Remote Sensing of Environment 209 (2018) 712–730

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Normalized Difference Flood Index for rapid flood mapping: Taking advantage of EO big data

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ARTICLE INFO

Keywords:
SAR
Flood mapping
EO big data
Flood index
Multi-temporal statistics

ABSTRACT

Climate change projections foresee an increasing number of intense precipitation events with consequent flash and riverine floods. An accurate and rapid mapping of these phenomena is a key component of effective emergency management and disaster risk reduction plans. Earth Observation big data such as the ones acquired by the Copernicus programme, are providing unprecedented opportunities to detect changes and assess economic impacts in case of disasters.

This paper presents an innovative flood mapping technique based on an index which is computed using multi-temporal statistics of Synthetic Aperture Radar images. The index compares a large amount of reference scenes to those acquired during the investigated flood and allows an easy categorization of “flooded” areas; either areas solely temporarily covered by water or areas with mixed water and vegetation. The method has been developed specifically to exploit Sentinel-1 data but can be applied to any other sensor. It has been tested for the 2010 flood of Veneto (Italy) and the floods of 2015 in Malawi and Uganda. Extensive qualitative analysis and cross-comparison with other state-of-the art methods, proved the proposed approach highly reliable and particularly effective, allowing a precise, simple and fast flood mapping. Compared to the maps produced for emergency management for the event analyzed, we obtained an overall agreement of 96.7% for Malawi and an average of 96.5% for Veneto for the 5 maps presented.

1. Introduction

New satellite constellations, such as the European Space Agency's (ESA) Sentinels, have started the era of Earth Observation (EO) big data (Hua-Dong et al., 2015; Ma et al., 2015; Yang et al., 2017) allowing to entering a new paradigm for disaster monitoring and EO data exploitation. Sentinel-1 (S1), a constellation of two radar satellites operational since October 2014, can monitor the entire Earth every 6 days, giving an unprecedented opportunity to access a large number of archived scenes (Potin et al., 2015; Torres et al., 2012). This allows statistical analysis to be performed on long time-series of data and new approaches in change detection (CD) analyses to be developed for mapping floods, assessing their economic impacts and managing emergency responses.

With a foreseen increase in the number of extreme precipitation events due to climate change and consequent flash and riverine floods (MunichRE, 2014), rapid and accurate mapping of floods is of key importance. Firstly, rapidity is key in emergency management (EM), with new cloud computing tools (Yue et al., 2013; Li et al., 2015; Yang et al., 2013) such as Google Earth Engine (GEE) (Google Earth Engine, Google, n.d) starting to play a fundamental role (Karamouz et al., 2013). Secondly, accuracy is required not only in EM, but also for better planning urban areas, for saving lives, for reducing economic losses and building more resilient livelihoods (de Moel et al., 2015; Mysiak and Luther, 2013; UNISDR, 2015). The big EO data of ESA's Copernicus programme is helping to move towards an improved flood risk assessment for both EM and better infrastructure planning (Twele et al., 2016).

The capability of near-real time flood mapping by means of EO data has already been demonstrated in the past (Horritt et al., 2001; Matgen et al., 2007; Brisco et al., 2011; Henry et al., 2006; Cossu et al., 2009; Martinis et al., 2015) and it is now regularly used by operational emergency response centers (Bessis et al., 2004; Mahmood, 2012) such as the European Copernicus Emergency Management Service (Copernicus EMS) or the International Charter on Space and Major Disaster (International Charter, n.d).

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https://doi.org/10.1016/j.rse.2018.03.006
Received 2 October 2016; Received in revised form 6 February 2018; Accepted 2 March 2018

Table 1
Summary of relevant literature in flood mapping in chronological order from the year 2000. The table specifies the data used, location, type of environment, size of the study area, method and key results. The last column (Key Results) reports "Quantitative result not available" whenever the study did not provide any quantitative results in terms of flood map extent accuracy. For the sake of completeness, the proposed method has been added in the last row.

Study	Data used/res./band	Location/landscape/study size/dates	Method/approach	Key results
1 - (Nico et al., 2000)	ERS-1/2/30 m/C	Béziers, France/urban, agricultural areas/ 10.000 km^2/January 1996	Interferometric coherence change detection	– Combined use of amplitude and interferometric coherence improved detection of flood compared to the use of amplitude only – Quantitative result not available
2 - (Horritt et al., 2001)	ERS-1/30 m/C	Oxford, UK/agricultural areas/250 km^2/December 1992	Active contour model	– Discrimination of thickly vegetated areas from flooded areas – 75% accuracy with respect to simultaneous aerial photo
3 - (Brivio et al., 2002)	ERS-1/30 m/C	Piedmont region, Italy/flat agricultural area/ 450 km^2/November 1994	Thresholding + DEM filling	– Estimation of flood peak extent – 96.7% map accuracy with respect to the official map created by the local government
4 - (Bazi et al., 2005)	ERS-2/30 m/C	City of Bern, Switzerland/urban, alpine/80 km^2/ May 1999	Unsupervised change detection	– Automatic unsupervised filtering and threshold selection – Simple and stable method – Accuracy similar to manual supervised thresholding – Quantitative result not available
5 - (Henry et al., 2006)	1) ENVISAT-ASAR/30 m/C 2) ERS-2/30 m/C	Elbe River, Dresden, Germany/urban, agricult. areas/–/August 2002	Thresholding	– Comparison of different polarization for flood detection – HH more suitable for flood detection compared to VV – HV improve the detection if combined with HH – 85% agreement with map derived from Landsat 7
6 - (Mason et al., 2007)	ERS-1/30 m/C and LiDAR DTM/2 m	Oxford, UK/flat agricultural area/40 km^2/ December 1992	Active contour model on SAR and DTM	– Automatic extraction of flooded area taking into consideration terrain elevation – The use of elevation data combined with SAR improved the accuracy – Quantitative result not available
7 - (Matgen et al., 2007)	1) ENVISAT-ASAR/30 m/C 2) LiDAR DEM/2 m	River Alzette, Luxembourg/urban, alpine/30 km^2/ January 2003	Thresholding + active contour model	– The use of elevation data combined with SAR improved the accuracy – Extraction of flood in vegetated areas – Quantitative result not available
8 - (Martinis et al., 2009)	TerraSAR-X/3 m/X	Tewkesbury, UK/urban, agricult. areas/ 1.500 km^2/July 2007	Thresholding + segmentation	– Unsupervised flood detection using locally computed thresholds – Computationally efficient compared to global thresholding – Operational rapid mapping – Use of DEM for improving accuracy – 95.5% overall accuracy on a subset of the dataset with respect to ground truth of the event
9 - (Schumann et al., 2010)	ENVISAT-ASAR/150 m/C	Po river, Cremona, Italy/urban, agricultural areas/ 1.250 km^2/June 2008	Thresholding + hydrologic modelling	– Verification of flood inundation models in near-real time – Quantitative result not available
10 - (Matgen et al., 2011)	ENVISAT-ASAR/150 m/C Radarsat-1/25 m/C	1) Red river, US/urban, agric. areas/4.500 km^2/ April 1997 2) Tewkesbury, UK/urban, agric. areas/800 km^2/ July 2007	Thresholding + region growing and change detection	– Automatic, objective and reliable flood mapping – 85% overall accuracy with respect to a map extracted from aerial photography
11 - Manjusree et al. (2012)	Radarsat-2/50 m and 3 m/C	Kosi subbasin, Darbhanga District, Bihar State, India/monsoonal climate, agricultural areas/ 25.000 km^2/October 2011	Thresholding based on incidence angle	– Delineation of flood water using high incidence angle SAR images – Retrieval of optimal threshold values – Quantitative result not available
12 - (Mason et al., 2012a, 2012b)	TerraSAR-X/3 m/X	Tewkesbury, UK/urban and rural flooding/ 70 km^2/July 2007	Thresholding + segmentation	– Automatic near-real time flood mapping in rural-urban areas – 89% overall accuracy with respect to aerial photographic data
13 - (Giustarini et al., 2013)	TerraSAR-X/3 m/X	Severn River, Tewkesbury, UK/urban areas/ 3 km^2/July 2007	Thresholding, region growing, change detection	– Automated, objective and repeatable flood detection in urban areas – 82% overall accuracy with respect to aerial photography-derived flooded areas
14 - Pulvirenti et al. (2014).	COSMO-SkyMed/3 m/X	Northwest Italy/urban, alpine, agricultural areas/ 1.700 km^2/November 2011	Segmentation + fuzzy logic	– Discrimination of artifacts caused by heavy rain or wet snow cover – Quantitative result not available
15 - Long et al. (2014)	ENVISAT/ASAR/150 m/C and Radarsat-2/6.25 and 12.5 m/C	Caprivi region, Namibia/tropical rural areas, wetlands/10.000 km^2/March 2009, March 2011, April 2012, March 2013	Change detection + thresholding	– Simple and fast method – Flood in vegetated areas – Frequency of flooding – Quantitative result not available
16 - (Ward et al., 2014)	ALOS-PALSAR/100 m/L Landsat TM 5/30 m/optical	Alligator Rivers region, northern Australia/wet-dry tropical floodplains/10.000 km^2/April to October 2009	Classification tree using spectral indices and segmentation	– Data fusion of optical and radar data – Understanding of floodplain inundation dynamics – Flood in vegetated areas

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