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Google earth engine based computational system for the earth and environment monitoring applications during the COVID-19 pandemic using thresholding technique on SAR datasets

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ABSTRACT

Observing the earth and environmental conditions during the COVID-19 pandemic lockdown along with travel restrictions headed to worse circumstance. These scenarios amplified the hurdles of flood management. In order to resolve these issues, an efficient and resilient geospatial framework with unconventional systems is also required for the generation of instantaneous results. Hence to avoid these deficiencies, the google earth engine based computational system integrated with analytical tools for large-scale data handling is introduced for the earth and environmental monitoring applications. The present study proposes a working model for geospatial data processing to understand socio-demographic implications with a web-based analytical interface. The research introduces a histogram-based thresholding approach for real-time surface water mapping along with precise data processing and analysis for automated monitoring. The study integrates geospatial datasets to a enhanced data processing methods in a web-based platform to deliver the required results for extensive planning and decision making. Furthermore, a similar type of work can be undertaken for other disaster management applications.

1. Introduction

Several remote sensing-based studies about the earth and environment monitoring applications like surface water mapping have focused on the utilization of optical sensors, but there are certain issues for the application of these sensors (Markert et al., 2020; Marquez et al., 2019). Remote sensors operate on various principles for recording the electromagnetic radiations from the land surface to offer a variety of information either collected from optical sensors or emitted by microwave sensors (Joshi et al., 2016; Ki et al., 2009). Thus, to resolve these issues, synthetic aperture radar (SAR) offers the wide capability to operate in all weather conditions but these are prone to more noise, unlike optical images. Being an active microwave sensor, SAR systems have gradually taken their pace for wider applications. It plays a significant role in the large-scale observation of the earth and environmental layers due to its cloud penetration capability (Mpakratsas et al., 2020; Surampudi and Yarrakula, 2020). It offers enormous potential, but it involves rigorous pre-processing sequences to bring the raw data in useable form by removal of noise.

Earth surface conditions during extensive and prolonged flooding cause a floodwater runoff from heavy seasonal rains affecting the vegetated environments. The developing countries are mostly affected by these conditions due to a lack of proper infrastructures, poor technological advancement, insufficient essential economic structures to predict the influence of the hazards or ways to mitigate these costs (Saleem et al., 2019; Towfiqul Islam et al., 2021). The Ganga-Brahmaputra plains are highly susceptible to regional floods due to their geographic setting and other hydro-geographic factors. These can also accumulate the excessive floods in the region during the monsoons seasons, which further leads to severe damages to life and property losses (Bui et al., 2019; H. Zhang, Zhao, Yang and Wu, 2020). Thus, there is significance in developing a high-performance automated computational system for the earth and environment monitoring applications.

It is well-known fact that the daily availability of datasets is required to understand the dynamics of the earth and the environment (Barbosa
Traditionally, ground-based surveys, in-situ measurements of landscape provide accurate results to monitor the earth and environmental conditions. Apart from these, ground-based surveys are more important during the observations of the inundation areas with in-situ measurements, which are expensive, time-consuming (Anusha and Bharathi, 2020; Hegarty-Craver et al., 2020; Pande et al., 2021a, 2021b). Also during the COVID-19 pandemic condition, these areas became inaccessible. The occurrence of the earth and environmental disturbances create a poorer situation during the COVID-19 pandemic. The COVID-19 norms allow a social and physical distancing along with essential lockdown to avert the spread of the pandemic, therefore the physical surveys and measurements may not be promising (ArunKumar et al., 2021). Hence, these led to the requirements for a satellite-based computational system for the earth and environment monitoring applications to perform the requisite geospatial analysis with analytical approaches (D. Kumar, 2016; Twele et al., 2016). The earlier studies suggest that the earth observation datasets from the SAR system are designed to spatially monitor the earth and environmental condition of any region to help the authorities for an immediate response (Ahamed and Bolten, 2017; Y. Chen et al., 2016). Various research studies implemented SAR-based systems to observe the surface water detection and measurements with supervised and unsupervised classification algorithms (Cao et al., 2019), some of them used object-based image analysis (Li et al., 2021; Nakmuenwai et al., 2017), and also threshold techniques, and hybrid methods (Biorestita et al., 2018). Out of all the methods, the thresholding based approach is assumed as the most common for SAR data processing (Agnihotri et al., 2019; Gasparovic and Klobucar, 2021).

The capability to precisely monitor the variations in inundations comprises uncertainties and probable biases to support the study for climatological dominant inundations. One of the techniques for flood plotting involves the use of very coarse resolution gravity data acquired by NASA during the Gravity Recovery and Climate Experiment (GRACE) mission. These may be combined with other datasets and satellite altimetry to estimate better surface water conditions (Lee et al., 2011). This raises the need for technological advancement with automated methods, increased computing power, and storage capabilities that have given rise to developing cloud-based computing platforms (Boothroyd et al., 2021; Malathi et al., 2019).

In modern times, the integration of artificial intelligence has overcome many of the limitations but the artificial neural network (ANN) lacks the power of predictive analysis, so it is generally integrated with fuzzy logic (Wang et al., 2019; H. Zhang, Shi, Wang, Hao and Miao, 2014). Several researchers participated in studying the various classification methods like supervised, unsupervised, band thresholding, algorithms, indices (Inman and Lyons, 2020; Y. Zhang, 2021). Among these, recent studies suggest the thresholding technique generate accurate results. Besides, advances in the field of hazard monitoring rely on the adaptation of hybrid algorithms and machine learning models that are well suited, flexible, and provide accurate hazard predictions. Several researchers confirmed that the machine learning models generate accurate predictions of hazards like floods, droughts, earthquakes, wildfires, landslides, gully erosion, and ground subsidence (Jian et al., 2020; Shahabi et al., 2020). Flood inundation maps are essential for future studies, emergency action plans, planning and development, flood insurance rates, and other related studies (Bui et al., 2019). Various data-driven models are developed and applied for flood mapping, which involves bivariate models of frequency ratio (Khosravi et al., 2019), the weight of evidence, and Shannon Entropy (Q. Q. Chen et al., 2021; Khosravi et al., 2016). In addition, several multivariate methods
are applied for the flood hazards like logistic regression (Pradhan, 2009), analytic hierarchy process, but these models have performance limitations, especially for non-flood regions.

The generation of robust and accurate water maps requires the use of geospatial techniques fused with web-based technology to accumulate big data from multiple sensors. The current works on objectives like (a) to evaluate the performance of an automated flood area inundation estimation, (b) Surface water mapping with the google earth engine (GEE) and the histogram-based from Otsu’s thresholding approach, and (c) to validate the surface water maps from multiple sources. The cloud-computing platforms provide on-demand access to high-performance computing abilities without the need to download images and maintain the hardware (Gilanifar et al., 2021; Jeansoulin, 2019; Kouadri et al., 2021; Sudmanns et al., 2019). It can also support the immense data storage facilities to resolve issues associated with a large volume of earth observation datasets (Neetu et al., 2019; Yang et al., 2011). Conventionally, data procurement and management, computational power, data storage, and processing time have been great hurdles, especially for the analysis of the time series datasets for large areas (Alberto et al., 2016; Wolski et al., 2017). Besides, this processing incapability with the limitations of remote sensing methods prevents the wide access of adopting automated techniques. In this regard, Google Earth Engine (GEE) is the best-suited platform for large area analysis with pre-processed Sentinel-1 images integrated with land and inland water applications. In recent times, many researchers have used Sentinel-1 data and cloud-based platforms like GEE for robust mapping of big datasets over large-scale areas (S. S. Chen et al., 2021; Kandekar et al., 2021; Kouadri et al., 2021; Vanama et al., 2020). The analysis determines the processing of Sentinel-1 SAR data sets for automated flood mapping technique influencing the accuracy of the generated maps and validating results by implementing data from the optical sensor like Sentinel-2. Moreover, visualizing the problem, spatially segregating the inundated areas, resilient spatial information, and accurate results with validation. As a result, it provides efficient results to support decision-makers with quick responses for flood monitoring, formulating measures and maintaining social distancing norms during COVID-19 (Khan and Ramsahai, 2021; Shahid et al., 2021; Syrowatka et al., 2021). Automation is required for an efficient approach to map and deliver robust accurate water maps; avoid expensive and time-consuming manual processing. Thus, the recent advances in auto-processing and executing unconventional approaches and algorithms in a cloud-based system enables faster access to the analyzed datasets. The work conveys the immense benefit of using high-resolution satellite images with minimal effort without data download and software requirements. These approaches can be used to understand the past and present situation to analyze the effect on the land use, the population, and its surrounding; to predict future transformations.

2. Materials and methods

2.1. Study area

The current work considers the Ganga-Brahmaputra plains for the detailed study as shown in Fig. 1. It encompasses the state of Bihar, West Bengal, Assam, Meghalaya, Tripura of the Indian subcontinent. The extent of the study area lies between 22°05′23″N to 27°49′37″N and 84°06′27″E to 95°89′28″E. The study region is severely affected by floods amid the COVID-19 pandemic, especially in the month of July and August. During the last years due to the uneven precipitation recurrent flooding occurred in the Indian sub-continent.

The major rivers along with their tributaries present in the Ganga-Brahmaputra plains brings a huge volume of water every year. The Ganga-Brahmaputra plains are characterized by distinctive hydrological as well as morphological characteristics with increasing human interventions in the fragile region causing large-scale erosion and devastating floods (Bhatt and Rao, 2014). The Ganga-Brahmaputra plains are characterized by large widths of channel belts; a rich source of alluvial soil; the presence of ox-bow lakes; alluvial islands; wetlands; and other related geomorphic features. The region is entirely confined by the Himalayas in the north, the Chota Nagpur plateau in the south, and the Delta in the east (Sinha and Tandon, 2014). The Ganga basin streams cross a Mesozoic-Tertiary flood basalt, Precambrian metamorphic, Archean granites, and gneisses. Relatively, the Brahmaputra basin is dominated by Mesozoic sandstone, shale, limestone, Precambrian acid intrusive, and Cambrian sedimentary rocks (Jha and Bairagya, 2011). There exist significant variations in the landform development drained by the major rivers that cause floods due to different tectonic-geomorphic factors. These include the presence of active hinterlands, excessive rainfall, peak discharges of major rivers, obstruction of drainage by infrastructure, low or high levels of groundwater, and low relief. The climate in the plains of Ganga-Brahmaputra experiences a monsoon-type of climate, the summers are hot, and the winters are cold. The southwest monsoon from the month June–September majorly contributes about (80–90) % of total rainfall (Bhatt et al., 2021).

Fig. 2. Constituents of google earth engine (GEE).
vegetation of this region is typically covered with tropical deciduous trees like peepal, teak, and Sal; mangroves in the Sundarbans; and coniferous trees in the hilly parts. The fauna of this region is rich in several large species of animal that involves Indian gazelles, elephants, antelopes, lions, horses, wild cattle, deer, and wild pigs in the forested regions; large herds of water buffalo in the wetter regions that graze on the riverbanks; Bengal tiger, crocodiles, and alligators found in the deltaic region. The aquatic life in the river water contains a variety of fishes like Rohu, Katla, and Hilsa (Bandyopadhyay and Ghosh, 2009). Agriculture is the main occupation with paddy being the main crop grown. The plain area is beneficial for having a good network of roads, railways, airports, and effective means of waterways along the rivers. Kolkata is one of the important ports on the river Hooghly connecting international ports.

### Table 1
Specification of datasets.

| Characteristics          | Sentinel-1     | Sentinel-2     |
|--------------------------|----------------|----------------|
| Sensor Type              | Microwave      | Optical        |
| Sensor complement        | C-band Synthetic Aperture | Multi Spectral Instrument |
| Polarization             | VV Polarization | B3-Green, B4-Red, B8-NIR |
| Bands                    | 1              | 12             |
| Wavelength               | 5.5 cm         | 442–2202 nm    |
| Swath                    | 250 Km         | 290 Km         |
| Spatial Resolution       | 20m            | 10m (resampled) |
| Temporal Resolution      | 6 days         | 5 days         |

### 2.2. Platform overview

Google Earth Engine (GEE) is a web-based platform to resolve big data problems to enhance the processing of satellite images for large-scale applications. This offers analysis-ready earth observations datasets at a global scale in cloud computing based infrastructure as shown in Fig. 2 for quick visualization and prototyping of the results. The GEE data catalogue holds a large repository of publicly accessible geospatial datasets including a variety of satellite and aerial imaging systems in the form of both optical and non-optical datasets of weather forecasts, environmental variables, topographic, and socio-economic datasets at global, national, and regional levels. The majority of earth observation remote sensing imageries like the entire Landsat collection of datasets, Sentinel satellites, MODIS images, and other relevant datasets are available for various applications.

GEE has more than 800 prebuilt functions in the earth engine library. Java script code editor in GEE is well suited for large-scale operational processing in this environment. This platform includes various in-built algorithms such as classification algorithms to scrutinize the data at a

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**Fig. 3.** Proposed research methodology.
planetary scale with minimal efforts (L. Kumar and Mutanga, 2018). It also includes MODIS images for various temporal analysis studies based on vegetation cover changes and thermal changes over the region (Campos-Taberner et al., 2018). Once an algorithm is recognized, users can easily develop systematic data products supported by earth engine.

Fig. 4. Data preprocessing.

Fig. 5. Processing of Sentinel-1 using Earth Engine Platform.

Fig. 6. The assessment of flood inundated results.

Fig. 7. Backscatter values of water and non-water pixel.
data resources. This platform provides several image classifications with single or multiple images. Supervised and unsupervised classification is used to assign pixels into one of many user-specified classes (Shetty, 2019). However, the supervised classification uses the expert-defined classes trained by the users. Some of the supervised classifiers include Classification and Regression Trees (CART), Random Forest (RF), Naïve Bayes, and Support Vector Machine (SVM) approaches (Bengtsson, Torres-pérez, & Mccullum, 2021).

All the automated operations are performed in bulk and parallel in Google CPUs and GPUs without manual download (Gorelick et al., 2017). This platform provides fast filtering and sorting capabilities that enable users to choose their desired datasets assigning different spatial and temporal specifications out of millions of images. It allows access to the same set of objects, automates batch processing tasks, and delivers highly interactive results. The readily accessible and preprocessed datasets make it easier for the users. The platform hosts Sentinel-1 GRD preprocessed data making use of SAR relatively easier. GEE is limited to selected data mining regression and classification models such as RF, SVM, and CART. Thus, it lacks an efficient and accurate segmentation algorithm (Amani et al., 2019). Complex machine learning algorithms are a little difficult in GEE due to their computational restrictions (Delancey et al., 2019). The complex SAR phase data cannot be stored in the GEE environment since they are not compatible with the tiling concept of the infrastructure. As a result, these applications that rely on phase information like polarimetry and Interferometric SAR applications are limited. It is difficult to download processed data for further analysis while performing a workflow in a third-party software environment. The users often face difficulties due to the enormous map size and internet speed limitations (Gorelick et al., 2017).

### 2.3. Datasets/Database used

The present study utilises satellite microwave and optical datasets. Corresponding, Sentinel-1A SAR images are retrieved during the pre-flood on June 20, 2020 and post-flood on July 30, 2020 in VV polarization. Earlier studies report that these datasets are best suited for flood mapping. The optical data from the Sentinel-2 satellite is acquired on June 20, 2020 and July 30, 2020 for validating the equivalent Sentinel-1A SAR images. Thus, the cloud-based image processing platform is used to deliver image analysis functionality. Furthermore, it is integrated with automated threshold approaches for robust processing to perform all tasks clearly with accurate results. Table 1 summarises the details of sentinel 1 and 2 datasets for flood monitoring.

### 2.4. Methodology

The detailed methodology is represented in Fig. 3 and data is processed with the following steps:

a) Database Creation

The remote sensing images are gathered to map and monitor the inundated areas during the recent flood event of 2020. The required Sentinel-1 satellite images are acquired for pre-monsoon and during the peak monsoon period. JRC surface water data is also used to obtain the permanent water pixels to make the inundated maps. It helps to observe the areas with permanent water presence throughout the year, areas with no water presence, and the areas with occasional water presence. The results are validated with the corresponding Sentinel-2 and google earth images.

b) Data Pre-processing

The google earth engine (GEE) processes the input layer datasets with integrated algorithms and geo-spatial techniques to generate the

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**Table 2** Impact of Flood Inundation over different states.

| States       | Geographical area (km$^2$) | Area under flood inundation (km$^2$) |
|--------------|-----------------------------|-------------------------------------|
| Bihar        | 94,165                      | 8762.32                             |
| Jharkhand    | 79,714                      | 820.27                              |
| Assam        | 78,436                      | 7628.10                             |
| West Bengal  | 89,752                      | 7072.36                             |
| Meghalaya    | 25,429                      | 250.28                              |
| Tripura      | 10,498                      | 235.21                              |
| Total Area   | 377,994                     | 24,768.54                           |

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**Fig. 8.** Water inundation during the pre-flood period on June 20, 2020.
required layer as shown in Fig. 4. The pre-processing techniques for Sentinel-1A images encompass orbit correction, thermal noise removal, radiometric calibration, and terrain correction. Furthermore, Sentinel-2 images are pre-processed to remove cloud cover. Cloud masking helps to identify and mask out the flagged clouds and these datasets are readily available as Image Collection in GEE. The JRC Global Surface Water dataset is also used to mask out areas covered with surface water for more than 10 months.

c) Data Analysis

The permanent water for more than 10 months is masked out through the JRC Global Surface Water datasets. To determine the water inundated areas, the data is categorized after pre-processing of Sentinel-1 images as explained in Fig. 5. The classification is based on two distinct classes is water and non-water. Threshold values are selected to isolate the non-water pixels from the water pixels. Otsu’s method is broadly applied in pattern recognition, feature analysis, and quantification. This method searches for a threshold to segment an image for further
processing. Otsu’s algorithm uses an optimal threshold-based clustering of the foreground (flooded) and background (non-flooded) pixels of the selected image. It assumes to achieve good results if the histogram of the original image comprises of two discrete peaks, one belongs to the foreground and the other belongs to the background.

d) Evaluation Design

The accuracy assessment of the classified image is achieved with a confusion matrix. The classified image derived from Sentinel-1 is validated using Sentinel-2 optical images. The classification of validation samples is derived from the decision tree approach. The generated validation samples from Sentinel-2 are overlaid on Sentinel-1 SAR images. Moreover, the results are also cross-checked with google earth imageries.

The correctness of Otsu’s method is regained by linking the generated flood inundation maps with the overall accuracy. The individual class accuracies are checked to validate the images. The overall justification of the classified images is executed as per the schematic given in Fig. 6 by comparison of flooded and non-flooded scenarios in google earth images.

3. Results

3.1. Backscatter values of water and non-water pixels

The backscatter values in Sentinel-1 SAR images depend on several factors like acquisition features, topography, soil moisture, land cover, and vegetation characteristics (Bhatt et al., 2021; Singh et al., 2020). It is observed that water illustrates a low backscatter response and appears in a dark tone due to specular reflection causing the majority of the radar signals to divert away from the sensor (Liu, 2016). The low backscatter can also be the same due to smooth topography, low soil moisture, a surface with low vegetation, and the presence of standing water in the fields.

The backscatter values from the generated maps helped to extract the water and no-water pixels followed by statistical metrics calculation. It is observed that the backscatter value of water class during peak-flood (26.51) exhibits low backscatter than the pre-flood (15.35) situation as shown in Fig. 7. Due to heavy flooding, the backscatter values showed low intensity and tends to fall towards more negative values.

3.2. Water inundation analysis

The impact of the flood is evaluated to understand the influence of the flood inundation in the regions. The quantification of the affected areas in pre-flood and peak flood scenarios are estimated by multiplying the cell size of the pixel with the total number of affected pixels as shown in Table 2.

Water inundation maps are generated for pre-flood as well as the peak-flood period as depicted in Fig. 8 and Fig. 9. The results show the total area submerged under floodwater. The total area covered by water is much less for pre-flood when compared to the peak-flood results. The figures in the results summarized the workflow which is used for processing the images and further estimated the total area affected due to the flood.

In Fig. 9, the google map of the study area is shown to display the extent of the study area of the pre-flood where there is no presence of
inundated regions. The major rivers like Ganga, Brahmaputra, and Kosi with other water bodies are visible at this stage. In contrast to this, Fig. 9, presents the peak-flood scenario with severely affected regions of Bihar, the Northern and central parts of West Bengal, and Assam. The rivers and water bodies are denoted with the light shade of blue whereas the flood water is presented with the dark blue. This is followed by some examples (A, B, and C) considered within the study area to visualize the changes and is explained later in the study.

It is noted that severe floods occur in parts of the upper catchment of River Ganga, Kosi, and the Brahmaputra and also at the confluence of River Ganga and Brahmaputra basin. As a result, induced devastating effects on the residents of these regions. This study exhibits a recent flood of July 2020 inundated a large portion of the 24,768.54 km² area of the lower Ganga-Brahmaputra plains. The maps represent blue for peak-flood maps in the flood inundated areas affecting most parts of the Indian sub-continent like Bihar, Assam, Tripura, and West Bengal. In addition to this, major parts of Bangladesh endure the devastating effects of the flood. The flood significantly affects the regions of Bihar (9.31%), Assam (9.73%), and West Bengal (7.89%) majorly, whereas the states of Meghalaya (0.99%), Tripura (2.24%), and Jharkhand (1.03%) are comparatively less affected. It is observed that severe floods in northern parts of Bihar, northern and central West Bengal, and the north-eastern part of Assam also in the central and western part of Bangladesh which is the confluence of both the basins experience frequent inundations. This shows that the upper catchments of the major rivers of the Brahmaputra and river Ganga get severely flooded, and the water gets accumulated at the confluence of both basins in Bangladesh that further leading to devastating effects. In contrast, the flood has the least impact on states of Meghalaya, Jharkhand, and Tripura due to its size and location. Images (A, B, and C) symbolized examples of selected regions undergoing severe floods.

3.3. Validation and assessment

The non-water samples are used for validation for understanding the variations in the backscatter values. It is observed that during the peak flood the backscatter values of water pixels are around (−26.51 dB) and it is much lower compared to the backscatter values of non-water pixels with (−23.64 dB). Contradictory, the backscatter values of the non-water pixels in the pre-flood shows a very low mean backscatter values of (−8.48 dB). The variations in the backscatter values occur due to surface roughness and rise in water inundation. The charts show the backscatter responses of water and non-water pixels in pre-flood and peak-flood situations as shown in Fig. 10 and Fig. 11. The results of the water inundation maps are compared with Sentinel-2 images. Thereafter extraction of the water and non-water pixel values is completed and google earth is used to assess the accuracy of extraction. Fig. 12 shows the sample locations (viz A, B, C) on the google earth engine. The resulting inundation maps for the given locations are analyzed to evaluate the accuracy using google earth imageries. The area submerged underwater in classified images for both scenarios of flooded and non-flooded are compared using the google earth images. The subsets of flood maps with their corresponding google earth images for before and during flood events are shown in detail. The results of the classification are presented through these images that help in the validation. This justifies the implementation of Otsu’s threshold method in this study.

The comparison analysis among locations A, B, and C indicates that these regions are severely affected by the flood. The accuracy assessment shows an overall accuracy of 95.63% for June 20, 2020 (pre-flood scene) and 94.16% for July 30, 2020 (peak-flood) with the kappa coefficient of 0.87 and 0.86 respectively. The individual class accuracy of the classification for both the water and non-water class in pre-flood and peak flood scenarios are extracted from the confusion matrix and depicted in
Fig. 13. The higher the classification accuracy metrics determined the best performance of Otsu’s algorithm for surface water mapping and classifying the water and non-water pixels. 

Figs. 14 and 15 shows a set of four images to compare the pre-flood and peak-flood situations. The first and second images show the SAR imageries of pre-flood and peak-flood conditions. The pixels with low greyscale intensity shows the presence of water whereas the pixels with dark greyscale indicates land features. The inundation maps show the flood inundation with a dark shade of blue whereas the permanent water with a sky blue colour. The other images show the google earth imageries of the corresponding areas. The validation of flood regions is also checked with the historical data sources of google earth images. The first example shows location A as shown in Fig. 13, covering the area of Bihar which is mostly affected by flood inundation. Fig. 16 shows the water pixels before the occurrence of rainfall in the Sentinel-1 SAR image to monitor the extent after the flood. Fig. 14 shows inundated areas derived with the thresholding of backscattering intensity. 

This analysis evaluates the efficiency of automated surface water mapping approaches for generating efficient inundation maps. Moreover, assessed Otsu’s threshold algorithm, produces surface water maps with moderate accuracy in real-time applications by utilizing the cloud-based GEE platform. The obtained results from the analysis are compared, validated and interpreted with the sample imageries.

4. Conclusion

The abrupt outbreak of the COVID-19 pandemic disrupted flood responses but the assessment of accurate inundated areas provides the ready solution for a valued and timely response during the parallel flood and pandemic condition. Although some researchers suggested that surface water mapping might obtain high errors depending on its environment and physiography. Likewise, Chapman et al. in his study (Chapman et al., 2015) observed high errors in flooded forested areas using a surface water mapping algorithm where the L-band SAR data is preferred to view the underlying water since the C-band SAR signal cannot penetrate the canopy structure. Furthermore, Martinis et al. (Martinis et al., 2018) remarked that in the arid regions where the surface is flat, the surface water mapping algorithm is found to have high errors of commission. Conversely, this study used the Lee Sigma filter, which can provide adjusted inputs for the algorithm of surface water mapping and provide better results. Lastly, additional tasks and parameters can be built upon this study which is not discussed here. This can provide highly customized results that can be applicable for some other regions. Data fusion techniques can also be implemented for automated surface water mapping and generating near real-time surface water maps for immediate disaster response and effective decision-making. The preparation of high-quality surface water maps can support the efforts of different sections of regional land-cover monitoring systems (Saah et al., 2019), ecosystem and environmental monitoring (Poortinga et al., 2018), and water-resources management (Aekakkararungroj et al., 2020). The study presents the significance of cloud-based data processing with geospatial analysis of multi-sensor data for real-time information generation. The study presents an assessment of the pre-processed SAR datasets and the potential of the automated technique to map, monitor and analyze the flood scenarios. Surface water maps are generated for the pre-flood and the peak-flood scenarios. Also, it is validated for checking the accuracy of surface water maps to provide actual results from the pre-processing steps and their effects on inputs of the applied algorithms for flood mapping. The results report that the recent flood of July 2020 has caused a severe threat to life and property. It is expected that a similar study can be adapted by the researchers, disaster mitigation communities, and other stakeholders for future preparedness in cases of emergencies. The automated techniques can be integrated with approaches that have great 

Fig. 15. (a) Parts of region shown as location B in Fig. 12 showing Ganga and Brahmaputra confluence. (b) Parts of Assam shown as location C in Fig. 12.
potential to deliver near real-time surface water maps and it can be a capable way for various applications like flood risk mapping, immediate disaster response, and support decision making for sustainable development of resources.

Author contribution

Dr Deepak Kumar (DK) conceived and designed the study, and Ms. Sukanya Ghosh (SG) performed the research, analyzed the data, and Dr Deepak Kumar (RK) has contributed to editorial input. Conceptualization, methodology and formal analysis: DK, SG; investigation: SG, DK; visualization: SG, DK; writing—original draft: SG, DK; writing—review and editing: DK, SG; All authors read and approved the final manuscript.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Not applicable.

Consent for publication

All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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