

FuelNet: An Artificial Neural Network for Learning and Updating Fuel Types for Fire Research

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Abstract—Wildfire is a significant driver of forest and land cover change in the central interior of British Columbia, Canada. Fuel type maps are a primary input to fire behavior calculations and simulation studies that assess wildfire threat at the landscape level. However, these thematic maps are not easily produced at the scale and speed needed to assess and mitigate wildfire threat on an annual basis. The objective of this research was to explore how an artificial neural network could be used with remotely sensed satellite imagery to map and update fuel types on an annual basis. We applied the artificial neural network over a 40 000-km² landscape in central interior British Columbia that burned from a megafire in 2017. Fuel maps were generated for the years 2014–2018, assessed through an independent validation, and evaluated against an existing fuel type map. The highest cross-validation overall accuracy during training was 66.5% and overall accuracy from the independent validation was 63.1%. Generally, the maps had fair agreement with the existing fuel type map (circa 2016), with Cohen's Kappa ranging from 0.28 in 2018 to 0.35 in 2015. Several recommendations are provided for future research using artificial neural networks for fuel typing such as assuring quality of training samples through rigorous standards, designing the network architecture, choosing appropriate cost functions and regularization, incorporating learning of temporal features, and identifying novel fuel types from the output activations.

Index Terms—Artificial neural network, Canadian forest fire danger rating system, fire behavior, fuel types, megafire, wildfire.

I. INTRODUCTION

WORLDWIDE, human, and environmental impacts from fire have increased despite a negative global trend in area burned [1]. Impacts from fire have increased so abruptly that we now refer to the most extreme events as “megafires” [2]. Though fires are a natural component of ecosystem dynamics, megafires are characterized by unprecedented impacts on human values and the environment [3], [4].

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Large areas are burned so intensely that megafires are dangerous and very challenging to control, yet they account for the majority of annual area burned and fire suppression expenditures in North America [3], [5]. Climate change is expected to exacerbate extreme fire behavior and lead to increased challenges for fire suppression and management [6]. Although global area burned has declined, the impacts from fire are increasing and this trend necessitates innovation in fire informatics for fire behavior modeling and prediction.

Fire behavior can be calmed significantly when a fire is limited by weather, terrain, or fuels [7]. Therefore, fire behavior models are widely used by fire management agencies to predict fire risk and threat using weather, terrain, and fuels as inputs [8]. Meteorological variables are usually sourced from the nearest weather station [7] or spatially interpolated over larger areas [9]. Both terrain and fuels are commonly mapped data layers in geographic information systems. While terrain maps remain valid for long periods of time, fuel maps can be very challenging to maintain and update because fuels are continuously modified by biotic and abiotic agents on an annual basis. Longer term drivers, such as forest management and succession, fire suppression, and climate change, can modify fuels over decades. Thus, fuel maps need to be regularly updated to remain useful for more than a few years.

The province of British Columbia in Canada maintains a wall-to-wall database of spatial forest inventory data that are also used to map fuel types [10]. The polygon-based inventory data are primarily collected and updated from interpretations of aerial imagery. Numerous attributes are interpreted about vegetation structure in each polygon including canopy cover, forest height, species composition, and stem density. Together with other ancillary information on land cover and disturbance history, these polygons are interpreted into Canadian Forest Fire Behavior Prediction System standard fuel types using expert knowledge and a massive decision tree with 371 end nodes [10]. The fuel type scheme developed for British Columbia represents decades of collective experience and expertise in fire behavior observations in a wide variety of environments. The resulting fuel map is used as an input to fire behavior simulations to provide a Fire Threat Rating across the province supports a variety of stakeholders.

Fuel maps that use decision-tree fuel type schemes are challenging to update quickly. Specifically, the inventory data used in the scheme are updated on a rolling basis across the province, so updated attributes are not available every

single year for every polygon. This process results in a patchwork mosaic of polygons with inconsistent data fidelity and reliability for generating a wall-to-wall fuel map.

Remote sensing can aid the process of updating fuel maps over large areas using Earth observing satellites and other remotely sensed data [11]–[14]. At fine spatial scales, light detection and ranging (LiDAR) has been used to characterize surface fuel beds and aerial fuels in the forest canopy [15]. LiDAR has also been used extensively with hyperspectral and spectroscopy to classify fuel types [16], [17]. Over larger areas, satellite imagery from Terra/Aqua [18]–[21], Landsat [22]–[26], Sentinel [27], Quickbird [14], [25], [28], Worldview [15], and Ikonos [29] have been used with variable success in different study areas around the world. A significant body of research has emerged over the last decade analyzing historical trends in land cover change using the long-term Landsat satellite archive [30]. State-of-the-art methods analyze time series of multispectral imagery to classify land cover and identify abrupt and gradual changes from temporal trends [31], [32]. General fuel types may be inferred from these classifications and may be further augmented by forest inventory data that provide additional information about vegetation structure [10].

Several methods have been applied to fuel type research using remotely sensed imagery. Among the most popular are object-based image analysis [11], [15], [19], [25], [33], [34] and the maximum likelihood algorithm [15], [21], [26], [35]. Clustering and classification and regression trees have also been popular methods, while only a handful of studies have applied machine learning methods like random forests [23], [36], [37] and artificial neural networks [21], [38] to the problem of fuel type mapping.

The objective of this research was to explore the use of an artificial neural network to learn and update the provincial fuel type classification map for a small area of central interior British Columbia, Canada using remotely sensed imagery.

II. STUDY AREA AND REMOTE SENSING DATA SETS

The study area was defined as a 200 km $\times$ 200 km (40 000 km²) square grid (using NAD 1983 BC Albers coordinate system) with a cell size of 30 m centered over the 2017 Elephant Hill megafire perimeter (51° 6' 30.57" N, 121° 12' 35.7" W; Fig. 1). This study area was selected due to the variation in fuel types and field-based monitoring that has been undertaken for the Elephant Hill megafire. The terrain is characterized by a plateau between the coast mountains in the southwest and the Rocky Mountains in the northwest [39] with elevation ranging from 81 to 2854 m.a.s.l. Climate is continental with the temperature difference between the mean warmest and coldest months ranging from 14 °C to 28 °C, according to available ClimateNA data [9]. Mean annual temperature (MAT) ranges from −4 °C to 10 °C and mean annual precipitation (MAP) ranges from 219 to 1622 mm with between 16% and 86% of precipitation falling as snow.

The terrain and climate support mostly dry interior forests composed of Douglas-Fir (*Pseudotsuga menziesii* var *glauca* (Beissn.) Franco), ponderosa pine (*Pinus ponderosa* Dougl.

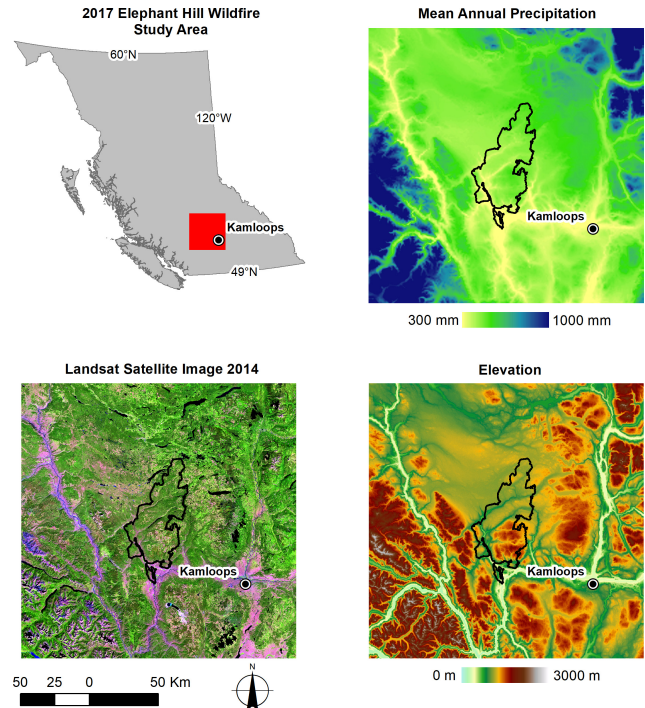


Fig. 1. Study area in British Columbia, Canada (red square), defined as a 200 km $\times$ 200 km square centered on the 2017 Elephant Hill wildfire (perimeter in black outline) at 51°6'30.57" N, 121°12'35.7" W.

ex Laws.), lodgepole pine (*Pinus contorta* var *latifolia* Douglas), and Engelmann spruce (*Picea engelmannii* Parry ex. Engelm.). Pockets of mixedwood forests with co-occurring deciduous trees (*Betula papyrifera* Marshall and *Populus* species) are commonly found in the valleys. In valley bottoms, nonforested areas are primarily covered by shrubs (*Artemisia tridentata* Nutt. and *Purshia tridentata* (Pursh) dc.) and grasses (*Agropyron spicatum* (Pursh) Scribn. and J.G.Sm. and *Stipa comata* Trin. and Rupr.). There are 12 major biogeoclimatic zones that occur in the study area and contribute to the diversity of fuel types in the landscape (ordered descending by area): Interior Douglas-Fir; Engelmann Spruce-Subalpine Fir (*Abies lasocarpa* (Hooker) Nutt.); Montane Spruce; Sub-Boreal Spruce; Interior Coastal Hemlock; Bunchgrass; Sub-Boreal Pine-Spruce; Ponderosa Pine; Coastal Western Hemlock (*Tsuga heterophylla* (Raf.) Sarg.); Mountain Hemlock (*Tsuga mertensiana* (Bong.) Carr.); and Alpine Tundra [40].

Fire regimes in the study area vary from frequent, low severity fires on the plateau to rare, high severity fires nearer the coast mountain range [41]. Estimated fire return intervals range from 4 to 50 years in the Interior Douglas-Fir and Ponderosa Pine zones to 250 years for the Coastal Western Hemlock and 350 years for the Engelmann Spruce-Subalpine Fir zone [41]. Nearer the coast mountain range, the fire return interval can exceed 5000 years [42]. Between 1919 and 2018, there were 2129 fires that burned at least 3 ha of the study area [43]. Approximately 85% of fires were caused by humans and 15% were caused by lightning. Human- and lightning-caused fires represented 79% and 21% of area burned, respectively. The

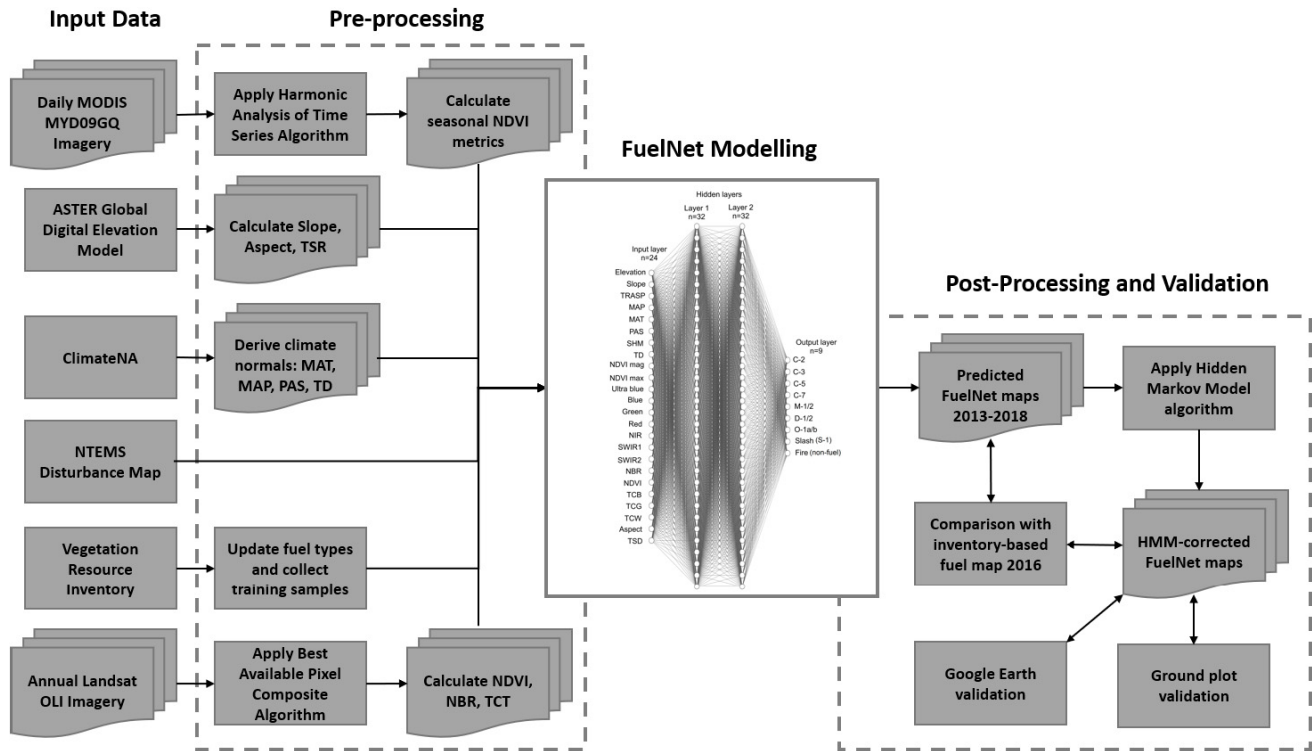


Fig. 2. Overview of workflow. Image in center is Fig. 3. Acronyms alphabetically (defined): Advanced Spaceborne Thermal Emission Radiometer (ASTER); hidden Markov model (HMM); mean annual temperature (MAT); mean annual precipitation (MAP); moderate resolution spectroradiometer (MODIS); normalized burn ratio (NBR); normalized difference vegetation index (NDVI); National Terrestrial Ecosystem Monitoring System (NTEMS); operational land imager (OLI); precipitation as snow (PAS); tasseled cap transformation (TCT); temperature difference (TD) of mean warmest and coldest months; topographic solar-radiation index (TSR).

mean date of ignition for human-caused fires was June 29 (± 1 standard deviation: May 9 to August 19) compared with July 24 (± 1 standard deviation: June 30 to August 17) for lightning-caused fires. The Elephant Hill megafire burned approximately 192 017 ha in the summer of 2017 and was the largest fire on record for the study area representing approximately 23% of total area burned by all fires in the last century of records.

Multiple satellite data sets were used as predictor variables in the classification process (Table I) and an overview of the entire workflow given in Fig. 2. Multispectral data were used to predict both inter- and intra-annual changes to fuel types and availability for combustion. Landsat 8 Operational Land Imager images representing the growing season (June 1 to September 30) between 2013 and 2018 and had less than 70% cloud cover were downloaded as surface reflectance products from the United States Geological Survey. Each pixel in the Landsat surface reflectance images were scored by distance to cloud and cloud shadow, presence of snow, and atmospheric haze to produce best available pixel composites following [44]. The Landsat best available pixel composites were used to provide interannual information on the state of fuels.

Since fuel characteristics and types may also vary seasonally, we utilized Moderate Resolution Imaging Spectroradiometer (MODIS) imagery with higher observation frequency to improve intra-annual characterization of fuels. MODIS imagery taken between 2013 and 2018 by the Terra satellite (afternoon orbital overpass for our study area) were downloaded as daily calculated surface reflectance from the

MYD09GQ product [45]. The normalized differenced vegetation index (NDVI) was calculated daily then further processed through the harmonic analysis of time series (HANTS) algorithm to remove noise in the seasonal NDVI time series following [46]. The HANTS algorithm was parameterized with three frequencies [46], fit tolerance was set to 0.05 (units of NDVI) [47], and the degree of overdeterminedness (DOD) was defined dynamically for each pixel time series according to (1) as follows [48]:

$$\text{DOD} = \frac{V_{\text{NDVI}}}{2} - 5 \quad (1)$$

where V_{NDVI} is the total number of valid NDVI values in the time series (i.e., noncloud). The HANTS algorithm was not applied to pixels with more than six missing values in the time series. Following the HANTS noise removal, two NDVI time series metrics were calculated for each year: maximum annual NDVI and annual NDVI magnitude, defined as the absolute difference between the maximum and minimum annual NDVI. These two intra-annual metrics of greenness were assumed to inform about leaf area change, which could be particularly useful for predicting grassland, deciduous, and mixedwood forests.

The Advanced Spaceborne Thermal Emission Radiometer (ASTER) Global Digital Elevation Model (DEM) Version 3 was used to derive terrain metrics [49]. Slope, aspect, and the Topographic Solar-Radiation Index were calculated from the DEM. In addition to the terrain and spectral data sets, five climate maps were generated from the historical baseline

TABLE I
SUMMARY OF GEOSPATIAL DATA SETS USED AS PREDICTOR VARIABLES TO TRAIN THE NEURAL NETWORK

Theme	Dataset	Derived Data	Year(s)
Spectral	Best Available Pixel (BAP) composites of surface reflectance bands (1-7) of the Operational Land Imager (OLI) onboard the Landsat 8 satellite	<ul style="list-style-type: none"> Ultra blue (band 1), blue (band 2), green (band 3), red (band 4), near infrared (NIR, band 5), shortwave infrared (SWIR 1-2, bands 6-7) Normalized Differenced Vegetation Index (NDVI) Normalized Burn Ratio (NBR) Tasseled Cap Transformation brightness (TCB), greenness (TCG), wetness (TCW) 	2013-2018
	Daily red and near-infrared surface reflectance bands of the Moderate Resolution Imaging Radiometer (MODIS) onboard the Terra satellite	<ul style="list-style-type: none"> Annual maximum daily NDVI (NDVI max) Annual magnitude change NDVI (NDVI mag) 	2013-2018
Terrain	Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (DEM) Version 2	<ul style="list-style-type: none"> Aspect (degrees) Slope (degrees) Topographic solar-radiation index 	2011
Climate	ClimateNA Version 5.5 historical climate normals (1961-1990)	<ul style="list-style-type: none"> Mean annual temperature (MAT, °C) Mean annual Precipitation (MAP, mm) Precipitation as snow (PAS, mm) Temperature difference between mean warmest and coldest months (TD, °C) Summer heat-moisture index (SHM) 	1961-1990
Ancillary	National Terrestrial Ecosystem Monitoring System disturbance map	<ul style="list-style-type: none"> Time since last known disturbance (TSD) 	2016

period 1961–1990 using ClimateNA Version 5.5 [9]: MAT; MAP; precipitation as snow; summer heat-moisture index; temperature difference between mean warmest month and mean coldest month (i.e., continentality). Finally, a disturbance map derived from the National Terrestrial Ecosystem Monitoring program was used to generate a time since last known disturbance map [50]. All raster data layers were resampled to 30 m and projected to NAD 1983 BC Albers using nearest neighbors for the disturbance map and cubic convolution for all other continuous data layers.

III. TRAINING THE ARTIFICIAL NEURAL NETWORK

A. Training Samples

Training samples were extracted from the current British Columbia Wildfire Service fuel layer. The fuels in this layer are typed into the Canadian Forest Fire Behavior Prediction System by applying a decision-tree algorithm [10] to a series of land cover and stand attributes found in the provincial vegetation resource inventory (VRI). The VRI is a set of polygons covering the entire province that are interpreted mostly from air photos and provide information about tree species, forest height, canopy cover, and stem density among others [51]. While comprehensive in spatial coverage, updates to the VRI can lag more than ten years from present, and inaccuracies can arise from the interpretation process. Thus, the quality and fidelity of the attributes used to type fuels can be unreliable for polygons that have not been interpreted or updated recently. To address these limitations, we applied a structured approach through a series of spatial overlays, queries, and calculations in a geographic information system

to remove polygons (i.e., samples) that were deemed to have poor quality for training purposes. This quality control process ensured that only the highest confidence polygons were available for selection as samples. Our first quality control step was to update the VRI polygons based on recent disturbances. We overlaid fire perimeters derived from the National Burned Area Composite data set produced by the Canadian Forest Service [52] and transferred the year of burn to the VRI polygons for fires that burned between 2003 and 2017. Next, we overlaid the cut block inventory data set [53] to the VRI polygons and transferred the year of harvest for cut blocks harvested between 1998 and 2017. We then updated the fuel type for every VRI polygon based on the decision-tree logic introduced in [10] for each year individually. Namely, this involved checking for a recent disturbance (e.g., fire or harvest), calculating time since last disturbance relative to the current year being processed (2013–2017), and then checking other attributes (e.g., stand height, age, stem density, and species composition) as necessary to assign a new fuel type. If a VRI polygon did not have an overlaying fire or harvest disturbance, then the fuel type was not changed. This assumption was reasonable because disturbance is the primary catalyst for changing fuel types from year to year.

Following the procedure to update the VRI fuel type, we applied a series of logical consistency checks and spatial operations to enhance the quality of training samples. Polygons that were missing data source identifiers for attributes considered to be central in the fuel type decision tree, namely stem density (stems per hectare), stand age (years), stand height (m), and canopy cover (%), were excluded from consideration. Only polygons derived from air photos acquired within the

last 10 years were included. Finally, a minimum mapping unit of 25,466 m² ($\pi 90^2$) excluded small polygons and a negative buffer (nibble) of 90 m was applied to any remaining polygons to remove potential edge-related mapping errors. The above steps were repeated annually to collect training samples from 2013 to 2017, which were rasterized to a 30 m cell size grid for the study area. Through this process, each labeled pixel was considered a potential sample (hereafter, “pixel samples”).

Training pixel samples were collected for nine fuel types (see Table II for a description of fuel types): Fire [non-fuel (NF)], C-2, C-3, C-5, C-7, D-1/2, M-1/2, O-1a/b, and S-1. Some fuel types were too rare to retrieve high-quality samples, so the rarer types were combined with a similar abundant type. For example, C-4 (regenerating Jack Pine (*Pinus banksiana* Lamb.) or Lodgepole Pine), S-2 White Spruce (*Picea glauca* (Moench) Voss), Balsam Fir (*Abies balsamiae* (L.) Mill.) slash, and S-3 (Coastal Cedar, Hemlock, Douglas-Fir slash) collectively represented less than 0.5% of total available pixel samples, so C-4 was grouped with C-3 (mature Jack or Lodgepole Pine), and S-2 and S-3 were grouped with S-1 (Pine slash). A balanced set of pixel samples were randomly selected for each fuel type class proportional to the abundance of that class in each year to extract 50 000 pixel samples per class for a total of 450 000 pixel samples across the years 2013–2017. For example, if a fuel type had an abundance of 890 000 pixel samples in 2013 and the total abundance of the fuel type across all years was 3 211 000 pixel samples, then 13 850 pixel samples (27.7%) were randomly selected from 2013 for inclusion in the final 50 000 pixel sample set for that fuel type. In total, the selected pixel samples represented a sampling rate of 2.7% of available pixel samples that met all of the aforementioned quality control standards.

B. Artificial Neural Network Model and Architecture

Initial testing was performed to optimize the neural network architecture in terms of cross-validation accuracy, efficiency, and speed. We tested multiple architectures by varying the size and number of hidden layers (shallow versus deep networks), implementing different activation functions, loss functions, and optimizers, and regularizing before achieving the final neural network architecture presented in Fig. 3. The number of input neurons was 24, equal to the total number of predictor variables (Table I). We found that the depth and size of the network did not appreciably change the accuracy, but deeper networks were less efficient and more costly with computer resources. Thus, we used two hidden layers comprised of 32 neurons, each activated using the rectified linear unit function [54]. The final output layer had nine neurons representing the nine fuel type classes that we wanted to predict and these neurons were activated using a softmax function [55]. Given this architecture, there were a total of 2153 trainable parameters calculated from (2): 800 in the first hidden layer; 1056 in the second hidden layer; and 297 in the output layer

$$\text{total parameters} = \sum_{l=1}^{L-1} (n_l * n_{l+1}) + n_{L+1} \quad (2)$$

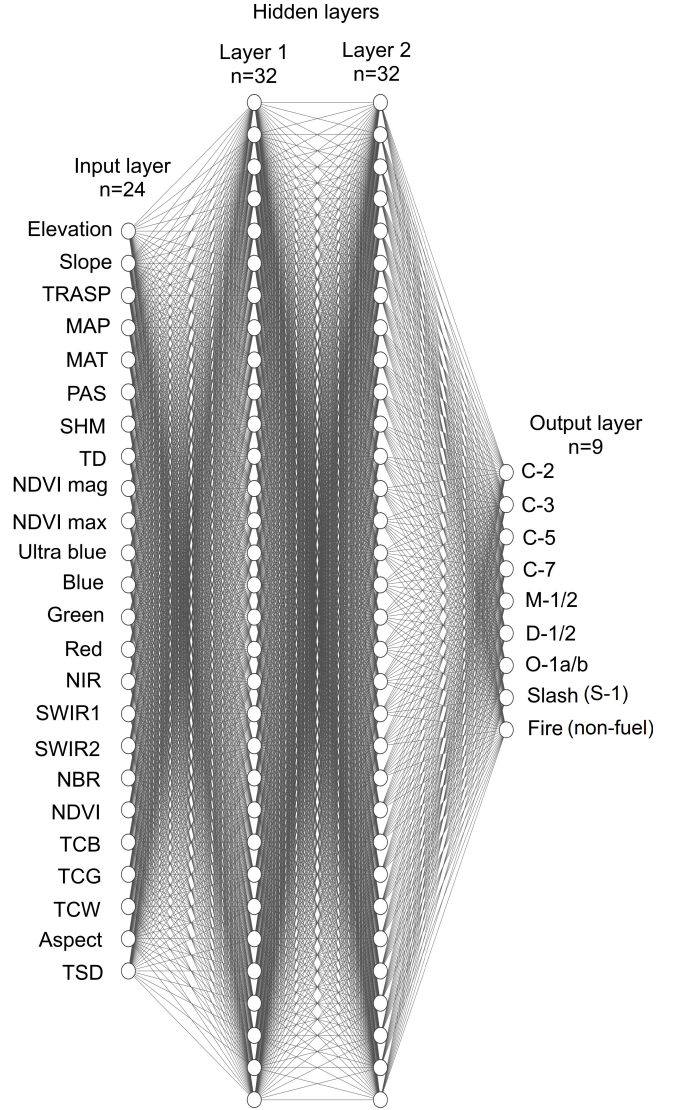


Fig. 3. Schematic of fully connected neural network architecture. Total neurons $n = 97$, total edges = 2080, and total parameters = 2153. Acronyms of input and output variables are defined in Table I.

where n_l is the total number of neurons in layer l and L is the total number of fully connected layers (input, hidden, and output). All input variables were standardized to a range [0,1] using the following equation:

$$\hat{x} = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (3)$$

The neural network was trained on the 360 000 pixel samples described in the previous section. The neural network was given the training set over 500 epochs, processed in batches of 128 samples using the Keras library [56]. We selected the number of epochs based on testing several different values ranging from 100 to 500 in tranches of 100. From these tests, we observed the change in model loss, accuracy, and processing time and determined that 500 epochs were suitable. The trainable parameters of the neural network were updated after each batch of training pixels was processed and accuracy was assessed over all training samples after each epoch. The

TABLE II

SUMMARY OF CANADIAN FIRE BEHAVIOR PREDICTION SYSTEM FUEL TYPES USED IN THIS STUDY AND CONSIDERATIONS FOR MAPPING FROM REMOTELY SENSED IMAGERY. WE USE THE CANADIAN FBP FUEL TYPES HERE AND THROUGHOUT THE MANUSCRIPT TO BE CONSISTENT WITH THE PUBLISHED LITERATURE. FOR A FULL REVIEW AND EXPLANATION ON THESE FUEL TYPES, PLEASE REFER TO [13]

Fuel type	Description	Remote sensing considerations
Fire (non-fuel)	Recent fire was coded as a non-fuel type following [13]. The rationale is that fuel abundance has been reduced by the previous fire such that future fire behavior is expected to be significantly lower or absent in the following post-fire years.	Fire is generally mapped from burn severity spectral indices such as Normalized Burn Ratio (NBR), which provide a continuous measure of change to vegetation. With the current fuel typing algorithm, there is no distinction between different fire severity levels (e.g., low, medium, high) when labelling a burnt stand as non-fuel. This presents a challenge for integrating remotely-sensed imagery into the fuel typing process because stands that burn frequently at low severity (such as in our study area) should not be typed as non-fuel after each burn as this would severely under-estimate calculations of fire behavior. Nonetheless, we did not alter the fuel typing algorithm logic and this is something that will need to be considered in future research.
C-2	Boreal Spruce (<i>Picea spp.</i>) overstory with continuous shrub understory layer, tree crowns extend nearly to the ground, and low-to-moderate downed woody fuels.	The conifer fuel types are mostly distinguished by structures below the canopy, which makes their detection from satellite imagery challenging. The spectral signatures of the different overstory species are similar and likely other non-spectral environmental factors (e.g., terrain and climate) will play an important role in distinguishing these fuel types.
C-3	Mature Jack (<i>Pinus banksiana</i>) or Lodgepole Pine (<i>Pinus contorta</i>) overstory with sparse conifer understory possibly present, sparse downed woody fuels and tree crowns separated from the ground.	
C-5	Red Pine (<i>Pinus resinosa</i>) and White Pine (<i>Pinus strobus</i>) overstory with moderate herb and shrub cover in the understory and tree crowns separated from the ground.	
C-7	Ponderosa Pine (<i>Pinus ponderosa</i>) Douglas-Fir (<i>Pseudotsuga menziesii</i>) associated overstory with discontinuous grasses and herbs in the understory except in conifer thickets. Downed woody fuels are sparse and tree crowns generally separated from the ground except in conifer thickets.	Due to the sparsity of trees and horizontal separation of crowns, this class is most likely to be confused with the O-1a/b grass fuel type. The seasonal greening effect from the grass understory component is likely visible from aerial and satellite imagery, which could also lead to confusion with the M-1/2 mixedwood class.
D-1/2	Aspen (<i>Poplar spp.</i>) overstory with conifer understory and co-dominance absent. Downed woody fuels are sparse with medium to tall shrubs and herb layers in the understory. The 1/2 codes distinguish different seasons for leaf-on (D-1) and leaf-off (D-2) conditions, which results in different fire behaviors. We did not distinguish seasonal fuel conditions, but they can still be used when calculating fire behavior.	Deciduous stands are primarily characterized from the seasonal spectral change in the red and near-infrared portions of the electromagnetic spectrum due to leaf-on conditions causing increases in chlorophyll and foliar moisture content. Therefore, it is important to have intra-annual seasonal spectral indicators to properly separate this class from other forested fuel types.
M-1/2	Mixedwood associations of boreal conifers and deciduous species. The 1/2 codes distinguish different seasons for leaf-on (M-2) and leaf-off (M-1) conditions for the deciduous component of the stand, which results in different fire behavior. Additionally, mixedwood stands are characterized by the percentage of the conifer component when calculating fire behavior.	Characterizing mixedwood stands is similar to deciduous stands except that the seasonal leaf-on signal of the deciduous component is attenuated by the percentage of conifer present. Classification approaches that use ensemble models or predict a vote or probability for each class can significantly aid in characterizing mixedwood stands. For example, predicting both a deciduous and coniferous class with probabilities can directly inform the percentage of conifer and allow for accurate mapping of mixedwood stands. Generally, a threshold is applied to the percentage of conifer to distinguish pure deciduous, pure conifer, and mixedwood stands. In our study, percentage conifer was available directly from the inventory data, so we constrained the mixedwood training samples between 40-60% conifer, inclusively.
O-1a/b	Continuous grass fuels either matted in the early spring (O-1a) or standing cured in the summer (O-1b). Continuous overstory is absent with any scattered trees not appreciably affecting fire behavior.	Like deciduous forests, grasslands are primarily characterized from seasonal changes in leaf pigments and cellular structure. Intra-annual measures of spectral indices are necessary to characterize grassland pixels as well as the state of the pixel as O-1a (live and green) or O-1b (dead and cured).
Slash	Moderate-to-heavy loading of downed, dead woody material following clear-cut harvesting. Fuels are generally piled with some shrub, grass, and herb layers present in subsequent years. Foliage retention and curing varies depending on species. Three types of slash are considered in the FBP system, which are collapsed into a single slash class in this study. The most abundant (>85%) type of slash in our study area is S-1 (Jack or Lodgepole Pine slash), so our slash class primarily represents fire behavior that would arise from the S-1 fuel type.	Different slash types in the FBP system generally rely on the species and geographic location of a harvested forest stand. Due to the high imbalance of training samples amongst the slash classes in our study area, we chose to simply predict any slash (recent harvest), but it is possible to work out the exact type of slash in a <i>post hoc</i> analysis that considers the biogeoclimatic zone and species. The species in the year prior to harvest can be derived from the time series to aid this process. For example, if a C-2 pixel was harvested, then the most appropriate FBP fuel type would likely be S-2 (White Spruce-Balsam slash).

categorical cross-entropy loss function was used to estimate loss $L(y, \check{y})$ using the following equation:

$$L(y, \check{y}) = \sum_{i=1}^m \sum_{j=1}^k (y_{ij} * \log(\check{y}_{ij})) \quad (4)$$

where $\check{y}_{ij}$ is the softmax activation (probability) for pixel i of m for fuel type j of k and y_{ij} is the one-hot encoded expected probability for fuel type j such that

$$y_{ij} = \begin{cases} 1, & i = j \\ 0, & i \neq j. \end{cases}$$

The adaptive moment estimator (“adam”) was used for stochastic optimization and learning [57]. To avoid overfitting with hundreds of epochs, L2 regularization $L2(y, \check{y})$ was applied to the categorical cross-entropy loss function above using the following equation:

$$L2(y, \check{y}) = L(y, \check{y}) + \left(\lambda * \sum_{j=1}^k \check{y}_{ij}^2 \right) \quad (5)$$

where the tuning parameter $\lambda = 0.0001$. The neural network was then applied to the input variables to predict the $k = 9$

fuel types for all M pixels in each year. The result was an M -by- k matrix of probabilities that a given pixel belonged to each fuel type. The fuel type with the maximum probability was selected as the predicted fuel type and all k fuel type probabilities for all M predicted pixels were output as images to aid interpretation. We refer to the predicted fuel type maps as “FuelNet” to distinguish from the inventory-based fuel type layer.

C. Postprocessing and Validation

Multiple strategies were undertaken to improve the quality of and to validate the predicted fuel maps. Natural non-fuels and water were extracted from the current inventory-based fuel layer and transferred into all annual FuelNet maps under the assumption that these fuel types were too easy to learn (thus leading to possible overfitting) and relatively constant through time. This eliminated the need to train the neural network on abundant and easy-to-learn classes while maintaining a consistent landscape across time. Despite the amount of information used in training and the quality of the pixel samples, fuel types could change through time independently of past and future years. As a result, abundant

TABLE III
HMM TRANSITION PROBABILITIES

	To								
From	Fire	C-2	C-3	C-5	C-7	D-1/2	M-1/2	O-1a/b	Slash
Fire	0.900	0.001	0.001	0.001	0.001	0.025	0.025	0.025	0.025
C-2	0.025	0.900	0.001	0.001	0.001	0.001	0.001	0.001	0.025
C-3	0.025	0.001	0.900	0.001	0.001	0.001	0.001	0.001	0.025
C-5	0.025	0.001	0.001	0.900	0.001	0.001	0.001	0.001	0.025
C-7	0.025	0.001	0.025	0.001	0.900	0.001	0.001	0.001	0.025
D-1/2	0.025	0.001	0.001	0.001	0.001	0.900	0.025	0.001	0.025
M-1/2	0.025	0.025	0.001	0.001	0.001	0.001	0.900	0.001	0.025
O-1a/b	0.025	0.001	0.001	0.001	0.025	0.100	0.100	0.900	0.001
Slash	0.025	0.001	0.001	0.001	0.001	0.100	0.001	0.100	0.900

and often illogical transitions between fuel types can result from noise and other errors such as georegistration of satellite imagery, atmospheric noise not masked out by the HANTS and best available pixel processes, and phenological changes and inconsistencies [50]. To correct for these unwarranted transitions, we applied a forward-backward hidden Markov model (HMM) algorithm [58] to filter the fuel maps and improve year-to-year consistency. The forward-backward HMM algorithm applies a transition probability matrix forward and backward for the observed time series of probabilities from the softmax activation of the neural network output layer. The unobserved “hidden” states of the Markov process (i.e., filtered fuel type sequence) are then inferred by calculating all possible fuel type sequences and the pixel time series is labeled with the most likely sequence (i.e., argument of the maximum probability).

The transition probability matrix given in Table III was defined to reflect higher probabilities to logical transitions and lower probabilities to illogical or unlikely transitions in fuel types from year to year. For example, the diagonal reflects a 90% probability of any fuel type remaining as the same fuel type in the following and prior years. We assigned a 10% probability to transitions we deemed to be probable based on vegetation succession, for example: grassland (O-1a/b) transitioning to deciduous (D-1/2) or mixedwood forest (M-1/2); and recent harvest (S-1) transitioning to deciduous or grassland. A 2.5% probability was assigned to other transitions that we deemed to be possible such as: any fuel type transitioning to recent fire (NF-fire); any forested fuel type transitioning to slash; recent fire transitioning to deciduous, mixedwood, grassland, or slash (e.g., postfire salvage); sparse conifer forest (C-7) transitioning to a closed conifer forest (C-3); grassland (O-1a/b) transitioning to sparse conifer (C-7); and mixedwood transitioning to deciduous or conifer (except C-7).

All other elements of the transition probability matrix were deemed to be unlikely or illogical and were assigned a 0.1% probability. The probability values (0.1%, 2.5%, 10%, and 90%) were derived from land cover maps described in [50], but we applied the probabilities using our expertise of how we would expect fuels could change over time. In part, our decisions were supported by the logic already established in the decision-tree algorithm for typing fuels, which relies on forest attributes that follow successional pathways [10]. In years when a pixel was missing due to persistent cloud,

haze, or smoke, we simply pushed forward the last known prediction for that pixel from a previous year. In most cases, this gap-filling approach simply used the predicted fuel type from the previous year, which was justified in most cases in the absence of disturbance. We quantified the number of transitions from year to year both before and after applying the HMM to our annual fuel maps. In addition, Cohen’s Kappa coefficient [59] was calculated between the current inventory-based fuel layer representing 2016 conditions and the HMM-adjusted and non-HMM-adjusted FuelNet maps to assess agreement between fuel maps for each year.

Independent validation was performed by randomly stratifying a set of 274 points proportionally to the fuel types in FuelNet 2016 and then interpreting the points using high spatial resolution imagery available in Google Earth Pro. An interpreter was trained to identify eight different fuel types: water (NF), natural NF (bare ground, ice, rock), recent fire (NF), recent harvest, conifer forest, mixedwood forest, deciduous forest, and grassland. Given the challenges associated with distinguishing between the four conifer fuel types without having access to information on surface fuels and stand density, we collapsed all conifer fuel types (C-2, C-3, C-5, C-7) into a single conifer fuel type for the validation. We validated both the inventory-based fuel layer and the predicted fuel map to estimate overall and class-level accuracies. Because the natural non-fuel and water classes were transferred directly from the inventory-based fuel map, the class accuracies for these fuel types are not the result of the neural network. In addition, we utilized a set of 75 permanent plots that were established in 2018 within the Elephant Hill megafire perimeter and randomly stratified by fire severity and biogeoclimatic zone. Tree data including tree species, density, height, and crown cover were collected at each 400-m² fixed-radius plot. These data, along with photos taken at each plot center, were used to interpret the plot to one of the fuel classes and then used to further interrogate overall and class-level accuracy of the FuelNet maps. This last step enabled us to estimate producer’s and user’s accuracies for the four conifer fuel types that could not be estimated from the interpretation of aerial imagery in the Google Earth validation. Finally, we quantified the area burned per fuel type in the 2016 FuelNet fuel map versus the inventory-based fuel map.

TABLE IV
PERCENTAGE OF INTERANNUAL TRANSITIONS BEFORE APPLYING THE HMM FOR ALL YEARS, 2013–2018

From	To	Fire	C-2	C-3	C-5	C-7	D-1/2	M-1/2	O-1a/b	Slash
Fire		0.79	0.34	0.13	0.00	0.27	0.17	0.10	0.21	0.03
C-2		0.33	10.20	0.83	0.18	0.46	0.08	0.66	0.01	0.35
C-3		0.18	1.06	10.74	0.05	0.41	0.41	0.38	0.10	0.27
C-5		0.01	0.26	0.07	5.02	0.09	0.33	0.30	0.01	0.05
C-7		0.79	0.67	0.42	0.11	19.71	0.93	0.68	0.73	0.12
D-1/2		0.10	0.12	0.45	0.30	0.77	6.55	0.42	0.55	0.25
M-1/2		0.16	0.81	0.43	0.23	0.57	0.44	7.53	0.23	0.17
O-1a/b		0.31	0.01	0.10	0.01	0.64	0.63	0.24	11.13	0.14
Slash		0.11	0.19	0.36	0.03	0.09	0.35	0.27	0.23	6.06

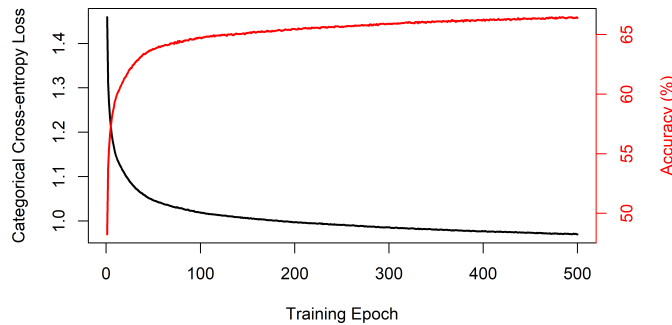


Fig. 4. Categorical cross-entropy loss and cross-validated accuracy as a function of training epoch. Accuracy was calculated as the percentage of correctly classified pixel samples out of total training pixel samples ($n = 360\,000$).

IV. EXPERIMENTAL RESULTS

The highest cross-validation overall accuracy during training of all years combined was 66.5% in epoch 481 and the lowest was 48.2% in epoch 1 (Fig. 4). Categorical cross-entropy loss was highest in epoch 1 (1.46) and lowest in epoch 500 (0.97) with minimal change in loss after epoch 100 (Fig. 4).

Prior to applying the HMM, approximately 22.3% of all pixels transitioned to a different fuel type from year to year, while 77.7% of all transitions remained in the same fuel type (Table IV). The highest rates of transitions to another fuel type occurred from C-7 to D-1/2 (0.9%), C-2 to C-3 (0.8%), and M-1/2 to C-2 (0.8%). Overall, C-7 was the least stable fuel type and most likely to transition to another fuel type in any given year (4.5% of transitions), followed closely by M-1/2 (3.0%) and D-1/2 (3.0%). Pixels were most likely to transition to C-2 (3.5%), D-1/2 (3.3%), or C-7 (3.3%) and least likely to transition to C-5 (0.9%), slash (1.4%), or fire (2.0%).

Cohen's Kappa statistic between the predicted FuelNet map and the inventory-based fuel map ranged from 0.2792 in 2018 to 0.3481 in 2014 (Fig. 5). The FuelNet maps showed declining agreeability with inventory-based fuel map after 2016. After applying the HMM, Cohen's Kappa statistic improved for the comparison for nearly all years with the exception of 2014. The years 2017 and 2018 showed the greatest improvement in terms of map agreement with the inventory-based fuel layer after applying the HMM.

Overall accuracy for the predicted fuel maps in all years was 63.1% based on independent validation (Table V). Water had 100% producer's accuracy and 62.5% user's accuracy, while

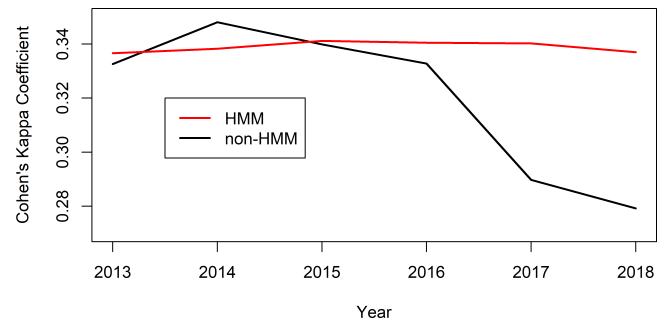


Fig. 5. Cohen's Kappa coefficient for the annual FuelNet maps (2013–2018) compared with the inventory-based fuel map showing the impact of applying the HMM on map agreeability. These comparisons exclude the water and natural NF classes, which all fuel maps share in common.

natural non-fuel had 57.9% producer's accuracy and 71.0% user's accuracy. Both water and natural non-fuel were not classes trained or predicted by the neural network, so when those classes were excluded from the error matrix then the overall accuracy attributable to FuelNet was 66.1%. Although user's accuracy of coniferous fuel types was high (96.7%), coniferous forests were generally confused with mixedwood and deciduous forests. Deciduous forests had the lowest class-level accuracy with 4.3% user's accuracy and 25.0% producer's accuracy. There was also high confusion between predicted grasslands and non-fuel with 39.5% user's accuracy for the grassland class.

A separate and independent ground plot validation on the forested fuel types is presented in Table VI. The ground plot validation resulted in user's and producer's accuracies that diverged from the aggregated "coniferous" class accuracy of the Google Earth validation given in Table V. User's and producer's accuracies were highest for C-7 (98.1% and 65.4%, respectively), which approximated the aggregated "coniferous" class user's and producer's accuracies (96.7% and 65.0%, respectively). Class accuracy was lowest for C-2, with 33.3% user's accuracy and 22.2% producer's accuracy. Overall accuracy for the forested classes in the ground plot validation was 78.7%, which was comparable with the 75.5% overall accuracy for all forested classes in the Google Earth validation. Both D-1/2 and M-1/2 had 0% user's and producer's accuracy, which were also the least common classes both in terms of predicted area and number of reference ground plots available.

The fuel types burned by the Elephant Hill megafire in 2017 are presented in Table VII for both the FuelNet

TABLE V

GOOGLE EARTH VALIDATION ERROR MATRIX FOR FUELNET MAPS IN ALL YEARS, 2013–2018. NOTE THE WATER AND NATURAL NF CLASSES ARE NOT PREDICTED AND THOSE CLASS ACCURACIES REFLECT THE CURRENT INVENTORY RATHER THAN THE NEURAL NETWORK. TOTAL INTERPRETED PLOTS $n = 274$

Predicted	Reference								User's accuracy
	Water	Coniferous	M-1/2	D-1/2	O-1a/b	Fire	Slash	NF	
Water	5	1	0	0	0	0	0	2	62.5%
Coniferous	0	119	1	1	0	1	0	1	96.7%
M-1/2	0	19	3	1	7	0	0	2	59.4%
D-1/2	0	18	0	1	2	0	1	1	4.3%
O-1a/b	0	11	0	1	15	0	1	10	39.5%
Fire	0	1	0	0	0	4	0	0	80.0%
Slash	0	7	0	0	3	0	4	0	28.6%
Non-fuel (NF)	0	7	0	0	2	0	0	22	71.0%
Producer's accuracy	100%	65.0%	75.0%	25.0%	51.7%	80.0%	66.7%	57.9%	
Overall accuracy = 63.1%									

TABLE VI

GROUND PLOT VALIDATION ERROR MATRIX FOR FUELNET 2016 FORESTED FUEL TYPES WITHIN THE ELEPHANT HILL MEGAFIRE. NOTE THE WATER, FIRE, AND GRASSLAND FUEL TYPES WERE NOT TARGETED FOR GROUND SAMPLING AND ARE EXCLUDED FROM EVALUATION HERE. TOTAL FORESTED GROUND PLOTS WAS $n = 75$

Predicted	Reference					User's accuracy
	C-2	C-3	C-7	D-1/2	M-1/2	
C-2	2	2	2	0	0	33.3%
C-3	4	6	0	0	0	60.0%
C-7	1	0	51	0	0	98.1%
D-1/2	0	0	0	0	0	0%
M-1/2	2	3	1	1	0	0%
Producer's accuracy	22.2%	54.5%	65.4%	0%	0%	
Overall accuracy = 78.7%						

TABLE VII

PERCENTAGE OF FUEL TYPES WITHIN THE ELEPHANT HILL MEGAFIRE PERIMETER FROM THE HMM-ADJUSTED FUELNET 2016 LAYER AND THE INVENTORY-BASED FUEL LAYER

Fuel type	FuelNet 2016	Inventory-based	FuelNet minus inventory-based
Fire	4.9%	0.0%	4.9%
C-2	16.8%	1.2%	15.6%
C-3	10.0%	33.9%	-23.9%
C-4	0.0%	0.1%	-0.1%
C-7	36.6%	31.9%	4.7%
D-1/2	1.3%	0.9%	0.4%
M-1/2	9.6%	4.9%	4.7%
O-1a/b	11.6%	21.1%	-9.5%
Slash	9.4%	6.0%	3.4%

2016 and inventory-based fuel maps. The FuelNet 2016 map predicted more C-2 (15.6%), M-1/2 (4.7%), C-7 (4.7%), and slash (3.4%) burned compared with the inventory-based layer. In contrast, the FuelNet 2016 map predicted much less C-3 (−23.9%) and O-1a/b (−9.5%) fuels was burned compared with the inventory-based layer. Within the Elephant Hill megafire perimeter, 4.9% more fire fuel type was predicted in FuelNet 2016.

The FuelNet 2016 prediction was compared against the inventory-based fuel layer in Fig. 6. Generally, the neural network predicted fuel types corresponding to elevation and climate envelopes, with the notable exception of recent harvest and slash. We interpreted the weights between the input neurons and the neurons in the first layer as indicators of variable importance with higher magnitude weights (positive or negative) contributing to greater control over neuron activation in the subsequent layers. Practically, this exercise provides some indication of how the input variables interact and pass information along the network. All climate variables and elevation provided the highest magnitude weights between the input neurons and the first layer (Fig. 7). Several spectral variables had high magnitude weights with at least one neuron in the first layer including NDVI seasonal maximum, Landsat Band 1 (ultrablue), Landsat Band 4 (near infrared), Landsat Bands 5-6 (shortwave infrared), and Tasseled Cap Wetness. Slope, TRASP, Tasseled Cap Brightness, and aspect all had low weights will all neurons, indicating relatively low importance compared with other variables. There were several neurons in the first layer with weights near zero for all input variables (neurons 2, 6, 7, 16, 21, 29), which suggest the training data could be learned by a simpler model architecture.

There were some positive and negative associations between input variables on specific neurons. The so-called “fire together wire together” associations were observed between climate variables: an inverse interaction between MAP and temperature difference continentality (negative-positive) on neuron 10 as well as a direct interaction (positive-positive) on neuron 22; and MAT and summer heat moisture index (positive-negative) on neuron 17. There were direct interactions between elevation, MAP, and precipitation as snow (negative-negative-negative) on neuron 15 and between elevation and NBR (negative-negative) on neuron 19. Inverse interactions were observed between MAP and Landsat Band 7 (positive-negative) on neuron 20 and between MAP and Landsat Band 6 (negative-positive) on neuron 28.

Class probabilities are given in Fig. 8 and were compared against the labeled fuel types provided by the interpreter in Fig. 9. The class probabilities provide an indication of confidence by the artificial neural network. Generally, the FuelNet

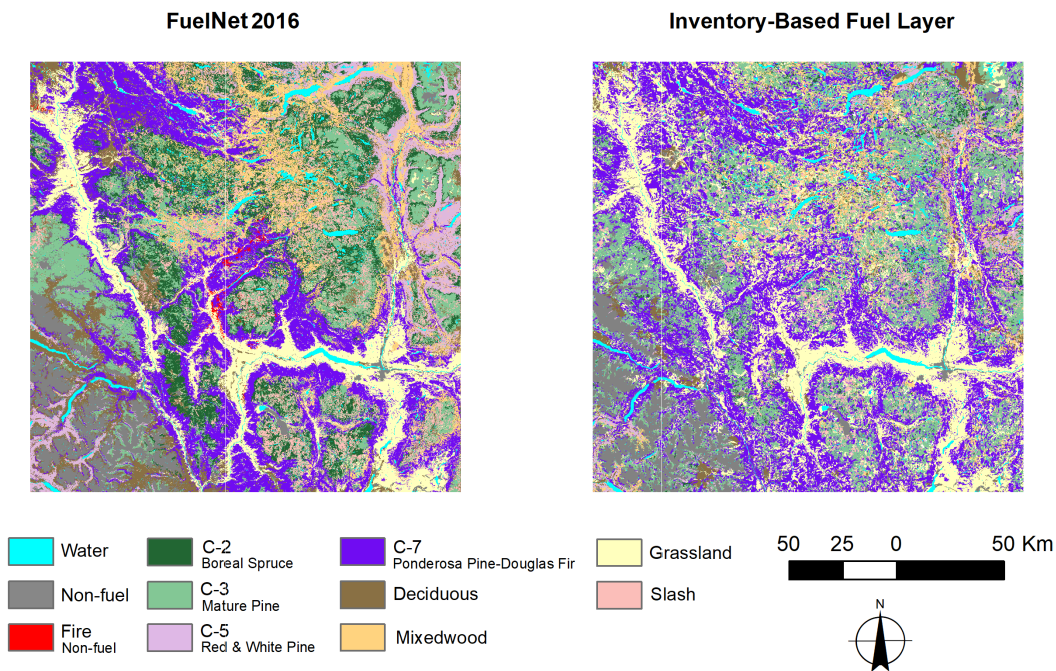


Fig. 6. Comparison of the predicted FuelNet 2016 map and the inventory-based fuel map.

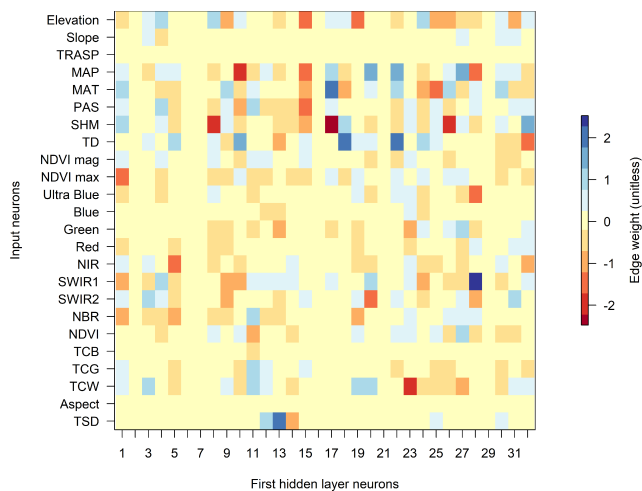


Fig. 7. Diagnostic matrix showing final weights of input variables on the neurons in the first layer of the neural network after training. Variable acronyms defined in Table I.

class probabilities were highest for the fuel type labeled by the interpreter with the notable exceptions of mixedwood and deciduous. Samples labeled as mixedwood by the interpreter showed a trend of increasing probability from deciduous to mixedwood to conifer by the artificial neural network, which suggests difficulty in predicting and interpreting pixels with varying proportions of conifer and deciduous trees. Similarly, the deciduous samples labeled by the interpreter indicated confidence of the artificial neural network was equally divided amongst conifer, mixedwood, deciduous, and grassland.

V. DISCUSSION

A. Benefits of Using Artificial Intelligence to Map Fuels

Artificial intelligence offers several advantages for mapping fuels. In British Columbia, significant effort has been made

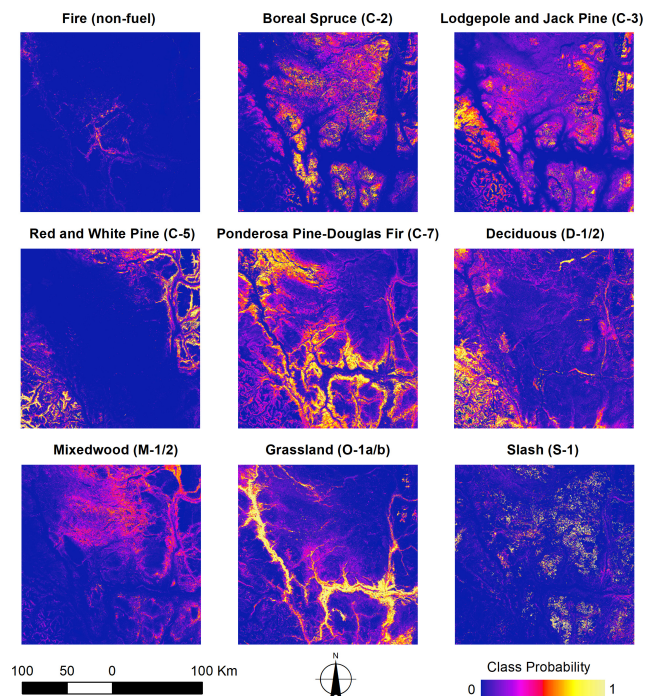


Fig. 8. Class probabilities for the FuelNet 2016 prediction.

to interpret forest inventory attributes into fuel types, which represents a large pool of labeled samples for any deep learning method that requires a large volume of training data. Beyond the initial investment of labeling millions of features, artificial intelligence methods are largely automated and flexible to update. By design, an artificial neural network is capable of classifying novel data as well as ingesting new training data to update the learning algorithm. Combined with temporally dense remote sensing data, deep learning methods

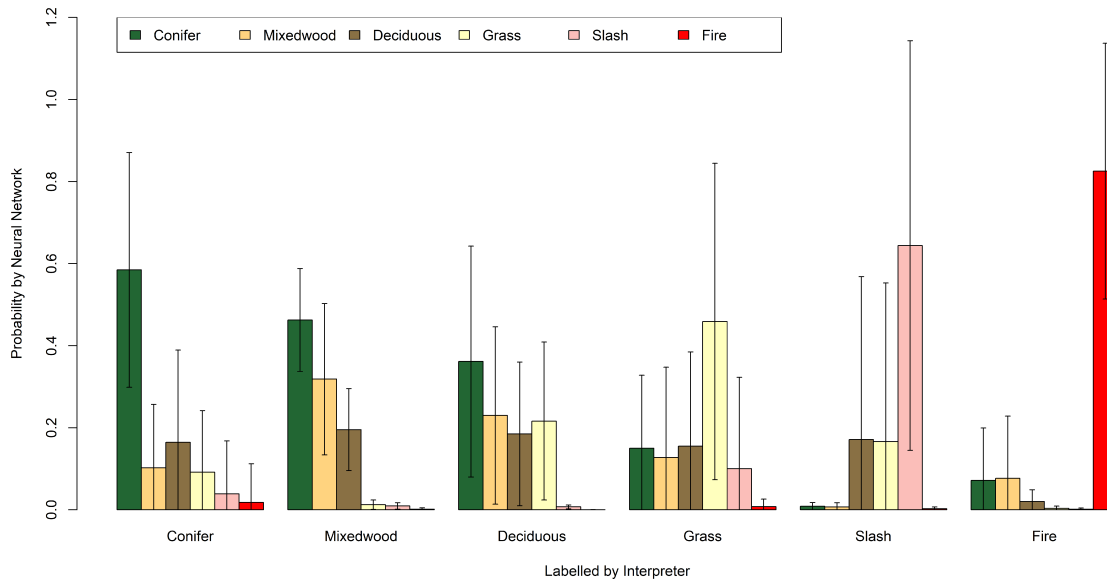


Fig. 9. Mean class probabilities from the neural network compared with labeled fuel type by the human interpreter for $n = 269$ plots across all years, 2013–2018. Vertical lines indicate ± 1 standard deviation.

are flexible for a wide range of classification problems [60]. These are important features of any process for updating large area fuel maps because the chance of encountering a novel fuel type increases with the area mapped, following Tobler's first law of geography: "near things are more related than distant things" [61].

B. Considerations for Using These New Fuel Maps

Our aim was to evaluate how an artificial neural network could be used with the existing fuel classification scheme in British Columbia. We provide extensive evaluation of these new mapped products in our study area, but we caution against using these maps as an authoritative singular source of fuel type information at the site or stand level. Our products should be used in concert with all available data sources to reach any conclusion about site-level fire risk and threat. At least within our study area, our analysis shows that the FuelNet maps are as reliable as existing maps for landscape-level forest planning and research.

The agreement between the inventory-based fuel layer and our predicted FuelNet maps was more or less as expected based on the approach we employed. The objective of this research was never to create a map that had perfect agreement with the current fuel layer because we were already aware of the shortcomings associated with the inventory-based approach. Instead, we hoped to provide some measure of consistency, both between the two methods and through time, which is part of the novelty of the proposed approach. The results demonstrated that the HMM helped to achieve both spatial and temporal consistency, as previously found by others in alternative land mapping and change detection contexts [50], [57], [62].

The user's accuracy of water was lower than expected (65%) due to how water is defined in the fuel type algorithm [10]. For example, water can be an open body of water, but also

forested and vegetated sites (e.g., swamps, bogs, fens) and even nonvegetated sites that no longer have standing or running water due to the short hydrological period at the time of the Google Earth Pro image interpretation. The fact that the interpreter labeled some water pixels as conifer and NF seems to support this idea. In terms of fire behavior modeling, water is treated the same as NF, so there would be no consequence for calculated fire behavior outcomes if these two classes were confused with each other.

The low user's accuracy for the slash class may partly be explained by a temporal lag between the satellite image used to make the prediction and the Google Earth Pro image that was interpreted. For example, slash was most often confused with coniferous forest, which suggests the interpreter was looking at a Google Earth Pro image of the site before it was harvested, while the harvest is detected in the Landsat satellite image acquired later in the year. A similar effect likely explains the low producer's accuracy for the NF class, which is not predicted, but derived directly from the inventory data set. Nearly 37% of interpreted NF samples were predicted to be grasslands or some other vegetated fuel type, which indicates that it was challenging for the interpreter to identify vegetation that may have been dormant, leaf-off, or otherwise not visible. Similarly, 29% of predicted NF samples were in fact vegetated by conifers or grasslands, which suggests that the inventory data are out of date in some areas.

The predicted fire fuel type observed in the FuelNet 2016 map within the perimeter of the 2017 Elephant Hill megafire is likely a training artifact. We experienced a challenge when training the neural network in the study area due to the unprecedented burning duration of the Elephant Hill megafire from July to October 2017. Because the target image date for acquiring satellite imagery was in August, some of the samples from the Elephant Hill megafire perimeter may not have been contemporaneous with the Landsat satellite imagery that we used for training. Therefore, it is possible that

some “burned” fire class samples were actually representing unburned conditions at the time of the Landsat satellite image and this would explain why we see the fire fuel type predicted for what otherwise might be some unburned vegetated fuel type. The low probabilities for the conifer and mixedwood forest fuel types with interpreter labeled fire samples also support this conclusion (Fig. 9). We chose to include this result rather than modify our workflow to demonstrate the possible limitations of mapping fuel types solely from an artificial neural network.

Accuracy of forested and grassland fuel types was mostly impacted by confusion between those fuel types. For example, user’s accuracy of the mixedwood (M-1/2) fuel type was 59.4% and was mostly confused with the coniferous fuel type. The deciduous (D-1/2) fuel type had the lowest user’s accuracy (4.3%), which was also most often confused with coniferous fuel types. Grassland (O-1a/b) was most often confused with coniferous fuel types, NF, and mixedwood. In the case of grasslands, phenological differences of vegetation in the satellite imagery may have contributed to confusion between the spectral signatures. Some training samples may have represented dry or dead grasses, which may spectrally look more like NF, while other training samples taken from the inventory may be out of date and not reflect coniferous forest encroachment at the interface of Ponderosa Pine-Douglas Fir (C-7) and grasslands.

Other studies that have used artificial neural networks to predict or classify fuel types have found similar accuracy levels to what we have reported here. Most recently, Alonso-Benito *et al.* [21] achieved 77% overall accuracy on 14 fuel type classes using a single-date ASTER image. Coluzzi *et al.* [63] achieved 78% overall accuracy on seven fuel type classes also using a single-date ASTER image. Vasconcelos *et al.* [38] stratified their results by land cover classes and reported overall accuracies that ranged from 33% on four fuel types in pine forest land cover to 75% in shrublands and other forest land cover types. However, these studies mapped relatively small areas (64–1920 km²) compared with our 40 000-km² study area. We found only one recent study that achieved or exceeded our reported level of accuracy of fuel type mapping over a larger study area and using a method other than an artificial neural network. Mitsopolous [64] validated the European ArcFuel fuel type map [65] across two of the most studied areas for fuel research in the world: Portugal and Greece. The overall accuracy of the clustering-based ArcFuel map was 67% in Portugal and 81% in Greece.

C. Challenges With Mapping Fuels

Fuel typing remains as much an art as a science because significant expertise is needed to identify the characteristics of fuels that will be important for fire behavior [66]. The current provincial fuel map in British Columbia is generated by applying a large decision tree to a set of mostly continuous forest inventory variables such as canopy cover, stand height, and stem density. Additional modifiers like past disturbances, stand age, and species composition can help bring possible fire behavior into focus, but there are still practical considerations.

First, the precision of forest inventory data is generally not sufficient for fuel typing because stand metrics are mostly estimated from air photos in British Columbia. For example, the difference between 25% and 26% crown closure in pure Douglas Fir stands can result in a polygon being labeled as deciduous/grassland (25%) or coniferous (26%) by the existing decision tree [10], which has significant implications for modeled fire behavior. Yet, air photograph interpreters are not likely to be able to resolve canopy cover to that precision. Second, forest inventory data in British Columbia are not updated province-wide on an annual basis. Even where updates to the forest inventory are obtained in a given year, those data are not immediately incorporated into the fuel typing process because the fuel map is also not updated on an annual basis. Third, updates to the decision tree fuel type algorithm can be very time-consuming and could be prone to errors. The 2017 update to the provincial fuel map contained 4 785 001 polygons for British Columbia, each with dozens of forest inventory attributes that combine into hundreds of unique nodes on a decision tree. Manually coding this decision tree can introduce errors into the process and revising the decision tree requires expert interpretation to accommodate any novel combinations of forest attributes into future updates.

D. How to Improve Artificial Neural Network Fuel Mapping

The results show that artificial neural networks can be a viable method for mapping and updating fuel maps using remote sensing data. Through an independent validation, we found that the artificial neural network performed as well as the decision tree classifier at a coarser thematic resolution. Still, we have a number of recommendations for improving large area fuel mapping with artificial neural networks.

- 1) *Training Data Quality and Quantity:* Artificial intelligence methods require a substantial amount of high-quality training samples in order to learn complex data patterns. In our study, we utilized the existing fuel map derived from a forest inventory data set as the source of training samples. These training data were further refined by using the most recent and reliable samples identified through a quality assessment. As a result, the artificial neural network did not improve map accuracy because it relied on the accuracy of the existing fuel map. Therefore, it is important to maintain high data quality standards when deciding how to select training data.
- 2) *Integrate Additional Remote Sensing Data:* Our approach relied solely on optical imagery and some ancillary geospatial data sets to map fuels. The practical advantage with this approach is that optical data are acquired very frequently and repeat imagery from satellites or aerial photography can provide rapid spectral information that is useful for updating fuel types described in Table II. More recent advances using imagery from unmanned aerial vehicles [67] and digital aerial photogrammetry [68] to produce 3-D point clouds from optical imagery show promise for mapping species composition and forest canopy structure, which are

important attributes for fuel type classification in British Columbia and across Canada (Table II). In addition, these methods have been successfully used together with machine learning to characterize burn severity within fires [69] and post-disturbance regrowth [67], which are both critically important for determining the appropriate postfire fuel type for a given location. While optical imagery can provide useful metrics to identify vegetation type and condition, active remote sensing imagery such as radio detection and ranging (RADAR) or LiDAR can help characterize the structural features that are important for distinguishing the finer-level fuel types as well as surface and ground fuels [70]. These 3-D data can also be used to aid the quality assurance process by filtering unreliable polygons used in training the artificial neural network.

- 3) *Expand Learning in Temporal Domain:* We used three variables that explicitly described the temporal domain: annual NDVI maximum and magnitude, and the time since last known disturbance map. The climate variables are arguably temporal, representing the period 1961–1990, but these variables were static across all predicted years. Explicitly linking the annual predictions of fuel types together could improve the learning for certain classes while also reducing the number of transitions between fuel types that require post hoc analysis (e.g., forward–backward HMM). Two possible ways to achieve this include: (future work a) deriving trend metrics from the multispectral time series such as the break point analysis used in [71] or (future work b) reconceiving the problem entirely as a trend-based prediction rather than a state-based prediction. In other words, instead of predicting fuel type states independently each year, future work b would involve learning and predicting fuel type sequences, from which the annual states could be derived or inferred. While future work a is a logical next step to improve the current artificial neural network in the temporal domain, future work b has the advantage of less human inference specified *a priori* and greater capacity for learning patterns and structures that are not obvious to human experts.
- 4) *Modify Architecture, Optimization, and Loss Function Parameters:* Although we used training pixel samples balanced by fuel type, the categorical cross-entropy loss function rewarded the optimization of overall accuracy. As a result, class-level accuracies were quite variable as evidenced by the validation. Therefore, future adaptation of FuelNet should consider cost-sensitive learning that applies weighted costs across the confusion matrix [72]. For example, the low user's and producer's accuracy for the mixedwood, deciduous, and grassland classes would invite a higher cost in a cost matrix to penalize the artificial neural network for optimizing the accuracy of other classes that are abundant and easier to learn like the coniferous class. In addition, the interpretation of weights could be useful for future studies considering which variables might be important or useful to predict fuel types.

- 5) *Identify Novel Fuel Types:* In addition to solving the typical classification problem, an artificial neural network can be used to identify novel and recombinant fuel types that would be otherwise impossible to identify with a hard classifier like a decision tree. For example, the activation of each class in the output layer can be used to assess relative “fit” in the existing classification scheme to identify pixels or areas that might require further examination.
- 6) *Improve Consistency Checks:* We did not provide any *post hoc* analysis beyond the forward–backward HMM. Future development of an artificial neural network algorithm to predict fuel types through time should integrate ancillary data to enforce logical state transitions, trends, and finer thematic resolution of fuel types. For example, biogeoclimatic zones can be used to separate the general harvest fuel type into the appropriate slash fuel type (i.e., S-1, S-2, or S-3). It would also be possible to integrate the inventory-based fuel layer and FuelNet so that all best available information is being utilized. Fire perimeters are commonly mapped and updated regularly in British Columbia and could be used to logically correct for predicted fire in the wrong year, like we observed at Elephant Hill. With multiple annual fuel maps, it is possible to substitute a higher confidence fuel type from a previous year for any illogical prediction. With some fire predicted a year early in 2016 for Elephant Hill, we could look to the 2015 fuel type map to determine what those pixels should have been. In the case of Elephant Hill, the areas predicted as fire in 2016 were mostly grasslands (O-1a/b) in 2015. As much as these consistency checks could be applied *post hoc* to the prediction by the end user, they could also be applied to the training samples by the future developer.

REFERENCES

- [1] S. H. Doerr and C. Santín, “Global trends in wildfire and its impacts: Perceptions versus realities in a changing world,” *Phil. Trans. Roy. Soc. B, Biol. Sci.*, vol. 371, no. 1696, Jun. 2016, Art. no. 20150345.
- [2] J. San-Miguel-Ayanz, J. M. Moreno, and A. Camia, “Analysis of large fires in European mediterranean landscapes: Lessons learned and perspectives,” *Forest Ecol. Manage.*, vol. 294, pp. 11–22, Apr. 2013.
- [3] J. Williams, “Exploring the onset of high-impact mega-fires through a forest land management prism,” *Forest Ecol. Manage.*, vol. 294, pp. 4–10, Apr. 2013.
- [4] S. L. Stephens *et al.*, “Temperate and boreal forest mega-fires: Characteristics and challenges,” *Frontiers Ecol. Environ.*, vol. 12, no. 2, pp. 115–122, Mar. 2014.
- [5] B. J. Stocks *et al.*, “Large forest fires in Canada, 1959–1997,” *J. Geophys. Res.*, vol. 108, no. 1, p. 8149, 2002.
- [6] M. Flannigan, A. S. Cantin, W. J. de Groot, M. Wotton, A. Newbery, and L. M. Gowman, “Global wildland fire season severity in the 21st century,” *Forest Ecol. Manage.*, vol. 294, pp. 54–61, Apr. 2013.
- [7] C. Van Wagner, “Development and structure of the Canadian forest fire weather index system,” Canadian Forestry Service, Ottawa, ON, USA, Forestry Tech. Rep. 35, 1987.
- [8] G. J. Cary *et al.*, “Comparison of the sensitivity of landscape-fire-succession models to variation in terrain, fuel pattern, climate and weather,” *Landscape Ecol.*, vol. 21, no. 1, pp. 121–137, Jan. 2006.
- [9] T. Wang, A. Hamann, D. Spittlehouse, and C. Carroll, “Locally down-scaled and spatially customizable climate data for historical and future periods for north america,” *PLoS ONE*, vol. 11, no. 6, Jun. 2016, Art. no. e0156720.

- [10] D. D. B. Perrakis, G. Eade, and D. Hicks, "British Columbia wildfire fuel typing and fuel type layer description," Natural Resour. Canada, Can. Forest Service, Pacific Forestry Centre, Victoria, BC, Canada, Inf. Rep. BC-X-444, 2018.
- [11] A. Alonso-benito, P. A. Hernandez-leal, M. Arbelo, J. A. Moreno-ruiz, and J. R. Garcia-lazaro, "Satellite image based methods for fuels maps updating," *Proc. SPIE*, vol. 9998, Art. no. 999821, Oct. 2016.
- [12] J. van Wagtenonk, R. E. Keane, and R. Burgan, "Mapping wildland fuels for fire management across multiple scales: Integrating remote sensing, GIS, and biophysical modeling," *Int. J. Wildl. Fire*, vol. 10, no. 4, pp. 301–319, 2001.
- [13] T. Xiao-rui, D. J. McRae, S. Li-fu, and W. Ming-yu, "Fuel classification and mapping from satellite images," *J. Forestry Res.*, vol. 16, no. 4, pp. 311–316, Dec. 2005.
- [14] L. A. Arroyo, C. Pascual, and J. A. Manzanera, "Fire models and methods to map fuel types: The role of remote sensing," *Forest Ecol. Manage.*, vol. 256, no. 6, pp. 1239–1252, Sep. 2008.
- [15] A. Alonso-Benito, L. Arroyo, M. Arbelo, and P. Hernández-Leal, "Fusion of WorldView-2 and LiDAR data to map fuel types in the canary islands," *Remote Sens.*, vol. 8, no. 8, p. 669, Aug. 2016.
- [16] S. Veraverbeke *et al.*, "Hyperspectral remote sensing of fire: State-of-the-art and future perspectives," *Remote Sens. Environ.*, vol. 216, pp. 105–121, Oct. 2018.
- [17] T. A. Varga and G. P. Asner, "Hyperspectral and lidar remote sensing of fire fuels in Hawaii volcanoes national park," *Ecol. Appl.*, vol. 18, no. 3, pp. 613–623, Apr. 2008.
- [18] R. Lasaponara and A. Lanorte, "Remotely sensed characterization of forest fuel types by using satellite ASTER data," *Int. J. Appl. Earth Observ. Geoinfor.*, vol. 9, no. 3, pp. 225–234, Aug. 2007.
- [19] M. A. Tanase and I. Z. Gitas, "An examination of the effects of spatial resolution and image analysis technique on indirect fuel mapping," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 1, no. 4, pp. 220–229, Dec. 2008.
- [20] M. J. Falkowski, P. E. Gessler, P. Morgan, A. T. Hudak, and A. M. S. Smith, "Characterizing and mapping forest fire fuels using ASTER imagery and gradient modeling," *Forest Ecol. Manage.*, vol. 217, nos. 2–3, pp. 129–146, Oct. 2005.
- [21] P. Herna, "Pixel and object-based classification approaches for mapping forest fuel types in Tenerife Island from ASTER data," *Mapa*, vol. 1989, pp. 306–317, Dec. 2013.
- [22] J. W. Van Wagtenonk and R. R. Root, "The use of multi-temporal landsat normalized difference vegetation index (NDVI) data for mapping fuel models in yosemite national park, USA," *Int. J. Remote Sens.*, vol. 24, no. 8, pp. 1639–1651, Jan. 2003.
- [23] A. D. Pierce, C. A. Farris, and A. H. Taylor, "Use of random forests for modeling and mapping forest canopy fuels for fire behavior analysis in Lassen volcanic national park, California, USA," *Forest Ecol. Manage.*, vol. 279, pp. 77–89, Sep. 2012.
- [24] E. N. Stavros *et al.*, "Remote sensing applications?: Society and environment use of imaging spectroscopy and LIDAR to characterize fuels for Fire behavior prediction," *Remote Sens. Appl. Soc. Environ.*, vol. 11, pp. 41–50, Aug. 2018.
- [25] G. Mallinis, G. Galidaki, and I. Gitas, "A comparative analysis of EO-1 hyperion, quickbird and landsat TM imagery for fuel type mapping of a typical mediterranean landscape," *Remote Sens.*, vol. 6, no. 2, pp. 1684–1704, 2014.
- [26] R. Lasaponara, A. Lanorte, and S. Pignatti, "Multiscale fuel type mapping in fragmented ecosystems: Preliminary results from hyperspectral MIVIS and multispectral landsat TM data," *Int. J. Remote Sens.*, vol. 27, no. 3, pp. 587–593, Feb. 2006.
- [27] S. Arellano-Pérez *et al.*, "Potential of sentinel-2A data to model surface and canopy fuel characteristics in relation to crown fire hazard," *Remote Sens.*, vol. 10, no. 1645, pp. 1–23, 2018.
- [28] I. Z. Gitas, G. H. Mitri, G. Kazakis, D. Ghosn, and G. Xanthopoulos, "Fuel type mapping in anapolis, crete by employing QuickBird imagery and object-based classification," *Forest Ecol. Manage.*, vol. 234, p. S228, Nov. 2006.
- [29] M. N. Giakoumakis, "Object-oriented classification modelling for fuel type mapping in the Mediterranean, using LANDSAT TM and IKONOS imagery—preliminary results," *Fire Res.*, vol. 5, pp. 1–13, Dec. 2002.
- [30] M. A. Wulder *et al.*, "Remote sensing of environment current status of landsat program, science, and applications," *Civil Environ. Eng.*, vol. 225, pp. 127–147, Feb. 2019.
- [31] T. Hermosilla, M. A. Wulder, J. C. White, N. C. Coops, and G. W. Hobart, "Regional detection, characterization, and attribution of annual forest change from 1984 to 2012 using landsat-derived time-series metrics," *Remote Sens. Environ.*, vol. 170, pp. 121–132, Dec. 2015.
- [32] M. A. Wulder, N. C. Coops, D. P. Roy, J. C. White, and T. Hermosilla, "Land cover 2.0," *Int. J. Remote Sens.*, vol. 39, no. 12, pp. 4254–4284, 2018.
- [33] A. Stefanidou, I. Z. Gitas, and T. Katagis, "A national fuel type mapping method improvement using sentinel-2 satellite data," *Geocarto Int.*, vol. 5, pp. 1–21, Apr. 2020.
- [34] A. Stefanidou, E. Dragozi, D. Stavrakoudis, and I. Z. Gitas, "Fuel type mapping using object-based image analysis of DMC and Landsat-8 OLI imagery," *Geocarto Int.*, vol. 33, no. 10, pp. 1064–1083, Oct. 2018.
- [35] D. Riaño, E. Chuvieco, J. Salas, A. Palacios-Orueta, and A. Bastarrika, "Generation of fuel type maps from landsat TM images and ancillary data in mediterranean ecosystems," *Can. J. Forest Res.*, vol. 32, no. 8, pp. 1301–1315, Aug. 2002.
- [36] S. H. Peterson, J. Franklin, D. A. Roberts, and J. W. van Wagtenonk, "Mapping fuels in yosemite national park," *Can. J. Forest Res.*, vol. 43, no. 1, pp. 7–17, Jan. 2013.
- [37] S. E. Sessie, H. Eagleston, L. Johnson, and E. Yurcich, "In-Situ and remote sensing platforms for mapping fine-fuels and fuel-types in sonoran semi-desert grasslands," *Remote Sens.*, vol. 10, no. 9, Aug. 2018, Art. no. 1358.
- [38] M. J. P. Vasconcelos *et al.*, "Regional fuel mapping using a knowledge based system approach," in *Proc. 14th Conf. Fire Forest Meteorol.*, Feb. 1998, pp. 2111–2123.
- [39] G. Scudder and I. Smith, "Introduction and Summary of the Montane Cordillera Ecozone," in *Assessment Species Diversity Montane Cordillera Ecozone*, G. Scudder and I. Smith, Eds. Ottawa, ON, Canada: Agriculture and Agri-Food Canada and Environment Canada, 2011, pp. 1–24.
- [40] D. A. Demarchi, "An introduction to the ecoregions of British Columbia," Ministry Environ., Victoria, BC, Canada, Tech. Rep., 2011. [Online]. Available: https://www2.gov.bc.ca/assets/gov/environment/plants-animals-and-ecosystems/ecosystems/broad-ecosystem/an_introduction_to_the_ecoregions_of_british_columbia.pdf
- [41] *British Columbia Forest Practices Code Biodiversity Guidebook*. British Columbia Ministry Forests, Victoria, BC, Canada, 1995.
- [42] N. C. Coops, T. Hermosilla, M. A. Wulder, J. C. White, and D. K. Bolton, "A thirty year, fine-scale, characterization of area burned in canadian forests shows evidence of regionally increasing trends in the last decade," *PLoS ONE*, vol. 13, no. 5, May 2018, Art. no. e0197218.
- [43] British Columbia Wildfire Service. (2020). *Fire Perimeters—Historical [data set]*. British Columbia Ministry of Forests, Lands, Natural Operations and Rural Development. Accessed: Nov. 23, 2020. [Online]. Available: <https://catalogue.data.gov.bc.ca/dataset/fire-perimeters-historical>
- [44] J. C. White *et al.*, "Pixel-based image compositing for large-area dense time series applications and science," *Can. J. Remote Sens.*, vol. 40, no. 3, pp. 192–212, May 2014.
- [45] E. Vermote and R. Wolfe, "MYD09GQ MODIS/Aqua surface reflectance daily L2G global 250 m SIN grid V006 [data set]," NASA EOSDIS Land Processes DAAC, 2015. Accessed: Nov. 23, 2020. [Online]. Available: <https://doi.org/10.5067/MODIS/MYD09GQ.006>
- [46] C. Maffei, S. Alfieri, and M. Menenti, "Relating spatiotemporal patterns of forest fires burned area and duration to diurnal land surface temperature anomalies," *Remote Sens.*, vol. 10, no. 11, p. 1777, Nov. 2018.
- [47] W. Jun, S. Zhongbo, and M. Yaoming, "Reconstruction of a cloud-free vegetation index time series for the Tibetan Plateau," *Mt. Res. Dev.*, vol. 24, no. 4, pp. 348–353, 2004.
- [48] G. J. Roerink, M. Menenti, and W. Verhoef, "Reconstructing cloudfree NDVI composites using Fourier analysis of time series," *Int. J. Remote Sens.*, vol. 21, no. 9, pp. 1911–1917, Jan. 2000.
- [49] T. Tachikawa *et al.*, "ASTER global digital elevation model version 2-summary of validation results," NASA Earth Resour. Observ. Sci. (EROS) Center, Sioux Falls, SD, USA, Tech. Rep., 2011. [Online]. Available: <https://pubs.er.usgs.gov/publication/70005960>
- [50] T. Hermosilla, M. A. Wulder, J. C. White, N. C. Coops, and G. W. Hobart, "Disturbance-informed annual land cover classification maps of canada's forested ecosystems for a 29-year landsat time series," *Can. J. Remote Sens.*, vol. 44, no. 1, pp. 1–21, 2018.
- [51] British Columbia Forest Inventory and Analysis Branch. (2019). *VRI—2019—Forest Vegetation Composite Rank 1 Layer (R1) [Data Set]*. British Columbia Ministry of Forests, Lands, Natural Resource Operations and Rural Development. Accessed: Nov. 23, 2020. [Online]. Available: <https://catalogue.data.gov.bc.ca/dataset/vri-2019-forest-vegetation-composite-rank-1-layer-r1>
- [52] *National Burned Area Composite [Data set]*, Edmonton, Alberta, Calgary, 2020.

- [53] British Columbia Forest Analysis and Inventory Branch. (2019). *Harvested Areas of BC (Consolidated Cutblocks) [Data Set]*. British Columbia Ministry of Forests, Lands, Natural Resource Operations and Rural Development. Accessed: Nov. 23, 2020. [Online]. Available: <https://catalogue.data.gov.bc.ca/dataset/harvested-areas-of-bc-consolidated-cutblocks>
- [54] R. H. R. Hahnloser, R. Sarpeshkar, M. A. Mahowald, R. J. Douglas, and H. S. Seung, "Digital selection and analogue amplification coexist in a cortex-inspired silicon circuit," *Nature*, vol. 405, no. 6789, pp. 947–951, Jun. 2000.
- [55] J. Bridle, "Probabilistic interpretation of feedforward classification network outputs, with relationships to statistical pattern recognition," in *Neurocomputing: Algorithms, Architectures and Applications*, F. Soulie J. Hérault, Eds. Berlin, Germany: Springer-Verlag, 1990, pp. 227–236.
- [56] F. Chollet. (2015). *Keras*. [Online]. Available: <https://keras.io>
- [57] D. P. Kingma and J. L. Ba, "Adam: A method for stochastic optimization," in *6th Int. Conf. Learn. Represent.*, 2015, pp. 1–15.
- [58] S.-Z. Yu and H. Kobayashi, "Practical implementation of an efficient forward-backward algorithm for an explicit-duration hidden Markov model," *IEEE Trans. Signal Process.*, vol. 54, no. 5, pp. 1947–1951, May 2006.
- [59] J. Cohen, "A coefficient of agreement for nominal scales," *Educ. Psychol. Meas.*, vol. 20, no. 1, pp. 37–46, Apr. 1960.
- [60] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, and B. A. Johnson, "Deep learning in remote sensing applications: A meta-analysis and review," *ISPRS J. Photogramm. Remote Sens.*, vol. 152, pp. 166–177, Jun. 2019.
- [61] W. R. Tobler, "A computer movie simulating urban growth in the detroit region," *Econ. Geogr.*, vol. 46, pp. 234–240, Jun. 1970.
- [62] W. Gong, S. Fang, G. Yang, and M. Ge, "Using a hidden Markov model for improving the spatial-temporal consistency of time series land cover classification," *ISPRS Int. J. Geo-Information*, vol. 6, no. 10, p. 292, Sep. 2017.
- [63] R. Coluzzi, I. Donna, A. Lanorte, and R. Lasaponara, "Mapping forest fuel types by using satellite ASTER data and neural nets," *Proc. SPIE*, vol. 6742, Oct. 2007, Art. no. 67420T.
- [64] *Advances in Forest Fire Research*, Mitsopolous, Larnaca, Cyprus, 2020.
- [65] M. Bonazountas, D. Kallidromitou, and A. Atyakopoulos, "ArcFIRETM/ArcFUELTM: Forest fire management geoplatform and fuel maps," *Forest Fires*, vol. 158, no. 2, pp. 67–78, 2012.
- [66] R. E. Keane and M. Reeves, "Use of expert Knowledge to develop fuel maps for wildland fire management," in *Expert Knowledge and Its Application in Landscape Ecology*, A. H. Perera, C. Drew, C. Johnson, Eds. New York, NY, USA: Springer, 2012, pp. 211–228.
- [67] T. R. H. Goodbody, N. C. Coops, T. Hermosilla, P. Tompalski, and P. Crawford, "Assessing the status of forest regeneration using digital aerial photogrammetry and unmanned aerial systems," *Int. J. Remote Sens.*, vol. 39, nos. 15–16, pp. 5246–5264, Aug. 2018.
- [68] T. R. H. Goodbody, N. C. Coops, and J. C. White, "Digital aerial photogrammetry for updating area-based forest inventories: A review of opportunities, challenges, and future directions," *Current Forestry Rep.*, vol. 5, no. 2, pp. 55–75, Jun. 2019.
- [69] J. Arkin, N. C. Coops, T. Hermosilla, L. D. Daniels, and A. Plowright, "Integrated fire severity-land cover mapping using very-high-spatial-resolution aerial imagery and point clouds," *Int. J. Wildl. Fire*, vol. 28, no. 11, pp. 840–860, 2019.
- [70] M. Fernández-Álvarez, J. Armesto, and J. Picos, "LiDAR-based wildfire prevention in WUI: The automatic detection, measurement and evaluation of forest fuels," *Forests*, vol. 10, no. 2, p. 148, Feb. 2019.
- [71] T. Hermosilla, M. A. Wulder, J. C. White, N. C. Coops, G. W. Hobart, and L. B. Campbell, "Mass data processing of time series landsat imagery: Pixels to data products for forest monitoring," *Int. J. Digit. Earth*, vol. 9, no. 11, pp. 1035–1054, Nov. 2016.
- [72] J. M. Johnson and T. M. Khoshgoftaar, "Survey on deep learning with class imbalance," *J. Big Data*, vol. 6, no. 1, p. 15, Dec. 2019.



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