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Using NASA Earth Observations to Create a Database and Determine Regional and Temporal Wildfire Susceptibility in Idaho Savannahs

DEVELOP Technical Report

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I. Abstract

Wildfires play an important role in ecosystem health, with many native plant species dependent on fire to complete their life cycle. Wildfires also burn dead vegetation, which recycles nutrients back into the soil. However, climate change has created favorable conditions in the western United States for larger and more frequent wildfires, which can disrupt ecosystems and human localities. Also, the invasion of cheatgrass (*Bromus testorum*) across the landscape has drastically increased the duration of the fire season by contributing to the fuel load. To prepare for the fire season in Idaho, the Bureau of Land Management (BLM) and the Idaho Department of Lands (IDL) use vegetation moisture measurements from the National Fuel Moisture Database to identify and allocate resources to regions with drier vegetation during the year. To supplement that database, this research analyzed the Normalized Difference Vegetation Index (NDVI) and surface temperature (ST) to investigate their ability to identify fire susceptible regions since both of these variables characterize the quality of vegetation, are gathered frequently, and are continuous. The data for each of these variables was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument aboard the Terra satellite from 2001 – 2014 and examined in shrubland and grassland habitats as determined by the 2011 National Land Cover Dataset. These land classes were analyzed due to the high abundance of fires occurring in these habitats every year. The NDVI and ST in each land class was compared across the state to the number of fires that occurred each year. On a smaller scale, individual burned regions were compared to unburned areas to determine if NDVI or ST had a unique signature in the months leading up to a fire. In addition to this analysis, precipitation data was gathered from a number of sources to assess their quality, accuracy, and relationship with fires across the region. The results and data gathered from this study will support Idaho Department of Lands (IDL) and Bureau of Land Management (BLM) in resource allocation early in the fire season and planning fuel load reduction activities following the fire season.

Keywords
Wildfire, savannah, fire susceptibility, fire risk

II. Introduction

Wildfires are natural ecological processes that support long term environmental sustainability and diversity but are also considered major disturbance mechanisms to human society. As humans expand further into wilderness areas, wildfires increasingly have a negative economic impact (Schneider et al., 2008). This vulnerability is apparent when considering the Charlotte Fire, which burned over 1,000 acres in June 2012 in the Mink Creek area south of Pocatello, ID. This fire destroyed 66 homes, forced the evacuation of 1,000 individuals, and caused roughly $7.2 million in damage (Hancock, 2012). Our research is classified in Idaho Disasters due to the deleterious effects of wildfires on the landscape and society.

The need for understanding fire susceptibility has been recognized since the turn of the 20th century when the northeastern United States experienced a series of extreme fire seasons (Donovan et al., 2008). Increasing human risk related to wildfire creates a need for advanced tools and applications that will aid emergency responders in identifying areas susceptible to fire, mitigating active fires, and developing post burn area rehabilitation strategies. Fire susceptibility has been addressed with the fire potential index (FPI) that was developed by Burgan, et al. (1998), and took into account the weather conditions, a fuel model map, and vegetation greenness using remote sensing. Since the development of this model, other studies have used various remote sensing variables to develop superior models in mapping fire susceptibility (Schneider et al., 2008; Newnham et al., 2010; Huesca et al., 2009). These models have been adopted by different wildfire management teams for real-time monitoring of fire susceptibility.

However, these models identify fire susceptible regions on a daily basis, with some having the ability to forecast fire susceptibility up to a week in advance. If wildfire management organizations were able to identify regions of increased fire susceptibility months in advance then proactive actions such as prescribed burns, fire-fighting resource allocation, and personnel preparedness can be taken. Currently, our end-users the Bureau of Land Management (BLM) and the Idaho Department of Lands (IDL) prepare for the fire season by measuring vegetation moisture and referring to the National Fuel Moisture Database to identify and allocate resources to regions with drier vegetation during the year. BLM has operational responsibility for wildland fire on approximately 250 million acres of public land in the U.S., including 12 million acres or 22% of the land base in Idaho. IDL is the primary state-level agency responsible for managing wildfire in Idaho. Being able to easily identify fire susceptible areas would help both parties allocate their limited resources to carry out fire management plans. We investigated the ability to use remote sensing to supplement their current practices since satellite imagery is gathered frequently and has continuous values across the landscape.

Our study area comprised of the expansive savannah ecosystems from the southern border of Idaho to 44.5°N and spans across the entire state from east to west. A majority of this region is classified as semi-desert scrub and grassland as identified by the 2011 National Land Cover Dataset (NLCD), most of which is located in The Big Desert (Figure 1). Although not analyzed in this study, land cover in this region included agricultural and residential areas along the Snake River and forested woodlands leading into the foothills of numerous mountain ranges. Yearly total precipitation in southern Idaho ranges from 20 to 30cm, of which 25 - 50% is snowfall. Vegetation in the savannah ecosystems is a mixture of native and non-native species. Native species include sagebrush (*Artemisia tridentata*) and rabbit brush (*Chrysothamnus nauseosus*) (Chen et al., 2011). An important invasive species, cheatgrass (*Bromus tectorum*), expands millions of hectares in southern Idaho. Cheatgrass is a highly flammable species and is primarily the reason for increased fire frequency in our study area (Laycock, 1991). Nearly 100% of the wildfires in this region occur between May and October,

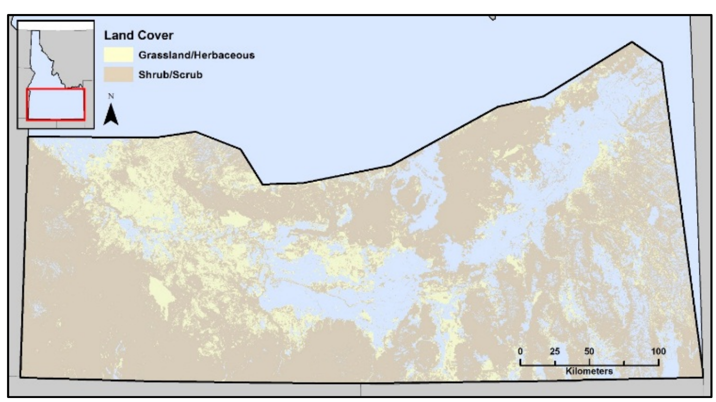


Figure 1: Map of study area in southern Idaho. Grassland and shrubland land classifications derived from the 2011 NLCD.

peaking in July and August, which are the warmest months in southern Idaho (Westerling et al., 2003).

Our study used remote sensing to identify fire susceptibility on a temporal and spatial basis. Temporally, we investigated the relationships between the number of fires each year compared to the normalized vegetation difference index (NDVI) and surface temperature (ST). We hypothesize that NDVI prior to the fire season is larger in years that have more fires because higher NDVI values are related to higher biomass, which provides more fuel for fires. Surface temperature was used as a proxy of vegetation moisture, higher temperatures is correlated with drier vegetation since there is little evapotranspiration (Sandholt et al., 2002). Spatially, we compared the NDVI between burned and unburned regions during the year. Similar to the temporal study, we hypothesize that regions that burned had a higher NDVI leading up to the fire since increased NDVI can indicate more fuel biomass. Precipitation was also investigated because its link with vegetation and soil moisture; there may be a decrease in wildfire activity in wetter years (Chen, 2014). Fires occurring since 2001 were identified for analysis, which coincides with the beginning of NDVI and ST observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument on the Terra satellite.

III. Methodology

Fire Data

Polygon shapefiles of fires occurring until 2012 in Idaho were obtained from the Interactive Numeric & Spatial Information Data Engine - Idaho (http://inside.uidaho.edu). Fire data since 2012 were obtained from the USGS Geosciences and Environmental Change Science Center GeoMAC Outgoing Datasets portal (http://rmgsc.cr.usgs.gov/outgoing/GeoMAC). Fires were classified as either a grassland or shrub fire depending on which land class a majority of its pixels belonged to; none of the fires had a majority of pixels outside of these land cover classes (Table 1). Although there are more fires occurring in the shrublands than grasslands, the grassland land cover has more fires per million acres of land (138.1ac) than shrublands (73.3ac). Our analyses only focus on the number of fires occurring each year since the number of acres burned is a direct result of wildfire management and their decisions on letting a fire burn out or creating fire barriers to prevent the advancement of wildfires.

Table 1: Fire statistics within the study region since 2001.

	Number of Fires		
Year	*Grass*	*Shrub*	*Total*
2001	58	82	140
2002	10	46	56
2003	16	59	75
2004	13	16	29
2005	50	76	126
2006	56	90	146
2007	36	103	139
2008	19	51	70
2009	15	32	47
2010	33	77	110
2011	39	55	94
2012	56	133	189
2013	48	102	150
2014	10	39	49
Total	459	961	1430

Yearly Analysis - ST

Surface temperature was analyzed across the study area in the grassland and shrubland land cover classes from 2001 to 2014. We used the MOD11A2 product from Terra MODIS which is an 8-day averaged dataset at a 1km resolution and stage 2 validation. Each 8-day composite was retrieved from the Land Processes Distributed Active Archive Center from January 9th, the first product of the year, to September

30th, since most fires have occurred by then. Our study area was completely contained within one MODIS tile. Data was scaled to Kelvin (scale factor = 0.02) and then converted to degrees Celsius.

Using zonal statistics, the median surface temperature value within grasslands, shrublands, and both land covers in the study area were calculated across each image date. The median, instead of the mean, was used to lower the influence of anomalous values, especially from neighboring land cover classes like agriculture. Results were plotted against the number of fires that occurred in the land cover classes and were visually assessed before pursuing further statistical analysis.

Yearly Analysis - NDVI

Name	**Description**
Start of Season Time (SOST)	Day of year at beginning of measurable photosynthesis
Start of Season NDVI (SOSN)	NDVI at day of year associated with beginning of measureable photosynthesis
End of Season Time (EOST)	Day of year at ending of measurable photosynthesis
End of Season NDVI (EOSN)	NDVI at day of year associated with ending of measurable photosynthesis
Time of Maximum (MAXT)	Time of maximum photosynthesis
Maximum NDVI (MAXN)	Maximum level of photosynthetic activity
Duration (DUR)	Length of photosynthetic activity (the growing season)
Green-up Amplitude (G-AMP)	Maximum increase in photosynthetic activity above the baseline (MAXN – SOSN)

We analyzed NDVI and number of fires from 2001 to 2014. The NDVI product used in this analysis was the MOD13Q1 product from Terra MODIS, which is a 16-day composite at a 250m resolution and stage 3 validation. Data was scaled (scale factor = 0.0001) to achieve values in the -1 to 1 range. The average NDVI on each day of a 16-day composite product was examined across the combined grassland/herbaceous and shrub/scrubland land cover classifications obtained from the 2011 NLCD. The NDVI pattern from each year was plotted and the vegetation phenology was derived. We adopted this methodology because peaks in NDVI earlier in the year may lead to more biomass fuel, which the 16-day composites will be able to capture. The different phenology metrics were then statistically compared to the number of fires occurring each year. Phenology metrics that were evaluated are described in Table 2, and a visual description is also available (Appendix: Figure 1). The average NDVI each imagery day was calculated to compare current NDVI conditions to historical averages and the annual NDVI time series from Jan - Sept were graphed to analyze year-to-year variation.

Brown-out Amplitude (B-AMP)	Maximum decrease in photosynthetic activity above the baseline (MAXN – EOSN)

Table 2: Vegetation phenology metrics derived from the United States Geological Survey.

Regional Analysis

In addition to examining temporal correlations with the number of fires each year, we wanted to use NDVI to spatially analyze fire susceptibility. We began by analyzing the year 2006, which had numerous large fires during the year in the study region. Twelve fires greater than 5000 acres were selected in order to ensure numerous NDVI pixels within the fire perimeter. We averaged the NDVI within a 250m buffer around lightning strikes (data obtained from the Bureau of Land Management) that occurred on the same day or the day prior to fire start. The previous day was included in case a lightning strike the evening before started a fire that was not reported until the following morning. Only five fires in 2006 had lightning strikes occur before or on the same day inside the fire perimeter (Figure 2). The NDVI around the lightning strikes, instead of the NDVI in the entire fire perimeter, was used because other areas of the fire may have not ignited if struck by lightning, rather it burned due to the spread of fire. Sometimes there was more than one lightning strike that met the criteria within a fire. Multiple lightning strikes in a fire were included since there is no definitive procedure in defining the lightning strike that originally caused the fire.

The NDVI around lightning strikes that did not lead to a fire were used as a control. Control lightning strikes were identified within 1 - 5km of the five fires that had lightning strikes. Strikes within 1km outside of the fire perimeter were not used in case lightning

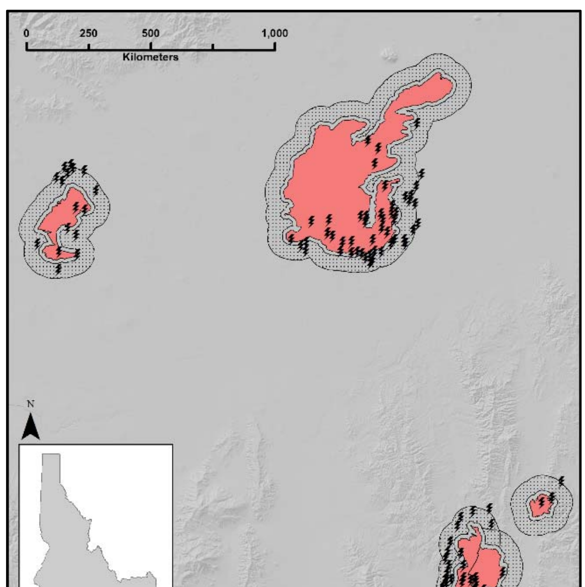


Figure 2: Fires (red) with lightning strikes on the same day or the day before the fire start. Lightning strikes during the same time period identified in 1-5km buffer outside fires.

coordinates were slightly inaccurate and to ensure the NDVI buffer would not overlap the fire perimeter. Control lightning strikes were limited to 5km outside of the fire to limit the variation in precipitation and other weather conditions between fire and control sites. Control strikes also needed to occur on the same days that the strikes within the fire occurred in order to keep as many variables constant across both lightning data sets. Lightning strikes were removed from the analysis if buffers overlapped or if there was a high density of strikes in a region.

Using zonal statistics, the average NDVI within each 250m buffer was averaged across the lightning strikes within the fire perimeters and outside the fires from February 18 - September 30th. The NDVI product described earlier is the same used in this analysis. Additional statistical analyses were conducted if individual days exhibited a significant difference in NDVI between lightning in fires and lightning outside of fires.

Precipitation

The precipitation component of this project focused on the availability of various data sources and establishing baseline precipitation statistics within the study area. Among the available datasets included *Agrimet* weather station data, *PRISM* precipitation, and *Modern-Era Retrospective Analysis for Research and Applications* (MERRA) ground moisture products. Statistics were compiled for each of these sources over a thirteen year time period (2001-2013).

Weather station locations along with various climate tables were downloaded from the US Bureau of Reclamation’s AgriMet website. Datasets are available at any time window from the 1980’s to present. Data analysis and manipulation included summing values for hydrologic water years (April to September) and ensuring relational database keys were created in order to join the data spatially with the weather station dataset. Graphing of annual precipitation trends reveal trends that can be compared with the data gathered from the other precipitation products.

The *PRISM* dataset includes *AgriMet* network weather station along with many other United States weather station network data. These datasets were acquired from the Northwest Alliance for Computational Science and Engineering (http://www.prism.oregonstate.edu/). Zonal statistics for the entire study area were then calculated for each year representing precipitation in inches. MERRA GWETTOP data, a NASA soil moisture product, was also analyzed to discover how correlated ground moisture was with precipitation. Monthly max values were averaged and compiled by year in order to compare against the AgriMet data.

IV. Results & Discussion

Yearly Analysis - ST

The surface temperature profile during the year was similar between the grassland and shrub land cover classes (Figure 3). Although they share a similar profile, the grassland surface temperature was significantly higher than shrubland temperature. Kaufmann et al. (2003) found a similar trend and

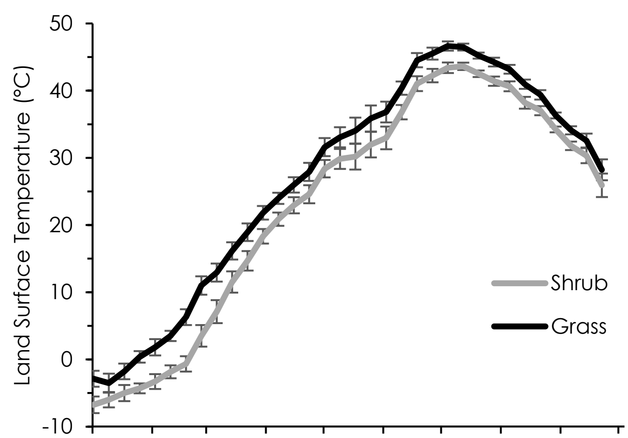


Figure 3: Average surface temperature between grasslands and shrublands. Vertical lines represent standard error.

explained that regions of higher NDVI will have a decrease in surface temperature during the summer. In our study, the NDVI of the shrublands was higher than grasslands in the summer which would account for the decrease in temperature (Appendix Figure 2). Kaufmann et al. (2003) also found that the NDVI in winter was inversely related to temperature; regions with higher NDVI had higher surface temperature due to its relationship with snow cover. Although there was not snow on the ground in late February through April in southern Idaho, cheatgrass establishes itself in late Fall and quickly emerges from the cold weather with a rapid growth cycle compared to native shrubs (Stewart & Hull, 1949). The presence of vegetation in the grasslands prior to the main growing season causes the increase in surface temperature as compared to the relatively bare soil in the shrublands (Tesař et al., 2008).

Since the temperature profiles for grasslands and shrublands were similar except for the few degrees Celsius difference throughout the year, we only analyzed surface temperature to number of fires for the total study area comprised of both land cover classes. The median temperature across the region was plotted for each 8-day composite for each year (Figure 4A). The surface temperature in June deviates between years with more fires and years with less fires. Further correlation analysis at each particular day (May 23, June 1, June 10; Figure 4B) revealed very weak correlations between the number of fires and the surface temperature. The lack of correlation could be due to a weak relationship between fires and surface temperature, but may also be due to the low spatial resolution of the data and the dependency of surface temperature largely from weather and not vegetation.

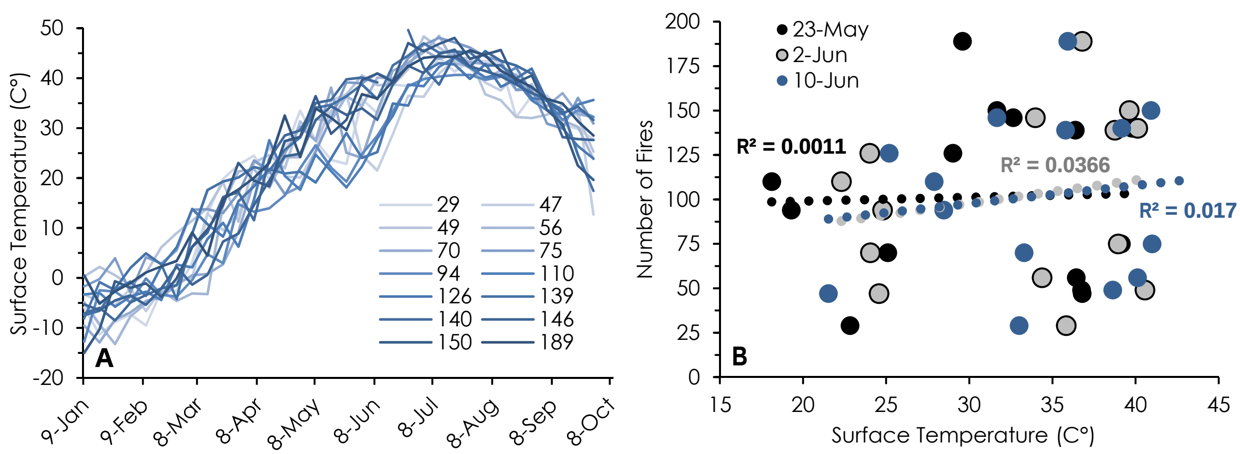


Figure 4: (A) Average surface temperature between grasslands and shrublands. Vertical lines represent standard error. (B) Correlation analysis for individual days and the fires each year.

Yearly Analysis - NDVI

NDVI derived phenology metrics overall had weak correlations with number of fires for a given year with the exception of SOST and DUR. These two metrics had the strongest correlation coefficients when analyzed with number of fires (-0.54 and 0.40, respectively). This data supports the hypothesis that more fires are positively correlated with an early growing season that lasts longer than average. Although most metrics did not have a correlation with fire, phenology is still important in considering an area's susceptibility to fire. The stage of the growing season when a fire first starts and the NDVI of the burned area leading up to the fire allows us to standard of phenology and NDVI conditions that need to exist for natural wildfire events to occur. Without defined thresholds such as these, it is difficult to identify areas with higher susceptibility to fire using NDVI phenology alone.

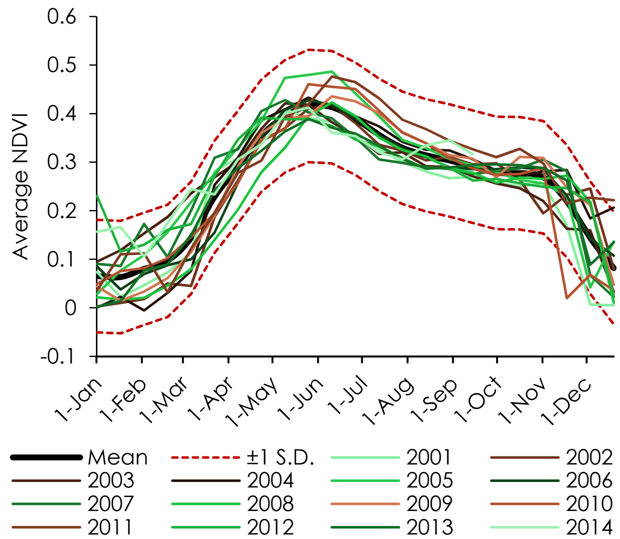


Figure 5: NDVI time series (2001-2014) including historic 16-day mean and standard deviations.

NDVI conditions for a specific year rarely fall outside one standard deviation of the historic average (Figure 5). Using the 16-day mean NDVI for a specific day across time series we can identify anomalous conditions with respect to current NDVI conditions above or below historic averages. In this study, the average NDVI for April 7th was calculated from the 2001-2014 time series (Figure 6B) and anomalous conditions for 2014 (Figure 6C) were identified by subtracting this average from the current April 7th, 2014 conditions (Figure 6A). Identifying areas where NDVI is lower than average at a specific time indicates that the vegetation there is not thriving, due to lack of precipitation or other environmental reasons, and has a higher susceptibility to fire than what is normally observed. On the contrary, if NDVI is unusually high, it may raise concern about higher fuel loads later in the fire season.

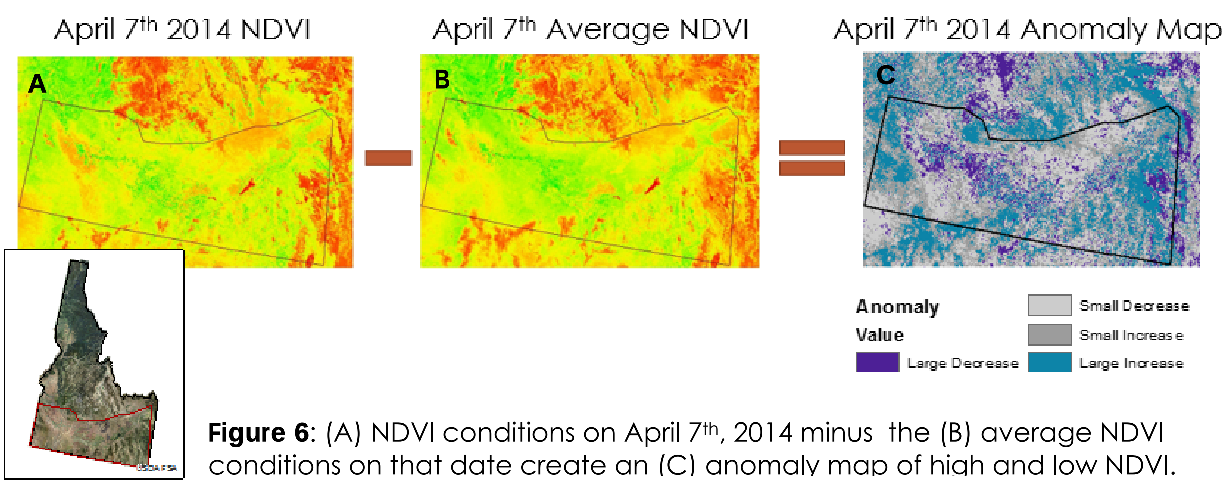


Figure 6: (A) NDVI conditions on April 7th, 2014 minus the (B) average NDVI conditions on that date create an (C) anomaly map of high and low NDVI.

Regional Analysis

There was a significant difference in NDVI between lightning strikes inside and outside of the fire perimeters prior to the 2006 fire season (Figure 7). On April 7th, the NDVI around lightning strikes inside of fires was significantly higher than NDVI at strikes outside of fires ($P < 0.03$). This increase in NDVI could indicate an increase in biomass (Wessels et al., 2006; Shippert et al., 1995), which provides more fuel and ignition potential for fires later in the season (D'Antonio & Vitousek, 1992). Towards the end of April there is a shift, control strikes have higher NDVI than strikes inside fires. Although this trend is not significant, it does provide potential evidence of vegetation senescence, making it more susceptible to fire ignition (Hardy & Burgan, 1999).

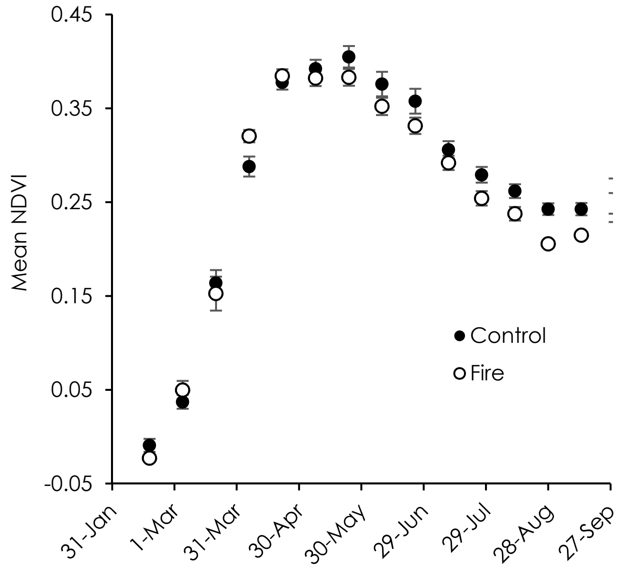
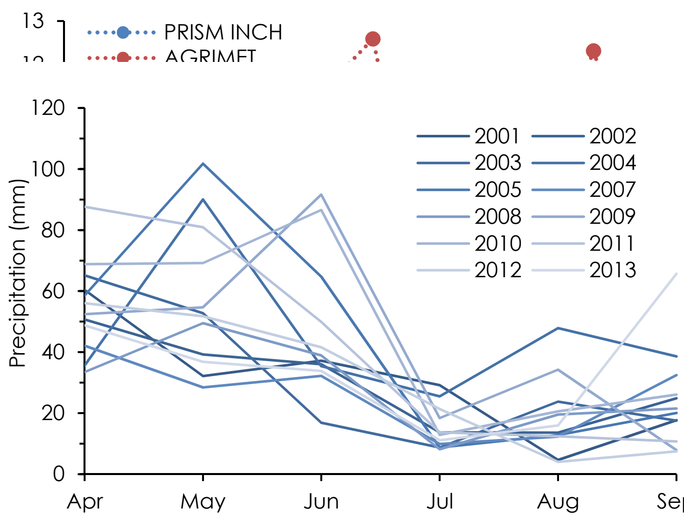


Figure 7: NDVI within 250m buffers of lightning strikes in fires (N=37) and outside of fires (N=59) in 2006. Bars represent standard error.

Since there was a significant difference on April 7th, we examined two more years (2010 and 2012) using the same procedure described in the methods. We analyzed the years separately, instead of pooling all years together, because inter-annual yearly trends are important in fire preparation. If the NDVI is higher on April 7th in some years while others exhibit no difference, then it becomes difficult to use this method as an early warning indicator of fire susceptibility. In 2010, the NDVI in fire locations was higher than control sites but was only nearly significant ($P = 0.54$). Also evident in 2010 is the switch in NDVI in which fire sites had a lower NDVI than control sites in late spring, possibly due to vegetation drying. However, this switch occurred in late May (Appendix Figure 3A), which is later than the switch in 2006. In 2012, the NDVI was higher inside fires than outside, but the significance drops ($P = 0.20$). There was no switch in NDVI in 2012, except during the fire season which is expected since the burned regions will drop in NDVI after the fire (Appendix Figure 3B). The general trend on April 7th is still present, and when the three years are pooled the NDVI in the fires is significantly higher than outside of the fires ($P < 0.01$).

Precipitation

Graphing the precipitation data from AgriMet precipitation shows the expected peaks and valleys of wet and dry years (Figure 8). When compared to the number of fires each year (Table 1), there is a strong correlation for dry years as might be expected, but



there are also interesting correlations in wet seasons. Similarly, Holden et al. (2007) found that the total number of days without rain and maximum amount of consecutive days without rain explained approximately 63% of the variance in total acres burned in the southwestern United States. Further research is needed to understand these trends better.

AgriMet stations are relatively sparse and discrete, which created a challenge when trying to understand specific precipitation conditions at specific fire locations far from a weather station. PRISM data is preferable to AgriMet data, which only provide data measurements at discrete intervals. The overall precipitation data from AgriMet and PRISM have a strong correlation (R = 0.69; Figure 8) but the larger number of weather data collection centers in the PRISM dataset allows for more accurate spatial interpolation in regions lacking precipitation data. Its relatively high resolution (4 km) and continuous nature made it the preferred precipitation dataset to work with (Figure 9).

Figure 9: PRISM maximum precipitation accumulation during hydrologic water year

While MERRA GWETTOP soil moisture data and precipitation data are not measured in the same way, there is a reasonable amount of correlation (R = 0.47 with Agrimet precipitation data). The role MERRA products might play with regard to fire susceptibility still remains unclear, but its availability and strong relationship with precipitation variables make it warrant future research.

Future Work

This research project is the first in a series of three. Our future terms will focus on building materials that the Bureau of Land Management and the Idaho Department of Lands need while in the field. One valuable resource is a vegetation cover map. Although the NLCD classifies areas based on vegetation and cover type, the wildfire agencies need maps that delineate vegetation species. Different vegetation types have different tolerances and susceptibilities to fire and also have direct implications on wildfire management. Many vegetation species in southern Idaho are introduced or are classified as a noxious weed, so management on these lands will be vastly different than in regions dominated by native flora.

Currently, the BLM and IDL use vegetation moisture measurements that are gathered throughout the state in order to make decisions on resource allocation. Although there are a few proxies of moisture content using remote sensing spectral bands, the soil moisture active passive (SMAP) satellite will provide direct readings of soil and vegetation moisture. We plan to validate SMAP measurements with ground-truthing data gathered in southern Idaho to validate its accuracy and usefulness in fire management. The vegetation moisture information that is currently collected is sparse and gathered every two weeks, so the potential for SMAP to fill gaps in this data is high. Although the low resolution (3km) will prevent wildfire managers from identifying the susceptibility of small land allotments, it can be used to pinpoint a drier vegetation region that managers can further investigate.

V. Conclusions

The Bureau of Land Management and the Idaho Department of Lands can use the results of this study in conjunction with their decision-making processes to identify areas of higher susceptibility. If these organizations know ahead of time the likelihood of fire across the state of Idaho, they can make decisions on firefighting resource allocation (M. Kuyper, pers. comm.). However, we didn't find a correlation with surface temperature or NDVI and the number of fires from year-to-year. The lack of a significant trend could be due to the spatial availability of the data. Image composites for both surface temperature and NDVI were used since they were already processed to integrate the best pixels, and the decreased number of files led to faster computing. Vegetation characteristics in grasslands and shrublands change quickly as a result of weather conditions, so measurements taken more often may warrant different results. The course resolution of both measurements may also interfere with trends.

The regional NDVI analysis indicated that April 7th may be a key time period in determining an increased biomass load in areas that burned later in the season. Although this trend was consistent for 3 years, it was not always significant, so its use as an early warning indicator of fire susceptibility will need to be used with caution. The switch in NDVI patterns prior to the fire season may also indicate increased drying in vegetation within fires, which makes the fuels more ignitable, but this trend was not evident in all study years.

Among the precipitation datasets explored this term, PRISM was found to have the highest resolution, is continuous, is easily accessible, and has a wide temporal scale. Further it is highly correlated to ground measurements taken from weather stations. While precipitation data are known to impact fire susceptibility and behavior, alone it is not strongly correlated with the number of fires in the study area.

Overall, remote sensing can be used for identifying fire susceptibility months in advance, but likely cannot be used to determine the number of fires that will occur that year. Other remote sensing products such as SMAP may hold the key for strong correlations with fire susceptibility.

VI. Acknowledgments

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VIII. Appendices

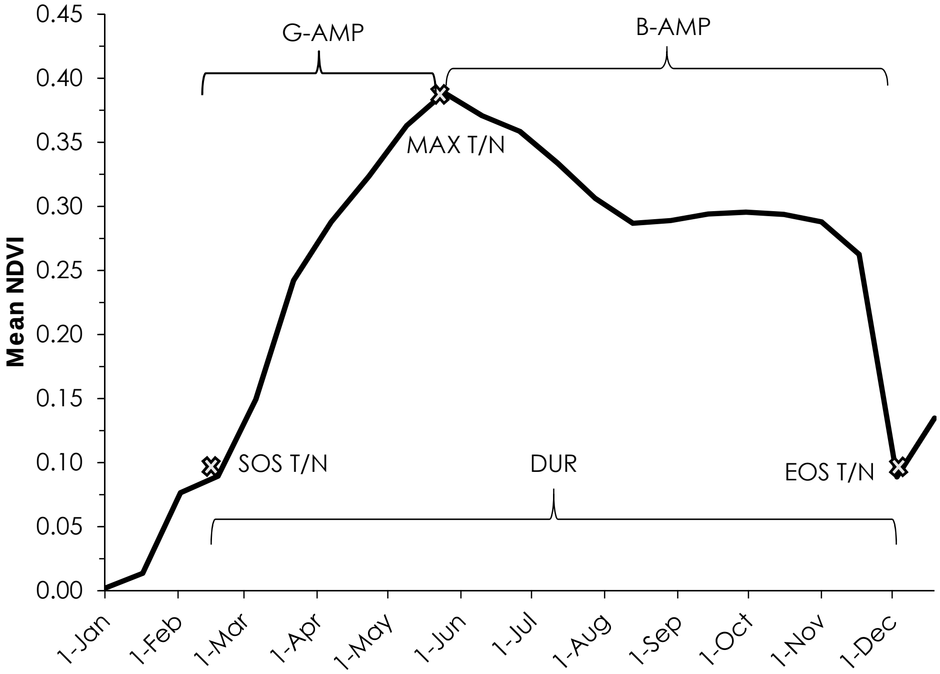

Figure 1: Phenology metrics visualized across 2013 NDVI in study area.

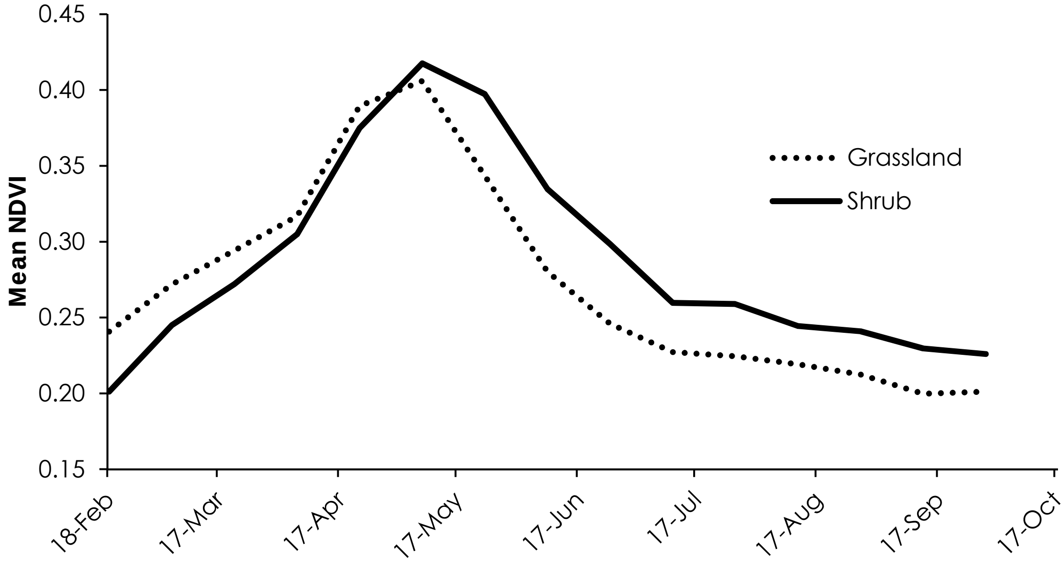

Figure 2: Average NDVI in 2006 between the grasslands and herbaceous land cover classes.

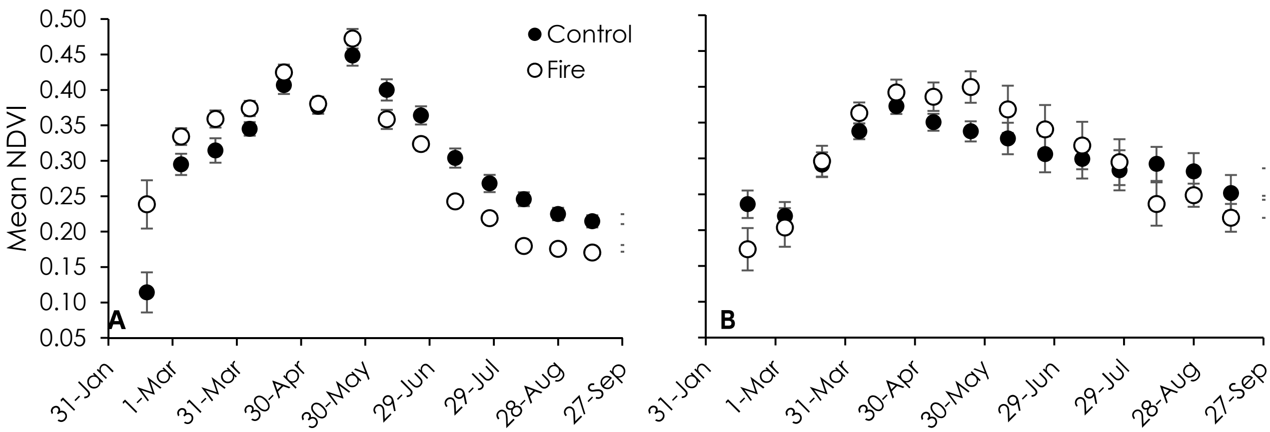

Figure 3: Average NDVI in 2010 (A) and 2012 (B) between the grasslands and herbaceous land cover classes.