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Automated Coastal Ice Mapping with SAR Can Inform Winter Fish Ecology in the Laurentian Great Lakes

La cartographie RSO automatisée des glaces côtières peut éclairer sur l'écologie des poissons durant l'hiver dans les Grands Lacs du Saint-Laurent

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ABSTRACT

Many freshwater lakes in the temperate zone undergo annual freeze-thaw cycles. Climate change has disrupted these patterns and altered habitat for many species including ecologically, economically, and culturally valuable fish species. To understand the relationship between ice cover and aquatic species, suitable data can be derived from remote sensing. We developed a novel ice classification method with minimal user input using freely available Sentinel-1 data and an adjacent and time-coincident validation dataset. Using image object segmentation and a random forest classifier, ice conditions were classified correctly with >85% overall accuracy. Our ice mapping efforts coincided with a telemetry dataset of tagged Walleye (*Sander vitreus*) and Northern Pike (*Esox lucius*) in Hamilton Harbor in western Lake Ontario. Between years with low and high ice covers (2017 and 2019, respectively), we found Walleye appeared to reduce their area of movement when the harbor was covered in ice. Our ice mapping tool can provide a quick and consistent method for agencies to adopt for freshwater resource management as well as provide ice cover information in coastal areas that are important overwintering habitat for many fishes.

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RÉSUMÉ

De nombreux lacs d'eau douce de la zone tempérée subissent des cycles annuels de gel-dégel. Les changements climatiques ont perturbé ces tendances et modifié l'habitat de nombreuses espèces, y compris des espèces de poissons qui ont une valeur écologique, économique et culturelle. Pour comprendre la relation entre la couverture de glace et les espèces aquatiques, des données appropriées peuvent être tirées de la télédétection. Nous avons mis au point une nouvelle méthode de classification des glaces avec une contribution minimale de l'utilisateur à l'aide des données Sentinel-1 disponibles gratuitement et d'un ensemble de données de validation adjacent et coïncident dans le temps. À l'aide d'une segmentation objet et d'un classificateur de type forêt aléatoire, les conditions de glace ont été classées correctement avec une précision globale >85%. Nos efforts de cartographie des glaces ont coïncidé avec un ensemble de données de télémétrie du doré jaune (*Sander vitreus*) et du grand brochet (*Esox lucius*) marqués dans le port de Hamilton, à l'ouest du lac Ontario. Entre deux années où la couverture de glace était faible ou élevée (2017 et 2019, respectivement), nous avons constaté que le doré jaune semblait réduire sa zone de mouvement lorsque le port était recouvert de glace. Notre outil de cartographie des glaces peut fournir une méthode rapide et uniforme que les organismes peuvent adopter pour la gestion des ressources en eau douce et fournir de l'information sur la couverture de glace dans les zones côtières qui constituent un important habitat d'hivernage pour de nombreux poissons.

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Introduction

Over half of the world's lakes have a seasonal cycle of surface water freezing that affects limnological and biological processes (Brown and Duguay 2011; Verpoorter et al. 2014). Variation in the duration and extent of lake ice cover can have economic, biological, and anthropogenic consequences and mapping interannual changes in ice cover can help us measure and better understand these consequences (Assel 2003; Duguay et al. 2006; Brown and Duguay 2011; Yang et al. 2020). Globally, the duration of winter ice cover in lakes is declining due to anthropogenic climate change (Magnuson et al. 2000; Lopez et al. 2019), with largely unknown consequences on aquatic ecosystems. Given human dependence on aquatic ecosystems, even during winter (Knoll et al. 2019), changes in ice cover may have broad reaching socio-economic consequences.

Due to the importance of lake ice measurements and the utility of more automated remote sensing processes, many researchers have undertaken projects to map ice cover with some level of automation. For example, Surdu, Duguay, Pour, et al. (2015) developed an approach for mapping thin ice cover in shallow Alaskan lakes with VV-polarized (vertical send, vertical receive) Synthetic Aperture RADAR (SAR) data and validated the outputs with predictions based on climatic variables. In the Great Lakes, Leigh et al. (2014) created an automated ice classification system dubbed "MAGIC" (MAp-Guided Ice Classification) that uses Iterative Region Growing Semantics (IRGS) to identify ice from HV-polarized (horizontal send, vertical receive) data over large spatial scales. A support vector machine (SVM) tool was applied to the image objects with expert input as training data to classify ice types in the outputs. These types of single-polarized data are susceptible to angle effects (Surdu, Duguay, and Fernández Prieto 2015) and wave action (Wang et al. 2018) so more studies are shifting to use multi-polarized data. To show the utility of dual-polarized HH/HV image data, Wang et al. (2018) used MAGIC on reduced resolution (100 m) Radarsat-2 data to delineate ice type boundaries in Lake Erie, which were then manually labeled/classified. Applications with random forest (RF) labeling have also been developed (Hoekstra et al. 2020) and use supervised classification on the output polygons to further reduce the requirement for user input and overall workload while still retaining high accuracy (>95%). Deep learning has become a popular tool within the field of remote sensing in recent years, and Tom et al. (2020) applied this technique to alpine lakes in Switzerland. They trained a two-class model (ice/water) from a large bank of existing Red-Green-Blue imagery (collected for another ice cover study) and observed high model accuracy (>84%) across all their field sites. With the transferability of their method as it exists in Google Earth Engine (GEE; Gorelick et al. 2017), it is feasible that this technique could also be applied across many locales, but such an exercise has yet to be undertaken.

The Laurentian Great Lakes constitute the largest aggregation of freshwater resources on the planet and are home to a wide diversity of aquatic organisms (Vadeboncoeur et al. 2011; Gronewold et al. 2013). Within the Great Lakes basin, ice mapping works were undertaken in the late 1990s and early 2000s by the Great Lakes Environmental Research Laboratory (National Oceanic and Atmospheric Administration, Ann Arbor, USA) and the Jet Propulsion Laboratory (California Institute of Technology, Pasadena, USA) (Bolsenga 1992). Data from ERS-1 (European Remote Sensing Satellite 1) were able to map snow ice and new lake ice in Lake Superior (Leshkevich et al. 1995). To obtain high quality accuracy/validation data, the Jet Propulsion Laboratory equipped a polarimetric scatterometer (C-band, full HH/VV/HV polarization) onboard U.S. Coast Guard vessels timed accordingly with Radarsat-1 and ERS-2 passovers of the area as part of the Great Lakes Winter Experiment 1997 (Nghiem and Leshkevich 2007). These data were used as a training library in further image classifications (Leshkevich and Nghiem 2007) and allowed for the discrimination of ice types (including brash ice and consolidated ice floes) within the Great Lakes, with noted difficulties due to the single polarization of the data. With the launch of Radarsat-2 quad pol and dual-pol ENVISAT ASAR data, the authors used the same reference library and found that multi-polarized data were less affected by wind and wave action (Leshkevich and Nghiem 2013). While the resulting ice classification library is a unique and helpful resource, the method has required a substantial amount of field data and relies on unique classification parameters for each polarization and incidence angle.

Similar to global patterns, ice cover breakup in the Great Lakes has been trending earlier in the year since the early 1800s (Duguay et al. 2006) while freeze up was stable for most of the 1900s (Assel et al. 1995). On an interannual basis, ice cover is highly variable, with some years seeing near complete ice cover and the following years largely open water (Wang et al. 2017); lake ice cover is not inherently predictable based on Great Lakes' climate models and therefore needs to be tracked (Wang et al. 2012). Ice conditions throughout the Great Lakes basin are determined by Canada's and the United States of America's ice services (Canadian Ice Service, CIS; U.S. National Ice Center, NIC) who calculate Great Lakes ice cover with several data sources including satellite data, weather data, and visual observations (Assel et al. 2002). Despite advances in automation, currently the methods these agencies employ require manual interpretation of data by analysts and are produced mainly to aid shipping. This time-consuming process produces accurate results for the main basin of the lakes, but often misses small embayments and coastal areas of the Great Lakes with shapes and/or sizes that do not meet the 1.275 km^2 grid of the exported data. From a biological perspective these small coastal areas are important sources of productivity and likely areas of aggregation for many freshwater fishes during the winter (Danz et al. 2007; Vadeboncoeur et al. 2011). Increasing the extent of these mapping initiatives to cover smaller, nearshore areas is necessary to capture the full extent of ice cover within the Great Lakes and to better understand how these coastal areas and the species that rely upon them are affected by changes in the extent and duration of ice cover.

In temperate freshwater ecosystems, winter is a critical time period that helps shape and structure aquatic communities, influencing primary productivity (Hampton et al. 2017) as well as higher trophic levels including fish (Hokanson 1977; Cunjak 1996; Shuter et al. 2012). For most fishes, decreased water temperature, ice cover, declining dissolved oxygen, and limited foraging opportunities in the winter result in reduced growth (Shuter and Post 1990; Cunjak 1996; Brönmark et al. 2008; Shuter et al. 2012) and increased mortality (Keast and Fox 1990; Casselman and Lewis 1996; Shuter et al. 2012). Despite the ecological importance of winter, practical challenges associated with sampling freshwater communities and observing individual behaviors have resulted in a knowledge deficit during this season (Salonen et al. 2009; Kirillin et al. 2012). Complicating our understanding of individual species, local variation in winter conditions may result in behavioral differences among populations of the same species (Shuter et al. 2012). This is largely driven by the strong selective pressures that occur during the winter since habitat selection and winter survival are intimately linked to the need for an individual to minimize energy expenditures (Brown et al. 2011). Despite the critical nature of winter biology and the need for proper year-round management of fish habitat (Cunjak 1996), little work has focused on the winter biology of fishes in large freshwater systems due to the challenges of sampling and tracking under ice (but see McMeans et al. 2020 and Marsden et al. 2021). While winter ecology is under-represented in the literature, McMeans et al. (2020) argue that the extent and duration of ice cover alters interaction and competition among fishes as well as biological activity compared to ice-off periods. Yearly variation in the extent and duration of ice cover can thus be an indirect source of stress for fishes, with the potential for community-level changes based on shifts in ice-cover. The techniques and approaches commonly used in remote sensing studies hold great promise in their application to the study of fish ecology (Dauwalter et al. 2017), particularly when used to map physical elements (such as ice cover) that can influence how fish interact with their habitat. By combining remote sensing approaches with techniques like acoustic telemetry, which allows for near-continuous positioning of fishes on stationary receivers (Cooke et al. 2013), we can capture dynamic changes in ice cover and the responses of fish to these habitat changes.

In this paper we detail a tool that is reproducible and uses open-source data to streamline ice cover mapping of the Great Lakes at medium resolutions (20 m), providing a quick and consistent method for agencies to adopt as well as provide fine-scale, detailed ice cover in coastal areas that are important overwintering habitat for fish. This approach uses freely available SAR images (Sentinel-1) to ascertain if a model can be developed that requires minimal user input with accurate (>85%) results. These methods are transferable to any other system where validation data exist concurrent with Sentinel-1 image acquisitions. To explore the needs for higher-resolution ice cover maps we contrast our findings from the derived ice cover maps in an embayment in western Lake Ontario (Hamilton Harbor) with concurrent ice cover maps in Lake Ontario. Finally, as a demonstration for how these data can be used to support studies of fish winter ecology, we have undertaken a preliminary investigation of the space- and depth-use of two freshwater fish species (Northern Pike [*Esox lucius*] and Walleye [*Sander vitreus*]) during ice-on and ice-off periods. These species were selected as they are ecologically important top predators that are known to be active during periods when ice is present (Northern Pike: Cook & Bergersen 1988; Kobler et al. 2008; Walleye: Hayden et al. 2014). Populations of both species are below historic levels in our study area (Whillans 1979;

Table 1. Date of image acquisition and associated start and end date for when telemetry-derived detections were associated with each image.

Image period	Image date	Image incidence angle,°	Start	End	Num. Northern Pike	Num. Walleye
X2017_A	1/10/2017	30.873	1/8/2017	1/12/2017	7	12
X2017_B	1/15/2017	41.372	1/13/2017	1/17/2017	7	13
X2017_C	1/22/2017	30.877	1/20/2017	1/24/2017	7	13
X2017_D	2/3/2017	30.879	2/1/2017	2/5/2017	7	14
X2017_E	2/20/2017	41.362	2/18/2017	2/22/2017	7	14
X2017_F	3/4/2017	41.361	3/2/2017	3/6/2017	7	14
X2017_G	3/16/2017	41.363	3/14/2017	3/18/2017	7	14
X2019_A	1/12/2019	30.912	1/10/2019	1/14/2019	10	11
X2019_B	1/24/2019	30.910	1/22/2019	1/26/2019	9	12
X2019_C	1/29/2019	41.362	1/27/2019	1/31/2019	8	12
X2019_D	2/10/2019	41.362	2/8/2019	2/12/2019	9	13
X2019_E	2/17/2019	30.904	2/15/2019	2/19/2019	8	14
X2019_F	2/22/2019	41.362	2/20/2019	2/24/2019	8	14
X2019_G	3/1/2019	30.912	2/27/2019	3/3/2019	9	13
X2019_H	3/6/2019	40.362	3/4/2019	3/8/2019	10	13
X2019_I	3/13/2019	30.913	3/11/2019	3/15/2019	9	14
X2019_J	3/18/2019	41.359	3/16/2019	3/20/2019	7	14
X2019_K	3/25/2019	30.916	3/23/2019	3/27/2019	6	14

The total number of individual Northern Pike (*Esox lucius*) and Walleye (*Sander vitreus*) available during each image period is also shown.

COA 1992; Boston et al. 2016) and there is considerable effort currently underway to improve conditions for these species. An exploration of their winter ecology in ice-on and -off situations is therefore helpful in describing their annual habitat requirements to inform both these remediation efforts as well as our more general understanding of their winter ecology.

Methods

Study site

Hamilton Harbor is a large (east-west axis = 8 km, north-south axis 5 km, surface area = 22 km^2) freshwater embayment (mean depth of 13 m, max depth of 26 m) situated at the western end of Lake Ontario (COA 1992; Smokorowski et al. 1998). It is a high-nutrient system (Charlton and Le Sage 1996) that historically provided habitat for many species of fish; however, years of industrial development and anthropogenic degradation have impaired water quality and biota (Smokorowski et al. 1998). Hamilton Harbor has been binationally designated for restoration and government (all levels) and non-government agencies have worked to describe ecosystem processes and restore them (COA 1992). Efforts to restore the harbor rely on knowledge of the ecology of inhabiting aquatic organisms so understanding their response to changing conditions, such as ice-cover, is essential.

Remote sensing of ice cover

Ice mapping was conducted using Sentinel-1 Level 1 Ground Range Detection (GRD) image data from the Copernicus program (European Space Agency) and processed in Google Earth Engine (GEE; Gorelick et al. 2017). Images were only available in Ascending, IW (Interferometric Wide Swath), 10 m, VV/VH polarized data for the dates used (see Table 1 for dates and incidence angles). The Javascript code to conduct these analyses can be found at the following link: https://code.earthengine.google.com/a6621784fb7ac9940f7cccbc253b18f0. The scenes were pre-processed on GEE, which used SNAP with thermal noise removal, radiometric calibration, and terrain correction using SRTM (Shuttle Radar Topography Mission) 30 m data and then finally converted to decibels via log scaling; Sigma Nought incidence angle correction was also applied throughout the images. The data were then segmented into image objects using SNIC (Simple Non-Iterative Clustering; Achanta and Susstrunk 2017) using a compactness of 2, connectivity of 8, and cluster seeds at 9-pixel increments. These inputs were chosen by comparing manual interpretation of select scenes and comparing against the geography of the image clusters. Each object included the mean of the input pixels (per band) as well as standard deviation (per band) and object area.

The classification was conducted using a Random Forest classifier within GEE with the maximum number of trees set to 500 and bag fraction set to 50%. The optimal tree depth was derived by plotting overall accuracy and observing a plateau therein up to the GEE-defined tree depth limit of 2,500 (Figure 2). To obtain training and validation data, ice coverage data concurrent with image acquisition dates were acquired from the National Ocean and Atmospheric Association's Great Lakes Environmental Research Laboratory historic ice coverage data (available at https://www.glerl.noaa.gov/data/ice/#historical). These data are derived jointly from the Government of

Canada (Canadian Ice Service) and the United States Government (U.S. National Ice Center) and are produced daily at a nominal resolution of 1.275 km^2. All pixels that can be mapped are given an ice cover to the closest 10% plus an additional 95% class. For our analyses, we separated these values into four bins: no ice (comprised of 0%, 10%, and 20%), low ice cover (30%, 40%, and 50%), medium ice cover (60%, 70%, and 80% ice cover) and high ice cover (90%, 95%, 100%). Each image was trained/validated with its own concurrent training/validation data. The training/validation data were spaced further apart than the classified data (1,250 m vs 20 m), which diminishes the likelihood for spatial autocorrelation amongst the sampled points. To further reduce this, the training data were derived from a randomly sampled 70% of the NOAA data within the Sentinel-1 image footprint and the remaining 30% were used for validation and accuracy assessment (overall, producer's, and user's accuracy). As the footprint of the image changes with acquisition date so does the total number of samples available for accuracy assessment, ranging from approximately 1,500–2,500 observations. In early and late season low-ice cover periods, the majority of these observations (~90%) were in the 0% class and there were fewer ice cover classes. To combat the issue of sampling bias due to the dominance of the 0% class, a stratified random approach was applied that reduced the number of training data points used in the RF model. With this stratification, the model subsamples a maximum of 500 points from the 0% or "no ice" class and up to 200 points from all other bins to reduce model bias toward the 0% class while maintaining the structure of the underlying data.

Independent validation of ice cover within Hamilton Harbor was conducted with coincident Sentinel-2 image data from February 27, 2017 and coincident Landsat 8 data from March 1, 2019. These were the only data available coincidentally without complete cloud coverage, which is a common problem in winter imagery of the Great Lakes area. A remote time-lapse camera that was directed at the mid-western portion of the basin throughout 2019 provided concurrent time-lapse images and these were compared manually to the mapping products (similar data do not exist for 2017). The RF classifier was applied to the image objects throughout the entire scene (including other areas within the Great Lakes covered by the input image data) to derive ice cover maps and these were exported from GEE as .tif files for further analyses.

Fish telemetry data collection/processing

An acoustic telemetry array has been deployed in Hamilton Harbor (Lake Ontario) since August 2015 (Brooks et al. 2017). The placement of some receivers has changed through time to adapt to dynamic underlying research questions; for the present works, receivers ($n = 22$) that were deployed for two periods of interest—January–March 2017 and January–March 2019 were selected (Figure 1). Fish capture (boat electrofishing and trap netting) and tagging followed the methods outlined in Brooks et al. (2019). Two types of transmitter tags were surgically implanted into adult Northern Pike and Walleye; tags either transmitted an individual fish code (Vemco V13, 31 mm length, dry mass 9 g, battery life 1,825 days) that was used to identify a fish's location or had a pressure sensor to provide an indication of depth (Vemco V13P, 39 mm length, dry mass 11 g, battery life 1,317 days) in addition to an individual's unique code. A typical implantation procedure lasted less than four minutes and fish were released back into the harbor at their point of capture once they responded to external stimuli. Detection data from each receiver were downloaded in the spring and fall of each year and data were filtered using the nominal-delay method in the Great Lakes Acoustic Telemetry Observation System package (Holbrook et al. 2019); this approach removes potentially erroneous detections when there is a gap between detections of 30 times the nominal delay of the transmitter. Data were further processed to remove individuals that either displayed no change in depth or no change in detection location for the duration of the study, indicators that the individual may have died or that their pressure sensor was malfunctioning (Brownscombe et al. 2019).

Detection data were split into separate time periods based on the date of acquisition for each image (Table 1). Detections from two days before and after the date of image acquisition were linked with that image period—this was the maximum time period that could be selected to yield distinct (i.e., non-overlapping) detection periods. Data were further randomly sub-sampled without replacement so that there were an equal number of detections ($n = 40$) for each individual fish per image period. This value represented the minimum number of detections by an individual for any image period.

Minimum convex polygons (MCP) set to encapsulate 95% of detections were calculated for each individual for each image period using the mcp function in the adehabitatHR package (Calenge 2006). MCPs have been applied to estimate the area used by fishes

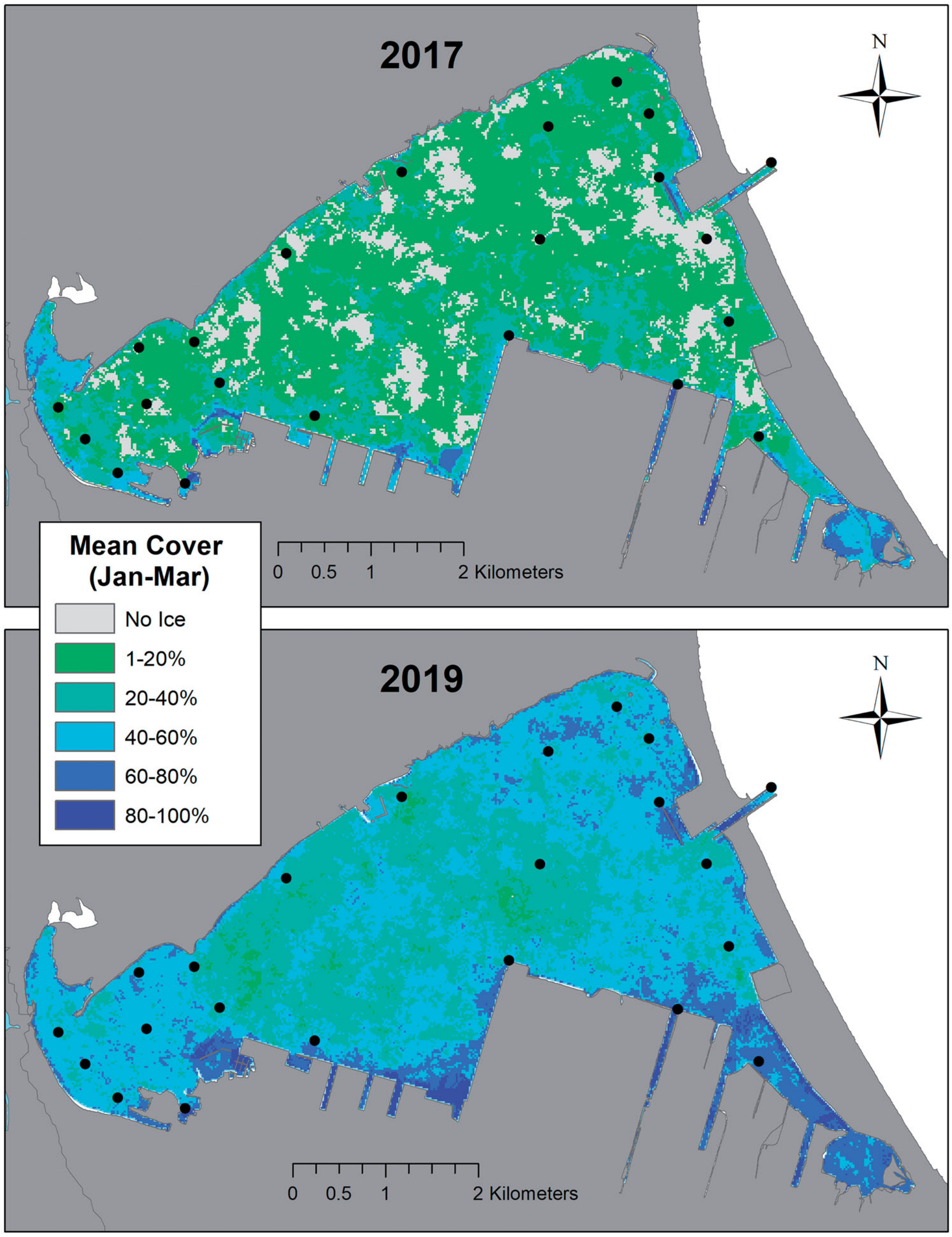

Figure 1. Mean ice cover for 2017 and 2019 in Hamilton Harbor, Lake Ontario. Fish telemetry receivers (black circles) were deployed to track tagged fish species. Mean ice cover is calculated by taking the bin class per pixel (no ice: 0, low: 40%, medium: 70%, high: 100%) and summing these over the duration of the datasets.

(Ebner et al. 2010) and provide a simple measure of the area used by an individual. MCPs can have errors when ranges are irregularly shaped or sampling effort is unequal, however, for the present study sampling effort is constant in fixed locations and less likely to be affected (Burgman and Fox 2003). The mean depth (m) for each individual was calculated from pressure sensor readings on the acoustic tag and linked to each image period. Finally, for each image period, the proportion of the harbor that was covered in ice was determined based on the image-derived estimate of ice cover for each image object. Ice cover is calculated by taking the bin class per pixel multiplied by a percentage: no ice: 0, low: 40%, medium: 70%, high: 100%. These data were linked to the individual-level MCP area and mean depth for each image period and used in the statistical models.

To visualize areas occupied by Northern Pike and Walleye during different image periods, a grid was created in ArcMap (10.7.1, ESRI 2019, Redlands, CA) with points spaced 75 m apart and for each image period, the total number of MCPs at each point was counted and then divided by the number of individuals detected during that image period to yield the

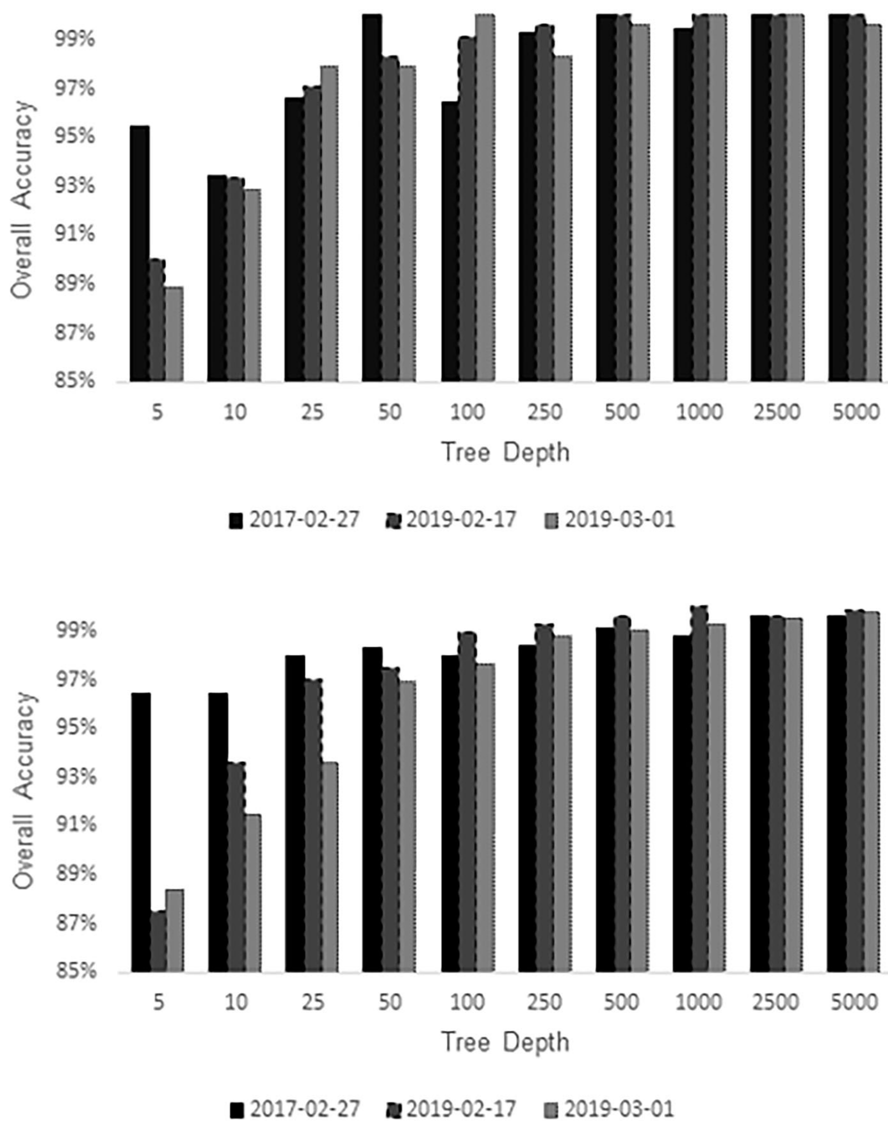

Figure 2. Overall accuracy as defined from the held back 30% validation data at given tree depths using (top) all ice cover bins and (bottom) the four bin (no ice, low, medium, high) ice cover model.

proportion of MCPs that overlapped at that location. These values were interpolated using the natural neighbor method (ESRI 2016) and a subset are presented for select image periods.

Statistical analysis

All analyses were conducted using R statistical software (R 3.6.1; R Development Core Team 2020). Linear mixed-effect models with restricted maximum likelihood estimates were used to explore the relationships between Day of Year or proportion of ice cover in the harbor and MCP area (ha) or mean depth (m) for both Northern Pike and Walleye. These models were fit using the lmer function in the lme4 package (Bates et al. 2015) with individual ID nested in year as a random effect. This model structure was necessary to account for individual differences in model intercept and the fact that data were available for most individuals in only one year. Both response variables (MCP area and mean depth) were log transformed to meet the assumptions of normality and heterogeneity in the residuals. Models were validated by plotting the residuals against fitted values. To determine whether harbor ice cover or Day of Year was a better predictor in the models, Akaike information criterion (AIC) values were used to compare relative accuracy with generated models. Lower AIC values indicate better fit (Akaike 1987) and the model with the lower AIC was selected for plotting.

Results

Data from February 17, 2019 were used to determine ideal tree depth as this date encompassed a variety of

Table 2. Accuracy assessment data for ice cover mapping using held-back validation data in the four bin class model.

Ice cover	2017 User's accuracy (%)	2019 User's accuracy (%)	All user's accuracy (%)	2017 Producer's accuracy (%)	2019 Producer's accuracy (%)	All producer's accuracy (%)
No Ice	99.5	99.4	99.4	99.9	99.9	99.9
Low	99.9	99.9	99.9	89.4	87.2	88.2
Medium	99.9	99.4	99.6	97.7	96.4	96.7
High	99.9	99.7	99.8	99.5	98.8	99.0
Overall accuracy 2017	99.7%	Overall accuracy 2019	99.5%	All overall accuracy	99.6%	

The data presented are mean accuracies of each category per bin, per year (2017/2019) and pooled (all data). With respect to the training and validation ice cover, no ice represents the 0%, 10%, and 20% classes, low ice represents the 30%, 40%, and 50% classes, medium ice represents the 60%, 70%, and 80% classes, and high ice represents the 90%, 95%, and 100% classes.

ice cover percentages. Overall accuracy was maximized after a tree depth parameter of 250 when using the full ice class data and 500 when using the binned classification approach (Figure 2). For the rest of the analyses, the tree depth was set to 500 as there was minimal differences in processing time with a tree depth of 250 vs 500.

Considering the metrics derived from the built-in validation dataset, accuracies are very high throughout the time periods analyzed (Table 2). The lowest mean accuracy was found in the "low ice cover" bin (87%), which had values from 74% to 99% for user's accuracy. Overall accuracy within this dataset was consistently high. Comparing the maps to optical datasets, our technique gives overall accuracy >85% (Tables 3 and 4). The March 23, 2017 image had low producer's accuracy in the low ice cover bin and low user's accuracy in the high ice cover bin as these two classes were the most confused in the dataset (no medium class pixels existed in this image; Table 3). The February 22, 2019 image had better overall accuracy and less confusion between ice classes (Table 4); the unobscured portions of the optical data were nearly completely covered in ice in this image. When comparing our outputs with the time-lapse camera data, the viewable area was mapped appropriately during all coinciding dates with good images. The camera's viewable area includes a boundary between ice and water identified in the western end of the harbor throughout 2019, which further verifies our methodology (Appendix 1).

As is the case with whole-lake ice cover, there were stark differences in ice cover in Hamilton Harbor between 2017 and 2019 (Figure 1). While small, shallow sub-basins were frozen in both years (in the western and southeastern portions of the harbor) there was a noticeable absence of ice cover in the core of the harbor in 2017. The timing of peaks in ice cover in Hamilton Harbor were similar between years (January 15, 2017 and January 29, 2019 as well as February 20, 2017 and February 22, 2019) but different from peak Lake Ontario times (Figure 3).

Table 3. Confusion matrix for random forest binned classification output (20 m resolution) against Landsat 8 data (30 m resolution) on March 23, 2017.

Ice cover	None	Low	High	Total	User's accuracy (%)
None	90	1	0	91	98.9
Low	1	4	0	5	80.0
High	7	7	5	19	26.3
Total	98	12	5	115	
Producer's accuracy	91.8%	33.3%	100%	Total accuracy	86.1%

This day had low overall ice cover in Hamilton Harbor and considerable cloud cover distorting the center of the harbor. With respect to the training and validation ice cover, no ice represents the 0%, 10%, and 20% classes, low ice represents the 30%, 40%, and 50% classes, and high ice represents the 90%, 95%, and 100% classes (the medium class was not represented in this image).

Table 4. Confusion matrix for random forest binned classification output (20 m resolution) against Sentinel-2 data (20 m resolution) on February 22, 2019.

Ice cover	Medium	High	Total	User's accuracy (%)
Medium	8	2	10	80.0
High	4	37	41	90.2
Total	12	39	51	
Producer's accuracy	66.6%	94.9%	Total accuracy	88.2%

This day had high overall ice cover in Hamilton Harbor and considerable cloud cover masking the northern portion of the harbor. With respect to the training and validation ice cover, medium ice represents the 60%, 70%, and 80% classes, and high ice represents the 90%, 95%, and 100% classes (the no ice and low ice classes were not represented in this image).

Maximal ice cover throughout the lake was earlier in 2017 (7 February) and later in 2019 (2 March). Hamilton Harbor was proportionally more frozen in the early season as well as the latter portions than Lake Ontario.

For both Northern Pike and Walleye, areas of high use were generally concentrated in the western part of the harbor (Figures 4 and 5). Specifically for Northern Pike, MCP areas in both years were largest in January, decreased in size in February, and remained small into March. The main difference between 2017 and 2019 was that by February and March all Northern Pike MCP areas were situated in the west end in 2019 whereas in 2017 some Northern Pike were detected in the deeper areas of the central and eastern harbor that were covered by ice in 2019 (Figure 4). For Walleye, there was evidence for a shift in the size and location

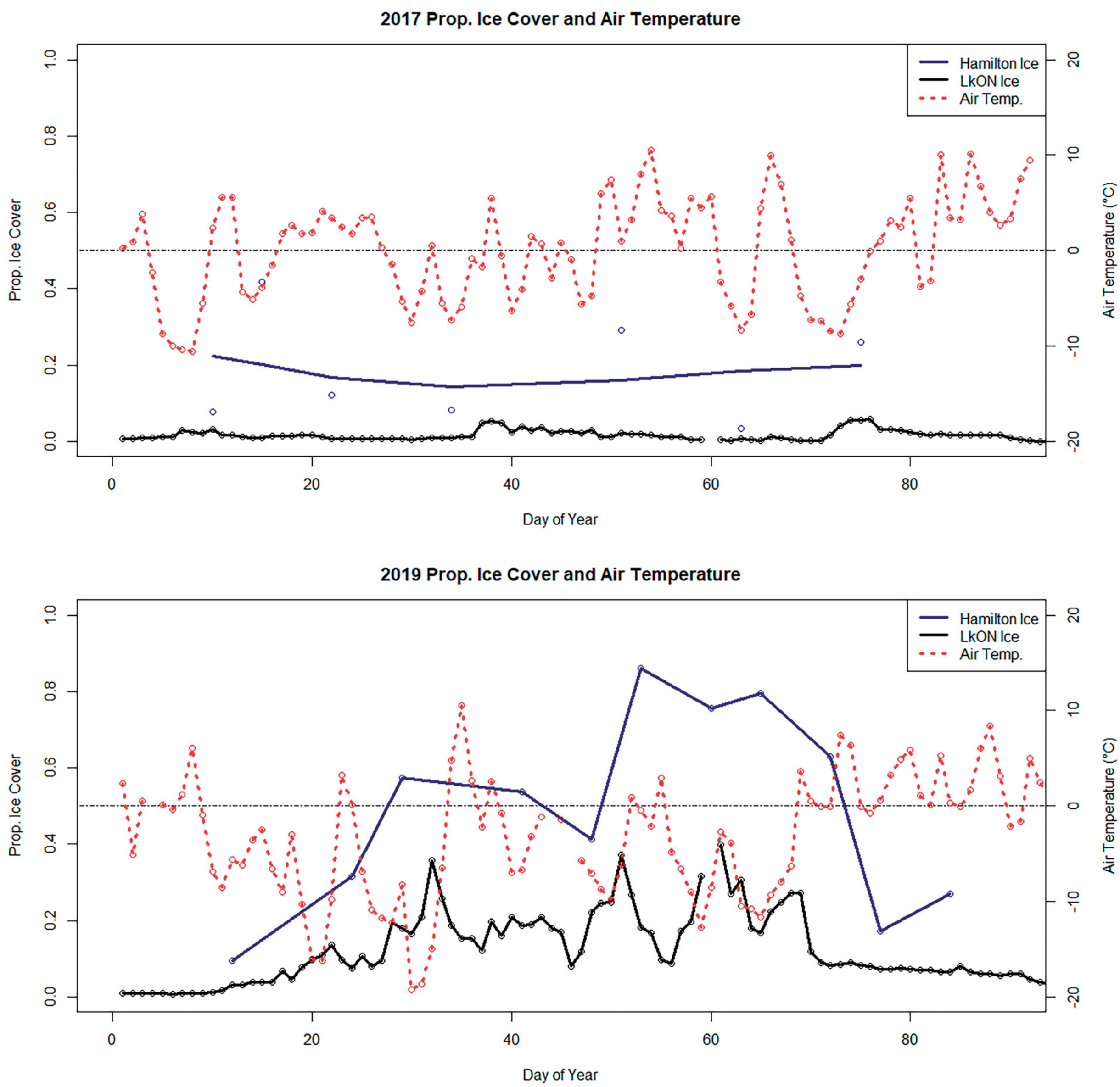

Figure 3. Lake Ontario (LkON) and Hamilton Harbor ice cover (%) and air temperature (°C) for 2017 and 2019 (air temperature data were taken from Environment and Climate Change Canada 2020, climate station 27529). A line at 0° Celsius is shown to more easily see the freeze/thaw boundary.

of MCP areas from January, when they were larger and focused in the center of the harbor, to February, when their MCPs were slightly smaller and more focused on the west end of the harbor (Figure 5). Reductions in the spatial coverage of Walleye MCP areas into March were more apparent in the 2019 dataset.

For Northern Pike, models using Day of Year had lower AIC values for both area and mean depth (Table 5). The Walleye depth model for Day of Year similarly had lower AIC values, but the area model with harbor ice cover had a slightly lower AIC. It should be noted that fixed effects for both the harbor ice cover and Day of Year models for Walleye area were significant (Table 5). For both Northern Pike and Walleye, all best fit models suggested that the area of habitat used (derived from MCP) declined through time or with increasing ice cover, and depth use decreased (i.e., fish moved upwards in the water column) through time (Figure 6).

Discussion

Ice mapping

The high accuracy of the method presented here shows its potential for mapping smaller sub-basins and coastal areas in the Laurentian Great Lakes. With

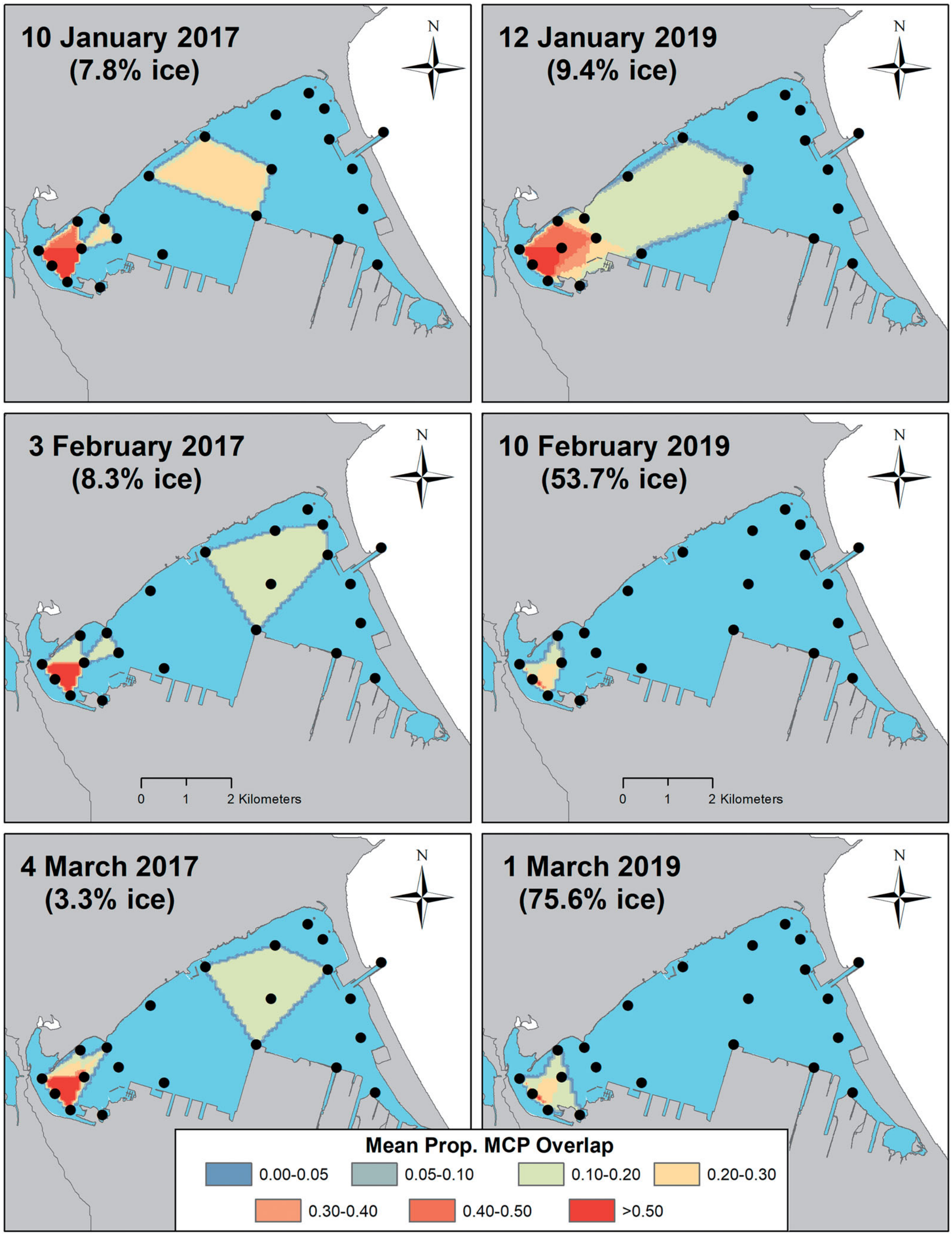

Figure 4. Minimum convex polygons (MCPs) of Northern Pike at labeled time points throughout 2017 and 2019. Greater proportions of MCP suggest higher activity in those polygons. Northern Pike continued to use deeper portions of the central and eastern harbor only in 2017 when ice cover was low, and both show a shift to using the western basin over time.

near-global coverage of Sentinel-1, these methods could be applied to other systems where validation data exist at larger scales. When comparing against the held-back validation data, the results are very good across ice covers even when certain categories have low input data. When compared against external optical datasets, the binned classification performs well under scenarios with high and low overall ice cover in Hamilton Harbor. The low ice cover date (February 27, 2017) saw a lower user's accuracy for high ice cover bins, which were predicted in small patches within the study area. Given the lower resolution of the optical dataset (Landsat 8, 30 m) it is possible that small ice floes exist in this area that cannot be captured with the available reference data. A preferable optical image on a date with a wide range of predicted ice cover could not be found within the Landsat and Sentinel-2 time series.

Comparing the time lapse camera in 2019 to the mapped data showed good agreement in ice cover for

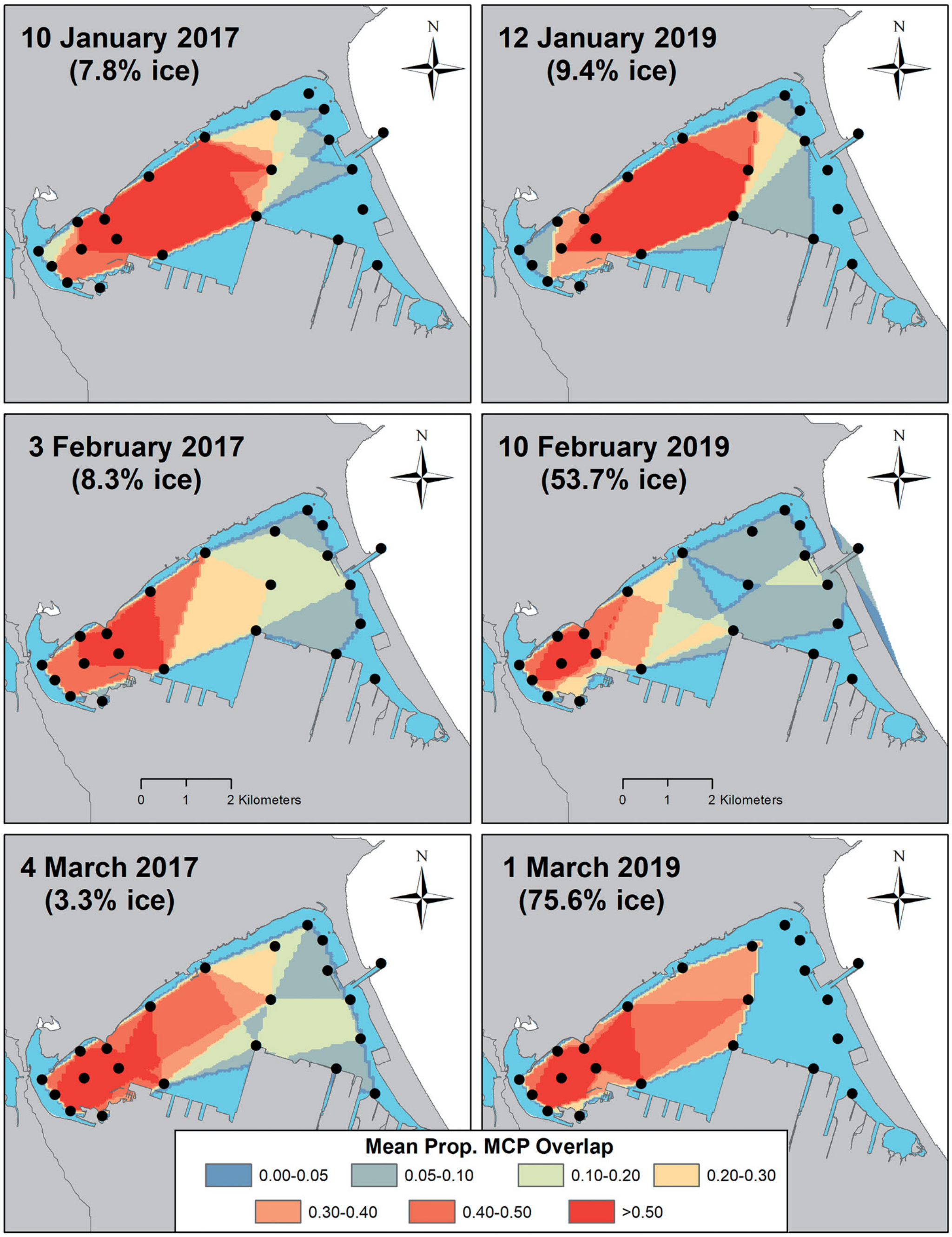

Figure 5. Minimum convex polygons (MCPs) of Walleye at labeled time points throughout 2017 and 2019. Greater proportions of MCP suggest higher activity in those polygons. Walleye had more reduced MCPs during the higher ice cover year (2019) shifting to increased use of the central and western portion of the harbor.

the areas captured. As seen with the time lapse camera, the nature of ice cover in the study area is very dynamic (as seen with the time lapse camera). While the western portion of the basin is somewhat protected from ice movement due to the dominant west winds in the area, there are frequent changes in the extent of ice cover in waters situated east of the previously noted ice-water boundary that is present in the frame of the time-lapse images There was a noticeable divide between an ice sheet in the western portion of the basin and open water that is well captured in imagery from the same date on February 17, 2019. The preceding decrease in ice cover was not able to be verified due to poor weather on the days surrounding image capture, though this decrease is likely partially explained by warmer air temperatures (discussed below). While these time lapse data were not intended for scientific purposes they can be utilized as a sufficient true-colour dataset for comparison and validation.

Table 5. Importance of the fixed terms, the variance of the random intercepts (Var.), and residual error of the random intercept (Resid. Err.) for the linear mixed-effects models exploring Northern Pike and Walleye mean depth and MCP area based on the proportion of Hamilton Harbor that was covered in ice (Prop. Ice Cover) and the Day of Year. Models with lower Akaike information criterion (AIC) scores were used for visualizing predicted trends (see Figure 6).

Species	Response	Model term	Year: ID Var.	Year Var.	Resid. Err.	DF	*p*-Values	AIC
Northern Pike	MCP Area	Prop. Ice Cover	0.577	0.000	3.068	1	0.089	585.1
	MCP Area	Day of Year	0.579	0.000	2.951	1	0.008	580.9
	Depth	Prop. Ice Cover	0.368	0.113	0.287	1	0.055	277.4
	Depth	Day of Year	0.375	0.126	0.252	1	<0.0001	261.1
Walleye	MCP Area	Prop. Ice Cover	0.075	0.000	0.426	1	0.0005	505.8
	MCP Area	Day of Year	0.082	0.000	0.434	1	0.009	511.4
	Depth	Prop. Ice Cover	0.016	0.005	0.043	1	0.017	−20.1
	Depth	Day of Year	0.017	0.000	0.021	1	<0.0001	−148.7

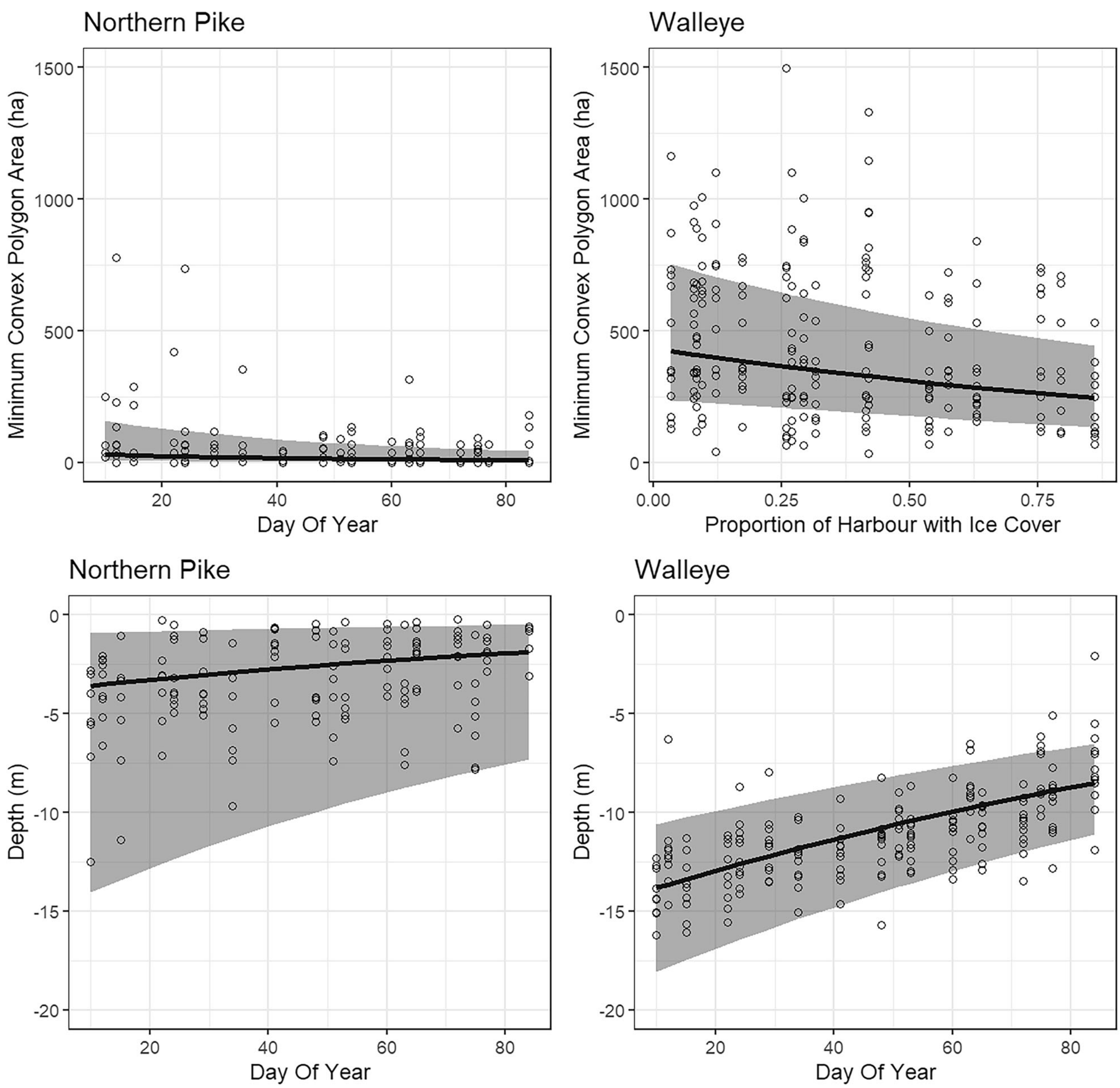

Figure 6. The predicted effects of day of year or proportion of the harbor covered in ice on mean depth (m) and the area of the 95% minimum convex polygons (ha) derived from their respective top models (see Table 5). Circles display observed data points and lines display predicted linear mixed-effects model trends with 95% confidence intervals.

A common source of error in remote sensing of ice with SAR data comes from wind roughening (i.e., waves) of the water's surface resulting in changes to backscatter values that appear as ice. Since the training and validation data are coincident with the input Sentinel-1 data, this problem is reduced as wavy water will still be fed into the model as water and not misinterpreted as ice. Furthermore, our tool is designed for nearshore areas where wind action can be less prevalent due to shoreline buffering. The impact of wind must still be considered as a potential source of error as those areas that experience high wave action (e.g., leading edges of barrier beaches, breakwalls) could see reduced model performance that would not be reflected in the accuracy assessments.

In a study by Singha et al. (2020), non-coincident training data were used to determine the applicability of an artificial neural network over a range of dates and incidence angles. Throughout a season ice can change its backscatter response due to properties of the ice and associated water/snow cover (Leigh et al. 2014; Surdu, Duguay, and Fernández Prieto 2015); changes in incidence angle can similarly affect backscatter and interpreted ice cover (Leshkevich & Nghiem 2013; Wang et al. 2018). Due to low total ice cover over western Lake Ontario throughout the study period, it was not possible to find a single date that covered all ice cover classes within the training dataset. We did attempt to use the closest available non-coincident imagery (i.e., <2 weeks difference between image acquisition) for training data, but obtained lower overall and within-class accuracy than when using coincident imagery (data not shown). Since ice cover charts are produced daily for the Great Lakes, we intend for this tool to only be used with coincident training data.

Lake Ontario has typically experienced ice onset just prior to January since the 1800s and ice cover ends by April and most often has its peak in mid-February (Duguay et al. 2006). Our mapped ice cover datasets in 2019 show a decrease in ice cover partway through the winter months before a rebound thereafter, which is also seen in analyses of more recent Great Lakes ice cover (Wang et al. 2017). A cause of this in Hamilton Harbor may be gleaned from concurrent air temperature data that show daily mean temperatures above 0 degrees Celsius for prolonged periods in late February 2019 (Environment and Climate Change Canada Climate Station 27529; Figure 3). Our data in Hamilton Harbor do not show a consistent agreement with larger Lake Ontario patterns, which stresses the need for regular fine-scale ice cover mapping. Our mapped maximal ice cover dates may not agree with maximal whole-lake ice cover due to regional variations and the much smaller size of the Harbor. In theory, the thermal mass of this water body would be much less than the entire Lake and thus more susceptible to weather conditions and temperature changes.

The ice mapping process derived here is easily accessible via a GEE script (source link in methods). All of the data and techniques are contained within the script except for the training ice cover maps, which were manually uploaded to GEE by the authors. The script has been written in such a way to be user accessible with the only required inputs being the area to be mapped (which is a modifiable polygon), date of the Sentinel-1 image required, and the relevant ice cover training file (uploaded by date). This does require the user to know the dates that imagery is available, but a print-out in the code lists all image dates available for the year in question. The code also provides a download option for the resultant image file and confusion matrices of the accuracy and validation datasets. With the script written in this way, we hope that others can take advantage of this mapping tool within GEE and outside in the program of their choice.

Embayments like Hamilton Harbor are ecologically important for fishes and other aquatic organisms and these areas have not previously been mapped at an appropriate resolution to study their residents' winter ecology. Although the primary focus of ice cover mapping is to support navigation, the present study demonstrates how shipping-focused mapping initiatives can be leveraged to support finer scale ice cover mapping. While the data presented here are for Hamilton Harbor, these techniques can be readily applied to other unmapped areas that have comparable ice cover maps in adjacent areas that can be used to train the model. For the Laurentian Great Lakes, this can include other areas known to support important fisheries and this approach can be used by regulatory agencies to support the management of fish and fish habitat.

Fish under ice

Quantifying winter severity remotely using measures of ice cover is an established method in the Great Lakes region that can be linked to regional climates (Assel 1980; Hewitt et al. 2018). Assumptions around fish responses to cold duration are not intuitive and depend on the species' life histories. Shortened winters under a warmer climate change scenario are beneficial to the growth of some fish species, as has been demonstrated in Smallmouth Bass (*Micropterus dolomieu*; Casselman 2002). In contrast, some commercially and recreationally important species require a minimum length of winter for their life history strategies. For example, Yellow Perch (*Perca flavenscens*) in Lake Erie have lower recruitment success after short, warm winters. Females of this species spawning in warmer water temperatures produce smaller eggs that hatch at lower rates and subsequently produce smaller larval fish than females spawning from colder (longer) winters (Farmer et al. 2015). For Northern Pike and Walleye winter is an important season, particularly for females since egg development occurs in preparation for spring spawning (Murry et al. 2008; Pierce et al. 2013; Zhao et al. 2008). As a result, both species actively forage in the winter months, which increases the potential for inter- or intraspecific competition for limited resources (as noted for Northern Pike; Knight et al. 2008). McMeans et al. (2020) demonstrated spatial segregation of two top predators (Lake Trout [*Salvelinus namaycush*] and Smallmouth Bass) during the winter. Although species distributions based on life histories were not the intent of the present works, our results suggest that while there is overlap in the core areas used by Northern Pike and Walleye (i.e., western Hamilton Harbor) during the winter, there is separation in the depth strata they occupy. Additionally, despite this overlap, core areas for Walleye were considerably larger than Northern Pike, suggesting they may be more active or wide-ranging during the winter. This type of habitat partitioning is important to document since it can help define how these two top predators are able to co-exist while also providing habitat managers with an indication of the types of overwintering habitat that are important for each species.

For both species, results suggest the area used by an individual decreases throughout the winter and, at least for Walleye, this reduction is better explained by the extent of ice cover than timing. As ectotherms, reductions in activity as temperatures decline and remain cold throughout the winter likely explain these reductions in area use, particularly for these two study species that are considered cool rather than cold-water specialists. The formation of ice during the winter further alters aquatic habitat for fishes beyond declines in temperature by reducing light intensity and preventing inputs of atmospheric oxygen (Shuter et al. 2012). For Walleye, it is possible that these additional habitat changes (e.g., declining oxygen) act to reduce their area of use during periods of ice-on. The already more restricted MCP of Northern Pike may be less affected by the presence of ice cover than Walleye, alternately there may not be sufficiently high resolution of telemetry positioning to detect a change in Northern Pike MCP during ice-on and off. For the present study, however, we are unable to determine the specific ecological drivers behind differences in space use between species or between periods of ice-on or ice-off. In other words, space use of fish was consistent with differences in ice cover but the specific drivers of that association are unclear. Moreover, we only have two years for comparison so some caution must be applied when interpreting this pattern. The shifts to shallower depths as the winter progressed observed for both species are similarly challenging to explain with the available data, however, both Northern Pike and Walleye spawn in the spring, so toward the end of the winter it is likely that shallow waters are occupied as they stage or begin to spawn in nearshore areas.

Acoustic telemetry has been used for decades to study fish under ice (e.g., Johnsen and Hasler 1977; Blanchfield et al. 2009; Hasler et al. 2009) and has been gaining in popularity to characterize the winter ecology of freshwater fishes (reviewed in McMeans et al. 2020; Marsden et al. 2021). The novel addition of RS-derived ice cover maps to such studies provides for continuous measure of winter conditions in the form of the location and duration of ice cover through a study system. The presence of ice cover can influence light penetration and oxygen availability in the water column, which influences fish behavior and ecology (Brown et al. 2011; Hampton et al. 2017). While these and other habitat variables can be monitored directly, they require in-person site visits or careful placement of instrumentation and would not cover the same spatial extent as RS without significant cost. As noted by Dauwalter et al. (2017), access to RS imagery with higher spatial and temporal resolution is increasing, making this imagery and derived products more readily available for inclusion in the development and implementation of fisheries research. The methods outlined herein take advantage of new RS products, software, and existing data to enhance the potential analyses of ice cover in the Great Lakes. The present study demonstrates a simple link between winter ice cover and the area and depth used by two freshwater piscivores. More in-depth explorations combining these two remote-based approaches, remote sensing and acoustic telemetry, can provide relatively fast, cost-effective methods to help fisheries scientists and managers better understand the behavior of fish under ice.

Conclusion

We have shown a promising remote sensing-based method for the analysis of ice cover in unmapped portions of the Laurentian Great Lakes that produces accurate results (>85%) with freely available Sentinel-1 data. By utilizing cloud computing and shareable code, this technique can be easily applied to other regions within the Laurentian Great Lakes or anywhere accurate validation data exist and there is sufficient spatial coverage by Sentinel-1. The resulting maps will provide previously unavailable information on ice cover dynamics in small, nearshore areas that are important overwintering habitat for many fishes. These maps can be combined with fish telemetry information from collaborative research networks such as the Great Lakes Acoustic Telemetry System (https://glatos.glos.us/) to further our understanding of winter fish ecology. This season poses many challenges for fishes, yet it is often understudied, therefore the integration of remote sensing and acoustic telemetry hold great promise for supporting future studies of fish ecology and ultimately more effective fish and fish habitat management.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Achanta, R., and Susstrunk, S. 2017. “Superpixels and polygons using simple non-iterative clustering.” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4651–4660.

Akaike, H. 1987. “Factor analysis and AIC.” In *Selected Papers of Hirotugu Akaike*, edited by E. Parzen, K. Tanabe, and G. Kitagawa, 371–386. New York, NY: Springer.

Assel, R.A. 1980. “Maximum freezing degree-days as a winter severity index for the great lakes, 1897–1977.” *Monthly Weather Review*, Vol. 108: pp. 1440–1446. doi:10.1175/1520-0493(1980)108<1440:MFDDAA > 2.0.CO;2.

Assel, R.A. 2003. Great Lakes ice cover, first ice, last ice, and ice duration: Winters 1973-2002. *NOAA Technical Memorandum* GLERL-125, 1–49.

Assel, R.A., Norton, D.C., and Cronk, K.C. 2002. A Great Lakes ice cover digital data set for winters 1973–2000. *NOAA Technical Memorandum* GLERL-121, 1–46.

Bates, D., Mächler, M., Bolker, B., and Walker, S. 2015. “Fitting linear mixed-effects models using lme4.” *Journal of Statistical Software*, Vol. 67(No. 1): pp. 1–48. doi:10.18637/jss.v067.i01.

Blanchfield, P.J., Tate, L.S., Plumb, J.M., Acolas, M.L., and Beaty, K.G. 2009. “Seasonal habitat selection by Lake Trout (Salvelinus Namaycush) in a small Canadian Shield Lake: Constraints imposed by winter conditions.” *Aquatic Ecology*, Vol. 43(No. 3): pp. 777–787. doi:10.1007/s10452-009-9266-3.

Bolsenga, S.J. 1992. “A review of great lakes ice research.” *Journal of Great Lakes Research*, Vol. 18(No. 1): pp. 169–189. doi:10.1016/S0380-1330(92)71283-0.

Boston, C.M., Randall, R.G., Hoyle, J.A., Mossman, J.L., and Bowlby, J.N. 2016. “The fish community of Hamilton Harbour, Lake Ontario: Status, stressors, and remediation over 25 years.” *Aquatic Ecosystem Health & Management*, Vol. 19(No. 2): pp. 206–218. doi:10.1080/14634988.2015.1106290.

Brönmark, C., Skov, C., Brodersen, J., Nilsson, A.P., and Hansson, L.-A. 2008. “Seasonal migration determined by a trade-off between predator avoidance and growth.” *PLoS One*, Vol. 3(No. 4): pp. e1957. doi:10.1371/journal.pone.0001957.

Brooks, J.L., Boston, C., Doka, S., Gorsky, D., Gustavson, K., Hondorp, D., Isermann, D., et al. 2017. “Use of fish telemetry in rehabilitation planning, management, and monitoring in areas of concern in the Laurentian Great Lakes.” *Environmental Management*, Vol. 60(No. 6): pp. 1139–1154. doi:10.1007/s00267-017-0937-x.

Brooks, J.L., Midwood, J.D., Gutowsky, L.F.G., Boston, C.M., Doka, S.E., Hoyle, J.A., and Cooke, S.J. 2019. “Spatial ecology of reintroduced walleye (*Sander vitreus*) in Hamilton Harbour of Lake Ontario.” *Journal of Great Lakes Research*, Vol. 45(No. 1): pp. 167–175. doi:10.1016/j.jglr.2018.11.011.

Brown, L.C., and Duguay, C.R. 2011. “The fate of lake ice in the North American Arctic.” *The Cryosphere*, Vol. 5(No. 4): pp. 869–892. doi:10.5194/tc-5-869-2011.

Brown, R.S., Hubert, W.A., and Daly, S.F. 2011. “A primer on winter, ice, and fish: What fisheries biologists should know about winter ice processes and stream-dwelling fish." *Fisheries*, Vol. 36(No. 1): pp. 8–26. doi:10.1577/03632415.2011.10389052.

Brownscombe, J.W., Lédée, E.J.I., Raby, G.D., Struthers, D.P., Gutowsky, L.F.G., Nguyen, V.M., Young, N., et al. 2019. "Conducting and interpreting fish telemetry studies: Considerations for researchers and resource managers." *Reviews in Fish Biology and Fisheries*, Vol. 29(No. 2): pp. 369–400. doi:10.1007/s11160-019-09560-4.

Burgman, M.A., and Fox, J.C. 2003. "Bias in species range estimates from minimum convex polygons: implications for conservation and options for improved planning." *Animal Conservation*, Vol. 6(No. 1): pp. 19–28. doi:10.1017/S1367943003003044.

Calenge, C. 2006. "The package adehabitat for the R software: Tool for the analysis of space and habitat use by animals." *Ecological Modelling*, Vol. 197(No. 3–4): pp. 516–519. doi:10.1016/j.ecolmodel.2006.03.017.

Canada-Ontario Agreement (COA). 1992. *Remedial Action Plan for Hamilton Harbour. Environmental Conditions and Problem Definition*. 2nd edition of the Stage 1 Report. Prepared for Ontario Ministry of the Environment and Environment Canada.

Casselman, J.M. 2002. "Effects of temperature, global extremes, and climate change on year-class production of warmwater, coolwater, and coldwater fishes in the Great Lakes basin." In *American Fisheries Society Symposium*, 39–60. American Fisheries Society.

Casselman, J.M., and Lewis, C.A. 1996. "Habitat requirements of northern pike (Esox lucius)." *Canadian Journal of Fisheries and Aquatic Sciences*, Vol. 53(No. S1): pp. 161–174. doi:10.1139/cjfas-53-S1-161.

Charlton, M.N., and Le Sage, R. 1996. "Water quality trends in Hamilton Harbour: 1987 to 1995." *Water Quality Research Journal*, Vol. 31 (No. 3): pp. 473–484. doi:10.2166/wqrj.1996.027.

Cook, M.F., and Bergersen, E.P. 1988. "Movements, habitat selection, and activity periods of Northern Pike in Eleven Mile Reservoir, Colorado." *Transactions of the American Fisheries Society*, Vol. 117(No. 5): pp. 495–502. doi:10.1577/1548-8659(1988)117<0495:mhsaap>2.3.co;2.

Cooke, S.J., Midwood, J.D., Thiem, J.D., Klimley, P., Lucas, M.C., Thorstad, E.B., Eiler, J., Holbrook, C., and Ebner, B.C. 2013. "Tracking animals in freshwater with electronic tags: Past, present and future." *Animal Biotelemetry*, Vol. 1(No. 1): pp. 5. doi:10.1186/2050-3385-1-5.

Cunjak, R.A. 1996. "Winter habitat of selected stream fishes and potential impacts from land-use activity." *Canadian Journal of Fisheries and Aquatic Sciences*, Vol. 53(No. S1): pp. 267–282. doi:10.1139/cjfas-53-S1-267.

Danz, N.P., Niemi, G.J., Regal, R.R., Hollenhorst, T., Johnson, L.B., Hanowski, J.M., Axler, R.P., et al. 2007. "Integrated measures of anthropogenic stress in the US Great Lakes basin." *Environmental Management*, Vol. 39(No. 5): pp. 631–647. doi:10.1007/s00267-005-0293-0.

Dauwalter, D.C., Fesenmyer, K.A., Bjork, R., Leasure, D.R., and Wenger, S.J. 2017. "Satellite and airborne remote sensing applications for freshwater fisheries." *Fisheries*, Vol. 42(No. 10): pp. 526–537. doi:10.1080/03632415.2017.1357911.

Duguay, C.R., Prowse, T.D., Bonsal, B.R., Brown, R.D., Lacroix, M.P., and Menard, P. 2006. "Recent trends in Canadian lake ice cover." *Hydrological Processes*, Vol. 20 (No. 4): pp. 781–801. doi:10.1002/hyp.6131.

Ebner, B.C., Lintermans, M., Jekabsons, M., and Dunford, M. 2010. "Convoluted shorelines confound diel-range estimates of radio-tracked fish." *Marine and Freshwater Research*, Vol. 61(No. 12): pp. 1360–1365. doi:10.1071/MF10043.

ESRI (Environmental Systems Research Institute). 2016. *Natural Neighbour* [online]. Available from: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/natural-neighbor.htm. (Accessed October 30, 2019).

Farmer, T.M., Marschall, E.A., Dabrowski, K., and Ludsin, S.A. 2015. "Short winters threaten temperate fish populations." *Nature Communications*, Vol. 6 pp. 7724. doi:10.1038/ncomms8724.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. 2017. "Google Earth Engine: Planetary-scale geospatial analysis for everyone." *Remote Sensing of Environment*, Vol. 202 pp. 18–27. doi:10.1016/j.rse.2017.06.031.

Gronewold, A.D., Fortin, V., Lofgren, B., Clites, A., Stow, C.A., and Quinn, F. 2013. "Coasts, water levels, and climate change: A Great Lakes perspective." *Climatic Change*, Vol. 120(No. 4): pp. 697–711. doi:10.1007/s10584-013-0840-2.

Hampton, S.E., Galloway, A.W.E., Powers, S.M., Ozersky, T., Woo, K.H., Batt, R.D., Labou, S.G., et al. 2017. "Ecology under lake ice." *Ecol Lett*, Vol. 20(No. 1): pp. 98–111. doi:10.1111/ele.12699.

Hasler, C.T., Suski, C.D., Hanson, K.C., Cooke, S.J., and Tufts, B.L. 2009. "The influence of dissolved oxygen on winter habitat selection by largemouth bass: an integration of field biotelemetry studies and laboratory experiments." *Physiological and Biochemical Zoology*, Vol. 82(No. 2): pp. 143–152. doi:10.1086/591806.

Hayden, T.A., Holbrook, C.M., Fielder, D.G., Vandergoot, C.S., Bergstedt, R.A., Dettmers, J.M., Krueger, C.C., and Cooke, S.J. 2014. "Acoustic telemetry reveals large-scale migration patterns of walleye in Lake Huron." *PLoS One*, Vol. 9(No. 12): pp. e114833. doi:10.1371/journal.pone.0114833.

Hewitt, B.A., Lopez, L.S., Gaibisels, K.M., Murdoch, A., Higgins, S.N., Magnuson, J.J., Paterson, A.M., Rusak, J.A., Yao, H., and Sharma, S. 2018. "Historical trends, drivers, and future projections of ice phenology in small north temperate lakes in the Laurentian Great Lakes region." *Water (Switzerland)*, Vol. 10(No. 1). doi:10.3390/w10010070.

Hoekstra, M., Jiang, M., Clausi, D.A., and Duguay, C. 2020. "Lake ice-water classification of RADARSAT-2 images by integrating IRGS Segmentation with pixel-based random forest labeling." *Remote Sensing*, Vol. 12(No. 9): pp. 1425. doi:10.3390/rs12091425.

Hokanson, K.E. 1977. "Temperature requirements of some percids and adaptations to the seasonal temperature cycle." *Journal of the Fisheries Research Board of Canada*, Vol. 34(No. 10): pp. 1524–1550. doi:10.1139/f77-217.

Holbrook, C., Hayden, T., Binder, T., and Pye, J. 2019. *glatos: A package for the Great Lakes Acoustic Telemetry Observation System*. R package version 0.4.0. https://gitlab.oceantrack.org/GreatLakes/glatos

Johnsen, P.B., and Hasler, A.D. 1977. "Winter aggregations of carp (*Cyprinus carpio*) as revealed by ultrasonic tracking." *Transactions of the American Fisheries Society*, Vol. 106(No. 6): pp. 556–559. doi:10.1577/1548-8659(1977)106%3C556:WAOCCC%3E2.0.CO;2.

Keast, A., and Fox, M.G. 1990. "Fish community structure, spatial distribution and feeding ecology in a beaver pond." *Environmental Biology of Fishes*, Vol. 27(No. 3): pp. 201–214. doi:10.1007/BF00001673.

Kirillin, G., Leppäranta, M., Terzhevik, A., Granin, N., Bernhardt, J., Engelhardt, C., Efremova, T., et al. 2012. "Physics of seasonally ice-covered lakes: A review." *Aquatic Sciences*, Vol. 74(No. 4): pp. 659–682. doi:10.1007/s00027-012-0279-y.

Knight, C.M., Gozlan, R.E., and Lucas, M.C. 2008. "Can seasonal home-range size in pike Esox Lucius predict excursion distance?" *Journal of Fish Biology*, Vol. 73(No. 4): pp. 1058–1064. doi:10.1111/j.1095-8649.2008.01989.x.

Knoll, L.B., Sharma, S., Denfeld, B.A., Flaim, G., Hori, Y., Magnuson, J.J., Straile, D., and Weyhenmeyer, G.A. 2019. "Consequences of lake and river ice loss on cultural ecosystem services." *Limnology and Oceanography Letters*, Vol. 4(No. 5): pp. 119–131. doi:10.1002/lol2.10116.

Kobler, A., Klefoth, T., Wolter, C., Fredrich, F., and Arlinghaus, R. 2008. "Contrasting pike (*Esox lucius* L.) movement and habitat choice between summer and winter in a small lake." *Hydrobiologia*, Vol. 601(No. 1): pp. 17–27. doi:10.1007/s10750-007-9263-2.

Leigh, S., Wang, Z., and Clausi, D.A. 2014. "Automated ice-water classification using dual polarization SAR satellite imagery." *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 52(No. 9): pp. 5529–5539. doi:10.1109/TGRS.2013.2290231.

Leshkevich, G.A., and Nghiem, S.V. 2007. "Satellite SAR remote sensing of Great Lakes ice cover, part 2. Ice classification and mapping." *Journal of Great Lakes Research*, Vol. 33(No. 4): pp. 736–750. doi:10.3394/0380-1330(2007)33.736:SSRSOG]2.0.CO;2.

Leshkevich, G., and Nghiem, S.V. 2013. "Great Lakes ice classification using satellite C-band SAR multi-polarization data." *Journal of Great Lakes Research*, Vol. 39(NO. S1): pp. 55–64. doi:10.1016/j.jglr.2013.05.003.

Leshkevich, G., Pichel, W., Clemente-Colon, P., Carey, R., and Hufford, G. 1995. "Analysis of coastal ice cover using ERS-1 SAR data." *International Journal of Remote Sensing*, Vol. 16(No. 17): pp. 3459–3479. doi:10.1080/01431169508954640.

Lopez, L.S., Hewitt, B.A., and Sharma, S. 2019. "Reaching a breaking point: How is climate change influencing the timing of ice breakup in lakes across the northern hemisphere?" *Limnology and Oceanography*, Vol. 64(No. 6): pp. 2621–2631. doi:10.1002/lno.11239.

Magnuson, J.J., Robertson, D.M., Benson, B.J., Wynne, R.H., Livingstone, D.M., Arai, T., Assel, R.A., *et al.* 2000. "Historical trends in lake and river ice cover in the Northern Hemisphere." *Science*, Vol. 289(No. 5485): pp. 1743–1746. doi:10.1126/science.289.5485.1743.

Marsden, J. E., Blanchfield, P. J., Brooks, J. L., Fernandes, T., Fisk, A. T., Futia, M. H., Hlina, B. L., et al. 2021. "Using telemetry data to explore the winter biology of freshwater fish." *Reviews in Fish Biology and Fisheries*.

McMeans, B.C., McCann, K.S., Guzzo, M.M., Bartley, T.J., Bieg, C., Blanchfield, P.J., Fernandes, T., et al. 2020. "Winter in water: Differential responses and the maintenance of biodiversity." *Ecology Letters*, Vol. 23(No. 6): pp. 922–938. doi:10.1111/ele.13504.

Murry, B.A., Farrell, J.M., Schulz, K.L., and Teece, M.A. 2008. "The effect of egg size and nutrient content on larval performance: Implications to protracted spawning in northern pike (Esox Lucius Linnaeus)." *Hydrobiologia*, Vol. 601(No. 1): pp. 71–82. doi:10.1007/s10750-007-9267-y.

Nghiem, S.V., and Leshkevich, G.A. 2007. "Satellite SAR remote sensing of Great Lakes ice cover, part 1. Ice backscatter signatures at C band." *Journal of Great Lakes Research*, Vol. 33(No. 4): pp. 722–735. doi:10.3394/0380-1330(2007)33722:SSRSOG]2.0.CO;2.

Pierce, R.B., Carlson, A.J., Carlson, B.M., Hudson, D., and Staples, D.F. 2013. "Depths and thermal habitat used by large versus small northern pike in three Minnesota lakes." *Transactions of the American Fisheries Society*, Vol. 142(No. 6): pp. 1629–1639. doi:10.1080/00028487.2013.822422.

Salonen, K., Leppäranta, M., Viljanen, M., and Gulati, R.D. 2009. "Perspectives in winter limnology: Closing the annual cycle of freezing lakes." *Aquatic Ecology*, Vol. 43(No. 3): pp. 609–616. doi:10.1007/s10452-009-9278-z.

Shuter, B.J., Finstad, A.G., Helland, I.P., Zweimüller, I., and Hölker, F. 2012. "The role of winter phenology in shaping the ecology of freshwater fish and their sensitivities to climate change." *Aquatic Sciences*, Vol. 74(No. 4): pp. 637–657. doi:10.1007/s00027-012-0274-3.

Shuter, B.J., and Post, J.R. 1990. "Climate, population viability, and the zoogeography of temperate fishes." *Transactions of the American Fisheries Society*, Vol. 119(No. 2): pp. 314–336. doi:10.1577/1548-8659(1990)119<0314:CPVATZ>2.3.CO;2.

Singha, S., Johansson, A.M., and Doulgeris, A.P. 2020. "Robustness of SAR Sea ice type classification across incidence angles and seasons at L-band." *IEEE Transactions on Geoscience and Remote Sensing*, 1–12. doi:10.1109/TGRS.2020.3035029.

Smokorowski, K.E., Stoneman, M.G., Cairns, V.W., Minns, C.K., Randall, R.G., and Valere, B. 1998. *Trends in the nearshore fish community of Hamilton Harbour, 1988 to 1997, as measured using an Index of Biotic Integrity*. Canadian Technical Report of Fisheries and Aquatic Sciences. No. 2230: xii + 97 p.

Surdu, C.M., Duguay, C.R., and Fernández Prieto, D. 2015. "Evidence of recent changes in the ice regime of lakes in the Canadian High Arctic from spaceborne satellite observations." *The Cryosphere Discussions*, Vol. 9(No. 6): pp. 6223–6274. doi:10.5194/tcd-9-6223-2015.

Surdu, C.M., Duguay, C.R., Pour, H.K., and Brown, L.C. 2015. "Ice freeze-up and break-up detection of shallow lakes in Northern Alaska with spaceborne SAR." *Remote Sensing*, Vol. 7(No. 5): pp. 6133–6159. doi:10.3390/rs70506133.

Tom, M., Aguilar, R., Imhof, P., Leinss, S., Baltsavias, E., and Schindler, K. 2020. "Lake ice detection from Sentinel-1 SAR with deep learning." Paper presented at ISPRS Congress 2020, Nice, France.

Vadeboncoeur, Y., McIntyre, P.B., and Vander Zanden, M.J., 2011. "Borders of biodiversity: Life at the edge of the world's large lakes." *BioScience*, Vol. 61(No. 7): pp. 526–537. doi:10.1525/bio.2011.61.7.7.

Verpoorter, C., Kutser, T., Seekell, D.A., and Tranvik, L.J. 2014. "A global inventory of lakes based on high-resolution satellite imagery." *Geophysical Research Letters*, Vol. 41 (No. 18): pp. 6396–6402. 2014GL060641. doi:10.1002/2014GL060641.

Wang, J., Bai, X., Hu, H., Clites, A., Colton, M., and Lofgren, B. 2012. "Temporal and spatial variability of Great Lakes ice cover." *Journal of Climate*, Vol. 25(No. 4): pp. 1318–1329. doi:10.1175/2011JCLI4066.1.

Wang, J., Duguay, C.R., Clausi, D.A., Pinard, V., and Howell, S.E.L. 2018. "Semi-automated classification of Lake Ice Cover using dual polarization RADARSAT-2 imagery." *Remote Sensing*, Vol. 10(No. 11): pp. 1727. doi:10.3390/rs10111727.

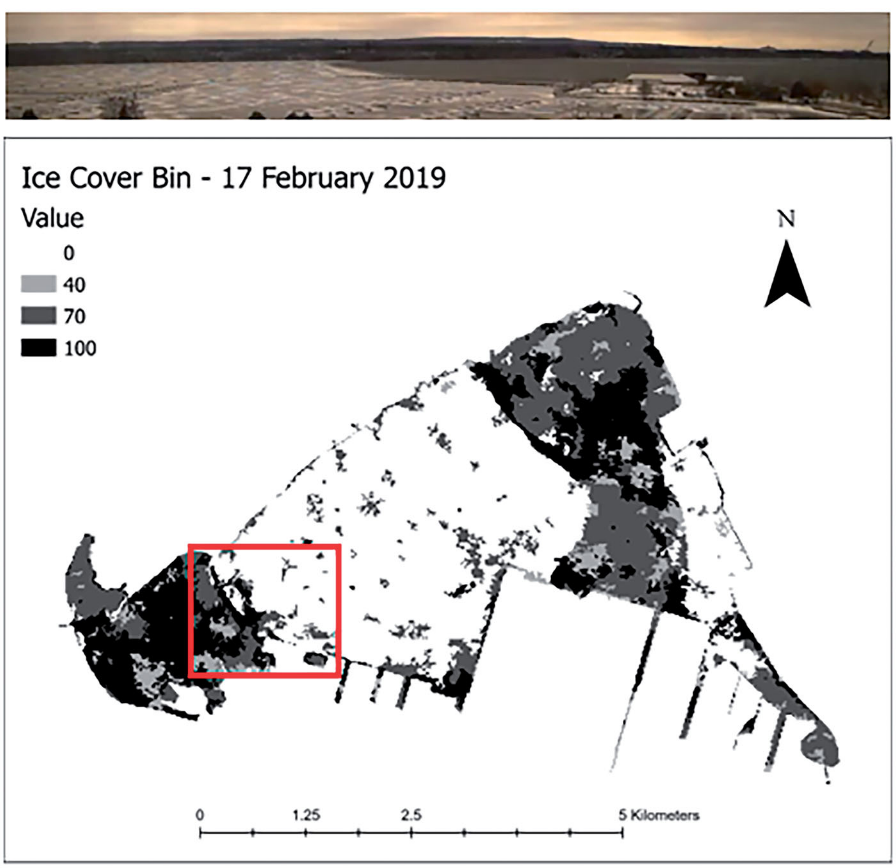
Wang, J., Kessler, J., Hang, F., Hu, H., Clites, A., and Chu, P. 2017. *Great Lakes Ice climatology update of winters 2012-2017: Seasonal cycle, interannual variability, decadal variability, and trend for the period*. NOAA Technical Memorandum GLERL-170, 1–14.

Whillans, T. 1979. "Historic transformations of fish communities in three Great Lakes bays." *Journal of Great Lakes Research*, Vol. 5(No. 2): pp. 195–215. doi:10.1016/S0380-1330(79)72146-0.

Yang, X., Pavelsky, T.M., and Allen, G.H. 2020. "The past and future of global river ice." *Nature*, Vol. 577(No. 7788): pp. 69–73. doi:10.1038/s41586-019-1848-1.

Zhao, Y., Shuter, B.J., and Jackson, D.A. 2008. "Life history variation parallels phylogeographical patterns in North American walleye (*Sander vitreus*) populations." *Canadian Journal of Fisheries and Aquatic Sciences*, Vol. 65(No. 2): pp. 198–211. doi:10.1139/f07-162.

Appendix



Appendix 1. Time lapse camera image (top) from February 17, 2019 matches ice/water boundary present in mapped ice (bottom; red rectangle).