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Using emerging technologies for monitoring surface water near railway tracks

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ABSTRACT

The level of water near the railway track is a major factor affecting the safety of train passage. Prolonged periods of heavy rainfall, rapid snowmelt, flash flooding, river flooding, beaver dams or blockage of a culvert result in a rise of water levels. This situation has been the major cause of many derailments in Canada and resulted in fatalities and serious injuries, damage to environment, loss of property, and service disruption. Railway companies strive to identify the development of problematic water levels in the area surrounding the track. This includes visual inspection performed by qualified track inspectors to visually identify waterway blockage and levels issues and air reconnaissance patrols that take place once or twice each year. These inspections rely on the inspectors' judgment and experience regarding the water level, have a limited range of coverage, and do not provide visibility on the water issue in the areas that are out of the vision range but still close enough to affect the track. The air reconnaissance patrol covers a larger area and provides a bird's eye view of all the waterways and identifies blockage of waterway but they are not as frequent. Recent advances in satellite-based remote sensors and tremendous development in unmanned aerial vehicle (UAV) have promoted the field of sensing surface water to a new era. National Research Council Canada and Transport Canada undertook a collaborative research project to evaluate the feasibility of using satellite imagery (including synthetic aperture radar and optical images) and UAV-based RGB images to detect water near railway tracks using data from two test sites in Canada. In addition, Transportation Safety Board (TSB) Rail Occurrence database and TSB's investigation reports were analyzed to identify the root causes of water-related derailment within Canada's rail network in the last few decades. 4 Canadian railway operators were also interviewed to better understand their main water related issues. The results of this project suggested that even though these technologies cannot entirely replace the current methods of water inspection, they offer an additional and inexpensive method to provide trackside water information to track inspectors. It was also indicated that further investigations and testing of technologies over same section of track would be required for drawing a definitive conclusion.

1 INTRODUCTION

The level of water near a railway track can be a major factor affecting the safety of train operations. Prolonged periods of heavy rainfall, rapid snowmelt, flash flooding, river flooding, beaver dams, blocked and under sized culverts or poor drainage design can result in a rise in water levels. The problems associated with high water levels include washout (a sudden release of a large quantity of water which quickly damages the trackbed), massive shear failure caused by submersion of track substructure, pier scour and undermining, and bridge foundation erosion that may occur with or without train loading. Such failures in a Centralized Traffic Control (CTC) territory often leave the track superstructure intact but unsupported. As a result, the washout is not visible until the train is a short distance away, when the train cannot be stopped or significantly slowed before reaching the washed-out track sections. This situation has been a major cause of many derailments in Canada and resulted in fatalities and serious injuries, damage to environment, and loss of property. Occasionally the track washout can be caused by another washout or culvert failure on a nearby road.

Railways strive to identify the development of problematic water levels in the area surrounding the track. This includes visual inspection performed by qualified track inspectors to visually identify waterway blockage and levels issues and air reconnaissance patrols that take place once or twice each year. When rainfall occurs over multiple days and a sustained accumulation is identified, the railways increase the number of special inspections ahead of train traffic. Also, when a certain area is expected to have a large amount of continuous rain or when a severe weather advisory is issued, the railway companies implement additional track inspections to monitor drainage along the railway right-of-way. These inspections rely on the inspectors' judgment and experience regarding the water level, have

a limited range of coverage, and do not provide visibility on the water issue in the areas that are out of visual range but still close enough to affect the track. The air reconnaissance patrols cover a larger area but they are not as frequent.

The historical weather data shows that precipitation has increased in many parts of Canada, and there has been a shift toward less snowfall and more rainfall (Bush and Flato 2019). In the future, climate change is expected to exacerbate flooding issues (Khaliq & Attar, 2017) and extreme precipitation is projected to increase in Canada under both low and high emission scenarios. An extreme precipitation event that now occurs every 50, 20, 10 years is expected to occur every 10, 5, and 3 years under high-emission scenarios (Bush & Flato, 2019), a significant change that will affect infrastructure in the future. It is also expected that warmer winters and earlier snowmelt will combine to produce higher winter stream flows. Therefore, to assist in the identification of future impacts from expected climate changes, it is imperative to develop new ways for water inspection in the vicinity of a railway corridor, particularly through the use of new and emerging technologies.

Recent advances in satellite-based remote sensing and the tremendous developments in unmanned aerial vehicle (UAV) technologies have promoted the field of remote sensing to a new level. These technologies can be adopted by railways (some have already started implementing them) to improve/supplement their current waterway inspection procedures for areas beyond the railway corridor as well as the extreme weather policies. National Research Council Canada (NRC) and Transport Canada undertook a collaborative research project to evaluate the potential of satellite imagery and UAV-based imagery to detect water bodies near railway tracks. The main goals of this project were to 1) investigate the major causes of water-related issues around railway tracks by analyzing historical occurrences within Canada's rail network and interviewing the railway operators in Canada and 2) evaluate the potential of UAV and satellite imagery to map water bodies near railway tracks by testing both technologies over two study sites located within Canadian railway network.

2 HISTORICAL OCCURENCES

NRC reviewed eight Transportation Safety Board (TSB) of Canada investigation reports in which washout and high water level were the main attributed causes of incidents (summarized in
Table *1*). It was found that in all of these occurrences, a special weather condition, such as heavy rainfall over 24 hours, above average rainfall over several days prior to the occurrence, above average daily temperature, etc. was involved. All these factors are anticipated to be more frequent under future expected climate. This review also indicated that seven of these occurrences happened over a section of track without any history of problems. In three such occurrences, an undetected beaver dam located out of the visual range was the major cause. It was also found that the time it takes for a water-related issue to develop and lead to a derailment is so variable and it may range between a month to a few hours.

NRC in collaboration with TSB created a subset of the Railway Occurrence Database (RODS) in which one of the major causes was water-related (e.g. washout, culvert failure, beaver dams, high-water level, subgrade failure, etc.). Washout was found to be the most frequent primary cause of the occurrences in this dataset followed by subgrade failure (Figure *1*a). The analysis also suggested that the main secondary factors were heavy rainfall followed by beaver dams. It also showed that despite the negative effect of climate change, there has been a declining trend in the number of water-related occurrences in the last 20 years. This can be attributed to more frequent and stringent water monitoring and management methods adopted by the railways. The analysis also suggests that June and July are the most critical months of the year in terms of water-related occurrences (Figure *1*b).

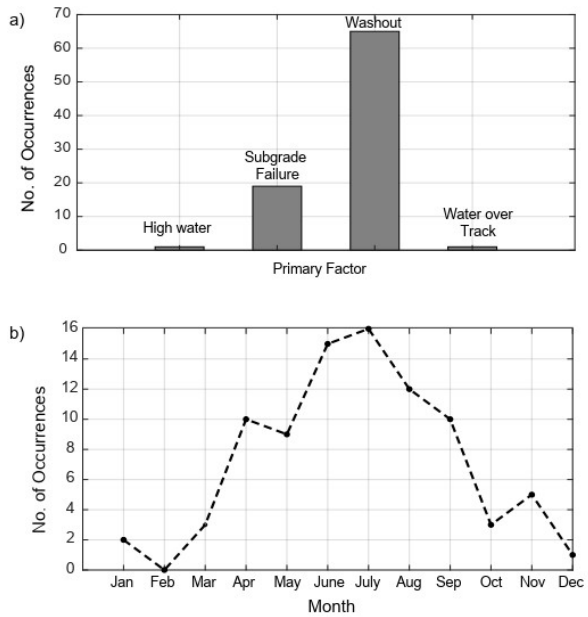

Figure 1. Plots show a) number of water-related occurrences vs primary cause/factor attributed and b) monthly distribution of water-related derailments.

3 INTERVIEWING RAILWAYS

NRC interviewed four Canadian railways (two class-I and two short lines) to obtain their perspectives regarding the major causes of water issues on their networks and to learn more about their current water inspection procedures. These interviews indicated that the water-related issues vary depending on the territories; however beaver dams and culvert failures seem to be the most common issues. The interviewees also indicated that, in their opinion, water issues have become more frequent in recent years due to the effects of climate change. They also indicated that in recent years, they have increased the size of the culverts to the next standard size whenever there is a need for a replacement to allow for higher expected water flow in the future. The information

collected during these interviews also suggested that the railway water inspections are undertaken more frequently than what is required by the regulators. Out of the four, one company indicated that it has evaluated the risk of extreme weather events on its network and identified areas prone to washout, flooding, and drainage issues. This risk assessment is also supplemented with a criterion used to define and trigger a special weather alert that automatically notifies the inspectors to increase their inspection frequency until the situation is eliminated.

Table 1. Summary of TSB's water related investigation reports

Occurrence	Involved beaver dam	Special environmental condition prior to the occurrence	Impeded external drainage	History of problem
Ottawa Valley; TSB report# R09H0006	Yes	Week before the occurrence, above average rainfall	Accumulated water exceeded the capacity of culvert	No
Canadian Pacific, TSB report# R13E0069	No	Abnormally warm temperature increasing seasonal run-off water from melting snow	Ice in the ditch restricted flow to the culvert	No
VIA Rail, TSB Report# R13W0124	No	5 days prior to occurrence, rapid melt of snowpack	Culvert plugged with ice	No
Huron Central, TSB report# R15H0092	No	Above average monthly precipitation	Culvert had either collapsed, sunk, and/or was plugged	Yes
VIA Rail, TSB report# R18W0168	No	Heavy rainfall prior to and on the day of occurrence	Culverts of nearby highway accumulated forest debris and failed	No
Canadian National, TSB report# R92T0183	Yes	Extremely heavy rainfall on the day of occurrence	No	No
Canadian Pacific, TSB report # R97T0097	Yes	Rapid melting of snow during the two weeks preceding the derailment	No	No
Canadian Pacific, TSB report # R13C0069	No	150 mm of rainfall in 48 hour period prior to derailment	No	No

Even though the other three companies did not perform any formal risk assessment, the discussions suggested that this kind of analysis is continuously performed by the inspectors on-site. The inspectors are familiar with their territories and from the experience, they know where the problematic sites are located and therefore, they plan for the inspection and mitigation measures accordingly. One of these companies also indicated that they use UAVs to inspect water in areas that are difficult for inspectors to reach. They indicated that UAVs are a useful tool that result in significant efficiency gains; however their use is limited as they can only be piloted by certified operators. All interviewed companies indicated that the current water inspection procedures are sufficient for safe railway operation but there is certainly room for improvement, especially using the new technologies.

4 METHODOLOGY

This section briefly discusses the basic principles of water detection from satellite and UAV images and introduces two test sections on Canada's rail network

that were used to evaluate the potential of these technologies.

4.1 Water detection using satellite data

One of the significant applications of remote sensing is to identify changes in water bodies on Earth. Surface water bodies are dynamic in nature, because they shrink or expand with time, owing to a number of natural and human-induced factors (Huang, et al, 2018). The process of identifying changes by observing different satellite images taken at different times is called change detection. Change detection quantitatively analyzes temporal effects by using the satellite images taken at different times (Bhavani, et al, 2018).

Satellite remote sensors can be divided into two categories: passive and active. Passive remote sensors respond to external stimuli. They record natural energy which is transmitted or reflected from Earth. Reflected sunlight is the main source of energy for passive remote sensors. On the other hand, active remote sensors use some internal stimuli to obtain information about the objects or phenomenon occurring on Earth (Rana, et al, 2017). Satellite-based optical sensors (also referred to as visible band sensors) are considered as passive, and microwave sensors (also referred to as Synthetic Aperture Radar (SAR) are considered as active types.
The multispectral nature of optical sensors provides some advantages for water detection, however their application in detecting surface water is constrained by several environmental factors, such as cloudy sky conditions, cloud shadows that may seriously affect water detection due to similar spectral characteristics between shadow and flood/standing water. Optical sensors also fail to image the water surface beneath flooded vegetation canopies (Alsdorf, et al, 2007).

SAR's use of long wavelength radiation has the ability to penetrate cloud coverage and certain vegetation coverage. It is independent of solar radiation and therefore they can work day and night under any weather conditions. Radar can measure amplitude (the strength of the reflected echo) and phase (the position of a point in time on a waveform cycle). The dielectric and geometric properties of various target surfaces affect the intensity of the backscatter signal and is the basis by which SAR differentiates features on the ground (Irwin, et al, 2017). Fresh water has a high dielectric constant and smooth water surfaces usually provide a specular reflection of microwave radiation; both of these attributes result in very little energy backscatter (appearing dark in the image). In contrast, land surfaces scatter much more energy back to the radar source due to surface roughness and volume scattering (White, et al, 2015). However, SAR-based estimates of the extent of surface water are hindered by wind roughening the water surface for the wavelengths used by most sensors (Alsdorf, et al, 2007). Also due to the side-looking nature of SAR, some areas on the ground surface may be misclassified when terrain or other features create regions of radar shadow (Mason, et al, 2010).

4.2 Water detection using UAV based RGB images

An RGB image is the true-colour image that one can see in everyday life. The abbreviation "RGB" stands for Red, Green and Blue, and it refers to the three colours of light (known as channels) used in image processing science. The three colours can be mixed together to form different colours and to produce colour images on screens.

Water detection methods can be categorized as: traditional methods (hand-crafted features such as colour, texture, etc.) or deep learning-based methods (to learn to extract informative and discriminative features). These also vary depending on whether the camera is fixed or moving, placed on a ground carrier or mounted on a UAV, and whether the methods work on a per-image basis (i.e., only spatial context taken into account) or on videos (i.e., temporal context also considered).

Water is detected based on cues such as colour, texture and reflections detected in stereo-range data, for example by Rankin (2004). That is, a pair of cameras used to generate range images from which reflections are detected. A range image contains the distances of given points in the scene to another point. This method is appropriate for ground vehicles and autonomous navigation. Only colour-based cues are insufficient as they lead to many false detections (e.g., in cases of snow, white rocks, sky regions, and overexposed imagery).

The texture-based water cue proposed in Rankin (2004) is focused on low texture water regions. Although their method was able to detect regions not detected by the colour-based cues only, it required proper thresholds to be set up and yet yielded false detections. In addition to colour- and texture-based cues, Rankin (2004) proposed stereo range reflection-based water cues as well. In Mettes, et al (2017), the dynamic texture of water surface was exploited in differentiating water regions from non-water regions. Their method is not applicable where the camera is moving, e.g., carried by a UAV. Mehra, et al, (2016) proposed a technique to detect stagnant water bodies based on classical hand-crafted features (e.g., Scale-invariant feature transform - SIFT).
Besides 2D imaging, some researchers, e.g., (U.S. Patent No. US 9,460,353 B2, 2016), have proposed the use of 3D imaging systems to detect water bodies based on certain characteristics which serve as cues for water's presence, similar to and expanding on the techniques described in Rankin (2004). However, the techniques suffer from many false detections.

Some researchers have addressed the problem of water detection in scenarios such as floods on roadways. An example of such a work is that by Sazara (2019) in which a suite of algorithms were proposed and evaluated. The paper states that remote sensing-based water detection methods lack local details which are needed to gain deeper information regarding the extent and severity of water on the inspected regions.

Kawaguchi (2016) proposed the use of infrared cameras to detect water and dike regions to monitor the water levels in urban water channels. Instead of using

RGB image sequences alone, Ghahremani, et al (2017) employ thermal images as well. However, the dataset and the proposed method seems to consider a fixed camera and as such are based on the assumption that non-water regions have no dynamic behavior compared to water region pixels.

Some researchers have investigated the use of UAVs to detect and monitor water levels. For example, Ridolfi, et al (2018) use a UAV to capture images in dam sites and exploit filter-based techniques to identify boundaries between water and non-water surfaces. Camera-based methods benefit from wide aerial coverage while fetching local details, in contrast to Internet-of-Things or sensor-based methods (Arshad, et al, 2019).

Another methodology for detecting water in single images is that of Han, et al, (2018). In their method, a deep learning method known as fully convolutional network (FCN) was modified to learn the reflection of objects and sky on the water.

Adhering to and in spite of the work required to meet strict safety and security regulations, many railways are investigating and deploying UAV technology for maintenance, surveillance, etc. (Federal Railroad Administration, 2018). The use of UAVs in the railway industry ranges from a passive role, such as rail inspection and surveillance, to an active role, including maintenance and on-site reparation. Even though UAVs are used in many areas such as bridge maintenance and inspection, railway infrastructure inspection, and object detection (e.g., vegetation, water, animals), the exploration of UAVs in preventing the accumulation of water around railway tracks due to flooding or snow-melting has not yet been extensively investigated by researchers. This is due to the fact that the detection of water bodies in RGB images, as those detected by UAV cameras, is a challenge. Water's shape and colour change frequently and continuously throughout a day. Further research work is needed in this area. The recent advancements in deep learning-based computer vision, especially with regards to convolutional neural networks (CNNs), motivates this study to investigate and evaluate CNNs for the task of water detection in RGB images captured by UAVs.

4.3 Test sites

Two sites were selected along Canada's rail network to evaluate the potential of Satellite and UAV images for mapping surface water. Site-I, located on Churchill subdivision (Manitoba), used for assessing Satellite images (optical and RADAR) and Site-II, located on a railway line in eastern Canada, used to investigate the potential of UAV images. The UAV is used by the owner of this line to inspect water bodies located around railway tracks and also in areas that are difficult for their inspectors to reach.

5 RESULTS AND DISUSSION

5.1 Satellite data

The freely available optical images from Landsat 8 and radar images from Sentinel-1 between May and October of 2019 (one image per month) were obtained for a section of track along Churchill subdivision.

The images obtained from the Landsat 8 are subject to many quality issues; in particular, problems with instrument saturation, topographic shading (where topography does not allow direct solar radiation), cloud shadows and instrument failure. The presence of cloud and cloud shadows decrease the accuracy of the results of remote sensing applications as they obscure the land surface, and the brightening effect of clouds and the darkening effect of cloud-shadows influence the reflectance of each band (Zhu & Woodcock, 2014). The band quality assessment (BQA) data for each image was first reviewed to evaluate its suitability for water mapping. The analysis of this information showed that out of the 8 images, 7 were affected by the presence of clouds and shadows and were therefore not appropriate candidates for water detection (an example is shown in Figure 2). This is a significant limitation that was noted by other researchers as well. This limitation prevented the mapping of the temporal variations of surface water using optical images.

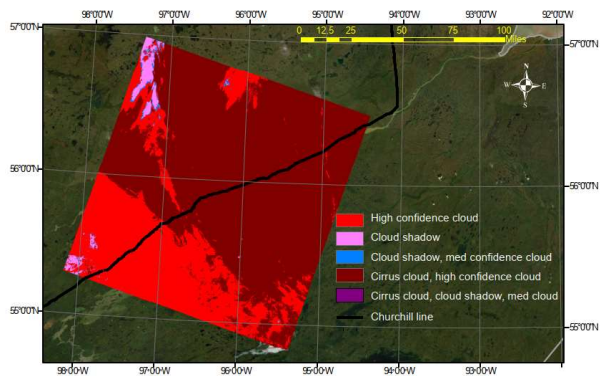

Figure 2. Quality assessment band for the optical image collected from Churchil subdivision on September 07, 2019.

Radar images from Sentinel-1 (Level 1 GRD images IW mode with pixel spacing of 10 m) were collected across the study region using the Alaska Satellite Facility website (https://search.asf.alaska.edu/#/). The analysis of radar images conducted based on a technique known as segmentation. This technique is the most commonly used approach to map surface water from radar imagery. In this method, all pixels with a backscatter coefficient lower than a specified threshold in an intensity image are mapped as water. This technique is useful for producing results quickly and inexpensively and is only suitable for calm open water with a specular backscatter response (Martinis, Twele and Voigt 2009) (White, Brisco and Dabboor, et al. 2015). Thresholding could be fixed, in which the threshold value is held constant throughout the image (which is the case in this project) or local (dynamic thresholding) which varies with the position of the pixels in the image. A suitable threshold has a direct impact on the classification of features in an image. It should be noted that before segmentation stage, some pre-

processing techniques are required to calibrate and filter the RADAR images. A more detailed discussion on pre-processing steps can be found in (Roghani, Mammeri, and Siddiqui, 2019).

Figure 3a presents the output intensity images for the image taken on Churchill test site on May 30, 2019 and Figure 3b shows its equivalent histogram and the threshold value used to extract water from other land features. Similar plots were created for each of the images taken between May and October 2019 and used to map variation of surface water over the test section. The results are presented in Figure 4.

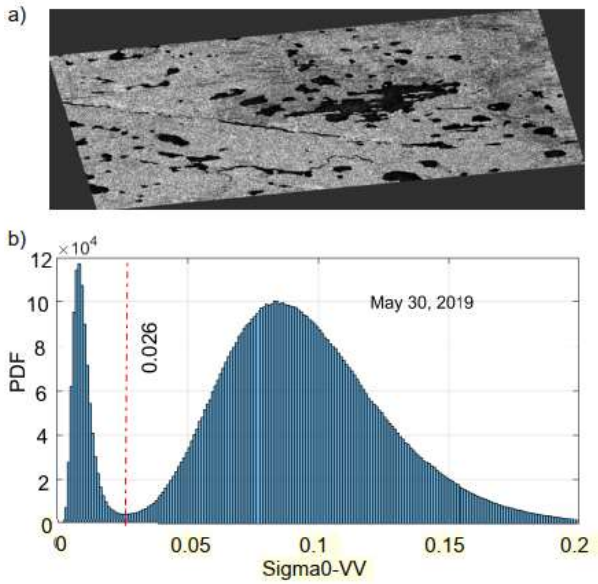

Figure 3. a) The VV polarization intensity image and b) the histogram of the intensity image histogram for the image taken Churchill test site on May 30, 2019 (the red dashed line shows the threshold used to extract water bodies).

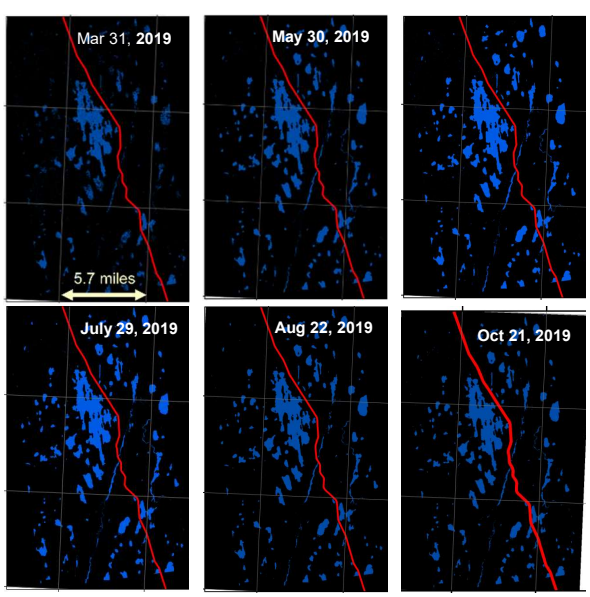

Figure 4. Surface water mapped using satellite data from Sentinel-1 near a section of track along Churchill line (the red line show the railway line).

The output images (mapped water shown in Figure 4) can be imported into a GIS-based software application (e.g. ArcGIS®) to detect temporal changes in water extent. This information can be aligned with the other datasets such as culverts and bridges locations, geology information, topography, and historical problematic areas allowing the track engineers to determine the high-risk areas.

5.2 UAV images

In this work, a deep learning model based on CNNs was developed for the segmentation of rail-tracks and water regions in UAV-based images, labelled as *RailWater-UNet.* This model is a multi-scale Fully Convolutional Neural network (FCN) designed in an encoder-decoder architecture inspired by U-Net (Olaf Ronneberger, 2015). For a given image, the model learns to identify and differentiate between different pixels (or groups of pixels) belonging to the different classes (water, railway track or other regions). The model is basically used to indicate whether a particular pixel (or group of pixels) belong to water, railway track or other regions in a given image. The dataset is split intro training and testing sets for respectively training and testing the model with.

The effectiveness of the model can be assessed using Mean Intersection over Union (mIoU). The mIoU metric gives a measure of how close the model's predicted regions match with the actual ground truth regions for various classes (e.g., water and railway track).

Different versions of the model were trained with the training set, varying the number of training rounds (i.e., epochs) used. Here, we present the results of three such versions: model trained for (i) 100 epochs, (ii) 300 epochs, and (iii) 500 epochs. The mIoU values for each model are summarized in Table 2. The closer an mIoU score is to 1.0, the better it is.

Table 2. Summary of testing set evaluation

Model (#epochs trained)	**mIoU**		
	Background	**Rail-track**	**Water**
100	0.940	0.512	0.660
300	0.944	0.545	0.673
500	0.944	0.544	0.673

The sample outputs of the Model500 are shown in Figure *5*. The left column shows the predicted segmentation mask overlaid on the input image while the right column shows the original input image.

The performance of the RailWater-UNet model could be further improved by incorporating ideas inspired by some well-known AI models such as ResNet-like skip connections (He, et al, 2016). Moreover, newer semantic

and unsupervised segmentation models could be studied in the context of rail and water segmentation.

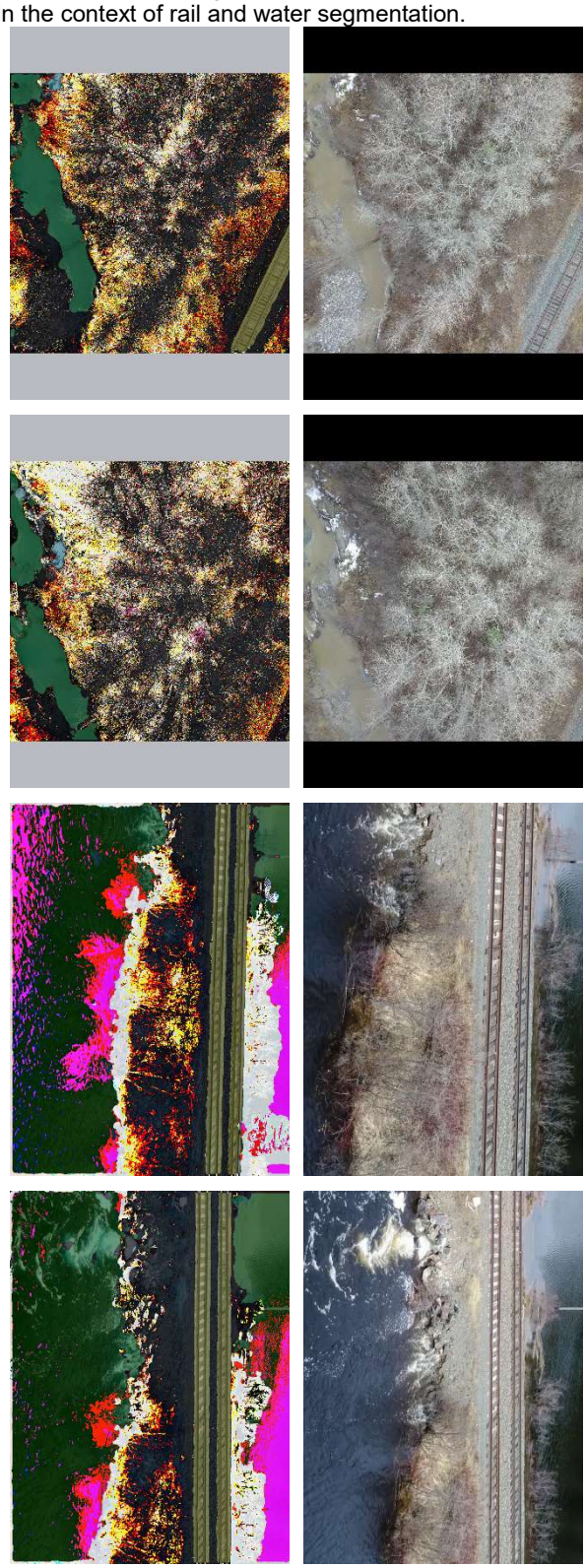

Figure 5. [Left Column] Sample prediction outputs (Greenish regions: Water, Yellowish regions: Railway track, others: background or ignored classes). [Right Column] Original test images.

5.3 Comparing Satellite and UAV results with hi-rail inspection

Table 3 compares the advantages and limitations of using UAV and satellite data for water inspection with hi-rail/visual inspection by considering five different indicators: spatial and temporal resolution, visibility range, water detectability, and cost of data acquisition. It should be noted that the information in this table reflects authors' opinion based on the preliminary results and may change as more data is available. In addition, for a true comparison, the advantages and limitations of these methods should be assessed by testing over same sections of track.

As it is described in this table, each method has its own advantages and limitations. Given the information obtained regarding the water-related derailments during the interviews and the review of TSB's investigation report, the current state of UAV and satellite technology does not allow for their use as the sole method for water monitoring near railway tracks. However, the limited observations from this project suggested that UAV and satellite imagery can provide supplementary information to hi-rail inspection.

Table 3. Comparing the advantages and limitations of various water monitoring methods.

	Satellite	UAV	Hi-rail
Spatial resolution	10 m ×10 m for sentinel-1, filtering would lower it further	Depending on resolution of camera and flight height	Human eye
Temporal resolution	6 days for sentinel-1	Flexible	1-2 times a week, could be more frequent**
Visibility Range	No limit	Depending on flight height, approximately ~10-50 m around the track	Right-of-way
Water detectability	Easy water detection due to water response to Radar signals	Challenging as colour of water differs	Human eye
Cost*	$	$$$	$$
Major limitation	Inadequate spatial and temporal resolution for water issues with ROW	A large dataset of images required for automating water detection process	Not automated, limited in range

* Cost of data acquisition
** Railways also conduct helicopter and/or drone inspections 1-2 times a year to supplement their hi-rail/visual inspections

6 CONCLUSIONS

National Research Council Canada and Transport Canada undertook a collaborative research project to evaluate the potential of satellite and UAV-based

imagery to detect water bodies near railway tracks. Four Canadian railway companies interviewed by NRC indicated that even though the current water inspection procedures are sufficient for safe railway operation, there is certainly room for improvement and complement the visual inspection done by the qualified Rail Inspector, especially using the new technologies. The interviewees also indicated that, in their opinion, water issues have become more frequent in recent years, an observation that is consistent with the results of recently published Canada's Changing Climate Report that suggests that extreme precipitation is expected to increase under both high and low emission climate scenarios. Therefore, to assist in the identification of future impacts from expected climate changes, it is imperative to develop new ways for water inspection in the vicinity of railway corridors, particularly through the use of new and emerging technologies.

The potential of satellite and UAV images were evaluated by testing them over two study sites. The results suggested that even though these technologies cannot replace the current methods of water inspection, they offer an inexpensive and effective method that provides information about the water issues that may not currently be available to track inspectors. The implementation of these technologies into a railway's water inspection methods could provide a better view of the problems occurring far from the track. This is especially useful during the springtime and heavy rainfalls to reduce the risk of water-related derailments.

Currently, NRC and Transport Canada are working on the next phase of this project whose main goal is to combine several different technologies into a single framework and evaluate their potential in water detection through limited field trials. These trials will include two types of sensors: LIDAR and high-resolution cameras (providing images within visible and infrared spectrum) from three different platforms: satellites (space), UAV (airborne), and hi-rail truck (at track level). The combination of various sensors and platforms provides a wide range of complementary information with different spatial and temporal resolutions as well as varying fields of view. These results are expected to provide the most comprehensive picture of the water situation near railway tracks and mitigate the risk of water-related derailments on Canada's rail network.

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