Predicting the Probability of High Fire Severity in Yellow Pine Mixed Conifer Forests in Northern San Bernardino National Forest

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1. Introduction

Nation-wide fire suppression was enacted in the early 20th century (Safford & Stevens, 2017) in an effort to protect timber resources and rural communities (Berry, 2007). These suppression policies have led to altered fire regimes, changes in forest composition and structure, and an increase in ladder fuels (Miller et al., 2009; Miller & Safford, 2017; Nigro & Molinari, 2019). Increased fuels in fire-suppressed areas are likely to precede more severe fires and potentially result in the loss of unique and critical ecosystems. This is partially due to a build up of ladder-fuels allowing fire to reach the tree canopy and resulting in high mortality (Miller et al., 2009; Miller & Safford, 2012). Additionally, climate change is expected to increase mean average temperature, increase the frequency of extreme temperature events, and reduce average precipitation (Hayhoe et al., 2004). These combined factors that contribute to fire severity threaten public safety, infrastructure, and watershed health (Savage & Mast, 2005; Moody et al., 2013; Calkin et al., 2014)

Yellow Pine Mixed Conifer (YPMC) forests are especially susceptible to being lost to high severity wildfires because they are in geographically isolated sky islands and consist of trees with non-seritonous cones (Minnich & Everett, 2001). The limited range of the trees' natural distribution is vulnerable to forest degradation as their mountain ranges are relatively non-contiguous, unlike the Sierra Nevada. Additionally, YPMC forests are limited in the ability to migrate in elevation as they are already found near the top of their range. These forests provide critical habitat for wildlife like the California Spotted Owl (*Strix occidentalis occidentalis*), who nest in old-growth areas with downed woody debris (Davidson, n.d.). YPMC forests also provide invaluable ecosystem services such as clean air, water, and carbon sequestration (Schimel & Braswell, 2005; Gonzalez et al., 2015; Hillberg et al., 2016). YPMC forests face many risks, and land managers need to understand best methods to conserve them.

A key component of YPMC forest conservation is understanding which variables facilitate high severity wildfires. There have been multiple studies that investigated how environmental variables contribute to high fire severity, but previous work has investigated large-scale geographic regions across multiple vegetation types (Parks et al., 2018) or studies were conducted in different climatic regions (Birch et al., 2015; Dillon et al., 2011; Haire & McGarigal, 2009). The proposed project will replicate Parks' (2018) study by modelling the probability of high fire severity but on a much finer scale that includes data on a single vegetation type, which will produce more representative results. By mapping the probability of high fire severity and identifying the variables that contribute to high fire severity, land managers can minimize the threat of losing YPMC forests and maintain ecosystem health and biodiversity.

2. Objectives

The objectives for this project are as follows:

1. Model the probability of high fire severity with the Random Forest (RF) package in RStudio (Version 1.2.1335) for YPMC habitat in northern San Bernardino National Forest.
2. Identify which variables are the most important in determining the probability of high fire severity.
3. Produce a map of key conservation areas in northern San Bernardino National Forest

The ultimate goal of this project is to assist with management strategies for our identified conservation areas.

3. Methods

3.1 *Project Area Selection*

We decided to focus solely on YPMC habitats because of the many consequences of losing this habitat-type from increasing threats of high fire severity. Additionally, SBNF has the most acreage of YPMC forests out of all four southern California National Forests (805,482 acres). SBNF is comprised of a northern and southern portion, but we chose to focus solely on the northern portion to create a more manageable dataset (Figure 1).

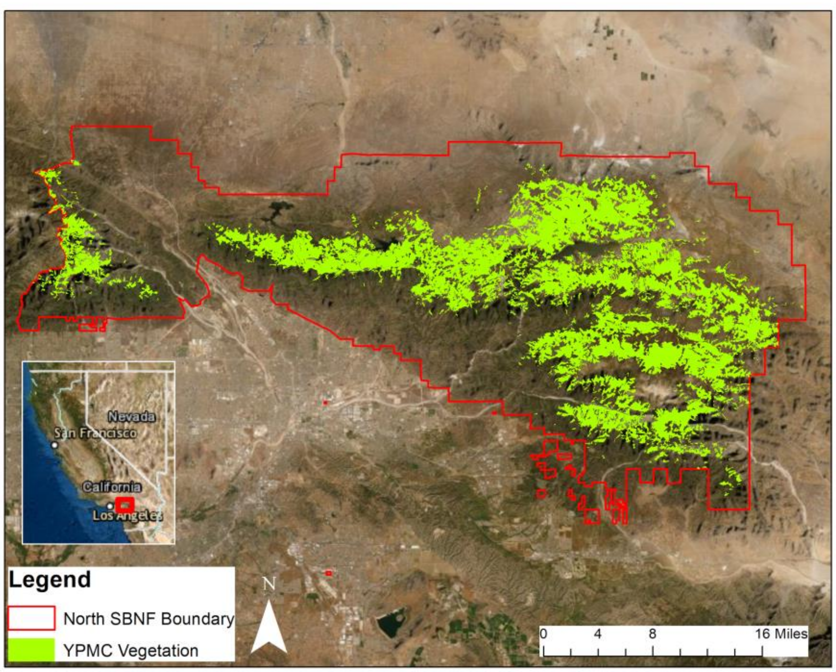

Figure 1. Study area (northern SBNF) and the YPMC habitat (805,482 acres).

3.2 *Programs*

Data processing and analysis was done in ArcGIS (Version 10.8.0.12790) and RStudio (Version 1.3.1073) (RStudio Team, 2020). We used the Random Forest package in RStudio (Liaw & Wiener, 2002) for our model.

3.3 *Data*

To find YPMC habitat type in northern SBNF, we downloaded CalVeg Zones (Ecoregions) from USDA National Dataset (USDA Forest Service, 2018). We selected four ecoregions (south coast, south interior, central valley, and central coast) and filtered for all species that form YPMC habitats (Appendix A). The list of YPMC species is based on other reports describing YPMC forest composition and conversations with USFS Province Ecologist, Dr. Nicole Molinari (Minnich & Everett, 2001; Safford & Stevens, 2017). We downloaded CalFire Fire Perimeter data (CALFIRE, 2020) to figure out which fires occurred in our assessment area between 1984 and 2018. We clipped the fire perimeter data to our study region and found a list of 20 fires (Appendix B).

With the list of fires in the project area, we downloaded corresponding fire bundle data from Monitoring Trends in Burn Severity (MTBS) (MTBS, 2017). Twenty 30-meter relative differenced Normalized Burn Ratio (RdNBR) GeoTIFF files were downloaded for each fire listed in Appendix B. We chose relativizing dNBR because it removes the biasing effect of pre-fire conditions (Miller et al., 2009). RdNBR data from MTBS takes pre- and post-fire imagery and assigns a severity value as a raster file. We used the 'Mosaic to New Raster' tool in ArcGIS and added all 20 rdnbr.tif files as inputs to merge into one raster. We assigned 32_BIT_SIGNED as the pixel type and assigned 1 band. In ModelBuilder, we reclassified the values of the merged RdNBR files (Appendix C) according to Miller and Thode's (2007) classification (Table 1). We did not include values less than 0 in our classification because those values represent unburned land and thus would not be valuable in our analysis. Lastly, RdNBR was converted from raster to point in ModelBuilder (Appendix C). We then projected the points onto our study area (Figure 2).

Predictor variables for the Random Forest model were based on variables that Parks et al. (2018) found most important (Table 2). For live fuels, we downloaded 16 Landsat images from climateengine.org, all of which were 30 m resolution. These images were downloaded on the same date listed from the RdNBR pre-fire imagery. This ensured that the same pre-fire vegetation was being analyzed to ensure consistency with our model. Additionally, some of the fires used the same pre-fire image, resulting in sixteen Landsat images instead of twenty. ClimateEngine pre-calculates normalized difference vegetation index (NDVI) raster files (Appendix D). NDVI is used to measure vegetation greenness and is used to calculate vegetation density (Landsat Normalized Difference Vegetation Index, n.d.). We used the 'Mosaic to New

Raster' tool in ArcGIS and added all 16 ndvi.tif files as inputs to merge into one raster. We assigned 32_BIT_FLOAT as the pixel type and assigned 1 band.

Table 1. RdNBR regression thresholds from Miller and Thode (2007).

Severity category	Sample Size	Predicted RdNBR
Unchanged	57,624	< 69
Low	56,807	69 - 315
Moderate	40,931	316 - 640
Severe	48,940	>=641

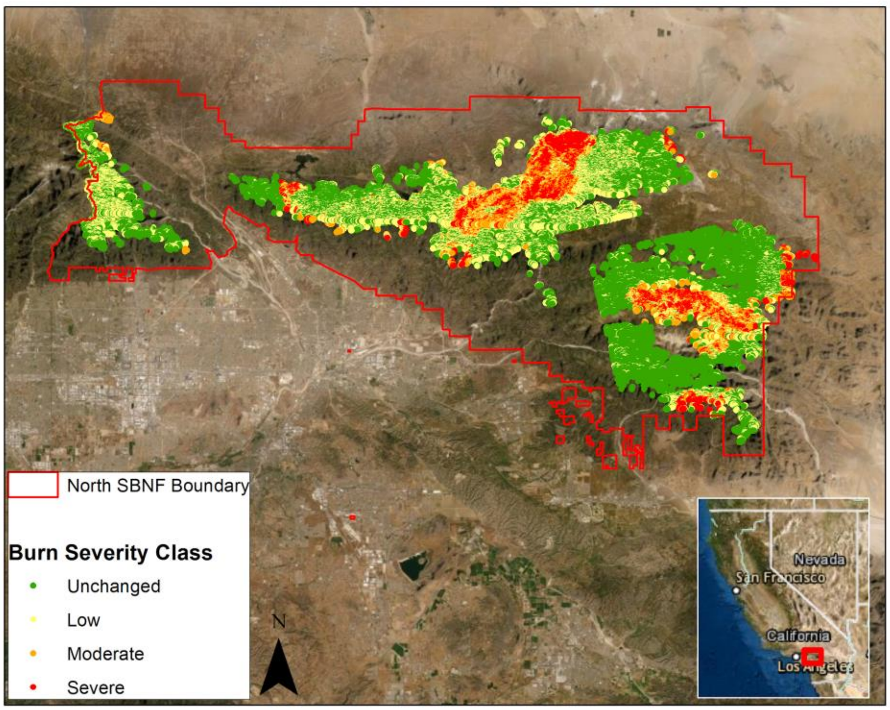

Figure 2. The burn severity classification projected into the project area. The burn severity has been clipped to the YPMC polygon inside northern SBNF.

Table 2. Variables used as predictors in modeling the probability of high-severity fire in YPMC forests in northern SBNF.

Group	Variable name	Description	Source
Live fuel	NDVI	Normalized differenced vegetation index. Pre-fire imagery downloaded on the same date as the MTBS burn severity imagery	http://climateengine.org/
Topography	Slope	Calculated from the digital elevation model of regularly spaced land elevation values at 1 arc-second (30 m)	https://www.usgs.gov/core-science-systems/ngp/3dep
	Elevation	Digital elevation model of regularly spaced land elevation values at 1 arc-second (30 m)	https://www.usgs.gov/core-science-systems/ngp/3dep
	TPI	Topographic positions index. TPI is a measure of topographic complexity	http://www.jennessent.com/arcview/tpi.htm (Jeness, 2006)
Climate	CWD	Climatic water deficit. Calculated as potential evapotranspiration minus actual evapotranspiration. Mean over the 1981-2010 time period	http://climate.calcommons.org/bcm
	Tmin	Minimum monthly temperature. Mean over the 1981-2010 time period	http://climate.calcommons.org/bcm
	Tmax	Maximum monthly temperature. Mean over the 1981-2010 time period	http://climate.calcommons.org/bcm

Topography predictor variables include slope, elevation, and topographic position index (TPI) from digital elevation model (DEM) data. DEM data is of 30 m resolution and was downloaded from the U.S. Geological Survey (USGS, 2017). We calculated the slope from the DEM using the Slope tool in ArcGIS. TPI was calculated from DEM data following protocol from Jeff Jenness (2006) and the topography toolbox in ArcGIS (Dilts, 2015). Climate variables from the Basin Characterization Model (BCM) include climatic water deficit (CWD) (mm), maximum temperatures (Tmax) (degrees Celsius), and minimum temperatures (Tmin) (degrees Celsius). CWD is a measure of potential and actual evapotranspiration and is used as an index of drought stress (Lutz et al., 2010). The dataset was created in 2014 and provided historical climate data from 1981 to 2010 at 270 m resolution (Flint et al., 2014).

The topography and climate variables were processed the same (Appendix E). Each variable was projected in NAD 1983 California Teale Albers and clipped to the YPMC polygon within northern SBNF. Once all variables were processed, we used them as inputs in our 'Extract Multi Values to Points' tool to combine all variables into one spreadsheet (Appendix F). This spreadsheet was converted into a .csv file to be used in RStudio.

We noticed that the climate data (Tmin, Tmax, and CWD) had missing values when we downloaded the data and clipped it to our project site. After exporting the .csv, we ran an analysis in RStudio to identify how many pixels had missing data. Slope has the highest percentage of missing data (19%), while the rest of the variables range between 3.5 to 4.2% of missing values (Appendix G). Since we anticipated those missing values, we got rid of all observations with any "NA" by using the drop_na() function in RStudio.

3.4 *Analysis*

Random Forests (RF) (Liaw & Wiener, 2002) is a machine learning algorithm that can handle complex interactions, which is ideal for studying the complexity of fire dynamics (Cutler et al., 2007). There are several advantages of using RF over linear regression models. First, RF has the ability to grow in complexity due to the ease of working with correlated predictor variables (Strobl et al., 2008). Secondly, as a non-parametric model, RF has less assumptions about the data distribution (Strobl et al., 2008). These advantages make RF desirable for our analysis as calculating fire severity is extremely complex and is variable over time (Fang et al., 2018).

RF generates an output plot that ranks the importance of each predictor variable, and is composed of many independent and uncorrelated decision trees. We used topography, climate, and live fuels data as our predictor variables, while burn severity (RdNBR) is our response variable. The final variable prediction is selected by the variable that was predicted the most by the individual trees. Bootstrap aggregations are employed by RF to train the model, and about 30% of the data is set aside to calculate the out-of-bag (OOB) error rate. We used the OOB error and class error to determine the accuracy of our model and to finalize our variable selection.

We performed correlation tests to see if any of the variables were highly correlated with one another. We found that elevation was moderately correlated with all climate variables and was thus removed from the final model (Figure 3). Additionally, all three climate variables are generally highly correlated with one another, though with the limited data, we did not want to remove any more variables. The issue with highly correlated variables is that RF will sometimes favor those variables (Strobl et al., 2008).

	elev	ndvi	tpi	cwd	tmin	tmax
elev	1.00000000	-0.48805926	0.081636606	-0.77641741	-0.872985557	-0.87394806
ndvi	-0.48805926	1.00000000	-0.088414229	0.30843079	0.410458680	0.35627193
tpi	0.08163661	-0.08841423	1.000000000	-0.04813748	-0.006519916	-0.06681983
cwd	-0.77641741	0.30843079	-0.048137483	1.00000000	0.661622147	0.83661793
tmin	-0.87298556	0.41045868	-0.006519916	0.66162215	1.000000000	0.63208143
tmax	-0.87394806	0.35627193	-0.066819834	0.83661793	0.632081429	1.00000000

Figure 3. Elevation showed high correlation with all three climate variables (cwd, tmin, and tmax).

We combined the unchanged, low, and moderate burn severity classes into one, because the purpose of this model is to predict the probability of high fire severity. Unchanged, low, and moderate severities were listed as “other” and assigned 0s, while high severity was listed as “high” and assigned 1s to create a binary classification. We chose these binary categories as our response variable and the topography, climate, and live fuels variables as our predictor variables. We then performed testing and training the data (script here). The train data had 2,000 observations and the testing data had 202,302 observations.

Because we had a high number of observations, we randomly sampled from the “other” and “high” category using the sample_n() function in the tidyverse package (Wickham et al., 2019). Our “other” factor in our model had a sample size of 155,362 observations, and “high” had a sample size of 48,490 observations. We then randomly sampled 20,000 observations each from the “other” and “high” categories. We wanted both factors to have the same number of samples as not to skew the results or overfit the data. We used the default number of trees of 500 with 2 variables tried at each split.

4. Results

When working with machine-learning algorithms, it is important to test and train your data (Miller et al., 2009). The training RF model had an OOB error rate of 26.25% and ranked Tmin, NDVI, and CWD as the top three most important variables for predicting the probability of high fire severity (Figure 4). Our testing RF model had an OOB error rate of 9.42%, which is indicative of the model being overfit. The testing RF ranked NDVI, Tmin, and TPI as the top three most important variables for predicting the probability of high fire severity (Figure 5).

```
Call:
 randomForest(formula = class ~ ., data = train, importance = TRUE)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 26.25%
Confusion matrix:
    0   1 class.error
0 705 295       0.295
1 230 770       0.230
```

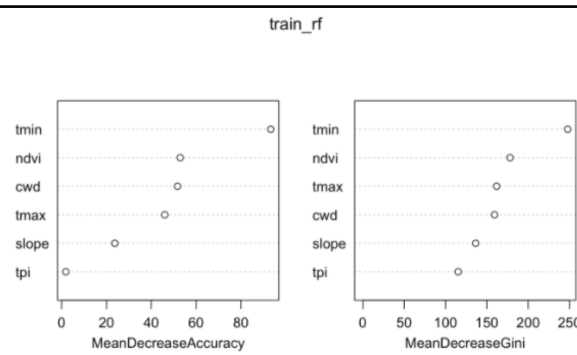

Figure 4. Results from our training data and model.

```
Call:
 randomForest(formula = class ~ ., data = test, importance = TRUE)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 9.42%
Confusion matrix:
       0     1 class.error
0 146845  7517  0.04869722
1  11532 36408  0.24055069
```

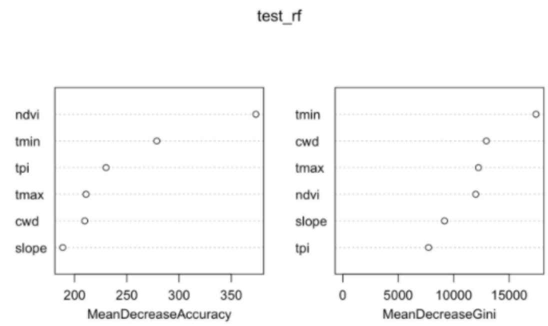

Figure 5. Results from our testing data and model.

Our final RF model contained 20,000 observations from the unchanged, low, and moderate (ULM) burn severity category and 20,000 observations from the high burn severity category. Our OOB error rate was 14.18%. The ULM category had an accuracy of 82.63% ([1- class error] * 100) and the High category had an accuracy of 89.01% (Figure 6). Our final RF model ranked Tmin as the most associated variable when predicting the probability of high fire severity (Figure 7). Next was NDVI, or live fuels, followed by CWD.

```
Call:
 randomForest(formula = class ~ ., data = combined_sample, importance = TRUE)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 14.18%
Confusion matrix:
      0     1 class.error
0 16526  3474      0.1737
1  2198 17802      0.1099
             0         1 MeanDecreaseAccuracy MeanDecreaseGini
ndvi  90.00812 224.89684            256.69093         3375.706
tmin  49.03226 209.83369            298.49453         5388.727
cwd   16.69527 136.29603            191.20504         3462.190
tpi   34.27826  85.96266             92.74022         1940.141
tmax  23.84608 142.61298            188.11323         3289.722
slope 67.27649 143.43779            140.46550         2418.242
```

Figure 6. The OOB error rate, confusion matrix, and mean decrease accuracy for the RF model output.

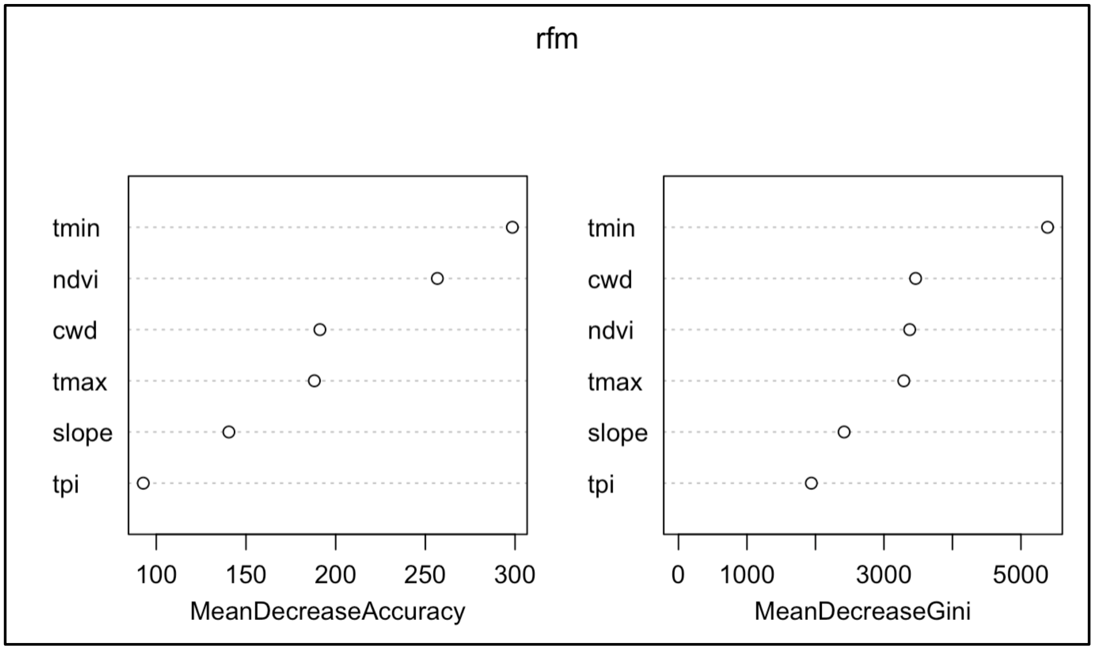

Figure 7. Output from our final Random Forest model showing Tmin ranked highest, followed by NDVI, and CWD.

Predictor variables can be non-linear and can correlate with one another, which makes it difficult to truly interpret the results from a RF model (Debeer & Strobl, 2020). RF also lacks a statistical population model, which means interpreting the variable importance in respect to high fire severity is challenging (Debeer & Strobl, 2020). Thus, we used a model agnostic tool called accumulated local effects (ALE) to examine how each high-ranking predictor variable was associated with high fire severity (Figure 8). Partial dependence plots were not used due to the correlation between variables (Molnar, 2020). Both NDVI and CWD increased rather linearly - as NDVI and CWD values increased (denser vegetation and more drought stress), the model predicts an increase in high fire severity. Live fuels (NDVI) above 0.5 results in a model prediction of an increase in high fire severity of 0.1 relative to the average prediction. Similarly, drought stress (CWD) above 800 results in a model prediction of an increase in high fire severity of 0.15 relative to the average prediction. Minimum temperature (Tmin) has a more complicated relationship with high fire severity; temperatures between -3 and 0°C had an increasing slope and maximized at a model prediction increase in high fire severity of 0.2 relative to the average prediction. This explains why Tmin was ranked highest by RF. However, temperatures greater than 0°C began to decline the model's prediction of high fire severity.

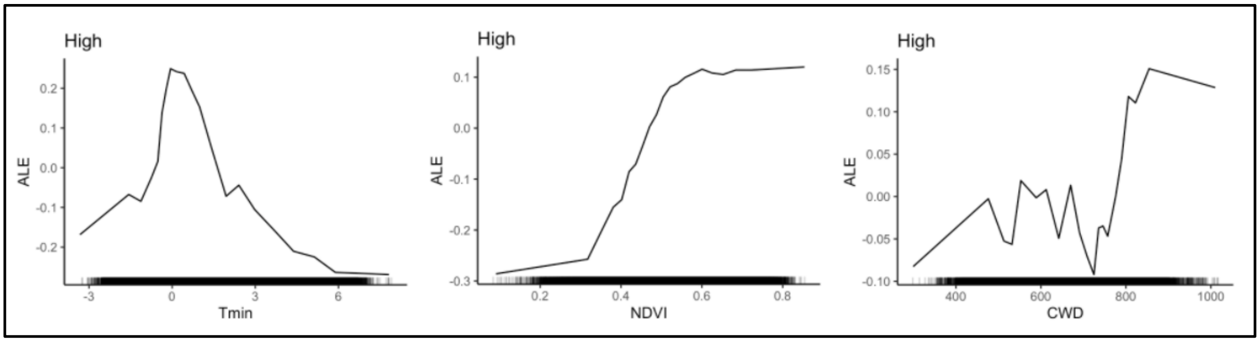

Figure 8. ALE plots for the top three predictors variables from our RF model. Both NDVI and CWD are more associated with high burn severity as their values increase. Tmin is associated with high burn severity for values less than ~0°C, but becomes less associated with high burn severity as minimum temperature increases.

Minimum temperatures between 0-2°C were mapped in an effort to see if they overlapped with high NDVI and high CWD (Figure 9). We did not find that minimum temperatures that increased the model's ability to predict high fire severity (0-2°C) overlapped with high NDVI. We believe that because Tmin is correlated with the climate variables (Tmin and CWD), that RF favored it in its decision trees. A study by Strobl et al. (2008) found that the RF algorithm shows a preference for correlated predictor variables, which we believe is the case for Tmin.

The results of high NDVI and high CWD improving the model's prediction of high fire severity relative to the average prediction makes sense when looking at a map of SBNF. We noticed that there are a few areas where both NDVI and CWD are high, which verifies that the two variables are ecologically intertwined and important in predicting the probability of high fire severity (Figure 10, 11).

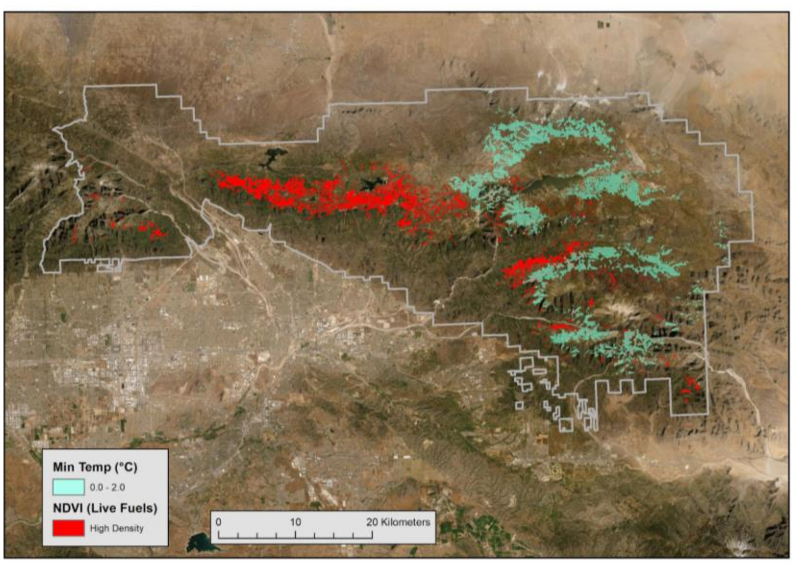

Figure 9. Minimum temperature (Tmin) between 0-2°C mapped in cyan. High NDVI values are seen in red. There are not many places within SBNF where these two variables intersect.

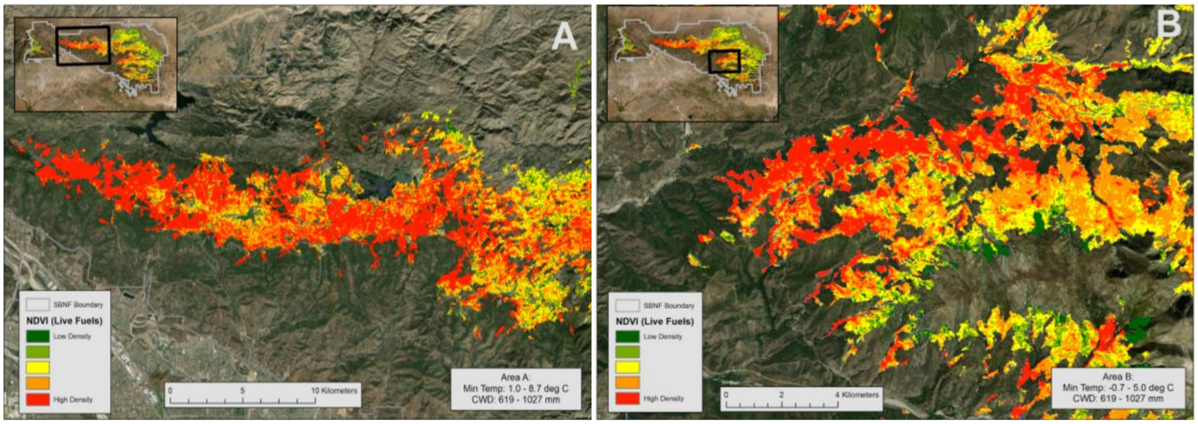

Figure 10. Two areas within SBNF where live fuels (NDVI) was high. High values of NDVI are approximately 0.6 to 09 (*NDVI, the Foundation for Remote Sensing Phenology*, n.d.). Tmin in these areas range from -0.7 - 8.7°C.

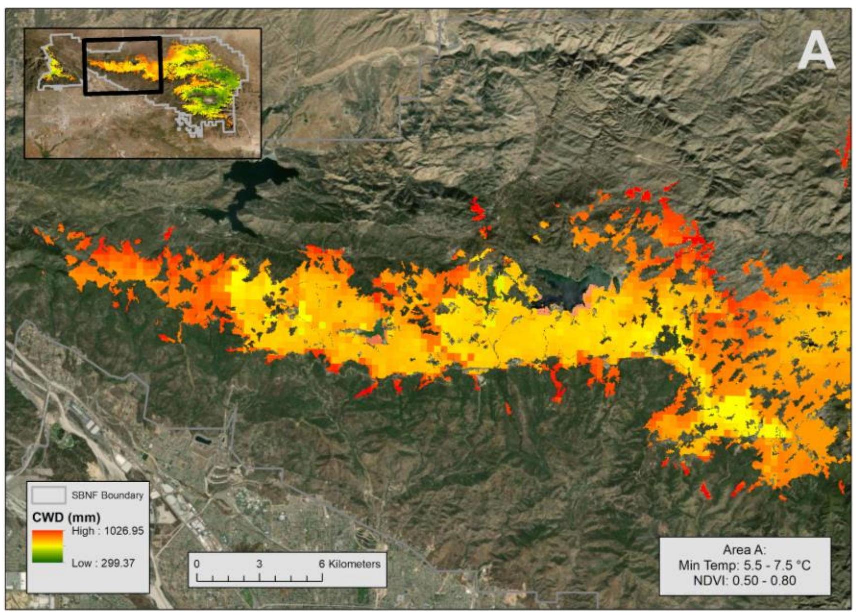

Figure 11. Area within SBNF where CWD deficit is high. This area also has high NDVI values, which range between 0.5 and 0.8. Minimum temperatures range from 5.5 - 7.5°C.

5. Conclusions

Our results from the Random Forests model are somewhat inconclusive regarding minimum temperatures, but they do show the importance of live fuels and climatic water deficit in high fire severity. Ecologically, this is important as forest evapotranspiration makes up a large majority of the total ecosystem water loss (Sankey et al., 2020) and thus contributes to the density of forest fuels. High water stress from high water deficits can physiologically weaken xylem tissues in trees and weaken their capacity to store moisture when moisture loss is high, which lessens a forest's resiliency against high fire severity (van Mantagem et al., 2013). In addition, high tree density indicates competition between neighboring trees for resources, including water, which can further detriment forest health under drought-like conditions and wildfires (Sankey et al., 2020; Woolley et al., 2011).

The results from our Random Forests model for high fire severity can shape local forest management decisions regarding wildfires. Identifying which variables contribute the most to the probability of high fire severity can aid in identifying specific fire management strategies that result in forest resilience and conservation. An effective fuels treatment plan may vary between different YPMC forests within southern California based on regional differences in vegetation structure, fire regimes, local topography, and weather (Syphard et al., 2011). Regardless, the remaining three National Forests in southern California face the same wildfire and environmental risks as our study area. We believe that the results from our Random Forests model could be directly applicable to forest management in all four southern California National Forests.

Limitations and Future Work

Future work should include additional variables that have been used by previous studies (Parks et al., 2018; Birch et al., 2015; Dillon et al., 2011). Because NDVI and CWD ranked high in the RF model and increased the model's probability of predicting high fire severity, we believe including normalized difference moisture index (NDMI) - which calculates plant water stress - would be a logical next step. We also did not include many weather variables besides temperature. Daily weather variables versus monthly averages would provide a better indication of how weather actually affects high fire severity. Parks et al. (2018) found that fire weather was the most significant predictor of high fire severity in the California south coast ecoregion, but we do not believe monthly averages truly reflect fire weather conditions. If more specific daily weather data becomes available, it would be an important addition to this model.

Due to the limitations of Random Forests, such as its preference for ranking correlated predictor variables as highly important (Strobl et al., 2008), we speculate whether or not minimum temperature (Tmin) is actually the most important variable in predicting the probability of high fire severity. Our results vary slightly from the findings of Parks et al. (2018), though their team did find that on average, NDVI was the most significant variable in predicting the probability of high fire severity out of all investigated ecoregions. The Basin Characterization Model dataset did not have average monthly temperatures, which may have been more representative of the temperature data. The Tmin and Tmax variables from the BCM dataset did not reveal useful information about fire severity and challenged what we know about high temperatures and their effects on vegetation and evapotranspiration.

Recommendations

Based on model results and considering the limitation of the model, we have developed potential management strategies to conserve YPMC forests in northern San Bernardino National Forest. Forest managers often use mechanical thinning to decrease vegetation and ladder fuels. Employing thinning in SBNF would result in forest areas with lower live fuels (NDVI). Forest thinning indirectly affects CWD; by reducing the number of trees in an area, competition for water resources also decreases. As CWD is reduced, trees become less drought-stressed and therefore more resilient to high severity fires (Sankey et al., 2020). Decreasing tree density through thinning will also protect YPMC forests from bark beetles and other pests (Sankey et al., 2020). We believe forest thinning is an ideal management strategy in areas where both live fuels and drought stress are high.

Another management strategy that can be employed is the use of prescribed burning. Prescribed burns require the manual removal of litter, duff (older, partially decomposed litter) and fine woody debris from the bases of large trees beforehand, which is abundant in YPMC forests (Dalrymple & Safford, 2013). Some recent findings show that raking litter away from the base of trees can reduce tree damage during prescribed burning (Dalrymple & Safford, 2013). The effectiveness of prescribed burns depends on fire severity, but once effective, prescribed burns help form clearings around trees that can be naturally maintained for 10–15 years (Dalrymple & Safford, 2013). These clearings can act as fuel breaks, reducing physical damage and tree mortality during a fire (Dalrymple & Safford, 2013). Additionally, Lyons-Tinsley & Peterson (2012) found that burning reduces mortality from future fires and promotes resiliency among trees at an early age. However, it is important to note that fuel consumption during prescribed burning is often highly variable and that variable outcomes should be anticipated (Levine et al., 2020).

Although both methods provide benefits to forest health, thinning and prescribed burning may take time to get approved due to public concerns and the potential impacts to sensitive species. Mechanical thinning and prescribed burns both decrease local air quality and the forest capacity to sequester carbon before the long-term benefits of reducing carbon emissions begin (Krofcheck et al., 2018). One concern about these forest health projects is the uncertainty of finding the right conditions for fuels treatments to effectively mitigate fire risk (Syphard et al., 2013). It is important to recognize that any fire treatment method is not a one-size-fits-all solution, and forest managers must think carefully on the best way to manage their forests to fit the local fire regimes. We have identified two areas of YPMC forest in northern SBNF where we recommend land managers to prioritize fire management efforts (Figure 12). Area 1 contains a high density of live fuels and high CWD. We recommend mechanical thinning only in this area. Prescribed burning may be an option only if weather conditions are right. Area 2 contains a high density of live fuels and moderate levels of CWD, which would we believe would benefit from both mechanical thinning and prescribed burning. Because California spotted owls do live in the area, it is important to leave some areas of YPMC forests untouched as they prefer coarse woody debris and multi-layered canopy cover for habitat (U.S. Fish and Wildlife Service, 2019). We believe our above recommendations will be one piece in conserving important YPMC habitat for many years to come.

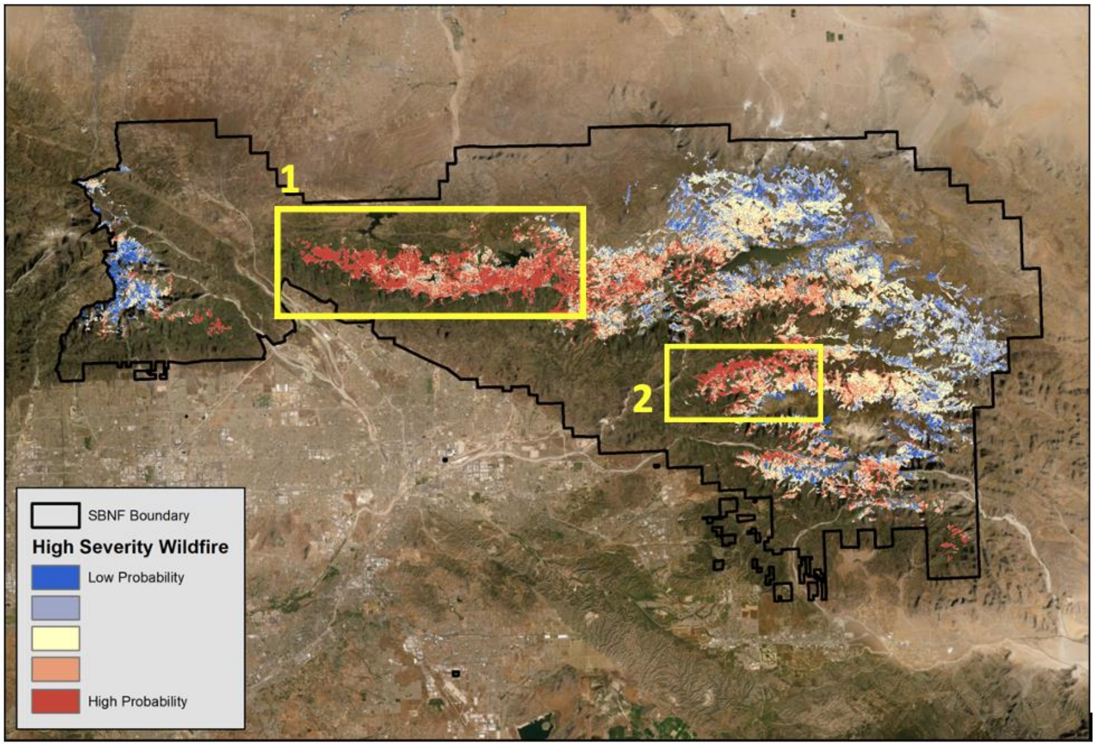

Figure 12. Highlighted in yellow are the areas where we predict the probability of high severity wildfires to be greatest and should be prioritized for YPMC conservation.

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Appendix A. Species filtered in each ecoregion (in ArcGIS) and the names of each species.

Ecoregion	Species Filtered
South Interior	EP
Central Valley	DP, EP, JP, MF, MP, PP, PW
Central Coast	DP, MP, PP
South Coast	DP, EP, JP, MF, PP

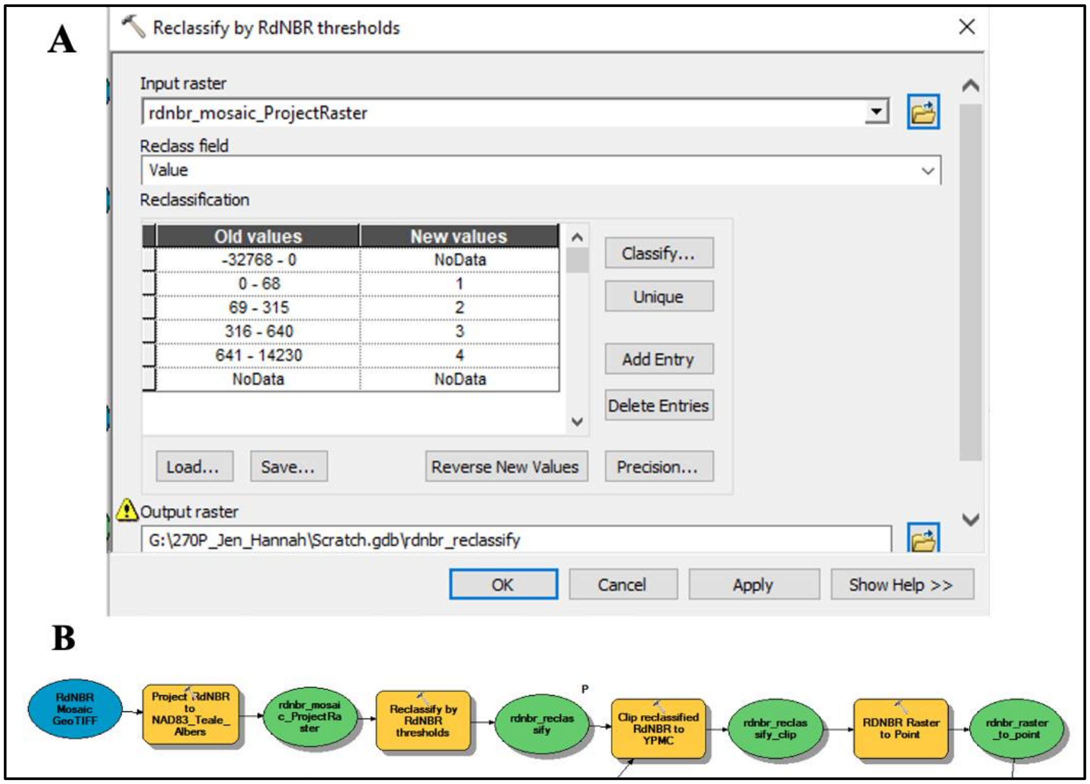
CalVeg Code	Species Name
DP	*Pseudotsuga menziesii*
EP	*Pinus jeffreyi* (eastside)
JP	*Pinus jeffreyi*
MF	Mixed conifer fir alliance
MP	Mixed conifer pine alliance
PP	*Pinus ponderosa*
PW	Ponderosa pine white fir alliance

Appendix B. Fires in northern SBNF between 1984 and 2018. There were more than 60 fires between this time but we filtered the fires for only northern SBNF and fires that intersected with our YPMC polygon. The first date listed is the date of which pre-fire Landsat imagery was taken by MTBS. The second date listed is the post-fire Landsat imagery taken by MTBS.

1. LYTLE (19840323_19850407)
2. TEXAS (19870702_19890723)
3. STOCKTON (19910713_19920613)
4. HEMLOCK (19960608_19980716)
5. MILL (19960608_19980716)
6. WILLOW (19980716_20000705)
7. HEMLOCK (20010505_20020524)
8. OLD (20030714_20040614)
9. MILLARD (20050703_20070709)
10. SLIDE (20060706_20080609)
11. GRASS VALLEY (20060706_20080609)
12. BUTLER 2 (20060706_20080609)
13. SHEEP (20090511_20100530)

14. HATHAWAY (20130607_20130623)
15. LAKE (20140829_20160623)
16. BLUE CUT (20160802_20170704)
17. PILOT (20160802_20170704)
18. HOLCOMB (20170618_20180621)
19. CRANSTON (20170720_20190710)
20. VALLEY (20170704_20190710)

Appendix C. (A) classification inputs of the 20 merged rdnbr.tif files and (B) model builder of RdNBR processing.



Appendix D. Selection for downloading Landsat imagery from climateengine.org with NDVI. calculated.

Variable:

Type: Remote Sensing

Dataset: Landsat 4/5/7/8 Surface Reflectance

Variable: NDVI (Vegetation Index)

Processing:

Statistic: Mean

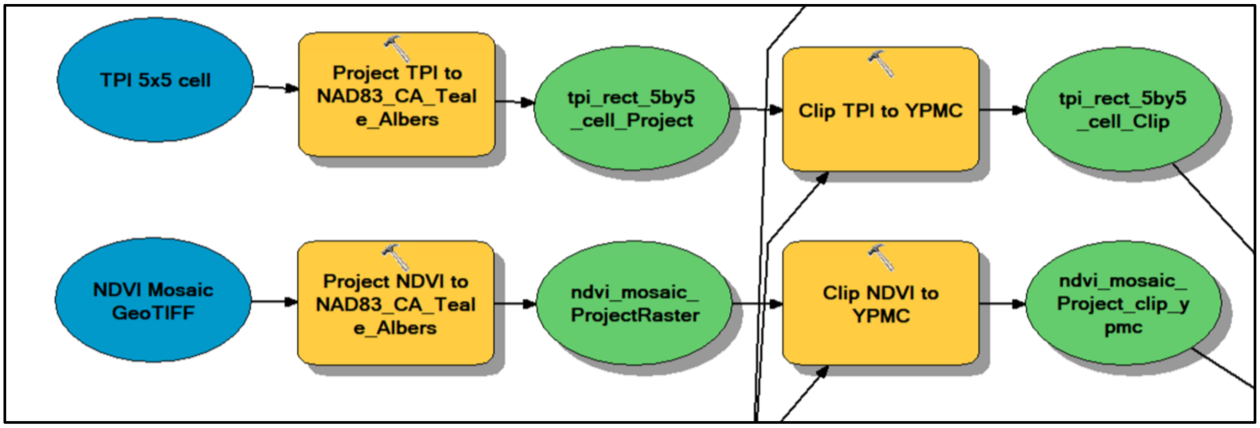
Calculation: Values

Time period:

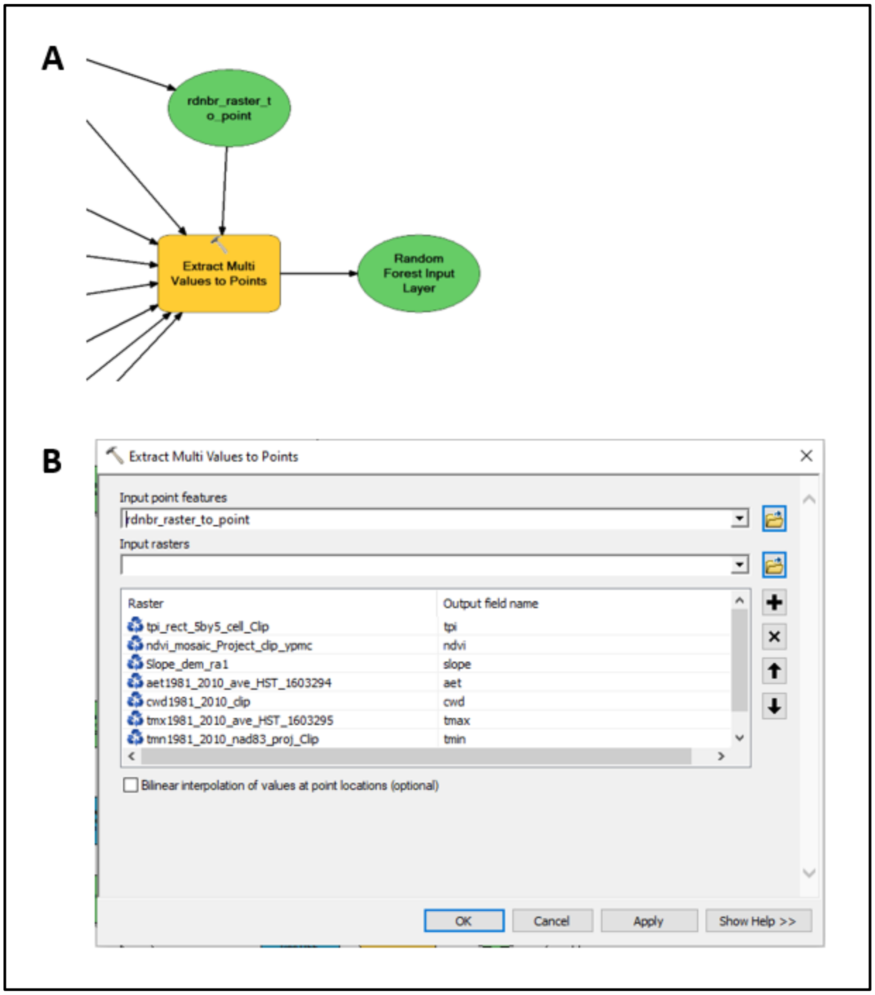
Custom date range: [enter date on rdnbr.tif file (first date is pre-fire)]

Download the image file at native resolution (30m)

Appendix E. Example of input/predictor variable geoprocessing in modelbuilder. All variables were projected to NAD 1983 and clipped to the YPMC polygon in our assessment area.



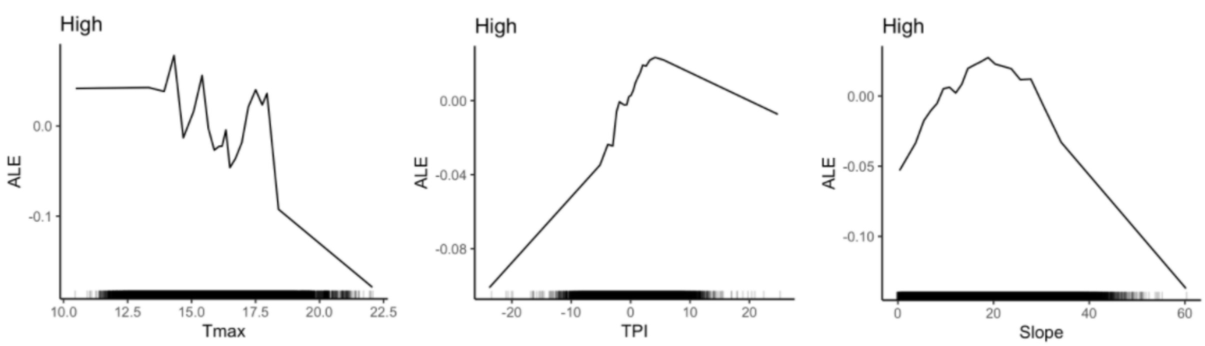
Appendix F. (A) ModelBuilder of Extract Multi Values to Points. RdNBR was used as the reference input point feature. (B) Input raster included all the processed live fuels, topography, and climate variables. Once processed, we were able to download a .csv file of all our points to be used in RStudio.



Appendix G. Analysis of missing data in each variable within our input CSV for the Random Forests model. Each variable is followed by the amount of table cells with NA values (n_miss) and the percentage of those cells out of all table cells (pct_miss).

variable	n_miss	pct_miss
slope	48510	18.92
tpi	10640	4.15
aet	9966	3.89
cwd	9966	3.89
ndvi	9509	3.71
tmin	9474	3.70
tmax	9390	3.66
OBJECTID	0	0.00
pointid	0	0.00
grid_code	0	0.00

Appendix H. ALE plots for the remaining variables in our model: maximum temperature (Tmax), topographic position index (TPI), and slope. Most variables never exceed 0.00, which indicates that these variables did not increase the model's prediction of high fire severity. As maximum temperature and slope increases, the model's prediction in high fire severity actually decreases.



Appendix I. Hyperlink for RScript used for the Random Forest Analysis:
https://ucsb.box.com/s/rusgmbalxcg0rnu4xdjoocguah6f324c