Mapping disturbance across California's rapidly changing forests

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Abstract

Disturbances shape assemblages and spatial patterns of flora and fauna across the globe, and accurate disturbance mapping can aid conservation science and decision-making. However, mapping and differentiating among disturbance types using remote sensing is challenging, especially in forests with hidden subcanopy disturbances. On federal lands in the western US, wildfire, drought, and fuels management are three primary disturbance agents of forest change. The US Forest Service's (USFS) Forest Activity Tracking System (FACTS) provides nationwide fuels management data on USFS lands, but has not been widely utilized to understand the drivers of forest change, partially due to missing data and spatial and temporal uncertainty. We compared fuels management areas as represented in FACTS with annual, remotely-sensed predictions of canopy loss (Mortality Magnitude Index in the eDaRT system for Landsat processing; MMI) and assessed their spatial and temporal accuracy. We determined that a temporal window spanning two years before to one year after the reported FACTS completion year accounted for 98.5% of high-change fuels management areas delineated using remote sensing and visually confirmed using NAIP imagery. Our approach indicates that FACTS, once buffered temporally (and possibly spatially, depending on the user's objectives), can provide reliable information on the history of fuels management. We used these data in conjunction with estimates of fire severity (composite burn index) and drought-related tree mortality (MMI) to characterize annual patterns in forest disturbance on USFS lands in the Sierra Nevada and Southern California from 2003 to 2022. We found that 73% and 76% of these regions were disturbed, respectively (25,000 km^2 across both regions). Of the 25,000 km^2 affected, wildfire was the dominant disturbance agent (17,204 km^2; 69%), followed by drought/other mortality (12,813 km^2; 51%), and fuels management (3,472 km^2; 14%), with some overlap between these categories across the 20-year span. These results underscore recent widespread disturbance agents and the possible transformation of California forests, changes that are having profound effects on biodiversity. The accompanying disturbance dataset and processing code provide new and potentially powerful opportunities for scientists and managers studying and stewarding these rapidly changing ecosystems.

Keywords

California; change detection; disturbance; drought; FACTS; fuels management; fuel reduction; fuel treatment; landscape; Sierra Nevada; Southern California

1. Introduction

Understanding the drivers of environmental change can facilitate appropriate and effective management interventions. In forest ecosystems, a multitude of disturbances can cause changes to forest structure and composition, result in tree death, and reset forest succession (Pickett and White 1985, Turner 2010). Natural disturbances such as wildfire (Bond and Keeley 2005), drought-induced tree mortality (Allen et al. 2010), insect outbreaks (Raffa, Grégoire, and Lindgren 2015), and windfall (Baumann et al. 2014), as well as anthropogenic disturbances such as tree harvesting (Kittredge Jr, Finley, and Foster 2003) and grazing (Öllerer et al. 2019) can all influence forest dynamics. Forest managers intent on guiding the conservation of particular forest characteristics must understand how natural and anthropogenic disturbances interact to influence change, and incorporate such knowledge into management prescriptions (Leverkus et al. 2021). As the frequency, size, and intensity of disturbances and their interactions accelerate in many forest systems (Burton, Jentsch, and Walker 2020), managers must also understand the nature and distribution of changing disturbances to optimize conservation decisions. Furthermore, financial investments by government or private entities in management activities are contingent upon accurate reporting thereof such that subsequent work is appropriately allocated based on actual work accomplishments.

Despite the importance of understanding disturbance processes, detecting and delineating the spatial and temporal boundaries of interacting disturbances is challenging (Stahl et al. 2023). Some disturbances, such as wildfire, can be discrete in space (have clear boundaries) and punctuated in time (have clear start and end dates). Other disturbances, like drought-induced tree mortality, are more gradual in nature, having ambiguous spatial footprints and start and end dates (Asner et al. 2015, Parry et al. 2016, Diaz et al. 2020). Discrete disturbances are relatively straightforward to map; gradual disturbances are not. Hidden subcanopy disturbances, such as surface fire or understory mechanical thinning, also challenge change detection (Jarron et al. 2020, Gao et al. 2020). Moreover, discrete and gradual canopy and subcanopy disturbances can interact in space and over time, creating a complex challenge in terms of attributing which factor was responsible for producing landscape change. Wildfire can occur within the context of an ongoing drought (Crockett and Westerling 2018); insect outbreaks can precede wildfires and influence their behavior (Wayman and Safford 2021); and so on. The increasing likelihood of disturbance interactions and the task of accurate disturbance mapping challenge managers' ability to understand and respond appropriately to landscape change and quantify disturbance impacts to sensitive species and biodiversity.

In western United States forests, wildfire is the dominant driver of landscape change and, as such, robust monitoring systems exist to track fire occurrence and severity (Eidenshink et al. 2007). Existing evidence, based on monitoring data produced by such systems, suggests that rapidly changing fire regimes have begun transforming western US forests (Coop et al. 2020, Parks and Abatzoglou 2020, Hagmann et al. 2021). Increasingly, though, other forms of forest disturbance are becoming more common and/or consequential and are typically more difficult to map with high precision. Drought-induced tree mortality has increased in western US forests in recent years (Williams et al. 2015, Crockett and Westerling 2018), but drought plays out over years, and sometimes trees do not die until after the drought has concluded (Young et al. 2017), challenging attribution. Although fuels management such as understory mastication, forest thinning, and other restoration projects regularly occur on USFS land, the pace and scale of this management needs to increase to mitigate fire and drought effects (North et al. 2015, Stephens et al. 2013). The US Forest Service maintains one of the largest databases describing the details of each of these projects: the Forest Activity Tracking System (FACTS). However, this system is error-prone and incomplete (Knight et al. 2022), and as such has not been widely utilized to understand the drivers of forest change. An improved understanding of the relative and absolute influences fire, fuels management, and drought on western US forest change, as well as the spatial and temporal distribution of these drivers, is critical for informing data-driven forest management moving forward.

Here, we present a novel approach for attributing forest change to fire, fuels management, and drought/other disturbance types across California's Sierra Nevada and Southern California, USA bioregions over the period 2003-2022. These regions are at the center of contemporary forest management issues and represent biodiversity hotspots experiencing rapid environmental change. Our approach integrates two previously existing spatiotemporal datasets (fire, drought) and introduces a new approach for vetting and attributing fuels management activities using existing databases. Specifically, we 1) assess the temporal and spatial accuracy of FACTS fuels management polygons, and 2) compile fire, fuels management, and drought/other disturbance into synthetic annual disturbance layers across a 20-year period for the Sierra Nevada, CA and Southern California study areas. We provide freely available geospatial raster datasets and code for managers and scientists to update the spatial dataset for new areas or in the future as forests continue to change. These methods and code for facilitating disturbance type summary – especially because they are accompanied by a rigorous accuracy assessment of fuels management activities actually used by land managers for reporting accomplishments – can serve as a much needed and repeatable approach to compare the relative proportions of the drivers of ecosystem change over time in national forests and will facilitate forest planning, biodiversity conservation, and new scientific advances.

2. Methods

2.1 Study area

Our study areas were limited to USFS land and encompassed 19,871 km^2 in the Sierra Nevada and 14,045 km^2 in Southern California. The climate is Mediterranean with warm, dry summers and cool, wet winters and elevations ranging from 226 to 3,972 m in the Sierra Nevada and 102 to 3,504 m in Southern California. The Sierra Nevada is primarily forested, including Sierra mixed conifer, subalpine forests, and oak woodlands, as well as non-forest areas including wet meadows, shrubfields, and rocky areas. The Southern California study area is more sparsely forested and is primarily characterized by oak woodland and chaparral shrubfields. Because we eliminated non-USFS ownership from our analyses, our study areas were a checkerboard pattern in some areas. The study landscape is primarily influenced by three disturbance types: a) fires of different sizes and severities, b) fuels management efforts by the USFS, and

c) drought that spiked at different times in the northern and southern Sierra Nevada, as well as in Southern California.

2.2 FACTS fuels management

The FACTS database provides nationwide data on activities related to fire, fuels, silviculture, and invasive species on USFS lands from as early as the 1850s up to the present, as well as treatments that are planned but not yet implemented. This database of spatially explicit polygons includes 113 attributes for each treatment polygon including treatment activity type, method, equipment used, award and completion date, funding information, project name, and National Environmental Policy Act (NEPA) details. Note that these spatial data are typically hand-delineated using background imagery and maps, and often by managers who are not necessarily trained in spatial analysis. Knight et al. (2022) compared FACTS data with remote sensing for the purpose of more accurately accounting for the area with fuels management across time, and found potential over-reporting. However, they did not deeply explore temporal accuracy or potential underreporting when fuels management was not in FACTS. Although this information-rich database could be a goldmine for researchers, it has not been widely used in forest or biodiversity science, in part because of missing data and uncertainty around the spatial and temporal accuracy of the records. This database is used extensively by the USFS for reporting, however, emphasizing the importance of thorough assessment and data validation.

We downloaded the FACTS Common Attributes shapefile for Region 5 (USDA Forest Service 2025) and exported only treatments awarded since 1980 that were located within the 10 km buffered study area. Although we were only interested in fuels management since 2003, activities can take over a decade to be completed, and we aimed to avoid removing potentially relevant data, so we looked as far back as 1980 to ensure that all activities in 2003 or later were considered. We filtered the FACTS dataset to a limited subset of activities representing fuels management. Specifically, we identified 97 (of 483) activity types representing fuels management (including prescribed fire, mechanical, and manual fuel reduction) and excluded wildfire and non-fuels management activities like planting or surveys, as well as low-impact and spatially broad activities like Christmas tree harvests (personal communication, S. Coppeto and T. Moore; see Table S.1 for full list of the 97 activity codes used). In cases where there was no recorded completion date, we noted the year of the award (i.e. the financial allocation, and the most recent of the two fields "award date" and "date award" if both were filled). Finally, we projected the filtered polygon fuels management layer to match the Mortality Magnitude Index (MMI) rasters describing canopy cover change (described in the following section).

2.3 Wildfire data and MMI prep

We mapped wildfire severity for the Sierra Nevada and Southern California study regions from 2000 to 2022. We used the random forest model developed by Parks et al. (2019) within Google Earth Engine (Gorelick et al. 2017) to predict a field-based metric of fire severity, the composite burn index (CBI), at a 30 m resolution. CBI characterizes the effects of fire on soils and vegetation on a continuous scale from 0 to 3 (unburned/unchanged to high-severity; Key and Benson 2006) and can be modeled as a function of several pre- and post-fire Landsat spectral indices, climate, and latitude (Parks et al. 2019). Specifically, we predicted CBI within wildfire perimeters ≥ 4 ha (Cova et al. 2023) obtained from the CAL FIRE Fire and Resource Assessment Program's historical fire perimeters geodatabase (CAL FIRE 2024).

We downloaded tiled annual 30 m rasters of MMI from the eDaRT system for Landsat processing (Koltunov et al. 2020, Slaton et al. 2025). Briefly, MMI represents an estimate of canopy cover loss as a proportional area within each 30 m pixel. Although the MMI is computed on an annual basis and MMI values are associated with the total canopy cover loss associated with a mortality event in the given year, in some instances MMI incorporates change over two years (e.g. where clear Landsat images were not available nearer in time to a discrete disturbance's timing). Importantly, the canopy cover loss conveyed by MMI could represent a variety of causes, including fire, fuels management, drought, disease, insect damage, windthrow, etc. We will henceforth refer to all disturbances other than fire and fuels management as drought, and while we acknowledge that some of these disturbed areas were not due to drought, we assumed that the majority of them were, based upon known – and often-times severe –

drought impacts documented in Calfornia, especially during 2004-2006 and 2014-206, and subsequent resulting insect and disease damag. Pixels were excluded from the analysis in cases where 1) the MMI could not be computed in the eDaRT algorithm (e.g. too few clear images were available in the search windows before and after disturbance to calculate change), 2) the pixel was burned in that or the previous 3 years (i.e. had a categorized CBI score of 0-3; essentially any pixel that fell within a fire polygon), and thus would already be categorized as "fire" and not need to be further analyzed using MMI. MMI pixels with a value < 10 were also excluded, since these low scores reflect relatively small changes in the canopy less likely to be driven by the major drivers of change of interest to us. Tiled MMI rasters were mosaicked and snapped to align with a tile in the center of each study area (Sierra Nevada or Southern California) by taking the maximum MMI value of each pixel in the areas where they overlapped. Finally, we clipped the mosaiced MMI raster for each year to the 10 km buffered study area.

2.4 FACTS fuels management temporal and spatial accuracy

In order to assess the spatiotemporal accuracy of the FACTS fuels management polygons, we first defined areas with clustered and substantial canopy cover loss in the northern portion of our study area (areas with comparatively less drought mortality to best isolate fuels management) annually from 2004-2022. For simplicity, we will refer to these high canopy change clusters as HCC clusters henceforth. While not all fuels management is visible in imagery or the MMI product, we reasoned that areas of clustered high MMI values would most often be associated with fuels management activities, which typically remove canopy cover within targeted continuous stands with distinct boundaries. To generate the HCC clusters, we first identified pixels with MMI > 20% (e.g. pixels with substantial canopy cover loss). We then used a 5x5 cell neighborhood to identify pixels where at least 60% (15/25) of pixels in the neighborhood had high canopy cover loss. We chose these relatively high thresholds to ensure that extraneous noise / drought in the MMI layers from one year to the next was eliminated and that most HCC clusters visually aligned with existing fuels management polygons (using NAIP imagery). Finally, we merged pixels that were orthogonally contiguous into patches and removed any patches < 0.9 ha (10 pixels) in area.

To assess the temporal accuracy of FACTS fuels management data, we compared the area where HCC clusters overlapped FACTS fuels management polygons, checking for HCC cluster area from five years before to five years after the reported completion year (e.g. activity date). We chose a five-year window around this date to include potential misreporting, as well as activities that took multiple years to complete. We thus compared HCC clusters from 2004-2022 that overlapped completion years from 2009-2017 (254 km^2). We then examined this distribution and determined a suitable temporal window, based on the FACTS completion date, that captured the majority of this change. We used that temporal window to guide further analyses and shape fuels management areas in our ultimate disturbance dataset.

To assess the spatial accuracy of FACTS fuels management polygons (and other fuels management activities), we visually examined NAIP imagery overlapping any instance where HCC clusters did not overlap probable FACTS fuels management (using the temporal window discussed in the previous paragraph). We wanted to focus this analysis on areas with relatively minimal drought (reasoning that drought could create these HCC clusters outside FACTS fuels management polygons, and these instances were not a relevant factor in this sub-analysis). We therefore performed this HCC cluster check for the northern 30% of the Sierra Nevada study area in 2013, 2015, and 2017 (covering 9,636 km^2 of the following counties: Butte, Lassen, Nevada, Plumas, Shasta, Sierra, Tehama, and Yuba). We deleted any high change area that overlapped a FACTS fuels management polygon with a completion date between one year before to two years after the year of change (based on the results from the analyses described in the previous paragraph). We then visually compared 1 m NAIP imagery (available every two years) before and after the year of the HCC cluster and classified the cluster's disturbance type as 1) edge, 2) drought, 3) open (i.e. non-forest), 4) wildfire, or 5) fuels management. We defined the HCC cluster as edge when it appeared to be a fuels management activity that extended from either a) the edge of USFS ownership or b) the edge of a FACTS polygon, indicating inaccurate treatment boundary mapping. The HCC cluster was classified as a) confirmed drought when red stage or needle drop was visible in the NAIP at the site of the HCC cluster or b) presumed drought when no disturbance was visible in the NAIP. These two subcategories were both considered to be drought. We classified areas as open when the area appeared to be grass, shrub, or rock in the NAIP. Although eDaRT does detect disturbances in non-forest areas, MMI is specifically calibrated for tree canopy cover loss. Because these regions had relatively few open areas, we assumed that errors resulting from these in the final dataset would be minimal. While recently burned areas should have been eliminated from potential HCC clusters, wildfire perimeters were not always accurately mapped, and we included this as a category after we noticed a few instances in the dataset where wildfire extended beyond the mapped boundaries. Finally, if the NAIP showed fuels management where there was no FACTS record (within the five-year temporal buffer), we noted whether it was a) shrub mastication or b) forest management. We also visually examined the spatial accuracy around boundaries of both USFS ownership and FACTS fuels management polygons to determine whether any additional spatial inaccuracies were present that were not captured by the HCC clusters. We performed an additional exploratory analysis to gain insight into an appropriate timeframe and method for fuels management polygons with missing completion dates in the FACTS database (Supplementary Material).

2.5 Annual disturbance compilation and assessment

We compiled fire, fuels management, and drought, and summarized disturbance area annually across 20 years for the Sierra Nevada and Southern California. Note that because the FACTS database only included USFS fuels management activities, we were only able to map disturbance on USFS land. When compiling the different disturbance types, fire took precedence (i.e. we classed any burned pixel in a given year as burned, even if that pixel also underwent fuels management, thus assuming that the primary disturbance agent in that pixel in that year would be fire). Similarly, we only determined drought for pixels that had neither burned nor undergone fuels management. Importantly, for this compilation, a given disturbance of each type spanned four years to capture either a) the temporal breadth of the disturbance, or b) the temporal uncertainty of the disturbance, explicitly for fuels management. This manifested as a lag after fire and drought to account for secondary fire effects or a prolonged period of drought and a temporal envelope around fuels management dates to account for both the temporal uncertainty associated with FACTS and fuels management activities that were implemented across multiple years. Because the span was four years across all three disturbance types, we were comfortable comparing the relative area of each disturbance type on the landscape across time.

We categorized the severity of burned pixels using the CBI scores described in section 2.3, where pixels with CBI ≥ 2.25 were classified as high severity fire, and pixels with CBI 0-2.25 were classified as low-moderate severity (Miller & Thode, 2007). Note that while a CBI score of 0 equates to unburned/very low severity areas within a fire perimeter, we wanted to err on the side of caution and attribute any potential disturbance within these areas to fire as opposed to other factors (like fuels management or drought). To account for secondary fire effects after the year of the fire (e.g. delayed tree mortality due to injury from the fire), we assigned a three-year lag period for any burned pixel of a given severity class. For instance, we classified a pixel that burned at high severity in 2010 as high severity in 2010-2013.

Because the results from the analyses described in section 2.4 did not provide a definitive path forward in terms of how to identify fuels management and drought, we calculated each disturbance type based on two disturbance scenarios (Fig. 1). We designated a maximum and minimum disturbance scenario using different methodologies to assess the importance of choosing one methodology over another. The minimum disturbance scenario only used fuels management polygons with a completion date (using the span of two years before to one year after the completion date; Fig. 1). Conversely, in the maximum disturbance scenario, we used fuels management polygons regardless of whether a completion date was entered in the FACTS database. When the completion date field was blank, we used a temporal range from the year of the award to three years thereafter. Also see Fig. S1 for a more detailed breakdown of the input data and decisions used to assess the FACTS data alone.

In the maximum disturbance scenario, we determined drought for any pixel that neither burned nor had fuels management in a given year. In the minimum disturbance scenario, we further excluded any pixels within 50 m of either a USFS ownership boundary or a fuels management polygon. In either case, if a pixel had an MMI > 10% in the given year, we classified it as drought and applied a three-year lag period so that the pixel remained “drought” for four years. Examples of the resulting disturbance types on NAIP imagery are shown in Fig. S2.

We first calculated the annual area affected by each disturbance type under the maximum and minimum scenarios to evaluate the range between the two scenarios, the trends of each disturbance type across the 20-year span, and the relative magnitude of each disturbance in relation to the other disturbance types. Because the difference between the two scenarios was minimal across the disturbance types and the two study areas, we used the maximum disturbance scenario to track cumulative disturbed area across time and to map each disturbance type and all disturbances across the full 20-year span.

3. Results

3.1 FACTS fuels management temporal and spatial accuracy

Across 254 km^2 of HCC clusters (2009-2017; Fig. 2a) that overlapped FACTS fuels management polygons within five years of the reported completion date, only 157 km^2 (62%) of the changed area (as determined using annual summaries of remote sensing detection methods) occurred on the same year of FACTS-reported completion (Fig. 2b). An additional 49 km^2 (19%) and 15 km^2 (6%) of HCC cluster area occurred one and two years before the completion year, respectively, and 10 km^2 (4%) of HCC cluster area occurred in the year after the completion year. In summary, within a four-year period (from two years before to one year after the fuels management completion year), 91% of HCC cluster area was accounted for by fuels management polygons (Fig. 2b).

Across 2013, 2015, and 2017, there was 42.9 km^2 of HCC cluster area total (overlapping FACTS fuels management polygons and not overlapping them). Clusters that overlapped FACTS polygons using the above four-year temporal window accounted for 35.7 km^2 (83%) of that total HCC cluster area. Of the remaining 7.2 km^2 (17%; 156 individual HCC clusters) that did not overlap FACTS fuels management polygons, drought accounted for the majority (85.6%) of unaccounted HCC cluster area (i.e. not overlapping with FACTS; Table S.2), and edge accounted for 3.6% of HCC cluster area, including fuels management that was not fully contained by the FACTS polygon. A similarly small proportional area (3.9%) was due to obvious fuels management activity that was not present in the FACTS dataset, although some of these were captured by FACTS fuels management polygons with dates outside the four-year span or missing dates. Other cases were completely absent from the FACTS dataset, though this was due to recent USFS land acquisition in at least one instance. The remaining categories also represented minimal area, with 5% and 1.9% of unaccounted for HCC cluster area occurring in unforested areas and mis-mapped wildfire area, respectively. In summary, across 42.9 km^2 of HCC cluster area, 83.2% overlapped with FACTS fuels management, 1.3% (0.5 km^2) was visually confirmed to be fuels management area not captured by our methods, 14.4% was drought, and 1.1% was misclassified for other reasons.

To estimate the relative rate of fuels management misclassification, we compared the proportion of HCC cluster area that did not overlap with FACTS fuels management polygons (using the four-year temporal window) and was visually determined to be fuels management (0.5 km^2) to the total fuels management HCC cluster area over the same area and timeframe (0.5 km^2 + 35.7 km^2 HCC cluster area that overlapped with FACTS fuels management polygons using the four-year temporal window). This yielded a 1.5% misclassification rate where fuels management would have been misclassified as drought.

3.2 Annual disturbance compilation and assessment

The difference between the maximum and minimum disturbance scenarios was narrow for nearly all disturbance types across both study areas (Fig. 4). The only exception was for drought in Southern California between 2003 and 2008. Overall temporal trends show drought pulses in 2007 and 2016 in the Sierra Nevada and 2015 in Southern California. Wildfire area also fluctuated, with a marked rise in burned area in the Sierra Nevada in 2020-2022. Fuels management was relatively constant from one year to the next, and generally the least prevalent driver of forest change. Fuels management varied between 2 and 4% of the land area each year in the Sierra Nevada, but was less than 2% each year in Southern California.

When we compiled disturbance across 20 years (2003-2022), 69% of USFS lands were disturbed across the Sierra Nevada and Southern California (~25,000 km^2 total; Fig. 5a; Table 1). Broken down by each disturbance type on USFS land, fire of any type burned 17,204 km^2 (51% of the total area and 69% of the total disturbed area; Fig. 5b; Table 1). Of that area, severe fire burned 7,343 km^2 (22% of the total area and 29% of disturbed area) and low/moderate severity fire burned 10,966 km^2 (32% of the total area and 44% of disturbed area; Fig. 5b; Table 1). Note that different disturbance types overlapped, and some areas burned in different fires at both high and low/moderate severity. Fuels management covered 3,472 km^2 (10% of the total area and 14% of disturbed area; Fig. 5c; Table 1), and drought impacted 12,813 km^2 (38% of the total area and 51% of disturbed area; Fig. 5d; Table 1).

4. Discussion

We produced a synthetic dataset of disturbances across 34,000 km^2, using existing data products collected by the USFS and derived from remote sensing. Using this synthetic dataset, we showed that substantial disturbances have occurred on USFS land over time and that the area affected by fire and drought far exceeds the area under active fuels management. Our method overcomes previous challenges of vetting and parameterizing uncertainty in one of the input datasets (FACTS) and combines the different disturbance types into one cohesive product. This product offers a resource for researchers and forest managers to investigate spatial and temporal disturbance trends, including their interaction, and the relationship of reported forest management activities to detectable changes on the landscape.

4.1 FACTS data can be a reliable fuels management data source

These analyses improve our understanding of the uncertainty and limitations of the FACTS database and indicate that with appropriate treatment of the data with the recommendations provided here, FACTS can be a reliable data set for tracking fuels management. Knight et al. (2022) examined some inaccuracies in the FACTS dataset that align with our findings. For instance, they found that disturbance was detected by remote sensing within about half of FACTS polygons across an eight-year timespan, and that the median difference in timing between the award year and the change in the remote sensing was 0 years. However, their investigation did not focus on exploring treatment timing in further detail (such as the temporal distribution of fuels management when it was not the same year as that reported) or exploring possible instances of fuels management that were more than 300 m beyond the borders of FACTS polygons. Similar to Knight et al. (2022), we found that the majority (62%) of fuels management detected by remote sensing appeared to occur on the completion year (often the same as the award year). While we did find some fuels management areas that were not represented in FACTS, these were minimal (1.5% of HCC cluster fuels management area) when a four-year temporal buffer was applied one year before to two years after the reported completion year.

One of our aims was to extend the applicability of the work done by Knight et al. (2022) in generating a robust fuels management spatial dataset. Specifically, we completed additional spatiotemporal assessment and filtering of the FACTS data to improve its applicability and robustness as a data product, and we combined the fuels management spatial data with additional disturbances to create a synthetic multi-disturbance dataset. Furthermore, our product offers some additional end-user flexibility in that a scientist or manager could tailor how they use the FACTS data depending on the magnitude of spatial and temporal error acceptable for their study design. For instance, if the objective was to isolate any area with moderate temporal resolution where canopy change could have been due to USFS fuels management (and not another disturbance agent), a four-year span (two years before to one year after the FACTS completion date) paired with a buffer around fuels management polygon boundaries would capture the majority of fuels management activity. If the objective was to identify areas where change could be attributable to drought, blocking out the above areas, as well as burned areas and any canopy change within a buffer around non-USFS ownership would help to exclude any areas affected by other disturbance types.

Although it may not be intuitive as to why the fuels management temporal buffer would extend a year beyond the completion date, we suspect that this was due more to a temporal mismatch between the

MMI and FACTS datasets as opposed to fuels management activities occurring after reported completion. Because the MMI data estimated canopy cover change between one growing season and the next, any fuels management that occurred in the fall or winter of a given year would not be detected by MMI until the following year. Therefore, if MMI (or similar remote sensing technology that detects change primarily from one growing season to the next) is being used in conjunction with FACTS, we advise users to accommodate this temporal mismatch by 1) attributing any detected change up to a year after fuels management completion to fuels management, as opposed to another disturbance type, or 2) instead of utilizing just the year, as we did in this analysis, utilizing the time of year of fuels management completion.

4.2 Disturbance trends on USFS lands over two decades

Our compilation of disturbances showed that 69% of USFS land area in the Sierra Nevada and Southern California has experienced wildfire, fuels management, drought, or a combination of disturbances across 20 years. Additionally, trends between the different disturbance types across time emerged, including an oscillating pattern of drought and wildfire. While this broad pattern is not surprising, these data facilitate analyses that examine more complex relationships between the spatial and temporal patterns of disturbance and their relationship to the flora and fauna of different landscapes. An examination of the 31% of the landscape that was not disturbed during this timeframe would also be insightful, revealing either potential disturbance refugia or areas that have sufficient fuel accumulation to be at higher risk of disturbance in the coming years.

In order to improve the utility of this product and workflow, we have published the code that generates the disturbance layers, as well as the annual disturbance rasters for the Sierra Nevada and Southern California at ___________________________. Base data needed to generate these disturbance layers are available for the state of California, though MMI does not extend to other states at this time. Also note that while MMI has been validated, it may be less accurate in predicting canopy change in certain areas, but see (Slaton et al. 2025). As part of our code, we embedded the MMI values associated with each disturbance type for each pixel for each year, which could allow a user to estimate relative disturbance intensity. While we did not examine MMI explicitly in its ability to determine disturbance intensity for either fuels management or drought, greater canopy cover loss associated with these disturbance types, should be reflected by more intense disturbance in the MMI. For instance, a preliminary investigation indicated higher MMI in treatment activity types that had more intense fuel reduction, including group selection and commercial thin activities (Fig. S3). While we encourage additional testing in this area, these findings suggest that relative intensity of fuels management or drought / other disturbances could be determined from this dataset. This dataset also incorporates salvage logging as a disturbance type at two different confidence levels.

4.3 Alignment with other research

While not strictly comparable, Asner et al. (2015) found that 10,000 km^2 of California forests experienced severe canopy water loss during the 2012-2015 drought, which is similar to our estimate of 12,813 km^2 of substantial canopy loss due to drought and other factors from 2003 to 2022 in the Sierra Nevada and Southern California. This recent drought killed a higher proportion of large trees that are important for both wildlife habitat and future wildfire resilience, and the effects of drought may be accelerating a species type conversion (Fettig et al. 2019).

Unsurprisingly, our results regarding the extent of severe wildfire were similar to previous studies, including larger fires overall (Cova et al. 2023, Westerling et al. 2006) and a high proportion of severely burned area on USFS land (Stevens et al. 2017) compared to the area burned at low or moderate severity. Similar to findings by Steel et al. (2023), drought and fire covered greater extents than mechanically treated area. Abatzoglou et al. (2021) predicted that burned area will continue to increase in the coming decades, with fire effects potentially amplified by drought through feedback loops. These findings corroborate arguments of many that the pace and scale of fuels management is slow and insufficient to prevent the loss of forest ecosystems in the face of climate change (Stephens et al. 2020, North et al. 2015). Part of the challenge of implementing fuels management has been uncertainty as to how these management actions, as well as in combination with other disturbance types, will affect native species and these ecosystems overall.

Many studies have examined how these disturbance types individually affect rare species or species communities, but few studies have considered multiple disturbance types as a complex spatiotemporal mosaic, perhaps in part due to the absence of a comprehensive data source. For instance, many researchers have examined the effects of fire (severity, spatial configuration, and patch size) on California spotted owls (*Strix occidentalis*), and found that they avoid large, severely burned patches for many years after fire, yet smaller high severity patches and low and moderate severity fire were not avoided by owls (Kramer et al. 2021, Jones et al. 2021, Roberts et al. 2011). Roberts et al. (2019) examined the effects of drought on the avian community and found that some species declined, while others increased. Stephens et al. (2014) showed that while many animal species were not affected by fuels management, California spotted owl occupancy declined. Pyrodiversity is a metric that captures the spatiotemporal aspects of fire, and Tingley et al. (2016) demonstrated a link between pyrodiversity and biodiversity, yet no such metric currently exists for disturbance overall. Steel et al. (2023) examined these different disturbance types in tandem in Southern California using the Knight et al. (2022) data to attribute declines in canopy cover and tall trees to different disturbance agents and predicted that more homogeneous disturbances, combined with the mortality of larger trees, would negatively impact habitat for old-forest specialists like the California spotted owl and fisher (*Pekania pennanti*), yet they did not have data on the movement or occupancy of these species. The comprehensive dataset that we developed here, combined with species distribution and movement information, can facilitate more nuanced investigations of the effects of these disturbances on biodiversity.

4.4 Management implications

Our findings will facilitate forest management and science in at least two important ways; (1) by demonstrating how the FACTS database can be integrated with remotely sensed data to accurately map fuels management history and drivers of forest disturbance; and (2) via our compilation of common disturbances into a fine-scale (30 m) series of annual rasters. The FACTS database holds vast and detailed data on USFS activities, yet it has been underutilized within and outside the agency due to uncertainties around its accuracy, how to appropriately incorporate this uncertainty into analyses, and the unwieldy size of the dataset. Here, we suggest ways to organize, filter, and buffer the data based on a potential user's objectives. Beyond FACTS, the disturbance rasters we compiled have a fine spatial (30 m) and temporal (annual, starting in 2003) scale, and could be utilized for numerous purposes. Some potential uses include 1) monitoring change across time in a given area (as we did here), 2) modeling how different disturbances (including salvage logging and disturbance intensity) influence forest structure or wildlife occupancy or habitat, and 3) planning study designs or reserves based on different disturbance histories or spatial patterns. For instance, these data are already being used to model spotted owl occupancy is effected by the different disturbance types (Ng et al. in review), attributing changes in spotted owl habitat to each disturbance type (Barry et al. in review), and weighing the slight decline in habitat after intense fuels management against the gains in habitat resilience in the face of wildfire when fuels management precedes wildfire, both in general and in the context of the spotted owl (McGinn et al. in review).

In summary, these ecosystems, as well as many areas around the globe, are changing in multifaceted ways and at an accelerating pace. Many have argued that the pace and scale of restoration efforts is too slow, and that we risk losing some of these species and ecosystems if we continue the status quo (Stephens et al. 2020, North et al. 2015). The slow speed of restoration is due, in part, to a lack of research on the effects of these disturbances on these systems and species, but in order to do this, scientists first need a comprehensive dataset that captures the facets of those disturbances, and we hope that this dataset can serve that purpose.

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References

Abatzoglou, John T, David S Battisti, A Park Williams, Winslow D Hansen, Brian J Harvey, and Crystal A Kolden. 2021. "Projected increases in western US forest fire despite growing fuel constraints." *Communications Earth & Environment* 2 (1):227.

Allen, Craig D, Alison K Macalady, Haroun Chenchouni, Dominique Bachelet, Nate McDowell, Michel Vennetier, Thomas Kitzberger, Andreas Rigling, David D Breshears, and EH Ted Hogg. 2010. "A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests." *Forest ecology and management* 259 (4):660-684.

Asner, Gregory P, Philip G Brodrick, Christopher B Anderson, Nicholas Vaughn, David E Knapp, and Roberta E Martin. 2015. "Progressive forest canopy water loss during the 2012–2015 California drought." *Proceedings of the National Academy of Sciences* 113 (2):E249-E255.

Baumann, Matthias, Mutlu Ozdogan, Peter T Wolter, Alexander Krylov, Nadezda Vladimirova, and Volker C Radeloff. 2014. "Landsat remote sensing of forest windfall disturbance." *Remote sensing of environment* 143:171-179.

Bond, William J, and Jon E Keeley. 2005. "Fire as a global 'herbivore': the ecology and evolution of flammable ecosystems." *Trends in ecology & evolution* 20 (7):387-394.

Burton, Philip J, Anke Jentsch, and Lawrence R Walker. 2020. "The ecology of disturbance interactions." *BioScience* 70 (10):854-870.

CAL FIRE. 2024. "Fire and Resource Assessment Program." accessed August 12. http://frap.fire.ca.gov/.

Coop, Jonathan D, Sean A Parks, Camille S Stevens-Rumann, Shelley D Crausbay, Philip E Higuera, Matthew D Hurteau, Alan Tepley, Ellen Whitman, Timothy Assal, and Brandon M Collins. 2020. "Wildfire-driven forest conversion in western North American landscapes." *BioScience* 70 (8):659-673.

Cova, Gina, Van R Kane, Susan Prichard, Malcolm North, and C Alina Cansler. 2023. "The outsized role of California's largest wildfires in changing forest burn patterns and coarsening ecosystem scale." *Forest Ecology and Management* 528:120620.

Crockett, Joseph L, and A Leroy Westerling. 2018. "Greater temperature and precipitation extremes intensify Western US droughts, wildfire severity, and Sierra Nevada tree mortality." *Journal of Climate* 31 (1):341-354.

Diaz, Vitali, Gerald A Corzo Perez, Henny AJ Van Lanen, Dimitri Solomatine, and Emmanouil A Varouchakis. 2020. "An approach to characterise spatio-temporal drought dynamics." *Advances in Water Resources* 137:103512.

Eidenshink, Jeff, Brian Schwind, Ken Brewer, Zhi-Liang Zhu, Brad Quayle, and Stephen Howard. 2007. "A project for monitoring trends in burn severity." *Fire ecology* 3 (1):3-21.

Fettig, Christopher J, Leif A Mortenson, Beverly M Bulaon, and Patra B Foulk. 2019. "Tree mortality following drought in the central and southern Sierra Nevada, California, US." *Forest ecology and management* 432:164-178.

Gao, Yan, Margaret Skutsch, Jaime Paneque-Gálvez, and Adrian Ghilardi. 2020. "Remote sensing of forest degradation: a review." *Environmental Research Letters* 15 (10):103001.

Gorelick, Noel, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore. 2017. "Google Earth Engine: Planetary-scale geospatial analysis for everyone." *Remote sensing of Environment* 202:18-27.

Hagmann, RK, PF Hessburg, SJ Prichard, NA Povak, PM Brown, PZ Fulé, RE Keane, EE Knapp, JM Lydersen, and KL Metlen. 2021. "Evidence for widespread changes in the structure, composition, and fire regimes of western North American forests." *Ecological Applications* 31 (8):e02431.

Jarron, Lukas R, Nicholas C Coops, William H MacKenzie, Piotr Tompalski, and Pamela Dykstra. 2020. "Detection of sub-canopy forest structure using airborne LiDAR." *Remote Sensing of Environment*:111770.

Jones, Gavin M, H Anu Kramer, William J Berigan, Sheila A Whitmore, R.J. Gutierrez, and M Zachariah Peery. 2021. "Megafire causes persistent loss of an old-forest species." *Animal Conservation*. doi: https://doi.org/10.1111/acv.12697.

Kittredge Jr, David B, Andrew O Finley, and David R Foster. 2003. "Timber harvesting as ongoing disturbance in a landscape of diverse ownership." *Forest Ecology and Management* 180 (1-3):425-442.

Knight, Clarke A, Ryan E Tompkins, Jonathan A Wang, Robert York, Michael L Goulden, and John J Battles. 2022. "Accurate tracking of forest activity key to multi-jurisdictional management goals: A case study in California." *Journal of Environmental Management* 302:114083.

Koltunov, Alexander, Carlos M Ramirez, Susan L Ustin, Michèle Slaton, and Erik Haunreiter. 2020. "eDaRT: The Ecosystem Disturbance and Recovery Tracker system for monitoring landscape disturbances and their cumulative effects." *Remote Sensing of Environment* 238:111482.

Kramer, Anu, Gavin M Jones, Sheila A Whitmore, John J Keane, Fidelis A Atuo, Brian P Dotters, Sarah C Sawyer, Sarah L Stock, RJ Gutiérrez, and M Zachariah Peery. 2021. "California spotted owl habitat selection in a fire-managed landscape suggests conservation benefit of restoring historical fire regimes." *Forest Ecology and Management* 479:118576.

Leverkus, Alexandro B, Simon Thorn, Lena Gustafsson, Reed Noss, Jörg Müller, Juli G Pausas, and David B Lindenmayer. 2021. "Environmental policies to cope with novel disturbance regimes–steps to address a world scientists' warning to humanity." *Environmental Research Letters* 16 (2):021003.

North, MP, SL Stephens, BM Collins, JK Agee, G Aplet, JF Franklin, and PZ Fulé. 2015. "Reform forest fire management." *Science* 349 (6254):1280-1281.

Öllerer, Kinga, Anna Varga, Keith Kirby, László Demeter, Marianna Biró, János Bölöni, and Zsolt Molnár. 2019. "Beyond the obvious impact of domestic livestock grazing on temperate forest vegetation–A global review." *Biological Conservation* 237:209-219.

Parks, Sean A, and John T Abatzoglou. 2020. "Warmer and drier fire seasons contribute to increases in area burned at high severity in western US forests from 1985 to 2017." *Geophysical Research Letters* 47 (22):e2020GL089858.

Parks, Sean A, Lisa M Holsinger, Michael J Koontz, Luke Collins, Ellen Whitman, Marc-André Parisien, Rachel A Loehman, Jennifer L Barnes, Jean-François Bourdon, and Jonathan Boucher. 2019. "Giving ecological meaning to satellite-derived fire severity metrics across North American forests." *Remote Sensing* 11 (14):1735.

Parry, Simon, Christel Prudhomme, Robert L Wilby, and Paul J Wood. 2016. "Drought termination: Concept and characterisation." *Progress in Physical Geography* 40 (6):743-767.

Pickett, S. T. A., and P. S. White. 1985. *The ecology of natural disturbance and patch dynamics*. Orlando, FL: Academic Press.

Raffa, Kenneth F, Jean-Claude Grégoire, and B Staffan Lindgren. 2015. "Natural history and ecology of bark beetles." In *Bark beetles*, 1-40. Elsevier.

Roberts, L Jay, Ryan Burnett, James Tietz, and Sam Veloz. 2019. "Recent drought and tree mortality effects on the avian community in southern Sierra Nevada: a glimpse of the future?" *Ecological Applications* 29 (2):e01848.

Roberts, Susan L, Jan W van Wagtendonk, A Keith Miles, and Douglas A Kelt. 2011. "Effects of fire on spotted owl site occupancy in a late-successional forest." *Biological Conservation* 144 (1):610-619.

Slaton, Michèle R, Alexander Koltunov, Kirk Evans, Tanya Kohler, and Laura Young-Hart. 2025. "Estimating canopy cover loss with Landsat dense time series: a Mortality Magnitude Index for the Ecosystem Disturbance and Recovery Tracker (eDaRT)." *International Journal of Remote Sensing* 46 (2):686-703.

Stahl, Amanda T, Robert Andrus, Jeffrey A Hicke, Andrew T Hudak, Benjamin C Bright, and Arjan JH Meddens. 2023. "Automated attribution of forest disturbance types from remote sensing data: A synthesis." *Remote Sensing of Environment* 285:113416.

Steel, Zachary L, Gavin M Jones, Brandon M Collins, Rebecca Green, Alexander Koltunov, Kathryn L Purcell, Sarah C Sawyer, Michèle R Slaton, Scott L Stephens, and Peter Stine. 2023. "Mega-disturbances cause rapid decline of mature conifer forest habitat in California." *Ecological Applications* 33 (2):e2763.

Stephens, S. L., J. K. Agee, P. Z. Fulé, M. P. North, W. H. Romme, T. W. Swetnam, and M. G. Turner. 2013. "Managing Forests and Fire in Changing Climates." *Science (New York, N.Y.)* 342 (6154):41-42. doi: 10.1126/science.1240294.

Stephens, Scott L, Seth W Bigelow, Ryan D Burnett, Brandon M Collins, Claire V Gallagher, John Keane, Douglas A Kelt, Malcolm P North, Lance Jay Roberts, and Peter A Stine. 2014. "California spotted owl, songbird, and small mammal responses to landscape fuel treatments." *BioScience* 64 (10):893-906.

Stephens, Scott L, A LeRoy Westerling, Matthew D Hurteau, M Zachariah Peery, Courtney A Schultz, and Sally Thompson. 2020. "Fire and climate change: conserving seasonally dry forests is still possible." *Frontiers in Ecology and the Environment* doi:10.1002/fee.2218. doi: doi:10.1002/fee.2218.

Stevens, Jens T, Brandon M Collins, Jay D Miller, Malcolm P North, and Scott L Stephens. 2017. "Changing spatial patterns of stand-replacing fire in California conifer forests." *Forest Ecology and Management* 406:28-36.

Tingley, Morgan W, Viviana Ruiz-Gutiérrez, Robert L Wilkerson, Christine A Howell, and Rodney B Siegel. 2016. "Pyrodiversity promotes avian diversity over the decade following forest fire." *Proceedings of the Royal Society B: Biological Sciences* 283 (1840):20161703.

Turner, Monica G. 2010. "Disturbance and landscape dynamics in a changing world." *Ecology* 91 (10):2833-2849.

USDA Forest Service. 2024. Appendix B: FACTS Activity Codes.

USDA Forest Service. 2025. Download National Datasets.

Wayman, Rebecca B, and Hugh D Safford. 2021. "Recent bark beetle outbreaks influence wildfire severity in mixed-conifer forests of the Sierra Nevada, California, USA." *Ecological Applications* 31 (3):e02287.

Westerling, Anthony L, Hugo G Hidalgo, Daniel R Cayan, and Thomas W Swetnam. 2006. "Warming and earlier spring increase western US forest wildfire activity." *Science* 313 (5789):940-943.

Williams, A Park, Richard Seager, John T Abatzoglou, Benjamin I Cook, Jason E Smerdon, and Edward R Cook. 2015. "Contribution of anthropogenic warming to California drought during 2012–2014." *Geophysical Research Letters* 42 (16):6819-6828.

Young, Derek JN, Jens T Stevens, J Mason Earles, Jeffrey Moore, Adam Ellis, Amy L Jirka, and Andrew M Latimer. 2017. "Long-term climate and competition explain forest mortality patterns under extreme drought." *Ecology Letters* 20 (1):78-86.

Table 1. Summary of the USFS-owned land disturbed by different disturbance agents across two decades from 2003-2022.

	Southern California		Sierra Nevada		Total		
	Area km^2	proportion	Area km^2	proportion	Area km^2	proportion	proportion of disturbed area
Total pixels	14,046	1.000	19,871	1.000	33,917	1.000	NA
Any disturbance	10,647	0.758	14,429	0.726	25,075	0.739	1.000
Any fire	7,891	0.562	9,313	0.469	17,204	0.507	0.686
Severe fire	3,211	0.229	4,131	0.208	7,343	0.216	0.293
Low/moderate fire	5,277	0.376	5,689	0.286	10,966	0.323	0.437
Fuels management	685	0.049	2,787	0.140	3,472	0.102	0.138
Drought	5,395	0.384	7,417	0.373	12,813	0.378	0.511

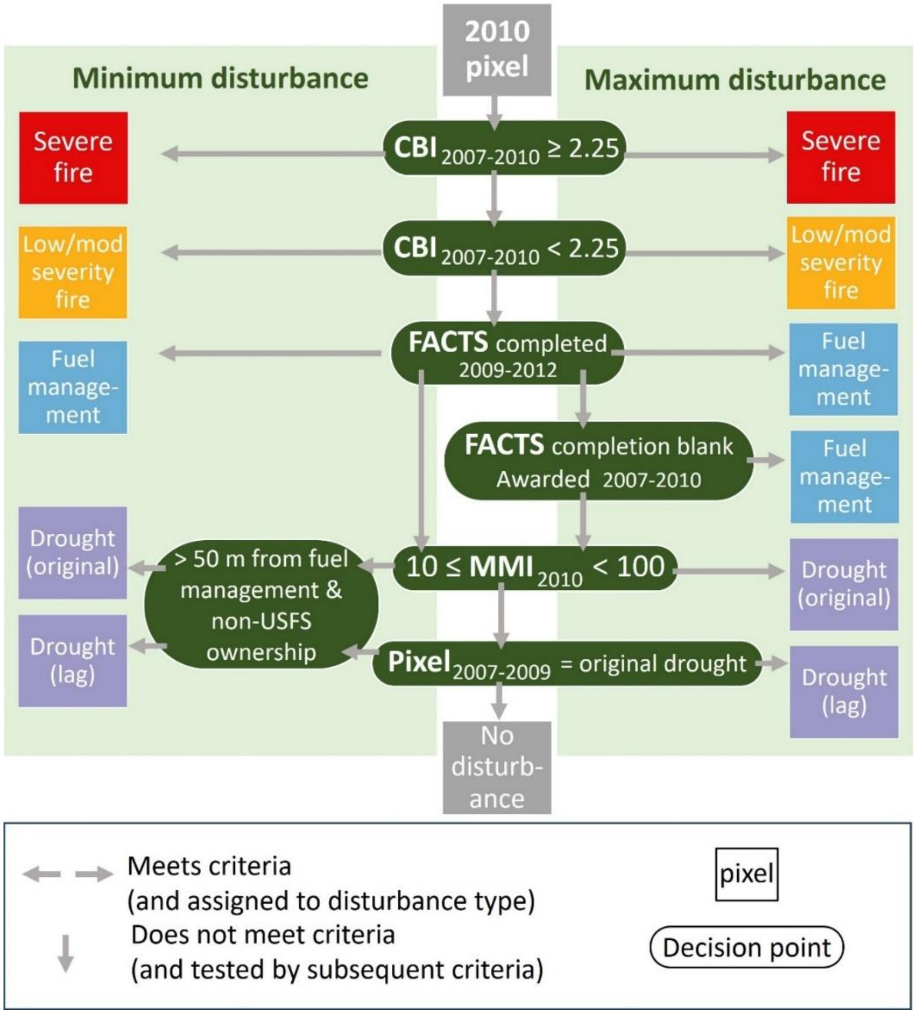

Figure 1. Decision tree for determining the disturbance type of an example pixel in 2010 under the minimum and maximum disturbance scenarios (light green boxes), based on the input data. The three main input datasets include the annual composite burn index (CBI), the USFS's Forest Activity Tracking System (FACTS), and the Mortality Magnitude Index (MMI). The unclassified pixel at the top is tested by a series of decision points (dark green ovals). If the pixel satisfies the condition of the decision point, it follows the arrows left and/or right (pertaining to the minimum and maximum disturbance scenarios, respectively) and is classified as the disturbance type in the square box. Otherwise, it continues down the decision tree to be tested by subsequent decision points. If it meets none of the criteria, it is classified as having no disturbance in the given year. Note that vertical arrows in the middle denote tests for both

disturbance scenarios, while arrows within the light green boxes are specific to the given disturbance scenario. Although drought is ultimately not classified into “original” (pertaining to drought in the given year) and “lag” (pertaining to drought classified in the preceeding three years), we included those terms here to clarify the workflow.

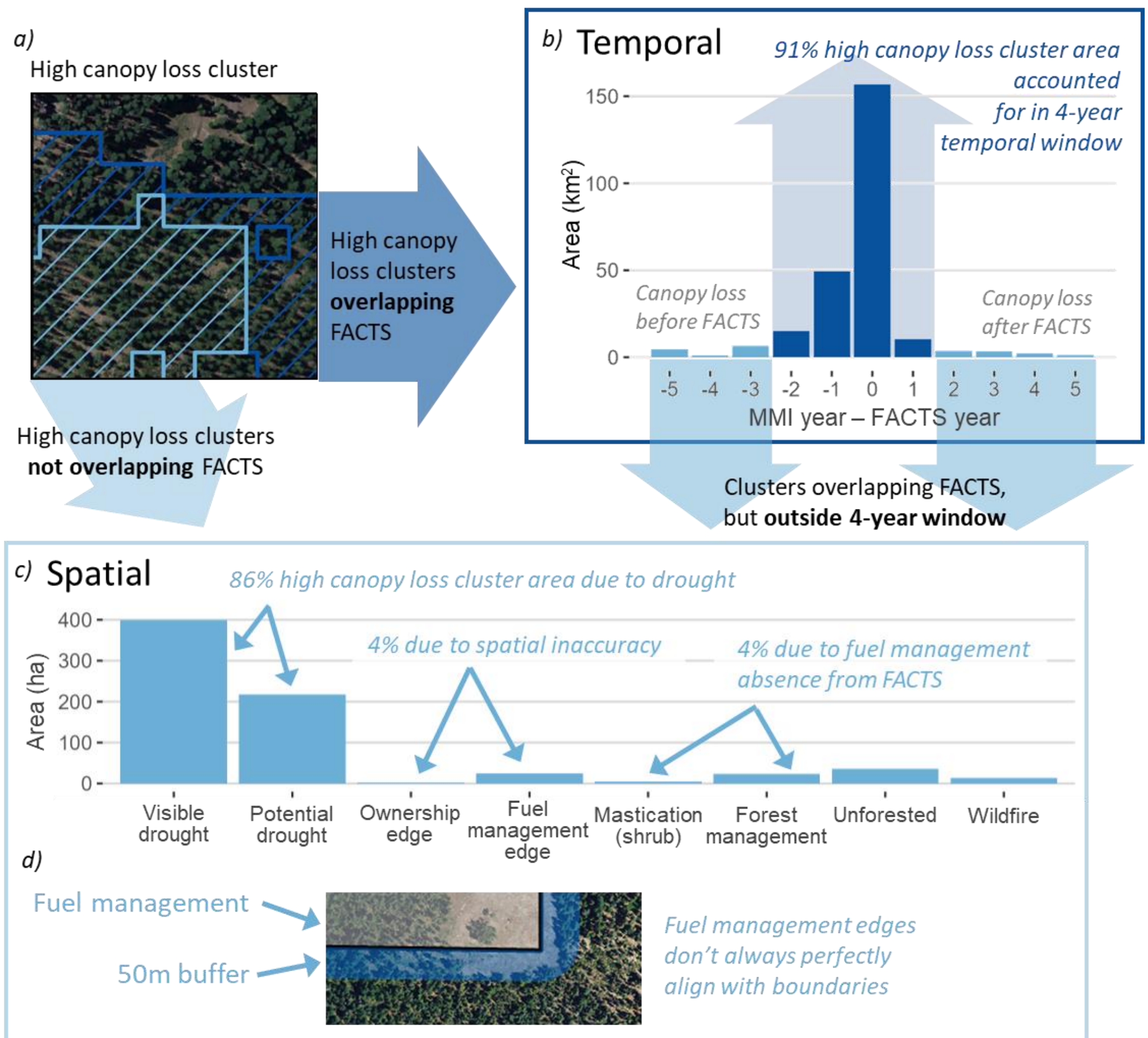

Figure 2. An example of a high canopy change cluster (HCC cluster) (a) illustrates the input data used for determining the (b) distribution of annual HCC cluster area in relation to the reported date of FACTS completion. For HCC cluster area that was not within a FACTS polygon (using the 4-year temporal window shown in dark blue: 2 years before to 1 year after the completion date), we determined the cause of change by visually examining NAIP imagery, summarized in the bar graph (c). Also note that there was often minor spatial inaccuracy (d) of forest management polygons and on USFS ownership boundaries that was insufficient to create an HCC cluster (often just one or two pixels wide).

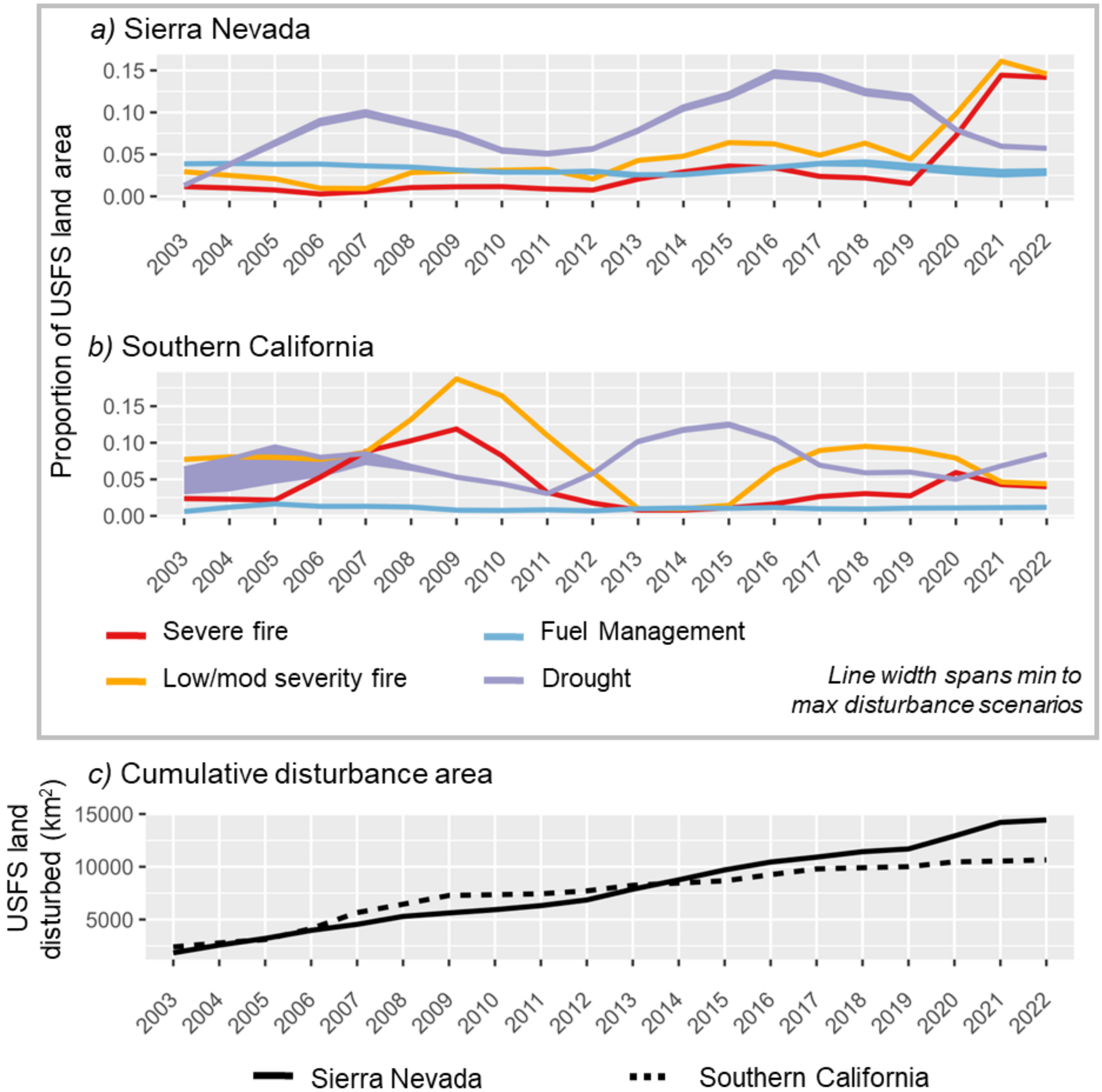

Figure 4. Proportion of the landscape affected by each disturbance type through time for (a) the Sierra Nevada (a), and Southern California (b). The line width represents the span between the minimum and maximum disturbance scenarios. Note that all four disturbance types span four years, so the relative heights of the lines in relation to one another, as well as over time, should represent the overall magnitude of that disturbance type on the landscape in comparison to the other disturbance types. We also display the cumulative disturbed area on USFS land (c) in the Sierra Nevada and Southern California study areas.

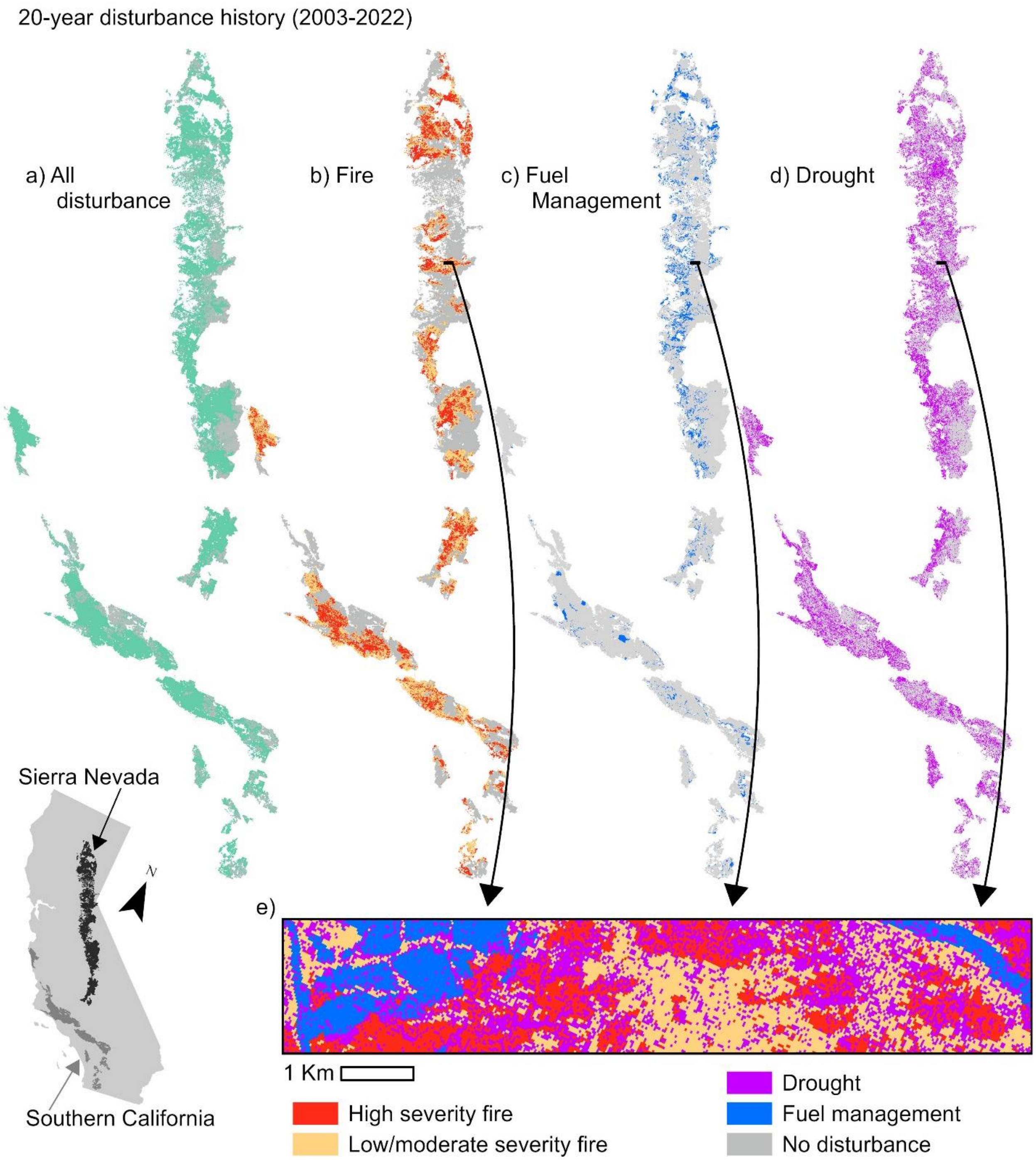

Figure 5. Maps of disturbances compiled across 20 years (2003-2022) in the Sierra Nevada and Southern California study areas using the maximum fuels management scenario (very similar in area and pattern to the minimum fuels management scenario. We display all disturbance types together (a), as well as wildfire (b), fuels management (c) and drought / other canopy mortality (d). We also show an inset map

(e) that is zoomed in to show the spatial characteristics of the different disturbance types; note that for the clearest view, the layers are displayed with drought on top, followed by fuels management, then fire.

Supplement

Table S.1 List of 97 activity codes (and descriptions) defined as "fuels management" that we considered for all analyses (out of 483 total activities).

Activity code	Activity description
1102	Landing Treated - Area Mitigated
1111	Broadcast Burning - Covers a majority of the unit
1112	Jackpot Burning - Scattered concentrations
1113	Underburn - Low Intensity (Majority of Unit)
1120	Yarding - Removal of Fuels by Carrying or Dragging
1130	Burning of Piled Material
1136	Pruning to Raise Canopy Height and Discourage Crown Fire
1139	Grazing and Range Mgt. for Hazardous Fuels Reduction
1150	Rearrangement of Fuels
1152	Compacting/Crushing of Fuels
1153	Piling of Fuels, Hand or Machine
1154	Chipping of Fuels
1160	Thinning for Hazardous Fuels Reduction
1180	Fuel Break
2000	Range Grazing Systems
2341	Range Cover Manipulation
2360	Range Control Vegetation
2370	Range Piling Slash
2510	Invasive - Pesticide Application
2530	Invasive - Mechanical/Physical
2540	Invasive - Cultural/Fire
2560	Invasive - Biocontrol, Livestock
3132	Recreation Removal of hazard trees and snags - Area
3340	Visual Resource Prescribed burning
3370	Precommercial thinning for visual
3380	Visual Resource Slash treatment
4101	Coppice Cut (EA/RH/FH)
4102	Coppice Cut (w/leave trees) (EA/RH/FH)
4111	Patch Clearcut (EA/RH/FH)
4113	Stand Clearcut (EA/RH/FH)
4115	Patch Clearcut (w/ leave trees) (EA/RH/FH)
4117	Stand Clearcut (w/ leave trees) (EA/RH/FH)
4121	Shelterwood Preparatory Cut (EA/NRH/NFH)
4122	Seed-tree Preparatory Cut (EA/NRH/NFH)
4131	Shelterwood Establishment Cut (with or without leave trees) (EA/RH/NFH)
4132	Seed-tree Seed Cut (with and without leave trees) (EA/RH/NFH)
4141	Shelterwood Removal Cut (EA/NRH/FH)

4142	Seed-tree Final Cut (EA/NRH/FH)
4143	Overstory Removal Cut (from advanced regeneration) (EA/RH/FH)
4145	Shelterwood Removal Cut (w/ leave trees) (EA/NRH/FH)
4146	Seed-tree Removal Cut (w/ leave trees) (EA/NRH/FH)
4148	Shelterwood Staged Removal Cut (EA/NRH/NFH)
4151	Single-tree Selection Cut (UA/RH/FH)
4152	Group Selection Cut (UA/RH/FH)
4162	Two-aged Coppice Cut (w/res) (2A/RH/FH)
4175	Two-aged Patch Clearcut (w/res) (2A/RH/FH)
4177	Two-aged Stand Clearcut (w/res) (2A/RH/FH)
4183	Two-aged Seed-tree Seed and Removal Cut (w/res) (2A/RH/FH)
4192	Two-aged Preparatory Cut (w/res) (2A/NRH/NFH)
4193	Two-aged Shelterwood Establishment and Removal Cut (w/ res) (2A/RH/FH)
4194	Two-aged Shelterwood Establishment Cut (w/res) (2A/RH/NFH)
4196	Two-aged Shelterwood Final Removal Cut (w/res) (2A/NRH/FH)
4210	Improvement Cut
4211	Liberation Cut
4220	Commercial Thin
4231	Salvage Cut (intermediate treatment, not regeneration)
4232	Sanitation Cut
4241	Special Products Removal
4242	Harvest Without Restocking
4270	Permanent Land Clearing
4455	Slashing - Pre-Site Preparation
4471	Site Preparation for Planting - Burning
4472	Site Preparation for Planting - Chemical
4473	Site Preparation for Planting - Other
4474	Site Preparation for Planting - Mechanical
4475	Site Preparation for Planting - Manual
4481	Site Preparation for Seeding - Burning
4482	Site Preparation for Seeding - Chemical
4483	Site Preparation for Seeding - Other
4484	Site Preparation for Seeding - Mechanical
4485	Site Preparation for Seeding - Manual
4491	Site Preparation for Natural Regeneration - Burning
4492	Site Preparation for Natural Regeneration - Chemical
4493	Site Preparation for Natural Regeneration - Other
4494	Site Preparation for Natural Regeneration - Mechanical
4495	Site Preparation for Natural Regeneration - Manual
4511	Tree Release and Weed
4521	Precommercial Thin
4530	Prune
4541	Control of Understory Vegetation- Burning

6101	Wildlife Habitat Prescribed fire
6103	Wildlife Habitat Precommercial thinning
6104	Wildlife Habitat Regeneration cut
6105	Wildlife Habitat Intermediate cut
6106	Wildlife Habitat Chemical treatment
6107	Wildlife Habitat Mechanical treatment
6133	Wildlife Habitat Slash treatment
6584	Anadromous Fish Thinning for Fish Habitat Improvement
6684	Inland Fish Thinning for Fish Habitat Improvement
7015	Site preparation for re-vegetation - prescribed fire
7050	Natural regeneration - prescribed fire
7065	Re-vegetation treatments - vegetation removal
7067	Re-vegetation treatments - herbicides
9008	Road Maintenance - Vegetation Reduction
9400	Right of Way Maintenance

Table S.2. Summary of visual comparison of the 156 high canopy cover change clusters that did not overlap a FACTS fuels management polygons (within two years before to one year after the completion date or within three years after the award date when a completion date was not entered), and therefore not considered fuels management in our analysis of disturbance. Note that this analysis was limited to eight counties in the northern Sierra Nevada (~30% of the Sierra Nevada study area) to limit the occurrence of drought. While we don't report the number of clusters in each category here, the proportions were similar to proportional areas.

	Area (ha)			Total Area (ha)	Proportion
	2013	2015	2017		
Edge	6.4	18.1	1.7	26.2	3.6
Fuels management outside FACTS polygon	6.4	16.5	1.7	24.7	3.4
Fuels management across USFS ownership	0.0	1.6	0.0	1.6	0.2
Drought	566.9	37.7	12.2	616.8	85.6
Confirmed drought (apparent in NAIP)	393.8	4.3	1.4	399.5	55.5
Presumed drought	173.1	33.4	10.8	217.3	30.2
Open	35.8	0.0	0.0	35.8	5.0
Wildfire	12.4	0.0	1.1	13.5	1.9
Fuels management	25.2	1.0	1.6	27.8	3.9
Mastication	4.5	0.0	0.0	4.5	0.6
Forest fuels management	20.7	1.0	1.6	23.2	3.2
Total	646.8	56.8	16.6	720.2	100.0

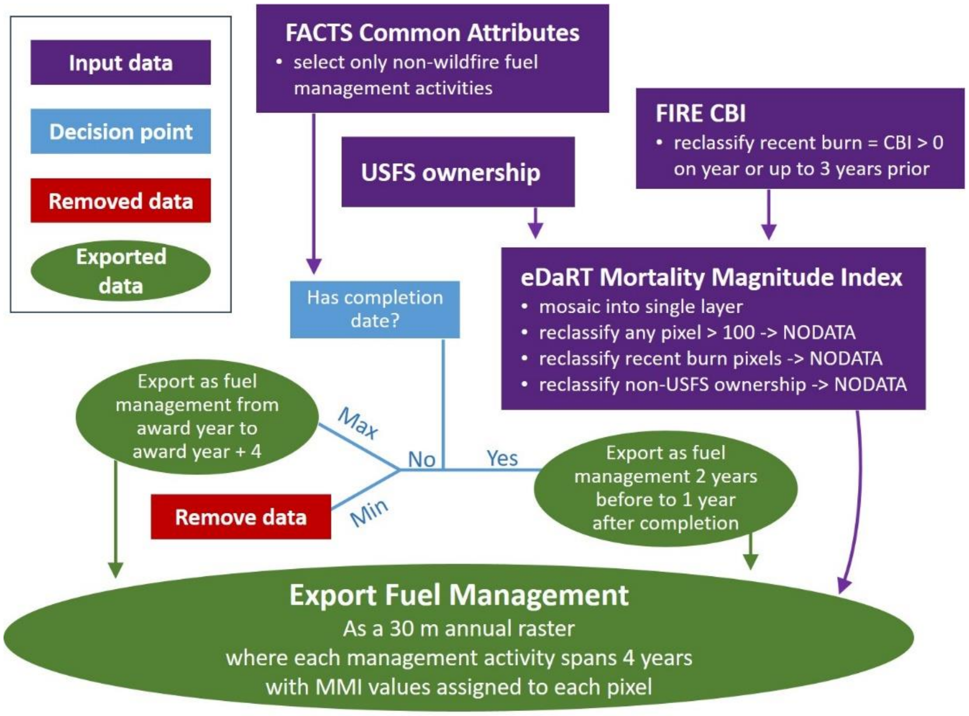

Figure S1. Decision tree for processing downloaded FACTS polygons into annual fuels management rasters. Note that we clipped all input data layers to the study area and ensured that they had the same projection as the MMI layers and that all rasters were snapped to the MMI raster grid (using a central study area tile). The ultimate data were exported as 30 m annual rasters where each fuels management polygon spanned 4 years and each treated pixel maintained the MMI value for that year to facilitate potential further splitting fuels management by activity intensity.

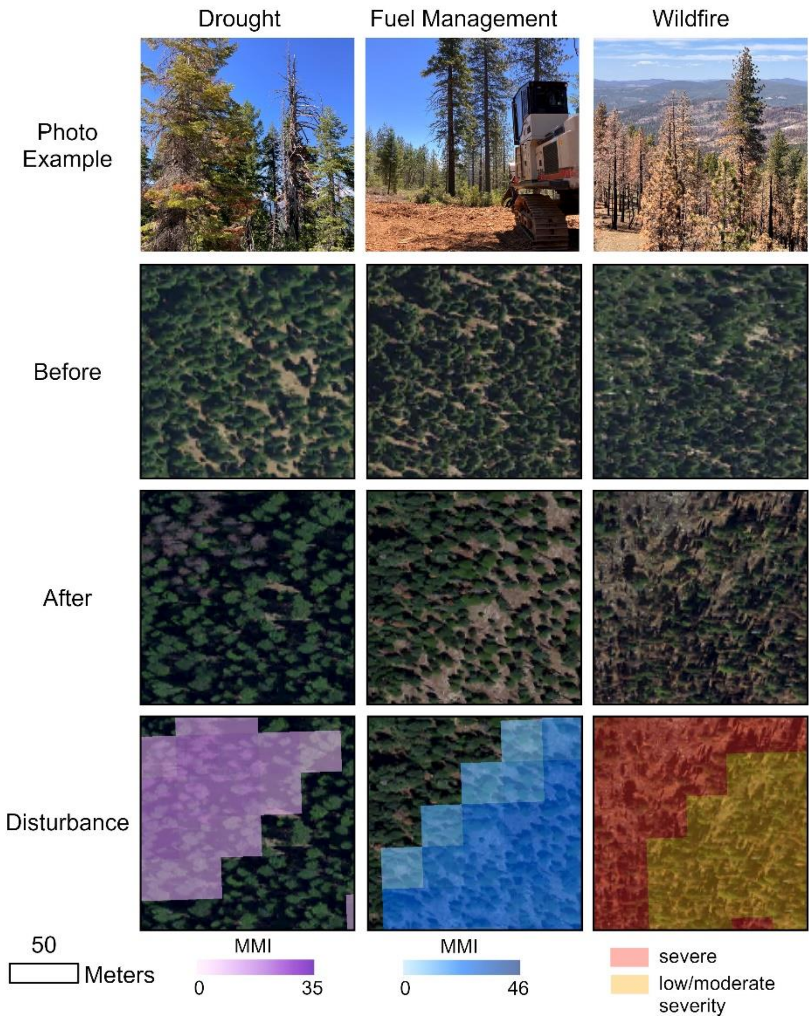

Figure S2. Examples of areas of different disturbance types, including wildfire (high and low-moderate severity), fuels management, and other canopy loss, including from drought, insects, and disease. While the most intense fuels management and drought areas are apparent in the NAIP, the MMI shows a much broader range of canopy loss.

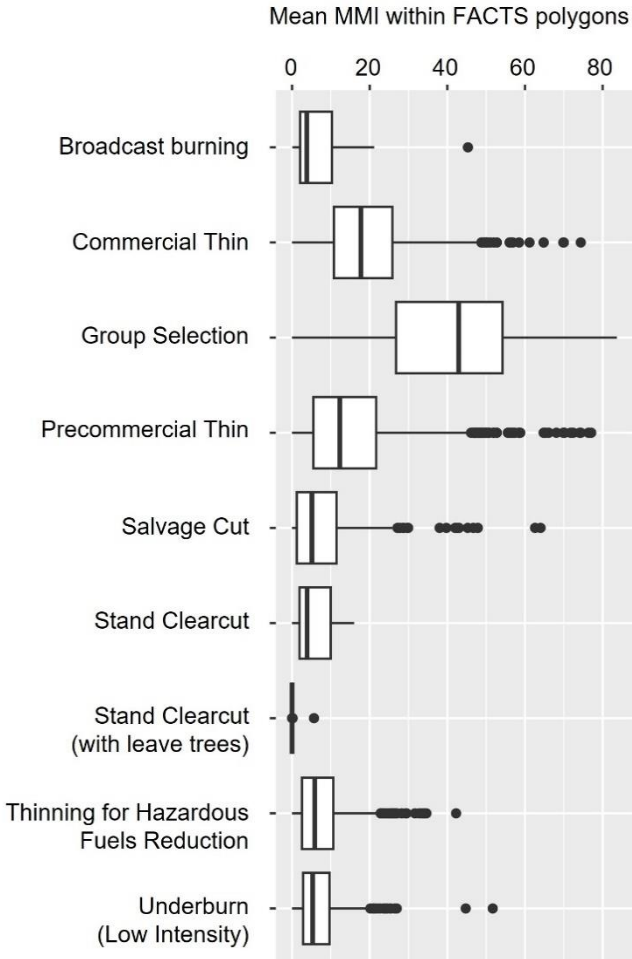

Figure S3. Mean MMI within FACTS polygons with different treatment activities. Note that for this analysis only treatments with a completion date were used, and the mean MMI from the maximum year from 2 years before to 1 year after treatment completion was used.

Missing FACTS data subanalysis

We explored an appropriate timeframe and method for fuels management polygons with missing completion dates in the FACTS database. The reason for a missing completion date could be due to a variety of factors, including: a) the activity had not been started, b) the activity had been started, but not completed, or c) the activity was completed, but never entered into the FACTS database.

Methods

First, we assessed the preponderance of fuels management activities between 2003 and 2024 without a completion date across time to be aware of how large this issue was for both older and more recently awarded activities. Next, we tried to determine whether we could use MMI to determine whether fuels management activities had begun. We did this by calculating the mean annual MMI within all completed fuels management polygons for each year from two years before completion to one year after (determined as an appropriate temporal envelope to capture the vast majority of canopy change from our analyses described earlier in this section). We recorded the maximum of these four values ("max mean MMI") and plotted the frequency of different max mean MMI values. Finally, we visualized the elapsed time between the award and completion dates for all fuels management activities between 2003 and 2024 that had a completion date that was not identical to the award date. We also calculated the proportion of activities that listed a completion date identical to the award date. We reasoned that this analysis would help us decide on an appropriate duration to capture the majority of fuels management activity when a completion date was not available.

Results

While 19% of treatments had no reported completion date between 2003-2024, older fuels management activity award dates were more likely to have a completion date entered into the FACTS database, whereas nearly half of polygons awarded more recently had with a blank completion date (Fig. S4a). Although there was a range of mean MMI values among completed fuels management polygons, 50% had a mean MMI of 0 (Fig. S4b). Finally, when examining the duration between the award and completion dates for fuels management polygons, 65% had an identical award and completion date. Of those that did not have identical dates, the majority (87%) were completed within one year, and 97% were completed within four years (Fig. S4c). While four years does not hold particular significance, it matched the temporal span we had identified in the first paragraph of this section, as well as the lag period for both fire and drought (making all disturbance types comparable in the final disturbance analysis) and seemed a reasonable span.

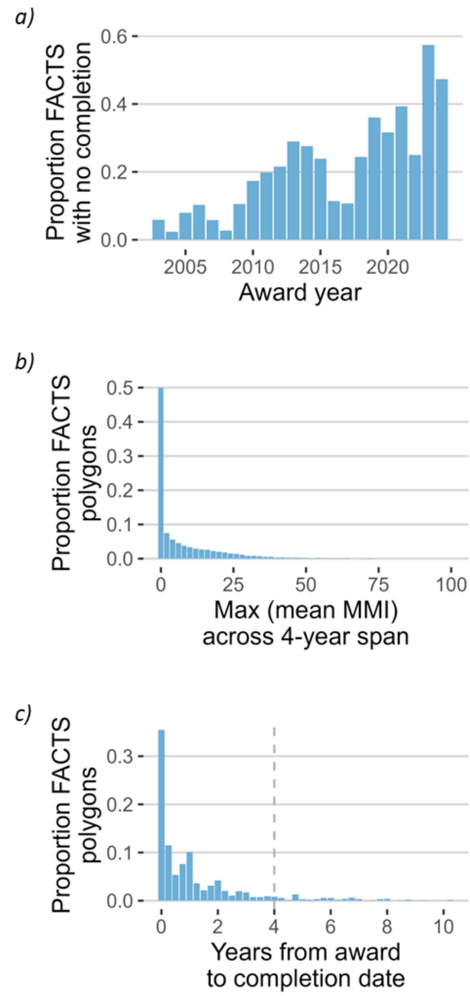

Figure S4. Panel a shows the proportion of FACTS fuels management polygons with a blank completion date field over time (using the year of the award date). Of fuels management activities with both an award and completion date between 2003 and 2024, panel b shows the frequency of mean MMI values within fuels management polygons (using the four-year temporal range and taking the maximum of annual mean MMI scores across the each polygon). Panel c shows the duration of time between the award and completion dates, though note that we removed any fuels management polygons from this panel if the award and completion dates were identical (66% of our original dataset). Also note that fewer than 8% of FACTS fuels management polygons had a duration > 4 years between award and completion.

Discussion
While we were not able to determine whether fuels management entries in the FACTS database with a blank completion date had begun, it ultimately did not substantially change the overall area affected by fuels management because of other spatially and temporally overlapping fuels management areas. Although we did not include the most recent two years for our analysis (2023 and 2024, where nearly half of fuels management polygons had blank completion dates), we did not notice a widening between the two scenarios in our dataset for more recent years (as the proportion of entries without completion increased), and while additional errors may enter the dataset for more recent years, this risk appeared to be minimal.