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Deforestation and reforestation in a world hotspot of fire-driven forest loss: trends in California conifer forests 1991–2023

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North America is a continental leader in fire-driven deforestation, with US western and Mediterranean-climate forests being major centers of forest loss. 25% of the average annual reforestation need in the western US is wholly in California, where background mortality rates are high, and recent droughts, insect outbreaks, and severe wildfires have led to increasing rates of forest loss. Our objective was to use a "ground up" approach to document fire-driven trends in California in deforestation severity and reforestation priority (treated synonymously here: DS/RP). Using field data on postfire conifer regeneration from across the State, we employed the POSCRPT (Postfire Spatial Conifer Regeneration Prediction Tool) platform to estimate postfire conifer regeneration probabilities at 900-m^2 spatial resolution from 1991 to 2023. We then overlaid our maps of natural regeneration probabilities with reforestation data from US Forest Service (USFS) records to estimate reforestation deficit. Using three definitions of DS/RP ("moderate," "high," and "acute"), we found that trajectories in all three classes were best explained by exponential growth with no significant evidence of attenuation toward saturation. By 2021–2023, fire-driven deforestation reached nearly 150,000 ha per year under our moderate DS/RP definition, and 86,000 ha under our high DS/RP definition. Mixed conifer, yellow pine, and Douglas-fir/hardwood forests experienced the most fire-driven deforestation since 1991, but acceleration in the rate of deforestation was highest in high-elevation forests. Private and USFS lands experienced the highest amounts and rates of increase in DS/RP during the study period, accounting for >93% of all reforestation need. On USFS lands, postfire reforestation efforts in California began to fall behind fire-driven reforestation needs after 2006; between 2016 and 2023 < 1.2% of deforested hectares were replanted. California is one of the world leaders in fire-driven forest loss (deforested hectares minus reforested hectares), with estimated 2001–2023 mean annual losses of 0.25 to 0.47% (high and moderate DS/RP classes, respectively) in the forest types we assessed. Successful reversal of these trends will likely require major reform to the reforestation pipeline and attenuation of long-term declines in reforestation funding, staffing, and capacity.

KEYWORDS
deforestation severity, forest loss acceleration, high-severity fire, POSCRPT, reforestation priority

Introduction

Worldwide rates of deforestation remain concerningly high, and wildfire is playing a progressively more important role in driving forest loss (Curtis et al., 2018; Tyukavina et al., 2022). North America is one of the continental leaders in fire-driven deforestation, with centers of forest loss in Canadian boreal and temperate forests, and US western and Mediterranean-climate forests (Safford and Vallejo, 2019; Coop et al., 2020; Davis et al., 2020; Guiterman, 2022). On the Canadian side of the border, federal and province investments in reforestation have increased apace (Government of Canada, 2020). However, on the US side of the border, federal budgets for public land reforestation and federal and state tree nursery capacity have both been dropping for decades (Dumroese et al., 2019), even as forest losses driven by drought, wildfire, and pest outbreaks mount (Cohen et al., 2016; Coop et al., 2020; Wang et al., 2022). As a result, current reforestation needs in the western US greatly outpace reforestation capacity, and the gap is growing (Dumroese et al., 2019; Fargione et al., 2021; Dobrowski et al., 2024). California may be the US state most acutely affected by the situation. 25% of the average annual reforestation need in the western US is located wholly in California, and although California is one of only three states with annual postfire planting capacities of ≥5,000 ha or more, this capacity is only about ¼ of the state's reforestation needs (Dobrowski et al., 2024). Approaching the problem from the "supply" side, another recent study found that California was one of three western states most likely to suffer large-scale regeneration failures in the future, taking current and projected climate and wildfire trends into account (Davis et al., 2023).

Most of California falls in the North American Mediterranean Climate Zone, where long summer droughts are typical and interannual variability in precipitation is higher than anywhere else in the US (Dettinger et al., 2011; Safford et al., 2021). This, combined with climate warming and intensifying multiannual droughts, has led to California forests experiencing the highest background (i.e., non-fire and non-epidemic-driven) rates of tree mortality in the western US (Van Mantgem et al., 2009). In recent years, huge areas of high severity fire and drought- and insect-driven mortality in conifer forests in California have further raised concerns about forest sustainability and the ability of degraded or type-converted forestlands to provide key ecosystem services. For example, Gonzalez et al. (2015) estimated that California carbon stocks had decreased by about 8% between 2001 and 2010, and Wang et al. (2022) demonstrated a 6.7% loss in forest cover in California between 1985 and 2021; both studies identified wildfire as the principal cause of the changes they measured. Future projections of forest cover and conditions in California portend an acceleration of current forest loss trends. Focused on soil drying, Goulden and Bales (2019) projected potential conifer mortality increases of 15–20% per degree C in the Sierra Nevada, and fire-focused studies project large losses in conifer cover across all ecoregions of the state if current fire severity trends continue unabated (Safford et al., 2012; Dettinger et al., 2018). Focused on carbon sequestration, Anderegg et al. (2022) projected that California will be the major US center of wildfire- and insect-driven forest mortality by the mid- and late-21st century, independent of the climate change scenario.

Forecasting future forest conditions in disturbance-prone landscapes like California is dependent on the existence of tools that can accurately project spatiotemporal patterns and trends pursuant to major forest disturbances. Although there are many widely used forest growth and yield and successional models, a major constraint with studies that use all of them is the general dearth of realistic tree regeneration data, especially for conifer-dominated forest (Carlson et al., 2012). The first 5 years after disturbance represent a window of opportunity for successful regeneration of most conifers, and this period sets the stage for either successful or failed recovery of forest cover and forest ecosystem services (Kashian et al., 2006). The importance of these early postfire years is reflected in National Forest Management Act and Forest Service regulations (e.g., Forest Service Handbook 2409), which mandate that productive forests be replanted within 5 years after a major stand-altering event. In California, 5 years also represent an important replanting threshold for managers, because strong shrub growth response after severe burning requires increasing investments in site preparation the longer the manager waits (McDonald and Fiddler, 2010; Bohlman et al., 2016).

Beginning in 2009, in collaboration with the University of California-Davis, the US Forest Service Pacific Southwest Region ("Region 5") embarked on an inventory and monitoring program of natural postfire regeneration of conifers in selected wildfires, focused on nonserotinous obligate seeding species and 5-year-old burns. Welch et al. (2016) summarized regeneration patterns across environmental and fire severity gradients and reported that postfire regeneration met Region 5 stocking standards (minimum levels of site occupancy for seedlings or saplings, assuming equidistant planting; USDA, 1989) in only 4 of 13 studied fires, and in the high fire severity class (≥75% basal area mortality of the prefire canopy) the median density of nonserotinous conifer seedlings was zero. Welch et al. also included a graphical pocket-guide that allowed foresters to assess in the field the likelihood that natural regeneration would meet Region 5 stocking standards. Shive et al. (2018) used the same dataset to build a spatially explicit model that combines spatial data on postfire basal area by species, topography, fire severity, and climate with an algorithm predicting seed dispersal. Safford et al. (2021) and Williams et al. (2021) introduced the acronym POSCRPT (Postfire Spatial Conifer Regeneration Prediction Tool) for the Shive et al. model. Stewart et al. (2021) subsequently refined POSCRPT and introduced the capacity to include postfire variability in seed arrival (i.e., low years and masting years) and precipitation in the 5-year seedling density predictions. More recently, the Region 5 database was used in Davis et al. (2023) western US metanalysis that concluded that fire severity x climate warming interactions were driving higher probabilities of postfire regeneration failures, especially in California and the Southwest.

Ensuring the persistence and sustainability of western US forests and the ecosystem services they provide over the long-term will require a multi-faceted approach, but a key first step is to determine the temporal and spatial landscape of reforestation needs. To this point, most assessments of wildfire-driven reforestation need in California and other western states have used the extent of high severity burning as the principal basis to determine reforestation needs [e.g., the USFS Region 5 deforested condition assessments, whose website was recently taken down; recent joint USFS-CalFire estimates (State of California, 2021); or Dobrowski et al. (2024), who added a distance buffer to accommodate potential seed rain], however this approach ignores many other factors that drive regeneration potential. In an important advance, a recent study by Davis et al. (2023) employed a similar approach to POSCRPT, combining a number of variables related to fire severity, climate, and seed availability to model conifer regeneration potential across the western US. This study found that California, Arizona, and New Mexico were the states most likely to suffer regeneration failures today and in coming decades.

Here, we deploy the most recent version of the POSCRPT tool to investigate California-specific trends in deforestation/reforestation needs over the period 1991–2023. One third of California (13.4 million ha) is forestland, and nearly half of that (6.4 million ha) is managed by USFS

Region 5 (Christensen et al., 2016). POSCRPT has become an important addition to Region 5's postfire reforestation and restoration planning pipeline (Meyer et al., 2021), and the tool has been deployed in projects on non-USFS lands as well. The objectives of our study are to: (1) describe the most recent version of POSCRPT; and, for the period 1991–2023: (2) use POSCRPT to estimate postfire regeneration probabilities in California non-serotinous conifer forests; (3) quantify spatial and temporal trends in fire-driven deforestation across California; and (4) assess the magnitude of reforestation deficit and progress on USFS lands.

Methods

Study system and model domain

Our study is focused on conifer-dominated forests and woodlands in California (Figure 1), with special focus on lands managed by the US Forest Service (USFS). The vegetation classification most often used by resource managers in California is the California Wildlife Habitat Relationships (CWHR) system (CDFW, 2014). CWHR includes 15 forest and woodland types dominated by conifers, and one other which can be nearly conifer-dominated (Montane Hardwood-Conifer). Of these 16 types, we conducted analyses on 11 (see below for rationale); the total area of forest analyzed was 71,764 km^2. The CWHR types which are listed in Figure 4, and their definitions/descriptions and the number of field plots sampled in each are provided in Supplementary Tables S1, S2. See Mayer and Laudenslayer (1988) for more information, as well as more recent modifications (2005) to the classification rules found at: https://nrm.dfg.ca.gov/FileHandler.ashx?DocumentID=65851&inline.

For some of our analyses we binned the CWHR types into four ecological groups that cohere based on environmental characteristics and species adaptations to fire (de Van Water and Safford, 2011, Safford and Stevens, 2017, van Wagtendonk et al., 2018, Safford et al., 2021). Douglas-Fir/Hardwood Forests (Douglas-Fir and Montane Hardwood Conifer CWHR types, often collectively referred to in California as "mixed evergreen" forests; Safford et al., 2021) are

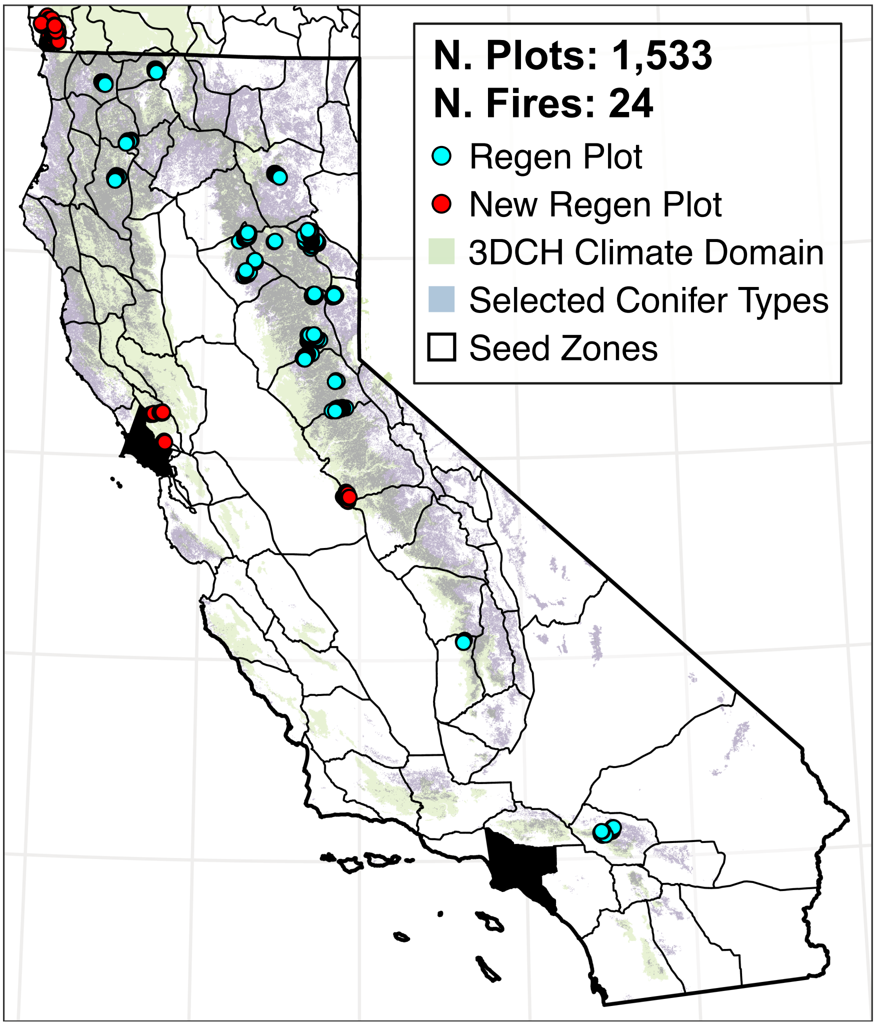

FIGURE 1
Locations of 1,533 postfire regeneration plots used to parametrize the POSCRPT model, including 299 newly measured plots from in California and southwest Oregon. A climatic domain for the training data is approximated using a 3-dimensional convex hull (3DCH) of three historical (1981–2010) climate variables: mean annual temperature, mean annual precipitation, and temperature differential. "Selected Conifer Types" refers to CWHR vegetation types included in this study. See text for details.

characterized by varying mixtures of Douglas-fir, a few other conifers, and numerous resprouting hardwood species, especially oaks (*Quercus* spp.). These forests are mostly lower elevation and are found in areas of relatively high precipitation. Yellow Pine Forests (Eastside Pine, Jeffrey Pine, Ponderosa Pine CWHR types) are dominated by Jeffrey pine and ponderosa pine and grow at low to moderate elevations in areas of low to moderate precipitation and intense summer drought. Mixed Conifer Forests (Klamath Mixed Conifer, Sierran Mixed Conifer, White Fir CWHR types) grow at low to moderate elevations (but often above Yellow Pine Forests) in areas of moderate to high precipitation and/or less severe summer drought. High Elevation Forests (Lodgepole Pine, Red Fir, Subalpine Conifer CWHR types) are found in the upper montane and subalpine zones, where snow comprises > 50% of annual precipitation.

Postfire regeneration data for model training and evaluation were collected in and surrounding postfire footprints in coniferous forests and woodlands of California and SW Oregon (Figure 1). Estimates of postfire regeneration, burn severity, and reforestation priority are reported across coniferous forests of California, excluding the following CWHR types: Redwood, Closed-Cone Pine-Cypress, Pinyon-Juniper Woodland, Juniper Woodland, and Undetermined Conifer. POSCRPT was originally built for USFS-managed yellow pine and mixed conifer forests of the Sierra Nevada and eastern Klamath Mountains. However, managers wanted conifer regeneration predictions outside the domain of the training data and almost immediately began to use the model for extrapolated predictions in these settings. To better meet this information demand and improve model performance in areas the model was already being used, we collected additional training data to expand the climatic and taxonomic domains of the model (Figure 1; Supplementary Table 1) and revised the model to improve the odds it would perform reasonably well outside these domains (see below). We excluded five mapped CWHR types from our analyses, either because we expected our regeneration model to not generalize well to their life history strategies (Redwood, which is a resprouter; Closed-Cone Pine-Cypress, which includes serotinous species), because they are invasive in some of their range and often considered undesirable in these contexts (Juniper, Pinyon-Juniper), or because they are a rare mapping artifact and not an actual vegetation type (Undetermined Conifer).

While we extrapolate POSCRPT predictions to some taxonomic contexts where training data are sparse or absent, these areas constitute a small proportion of coniferous area in California and an even smaller proportion of high severity fire and reforestation need. For instance, though we lack training data above 2,500-m elevation and have sparse data for subalpine conifer species in our current training dataset, the model accounts for seed production from these species, and we lack evidence or inference that it will perform particularly poorly in these areas. To provide a more complete picture to readers, we included subalpine conifers in our analyses, which constitute < 4% of coniferous forest and woodland area in California, even as we caution managers making decisions on the ground to use their best judgement interpreting out-of-domain predictions. See Supplementary Table S1 and Supplementary Figure S1 for information on our training data.

Field data collection

The postfire regeneration database was built from field data collected by Welch et al. (2016) plus more recent additions and subtractions described in Shive et al. (2018) and Stewart et al. (2021). See these references for protocol details. In general, 60-m^2 circular plots were located at the nodes of a 200-m grid overlaid on wildfires and adjacent unburned lands, stratified by seven fire severity categories and slope, aspect, and elevation classes. Seedlings found within a plot were inventoried, and data on site characteristics, ground cover, and distance to nearest surviving seed trees (among other things) were collected. We supplemented the composite dataset with 299 additional 5-yr postfire plots from five fires that burned in 2017 in California and southwestern Oregon: Chetco Bar ($N = 97$), Atlas ($N = 52$), Adobe ($N = 30$), Detwiler ($N = 66$), and Nuns ($N = 54$).

New data collections were targeted at expanding the climatic and geographic domain of the dataset. Specifically, we sought to collect data that would remedy deficiencies in the previous version of the model. These deficiencies included: (1) unrealistically high predictions of conifer regeneration probability in areas of very high precipitation (e.g., mean annual precipitation > 1,500 mm/yr); and (2) lower than expected influence of seed availability on conifer regeneration, leading to unrealistically high predictions of conifer regeneration in areas distant from plausible seed sources. Accordingly, we targeted additional data collection to areas with higher precipitation and areas more distant from potential seed sources.

Regeneration model improvements

Details related to the development of the POSCRPT model are found in Shive et al. (2018) and Stewart et al. (2021). Given the use of POSCRPT by managers outside of the domain of the original training data, we undertook improvements to enhance the models' generalizability to these areas. We updated our previously published hierarchical model of postfire conifer regeneration with newly collected data (see above), spanning a wider range of geographic and climatic conditions. The revised dataset includes measurements from 1,533 study plots in 24 wildfires that burned from 2004 to 2017 in California and southwestern Oregon. Model updates also include refinements for enhanced capture of mechanistic processes and improved out-of-sample predictive accuracy (see below). POSCRPT was fit as a binomial shape-constrained additive model with smooth terms for burn severity, 5-year postfire precipitation, insolation, and slope, and a monotone increasing smooth for seed availability. Smoothing parameters were estimated using the extended Fellner-Schall algorithm and model coefficients were optimized using the Broyden-Fletcher-Goldfarb-Shanno algorithm. Model skill was assessed using leave-one-fire-out (LOFO) cross-validation.

We refined the geospatial predictors used in Stewart et al. (2021) to better capture mechanisms and improve out-of-sample model performance. We made improvements in four areas: seed availability, burn severity, postfire precipitation, and solar insolation. Predictor units are shown in Figure 2. First, we expanded seed-availability estimates to all conifer taxa in the LEMMA GNN dataset, updated basal area estimates to rely on LEMMA GNN version 2020.1 (Ohmann and Gregory, 2002; Ohmann et al., 2011), and updated the process for estimating seed availability to account for basal area loss from multiple repeated wildfires. We replaced the Gaussian dispersal kernel with a more realistic exponential-power kernel ($\alpha = 0.5$, $\beta = 50$ m), yielding a moderately fat-tailed kernel (Bullock et al., 2017), and updated the units of allometrically estimated seed production from number produced to mass produced (i.e., larger seeds have higher survival, Greene and Johnson, 1994). Second, we replaced RAVG burn-severity inputs with Google Earth Engine–derived severity following Parks et al. (2018, 2021), providing standardized coverage across fires of all sizes

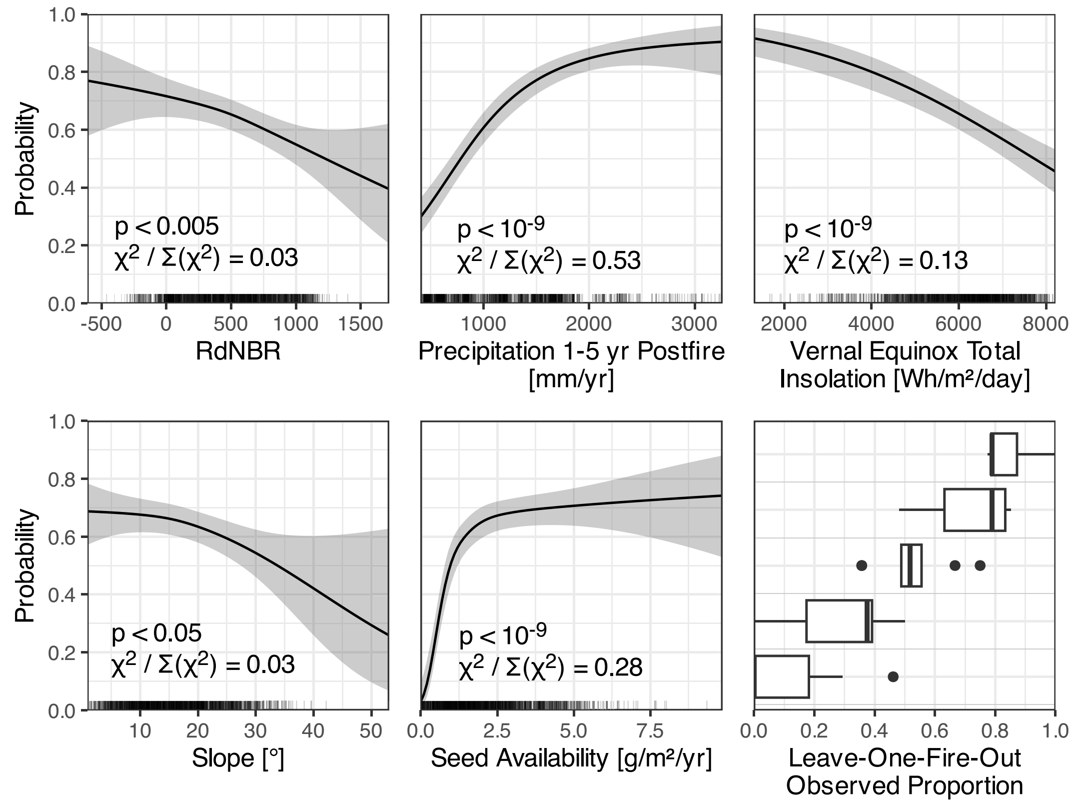

FIGURE 2
Marginal response curves (first five panels) and a leave-one-fire-out (LOFO) reliability diagram (bottom right) for the conifer regeneration model. Each response curve shows the predicted probability of regeneration across the range of one predictor—holding all others at their mean—with associated p-values and percent of model χ^2 explained. The LOFO reliability diagram depicts out-of-sample model performance with standard Tukey-style box-and-whisker statistics; bold, vertical bars represent the median. The LOFO AUC is 0.804 with LOFO classification error rate of 0.277.

TABLE 1 Deforestation levels.

Reforestation priority/deforestation severity	Definition/notes
Moderate	≥ 50% tree basal area mortality; current USFS Region 5 guidance focuses reforestation efforts on coniferous forest in this class.
High	≥ 75% tree basal area mortality and <50% probability of natural conifer regeneration.
Acute	≥ 90% tree basal area mortality and <10% probability of natural conifer regeneration.

Classes of postfire reforestation opportunity and deforestation level used in this paper.

and jurisdictions. Following advice from Jay Miller (US Forest Service, retired), we applied a small Gaussian spatial smooth ($\lambda = 50$ m) to RdNBR with difference, which improved fit with basal area loss data. Third, we simplified postfire climate predictors by focusing on cumulative precipitation in the first five water years after fire and downscaled PRISM precipitation to 30-m resolution using local lapse rates (PRISM Climate Group, 2022). Finally, we replaced the phenomenological variable "aspect" with the more-mechanistically-linked variable "vernal equinox solar insolation", estimated using the r.sun algorithm (Hofierka and Suri, 2002) and a 30-m DEM (USGS, 2020) covering a 10 k-m buffer around our study region.

Deforestation and reforestation trajectories

To assess deforestation trends, we generated statewide 30-m (900-m^2) resolution maps of fire-driven tree basal area mortality (1991–2023) and probability of postfire conifer regeneration (1991–2023) and overlayed them on static maps of vegetation type, land ownership, and region. To assess reforestation trends, we overlayed maps of reforestation progress (1992–2024) on this stack. We limit analyses of reforestation trends to USFS lands where the USFS FACTS database (Forest Activity Tracking System; https://data.fs.usda.gov/geodata/edw/datasets.php) has coverage over our study period. We used the 2015 version of the California "FVEG" vegetation map[1] and the 2025 version of the California landownership database.[2] We parsed regional trends using the Jepson Ecoregions (Hickman, 1993) and California Seed Zones (Buck et al., 1970). All maps were converted to a common 30-m (900-m^2) resolution raster grid (USA Contiguous Albers Equal Area Conic projection).

We sought to capture a metric of fire-driven deforestation that incorporates a longer-term view of forest trajectory by combining estimates of fire severity (i.e., percent basal area tree mortality) with

1 https://map.dfg.ca.gov/metadata/ds1327.html
2 https://data.cnra.ca.gov/dataset/california-land-ownership

natural regeneration probability. For each pixel-year combination we classified deforestation severity (aka reforestation priority) into three classes (Table 1). The *Moderate* class is simply the deforested-condition threshold used by USFS Region 5, defined as ≥ 50% tree basal area mortality. The *High* and *Acute* classes take a longer-term view and incorporate more information by including both basal area mortality and probability of natural regeneration. We defined the *High* class as ≥ 75% basal area mortality and < 50% probability of natural conifer regeneration and the *Acute* class as ≥ 90% basal area mortality and < 10% probability of natural conifer regeneration.

Our conifer regeneration probabilities represent the probability that a 60-m^2 (1/70th acre) sampling plot will contain at least one live conifer seedling 5-years postfire. To contextualize these probabilities in terms of traditional, uniform-density tree-per-acre (TPA) stocking targets used by the USFS we can make the simplifying (but imperfect) assumption that, due to local competition, multiple trees in a 1/70th-acre plot would be redundant for long-term forest regeneration. Accordingly, a 50% regeneration probability would roughly translate to the equivalent of about 35 uniformly distributed TPA (i.e., 0.5 × 70) and a 10% regeneration probability would roughly translate to about 7 uniformly distributed TPA. Obviously, this simplifying assumption has some weaknesses (e.g., younger trees compete on smaller spatial scales, competition is counterbalanced by facilitation), however with proper contextualization we believe it is still useful as a rough and simple heuristic. The 60-m^2 plot size used to build the POSCRPT model limits our ability to directly make similar translations for rough equivalence for targets of > 70 uniformly distributed TPA, although simplifying assumptions about spatial distributions of seedlings may be used for rough estimates of regeneration probability for plots of smaller sizes, and higher uniform-density-equivalent TPA targets.

We quantified annual deforestation from 1991 to 2023 and evaluated alternative temporal trend models representing linear, exponential, and sigmoidal dynamics in the growth of fire-driven deforestation. We compared these forms because, absent major changes in policy, management, or environmental forcing, recent dynamics may provide a useful first-pass estimate of near-term future trajectory. For each priority class, we fit three candidate models (softplus-linear, exponential, and logistic) using maximum likelihood under a common Gamma error distribution to reflect positive support and increasing variance with the mean. The softplus-linear model provides an approximately linear trend for large values while constraining all values to remain positive. For ecological groups, which included some years with zero DS/RP, we added a small constant (ϵ = 0.01 ha) to all annual values to accommodate these zeros while preserving relative magnitudes. Time was centered for numerical stability. We compared models using AICc and used Vuong non-nested likelihood ratio tests to assess whether exponential, sigmoidal, and linear trajectories were statistically distinguishable. For exponential fits, we converted fitted growth rates to implied doubling times, with confidence intervals estimated via the delta method.

To quantify USFS reforestation activity we accessed records of the following activities from the USFS FACTS database: "Plant Trees," "Fill-in or Replant Trees," "Fill-in Seed or Reseed Trees," and "Seed (Trees)." We summarized postfire reforestation activity occurring within 3 years postfire, 5 years postfire, and occurring by the end of 2024. We downloaded the FACTS database in January 2025, and included all FACTS records through 2024. All records were rasterized to a 30-m resolution grid. Consistent with Knight et al. (2022), we used reported accomplished area rather than raw polygon area to quantify reforestation extent, proportionally weighting 30-m pixels within each polygon to adjust for area discrepancies; in our dataset, reforestation polygons were 36.1% larger than reported area in aggregate (median absolute difference = 0.23 ha; median relative absolute difference = 6.2%). Overlapping or repeated postfire reforestation treatments were uncommon and counted cumulatively, which may result in slight overestimation of reforested land area.

Results

Predictive model

Our model revisions resulted in improved leave-one-fire-out (LOFO) predictive performance metrics and an expanded environmental domain of the data used to train and validate the model. The LOFO AUC of the revised model was 0.804 (bootstrap 95% CI: 0.781–0.825; previous model was 0.775). Figure 2 summarizes relative predictor importance using each term's partial Wald chi-square standardized by the sum across model terms, with postfire precipitation and seed availability contributing most strongly. The LOFO classification error rate was 0.277 (previous model was 0.287). Newly collected data expanded the environmental domain the model was trained on into areas of lower conifer seed availability, hotter and wetter climates, and lower elevations (see Supplementary Figure S1).

Notable qualitative differences between the revised POSCRPT model and the previous best-performing all-conifer regeneration model include the following. (1) The new model shows attenuated increases in regeneration probability for marginal increases in precipitation above ≈ 1,500 mm/yr. In contrast, previous versions of the model predicted unrealistically high probability of conifer regeneration under the highest precipitation conditions. (2) The new model puts more weight on seed availability (proportion χ^2 explained jumps from 0.06 to 0.28) resulting in more realistic predictions in areas that are distant from potential seed sources. (3) The new model better accounts for topographic shading, resulting in increased predicted probability of regeneration in settings such as south-facing valley bottoms. (4) The LOFO reliability diagram suggests the revised model has a tendency for modest underprediction of regeneration probability in the lowest and highest quintiles (Figure 2).

Deforestation and reforestation trajectories

Between 1991 and 2023, the trend in fire-driven deforestation in coniferous forests of California was best explained by an exponential trajectory (Table 2**;** Figure 3). Across all three reforestation-priority classes (moderate, high, acute), exponential models had the lowest AICc and highest weights (0.78–0.79), outperforming both logistic and linear alternatives (Table 2). Vuong tests indicated that exponential and logistic trajectories were statistically indistinguishable (moderate: $p = 0.36$; high: $p = 0.39$; acute: $p = 0.71$), whereas both nonlinear forms outperformed linear growth (exponential vs. linear—moderate: $p = 0.031$; high: $p = 0.007$; acute: $p = 0.053$; logistic vs. linear—moderate: p = 0.031; high: p = 0.007; acute: $p = 0.053$). Taken together, the evidence indicates accelerating, nonlinear growth without statistically detectable attenuation toward saturation, with implied doubling times of 5.42 years (95% CI: 3.86–6.98) for moderate priority, 4.44 years

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TABLE 2 Trend analyses of conifer DS/RP show consistent support for exponential growth dynamics across moderate, high, and acute priority classes (AICc weights ≈ 0.78–0.79).

DS/RP level	Exponential		Logistic		Linear	
	ΔAICc	Weight	ΔAICc	Weight	ΔAICc	Weight
Moderate	0.000	0.784	2.603	0.213	11.566	0.002
High	0.000	0.786	2.603	0.214	16.669	0.000
Acute	0.000	0.783	2.602	0.213	10.694	0.004

Logistic models were weaker alternatives (ΔAICc ≈ 2.60), and linear trends were strongly unsupported (ΔAICc > 10), indicating accelerating rather than linear change through time.

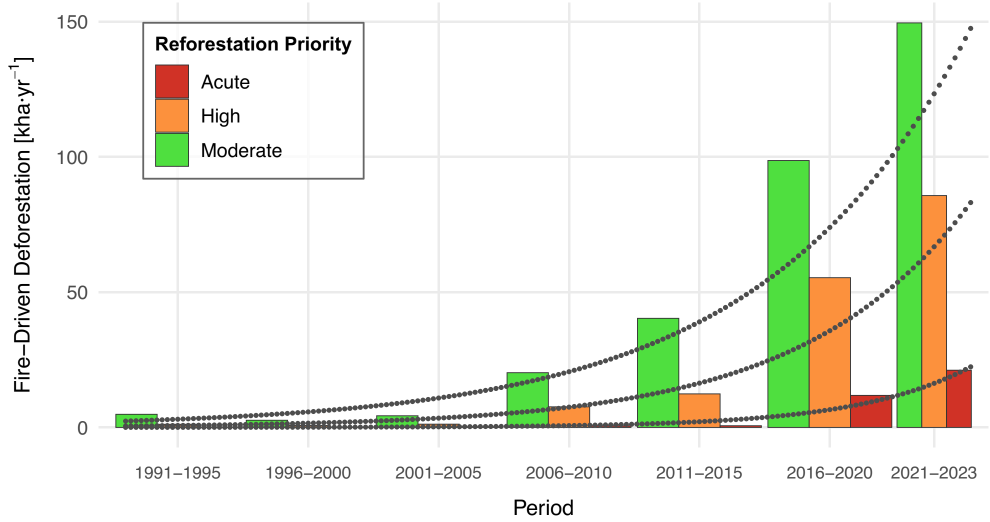

FIGURE 3
Rates of fire-driven deforestation in coniferous forests of California from 1991 to 2023. Best-fit regression lines fit to annual data (i.e., exponential, Table 2) are drawn for each priority/severity classes (top: moderate, middle: high, bottom: acute).

(3.38–5.49) for high priority, and 3.05 years (2.45–3.64) for acute priority (Table 3).

The area of reforestation need was near zero in the 1990s but began to rise in the 2000s. The area of reforestation need was highly dependent on the definition of restoration need used. In the 2021–2023 period, the conservative Region 5 Guidance-based estimate of need ("50% rule," our "moderate priority" class) was 1.74 times higher than the need identified by our high priority definition, and 7.07 times higher than the need according to our acute priority definition. See Figure 3 for best fit regressions of trajectory.

By far the greatest fire-driven forest loss occurred in the Sierra Nevada mixed conifer CWHR type, followed by the Douglas-fir CWHR type in northern and northwestern California; these are also the forest types and regions with the largest area of reforestation need, independent of the definition of need (Figure 4; see Supplementary Table S3 for data). Other CWHR forest types with large areas at risk of natural regeneration failure of nonserotinous conifers include Montane Hardwood-Conifer, Klamath Mixed Conifer, White Fir, Red Fir, Ponderosa Pine, and Eastside Pine (mix of ponderosa and Jeffrey). There is a rising temporal trend noticeable in all of the CWHR types, with the two biggest years being 2020 and/or 2021 for all the forest types. See Supplementary Figure S2 for a summary of patterns across all analyzed forest types, and Supplementary Figure S3 for the area of high severity (>75% basal area mortality) burning and probability of natural regeneration by CWHR type. Supplementary Figure S5 is an alternative portrayal of Supplementary Figure S2, using the Jepson Ecoregions as the principal data stratification rather than the CWHR types.

Similar patterns were observed across our four ecological groups and their three deforestation severity classes (Figure 5), where exponential trajectories consistently received the strongest AICc support and linear models performed most poorly (AICc weights for the exponential trajectory ranged from 0.48 to 0.78 across the 12 comparisons). Logistic models were occasionally competitive but not statistically distinguishable from exponential growth ($p > 0.5$), reinforcing the conclusion that early-stage accelerating dynamics prevail across forest types. The highest percentage of forest loss is occurring in the middle elevation ecological groups (yellow pine and mixed conifer, Figures 5B,C), with intermediate loss in the Douglas-fir/hardwood group and lowest overall in the high elevation group (Figures 5A,D). Estimated doubling times varied by ecological group and priority class, often with overlapping confidence intervals, but were generally fastest for the high-elevation group and slowest for the yellow-pine group (Table 3; Figure 5).

Postfire reforestation needs in California are primarily located on private and USFS lands. Private lands experienced about 644,000 ha/298,000 ha of deforestation (moderate priority/high priority) across our study period in the 11 evaluated CWHR forest types, and USFS lands lost forest on about 574,000 ha/315,000 ha (moderate/high) in the same forest types. Together, these constitute >93% of the total across all ownerships (Figure 6). Most years the area of private land burning at high severity is higher than the area of USFS and other

TABLE 3 Estimated doubling times for annual fire-driven deforestation in California, 1991–2023, reported for all coniferous forests and for our four ecological groups by severity class.

Ecological group	DS/RP level	Doubling time [yrs] (95% CI)
All conifers	Moderate	5.42 (3.86–6.98)
	High	4.44 (3.38–5.49)
	Acute	3.05 (2.45–3.64)
Douglas–fir/hardwood	Moderate	4.45 (3.30–5.59)
	High	3.97 (3.10–4.84)
	Acute	3.14 (2.49–3.78)
High elevation	Moderate	2.97 (2.36–3.58)
	High	2.27 (1.83–2.70)
	Acute	1.41 (1.22–1.61)
Mixed conifer	Moderate	3.69 (2.89–4.50)
	High	3.00 (2.39–3.61)
	Acute	2.50 (1.94–3.07)
Yellow pine	Moderate	10.62 (4.13–17.10)
	High	7.15 (3.87–10.42)
	Acute	3.65 (2.58–4.71)

federal lands. However, the 2021–2023 period was a notable exception, where USFS deforested lands in the 11 assessed CHWR types were about 259,000 ha/159,000 ha (moderate/high) and private deforestation was about 165,000 ha/87,000 ha. The period 2021–2023 also saw high amounts of fire-driven deforestation on National Park Service lands (21,160 ha/9,300 ha; Figure 6). See Supplementary Figure S4 for an alternative version of Figure 6, where the area of high severity (>75% basal area mortality) burning is integrated with the probability of natural regeneration by ownership type.

Reforestation deficit on forest service lands

On USFS lands between 1991 and 2023, the rate of postfire conifer reforestation has not kept up with reforestation needs (Figure 7; Supplementary Table S4). Reforestation becomes more challenging as time elapses; most reforestation occurred within 3 years postfire. Rates of deforestation in all three classes of fire-driven deforestation severity accelerated over time, with annual means more than doubling in each of the priority classes between 2011–2015 and 2016–2020 (and more than tripling in “high” and “acute”) and then more than doubling again in the shortened 2021–2023 period.

In contrast, rates of postfire reforestation peaked following the fires of the 2006–2015 period and have since greatly declined, even as reforestation needs have increased by orders of magnitude. Areas of acute reforestation need had a lower probability of being reforested than areas of moderate or high reforestation need. Across the entire study period, the percentage of USFS Region 5 reforestation need replanted in the 11 assessed CWHR types was 8.13% of the moderate class, 8.21% of the high class, and 2.75% of the acute class (Figure 7). For 2016 to 2023 fires, 1.16% of the moderate priority class was replanted, compared to 1.24% of the high priority class, and just 0.72% of the acute class. The cumulative USFS Region 5 reforestation deficit in the assessed forest types—the difference between reforestation need and actual reforestation—was 528 kha (19.0% of USFS coniferous forest area in California) for the moderate class, 289 kha for the high class (10.4% of USFS coniferous area), and 68 kha (2.4% of USFS coniferous area) for the acute class. This equates to annual unreplaced losses of forest cover of 0.32–0.58% (high and moderate priority, respectively). Almost all this loss occurred after 2001, since which the annual mean annual USFS restoration deficit was 0.45–0.82% (high and moderate priority, respectively) of the assessed USFS forests.

Reforestation needs by seed zone: the 2020 and 2021 fire seasons

2020 and 2021 were by far the most significant years for high severity burning and deforestation in our period of analysis. In Figure 8 we plot the high priority reforestation need by California seed zone for those 2 years, as a percent of the total conifer forest in the seed zone. Although there are areas of enhanced need throughout the central and northern California montane forests, three areas stand out (Figure 8): (1) The northern Inner Coast Ranges on the Mendocino National Forest and surrounding lands (driven principally by the Mendocino Complex Fire in 2018 and the August Complex Fire of 2020); (2) The northern Sierra Nevada boundary with the southern Cascades, on the Plumas and Lassen National Forests and surrounding lands, driven by a long list of large, severe fires starting already in the early 2000s and culminating with the North Complex Fire in 2020 and the Dixie Fire in 2021; (3) The southwestern Sierra Nevada, principally on the Sequoia National Forest and Sequoia-Kings Canyon National Parks and surrounding lands, driven by multiple fires, most recently the Castle Fire of 2020 and the KNP Complex Fire of 2021.

Discussion

Based on a set of POSCRPT-centered analyses, our results document the following salient patterns and trends: (1) Fire-driven deforestation/reforestation need (DS/RP) in California between 1991 and 2023 increased at an exponential rate, reaching nearly 150,000 ha per year using our “moderate priority” definition and nearly 86,000 ha per year in our “high priority” class between 2021 and 2023. (2) Overall, the mixed conifer forest ecological group experienced the most fire-driven deforestation since 1991, followed by the Douglas-fir/hardwoods group, the yellow pine group, and finally the high elevation forest group. (3) The rates of exponential growth in deforestation are highest for the high elevation forest ecological group, followed by the mixed conifer group, and then the Douglas-fir/hardwood group. (4) Private and USFS lands experienced by far the highest amounts and rates of increase in DS/RP during the study period, and accounted for 93.4% of moderate DS/RP, 94.4% of high DS/RP, and 96.0% of acute DS/RP. (5) During the study period, postfire reforestation efforts on USFS lands in California began to lose ground to fire-driven reforestation needs after about 2006; between 2016 and 2023 only a small fraction (< 1.2%) of deforested hectares was replanted. (6) Over the entire study period, reforestation progress on USFS lands did not keep pace with our metric of reforestation priority: a total of 8.21% of high priority areas were reforested while only 2.75% of acute priority areas were reforested. (7) The greatest reforestation needs in our study period were driven by the effects of the 2020 and 2021 wildfires, which deforested large areas of the conifer land base in the northern Inner Coast Ranges, at the boundary between the northern Sierra Nevada and

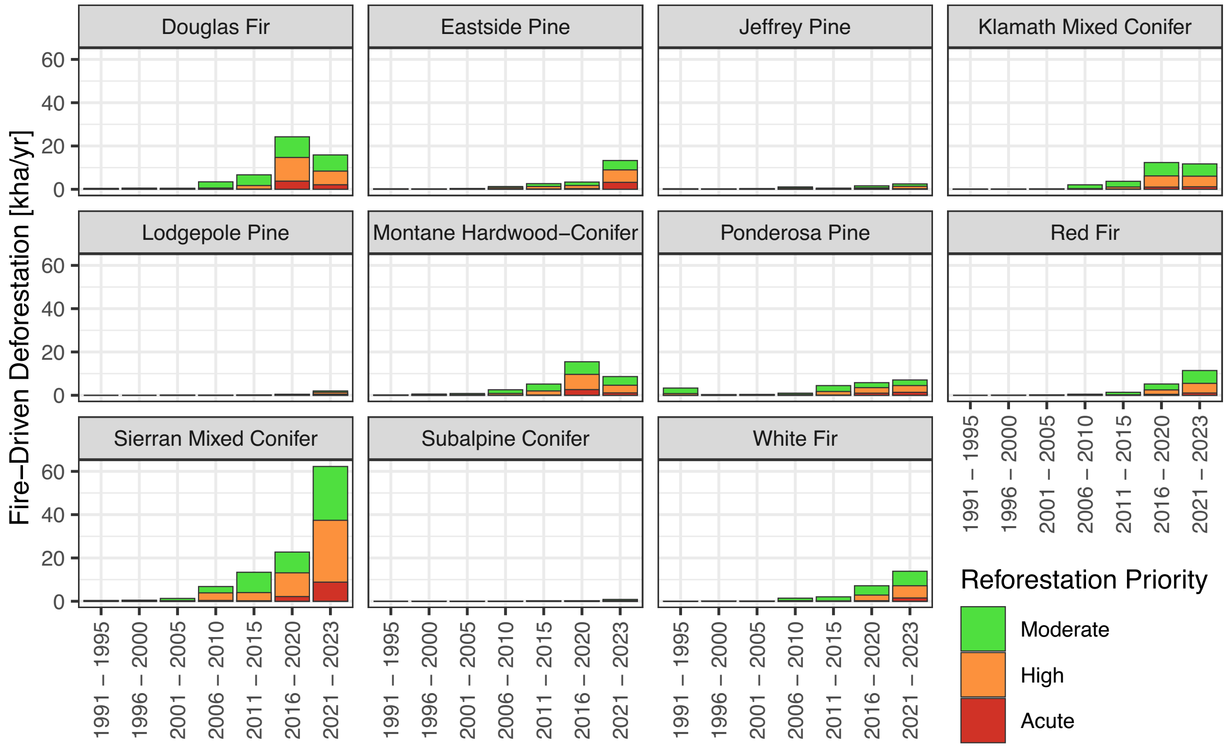

FIGURE 4
Rates of fire-driven deforestation for 11 vegetation types across California between 1991 and 2023. Priority categories are nested and overlapping such that lower levels include higher levels. See Supplementary Table S3 for tabular representation of these data.

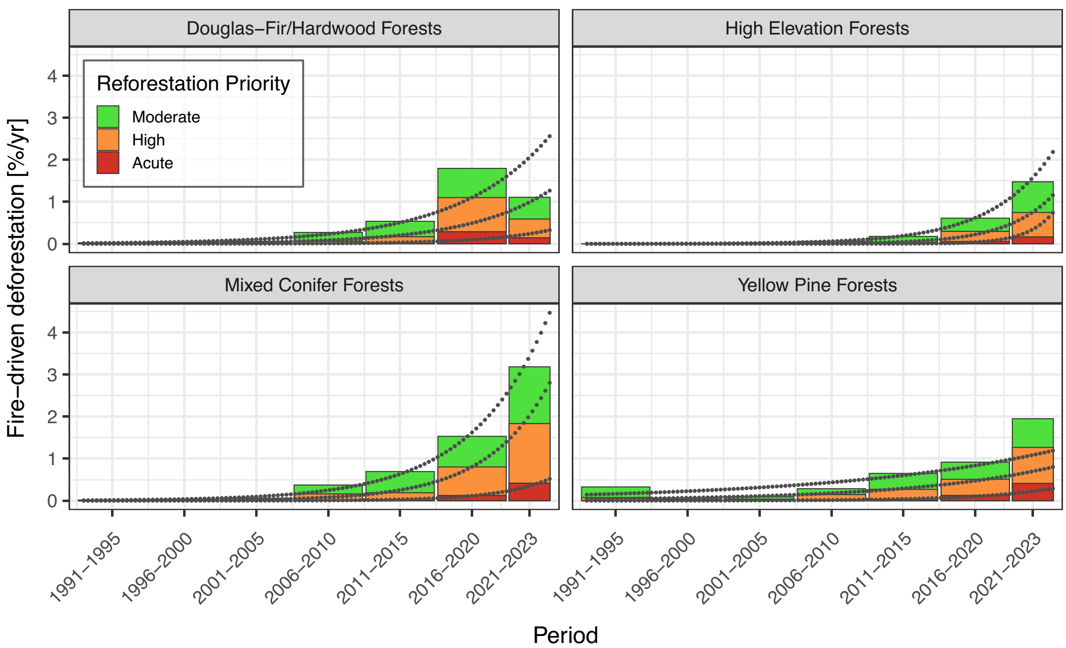

FIGURE 5
Deforestation trends in California as a percent of total forested area per year for four forested ecological groups. **(A)** Douglas-Fir/Hardwood, **(B)** Yellow Pine, **(C)** Mixed Conifer, and **(D)** High Elevation Forests. Best-fit exponential regression lines fit to annual data are drawn for each severity classes (top: moderate, middle: high, bottom: acute). Severity categories are nested and overlapping such that lower levels include higher levels.

South Cascades, and in the southwestern Sierra Nevada. (8) In terms of percent loss per year, the overall rate of deforestation in California since 2001 is among the world's highest.

In California, the rate of fire-driven deforestation has grown quasi-exponentially over time with no significant evidence for attenuation toward saturation. Most of the reforestation need is found in low

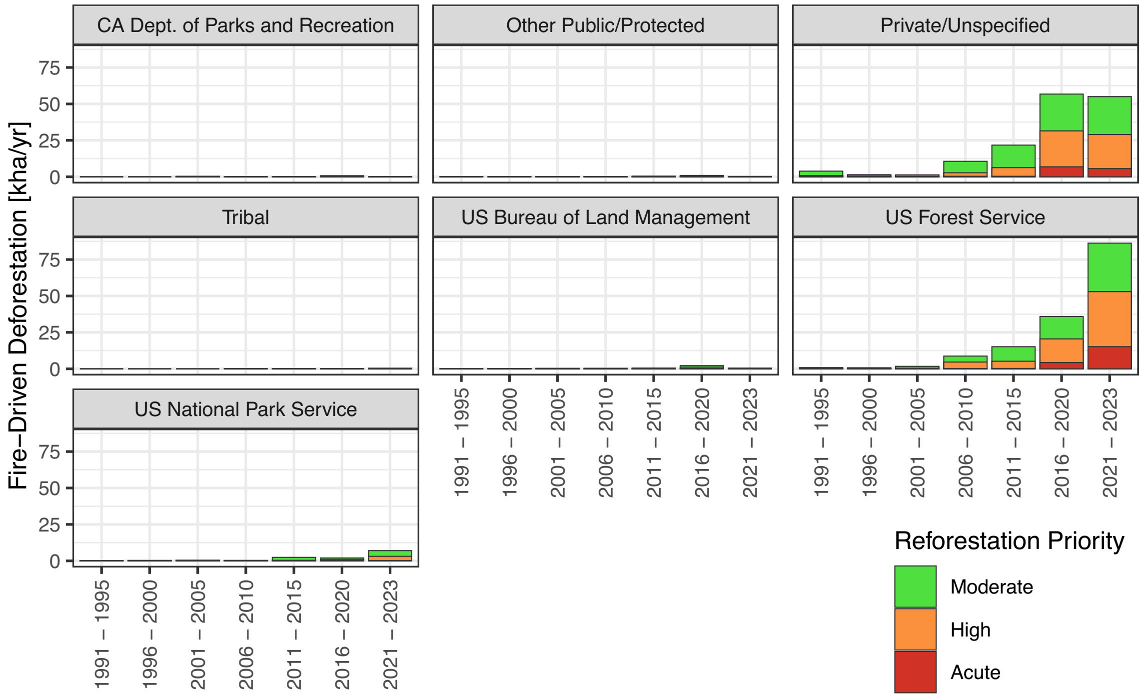

FIGURE 6
Rates of fire-driven deforestation for 7 ownership types across California by reforestation priority and period. Priority categories are nested and overlapping such that lower levels include higher levels. See Supplementary Table S4 for tabular representation of these data.

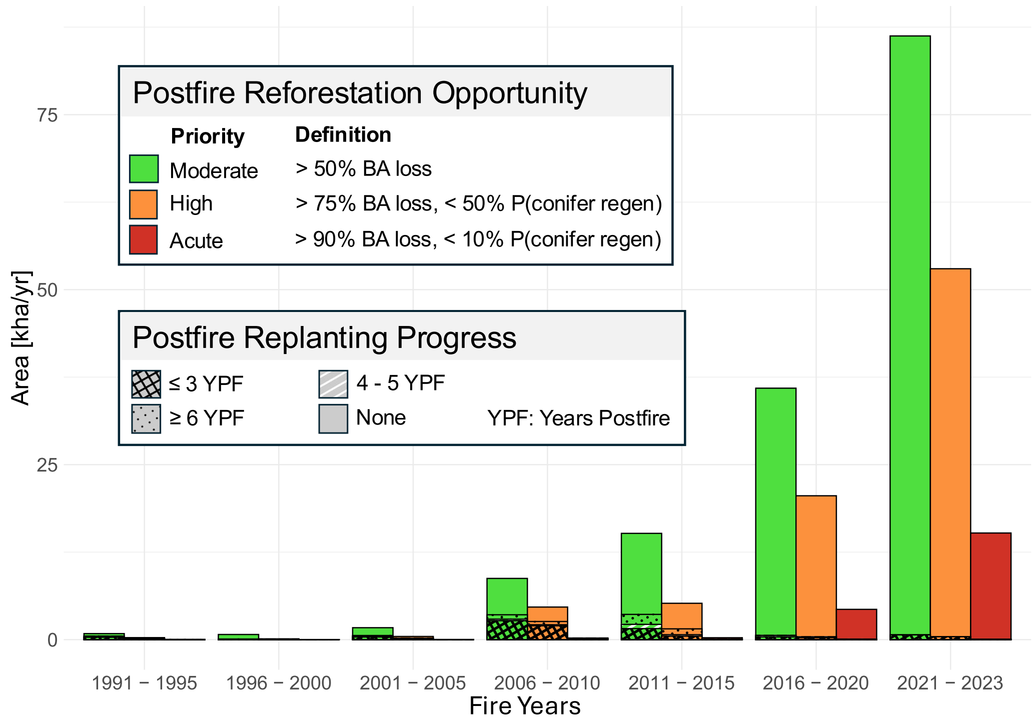

FIGURE 7
Rates of fire-mediated conifer deforestation severity/reforestation priority and subsequent replanting progress on USFS lands in California. Figure includes eleven coniferous forest types where our methods apply. Each period is 5 years in length, except the final period, which is 3 years. Replanting progress is measured using reported areas from the USFS FACTS database, with its position on the *x*-axis tied to the year of the fire and its timing after the fire depicted via patterns. YPF = years postfire. See Supplementary Table S5 for tabular representation of these data.

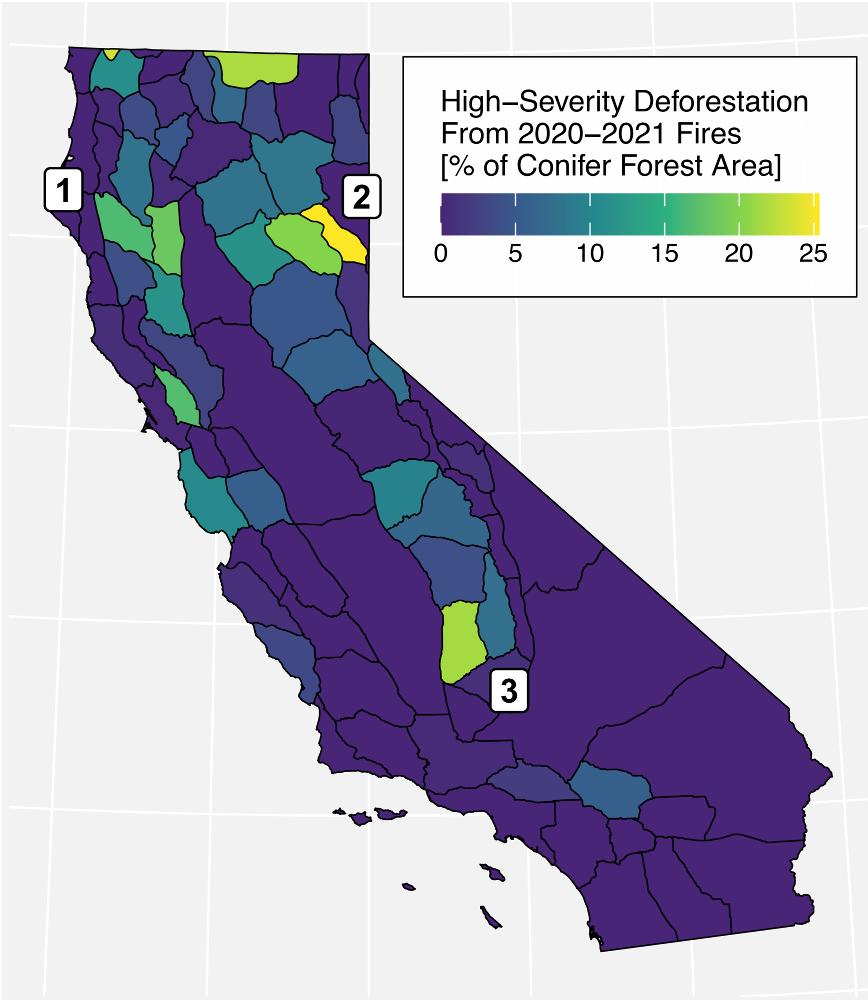

FIGURE 8
High priority postfire conifer reforestation opportunities emerging from the 2020 and 2021 wildfire years as a proportion of total coniferous forest area by California seed zone (Buck et al., 1970). Total conifer forest area is calculated using the 11 CWHR types where we apply the regeneration model.

and middle elevation forests, such as Mixed Conifer Forests, Douglas-Fir/Hardwood Forests, and Yellow Pine Forests. These are the forest types that constitute the majority of productive forestland in California, and which form the backbone of private forest holdings, commercial timberlands, and lands managed by the USFS. These are also the forest types most negatively affected by fuel accumulation and stand densification driven by long-term fire exclusion and selective logging-driven loss of fire-tolerant tree species (Safford and de Water, 2014; Safford et al., 2021; Williams et al., 2023). Under the moderate priority reforestation need class, most DS/RP in California occurred on private and commercial lands, but reforestation needs were higher on USFS lands in the high and acute categories. Private lands experience much higher numbers of ignitions than federal lands (Keeley and Syphard, 2018), and the industrially managed portion of privately owned forestland (about 36% of private lands; Christensen et al., 2016) has a tendency to burn at higher severity than federal lands (Levine et al., 2022). This is ironically due in part to the relative rapidity and success of postfire reforestation efforts on private industrial lands (Stephens et al., 2020), which generate continuous stands of young trees that are highly susceptible to high severity burning (Thompson et al., 2011; Zald and Dunn, 2018).

We estimate that the USFS reforestation backlog in California using our moderate priority category (equivalent to the "50% rule" used by USFS Region 5) is about 7.4% of the total forested area we analyzed, and about 4.1% when we apply our high priority. We have fewer data on the other ownership classes, but we can make some assumptions to calculate overall restoration deficit using the moderate and high priority classes. During our study period there were about 227,895 (moderate priority) or 105,492 (high priority) ha of private industrial forestlands that were deforested by fire in California, and those lands are nearly always salvage harvested and replanted within a few years. Of the c. 415,875 (moderate priority) or 192,508 (high) ha of private nonindustrial forest lands (mostly smallholders) that were deforested, we estimate, based on Waks et al. (2019), that up to about 60% of those hectares are ultimately reforested (this is likely an overestimate; S. Kocher, UC Cooperative Extension, pers. comm.), which produces restoration deficits of 166,350 ha (moderate) or 76,963 (high) ha. We assume that the remaining 13% of the California forestland total (mostly other federal, but also tribal and state and local) is not reforested in most cases, or that efforts are small enough in area to not greatly affect our calculations. These assumptions—which each introduce some uncertainty into our final numbers—yield a conservative estimate of an overall 1991–2023 restoration deficit (aka unreplanted deforestation) of about 791,000 ha across all ownerships for the CWHR types we assessed under the moderate priority, and 416,600 ha under the high priority. Overall conifer forest loss (deforested hectares minus replanted hectares) for 1991–2023 comes to about 11% (moderate priority) or 6% (high). Our high priority estimate is close to the 6.7% loss in California-wide forest cover estimated by Wang et al. (2022) for the period 1985–2021, based on remotely sensed imagery and which they ascribed mostly to fire effects. Taken together, these numbers suggest that California is one of the world leaders in fire-driven forest loss, with an annual average loss of 0.18–0.32% (range from our data and Wang's) between 1991 and 2021, and an annual loss of 0.25–0.47% between 2001 and 2023 (our data only), vs. 0.15% per year worldwide since 2001 (Tyukavina et al., 2022; Global Forest Watch, 2025).

In recent decades, federal resource management agencies have experienced a catastrophic drop in their ability to reforest burned conifer forests in California and across the western US. This is partly due to the loss of funding (which historically came mostly from timber harvest receipts, which have dropped significantly since the 1980s), staff, and nursery facilities over the last three to four decades (Dumroese et al., 2019; Stewart et al., 2021; Dobrowski et al., 2024), and partly due to the huge increase in the area of severely burned forest over the same period (Safford et al., 2022; Williams et al., 2023). The huge and growing gap between reforestation need and Federal reforestation implementation threatens a long list of ecosystem services conveyed by functioning forests, including carbon sequestration, hydrological services, erosion and sedimentation reduction, recreation, numerous provisioning services (lumber, biomass, firewood, fruits and nuts, hunting, etc.) habitat creation and maintenance, and biodiversity (Brockerhoff et al., 2017). Numerous efforts have highlighted the importance of comprehensive reform to resolve the problem (e.g., Stewart, 2020; State of California, 2021; USDA, 2022; USDA, 2024). "Reforestation pipeline" constraints and solutions are covered in depth elsewhere (see especially Dumroese et al., 2019; Stewart et al., 2021; Fargione et al., 2021; Dobrowski et al., 2024; USDA, 2024), but decisions of where, when, and how much to plant—which we are focused on here—are of similar importance.

For USFS Region 5, our data show that areas of moderate and high reforestation need are much more likely to be reforested than areas of acute reforestation need. Areas of high reforestation need were only marginally more likely to be replanted than areas of moderate reforestation need. This raises questions related to when and where the USFS and other landholders should conduct conifer reforestation, given the financial and capacity constraints to action. Welch et al. (2016) found that in the burned forests they studied, areas with <75% mortality were more likely than not to naturally regenerate to Region 5 stocking standards (which are likely too high given current climate trends; see below). Another concern is that Region 5's "50% rule" (our moderate priority class) only considers tree mortality, and ignores probabilities of postfire seedling recruitment and other important factors such as burn patch size, climate, and distance to nearing living seed trees, all of which are key inputs to POSCRPT (Safford, 2021). The continued application of the 50% rule seems questionable under current and projected trends in budget, capacity, seedling availability, and wildfire severity. Our analyses show that the magnitude of reforestation need is already enormous under the high and acute reforestation need classes. Targeting the moderate reforestation need class (which extends down to 50% basal area loss) includes lands that do not need to be replanted, robs funding and staff time from higher priority areas, makes progress seem impossible (the area considered for reforestation is reduced considerably in the high and acute priority classes), and results in budget and capacity planning that is a lesson in futility. With respect to the final point, see the USFS Region 5 Reforestation Implementation Plan (USDA, 2024), which proposed a return to historical levels of reforestation capacity, which were projected to eliminate the reforestation backlog on USFS lands—calculated based on the 50% rule—in 23 years (and which did not include increasing rates of forest loss in their calculations). The alternate proposal in USDA (2024) was an "unprecedented" ramping up of staff and effort, with the payoff being a 13-year runway instead of 23. Of course, with the Trump administration cuts to USFS budget and staff, both proposals are unlikely to get off the ground.

There are numerous other recommendations in the literature for improving and streamlining postfire planting on USFS and other lands. For example, concern has been voiced about the typically high density of planted seedlings on federal lands in light of the increasing probabilities of severe droughts and wildfires and the concurrently decreasing probability of stand maintenance and precommercial thinning; the grid pattern of most (even non-commercial) planting, which does not follow natural environmental gradients and does not mimic natural clumping patterns; and the lack of clear guidance as to the use of and movement of genotypes and species that are better adapted to future climates rather than the climate of the recent past (e.g., Welch et al., 2016; North et al., 2019, 2022; White and Long, 2019; Koontz et al., 2020; Meyer et al., 2021; Marsh et al., 2022). The USFS National Forest System Reforestation Strategy (USDA, 2022) notes that "Reforestation, whether natural regeneration or planting, needs to consider future ecological conditions, forest community structure, wildfire risk, and other factors," but very little in the way of implementing standards or guidelines have been developed for these goals.

Reforestation efforts need to balance need with likelihood of success. Experience and scientific study show that landscapes vary hugely in their ability to support robust seedling survival and growth (e.g., Gray and Spies, 1997; Gray et al., 2005; Marshall et al., 2023). Very warm and/or dry, severely burned areas with no seed sources are unlikely to regenerate to forest without planting (Sorenson et al., 2025), but planting success in such locations is often very low (Smith, 2024). Such sites are also more likely to become uninhabitable for conifers under continued climate warming (Young et al., 2019; Petrie et al., 2023; Holden et al., 2024). Plantings in moist, lightly burned areas are likely to succeed, but are often superfluous as there are plenty of nearby seed sources (and indeed, the loss of some conifer basal area and density is a positive thing in many of these sites; White and Long, 2019). Site productivity is an important integrating metric that correlates closely with reforestation success. Smith (2024), in a review of USFS reforestation activities in California, found that—for FIA productivity classes that had at least 2000 acres of treatment in the USFS FACTS database—FIA class 3 (moderately high productivity) supported an average of 44% planting success, classes 4–6 averaged about 30%, and class 7 (very low productivity) averaged c. 7%. Overall, in California with its bone dry summers, it seems that basing planting patterns on fine- and meso-scale moisture and productivity gradients on the landscape would be an avenue to greater success (North et al., 2019). Of course, this would require a more nuanced approach to planting and more upfront planning. An example to follow might be planting methods practiced in some of the drier Mediterranean Basin regions, such as southeastern Spain or Israel, where great care is often taken in choosing planting sites, such as topographic depressions and deep soil pockets that can capture and retain water (Vallejo et al., 2012, Safford and Vallejo, 2019; G. Atsmon, Israeli Forest Service, pers. comm.).

Another common planting practice in the Mediterranean Basin that is still a rarity in the western US is the mixing of hardwood/broadleaf species and conifer species. Hardwoods like oaks are generally less resistant than pines to the direct effects of extreme drought, but they are less susceptible to insect attack, and—as resprouters—they are much more resilient to fire. Postfire restoration projects in the Mediterranean Basin often include a mix of conifers (mostly pines) and resprouting hardwood trees and shrubs—e.g., oak (*Quercus* spp.), madrone (*Arbutus* spp.), pistachio (*Pistacia* spp.), carob (*Ceratonia siliqua*), *Rhamnus* spp.—that are included to increase resilience to fire, more rapidly cover soil after severe burning, and augment habitat heterogeneity and ecosystem service provision (Safford and Vallejo, 2019). Both empirical observation and modeling forecasts that include climate and fire trends suggest a drift away from nonserotinous conifers and toward hardwood species in California's lower elevation mountains (Lenihan et al., 2008; Safford et al., 2012; McIntyre et al., 2015). Management facilitating such transitions thus constitutes a form of climate change adaptation (Safford and Vallejo, 2019; Swanston et al., 2020). Hardwoods are already a major component of the Douglas Fir and Montane Hardwood-Conifer CWHR types, and their rate of deforestation is attenuated by their hardwood component, which resprouts with high success rates even after severe burning (Safford et al., 2021). In these forest types, postfire reforestation of conifers on noncommercial land may be a lower priority where management is focused on long-term ecosystem sustainability and climate change mitigation or adaptation (Long et al., 2023).

Our POSCRPT model revisions resulted in higher accuracy and lower error, and adding new data expanded the environmental domain of the model to areas of lower seed availability, lower elevation, and hotter and wetter environments. In the future we would like to add more high elevation (especially lodgepole pine and subalpine) fires to our dataset, and we would like to include regeneration probabilities for serotinous species as well. Forest fires become less prevalent with elevation, but recent science indicates that the area and severity of fires in high elevation forests are both increasing (Schwartz et al., 2015; Williams et al., 2023), and our data show that these forests are seeing the most rapid acceleration of exponential growth in deforested area. POSCRPT is currently data-poor in these forest types. Serotinous species like knobcone pine (*P. attenuata*) and various cypress (*Hesperocyparis*) species are well positioned to take advantage of high severity burning, as their cones usually require hotter burning, and their seedlings are freed from heavy interspecific competition for the first years of their life. As long as fire frequencies do not greatly increase, the shift toward more severe burning could theoretically result in expansion of serotinous conifers in California. Such an expansion may already be occurring in knobcone pine (Reilly et al., 2018). A model for the effects of increasing human influence on the fire regime on serotinous species is the Mediterranean Basin, where serotinous species are less numerous than in California, but they are much more dominant on the landscape (Ne'eman and Osem, 2021).

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

HS: Writing – review & editing, Visualization, Conceptualization, Supervision, Funding acquisition, Project administration, Writing – original draft, Validation. JS: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization, Methodology.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/ffgc.2026.1764379/full#supplementary-material

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