Fall 2019

Great Basin Ecological Forecasting

Integrating NASA Earth Observations into Live Fuel Moisture Models to Improve Wildfire Timing and Severity Forecasting in the Eastern Great Basin

DEVELOP Technical Report
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1. Abstract
The eastern Great Basin (EGB) covers approximately 411,000 km^2 within the states of Arizona, Colorado, Idaho, Utah, and Wyoming. Since the 1950s, wildfires have increased in both frequency and size within the EGB and neighboring states. Partners at the Bureau of Land Management (BLM), the Idaho Department of Fish and Game, the National Weather Service, and the Great Basin Coordination Center (GBCC) are particularly concerned with Live Fuel Moisture (LFM). Living vegetation that fuels wildfires, referred to as live fuel, requires greater energy input to combust when wet and less energy input to combust when dry, making LFM a vital measurement for predicting wildfire risk and severity. To increase spatial coverage for the EGB from the 155 *in situ* observation sites, the NASA DEVELOP team modeled LFM using satellite data from Aqua and Terra Moderate Resolution Imaging Spectroradiometer (MODIS) and Suomi National Polar-orbiting Partnership (NPP) Visible Infrared Imaging Radiometer Suite (VIIRS). The team incorporated remotely sensed data into machine learning modeling techniques, such as the Random Trees Classifier through ArcGIS Pro, to develop a predictive model of LFM. The remotely sensed data included vegetation indices, land surface temperature, evapotranspiration, and topographic variables. Model accuracy was evaluated by testing generated values against historical data obtained from partners at the BLM and the GBCC. The LFM model benefitted partners by improving the spatiotemporal resolution for wildfire forecasts. While model accuracy averaged at 8.2%, the LFM trend developed from model classification was useful for resource allocation and improved emergency response to wildfires within the EGB.

Keywords
remote sensing, wildfire, live fuel moisture, NDVI, evapotranspiration, soil moisture, MODIS, VIIRS

2. Introduction

2.1 Background Information
Wildfires are a major source of disturbance for vegetation and are difficult to manage, regardless of the ignition source. They can impact water quality and watershed susceptibility to erosion and flooding for months, even years, after a burn period ends (United States Geological Survey [USGS], 2018). The frequency, size, and severity of wildfires have increased across the western United States since the 1950s (Davis & Weber, 2018). While wildfires are beneficial to ecosystem health relative to plant succession regulation and species composition, they also threaten property and human life (Leblon, Bourgeau-Chavez, & San-Miguel-Ayanz, 2012). An analysis of the variables that contribute to wildfire risk and severity allows for improved response efforts and resource management. For land managers, live fuel moisture (LFM) is a key indicator for wildfire occurrence and behavior, as it relates to the rate of spread and potential for ignition (Danson & Bowyer, 2004).

Current research on wildfire forecasting uses remote sensing data to examine variables such as land surface temperature (LST), evapotranspiration (ET), and vegetation indices to estimate LFM. Several studies have evaluated the accuracy and reliability of using these remotely sensed LFM inputs as a means to extrapolate wildfire potential (Danson & Bowyer, 2004; Dennison, Roberts, Peterson, & Rechel, 2005). As previous studies of LFM have not incorporated all variables used in this study, or have not covered the entire eastern Great Basin (EGB), a comprehensive analysis was necessary. This comprehensive analysis included a predictive model for wildfires that incorporated LST, ET, elevation, aspect, and a Normalized Difference Vegetation Index (NDVI) across the entire EGB.

Prior to this study, land managers in the EGB exclusively relied on field samples for measuring LFM. In the EGB these field samples are taken from 155 field observation sites that cover 411,759 km^2 of semi-arid ecosystems in Arizona, Colorado, Idaho (ID), Utah (UT), and Wyoming, with the majority of the study area covering ID and UT. Land managers with the Bureau of Land Management (BLM), the Idaho Department of Fish and Game (IDFG), the Great Basin Coordination Center (GBCC), and the National Oceanic and Atmospheric Administration (NOAA) use these field sites and LFM observations to estimate wildfire timing and severity and to make decisions on resource allocation and deployment. In order to provide an effective

LFM model for the EGB, the 2019 Fall NASA DEVELOP Great Basin Ecological Forecasting team conducted an analysis during peak wildfire season, April through September. Based on the availability of satellite data and *in situ* measurements, the team developed a model using data from the years 2016 and 2017. Spatial resolution for LFM increased from 2,600 km^2 to 250 m^2 through the development of a predictive LFM model. The team then conducted validation between remotely sensed data from NASA Earth observations (EO) and *in situ* LFM measurements prior to analyzing correlation strength to ensure model accuracy.

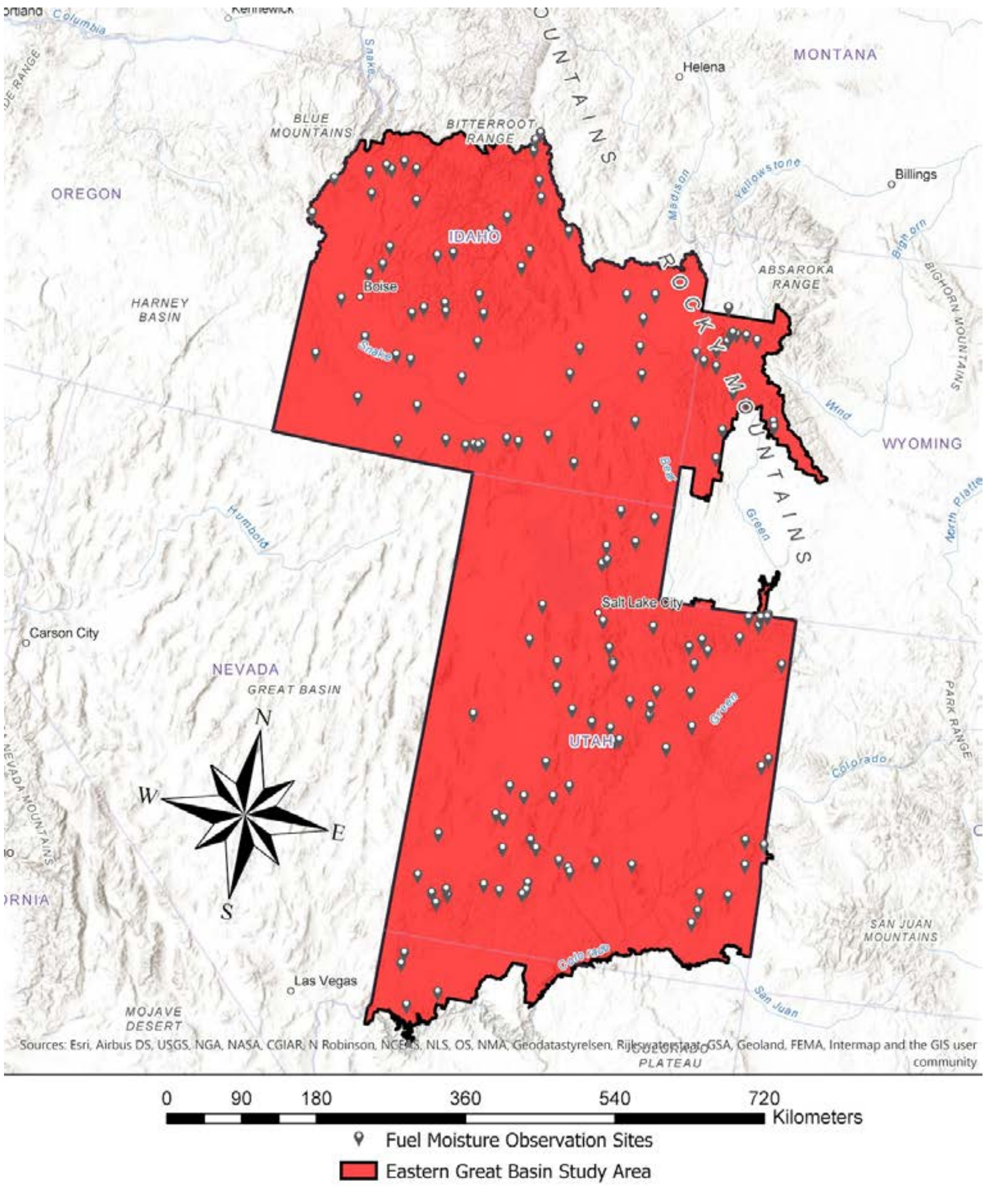

Figure 1. The eastern Great Basin (EGB) study area in AZ, CO, ID, UT, & WY. The 155 fuel moisture observation sites serve as the locations for *in situ* LFM measurements.

2.2 Project Partners & Objectives

The partners for this project were the Southeast Regional Office of the Idaho Department of Fish and Game (IDFG), the Upper Snake Field Office of the Bureau of Land Management (BLM), the Pocatello office of the NOAA National Weather Service (NWS), and the Great Basin Coordination Center (GBCC). The BLM and NWS are the primary end users and will use our predictive model to supplement *in situ* observations of LFM. This project benefited the end users and partners at the GBCC by streamlining the decision-making process and, if feasible, by providing a LFM predictive model that could be applied to the remaining Geographic Area Coordination Centers (GACC) across the US. The BLM and NWS provide wildfire safety warnings to communities based on estimated risk derived from the *in situ* LFM measurements. When wildfires occur, the BLM and NWS mobilize response resources, such as firefighters, helicopters, and volunteers, to protect the environment and human health.

The primary objective of this study was to evaluate the feasibility of determining LFM from remotely sensed data such as ET, LST, NDVI, and topography. The team validated derived LFM values from Moderate Resolution Imaging Spectroradiometer (MODIS), and Visible Infrared Imaging Radiometer Suite (VIIRS) satellite imagery against *in situ* measurements of LFM in the EGB. This comparison evaluated the accuracy in estimating LFM in the semi-arid climate of the EGB. In order to determine the validity of deriving LFM values from remotely sensed data, we used a confusion matrix to evaluate the correlation strength of multiple data inputs to determine which inputs best matched the *in situ* datasets. Finally, we established a baseline for the Spring 2020 DEVELOP team to create a forecasting model of LFM into the 2020 fire season.

3. Methodology

3.1 Data Acquisition

The team received *in situ* measurements of LFM from the BLM for the years 2016 and 2017 and used the BLM's Fuel Moisture Sampling Guide as an outline for fuel moisture classification (Pollet & Brown, 2007). Based on project partner classification needs, we altered the six classes described in the BLM's guide to produce the class divisions in Table 1. These LFM divisions classified the *in situ* observations for analysis. The team downloaded the United States Department of Agriculture (USDA) and the United States Geological Survey (USGS) Landfire existing vegetation cover (EVC) and existing vegetation types (EVT) for the study area. Additionally, we downloaded USGS National Elevation Dataset (NED) in order to create aspect, slope, elevation, and hillshade rasters at a 10 m spatial resolution.

Table 1
Fuel Classification Types used for LFM model (Pollet & Brown, 2007)

Class	Live Fuel Moisture Range (Percent)
1	0-74
2	75-99
3	100-124
4	125-149
5	150-199
6	200 & above

For NASA EO data, the team utilized NASA EARTHDATA and the Land Processes Data Archive Center (LP DAAC) Application for Extracting and Exploring Analysis Ready Samples (AppEEARS). The project team downloaded Aqua and Terra MODIS ET as well as Suomi National Polar-orbiting Partnership (NPP) VIIRS LST and NDVI data as GeoTIFFs. Full descriptions of the data are outlined in Table 2.

Table 2

List of Sensors and Data Products utilized for this project

Platform and Sensor	Data Product	Dates	Acquisition Method
Aqua MODIS	MYD16A2 Net Evapotranspiration 8-Day L4 Global 500m SIN Grid V006	April to September 2016 & 2017	EARTHDATA
Terra MODIS	MOD16A2 Net Evapotranspiration 8-Day L4 Global 500m SIN Grid V006	April to September 2016 & 2017	EARTHDATA
Suomi-NPP VIIRS	VNP21A1D Land Surface Temperature and Emissivity Daily L3 Global 1km SIN Grid Day V001	April to September 2016 & 2017	LP DAAC AppEEARS
Suomi-NPP VIIRS	VNP13A1 Vegetation Indices 16-day L3 Global 500m SIN Grid V001	April to September 2016 & 2017	LP DAAC AppEEARS

3.2 Data Processing

The team primarily conducted data processing using Esri ArcGIS Pro. We used USGS NED 10 meter Digital Elevation Models (DEMs) to develop aspect and elevation layers. In order to create training and testing points for the development of a predictive LFM model, the team organized the *in situ* data into the six LFM classes and separated it into 24 different time periods during the two year study period. Since the study period covers the six months of April through September during 2016 and 2017, the team divided each month into two periods in order to conduct an independent analysis on the first and second half of each month. Additionally, this was done to correspond with the field sampled data and to provide finer temporal resolution of the output data. Aqua and Terra MODIS ET, Suomi-NPP VIIRS LST and NDVI, and NED data were resampled to 250 m and reprojected to NAD 1983 Albers Equal Area Conic for layer consistency. Prior to model development, six-layer composite images were made for each of the 24 time periods within the study period. These composite images were layered with elevation, Aqua MODIS ET, VIIRS LST, VIIRS NDVI, Terra MODIS ET, and aspect from the given time period. The team clipped the composite images to the study area and masked out all nonburnable areas using the Landfire Fire Behavior Fuel Models (FBFM) 40 land cover raster. Finally, the team split *in situ* data points for each time period into 60% training and 40% testing points using random point generation. These training and testing points were used to independently train and validate the Random Trees Classifier (RTC) tool in ArcGIS Pro.

3.3 Data Analysis

Using the RTC, the team created a predictive LFM model for conducting data analysis. For each of the 24 time periods, the *in situ* training points trained the RTC to classify LFM using the corresponding composite image for the given time period. The model classified LFM of sagebrush for each 250 m^2 cell throughout the study area. In order to isolate sagebrush for classification, we utilized the Landfire EVT raster and masked out all other vegetation and land cover types. Using the RTC, the team made an LFM classification image for each time period using 60% of the *in situ* LFM observations. Then, a confusion matrix validated each model output to demonstrate the correlation strength between satellite and *in situ* datasets. This validation used the *in situ* testing points, which accounted for 40% of the total *in situ* points for the given period. After the completion of the classification and validation, the team made three polygons: one incorporating the border between Idaho and Utah, one exclusively in Idaho, and one exclusively in Utah (*Figure 2*). These polygons covered the primary areas of interest for project partners. Next, the team calculated zonal statistics for each time period, and in each of the three polygons, in order to understand the annual trends of LFM during peak fire season. Finally, the mean and median outputs from the zonal statistics were exported to Microsoft Excel and used to develop trend lines of LFM.

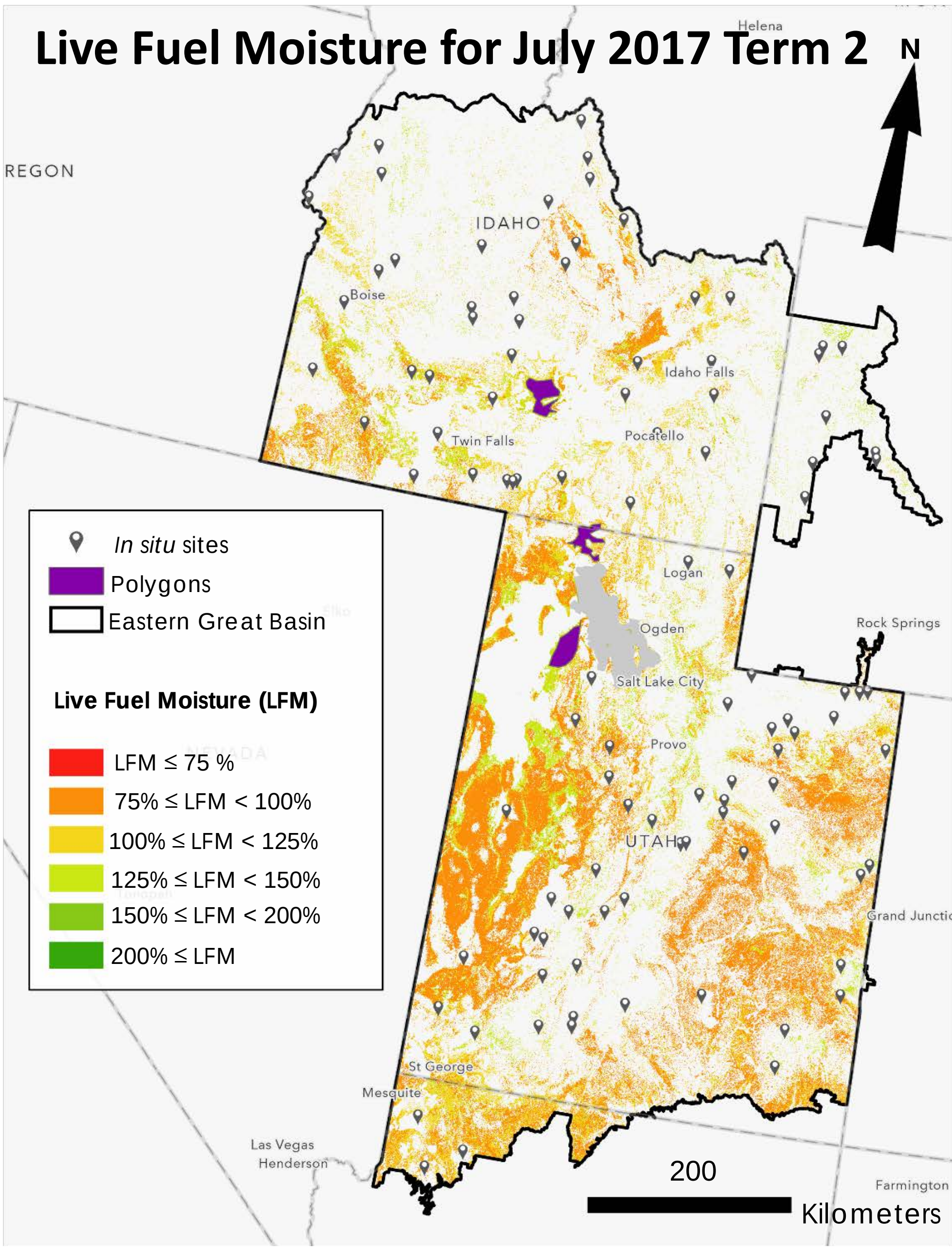

Figure 2. The EGB study area during the second term of July 2017 showing the three polygons used for classification trend analysis. The three polygons cover sagebrush dominated areas that are frequented by project partners but do not include any *in situ* sites. This allowed for unbiased statistics.

4. Results & Discussion

4.1 Analysis of Results

Our team developed 23 classification maps for April through September of 2016 and 2017. The second term of April in 2017 did not have a classification made due to a lack of *in situ* data. The average overall accuracy achieved in model classification was 8.2% with the highest overall accuracy achieved being 34.6% for the first term of July in 2017 (*Figure 3*). The lack of model accuracy was attributed to a lack of *in situ* data and gaps in VIIRS LST data, which were used to train and test the model. The mean number of training points was 28.3, with the mean number of testing, or validation points, being 18.9. While the accuracy for each classification was low (Table 3), the images were useful for the development of yearly LFM trend lines (*Figure 4 a, b, & c*).

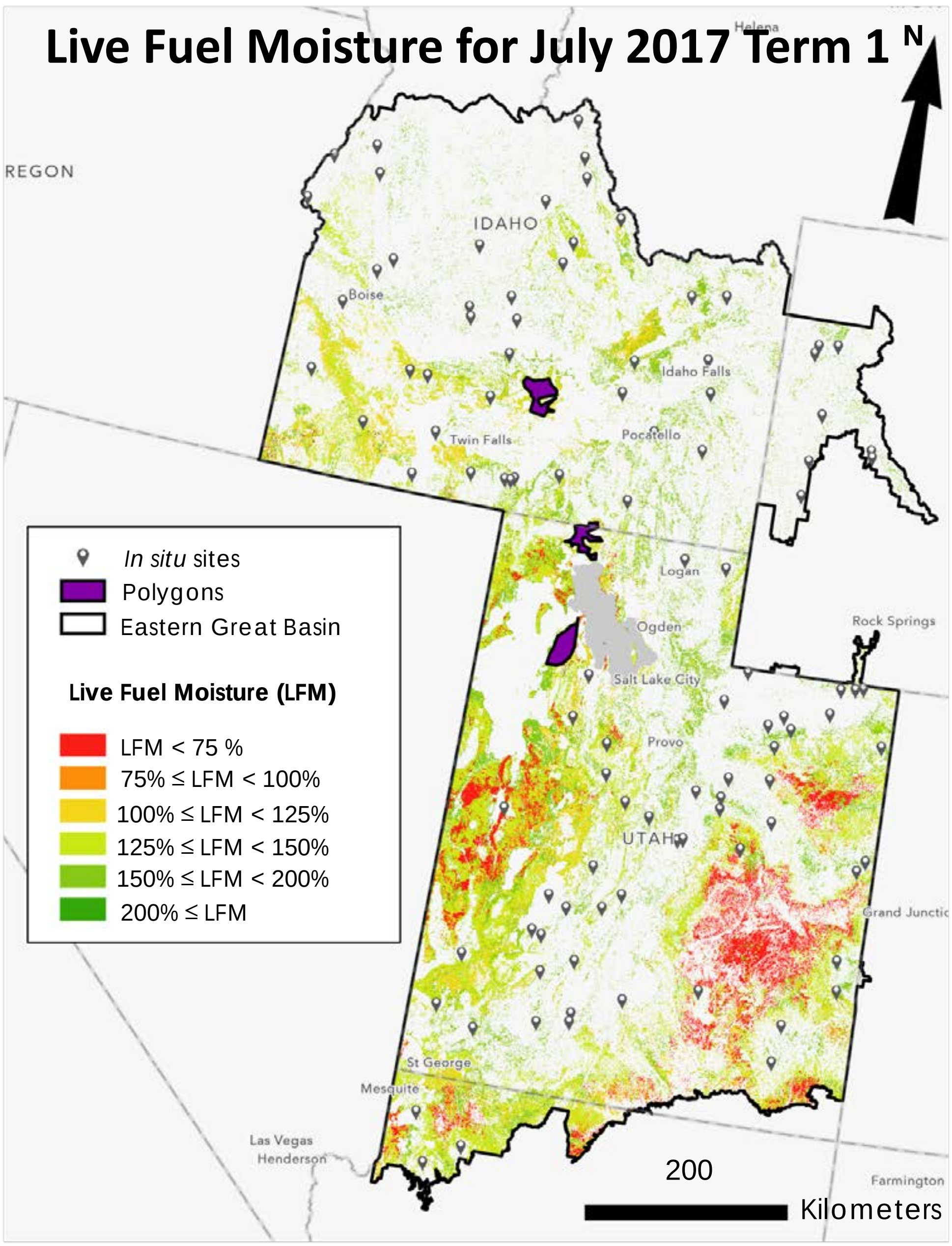

Figure 3. The EGB study area with LFM of sagebrush classified during the first term of July in 2017. This image depicts the variability in LFM percentages that exist during a peak wildfire month.

Table 3
LFM Model Accuracy

Term	Train Accuracy (%)	Overall Accuracy (%)
1-15 April 2016	100	0
16-30 April 2016	100	0
1-15 May 2016	82.6	0
16-31 May 2016	100	0
1-15 June 2016	95.0	0
16-30 June 2016	100	4.2
1-15 July 2016	100	13.3
16-31 July 2016	100	25.0
1-15 August 2016	97.7	13.3
16-31 August 2016	96.4	5.2
1-15 September 2016	97.1	9.1
16-30 September 2016	100	9.1
1-15 April 2017	100	0
16-30 April 2017	NA	NA
1-15 May 2017	88.5	0
16-31 May 2017	100	0
1-15 June 2017	100	0
16-30 June 2017	100	10.0
1-15 July 2017	100	34.6
16-31 July 2017	96.9	14.3
1-15 August 2017	100	20.8
16-31 August 2017	100	5.6
1-15 September 2017	100	17.4
16-31 September 2017	100	6.7

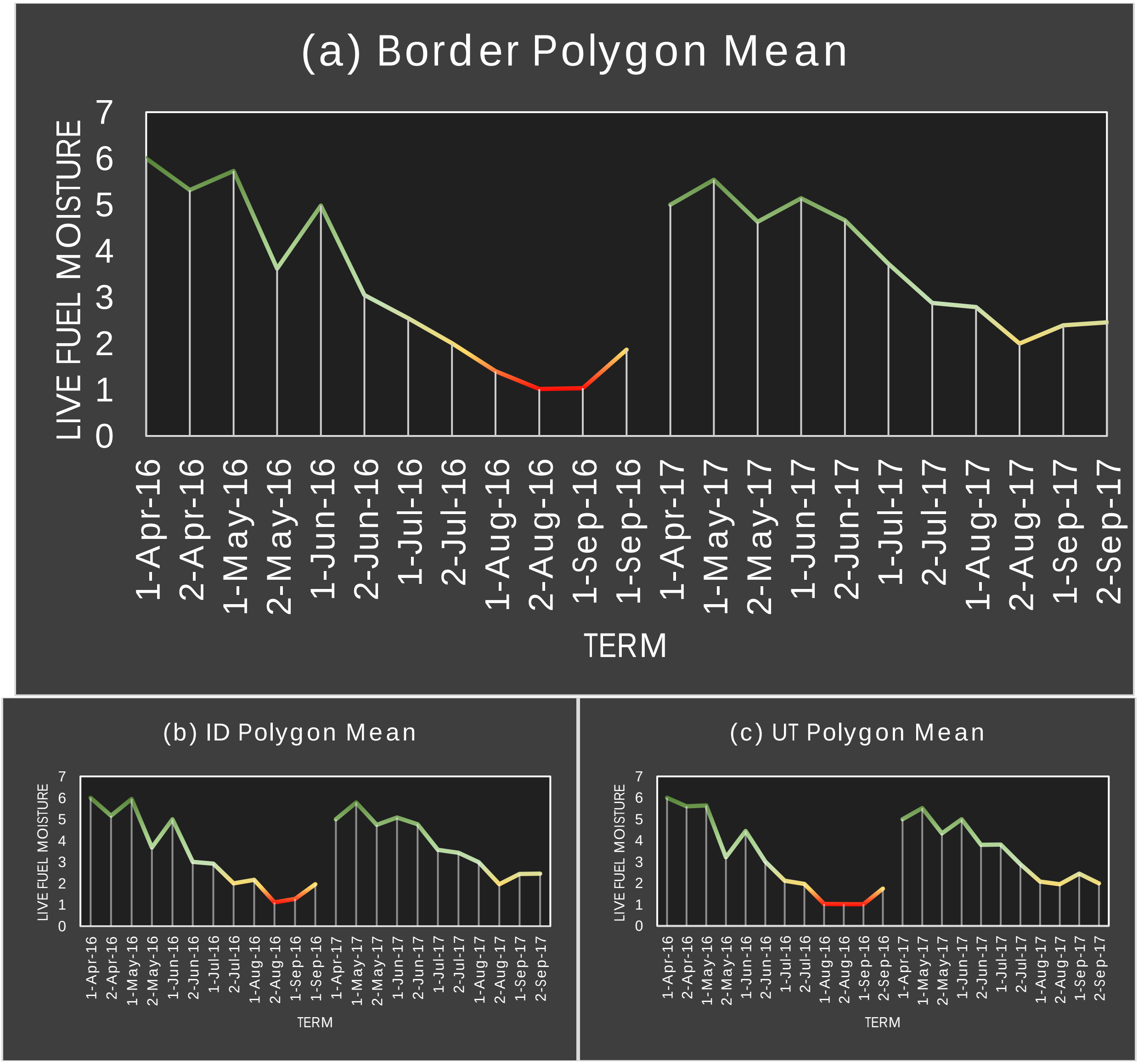

Figure 4 (a, b, & c). These images show the LFM classification average for each of the three polygons where zonal statistics were calculated. The second term of April 2017 is missing in all three graphs. This is due to insufficient data, and an inability to make a classification image. In all three polygons, the lowest mean LFM occurred between the months of July and September of 2016, with the highest mean LFM occurring in April of the same year. These trend lines follow predicted LFM percentages for these months, showing a decreased plant moisture during summer months, and higher LFM during late spring.

4.2 Future Work

Incorporation of meteorological data along with the LFM predictive model would be helpful for our end users to maintain a more comprehensive dataset for estimating potential wildfire risk and severity. Climate data depicting El Niño Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) are linked to persistent droughts and could benefit land managers by providing multi-year cyclical predictions of wildfire risk and severity (Cole & Overpeck, 2002). Additionally, a forecasting model linked to ENSO and PDO patterns could expedite wildfire prediction and further advance response efforts for our partners and their organizations (Hessl, McKenzie, & Schellhaas, 2004). A forecasting model could also incorporate lightning strike data from the Geostationary Lightning Mapper (GLM) through the Geostationary Operational Environmental Satellites R-Series (GOES-R), where lightning could be a primary contributor to the formation of wildfire events in the EGB (Dowdy & Mills, 2012). A combined analysis of these variables could provide greater insight toward generating a forecasting tool for our end users that integrates climate and meteorological data for predicting wildfire frequency in the EGB region (Collins, Omi, & Chapman, 2006). After discussion with project partners, more *in situ* data will be added to the model by georeferencing sagebrush points to the 1 km surrounding partner measurement sites. This may increase model accuracy by increasing the number of training and testing points. Furthermore, using data collected from *in situ* observations, MODIS, VIIRS, and this team's predictive model, the Great Basin Ecological Forecasting II project will develop a forecasting model that our end users will be able to use during the 2020 fire season.

5. Conclusions

Historically, partners used *in situ* LFM measurements as their main predictor of wildfire risk in the EGB. With the addition of the team's LFM model classifications, partners received increased spatial awareness, approximately 10 times finer than *in situ*, regarding the behavior of LFM. Additionally, partners were able to use the developed trend lines to further understand the rate of change of LFM during peak fire season. The study demonstrated that the development of a LFM model using *in situ* measurements and NASA EO datasets is feasible, but increases in the accuracy would require more *in situ* observations and fewer gaps in VIIRS LST data. Additionally, our study was in agreement with past studies that indicated LST, ET, and NDVI as key variables influencing LFM (Burgan, Hartford, & Eidenshink, 1996; Chuvieco et al, 2004). While the model classifications featured low accuracy when compared to ground truth data, the statistics derived from these classifications were useful for profiling the behavior of LFM through mean and median trend analysis. Since dependent classification was successful, the development of more *in situ* points through georeferencing might increase model accuracy. As expected, LFM was much higher in the late spring than it was in summer months, and large variations between the two terms of each month occurred when there were intense weather events. In addition to the trends and classification developed by the team during this term, the partners will benefit from a forecasting model that will be developed in the spring.

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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
ENSO - El Niño Southern Oscillation
EO – Earth observations; Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time
ET – Evapotranspiration
EVC – Existing Vegetation Cover
EVT– Existing Vegetation Type
FBFM – Fire Behavior Fuel Models
GACC – Geographic Area Coordination Center
GBCC – Great Basin Coordination Center
GIS TReC – Geographic Information Systems Training and Research Center
GLM – Geostationary Lightning Mapper
GOES-R – Geostationary Operational Environmental Satellites R-Series
IDFG – Idaho Department of Fish and Game
In situ – on-site, ground truth
LFM – Live fuel moisture
LST – Land surface temperature
MODIS – MODerate Resolution Imaging Spectroradiometer
NED – National Elevation Dataset
NDVI – Normalized Difference Vegetation Index
PDO – Pacific Decadal Oscillation
RTC – Random Trees Classifier; Tool used in ArcGIS Pro to develop the predictive LFM model
Suomi-NPP – Suomi National Polar-Orbiting Partnership
VIIRS – Visible Infrared Imaging Radiometer Suite

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9. Appendices

Table A1

Primary Datasets

Dataset	Date	Use	Acquired From	Level	DOI
Aqua MODIS version 6 8-day Global 500 m (MYD16A2)	2016 to 2017	ET	NASA EARTHDATA	Level 4	10.5067/MODIS/MYD16A2.006
Suomi-NPP VIIRS version 1 daily Global 1000 m	2016 to 2017	LST	NASA LP DAAC AppEEARS	Level 2	10.5067/VIIRS/VNP21A1D.001
Suomi-NPP VIIRS version 1 16-day Global 500 m pre-processed NDVI	2016 to 2017	NDVI	NASA LP DAAC AppEEARS	Level 3	10.5067/VIIRS/VNP13A1.001
Terra MODIS version 6 8-day Global 500m (MOD16A2)	2016 to 2017	ET	NASA EARTHDATA	Level 4	10.5067/MODIS/MOD16A2.006

Table A2

Ancillary Datasets

Dataset	Date	Use	Acquired From	Level	DOI
GBCC LFM *in situ* measurements	April 2, 2016 to September 30, 2016 ; April 1, 2017 to September 20, 2017	Validation for model outputs	GBCC & BLM	NA	NA
Landfire Land Cover Datasets	2018	Defining EVT and sagebrush classification	USDA & USGS	NA	NA
Landfire 40 FBFM	2005	Fuel type classification and masking out of nonburnable areas	BLM	NA	NA
NED	2012	Calibration of model	USGS	NA	NA