**NASA DEVELOP National Program**



GIS Training and Research Center, Pocatello, Idaho

*Summer 2015*

Idaho Disasters III

Using Landsat Earth Observations to Identify Increased Fire Susceptibility Due to Invasion of Cheatgrass (*Bromus tectorum)*

 **Technical Report**

Rough Draft – June 25, 2015

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# I. Abstract

[Placeholder - do not put anything here until the final draft submission. The abstract in the project summary is where the working draft of the abstract should “live”]

**Keywords**

Remote sensing, wildland fire, cheatgrass, fire susceptibility, semi-arid savanna, ecosystem change.

# II. Introduction

## Overview

Wildfire is a primary driver of change in the semi-arid savanna ecosystems. Though fire often plays an essential role in wildland ecology and helps maintain natural processes, too many occurrences of wildfire can deplete resources and facilitate a loss of biodiversity (Oppenheimer, 2013). An increase in wildfire activity not only disrupts ecosystems, it also costs the United States tremendous amounts of money every year. According a recent report issued by Headwaters Economics, estimates of wildland fire costs have tripled from less than $1 billion in the 1990’s to more than $3 billion on average since 2002 (Gorte, 2013). However, the costs of wildfire management may be much more. These assessments from Headwaters Economics reflect the direct suppression costs and did not take into account the costs spent in wildfire protection and mitigation. It is estimated that the Bureau of Land Management spends about $40/ha in fire protection efforts and around $77/ha in land rehabilitation after a burn. (Pellant et al. 2004). These costs are expected to increase in response to increasing wildfire size, frequency and severity. A twenty-seven yearlong study conducted by Dennison et al., found that the total fire area across the Western United States, has increased on average at a rate of 221 mi² (355 km²) per year (Dennison, 2014). One of the primary drivers of these expanding wildfire regimes is the presence of invasive species, namely *Bromus tectorum*, or more commonly known as cheatgrass.

Present in Idaho rangeland and throughout the Great Basin, cheatgrass is a non-native species that has overwhelmed native vegetation and has altered many of the ecological dynamics of this fragile landscape. Due to its ability to rapidly invade disturbed areas and increase frequency of wildland fires, it has perpetuated a continuous cycle of wildfire recurrence and subsequently transformed sagebrush dominated landscapes into cheatgrass dominated monocultures (Brooke & Antonio *et al.*, 2010; Mealor & Mealor *et al.*, 2013). Cheatgrass is a self-pollinating, winter annual that has the potential to germinate in either the fall or early spring. It proliferates rapidly and has the ability to sustain its population throughout drought cycles because its seeds are viable for up to 5 years (Pellant, 1996). Cheatgrass germinates much earlier in the growing season than native species, outcompeting native plants by consuming water and soil nutrients. This creates a more difficult ecosystem for native vegetation to thrive. Researchers suggest that cheatgrass dominates 2.5 million ha of former sagebrush-grass rangelands in Southern Idaho and roughly 10.1 million ha in the Great Basin (Laycock, 1991; Pellant et al, 2004). This mass invasion is thought to have been aggravated by overgrazing, land misuse and abandonment, and an increase in fire regimes (Laycock, 1991). The presence of invasive plants such as cheatgrass create a positive feedback cycle that promotes wildfire. Because cheatgrass grows, reproduces and dies so quickly; it becomes a fine fuel that ignites easily. This in turn clears the landscape and facilitates cheatgrass populations to become established before the next growing season. This has forever changed the fire regime in many areas, extending the fire season and causing landscapes to burn more frequently (Mealor *et al.,* 2013, Pellant, 1996; Stewart & Hull, 1949). Cheatgrass promotes itself due to its ability to quickly invade and monopolize the landscape, and as a result, cheatgrass has altered both the spatial and temporal conditions in a shrub-steppe system (Brooks et al., 2010).

A study by Balch, J. K., Bradley, B. A., D'Antonio, C. M., & Gómez‐Dans, J. found that cheatgrass-dominated landscapes were more than were four times more likely to ignite than native vegetation types. They also documented that these cheatgrass controlled landscapes were more vulnerable to the largest fires recorded during this twenty year study (Balch et al., 2013). Cheatgrass is flammable 4 to 6 weeks sooner than native plants and is susceptible to wildfire 1 to 2 months longer than native perennials (Platt and Jackman, 1946). The “cheatgrass-wildfire cycle” can be detrimental to the native ecosystems affected by frequent fires because excessive wildfires reduce native plant diversity and recovery times. An excess of desiccated cheatgrass has increased the frequency of wildland fires with intervals now less than 5 years on average in certain southern Idaho rangelands (Pellant, 1990).

There have been numerous studies that have attempted to delineate cheatgrass from the landscape using remotely sensed technologies and a variety of methodologies. Landsat TM/ETM+, Advanced Very High Resolution Radiometer (AVHRR), and Moderate Resolution  Imaging Sprectro-radiometer (MODIS) have been used to detect the amplified precipitation response of cheatgrass using Normalized Differenced Vegetation Index (NDVI) image differencing techniques for years that had experienced high levels of rainfall (Bradley and Mustard, 2005; Clinton and Potter et al., 2010). Other studies have used the early phenology (green-up and senescence) of cheatgrass to map its distribution from differenced images combined with decision-tree-based-classification (Peterson, 2003; Bradley and Mustard, 2008, Baraldi and Puzzolo et al., 2006). These studies employ vegetation indices to help delineate cheatgrass and the (NDVI),

$NDVI= \frac{NIR-RED}{NIR+RED}$, (1)

is commonly used. This index measures the unique ability that plant cells have to absorb visible light and reflect near-infrared light. Analyzing this proportion can determine how much biomass is undergoing photosynthesis. However, NDVI is strongly affected by soil reflectance in areas of low vegetation cover, often leading to an overestimation of reflectance values at a given pixel (Qi and Chehbouni *et al.*, 1994; Rondeaux & Steven *et al.*, 1996) and may not be appropriate for use in areas where there is a high percentage of bare ground. In these instances the Soil adjusted Index (SAVI),

$SAVI= \frac{NIR-RED}{\left(NIR+RED+L\right)}×\left(1+L\right),$ (2)

is used with similar calculations to NDVI, but with an adjustment for soil reflectance.

This formula has undergone refinement with the most recent being MSAVI2,

$mSAVI2= \frac{\left(2×NIR +1 - \sqrt{\left(2×NIR+1\right)^{2}-8×\left(NIR-RED\right)}\right)}{2}$, (3)

that has progressively minimized the effects of bare soil reflectance by utilizing a self-adjusting *L* value. Because of the sparse vegetation cover located in the study area, this method was chosen to measure photosynthetic activity.

The phenology of a region changed between years and the phonological synchronization of satellite imagery can help narrow down imagery selection (Weber, 2000). Researchers have found that environmental conditions, especially perception and temperature play a strong role in cheatgrass germination (Richards, 2013; Miller & Franklin, 2002). A study by Miller and Franklin (2002) found the best predictors for cheatgrass germination was mean daily air temperature and growing degree-days (GDD),

$GDD=\frac{Tmax+Tmin}{2}-Tbase ,$ (4)

and concluded that annual weather effects cheatgrass germination more than area disturbance for all seasons.

## Objectives

The objectives of this study were to create a vegetation distribution map using imagery from the Landsat 8 Operational Land Imager (OLI) and decision-tree-based-classification to identify areas with higher presence of cheatgrass (*Bromus tectorum)* in the Idaho rangelands, and therefore, higher fire susceptibility. The results of this project will support decision making processes by the Bureau of Land Management (BLM) and Idaho Department of Lands (IDL) to better allocate resources prior to the beginning of the wildfire season and to better implement ecosystem recovery efforts following a wildland fire.

## Study Area

The study focused on the semi-arid savanna rangelands in southeast Idaho known as the Snake River Plain. The Snake River Plain is located in southern Idaho and stretches east to west 400 miles (640 km) from Wyoming to Oregon. The Snake River Plain was formed as a result of the movement of the North American tectonic plate over the Yellowstone hotspot. Geologists believe that this hotspot was formed around 16 million years ago and has traced a path through the landscape to its present location, Yellowstone National Park (Smith and Braile, 1994). This volcanic activity has modified the landscape, creating a 70 mile (110 km) channel that has crosscut the basin and range patterns of the Rocky Mountains and has significantly altered the climate of this area. While most of the Western United States is situated within the rain shadow of the Sierra Nevada, the Cascades and the Olympic mountains, The Snake River Plain funnels precipitation through a moisture channel extending from the Pacific Ocean to Yellowstone. While most of the Snake River Plain itself is semi-arid, this region receives an abundance of precipitation and forms the headwaters of the Snake River. From Yellowstone, the Snake River flows west through the desiccated countryside and sustains a tremendous diversity of plant and animal species. Many of the shrub species that dominate this landscape include Big Sagebrush (*Artemisia tridentata*), Rocky Mountain Juniper (*Juniperus scopulorum*), and Antelope Bitterbrush (*Pursia tridentata*). The understory is comprised of a variety of forbes and grasses, including Bluebunch Wheatgrass (*Pseudorogneria spicata*), Indian Ricegrass (*Oryzopsis hymenoides*), Crested Wheatgrass (*Elymus lanceolatus*), Bottlebrush Squrreltail (*Elymus elymoides*), needle-and-thread grass (*Stipa comata)*, and Cheatgrass (*Bromus tectorum*). Many species of animals that also inhabit this area include coyote (*Canis latrans*), mountain lion (Puma concolor), pronghorn antelope (Antilocapra americana), greater sage-grouse (Centrocercus urophasianus), rainbow trout (*Oncorhychus mykiss*), golden eagle (*Aquila chrysaetos*), and substantial populations of elk (*Cervus canadensis*) and mule deer (*Odocoileus hemionus*).

## Study Period

The study period for this project was April-September, 2013 and 2014; April – June, 2015. These months encapsulate the growing season. Twenty-three images were obtained from Landsat 8 Operational Land Imager (OLI) focusing on WRS-2 Path 39 Row 30. The minimum, maximum, average daily temperature, daily precipitation, relative humidity, and growing degree days were downloaded from ArgiMet – the cooperative agricultural weather network for every day of the study period.

This project falls under the NASA Natural Disaster Applications Area by seeking to improve wildfire susceptibility forecasting and enhance management practices by providing information allowing land managers to make better, more informed decisions.

## Project partners

The Bureau of Land Management (BLM) and Idaho Department of Lands (IDL) were the end-users for this project. Currently, these agencies rely on vegetation moisture measurements as well as field observations to support decisions regarding allocation of helicopters, dozers, and other fire suppression equipment across fire management zones throughout Idaho. These observations are collected at two week intervals. Due to the large extent of the area of concern, field observations are not capable of providing a comprehensive assessment of vegetation distribution throughout the agency’s respective management zone. Furthermore, the positive feedback cycle between cheatgrass and wildland fire is well understood within these organizations, but there is no process currently implemented that communicates cheatgrass distribution information to decision makers. The results of this research support decision making by land managers by providing vegetation distribution data products at local and regional scales, allowing managers to visualize areas with increased fire susceptibility by identifying dominant vegetation at a particular site. The NASA RECOVER project team serves as a boundary organization whose purpose is to distribute critical fire related information to end-users for a specific site via a web map application. Data products produced by this study will be disseminated via the RECOVER project team to be used by end-users.

# III. Methodology

## Data Acquisition

### Landsat 8 OLI

Level 1T Landsat 8 Operational Land imager (OLI) imagery were acquired from the USGS Earth Explorer web application in GeoTIFF format for WRS-2 Path 39 Row 30. The images selected, from late March through late September, comprise of the complete growing season, or hydrologic water year, during which vegetation experiences a full growth cycle.  Images from this time range were acquired for 2013 and 2014, as well as available imagery since late March for the year 2015 (*Appendix A)*.  Selected imagery maintained less than 20% cloud cover.

### Climate Data

Historic meteorological data were obtained from the Bureau of Reclamation’s AgriMet weather system. Daily air temperature, daily precipitation, and GDD were collected in order to determine which, of the Landsat 8 OLI time series, coincided with the time that cheatgrass is actively growing while other vegetation species are not.  Specifically, days that received early precipitation were scrutinized to evaluate cheatgrass location. Temperature and precipitation were then analyzed to determine the days when cheatgrass green up would be more active.

### Classification sites

To help delineate vegetation dominance in the study area, five classifications of land cover were determined; bare ground, cheatgrass, mixed vegetation, montane forest/ western Juniper, and sagebrush/ herbaceous. Classification sites were created using 2013 NAIP imagery with a .5m resolution, 2015 UoG ground truth observations, cheatgrass points from Clinton *et al.*, 2010 study that used remote sensing and a based time-series analysis to detect cheatgrass phenology, and field observations collected by Idaho State University GIS Training and Research Center staff during the summer months of 2014 and 2015. The total number of classifications for land cover dominance were 14 bare ground, 43 cheatgrass, 17 mixed vegetation, 63 montane forest/ western Juniper, and 128 sagebrush/ herbaceous with a total of 266 observations.

A classification tree (CT) analysis was used because it is data driven and allows for the development of a decision tree training and model validation from this dataset (Miller & Franklin, 2002). In the Idaho rangeland, cheatgrass tends to grows better with a southwest aspect and a slope of < 30% (S. Mavor, personal communication, June 19, 2015). Topography- related variables, aspect and slope, along with climate variables, precipitation and temperature, were used to help determine vegetation distribution. Each of the five classes were randomly divided into 50% training sites that were used to build the model and 50% test sites that were used to assess the accuracy of the model.

## Data Processing

Corrections for atmospheric effects were applied to the L1T Landsat 8 OLI imagery using the *Cos*(t) model and calculations to derive surface reflectance from multispectral bands were computed using the IDRISI TerrSet Landsat archive import module.

Imagery selected for further processing was considered to be at the green-up phase of cheatgrass. Pheno-Calc, a software package developed at the GIS Training and Research Center and available at the organizations website (http://giscenter.isu.edu), was used in combination of AgriMet historical meteorological records, to determine GDD for cheatgrass green-up in each study year. Pheno-Calc was used to match days of the year that are phonologically similar to selected days of another year. The time period identified as meeting this criteria was a base temperature of 35 degrees Fahrenheit a GDD of 400 with a 10% tolerance. 400 GDD was selected after Pheno-Calc and AgriMet historical meteorological records analysis of the results for early spring cheatgrass phenology by Boyte, S. P., Wylie, B. K., Homer, C. G., & Major, D. J.

The ideal imagery that met our study window and was available from Landsat 8 (OS) with less than 20% cloud contamination were selected.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Year | Month | Day  | GDD | Average Precipitation (in) | AverageTemperature(F) |
| 2013 | 5 | 15 | 652.385 | 0.65 | 65.51 |
| 2014 | 4 | 16 | 390.11 | 2.27 | 43.13 |
| 2015 | 4 | 19 | 466.55 | 0.53 | 49.75 |

From the selected imagery, mSAVI2 (Qi & Huete *et al.*,1994) and Tasseled-Cap-Transformation Brightness, greenness, and wetness (Kauth & Thomas, 1976) were derived. These indices were evaluated for their ability to identify the spectrally distinct land cover classes defined as Herbaceous/Shrubland and Montane Forest from the 2011 National Land Cover Dataset (NLCD).

The Modified Soil-adjusted Vegetation Index was calculated to produce phenology graphs. Two habitat types were compared where cheatgrass is most likely to grow, montane forest/Western Juniper and Herbaceous/Shrubland. These cover types were imported into Arcmap 10.3 and zonal statistics were calculated to determine areas with high mSAVI values. The phenology graphs were used to determine the days when cheatgrass was most likely to grow.

## Data Analysis

Training sites used in the Classification Tree Analysis (CTA) were analyzed for class purity, or the degree of spectral similarity between points belonging to the same class.  Training sites that fell outside the acceptable range were removed from training dataset. CTA was used to classify individual pixels based upon spectral signatures exposed in the mSAVI and TCT indices and identified using the training sites.  Analysis results were analyzed for its ability to discriminate the classes based on the spectral signature of each class.  Once sufficient separation between spectral classes was identified, the model results were accepted for further evaluation.

# IV. Results & Discussion

Insert images, graphs, maps, charts, etc. here. Choose the most important results to highlight here. No word cap, but two to six pages is a good range.

Things to discuss:

* Analysis of Results: What can you tell from your graphs, images, etc? What does this mean for your project?
* Errors & Uncertainty: What factors could you not account for, what things didn’t work out like you expected they would, etc.
* Future Work: If this project was to be selected for another term, what would be the focus? What other areas would be of interest?

# V. Conclusions

Final conclusions. Word count: 200-600 (~a page).

# VI. Acknowledgments

We would like to thank our science advisors, Keith Weber, Dr. Mark Carroll, and Dr. John Schnase as well as Margaret Wooten for their guidance and feedback throughout the life of this project.  We extend a special thanks to Ryan Howerton at the GIS TReC for his assistance in collecting field observations used as part of this research as well as taking quality photos of the DEVELOP team.  We would also like to thank past DEVELOP team members Kiersten Newtoff, Kyle Sowder, Katherine Bradford, Andrea Bodenberg, and Eric Smith for their contributions to this research.

This material is based upon work supported by NASA through contract NNL11AA00B and cooperative agreement NNX14AB60A.

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Interactive Plot Viewer

Nomenclature Viewer

# IV. Appendices

## Appendix A

**Landsat 8 Image Acquisition Table**

Table lists Landsat 8 OLI imagery acquired with imagery selected for analysis highlighted

|  |  |  |
| --- | --- | --- |
| **Data Product** | **Data Processing Level** | **Imagery Date** |
| LC80390302013135LGN01 | L1-T | May 15, 2013 |
| LC80390302013151LGN00 | L1-T | May 31, 2013 |
| LC80390302013167LGN00 | L1-T | June 16, 2013 |
| LC80390302013183LGN00 | L1-T | June 31, 2013 |
| LC80390302013215LGN00 | L1-T | July 2, 2013 |
| LC80390302013231LGN00 | L1-T | July 18, 2013 |
| LC80390302013231LGN00 | L1-T | August 3, 2013 |
| LC80390302013279LGN00 | L1-T | August 19, 2013 |
| LC80390302014090LGN00 | L1-T | September 4, 2013 |
| LC80390302014106LGN00 | L1-T | March 31, 2014 |
| LC80390302014122LGN00 | L1-T | May 2, 2014 |
| LC80390302014154LGN00 | L1-T | June 3, 2014 |
| LC80390302014170LGN00 | L1-T | June 19, 2014 |
| LC80390302014186LGN00 | L1-T | July 5, 2013 |
| LC80390302014202LGN00 | L1-T | July 21, 2014 |
| LC80390302014250LGN00 | L1-T | September 15, 2014 |
| LC80390302014266LGN00 | L1-T | September 23, 2014 |
| LC80390302015077LGN00 | L1-T | March 18, 2015 |
| LC80390302015093LGN00 | L1-T | April 3, 2015 |
| LC80390302015109LGN00 | L1-T | April 19, 2015 |