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Research, part of a Special Feature on The Many Facets of Forest Resilience in the Lake Tahoe Basin

Forest management under uncertainty: the influence of management versus climate change and wildfire in the Lake Tahoe Basin, USA.

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ABSTRACT. Climate change will accelerate forest mortality due to insects, disease, and wildfire. As a result, substantial resources will be necessary where and when forest managers seek to maintain multiple management objectives. Because of the increasing managerial requirements to offset climate change and related disturbances, the uncertainty about future forest conditions is magnified relative to climate change alone. We provide an analytical approach that quantifies the key drivers of forest change—climate, disturbance, and forest management—using scenarios paired with simulation modeling to forecast and quantify uncertainties in the Lake Tahoe Basin of California and Nevada (USA), a montane seasonally dry conifer forest. We partitioned uncertainty among climate change (including associated changes to wildfire and insect outbreaks), forest management (including thinning, prescribed fire, and fire suppression), and other sources using a fully factorial experimental design and analysis of variance. We focused on three metrics that are important for forest management objectives for the area: forest carbon storage, area burned at high severity, and total area burned by wildfire. Management explained a substantial amount of variance in the short term for area burned at high severity and longer term carbon storage, while climate explained the most variance in total area burned. Our results suggest that simulated extensive management activities will not meet all the desired management objectives. Both the extent and intensity of forest management will need to increase significantly to keep pace with predicted climate and wildfire conditions.

Key Words: *climate change; forest management; scenario planning; uncertainty; wildfire*

INTRODUCTION

We are experiencing unprecedented global change and these changes will accelerate in the coming decades. Globally, forests are subject to many drivers of anthropogenic change (McIntyre et al. 2015, Franklin et al. 2016, Balch et al. 2017) that may reduce their capacity to deliver expected levels of ecosystem services (Asner et al. 2015). Because these anthropogenic drivers interact in surprising ways and their future magnitude is also uncertain, the future of forests are highly uncertain (Millar et al. 2007, Lindner et al. 2014, Luce et al. 2016, Wang et al. 2016, Boulanger et al. 2018). Natural resource managers must account for uncertainty when making decisions (Nichols et al. 2011, Lindner et al. 2014) but climate change magnifies uncertainty and can be a barrier to management action (Polasky et al. 2011, Adams 2013, Scheller and Parajuli 2018).

Despite decades of progress, there remain many sources of uncertainty that constrain our capacity to understand and forecast future forests, including parameter uncertainty (the data that feed into the models), model uncertainty (reflecting our overall understanding of how the system operates), and inherent uncertainty (unresolvable uncertainty; Higgins et al. 2003, Morin and Thuiller 2009, Reyer et al. 2016). Nevertheless, within the domains of forest ecology and management there are opportunities to quantify and evaluate the sources of uncertainty through the use of scenario planning. Scenarios in combination with forecasting models are a common approach to quantifying uncertainty by attempting to identify outcomes from a variety of inputs, states, and actions (Peterson et al. 2003). By identifying the plausible or potential bounds of the primary drivers of system change, uncertainty due to each (or neither) can be estimated (Polasky et al. 2011). In the case of forests and climate change, the climate forecasts themselves are a substantial source of uncertainty as they reflect a range of social, economic, and technologic variables themselves (Van Vuuren et al. 2011). Model uncertainty can also be substantial (Petter et al. 2020). Forest disturbances contribute considerable uncertainty to our understanding of forest futures (Hicke et al. 2006, Millar et al. 2007, Littell et al. 2010, Scheller et al. 2011, Anderegg et al. 2015, Seidl et al. 2016, Bognounou et al. 2017, Coen et al. 2018, Stephens et al. 2018). On the contrary, negative feedbacks among disturbances, in combination with ecological memory, may reduce uncertainty. Disturbances do not necessarily compound; there can be negative feedbacks among disturbances that tend to reduce the magnitude (i.e., tree mortality) of subsequent disturbances such as with insects and high severity fire where fire risk is reduced after needle drop (Meigs et al. 2016). Forested landscapes have long ecological memories (Sun et al. 2013, Johnstone et al. 2016)—consisting of the biotic elements, their age, and spatial distribution—that limit their future behavior (Rhemtulla et al. 2009, Loudermilk et al. 2013, Perring et al. 2016).

We provide an analytical approach that quantifies the key drivers of forest change, climate, disturbance, and forest management using scenarios paired with simulation modeling to forecast and quantify future uncertainties. We focused on uncertainty generated by climate change (including associated changes to wildfire and insect outbreaks), forest management (including thinning, prescribed fire, and fire suppression), and other sources using a fully factorial experimental design (similar to Seidl and Lexer 2013); we conducted an analysis of the variance generated by uncertainty (e.g., Seidl and Lexer 2013).

Our combination of scenarios and modeling enabled forecasting of an array of potential futures as dictated by climate and management. The information generated can subsequently inform long-term strategic management planning (Sturtevant et al. 2007), which can, in turn, answer this question: Can management continue to guide outcomes on this landscape in spite of changing climate?

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Table 1. Management scenario broken down by intent and treatment type, by hectares, annually (approximate, rounded).

Scenario	Management specifications	Mechanical	Hand	Prescribed fire	Total	Percent of landscape treated annually	Stand minimum re-treatment time	Natural ignitions as managed fires
1	The only management activity was to suppress fires.	0	0	0	0	0%	0	No
2	Management activities were focused on forest thinning in the wildland-urban interface (WUI). This management strategy was designed to provide a buffer of defensible space around human-built structures and property. It treated ~2% of the vegetated area each year, all in the WUI. This scenario most closely resembled current management activities in the Lake Tahoe Basin. Fire suppression efforts remain the same as Scenario 1.	350	950	0	1300	2%	20	No
3	This scenario builds upon Scenario 2 by expanding management activities into the remaining forested landscape beyond the WUI and used predominantly mechanical and some manual methods to thin the forest and reduce biomass. It treats approximately 6.7% of the vegetated area each year. Fire suppression efforts remain the same as Scenario 1.	1200	3800	0	5000	7%	11	No
4	This scenario builds upon Scenario 2 by expanding management activities into the remaining forested landscape. Scenario 4 uses primarily prescribed fire and managed wildfire. This scenario treats approximately 4% of the vegetated area each year. Fire suppression efforts were the same as Scenario 1 in WUI areas but natural ignitions were allowed to burn for resource objectives in the wilderness areas.	250	1000	1800	3050	4%	20	Yes, in wilderness
5	This scenario builds upon Scenario 4 by greatly expanding the use of prescribed fire. This scenario treats a approximately 7.2% of the vegetated area each year, slightly more than Scenario 3, but with the majority of treatments (75%) being prescribed fire. Fire suppression efforts were the same as Scenario 1 in WUI areas but natural ignitions were allowed to burn for resource objectives in the wilderness areas.	250	1000	6600	7850	11%	20	Yes, in wilderness

We assessed three metrics that we forecasted through time that reflect present day management objectives, including the restoration of a more natural fire regime dominated by low-intensity fire; the reduction of high-risk, high-intensity wildfires; and the maintenance of potential C sequestration. We address this issue within the Lake Tahoe Basin (LTB), which is well-suited for landscape modeling because (1) the forests are mostly in public ownership, which allows for a unified approach to forest and fire management, (2) wildfires there have been historically confined within its steep basin boundaries, and (3) the climate is expected to warm but will remain characterized by winter snow and dry summers.

METHODS

Our analysis was a component of a larger effort to examine social and ecological resilience in the Lake Tahoe West (LTW) study area under alternative management strategies as part of a collaborative landscape restoration effort. This larger effort is the subject of various articles in this special feature, and more information about that project is available here: https://www.nationalforests.org/regional-programs/california-program/laketahoewest. This core of this effort involved modeling ecological change in the forests of LTW over time.

We forecast climate and management interactions using the LANDIS-II simulation modeling framework; LANDIS-II simulates management and climate forcings to quantify uncertainty (Scheller et al. 2007). We simulated five management strategies varying in overall intensity and specific management activities deployed (Table 1) and eight climate projections in a fully factorial design. We selected our 40 scenarios to reflect the full range of plausible climate and management projections that were then replicated three times, therefore encapsulating most of the uncertainty from both (while recognizing that there is potential uncertainty beyond what is currently regarded as plausible). The behavior of the dominant disturbances, wildfire and insects, were dependent upon both climate and management.

Metrics

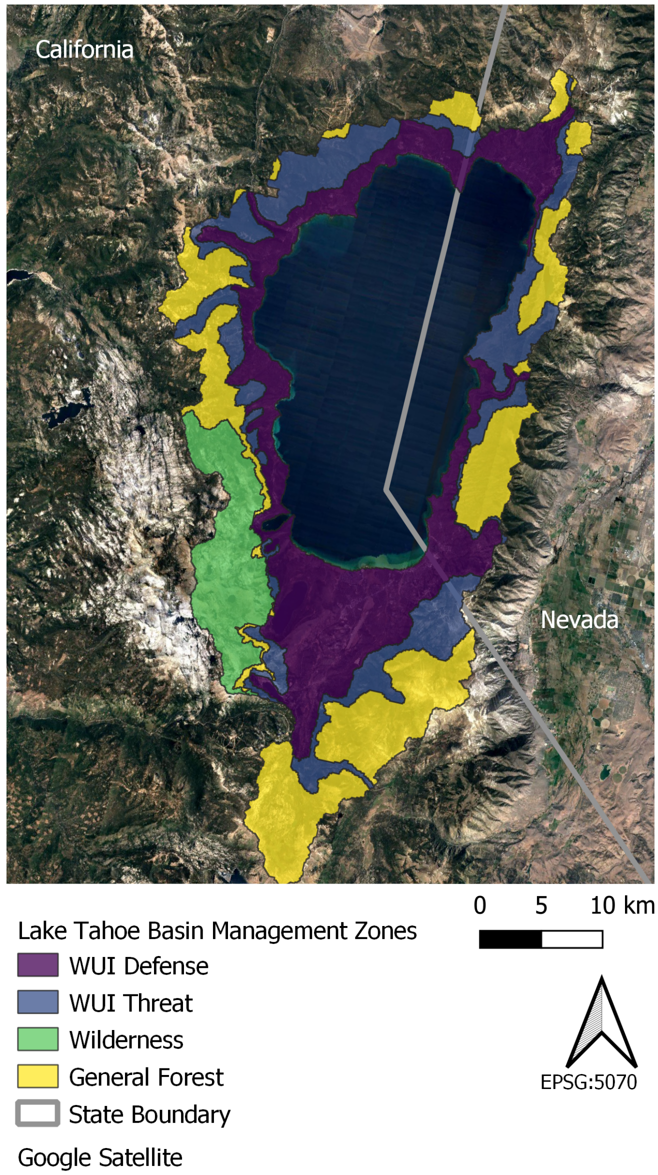
A variety of metrics were used to evaluate social and ecological resilience as part of the larger LTW research effort; these metrics were selected and constructed with input from a group of stakeholders as well as the research team (see Abelson et al. 2022). For this analysis, we examined three metrics that reflect important landscape dynamics relevant to forest management: (1) area burned at high intensity, (2) total area burned by wildfire; and (3) landscape carbon density. Note that our fire module was set up to represent fire intensity, specifically to approximate different classes of flame lengths and crown fire, but it serves also a measure of fire severity (Scheller et al. 2019). Although many dimensions of fire regime are important to consider, area burned at high-intensity may be more informative than percent area burned at high-intensity or severity. Area burned at high severity has been widely reported as a measure of departure in fire history studies (e.g., Safford and Stevens 2017), but that measure has potential to distort understandings of landscape change. For example, if a small area burns mostly at high-intensity in one year, followed by a large area mostly at low-intensity in another year, that outcome may be very consistent with a resilient landscape condition. However, if those relationships are switched, i.e., a small area at low-intensity followed by a large area at high-intensity, that outcome is indicative of departure from reference conditions. However, a metric based upon average percent high-severity does not effectively distinguish between those two outcomes.

Total area burned by wildfire is an important process variable, although in itself is not generally indicative of ecological resilience for fire-adaptive landscapes. Area burned by wildfire is important for understanding larger social and ecological processes, such as costs of suppression, smoke emissions, and restoration of functional fire, which were important indicators to stakeholders (Abelson et al. 2022). Carbon storage, both within the forested landscape and overall system (including wood products) represents another value important to some stakeholders (especially because funding programs have been established to support management that stores carbon). For this analysis, we considered carbon density, or mass per unit area (Mg ha^{-1}) within the landscape as a measure of this social-ecological value. We focus on these three indicators to consider resilience in fire-adapted ecosystems under climate change. Much recent research has suggested potential to both restore fire and secure carbon stores (e.g., Krofcheck et al. 2017, Loudermilk et al. 2017, Liang et al. 2018). However, some research has also suggested that carbon stocks in contemporary forests of the Sierra Nevada have exceeded historical references in some areas with a long-history of fire suppression (Harris et al. 2019), which suggests that reductions in carbon may be consistent with ecological restoration. Therefore, this analysis sheds light on important trade-offs when considering alternative management strategies in light of climate change.

Study area

The Lake Tahoe Basin (LTB) consists of 70,000 ha of predominantly forested land around Lake Tahoe in the Sierra Nevada of California and Nevada, USA (Fig. 1). The majority of the LTB forested area is under the management of the USDA Forest Service. The climate is a Mediterranean-influenced continental climate with warm to hot summers and most of the precipitation falling as snow in the winter. Annual precipitation averages a little over 1000 mm per year (ranging from 400 mm to 2000 mm; Fig. A1.1), with a mean minimum monthly temperature average around -7 °C and mean maximum monthly temperature around 24 °C (PRISM 30-year averages; Fig. A1.2). Most forests are mixed conifer, with the composition varying across topography and soils. At higher elevations, red fir (*Abies magnifica* A. Murr.) dominates, while in lower elevations Jeffrey pine (*Pinus jeffreyi* Grev. & Balf.) and white fir (*Abies concolor* Gord. & Glend.) dominate. Sugar pine (*Pinus lambertiana* Dougl.) and incense-cedar (*Calocedrus decurrens* (Torr.) Florin) are important components of the lower elevation forests. Shrub fields exist throughout elevation classes, featuring species primarily from the *Ceanothus* and *Arctostaphylos* genera.

Fig. 1. Map of the Lake Tahoe Basin. WUI, wildland-urban interface.



Much of the basin was heavily logged beginning in the late 19th century to support mining operations in the greater area (Taylor 2004). Following the subsequent recovery of the forests and the institution of fire suppression policies, the present-day forests have become denser and feature more shade-tolerant tree species at the expense of less shade-tolerant pines (Barbour et al. 2002). Loudermilk et al. (2013) project that this trend will continue over the next 80 years. Wildfires were much more frequent prior to Euro-American settlement, with small fires happening nearly every year in some watersheds, while larger fires occurred once every 35 years (Taylor and Beaty 2005). Several species of bark beetles are also present in the Basin and have caused mortality across large areas of forest (Scheller et al. 2018).

Forest and disturbance modeling

We chose the LANDIS-II simulation framework because it simulates forest succession, disturbance, and management over long time periods and wide spatial extents (Scheller et al. 2007). In LANDIS-II trees and shrubs species are modeled individually as species-age cohorts, each species has its own life history attributes (e.g. shade tolerance, fire tolerance, dispersal ability, etc.), and multiple cohorts can occupy the same space. This allows species to respond uniquely to the multiple and interactive drivers (Scheller et al. 2007). Moreover, each species has its own range of temperature and water optimums, and so each responds to the future climate projections differently. Cohort establishment, likewise, was dependent on climate conditions, and it was assumed that there would only be natural regeneration on this landscape. Species parameters are detailed in Loudermilk et al. (2013), Kretchun et al. (2016), and Scheller et al. (2018). Initial aboveground biomass results were validated against Wilson et al. (2013; see Appendix 1 for supplemental methods and Fig. A1.4).

The ignition, spread, and intensity of fires (both wild and prescribed) were modeled using the Social-Climate Related Pyrogenic Processes (SCRPPLE v. 2.1) extension (Scheller et al. 2019). Simulated fire regimes are sensitive to climate; recent wildfires (2000–2016) were used to parameterize fire spread and size. Five fire experts working in the region provided their estimates of the mortality of three fire intensities for varying species and age combinations.

Three beetle species—Jeffrey pine beetle (*Dendroctonus jeffrey*), mountain pine beetle (*Dendroctonus ponderosae*), and fir engraver beetle (*Scolytus ventralis*)—that cause the majority of insect mortality within the LTB, as well as white pine blister rust (*Cronartium ribicola*), were simulated using a modified version of the Biological Disturbance Agent (BDA v.2.0.1) extension (Sturtevant et al. 2004); the modification triggers outbreaks following climate water deficit (CWD) and minimum winter temperature thresholds. The extension requires insect-specific resource requirements and assigns a species-specific vulnerability that varies by age. Mortality at an outbreak site is determined by tree species' age and host susceptibility probabilities based from empirical field studies (Egan et al. 2010, 2016) and expert opinion. The parameters for insect spread and their resultant mortality are outlined in Kretchun et al. (2016). Additionally, results from the Insect and Disease Detection Survey (1993–2017) were used to validate the model results under historical climate conditions (see Fig. A1.5). However, there were challenges associated with using a climate threshold as a trigger approach as it ignores the brood mechanics and so does not capture the epidemic "wave" pattern of Egan et al. (2016). As such, the model underestimates peaks and overestimates troughs; instances where population dynamics override climate controls. All model parameters, and the model and extension versions used, are available on GitHub at: https://github.com/LANDIS-II-Foundation/Project-Lake-Tahoe-2017/.

Management modeling

We developed five scenarios that represent unique approaches to achieving multiple management objectives: restore a low-intensity fire regime; reduce the risk of high-intensity fires; and maintain carbon sequestration. These scenarios were co-developed with managers representing multiple agencies operating within LTB along with input from stakeholder groups operating in the region. For details of area treated annually and treatment frequency for each scenario, see Table 1. Scenario 1 features no fuels management paired with a high fire suppression. Scenario 2 focuses on reducing wildfire hazard in wildland-urban interface (WUI) area (1.5 miles from urban development) through hand or mechanical thinning (based upon accessibility) along with high effort fire suppression; it was closest to the current, business-as-usual strategy because understory prescribed burning has been rather limited. Scenario 3 increases the intensity and extent of vegetation thinning treatments. This scenario focuses on hand and mechanical treatments in the WUI and general forest, with hand treatments occurring in the wilderness as well. Scenario 4, the fire-focused strategy, uses prescribed and managed natural ignitions, along with some limited thinning in the WUI (akin to Scenario 2) to reduce fuels and restore forest structure. Prescribed fire was constrained to be low-intensity fire only, based upon guidance from managers regarding their intent. Scenario 5 was similar to Scenario 4, but with higher levels of prescribed burning. In Scenario 4 and Scenario 5, natural ignitions were not suppressed in management zones outside of the WUI. The amount of area treated under the five scenarios ranges from 0% to 11% of the landscape annually. The amount removed by thinning treatments were based on recent treatments within the Basin, and moreover followed the same approach of a thin-from-below up to a set diameter size class (27 cm dbh for hand thinning, 61 cm dbh for mechanical thinning) and slope restrictions (< 30%) for mechanical operations.

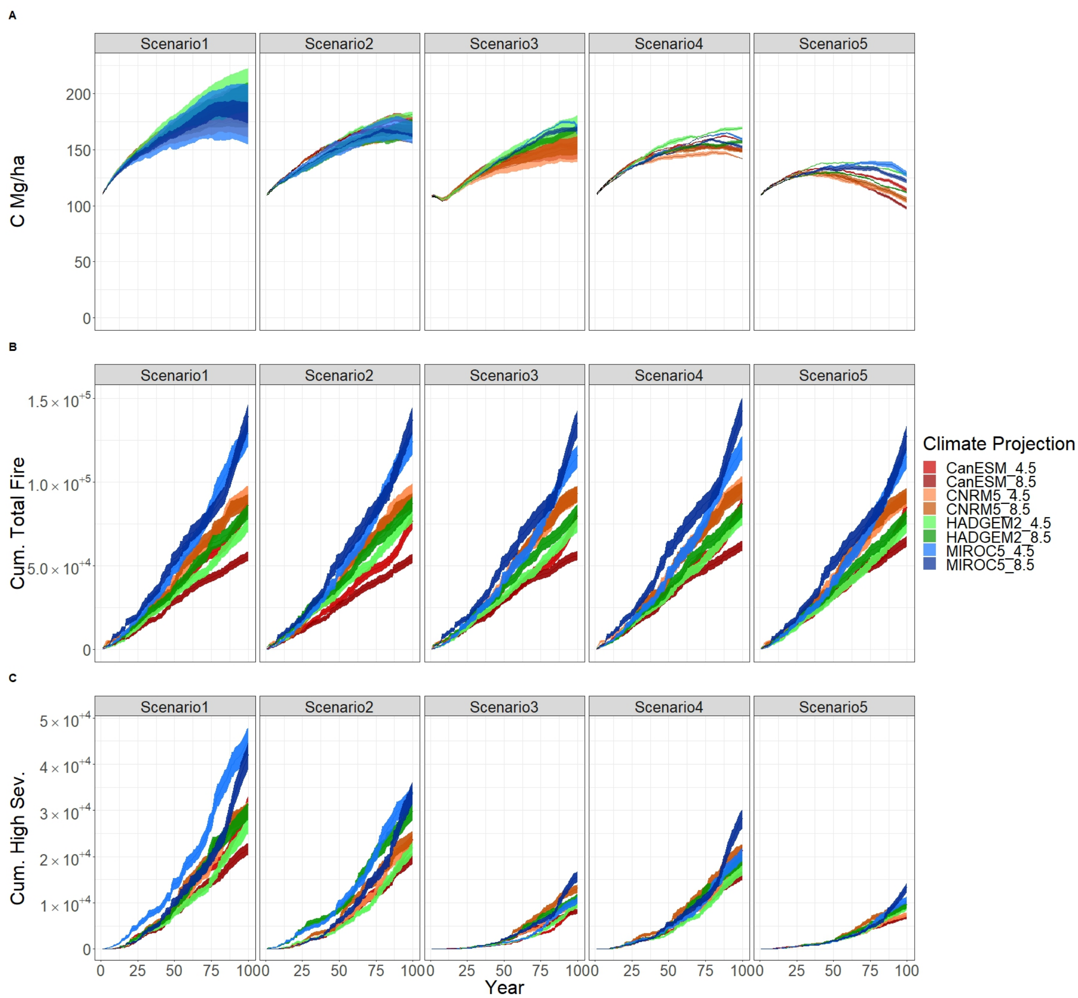
Climate modeling

In keeping with the 4th California Climate Assessment, future climate projections were derived from four Global Change Models (GCM; CanESM2, CNRM5, HADGEM2, and MIROC5) under two different relative concentration pathways (RCP) (4.5: which is an "optimistic" scenario of emissions; and 8.5: which represents a "business-as-usual" uncontrolled emissions scenario) using the localized constructed analogs downscaling methodology (Pierce et al. 2014). Climate futures ranged substantially with respect to precipitation: some projecting an increase of around 30% more annual precipitation (CanESM2 8.5), others projecting an almost equivalent decrease (MIROC5 8.5). With the CanESM2 8.5 projection, summers were projected to see an increase in summertime precipitation. Under the MIROC5 GCM, the area is expected to see increasing frequency and persistence of summertime droughts (Fig. A1.3).

Analysis

In order to differentiate between management and climate sources of uncertainty, an analysis of variance was performed using climate and management scenario as group factor variables for every time step of the model run and for our three metrics (landscape carbon density; area burned at high-intensity, and total area burned by wildfire). This analysis was repeated using decadal averages of each metric to reduce temporal autocorrelation associated with persistent climate events like multi-year droughts. We also examined a climate by management interaction effect although doing so produced too few degrees of freedom at the annual or decadal scale. The analysis was performed using the "car" package (3.0) in R (3.5.2). The reported explained variance is in terms of the sum of squares (SS), which can be apportioned into treatment effect and error. Error represents other sources of variation not explained by climate or

Fig. 2. Landscape level results for carbon and fire metrics by climate projection and management scenario through model year 100. (A) Projected landscape C density, in megagrams per hectare, for the Lake Tahoe Basin by management scenario, by climate projection. (B) Cumulative number of hectares that burned at any intensity by climate projection. (C) Cumulative number of hectares that burned at high intensity by climate projection. Ribbons represents +/- 1 standard deviation across 3 replicates.



management and results from stochastic model behavior not specifically related to climate or management, e.g., randomized ignition locations and seed dispersal.

RESULTS

Total area burned by wildfire

Climate was the main driver for total area burned. Despite the different approaches taken with respect to management practices among the different scenarios, there was little difference in the total area of wildfire (Fig. 2B).

Area burned at high intensity

The area of high intensity (> 8' flame length) fire was most limited under the intensive third scenario (Fig. 2C). The influence of climate on high-intensity area burned was closely tied to the precipitation values for each climate projection (Fig. A1.1). As a result of increasing summertime precipitation, the CanESM2 8.5 climate projection resulted in the least of amount of high-intensity fire. The persistent droughts toward the end of the century forecast under the MIROC5 RCP 4.5 and 8.5 climate projections resulted in the largest high-intensity area burned by the end of the century (approximately 2-3 times higher than the CanESM2 RCP 8.5 projection; Fig. 2C).

Landscape carbon density

Our simulations project that forest carbon would increase through time as this forest recovers from historical logging. There was not a substantial amount of variation among the climate projections until the end of the century, when there was the greatest divergence among the different climates (Fig. 2A). The intensive mechanical treatment scenario (Scenario 3, subjected to the most thinning, produced an initial decline in C density (Fig. 2). However, this was offset over the century as the thinned stands were less likely to experience high-severity fire, resulting in a higher rate of carbon sequestration. The high fire use scenario (Scenario 5) had the lowest C density at the end of the century, in part due to greater removal of C in surface fuels, dead wood, and standing biomass from long-term use of prescribed fire (as compared to hand or mechanical thinning treatments used in Scenario 3).

Variance decomposition

Group predictors (climate and management scenario) explained a range of variation in landscape C density, total area burned, and area burned at high intensity, ranging from 11 to 98% of variance (adjusted R-squared) in a given year (Figs. 3, 4, and 5). Management strategy and climate projection explained substantially more of the variation in landscape C density (and were always significant; Fig. 5) as compared to total area burned or high-intensity area burned (Figs. 3 and 4, respectively). This difference highlights the uncertainty of fire generally and indicates that there are other sources of uncertainty, including the stochastic numbers of fires and their locations.

Fig. 3. Variance decomposition through time for climate and management factors for high severity fire area. Proportion of variance, in terms of sum of squares explained by factor (climate, management, error), each year (left), and each decade (right) through time for the area burned by high severity wildfire. Also included is the adjusted R-squared for each model for each timestep. Panel C and D show P-value for each factor.

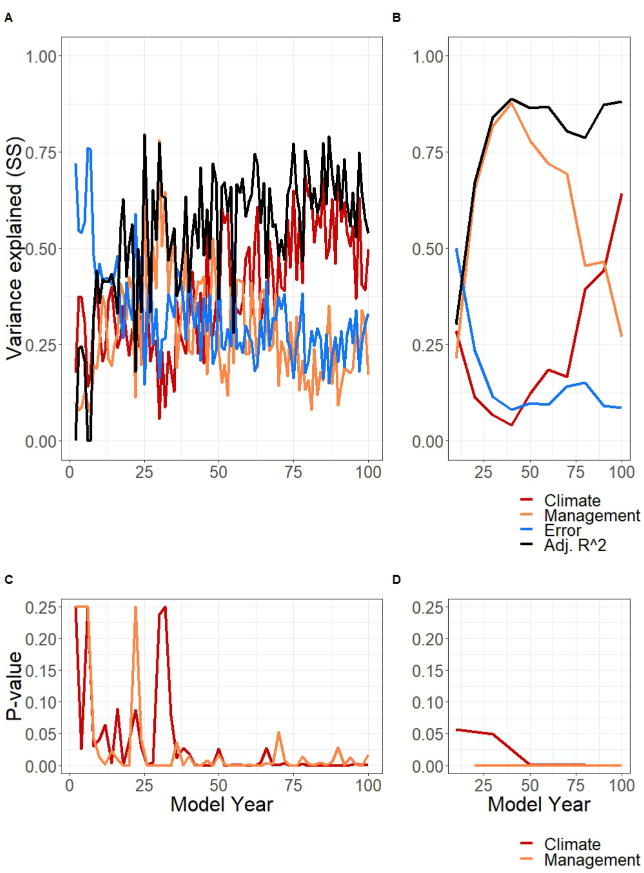
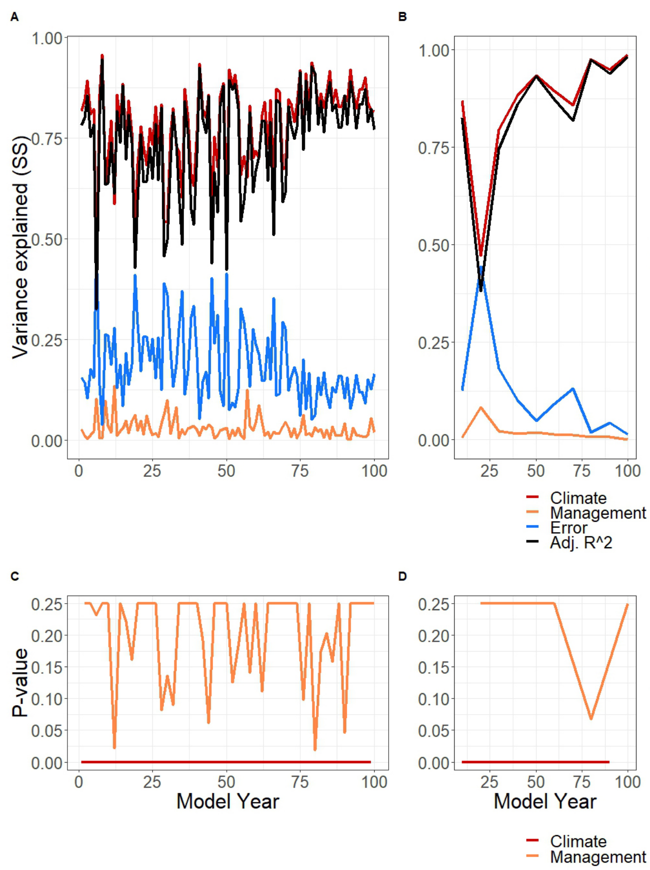
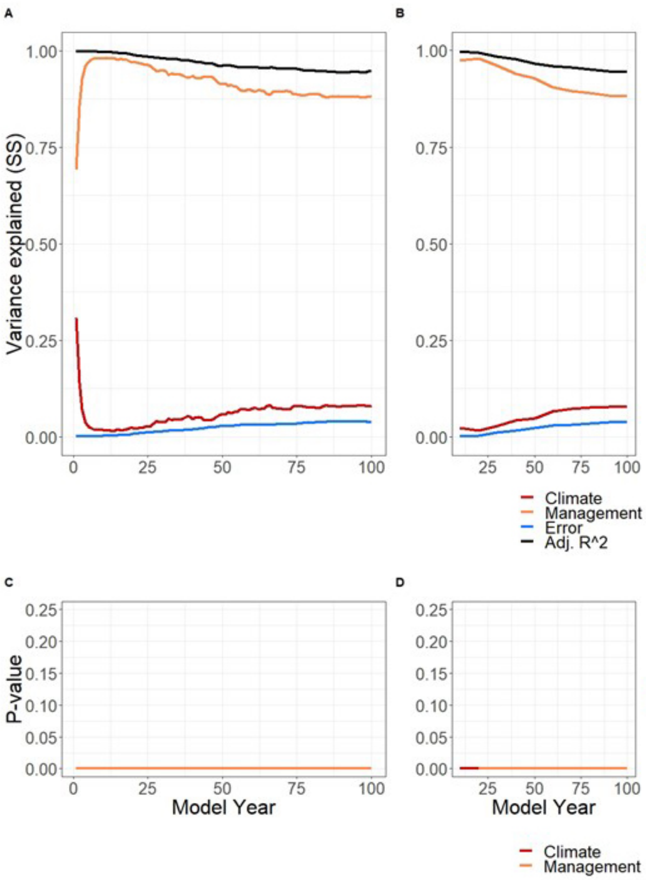


Fig. 4. Variance decomposition through time for climate and management factors for total wildfire area. Proportion of variance, in terms of sum of squares explained by factor (climate, management, error), each year (left), and each decade (right) through time for the total area burned by wildfire. Also included is the adjusted R-squared for each model for each timestep. Panel C and D show P-value for each factor.



For total area burned, management explained less variance than with high-intensity fire at annual and decadal time scales. Climate was the main driver of total area burned, while management was the main driver of area burned at high-intensity (Fig. 3). For high-intensity fire, climate explained more variance than management although the error term—functionally the stochasticity of disturbance within the model—accounted for much of the total variance (Fig. 4A). When aggregated to a decadal time step, management explained substantially more variance in the area of high severity fire (see Fig. 4B). At the decadal scale, large fluctuations in climate are averaged out (wet years can follow dry years, except during periods with multi-year droughts forecast), while the area treated was deterministic (i.e., determined by the management scenarios).

Fig. 5. Variance decomposition through time for climate and management factors for mean total carbon. Proportion of variance, in terms of sum of squares explained by factor (climate, management, error), each year (A), and each decade (B) through time for the mean total landscape carbon. Also included is the adjusted R-squared for each model for each timestep. Panel C and D show P-value for each factor.



DISCUSSION

Uncertainty regarding future forest conditions has important implications for derived social values, including ecosystem services (Hou et al. 2013, Hamel and Bryant 2017). From carbon storage to wildlife habitat, forest benefits are dependent on the interactions of climate, disturbance, and management. When those benefits drive the local economy, such as recreation in the Lake Tahoe Basin, quantifying the contribution of individual drivers improves decision making regarding the forest and the benefits in question, which is the focus on another manuscript in this special feature (Abelson et al. 2022). We focused on the primary sources of uncertainty—climate and management and interactions with fire—in our simulations of forest landscape change in order to assess the ability of management generally to shape future forest conditions. Our results suggest areas where management can have the greatest influence (high-intensity fire ~ landscape C density > total area burned). Although this landscape is unique in its centralized ownership, which may limit the broader applicability of this study, there is now greater movement toward whole landscape planning for the State of California.

The amount of area treated was more important in reducing area of high-intensity fire than the type of treatment used: as the area treated increased, the area burned by high-intensity fire declined because a fire would have a larger likelihood of intersecting a treated area. This is evident from the order of the results in Figure 2C and how they align with the number of hectares treated in each management scenario (i.e., 1, 2, 4, 3, 5). However, the variance explained by management waned as climate change uncertainty increased over the century, implying that the effectiveness of management may decline after 40 years. Management efforts within the LTB may need to increase substantially through time, more than managers considered when co-designing the management strategies tested. In the near term, more aggressive initial treatment may delay widespread mortality, and in the long term, promote the transition to a more drought-tolerant species mix (Elkin et al. 2015). In general, our results suggest that to increase the capacity of LTB forests to remain forests, management would need to cover a greater proportion of the landscape in a shorter period of time (Drever et al. 2006). Without this increased level of investment and activity, the rate of change brought by management actions may not keep the forest within a desirable condition (Johnstone et al. 2016).

Fuel treatments (hand and mechanical thinning) locally reduce fire intensity and rate of spread. The extent to which this holds true at the landscape-scale is debated (Campbell et al. 2012, Restaino and Peterson 2013), because in low-ignition environments there is only a small chance that fire will intersect with a treatment. At the same time, climate change and associated higher temperatures will reduce fuel moisture and will generate larger and more intense fires (Westerling and Bryant 2008). Our results suggest that management reduces fire intensity at landscape scales when the accumulation of treated area is large enough that there is a high chance a wildfire will intersect a treatment. This finding is consistent with other studies in the region that have found that both area treated and incidence of wildfire would need to increase from recent historical levels for that intersection to take place (Chiono et al. 2017, Krofcheck et al. 2017), and that there may be thresholds of area treated above which that have even greater effectiveness in reducing the risk of high severity fire (Stevens et al. 2016). The variance in area of high-intensity fire and total area burned explained by management declined over the century, which reflects the warming and drying trend of climate change.

In addition to management and climate uncertainty, we estimated the error term or unexplained uncertainty, which is the variance unexplained by either management or climate alone. This variance is not the same as error propagation, which is the combination of all the uncertainty of all the variables used in the development of these results (Morgan et al. 1990). In our modeling framework, unexplained variance of landscape C density may include a fire-by-climate effect: as the climate warms, the number of fires increases, but probabilistically. A given warm and dry day may or may not produce multiple wildfires. Therefore, the "inherent" variance (Higgins et al. 2003) increases over time in parallel with climate for our estimates of landscape C density. In contrast, the inherent variance remained relatively constant for total and high-intensity area burned because maximum area burned for each fire was a linear function of climate (Scheller et al. 2019).

Although there is and always will be uncertainty about the future, management has an important role to play in shaping the future forest conditions. Management actions can shape landscape conditions in spite of climate uncertainty up to a certain point. Areas, or metrics, where management is less effective suggests the need for new thinking about the kind (planned vs. reactionary), intensity, rate, or placement of treatments. Given the recent extremity of the climate conditions across the western U.S. only highlights the need for treatment and the need for new thinking.

Responses to this article can be read online at:
https://www.ecologyandsociety.org/issues/responses.php/13278

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Data Availability:

The model parameters and code used in this analysis that support the findings of this study are openly available in: https://github.com/LANDIS-II-Foundation/Project-Lake-Tahoe-2017/. This code has been archived on zenodo.org at: https://doi.org/10.5281/zenodo.4644579.

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This file includes:

Supplementary methods
Tables A1.1 to A1.7
Figures A1.1 to A1.9
Supplementary references

Supplemental Methods:

Climate projections

A combination of 8 projections were used from 4 different global change models (GCMs) at two relative concentration pathways (RCPs). The RCPs chosen were 4.5 and 8.5, the former representing an emissions-controlled future, while the latter represents an uncontrolled emissions future. The particular combination is based on recommendations from Pierce et al. 2016. The LANDIS model utilizes the following climatological variables: daily precipitation (Fig. A1.1 and A1.2), daily maximum temperature (Fig. A1.3), daily minimum temperature, daily average windspeed, and daily average wind direction that are averaged across the Level II EPA ecoregions in the study area.

Forest succession

NECN (v6.5) simulates both above and belowground processes, tracking C and N through multiple live and dead pools, as well as tree growth (as net primary productivity--a function of age, competition, climate, and available water and N). Soil moisture, as well as movement across the dead pools: wood and litter deposition and decomposition, soil accretion and decomposition are based on the CENTURY soil model (Parton et al. 1983, Scheller et al. 2011). Carbon estimates by pool were validated against Wilson et al. (2013) at the ecoregion level, where the model overestimated total C for only one region but was within one standard deviation for all others (Fig. A1.4). Forest growth estimates using the climate data for year 2010-2015 for the region were calibrated against the MODIS 17a3 product annual mean for 2000 – 2015 (Fig. A1.5). Mean landscape value for MODIS was 393 g C/m ^2 (sd 134), while for LANDIS the mean value was 320 g C/m^2 (sd 312). Reproductive success is dependent on temperature and water.

Fire modeling

The SCRPPLE extension (v2.1) models ignitions by drawing the number of ignitions from a zero-inflated Poisson distribution and allocates them across the landscape with a weighted ignition surface for each type of fire modeled (Scheller et al. 2019). The weather influence on fire is based on the Fire Weather Index (FWI) measures created by the Canadian Fire Prediction System (1992). There are three categories of fires that can be modeled: lightning, accidental (i.e., human started), and prescribed fire. The extension also includes the ability to explicitly set fire suppression effort levels across the landscape as well as by ignition type, where the suppression parameter reduces the probability of fire spread from one cell to another. Effort levels can range from 0 to 3, where 0 is no suppression attempted, to 3 which represents high effort and was designed to mimic current suppression efforts in the Basin (Fig. A1.6). However, suppression effectiveness can be limited by weather as well, a maximum wind speed parameter can limit suppression to days only when resources can be deployed safely. That parameter was set at wind speeds of 11 meters per second (~25 miles per hour) in consultation with regional fire personnel. Prescribed fires follow a set of weather prescriptions for when fires can occur (Table A1.2).

Contemporary wildfires (2000-2016, from CalFIRE FRAP) were used to parameterize fire spread and size from the Central Sierra Nevada in order to increase the sample size of fires. Mean annual fire area (in ha) for observed data was 117 hectares per year (SD = 309), for modeled data, the mean value was 122 hectares per year (SD = 210). In order to move from fire intensity to fire severity (to encompass the mortality associated with fire), five fire experts working in the LTB provided their estimates of mortality for varying species, age, and intensity combinations. More details about the parameterization of the fire extension are found in Scheller et al. (2019). Suppression effort and fire spread are calibrated at the same time in order to try to account for both forces in recreating the contemporary fire regime.

The model calculates three levels of fire intensity, roughly corresponding to flame lengths of: 1) less than 4 ft, 2) between 4 ft. and 8ft., and 3) greater than 8ft. While ignitions are based off of climate, fire intensity is based off of fuel loading within each cell. LANDIS calculates fuel loadings based on the current year's litter, duff, and downed and dead woody debris. When a threshold of fine fuels is exceeded in a cell, the fire intensity increases. This threshold is based off a value of ~1100g/m^2 or about 5 tons per acre of fine fuels. The other threshold is based on ladder fuels: a combination of specific species, under a certain age, and over a certain amount of biomass per area, contribute to intensity. Those species contributing to ladder fuels are: Jeffrey Pine, white fir, and incense-cedar, and the cohorts in the cell have to be younger than 40 with a biomass greater than 2000g/m^2 (9 tons per acre). When one threshold is exceeded, fire intensity increases. When both thresholds are exceeded, fire intensity is at its highest. High intensity fire spreads as high intensity fire. To validate fire intensity for the Basin, the targeted fire intensity value for any of the larger multi-day fires was 40% high, 40% mid, and a 20% low intensity, with high intensity less than 60% of the total fire area. These targets are based on long-term averages calculated for the Northern half of the Sierra Mountains (which includes the Lake Tahoe footprint) using the Monitoring Trends in Burn Severity Composite Burn Index data. Over the entire data period (1984-2020), the percentage of area burned at high severity was 41% each year (with 36% and 22% for moderate and low severity respectively), with up to 58% of area burning at high severity in 2007, see Table A1.7.

Insect modeling

A modified version of the Biological Disturbance Agent extension (Biomass BDA v.2.0) (Sturtevant et al. 2009) was used to simulate insect outbreaks for three species of insects: Jeffrey pine beetle (*Dendroctonus jeffrey*), mountain pine beetle (*Dendroctonus ponderosae*), and fir engraver beetle (*Scolytus ventralis*). The extension requires insect-specific resource requirements and assigns a species-specific vulnerability that varies by age. Cells are probabilistically selected for disturbance based upon the species host density at a given site and the presence of non-hosts reduce disturbance probability. The parameters for spread and mortality are outlined in Kretchun et al. (2016), see Table A1.5 and Table A1.6 below. Mortality at an outbreak site is subsequently determined by species' age and host susceptibility probabilities based from empirical field studies (Egan et al. 2010, 2016) and expert opinion, see Table A1.2 below. The insects had differing rates of spread per year from previous outbreaks. Mountain Pine Beetle had positive neighbor effects, where pheromones promoted more rapid spread when there were neighboring populations. All insects were able to exploit recently burned stands up to 10 years after a fire. Following mortality, dead biomass remains on site and moves to the downed woody debris C pool and the fine woody debris C pool.

However, unlike Kretchun et al. (2016), the trigger for an outbreak was changed to be responsive to climate signals. This is because for many beetle species climate influences outbreaks in three ways: low winter temperatures cause beetle mortality; year-round temperatures influence development and mass attack; and drought stress reduces host resistance. Here, we modeled climate influences as a function of drought and mean minimum winter temperature, recognizing that the full suite of climatic influences is necessary for a fully mechanistic model. So long as annual climatic water deficit exceeded a set threshold, in conjunction with mean winter minimum temperatures exceeded a certain threshold, outbreaks could occur. A comparison between the modeled and observed outbreak dataset (USFS Aerial Detection Survey: https://www.fs.fed.us/foresthealth/applied-sciences/mapping-reporting/index.shtml) found an overestimation of frequency of occurrence but an underestimation of area impacted by insects (Fig. A1.7). However, there was unprecedented mortality across the Sierras due to the drought in California that lasted from 2012-2016, and the cause of the mortality has not been definitively attributed to insects or drought given that field studies are retrospective (e.g., Fettig et al. 2019, Restaino et al. 2019). While the ADS data were the main source of such insect mortality data; there are significant limitations with the data. Not all areas receive a fly-over each year and very few areas that are marked as having mortality receive on the ground verification. A newer dataset developed by the R5 Remote Sensing Research Team uses LANDSAT images to assess changes in canopy cover through time. From personal communication with Michele Slaton (USFS) who helped develop this data product, the amount of area affected by insects is far less than what is reported by the Aerial Detection Survey possibly due to the limited accuracy of fly-over mapping. However, these data are still provisional as their manuscript is in review.

Supplemental Tables:

Table A1.1. Suppression effort levels and effectiveness on fire spread probability.

	Fire Weather Index Thresholds		Effort Level		
Fire Type	Low-mod	Mod-high	Low	Moderate	High
Accidental	40	60	0	5	10
Lightning	40	60	0	5	10
Rx	40	60	0	0	0

Table A1.2. Prescribed fire parameters used for Scenario 5

Prescribed Fire Parameters	
MaximumRxWindSpeed	6.6 (m/s)
MaximumRxFireWeatherIndex	55 (unitless)
MinimumRxFireWeatherIndex	10 (unitless)
MaximumRxFireIntensity	1 (low)
NumberRxAnnualFires	364 (days of year allowable, subject to climate constraints)
FirstDayRxFires	1 (first julian day for allowable fire, subject to climate constraints)
TargetRxSize	72 (hectares)

Table A1.3. Species parameters used in modeling.

Name	Longevity	Sexual maturity age	Shade tolerance	Fire tolerance	Seed effective dispersal distance (meters)	Maximum dispersal distance (meters)	Vegetative Reproduction Probability	Minimum age veg reproduction	Maximum age veg reproduction	Post-fire regeneration
Pinus jeffreyi	500	25	2	5	50	300	0	0	0	none
Pinus lambertiana	550	20	3	5	30	400	0	0	0	none
Calocedrus decurrens	500	30	3	5	30	1000	0	0	0	none
Abies concolor	450	35	4	3	30	500	0	0	0	none
Abies magnifica	500	40	3	4	30	500	0	0	0	none
Pinus contorta	250	7	1	2	30	300	0	0	0	none
Pinus monticola	550	18	3	4	30	800	0	0	0	none
Tsuga mertensiana	800	20	5	1	30	800	0.0005	100	800	none
Pinus albicaulis	900	30	3	2	30	2500	0.0001	100	900	none
Populus tremuloides	175	15	1	2	30	1000	0.9	1	175	resprout
Non-N fixing, Resprouting	80	5	2	1	30	550	0.85	5	70	resprout
Non-N fixing, Seeding	80	5	2	1	30	1000	0	0	0	none
N fixing, Resprouting	80	5	1	1	30	500	0.75	5	70	resprout
N fixing, Seeding	80	5	1	1	30	800	0	0	0	none

Table A1.4. Harvest removals prescription tables

		Abies concolor	**Calocedrus decurrens**	**Pinus jeffreyi**	**Abies magnifica**	**Pinus contorta**	**Pinus lambertiana**	**NonnResp**	**NonnSeed**	**FixnResp**	**FixnSeed**
Hand Thinning	Age range	1-60	1-64	1-52	1-60	1-73	1-52	10-200	10-200	10-200	10-200
Scenario 1 - 5	Percent removed	-66%	-66%	-66%	-66%	-66%	-66%	-5%	-5%	-5%	-5%
Trees up to 11” dbh	Age range	61-70	65-78	53-68	61-75	74-88	53-64				
	Percent removed	-39%	-39%	-39%	-39%	-39%	-39%				
Mechanical Thinning		**Abies concolor**	**Calocedrus decurrens**	**Pinus jeffreyi**	**Abies magnifica**	**Pinus contorta**	**Pinus lambertiana**	**NonnResp**	**NonnSeed**	**FixnResp**	**FixnSeed**
Scenario 1, 2, 4, 5	Age range	1-60	1-64	1-52	1-60	1-73	1-52	10-200	10-200	10-200	10-200
Trees up to 24” dbh	Percent removed	-93%	-93%	-93%	-93%	-93%	-93%	-30%	-30%	-30%	-30%
	Age range	61-65	65-71	53-60	61-68	74-80	53-58				
	Percent removed	-70%	-70%	-70%	-70%	-70%	-70%				
	Age range	66-70	72-78	61-68	69-75	81-88	59-64				
	Percent removed	-65%	-65%	-65%	-65%	-65%	-65%				
	Age range	71-75	79-84	69-76	76-82	89-96	65-70				
	Percent removed	-57%	-57%	-57%	-57%	-57%	-57%				
	Age range	76-80	85-91	77-85	83-90	97-105	71-77				
	Percent removed	-45%	-45%	-45%	-45%	-45%	-45%				
	Age range	81-84	92-99	86-95	91-97	106-115	78-83				
	Percent removed	-32%	-32%	-32%	-32%	-32%	-32%				
	Age range	85-89	100-107	96-105	98-104	116-125	84-90				
	Percent removed	-23%	-23%	-23%	-23%	-23%	-23%				
	Age range	90-93	108-115	106-115	105-112	126-136	91-97				
	Percent removed	-17%	-17%	-17%	-17%	-17%	-17%				
	Age range	94-98	116-125	116-126	113-120	137-148	98-104				
	Percent removed	-13%	-13%	-13%	-13%	-13%	-13%				
	Age range	99-103	126-135	127-138	121-127	149-161	105-112				
	Percent removed	-8%	-8%	-8%	-8%	-8%	-8%				
	Age range	104-108	136-145	139-151	128-135	162-176	113-120				

	Percent removed	-4%	-4%	-4%	-4%	-4%	-4%				
Mechanical Thinning		**Abies concolor**	**Calocedrus decurrens**	**Pinus jeffreyi**	**Abies magnifica**	**Pinus contorta**	**Pinus lambertiana**	**NonnResp**	**NonnSeed**	**FixnResp**	**FixnSeed**
Scenario 3	Age range	1-60	1-64	1-52	1-60	1-73	1-52	10-200	10-200	10-200	10-200
Trees up to 38" dbh	Percent removed	-95%	-95%	-95%	-95%	-95%	-95%	-30%	-30%	-30%	-30%
	Age range	61-65	65-71	53-60	61-68	74-80	53-58				
	Percent removed	-95%	-95%	-95%	-95%	-95%	-95%				
	Age range	66-70	72-78	61-68	69-75	81-88	59-64				
	Percent removed	-85%	-85%	-85%	-85%	-85%	-85%				
	Age range	71-75	79-84	69-76	76-82	89-96	65-70				
	Percent removed	-85%	-85%	-85%	-85%	-85%	-85%				
	Age range	76-80	85-91	77-85	83-90	97-105	71-77				
	Percent removed	-85%	-85%	-85%	-85%	-85%	-85%				
	Age range	81-84	92-99	86-95	91-97	106-115	78-83				
	Percent removed	-75%	-75%	-75%	-75%	-75%	-75%				
	Age range	85-89	100-107	96-105	98-104	116-125	84-90				
	Percent removed	-70%	-70%	-70%	-70%	-70%	-70%				
	Age range	90-93	108-115	106-115	105-112	126-136	91-97				
	Percent removed	-60%	-60%	-60%	-60%	-60%	-60%				
	Age range	94-98	116-125	116-126	113-120	137-148	98-104				
	Percent removed	-35%	-35%	-35%	-35%	-35%	-35%				
	Age range	99-103	126-135	127-138	121-127	149-161	105-112				
	Percent removed	-20%	-20%	-20%	-20%	-20%	-20%				
	Age range	104-108	136-145	139-151	128-135	162-176	113-120				
	Percent removed	-10%	-10%	-10%	-10%	-10%	-10%				
	Age range	109-120	146-180	152-240	136-180	177-230	121-160				
	Percent removed	-10%	-10%	-10%	-10%	-10%	-10%				
	Age range	121-125	181-200	241-252	181-190	231-250	161-180				
	Percent removed	-5%	-5%	-5%	-5%	-5%	-5%				

Table A1.5. Insect disturbance inputs by insect

	Fir Engraver		**Jeffrey Pine Beetle**		**Mountain Pine Beetle**	
	Parameter	Source	Parameter	Source	Parameter	Source
Dispersal Rate	1000 m/year	Jactel (1991)	600 m/year	Egan (personal comm.)	400 m/ year	Safranik (2006)
Neighborhood Effect	N/A	USFS Fir Engraver Facts (2017)	N/A	N/A	Yes, 2x	Safranik (2006)
Disturbance Modifier	Fire: 100%, 10 years	Schwilk 2006	Fire: 100%, 10 years	Schwilk 2006	Fire: 100%, 10 years	Schwilk 2006

Table A1.6: Insect disturbance parameters by insect by host species

		Susceptibility			Mortality			
	Target Species	*Age Class 1*	*Age Class 2*	*Age Class 3*	*Age Class 1*	*Age Class 2*	*Age Class 3*	*Source*
Fir Engraver	*Abies concolor*	0-10, 0%	10-60, 65%	60+, 75%	0-10, 0%	10-60, 8%	60+, 12%	Ferrell 1994, Schwilk 2006, Egan (personal comm)
	Abies magnifica	0-10, 0%	10-60, 45%	60+, 55%	0-10, 0%	10-60, 8%	60+, 12%	
Jeffrey Pine Beetle	*Pinus jeffreyi*	0-20, 10%	20-30, 80%	30+, 80%	0-40, 5%	40-120, 18%	120+, 8%	Egan et al. 2016
Mountain Pine Beetle	*Pinus albicaulis*	0-20, 33%	20-60, 66%	80+, 80%	0-20, 5%	20-60, 15%	80+, 20%	Safranik (2006), Cole and Amman (1980)
	Pinus lambertiana	0-20, 33%	20-60, 66%	80+, 80%	0-20, 5%	20-60, 25%	80+, 30%	
	Pinus contorta	0-20, 33%	20-60, 66%	80+, 80%	0-20, 5%	20-60, 15%	80+, 20%	
	Pinus monticola	0-20, 33%	20-60, 66%	80+, 80%	0-20, 5%	20-60, 25%	80+, 30%	

Table A1.7. Percent of fire severity type by class based on MTBS thematic burn severity for the Northern Sierras

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1994	1996	1997	1999	2000	2001	2002	2003	2004
High severity	23%	16%	21%	32%	39%	37%	41%	6%	68%	48%	21%	17%	28%	45%	50%	31%	8%	42%
Moderate severity	30%	17%	52%	39%	35%	41%	35%	52%	23%	29%	56%	41%	49%	36%	37%	41%	51%	36%
Very low/low severity	47%	67%	27%	29%	27%	22%	24%	42%	9%	22%	23%	42%	24%	19%	13%	29%	41%	23%
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**		**Total**
High severity	32%	27%	58%	30%	20%	15%	5%	34%	42%	54%	45%	36%	38%	38%	37%	50%		41%
Moderate severity	42%	52%	29%	48%	39%	45%	39%	48%	37%	24%	32%	43%	37%	40%	39%	26%		36%
Very low/low severity	26%	21%	12%	22%	41%	39%	56%	18%	22%	21%	23%	22%	26%	21%	24%	24%		22%

Supplemental Figures:

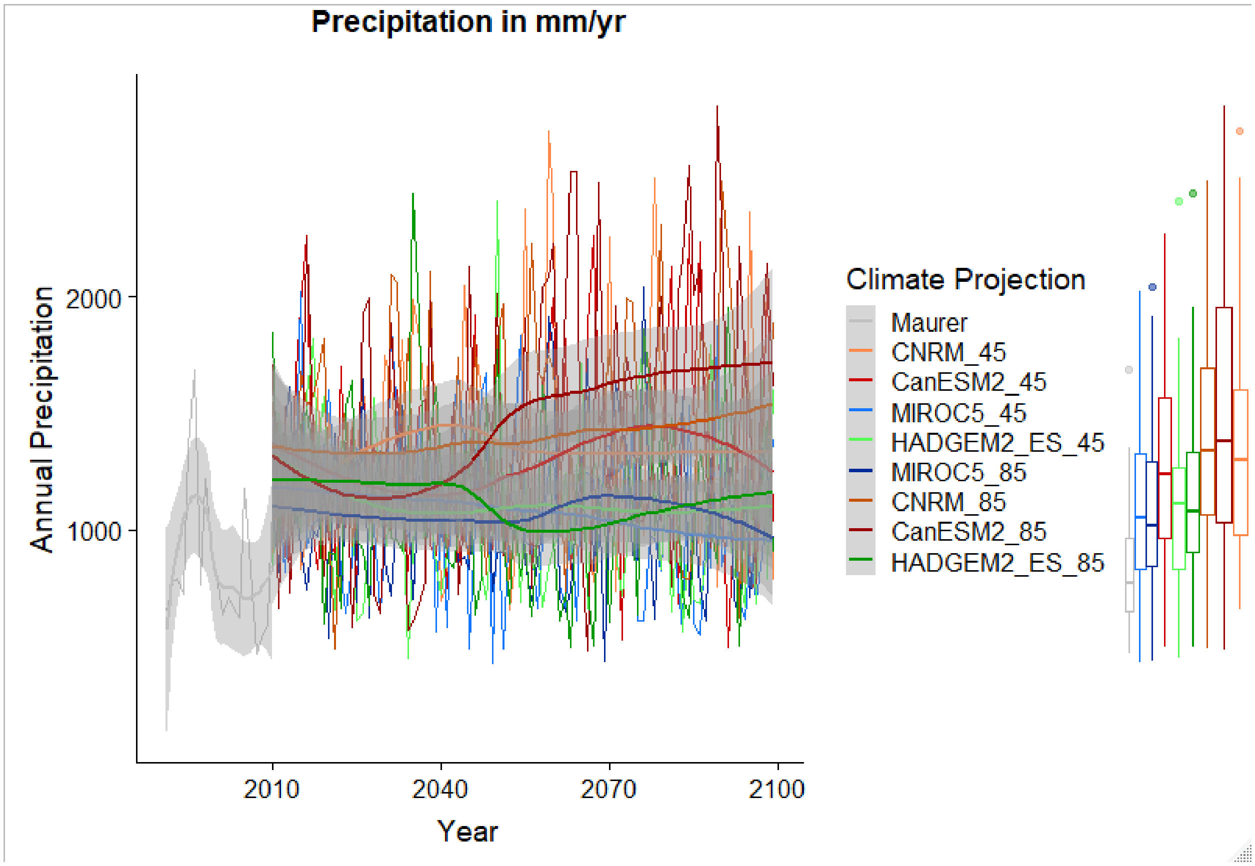

Fig. A1.1. Projected precipitation in mm yr^{-1}, lines of best fit are GAM estimated, and boxplots represent distribution of annual precipitation for the years 2090-2100.

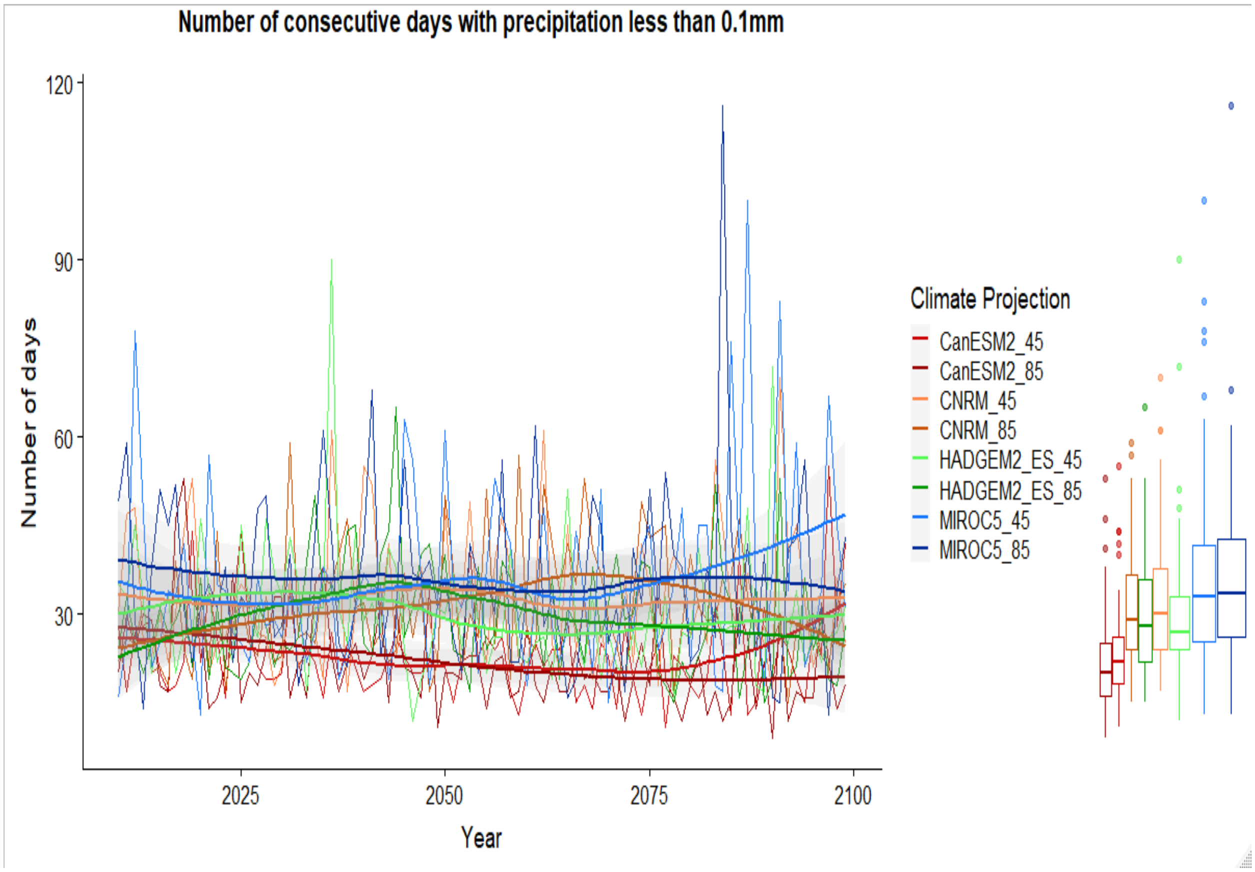

Fig. A1.2. Projected number of consecutive days with no precipitation, lines of best fit are GAM estimated, and boxplots represent distribution of consecutive days per year for the years 2090-2100.

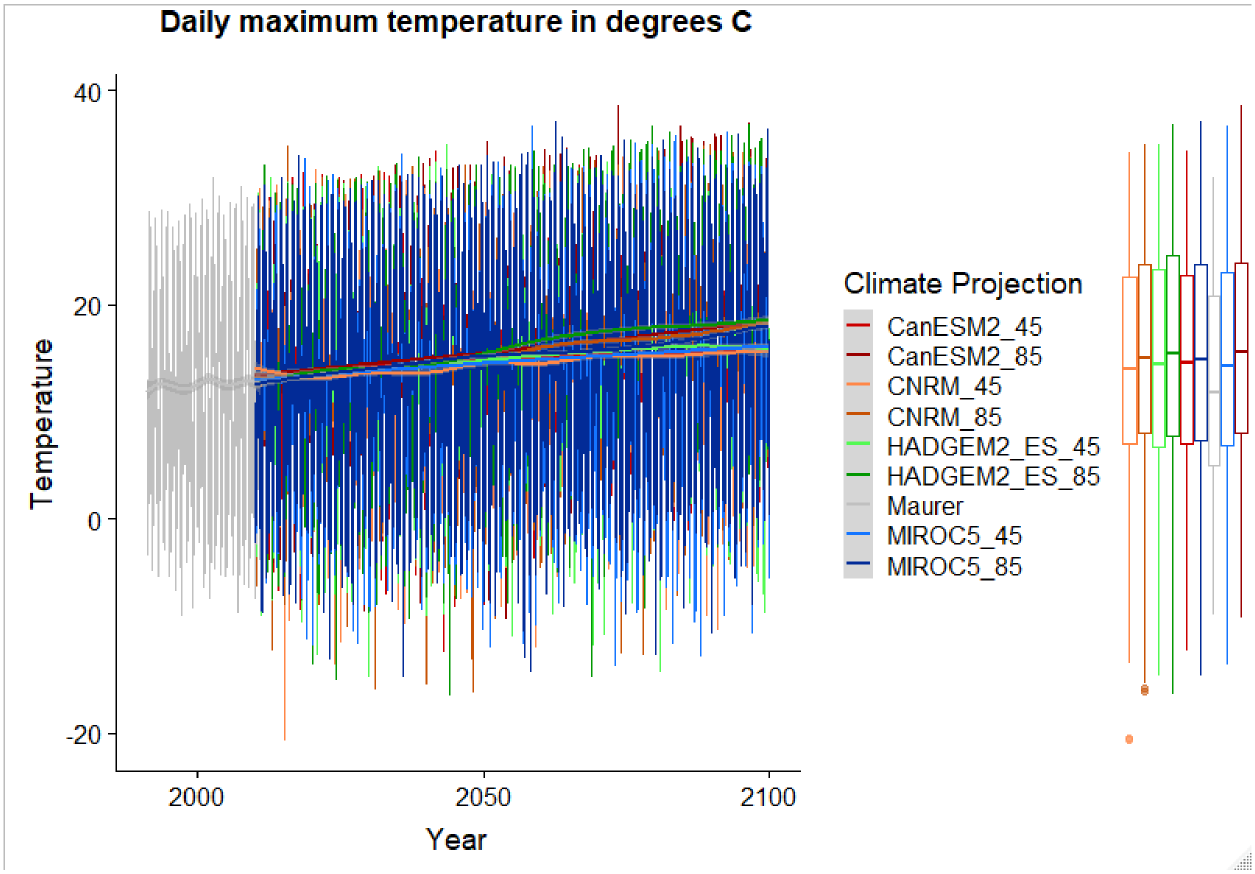

Fig. A1.3. Projected daily maximum temperature in degrees C, lines of best fit are GAM estimated, and boxplots represent distribution of daily temperatures for the years 2090-2100 for the future climate projections.

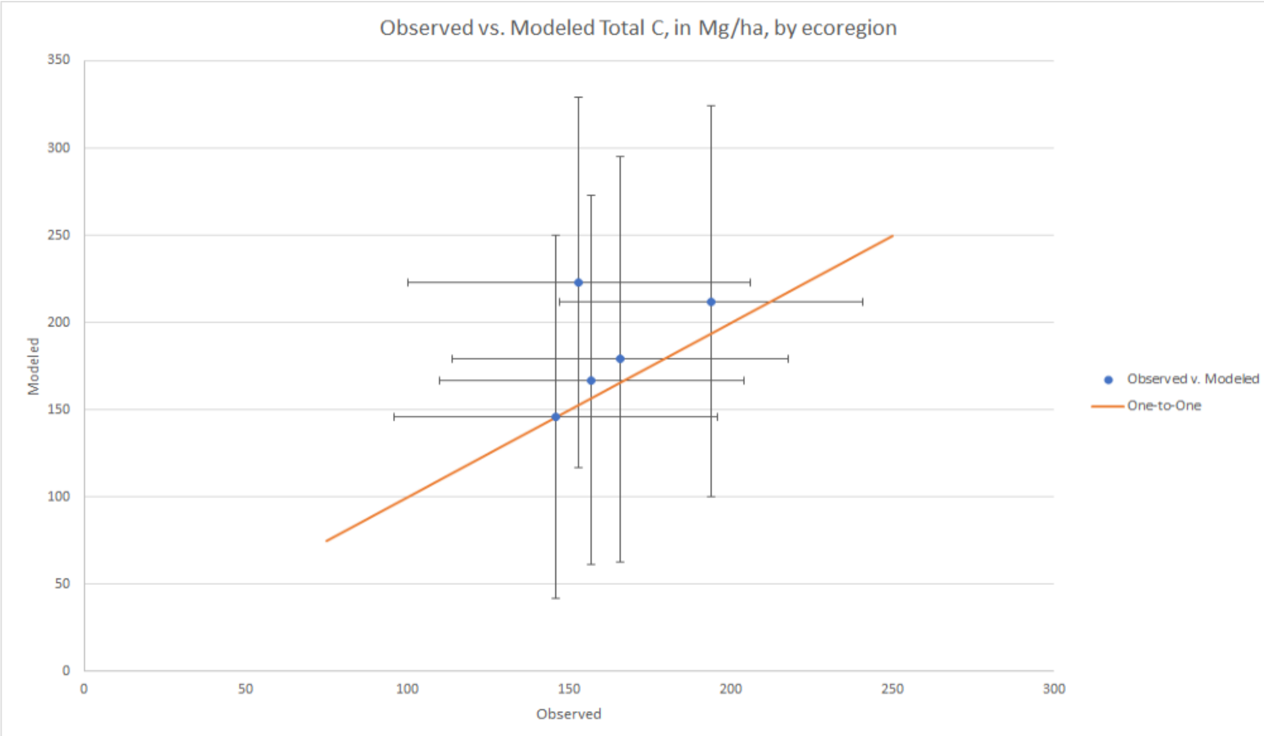

Fig. A1.4. Observed versus modeled total C, in megagrams C per hectare, by ecoregion, error bars represent +/- 1 standard deviation.

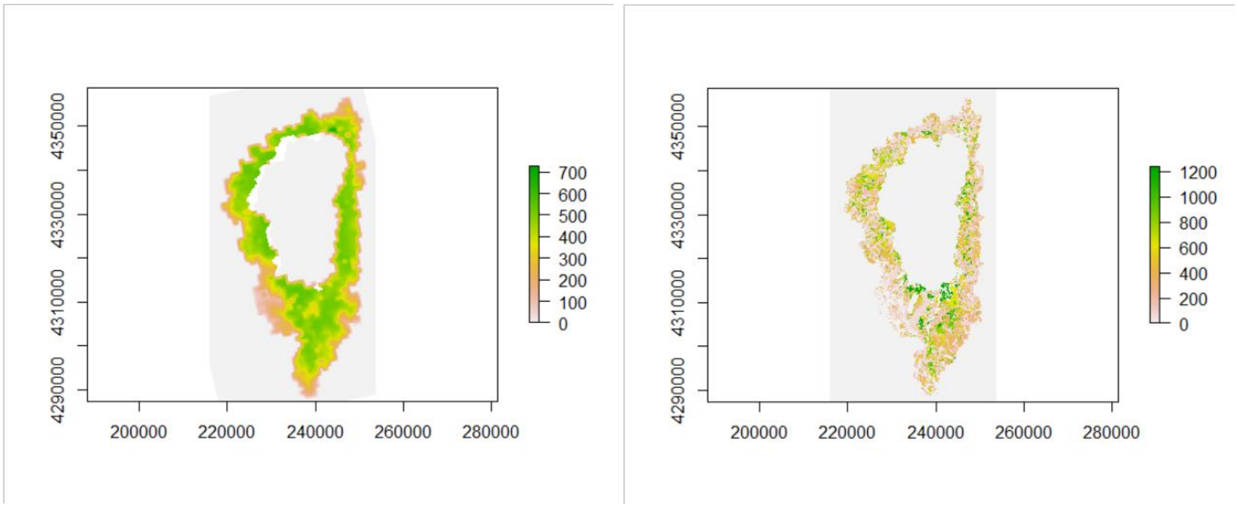

Fig. A1.5. Comparison of MODIS (left) and LANDIS (right) estimates of Net Primary Productivity in g C/m ^2. Mean landscape value for MODIS was 393 g C/m ^2 (sd 134), while for LANDIS the mean value was 320 g C/m^2 (sd 312).

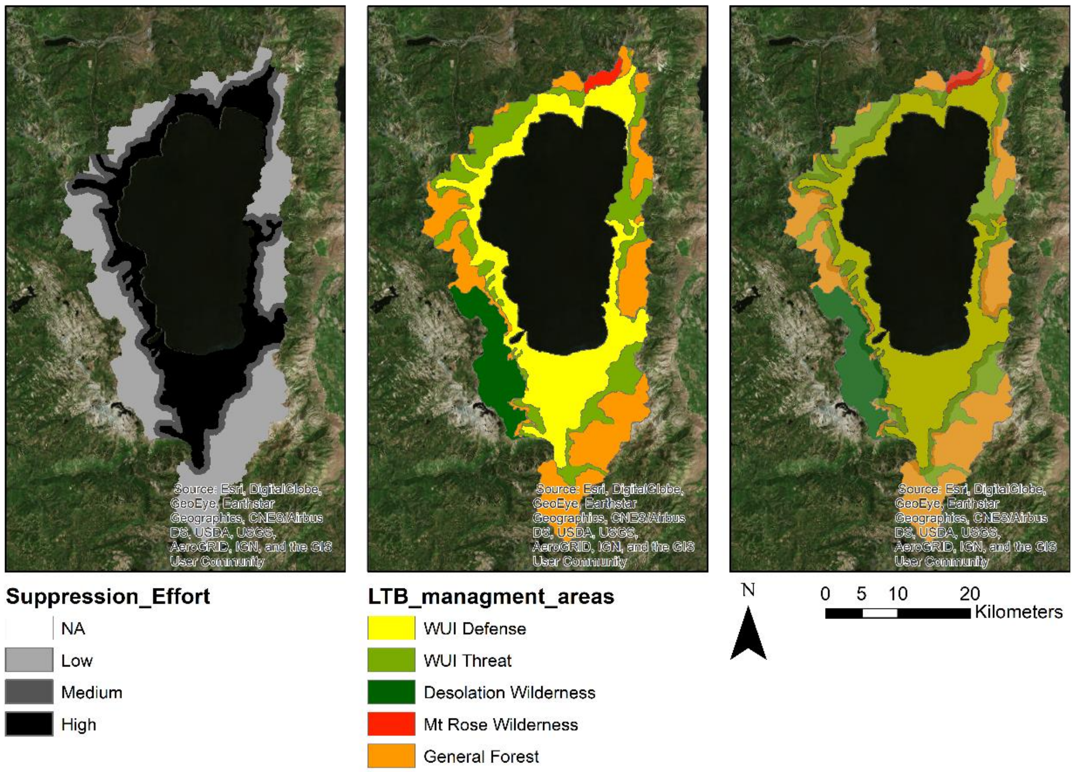

Fig. A1.6. Map of suppression effort (left), management zone (middle), and the overlay of the two (right).

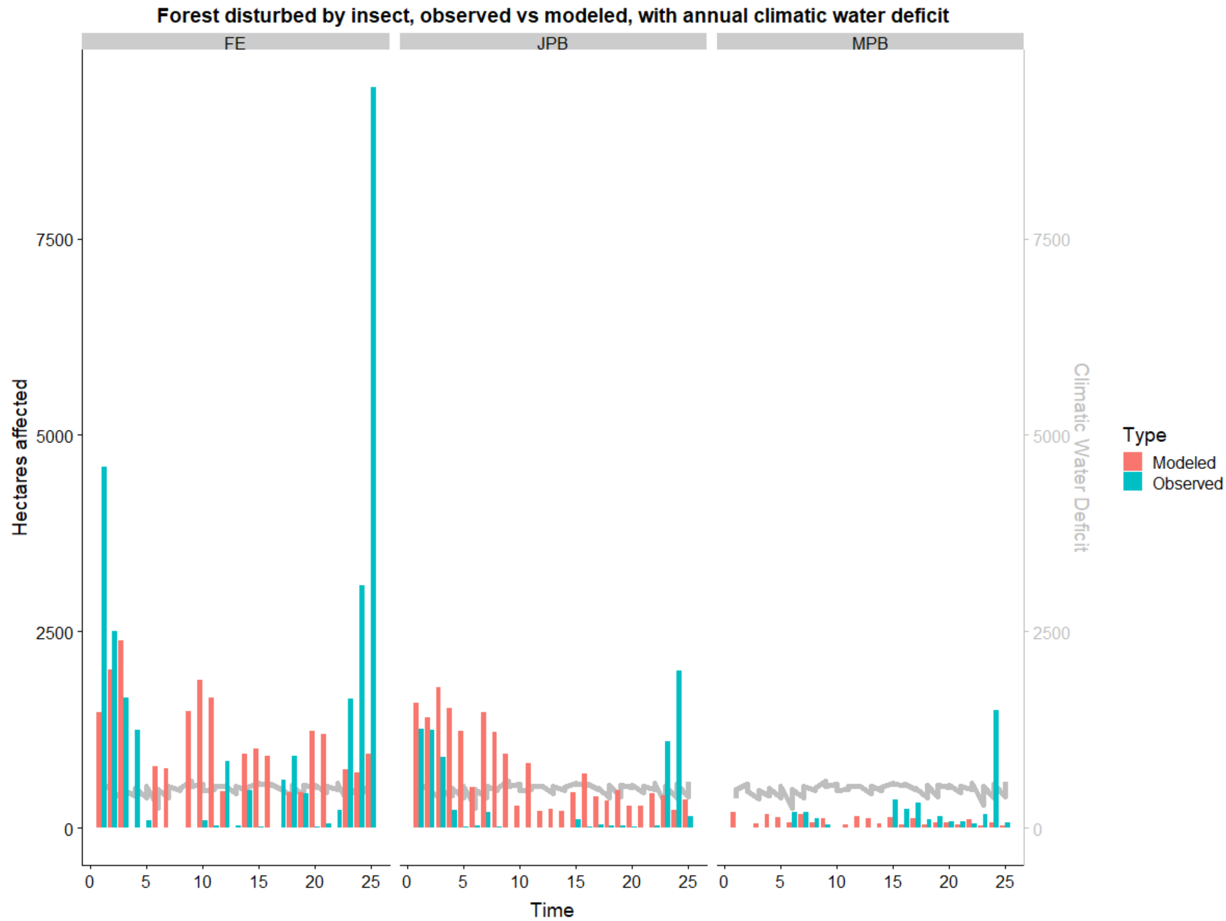

Fig. A1.7. Observed versus modeled number of hectares affected by insect/mortality agent. Time 0 is equal to 1990, with Time 22-25 corresponding to the 2012-2015 California drought. FE is fir engraver beetle (*Scolytus ventralis*), JPB is Jeffrey pine beetle (*Dendroctonus jeffrey*), and MPB is mountain pine beetle (*Dendroctonus ponderosae*).

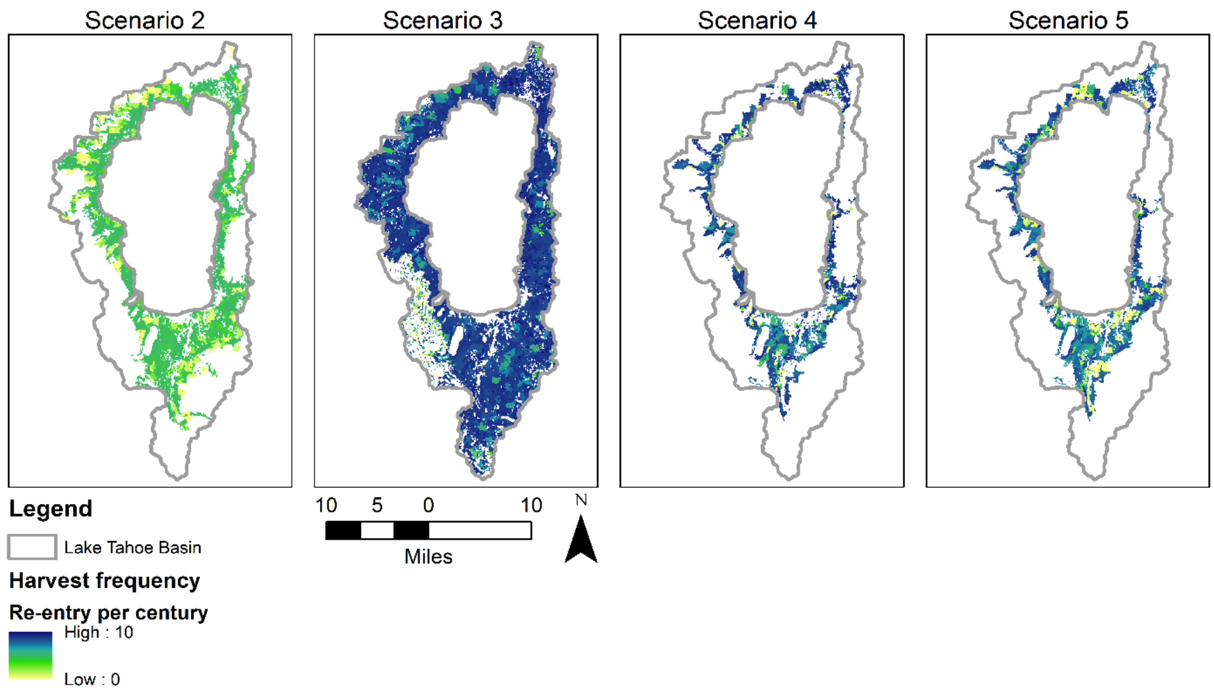

Fig. A1.8. Harvest return frequency by management scenario. Treatments were expanded beyond the WUI area in Scenario 3. Scenarios 3 through 5 had a higher intended treatment frequency.

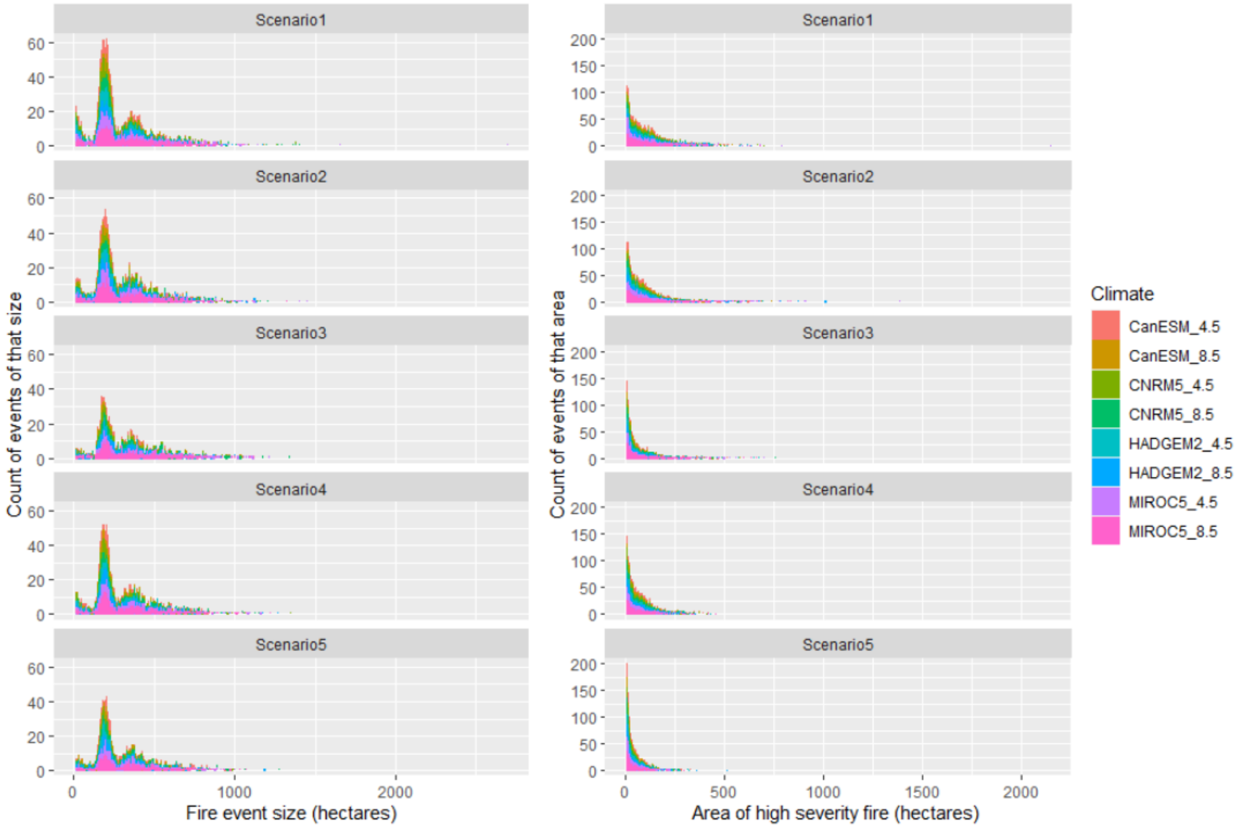

Fig. A1.9. Histogram of fire sizes (left) and high severity fire area (right) by scenario and by climate

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