Understanding spatial variation in grassland fuels to inform wildfire risk mitigation strategies in the Front Range

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Executive Summary

Grassland wildfires are increasing in frequency with great potential to damage human lives, health, and property. However, relatively little is known about the factors that influence grassland wildfire risk such as variation in grassy fuels across the landscape and through time. This lack of understanding of grassland fuel variation hinders managers' ability to make informed decisions on fuel management. Here we quantified variation in grassland fuel characteristics across the Front Range landscape to better understand fuel variation and the factors that influence it. To do this we surveyed fuel characteristics across a range of grassland types and combined this with spatial information on vegetation types, soil texture, topography (elevation, slope, aspect, water accumulation), plant cover, and prairie dog presence to determine the extent to which we can predict fuel characteristics. We find that the factors affecting fuel characteristics vary but that we can predict fuel characteristics relatively well using simple models (R^2 from 0.44-0.98). Overall, prairie dog presence and perennial plant cover have consistent effects on fuel characteristics where prairie dogs reduce fuel while higher perennial cover increases fuel. Topography, soil, and vegetation type have some effect, but are less consistent. We also conducted a simulated fire behavior modeling exercise that showed that fire spread rates are influenced by fuel levels and moisture, suggesting that decreasing fuel loads or increasing fuel moisture can decrease fire spread rate. Overall management implications are as follows:

-The areas with the greatest fuel loads are places without prairie dogs and that have high perennial plant cover.

-Ruderal and smooth brome communities tend to have the highest biomass besides cattails.

-Reducing fuel loads and increasing fuel moisture by promoting plants with high moisture tissues should reduce fire spread rates under high wind conditions

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Abstract

Grassland fuels are severely understudied, and their variation is often underestimated in fuel models used for fire modeling. However, understanding their variation can be extremely useful for making management decisions about when, where, and whether to attempt fuel reduction treatments. To better understand how grassland fuel characteristics vary across the Front Range landscape, we set up a network of 120 fuel monitoring plots across the primary grassland types in the region. We measured fuel characteristics during midsummer (July) and fall (October) to determine spatial and temporal variation in grassland fuel structures. We found that vegetation type has large consequences on fuel characteristics and that a combination of vegetation type, topography, soils, prairie dog presence, and vegetation cover can predict fuel characteristics moderately well (R^2 from 0.44-0.98). We also conducted a fire modeling exercise to investigate how fuel loads, fuel moisture, and wind interact to affect fire behavior. This exercise shows that fire spread is sensitive to fuel moisture and fuel loads in a non-linear way where spread rate can be slower than the wind speed when moisture is higher and fuel loads are lower. Overall, these results have implications for determining areas of higher priority fuel management due to high productivity.

Keywords: grassland, fire behavior, fire risk, fuel, biomass, moisture

Introduction

With rapidly increasing urbanization and suburban sprawl throughout much of the United States, the Wildland Urban Interface (WUI) is vastly increasing in extent and complexity (Radeloff et al. 2005). Because wildfires that reach developed areas can have catastrophic consequences for human life and structures, the rapid increase in WUI heightens the criticality of effective wildfire risk mitigation strategies (Shuman et al. 2022). The Marshall Fire is a tragic reminder of the rising threat to life and property. The destructiveness of the Marshall Fire was due, in part, to extreme weather conditions (Keeley and Syphard 2019; Fovell et al. 2022). Climate changes including warmer temperatures, more extreme winds, and changing seasonal moisture distribution are creating conditions that foster extreme wildfires (Abatzoglou and Williams 2016; Schoennagel et al. 2017). While weather conditions are outside of the control of local land managers and property owners, all expectations are that grassfires will occur at increased frequency in the future. Thus, innovative action is needed to counteract the increasing risk of grassfire damage in WUIs (Shuman et al. 2022).

Landscape factors play a crucial role in determining effective fuel treatment strategies, as fire risk depends on topography, wind, vegetation characteristics, weather, and climate (Salis et al. 2018). Research has documented the optimal amount and configuration of fuel management treatments in forested landscapes (Cochrane et al. 2012; Martinson and Omi 2013). Yet, fuel management in grasslands differs from forests in several important ways: importantly, productivity exhibits great spatial variation as well as seasonal variation due to cool (early-season) and warm (late-season) grasses in different parts of the landscape (McGranahan et al. 2013, 2018). Cool season grasses are likely to generate dead, flammable fuel earlier in the season compared to warm season grasses, while areas dominated by warm season grasses will stay green later in the season. In addition, spatially variable soil characteristics, moisture availability, land use, and topography influence fuel accumulation and species that dominate a site (Maestas et al. 2022). Fuel moisture is also highly variable in senesced grassland fuels, as they are characterized as 1 hour fuels because they rapidly (on the scale of hours) acclimate to the atmospheric relative humidity. This spatial and temporal variability in fuel characteristics in grassland landscapes is often overlooked in fire behavior modeling and risk assessments (Figure 1).

Thus, changing environmental conditions and rapid WUI expansion makes understanding of grassland fuel variation and how it influences fire behavior increasingly important for reducing wildfire risk and protecting human life and property. In this study, we had two main objectives. First, we measured spatial and temporal variation in grassland fuel characteristics and determined how this variation is related to topography (elevation, slope, aspect, and water accumulation), soil texture, prairie dog presence and vegetation type. We then used this information to extrapolate fuel characteristics across space to provide maps of grassland biomass and height for properties owned by open space agencies in Boulder and Jefferson Counties. Second, we used simple fire models to determine how different fuel characteristics and wind determine fire behavior. Combined, these objectives will provide detailed information about how fuels vary across the landscape and over time to increase fire model accuracy and to provide guidance for fuel management strategies throughout Boulder and Jefferson Counties.

Methods

Plot Selection

To measure fuel characteristic variation across space, we established a network of 120 fuel monitoring plots spread across properties managed by Boulder Open Space and Mountain Parks (BOSMP), Boulder County Parks and Open Space (BCPOS), Jefferson County Open Space (JCOS), and City of Longmont Public Works and Natural Resources (LPWNR). These monitoring plots were split between eight broad vegetation types and the number of plots representing each vegetation type depended on how frequently these vegetation types occur on the landscape (Table 1). The target vegetation categories were determined jointly with agency representatives as the broad classification that could represent most of the grassland vegetation types in the region. The shortgrass category are areas dominated by grama grasses, the ruderal category includes communities dominated by cheatgrass, tall oatgrass, kochia, Russian rye, and crested wheatgrass, the tallgrass represents communities with short and mixed grass species but with abundant big bluestem, wet grassland represents communities with species that require consistently moist soils, the mixed grass category is often dominated by western wheatgrass, the smooth brome category indicates areas dominated by smooth brome, the mesic tallgrass indicates areas dominated by big bluestem, Indiangrass, and switchgrass, and the cattail category represents areas dominated by cattails.

Plot selection was guided by using digitized vegetation maps from BOSMP, BCPOS, and JCOS. These vegetation maps include polygons that are assigned to vegetation classes based on the US National Vegetation Classification system at the alliance level. In addition, we visited field sites to ensure that our plots were in representative examples of each vegetation type and spread across space while accounting for accessibility. Thus, plots were placed within 0.5 miles from roads or trails. Field sites were scouted for suitability of vegetation and accessibility in May/June, 2023 and final plot locations were determined after this scouting (Figure 2).

Field Surveys

All plots were surveyed twice, once in July, 2023 and again in October, 2023. Two plots were lost between samplings due to mowing that destroyed the permanent markers. However, several other plots were mowed and the plot markers were either avoided by the mowers or survived mowing (114 of the 120 original plots were resurveyed in October). Each plot consists of a randomly-placed center point, marked with rebar that extends ~6 inches above ground capped with an orange safety cap. Each plot has four subplots (except for cattail plots, which have two subplots) three meters away from the center point in each cardinal direction.

At each subplot, we placed a quadrat measuring 75cm by 50cm (except in cattail plots and a few other highly productive plots where the quadrat measured 75cm x 25cm). We identified up to three dominant species in each subplot and estimated their aerial coverage in cover classes (1-5%, 6-25%, 26-50%, 51-75%, 76-95% and 96-100%). We also estimated the percent of the vegetation that was green vs brown (to the nearest 1%, summing to 100%) and the percent cover of grasses, non-grasses, bare ground, rocks, and other cover types (to the nearest 1%, summing to 100%). We measured the height of standing vegetation (biomass from this year) and litter (biomass from previous years) in three random locations to the nearest centimeter. To measure standing vegetation height, we did not straighten vegetation and measured to the tallest intersecting vegetation at the measurement point. Finally, we used a handheld NDVI meter (Trimble Greenseeker) held at approxmately 1 meter above the ground to estimate the Normalized Difference Vegetation Index (NDVI) of the entirety of each subplot, measured soil moisture using a TDR meter (Spectrum Technologies, FieldScout TDR 300 meter) and took a photograph to calculate a green chromatic coordinate and for later reference. We also identified whether plots had signs of disturbance such as grazing, prairie dogs, or soil disturbance.

We harvested biomass of standing vegetation and litter separately at each subplot. We clipped all standing vegation within one inch of the ground and put all that biomass in one bag then clipped and gathered all dead biomass from previous years while being careful to avoid gathering rocks and other debris that was not part of the plant growth in the subplot (e.g., wood, animal scat). This litter was put into a separate bag to enable distinguising between current year biomass that generally stands more upright from previous biomass that lays flatter on the ground. We recorded fresh weight of each sample within 1 hour of sample collection then dried the samples for at least 48 hours at 60C before measuring dry mass. In total, each sampling round we collected approximately 120 plots * 4 subplots * 2 samples (one standing and one litter biomass) * 2 rounds of sampling = 1920 biomass samples.

Fuel Characteristics Analyses

First, we calculated six fuel characteristics that are highly relevant to fire behavior including average vegetation height (cm), total dry biomass (tons/acre), standing dry biomass (tons/acre), litter dry biomass (tons/acre), standing fuel moisture (%), and litter fuel moisture (%). Fuel moisture was calculated as the difference between the fresh and dry mass divided by the dry mass of each sample. We also calculated the mean height of each plot by taking the mean of the three standing vegetation height measurements.

We used several approaches for examining variation in fuel characteristics and the extent to which fuel characteristics are predictable by topography, edaphic, and vegetation variables. To do this, we calculated topographic variables for each plot including elevation, slope, aspect, and water flow accumulation from a digital elevation model from the USGS with a 1 arcsecond resolution (USGS EDNA). For analysis purposes, we take the cosine of aspect to convert the values into a north/south vs. east/west orientation. In addition, we used soil particle size category from the USDA soil survey maps (https://websoilsurvey.nrcs.usda.gov/app/), the presence of prairie dog colonies from BOSMP and BCPOS prairie dog colongy survey maps from 2021-2023 and vegetation cover estimates (for annual plant, perennial plant, litter, and bare categores) from the rangeland analysis platform (https://rangelands.app/). We then fit a linear model with each fuel characteristic as the dependent variable (standing biomass, litter biomass, total biomass, standing plant moisture, litter moisture), then the topography, soil, and vegetation type and cover as predictors. These models did not include interactions, as we did not have enough data to fit all interactions. We then performed a stepwise backwards model selection proceedure to determine the simplest model baised on delta AIC values to predict each fuel characteristic using the step function R (RCoreTeam 2022). We removed cattail plots from this modeling analysis because these cattail plots are not representative of overall grassland fuel characteristics.

Spatial Prediction of Biomass and Height

We produced maps of predicted biomass and height by using the predict function in R to calculate predicted fuel characteristics based on the simplest fitted linear model for each pixel at 1 arcsecond resolution for all areas that had vegetation mapping. To do this, we rasterized the vegetation category, prairie dog presence, and soil characteristics shapefiles at the same pixel size as the digital elevation model to serve as predictor input data along with the rasters produced by the rangeland analysis platorm on plant cover. We include the locations of our study points colored by their residuals as an indication of how well those areas fit the models (see provided map package file). We do not provide maps of fuel moisture because moisture is so variable thorugh time that we do not believe that we can produce a reliable map of fuel moisture based on our data at this time. Further work to incorporate time of sampling (both date and time of day) and a wider range of seasonal sampling will help to improve the moisture analysis. Also, due to a lack of vegetation mapping on City of Longmont properties, we were unable to map those areas, but would be excited to expand to those areas if vegetation maps were available.

Fire behavior modeling

To assess the extent to which fuel characteristics or weather conditions influence fire behavior, we used BehavePlus 6 (https://www.frames.gov/behaveplus/software-manuals) to calculate fire behavior metrics including fire rate of spread, fireline intensity, and flame length at a range of biomass, fuel moisture, and wind speeds. To do this, we modified the standard shortgrass fuel model (the standard gr2 fuel model),is which is similar to the grassland fuel model most often used in this region (Figure 1, yellow represents gr2, low load arid grassland). We then modified the biomass, height, and moisture then ran simulations at a range of wind speeds. To modify biomass and height, we fit a relationship between height and biomass from our field surveys and used that relationship to create scenarios where height and biomass change together to retain realistic fuel density (combination of fuel height and biomass). We found that fuel bed height is a function of total biomass as follows: total biomass (tons per acre) = fuel bed height (feet) * 0.67. We modeled total biomass ranging from 0.5 to 5.5 tons per acre by 0.5 ton intervals with corresponding fuel bed heights ranging from 0.33 to 3.67 ft. Because we were looking to model dormant season fire behavior, we put all of the fuel in the dead category. The other parameters that we varied included fuel moisture, ranging from 1 to 10% and wind speed, ranging from 0 to 40 miles per hour in intervals of 5 miles per hour. The other parameters were kept constant across model runs and include the standard shortgrass static fuel charateristics and a slope of 5%. We recorded fire spread rate (chains per hour), fireline intensity (btu/ft/s), and surface fire flame length (ft) across the variation in fuel loading, fuel moisture, and wind speed.

Results

Fuel Characteristics Analysis

There was substantial variation in all fuel characteristics. Cattail plots were the most distinct, with substantially higher biomass, height, and moisture (Figure 3). Besides cattails, the other vegetation types had similar biomass. Many plots had much greater biomass than what is present in the standard gr2 fuel model (1 ton per acre) and the fall survey generally had slightly lower biomass compared to the summer survey. Generally, there is approximately twice the biomass in the standing portion compared to the litter with an average of 1 ton per acre in the standing portion and 0.5 tons per acre of litter. After cattails, ruderal and wet grassland plots tended to have the tallest plants. Overall, moisture for both standing and litter biomass was highly variable between vegetation types. Fall samples of standing biomass moisture were much lower than summer, likely because most plants were senesced by the time of fall sampling. Moisture levels tended to be higher in areas that are characterized by wet-loving plants like cattails, wet grasslands, and mesic tallgrass sites and litter moisture tended to be lower than standing biomass moisture (Figure 3).

Our models explained approximately 44% - 98% of the variation in fuel characteristics (Table 2). This is using a model that only includes vegetation type, topography variables, soil texture, plant cover, and prairie dog presence. The best models for prediction varied by fuel characteristic. Biomass (either total or standing vs. litter) was best predicted by prairie dog presence, vegetation type, and one of elevation, perennial plant cover, and aspect (Table 2, Figures 4-6). On the other hand, standing and litter moisture were best predicted by different variables. They both share perennial plant cover as a predictor, but standing moisture as most related to aspect and litter cover while litter moisture was most related to elevation, bare ground, soil texture, and vegetation type (Table 2, Figures 7-8). Standing moisture was highest in areas facing west southwest and north northwest. Finally, height was best predicted simply by elevation and prairie dog presence (Table 2, Figure 9). Interestingly, our models fit best on litter values, although the best fit was for predicting height. The very high R^2 for height is surprising but likely due to overwhelming and consistent effect of prairie dog presence on determining plant height. Prairie dog presence had a strong effect on all the fuel characteristics that we measured.

Fire modeling

Our fire modeling exercise shows a few trends. First, as fuel load increases, we tend to see more extreme fire behavior for all metrics, but the increase in these metrics slows down as you have higher fuel loads. Fuel moisture plays an important role in reducing fireline intensity, but only a minor role in reducing flame length. The rate of spread results are interesting because they indicate that the rate of fire spread is primarily limited by wind speed, but rate of spread begins to become limited by fuel load at higher fuel moisture levels (Figure 10). These fire behavior measurements are all quite extreme, likely due to the parametrization of these models, and thus probably don’t represent realistic values. However, the relative differences are still informative in understanding how fuel, wind, and moisture combine to influence fire behavior. More work is needed to use this sort of exercise for prediction of actual fire behavior metrics.

Discussion

Our survey of grassland fuels reveals substantial spatial variation in fuel characteristics. We find that much of this variation is related to vegetation type, but other variables like topography, vegetation cover, prairie dog presence, and soil texture also help to predict variation in fuel characteristics. Our fire modeling exercise also confirms the importance of variation in fuel levels and fuel moisture, especially when it comes to the rate of spread. These results should aid in considering prioritization of areas that might be potentially more hazardous due to their fuel characteristics. Generally, areas with higher total and standing biomass and lower fuel moisture should be more hazardous from a fire spread perspective and our analyses show the areas that we might predict to have higher biomass and lower fuel moisture.

The consistent importance of prairie dog presence in predicting variation in fuel characteristics indicates that prairie dog activities have large impact on fuel characteristics by greatly reducing biomass. In addition, vegetation type influenced several fuel characteristics, indicating that differences between species that dominate different areas can play a large role in determining fire behavior. The importance of different species is due, in part, to different productivity between species which could result in increased flammability, something that merits further investigation. Notably, we find that the fuel measurements that we made differ from those in the gr2 fuel model that predominates around the region. While the gr2 fuel model includes a fuel load of ~1 ton per acre and a depth of 1 foot, we find that grassland fuel loads vary from 0.3 to 10 tons per acre with fuel depths of 1 inch to 3 feet. Being able to predict the spatial arrangement of fuel characteristics will be critical to creating better fuel models to more accurately model fire behavior. Our modeling including a few simple predictors yielded variable, but overall, relatively good fits (R^2 ranging from 0.44 – 0.98). Increasing our fuel data and gathering more targeted predictors should only improve our prediction and is a goal of future research. This will likely be especially important as we try to predict across years, as annual weather can be very important in determining fuel production. This year had above average precipitation through the spring and summer, likely resulting in high productivity. In the future we will compare our measures of biomass with those estimated by the rangeland analysis platform to help determine whether that product is reliable for understanding biomass production across the Front Range landscape.

The differences in which factors predict fuel characteristics is interesting for understanding grassland structure. The first important point is that prairie dogs are very effective in reducing biomass, and they have a significant effect on all fuel characteristics. Plant cover variables are also important for many fuel characteristics, but the type of plant cover that is important varies between fuel characteristics. For biomass (total, standing, and litter), perennial plant cover was important, a result that is not surprising, as where there are more plants there should be more biomass. For topographical variables, only aspect and elevation were important, showing a trend toward shorter plants, higher litter moisture, and lower standing biomass at higher elevations and a tendency toward higher standing moisture and total biomass in west southwest and north northwest facing areas. We expect that we will be able to increase our predictive power for many fuel variables by using more complex models or machine learning approaches that can incorporate interactions or non-linear relationships between variables and this will be the focus of future modeling efforts, especially as we gather more data.

Our fire behavior modeling exercise, while theoretical, shows interesting patterns between fuel loading, fuel moisture, and wind in how fires behave. Probably most interesting is how fire spread can shift from being limited by wind to being limited by fuels at low fuel levels. This relationship changes as fuel moisture increases as fuel loading when fire spread is limited by fuel rather than the wind speed gets higher. This might suggest the usefulness of promoting plants that retain higher fuel moisture as a method of slowing fire spread under high winds as well as reducing fuel loads overall. The other fire behavior metrics did not show clear non-linearities in their responses, primarily showing that higher fuel moisture, lower fuel loads, and lower wind speeds result in less extreme fire behavior. It would be useful to compare the values from our modeling exercise to real fire behavior to determine more appropriate parameterization of our models to increase the usefulness of this exercise for generating predictions of fire behavior instead of just examining relationships between fuels and wind. We can also include topography in this model to determine the importance of slope in these relationships.

Taken together our results capture the variation of midsummer and fall fuel characteristics and suggest that this variation could play a critical role in how fires are likely to behave across the landscape. The places with highest fuel loads are likely to be patchy and targetable with management if fuel reduction treatments are a goal. In addition, methods of increasing fuel moisture may be successful in slowing fire spread to allow for greater ability for first responders to control a fire. We hope that better understanding the predictors of fuel characteristics and how this plays out across the landscape can help to prioritize potential fuel management treatments. The maps of predicted biomass values across open space properties should aid in this. However, we also plan to test these fuel treatment methods and measure any potential tradeoffs that these methods might have in other ecosystem functions like soil health and biodiversity. Understanding the potential unintended effects of fuel treatment methods like mowing, grazing, and prescribed fire will be critical to responsibly applying these methods to meet both fire risk reduction and grassland management goals.

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Table 1: Plot distribution by vegetation type and management organization. Numbers indicate the number of plots surveyed in each category split by organization. Percentages in the total column indicate the percentage of our plots in that category first, then the percentage of the landscape that were classified into these categories based on reclassifying USNVC Associations from vegetation maps provided by BCPOS, BOSMP and JCOS.

Vegetation Type	BCPOS	BOSMP	JCOS	LPWNR	Total (study plots, landscape)
Shortgrass	3	0	2	0	5 (4%, 3%)
Ruderal	11	2	9	10	31 (28%, 30%)
Tallgrass	2	4	3	0	9 (9%, 17%)
Wet Grassland	1	4	0	0	5 (4%, 5%)
Mixed Grass	13	20	8	4	45 (39%, 34%)
Smooth Brome	1	4	0	1	6 (5%, 9%)
Mesic Tallgrass	0	7	0	0	7 (6%, 2%)
Cattail	2	0	1	3	6 (5%, <0.1%)

Table 2: ANOVA table of linear model results for each fuel characteristic. Values reported are F-value (numerator df, denominator df) then p-value. P-values below 0.05 are bolded. Asterisks indicate those terms that were retained in the best model after backwards stepwise model selection and thus comprise the simplest predictive model. R^2 for the simplest model used in predicting fuel characteristics maps are reported at the end of the table.

Term	**Total Biomass**	**Standing Biomass**	**Litter Biomass**	**Litter Moisture**	**Standing Moisture**	**Height**
Elevation	0.2 (1 , 79) 0.64	4.9 (1 , 79) **0.03***	3.6 (1 , 79) 0.06	3.5 (1 , 79) 0.07*	2 (1 , 79) 0.16	4.2 (1 , 79) **0.04***
Slope	2.8 (1 , 79) **0.1**	4.5 (1 , 79) 0.04	0.2 (1 , 79) 0.67	1 (1 , 79) 0.31	0 (1 , 79) 0.95	1.3 (1 , 79) 0.26
Aspect	2.4 (1 , 79) 0.12*	0.5 (1 , 79) 0.46	0.1 (1 , 79) 0.78	0 (1 , 79) 0.93	5.5 (1 , 79) **0.02***	24.4 (1 , 79) 0
Prairie Dog Presence	55.6 (2 , 79) **<0.001***	33.7 (2 , 79) **<0.001***	55.8 (2 , 79) **<0.001***	193.1 (2 , 79) **<0.001**	63.7 (2 , 79) **<0.001**	>900 (2 , 79) **<0.001***
Annual Plant Cover	0.3 (1 , 79) 0.6	1.1 (1 , 79) 0.29	0.2 (1 , 79) 0.64*	0.2 (1 , 79) 0.69	0.5 (1 , 79) 0.46	0.1 (1 , 79) 0.74
Bare Ground Cover	7.1 (1 , 79) **0.01**	3.3 (1 , 79) 0.07	11.5 (1 , 79) **<0.001***	1.2 (1 , 79) 0.27*	1.2 (1 , 79) 0.28	1.1 (1 , 79) 0.31
Perennial Plant Cover	1.2 (1 , 79) 0.29*	1.4 (1 , 79) 0.24*	0 (1 , 79) 0.9*	0 (1 , 79) 0.98*	0.2 (1 , 79) 0.66*	0.4 (1 , 79) 0.53
Litter Cover	0.4 (1 , 79) 0.55	1.3 (1 , 79) 0.26	0.1 (1 , 79) 0.74	7.7 (1 , 79) **0.01**	0.4 (1 , 79) 0.55*	0 (1 , 79) 0.83
Vegetation Type	2 (7 , 79) 0.06*	1.6 (7 , 79) 0.14	2.6 (7 , 79) **0.02***	2.2 (7 , 79) **0.04***	1.4 (7 , 79) 0.2	1.3 (7 , 79) 0.25
Soil Texture Class	0.7 (11 , 79) 0.78	0.5 (11 , 79) 0.89	0.7 (11 , 79) 0.72	2 (11 , 79) **0.03***	0.6 (11 , 79) 0.79	0.7 (11 , 79) 0.74
Water Flow Accumulation	0.5 (1 , 79) 0.46	0.7 (1 , 79) 0.4	0 (1 , 79) 0.91	0.1 (1 , 79) 0.75	0.1 (1 , 79) 0.73	0.1 (1 , 79) 0.7
R^2	0.6	0.44	0.61	0.84	0.57	0.98

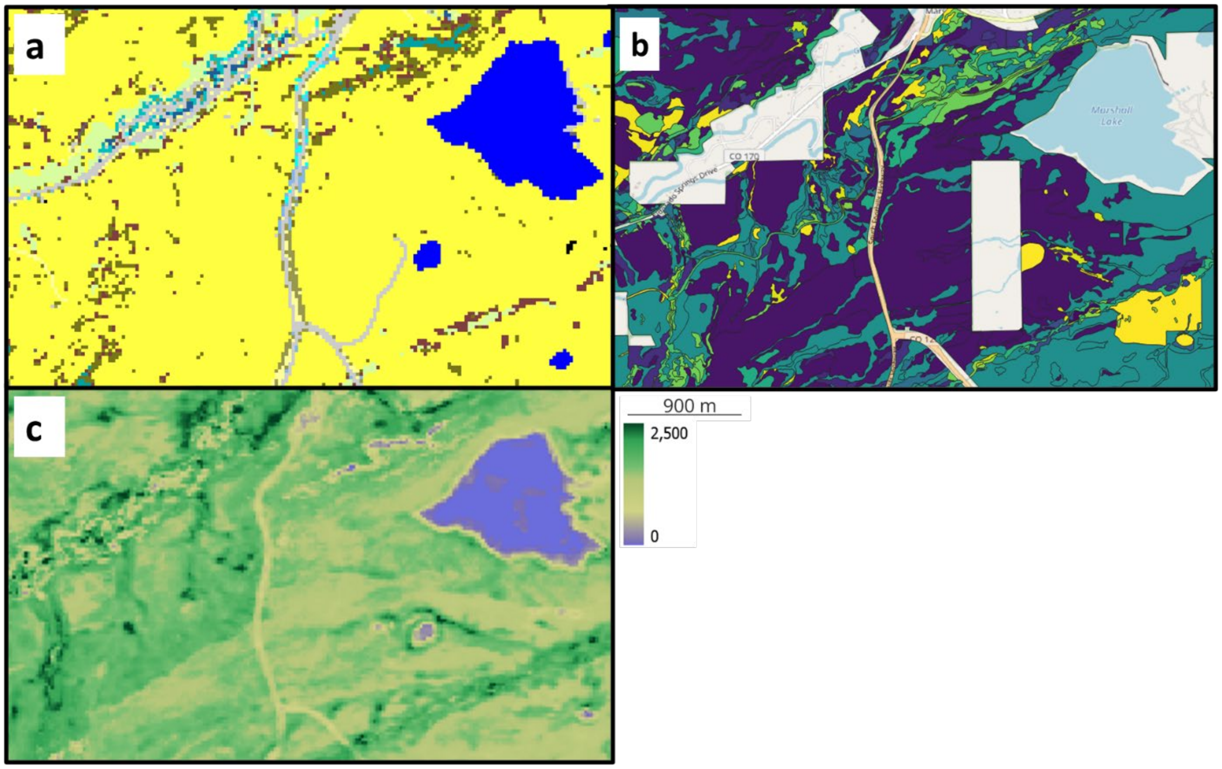

Figure 1: Maps of a section of grassland landscape managed by the City of Boulder. LANDFIRE fuel model, which considers all grasslands sharing a single fuel characteristic (a) compared to grassland type (b) and vegetative biomass (c, lbs/acre)

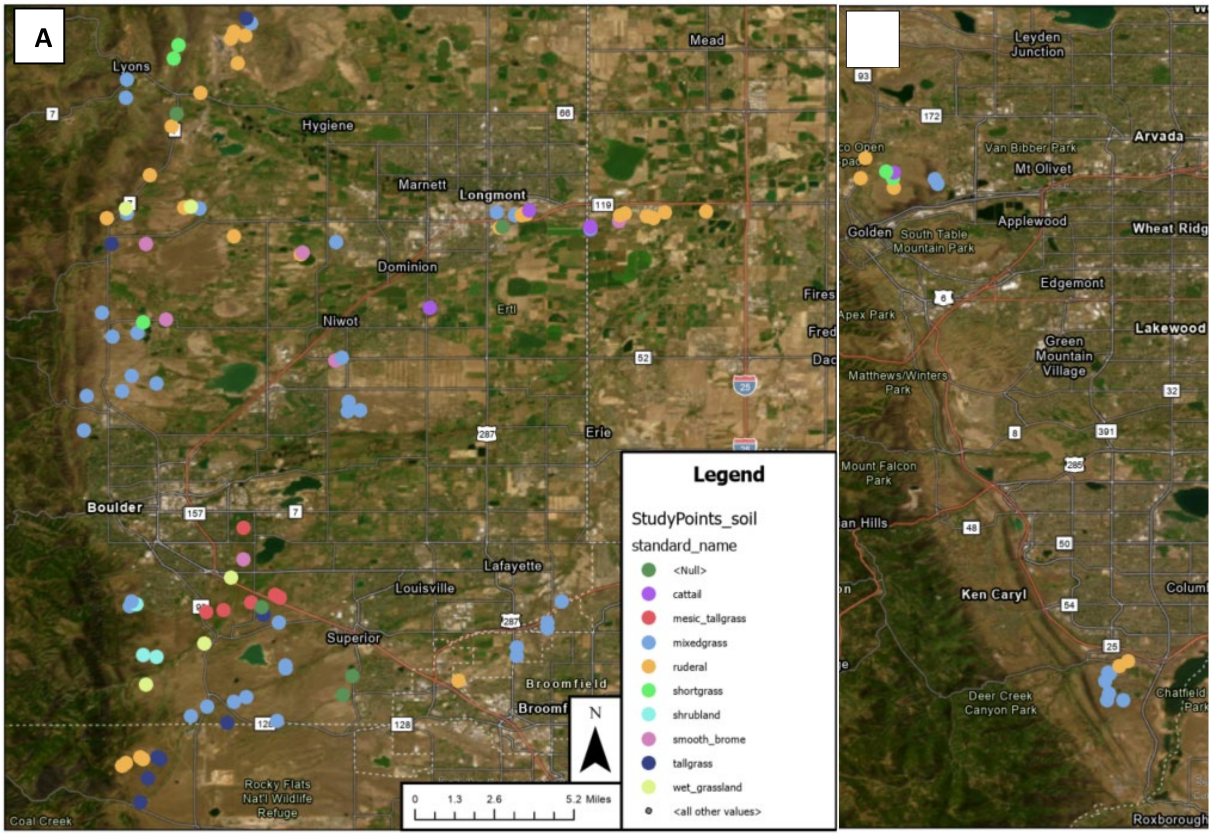

Figure 2: Map of plot locations across Boulder and Jefferson Counties. (A) Northern plots and (B) Southern plots. Plots are colored by their vegetation type.

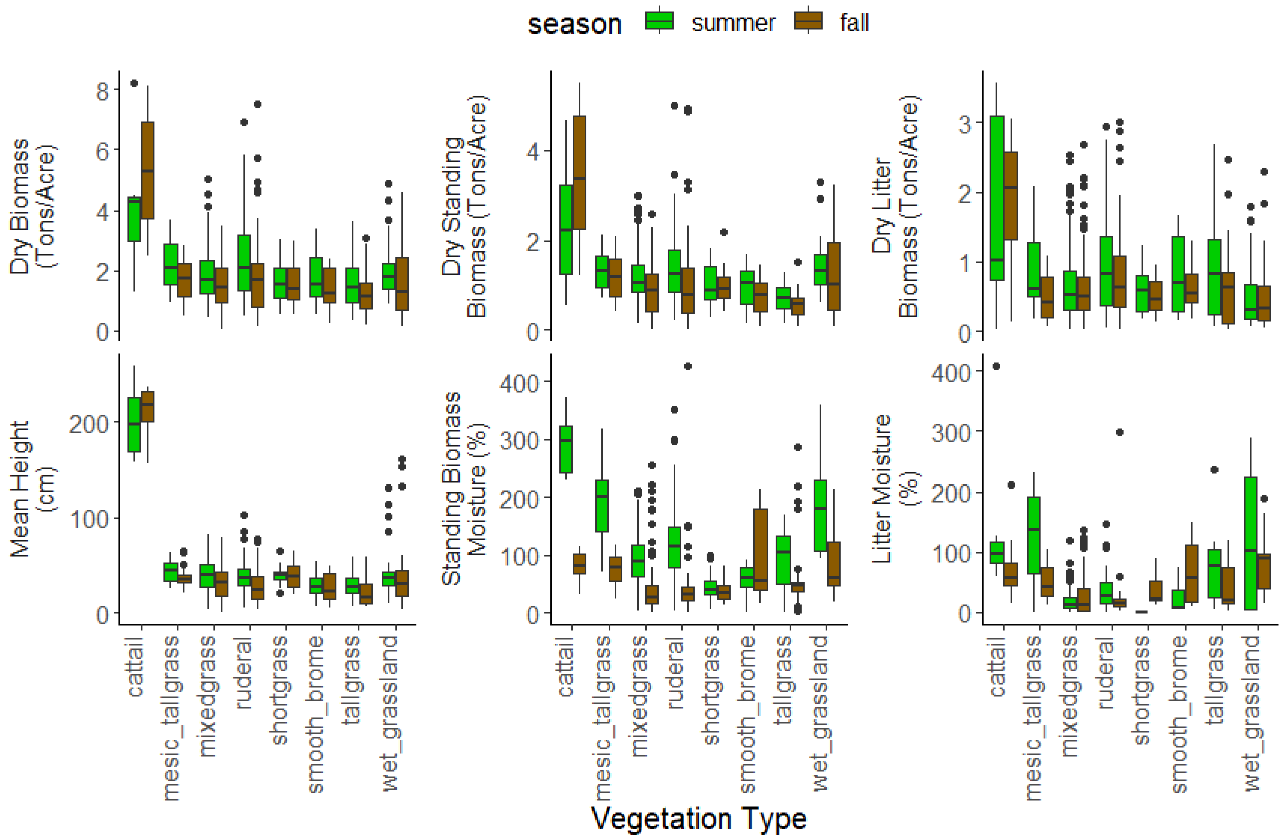

Figure 3: Fuel characteristics by vegetation type. Dry biomass includes both standing and litter biomass combined, while standing and litter biomass are also presented separately. Mean height is only of standing biomass and moisture measurements are the percentage of the dry masses that is water. Colors of boxplots indicate the season of sampling with green indicating summer (July) and brown indicating fall (October) sampling.

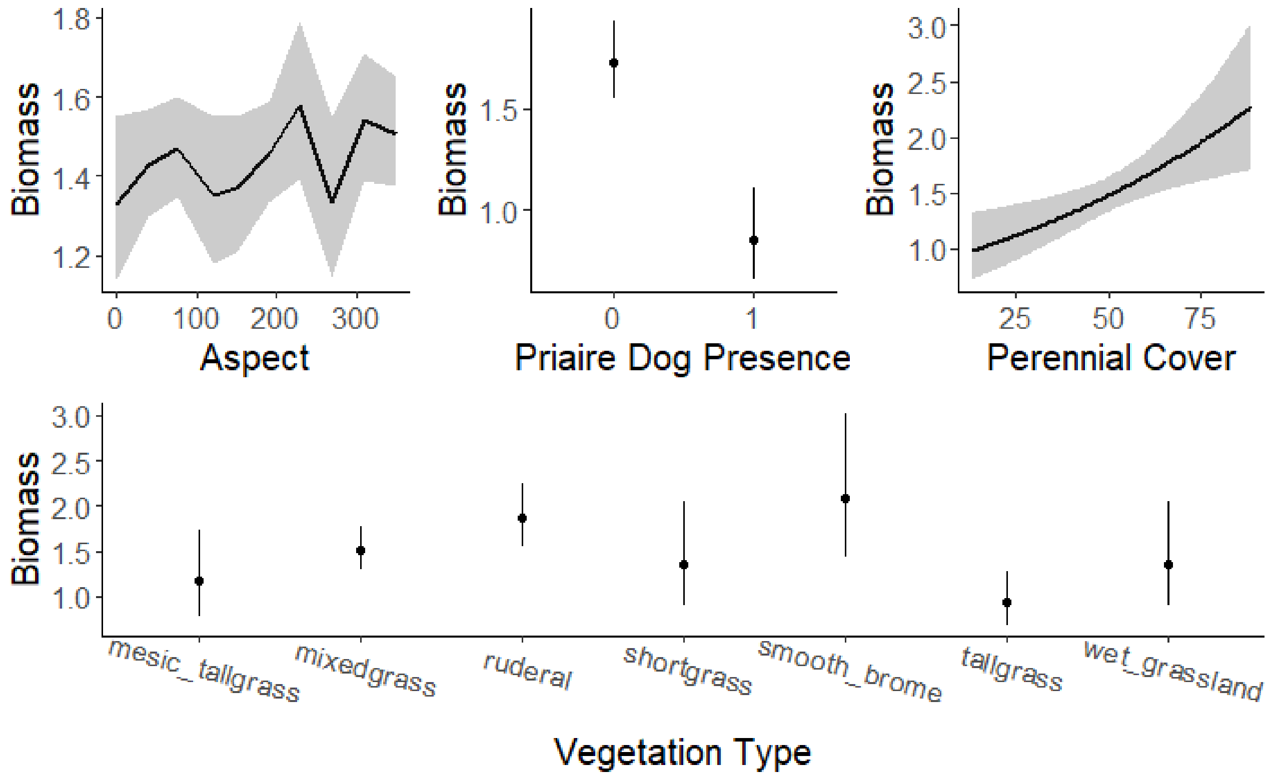

Figure 4: Predicted effects of predictor variables on biomass. These are model predictions made by the reduced model after stepwise model selection. Shaded areas indicate 95% confidence intervals. Aspect refers to the direction a slope is facing in degrees as if reading a compass where 0 and 360 are north, 180 is south, etc.

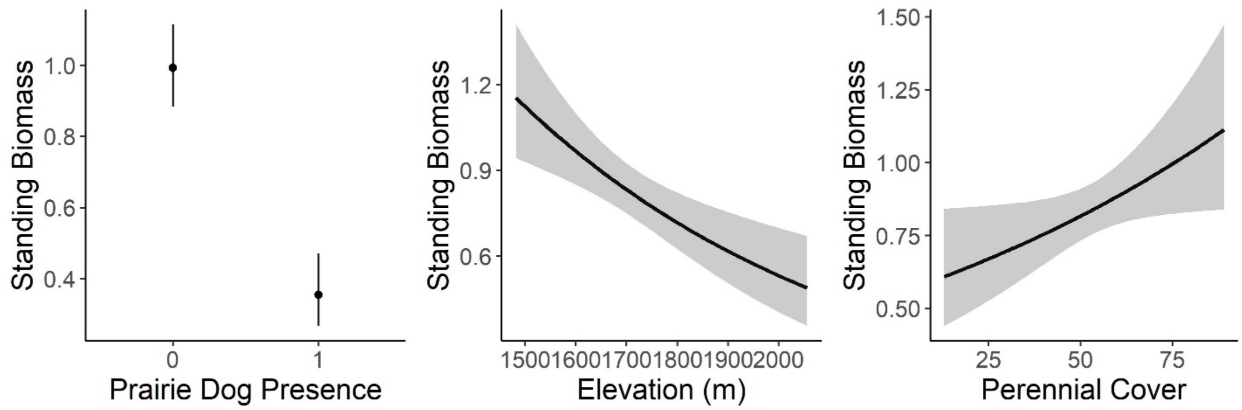

Figure 5: Predicted effects of predictor variables on standing biomass. These are model predictions made by the reduced model after stepwise model selection. Shaded areas indicate 95% confidence intervals.

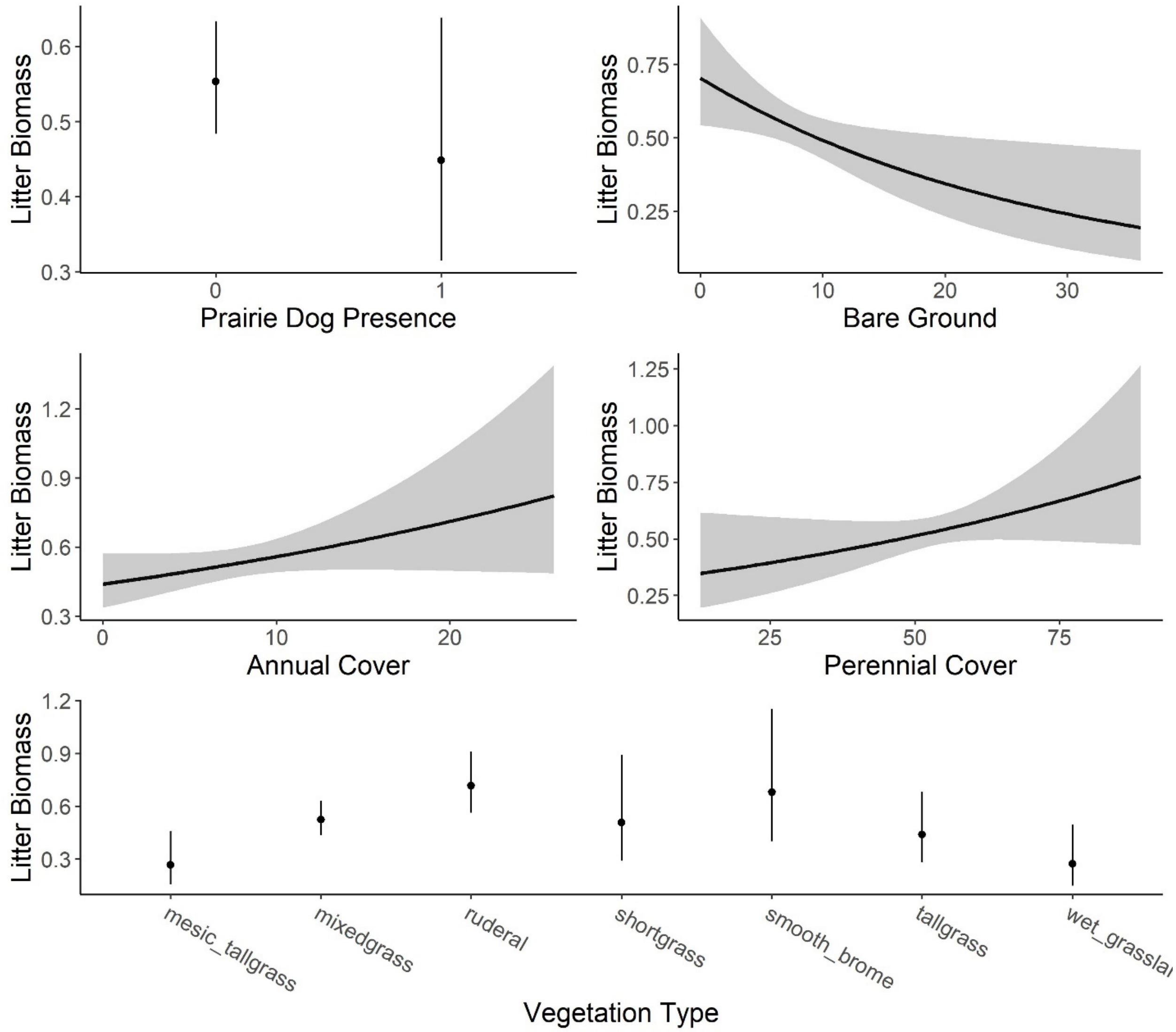

Figure 6: Predicted effects of predictor variables on litter biomass. These are model predictions made by the reduced model after stepwise model selection. Shaded areas indicate 95% confidence intervals.

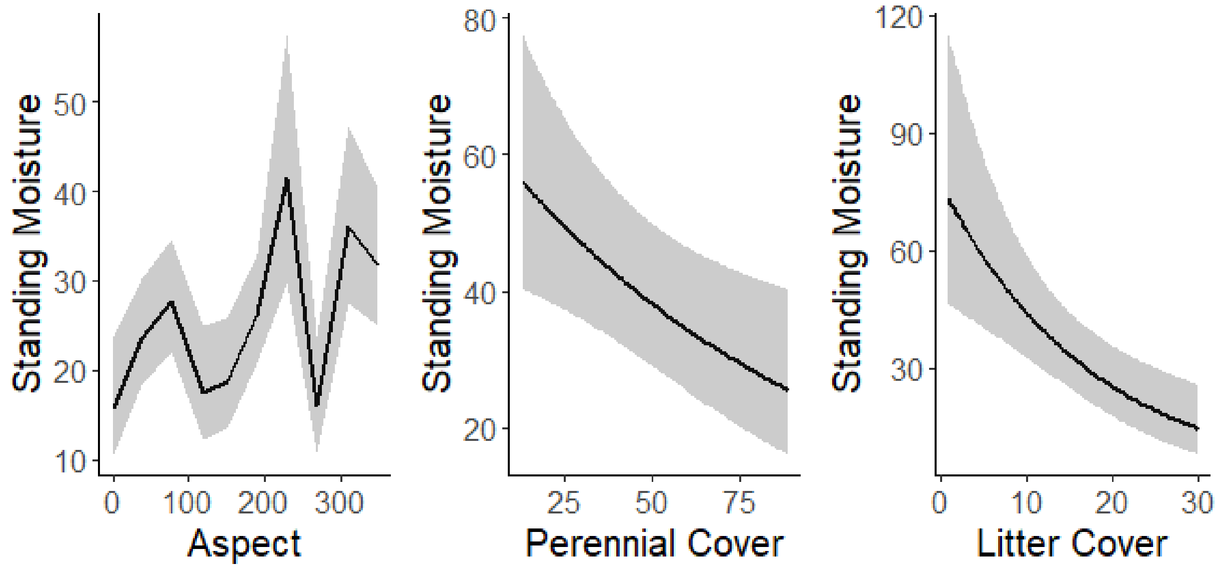

Figure 7: Predicted effects of predictor variables on standing moisture. These are model predictions made by the reduced model after stepwise model selection. Shaded areas indicate 95% confidence intervals. Aspect refers to the direction a slope is facing in degrees as if reading a compass where 0 and 360 are north, 180 is south, etc.

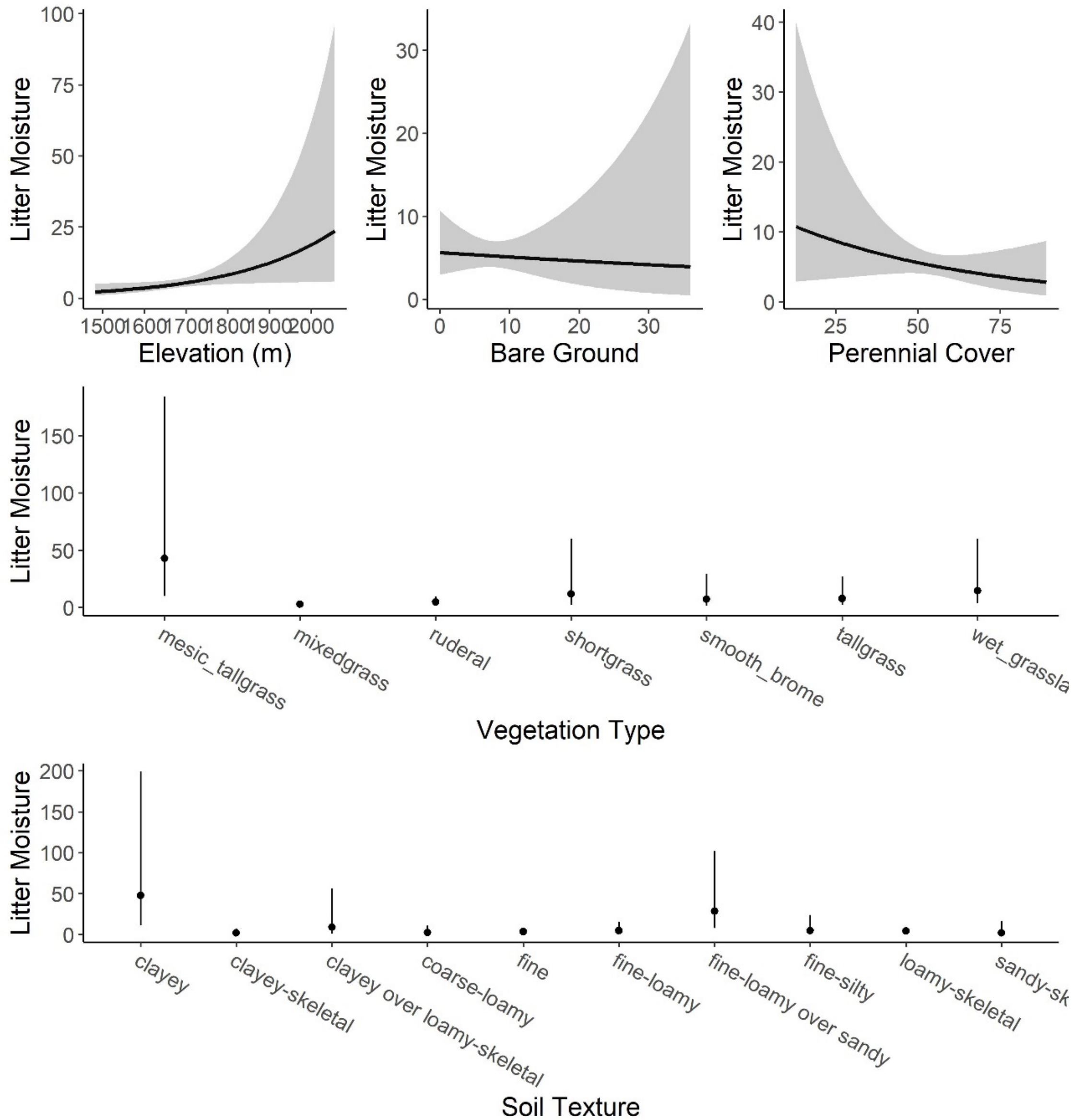

Figure 8: Predicted effects of predictor variables on litter moisture. These are model predictions made by the reduced model after stepwise model selection. Shaded areas indicate 95% confidence intervals.

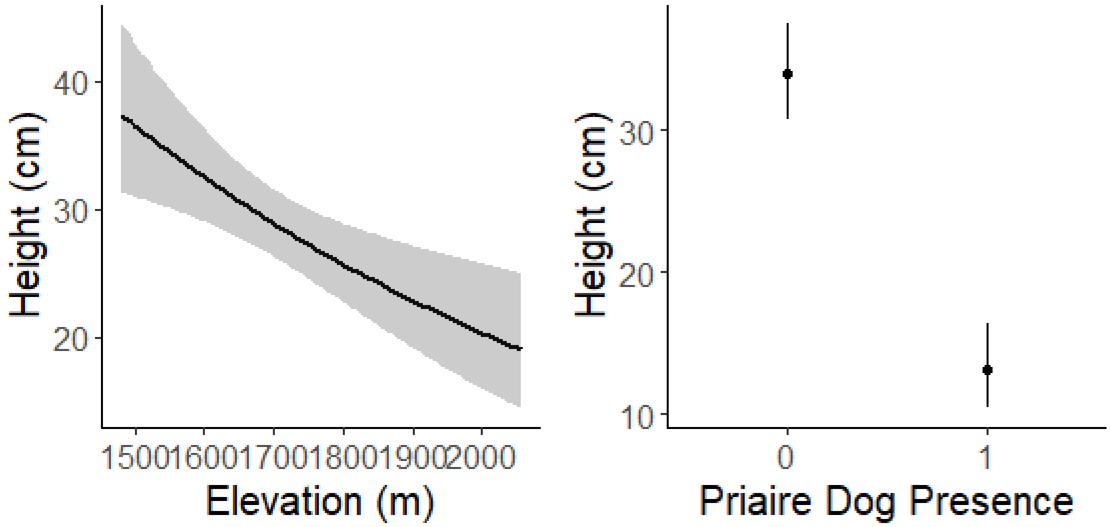

Figure 9: P Predicted effects of predictor variables on fuel bed height. These are model predictions made by the reduced model after stepwise model selection. Shaded areas indicate 95% confidence intervals.

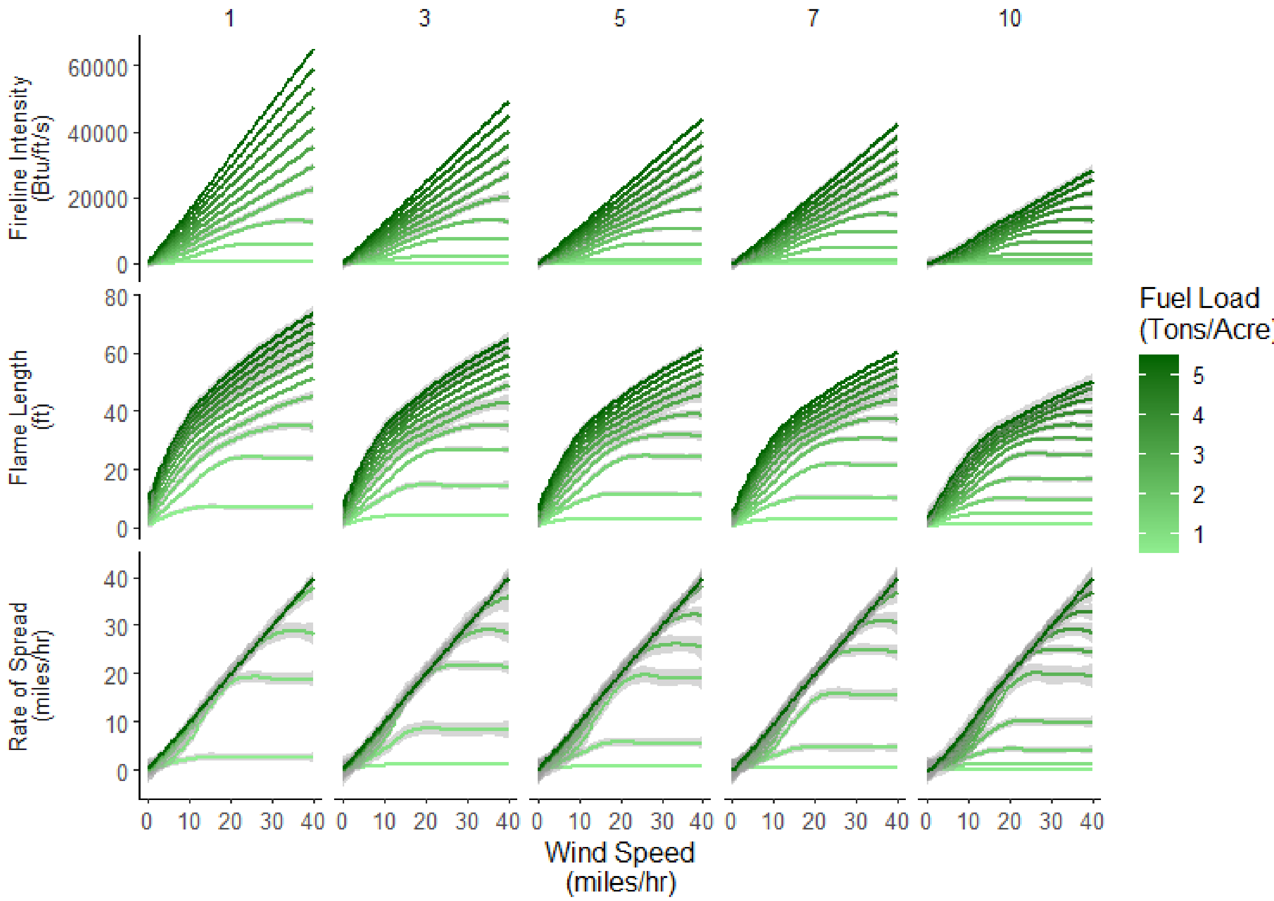

Figure 10: Results of BehavePlus modelled fire behavior under a range of fuel loads, wind speeds, and fuel moisture. Wind speed variation is graphed along x-axis, line colors indicate fuel loads while columns of graphs are arranged by fuel moisture, from 1% (left) to 10% (right). Higher fuel load lines overlap in the rate of spread graph.