Forest Ecology and Management 542 (2023) 121102

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Vegetation type change in California's Northern Bay Area: A comparison of contemporary and historical aerial imagery

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ARTICLE INFO

Keywords:
Vegetation change
Mixed hardwood forests
Shrublands
Historical ecology
Aerial photography
Wildland urban interface
Object-oriented remote sensing

ABSTRACT

The North Bay area of California is a populous and ecologically diverse area that has experienced significant changes in the past century, as well as a series of recent wildfires, after over a century of fire suppression practices. While much research has been conducted quantifying drivers and patterns of vegetation change in conifer-dominated ecosystems, and how such changes have influenced current trends in fire behavior, studies of similar focus and scale are rarer in non-conifer ecosystems, including mixed-hardwood forests or shrub-dominated ecosystems in central and coastal Northern California. This is despite the fact that ecosystems other than conifer forests make up the majority of area burned in California wildfires. As such, expanding research focused on patterns of large-scale vegetation change as a possible driver of this trend in this area is a priority. In this study, we sought to map the overall extent and patch sizes of broad vegetation classes across a 52,000 ha study area based on historical (1948) and contemporary (2014) aerial imagery and to investigate shifts in vegetation patterns, as well as potential pathways and drivers of detected changes. We classified vegetation types through segmenting our imagery into homogenous polygons, and assigning broad vegetation categories using a random forest algorithm. We then analyzed patterns of change using spatial statistics and conditional inference tree analyses. We detected a large increase (12%) in the relative landscape proportion and average patch size of the forest class, characterized by dense tree canopy cover. Woodlands and shrub patches were most susceptible to type change, with the majority (57% and 65%, respectively) of converted areas subsequently identified as denser forest stands. By contrast, herbaceous and forest patches were most persistent. We additionally found that disturbance history, specifically whether an area burned or not, and topographic variables, including elevation and aspect, were important influences on the likelihood of vegetation persistence, while slope and water availability were not. Historical aerial imagery, which provides fine resolution and accurate data over a large spatial scale, is a useful tool for detecting landscape-scale vegetation shifts in ecosystems where widespread vegetation monitoring was not common historically. The marked increase in dense forest we detected, specifically due to the conversion of large areas of shrub and woodland vegetation may correspond to higher surface and ladder fuel load and continuity, and potentially higher wildfire risk. Fuel reduction treatments typically implemented in conifer-dominated forests may also be warranted in these mixed hardwood forests. However, more research is needed to understand drivers of change in non-conifer-dominated ecosystems in California and how such change influences wildfire behavior.

1. Introduction

The occurrence of large wildfires in California's wildlands has rapidly increased, with the majority of the most destructive wildfires in the state's recorded history occurring in the past decade alone (CAL FIRE, 2022). Much work has been conducted quantifying how the implementation of fire suppression and exclusion policies in the 19th and 20th centuries, and their resulting impact on fire regimes, have contributed to landscape-scale changes in conifer-dominated ecosystems (Ansley and Battles, 1998; Dolanc et al., 2014; Stephens et al., 2015,

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https://doi.org/10.1016/j.foreco.2023.121102
Received 13 March 2023; Received in revised form 8 May 2023; Accepted 10 May 2023
Available online 22 May 2023

Collins et al., 2016; Hagmann et al., 2021). Other studies have additionally focused on how these changes contributed to observed trends in fire frequency and effects in the past few decades (Steel et al., 2022; Cova et al., 2023; Williams et al., 2023). However, the impacts of fire exclusion in non-conifer ecosystems, including mixed-hardwood forests or shrub-dominated ecosystems, especially those in central and coastal Northern California, are not well understood, despite the fact that ecosystems other than conifer forests can make up the majority of area burned in California wildfires (Calhoun et al., 2022).

The North Bay area of California, including Sonoma, Napa and Solano counties, has experienced a series of several large wildfires over the past decade. The North Bay fires of October 2017 were among the deadliest and most destructive wildfires in California's history, with 44 fatalities and nearly 9000 structures lost (Nauslar et al., 2018). Since 2017, there have been three fires >10,000 ha in this region, including two >20,000 ha and one >120,000 ha. For comparison, only 2 fires >10,000 ha in these counties occurred in the 100+ years preceding 2017 (FRAP, 2021).

Possible factors contributing to this trend include the rapid and widespread expansion of wildland urban interface (WUI) areas within the region, which is associated with increased risk of ignition (Hammer et al., 2009), as well as long-term drought and extreme fire weather conditions driven by climate change. Climate, weather, terrain, and fuels all drive fire behavior (Estes et al., 2017), and it is also possible that fuels conditions and/or changing vegetation conditions contributed to the extreme fire behavior experienced in this region in recent years. However, the relative importance of the different factors such as fuels in predicting fire severity is not well understood in most coastal Californian ecosystems. A comprehensive understanding of the dynamics driving fire patterns in this area is especially complicated due to its diversity of microclimates, topography and vegetation types, as well as the rapid development and urbanization the area has experienced over the past several decades (Huang et al., 2020). Given the devastating ecological, social, and economic impacts of the recent large wildfires in this region, coupled with the relative scarcity of published science on disturbance dynamics in these ecosystems, investigations into potential vegetation change and other possible drivers of fire activity are warranted.

Landscape-scale vegetation patterns influence (and are influenced by) a range of ecosystem processes including wildfire and disturbance regimes (e.g., Turner and Romme, 1994; Hessburg et al., 2007), and significant shifts in these patterns may alter these processes and their interactions (Hessburg et al., 2005; McLauchlan et al., 2020). For example, increasing patch size of dense forest when compared to historical conditions has been observed in coniferous forests adapted to a frequent fire regime throughout western North America (Hagmann et al., 2021), and is associated with greater susceptibility to stand replacing fire (Steel et al., 2022; Stephens et al., 2022). It is unclear whether woodland and mixed hardwood forests have undergone similar changes in vegetation patterns, and if so to what extent they may be contributing to the recent increase in fire activity. Knowledge of the patch size distributions and geographic settings of different vegetation types, and how they may have shifted over time, can improve our understanding of landscape resilience in these landscapes (Hessburg et al., 2019). In addition, habitat patch size is known to influence wildlife abundance and species richness in this area, and a better understanding of how vegetation patterns have changed could be informative for wildlife management (Lawrence et al., 2018).

Assessment of historical vegetation and comparison to contemporary conditions could offer some insight into how vegetation patterns changed over the last half-century in this area. Environmental history and historical ecology research can provide a baseline from which one can evaluate change, and possibly the degree of departure from an assumed natural condition. Such information can provide valuable context to inform management decisions (Swetnam et al., 1999; Rhemtulla and Mladenoff, 2007; Beller et al., 2020). However, data quantifying historical vegetation conditions in non-conifer dominated ecosystems of California are rare, particularly at the landscape level. This is likely due to a number of factors, including the high proportion of land in private ownership, and the fact that the majority of the dominant species have lower commercial value thus were not included in the early timber surveys conducted in the early part of the 20th century. Furthermore, the lack of more conventional natural resource commodity uses has led to less controversy over land management objectives, hence less overall attention (including funding) to studying these ecosystems.

While historical field plot data in these vegetation types are limited, aerial photography surveys were conducted over California throughout the 1940s and provide the opportunity to conduct landscape scale vegetation cover comparisons with contemporary imagery. Aerial photography is a commonly used tool to quantify landscape change (Morgan et al., 2010). Aerial photography is unique and particularly useful for ecological analysis of historical conditions, as it provides a continuous and high-accuracy snapshot of conditions over a large spatial area, and may serve as the only source of high-resolution spatial data to address shifting vegetation dynamics in many areas where widespread vegetation surveys were not common (Kadmon and Harari-Kremer, 1999; Lauvaux et al., 2016; Lydersen and Collins, 2018). Methods for assessing landscape change from aerial photo comparison include manual interpretation and digital analysis techniques (i.e. pixel-based or object-based image analysis) (Hay et al., 2003; Morgan and Gergel, 2013). Manual interpretation of aerial photos, the long-term standard method for photo-interpretation, is labor-intensive and may introduce observer-error and subjective or biased identification (Wulder et al., 2008; Morgan and Gergel, 2013). The technology associated with digital analysis has improved rapidly over the past few decades, and program-based classification is increasingly employed as an efficient means of photo interpretation and analysis for landscape-scale ecological studies (Varga et al., 2014). However, as historical aerial photos were generally taken in black and white, this limits the amount of extractable information in the images used for digital classification schemas when compared with contemporary imagery, posing challenges in these types of analyses (Morgan and Gergel, 2013; Eitzel et al., 2015).

For this study we used aerial photographs from the late 1940s mosaicked into a continuous orthorectified photomosaic to classify and characterize historical vegetation conditions and patterns across the landscape and then compared this to contemporary imagery captured in 2014, just preceding the series of large and destructive wildfires in the study area. Our specific objectives for this study were to

1) Classify vegetation types across broad categories for our historical photo dataset and contemporary imagery in order to quantify landscape-scale vegetation patterns for both time periods.

2) Assess major changes and pathways of change in vegetation types across the study area.

3) Evaluate drivers and important variables for vegetation change, especially from non-forested to forested patches.

Our hypotheses connected to these objectives were as follows: 1) A shift towards greater proportions and patches sizes of woody vegetation in the contemporary landscape given the continued absence of frequent fire in this area (Stephens et al., 2018); and 2) greater change in vegetation patterns would occur in more productive biophysical settings (i.e., greater moisture availability) (Bernal et al., 2022).

2. Methods

2.1. Study area

The study area is located primarily in California's Napa, Sonoma, and Solano counties approximately 50–90 km inland of the coast. This region is characterized by highly variable topography and a diverse array of vegetation types, as it sits at the intersection between the Central Valley and North Coast bioregions (Stuart and Stephens, 2006; Wills, 2006). Wildland vegetation in the area consists primarily of coniferous forests, mixed hardwood forests, oak woodlands, chaparral,

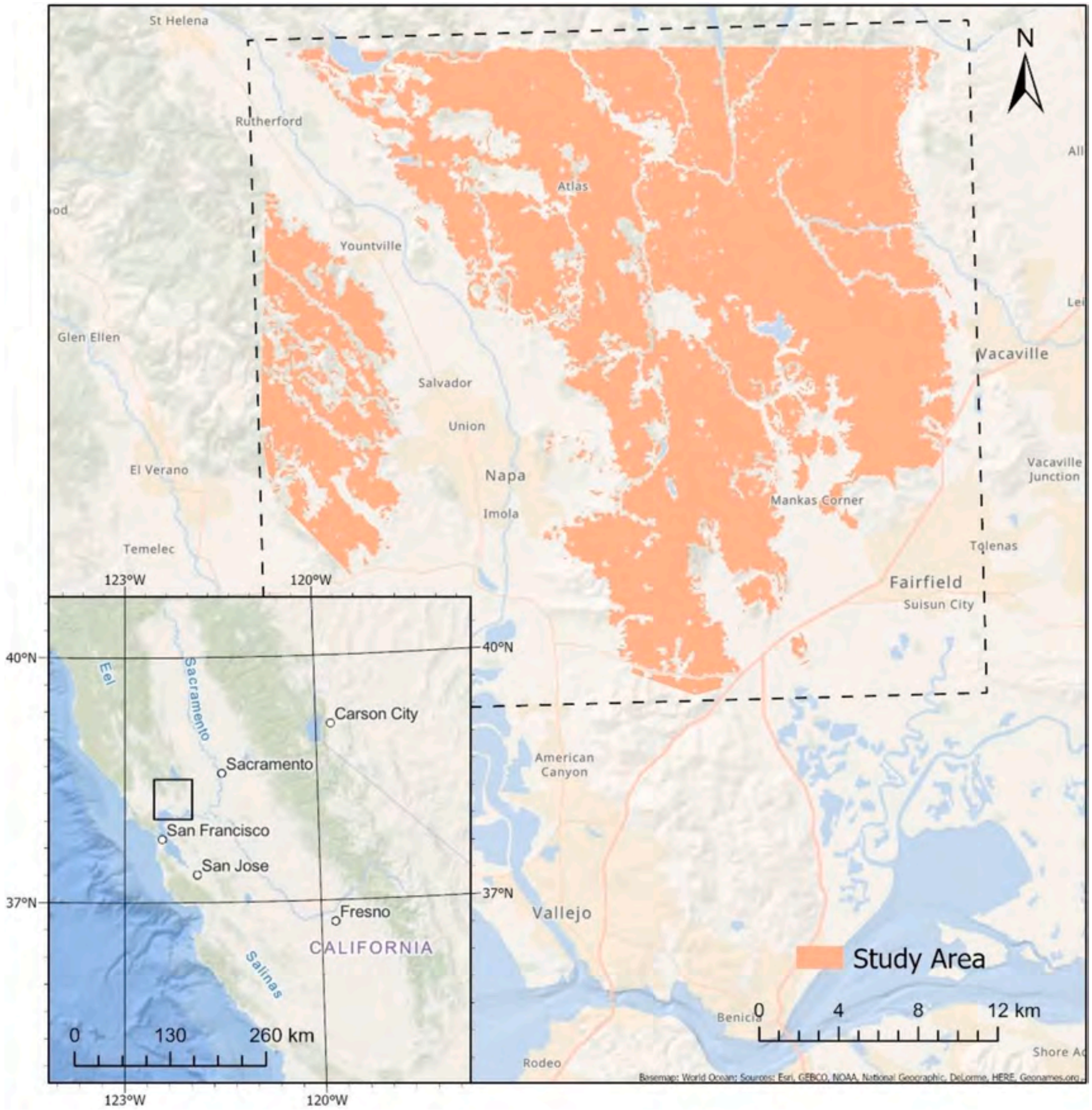

Fig. 1. Map of study area. The larger map identifies the approximate focus area of our study within Northern California for geographical context while the inset map shows our exact study area that intersects Napa, Sonoma, and Solano counties. Map was generated using ArcGIS Pro (ESRI 2020).

montane scrub, and annual grasslands. Much of this area is highly altered both from agricultural and pastoral land use as well as urban and suburban development, a significant portion of which is in the WUI zone. The climate is Mediterranean with cool wet winters and hot dry summers, though the diverse topography results in a diversity of microclimates across the landscape. Historical fire regimes in this area were variable because of the diverse vegetation types. Historical fire studies have revealed that fire occurred most frequently in grasslands and oak woodlands, which typically experienced very short fire return intervals from regular Indigenous burning (Stuart and Stephens, 2006; Stephens et al., 2007).

We initially defined our study area based on available field plot data from the Wieslander Vegetation Type Mapping (VTM) surveys conducted in the 1920s and 30s (Kelly et al., 2005). We intended to use the field plots to aid in classification of vegetation types in the historical aerial imagery. However, given the fine-scale resolution of the images and our intended classification scheme, as well as uncertainty in the precise location of the VTM plots (Doherty et al., 2006), we did not use the VTM plot data in our final analysis. The study area was delineated by generating a minimum bounding area convex hull polygon with a 500 m buffer using the spatial locations of available VTM plots in ArcGIS Pro (ESRI, 2020). As we wanted to look primarily at wildland vegetation for classification purposes, we removed areas that were developed in both the 1948 and 2014 imagery using publicly available county-level municipal datasets including Solano County's City Boundary shapefile (Solano County, 2022), Napa County's Municipal Zoning shapefile (Tangen, 2002), the USFS CALVEG dataset (U.S. Forest Service, 2018), and the 2016 National Land Cover Database (NLCD) (Dewitz and U.S. Geological Survey, 2021). Aquatic areas were also clipped from the study area using the NLCD dataset. Both sets of imagery were subsequently visually inspected and remaining developed areas were removed manually. This resulted in a final study area comprising approximately 52,500 ha for our analysis (Fig. 1). All processing of spatial datasets and imagery for this step was performed in ArcGIS Pro.

2.2. Image acquisition and photo processing

All images for this study were acquired from the USGS Earth Explorer Portal (https://earthexplorer.usgs.gov/) between September 7th and 9th, 2021. A series of historical aerial photos from 1948 were processed to assess historical vegetation type distribution across the study area. A 1-m resolution mosaic of National Agriculture Imagery Program (NAIP)

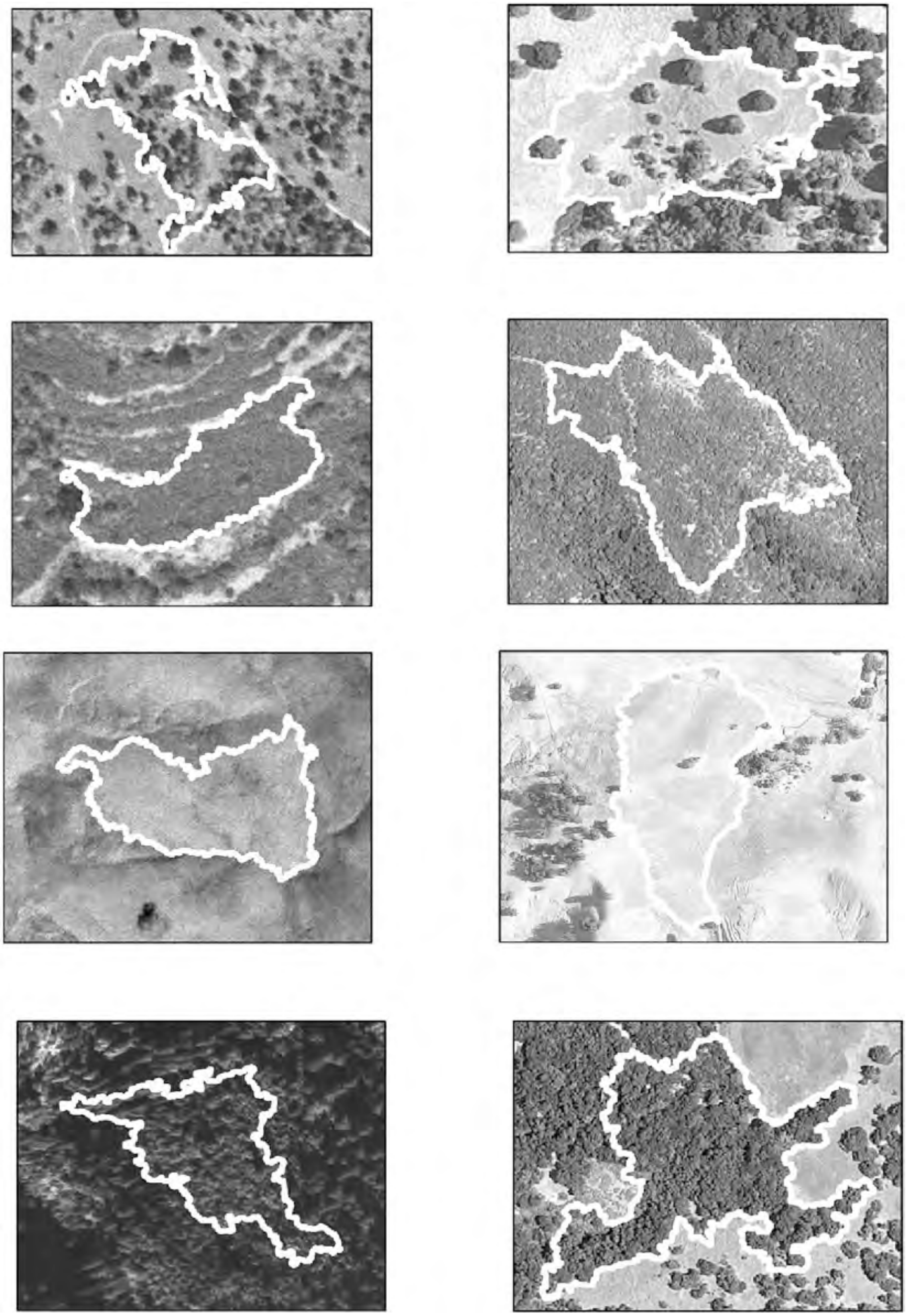

Fig. 2. Example training polygons of different vegetation types for 1948 imagery (Left) and 2014 Imagery (Right). Vegetation types from top to bottom are: woodland, shrub, herbaceous, and forest.

imagery taken over the study area in 2014, which was already georectified, was used to assess contemporary vegetation conditions and landscape level vegetation changes.

Historical aerial photos in black and white were taken of the study area in March and April of 1948. Flights were conducted during the middle of the day to minimize shadowing in the photos. These images were digitized by the USGS at a resolution of 1000 DPI. We used Catalyst Professional Toolbar's Historical Airphoto processing and Orthoengine software to georeference, orthorectify, and mosaic the historical images (Catalyst, 2021). We used the image file metadata, including coordinates for the corner of the photograph, to generate a rough mosaic of all images across the study area. We used the 2014 NAIP imagery and a 1/3 arcsecond DEM as a reference for our alignment. Using Orthoengine software, we ran 9 coarse alignments and 3 fine alignments with reference imagery to generate and collect ground control and tie points (GCPs and TPs, respectively). The results of each alignment were inspected and high RMS error points were deleted. To ensure that each image had at least 3 ground control points, some points were manually added or adjusted to improve accuracy. Our final model had an average X and Y RMS error of <4 m for ground control points, and <1 m for tie points. Orthorectified images were then mosaicked in Catalyst's Mosaic toolset (Catalyst, 2021). Cutlines between individual input images were autogenerated and adaptive normalization was applied to the mosaic to normalize brightness across the entire study area. The mosaic was then visually inspected and some cutlines were manually adjusted. A high resolution orthomosaic TIFF file with 0.5 m pixel size was generated using the Python scripts provided by the Mosaic software. The generated photomosaic was subsequently clipped to the identified study area for our vegetation classification analysis.

2.3. Segmentation and classification

2.3.1. Segmentation

In order to identify continuous vegetation patches in our imagery to subsequently classify as one of the broad vegetation categories, we ran a multiresolution segmentation algorithm on both our clipped historical and contemporary photomosaics in eCognition Developer 10.2 (Trimble, 2022). Multiresolution segmentation is a method of partitioning individual pixels that make up digital images into "objects" through an algorithm that pairs similar adjacent pixels into segments of varying sizes (Baatz and Schäpe, 2000; Rahman and Saha, 2008). Users of eCognition can manually adjust values for a set of three parameters that control size and shape of resulting segments that include scale (influencing the average object size), shape (the relative influence of object shape vs. color), and compactness (influencing the smoothness/roughness of the object's perimeter) (Gupta and Bhadauria, 2014; Trimble, 2021).

We ran segmentation using several different parameter options, visually inspecting the resulting shapefile to determine homogeneity of vegetation within identified polygons. For the 1948 photomosaic, we used a scale setting of 225, a shape setting of 0.2, and a compactness setting of 0.5, resulting in a layer containing 114,917 polygons, or "objects" identified within the study area.

Following Lydersen and Collins (2018), we converted the 2014 NAIP imagery to black and white to ensure a comparable analysis to the historical imagery and ran a multiresolution segmentation algorithm in eCognition. Preliminary segmentation at the same scale as used in the historical imagery produced fewer and overly simplistic objects, likely due to the relatively larger pixel size of the contemporary imagery (1 m vs. 0.5 m). The scale parameter for multiresolution segmentation was adjusted and segmentation was run at several intervals to have roughly equivalent number of patches identified and then visually inspected for homogeneous vegetation patches. Our final segmentation parameters for the contemporary imagery were a scale value of 100, a shape value of 0.2, and compactness of 0.5, resulting in a layer containing 114,707 identified polygons, comparable to the number of polygons for our 1948 segmentation.

2.3.2. Classification of historical and contemporary segments

We classified our segments by broad vegetation type using random forest analysis, which has frequently been employed in land-cover mapping analyses (Mishra and Crews, 2014; Pal, 2005; Lydersen and Collins, 2018). Historical aerial imagery, and specifically black and white imagery, poses significant challenges and limitations when it comes to large-scale automated identification, as the traditional tools for contemporary imagery which often use multiple color bands are not available. Image attributes for black and white images are limited to texture (i.e. relative heterogeneity and spatial distribution of intensities) and brightness (i.e. how light or dark a pixel is) variables, which may diminish the ability of identification tools to classify vegetation type beyond broad categories such as herbaceous vs. woody vegetation (Eitzel et al., 2015). In addition, more detailed discrimination of vegetation types from historical aerial photographs may be compromised by issues such as increasing distortion at photo edges (Fensham and Fairfax, 2007) and an inability to differentiate tree crowns from shadows (Platt and Schoennagel, 2009).

As we were limited in specificity of identification classes, we opted to identify polygons for both sets of imagery to one of four broad vegetation classifications based on the dominant vegetation type for both sets of imagery. Our broad vegetation type classes, designed to be identifiable by relative shade and texture, were "Herbaceous" (none to extremely sparse woody vegetative cover), "Shrub" (dominated by shrubs), "Woodland" (low to moderate tree cover throughout the polygon), and "Forest" (dense, continuous tree cover within the polygon) (Fig. 2).

Following the segmentation of our imagery sets into polygon layers, we calculated a suite of texture and brightness variable attributes for each polygon in eCognition to be used for our random forest classification. These attributes are generated from member pixels for each polygon from the source imagery. The variables we extracted for each polygon included: brightness variables (mean brightness, standard deviation, median, 25th, 50th, and 75th percentiles, minimum, maximum and skewness of the segment pixels) and texture variables (homogeneity, contrast, dissimilarity, entropy, angular second moment, mean, and standard deviation).

We used a random point generator in ArcGIS Pro (ESRI, 2022) to select 300 polygons across the entire study area for both the contemporary and historical segmented datasets to be used as a training sample for our classification algorithm. Training polygons for both imagery sets were manually classified by a single person in a single sitting to limit observer bias. In general, polygons were homogeneous in terms of cover type, but in the case where polygons contained more than one vegetation class, the majority coverage type was assigned.

For each time period, we applied the "random forest" function in the randomforest R package (Liaw and Wiener, 2002) to a dataset containing the assigned vegetation class of the manually classified polygons, as well as the full suite of seven texture and nine brightness attributes. We subsequently ran the "tune RF" function to determine the optimal number of variables for each dataset, and adjusted our algorithm to minimize out of bag error for our samples. This resulted in separately optimized classification models for both contemporary and historical polygons.

We then applied our optimized random forest models to all generated polygons (separately for each time period), using their associated texture and brightness attributes as inputs with the "predict" function. This resulted in a dataset containing a predicted vegetation class for every polygon in both time periods. Classified polygon layers were also subsequently used to generate a raster of vegetation types at 1 m resolution across the study area for both time periods using the "Polygon to Raster" tool in ArcGIS Pro.

2.3.3. Accuracy assessment

In order to conduct a post-classification accuracy assessment for both time periods, we generated a sample of 100 random points per predicted class across the study area ($n = 4$) for each time period ($n = 2$; 800 total), which were manually identified using each time period's aerial photomosaic. We compared manually assigned class to predicted class at each accuracy assessment point and used the resulting error rates to calculate overall, user's, and producer's accuracy estimates for each class.

2.4. Analysis of vegetation change patterns

Following Lydersen and Collins (2018), and using the equations described in Olofsson et al. (2014), we used the error rates obtained from our accuracy assessment to generate 95% confidence intervals on the predicted landscape proportions of each vegetation type for both

Table 1
Area-Weighted mean patch size for both time periods in hectares. Average forest patch sizes increased dramatically, while woodland and shrub patches were observed to shrink between the two time periods.

	Area-Weighted Mean Patch Size (ha)			
Year	Forest	Herbaceous	Shrub	Woodland
1948	58.7	252.4	618.1	181.5
2014	871.1	283.2	448.4	55.7

time periods to see if significant differences could be detected in predicted cover proportions between the two photomosiacs. We used our 1 m vegetation class raster datasets and the "Compute Change Raster" tool in ArcGIS Pro to calculate the categorical differences between the two time periods on a pixel by pixel basis. We then used the changed areas identified by this tool to look at total changed area, and common pathways of change in the landscape. To assess how vegetation type continuity may have changed across the landscape during the study period, we calculated the average patch sizes of different vegetation types for each time period. To generate continuous vegetation patches, we dissolved polygons of the same predicted vegetation type into multipart features and exploded into singlepart polygons of one continuous vegetation type, and calculated the area of each dissolved polygon. We then calculated the area-weighted mean for each vegetation type for both sets of imagery.

To further investigate possible drivers of landscape change, and determine relative importance of topographic, climatic, and disturbance history on vegetation type change, we conducted a conditional inference tree analysis on sampled points throughout the study area. We generated a set of 6500 random points in ArcGIS Pro across the study area with a minimum distance of 250 m in between points to reduce spatial autocorrelation. For each random point we then calculated the following variables: slope, aspect category, elevation, mean climatic water deficit (CWD), mean actual evapotranspiration (AET), vegetation class for each of the two time points, and a binary variable for if the sample point experienced fire during the study period (1948–2014). Elevation, aspect, and slope were extracted to sample points from a National Elevation Dataset digital elevation model (DEM) raster layer (USGS, 2022). AET and CWD were obtained from the Basin Characterization Model dataset of historical monthly water balance (Flint et al., 2013). Fire history for each point was obtained using CAL FIRE Fire and Resource Assessment Program's (FRAP) Fire Perimeter dataset (FRAP, 2021). Aspect was converted into a categorical variable with four categories: northeast-facing (0–90°), southeast-facing (91–180°), southwest-facing (181–270°), and northwest-facing (271–360°) slopes.

Understanding drivers of vegetation type change to and from our forest class was of particular interest for this study given their potential connection to the removal of fire from these landscapes (Stephens et al., 2007, Stephens et al., 2018). As such, we split our dataset of randomly generated points into two subsets for analysis: 1) points identified as forest in 1948 and 2) points identified as all other vegetation types in 1948. For points originally identified as forest, we generated a binary outcome variable for if they experienced forest "loss", i.e. were classified as a non-forest vegetation type in 2014. For points identified as non-forest vegetation types in 1948 we generated a binary outcome variable for if they experienced forest "encroachment", i.e. were subsequently classified as forest in 2014. We assessed covariance between all variables using Pearson's correlation coefficient and removed CWD given its high correlation with AET ($r = -0.87$). To generate our conditional inference trees for sample points, we used the R package "Party" (Hothorn et al., 2006) and applied the "ctree" function which employs an unbiased recursive partitioning algorithm, using significance tests to select and optimize partitioning of the data. For points identified as forest in 1948, topographic variables, AET, and if the site experienced fire were included as predictors. For points identified as non-forest classes in 1948, in addition to the above variables we included 1948 vegetation type to assess which non-forest classes were most susceptible to conversion.

3. Results

Overall out-of-bag (OOB) error rates for our selected random forest classification algorithm for 1948 segments and 2014 segments were 26.3% and 22.6%, respectively (Table A1). The shrub class had the

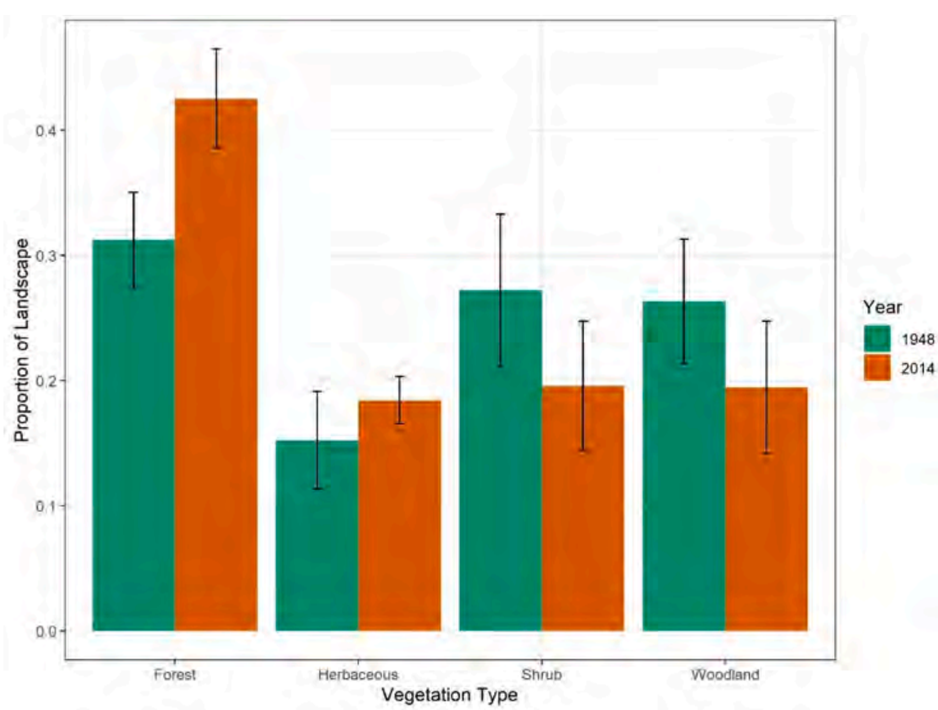

Fig. 3. Bar graph comparing predictions for the proportion of the landscape of each vegetation type for 1948 and 2014 imagery, including 95% confidence intervals derived from post-classification accuracy rates. Our forest class was the only class that exhibited significant change in relative landscape proportions.

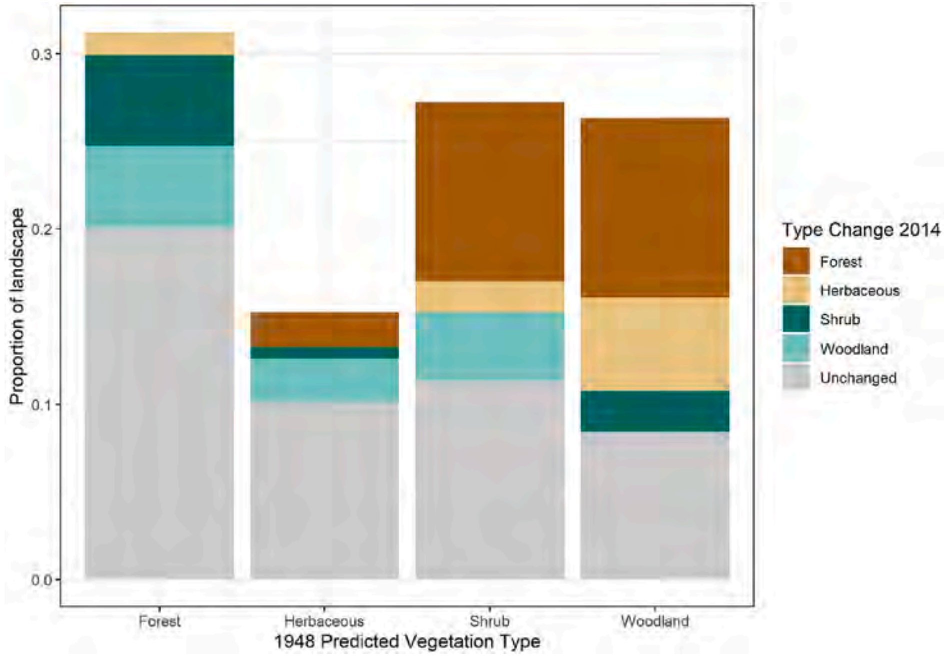

Fig. 4. Proportions of landscape of different vegetation classes in 1948 and 2014 (including areas that were unchanged in contemporary imagery from each class) as proportion of the overall sampled landscape.

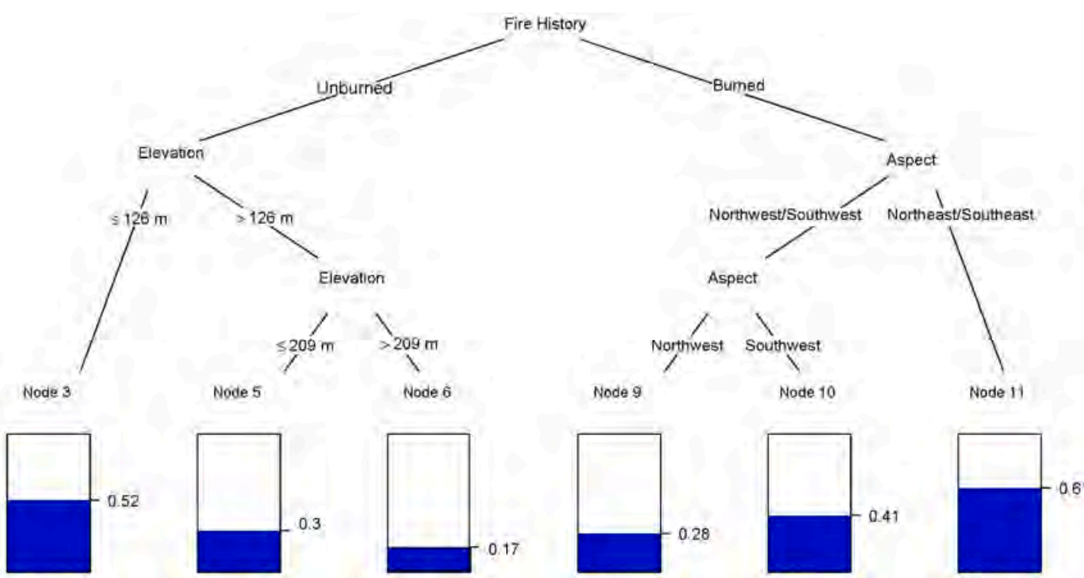

Fig. 5. Conditional Inference Tree results for points identified as forest in historical imagery. The proportions at the bottom represent the likelihood of conversion to a non-forest vegetation class, or forest loss over the study period. Our results showed that fire history held the most influence over type conversion for forested sites, followed by topographic variables such as aspect and elevation.

highest error, which was comparable for both time periods (33.3% for 1948 and 32.9% for 2014). Our forest class had the lowest OOB error rate for 1948, while herbaceous cover had the lowest OOB error rate for 2014 imagery. Overall accuracy rates for our post-classification assessment of predicted vegetation classes for both time periods were comparable at 86% and 87% for 1948 and 2014, respectively (Table A2).

3.1. Vegetation change analysis

Our change detection raster analysis showed that 50.1% of the land area remained unchanged, and 49.9% of the area was identified as having a classification change. In terms of relative proportions of vegetation cover across the landscape, we detected increases in forest and herbaceous cover, and decreases in shrub and woodland cover between the two time periods (Fig. 3).

Among pixels identified as having a vegetation class change between the two images, the most common transition (10.3% of the landscape) was in areas that were identified as woodlands in the historical imagery and subsequently identified as forest in the contemporary imagery. The next most common transition (10.2% of the landscape) was in areas identified as shrublands in the 1948 imagery and then identified as forest in the 2014 imagery (Table A3). In general, shrub and woodland were more likely to transition to another vegetation class, with only 42% and 32% remaining in the same class, respectively. In contrast, the majority of area originally identified as forest and herbaceous in the 1948 imagery remained in the same predicted class in 2014 (64% and 66% of the area in that class, respectively) (Fig. 4).

We found that average patch size of our forest cover type increased over tenfold during the study period. Herbaceous cover patch size was also found to have increased, while shrub and woodland patch sizes decreased (Table 1).

3.2. Conditional inference tree analysis

Our first conditional inference tree analysis in areas identified as forest in the 1948 imagery indicated that if the sample point had burned or not was the most important variable in determining if forest vegetation persisted in the 2014 imagery, with areas that had experienced fire more likely to convert from forest to another vegetation. Elevation and aspect exhibited significant, but secondary influence on persistence of forest vegetation type, with higher elevation sites and northwest-facing slopes less likely to convert from forest to another vegetation class (Fig. 5).

Our second conditional inference tree analysis investigating change among non-forest vegetation types found that 1948 vegetation class was the strongest predictor of vegetation class conversion to forest, with herbaceous cover the least likely to experience conversion. Aspect, elevation, and fire history were also found to exhibit significant influence on the likelihood of type conversion to forest cover (Fig. A1). The sites that were least likely (≤25% probability) to convert to forest included herbaceous areas, shrubland and woodland on SE facing aspects, and woodlands < 127 m elevation. The sites most likely (≥59% probability) to convert to forest occurred over 195 m elevation and included shrub and woodlands on NW facing aspects, unburned woodland on NE and SW facing slopes, and burned shrub or woodland on SW facing aspects > 587 m in elevation.

4. Discussion

Our analyses of mid-20th century and contemporary landscape-level vegetation patterns in the Northern Bay Area region of California demonstrated changes in the relative abundance and patch characteristics of four broad vegetation classes. Most notably, both forest cover proportion and patch sizes increased, indicating a shift towards larger and more continuous stands of dense tree canopy throughout the region. We found that woodlands and shrublands were most susceptible to conversion among the vegetation classes we mapped, with the majority of converted areas of these vegetation classes becoming forest. This trend towards an increased landscape-level proportion and increased continuity of forest cover is consistent with other studies investigating landscape-scale vegetation change in historically fire-prone forests following many decades of fire suppression and exclusion (Miller, 1999; Hessburg et al., 2005; Grossmann and Mladenoff, 2007; Lydersen and Collins, 2018). While much less is known about the historical vegetation patterns in these ecosystems, relative to conifer-dominated ecosystems, this work provides robust evidence of change at least over the last 65 years.

Among our assigned vegetation classes, woodlands, characterized by sparse tree canopy cover, changed most readily to another vegetation type. Approximately 30% of the area identified as woodland in the historical imagery persisted as woodlands in the 2014 imagery. Of converted woodlands, the greatest proportion by far was subsequently identified as forest in the contemporary imagery, suggesting densification of tree canopy within woodland stands. One possible driver of this pattern is the continued infilling associated with the removal of frequent fires from this landscape, which began well before the early (1948) imagery. In a nearby area (<20 km away) dominated by *Sequoia sempervirens,* Finney and Martin (1992) reported historical mean fire intervals between 6 and 23 years. Based on these reconstructed fire frequencies and the overall lack of lightning during the dry season in the area, Finney and Martin concluded that Indigenous fire use must have augmented, if not dominated, this landscape. It is likely that similar Indigenous fire practices influenced historical vegetation density and composition in our study area as well. Woodland areas that were least likely to experience conversion to forest were on southeast-facing slopes and areas < 127 m in elevation. These areas may be more limited by edaphic conditions, i.e., less productive, and therefore, less likely to experience significant infilling in the absence of recurring fires.

Fire is known to be a key ecological process in the maintenance of more open woodland and savanna ecosystems both worldwide and regionally (Grossmann and Mladenoff, 2007; Staver et al., 2011; Scholtz et al., 2018), and the prolonged absence of fire is known to cause shifts in vegetation towards denser and more continuous forested stands, often through the encroachment of conifers (Russell and McBride, 2003; Gedalof et al., 2006; Engber et al., 2011; Lake et al., 2017, Schriver et al., 2018; Sartin, 2022). Our results were consistent with several studies documenting the encroachment of Douglas-fir (*Pseudotsuga. menzesii*) into open oak (*Quercus sp.*) stands over a wide swath of Northern California's woodlands throughout the past century (Barnhart et al., 1996; Cocking et al., 2012; Cocking et al., 2015. Barnhart et al. (1996) recorded a similar pattern of encroachment and loss of open oak woodlands in Annadel State Park, just outside of our study area. In another nearby site (Pepperwood Preserve), Evett et al. (2013) similarly noted increased tree density and a decrease in the median size of open areas by 35% in side-by-side photo comparisons of 1942 and 2000 aerial imagery, as well as an increasing occurrence of Douglas-fir across the site in contemporary field surveys when compared with historical surveys. Another study examining stand structure, regeneration, and age dynamics in oak stands on California's North Coast found that while the majority of oaks established sometime during the 19th century, the majority of Douglas-fir trees established after 1950 (Schriver et al., 2018) aligning with the time frame of this study. The fact that much of this Douglas-fir establishment occurred well after the cessation of frequent fires in this area (ca. late 1800 s) suggests that removal of frequent fire may not be the only process influencing infilling of the areas. Changing livestock grazing patterns could be another factor; however, this is only speculative as we could not find reliable records indicating major changes in grazing patterns over the study period. Transition of shrubland to forest was also common at our study site, and may similarly be attributed to reduced frequency of fire between our two time points. Reduction in montane chaparral has been observed in mixed conifer landscapes in northern California due to fire exclusion (Nagel and Taylor, 2005; Lauvaux et al., 2016), and the encroachment of conifers into shrub-dominated areas has been documented in nearby coastal California ecosystems (McBride, 1974; Evett et al., 2013). This was evident in a study of coastal vegetation change in California between 1985 and 2010 using remotely-sensed data, which found that the greatest shifts in vegetation type in Northern California were from shrub to forest cover, likely due to fire suppression (Hsu et al., 2012). However, it is worth noting that these documented shifts are in contrast to vegetation change patterns in southern California, where conversion of chaparral to annual grassland due to drought and increased frequency of fire is a major concern (Syphard et al., 2019a; Jacobsen and Pratt, 2018; Park and Jenerette, 2019). Impacts of increasing fire frequency on vegetation persistence has been studied in conifer-dominated landscapes in northern California (e.g., Steel et al., 2021), but future work could focus on the impacts of increased fire frequency, as occurred at our study site after the 2014 imagery analyzed here, in more coastal northern California landscapes.

In addition to a reduction in overall cover, we found that the woodland class became more fragmented over time, with area-weighted patch size around three times smaller in 2014 versus 1948. The changes experienced by woodlands occurred both through densification (i.e. conversion to forest) and loss of tree canopy cover (i.e. conversion to herbaceous). While tree densification accounted for the majority of this change in woodlands, which could lead to increased risk of high severity fire, conversion of woodland to herbaceous could negatively impact wildlife habitat (Garrison and Standiford, 1997). For example, some fragmentation of woodland habitat towards open pasture can negatively impact species that rely on large tracts of woodland, specifically raptors and large mammals (Merenlender and Crawford, 1998; Heaton and Merenlender, 2000).

In contrast to woodland and shrub vegetation types, herbaceous vegetation was the most stable between the two time periods, with nearly 70% of herbaceous areas in the historical imagery remaining as herbaceous in the contemporary imagery. Woody encroachment of grasslands, prairies and savannah has been of ecological concern and interest (Archer et al., 2017; Staver et al., 2011;Cuthrell, 2013), and we expected to see a similar shift in this study. Loss of prairie and grassland areas from the absence of widespread, frequent fires has been documented in northern coastal California. In a notable example, it has been estimated that fire exclusion may have resulted in the loss of up to 44% of the woodland and prairie lands in the Bald Hills of Redwood National Park (Fritschle, 2008). Evett et al. (2013) additionally documented a decrease in grassland area at nearby Pepperwood Preserve by 10% since 1942. However, as our study area is positioned within a relatively populous, majority privately owned and agricultural region, both the persistence of herbaceous cover and its increases in proportion across the landscape are possibly due to land use priorities in the area. The maintenance of herbaceous and open areas for livestock grazing and other agricultural uses through shrub and tree removal (Bolsinger, 1988; Mensing, 2006) is a possible explanation. Most of the area that converted to grassland were classified as woodland in 1948 and may reflect areas where oaks were removed in order to increase range productivity (Bolsinger, 1988; Merenlender and Crawford, 1998).

Site conditions were among the most important variables explaining change in cover in both of our conditional inference analyses. Somewhat predictably given the landscape proportion changes we observed in our results, we found that historical vegetation class was the most influential predictor of conversion to forest, with woodland and shrub vegetation classes more likely to convert. In general, areas more likely to convert to forest occurred at greater elevation and on more northwesterly aspects. These more productive sites may be more reliant on fire to maintain a more open vegetation type than lower elevation, drier, southeasterly sites (Bernal et al., 2022).

Disturbance history, specifically whether the sample point experienced a fire during the study period, was the most important variable in determining the likelihood of loss of forest vegetation between the two time points. Nemens et al. (2018) demonstrated that, wildfire's return to a long fire-excluded landscape may promote oak woodland reestablishment in encroached stands as oaks vigorously regenerate following crown-kill by wildfire. This process is a possible driver of the conversion of forested areas to woodlands we observed in approximately 14% of forested areas identified in the historical imagery. Moreover, our results suggest that the exclusion of fire likely contributed to the expansion or persistence of dense forest stands in this area, as discussed previously. By the time of the historical imagery, the landscape had already experienced many decades of enforced fire suppression and exclusion, so it's likely that continued fire removal in the area may have increased dense tree cover in the unburned portions of the study area (Lightfoot et al., 2013), while the few large fires experienced during our study period may reestablish a more open stand structure that was more widespread across the landscape prior to the 20th century.

The greater than tenfold growth in area-weighted mean patch size of the forest type indicates a marked increase in continuity of vegetation patches with dense tree cover in our study area. Our observed increase in patch size of dense forest stands is consistent with several other studies comparing historical and contemporary conditions in fire-adapted western US forests that found higher tree densities, increased patch size of continuous forest cover, and simplified heterogeneity (Hessburg and Agee, 2003; Hessburg et al., 2005; Lydersen and Collins, 2018; Safford and Stevens, 2017). Comparisons of aerial photographs between 1932 and 1999 in a 52,000 ha watershed in the Gila National Forest in New Mexico similarly showed that vegetation dynamics shifted under a period of reduced fire frequency from open-structured vegetation to denser-canopy forests and woodlands, with the total proportion of the landscape covered by dense overstory canopy increasing over 30% during the study period (Miller, 1999). In conifer-dominated forest types, increased patch size of dense continuous forest cover has generally been associated with greater vulnerability to high-severity fire (Hessburg et al., 2005; Koontz et al., 2020).

A small number of previous studies have sought to understand how densification and conifer encroachment in oak woodland stands may have influenced fire behavior, and overall stand resilience to fire. In oak woodland stands, densification may lead to an increase in ladder fuels, increasing the chance of crown fire and fire-induced mortality when wildfire moves through the stand (Cocking et al., 2012; O'Gorman et al., 2022). Additionally, woody fuel deposition and accumulation rates tend to be higher in more densely forested stands (van Wagtendonk and Moore, 2010; Engber et al., 2011); thus, the significant overstory changes we observed through the conversion of non-forest vegetation to dense and more continuous forest patches may also correlate to elevated ground or surface fuel loads and fuel continuity conditions in our study area.

Surface and ground fuel load changes are known to alter fire behavior (Scott and Reinhardt, 2001, Thaxton and Platt, 2006). It is possible that the increased levels and greater continuity in ground, surface, and ladder fuels our results suggest impacted fire behavior in the catastrophic wildfires that occurred shortly after our contemporary imagery was captured. It has alternatively been suggested that conifer encroachment into oak woodlands may actually dampen fire effects (i.e. intensity and temperature) and disrupt the main mechanism in maintaining a more open stand structure in woodland/grassland ecosystems (Engber et al., 2011). However, as those results are mainly hypothesized to be a result of the higher fuel moisture of woody fuels during wetter conditions (i.e. prescribed burning windows), how this could impact wildfire in severe burning conditions or under climate change, is uncertain. More research is needed in mixed hardwood and oak-dominated stands to fully understand how changes in overstory conditions may affect ground and surface fuels, fire behavior patterns, and wildfire outcomes.

Another interesting component to our study area that merits further investigation is how ownership within the study area might have influenced management practices, and, in turn, vegetation changes across the landscape. Only 16% of our study area is publicly owned, and the vast majority of the land within the three counties that our study area intersects-Napa, Sonoma, and Solano- is privately-owned (with 26, 13, and 12 % of the land base publicly owned, ranking 38th, 48th, and 50th out of California's 58 counties, respectively, in terms of proportion of public lands). These ownership patterns result in greater proportions of WUI relative to other areas in the state (Syphard et al., 2019b), and with that greater likelihood of structure loss from wildfire (Kramer et al., 2019). Furthermore, climate and land use projections for this area demonstrate greater likelihood of structure loss from wildfire (Syphard et al., 2019b).

There are a number of limitations in our study that may have influenced our results. Most significantly, our use of historical aerial imagery as our singular source of data for historical vegetation type did not allow us to validate our classification and training dataset using field data as could have occurred if using contemporary imagery (Bradter et al., 2011; Mishra and Crews, 2014). Though we explored the use of Weislander Plot Data to assist in validation, the lack of exact location data for these plots prevented us from using this data source. Misclassification is inherent to some extent in remote sensing, and there is a chance that polygons were misclassified by our random forest algorithm in either time period, leading to potential inaccuracies in estimation proportions and types of change between the two photos. Additionally, it is also possible that the manual classification of our training dataset contained some classification errors, which are not captured or quantified in our accuracy assessment or confusion matrix. The fact that our historical imagery was black and white and of varying quality across frames also provided additional challenges in our analysis, leading to our use of broader vegetation and life form categories rather than identifying to species or taxa.

5. Conclusion

Non-conifer and coastal range ecosystems in California are understudied, especially from a fire ecology perspective. Though urbanization, development, and expansion of the WUI are certainly among the primary drivers of vegetation change in our study area, our results indicate that large areas of wildlands throughout the greater Bay Area and Northern California have experienced shifts in landcover and vegetation type over the past 70 years, specifically through the densification and expansion of forested areas and conversion of woodland and shrubland areas across the landscape. We found unburned, higher elevation, and Northwest-facing areas were more likely to persist as forest vegetation, while higher elevation or Northwest-facing shrub and woodland sites were more likely to convert to forest.

Deepening our understanding of past conditions as well as the drivers and patterns of change is a crucial component of building resilience, especially across a landscape so shaped by disturbance. Our study emphasizes that the use of widely available historical aerial imagery is an increasingly valuable tool in the evaluation of landscape-level vegetation changes from historical conditions, especially as the processing and analysis tools for this method continue to improve. Additionally, the assessment of landscape-scale vegetation changes over time may contribute to helping inform management priority areas and activities. For example, areas identified as having converted to forest (mainly from shrub and woodland types), as well as large patches of continuous forest cover may be ideal targets for restoration treatments.

Funding

This work was accomplished with funding the California Department of Forestry and Fire Protection under the California Initiative for Research on Fire and Forests partnership (agreement number 8CA05327).

CRediT authorship contribution statement

Hannah M. Fertel: Methodology, Investigation, Formal analysis, Software, Resources, Data curation, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Brandon M. Collins:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition. **Jamie M. Lydersen:** Conceptualization, Resources, Writing – review & editing. **Scott L. Stephens:** Conceptualization, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

Many thanks to Dr. Zack Steel, Ashley Grupenhoff, and Dr. Daniel Foster for general analysis advice and guidance. We are also grateful to Dr. Maggi Kelly for sharing subject matter expertise on potential methodology and analysis approaches. This research benefited from the support and services of UC Berkeley's Geospatial Innovation Facility (GIF), gif.berkeley.edu.

Appendix A

Figs. A2 and A3

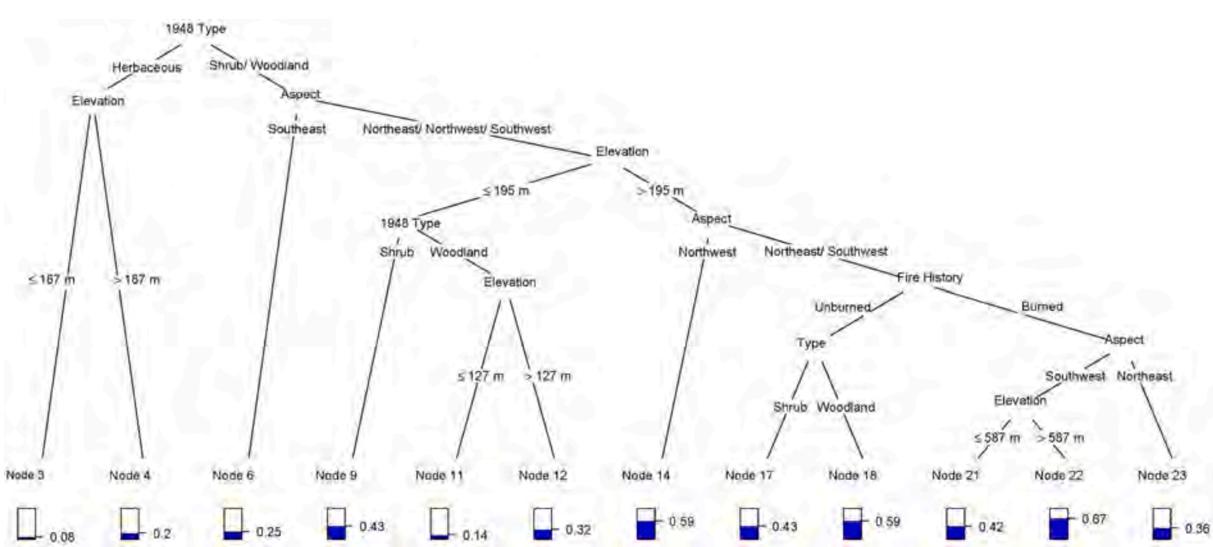

Fig. A1. Conditional Inference Tree results for points identified as non-forest in historical imagery. The proportions at the bottom represent the likelihood of conversion to forest class, or forest gain over the study period.

Table A1
Confusion matrix from Random Forest Classification Algorithm for both imagery time periods.

		Forest	Herbaceous	Shrub	Woodland	Total	Omission Error
1948	Forest	72	0	14	7	93	22.58%
	Herbaceous	0	32	4	8	44	27.27%
	Shrub	14	3	52	9	78	33.33%
	Woodland	11	5	4	65	85	23.53%
	Overall 1948 OOB Error: 26.3%						
2014	Forest	99	0	14	7	120	17.50%
	Herbaceous	0	49	1	5	55	10.91%
	Shrub	18	1	47	4	70	32.86%
	Woodland	11	6	1	37	55	32.73%
	Overall 2014 OOB Error: 22.6%						

Table A2
Error rates from post-classification accuracy assessment of predicted vegetation classes. We calculated Producer's Accuracy (complement of the Omission Error), User's Accuracy (complement of Commission Error) and Overall Accuracy using randomly generated points that were subsequently manually identified across the classified landscape layer. Herbaceous cover had the highest producer's accuracy for both time periods, meaning herbaceous was the least likely vegetation class to be misclassified. Woodland had the lowest producer's accuracy for 1948 (83%) and Forest the lowest for 2014 (82%). User's accuracy was highest for the Forest class and lowest for the Shrub class in both time periods, meaning misclassified polygons were least likely to be interpreted as Forest and most likely to be interpreted as Shrub.

	1948		2014	
	Producer's Accuracy	**User's Accuracy**	**Producer's Accuracy**	**User's Accuracy**
Forest	0.85	0.95	0.82	0.97
Herbaceous	0.90	0.90	0.94	0.93
Shrub	0.86	0.72	0.90	0.78
Woodland	0.83	0.86	0.83	0.8
	Overall Accuracy		**Overall Accuracy**	
	0.86		0.87	

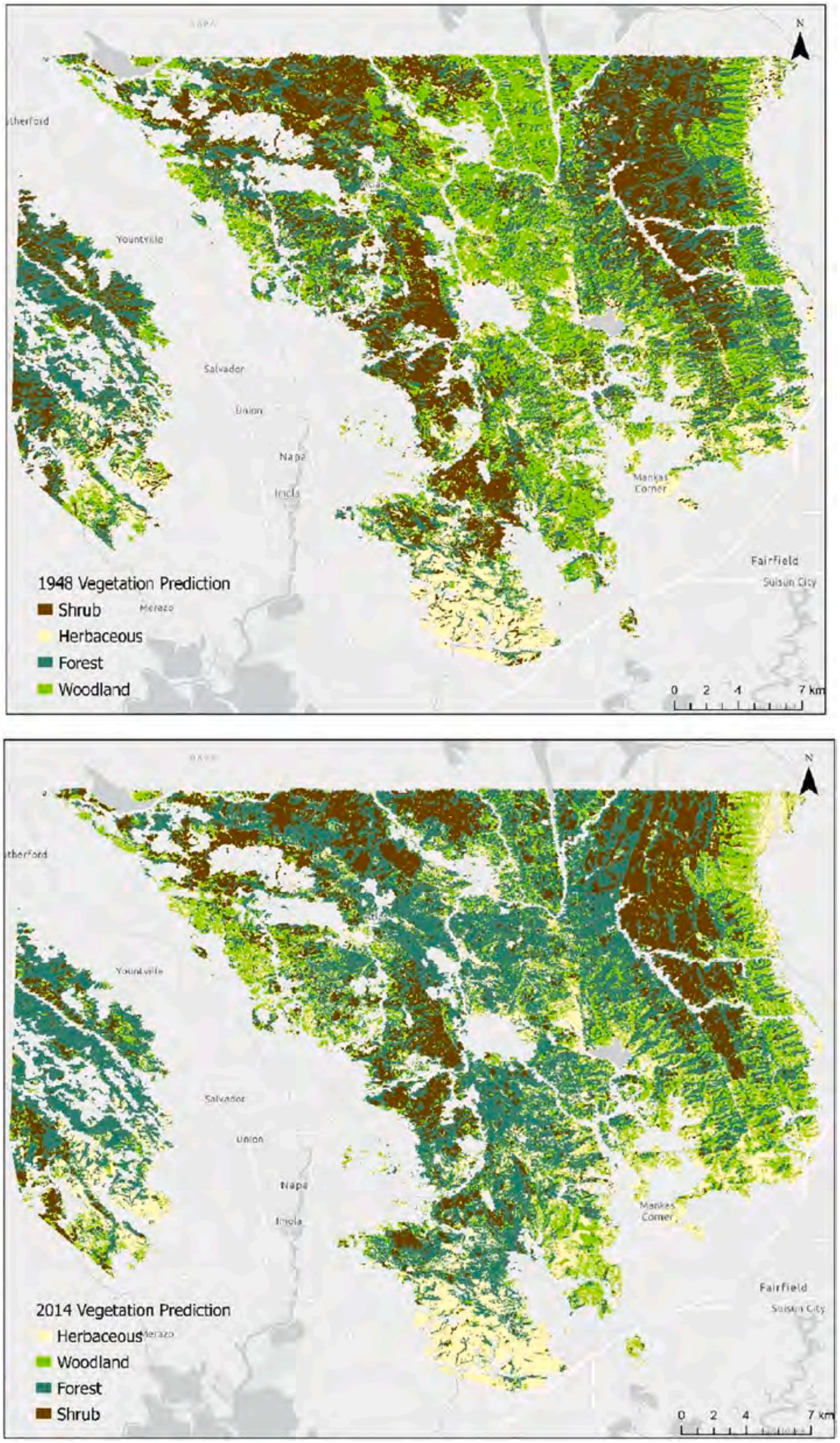

Fig. A2. Maps showing vegetation type classification generated from our random forest models for 1948 (top) and 2014(bottom). The increased forested area and continuity of forest vegetation type can be observed in the bottom map.

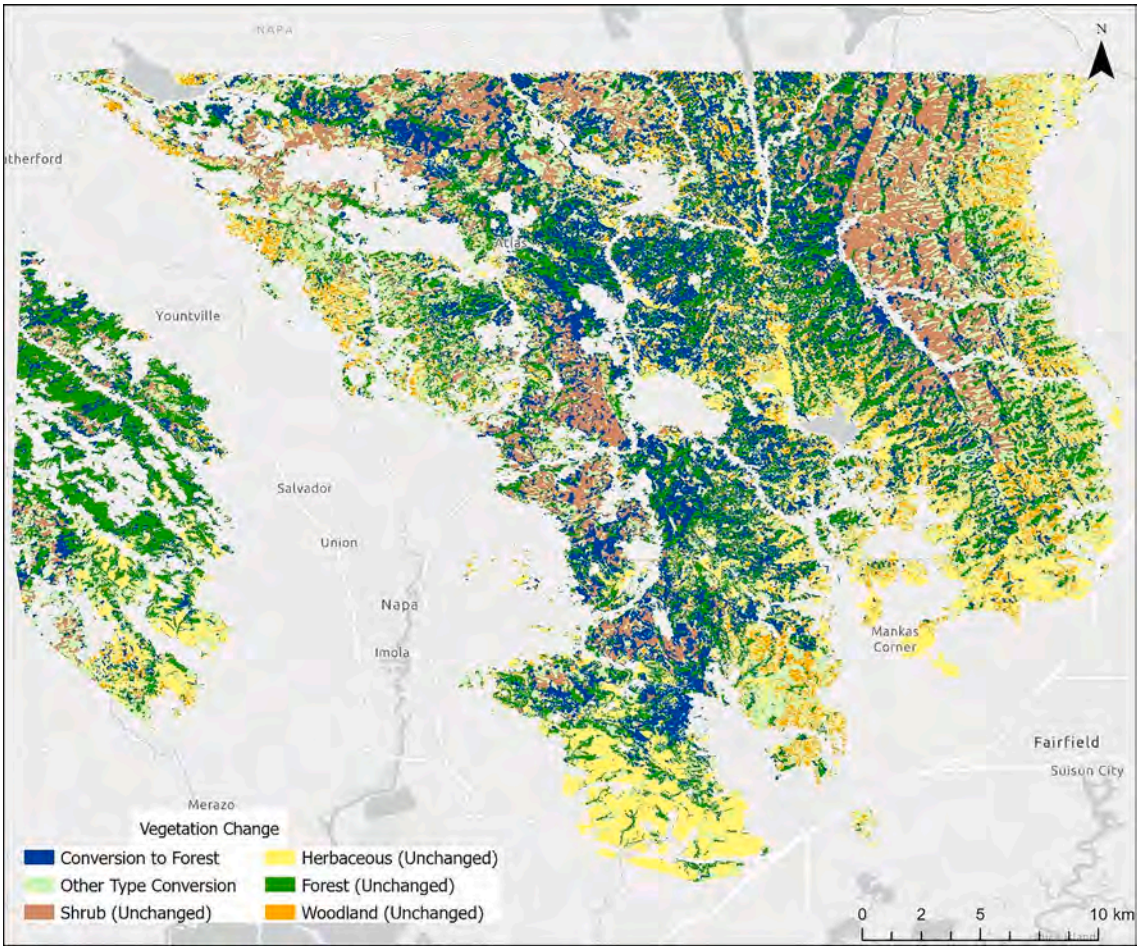

Fig. A3. Map showing areas that remained in the same vegetation class between 1948 and 2014, as well as areas that converted to forest or other vegetation classes.

Table A3
Table showing the results of our change analysis with each vegetation class combination between the two sets of imagery as a percentage of the entire study area and as a percentage of the 1948 class.

1948 Class	2014 Class	Percentage - Total Study Area	Percentage - Total 1948 Class Area
Forest	Forest	20.1%	64.3%
Forest	Herbaceous	1.3%	4.1%
Forest	Shrub	5.2%	16.7%
Forest	Woodland	4.7%	15.0%
Herbaceous	Herbaceous	10.1%	66.5%
Herbaceous	Forest	1.9%	12.8%
Herbaceous	Shrub	0.7%	4.4%
Herbaceous	Woodland	2.5%	16.3%
Shrub	Shrub	11.4%	41.7%
Shrub	Forest	10.2%	37.6%
Shrub	Herbaceous	1.8%	6.5%
Shrub	Woodland	3.9%	14.2%
Woodland	Woodland	8.4%	32.0%
Woodland	Forest	10.3%	39.0%
Woodland	Herbaceous	5.3%	20.0%
Woodland	Shrub	2.4%	9.0%

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