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ORIGINAL ARTICLE

Predicting Soil Temperatures Associated with Reintroduction of Prescribed Burning in Western Coniferous Forests

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Abstract

Elevated soil temperatures resulting from reintroduction of prescribed fire into long unburnt stands have been associated with unintended tree mortality. Several models exist to predict soil temperatures resulting from soil heating by fire; however, data to develop and validate these models are limited. A model to predict soil temperature at depths up to 25 inches (0.63 m) was developed from a data set from 46 prescribed burns in coniferous forests in national forests and parks in Arizona and California. Soil temperature was less than 140 °F (60 °C) at depths greater than 6 inches (0.15 m) and constant below 10 inches (0.25 m). Using a Bayesian generalized nonlinear additive model, nine models formed from combinations of soil and humus moisture contents, fuel consumption and tree species were fit to soil temperature data for *Pinus ponderosa, P. lambertiana*, and *Sequoiadendron gigantea*. Bayesian R^2 for the full model and the reduced model containing tree species and fuel consumption was 0.70 and 0.67, respectively. The Bayesian model predicted higher maximum temperatures than two soil heating models in the First Order Fire Effects Model. Based on parsimony, the model using fuel consumption and tree species is recommended for use.

Keywords Temperature · Fire · Humus · Bayes · *Pinus* · *Sequoiadendron* · Soil · Consumption

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Introduction

Prior to European settlement, the composition and structure of southwestern ponderosa pine (*Pinus ponderosa*) forests were quite different from today. The open, park-like pre-settlement stands characterized by widely-spaced older trees and sparse pockets of younger trees had vigorous and abundant herbaceous vegetation (e.g. Cooper 1960; Biswell et al. 1973). These conditions were noted throughout much of the range of ponderosa pine (Agee 2000; Johnston et al. 2016), particularly on drier sites. These forest conditions were maintained by fires burning on a frequent, regular basis in light surface fuels of grass and pine needles. There is an extensive literature describing relative amount of fire attributed to lightning and anthropogenic ignitions (Condie and Raish 2003; Raish et al. 2005; Stan et al. 2014; Whitehair et al. 2018; Roos et al. 2019, 2021). In southwestern ponderosa pine, light surface fires burned at intervals averaging less than 10 years and as often as every 2 years (e.g. Weaver 1951; Dieterich 1980; Fulé et al. 1997; Heinlein et al. 2005).

The change of the pre-settlement fire regime in southwestern ponderosa pine ecosystems started with extensive livestock grazing in the late nineteenth century when fine, surface grass fuels were reduced (Faulk 1970). Subsequently, ponderosa pine regeneration increased because of reduced understory competition, less fire mortality, and more mineral soil seedbeds (Cooper 1960). In the early 1900's, forest practices, primarily fire suppression, further reduced the ecological role of fire. These practices lead indirectly to stagnation of naturally regenerated stands and unprecedented fuel accumulation (Biswell et al. 1973). With a greatly altered fire cycle, unprecedented and unnaturally large amounts of surface and ground fuels have accumulated (Kallander 1969). Sackett (1979) reported average loadings of naturally fallen fuels at 49 Mg ha^{-1} (22 tons per acre) for 62 southwestern ponderosa pine stands. Harrington (1982) verified the heavy fuel loadings with an average of 76 Mg ha^{-1} in southeastern Arizona. Because of the risk posed by these accumulated fuels in southwestern ponderosa pine, a study was established in 1976 and 1977 to reintroduce low intensity prescribed fire in these forests in northern Arizona and extensive results have been reported (e.g. Sackett 1980; Covington and Sackett 1984, 1992; Peterson et al. 1994; Covington et al. 1997; Sackett and Haase 1998, 2008; Scudieri et al. 2010; Weise et al. 2019). The results from this study and numerous others in the western US have contributed in part to the scientific basis for the recently announced USDA/USDI Wildfire Risk Reduction Strategy (USDA Forest Service 2022).

Mortality of mature, large ponderosa pines following the reintroduction of fire in 1976 and 1977 in stands with heavy accumulation of fuels around the base of the trees was observed within 2 years of fire reintroduction. As prescribed fire has been reintroduced in both the western and southern US, managers noted unanticipated mortality in ponderosa, Jeffrey, and sugar pines (e.g. Stephens and Finney 2002; Van Mantgem et al. 2013) as well as longleaf pine (Varner et al. 2007), which was sometimes associated also with pine beetle attack (Fettig et al. 2010). Identifying the causes of postfire mortality is complex and different approaches have been taken to identify causal factors which include foliage loss interrupting the tree's ability to photosynthesize as well as belowground damage to fine roots and damage to the cambium (e.g. Martin 1963; Ryan and Frandsen 1991; Swezy and Agee 1991; Kelsey and Joseph 2003; Jones et al. 2006; Michaletz and Johnson 2007; Varner et al. 2007; Weise et al. 2016; Cansler et al. 2020; Fettig et al. 2022). Because prescriptions used to reintroduce fire into unburnt stands typically call for relatively small flames and low fireline intensities (heat release rates) to prevent damage to the overstory trees, we deduced that the mortality observed in stands where fire had been reintroduced was associated with damage to the trees in the soil or lower portions of the tree bole. As a result a thermocouple-based system to measure temperatures in the soil and tree cambium was developed (Sackett and Haase 1992). The system was also used to study the impact of repeated prescribed burns on ambient soil temperatures in southwestern ponderosa pine (Weise et al. 2019) as well as on buried cultural resources such as obsidian (Deal 2002). At the time this system was designed, thermocouples had been used to measure temperatures in at least one other study involving prescribed burning in ponderosa pine (Ryan and Frandsen 1991).

There are numerous models, statistical and biophysical, which have been developed to predict tree mortality following fire. The review by Hare (1961), while somewhat dated, provides the basis for the instantaneous temperature of 140 °F (60 °C) causing plant cell death. This review also discussed the importance of time exposure to heat fluxes at temperatures below this lethal threshold. A recent review questioned the usefulness of this instantaneous temperature (Pingree and Kobziar 2019) due to heterogeneity in the soil environment, organisms' physiological attributes and temperature tolerance, and complexity of soil heat transfer. The review did not find any studies showing that a one-minute exposure to this temperature resulted in organismal depth.

Models to predict soil temperature resulting from fire are available (e.g. Steward et al. 1990; Pafford et al. 1991; Campbell et al. 1995; Albini et al. 1996; Preisler et al. 2000; Enninful and Torvi 2008; Massman et al. 2008; Choczynska and Johnson 2009; Busse et al. 2010; Massman 2015, 2021; Brady et al. 2022). Of these models, two (Campbell et al. 1995; Massman 2012, 2015, 2021) have been implemented in the First Order Fire Effects Model (FOFEM) version 6.7 (Lutes 2020) which can be used to predict fire effects in a wide range of North American ecosystems. These soil temperature models predict the downward heat flux at the soil surface (Btu ft^{-2} h^{-1}, W m^{-2}) from fuels information and then predict the temperature at different depths based on duration of heating and soil characteristics. Fuel consumption is used to estimate the downward heat flux.

While several models have been developed and subsequently validated with measured soil temperature data, the data have often originated from simplified experiments in homogeneous soils in a laboratory. Soil temperatures during fires have been measured less frequently (Robichaud et al. 2018). These data have been difficult to obtain yet are necessary to understanding the impacts of fire on soil physical and biological processes as well as impacts on the plants rooted in the soil. This manuscript presents the development of a statistical model to predict soil temperatures at depths of up to 25 inches (0.63 m) using fuel loading (tons per acre,

Table 1 Summary of prescribed burns from which soil temperatures were measured

Species	Locations	Rx burns	TC Sites	Hours
Pinus ponderosa	Coconino NF, Kaibab NF, Apache-Sitgreaves NF, Lassen NF, San Bernardino NF, Yosemite NP	30	123	11,341
P. lambertiana	Eldorado NF, Sequoia-Kings Canyon NPs, Yosemite NP	15	64	9449
P. jeffreyi	Humboldt-Toiyabe NF	1	5	140
Sequoiadendron giganteum	Sequoia-Kings Canyon NPs	12	39	6354

Mg ha^{-1}), humus moisture content and soil moisture content as predictor variables for three western conifers: ponderosa pine (*Pinus ponderosa* Laws), sugar pine (*P. lambertiana* Douglas) and giant sequoia (*Sequoiadendron giganteum* (Lindl.) J. Buchholz). Some of the giant sequoia and sugar pine data were previously used to develop a stochastic model based on the heat conduction equation to predict risk from elevated soil temperatures in giant sequoia stands (Preisler et al. 2000) and as a validation data set for the non-equilibrium HMV model (Massman 2015; Robichaud et al. 2025) (https://www.fs.usda.gov/rmrs/projects/high-soil-temperature-data-archive). A comparison between the Campbell and Massman models using some of these data found that the Massman HMV model was consistently more accurate than the Campbell model (Robichaud et al. 2025).

Methods

Field Data Description

Forty-six prescribed burns between 1980 and 2005 that reintroduced fire in national forests and national parks in Arizona and California produced the temperature data (Burke et al. 2024a, 2024b) used to develop the statistical model (Table 1). Type K (chromel–alumel) sheathed thermocouples connected to Campbell Scientific[1] data loggers (Sackett and Haase 1992) measured soil temperatures at depths up to 25 inches (0.63 m) below the Oe-A (Soil Survey Staff 2024) interface adjacent to large tree boles and under the tree crown away from the zone where forest floor material mounds around the bole (e.g. Ryan and Frandsen 1991). The terms "litter" and "duff" refer to the Oi and Oe/Oa soil organic layers (Keane 2015). The Oe and Oa layers are also referred to as the "fermentation" and "humification" layers in forest soils, respectively (Spurr and Barnes 1980). The tree species measured were ponderosa pine (*Pinus ponderosa* Laws), sugar pine (*P. lambertiana* Douglas) and giant sequoia (*Sequoiadendron giganteum* (Lindl.) J. Buchholz). While giant sequoia

[1] The use of trade or firm names in this publication is for reader information and does not imply endorsement by the US Department of Agriculture of any product or service.

stands at Sequoia and Kings Canyon National Parks were the first locations in the western United States where prescribed fire was reintroduced following years of fire suppression (Kilgore and Briggs 1972; Bancroft et al. 1985), park managers identified a need for information on the below-ground impacts of prescribed burning after noting large tree mortality following low intensity prescribed burns in order to manage the groves with the best available science (Haase and Sackett 1998). Temperature measurements under Jeffrey pine (*P. jeffreyi* Balf.) were collected from a single prescribed burn in Nevada. Due to similarities in needle width (Jeffrey 0.067–0.087 inches, 1.7–2.2 mm; ponderosa 0.055–0.067 inches, 1.4—1.7 mm) (Haller 1962) and length (Harlow et al. 1979), the Jeffrey pine data were combined with the ponderosa pine data. The 46 fires present a range of fuel conditions commonly encountered in unburnt stands; the environmental conditions during the prescribed burns were typical conditions prescribed for the location.

Within each burn, usually six soil temperature sites were randomly selected near the bole of each selected tree, midway to the tree's canopy dripline, and near the tree's canopy dripline. Sites were avoided where there was excessive disturbance by wildlife and/or people. Sample holes were dug by hand and sheathed thermocouples installed while kneeling on a piece of plywood to prevent compaction and edge collapse of the hole to protect the site. A 6 × 18-inch (15.2 × 45.7 cm) rectangle was cut in the forest floor down to mineral soil and all organic material (litter, duff, woody) was removed intact. As each hole was dug, the forest floor material and soil were placed on a sheet of plastic to further protect the unburnt fuels in proximity to the hole. Depth of the hole varied by species and study site; however, a minimum depth of 12 in (30.5 cm) was used for all burns. Sheathed thermocouple dimensions were 12 inches (30.5 cm) long and 3/16-inch (0.48 cm) diameter. The thermocouples were inserted horizontally into the vertical soil wall at several depths below the Oe-A (duff-mineral soil) interface with one thermocouple positioned at the interface (reference depth = 0 inch). The excavated soil and removed forest floor were replaced to restore the pedon. The time constant for the sheathed thermocouples, i.e. the timelag for the thermocouple voltage output to reach 63 percent of maximum change in response to the temperature change, was ~ 22 s and the response time to reach 99.9 percent of the voltage change was ~ 110 s. This responsiveness was deemed sufficient for the slow rate of temperature change due to low thermal conductivity. Soil thermal conductivity can range from 0.2 to 3 W m^{-1} K^{-1} (0.1 to 1.7 Btu hr^{-1} ft^{-2}) for soil moisture content up to 50 percent (Campbell et al. 1994).

Soil moisture content (oven-dry basis) samples were taken in 2-inch (5.1 cm) depth increments at the same time the hole was being dug. These soil samples were sieved to 0.079 inch (2 mm), placed in soil tins, sealed for further processing and weighed in the field. Postburn soil moisture content samples were taken within the hole from walls that did not contain the thermocouples. Soil samples were dried at 221 ^{0}F (105 ^{0}C) in a forced-air convection oven until weight loss was no longer detected (ASTM D4442–16 2020).

Relating duff loading and consumption to duff depth is a well-established approach (e.g. Beaufait et al. 1975; Little et al. 1986; Brown et al. 1991; de Groot et al. 2009; Prichard et al. 2017). This approach was applied to estimate forest floor loading by including the litter layer and woody material. To develop site-specific regression equations for each prescribed burn to predict forest floor fuel loading at the temperature monitoring sites using depth, three 1 ft^2 (0.9 m^2) square samples (Sackett 1979; Sackett and Haase 1992) were randomly located close to the bole of a tree, halfway to the canopy dripline, and close to the drip line under the tree canopy. Litter, duff and woody material comprised the forest floor sample. This arrangement captured the range of forest floor depth in a selected burn area. For each square sample, depth of the forest floor material (surface to mineral soil) was measured at the midpoint of each side. Fuel samples were dried in a convection oven at 185 ^{0}F (85 °C) until weight loss ceased. At least 10 forest floor samples were collected within the general area of the temperature measurement trees. For each species, a simple linear regressions relating forest floor loading to depth was fit (Sackett and Haase 1991; Haase and Sackett 1998) (Eq. 1—Eq. 3) where *depth* was the vertical distance from the surface to the mineral soil (mm) and forest floor loading (*L*) was tons per acre (multiply by 0.224 for kg m^{-2}).

To determine the depth of consumed fuel, five forest floor consumption pins were installed in a horseshoe pattern beyond the ends of the thermocouples and a small wire was twisted on each pin to mark the top of the forest floor. The vertical distance from the wire to the remaining fuel was measured postburn to provide estimates of pre and postburn loading from the regression equations and thus estimates of fuel consumption (by difference).

$$L = 0.224\left[12.27 + 1.42(depth)\right] \; ponderosa\,pine \tag{1}$$

$$L = 0.224\left[-2.13 + 12.53(depth)\right] \; sugar\,pine \tag{2}$$

$$L = 0.224\left[12.33 + 10.64(depth)\right] \; giant\,sequoia \tag{3}$$

Statistical Modelling

Maximum temperatures (°F) were converted to the Rankine scale ($°R =° F + 459.67$) so that a value of 0 indicated absolute zero making the log maximum soil temperature interpretable. Maximum soil temperature $\left(Tmax_{ij}\right)$ was computed at each depth (j) for each fire (i). Based on graphical inspection, $log(Tmax)$ appeared to decay exponentially over depth. Taking a generalized nonlinear modeling approach (Pinheiro and Bates 2000), the exponential decay was modelled while letting the rate of decay be a function of the fuel loading data and moisture content:

$$Tmax_{ij} \sim Log - Normal\left(\mu = \beta_0 + \exp\left[\beta_{1i} - depth_i \exp\left\{\beta_{1i}\right\}\right], \sigma\right) \tag{4}$$

where β_0 is log maximum temperature at infinite depth, $\exp\left\{\beta_{1i}\right\}$ is the difference between the log maximum temperature of fire i at the Oe/A soil horizon ($depth = 0$) and $depth = \infty$, and $\exp\left\{\beta_{1i}\right\}$ is also the exponential rate of decay of log max temperature over depth, and σ is the error standard deviation of the natural log of the maximum temperature which does not change with depth. We assumed the parameter β_{1i} was a function of the moisture content of the humus and the soil as well as the amount of forest floor which was consumed; this function took the form of a generalized additive model

$$\beta_{1i} = Species_i + f_1\left(\left\{L_{Consumed}\right\}_i\right) + f_2\left(\left\{M_{humus}\right\}_i\right) + f_3\left(\left\{M_{soil}\right\}_i\right) \quad (5)$$

where *Species* is ponderosa pine, sugar pine or giant sequoia, $L_{Consumed}$ is estimated fuel consumption, and M_{humus}, M_{soil} are the oven-dry moisture content of the humus layer and the mineral soil, respectively. Each of the functions f_1,f_2,f_3 were fit using thin plate smoothing splines (Wood 2017).

Prior Selection Weakly informative prior distributions were chosen. A normal prior for β_0 with $\mu = 6.8, \sigma = 0.31$ was chosen. The value 6.8 was chosen since exp(6.8) = 898. While this value is close to the ignition temperature of paper (910 °R, 505.5 K), the concept of ignition temperature is unsettled (Babrauskas 2003). For example, a recent study reported ignition temperature for smoldering peat ranged from 977 to 996 °R (543 to 553 K) and for flaming combustion 1005 to 1734 °R (558 to 963 K) as moisture content ranged from 10 to 100 percent (Lin et al. 2019). Using the low ignition temperature for flaming combustion of 1005 °R (558 K) resulted in a value of 6.9 which was sufficiently close to 6.8. The value 0.31 was chosen as the prior standard deviation as two standard deviations below and above the mean contained about 95% of the prior probability for maximum temperature. These distributional parameters for β_0 resulted in a range of 483 to 1669 °R (23 to 1209 °F) which covered much of the range of measured temperature at the Oe/A interface (Fig. 1). Given that this range of possible temperature values is 1186, we would expect the maximum effect size for β_{1i} to be less than ln[ln(1186)] ≈ 2.0. For the tree species intercepts a normal prior ($\mu = 0, \sigma = 0.5$) was chosen. All other priors were set to the defaults provided by the *brms* package. A half-normal distribution with standard deviation 0.31 was chosen as the prior on σ (Byers 2005). Given these assumed prior distributions, the Bayesian approach estimated the parameters using the posterior distribution (observed soil temperatures).

Model Selection and Inference All combinations of terms that included at least one of the functions f_1, f_2, and f_3 were fit for a total of 7 models; the eighth model was tree species alone. The Bayesian generalized nonlinear additive model approach was computationally slow to implement. The bottleneck was using additive models, rather than linear, to incorporate covariate information. The full model including f_1, f_2, and f_3 took 3 days to run using 12 processors to generate 12 Markov chains. The reduced models using 4 cores and 4 Markov chains required less time. Several measures of fit based on the posterior distributions were calculated to select the final model. These measures included an R^2 developed for Bayesian models (Gelman et al. 2019) and the expected log pointwise predictive density (ELPD) from leave-one-out cross validation with Pareto-smoothed importance sampling (PSIS-LOO) (Vehtari et al. 2017). The differences in ELPD can be put on a deviance scale by simple multiplication.

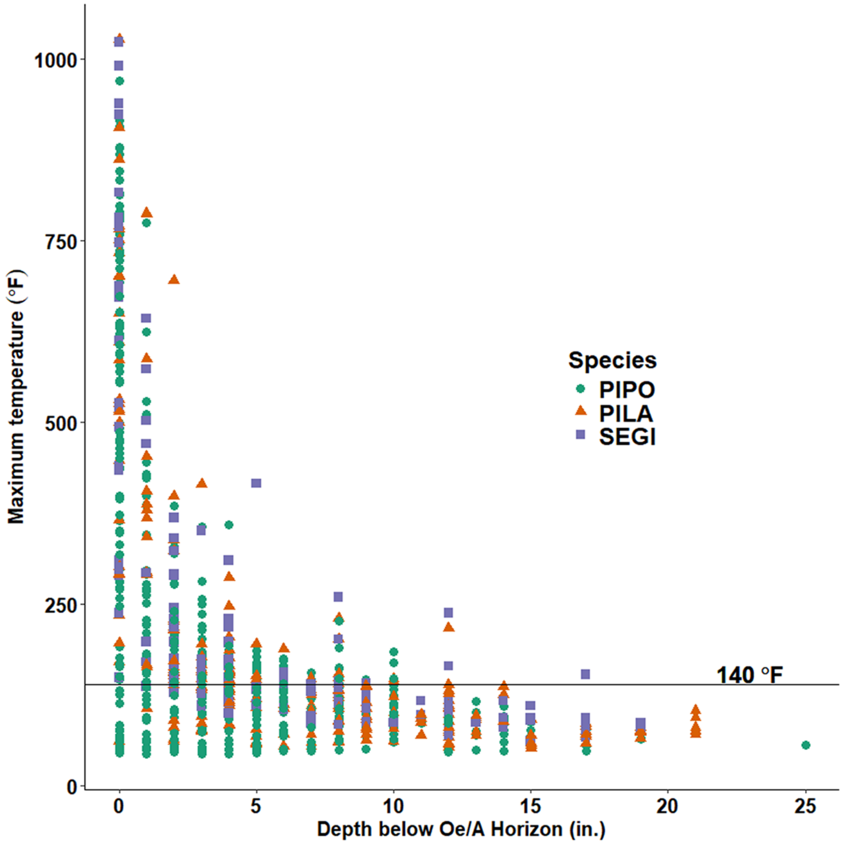

Fig. 1 Maximum soil temperature measured at different depths below Oe/A horizon during prescribed burns for different western conifers

Software Details The generalized nonlinear model was implemented in a Bayesian framework using the *brms* version 2.12.0 (Bürkner 2017, 2018) and *mgcv* version 1.8–31 (Wood 2017) in the R version 4.4.2 statistical computing environment (R Core Team 2024). A Hamiltonian Monte Carlo algorithm was used by the *brms* package to produce samples from the joint posterior distribution of the model parameters (Neal 2011). This algorithm ran 12 or 4 Markov chains in parallel for 2000 iterations with burn-in/warm-up of 1000 iterations. For the No-U-Turn sampler (NUTS) (Hoffman and Gelman 2014), the size of the maximum binary tree depth was set to 15 and the adapt delta was set to 0.99 which improved algorithm performance over the default values at the cost of slower total run time. All parameter chains converged according to the R-hat diagnostic (Vehtari et al. 2021).

Results

In the present study, 30 of the 46 prescribed burns reintroducing fire to long unburnt stands occurred in ponderosa pine (Table 1). Sugar pine and giant sequoia occurred together in the prescribed burns at Sequoia-Kings Canyon National Parks. Mean fuel depths at the time of fire reintroduction were similar as were the ranges (Table 2). The mean initial fuel loadings were also similar. The geometric mean of fuel consumption percentage was 73.4, 84.1 and 94.5 percent for ponderosa pine, sugar pine and giant sequoia, respectively. While fuel consumption range was nearly 0 to 100 percent, the mode (most frequently occurring data point) for all three species was 100 percent. Pearson's correlation coefficient (r) for fuel consumption with humus moisture content and soil moisture content differed between species. For ponderosa pine, fuel consumption was not significantly correlated with humus moisture content ($p = 0.79$) and was negatively correlated ($r = -0.22$, $p = 0.01$) with soil moisture content (Table 3). For giant sequoia and sugar pine, fuel consumption was significantly positively correlated with both humus and soil moisture content.

Over 26,000 h of temperature monitoring occurred. The average length of monitoring per thermocouple site was 163, 148 and 92 h for giant sequoia, sugar pine and ponderosa pine or 6.8, 6.2 and 3.8 days, respectively. The data were trimmed by removing the recorded temperatures after the thermocouples returned to ambient levels. The intercepts and the slopes of the regressions predicting the fuel loading L differed between sites (Table 4). While the coefficients differed, the mean initial fuel loading was similar between the two pine species as indicated by overlapping 95 percent confidence intervals (Table 2). Mean fuel loading under giant sequoias was greater as the 95 percent confidence interval did not overlap with the pine means. The consumed fuel loading was similar for the pine species and larger for giant sequoia. The percent of fuel consumed for sugar pine was intermediate between the low of ponderosa pine and the high of giant sequoia. The humus moisture content was lower for giant sequoia compared to the pines.

The number of times in which the temperature exceeded 140 °F (60 °C) was appreciable at depths up to 10 inches (25.4 cm) for all three species and at depths of 17 inches (43.2 cm) under giant sequoia (Table 5, Fig. 1). Below 10 inches depth, the temperatures for all three species tended to plateau. While there were fewer instances when temperature exceeded 212 °F (100 °C), this temperature was exceeded at a depth of 4 inches (10.2 cm) for the pines and at 12 inches (30.5 cm) in giant sequoia. Plant cell death occurs somewhere between these temperatures (e.g., Hare 1961; Pingree and Kobziar 2019; Salladay and Pittermann 2023).

Based on the model formulation, all models included an effect for species (Table 6). The 9 models considered here ranged from the full model containing fuel consumption, humus and soil moisture content to a model containing only the species effect. Plots of the fitted and observed maximum temperatures against fuel consumption, humus moisture content and soil moisture content exhibited similar behavior. At the Oe/A interface ($depth = 0$), there was a great deal of scatter in both observed and fitted values (Fig. 2). As depth increased, both the observed and fitted

Table 2 Forest floor characteristics associated with soil temperatures resulting from prescribed burning by species

Species	Depth[1]	Loading[2]		Fuel Consumption[3]	Humus MC[4]
		Initial	Consumed		
Pinus ponderosa	10.8 (9.9, 11.7)	38.6 (34.0, 43.8)	28.4 (23.5, 34.8)	73.4 (66.6, 80.8)	36.1 (31.4, 41.4)
P. lambertiana	9.3 (8.0, 10.6)	32.9 (27.7, 39.1)	29.2 (23.5, 36.3)	84.1 (76.7, 92.1)	46.7 (36.9, 59.0)
Sequoiadendron giganteum	10.4 (8.6, 12.2)	46.3 (40.2, 53.4)	44.5 (38.3, 52.2)	94.5 (90.8, 98.3)	23.6 (18.5, 30.3)

[1]Values are mean fuel depth in cm (95 percent confidence interval)

[2]Values are geometric mean fuel loading in tons per acre (95 percent confidence interval). Tons per acre × 2.245 = Mg per ha

[3]Values are geometric mean of fuel consumption as percentage (95 percent confidence interval)

[4]Humus moisture content dry weight basis in percent. Values are geometric mean (95 percent confidence interval)

Table 3 Correlation of fuel consumption with preburn humus and soil moisture content for initial prescribed burns by species

Species	Humus[1]	Soil
Pinus ponderosa	0.02 (0.78)	−0.21 (0.01)
P. lambertiana, Sequoiadendron giganteum	0.47 (0.006)	0.33 (0.04)

[1]Values are Pearson's *r* (*p*-value)

Table 4 Coefficient estimates for fitted linear regressions to predict forest floor loading (g ft^{-2}) from forest floor depth (mm)

Species	Unit	Location	Intercept	Slope
Pinus ponderosa	Coconino NF	Chimney Spring	26.20	9.63
		Limestone Flats	99.59	9.43
		Fort Valley	−248.77	13.81
		Bald Mesa	−119.10	8.98
	Kaibab NF	Kaibab	−291.94	12.25
	Apache-Sitgreaves NF	Kettle	−82.03	10.00
	Yosemite NP	YOSE-2	−82.86	8.56
		YOSE-3	−125.95	9.31
		YOSE-4	515.36	2.23
	Lassen NF	Blacks Mountain	−171.30	9.91
	San Bernardino NF	Frog	−240.1	10.71
P. lambertiana	Yosemite NP	YOSE-1	−3.99	8.79
	Eldorado NF	Baltic Ridge	127.40	7.06
	Sequoia-Kings Canyon NPs	SEKI-1, 2, 3, 4, 5, 6, 7, 8, 9	−38.39	10.27
		SEKI-11	−58.58	12.03
		SEKI-11 Reentry 4	−267.62	12.69
		SEKI-11 Reentry 7	77.67	7.36
		SEKI-11 Reentry 9	−188.68	13.16
		SEKI-12	68.88	5.83
P. jeffreyi	Humboldt-Toiyabe NF	Mills Canyon	130.80	3.86
Sequoiadendron giganteum	Sequoia-Kings Canyon	SEKI-1, 2, 3, 4, 5, 7, 8, 9	262.11	8.73
		SEKI-6	−16.67	8.89
		SEKI-11 Reentry 2, 6	−22.71	10.50
		SEKI-11 Reentry 4	−399.44	15.02
		SEKI-11 Reentry 7	156.09	6.89
		SEKI-11 Reentry 9	387.11	0.17
		SEKI-12	8.07	9.97

values became nearly constant. Recall that the prior distribution of β_1 was assumed to be normal (0, 0.25). The baseline posterior distributions, while normal, differed by species (Fig. 3). The means for β_1 for the two pine species were more similar than

Table 5 Number of instances when sheathed type K thermocouples measured hourly soil temperature ≥ 140 °F (60 °C) and ≥ 212 °F (100 °C) by depth below soil organic layer during reintroduction of prescribed burning into long unburnt stands

Species	Depth (inches)												
	0	1	2	3	4	5	6	7	8	9	10	12	17
140 °F													
Pinus ponderosa	1105	576	510	439	173	189	81	41	42	11	21		
P. lambertiana	557	360	400	180	319	71	51	8	118		38	22	
P. jeffreyi		2											
Sequoiadendron giganteum	588	238	359	85	270	112	26	2	208	5		176	56
212 °F													
Pinus ponderosa	703	218	93	54	3	1							
P. lambertiana	329	162	112	31	36				5			2	
P. jeffreyi													
Sequoiadendron giganteum	380	126	138	6	32	70			33			46	

Table 6 Estimated measures of fit for models to predict maximum soil temperature at various depths below the Oe/A1 interface resulting from reintroduction of fire for three western conifers

Model[1]	R^2			Goodness of fit[4]		
	Mean[2]	2.5[3]	97.5	Deviance	Diff	$\hat{p}_{loo}$
CHS	0.70	0.70	0.71	482,204		62.4
CH	0.69	0.68	0.69	483,628	1424	45.5
CS	0.68	0.68	0.69	484,103	1899	46.3
HS	0.64	0.63	0.64	489,981	7777	58.2
C	0.67	0.67	0.67	485,383	3179	29.4
C2	0.67	0.66	0.67	485,560	3356	26.6
H	0.61	0.61	0.62	492,231	10,027	31.6
S	0.62	0.61	0.62	491,515	9311	36.5
Sp	0.59	0.59	0.60	493,744	11,540	10.1

[1]All models included Species (Sp). C denotes $L_{Consumed}$= fuel consumption, H denotes M_{humus}= humus fuel moisture content, S denotes M_{soil}= soil moisture content. C2 model combined *Pinus lambertiana* and *Pinus ponderosa* into *Pinus* spp

[2]R^2 is the variance of the predicted values divided by the variance of predicted values plus the expected variance of the errors (Gelman et al. 2019)

[3]R^2 quantiles from the modelled posterior probability distribution

[4]Deviance is the expected log pointwise predictive density (ELPD) multiplied by −2 to put it on a deviance scale (Vehtari et al. 2017). Diff is the difference between the deviance for the full model and each reduced model. $\hat{p}_{loo}$ is the estimated effective number of parameters in the model

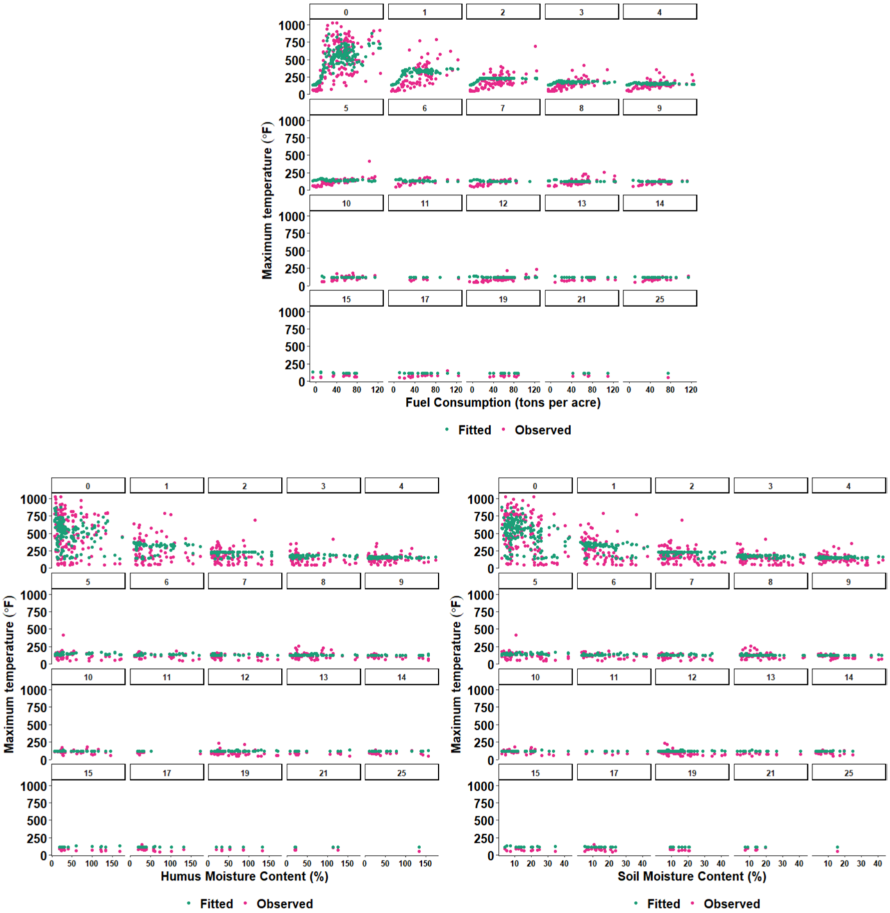

Fig. 2 Observed and fitted maximum soil temperatures by depth below Oe/A horizon by preburn fuel loading (top), humus moisture content (bottom left) and soil moisture content (bottom right)

the mean for giant sequoia. As a result of the similarity between the pines, the C2 model combined the two pine species (PILA, PIPO) into a single category (Table 6).

The amount of variation (as measured by a Bayes R^2) in the predicted posterior distribution accounted for by the full model (CHS) was greatest (Table 6) while the species only model was least (Sp). The CS and CH models accounted for nearly as much variation with roughly 1/4th fewer effective parameters and only slightly more deviance. The consumption only models (C, C2) accounted for nearly as much variation with slightly less than half of the effective number of parameters. The 2.5 and 97.5 quantiles for R^2 are analogous to a 95 percent confidence interval. While the difference between the quantile values for each were similar ($\leq$0.01) for all nine models, the consumption only models accounted for more variation than the soil moisture and humus moisture only models and nearly as much as the CS, CH, and CHS models. For the CHS model, the predicted values of maximum soil temperature

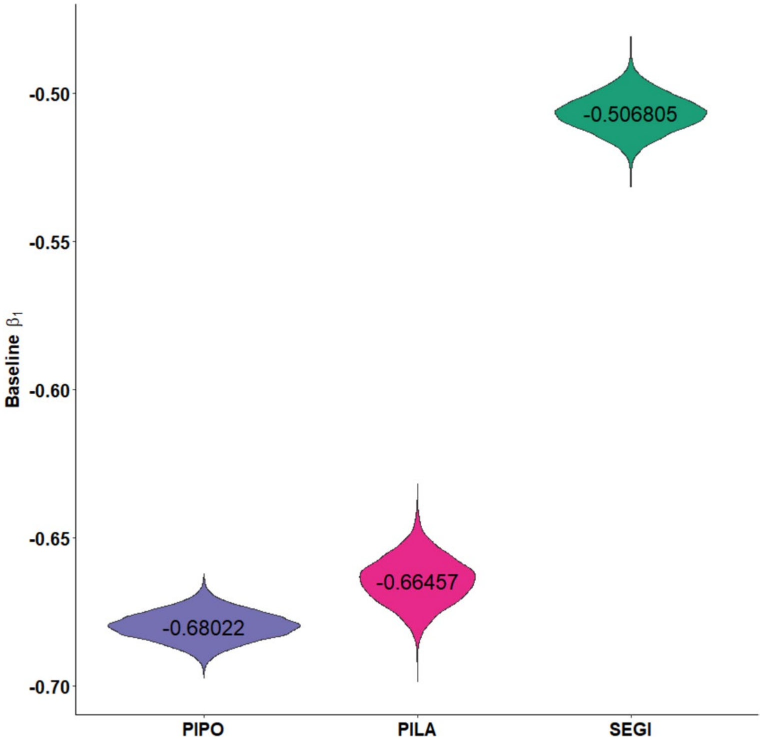

Fig. 3 Posterior distribution of species effect used to predict maximum soil temperature under three western conifers subjected to prescribed burns. The means of the posterior distributions are shown within each distribution

for each species plotted against fuel loading, humus moisture content, and soil moisture content exhibited similar patterns (Fig. 2). The variability in the predictions was greatest at the mineral soil surface (depth = 0) and decreased as depth increased. At 10 inches below the Oe/A interface, the maximum temperatures were essentially constant for all three predictor variables.

The full model (CHS) contained an estimated 62 parameters $\left(\widehat{p}_{loo}\right)$ while the three two-variable models contained 46 to 58 parameters (Table 6). The single variable models contained 27 to 37 parameters and the species only model contained 10 parameters. While the estimated deviances for the two-variable models containing consumption were close to the CHS model, the deviances of the consumption only models were third in terms of being closest to the CHS model. Using parsimony, amount of variation explained and the deviance, the fuel consumption model with three species (C) was selected for further comparison with the full model. The combined pine species consumption model (C2) parameters are contained in the supplemental data.

For the CHS model, to illustrate the shape of the fitted model for a particular combination of species, fuel consumption, humus moisture content and soil

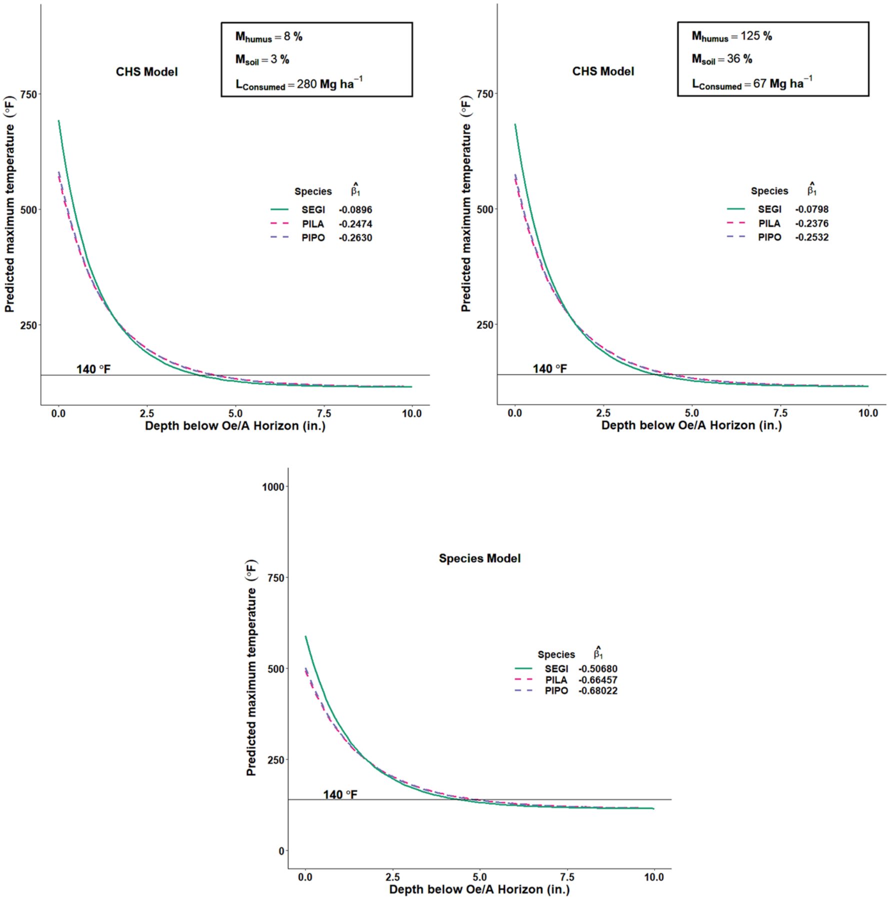

Fig. 4 Maximum soil temperature estimated using fuel consumption, humus moisture content and soil moisture content for three species of western conifers for a dry scenario (left) and a wet scenario (right). The bottom plot shows the fitted curve for the model with species only

moisture content, two scenarios were created – a dry scenario and a wet scenario (Fig. 4) for the three tree species. Note the similarity in the curves. The posterior distribution of β_1 (Fig. 3) showed that the two pine species were similar and giant sequoia was different. This is demonstrated by the overlapping curves for PILA and PIPO and a different curve for SEGI (Fig. 4). It is important to note that scale on the y-axis in Fig. 3 exaggerates the difference between species. The mean β_1 for each species without the addition of fuel loading, humus moisture content or soil moisture content were −0.66457, −0.68022, and −0.50680 for PILA, PIPO and SEGI, respectively. The corresponding values for e^{β_1} were 0.51, 0.51 and 0.60, respectively. With species alone, the model predicted maximum soil temperature of 500 to 600 °F (260 to 316 °C) (Fig. 4). Inclusion of humus moisture content, fuel consumption and soil moisture content was necessary to increase

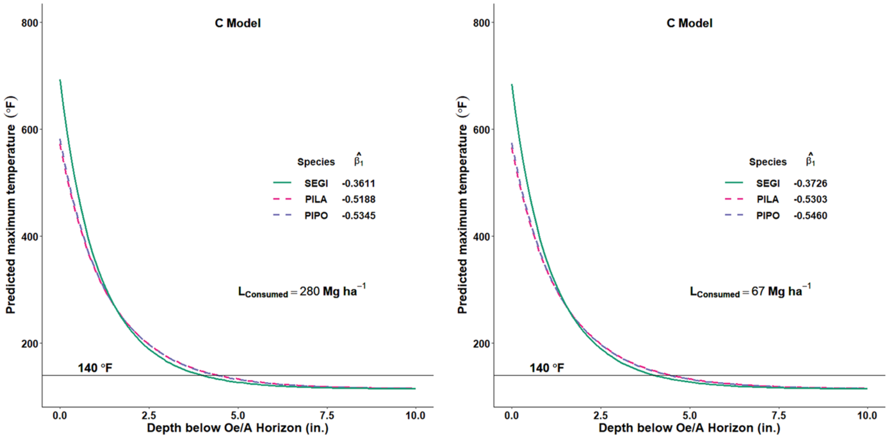

Fig. 5 Maximum soil temperature estimated using fuel consumption, humus moisture content and soil moisture content for three species of western conifers for high fuel consumption (left) and low fuel consumption (right) scenarios

Table 7 Summary of maximum soil temperature (°F) predictions from the Bayes (CHS, C), Campbell and Massman models for two scenarios

		Model			
Scenario	Depth	CHS	C	Campbell	Massman
Giant sequoia	2	228	225	149	163
	4	154	144	97	131
	10	115	114		
Ponderosa pine	2		216	120	115
	4		167	93	95
	10		121		

predicted temperatures to 800 to 1000 °F (427 to 538 °C). Using the same amount of fuel consumption, the maximum soil temperatures for different depths were also plotted for the fuel consumption only (C) model (Fig. 5). Again, note the similarity in curves. While the values of $\widehat{\beta}_1$ differed between the two models and between species, the maximum temperatures were similar and dropped below 140 °F (60 °C) at a depth of about 5 inches (12.7 cm) which was consistent with much of the observed data (Fig. 1). The fitted coefficients for all 9 models are contained in the Supplemental material.

Even though the fitted model assumed that the coefficients were functions of soil moisture, humus moisture content and fuel consumption (Eq. 5), the process to estimate maximum soil temperature for a specific depth is straightforward. The following two examples illustrate how maximum soil temperature can be estimated using the Bayesian model. Comparison with the Campbell and Massman model predictions in FOFEM 6.7 (Lutes 2020) is also presented (Table 7).

Example 1 – First Prescribed Burn in a Giant Sequoia Grove

A prescribed burn is planned for May in a giant sequoia grove that has not been burned in recorded history. Using the Giant Sequoia photo series (Weise et al. 1997), it was determined that the forest floor conditions look like "Mountain Home Grove 3" with an estimated fuel loading of 33.1 tons per acre (74.2 Mg ha^{-1}). Because there was good precipitation over the winter, the soil moisture content is 40 percent and the humus moisture content is 100 percent. Prior experience suggests that all the forest floor material will be consumed. From the supplemental data, the coefficients for species (giant sequoia), fuel consumption (33 tons per acre), soil moisture content (40 percent) and humus moisture content (100 percent) are −0.507, 0.052, 0.034 and −0.298, respectively, for the CHS model. The coefficients for the C (consumption only) model are −0.555 (species) and 0.072 (fuel consumption). The intercept term β_0 ranged from 6.349 to 6.353 for the 9 models so 6.35 was used for all calculations. From Eq. 5, $\beta_1 = -0.507 + 0.052 - 0.298 + 0.034 = -0.719$. Using Eq. 6, the maximum soil temperature *Tmax* would be 228, 154 and 115 °F (109, 68, 46 °C) at 2, 4 and 10 inches (5.1, 10.2, 25.4 cm) below the Oe/A horizon, respectively (Table 7). For the C model, $\beta_1 = -0.555 + 0.072 = -0.483$ and *Tmax* would be 225, 144, 114 °F (108, 62, 45 °C) for the same depths. If the C2 model was used, $\beta_1 = -0.553 + 0.074 = -0.479$ resulting in the same *Tmax* values (after rounding).

In FOFEM 6.7 (Lutes 2020), SAF forest type 243 Sierra Nevada Mixed Conifer (Eyre 1980) was chosen to represent giant sequoia/sugar pine (SMFDB 027 variant). Assuming forest floor loading of 45 tons per acre, a fall burn under very dry conditions with 100 percent consumption of duff and 100 percent consumption of litter and woody fuels, *Tmax* at 2 and 4 inches (5, 10 cm) from the Campbell model (Campbell et al. 1995) and Massman models was calculated (Table 7). The FOFEM models predicted lower temperatures than the CFS and C models and were limited to depths of 5.1 inches (13 cm). Both FOFEM models did predict temperatures greater than 140 °F at 2 inches which agreed with Table 5.

$$Tmax = -459.67 + \exp\left(6.35 + \exp\left[\beta_1 - depth \times \exp\left\{\beta_1\right\}\right]\right) \qquad (6)$$

Example 2 – Chimney Springs (AZ) Fire Reintroduction

Fire was reintroduced to a ponderosa pine stand on the Ft. Valley Experimental Forest near Flagstaff, AZ in 1976 to reduce fire risk (Sackett 1980). Estimated fuel loading was 15.2 tons per acre (34.0 Mg ha^{-1}) and 9.5 tons per acre (23.3 Mg ha^{-1}) were consumed. Antecedent rainfall was less than normal rainfall for the summer and fall so the fire was conducted at night to moderate the burning conditions. No information on soil or humus fuel moistures were reported so the C model was used. From the supplemental data, the species coefficient was −0.626 and the fuel loading coefficient was −0.564. From this $\beta_1 = -0.626 - 0.564 = -1.19$ and *Tmax* at 2, 4, and 10 inches (5.1, 10.2, 25.4 cm) would be 216, 167 and 121 °F (102, 75, 50 °C), respectively (Table 7).

The predictions from FOFEM 6.7 for a fall burn in interior west ponderosa pine forest with assumed natural fuel loading of 22.5 tons per acre, very dry, and 60 percent consumption, were less than the C model at 2 and 4 inches (5, 10 cm) (Table 7). Neither FOFEM model predicted *Tmax* of 140 °F at 2 inches unlike the observed data (Table 5). While a significant proportion of trees died following these fires (Harrington and Sackett 1990), the reduction was primarily in the sapling and pole-sized trees. The causes of tree mortality were not described (crown damage, root damage); however, the C model did predict instantaneous lethal temperatures at 2 and 4 inches.

Discussion

Reintroducing prescribed burning into long unburnt stands with large fuel accumulations has been and continues to be a challenge to forest managers in the United States in many forest types (Wade et al. 1998; Scheller et al. 2005; Ruth et al. 2007; Webster and Halpern 2010; Nemens et al. 2019). While much progress has been made to improve the knowledge managers need, fire reintroduction still carries risk. One of those risks is damaging the tree and soil resources by the unintended consequences of soil temperatures elevated above the limits where biological activity can occur. For the data presented here, killing temperatures were observed at depths of 4 to 6 inches into mineral soil. For the stands where fire was reintroduced, fuel consumption was relatively high and often complete when the fire spread across the surface of the forest floor and humus fuel moisture approached 200 percent (Haase and Sackett 1998).

High levels of fuel consumption have been reported in other prescribed burns in giant sequoia (Kilgore 1973; Stephens and Finney 2002). Using temperature-sensitive chemicals, temperatures as high as 750 °F (399 C°) at a depth of 1.75 inches (4.45 cm) and 200 °F (93 °C) at a depth of 7 inches (17.8 cm) were observed in a prescribed burn in a long unburnt sequoia stand (Kilgore 1973); however, using these chemicals can only provide an estimate of maximum temperature (Iverson et al. 2004). As a result of this high level of fuel consumption and heat generation for a wide range of soil and humus moisture content for these three species (PIPO, PILA, SEGI), an understanding of this unseen impact from fire reintroduction into similar stands may be useful (although it was noted by observant forest managers who identified this problem in the 1970 s). Fire reintroduction in unburnt longleaf pine did not result in such high levels of fuel consumption, even in stands with relatively dry organic layers (Varner et al. 2007). However, the maximum soil temperatures observed following reintroduction of fire in a long unburnt longleaf pine stand found that temperatures did not exceed 140 °F (60 °C) at 4 inch (10.2 cm) depth (Kreye et al. 2020). In this latter study, fuel consumption was reported as the depth of duff burned instead of fuel loading consumed.

For giant sequoia, ponderosa pine and sugar pine, the greatest variability of maximum soil temperature was noted in the top 4 inches of mineral soil (Fig. 1). This zone is particularly critical because a significant amount of fine root mass is found there (Berndt and Gibbons 1958; Swezy and Agee 1991; Dumm et al. 2008; Bartley

2023). Prior to and because of the measurement of these potentially lethal temperatures within this critical zone, various mechanical methods have been proposed as a means to reduce large accumulations of fuel around high-value trees (Thomas and Agee 1986; Fowler et al. 2010; Hood 2010).

Prescribed burning has been shown to cause stress in several conifers resulting in the formation of ethanol in plant tissues (e.g. Kimmerer and Kozlowski 1982; Kelsey and Joseph 2003; Kelsey and Westlind 2017) which can serve as an attractant for various insects that then attack stressed trees (Sullivan et al. 2003). While 140 °F (60 °C) may be recognized as a near-instantaneous lethal temperature limit, the effects of longer term exposure of plant tissue to elevated temperatures are also recognized (Seidel 1986; Kelsey and Westlind 2017). Kelsey and Westlind (2017) presented a model of ethanol formation resulting from prolonged exposure to temperatures below 140 °F (60 °C). The data and fitted model presented here showed that temperatures above ambient soil temperature, yet below lethal temperature, were observed at depths of up to 10 inches (25.4 cm). These temperatures may be sufficient to cause formation of ethanol in the roots of the trees. Similarly, temperatures measured in ponderosa pine cambium in Arizona ranged from 60 to 230 °F (16 to 110 °C) (Sackett and Haase 1998) suggesting that the cambial cells may have produced ethanol aboveground potentially attracting bark beetles. In addition to ethanol being formed within tree cells, ethanol is a well-known product of the pyrolysis and burning of wildland fuels (e.g., Simpson et al. 2011; Weise et al. 2023) and could serve as an attractant if the concentration is sufficient to be detected by bark beetles. This brief discussion illustrates the complexity associated with the physical and chemical aspects of the interactions between forest trees, insects and fire as related to tree mortality.

The soil temperature models currently available in the FOFEM (Campbell et al. 1995; Massman 2012, 2015, 2021) include factors that can affect soil temperature and are theoretically derived. In these models, soil temperature is sensitive to soil moisture content. For the present data, while soil and humus moisture content alone were each significant predictors of maximum soil temperature, fuel consumption was the single variable most related to maximum soil temperature. Fuel consumption was sometimes correlated with humus and soil moisture content in the present study (Table 3) which would affect the statistical fitting of models. The two-variable models (CS, CH) showed that soil and humus moisture content improved the fit of the model for maximum soil temperature but contained substantially more parameters. An important characteristic of the Massman model is that it produces soil temperature as a function of time unlike the models developed in this paper which only predict point estimates of the maximum temperature. The original data (Burke et al. 2024a, 2024b) are temperature observed on a hourly time step at various depths which could be used to further validate the Massman model.

Robichaud et al. (2025) used a portion of the data from this study to compare predictions from the Campbell and Massman models with the observed data. The comparison was focused on depths of 0.75 and 1 inch (1.9, 2.5 cm) and found that the Massman model provided better predictions than the Campbell model. However, as the two examples above showed, temperatures from both models were appreciably lower than the temperatures from the CHS and C models at depths of 2 and 4 inches (5, 10 cm). This is not an uncommon result when a theoretical model based on physical processes is compared to a statistical model fit to a specific data set. Both model types have their uses (Roberts et al. 2017); an important consideration for statistical models is extrapolating them beyond the data which is not a limitation for a model describing physical processes.

The output that the FOFEM models produced only went to a depth of 5.1 inches (13 cm) in the mineral soil; the data and the models agreed that the highest temperatures occurred within this region. Soil biological activity generally occurs within the top 12 inches (30 cm) of the mineral soil; in this study, fire-caused increases in temperature were approaching ambient conditions and stabilized at 10 inches (25 cm) depth. While not elevated to potentially lethal temperatures, the temperatures at these lower depths may have an effect of biological activity so the ability to predict fire-elevated temperature at depths greater than 4 inches might be desirable. The statistical models developed in this paper predict temperatures at these depths based on the data while the two FOFEM models did not. There may be settings in the FOFEM program which allow predictions at greater depths.

Fuel consumption rate determines the heat flux which propagates into the soil. Radiant heat fluxes in the original laboratory experiments for the Campbell and Massman models were 3.4 and 4.8 Btu s^{-1} ft^{-2} (39 and 54 kW m^{-2}) (Campbell et al. 1995). In a study of smoldering combustion of peat moss, heat fluxes of about 0.35 Btu s^{-1} ft^{-2} (4 kW m^{-2}) were observed (Schneller and Frandsen 1998). The range of fluxes described for surface fires in Massman (2012) was 0.9–8.8 Btu s^{-1} ft^{-2} (10–100 kW m^{-2}). For the present study, assuming fuel consumption of 100 tons per acre (224 Mg ha^{-1}) for a prescribed burn reintroduced into SEGI that burned for 92 h, and a duff heat of combustion content of 8600 Btu lb^{-1} (20 MJ kg^{-1}) yields an average heat flux of 0.13 Btu s^{-1} ft^{-2} (1.5 kW m^{-2}) which is smaller than any of the reported fluxes. This calculation did not include any adjustments for the moisture content of the humus. Drier humus would result in shorter burn times increasing the calculated heat flux. While it is possible to infer heat flux rates from the measured temperature profiles at a given depth (Haase and Sackett 1998), several assumptions are necessary and beyond the scope of this paper.

Conclusions

A statistical model has been developed to use fuel consumption to predict maximum soil temperatures resulting from the reintroduction of prescribed burning into long unburnt stands with deep accumulations of forest floor material. The full Bayesian generalized multivariate non-linear multilevel model contained 62 terms for species, fuel consumption, humus moisture content and soil moisture content. Eight reduced models were compared to the full model and the reduced model with species and fuel consumption contained substantially fewer terms, performed nearly as well as the full model and is suggested for use. Variability in maximum soil temperature decreased rapidly from the Oe/A horizon and was relatively constant by 10 inches (25.4 cm) below the horizon. The models for ponderosa pine and sugar pine were more similar than the model for giant sequoia. All models predicted lethal temperatures at depth of 4 to 6 inches (10.1 to 15.2 cm). The models were relatively insensitive to differences in species. The model can be used to estimate maximum soil temperatures at depths up to 25 inches (0.63 m) and fuel consumption up to 125 tons per acre (280 Mg ha^{-1}).

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Declarations

Competing interests The authors have no competing, relevant financial, or non-financial interests to disclose.

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