Testing Urban Flood Mapping Approaches from Satellite and In-Situ Data Collected during 2017 and 2019 Events in Eastern Canada

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Abstract: The increasing frequency of flooding worldwide has driven research to improve near real-time flood mapping from remote-sensing data. Improved automation and processing speed to map both open water and vegetated area flooding have resulted from these research efforts. Despite these achievements, flood mapping in urban areas where a significant number of overall impacts are felt remains a challenge. Near real-time data availability, shadowing caused by manmade infrastructure, spatial resolution, and cloud cover inhibiting optical transmission, are all factors that complicate detailed urban flood mapping needed to inform response efforts. This paper uses numerous data sources collected during two major flood events that impacted the same region of Eastern Canada in 2017 and 2019 to test different urban flood mapping approaches presented as case studies in three separate urban boroughs. Cloud-free high-resolution 3 m PlanetLab optical data acquired near peak-flood in 2019 were used to generate a maximum flood extent product for that year. Approaches using new Lidar Digital Elevation Models (DEMs) and water height estimated from nineteen RADARSAT-2 flood maps, point-based flood perimeter observations from citizen geographic information, and simulated traffic camera or other urban sensor network data were tested and verified using independent data. Coherent change detection (CCD) using multi-temporal Interferometric Wide (IW) Sentinel-1 data was also tested. Results indicate that while clear-sky high-resolution optical imagery represents the current gold standard, its availability is not guaranteed due to timely coverage and cloud cover. Water height estimated from 8 to 12.5 m resolution RADARSAT-2 flood perimeters were not sufficiently accurate to flood adjacent urban areas using a Lidar DEM in near real-time, but all nineteen scenes combined captured boroughs that flooded at least once in both flood years. CCD identified flooded boroughs and roughly captured their flood extents, but lacked timeliness and sufficient detail to inform street-level decision-making in near real-time. Point-based flood perimeter observation, whether from in-situ sensors or high-resolution optical satellites combined with Lidar DEMs, can generate accurate full flood extents under certain conditions. Observed point-based flood perimeters on manmade features with low topographic variation produced the most accurate flood extents due to reliable water height estimation from these points.

Keywords: optical; radar; sensor network; citizen science; aerial surveillance; DEM

1. Introduction

In the spring of 2017, large regions in Canada’s provinces of Quebec and Ontario experienced severe flooding caused by consecutive record-setting rain events during snowmelt from early April to mid-May. The most heavily impacted portions extended more than 400 km from west of the City
of Ottawa on the Ottawa River to Lac St-Pierre along the St-Lawrence (Figure 1). Upwards of 2400 residences were flooded in 146 communities in Quebec, forcing mass evacuations and declaration of a state of emergency. First responders in Gatineau, Quebec evacuated more than 500 people while across the river in Ottawa, people in approximately 350 residences were displaced [1,2].

Two years later in the spring of 2019, flooding affected the region once again, including many of the same communities along the Ottawa and St-Lawrence Rivers. From late April to early May, many rivers exceeded record water levels reached during the 2017 flood [3]. In Quebec, 51 municipalities were flooded, including most of those affected in 2017. More than 6000 residences were inundated in these municipalities with several in the greater Montreal area, while an additional 3500 were isolated due to flooded roads and landslides resulting in more than 13,500 disaster victims [4]. Unlike in 2017, a breach of the dike in the town of Sainte-Marthe-sur-le-Lac flooded a significant portion of the municipality, forcing more than 6500 people to leave [5]. In the Outaouais region, Gatineau and communities westward were particularly impacted by the flood. Insured damages from the 2019 flood totaled $201 million across Ontario and Quebec [6].

![Map of Central Canada showing flooding areas](image)

**Figure 1.** The approximate east-west extent of the region of Central Canada along the Ottawa and St-Lawrence Rivers affected by the 2017 and 2019 flood events, with three urban borough regions of interest used as urban flood mapping case studies shown as red dots. Black dots show hydrometric station locations 1. 02OA107; 2. 02OA013; 3. 02OA033; 4. 02MC005; 5. 02OA039; and 6. 02OA016 referred to in Figure 2.

A state of emergency was declared for both flood events, activating Canada’s Emergency Geomatics Services (EGS) and the International Charter on Space and Major Disasters. The EGS maps floods from satellite imagery in near real-time to prioritize resources where needed most to help mitigate impacts. Flood maps are normally generated from Canada’s RADARSAT-2 (RS2) imagery and RADARSAT Constellation Mission (RCM) going forward; however, activation of the International Charter on Space and Major Disasters provides additional observations from up to 34 satellites belonging to 17 member space agencies. The majority of data received through the Charter during both events was radar, which is able to detect water beneath continuous cloud cover that is
normally present during flooding. However, some optical data were also received and processed both years, including high-resolution imagery acquired under clear-sky conditions.

The EGS has been mapping floods in Canada and internationally since 2004, redeveloping its operational flood mapping methods from manual to fully automated prior to 2017 to improve consistency and efficiency. These improvements not only enable repeatable and simultaneous processing of multiple images quickly, but also perform well on different satellite data received through the Charter. New methods exploit information contained in existing water products to map open water by training and applying machine learning algorithms. Flooded vegetation is mapped next by region growing from open water based on sensor-specific channels and thresholds. In the case of radar, a high-intensity threshold is applied to a co-polarization channel (normally HH) because flooded vegetation has a high backscatter in radar due to double-bounce scattering between the horizontal water surface and vertical vegetation stems [7]. In optical sensors, a moderately dark threshold applied to a long-wavelength channel can be used to detect flooding beneath vegetation before leaf growth in spring. While new methods have been shown to work well in most settings, including rural and moderately dense suburban areas with sparse to thick vegetation [8], urban flood mapping remains a challenge due to double-bounce and the layover of manmade targets in radar, cloud cover in optical sensors, and shadowing in both radar and optical sensors. For this reason, flood mapping in dense urban environments is seldom attempted by EGS unless appropriate data become available during the event. Unfortunately, a significant amount of the impact from flooding is felt in these dense urban environments and therefore, research is needed to help address this information gap [9].

A substantial amount of urban flood mapping research has focused more on risk and less on near real-time mapping for current situational awareness [10]. Despite advances in recent years, remote-sensing of urban flooding remains a challenge [11]. Different approaches including the use of high-resolution radar and change detection [11] have been developed; however, the relatively small footprint of high-resolution data limits its coverage to an area on the order of a few square kilometers, which is much smaller than the region impacted by the 2017 and 2019 floods. Optical fusion of coarse-resolution MODIS and medium resolution Landsat [12] was used to generate flood maps with an accuracy of around 90% following the 2005 flood in New Orleans from Hurricane Katrina. While data fusion combines the advantages of daily revisit from coarse-resolution data with the detail of medium-resolution imagery, fundamental limitations of optical sensors are still present due to cloud cover combined with a lack of detail from moderate resolution sensors to detect street-level flooding. High-resolution optical imagery has been shown to perform well for surface water mapping in Olthof [13] and integrated with Digital Terrain Model (DTM) data using machine learning for flood mapping in Lamovec et al. [14]. Both studies demonstrate the advantages of these data in terms of detail, but limitations persist in urban areas depending on building density and shadow, while clouds continue to restrict their usefulness for near real-time flood mapping. Finer resolution airborne photography and UAV imagery [15] acquired below the cloud cover provide the most detail but their limited footprint, barriers due to regulations in Canada, timing, and deployment restrict their usefulness for operational flood mapping.

Numerous studies have explored SAR’s ability to penetrate cloud cover to map flooding [16]. SAR flood mapping has the ability to identify open, non-vegetated areas with high accuracy, but ambiguity in the returned signal may occur within more complex environments such as dense vegetation and urban areas [17]. Urban flood mapping with radar is limited due to factors already mentioned, including double-bounce, layover, and shadowing. However, two promising approaches have been developed in recent years including intensity differencing between pre-flood and flooded images in areas masked to remove shadow and layover by [11]. This approach relies on enhanced double-bounce backscatter due to horizontal asphalt and concrete surfaces becoming inundated with water that has a higher dielectric constant. Results using 3 m TerraSAR-X data produced flooding over detection errors at greater than 2% of the study area, under detection in mostly masked ‘unseen regions’ in the range of 16% and total errors around 18% compared to near-simultaneous aerial photography [11].
With the advance of SAR technology, the ability to perform interferometric analysis on a global scale has increased substantially. A second promising approach using radar involves interferometric Coherent Change Detection (CCD) for urban flood detection by Chini et al. [18]. Their rationale for the application of CCD was that urban environments are consistently characterized by relatively high coherence values and that floodwater causes a significant, detectable decrease in coherence. Their methods first identify double-bounce features (i.e., buildings with orthogonally oriented facades to the SAR look direction) in the SAR images using a multi-temporal technique; and subsequently detects the coherence drop-off in the aforementioned double-bounce map caused by floodwater. This approach was tested using 5 m and 20 m Sentinel-1 (S-1) images over three areas around the city of Houston that were flooded due to Hurricane Harvey, and good agreement was achieved with high-resolution optical images acquired shortly after the hurricane’s passage [18].

The recent acquisition of high-resolution Lidar elevation data over parts of Canada from NRCan’s high-resolution digital elevation model (HRDEM) series [19] presents EGS with new data to assist with urban flood mapping. Urban flood extents can be mapped using a 1-dimensional model with elevation data and local water level [20], which can vary due to wind, obstructions, water flow, bathymetry, and channel width. Local water levels may be determined by intersecting mapped flood extents with topographic data, by measuring water level directly, or by locating a flood perimeter in-situ combined with topographic data. Once the water level at the shoreline of an urban area has been established, it can be used to map water by flood-infilling adjacent ‘unseen’ urban land located at lower elevations. An assumption of this approach is that local flooding that occurs over an extended period of time reaches an equilibrium state so that water levels are constant across the flooded area. In areas where persistent strong currents and wind combine with obstructions for the duration of the flood event, these assumptions may not be valid.

Several studies have attempted to fuse remotely sensed flood extents with DEM data in order to determine the water level in rural areas. Reported errors from different studies using both optical and radar satellite-derived flood extents and DEM data ranged from 0.1 m up to 2 m when assessed against field data and model outputs [9]. It should be noted that the magnitude of errors will depend on local topography and satellite spatial resolution since a one-pixel error in flood extent will produce a greater water level error at coarser spatial resolutions and/or in areas of steep nearshore topography. At the upper limit of this error range, fusion for the purpose of establishing water levels for urban inundation modelling are not useful; however, at the lower end, water height may be sufficiently accurate to map urban flooding with DEM data.

The development of sensor networks in cities including traffic cameras, Wi-Fi, and GPS infrastructure and the use of their data for the benefit of its citizens has brought about the concept of ‘smart cities’ [21]. In-situ cameras have been used to monitor rivers’ water level [22] and flow velocity [23] for urban flood monitoring [24], as well as river ice to assess ice-jam risk [25]. Mobile sensors and citizen science provided data to map urban floods in 2017 in two separate boroughs in Ottawa and Montreal [8], but proved unreliable in 2019 due to a lack of users of EGS’s Citizen Geographic Information (CGI) application. Establishing a permanent sensor network or leveraging and enhancing existing networks, such as traffic cameras, should prove more reliable to acquire systematic information on a current flood situation [24]. Location analyses based on previous flooding and simulation can be performed to determine an optimal spatial coverage with a minimal number of sensors.

This paper examines different approaches using case studies to guide the development of operational urban flood mapping tools. Operational methods must produce accurate urban flood maps at the street or property level, require as few readily available inputs as possible and be efficient enough to be able to integrate with larger-area flood maps derived from other data sources such as radar within the four-hour product dissemination window required of EGS for near real-time flood response. Case studies use data collected during 2017 and 2019 flood events in Eastern Canada and focus on three separate boroughs in the larger study area that flooded in at least one of the two flood years, including Sainte-Marthe-sur-le-Lac, Pointe-Gatineau, and Pierrefonds on the Island of Montreal (Figure 1). Each case study relies on different sources of data and information that may or
may not be available for a particular time and flood event depending on weather conditions such as cloud cover for optical satellite imagery. Other than Lidar DEM data and high-resolution optical satellite imagery that was fortunate to be captured nearly cloud-free during the 2019 event, RS2 flood maps, citizen geographic information and simulation based on in-situ flood observations are also used to test different approaches.

2. Data

2.1. Remote Sensing Data

2.1.1. RADARSAT-2

Nineteen RS2 images processed by EGS during the 2017 and 2019 activations over the flood-affected regions in Eastern Canada were used to generate flood maps. Sixteen of those scenes were acquired over the greater Montreal area from the Ontario/Quebec border to east of the Island of Montreal. Eight Montreal scenes were imaged in 2017 from April 23 to May 21 while the remaining eight were from April 20 to May 18, 2019. An additional three scenes were captured over the Ottawa-Gatineau region from the town of Arnprior located approximately 50 km west of Ottawa on the Ottawa River to Hawkesbury nearly 90 km to the east. One Ottawa-Gatineau scene was acquired on May 7, 2017 with the remaining two on April 30 and May 20 of 2019. Data consist of dual-polarization channels representing HH and HV gridded at 8 or 12.5 m resolution. Flood maps were generated for each scene using the latest RS2 flood tools to ensure map consistency as small changes have been made to the software since it was initially developed. Flood maps show areas of permanent water, open water flooding, and flooded vegetation in shrub and treed areas.

2.1.2. Sentinel-1

Current EGS flood extraction methods rely on SAR backscatter and therefore, InSAR capable RS2 data were not acquired over Gatineau and Sainte-Marthe-sur-le-Lac for the 2017 or 2019 floods. Instead, this study utilized data from the S-1 SAR constellation to test urban CCD over Gatineau and Sainte-Marthe-sur-le-Lac for 2019, which provides global C-band coverage from two satellites of the earth’s landmasses bi-weekly. Five dual-polarization (VV+VH) S-1A Interferometric Wide (IW) Single Look Complex (SLC) images simultaneously covering both Gatineau and Sainte-Marthe-sur-le-Lac were acquired in May of 2019 during the flood event and into June post-event (Table 1). IW is acquired at a 5 m by 20 m spatial resolution and is the main acquisition mode consistently collected over Gatineau, QC and Sainte-Marthe-sur-le-Lac, QC. Available repeat-pass data were collected every 12 days with a single IW swath covering both municipalities.

Table 1. S-1 IW image dates for urban flood mapping using CCD, with significant flood events in Gatineau and Sainte-Marthe-sur-le-Lac.

| Acquisition Time [UTC] | Polarization | Incidence Angle (°) (IW1/IW3) | Resolution (m) (Range × Azimuth) | Pixel Spacing (m) (Range × Azimuth) | Orbit |
|------------------------|--------------|-------------------------------|----------------------------------|-----------------------------------|-------|
| 2019-05-02 T22:52:18   | VV           | 33.7/43.7                     | 5 × 20                           | 2.3 × 13.9                        | Ascending |
| 2019-05-14 T22:52:19   | VV           | 33.7/43.7                     | 5 × 20                           | 2.3 × 13.9                        | Ascending |
| 2019-05-26 T22:52:19   | VV           | 33.7/43.7                     | 5 × 20                           | 2.3 × 13.9                        | Ascending |
| 2019-06-07 T22:52:20   | VV           | 33.7/43.7                     | 5 × 20                           | 2.3 × 13.9                        | Ascending |
| 2019-06-19 T22:52:21   | VV           | 33.7/43.7                     | 5 × 20                           | 2.3 × 13.9                        | Ascending |
1. Gatineau is captured by IW sub-swath 1 (IW1) and Sainte-Marthe-sur-le-Lac is captured by IW sub-swath 3 (IW3).

2.1.3. High-Resolution Optical

PlanetScope multispectral imagery was provided free of charge from Planet to promote its data for flood mapping during the 2019 flood activation, covering almost the entire study area under near-complete clear-sky conditions. PlanetScope data are acquired by a constellation of more than 120 CubeSat satellites providing daily global land surface coverage at 3 m spatial resolution. Multispectral data consisting of blue (455–515 nm), green (500–590 nm), red (590–670 nm), and NIR (780–860 nm) were provided in UTM zone 18N projection at Level 3B representing orthorectified Surface Reflectance imagery. Eight separate regions, each consisting of one to four scenes were imaged on different dates from April 28 to May 8, 2019, with the majority of data acquired late April. One RapidEye scene acquired May 5, 2019 was also provided to fill small gaps in the Ottawa-Gatineau region where PlanetScope was cloudy, with 5 m multispectral data that included similar bandwidths as PlanetScope in addition to a red edge band located at 690–730 nm.

2.2. DEM

Canada’s new High-Resolution Digital Elevation Data Model (HRDEM) Lidar-derived elevation data were downloaded and mosaicked to cover the Montreal and Ottawa/Gatineau study areas [19]. The complete dataset includes elevation of the terrain surface, slope, aspect, and shaded relief, forming a 1 m spatial resolution digital terrain model in 10 km × 10 km tiles with floating point precision. Positional accuracy is stated as generally being better than 1 m while no assessment of vertical accuracy has been conducted for the elevation product to date. However, an error analysis of a 2 m Lidar DEM acquired by aircraft over a portion of South Carolina can serve as a reference, where a range of elevation RMSE between 0.17 m and 0.26 m was calculated [26]. Lidar elevations were resampled using bilinear interpolation to different spatial resolutions and extents depending on the case study.

2.3. Hydrometric Data

Environment Canada operates a network of approximately 2100 hydrometric stations through the Water Survey of Canada. Stations are mostly located in Southern Canada, transmitting data in real-time and making them publicly available online within hours. Available real-time 15-minute water level data for the current year [27] and archived daily historical data [28] were downloaded for six stations located east and south of the Island of Montreal on the Lake of Two Mountains, Lake St-Louis, and the St-Lawrence River for years 2000–2019, except for one station that began recording in 2009. Median and maximum water levels were calculated for the available period for each station to provide reference levels for spatial and temporal comparisons. Two stations located in the Lake of Two Mountains above a dam at Sainte-Anne-de-Bellevue showed water level changes consistent with one another, exhibiting peak above long-term median water levels of over 2.5 m on May 5, 2017 and April 29, 2019 for the two flood years. Below the dam, water levels at the remaining four stations behaved similarly, peaking around 1.2 m above long-term median levels between May 6 and May 18, 2017 and May 14 to May 28, 2019 for the two years and remained near peak levels for nearly the entire month of May (Figure 2). Extreme water level changes east and north of the Island of Montreal in the Lake of Two Mountains produced the most severe flooding in communities along its shoreline.
Figure 2. Hydrometric water levels above long-term medians for six stations located east and south of the Island of Montreal on the Lake of Two Mountains (02OA107 and 02OA013), Lake St-Louis (02OA016 and 02OA039) and the St-Lawrence River (02OA033 and 02MC005) for the spring of 2017 (top) and 2019 (bottom).

Data from three stations located on the Ottawa River were also downloaded to provide water level data for the region beginning in 2000, 2011, and 2018, and ending in year 2019. Peak water heights greater than 3 m above long-term median levels were reached at hydrometric stations near Gatineau around May 7, 2017 and April 30, 2019.

2.4. Citizen Geographic Information

A Citizen Geographic Information (CGI) mobile application for Android was developed and made available to trusted users prior to the 2017 flood season [29]. The application provides notification of an upcoming satellite overpass when the user is requested to take pictures of flooding and complete a short smart survey to describe its context. Information including the survey, picture, and photo azimuth is geotagged and automatically uploaded to a geodatabase. The application was
originally intended to help quickly quality-control flood maps prior to their release; however, it was also used during the 2017 flood season to map urban flooding in Gatineau and along Pierrefonds Boulevard on the Island of Montreal. Eighty observations were submitted in the severely impacted borough of Pointe-Gatineau on May 8, 2017, while an additional 58 observations along Pierrefonds Boulevard on Montreal’s West Island were received on May 9, 2017.

2.5. NASP

From May 7–16, 2017, Transport Canada’s National Aerial Surveillance Program (NASP) aircraft acquired oblique pictures of flooding along approximately 600 km of waterfront from Pembroke, Ontario eastward to Quebec City. Four separate flight zones were defined, with flights rotating through each flight zone over a 10-day period. Pictures captured every 5 s during flights totaled nearly 14,000 images taken during the 11-day period. These pictures were used to populate an interactive web map through ArcGIS Online for distribution to help quality-control flood maps as they were generated from satellite imagery.

The NASP was activated again in 2019, capturing approximately 3500 still frames on April 25 and 29, 2019 along the same corridors as 2017. In addition, simultaneous video was acquired during the April 29 flight generating approximately 50 minutes of video footage. Still frames were extracted from the video at 2-s intervals, producing nearly 1500 frames. Image metadata including date, time, aircraft, and target location were imbedded in each image frame, requiring automated Optical Character Recognition (OCR) [30] to extract and make use of in the online web map. After OCR was applied and quality control performed, approximately 300 frames that had all metadata extracted accurately were used to populate the database with additional observations.

3. Methods and Results

3.1. Flooding Algorithm

A simple 1-dimensional flood simulation algorithm was developed to map urban flooding that uses a DEM and one or more flood perimeter locations determined from a flood map, satellite image, or in-situ by camera or GPS. Points observed along the flood perimeter are overlain on the DEM first to determine floodwater height by sampling the DEM at the shoreline location. In the following case studies, flood perimeters were obtained using RS2 flood maps, CGI, by simulating point observations along roads in three boroughs as potentially captured by sensor networks including traffic cameras, and also by simulating observations in different locations around a flood perimeter. Once flood perimeter locations and corresponding water heights are determined, they serve as seeds for iterative flood-filling of adjacent elevations below the established water height. The process continues until no adjacent elevations are found below the water height or when a water body is encountered in the input flood map, at which point the entire basin is flooded.

3.2. Case Studies

3.2.1. PlanetScope 3 m

High-resolution optical imagery acquired during near peak-water levels was classified to map the maximum flood extent for 2019. Hydrometric data showed that water levels peaked around the end of April to early May in the Lake of Two Mountains, breaching the dike eastward in Sainte-Marthe-sur-le-Lac on April 27. Flood extents were mapped using PlanetScope’s NIR surface reflectance by applying a dark threshold value to mosaicked tiles representing eight separate regions. The threshold value was selected by inspecting reflectance values of dark water located in the middle of lakes while attempting to minimize commission error with other dark features such as urban shadow and wet fields. Commission error was further reduced by sieving small dark objects not representative of water bodies but more likely of shadow. Once sieved, only larger dark objects remained, representing seeds of water bodies that were subsequently region-grown into areas darker than a brighter multiple of the original threshold value. Individual parameters were modified slightly
between regions to obtain an optimal result based on visual inspection. NIR dark threshold values ranged between 800 and 1500 Digital Numbers (DN = surface reflectance x 1000) or 0.8 to 1.5% reflectance, sieve sizes varied from 300 to 500 pixels and region growing thresholds were between 1.6- and 1.9-times original threshold values (e.g., 1280 to 1520 DN for the 800 DN threshold). Some manual editing was performed to generate the final product (Figure 3), mainly by removing fields and other features mapped as water that may have been flooded but were not directly connected to the main channels of interest.

Figure 3. The 2019 maximum flood extent product generated from a combination of PlanetScope and RapidEye optical imagery acquired near peak-flood (main panel) with flood extents of the three study areas over Sainte-Marthe in 2019, and Gatineau and Pierrefonds in 2017 (right panels).

An assessment of the maximum flood extent map was conducted by visually interpreting NASP oblique images and still frames captured by video in the Pontiac region just east of Ottawa/Gatineau. Samples were selected in the flood zone and 150 m beyond according to the maximum flood extent product. The flood zone represented the area mapped as water in the flood product that was not permanent water according to Canada’s National Hydrometric Network base data (NHN) [31]. A total of 2808 points were established in the flood zone and on land in the adjacent 150 m buffer using a regular grid spacing. Of these points, 1191 were interpretable in the oblique images as either land or flood. An assessment conducted on the final maximum flood extent product against reference points interpreted from NASP images produced an overall accuracy of 95.6% and a kappa statistic of 91.1%, with well-balanced user and producer accuracies suggesting minimal bias in the classification towards either land or flood (Table 2). This product will serve as one of several ‘ground truth’ references in subsequent analyses.
Table 2. Classification accuracy of the maximum flood extent product mapped from Planet high-resolution optical imagery.

| Class          | Reference | Land | Flood | Column Total |
|----------------|-----------|------|-------|--------------|
|                | Land      | 479  | 27    | 506          |
| Flood          | 25        | 660  | 685   |
| Column Total   | 504       | 687  | 1191  |

Overall Accuracy = 95.6%

Producer’s Accuracy (omission error)  
Land = 95.0% (5.0%)  
Flood = 96.1% (3.9%)

User’s Accuracy (commission error)  
Land = 94.7% (5.3%)  
Flood = 96.4% (3.6%)

Kappa Statistic = 91.1%

3.2.2. RADARSAT-2

Urban flood maps were generated using the sixteen RS2 images from 2017 and 2019 over the Montreal region by combining satellite flood maps with DEM data. Because radar flood maps currently exclude flooding in urban areas, flood boundaries and associated water heights are not reliable along urban shorelines, and therefore, attempts were made to estimate water heights from adjacent, suburban, and rural flood perimeters. Only Horton’s orders 8 and 9 [32] representing main channels were used to map onshore urban areas between dams to the east and west to avoid large, manmade changes in water height. Local water heights were first established along flood boundaries by overlaying flood maps on Lidar DEM data. Urban shorelines were removed from the flood boundaries using the 2010 land cover of Canada [33] and tests were conducted using interpolation and smoothing to retrieve urban shoreline elevations from adjacent water heights. Interpolators including bilinear inverse distance weighting and smoothing using general additive models were tested using a range of input parameters specific to each method. Once local urban water heights were estimated in this manner, flood filling was performed into urban areas using the developed flood-filling algorithm and Lidar DEM data.

This approach is similar to methods developed in Mason et al. [34], who refine urban flood extents using water heights of nearby rural areas determined by intersecting flood boundaries with a Lidar DEM. Their approach is more sophisticated than ours since they first map urban water in unmasked regions of non-shadow or layover areas determined by a SAR simulator. An initial rural classification is used to determine backscatter and water height threshold inputs needed to classify adjacent urban areas. Dark pixels in unmasked urban regions assigned as water based on the previously determined backscatter threshold then serve as seeds for subsequent region growing into ‘unseen’ areas using a water height threshold and Lidar DEM. An important difference in our approach is that we rely entirely on Lidar elevation to map urban flooding from the shoreline, whereas Mason et al. [34] use a combination of backscatter and elevation. Their method requires additional processing to run a SAR simulator to identify shadow and layover, potentially increasing the latency between data reception and product dissemination.

We estimated water height errors for the 16 RS2 flood maps using hydrometric water heights from the six stations around Montreal as a reference. For each station and RS2 acquisition date, hydrometric water heights were compared to the nearest mapped shoreline elevation obtained from the methods described above. The Root Mean Square Error (RMSE) was calculated between shoreline elevations mapped in 16 RS2 scenes and nearest reference water heights at the six hydrometric stations on the RS2 acquisition dates. For a sample size of 96 RS2 – station pairs, a mean error of 0.35 m was obtained with an RMSE of 1.2 m. [35] generated flood masks from 12.5 m RADARSAT-1 imagery to estimate floodwater levels using a 1 m LiDAR DEM and concluded that RADARSAT-1 imagery is not appropriate for such detailed analysis. In the same study, more detailed 3 m TerraSAR-X imagery was tested using the same approach, producing an underestimation of 1.17 m compared to water gauge measurements.
After flood filling of adjacent urban areas from shoreline elevations derived from RS2 flood maps, a thorough examination was conducted against known flooded urban areas based on visual interpretation of NASP images and other reference data acquired on corresponding dates (Figure 4). Results showed that when combined, all classifications predicted urban flooding in areas that flooded at least once during the 2017 or 2019 event according to reference data, or are prone to flooding according to risk maps produced by the Province of Quebec [36]. However, there was poor correspondence overall between predicted and known flooding for a specific date and area. Attempts were made to generate consistent results by changing input water height smoothing and interpolation parameters, which improved flood predictions for specific areas and dates but worsened them in others. Thus overall, errors in mapped flood extents and DEM data, as well as errors caused by smoothing and interpolating urban shoreline water heights from adjacent areas using data and methods tested in this case study, currently appear to be too great to accurately predict urban flooding.

![Montreal 20170506](image)

**Figure 4.** RS2 flood map from May 6, 2017 used to approximate water levels along urban shorelines, with examples of adjacent flood-filled urban areas using Lidar DEM data. On individual dates, examples of known errors of commission, omission, as well as correctly mapped urban flooding according to independent National Aerial Surveillance Program (NASP) and Citizen Geographic Information (CGI) data are shown in boxes 1–3.

3.2.3. Sentinel-1 CCD

This case study aimed to loosely replicate the methodology developed by Chini et al. [18] by applying CCD to two flooded neighborhoods in Gatineau and Sainte-Marthe-sur-le-Lac, Quebec during the spring of 2019 (Figure 5).
A SAR resolution cell represents a mixture of many natural scatterers and the returned signal represents the coherent sum of those returns [37]. Spatial coherence is calculated as the magnitude of the complex correlation coefficient applied to a small moving window over an interferogram, which represents the phase difference between two complex SAR images [37,38]. It is normalized between zero and one, with zero indicating random phase noise and one indicating constant phase between the two images or the absence of phase noise. In an urban environment with limited vegetation, the return signal will ideally be a strong, consistent double-bounce from the radar interaction with stable building facades orthogonal to the SAR antenna [39]. Previous urban flood CCD methods estimated coherence ($\gamma$) from an interferogram formed between two SAR images acquired prior to the flood-event (pre-event coherence, $\gamma_{pre}$) and from an interferogram formed between a SAR image acquired before the flood-event, and another acquired during the flood-event (co-event coherence, $\gamma_{co}$) [18,39]. $\gamma_{pre}$ provides a baseline coherence image to map coherent areas representative of stable features (e.g., buildings, sparse vegetation) with coherence values close to one. The baseline coherence or $\gamma_{pre}$ is subsequently compared to $\gamma_{co}$. This event coherence image will still have values closer to one in baseline stable areas that have remained unchanged, while changes in the spatial distribution of scatterers within a resolution cell due to vegetation, snowmelt, and water level will result in lower coherence. Subtraction of the two coherence images produces small differences in areas that have remained unchanged between pre- and co-event pairs, while large coherence differences are representative of baseline stable areas that have undergone random phase changes due to the event.

For this study, the baseline interferogram was generated from SAR images acquired after the flood-event (post-event coherence, $\gamma_{post}$) due to a decision by S-1 mission management to switch polarization just prior to the 2019 floods in order to set up and calibrate ground transponders for the new RCM mission [40]. The integrity of the results should be maintained with the use of $\gamma_{post}$ since Chini et al. [18] reported a return to relatively high coherence values in post-event interferograms following Hurricane Harvey. To improve efficiency, rather than identify double-bounce features in the SAR imagery prior to the application of CCD as in Chini et al. [18], we rely instead on the 30 m Land Cover Classification product [33] to limit changes to urban areas that are assumed to have a high enough coherence to be sensitive to flooding. S-1 IW mode used in the current case study has relatively coarse spatial resolution compared to Strip Map tested by Chini et al. [18], which means there will be a larger assortment of natural scatters within each resolution cell. Still, the dominant scatterers (e.g., double-bounce returns from building façades, orthogonal to the sensor look direction)
and limited vegetation in urban areas should provide relatively consistent phase returns that result in high coherence values [39,41].

Several decorrelation factors affect InSAR coherence [37], including baseline, volumetric, and temporal decorrelation. Chini et al. [18] found the spatial baseline decorrelation to be negligible for S-1 interferometric pairs with perpendicular baselines under 90 meters. Volumetric decorrelation is the result of the microwave signal passing through a scattering medium such as a tree canopy, resulting in a loss of coherence due to changes in vegetation growth, vegetation orientation, and dielectric properties between interferometric pairs [37,39]. Temporal decorrelation can play a significant role in the coherence of a resolution cell since any surficial changes between SAR images will have an effect on the returned phase information. S-1 has 12-day repeat orbit over Gatineau and Sainte-Marthe-sur-le-Lac, which should help minimize temporal decorrelation due to factors other than floodwater. However, during springtime when flooding generally occurs in Canada, other factors such as snowmelt and vegetation green-up can contribute to temporal decorrelation.

In Sainte-Marthe-sur-le-Lac, the dike breach that occurred on April 27, 2019 was not repaired until May 5, 2019 [42] (Table 3). For this test location, \( \gamma_{oo} \) was generated using the May 2 and May 14, 2019 S-1 IW image acquisitions, while \( \gamma_{post} \) was generated using the May 26 and June 7, 2019 image pair (Tables 3 and 4). In Gatineau, water levels rose to critical levels in April 2019, causing the City of Ottawa to declare a 49-day state of emergency from April 25 to June 12, 2019 [43] (Table 4). Water levels did not recede in Gatineau until well into May 2019. Therefore, a longer 24-day interferometric pair between May 2 to May 26, 2019, was used to generate \( \gamma_{oo} \) for Gatineau and \( \gamma_{post} \) was generated using the June 7 and June 19, 2019 pair. For both test sites, a 12-day temporal gap representing consecutive repeat passes in the post-event pair was used to ensure that coherence was minimally affected by post-flood cleanup activities (Tables 3 and 4).

Table 3. S-1 image dates for urban flood mapping using Coherent Change Detection (CCD), with significant flood events in Gatineau and Sainte-Marthe-sur-le-Lac, QC.

| Date (2019) | Gatineau, QC | Sainte-Marthe-sur-le-Lac, QC |
|-------------|--------------|------------------------------|
| April 25    | State of emergency declared (Ottawa) | Dike breach |
| April 27    | NASP         | NASP |
| April 29    | S-1 event acquisition | S-1 event acquisition |
| May 2       | Peak water level | NASP |
| May 3       | NASP         | NASP |
| May 5       | Dike repaired | S-1 post-event acquisition |
| May 14      | S-1 post-event acquisition | S-1 post-event acquisition |
| May 26      | S-1 post-event acquisition | S-1 post-event acquisition |
| June 7      | State of Emergency lifted (Ottawa) | S-1 post-event acquisition |
| June 12     | S-1 post-event acquisition | |
| June 19     | S-1 post-event acquisition | |

Table 4. InSAR coherence data used to map urban flood in Gatineau and Sainte-Marthe-sur-le-Lac, Quebec.

| InSAR Coherence | Interferometric Pair | Area (QC.) | Pixel Spacing (m) (gr. rg. x az.) | Temporal Baseline (days) | Perpendicular Baseline (m) | Window Size (pixels) |
|-----------------|----------------------|------------|----------------------------------|--------------------------|---------------------------|-----------------------|
| \( \gamma_{oo} \) | 2019-05-02 & 2019-05-26 | Gatineau | 25.2 x 27.9 | 24 | 2.3 | 5 x 5 |
| \( \gamma_{post} \) | 2019-06-07 & 2019-06-19 | Gatineau | 25.2 x 27.9 | 12 | 43.6 | 5 x 5 |
| \( \gamma_{oo} \) | 2019-05-02 & 2019-05-14 | Saint-Marthe- | 27.0 x 27.8 | 12 | 6.4 | 5 x 5 |
Both areas were multi-looked to create square pixels of approximately 28 m in size. Interferograms were filtered using the Goldstein-Werner adaptive filter [44], which does a good job of contrasting areas of high and low coherence. The coherence for each interferometric pair was generated using a 5 × 5 pixel window to maintain a high level of detail. The resultant $\gamma_{\text{co}}$ and $\gamma_{\text{post}}$ were then geocoded, differenced, masked using the urban land cover class, and thresholded to produce urban flood extents.

An accuracy assessment of the CCD product over Sainte-Marthe-sur-le-Lac, was conducted against reference points labelled using the maximum flood extent product generated from high-resolution optical imagery and confirmed by NASP (Figure 3). The Sainte-Marthe-sur-le-Lac urban flood product was combined with open water and vegetation flooding mapped from RS2 on May 3, 2019. After clipping the maximum flood extent to the borough, a 150 m buffer was created around the CCD flood perimeter and a 500-point random sample was generated inside the buffer (Figure 6). Points were labelled by intersecting flood extents generated from PlanetScope imagery acquired on April 29, 2019 and WV-3 imagery acquired May 5, 2019 and assigned as either flooded or non-flooded where both sources of high-resolution imagery agreed (Figure 7). An overall accuracy of 79.0% was achieved with low producer's accuracy for the flood class (Table 5), suggesting an under-prediction of the true amount of floodwater by CCD. A Kappa statistic of 57.5% suggests moderate agreement between reference and classification points. While the overall extent is well captured by CCD in Gatineau (Figure 8) and in Sainte-Marthe-sur-le-Lac (Figure 7), of the 500 random sample points within the flood buffer around Sainte-Marthe-sur-le-Lac, 123 were omitted since they did not depict the same class in both high-resolution image dates and most of these were located close to the flood margin where errors are generally highest. Despite omitting these points, agreement was only deemed marginal while the resolution of the source S-1 data lacks street-level flooding detail, limiting its usefulness for disaster response compared to the ~3 m resolution of the optical imagery used to map the maximum flood extent.

![Figure 6. CCD urban flood extents of Sainte-Marthe-sur-le-Lac with the maximum flood extents from high-resolution optical imagery and validation points interpreted as either flood (blue) or land (green) from NASP imagery acquired on April 29, 2019.](image-url)
Figure 7. Sainte-Marthe-sur-le-Lac: (a) High-resolution natural colour image from GoogleEarth™; (b) urban flood extents derived from a PlanetScope NIR image acquired on April 29, 2019; (c) urban flood extents derived from a WorldView-3 image acquired on May 5, 2019; (d) urban flood extent derived from thresholding a CCD image between $\gamma_{post}$ and $\gamma_{co}$. Background classification for panels b-d is an EGS RS2 flood map from May 3, 2019.

Figure 8. Gatineau: (a) High-resolution natural colour image from GoogleEarth™; (b) urban flood extents derived from a Pleiades-1B NIR image acquired on April 28, 2019; (c) urban flood extents
derived from a RapidEye-5 image acquired on May 5, 2019; (d) CCD urban flood extent derived from γpost and γco. The background classification for panels b-d is an EGS RS2 flood map from April 30, 2019. Note that urban flooding refers to floodwaters detected in high-resolution optical imagery or CCD and not in RS2.

Table 5. Classification accuracy of the CCD flood extent product over Sainte-Marthe-sur-le-Lac mapped from Sentinel-1 imagery.

| Class       | Reference | Land  | Flood | Row Total |
|-------------|-----------|-------|-------|-----------|
| Land        |           | 174   | 59    | 233       |
| Flood       |           | 18    | 116   | 134       |
| Column Total|           | 192   | 175   | 367       |
| Overall Accuracy |       | 79.0% |       |           |
| Producer’s Accuracy | | 90.6% (9.4%) |       |           |
| User’s Accuracy |       | 74.7% (25.3%) |       |           |
| Kappa Statistic |     | 57.5% |       |           |

3.2.4. CGI

Point flood perimeter locations were determined from CGI pictures taken on May 8 and 9, 2017 in Gatineau and Pierrefonds, respectively. For efficiency sake, flood perimeters were assumed to occur sufficiently close to where CGI pictures were taken to use their locations directly rather than trying to interpret flood boundary locations in all 138 pictures. Once flood perimeter and water levels were established using CGI picture locations, the full flood extents were mapped in each borough using the flood-filling algorithm and DEMs (Figure 9). In Gatineau, NASP photos acquired in both 2017 and 2019 and a 2017 maximum flood extent product generated by combining multiple EGS flood products from the 2017 event from both optical and radar [45] were used to confirm modeled extents. These independent sources of validation data showed similar flooded area for the Gatineau region in 2017 and 2019, since many of the same roads were flooded both years. In Pierrefonds, flooding was much less severe in 2019 compared to 2017 according to NASP and PlanetScope imagery due to underground infrastructure renovations performed since 2017 to reduce flooding [46].

Figure 9. Urban flood extents generated using LidarDEM and CGI data collected May 9, 2017 in Pierrefonds on an EGS RS2 flood map from May 6, 2017 (left), and May 8, 2017 in Gatineau on an EGS RS2 flood map from May 7, 2017 (right).

Flood simulations using CGI in Gatineau were good overall, agreeing well with both NASP and 2019 PlanetScope satellite imagery. Some commission error existed to the north and west of the true
flood area where many CGI observations were acquired. This was likely due to the fact that instructions provided to CGI volunteers did not request observations at the flood perimeter and no attempt was made to precisely locate the flood perimeter in CGI images. Rather, it was somewhat falsely assumed that CGI locations would be sufficiently close to the flood margin to use them as perimeter locations. In most cases, this assumption must have been correct; however, in the area where commission error was noted, this was likely not the case.

There was a similar outcome in Pierrefonds, where the length of flooding along Pierrefonds Boulevard was modeled correctly using CGI, but the perpendicular flood extent was overestimated. This overestimation was determined using an additional source of high water mark information from photos taken during the 2017 event that were exceeded by the predicted flood extent. While not verified by careful examination of all CGI images, the cause of this overestimation is likely the same as in Gatineau.

3.2.5. Simulation Based on Single In-Situ Flood Extent Observation

Use of CGI, traffic cameras, web cameras, or other sensor networks can provide in-situ flood perimeter observations. The feasibility of using existing sensors, or establishing the location of new sensors that will enable mapping of the full range of flood extents, can be determined through simulation. Existing traffic cameras generally point in the direction of a road and therefore, traffic camera images may be used to observe point-based flood perimeter locations along the road. When establishing new sensors in areas not imaged by traffic cameras, the location and direction of the sensor along a road should be considered in order to maximize the amount of potential information that can be obtained with the smallest number of sensors.

Three neighborhoods where flooding occurred in 2017 or 2019 were considered for simulation, including Pointe-Gatineau that flooded both years, Pierrefonds that experienced significant flooding in 2017, and Sainte-Marthe-sur-le-Lac that flooded in 2019 after the dike breached. A range of possible point observations of the flood perimeter along roads that flooded during these events was used to simulate full flood extents in these neighborhoods. Road sections along 22nd Avenue in Sainte-Marthe-sur-le-Lac, Pierrefonds Boulevard in Pierrefonds, and Rue Saint Louis in Gatineau were considered in each of the three boroughs. Along each road section, one hundred evenly spaced point observations served as seeds for flooding. For each flood perimeter seed point location, the flood-filling algorithm was applied with Lidar DEM data (Figure 10).

![Figure 10](image.png) A range of simulated urban flood extents represented by different shades of pink, flood-filled using a Lidar DEM seeded from single flood perimeter observations represented by black dots along Pierrefonds Boulevard.
To validate the output, 2017 NASP photos of Gatineau taken on May 8, and of Pierrefonds on May 7 were used to identify flooded intersections, parking lots, fields, and other flooded features in each borough. Both dates correspond to maximum water levels according to hydrometric data recorded at a minimum of one co-located station, and should therefore represent near-maximum flood extents in both locations. NASP photos were interpreted visually and flooded locations were placed on high-resolution imagery in Google Earth, with attempts made to capture flooded features located close to the perimeter to approximate full extents. PlanetLab imagery and derived maximum flood extents were used to verify simulated flood extents in Sainte-Marthe (Figure 11).

Figure 11. Validation of simulated flood extents from single flood perimeter observations combined with Lidar DEM data along roads in each of the three boroughs, using visual interpretation of NASP, corresponding high-resolution optical imagery (to the right of each simulation), and the 2019 maximum flood extent product outlined in light blue on maps and in red on images.
In all three locations, simulated flood extents derived from point observations of the flood perimeter agreed well with reference data. In Pierrefonds, all but two of 28 points interpreted as flooded in NASP were included in the simulated flood extent. These points were disconnected from the main flood area by a slight elevation gain, effectively stopping the flooding algorithm from infilling. A similar result can be seen in Sainte-Marthe, where two distinct neighborhoods were flooded, separated by slightly higher elevations that prevented water from flowing between the two. In the case of Gatineau, all 31 points interpreted as flooded according to NASP were within the simulated flood extents. However, a highway intersection and overpass that disconnected the eastern and western flooded areas required two separate observations to capture the entire flood that extended beneath the overpass. Since the elevations at both observation points were within less than 10 cm, it should be possible to locate a point on the road on the opposite side of the overpass at the same elevation and propagate the flood extent separately from there. Similarly, in the case of Sainte-Marthe, flooding in the second neighborhood can be simulated using a separate observed flood perimeter point location, or a water height measurement may be extended from one neighborhood into the adjacent neighborhood to simulate its flooding (Figure 11).

Based on the full set of simulations in each borough, it was determined that only a section along each road needs to be monitored to capture the full range of flood extents from initial flooding to extents greater than those observed in 2017 and 2019. It was estimated that a 766 m long section of 22nd Avenue in Sainte-Marthe, a 1652 m section of Pierrefonds Boulevard, and 555 m and 366 m sections to the east and west of the highway need to be monitored to simulate the range of historical flooding observed in each borough. All of these sections of road are relatively straight; therefore, their full lengths may be visible from a single camera vantage point, although this needs to be verified. The most effective way to monitor, whether by existing traffic cameras, installation of new web cameras, or by CGI, still needs to be determined.

3.2.6. Simulation Based on Point-Based High-Resolution Optical Satellite Flood Extent Observation

High-resolution optical data has been shown to produce reliable flood extents; however, clear-sky coverage of an entire flooded borough may not be available during the event. Similar to the approach of using in-situ point observations of flood extents, available optical remote-sensing imagery may be clear enough to observe some of the flood perimeter through holes in cloud cover. An experiment was designed to test this approach using the maximum flood extent product generated from optical data described earlier in conjunction with DEM data.

The portion of the Pointe-Gatineau study area east of the highway was chosen for this analysis since it includes diverse land cover including vegetation. The maximum flood extent was generated from 5 m RapidEye over this borough, and therefore, the native 1 m resolution Lidar DEM was resampled to 5 m to match using bilinear interpolation. A vector of the maximum flood extent was clipped to the area and a series of 70 sample points was generated at equal spacing along the perimeter (Figure 12). Imagining the flood perimeter was observable through the clouds at each of these point locations, and 70 full flood extents were simulated using each point as a seed in the flooding algorithm. These simulated extents were then validated individually against the full flood extents from the maximum flood extent product. The kappa statistic was used to measure the accuracy of each simulated product against the maximum flood extent to remove the effect of random agreement. Accuracy was examined in relation to the topographic variability of each seed point location, measured as the elevation standard deviation in a 3 × 3 pixel surrounding window. In addition, the cover type beneath each seed pixel was visually interpreted in Google Earth to determine its effect on simulated flood extent accuracy.
Figure 12. Location of imaginary flood perimeter observations used to flood-fill the borough of Pointe-Gatineau using the Lidar DEM.

According to the 5 m DEM, water height sampled at 70 points along the flood perimeter to the east of the highway was 44.87 m asl, with a standard deviation of 0.52 m and a range from 42.70 m to 44.87 m, or just over 2 m. Kappa values of simulated flood extents compared to maximum flood extents from each of these 70 seed locations ranged from 0 to 0.746, and were found to be significantly inversely related to seed location surface roughness \( (r = -0.49, p < 0.05) \) (Figure 13). In other words, seed locations with higher local topographic variation generated poorer flood simulations than those that were flatter in their immediate vicinity. Most of those locally flatter seed locations that produced better simulations represented manmade features such as roads, sidewalks and grass, while those that produced poorer simulations represented taller vegetation located on the riverbank, in gullies and ditches, or adjacent to creeks. Overall, it appears that taller vegetation is more often located in natural, topographically complex areas, while manmade features tend to be flatter.

Figure 13. The relationship between the surface roughness surrounding single point-based flood perimeter observations and accuracy of flood extents derived from flood-filling the Lidar DEM.

The above suggests that errors in the flood perimeter seed location and local topographic variation relate to the quality of output simulated flood extents. Even at the 5 m spatial resolution of
RapidEye, there is ambiguity in the precise location of the flood boundary due to the sensor’s point spread function and subpixel mixing. Within $3 \times 3$ windows surrounding seed pixels, the standard deviation in elevation can be as high as 1 m or more. Thus, an error of one pixel, or 5 m in the interpreted location of a flood perimeter from optical imagery can lead to an error of 1 m or more in its height estimation. This error in floodwater height will cause a significant overestimation, or underestimation of simulated flood extent using the flooding algorithm and Lidar DEM. However, if observed flood perimeter locations through holes in clouds represent manmade features that are relatively flat, then the exact flood perimeter location to within a pixel becomes less important. This result corroborates good simulation results achieved by simulating CGI or sensor network flood perimeter locations along roads that are relatively flat or progressively sloped. Fortunately, urban areas have many manmade, flat features that can serve as seed locations for flood simulation, and therefore, cloudy optical data may be of use to predict accurate urban flood extents if flood perimeters on such features are observable through holes in cloud cover.

4. Discussion

These case studies were conducted to evaluate approaches to develop a reliable, operational urban flood mapping tool using readily available data. EGS operational requirements dictate that flood maps are to be made available within four hours of data reception. In this case, less reliance on external data providers to feed operational mapping is preferred in order to ensure reliable delivery within the allotted timeframe. When used in conjunction with a high-resolution DEM, CGI data can produce excellent urban flood mapping results as long as they are acquired according to specification, which requires observations along the flood perimeter on relatively flat, preferably manmade terrain, or in a best-case, along a specified road segment. However, unless these observations are acquired systematically, their availability on an opportunistic and best effort basis may not be reliable enough for repeatable, frequent flood mapping. If users can be established in different municipalities prone to flooding, preferably from the municipal government or emergency management, then either they can generate maps themselves or provide data to EGS to do so on their behalf.

Sensor networks may be preferable to provide the same point-based observations of flood perimeters along important road segments. The use of such observations along predefined road segments provides the advantage of being able to simulate flood extents before a flood, making this approach faster and more reliable than generating extents on the fly. A database of point-based flood perimeter observations along roads and corresponding flood extents can be used to quickly access flood area information during an urban flood event.

Table 6. Summary of methods and results from presented case studies.

| Mapped Using Remote Sensing Data Only |
|---------------------------------------|
| Data | Method | Accuracy | Validation |
|------|--------|----------|------------|
| High-resolution optical | Dark-object thresholding and region growing | 91.1% kappa | NASP |
| Sentinel-1 | Coherence Change Detection (CCD) | 57.5% kappa | High-resolution optical |

| Flood-filling algorithm using Lidar DEMs and flood perimeters |
|---------------------------------------------------------------|
| Data | Method | Accuracy | Validation |
|------|--------|----------|------------|
| RADARSAT-2 Citizen Geographic Information (CGI) | Mapped flood perimeters | Variable between boroughs and dates | NASP, CGI, flood risk maps |
| Simulation | Observed in-situ | Slight overestimation due to lack of CGI screening and pre-processing | NASP, high-resolution optical, independent observations |
| Simulation | Observed in-situ along roads or by traffic camera | 92.8% overall accuracy or greater | NASP |
### Table: Observed in-situ or through cloud in high-resolution optical imagery

| Simulation | Observed in-situ or through cloud in high-resolution optical imagery | 0 - 74.6% kappa depending on local flood perimeter topographic variation | High-resolution optical

Previously, high-resolution optical satellite data were seldom used for urban flood mapping due to fundamental limitations including long revisit times as well as price [16]. High-resolution 0.2 m natural color (RGB) optical imagery from an Unmanned Aerial Vehicle was tested in Shen et al. [16], achieving a kappa of 74.6% against visually interpreted validation samples. In a comparison of different optical data for waterbody extraction in a rural setting, Jakovljević et al. [47] obtained a kappa of 79% using RapidEye. Both studies achieved a lower kappa than what was obtained in the current study despite applying more sophisticated machine learning as opposed to dark-object thresholding. In Shen et al. [16], a poorer result is most likely due to a lack of NIR and confusion between soil, vegetation, and turbid water in visible bands. In addition, both studies applied only per-pixel classification and no post-processing, whereas in the current study, sieving of smaller dark objects and region growing after initial thresholding was used.

When available, clear-sky optical remote sensing data can be used to accurately map flood extents using simple thresholding of a long wavelength channel such as NIR followed by region-growing (Table 6). However, when overlaid on the DEM, the derived 5 m resolution maximum flood extent perimeter in Pointe Gatineau exhibited considerable height variation, suggesting that there is likely some error in the mapped flood boundary. Subpixel mixing and the sensor’s point spread function causes blurring of the flood perimeter, making it difficult to detect accurately to within a pixel. Simulation showed seed pixels along the flood perimeter analogous to in-situ point observations used to predict flooding with the DEM can be generated from high-resolution optical remote-sensing provided they are located on flat, preferably manmade features. The effect of flood boundary errors causing errors in water height is exacerbated in areas with high topographic variation and also in maps generated from coarser resolution EO data. Tasking of Planet’s SkySat imagery can provide sub-metre resolution data up to twice daily for any location on Earth, enabling high-repeat revisit that increases the chance of obtaining clear-sky observations, or provides more frequent flood progression monitoring. Furthermore, simulation showed that the entire flood extent does not need to be observed to use of high-resolution optical data. Combining partial flood perimeters observed through cloud with Lidar DEM data should significantly enhance the use of high-resolution optical imagery for flood mapping.

Flood boundary locations from RS2 data adjacent to urban areas were used to interpolate flood height along urban shorelines for subsequent flood filling using the algorithm and Lidar DEM data. In addition to uncertainties in the mapped flood perimeter that are greater in RS2 than in RapidEye simply due to differences in spatial resolution, urban water height interpolation and smoothing errors were also introduced in this approach. When combined across all 19 R2 scenes tested over the three study areas, maps predicted areas that flooded at least once during the 2017 or 2019 flood events. However, predicted urban flooding in individual boroughs for single scenes seldom showed correspondence between the scene’s acquisition date and flood event date. Therefore, while this approach did not prove useful to predict individual flood events, combined maps were able to predict boroughs vulnerable to flooding. This may not be the most efficient way to flag these areas; however, prior knowledge of flood-prone areas from these analyses corroborates flood hazard maps that are useful and necessary to limit urban flood mapping efforts to vulnerable boroughs.

CCD has shown promise for urban flood mapping in other studies, and this promise is confirmed here. Previous studies report good agreement between CCD flood extents and near coincident high-resolution optical images, crowdsourced reference points and inundation models [18]. Combined coherence and intensity achieved between 0.68 and 0.72 kappa in Li et al. [48], which is greater than the kappa of 0.58 we achieved using coherence only (Table 5). A second study using coherence and intensity achieved overall accuracies of 70% against hydraulic model simulations using intensity only, increasing to 79% when incorporating coherence [49]. This result aligns well
with ours, wherein we achieved 79% overall accuracy over Sainte-Marthe using only coherence (Table 6).

While our achieved accuracies were not high enough to map flooding on a street basis, there were limitations related to data used in this study that may be overcome to some extent if better data were available. The 20 m resolution of available S-1 data used in this study severely limited the accuracy of the mapped flood perimeter due to the influence of non-persistent scatterers such as vegetation. Additionally, decorrelation factors including temporal decorrelation due to springtime snowmelt and vegetation growth, as well as anthropogenic influences such as cleanup after the flood, likely contributed to changes in coherence as well. A 24-day co-event S-1 image pair used to capture the maximum flood extent in Gatineau may have exhibited greater decorrelation due to a higher temporal baseline than the 12-day pair in Sainte-Mathe-sur-le-Lac. Strip-Map S-1 data used in Chini et al. [18] with its higher spatial resolution than the Interferometric Wide data employed here could have produced better results due to greater detail and fewer subpixel scatterers. RCM, with its higher spatial resolution and potential for more frequent repeat passes, may offer a greater ability to map urban flood progression with sufficient detail to detect street-level flooding. However, limitations persist with current missions. Standard repeat high-resolution acquisitions with sufficient coverage to map several affected boroughs in an area the size of the 2017 or 2019 flood-affected areas currently do not exist. Additionally, the four to 6-day exact repeat cycle of RCM and S-1, respectively, may not provide sufficient frequency to provide useful near-real time flood products in an operational setting.

Future work will explore the potential of combining hydrometric data with lidar DEMs to predict urban flood extents by testing approaches and outputs against numerous data sources used in this paper. For urban CCD, as RCM data become more readily available, higher spatial and temporal resolutions will be evaluated over urban flood events. Promising results have been achieved integrating coherence and intensity data together [48,49]. We believe that a synergistic relationship between intensity and coherence could also be exploited with the aforementioned benefits associated with RCM data.

5. Conclusions

While significant progress has been made on automated open water and vegetated area flood mapping in rural to suburban areas, near-real-time operational flood mapping in dense urban settings remains a challenge. The goal of this research was to develop accurate, simple urban flood mapping approaches to guide near real-time response efforts. Case studies using remote sensing imagery on its own showed that high-resolution optical data, when available through cloud cover that often persists during flooding, can be used to generate accurate flood extents using simple dark object thresholding and region growing. A multi-temporal radar that can penetrate cloud cover showed promise using Coherent Change Detection; however, resolution, coverage and revisit frequency of current missions do not allow product generation within the four-hour EGS map dissemination window with sufficient detail to guide emergency response efforts. Despite this, the feasibility of this approach demonstrated in previous studies is confirmed here, requiring only better data that should become available from future missions. Use of lidar DEMs and flood perimeter observations from remote sensing or in-situ showed promise in certain cases. Flood perimeter estimation from 8 m–12.5 m resolution RS2 flood maps was too coarse and therefore inaccurate to be used to reliably fill full urban flood extents. The potential of traffic camera imagery or other in-situ flood perimeter observations was demonstrated through simulation of point-based flood perimeter observations along roads that served as seeds to infill full flood extents. Generated urban flood areas showed high agreement with independent sources of flood extent information using this approach. The reason for such high agreement was determined by simulating multiple point observations around the flood perimeter, as potentially observed from high-resolution satellite imagery, CGI, or other sensors. These simulations showed that observed flood perimeter locations may be reliably used to flood fill urban areas if they occur on relatively flat, preferably manmade features such as roads to minimize errors in water height estimated from the DEM.
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