International Journal of Applied Earth Observation and Geoinformation 34 (2015) 70–77

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

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

Accounting for image uncertainty in SAR-based flood mapping

L. Giustarini[a,*], H. Vernieuwe[b], J. Verwaeren[b], M. Chini[a], R. Hostache[a], P. Matgen[a], N.E.C. Verhoest[c], B. De Baets[b]

[a] Centre de Recherche Public – Gabriel Lippmann, Belvaux, Luxembourg
[b] KERMIT, Department of Mathematical Modelling, Statistics and Bioinformatics, Ghent University, Coupure links 653, 9000 Gent, Belgium
[c] Laboratory of Hydrology and Water Management, Ghent University, Coupure links 653, 9000 Gent, Belgium

ARTICLE INFO

Article history:
Received 22 January 2014
Accepted 23 June 2014
Available online 26 July 2014

Keywords:
Flood mapping
Speckle
Bootstrap
Synthetic aperture radar
Uncertainty

ABSTRACT

Operational flood mitigation and flood modeling activities benefit from a rapid and automated flood mapping procedure. A valuable information source for such a flood mapping procedure can be remote sensing synthetic aperture radar (SAR) data. In order to be reliable, an objective characterization of the uncertainty associated with the flood maps is required.

This work focuses on speckle uncertainty associated with the SAR data and introduces the use of a non-parametric bootstrap method to take into account this uncertainty on the resulting flood maps. From several synthetic images, constructed through bootstrapping the original image, flood maps are delineated. The accuracy of these flood maps is also evaluated w.r.t. an independent validation data set, obtaining, in the two test cases analyzed in this paper, *F*-values (*i.e.* values of the Jaccard coefficient) comprised between 0.50 and 0.65. This method is further compared to an image segmentation method for speckle analysis, with which similar results are obtained. The uncertainty analysis of the ensemble of bootstrapped synthetic images was found to be representative of image speckle, with the advantage that no segmentation and speckle estimations are required.

Furthermore, this work assesses to what extent the bootstrap ensemble size can be reduced while remaining representative of the original ensemble, as operational applications would clearly benefit from such reduced ensemble sizes.

Introduction and objective

Rapid flood mapping, together with uncertainty assessment and delivery of flood maps, are of considerable importance for response activity planning during emergencies and as a support for long-term risk management. Given its cloud penetrating and night/day operational capabilities and its skill in capturing the different scattering behavior between flooded and non-flooded areas (Pierdicca et al., 2013), synthetic aperture radar (SAR) constitutes a valuable source of information to provide flood maps. Such maps can then be used for the calibration or validation of hydraulic models (Di Baldassarre et al., 2009; Hostache et al., 2009; Montanari et al., 2009; Stephens et al., 2012; Mason et al., 2012; Schumann et al., 2014). Hydraulic information derived from flood maps, such as flood extents or water stages, can also be employed in a data assimilation (DA) framework in order to improve model predictions (Matgen et al., 2010; Hostache et al., 2010; Giustarini et al., 2011).

Flood maps derived from SAR observations are the result of image processing procedures. Given that there is no perfect procedure and no best practice on selecting one over another, the chosen mapping procedure may introduce errors or uncertainties in the retrieved flood map. Furthermore, SAR observations are susceptible to sources of uncertainty due to imaging characteristics (*e.g.* imaging modes, speckle, resolution) and ground perturbations (*e.g.* wind, trees, buildings masking water, terrain geometry). Therefore, it is important to assess the impact of these uncertainties on the final flood map. Without this information, model calibration/validation or DA activities could yield suboptimal results (Quaife et al., 2008).

In order to assess uncertainty in flood delineation methods, the few approaches proposed in literature employ an ensemble of flood maps (Schumann et al., 2008; Di Baldassarre et al., 2009). However, the number of ensemble members and the procedure to obtain the different ensemble members tend to be subjective. For example, Schumann et al. (2008) investigated uncertainty in SAR-derived water stages, for a single SAR image and a single flood mapping

* Corresponding author at: 41, rue du Brill, L-4422 Belvaux, Luxembourg. Tel.: +352 470261 479.
E-mail address: giustari@lippmann.lu (L. Giustarini).

http://dx.doi.org/10.1016/j.jag.2014.06.017
0303-2434/

procedure, identifying two main sources of uncertainty. The first one corresponds to the parameter value applied to classify a pixel as flooded (*i.e.* wet/dry classification threshold), whereas the second one stems from the geocoding of the image itself. They decided to test four different threshold values and fifty image geocodings, to obtain an ensemble of flood maps and corresponding SAR-derived water levels. In a second study, Di Baldassarre et al. (2009) considered uncertainty due to both the available SAR image and the applied procedure. They computed ten flood maps, combining two available SAR images, acquired at nearly the same time but having a different resolution, with five different flood mapping procedures. These case studies show that it is important, yet not trivial, to correctly and objectively quantify uncertainty in flood mapping. In flood mapping, uncertainty principally stems from the image input to the algorithm and from the algorithm itself.

The flood mapping procedure (Giustarini et al., 2013) employed in this paper, deterministically fits its parameter values to a given SAR image. The uncertainty we focus on stems from image uncertainty, which is propagated through the flood mapping procedure.

SAR image uncertainty is mainly due to speckle, leading to random changes in the pixel's brightness and usually hampering decision making on a pixel basis (Oliver and Quegan, 1998). This phenomenon occurs where distributed targets are imaged and the pixel is therefore representative of the contributions coming from many scatterers with random phase. These contributions cause interference and result in speckle. In an amplitude or intensity image, speckle appears as a noise-like multiplicative modulation of backscatter. As a consequence, the individual value of a pixel represents a rather inaccurate measurement of its true backscatter. In order to account for speckle in uncertainty analysis, each pixel can be characterized by its speckle distribution, which is different for each particular land cover class. This speckle characterization can be accomplished with speckle reconstruction techniques (Frost et al., 1982; Durand et al., 1987; Lee et al., 2009), which try to approximate the backscatter over the entire image, or with segmentation methods, which hypothesize the presence of structures in the image and are potentially powerful techniques for extracting information from SAR images (Lee and Jurkevich, 1989; Horritt, 1999; Zhang et al., 2008; Sui et al., 2012). These latter methods assume that the image is composed of relatively homogeneous regions, whereas adjacent regions are separated by edges corresponding to changes in some local statistic, such as mean brightness or texture (Caves et al., 1998). The assumption of a uniform backscatter within each segment is useful to extract speckle from the given image by first segmenting the image into uniform regions and by then extracting the speckle distribution of each region.

In this work, differently from already published methods, a non-parametric bootstrap method is proposed to account for the influence of speckle. Bootstrap methods (Efron, 1979; Efron and Tibshirani, 1993) belong to the class of resampling methods in which multiple new samples are drawn from the data sample at hand in order to estimate a statistical unknown population parameter. Resampling methods are generally used when it is not straightforward to use the classical statistical methods in the estimation of the parameter, for instance, when one disposes of a small data set. In this work, only one SAR image is available, which can be regarded as a set of pixels that represents the best guess about the population from which the image was formed. A first advantage of the proposed bootstrap method is that it is fully automatic, in the sense that it does not require specific knowledge on image processing, in contrast to, *e.g.* segmentation methods. Moreover, while image segmentation could result in a rather time-consuming process, particularly for large images, the proposed method should be rather independent of the image size in terms of process time. Eventually, since the bootstrap method can result in a large set of bootstrap data sets, we also assess the smallest appropriate number of data sets needed to still adequately describe the uncertainty in the flood maps due to speckle.

Methodology

Flood mapping procedure

In this work, the flood mapping procedure described in Giustarini et al. (2013) and based on Matgen et al. (2011) is applied for flood delineation. It is a hybrid procedure combining backscatter thresholding, region growing and change detection w.r.t. an available reference image. The procedure assumes that the histogram of backscatter values in a SAR flood image can be modeled as two partially overlapping histograms: one histogram derived from the backscatter values representing "open water" in the image and the other one from the backscatter values representing the non-flooded areas (Ulaby et al., 1986). The flood mapping method is based on fitting a scaled gamma curve to the backscatter values that represent "open water" in the flood image:

$$f(\sigma^0; k, \sigma_m^0)\frac{(\sigma^0-\sigma_1^0)^{k-1}}{((\sigma_m^0-\sigma_1^0)/(k-1))^k\,\Gamma(k)}\exp\left(-\frac{(\sigma^0-\sigma_1^0)(k-1)}{\sigma_m^0-\sigma_1^0}\right) \quad (1)$$

where k is the shape parameter of the scaled gamma curve, σ^0 is the backscatter value of a pixel in the SAR image, σ_m^0 is the mode of the scaled gamma curve and σ_1^0 is the minimum backscatter value in the SAR image, applied so that the curve only takes positive values. Next, a sequence of three steps, optimized backscatter thresholding, region growing, and change detection, is applied on the flood image and on a pre- or post-flood reference image with the same imaging characteristics (track, orbit, polarization, acquisition mode). In the first step, based on the fitted curve, a backscatter threshold parameter σ_{thr}^0 is determined, and the flooded area is extracted by selecting the pixels with a backscatter value lower than σ_{thr}^0. Concerning the second step, the region growing parameter σ_{rg}^0 is the one on whose basis pixels in the vicinity of the water bodies are included in the flood area. The change detection parameter $\Delta\sigma^0$ is defined as the required minimum change in backscatter between the reference and the flood image for a pixel being retained as flooded. The second and the third step, *i.e.* region growing and change detection, are simultaneously and iteratively performed. This means that several different σ_{rg}^0 values are sequentially tested and a corresponding $\Delta\sigma^0$ is optimized for each tested σ_{rg}^0 value. At the end of each iteration, the histogram of "open water" pixels is computed and it is compared with the initially calibrated theoretical gamma curve. The parameter set (σ_{rg}^0, $\Delta\sigma^0$) providing the lowest RMSE value, computed between the histogram of "open water" pixels and the theoretical gamma curve, is set as optimal.

Since no manual and subjective input is required from the end user, the procedure enables automated, objective and repeatable flood detection. The parameters, σ_m^0 and σ_{thr}^0 only depend on the histogram shape and the gamma curve optimized on it, whereas σ_{rg}^0 and $\Delta\sigma^0$ also depend on the geographical patterns in the SAR image.

The flood mapping procedure automatically optimizes its parameters in a deterministic way for a couple of given input SAR images. However, the uncertainty stemming from the image acquisition process, affecting the actual images used as input to the flood mapping procedure, influences the parameter values. In order to take into account this uncertainty and its effect on the pixel histogram and flood mapping classification accuracy, several synthetic flood images are generated and provided as input for the procedure itself. It has to be noted that only for the flood image, synthetic images are generated, whereas the reference image is