Title: Estimating the influence of field inventory sampling intensity on forest landscape model performance for determining high-severity wildfire risk

Authors: Hagar Hecht[1,4], Dan J. Krofcheck[2,4], Dennis Carril[3], Matthew D. Hurteau[4]

[1] Spatial Informatics Group Natural Assets Lab

[2] Sandia National Laboratory

[3] Santa Fe National Forest

[4] Department of Biology, University of New Mexico

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Abstract

Fire has historically been an integral part of forests in the Southwestern US. However, a policy of fire exclusion in the past century together with a warming and drying climate, created forests which are more susceptible to fires, resulting in uncharacteristic wild-fires with large high-severity patches. Managers use a combination of thinning and prescribe burns to reduce forest density to help mitigate the risk of high-severity fires. However, these treatments are labor intensive and expensive, therefore it is important to optimize the effect of this work. Landscape simulation models can be a useful tool to help identify high risk areas and assess the effects of treatments, and are applicable over large areas, however, uncertainties in these models can limit their utility in decision making. In this study we examined one aspect of the underlying uncertainties, the initial vegetation layer. We extended a study by Krofcheck et al., (2019) and simulated wildfires and management in the Santa Fe fireshed using over 1000 new additional inventoried plots with which we interpolated the initial forest conditions. We found that using an increased number of inventory plots improved representation of the forest in its entirety and allowed to model a wider range of biomass. In addition, in forest types that were not frequently inventoried the simulated biomass was significantly dependent on the number of plots used for the initial forest interpretation. The consequential difference in biomass and its geographical distribution resulted in a shift of areas with high probability of high-severity fires, causing a shift in management areas. Although management consistently reduced probability of high-severity fires, the carbon dynamics depended on number of plots used for forest interpretations. Net ecosystem carbon balance (NECB) was always negative in the first years of the simulations when thinning happened but transitioned to ecosystem carbon intake was faster when using more plot data. We conclude that the initial forest layer is significant in its effect on fire and carbon

dynamics and is dependent on both number of plots available and a sufficient representation of the forest in its entirety. Operationalizing forest landscape models will require managers and researchers to work together and develop a forest inventory design applicable to this kind of work and determine the acceptable amount of uncertainty that will allow the use of these models for decision making.

1. Introduction

Contemporary forest fuels management in the southwestern US involves a combination of thinning small diameter trees and prescribed burning to reduce tree density, ladder fuels, and surface fuels, which can reduce the risk of high-severity fire (Agee & Skinner, 2005; North et al., 2021; Safford et al., 2012). Yet, these treatments can have varying degrees of effectiveness for reducing the risk of high-severity fire and the per unit area costs range from tens to hundreds of dollars per hectare for prescribed burning to several thousand dollars per hectare for thinning and hand-piling the cut material (the most expensive treatment; Krofcheck et al., 2017; McIver et al., 2012; Shive et al., 2013). The most effective approach for reducing the risk of high-severity fire, especially in areas where consequences are greater (e.g. the wildland-urban interface), is small diameter tree thinning combined with prescribed burning. In the southwestern US, thinning combined with prescribed burning is one of the most expensive treatment combinations because the trees are not merchantable. Thus, preparing a landscape to receive fire and reduce high-severity wildfire risk is contingent upon using thinning treatments in a manner that they facilitate prescribed burning and managing natural ignitions for resource benefit over a larger fraction of the landscape (North et al., 2021; York et al., 2021).

The goals of management vary in terms of desirable outcome and planned timeline, and are often a balancing act of multiple objectives that can include in addition to fire severity reduction and forest restoration, watershed protection, habitat conservation, and carbon stabilization (Hurteau et al., 2013; Jones et al., 2022; Latif et al., 2022; Smith et al., 2011). Achieving near-term objectives, such as reducing the risk of high-severity wildfire to communities, and long-term objectives, such as managing for carbon storage to help regulate the climate, requires evaluation of trade-offs in both time and space. Accounting for trade-offs between management objectives across different temporal and spatial scales becomes increasingly difficult as the number of objectives and interactions between them increases, requiring the use of forest landscape models to better understand treatment scenarios and their possible outcomes (Ager et al., 2010, 2022; Finney et al., 2007; Krofcheck et al., 2019).

As resources available for management are limited, using them in the most advantageous way is crucial, and optimizing treatment placement has been another subject of forest landscape simulation studies (Ager et al., 2013; Krofcheck et al., 2018; Wei et al., 2008). In the case of wildfire, identifying landscape positions that have the highest probabilities of burning at high-severity can help managers efficiently locate forest treatments. However, uncertainties in model output can limit their utility for decision-making. These uncertainties can be due to model structure (Petter et al., 2020), key processes being absent from models (Stephens et al., 2022), or due to errors in the underlying data such as climate projections or the use of a generalized vegetation parameterization (Remy et al., 2019). With all landscape vegetation models, the simulation is heavily influenced by the representation of vegetation conditions across the landscape. Uncertainty in the initial characterization of vegetation structure will likely propagate and amplify as dependent processes are simulated in the model, such as vegetation competition, drought, and wildfire. These compounding uncertainties increase the challenges associated with using landscape models to inform decision making at any spatial or temporal scale, and therefore it is critical that we 1) develop a more rigorous understanding of how the uncertainty in the model inputs affects variability in model output, and 2) identify mechanisms to constrain that uncertainty with additional data.

In this study we evaluated the effects of forest inventory sample size on variability in the initial vegetation layer for an ecosystem model for the Santa Fe Fireshed in northern New Mexico. We leveraged prior research by Krofcheck et al. (2019) that evaluated thinning treatment placement optimization and its effects on forest carbon dynamics in the Santa Fe Fireshed and additional inventory data from the US Forest Service to quantify how the number of inventory plots influences model estimates of the high-severity wildfire. We compared our results to those of Krofcheck et al. (2019) to determine the effect of additional inventory data on forest treatment placement.

2. Methods

2.1. Study area

We conducted simulations in the Santa Fe fireshed, located in the Sangre De Cristo Mountains, east of Santa Fe, New Mexico. The fireshed is approximately 48,000 ha and has an elevation ranging from 1900 to 3700 m. The prominent vegetation changes with elevation and is comprised of piñon-juniper (*Pinus edulis, Juniperus monosperma*) woodlands at lower elevations, ponderosa pine (*P. ponderosa*) at mid-elevations and mixed-conifer forest and spruce-fir (*Picea spp, Abies spp.*) at high-elevations. There are occurrences of gambel oak (*Quercus gambelii*) and quaking aspen (*Populus tremuloides*) stands in recently disturbed areas in the mid- and high-elevations. At lower elevations, the Sobordoro soils have a silty clay skeletal mixture, which transitions to loam-dominated soils at higher elevations. Mean climatic conditions over the period 1980–2015 included mean annual temperature of 9.4 °C and mean annual precipitation of 360 mm, with greater than 50% falling as snow in the winter months at higher elevations (Thornton et al., 2012).

2.2. Model and Parametrizations

As the starting point for our modeling experimentation, we replicated the model inputs, landscape structure and all parameterizations used in Krofcheck et al. (2019), and fixed all random seeds used to govern stochastic draws from distributions in the succession and wildfire components of the model. Our ultimate goal was to ensure that any differences we observed relative to the previously published work could be attributed to our experimental manipulations. The full modeling structure and parameterization are described below.

We used the Landscape Disturbance and Succession II (LANDIS-II) model (Scheller et al., 2007) with the photosynthesis and evapotranspiration (PnET) succession, Dynamic Fuels and Fire, and Biomass Harvest extensions to simulation forest growth and disturbance using a 100m resolution. The core model simulates forest growth and succussion for each pixel (henceforth referred to as site) using a demography-based approach to track species-specific age cohorts of biomass. Each species is parameterized independently with a unique set of parameters that govern their growth, succession, dispersal, and mortality across a spatially explicit landscape (Scheller et al., 2007). We used the (PnET) succession extension (de Bruijn et al., 2014), based on elements of the PNET-II model (Aber et al., 1995). The PnET succession extension models carbon and water flux using species-specific physiological parameters. We used the parameters previously validated by Remy et al. (2019) for this area, which were obtained from previously published data and the TRY database, and validated against eddy covariance tower data (Gustafson et al., 2015; Kattge et al., 2011; Remy et al., 2019). We used the Dynamic Fuels and Fire extension (Sturtevant et al., 2009) to simulate wildfires. This extension was parameterized for the study area by Krofcheck et al. (2019) using regional fire size data from Geospatial Multi-Agency Coordination (https://rmgsc.cr.usgs.gov/outgoing/GeoMAC/historic_fire_data/), previously published fuels data (Forestry Canada Fire Danger Group, 1992; Hurteau et al., 2016; Krofcheck et al., 2017; Syphard et al., 2011), and climate projections from the Multivariate Adaptive Constructed Analogs v2 collection to develop fire weather distributions (https://climate.northwestknowledge.net/MACA/). We used the Biomass and Harvest extension (Gustafson et al., 2000) to simulate thinning treatments.

We used a Cross between three elevation zones (https://datagateway.nrcs.usda.gov/) roughly corresponding to the vegetation transitions determined by the Southwest Regional Gap Analysis (https://swregap.org/) and six soil types (State Soil Geographic dataset, https://datagateway.nrcs.usda.gov/) to define 18 unique edaphic and climatic zones. These were used as ecoregions in the LANDIS-II core model and PnET succession extension. We used the same three elevation zones to define three different fire regions, which the model requires to define areas of similar fire weather, fire size distribution, and number of attempted ignitions.

We used monthly climate data, radiation, and atmospheric carbon dioxide concentration produced by Krofcheck et al. (2019). These were based on projections from the Localized Constructed Analogs statistically downscaled climate projection from five climate models forced with Representative Concentration Pathway 8.5 from the Coupled Model Inter-comparison Project Phase 5. The climate models chosen were Community Climate System Model (CCSM), Centre National de Recherches Météorologiques (CNRM), Flexible Global Ocean-Atmosphere-Land System Model (FGOALS), Geophysical Fluid Dynamics Laboratory (GFDL), and Model for Interdisciplinary Research on Climate (MIROC5-ESM 2) as their projections capture the range of temperature and precipitation for the study area.

2.3. Initial Communities Data

The initial communities layer is the base vegetation layer that sets the starting conditions for the exchange of carbon, water, energy, species interactions, disturbance effects, and other landscape processes. Given the importance of vegetation conditions for determining an optimal solution for thinning treatments, representing the spatial distribution of actual forest conditions well is central to generating simulation outputs that are useful to management decision-making. The initial treatment optimization study in this landscape (Krofcheck et al., 2019) used 68 Forest Inventory and Analysis (FIA) plots from within the Santa Fe National Forest that had been inventoried in 2010 or later and had not burned since 2005 (Fig. 1). Forest types represented by the FIA plots were piñon-juniper, ponderosa pine, Douglas-fir (*Pseudotsuga menziesii*), Engelman spruce (*Picea engelmannii*) and limber pine (*Pinus flexilis*). The latter three were grouped into a general mixed-conifer forest type. The authors then used elevation, transformed aspect using Topographic Radiation Aspect Index, TRASP (Roberts & Cooper, 1989), and a tasseled cap transformation of spectral data from Landsat 8 (available at https://www.usgs.gov/landsat-missions/landsat-8) as predictors for Random Forest models and used the rfUtilities library (Evans & Murphy, 2018) to select the most parsimonious model for each forest category separately. Existing vegetation classification from the Southwest Regional Gap Analysis (SWReGap, https://swregap.org/) using the 'yaImpute' library (Crookston & Finley, 2008) was used to stratify the measured plots for the imputation. We determined plot sampling intensity by calculating the relative area of land each plot represents within its forest type.

To evaluate the influence of additional plot data on the initial communities layer and its effects on model behavior, we used data collected as part of the planning process by the US Forest Service. These data were located entirely within the study area and included 1072 plots from 111 stands inventoried in 2011, where each stand included between 3 and 31 plots (Fig. 1). Plot data were collected using a common stand exam protocol using variable radius plots. The specific Basal Area Factor (BAF) prism chosen for each stand was a function of stand density and they ranged from 10 to 30 BAF. We had coordinates for the centroid of each stand, but not for each individual plot, which effects the imputation process. We used the tree data from each plot to determine a specific forest type and generalized category (e.g. piñon-juniper, ponderosa pine, mixed-conifer), corresponding to the FIA classification, and added an aspen forest type, resulting in a total of four generalized forest types. We also defined non-forested areas and included two generalized species parameterizations to represent shrubs that resprout and shrubs that do not resprout following fire. We used all FIA and common stand exam (CSE) plot data (n=1140) to generate a new initial communities layer following the same method as Krofcheck et al. (2019) in R v4.1.2 (R Core Team, 2021).

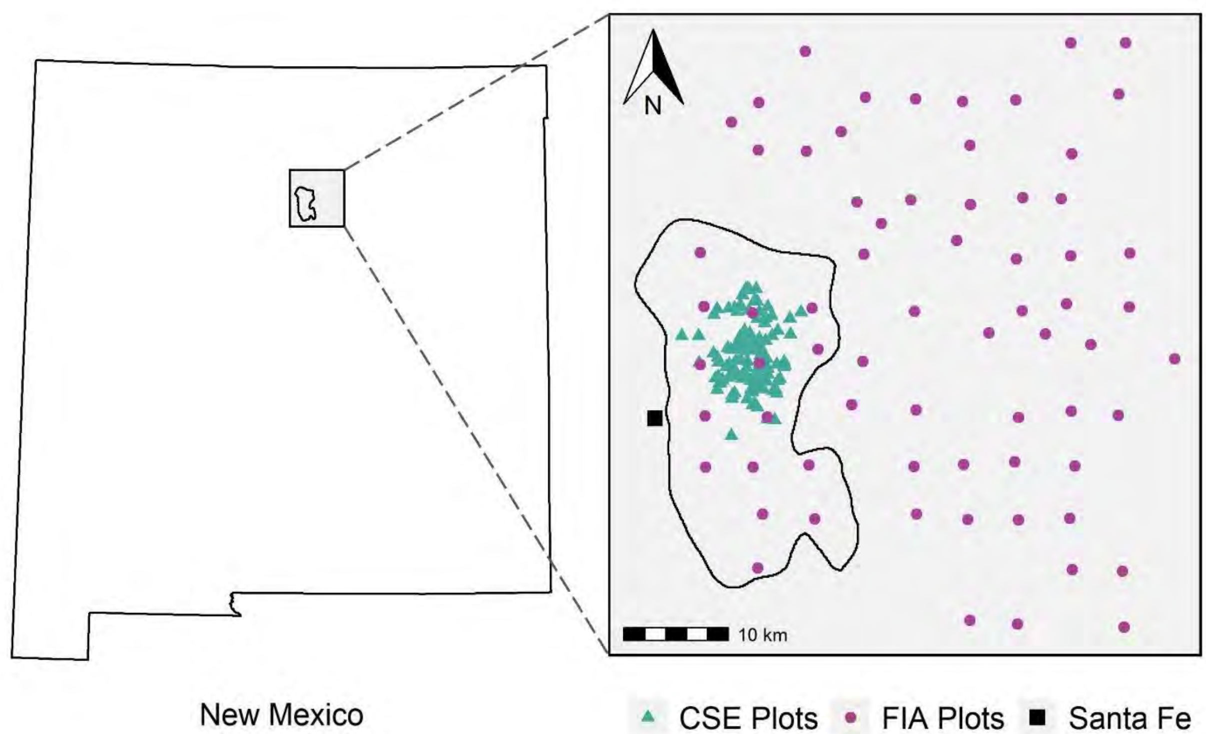

Fig. 1. Study area boundary with approximate Forest Inventory and Analysis (FIA) plot locations (n = 68) and the Common Stand Exam (CSE) plots (n = 1072) represented by stand locations (n = 111). Each stand contains between 3 and 31 plots.

2.4. Simulation Analysis

Given the importance of the initial communities layer for determining where high-severity fire probability is greatest on the landscape, we sought to estimate the uncertainty in the initial communities layer from not having coordinates for every CSE plot because the USFS data applies coordinates for a stand to all plots sampled in the stand. We also sought to estimate the uncertainty due to the number of plots used to interpolate the initial communities layer.

To estimate the uncertainty in the initial communities layer that is due to not having coordinates for all CSE plots, we re-ran interpolations randomly selecting one plot for each set of stand coordinates. This led to 31 initial communities layers, which we used to initialize the model with the five climate projections, for a total of 155 simulations. We compared the aboveground carbon following model initialization of these initial communities layers with the initial communities layer that we created using all plot data and that we used for our management simulations. We calculated the difference in aboveground carbon between each layer and the one we used in our simulations to determine how much the initial communities layer is influenced by this source of uncertainty.

Inventory data can be costly to collect and limited data availability for developing the initial communities layer is a source of uncertainty that can influence identifying locations with a high probability of high-severity fire. To determine the influence of the number of plots used in the development of the initial communities layer, we produced five additional initial communities layers with differing numbers of underlying plot data. For four of the five layers, we halved the number of CSE plots used in the interpolation each time (e.g. 536, 268, 134, 67) and combined those with the FIA data. For the fifth initial communities layer, we only used the 68 FIA plots. For each of the layers, we randomly selected plots from each forest type proportional to the prevalence of each forest type on the landscape. We then initialized the model using each of these initial communities layers using the five climate projections and compared the aboveground carbon following model initialization to that of the initial communities layer that we used for our simulations.

We quantified differences between our primary initial communities layer and that of Krofcheck et al., (2019) by comparing the difference in quantity and distribution of aboveground carbon at the beginning and end of the simulations. We ran an independent t-test to assess the difference in carbon between the two studies at each site every 10 years for each of the climate models, and computed the percent of area with a significant difference ($p < 0.01$) in aboveground carbon. We compared treatment location as determined by the probability of high-severity fire between our initial communities layer and that of Krofcheck et al. (2019). We calculated Net Ecosystem Carbon Balance (NECB) by subtracting carbon lost from the system (treatment and wildfires) from carbon gained (photosynthesis) and then relativized the treatment scenario NECB values to the no-management scenario for both our simulations and those of Krofcheck et al. (2019). Data processing and analysis was conducted using R v4.1.2 (R Core Team, 2021).

2.5. Treatment scenarios

To develop the optimized treatment placement scenario, we first ran simulations that included no management to identify locations where landscape conditions were such that there was a high probability of high-severity wildfire. We ran the no-management simulations using the same five projected climate data sets and fire weather data described above. We ran 25 replicate simulations using each of five projected climate data sets, for a total of 6250 simulation years. We used fire severity raster data from these model outputs to quantify the probability of high-severity by dividing the number of years with high-severity fires by the total number of fire years per site. We then identified sites with a probability of high-severity fire greater than 0.3 and targeted those locations in the treatment scenario simulations, assigning treatment to those areas first.

To determine the type of treatment we used the probability of high-severity fire in combination with slope and forest type. We limited our management simulations to the ponderosa pine and dry mixed-conifer forest where the combined ponderosa pine and Douglas-fir aboveground carbon was at least 65% of the total. We used the same thinning and prescribed burning treatments as Krofcheck et al. (2019), which were designed to approximate common treatments for the region. Thinning treatments simulated thinning from below by removing approximately 30% of the biomass, preferentially removing the youngest cohorts (Hurteau et al., 2011, 2016) and was only applied to ponderosa pine forest and confined to slopes <30%, to account for a common limitation on mechanical thinning. We simulated prescribed burning based on historic mean fire return intervals, with all ponderosa pine burned using a 10-year return interval and forests co-dominated by ponderosa pine and Douglas-fir burned using a 15-year return interval. The forest type and probability of high-severity fire are highly dependent on the initial communities layer which defines the initial forest conditions. As a result, our treatment placement map differed substantially from the one in Krofcheck et al. (2019).

To examine the effects of the treatment on the landscape we produced a new probability of high-severity fires raster and calculated the difference in aboveground carbon between the management and no management scenarios of this study at the end the simulations.

We ran simulations over a 50-year period, using climate model projections for years 2000-2050. We ran 25 replicates for each of the five climate projections, totaling 125 simulations each for the no-management and management scenarios. Fire weather distributions tracked projected climate and were updated each decade to account for changes in temperature and precipitation.

3. Results

Our comparison of the 31 initial communities layers derived from randomly selecting plots from the forest stands sampled by the USFS indicated that the specific plots selected to represent each stand had a relatively small influence on aboveground carbon. The total aboveground carbon of the whole fireshed in teragrams at year 1 of the simulations was similar when comparing simulations within each of the five climate models, and the median for all 155 simulations and across the five climate models was 3.601 Tg of carbon with an interquartile range (IQR) of 0.146 Tg. (Fig. S1a). We calculated the difference between the year 1 aboveground carbon of the initial communities layer we used for our management simulations (hereafter new layer) and the mean of year 1 aboveground carbon generated from replicate simulations of the 31 initial communities layers and found that only 560 hectares of the total 48,957 ha within the study area had a difference of more than 20 Mg ha^{-1} of carbon, the median of the difference was -0.068 and the IQR was 0.859 Mg ha^{-1} of carbon (Fig. S1b). Typically, grid cells that had higher carbon values than those in the new layer were the aspen forest type and grid cells that had lower carbon values than the new layer were dominated by limber pine or ponderosa pine forest with a large limber pine component. This result is likely due to the fact that these forest types are less common in the CSE plot data set.

The aboveground carbon distributions for ponderosa pine and mixed-conifer forests were fairly similar to the new layer, regardless of the number of plots used to develop the initial communities (Fig. 2a). Estimates of aspen carbon differed substantially from the new layer, with median values decreasing by 12.22 Mg ha^{-1} or more (Fig. 2a). For piñon-juniper, median values were fairly consistent regardless of the number of plots used to develop the initial communities layer, but variability decreased substantially when fewer than half of the available plots were used (Fig. 2a), demonstrating the importance of adequate sampling to capture the variability in vegetation conditions (Fig. S2). The density distribution of aboveground carbon was similar for the new layer developed using all 1072 plots and the layer developed using half the plots. However, the layers that used fewer than half of the plots had decreased variability and were underestimating lower carbon grid cells of approximately 30 Mg C ha^{-1} and lower (Fig. 2b). The reduction in carbon variability with decreased numbers of plots used to inform the initial communities layer, when mapped spatially, shows that the largest discrepancies between the new layer and the others occurs in the vegetation types (e.g. aspen and piñon-juniper) that are sampled less intensively than the more common ponderosa pine and mixed-conifer forest types (Fig. 2c).

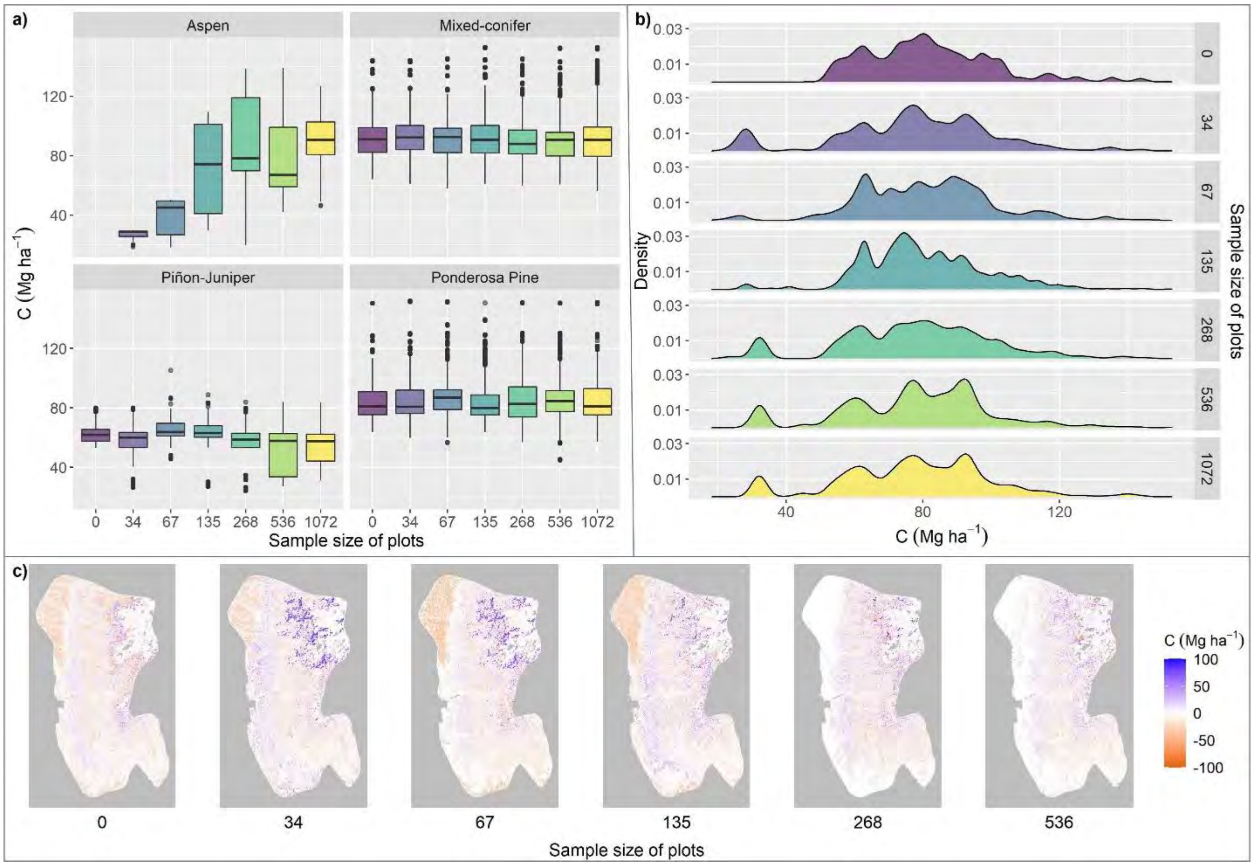

Fig. 2. a) Boxplot of aboveground carbon per site at year 1 of the simulation using different initial communities layers separated by forest type. X axis indicates number of available new plots in addition to 68 FIA plots used to create the initial communities layer. b) Density distribution of aboveground carbon at year 1 of the simulations for each of the initial communities layers. c) Difference in aboveground carbon at year 1 between the new initial communities layer developed using all 1072 plots and initial communities layers developed using fewer plots. Positive values indicate higher aboveground carbon in the initial communities layer developed using all 1072 plots.

When we compared the model results from our initial communities layer developed using the 68 FIA plots in addition to the 1072 CSE plots (new layer) with those from the Krofcheck et al. (2019) initial communities layer developed using only the FIA plots (hereafter 'old layer') we found the new layer results in higher overall aboveground carbon and greater carbon variability following model initialization (Fig. 3a, b), with statistically significant differences occurring at the site-scale (Fig. 3c). While these differences persisted throughout the 50-year simulation period, the difference in aboveground carbon between the new and old layer decreased by the end of the simulation period (Fig. 3c).

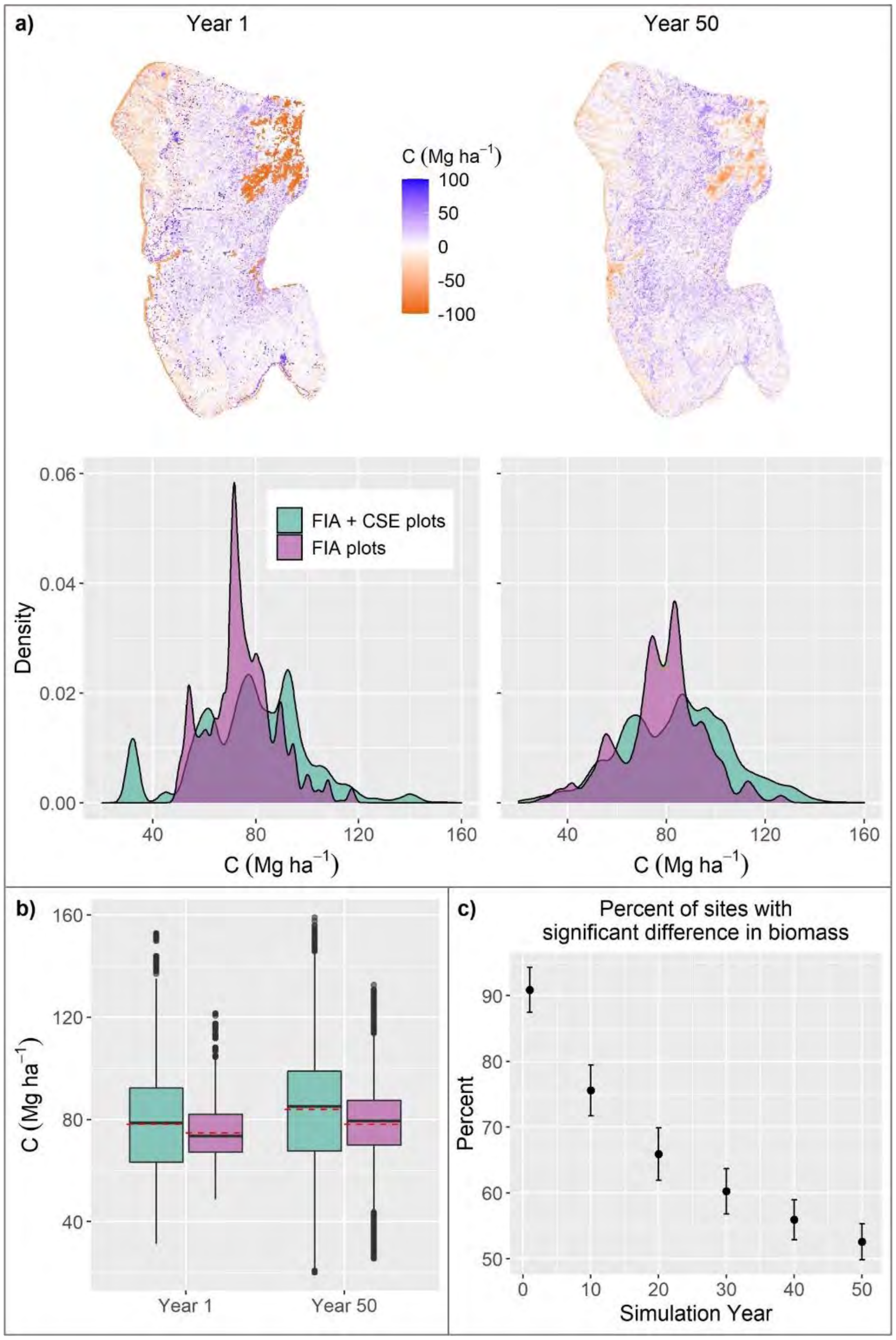

Fig. 3. a) Comparison of aboveground carbon when using FIA plots only (Krofcheck et al., 2019) and FIA + CSE plots (this study) for the no management scenarios. Top is the difference in aboveground carbon. Positive values indicate this study has a higher value than the previous study. Bottom is density plots. Left column is year 1 of the

simulations and right column is year 50. b)Boxplot of aboveground carbon in each of the studies for year 1 and 50. Red line is the mean. c) Percent of sites with significantly different aboveground carbon ($p < 0.01$ for t-test). Points are mean for all climate models and error bars are standard deviation.

The differences in aboveground carbon density between the new and old layers led to differences in the spatial distribution of the probability of high-severity fire (Fig. 4a). Given these differences, the distribution of thinning and prescribed fire treatments varied between the old and new layers (Fig. 4b). The carbon density and resultant probability of high-severity fire from the new layer resulted in areas identified for thinning and burning combined or burning alone shifting east and up in elevation. The new treatment map also had approximately 2000 ha fewer identified as requiring thinning when compared to the old treatment map (Fig. 4b right).

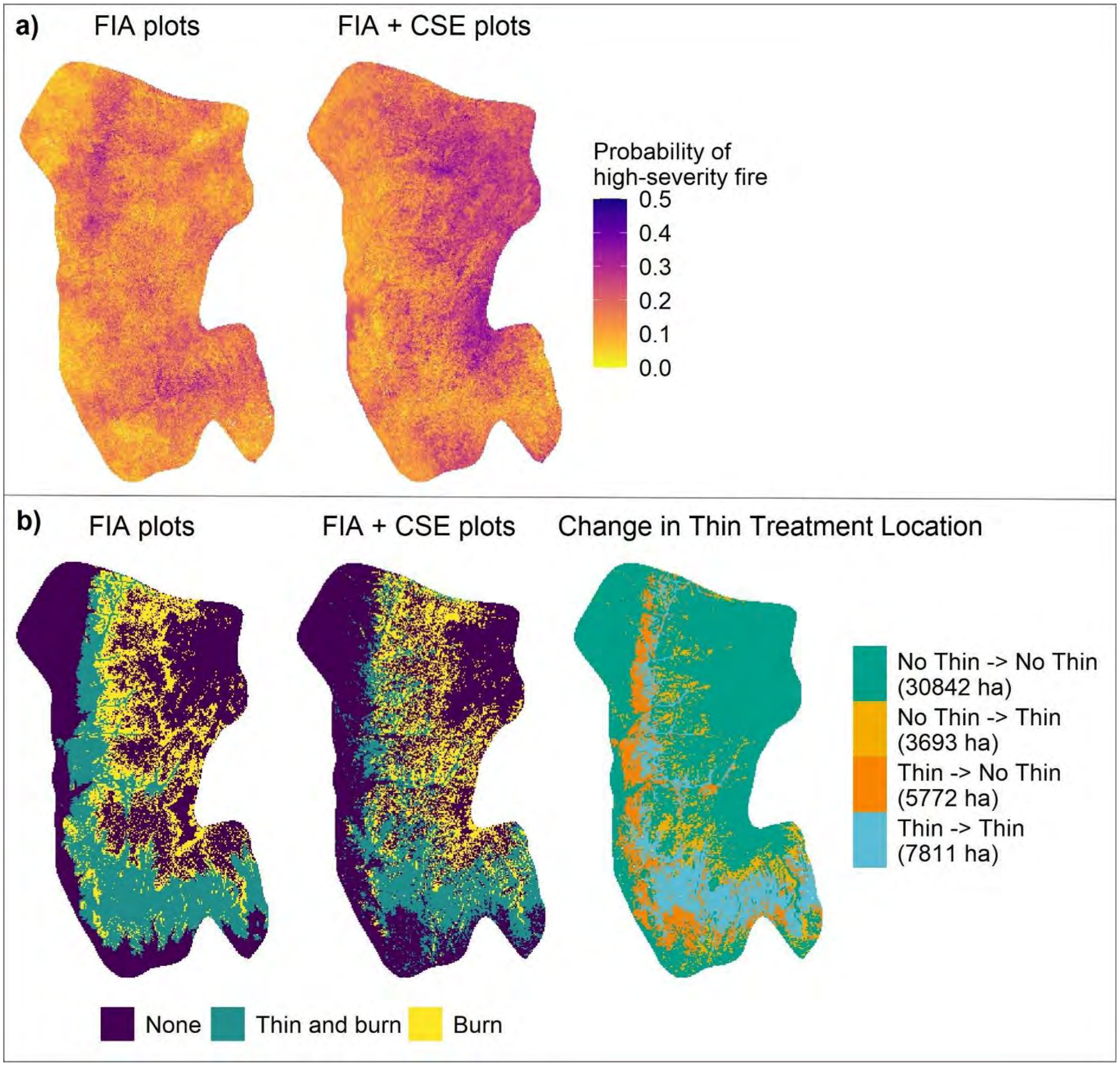

Fig. 4. a) Probability of high severity fire in Krofcheck et al., 2019 (FIA plots) and this study (FIA + CSE plots). b) The optimized treatment map from Krofcheck et al, 2019 (left), treatment map for this study (middle) and the changes in thinning treatment locations (right). Each zone indicates the type of treatment in Krofcheck et al., 2019, and what it has changed to, for example, yellow indicates areas that were not thinning in the previous study and were designated to undergo thinning in the new study.

We compared the simulation outputs of the management and no-management scenarios using the new initial communities layer and found that the management scenario, as expected, decreased the probability of high-severity fire where treatments were implemented (Fig. 5a). The reduction in high-severity in the management scenario led to an increase in landscape carbon storage over the 50-year simulation compared to the no-management scenario (Fig. 5b). The carbon increases were primarily in areas that were treated because the treatments reduced fire severity, while in areas that were untreated there was little difference between the management and no-management scenarios.

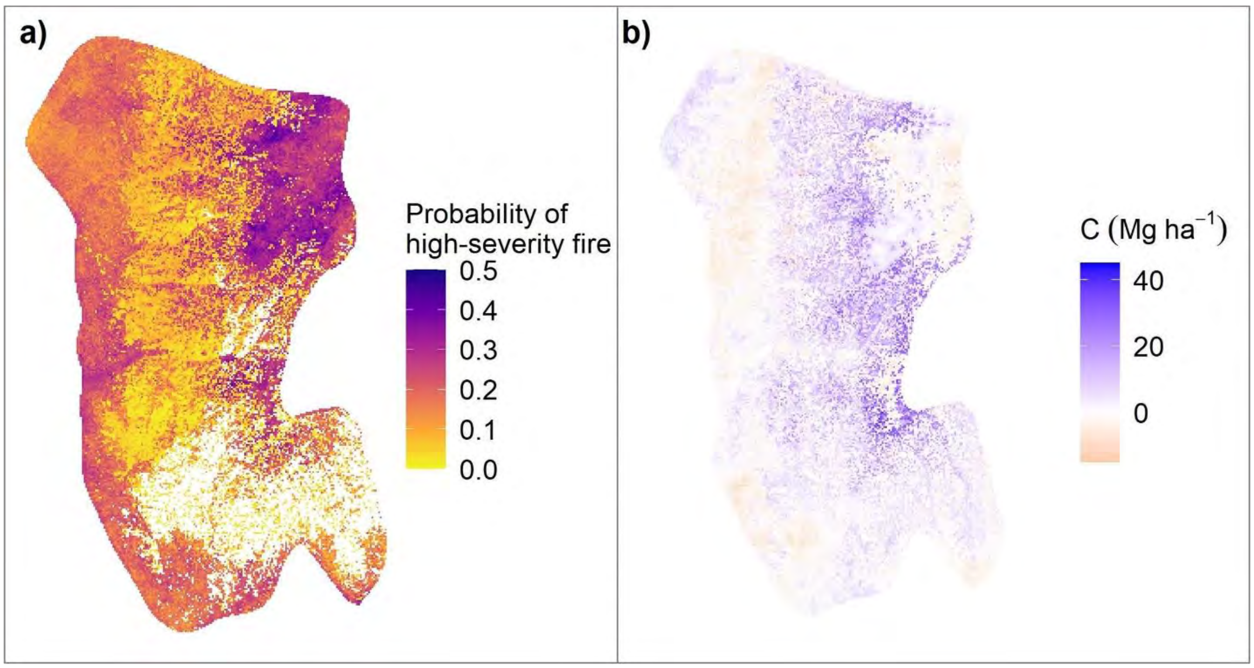

Fig. 5. a) Probability of high severity fire for the management scenario in this study. b)Difference in aboveground carbon at the end of 50 years of simulation between the management and no management scenarios in this study using the new initial communities layer. Positive values indicate higher carbon in the management scenario.

Given the differences between the new and old layers in terms of probability of high-severity fire and resultant treatment location, we compared the effects of the management scenario on cumulative NECB relative to the no management scenario. We found similar trends for both the new and old initial communities layers. The greater carbon density in simulations using the new layer resulted in larger decreases from thinning and burning treatments early in the simulation period compared to simulations using the old layer (Fig. 6). Transition to positive cumulative NECB relative to no-management scenario occurred faster in simulations using the new layer (~18 years) than in simulations using the old layer (~24 years). This difference is due to the fact that the landscape carbon density is higher for simulations with the new layer.

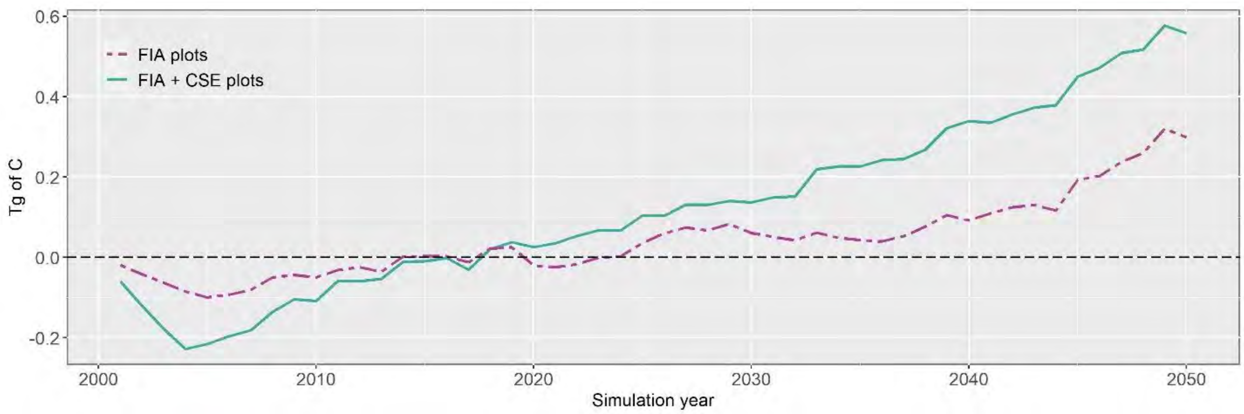

Fig. 6. Cumulative net ecosystem carbon balance (NECB) of the optimized scenario of the previous study (Krofcheck et al., 2019) and the management scenario of this study relative to the no management scenarios of the respective studies. NECB is the balance between carbon intake from photosynthesis and carbon loss due to thinning, prescribed burns, and wildfires. Positive values indicate more carbon intake to the system in the management scenario relative to the no management scenario.

4. Conclusions

The frequency and severity of wildfires is predicted to increase as the climate gets hotter and drier, but mitigating these events is possible by restoring ecologically appropriate fire. Given the size of the area in the Southwestern US that has missed multiple fire return intervals, there is more area requiring management than there are resources to support management. Forest landscape models can help identify landscape positions with the highest probability of high-severity wildfire, but their utility for management planning is based on how well the model represents actual conditions. Operationalizing forest landscape models that have largely been research tools to-date will require forest managers and researchers working collaboratively to both inform forest inventory sample design and to determine the amount of uncertainty in model output that is acceptable when using model outputs to inform decision-making.

5. Acknowledgements

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