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Towards operational SAR-based flood mapping using neuro-fuzzy texture-based approaches

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ABSTRACT

Synthetic Aperture Radar (SAR) data are currently the most reliable resource for flood monitoring, though still subject to various uncertainties, which can be objectively represented with probabilistic flood maps. Moreover, the growing number of SAR satellites has increased the likelihood of observing a flood event from space through at least a single SAR image, but generalized methods for flood classification independent of sensor characteristics need to be developed, to fully utilize these images for disaster management. Consequently, a neuro-fuzzy flood mapping technique is proposed for texture-enhanced single SAR images. Accordingly, any SAR image is first processed to generate second-order statistical textures, which are subsequently optimized using a dimensionality reduction technique. The flood and non-flood classes are then modelled within a fuzzy inference system using Gaussian curves. Parameterization is achieved by training a neural network on the image through user-defined polygons. The results of the optimized texture-based neuro-fuzzy classification were compared against the performance of the SAR image alone and that of SAR enhanced with randomly selected texture features. This approach was tested for a COSMO-SkyMed SAR image at two validation sites, for which high resolution aerial photographs were available. An overall accuracy assessment using reliability diagrams demonstrated a reduction of 54.2% in the Weighted Root Mean Squared Error (WRMSE) values compared to the stand-alone use of SAR. WRMSE values estimated for the proposed method varied from 0.027 to 0.196. A fuzzy validation exercise was also proposed to account for the uncertainty in manual flood identification from aerial photography, resulting in fuzzy spatial similarity values ranging from 0.67 to 0.92, with higher values representing better performance. Results suggest that the proposed approach has demonstrated potential to improve operational SAR-based flood mapping.

1. Introduction

Floods are widely accepted as the most ubiquitous of all natural disasters and an alarming increase in their frequency has been evident for the last few decades (Schumann et al., 2009b). The global socio-economic impacts of flooding are likely to increase as a result of climate change impacts and population growth (CRED and UNISDR, 2015). As satellite data provide a cost-effective, near real-time solution for operational flood mapping, it becomes imperative to exploit its full potential for flood management (Giustarini et al., 2016). Furthermore, satellite-derived flood extent maps can improve flood forecasting skill by allowing more accurate hydraulic model calibration and validation (Grimaldi et al., 2016; Wood et al., 2016), through direct assimilation of flood extent (Hostache et al., 2015; Lai et al., 2014) or spatially distributed water levels derived using digital elevation models (DEM) (García-Pintado et al., 2013, 2014; Giustarini et al., 2011; Hostache et al., 2009, 2010; Lai and Monnier, 2009; Mason et al., 2012; Matgen et al., 2010).

Synthetic Aperture Radar (SAR) data have proven to be the most useful for the spatial characterization of floods, due to their all-weather, all-day imaging capabilities (Smith, 1997). Inundated pixels often appear dark on SAR images, as specular reflection reflects the radar signal away from the sensor, resulting in low recorded backscatter (Hostache et al., 2009). This usually results in a high land-water contrast and so several flood mapping approaches utilize this characteristic, including but not limited to; radiometric thresholding (Hostache et al., 2006), automatic thresholding (Chini et al., 2017; Twele et al., 2016), region-growing (Boni et al., 2016), object oriented classification (Pradhan

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et al., 2016), pixel based supervised classification (Voormansik et al., 2014), and change detection (Giustarini et al., 2013; Long et al., 2014).

Most of the aforementioned approaches rely on a clear separation between land and water pixels achieved at the classification boundary, which is improbable in practice due to an overlap in the class distributions. As shown by O'Grady et al. (2014), even for images exhibiting significant class separability, > 2% of pixels will be misclassified even if the central data value is accurately identified for binarization. Furthermore, SAR images are affected by speckle noise, which causes random backscatter variations within homogeneous image features, making SAR-based classification significantly more challenging (Giustarini et al., 2015). Moreover, the SAR imaging geometry at the time of acquisition, especially the local incidence angle, substantially contributes to backscatter variability (O'Grady et al., 2013, 2014). Factors like submerged vegetation, wind or rain, which roughen open water surfaces and thus alter the backscattering behaviour, may contribute to under detection. Conversely, dark or smooth urban surfaces such as asphalt and concrete, which generate low backscatter similar to water, may lead to over detection (Martinis et al., 2015).

Given that the sources of uncertainty are numerous, stakeholders stand to benefit from a clear representation of these on the resulting flood maps. Probabilistic flood maps provide a unique opportunity for an objective characterization of the various uncertainties associated with SAR-based flood mapping. Multi-algorithm map ensembles, which indicate the possibility of inundation at each pixel, have been proposed to account for the subjectivity in the choice of an appropriate classification algorithm (Schumann et al., 2009b; Schumann and Di Baldassarre, 2010). Such maps have also proved useful for fuzzy model calibration, as the information content of SAR imagery could be extracted while accounting for observational uncertainties (Di Baldassarre et al., 2009). However, the number of ensemble members and the specific algorithms chosen for this exercise could still be subjective (Giustarini et al., 2016).

Similar to the ensemble mapping technique, Schumann et al. (2008) proposed the use of multiple equally plausible thresholds for the land-water interface. Building on this, the merit of acknowledging the uncertainty in the SAR thresholding for flood model calibration was demonstrated (Schumann et al., 2014), with the threshold varied across the whole range of plausible backscatter values to ensure objectivity and to optimize information extraction from the SAR image. Each model simulated binary flood map (water and no water) resulting from a particular parameter set was then compared to all the binary SAR-based maps generated. Although this approach is theoretically promising for model calibration, it remains a computationally intensive exercise which may be unsuitable for operational applications.

More recent studies have used the Bayesian principles of conditional probability, where each pixel is assigned a flood probability based on its backscatter value (Giustarini et al., 2016). Here the probability distributions for flood and non-flood classes were first estimated from the empirical histogram of SAR backscatter values and parameterized as a mixture of two Gaussian functions using the Levenberg–Marquardt algorithm (Marquardt, 1963). The reliability statistic used in the study exhibited a keen sensitivity to the prior probabilities assumed, though authors showed that using a prior value of 0.5 was mostly acceptable. Subsequent research on this method used a time-series of SAR data to parameterize the probability distributions (Schlaffer et al., 2017). The results showed that the varying imaging geometries, the incidence angle in particular, had a large impact on class separability. This implies that reliance on SAR backscatter alone is unable to account for uncertainties contributed by wind and rain conditions, mixed land covers, or water lookalike surfaces. However, these studies established that a reasonable probabilistic definition of flooding at each pixel was possible by modelling the backscatter distribution using some non-linear regression technique, if complementary information was available or priors were accurately estimated.

Ideally, the inclusion of ancillary datasets within this Bayesian framework could eliminate one or more sources of errors in SAR-based flood extraction (D'Addabbo et al., 2016). Integration with a detailed land cover map for example, allows differentiation between water and water lookalike regions in the SAR image (Pierdicca et al., 2008). Several approaches have been proposed for the integration of these separate information layers, from Bayesian networks (Refice et al., 2014) to fuzzy inference systems (Pulvirenti et al., 2013, 2014). A key limitation of such approaches is the assumption that suitable supporting datasets are available for the area of interest, which is often inaccurate especially for developing regions. Moreover, the present cohort of fuzzy rule-based approaches utilizes theoretical electromagnetic backscattering models for parameterization. Given that these are wavelength specific, they typically limit transferability of fuzzy approaches across the range of SAR satellites. Therefore, this study introduced a texture-based image enhancement approach to improve single image flood mapping, which can incorporate the spatial autocorrelation amongst pixel values to minimize the impact of sensor parameters.

Since texture can be derived from the SAR image, it also reduces the dependence on ancillary or complementary datasets. However, state-of-the-art texture based mapping approaches also struggle with the subjectivity in selecting application appropriate texture features, suitable window sizes, and optimal direction for identifying the feature of interest. These challenges currently significantly limit the use of texture in SAR based flood mapping (Di Baldassarre et al., 2011). Consequently, a SAR texture optimization technique is proposed in this paper to improve the utilization of texture in single image flood mapping and address these open research questions.

The optimized texture bands were considered alongside the SAR intensity image, within a neuro-fuzzy classifier to generate a fuzzy flood map. Gaussian membership functions were chosen to represent the backscatter distribution of each class, based on the image histogram as in the probabilistic mapping approaches (Giustarini et al., 2016; Schlaffer et al., 2017). However, using the neural network for a data driven parameter estimation of these membership functions removes the need for identification of suitable prior probability distributions. Training the classifier on the image to be processed, offers the additional advantage of accounting for image specific backscatter variability, caused by the reference incidence angle or wind effects.

Given a filtered SAR image, the ideal window size for texture estimation is first determined through semivariogram analysis. This is followed by an estimation of omnidirectional Grey Level Co-occurrence Matrices (GLCM) from which texture features were derived. An independent component analysis was then used to condense the maximum possible information into minimum bands, which were then added to the SAR image prior to classification. The class distributions were modelled as Gaussian functions within a fuzzy inference system, and parameterized using training data from the image itself.

The resulting maps were evaluated using aerial photographs through reliability diagrams, as well as a fuzzy validation exercise novel to flood mapping literature. The fuzzy map comparison accounts for the uncertainties in manual shoreline extraction for validation data as well. The classification performance of the SAR image with added optimized texture bands was compared against a SAR image without any texture addition and a SAR image with some randomly selected texture features added. Finally, a land-use specific analysis was conducted to assess the spatial variability of classifier performance, to facilitate an area appropriate choice of classifiers for flood mapping.

2. Study area and data

2.1. Study area

The Clarence Catchment of New South Wales, Australia, which spans an area of 22,700 km^2 was selected as the study site to test the mapping approach. Fig. 1 illustrates the geographic location of the