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# Characterization of ice coverage in the St. Lawrence River using satellite imagery and an operational ice status index

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The St. Lawrence River is part of an important international shipping route, with numerous shoreline communities and major infrastructure such as dams and hydroelectric power generation stations. In winter, ice is a crucial consideration in water management decisions on the upper part of the St. Lawrence, from Lake Ontario to Montreal. The water management board and hydroelectric companies closely monitor river ice conditions at two key locations, Lake St. Lawrence and Beauharnois Canal. River flow is usually reduced to encourage the formation of a stable ice cover and prevent problematic ice jams; once this cover forms, flow may be increased. Since the year 2000, detailed observations have been made on ice cover presence and stability, and a numeric ice status index has been recorded for each day of the ice season. The availability of remotely-sensed data, such as satellite imagery, affords another way to monitor ice conditions. Satellite-based optical imagery was used to classify pixels on the St. Lawrence River as either ice or water. The percent coverage of the surface by ice was then calculated over each area for images from 2013 to 2022. This satellite-derived ice coverage was compared with the ice status indicator timeseries, and preliminary correlations were established. Several machine-learning methods for synthetic aperture radar (SAR) imagery analysis were also tested and summarized.

### 1. Introduction

The Lake Ontario – St. Lawrence River flow is managed according to a regulation plan to meet, as best as possible, the needs of various interests (International Joint Commission, 2014). The upper section of the St. Lawrence, from Lake Ontario to Montreal, is closed to ship traffic during the ice season. A major concern around water management at that time is the maintenance, through dam operations, of acceptable water levels to protect municipal water intakes. When the water level is high in Lake Ontario, winter flows are maintained as high as possible to reduce the risk of flooding the following spring. River ice can complicate the achievement of those objectives, but some management of ice processes is possible.

Promoting the development of a stable ice cover upstream of critical infrastructure is a technique used by operators on various rivers (see, e.g., Tuthill, 1999; Bunch, 2018; Ontario Power Generation, 2021). Ice jams – and subsequent flooding – are less likely if a thick and stable ice cover is present; thinner ice can more easily break up and form a jam. An ice cover helps to avoid the open water conditions that are favourable for the formation of frazil ice, which can clog municipal or industrial water intakes, or contribute to ice jams. The progression of a stable ice cover may be encouraged by reducing the river flow through dams during the critical time of ice formation. Lowering the flow also reduces turbulence and further discourages the formation of frazil ice. Since flow regulation began on the upper St. Lawrence River in 1960, ice jam issues have mostly been averted (International Lake Ontario–St. Lawrence River Board, 2019). Ice control structures, such as ice booms, are also part of the seasonal operations to optimize ice coverage (Ontario Power Generation, 2019; Abdelnour et al., 2019). Further information on mitigation measures for floods caused by river ice is given in Barrette et al. (2025).

River ice monitoring and short-term forecasting are important for day-to-day water management decisions on the upper St. Lawrence. During the ice season, ice presence and stability are monitored at key locations and a daily numeric indicator is assigned to help guide decision-makers. Presently, ice observations on the upper St. Lawrence are mainly visual, from shore and aircraft. Optical satellite data are sometimes consulted, but are not a regular part of the ice monitoring operations. The availability of remotely-sensed data affords new ways to monitor and quantify the ice and to complement daily operations. Satellite imagery has been used successfully in operations on several other Canadian rivers, and methods are being explored for the upper St. Lawrence. Satellite imagery is also useful on a second front: understanding historical ice conditions.

### 2. Objectives

The present paper describes the following two efforts for the Beauharnois Canal and Lake St. Lawrence sections of the river system (shown in Figure 1):

- 1) The analysis of ten years of archived optical imagery and comparison of the seasonal ice coverage with daily ice status indices available. These indices, described herein, are a valuable and unique set of validation data.
- 2) The exploration and testing of automated methods to process synthetic aperture radar (SAR) imagery. The aim of this work is to advance the development of an ice cover characterization tool that can be applied not only to the upper St. Lawrence River, but also to other river reaches.



Figure 1. Areas of interest for ice monitoring and analysis on the upper St. Lawrence River.

### 3. Ice monitoring on the upper St. Lawrence River

The boundary waters of the St. Lawrence River are managed by the International Joint Commission (IJC) through its various boards and committees, which have members from Canada and the USA. Ice is monitored primarily at Lake St. Lawrence and the Beauharnois Canal, which are two reaches of the river system for which flow adjustments can influence ice conditions (personal communication, J. Ferguson, April 4, 2025). Visual observations are made from key locations on shore, and are supplemented by photos and observations from dedicated aircraft flights. Water levels are also closely monitored for potential rise due to ice presence.

For the upper St. Lawrence, a special labelling system called the Ice Status Indicator (ISI) has been devised to quantify ice coverage and stability. Each ice season, a daily ISI value is assigned to each of Beauharnois Canal and Lake St. Lawrence:

- ISI = 0: Open water conditions or marginal ice cover.
- ISI = 1: There is a significant ice cover, but a stable ice sheet has not yet formed.
- ISI = 2: A stable ice cover has been achieved, which can accommodate normal discharge.

From 1960 to 1999, before the use of the ISI system, visual observations of the initial freeze-up and final break-up dates of the ice have been recorded at both Lake St. Lawrence and Beauharnois Canal. Since the year 2000, daily records have been kept of the ISI numeric value, often along with explanatory text from the ice observers. This record of ice conditions is used by the IJC in their water regulation and routing modelling, for example, as an input to evaluations of potential changes to the water regulation plan. The ISI record is a valuable source of information on freeze-up, mid-winter break-ups and ice cover stability throughout the ice season. The use of the ISI in

climate change studies and modelling of future ice conditions is described in Barrette and Sudom (2025) and in Sudom et al. (2024). Examples of the ISI record for one season at each area of interest are shown in Section 5.2, and ten seasons of ISI data at each site are plotted in Section 5.3.

### 4. Background on river ice monitoring and satellite data applications

At other rivers, various methods are used to observe and analyze river ice; a good recent overview is given by Zakharov et al. (2024). The ISI system described above is unique to the upper St. Lawrence River, but the U.S. Geological Survey (USGS) uses a similar "ice flag" system to indicate ice presence (Ayyad et al., 2025).

In recent years, satellite sensors, including both optical and synthetic aperture radar (SAR), have become important for river ice classification. Optical sensors passively collect images in which ice cover can generally be intuitively interpreted, similar to a photograph. However, a useful image of the earth's surface cannot be captured if it is covered by clouds, and some sensors depend on the visible light spectrum (and therefore only work during daylight hours). SAR sensors are insensitive to cloud cover and sunlight, which is advantageous for monitoring rivers on a regular basis. The disadvantage is that distinguishing between ice and water in a SAR image is more challenging than in an optical one. SAR sensors are active, in that they send and receive a signal. The resulting backscatter data must then be processed in order to classify pixels as either ice or water. Since the backscatter depends on radar wavelength, polarization and incidence angle, the threshold for classifying ice or water must be matched to the sensor configuration – a robust, configuration-independent method is not available (Sobiech and Dierking, 2017).

SAR imagery can cover a broad area, and algorithms can be developed to automate the ice analysis. SAR data are used in the operational monitoring of ice conditions and ice jam flood risk management in a number of Canadian rivers. Three models used in Canada for automated analysis of SAR images – ICEMAP-R by INRS, RIACT by C-CORE and IceBC by NRCan – are compared by Plante Lévesque et al. (2019). The authors highlight that each method has its limitations depending on the ice conditions at the time of image capture and the geometry of the river to be analyzed. A recent paper reported on the merging of the outputs of those three models to create an ensemble system (Plante Lévesque et al., 2025). Van der Saanden et al. (2021) review a number of approaches that have been developed to extract ice cover information from imagery, and present their own method, which was tested in five rivers across Canada. Examples of rivers for which SAR-based ice classification is used operationally include the Churchill River project in Labrador (Lynch et al., 2021; <u>https://www.churchillriver.app/</u>), the Exploits River in Newfoundland (<u>https://www.exploitsriver.app/</u>), and several rivers in Québec (INRS, 2025).

Rubbled or rough ice types are generally easier to distinguish from water, since they give greater backscatter of the radar signal. Accurately distinguishing between water and smooth freshwater ice, especially thin or wet ice, remains a challenge and advances continue to be made (Unterschultz et al., 2009; Sobiech and Dierking, 2017; Scott et al., 2020; van der Saanden et al., 2021; de Roda Husman et al., 2021). Techniques involving optical imagery or multiple data sources are also evolving (see, e.g., Temimi et al., 2023; Plante Lévesque, 2024).

## 5. Analysis of ice cover from optical imagery of the upper St. Lawrence River

In this paper, the utility of optical (visual) satellite imagery in the classification of ice cover vs. open water was assessed for the two river areas of interest shown in Figure 1. An ice cover data set was derived for 10 years of imagery. The longer-term goal of this work is to use the optical imagery as "ground truth" labels for testing automated methods for ice detection in SAR images, as described in Section 6. For the present paper, the satellite-derived ice coverages were compared with the ISI data set described in Section 3.

## 5.1. Methodology

Optical images were obtained from three sources: moderate resolution imaging spectroradiometer (MODIS) data from NASA Worldview, Sentinel-2 data from Copernicus, and PlanetScope highresolution data (available through an academic license). The image annotation process was conducted using CVAT (Computer Vision Annotation Tool) (<u>https://cvat.ai/;</u> available at <u>https://github.com/cvat-ai/cvat</u>) and QGIS (<u>https://qgis.org/</u>) to create segmentation masks that identify each non-land pixel in the regions of interest as either ice or water. Since a SAR image analysis method was the main goal of this project, the labelling was done on SAR image pixels, using the optical images as a guide.

## 5.2. Example of analysis for one winter season

## 5.2.1. Lake St. Lawrence, winter 2021-22

An example is given of the ice coverages calculated for one season (winter 2021-22) at Lake St. Lawrence, using the methodology described in Section 5.1. Examples of optical images used in the analysis are given in Figure 2, and the ice coverages are compared to the ISI record in Figure 3.



Figure 2. Optical images of Lake St. Lawrence used for labelling of pixels as ice or water.



Figure 3. The winter 2021-22 season for Lake St. Lawrence; the ISI values give an indication of ice conditions as they pertain to water management operations. This may be compared with the ice coverage derived from satellite images such as those in Figure 2.

### 5.2.2. Beauharnois Canal, winter 2021-22

An example is given of the ice coverages calculated for one season (winter 2021-22) at Beauharnois Canal, using the methodology described in Section 5.1. Examples of optical images used in the analysis are given in Figure 4, and the ice coverages are compared to the ISI record in Figure 5.



Figure 4. Optical images of Beauharnois Canal used for labelling of pixels as ice or water.



Figure 5. The winter 2021-22 season for Beauharnois Canal; the ISI values give an indication of ice conditions as they pertain to water management operations. This may be compared with the ice coverage derived from satellite images such as those in Figure 4.

### 5.3. Comparison of ten seasons of ISI and satellite imagery analysis

### 5.3.1. Lake St. Lawrence

Optical images from ten seasons of satellite data were analyzed using the methodology described in Section 5.1. The percent ice coverage of Lake St. Lawrence from each image is compared to the seasonal daily ISI data in Figure 6. In Figure 7, the box and whisker plot gives an indication of the ranges of ice coverage that correspond to each ISI value:

- An ISI of 0 for the Lake corresponds to up to about 40% ice coverage,
- An ISI of 1 or 2 generally corresponds to over 90% ice cover.

An ISI value of 0 often does not correspond to zero ice coverage – it could mean that there is significant border ice but the centre of the channel is ice-free, or that there is no substantial ice cover at key observation points. In terms of ice coverage percentage, no difference is apparent between the ISI values of 1 and 2. This suggests that the operational choice between an ISI of 1 or 2 is likely based on ice thickness, rather than solely the percent of the lake area covered by ice. The three outlier points in Figure 7 are for dates at the very start or very end of the ice season, and could be ignored.



Figure 6. Lake St. Lawrence: 10 seasons of ISI data compared with satellite optical imagery analysis of ice cover.



Figure 7. Comparison of ISI and satellite-derived ice cover of Lake St. Lawrence. The satellitederived ice coverage points correspond to 42 imagery dates with ISI = 0, 9 dates with ISI = 1, and 20 dates with ISI = 2.

#### 5.3.2. Beauharnois Canal

Similar to the analysis of the Lake St. Lawrence, optical images of Beauharnois Canal were assessed. The percent ice coverage of the Canal from each image is compared to the seasonal daily

ISI data in Figure 8. The box and whisker plot of Figure 9 gives an indication of the ranges of ice coverage that correspond to each ISI value:

- An ISI of 0 for the Canal generally corresponds to less than 10% ice coverage
- An ISI of 1 corresponds to about 30% to 60% ice cover
- An ISI of 2 generally corresponds to over 70% ice cover.

In Figure 9, the outlier points for ice coverages with an ISI=2 are for dates at the very end of the ice season. At this point the ice cover might have disintegrated but, for the purposes of water management and flow regulation, an ISI of 2 might be maintained.

It is apparent that, for the years examined, an ISI value of 2 corresponds to greater ice coverage of the Lake St. Lawrence area than of the Beauharnois Canal area.



Figure 8. Beauharnois Canal: 10 seasons of ISI data compared with satellite optical imagery analysis of ice cover.



Figure 9. Comparison of ISI and satellite-derived ice cover of Beauharnois Canal. The satellitederived ice coverage points correspond to 32 imagery dates with ISI = 0, 7 dates with ISI = 1, and 30 dates with ISI = 2.

#### 6. Preliminary analyses of ice cover from SAR imagery of the upper St. Lawrence River

Work is ongoing to develop an automated method to classify river ice cover for the upper St. Lawrence from SAR images. The progress to date is summarized below. The goal is to develop methods that can be used in near real time to supplement daily ice monitoring activities.

#### 6.1. Methodology

As described in Section 4, analysis is needed to interpret SAR images. The general methodology for pre-processing in this project is shown in Figure 10. The pre-processed image examples in Figure 11 illustrate that visually distinguishing ice and water is not trivial. The SAR analysis methods tested in this project employ machine-learning methods. Optical imagery (Section 5) was used for "ground truth" ice coverage data for model training. Optical images were sought for the same dates as the SAR imagery data set. If an optical image was not available on the same day as the SAR image, images 1-3 days before and after the SAR image were sought. If two optical images were available and the conditions looked to be unchanged between them, one of those images was used to label the SAR image. The imagery analysis dataset was then split into folds. For each fold one year was held out for model testing and the others were split into training and validation sets with an 80/20 split. Model accuracy was assessed by comparing the model results for the held-out dates against the imagery analysis on the basis of correctly-modeled pixels.



Figure 10. Illustration of the data pre-processing steps for a SAR scene acquired on February 3, 2013. (a) Original SAR image for Lake Ontario / upper St. Lawrence River; (b) calibrated output; (c) land mask; (d) pre-processed image for Lake St. Lawrence with land removed and cropped; (e) pre-processed image for Beauharnois Canal with land removed and cropped. Reproduced from Scott et al. (2025).



Figure 11. Pre-processed SAR images of Lake St. Lawrence (left) and Beauharnois Canal (right).(a) Images from December 5, 2021, which correspond to a time with no ice at either location. (b) Images from January 22, 2022; these may be compared with the optical images on the same date in Section 5.3, which show full ice coverage for Lake St. Lawrence, and about 75% ice coverage for Beauharnois Canal.

The initial approach was to consider this as an image classification problem and use a convolutional neural network (CNN), where each image (or, in this case, a patch from the SAR image) has a single label (for more information on this type of approach, see Scott et al., 2020). The CNN ice classification model was tested for Beauharnois Canal and worked well (Traxler et al., 2024). However, such an approach was not optimal for Lake St. Lawrence since ice conditions are much more heterogeneous (i.e., a patch of the image can easily have mixed ice and water). Also, the presence of many islands meant that image patches could have a high fraction of land, making it difficult for the model to obtain sufficient spatial context for learning. Several model iterations were subsequently tested by Qu et al. (2024) for both the Canal and Lake St. Lawrence. The best performance was obtained from a learnable weight graph neural network (GNN), which achieved an accuracy of 81% to 89% for five years of data. Most recently, another deep learning approach called UPerNet was tested with an expanded ten-year data set. The UPerNet structure is similar to U-Net, which is a more standard approach to using SAR data for deep learning than GNN (see, e.g., Radhakrishnan et al., 2021). Details on the UPerNet model architecture used in the present study are given in Scott et al. (2025). The pixel-to-pixel capability of the UPerNet model means that each patch can have a variety of labels. The method requires little pre-processing and can ingest large patches (i.e., 400 by 400 pixels) of a SAR image that are chosen at random from the training data set of full-scale imagery. The method is thus more translatable from one region to another. In our testing, the expansion of the data set to 10 years of imagery required using data from two different SAR sensors (RADARSAT2 and Sentinel 1). Visual inspection of the RADARSAT2 and Sentinel 1 data showed differences in the two sets of imagery due to spatial resolution and imaging characteristics. For the present iteration these two datasets were merged, however the deep learning approach may benefit from different hyperparameters for each dataset, which was not explored at this stage. This is likely a contributing factor to the model accuracy being lower than expected. The baseline UPerNet model resulted in an annual mean accuracy of 69%. The method was also tested with the inclusion of air temperature and precipitation as context for the model. Model variations with weather conditions from the day of image collection, and for a 5-day window, were tested. The version with 5 days of weather showed an average improvement in accuracy of 5%, with five of the ten years tested having an accuracy of 75% to 99%. For two other years, the inclusion of weather data decreased the ice prediction accuracy. Work is ongoing to refine the model.

### 6.2. Example of SAR imagery analysis results for Beauharnois Canal

For illustration purposes, the results from the earlier model for 5 years of SAR imagery of Beauharnois Canal are presented in Figure 12. As in previous plots, the ISI record is plotted for comparison. Figure 13 shows the correlation between the ISI and the ice coverage from the analyzed SAR images. Correlations are similar to those in Figure 9, but the SAR data show a greater range in the ISI categories 1 and 2. The outliers are mainly at the very start or very end of seasons, for 2 reasons (1) determining when the ISI should move from 0 to 1 or from 2 to 0 requires a judgement call on the part of the operator and depends on factors other than the ice condition, and (2) ice conditions in SAR images are more difficult to assess when the ice is thin or when water is present on its surface.



Figure 12. Ice coverage on Beauharnois Canal derived from SAR imagery analysis for winters from 2016 to 2021, compared with ISI observations.



Figure 13. Comparison of ISI and satellite-derived ice cover of Beauharnois Canal. The satellitederived ice coverage points correspond to 20 dates with ISI = 0, 14 dates with ISI = 1, and 36 dates with ISI = 2.

### 7. Conclusions and recommendations

The Ice Status Indicator or ISI system, currently used to help with decision-making around water management for the St. Lawrence River, is based on visual observations of ice and monitoring of its effects on water levels. Satellite imagery opens up the possibility of augmenting visual ice observations with more information on the ice cover. At the same time, the ISI data, now in their twenty-fifth year of collection, are a valuable and unique set of validation data.

The utility of both optical and SAR satellite imagery was explored for the upper St. Lawrence River. Archived optical imagery was used to derive ice coverage data for 71 SAR scenes of Lake St. Lawrence and 69 scenes of the Beauharnois Canal over a span of 10 years. The seasonal ice coverage was compared with the record of daily ISI. An ISI of 0 for Lake St. Lawrence corresponds to up to about 40% ice coverage, while an ISI of 1 or 2 corresponds to over 90% ice cover. For Beauharnois Canal, an ISI of 0 generally corresponds to less than 10% ice coverage, an ISI of 1 corresponds to 30% to 60% ice cover, and an ISI of 2 corresponds to over 70% ice cover. Initial results of SAR imagery analysis were also presented for Beauharnois Canal, and these align with the optical imagery analysis.

These thresholds provide quantitative bounds on the ice coverage and supplement other work by the authors that employed the ISI data (Sudom and Barrette, 2024; Barrette and Sudom, 2025). For example, if an ISI of greater than zero was recorded for Lake St. Lawrence for a certain number of days in a season, it is likely that the ice covers at least 90% of that river reach for those days. This allows one to have some understanding of historical conditions at times for which ISI was recorded, but satellite images were not regularly collected. The ice coverage thresholds could also be applied to the future ice presence predictions by the authors. This information could be useful for other fields, e.g., ecology or biology.

The ISI record could also be used to help validate SAR data for dates on which no optical satellite validation images are available. The advantage of the ISI is that it is a complete daily data set from year 2000 onward – unlike optical imagery. The meaningfulness of any correlations between the ISI and ice coverage relies upon the operators' use of a consistent definition of ice presence for each ISI category throughout time (which does appear to be the case). Caution must be used in applying the ISI data especially at the end of the ice season, when decisions on ISI are more likely to reflect variables other than ice conditions.

In addition to the historical imagery analysis, several machine-learning methods to process synthetic aperture radar (SAR) imagery were calibrated, and trained and tested with an optical imagery-based data set. A method to map ice presence in near real time could supplement current monitoring on the upper St. Lawrence River. Generalized SAR image analysis methods do not yet exist; models must be recalibrated based upon the configuration of the satellite. The main aim of the work is to move toward an ice cover characterization tool that could be applied not only the upper St. Lawrence, but to other rivers as well. Care was taken to consider the ease of translating the model to other areas. The model needs further testing to resolve issues around the merging of multiple SAR sources. The model performance was enhanced by the inclusion of weather data in its architecture; this result is promising and the concept will be explored further. In general, more work is needed to resolve the issues that SAR analysis methods seem to have with ice/water classification under certain ice and weather conditions.

#### Acknowledgments

This research was supported by the NRC's Climate Resilient Built Environment Initiative, in support of delivering the Government of Canada's Adaptation Action Plan, and towards achieving commitments under the National Adaptation Strategy. The initial work on this topic was supported by the International Joint Commission (IJC), as part of a project carried out by the NRC. The IJC's International Lake Ontario–St. Lawrence River Board is thanked for their provision of the ISI record used in this project, as well as helpful conversations on ice monitoring and water management operations. Hydro Québec also contributed useful information on operations on the St. Lawrence River. The authors would like to thank our colleague Richard Burcher for his assistance with satellite imagery data. Discussions with Paul Barrette were very helpful in focusing and refining this paper. Comments provided by Jamie Ferguson and Saber Ansari on the manuscript are gratefully acknowledged.

### References

- Abdelnour, E., Abdelnour, R., & Pelletier, L., 2019. *Ice Management of the Beauharnois Canal* with Redesigned Ice Booms. <u>https://cripe.ca/docs/abdelnour-et-al-2019-pdf</u>.
- Ayyad, M., Temimi, M., Abdelkader, M., Henein, M.M.R., Engel, F.L., Lotspeich, R.R., & Eggleston, J.R., 2025. *RIce-Net: Integrating ground-based cameras and machine learning for automated river ice detection*. Environmental Modelling & Software, Volume 190, 2025, 106454, <u>https://doi.org/10.1016/j.envsoft.2025.106454</u>.
- Barrette, P. & Sudom, D., 2025. Using an operational index to foresee future ice scenarios in the Upper St. Lawrence River. CGU HS Committee on River Ice Processes and the Environment 23rd Workshop on the Hydraulics of Ice Covered Rivers, St. John's, Newfoundland and Labrador, Canada, June 9-12, 2025.
- Barrette, P., Ghobrial, T., & Kolerski, T., 2025. On floods caused by river ice: an overview of mitigation measures. NRC report NRC-OCRE-2024-TR-027. https://doi.org/10.4224/40003460.
- Bunch, K., 2018. Managing Great Lakes Ice: Preventing Jams and Keeping Water Flowing. International Joint Commission. <u>https://www.ijc.org/en/managing-great-lakes-ice-preventing-jams-and-keeping-water-flowing</u>.
- De Roda Husman, S., van der Sanden, J. J., Lehrmitte, S. & Eleveld, M., 2021. *Integrating intensity and context for improved supervised river ice classification from dual-pol Sentinel-1 SAR data*. International Journal of Applied Earth Observation and Geoinformation, 101, 102359, 1-10. <u>https://doi.org/10.1016/j.jag.2021.102359</u>.
- Institut national de la recherche scientifique (INRS), 2025. A major breakthrough for river ice monitoring in Québec. March 24, 2025. <u>https://inrs.ca/en/news/a-major-breakthrough-for-river-ice-monitoring-in-quebec/</u>
- International Joint Commission, 2014. Lake Ontario St. Lawrence River Plan 2014: Protecting against extreme water levels, restoring wetlands and preparing for climate change. https://ijc.org/sites/default/files/IJC\_LOSR\_EN\_Web.pdf.
- International Lake Ontario-St. Lawrence River Board, 2019. *Quarterly Newsletter: Winter 2019*. <u>IJC-Newsletter-WINTER-2019-English-1.pdf</u>.

- Lynch, M., Briggs, R., English, J., Khan, A. A., Khan, H., & Puestow, T., 2021. Operational Monitoring of River Ice on the Churchill River, Labrador. In Proceedings of the 21<sup>st</sup> Workshop on the Hydraulics of Ice Covered Rivers, Saskatoon, SK, Canada (Vol. 29).
- Ontario Power Generation (OPG), 2019. *Ice booms keep rivers flowing and winter's deep freeze at bay*. <u>https://www.opg.com/news-and-media/our-stories/story/ice-booms-keep-rivers-flowing/</u>.
- Ontario Power Generation (OPG), 2021. *OPG's hydro operations not frazzled by frazil ice*. https://www.opg.com/stories/opgs-hydro-operations-not-frazzled-by-frazil-ice/.
- Plante Lévesque, V., Gauthier, Y., Tolszczuk-Leclerc, S., Van Der Sanden, J., Drouin, H., Chokmani, K., & Bernier, M., 2017. *Comparative analysis of river ice mapping tools from satellite radar data*. In 19<sup>th</sup> Workshop on the Hydraulics of Ice Covered Rivers, pp. 10-12.
- Plante Lévesque, V., Karem, C., Yves, G., & Monique, B., 2025. *IceEB: An ensemble-based method to map river ice type from radar images*. International Journal of Applied Earth Observation and Geoinformation, 136, 104317.
- Plante Lévesque, V., Persent, M. A., Lhissou, R., Chokmani, K., Gauthier, Y., & Bernier, M., 2024. How Ice Mapping Can Help Manage and Prevent Ice Jams: Remote Sensing Monitoring of the Saint-François River, Québec. Canadian Journal of Remote Sensing, 50(1). https://doi.org/10.1080/07038992.2024.2391972.
- Qu, Y., Soleymani, A., Sudom, D., & Scott, K. A., 2024. Learnable Weight Graph Neural Network for River Ice Classification. Proceedings, 110(1), 30. https://doi.org/10.3390/proceedings2024110030
- Radhakrishnan, K., Scott, K.A. & Clausi, D., 2021. Sea ice concentration estimation: Using passive microwave and SAR data with a U-Net and curriculum learning. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 14, pp. 5339–5351, 04 2021.
- Scott, K.A., MacMillan, C., and Soleymani, A., 2025. *River Ice/Water Classification Using SAR Data*. University of Waterloo report for the NRC. Available through <u>https://nrc-publications.canada.ca/</u>.
- Scott, K.A., Xu, L., & Kheyrollah Pour, H., 2020. Retrieval of ice/water observations from synthetic aperture radar imagery for use in lake ice data assimilation. Journal of Great Lakes Research, Volume 46, Issue 6, pp. 1521-1532, https://doi.org/10.1016/j.jglr.2020.08.018.
- Sobiech, J., & Dierking, W. (2013). Observing lake- and river-ice decay with SAR: advantages and limitations of the unsupervised k-means classification approach. Annals of Glaciology, 54(62), 65–72. https://doi.org/10.3189/2013AoG62A037.
- Sudom, D., Barrette, P., & Burcher, R., 2024. *Plausible scenarios for future ice conditions in the St. Lawrence River.* NRC report NRC-OCRE-2023-TR-029, March 2024. https://doi.org/10.4224/40003396.
- Temimi, M., Abdelkader, M., Tounsi, A., Chaouch, N., Carter, S., Sjoberg, B., Macneil, A., & Bingham-Maas, N., 2023. An Automated System to Monitor River Ice Conditions Using Visible Infrared Imaging Radiometer Suite Imagery. Remote Sensing, 15(20), 4896. <u>https://doi.org/10.3390/rs15204896</u>.
- Traxler, C., Qu, Y., and Scott, K.A., 2024. *Ice/water classification in the St. Lawrence River*. University of Waterloo report for the NRC. Available through <u>https://nrc-publications.canada.ca/</u>.
- Tuthill, A.M., 1999. *Flow Control to Manage River Ice*. US Army Corps of Engineers. Cold Regions Research & Engineering Laboratory Special Report 99-8, July 1999.

https://damfailures.org/wp-content/uploads/2021/04/OR\_Flow-Control-to-Manage-River-Ice.pdf.

- Unterschultz, K.D., van der Sanden, J., & Hicks, F.E., 2009. Potential of RADARSAT-1 for the monitoring of river ice: Results of a case study on the Athabasca River at Fort McMurray, Canada. Cold Regions Science and Technology, Volume 55, Issue 2, pp. 238-248. <u>https://doi.org/10.1016/j.coldregions.2008.02.003</u>.
- Van der Sanden, J.J., Drouin, H., & Geldsetzer, T. 2021. An automated procedure to map breaking river ice with C-band HH SAR data. Remote Sensing of Environment, Volume 252, January 2021, 112119. <u>https://doi.org/10.1016/j.rse.2020.112119</u>.
- Zakharov, I., Puestow, T., Khan, A. A., Briggs, R., & Barrette, P., 2024. *Review of River Ice Observation and Data Analysis Technologies*. Hydrology, 11(8), 126. https://doi.org/10.3390/hydrology11080126.