PREDICTING FIRE INTENSITY USING VEGETATION, FUEL, AND WEATHER VARIABLES

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ABSTRACT

When applying prescribed fire to achieve various management objectives, forest managers benefit from being able to accurately predict fire behavior with site- and time-specific data. At the William B. Bankhead National Forest in northcentral Alabama, we used three levels of thinning (none, light, heavy) and three fire return intervals (no fire, 9-year return, 3-year return) in mixed pine-oak (*Pinus* spp.-*Quercus* spp.) stands to move stands toward more desirable structures. After 38 fires over 12 years, we amassed a substantial store of thermocouple temperatures and burn condition data. We modeled maximum thermocouple temperature as a surrogate for fire intensity by using a mixed effects model that incorporated stand and vegetation variables, fuel loading measurements, and weather data. The random portion of our model estimated low correlation of maximum temperatures within stands, but moderate correlation within plots (plots were nested within stands). The fixed effects portion of our model revealed associations of maximum temperature with several vegetation (importance values of oaks and pines, seedling counts of pines and other species), fuels (loadings of both bark and duff), and weather variables (average ambient temperature and relative humidity over the 24 hours prior to ignition, fuel temperature, and fuel moisture).

INTRODUCTION

Forest managers must frequently balance multiple objectives in their stewardship duties. The general concept of achieving and maintaining healthy and resilient forests may imply a number of specific goals, including but not limited to maximizing floral and fauna biodiversity, managing the economic timber resource, facilitating recreational opportunities, enhancing forests' roles in providing clean air and water, and establishing wildlife habitat (USDA Forest Service 2004). Of the many tools forest managers have at their disposal, prescribed fire holds a unique place. On a general level, with wildland fires having been artificially suppressed for much of the 20th century, the use of prescribed fire can provide a return to a more natural state, restoring a process that has been diminished or lost. More specifically, prescribed fire may increase light in the understory, change the prevailing species mix, and alter fuel loading and structure (Brose and others 2013).

While prescribed fire is a tool that may offer many benefits, the relationship of fire to other elements within an ecosystem is complex. Forest stand characteristics, fuel composition, and fire behavior all interrelate in feedback loops (fig. 1). In this context, applying prescribed fire to achieve specific silvicultural outcomes is anything but simple. Consequently, the more that can be learned about the relationships among these elements, the better equipped forest managers will be to effectively apply prescribed fire. Our analysis seeks to inform one aspect of this system, by identifying associations between fire behavior and vegetation. Specifically, the primary objective of this analysis was to assess the null hypothesis of no association between the forest's vegetation species mix and maximum thermocouple temperatures, while controlling for other factors that affect fire intensity.

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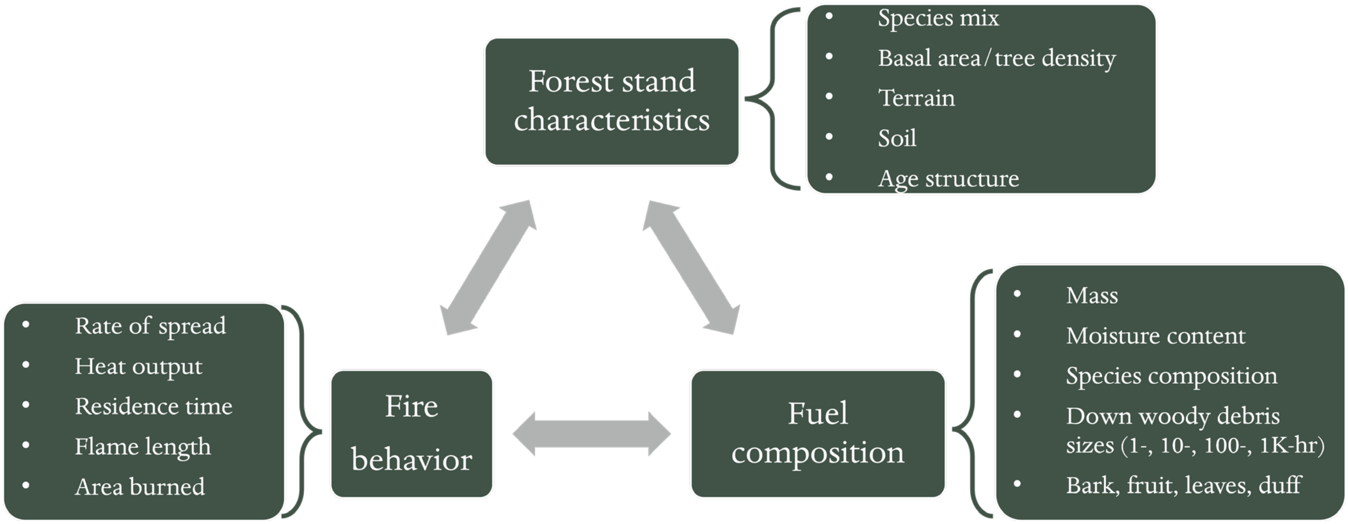

Figure 1—Forest-fuels-fires feedback loops: predicting fire behavior requires understanding how forest stand characteristics and fuel composition both influence and are influenced by fire behavior. Each of the three constructs in this feedback loop (fire behavior, forest stand characteristics, and fuel composition) is composed of several individual empirical metrics. For example, fire behavior is described by metrics such as rate of spread, heat output, residence time, flame length, and area burned.

METHODS

The William F. Bankhead National Forest (BNF) is a 180,000-acre national forest located in northcentral Alabama. The treatment stands, all located in the northern portion of the BNF, were selected to be similar based on average stand age, composition, and size. They ranged in area from 22 to 46 acres, in age from 30 to 60 years old, and in pretreatment basal area from 143 to 188 square feet per acre. The study sites were mixed pine-hardwood forests, dominated by loblolly (*Pinus taeda*), with lesser amounts of Virginia (*P. virginiana*) and shortleaf (*P. echinata*) pine. Upland oaks were common and included chestnut (*Quercus prinus*), white (*Q. alba*), northern red (*Q. rubra*), scarlet (*Q. coccinea*), black (*Q. velutina*), and southern red (*Q. falcata*) oaks. Other hardwoods included yellow-poplar (*Liriodendron tulipifera*), red maple (*Acer rubrum*), and black cherry (*Prunus serotina*), among others.

Part of the original goal of the study was to test varying levels of management disturbances for their effectiveness at shifting the species mix toward greater hardwood dominance, particularly oak. The nine treatment levels (eight treatments and one control) were the result of a 3 by 3 factorial design incorporating two disturbance factors at three levels each. The three thinning levels (mechanical thinning from below) were no thinning, light thinning [target residual basal area (BA) of 75 square feet per acre], and heavy thinning (target residual BA of 50 square feet per acre). Prescribed burns occurred at three frequencies: no burns, infrequent burns (every 9 years), and frequent burns (every 3 years). Only the infrequent and frequent burn treatments are relevant for this analysis, hence six treatments were included in the data used here.

Four replications (blocks) were initiated from 2006 through 2008; each block consisted of nine stands, one for each treatment level. Each stand was surveyed and marked with five permanent measurement plots. Thinned stands received a single thinning treatment to the desired residual BA prior to burning. A total of 38 landscape-scale prescribed fires, usually encompassing multiple treatment stands, were conducted over 12 years. The low- to moderate-severity prescribed fires all took place during the dormant season from January through early April and used backing fires or strip head fires to ensure that only surface fires occurred. For details, see Schweitzer and others (2016).

Data Collection

Dependent variable: maximum thermocouple temperature

Fire temperature data were recorded for most prescribed fires. We followed methods from Iverson and others (2004) for distributing six to eight HOBO data recorders (HOBO U12 Series Datalogger) and thermocouple probes (TCPs) (HOBO TCP6-12 Probe Thermocouple Sensor, Onset Computer Corporation, Cape Cod, MA) per measurement plot per burn. Dataloggers were buried approximately 6 inches deep, and litter and duff layers were replaced over mineral soil after burial. The thermocouple probes were installed in a vertical orientation with the tips approximately 10 inches above the litter layer. Temperatures were recorded together with date-time stamps every 2 seconds from the morning before through the night following the burn. For this analysis, only the maximum recorded temperatures were used, and no data was used if the maximum temperature did not exceed 90 °F. Although we did not view the burn temperatures as precise measurements of fire intensity, in the sense of heat transfer, we maintain that they provided a useful index for comparing fire intensity among locations or among different fires. Thermocouple-based data also carry further advantages, which are addressed in more detail in the Discussion.

Covariates: stand data

After stands were assigned to treatments, each was surveyed using five permanent measurement plots. For each plot, soil type, aspect, slope percentage, and elevation were recorded.

Covariates: weather data

Hourly weather data for each burn date and 7 days prior to each burn were obtained from the MesoWest weather database maintained by University of Utah (2022). Relevant data fields included air temperature (°F), relative humidity (RH, percent), wind speed (miles per hour), wind direction (degrees), wind gust maximum speed (miles per hour), precipitation accumulation (inches), fuel temperature (°F), and fuel moisture (percent). The preburn date air temperature, relative humidity, and precipitation variables were averaged over varying time windows (e.g., 24 hours, 48 hours, 72 hours, etc.) prior to ignition to investigate the effect that weather preceding the burn date would have on the fire temperatures. Burn date weather was matched to the fire temperature data according to the weather time stamp most closely matching fire ignition time.

Covariates: fuels data

In each permanent measurement plot, fuel loads were measured after leaf fall and before the prescribed burn for that cycle. To collect these data, two 50-foot planar intercepts were established in each plot (Brown 1974). For each transect, two distances were randomly selected. At each distance, two 1-foot square samples were marked, one at 3 feet to the left, the other at 3 feet to the right of the planar intercept. In these 1-square-foot sample areas, all down woody debris was collected and separated into the following categories: bark, fruit, leaves, duff, 1-hour fuels, and 10-hour fuels. At the lab, samples were oven dried in paper bags at 175 °F for 48 hours (72 hours for duff); immediately after drying, samples were weighed to 0.00035 ounces (0.01 grams) using an Ohaus 810-g precision scale. The fuels variables were invariably and highly right skewed; therefore, model building used the natural log-transformed versions of these measures.

Independent variables of primary interest: vegetation data

The primary research interest lay in determining associations between vegetation data and prescribed fire intensity. All vegetation data were collected prior to thinning and then in the summer before each prescribed burn. Regeneration data (understory reproduction, i.e., seedlings and stems <1.5 inches diameter at breast height, d.b.h.) were tallied within a 1/100-acre subplot with center at plot center. Tallies were recorded by species and size class (this analysis uses only the aggregate counts across all the reproduction size classes and divides the total counts by 1,000). Midstory trees (d.b.h. ≥1.5

inches, but <5.6 inches) were tagged and counted within a 1/40-acre subplot with center at plot center. Overstory trees (d.b.h. ≥5.6 inches) were tagged and counted within a 1/5-acre subplot with center at plot center. For the midstory and overstory, species and d.b.h. were recorded for every tallied tree in the respective subplots. For this analysis, species were aggregated into four groups: oak, pine, red maple, and other species. An index, the importance value (IV), was used to aggregate the high dimensional vegetation data for the midstory and overstory. The IV is an equally weighted average of the relative density (stems per acre) and relative dominance (BA per acre) of each species group (Cottam and Curtis 1956, Crow and others 2002).

This analysis utilizes data through four burn cycles for all four blocks; thus, frequently burned stands received four fires, while infrequently burned stands received two fires. Further background on the study and analysis on other research questions may be found elsewhere (Craycroft and Schweitzer 2023; Schweitzer and others 2016, 2019).

Statistical Analysis

Although we had a high number of temperature measurements, the data were not independent. There was spatial correlation, with plots nested within stands. There was also temporal correlation, because stands within the same blocks were generally ignited under the same weather conditions. And there were repeated measures over time. Hence it was critical to not treat the data as a simple random sample. We therefore employed a mixed effects model approach to address these various sources of dependence, as specified in the following model statement:

$$\ln T_{ijk} = X_{ijk}\beta + \alpha_k + \alpha_{j|k} + \epsilon_{ijk}$$

where

ln is the natural log operator

T_{ijk} is the maximum TCP temperature for observation i, in plot j, in stand k

X_{ijk} is the vector of covariate values associated with observation ijk

β is the vector of coefficients capturing the relationships between the fixed effects and the outcome

α_k is the random intercept for stand k

$\alpha_{j|k}$ is the random intercept for plot j nested within stand k

ϵ_{ijk} is the true noise term for each observation

We treated stand (the combination of treatment and block) and plot nested within stand as random effects, while all other covariates plus year, day of year, and time of day were treated as fixed effects.

To develop this mixed effects model, we used the protocol described by Zuur and others (2009). First, we estimated a model with all possible covariates, plus all reasonable interaction terms. Using that model, we sought the optimal random structure using restricted maximum likelihood and Akaike's Information Criteria (AIC). Third, given the optimal random structure, we sought the optimal fixed structure using maximum likelihood to compare nested models and removed nonsignificant covariates. A threshold of $\alpha = 0.05$ was used for assessing statistical significance. In the final model validation step for the best fitting model, plots of residuals against predicted values, against included covariates, and against excluded covariates were all examined for systematic unexplained variation. Analysis was conducted in R Version 4.1.1 (R Core Team 2021).

RESULTS

The 38 prescribed fires over the course of the four burn cycles included in this analysis generated 1,389 individual temperature time series. Average maximum TCP temperature was 344 °F [±166 °F, standard deviation (SD)]. The majority of the maximum temperatures were in the 200–500 °F range, but some reached above 800 °F (fig. 2). Distributions of maximum burn temperatures did not vary greatly among the different treatments (fig. 3).

The best fitting mixed effects model included the covariates summarized in table 1. The only vegetation variables that displayed a statistically significant association with the maximum TCP

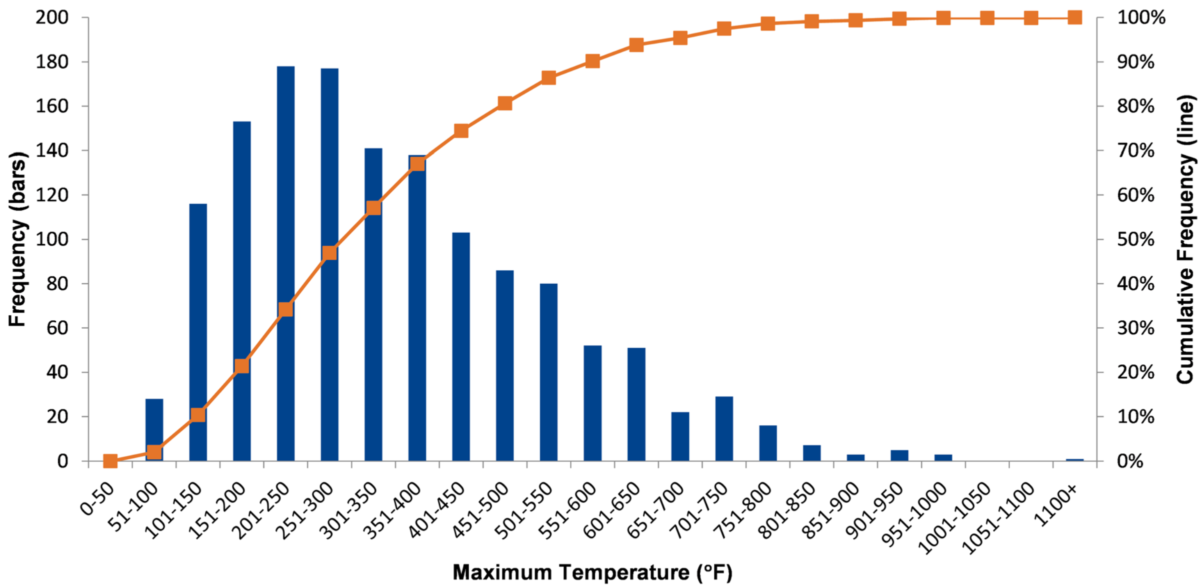

Figure 2—Histogram of maximum thermocouple probe (TCP) temperatures for 38 dormant season prescribed fires on the William B. Bankhead National Forest, AL. Fires included one or more study stands, each stand contained five measurement plots, and each plot received from six to eight probes; this resulted in 1,389 maximum TCP values. The bars in the histogram represent the frequency (left axis) of maximum TCP values within 50-degree intervals, while the line on the graph illustrates the cumulative frequency (right axis).

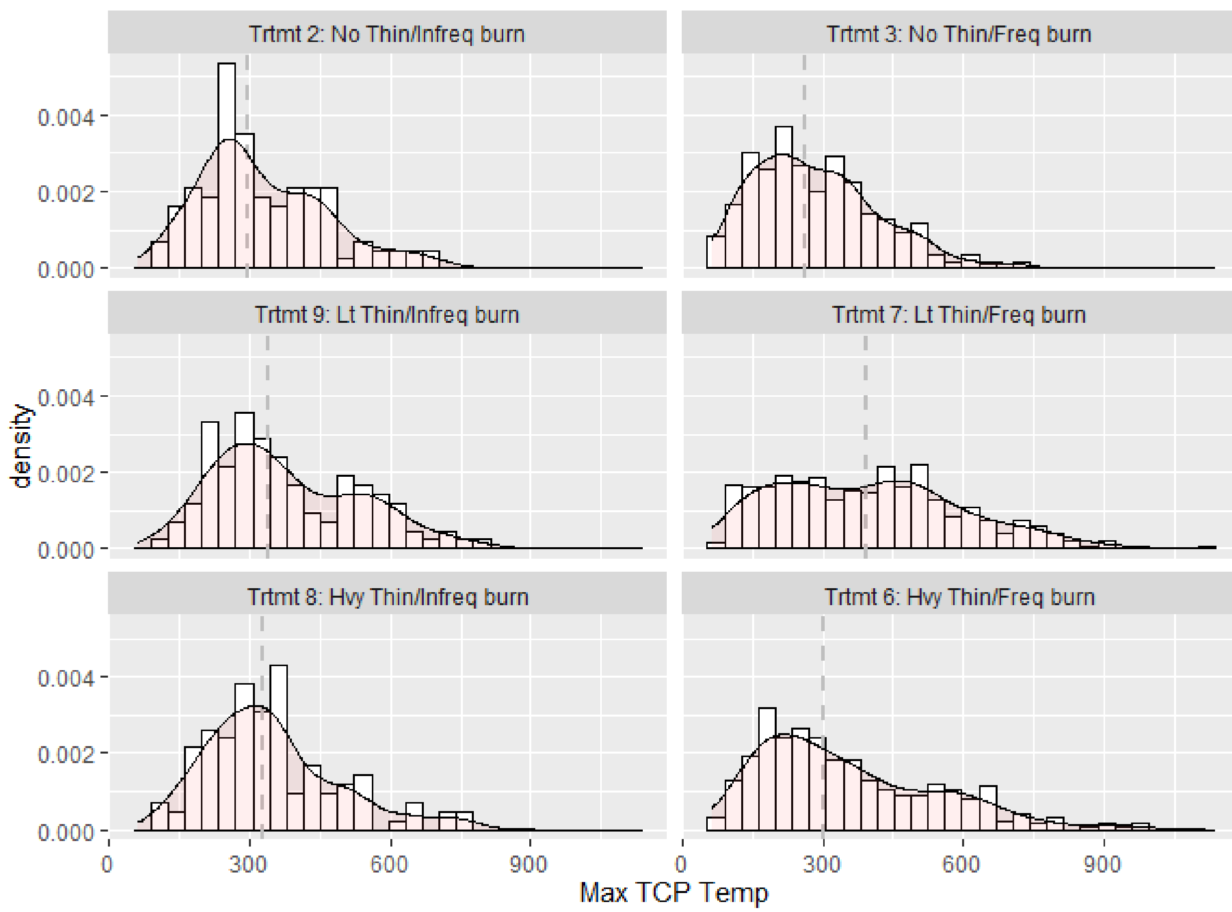

Figure 3—Maximum thermocouple probe (TCP) temperature density histograms by treatment for 38 dormant season prescribed fires on the William B. Bankhead National Forest, AL. Trtmt: treatment. Infreq: one burn every 9 years. Freq: one burn every 3 years. Lt Thin: thinning to residual basal area (BA) of 75 square feet per acre. Hvy Thin: thinning to residual BA of 50 square feet per acre. We used density, not frequency, histograms because the infrequent burn treatments (left column) contain roughly half as many observations as the frequent burn treatments (right column); plotting frequencies would cause the infrequent burn histograms to be squashed, making comparisons between the columns more difficult. Dashed vertical lines indicate the median for each treatment.

temperatures were the IVs for oaks and pines, and the seedling counts for pines and others. Other statistically significant covariates included time of day, day of year, averages of relative humidity and air temperature for the 24 hours preceding ignition, bark mass, duff mass, fuel temperature and fuel moisture, year, and three interaction terms. Table 2 organizes the statistically significant fixed effects by their relative importance in explaining variation in the maximum temperatures.

The model was built using the log-transformed outcome to address the right-skewed temperature distribution and the heteroscedasticity in the data; consequently, the estimated coefficients all describe effects on the log scale. To interpret covariate effects on the original scale of burn temperature, we assumed changes of one SD of each fixed effect term in turn (holding all other covariates constant), and then back-transformed the resulting impact from the log scale to the original scale. For example, a one SD increase in the IV for oak was associated with a 23 °F increase in predicted maximum burn temperature, holding all other covariates constant (table 3).

Table 1—Estimated coefficients and significance levels for fixed effects model used to predict maximum thermocouple probe temperature as a surrogate for fire intensity for 38 prescribed fires on the William B. Bankhead National Forest, AL

Variable category	Variable	Coefficient	*P*
Vegetation	Importance value, oak	0.0052	0.006
Vegetation	Importance value, pine	0.0038	0.004
Vegetation	Total seedlings, pine[1]	0.0115	0.045
Vegetation	Total seedlings, other species[1]	-0.0145	<0.001
Fuels	Bark weight (ln)	0.2495	0.024
Fuels	Duff weight (ln)	-0.1359	<0.001
Weather	Air temperature[2]	0.0656	<0.001
Weather	Relative humidity[2]	0.0371	0.010
Weather	Fuel temperature	-0.0163	0.048
Weather	Fuel moisture	-0.1429	0.034
Weather	Start time	-2.8137	0.002
Weather	Julian day of burn	-0.0355	<0.001
Weather	Year[3]	–	<0.001
Interaction	Air temperature x Relative humidity	-0.0009	0.001
Interaction	Fuel temperature x Fuel moisture	0.0022	0.017
Interaction	Time x Julian day of burn	0.0645	<0.001

ln = natural log .
[1] Seedling counts were divided by 1,000 to obtain more meaningful coefficients.
[2] Averages of air temperature (°F) and relative humidity for the 24 hours prior to burn start time.
[3] Year was treated as a factor variable; hence there was a different coefficient (not shown) for every value other than 2007, the reference year.

Table 2—Fixed effects model variables ranked by relative importance in explaining variation in maximum thermocouple probe temperature for 38 prescribed fires on the William B. Bankhead National Forest, AL

Category	Variable name
Weather	Julian day of burn
Weather	Air temperature, 24 hours pre-ignition
Weather	Time of day
Weather	Relative humidity, 24 hours pre-ignition
Vegetation	Importance value, pine
Vegetation	Importance value, oak
Vegetation	Total seedlings, other species
Fuels	Duff weight
Weather	Fuel moisture
Weather	Fuel temperature
Vegetation	Total seedlings, pine
Fuels	Bark weight

Relative importance was determined by *P*-values, model AIC changes, and considering if a variable was also included in interaction terms or not.

Table 3—Effect on maximum thermocouple probe temperature (original scale) of a one standard deviation change in four vegetation variables in the mixed effects model

	Importance value		Total seedlings	
Factor	Oak	Pine	Pine	Other species
Model coefficient	0.00525	0.00382	0.01150	-0.01447
1 standard deviation (SD)	13.8	19.7	3.1	4.2
1 SD change (log scale)	0.0724	0.0752	0.0359	-0.0609
Change[1]	23.5	24.5	11.5	-18.4

[1] Change in median maximum thermocouple probe temperature at original scale (°F).

DISCUSSION

A long-held view of fire behavior is that intensity is a product of weather, topography, and fuels (Rothermel and Deeming 1980, Varner and others 2015). Each of these three components are broad concepts comprising many individual elements; ascertaining the relative importance of the concepts to fire behavior has been a focus of much research (Bessie and Johnson 1995, Hély and others 2001, Wenk and others 2011). The main question driving this analysis was not which component had the highest relative importance, but rather, after controlling for weather and fuels, which vegetation variables, if any, had a statistically significant association with maximum TCP temperature. We view maximum TCP temperature as a useful index for fire intensity even if it does not fully describe the heat transfer effects that occur. Teasing out the influence of vegetation requires conditioning models on those other factors. Indeed, weather variables played the largest role in explaining maximum TCP temperatures in this model (table 2). We highlight that the averages of air temperature and relative humidity over the 24 hours prior to ignition were more strongly associated with the outcome than air temperature or relative humidity strictly from the burn start time. Many studies reporting weather conditions prevailing during prescribed burns present those conditions only at ignition time or averaged over the duration of the burn (e.g., Iverson and others 2004, Wenk and others 2011). In our model building process, we also tested 48-, 72-, 96-, and 120-hour prior averages; while relationships were found for several of these, the strongest association here and best improvement in overall model fit was achieved with the 1-day prior averages. These results suggest that in reporting on fire research, it may be most useful to present weather conditions for 24 or more hours preceding the burn.

With respect to vegetation variables, none of the midstory importance values were significant in this model. Dormant season fires primarily consume leaf litter and thus it is likely that the overstory size class simply provides so much more leaf litter that the effect on burn temperatures from the overstory overwhelms any effect of the midstory as related to species distribution. The overstory species groups that showed significant associations were oaks and pines, with higher IVs in each case implying higher maximum TCP temperatures. The IV for red maple was not significant; it is conjectured, however, that an increase in IV for red maple would be accompanied by a decrease in IV for oaks or pines or both, and hence would tend to lead to a decrease in maximum TCP temperatures. The IV for the other species group was omitted as a candidate variable (linear dependence among the independent variables would result if all four IVs for a size class were included together). For the understory, seedling totals for the other species group and for pines were statistically significant, with higher pine seedling counts associated with higher maximum TCP temperatures, and higher seedling counts for the other species group (i.e., nonoaks, pines, or red maples) associated with lower temperatures.

Of the six categories of dead fuels tested in this analysis (bark, fruit, leaves, duff, 1-hour, and 10-hour), only bark and duff were statistically significant. We have found that the category of fuel that is most consistently and completely consumed by these prescribed fires is leaves (Craycroft and Schweitzer, unpublished), which is somewhat different from the experience of another recent study involving prescribed fire and thinning in the South (Vander Yacht and others 2019). Nevertheless, in this analysis, the mass of leaves in the aggregate does not appear to have a significant effect on fire temperatures after controlling for other variables. Therefore, it may be of interest to quantify fuel loads not just by size and type, but also by species; this may also enable assessment of how similar combustion and flammability results in the field are compared to lab experiments (Kreye and others 2023, Varner and others 2015). This study, however, did not capture that aspect of fuel loads.

With fire being such a dynamic phenomenon and acknowledging that feedback loops influencing fire behavior are complex, it is interesting that this model suggests associations between maximum TCP temperature and several vegetation variables, even after conditioning on weather and fuels. Also, certain other covariates such as slope steepness and aspect, while significant in models where those were the only independent variables, were not statistically significant after conditioning on the other covariates included here. Meanwhile, the random components of the model suggest that there is relatively high variation yet unexplained by the model. This is understandable given the complex nature of fire as well as of the general categories of independent variables (vegetation, fuels, weather) and the consequent difficulty of fully capturing these constructs with a relatively small number of individual variables.

Several issues have been raised regarding the utility of TCPs for capturing fire behavior. Experiments have demonstrated lags between actual heating and when higher temperatures are recorded (Iverson and others 2004), and between the removal of heat and when lower temperatures are recorded (McGranahan 2020). Furthermore, data measurements depend upon the physical properties of the materials making up particular probes (Bova and Dickinson 2005). The orientation in which TCPs are installed also affects fire behavior estimates (Coates and others 2018).

Nevertheless, TCPs offer several important practical benefits. Compared to temperature sensitive paints, TCPs enable a time series of temperature measurements, rather than a single maximum temperature estimate. The data are measured on a continuous scale, rather than comparatively wide-ranged discrete temperature intervals, as with paints. TCPs provide ambient temperature readings and so can be used to compute duration of heating above ambient. More technologically advanced radiometers can more accurately measure actual energy flux but are more expensive than TCPs. The utility of TCP data means that a better approach than forsaking such data is treating it more as an index rather than an exact expression of fire intensity.

Finally, comparisons across burns, or across locations during the same burn, may provide valid and insightful results when care is taken to standardize the calibration and installation of the devices. Utilizing the full temperature-time profile provided by these devices, rather than the single metric of maximum TCP temperature, is the object of the next phase of this study.

CONCLUSIONS

Restoring fire as a disturbance and process in mixed pine-hardwood forests is an important step towards creating desired ecosystem functions and structures. However, effectively applying prescribed fire requires understanding how multiple factors, such as fire behavior, forest characteristics, and fuel composition interrelate in feedback loops. This understanding can best be achieved via long-term studies that comprehensively examine all aspects of these loops.

The ongoing research study at the BNF is an example of such a study, valuable due to both its longevity and its broad scope of data collection. After implementing 38 landscape-scale prescribed fires over 12 years, representing four cycles of frequent burning and two cycles of infrequent burning, we were able to couple data across weather, fuels, and vegetation to discern variables driving maximum TCP temperature as a surrogate for fire intensity. Using a mixed effects model, we controlled for factors affecting fire intensity and found that maximum TCP temperature was related to the IV of oaks and pines, bark and duff fuel loads, and weather. Continuing research both in this and in similar studies will serve to further refine our understanding of the dynamic feedback loops involving fires and forests.

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