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Flood extent delineation using Sentinel-1 data as information source: systematic review of processing methods

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ABSTRACT

Delineating the flood extent using SAR data has been an unexceptional activity since the launch of the first sensors. The methodologies applied to image classification vary in complexity and accuracy and, for Sentinel-1, the technical procedures must be adapted considering their polarization, band, temporal resolution, and other factors. Considering these aspects, this article aimed to realize a systematic literature review discussing the most frequent methodologies applied to flood mapping classification employing Sentinel-1 data; describe the preferred methods by areas of expertise; and, inform about their accuracy level. Results indicate that thresholding is the most common methodologies used to flood delineation whatsoever is the researcher area of work. Excellent accuracy levels (reaching 99%) can be obtained using thresholding as the major method, with refinement provided by additional procedures to correct limitations and misclassification. The Sentinel-1data is a good source of information to realize classification in flooded areas but has its limitations in small areas. The choice of methodology for processing SAR data is subjective and requires specific knowledge in the remote sensing field from who executes a hydrological study.

Keywords: Flood mapping, thresholding, synthetic aperture radar, remote sensing.

Delineamento de extensão de inundação usando dados Sentinel-1 como fonte de informação: revisão sistemática dos métodos de processamento

RESUMO

Delinear a extensão da inundação usando dados SAR tem sido uma atividade comum desde o lançamento dos primeiros sensores. As metodologias aplicadas à classificação de imagens variam em complexidade e precisão e, para o satélite Sentinel-1, os procedimentos técnicos devem ser adaptados considerando sua polarização, banda, resolução temporal, entre outros fatores. Considerando esses aspectos, este artigo teve como objetivo realizar uma revisão sistemática de literatura discutindo as metodologias frequentemente aplicadas à classificação do mapeamento de inundações empregando dados do Sentinel-1; descrever os métodos preferidos por áreas de especialização do analista; e, informar sobre seu nível de precisão. Os resultados indicam que a limiarização é a metodologia mais comum utilizada para o delineamento de inundação, seja qual for a área de trabalho do pesquisador. Excelentes níveis de precisão (cerca de 99%) podem ser obtidos usando a limiarização como o método principal, com refinamento fornecido por procedimentos adicionais para corrigir limitações e erros de classificação. Os dados do Sentinel-1 são uma boa fonte de informação para realizar a classificação em áreas inundadas, mas têm suas limitações em áreas pequenas. A escolha da metodologia para o processamento de dados SAR revela-se subjetiva, inerente ao campo de estudo do pesquisador, e requer conhecimento específico na área de sensoriamento remoto de quem executa um estudo hidrológico.

Palavras-chave: Mapeamento de inundação, limiarização, radar de abertura sintética, sensoriamento remoto.

Introduction

Due to their increase in the last decades, floods have become a major concern in most part of the developed and developing countries. According to the last report from the Centre for Research on the Epidemiology of Disasters (CRED) from EM-DAT, in the period of 2006-2015, hydrological disasters took the largest part of occurrences in world, with approximately 50.5%. Hydrological disasters, a group that contain flood events, landslides, and wave action, remain ahead of the meteorological, climatological, and geophysical disasters podium (Guha-Sapir et al., 2016). Exemplifying with literature, large floods have been measured in countries as China (Tsyganskaya et al., 2018; Wan et al., 2019; Qiu et al., 2021); Pakistan (Zhang et al., 2020); Bangladesh (Uddin et al., 2019; Hassan et al., 2020); Vietnam (Phan et al., 2019), and many others. These data corroborate with studies which indicate that, besides the USA, developing countries like China, India, Indonesia, Vietnam, and others have the most frequently hit by disasters, with flood being the first cause of disaster deaths (Guha-Sapir et al., 2016).

For the affected countries, there is an intrinsic importance in the flood mapping and monitoring earlier than the flood mitigation and flood prevention (Qiu et al., 2021). In the urban planning field of knowledge, the evaluation of the potential flood through maps represents the basis for land planning and policy decision oriented towards the best local uses (Ruzza et al., 2019). Flood mapping can be done with field data supported by mathematical models and geomatic. In both cases, the remote information obtained via satellite data represents a good complementary source to in-situ and ancillary data conceived as ground truth. When used jointly, they can provide information in historical retrospectives, feed hydrological and climate models, contribute to the creation of local inventories, and retrieve information to support flood management, emergency response and designing emergency plans (Perrou et al., 2018; Elkhrachy et al., 2021).

During the occurrence of floods, the fieldwork for mapping and obtaining correct information must be done immediately after the event (Paixão et al., 2018; Uddin et al., 2019; Elhag and Abdurahman, 2020). This task is very dangerous because collecting hydrological information in the field, such as river velocity, discharge, and maximum depth, requires technical teams at inaccessible locations (Alves, et al., 2020; Moya et al., 2020) and many urban systems may be inaccessible due to the damage in telecommunication and transportation facilities (Agnihotri et al., 2019). In this condition, the use of images acquired by remote sensing becomes an important tool for retrieving information, that is difficult to access in the field, in order to calibrate or validate flood models without direct contact with the flooded area (Ouled Sghaier et al., 2018; Zotou et al., 2020).

To help with remote flood measurements, radar data have been used for decades. The number of satellites that contain microwave sensors has increased greatly, which has allowed the expansion of studies in watersheds that are poorly monitored and the improvement of flood mapping techniques. However, the availability of sensors that cover the entire Earth's surface with images in high resolution quality and with frequent revisiting is still low. When both factors are available, the gratuity of images is a rare factor, which can make it difficult to analyze some locations (Agnihotri et al., 2019). Nevertheless, middle or low-income countries have an interest in radar mapping techniques with low or no cost, with automated processing chains and easy-to-use techniques. To fill this gap, the Sentinel-1 series of sensors are responsible for the collection of surface data with a high to medium spatial and temporal resolution (Agnihotri, 2019). These images are free of charge and can be used in flood mapping around the world due to the almost entirely surface cover.

The Sentinel-1 is a mission promoted by the European Space Agency (ESA) in the Copernicus Programme to form a constellation of satellites that offers free SAR images from the entire globe in a revisit frequency of 6 days. The first satellite was launched in 2014 (Sentinel-1A) and the second was launched in 2016 (Sentinel-1B), equipped with a C-band sensor (Cao et al., 2017; Carreño Conde and De Mata Muñoz, 2019).

A great range of processing methods can be applied to SAR data in order to extract the flood extent, but there are some factors that need to be considered when analyzing the results provided. Polarizations, wavelength, spatial and temporal resolution, are examples of very important variables to examine when one chooses the target under study. For instance, Di Baldassarre et al. (2009) applied five different techniques to separate the maximum possible inundation with SAR data: visual interpretation, histogram threshold, active contour, image texture variance and Euclidean distance. Sentinel-1 images were not available at the time, instead Envisat ASAR and ERS-2 SAR images were used for sensitivity analysis maps of the LISFLOOD-FP hydrodynamic model.

Zhang et al. (2020) indicate that the most common SAR-based techniques used to extract the flood extent are thresholding methods, image segmentation, statistical active contouring, rule-based classification and data-fusion procedures (Melkamu et al., 2022). Among these methods, the most successful methodology mentioned is the threshold-based delineation (Wan et al., 2019). Cian et al. (2018) have made a review on the literature in flood mapping since the year 2000, describing the satellite/sensor used, the study site, the method employed, and the key results. The most used method is thresholding with the addition of other refinement methods. There is not a specific focus on Sentinel-1 articles because the launching date of this satellite is relatively recent.

Taking into consideration the great amplitude of methodologies found in the literature for SAR data, only a few recent articles are presenting the methodologies specifically destined to the freely available Sentinel-1 images, in the light of their peculiarities like polarization, frequency, band, spatial resolution and imaging mode, for example. The study aimed to conduct a systematic review on the use of radar images from Sentinel-1 (S1) in flood mapping worldwide, focusing on the primary objectives: (a) describe what are the most frequent techniques employed during the image processing to distinguish water from other features; (b) verify if there is a group of techniques preferred by some studying areas, i.e., hydrologists and geoscientists; and (c) indicate the techniques that can be used considering the classification accuracy level desired.

The research questions that undergo this study are:

1. Which are the recurrent methodologies (including the simplest to the most advanced) employed in the processing of Sentinel-1 images alone when delineating the flood extent area?

2. There are preferences in the types of methods chosen for the flood mapping when the analyst's area changes? (this is a specific aspect of the analysis that was never found, in the best of our knowledge, under discussion in the literature).

The final task is to evidence between the reviewed methods, their easy applicability to the free Sentinel-1 images, and delineate the balance between the accuracy obtained and the difficulty implementing. The Development section is organized by titles as follows: the first part describes the method and the rationale used to realize the systematic review; the following section describes the first results found through a rapid bibliometric analysis; the third section discusses the necessity or nor for the implementation of the pre-processing step in Sentinel-1 methodologies; and the next section, presented the most relevant methodology used to process Sentinel-1 images, and gives a glimpse of the tendencies of research in hydrological field of work; the last section concludes the findings in this article.

Development

Methodology of systematic review employed

A systematic review of the peer-reviewed literature concerning the use of Sentinel-1 radar images to map flooding was realized. A research process was carried out utilizing the methodology described in the PRISMA 2020 document (Page et al., 2020).

PRISMA is a specific method for a systematic review that describes a fixed procedure for developing the collection of articles and how to analyze them. It allows reproducibility of the research and reduces bias during the sequence of screening and eligibility. In this case, generally, the author analyses the literature without collecting field data or describing original or primary data.

The analysis was conducted following the research questions, clearly formulated prior to the database search. The articles were identified through search in CAPES database that includes approximately 294 databases that contain journals, theses, dissertations, open files and patents. The CAPES system allows the researcher to carry out unlimited searches, with several constructions of keywords and save them in a specific space identified by an individual access login. It is possible to store all articles and publications with date and time of access, identifying them for later consultation.

The research was carried out during the months of June and July 2021 through a detailed article evaluation procedure, seeking to reduce possible bias and loss of relevant information. The search string “Sentinel-1” AND “flood” OR “flooding” was used to retrieve all the articles present in the database that would include these keywords, even if they were only in the article’s reference as a cited paper title or had been used in the text without being the main subject of the paper but as an example. The main objective was to capture most of the available articles containing the chosen keywords, so the screening and identification steps were more demanding.

The grey literature and articles present on annals or proceedings from events, even the peer-reviewed, were excluded. Only articles published in journals and described as research or original papers were considered in the first selection (identification stage), which excluded the category of review articles with tangent themes also.

The searching procedure considered only the period of 2014 to 2021, to include the year that Sentinel-1 have been launched into space and the following years in activity till the recent day. The list of items used to select articles during the *screening step* are described in

Table 1.

Table 1 – Main criteria applied to papers in the screening step of the assessment.

Criteria	Rationale
The methodology should be applied preferably on the Sentinel-1 images.	There are other SAR images obtained from diverse sensors, that differ from the Sentinel-1 in terms of polarization, temporal resolution, spatial resolution, among other factors.
The context of the article should be focused mainly in the flood extent mapping (water target).	There are a great number of methodologies that can be applied to SAR images, but the object of interest in the image must be defined in advance because every target has different behavior and requires specific processing methods.
The methodology should be described in detail.	There are articles that use the methodologies to observe factors other than the image processing, like damage analysis, water body measurements outside the flood event, reservoirs limit calculations, etc.

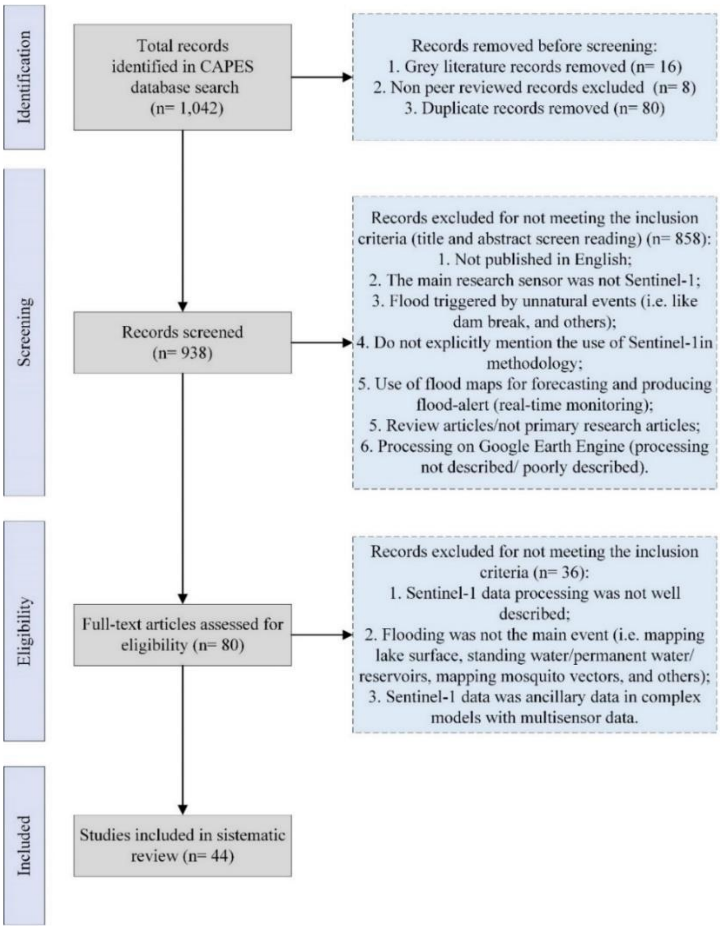

Figure 1 – The PRISMA diagram constructed to show the four phases conducted throughout the systematic review.

The *Identification* step is the simplest of all, and consists of performing the initial inspection of possible articles based on keyword research. The *Screening* step consisted in the reading of all of the titles and the complete abstracts of the total records identified in the database. In this case, most part of the articles were excluded for not being inside the main criteria explained in Table 1.

Other reasons for exclusion in this step can be identified in the PRISMA diagram (Figure 1). *Eligibility* step included a new reading of titles, abstracts, and complete introduction and conclusion. The articles were not read entirely in this occasion because the detailed information stand in methodology, which are the longest part in research articles and focus of the next step. At last, the *Included* articles (n=44) were read in the full content, in order that the methodology could be analyzed in depth. Figure 1 presents in the blue dashed boxes the reasons to exclude the articles under review.

Rapid bibliometric analysis

The first part of the systematic review was conducted through a rapid bibliometric analysis with help of R environment through the *Biblioshiny* package, specifically made for quantifying information about the articles under evaluation (Aria and Cuccurullo, 2017).

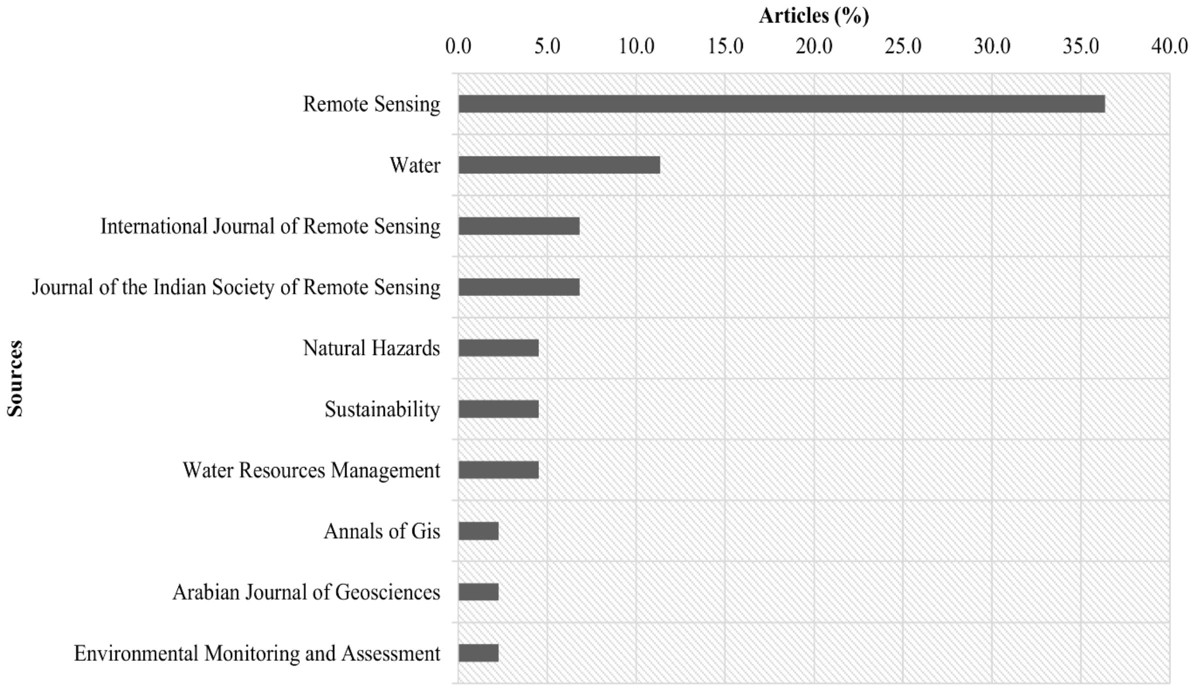

Figure 2 – Ten most relevant journal sources of the articles reviewed for Sentinel-1 flood mapping.

Figure 2 presents the ten most relevant journals that have published the articles included in the review. *Remote Sensing* journal is the most important in the universe of 18 sources that contain Sentinel-1 studies focused on flood water mapping, with 36.4% of the publication total amount (n= 16 studies). In second position comes *Water* journal, demonstrating that publications in the water resources field are adapting methodologies to incorporate more of SAR data in their study areas. Despite the fact that *Remote Sensing* is the most prolific journal in the Sentinel-1 flood mapping publications, it is worth mentioning that the number one reference source for the papers published is *IEEE Transactions on Geoscience and Remote Sensing* and other specific remote sensing journals. Such information delineates the tangent movement that other areas (i.e., hydrology, hydraulic, geography, etc.) are performing to include SAR data in non-traditional hydrologic assessments and methodologies.

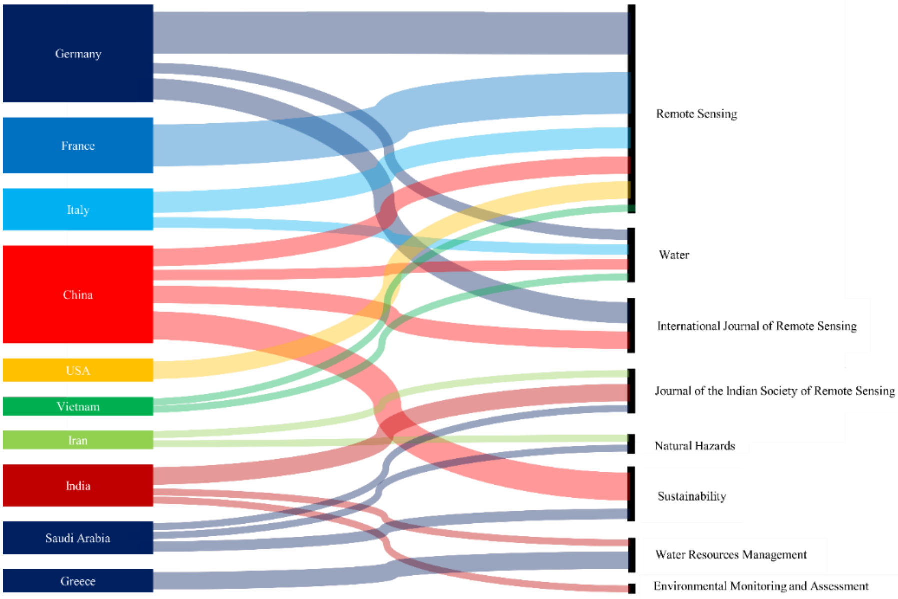

Figure 3 – Sankey diagram for the eight most relevant journals that most prolific countries contribute.

The leading countries that contribute to eight most important journals reviewed are shown in Figure 3. The top ten countries are relatively dispersed across the globe, with a remarkable absence of relevant publications from Latin American countries. Among those, there are countries with lower middle income, upper middle income and high income, signalizing that freely available data such as Sentinel-1 have been used for research in several universities and research centers. It is evident that the great contributions for the journal Remote Sensing come from three countries, that receive grants and financing dedicated to the SAR and remote sensing for the environment research. For Germany, France, and Italy the source of income has been provided by the German Aerospace Center (DLR), French National Centre for Scientific Research (CNRS), and CIMA Research Foundation, respectively.

Figure 4 exhibit the level of partnership that research centers, institutions and universities maintain with each other for publication and new methodology diffusion. The data provide an overview of the scientific collaboration and the research communities constructed around the world. The participation of more than one country denotes high international cooperation or studies with multi-sites of interest. Germany shows the top trend in single country publications, and the rest of the countries under analysis indicate a tendency to have half part of the publications alone and the other half in multiple country collaboration.

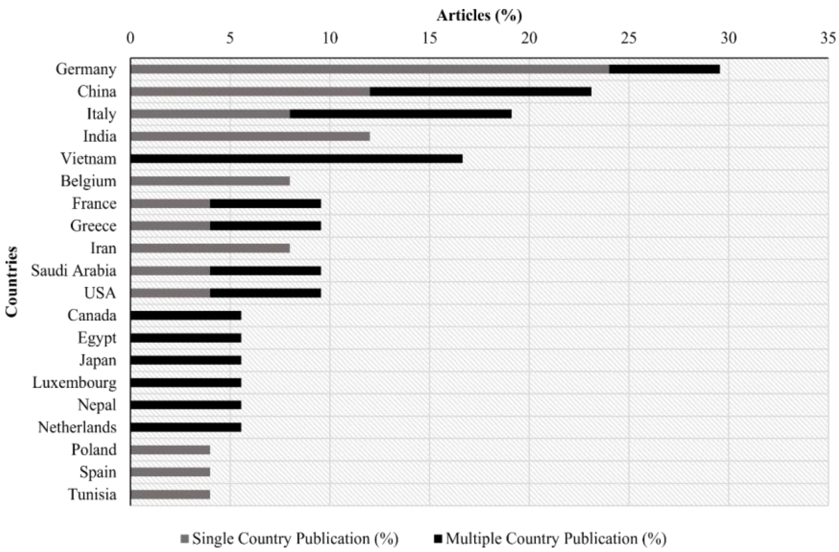

Figure 4 – Production of articles with single country publication and multiple country publication.

Using the abstract words to analyze the predominant words in the text, we formulate the word cloud that describes the frequency of words with the size of the letters illustrated. The words “flood”, “water”, “SAR”, “data” and “sentinel” are the most important in the articles reviewed because of their size in the word composition. The colors do not have a meaning in this case and are randomly applied in the package. Two words can be evidenced in Figure 5: "method" (in dark brown) and "thresholding" (in purple), which together manifest the predominance of thresholding between the methodologies found out to flood mapping. This result shows that the use of a greater number of words in the analysis (abstract words) allows terms that refer to the methodologies to be identified, however, the analysis using only the article's keywords does not explicitly show the methodologies.

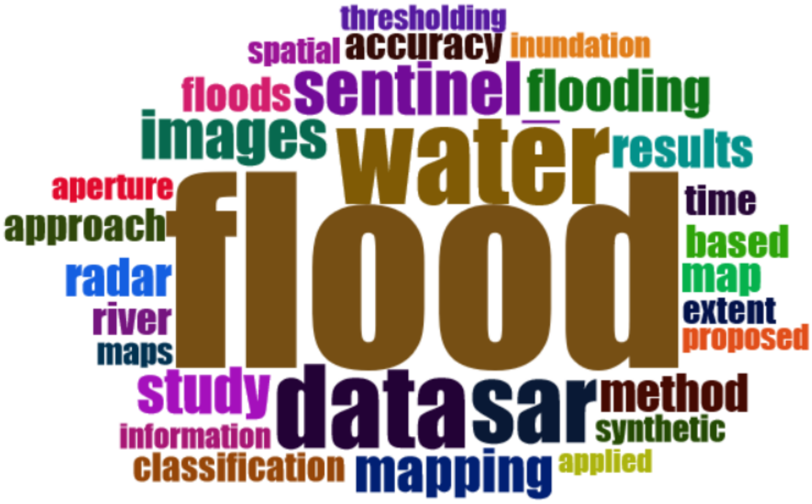

Figure 5 – Word cloud representing the predominance by their size of words in the abstracts of paper under review.

Among various SAR-based processing techniques for flood mapping are found visual interpretation, histogram thresholding, image segmentation, active contouring, rule-based classification, texture measures, data fusion approaches, change detection methods, neural network, fuzzy classifications, and others (Cao et al., 2019; Zhang et al., 2020; Kuntla and Manjusree, 2020; Melkamu et al., 2022). For Phan et al. (2019) the flood detection methods can be divided into three categories: thresholding combined techniques, complex prediction models, and machine learning (ML) approaches. Many of these methods are based on intensity data, but some use interferometric coherence and polarimetric indices when full or partial data are available (Cazals et al., 2016; Liang and Liu, 2020). The next session presents the concepts that underlie those techniques in the studies reviewed and initiate the second part of the systematic review.

Pre-processing Sentinel-1 data prior to flood mapping

In general, pre-processing SAR images shows off in the majority of the articles, and is an important phase when the methods involve thresholding, contour extraction, pixel-based classifications, among others. Pre-processing is a preparation of the data realized to correct effects in the projection, in the swath, speckle, and other distortions. Through Copernicus Open Access Hub, the Sentinel-1 constellation distributes two product types: Ground Range Detected (GRD) and Single Look Complex (SLC). Ground Range Detected images have been projected to the ground using an ellipsoid model, then applied a multi-looking for each burst, which is merged into sub-swats and made available to the user. A more profound discussion over data preparation made by the space agency prior to user distribution can be found in the Filipponi (2019) article. Single Look Complex (SLC) images also have a minimum pre-processing before being made available to users, because more quantity of information is contained in SLC. Thus, when using SLC images, the analyst has to know that image is still in slant range, under certain compression, and has a large swath width when downloaded. More information about SLC data pre-processing is reported in (ESA, 2022).

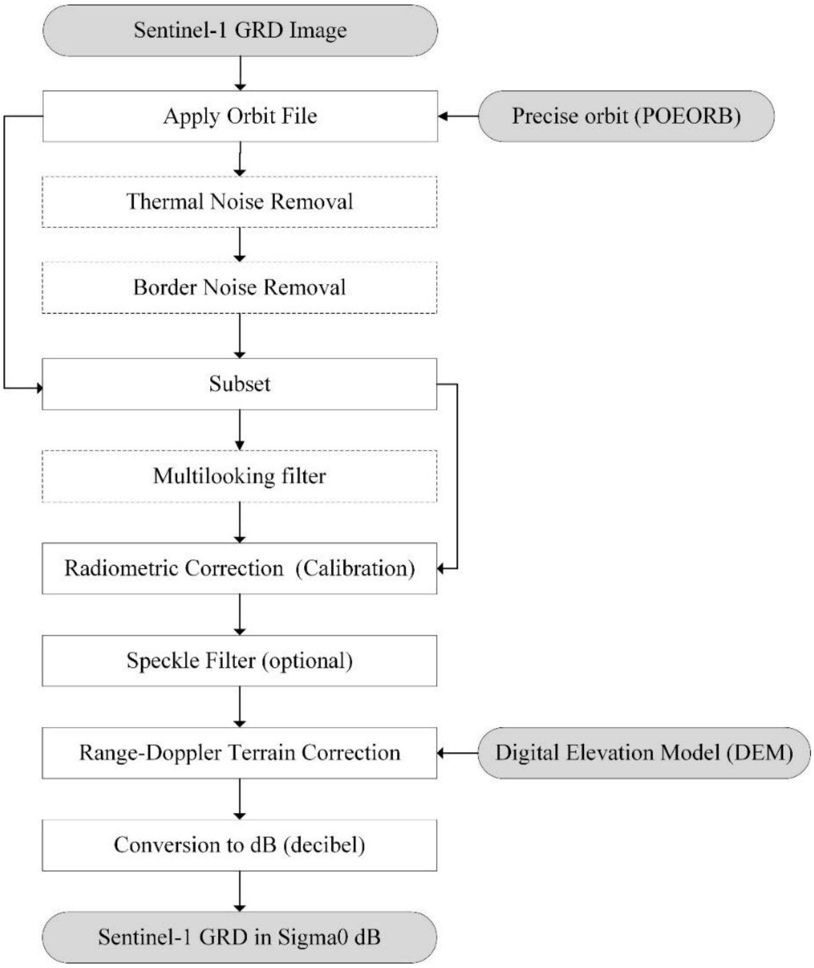

Figure 6 – Sentinel-1 data pre-processing workflow in SNAP. Source: adapted from Filipponi (2019) and Zotou et al. (2020).

The recommended framework to be applied in Sentinel-1 GRD data is presented in Figure 6. The structure contains the pre-processing step common to all articles that deal with Sentinel-1, as a recommendation, not a methodological obligation. For Benzougagh et al. (2022), the pre-processing recommended is designed to follow a sequence that prevents the propagation of errors or the loss of data through the steps. For Ouled Sghaier et al. (2018), for instance, the application of the framework was not necessary because the image analysis uses a texture descriptor not sensitive to noise and based on local statistics for homogeneous regions (open water). In the case of texture analysis, the speckle filter is not used for smoothing. Also, when delineating water bodies and flood features with small size, is not recommended apply a filter with large window, at risk of image degradation to the point where water cannot be distinguished.

The multilooking step is in dashed line because GRD images are already multilooked when they are made available to final user (Twele et al. 2016). Thus, using the multilooking tool as a filter can further degrade spatial resolution and is not indicated to mitigate speckle in GRD images used for water extraction (Amitrano et al., 2018; Elhag and Abdurahman, 2020).

The tools for thermal noise removal and border noise removal are optional steps, the last one used when dealing with subset images, cropped from bigger data. Thermal noise is background energy caused by the microscopic motion of electrons due to temperature and can also be removed in pre-processing (Phan et al., 2019; Tanim et al., 2022).

At the end of the processing framework to obtain the backscatter coefficient in decibel, the standard equation (1) is applied through a conversion tool, where A is the amplitude of the SAR image in the complex domain (Lin et al., 2019). The backscatter coefficient values range between an interval that promotes a reduction in contrast in some parts of the image while highlighting others. Those values can be interpretated through histogram to define the threshold values, for example.

$$\sigma^0 = 10\log_{10} A^2 = dB \qquad (1)$$

In all of other papers under review, the framework has been used in some manner, following the complete steps or skipping and changing any of them. Tsyganskaya et al. (2018) applied the radiometric calibration, a Range-Doppler terrain correction, the co-registration of the individual SAR data, and last a speckle filtering. Co-registration of image data is presented as essential procedure to position correctly the pixel in space, but is out of the usual pre-processing framework because is dependent of the required methodology employed further, usually change-detection methods (Perrou et al., 2018).

Zotou et al. (2020) used the Sentinel-1 images to validate the performance of a hydrodynamic 1D model, using SAR data as a reference to observed data (validation). The pre-processing applied is similar to previous workflow with slightly difference in some suppressed steps. In a study with time-series of Sentinel-1 images in SLC form, the data required the pre-processing step, but with small differences compared to the GRD framework (Ouled Sghaier et al., 2018). The SLC images needed a specific methodology in an almost fixed chain of steps, which include calibration, deburst (TOPSAR in SNAP software), and multilooking in this specific sequence, for example. Pre-processing of SLC images on Google Earth Engine is still not implemented until this data, and must be done in SNAP software.

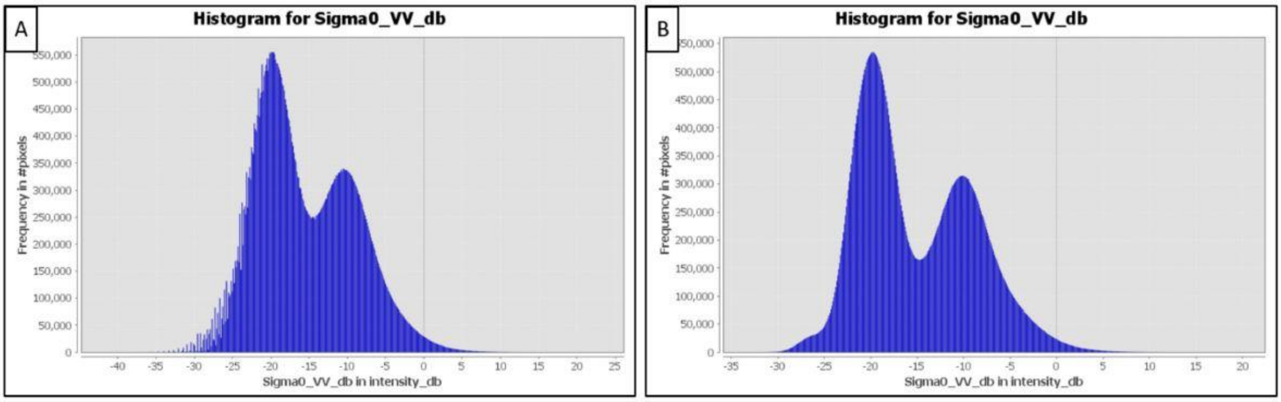

Figure 7 – The effect of speckle filter in the histogram of a SAR image in VV polarization. Source: Budiman et al. (2021).

The pre-processing framework can be automated using the graph processing tool (GPT) that comes with SNAP environment in Sentinel-1 Toolbox (S1TBX) (Kuntla and Manjusree, 2020). It can be automated either with Google Earth Engine (GEE) for GRD data (Phan et al., 2019; Qiu et al., 2021). In the seminal work of Twele et al. (2016) a graph process was implemented to prevent user intervention and facilitate pre-processing of substantial amount data. As the most cited article, Twele et al. (2016) work has been extremely important among the documents in this review, being present in 20% of our references. The reason for this may be the year of publication, being the oldest among all the documents considered in the review analysis. But the relevance in the content cannot be disregarded, since the article references are not time-limited. The work of Martinis et al. (2018) is an example of an improvement of the original framework created by the previous authors, adding some new features and processing steps adapted to a specific study site in arid areas.

A simple version of the pre-processing workflow was applied to pre-process a Sentinel-1 image, before the automatic histogram thresholding and fuzzy-set approach to refine the flood classification (Zhang et al., 2020). Comparing to the Figure 6, the steps were rearranged in other sequence, implying that there is not a rigid chain established for GRD images. In Perrou et al. (2018), the pre-processing steps were followed until the speckle filter, then instead of making the terrain correction shortly thereafter, was performed the classification method chosen by the authors. The terrain correction by the Range-Doppler tool was the last step in the entire flowchart described. Pre-processing is not a rigid sequence of steps but is a needed procedure prior to application of any methods described in the following.

There are a great number of SAR-based flood detection algorithms developed today. Most part of them still requires a certain amount of user interaction, either in the steps of data collection, pre-processing, application of the chosen method, or integration of processing chains. The demand for user skills to manage all the steps of the adopted procedure is not a problem but certainly is dependent on the focus of the research, the applicability of the method, and the discernment in interpreting the necessity of some steps or not (Bioresita et al., 2018). The Figure 8, presents an overview of the methods most cited and used in researches. The category of “Thresholding+other methods” considers the thresholding as a method used together with several approaches, even those mentioned in the other categories that participate in the graph, to improve the classification of the flood mapping. The category “Others” gathers all the methods that cannot fit in one of the previous classifications adopted.

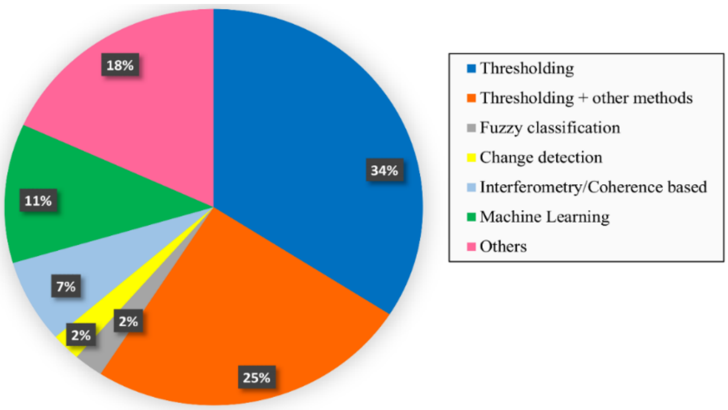

Figure 8 – Most cited methods applied in the articles under review (in percentage).

In Table 2 (supplementary material) are presented the summary of the articles revied, their methodologies, and main topics related to the conclusions. The next sessions present some methods compiled in Figure 8 and discuss the relevant aspects introduced by their authors.

Histogram thresholding method

The histogram threshold method produces a binary image by defining the separation threshold value between gray level histogram intensity classes corresponding to different targets on the surface. The intensity backscatter value in fully submerged or open water areas is very low, and defining a value below a given threshold can identify all the flood areas (Ouled Sghaier et al., 2018). This technique is simple to apply, as the numerical separation criteria defines which parts of the pixel distribution correspond to the "flood" and "non-flood" regions (Di Baldassare et al., 2009).

The method performs very well, but when the threshold value is empirically chosen the value is specific to each dataset provided, and cannot be considered a parameter to other studies in absolute values. Zotou et al. (2020) study observed that most part of relevant studies relying on radar mapping uses either manual delineation for flood recognition or threshold techniques for extraction of water surfaces.

Nevertheless, threshold remains the most common way to recognize flood, since the delimited flood area is highly sensitive to the threshold values applied, wavelength, incidence angle and dielectric properties of objects (Zhang et al., 2020; Benzougagh et al., 2022). When using the thresholding procedure is essential to mask out or remove other sources of specular reflection (lookalike water) as urban areas, streets, roadways and shadowing produced by distortions (Ouled Sghaier et al., 2018; Chithra et al., 2022).

The threshold methodology is also called “binarization process” in Tripathi et al. (2020) and Perrou et al. (2018), “adaptive threshold method” in Phan et al. (2019) and “dynamic threshold method” in Qiu et al. (2021), with a description that matches the histogram threshold method defined by Otsu (1979) or its modified versions. The Otsu's method is a non-parametric (essential for radar data) and unsupervised method, and was proposed on the basis of the calculation of maximum between-class variance and the minimum within-class variance, to maximize the separability of the desired objects (foreground must occupies more than 30% of the subset) and its background from a bimodal or multimodal histogram (fails in a unimodal distribution) (Ruzza et al., 2019; Qiu et al. 2021). In some studies, the processing method using Otsu’s threshold is considered famous and a reference already presented through literature and discussed in so many articles, that a description of his use is presented only in the supplementary material that accompanies the publication (Debusscher et al., 2020).

One difficult aspect related to Otsu's thresholding method is the requirement for a bimodal distribution, which leads to the necessity to split SAR images into small squared parts balancing low and high intensity values called tiles. This procedure originates the tile-based, split-based approach (SBA), modified split-based approach (MSBA), chessboard segmentation-based approach, or multi-segmentation approach associated with thresholding technique (Bioresita et al., 2018; Cao et al., 2019; Moya et al., 2020; Kuntla and Manjusree, 2020; Antzoulatos et al., 2022). The split-based and the tiles are employed in methodologies that want to analyze the entire image downloaded from the original source. In this approach, generally, occurs an automatic sweeping over the image because the near range and the far range pixels does not have a similar backscattering for the whole scene (Cao et al., 2019). When the analyst has a small portion of the image, called subset, this procedure can be ignored since the thresholding will probably behave the same in the entire image.

As a consequence, the literature recognizes two categories for the thresholding, as presented in Figure 9, the global (considering an entire image) and the local threshold (considering each tile from the original image) (Liang and Liu, 2020). And a known problem in the case of the popular local thresholds is that can occur over/underestimation of the optimal value due to local variation in the values of backscattering and because of the side-looking sensor (Amitrano et al., 2018).

Using more refined methodologies, there are several ways to define the threshold value described in the literature, and those cases also consider other features in the image under analysis, like urban areas, vegetation or crops, sand areas, and paved places.

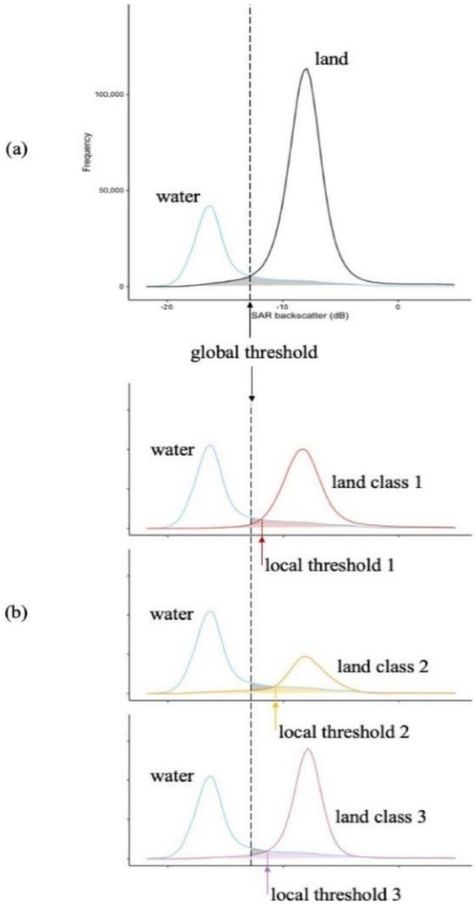

Figure 9 – Example of global and local thresholding approaches using the intensity histogram values to determine the optimum values for binary image classification. Source: Liang and Liu (2020).

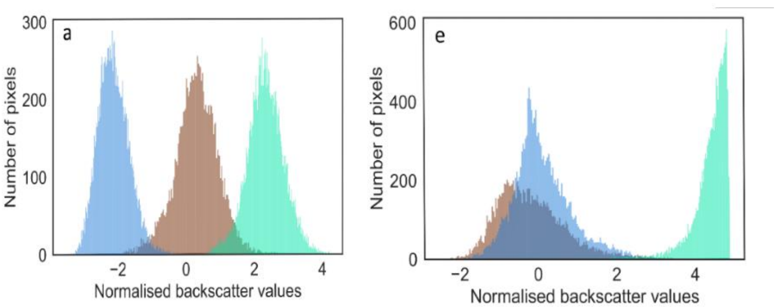

Figure 10 – Histogram distributions based on training data used in Random Forest model to extract the threshold values for each class, i.e., temporary open water (TOW) in blue, temporary flooded vegetation (TFV)in green, and dry land in brown, using a normalized dataset in VV polarization (a) and a ratio between VV/VH (e). Source: Tsyganskaya et al. (2018).

The method applied in Tsyganskaya et al. (2018) and Tsyganskaya et al. (2019), describe a multi-temporal evaluation with pixel-based and object-based classifications (Figure 10). The first classification was carried out using a Random Forest algorithm, which provided in ultimate instance a group of threshold values automatically derived for temporary open water (TOW), temporary flooded vegetation (TFV) and dry land (DL) classes. In this case, the manually approach was considered less robust, especially for flooded vegetation separation. And as a second classification step, a clustering approach with K-means algorithm was used to perform an unsupervised image segmentation (object-based classification).

The approach of the aforementioned article considered a time series data for the extraction of features on the Sentinel-1 SAR images. The characteristics indicate a tendence on temporary open water to show lower backscatter values in a VV polarization, and the temporary flooded vegetation had an increase in these values during the analyzed period. This perception is something that have been used during manual thresholding, when one searches for lower values to delimit classes of water and non-water. Lower values can be explained by the specular reflectance of open waters, and increase in values can also be explained by the double- or multi-bounce reflectance of SAR signal, characteristic for vegetation and urban areas. However, the type of vegetation analyzed (TFV can be dense forest, shrub forest, grasses, among others) influences the backscatter pattern locally, obtaining different values of parameters and indices derived from the polarizations in each specific case (Tsyganskaya et al., 2018; Tsyganskaya et al., 2019).

From the normalized image presented in Figure 10, we perceive that the analyst can choose to transform the intensity of a SAR image so the data can be easily manipulated. Previous studies have also shown that backscatter intensity values follow a Gamma distribution by pattern (Liang and Liu, 2020). The problem for SAR data is that a probability distribution that approximates the Gamma distribution does not perform well in a large part of usual classification methods. In this case, specific methods for processing SAR data need to be applied or data has to be transformed to a Gaussian distribution. The analyst needs to be aware that the transformation to a Gaussian distribution can lead to other problems, like the multiple peaks (Cao et al., 2019).

For Martinis et al (2018), the intensity histogram can be misleading because of the behavior of open water and sand lookalike and overlapping distributions. When dealing with an arid environment, the analyst must be aware that sand areas can lead to an overestimation of the flooded areas. The spectral behavior of both samples can be seen in Figure 11. In this case, the use of a histogram analysis through threshold cannot be precise and not recommended alone.

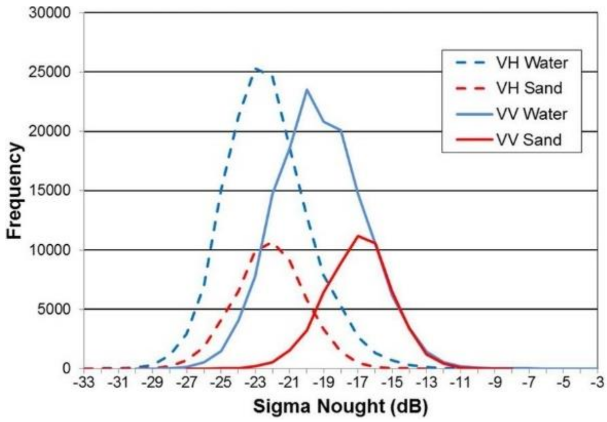

Figure 11 – Spectral behavior of intensity values overlapping in the histogram for VV and VH polarized data from Sentinel-1. Source: Martinis et al. (2018).

To solve some setbacks, the estimation of a probability distribution function (PDF) can work to soften the histogram through the clipping, and produce an enhancement in the information for low intensity areas (Amitrano et al., 2018). Zhang et al. (2020) estimated a PDF function from classes of water and non-water samples, which provided the global statistical distributions of the backscattering coefficients to evidence the thresholding. The PDF function used the backscattering intensity, the number of looks, and a hypergeometric function as basic variables to the equation. As complementary steps, the refinement of the map was carried out through the removal of misclassified areas through a process based on fuzzy logic, and a post-processing with a morphological dilation tool at the end.

In a similar procedure, Wan et al. (2019) have applied the threshold technique through the PDF function to global values using a gamma distribution. In this case the intensity histogram is assumed to be bimodal (Figure 12). The method derived four values of threshold defined from PDF theoretical distribution, which were applied to following steps, i.e., pixel-based and object-based classification. Sharifi (2020) also used a gamma

PDF to derive two threshold values, following a machine learning classification based on Relevance Vector Machine (RVM) procedure.

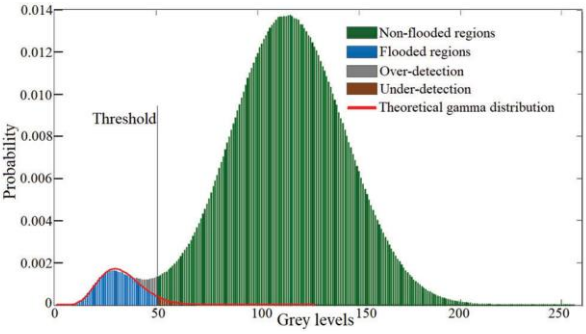

Figure 12 – Four thresholds defined regions of flooding, non-flooding, over and under-detection derived from PDF distribution. Source: Wan et al. (2019).

Quang et al. (2019) presented a methodology for thresholding named Hammock Swing Thresholding (HST). The name was due to the behavior found in the graph comparing the curves of residual (RE) and the percentages (P) of mutual flooded pixel values in Sentinel-1 and HEC-RAS water masks. Analyzing these two curves, is possible to determine the threshold value to classify the SAR image. The concept brought in the article deals with fixing a threshold value applied to a SAR image, while minimizing the total absolute values of the difference between layers of the SAR and HEC-RAS binarized output rasters. The central idea is to invert the current perspective: use the water masks from hydrodynamic models to set the threshold values (Quang et al., 2019). Figure 13 shows the graphical presentation of the HST for the Sentinel-1 image.

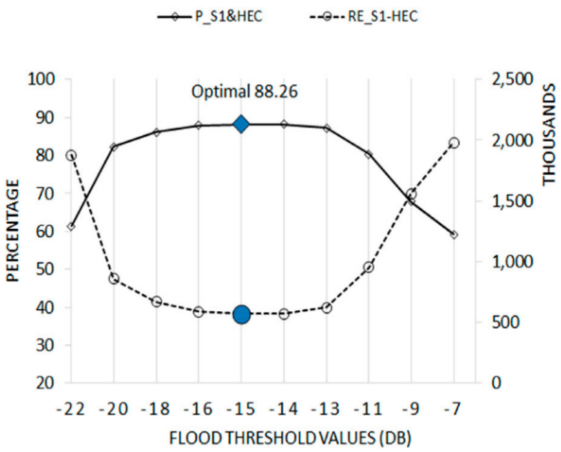

Figure 13 - Graphical presentation of Residue (R) and Percentage (P) for Sentinel-1 data comparison for Hammock Swing Threshold. The blue point indicates the optimal value for threshold. Source: Quang et al. (2019).

Considering similar use of hydrodynamical models and hydrological parameters associated with SAR image thresholding, Sentinel-1 images coupled with river level data from gauge stations were used to map flood extent through the application of the threshold technique (Agnihotri et al., 2019). The inundation period was long enough to allow the recollection of about 2 months of flood data with SAR images. These data were validated with pre- and post-flood mapping using Sentinel-2 images, processed through the MNDWI spectral index specific for water mapping in optical images. It is also very common that simulated flood maps produced in hydrodynamic models are validated through comparison to SAR images post flood classification. Both maps are submitted to statistical analysis at the final processing to evaluate the difference between the resulting areas (Melkamu et al., 2022).

We must be aware that even Sentinel-1 SAR images have their own limitations with thresholding methodology. Elkhrachy et al. (2021) mentions the low values of the goodness of fit when comparing the flooded areas extracted from SAR data and the flooded areas obtained through HEC-RAS 1D simulation. It is obvious that this kind of mismatching spatial resolution can be problematic when evaluating the results. That is why the spatial resolution of 10 meters (average) needs to be considered when establishing validation statistics.

In a different perspective, Cian et al. (2018) proposed a methodology based on the definition of a threshold from values extracted according to two indices specific for radar images, considering normalized values to establish statistical analysis: Normalized Difference Flood Index (NDFI) and the Normalized Difference Flood in short Vegetation Index (NDFVI). Both values determined thresholds to separate the classes of temporary open waters and of flooded vegetation in shallow areas. The advantages in using parameters like indexes are the absence of subjectivity in the procedure of choosing values since it has low user-dependency; the robustness and simplicity in implementation; and the possibility to apply to other sensors beyond Sentinel-1.

For Wan et al. (2019) the threshold method alone is not sufficient to delineate the flood extent. Additional approaches improve the quality of mapping floods because most algorithms depend on ancillary data. There is a tendency in articles to use the SAR image as the main data to perform classification, but additional optical images and Digital Elevation Models (DEM) are the most common ancillary, when available, to improve results. Studies relying only on SAR data in the entire processing approach are still very rare and compose a gap in the literature to be explored.

Visual interpretation and manually classification

The Visual Interpretation is a basic method applied during the first contact to image analysis. There are several numbers of studies that describe this technique as an important diagnose, but as a pre-processing phase when the analyst searches for a previous delineation on the area of interest. In these circumstances, the flood extent and other inundation relevant attributes can be digitized manually or with simple SIG tools (Di Baldassare et al., 2009).

Associated to the thresholding concept, another name given to visual interpretation is Valley Emphasis, which consists in choosing the minimum backscatter values for water delineation according to the grayscale intensity histogram. The term "valley" is linked to the valley found out between two peaks of a bimodal distribution. Usually, the inspection over histogram is made on a manual basis, as well as the threshold value choice. Ruzza et al. (2019) indicate that the Valley Emphasis method has limitations for extracting mixed water pixels, removing background noise, and shadowing effect.

Manually classification uses the threshold value that determines a point between peaks of a bimodal histogram or in the bottom rim of a single peak for a unimodal distribution in order to separate classes (Ruzza et al., 2019; Chithra et al., 2022). In this case, the simplest way to define the threshold value is to collect samples of flooded rivers and water areas (similar to sample training), and with the general statistics of decibel values apply band math (Carreño Conde and De Mata Muñoz, 2019; Elkhrachy et al., 2021; Zotou et al., 2020).

One example of the empirical equation created specifically to a SAR dataset is described in Budiman et al. (2021), as:

$$255 * (if\ \sigma_{0_{VV}} < -7.23\ \ and\ \sigma_{0_{VV}} > -14.22\ \ then\ 1;\ else\ 0)$$

Where the values -7.23 and -14.22 are empirical constants found for the data from the histogram in decibel. Another example of sample points used to determine the threshold is in Benzougagh et al. (2022). This research indicates that the feature class histograms can be applied to a statistical threshold-based approach (STA), which consists in extract the values related to percentages of the points distribution. Pixel samples are used to recognize the histogram behavior in different sites for specific feature classes and determine the best value in future inundation maps through supervised classification.

In Perrou et al. (2018) the histogram investigation was made in logarithmic scale, to visually identify the valley between the peaks. The choice of threshold value occurred after numerous manual trials. In the sequence, a band math tool was applied for classification according to a mathematical expression containing the value found out. A similar technique was applied in Agnihotri et al. (2019), with a thresholding value applied through band math operation in SNAP software to binarize the image.

Another way to manually classify a SAR image through visual interpretation is using RGB composition. In Carreño Conde and De Mata Muñoz (2019), a RGB composition is used to visualize multi-temporal modifications in the scene, facilitating the terrain change detection through the color composition. The method is based on the composition of pre- and post-flood images with the bands of RGB primary colors assigning red to the image before the event, and the images after the event in green and blue to favor the flood visualization (Moya et al., 2020). In other works, the RGB composition can be done with intensity and coherence maps, prioritizing the flood images in the blue and green, and the reference image in red band (Chini et al., 2019; Li et al., 2019; Elhag and Abdurahman, 2020).

Histogram texture measures

This technique relies on the histogram analysis, through simple statistical methods that consider blocks of data surrounding the object under analysis. The method considers the information about the arrangement in the surface of the environment. Algorithms use “statistical properties of a neighborhood of pixels” to delineate the boundaries, which can be computed using a moving window (Haralick et al., 1973; Di Baldassare et al., 2009). In a recent approach, Ouled Sghaier et al. (2018) used Structural Feature Set (SFS) method, which is a local texture descriptor. The SFS was associated with six measures obtained from a histogram using local statistics to decide whether a pixel belongs to a specific class. This approach usually does not require the preprocessing step, because the search for flood areas and other classes is based on locating homogeneous objects. In this case, the influence of isolated pixels is not representative inside the equations. At the same time, the method calculates two different threshold values for the pixel homogeneity measurement, allowing delineation of a class containing roads, streets, urban areas, and floods, with the brightness of pixels varying between objects. Some of the threshold values are fixed experimentally considering the size of targets (Ouled Sghaier et al., 2018).

The texture is one important characteristic to delineate objects or regions, and SAR images have a backscatter behavior that can produce good responses with textural classificators. Amitrano et al. (2018) used the classic Haralick textural features, using the dissimilarity window to data classification. Good performances can be obtained using homogeneity and contrast, for instance. For Liang and Liu (2020) the use of texture classificator was applied for delineation of the non-flooded pixels, deriving them with the mean shift function implemented in a proprietary SIG. The function works in a kernel iteratively until the shifting is full of pixels, resulting in lots of patches with same texture and backscatter intensity. In this case, the gray-scale values are intrinsically connected to the texture statistics to produce the clusters of same class.

Active contour model

In this approach, the boundaries of a feature are demarcated by a contour tool that works through an energy function, which uses nodes and straight-line link vectors for segmentation. The models are based on the weighted values corresponding to the sum of differences between average backscatter values outside and inside the segmentation area of interest. The working principle is similar to the region growth algorithm that requires an initial contour position or a “seed” to start the procedure (Di Baldassare et al., 2009), usually relying on high resolution SAR images (Zhang et al., 2020).

Generally used for small regions, the active contour models are part of the computer vision research, which groups pixels already pre-processed into objects with little parameters and post-processing. The advantage of this technique is the fast classification (Debusscher and Van Coillie, 2019). For Debusscher and Van Coillie (2019), the choice of the seeds was made with trial and error, which implies in a quantity of manual work and uncertainty associated. The shortcomings of this approach are the need of supervision to work, and the handicaps during urban classification in narrow streets, paved areas, and other lookalike water features.

Fuzzy classifications

The concept of fuzzy classifications is ancient in remote sensing literature, having its definition developed through the years as a classifier that allows multiple possible truth values to find a possible conclusion. This method emulates the human process of decision whose set different degrees of membership to a variable. In Amitrano et al. (2018) the classification of flood maps used the fuzzy method as the main approach, differing in the techniques to define the threshold of the flooding intensity pixels. In the study, the use of a fuzzy set of parameters avoided the use of a traditional thresholding, and the classes of “flooded” and “non-flooded” were assigned through the defuzzification probability maps.

When associated with the thresholding method, as a refinement, the fuzzy-based approach work as a post-processing tool to remove areas that look like water but can be classified as other feature class. The threshold values used in first classifications are also employed in the fuzzy set rules amongst with other ancillary data values (Zhang et al., 2020), meaning that initial classification is mandatory to build the fuzzy refinement (Twele et al., 2016).

Change detection

Change detection is a technique that perceive the differences in the surface through a time-series of images. With the methodology, the abrupt changes of natural disasters in the environment can be easily detected. This method is based on using two or more images from the same sensor, with same orbit track and polarization, and the same coverage, to compare the pre-event pixels to co-event or post-event (Li et al., 2018). The advantage of using Sentinel-1 data for this procedure, is that the SAR sensor have a large archive to be exploited since its launch in 2014, constructing a series of sequence images, and not only for flood purposes.

Being the change detection a technique that encompasses all the diversity of possible methods already tested; Li et al. (2018) mentions that a good change detection method using SAR data needs to follow some statements:

a) Be capable of selecting an adequate image;

> b) Be capable of handling highly imbalanced distribution between flooded and unflooded areas;
> c) Be robust to speckle noise while preserving the detailed flooded information (Li et al., 2018, p. 02).

Change detection and thresholding can be used in separate ways and in joint methods, being notable in literature that most of change detection methods use thresholding and filtering techniques (Cao et al., 2017). In Amitrano et al. (2018) the pre-processed Sentinel-1 images were used to compute a change index using one equation that feeds the posterior fuzzy classification with parameter values. Chini et al. (2019) demonstrated that change detection can use an adaptive thresholding and contextual information through region-growing algorithm to detect multi-temporal differences.

In other articles, the change detection has a more complex approach. The method was implemented through and automatic three step chain of processing: (1) pre-processing to obtain a ratio image, (2) automatic coarse detection based on a threshold to define 3 classes for study site, and (3) a post-classification with energy functions defined with a Markov Random Field (MRF) model (Cao et al., 2017). In the described case, the ratio operator can be defined as an unsupervised change detection classificator. Li et al. (2018) proposed an intricate chain of steps introducing the use of a Jensen-Shannon (JS) divergence-based index to select the adequate reference image, followed by a saliency-guided generalized Gaussian mixture model (SGGMM) to calculate the difference in images.

Connecting this section with the next one, recent works have been presenting a wide composition of methodologies being employed in a single research. It is possible and has become very common when the test of several scenarios with different methods that originally were seen apart in literature are united for flood classification improvements or in extensive comparison procedures. In Tanim et al. (2022), for example, a fuzzy classification made use of a set of rules based on thresholding values to delimitate flood class features, while a machine learning model was set up to be compared with the fuzzy results. In this case, the authors called the machine learning models supervised versions of classification, against the unsupervised method presented by a fuzzy model.

Machine learning methods

Machine learning (ML) is a great area that develops a large number of algorithms and software dedicated to analyzing data from different sources. Their focus relies on the use of data to train a model, and teach to learn patterns from the data, learning from the experience that a user provides by setting up initial parameters (Goodfellow et al., 2016). Eventually, the apprentice model has to demonstrate a certain performance to be considered a good predictor for an event. In this manner, machine learning cannot be used directly in a real-time flood forecast, because the model has to be trained and learned before showing results.

The most common ML classification methods are Artificial Neural Networks (ANN), k-Nearest Neighbors (kNN), Decision Trees (DT), Support Vector Machines (SVM), Random Forest (RF) (Hassan et al., 2020; Antzoulatos et al., 2022; Tanim et al., 2022). The most common ML methods found in this review are Support Vector Machine and Random Forest models. SVM is a non-parametric regression-based method situated on the classical binary classification that defines a hyperplane from a subset of data points. The subset data are nearest to the class boundary during classification, and these data points are known by support vectors. The model can ingest ancillary data to perform better results (Hassan et al., 2020; Moya et al., 2020).

Despite the good performance that machine learning methods provide during classification, SVM classifier were optimized with kernel function Radial Basis Function (RBF) using cross-validation to refine the results (Phan et al., 2019). The method was compared to other classifiers as XGBoost, Random Forest, and threshold-based classifications, with SVM resulting in the best performance for the case. The classifiers were constructed and trained in Python programming, which has a dedicated library for machine learning called Scikit-learn. Implementation of machine learning plugins ready for final user can be found also in SIG environments, like QGIS, ArcGIS, ENVI and MATLAB. Similarly, in Panahi et al. (2022), the SVM classifier was called hybrid machine-learning after a series of metaheuristic optimization procedures were employed in a coupled way to improve the original method. In those cases, the hybrid combination performs better than the standalone SVM, with accuracy reaching up to 91%.

Another work in machine learning using probabilities to classify SAR data considered a Relevance Vector Machine (RVM) based on Bayesian formulation model. The RVM can be used in the case of limited training data available. The method differs from a SVM because a hyperplane is constructed to each weighted parameter in RVM instead of having a shared hyperplane (Sharifi, 2020).

In Tsyganskaya et al. (2018) and Tsyganskaya et al. (2019) Random Forest was applied to identify the TOW and TFV, as already explained previously. Conceptually, the RF is an ensemble learning method, using a collection of decision trees with training data. For the authors, random forest is a robust method for SAR data, because outliers and noise do not have great effect in model.

Random Forest is also considered a supervised learning algorithm, capable of identifying more than two feature classes, which is a limitation in classical thresholding. In Keerthana et al. (2022), 7000 training samples combined with 50 to 150 decision trees were used to determine land use classes such as flood, urban areas, rice and other plantations, shrubs, dense forest, and others. In the same paper, the thresholding method was employed in the final refinement steps, to produce a binary map of chosen areas. This example shows how the methodologies presented in this review can be used in various arrangements.

Interferometry and coherence-based methods

The interferometric method uses a pair of SLC images, with amplitude and phase, to generate a third complex image that calculates the difference in phase between two images. Using the phase information could help better interpreting the changes in the pixels during the flood event over time. The coherence is an important measure of the quality of an interferogram, deriving the correlation level between the interferometric pair of SAR images (Paradella et al., 2021) and it is related to the spatial arrangement of scatters and their geometric changes (Chini et al., 2019).

Interferometric SAR (InSAR) can be used to monitor floodplains and their behavior joint with intensity data, exploring the gaps in the latter. Several works have showed the improvement provided by the synergistic combination of these two data. InSAR is usually applied in flood occurred inside urban areas, where the double bounce effect brings a brighter return compared to the flooded areas, but can be confused when classifying paved sites and roads, which have a similar low backscatter with water features in intensity. The use of coherence data with long baselines does not produce loss of information, because the built-up area remains the same through time; this cannot be true to rural and vegetated areas that change (Chini et al.,2019), and require a short temporal baseline for interferograms (Refice et al., 2014). Fortunately, Sentinel-1 has a good spatial and temporal baseline that can reduce possible degradation or decorrelation through false alarms.

The method employed in the work of Chini et al. (2019) uses the coherence to detect differences in the Sentinel-1 pixels through time, focusing on identifying the building footprints and the flooded patches, extracting the buildings from the original image. Li et al. (2019) introduces the Bayesian network for flood mapping combining information from intensity and coherence in a single stack, because they provide different information of a scene: intensity supply information on surface roughness and their backscattering, while coherence measures the changes in the scatters between acquisitions. As final processing, the authors apply a fully-connected Conditional Random Field (CRF) to refine classification.

Pulvirenti et al. (2021) presents the construction of a Persistent Scatterers (PS) map inside the urban areas during the InSAR analysis, combining both interferometric products. Persistent scatters are a combination of high backscatter and temporal stability, like buildings, exposed rocks, roads, etc. and have been used to map displacements, landslides and earth movement. So, this approach was complemented by data containing coherence and the interferometric phase, searching for reduce omissions and errors in flood classification.

Choice of SAR processing method by different areas of expertise and accuracy level

Inside a universe of 44 articles reviewed, most of them were published in journals directly linked to the development and testing of new methodology in remote sensing (75%). When considering papers that use SAR data as a source of information associated with the hydrological and hydrodynamic models the percentage of studies is fewer (25%). In the last case, journals that publish studies with SAR and hydrological modeling together are Environmental Monitoring and Assessment; IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing; Natural Hazards; Journal of the Indian

Society of Remote Sensing; Journal of Flood Risk Management; Frontiers of Earth Science; Remote Sensing; Water; and, Water Resources Management.

Data also reveals the curious information that 100% of studies that combine radar data processing in hydrological studies use the thresholding method to classify SAR data. It was observed that when the analyst is not working directly with processing radar data as the main area of study, there is a tendency to present more information over the basics and characteristics of SAR and pre-processing data that are not presented in other works focused only in methodological development, testing and validation. In the last scenario, it is implied that their reader already knows the basics of SAR and it is interested in novelty.

The methodological development in hydrological studies aims at the flood event reproduction and their analysis, and consequently, in none of these articles, the cutting-edge SAR processing methodologies have been used. This is a major gap found in this review directed to the Sentinel-1 satellite, for other satellites there may be similar review information in the literature due to the similarities found in the characteristics of the images and in the space sensors available. The hydrological analyst dominates only one area of research, and all the processing applied to SAR data is simple. This is a trend that can be seen in Perrou et al. (2018) and in Melkamu et al. (2022) when describing pre-processing flowchart as a major part of the research and leaving the flood classification method as secondary information.

The authors that compose the studies using SAR data joint with hydrological modeling belong to study areas and university departments of Geography; Electronics; Civil Engineering; Geoinformatics; Hydrology and Water Resources; Hydraulic; Environmental Engineering and Agriculture; Biology; and, at last, Remote Sensing. In this set, there are only two articles financed by big governmental agencies and directly linked to the specific studies in remote sensing dedicated to national science and development (Perrou et al., 2018; Quang et al., 2019). All the agencies mentioned previously (i.e., DLR, CNRS, CIMA) does not have researchers participating in hydrological studies explicitly mentioned.

In general, the most common and well-established method used to process Sentinel-1 data is employed by the hydrologic area of study: the thresholding. The advantage is to use a method that is well recognized, and that works in a simple way and in almost every software existing. The disadvantages are the fact that better and advanced methods can be found in literature, with better accuracy in classification maps, but they require deepening in the remote sensing research area. In this perspective, there still a few numbers of articles being published that gather hydrological modeling and SAR processing methods, both in their cutting-edge form.

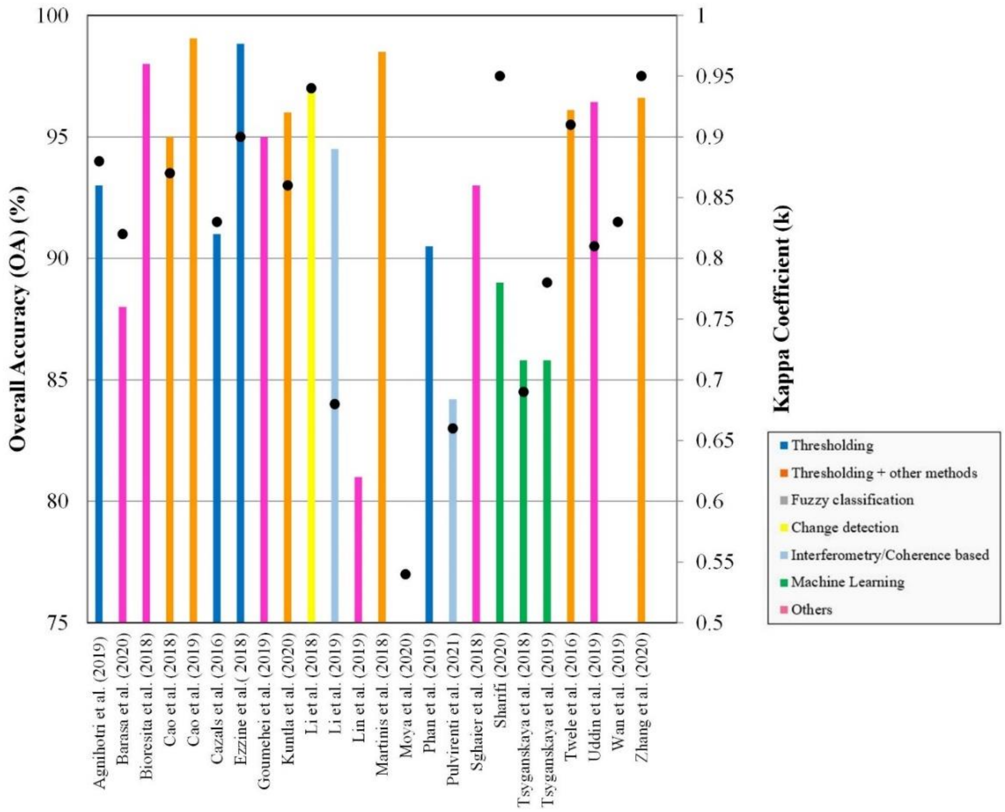

Figure 14 – Overall accuracy (OA) in the colored bars and Kappa Coefficient (k) in the black points for reviewed articles. Some cases present only one value because not all of them explicitly mention both success metrics.

In one topic all the articles seem to agree: the SAR image, either from Sentinel-1 or from another sensor, can produce an overview of the flooded area that helps to produce almost any analysis that a researcher can design. SAR data provides information when optical sensors are not available, and this can make a great difference in some sites with scarce flood monitoring. Moreover, all of the methods need DEMs to be pre-processed, and flooding maps for validation purposes produced via optical images or field data collected. The SAR image can be used in a single way in few applications.

In the end, remains clear that any type of classification or sequence of steps chained into a classification flowchart can produce a good and very accurate flood classification for a radar image like Sentinel-1. Figure 14 shows the Overall Accuracy (OA) and the Kappa Coefficient (k) for some of the articles in review, not all the 44 papers appear in the graphic because they do not always use a standard to measure success in classification. The articles not presented in Figure 14 employed F1-measures; Detection Rate (DR) and False Alarms (FA); F-score; Critical Success Index (CSI); Root Mean Square Error (RMSE); Global Variation; Goodness of fit; comparison of flooded areas in kilometers, and some articles do not describe any classification metric.

Most of the methodologies presented throughout this article can produce a classification with Overall Accuracy above 80% and Kappa Coefficient above 0.54 in the majority of the cases. The work of Amitrano et al. (2018) shows this clearly: the best method proposed by the authors can produce a 91% to 99% agreement with the ground truth information. Nevertheless, the worst method used in the comparison, threshold-based segmentation with global values, delivered an accuracy of 88% in the best performance. The work of Cao et al. (2019) is based on a thresholding technique with several refinement procedures, and presents an accuracy of 99.05% of classification maps compared to the validation dataset produced from Landsat-8 image, in the absence of field data collected as observed data. There is no clear evidence that one classification method produces better results than other, but being the prevailing method, thresholding alone or with refinement techniques have been used many times and have been improved over time.

The choice of a proper method to process Sentinel-1 data towards a flood map with high accuracy remains with the analyst, which is the one who has to consider aspects such as processing time; computational demands and hardware and software available to the processing steps; expertise to execute the methodologies; the necessity to supervise the whole processing and choose parameters during the procedure, among others. If the analyst belongs to the remote sensing area, the cutting-edge methods concentrate now in machine learning, specifically in deep learning. If the analyst belongs to water resources areas and their branches, there is a wide range of methods that can be tested to improve accuracy in the hydrological and hydrodynamic models, just taking advantage of the knowledge available.

Conclusions

The proposed article intended to produce a literature review evaluating the methodologies based on entirely costless and open access SAR data. For the first time, the Sentinel-1 satellite provides freely available SAR data to every user with an account on the ESA website (Cazals et al., 2016). That is relevant opportunity to countries with low resources to use high quality data with good spatial and temporal resolutions for flood mapping and hydrological studies.

The use of a single pair of words like “flood” and “Sentinel-1” can give us a sum of articles that go from hydrology and the use of SAR image as ancillary data to modelling, reaching the cutting-edge on methodological development of SAR processing techniques used for flood extent detection in developed countries. Some articles focus on the object of interest related to the floodmaping, as flooding areas near arid sites, flooding in mangroves, rice paddy fields, urban flooding, flooding that can cause land displacement, and other. Unfortunately, Sentinel-1 cannot monitor very small water bodies and catchments because of its spatial resolution (~10m) and terrain effects (Qiu et al., 2021).

We conclude that thresholding technique is the most important and rapid method for flood mapping or water delineation in small or global-scale applications, and determine the appropriate threshold for the image is the great challenge (Cao et al., 2019). Other post-processing methods including object-based classification, region growing, segmentation techniques, change detection, and machine learning are complementary when combined with the thresholding procedure. Innovations in the field of flood mapping using SAR have been noticed in deep learning models and interferometric-based processing.

Appears to be clear that studies focusing on flood mapping working only with the proposition, test and validation of new methodologies for SAR data are concentrated in understand the process of mapping with high accuracy, instead of understanding the development of the flood event and the hydrodynamic of the flood wave throughout the floodplain. Inside the hydrological field of study, the development of a hydrodynamic model can inform about intrinsic characteristics that cannot be capture by an instantaneous SAR image taken from space. The use of a SAR data is limited in the interpretations as is for the hydrodynamic model, that needs validation procedures with observed data and ground truth information. The limitations found in this review are the lack of knowledge about why researchers choose the methodologies used in their studies and what are the aspects they use to consider one specific pathway through developing studies instead of another one. We can only suppose that trials and error are an important part of the science of flood mapping.

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Supplementary Material

Table 2 – Summary of the articles reviewed presenting the authors, study site, methodologies applied (with numbers to indicate their use to comparison), and the key findings.

Nº	Author (year)	Study site	Method/approach	Key findings
1	Agnihotri et al. (2019)	Ramganga River Basin, India	Thresholding	SAR data can be successfully used associated with optical data (cloud-free) to assess the large-scale river changes in morphology pre- and post-flood phenomena.
2	Amitrano et al. (2018)	1) Parachique, Peru 2) River Ouse, UK 3) Ballinasloe, Ireland 4) Poplar Bluff, USA 5) Lachlan River, Australia	1) Fuzzy classification using Haralick textural features, 2) Fuzzy classification using change detection indexes.	Both methods lack any supervision to be performed in SAR images due to the fuzzy selection of parameters. The method based on the Haralick textural features can be very fast. And the method with change detection index does not degrade the spatial resolution in the despeckling process.
3	Barasa and Wanyama (2020)	Uganda, East Africa	Classification using segmentation algorithm called Mean Shift	The study demonstrates the possibility to use classified SAR images to develop transects that cross pixels and can provide information about what occurred in the frontiers between water bodies and upland areas from DEM.
4	Berezowski et al. (2020)	Biebrza River, Poland	Thresholding	The best combination of scenarios was obtained from VV polarization, water levels (instead of discharge), and the river zone nearest the regular channel used,
5	Bioresita et al. (2018)	1) Keenagh Beg, Ireland 2) River Ouse, England 3) Liguria and Piedmont, Italy	Finite Mixture Model	Narrow rivers (below the minimum for feature size detection) with less than 100 m widths are difficult to detect. This can be caused by the 100m² pixel size associated with the handicap to detect flooding under vegetation in C-band.
6	Budiman et al. (2021)	Al-Lith Watershed, Saudi Arabia	Thresholding	Choose the right dB value for water delineation can be tricky because flat sand can be misidentified as water due to their similar backscatter behavior.
7	Cao et al. (2017)	1. Kavala region, Greece 2. Evros River, Greece and Turkey	Change detection using Ratio calculation + Automatic detection of 3-class defining thresholds + Post classification with GCO solver for MRF model	The proposed method allows delineating 3 classes in the flood mapping, achieving about 95% of overall accuracy.
8	Cao et al. (2019)	Jialing River, Sichuan Basin, China	Multi-scale segmentation-based tiles + Non-parametric histogram-based thresholding algorithm + Region growing + Classification refinement	The refinement of the results with region growing method creates a more precise mapping when compared with traditional approaches like Otsu's thresholding. Based on the reference map from the Landsat image, the accuracy of the method achieves one of the best results found out in recent literature (i.e. 98.82%).

Table 2 – Summary of the articles reviewed presenting the authors, study site, methodologies applied (with numbers to indicate their use to comparison), and the key findings (continuation).

Nº	Author (year)	Study site	Method/approach	Key findings
9	Cazals et al. (2016)	Poitevin marsh, France	Hysteresis thresholding algorithm	The detection of the limits between the classes of ponds and grasslands is difficult because of the presence of water in the middle of the grass in the field scale. In some marshes there is vegetation covering the water areas so the flooding beneath is not detected for the C-band sensor, resulting in high values of omission errors.
10	Chini et al. (2019)	Houston, Texas, USA	Change detection using preliminary detection of building areas + Interferometric SAR data coherence to detect flood pixels	The flood detection is effective when is used a short temporal baseline for the co-event image pairs to extract the coherence.
11	Cian et al. (2018)	1) District of Chikwawa and Nsanje, Malawi 2) Veneto, Italy 3) Teso region, Uganda	Thresholding from indexes	The use of thresholds based on indexes associated with the change detection technique can be an easy way to determine the values removing the subjectivity in the process
12	Carreño Conde and De Mata Muñoz. (2019)	Ebro River, Spain	1) RGB composition 2) Threshold	SAR images are a great tool to complement the flood maps generated by the governments, which usually requires hydrological studies with field analysis, orthophotography, historical studies, among others.
13	Debusscher and Van Coillie (2019)	Demer river, Belgium	Active contour model with graph-based representation	When there is a numerous small flood zones in the study area, it is important to have numerous seed pixels in all of the regions so the active contour model works properly.
14	Debusscher et al. (2020)	1) Patna City, India 2) Beira City, Mozambique	Otsu's thresholding + Morphological operations + Graph-based approach	The graph-based approach is fast, effective, and simple to understand the flood dynamics in the floodplain through time and space, but can have an elevated computation time processing when features are more dispersed.
15	Elhag and Abdurahman (2020)	Tabuk City, Saudi Arabia	Thresholding	Arid areas are difficult to identify when there is a flooding event because they have similar backscatter.
16	Elkhrachy (2017)	Wady Najran City, Saudi Arabia	1) Image difference (raster calculator) 2) Local adaptive Threshold, 3) Otsu's thresholding 4) K-means,	Otsu's method showed the best fit between HEC-RAS and SAR flooded areas, nevertheless it shows the biggest flooded area which can be due to overestimation when choosing a unique value for the entire image.
17	Elkhrachy et al. (2021)	New Cairo City, Egypt	Thresholding	The use of the 90th percentile of threshold values extracted from histograms performs better than the median values of samples.
18	Ezzine et al. (2018)	Medjerda River, Tunisia	Thresholding	Considering the kappa index and the overall accuracy, the best polarization for flood delineation in the study area is VH.

Table 2 – Summary of the articles reviewed presenting the authors, study site, methodologies applied (with numbers to indicate their use to comparison), and the key findings (continuation).

Nº	Author (year)	Study site	Method/approach	Key findings
19	Goumehei et al. (2019)	Iran	Supervised contextual classification using Wishart Markov Random Field (WMRF)	The method achieves high accuracy without any ancillary data to support supervised classification.
20	Hassan et al. (2020)	Bay of Bengal, Bangladesh	Support Vector Machines (SVM)	The methodology of post-processing can analyze the vulnerability of flooding spots considering variations in time and space for a rapid assessment and relief operations at-risk areas.
21	Kuntla and Manjusree (2020)	Ganga River, India	Multi-segmentation + Otsu's thresholding + Majority filter + Mask out permanent rivers and hill shadow	The procedure was built to process the entire SAR image, generating little tiles from the original. The automatic procedure of delineating the flood from the SAR image takes only 9 minutes in the python module.
22	Li et al. (2018)	1) Evros River, Greece 2) Wharfe River and Ouse River, United Kingdom	Change Detection using JS divergency index+ Saliency detection based on log-ratio image + Probabilities based on EM on GGMM	The method presents a very useful way to choose the best image (dry image) between a set of reference images to compare with the flooded image.
23	Li et al. (2019)	1) Houston, USA 2) Joso, Japan	Unsupervised classification using SAR intensity and interferometric coherence under Bayesian network fusion framework	The synergistic use of SAR intensity and coherence provides an improvement in urban flood information than using the traditional intensity analysis
24	Liang and Liu (2020)	Ascension Parish, Louisiana, USA	Global thresholding and morphological processing + Local Thresholding + Clustering + Imposition of hydrological constraints	To avoid the speckle noise, the method applied morphological operations and the intersection of the two polarization images (VV+VH) instead of using speckle filters in SNAP
25	Lin et al. (2019)	Lumber River, North Carolina, USA	Distribution normalization (z-score) and Bayesian probability approach	The approach has improved performance when compared to optimal uniform threshold.
26	Martinis et al. (2018)	Webi Shabelle River, Somalia and Ethiopia	Automatic thresholding for flood. Empirical threshold for sand areas.	Longer time series improves accuracy for better covering the seasonal effects of the land cover. The proposed approach only works in areas where the flooding does not occur in the same area where there is sand, otherwise, it would be impossible to distinguish one from another.
27	Mehrabi (2021)	Kashkan river, Iran	Threshold (for flooding) and SBAS-InSAR (for subsidence)	Sentinel-1 can be an excellent data source for mapping the limits of flood and the subsidence ad uplift caused by the accumulated water.

Table 2 – Summary of the articles reviewed presenting the authors, study site, methodologies applied (with numbers to indicate their use to comparison), and the key findings (continuation).

Nº	Author (year)	Study site	Method/approach	Key findings
28	Moya et al. (2020)	Okayama and Nishikan City, Japan	Support Vector Machines	There is a moderate agreement between flood classification results when using training data from past events (better classification results) compared to using training samples from the current event year.
29	Perrou et al. (2018)	Strymon/Struma River basin, boundaries of Bulgaria, Greece, and Serbia	1) Thresholding segmentation technique 2) RGB composition (for change-detection)	Results provided by Sentinel-1 data used for flood mapping have a high correlation with the ancillary data found in hydro-meteorological records.
30	Phan et al. (2019)	Red River Delta, Vietnam	1) Otsu's thresholding method (flood mapping) + Morphological transformation refinement (opening and closing) 2) Support Vector Machines (SVM) (for rice mapping)	The SVM method was tested for rice mapping using four classifying datasets including the VV, VH, VVVH, and the ratio ((VV-VH)/(VV+VH)), with the VVVH being the best classifier amongst all.
31	Pulvirenti et al. (2021)	Shabelle river, Beletweyne, Somalia	InSAR Persistent Scatters (PS)	The methodology proposed opens the way to a new urban flood monitoring using PS approach, joint with interferometric phase to correct some high coherence flood pixels. The work demands the process of data training and calibration of the stack images, being considered a methodology that takes time for preparation before implementation.
32	Qiu et al. (2021)	Pearl River Basin, China	Thresholding	SAR data provides spatial continuity for flood propagation analysis. Pre- and post-processing can be automated in Google Earth Engine (GEE) for municipalities.
33	Quang et al. (2019)	Lower Mekong River basin, Vietnam	Hammock Swing Thresholding	Thresholding approaches are a robust and simple manner to rapid and automatic flood mapping, but finding the threshold value is challenging since it is not always constant for every region.
34	Ruzza et al. (2019)	Bicol River, Philippines (Camarines Sur Province)	1) Valley Emphasis, 2) Otsu's thresholding, 3) K-means clustering	All methods can provide a total flooded very closely among each other. K-means Clustering performed better in results and has advantages as low computation time and automatic procedure.
35	Ouled Sghaier et al. (2018)	1) Richelieu River, Canada 2) Evros River, Greece 3) Dez River, Iran	Local Texture Descriptor + Morphological Filter + Fusion Technique	Method performs with higher metrics with a high-resolution sensor like RADARSAT-2 (8 m) than with Sentinel-1 (12 m). The methodology is not good for flooded vegetation mapping.

Table 2– Summary of the articles reviewed presenting the authors, study site, methodologies applied (with numbers to indicate their use to comparison), and the key findings (continuation).

Nº	Author (year)	Study site	Method/approach	Key findings
36	Sharifi (2020)	Gorgan River, Iran	Thresholding + Relevance Vector Machine (RVM)	Thresholding is a method that provides over- and under-detection regions in flooded areas. The RVM proposed method does not need auxiliary data to work and uses limited data for training the algorithm.
37	Tripathi et al. (2020)	Kosi River Catchment, India	Thresholding	Methodology not complex with low cost of implementation when high-resolution satellite data are not available.
38	Tsyganskaya et al. (2018)	Zambezi and Chobe River, Zambia, Zimbabwe and Botswana	Pixel- (random forest) and object- (K-means) classification + Random Forest providing threshold values + Mask out features with specific indices	SAR data can be normalized with distributions that allow comparability between classification results. Mask out shadow, permanent water body and other features can improve final accuracy. The technique presented can deal with a time series of non-sequential or irregular Sentinel-1 images.
39	Tsyganskaya et al. (2019)	1) Chobe-Sambesi floodplain, Namibia 2) Evros Catchment, Greece 3) Yangtze River, China	Pixel- (random forest) and object- (K-means) classification Random Forest providing threshold values Mask out features with specific indices	There is a tendency of Temporary Open Water (TOW) have the most important feature varying between Z-score VV or Z-score VV+VH for Random Forest. For Temporary Flooded Vegetation (TFV) does not exist a pattern for attributes (each region and country have its own pattern)
40	Twele et al. (2016)	Evros River, Grece	Automatic Threshold + Fuzzy-based logic classification + Region growing refinement + Mask out with HAND index	The work presents a fully automated processing chain for inundation mapping for Sentinel-1 data, including pre-processing steps. The thematic classification accuracy is slightly better in VV polarization than in VH polarization (available in Sentinel-1), but superior results can be achieved is in HH (not available in all Sentinel-1 data).
41	Uddin et al. (2019)	Bay of Bengal, Bangladesh	Rule-based (called knowledge-based analysis)	Method uses freely available free-of-charge data which is important for less developed countries (but uses lots of proprietary software to apply the procedure).
42	Wan et al. (2019)	Jilin Province, China	Histogram Threshold + Pixel- and object-based classification	Compared to flood monitoring via discrete hydrological data, the use of Sentinel-1 provides spatial and temporal continuity in the analysis.
43	Zhang et al. (2020)	Indus and Chenab River, Pakistan	Automatic Threshold + Fuzzy Approach + Morphological Operations	The suggested processing chain is rapid and automatically executed after the pre-processing step. The classification result can be greatly improved using the fuzzy-logic algorithm after the automatic thresholding procedure.

Table 2 – Summary of the articles reviewed presenting the authors, study site, methodologies applied (with numbers to indicate their use to comparison), and the key findings (continuation).

Nº	**Author (year)**	**Study site**	**Method/approach**	**Key findings**
44	Zotou et al. (2020)	Pineios River Basin, Greece	Thresholding	SAR extracted inundation boundary based on thresholding technique is considered a ground truth to compare with the hydrodynamic model, but the model can have a low fit rate with the classification data.