Int J Appl Earth Obs Geoinformation 87 (2020) 102031

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

Maintaining accurate, current, rural road network data: An extraction and updating routine using RapidEye, participatory GIS and deep learning

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ARTICLE INFO

Keywords:
Convolutional neural network
Road extraction
Machine learning
Forest road networks
Ursus arctos
Remote sensing

ABSTRACT

Accurate and current road network data is fundamental to land management and emergency response, yet challenging to produce for unpaved roads in rural and forested regions using traditional cartographic approaches. Automatic extraction of roads from satellite imagery using deep learning is a promising alternative gaining increasing attention, however most efforts have focused on urban paved roads and used very high spatial resolution imagery, which is less frequently available for rural regions. Additionally, road extraction routines still struggle to produce a fully-connected, vectorized road network. In this study covering a large forested area in Western Canada, we developed and evaluated a routine to automatically extract unpaved road pixels using a convolutional neural network (CNN), and then used the CNN outputs to update a pre-existing government road network and evaluate if and how it would change. To cover the large spatial extent mapped in this study, we trained the routine using moderately high-resolution satellite imagery from the RapidEye constellation and a ground-truth dataset collected with smartphones by organizations already operating and driving in the region. Performance of the road extraction was comparable to results achieved by others using very high-resolution imagery; *recall* accuracy was 89–97%, and *precision* was 85–91%. Using our approach to update the pre-existing road network would result in both removals and additions to the network, totalling over 1250 km, or about 20 % of the roads previously in the network. We discuss how road density estimates in the study area would change using this updated network, and situate these changes within the context of ongoing efforts to conserve grizzly bears, which are listed as a Threatened species in the region. This study demonstrates the potential of remote sensing to maintain current and accurate rural road networks in dynamic forest landscapes where new road construction is prevalent, yet roads are also frequently de-activated, reclaimed or otherwise not maintained.

1. Introduction

Accurate and up-to-date information on the location of roads is an increasingly fundamental dataset for a wide range of planning, emergency response, conservation and research activities globally (Barrington-Leigh and Millard-Ball, 2017). However, the routine mapping of roads and their associated attributes is often lacking, especially in more rural and forested regions where roads are often unpaved (Prendes et al., 2019; Workman et al., 2016). Even small changes in rural road networks can have large impacts on human wellbeing (e.g., access to markets and services), environmental integrity and wildlife health (e.g., habitat fragmentation, increased risk of mortality). A particular concern in rural areas is understanding how road networks alter the fundamental landscape structure, which can result in cascading ecological implications (Bennett et al., 2011). Such understanding requires accurate road network data, which can be difficult to produce and maintain since unpaved road networks are often highly dynamic. For example, in areas with intensifying exploitation of timber, minerals, fossil fuels and arable land, new road construction may be very rapid as infrastructure is developed to access sites and transport materials (Laurance and Balmford, 2013). Meanwhile in areas with ongoing land reclamation or rural abandonment, previously existing unpaved roads may no longer be accessible once vegetation regrows. These realities present challenges to maintaining rural road network databases using traditional cartographic approaches such as physical mapping with GPS or manual delineation from photo-interpretation.

An alternative (or complementary) approach is to automatically extract road information from remote sensing data – particularly imagery acquired from space or air borne sensors. Since the early 1980's, a

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https://doi.org/10.1016/j.jag.2019.102031
Received 12 September 2019; Received in revised form 2 December 2019; Accepted 6 December 2019
Available online 17 December 2019

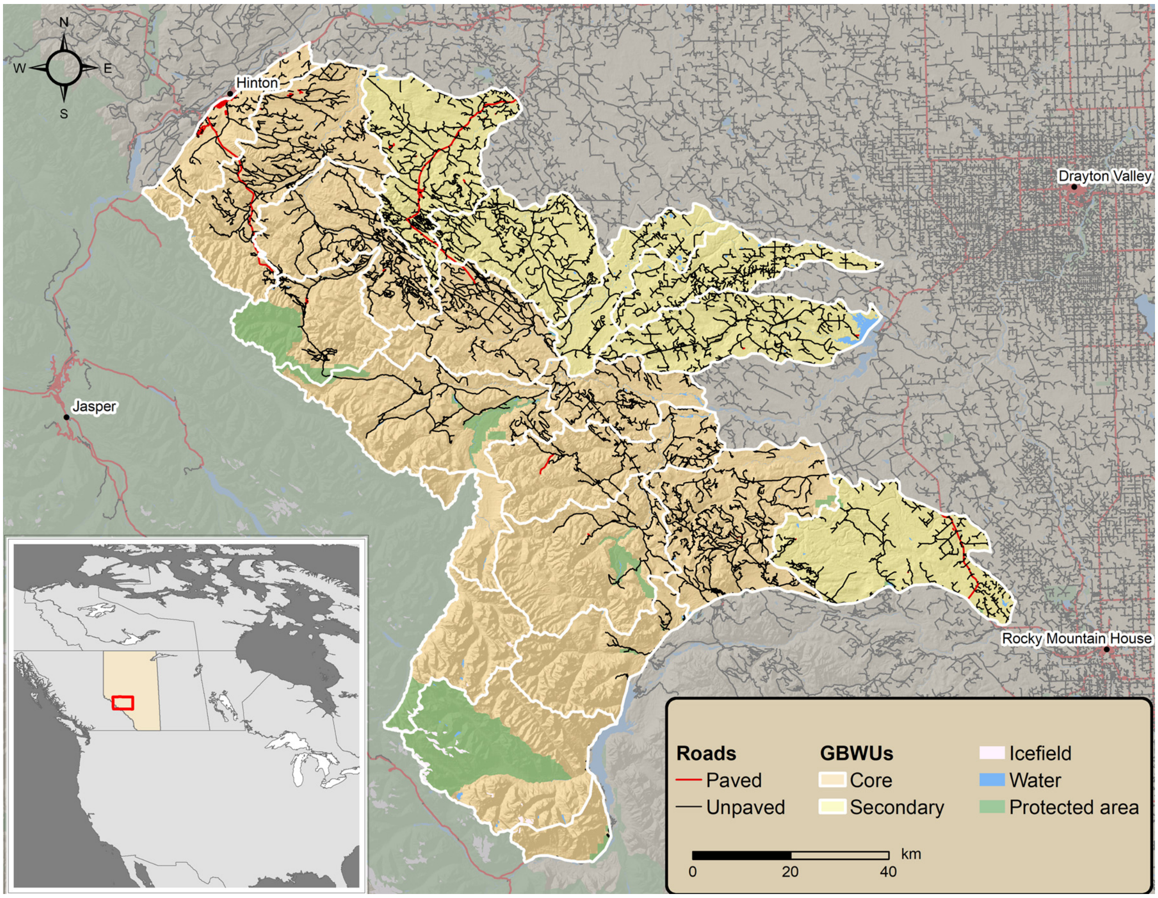

Fig. 1. Map of the study area, which corresponds to the 22 grizzly bear watershed units (GBWUs) that make up the recovery zone within the Yellowhead Bear Management Area. The roads shown are the pre-existing, publicly available road network dataset.

large number of road extraction approaches have been investigated with ranging degrees of success (see review by Wang et al., 2016, amongst others). Most recently, convolutional neural networks (CNNs) – a form of deep machine learning – have shown marked improvement over conventional image classification for high level feature extraction computer vision tasks, including road extraction (Gao et al., 2019). By training a CNN on many examples of road segments across a variety of conditions, the CNN is able to use both variations in the brightness of the road surface and local morphology to help in road extraction without significant pre-processing, and generally achieving better results than other approaches (e.g., Alshehhi et al., 2017; Das et al., 2011; Gao et al., 2019; Xu et al., 2018).

To date, most deep learning road extraction efforts have focused on mapping paved roads in urban locations and utilized very high spatial resolution imagery (i.e., ≤ 1 m pixels), which may limit their applicability to unpaved road networks (Xu et al., 2018) for several reasons. Firstly, models built on urban datasets may perform poorly in rural areas due to differing road surface conditions and surrounding land covers. Additionally, even if urban models can be successfully applied to rural roads, the limited temporal and spatial coverage of very high resolution imagery is typically not adequate for frequent mapping over large extents, and such imagery is less available in rural regions. Therefore, road extraction techniques applicable across broad spatial extents in rural and forested regions are still lacking.

In this study, we evaluated a CNN road extraction routine for unpaved roads using moderately high-resolution RapidEye imagery (5 m pixels) covering a large area in the Rocky Mountain foothills of Western Alberta, Canada. The RapidEye constellation of commercial satellites enables frequent imaging over large areas while maintaining relatively fine spatial resolution (Tyc et al., 2005), making it a strong candidate for extraction and monitoring of rural road networks over time. To obtain training and validation data over a large area and close in time to the imagery acquisition, we took a participatory approach and recruited people already working and driving in the study region to use a road-tracking application that can be installed on most mobile devices.

We chose to focus this study in Western Alberta due to the dense and dynamic network of unpaved roads serving local forestry, mining and oil and gas activities, and concerns over the implications of current and expanding road networks for the recovery of grizzly bears (*Ursus arctos*) present in the region. The provincial government listed the grizzly bear as 'Threatened' in 2010 in response to low population estimates and high levels of human caused mortality and initiated efforts to support and monitor population recovery. As part of these efforts, road density thresholds have been recommended for sensitive habitat to limit overdevelopment and human access (Alberta Environment and Parks, 2016). These thresholds were based, in part, on studies showing that mortality risk is higher for bears near roads (Benn and Herrero, 2002; Boulanger and Stenhouse, 2014) and highlight the need for up-to-date road network datasets for the region.

The principle objective of this study, therefore, was to develop and evaluate the accuracy of automated extraction of unpaved roads across a large grizzly bear recovery area using a CNN trained with RapidEye satellite imagery. We also developed a semi-automated routine to update a pre-existing road network dataset and discuss how road densities across the region might change when calculated on an up-to-date dataset. This study demonstrates the potential of moderately high-resolution imagery, participatory data collection and deep learning to map rural roads across large areas, and highlights the importance of maintaining up-to-date road network datasets in dynamic landscapes.

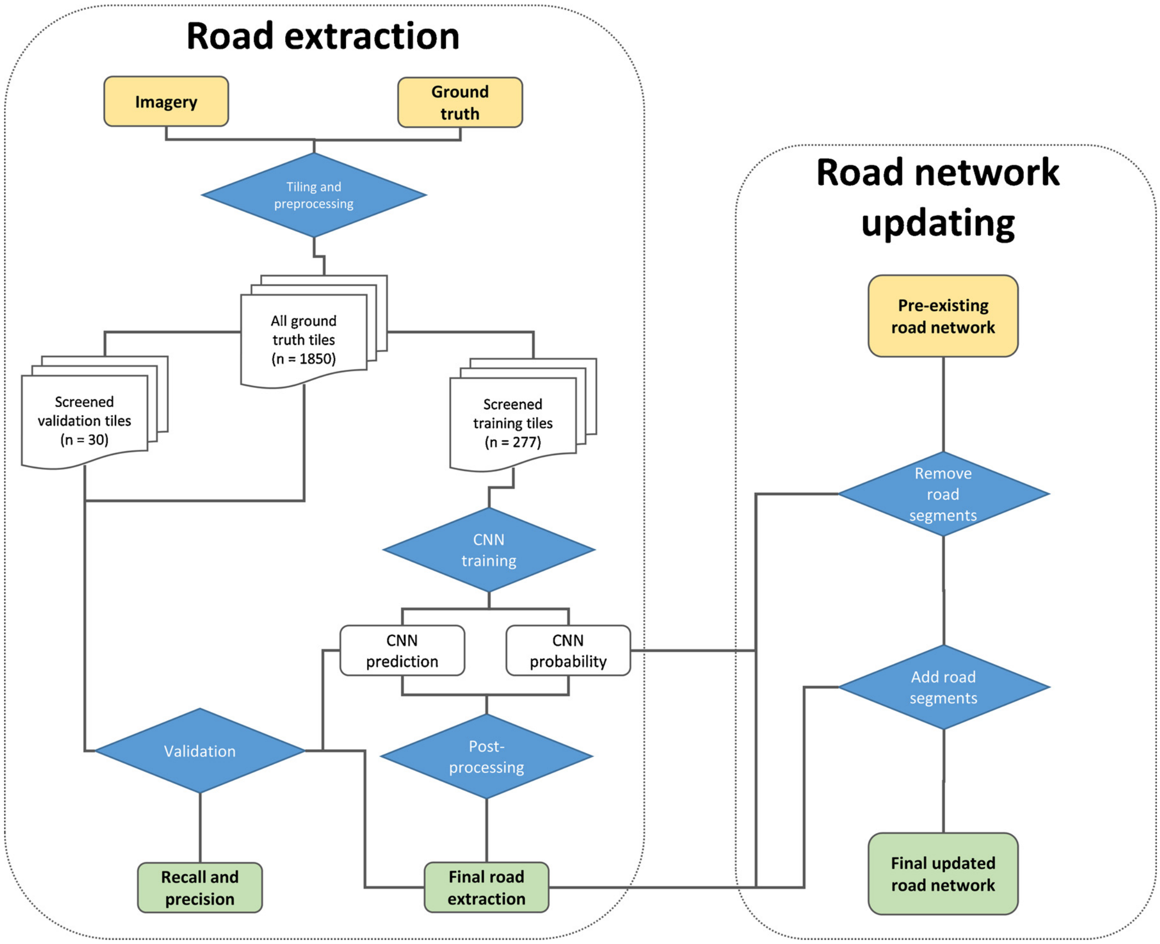

Fig. 2. Schematic of the road extraction routine and subsequent updating of the existing publicly available road network.

2. Materials and methods

2.1. Study area

Our study area was the grizzly bear recovery zone within the Yellowhead Bear Management Area (Alberta Environment and Parks, 2016) in Alberta, Canada (Fig. 1), which has been separated into 'Core' (n = 16) and 'Secondary' (n = 6) grizzly bear watershed units (GBWUs) (Nielsen et al., 2009). It covers approximately 12,000 km^2 of the Rocky Mountain foothills, bounded by Jasper National Park to the west and the more populated lowlands to the east. The area is primarily public land with mixed land uses related to industrial-scale natural resource extraction (i.e., open-pit coal mining, forestry, and oil and gas development) and recreation, leading to a dynamic and dense network of roads and other linear features such as pipelines and seismic lines. Land cover within the foothills consists of conifer, mixed, and deciduous forests as well as bogs, meadows, and forests regenerating from limited wildfire activity and widespread forest harvesting (Franklin et al., 2001). The climate is typically long cold winters and cool wet springs, with prolonged snow cover at higher elevations (Janz and Storr, 1977).

2.2. Data and preprocessing

2.2.1. Satellite imagery

We utilised orthorectified (Level 3A) RapidEye satellite imagery acquired between August 8 and September 17, 2017. We mosaicked image tiles, visually choosing the best image when overlapping tiles were available (approximately 15 % of the study area). Cloud cover was low (approximately 0.5 % of the study area) and the angle of observation averaged 8.8 % off-nadir (SD = 4.9 %).

2.2.2. Participatory ground truth

In order to create an accurate ground truth dataset of known roads in the study area, we asked organizations working in the region to have their employees use a free road tracking application while driving roads during their daily work activities. The application – RoadLab Pro – was designed as a data collection tool for the World Bank (see progressana.com) and utilises the GPS and the accelerometer on a smartphone or tablet to automatically map driving location and speed. We provided the application to six different users working for industrial and non-profit organizations operating in the region. Data was collected between June 2018 and March 2019 for approximately 1000 km of roads.

2.2.3. Existing road networks

The Government of Alberta maintains an authoritative source of publicly available road data for the province. To understand how this existing road network would change if updated using our routine, we downloaded the road network through the GeoDiscover Alberta data portal in October 2017 and selected all non-paved roads for the study area. Non-paved roads in the region consist of one- and two-lane roads with both earth and gravel surfaces ranging from 5 to 12 m in width. We also obtained a road network dataset from West Fraser – a local forestry company – that identified active and de-activated forestry roads within their Forest Management Area. This dataset covered a subset of the study area, and we used it to help determine a CNN probability threshold to remove roads from the publicly available road network (see Section 2.4).

2.2.4. Tiling of data and preprocessing

In order to create an input dataset for the CNN, we first needed to extract RapidEye image tiles with complete ground truth coverage. To create a candidate set of input tiles, we extracted 300 × 300 pixel tiles (2.25 km^2) from both the RapidEye imagery and the preprocessed ground truth data. We ignored areas more than 1750 m from roads in the ground truth dataset to limit the number of tiles to a manageable size and minimize the chances of including tiles with roads that were not driven during ground-truth data collection. This produced 1850 candidate tiles, which we manually screened to choose only tiles for which all visible roads were in the ground truth dataset. This resulted in 307 screened tiles, 90 % of which were randomly chosen for training (n = 277), leaving 30 tiles for independent validation (Fig. 2). For CNN training and prediction, we extracted the red, green and blue (RGB) RapidEye bands and rescaled each band from 0 to 1 based on the minimum and maximum of each tile.

2.3. Road extraction

2.3.1. Convolutional neural network (CNN)

We trained the CNN using the SegNet architecture designed to provide pixel-wise image segmentation (Badrinarayanan et al., 2017) and programmed in Python 3.6 using the *PyTorch* library (Paszke et al., 2017). Data inputs consisted of 64 × 64 pixel patches from the screened training tiles. For each epoch, 10,000 random sub-samples were drawn and each sub-sample was randomly flipped, mirrored, or unaltered. We used a base learning rate of 0.01, stochastic gradient descent optimization with momentum (0.9) and weight decay (0.0005), and a scheduler to decrease the learning rate by a factor of 10 after two, five and seven epochs (however five epochs was deemed sufficient to minimize loss). Due to the imbalanced nature of sparse road pixels relative to abundant non-road pixels, class weighting was applied in the loss function based on the abundance of each class in the dataset, resulting in a weight of 0.95 for the road class and 0.05 for the non-road class.

2.3.2. Post-processing

To refine the initial binary CNN prediction, we implemented a two-step post-processing approach utilizing both the binary prediction and probability output obtained from the trained CNN (Fig. 2). Post-processing is commonly required to improve road extraction performance by removing small or non-linear regions and connecting broken road segments (Alshehhi et al., 2017; Das et al., 2011; Gao et al., 2019). We developed a relatively simple and quick post-processing workflow, adapted from Das et al. (2011), using thresholds associated with properties of labeled image regions that can be created with freely available image processing tools.

In the first post-processing step, applied to each tile, we grouped the binary CNN prediction into contiguous regions and, for each unique region, extracted the mean probability of being a road (derived from the CNN probability output) along with the eccentricity of that region – a measure of the elongation of the region, ranging between zero and one. To eliminate small regions suspected not to be roads, we removed all very small regions (< 20 pixels) and those small regions (< 200 pixels) with a low mean probability (< 0.05) or low eccentricity (< 0.95). To connect nearby road segments, we applied a dilation filter using a 15 × 2 pixel ellipse oriented along the longest axis of the region, and reclassified any non-road pixels as roads where two or more dilated regions overlapped. For the second post-processing step, we mosaicked together all tiles and again identified unique contiguous regions. We then removed all remaining regions containing less than 200 pixels, and any large regions (≥200 pixels) suspected to be non-linear based on the ratio of the region area to the minimum convex area of the entire region (ratio > 0.30 was removed). All thresholds were selected based on visual inspection of early results and histograms, however, results were not highly sensitive to small changes in the threshold values.

2.3.3. Validation of road extraction

To quantify the performance of the road extraction routine, we calculated three validation metrics – *recall* (i.e., completeness), *precision* (i.e., correctness) and *quality* – at the pixel scale. We allowed for a buffer of 25 m (Heipke et al., 1997; Wiedemann, 2003) to account for the positional uncertainty of the RoadLab Pro ground data and the 5 m spatial resolution of the RapidEye imagery. Since we were primarily interested in accurately mapping presence or absence of road segments rather than the precise positional location of roads, we deemed a 25 m buffer to be suitable. *Recall* is therefore the percent of known roads correctly predicted within 25 m and *precision* is the number of predicted road pixels that were actually within 25 m of a known road. *Quality* is a measure of overall goodness, taking into account both *recall* and *precision*, and calculated as:

$$Quality = \frac{Recall \times Precision}{Recall - Recall \times Precision + Precision}$$

We validated both the initial CNN road prediction and the final extraction to evaluate the degree to which post-processing improved results. We validated the screened training and validation tiles, as well as all the candidate tiles covering the ground truth dataset to gauge if the CNN model was biased toward screened tiles. Since not all roads were driven in every candidate tile, *precision* could not be calculated using the ground-truth dataset alone. Therefore, we took a random subset of 307 candidate tiles (to equal the number of screened training tiles) and manually delineated all the roads in each of these tiles to calculate *precision* across the entire ground-truth network area.

2.4. Updating the existing road network

Going from a pixel-wise road extraction to a vectorized road network remains challenging (Xu et al., 2018), therefore we developed a semi-automated approach to update the existing publicly available road network using outputs from our road extraction routine (Fig. 2). The first step was to remove segments from the existing road network that were unlikely to be driveable roads. For each road segment in the existing network, we first calculated the mean probability of being a road (derived from the CNN probability output) and the percent of that segment that was predicted as a road in the final road extraction. We then removed road segments if the proportion of the segment predicted as road in the final extraction or the mean probability were below certain thresholds identified by comparing the values for de-activated (includes reclaimed roads) versus active forestry roads, which were available for a portion of the study area (see Section 2.2.3). The probability threshold was set at the 10th percentile of active roads and the proportion threshold set at 10 %. Adding in new roads not present in the existing network required a more manual approach. Road pixels present in the final road extraction that did not already overlap with segments in the existing road network were visually examined and manually connected to the existing road network.

To evaluate how the existing road network would change if updated using our approach, we calculated the length of roads that would be removed and added, respectively. We also calculated road density (km of road per km^2) for the study area before and after updating the network. Road density is an important indicator of the impact of roads on wildlife (e.g., Boulanger and Stenhouse, 2014), and for this region road density thresholds have been set for GBWUs within the recovery zone for threatened grizzly bear populations (Alberta Environment and Parks, 2016). We calculated changes in road density for each of the GBWUs within our study area and, for visualization purposes, road density changes calculated using a 7.44-km radius moving window, representing the average daily movement rate of grizzly bears in the

Table 1
Road extraction accuracies before and after post-processing.

Dataset	No. tiles	CNN binary prediction			Final road extraction		
		Recall	*Precision*	*Quality*	*Recall*	*Precision*	*Quality*
All ground truth tiles	1850	0.97	*0.72	0.70	0.89	*0.87	0.79
Screened validation tiles	30	1.00	0.78	0.78	0.97	0.91	0.89
Screened training tiles	277	0.99	0.74	0.73	0.91	0.85	0.78

* Signify they were taken from a random sub-sample of equal size to the screened tiles (n = 307) taken from the original ground truth dataset and manually delineated to validate precision of road detection across the entire ground truth dataset (see Section 2.3.3).

region (Nielsen et al., 2016).

3. Results

3.1. Road extraction

The final road extraction had high recall (0.89) and precision (0.87) across the entire ground-truth dataset (Table 1). The initial CNN output tended to over-predict roads, as indicated by very high recall (0.97) and lower precision (0.72). False positives in the initial CNN prediction were most commonly associated with streams and rivers (Fig. 3) and, to a lesser extent, clouds and vegetated linear features such as gas pipelines. False negatives were most likely to occur where roads were surrounded by exposed soil and rock (e.g., open pit mines), occluded by forest canopy or under cloud shadows.

The post-processing steps improved the precision of the road extraction to 0.87 by removing uncertain predictions from the CNN as well as small, isolated and non-linear regions. Post-processing tended to successfully remove wide river sections and vegetated linear features (Fig. 3b and c), however narrower river sections were less likely to be removed (Fig. 3d). The drop in recall from 0.97 to 0.89 after post-processing shows that some regions that were actually roads were removed during the post-processing steps.

Recall and precision for the held-out validation dataset (n = 30) were higher compared to the entire ground truth dataset both before and after post-processing, which suggests that the algorithm may be biased toward the types of roads in the screened tiles that were used for CNN training and validation. Screened tiles were restricted to locations where all roads within 2.25 km^2 (i.e., the size of one tile) were driven during ground data collection. These tiles may be more likely to contain isolated roads surrounded by relatively homogenous forest compared to the entire study area, where mining and forestry activities can result in dense road networks surrounded by more heterogeneous land covers.

3.2. Road network updating

De-activated forestry road segments had a lower CNN-derived probability compared to active forestry roads (Fig. 4), demonstrating that the CNN probability output is useful for automatically removing old de-activated roads. After we removed suspected non-roads from the existing network using set thresholds and added in new roads using a semi-automated approach, our final updated road network differed substantially from the existing network in some areas (Fig. 5). Prior to updating, there were 6202 km of roads in the study area according to the public database. During updating, we removed 867 km of unpaved roads, equivalent to about 15 % of the original network, and added 383 km of new roads, equivalent to 8 % of the total updated road network. Updating the existing road network using this approach would increase the road density for some regions of the study area and decrease it for others (Fig. 6 and Table 2). After updating, the maximum road density at the grizzly bear daily movement scale was 1.68 km km^{-2} and changes ranged from -0.33 to +0.22 km km^{-2} (Fig. 6). At the watershed scale, road density decreased for 14 GBWUs, increased for two GBWUs, and was unchanged for six GBWUs (Table 2). Most apparent changes were associated with forestry roads, i.e. vegetation regrowth on de-activated roads and construction of new roads for logging. However, some of the decreases in road density in the northwest of the study area were associated with open-pit mining roads, likely either a result of reclamation activities or the fact that the CNN had difficulty extracting gravel roads surrounded by exposed bedrock.

4. Discussion

4.1. Road extraction

Our CNN-based road extraction routine trained with RapidEye imagery achieved reasonably high performance for unpaved rural roads. *Recall*, *precision* and *quality* metrics were comparable to studies using higher resolution imagery to extract paved roads across much smaller areas using deep learning (e.g., Gao et al., 2019; Xu et al., 2018) and other approaches (e.g., Miao et al., 2015; Zhou et al., 2019). The lower cost and broader spatial and temporal coverage of RapidEye and similar sensors (e.g., onboard the French SPOT satellites) would enable more frequent road network mapping over larger areas compared to very high-resolution imagery. RapidEye imagery is not free, however (costs are currently around $1.00 per km^2, depending on volume and academic discounts), and it would be worth exploring whether freely available imagery (e.g., from Landsat, Sentinel) can provide adequate extraction of unpaved roads. In our study region, the roads of interest were typically at least one to three pixels (i.e., 5–15 m) wide, which suggests coarser resolution imagery may not be adequate. Additionally, RapidEye imagery may not be suitable for detecting smaller roads and tracks less than one pixel wide (e.g., emergency access, ATV routes).

The use of deep learning algorithms such as CNN has expanded greatly within the past 5 years and is proving to be a useful tool in extracting features and objects from remotely sensed imagery. Recent advances in computing power and the ability to apply deep learning algorithms in a spatial context allows users previously unable to utilise the power of CNN, to now be able to do so. However, the initial output from the CNN did not produce a satisfactory road extraction for this study, and post-processing appears to remain a critical step to improve performance across a range of landscape conditions (Alshehhi et al., 2017; Das et al., 2011; Gao et al., 2019). Roads are difficult objects to classify due to their spectral similarity to other high albedo objects such as bare soil and rock, and their morphological similarity to other linear features such as rivers and pipelines. Our simple post-processing approach improved the overall quality of our road extraction by about 13 % (Table 1), but required setting thresholds to filter out small and non-linear regions and connect broken segments. These thresholds are likely site dependent and a function of both the spatial resolution of imagery and the inherent patterns of the landscape. Cross-validated approaches could be used to identify thresholds for a given region, thus enabling a purely automated approach.

4.2. Road network updating

Even after post-processing, a pixel-based road extraction is difficult to convert into a fully connected vectorized road network for

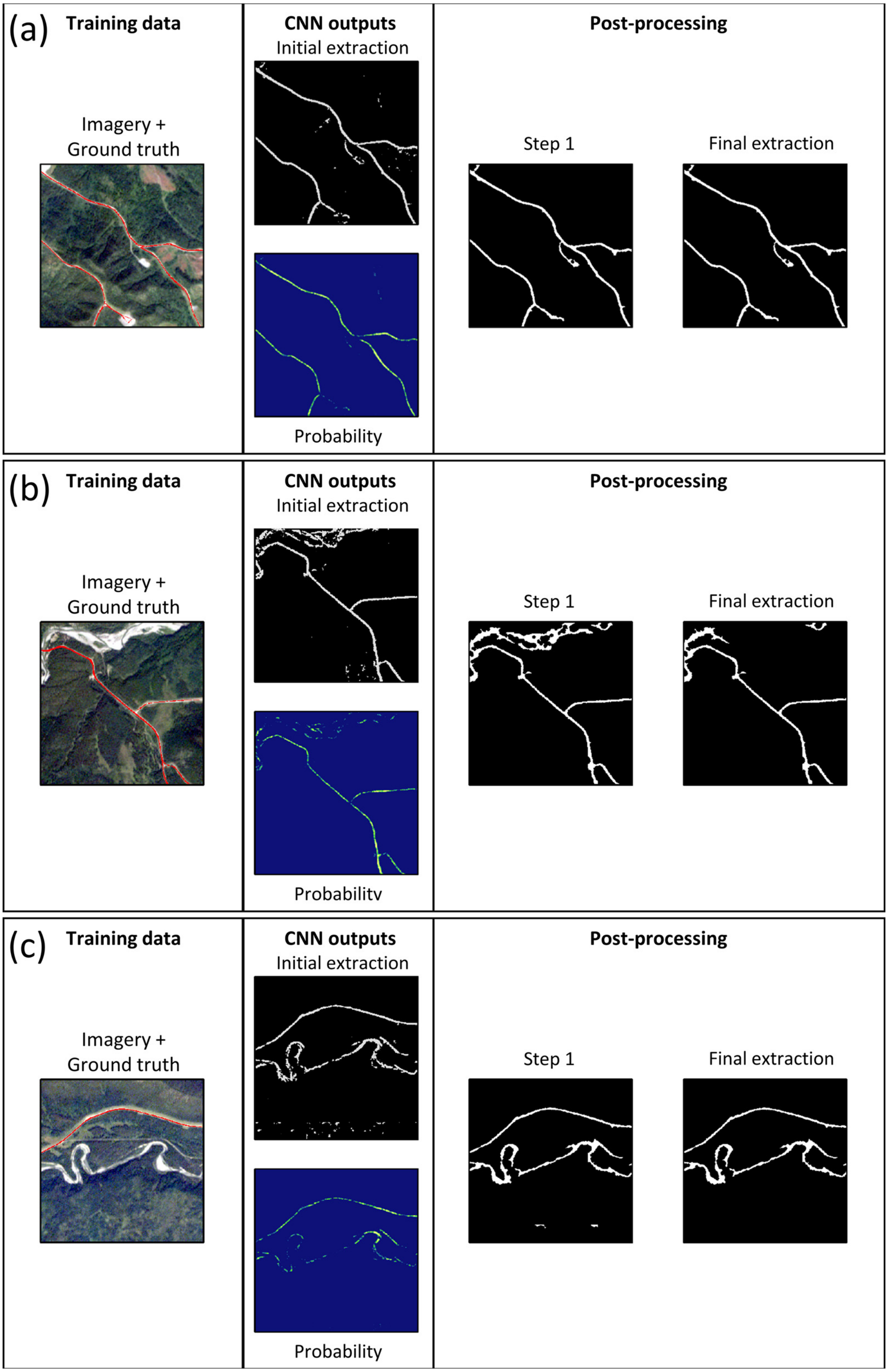

Fig. 3. Examples of final road extractions and intermediate steps for various training tiles. For each panel: 'Input data' shows the RapidEye image overlaid with ground truth data in red; 'CNN outputs' are the initial binary road prediction and the road probability (brighter = higher probability) produced by the CNN; and 'Post-processing; shows the binary road prediction after the two post-processing steps. Panel (a) shows a tile with good CNN performance even without post-processing, panel (b) shows a tile with poor initial CNN predictions, but good performance after post-processing, and panel (c) shows a tile with poor performance even after post-processing. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

navigation (Xu et al., 2018). While crowdsourced road networks such as OpenStreetMap provide increasingly complete datasets (Barrington-Leigh and Millard-Ball, 2017), they are less likely to include rural roads such as forestry logging roads (e.g., see supplementary material in Ibisch et al., 2016), and we found OpenStreetMap to be far from complete in our study area. In similar locations where a partial or out-of-date road network dataset exists, using a CNN-based road extraction to update the pre-existing network, as we have done here, may be a suitable approach. Our approach to remove road segments from the existing network that likely no longer exist (e.g., are now overgrown) can be fully automated once thresholds are defined. Our method to add in new roads required manual delineation, but was relatively fast since we only had to connect extracted road segments that did not already exist in the road network, rather than visually examine the entire image

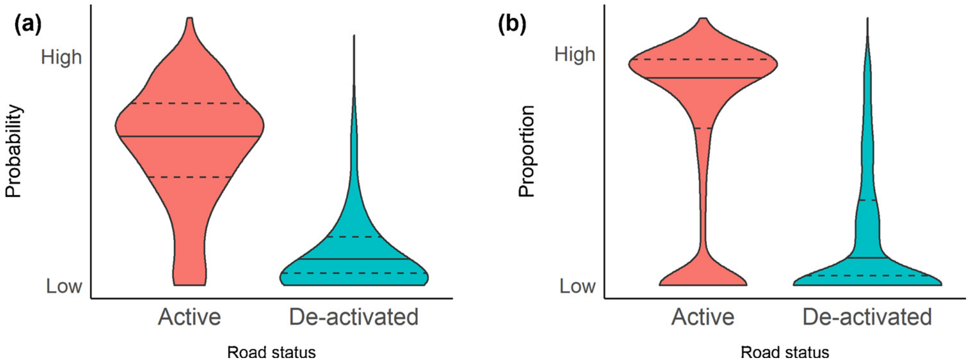

Fig. 4. Violin plots comparing known active and de-activated forestry roads. Panel (a) is the mean CNN road probability within 25 m of forestry road segments and panel (b) is the proportion of area within 25 m of forestry road segments predicted as a road in the final road extraction. Solid lines indicate median and dashed lines indicate the 25th and 75th percentiles. Y-axis range is the highest and lowest observed values, shown on a log scale.

to discover new roads or manually delineate the entire network from scratch. It is also possible that new roads could be automatically added to the existing network from the road extraction using least-cost path, tensor voting, active contour or fast marching method algorithms (e.g., Miao et al., 2015; Zhou et al., 2019).

The possible road network changes we identified in our study area highlights the contribution of remote sensing to policy makers, land managers, researchers and others that rely on accurate and up-to-date road datasets. Even within this Canadian study area, where road data is frequently updated and shared publicly, we estimated that changes to the pre-existing road network could exceed 20 % of its current length. Two-thirds of this change came from removing old roads, which suggests that the public dataset in Alberta is less likely to reflect de-activated or otherwise overgrown roads than it is to include newly constructed roads. New roads are likely easier to identify during manual delineation from satellite imagery or can be added from information included in permit applications. By contrast, knowing when to remove an old or de-activated road would generally require a site visit or careful photointerpretation.

Up-to-date rural road network data are essential to sustainable forest management (Bennett et al., 2011; Selva et al., 2015), and in our study area road density is a key metric for the provincial grizzly bear recovery plan. The provincial government has recommended that open-access road densities within GBWUs should not exceed 0.6 km/km^2 in Core recovery zones and 0.75 km/km^2 in Secondary recovery zones (Alberta Environment and Parks, 2016). We identified one GBWU where updating the existing road network using our method would change the estimated road density from above the recommended threshold to be below it (Table 2). We also identified several areas where updating the existing road network could result in road density changes at the grizzly bear daily movement scale exceeding 0.15 km/km^2 (Fig. 6). However, more ground data and methods to classify newly detected roads are needed to confirm these numbers. For example, the provincial road density recommendations are for open-access all weather gravel roads, which do not usually include temporary tracks within new forestry cut-blocks. These tracks are often impassable and generally replanted to return to a forested state, though they tend to appear as roads in satellite imagery for at least a year or two, which may account for some of the road density differences in our study. One simple solution would be to mask roads within recent cut-blocks from analysis. Additionally, a remote-sensing based approach allows for repeated updating of road networks over time, which would not only reveal changes and trends, but also enable improved accuracy by filtering out temporary tracks and other single-year misclassifications using time averaging or a Hidden Markov Model (e.g., Hermosilla et al., 2018).

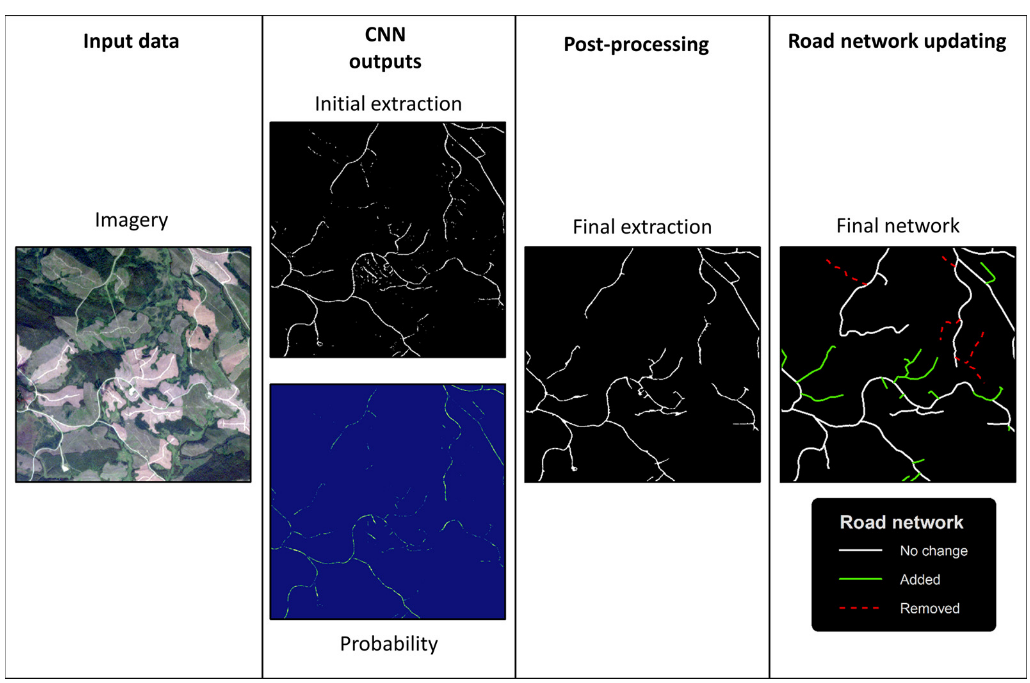

Fig. 5. Example of how updating would change the existing publicly available road network in an area with recent forestry activity.

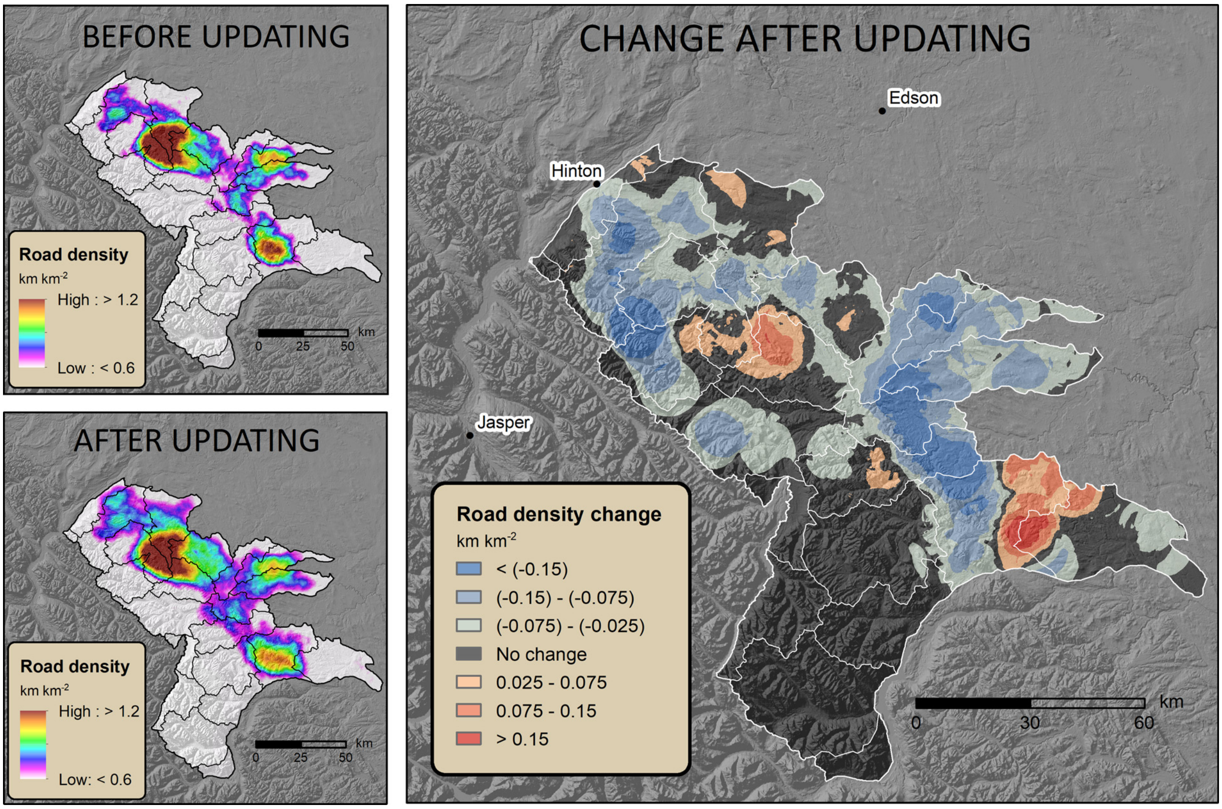

Fig. 6. Change in road density in the study area before and after updating the existing road network. Road density was calculated using a 7.44-km^2 radius moving window. Outlines within the study area represent the 22 grizzly bear watershed units (GBWUs).

Table 2
Road density before and after updating the existing road network at the scale of individual grizzly bear watershed units (GBWUs). Only GBWUs with at least 100 km of roads are shown (16 out of 22 GBWUs shown; all those removed were in the 'Core' recovery zone). GBWUs highlighted in bold indicate a change that crosses the recommended road density threshold for the respective habitat type.

GBWU	Area (km^2)	Road density ($km\ km^{-2}$)		
		Before	*After*	*Change*
Core recovery zone				
Y86	782.4	0.27	0.26	−0.01
Y77	834.1	0.31	0.27	−0.04
Y69	491.7	0.52	0.42	−0.10
Y81	611.8	0.56	0.47	−0.10
Y53	295.7	0.68	0.66	−0.02
Y56	858.5	0.82	0.70	−0.12
Y79	361.6	0.92	0.75	−0.17
Y82	840.9	0.88	0.85	−0.02
Y70	523.8	0.87	0.89	0.02
Y61	648.5	1.02	0.98	−0.04
Secondary recovery zone				
Y87	811.0	0.47	0.50	0.03
Y65	**365.9**	**0.80**	**0.69**	**−0.11**
Y73	618.8	0.95	0.81	−0.14
Y66	432.6	1.11	0.97	−0.14
Y63	570.8	1.04	0.98	−0.06
Y57	710.3	1.06	1.03	−0.03

5. Conclusions

We demonstrated that in rural landscapes even moderately high-resolution RapidEye imagery can provide valuable information on road locations. This finding is encouraging, as it would enable more frequent mapping over larger areas compared to the current availability and cost of very high-resolution imagery. Despite the advances in CNN, post-processing remains a critical step for satellite-based road extraction and it is still challenging to produce a fully connected, vectorized road network directly from imagery. We introduced a routine to update an existing road network by automatically removing old, overgrown roads flagged during road extraction. New roads had to be added in manually, which was time consuming and somewhat subjective, though aided by the road extraction output. Ideally, new roads would always be inventoried during construction by the entities creating them and end up in a digitized spatial database. However, there would still be a need to remove old roads from the database in dynamic landscapes where roads are frequently de-activated, reclaimed or otherwise not maintained. To maintain accurate and current road network datasets in such landscapes, we would recommend (1) creating an initial road network through a combination of automated road extraction and semi-automated updating of available road network datasets, (2) developing stricter requirements for documenting newly constructed roads, and (3) removing old roads from the network using a routine like the one introduced in this study. Ground data is necessary to validate steps 1 and 3. We found the use of participatory approaches to collect ground data particularly useful to gather training and validation data over a large area at minimal cost.

Intellectual property

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

Authorship

All listed authors meet the ICMJE criteria. We attest that all authors contributed significantly to the creation of this manuscript, each having fulfilled criteria as established by the ICMJE.

Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

Acknowledgements

This research was supported by the Grizzly-PAW project (NSERC File: CRDPJ 486175 – 15, Grantee: N.C. Coops, FRM, UBC), in collaboration with fRI Research and FRIAA, Alberta Newsprint Company, Canfor, Cenovus, Repsol, Seven Generations Energy, Shell Canada, TransCanada Pipelines, Teck Resources, West Fraser, Westmoreland Coal, and Weyerhaeuser. More information at: http://paw.forestry.ubc.ca/. We thank the following for their help in coordinating ground data collection: Isobel P. and Cam M. (fRI Research), Bernie M. (Canfor), Ryan S. and Cheryl R. (Shell Canada), Michael H. and Kelsey R. (Westmoreland Coal).

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