# **Chapter 12 Flood Mapping from Multi-Sensor EO Data for Near Real-Time Infrastructure Impact Assessment: Lessons Learned from the 2017 Spring Flood in Eastern Canada**



**Ian Olthof, Simon Tolszczuk-Leclerc, Brad Lehrbass, Victor Neufeld, and Vincent Decker**

# **12.1 Introduction**

The Emergency Geomatics Services (EGS) is a section within the Canada Centre for Mapping and Earth Observation, Natural Resources Canada, responsible for providing geospatial intelligence during natural disasters including fooding. EGS maps foods to help mitigate impacts on people and infrastructure by providing an overview of current food extents that allow emergency responders including the military to prioritize and deploy help where it is needed most. Mitigation measures include shutting down power and gas transmission lines, erecting sandbag walls to protect buildings and other infrastructure, as well as mass evacuations to safeguard people from fooding.

On 23 April 2017 EGS was activated by Public Safety Canada for fooding caused by snowmelt and heavy precipitation in communities located on the Ottawa River between the Quebec–Ontario provincial border and Lake of Two Mountains, Canada. As record amounts of precipitation continued to fall into May 2017, the activation area expanded to include the Ottawa River from west of Ottawa to east of Montreal as far as Lac St-Pierre further downstream (Fig. [12.1\)](#page-1-0).

At the outset of the 2017 flood, EGS was in the midst of changing its operations; from the way, it extracted surface water extents from satellite imagery to the incorporation of citizen geographic information to improve its food map products. This chapter describes lessons learned amid this transition during EGSs' 2017 springtime flood activation in Eastern Ontario and Western Quebec. Data received by EGS

I. Olthof ( $\boxtimes$ ) · S. Tolszczuk-Leclerc · B. Lehrbass · V. Neufeld · V. Decker

Emergency Geomatics Services, Canada Centre for Mapping and Earth Observation, Natural Resources Canada, Ottawa, ON, Canada

e-mail: [ian.olthof@canada.ca](mailto:ian.olthof@canada.ca)

<sup>©</sup> Springer Nature Switzerland AG 2021 275

V. Singhroy (ed.), *Advances in Remote Sensing for Infrastructure Monitoring*, Springer Remote Sensing/Photogrammetry, [https://doi.org/10.1007/978-3-030-59109-0\\_12](https://doi.org/10.1007/978-3-030-59109-0_12#DOI)

<span id="page-1-0"></span>

**Fig. 12.1** 2017 food activation area from west of Ottawa to Lac St-Pierre

used to generate accurate and consistent near real-time food information is listed, including satellite imagery, as well as airborne and ground-based reference data used to improve and validate food maps. The transition that was taking place within EGS to update surface water mapping methods is described as this coincided with the 2017 activation. Due to the challenges faced by processing vast quantities of satellite imagery received during the event, EGS decided to adopt the new methods due to improved mapping efficiency and consistency. The rationale for this transition including advantages of the new methods are explained.

# *Background*

In the year prior to the 2017 activation, EGS had made signifcant progress on automated surface water mapping to extract both open water and fooded vegetation extents from optical and radar satellite data. This work was ongoing within Public Safety's floodplain characterization programme with the goal of generating useful information for EGS, including historical surface water maps to help precisely delineate foodplains as well as calibrate satellite food models for operational mapping. This new methodology for automated food mapping was demonstrated using historical optical satellite imagery from the Landsat mission obtained through the USGS in Olthof [\(2017](#page-14-0)).

This methodology was subsequently adapted to single and dual-polarization radar imagery from RADARSAT-1 and 2 and work began to generate historical surface water maps over the Saint John River foodplain to compare with optical data with the eventual goal of seamlessly integrating information derived from both sensors (Olthof and Tolszczuk-Leclerc [2018](#page-14-1)). The overarching objective of this work was to produce a robust, accurate, automated and effcient methodology to map surface water from a range of sensors for both operational and historical food mapping with minimal user intervention. The large data volumes of satellite imagery that exist in historical archives necessitated the transition from manual methods to full automation, while effciency is needed since EGS has set a goal to publish maps within 2–4 h of satellite data reception to provide current emergency situational awareness. The 2–4 h timeframe includes several time-consuming steps from data download, processing, quality control including editing when necessary, to map production and publishing.

At the request of Public Safety Canada, the International Charter on Space and Major Disasters was activated on 6 May 2017 for fooding in Southern Quebec. The Charter members consist of 17 space agencies from around the world who provide free imagery from 34 satellites to relief organizations working in areas affected by natural or manmade disasters. Upon activation, the methodology was applied to data from different sensors received through the Charter in addition to Canada's own RADARSAT-2. The majority of data were from radar satellites, providing the ability to detect water through cloud during near continuous cloud cover that was present in the weeks of fooding. Fortunately, the methodology proved to be suffciently reliable to be adapted to other sensors that include different radar wavelengths, polarizations and spatial resolutions, requiring specifcation of only three sensor-specifc parameters to account for these differences.

### *Data*

Satellite, airborne, ground-based and ancillary data layers were integrated to provide near-real-time food maps that were quality checked on a best effort basis prior to release to government agencies and the public.

#### **Satellite Imagery**

EGS tasks Canada's RADARSAT-2 satellite to image food-prone regions through acquisition plans prior to the springtime food season and gets priority tasking during an emergency activation. EGS tasks RADARSAT-2 dual-polarization imagery in standard or wide-mode to ensure sufficient coverage over the affected region. Through the Charter, EGS received both optical and radar imagery from a number of different satellite sensors with detail ranging from sub-metre to 250 m resolution and coverage from tens of square kilometres to thousands (Table 12.1).

**Table 12.1** Satellite provided by the International Charter on Space and Major Disasters to the Emergency Geomatics Services during the 2017 food.





Priority needed to be given to the best available scenes due to the volume of data received through the Charter. From April 23 to May 24, 112 scenes were evaluated for map production and publishing, the majority of which were discarded due to excessive cloud cover in optical, high wind in radar or some other quality issue. Of the 112 scenes, 41 were processed to some degree and 22 were fully processed and published as maps simultaneously on the Federal Geospatial Platform (FGP) used to disseminate food products internally to government and Open Maps to the public.

### **NASP**

From May 7–16, 2017, Transport Canada's National Aerial Surveillance Program (NASP) aircraft were tasked to acquire oblique pictures of the fooding along approximately 600 km of the waterfront from Pembroke, Ontario eastward to Quebec City. Four separate fight zones were defned, with fights rotating through each fight zone over the 10-day period. Pictures captured every 5 s during fights totaled nearly 14,000 images taken during the 11-day period. These pictures were used to populate an online interactive web map through ArcGIS Online to distribute information and help improve and validate food maps as they were generated from satellite imagery (Fig. [12.2\)](#page-4-0).

<span id="page-4-0"></span>



Prior to the activation, a beta version Citizen Geographic Information (CGI) application was released to select trusted users to acquire near real-time in-situ food information. The application notifes users of a satellite overhead about to acquire an image, at which time the user is requested to take a geotagged picture of fooding and upload it to a central geodatabase for analysis. The image metadata also includes azimuth, enabling co-registration of features in CGI pictures with features in the satellite image. When available, this information is used to verify food extents in satellite products and better tailor products by correcting obvious errors before release on the FGP and Open Maps.

### **LIDAR HRDEM**

Canada's new High-Resolution Digital Elevation Data Model (HRDEM) LIDARderived elevation data were made available to EGS prior to their offcial release to the public over portions of the food-affected area where available. The complete dataset includes elevation, slope, aspect and shaded relief for a digital terrain model available at 2 m spatial resolution in 20 km  $\times$  20 km tiles with floating-point precision. Tiles covering urban areas where CGI data were acquired were used to improve food mapping in locations where remote sensing has traditionally had diffculties mapping water due to obstructions including buildings.

### **Water Occurrence**

A water occurrence map was obtained from a global product generated from 32 years of historical Landsat data by the European Commission (Pekel et al. [2016\)](#page-14-2). Water occurrence is also referred to as inundation frequency because it maps the percentage that water has been observed at each location in satellite imagery. It is generated by overlaying a time-series of water maps and for each pixel location, counting the number of times water is detected divided by the total number of valid observations. These maps have been produced at a global scale to support applications including water resource management, climate modelling, biodiversity conservation, food security and food response mapping.

# **12.2 Emergency Geomatics Services New Operational Flood Mapping Methods**

### *Open Water Mapping*

The new EGS food mapping methodology performs multi-channel supervised machine learning classifcation of available radar polarizations to map open water, and then bright threshold region growing from open water to map fooded vegeta-

### **CGI**

<span id="page-6-0"></span>

Fig. 12.3 New methodology put into operations for the 2017 flood activation

tion (Fig. [12.3](#page-6-0)). Smooth open water is a specular surface that produces a dark appearance in radar imagery caused by single bounce of incident radiation away from the sensor. Previously, EGS mapped open water using the traditionally accepted method of single polarization interactive dark image thresholding even when multiple polarizations were available (Bolanos et al. [2016;](#page-14-3) Li and Wang [2015\)](#page-14-4). While thresholding has been shown to perform well for open water under ideal conditions, water surface roughness due to ice that is sometimes present during the spring food season as well as waves can increase backscatter to a level where a single threshold value cannot reliably separate water from land (Henry et al. [2006](#page-14-5)). Automated methods used to determine optimal threshold values are compromised by these factors, while manual thresholding can better tune the value to minimize errors of omission and commission. Even still, a signifcant amount of post-processing is often required to reduce errors to an acceptable level (White et al. [2014\)](#page-14-6).

Information contained in multiple radar polarizations can help to reduce errors in open water extraction; however making use of this information requires an approach other than single band image thresholding. The supervised multispectral classifcation has long been used in terrestrial remote sensing applications, but has seen limited use for surface water mapping from radar. One challenge is that supervised classifcation approaches require spectral signatures for each class to train a classifer, for example, signatures representing land and water in the case of water extraction. The use of standard spectra to classify land and water will not achieve an optimal classifcation result for several reasons. First, the spectral variability of water in radar due to wind and ice can cause confusion between water and land. Second, spectral signatures of land also vary due to the presence of several land cover types that change through time because of vegetation phenology, moisture and atmosphere. An additional complicating factor is that in order to perform traditional multispectral classifcation such as minimum distance or maximum likelihood, separate signatures must be sampled for all land cover types present in the scene.

To deal with these limitations, an automated open surface water extraction methodology that is an extension of one already developed in Olthof [\(2017](#page-14-0)) was implemented. The approach makes use of recently available inundation frequency products from historical Landsat data (Pekel et al. [2016](#page-14-2); Olthof [2017\)](#page-14-0) to sample all scene-specifc signatures representing every land and water class present in the image. Land signatures are extracted where inundation has never occurred (0% occurrence) based on historical inundation maps, while water signatures are extracted where water has always been observed (100% occurrence). Sampled, scene-specifc signatures are used to train the C50 (See5) decision tree machine learning algorithm that classifes the entire image into the water versus land. Machine learning is used because it does not assume a statistical distribution and can handle vast amounts of training data to precisely tune the classifer.

## *Flooded Vegetation Mapping*

A signifcant amount of fooding in Canada occurs in vegetated areas, which has lead to considerable research to improve fooded vegetation mapping in recent years. Flooded vegetation presents a challenge to remote sensing because the signal must penetrate the vegetation layer to sense water below. While optical remote sensing has a limited capability to detect fooding beneath vegetation and can do so reliably only during leaf-off in the early spring or late fall, radar is able to detect water beneath leaf-on canopies under many conditions. Radar is an active sensor that is side-looking, causing double bounce of the incident beam frst off horizontal water surfaces beneath the canopy, and second off vertical trunks and stems acting as corner refectors before returning to the sensor (Hess et al. [1990](#page-14-7)). Leaf size, wavelength and incidence angle are all factors that affect water detection beneath vegetation from radar, with longer wavelengths relative to leaf size (Townsend and Walsh [1998\)](#page-14-8) and shallower incidence angles (White et al. [2015](#page-14-9)) generally providing greater signal penetration through the canopy.

Double bounce off fooded vegetation causes a high-intensity return to the sensor, producing a bright signal in radar imagery particularly in like-polarization channels (e.g. HH). Bright target thresholding has been used in the past to map fooded vegetation; however, this approach was never operationalized by EGS because it leads to signifcant commission error caused by the presence of other corner refectors such as buildings and rock outcrops in the scene. Post-classifcation editing in a GIS environment can be performed to help reduce commission error, but

this relies on ancillary data layers that may be out of date or contain errors. Manual editing has also been done to improve food products but is both time-consuming and subjective in the absence of reliable ancillary information. A robust fooded vegetation extraction methodology independent of ancillary data requirements is preferred for emergency food mapping for product quality, improved processing speed and efficiency.

To minimize processing time and commission error, the new methodology maps fooded vegetation by iteratively region growing from open water into adjacent bright intensity areas characteristic of double bounce using a bright threshold value criterion. Region growing has the advantage over thresholding the entire image by assigning only adjacent pixels to the fooded vegetation class, thereby reducing commission errors caused by double bounce elsewhere in the scene. Double bounce off buildings adjacent to open water was corrected using the urban class from a recent Landsat land cover of North America (Latifovic et al. [2017](#page-14-10)), which was generated including information from Canada's road network layer. Once the frst region growing using a bright threshold value is complete, a second region growing is performed using a dark threshold value from open water and fooded vegetation to help infll dark areas contained within bright fooded vegetation and better connect nearby areas of open water. Both instances of region growing stop when either no additional adjacent pixels meet the threshold criterion or after a set number of iterations. Open water and fooded vegetation are subsequently improved using morphological operators to infll small land areas entirely surrounded by water, followed by fltering and sieving to reduce both errors of omission and commission.

Because the methodology relies on signatures extracted from each scene to classify open water, and only user specifcation of radar polarization, bright and dark threshold values are needed to map fooded vegetation, the approach is sensorindependent. As new charter data was received during the activation, tools were modifed to accept the number of polarizations available to work on single polarization (e.g. TerraSAR-X), dual-polarization (e.g. Sentinel-1) and quad-polarization (e.g. RADARSAT-2) (Fig. [12.4\)](#page-9-0). Where multiple polarizations are available, specifcation of the polarization to use for fooded vegetation region growing must be specifed. Generally, the polarization with the best contrast between fooded vegetation and surrounding water and land is selected. Where available, like-polarization provide the best contrast, for example, HH in RADARSAT-2.

### *Urban Flood Mapping*

A major shortcoming of the approach applied to radar data was its inability to accurately map open water in urban environments. The presence of buildings causing shadow made dark water target detection impossible, while confdence that any detected dark targets were water was low. Further, urban areas located on the water were often mapped as fooded vegetation due to the presence of corner refectors

<span id="page-9-0"></span>

**Fig. 12.4** Example of multi-sensor food mapping using the new operational methodology from RADARSAT-2 (interior white box), and TerraSar-X (outside), showing the consistency in mapping open water and fooded vegetation between sensors

such as road and buildings producing a high-intensity return. Post-classifcation improvements were made with land cover data to remove fooded vegetation in urban settings; however, this also removed any real water that was detected.

As Citizen Geographic Information (CGI) data submitted during the event became available during the activation, tests began on using it in combination with newly available LIDAR HRDEM data to improve urban food mapping. A total of 394 observations were submitted across three food-affected regions including Lac St-Pierre, Montreal and Lake of Two Mountains, and Ottawa-Gatineau between March 29 and April 14, 2017. The use of LIDAR data for food mapping requires a local water depth measurement, which can be estimated from CGI data assuming the observer is taking pictures at or near the food perimeter and can be verifed by looking at the pictures themselves. Once an elevation along the food perimeter has been established from CGI, the full local food extent can be mapped by flling adjacent pixels below the established food elevation at the food perimeter, as shown in Fig. [12.5](#page-10-0) using 80 observations submitted in Gatineau 6 April 2017. The extent to which inflling can be done varies with the degree of local variation in the geoide. For example, if a single elevation threshold were applied to a LIDAR DEM from Ottawa to Montreal, fooding would be under predicted in Ottawa and simultaneously over predicted in Montreal due to the slope of the geoide from Ottawa to Montreal that causes water to fow in that direction. While the extent of urban fooding is considerably less than the distance between Ottawa and Montreal, CGI data acquired in Montreal's West Island should not be used to estimate urban fooding in the East End. Therefore, local CGI data can be used to estimate local residential/urban fooding from inland to the nearest adjacent permanent water body, but not between separate, distant locations.

<span id="page-10-0"></span>

**Fig. 12.5** Use of Crowdsourced Geographic Information (CGI) data acquired on 6 April 2017, and a new LIDAR DEM to improve urban food mapping in Gatineau, Quebec, combined with a RadarSat-2 food product from 7 April 2017

#### **Limitations and Lessons Learned**

Currently available global historical dynamic surface water maps used to train machine learning have known limitations due to input optical Landsat imagery that is the only medium resolution data available with its spatial and temporal coverage. First, optical data does not penetrate cloud and therefore, maximum water extents during cloudy, rainy events including a signifcant percentage of foods such as the 2017 event are not fully captured. In addition, optical remote sensing has a limited capability to detect water beneath vegetation, while fooded vegetation comprises a high percentage of the overall food area on many foodplains in Canada. Lastly, because the product is global in scale, it is not optimized to Canada's specifc geography or seasonality. All of these factors generally lead to water omission errors. Nevertheless, the new food mapping methodology is robust enough to overcome these limitations and Pekel's occurrence map proved very useful during the 2017 activation.

The availability of historical radar imagery from Canada's RADARSAT mission going back to 2008 combined with the advantages cloud penetration and the ability to map fooded vegetation suggest that separate dynamic surface water maps should be generated from these data over Canada. While current global products contain error, machine learning used to classify open water is known to be very robust to errors in training data (Ghosh et al. [2016;](#page-14-11) Olthof and Tolszczuk-Leclerc [2018\)](#page-14-1). Therefore, even if global maps omit the water, errors in training data extracted using these maps should be relatively small compared to the overall training sample size. The activation season was also considered successful using a global historical map product as input, further supporting the use of Pekel's map. However, the more extreme the food event, the more errors will be introduced when relying on a product that omits water in favour of land. Currently, EGS has no sense of the level of improvement that can be achieved with better historical information. For this reason, work will continue to generate Canadian products tuned to our geography and seasonality from historical optical and radar imagery over select foodplains in Canada. With support, the historical RADARSAT archive can be exploited for this purpose as is ongoing along the Saint John River, NB. Finally, the complete historical and operational surface water mapping approach is iterative as current food products are used to update and improve historical inundation products, which will then in turn be used to produce food products next season. As scenes are added to the time-series of water maps, both historical and near-real time water maps should continue to improve.

In addition to falsely detecting fooded vegetation by region growing in urban areas adjacent to open water, a second limitation of the methodology relates to the local topography of riverbanks. Where riverbanks are steep and roughly parallel to the SAR orbit, fooded vegetation will also be falsely detected due to a high backscatter caused by steep local incidence angles. Using ancillary datasets such as slope and aspect based on look direction can help reduce these errors by removing fooded vegetation on slopes above a certain grade. Work is still needed on the best approach to integrate digital elevation data to improve food maps, particularly in areas of fooded vegetation. Factors such as the quality and resolution of the DEM in relation to the resolution of satellite imagery and decisions on whether to incorporate the DEM directly into region growing, to use it to create a processing mask of fat areas where surface water can pool, or to use it in post-processing still need to be considered.

Editing of flood maps is still required to remove either false detections or those that are not of interest for public safety. However, false detections appear to be relatively rare, and those detections that are not of interest to public safety could be relevant to other potential users. Enhancing flood products with ancillary information to target these users may be an avenue worth pursuing to make food maps of value to a wider audience. For example, fooding is consistently detected in agricultural felds, while visual observations confrm that this is a common occurrence during the food season. These detections are ephemeral and are currently being removed from food maps, but they may be relevant to agricultural production as tilling and seeding are delayed by standing water in felds. Agriculture Canada and crop insurance companies may be interested from a crop inventory perspective to know if crops will be planted late, how much and where. The intersection between food maps and land cover may be suffcient to characterize different types of fooding in terms of longevity and impacts on different stakeholders.

EGS is generally most active in the response phase of the emergency management cycle that includes mitigation, preparation, response, recovery. However, a request was made to generate maximum 2017 flood extent polygons over the activation region to help evaluate food risk. Due to the nature of emergency mapping, accuracy assessments are performed on a best effort basis within the 4-h period that the EGS has to generate and distribute its food extent polygons. Nonetheless, accurate maximum flood extent maps are considered a valuable product to the emergency management and land planning communities during the recovery phase. EGS undertook work to generate a maximum food extent product that spans all of the affected areas that were mapped at least once by our services. To achieve this, the highest resolution products generated closest to the timing of peak food were selected, reviewed using all available datasets and merged, including urban food products in Gatineau and along Pierrefonds Boulevard on the Island of Montreal generated from CGI and the LIDAR DEM. Each product was initially assessed separately against very high-resolution satellite imagery (Worldview, Pleiades) medium resolution optical satellite imagery (Sentinel-2, Landsat), crowdsourced feld observation (photography and surveys) and oblique aerial photography acquired by NASP before publishing. Each flood extent polygon was edited and its accuracy improved where errors were noted compared to reference data.

A more formal accuracy assessment of the fnal maximum food extent product was subsequently conducted using visually interpreted NASP oblique airphotos as a reference. Interpretation was performed by putting placemarks in Google Earth at locations interpreted as either food or land at the time of the NASP photo acquisition. Because assigning points in open water under normal non-food conditions would artifcially infate classifcation accuracy, reference points were located near the food margin with fooded points interpreted as locations that were inundated in NASP photos but were interpreted as land in Google Earth during baseline, non-

<span id="page-13-0"></span>

**Fig. 12.6** Maximum food extent of the activation area generated by combining food maps of different sub-regions

flood conditions. Land points were interpreted just beyond the flood margin as permanent land before and during the food event. A total of 793 points were collected in this manner from a subset of 1475 photos acquired from west of Ottawa to east of Lac St-Pierre from 7 May 2017 to 16 May 2017. The maximum food extent is a mosaic of different food products acquired on different dates that may not correspond precisely to the acquisition dates of co-located NASP. Consecutive dates checked in many locations showed consistent food margins, suggesting differences in the timing of a few days between NASP and satellite acquisitions likely had a minimal effect on overall accuracy but may have led to error in some cases where flood margins changed significantly over a short period of time. Despite these potential issues, an overall accuracy of 86.2% was obtained for this product using the assessment methodology outlined above. The result is a validated complete and uniform maximum food extent product shown in Fig. [12.6](#page-13-0).

### **12.3 Conclusions**

The 2017 EGS food activation was considered a success by clients, stakeholders and management at CCMEO. EGS operations adopted new methods to extract open water and fooded vegetation from multiple sensors that were developed the previous year on historical satellite data, which proved to be reliable and robust on a range of sensor data received through the International Disasters Charter. Feedback received from Public Safety Quebec was extremely positive, stating that new products were signifcantly improved over ones previously generated by EGS during the 2011 Richelieu River activation, particularly in areas of fooded vegetation that were mapped operationally for the frst time. Rather than relying on global inundation products from optical data, work on historical inundation frequency integrating radar data should continue for foodplain characterization to better tailor products to the Canadian context and assess the level of optimization that is still possible. Finally, EGS envisions enhancing our flood products through ancillary data integration to further improve them and to make them more relevant to a wider set of users and stakeholders.

## **References**

- <span id="page-14-3"></span>Bolanos, S., D. Stiff, B. Brisco, and A. Pietroniro. 2016. Operational surface water detection and monitoring using RADARSAT-2. *Remote Sensing* 8: 285.<https://doi.org/10.3390/rs8040285>.
- <span id="page-14-11"></span>Ghosh, A., N. Manwani, and P.S. Sastry. 2016. On the robustness of decision tree learning under label noise. *arXiv*: arXiv:1605.06296.
- <span id="page-14-5"></span>Henry, J.-B., P. Chastanet, K. Fellah, and Y.-L. Desnos. 2006. Envisat multi-polarized ASAR data for food mapping. *International Journal of Remote Sensing* 27: 1921–1929. [https://doi.](https://doi.org/10.1080/01431160500486724) [org/10.1080/01431160500486724.](https://doi.org/10.1080/01431160500486724)
- <span id="page-14-7"></span>Hess, L.L., J.M. Melack, and D.S. Simonett. 1990. Radar detection of fooding beneath the forest canopy: A review. *International Journal of Remote Sensing* 11: 1313–1325. [https://doi.](https://doi.org/10.1080/01431169008955095) [org/10.1080/01431169008955095.](https://doi.org/10.1080/01431169008955095)
- <span id="page-14-10"></span>Latifovic, R., D. Pouliot, and I. Olthof. 2017. Circa 2010 land cover of Canada: Local optimization methodology and product development. *Remote Sensing* 9: 1098. [https://doi.org/10.3390/](https://doi.org/10.3390/rs9111098) [rs9111098.](https://doi.org/10.3390/rs9111098)
- <span id="page-14-4"></span>Li, J., and S. Wang. 2015. An automatic method for mapping inland surface waterbodies with Radarsat-2 imagery. *International Journal of Remote Sensing* 36: 1367–1384. [https://doi.org/1](https://doi.org/10.1080/01431161.2015.1009653) [0.1080/01431161.2015.1009653.](https://doi.org/10.1080/01431161.2015.1009653)
- <span id="page-14-0"></span>Olthof, I. 2017. Mapping seasonal inundation frequency (1985–2016) along the St-John River, New Brunswick, Canada using the Landsat archive. *Remote Sensing* 9: 143. [https://doi.](https://doi.org/10.3390/rs9020143) [org/10.3390/rs9020143](https://doi.org/10.3390/rs9020143).
- <span id="page-14-1"></span>Olthof, I., and S. Tolszczuk-Leclerc. 2018. Comparing Landsat and RADARSAT for current and historical dynamic food mapping. *Remote Sensing* 10: 780. [https://doi.org/10.3390/rs1005](https://doi.org/10.3390/rs10050780) [0780.](https://doi.org/10.3390/rs10050780)
- <span id="page-14-2"></span>Pekel, J.-F., A. Cottam, N. Gorelick, and A.S. Belward. 2016. High-resolution mapping of global surface water and its long-term changes. *Nature* 540: 418–422. [https://doi.org/10.1038/nature](https://doi.org/10.1038/nature20584) [20584](https://doi.org/10.1038/nature20584).
- <span id="page-14-8"></span>Townsend, P.A., and S.J. Walsh. 1998. Modeling foodplain inundation using an integrated GIS with radar and optical remote sensing. *Geomorphology* 21: 295–312.
- <span id="page-14-9"></span>White, L., B. Brisco, M. Dabboor, A. Schmitt, and A. Pratt. 2015. A collection of SAR methodologies for monitoring wetlands. *Remote Sensing* 7: 7615–7645. [https://doi.org/10.3390/](https://doi.org/10.3390/rs70607615) [rs70607615.](https://doi.org/10.3390/rs70607615)
- <span id="page-14-6"></span>White, L., B. Brisco, M. Pregitzer, B. Tedford, and L. Boychuk. 2014. RADARSAT-2 beam mode selection for surface water and fooded vegetation mapping. *Canadian Journal of Remote Sensing* 40: 135–151.<https://doi.org/10.1080/07038992.2014.943393>.