Weather and fuel as modulators of grassland fire behavior in the northern Great Plains

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# Abstract

Fuel and fire weather conditions interact to affect wildland fire behavior, but little is known about how these variables affect fire behavior in the northern Great Plains of North America. Data that are available consist mostly of reports based on temperature-time data from thermocouples, and neither consider rate of spread or statistically test the influence of fire environmental variables. We measured fuel load and fuel moisture ahead of prescribed fires in southwestern and central North Dakota, USA, and used a unique multi-channel thermocouple array to measure rate of spread, soil surface temperature, and flame temperature in the plant canopy, which we compared with fire weather data taken from nearby weather stations. Canopy temperatures averaged 225oC during spring burns in central North Dakota and 250oC during fall burns in southwestern North Dakota. Surface temperatures averaged just above 100oC, although 50% of observations were 60oC or less. Regression analysis indicated that wind speed drove faster rates of spread while higher fuel loads and lower fuel moisture produced higher canopy temperatures. None of our measurements explained variability in soil surface temperature, likely because ground-level heating remained low. We highlight the differential responses among fire behavior metrics to different components of the wildland fire environment. These results can help wildland fire managers better match burn conditions to desired outcomes and fire ecologists match measurements to specific ecological responses. We also discuss knowledge gaps that remain in understanding how land management and ignition patterns interact to effect variability in fire behavior, and what fire scientists need to learn about the relationships between atmospheric moisture and fuel curing in grassland systems.

**Key words:** Grassland fire ecology and management; Prescribed fire; Rangeland fire management; Robust wildland fire science; Wildland fire science in working landscapes

# Introduction

More than simply the result of combustion of vegetation, fire behavior in wildland environments is multi-faceted, with different components producing different effects on the surrounding environment and organisms within. Most wildland fire scientists describe fire behavior in terms of *rate of spread*—how quickly a flame front moves through a fuelbed—and *intensity*—a suite of measurements of how much energy is released by combustion, often expressed as a rate of energy release over time (McGranahan and Wonkka 2021).

Wildland fire behavior is controlled by interactions between several abiotic and biotic factors, and understanding them is critical to safe and effective wildland fire management (Benson *et al.* 2009). *Abiotic factors* include those determined by the physical environment, such as wind speed and atmospheric moisture content. Wind speed has long been recognized as a primary driver of fire behavior, especially in well-cured grassland fuels (Cheney and Gould 1995; Kidnie and Wotton 2015; Whittaker 1961). Two measures of atmospheric moisture content—relative humidity and vapor pressure deficit—are associated with fire growth (Sedano and Randerson 2014; Evett *et al.* 2008; Reid *et al.* 2010).

*Biotic factors* relate principally to the vegetation biomass available for combustion. Overall, fire spread and energy release rates increase as more fuel is available to burn; the structure and arrangement of plant biomass is also important. Greater fuel load attributable to longer time-since-fire increased fire temperature; spatial variability in fuel load and patchy distribution of fine fuels contributed to spatial variability in fire behavior (Patten and Cave 1984; Gibson *et al.* 1990; Gomes *et al.* 2020). Furthermore, fine-leaved grasses burn more completely and hotter than an equal mass of forbs (Wragg *et al.* 2018). Finally, fuel moisture content is an especially important driver outside of the highly-cured context of wildfire seasons (Sparling and Smith 1966; Kidnie and Wotton 2015). Together, variability in flammability traits and curing rates among species that comprise grassland fuelbeds contributes to variability in fire behavior (Cardoso *et al.* 2018; McGranahan *et al.* 2016).

How and where within the wildland fire environment fire behavior measurements are made matters a great deal to assessing fire effects. For decades, fire ecologists have measured fire behavior as *flame temperature* via various methods, including arrays of temperature-sensitive paints (e.g., Whittaker 1961; Smith and Sparling 1966; Bailey and Anderson 1980) or by recording air temperature as a flame front passes over a thermocouple connected to a datalogger (e.g., Strong *et al.* 2013; Russell *et al.* 2015). Despite its popularity among fire ecologists, temperature alone is a poor response variable fraught by several issues in collecting and interpreting thermocouple data (see review by McGranahan 2020). Firstly, a considerable amount of variability in temperature attributable to sensor placement relative to both the ground and the fire. There is neither a standard for placing thermocouple probes in the wildland fire environment nor consistency in vertical temperature profiles. Most observations of surface fire temperature profiles describe an inverse, linear relationship between height and temperature (Smith and Sparling 1966; Patten and Cave 1984; Archibold *et al.* 2003), although Ramsay and Oxley (1996) found the highest temperatures at the top of a 1 m profile and the lowest temperatures at 30 cm, while Frost and Robertson (1987) and Bailey and Anderson (1980) present evidence that the highest temperatures occur midway up the profile. At least some of this variability might be due to differences in surface vs. canopy temperature among head and back fires (Trollope 1978). Secondly, many factors that contribute to variability in temperatures recorded by thermocouples are attributable to the nature of the sensor rather than the nature of the fire. Thus, reporting ‘device temperatures’ alone impedes comparisons between studies; Bova and Dickinson (2008) present a standard calibration of thermocouple probes, while McGranahan (2021) simply uses the timestamps of peak heating across an array of several thermocouples to calculate rate of spread. Using rate of spread as the response variable makes moot the third issue with temperature as a fire behavior metric: temperature of the media around a probe is a poor proxy for the thermal experience of an organism. Measures of intensity or energy flux are more biologically relevant (Kremens *et al.* 2012; Smith *et al.* 2016).

In the North American Great Plains, most reports of grassland fire behavior consist of temperatures derived from thermocouples, and there are few data on rate of spread. Soil surface temperatures in South Dakota tallgrass prairie ranged from 200-500oC during spring burns, and were greatest under lower fuel loads (Ohrtman *et al.* 2015); fires in Saskatchewan mixed grass prairie exceeded 300oC 5-10cm above the soil surface in spring, summer, and fall (Archibold *et al.* 2003). Mean temperatures in experimental burns in eastern Montana ranged from 172-222oC in the summer to 253oC in the spring (Strong *et al.* 2013; Russell *et al.* 2015). To our knowledge, no studies on grassland fire in the northern Great Plains region has explicitly tested the effect of fire weather on fire behavior.

Our objectives were to (1) describe the range of variability in three measures of fire behavior—rate of spread, canopy temperature, and soil surface temperature—during prescribed burns in typical fuelbeds of the northern US Great Plains, and (2) explain variability in fire behavior in terms of abiotic and biotic conditions. Our analysis emphasizes the differential effects of environmental variables among the three responses, and the multidimensional relationship between these different measures of grassland fire behavior.

# Methods

## Study locations

We sampled 25 prescribed fires at two locations in central and southwestern North Dakota, USA. At both locations, sampled grasslands are included in a patch-burn grazing study that requires a portion of each experimental unit to be burned each year (Spiess *et al.* 2020). Fire sizes ranged from 8-16 ha. Typical ignition patterns consisted of downwind backing fires followed by either ring ignition and primarily head fire spread, when fuels were conducive; when fuels were sparse or higher-moisture, flanking fires and strip ignitions were employed as necessary to ensure fire spread through the entire burn unit.

In central North Dakota, we sampled 15 spring (May) fires at the North Dakota State University Central Grassland Research Extension Center near Streeter, ND (46.718686 N, 99.448521 W). Burned grasslands at this location are divided into two 260 ha blocks with four, 65 ha pastures each in which either an 8- or 16-ha patch is burned each spring. Located in a mixed-grass prairie ecoregion, this location has a rolling topography and receives an average of 468 mm annual precipitation. Vegetation is mixed-grass prairie invaded by exotic, C3 grasses; stands are dominated by *Pascopyrum smithii*, *Nassella viridula*, *Poa pratensis*, *Bromus inermis*, *Koeleria macrantha*, *Artemisia* spp., *Solidago* spp., and clumps of *Glycyrrhiza lepidota* and *Symphoricarpos occidentalis*.

In southwestern North Dakota, we sampled ten, 16-ha fall (October) fires in two blocks at the North Dakota State University Hettinger Research Extension Center, Hettinger, ND (46.004443 N, 100.646477 W) with mean annual precipitation of 380 mm. Topography is consistently flat. Located in a shortgrass prairie ecoregion, these pastures are dominated by introduced C3 grasses *Thinopyrum intermedium*, *Bromus inermis*, *Agropyron cristatum*, and *Poa pratensis*, along with the non-native legume *Medicago sativa*.

## Data collection

We measured each fire with 27 a set of 9, 1 m equilateral triangle plots arranged in a nested fashion such that three 10 m triangles, each containing 3, 1m plots, were placed 100 m apart to form a total plot area of 0.433 ha with 27 sample points positioned at the centroid of each burn unit. This fractal design is modified from the Sierpinksi triangle described by Dorrough *et al.* (2007) and applied to measuring wildland fire spread by McGranahan (2021). Although the logarithmically-scaled nested design was intended for geospatial analysis of point-level data, for our analyses here we calculate averages from the finest (1 m) scale.

**Fuel data** were collected no more than three hours prior to fire ignition. We clipped and collected all fuels in a 25 × 25 cm quadrat positioned 0.5 m away from each 1 m triangle vertex; the three measurements per plot were averaged prior to analysis. Fuel samples were initially placed in airtight plastic bags to retain moisture, and then weighed, dried to constant mass at 60o for 48 hours, and reweighed. These data were used to calculate percent fuel moisture content (expressed on a dry-weight basis) and fuel load (kg/ha) for each plot (n = 9 subsamples for each fire).

**Fire behavior data** were recorded as temperature (o) associated with the advancing flame front at each of the 27 points arranged in 9, 1 m triangles at the center of each burn unit. Data were recorded with the open-source FeatherFlame thermocouple datalogger system (McGranahan 2021). Briefly, the FeatherFlame system reads overbraided, ceramic fiber-insulated K-type thermocouples (Omega, Norwalk, CT) connected to an Arduino-based datalogger assembled from Adafruit Feather breakout boards (M0 Adalogger, datalogging shield, and OLED display; Adafruit Industries, LLC, New York City, NY) and housed inside water-resistant Pelican (Pelican Products, Inc, Torrance, California) cases. The low cost of open-source systems make multiple units more affordable than proprietary data loggers with no sacrifice in data quality (McGranahan and Poling 2021).

At each 1-m triangle—the individual observational unit in the nested plot design—we used four thermocouples to a single FeatherFlame datalogger. Three thermocouples measured flame temperature 15 cm above the soil surface at each 1 m vertex while a fourth thermocouple recorded soil surface temperature at a representative point within the 1 m array. The soil thermocouple was placed on mineral ground, perpendicular to the soil surface, below plant litter. Dataloggers recorded thermocouple temperatures at 1.5 Hz.

For each fire event, we determined the time and value of the maximum temperature (o) as the flame front encountered each thermocouple. We calculated the Maximum flame temperature (o) 15 cm above soil surface for each plot as the mean of the thermocouple readings from its vertices. We calculated the rate of spread (m/s) of the flame front as it passed through each plot using the maximum temperature timestamps following equations 1 and 2 from Simard *et al.* (1984).

**Fire weather data** were obtained after each fire from records made available by the North Dakota Agriculture Weather Network, the statewide mesonet system with sensor arrays at both experimental stations. We downloaded hourly relative humidity (%), dew point (o), air temperature (o), and average wind speed (km/h). From these data we calculated atmospheric vapor pressure (e) and saturation vapor pressure (es) and used these quantities to determine the vapor pressure deficit (VPD = e - es) for the hour in which each fire behavior observation occurred. These data capture hourly trends in weather at the meso-gamma scale (2-20 km; Orlanski 1975), and are reliably connected to our fire behavior measurements via time stamps provided by the dataloggers. The Hettinger mesonet array is 3–8 km from burned pastures, while the Central Grasslands mesonet array is 1–7.5 km from burned pastures. We found a high degree of consistency between these meso-scale data and fire weather records made on the fireline during operational periods, and the open rangeland physiognomy with flat to rolling terrain precludes substantial microsite differences in weather between these records and the conditions at each fire behavior sample point.

## Data Analysis

Prior to analysis, we ensured statistical power across 167 observational units by using multiple imputation to interpolate missing datapoints, as missing field data occurred for three rate of spread samples (2% of total), 29 fuel load values (17%), and 46 soil surface temperature values (27%). We used the multiple imputation method in the *mice* package (Van Buuren and Groothuis-Oudshoorn 2011) in the R statistical environment (R Core Team 2020) to fill in these missing values. The procedure simulated 100 datasets with different, but reasonable, values for the missing data based on patterns in the existing data. We then scaled all variables to a common range within each imputed dataset, performed regression analysis on each *mice*-generated dataset, and report composite statistical results pooled from the results of the 100 individual regression models.

**Multivariate analysis** We first conducted a multivariate analysis to assess composite relationships among the fuel, weather, and fire behavior responses. We used Principal Components Analysis (PCA) fit with the ‘rda’ function in the *vegan* package for R (Oksanen *et al.* 2017). We performed post-hoc group (location) and gradient (fire weather) analysis with the vegan ‘envfit’ function, stratified by year.

**Regression analysis** We assessed weather and fuel effects on three fire behavior response variables: Maximum flame temperature (o) 15 cm above the soil surface (mean of three thermocouples), Maximum soil surface temperature (o; single thermocouple), and Rate of spread (m/s) through each 1 m equilateral triangle plot. Because all three response variables were best modeled with a gamma distribution, we fit generalized linear mixed-effect regression models for each response with the ‘glmer’ function from the *lme4* package in R (Bates *et al.* 2015). Fixed effects consisted of weather and fuel variables, as described above. The random-effect term was constructed to account for spatial non-independence within locations and nested variance within sample plots, and the effect of repeated measurements within each location. Due to concerns about colinearity between relative humidity and vapor pressure deficit because they are derived from the same variables, vapor pressure deficit was excluded from regression analysis for all three response variables.

# Results

Most measures of fuel, fire weather, and fire behavior showed considerable variability within each location, although rates of spread were generally low (Fig. 1). Principal Components Analysis indicated fire behavior patterns were consistent across locations (P = 0.11), although the fall season in Hettinger—our semi-arid location in southwestern North Dakota—tended to have drier air and hotter fires (Fig. 2). Spring fires in the Central Grasslands were conducted under warmer and more evaporative (VPD) conditions than fall fires at Hettinger. The first two axes of the Principal Components Analysis (Fig. 2) explained 86% of overall variance in the fire behavior dataset. The first axis (52% variance explained) was most strongly associated with canopy temperature and rate of spread, while the second axis was more strongly associated with soil surface temperature. Dew point was marginally related (p < 0.05) and inversely associated with canopy temperatures and rate of spread dew point had marginally significant association with variation in fire behavior.

Fires at both locations were characterized by considerable variability among sub-plots. Within the plant canopy, half of the fires (13) exceeded 325oC, but only four of those fires had >50% of individual sample plots within the burns reach an average of 325oC. Sparse fuels meant that fire did not spread to some individual plots in some burns despite strip ignitions. Among plots that burned, less than half exceeded 100oC at the soil surface (49 of 121 plots). A majority of the 21 fires had at least one plot exceed 100ºC at the soil surface (18 of 21 fires), seven had over half of the plots exceed 100oC at the soil surface and only one fire had all plots reach this (a spring Central Grasslands fire). Only 10 fires reached 325oC on the soil surface, with most of these fires reaching this point in only one plot and never in more than half of the plots.

The effects of fuel and fire weather predictor variables varied across the three response variables (Fig. 3). Fires spread faster with higher wind speeds (t = 2.92, P < 0.01), but no other variable had a statistically-significant association with rate of spread (Table 1). Temperatures in the plant canopy (15 cm above the soil surface) increased as fuel load increased (t = 2.82, P = 0.01) and decreased as fuel moisture increased (t = -2.16, P = 0.04). No fuel or weather variable included here had statistically-significant associations with soil surface temperature (Table 1).

# Discussion

In our comparison of three measurements of fire behavior—rate of spread and maximum temperature recorded on the soil surface and 15 cm above the soil surface—against fuel and fire weather variables, we found considerable variability in which predictor variables were associated with different measures of fire behavior. These data directly support the safe and effective application of prescribed fire in the region. Some results are straightforward and consistent with decades of fire safety science; e.g., faster rates of fire spread associated with higher wind speed and lower relative humidity. Other results add nuance to an ecological understanding of how fire behavior relates to fire effects—e.g., factors like fuel load and fuel moisture were related with canopy temperature but not soil surface temperature, which suggests that direct effects on belowground plant tissue and soil biota are not correlated with aboveground heating and fire spread.

To our knowledge, this is the first study from the northern Great Plains to scrutinize the factors that influence fire behavior, and the first to combine reports of fire spread and temperature data from thermocouples. Most published research on fire spread in the Great Plains is derived from computer simulations (McGranahan *et al.* 2013; Yurkonis *et al.* 2019; Overholt *et al.* 2014). The few field studies from the region mostly report temperature data from thermocouples and rarely incorporate fuel and fire weather data into the analysis; when such information is provided, it is typically included in the study description, not as data. Given the high degree of variability in the wildland fire environment, a mechanistic understanding of grassland fire dynamics will require collect fuel, fire weather, and fire behavior data in a spatially and temporally consistent manner to facilitate statistical analyses of their relationships (McGranahan and Wonkka 2018; Hiers *et al.* 2020).

Mean temperatures recorded in this study are consistent with other reports from northern rangelands. In central Alberta grassland, Bailey and Anderson (1980) observed that surface temperatures varied between 110oC and 165oC for backfires and headfires, respectively, and headfires averaged 200oC 15 cm above the ground; temperatures generally tracked with fuel load. Surface fires through jack pine barrens in Ontario had a similar range as ours: 140-545oC (Smith and Sparling 1966). In our study, average 15-cm temperatures were 225oC during spring burns in central North Dakota and 250oC during fall burns in southwestern North Dakota; surface temperatures at both locations generally averaged just above 100oC (Fig. 1).

Discrepencies between our data and others reported in the region are consistent with what would be expected when differences in the fire environment are considered. For example, Ohrtman *et al.* (2015) reported a wide range of maximum temperatures at the soil surface—150-500oC—that was generally explained by variability in annual productivity and clipping frequency. Our fires were also cooler than those reported by Archibold *et al.* (2003) in Saskatchewan: using the mid-point of observations made at 10 cm and 20 cm as a comparison, spring fires reached 314oC and fall fires reached 298oC. But Archibold *et al.* (2003) also reported substantially lower fuel moisture in each season and they had approximately three times the fuel load, likely due to an absence of grazing management on the remnant prairie. With greater variability in fuel load and fuel moisture, we might also expect to see these factors have greater influence on aboveground flame temperatures. For example, in Colorado, Augustine *et al.* (2014) observed a strong linear relationship between fuel load and temperatures ranging from 60-200oC, but their fuel load also ranged from 0.2 to 1.2 t/ha.

Although one must look beyond the northern Great Plains for comparable data on fire spread, our results are consistent with international reports. For example, our data match the pattern from Australian grassland, where Cheney *et al.* (1993) found a statistical relationship between rate of spread and both wind speed and fuel moisture, but not total fuel load. Their fires traveled at rates similar to the vast majority of ours (1-2 m/s), with slightly higher fuel loads and slightly lower relative humidity. Wind was by far their most important variable, followed by dead fuel moisture, consistent with patterns in our data. Likewise, Cruz *et al.* (2015) observed fire spread rates up to 2 m/s in fully-cured grassland fuels with fuel loads at the upper end of our samples.  
In comparing our results to these studies, it appears the trigonometric method of calculating rate of spread through the thermocouple array (Simard *et al.* 1984) overestimates rate of spread, but there is no indication that using this measure of spread as a scaled response variable in regression models presents error in interpreting the relative effect of fuel and weather predictors.

Interestingly, Cheney *et al.* (1993) found that fires spread faster in undisturbed pastures compared to those that had been cut, which they attribute to differences in fuel structure (height, bulk density) rather than fuel load. This might have implications for fire behavior in our region, where invasive species like *Poa pratensis* generally increase aboveground plant biomass but do so by adding thick dense litter at the soil surface, rather than standing dead fuel in the plant canopy (Gasch *et al.* 2020). While difficult to tease apart statistically in the present data, many burn units in our mesic location in central North Dakota were dominated by *P. pratensis* and indeed, that location tended to have higher fuel loads and lower rates of spread (Fig. 1), consistent with simulations of fire spread through those *P. pratensis*-dominated prairies (Yurkonis *et al.* 2019).

Much is made of the difference in fire behavior between head and back fires in the fire ecology literature, and while we expect these differences translate to different fire effects in our system, making distinctions between fire types is difficult in both our data and our management. Trollope (1978) emphasized that while head fires move faster and generally release more energy, back fires effect greater heating at the ground level. One would expect, then, that back fires would have more opportunity to burn down through even thick *P. pratensis* litter to mineral soil. Unfortunately, our results offer little insight into what fuel or weather variables enhance litter combustion, likely because most of our fires never got very hot at the soil surface—50% of our observations were less than 60oC, and 60% less than 1000C (Fig. 1). Nor can we differentiate the direction of fire spread with the current trigonometry applied to the triangular thermocouple arrays (Simard *et al.* 1984), although it would theoretically be possible to compare spread direction to wind direction if the latter data were available at a fine enough scale. But in these pastures, the functional difference between head and back fires might be moot. Because our fuels were often sparse, sometimes only marginally cured, and prescriptions precluded taking advantage of higher wind or lower relative humidity to mitigate fuel limitations, we often employed substantial interior ignitions using strip, point, flanking, and spiral patterns that sent flame fronts towards our sensors in all possible directions at different times. Differences in ignition patterns create additional spatial variability in fire behavior and burn severity (Williams *et al.* 2015). Our data are certainly useful in describing the variability in fire behavior across these burns, but do not inform the relationship between ignition pattern and fire behavior. Thus, future research on fire behavior in the northern Great Plains should use experimental plots with consistent fuelbeds to explicitly compare head and back fires set via line ignitions, akin to the experimental burning program described by Cruz *et al.* (2015) in Australia.

A more detailed analysis of fuelbed effects on fire behavior also ought to separate fuels into live and dead components, and consider the moisture content of each along with fuel load ratios. We report here the fine fuel moisture content of the entire fuelbed, consistent with descriptive, post hoc statistical approaches to describing fire behavior (Cruz *et al.* 2015; Trollope and Potgieter 1985; McGranahan *et al.* 2016). But predictive fire behavior models accommodate inputs for live and dead fuel categories (Scott and Burgan 2005), and Kidnie *et al.* (2015) found that four categories of live, dead, and senescent fuels best represented differences in grassland fuel moisture scenarios. Although parsing live and dead fuel moisture in the present analysis would probably not better explain variability in our dataset, it would likely contribute to better predictions of fire behavior relative to management objectives if information on fuel moisture content were available prior to ignition. Unfortunately, the standard clipping and drying method is not compatible with providing day-of fuel moisture data, and visual assessments based on color tend to over-predict curedness (Kidnie *et al.* 2015). However, electronic devices can provide accurate and instantaneous measurements of grassland fuel moisture (McGranahan 2019).

Research must also address the influence of atmospheric moisture conditions on prescribed fire behavior. Several broad-scale, post-hoc analyses of wildfire conditions conclude that atmospheric moisture is an important driver of burned area (Sedano and Randerson 2014; Evett *et al.* 2008; Reid *et al.* 2010). But experiments that explicitly test the immediate effect of relative humidity on fire behavior report no appreciable effect on surface fire temperatures or rate of spread (Sparling and Smith 1966; Trollope and Potgieter 1985). It is likely that atmospheric moisture plays a larger role in modulating fuel moisture content prior to combustion than affecting instantaneous fire behavior itself—consider how fire behavior models take fuel moisture as a parameter and not relative humidity, but include relative humidity as an input to determine fuel moisture content (Rothermel 1983; Cruz *et al.* 2016).

The most appropriate measure of atmospheric moisture content might also be unresolved. We focused our analysis here on relative humidity because it is so common in fire behavior models and fire weather forecasts. But vapor pressure deficit has also been identified as an important driver of fire spread and intensity (Gomes *et al.* 2020). In fact, Srock *et al.* (2018) suggest vapor pressure deficit might be a better measure of atmospheric moisture content for fire predictions, but the Hot-Dry-Windy index they developed to incorporate vapor pressure deficit operates at synoptic scales beyond the spatial extent and operational periods of prescribed burns. Given that substantial changes in atmospheric moisture changes in recent decades are expected to strengthen over the 21st century (Seager *et al.* 2015; Ficklin and Novick 2017), understanding how these dynamics affect fire behavior will be an essential component of managing resilent fire regimes.

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Table 1: Results of generalized linear mixed effect regression models testing three measure of fire behavior against potential predictor variables. Statistics reflect pooled results of 50 imputed datasets using the *mice* package in R; see Methods.

|  |  |  |  |
| --- | --- | --- | --- |
| Response | Model term | t *df* | P |
| Rate of spread |  |  |  |
|  | Wind speed | 3.16 *101* | < 0.01 |
|  | Fuel moisture | -1.12 *43* | 0.27 |
|  | Fuel load | 0.95 *46* | 0.35 |
|  | Relative humidity | -0.47 *89* | 0.64 |
| Canopy temperature |  |  |  |
|  | Fuel load | 2.82 *54* | 0.01 |
|  | Fuel moisture | -2.16 *41* | 0.04 |
|  | Relative humidity | -1.19 *120* | 0.24 |
|  | Wind speed | 0.02 *132* | 0.99 |
| Surface temperature |  |  |  |
|  | Relative humidity | -1.19 *75* | 0.24 |
|  | Fuel load | -0.48 *20* | 0.64 |
|  | Fuel moisture | -0.47 *40* | 0.64 |
|  | Wind speed | 0.06 *50* | 0.95 |

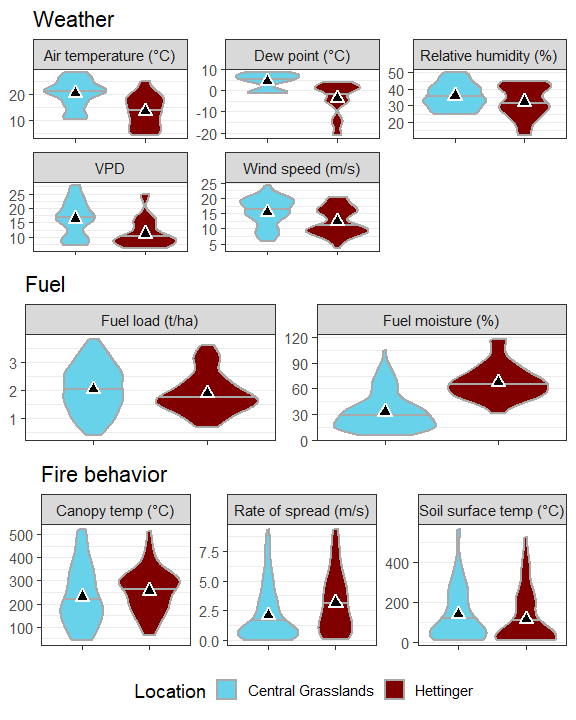
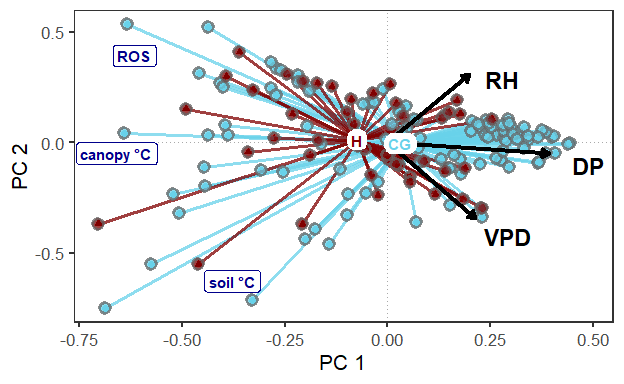
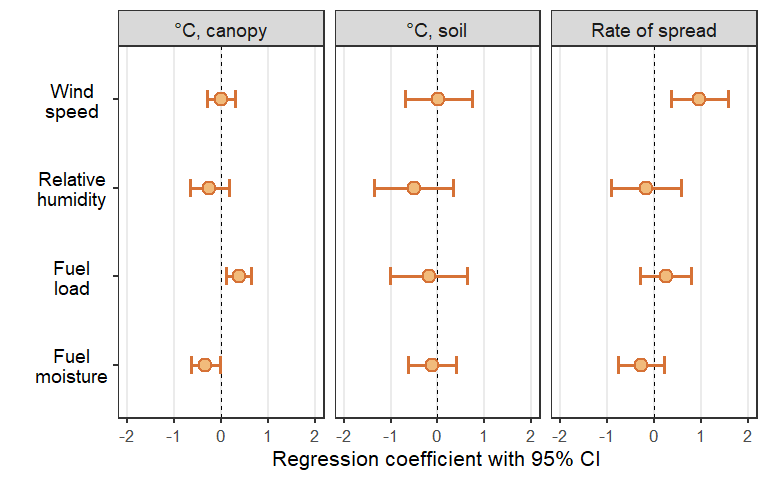
Figure 1: Distribution of weather, fuel, and fire behavior data for fires in southwestern North Dakota (Hettinger, dark maroon) and central North Dakota (Central Grasslands, light blue) sampled from 2017 to 2019. Summary statistics include median (horizontal gray lines) and means (triangles). VPD = Vapor pressure deficit.

Figure 2: Principal Components Analysis of fire behavior data (response variables in blue; rate of spread (ROS), temperature above surface (canopy ºC), and temperature at soil surface (soil ºC) for prescribed burns on rangeland at Hettinger (H), in southwestern North Dakota, and Central Grasslands (CG), in central North Dakota. No difference between locations (P = 0.11). Total variance explained in these two axes = 86%. 

Figure 3: Regression coefficients and 95% confidence intervals for fuel and weather terms from models for maximum temperature at 15 cm above the soil surface (canopy), maximum temperature at the soil surface (soil) and rate of spread.