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River flood mapping in urban areas combining Radarsat-2 data and flood return period data

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ABSTRACT

Near-real-time flood maps are essential to organize and coordinate emergency services' response actions during flooding events. Thanks to its capacity to acquire synoptic and detailed data during day and night, and in all weather conditions, Synthetic Aperture Radar (SAR) satellite remote sensing is considered one of the best tools for the acquisition of flood mapping information. However, specific factors contributing to SAR backscatter in urban environments, such as shadow and layover effects, and the presence of water surface–like radar response areas, complicate the detection of flood water pixels. This paper describes an approach for near-real-time flood mapping in urban and rural areas. The innovative aspect of the approach is its reliance on the combined use of very-high-resolution SAR satellite imagery (C-band, HH polarization) and hydraulic data, specifically flood return period data estimated for each point of the floodplain. This approach was tested and evaluated using two case studies of the 2011 Richelieu River flood (Canada) observed by the very-high-resolution RADARSAT-2 sensor. In both case studies, the algorithm proved capable of detecting flooding in urban areas with good accuracy, identifying approximately 87% of flooded pixels correctly. The associated false negative and false positive rates are approximately 14%. In rural areas, 97% of flooded pixels were correctly identified, with false negative rates close to 3% and false positive rates between 3% and 35%. These results highlight the capacity of flood return period data to overcome limitations associated with SAR-based flood detection in urban environments, and the relevance of their use in combination with SAR C-band imagery for precise flood extent mapping in urban and rural environments in a crisis management context.

1. Introduction

The capacity of spaceborne Synthetic Aperture Radar (SAR) remote sensing for near-real-time flood detection and mapping has been demonstrated by numerous studies over the last decade (Henry et al., 2006; Greifeneder et al., 2014; Schumann et al., 2011; Schumann et al., 2012; Pulvirenti et al., 2014). Many civil protection organizations now use airborne and satellite SAR imagery to support the development of assistance plans to reduce human and material consequences of flooding events (Bhatt et al., 2016; Boni et al., 2009; Kussul et al., 2014; Martinis et al., 2015; Pulvirenti et al., 2013; Zhang et al., 2002).

Accurate flood detection is of the utmost importance in urban areas, where high population concentrations and critical infrastructures often make the economic and social impacts of a flood event very high. However, specific factors contributing to SAR backscatter hamper flood water detection in built-up environments. In particular, the side-looking nature of SAR sensors can cause objects such as buildings and tall vegetation, oriented parallel or roughly parallel to the satellite track, to produce shadow and layover effects (Soergel, 2010). The magnitude of these geometric distortions, which may hide important sections of the ground from the sensor, is a function of wavelengths, radar look angle, and polarization (Mason et al., 2014; Schumann et al., 2009). In addition, large, permanent, specular-like reflection surfaces typical of urban areas, such as roads and parking lots, may be confused with open water regions, thereby increasing flood detection errors (Mason et al., 2010).

In order to limit the impact of these effects on flood detection accuracy, the methods that have been developed for flood detection in urban areas using SAR imagery have taken advantage of a variety of tools and sources of ancillary information. For instance, in the algorithm for near-real-time flood detection in urban areas using TerraSAR-X images presented by Mason et al. (2010, 2012), a SAR end-to-end simulator (Speck et al., 2007) was run in conjunction with high-resolution LIDAR data of the urban area of Tewkesbury (UK) to generate a map of shadow and layover effects. Masking these effects during near-real-time processing enabled 75% of the unmasked flooded pixels to be correctly classified in urban areas. Furthermore, in Mason et al. (2014), the

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same SAR simulator and high-resolution LIDAR data were successfully used in a double-scattering strength measurement method for flood detection in the layover regions of the same TerraSAR-X image.

In Giustarini et al. (2013), areas affected by shadow effects, permanent water surfaces, and other surfaces characterized by specular-like reflections are identified by detecting changes in backscatter intensities between a high-resolution TerraSAR-X flood image and a non-flooded reference image. These areas are then masked out from the final flood map to reduce false alarms.

In addition, Chini et al. (2012) and Pulvirenti et al. (2015) demonstrated that combining the complex coherence information extracted from COSMO-SkyMed interferometric pairs with intensity information can greatly assist in the detection of flooded areas in both urban and rural environments and reduce flood detection omissions produced by approaches based solely on intensity analysis.

These algorithms enable flood water detection in urban areas with reasonable accuracy, but it is worth mentioning that the use of shadow and layover masks results in non-identification of the flooding status of a significant part of the flooded urban areas (e.g., 39% in the study by Giustarini et al. (2013)). Moreover, the availability of an adequate non-flooded SAR reference image (identical orbit track and polarization, similar state of vegetation, etc.), required by a change-detection approach, of a SAR simulator, or of adequate SAR interferometric pairs, is not always guaranteed.

Simple hydraulic considerations have also been used in several image-processing algorithms to guide the detection of flooded pixels in urban and rural areas (see Pierdicca et al., 2008; Pulvirenti et al., 2011; Mason et al., 2012 or Schumann et al., 2011). In this approach, information from surface elevation data, which have the advantage of being available for most rivers worldwide, is exploited. However, such algorithms restrict the integration of hydraulic considerations to simple elevation and proximity analysis. To our knowledge, no example can be found in the recent literature of the explicit integration of hydraulic data within SAR image-processing algorithms for flood detection in urban and rural areas. Such data, which could include information about a river's flooding pattern or the specific hydraulic characteristics of a floodplain, could be of great use in areas where SAR-based flood detection remains a challenge.

Therefore, the objective of the present study is to demonstrate how a combination of very high resolution SAR imagery and hydraulic data can yield effective near-real time flood delineation in urban areas. More specifically, we rely on the use of the flood return period, estimated at each point of the floodplain. Note that the flood return period, which can be defined here as the average number of years between two flood occurrences of the same magnitude, will be referred to as "RP" in the following sections. The underlying hypothesis is that this parameter, which relates to the hydrologic and hydraulic characteristics of the floodplain and the flooding event, might allow the identification of flooded pixels, even in areas where SAR remote sensing is limited. In order to confirm this hypothesis, an innovative approach was developed and evaluated by using two very-high-resolution RADARSAT-2 images (C-Band, HH polarization) acquired during the 2011 Richelieu River flood (Canada) with different acquisition parameters and water surface conditions.

2. Methodology

The proposed method (depicted in the flowchart in Fig. 1) provides near-real-time flood extent mapping in urban and rural areas using a high-resolution SAR C-Band HH-polarized flood image as input data. Horizontal polarization is preferred over vertical polarization or cross polarization as it generally yields the highest contrast between open water and upland locations (Brisco et al., 2008). The SAR image must be speckle-filtered (Senthilnath et al., 2013), geocoded, and calibrated to obtain backscatter values.

RP data estimated for each point of the study area are also required. These values are generally estimated using one dimensional (1D) or two-dimensional (2D) hydraulic modelling. If such data is not available for the study area, an alternative method for RP estimation at each point of the study area is described in Section 2.1. This estimation should be carried out prior to near-real-time operations.

The first step in near-real-time operations is the detection of open water flooded areas on SAR flood image using an approach that combines object-oriented segmentation, calibration of the statistical distribution of "open water" objects' mean backscatter values, and thresholding-based fuzzy classification. This initial classification of "open water" objects is then refined using the degree of membership of each object in the "open water" set and its maximum RP. Following this classification refinement, the RP associated with the maximum extent of the refined "open water" classification is extracted. Finally, floodplain points for which the RP is less than or equal to this maximum RP are selected to create the final flood map. These near-real-time processing steps will be described in detail in the following sections.

2.1. Method for flood return period estimation

RPs are usually computed, for some selected RPs, using a 1D or 2D hydraulic model forced by statistically estimated hydrological inputs. Hydrological and hydraulic models, set up for a given area, are generally not available for the public. However, their outputs in terms of RP shorelines or extents are publicly released, for some selected RPs. Between 3 and 5 RP shorelines are usually made available, depending on the country or region, and are widely used as risk criteria for land use planning. Therefore, the RP of most points of the floodplain remain unknown. Running a hydraulic simulation can be complex and time consuming. We hereby propose a simple and efficient method to estimate the RP at each point of the floodplain, based on the available RP shorelines in the study area and on topographic elevation data. A flowchart of this method is presented in Fig. 2.

The inputs to this method are:

1. Available RP shorelines for the river. The positions of such shorelines along the river are estimated using 1D or 2D hydraulic modelling, and they are often made available in the form of polygons or polylines. A minimum of three different RP floodplain shorelines are required to estimate consistent RP at each point of the floodplain.
2. Water height values at the river centreline associated with each RP shoreline available. The water-surface elevations at the river centreline are also estimated by using either a 1D hydraulic model (in which case one value of water height at the river centreline coincides with the values of water height of the given section) or a 2D hydraulic model (in which case a water height value is available for each cell of the model at the river centreline, including one value for each cell located along the river centreline).
3. A high-resolution digital elevation model (DEM) of the ground elevations in the area. In order to allow extraction of accurate water levels along the RP shorelines, this DEM should be the same as the one used to estimate the position of these shorelines. If this DEM is not available, a DEM with identical vertical and horizontal accuracies must be used. Also, the user must ensure that no major changes in ground elevations occurred between the time the flood return shorelines were estimated and the time the alternative DEM was produced. It should be noted that the higher the vertical and horizontal accuracies of the DEM used are, the more precise the RP estimation at each point of the floodplain should be.

RP estimation at each point of the floodplain follows three steps. In order to facilitate understanding of this procedure, its different elements are gathered in a single figure (see Fig. 3), which also presents an example of RP of a point in the floodplain.

First, the elevations of the water surface associated with each RP are generated, using a spatial interpolation technique. This involves the creation and aggregation of the points used for the generation of each