# A Comparison of Post Wildfire Regeneration of Invasive and Pioneer Species

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**Abstract:** Wildfire is a destructive event that has the potential to occur in any region where forests exist. A natural and balanced regeneration of vegetation is paramount to forest and animal health after a wildfire is extinguished. Monitoring and understanding regeneration patterns can aid environmental professionals in promoting healthy forest regeneration. This study focuses on post wildfire vegetation regeneration in Glacier National Park, Montana. Two fire perimeters from the 2003 fire season are used to identify and map the regeneration using multispectral imagery. Cheatgrass, an invasive species, and western larch, a pioneer species are identified, mapped, and analyzed using remote sensing techniques.

An object-based image analysis classification workflow is presented to demonstrate how species are identified and classified. Normalized Difference Vegetation Index (NDVI) and Normalized Difference Burn Ration (dNBR) indices are utilized to identify burn areas and new vegetation growth. The results reveal regeneration behaviors of the vegetation species and how they relate to overall patterns of burning and other environmental factors. The results show that western larch thrived in the post wildfire regeneration period by out-competing other species to generally occupy larger amounts of land than previously occupied. Little direct competition was found between the species as cheatgrass was found to occupy steeper south facing slopes while western larch was found on less inclined slopes. There was also a distinct separation of these species when evaluating elevation as cheatgrass was consistently found regenerating in higher elevations. Western larch was found to correlate strongly with low to moderate burns while cheatgrass was found in more severely burned areas.

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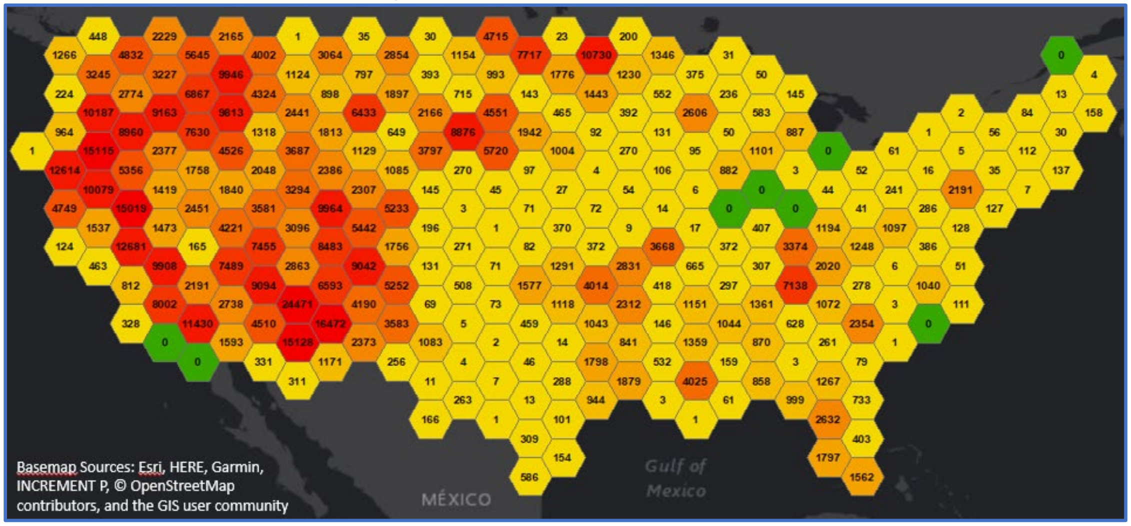
## 1. Introduction

The ability to monitor long term post wildfire regeneration is essential to understanding and controlling the spread of invasive vegetation species and variations in the extent of pioneer species. Beginning in the 1980s, there has been a dramatic increase in wildfire throughout the United States (Westerling, 2016). Data from the National Interagency Fire Center (Figure 1) shows 589,280 wildfires that occurred from 1980 to 2016. Wildfire presents an opportunity for a forest ecosystem to renew itself with healthy growth. Some native species such as western larch (Larix occidentalis) have the ability to thrive in post fire environments as the tree's bark is capable of resisting fire which allows for rapid reseeding and establishment of saplings (Scher, 2002). Post-fire conditions also present an ideal opportunity for harmful invasive species to flourish during regeneration (Brooks & Lusk, 2008).

**Figure 1.** US Wildfires 1980-2016



Basemap Sources: Esri, HERE, Garmin, INCREMENT P, © OpenStreetMap contributors, and the GIS user community

The United States Department of Agriculture (2018) defines invasive species as a non-native organism whose introduction causes economic or environmental harm, or harm to human, animal, or plant health. Invasive species are typically introduced through the spread of their seed by birds, wind, or humans who unknowingly transport seed. Hallmark tendencies of invasive species include high seed yields, aggressive root systems that choke out surrounding species, or chemicals that hinder the growth of nearby vegetation (United States Department of Agriculture, 2018).

Invasive species can have devastating impacts on the ecosystem that include competition with native species for essentials of life such as moisture, nutrients, daylight, and growing space. Additionally, long term plant diversity can be affected which eventually can lead to a deterioration of wildlife habitat and potential food resources being replaced by invasive species. Finally, these species can affect water quality and lead to increased erosion of soil (United States Department of Agriculture, 2018).

Cheatgrass (*Bromus tectorum*) is one of these invasive species and is especially invasive because it germinates in both spring and fall. This germination period allows cheatgrass to seed earlier than other native plants, which encourages rapid establishment in disturbed areas. Cheatgrass is also extremely flammable when dried, introducing the threat of a cycle where it can burn and then develop a dominant stranglehold where it begins to alter the local ecosystem during regeneration (Weber, 2017).

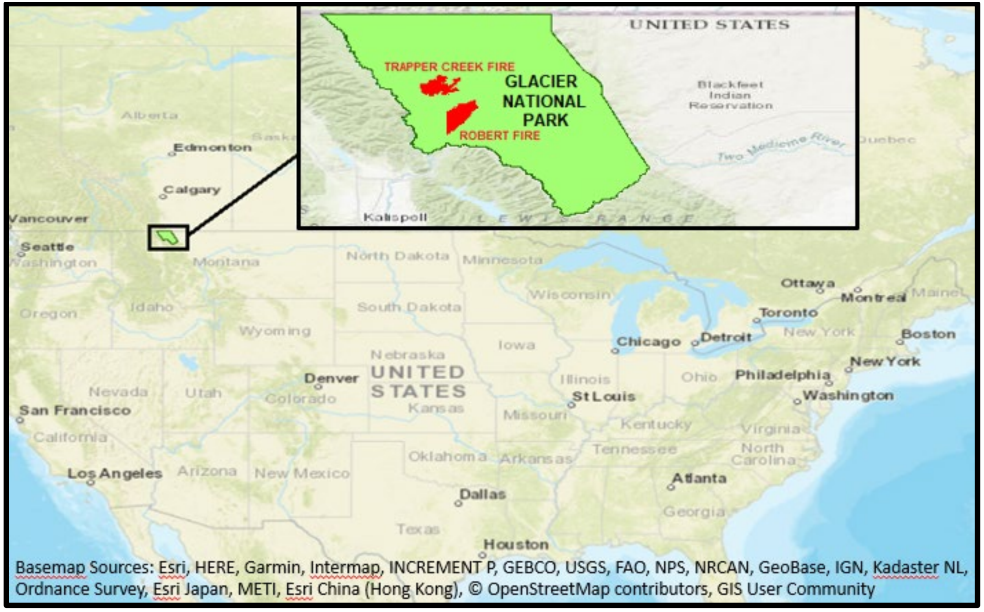
This study will present a workflow that uses object-based image analysis within Esri ArcMap 10.6 to classify and analyze long term post wildfire regeneration within Glacier National Park. The analysis will focus specifically upon the extent of western larch and cheatgrass during post-fire regeneration. The methodology successfully classified each species to at least an 80% class accuracy, which allows for reliable analysis of the regenerative growing conditions.

## 2. Methods

### 2.1 Study Area

The Robert and Trapper Creek fires (Figure 2) occurred during the 2003 burn season. These fires account for over 30,000 acres of burned land when combined. The land covers of these burn areas consist of mountains, alpine meadows, glacial valleys, and coastline of large glacial lakes.

**Figure 2.** Location of the study areas within Glacier National Park.



Basemap Sources: Esri, HERE, Garmin, Intermap, INCREMENT P, GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), © OpenStreetMap contributors, GIS User Community

### *2.2 Datasets*

LANDSAT 7, LANDSAT 8, and National Agriculture Imagery Program (NAIP) imagery was downloaded for the years of 2003 through 2017 from the (USGS) Earth Explorer website. LANDSAT 7 images were selected before the fires in the summer of 2003 and in the summer of 2004. LANDSAT 8 images were obtained for July 2017. NAIP imagery was selected during September 2017 for the vegetation classification. Fall was chosen for the classification due to western larch appearing yellow/orange as it prepares to drop its needles before the winter and cheatgrass appearing more green than surrounding vegetation leading into the fall. These color differences allow for more accurate classification. Pre-fire images were found mere days before the wildfire began. However, post-fire images had to be taken from the following summer due to the several weeks that the fires burned. By this time the imagery became very cloudy and nearly unusable. It was critical to obtain post-fire imagery before regeneration began to ensure the post-fire indices were created properly. The LANDSAT images from all years were used to create NDVI and NBR indices for analysis after the vegetation classification.

A 10-meter Lidar Digital Elevation Model (DEM) was secured from the National Park Services (NPS) Integrated Resource Management Applications (IRMA) portal. The NPS mosaicked the data from USGS 7.5’ quadrangle data. The DEM was used to analyze slope and aspect.

High resolution vegetation species polygons and points mapped by the NPS were harvested from the NPS Vegetation Inventory Project. This high-resolution dataset was developed from multiple sources to form the most accurate vegetation classification data of Glacier National Park. The data contains the best of aerial photographs and extensive field surveys from 1997 to 2000. This data served as the baseline for vegetation species classification and creation of training data polygons.

Soil survey polygons were selected from the National Park Services (NPS) Integrated Resource Management Applications (IRMA) portal. This data is developed by the National Cooperative Soil Survey and was constructed largely using local soil scientists with experience in surrounding landscapes. This data was used during analysis to determine where each species is likely to be found during regeneration.

### *2.3 Indices*

Indices used for analysis include NBR, dNBR, NDVI and dNDVI. NBR is used for mapping burn severity and is computed (Figure 3) using the near infrared and short-wave infrared spectral bands. Near infrared strongly reflects vegetation while the short-wave infrared reflects weakly (Wasser & Cattau, 2018). The NBR was calculated from LANDSAT imagery before and after each fire. The pre-fire numbers are then subtracted (Figure 4) from the post fire numbers to get the final Normalized Difference Burn Ratio (dNBR) values. dNBR reveals where the most severe burns occurred within a burn perimeter.

**Figure 3.** Normalized Burn Ratio

$$\boxed{NBR = \frac{NIR - SWIR}{NIR + SWIR}}$$

**Figure 4.** Normalized Difference Burn Ratio

$$\boxed{dNBR = NBR_{pre} - NBR_{post}}$$

Normalized Difference Vegetation Index (NDVI) is a classic measuring stick for evaluating vegetation health and is useful for evaluating post burn areas. It is computed (Figure 5) using the near infrared and red bands. Since vegetation is highly reflective in the near infrared portion of the electromagnetic spectrum and highly absorptive in the visible red spectrum, these contrasts are used as an indicator of vegetation status (Yichun et al, 2008). NDVI can also be normalized by subtracting (Figure 6) the pre-fire numbers from the post-fire numbers to get normalized NDVI (nNDVI). nNDVI essentially shows where regeneration is strongest since the fire occurred. nNDVI was also used as a quality check on dNBR. The areas with the most severe burns should align with the areas experiencing the greatest regeneration.

**Figure 5.** Normalized Difference Vegetation Index

$$\boxed{NDVI = \frac{NIR-R}{NIR+R}}$$

**Figure 6.** Normalized Normalized Difference Vegetation Index

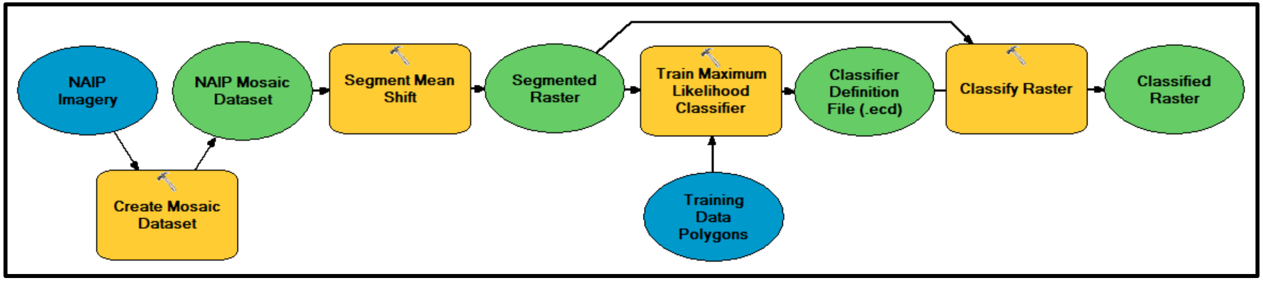
$$\boxed{nNDVI = NDVI_{pre} - NDVI_{post}}$$

*2.4 Process*

Object-based image analysis is a classification method that focuses on grouping similar pixels into groups called objects. These objects are then classified based on spectral, spatial, and pixel detail. This form of classification mimics how the human eye sees and classifies an image. For example, when looking at a green field, the human eye does not analyze each individual pixel. Instead, human eyes group the green pixels together into a single object, and then define that object as a field. This type of classification lays the groundwork for automated classification workflows. With high quality imagery and the appropriate settings, object-based image analysis can be an extremely accurate form of automated classification (Bradley, 2014). The object-based image analysis workflow is an iterative process that allows for refinement of the classification. Quality checks are used to ensure accuracy along the way.

The object-based image analysis workflow (Figure 7) was completed entirely within ArcMap and successfully classified vegetation species for analysis. A clear step by step process was defined to provide consistency so the exact same process was utilized for both burn areas. Creation of a defined process allowed for fine tuning of the workflow to create the most accurate classification possible.

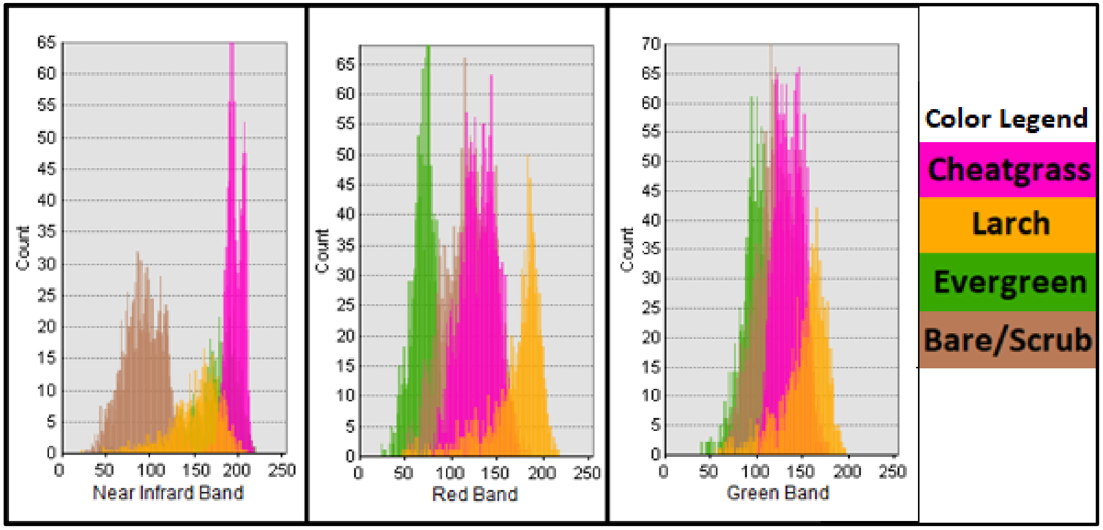
**Figure 7.** Object-Based Image Analysis Workflow



The workflow begins with creating a mosaic dataset of the NAIP imagery. All images that cover the burn perimeter are then added into the proper dataset. The result is a seamless image that allows for smooth running of geoprocessing tools needed to complete the classification process.

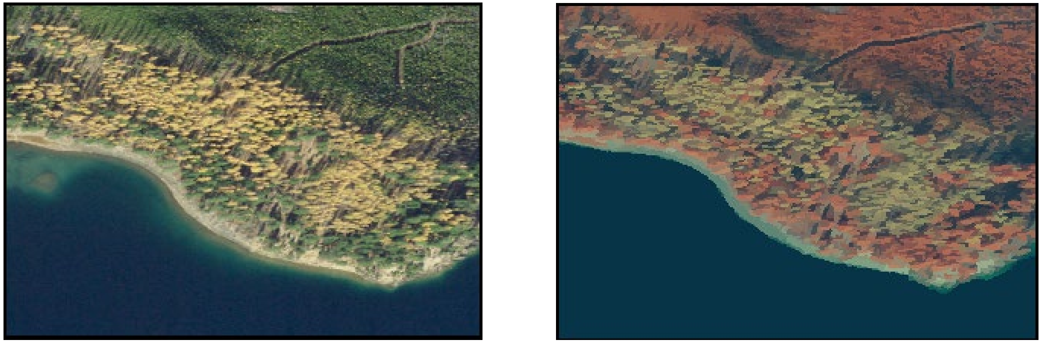
The near infrared (band 4), red (band 1), and green (band 2) bands were used for this classification. The decision to use this specific band combination was the result of a spectral band analysis completed via the Training Sample Manager. Histograms (Figure 8) show each spectral band was capable of differentiating between the desired classes.

**Figure 8.** Spectral band analysis within Training Sample Manager



The mosaic was then passed into the Segment Mean Shift tool where the pixels are grouped into objects (referred to by Esri as segments). The objects are based on specific spectral, spatial, and pixel detail. This is where the spectral image bands are utilized. Using a trial and error process it was discovered that the following Segment Mean Shift settings were best for this classification. Spectral Detail – 18; Spatial Detail – 18; Minimum Segment Size in Pixels – 80. Accuracy assessments and visual inspection found this combination of settings to be the best for classifying relatively small patches of differing vegetation species while providing a result that is ready for analysis. The minimum pixel size of 80 greatly increased the accuracy of the classification by eliminating small misclassifications caused by a few pixels that were discolored due to shadow, sun reflection, or other unexpected environmental factors. This process results in the segmented image (Figure 9) that will be used for classification.

**Figure 9.** Original NAIP image and result of Segment Mean Shift tool



Original NAIP

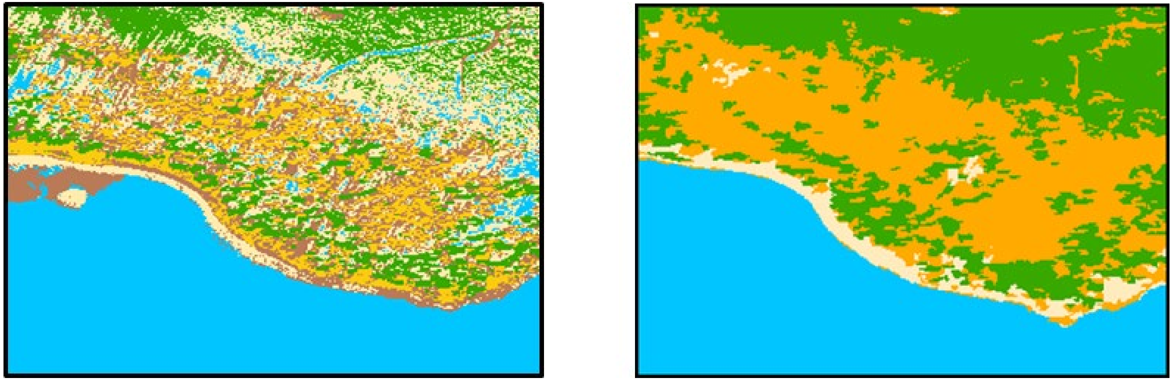
Segmented image

The segmented raster was then coupled with training polygons that were created from known vegetation data provided by the NPS. This training process utilized the Maximum Likelihood Classifier. The creation of training data polygons took place within the Training Sample Manager where the NPS vegetation species data was verified on imagery. Polygons were manually added to the training dataset for each species being classified. Visually verifying the training data on imagery greatly reduced the chance for error. Settings were specified to allow the training process to focus specifically on segment attributes of Color, Mean, Count, and Compactness. These settings were found to be the best after a trial and error process to verify which settings provided the best result. This training process led to the creation of an Esri classifier definition (.ecd) file. This file holds all training data information to be used for the final classification with the segmented raster.

The final step is to complete the classification by directing the .ecd file to classify the segmented raster based on the specified training data and settings. This is done via the Classify Raster tool. The result is a raster that is classified based on the object-based image analysis workflow described within this report. Comparisons were made between the object-based image analysis result and a traditional unsegmented result (Figure 10). The comparison revealed this object-based image analysis workflow created a more generalized and meaningful result that was ready for analysis and mapping.

The process described above is iterative and was repeated several times before the final classification was completed. Feedback loops through each step of this process allows for continual refining of the settings. This approach encourages continued improvement of the output until it meets quality and/or accuracy standards.

**Figure 10.** Comparison of traditional and segmentation classification



Traditional (unsegmented)

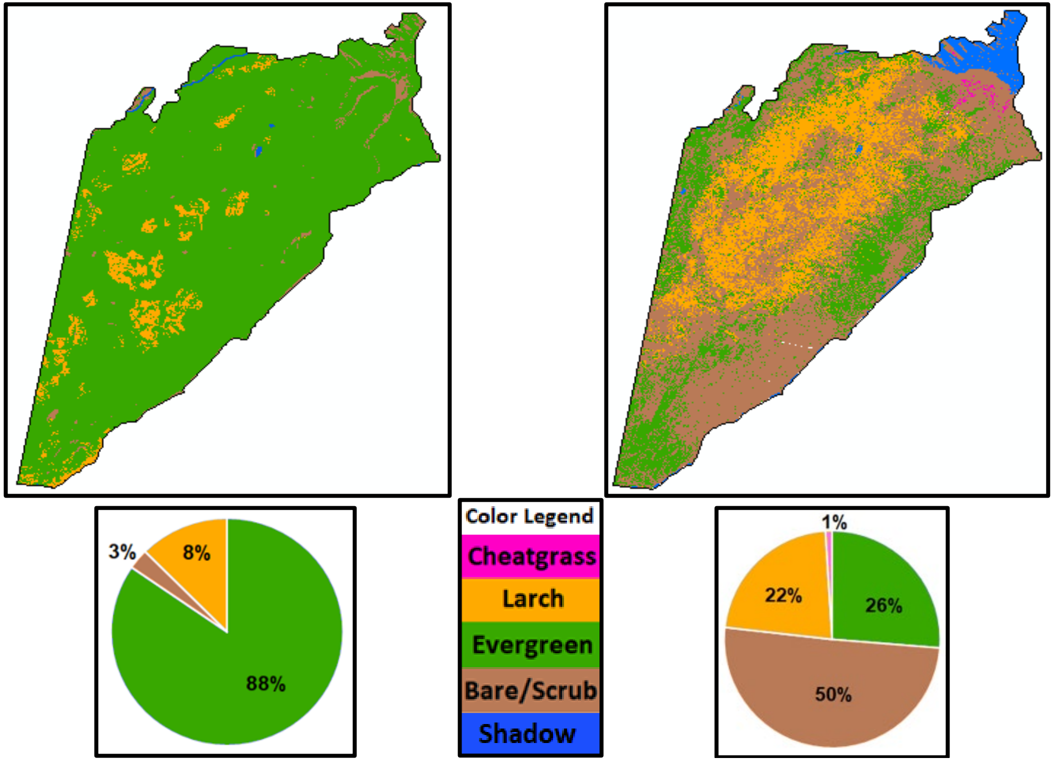
Segmentation

## 3. Results and Discussion

### *3.1 Classification Results*

The classification results from both the Robert (Figure 11) and Trapper Creek (Figure 12) fires reveal that what was once primarily evergreen forest has been replaced primarily by bare/scrub/brush areas. The results also show western larch weathering the fire well with only a 2% decrease in total area within the Trapper Creek perimeter and increasing from 8% to 22% in the Robert perimeter. The 14% increase within the Robert perimeter is something that was expected to be seen from a pioneer species like western larch. The disturbance provided an opportunity for this species to continue its germination cycle that excels in disturbed areas. The 2% decrease in western larch found at the Trapper Creek perimeter can be attributed to shadows in the imagery where western larch would have been expected to grow in addition to some higher burn ratios within the perimeter. An introduction of cheatgrass was also found at both sites. The cheatgrass accounts for approximately 1% of the landcover within the regenerating perimeters. This is something to be concerned about when considering the overall size of these perimeters and considering how quickly cheatgrass can spread once established in an area. Cheatgrass was found primarily in the western portion of both burn areas. Analysis was done to further investigate competition between these species and to pinpoint post-fire conditions these species favor during regeneration.

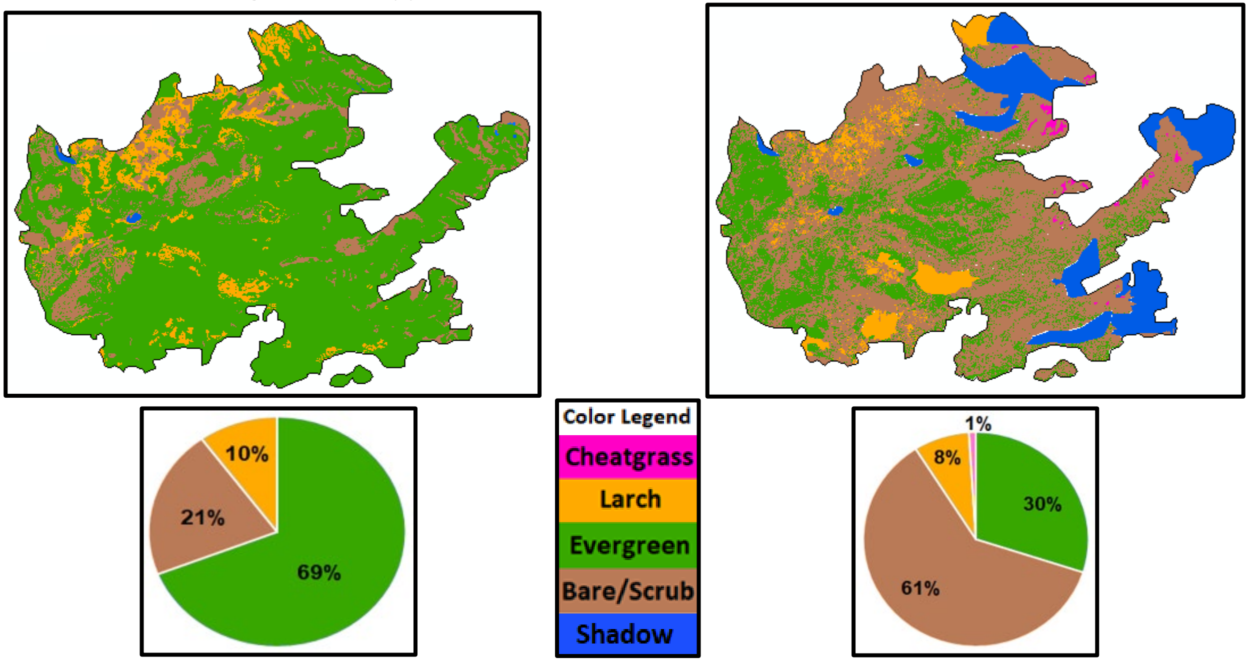
**Figure 11.** Robert Fire before and after classification results



Robert before

Robert after

**Figure 12.** Trapper Creek Fire before and after classification results



Trapper Creek before

Trapper Creek after

### *3.2 Accuracy Assessment*

A site-specific accuracy assessment was performed on the classified data to find the producer's, user's, and overall accuracies. The NPS Vegetation Mapping Inventory Program requires a minimum class accuracy goal across all vegetation and land cover classes of 80% (Cook, 2016). This process began by generating random points in ArcMap across the AOI while also making an effort to include the different classes that were defined. Some manual adjustments were made in instances where the points generated areas containing shadow, cloud, etc. Approximately 50 points per class were an effective number of reference points; however, these numbers changed due to different amounts of area for each class within the AOI. Western larch and evergreen ended up with significantly more reference points. The points were converted to raster and combined with a classified raster created with the object-based image analysis process. This combined class was put into the Pivot Table tool in Excel to create the error matrixes (Figures 13 & 14).

**Figure 13.** Robert fire accuracy assessment

**Robert Fire Classification Error Matrix**

| | | **Reference** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Classes | Evergreen Forest | Water | Shrub/Bare | Snow | Larch | Cheatgrass | **Total (classified as)** | **User's Accuracy** |
| **Classified** | Evergreen Forest | 68 | 0 | 0 | 0 | 2 | 2 | **72** | **94%** |
| | Water | 0 | 24 | 1 | 7 | 1 | 0 | **33** | **73%** |
| | Shrub/Bare | 3 | 0 | 43 | 0 | 3 | 2 | **51** | **84%** |
| | Snow | 0 | 6 | 1 | 18 | 0 | 0 | **25** | **72%** |
| | Larch | 4 | 0 | 2 | 0 | 69 | 1 | **76** | **91%** |
| | Cheatgrass | 0 | 0 | 3 | 0 | 0 | 25 | **28** | **89%** |
| | **Total (Training data)** | **75** | **30** | **50** | **25** | **75** | **30** | **285** | |
| | **Producer's Accuracy** | **91%** | **80%** | **86%** | **72%** | **92%** | **83%** | | **87%**<br>**Overall Accuracy** |

**Figure 14.** Trapper Creek fire accuracy assessment

**Trapper Creek Fire Classification Error Matrix**

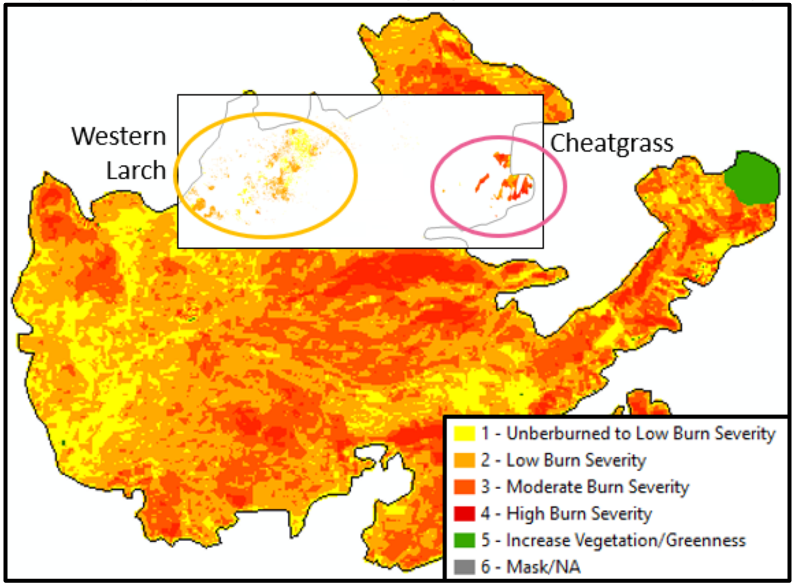
| | | **Reference** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Classes | Evergreen Forest | Water | Shrub/Bare | Snow | Larch | Cheatgrass | **Total (classified as)** | **User's Accuracy** |
| **Classified** | Evergreen Forest | 68 | 1 | 1 | 0 | 1 | 0 | **71** | **96%** |
| | Water | 0 | 23 | 0 | 2 | 0 | 0 | **25** | **92%** |
| | Shrub/Bare | 3 | 0 | 44 | 1 | 2 | 1 | **51** | **86%** |
| | Snow | 0 | 5 | 0 | 22 | 0 | 0 | **27** | **81%** |
| | Larch | 4 | 0 | 3 | 0 | 71 | 3 | **81** | **88%** |
| | Cheatgrass | 0 | 1 | 2 | 0 | 1 | 26 | **30** | **87%** |
| | **Total (Training data)** | **75** | **30** | **50** | **25** | **75** | **30** | **285** | |
| | **Producer's Accuracy** | **91%** | **77%** | **88%** | **88%** | **95%** | **87%** | | **89%**<br>**Overall Accuracy** |

When looking into the accuracy results, there are a few points that stick out. The 87% and 89% that represents overall accuracy does not represent a steady percentage across all classifications. When looking at the error matrix, the diagonal values represent correctly classified points while non-diagonal values represent misclassifications. It can be seen that the most common misclassifications involve water and snow being confused for one another. These misclassifications are reflected in the producer's and user's accuracy for those classes; snow and water tend to have lower accuracies in these categories. The ratings show the results are of good quality, but do have some inaccuracies. All vegetation classes meet the 80% minimum class accuracy requirement. Snow and water accuracies fell just below 80% accuracy. This was viewed as acceptable since these two classes were confused for each other in most instances and were not integral to the final analysis. Western larch and cheatgrass exceeded 80% accuracy with values in the high 80s and low-mid 90s percentages.

*3.3 Analysis*

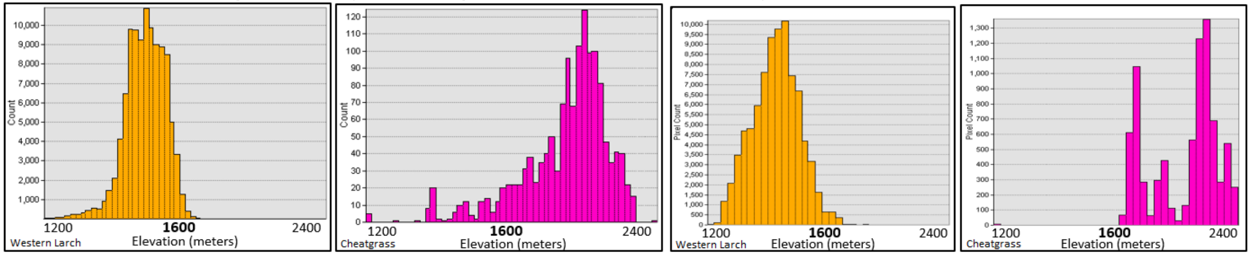
When looking at the effects of burn severity on regeneration, it was revealed that cheatgrass can consistently be found in areas that suffered more severe burns. The western larch was found regenerating in areas that suffered low to moderate burns. This suggests that cheatgrass is more suited to quickly take advantage of areas experiencing higher levels of disturbance. Western larch was not excluded from regenerating in severe burn areas, but was more abundant in the lesser burned areas. An inset map of the Trapper Creek Fire (Figure 15) shows the common trend of cheatgrass regenerating in more severe burn areas. This trend was found within both perimeters.

**Figure 15.** Map of Trapper Creek Fire showing regeneration locations compared to dNBR



The classified results were also compared to elevation data. This revealed species preferences in regards to total elevation, slope, and aspect. When looking at elevation (Figure 16) it was found that there is a decisive break at approximately 1600 meters where western larch is found below and cheatgrass is found above. This 1600 meter break was found in both the Robert and Trapper Creek regeneration patterns.

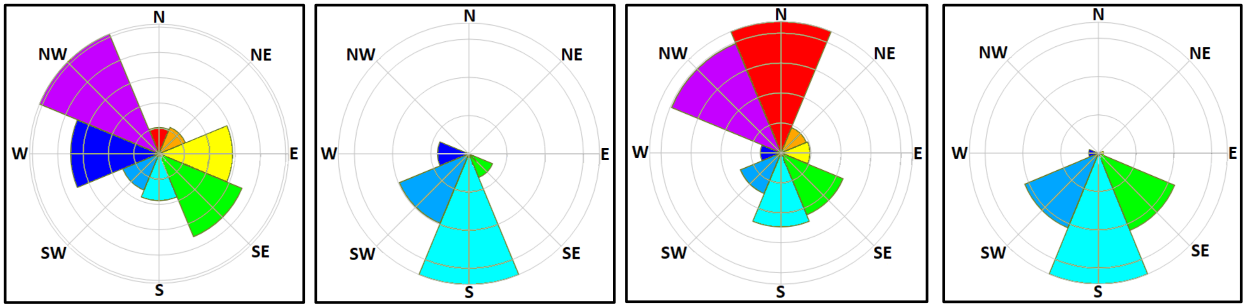
**Figure 16.** Species regeneration locations compared to total elevation



Robert – larch Robert – cheatgrass Trapper – larch Trapper - cheatgrass

Aspect analysis (Figure 17) revealed western larch regenerating on terrain facing in all directions. Western larch did appear to slightly favor north facing slopes that provide more shade for seedlings. This is a result that agrees with historical western larch regeneration patterns (Scher, 2002). Cheatgrass on the other hand was revealed to be greatly affected by aspect. In both burn perimeters cheatgrass was found to regenerate in areas that face primarily to the south. South facing slopes in Montana are exposed to more sunlight and are an ideal situation for cheatgrass to invade. Other species have issues growing in bare areas that receive increased sunlight, whereas cheatgrass can be more effective (Peeler & Smithwick, 2018).

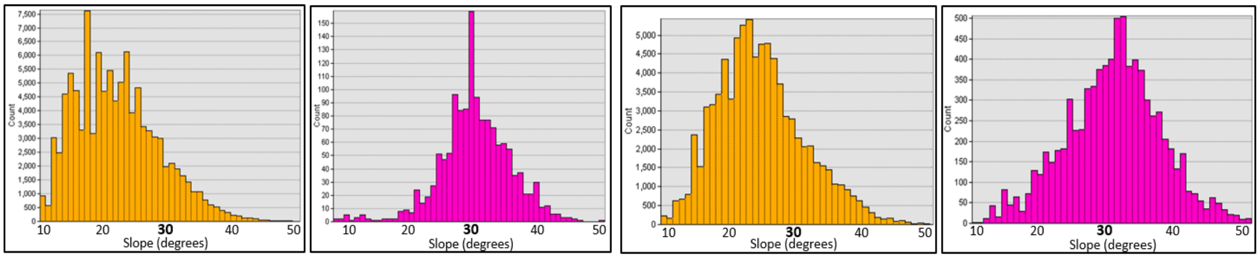
**Figure 17.** Compass roses displaying regeneration aspect



Robert – larch Robert – cheatgrass Trapper – larch Trapper – cheatgrass

Slope analysis (Figure 18) revealed that cheatgrass was found on steeper average slopes (5°-50°) than the western larch. This result was expected due to the fact that cheatgrass was found at higher overall elevations. Higher elevations and steeper slopes typically go hand in hand. Western larch was generally found on slopes ranging between 0° and 35°. Both cheatgrass and western larch were found at all slopes but there was a large difference where each species was found on average.

**Figure 18.** Species regeneration locations compared to total elevation



Robert – larch Robert – cheatgrass Trapper – larch Trapper - cheatgrass

The final analysis involved comparing the regeneration of western larch and cheatgrass to soils types. When investigating western larch, it was found overwhelmingly in a silty clay loam glacial till. This was found to be true in both burn perimeters. This type of glacial till provides nutrients and minerals to help grow healthy plant life (Sher, 2002). It must also be mentioned that both burn perimeters are made up of at least 65% of glacial till. Cheatgrass on the other hand was found in a few different primary soils throughout both burn areas that include Moderate QA Colluvial Forest, QA Rock Outcrop & Shallow Soils, Deep QA Colluvial Forest, and Shallow QA Colluvial Forest (Dutton et al, 2001). These soils are mostly moderate to shallow depths that are or can be rocky in nature, the exception being the Deep QA Colluvial Forest. These results reveal that cheatgrass is regenerating in less favorable soil types when compared to western larch.

## 4. Conclusion

### *4.1 Analysis Conclusion*

The results of the analysis reveal that western larch appears to out-compete cheatgrass in the overall regeneration. Western larch pioneered low to moderately disturbed areas that were primarily at lower elevations. Western larch was also found in soils that were of good condition for regenerating vegetation. Western larch regenerating in these areas will also garner a positive affect on the local ecosystem since it is natural to the region. The results also indicate that western larch regenerated in a manner that was expected of a pioneer species.

During each phase of the analysis cheatgrass was found to be growing in instances that may not be favorable to most vegetation. Cheatgrass was found in areas with more severe burns than the other classes. Cheatgrass was not exclusive to the higher burn areas but did trend toward favoring the more severe burns. Cheatgrass was also found on steeper slopes facing in a southerly direction and at higher elevations. Cheatgrass was able to replace native vegetation due to increased severity in growing conditions such as exposure to weather, high winds, and extreme sun exposure.

These findings suggest that heightened monitoring of the most severe burn areas, especially those that may be hindered due to poor growing conditions (soil, slope, aspect), should continue over the long term to ensure a healthy regeneration is occurring. The results have identified areas where invasive species are likely to occur after a wildfire. This information can be used to map future potential burn areas for the purpose of responding to invasive vegetation. All burn perimeters should continue to be monitored in addition to the heightened monitoring mentioned above.

### *4.2 Lessons Learned*

There are some lessons learned from this process to remember for similar workflows in the future. This workflow must be tailored to work with the type of imagery that is being used and to specifically look for the type of features that are to be classified. An iterative workflow, similar to the one used for this analysis, that allows for quality feedback loops is highly recommended. This allows for continued refinement of the process to ensure the most accurate results possible. An accuracy assessment of the final results is also required. This workflow is also a great candidate for automation. Automation of this workflow will reduce human error, increase consistency, and create a quicker streamlined output, especially in instances where large areas are being analyzed.

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