Sentinel-1 remote sensing data and Hydrologic Engineering Centres River Analysis System two-dimensional integration for flash flood detection and modelling in New Cairo City, Egypt

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Abstract
Digital surface models, land use and rainfall data were used to simulate water areas using Hydrologic Engineering Centres River Analysis System (HEC-RAS) software. Multi-temporal synthetic aperture radar (SAR) was used for the detection of flood prone area to calibrate HEC-RAS, due to the lack of data validation in the New Cairo City, Egypt. The thresholding water detection method was applied to two Sentinel-1 images, one pre- and one post-flash flood event from April 24 to 27, 2018. The threshold method was used to detect water areas from SAR Sentinel-1 images. Feature statistical agreement $F_1$ and $F_2$ values ranged from 73.4 to 77.7% between water areas extracted based on backscattering values between 19.97 and 16.53 in decibels (dB) and reference water areas obtained using an optical image of the Sentinel-2 satellite. The similarity between simulated HEC-RAS two-dimensional (2D) of water areas and

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reference water areas based on SAR data ranged between 74.2 and 89.7% using feature statistical agreement values $F_1$ and $F_2$. It provides a clear suggestion that, in the absence of field observations, SAR data can be used to calibrate the model. Two flood hazard maps created based on water velocity and depth were obtained from HEC-RAS 2D simulation. The obtained maps indicated that 11% of the roads and 50% of the buildings in New Cairo City are exposed to high hazard areas. Furthermore, 28% of the bare land is situated in a very high vulnerability area. We recommend the use of obtained hazard map in supporting emergency response, and designing effective emergency plans.

**KEYWORDS**

flood hazard maps, hydraulic modelling, rainfall data, New Cairo City, remote sensing, SAR data

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### 1 | INTRODUCTION

A flash flood can be a direct response to very intense rainfall or dam break (Costache, Hong, & Pham, 2020). Coastal or river flash floods can cause flooding in urban areas where most of the areas contain impervious elements such as roads, streets and buildings. Flooding in urban areas occurs when the sewage and drainage systems are not capable of absorbing the high-intensity rainfall. During the heavy rainfall events, the water collects and gathers speed before coming together in areas with steep slopes. As a result, the water has the power to carry away debris, rocks, trees, cars, and structures and cause serious vulnerability (Borga, Stoffel, Marchi, Marra, & Jakob, 2014; Schumm, 1977). Natural disasters caused by flash floods are among the most harmful events in terms of social and economic losses, both worldwide and in Egypt. Many countries in Europe and others, such as China, the Unites States, Myanmar, the Philippines, Pakistan, Iran, Saudi Arabia and Venezuela, have been affected and suffered from floods. In Spain, the direct economic losses resulting from floods in the period 1987–2000 was 12 billion euros (Díez-Herrero, Huerta, & Isidro, 2009).

Egypt's climate is a mixture of arid and semi-arid, with most of the area being desert. There is very little rainfall in the southern and western deserts. The Mediterranean and Red Sea coasts regions are characterised by heavy rainfall, with an annual average rainfall of 200 mm between 1961 and 1990 (Abdel-Shafy & Aly, 2002; El-Ghani, Huerta-Martinez, Hongyan, & Qureshi, 2017). Like the rest of the world, Egypt has suffered losses of human life and property due to flash floods; on November 2, 1994 almost 600 people were killed and many houses were destroyed in Drunka village (UNDHA, 1994). The worst flash flood of recent decades occurred on January 18, 2010 in Wadi El Arish, where six civilians died, hundreds of people were injured or went missing, and over 2,000 buildings collapsed fully or partially because the surface of the water was 2 m above the ground (IFRC, 2010; Moawad, 2013). Egypt's financial losses as a result of floods in May 2014 were estimated at $150 million (Abdel-Fattah et al., 2017). In addition to economic losses, the degree of human loss is on the rise, as at least six people were killed in the October 2015 flood in Alexandria, while in November of the same year 25 people were killed in Beheira Governorate. In November 25, 2015 people were killed in only the province of Beheira (FloodList, 2015). In October 2016, a rainstorm struck the north-western region of Egypt, killing at least 73 and wounding 30 people (Elnazer, Salman, & Asmoay, 2017; FloodList, 2016; IFRC, 2017). In April 2018 and October 2019, several flash floods occurred in New Cairo City, which caused the evacuation of many residents, property damage, considerable economic losses and the death of seven people (FloodList, 2018; FloodList, 2019).

Many studies have attempted to assess the effect of flash floods in regions of Egypt; for example, the Sentinel-1/2 images were used to assess flash floods in the Wadi El-Natrun region, Egypt (Sadek et al., 2020). The geomorphological map for the most vulnerable sub-basins along the St. Katherine road, southern Sinai, Egypt, is described (Youssef, Pradhan, & Hassan, 2011). By using both remote sensing data and GIS software, the hydrological modelling method was used to quantify the flash flood hazards in the area of Abu Dabbab, Egypt (Abou El-Magd, Hermas, & el Bastawy, 2010). However, few of these studies used a two-dimensional (2D) modelling technique or focused on New Cairo City.

Because of the serious effects of floods on humans and the economy, many studies have been carried out to examine flood hazard and its impact on urban areas (van Alphen, Martini, Loat, Slomp, & Passchier, 2009), presented experiences and illustrative examples of different types of flood maps across European countries.
Increasing attention has been paid in the last few decades to the effects of floods and initiatives that could be introduced to mitigate the effects of a flood (de Moel, van Alphen, & Aerts, 2009).

There are many different flood modelling methods to determine flood inundation, such as hydrological and hydraulic (Zaharia, Costache, Právlík, & Minea, 2015). A detailed review of different flood modelling methods can be found in Teng et al. (2017). Many researchers have used Hydrologic Engineering Centres River Analysis System (HEC-RAS) for flood modelling (Horritt & Bates, 2002). Although the aim of any hydraulic modelling is to precisely simulate the actual flow conditions, the 2D modelling methods have many benefits over hydraulic 1D model. The entire region is split into small cells instead of using cross sections, and the fluid equations are solved at the centre of each cell (Tayefi, Lane, Hardy, & Yu, 2007). The 2D hydraulic modelling requires few modelling assumption and user assessment. The 2D model also produces an accurate description of complex conditions such as multiple channels, tidal rivers, and skewed roadway or bridges. Flash flood inundation modelling is primarily used to forecast the consequences of heavy rainfall events by simulating the flow accumulation. HEC-RAS 2D software is used to determine the movement and timing of runoff in the studied areas, which helps to determine water depth, water velocity, or flood extent. The simulated results should be calibrated by using real observations, which are then used them to obtain flood hazard maps and evaluate flood vulnerability.

Remote sensing satellite images are used for calibration in the absence of real hydrological observations. After manual user interaction with data processing programs, flood extent maps were derived from synthetic aperture radar (SAR) data, which can be used to provide valuable information for the successful management of flash flood disasters. Many researchers suggest the application of SAR images to detect floods prone areas using remote sensing images (Anusha & Bharathi, 2020; Cao, Zhang, Wang, & Zhang, 2019; Elkhrachy, 2018; García-Pintado et al., 2015; Giustarini et al., 2011; Hong Quang et al., 2020; Li, Martinis, Plank, & Ludwig, 2018; Schlaffer, Matgen, Hollaus, & Wagner, 2015; Schumann, di Baldassarre, & Bates, 2009; Shahabi et al., 2020; Twele, Cao, Plank, & Martinis, 2016). In the case that there are no data to calibrate, the simulated HEC-RAS Sentinel-1 images were used to assess the performance of a hydraulic model. (Zotou et al., 2020) reported that, the hydraulic model performance ranged between 61.04 and 65.49%. High-resolution (5 m) Radarsat-2 SAR images and time series were used to calculate water level to validate the 1D HEC-RAS model, 0.28 m was the best root mean square error between SAR and simulated water level (Desrochers, Trudel, Peters, Siles, & Leconte, 2020). (Yu & Lane, 2006) calibrate the model using higher spatial resolution airborne remote sensing data. They reported a small change in the model resolution had an effect on the quality of the obtained output. Shallow water of a flat floodplain was simulated using a 2D model and validated using SAR data, with a suitable accuracy of the modelling being obtained by Horritt (2000). The effect of SAR images uncertainty on the hydraulic model was evaluated and a good performance was achieved if water elevation was used during the calibration step. A lower accuracy was obtained if pattern matches of SAR information was used (Stephens, Bates, Freer, & Mason, 2012). SAR and optical data were merged to flood fusion, with an increase in the accuracy of results compared to the use of a single water mask (D’addabbo, Refice, Pasquariello, & Lovergine, 2016). It is important to further resolve sources of uncertainty such as the coarse spatial resolution of currently available radar scenes, georeferencing errors, and the selected techniques of image filtering and classification (Matgen, Schumann, Henry, Hoffmann, & Pfister, 2007).

Based on the two separate approaches to flood detection (HEC-RAS 2D modelling and satellite SAR images), the main purpose of the current study is to integrate them to obtain the benefits of both methods and to resolve the absence of hydrological observations data to calibrate simulation results. The secondary aim is to create flood hazard maps that identify potential degrees of flood hazard vulnerability within the study area for each land use type. To do so, the HEC-RAS 2D software was used to simulate flash floods and SAR data from the Sentinel-1 mission, supported by the European Space Agency, were used to extract water extent during a flash flood that hit the study area on April 24, 2018. Two SAR images, one acquired before the flood event, on April 9, 2018, and one acquired after the flood occurred, on April 27, 2018, were processed and used as reference data for the HEC-RAS 2D calibration step. Once the validation process was completed, the water velocity and depth data were used for the purpose of producing hazard maps. Flood vulnerability over several land use types in the study area were calculated and visualised using ArcGIS 10.4 software. Overall, the results of this research serve as a valuable reference to support policy and decision making for future planning and development in the current study area.

2 STUDY AREA AND USED DATA

New Cairo is a city covering 500 km², situated in the south-east of Cairo Governorate. An area of about
640 km² with an elevation ranging from a minimum of 41 m to a maximum of 572 m above mean sea level was chosen to investigate flash floods. The study area is shown in Figure 1.

The climate of Cairo city is characterised as a four-season hot desert climate. The study area receives most of the rainfall events during November–April. Daily rainfall for the study area was collected from the NASA prediction of worldwide energy resources (POWER) project, which provides complete weather data worldwide with 0.5° spatial resolution. The average annual precipitation in the watershed is 51.2 mm/year based on historical weather records for 1981–2018 downloaded from the POWER website (https://power.larc.nasa.gov/data-access-viewer/), as shown in Figure 2.

2.1 Data

Flood hazard mapping and management requires the preparation of spatial data including a precise digital model (DSM) or digital elevation model (DEM). These models includes all topographical features with their correct geometric dimensions and elevations; land surface cover details to determine roughness coefficients and hydrological information such as rainfall data and water level time series. Data requirements are described in detail in the following sections.

2.2 Hydrological data

Although rainfall stations are regarded as the most accurate and direct source of rainfall information, their distribution in most parts of the world is sparse (Chow, 1964). Over the last three decades, satellite-based rainfall data are able to overcome the limitation of data sparsity by providing continuous rainfall estimates at fine spatial and temporal resolutions.

Global satellite mapping of precipitation (GSMaP) and integrated multi-satellite retrievals for global precipitation measurement (IMERG) provide satellite-based precipitation data. GSMaP, provided by Japan Aerospace, delivers worldwide hourly rainfall rates with a spatial resolution of 0.1 × 0.1°. The GSMaP data are based on the algorithms that combine observational data from microwave and infrared radiometers from multiple satellites (Kubota et al., 2007). Many worldwide studies have attempted to evaluate the accuracy of IMERG and GSMaP surface rainfall data, for example, China (Chen & Li, 2016; Ning, Wang, Jin, & Ishidaira, 2016; Zhao et al., 2018), Japan (Kubota et al., 2007), Brazil (Rozante, Vila, Barboza Chiquetto, Fernandes, & Souza Alvim, 2018), Iran (Sharifi, Steinacker, & Saghaﬁan, 2016), Bangladesh (Islam, 2018), and Myanmar (Yuan et al., 2019). Most of their results show that the accuracy of GSMaP is slightly higher than IMERG. (Derin et al., 2016) investigated the rainfall data over nine complex terrain regions around the globe and the authors conclude that precipitation products are highly dependent on the structure of the rainfall. GSMaP real-time satellite rainfall data were used in this study to estimate rainfall in the study area. We collected rainfall data from April 24 and 27, 2018. Figure 3 shows the obtained rainfall information from the GSMaP website (https://sharaku.eorc.jaxa.jp/GSMaP/index.htm).

2.3 Topography

DSM and DEM are the most important data inputs for flash flood modelling, while the geometric data of floodplains and river channels were extracted from surface
topography information of the study area. The DSM describes the surface of the earth and contains all things on it. Unlike a DSM, the DEM depicts the shape of the bare ground without any objects such as vegetation and structures.

As a result of expansion of satellite-based innovations in the past 30 years, many DSM and DEM sources have been produced, which vary from low to high resolutions.

For developing countries and data-sparse regions, coarse-resolution DEMs such as the shuttle radar topography mission (SRTM) 30 m and advanced spaceborne thermal emission and reflection radiometer (ASTER) 30 m are freely available and can be used for flood mapping and modelling. In the current study, the advanced land observing satellite (ALOS) 30 m DSM for the study area (shown in Figure 4) was freely downloaded from the ALOS website (http://www.eorc.jaxa.jp/ALOS/en/aw3d30/) and used as data with HEC-RAS software.

2.4 | Sentinel-1 data

Using microwave data, water bodies (such as rivers) or flooded areas appear as black spots. SAR penetrates clouds and dense vegetation, which makes it suitable for detecting water areas in all weather conditions (Bolanos, Stiff, Brisco, & Pietroniro, 2016; Henderson & Lewis, 1998; Mason, Giustarini, Garcia-Pintado, & Cloke, 2014).

During times of flood events, remote sensing data such as optical or microwave data can be used to detect water bodies because of the lower backscatter reflected to
SAR instruments compared with dry areas. Two polarizations (vertical transmit, horizontal receive (VH), and vertical transmit, vertical receive (VV) for the ground range detected product with 10 m spatial resolution of Sentinel-1 satellite images acquired on April 27, 2018 were freely downloaded from the Land Viewer website (https://eos.com/landviewer). Sentinel Application Platform (SNAP) 7.0 software was used to process of SAR images. Fundamental SAR image processing steps include radiometric calibration, speckle filtering, terrain correction and sigma naught value calculation for VH and VV polarizations. To improve visualisation of water areas, it is recommended to convert the backscattering in decibels (dB) of $\sigma_{VV}$ and $\sigma_{VH}$ (Cian, Marconcini, & Ceccato, 2018; Rahman & Thakur, 2018).

2.5 | Land use

The maximum likelihood (ML) classifier was used in this work. It is a supervised classification method derived from the Bayes theorem (Costache, Bao Pham, et al., 2020). Every pixel is classified to the most likely class or labelled as unclassified if the probability values are all below a threshold (Lillesand, Kiefer, & Chipman, 2015). Four steps are required to obtain land use map using the ML method; the number of layers should be determined; the training sample for each class should be selected; mean vector and covariance matrix for each training sample layer should be estimated. Finally, each pixel in the satellite image is classified based on a covariance matrix and mean vector. Figure 5 shows the processing methodology to obtain a land use map using ArcGIS 10.4 software.

Land use map provide details of thematic classes in the study area including; buildings, roads, bare land, water and vegetation. Sentinel-2 data are an earth observation satellite that acquires downloadable images free of charge with a spatial resolution of 10 m. A Sentinel-2 image acquired on April 24, 2018 was downloaded from the Land Viewer website (https://eos.com/landviewer) and classified to obtain a land use map. The supervised classification method was used to generate land cover maps based on ground truth data. Training samples of clearly identified categories such as buildings, green areas and roads were assigned first, then the algorithm searches for pixels that have the same digital number; the ML classification method was conducted for this step. Five land use layers were extracted, as shown in Figure 6.

Furthermore, testing of 217 random samples of the obtained land cover map with a Google Earth image at the same acquisition time was carried out. With an expected accuracy of 85% and allowable error of 5%, the minimum sample size will be 203 ground control points to assess the accuracy of the land use classification map (Olofsson et al., 2014). The overall accuracy and kappa value obtained were about 87.1 and 81.5%. Different land use types considered for flood modelling include the bare land (56%), buildings (23%), roads (18%), water (0.1%), and green areas (2.9%), as shown in Figure 7.

2.6 | Roughness coefficient

The roughness coefficient $(r)$ must be between 0 (maximum roughness) and 1 (hydraulically smooth). As well as topographic and rainfall data, the hydraulic modelling step requires the study area’s hydraulic roughness to be defined (Costache, Pravalie, Mitof, & Popescu, 2015). Hydraulic roughness assessments are generally based on an expert experience, using either visual surveys or satellite imagery. Once we have land use data for the study area, Manning’s $n$ can be estimated based on Manning’s $n$ (Straatsma & Baptist, 2008) or Chow’s $C$ (Chow, 1959), and assigned according to the land cover map. Table 1 shows the roughness coefficient for the classified land use cases.
METHODS

The methodology used for the analysis is provided in Figure 8. The DSM, land use map and rainfall data were used to perform an unsteady flow analysis. The software outputs were flood inundation and water depth and velocity for the period April 24 and 27, 2018. Simulated inundation extent and water depth are usually calibrated and validated by using gauge information or observed water depth in the study area. For our study field, there were no available gauge readings or measurements of water depth; thus, radar images were used for model validation and calibration.

3.1 Hydrological modelling using HEC-RAS 2D

HEC-RAS 2D hydraulic software was used in the current research for unsteady flow analysis. The free software HEC-RAS 2D 5.0.6 version has the ability to simulate and model 2D surface flow (Brunner, 2010). The aims of hydrologic analysis were to determine the discharge, its route and the areas that might have been affected by a flood episode during the flash flood period (April 24 and 27, 2018). The HEC-RAS 2D model require a DSM for the study area, land use maps, Manning’s n values for each land use class and rainfall information. The GSMaP rainfall time series was used to determine unsteady flow boundary conditions. All input layers were projected in the Universal Transverse Mercator coordinate system zone 36N. The output of this analysis was images illustrating water depth, velocity, flood extent, and areas affected by a possible flood event.

3.2 SAR techniques for the detection of flood prone area

There are many techniques to detect water bodies from SAR image backscatter: histogram thresholding methods (Chini, Hostache, Giustarini, & Matgen, 2017; Liang & Liu, 2020), interferometric coherence calculation (Chini et al., 2019), a region growing algorithm and active contour mode (Teatini et al., 2012) and object-oriented classification (Horritt, Mason, & Luckman, 2001).

In the present study, the histogram method was used to compute best threshold values to detect water bodies. The Sentinel-1 image histogram shows the frequency of various backscattering intensities for each pixel, one intensity values is expressed by each bar. The valley point between two peak points represents a threshold backscattering coefficient that distinguishes between water and non-water region (Nixon & Aguado, 2019).

The Nile River is located in the west of study area, approximately 13 km away, and it is detectable in the SAR images. Therefore, 17 well-distributed polygons manually drawn within the permanent water of the Nile River were used to calculate the statistical analysis of image histograms. The polygons appear in red in Figure 9a. The water bodies were extracted based on histogram threshold values. To calculate the accuracy of threshold values, the extracted permanent water area of the Nile River from each threshold value was compared to another reference water area extracted based on a true colour Sentinel-2 image acquired on April 24, 2018, as shown in Figure 9b. The flow diagram depicting SAR threshold value calculation is shown in Figure 9c.
FIGURE 8  Flowchart of the present study

FIGURE 9  Water bodies extraction by Sentinel-2. (a) Water polygons; (b) Sentinel-2 true colour image; and (c) methodology
3.3 | Accuracy assessment of simulated and SAR water extent

To determine and compare how well the raster layers of the flood prone area obtained by SAR images fit with the raster of flooded areas simulated by HEC-RAS 2D, two scales, feature agreement statistics $F_1$ and $F_2$ are used as shown in Equations (1) and (2) (Bates & De Roo, 2000; Lim & Brandt, 2019b; Mason, Bates, & Dall’Amico, 2009):

$$F_1 = \frac{A}{A+B+C} \times 100$$

$$F_2 = \frac{A-B}{A+B+C} \times 100$$

where $A$ is the total number of pixels showing a perfect match between SAR and the simulated model, $B$ is false or overestimated matches, and $C$ is the missing or underestimated pixels. More details about different verification scales for raster and vector data can found in Hunter (2005) and Lim and Brandt (2019a). The $F$ values range from 0 to 100%, where 100% is the maximum performance.

4 | RESULTS AND ANALYSIS

4.1 | HEC-RAS 2D simulated water extent area

The simulated inundation extent, water depth and velocity were generated based on data inputs using HEC-RAS 2D version 5.0.6. The output quality was calibrated by comparing water areas with SAR images. The time duration of the simulation was determined from the start of the rainstorm on April 24, until the time of the only available Sentinel-1 radar images on April 27, 2018; users can calculate outputs at any selected time within the defined processing time period. Figure 10 shows the water extent area on April 27, 2018 at 3:00 p.m. (the time of the radar image). The total water area was calculated as 94.5 km$^2$, and the total study area was 639.4 km$^2$, which means that 14% of the total study area was flooded at that time based on the results of simulation.

4.2 | SAR threshold value for water detection

To detect water areas correctly based on SAR data, the threshold values must be carefully calculated and compared with another more accurate method. In the current work, we extracted a water area of a portion of the Nile River using Sentinel-2 colour images as a reference water area to obtain the best threshold SAR value. The reference water area of the Nile River area from the Sentinel-2 image after image processing and classification by ArcGIS 10.4 was found to be 12.2 km$^2$. The same Nile area appearing in SAR images was selected and processed with different polarizations using SNAP 7.0 software. The statistical information and histograms of 17 polygons drawn in the Nile water area were used as training samples. Figure 11 shows the calculated histograms of SAR training samples for different polarizations of the two SAR images.

The histogram results indicate that, for VH polarisation, the mean value to detect water area is 16.3 dB during a flood, and 15.8 dB prior to a flood event. The appropriate mean pixel values of 19.2 and 18.5 dB could be used to detect water areas before and after a flood event for a Sentinel-1 SAR image with VV polarisation. Two threshold values, mean value and 90th percentile, were used to test their appropriateness to detect water areas. At each threshold value, the Band Math tool of the SNAP program was used to obtain raster layers, including areas with water and with no water based on the following condition:

$$\text{if } \sigma_{(\text{VH or VV})} \text{ dB} < \text{ (threshold) then 255 else 0}$$

where the value 255 represents a pixel with water, and 0 a pixel with no water.

By comparing the reference water area obtained by Sentinel-2 images and the water area obtained at each
threshold value, the accuracy can be calculated. Fit scales for each threshold value are presented in Table 2.

The best fit value was 77.7% at the 90th percentile threshold value for VH polarisation, and the worst is the mean threshold value for VH polarisation. The differences between the extracted water area using SAR and optical remote sensing imagery range between 27 and 59.8%: the 90th percentile threshold pixel value has the smallest water differences for VV and VH polarisation.

4.3 SAR reference water area

The 90th percentile threshold was used as an appropriate pixel value to extract water areas using SAR images. The best thresholds for the Sentinel-1 SAR image acquired on April 9, 2018 were determined to be 16.53 and 19.38 dB for VH and VV polarizations, respectively. For the image acquired on April 27, 2018, the threshold values were 16.93 and 19.7 dB. Figure 12 shows four extracted water areas based on the best threshold values for pre- and post-flooding SAR images. The results of VH image polarisation yielded water areas bigger than those obtained by VV polarisation. The obtained water areas were between 304.7 and 62.6 km². The areas that had some buildings suffered from backscattering of SAR values and had few wet areas; some shadow areas were classified as water areas, as can be seen in Figure 12. According to the height orientation, material and shape of buildings, some researchers clarified the low backscattering of SAR values inside areas with

### TABLE 2

| Threshold          | Polarisation | Sentinel-2 Flood area (km²) | SAR Diff % | A     | B     | C     | F1    | F2    |
|--------------------|--------------|----------------------------|------------|-------|-------|-------|-------|-------|
| 90th percentile    | VV           | 12.2                       | 8.9        | −27.0%| 222,113| 11,254| 67,306| 73.9% | 77.6% |
| Mean               | VV           | 4.9                        | 59.8%      | 195,069| 4,511 | 101,093| 64.9% | 66.4% |
| 90th percentile    | VH           | 9.12                       | −25.2%     | 220,934| 12,888| 66,980| 73.4% | 77.7% |
| Mean               | VH           | 8.2                        | −32.8%     | 190,219| 4,876 | 105,707| 63.2% | 64.9% |

Abbreviations: SAR, synthetic aperture radar; VH, vertical transmit, horizontal receive; VV, vertical transmit, vertical receive.
buildings (Koppel, Zalite, Voormansik, & Jaghuber, 2017). They reported that building height has the strongest effect on backscatter values for both VH and VV polarizations. Backscatter mean values increase with increasing building heights. The heights of most of the buildings inside the study area do not exceed two or three floors. For this reason, we find that the lowest reflectance values within the building areas.

Furthermore, using Erase Tool in ArcMap, the water areas in pre-flood images were removed from the water areas of post-flood images to obtain the final reference water extent. Figure 13 shows the final reference SAR water areas that were used to calibrate the HEC-RAS. The extracted water areas were 99.9 and 76.8 km² for VV and VH polarizations, respectively.

### 4.4 Accuracy assessment of validation

It is noted that, to calculate scales F1 and F2, the values A, B and C should be calculated first. Hence, the simulated HEC-RAS 2D water surface on April 27, 2018 at 3:00 p.m. (Figure 10) and SAR reference water areas (Figure 13) were converted from polygons to raster layers and reclassified, where pixels with water get a pixel value of 255, and pixels with no water get a pixel value of 0. After that, by using the Raster calculator tool in ArcGIS, two raster layers were subtracted to obtain the values A, B, and C. Figure 14 shows the results for VH and VV polarizations, where −1 represents overestimation (B value), 0 represents a perfect match (A value), and +1 represents underestimation (C value).

Table 3 shows appropriate agreement scales between the two compared water areas. VH SAR polarisation had the highest performance in terms of F-statistics, from 76.6 to 89.7%. The results of VV polarisation showed more wet areas than HEC-RAS 2D, while those of VH showed less. This means that at least 74.2% of the estimated water area was similar to the SAR data. A best fit value of 89.7% was found for F2, showing that the estimated water areas by HEC-RAS 2D simulation and SAR images were similar. The worst fit result between
simulation results and reference water areas of 74.2% was found for F1.

4.5 | Flood hazard maps

Flood hazard maps show areas at risk from flooding according to three probabilities: low, medium and high hazard classes. For each level, three parameters should appear on flood hazard maps: water depth, velocity, and water area (Alkema & Middelkoop, 2005; Diek, 2018; Golz, Weller, & Jüpner, 2016; Van Alphen et al., 2009). Table 4 shows limits of water depth and velocity values that were used to classify hazard intensity.

Figure 15a,b shows hazard maps for the study area based on water velocity and depth. The maximum simulated water depth is divided into three hazard classes, that is, 0–0.5, 0.5–2, and >2 m. The maximum simulated velocity hazard map shows flow velocity from 0 to >2 m/s by colour shading. Maximum and minimum simulated flood inundation extents were calculated as shown in Figure 15.

4.6 | Land use vulnerability estimation to flood hazard

By overlying velocity and water depth maps with land use map, the vulnerability areas can be calculated for each land use type. With the exception of bare soil land use, the buildings are the most places in exposure to risk. It is noted that, the percentage of 35.6% buildings and 29.6% are roads located in severe areas based on water depth hazard. On the other hand, the percentage of exposed area based on water velocity hazard maps are greater, which is, reaching 38.6% for buildings and 29.7% for roads. Most of the bare land areas are located in high-hazard areas due to the expectation of flash floods; the percentage located in high-hazard areas reached 34.1% based on velocity hazard, and therefore it is forbidden to construct buildings or facilities in those areas without proper protecting, as shown in Table 5.

5 | DISCUSSION

The threshold method was used for flooded area extraction from pre- and post-flooding Sentinel-1 images. The feature statistical agreement $F_1$ and $F_2$ values of backscattering threshold values (19.97 and 16.53 dB) were between 73.4 and 77.7% at both used SAR polarizations. To calibrate hydraulic model, the SAR data outputs are considered to resolve the gap or absent of calibration information. The agreement values $F_1$ and $F_2$ between simulated results and SAR data were 74.3 and 89.7% for alternative polarizations. Using the thresholding approach for flood mapping is simple, rapid, and robust. By comparing our obtained results
with researchers investigated optimal thresholds SAR scattering to detect water areas, Hong Quang et al. (2020) reported best agreement 88.3% between water levels and calibrated water extent with the HEC-RAS 2D. Moreover, the accuracy of water area extracted by Sentinel-1 data compared to Sentinel-2 optical flood extent was ranging between 87 and 71.5% for the two polarisations (Clement, Kilsby, & Moore, 2018).

There are many explanations to clarify the differences between water areas obtained by SAR data and modelling approaches. The flooded area analysis based on SAR images has some uncertainties that affect the output. Satellite images are not available for all places in any times, which create a time difference between the beginning of the flood and the acquisition of satellite images. In the current study, the rainstorm started on April 24, 2018 at 5:00 p.m. and the SAR images were acquired on April 27, 2018 at 3:00 p.m. However, there are some problems associated with SAR images, that is, scattering of signals when the mirror send back the signals and sensors do not receive the signals. Furthermore, not all the black areas are necessarily to be detect as flooded areas. For some land use, such as buildings or shadow areas, the SAR method to detect shallow wet areas generally fails to detect flood areas. In addition, due to the lack of detail in low-resolution SAR images, detecting flooded areas in urban regions can be very difficult (Schumann, Neal, Mason, & Bates, 2011). Moreover, misalignment or geographical shift between SAR images and DEM files can result from inaccurate georegistration.

The hydraulic method has also some reasons for uncertainty that affect the accuracy of HEC-RAS 2D outputs. For instance, DEM with a spatial accuracy of 30 m is not sufficient to study of urban flood analysis, as some previous studies have recommended not to use more than 10 m resolution DEM. An increase in the percentage of wet areas with values varying around 33–45 and a 5%
positive change in travel time using coarser DEM with the HEC-AS program was reported in Casas, Benito, Thorndycraft, and Rico (2006), Cook and Merwade (2009), and EXCIMAP (2007). Moreover, previous studies did not fully agreed on anticipating rainfall patterns and intensity from satellite data within our study area, that contributes to uncertainties that affect the performance of study results by Salem Nashwan, Shahid, and Wang (2019).

6 | CONCLUSION AND RECOMMENDATION

In this article, flood hazard mapping, flood extent and vulnerability in New Cairo City in Egypt, were investigated using HEC-RAS 2D modelling software. A preliminary and essential stage in management is to carry out a flood hazard assessment, including a detailed analysis of risk factors, such as hazard, exposure and vulnerability. Flood hazard maps are used to prevent new areas of urban areas from risk to building up, reduce existing risks and to adapt to changes in risk factors. Moreover, it helps us plan to reach a particular area if the depth map is available, and for relief during the event of flood.

To get the best SAR backscattering pixel values for the detection water areas, statistical analyses and histograms of some manually drawn polygons in the permanent water area of the Nile were calculated. Based on histogram information, 90th percentile and mean SAR backscattering pixel values were tested to detect the water area and compared with another more accurate method such as optical images acquired with Sentinel-2 satellite images. The feature statistical agreement $F_1$ and $F_2$ values for water areas ranged between 63.2 and 77.7% for SAR data and optical data. The 90th percentile threshold value was used to detect water bodies using SAR images with VH and VV polarizations to validate the simulation results. The fit agreement between SAR data and HEC-RAS 2D simulation water areas ranged between 74.2 and 89.7% for feature statistical agreement $F_1$ and $F_2$.

After the simulation was conducted by HEC-RAS, the water extent area, water depth and velocity were imported to ArcGIS software to produce flood hazard maps. In this study area, the majority of losses were structural, with 8% in a very high hazard zone, and 11% of the road area also in a high hazard zone. From the findings of the current study, it was also found that 28% of the bare land is situated in a very dangerous area.

From the current study, the low-cost produced flood hazard maps have a suitable drawing scale and contain various flood parameters such as hazard degree, water depth, velocity and water extent area, which are the bases of planning decisions to determine appropriate land uses and development types. For emergency planning and management, subsequent maps showing detailed flood metrics such as levels of risk on the main roads of the city and water depths during floods are very relevant. Therefore, we suggest that the created maps be used to raise public awareness and to reduce economic and social losses within the study area in coordination with the decision makers.

Low image resolution and Noise such as speckle are a major disadvantages and limitation of using SAR images to detect flood extent area. The position accuracy of SAR images affected by input elevation data during georeferencing process; mostly, the free cost, low resolution, and accuracy SRTM or ASTER DEM are used to achieve georeferencing step. The more time between occurrence of the flood and the SAR images acquired, the less accuracy of water extent area expected. Used high-resolution multi-temporal SAR images is considered an area of future research.

CONFLICT OF INTERESTS
The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT
Data sharing is not applicable to this article as no new data were created or analyzed in this study.

| Land use   | Hazard based on water depth | Hazard based on water velocity |
|------------|-----------------------------|-------------------------------|
|            | High (km²) | %       | Medium (km²) | %    | Low (km²) | %     | High (km²) | %       | Medium (km²) | % | Low (km²) | %     |
| Buildings  | 4.71       | 3.1     | 26.77        | 17.8 | 26.15      | 17.4 | 11.81       | 7.9     | 13.01        | 8.7 | 32.97   | 22.0   |
| Bare soil  | 9.21       | 6.1     | 60.54        | 40.3 | 65.95      | 44.0 | 51.17       | 34.1    | 43.43        | 28.9 | 41.88   | 27.9   |
| Roads      | 3.66       | 2.4     | 20.89        | 13.9 | 19.88      | 13.3 | 16.70       | 11.1    | 14.55        | 9.7  | 13.40   | 8.9    |
| Water      | 0.02       | 0.0     | 0.14         | 0.1  | 0.11       | 0.1  | 0.06        | 0.0     | 0.08         | 0.1  | 0.14    | 0.1    |
| Green      | 0.55       | 0.4     | 3.66         | 2.4  | 3.06       | 2.0  | 1.35        | 0.9     | 2.34         | 1.6  | 3.59    | 2.4    |
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