated by winter snow. Temperatures from nearby weather stations at similar elevations vary from average January daily minimum temperatures of −5 °C to average July daily maximum temperatures of 25 °C (2000–2015; http://www.wrcc.dri.edu/; stations: White Wolf, Crane Flat).

The basin is covered by coniferous forests (dominated by *Pinus jeffreyi, Abies magnifica, A. concolor and P. contorta*), shrublands (dominated by *Ceanothus cordulatus*), meadow environments containing grasses and forbs (including both dryland and wetland obligate species), and extensive exposed bedrock (Collins et al., 2007). The ICB was not logged and experienced minimal impacts from livestock grazing (Collins and Stephens, 2007). Fire suppression began in ICB in the late 19th Century (Collins and Stephens, 2007) and continued until 1972, when Yosemite National Park began its "Natural Fire Management" program (van Wagtendonk, 2007). Yosemite National Park began mapping fire perimeters in the 1930s; the 99 lightning fires that ignited within ICB between 1930 and 1973 were suppressed, keeping each fire under 5 ha, and only 27 ha total burned during this period (van Wagtendonk, 2012). The ICB's first 20th century fire over 5 ha in size was the 1600 ha Starr King fire in 1974. Since then, there have been 27 fires over 20 ha in size, and over 100 smaller fires (Figs. 2 and 3). Fifty-two percent of the total basin area and ≈75% of the vegetated area have burned since 1972 (Fig. 1). Fire frequency and extent during the managed wildfire period beginning in 1972 are comparable to pre-suppression historical estimates (a 6.8 year recurrence interval, versus 6.3 historically, based on fire scar measurements, Collins and Stephens, 2007).

2.2. Data sources

This study makes use of aerial photos, historical maps, and ground reference data to delineate patches of vegetation with common compositions. Aerial imagery is increasingly popular for historical vegetation change analysis, and new computer products are increasing the objectivity and reproducibility of classification of aerial photos (Morgan et al., 2010, Hessburg et al., 2000). Aerial imagery offers several advantages for historical vegetation mapping. Given its high resolution, it is often possible to identify individual trees and large shrubs within the image, allowing manual interpretation of images and object-oriented classification. This contrasts with relying on interpretation of spectral signatures for classification, as would be required if the reconstruction were to be based upon satellite records such as Landsat. Although Landsat imagery is available on more frequent time intervals and with greater spectral resolution, the coarse spatial resolution (80 m from 1972 to 1978, 40 m for 1978 to 1982, and 30 m afterwards, landsat.usgs.gov) reduces accuracy when identifying different vegetation types and mapping them to changes in the landscape. Use of a high spatial resolution product is particularly important because no ground truth data are available for the earliest part of our analysis.

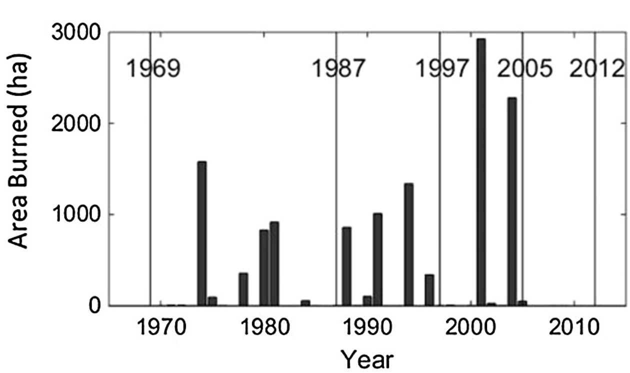

Fig. 2. ICB fire history. Total ha burned each year in the context of years mapped (vertical lines). Prior to 1974, no fires over 5 ha in area had burned since at least 1930.

The earliest aerial imagery of the ICB comes from a set of black and white images taken by Cartwright Aerial Surveys in 1969 and 1970, provided by the Yosemite National Park Archive. This imagery was digitized to yield an approximately 0.5-m spatial resolution and represents the fire-suppressed condition of the watershed (Fig. 2).

National Aerial Photography Program (NAPP) aerial imagery from 1987, 1988, and 1997 (available from U.S. Geological Survey) were used to map the changing state of ICB vegetation following the institution of the managed wildfire regime. Images from 1987 and 1988 were combined to maximize spatial coverage of the watershed. NAPP imagery was recorded using color infrared film and has been digitized to yield 1-meter resolution.

The highest quality images of this area are from 2005 and 2012 National Agriculture Imagery Program (NAIP) datasets (Farm Service Agency and USDA, 2015). The NAIP imagery was captured digitally at a spatial resolution of 1 meter, a radiometric resolution of 8 bits, and contains red, green, and blue bands as well as an infrared band.

All images other than those from NAIP required orthorectification prior to classification. We used the ERDAS Imagine Leica Photogrammetry Suite (http://www.hexagongeospatial.com/products/producer- suite/erdas-imagine), NAIP imagery for reference, and a LiDAR elevation map (Kane et al., 2015) for orthorectification. Where two or more images overlapped, the best of those images was chosen manually, in ArcMap (http://desktop.arcgis.com/en/arcmap/), based on the clarity of individual objects (influenced by plane angle, contrast, glare, etc.).

Table 1 contains details on the imagery sources used in this project. Although the images vary in terms of color and resolution, they all have high enough quality to allow visual identification of vegetation types, allowing us to confidently track changes in vegetation over time using methods similar to other studies of landscape evolution (e.g. Laliberte et al., 2004; Ellis et al., 2006).

We used existing vegetation maps of Yosemite to assist with mapping as much as possible. However, such maps are only available for a limited number of years, and most have lower spatial resolution than our analyses require. The 1997 Yosemite National Park vegetation map (available at irma.nps.gov) provided the finest spatial resolution, and was used to verify the approximate extent of the different vegetation types where appropriate (e.g. we could not use the 1997 park map to verify our 2012 map in areas that had burned after 1997).

2.3. Vegetation mapping

Vegetation classification was performed in eCognition (produced by Trimble, www.ecognition.com), an object-based analysis tool which uses color band values, texture, and shape to classify image objects. Object-based analysis facilitates the use of texture in classification, and also avoids the challenges associated with pixel based analysis, including unmixing of spectral information in areas with fine-scale heterogeneity in land cover (Blaschke et al., 2014), and changing availability of color and infra-red bands across the images. Each individual image was processed separately, as differences in attributes such as brightness and flight angle between images precluded our ability to use the same algorithm across all images, even within the same year. The use of a supervised classification method ensured that classification meaning was consistent across all images despite slight changes in the specific classification algorithms.

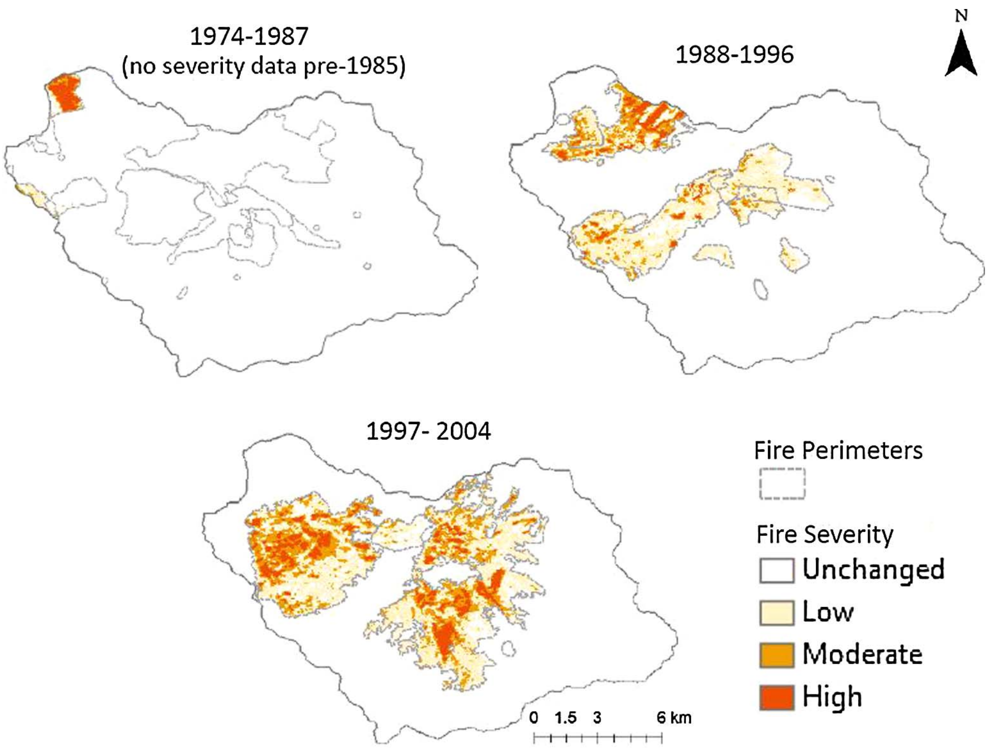

Fig. 3. Maps of fire extent and severity in the time intervals between aerial images. Fire severity, calculated using RdNBR according to Miller and Thode (2007), is shown for all fires starting in 1985 when RdNBR data is available. No large fires occurred between 2004 and 2012.

Table 1
Imagery details. Images were either black and white, color infrared (false color images representing infrared reflectance), or four-band images including red, green, blue, and infrared reflectance. Imagery sources included the Yosemite National Park archives, the United States Geological Survey (USGS) NAPP program, and the United States Department of Agriculture (USDA) NAIP program. All imagery taken prior to 2005 needed to be georeferenced prior to imagery analysis. The image resolution was 1 m or better for all images. *The 1997 NAPP imagery contained small regions of glare that made individual objects harder to distinguish.

Year	Film type	Imagery source	Georeferenced?	Resolution (m)
1969, 1970	Black and White	Yosemite National Park	No	~0.5
1987, 1988	Color Infrared	NAPP, USGS	No	1
1997	Color Infrared	NAPP, USGS	No	1*
2005	Red, green, blue, IR	NAIP, USDA	Yes	1
2012	Red, green, blue, IR	NAIP, USDA	Yes	1

All years were classified into at least six land cover classes: rock, water, conifer forest, shrub, sparse meadow, and dense meadow. A seventh cover class, aspen, was added for the 1997 NAPP and all NAIP images. Meadows are defined as areas dominated by grasses and forbs; dense meadows have little to no bare ground and appear green in color summer aerial photographs (bright red in color infrared images), while sparse meadows have larger amounts of bare ground and appear brown in color photographs or green/beige in color infrared. The dense meadow category encompasses wetlands, but the aerial image analysis does not reliably separate true wetlands from areas with dense summer grass. Areas of standing dead trees with no discernible understory were classified as sparse meadows.

The 1969 black and white imagery was degraded both spatially and radiometrically, prior to classification, to enhance the capabilities of the texture algorithms and speed processing time (Caridade et al., 2008). The original data was 8-bit, ≈0.5 m resolution and was degraded to 4-bit, 2 m resolution. Only non-overlapping portions of the images were processed in eCognition to eliminate redundancy and to speed processing. Bodies of water were entered via ArcMap after the initial eCognition classification using delineations from NAIP imagery in order to retain smooth outlines that were not always captured in the degraded black and white imagery. Some images captured more fine-scale heterogeneity than others. To compensate for this effect, we merged any polygon with an area less than 700 m^2 with the largest adjacent polygon. The value of 700 m^2 was chosen to minimize the number of polygons removed while visually maximizing the similarity in types of structures captured in different maps. Using polygons of this size also assures that the slight differences in spatial resolution between imagery sources will not affect our final analyses, since the differences in resolution (< 1 m^2) are orders of magnitude smaller than our minimum mapping unit of 700 m^2.

To classify the images, we first identified exposed rock using color imagery, which helped to distinguish it from grassland, bare ground and sand. Ground reference locations of bare ground, solid rock, and sand helped in identifying the slight differences in color between these similar looking areas. Under the rationale that fire occurrence would not affect the distribution of the "rock" land cover type, the mapped locations of granite outcrops from later images were used directly in classifying the 1969 photographs. Maps of rock outcrops created using NAIP imagery were uploaded into eCognition as a thematic layer, using the "assign class using thematic layer" algorithm.

Portions of the 1997 aerial images were of lower quality than other years due to blurring or heavy glare that made it difficult to identify vegetation (such problems occurred over < 20% of the total area). To compensate for this, and to incorporate as much independent information into the classification as possible, we included the Yosemite National Park Service (NPS) vegetation map (irma.nps.gov) as a thematic layer in eCognition for the 1997 classification. Including the 1997 NPS map, which was created using aerial imagery originally, helped us to delineate some of the boundaries between vegetation types as well as identify vegetation types in areas with high levels of glare. A slight disadvantage of incorporating the 1997 map was that the boundaries of some vegetation patches were smoother than would otherwise be created in eCognition. These smoothed boundaries could affect certain patch properties such as fractal dimension, but are not expected to alter total area of either individual patches or types of land cover in a measurable way. Although it would have been simpler to use the 1997 NPS map instead of creating our own map for 1997, initial tests showed that we could not directly compare the NPS map to our other vegetation maps because of differences in the level of spatial detail and shape complexity captured.

For imagery not obtained from NAIP, unclassified sliver polygons remained in the exported classification in areas where individual images did not overlap perfectly. These slivers were classified manually in ArcMap. There were some small areas (< 10%) of the watershed that were not covered by the available imagery. These missing areas do not include any of the areas where stand-replacing fire occurred in ICB. We therefore gap-filled these sites from the closest (in time) vegetation map that covered the missing areas.

2.4. Comparison with other data products

We compared our maps to the publicly-available LANDFIRE product, a 30 m resolution map of existing vegetation cover (EVT) for 2012, an estimate of 'peak' vegetation cover (for fire suppressed conditions), and a mapped estimate of pre-European settlement vegetation cover (pre-fire suppression) referred to as the biophysical settings or BPS map (LANDFIRE, 2012). Comparing our 2012 map to the EVT product allows us to verify that our maps agree with publicly available estimates of different types of land cover. Comparing our 1969 map to the peak vegetation cover allowed us to see whether a century of fire suppression created the expected land cover in this area. Comparing our 2012 map with the BPS layer allowed us to compare the landscape's current condition to what the landscape likely resembled prior to fire suppression.

2.5. Accuracy assessment

The 2012 map was validated using 230 ground reference points mapped in 2013–2015. We mapped these points with a handheld Garmin GPS unit, with the goal of capturing transitions in vegetation cover type as well as mapping multiple examples of large stands within each cover class. Due to the inaccessibility of portions of the ICB, mapping was generally limited to within 1.5 km of hiking trails. Sixty-six points were removed because they were within 50 m of another ground reference point for the same vegetation type, in order to avoid skewing the results. The mapped locations of ground truth points were verified by comparing field notes to 2012 aerial images. We manually classified an additional 300 randomly selected validation points from the aerial imagery, in order to cover a broader area and increase the total number of validation sites.

We were unable to use the Yosemite NPS Vegetation map from 1997 for additional validation due to the mismatch in resolution between the NPS map and our product. Not only do the maps we produced provide finer spatial resolution than the Yosemite NPS vegetation map, they are also more discriminatory in assigning an area as "forest". In contiguous patches with less than ≈15% vegetation cover, we classified the patch as bare ground or rock, even if the park map labeled it as forest due to the presence of sparse trees.

Other than the NPS map, no independent information is available to validate the maps for earlier years. Earlier classifications were validated by selecting random points in ArcMAP, visually identifying those points as belonging to one of the five vegetation classes, and then using these random points for validation. These points were selected using the Create Random Points tool in ArcMap, keeping a minimum of 50 m between any two points. The goal was to have 500 total points, distributed proportionally among vegetation types, in each year. If needed, extra points were added in order for each mapped vegetation class to include at least 10 verification points. Any large vegetation areas identified as being misclassified were manually corrected until overall accuracy reached 90%.

We used confusion matrices to calculate accuracy within each vegetation class for each year. Confusion matrices give the number of validation points mapped as a certain class (rows) which are identified as each vegetation class using visual inspection of the photos or actual ground reference points (columns). *Reliability*, also known as "user's accuracy", is the proportion of points mapped as belonging to a certain class which are classified correctly. *Overall Accuracy* is the proportion of points where the vegetation is mapped correctly, or the sum of values along the diagonal of the confusion matrix divided by the number of data points.

In addition to accuracy for individual years, we used transition confusion matrices to calculate our accuracy in capturing different transition types. The transition confusion matrix is the same as an individual confusion matrix, except that instead of dividing the map into individual vegetation classes it uses categories such as "conifer to conifer" or "conifer to shrub" (which would represent areas which remain conifer or that transition from conifer to shrub, respectively; Congalton and Green, 2008). We created these transition confusion matrices for all sequential map pairs (e.g. 1969–1988 and 1997–2005) as well as for the larger time lags of 1969–2012, 1969–1997, and 1997–2012.

2.6. Identifying landscape change

Total cover was calculated for each vegetation type in each image. Because of the steep topography in this area, we adjusted area for the slope of the landscape in order to avoid underestimating land cover in steep areas (Dorner et al., 2002). We used our measures of classification accuracy for each vegetation type in each image in order to determine the statistical significance of our estimated changes in total area for each vegetation type (following Congalton and Green, 2008). For each map, we calculated the areas of each vegetation class that were converted into another class in a later map. For example, what proportion of the shrublands in 1969 remained as shrubland in each mapped year, and what proportion converted to each of the other vegetation classes?

Changes in patch sizes and distributions between the fire-suppressed and the contemporary condition were assessed using the FRAGSTAT software package (McGarigal et al., 2012). The landscape metrics we selected can be divided into two categories: landscape diversity metrics, which describe how heterogeneous a landscape is, and within-class properties, which describe the behavior of a specific vegetation class.

2.6.1. Landscape diversity metrics

Diversity indices have been shown to capture fire-related landscape changes well (Romme, 1982). They describe heterogeneity by measuring how patches of vegetation are distributed spatially across the landscape. We evaluated the following diversity metrics:

Shannon's Evenness Index (SHEI) is the Shannon's Diversity Index (calculated using information theory) divided by the maximum diversity given the number of cover types present (McGarigal et al., 2012). An evenness index of 1 would mean that all vegetation types were equally represented in the landscape; higher evenness means more landscape diversity.

Simpson's Evenness Index (SIEI) is similar, but is calculated using the probability that any two cells selected at random would be different patch types (McGarigal et al., 2012). Again, a value of 1 would mean that all patch types cover an equal area, and a value near 0 would mean that one type dominated nearly all of the landscape. We include both evenness indices in order to verify that the exact method of calculating evenness does not affect our results.

Aggregation Index (AI) is a measure of how much each vegetation type is clumped into a few large groups (high aggregation) or spread into many small groups (low aggregation).

2.6.2. Patch properties within each class

Patch properties describe local-scale heterogeneity and the size and shape of individual vegetation patches. For this study, we selected metrics which have been shown to be consistent across many different landscapes (Cushman et al., 2008):

Largest patch percent area (LPI) gives the percent of the total vegetated area taken up by the largest contiguous vegetation patch within each vegetation class. This metric gives an idea of the maximum area dominated by a single type of overstory.

Fractal dimension (FRAC) measures how complex and plane-filling the shapes are by using the relationship between the area and perimeter of a patch. As the dimension approaches 2, perimeter is maximized for a given area of coverage, while for simple geometries such as squares or circles the dimension is 1 (McGarigal et al., 2012).

For example: a vegetation class with a low fractal dimension whose largest patch covers a large area indicates a spatially homogeneous region. On the other hand, a high fractal dimension suggests an increase in the total length of boundaries between patches of different types, thus increasing local heterogeneity.

In addition to these metrics, we calculated the mean and standard deviation of the areas of all patches within each vegetation class. These measures help capture the changes in the distribution of patch sizes.

2.7. Varying resolution

Spatial resolution can significantly affect the computed values of landscape-scale metrics (Wu, 2004; Kelly et al., 2011). We tested the sensitivity of our metrics to resolution by converting our vectorized vegetation maps into raster maps at resolutions of 5, 30, 90, and 500 meters (FRAGSTATS requires converting vectorized maps into gridded datasets). We re-calculated all metrics with these varying-resolution maps and compared the results to each other.

3. Results

3.1. Vegetation mapping

The final vegetation maps created from each set of aerial images reveal clear changes over time (Fig. 4). Many forested areas are replaced by other vegetation types (Figs. 4–6), and some shrub patches expand into high severity burn areas (which can be seen by comparing Fig. 3 and 4). Fig. 5 shows the total landscape area covered by each vegetation type in each year (adjusted for land surface slopes). There were significant changes in total area for every land cover class from 1969 to 2012. However, the significance of some image-to-image changes within that time span are unclear when the change is less than our level of classification accuracy (Fig. A.1).

Across the whole 1969–2012 period, conifer cover decreased by 21 km^2 (24%), shrublands increased by 4 km^2 (35%), sparse meadow area increased by 17 km^2 (199%) and dense meadows grew by 1 km^2 (161%). Sparse meadow area increased significantly from 1969 to 1997 after which any changes in area were too small to be detected. Shrublands initially decreased in area, but then increased. This pattern likely arose from a delay in colonization of burned areas by shrubs. Dense meadow area generally increased, but dropped slightly between 2005 and 2012, possibly due to drought conditions in 2012 (http://droughtmonitor.unl.edu/). In 2012, it had been 8 years since the most recent stand replacing fire in ICB, and vegetation had grown into some of the large, sparsely vegetated patches present in 1997 and 2005. The 1997 and 2005 maps were created from imagery taken relatively soon after large fires with a high amount of stand-replacing area (nearly 2000 ha burned from 1994 to 1996, and a 2000 ha fire burned in 2004; Fig. 2). These fires created large areas of sparsely vegetated grassland. Although woody recruitment into these burned sites may have begun in 1997 and 2005, any seedlings or saplings would be too small to detect in aerial photography.

Most of the area covered by the 1969 conifer forest (61–73%) was also conifer-dominated in 2012 (Fig. 6, Table A.6), either because it did not experience large, stand-replacing fire or conifers had regrown post-fire. Approximately 10% of the conifer area transitioned to shrubland by 2012, 16–26% to sparse meadow, and 2% to dense meadow. Areas dominated by shrubs in 1969 either remained as shrubs in 2012 (40–44%), transitioned to conifer (24–52%), or were replaced by sparse meadows (19%) and a negligible portion shifted to dense meadow. Most 1969 sparse meadows remained sparsely vegetated (54%), but a large portion transitioned to forest (39%). There was very little dense meadow present in the basin in 1969, and conifers encroached upon up to 40% of this area by 2012; but overall dense meadow area increased primarily from the burning of conifer forests (Fig. 6, Table A.6). For the 1987/8–2012 period, results are similar but only 43% of 1987/8 sparse meadow remains sparse meadow in 2012, and 20% transitioned to shrubs (Table A.8).

3.2. Comparison with other data products

In comparing our maps to LANDFIRE, we found reasonable

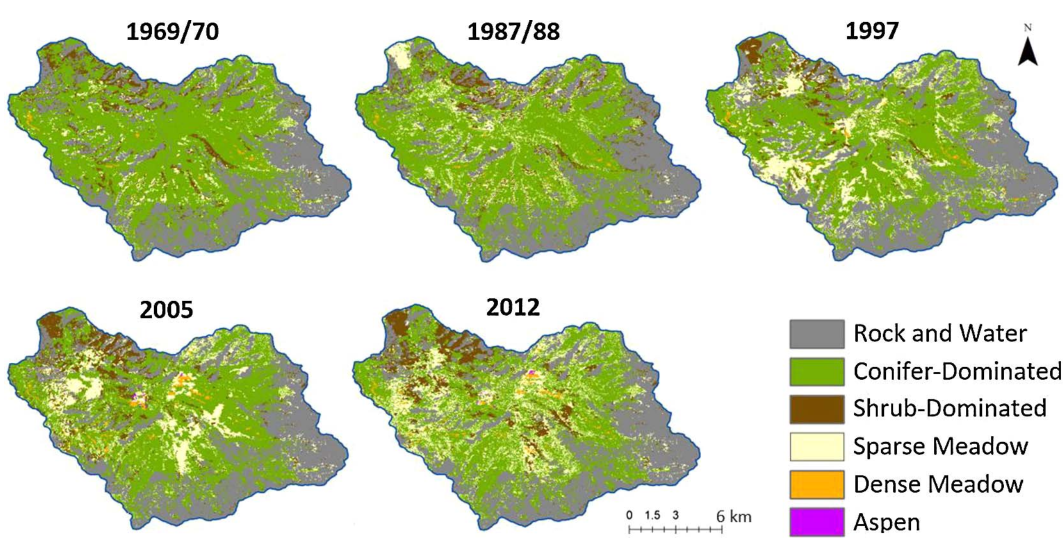

Fig. 4. Maps created from aerial imagery in five different decades showing non-vegetated areas (rock and lakes), conifer forest, shrublands, sparse meadows, dense meadows, and aspen stands.

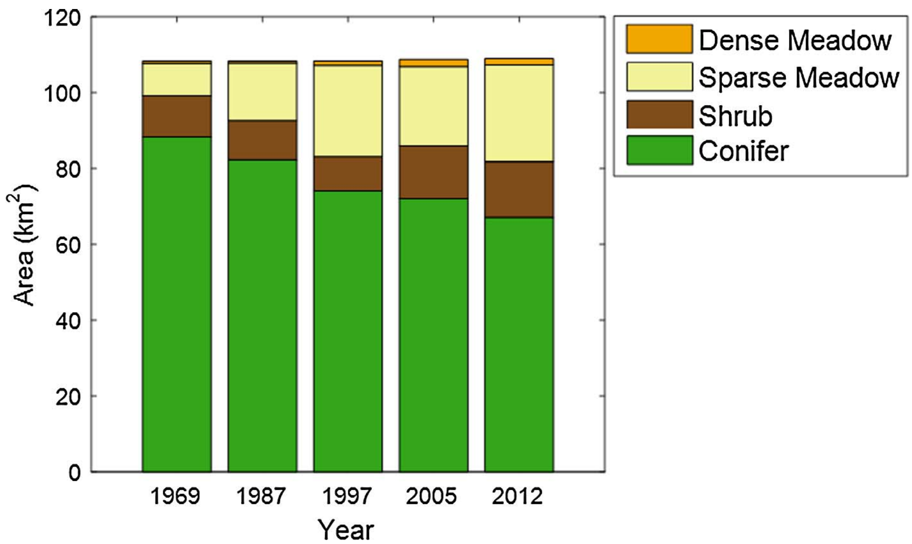

Fig. 5. Total area of each vegetation class for each year's map. Conifer cover steadily decreases. Shrub area decreases initially but then increases as burned forests and shrublands are colonized by shrubs. Sparse meadow initially increases dramatically but levels out by 1997, while dense meadow area increases slowly and steadily.

agreement between the 2012 EVT layer and our 2012 map (54% forest cover versus our estimate of 41% forest cover, and 4.5% shrubland cover versus our estimate of 8.7%). Some of the differences in cover between the EVT layer and our 2012 map partly arise from discrepancies in the criteria for classification as barren/sparsely vegetated – only 20% of ICB was classified this way in EVT, versus 33–36% in our maps. EVT does not distinguish between dense and sparse meadows, preventing a direct comparison of these values. The LANDFIRE peak vegetation layer was similar to our 1969 vegetation map. The BPS layer, however, did not closely resemble the current landscape. For example, the BPS layer suggests 79% of the watershed would support forests, but only 1% would be shrubland. This is more consistent with the 1969 fire suppressed conditions in ICB than conditions under the current fire regime.

3.3. Accuracy assessment

According to our verification points, greater than 85% total accuracy in the classification was achieved in each year's vegetation map, ranging from 87% for 2012 to 94% for 1969. Accuracy varied between vegetation classes (Table 2). Confusion matrices, detailing sources of error in the classifications for different years, are provided in Appendix A. Confusion matrices for changes over time, using the methods of Congalton and Green (2008), are also presented in Appendix A.

Table 2
The reliability (proportion of the vegetation map that is classified correctly) of our vegetation maps varies between years and vegetation classes.

Year	Conifer	Shrub	Sparse Meadow	Dense Meadow	Overall
1969	0.97	0.88	0.80	0.90	0.94
1988	0.96	0.87	0.77	0.80	0.92
1997	0.91	0.91	0.88	0.80	0.90
2005	0.95	0.89	0.94	1.00	0.92
2012	0.89	0.94	0.78	0.90	0.87

Collapsing all changed versus unchanged points, 94% of the area mapped as remaining unchanged is truly unchanged, and 76% of the area mapped as having changed vegetation class from 1969 to 2012 actually experienced a change. Within the areas of change, transitions from one vegetation class to another were captured with variable accuracy, ranging from only 14% for the uncommon sparse-shrub transition, to 93% accuracy for the conifer to dense meadow transition.

Common classification errors included bare ground being classified as conifers, due to shadows being misclassified as trees by the eCognition algorithm. The eCognition algorithms also sometimes had difficulty differentiating between shrubs and trees. Other sources of error include low camera angles in parts of some images, which impairs detection of edges, particularly at forest boundaries, and can result in

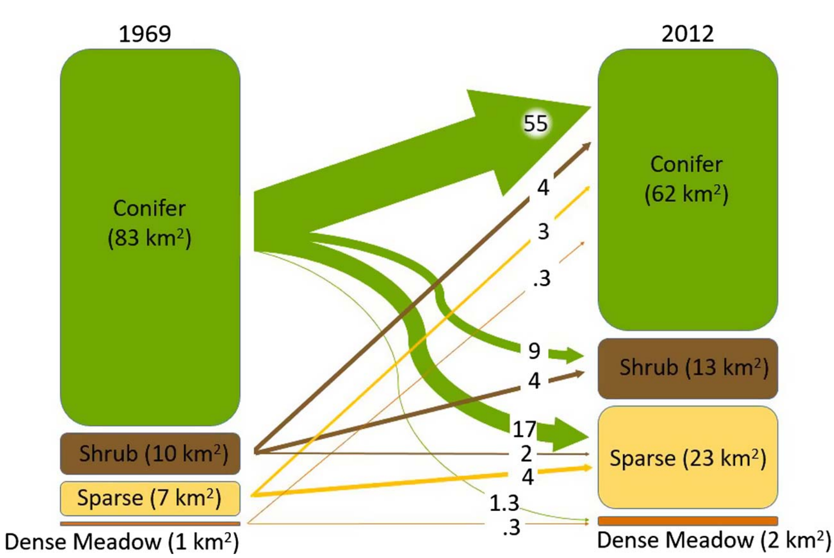

Fig. 6. Land cover type transitions from 1969 to 2012. Box areas are proportional to the total area of each vegetation type in each year. The numbers on each arrow give the area in km^2 which experienced each type of transition, and the width of each arrow is proportional to this value. All transitions covering more than 0.25 km^2 are included.

trees obscuring small meadow or rock features. It should also be noted that the rigor of the accuracy assessments was not constant across the maps: For the 2012 map, actual ground reference points were included in the accuracy assessment in addition to manually classified points from the aerial photograph. This is likely why the 2012 map accuracy is slightly lower than that of the other maps.

3.4. Varying resolutions

We calculated patch-level and landscape-level indices at resolutions from 5 m to 500 m. None of the indices changed significantly with scale, except for a few individual values at the 500 m level. At all scales, the trend of each metric over time remains the same. This scale-independence gives us high confidence that these indices accurately represent changes in the vegetation structure, rather than being an artifact of the mapping process. Because of these results, we did not deem it necessary to present results from various spatial resolutions. Therefore, all further results in this paper are calculated from maps at 5 m resolution. The supplementary material gives examples of some of these calculations (Table A.9).

3.5. Identifying landscape change

FRAGSTAT operates on planar area, which can be problematic in highly sloping regions. Correcting total vegetation areas to account for surface slope increased total area in the 2012 image by 4% for conifers and sparse meadows, 7% for shrubs (which generally grow in steeper areas), and 1% for dense meadows (generally found on relatively flat ground). While this correction was incorporated into our calculations of total coverage, the differences were not large enough to require modifying FRAGSTAT calculations.

Using landscape metrics offers a quantitative measure of the increased spatial complexity in the ICB. Fig. 7 shows consistent and parallel increases in both Shannon's and Simpson's evenness indices, and a decrease in the aggregation index (meaning the landscape became more fragmented). We measured a steady increase in both Shannon's Evenness Index (from 0.44 to 0.70) and Simpson's Evenness Index (from 0.42 to 0.73) for the 1969 to 2012 period. The aggregation index decreases from 95 to 87 over this period, although not monotonically, showing a trend towards more distributed vegetation patches over time. Aggregation index increases between 1988 and 1997, and remains fairly high in 2005 (although it is still lower than in 1970). This temporary increase in aggregation index is mainly due to several large areas that burned with a large component of high severity only a few years before the images were taken, resulting in large areas of sparse meadow which had not yet re-grown with other vegetation.

Patch sizes also changed in response to fires. Mean patch size, standard deviation of patch sizes, and LPI decreased over time for conifers (Fig. 8a–c). These indices either remained steady or increased for all other vegetation classes (Fig. 8a–c). The large 1997 and 2005 sparse meadow LPI values are due to a large burned area that hadn't grown back yet (Fig. 2). By 2012, much of this sparse meadow had regrown with shrub or conifers. Area-weighted fractal dimension showed an increasing trend for all vegetation classes, suggesting that the vegetation patches are adopting an increasingly complex suite of geometries (Fig. 8d). The fractal dimension increased even during the fire-free period of 2005 to 2012, suggesting that regeneration processes as well as fire contribute to increasing vegetation patch shape complexity as patches of new vegetation grow in portions of previously homogeneous areas (such as a small shrub patch growing within a sparse meadow, or conifer regenerating in one area of a shrub field). Data from 1997 are omitted from Fig. 8d. When initially calculated, the 1997 image had an anomalously low fractal dimension. This image was partially classified using the Yosemite Vegetation Map to compensate for low aerial imagery quality, and we interpret the low fractal dimension as arising from the smooth patch edges created in areas strongly affected by inclusion of the 1997 NPS map, compared to the more uneven edges created by eCognition using imagery alone. These smoothed edges do not affect the entire map, and should not cause relevant changes in patch sizes, only in their edge shapes.

4. Discussion

These results suggest that the re-introduction of fire to the ICB through the managed wildfire regime has increased landscape heterogeneity and complexity, primarily by fragmenting and reducing the area covered by conifer forest. All measures of heterogeneity, both landscape metrics and patch metrics, showed that heterogeneity increased from 1969 to 2012. Although landscape metrics can be challenging to directly relate to ecological outcomes, and only reflect selected kinds of landscape change (Li and Wu, 2004), the trends in landscape metrics that we have identified in the ICB appear to be both informative and robust: Multiple metrics point towards the same trend of increased heterogeneity and complexity, the metrics were independent of the resolution of the datasets used for their computation, and the metrics we used have been independently shown to be ecologically relevant across many landscapes (Cushman et al., 2008). Furthermore, our results are consistent with recent field studies which have identified high levels of contemporary landscape heterogeneity in the ICB (Collins et al., 2016).

Although we cannot directly attribute all observed changes to fire (and some small areas of change are likely due to succession or other disturbances) it is clear the wildfire is the dominant change agent in the ICB. Analysis of Landsat imagery shows the largest changes in

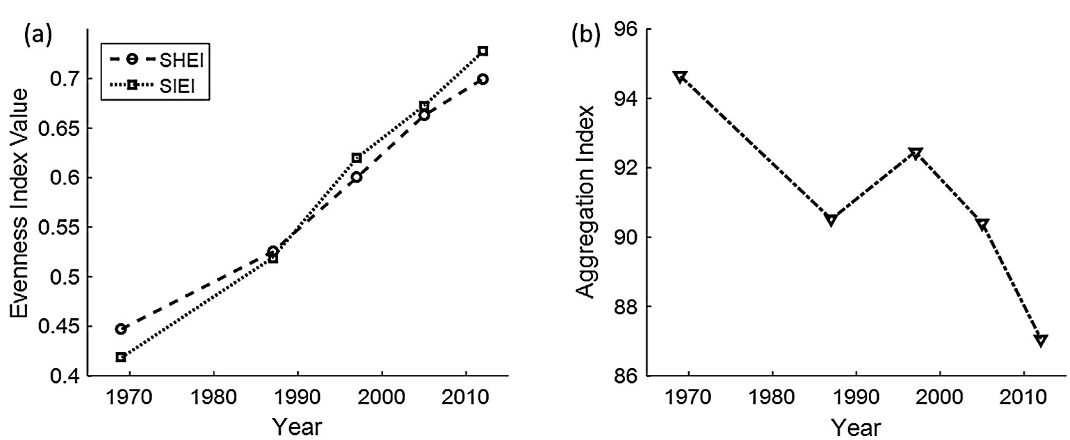

Fig. 7. Landscape Indices. (a) Shannon Evenness Index (SHEI) and Simpson's Evenness Index (SIEI) both increase over time, indicating an increase in landscape heterogeneity. (b) The landscape aggregation index has a downward trend over time which also is a measure of increasing heterogeneity.

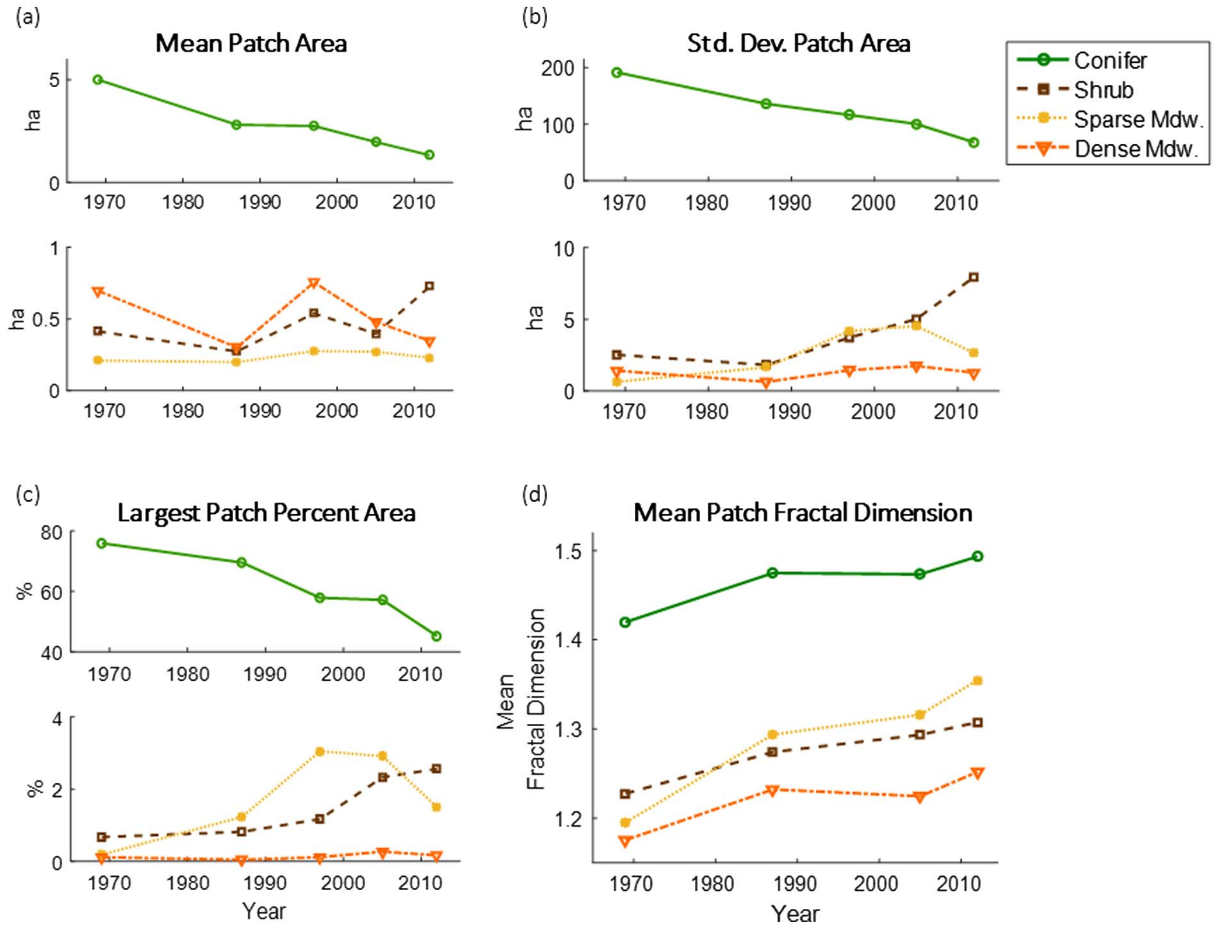

Fig. 8. Patch size metrics over time for the four main vegetation classes: conifer, shrub, sparse meadow (mdw.), and dense meadow (mdw.). Conifer is shown separately from other classes for ease of viewing when its metric varies largely from the others. (a) Mean patch area in hectares. (b) Standard deviation of patch areas within each class. (c) The percent of the vegetated landscape covered by the largest patch of each vegetation type (LPI). (d) Mean fractal dimension; the only metric which generally increases over time regardless of vegetation type.

vegetation cover are all within areas that have burned: within burned areas, 10% of the land experienced decreases of over 90% of vegetation in patches of up to 10 ha, compared to only 0.3% of unburned areas in patches of under 1 ha (Appendix C, Kennedy et al., 2010). Comparing Figs. 3 and 4 also reveals clear relationships between areas that burned at high severity and areas that experienced large-scale vegetation type conversion. In addition, extensive areas of burned logs are present in contemporary shrubland and meadow locations, demonstrating the role of fire in changing the landscape. Further work using this dataset will explore the drivers which determine when moderate or high severity burn areas convert to new vegetation types versus re-growing with the same vegetation type.

A range of ecological consequences may be expected to follow from the increased landscape complexity in the ICB. From the literature, and from awareness of the requirements of many plant species in the ICB (e.g. species dependent on open areas or on recruitment under shrub canopies), we would anticipate increases in biodiversity from the re-establishment of fire regimes (Seiferling et al., 2014; Bird et al., 2008). There is some evidence of such increases occurring in ICB. Pollinator diversity in ICB is positively correlated with diversity in understory vegetation and fire history (Ponisio et al., 2016). Using the understory vegetation data from Ponisio et al. (2016), we found that understory vegetation richness and total understory cover in the ICB is slightly elevated in open areas compared to forests, on average, and richness appears to be affected by local fractal dimension, although these relationships are subject to high variability and not statistically significant (Appendix B). This understory dataset also shows 82 understory plant species that were found within ICB in meadows or shrub fields but never found in any of the 89 forested plot surveys, suggesting that increasing non-conifer cover could expand habitat for such species (Appendix B).

We would also anticipate that increased fragmentation and reduced patch sizes in the landscape would decrease connectivity of available fuels (Miller and Urban, 2000a), reducing the risk of extreme fire in the ICB. Although this study does not investigate fuel connectivity directly, Collins et al. (2009) found many areas of self-limiting fires within the ICB. Therefore, reduced connectivity of conifer fuels is likely reducing fire spread, while the smaller increase in shrub area does not appear to have a strong effect (despite the fact that shrublands propagate fire relatively easily).

Finally, there is a possibility for the landscape-level changes to have hydrologic relevance. Our maps show a decrease in forested area of more than 20%, which has been shown to be a large enough effect to cause measurable streamflow changes in many other watersheds (Wine and Cadol, 2016; Brown et al., 2005). Dense forests are likely to have the greatest water use of the vegetation types in the ICB (Goulden and Bales, 2014), meaning that reduction in forest cover likely translates to reduced overall loss of water through transpiration. In addition, replacement of dense forests with sparser forest cover, shrubs and open areas may increase snow retention and reduce water loss from canopy evaporation and sublimation (Lundquist et al., 2013; Grant et al., 2013). Potentially, managed wildfire could therefore provide a forest management approach consistent with contemporary interest in supporting streamflow yields from Sierra Nevada watersheds and reducing drought stress in forests (Grant et al., 2013; Boisramé et al., 2016).

The use of aerial photography for mapping vegetation change was effective, but was also time consuming and required finding and purchasing imagery from multiple sources. Since landscape analysis results were similar at 30 m and 5 m scales, the 30 m resolution of recent Landsat imagery may be sufficient to describe changes in landscape patterns from fire, provided that the imagery can be classified accurately. Land cover maps of forested areas created with Landsat data have been shown to reach accuracies of 85%, though validation of older Landsat data is problematic if higher resolution photos or field data is not available (Wickham et al., 2013).

We chose to use the simplest vegetation classification possible in order to reduce the levels of uncertainty and in order to devote our time to classifying as many images as possible. Further work could use other methods to do more fine-scale classification of forests into classes based on age, density, or habitat type. However, species classification would be problematic, especially for the non-color imagery. Combining this imagery with LANDSAT information might provide more details in terms of stand composition, but with a lower spatial resolution and limited validation data.

Our accuracy assessment suggested that individual maps had high accuracy, but classification errors arose when mapping specific transitions over time from one land cover class to another. Despite classification errors, the most common transitions were clearly from conifer forest to either shrub or sparse meadow. These observed transitions are consistent with the known biology of the dominant species in the ICB. For instance, the dominant shrub species (*C. cordulatus*) establishes quickly in severely burned areas thanks to its ability to propagate both via seed and re-sprouting (www.feis-crs.org/feis/), and sparse meadow conditions are likely to prevail during the period required for tree establishment after fire if conditions are not favorable to fast grass or forb recruitment.

Wildfires are known to affect the establishment and maintenance of mountain meadows, although most work focuses on forest encroachment on meadows rather than creation of new meadows in previously forested areas (Ratliff, 1985; Helms and Ratliff, 1987). We observed some encroachment of forests into meadows during the study period, which is likely associated with the fire-intolerant *P. contorta* which grows in a variety of moisture conditions and commonly encroaches on meadows (Helms and Ratliff, 1987). Removing conifer trees with fire or other means can also restore aspen stands (Jones et al., 2005, Krasnow and Stephens, 2015). Although we could not positively identify tree type in the black and white photos, our field observations show that at least one of the large aspen stands mapped in 2012 grew following high severity fire in a conifer-dominated forest.

There may be complex interactions between the land cover classes that our large-scale analysis cannot capture. For example, *P. jeffreyi*, *A. magnifica*, and *A. concolor* have been shown to have higher post-fire seedling survival rates in *Ceanothus*-dominated patches compared to bare patches (Zald et al., 2008). Fires are also likely causing changes in species composition that could not be captured by our maps. For example *P. jeffreyi* is more fire tolerant (Stephens et al., 2008) and generally grows in relatively dry soil (Fowells et al., 1965; Fites-Kaufman et al., 2007), while *P. contorta* is fire-intolerant but readily grows in open, moister areas following fire (Helms and Ratliff, 1987; Stuart and Sawyer, 2001). These species would be expected to fill different niches in a landscape with frequent fire.

All computed landscape-level metrics showed clear trends, rather than appearing to saturate or approach a dynamic equilibrium. This suggests that the restored fire regime has probably not yet returned the ICB landscape to a state of 'natural variability' in which the landscape structure remains within a range set by natural habitat and disturbance conditions rather than human intervention (Swanson et al., 1994). Model predictions suggest that restoration of similar landscapes having experienced a century of fire suppression could take over 200 years (Miller and Urban, 2000b), without factoring in the complications implied by non-stationary climate. The landscape of the ICB today conforms to the description of historical Western US forests given by Hessburg et al. (2015) – a patchwork of small (< 100 ha) to large (1000–10,000 ha) patches of vegetation including forest, shrubland, grassland, bare ground, and dead trees – suggesting that the current landscape is beginning to approximate the conditions that prevailed before fire suppression and is adapting to the new climate. There are few guidelines available to assist with the restoration of landscape-scale heterogeneity to fire suppressed forests (Collins et al., 2016). The analyses presented here provide an important resource: a detailed description of the heterogeneity caused by a natural fire regime in the Sierra Nevada, and thus an approximation for landscape-level targets for alternative management regimes, or guidance as to what could be expected if managed wildfire were introduced into other Sierran forests.

5. Conclusion

The alleviation of fire suppression in the ICB reintroduced an agent of change to a landscape which had been artificially protected for 100 years. Landscape metrics do not appear to have stabilized or peaked, suggesting that the landscape is still recovering from the history of fire suppression or adapting to the new climate. We might expect the landscape to ultimately come into a dynamical equilibrium set by the fire regime and local climate, in which individual points on the landscape may change but the landscape composition and patch characteristics are approximately stationary (or vary within a natural envelope). However, the ICB does not yet appear to have reached such a state and possibly it never will. While it is unclear what the end point of the managed wildfire regime is likely to be in terms of landscape composition, especially in light of climate non-stationarity, it is clear that frequent, mixed severity wildfires in the ICB reintroduced heterogeneity to the landscape and increased the amount of non-forest land cover.

Clearly, there are many potential benefits to adopting wildland fire use (Stephens et al., 2016). There are nearly 10,000 km^2 of wilderness area in the Sierra Nevada within the same climate zone as the ICB, where wildland fire use could likely be implemented safely and successfully (Boisramé et al., 2016). Despite the long timescales that might be required to restore forests to a new natural state, in the ICB forty years were clearly sufficient to impose changes that could increase biodiversity, reduce plant water consumption, decrease the risks of extreme fire and enhance the resilience of forests.

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Appendix D. Data and Maps

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2017.07.034. These data include Google maps of the most important areas described in this article.

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