



Technical Report

Integrating satellite and instrumented hi-rail truck data into current railway water inspection procedures to improve its effectiveness amidst changing climate conditions

Prepared for: Ontario Northland Transportation Commission

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March 31, 2026

Project: A1-022939

Report Number: AST-2024-0014

Version 2.0



Change control

Version	Date	Description	Lead Author
0.1	March 29, 2024	Draft Report	A. Roghani
1.0	April 15, 2024	Initial release	A. Roghani
2.0	March 31, 2026	TC Publication to Federal Open Science Repository of Canada	A. Roghani

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- **Dr. Alireza Roghani**, as the primary technical lead of this project, made contributions to the project's development and planning, guided the research direction, analyzed data, and drafted the report.
- **Dr. Juan Pablo Arroyo-Mora and Dr. Margaret Kalacska**, led the satellite component of this project. Their responsibilities included acquiring, analyzing, and interpreting satellite imagery, as well as drafting Section 1: Using satellite imagery for mapping water of this report.
- **Sylvie Chenier**, is the project manager and provides coordination efforts between the tasks and teams, including coordination of the sections of the report.
- **Dr. Samy Metari, Dr. Taufiq Rahman**, led the hi-rail portion of this research project, including the data collection, analysis, interpretation, and drafting Section 4 of this report: Using instrumented hi-rail truck for water mapping.
- **Fatma Usta and Chengbi Dai**: led the development of the dashboard.
- **Ehsan Raei**, contributed to the analysis of hi-rail data and the development of the dashboard.

Acknowledgement

The authors would like to thank the following people for their help throughout this project:

- **Vincent Konadu**, Ontario Northland Transportation Commission: For contributing input into the project deliverables and aiding with the client data transfer;
- **Paul-Andre Lajeunesse**, Ontario Northland Transportation Commission: For ONTC Director-level project support;
- **Yan Liu**, National Research Council Canada: For his invaluable efforts in developing the dashboard platform and participation in the project;
- **Dr. Abdelhamid Mammeri**, National Research Council Canada: For leading the Intelligent Transportation System (ITS) team and contributing to the hi-rail component of this project;
- **Ryan Pelletier**, Ontario Northland Transportation Commission: For leading and ensuring safe navigation during field data collection along ONR right of way;
- **Paul Michael Pilkington**, Ontario Northland Transportation Commission: For additional ONTC contribution and project support;
- **Joe Viscek**, Ontario Northland Transportation Commission: For his efforts in leading the project on behalf of ONTC, his invaluable input as a client in regards to railway needs and focus, and for coordinating onsite data collection and data transfer.

Executive Summary

The National Research Council Canada (NRC) partnered with (Ontario Northland Transportation Commission) ONTC to advance NRC's current framework using remote sensing technologies to monitor surface water along ONTC's right-of-way, specifically using satellite imagery and instrumented hi-rail trucks. The aim of this project is to help ONTC integrate the satellite and hi-rail-based water monitoring data into its water inspection toolbox. This report presents the results of this project.

The NRC, in collaboration with ARSL, investigated the potential of PlanetScope and Sentinel-2 satellite imagery platforms for mapping surface water along ONTC's rail network. This investigation included a comparative analysis of their abilities to map small water bodies. The results from various test sections indicated that PlanetScope's superior resolution was beneficial for the project's objectives. Without it, the numerous small water bodies present along the ONTC network could not be accurately mapped, using the Sentinel-2 platform alone. Additionally, the PlanetScope has advantages over Sentinel-2 for mapping surface water over time due to its ability to handle cloud cover and its temporal resolution which is required for accurate water detection.

Subsequently, the PlanetScope was selected to generate a map of the surface water area over the entire 700 miles of ONTC railway network, with a buffer zone of 0.5 mile on each side of the rail line. This mapping was carried out on three separate occasions throughout 2023, in May, July, and October and included processing 335 PlanetScope images. To enhance the accuracy of surface water mapping, a wetland classification layer was incorporated, as wetlands often present a unique challenge in surface water classification. The dense surface vegetation can impede the identification of areas with high water content and flooding potential. Additionally, a watercourse layer, indicating the direction of water flow, was extracted from the Ontario Hydro Network (OHN) database and used to supplement the water classification.

A hi-rail truck was equipped with LiDAR, RGB Cameras, Infrared Cameras, and a GNSS-IMU to develop a data acquisition (DAQ) system capable of collecting data in different sensing modalities and multispectral bandwidths. A high-capacity computer, a portable power system to supply power to all electrical components, and a monitor were installed inside the vehicle. The instrumented hi-rail truck was deployed for data collection between Mi. 0 – 57 of the Kirkland Lake Subdivision (approximately 90 km) for two runs conducted on July 13 and October 26, 2023. To measure water levels, a novel algorithm was developed using the data acquired from the different 2D and 3D sensors. The 3D map of the environment was generated using simultaneous location and mapping (SLAM) algorithms applied to the raw LiDAR point cloud. The locations of water bodies were identified in the 3D map and confirmed with RGB cameras. The water level was then calculated using a fixed reference point on top of the rail and one or more reference points surrounding the water body. The elevation difference between the water surface and the top of rail was calculated, with smaller values indicating water bodies closer to track surface and thus posing a higher risk for railway operations. Efforts were made to automate the process of water detection using 2D RGB/thermal images, but existing deep learning models had difficulty generalizing the detection of water due to differences in water appearance between training and testing images. Future work will focus on automating the water detection process by developing several algorithms which would use the fused 2D and 3D sensor data to extract the 3D points surrounding the water surfaces.

An interactive online dashboard was developed by the NRC to display the results obtained from the satellite and hi-rail truck. Hosted on a secure cloud, this web-based dashboard is accessible to ONTC and is designed to provide valuable information to decision-makers in an easily accessible format.

The outcomes of this project provided significant insights into the benefits, capabilities, and constraints of measurements derived from satellite and hi-rail platforms. More importantly, it highlighted the limitations and advantages of integrating this data into a web-based dashboard that can be utilized by the ONTC to make informed decisions regarding water inspection. Currently, the dashboard functions primarily as a viewer for the available data. However, it holds the potential to evolve into a risk mapping dashboard, where various layers of data can be integrated to identify areas within the network that require action. This information could also be leveraged for capital investment decisions or for prioritizing maintenance activities.

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1 Introduction

The level of water near a railway track can be a major factor affecting the safety of train passage. Prolonged periods of heavy rainfall, rapid snowmelt, flash flooding, river flooding, beaver dams, blocked culverts, or poor drainage design can result in a rise in water levels. Climate change is expected to exacerbate flooding issues [1] 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, and 10 years is expected to occur every 10, 5, and 3 years under high-emission scenarios [2], a significant change that will affect infrastructure in the future.

Through previous research projects, the National Research Council Canada (NRC) Automotive and Surface Transportation and Aerospace Research Centers, in collaboration with Applied Remote Sensing Lab (ARSL) at McGill University, demonstrated the potential of satellite, Remotely Piloted Aerial System (RPAS), and instrumented hi-rail truck imagery to inspect surface water near railway tracks. The results of these studies provided valuable information regarding the operational challenges of these systems, the advantages and limitations of the measurements from each platform, the minimum specifications required to attain results, the challenges in developing highly effective AI algorithms, and the potential application of the measurements for monitoring other track features.

In 2023, the NRC partnered with ONTC to advance its current framework using remote sensing technologies to monitor surface water along ONTC's right-of-way, specifically using satellite imagery and instrumented hi-rail trucks. The aim of this project is to help ONTC to integrate the satellite and hi-rail based water monitoring data to its water inspection toolbox. This report presents the results of this project.

2 Objective and scope of work

The objective of this project was to advance the development and implementation of emerging technologies, tools, and approaches to address the increasing risks of water-related issues projected under climate change on Canada's rail sector. To this end, the NRC assisted ONTC in integrating remote sensing technologies into its water monitoring methods. The remote sensing technologies used in the study include satellite imagery and instrumented hi-rail trucks. To facilitate the implementation of these technologies into ONTC's system, an online dashboard/tool was also developed that allows ONTC's engineers to view the results of the satellite and hi-rail data processing along with other layers of track and environment data. This is a critical incremental step in integrating these technologies into ONTC's current water monitoring toolbox.

The following provides a high-level overview of the tasks accomplished during this project:

Satellite:

1. The imagery from the PlanetScope and Sentinel-2 platforms was compared and the level of detail that can be extracted from each one was compared. PlanetScope was selected as the platform best suited for water mapping in this project; and
2. Using Google Earth Engine, the satellite images from PlanetScope were processed, and a map of surface water area (spatial variations) was created for over the entire ONTC's rail system (~700 mi.) over 3 time periods in May, July, and October 2023.

Hi-rail:

1. The hi-rail truck was instrumented for field deployment on ONTC's tracks;
2. Two (2) separate field trials were conducted using the instrumented hi-rail truck on July 13 and October 26, 2023, between Mi. 0 – 57 of the Kirkland Lake Subdivision (approximately 90 km); and
3. The images and collected data were analyzed and new and previously developed water detection algorithms were used to:
 - a. Create 3D point clouds from track level for the entire Kirkland Subdivision;
 - b. Create a map through which water within the right-of-way is visible; and
 - c. Calculate the distance between surface water and the track surface.

Dashboard:

1. An interactive online dashboard was developed and hosted on a secure cloud to display results from the satellite and hi-rail truck. This dashboard, accessible to ONTC, consists of two distinct sections, allowing for the review of various data layers in an environment similar to ARC GIS as well as viewing and manipulating of 3D point clouds generated from hi-rail LiDAR measurements; and
2. Supplementary data was added to the dashboard to assist ONTC in evaluating water conditions along its network. This includes the locations of wetlands, water flow direction, and a track asset database. Furthermore, to demonstrate the potential of the dashboard for future expansion, track testing data including geometry defects and rail flaw defects were also integrated into the dashboard.

It is important to note that the detailed dashboard information is not presented in this report, as it contains ONTC's sensitive data.

3 Using satellite imagery for mapping water

Satellite based water mapping is a common activity for several Earth observation applications and is key for monitoring surface water changes over time [3]. The overall objective of this section is to implement existing software tools to process satellite images (i.e., Google Earth Engine) to create a map of the surface water area over the 700 miles of the ONTC railway network for the year 2023. A secondary objective was to identify which satellite platform, the European Space Agency (ESA) Copernicus Sentinel-2, or the PlanetScope Dove Constellation, provided better results for surface water mapping. Table 1 compares the main characteristics of the satellite sensors, while Figure 1 showcases the bands of the three PlanetScope Dove constellations, and ESA’s Sentinel-2A spectral bands.

Table 1. PlanetScope Dove and Sentinel-2 revisit times, spatial resolution and cost comparison.

Characteristics	PlanetScope	Sentinel-2
Revisit Time (Temporal res.)	Daily	10 days with each satellite (Sentinel 2A and 2B). Five days with combined satellites.
Pixel size (Spatial res.)	3 m resampled	Four 10-m bands, six 20-m bands, and three 60-m bands (13 bands).
Availability of free imagery	N/A	Unlimited

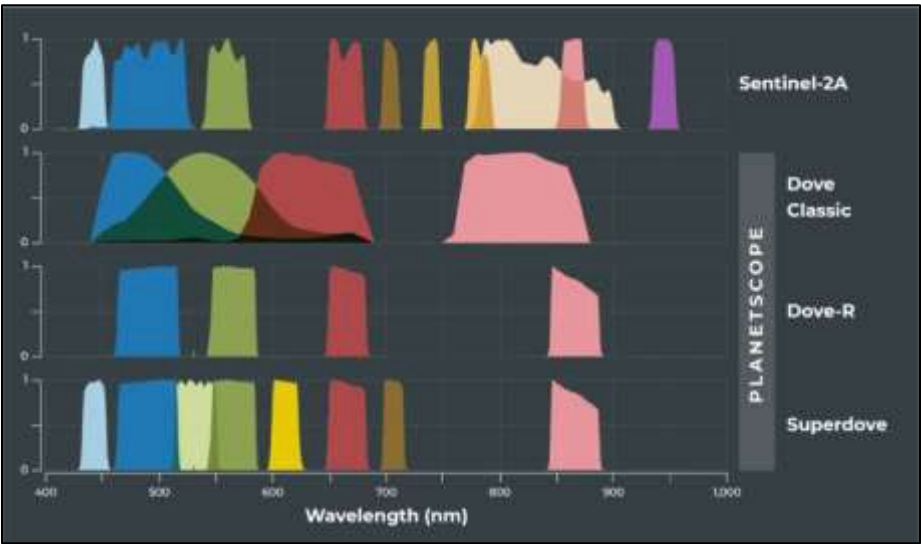


Figure 1. Spectral band comparison between Sentinel-2A and PlanetScope constellations. For this study, the Superdove constellation was used. Source: Harrison et al. 2021.

3.1 Study Area and ancillary data

The 700 miles of the ONTC railway network is located mainly in Ontario, with a small section located in Quebec, west of Rouyn-Noranda (Figure 2). This vast network is divided in eight subdivisions, passing through various wetland ecosystems – bogs, fens, swamps and marshes. Wetlands are a key consideration for surface water classification, because in many instances, surface vegetation impedes the identification of areas with high water content and flooding potential. For this reason, a wetland classification for both the Ontario network, and the small area in Quebec is provided to supplement the surface water mapping data generated for this report. The data description for the wetlands layers were taken from [4] (Ontario) and [5] (Quebec) while and the interactive online map for Ontario can be found at [6].



Figure 2. ONTC railway network subdivisions for surface water assessment based on three time periods in 2023.

A second layer was acquired to supplement the water classification with the water flow direction. The Ontario Hydro Network (OHN) database includes the location of watercourses in the province. According to the data description document [7], a watercourse is defined as a “*line features (natural and constructed) that describe various realizations of flowing water at a medium scale of 1:10K in Southern Ontario, 1:20K in Northern Ontario and 1:50K in the Far North*”. Figure 3 shows an example of the ancillary data for the wetlands and watercourses.

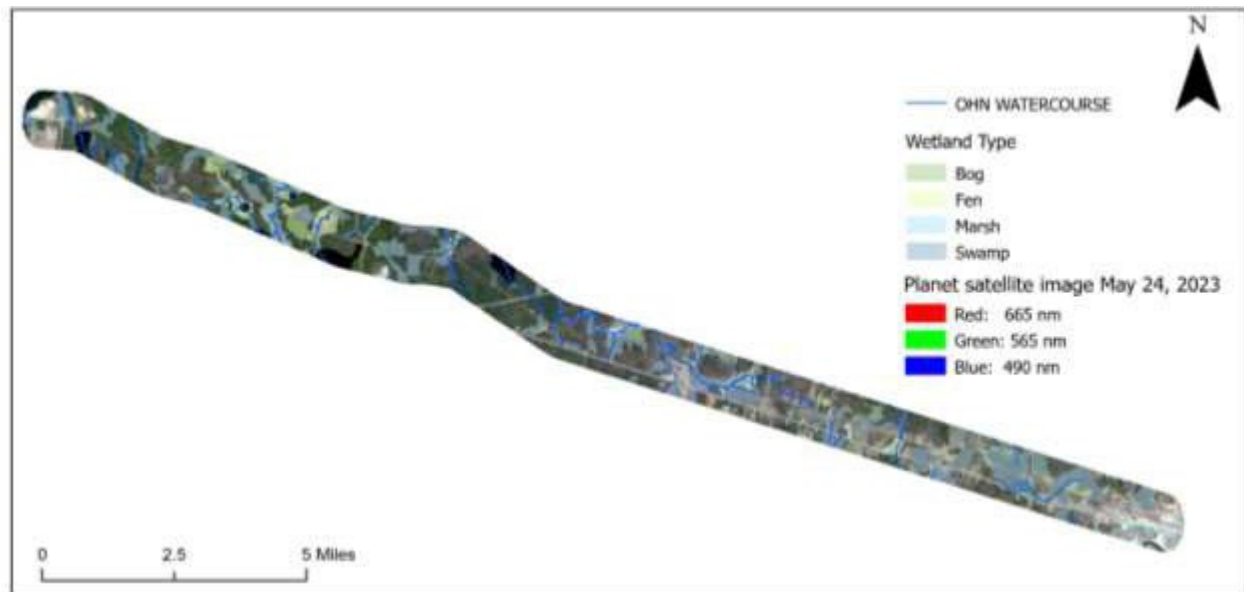


Figure 3. Example for the Pagwa Railway Subdivision with the Ontario Hydro Network layers: Wetlands and Watercourses.

3.2 Methods

A key factor in periodically mapping surface water is the availability of imagery with low or no cloud cover. In this project, the threshold for considering an image suitable for analysis was set at 20% cloud cover. To select the optimal satellite option for multitemporal surface water mapping, the effect of cloud cover on imagery availability was evaluated. This evaluation also considered the temporal resolution, which refers to the time it takes for a satellite to complete an orbit and revisit the same observation area. Based on these two parameters, the PlanetScope Dove Constellation emerged as the most suitable option for mapping surface water over time (see results Section 3.4). Moreover, one of the goals of this project was to compare the Sentinel-2 (no cost) outputs with the PlanetScope Dove Constellation (available for a fee) outputs for water surface mapping. A preliminary analysis was conducted on two selected areas that contain large (rivers) and small (streams) water bodies (Figure 4).

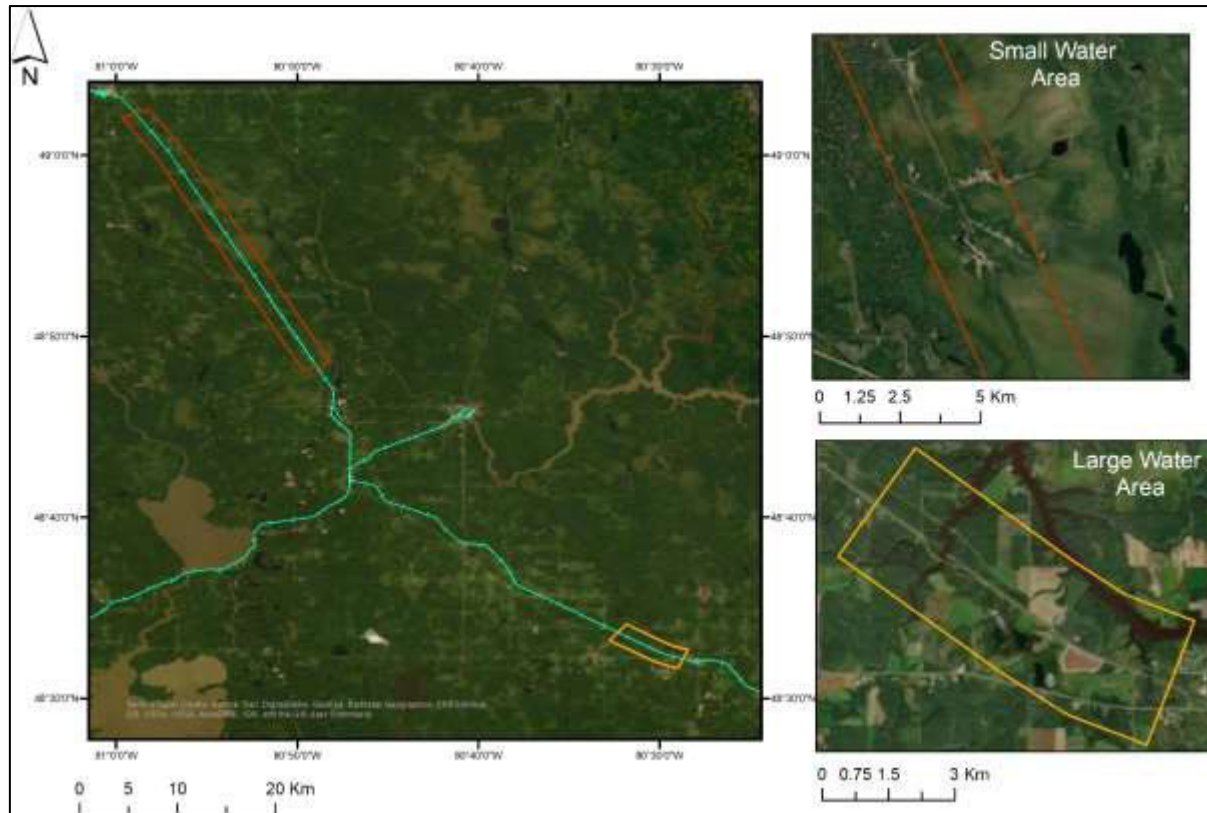


Figure 4. Sample area for comparing Sentinel-2 and the PlanetScope Constellation imagery for surface water mapping.

The general process used to generate surface water from the PlanetScope Constellation is shown in Figure 5. Given the large extent of the study area with 700 miles of railway network, railway subdivisions were used to simplify data acquisition, processing and presentation of the results. Table 2 shows the network subdivision names, railway length, and area based on a half a mile buffer around the railway tracks.

Table 2. ONTC subdivisions for surface water mapping from the PlanetScope Constellation.

Subdivision	Length (mi)	Area km ²
Island Falls	192.6	508.3
Kapuskasing	141.3	353.1
Pagwa	22.1	64.7
Devonshire	37.9	73.1
Iroquois Falls	8.5	21.5
Ramore	119.8	259.5
Kirkland Lake	62.8	159.7
Temagami	151.8	314.4
Total		1,754.3 km ²

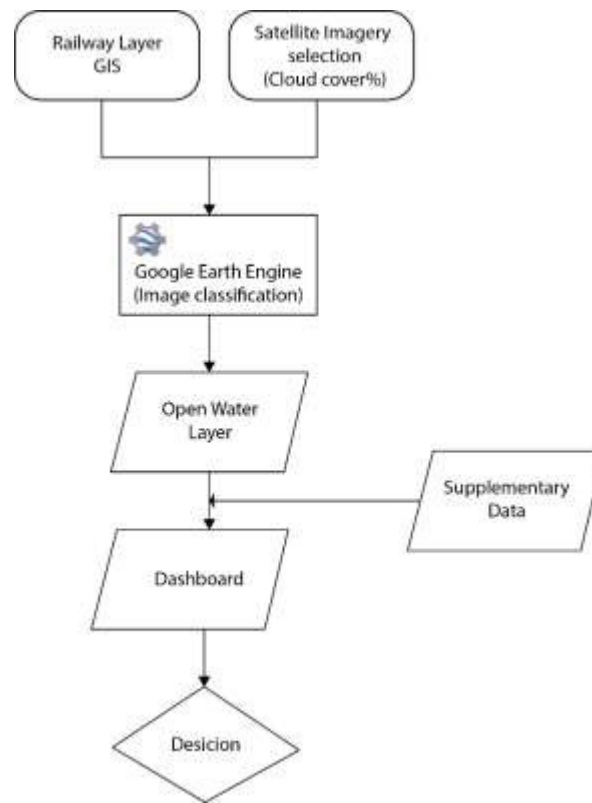


Figure 5. Flow chart showing the overall steps for surface water mapping for the ONTC railway network.

Based on the cloud cover and PlanetScope image availability, the months of May, July and October were selected to map surface water in the eight subdivisions. Section 3.3 describes the general approach in Google Earth Engine (GEE) used in this study. A total of 121 Planet images were used for May, 91 for July and 123 for October (335 total).

3.3 GEE surface water mapping

Despite the success of small-scale surface water mapping approaches such as the use of indices like normalized difference water index (NDWI) [8], in the ecosystems surrounding the ONTC rail network, a different approach was needed that was less sensitive to differences in illumination conditions, water quality (e.g., turbidity) and remained sensitive to water from the different wetland classes. The overall approach was based on a modification of the Otsu thresholding technique [9] commonly used for the analysis of synthetic aperture radar (SAR) data, however, maximizing the high absorption property of water in the near infrared wavelengths. The modified method employed here incorporates multiple histogram-based thresholds to separate water with a range of turbidities and other characteristics such that regardless of the number of different land cover classes in the scene, ultimately, each water type becomes an inter-class variance problem between two classes. An edge detection filter, a mode reducer kernel, a water body area threshold of 10 m² (i.e., larger than 3 connected pixels) and a focal mode filter are used to clean up the classification to minimize erroneous detections due to shadows, or other landscape elements (e.g., certain materials in an urban context).

3.4 Results

The results for determining the number of cloud-free images within an example area of the Ramore Subdivision (as shown in Figure 6) showcases the importance of the daily revisit imagery acquisition from PlanetScope compared to Sentinel-2. Despite having two satellites (2A and 2B) that acquire data every five days, Sentinel-2 was less effective in this context. Due to the large area of the ONTC network, it was difficult to acquire cloud free data for the July period and the time span for the different subdivisions was greater in July, 2023 than for May or October, 2023.

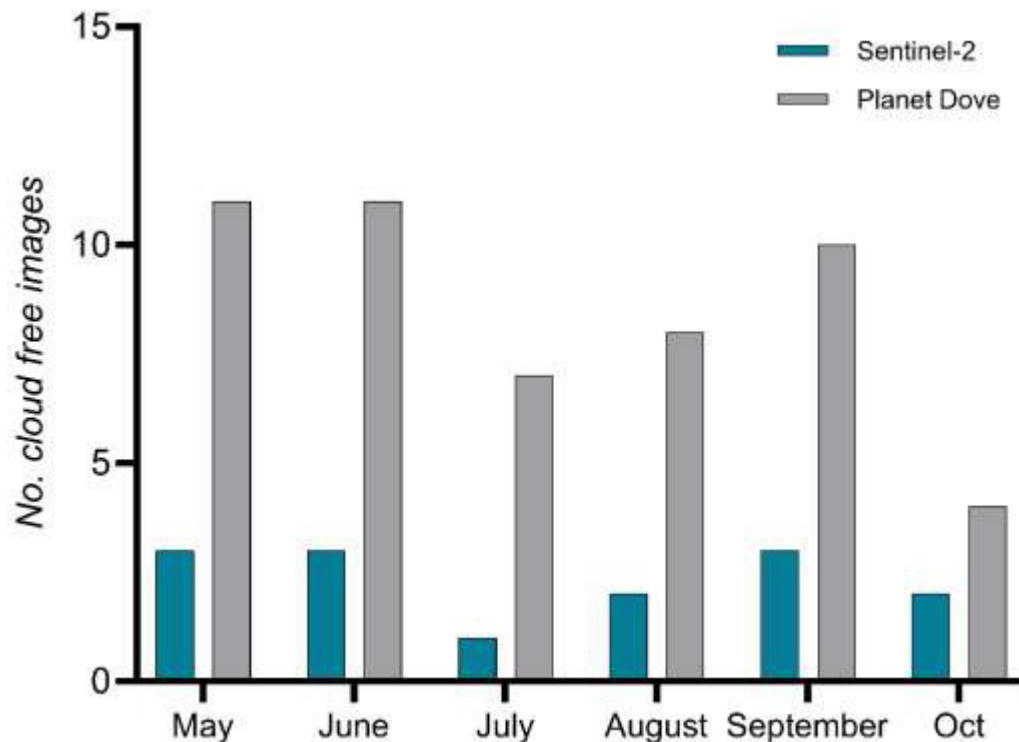


Figure 6. Satellite imagery availability comparison between Sentinel-2 and the PlanetScope Constellation for an area within the ONTC Ramore Subdivision for 2023.

When comparing the effects of the spatial resolution on the surface water classification (Figure 7) for small and large water bodies, the results clearly show the better detection that can be achieved with imagery from the PlanetScope Constellation (3m resampled pixels) compared to Sentinel-2 (10m and 20m pixels). For instance, the PlanetScope constellation more effectively captured narrow linear water features due to its smaller pixel resolution. Additionally, the representation of the watercourse is better defined with the PlanetScope Constellation (Figure 7).

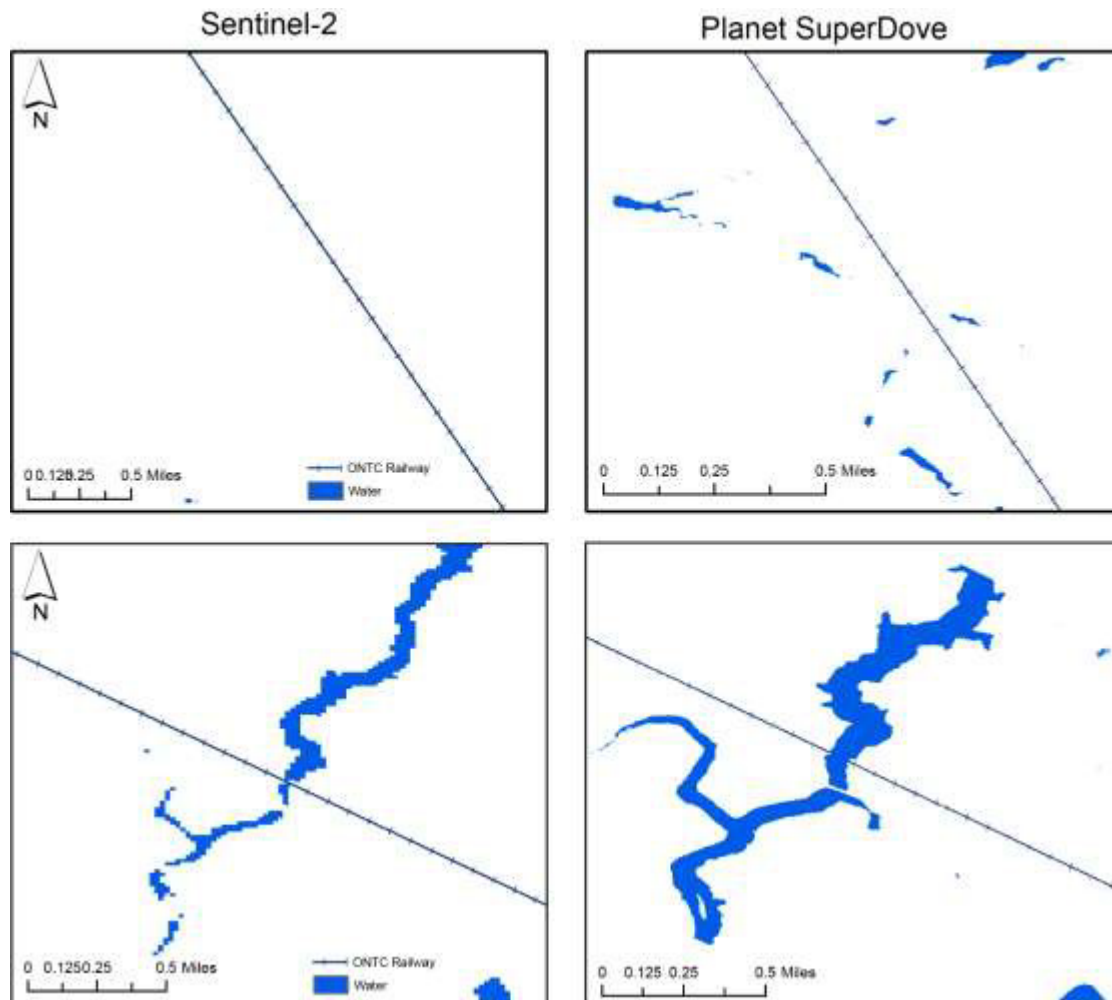


Figure 7. Sentinel-2 and PlanetScope Constellation surface water mapping comparison for small and large water courses with examples from the Ramore subdivision.

An example of the water classification results from the Pagwa Subdivision, derived from the PlanetScope imagery for May 24, 2023, is shown in Figure 8. Table 3 shows the total area of open surface water mapped for each subdivision during the three time periods. The surface water results reveal relatively small water surface changes for most subdivisions during the three time periods except for Island Falls and Kapuskasing. There is a notable decrease in water level in the large rivers and smaller streams in Island Falls between the May and July/October time periods. In the large rivers sections of river bottom are visible in July and October in comparison to May. In contrast, for Kapuskasing, it is not possible to directly observe the water extent in July in many of the water bodies that are present in May and October due to an overgrowth of vegetation. As such, only 4.17 km² of open water was mapped in July in comparison to 8.81 km² in May and 8.03 km² in October.

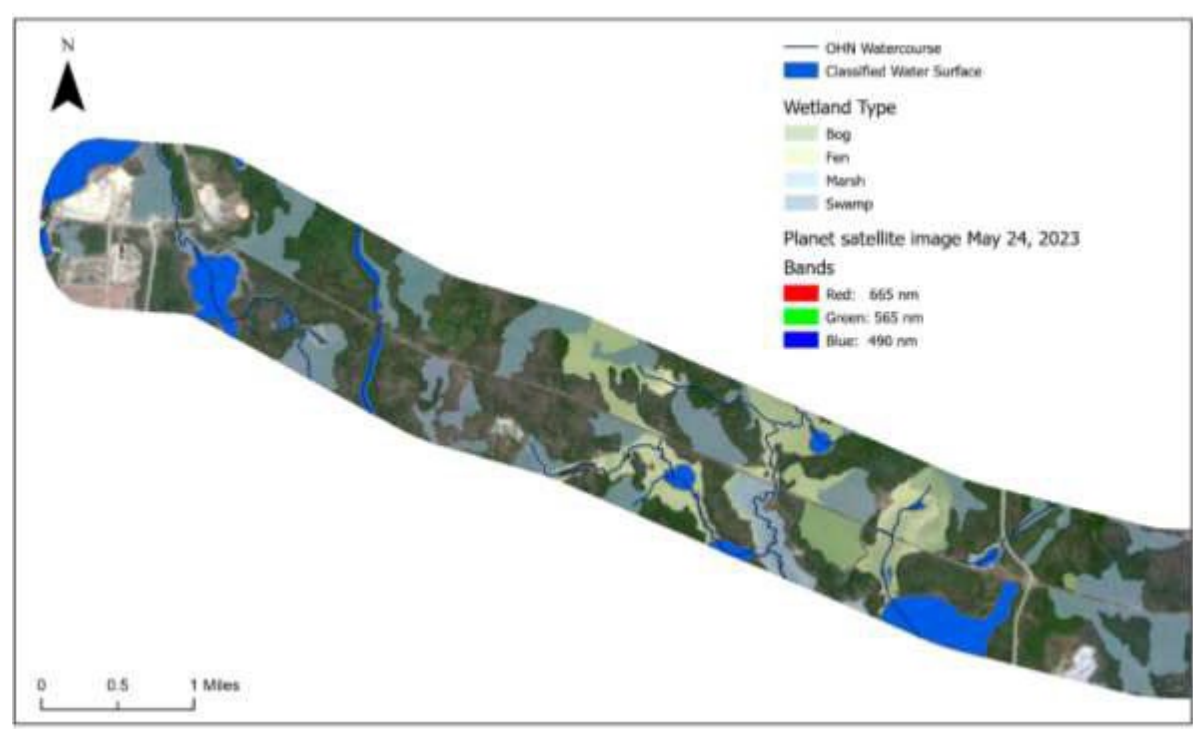


Figure 8. Example of surface water classification for a railway section in the Pagwa Subdivision based on PlanetScope imagery from May 24, 2023.

Table 3. Total water surface area (km²) for the ONTC subdivisions during the three time periods.

Subdivision	May 2023	July 2023	October 2023
Island Falls	23.68	18.64	17.56
Kapuskasing	8.81	4.17*	8.03
Pagwa	2.01	1.58	1.85
Devonshire	0.75	0.73	0.81
Iroquois Falls	0.11	0.09	0.10
Ramore	13.43	9.81	13.24
Kirkland Lake	8.64	8.48	10.42
Temagami	30.38	26.50	28.64

3.5 Conclusions and recommendations

Despite the daily temporal revisit of the PlanetScope Constellation, the large area encompassed by the ONTC railway network (700 miles) presents challenges for satellite-based surface water classification, especially related to the acquisition of cloud-free imagery. One aspect that needs to be considered in the multitemporal surface water mapping methodology is time coherence. This refers to the chance of getting minimal cloud cover satellite data within a short period of time for all of the subdivisions, or at the subdivision level. High time coherence would involve acquiring data for all subdivisions within one to two days difference, while low time coherence would be to acquire the satellite data across different dates for all subdivisions, or within a subdivision. For example, for the acquisition of the PlanetScope imagery for May and October, the cloud free data span four dates respectively (May 13, 21, 22 and 24; Oct 1,2,3,4). In contrast, for July nine dates were needed (July 1, 3, 4, 13, 14, 21, 22, 23, 25). This time coherence aspect might be important for capturing potential local changes in water levels that might affect railway safety, for example a considerable increase in water surface area at a specific location.

The comparison between Sentinel-2 and the PlanetScope constellation clearly highlighted the advantages of PlanetScope's higher spatial resolution. However, given the complexities of water mapping, such as vegetation cover in different water bodies and turbidity, there are limitations in detecting the surface water. Moreover, it was found that small meanders are more difficult to map due to their narrow width and complex curvilinear features. Thus, for improving the overall understating of some of the hydrological aspects in the ONTC railway network, this work benefited from the integration of two other datasets to supplement the surface water classification. First, the integration of the wetland classification dataset [4] provided information on the spatial extent of four wetland categories across the entire ONTC network: bogs, fens, marshes and swamps. These wetland categories are key as they can identify areas with flooding potential, such as swamps, even if water is not visible in the satellite image due to vegetation cover. Second, the Watercourse spatial layer [10] provides a very detailed one-time map of all water courses as line features capturing small streams. Further work could take advantage of the multitemporal surface water classification shown here, and in combination with the Ministry of Northern Development, Mines, Natural Resources and Forestry (OMNRF) products, model potential risk areas, where high temporal resolution mapping would be warranted.

The water mapping approach used here captures surface water at the landscape level, however, to better understand potential risk due to increases in water surface and more importantly water levels, technologies such as RPAS [11] or instrumented hi-rail truck (see Section 4 in this report), are needed to fill spatial gaps. These supplementary technologies are important, as abrupt changes in water level cannot be captured by satellite-derived products. Integration of the water surface products onto the dashboard, would allow the user to revise specific areas or polygons to assess changes in the surface water. It is recommended that this analysis be extended to a larger time span, e.g. eight months to identify the areas where changes in water surface are more significant. Given the large area of the ONTC railway, optimizing areas for further analysis not only reduce the cost of using PlanetScope imagery, but also identify areas where the implementation of drone or hi-rail truck are needed.

The large number of PlanetScope images used in this study (335 images), showcases the substantial utility of Google Earth Engine for processing these data, otherwise making it too resource demanding in terms of computational requirements. Despite the benefits of the computational power of Google Earth Engine, the changes in illumination conditions at the higher latitudes (e.g., up to ~1 hr time difference)

images of different parts of a subdivision required manual intervention to set and verify the detection threshold levels based on the conditions. In addition, highly turbid water required processing at a 'local scale' where the model parameters may be different for a single turbid river from the rest of the subdivision or large section of the subdivision. As such, to maximize the accuracy of the results, manual oversight is required.

It is important to reiterate that in the ecosystems present along much of the ONTC rail network, the lack of observable surface water from satellite imagery does not necessarily indicate a lack of water. This is an especially important consideration in July, where high vegetation biomass in marshes and swamps predominantly obscure the water under floating and/or emergent plants. The significant decrease in water mapped in the Kapuskasing Subdivision in July versus May or October for example, does not indicate less water in the region. The small water bodies are simply obscured from direct observation from satellite imagery. Rather than relying on the extent of surface water as the primary indicator, other contextual factors such as the type of water body (e.g., stream with beaver dam) in the vicinity of the track or tracks passing through swamp or marsh classes are important factors that should be considered.

4 Using instrumented hi-rail truck for water mapping

The published literature identified in this work provides only a few reports of employing instrumented hi-rail trucks for railway track inspection purposes. One example is provided by Federal Railway Administration (FRA) of the US Department of Transportation (USDOT) in 2016 in which a hi-rail truck instrumented with LiDAR, IMU and GPS receivers was used to test the potential of 3D maps generated from the sensors to assess safety at grade crossings [12]. One of the advantages of the hi-rail trucks is that they offer a more convenient and accessible method for data collection from railway tracks because of their high payload capacity and superior availability. A hi-rail truck can carry an equipment payload several orders of magnitude greater than a RPAS. Unlike satellite imaging, data collection from a hi-rail vehicle can be conducted on demand, which highlights the exceptional availability of this technology. In addition, deploying a hi-rail truck with mapping and sensing equipment will not impose additional downtime for the tracks, because hi-rail trucks are already used regularly by track inspectors to conduct their visual inspection duties mandated by regulators.

In this project, a hi-rail truck (Figure 9) was instrumented with a suite of sensors and auxiliary components to develop a complete data acquisition (DAQ) system that can acquire environmental data in different sensing modalities and multispectral bandwidths. The data provided by the DAQ system facilitated the detection and tracking of water bodies around railway tracks.



Figure 9. Instrumented hi-rail truck.

4.1 DAQ system hardware

The DAQ system features a number of sensors as described in Table 4. In addition to these sensors, a high-capacity computer was deployed inside the hi-rail truck to host the supporting software and to facilitate the data acquisition task. A portable power system provided the necessary electrical power to all system components. In addition, a monitor was placed inside the hi-rail vehicle to provide in-vehicle visualization (Figure 10).

Table 4. Sensor suite deployed on the instrumented hi-rail truck.

Sensor	# Deployed	Description
LIDAR	1	Velodyne VLP-32 905 nm wavelength 16 channel 360° horizontal FOV 30° vertical FOV 200 m maximum range
RGB Camera	2	Stereolabs Zed 2i 120° FOV Resolution: 1920X1080
Infrared Camera	2	FLIR BOSON ADK Long wavelength infrared (8-14 μm) 24° horizontal FOV 19.2° vertical FOV Resolution: 640 X 480
GNSS-IMU	1	Xsens MTi-G-710 GNSS/INS solution MEMS implementation Up to 2000 Hz data rate



Figure 10. Auxiliary components for the DAQ (left) and in-vehicle visualization (right).

4.1.1 DAQ system software

A software stack hosted on the in-vehicle computer and based on the Robot Operating System (ROS) was developed to facilitate data acquisition and real-time visualization. The organization of the software stack is presented in Figure 11. The software included vendor-supplied and custom drivers to translate binary sensor data into ROS messages. It also included nodes that captured these published ROS messages to save to the local storage of the computer in ROSBAG¹ format for each message.

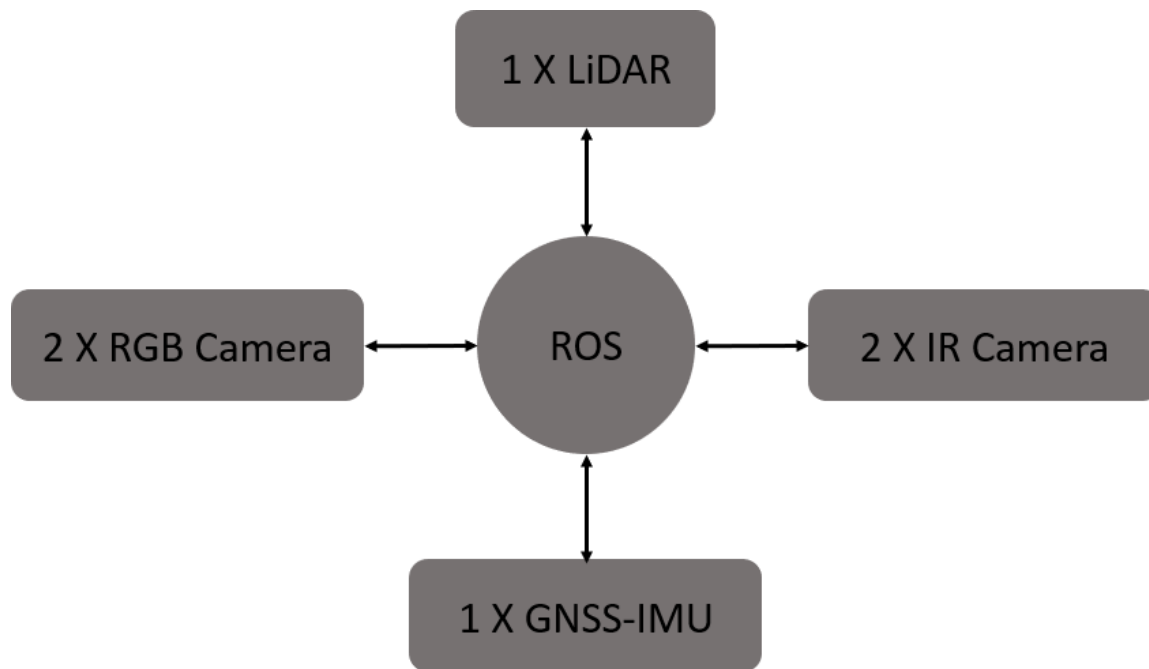


Figure 11. DAQ system software block-diagram.

A typical data acquisition pipeline in a ROS is schematically described in Figure 12. The sensor connects to the ROS computer via a data interface such as USB, Ethernet, etc. The data interface converts the physical signal into binary data. An appropriate ROS driver parses the binary data into standard or custom ROS messages (e.g., image message, IMU message, point cloud message, etc.). The driver makes these messages available to other nodes under a “publish-subscribe” model. Other nodes such as a DAQ node can subscribe to these messages, and as soon as the messages become available, the node can store them in local storage (e.g., a hard-drive). Other nodes such as a visualization node or a perception algorithm node can also make use of the incoming data by subscribing to the messages published by the driver.

¹ It is a binary format that stores acquired sensor data with accurate timestamps.

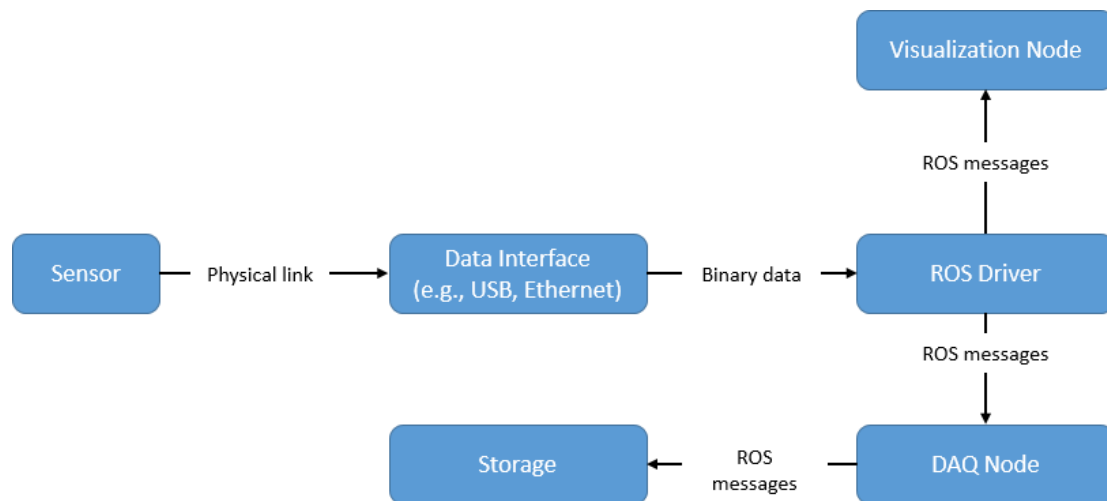


Figure 12. ROS data acquisition pipeline.

4.2 Data acquisition

The instrumented hi-rail truck was deployed for data collection between Mi. 0 – 57 of the Kirkland Lake Subdivision (approximately 90 km) for a total of two runs. An aerial map of the route is presented in Figure 13. The first and second runs were conducted on July 13 and October 26, 2023, respectively. The two runs yielded a total of 2.9TB of binary data in ROSBAG format. The bagged data included the 3D point cloud from the LiDAR, RGB images, grayscale infrared images, GPS coordinates, and inertial data (vehicle speed, heading, etc.). The binary ROSBAG format saves all these different data streams under a common timestamp. This temporal consistency among different data streams was crucial in implementing the time-sensitive data fusion tasks.

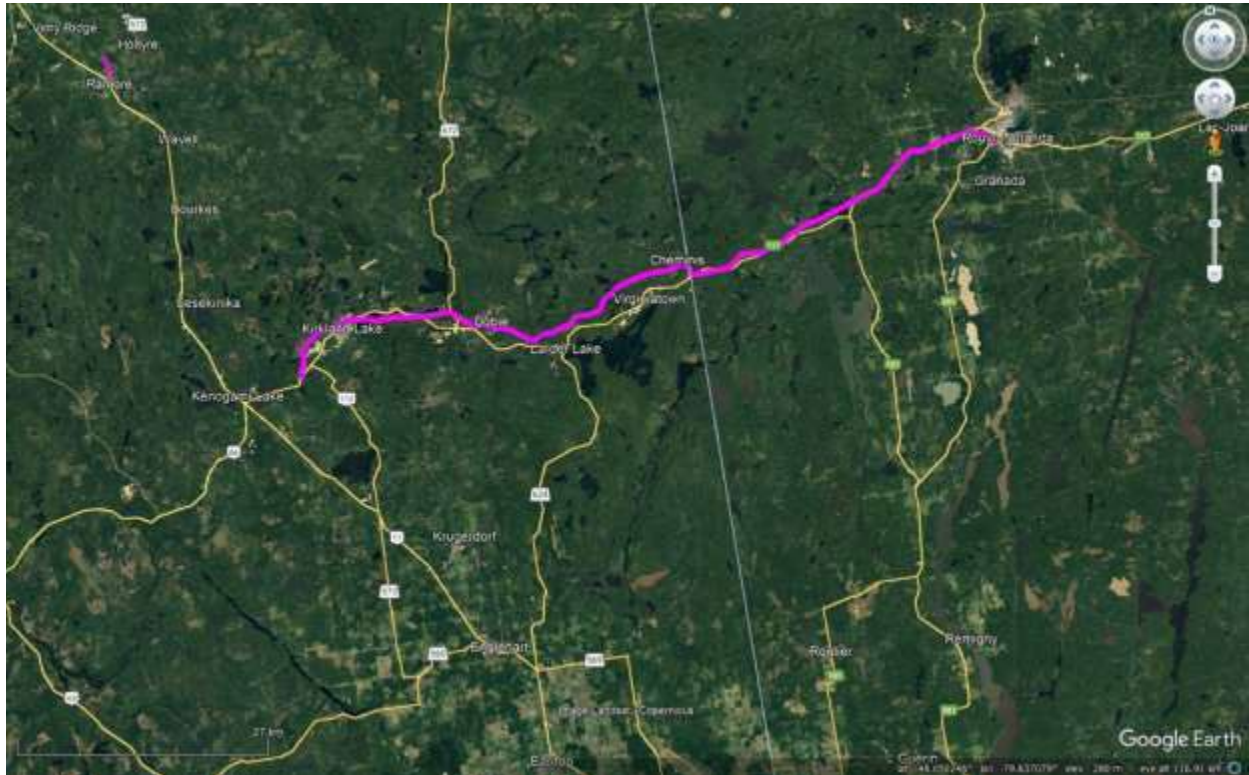


Figure 13. Study area (Kirkland Lake Subdivision) for ONTC-NRC instrumented hi-rail truck field work, with collected water level data along rail right of way to be modeled through algorithms to identify potential hazard areas.

The recorded data in the ROSBAG format can be replayed with accurate time deltas to provide a convenient pipeline for rapid prototyping of data processing algorithms. For example, Figure 14 shows LiDAR, RGB and IR camera data visualized in a data replay exercise. This provides an opportunity for track engineers to view data later as if they are inspecting the track from a hi-rail truck in the field.

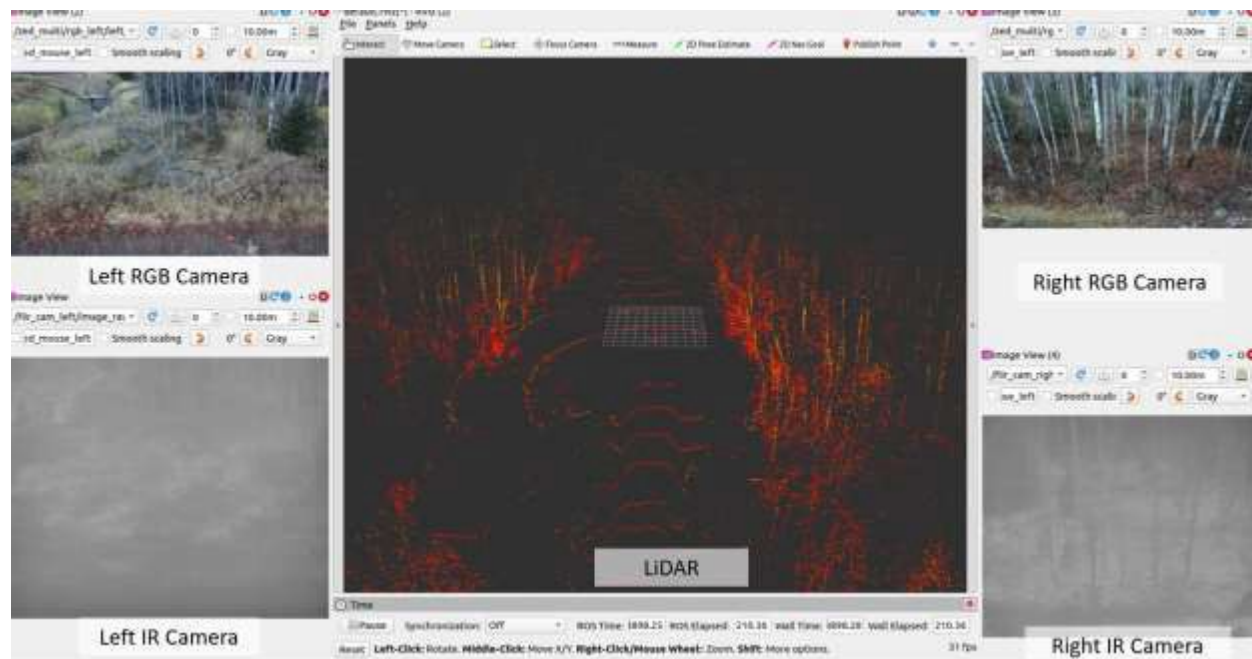


Figure 14. ROSBAG data being visualized.

The data processing tasks are very resource intensive, requiring high GPU, CPU and memory resources, and involve the following steps:

- (1) reading binary files from local/cloud storage;
- (2) de-serializing the binary sensor data into appropriate formats; and
- (3) evaluating perception algorithms on the formatted data, etc.

4.3 LiDAR data processing

In this project, the measurements from scanning LiDAR and the IMU data were fused together to construct a 3D map of the scanned locations using simultaneous localization and mapping (SLAM) techniques. The algorithm presented in [13] with some project-specific enhancements was utilized to build 3D point cloud maps as shown in Figure 15. It is important to note that these 3D point cloud maps are available for ONTC via the dashboard to view and even make required measurements.

The LiDAR used in this project is optimized for scanning speed and for detecting roadway elements such as vehicles and pedestrians. Using this LiDAR to map railway tracks and surrounding environments is an important outcome of this project, which may create new research directions for track inspection using emerging technologies. It should be noted that a higher resolution LiDAR will provide a finer 3D map of the environment. For example, the geometric features from the culvert and the embankment in Figure 15 will be more pronounced if a higher resolution LiDAR is used.



Figure 15. 3D point cloud map showing a railway track, a farm crossing, and the surrounding area.

4.4 Water level measurement:

In order to measure the water level, a novel algorithm was developed. The environment around the railway tracks was acquired using different 2D and 3D sensors, namely, RGB and thermal cameras, and a 32-channel LiDAR. The 3D map of the environment (see Figure 16) is generated using SLAM algorithms applied to the raw LiDAR point cloud. An in-depth analysis of the LiDAR 3D maps reveals that the water bodies in the 3D map contain very few 3D points (see Figure 16, areas highlighted in red). The absence of points is mainly due to the absorption properties of the laser pulses by the water. Recall that the LiDAR wavelength is located in the near-infrared spectrum. The laser pulses are absorbed by water and therefore do not generate reflected returns on water bodies. This produces void regions within the LiDAR point cloud.

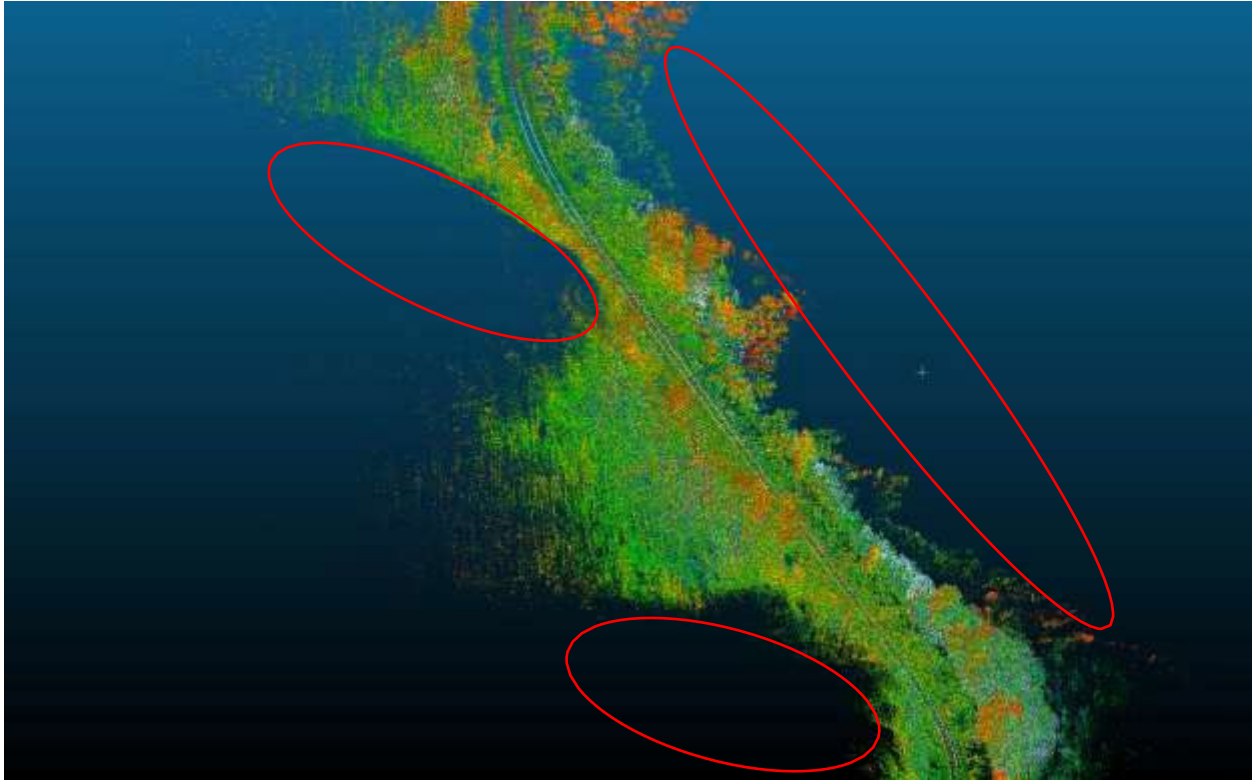


Figure 16. 3D map of the environment around the railway tracks (Kirkland Subdivision, Mile posts 44.5 – 44.75).

In order to measure the water level, a preliminary step is to locate the water bodies in the 3D map. Void regions within a 3D map most likely correspond to water bodies, as shown in Figure 16. To confirm that, water bodies must also be identified from other sensors, RGB cameras in this case. Figure 17 shows two images acquired by the east-side RGB camera at mile posts 44.59 and 44.63. Water bodies shown in Figure 17 confirm that the right void region within the 3D map in Figure 16 corresponds to a water area.



Figure 17. Water bodies acquired by the east-side RGB camera (Kirkland Subdivision, Mile posts 44.59 (left) and 44.63 (right)).

Once the water bodies are located in the 3D map, the algorithm dedicated to calculating the water level, described by the following steps, is used:

- Identify a fixed reference point located on top of the rail, and measure the elevation at that point;
- Identify one or more reference points surrounding the water body and measure the elevation of the water on those points; and
- Measure the water level with respect to the reference point.

4.4.1 Elevation of the reference point:

The water level measurements are mainly based on the LiDAR 3D map because the distances between the 3D points in the map correspond to the actual distances in the world coordinates. The algorithm needs at least one reference point to measure the water level with respect to this point. By analyzing the 3D map of the scene, the top of rail surface was identified as a good candidate to set as a reference point (see Figure 18, left reference point) because its location is fixed. This allows measuring the change in water levels across different seasons because the reference point used for the calculation is always located at the same position in the 3D map. To measure the elevation at the reference point, first a 3D segmentation technique is applied around that point to extract the 3D points whose depth is close to reference point's depth. The objective is to calculate the elevation based on several 3D points to avoid outliers. The elevation corresponds to the average of depths of these 3D points that were extracted by the 3D segmentation technique.

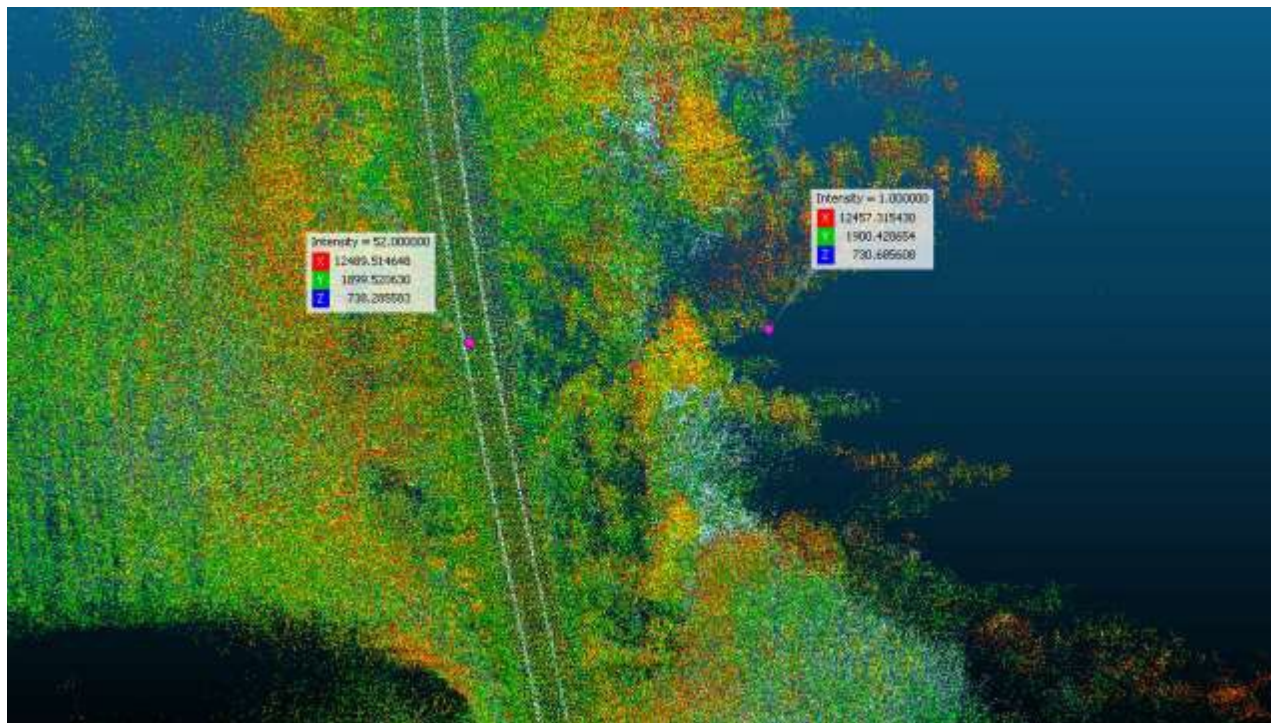


Figure 18. Reference points of the railway track and the water body in the 3D map.

4.4.2 Elevation of water body:

The elevation of water bodies should be calculated based on the depth of 3D points in the map. However, as explained above, water surfaces contain almost no points in the 3D map. To address this issue of lack of points, the algorithm uses 3D points belonging to the surroundings of water bodies (see Figure 18, right 3D point). These edge points are located at the intersection of the water surface with the ground, and therefore have a depth equal to that of the water surface. A 3D segmentation is applied around the edge point to extract neighboring points. Then a clustering is performed to keep only points whose depth is very close to the edge point's depth. The elevation of the water surface is the average of depths of the remaining points.

4.4.3 Level of water body:

The elevations of water surfaces and rails (measured in the above subsections) are expressed in the 3D map coordinates. However, distances between the 3D points in the map correspond to the real distances in the world coordinates. Thus, the water level is expressed as the difference between elevation of rails and the elevation of water surface.

4.5 Automate/semi-automate the process of water detection:

In addition to the algorithm dedicated to measuring the water level, further research and development work has been performed with the aim of automating the water detection process using 2D RGB/thermal images.

4.5.1 Water detection based on 2D RGB/thermal images:

The first objective was to investigate existing deep learning models that are already trained on 2D water images. A Fully Convolutional Network (FCN) model [14] dedicated to the detection of water from a single RGB image was adapted and tested on the RGB images acquired from the hi-rail. Although the FCN model performs well on images for which it was trained (see Figure 19 and Figure 20), it had great difficulty generalizing. i.e. to detect water in the railway images (see Figure 17). This is mainly due to the large difference in water appearance between the images used to train the FCN model and the railway images tested by the same model.



Figure 19. Off-road image used in the training of the FCN model.



Figure 20. On-road image used in the training of FCN model.

A Convolutional Neural Network (CNN) model built and trained by the NRC team on a set of thermal images during a previous research project (see Figure 21) was also tested on the thermal images acquired on ONTC line. The CNN model could not generalize the detection of water due to the difference in water signatures between the thermal images used to train the CNN model (see Figure 21) and the thermal images tested by the same model (see Figure 22). The NRC speculates that this could be related to the ambient temperatures in which these data were collected, affecting the water signature in thermal images.

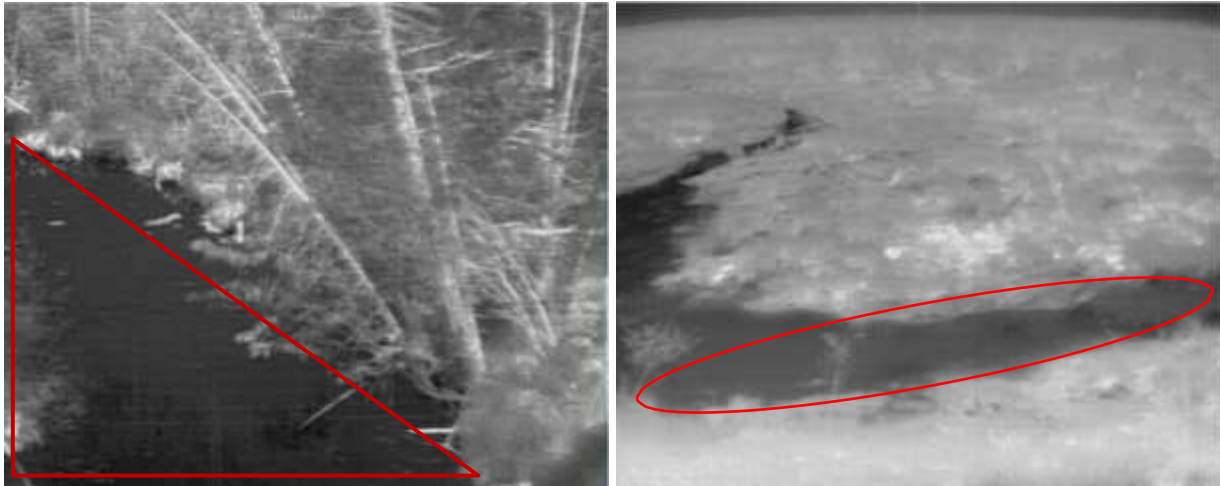


Figure 21. Two thermal images of water bodies (highlighted in red) used in the training of the CNN model.



Figure 22. Thermal image of a water body highlighted in red.

Both deep learning models (FCN and CNN) that were tested on RGB and thermal images, respectively, to detect water bodies did not give satisfactory results. This is due to the sensitivity of the models to the appearance of water surfaces in the training data.

4.5.2 Water detection based on Structure from Motion (SfM) 3D map:

Another approach that was investigated consists of detecting water bodies in the LiDAR 3D map. Water surfaces contained little to no 3D points in the LiDAR 3D map, as seen in Figure 16. That makes the water detection task in the 3D map very complex. To overcome this challenge resulting from a lack of 3D points, the SfM photogrammetry technique was investigated [15]. Structure from motion is a photogrammetric imaging technique intended to estimate the 3D structure of the scene (see Figure 24) from a set of 2D images (see Figure 23). The main goal behind generating the SfM 3D map is to have a

new 3D representation of the scene where the water bodies are clearly distinguished by a set of 3D points (see Figure 24). For future work, the SfM 3D map will be used to automate the water detection process, according to the following steps:

1. Develop a new algorithm to locate the water body within the SfM 3D map;
2. Fuse the SfM 3D map with the LiDAR 3D map using the iterative Closest Point (ICP) algorithm [16];
3. Extract the water region from the LiDAR 3D map based on the 3D Region of Interest (ROI) of water body identified in the SfM 3D map; and
4. Measure the water level based on the water region extracted from the LiDAR 3D points.



Figure 23. Four different points of view of the same scene.



Figure 24. SfM 3D map generated based of 2D RGB images of the same scene (see Figure 23).

4.6 Conclusions and future work:

The research work performed within the framework of automated/semi-automated detection of water bodies as well as the algorithm dedicated to measuring water levels has been described in the sections above. The process involved locating water bodies using a 3D map created from the LiDAR data and filling in gaps with images from the RGB cameras. Algorithms were then developed to calculate water levels. The lessons learned and recommended future work includes:

- The deep learning models dedicated to the detection and recognition of water bodies are very sensitive to the training data (RGB/thermal images);
- A large and diverse set of data should be annotated to build a robust deep learning model;
- The absence of 3D points at the water surfaces in the LiDAR 3D map is a constraint for the measurement of water levels;
- The SfM 3D map is a novel method to obtain a 3D representation of the scene;
- A robust solution to automate the detection of water should include several algorithms using both 2D and 3D sensors. For example, the results obtained with a deep learning model applied to RGB images can be fused (decision level) with the results of another deep learning model applied to thermal images as well as with the results of water detection in the corresponding SfM 3D map; and
- The LiDAR 3D map should be fused (signal level) with the SfM 3D map to localize the water bodies in the LiDAR 3D map and extract the 3D points surrounding the water surfaces.

5 Conclusion and future work

This section provides an overall conclusion for the project. More detailed discussions and conclusions can be found at section 3.5 for satellite and section 4.6 for hi-rail part of this study.

The NRC, in collaboration with ARSL at McGill University and ONTC, performed an extensive field investigation by employing satellite images and an instrumented hi-rail truck at several test sites along the ONTC railway line to demonstrate the potential of these technologies for monitoring surface water near railway tracks. The measurements from the two platforms (satellite and hi-rail truck) and various sensors provided a wide range of complementary information with different spatial and temporal resolution as well as field of view. These results were implemented into a dashboard for easy viewing and interpretation to be utilized by key decision makers in ONTC.

The large area covered by the ONTC railway network presents challenges for satellite-based surface water classification due to the need for cloud-free imagery and the likelihood of getting minimal cloud cover satellite data within a short period which could be important for capturing potential local changes in water levels that might affect railway safety. Other contextual factors such as the type of water body (e.g., stream with beaver dam) in the vicinity of the track or tracks passing through swamp or marsh classes are important risk factors that should be considered in addition to the extent of surface water.

During the satellite imagery study, the comparison between Sentinel-2 and PlanetScope showed the advantages of the higher spatial resolution of PlanetScope imagery, but there are still limitations in determining the surface water due to vegetation cover, and in the cost of purchasing the PlanetScope images. The study benefited from the integration of two province-level datasets that supplement the surface water classification. The use of drones or instrumented hi-rail trucks can help to fill spatial gaps and capture abrupt changes that cannot be captured by satellite-derived products. Despite the computational power of Google Earth Engine, manual oversight is still required to maximize the accuracy of the results.

A hi-rail truck instrumented with a suite of sensors (LiDAR, RGB camera, and longwave infrared camera) was used to measure the water level as well as changes in water level. This was done by locating the water bodies through a 3D map that was created using LiDAR data, and filling in the void regions using images acquired by RGB cameras. Algorithms were developed to calculate water levels based on a reference point, which was chosen as the top of rail surface, to the edge of the water body. Future work will focus on automating the water detection process by developing algorithms which would use the fused 2D and 3D sensor data to extract the 3D points surrounding the water surfaces.

An interactive online dashboard has been developed and made available to ONTC to support visualization and analysis of satellite and hi-rail truck data. The platform enables ONTC users to access and explore relevant network and condition information through a secure environment.

The outcomes of this project provided significant insight into the benefits, capabilities, and constraints of measurements derived from satellite and hi-rail platforms. More importantly, it highlighted the limitations and advantages of integrating this data into a web-based dashboard that can be utilized by the ONTC to make informed decisions regarding water inspection. Further studies and advances in the framework of

these technologies would provide additional information for a more complete picture of the water distribution. The following recommendations are made:

- Consider extending the satellite analysis to a period of 8-12 months. This will help identify regions where significant changes in water surface levels occur, making them prime candidates for satellite monitoring. This approach will not only optimize the use of PlanetScope imagery, thereby reducing costs, but also pinpoint areas where the deployment of drones or an instrumented hi-rail truck is necessary;
- Rather than relying on the extent of surface water as the primary indicator from satellite imagery, other contextual factors such as the type of water body (e.g., stream with beaver dam) in the vicinity of the track or tracks passing through swamp or marsh classes are important risk factors that should be considered;
- Additional improvements and automation requirements have been identified related to the results of the instrumented hi-rail truck data analysis:
 - A robust solution to further automate the detection of water should include several algorithms using both 2D and 3D sensors;
 - The LiDAR 3D map should be fused (signal level) with the SfM 3D map to localize the water bodies in the LiDAR 3D map and extract the 3D points surrounding the water surfaces; and
 - A deep learning model would benefit from annotating a large and diverse set of data.
- Currently, the dashboard functions primarily as a viewer for the available data. However, it holds the potential to evolve into a risk mapping dashboard, where various layers of data can be integrated to identify areas within the network that require action. This information could also be leveraged for capital investment decisions or prioritizing maintenance activities.

Acronyms and abbreviations

ARSL	Applied Remote Sensing Lab at McGill University
CNN	Convolutional Neural Network
DAQ	Data acquisition
FCN	Fully Convolutional Network
FRA	Federal Railway Administration
GEE	Google Earth Engine
ICP	Iterative Closest Point
ITS	Intelligent Transportation System
LiDAR	Light Detection and Ranging
NDWI	Normalized difference water index
NRC	National Research Council – Automotive and Surface Transportation and Aerospace Research Centers
OHN	Ontario Hydro Network
OMNFR	Ontario Ministry of Northern Development, Mines, Natural Resources and Forestry
OMNR	Ontario Ministry of Natural Resources and Forestry
ONTC	Ontario Northland Transportation Commission
RGB	Red, green, and blue wavelengths
ROI	Region of Interest
ROS	Robot Operating System
ROW	Right of Way
RPAS	Remotely Piloted Aerial System
SAR	Synthetic aperture radar
SfM	Structure from Motion
SLAM	Simultaneous localization and mapping
USDOT	US Department of Transportation

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