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

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Abstract

Fuel and weather interact to affect wildland fire behavior, but little is known about associations between these variables in the northern Great Plains of North America. Few studies consider rate of spread or statistically test the influence of fuel and weather. We measured overall fuel load and moisture ahead of prescribed fires in North Dakota, USA, and used a thermocouple array to measure two-dimensional rate of spread, soil surface temperature, and aboveground flame temperature, to compare with fire weather data. Flame temperatures averaged 225°C during spring burns and 250°C during fall burns, and were generally higher with greater fuel loads and lower overall fuelbed moisture. Surface temperatures averaged ≈100°C, although 50% of observations were ≤60°C. Fires spread at an average of 2.5 m min^{-1}, increasing with wind speed. As such, prescribed fire in northern Great Plains working rangeland appear to spread slowly and effect low soil surface temperatures, often limited by high fuelbed moisture. Fire behavior measurements respond differently to variability in fuel and weather. Belowground heating is likely minimal. We suggest ecologists ought to consider which fire behavior measurements best relate to fire effects, and managers consider weather and ignition pattern mitigations when fuels constrain desired fire behavior to ensure effective burns.

Keywords: Grassland fire ecology and management, Prescribed fire, Rangeland fire management, Robust wildland fire science, Wildland fire science in working landscapes

Introduction

Prescribed fire is used widely for ecosystem management around the world (Weir and Scasta, 2022). More than simply the result of combustion of vegetation, wildland fire behavior 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 among 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 (Whittaker, 1961; Cheney and Gould, 1995; Kidnie and Wotton, 2015). Two measures of atmospheric moisture content—relative humidity and vapor pressure deficit—are also associated with fire growth (Evett et al, 2008; Reid et al, 2010; Sedano and Randerson, 2014).

Biotic factors relate principally to the amount and nature of plant biomass available for combustion. Overall, energy release rates increase as more fuel is available to burn. The structure and arrangement of vegetation is also important. Greater fuel load attributable to longer time-since-fire increases fire temperature, and spatial variability in fuel load and patchy distribution of fine fuels in turn drive 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 (Cruz et al, 2015; Kidnie and Wotton, 2015; McGranahan et al, 2016; Cardoso et al, 2018).

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 is 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. flame 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 (e.g., Walker and Stocks, 1968). 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 200-500°C during spring burns, and were greatest under lower fuel loads (Ohrtman et al, 2015); fires in Saskatchewan mixed grass prairie exceeded 300°C 5-10 cm above the soil surface in spring, summer, and fall (Archibold et al, 2003). Mean temperatures in experimental burns in eastern Montana ranged from 172-222°C in the summer to 253°C 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, soil surface temperature, and flame temperature 15 cm above soil surface—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 factors. Our analysis emphasizes the differential effects of environmental variables among the three measures of fire behavior, and the multidimensional relationship among these responses during prescribed burns conducted at scales consistent with land management in the region.

Methods

Study locations

We sampled 25 prescribed fires at two locations in central and southwestern North Dakota, USA (Maps in Supplemental Information Figure 1). 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). The majority of the burn units were 16 ha, while a small set were 8 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 introduced, C_3 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 C_3 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 a set of 9, 1-m equilateral triangle plots arranged in a nested fashion such that three 10 m triangles, each containing 3, 1-m 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 (a schematic of this layout is presented in Supplemental Information Figure 2). 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 microplot) scale, consistent with the method of locating multiple microplots within larger burned areas to characterize spatial variability within fires (Fernandes et al, 2000).

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 60°C 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 m^2) for each plot (n = 9 subsamples for each fire).

Fire behavior data were recorded as temperature (°C) associated with the advancing flame front at each of the 27 points arranged in 9, 1-m triangular microplots at the center of each burn unit. Data were recorded with the open-source FeatherFlame thermocouple datalogger system (McGranahan, 2021), logging at 1.5 Hz. The FeatherFlame system reads overbraided, ceramic fiber-insulated, 20-gauge 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 cases (Pelican Products, Inc, Torrance, California). 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). More details on the datalogger system are available in Supplemental Information.

Another advantage of the multi-channel datalogger is the opportunity to calculate *two-dimensional rate of spread* from the arrival time of the flame front at vertices of a thermocouple array logged to a common timestamp. While one-dimensional rate of spread requires direct observation of a flame front moving perpendicular to a vector of fixed points, two-dimensional rate of spread is ideal for larger-scale fires in which direct observation is infeasible and the exact angle of approach for oncoming flame fronts is not known (Finney et al, 2021). Here, we calculate 2-D rate of spread through the 1 m triangular microplots using trigonometric equations from Simard et al (1984).

At each 1 m triangular microplot—the observational unit in the nested plot design—we used four thermocouples connected 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. Beads of the thermocouple probes extended at least 3 cm from the supporting apparatus, to which the insulated lead was attached with wire. The soil thermocouple was placed on mineral ground, perpendicular to the soil surface, below plant litter.

For each fire event, we determined the time and value of the maximum temperature (°C) as the flame front encountered each thermocouple. We calculated the maximum flame temperature (°C) 15 cm above soil surface for each microplot as the mean of the thermocouple readings from its 3 vertices. We calculated the rate of spread (m min^{-1}) of the flame front as it passed through each microplot using the maximum temperature timestamps as arrival times following equations from Simard et al (1984), which are presented in full in Supplemental Information.

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 (°C), air temperature (°C), and average wind speed (m s^{-1}). From these data we calculated atmospheric vapor pressure (e) and saturation vapor pressure (e_s) and used these quantities to determine the vapor pressure deficit ($VPD = e - e_s$) 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%) due to logistical and time constraints during the operational burn periods. 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 50 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 50 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 (°C) 15 cm above the soil surface (mean of three thermocouples), maximum soil surface temperature (°C; single thermocouple), and rate of spread (m min^{-1}) through each 1 m triangular microplot. 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 random variance among locations, spatial non-independence within locations and nested variance within sample plots, and the effect of repeated measurements within each location. Due to concerns about collinearity 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 flame 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 flame temperatures and rate of spread.

Fires at both locations were characterized by considerable variability among sub-plots. Above the soil surface, half of the fires (13) exceeded 325°C, but only four of those fires had >50% of individual sample plots within the burns reach an average of 325°C. Sparse fuels meant that fire did not spread to some individual plots in some burns despite strip ignitions. Among plots that burned, fewer than half exceeded 100°C at the soil surface (49 of 121 plots). A majority of the fires (18) had at least one plot exceed 100°C at the soil surface, seven had over half of the plots exceed 100°C at the soil surface, and only one fire had all plots reach this (a spring Central Grasslands fire). Only 10 fires reached or exceeded 325°C 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.

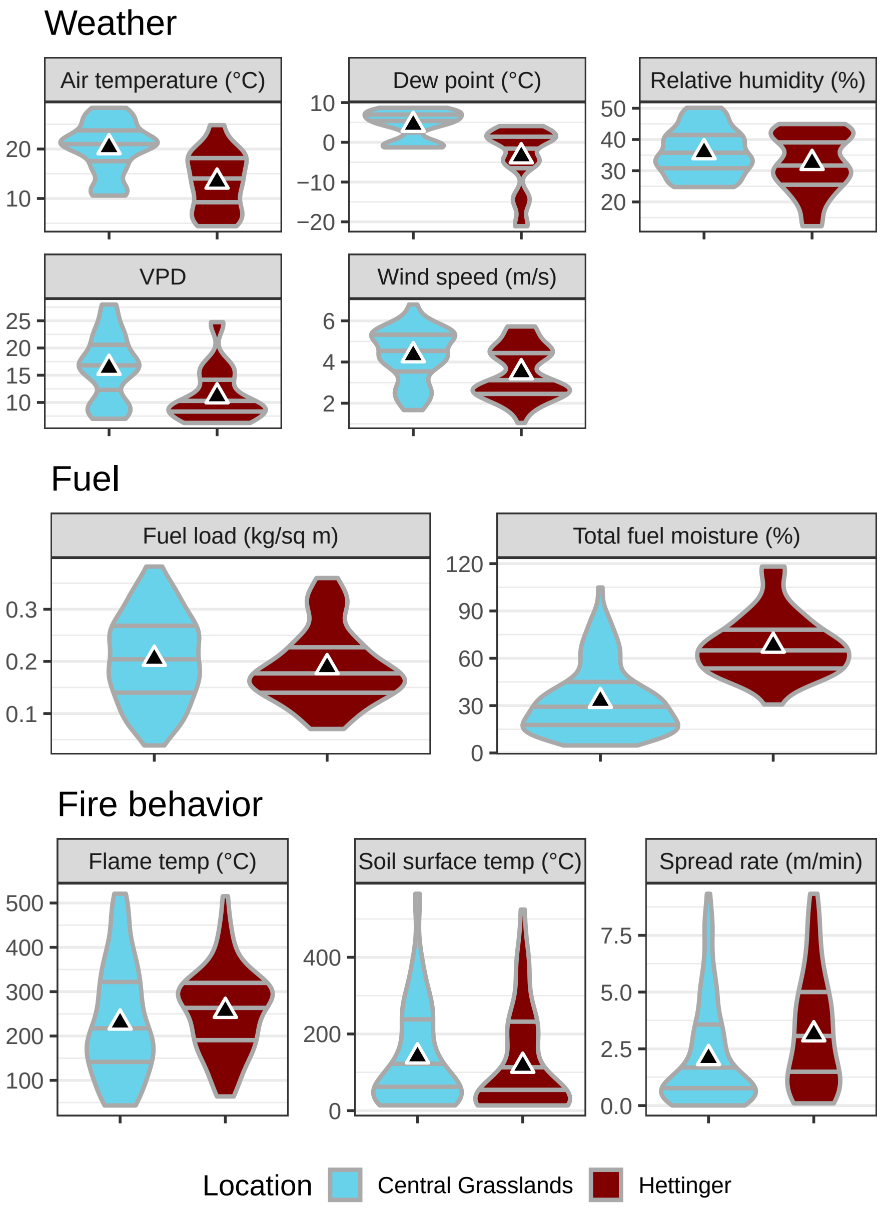

Fig. 1 Distribution of weather, fuel, and fire behavior data for fires in southwestern North Dakota (Hettinger, dark maroon) and central North Dakota (Central Grasslands, light blue). Horizontal gray lines denote 25%, 50% (median) and 75% quantiles; triangles are arithmetic means. Means and standard deviation are also reported in Supplemental Information Table 1. VPD = Vapor pressure deficit.

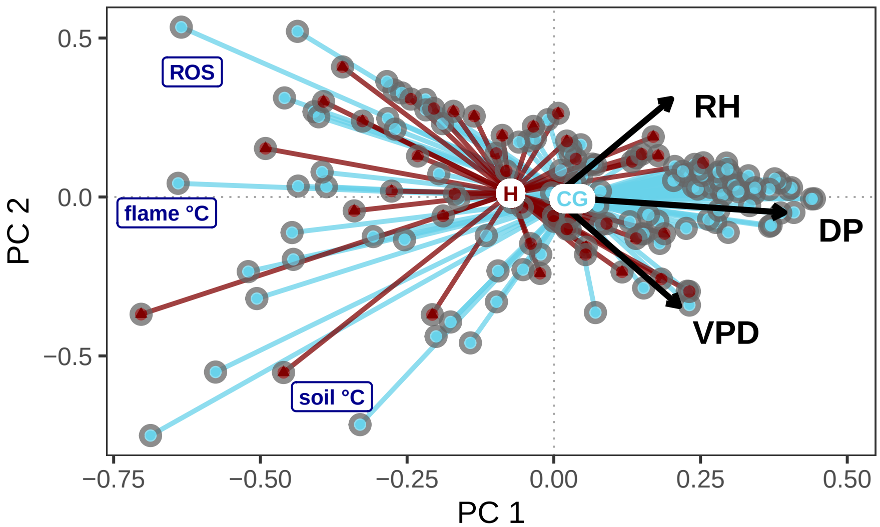

Fig. 2 Principal Components Analysis of fire behavior data (response variables in blue; rate of spread (ROS), temperature above surface (flame °C), and temperature at soil surface (soil °C) for prescribed burns on rangeland at Hettinger (H), in southwestern North Dakota, and Central Grasslands (CG),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

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). Aboveground flame temperatures 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

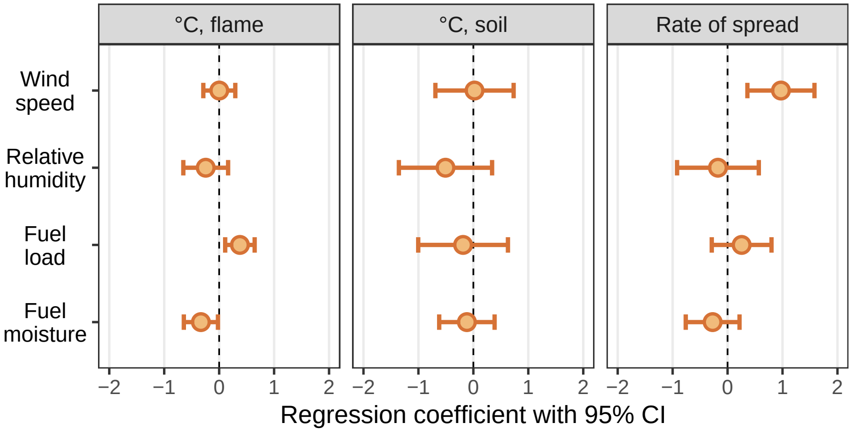

Fig. 3 Regression coefficients and 95% confidence intervals for fuel and weather terms from models for maximum temperature at 15 cm above the soil surface (flame), maximum temperature at the soil surface (soil), and rate of spread.

Table 1 Results of generalized linear mixed effect regression models testing three measure of fire behavior against four potential predictor variables. Statistics reflect pooled results of 50 imputed datasets using the *mice* package in R, see Methods. Vapor pressure deficit included for Rate of spread only due to statistically-significant difference between GLMM regression results that included VPD compared to RH alone (Wald = 5.32, $P = 0.02$), while temperature models had no such difference.

Response	Model term	t_{df}	P
Rate of spread			
	Wind speed	$2.92_{108.0}$	< 0.01
	Vapor pressure deficit	-2.31 108.1	0.02
	Relative humidity	-1.66 80.8	0.10
	Fuel load	1.16 49.9	0.25
	Fuel moisture	-0.68 62.9	0.50
Canopy temperature			
	Fuel load	2.82 54.2	0.01
	Fuel moisture	-2.16 40.9	0.04
	Relative humidity	-1.19 120.4	0.24
	Wind speed	0.02 132.4	0.99
Surface temperature			
	Relative humidity	-1.19 74.8	0.24
	Fuel load	-0.48 20.1	0.64
	Fuel moisture	-0.47 40.1	0.64
	Wind speed	0.06 49.5	0.95

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 are 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 overall fuelbed moisture were related with flame 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; Overholt et al, 2014; Yurkonis et al, 2019). 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 (Hiers et al, 2020; McGranahan and Wonkka, 2018).

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 110°C and 165°C for backfires and headfires, respectively, and headfires averaged 200°C 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 (140-545°C, Smith and Sparling, 1966). In our study, mean 15-cm temperatures were 225°C during spring burns in central North Dakota and

250°C during fall burns in southwestern North Dakota; surface temperatures at both locations generally averaged just above 100°C (Fig. 1).

Discrepancies between our data and others from 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—150-500°C—that was generally explained by variability in annual productivity and clipping frequency, which altered fuel load. 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 to our 15-cm values, spring fires reached 314°C and fall fires reached 298°C. 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 on the remnant prairie. A previous study reported similar results—temperatures approaching 500°C when fuel loads averaged 2.8-4.5 t ha^{-1} (Archibold et al, 1998). 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 60-200°C, but their fuel load also ranged from 0.2 to 1.2 t ha^{-1}.

Fires at both of our locations spread much more slowly than most reports from other grasslands, due primarily to high fuelbed moisture content and little opportunity for mitigation by wind or lower atmospheric moisture (Fig. 1). Perhaps the most variability in fire spread was reported by Sneeuwjagt and Frandsen (1977) from prescribed grass fires in California and Washington, where rates of spread ranged from 0.2-61 m min^{-1}. From grassland fires in South Africa and Kansas, USA, Trollope et al (2002) reported average spread rates of 24 and 32 m min^{-1}, respectively, for head fires and 0.12 and 0.14 m min^{-1}, respectively, for back fires. In a tallgrass prairie in Texas, Clements et al (2019) recorded fire spreading between 72-150 m min^{-1} with the wind and 48 m min^{-1} for flanking fires. Likewise, fires through cured grass fuelbeds in Australia spread much more rapidly than we observed—up to 18-180 m min^{-1} (Cheney et al, 1993; Cheney and Gould, 1995; Cruz et al, 2015). Through partially-cured stands, though, Cruz et al (2015) found spread rates dropped to 3-44 m min^{-1}, approaching our location averages of 2.1 and 3.1 m min^{-1}. Consistent with our finding that only wind speed had a statistically-significant effect on increasing rate of spread (Fig. 3), Cheney et al (1993) found that wind was by far the most important variable to spread rate.

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 60°C, and 60% less than 100°C (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.

The functional difference between head and back fires in the fuelbeds reported here is likely 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. While Williams et al (2015) did show that different ignition patterns created additional spatial variability in fire behavior, the effect of shorter line ignitions and spot ignitions was to mitigate the high severity of wildfire and long line ignitions in highly-flammable spinifex fuelbeds. In our case, we had to manipulate ignition pattern just to get fire to carry. 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 (1) 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, and (2) attempt to at least address severity, if not fire behavior, in wildfire scenarios via remote sensing and/or modelling.

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. Explicitly measuring litter moisture might also be valuable, especially when variability in belowground heating is expected to influence first-order fire effects. We report here the overall fuel moisture content of the entire fuelbed, consistent with descriptive, post hoc statistical approaches to describing fire behavior (Trollope, 1978; Trollope and Potgieter, 1985; Bidwell and Engle, 1992; Trollope et al, 2002; 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. With this in mind, Cruz et al (2015) employed a hybrid approach in which fuel moisture was measured for the various components, from which a weighted average was used as a predictor variable in regression analysis. They subsequently found that overall degree of curing, not simply live fuel moisture, was the most important variable in explaining the dampening effect of fuel moisture on fire behavior.

Often, time and resource constraints preclude the separation of fine plant material by live and dead class, and overall fuelbed moisture content is the best available data for managers. 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 overall fuelbed 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 (Evett et al, 2008; Reid et al, 2010; Sedano and Randerson, 2014). 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 resilient fire regimes.

This study is novel in that it examines the fire environment at a spatial scale consistent with land management in the region using realistic ignition scenarios. To our knowledge, no other study in the northern Great Plains has reported the behavior of fires larger than experimental plots. Integrating research into management almost invariably requires trade-offs; two already discussed above include (1) measuring only the overall moisture content of the entire fuelbed, being precluded from parsing fuel into live, dead, and litter components, and (2) measuring two-dimensional rate of spread of fire fronts within the burn unit without being able to associate them with wind direction. But these are the respective conditions under which prescribed fire managers in the region decide whether to burn, and ensure fire spread objectives are met. Research conducted at the spatial scales at which management occurs helps managers trust the transfer of knowledge from studies to working landscapes (Sayre, 2005; Cacciapaglia et al, 2012). For example, all of our fire behavior measurements were made more than 50 m from the initial fire line, the distance identified in simulations and used in wildland fire science to allow flame fronts to achieve a quasi-steady state in spread rate (Fernandes et al, 2000; Sutherland et al, 2020), which is obviously precluded in studies that employ small plots.

Supplementary Information. Supplementary Information containing additional information on the study location, rate of spread calculations, and R script is available in the online version of the paper.

Acknowledgments. We appreciate support from the North Dakota State Agricultural Experiment Station, including K. Sedivec at the Central

Grasslands REC and C. Schauer and B. Geaumont at the Hettinger REC. We recognize funding from the University of North Dakota Department of Biology, USDA-NIFA Hatch project number ND02393, and USDA-NIFA AFRI award number 2018-67020-27856. We appreciate the technical assistance of several North Dakota State University graduate students and faculty for assistance with prescribed burning. L. LaFond, C. LaFond, and E. Wahl assisted with datalogger assembly. J. Spiess, J. Cutter, M. Lakey, B. Poling, and A. Steele assisted with sensor deployment and data collection.

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