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ORIGINAL PAPER

Spatial distribution of wildfire threat in the far north: exposure assessment in boreal communities

Jennifer I. Schmidt[1] · **Robert H. Ziel**[2] · **Monika P. Calef**[3] · **Anna Varvak**[3]

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Abstract

Increased wildfire activity has raised concerns among communities about how to assess and prepare for this threat. There is a need for wildfire hazard assessment approaches that capture local variability to inform decisions, produce results understood by the public, and are updatable in a timely manner. We modified an existing approach to assess decadal wildfire hazards based primarily on ember dispersal and wildfire proximity, referencing landscape changes from 1984 through 2014. Our modifications created a categorical flammability hazard scheme, rather than dichotomous, and integrated wildfire exposure results across spatial scales. We used remote sensed land cover from four historical decadal points to create flammability hazard and wildfire exposure maps for three arctic communities (Anchorage and Fairbanks, Alaska and Whitehorse, Yukon). Within the Fairbanks study area, we compared 2014 flammability hazard, wildfire exposure, and FlamMap burn probabilities among burned (2014–2023) and unburned areas. Unlike burn probabilities, there were significantly higher in exposure values among burned and unburned locations (Wilcoxon; $p < 0.001$) and exposure rose as flammability hazard classes increased (Kruskal–Wallis; $p < 0.001$). Very high flammability hazard class supported 75% of burned areas and burns tended to occur in areas with 60% exposure or greater. Areas with high exposure values are more prone to burn and thus desirable for mitigation actions. By working with wildfire practitioners and communities, we created a tool that rapidly assesses wildfire hazards and is easily modified to help identify and prioritize mitigation activities.

Keywords Alaska · Yukon · Urban · Hazard · Mitigation · Fire

✉ Jennifer I. Schmidt
jischmidt@alaska.edu

1 Institute of Social and Economic Research, University of Alaska Anchorage, Anchorage, AK 99508, USA

2 International Arctic Research Center, University of Alaska Fairbanks, Fairbanks, AK 99775, USA

3 Soka University of America Aliso Viejo, Aliso Viejo, CA 92656, USA

1 Introduction

Wildfire activity around the world has been increasing, and there appears to be no indication that feedback mechanisms will limit increases (Abatzoglou et al. 2021; Barlow et al. 2020; Chisholm et al. 2016; Grabinski and McFarland 2020; Kelly et al. 2020). Reasons for this increase include historic fire suppression (Doerr and Santin 2016; Parisien et al. 2020; Parks et al. 2015), climate change (Abatzoglou and Williams 2016; Mueller et al. 2020; Schoennagel et al. 2017; Scholze et al. 2006), land use (Silveira et al. 2020), and vegetation shifts (Hagmann et al. 2021; Schoennagel et al. 2017). Coupled with the rapid expansion of the transition zone between forested areas and human development often called the wildland–urban interface (WUI) (NWCG 2009; Radeloff et al. 2018) places thousands of communities at risk (NASF 2021). The US Forest Service has gone as far as to say the USA is dealing with a wildfire crisis (USFS 2022). National efforts have been made to assess wildfire hazards and risks, but often they do not incorporate localized datasets (Scott et al 2020), lack regional factors (USFS 2020), and utilize a spatial resolution that is too coarse to be used effectively by communities (Ager et al. 2015). For example, one national effort only has two categories for wildfire risk in Anchorage, Alaska, which is not overly helpful for making local decisions (USFS 2020). Ager argues for a more localized approach that aligns with planning and actions. Our proposed method uses a finer spatial resolution (30 m) that captures more subtleties than national efforts that is regionally adjusted for Alaska (Napoli et al. 2021; USFS 2020). There is a critical need to provide concrete information about the hazards and risks that these high-latitude communities face given they are faced with increased wildfire activity (Grabinski & McFarland 2020; York et al. 2020), losses of homes and property due to wildfire (Bhatt et al. 2021; Rasker 2015), and a wildland–urban interface (WUI) on the precipice of potentially deadly events, given shrinking wildland fire response crews and capacity (Thompson et al. 2023). While it has been acknowledged that wildfire activity is increasing in the Arctic (Kelly et al. 2013; Masrur et al. 2018), very little work has been done to assess wildfire hazards and risk in northern boreal and tundra ecosystems (Wimberly et al. 2004; Zhang et al. 2021).

Currently, wildfire risk assessment processes use fire spread models to determine the manifest hazard (Parisien et al. 2019, 2005; Scott 2013), estimating exposure based on the modeled fire intensity at each location. These fire models demand detailed descriptions of fuelbed characteristics, windspeed and direction, fuel moisture and flammability, and terrain characteristics to model fire spread and intensity. They combine a measure of burn frequency with the estimated intensity to produce the exposure estimate, subject, of course, to the accuracy of the critical assumptions required for all these listed factors. We modified the wildfire exposure assessment method (Beverly et al. 2010, 2021) to determine the likelihood and significance of wildfire flammability hazards to the values at risk in communities of interest. Our paper builds on the original method by using the Alaska model fuel guide (AWFCG 2018) to inform changes from dichotomous flammability scores into categorical values that provide a deeper understanding of the hazard at its source location.

Promoting wildfire-resilient communities is not only about identifying hazards and risks, but also about effectively communicating these. The National Fire Plan strategy emphasizes information sharing and gathering feedback (USDA 2001). There is a critical need for wildfire risk mapping tools that can be easily understood and used by communities and land managers to promote wildfire-resilient communities (Cao et al. 2016; Meyer et al. 2015; Mozumder et al. 2009). The modified exposure method is still rapid and straightforward, uses fewer subjective inputs, and produces results comparable to more complicated processes (Beverly et al. 2010, 2021). One issue we identified with our public engagement was the confusion caused by using various scales to assess wildfire hazards which are based on dispersal mechanism and wildfire proximity (i.e., long and short distance). This can be confusing when attempting to communicate science. Which product should be displayed to the public? Which classification should be used for fuel treatment planning? We further refined the exposure method to provide a single integrated output that can be displayed and used by public and wildfire practitioners; it integrates wildfire exposure derived from differing hazards where appropriate. The integrated approach provides a clearer understanding of wildfire hazards without overstating the hazard or minimizing the threat from the landscape-level process.

This study is intended to demonstrate that the exposure assessment method employed here is simple and adaptable enough to be used as frequently as needed to update conditions based on changes in hazards after wildfires and specific fuel treatments intended to reduce hazards. The ability of this exposure method to effectively represent changes over time will be shown using four decadal (1984, 1994, 2004, and 2014) instances in three Arctic communities (Anchorage and Fairbanks, Alaska, USA and Whitehorse, Yukon, Canada). Each is in the boreal forest but reflects different ecoregions, wildfire histories, and social demographics. However, among them, the landscape characteristics are of paramount importance. There is a critical need to support easily applied methods that can assess wildfire hazards and the threats they pose, provide information that can be used for hazard fuel reduction actions like fuel treatments and other actions, and provide tools that can be easily used by land managers and wildfire practitioners.

2 Study areas

Our three study areas (Fig. 1) include two areas from Alaska, USA—Anchorage (2704 km^2) and Fairbanks (15,077 km^2)—and one from the Yukon Territory, Canada—Whitehorse (12,305 km^2). They were selected because they contain a large WUI within the Arctic boreal forest region and communities expressed interest in assessing hazards. The Municipality of Anchorage (n = 291,247 population) boundary defines this study area and encompasses the largest community in the North America Far North: Anchorage proper (n = 288,970) and several other smaller communities (US Census Bureau 2020). This area is greatly influenced by a maritime environment with mild summers (July mean = 14.3 °C) and a moderate amount of annual precipitation (mean = 839 mm). To the north, the community of Fairbanks (n = 31,410) has hotter summers (July mean = 17.6 °C) and minimal precipitation (mean = 375 mm) (Climate data 2022) and is the largest community within the Fairbanks North Star Borough (FNSB, n = 95,655). Our boundary for this region was chosen based the boarders of the FNSB, where residents live within those boundaries, previously collected aerial imagery, and a sufficient buffer to allow wildfire to move into the region. Whitehorse is the capital of Yukon and its largest community (n = 28,201; Statistics Canada 2021). The study area boundaries were drawn with community wildfire experts to capture surrounding communities and likely directions that would capture encroachment of a wildfire, especially from the south. The climate in Whitehorse comprises cooler summers (July mean = 13.1 °C) and moderate precipitation (463 mm) (Climate data 2022).

Burnable areas within our study areas differ (Table 1) due to maritime influence on climate and vegetation, topography, and population density. Burnable areas are defined as places not covered by ice, glacier, water, or barren. Historically and recently, Fairbanks

Fig. 1 Three study areas in Anchorage and Fairbanks, Alaska and Whitehorse, Yukon used for our wildfire exposure analysis. Boundaries reflect either local government jurisdictions with refinements based on where residents live or suggestions from local authorities

Table 1 Wildfire history within the landscape in the three AURA community study areas. Burnable areas are places not covered by ice, glacier, water, or barren

		Time Period				
		1974–1983	1984–1993	1994–2003	2004–2013	Initial burnable area (km^2)
Anchorage	Number of fires	171	88	81	138	1,898
	Area burned (km^2)	6.3	1.2	3.3.0	7.9	
	% Change in burnable area	– 0.3%	– 0.1%	0.4%	– 0.2%	
Fairbanks	Number of fires	686	1083	835	723	14,591
	Area burned (km^2)	339.2	213.8	183.0	3032.8	
	% Change in burnable area	– 2.3%	– 1.5%	– 1.3%	– 20.8%	
Whitehorse	Number of fires	237	371	283	122	10,986
	Area burned (km^2)	0.42 km^2	9.4	82.6	0.24	
	% Change in burnable area	0.0%	– 0.1%	– 0.8%	0.0%	

has had the most area burned, with 20% of the landscape burning in the last decade compared to less than 1% in the other two areas. The higher portion of the landscape burned in Fairbanks reflects the lack of a maritime influence, resulting in warmers summers with more lightning activity and the greater extent of woodland and boreal black spruce forests encouraged by widespread permafrost.

3 Methods and data

3.1 Land cover classification resource and area modifications

We used the Arctic Boreal Vulnerability Experiment (ABoVE) Landsat-derived annual dominant land cover classification, which provides a critical depiction of land cover that encompasses all three community areas (Wang et al. 2019). It provides 31 annual depictions (1984–2014) that capture changes due to disturbances and development that can inform projections of change in the future. No other dataset was found that could provide a combination of classification accuracy and precision, resolution of spatial distribution, or history of landscape changes that were critical to evaluating changes to hazard and risk across the three areas (NALCMS 2015; NRC 2015; Landfire 2016; NLCD 2016).

We used four years to represent historic decadal instances (1984, 1994, 2004, and 2014) for this wildfire hazard assessment. Of these, 2014 represents the baseline landscape characterization to which other instances are compared because it is the most current and most recognizable by residents. The land cover classification includes 16 categories (Table 2) while providing important distinctions in non-forest and disturbed categories. It includes the unnamed NA class, which generally represents persistent ice and snow at high elevations. The ABoVE data have a single evergreen category, although those forests are dominated by different evergreen species combinations. Evergreen tree species can vary in their flammability and wildfire behavior so we found it necessary to refine this category to contain black and white spruce, hemlock, lodgepole pine, and subalpine fir depending on the study area (Online Appendix 1). For each decade, we distinguished four additional evergreen categories that were reclassified from the evergreen forest class based on the ecoregion and vegetation native to each study area (Online Appendix 1) (Wiken et al. 2011). This breakdown allows us to highlight important variations found in each of the three areas.

In boreal Alaska, there are two dominant evergreen forests: black spruce (*Picea mariana*) and white spruce (*Picea glauca*). Black spruce prefers acidic, poorly drained soils; white spruce is more often found on well-drained, south-facing slopes (VanCleve and Viereck 1981; Viereck and Little 1972). In the Whitehorse area, the evergreen forest is primarily dominated by white spruce and/or lodgepole pine (*Pinus contorta*). We trained a gradient boosted decision tree machine learning model using the XGBoost package (version 1.0.1) in R (version 3.6.3, https://xgboost.ai/) using aspect, slope, elevation, climate factors, pH, and time since last fire to differentiate evergreen forests dominated by black spruce and other spruce in Anchorage and Fairbanks, and in Whitehorse lodgepole pine was differentiated from other spruce (Calef et al. 2023). The boost approach uses multiple random decision trees to correct prediction errors (Chen and Guestrin 2016). In Fairbanks, the other evergreen category represents white spruce. However, in Anchorage and Whitehorse there was a need to further reclassify the other evergreen category because of the diversity in the evergreen present.

Table 2 Hazard rating assignments for cover types used in classifying the landscape in the three AURA study areas. The areas are Anchorage (A), Fairbanks (F), Whitehorse (WH), and all three (All). Published methods are based on previous work (Beverly et al. 2010, 2021) and modified as described in the methods section

Dom	Veg Type	Published Method Hazard Ratings			Modified Hazard Ratings		Hazard Class
		500 m	100 m	30 m	500 m-adj	100 m-adj	
All	Evergreen Forest	**1**	**1**	**1**	**100**	**100**	**Very High**
All	Woodland	**1**	**1**	**1**	**100**	**100**	**Very High**
F, Wh	Mixed Forest	**1**	**1**	**1**	***75***	***75***	***High***
A	Mixed Forest	**1**	**1**	**1**	**50**	***75***	***Mod/ High***
All	Open Shrub	0	**1**	**1**	*20*	**50**	**Low/Mod**
All	Tussock Tundra	0	**1**	**1**	*20*	**50**	**Low/Mod**
All	Fen	0	**1**	**1**	*20*	**50**	**Low/Mod**
All	Low Shrub	0	0	**1**	*6*	*30*	*Low*
All	Tall Shrub	0	0	**1**	*6*	*30*	*Low*
All	Herbaceous	0	0	**1**	*6*	*30*	*Low*
All	Sparsely Vegetated	0	0	0	0	0	Very Low
All	Bog	0	0	0	0	0	Very Low
All	Shallows/Littoral	0	0	0	0	0	Very Low
All	Barren	0	0	0	0	0	Very Low
All	Water	0	0	0	0	0	Very Low
All	NA (Ice/Snow)	0	0	0	0	0	Very Low
Vegetation Classification Modifications							
A, F	Black Spruce	**1**	**1**	**1**	**100**	**100**	**Very High**
Wh	Lodgepole Pine	**1**	**1**	**1**	**100**	**100**	**Very High**
Wh	Sub-Alpine Fir	**1**	**1**	**1**	***75***	***75***	***High***
A	Hemlock	**1**	**1**	**1**	*20*	**50**	**Low/Mod**

In Anchorage, the other spruce was further distinguished with hemlock (*Tsuga mertensiana*). The flammability of hemlock was differentiated from spruce in an earlier land cover classification used for wildfire hazard assessment (Goodrich et al. 2008). In each decadal land cover classification, other evergreen forests were reclassified, and hemlock forests were identified in an earlier assessment. The remaining evergreen forests represent white spruce. In Whitehorse, we added subalpine fir (*Abies lasiocarpa) forests as distinct and important evergreen forests.* To identify them, we used a 5 K vegetation inventory dataset that covered 63% of our study area (Government of Yukon 2012). In areas overlapping the other evergreen category in ABoVE and the subalpine fir in the 5 K dataset, the other evergreen forest was reclassified as subalpine fir. For areas not covered by the 5 K dataset, we first determined a lower elevation threshold for subalpine fir since it is known to grow at higher elevations (610–1524 m) (Alexander et al. 1984; Government of Yukon 2022). Areas on the 5 K map were reclassified as subalpine fir if they were other evergreens and above 1200 m. Like Fairbanks and Anchorage, the remaining other evergreen represents white spruce. Decadal vegetation datasets are archived with the NSF Arctic data Center (https://arcticdata.io/).

3.2 Boreal wildfire exposure assessment methods

The only assumptions imposed on exposure assessment are the flammability hazard rating based on land cover type and the distance from which the hazard (embers transmission and surface intensity) can effectively be projected. With its use of circular neighborhood focal statistics of hazard ratings (ArcGIS Pro 2.9.1), exposure ranking makes no assertion about wind speed and direction, fuel moisture and drought, or the topography of the landscape (Beverly et al. 2010). Instead, our basic assertions of hazard potential are employed to estimate the relative likelihood of impact without an attempt to produce simulated probabilities. This approach shifts attention to distribution and relative flammability of vegetative cover in our study areas.

The original wildfire exposure assessment method identifies 500, 100, and 30 m exposure neighborhoods. The 30 m neighborhood was not practical with the available 30 m land cover data. Figure 2 outlines the exposure assessment method adapted from the published method (Beverly et al. 2010, 2021). The initial two steps are the same: vegetation classification into a flammability hazard rating and the creation of exposure within defined

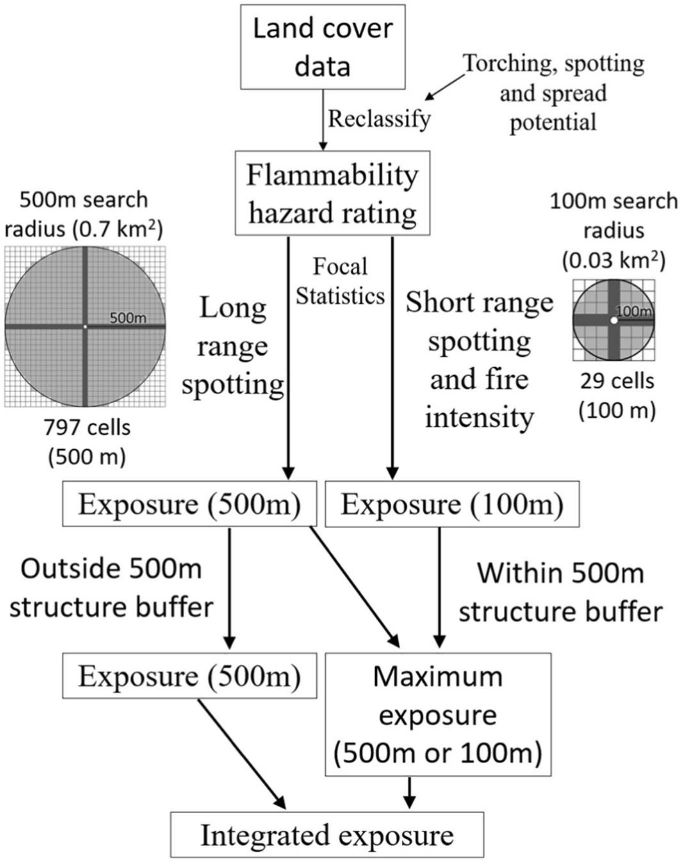

Fig. 2 Exposure assessment method process flowchart adapted from Beverly et al. (2010, 2021). Boxes represent maps produced

surrounding spatial neighborhoods. The three differences are (1) changing from a dichotomous classification of the flammability hazard rating (see next section), (2) the use of the 30 m (m) hazard classification to inform the flammability hazard rating at the 100 and 500 m scales, and (3) the integration of 500 and 100 m to create an integrated exposure map.

3.3 Flammability hazard rating

Hazard is any condition that can cause damage, loss, or harm to people, infrastructure, equipment, natural resources, or property (Scott 2013). In the case of a wildfire, anything that can burn during a fire (i.e., fuel) is a hazard (USDOI 2015). The first step is to reclassify land cover into a flammability hazard, which is based on the potential for each land cover class to burn with sufficient intensity to threaten nearby values. Land cover classifications do not explicitly characterize fuel and flammability distinctions; however, we found flammability distinctions, and the resulting hazard ratings, to be closely related. The original exposure approach treated hazard potential at the most basic level, assigning ones or zeros (true or false). We have modified the approach to provide a more nuanced, scaled hazard rating from 0 to 00 (Table 2). The intermediate ratings give the hazard classification finer spatial resolution because they identify more of the variation in vegetation and flammability. Table 2 shows how the vegetation types produced for the three areas are reclassified into flammability hazard ratings and class. The three intermediate hazard classes were identified to reflect vegetation (moderate hazard) that becomes a hazard at the 100 m analysis radius and then separately vegetation (low hazard) that becomes a hazard at the 30 m analysis radius in the published method, representing progressively less hazardous vegetation. Mixed forest is a combination of evergreen and deciduous, so that value was reduced, but still kept higher because of the presence of highly flammable evergreen. Online Appendixes 2 and 3 provide descriptions of each land cover class and how they relate to flammability and wildfire activity.

The two neighborhood sizes considered, 500 and 100 m circles, reflect two primary wildfire threats, long- and short-range spotting potential (Fig. 2) that includes some consideration of direct fire impact. The larger search radius emphasizes the long-range spotting potential associated with evergreen and mixed forests; the smaller radius incorporates additional intermediate hazard emphasis for other land cover types that can produce short-range spotting and sufficient surface intensity as threats (Online Appendixes 2 and 3). Crown fire and the associated torching/spotting fire behavior potential provide the maximum hazard in the assessment process. A score of 1 (published method) or 100 (modified method) was reserved for the spruce, lodgepole pine, and woodland types, which are most likely to produce significant crown fire behavior or torching frequency and spotting distance (Table 2). Ratings are higher for the 100 m than 500 m scale because it reflects more intense fire activity closer to threatened values. Based on local observations in Anchorage, the mixed forest category within the ABoVE data is largely dominated by less flammable deciduous canopies after several recent spruce beetle infestations, so it was given a lower hazard rating (50) than Fairbanks and Whitehorse (75) (Table 2).

3.4 Wildfire exposure ranking

The second step integrates individual *flammability hazard ratings* into a composite ranking for the 500 m (0.7 km^2) and 100 m (0.03 km^2) circular neighborhoods surrounding individual locations (Fig. 2). Assumptions about the hazard (spotting distances, spotting potential, and surface fire intensity) are inferred in the neighborhood radius to represent comparative *wildfire exposure rankings*. The focal statistic tool is used to sum the hazard rating within the 500 and 100 m circles surrounding each raster location. To produce a more easily understood exposure ranking, the result is divided by the number of cells within each circle (797 or 29) and rounded to an integer value for a result between 0 and 100. There is an edge effect for our study areas as the distance to the area boundary falls below 500 or 100 m, depending on the radius used. But given the size of our study areas, the edge effects are minimal. With these rankings, the threat to values distributed across the study areas can be compared by referencing the *wildfire exposure* at each location. *Exposure* is the potential contact of an entity, asset, resource, system, or geographic area with a hazard (Thompson et al. 2016). Exposure classes were created based on exposure values: very low (0–19), low (20–39), moderate (40–59), high (60–79), and extreme (80–100). To explore changes in exposure over time, we calculated the percentage of areas within each exposure class and the mean exposure value across decades and among the three study areas.

3.5 Integrating exposure rankings

The 100 and 500 m exposure assessments need to be applied across analysis areas where each is most appropriate and integrated into a single product that distributes exposure based on both assessments. These exposures are not fully independent because long-range spotting reflected in the 500 m radius can bring the threat within the 100 m radius, nor are they contingent because fires can threaten independently from distant and nearby sources. This integration needs to reflect the higher ignition frequency found concentrated in areas of human habitation and activity. And it needs to address the more local threat of fires within those same areas due to increased frequency of barriers to fire spread and the more effective suppression response to protect values there. The 100 m analysis radius emphasizes the hazards close by and reflects the increased frequency of wildfires, especially human caused, by evaluating hazard ratings within the much smaller analysis area (0.03 km^2 for 100 m radius versus 0.72 km^2 for 500 m radius).

To emphasize these nearby ignitions and smaller fire sizes, structures have been identified as the locations where key values exist and where human ignitions are common and problematic. Represented with a 500 m buffer around all structures in each study area, the area can be considered our delineation of the WUI extent. Structure information was obtained for each decade to the extent possible for each community. We started with the current buildings layer (i.e., near 2014) for each community and then worked backwards through the decades deleting buildings that were not observed with aerial imagery. Supplementary information from Microsoft buildings was used for 2014 as needed (Microsoft 2018). As we went back to the 1980s coverage for the entire study areas was not available, so we used the 1994 and if there was no historic imagery for 1984 the buildings remained in place. The Municipality of Anchorage (MOA) in-house GIS department provided aerial imagery from 1990 (1 m), 2004/2006 (1 m), and 2015 (1 m) that covered the entire area with limited details (MOA 2019). For 1984, we used Landsat (30 m) (USGS 2023), but it only covered the immediate Anchorage area (outlying communities were excluded) and it was primarily used to identify larger areas that were not disturbed in 1984 compared with 1994. In Fairbanks, the FNSB provided pictometry data for 2014 and 2009 with a meter or less resolution (FNSB 2019). Spot 5 data from 2003 and 2004 (2.5 m) and a combination of Quickbird (2.8 m, 2002–2003) and Digital Ortho Quad (1 m, 2007) were used for 2004. Orth mosaiced images from

2006 created by the City of Whitehorse were used, but again we were limited to the Whitehorse city limits with our data (City of Whitehorse 2006). Alaska High Altitude Aerial Photography from 1985 was used (NASA 1986) provided excellent detail for buildings, but the extent was limited to the city of Fairbanks (outlying communities were excluded). Government of Yukon provided aerial imagery for 2014 (Yukon 2019) and we used background imagery in ArcGIS Pro. Orthomosaiced imagery from 2006 was obtained from the City of Whitehorse (City of Whitehorse 2006). The National Air Photography Library of Canada from 1985 and 1995 was used which provided excellent detail for buildings, but the extent was limited to the city of Whitehorse (outlying communities were excluded) (NRC 2022a, b).

Integration of the two assessments could simply assign the 100 m exposure ranking for areas within the 500 m structure buffer and the 500 m exposure ranking elsewhere. However, while the 100 m exposure distributions generally produce higher exposure, there are situations where the exposure is directly from long-range spotting, especially when structures are themselves highly flammable and where the nearby cover produces low exposure estimates. Integration of these exposures should assume the maximum exposure from the two assessments within a neighboring area around the identified values and utilize the 500 m exposure elsewhere. Within this 500 m structure buffer area used the higher of the two raster values, comparing the 100 or 500 m exposure rankings at each location. This 500 m structure buffer changed each decade based on the spatial distribution of structures. Not having an urban category in the ABoVE database surprisingly was a strength because it allowed us to capture vegetation nestled between structures in the WUI extent. Outside this area, we used the 500 m exposure value. The integration of the modified 100 and 500 m scales within a 500 m buffer has the potential to affect the distribution of exposure values within the WUI. To assess the influence of the two scales on exposure, we calculated the total area where the exposure value was greater within the 100, 500 m, or equal to the 500 m buffer of structures in our study areas. The decadal vegetation datasets are archived with the NSF Arctic data Center (https://arcticdata.io/).

3.6 FlamMap wildfire modeling

We used FlamMap (Finney 2006) to calculate burn probabilities for the Fairbanks study area since this was the only area with significant wildfire activity. The goal was to compare how well wildfire exposure versus burn probabilities aligned with subsequent wildfire activity (2014–2023, total 959.1 km^2). We classified the exposure into the five categories listed above and used Jenks natural breaks (Jenks 1967) on the entire study area to identify five classes of burn probabilities. We calculated the percent of each class for the entire study area and within burned areas. Based on a wind rose from the Fairbanks International Airport for the fire season (June–August, 2000–2020, 1200–2200 h) (IEM 2022), we ran two FlamMap simulations with 20 mph wind directions from the west–southwest and northeast. The crosswalk table to create the landscape file was created using the Alaska fuel model guide (AWFCG 2018; Online Appendix 4). The fuel moisture settings were determined using crosswalks from calculated fuel moisture codes in 2014 using the same weather station (AFF 2022; Online Appendix 4). The simulation was run with human ignitions (1974–2000; AICC 2023) and then 76,817 random ignitions each for a 600-min simulation with a 0.15 spotting probability.

3.7 Validation of products

Flammability hazard ratings represent the source of the wildfire threat. To be effective, the hazard rating for each land cover type needs to demonstrate its differential flammability in burned area frequency. Therefore, land cover and flammability classes in the high to very high categories should occur more often than other classes within areas that have burned because their properties are more likely to produce threatening fire behavior. In turn, burned area should occur in areas with higher exposure values if exposure represents likelihood effectively. Based on these assumptions, exposure values should be greater in burned than unburned areas and this should hold true among each flammability hazard class. The Fairbanks study area experienced the greatest extent of fire disturbance among the three areas (Table 1) so we used the wildfire history in this are to assess whether there were significant differences in the area burned among the hazard classes and the vegetative types included. To account for spatial autocorrelation, we created a 500-by-500 m grid and, at the centroid of each cell, recorded the integrated exposure values, flammability hazard class, and land cover. An Anderson–Darling normality test (Thode 2002) on the exposure values indicated that they were non-normally distributed (Online Appendix 5), we used nonparametric statistics (R package nortest; $n = 55{,}292$, $A = 1165$, p value < 0.001). We used wildfire scars for Alaska to identify whether each centroid was burned or unburned between 2014 and 2023 (AICC 2023). To determine whether there was a significant difference in the distribution of the exposure values between burned and unburned areas we used the post hoc Wilcoxon rank-sum test (Wilcoxon 1945). To visualize the difference, we created cumulative distribution curves of exposure values for burned and unburned centroids. The nonparametric Kruskal–Wallis test was used to test if the exposure distribution differed significantly among any flammability hazard classes (Kruskal and Wallis 1952). This was followed up with a Dunn's test to post hoc test for differences among each flammability hazard class comparison (Dunn 1964). Meanwhile to test for differences between the classes, we used the Wilcoxon rank-sum test with a Bonferroni correction since multiple tests were performed (Benjamini and Yekutieli 2001). An exact binomial test was used to assess whether the distributions of land cover differed between burned and unburned areas (Clopper and Pearson 1934). This test was only done on land cover types that were present more than 10 times within a category. All statistical tests were performed with R (version 4.3.1) at the 5% significance level.

4 Results

4.1 Overview

The land composition of the three areas differed, with Anchorage containing the least amount of burnable land, due in part to the large urban footprint and mountainous regions (Table 3; Fig. 3). Nearly half of the land cover in Fairbanks (46%) and Whitehorse (48%) has a very high flammability hazard rating, while only 10% of this class occurs in Anchorage. Even though Fairbanks and Whitehorse have comparable amounts of flammable land cover types, wildfire activity in Fairbanks is much greater than in Whitehorse (Table 1). This translated into a greater percentage of the 2014 exposure

Table 3 Comparison of 2014 land cover distributions among three AURA areas in this assessment. Land cover based on ABoVE NASA data (see methods). Data are sorted from highest hazard class to lowest. Non-burnable areas are ice, snow, water, and barren

Land cover class	Anchorage (%)	Fairbanks (%)	Whitehorse (%)
Black spruce	0	19	NA
Lodgepole pine	NA	NA	13
White spruce	5	8	26
Woodland	4	20	8
Mixed forest	13	9	2
Subalpine fir	NA	NA	8
Fen	1	6	3
Hemlock	2	NA	NA
Open shrubs	3	0	2
Tussock tundra	0	0	0
Deciduous forest	8	9	1
Herbaceous	17	5	8
Low shrub	0	4	3
Tall shrub	9	10	8
Barren	22	2	5
Bog	0	0	0
Ice/snow	6	0	0
Shallows/littoral	0	0	0
Sparsely vegetated	8	7	8
Water	2	1	5

values occurring within the very high category in Fairbanks (32%) and Whitehorse (32%), with only 1% in this class for in Anchorage.

4.2 Flammability hazard ratings

Figure 4 illustrates the use of the land cover layer to create the original and our modified flammability hazard ratings. The use of a range (0–100) allows for more insight into the distribution of hazardous fuels than the original binary classification system.

Figure 5 shows that while there is a significant plurality with 46% of the land area in the very high flammability hazard class (rating of 100) while the very high hazardous area supported 75% burned areas. The distribution of flammability hazard classes between burned and unburned areas among land cover types was significantly different ($\chi^2 = 33{,}518$, d$f = 16$, $p < 0.001$). When the burned area in each hazard class is divided by the total land area in that hazard class, the percentages are distinctly highest (11%) in the very high class and decline (as intended), as shown in the inset table in Fig. 5.

4.3 Exposure ranking assessment

Exposure values from 2014 in burned versus unburned areas were significantly different (Wilcoxon rank-sum test, $W = 143{,}926{,}461$, $p < 0.001$). Mean exposure values of burned centroids were nearly 50% higher ($n = 3{,}792$; mean = 79.11; Std = 24.0) than unburned ($n = 51{,}490$; mean = 54.6; Std = 30.9). A cumulative distribution showed 80% of the burned distribution is composed of exposure values 63 or higher, while unburned areas the 80%

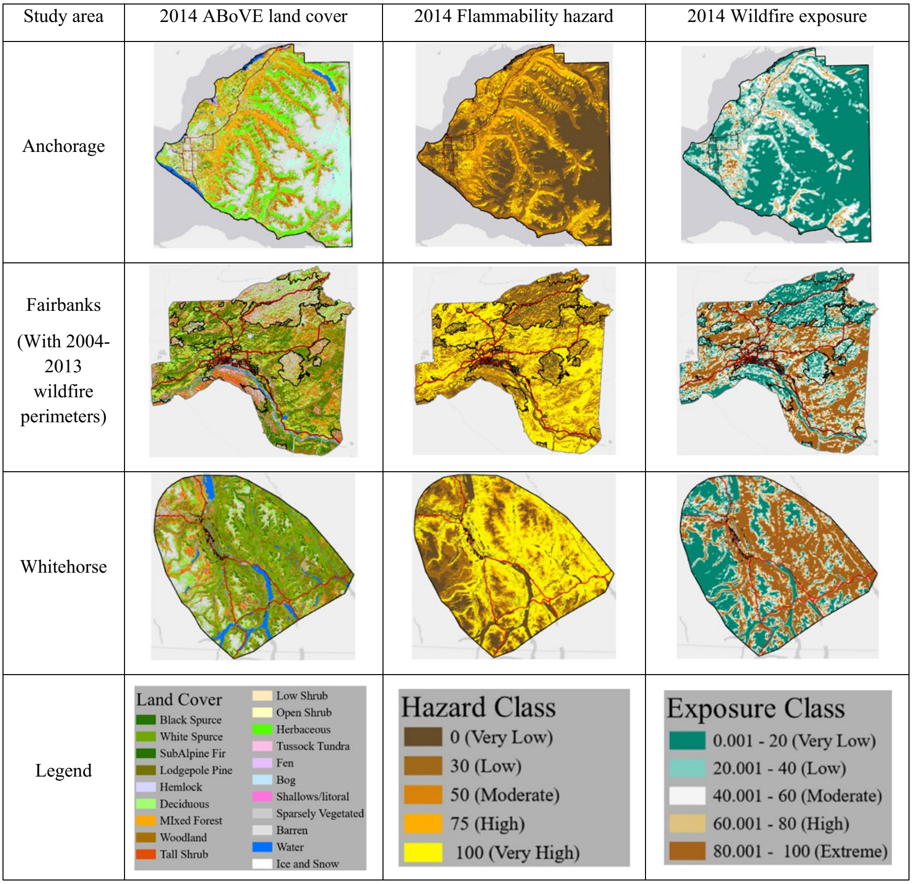

Fig. 3 Results from the land cover, hazard flammability rating (500 m), and integrated wildfire exposure ranking among Anchorage (row 1), Fairbanks (row 2), and Whitehorse (row 3) study areas in 2014

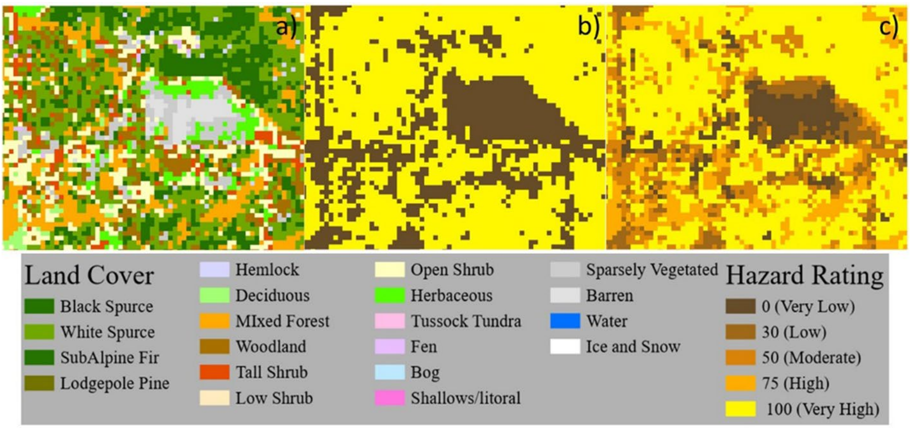

Fig. 4 Land cover; legend in Fig. 3 (**a**) and flammability hazard for an area near a high school in Anchorage. Published method 500 m hazard (**b**) and modified hazard ratings (**c**), as described in Sect. 2.3.1

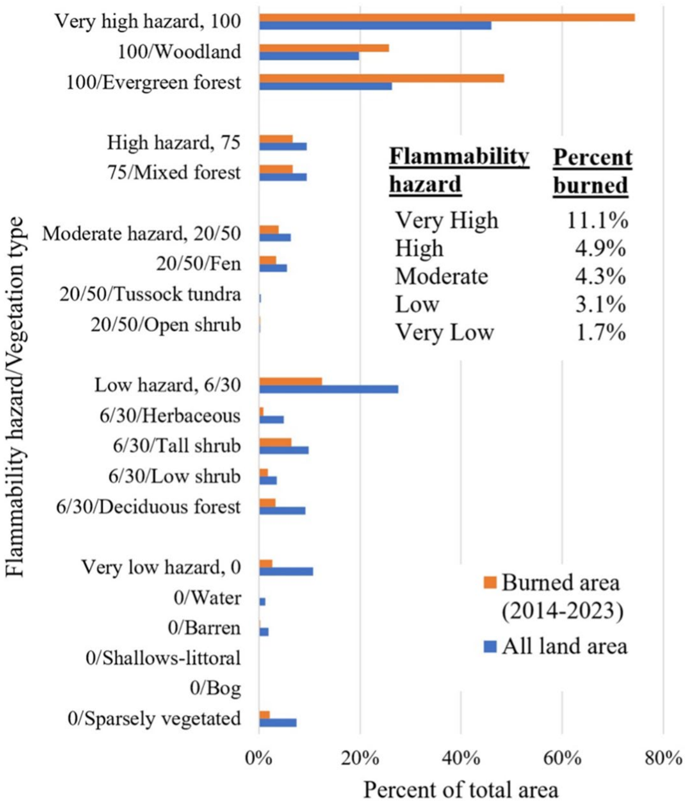

Fig. 5 Hazard rating distribution by vegetation type for all lands and for burned areas in Fairbanks. The burned area is divided by all land areas in each flammability hazard class to portray the relative likelihood (burned/all) of burning across the Fairbanks landscape. Numbers indicate the hazard rating at the 500 m/100 m scale. [a]Indicates a sample size < 10, so no binomial is test performed. All other vegetations had a significantly different distribution between burn than null (binomial exact test, $p < 0.001$)

distribution includes values down to 22 (Online Appendix 5). The box plot in Fig. 6 shows the utility of exposure rankings for distinguishing burned and unburned locations in each hazard class, with median values for burned areas distinctively higher. In fact, important thresholds in exposure rankings can be recognized, with levels of around 30 (lowest 25th percentile levels of burned exposure distributions) providing an important minimum for identifying any plausible threat and around 70 (low whisker bound for burned high and very high hazard classes) for elevated likelihood. Figure 6 illustrates the difference between hazardous fuels and exposure with the outliers observed among the lowest and highest hazard classes. Kruskal–Wallis test indicated a significant difference in exposure distributions ($\chi^2 = 31{,}043$, d$f = 4$, $p < 0.001$) among flammability hazard classes (Fig. 6), while a Dunn's test showed a significant difference in exposure distributions among the flammability hazard classes (Online Appendix 5). Since exposure is smoothed you can have interspersed highly flammable vegetation and unburned within each flammability hazard class (Kruskal–Wallis $\chi^2 = 31{,}095$, d$f = 4$, $p < 0.001$).

Areas that burned tended to occur in areas with wildfire exposure scores in the higher categories, unlike burn probabilities (Table 4). Instead the majority of burned areas fell

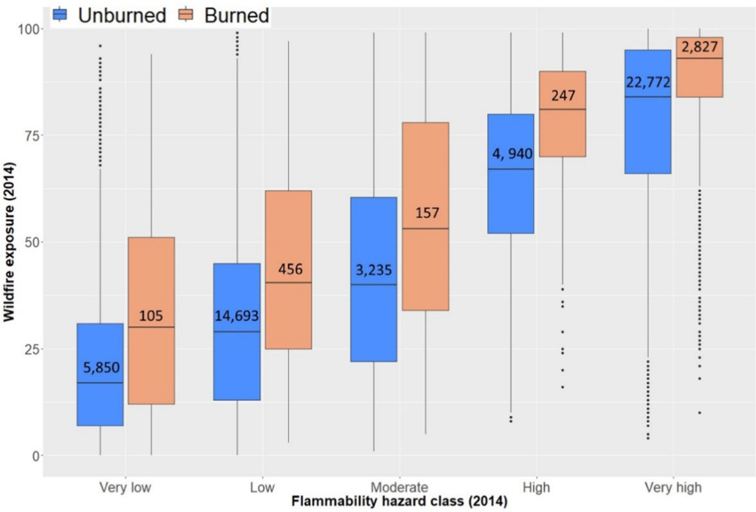

Fig. 6 Box plot of 2014 integrated exposure values by burned (2014–2023) and unburned areas among flammability hazard classes with the median, 25th, and 75th percentile. Whiskers indicate a value 1.5 times the percentile, and dots indicate values more than 1.5 times the percentile. Values are the number of points within each box plot. Significant differences in exposure distributions occurred between burned and unburned (Wilcoxon), among flammability hazard classes (Kruskal–Wallis), and within each flammability hazard class (Wilcoxon; Online Appendix 5)

Table 4 Distribution of wildfire exposure (2014) and burn probability from Flammap within burned and unburned (2014–2023) areas with the Fairbanks study area. Wildfire exposure categories are 0–20%, 20–40%, 40–60%, 60–80%, and 80–100%. Categories for burn probability are based on Jenks (1967) natural breaks (0–0.002, 0.002–0.007, 0.007–0.015, 0.015–0.029, 0.029–0.066)

Categories	Wildfire exposure		Burn probability	
	Unburned (%)	Burned (%)	Unburned (%)	Burned (%)
1 (lower)	18	4	43	12
2	17	7	37	68
3	17	9	16	19
4	18	16	3	1
5 (higher)	31	65	2	0

within the second lowest burn probability category. The difference between burn probabilities in burned areas (mean = 0.005; Std. = 0.003) and unburned (mean = 0.004; Std. = 0.006) was negatable.

4.4 Integrated exposure

Figure 7 shows the results from the modified (a) 500 m (b) and 100 m scales along with (c) their integration. The modified 500 m exposure ranking result shows broad gradients that range from extreme exposure outside developed areas to very low exposure in the heart of structure concentrations. In Fig. 7b, the 100 m exposure result exhibits both more extreme

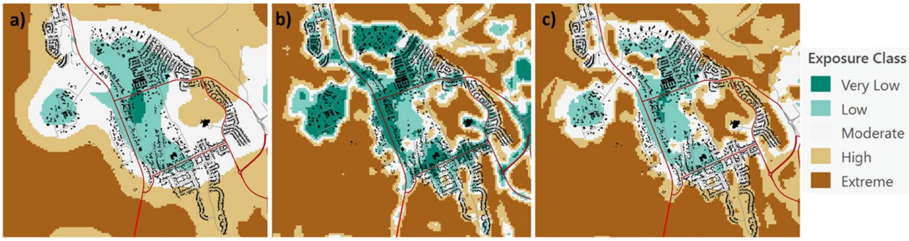

Fig. 7 Wildfire exposure ranking in the Whitehorse area. **a** Modified 500 m exposure; **b** modified 100 m exposure; **c** integrated maximum exposure within 500 m of structures. Structures in black; roads in brown

and very low exposure areas bounded by tight gradients between them. In multiple examples, extreme fire events, such as boreal crown fires, have proven the ability to penetrate deep into developed areas, suggesting that exposure is higher than estimated by the very low 100 m levels shown in this example. Capturing wildfire exposure rankings is important for communities that have interwoven vegetation and development such as our three communities: Anchorage (max: 28%, 100 m: 28%; 500 m 3%), Fairbanks (max: 53%, 100 m: 49%, 500 m: 36%), and Whitehorse (max: 62%, 100 m: 54%; 500 m 51%).

The maximum exposure assessment within 500 m of structures (Fig. 7c) derived from the 100 and 500 m exposure results exhibits important similarities when compared to the 100 m assessment. Many of the extreme exposure features displayed in the 100 m assessment are retained. However, much of the very low hazard in the immediate vicinity of structures has been increased to reflect the slightly higher hazard from the 500 m assessment, which reinforces the wildfire hazard potential surrounding structure locations in the Whitehorse study area.

Exposure values were lowest among the Anchorage study area and the WUI (Table 5). Most of the study area in Anchorage was in very low exposure, but among where residents live, the most common classification was low. In the Fairbanks and Whitehorse study areas, both residents and the entire area were more often in very high exposure. Whitehorse has nearly a quarter of the study area within very low exposure, but this has declined over the decades as the presence of very high exposure has increased (Table 5).

5 Discussion

5.1 Overview

In the case of the boreal communities studied here, the significant and growing threat comes primarily from large fire growth arising from crown fire potential of evergreen trees and flammable shrubs that can advance fires past barriers and less flammable vegetation (Westhaver 2017). Only once fires reach the immediate vicinity of values in these communities is the potential influence by surface fuels and intermediate fire intensities significantly represented. The exposure assessment method described here provides a rapid tool that communities can use for assessment and to make informed mitigation and planning decisions. The increase in wildfire activity (Abatzoglou et al. 2021; Bhatt et al. 2021; Kelly et al. 2020), highly altered landscape, and increase in the WUI (Radeloff et al. 2018) over the last decade (Bento-Gonçalves and Vieira 2020; Calkin et al. 2014) has made clear

Table 5 Percentage of each integrated exposure score and mean value for the decades examined among our study areas. The magenta color breaks are < 10%, 10–25%, 26–50%, and > 50%

Area	Exposure class	Wildland–urban interface				Study area			
		1984	1994	2004	2014	1984	1994	2004	2014
Anchorage	Very low	*18%*	*17%*	*18%*	*16%*	***57%***	***56%***	***57%***	***57%***
	Low	**31%**	**31%**	**31%**	**31%**	*21%*	*21%*	*22%*	*22%*
	Moderate	*23%*	*23%*	*23%*	*25%*	*14%*	*14%*	*14%*	*14%*
	High	*22%*	*23%*	*21%*	*21%*	7%	7%	7%	6%
	Extreme	7%	7%	6%	6%	1%	1%	1%	1%
Fairbanks	Very low	7%	6%	6%	6%	*11%*	*10%*	*10%*	*18%*
	Low	**27%**	*25%*	*24%*	*21%*	*14%*	*13%*	*13%*	*17%*
	Moderate	*19%*	*20%*	*19%*	*20%*	*16%*	*16%*	*16%*	*16%*
	High	*19%*	*20%*	*21%*	*22%*	*20%*	*21%*	*20%*	*18%*
	Extreme	**28%**	**29%**	**30%**	**31%**	**39%**	**40%**	**40%**	**31%**
Whitehorse	Very low	*14%*	*12%*	*11%*	9%	**28%**	**26%**	*25%*	*24%*
	Low	*18%*	*16%*	*15%*	*15%*	*10%*	*10%*	*10%*	*10%*
	Moderate	*13%*	*14%*	*14%*	*15%*	*11%*	*11%*	*11%*	*11%*
	High	*16%*	*18%*	*18%*	*19%*	*16%*	*16%*	*16%*	*16%*
	Extreme	**38%**	**41%**	**42%**	**43%**	**35%**	**38%**	**39%**	**39%**
Anchorage	Mean exp	44	45	43	44	22	23	22	22
Fairbanks	Mean exp	58	60	60	56	64	65	65	56
Whitehorse	Mean exp	61	64	66	58	55	57	58	58

that science-based methods to assess wildfire hazards are needed (Ager et al. 2015; Cao et al. 2016; Meyer et al. 2015; Mozumder et al. 2009). The methods and tools developed here help address the need to create science-based and understandable results on how to perceive hazards and risks. While Quantitative Wildfire Risk Assessment is a common approach (Allaire et al. 2018), many people struggle with how to interpret this information (Visschers et al. 2009). Additionally, feedback from communities and agencies is more easily applied and hazard changes are generated much more quickly and easily than can be accommodated by typical wildfire spread and growth models, such as FlamMap burn probability, FSIM, and Burn-P3 (Finney 2006; Finney et al. 2011; Parisien et al. 2005), improving the opportunity to co-produce a product, which is needed between researchers and practitioners (Adams et al. 2017). Co-production helps increase the acceptance of science, trust in results, and use among decision makers and wildfire practitioners (Glenn et al. 2022). We have modified previous efforts to provide an integrated wildfire exposure map that captures multiple spatial scales with an understandable five-category classification approach.

5.2 Flammability hazard ratings

The results indicate that flammability hazard classes relate closely to burned area frequency (Fig. 5). This approach adequately identifies areas with increased potential for wildfire activity; 80% of the areas that subsequently burned were within the very high flammability class from the assessment of the 2014 landscape. This speaks to the utility of both the coarse yet high resolution ABoVE vegetation classification effort (Wang et al. 2019) and the flammability hazard ratings assigned to each vegetation class. Hazard ratings were based primarily on the torching and spotting potential in the boreal biome. Even though flammability hazard rating maps are intermediate products, they have the potential to be very useful to identify areas for vegetation removal or thinning. These maps can be used to identify small concentrations of high and very high flammability hazards in areas of otherwise moderate and lower hazard that can ignite, but are less likely to spread.

5.3 Exposure ranking assessment

Given the utility of hazard classification in identifying the wildfire threat spatially, risk assessments have historically used it for that purpose. However, *wildfire exposure assessment* captures the importance of hazard juxtaposition for increasing fire spread potential and the resulting potential likelihood of wildfire impact by averaging the hazard level of all area within the analysis circle around the location. Due to the use of focal statistics, *wildfire exposure* represents the potential for a flammability hazard to reach and impact specific locations, even if the hazard at the destination may be lower. In the boreal landscapes considered here, exposure is enhanced dramatically by crown fire that commonly casts embers from the source location up to 500 m from the source location onto the vicinity of structures, igniting them and threatening the habitations they represent (Beverly et al. 2010; Bierwagen 2005; Page et al. 2019). By examining and averaging flammability hazards from the area surrounding individual locations, exposure highlights how likely it is that hazard may reach that location and, once there, impact it as smoke, heat, and fire. Recent lessons from wildfires have shown us that embers are what ignite most structures (Cohen 2000; Westhaver 2017).

5.4 Integrated exposure

As stated in published evaluations of the exposure assessment method (Beverly et al. 2010, 2021; Beverly and McLoughlin 2019), the initial greatest hazard from boreal wildfire potential is long-range spotting from extreme events that can breach significant barriers and vegetation types with lower flammability hazards. Once a wildfire enters a community, smaller-scale factors become important, such as the flammability of the buildings themselves (Knapp et al. 2021; Syphard et al. 2017). One advantage of using the maximum of the 100 and 500 m scales is that 100 m alone fails to adequately recognize the potential for long-range spotting and buildings as fuel; with remote sensed vegetation data, these pixels are often classified as barren. By incorporating the 500 m when it is greater, the result maintains at least some exposure value when there is sufficient long-range threat. This minimizes the risk of underestimating wildfire hazards and risks to communities, which can provide a false sense of confidence (Beverly et al. 2021). Natural causes, such as lightning, produce fewer fires overall (Brey et al. 2018; Grabinski and McFarland 2020) and are more randomly distributed across a landscape. The threat from these fires is associated with the distribution of hazards over the larger area, as reflected in the 500 m assessment. Thus, the 500 m scale is most appropriate outside of our 500 m structure buffer. The 100 m maps depict the different local information about exposure to nearby ignitions (Fig. 7b), they underestimate exposure from large tracts of forested lands, such as wildlands outside the WUI, as well as parks and refuges within. The 500 m captures this danger, so the use of the maximum of either scale (i.e., 100 or 500 m) around structures better captures wildfire potential and exposure.

5.5 Applications

One tool used to address wildfire hazards and risks is community wildfire protection plans (CWPPs) (Jakes et al. 2011). Some of the goals of CWPPs are to communicate risks to the public and to identify areas that may benefit from hazard-reduction activities. Our integrated exposure approach provides a rapid tool where there is no need to run specialized wildfire simulation models; rather, it can be utilized by Geographic Information Systems (GIS) and fire departments within communities. The model can be re-run quickly to refine results and incorporate feedback from residents or peers such as incorporating potential fuel treatments, different vegetation categories, vegetation changes due to infestation mortality and development. Reaching out to the public, incorporating feedback, and treating the creation of hazard and exposure maps as a process align with the best practices for risk and crisis communication and the acceptance of risk reduction actions (Steelman and McCaffrey 2013). Our hazard maps were presented to local government structures with repeated feedback and subsequent improvements, which is possible due to the less data-demanding and time-consuming approach than found in other stochastic wildfire models. We have also developed an ArcGIS Pro tool that allows users to choose their input vegetation, create a reclassification table, and a buildings layer to create their own flammability hazard and exposure layers. Providing categories that are clear and understandable is key to hazard and risk communication; previous research on flood risk mapping found five categories to be optimal (Fuchs et al. 2009). Providing effective communication about hazards improves resilience and, in the case of wildfires, increases social acceptance of more flexible wildfire management options (McCaffrey and Olsen 2012; Steelman and McCaffrey 2013).

Using the concept that exposure projects the flammability hazard beyond its source to locations where values exist, our exposure maps can be combined with value measures to produce *relative risk ratings* that identify where values need protection. Exposure, as a likelihood measure is often based on either historic frequencies. More recently, stochastic simulation fire occurrence and spread has been used to represent likelihood as probabilities. But risk is not able to predict the future. It is a measure of uncertainty in evaluating potential losses. Wildfire Exposure Ranking provides a scaled likelihood estimate for the risk assessment process by cumulating surrounding hazards and reflecting changes in landscape hazard over time. Risk rating is the logical next step, but to ensure that results are accurate and useful, communication and partnership with communities are needed to assess the values distribution.

Based on our four-decades analysis, the Whitehorse study area is of the most concern, with increases both within and outside the WUI (Table 5). This is largely due to the lack of wildfire activity. Table 1 supports the claim that Whitehorse is “at the edge of a blowtorch” (McKay 2018; Parisien et al. 2020). The Fairbanks study area has overall seen declines in wildfire exposure, largely due to increased wildfire activity outside the WUI (Table 1). However, within the WUI, high and very high wildfire exposures have increased (Table 5). In our results, it is certain that climate change is one of the driving factors of wildfire activity and exposure (Abatzoglou and Williams 2016; Littell et al. 2009; Wang et al. 2015). There is a need to incorporate climate change scenarios into wildfire risk models. However, incorporating and isolating the effects of climate can be challenging because vegetation changes from development. In WUIs, development and associated changes to land use and vegetation are often drivers of wildfire risk (Bryant and Westerling 2014) (Table 5). Previous modeling efforts have incorporated climate change by altering the fire weather based on climate predictions, but use static vegetation and fuels layers to compare model outputs ignoring development (Riley and Loehman 2016). Future efforts will focus on incorporating climate and development of scenarios to assess future wildfire hazards and risks. Again, by minimizing other data requirements, others can use this approach to focus on the identification of development strategies that are more wildfire resilient.

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Declaration

Conflict of interest The authors have not disclosed any competing interests.

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