IAHR AIRH
Hosted by
Spain Water
and IWHR, China

27th IAHR International Symposium on Ice
Gdańsk, Poland, 9 – 13 June 2024

A logic-driven assessment to refine SAR-based river ice classifications.

Stephanie Saal[1], Benoit Turcotte[1], Mederic Girard[1], Ashley Dubnick[1]
[1]Yukon University Research Centre
[1]500 University Drive, Whitehorse, YT, Y1A 5K4
ssaal@yukonu.ca

Radar remote sensing provides useful information to differentiate river ice conditions and ice cover types in large rivers. However, false classifications are common, especially at the end of winter, due to water on ice as well as wet snow. These situations can present challenges to end users, such as water resources managers and flood forecasters. In this study, we design a logic-driven assessment to refine existing classifications to distinguish between areas of water or wet snow on ice and open water. It is uncommon for river segments to experience ice cover, followed by open water, then ice cover again, within three consecutive radar images. Our decision tree analysis therefore assumes that river segments that are classified as water, but classified as ice in the radar images before and after, represent water or wet snow on ice. We examine the potential of this approach on two rivers in the Yukon Territory, Canada. The Äshèyi Chù (Aishihik River) is a narrow, regulated river with a relatively steep slope (0.3%) and commonly experiences flood issues at freeze-up. The Chu kon' dëk (Yukon River at Dawson) is a much larger, low gradient (0.04%) river with a history of ice jam related flooding. Pixels are tested based on this concept, and a clustering approach is applied to reduce noise. The success of the algorithm is assessed using drone imagery and Sentinel-2 optical imagery. We show that using logic can offer ways to refine river ice classification, that is meaningful to the end user.

Keywords: River Ice; SAR; Sentinel-1; Classification; Mapping; Floods

1. Introduction

Winter hydrological processes can have significant impacts on cold region ecosystems (Prowse 2001) and infrastructure (Burrell et al. 2021). In turn, flow regulation during months of high energy demand is also known to affect ice processes (Huokuna et al. 2022) with potential consequences on channel stability and habitats. Understanding the impact of high and varying streamflow on river ice and hydraulic conditions can be challenging, especially at locations with limited road access. Therefore, remote sensing represents an opportunity to collect valuable river ice coverage data and observations that can inform short- and long-term decision making.

Ice detection using radar waves is based on differences in signal backscatter for surfaces of different roughness. Calm water is a specular surface, which reflects the radar signal away from the satellite. This will show up as a dark area in the resulting image, since no or minimal signal is received by the satellite. Ice, however, has varying degrees of surface roughness, which causes the radar signal to interact with the surface and consequently results in backscatter of a portion of the signal to the satellite, with pixel brightness proportional to the backscatter ratio. In principle, a smooth ice cover, such as sheet ice, results in some backscatter, while a rough ice cover, such as an ice jam, causes more backscatter (Palomaki and Sproles 2022). This basic concept allows us to produce classifications that distinguish open water from ice cover, and even different types of ice, uncompromised by cloud cover or daylength. Over the years, several jurisdictions have used satellite-based ice maps to provide users with critical river channel information for purposes such as supporting winter navigation (e.g., on the St. Lawrence River and Estuary) or forecasting water level variations caused by a sudden change in ice condition (e.g., on the Peace River in Alberta).

Classification, however, becomes more complex when we find water or wet snow on top of an ice cover (Stonevicius, Uselis, and Grendaite 2022). During a water on ice event, the radar waves will interact with the water on top of the ice instead of the ice underneath (van der Sanden, Drouin, and Geldsetzer 2021). C-band synthetic aperture radar (SAR) products are commonly used for river ice detection, due to their high spatial resolution and frequent repeat cycle. When snow is dry, it is basically invisible to C-band waves (wavelength of 5.6 cm), and the waves interact with the surface underneath instead. If snow is wet and hence saturated, however, the interaction of the waves with snow is similar to that of water, and the signal is reflected away from the satellite (Bernier et al. 2017; Lievens et al. 2019). As a result, during a water or wet snow on ice event, minimal signal will be returned to the satellite and the spectral signature is like the one of calm water (van der Sanden et al. 2021). This presents challenges for the end users, such as flood forecasters, who need to know if a section of river is still ice covered or if the ice cover has moved downstream.

Since wet snow or water on ice conditions push the boundaries of the satellite capabilities, we propose here to make use of knowledge we have about rivers and ice cover formation to drive a refinement of classification using logic. For instance, it is well known that an ice cover, especially when it is thick and complete, cannot melt suddenly when upstream ice is present over a long distance, since any heat carried by the river would melt the upstream ice cover. Moreover, a sudden local breakup event usually results from a water level or flow fluctuation, with pieces of broken ice cover (i.e., ice floes) accumulating somewhere downstream. Finally, a complete ice cover is not likely to form overnight if there is a complete ice cover in the river reach located immediately upstream. Since several processes may cause water to accumulate on the ice cover (e.g. an increase in discharge in a small river, rain-on-snow, high air temperatures, etc.), it can be assumed that the ice cover, although no longer detected by radar, is still in place and relatively intact.

In this paper, we test a logic-driven approach to refine river ice classification. We examine river ice classification products as a time series and use an algorithm to look at radar classification product sequences that exhibit ice, then water, and then ice again.

2. Study Area

Two rivers were examined in this study – the Äshèyi Chù (Aishihik River), which is a small river used for power generation in southwest Yukon, and the Chu kon' dëk (Yukon River at Dawson), which is the major watercourse flowing through the Yukon Territory. Both rivers experience flooding issues due to ice jams and are hence examined for changes in ice cover conditions.

The Äshèyi Chù (Aishihik River) is located on the traditional territory of the Champagne and Aishihik First Nations (CAFN), in the southwest of the Yukon Territory, Canada. It is fed primarily by Äsheyi Män (Aishihik Lake). The CAFN settlement of Äsheyi (Aishihik) is situated at the north end of the lake. The name "Äsheyi" is of Tlingit origin and means "the head of the lake" (Champagne and Aishihik First Nations 2023). The watershed area of the river at Canyon is 4,300 km (Mcparland, Mckillop, and Pearson 2021). It drains into the Dezadeash River, which outlets into the Alsek River and then into the North Pacific Ocean. The Äshèyi Chù is a narrow (15m to 50m wide) river with a relatively steep slope (0.3%). This river is highly dynamic, with a frequency of 0.08 to 0.26 meander cut-offs/year. In 1975, the Äshèyi Chù became a regulated river for power hydroelectricity production with the establishment of the Aishihik Generating Station (AGS) (Mcparland et al. 2021). Winter flows, largely imposed by daily fluctuations in energy demand, have historically varied from less than 5 m^3/s to more than 20 m^3/s. From confluence of the East- and West-Aishihik Rivers, the river flows for approximately 30 km and passes through the CAFN community of Canyon. Flooding issues occur at that location, but also at several floodplain locations, mainly due to mid-winter ice jams, with consequent overflow and aufeis development.

The Chu kon' dëk is the most significant and largest river of the territory. The origin of its waters extends as far as the Atlin Lake area of northern British Colombia, more specifically from the discharge coming out of the Juneau Icefield. The river flows through the Yukon Territory and the U.S. state of Alaska, covering a distance of around 3185 km. Previous work suggests that the gradient of the river is around 0.05% when considering the 900 km stretch of channel from Whitehorse, the capital of the Yukon Territory, to the Alaska Border (Saal, Boyd, and Turcotte 2023). Dawson City, located along the Tágà Shäw, is susceptible to both ice jam and open water flooding. The Chu kon' dëk at Dawson City is approximately 360 m wide and has a depth of about 4 m with an annual flow ranging from about 500 m^3/s at the end of winter to about 10,000 m^3/s in June. The community has been subject to several floods, with the 1979 ice jam flood being the most notorious event on record. Although mitigation structures exist around the community, flood risk can still be reduced, including through flood forecasting (Turcotte and Saal 2022).

3. Input Data Sources

Two classification products we tested. The product of the narrow Äshèyi Chù is based on Sentinel-1 vertical-vertical (VV) imagery, while the product of the Chu kon' dëk stems from Radarsat-2 and Radarsat Constellation Mission (RCM) data.

The first classification product was created as part of a research project conducted by YukonU on the Äshèyi Chu. The objective of the project was to develop a river ice model that can inform flow management in a perspective of reducing downstream impacts (Fang et al. 2023; Saal, Turcotte, et al. 2023) Since river ice model development depends on the availability of data about ice coverage conditions on the Äshèyi Chu, an algorithm was developed to detect ice and water using Sentinel-1 imagery.

One goal was to identify locations of early season ice bridging, therefore distinguishing the specific type of ice was not necessary. Additionally, ice type would have been difficult to identify, given the small width of the river. While SAR technology is applied to large rivers of Canada, the ability of Sentinel-1 to detect ice on a narrow, 15 to 50m-wide river, had, to our knowledge, not been previously explored. In this hydrological context, Sentinel-1's 10 m grid cells in interferometric wide swath appear coarse. This is further complicated by the appearance of speckle. While filters are applied when working on wider rivers, we did not have this luxury due to the decrease in resolution resulting from filtering. The approach that was applied instead was to calculate a significant cluster size of a given classification. If a class cluster was below threshold, the area was removed as speckle and did not receive a classification. The resulting product contains the classes water and ice, as well as no data areas that were removed as speckle. Another layer of complexity materialized after December 23rd, 2021, when the Sentinel-1 platform lost half of its capacity due to the failure of the Sentinel-1B satellite (European Space Agency 2023). As a result, only Sentinel-1 imagery of the ascending path was explored during this study.

C-Core, a company specialized in remote sensing based in Newfoundland in Eastern Canada, started to produce ice maps on the Chu kon' dëk near Dawson City for the Yukon Government (Department of Environment) in 2015. The maps were initially based on RADARSAT-2 but can rely on RCM data from 2021, with more frequent acquisition.

4. Algorithm

The algorithm was coded to run in Python for ArcGIS. As an initial step, data sources were prepared to fit to the same schema. After that, the same code could be applied to any classification data source. Since the objective was to identify river sections that were classified as water, but that are actually ice-covered sections with water or wet snow on the surface, only the two classes, water and ice, were required to feed into the process. Hence, input data with more detailed classifications (e.g., ice cover types) were simplified to the same schema, in which water equals zero and ice equals one. When an input dataset contained a "water on ice" class, it was reclassified as ice, since the ice had already been identified.

A second dataset for every image was created to identify cluster size. As SAR data contains noise in the form of speckle, using a significant cluster size of the water and ice classes prevented correcting single pixels that may just have been speckle. The cluster size was calculated and assigned to every pixel within a cluster.

The basis of the logic applied was that:

> If a pixel is classified as water in the current image, but classified as ice in the previous and the consecutive image;
>
> AND
>
> If a pixel belongs to a cluster larger than 10;

It is reclassified as water on ice.

To avoid computational costs, this logic was simplified as much as possible. As such, simple raster math was applied to the images. This avoided testing every pixel individually and was hence more efficient. The input image was reclassified into a binary dataset, where 0 equals water and 1 equals ice. $Image_{T}$ is the image that is to be assessed. $Image_{T-1}$ is the image before the image in question, and $Image_{T+1}$ is the image after. During the first step, the following calculation was applied (Test 1):

$$Image_{T-1} - Image_{T} + Image_{T+1} = ImageTest_{1} \quad \textbf{[1]}$$

When the sequence of classified images represents ice/water/ice, expressed in numbers as 1/0/1, the result of the calculation would be 2, indicating a water or wet snow on ice event.

The cluster size was calculated for all images as well, using the non-simplified polygon sizes of the water and ice classes. The cluster size was then reclassified as 0 when cluster size was not sufficient, and 1 when cluster size was sufficient, and then assigned to every pixel. Again, simple raster math was applied to test if cluster size was sufficient in every image, using (Test 2):

$$ClusterImage_{T-1} + ClusterImage_{T} + ClusterImage_{T+1} = ImageTest_{2} \quad \textbf{[2]}$$

If cluster size was sufficient for a pixel on every image, the result would be 3.

Finally, image testing was completed by combining (Test 3):

$$ImageTest_{1} + ImageTest_{2} = ImageTest_{3} \quad \textbf{[3]}$$

When the sequence from test 1 was ice/water/ice, resulting in value 2, and cluster size was sufficient for a given pixel in all three images in test 2, resulting in value 3, the sum value was 5.

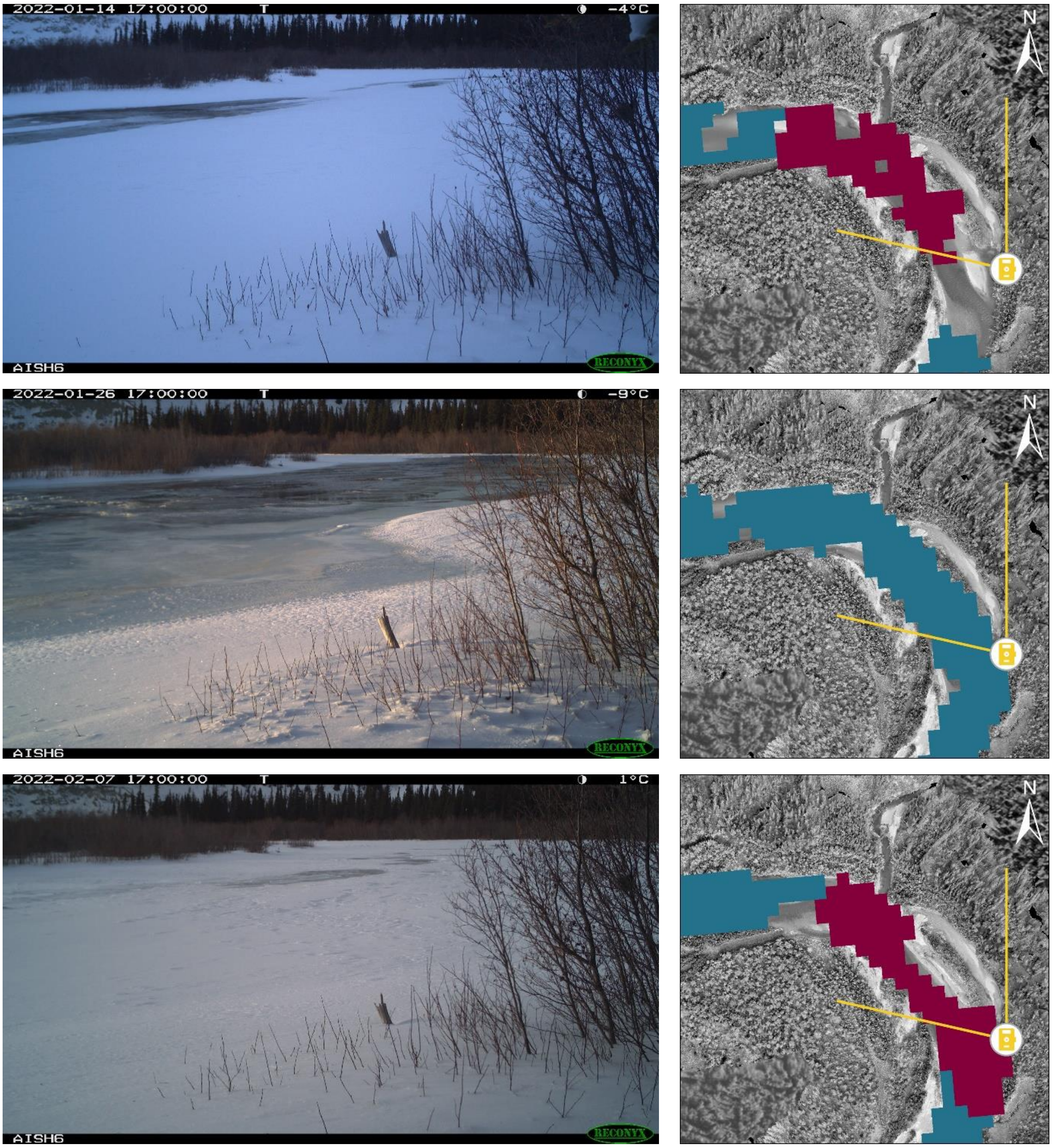
The resulting image was then reclassified from 5 to 50, representing water or wet snow on ice, with 0 being all other values. In the last step, the output image was merged with the original input. Images were mosaiced to the max value. This resulted in the output image from this algorithm only overwriting the input values in the case of water on ice, while other original classes stayed the same.

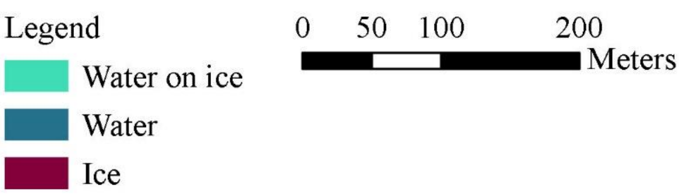
5. Results

Three winters were analyzed for the Äshèyi Chù. Several game cameras were deployed by a consultant (Morrison Hershfield) along the river each winter. During the study period, eight overflow events (OE) lined up with Sentinel-1 overpasses. In two instances, ice was detected, and there was no need to apply the algorithm. Since the classification product of the Äshèyi Chù has some areas that are not classified as these were removed as speckle, it is possible that an OE area doesn't have a classification in one of the three images. This occurred in three instances. During three of the eight other OEs, overflow was classified as water, and the images before and after as ice. In these cases, the algorithm was successfully applied.

Figure 1 shows an OE sequence that occurred at km 18 (with Km 0 starting upstream at the tailrace of the Aishihik Generating Station) on January 26th, 2022. The left column contains game camera photos, exhibiting a largely snow-covered ice cover on January 14th, the overflow event on January 26th, and a return to previous conditions on February 7th.The corresponding Sentinel-1 classifications are shown on the right. The algorithm was applied to the three images. In the bottom right corner, we can see the results of the refined classification, including a water on ice class. When looking at the remaining areas that are included in the frame of the game cameras where the algorithm was applied, no sections were falsely corrected as water on ice.

Three Unmanned Aerial Vehicle (UAV) orthomosaics were available near Sentinel-1 overpasses. In one case, river ice and water were classified correctly, and no improvement was needed. In another image, there were two instances where snow on ice was classified as water. However, the area was also classified as water in the previous image. Hence, the algorithm could not be successfully applied. In the third image, areas with snow on ice were classified as water. In this case, the previous and following images contained the ice class for this area, and the algorithm was used to improve the classification. Figure 2 shows the orthomosaic from December 21st, 2021, with the improved classification overlayed below. In the northern end of the image, we can see a narrow ice dam that was previously classified as water. In the southern section of the image, we can observe a snow-covered area with some possible overflow, also previously classified as water. While it is impossible to obtain the moisture content of the snow from looking at UAV imagery, it is assumed that this was a wet-snow-on-ice condition. As above, no false corrections were observed.





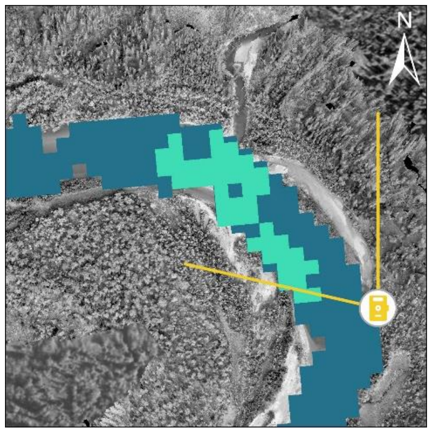


Figure 1. Game camera photos for km 18 with corresponding Sentine-1 classifications for 14-01-2022 (top), 26-01-022 (center), and 07-02-2022 (bottom). The improved classification includes the overflow event seen in the photo of 26-01-2022 (bottom right).

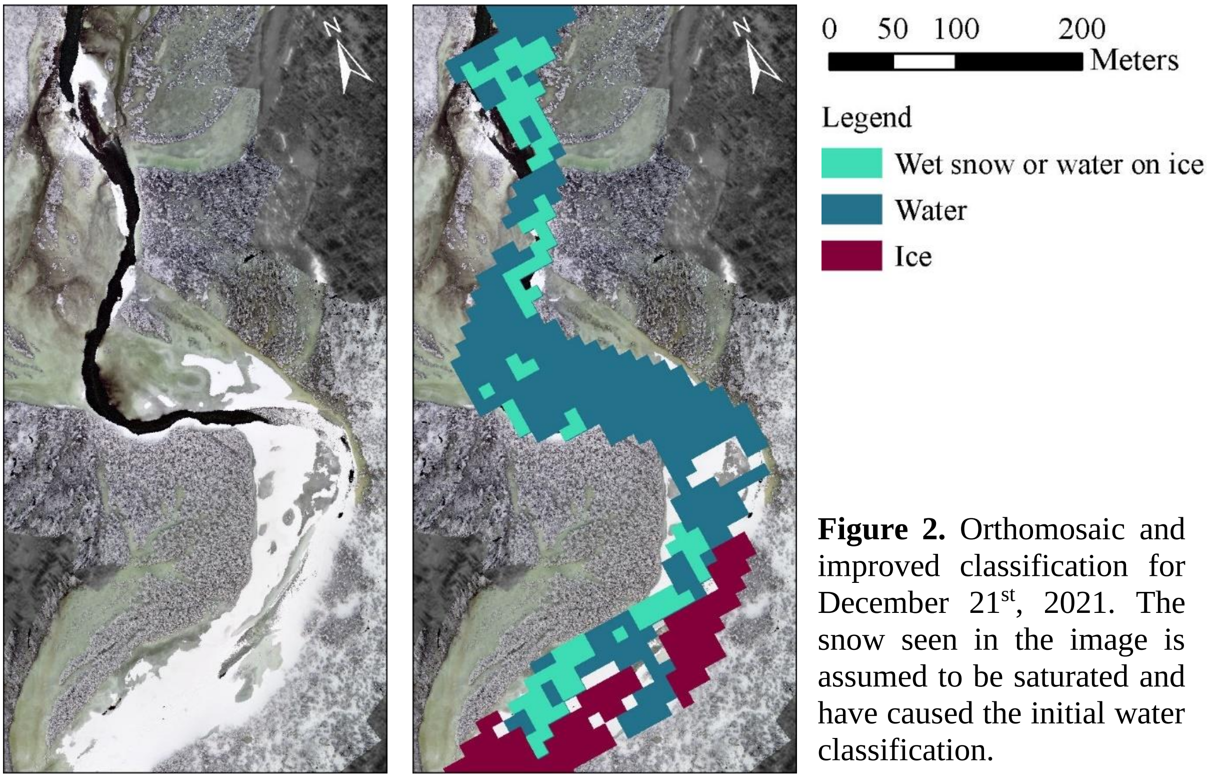


Figure 2. Orthomosaic and improved classification for December 21st, 2021. The snow seen in the image is assumed to be saturated and have caused the initial water classification.

Since the number of available C-Core classified scenes for the Chu kon' děk was limited, and a classification before and after the image in question was required for this algorithm, only a few relevant examples were used for this project. We were able to track down an example in the 2018 data to test the approach.

The top row in Figure 3 shows Copernicus Sentinel-2 2018 visible images of the corresponding classification dates. The image in question is from May 3rd, 2024, shown in the center column of the figure. While some open water exists within the scene, wet snow and water on ice received the same classification. We can see in the classification scheme, that C-Core acknowledges the difficulty of distinguishing between open water and water on ice, as the class is named "Water or possibly water on ice". The improved classification after application of the algorithm is shown at the bottom.

Overall, the algorithm was able to detect locations of wet snow and water on ice, while maintaining locations of open water. There are some locations that do not display the new class. This is due to these areas also being classified as water in the May 1st image, even though they displayed snow on ice.

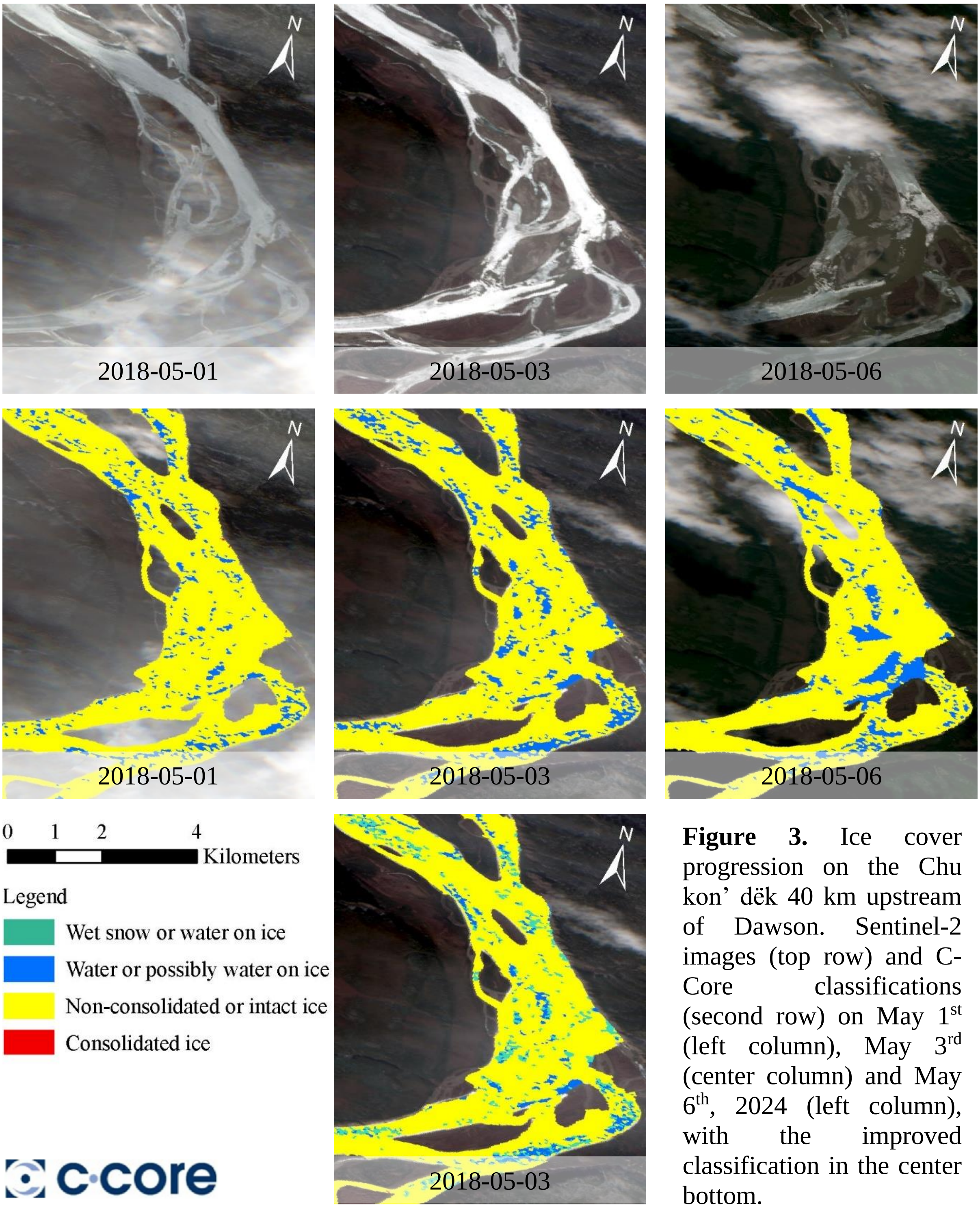


Figure 3. Ice cover progression on the Chu kon' dëk 40 km upstream of Dawson. Sentinel-2 images (top row) and C-Core classifications (second row) on May 1st (left column), May 3rd (center column) and May 6th, 2024 (left column), with the improved classification in the center bottom.

6. Discussion

This research project aims to improve the accuracy of ice condition classification using radar products using logic. As a first phase to this project, we explored the development of a simple algorithm that reclassifies water as water-on-ice, especially during the mid-winter period, where ice is unlikely to melt and then reform quickly, but where overflow events or wet-snow events are common. Optical imagery, especially when viewed in false-colour, can easily reveal this type of event, but unfortunately, cloud coverage and the short days limit the use of Sentinel-2 imagery during winter in Yukon.

The algorithm presented in this paper takes a sequence of images into account to improve the channel classification. For the case of the Äshèyi Chù, although the river is very narrow and somewhat steep, this approach seemed appropriate, especially considering that Sentinel-1A images are 12 days apart, and overflow or wet snow events are not likely to persist over this time period. When a data source with a more frequent acquisition period (e.g., RCM) is used for classification, however, several images before and after the image in question should be integrated in the algorithm. Air temperature data, which are readily available, could also be used to discard some water classifications.

One limitation of this approach, as presented in this paper, is that it can't be applied in an operational, or near real time context in which imagery interpretation would be required as soon as possible after the acquisition of the radar image. Since at least one image after the image of interest is required, a delay is induced, which represents at least 12 days when relying on the Sentinel-1 platform (keeping in mind that it is down to one satellite). This approach is hence mainly of use when analyzing river ice patterns over a long period, which is the case for our team in the context of creating ice coverage data for river ice model development and calibration.

More classification errors are likely to occur during breakup. When there is a sequence of ice cover, followed by open water, followed by an ice jam, the open water would be incorrectly changed to flooded ice (which is the case of some pixels in Figure 3). This could be mitigated by taking the roughness of the detected ice into account. Consequently, if the backscatter suggests an increased surface roughness, which means the scene is likely to contain an ice jam, the image sequence would be excluded from the algorithm.

Future steps of this research could involve: 1. Including hydrometeorological information into the classification, 2. Adding a roughness component to improve the reliability of the classification, 3. Testing RCM products and applying the methodology to other rivers where users see benefits. 4. Expanding the time series where appropriate.

7. Conclusion

This paper presented a thought experiment of how radar-based river ice classifications can be improved beyond backscatter. The radar community acknowledges the limitations around detecting ice when the ice is covered by a layer of water or wet snow. Within the C-Core classification for example, the first class is labelled "Water or possible water on ice", accounting for the fact that the radar interacts with the topmost layer. In this paper we show that creative thinking opens up the possibility to refine classifications in a way that contains important and accurate information for the end-user, without the need to use multiple other sources of information to confirm river ice conditions.

References

Bernier, Monique, Jean-Pierre Dedieu, Yannick Duguay, and Guy Seguin. 2017. "Snow Water Equivalent Estimation Using High Resolution SAR Data." Pp. 1351–54 in 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Fort Worth, TX, USA. IGARSS 2017 - 2017 IEEE International Geoscience and Remote Sensing.

Burrell, Brian C., Benoit Turcotte, George Comfort, and Joe Groeneveld. 2021. "Infrastructure and River Ice: An Overview." Pp. 1–27 in 21st CGU-HS CRIPE Workshop on River Ice, Saskatoon, SK, August 29 – September 1.

Champagne and Aishihik First Nations. 2023. “Äsheyi (Aishihik).” Retrieved December 6, 2023 (https://cafn.ca/territory/asheyi-aishihik/).

European Space Agency. 2023. “ESA - Mission Ends for Copernicus Sentinel-1B Satellite.” Retrieved December 6, 2023 (https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1/Mission_ends_for_Copernicus_Sentinel-1B_satellite).

Fang, Heyu, Yuntong She, Mark Loewen, Benoit Turcotte, and David Andres. 2023. “Modelling Freeze-up Processes in a Small-Steep-Regulated River.” Pp. 1–17 in 22nd CGU-HS CRIPE Workshop on River Ice, Canmore, AB, Canada, July 9-12.

Huokuna, Mikko, Mike Morris, Spyros Beltaos, and Brian C. Burrell. 2022. “Ice in Reservoirs and Regulated Rivers.” International Journal of River Basin Management 20(1):1–16. doi: 10.1080/15715124.2020.1719120.

Lievens, Hans, Matthias Demuzere, Hans Peter Marshall, Rolf H. Reichle, Ludovic Brucker, Isis Brangers, Patricia de Rosnay, Marie Dumont, Manuela Girotto, Walter W. Immerzeel, Tobias Jonas, Edward J. Kim, Inka Koch, Christoph Marty, Tuomo Saloranta, Johannes Schöber, and Gabrielle J. M. De Lannoy. 2019. “Snow Depth Variability in the Northern Hemisphere Mountains Observed from Space.” Nature Communications 10(1). doi: 10.1038/s41467-019-12566-y.

Mcparland, Dan, Robin Mckillop, and Forest Pearson. 2021. “Fluvial Geomorphological Responses to River Ice Dynamics Downstream of a Hydroelectric Facility, Southwest Yukon.” in 21st CGU-HS CRIPE Workshop on River Ice, Saskatoon, SK, August 29 – September 1.

Palomaki, Ross T., and Eric A. Sproles. 2022. “Quantifying the Effect of River Ice Surface Roughness on Sentinel-1 SAR Backscatter.” Remote Sensing 14(22). doi: 10.3390/rs14225644.

Prowse, Terry D. 2001. “River-Ice Ecology. I: Hydrologic, Geomorphic, and Water-Quality Aspects.” Journal of Cold Regions Engineering 15(1):1–16. doi: 10.1061/(ASCE)0887-381X(2001)15:1(1).

Saal, Stephanie, Joseph Boyd, and Benoit Turcotte. 2023. Developing 3D Profiles for Major River Systems of the Yukon - Preliminary Results. Prepared for the Water Resources Branch, Department of Environment, Government of Yukon. Whitehorse.

Saal, Stephanie, Benoit Turcotte, Ashley Dubnick, and Mederic Girard. 2023. “An Algorithm for Remotely Detecting River Ice on a Narrow River.” P. 1 in 22nd CGU-HS CRIPE Workshop on River Ice, Canmore, AB, Canada, July 9-12. Canmore.

van der Sanden, J. J., H. Drouin, and T. Geldsetzer. 2021. “An Automated Procedure to Map Breaking River Ice with C-Band HH SAR Data.” Remote Sensing of Environment 252. doi: 10.1016/j.rse.2020.112119.

Stonevicius, Edvinas, Giedrius Uselis, and Dalia Grendaite. 2022. “Ice Detection with Sentinel-1 SAR Backscatter Threshold in Long Sections of Temperate Climate Rivers.” Remote Sensing 14(7). doi: 10.3390/rs14071627.

Turcotte, Benoit, and Stephanie Saal. 2022. Flooding in Dawson: Exposure Analysis and Risk Reduction Recommendations. Presented to the Infrastructure Branch of the Department of Community Services, Government of Yukon. Whitehorse.