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Great Basin Ecological Forecasting II

Assessing and Forecasting Live Fuel Moisture Content of Wildfire Fuels for the Eastern Great Basin to Improve Wildfire Timing and Severity Predictions

DEVELOP Technical Report

Final Draft – April 2nd, 2020

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1. Abstract
The eastern Great Basin (EGB) extends throughout the states of Arizona, Colorado, Idaho, Utah, and Wyoming, covering approximately 411,000 km². In recent years, wildfires in the EGB have increased in frequency and size, representing a growing concern for our partners at the Bureau of Land Management (BLM), the National Weather Service (NWS), and the Great Basin Coordination Center (GBCC). Live fuel moisture (LFM) is an important factor in predicting wildfire risk, as dry vegetation requires less energy to combust than wet vegetation. Land managers currently derive LFM levels from just 165 *in situ* sites in the EGB. In order to provide partners with a more accurate assessment of LFM, the team used data from the National Elevation Dataset, Aqua and Terra Moderate Resolution Imaging Spectroradiometer, and Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite. These datasets include vegetation indices, evapotranspiration, and topographic variables, which were used to create biweekly forecasts of LFM throughout the EGB. An accuracy assessment was conducted using historical *in situ* data from our partners at the BLM and the GBCC. This model allowed our partners to make informed decisions regarding resource allocation in response to the predicted timing and severity of wildfires in the EGB.

Keywords

live fuel moisture, remote sensing, wildfire, evapotranspiration, NDVI, EVI2, MODIS, VIIRS

2. Introduction

2.1 Background Information
Wildfires are an important part of the ecosystem in the eastern Great Basin (EGB), a 411,000 km^2 region covering portions of Arizona, Colorado, Idaho, Utah, and Wyoming. Wildfires improve ecosystem health by regulating plant succession and species composition (Leblon, Bourgeau-Chavez, & San-Miguel-Ayanz, 2012). However, wildfires can threaten human lives and infrastructure (Leblon, Bourgeau-Chavez, & San-Miguel-Ayanz, 2012). Additionally, wildfires promote the spread of invasive species, such as cheatgrass (*Bromus tectorum*), which has changed the species composition in the EGB (Pilliod, Welty, & Arkle, 2017). Changes in vegetation, climate, and land use are all contributing to the increase in frequency and size of wildfires in the western United States (Davis & Weber, 2018; Dennison, Brewer, Arnold, & Moritz, 2014; Pilliod, Welty, & Arkle, 2017). Due to the rising concern related to the impacts of wildfire on human resources, predicting wildfire ignition and severity can help managers make well-informed decisions regarding resource allocation. While many factors influence the ignition and severity of wildfires, one strong natural indicator is live fuel moisture (LFM) (Yebra et al., 2013; Nghiem et al., 2014).

Currently, there are 165 *in situ* LFM measurement locations in the EGB, allowing for approximately one sample per 2,600 km^2. However, the majority of sampling occurs in Idaho and Utah with gaps of up to 100 km between sites. Increasing the spatial resolution of LFM measurements would allow our partners at the Bureau of Land Management (BLM), the Great Basin Coordination Center (GBCC), and the National Weather Service (NWS) to better predict wildfires. In order to accomplish this, our team created a forecasting model to predict LFM for May through September using remotely sensed data and *in situ* measurements. The model was validated using LFM measurements from 2019 and can be used to forecast LFM during future fire seasons.

During the Fall 2019 NASA DEVELOP term, a model was created to validate LFM in the EGB. This model used elevation, aspect, evapotranspiration (ET), land surface temperature (LST), and the Normalized Difference Vegetation Index (NDVI) to make predictions about LFM. Using *in situ* measurements as validation, the model had an average accuracy of 8.2%. This term, our team further refined the model with additional inputs to increase accuracy and to create biweekly LFM forecast maps. To supplement the model, Enhanced Vegetation Index 2 (EVI2) was selected because EVI2-based LFM estimations can predict the start of a fire season and highly correlate with LFM *in situ* measurements (Myoung et al., 2018). Normalized

Difference Water Index (NDWI) was selected because NDWI levels can support LFM seasonal monitoring due to the inclusion of a water absorption band, whereas NDVI relies on the "greenness" instead of true moisture (Dennison, Roberts, Peterson, & Rechel, 2004). Leaf Area Index (LAI) was selected because it is representative of vegetation biomass, which is related to LFM (Myoung et al., 2018). Fraction of Absorbed Photosynthetically Active Radiation (FPAR) was selected due to its relationship to vegetation productivity and thus, it may correspond to how much water a plant is using (Yu et al., 2018).

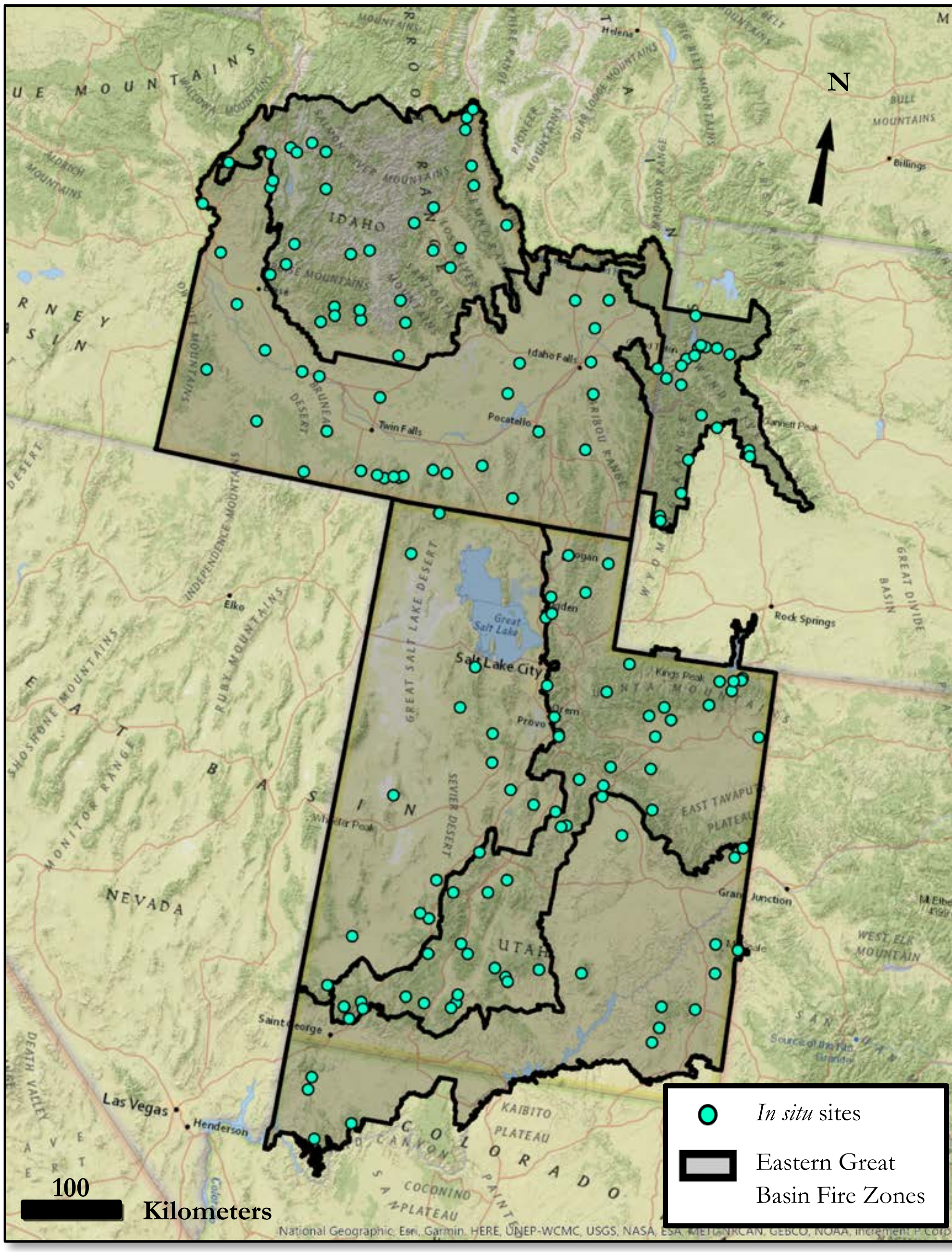

Figure 1. The EGB study area in AZ, CO, ID, UT, & WY. There are 165 *in situ* LFM observation sites.

2.2 Project Partners & Objectives

Our partners for this project were the Upper Snake Field Office of the Bureau of Land Management (BLM), the Pocatello office of the National Oceanic and Atmospheric Administration (NOAA) National Weather

Service (NWS), and the Great Basin Coordination Center (GBCC) under the National Interagency Fire Center (NIFC). The BLM and the NWS were the end users of the forecasting model, as they issue wildfire safety warnings and allocate resources based on LFM estimations. Our LFM forecasting model increased the spatial resolution of LFM estimates across the EGB, allowing our partners to make better-informed decisions regarding resource allocation to combat wildfires.

The primary objective of this project was to refine an existing predictive LFM model to forecast LFM for future fire seasons in the EGB. Our team refined the existing model and determined the accuracy of this updated model by validating against *in situ* LFM measurements. The model utilized *in situ* LFM measurements, topographic variables, Moderate Resolution Imaging Spectroradiometer (MODIS) data, and Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (VIIRS) data to forecast LFM across the EGB.

3. Methodology

3.1 Data Acquisition

Our team acquired *in situ* measurements of LFM from the National Fuel Moisture Database for April 1st through October 31st of 2019. These measurements are taken biweekly by land managers at 165 measurement points across the Eastern Great Basin by weighing sampled vegetation while it is wet (wet weight) and after it has been thoroughly dried (dry weight). The LFM measurement is computed according to Equation 1 below.

$$\text{Live Fuel Moisture} = \frac{(\text{wet weight of sample - dry weight of sample})}{\text{dry weight of sample}}$$

Equation 1. Formula used to determine LFM measurements in the National Fuel Moisture Database.

We downloaded existing vegetation type (EVT) data for the EGB in 2018 from the LANDFIRE dataset. Additionally, the team downloaded data from the USGS National Elevation Dataset (NED) in order to create aspect and elevation rasters at 10-meter spatial resolution. NASA Earth observation (EO) data were downloaded from NASA EARTHDATA and the Land Processes Distributed Active Archive Center (LP DAAC) Application for Extracting and Exploring Analysis Ready Samples (AppEEARS). The Suomi National Polar-Orbiting Partnership (Suomi-NPP) Visible Infrared Imaging Radiometer Suite (VIIRS) provided NDVI, FPAR, LAI, and EVI2, while Aqua and Terra Moderate Resolution Imaging Spectroradiometer (MODIS) provided the team with ET and surface reflectance. All data were acquired for April 1-October 31, 2019 (Table 1).

Platform and Sensor	Data Product
Suomi-NPP VIIRS	VNP13A1 Vegetation Indices 16-Day L3 Global 500 m SIN Grid V006
Suomi-NPP VIIRS	VNP15A2H Leaf Area Index/FPAR 8-Day L4 Global 500 m SIN Grid V006
Aqua MODIS	MYD16A2 Net Evapotranspiration 8-Day L4 Global 500 m SIN Grid V006
Terra MODIS	MOD16A2

	Net Evapotranspiration 8-Day Global 500m SIN Grid V006
Terra MODIS	MOD09A1 Surface reflectance 8-Day Global 500m SIN Grid V006

Table 1. List of sensors and data products

3.2 Data Processing

Data processing was conducted primarily using Esri ArcGIS Pro 2.5. Initially, the historic fuel moisture dataset was modified to include "Term" and "UID" fields. Each month was divided into two periods, term 1 (the 1st through the 15th of the month) and term 2 (the 16th through the last day of the month). This table was then used to create a feature class by utilizing latitude and longitude of the field sampling sites; this feature class was later used as a model input. Next, a buffer was created around the USGS NED dataset, in order to accurately resample the study area boundaries. Then, aspect and elevation rasters were created from the NED dataset that included the buffer. These rasters were then clipped to the study area.

Further data processing occurred within the LFM forecasting model that was built in ArcGIS Pro's Model Builder. This processing is summarized in Appendix A. First, the fuel type of interest was selected, along with the term to which to be forecasted. For the construction and validation of the model, our team selected all sagebrush species as the fuel of interest, but end users are able to select other fuel types if desired. The desired study area is then selected—all further processing will be clipped to this area. To validate the model using 2019 data, we selected the entire EGB as the study area. Future users can use fire zones within the EGB or other polygons that include an area of interest. Time 1 and Time 2 data inputs (Appendix A, blue ovals) are selected for the term of interest (e.g. forecasting for Term 1 of July requires Term 1 June and Term 2 June as data inputs). These inputs include LAI, FPAR, Aqua ET, Terra ET, EVI2, NDVI, and surface reflectance as rasters and *in situ* LFM measurements as feature classes. Before the linear regression runs, NDWI is calculated from surface reflectance, using Equation 2.

$$\text{NDWI} = \frac{\rho_{857} - \rho_{1241}}{\rho_{857} - \rho_{1241}}$$

Equation 2. Formula used to derive NDWI from surface reflectance bands of wavelength ρ_{857} and ρ_{1241}.

The Linear Regression (Appendix A) uses R-ArcGIS Bridge to leverage R's capabilities in conjunction with ArcGIS Pro to compute a linear regression equation between the Time 1 and Time 2 rasters for each EO data product and the *in situ* LFM measurements. The computed equation is then used to predict a Time 3 raster for each variable. The elevation and aspect rasters are used as constant inputs into the model (no linear regression is conducted for these inputs). The prediction rasters and topographic variables are then composited. This composited image is used as an input into the Train Support Vector Machine (SVM) Classifier tool, which is trained using the predicted *in situ* LFM measurements. The SVM generates a classifier which is used to populate an LFM forecast raster. This LFM forecast raster is a classified map that categorizes LFM into 6 classes according to BLM guidelines (Appendix B). Finally, the classified maps were masked to include only shrubland using a LANDFIRE shrubland layer, as the model was trained using only sagebrush LFM measurements. This process was completed for each term between May and September, 2019 to create a classified raster for each term (Figure 2, Appendix C).

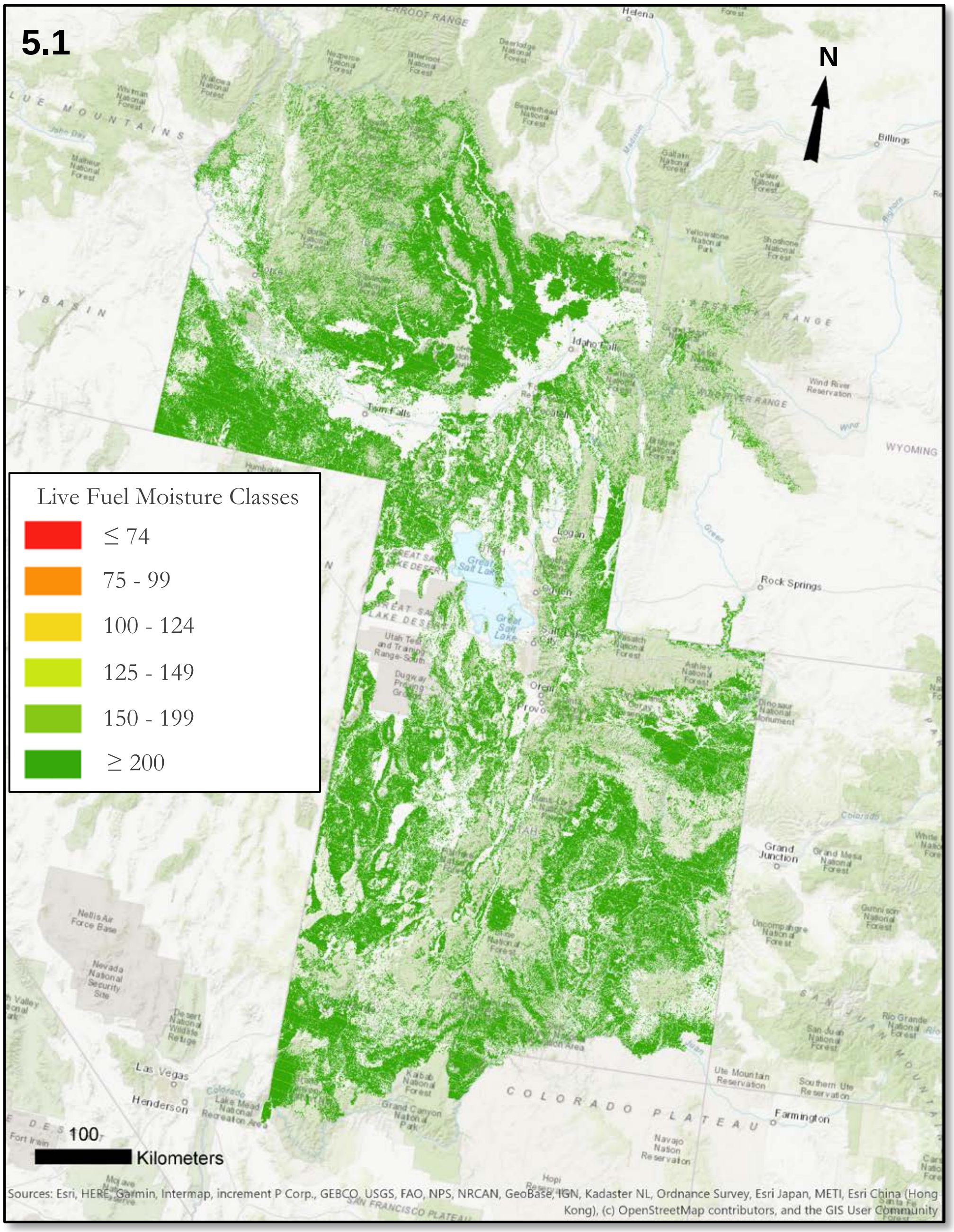

Figure 2. Live Fuel Moisture forecast for May Term 1, 2019 (Term 5.1)

3.3 Data Analysis

We validated the predictions generated by the LFM forecasting model against *in situ* LFM measurements taken during the forecasted term. In order to determine model accuracy, we computed a confusion matrix in ArcGIS Pro that compared the classified map and the *in situ* data for the forecasted term. The validation points were taken from the term 3 *in situ* measurements (if forecasting to 1st term of July, *in situ* points from 1st term of July were used to validate). The confusion matrix takes the actual class value of the *in situ* point and compares it to the forecasted value on the classified map where the *in situ* point is located. If the class value of the *in situ* point matches the classified map's value, the confusion matrix identifies it as a success. This is done for all validation points available for the forecasted term (Figure 3). The confusion matrices provide an overall accuracy of the classified map, which indicates how often our model is predictcting correct LFM at each measurement site.

4. Results & Discussion

4.1 Analysis of Results

The classified forecast maps can be seen in Appendix C. These forecasts show that LFM is predicted to be highest in May, and decreases throughout the season, as expected during a typical fire season. There appears to be the most variation throughout the EGB later in the fire season, particularly in August. The results of our confusion matrices showed overall accuracies that were highly variable (Figure 3, Appendix D). The average accuracy of our model was 13.65%. The majority of the low accuracies occurred in the beginning of the fire season, from May to the beginning of July. For these first 5 terms, the accuracy ranged from 0% to just 1.56% (Figure 3). This indicates that the model was not able to accurately predict LFM in the beginning of the 2019 fire season, when LFM was highest. These low accuracies in the beginning of the fire season may be due to the scarcity of *in situ* points against which we validated the model results. There are fewer *in situ* measurements collected during these early terms because there may still be snow at some sampling locations or frequent precipitation, which prevents *in situ* sampling of LFM (Figure 3, Appendix E). Having fewer points against which points to validate decreases the likelihood of a correct prediction because the sample size is too low. In general, accuracy increases are the number of *in situ* measurements for training and validation increases (Figure 3).

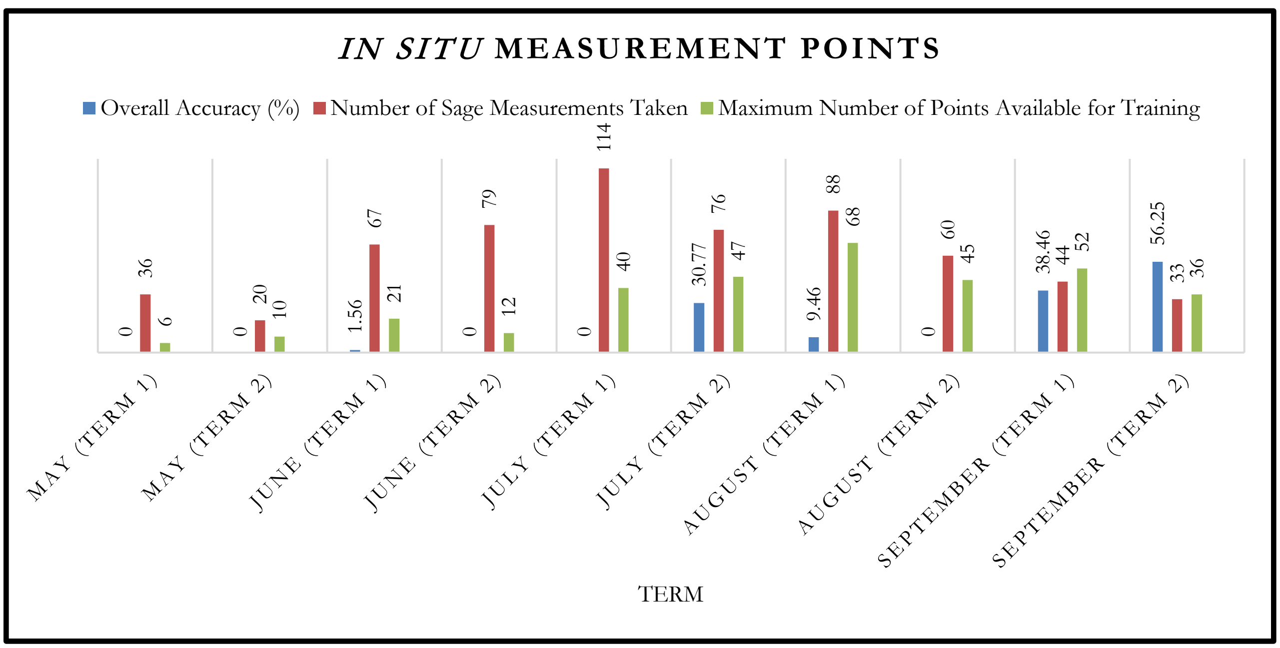

Figure 3. Overall accuracy, the number of *in situ* measurements taken in the EGB that are available for validation, and the maximum number of *in situ* measurements available for training for each term.

Notably, the classifed map for the second term of August appears to overall have higher LFM than the first term of August (Appendix C). This is not expected, as it is anticipated that LFM would continue to decrease continuously from July to September due to dry conditions. It is possible that this high LFM in August is due to higher-than-average precipitation that occurred during the beginning of August (National Weather Service, 2019). Due to the biweekly nature of our forecasting model and the lag between a precipitation event and the uptake of moisture by vegetation, this event would not be represented until the next forecast, term 2 of August, when LFM increased. Furthermore, the second term of August has a 0.00% accuracy; along with its higher LFM and this low accuracy may be due to having fewer measurements taken for the term than for previous terms.

The main limitation of this model is the number of *in situ* measurements available to train and validate the model. Although there are 165 sampling locations throughout the EGB, not every location samples sagebrush, which was the primary fuel of interest for this study. Additionally, not every sampling location (of the 165) is sampled during every term, meaning many fewer measurements are used by the model. This not only limits the number of training points, but also limits the number of points on which we validate the model. Furthermore, not all of the sage measurements that were taken in each term can be used to train the model. In order to run the linear regression, only sites that were sampled for sage during both the first term and second term may be used to train the model. Then, SVM uses just 60% of those measurements as training points. These limitations result in very few points available for training and the model (Figure 3), which decreases the model's accuracy.

Despite the low average accuracy of the classified maps produced by the model, the model can still be useful for future fire seasons. Although accuracy is low at the beginning of the season, the maps still represent when the "green-up" phase stops and the risk of fire begins increasing as LFM decreases. The forecasts are most accurate when LFM is low, which provides vital information about when fire risk will be at its peak due to low LFM.

4.2 Future Work
Further refinement is required to increase model accuracy and better forecast LFM in the EGB. This may be done by incorporating weather forecasts, such as temperature, relative humidity, precipitation, and wind speed as input parameters. Before a fire ignites, land managers and meteorologists rely heavily on weather factors to gauge wildfire risk level (Nghiem et al., 2014). Nghiem et al. (2014) found that their empirical LFM model was improved by including temperature, and found that incorporation of daily minimum temperature resulted in the highest improvement. Thus, adding weather variables could improve our model. Our team attempted to incorporate weather variables into the model, but were not able to due to time constraints and data processing time. Our partners could easily add weather forecasts, acquired from the National Blend of Models Dataset (NBM), into the model as an input parameter, which may increase the accuracy for the 2020 fire season and beyond.

Previous studies have shown that soil moisture data from the Soil Moisture Active Passive (SMAP) L-band radiometer (SMAP) correlates with live fuel moisture (Jia, Kim, Nghiem, & Kafatos, 2019). Our team was interested in incorporating SMAP data into the model as a monthly parameter. However, due to processing time and the feasibility of integrating the processes into our model during this ten-week project, our team opted to exclude SMAP data. An additional study with fewer time constraints could benefit from incorporating SMAP soil moisture data into the LFM forecasting model. SMAP data could also be more useful in refining the model when used for smaller regions such as fire zone study areas in comparison to the larger EGB study area.

Another dataset that should be pursued in future LFM forecasting models is the ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS), which measures the temperature of vegetation as an indicator of water stress (Greicius & Dunbar, 2018). This dataset was considered for the project, but it was ultimately excluded due to a lack of data in our study area. Other study areas with more ECOSTRESS coverage could benefit from including vegetation surface temperature data.

Additonally, future researchers could modify the model to rely on a single script in order to produce LFM forecasting maps. Currently, the LFM model requires 29 input parameters and a few exterior geoprocessing steps; conversely, a script may require fewer input parameters allowing for a more user-friendly experience. Refining the model by using one script could decrease processing time and reduce error when running the model.

5. Conclusions

The results of this project indicate that a remotely sensed forecasting LFM model is feasible for the EGB, and our methods may be applied to other geographical areas that would benefit from such a model. Our model is able to predict the spatial variation of LFM across the EGB at a spatial resolution that is approximately ten thousand times higher than what was provided by the *in situ* measurements, resolving down from approximately 2,600km^2 to just 250m^2. However, the prediction accuracy varies considerably, and the model forecasted especially low accuracy early in the fire season. In order to determine if this is a flaw of the model or due to a lack of data, more results should be generated and additional *in situ* data should be included. We believe the model accuracy could also be improved by using soil moisture, water stress, and weather data as inputs. Overall, the forecasting model provides land managers with the abiity to predict LFM in the EGB at a finer resolution than previously possible. This method will help improve predicting fire risk, allocating resources, and protecting human lives.

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7. Glossary

AppEEARS – Application for Extracting and Exploring Analysis Ready Samples
BLM – Bureau of Land Management
DEM – Digital Elevation Model
EGB – eastern Great Basin
EO – Earth observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time
ET – Evapotranspiration
EVT – Existing Vegetation Type
EVI2 – Enhanced Vegetation Index
FPAR – Fraction of Absorbed Photosynthetically Active Radiation
GBCC – Great Basin Coordination Center
in situ **–** on-site, ground truth
LAI – Leaf Area Index
LFM – Live Fuel Moisture
LP DAAC – Land Processes Distributed Active Archive Center
MODIS – MODerate resolution Imaging Spectroradiometer
NBM – National Blend of Models
NED – National Elevation Dataset
NIFC – National Interagency Fire Center
NDVI – Normalized Difference Vegetation Index
NDWI – Normalized Difference Water Index
NOAA – National Oceanic and Atmospheric Administration
NWS – National Weather Service
Suomi-NPP – Suomi National Polar-Orbiting Partnership
USDA – United States Department of Agriculture
USGS – United States Geological Survey
VIIRS – Visible Infrared Imaging Radiometer Suite

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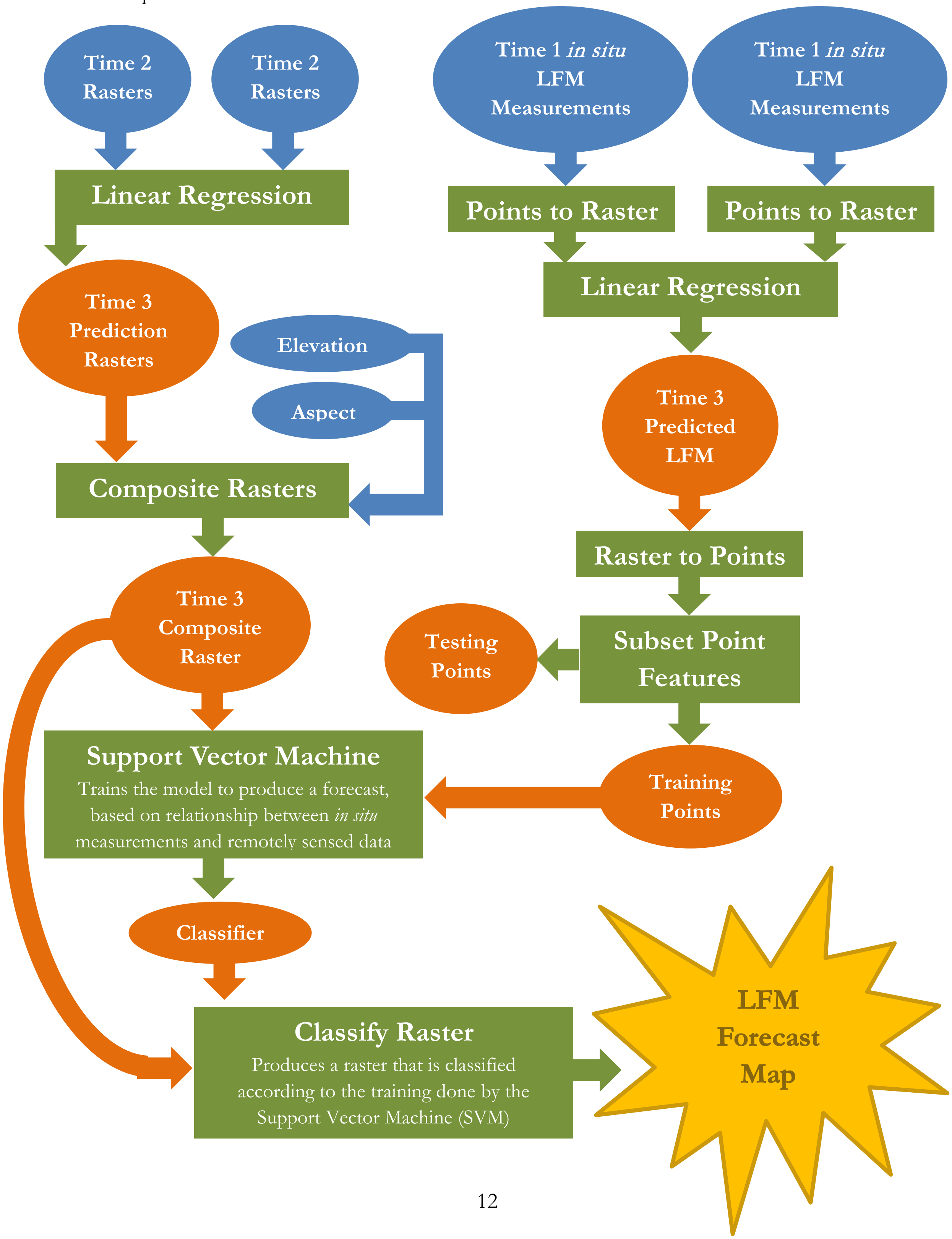
9. Appendices

Appendix A

Workflow of the LFM model built in ArcGIS Pro. Blue ovals indicate user-input features, green squares indicate processes run, and orange ovals indicate datasets produced within the model. The environment in which the model is run indicates that layers are all resampled to a 250m resolution and reprojected to NAD 1983 Albers Equal Area Conic USGS.



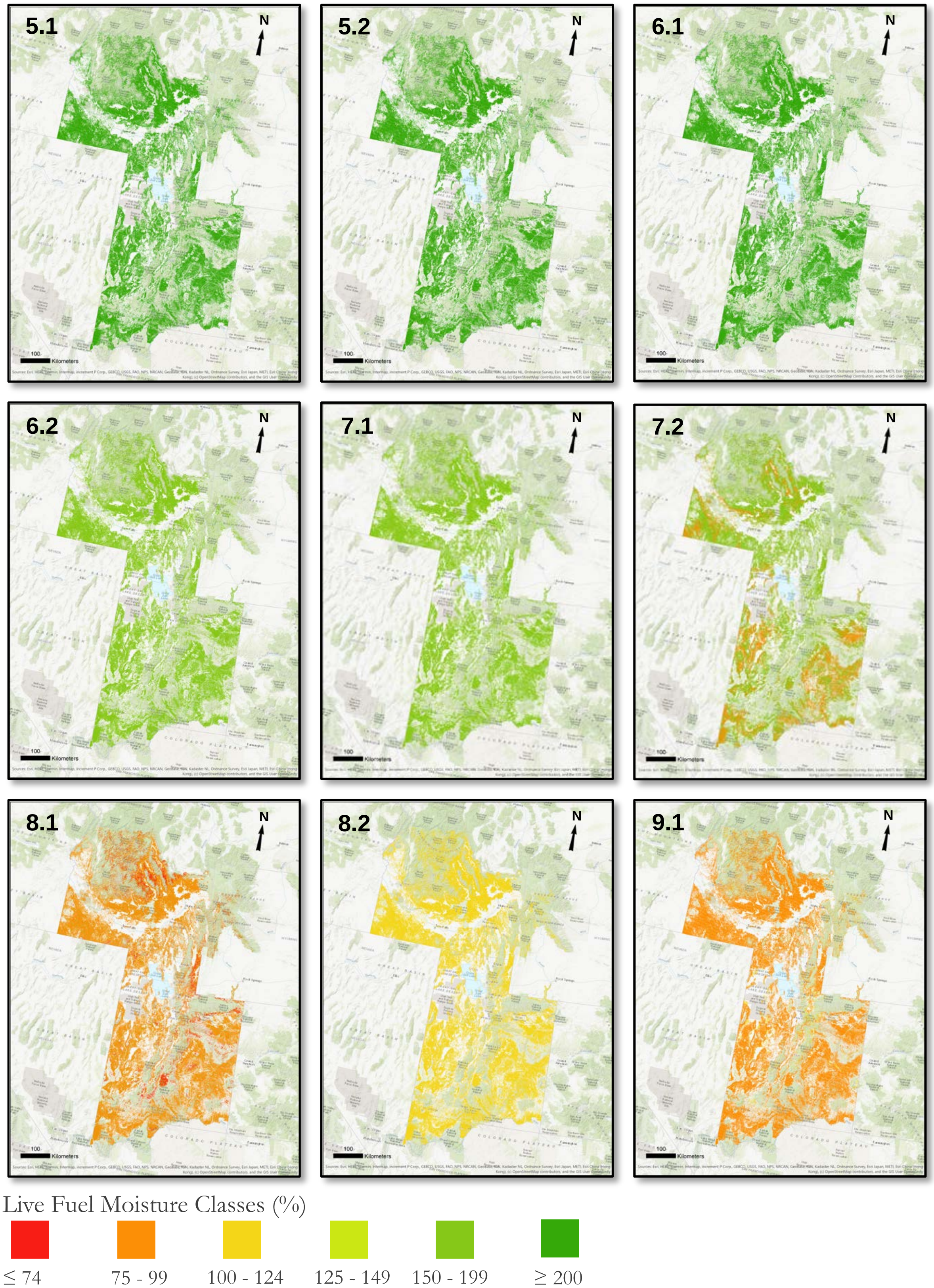
Appendix B

Classes represented in the classified LFM forecase maps based on BLM guidelines.

Class	Live Fuel Moisture Class (%)
1	≤ 74
2	75-99
3	100-124
4	125-149
5	150-199
6	≥ 200

Appendix C

Live Fuel Moisture Forecasting Maps for the 2019 fire season.



Appendix D

Overall accuracy of the predicted LFM map for each term as calculated in the confusion matricies. *This term included Aqua MODIS surface reflectance in calculating NDWI, rather than Terra MODIS surface reflectance – a potential source of error.

Term	Overall Accuracy (%)
May (Term 1)	0.00
May (Term 2)	0.00
June (Term 1)	1.56
June (Term 2)	0.00
July (Term 1)	0.00
July (Term 2)	30.77
August (Term 1)	9.46
August (Term 2)	0.00
September (Term 1)	38.46
September (Term 2)	56.25*

Appendix E

Number of LFM sage measurement sites per term in 2019. These points were used for training and validating the model. There are fewer points available early in the fire season. The maximum number of points available for training the model was calculated by taking 60% of the minimum number of training sites available from the previous two terms.

Term	Number of LFM Sage Measurements taken in 2019	Maximum Number of Points Available for Training
April (Term 1)	11	N/A
April (Term 2)	18	N/A
May (Term 1)	36	6
May (Term 2)	20	10
June (Term 1)	67	21
June (Term 2)	79	12
July (Term 1)	114	40
July (Term 2)	76	47
August (Term 1)	88	68
August (Term 2)	60	45
September (Term 1)	44	52
September (Term 2)	33	36