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A landscape model of variable social-ecological fire regimes

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ABSTRACT

Fire regimes are now recognized as the product of social processes whereby fire on any landscape is the product of human-generated drivers: climate change, historical patterns of vegetation manipulation, invasive species, active fire suppression, ongoing fuel management efforts, prescribed burning, and accidental ignitions. We developed a new fire model (Social-Climate Related Pyrogenic Processes and their Landscape Effects: SCRPPLE) that emphasizes the social dimensions of fire and enables simulation of fuel-treatment effects, fire suppression, and prescribed fires. Fire behavior was parameterized with daily fire weather, ignition, and fire-boundary data. SCRPPLE was initially parameterized and developed for the Lake Tahoe Basin (LTB) in California and Nevada, USA although its behavior is general and could be applied worldwide. We demonstrate the behavior and utility of our model via four simple scenarios that emphasize the social dimensions of fire regimes: a) Recent Historical: simulated recent historical patterns of lightning and accidental fires and current patterns of fire suppression, b) Natural-Fire-Regime: simulated wildfire without suppression, accidental fires, or prescribed fires, holding all other factors the same as Recent Historical, c) Enhanced Suppression: simulated a doubling of the effectiveness of suppression, holding all other factors the same as Recent Historical, and d) Reduced Accidental Ignitions: within which the number of accidental fires was reduced by half, holding all other factors the same as Recent Historical. Results indicate that SCRPPLE can recreate past fire regimes, including size, intensity, and locations. Furthermore, our results indicate that the 'Enhanced Suppression' and 'Reduced Accidental Ignitions' scenarios had similar capacity to reduce fire and related tree mortality over time, suggesting that within the broad outlines of the scenarios, reducing accidental fires can be as effective as substantially increasing resources for suppression.

1. Introduction

Fire regimes are now recognized as the product of social processes (Abatzoglou and Williams, 2016; Balch et al., 2017; Bowman et al., 2011; Moritz et al., 2014; Nagy et al., 2018; Syphard et al., 2017; Spies et al., 2018) whereby fire on any landscape is the product of human-generated drivers: climate change (Westerling, 2016), historical patterns of vegetation manipulation (e.g., through logging)(Taylor et al., 2016; Marlon et al., 2012), invasive species (Balch et al., 2013), active fire suppression (Baker, 1992), ongoing fuel management efforts (Loudermilk et al., 2014, Krofcheck 2017), prescribed burning (Stephens and Finney, 2002), and accidental ignitions (e.g., careless campers; Balch et al., 2017). In many areas and times, the social dimensions of fire may be as or more important than the purely ecological (e.g., fuel accumulation through succession, lightning strikes) (e.g., Taylor et al., 2016). Consequently, understanding human-driven changes in fire regimes and the potential impacts of fires on human and natural systems is critical for shaping policy and management responses.

Simulating fires and fire regimes is a common approach for elucidating the causes and effects of fire due to the difficulties of experimentation and the societal need for information about risks and management options. There are a broad range of stand-alone fire models available, each designed for specific purposes. These include models that predict ignition type and quantity, fire size, and total area burned within regions and ecoregions (e.g., Abatzoglou and Williams, 2016; Balch et al., 2017; Dennison et al., 2014; Stavros et al., 2014), combined statistical models of both number of ignitions and fire-size (Westerling et al. 2011), or pixel-level environmental suitability for fires (Hawbaker et al., 2013; Davis et al. 2017; Parisien and Moritz, 2009; Parisien et al., 2011). At finer spatial scales, a range of statistical methods have been used to predict ignitions in both space and time

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(Syphard et al 2008; Sturtevant and Cleland, 2007; Prestemon et al., 2012; Yang et al., 2015). Fire spread has been simulated with cellular automata models (Baker, 1992; Hargrove et al. 2000), empirical and semi-empirical fire behavior and spread models parameterized from laboratory experiments or field data (e.g. FARSITE, Finney, 1998), and physics-based combustion and spread models (e.g. the Wildland Urban Interface Fire Dynamics Simulator, Mell et al. 2007 or the Coupled Atmospheric Weather-Fire Experiment, Coen et al., 2013). These approaches to modeling ignition and fire spread are designed for landscape scales and interact with vegetation patterns, fuel loads, topography, and weather, but do not directly incorporate vegetation change or feedbacks among human activities, vegetation, climate, and fire over time.

In contrast, landscape simulation models can integrate feedbacks among human actions (e.g., logging), fire, and vegetation, as well as other dimensions of landscape change that alter vegetation and succession, including insect outbreaks, and climatic effects on regeneration and growth. Furthermore, landscape simulation models can represent direct human modifications to the fire regime. Such modifications include human effects on ignition rates (Chas-Amil et al., 2015), the likelihood of suppression success (Ntaimo et al., 2004), and the impact of fuel treatments that reduce fire spread and/or mortality (e.g., Loudermilk et al., 2014; Krofcheck et al., 2017; Ager et al., 2017). Currently, few landscape simulation models incorporate ignitions, spread, mortality, and a full suite of human activities in addition to feedbacks with climate and emergent vegetation; Envision contains many of these processes although follows a state-and-transition succession sub-model (Spies et al., 2017).

Parameterization of fire models typically emphasizes calibration to broad-scale metrics characterizing the recent fire regime (e.g., fire size distribution, fire rotation period). Less effort has been made to parameterize fire models to fine-scale and short-term metrics characterizing individual fire progression, in part because the data required to do so are either lacking or difficult to acquire. Daily satellite active fire detections (Giglio et al., 2003) have been demonstrated to track the progression of large wildfires (Veraverbeke et al., 2014) and used to update fire spread simulations (Pinto et al., 2016; Coen et al., 2018); however, limited effort has been made to fully parameterize fire spread simulations entirely from remote sensing and geospatial data (Duff et al., 2013; Sá et al., 2017). Consequently, we also sought to create a fire projection model that could be parameterized from available exogenous (e.g., remote sensing, expert opinion) and endogenous (vegetation data existing within a modeling framework, e.g., tree species, ages, biomass) data. Input variables (e.g., those relating daily climate to probability of ignition) should be tractable with solutions that can be estimated from remotely sensed data and/or readily resolved using spatial data and/or derived from local fire expertise.

Therefore, we developed a new fire model (Social-Climate Related Pyrogenic Processes and their Landscape Effects: SCRPPLE) that emphasizes the social dimensions of fire, and captures, 1) human ignitions, accidental or via prescribed fire; 2) the spatial and temporal patterns of prescribed fires; 3) fuel-treatment effects; 4) the spatial patterns of fire suppression. In addition, SCRPPLE captures the effects of topography, fuels, and climate. We emphasized parameterization using landscape-scale datasets that have recently become more widely available (see Table 1). Finally, the approach allows for targeted emphasis on different processes. If suppression is not practiced on the landscape, it can be readily disabled. The fire model described could be operated without any information except the relationship between ignitions, spread, and Fire Weather Index (FWI) (Van Wagner, 1987).

SCRPPLE was initially developed for the Lake Tahoe Basin (LTB) in California and Nevada (Fig. 1). Even though our model was initially parameterized for LTB and the initial suite of assumptions reflect the fire dynamics of this area, our approach and these assumptions are broadly applicable to landscapes worldwide where fire is driven by both social and physical processes. Both anthropogenic and non-human factors drive fire regimes in the LTB. Because of the value and density of people and structures, fuel treatments (i.e., vegetation management that reduces surface and mid-story 'ladder' fuels) and prescribed fire are both actively deployed. Accidental ignitions predominate. The arrangement and amount of fuels are a primary concern due to historical patterns of land use (e.g., a relatively young and even-aged forest age structure determined by historical logging events, Loudermilk et al., 2013) and future fire regimes are likely to be substantially shaped by climate change (Yang et al., 2015). In this paper, we present the SCRPPLE modeling approach and demonstrate model behavior using four scenarios for LTB that explicitly integrate multiple types of human actions and show the utility of our approach for assessing the trade-offs among approaches for reducing fire on the landscape.

2. Methods

The initial implementation of SCRPPLE is within the LANDIS-II landscape change framework; LANDIS-II represents vegetation succession (Scheller et al., 2007), forest harvest and fuel treatments (Syphard et al., 2011), and insect mortality (Sturtevant et al., 2004). Details about LANDIS-II implementation, computational requirements, operating systems, and open-source code can be found at www.landis-ii.org. LANDIS-II has two existing fire extensions: the Base Fire extension which does not include climatic effects (He and Mladenoff, 1999) and the Dynamic Fire extension which does not explicitly include anthropogenic processes (Sturtevant et al., 2009). Here we focus on the details of the new SCRPPLE fire extension which consists of four primary algorithms: Ignition (including human ignitions), Spread (including the effects of suppression and fuel treatments), Fire Intensity, and Fire Mortality. These algorithms simulate three separate types of fires: Lightning, Human Unintentional ('accidental'), and Prescribed Fire ('RxFire') allowing each fire type to have its own ignition and suppression and intensity patterns. The extension assumes that if suppression is constant, lightning and accidental fires will behave similarly in regard to spread and mortality under the same weather and wind speeds. Prescribed fires may be limited by FWI and wind speed. All model code is available at: https://github.com/LANDIS-II-Foundation/Extension-SCRPPLE. Details about input formats, keywords, etc., are provided in the associated user guide: http://www.landis-ii.org/extensions/scrapple

2.1. Ignition

Our ignitions follow a "supply and allocation" model whereby the supply of ignitions is generated from a zero-inflated Poisson model and then ignitions are allocated across the landscape with an ignition surface. For accidental and lightning fires, the number of ignitions per day was determined by relating the number of ignitions (by each of three the fire types: accidental, lightning, prescribed) to Fire Weather Index (FWI). The Canadian Fire Prediction System (1992) is used to calculate FWI as a smoothed average that integrates long- and short-term variation in precipitation and temperature. FWI is calculated for each day of the year and the appropriate number of ignitions are generated for each day.

The following equation was fit to ignition and FWI data (Table 1):

$$\text{Number of fires} = e^{\beta 0\ +\ \beta 1 * \text{FWI}} \tag{1}$$

This assumes a zero-inflated Poisson distribution (Zuur et al., 2009) and uses a log link function requiring a fit of β0 and β1 that vary by ignition type and the estimated non-zero portion of the ignition response. For fractional ignitions (e.g., number of ignitions = 1.6), rounding determines the number of ignitions (e.g., number of ignitions = 2).

Prescribed fires ('RxFire') are routinely deployed to reduce fine fuels (Agee and Skinner, 2005) and there are calls to substantially increase

Table 1
The following data sources were used to parameterize Lake Tahoe West.

Data	Source
Daily fire perimeters	GEOMAC from all available years (2000-2016). Data required preprocessing, which included year-to-year attribute name standardization, date convention standardization, geographic coordinate standardization, removal of blank or missing records, elimination of duplicate record days, elimination of days with 'negative' fire spread, and conversion to raster format. https://rmgsc.cr.usgs.gov/outgoing/GeoMAC/historic_fire_data/
Fire Weather Index (FWI), Daily	Daily FWI was calculated using equations internal to the Climate Library (Lucash et al. 2017). Climate data used was Mauer daily gridded historical climate data available through the USGS GeoDataPortal. https://cida.usgs.gov/gdp/. The climate data was produced for EPA level II ecoregions, which was then resampled into 900 m^2 pixels to make it consistent with all other input maps.
Fine fuel loads	Fine fuel load maps were developed using LANDFIRE cover types and the associated fuel loading information (Reeves et al., 2006) https://www.landfire.gov/documents/FuelProceedings.pdf
Daily wind speed	Daily wind speed data used were summarized by the USGS GeoDataPortal, using the same EPA region mapping approach and resolution resampling as the FWI data.
Daily wind direction	Because a continuous surface of historical daily wind direction is not available, we estimated wind direction as the direction of fire spread; daily fire polygon centroid-to-centroid azimuth was used as daily wind direction. Wind direction is not a direct input to fire spread, but rather is included in the effective wind speed calculation.
Burn intensity	Forest Service Region 5 GeoSpatial Information Center https://www.fs.usda.gov/detail/r5/landmanagement/gis/?cid=STELPRDB5327833

their use (e.g. State of California Executive Order B-52-18). For RxFire, a set number of fires are generated per year, based on expert input and/or scenario design. RxFires are attempted sequentially (by day of year) until the expected number of fires is successfully ignited. Prescribed fire is often used under weather conditions different from wildfires. Therefore, our model allows conditions to be placed on RxFire ignitions including a minimum FWI (necessary to maintain fire spread) below a maximum FWI (conditions under which prescribed fire would be avoided), and a maximum wind speed (again, conditions under which prescribed fire would be avoided).

A continuous weighted surface of historical ignitions for the entire landscape is required for each of the three ignition types and used to allocate ignitions. For regions where the spatial pattern of ignitions is weak or unknown, this surface can be a constant value or a smoothed average of ignition rates. For other regions, the spatial pattern of ignitions could be projected based on climate change estimates (e.g., Yang et al., 2015). All available sites are then shuffled using an algorithm that biases selection by the ignition probability maps. The list of ignitions sites is re-shuffled at the beginning of each year. In combination, the three ignition sources generate the total number of fires per year per fire type and are dependent upon FWI.

2.2. Fire spread (growth)

From the point of ignition, fire can spread to each adjacent cell (i.e., four nearest neighbors) dependent upon a probability of spread (Pspread). Fire spread is from cell-to-cell and determines fire size. A fire will continue burning until no more cells are selected for spread. Probability of fire spread is estimated using a general equation relating event probability to FWI (Beverly and Wotton, 2007), that creates a 0–1 probability function which is then applied at a daily time step to determine the success of cell-to-cell fire transmission:

$$\text{Probability of Fire Spread} = \text{Pspread} = 1 / 1 + e^{\beta 0} \tag{2}$$

Where β0 is the probability of spread into a site, given conditions on that site:

$$\beta 0 = \beta 0' + \beta 1 * \text{FWI} + \beta 2 * \text{EffectiveWindSpeed} + \beta 3 * \text{FineFuels} \tag{3}$$

Where EffectiveWindSpeed is an adjusted wind speed whereby reported wind speed and direction for the region (from meteorological stations) is downscaled to individual sites by accounting for slope angle and the slope azimuth relative to the wind direction (Nelson 2002). EffectiveWindSpeed also incorporates the intensity of the neighboring cell from which the fire is spreading (see intensity calculations below). A high intensity fire burning upslope generates a greater EffectiveWindSpeed than a moderate or light fire. This in turn feeds back into the estimate of fire intensity (see below), creating self-sustaining high-intensity fires under certain conditions.

During model execution, fire fuels are estimated from endogenous (internal to the model framework) litter estimates. During model execution, fine fuels are spatially and temporally variable and reflect reductions from fuel treatments and fires, and additions from overstory mortality, e.g., from insect outbreaks (e.g., Sturtevant et al., 2009), as calculated within an appropriate LANDIS-II succession extension.

A fire will spread until it has reached a maximum area for the day, or no cell-to-cell spread is predicted to occur due to fuel limitations or suppression activities (below). Maximum area was determined

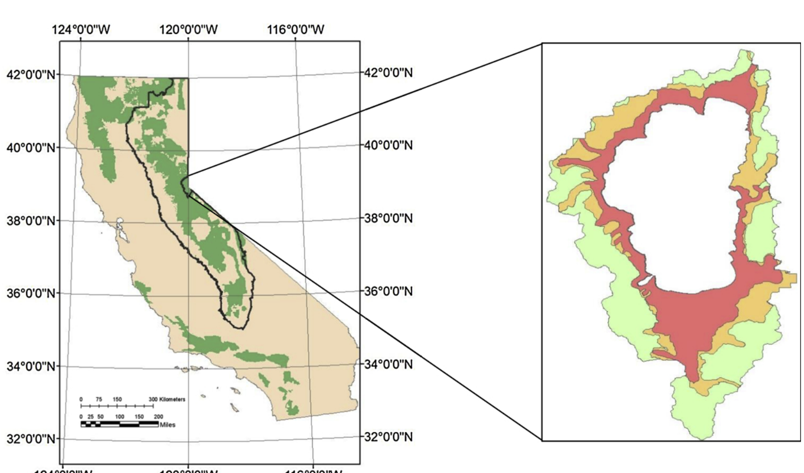

Fig. 1. Sierra Nevada analysis area for generating fire extension parameters for the Lake Tahoe Basin, outlined in black. Green areas in state map represent Forest Service administrative boundaries. Colors in inset represent wildland-urban interface zones delineated by Tahoe Basin Management Unit land managers: wildland-urban interface (red), wildland-urban intermix (orange), wildland (green) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

empirically:

$$\text{Maximum daily spread area} = \beta 0 + \beta 1{*}\text{FWI} + \beta 2{*}\text{EffectiveWindSpeed} \quad (4)$$

Maximum daily spread is an overall limit to daily area burned and therefore calculated separately from cell-to-cell fire spread. Maximum area spread parameters were derived using a fitted generalized linear model (‘glm’ in the R statistical software). Both cell-to-cell spread and maximum daily fire spread are updated with daily FWI estimates until the fire can no longer spread (e.g. disconnected fuels, low FWI, or suppression is applied).

2.3. Suppression

Suppression is simulated as the capacity to reduce the probability of fire spread and is unique for each fire type. Our suppression algorithm was designed in collaboration with fire managers and approximates the decisions made when deciding whether to suppress and the overall suppression effort. Suppression was implemented as four zones per fire type: none, minimal, moderate, maximal suppression. Each zone is assigned an integer reflecting suppression effectiveness that reduces P_{spread} as a fraction (suppression effectiveness / 100). Zones are input as unique maps for each fire type. The unique maps allow for different kinds of suppression dependent upon circumstances. For example, lightning generated fires may be allowed to spread in remote areas of a landscape. Accidental fires may be heavily suppressed in all areas. Prescribed fires are typically suppressed in all areas except where the fires are intentionally introduced although they can escape. These zones should be based on current or anticipated management efforts.

Suppression effectiveness can vary as a function of FWI; more resources for suppression are typically allocated during extreme fire weather (higher FWI). Two FWI breakpoints determine when suppression efforts (effectiveness) increase. In addition, a maximum daily wind speed limits suppression to days when resources can be safely deployed; if daily wind speed exceeds the maximum limit, suppression does not occur.

2.4. Fire intensity

We developed three classes of fire intensity, Low: < 1.2 m (< 4 feet) flame lengths; Moderate: 1.2–2.4 m (4–8 feet); and High: > 2.4 m (> 8 feet). These intensity classes correspond to metrics of intensity commonly used by fire managers. Corresponding mortality classes were also defined (see below).

Unlike fire ignition and spread, empirical data of fire intensity are not available at the regional scale. Differenced Normalized Burn Ratio (dNBR) is a metric of severity and does not readily translate into a metric of intensity. Therefore, we used a multi-condition risk approach to determine whether a site burned at low, moderate, or high intensity. We defined three risk conditions based on fine and ladder fuels (Schoennagel et al., 2004) and fire spread (Agee et al., 2000):

1 Does the mass (g m^{-2}) of fine fuels exceed a calibrated threshold?
2 Does the mass (g m^{-2}) of ladder fuels exceed a calibrated threshold? Ladder fuels are assigned via a list of species with maximum ages that can be regarded as ‘ladder fuels’. For example, *Abies concolor* aged 0–25 might be regarded as ladder fuels.
3 Is the fire intensity of the source site (the neighboring site from where a fire spread) high intensity? A high intensity fire will promote higher intensity fire as it spreads.

The default is low intensity. If one of these three conditions is true, the intensity become moderate. If two or more conditions are true, the fire is high intensity.

2.5. Fire mortality

Fire mortality varies depending on fire intensity and the tree species and ages present. A low intensity fire, for example, may cause extensive mortality if the forest is dominated by fire-intolerant tree species. For each fire intensity class, a fire mortality table is defined that includes the age ranges and associated probability of mortality for each tree species. A single random number is generated (a global function within the LANDIS-II framework) for each burned site (ensuring a consistent effect on all trees). If $P_{mortality}$ (from the corresponding fire mortality table) exceeds the random number, the species-age cohort is killed (100% mortality).

3. Model parameterization and application

3.1. Study area

We parameterized and applied our fire model to the Lake Tahoe Basin (LTB; Fig. 1). LTB is a dry conifer forest on the east side of the Sierra Nevada with a high average snowpack (50–150 cm) and dry summers. Although LTB is now largely a recreational destination, it was heavily logged at the end of the 19th century and the forests today reflect recovery from these past land uses (Loudermilk et al., 2013). Historically, fires were frequent (occurring every 3–20 years) (Nagel and Taylor, 2005), but have been actively suppressed since the early 20th century. In addition, fire ignitions have substantially shifted in frequency and location with about 80% of fires started accidentally by humans and typically near the lake shore whereas most lightning fires occur on ridgetops (Short, 2013). Prescribed fire has historically been limited in scale and located only within the wildland urban interface (Loudermilk et al., 2013) although recent efforts intend to expand prescribed fire to the broader watershed. Climate change is expected to increase annual temperatures, increase fire season duration, and increase the probability of extended droughts (Loudermilk et al., 2013) and ignition locations (Yang et al., 2015).

3.2. Model parameterization

In order to parameterize ignitions, historical fire data from 1992 to 2013 for the LTB (Short, 2013) were used to estimate the relationship between daily number of ignitions and FWI; we included only fires that spread to ≥ 1 ha. Ignitions within the historical data set were separated by ignition type into lightning (coded as ‘lightning’ within the Short data) and human accidental (many codes, including ‘campfire’, ‘arson’, and ‘child’, were combined). Daily historical FWI was calculated from daily temperature and precipitation data (PRISM) as implemented within the Climate Library of LANDIS-II (Lucash et al. 2017), which produced daily FWI values for our period of record. A zero-inflated Poisson distribution of fire ignitions was then fitted (using the ‘zeroinfl’ function within the ‘pscl’ package in R), producing estimates for β0 and β1 in Eq. (1). This was done for both lightning ignitions and human accidental ignitions. The analysis was conducted using the likelihood package in R (R Core Team 2014). We verified ignition behavior by testing Eq. (1) using random FWI values produced by a random number generator within R. To validate fire ignitions, we ran simulations to assess whether fire ignition parameters recreated the appropriate number of fires given a particular FWI value. We also validated each ignition type such that the spatial patterns of fire ignitions provided by the input maps generally match the spatial patterns of fire ignitions by type. The Short (2013) data were also used to define an ignition surface for each fire type. The cumulative number of ignitions by fire type by cell were used as inputs; the model subsequently translates these data into weights whereby cells with higher weights are preferentially selected for ignitions.

To parameterize spread within the LTB, we used the Sierra Nevada boundary defined by the Sierra Nevada Conservancy (see Fig. 1). We chose this area as being broadly representative of the conditions found in the LTB and containing more fires than the LTB alone, providing a larger sample size for model fitting. Fire perimeters were polyline layers and each of the fire spread variables were raster datasets (Table 1). Unsuccessful and successful spread cells were then identified and tracked throughout the period of record. 'Unsuccessful' cells were defined as those that fell on a fire perimeter that did not burn on the following day. To estimate the fire spread parameters, spatial data are needed for daily FWI, daily wind speed, daily wind direction, and fine fuel loading (Table 1) for a set of reference fires. Daily fire perimeters are then overlain on each of the datasets to extract successful and unsuccessful spread areas and assigned to a given day of the fire (both year and day-of-year). Maximum spread area was drawn from the GEOMAC fire perimeter data (Table 1) and was defined as the day-to-day increase in area of fire perimeters.

Suppression zones, intensity, and the FWI breakpoints were determined via consultation with cooperating fire managers. Similarly, the probability of mortality (given the above intensity calculation) estimates were collected using expert opinion, whereby available fire experts for the LTB provided independent estimates of mortality (provided via on-line survey) for varying species and age combinations. These data were collected independently and collated and areas of disagreement (indicated by a range among experts > 0.35) discussed and refined.

Our model design utilizes current estimates of fine fuels, coarse fuels, and ladder fuels. The LANDIS-II framework provides projections of fuel loads in response to vegetation growth, mortality, and disturbances, eliminating the need to categorize sites into fuel classes, which, by design, simplifies and averages landscape variation in fuels. For example, utilizing continuous fuel information will allow differentiation based on intensity and time-since insect defoliation or mortality, rather than a single fuel type for post-insect outbreaks.

3.3. Model calibration and validation

Prior to applying the model to forecasting unique scenarios, we calibrated and validated the model against historical fire regimes. We assessed model accuracy by comparing model outputs against historical fire data from the LTB including fire rotation period (years), the distribution of fire sizes, and estimates of intensity. Our calibration assumed that suppression in the Sierra Nevada broadly represented fire suppression in LTB; therefore, fire suppression efforts were parameterized via inputs from local fire managers.

To calibrate the relative total area of our three fire intensity classes, we compared simulated burned area for each intensity class against empirical estimates of ratio of area burned in three similar severity classes. Although intensity and severity are not equivalent, empirical intensity data are not available and so we used severity as the best available proxy. Historical fire severity data were drawn from the same broad Sierra Nevada geography as spread parameters, avoiding potential sampling bias towards small high intensity fires which are most prominent in the Basin (Table 1).

3.4. Model application

We demonstrated the behavior and utility of our model via four simple scenarios that emphasize the effects of human activities on fire regimes. The scenarios were run on the Lake Tahoe Basin (LTB) landscape. We simulated a randomized historical climate (1992–2011) whereby historical climate was randomly arranged (with replacement) on an annual basis (although note that this approach does not capture longer-term climatic trends, e.g., Kitzberger et al., 2007). Each scenario was simulated for 100 years (the duration of available downscaled climate projections) at a 1 ha resolution with four replicates per scenario; the number of replicates reflected intra-scenario variation and available computing time.

Fire was simulated using SCRPPLE while other processes were simulated using pre-existing model components within the LANDIS-II framework. We simulated succession (including seed dispersal, regeneration, and competition for water, light, and nitrogen) using the Net Ecosystem Carbon and Nitrogen (NECN) Succession extension v5.0 (Scheller et al., 2011). NECN simulates the regeneration and growth of tree and shrub species-age cohorts; limitations include sunlight (for regeneration), mineral Nitrogen, available soil water, and temperature. NECN tracks above and belowground live C (as woody and non-woody components for each cohort), detrital C (duff and large woody debris), and soil organic carbon (SOC which decays and transforms following the three pool structure of the CENTURY soil model; Parton et al., 1983). To estimate initial conditions, we used an imputation of inventory data; details of LTB succession parameterization, including imputation of the initial vegetation conditions, are found in Loudermilk et al. (2013). Climate data was identical for both NECN and SCRPPLE (Table 1).

Our scenarios were as follows:

a) Recent Historical: We simulated recent historical patterns of lightning and accidental fires and current patterns of fire suppression (Fig. 1). Ignition data were calculated as described above and using data described in Table 1. Suppression data were estimated via extensive interviews with fire managers responsible for LTB. Fuel treatments and prescribed fires were not included.
b) Natural-Fire-Regime: We simulated wildfire without suppression, accidental fires, or prescribed fires, holding all other factors the same as Recent Historical.
c) Enhanced Suppression: In this scenario, the resources devoted to suppression doubled the effectiveness of suppression, holding all other factors the same as Recent Historical.
d) Reduced Accidental Ignitions: In this scenario, the number of accidental fires was reduced by half, holding all other factors the same as Recent Historical, representing an alternative to Enhanced Suppression whereby resources were allocated to reducing accidental ignitions rather than suppression. Such reductions could be achieved variously, including education (e.g., Smokey Bear), camping restrictions, fireworks and firearms restrictions, or other; the associated human activity is less defined than in the case of fire suppression or fuel treatments.

4. Results

4.1. Model validation

To validate model behavior, we compared simulated patterns against historical patterns. Accidental human ignitions accounted for about 78.7% of recorded ignitions, while lightning ignitions accounted for 20.3% of recorded ignitions in the LTB during the calibration period. The spatial distribution of ignitions follows distinct patterns such that fires started accidentally cluster near the lake shore and most lightning ignitions occur on ridgetops. The weighted surfaces for

Table 2
Parameters estimated for four SCRPPLE equations. Coefficients for: intercept (β0), fire weather index (β1), effective wind speed (β2), and fine fuels (β3).

Equation	Parameters			
	β 0	β 1	β 2	β 3
Ignitions (Human accidental)	−3.3	0.03	NA	NA
Ignitions (Lightning)	−4.5	0.03	NA	NA
Spread probability	−36.0	0.6	0.915	0.022
Maximum spread area	−80	2.0	2.6	NA

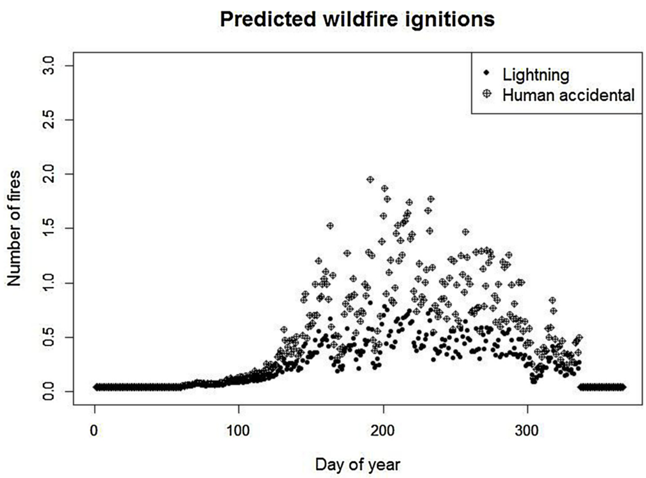

Fig. 2. Predicted human accidental and lightning ignitions per day for a single year (1993). Fractions are rounded to the nearest integer; number of fires < = 0.5 results in no fires.

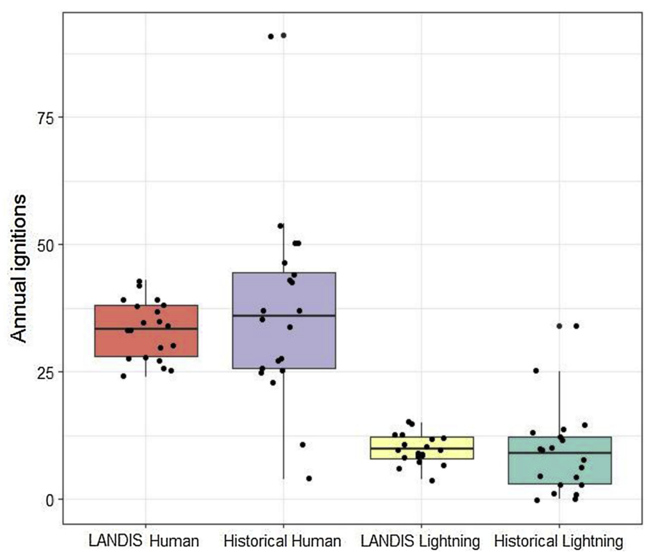

Fig. 3. Simulated and observed human and lightning caused ignitions for 20-year period (1992–2011). Box plots represent interquartile range, while dots represent individual annual ignitions.

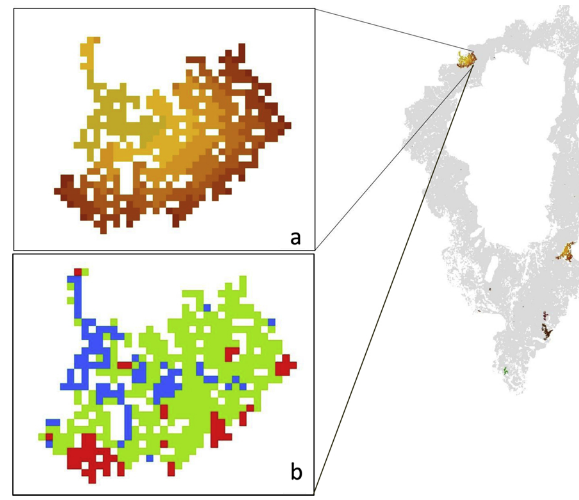

Fig. 5. An example of a) fire spread and b) fire intensity for a single simulation year of the 'business-as-usual' scenario within the Lake Tahoe Basin. A single fire is highlighted to demonstrate spread and emergent intensity patterns of individual large fires. This example fire burned 467 ha in 7 days, and was caused by an accidental human ignition on July 22nd (Julian day 203). Darker reds in the spread map (a) indicate later Julian days. Colors in the intensity map (b) represent three intensity classes (blue = low, green = moderate, red = high) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

ignitions captured patterns that demonstrated human (accidental ignitions) and natural influences on the spatial distribution of ignitions. Ignition parameterization (Table 2) produced the expected distribution in the number of ignitions within a year given seasonal weather conditions (Fig. 2), with both human accidental and lightning ignitions increasing with the FWI during the summer. Annual values approximated historical averages of both lightning and human accidental ignitions, although with reduced variability (Fig. 3). Probability surfaces allocated a realistic spatial distribution of fire which followed observed patterns (Short, 2013); simulated burn patterns are directly related to ignition patterns, with more frequent, smaller fires occurring at lower elevations where human accidental ignitions are typical (Fig. 4). Fire intensity was mixed (by total area: 42.8% low intensity, 35.9% mid intensity, and 24.3% high intensity for business-as-usual scenario) for most fires with an overall balance of the three intensities matching the estimates from the Forest Service's MTBS-derived burn severity maps.

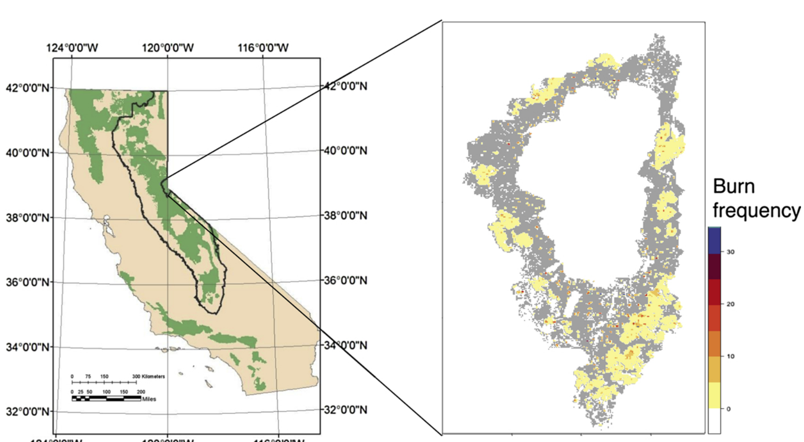

Fig. 4. Burn frequency (number of times a pixel burned) of 100 years of a single replicate of the 'business-as-usual' scenario across the Lake Tahoe Basin. Darker reds indicate pixels that burn more often, grey areas represent active pixels that experienced no fire during this particualr replicate. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

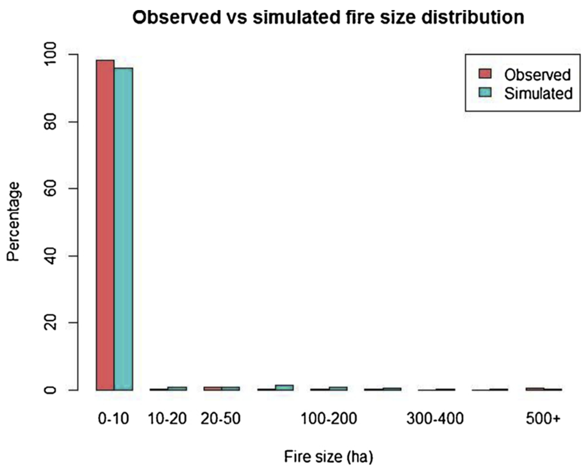

Fig. 6. Fire size distributions of recorded fires (Short, 2013) and calibrated SCRPPLE fire regimes. Historical data was from 20-year reference period, SCRPPLE outputs were drawn from all 100 years of a single simulation under Recent Historical scenario.

4.2. Fire size and spread

Our fire spread parameterization (Table 2) produced highly variable shapes and within patch heterogeneity of intensity (Fig. 5), dependent on local fuels, topography, and daily fire weather. Fire sizes varied with daily fire progression matching equation 4 (Table 2), indicating that physical barriers were not a frequent limit to fire spread in this landscape. Most (98%) historical fires in the Sierra Nevada Mountains were small (i.e., < 20 ha), but fires larger than 100 ha accounted for most burned area. Our approach captured this fire-size distribution (Fig. 6). Additionally, our approach allowed for the creation of unburned islands within perimeters, which are important ecologically and may cover up to 37% of the area within a perimeter (Kolden et al., 2012).

4.3. Model performance under different management scenarios

Our four scenarios demonstrate a consistent increase in high intensity fires and a decline in low intensity fires due to succession and increased fuel loading. Across the four management scenarios, 'Enhanced Suppression' had the highest proportion of low-intensity

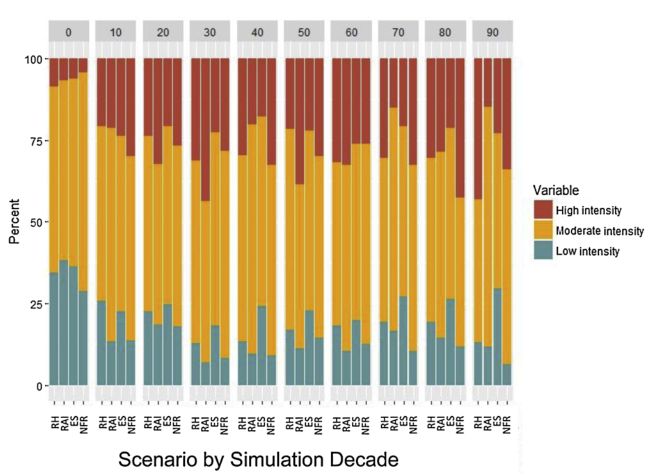

Fig. 7. Mean percentage of three fire intensities (high indicates > 2.4 m flame length, moderate indicates 1.2–2.4 m flame length, low indicates < 1.2 m flame length) for four scenarios (replicated four times) simulated over 100 years for the Lake Tahoe Basin, binned by decade. With respect to scenarios, 'RH' represents Recent Historical, 'RAI' represents Reduced Accidental Ignition, 'ES' represents Enhanced Suppresion, and 'NFR' represents Natural Fire Regime.

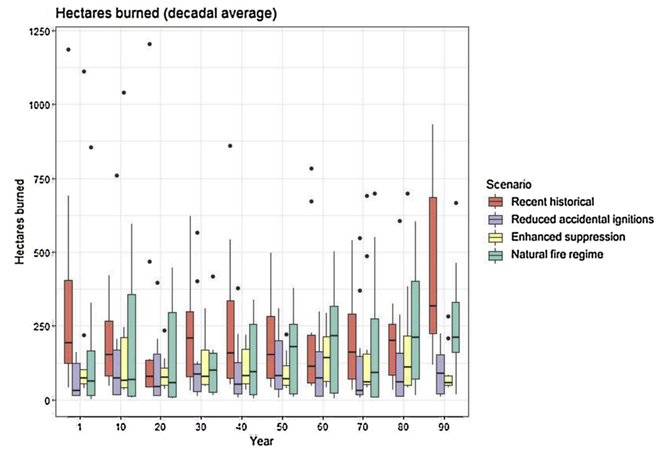

Fig. 8. Area burned (ha) for four scenarios simulated over 100 years for the Lake Tahoe Basin, binned by decade. Individual boxplots represent annual area burned within a decade across four replicates. Dots above boxplots represent years which exceeded interquartile range of annual area burned.

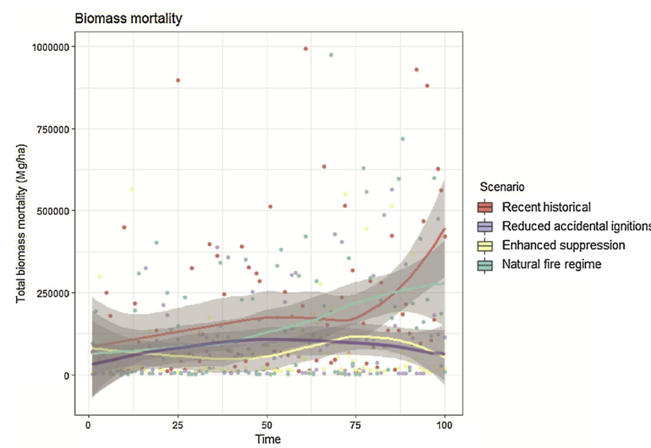

Fig. 9. Mortality (g biomass m^{-2}) for four scenarios simulated from 2010 to 2110 for the Lake Tahoe Basin. Lines represent smoothed conditional mean (loess), grey envelopes represent the standard error of those smoothed means. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

fires (Fig. 7). In contrast, the area burned was more variable over time; the 'Natural' fire regime scenario burned the least area overall and 'Recent Historical' and 'Reduced Accidental Ignitions' had the largest area burned (Fig. 8). The total mortality shows a clear trend of increasing and higher mortality for 'Recent Historical' and 'Enhanced Education' (Fig. 9). In summary, 'Recent Historical' resulted in the most active fire regime although the fraction burned as high intensity was not exceptional. Particularly after year 75, Recent Historical produced more intense fires, more total area burned, and more biomass killed than any other scenario. Recent Historical included accidental fires which account for differences with the 'Natural' scenario. The 'Enhanced Suppression' and 'Reduced Accidental Ignitions' scenarios were broadly similar and had the lowest total area burned and lowest mortality after 75 years (Figs. 8 and 9).

5. Discussion

Fire regimes are changing rapidly in response to human actions that affect ignition and suppression patterns, fuel management, and climate change. Given the rapid rate of change, there is a great need to expand our capabilities to simulate, integrate and understand feedbacks among human actions that will alter vegetation, succession, and disturbances.

In response to this need, we developed a new approach to simulate natural, accidental, and prescribed fires in the LANDIS-II landscape simulation model.

Although SCRPPLE was able to approximate the historical fire size distribution, individual fire shapes have been notoriously difficult to estimate (Keane et al., 2004; Duff et al., 2013; Sá et al., 2017),. Ellipses form the basis for many fire simulations (e.g., Finney, 2002), although the formation of an actual ellipse would require constant wind direction and minimal topography. Our simulated fire shapes are neither ellipses nor circular; rather each is complex with inclusions of unburned patches and with patchy fire intensity reflecting the complex terrain, shifting wind directions, and variable fuels. Unburned patches and within-fire heterogeneity represent critical biological refugia that are important seed sources for post-fire vegetation recovery (Kolden et al., 2012; Fornwalt et al., 2018). Our approach simulated fire size distributions that mirrored the fire size distribution of LTB as well as the shape of individual fires and within-fire heterogeneity, representing an advance in the capabilities of fire models to realistically represent the ecological impacts of fires for testing different management scenarios.

Our design also improved the capacity to utilize expert opinion, allowing for rapid development of simulation scenarios. For instance, the intensity classes are flexible and can be modified to suit fire managers' typology and experience. For this study, fire intensity classes were based on flame length bins that fire managers use regularly to make decisions around planning and resource deployment. Manager familiarity with this metric enabled the efficient utilization of expert opinion and allowed their input to come from a place of field-based knowledge. Explicit recognition and interface with manager expertise facilitates co-production of scenarios and, ultimately, utilization of the knowledge produced (Gustafson et al., 2006).

In addition, our fire simulation approach has improved capacity to utilize remotely sensed data and fire databases, where available. Doing so, we intentionally chose to move away from a Rothermel-style 'physics engine' to a geospatial data-driven 'landscape engine' whereby we focused on capturing landscape-scale determinants of fire behavior rather than fine-scaled experimentally-derived determinants (see also Stavros et al., 2018). Our approach is more congruent with the intended use of landscape-scale modeling: understanding disturbance consequences across many thousands of hectares and over many decades and fire regimes respond dynamically to climate whereas fire regimes are prescribed in a top-down manner in many landscape simulation models (e.g., Keane et al., 2004). This opens some exciting possibilities to understand how fire regimes may evolve over time and is critical for understanding the consequences of shifts in fire weather, ignition patterns, management strategies, other disturbances, and feedbacks with vegetation change. In addition, our approach facilitates sensitivity testing (i.e., a reduced parameter set), uncertainty analysis, and cooperative scenario building.

Every model approach has inherent limitations and SCRPPLE is no exception; it requires substantial spatial and temporal data for sufficient parameterization. However, these data needs are already being met, given the large amount of remotely sensed imagery that has been collected over active fires (e.g., Duff et al., 2013; Sá et al. 2017). Specifically, our application of daily fire perimeters to calibrate spread rates represents a novel application of remote sensing to inform a fire spread model. In addition, SCRPPLE does not simulate social processes themselves, rather it simulates the actions that result from social or cultural preferences. Agent-based models are increasingly capable of simulating learning, networking, and decision-making (Sotnik, 2018) and could in the future substitute for our suppression and fuel treatment algorithms.

5.1. Implications from the Lake Tahoe Basin

SCRPPLE provides a new framework to simulate interactions among human activities, vegetation, climate, and fire in a bottom-up fashion. Although we parameterized and evaluated SCRPPLE for the LTB, as an extension of the flexible and widely-applied LANDIS-II platform, SCRPPLE is suitable for application to forest landscapes worldwide. Importantly, SCRPPLE can make use of geospatial data and expert opinion to parameterize fire ignition rates, spread, behavior and effects. Such data requirements can be met in many places with MODIS active fire data (Giglio et al., 2016; Benali et al., 2016; Veraverbeke et al., 2014), which tracks fire ignitions and fire spread. Likewise, daily weather data suitable for calculating FWI are widely available from NCEP/NCAR Reanalysis daily weather data (https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.html). By explicitly including anthropogenic processes in SCRPPLE and parameterizing with widely-available metrics of fire behavior, the resulting simulations are suitable for evaluating the effectiveness of different management strategies for maintaining ecosystem services and enhancing ecosystem resilience in the face of climate change and human development.

The simulation results for our different scenarios highlight the potential for LANDIS-II to assess socio-ecological dimensions of fire regimes. Notably, the similar ability of 'Enhanced Suppression' and 'Reduced Accidental Ignitions' to reduce fire and related tree mortality over time suggests that within the broad outlines of the scenarios, reducing accidental fires (via education or other social processes, unspecified) can be as effective as substantially increasing resources for suppression. Because costs of fire suppression have increased markedly in recent years (Bladon, 2018), our Reduced Accidental Ignitions scenario implies that considerable cost savings are possible via social pathways. Consideration of the social dimensions of fire will become increasingly important as the wildland urban interface expands (Radeloff et al., 2018) and we move into the era of 'managed wildfire'. Explicit consideration of human activity allowed us to untangle multiple correlated factors, e.g., accidental fires and fire suppression efforts are highly spatially correlated. Next steps are to consider climate change effects on LTB fire regimes and the interactions between fuels management (reducing fuel quantities) and fire regimes.

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