Change detection approaches for flood extent mapping: How to select the most adequate reference image from online archives?

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1. Introduction

In recent years the increased volume and accuracy of remote sensing data have been used to develop new hydrology-related products that support and advance flood forecasting and disaster management worldwide. Synthetic Aperture Radar (SAR) images, in particular, have become an important asset in many flood monitoring studies. Existing image-processing techniques exploit the low signal returns of active radar pulses on open water surfaces to derive flooded areas from SAR imagery (e.g.: Oberstadler et al., 1997; Townsend, 2001; Hostache et al., 2009; Martinis et al., 2011; Mason et al., 2010). Because of their all weather day–night image acquisition capability, SARs are thus the most suitable instruments for high-resolution flood mapping from space. When a flood unfolds, targeted radar observations enable the acquisition of remote sensing data when needed. By combining the data stemming from different sensors and/or from constellations of the same sensor (e.g.: COSMO SkyMed constellation) it is possible to build sequences of SAR flood images acquired during the same storm event (see, e.g. the data sets of Schumann et al., 2011; Pulvirenti et al., 2011, acquired over a single event flood hydrograph).

Moreover, for an extreme event, the International Charter Space and Major Disasters ( http://www.disasterscharter.org ) offers authorized stakeholders in flood management the possibility to request the tasking of space and associated ground resources of the member agencies’ SAR satellite missions in order to obtain a plenitude of data documenting the event.

However, there are still a number of issues that need to be addressed in order to ensure the efficient production and dissemination of flooding-related products derived from SAR data. Matgen et al. (2011) showed that change detection approaches using reference images substantially improve the accuracy of SAR-based flood delineation. When water goes over bank, abrupt changes of the backscattered signal on inundated terrain are observed (Martinis et al., 2011). Reference images that show the area under “normal conditions” are thus useful for determining changes that can be imputed to flooding (Singh, 1989). According to O’Grady et al. (2011) the ambiguity resulting from low backscatter values from non-flooded areas can be reduced via image differencing approaches. In the past, little attention has been given to the objective retrieval of the most adequate reference image. This is surprising as flood maps obtained via change detection are highly dependent on the type of reference image used. For example, Matgen et al. (2011) argue that pre-flood images need to be selected carefully for the risk of under-detecting the true extent of flooding.
to be minimized. In change detection applications, for practical reasons, the first non-flood image that is found in the archive is often used as reference, although it is not necessarily the most appropriate (Jones et al., 2009). For each flood image, O’Grady et al. (2011) selected the latest available image covering all the azimuth extent of the area of interest and occurring prior to the beginning of the flood event. While these somewhat pragmatic approaches might be appropriate as long as the amount of sample images acquired over a given area of interest is relatively limited, the progressive built-up of increasingly large archives of SAR imagery acquired over the last two decades has paved the way for more enhanced methods. Such online databases of SAR imagery are nowadays accessible online and can be rapidly exploited for flood monitoring applications (e.g. the European Space Agency’s G-POD Faire application, http://gpod.eo.esa.int/). Hence, new opportunities have emerged for selecting reference SAR images for flood mapping applications more objectively and more reliably (Jones et al., 2009), thereby potentially enabling an improvement in SAR-based flood mapping.

Due to the high variability of backscattering values over a given region of interest as a result of different factors, namely the atmospheric forcing (e.g. precipitation, evaporation, transpiration, wind), the acquisition characteristics (e.g. wavelength, polarization, incidence angle), the soil–water redistribution processes related to terrain, soil and vegetation characteristics (e.g. changes of river channel courses), the yearly vegetation cycle and land use changes (Ulaby and Dobson, 1989; Singh, 1989; Lunetta et al., 2004) the task of selecting a reference image is far from being trivial. Numerous definitions of the term “reference image” are in fact possible and depending on what is considered as a good reference, contrasting results might be obtained in a flood mapping exercise. In a related topic, the tracking of soil moisture dynamics using change detection methods, the historically “driest” image is normally used as the reference image (Moran et al., 2000). Wagner et al. (1999) and Pathe et al. (2009) apply this type of approach for retrieving soil wetness indexes from historical time series of coarse resolution scatterometer and ScanSAR measurements. Their method is based on the scaling of backscattering coefficients between dry and wet reference values which can be extracted from long historic time series. A similar approach may in principle be applied to SAR-based flood mapping applications but given the fact that for water bodies mapping it is fundamental to work at the highest possible resolution (while for soil moisture also measurements with a spatial resolution of 1 km or lower are sufficient for many applications (Bartalis et al., 2007)) the costs involved in reprocessing long time series become problematic, particularly if larger regions or the whole global land surface is considered. Therefore, another more cost-economic option is to statistically analyse the backscattering behaviour of a limited selection of historic SAR images over a given spatial and temporal domain and to consider the most “normal” image as the best reference for flood detection.

Geared towards a more accurate delineation of flooded area using change detection techniques, the main objective of this study is to introduce a methodology for the automatic and objective identification of reference SAR images. The underlying research questions are focused on a better understanding of the spatio-temporal variability of radar backscattering values in relation to floods and the characterization of this variability via anomaly indexes. The proposed methodology will be evaluated in three case studies in contrasting climatic regions. More broadly, the paper intends initiating a discussion on what is the most adequate reference image for flood mapping.

2. Method

This section proposes a method for retrieving from an online archive the most adequate reference image for the delineation of flooded areas. To support the selection procedure, we propose several processing steps. First, a number of guidelines are formulated for identifying a priori candidate images. Next the sample is analysed in order to establish a characteristic backscattering profile for a given area of interest. Based on the highlighted backscattering statistics, two anomaly indexes are assigned to all candidate images in order to identify the best reference image. The proposed methodology includes the following processing steps: (i) sample collection: identification of candidate images, (ii) anomaly index1 expressing the likelihood of flooding on candidate image, and (iii) anomaly index2 expressing the statistical representativeness of the backscatter distribution inferred from candidate image. Optionally, we propose to compute an additional anomaly index3 that is a combination of index1 and index2. The index computation does not make use of the flood image. The imaging properties of the flood image only condition the imaging characteristics of the candidate images.

2.1. Sample collection

The collection of a representative image sample is the first step of the analysis. The acquisition characteristics of the crisis image condition the composition of the sample. It is therefore necessary to establish and follow a standardized protocol in order to minimize backscatter variability that is unrelated to flooding. For example, if two SAR images are acquired from different satellite tracks, the difference of pixel backscatter between these two images is also due to a difference in incidence angles (Ulaby and Dobson, 1989). Although backscatter normalization with respect to the incidence angle could be applied as proposed in Bartalis et al. (2007) for coarse resolution microwave remote sensing imagery, in high and very high resolution SAR imagery typically used for flood mapping the geometric distortions caused by differences in incidence angles significantly complicate the detection of changes caused by flooding. Similarly, if two images have been acquired with different polarizations, the difference of pixel backscatter between these two images is likely dominated by the difference in polarization (Ulaby and Dobson, 1989). Thus, if two images stemming from various polarizations and/or satellite tracks are used for change detection, it becomes difficult to determine whether detected changes have their origin in a flood or if they result from differences related to the imaging properties. Consequently, we propose to select as a priori candidates all images acquired from the same track and with the same polarization as the considered flood image. It is worth noting that we assume here that the equality of tracks implies an identical local incidence angle. If this assumption becomes erroneous, then the candidate images might have the same local incidence angle than the flood image. Moreover, in some regions of the world with season-dependent flooding (e.g. rainy season in tropical regions), it could be necessary to select as candidates only images acquired in the same period of the year as the crisis image.

Hence, images have to satisfy some preliminary conditions before being inserted into the image sample: they have to be acquired (i) with the same sensor and imaging mode as the flood image, (ii) from the same track as the flood image, (iii) with the same polarization as the flood image, and (iv) in the same period of year as the flood image (optional). The last requirement is optional, as the size of the associated time window would need to be determined separately for each individual area of interest. Often additional data are not available for limiting the statistical analysis on specific time periods. It is also important to note that in order to have a large and unbiased sample it is of paramount importance to systematically acquire imagery over all parts of the Earth’s surface and not only opportunistically in the event of a disaster.
2.2. Sample analysis

Once collected, the samples are statistically analysed. The main concept is that past observations enable the computation of site-specific backscattering profiles. The specular reflection of microwaves on inundated terrain with limited wind leads to a very low signal return (i.e. low backscattering coefficients) (Ulaby and Dobson, 1989). Consequently, a flood image contains an exceptionally high number of pixels with very low backscatter values. Moreover, in the event of a flood, soils are in general wet and often close to saturation. The increase of the soil dielectric constant with increasing water content leads to an enhanced signal return (Lievens et al., 2010). Consequently, flood images often exhibit an increased number of pixels with high backscatter values unless the inundation does not occur over the area where it rained (e.g. floods in arid regions) or the surrounding soils were already saturated prior to the flooding (e.g. floods in tropical regions). Moreover, it is important to avoid selecting a wind-affected SAR image as reference image. This could lead to a significant under-detection of the actual flooding extent. Since the PDF of such an image is expected to be markedly different to the median one, we propose an anomaly index that significantly reduces this risk. Moreover, the impact of wind among other phenomena illustrates the necessity to combine two anomaly indexes in order to detect good reference images.

Therefore, a first anomaly index should express an image’s spread in the distribution of backscattering values. There is a high likelihood that images exhibiting an irregularly large spread are affected by flooding. The proposed index expresses the distance between the 5% and 95% percentiles inferred from the image histogram. The 5% (resp. 95%) percentile is the backscatter value below which 5% (resp. 95%) of the observations are to be found. It has to be noted that permanent water bodies need to be masked out a priori in order to reduce their impact on the low percentiles of the distribution of backscattering coefficients. Moreover, the masking of permanent water bodies can significantly reduce the well-known problem of high backscatter due to waves caused by wind over large water bodies. Different approaches for detecting permanent open water surfaces have been introduced in the literature (e.g. Bartsch et al. (2008)). It is important that after the masking procedure less than 5% of the pixels correspond to permanent water bodies. Index1 is defined as follows:

\[ \text{index}_1(i) = P_{5\%} - P_{95\%}, \]

where \( P_{5\%} \) and \( P_{95\%} \) are, respectively, the 5% and 95% percentiles of the backscattering values of the candidate image \( i \). Index1 is rescaled between 0 and 1 in order to render its interpretation more easily transferable from one test case to another. A second anomaly index2 evaluates the degree to which the backscatter distribution inferred from one image reflects the backscattering behaviour inferred from the full sample. The main idea here is that a reference image for flood detection is required to have a statistical distribution of backscatter values that closely follows the median distribution inferred from a representative sample of candidate images. Anomaly index2 quantifies the distance between the backscatter statistical distribution of a candidate image and the median backscatter statistical distribution over the sample of candidates (see Eq. (2)).

\[ \text{index}_2(i) = \left| \bar{f} - f(i) \right| \]

The empirical distribution \( f \) corresponds to the distribution of backscattering values of any given image \( i \). The reference distribution \( \bar{f} \) is the median backscattering distribution. It is obtained from the full sample of SAR images by first calculating the median backscattering values for each pixel over the whole image sample and next arranging all the median backscattering values from lowest value to highest value. The median is used instead of the mean because it is less influenced by extreme values and outliers, the latter being potentially caused by measurement errors. The median backscatter distribution represents a reference distribution that is in most regions not strongly affected by flood pixels characterized by very low backscattering values. Like index1, index2 is rescaled between 0 and 1.

Depending on the kind of reference image that is targeted, index1 or index2 might be preferable. If the reference image is supposed to be the “driest” image in the sample, the image with the lowest index1 value might be selected as the most adequate one. If, on the other hand, the reference image is expected to represent a median backscatter behaviour the image with the lowest index2 might be the best choice. Here it is worth noting that the image with the lowest index2 may potentially represent a flood.

A compromise solution would be to identify the best reference image within the candidate list by combining the anomaly indexes 1 and 2, as follows:

\[ \text{index}_3(i) = \sqrt{\text{index}_1^2(i) + \text{index}_2^2(i)} \]

While it is helpful to first consider the two anomaly indexes separately, the best reference image for flood mapping applications may arguably be the candidate image having the lowest index3 value. A value close to 0 is assigned to an image that is comparatively dry and representative for an area’s normal backscattering behaviour.

3. Results

3.1. Study areas and image sample collection

The proposed method was tested and evaluated using three case studies: the Severn River (UK), the Red River (ND, USA) and the Meghna River (Bangladesh). These test sites have been chosen because they are characterized by markedly different climatologies and flooding mechanisms, thereby enabling a preliminary evaluation of the potential applicability of the method at global scale. The three selected river systems are representative for, respectively, humid temperate (Severn River), humid continental (Red River) and subtropical monsoon (Meghna River) climates.

The sample collection is considerably facilitated by logging into the customized version of the European Space Agency’s GPD FAIRE 2.0 (see http://gpd.eo.esa.int/) application. This customized version of GPD, which was developed in the framework of this study, is hosting an import filter enabling the retrieval, from the GPD’s rolling archive, of all ENVISAT images acquired with the same imaging mode, the same polarization, from the same track and at the same period of the year as a pre-selected crisis (i.e. flood) image. The SAROTEC customisation of FAIRE 2.0 is an automatic procedure. The user only needs to define the coordinates of the AOI and to select the crisis image from the archive. The tool further enables the calibration and co-registration of all selected images and the publication of the results on a FTP server from where the data can be accessed by users. Note that in our case studies we did not make use of the possibility offered by GPD to restrict the statistical analysis to specific time periods. This is because the number of sample images acquired in Wide Swath Mode satisfying the main selection criteria is still rather low.

Once the sample collection was concluded, a visual check of each candidate image was carried out. The objective of this preliminary check was to determine whether a flooding is visible on the sample or not and to provide a possible explanation for the observed backscatter distribution. This interpretation further allowed describing the magnitude of flooding (here defined by an indexing value ranging between 0 and 4). A magnitude of flood equal to 4 indicates the maximum flood extent that was observed.
in the full sample, and a value of 0 indicates the absence of flooded areas on the candidate image. The flags assigned to the SAR images included in an area’s sample are useful for evaluating the outcome of the automatic procedures outlined in Section 2.

The next sections present the application of the proposed methodology in three flood prone sub-reaches of the Severn, Red and Meghna rivers.

3.2. Severn River

On July 23, 2007 an ENVISAT Advanced SAR Wide Swath Mode image was acquired during a one-in-150-year flood that took place on the lower Severn around the city of Tewkesbury. Potential reference images for flooding-related change detection were retrieved from the online archive using as selection criteria the imaging characteristics of this crisis image. Fig. 1 illustrates the samples that have been extracted and pre-processed using the customized version of GPOD FAIRE 2.0. All candidate images have been acquired from track 144 in Wide Swath Mode and VV polarization. From Fig. 1 it is clear that SAR images acquired on 08Mar07, 26Jul07 and 17Jan08 exhibit large scale river inundation. The presence of flooding on these three images can be linked to the quasi-bimodal shape of the candidate image histograms shown in Fig. 2. The images exhibiting flooding are easily identifiable due to the lower tail ends on the corresponding histograms, while the histograms of no-flood images are generally uni-modal. The increase in spread and skewness as a result of the higher frequencies of low backscattering values (due to flooding) and high backscattering values (due to increased soil moisture) can be observed. This result illustrates that the range of backscatter values in flood image histograms is typically larger than in no-flood images. At first sight the higher frequencies of high backscatter values in the flood images are not obvious from the histograms of Fig. 2. However, when having a closer look at this figure, one can observe that for the 17Jan2008 flood image, for instance, the frequency of high backscatter (around −5 dB) is significantly higher than for the other images. We argue that this is due to an increase of soil moisture in the surrounding areas. However, it is possible that a flood occurs in an otherwise dry area, for example when runoff was generated by rainfall that fell in the upper parts of a river basin. In this case one can expect that there would be no increase of the higher percentiles. It remains to be seen if the expected decrease of the lower percentiles would still separate the flood image from all other no-flood images included in the sample.

Fig. 5a shows index1 values calculated for each image included in the sample. In Fig. 5, the three different columns refer to the three different test cases whereas the three different lines refer to the three different anomaly indices. The colour and label of each point indicate the magnitude of flooding obtained through visual analyses, with values ranging between 0 and 4.

When looking at Figs. 1 and 5a, one can see that, generally speaking, the higher the value of index1, the larger the flood extent on the corresponding candidate image. This highlights the capability of index1 to discriminate between flood and no-flood images. Fig. 5b illustrates that the image with the lowest anomaly index2 (i.e. 12Mar09) has also the lowest index1 value. This result shows that the most representative image over the sample is a non-flood image. On the right column, Fig. 5c shows the combined anomaly index3 values.

3.3. Red River

Candidate images for the Red River case study are presented in Fig. 3. These stem from track 69 and were acquired in Wide Swath Mode (WSM) and VV polarization, which are the imaging characteristics of the crisis image acquired on 27Mar10. The extraordinary magnitude of flooding is underlined by the fact that, besides the crisis image, no other image exhibits significant flooding. Fig. 5d–f indicates the anomaly indexes obtained for the Red River test case. Fig. 5d demonstrates a good capability of index3 for identifying images with large scale flooding. However, images exhibiting low magnitude flooding (red dots) cannot be easily separated from no flood images (black dots). This can be explained by the fact that surface water influences the backscattering characteristics of a comparatively small fraction of the image, thereby not significantly impacting the anomaly index1. In Fig. 5e, the image that appears as the most representative in terms of backscatter statistical distribution does not exhibit significant flooding. Moreover, it is worth noting that the 16Jan2010 image has the highest index3 value and does not exhibit any flooding. On this image we observe a strong contrast between the riparian zone exhibiting high backscatter values and the surrounding farmland outlined in dark colours. This high index3 value is probably due to snow cover on the image that renders the backscatter distribution on this image atypical. Snow cover and also freeze imply low signal returns, which could be mistakenly associated with flooding. This highlights a strong variability of the backscatter on the different candidate images. Finally Fig. 5f shows that the best reference image proposed by index3 is actually exempt of flooding.

3.4. Meghna River

Candidate images for the Meghna River test case are presented in Fig. 4. All samples stem from track 90 and have been acquired in Wide Swath Mode (WSM) with VV polarization. It is worth noting that a significant number of images exhibit very large scale flooding (i.e.: 3 images out of eight candidates). In Fig. 5g–i anomaly indexes are assigned to all images obtained in the framework of the Meghna River case study. The capability of index3 to allow the
discrimination of large-scale flood images is further confirmed in Fig. 5g. In Fig. 5h one can notice that the backscatter distribution of one of the relatively dry candidate images, namely the 14May07 image, deviates from the median backscatter distribution calculated over the whole candidate sample. This result confirms that in some regions that are prone to flooding, a dry situation may appear as exceptional from a statistical point of view. Moreover, the candidate with the most representative backscatter
distribution corresponds to a flood image (see Fig. 5h). This result reflects the high number of flood images in the sample. The Meghna River test site is interesting because its results mean that in some particular hydrological regimes the regular presence of surface water on large fractions of the area of interest may indeed dominate the median behaviour of backscatter. Fig. 5i shows that index\textsubscript{3} is a good compromise between representativeness and absence of flooding since it selects the 18Feb08 image as reference image.

4. Discussion

4.1. Insights from three case studies

In three case studies index\textsubscript{1} proofed to be a powerful discriminator between flood and no-flood images. Anomaly index\textsubscript{1} may thus be used to automatically flag all flood images that are included in the archive. In an operational context this kind of index could be used for rapidly evaluating the likelihood of flooding on newly
acquired imagery and for issuing timely flood warnings if critical thresholds are exceeded.

Anomaly index3 aims at identifying images with backscatter distributions that are representative for a given area of interest. However, in this particular context, the idea of statistical representativeness is debatable and different conflicting interpretations are possible. In our study, we consider as representative a backscatter distribution that closely follows the median distribution calculated over a sample of candidate images. However, the median is clearly influenced by the number of images included in the sample and more specifically by the composition of the image sample. For instance, a sample may not reflect the true backscatter-sampling behaviour of a region due to an exceedingly large number of flood images included in the sample. In fact, it is important to bear in mind that the number of flood images obtained as part of emergency acquisitions can potentially generate a biased sample composition. Moreover the Meghna River test case highlights that the choice of an adequate reference image is conditioned by a region’s climatology. During the rainy monsoon season from June to October a flood-exhibiting image might be the most representative. As a matter of fact, for regions of the world having strong seasonal climate variability, it is important to consider in what period of the year an image was acquired. In other words, in such areas, it might be necessary to limit the application of flooding-related change detection approaches to images acquired in the same period of the year.

The backscatter signature of the flood image is not considered. For the selection of the most adequate reference image, we believe that permanent water bodies are rather irrelevant as they impact the statistics of all images in a similar way. However, the subsequent flood mapping approach first extracts all permanent water bodies from the selected reference image and removes the corresponding pixels from the flood map (see Matgen et al., 2011).

Furthermore, in all three case studies, index3, which is computed as the combination of the two first anomaly indexes, appears to be a robust tool for determining the most adequate reference image for flood detection. Hence, we advocate its use for automatically flagging potential reference images included in a SAR archive. We hypothesize that the image with the lowest anomaly index3 is the most adequate reference image. This hypothesis obviously needs to be verified and validated. As a preliminary analysis of the assumption’s validity, we carried out a sensitivity analysis for the Severn River case test case.

4.2. Sensitivity analysis

The aim of the sensitivity analysis proposed here is to evaluate if a reference image with an associated lower value of index3 indeed leads to a higher classification accuracy. The Severn River flood in late July 2007 was not only observed from the ENVISAT platform as mentioned earlier but also by the high resolution SAR on-board TerraSAR-X satellite. The TerraSAR-X image (July 25, 2007) was acquired 39 h before the ENVISAT WSM image flood image (July 26, 2007). It is important to note that the flood extent did not change significantly between the two image acquisitions (Schumann et al., 2011). The spatial resolution of the TerraSAR-X image is 3 m, which means that the spatial resolutions of the two images differ by a factor of 50. As a matter of fact, we consider the flood extent derived from the TerraSAR-X image as the benchmark against which the flooded areas obtained from multiple combinations of flood and reference ENVISAT images are evaluated. Matgen et al. (2011) proposed a method for flood mapping using SAR images that is based on a sequence of backscatter thresholding, region growing and change detection processes. Reference images are used to eliminate from the flood maps those regions that produce a permanent flood-like radar response (e.g. permanent water bodies, smooth tarmac, shadow areas or dry sand deposits), thereby potentially reducing the risk of significantly over-detecting the amount of flooding. The method has been applied on the TerraSAR-X image using a post-flood reference image acquisition on July 22, 2008 from the same orbit track and with the same polarization. The method is also applied on the ENVISAT WSM crisis image from July 26 and using as reference images the different images introduced in Section 3.2. Fig. 6 shows the relationship between the reference images’ index3 values and the accuracy of the resulting flood extent maps. The latter is expressed as the percentage of correctly classified pixels (with respect to the number of pixels in one candidate image). It can be clearly observed in Fig. 6 that images with associated low index3 values provide better accuracies. Furthermore it can be noted that the image with the lowest index3 provides one of the best classification accuracies, as hypothesized previously. In light of the results shown in Fig. 6 it can be concluded that several reference images give a comparable classification accuracy. Only the use of reference images exhibiting themselves large scale flooding leads to a significant drop in performance. This result seems to indicate that it is crucial not to select a flood image as reference image. Even though this result clearly needs to be confirmed in additional case studies, we would argue that the proposed anomaly indexes do provide some certainty for the selection of an adequate reference image.

Moreover, there are multiple potential uses of these indexes, the most obvious one being the selection of the most appropriate reference image for change detection-based flood mapping. With respect to the presented anomaly index3, we could further imagine that this index can be used to identify flood images in an image archive or to issue flood alert warnings if critical thresholds are exceeded on recently acquired images. One possible exploitation of this could be to flag new images as “flood images” if their associated index3 value is high. Moreover, in both cases, the exceeding of a threshold could be used to automatically run a flood extent extraction algorithm. Consequently, the presented anomaly indexes could be used to build time series of flood extent data from historical and recent SAR images.

5. Conclusion

In flood management applications, an efficient processing of SAR images is required in order to shorten the time delay between
the image acquisition and the extraction and dissemination of flooding-related information. Flood delineation algorithms based on change detection are an important asset in such remote sensing-based flood monitoring systems, however, little attention has been given on how to select an adequate reference image for flood detection. In this study, a method was introduced enabling the reliable retrieval of reference images from online SAR image archives.

The sample includes all images acquired with the same polarization, from the same track and, if necessary, in the same period of year. The method consists of the systematic flagging of SAR images with anomaly indexes resulting from the statistical analysis of regional time series of backscattering values. An anomaly is here defined as (i) an increase of the spread of the distribution of backscatter values and as (ii) the deviation from an established trend. The proposed anomaly index $I_3$ expresses the distance between the 5% and 95% percentiles. The proposed anomaly index $I_3$ is a form of distance measurement between an empirical distribution function and a reference distribution function. The reference distribution is the distribution of the median backscattering values inferred from the full sample. To identify the optimal reference image, one approach could be to use anomaly index $I_3$, which integrates the complementary information provided by the anomaly indexes 1 and 2. We hypothesize that the SAR image with the lowest combined anomaly index $I_3$ is the most adequate reference image for flooding-related change detection application. However, in some regions the individual use of anomaly indexes 1 and 2 yields very similar orders of preference, with the additional advantage of a more straightforward scientific interpretation.

The proposed method was tested and evaluated in three case studies: the Severn River (UK), the Red River (USA) and the Meghna River (Bangladesh). The three areas of interest are characterized by markedly different climatologies and flooding mechanisms. In each trial case, the proposed approach reliably detected all flood images and extracted adequate reference images from an online archive of ENVISAT ASAR WSM images. However, the case studies also revealed a need for building several layers of security in order to avoid wrong flaggings caused by backscatter variations that are not due to flooding (e.g. measurement errors, impact of snow cover, freeze, irrigation and other). Moreover, the proposed approach, if implemented on high performance computing systems such as the European Space Agency’s Grid Processing On Demand (GPOD) environment, ensures a very efficient processing of SAR imagery. The results of this study are timely, because recent and upcoming SAR missions provide an unprecedented volume of data for flood monitoring applications.

At the moment, the low temporal resolution is a serious limitation of any systematic SAR-based flood monitoring system. However, the short-term target of our R&D activities is the flooding-related exploitation of data generated by the upcoming ESA SENTINEL-1 SAR mission. Today’s SAR instruments are typically able to acquire backscatter imagery in a large number of imaging modes. This has led to a quasi arbitrary coverage of the global land surface area in the different modes during different times. This has clearly been a significant hurdle to the operational use of the data. The Sentinel-1 satellites will be operated following a predefined and fixed acquisition scenario. The two planned Sentinel-1 SAR instruments will provide complete coverage over Europe and Canada within about 2 days and of all global land surface areas within less than 6–8 days. Moreover, in the event of an extraordinary emergency situation (e.g. large scale flooding), the Sentinel-1 SAR allows reacting to special requests by authorized users. Both features will help to develop systematic and automatic SAR-based flood monitoring systems. In this context, we believe that the approach presented in the submitted manuscript can be an important asset.

First results of a sensitivity study indicate how the selection of a reference image impacts the results in SAR-based flood delineation using change detection techniques. It appears that the choice of a reference image has a significant impact on the classification accuracy of the obtained flood maps, with reference images exhibiting flooding themselves yielding markedly less accurate flood inundation maps. Some problems remain for SAR-based flood detection, that cannot be addressed via change detection approaches. For example, in areas where the vegetation is dense or in areas affected by double-bounce the inundation cannot be easily retrieved.

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