High Resolution Inventory Solutions (HRIS)
2018 Same-Year Burn Severity Analysis
CHINOOK COMMUNITY FOREST

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EXECUTIVE SUMMARY

The wildfires that took place within the Chinook Community Forest (CCF) boundary during the summer of 2018 affected over 7,000 hectares. The level of changes to vegetation and soil, and impacts to stand productivity often vary a great deal across natural landscapes in the wake of wildfire. The satellite imagery derived same-year burn severity index is a useful estimator of the amount of vegetation cover consumed in the wildfire. These satellite derived estimates were then used to develop a predictive model for burn severity rating for all stands in the HRIS inventory as functions of stand attribute and site characteristics at the microstand scale.

The majority of the burned areas were classified as low and moderate severity, at 45% and 43% respectively, with 12% classified as high severity indicating significant losses in tree cover representing roughly 850 ha and an estimated 41,000 cubic meters of merchantable timber (trees > 12.5 cm dbh) in the highest severity class affected by the fire. These results should be used to better understand the impact of the 2018 wildfires to aid in timber loss estimates, salvage, and rehabilitation planning.

Average autumn temperature, frost free days, basal area of black spruce, and presence of dead trees were the strongest predictors of burn severity; these stand variables explained approximately 30% of the variation within the predicted severity ratings. The burn severity prediction model developed for the community forest is intended to help areas with higher potential for timber losses in the event of future wildfires and in so doing, assist with fire loss management and mitigation planning. This severe burn rating model estimates indicate that 17,500 ha of forest across Chinook CF are in the high burn severity category, with another 14,000 ha in the very high severity class.

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HRIS BURN SEVERITY INVENTORY ATTRIBUTES

THE SAME-YEAR BURN SEVERITY INDEX AND CLASSIFICATION

HRIS ATTRIBUTE NAME = BURN_SVI_SY18 / BURN_SVC_SY18

Description: This index is widely used in forestry and remote sensing research as an indicator of fire disturbance and vegetation impact immediately after a fire event (properly called same-year burn severity). The vegetation signal is measured from satellite before and after a fire and the burn severity index increases with the amount of vegetation loss (both green and woody biomass) and the degree of charring of the trees and soils.

Value ranges:

BURN_SVI: 0-2000. Higher value indicates higher burn severity
BURN_SVC: 0=Unburned ; 1=Low ; 2=Moderate ; 3=High

Uses: It is known to be a strong predictor of long-term tree mortality and stand replacement (potential inventory losses). Can also be used to plan timber salvage work.

THE HRIS SEVERE BURN PROBABILITY INDEX AND CLASSIFICATION

HRIS ATTRIBUTE NAME = BURN_SVPI / BURN_SVPC

Description: A site specific statistical model developed by forest scientists using HRIS data to predict the likelihood of a given stand of trees burning very severely in the event of a wildfire, based on the observed burn severity patterns on the landscape following a given fire event. It describes the probability of a very intense, potentially stand-replacing fire impact for any treed microstand on the landscape. The predictive model takes into account stand attributes, terrain and climate characteristics.

Value Ranges:

BURN_SVPI: 0-100. Higher value indicates higher probability of severe burn
BURN_SVPC: 0=n/a ; 1=Low ; 2=Moderate ; 3=High; 4=Very High

Uses: This microstand attribute can be used to help plan and target fire risk mitigation efforts around higher severe burn-risk areas to minimize potential losses for future wildfires.

PROJECT BACKGROUND

"***Across almost all biomes, fire season has lengthened for 25% of the Earth's vegetated surface and the burnable area has doubled since 1979***" (1)

Wildfire risk has been increasing in the Western Canadian landscape for many decades driven by historical forest fire suppression and increasing instability of global climate patterns. The impact of recent large wildfires, also referred to as megafires, on the British Columbia forestry sector has been a challenge to manage and even more difficult to mitigate without detailed knowledge of the forest conditions and fuel loads that can lead to wildfires getting out of control. Highly accurate forest inventory information and detailed measurements of the fire severity across the Chinook Community Forest landscape allow us a unique opportunity to investigate the relationship between the forest stand characteristics that were burned in the 2018 wildfires and how severely the fire affected the vegetation at the HRIS microstand scale using remote sensing technology to improve the understanding of existing and potential inventory impacts for destructive wildfire events such as this.

In the first phase of this high resolution wildfire inventory analysis we delineated the spatial extent of the 2018 wildfire within the Chinook Community Forest boundary using satellite imagery and analyzed the burned area by land cover and major stand species types. In this second phase, the severity of the wildfire is quantified in terms of the measurable impact on the vegetation inventory immediately following the fire to facilitate timber damage or loss estimation and salvage planning. Further to this, a statistical model based on the 2018 fire event was developed to rank any given treed microstand in terms of a relative burn severity rating. This predictive model was applied to all the microstands in the 2017 inventory in order to assist with identifying priority areas for fuel management in pursuit of fire risk reduction.

SPECIFIC OBJECTIVES

1. Evaluate the 2018 same-year burn severity across the 2017 HRIS inventory.
2. Generate a burn-severity index and classification attribute for the burned areas of CCF.
3. Describe how the burn severity classes relate to the landscape and inventory characteristics of the burned vegetation.

4. Develop a statistical model to predict potential burn severity levels across the remaining CCF inventory based on the observed 2018 burn severity data.
5. Identify stand characteristics that were most relevant for predicting burn severity (causal or otherwise correlated) that may be useful from a fire risk management/mitigation perspective.
6. Add the results to the HRIS Web Viewer for easy visualization of the spatial distribution of the actual and predicted burn severity across the CCF.

Fire Intensity vs Fire/Burn Severity

The distinction between fire or burn intensity and severity is important. Our analysis is focused on the burn severity, as an indicator of the relative reduction in vegetation cover, rather than the fire intensity, which describes the fire behaviour itself (the amount of energy released per unit length of fireline (12)). The definitions of each are made clear in the following excerpt from northernrockiesfire.org:

"Fire severity is a measure of the physical change in an area caused by burning (Sousa 1984). Although fire intensity is a key component of burn severity, these are two distinct features of fire; the terms are often incorrectly interchanged.

Used correctly, fire intensity refers to the rate at which a fire produces heat at the flaming front and should be expressed in terms of temperature or heat yield. Fire severity, on the other hand, describes the immediate effects of fire on vegetation, litter, or soils. It is most commonly used to describe fire's effects on the primary tree cover. Unlike fire intensity, fire severity "cannot be expressed as a single quantitative measure that relates to resource impact" (Robichaud et al. 2000). Instead, fires are typically ranked from low to high severity based on the postfire appearance of soil, litter, vegetation, or other resource of interest (Robichaud et al. 2000).

Burn severity depends not only on the amount of heat generated along the flaming front of a fire (i.e., intensity) but also on the duration of the burn. Duration is a function of the fire's rate of spread and subsequent smoldering time. Both depend on weather conditions and the nature of the forest fuels. Rate of spread is additionally influenced by topography and wind speed. A ground fire smoldering in level terrain, for instance, may travel only one foot in a week. At the other extreme, a wind-driven crown fire can race through 15 miles of forest in just one hour (Pyne 1982).

While a fast-moving, wind-driven fire may be intense, a long-lasting fire that just creeps along in the forest underbrush could transfer more total heat to plant tissue or soil. ***In this way, a slow-moving, low-intensity fire could have much more severe and complex effects on something like forest soil than a faster-moving, higher-intensity fire in the same vegetation. For this reason, the terms fire intensity and fire severity are not synonymous and interchangeable*** *(Hartford and Frandsen 1991)."*

Same-Year Burn Severity

The main purpose of mapping and measuring wildfire burn severity remotely for forest management is to provide a rapid estimate of the spatial extent and degree of damage to the forest vegetation and ecosystem. Burn severity measurements from satellites can help quickly assess potential stand losses due to tree mortality, facilitate timber salvage planning, provide insights for stand recovery timelines, and plan wildfire risk mitigation strategies. The same-year burn severity (SYBS) is an estimate of immediate fire-induced changes to the vegetation as measured by comparing the spectral characteristics of the vegetation immediately before and after the fire event in the near-infrared and short-wave infrared spectrum.

Remotely sensed SYBS metrics relate directly to the amount of green and woody vegetation biomass loss, as well as the level of charring and ash creation for a given area as observed from remotely sensed imagery. The accuracy of these indices for predicting vegetation disturbance and long-term fire impact in forest environments is generally quite high, but is subject to the timing and quality of the imagery used. If post-fire imagery is captured after significant understory regrowth occurs then the signal will be affected and the accuracy of the burn severity impact will likely be reduced. Similarly, logging and other changes to the forest that occur between the imagery capture and fire dates can introduce errors in the burn severity estimates if they are not otherwise accounted for.

Despite some of the challenges of using remotely sensed estimates of burn severity, the SYBS has proven to be very useful for evaluating the immediate impact of a wildfire on vegetation, specifically looking at losses to ecosystem structure and function as well as for estimating changes to timber quality, tree mortality, and stand productivity. A 2009 study found that high burn severity classes from satellite based same-year burn indices were successful in estimating the percent change in canopy cover and stand basal area after a fire with 70-90% accuracy (2).

A 2016 study by Lydersen et al. of the US Forest Service Pacific Southwest Research Station showed that the high burn severity class had a strong association with tree mortality measured the year following the fire (3). Based on 195 ground plots, their findings support the use of remotely sensed burn severity metrics for fire impact assessments:

“The high-severity category clearly captured stand-replacing fire effects (>95 % basal area mortality, >99 % tree density mortality), with typically all trees exhibiting high levels of crown consumption and

scorching. In other severity categories, most large-sized and intermediate- sized trees survived, and moderate-severity fire favored survival of shade-intolerant species. Results suggest that both the initial and extended burn severity satellite assessments give an accurate representation of forest structural change in mixed-conifer forests following fire, particularly those of high severity."

The BC Ministry of Forests, Lands Natural Resource Operations and Rural Development (BC MFLNRORD) provides a same-year burn severity for notable wildfire events in the province*; however, the datasets are generated at low resolution and the spatial feature boundaries follow rough outlines of the fire extent that do not relate directly to existing forest inventory stand units.

Aligning burn severity indices with high resolution or enhanced forest inventory data provides a unique opportunity to relate burn severity and stand damage estimates directly to an inventory database to explore the connection between stand properties and potential fire impacts and inventory loss risk levels. In this analysis of the 2018 wildfire event for Chinook Community Forest, we generated same-year burn severity indices and classes for each HRIS microstand and then developed a model to predict the potential for severe burn impacts on any given microstand in the inventory based on the patterns of burn severity, stand characteristics and site properties observed in the 2018 wildfires.

* https://catalogue.data.gov.bc.ca/dataset/2018-same-year-burn-severity

METHODS

Burn Severity Classification

The wildfire burn severity was calculated using the delta Normalized Burn Ratio (dNBR) method, a common remote sensing index for measuring fire impact on vegetation that takes the difference between the post-fire normalized burn ratio (NBR) and pre-fire NBR (4). The NBR pronounces the differences in reflectance of short-wave infrared (SWIR) and near-infrared (NIR) wavelengths of light which shift in relative intensity on the landscape after a fire event caused by changes in vegetation biomass and blackening of surfaces.

$$NBR = (SWIR - NIR) / (SWIR + NIR) \qquad \text{eq.1}$$

$$dNBR = NBR_{Pre\text{-}Fire} - NBR_{Post\text{-}Fire} \qquad \text{eq. 2}$$

The dNBR is a measure of fire-related vegetation change across the landscape and can be directly compared between locations and fire events, unlike burn indices that are based on post-fire imagery alone where the magnitude is relative within a given area and is often of limited use and accuracy. Using the same pre-fire and post-fire cloud-free imagery from phase 1 of the project (2020/07/26 and 2020/10/04) the dNBR was calculated across the full extent of the CCF.

The original dNBR values were then made positive by adding the minimum value and rescaled by 1000 to create a new index scale between 0 and 2000 for easier interpretation and mathematical operations. The average rescaled dNBR value was applied to all HRIS microstands to represent the Same-Year Burn Severity Index (BURN_SVI_SY18). This index was further classified into 4 burn severity categories to create the Same-Year Burn Severity Classes from 0 to 4 with the following breakpoints based on the natural breakpoints in the distribution of the data and then adjusted to closely align with the classification methods of BC MFLNRORD:

Table 1: Same-Year Burn Severity Classification Scheme

Class Number	Class Name	Breakpoints
0	**UNBURNED**	**dNBR < 1200**
1	**LOW**	**1200 ≦ dNBR < 1450**
2	**MODERATE**	**1450 ≦ dNBR < 1700**
3	**HIGH**	**dNBR > 1700**

Since the dNBR value is also influenced by non-fire related vegetation changes such as logging or seasonal leaf shedding, there were a number of deciduous areas outside of the wildfire extent that were incorrectly classified as low or moderate burn severity. To avoid these false positives in the observed burn severity classification, microstands outside the burn delineation boundary from phase 1 of this project were also assigned a class of 0 for unburned in the BURN_SVC_SY18 inventory data. The severity index, however, was not zeroed outside the burn boundary so that the natural variability in the dNBR could be observed and related to non-fire vegetation changes of interest such as stand deciduousness and tree removal.

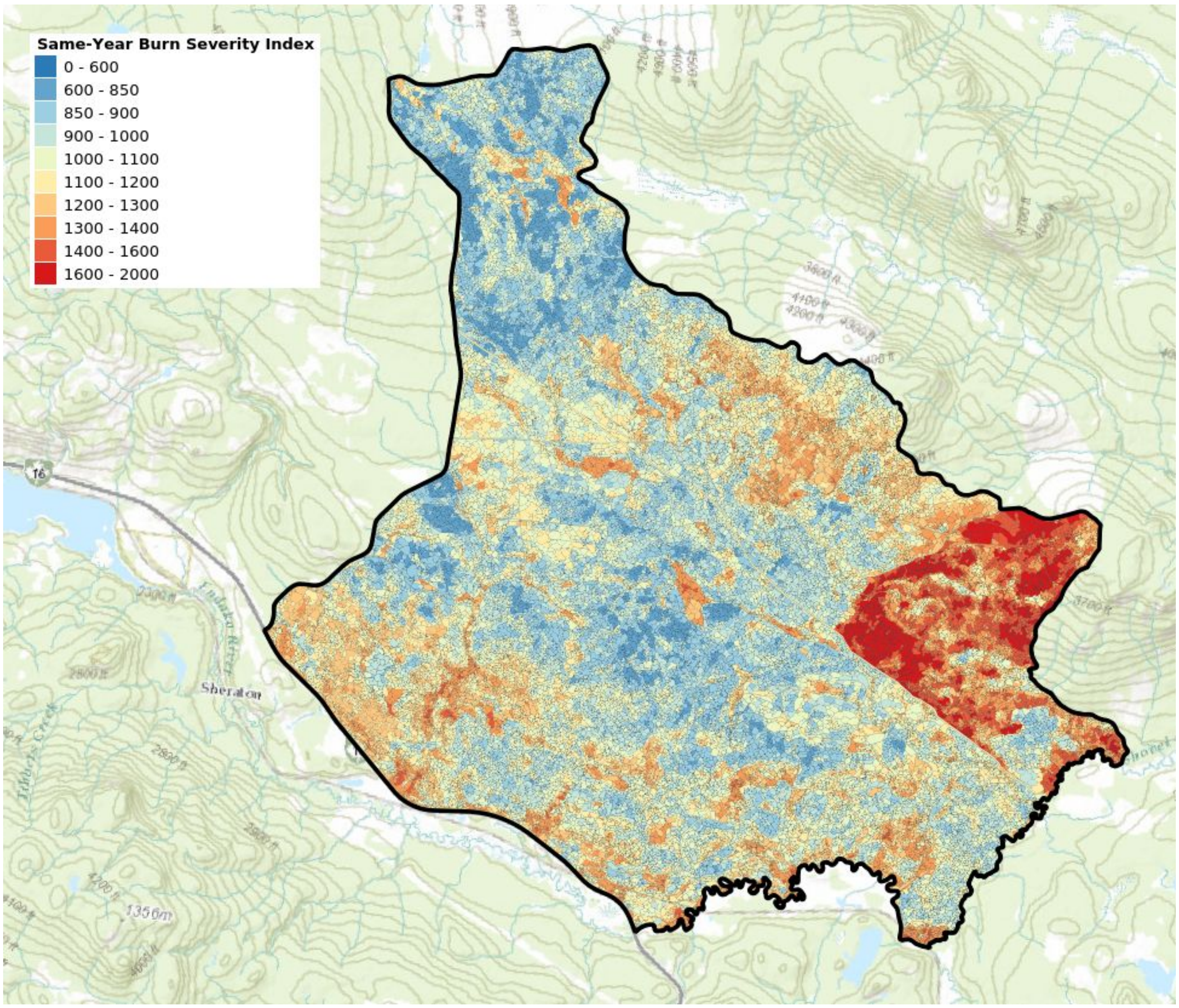

Figure 1. Burn Severity Index across Chinook CF Subregion D before index correction showing areas outside of the burn extent (in red) with higher index values caused by deciduous trees and non-treed vegetation losing green leaf area between July and October.

Predictive Modeling of Burn Severity Probability

Several areas within the wildfire burn boundaries did not show signs of burn impacts despite being surrounded by wildfire, suggesting specific landscape and vegetation characteristics strongly resist wildfire propagation. In addition, the burn severity distribution across the landscape appears to follow specific patterns with respect to the stand structure, composition, and topographic position of a given area. To test the predictive relationship between these stand characteristics and satellite-based burn severity indices, a multivariate analysis and predictive model was developed based on the burned areas of CCF.

Of the 31,750 microstands that were within the burned area boundary, 2,149, representing extreme cases, were selected to be used for the model training dataset based on the spatial intersection with a 5 ha grid to avoid spatial autocorrelation in the analysis which can decrease model precision and predictive power (5). Only treed microstands were used in the model as they contained all the relevant inventory attributes. For that reason the predictive model was only developed for treed areas and aspen dominated stands were excluded due to the effect of fall leaf shedding changing the burn severity index values and introducing false burn severity noise in the analysis.

Climate indices, site elevation, slope, aspect, and derivatives of the interactions between these variables were also added to the inventory variables and used as predictors in the model. These variables are known to interact with how wildfire spreads and can influence the condition of the vegetation fuel itself and therefore play a role in overall wildfire risk levels. In total, we started our prediction modelling with 130 predictive variables and selected 51 for the final regression models.

Starting with the 2,149 observations, dominant aspen stands were first removed, and the remainder were classified into 6 classes using a weighted dNBR using fuzzy C-Means classification. To begin with moderate burn severity classes could not be easily separated from the high and low burn severity classes using the predictor variables so the initial burn severity analysis focussed on differentiating the observed high versus low severity impact classes. Logistic regression (log odds) analysis was used to differentiate high from low burn severity for a given microstand as a function of structural, topographic, and climatic variables. This was repeated 6 times using sub-samples of the training data. The models varied with respect to variable selection and the associated estimation of variable coefficients. The estimates from each of the 6 models were averaged to produce a final number (p-value) between 0, and 1, where the former represents a relatively low ranking in terms of potential burn severity and the latter indicating a high ranking.

RESULTS

Burn Severity Mapping By Microstand

As previously described, there were 3 separate areas within CCF that experienced significant wildfire impacts (figure 3). In total, 7,155 ha of land were assigned a burn severity class. 3,208 ha (44.9%) of that was classified as low severity, 3,046 ha (42.6%) was classified as moderate burn severity, and 897 ha (12.5%) was classified as high burn severity. These numbers include all land cover types within the burned area extent.

85% of the area that burned was treed (6,090 ha) with 43% of the burned treed area classified as low, another 43% as moderate, and 14% as high burn severity. Ninety-four percent of the area burned was classified as upland and there were significant differences in the proportion of burn severity classes for upland and lowland areas (figure 2). For a breakdown of burn classification by vegetation type see figure 4.

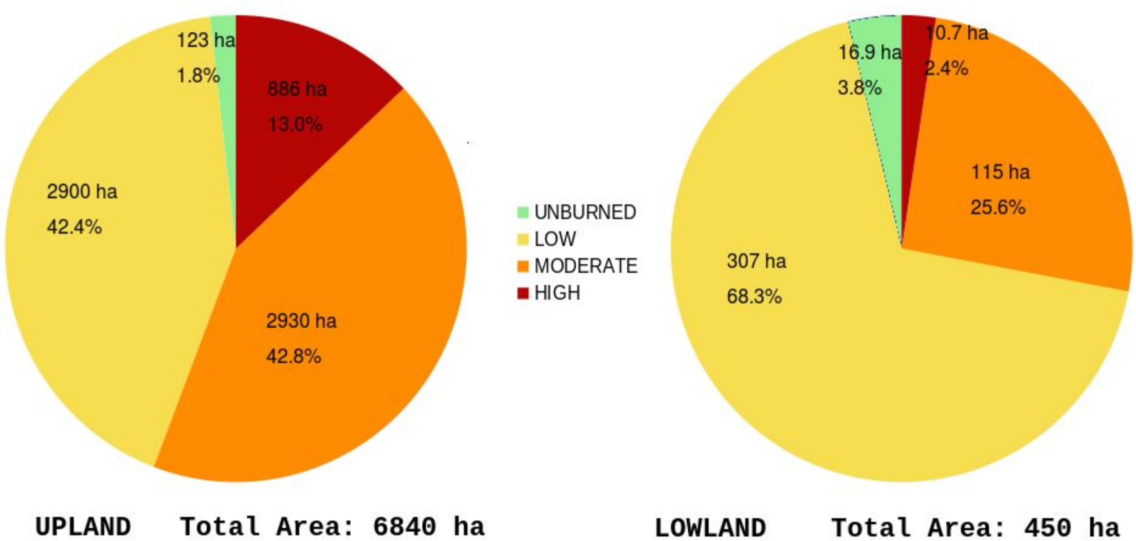

Figure 2. Burn Severity Class Areas By Upland Vs Lowland Land Cover Types

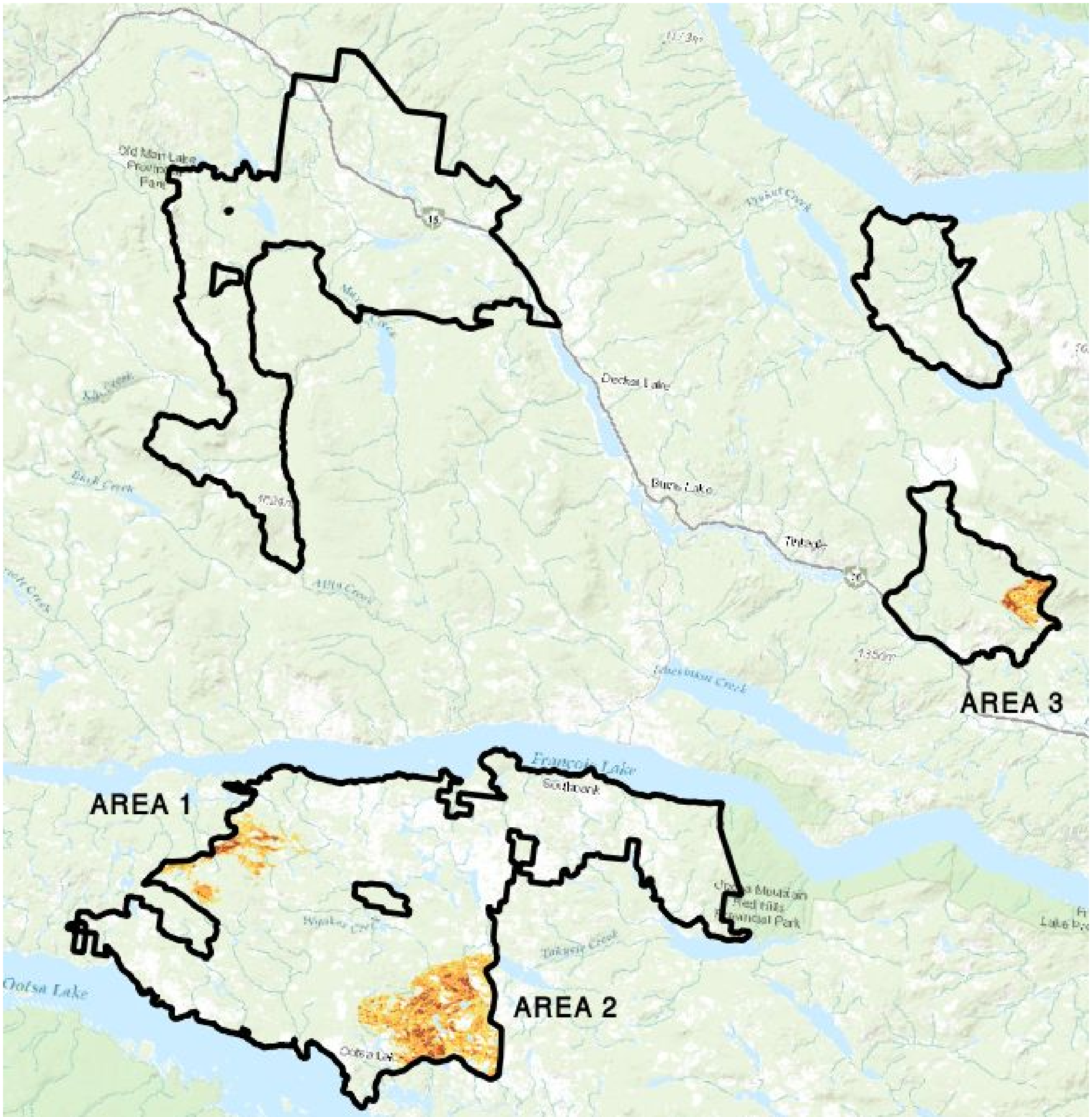

Figure 3: Wildfire burn severity locations (orange-red) between July and October 2018 within the CCF project boundary (black line) identifying the three areas of major wildfire presence.

Visit the interactive HRIS online viewer to explore this map in more detail (viewer.hris.tesera.com)

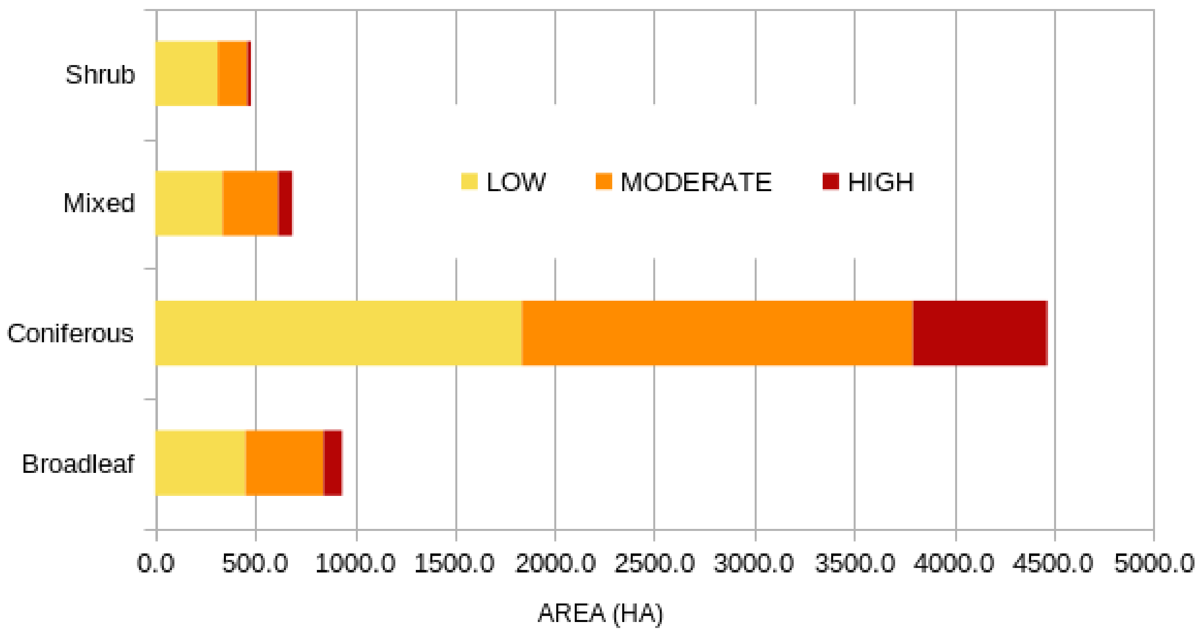

Figure 4. Burn Severity Area by Vegetation Sub-Type (lcc4)

While related studies show that ground observations of low and moderate burn severity classes using these satellite measurements do not have strong relationships with specific burn impact metrics, they still provide useful insights about general fire impacts and suggest that these stands in lower burn severity classes typically demonstrate high tree survival, less timber loss, minimal seedbank damage, and faster vegetation regrowth and recovery rates.

The high burn severity class areas, however, often correspond very well with ground assessments of fire damages and tree losses, which means the results obtained indicate that up to 836 ha of treed area may have experienced high tree mortality and potential stand replacing impacts from this wildfire. Figure 5 provides an estimate of total merchantable volume (for trees > 12.5 cm diameter) by burn severity class and leading stand species with the total volume in the high severity classification to be used as an indicator of potential timber losses.

Figures 6 through 8 provide a distribution map of the burn severity classes across the three areas affected by the 2018 wildfires. More detailed geospatial visualisations of these results can be found on the HRIS online spatial database viewer.

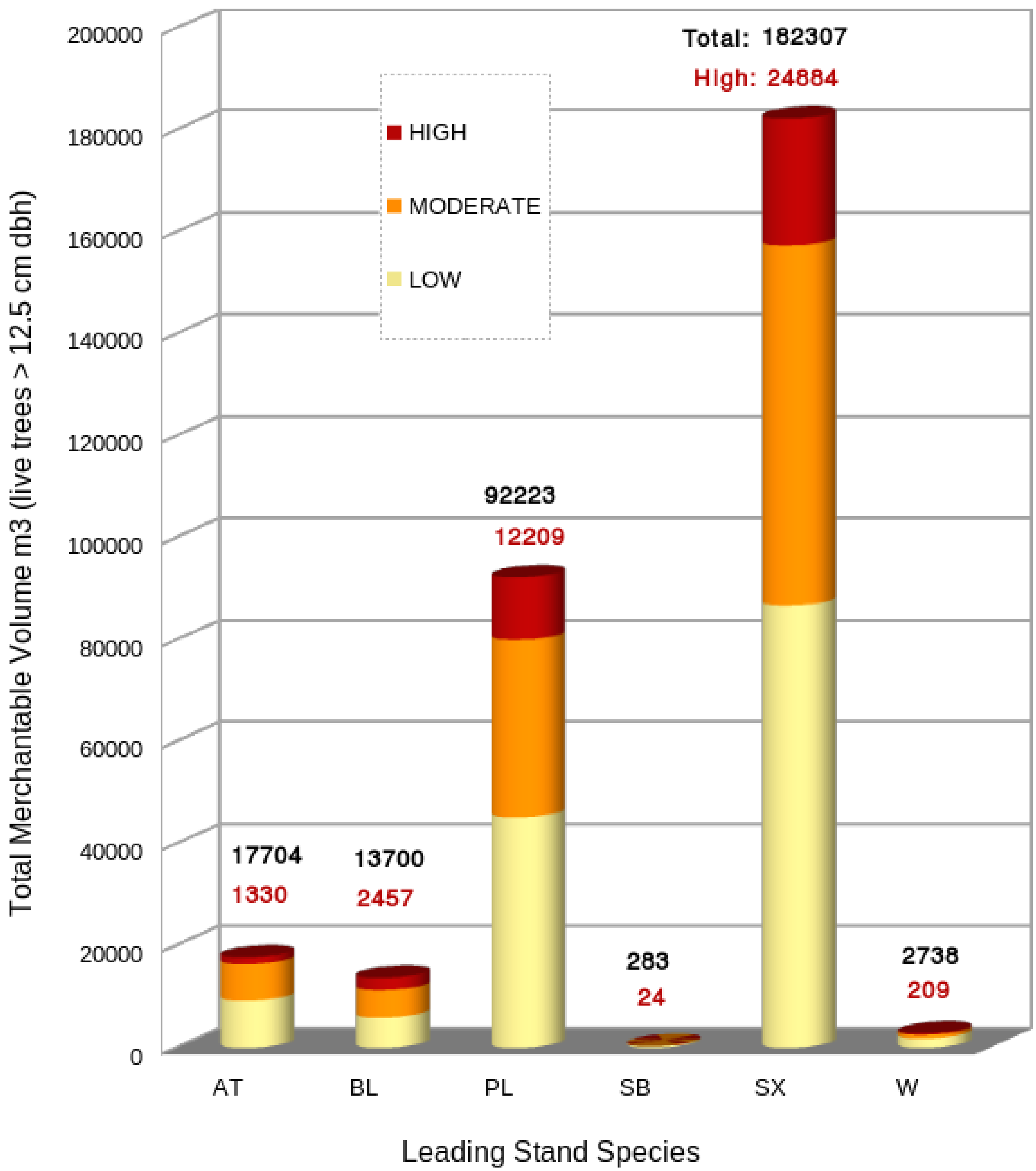

Figure 5. Total Merchantable Volume for Trees > 12.5cm DBH in each Burn Severity Class by Leading Microstand Species. Estimates based on area-weighted MVPH for each HRIS microstand affected by fire. Values in red are for the high severity class estimating complete timber losses in those stands.

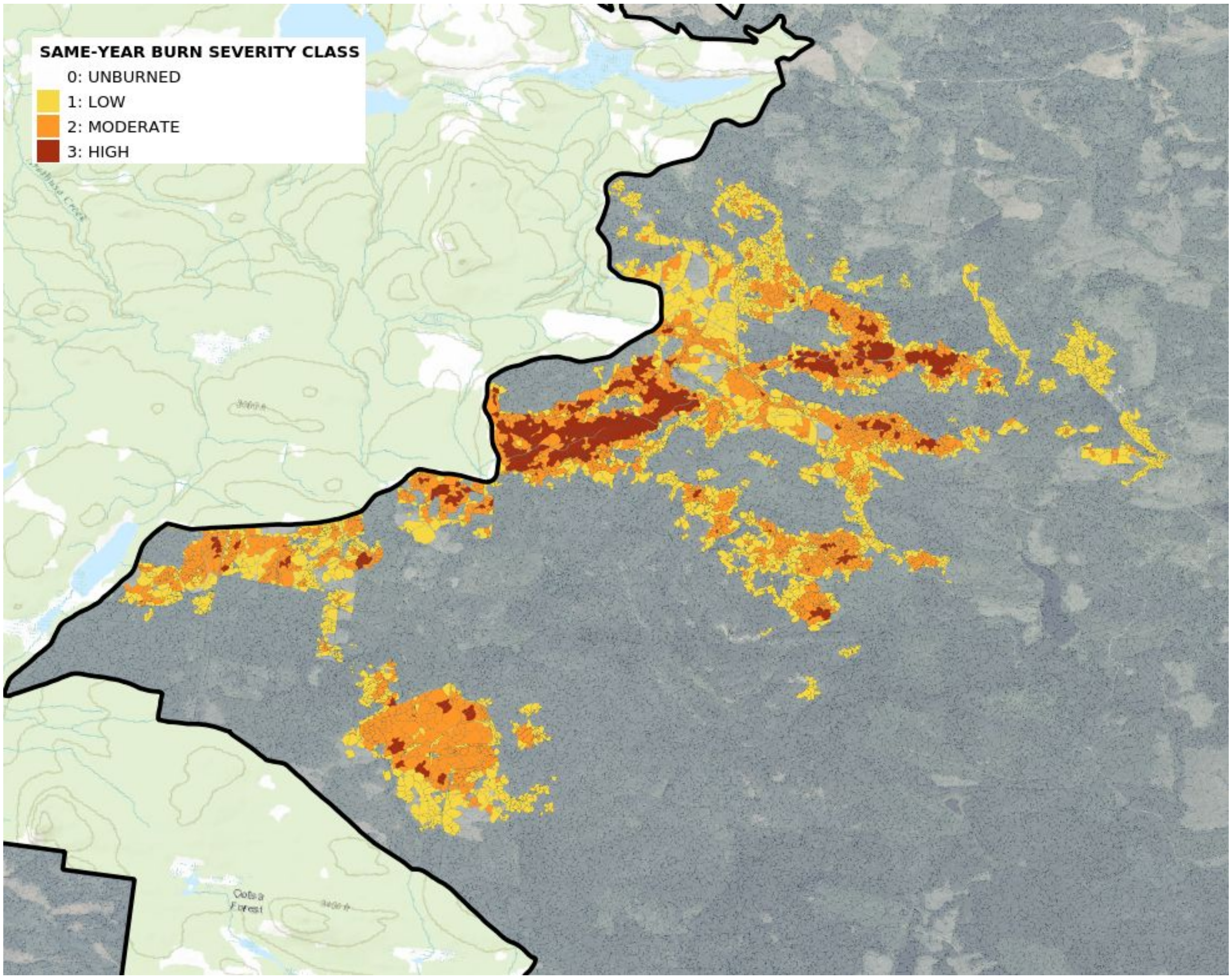

Figure 6. Burn Severity Distribution Map of Burned Area 1

Visit the interactive HRIS online viewer to explore this map in more detail (viewer.hris.tesera.com)

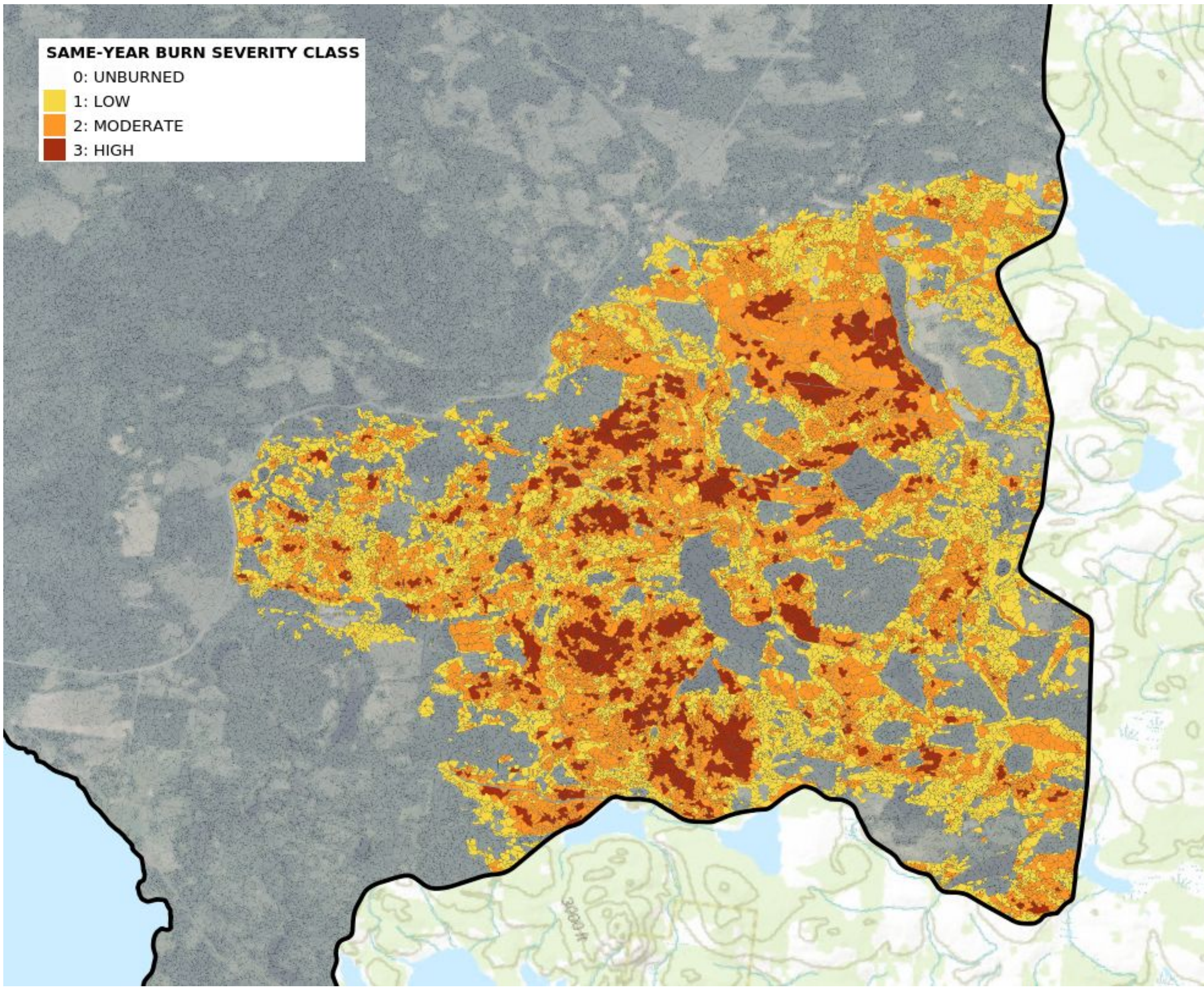

Figure 7. Burn Severity Distribution Map of Burned Area 2

Visit the interactive HRIS online viewer to explore this map in more detail (viewer.hris.tesera.com)

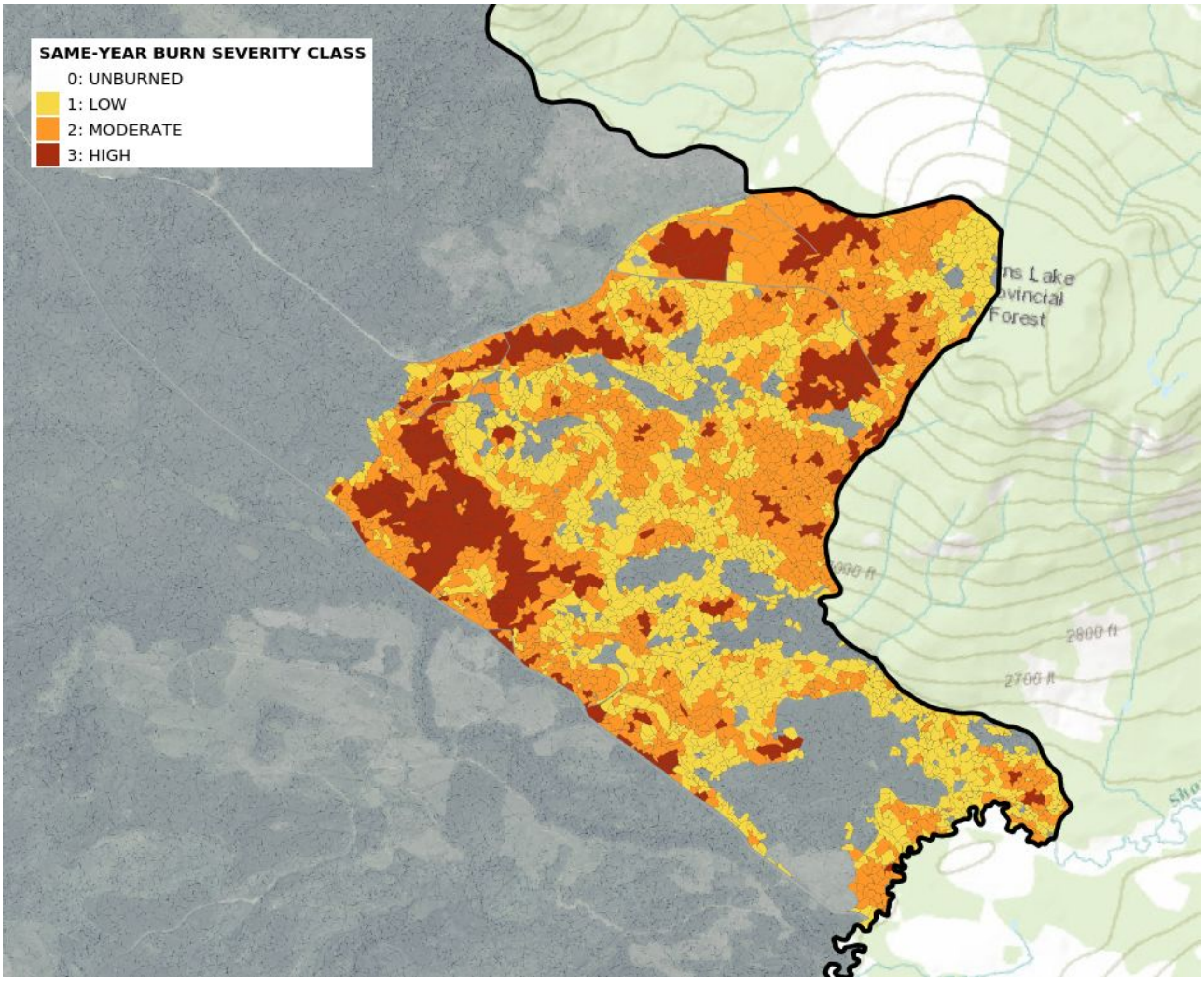

Figure 8. Burn Severity Distribution Map of Burned Area 3

Visit the interactive HRIS online viewer to explore this map in more detail (viewer.hris.tesera.com)

Trends in Burn Severity Stand Attributes

Compiling and comparing the average values of stand attributes across the different burn severity classes revealed some notable trends (see table 2). There were consistent patterns observed in several stand characteristics that have known associations with fire risk, such as increasing percentages of dead trees (DEAD_PCT) in a stand, both by basal area and by tree counts, with increasing burn severity.

Table 2. Average Microstand Attributes of Interest by Burn Severity Class.

ATTRIBUTE	UNBURNED	LOW	MODERATE	HIGH
Average - DEAD_PCT	18.4	22.2	27.1	29.7
Average - AGE	53.0	58.8	58.9	63.1
Average - SI	14.0	14.7	14.8	16.2
Average - HL_L	10.9	12.6	11.9	13.2
Average - CC_PCT	32.3	34.6	31.0	38.2
Average - TPH_L_001	1160	1120	977	1205
Average - TPH_D_001	348	432	502	588
Average - BPH_L_001	15.3	16.6	14.2	16.9
Average - BPH_D_001	6.0	7.5	8.0	9.4
Average - MQD_LD_001	10.4	11.4	11.1	12.3
Average - GINI_LD_001	0.45	0.48	0.48	0.53
Average - CDI_LD_001	0.13	0.14	0.15	0.17

These results are somewhat unexpected as recent research has shown that dead tree presence and volumes in a forest do not increase burn severity or fire risk in western north American forests (7)(8). However, there is no data available within this scope of this work to support the assumption that it is the dead trees specifically that are contributing to the increased observations of higher burn severity levels in a stand, it's possible that other stand attributes which may be related to the presence of dead trees, such as more understory biomass or drier stand conditions due to greater canopy openness, are driving this relationship. These relationships are simply indicators that have been developed based on empirical observations of burn severity via satellite; they are not to be interpreted in terms of cause and effect relationships within this context. For that one would require a deeper understanding of the physical process.

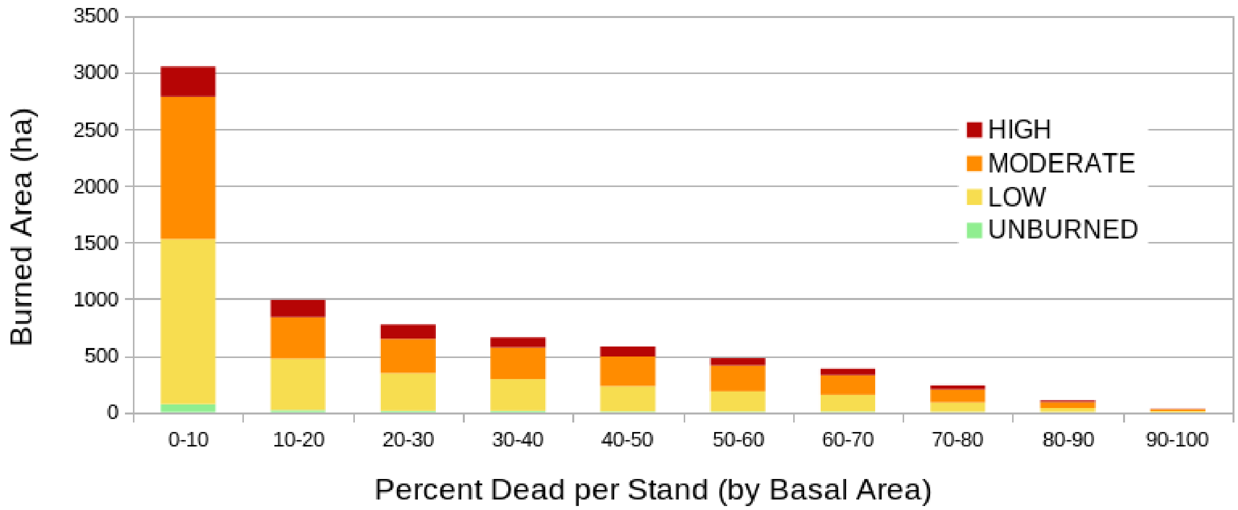

Figure 9. Burned area and Severity by Percent Dead per Microstand. Far less area in total was burned for stands with higher percentages of dead trees, yet stands with higher burn severities, on average, had higher proportions of dead trees.

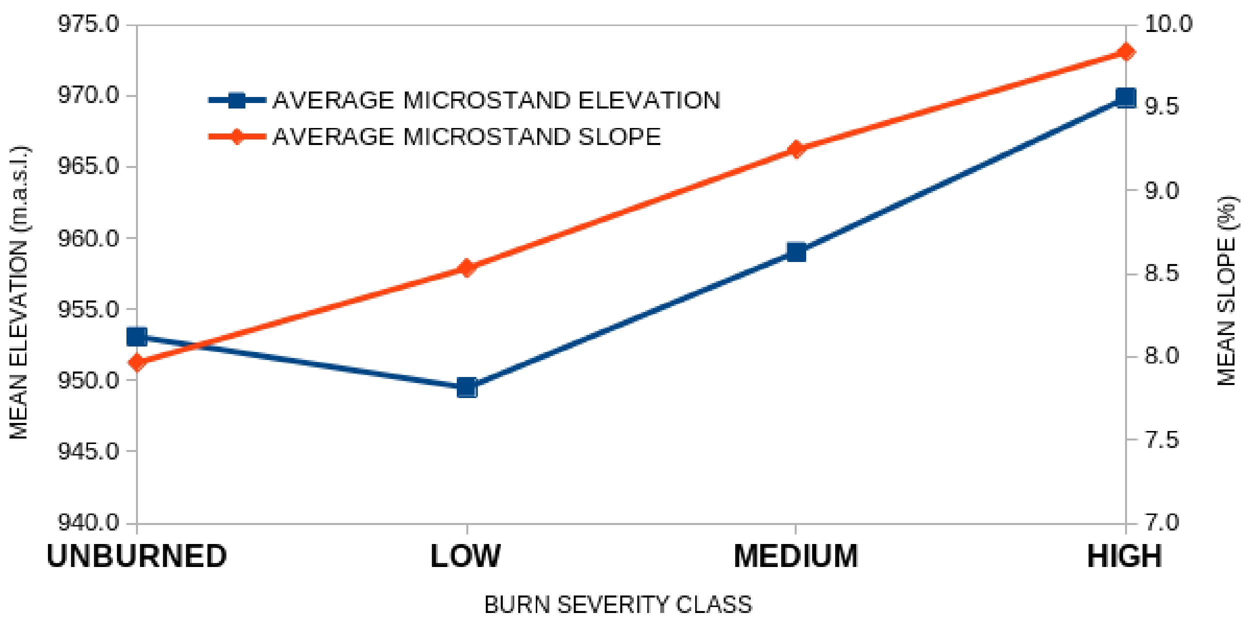

Figure 10. Mean Microstand Elevation and Slope Across Burn Severity Classes. Average site elevation and slope are higher for areas with higher observed burn severity.

Predicting Potential Burn Severity

In the final analysis the burn classification was applied to treed areas, including those outside of the area burnt in the 2018 fires. Areas that were not treed, or that were treed, but were classified using silviculture survey data (from RESULTS) instead of HRIS attribution, were not used to develop the burn classification model; these are represented as "Non Treed" (Table 3). The initial classification that was derived based on 6 classes was reduced to 4 remaining classes (Low, Moderate, High, and Very High) to acknowledge the ambiguity, particularly with respect to the low versus moderate severity ratings. The model-based estimates (p-values) and associated classifications are simply the best estimates for a relative ranking of the potential burn severities based on the experience gained from the 2018 fires, as interpreted by way of use of satellite imagery.

In total, the burn severity prediction model was applied to 91,550 ha of treed area across CCF. The model estimates resulted in approximately 60,000 ha being assigned to Low and Moderate severity classes, 17,500 ha in the high severity class, and 14,000 ha in the very high risk class. See table 3 for a more detailed breakdown of areas in each class.

Table 3. Average stand attribute for predicted severe burn probability class.

ATTRIBUTE	NON TREED	LOW	MODERATE	HIGH	VERY HIGH
AREA HA	40924.9	38219.4	21848.1	17475.9	14015.2
AREA %	30.9	28.8	16.5	13.2	10.6
SLOPE	6.4	7.4	9.0	9.2	10.6
ELEVATION	805.1	955.8	893.0	925.4	930.1
DEAD %	0.0	18.3	25.9	32.0	42.5
LOREY HEIGHT	0.0	15.9	16.1	15.6	14.9
SITE INDEX	6.2	19.8	19.1	17.8	16.3
BPH_D_125	0.0	5.2	7.0	8.1	9.2
TPH_L_125	0.0	547.7	459.0	394.2	302.0
CROWN CLOSURE %	0.0	53.9	47.1	43.7	38.0

Table 4 provides a list of stand and site variables that influenced the predicted severity ratings, ranked from most to least important. These are empirical rankings concerning potential burn severity. They are a reflection of the 2018 fires, and of the methods used to assess burn severity, and of the methods used to relate these severities to structural, climatic, and terrain indices. They are not forecasts of what might happen under different circumstances and scenarios and they are based on empirical evidence, in contrast to techniques that use an understanding of the underlying physical processes to accomplish similar objectives.

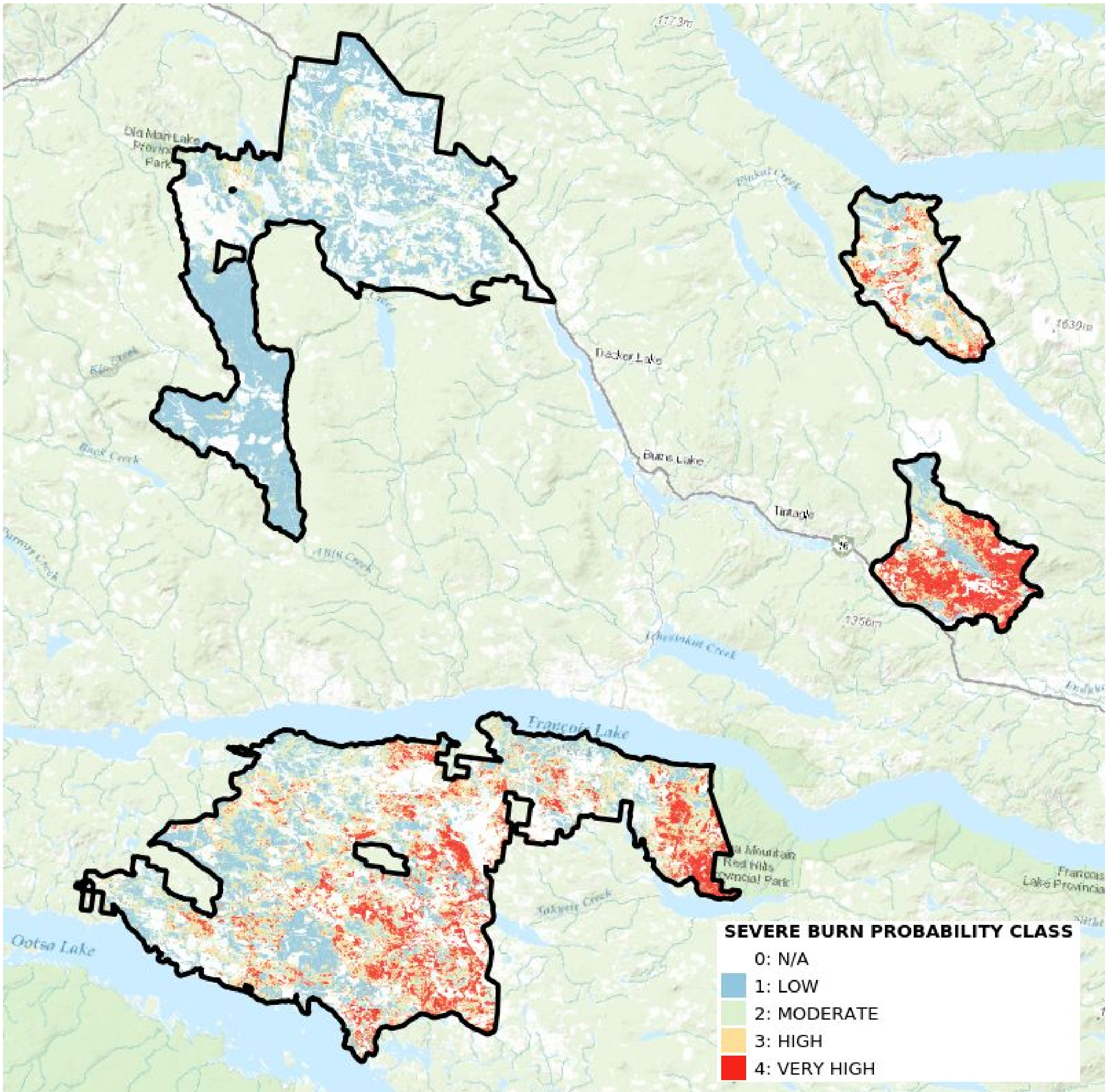

Figure 11. Spatial Distribution of Predicted Severe Burn Probability Classes. An index and probability class for post-fire severe burn levels related to high tree damage and mortality risk was applied to all microstands across the Chinook Community Forest HRIS.

The distribution of higher burn severity rated areas was largely located in the south to southeast region of Chinook CF (figure 11). Little to no high burn severity predicted areas were found in the Chinook A sub-region. This is not to say that these northern areas are not likely to experience significant fire risks during a high fire risk seasons, but rather that the stand characteristics of these sites suggest that a wildfire is less likely to result in high burn severities.

As the empirical model suggests, frost free days and autumn temperatures are important predictors, it’s likely also that tlower fire severity rated areas have cooler climates that retain more moisture as they are typically at higher elevations, putting them at lower risk for high burn severities. There are other factors already described that strongly influence these stand predictions, such as percent dead trees, though one worth noting again is the presence of Black Spruce (Picea mariana) which is a well known fire promoting species (9). The list of variables in Table 4 provides more insights as to the relative influence of the factors used to derive the results.

Model Accuracy

A post-hoc analysis comparing the predicted burn severity to the actual burn observations within the burned area revealed this model has a moderate but acceptable level of predictive error that varies as expected with the magnitude of the burn severity prediction. The model accuracy averages 70% for the highest and lowest burn severity classes and drops to about 25% for the moderate burn severity class. These intermediate severity classes tend to have the highest level of uncertainty and error when comparing ground observations to remote indices in other similar studies (2)(3)(4). A more robust test of the model would involve evaluating the model forecasts in an area with similar forest types that also burned, but was located outside the area used to select the training data. One might also evaluate the model at some later date should new fires occur in an area where predictions have already been made. Finally, ground plots could be used to evaluate the reliability of estimates, particularly where they have been established prior to the burn, and are accompanied with appropriate ground measures to underwrite more substantive burn severity rating.

Table 4. Summary results for microstand burn severity prediction model as a function of climatic, stand structure, and terrain attributes. Higher loadings indicate stronger influences in the model.

	CLASSES-ORIGINAL-MEAN VALUES								
VARIABLES	1	3	4	6	SIGN	#EQ.	LOADINGS	DESCRIPTION	UNITS
Tave_at	2.3	2.7	2.8	2.8	+	1	4.69	Average autumn tempereature	degrees C
eFFP	251.0	252.0	252.8	253.3	+	6	4.43	Day of year frost free period ends	# of days
SB_BA	0.3	0.0	0.0	0.0	-	6	3.94	Black spruce basal area	m2/ha
DEAD_PCT	19.7	26.3	31.4	42.5	+	1	3.06	Dead tree percent of basal area	%
BPH_D_125	5.8	7.3	8.3	10.5	+	1	3.01	Basal area per hectare dead trees (> 12.5 cm dbh)	m2/ha
TPH_L_125	547.6	480.5	431.9	360.4	-	3	2.82	Live trees per hectare (> 12.5 cm dbh)	#/ha
PL_BA	8.1	6.3	4.8	3.1	-	1	2.76	Lodgepole pine basal area	m2/ha
CDI_LD_001	0.1	0.2	0.2	0.2	+	1	2.75	Cumulative distribution index (0-uniform;1-two layered; 0.5-complex)	n/a
Tmax_sm	17.7	18.4	18.5	18.9	+	1	2.60	Maximum summer temperature	degrees C
STVI_LD_001	0.2	0.3	0.3	0.3	+	2	2.45	Structural Variation Index ; 0 uniform; 1-complex (Staudhammer & Lemay)	n/a
RH_at	69.4	67.9	67.7	67.0	-	1	2.41	Autumn mean relative humidity	%
EMT	-40.8	-40.9	-41.0	-41.4	-	5	2.40	Extreme minimum temperature over 30 years	degrees C
Tmin_wt	-12.7	-12.8	-12.9	-13.1	-	1	2.35	Minimum winter temperature	degrees C
MBD_LD_001	20.7	22.4	22.0	23.1	+	1	2.35	Mean live plus dead tree basal area weighted dbh	cm
TPH_LD_001	4074.9	2866.3	2642.9	2572.2	-	5	2.22	Live plus dead trees per hectare (> 1 cm)	#/ha
RH_sp	61.0	59.6	59.4	58.8	-	1	2.06	Spring relative humidity	%
Rad_sm	19.3	19.3	19.5	19.7	+	1	2.02	Summer solar radiation	MJ/(m2 d)
RH	64.3	62.8	62.6	61.9	-	2	1.98	Mean annual relative humidity	%
SLNELEV	49.5	57.3	58.7	70.8	+	3	1.87	Slope*LN(ELEV+1)	n/a
SLNELEV_norm	-0.2	0.0	0.0	0.3	+	3	1.87	Normalized Slope*LN(ELEV+1)	n/a
AGE	62.2	66.5	70.1	73.8	+	2	1.73	Stand age	years
MQD_LD_001	12.8	13.7	13.7	13.6	+	6	1.71	Mean live plus dead tree quadratic dbh (> 1 cm dbh)	cm
TPH_D_001	527.1	629.4	749.1	1028.9	+	6	1.57	Dead trees per hectare > 1 cm dbh	#/ha
MAR	10.9	10.9	11.0	11.1	+	5	1.50	Mean annual solar radiation	MJ/(m2 d)
MVPH_D_125	23.6	29.8	33.7	41.2	+	2	1.45	Mean dead tree merchantable volume Per hectare > 12.5 cm dbh	m3/ha
CC_PCT	54.7	50.7	48.6	45.2	-	1	1.31	Crown closure percent	%
GVPH_LD_001	181.1	185.2	186.2	189.4	+	1	1.27	Gross volume per hectare live plus dead trees > 1 cm dbh	m3/ha
SI_PL	19.1	18.3	17.3	16.2	-	2	1.14	Lodgepole pine site index	m
DD5_wt	4.2	4.1	4.3	4.8	+	1	1.02	Winter degree days < 5 degrees C	degree days
SI	19.1	18.8	17.9	17.2	-	3	1.00	Site index	m
DD18_sp	1.6	1.8	1.8	1.9	+	2	0.96	Spring degree days above 18 degrees	degree-days
BL_BA	2.4	1.2	1.5	2.4	+	5	0.87	Basal area - Subalpine fir	m2/ha
SX_BA	8.2	8.2	7.6	5.0	-	2	0.74	Spruce basal area	m2/ha
GVPH_L_125	129.9	133.2	130.6	134.8	+	2	0.60	Gross volume per hectare live trees (> 12.5 cm dbh)	m3/ha
W_BA	0.9	0.7	0.4	0.2	-	6	0.57	Willow basal area	m2/ha
HL_L	15.2	15.8	15.6	15.4	+	2	0.47	Lorey's mean tree height (living trees)	m
MCMT	-10.2	-10.2	-10.2	-10.3	+(4)/-(1)	5	0.46	Mean coldest month temperature	degrees C
HD_L	16.9	17.5	17.3	17.1	+	1	0.43	Dominant tree height (living trees)	m
SLOPCASP	0.2	0.2	0.1	-0.1	-	1	0.40	Slope*Cos(Aspect)	n/a
SLOPCASP_norm	0.0	0.0	0.0	0.0	-	1	0.40	Normalized Slope*Cos(Aspect)	n/a
TPH_LD_125	698.5	671.5	650.0	647.3	-	1	0.39	Live plus dead trees per hectare Greater than 12.5 cm dbh	#/ha
BPH_LD_001	33.8	33.4	33.3	32.9	+(2)/-(2)	4	0.28	Basal area per hectare live plus dead trees (> 1 cm dbh)	m2/ha
MTD_LD_001	11.5	11.6	11.4	10.6	+(2)/-(3)	5	0.22	Mean live plus dead tree dbh > 1 cm dbh	cm
SLNELEVCA	24.6	28.0	19.2	-13.1	-	1	0.19	SLNELEV*Slope*Cos(Aspect)	n/a
SLNELEVCA_norm	0.0	0.0	0.0	0.0	-	1	0.19	Normalized SLNELEV*Slope*Cos(Aspect)	n/a
GVPH_D_125	0.7	1.5	1.0	1.5	+	2	0.11	Gross volume per hectare dead trees (> 12.5 cm dbh)	m3/ha
maxP	0.2	0.6	0.7	0.9	na	0	0.00	Mean maximum p-value	p-value
meanP	0.1	0.5	0.6	0.9	na	0	0.00	Mean p-value	p-value
meanPdNBR	0.0	-0.1	-0.1	-0.1	na	0	0.00	Mean P digital number (Weighted inversly in proportion max-min)	n/a
minP	0.1	0.4	0.4	0.8	na	0	0.00	Mean minimum p-value	p-value
N (Original)	1838.0	6932.0	4184.0	311.0	na	0	0.00	Number of observations originally Assigned to each class	#
New Class	0.0	1.0	2.0	3.0	na	0	0.00	Newly assigned class number	n/a

SUMMARY AND RECOMMENDATIONS

Wildfire impacts on stand damages, tree survival and mortality, replacement and regrowth are important for inventory management, but can be challenging to measure over large areas of forest. Satellite-based multispectral reflectance data allows us to rapidly create burn severity indices for very large areas with minimal cost to evaluate wildfire damage immediately after a fire event. There are known limitations with some of these indices, such as cloud cover and non-fire vegetation change signal noise sources, however they have proven to be useful indicators of short and long-term stand losses with strong associations with high and low burn severity impacts.

Advances are still being made to improve these remote indices to overcome these limitations. The Relativized Burn Ratio (RBN) has more recently been proposed by some to increase the signal to noise ratio in lower and moderate burn severity classes, and may become the severity index of choice for future forest fire damage assessments (10), though other studies suggest the best index to use is often specific to the type of forest and the fire damage attributes of interest. As these indices only provide relative burn severity ratings, in order to relate them to post-fire stand properties they need to be paired with ground observations. Nonetheless, the burn severity classification based on these remote observations provide valuable information for immediate remediation or salvage planning for large forest management areas where higher priority zones and stand types need to be easily identified, and to further speed up the timber loss estimation process for longer term inventory recovery planning.

In developing a predictive model between the stand and site characteristics and the observed burn severities for Chinook Community Forest it was possible to relate a new classification scheme for burn severity rating for the rest of the HRIS inventory. It should be noted once again that this severe burn probability index describes the relative potential for a stand replacing disruption in the wake of wildfire. It does not impart a direct estimate of fire risk with consideration for a wide range of scenarios, for example based on types of ignition, location of initiation, terrain, weather (as opposed to climate), types of fuels and their condition, neighbouring stand conditions, access, locations of fire suppression equipment and fire suppression responses, and subsequent unfolding of weather events, etc. In general, the severity ranking and the risk of a stand replacing fire event may be related under the assumption that stands that have greater susceptibility toward high severity burn, are more likely to burn in the first place. However, other research has shown that the connection between fire intensity and the burn severity impact on the land and vegetation is still not clear, and that in some forest types it has been reported that higher intensity, fast moving fires, often results in less severe ecosystem responses in fire adapted landscapes, in other words a lower burn severity (11).

It's worth noting that related work examining the relationship between topographic, climatic and forest attributes supports some of the findings and conclusions in this project. Kane et al (2015) found that lidar based forest structural attributes were not strong predictors of burn severity patterns across the landscape in another type of forest in California, but that climatic and terrain variables had the best ability to explain burn severity observations (12). They also found that spatial autocorrelation was a very important factor in the models generated and further support methods such as the 5 ha sample gridding for reducing this effect to ensure models are more widely applicable and less biased by location.

Potential Next Steps

In order to improve on these results and create a model that can describe more specific and longer term ecosystem responses to fire damage, including tree mortality estimates, there are several next steps that could be taken. The first would be to establish ground plots in the burnt areas from the 2018 wildfires to measure the degree of change in microstands since the 2017 HRIS inventory so that the burn severity models could be calibrated to these observations. The other would be to create a between-year burn severity index for the years following the fire, in this case 2019 and 2020, which would describe observed difference between pre-fire stand conditions, the immediate post-fire stand conditions (same-year), and then contrast these changes to the years following to measure vegetation regrowth and recovery. Comparing these satellite time-series burn-severity indices to ground plot data would enable accurate estimates of tree survival, mortality, potential soil and seedbank damages, and impacts to long-term site productivity for the full extent of the area burned in 2018. Such work would lay a strong foundation to apply the same model to any area newly affected by fire within the Chinook region in order to quickly estimate inventory loss and damages with a high level of precision and detail after another wildfire event.

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