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Forecasting Fine Fuels in the Intermountain West Rangelands

Mira Ensley-Field
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FORECASTING FINE FUELS IN THE INTERMOUNTAIN WEST RANGELANDS

by

Mira Ensley-Field

A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in

Ecology

Approved:

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Major Professor Committee Member

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Committee Member Interim Vice Provost
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UTAH STATE UNIVERSITY
Logan, Utah

2022
Land managers in the Intermountain West begin making firefighting resource allocation decisions in early spring, but wildfire risk varies regionally and these spatial patterns can change from year to year. The objective of this thesis project is to develop a fine fuels forecast to help fire managers anticipate spatial variation in fuel loads before the start of the fire season. In Chapter 1 we compile and analyze the methodologies of the historical record of fine fuel loads reported to the Great Basin Coordination Center. Based on our data analysis, we developed a series of recommendations for improving the methods used to sample fine fuels in the future as well as more broad ideas for how land managers can use emerging technologies to more effectively monitor fine fuels. In Chapter 2, we combined this historic record of fine fuel measurements with a newly available remotely-sensed dataset of herbaceous productivity from the Rangeland Analysis Product (RAP) and modeled the ecological process of fine fuels accruing in and leaving a system. We built a Bayesian state-space model where the latent fuel at a location depends on the fuel load of the previous year and the current year’s productivity.
We then forecasted RAP productivity using remotely sensed data available in Google Earth Engine in early spring. Finally, we combined these models to forecast fuel loads based on forecasted productivity. These results left us with three main takeaways; 1) improvements and a greater quantity of fine fuel data measured are needed to produce a fine fuels forecast with usefully narrow confidence intervals, 2) remotely-sensed productivity datasets are meaningfully related to on-the-ground fine fuels and would be a useful tool for land managers in early spring, and 3) ecological forecasts of remotely-sensed productivity is a promising future direction of research. Our efforts have useful implications for how land managers can use already existing remotely-sensed data and remotely-sensed data forecasts for early spring fire planning decisions as well as needed recommendations for how to better focus the large amount of effort that goes into fine fuels monitoring in early spring.
The objective of this thesis project was to develop a fine fuels forecast to help fire managers anticipate spatial variation in fuel loads before the start of the fire season. In Chapter 1 we compile and analyze the methodologies of the historical record of fine fuel loads reported to the Great Basin Coordination Center. Based on our data analysis, we developed a series of recommendations for improving the methods used to sample fine fuels in the future as well as more broad ideas for how land managers can use emerging technologies to more effectively monitor fine fuels. In Chapter 2, we combine this historic record of fine fuel measurements with a newly available remotely-sensed dataset of herbaceous productivity from the Rangeland Analysis Product and model the ecological process of fine fuels accruing in and leaving a system. We build a model where the amount of fuel at a location depends on the fuel load of the previous year and the current year’s productivity. We then forecasted the remotely-sensed herbaceous productivity. Finally, we combine these models to forecast fuel loads based on forecasted productivity. These results left us with three main takeaways; 1) improvements and a greater quantity of fine fuel data measured are needed to produce a fine fuels forecast with usefully narrow confidence intervals, 2) remotely-sensed productivity datasets are meaningfully related to on-the-ground fine fuels and would be a useful tool for land managers in early spring, and 3) ecological forecasts of remotely-sensed productivity is a promising future direction of research. Our efforts have useful implications for how land
managers can use already existing remotely-sensed data and remotely-sensed data forecasts for early spring fire planning decisions as well as needed recommendations for how to better focus the large amount of effort that goes into fine fuels monitoring in early spring.
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Mira Ensley-Field
Because the second chapter of this thesis has been prepared as a standalone manuscript in journal format, there is some redundancy between chapters. We additionally have a GitHub code repository (https://github.com/mensleyf/finefuel4cast) where all code needed to run the models of Chapter 2 are available and we reference a dataset we published on Zenodo (https://zenodo.org/record/4382488#.YSfT9Y5KguU) multiple times throughout.
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CHAPTER 1
INTRODUCTION

Wildfires across ecosystems in western North America are occurring over greater spatial extents and more frequently than in the past several decades (Westerling et al., 2006). The anthropocentric, and economic costs of wildfires are monumental (Mietkiewicz et al., 2020; Morris and Rowe, 2014). Predicting wildfire risk in the early season can help land managers mitigate these consequences (Dunn et al., 2020). This is a pilot study exploring the possibility of developing a fine fuels forecast to help land managers in the Intermountain West optimize wildfire preparedness and response.

Throughout this project, we focus on wildfires in the rangeland ecosystems of the Intermountain West. By this, we mean the desert shrublands, sagebrush steppe, and rangelands stretching between the Rocky Mountains on the east and the Sierra Nevada and Cascade Ranges on the west. This system is characterized by low precipitation and intermittent shrub and perennial grass vegetation (D’Antonio and Vitousek, 1992), and includes rapidly expanding exotic annual grasslands, recently estimated to make up 20% of the Intermountain West (Smith et al., 2021b).

The Intermountain West rangelands (IWR) require different fire management strategies than other fire-prone ecosystems because they are fuel-limited. For ecosystems with large size classes of fuels (e.g. forests); the amount of biomass increases yearly barring any disturbance with productivity varying along with stand age, climate, and other factors (He et al., 2012). High risk years occur when it is dry enough for these fuels to ignite and for fire to spread (Abatzoglou and Kolden, 2013; Westerling et al., 2006). In grasslands and shrublands, the relationship between fire and climate is less directly
linked. It is the continuity of fuels in the landscapes that limits fire ignitions and spread. Recent studies in grasslands and shrublands in the IWR show that in the past 30 years, favorable antecedent climate of above normal precipitation leads to increased area burned through higher productivity and an associated increases in biomass and fuels (Littell et al., 2009; Pilliod et al., 2017; Smith et al., 2021a).

Fine fuels arise from the plant biomass in a landscape and the IWR is undergoing rapid changes to its vegetation from historic shrubland to annual grasslands (Smith et al., 2021b). Historically, the sagebrush steppe had low fuel loads and continuity, with shrubs and bunchgrasses separated by bare-ground interspaces (Reisner et al., 2013) and relatively long fire return intervals (FRI). FRI varies spatially and by vegetation communities, but has been estimated at >50 years for almost all vegetation communities throughout the IWR’s extent (Balch et al., 2013; Mensing et al., 2006; Whisenant, 1990). Annual exotic grasses, such as cheatgrass (*Bromus tectorum*), have been invading the IWR and increasing fuel continuity and cover (Smith et al., 2021b). Native vegetation conversion to exotic annual grasslands, recently estimated at 400,000 acres per year (Smith et al., 2021b) is leading to FRI less than five years in some locations (Whisenant, 1990), and creating a positive feedback loop leading to the exclusion of the relatively fire intolerant sagebrush and native bunchgrasses (Balch et al., 2013; D’Antonio and Vitousek, 1992; Davies and Nafus, 2013; Davies et al., 2021; Bradley et al., 2018).

While productivity of all vegetation in dryland systems is sensitive to precipitation (Holmgren et al., 2006), cheatgrass and other annual grasses are particularly sensitive to precipitation compared with native perennial vegetation (Bradley and Mustard, 2005) heightening inter-annual variability in fuel loads compared to native land
cover. In addition to being more sensitive to precipitation, systems dominated by exotic annuals have higher and more continuous fuel loads in general (Davies and Nafus, 2013; Mahood et al., 2021), shorter fire intervals (Balch et al., 2013), and earlier phenology (Clinton et al., 2010) so that fine fuels dry out and become flammable earlier in the season.

Organizations charged with wildfire management in the west rely on many inputs to prepare for the upcoming fire season, including weather forecasts, plant community composition, and fine fuel measurements (Dickson et al., 2006; Sandberg et al., 2001). While fine fuels loading data is a critical piece of information for fuel-limited systems, this data cannot be accurately collected until grasses have finished growing. Furthermore, this data source is time-intensive to gather. Organizations that manage wildfires would benefit from spatially extensive, early-season fuel loading maps to prepare for fire season in early spring.

Researchers are creating spatially extensive forecasts and near real time maps of herbaceous productivity. Fuelcast (“fuelcast.net,” n.d, www.fuelcast.net), GrassCast (Hartman et al., 2020), and the Rangeland Analysis Platform (Allred et al., 2021; Jones et al., 2021) are excellent examples of these tools. However, fuel loads are not the same as remotely sensed productivity datasets. Fuel loads refers to all biomass in a system, including litter, duff, and biomass from previous seasons’ growth, not just the current year’s production. Conversely, fuel load does not include current year biomass that gets grazed, decomposed, or blown away. Fuel loads are a result of the ecological process of productivity turning into biomass and accruing in a system, as well as leaving a system through herbivory, decomposition, and disturbances. So while productivity forecasts and
real time data are useful, they do not provide direct information about the on-the-ground fuel loads that land managers historically use to make inferences about the upcoming fire season.

In Chapter 2, we discuss the methods we used to compile the fine fuels monitoring data and metadata from the BLM and the additional data we added from SageSTEP (Sagebrush Steppe Treatment Evaluation Project, https://www.sagestep.org/). We analyze the fuel data collection methods, describe the dataset, and offer recommendations to improve these data. In addition, we published the dataset on Zenodo in the winter of 2021.

In Chapter 3, we build a forecast for fine fuels across IWR for 2021. To accomplish this, we developed two models which we combine to forecast fine fuels. Our first model is a Bayesian state-space model that represents the process of plant biomass production turning into fine fuels, and fuel leaving the system using our compiled fine fuels dataset from Chapter 2, and the RAP (Rangeland Analysis Platform) aboveground annual and perennial grass and forbs dataset. Our second model predicts each year’s production of grass and forb biomass from the RAP using remotely-sensed data available in early spring from 1987-2020, and uses the relationships between covariates found across these years to forecast production for 2021. After developing these two models, we combine them to create a forecast of fine fuels for the year 2021, and hindcasts for years 1987-2020, accounting for all relevant sources of uncertainty from both models.

This study explores a missing link between remotely sensed productivity data and on-the-ground biomass monitoring data with important implications for land managers. Modeling and forecasting productivity with remote sensing is an active area of research
and has potential for many applicable uses in addition to wildfire risk. However, annual productivity estimates are not the same things as on-the-ground fuels. This study investigates this important relationship between productivity and on-the-ground fuels to provide a clearer link for land managers interested in using these data for wildfire risk, and provides a close look at improvements needed to create a fine fuel forecast for the Intermountain West.

References


CHAPTER 2

COMPILING AND ANALYZING OBSERVATIONS OF FINE FUELS BETWEEN 1996 AND 2020

Abstract

Land Management agencies in the Intermountain West use information about regional variation in fuel loads to optimally allocate firefighting resources at the start of the fire season. While static maps work well for large fuel classes, fine fuels, the driver of rangeland fires, vary dramatically from year-to-year. While this is common knowledge among land managers, we are not aware of any dataset of fine fuel loads that could support quantitative analysis. Our goal in this chapter is to compile and determine the quality and consistency of current fine fuels data collection efforts. To do this, we compiled a historical record of fine fuel loads reported to the Great Basin Coordination Center, supplemented by control plots from the SageSTEP project cheatgrass sites. We analyzed the methodologies used to measure these fine fuel loads and then examined the spatial and temporal autocorrelation of these data. We also compiled subsample data aggregated to create site-level estimates of fine fuel loads from field offices who retained those records, and collected our own subsample data in a subset of BLM field offices to improve our understanding of scale and spatial heterogeneity. We found that BLM field offices that have collected fuel load data have different definitions of what biomass components constitute fine fuels, make different decision about placing hoops for random sampling, and base site estimates on anywhere from one to twelve subsamples. Based on our data analysis and comparison, we offer a series of recommendations for improving the methods used to sample fine fuels in the future.
Introduction

The frequency, size, and severity of wildfires in western North America has been increasing across almost all ecoregions (Dennison et al., 2014; Westerling, 2016), and wildfire trends have been an area of serious concern for scientists, private landowners, and federal agencies alike. Wildfires in the grasslands and sagebrush steppe of the Intermountain West are no exception. Increased fuel loadings, exotic annual invasions, climate change, and anthropogenic ignition sources all play a role (Fusco, 2019; Balch, 2017). From an ecological perspective, increases in the frequency intensity, and size of wildfires in the Great Basin region are leading to changes in plant community composition, altered grass-fire cycles, shortened fire intervals, and losses of the historic native-dominated shrublands (Balch et al., 2013). These changes have cascading effects on iconic sagebrush dependent species such as the Greater sage grouse (Coates et al., 2016) as well as large scale impacts on carbon fluxes (Bradley et al., 2006). These wildfires also come with high economic costs; the lowest annual estimates of wildfire costs in the US are over $70 billion (Thomas et al., 2017).

The wildfire regime of Intermountain West Rangelands (IWR) is considered fuel-limited, as opposed to ignition or climate-limited. In climate-limited systems, normal climate conditions reduce the number, extent, and severity of wildfires as the landscapes are too wet to ignite. In fuel-limited systems however, wet years can lead to high productivity, high fuel build-up, and more serious wildfire risks. Trends so far in the IWR indicate that for wet years, which build up fuel loads, pose a high risk for wildfires if they are followed by one or multiple dry years (Pilliod et al., 2017). Additionally, the historic perennial grasslands and sagebrush steppe of the Intermountain West are undergoing
conversion into annual grasslands at a rate nearing 200,000 ha/year (Smith et al., 2021), changing the amount, structure, and timing of fuels and shortening fire intervals (Balch et al., 2012).

There are ten Geographic Area Coordination Centers (GACC) across the United States involved in wildfire management. The personnel and gear required to fight fires is considerable, and the logistics effort needed to put resources in place to respond to wildfires is enormous. In the Intermountain West, fire risk is higher in some regions than others in any given year, and these high risk regions may change from year to year. The Great Basin GACC attempts to optimize resource placement (e.g. fire engines) in early summer before the start of the fire season, and dynamically manages resource allocations throughout the season.

The Great Basin GACC makes these allocation decisions using fine fuels data and weather forecasts (Predictive Meteorologist Shelby Law, personal communication). Fine fuels refers to small, easily dried out plant material common in grasslands as opposed to large scale woody material common in forest systems (NWACFIRE). In the grasslands and shrublands of the Intermountain West, it is herbaceous material that tends to have high variation year to year as well as the greatest ability to dry out and become flammable as the season progresses (Pilliod et al., 2017; Scott and Burgman, 2005). Starting in 1996, BLM districts began monitoring fine fuel loads at established sites, which they report to the GACC in the early summer. These sites are monitored using destructive sampling. BLM personnel wait until grasses have cured before going to the site, throwing down hoops, and clipping all fine fuels. They then scale this measurement up to provide an estimate of lbs/acre of fine fuels (BLM Fire Specialists, personal
communication). The GACC personnel usually compare a field office's current fuel monitoring data to the long-term average to anticipate if the current season will have higher than normal fuel loads (Shelby Law, personal communication.)

Given the importance of fine fuels for land managers of the Intermountain West, the goal of this chapter was to determine the quality and consistency of current data collection efforts. This is necessary in order to identify ways to improve data quality and make the dataset more valuable and useful, and as a first step before conducting quantitative analyses on the fuels data.

Methods

Compiling data

To compile the fine fuels dataset, we reached out first to fuel specialists in the BLM in the Great Basin. We received a list of contacts from Predictive Meteorologist Shelby Law with the GACC for fuel specialists working in BLM field offices across the region. We also included data from the control plots of grassland sites of SageSTEP.

These data were collected using different methodologies. The general protocol for measuring biomass through destructive sampling is to clip all fine fuels that fall within a hoop or quadrat of a known area. Generally, multiple hoops (subsamples) may be clipped, and may be further processed, dried in an oven or lab space, or simply weighed in the field. These subsamples are all combined to come up with an estimate for the amount of fine fuels at the site. We asked all field offices and SageSTEP a series of questions and read their SOPs (Standard Operating Procedures) when available. We came up with ten categories to classify the methods used to decide how to place quadrats/hoops
to take a subsample, the number of subsamples taken, the composition of the subsamples, and any processing done to estimate weight from the samples. We then assembled a file classifying the different methods used by each field office. We converted all sample data gathered from the field to lbs/acre units. These data are now freely available on Zenodo (https://zenodo.org/record/4382488#.YSU6HIhKhmM) with the exception of SageSTEP data, which is available upon request.

Spatial extent of fine fuels data

The sites we included from the BLM and SageSTEP field offices were located across six US States in the Intermountain West (Fig. 1), representing eleven BLM district offices, fourteen BLM field offices, and four field sites from SageSTEP. Often, one field office would collect monitoring data from neighboring field offices, and not all BLM field offices in these states monitored fine fuels. Together, these eighteen data collection groups span six ecoregions from the Arizona/New Mexico Plateau to the Columbia Plateau with the majority of points (94%) classified as grassland and open shrublands by the National Land Cover Dataset. A total of 1264 data points, with each data point representing one yearly measurement at one site, were compiled with the majority of observations (86%) occurring since 2007.
Subsample data

After preliminary analysis of the compiled data, we reached out again to fuel specialists to see if any field offices retained their records of subsample data from the field. Most field offices had only fuels data available at a site level, and did not retain records of the individual subsamples taken for each site. However, Boise and Elko field offices gave us their subsample data, and we compiled these separately. In addition, we spent several weeks in the summer of 2020 visiting sites and collecting our own subsample data in the Southern Nevada, Fillmore, Salt Lake City, and Upper Snake field offices using a protocol we developed (see Appendix A and B). At these four field

Figure 1. A total of 1264 measurements of fine fuel loads were collected between 1996 and 2020 by fuel specialists in the Bureau of Land Management and in control plots of the Sagebrush Steppe Treatment Evaluation Project.
locations, we sampled within 10m of the coordinates from established fuel monitoring sites and collected 10 subsamples per site using a 0.5758 m² hoop. We collected all grass, forbs, and litter biomass, and we oven dried all subsamples for 24 hours at 65 °C.

Quantitative analysis performed

After we analyzed the methodology used to collect these data, we wanted to understand the spatial and temporal heterogeneity of these data. There were three spatial scales that we focused on to understand fine fuel measurements; 1) variation among field offices, 2) variation among all sites, and 3) variation among subsamples within sites. We define ‘field offices’ as the 18 collection groups that include 14 BLM field offices and 4 SageSTEP field sites; this is the ‘collecting_field_office’ column in Table 1 and Table 2. By ‘site’ we are referring to the permanent locations where fuel specialists return and measure fine fuel loadings from year to year.

Among field offices (1), we aggregated our data to the long-term mean and (temporal) standard deviation of each site within a field office. We then took the mean of these means and the mean of the standard deviations from each field office.

At the site level (2), we looked at heterogeneity by calculating the long-term mean and standard deviation for each site, without aggregating to the level of field office. We then calculated the standard deviation among long-term site means to look at spatial heterogeneity, and calculated the mean of the within-site standard deviations to characterize temporal heterogeneity. We also calculated the temporal autocorrelation of measurements within individual sites.

The third scale we analyzed, ‘subsamples’, refers to the individuals hoops or quadrats of known areas that are placed at a site and averaged to come up with a site level
estimate of fine fuels. To quantify heterogeneity at this scale (3), we calculated the
standard deviation among the subsamples used to estimate the site-level fine fuel load
measurement, and then calculated the mean standard deviation across sites. We then
conducted a power analysis to understand how many subsamples would be needed to
estimate fine fuel load with an 80% confidence interval around 300 lbs/acre.

Results

We compiled a total of 1264 site-level fine fuel measurements from BLM field
offices and SageSTEP control plots, collected between 1996 and 2020. These fine fuels
data, the methodology data, and an explanatory key for each can all be found in the
dataset we published on Zenodo (https://zenodo.org/record/4382488#.YSU6HlhlKhM).
We include an additional summary table of methodology (Table 1 and Table 2) and
summary table of the mean and standard deviation of these data at the field office level
(Table 3.)
Table 1. Methods used to collect fine fuels site level data. ‘Y’ means ‘Yes’ and ‘N’ means ‘No’, abbreviated for space.

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<td>lbs</td>
<td>3</td>
<td>random/represent</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>0.84</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Twin_Falls</td>
<td>lbs</td>
<td>3</td>
<td>representative</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>0.89</td>
<td>N</td>
<td>oven</td>
</tr>
<tr>
<td>Upper_Snake</td>
<td>tons</td>
<td>2</td>
<td>random</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>0.84</td>
<td>N</td>
<td>air</td>
</tr>
<tr>
<td>Pocatello</td>
<td>lbs</td>
<td>3</td>
<td>random/represent</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>0.89</td>
<td>N</td>
<td>oven</td>
</tr>
<tr>
<td>Fillmore</td>
<td>lbs</td>
<td>4</td>
<td>random</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>1</td>
<td>N</td>
<td>oven</td>
</tr>
<tr>
<td>Boise</td>
<td>lbs</td>
<td>12</td>
<td>random/represent</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Ys</td>
<td>1</td>
<td>N</td>
<td>oven</td>
</tr>
<tr>
<td>Arizona_Strip</td>
<td>lbs</td>
<td>1</td>
<td>representative</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>0.222967</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Tule_Desert</td>
<td>lbs</td>
<td>1</td>
<td>random</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>0.891869</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>SageSTEP</td>
<td>grams</td>
<td>8</td>
<td>random</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>0.25</td>
<td>N</td>
<td>oven</td>
</tr>
</tbody>
</table>
Table 2. Key with additional details on what the columns of Table 1 mean.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>collecting_field_office</td>
<td>The field office that collected fine fuel measurements. Frequently, one field office would measure fuels for the entire district.</td>
</tr>
<tr>
<td>sample_units</td>
<td>Most field offices measured originally in grams and converted to pounds when reporting their data. However, some field offices switched to tons and we converted them back, potentially losing data precision in rounding.</td>
</tr>
<tr>
<td>subsamples</td>
<td>How many hoops or quadrats fuel specialists would lay and collect from at a given site.</td>
</tr>
<tr>
<td>subsample_sel</td>
<td>How fuel specialists were told to place their hoops. ‘Random’ means entirely random placement; either throwing the hoop without looking or placing it at a predetermined point along a predetermined azimuth. “representative” means that fuel technicians intentionally placing hoops in locations that seemed representative of the entire site. “random/representative” indicates a pseudo random approach where technicians would toss in the general direction of a representative region while looking, but not directly placing the hoop.</td>
</tr>
<tr>
<td>grass</td>
<td>Whether fuel specialists would include grass biomass, if found, in their sample.</td>
</tr>
<tr>
<td>forbgs</td>
<td>Whether fuel specialists would include forb biomass, if found, in their sample.</td>
</tr>
<tr>
<td>shrubs</td>
<td>Whether fuel specialists would include shrub biomass, if found, in their sample. The ‘Upper_Snake‘ field office collects shrub biomass separately and we did not include in our compiled ‘biomass’ data to keep all data comparable. While the ‘Salt_Lake_City’ and ‘Fillmore’</td>
</tr>
<tr>
<td>Description</td>
<td>Details</td>
</tr>
<tr>
<td>------------------------------</td>
<td>---------</td>
</tr>
<tr>
<td>‘collecting_field_offices’</td>
<td>would collect shrub biomass if found, their sites are dominated by herbaceous plants.</td>
</tr>
<tr>
<td>litter</td>
<td>Whether fuel specialists would include litter biomass, if found, in their sample.</td>
</tr>
<tr>
<td>sample_size</td>
<td>The size of the hoops used to take samples in meters squared.</td>
</tr>
<tr>
<td>conversion factors</td>
<td>Many field offices would record the color of cheatgrass (<em>Bromus tectorum</em>), a major component of fuel biomass, at the time of measurement. Green, uncured, cheatgrass biomass was multiplied by 0.37 to estimate the dry component of its biomass, while purple uncured cheatgrass was multiplied by 0.53.</td>
</tr>
<tr>
<td>drying</td>
<td>All field offices only collected data when it felt dry to the touch, but some additionally dried it by air or in an oven before recording weights.</td>
</tr>
<tr>
<td>comments</td>
<td>I’ve attempted to summarize major differences in methodology that may affect measurements above. I’ve noted here a few other differences unique to a field office that could also complicate comparison of fuel measurements.</td>
</tr>
</tbody>
</table>
Table 3. The average and standard deviation of all sites within a district, arranged in descending order. ‘Saddle_Mountain(SageSTEP)’ had only one control plot we used.

<table>
<thead>
<tr>
<th>collecting_field_office</th>
<th>abbreviation</th>
<th>mean (lbs/acre)</th>
<th>standard deviation (lbs/acre)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twin_Falls</td>
<td>TF</td>
<td>3757.222</td>
<td>994.344</td>
</tr>
<tr>
<td>Upper_Snake</td>
<td>US</td>
<td>3526.518</td>
<td>1675.275</td>
</tr>
<tr>
<td>Boise</td>
<td>BO</td>
<td>2909.833</td>
<td>1087.22</td>
</tr>
<tr>
<td>Pocatello</td>
<td>PO</td>
<td>2066.032</td>
<td>944.6364</td>
</tr>
<tr>
<td>Southern_Nevada</td>
<td>SN</td>
<td>1897.84</td>
<td>756.6197</td>
</tr>
<tr>
<td>Fillmore</td>
<td>FI</td>
<td>1376.443</td>
<td>959.6319</td>
</tr>
<tr>
<td>North_Ely</td>
<td>NE</td>
<td>1139.972</td>
<td>423.7453</td>
</tr>
<tr>
<td>Elko</td>
<td>EL</td>
<td>1108.658</td>
<td>944.9444</td>
</tr>
<tr>
<td>Winnemucca</td>
<td>WI</td>
<td>938.5883</td>
<td>661.2066</td>
</tr>
<tr>
<td>Arizona_Strip</td>
<td>AZ</td>
<td>900.875</td>
<td>472.7402</td>
</tr>
<tr>
<td>Mount_Lewis</td>
<td>ML</td>
<td>682.4063</td>
<td>408.2841</td>
</tr>
<tr>
<td>Moses_Coulee (sageSTEP)</td>
<td>MC*</td>
<td>610.0796</td>
<td>273.9909</td>
</tr>
<tr>
<td>Salt_Lake_City</td>
<td>SL</td>
<td>531.4615</td>
<td>485.8012</td>
</tr>
<tr>
<td>Tule_Desert</td>
<td>TD</td>
<td>477.25</td>
<td>559.0919</td>
</tr>
<tr>
<td>Saddle_Mountain(sageSTEP)</td>
<td>SM*</td>
<td>412.633</td>
<td>NA</td>
</tr>
<tr>
<td>Tonopah</td>
<td>TO</td>
<td>228.954</td>
<td>264.2816</td>
</tr>
<tr>
<td>Onaqui(sageSTEP)</td>
<td>ON*</td>
<td>159.7641</td>
<td>134.0567</td>
</tr>
<tr>
<td>Owyhee (sageSTEP)</td>
<td>OW*</td>
<td>117.8936</td>
<td>114.942</td>
</tr>
</tbody>
</table>
Units

Most field offices collected, recorded, and reported weights of biomass in units of pounds, however some field offices’ biomass data (Salt Lake City, Upper Snake) were available only in tons, resulting in some loss of information due to rounding. SageSTEP data was collected and reported in grams.

Subsamples

The majority (67%) of field offices used fewer than five subsamples per site, with 74% of all individual site estimates based on fewer than five subsamples. A few field offices (Tule Desert, North Ely, Arizona Strip) collected only one subsample per site (Fig. 2).

Figure 2. The number of subsamples (individual hoops of biomass) taken to measure site level fine fuels by each field office. The number of site level fine fuel observations measured by each field office between 1996 and 2020 are arranged in ascending order on the y axis, and the different field offices and the number of subsamples they took are on the x axis. We use the same color scheme grouping field offices geographically for the remainder of this thesis.
*Subsample site selection*

We did not ask field offices how site locations were originally chosen, as many sites were established by fuel specialists who no longer work for the same office. Generally, these sites were established in grasslands and shrublands where field offices thought it was most important to monitor fuels. We did ask fuel specialists how they placed their quadrats or hoops once they arrived at these sites. Seven field offices placed hoops and quadrats completely at random, and two field offices directly placed hoops in areas that looked representative. The remaining five field offices used an intermediate between completely random and completely chosen for hoop placement. 31.3% of hoops were located completely at random, 46.2% fell in the intermediate category of random and representative, and 22.46% were non-random and representative.

*Sample composition*

The definition of what kinds of plant material (grass, forbs, shrubs, litter) should be included in fine fuel estimates differed among field offices (Table 1). While some fuel specialists (Fillmore and Salt Lake City) told us they would include shrub biomass as fine fuels if found in their hoops, none of their sites had any shrubs, so we were not concerned about this discrepancy. Other field offices (SageSTEP and Upper Snake) collected woody biomass components as separate categories and we did not include them when compiling our fine fuels dataset. All field offices considered grasses as fine fuels and all but two field offices (Elko and Arizona Strip) considered forbs to be fine fuels. We did not have the chance to visit any Elko or Arizona Strip sites, and it is possible that there was little to no forb biomass at their fuel monitoring sites. Whether litter was included as a
component of fine fuels was the most split category with seven field offices explicitly including litter as a component of fine fuels and the remaining seven not doing so.

**Conversion**

BLM field offices monitor fine fuel loads to provide information to the GBCC to make early season fire resource allocation decisions. For this reason, they tried to sample and report fuel loads earlier in the season (see Fig. 3). BLM field offices needed to compromise between collecting data early enough for it to be useful, but late enough that the new year’s biomass had grown and dried out. As many fuel monitoring sites had large amounts of cheatgrass, some BLM field offices would note if the cheatgrass seed was green or purple, an indication of whether it was fully cured or not. These field offices would multiply green cheatgrass weights by 0.37 and purple cheatgrass by 0.53 to help account for early sampling. These two conversion numbers were consistent throughout all

**Figure 3.** The collection date of site level fine fuel samples between 1996 and 2020. Colors represent the collection dates, and the size of points and y axis represents the number of samples collected on that date.
field offices that mentioned this practice as part of their methodology, though I have found no scientific literature of where these conversion factors came from.

Drying

Conversations with field offices indicated that all fuel specialists followed the general practice of not sampling during or immediately following precipitation events. However, six field offices always oven dried their samples, two air dried their samples, and the remaining field offices generally did not dry samples before weighing them. In our separate 2020 field season, we did not samples during or following precipitation events. We weighed our 140 samples before and after oven drying and found oven drying reduced weights by an average of 6%.

Quantitative Analysis

Field office

At the broadest spatial scale, mean fine fuel loads for each field office ranged from 118 lbs/acre (Owyhee) to 3757 lbs/acre (Twin_Falls) and the mean of all field office fine fuel measurements was 1269 lbs/acre with a standard deviation of 657 lbs/acre (Table 3; Fig. 4).

Site

To evaluate variation among sites, instead of aggregating each site’s long-term mean to the level of field office, we calculated the mean of all sites’ long-term means and standard deviations (Fig. 4). We found the mean yearly site-level fuel measurement was 985 lbs/acre, which ranged from 37 to 6280 lbs/acre, and the mean standard deviation of
a site was 547 lbs/acre. As not all 198 locations were monitored more than once, the mean of the standard deviation is based on 151 locations. Sites with high average fuel loads have higher variation over time (Fig. 5). Taking the mean of the inter-annual standard deviation within a site gives us information about the mean temporal variation found in our sites. To look at spatial variation among our sites, we additionally calculated the standard deviation of all the long-term site means, which was 1058 lbs/acre.

For sites that were monitored more than once, we also looked at the autocorrelation of a site’s measurements over time. The mean autocorrelation coefficient across all plots did not indicate autocorrelation (-0.16±0.30, Fig. 6.)

**Average fine fuel load by field office**

**Figure 4.** Average fine fuel load of each field office. Bars represent one standard deviation and field offices are arrange by general geographic area of BLM field offices (Nevada, Idaho, Utah, Arizona) followed by SageSTEP sites (Utah, Oregon, Washington). Colors of each field office are the same as in Figure 2.
Subsamples

Within the subset of data for which we had subsample data in the Boise, Elko, Salt Lake City, Fillmore, Upper Snake and Southern Nevada field offices, the mean standard deviation among subsamples used to come up with a site level estimate for one year was 528 lbs/acre. Our power analysis demonstrated it would take an average of 7 subsamples to be within a 300 lbs/acre margin of error 80% of the time.

Figure 5. Long-term site mean and standard deviation. The x axis shows the long-term site level means and the y axis shows the standard deviation among all measurements taken at a site. Colors show different field offices’ sites.
Discussion

High spatial heterogeneity

Between field offices, our first scale of quantitative analysis, we found a high standard deviation (1128 lbs/acre). While this could represent true spatial differences in fine fuel loads, it could also reflect differences in methods used to measure fuel loads. At the second scale, among the long-term means of site-level measurements, we found the standard deviation among long-term means of all sites was 1058 lbs per acre, which could likewise be explained by the different methods used to measure each site. Temporal heterogeneity, the mean standard deviation among all measurements at the same site, was lower, at 547 lbs acre. This variation could also be explained by differences in methods used to measure fine fuel loads, but in general, each site is being sampled by the same

Figure 6. Autocorrelation in fine fuels per site. The dark green lines represent the mean autocorrelation across all sites and corresponding 90% confidence interval. The light green lines show each individual site’s autocorrelation.
field office using the same methods. That being said, field offices that estimate site level
fuel loads using very few subsamples likely have higher variability at the same site
among years than those that used more subsamples. As shown in Figure 4, we did not see
significant autocorrelation among sites between years.

For the yearly subsample scale, the data we were able to compile and collect
indicates that taking only a few subsamples for a site can lead to poor estimates of mean
fuel load.

The high variability at these scales could mean that fine fuel loads are truly
heterogeneous across space and time and also that the methods used to measure them are
highly variable and result in noisy data. During our own subsample data collection
efforts, we noted that drying fuels in the oven, careful quality control for dirt and rocks,
and randomly tossing hoops can have impacts on fuel estimates. However, even with our
own standardized protocol and the relatively large number of subsamples collected, we
still found high heterogeneity among subsamples at sites, between sites at the same field
office, and among field offices. Taking more subsamples to account for high
heterogeneity makes estimating the amount of fine fuels in a landscape a time-consuming
process. However, with high spatial heterogeneity, taking only a few subsamples might
result in site estimates with such high sampling error that useful comparisons among
years or locations are difficult.

Importance of standardized methods

As shown in Figures 2 and 3, fuel specialists in the BLM across the Intermountain
West use different methods to estimate site-level fine fuels. Most notably, they do not
share a consistent definition of what biomass should be included in sampling, many field
offices do not select subsample places randomly, and the number of subsamples taken per site is often very low. Different field offices have different lab spaces available for drying samples, different numbers of personnel available to help data collection efforts, and different landscapes and types of biomass present in their systems. These differences make a varied approach to sampling understandable, but it may limit the utility of quantitative analysis.

In Chapter 2, we integrated this compiled dataset with remotely-sensed data on herbaceous primary production (Robinson et al., 2019). After converting the fine fuels dataset and the productivity dataset to units of lbs/acre, we would expect a consistent ratio of fuel to productivity if the error from each data source is low, regardless of spatial differences in the amount of fuels between field office sites. We might expect this ratio to be around 1:1 if fuel carryover is low, and greater than 1:1 if fuel carryover is high. We found instead a high variability in fuel to productivity ratios. Some observed fine fuel measurements from the Southern Nevada field office were more than 100 times higher than the productivity of the same year, and ratio differences of extremely large magnitudes were not uncommon. Even after averaging all years of data and all sites within a field office, some field offices systematically had much higher fine fuel biomass compared to productivity. While differences in methods is understandable when compiling a dataset of this scope, finding differences in ratios on the scale of orders of magnitude suggests that a more consistent methodology would be useful.

Standardized methodology in science is rightfully held as the gold standard, and a standardized protocol for BLM fuel specialists monitoring these sites would be an improvement. So long as data collection methods are consistent from year to year within
a field office, temporal comparisons can be made from one site to its previous fuel loads. The GACC does indeed compare a field office’s reported data to previous years to identify a higher-than-normal fuel year for a region, and does not frequently compare fuel estimates between field offices. However, a standardized protocol could greatly improve intra-office, year-to-year comparisons, as well as within-year comparisons among sites. This would benefit the GACC as well as future researchers interested in using this long-term monitoring data for quantitative analyses.

**Recommendations**

We have a series of recommendations to improve the quality of this dataset that should be cost-effective enough to be implemented across BLM field offices: 1) more subsamples per site, 2) consistent definition of fine fuels, 3) random subsample selection with standardized rejection criteria, and 4) skipping conversion terms for uncured fuels.

We would recommend at least seven subsamples per site. Sites with higher mean fuel loads generally have higher variation, and require more subsamples, while low fuel load sites require fewer. Taking more subsamples will only improve estimates, and with the high spatial heterogeneity of the Intermountain West landscapes, most sites require more subsamples than currently being collected.

We recommend defining fine fuels as all annual and perennial forbs and grasses, as well as any litter on the ground. This definition would exclude shrub biomass. Many field offices ended up using this definition in practice, as they were monitoring sites where there were no shrubs, but a more explicit definition is needed.

Many field offices simply toss the hoop behind their shoulder to randomly place it, which we think is a good practice. Rejecting random hoop tosses should be
uncommon, limited to cases when the hoop falls on a trail, rock, or other unrepresentative patch that occupies >50% of the hoop’s area. Taking more subsamples reduces the need to place hoops directly on places that seem representative, or reject randomly selected hoop locations.

We recommend field offices do not multiply biomass weights of cheatgrass to account for its color at the time of sampling. All field offices that use conversions for uncured fuels use the same conversion factors. This is good. However, we were not able to find supporting scientific literature indicating where these conversion factors come from or that they are used outside of BLM field offices. SageSTEP and other scientists that measure biomass do not have a specific correction factor for early sampling for cheatgrass. We would recommend field offices try to time sampling so that grasses have cured.

*Alternative methods to collect fine fuels data*

Given the difficulty of collecting high quality fine fuels data by hand, we recommend the BLM consider alternatives based on new technology, such as photogrammetry and LIDAR from Unmanned Aerial Systems (UASs). Compared to LIDAR, photogrammetry is relatively cheap and has shown promise in a large number cropland agricultural studies (Walter et al., 2018; Gruner et al., 2019; Gil-Docampo et al., 2020) as well as few studies in pasture and forage areas (Lussemt al., 2020; Adrein et al., 2019). Unmanned aerial vehicles (UAVs) equipped for photogrammetry cost <$2,000 and it takes just a few minutes in the field to collect biomass data with pointclouds, compared to hours for destructive sampling. Operating UAVs and processing the resulting pointcloud data requires expertise, but flight design software and data analysis
tools are increasingly cheap and can be open-source as well as user-friendly. Furthermore, point cloud .las files resulting from flight plans can be analyzed in a standard script shared by all field offices, as opposed to methods for destructive sampling, collection, processing, and recording that are often dependent on the personnel, equipment, and lab space available at each field office. This data would also allow further research into quantifying fuel continuity and structure.

Actively gathered, remotely-sensed data using UASs is an exciting direction for the future of fuel monitoring and wildfire management. On-the-ground and satellite data will continue to be extremely useful datasets and we hope they will continue to be collected. With these historical datasets, we were able to develop models with important implications about fuel loading as will be described in the next chapter. However, the sampling uncertainty touched on here, and more extensively in the next chapter, show the need for a new approach to fuel monitoring. We are excited about the potential for UAS data that creates a compromise between the strengths and weaknesses of the manually gathered and remotely-sensed datasets we studied.

References


CHAPTER 3
FORECASTING FINE FUELS IN THE INTERMOUNTAIN WEST

Abstract

Land Management agencies in the Intermountain West use information about regional variation in fuel loads to optimally allocate firefighting resources and funding at the start of the fire season. While static maps work well for large fuel classes, fine fuels, the driver of rangeland fires, vary dramatically from year-to-year. Our goal was to develop a fine fuels forecast to help fire managers anticipate spatial variation in fine fuel loads before the start of the fire season. We compiled a historical record of fine fuel loads reported to the Great Basin Coordination Center and combined it with the Rangeland Analysis Platform (RAP) herbaceous productivity dataset. Using a Bayesian State-Space approach, we (1) built a process model in which the fuel at a location depends on the fuel load of the previous year and the current year’s productivity. The state-space approach allowed us to estimate latent fuel loads across the Intermountain West accounting for both process and observation error. We then (2) forecasted RAP productivity using remotely sensed data available in early spring. Finally, we (3) combined these models to forecast fuel loads based on forecasted productivity and the outputs of our state-space process model, and quantified the associated uncertainty. We found that current year productivity is twice as important (0.25 +/-0.03) as the previous year’s fuel load (0.13+/-0.04), though the process uncertainty of this relationship is high (0.73+/-0.03). Our forecasts of RAP productivity were relatively easy to create and reduced mean absolute predictive error by 13% compared to a strong null model without early season weather covariates. The resulting fine fuels forecast has high uncertainty, with most uncertainty coming from
the process error of our first model relating latent fuel load state changes over time. Our efforts to create a fine fuels forecast by integrating on-the-ground measurements with remotely sensed data shows that in its current state, a fine fuels forecast is too uncertain to be useful, but productivity forecasts show promise as a short-term ecological forecast.

Introduction

Wildfires have regulated our atmospheric composition, shaped the distribution of terrestrial plant communities, and affected the culture and history of humankind. Over the course of mere hours to weeks, this simple chemical reaction leads to dramatic changes in air quality, plant communities, and ecosystem functions. With 3% of Earth’s surface burning annually (van der Werf et al., 2017) short-term fire disturbance events are familiar to most of earth’s residents. While humans have used fire to modify ecosystems for centuries (Keeley, 2002), in the past several decades the fire regimes of many regions have been changing rapidly (Andela et al., 2017; Jolly et al., 2015). In the Intermountain West Rangelands (IWR), a hotter, drier, and more variable climate (Jolly et al., 2015; Westerling et al., 2006), legacy effects from historic fire suppression policies (Schoennagel et al., 2017) increasing human ignitions (Radeloff et al., 2018), and plant landscapes increasingly dominated by exotic annual grasses (Davies et al., 2021; Duell et al., 2021) are swiftly changing fire regimes and necessitating changes in the way land managers prepare for and respond to wildfire season.

In the sagebrush steppe and semi-arid drylands of the Intermountain West, the amount of fuel in landscapes is the main driver of wildfire risk. In general, wildfires can be limited by fuel loads, climate conditions, and ignition sources. Most drylands are fuel-limited; it is frequently hot and dry enough for fires to ignite, but so long as fuel loads
and continuity are low, these ignitions do not spread. However, in fuel-limited systems, wet years can lead to high productivity, high fuel build-up, and more frequent wildfires. In the sagebrush steppe of the Intermountain West, fine fuels are of particular concern. Fine fuels are the small, easily dried out plant materials common in grasslands and shrublands (NWACFIRE) that ignite easily, carry fire rapidly, and vary significantly from year to year (Davies and Nafus, 2013). Research so far in the IWR indicates that one to three wet years with increased productivity builds up fuel loads and increases the probabilities of wildfires (Balch et al., 2013; Pilliod et al., 2017) and this lagged response of fire to precipitation has been observed in other ecosystems as well (Littell et al., 2009).

Historically, the sagebrush steppe had low fuel loads and continuity, with shrubs and bunchgrasses separated by bare-ground interspaces (Reisner et al., 2013) and relatively long fire return intervals (FRI). FRI for sagebrush steppe was estimated at 60 years by Whisenant (1990) and Balch et al (2013) estimated the FRI for native land cover in the Great Basin at 294 years. Annual exotic grasses, such as cheatgrass (Bromus tectorum), have been invading the IWR and increasing fuel continuity and cover. Native vegetation conversion to exotic annual grasslands, recently estimated at 400,000 acres per year (Smith et al., 2021b), is leading to FRI less than five years in some locations (Whisenant, 1990), Chambers et al., 2008) and creating a positive feedback loop leading to the exclusion of the relatively fire intolerant sagebrush and native bunchgrasses (Balch et al., 2013; Bradley et al., 2018; D’Antonio and Vitousek, 1992; Davies and Nafus, 2013; Davies et al., 2021). While productivity of all vegetation in dryland systems is sensitive to precipitation (Holmgren et al., 2006), cheatgrass is particularly sensitive to
precipitation compared with native vegetation (Bradley and Mustard, 2005) heightening inter-annual variability in fuel loads compared to native land cover.

While changes in climate and historic vegetation paint worrying long-term projections for wildfire management in the IWR, in the short term, fire preparation and response does help mitigate the ecological and human impacts of wildfires (Dunn et al., 2020). Organizations charged with wildfire management in the west rely on many inputs including weather forecasts, plant community composition, and fine fuel measurements (Syphard et al., 2018) to prepare for the upcoming fire season. The Great Basin Geographic Area Coordination Center (GACC), which spans Utah, Nevada, and parts of Idaho, Wyoming and Arizona, is headquartered in Salt Lake City and works with the Regional Fire Directors and Managers from the State and Federal agencies to manage firefighter crews, engines, and air support during wildfire season. One part of management is optimizing placement of firefighting resources in the early spring based on which regions face the highest wildfire risk. One important input used by the GACC comes from BLM districts’ measurements of fine fuel load in the early summer (Predictive Meteorologist Shelby Law, personal communication). While fine fuels loading data is a critical piece of information for fuel-limited systems, this data cannot be accurately collected until grasses have finished growing and curing. Furthermore, this data source is time-intensive to gather and each BLM field office only monitors a handful of locations. Organizations like the GACC would benefit from spatially extensive, early-season fuel loading maps to optimally allocate fire-fighting resources at the beginning of each fire season.
Researchers are creating spatially extensive forecasts and near real time maps of herbaceous productivity. Fuelcast (www.fuelcast.net), GrassCast (Hartman et al., 2020), and the Rangeland Analysis Platform (Jones et al., 2021) all provide guided user interface applications where anyone can look at herbaceous productivity. These tools are an excellent start to helping land managers anticipate the fire season. However, fuel loads are not the same as productivity. Fuel loads refers to all biomass in a system, including litter, duff, and biomass from previous seasons’ growth, not just the current year’s production. Conversely, fuel load does not include current year biomass that gets grazed, decomposed, or blown away. Fuel loads are a result of the ecological process of productivity turning into biomass and accruing in a system, as well as leaving a system through herbivory, decomposition, and disturbances. So while productivity forecasts and real time data are useful, they do not provide direct information about the on-the-ground fuel loads that organizations like the GACC rely on.

An ecological forecast of fine fuels, not just productivity, would provide agencies like the GACC a forecast most relevant to their current decision workflow. The combination of remotely sensed productivity estimates and historic records of fine fuels monitoring data provide an opportunity to build and test a fine fuels forecast. This is a pilot study exploring the possibility of forecasting fuel loads in drylands of the IWR by integrating remotely-sensed productivity estimates and fine fuels monitoring data. Our overall goal was to determine if we could forecast fine fuels with low enough uncertainty to help Great Basin land managers allocate fire suppression resources. We also wanted to answer two basic research questions: 1) what is the relative importance of fuel carryover
vs. new production and 2) how accurately can we forecast peak growing season productivity using only data available early in the growing season?

**Methods**

We developed two models (Fuels Model and Productivity Model) which we combine to forecast fine fuels. The Fuels Model is a Bayesian state-space model that represents the process of plant biomass production turning into fine fuels, and fuel leaving the system. The Productivity Model uses a hindcast approach to model each year’s production of grass and forb biomass using remotely-sensed data available in early spring. After developing these two models, we combine them to create a forecast of fine fuels (Fuels Forecast) for the year 2021, and hindcasts for years 1987-2020, accounting for all relevant sources of uncertainty from both models.

**Fuels Model Data**

*Fuels data*

The data used to create the Fuels Model was collected by Bureau of Land Management (BLM) fuel specialists. After grasses have cured, fire personnel visit pre-selected sites, place hoops with known areas, and clip all fine fuels within hoops. They then scale this measurement up to estimate lbs/acre of fine fuels (BLM Fire Specialists, personal communication). The methods involved in estimating site level fuel loads vary widely; different sized hoops are used, different numbers of hoops are placed, hoop placement is randomized differently (or not at all), and specific definitions of what constitutes ‘fine fuels’ differs between BLM fuel specialists (BLM fuel specialists, personal communication). We compiled and published these data
We additionally included data from SageSTEP control treatment plots located in their grassland and shrubland sites. More information on the methods can be found in Table 1 from Chapter 2.

We also compiled subsample data available from the Boise and Elko field offices and spent several weeks in the summer of 2020 visiting sites and collecting our own subsample data in the Southern Nevada, Fillmore, Salt Lake City, and Upper Snake field offices. At these four field offices, we sampled within 10m of the coordinates from established fuel monitoring sites and collected 10 subsamples per site using a 0.5758 m² hoop. We collected all grass, forbs, and litter biomass and we oven dried all subsamples for 24 hours at 65 C.

The sampling sites used for the Fuels Model are located across six US States in the IWR (Fig. 7) representing eleven BLM district offices, fourteen BLM field offices, and four field sites from SageStep. These sites span six ecoregions from the Arizona/New Mexico Plateau to the Columbia Plateau with the majority of points (94%) classified as grassland and open shrublands. A total of 1264 data points at 198 sites were compiled with the majority of observations (86%) occurring since 2007.
Figure 7. Site and region map
A) Field site sampling locations and spatial extent of Productivity and Fine Fuels Forecast
B) Percent herbaceous cover (RAP). Pixels not classified as grasslands and shrublands by NLCD dataset are black.
C) Mean herbaceous productivity 1986-2020 (RAP). Pixels not classified as grasslands and shrublands NLCD dataset are black.
D) Variance of herbaceous productivity 1986-2020 (RAP). Pixels not classified as grasslands and shrublands by NLCD dataset are black.
An expanded figure that includes the landcover and ecoregions of this region can be found in Appendix E.1
Productivity data

The plant productivity data we used is derived from the Rangeland Analysis Platform (RAP) developed by the Numerical Terradynamic Simulation Group at the University of Montana. RAP uses a Landsat-derived GPP model (Jones et al., 2018) along with a Plant Function Type fractional cover data set (Robinson et al., 2019) to model productivity and partition it into component categories (e.g., annual forbs) on a spatial resolution of 30m². By incorporating plant functional type data, this model provides more accurate productivity estimates, especially for shrubland systems often underestimated with MODIS17, and produces estimates in weight per area, a more interpretable output than other remotely-sensed data products. To represent the biomass that turns to fine fuels, we summed the annual forbs and grasses and perennial forbs and grasses categories. These data were downloaded from Google Earth Engine (Gorelick et al., 2017) at a 30x30m scale and the scripts to do so are available in our finefuel4cast Github repository (https://github.com/mensleyf/finefuel4cast). We removed one location misclassified by the NLCD (National Land Cover Dataset) as open water that accordingly had unrealistic herbaceous productivity estimates. The Fuels Model used RAP productivity data for 148 locations across the IWR where on-the-ground fuel monitoring was conducted.

We chose the Rangeland Analysis Platform’s herbaceous productivity dataset for a few reasons we will highlight here. In the early stages of this project, we compared the RAP dataset with NDVI, the other remotely sensed data product related to productivity that was available on a similar time scale. (NIRv and SIF are other promising RS datasets with improved performance for dryland systems, but not available until after 1996.)
NDVI is an important input into the RAP data, but NDVI has many noted caveats in dryland systems and often fails to capture inter-annual variation (Biederman et al., 2017; Smith et al., 2021b). Our exploratory analysis of time series of RAP and NDVI data at our fuel monitoring sites showed that the RAP dataset was less temporally variable, and we note that high variability over time may not be related to capturing inter-annual variability, and might instead only relate to a more noisy data stream. The RAP dataset performed well compared to NDVI on AIM data and flux tower data out (Jones et al., 2018; Robinson et al., 2019), and allows us to remove tree and shrub biomass which may be what drives some of the inter-annual variability of NDVI data that we are not trying to capture.

_Productivity forecast data_

To forecast RAP productivity data, we used all pixels within a bounded polygon of the IWR and downloaded spatial and weather data all at a 4000m² resolution (see Fig. 8). We downloaded all data from Google Earth Engine (Gorelick et al., 2017) temporally aggregated to monthly, seasonal (several months), and annual scales. Our definition of IWR includes all pixels classified by the National Land Cover Dataset (NLCD) as grasslands and shrublands. In addition to the RAP herbaceous productivity data, we also included the RAP fractional cover type dataset. We used precipitation, maximum temperature, and vapor deficit from METDATA developed by Abatzoglou (2013). These derived data are interpolated from the North American Land Data Assimilation System Phase 2 NLDAS-2 dataset, available at high temporal resolution (hourly) but low spatial resolution (12km) and the Parameter-elevation Regressions on Independent Slopes Model (PRISM, Daly et al., 2008) available at high spatial resolution (800m²) and low temporal
resolution. We downloaded USDA soil texture classes from Hengl (2018), to use as a binomial classification of loamy versus non-loamy soils, and surface soil moisture data from SMAP/ NASA-USDA Global Soil Moisture Data.

We explored using many additional covariates and applied ridge regressions to prevent over-fitting. However, we found a simple linear regression model performed similarly to the ridge regressions and high numbers of additional covariates did not improve predictions.

To visualize spatial autocorrelation, we mapped residuals by year (Appendix Fig. E.2) and constructed variograms of the residuals for each year. We found significant autocorrelation in the residuals, but the spatial patterns of over and underestimation shifted from year to year. Accounting for and reducing spatial autocorrelation in a single year may be possible but would not improve our forecast because of the temporal variability in the spatial autocorrelation structure.

Fuels model

We used a Bayesian state-space approach (Fig. 8) to model the ecological process of fine fuels accumulation and turnover. State-space models represent a system that changes over time (process model) where the observations of that system are imperfect and treated as samples drawn from a true underlying true state (observation model). A simpler approach is to assume that the observed data represents the true state of a system, and only model the process. However, we know that the fine fuel monitoring data were measured using different methodologies depending on the field office conducting sampling, are on a far finer spatial scale than the remotely sensed productivity data, and are derived from subsamples coming from a spatially heterogeneous state variable.
Furthermore, separating the process and observation errors allows us to quantify the uncertainties associated with each.

The Observation Model (Eq. 1) relates the true, or latent, underlying fuel \( f_{x,t} \) at site \( x \) and time \( t \) to the observed fuel \( F_{x,t} \) at that time and place, with observation uncertainty \( \sigma_o^2 \).

\[
F_{x,t} \sim \text{Normal}(f_{x,t}, \sigma_o^2) \quad \text{(Eq. 1)}
\]

Our process model (Eq. 2) relates the latent fuel state \( f_{x,t} \) to the amount of fuel at that site in the previous time step \( f_{x,t-1} \) and the amount of aboveground herbaceous productivity of the current time step \( P_{x,t} \) with process uncertainty \( \sigma_p^2 \). The process uncertainty term accounts for all the ecological processes that control fine fuels not
directly accounted for in Eq. 2 (e.g. spatially heterogeneous grazing not accounted for by our spatially uniform carryover term).

\[ f_{x,t} \sim \text{Normal} (\alpha * f_{x,t-1} + \beta * P_{x,t}, \sigma^2_p) \] (Eq. 2)

In our process model (Eq. 2), the \( \alpha \) parameter is an autoregressive term that determines the amount of fuel carryover in a system. An \( \alpha \) value of 1 would indicate that all fuel from the previous time step is carried over, while a value of 0.5, would indicate that only half of the fuel from the previous time step is carried over, with the remainder lost to processes such as grazing and decomposition. The \( \beta \) term is a conversion term for the portion of productivity that becomes fine fuel biomass in the system. Similar to \( \alpha \), \( \beta \) can be thought of as the proportion of biomass production that ultimately becomes fuel.

We chose to implement the state-space model using a Bayesian framework. This approach allowed us to incorporate our knowledge of these datasets and the system through priors, propagate uncertainties, and handle missing data. For our final model, we standardized each fuel data point by subtracting the site’s long-term mean and dividing by the site’s standard deviation. We filtered out locations that were not monitored more than twice and periods of time among included sites that were not monitored frequently, so the final model runs on 148 locations for various time spans between 1996 and 2020 for each location. The number of fuel subsamples taken at each site varied by site and year, but we expect that our estimation of the true, latent mean fuel load would be more accurate in locations with a greater sample size. In other words, we can more reliably estimate the true fuel load with 6 samples than 1. Our observation model accounted for this by reducing observation uncertainty as a function of sample. Further model development details are provided in Appendix F, and all code is provided in the
finefuel4cast repository. The final version of this model is run using 1110 fuel observations, 1165 productivity data points, and produces 1165 latent fine fuel estimates.

We relied on our knowledge of the system, initial data exploration, and an additional compiled dataset of subsamples of fine fuel observations to set priors for this model. We set a relatively informative observation error prior using subsample data compiled from the Elko and Boise field offices which kept field sheets, and additionally from subsample data we collected in the summer of 2020. We also looked at the autocorrelation of the fine fuels dataset and time series between the fine fuels dataset and our productivity dataset to help us understand their relationship. We set relatively non-informative priors for the $\alpha$ and $\beta$ parameters. As we did not have any information on the process error of this model, we used a truncated normal distribution with a large standard deviation to ensure the resulting posterior distribution was informed by data. We also conducted sensitivity analysis for a wide range of the mean and standard deviation of each of our priors, as well as the fixed initial uncertainty term we used.

**Computation**

The Fuels Model was fit with the Hamiltonian Monte Carlo (HMC) sampler using the “rstan” package (Stan Development Team 2020). The final models we use are run with four chains of 20000 iterations with 10000 iterations as a warmup while models used for checking and validation are run for four chains of 2400 iterations with 2000 iterations as warmup to reduce memory and computational use. All model fitting was conducted in R (R Core Team 2021).
Fuels model validation and checking

We checked and validated the Fuels Model in five ways: 1) simulation, 2) monitoring parameter convergence, 3) posterior predictive checks, 4) coverage, and 5) sensitivity analysis of the priors. First, we (1) simulated a dataset with the same structure as our ecological process model (Eq. 1) using actual productivity data from Fuels Model sites. We set parameter values similar to our actual results and fit the Fuels Model to these simulated data to test whether we could recover the true parameter values. To confirm our model would recover the carryover ($\alpha$) and conversion ($\beta$) parameters even if our relatively informative observation error prior was incorrect, we ran simulations with a range of observation error values and a higher carryover ($\alpha$) and lower conversion ($\beta$) value than our model estimated. Our goal was to see how wrong we could be about our informative observation error prior before we would not retrieve underlying parameters correctly. (2) We assessed convergence using the “shinystan” package to visually examine traceplots, and we checked all r-hat values were less than 1.05. (3) We used posterior predictive checks to ensure that model predictions were no more extreme than our observed fine fuel observation data. We looked at the resulting deviance between our simulated and actual data and calculated posterior $P$-values to check that the predictions from our model came from a similar distribution as the observed data. One of the difficulties in using state-space models is that the true fine fuels value is not directly observed and thus calculating residuals between predictions and the true state is not possible. Instead of analyzing the residuals for model selection, we analyzed coverage. (4) We checked coverage by using the parameters from our state-space model to predict the latent fuel state at $t+1$ years, and checked if the observed data at $t+1$ fell within an
80% confidence interval of the prediction 80% of the time. (5) We ran our model on a wide range of priors for each parameter to assess sensitivity of posterior distributions to priors. We checked that posterior distributions were not changing dramatically across realistic prior ranges, and determined the ranges of priors that would result in model convergence.

*Productivity forecast model*

We forecast the annual productivity of the upcoming growing season using information available in early spring about the previous years’ growing season, long-term site information of a location, weather and NDVI data available by March, April, or May. To create a forecast for 2021, we created productivity hindcasts for each year between 1987 and 2020 by building a linear regression for all pixels within our spatial extent using only data available in the early March for each year.

Our modeling efforts focused on covariates that varied in time. We standardized climate variables we downloaded from GRIDMET, such as precipitation, from October of the previous year through March of the current year. Our idea with the standardizing approach was that subtracting the long-term mean from each pixel was a way of having each covariate represent an anomaly from the long-term mean. An average year would result in a data point around zero, while an anomalously dry year would be further from zero. We divided by standard deviation in part to put variances on the same scale, which was especially important given the different units all these climate data were available in. For a full list of covariates, see Appendix C. We also used standardized NDVI of February the one month lag time because of NDVI data becomes available later than the GRIDMET weather data. We standardized herbaceous productivity as well as all other
covariates that were not either binary variables (loamy vs non-loamy soils) or already fractional (fractional AFG cover and fraction of precipitation fallen compared to long-term average).

Forecasting a standardized response variable using standardized covariates, meaning all locations are centered at zero with standard deviations of one, helps our model focus on the temporal dynamics of factors affecting productivity rather than changes in average productivity across space. Modeling variation in productivity across space is relatively easy compared to modeling variation in productivity across time. We additionally included surface soil moisture and bulk density covariates from SMAP, and an interaction between precipitation and surface soil moisture to allow variation among sites in sensitivity to current year weather.

We assessed our forecast by comparing it with three other models: 1) a null model fit without early spring weather, 2) a model that includes monthly climate data for the whole growing season as covariates and 3) a model that includes monthly climate data and monthly NDVI for the whole growing season as covariates. Comparing our forecast with the null model shows how much an improvement the early season climate data adds. Comparing the models with monthly climate, and monthly climate and NDVI for the whole growing season show an upper bound of how well this approach could predict productivity if we were not forecasting but instead were working with all available data about the focal growing season.

The goal of our productivity forecast model was prediction, not inference, however we provide a table of the coefficients of this model (Appendix C and D) for readers who are interested.
Fine fuels forecast model

To combine our two models into the Fine Fuels Forecast, we sampled 500 draws from the MCMC chains of the Fuels model for fuel carryover ($\alpha$), productivity conversion ($\beta$), and process error ($\sigma^2_p$). As we are forecasting the latent, true fine fuel load, we did not include observation error. To quantify the Productivity Forecast parameter error, we drew 1000 samples from the variance-covariance matrix of coefficients in the Productivity Forecast model, and we estimated Productivity Forecast process error from the variance of the residuals.

We started each year’s Fine Fuels Forecast with ten year spin-up using productivity data from t-10 as the initial conditions. We ran simulations of initial starting values to ensure ten years was a long enough spin-up for initial condition uncertainty to fall out of the model. We then ran this model for ten years over 500 iterations, and for the final year used hindcasted productivity data for years 1988 through 2020 and forecasted data for year 2021. We included the process error and parameter error from the Productivity Forecast for the 500 iterations in this last year. These runs for 1988 through 2021 included all sources of uncertainty.

As land managers in the Great Basin GACC already have a good understanding of average spatial variation in fuel loads across the region, we focused our forecasts on temporal variation. We back transformed our forecast from units on the standardized normal scale to display them as percentages above and below the long-term average of each location.

We then partitioned the uncertainty from these sources of error in our model by repeating our Fine Fuels Forecast with different combination of error sources removed.
for a subset of 100 randomly selected locations. For instance, to estimate how much uncertainty in our model comes from the process uncertainty from the Productivity Forecast model, we used point estimates of alpha and beta, and added Productivity Forecast model process uncertainty by adding a normally distribution centered around zero with a standard deviation set to process uncertainty. We repeated this 500 times, with the only source of variation coming from the added normal distribution with a standard deviation set to process uncertainty. To estimate uncertainty from parameter uncertainty of alpha and beta from the Fuels Model, we used 500 draws from the MCMC chains for $\alpha$ and $\beta$, and did not add additional error distributions. We checked all single sources of error and all two-way combinations by calculating the mean of the variances of the 500 forecast iterations produced by each.

**Results**

*Fuels model*

The mean of the posterior distribution of the fuel carryover term $\alpha$ was low (0.13+-0.04) and the production conversion term, $\beta$, was about twice as high (0.25+-0.03), with a tighter distribution. Our observation error was high (0.84 +/- .07), and our process error (0.73 +/- .03) was also fairly high (Fig. 9).
In conducting the prior sensitivity analysis, we found that the posterior distributions of our conversion and carryover terms were fairly stable. Large changes in the mean and standard deviation of their respective priors had small effects on the resulting posterior distribution (Appendix Fig. E. 3). The posteriors of the observation and process error (see Appendix Fig. E.4) were far less stable, showing sensitivity to large changes in the priors. We found that vague priors on observation and process error led to models that did not easily converge on the observation error ($\sigma^2_o$) and process error.
error ($\sigma^2_p$) distributions, as indicated by their traceplots and r-hat scores (Appendix Fig. E.4).

Our model produced acceptable coverage for a wide range of priors. While changing priors affected the amount of uncertainty associated with observation vs process error terms, the overall uncertainty predicted at t+1 was almost always accurate (Appendix Fig. E.5).

In addition to assessing sensitivity to priors, we also validated our model using simulated data. Our model retrieves parameters set similar to our results accurately (see Appendix Fig. E.6). As our model relied on an informative prior for observation error ($\sigma^2_o$), we also tested to see what would happen if our prior for observation error ($\sigma^2_o$) was incorrectly specified and the carryover term, $\alpha$, was higher than our initial results indicated (Appendix Fig. E.7). Our model accurately retrieves the carryover term $\alpha$ and conversion term $\beta$ for a wide ranges of observation error ($\sigma^2_o$) values, but accurately retrieves the observation error ($\sigma^2_o$) and process error ($\sigma^2_p$), terms for a relatively narrow range of observation error ($\sigma^2_o$) values. As shown in Appendix Fig. E.7, so long as observation error is between 0.01 and 1.2, the simulated carryover and conversion terms fall are retrieved within a 95% confidence interval by our model. On the raw scale, by back-transforming the observation error off of the standardized scale, this indicates the observation error in this first simulation can range from 1100 to 2330 lbs/acre before our model fails to retrieve the carryover and conversion terms.

Likewise, we tested to see what would happen if our prior for observation error ($\sigma^2_o$) was incorrectly specified and the conversion term, $\beta$, was lower than our initial results indicated (Appendix Fig. E.8). The range for correct retrieval of a conversion ($\beta$)
term set to 0.1 (instead of 0.25 ±0.03 as in the results from our real data) is slightly larger; with correct retrieval within a 95% confidence interval for observation error ($\sigma^2_o$) ranging from 0.01 to 1.4.

**Productivity forecast**

Our productivity hindcasts, based on spatially varying covariates, and temporally varying covariates available in March, April, or May, outperformed the null model (Fig. 10). We found a 12% reduction in the mean absolute predictive error (MAPE) of the March Productivity Forecast compared to the null. The model that included monthly climate and NDVI data for the whole growing season reduced the MAPE by 8.5% compared to the forecast model.

![Figure 10](image)

**Figure 10.** The ‘Null’ model contains only spatial and previous year covariates and excludes early spring information; the ‘Forecast’ model additionally includes early spring information and the ‘Hindcast’ model adds in monthly weather and ndvi covariates through September. Compared with the null model, the forecast model has a 13% improvement in absolute error across all years while the hindcast model shows a 21% improvement. All models show variation in prediction performance in different years.
**Fuels Forecast**

We used historic productivity data and the output posterior distributions from our Fuels Model to estimate latent fuel loads up through 2020, and then used our Productivity Forecast to create three 2021 forecasts based on data available in March, April and May (Fig. 5). While our forecast does indicate that some regions of the IWR are likely to be above their long-term average, the 80% confidence intervals show that for most areas our model predicts a reasonable chance of fuels being either above or below their long-term average, indicating high uncertainty in our 2021 forecast.

![Figure 11](image)

**Figure 11.** Forecast and 80% confidence interval created for the 2021 fire season using data available in March. Yellow pixels indicate an estimate of 0% difference, green pixels indicate below the long-term average, and red indicates above long-term average.
We created a time series of hindcasts (Fig. 12) using forecasted productivity data, and calculated the mean percent above or below the long-term average for the region. We did this to understand whether 2021 was in any way a particularly difficult to forecast year, as well as so we could see if land managers would have found our hindcasts useful for the years we made them. We found that there are regions and years for which our model does indicate a stronger certainty that the fuel load will be above and below the long-term average, but in general the high uncertainty of 2021 is not an exception.

**Figure 12.** Time series of fine fuel hindcasts and forecast by district. We created hindcasts of fine fuels forecasts we could have provided BLM field offices in March of the year using the posterior output distributions from the Fuels Model and hindcasts of the productivity data. Each plots shows the average percent above or below long-term average of that year across all pixels falling within a given district offices.
To understand how to improve our model, we quantified sources of uncertainty. We found the main source of error was the process error uncertainty ($\sigma^2_p$) from our Fuels Model, followed by process error from the 2021 Productivity Forecast (Fig. 13). We additionally created hindcasts similar to Figure 12 of our productivity model, available in Appendix E.9.

Figure 13. Sources of uncertainty in 2021 Forecast. The gray area represents the total forecast variance from running our model with all sources of uncertainty. Each colored distribution represents the resulting variance with all but one source of uncertain removed or fixed as indicated by the title. Total uncertainty came mostly from process uncertainty in the Fuels Model (green), followed by process uncertainty in the Productivity Model (blue). Parameter uncertainty from each model contributed little to the overall variance of the forecasts, and initial condition uncertainty had dropped to nearly zero by year 2021.
Discussion

Our goal was to create a short-term ecological forecast of fine fuels, instead of the more commonly forecasted productivity, by combining remotely-sensed data on productivity with manually collected fine fuels data. We draw three main lessons from our results: 1) the on-the-ground fine fuels dataset does not contain as much information as we hoped due to high observation error and possible sampling biases. We offer recommendations for a standardized methodology that would improve this dataset and future fine fuel forecasts, but as it stands our fine fuel forecast is too uncertain to be useful. 2) Fuel loads appear to depend more on conversion of productivity into fuels than carryover of fuels from one year to the next. 3) Useful ecological forecasts of productivity are feasible and worth pursuing.

(1) Would our fine fuels forecast be useful to managers?

Our fine fuels forecast was likely too uncertain to produce precise forecasts that would be useful for land managers. In hindcasts for 34 years from 23 districts, there were zero instances where we forecasted with 80% confidence that fuels would be higher or lower than normal. Fig. 6 shows examples of these hindcasts for four of these districts; the rest can be reproduced using code from the finefuel4cast Github repository. A model that predicts every year will be an average year cannot help land managers make these decisions.

However, this work did provide ideas for how to improve forecasts. Most of the uncertainty in our fine fuels forecasts came from the process error in the Fuels Model (Fig. 13). While observation error was also high in the fuels data, our forecast was based on the latent state of fine fuels, meaning that the observation error falls out of our final
forecast uncertainty. However, the high observation error in the fuels data prevented us from exploring more complex models that might have helped reduce the process error (see Appendix E.4). For example, high variation in the ratio of observed fine fuels to productivity across the BLM districts forced us to model the data on a standardized scale, potentially obscuring real spatial variation in fuel carryover and conversion.

Increasing the quantity and quality of the field data could allow us to fit additional parameters in our Fuels Model, such as random and fixed effects on the carryover ($\alpha$) and conversion ($\beta$) terms to account for spatial variation across ecoregion or landcover type. Accounting for these sources of variation could reduce process error. Essentially, there is not enough information in the fine fuels observation data to allow us to reduce process error by fitting a more complicated model, perhaps one that would consider effects of grazing, decomposition rates, and other ecological processes on fuel carryover and conversion.

If manual measurements of fine fuels will continue to be collected, relatively minor changes in methodology could increase their utility. For example, all field offices should follow a Standard Operating Procedure. Ideally, this procedure would call for collection of more subsamples, place hoops and quadrats randomly, and clearly define what biomass is included in the definition of ‘fine fuels’. We also recommend exploring the use of Unmanned Aerial Systems to monitor fine fuels, which would help reduce inter-field office methodological differences and provide more spatially extensive sampling of fine fuels in far less time.
(2) What is the relative importance of fuel carryover vs. new production?

Our results indicate that new production is more important than fuel carryover in predicting fuel loads. This result is directly useful to land managers. We have noticed that fuel specialists do not always measure every fuel monitoring site every year, and some years they do not report their measurements to the Great Basin GACC until late spring. It is true that some regions of the IWR always have higher fuel loads, indicating there is spatial variation in fuel loads. These regions may almost always need more fire suppression resources than others. However, for a given region, fire risk varies by year. In years when fuel monitoring happens late or not at all, it is important to know whether a previous year’s fuel monitoring can be used to help fire preparation for a current year. Our results indicate it is better to use current year productivity information than last year’s fuel monitoring data.

While our knowledge on the importance of fuel carryover vs new production is limited, researchers have investigated fuel decomposition in dryland systems as well lagged fire risk from previous year’s productivity. We know there is grazing across the IWR (Howery, n.d.) which can reduce fuel (Strand et al., 2014), and that photodegradation is a large driver of decomposition in desert systems (Austin and Vivanco, 2006). However, we are not aware of any attempt to quantify what proportion of biomass is decomposed, consumed, or leaves the system through other means (e.g. wind, fire). Researchers have also found that antecedent climate of above normal precipitation leads to increased area burned through higher productivity (Littell et al., 2009; Pilliod et al., 2017; Smith et al., 2021a) which lends support to fuel carryover occurring in drylands. Our model indicates that a large proportion of fine fuels, though
not all, leaves the system every year, and we would expect only small amounts of lagged fire responses to be due to fuel carryover alone.

Despite the limitations of our fine fuels dataset, prior sensitivity analyses and the range of values retrieved with our simulated dataset give us confidence in the robustness of our $\alpha$ and $\beta$ estimates. In the Appendix, Fig. 2 through Fig. 5 show how our model responds to changes in priors. The carryover ($\alpha$) and conversion ($\beta$) terms do not change meaningfully or systematically across changes to their own priors, or changes in the other parameters’ priors, and our efforts to retrieve known parameters from simulated data indicated we would need to be very incorrect in our priors on the observation error before our model would underestimate fuels carryover and overestimate conversion.

The relatively high productivity conversion parameter ($\beta$) is good news for land managers and ecological forecasters. Many groups are making productivity forecasts, such as Fuelcast (www.fuelcast.net) and GrassCast (Hartman et al., 2020). Our results indicate that land managers could rely on these outputs as reasonable proxies for fine fuels.

*Forecasting productivity*

While our fuels forecast was extremely uncertain, we were more successful in forecasting one key input in the fuels model: productivity. We created early spring forecasts of productivity so our fine fuels forecast would be available before the start of fire season. For IWR rangelands, the growing season starts in early spring and continues through summer. Because of the relatively quick turnover of remotely-sensed weather
data and satellite imagery, our forecasts included early spring predictor variables through March, but not the rest of the season.

We found that a reasonable portion of variation in the upcoming year’s herbaceous productivity can be explained with weather data that occurred from October through March. In fact, we were surprised that inclusion of additional monthly climate and NDVI data for the rest of the year, doubling the number of covariates compared with our relatively simple model, did not improve the forecast more (see Fig. 4).

We were focused on forecasting herbaceous productivity as an input for our fine fuels forecast, but our forecast could be useful for other purposes as well. An ecological forecast of herbaceous productivity can be useful for ranchers seeking to optimize managing cattle and could be potentially useful, especially in light of our results about the conversion parameter (β) for optimizing prescribed burns, thinning, and other fuel reduction efforts.

**Conclusion**

Our forecast of fine fuels has too much uncertainty to be a useful tool for land managers. However, by partitioning the sources of uncertainty in our forecast, we know that increasing the quality and/or quantity of the observed fine fuels dataset we compiled could improve the future fine fuels forecast. Better data collection could allow us to simplify some measures we took, such as standardizing all data, and it would allow researchers to experiment adding in fixed or random effects on parameters in the process model to understand how fuel carryover and conversion vary spatially. We still believe that a fine fuels forecast data product would be very useful for land managers, and improvements in data collection efforts are worth pursuing. In addition to helping
organizations like the GACC be better prepared for the upcoming fire season, a stronger fine fuels forecast could also help target efforts of fuel management, optimizing prescribed burns, grazing, and other fuel reduction efforts.

Despite high uncertainty of the fuels forecast, we did find reason to believe that productivity is strongly related to fine fuels. It appears that the process of productivity turning into fuels is more important than fuel carryover from one year to the next, at least in the Intermountain West. We are therefore encouraged by the relative ease with which we built the Productivity Forecast Model with Google Earth Engine datasets, and the relatively low contributions of this model to the uncertainty of our fine fuels forecast. It is further encouraging given the efforts of many researchers to produce ecological forecasts of productivity with guided user interfaces for large spatial extents.

Longer and more severe fire seasons will continue so long as our climate becomes warmer, and the historical sagebrush steppe and perennial grasslands transition to exotic annual grasslands. Projecting the long-term future of IWR landscapes and fire regimes remains uncertain, but short-term ecological forecasts in the face of rapid change could help optimize wildfire preparation and response which would help mediate the immediate anthropocentric, economic, and ecological impacts. Improving forecasts relies on a cycle of making forecasts, finding out why they fail, and identifying how to improve them (Dietze et al., 2018). Our initial attempt is too uncertain to be a useful tool, but the ecological, anthropogenic, and economic costs of wildfires (Thomas et al., 2017) and potential value of a short-term fine fuels forecast to land managers means we should keep trying.
References


CHAPTER 4

CONCLUSION

This thesis explored the possibilities of leveraging an on-the-ground fine fuels dataset with newly developed remotely-sensed data products to build a fine fuels forecast. Our efforts led to insights about the process of fine fuels carryover and conversion, the potential of forecasting productivity data, and the sources of uncertainty in our fine fuels forecast.

In Chapter 2, we discussed the methods we used to compile the fine fuels monitoring dataset we published on Zenodo, and quantitative analysis we conducted to better understand the spatiotemporal heterogeneity in these data. We recommend BLM agencies adopt a Standardized Operating Procedure to standardize their data collection efforts, and we recommend in general that field offices 1) specifically define the types of biomass that constitute fine fuels, 2) collect more subsamples, and 3) randomly place hoops used to collect subsamples. We also highlight the potential for switching from destructive sampling of fine fuels to measurements using Unmanned Aerial Systems to monitor a far wider spatial extent of these data in far less time that would allow for higher standardization and data comparisons.

In Chapter 3, we built our 2021 fine fuels forecast using two models. The Fuels Model we built to model the process of productivity turning to fine fuel. This Bayesian state-space model integrates our compiled on-the-ground data with the newly developed RAP remotely sensed dataset. Our approach corroborates what many other land managers have noticed about fine fuel loads: there is high variance and independence from year to year. Our estimates of the fuel carryover term indicate that the yearly fuel monitoring is
useful given how much fuel loads can change from one year to the next, and our high fuel conversion term indicates that productivity forecasts are relevant inputs to making fire season decisions.

Our forecast of herbaceous productivity illustrated that the year’s productivity can be well forecasted even with only remotely sensed data available in early spring. It also highlights potential uses of Google Earth Engine for making forecasts given the quick turnaround on data availability.

The uncertainty of our final forecast of 2021 is high enough that it does not provide conclusive information for land managers. Likewise, our hindcasts of latent fuel do not have narrow enough confidence intervals to have provided conclusive reason for actions. While we were able to ignore observation error from the fine fuels dataset in propagating latent fuels, this observation error put limits on fitting extra parameters in the Fuels Model that could reduce our process error. A better Fuels Model may be possible in the future with more data, and more standardized methods used to collect data.

We hope this thesis will provide land managers with a stronger idea of how to use productivity data to supplement manually gathered fine fuels data, as well as refine destructive sampling fine fuel data collection and experiment with other ideas of monitoring these data.
APPENDICES
Fine Fuel Collection Standardized Operating Procedure

Contents

Introduction: 75

This is a draft of a standardized protocol for fine fuel collections based largely off protocols and conversations with BLM fire fuel specialists across many field offices in the Great Basin.

Materials: 76

A GPS with your plot coordinates, clippers, data sheets, bags for collecting samples, a hoop (9.6 ft^2), an oven for drying samples (ideally), and a balance.

Terms: 76

Definitions of terms we use in this protocol.

“Fine Fuels” definition 77

Fine fuels will include all grass, all forbs, and litter (dead plant material, including small twigs) but will NOT include living shrub material.

Sample Placement: 78

Go to the GPS location. Throw the hoop over your shoulder, without aiming. If it lands in an area that is clearly unrepresentative, you can reject the point and throw again, but don't directly choose a spot to place it.

Samples per plot: 79

Take at least 6 subsamples (measurements of fine fuels with hoop or quadrat) at each plot. Feel free to take more if desired!

Timing: 79
Sample once grasses have cured, and try not to measure soon after precipitation. The GACC would like data as early as possible though, so you may have to measure before grasses have finished curing at some of your sites. There's a correction factor for cheatgrass we can use to partially account for this.

Sample clipping: 80

All grass, forbs, and old standing dead whose stem originates in the hooped area should be clipped along with any litter that is >50% within the hooped area.

Sample drying: 80

Dry all herbaceous biomass in an oven at 65C or 150F for 2-5 days or until the weight between time points stops changing. If there is no way to dry the fine fuels collected in an oven, weights can be taken in the field or air-dried.

Scaling subsamples to field plot: 81

We have included an excel spreadsheet to scale up your weight (in grams) to lbs per acre. Feel free to modify it, or use something that has worked for you in the past. This also has the data format for reporting data to the GACC (most important is that it includes coordinates (NAD83), the sampling date, the fuel loading, and units).

Literature Cited: 82
Introduction:

Many BLM field offices in the Great Basin have been collecting fine fuel loading data for over twenty years. These data help districts compare the current year to previous years’ fuel loads and request additional resources for years when the fuel load is especially high. Agencies such as the GACC (Great Basin Coordination Center) receive the fine fuel numbers from these BLM field offices, and use these data to make decisions about fire resource allocation in the beginning of the season. These data also could provide a strong foundation for basic research on fine fuels. One shortcoming that complicates use of these data however, is that BLM districts often use different methodologies to measure fine fuels which makes comparisons between districts and broader ecological questions complicated and uncertain.

The Adler Lab has compiled fine fuels data from across the Great Basin in conjunction with the GACC and with the help of the fire specialists that monitor fuels across these BLM field offices. We hope to create a model for forecasting fine fuel loading using productivity models derived from Landsat imagery. The field measurements are the ground-truthed dataset. A regional forecast would provide more spatially extensive, dynamic, and less labor-intensive estimates of fine fuels for the Great Basin to help both with early seasons resource allocation. However, current methodological differences among districts complicate the use of the historical fine fuels data.

We would like to develop a standardized fine fuel loading protocol that can be used across the BLM districts. As part of this effort, we can conduct field work to understand the magnitude and direction different methods may have on fine fuel
measurements. This will help us calibrate the historic measurements taken with these
different methodologies in order to make them comparable.

We realize that finding a standardized method that can be applied on such a broad
scale and communicating it with the many personnel who are involved will be difficult.
We also realize that the real experts are the people who have been doing the direct fuel
sampling and working directly in the systems they measure. It is our hope therefore, that,
we will receive significant suggestions and feedback from you and that this protocol will
be facilitated by us, but not written by us. The end goal is to eliminate systematic error
that makes comparing fine fuel loading data difficult, but there are many ways we can get
there. What we have written so far is based largely off email correspondences, phone
conversations, and existing protocols that you have shared with us.

Materials:

Hoop (ideally 9.6ft^2)

Clippers

Oven

Bags (large brown bags should be sufficient)

Sharpies

Binder clips

Scale accurate to 0.1 grams for lab measurements

Spring scale accurate to 1g for field measurements (only if necessary)

Data sheets

GPS

Terms:
Sample: Fine fuel load samples taken in one hoop. Multiple samples are taken per field plot.

Field plot: The GPS coordinates of a location where multiple samples are taken. These are scaled up to lbs/acre.

Fine Fuels: plant material that can dry easily and carry fire. Includes grasses, forbs, and litter.

Litter: Plant material loose on the ground, no longer attached to plants or rooted to the ground. Includes grass, leaves, needles, any small plant material (<0.25 inch)

Old standing dead: Dead plant material that is still rooted and connected to the ground

“Fine Fuels” definition

“Fine Fuels” or “Flash Fuels” are plant materials that can dry easily, carry fire, and are a useful measurement to summarize and define an area’s susceptibility to fires. A few specific definitions confirm this;

Flash Fuels: Fuels such as grass, leaves, draped pine needles, fern, tree moss and some kinds of slash, that ignite readily and are consumed rapidly when dry. Also called fine fuels. (from Northwest Area Command Fire [NWACFIRE] with the Forest Service) https://www.fs.fed.us/nwacfire/home/terminology.html

Fine Fuels: Fast-drying dead or live fuels, generally characterized by a comparatively high surface area-to-volume ratio, which are less than ¼ inch in diameter and have a timelag of one hour or less. These fuels (grass, leaves, needles, etc) ignite readily and are consumed rapidly by fire when dry. See also: Flash Fuels (from NWCG Glossary of Wildland Fire, PMS 2015)
A key question is whether or not to include shrubs. While not as likely to dry out and carry fire as grass, shrub foliage is not irrelevant. For fine fuel load in the Great Basin, it is herbaceous material that tends to have high variation year to year compared to larger scale woody material as well as the greatest ability to dry out and become flammable as the season progresses (Piliod et al 2017). Sampling shrubs can be difficult and they do not vary year to year as much as herbaceous fuels (Doug Shinnerman, personal communication, Scott and Burgman, 2005). For these reasons, we propose to collect grasses, forbs, litter and old standing dead, but not shrub material. Only biomass above the ground should be clipped, as close to the ground as possible. Care should be taken that dirt, roots, and rocks are not accidentally included.

Sample Placement:

The goal of sampling is an accurate representation of fuel loading at a landscape level. To accomplish this, it is necessary to avoid systematic bias in the selection of areas to sample, and to collect sufficient samples to account for variation. To select the spot in which to place the hoop, a degree of randomization is necessary to avoid potential bias. A method that has been widely employed in the BLM is walking to the GPS coordinates of a given field plot, and throwing the hoop without looking behind.

1 Historically, all districts with data/methods in the Great Basin have collected grass, most collected forbs, some collected shrubs, and some collected litter.

2 If field offices want to continue collecting live shrub material—it is completely fine. However, it should be reported as a separate category than other fuel loading components so that comparisons are easy to make. The exclusion of shrubs and woody materials is definitely something we are open to discussion on! Another possibility is for all districts to collect woody material/shrubs as a separate category.
your shoulder. 3If the hoop lands in a spot that is not representative, rejecting the placement and randomly selecting another can be justified. Examples of a justified rejection would include if the hoop lands on an uncommon shrub patch, on a path, or in some location that is clearly not representative of the region.

Since each field plot will have six subsamples (next section) placing the hoop in a spot that is higher or lower in fuel loading than normal is fine. Rejecting a placement spot should be uncommon.

Samples per plot:

Taking multiple samples at each plot ensures that a few high or low fuel measurements don’t have undue influence on the overall landscape estimate. However, sampling is time consuming. We therefore recommend each field plot take six samples at each field plot.4

Timing:

Ideal timing of fine fuel measurement has to balance the ability to report numbers early so that the GACC and other agencies can make decisions, but late enough that the grasses/forbs have had time to cure. The GACC begins making fire resource allocation decisions at the beginning of May, but for many sites this would be far too early to

---

3 Another approach is to use azimuths and distances along a transect to sample. This approach is slightly more complicated, but achieves the same end of randomization. We do not believe this will lead to a difference in the end result, so if this method is preferred, that is fine. We’re also open to discussions about whether this method is better and should be universal.

4 Taking more subsamples is completely fine! It will change the excel spreadsheet and data forms we’re including, but again, our goal is to eliminate systematic differences in fine fuel load estimates and taking additional subsamples is completely fine.
sample and waiting until later is best. In situations when sampling must take place before cheatgrass has cured and when cheatgrass is a major contributor to loading, a conversion factor can be used on the cheatgrass subsample of the fuel load. In these cases, cheatgrass should be collected and weighed separately from the rest of the biomass. Timing will vary per district, but sampling within 24 hours of a rain event is not advisable unless there is an oven to dry samples and as soon as to when grass is cured is best.

Sample clipping:

All grass, forbs, and old standing dead whose stem originates in the hooped area should be clipped along with any litter that is >50% within the hooped area. Fine fuels should be placed in a labeled bag (ie Tungsten_6/15/2019_sample1). Separate uncured cheatgrass into separate bags if necessary and place in labeled bags (ie purple_cheatgrass Tungsten_6/15/2019_sample1). We’ve created an excel spreadsheet (“data_collection.xlsx”) which has an options in different tabs for field sheets that can be printed and brought along to record date and the labeled names of samples taken.

Sample drying:

If there is an oven (preferred) to air-dry samples:

Samples should be dried in a drying oven at 65 C (~150 F) for 48-120 hrs (2-5 days). (Taken from NEON Herbaceous Biomass SOP) and then weighed. Samples should be air-dried for 2-5 days. Samples can be considered fully dry when the weight difference between the latest two timepoints for a subsample of 10 of the samples is equal to zero, or
the weight difference is within $\pm 1\%$. If that happens before 5 days have passed (which is likely) then weights can be taken and recorded.

After being removed from the drying oven, samples will slowly begin taking in moisture from the air. For these reasons, it is good to zero the scale and weigh the samples quickly after removal. Weights should be taken with a scale accurate to $\sim 0.1$ gram.

*If no oven for drying and weights were taken in field or air-dried:*

If there is no oven present in the BLM facilities (ie samples are weighed in the field or air-dried), we would like to receive one sample from the six taken from each plot so that we can see approximately what impact no oven drying has on the recorded sample to better compare it with other districts using different methods. Drying in an oven vs no drying or air-drying does have potential to change the final weight estimated significantly, so it is important we try to calibrate different methods. (Please email me if this will be the case and we can work something out.)

**Scaling subsamples to field plot:**

Once weights for each of the six subsamples have been obtained, we’ve prepared an excel spreadsheet (“data_collection.xlsx”) that can scale these estimates up to lbs per acre for three common hoop sizes and assuming 6 subsamples per field plot. Feel free to modify this to suit your purposes, or continue using a past spreadsheet that is already familiar.

Included in this spreadsheet is the correction factor for uncured cheatgrass. Most districts have been converting weights by a conversion factor of 0.37 for uncured green cheatgrass
and 0.53 for purple cheatgrass. We’ve also included a tab for weights that were taken in the field or air-dried that will need an oven-dried correction factor to add in.

The final tab has the format the GACC would like to receive your data. For coordinates, we would ideally like them to be in NAD83 (espg 4269).

Literature Cited:


Personal communication:
Doug Shinnerman
David Pilliod
Shelby Law
## APPENDIX B: FINE FUEL COLLECTION SOP FIELD SHEET

<table>
<thead>
<tr>
<th>Sample</th>
<th>Bag Name</th>
<th>Dry weight (grams)</th>
<th>Green cheatgrass? (Y)</th>
<th>Purple cheatgrass? (Y)</th>
<th>Corrected lbs</th>
<th>Mean per subsample</th>
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<tr>
<td>1</td>
<td></td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td></td>
<td>0.0</td>
</tr>
<tr>
<td>2</td>
<td></td>
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<td>0.0</td>
<td>0.0</td>
<td></td>
<td>0.0</td>
</tr>
<tr>
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<td></td>
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<td>0.0</td>
<td>0.0</td>
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<td>0.0</td>
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<td>0.0</td>
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<tr>
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<td></td>
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</tr>
</tbody>
</table>

Mean of subsamples (grams): 0.0 0.0 0.0

Mean of subsamples (lbs): 0.0 0.0 0.0

Hoop size (ft^2): 9 9.5 10.3

Feet^2 per acre: 43560 43560 43560

Lbs per acre: 0.0 0.0 0.0

Comments:
### APPENDIX C: COVARIATES IN PRODUCTIVITY FORECAST MODEL

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<thead>
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<th>dataset_source</th>
<th>GEE_name</th>
<th>GEE_script</th>
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<td>rangeland-analysis-platform</td>
<td>RAP_gee_tiffs</td>
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<td>prev_z_agb</td>
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<td>RAP</td>
<td>rangeland-analysis-platform</td>
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<tr>
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<td>z_pr</td>
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<td>'IDAHO_EPSCOR/GRIDMET'</td>
<td>temporal_gee_tiffs</td>
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<tr>
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<td>NOAA/CDR/AVHRR/NDVI/V5</td>
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<tr>
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<td>NASA_USDA/HSL/SMAP_soil_moisture</td>
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<tr>
<td>z_bulk_dens</td>
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<td>USDA</td>
<td>&quot;OpenLandMap/SOL/SOL_TEXTURE-CLASS_USDA-TT_M/v02&quot;</td>
<td>spatial_gee_tiffs</td>
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<td>USDA/GRIDMET</td>
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APPENDIX D: COEFFICIENTS OF PRODUCTIVITY FORECAST MODEL

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<tr>
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</tr>
</tbody>
</table>

Appendix D. Table of coefficients of covariates of productivity forecast model
We did not construct our forecast model with the intent of drawing inferential conclusions, but we were interested nonetheless in which variables were important in our model. We also provide a correlation matrix of the weather covariates in Appendix E.9 for readers who are interested.
Appendix E.1 Expanded site and region map
A) Field site sampling locations and spatial extent of Productivity and Fine Fuels Forecast
B) National Land Cover Dataset (USGS)
C) US Ecoregions L3 (EPA)
D) Percent herbaceous cover (RAP). Pixels not classified as grasslands and shrublands by NLCD dataset are black.
E) Mean herbaceous productivity 1986-2020 (RAP). Pixels not classified as grasslands and shrublands NLCD dataset are black.
F) Variance of herbaceous productivity 1986-2020 (RAP). Pixels not classified as grasslands and shrublands by NLCD dataset are black.

All 34 years of spatial residuals can be created by running code in the finefuel4cast repository. These results are on the standardized scale where red indicates over prediction and green indicates under prediction.
Appendix E.3: Sensitivity Analysis: carryover (alpha) and conversion (beta)

On the y axis we show changes in the 95% confidence intervals of all parameters in our model (carryover, conversion, observation error, process error) as we change priors distributions one at a time (x axis). Our model is not sensitive to changes in the carryover (alpha) and conversion (beta) parameters’ priors. Full code and additional analysis can be found in https://github.com/mensleyf/finefuel4cast
Appendix E.4: Sensitivity Analysis: observation error (sig_o) and process error (sig_p)

On the y axis we show changes in the 95% confidence intervals of all parameters in our model (carryover, conversion, observation error, process error) as we change priors one at a time (x axis). Our model is more sensitive to changes in the observation error (sig_o) prior’s mean and variance terms relative to the process error term, but is also somewhat sensitive to changes in the process error (sig_p) parameter’s priors.
Appendix E.5: Sensitivity Analysis: Coverage plots

We predicted the latent fuel state at $t+1$ years, and checked if the observed data at $t+1$ fell within an 80% confidence interval of the prediction 80% of the time. We ran four versions with all sources of uncertainty, only process uncertainty, only observation uncertainty, and only parameter uncertainty to see how the partitioning of uncertainty changed as the priors changed.
Appendix E.6. Simulation retrieval of simulated dataset similar to our results

The x axis has the four known values of our simulated data, the y axis shows the 95% confidence intervals of our model’s estimates of those values. If the model retrieved the values, the points should fall on the 1:1 line.
Appendix E.7: Simulation retrieval of higher alpha

Our model retrieves the carryover (alpha) and conversion (beta) terms correctly for relatively wide range of observation error (sig_o) set values, before our model begins underestimating carryover.
Appendix E.8: Simulation retrieval of higher beta

Our model retrieves the carryover (alpha) and conversion (beta) terms correctly for relatively wide range of observation error (sig_o) set values, before our model begins underestimating carryover.

Appendix E.8. Simulation retrieval of lower beta
Our model retrieves the carryover (alpha) and conversion (beta) terms correctly for relatively wide range of observation error (sig_o) set values, before our model begins underestimating carryover.
Appendix E.9 Time series of fine fuel hindcasts and forecast by district

We created this figure to compare it to Fig 12 in the main text, with the same four districts shown. All district plots can be made from our code repository, and we find that the productivity forecast does have many instances of a 90% confidence interval indicating a above or below long-term average year.
Appendix E.10 Correlation matrix of weather covariates

We created a correlation matrix with our weather covariates to better understand how they were related. The size and color of each dot shows the magnitude of correlation, and blue colors indicate positive correlation while red indicates negative correlation.
Fuels Model Development

Developing the final form of the Fuels Model involved high amounts of trial and error. We explored many paths of different model structures and data transformations before settling on the high density, standardized data route. We will briefly explain some of the routes we attempted and why we ultimately did not follow them here, and some other considerations we think some readers may be interested in.

Model Structure Choices:
- Random and Fixed Effects
- ‘High density’ sites and years
- Intercept Term
- Model initialization
- Observation error (sig_o)

Data transformations:
- Raw
- Log
- Deviations
- Standardized

Model Structure Choices

1. Random/Fixed effects

We added the National Land Cover Dataset (NLCD) produced by USGS in 2016 at a scale of 30m using Landsat imagery and the level III ecoregions data from the EPA to our compiled fine fuels observation dataset for each site monitored by SageSTEP and the BLM. We thought the alpha and beta parameters may have differed spatially and these additional site data could help differentiate how fuel carryover and conversion differed in grasslands vs shrublands or different ecoregions. However, the resulting
posteriors did not differ meaningfully so we chose to go with the more parsimonious model. As noted in our manuscript, we suspect we need more fine fuels observation data and better data collection methods to be able to detect small changes in the carryover and conversion parameters across the IWR.

We also wondered if random effects by field office on a/b/sig_o might help the model because of the differing methodologies used by each, but likewise did not find meaningful differentiation in the posterior effects.

2. High density sites and years

A traditional matrix format of our data would include 198 rows representing all sites where fine fuels were ever monitored and 25 columns representing all years (1996-2020) that at least one fine fuel site was monitored. This matrix would be 75% filled with missing values because so many sites were only sampled once or twice and because the vast majority of field offices did not start monitoring fuels and/or keeping track of their measurements until much more recently.

We realized these large amounts of non-randomly missing data were an issue early on, and our initial solution was to reduce our matrix format of fine fuels data to include only locations that had been monitored more than once, and only years since 2007, which included 86% of our total compiled data. This resulting 161 locations x 14 years matrix had <50% of data ‘missing.’ By ‘missing’ we mean that the posterior for that location and year’s latent fuel load was based only on productivity and the past and future fine fuel observations, and there was no current year fine fuel measurement. With the 2007-2020 approach, we were including 1071 out of 1264 data points.
However, we tested increasing percent missing data in our simulation and found that even by 30% missing data, our parameters were retrieved noticeably more poorly. So, we configured a more complicated approach. We wrote an algorithm that runs over our entire 198x25 fine fuels observation matrix, and produces metadata we feed into rstan about which locations to include, and which years to include for each location. This approach let us include 148 locations, with a different number of years for each location, and 1110 total measurements. While the fine fuels observed data (‘O’ in our stan code) is still a 148 location by 25 years matrix, each location (row) is run over a different number of years. The output of latent fuel load (‘Fvec’) has 1165 values, so only 5% of the estimates are based on ‘missing’ data.

3. Intercept term

Not including intercept terms forces a model to predict a response of zero when all covariates are zero. For many ecological processes, including our Fuels Model, this is fairly reasonable. Without any fuel present in the system the previous year and without any productivity, the fuel load of the current year should be zero. But forcing a model through zero also means that if the response data is systematically higher than the covariate data, the coefficients on the covariate data may misrepresent the relationship because they are being forced to rescale the prediction to the scale of the response variable.

We calculated correlations, variances, and ratios of our productivity and fine fuels dataset. While correlated (correlation is 0.4 between raw fine fuels and productivity data), the fine fuels data set had much higher mean standard deviation per location (554 vs 170 lbs/acre.) We would expect the ratio of fuel to productivity to be generally around one if
these two data sets were on the the same scale. While we converted all data to lbs/acre, this did not seem to cause these two datasets to be on the same scale. Most ratios were greater than one, and some were orders of magnitude higher than the corresponding productivity estimate. And while there were occasionally fine fuel to productivity ratios <1, in general, productivity was lower than the fine fuel observed dataset. The mean ratio was 3.4, which we interpreted as either the fine fuel observation data sets is systematically overestimating fine fuel loads, or the RAP productivity dataset is systematically underestimating it. For these reasons, we looked into including an intercept term.

However, the intercept term complicated the interpretation of our model ecologically, in that we don’t actually believe there would be fuel in Intermountain West ecosystems without any productivity or previous year fuel. It additionally adds another parameter that our model has to estimate, which makes it slower and can lead to identifiability issues. We ended up addressing this problem instead by standardizing our data (see Data Transformations section).

4. Initializing the model

We created a simulation to see if and how long locations with different initial values, but with the same annual productivity values, would take to converge at a latent fuel estimate. We use the process equation used in our Fuels Model and point estimates for the carryover and conversion terms from the final version. We start initial values at time zero at a wide range of values. We found that within a few years estimates were similar, and within ten years even unrealistically extreme differences in initial values had disappeared (see figure 2). This happens because the fuel carryover term, alpha, is
conveniently low, and the impact of the initial values decreases each year. If fuel carryover was a significant contributor to next year’s fuel, initial condition uncertainty could be a bigger source of error in our forecast.

In the Fuels Model, we began the initial latent fuel load of each location coming from a normal distribution centered at the previous year’s productivity (the ‘P0’ term) with a fixed standard deviation of 0.8. We also fit the a model with this term as a parameter estimated in stan, as well as examined runs of the model with this fixed term increasing between 0.1, and 2 by 0.1. Extremely low fixed values result in increases in the carryover term and observation error, while higher values have higher process error and lower carryover term parameter estimates. We think 0.8 is a decent compromise.

5. Observation error (sig_o) (Fig 3)

We noted many differences in the methods between field offices in the ‘methods.csv’ file. We hope that standardizing the data accounts for some of this. There is clearly high spatial heterogeneity in fuel loads in the Intermountain West, which we documented through our own field work as well as compiling subsample data. Different subsamples within 10m of each other could vary significantly. It seems clear to us that all field offices should likely be collecting more subsamples, although our data is from only a part of the IWR and we do not know if there are areas in the IWR where the fuel landscapes are more homogenous. For these reasons, we looked into ways to structure our model to take into account that each fuel measurement was based on a different number of subsamples. We did this by dividing the sig_o term by the square root of the number of subsamples taken. We looked into model structures without this added piece
of data, and found this including it helped convergence greatly and made more sense because we set the sig_o prior based on these subsample data.

**Data transformations:**

1. *Log-transformed vs deviations vs standardized log-transforming*

   We initially log transformed our fine fuels and productivity data as neither were normal distributions. Both distributions are left-skewed, nonzero distributions with means of x and y respectively. However, while log-transformations make our data look more normal, it doesn’t address that they have different means and variances. We eventually realized that this was forcing the fuel carryover term to account for these differences in means and variances.

   After experimenting with adding an intercept as mentioned earlier, we tried to address this by calculating deviations from the mean for each location. This meant that both the productivity and fine fuels observation dataset were centered around zero for each location, and our carryover term no longer had to put these two data products on the same scale. We liked this approach as it allowed our data to be on the raw scale and easily interpretable fine fuel estimates in lbs/acre below or above average. However, the fine fuels data still had far higher variance. The higher variance we realized was still forcing the alpha term to act as a smoothing term between the two models.

   Our final solution was to standardize both datasets. This allowed us to confidently interpret the ecological meaning of our carryover and conversion terms without worrying the carryover term was rescaling data because of systematic differences in their lbs/acre estimates and smoothing the latent fuel estimates because of the high variance in the fine
fuels data. Afterwards, we transformed our data back to the raw scale and also report it as a percent above the long term normal scale to help with interpretation.
VITA

Mira Ensley-Field

Research Assistant (September 2019 - 2021)

Adler Community Ecology Lab: Quantitative ecologists exploring plant community dynamics in space and time and creating models for forecasting at scales useful to land managers.

- Collaborated with land managers in Bureau of Land Management to organize, compile, analyze and publish fuel monitoring dataset of Intermountain West
- Paired automated forecast of grass productivity through Google Earth Engine and a Bayesian State-Space Model to create early forecasts of wildfire for land managers
- Mentored other students to help with running code, models, and simulations
- Participated as data analyst in multiple global and regional projects; including global human impacts on phenology and economics of rangeland forage production in Utah

Field Technician (March 2018 – September 2019)

National Ecological Observatory Network: Network of field sites using standardized protocols to provide open data for scientists studying continental-scale research.

- Successfully led outdoor teams to collect field data using standardized protocols with strict adherence to data quality across diverse field sites
- Performed quality assessment and control on data collected by terrestrial ecology team
- Wrote R code to assess change and compare percent cover of plant diversity data year to year
- Managed documentation and samples of herbarium, create automated labeling code and process, and doubled the size of plant herbarium in one field season

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Publications: