Urban flood mapping using Sentinel-1 and RADARSAT Constellation Mission image and Convolutional Siamese Network

Nafiseh Ghasemian Sorboni
nghasem2@uwo.ca

University of Western Ontario Faculty of Social Science: Western University Faculty of Social Science
https://orcid.org/0000-0002-8907-9784

Jinfei Wang
University of Western Ontario Faculty of Social Science: Western University Faculty of Social Science

Mohammad Reza Najafi
University of Western Ontario Faculty of Engineering: Western University Faculty of Engineering

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Abstract

Urban floods can affect people’s lives and properties, therefore, urban flood mapping is crucial for reliable risk assessment and the development of effective mitigation strategies. With the advent of high spatial and temporal resolution satellite images, remote sensing has become popular for urban flood mapping. Synthetic Aperture RADAR (SAR) sensors can capture image data during a flood event because their emitted signal can penetrate through the clouds. However, they have some limitations, such as layover, shadowing, and speckle noise, that might challenge their usage, especially for urban flood mapping. Deep Learning (DL) algorithms have been widely used for automatic urban flood mapping using remote sensing data, but the flood mapping accuracy achieved using SAR and DL algorithms is still uncertain. This paper proposes a DL-based change detection framework, Convolutional Siamese Network (CSN), for flood mapping in three urban areas: parts of Ottawa, ON and Gatineau, QC, Abbotsford, BC, and Leverkusen, Germany. The dataset applied were Sentinel-1 and dual-polarized RADARSAT Constellation Mission (RCM) data. The applied data were captured in C-band, and their resolutions were 10m and 5m for Sentinel-1 and RCM, respectively. Comparison with other DL-based segmentation algorithms, including Unet, Unet++, DeepLabV3+, and Siamese-Unet, confirmed the reliability of the proposed CSN. It was inferred from the flood class accuracies that Sentinel-1 data medium resolution might hinder its application for urban flood mapping. Further, RCM data was also tested in both urban and non urban areas, and a precision of 0.79 was achieved for the non urban case.

1. Introduction

Urban flood mapping is challenging due to the complicated structures in cities, such as buildings, sidewalks, road culverts, and utility holes. Two types of satellite products are available for producing flood maps using remote sensing data, including optical and SAR images. Optical images are not always available during a flood event because they are affected by dense cloud cover. SAR sensors, however, can capture images from the flood-affected areas at longer electromagnetic wavelengths making it possible for the SAR signal to penetrate within the cloud cover. Besides, since the SAR sensor is active, it is not dependent on the sunlight. So, SAR images are available in all weather conditions and during day and night. This characteristic makes SAR data suitable for flood mapping.

Generally, three specific features can be extracted from a SAR image, intensity, polarimetry decompositions, and InSAR coherence. Intensity is a measure of the reflective strength of an object, polarimetry decomposition gives the polarimetric discriminators that can be used for classification and image interpretation, and interferometric coherence (correlation) is a measure for the accuracy of the determined radar signal, and its value decreases by temporal changes. While intensity reflects the electromagnetic characteristics of the radar backscattering, it is affected by the speckle noise. Besides, flood mapping based solely on intensity data might result in erroneous flood maps because of the complex structures in urban areas. Vertical structures, like buildings, can enhance the double bounce scattering effect, which can be further intensified when the floodwater covers the bottom of the tree. Coherence data are complementary in flood mapping studies using the SAR dataset (Pulvirenti et al., 2021; Olthof and Svacina, 2020), and the coherency maps show high values in urban areas because of the stability of urban structures during short time intervals. When producing a flood map, a coherency map can complement the intensity data and improve flood mapping accuracy (Zhang et al., 2021). Besides, steady targets such as buildings make InSAR coherence data useful for urban areas with limited vegetated regions. When vegetation cover is limited, any decrease in coherence values in an InSAR time series can be translated into a flood event. Also, speckle noise is reduced when producing coherency images because the noise is averaged when integrating the two SAR images. As mentioned before, because of the dynamic behaviour of the vegetated areas (due to growth), it is not evident that the coherence change is related to the vegetated areas or flood. Sometimes this problem is addressed using SAR images with a short revisit time, less than five days, like COSMO-SkyMed, but such datasets are not accessible quickly, especially for flood hazard management studies in which time plays a vital role (Pierdicca et al. 2018). Another limitation when using SAR data for flood extent mapping in urban areas is the shadowing effect. The shadowing effect in
a SAR image happens when the SAR signal does not reach some regions because higher objects create an obstacle between the SAR antenna and the area (Bouvet et al. 2018). The shadowed areas on the image are overlooked when performing flood extent mapping using SAR data.

Flood extent mapping techniques can be categorized into four groups based on the theories applied; 1- Hydrologic/Hydraulic modelling 2- Multi-Criteria Decision Analysis (MCDA) 3- Machine Learning 4- Hybrid methods. Hydrologic models can simulate runoff values during a flood event, and Hydraulic models provide information on flow movement and inundation depth in areas near a river network. Multi-criteria techniques assign a weight to each flood indicator, such as topographic, hydrologic, climatic, and anthropogenic parameters, to produce a final flood risk map. Machine learning approaches, aka Artificial Intelligence techniques, use training data to discriminate between flooded and dry areas based on geospatial input features. Hybrid techniques use a combination of previously mentioned methods to model flood events, such as integrating hydraulic modelling and the Analytical Hierarchical Process (AHP) technique to produce a flood risk map (Nguyen et al. 2021).

Deep Learning, aka deep structured learning, is a machine learning technique based on artificial neural networks with representation learning. Although ML algorithms such as neural networks, random forest, and support vector machines have proven promising methods for flood mapping, DL methods, especially CNNs, have shown higher capability than the previous ML methods to extract features at different scales such as edges and objects (Muñoz et al., 2021). Li et al. (2019a) introduced a CNN to produce a flood map in Houston, USA, during Hurricane Harvey in August 2017 based on TerraSAR-X intensity and coherence data. This study focused on fluvial flooding, and its efficiency for coastal or pluvial flooding was not examined. Some DL-based segmentation models such as Unet, Unet++, and DeepLabV3 have been proposed in the literature for flood mapping, and they have achieved promising results on both optic and SAR images. Wang et al. 2021, proposed a DL model based on Unet for flood water extraction in Poyang Lake in China using Sentinel-1 SAR images. Jaisakthi et al. 2021, proposed a modified Unet algorithm for flood detection using Planet Scope images and reported an overall accuracy of about 70% on validation data. The flood masks in this work were not compared with any ground truth dataset. Konapala et al. 2021, used Unet for flood inundation mapping using Sen1Floods11 data, including Sentinel-1 and Sentinel-2 images from 11 flood events around the globe. After adding elevation data to the input, the flood median F1 score improved from 0.62 to 0.73 compared with using only Sentinel-1 bands. Chen et al. 2022 proposed a Siamese Network based on Unet for building change detection in very high-resolution remote sensing images and reported promising accuracies after comparison with ground truth data. Their method was not tested for flood-induced changes in satellite images.

Convolution Siamese Network (CSN) is one type of DL algorithm that has been applied for change detection (Yang et al. 2021; Wang et al. 2020; Chen et al. 2020). This method highlights changed areas using a bi-temporal remote sensing dataset. CSNs use two parallel CNN in their internal architecture and are used in change detection problems. In CSN, one CNN focuses on the pre-event image and the other works on the co-event image. In this way, CSN is more applicable for change detection problems (here flood mapping) than the usual CNN network. Some recent studies have used Siamese Networks for remote sensing change detection applications. For example, Jian and Li (2021) applied a Siamese Network called S3N. This network used Visual Geometry Group (VGG) as subnetworks and was applied to detect changes in various types of remote sensing data, including panchromatic, MS, SAR, PolSAR and NDVI images. The problem of high computational cost and lack of training data was addressed by applying the transfer learning strategy. They concluded that their proposed architecture is more computationally efficient than state-of-the-art techniques while giving comparable results to the existing methods. Wang et al. (2021) presented a fully CSN trained on Focal Contrastive Loss (FCL) to address the imbalanced data problem by focusing on the samples with fewer train data. Zhang et al. (2022) proposed a Siamese Residual Multi-kernel Pooling module (SRMP) to improve the high-level change information extraction from optical images. A feature difference module was also proposed to extract low-level features and help the model generate more accurate details. In another work, a Siamese Segmentation Network, SiHDNet, was proposed for...
building change detection. The proposed method was based on deep, high-resolution differential feature interaction. The difference map was created through a special fusion module to obtain sufficient and effective change information. The final binary change map was acquired through the improved spatial pyramid pooling module (Liang et al. 2022). Yang et al. (2021) proposed a new change detection algorithm based on the Siamese Network, MRA-SNet, for building, road, and land cover change detection in optical remote sensing images. The UNet network was used as the backbone architecture, and the bitemporal images were imported separately to the encoder. The ordinary convolution blocks were replaced with Multi-Res blocks to extract spatial and spectral features of different scales in remote sensing images. These studies however were all based on optical image data for change detection, and they did not address the challenges associated with the SAR change detection problem. Recently, Siamese Networks have been used for flood mapping studies. Zhang et al. (2022) proposed a domain adaptation-based multi-source change detection method for heterogeneous remote sensing images. The Landsat-8 image was used as a pre-event, and the Sentinel-1A image was used as the co-event for flood mapping of the 2017 California event. The area studied for flood mapping in this work covered agricultural lands, not dense urban areas.

In this study, flood extent mapping is considered a change detection problem, thus CSN is applied to discern between flooded areas and non-flood regions. The contribution of this research is the use of the SAR data and a deep learning-based change detection algorithm, Convolutional Siamese Network (CSN), for urban flood mapping. Because of the SAR limitations, including geometric distortions such as layover, shadowing effects, and speckle noise, the use of SAR data for flood mapping is already a challenging task. In addition, deep learning for flood mapping can be a challenge because of the high computational burden that these algorithms add to the process. Hence, the use of SAR and deep learning algorithm for flood mapping is examined in this study. Producing flood maps in urban areas is more challenging than in rural or open areas because of the complex structures in the cities. To the best of our knowledge, this is the first study using SAR data and CSN for urban flood mapping.

The structure of this paper is as follows, Section 2 presents the study area and dataset applied. Section 3 describes the methodology and Section 4 discusses the results. Section 5 presents a discussion of the obtained results, followed by the conclusion in Section 6.

2. Study Area And Dataset

More extreme flood events have been happening in Canada in recent years, such as the 2019 Ontario-Quebec and 2021 B.C flood events. The current floods are also more straightforward to study after the launch of the Sentinel-1 satellite in 2014. Other flood events were the July 2021 European flood events, such as the flood event in Germany. The flood mapping for Leverkusen city in Germany was also investigated to show the generalization of the proposed CSN to other areas and because of the availability of the ground truth data. Figure 1 shows the location of these case studies on the map.

2.1. 2019 Ontario and Quebec flood event

Heavy rainfall from mid-April until mid-May and snowfall accumulation 50% greater than expected caused flooding in eastern Ontario and southern Quebec. This event was among the top ten natural disasters of the year and was even more severe than the flood event in 2017. The Ottawa River peak height went beyond the values recorded in 2017, about 30 cm. Ottawa and Gatineau were among the affected municipalities. These cities and nearby regions experienced a severe flood causing 111 homes to evacuate, 923 people injured, and insured losses from this event cost about $201 million across Ontario and Quebec (Olthof, I. and Svacinia, N., 2020).

Figure 2 shows the extent of the study area, which includes parts of Ottawa and Gatineau cities.
The dataset used for this case study was presented in Table 1.

<table>
<thead>
<tr>
<th>Case study/event</th>
<th>Data</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019 Ontario and Quebec flood, CA</td>
<td>Sentinel-1 Level-1A GRD</td>
<td>Data type: intensity SAR image</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Resolution: 10 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Imaging mode: IW</td>
</tr>
<tr>
<td></td>
<td>Sentinel-1 Level-1A SLC</td>
<td>Data type: interferometry SAR image</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Resolution: 10 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Imaging mode: IW</td>
</tr>
<tr>
<td></td>
<td>SRTM DEM</td>
<td>Resolution: 30m</td>
</tr>
</tbody>
</table>

### 2.2. 2021 BC flood event

The 2021 Pacific Northwest floods include a series of floods that influenced British Columbia, Canada, and neighboring Washington state in the United States. Heavy rains caused flooding in parts of southern British Columbia and the northwestern United States, starting from November 14 until December 17. In December, the Insurance Bureau of Canada reported that the flooding was the costliest natural disaster in British Columbia's history, costing at least 450 million CAD in insured damage. The natural disaster provoked an emergency state for British Columbia, and at least five people were killed, and ten others were hospitalized during the event. The Nooksack River flows north of Bellingham in Washington State. The floodwater ended up in the Sumas River, and the water flowed northeast, crossing the border into Abbotsford. Figure 3 shows Abbotsford city and the selected region on the map.

The dataset used for flood extent mapping in Abbotsford was presented in Table 2.

<table>
<thead>
<tr>
<th>Case Study/event</th>
<th>Dataset</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2021 BC flood, CA</td>
<td>RADARSAT Constellation Mission (RCM)</td>
<td>Data type: SAR image</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Resolution: 5m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Imaging mode: Stripmap</td>
</tr>
<tr>
<td></td>
<td>Gridded CDED format DEM</td>
<td>Resolution: 25m</td>
</tr>
</tbody>
</table>

### 2.3. 2021 Germany flood event

In July 2021, several countries in Europe experienced severe floods. Some of these floods caused severe impacts on lives and properties. The floods started in the United Kingdom and later affected several river basins across Europe, including Germany. The states of Rhineland-Palatinate and North Rhine-Westphalia were particularly hard hit, causing 196 death tolls. Further down the Rhine river, the heaviest rainfall ever measured over 24 hours caused flooding in cities including Cologne and Hagen, while in Leverkusen, 400 people had to be evacuated from a hospital. Figure 3 shows the Leverkusen city location and the Rhine river on the map.

The dataset used for flood extent mapping in Leverkusen was presented in Table 3.
Table 3
Dataset used for Leverkusen case study

<table>
<thead>
<tr>
<th>Case Study/event</th>
<th>Dataset</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2021 Leverkusen flood, Germany</td>
<td>Sentinel-1 Level-1A/B GRD</td>
<td>Data type: intensity SAR image</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Resolution: 10m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Imaging mode: IW</td>
</tr>
<tr>
<td></td>
<td>Sentinel-1 Level-1A/B SLC</td>
<td>Data type: interferometry SAR image</td>
</tr>
<tr>
<td></td>
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<td>Resolution: 10m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Imaging mode: IW</td>
</tr>
<tr>
<td></td>
<td>SRTM DEM</td>
<td>Resolution: 30m</td>
</tr>
</tbody>
</table>

2.4. Input Data for flood mapping using CSN

Both intensity and coherence data were used in this study. Sentinel-1 GRD datasets were used for producing intensity data. One image before the flood event and the other during the flood was selected. The raw pixel values were converted to the radar backscatter coefficient (σ°) using the calibration toolbox in SNAP software. Also, the Sentinel-1 SLC dataset was used to produce the coherency feature maps for both the pre and co-event flood images. The coherency maps between two dates were computed in the SNAP software for both VV and VH images using the procedure shown in Fig. 5.

For the 2019 Ontario and Quebec case study, one coherency map was computed between 27th Mar and 8th Apr (two dates before the flood event). Another was computed between 14th May and 8th Apr (one date during and another before the flood event). For Abbotsford city, three high-resolution dual-polarized RCM intensity images were available for the flood event. Two RCM3 data were available, one from the flood event on 18th Nov and the other after the flood event on 30th Nov. Also, one RCM2 data was available during the flood event on 19th Nov that was used as the co-event test image. There was no RCM SLC data available for the area during the flood event. For the Leverkusen region (Germany), Sentinel-1A/B intensity and coherency data were used for flood mapping. The pre-event intensity data were captured on the 7th (S1B) and 10th (S1A) of July. The pre-event coherency maps were extracted from 24th Jun and 6th Jul, and two sets of co-event counterparts were computed between the 18th and 6th (S1A) July and 19th and 7th July (S1B). The input features used for flood mapping in the three case studies were shown in Table 4.
Table 4
Input dataset

<table>
<thead>
<tr>
<th>Data type</th>
<th>Date(s) (Ottawa, ON and Gatineau, QC)</th>
<th>Date(s) (Abbotsford, BC)</th>
<th>Date(s) (Leverkusen, Germany)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intensity</td>
<td>Pre-event</td>
<td>Co-event</td>
<td>Post-event</td>
</tr>
<tr>
<td></td>
<td>09/04/2019 (train/test)</td>
<td>2019/04/25 (train)</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>07/05/2019 (test)</td>
<td>2019/04/25 (train)</td>
<td>-</td>
</tr>
<tr>
<td>Coherency</td>
<td>Pre-event</td>
<td>Co-event</td>
<td>Post-event</td>
</tr>
<tr>
<td></td>
<td>09/11/30 (train/test)</td>
<td>2019/11/18 (train)</td>
<td>-</td>
</tr>
</tbody>
</table>

3. Methodology

3.1. Flood mapping using CSN based on a change detection framework

In this study, flood mapping was conducted based on a deep learning-based change detection technique called Convolutional Siamese Network (CSN). Siamese networks are generally based on two CNN networks running parallel and having the same parameters, identical in number and value. One CNN network is applied on the pre-event image and the other one on the co-event image. Because of the high heterogeneity in the image scene, the input image bands need to be divided into more homogenous regions or image segments with size \((H, W, N)\), which denote the height, width, and the number of input bands for each input image segment (image patch hereafter), respectively. The size of the image patch depends on the CNN input layer configuration. In this study, the input layer has been designed to accept image patches with a size of 32×32. The patch size was set based on experimental experience, a very small patch size reduces the information content and a very large patch size increases the processing time. So, it is a balance between the information content imported to the network and processing time. Input image bands are segmented into regions with sizes \((32, 32, N)\) to be compatible with the input layer, and the central pixel label in each image patch is used as the target label. The proposed CSN has three blocks (subnetworks), the first block is the input layer, the second is the feature extraction, and the third is the prediction block. Figure 6 shows how the three blocks have been embedded into the network, and Figs. 7–9 show the graphical abstracts for each block.

The configuration of train data depends on the loss function applied in the feature extraction phase. For example, if the Triplet Loss function is used, a triplet set of image patches \([\text{anchor}, \text{positive}, \text{negative}]\) is imported into the network. In the case of a Contrastive Loss function, the input training set will be a duplet set of image patches, \([\text{positive}, \text{negative}]\), and the anchor patches will be removed from the training data. The 2D image patch is converted into a 1D feature vector.
using the convolution and pooling layers in the feature extraction block. The user defines the feature vector size, which is called the embedding dimension. Convolution layers extract the 2D feature maps, and pooling layers make the extracted feature maps more abstract and extract the gist of information from the feature maps. Some CNN networks have been designed, by computer vision experts, and trained on big RGB image databases, such as Image Net. These pre-trained CNN networks such as VGG16, VGG19 (Simonyan, K. and Zisserman, A. 2016), Resnet50 (He et al. 2015), and inception_v3 (Szegedy et al. 2015) are available via the TensorFlow library in Python. These model parameters can be kept fixed and used for other classification problems. Although the use of pre-trained models is valuable for flood mapping studies to create a map in the shortest possible time, because the input data was a SAR image with different textural information than the RGB image, both pre-training and training from scratch (when all the network parameters are trained from the very beginning) strategies were tested to evaluate which works better for the SAR data. The Resnet50 and VGG16 were used as the backbone CNN architecture because they have been previously found effective for image feature extraction. Although the applied CNN architectures here were Resnet50 and VGG16, the methodology is not limited to a specific architecture and can be generalized to other pre-trained CNN models. The imported train data via the input layer is used to adjust the feature extraction block parameters (CNN parameters). The CNN parameters are adjusted based on the loss function values, i.e., if the loss value is high, the parameters are changed to reduce the loss value.

### 3.1.1. Train Data Preparation

When using DL algorithms for flood mapping, train and test/ground truth data should not overlap for reliable accuracy assessment. In this paper, parts of the ground truth flood masks were set aside for training the DL algorithms. Figure 10 shows the flood masks used as train data for the case studies.

### 3.1.2. Training CSN

Two scenarios were tested for training the backbone CNN models in CSN. In scenario one, the CNN networks were Trained From Scratch (TFS), and all the parameters were trained from the beginning. In the second scenario, Transfer Learning (TL) was applied. TL means that the CNN model parameters are kept fixed based on their values obtained by training on popular RGB image databases like Image Net, and only the newly added fully connected layers (the topmost layers) are trained. The TR method was tested for the 2019 Ontario and Quebec flood events and compared with the TFS method. For the other case studies, only TFS was used because of the higher accuracy result it achieved for the 2019 flood event case study.

Popular backbone architectures, such as Resnet50 and VGG16 mainly accept three input feature bands because they have been trained on three-band RGB images. One problem when using these networks for remote sensing images is that the number of feature bands \(N\) is usually higher than three. A PCA transformation was applied to the train data, and the number of PCA components was set to three to make \(N\) (number of input feature bands) the same as the backbone networks.

For training the CSN, the network parameters, including the number of epochs, batch size, learning rate, and optimizer function, need to be set. Another critical parameter that needs to be set, especially for CSN, is the feature space vector dimension, aka embedding dimension. Table 5 shows the assigned values to these parameters.
The CSN was implemented using the Tensorflow library in Python. In Tensorflow, it is possible to set an early stopping condition to prevent overfitting. The condition is set so that the training will be stopped if the validation loss does not change during 50 epochs.

When training a deep learning model, it is often helpful to lower the learning rate as the training progresses. One of the strategies available in Tensorflow for reducing the learning rate is exponential decay in which the initial value of the learning rate is reduced exponentially. The parameters for exponential decay include initial learning rate, decay rate and decay step. These parameters were presented in Table 5.

### 3.2. Accuracy assessment

The accuracy assessment in this paper was achieved using three metrics (Chen et al. 2022; Jiang et al. 2021; Konapala et al. 2021), including precision, recall, and F1 score. These metrics have been described in Table 6. In this Table, TP (True Positive), refers to the number of correctly classified flood pixels, TN (True Negative) is the number of correctly detected background pixels, FP (False Positive), refers to the number of wrongly identified flood pixels, and FN (False Negative), is defined as the number of pixels classified incorrectly as background.

### 4. Results

This section presents the experiments conducted for each case study, including the 2019 Ontario and Quebec, 2021 Abbotsford, and 2021 Leverkusen flood events. The flood mapping results and comparison with other DL methods have been included for each case study. A comparison between TL and TFS strategies has also been included for the 2019 flood event case study, and the same training strategy was used for other case studies based on the higher accuracy results achieved for TFS.

#### 4.1. 2019 Ottawa River flood
4.1.1. Flood map for Ottawa and Gatineau area

Figure 11 shows the contingency map created using the proposed CSN for the Ottawa and Gatineau area overlaid onto the Government of Quebec flood mask. The original flood mask was in the vector format, and it was converted into the raster format for compatibility with the produced flood mask. Results show that although the proposed CSN overestimated the flood area, especially in the residential areas, this result was in agreement with previous study by Tanim et al. (2022) when using Sentinel-1 data for flood extent mapping. Because of the medium resolution (10m) of Sentinel-1 images, there is a high chance of mixed flood and non-flood pixels that might cause overestimation.

4.1.2. Comparison with other Deep Learning techniques

Figure 12 compares the proposed CSN with four other state-of-the-art deep learning algorithms, including Unet, Unet++, DeepLabV3+, and Siamese-Unet for the 2019 Ottawa River flood event. For all flood events in the comparison section, the backbone architecture was VGG16 and the Loss function was Contrastive Loss. The input data for all the methods in this section were Sentinel-1 intensity and coherency data and a 30m resolution SRTM DEM data to help the deep learning algorithms to differentiate between the low and high-lying lands. Based on the bar plot, Siamese-Unet and the proposed Siamese Network performed better than other DL algorithms. Although Siamese-Unet showed higher flood precision, recall, and F1 score, its low background recall rate indicates flood overestimation. The proposed Siamese Network shows higher background accuracy than Siamese-Unet, and its accuracy indices are more balanced between flood and background classes.

4.2. 2021 Abbotsford Flood

4.2.1. Flood map for Abbotsford area

Figure 13 shows the flood map created using the proposed CSN for the Abbotsford area. Based on the figure, it is evident that the proposed CSN algorithm detected some fragmented flood areas across the city in the roads and residential parts.

4.2.2. Comparison with other Deep Learning techniques

Figure 14 compares the proposed CSN with four other state-of-the-art deep learning algorithms, including Unet, Unet++, DeepLabV3+, and Siamese-Unet for the urban area in Abbotsford, BC. The input data for all the methods were dual-polarized HH and HV RCM intensity and a 25m resolution DEM data. Based on the bar plot, it is apparent that the accuracy indices achieved for the background areas were higher than flooded regions because of the higher number of train data available for the background class. Another reason for this might be the limitation of the dual-polarized RCM data used for Abbotsford city. The RCM images applied were in HH and HV polarization modes. Based on the literature, the most suitable polarization in C-band SAR data for urban flood mapping is the VV mode (Pramanick et al., 2022). It is also notable that the within-class accuracy distribution in Unet, Siamese-Unet, and our proposed CSN was more balanced than the Unet ++ and DeepLabV3+. In other words, the values achieved for the precision, recall, and F1 score in each class were closer in the Unet, Siamese-Unet, and the proposed method than Unet ++ and DeepLabV3+. Although DeepLabV3 + achieved 0.85 precision for background class and 0.94 recall rate for flood regions, it is still unreliable because of its low recall value for background class and low precision value for flood class. Siamese-Unet had a comparable performance with the proposed CSN (because they both use change detection for flood map generation), but it achieved a lower recall rate on the background, about 6%, than the proposed CSN. Besides, it achieved a higher flood recall rate, about 5%, than the proposed CSN. The low accuracy indices achieved for the flood areas in all the applied deep learning algorithms confirm the SAR data limitation for urban flood mapping applications. This result is in agreement with previous studies that used SAR data for urban flood mapping (Li et al. 2019b; Lin et al. 2019).
The method was also tested in an agricultural area near Abbotsford to further investigate the reliability of the proposed CSN. Figure 15 shows the flood mapping accuracy results for this area. While Unet ++ and DeepLabV3 + resulted in low flood accuracies, the proposed CSN achieved precision and F1 score of 0.71 and 0.6, which were the highest among all the methods, and the method achieved more balanced accuracies between background and flood classes.

Figure 16 shows the contingency map of the proposed CSN for this suburban area. The low recall rate value for the proposed CSN shown in the bar chart can be justified by so many missed flood areas (red regions) on the map, and the reported high precision index of 0.79 is because the number of false alarms is relatively low, and most predicted flood areas are consistent with the ground truth data.

4.3. 2021 Leverkusen Flood

4.3.1. Flood map for Leverkusen area

Figure 17 shows the flood map created using the proposed CSN for the Leverkusen city overlaid onto the rasterized ground truth data. The original ground truth data available via the Copernicus Emergency Management Website (European Union, 1995–2022, 2021) were in the vector format. The data was converted to the raster format for compatibility with the produced flood maps. Similar to the results obtained for the Ottawa and Abbotsford areas, the flood map produced using the proposed CSN shows overestimation compared with the reference data, and some granule noisy flood patterns can be seen on the map. In terms of capturing the permanent water bodies, the Rhine river width mapped using the proposed method is thinner than the river width in the reference data.

4.3.2. Comparison with other Deep Learning techniques

Figure 18 compares the proposed CSN and the previously mentioned deep learning algorithms, including Unet, Unet++, DeepLabV3+, and Siamese-Unet. It can be seen that Unet ++ achieved acceptable precision, recall, and F1 score rates of 0.79, 0.95, and 0.86 for flood areas, but the method resulted in high false alarms and mixed many background pixels with the flood. Further, Unet acquired higher background precision and recall indices than Unet ++ and DeepLabV3+.

DeepLabV3 + achieved a high recall rate of 1 for the background class, but it could not detect any flood pixel in the scene. The proposed CSN and Siamese-Unet achieved the highest background precision of 0.93 among all the deep learning methods and had comparable performance because they both use Siamese architecture for flood map generation. The proposed method could not achieve high precision, recall, and F1 score for the flood areas.

5. Discussion

5.1. Comparison of flood maps in terms of CSN backbone architecture

One of the uncertainty sources in the proposed CSN is the type of backbone architecture applied for the feature extraction. Figure 19 compares the accuracy indices for the three case studies in terms of two kinds of networks used for feature extraction, including Resnet50 and VGG16. It can be inferred from the figure that the flood precision rate after changing the feature extractor from Resnet50 to VGG16 improved by 0.02, 0.02, and 0.08 for the Gatineau area, Abbotsford, and Leverkusen, respectively. In terms of recall rate, except for the Gatineau area, for the other two case studies, the index dropped by 0.19 and 0.64 after changing the backbone architecture to VGG16. Finally, the F1 score improved by 0.03 and 0.1 for the Gatineau area and Leverkusen areas but dropped by 0.01 for Abbotsford after using VGG16 as the feature extractor. Based on the obtained accuracy indices for the three case studies, it can be induced that VGG16 generally achieved higher flood accuracy than Resnet50. It is worth mentioning that there is no best feature architecture.
extractor and the selection of the most suitable feature extractor for the Siamese Network depends on different factors such as the type of input data in terms of being optical, SAR, or topography data. Additionally, the selection can be affected by the case study, and a feature extractor might work for one case study but might not be suitable for the other case studies. Further, for the Abbotsford case study, the accuracy indices are more balanced between the background and flood classes than Gatineau and Leverkusen (Fig. 19). The reason for more similar results between Gatineau and Leverkusen areas is the type of input data applied for these case studies. While for the Abbotsford area, the RCM dual-polarized intensity bands in HH and HV channels were tested, for Gatineau and Leverkusen, Sentinel-1 intensity and coherency data in VV and VH channels were applied for flood mapping.

### 5.2. Effect of using different loss functions

Another uncertainty source in CSN is the loss function applied for training the feature extractor Network. Three loss functions, including Contrastive Loss, Weighted Double Margin Contrastive Loss (WDMCL), and Triplet Loss, were used in this study to assess the CSN sensitivity to the loss function applied.

Figure 20 shows the Gatineau case study’s bar chart for flood and background accuracy indices. The flood recall rate improved after increasing flood sample weights. The background precision did not drop significantly after increasing flood sample weights and reducing background sample weights simultaneously, but its recall rate dropped. In other words, after decreasing background samples’ contribution to the training process, the recall rate decreased. Looking at the bar chart more carefully, after changing from Triplet Loss to WDMCL, the recall rate increased by 0.43 and by 0.47 after changing from Contrastive Loss to WDMCL. Although using WDMCL effectively increased the flood recall rate, the flood precision did not change after changing the loss function formulation. The flood precision index might be more affected by the input data type (optic, SAR or topography data) than the background and flood samples distribution.

Figure 21 shows the same bar chart as Fig. 20 for Abbotsford city. Based on the figure, all three loss functions resulted in similar flood precision accuracy. Besides, the flood recall rate improved after emphasizing flood class in the WDMCL formulation. In terms of flood precision index, all three loss functions had comparable performance, achieving precision values lower than or equal to 15%, which means that in almost only 15% of the cases, the detected flood pixel had consistency with the reference data. This low precision index might be related to the limitations of using only the SAR intensity data for flood mapping. Although the complementary role of SAR coherency and polarimetry data can be inferred from the literature, the only high-resolution RCM data available for the area was the intensity, adding limitations to examining the effect of other SAR products, such as polarimetry and coherency, for flood extent mapping.

Looking at the bar chart more carefully, it can be observed that the F1 score achieved for the WDMCL is about 6% higher than the corresponding values for the Contrastive and Triplet Loss functions. While Contrastive and Triplet Loss functions achieved an F1 score of about 16%, the WDMCL achieved a 24% because of its significantly higher recall value of 68%. Another important point worth mentioning is that although adding more weight to the flood samples in the WDMCL improved the recall index, this strategy did not help increase the precision index for flooded areas in the SAR image. The flood recall rate improved by 0.51 compared to the Triplet and by 0.19 compared to the Contrastive Loss Functions. At the same time, after decreasing the emphasis on background class in WDMCL, the recall rate dropped by 0.21 and 0.32 compared to Contrastive and Triplet Loss functions, respectively.

Figure 22 shows the accuracy indices for the background and flood classes for the Leverkusen case study in terms of the Loss Function applied in the CSN. A similar trend to the Gatineau area and Abbotsford cases regarding flood recall value increase after changing the loss function to WDMCL can be seen. Precision values were not significantly affected by the loss function, and the index remained at the exact value of 0.93 and 0.07 for the background and flood classes, respectively. It can be inferred from the bar chart that although Contrastive Loss achieved the highest flood recall rate of 0.99 among the loss functions, it could not achieve an acceptable flood precision index, and its value remained as low as
in other cases. On top of that, the Contrastive Loss function resulted in a poor background recall index of 0.01, which was considerably lower than its counterparts for the WDMCL and Triplet Loss functions which were 0.68 and 0.88, respectively.

5.3. Effect of adding DEM data on flood mapping accuracy

Figure 23 shows the F1 score values for three case studies for the background and flood classes before (BF) and after (AF), adding DEM data to the SAR dataset. It is evident from the bar chart that the background F1 score improved in all three case studies. For the flood class, while the F1 score for flood pixels improved by 1% for the Gatineau area, it dropped by 6% and 1% for Abbotsford and Leverkusen areas, respectively. The decrease in flood detection accuracy might be related to the DEM data resolution. The DEM spatial resolution was between 25-30m, about 2.5-3 times lower than the spatial resolution of Sentinel-1 and about 5–6 times lower than the spatial resolution of RCM data. Because of the averaging operation in low-resolution DEM data, there is a high chance of mixed high and low-lying lands present in one sampling area. These mixed samples/pixels can increase flood mapping commission and omission errors.

Another critical point inferred from the bar chart is that the background accuracy increase was more significant after adding DEM in Leverkusen than in Abbotsford and Gatineau because the studied area in Leverkusen was larger, and the elevation variation was more significant than in the others. In other words, the elevation variation for the Leverkusen region, a catchment near the Rhine river, is more significant than the Abbotsford case study, which was a relatively small area with lower elevation variation than the Leverkusen region. The exact wording holds for the Gatineau area. The accuracies reported in this section for Gatineau were for a small area at the Gatineau Hull and Ottawa rivers with a smooth elevation variation.

6. Conclusions

In this study, urban flood mapping using SAR data through a CSN was explored and validated against ground truth data for three flood events in Ottawa, ON and Gatineau, QC, Abbotsford, BC, and Leverkusen, Germany. Also, CSN was compared with three of the state-of-the-art DL algorithms, including Unet, Unet++, and DeepLabV3+. For the sake of comparison with a network with similar architecture and taking advantage of Unet encoder-decoder architecture, Siamese-Unet was also compared with the proposed CSN. Also, the proposed CSN was tested in an agricultural area to investigate the reliability of the method. The precision index improved by 0.6 compared with the urban case. This result is in agreement with previous studies that reported lower accuracy indices for dense urban areas than non-urban. The results indicated that Sentinel-1 data can detect flooded areas with average accuracy above 0.5. Besides, RCM dual-polarized C-band HH and HV intensity channels were tested for flood mapping in Abbotsford city. The results showed that RCM data can achieve high flood precision in less urbanized areas. The effect of loss function on the CSN performance was also examined. It was inferred from the results that CSN is sensitive to the loss function selection, and the use of WDMCL can improve flood recall at the cost of deteriorating the background recall index. Another important finding was that the loss function selection had no contribution to the precision index. Precision is more affected by the input data type and the normalization method applied to the input data. The effect of adding DEM data on flood mapping accuracy was also explored. Although the F1 score for the flood class saw no significant improvement, the results confirmed the DEM data efficiency for improving the F1 score for the background class.

Declarations

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Author Contributions

Nafiseh Ghasemian Sorboni and Jinfei Wang contributed to the data collection. The first author did the analysis and prepared the first draft of the manuscript. All authors, Nafiseh Ghasemian Sorboni, Jinfei Wang and Mohammad Reza Najafi, contributed to the research concept and design, commented on the previous manuscript versions and read and approved the final version.

References


**Figures**

![Map of geographic extent of case studies](image)

**Figure 1**

Geographic extent of case studies on the map; a) Ontario-Quebec and BC case studies. b) Germany case study.
Figure 2

Study area for the 2019 Ontario and Quebec flood event
Figure 3

Abbotsford, BC case study

Figure 4

Leverkusen case study

Figure 5
the procedure used in SNAP software for producing the coherency map

**Figure 6**

Different blocks in Flood Map generation using CSN

**Block 1 and 2: Input layer and feature extraction using Resnet50**

Block 1: Input Layer

Block 2: Feature extraction

Convolutional Siamese Network

Training Resnet50 and/or FC layers
Figure 7

Graphical abstract for blocks 1 and 2

**Block 3: Prediction layer (training phase); assigning Flood and No Flood labels**

\[
F_{\text{positive}} = \begin{bmatrix}
  f_1 \\
  f_2 \\
  \vdots \\
  f_n
\end{bmatrix} \\
F_{\text{negative}} = \begin{bmatrix}
  f_1 \\
  f_2 \\
  \vdots \\
  f_n
\end{bmatrix}
\]

\[
\begin{bmatrix}
  F_{\text{positive}} \\
  F_{\text{negative}}
\end{bmatrix}
\]

![Graphical abstract](image)

**Figure 8**

Graphical abstract for block 3 (training phase)
Block 4: Prediction layer (test phase); assigning Flood and No Flood labels

Figure 9

Graphical abstract for block 3 (test phase); the dates are related to the 2019 Ontario and Quebec flood event
Figure 10

Train masks applied for flood detection; a) Ottawa and Gatineau area; b) Abbotsford, BC (agricultural area); c) Leverkusen, Germany; The blue and black shades were used for showing train data for the flood and background areas, respectively.
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Comparison of the proposed CSN with Unet, Unet++, DeepLabV3+, and Siamese-Unet for Abbotsford, BC (Urban), CA

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Figure 17

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Figure 18

Comparison of the proposed CSN with Unet, Unet++, DeepLabV3+, and Siamese-Unet for Leverkusen, Germany

Figure 19
Comparison between the proposed CSN performance in terms of feature extractor for Gatineau, Abbotsford, and Leverkusen case studies

Figure 20

background and flood accuracy indices for Contrastive Loss, WDMCL, and Triplet loss functions in Gatineau, QC
Figure 21

Background and Flood accuracy indices for Contrastive Loss, WDMCL, and Triplet loss functions in Abbotsford, BC.
**Figure 22**

Background and flood accuracy indices for Contrastive Loss, WDMCL, and Triplet Loss functions in Leverkusen, Germany.

**Figure 23**

Effect of adding DEM data on the F1 score for the background and flood classes in Gatineau, Abbotsford, and Leverkusen case studies; BF is an acronym for Before Flood and AF is an acronym for After Flood.