FLOOD MAPPING AND DAMAGE ASSESSMENT USING SENTINEL – 1 & 2 IN GOOGLE EARTH ENGINE OF PORT BERGE & MAMPIKONY DISTRICTS, SOPHIA REGION, MADAGASCAR

Penchala Vineeth Kurapati (1), Ashish Babu (1), Solo Tahiana Rajosarimalala (1), Kesava Rao Pyla (2)

[1] Project Scientist, Centre on Geo-Informatic Applications in Rural Development, Ministry of Agriculture, Livestock and Fisheries, Nanisana, Antananarivo, 101, Madagascar
[2] Associate Professor & Head, Centre for Geo-Informatic Applications in Rural Development, National Institute of Rural Development and Panchayati Raj, Telangana, 500030, India
Email: penchala.vineeth3@gmail.com; ashishbabu619@gmail.com; trajosarimalala@gmail.com; kesava.nird@gov.in

KEY WORDS: flood mapping; sentinel-1; damage assessment; sentinel-2; Google Earth Engine

ABSTRACT: Flood is the gravest natural disaster where Madagascar is facing, it is necessary for the government and disaster experts to monitor and assess the damage. The adoption of traditional approach is time taking and expensive, with the advances in remote sensing techniques and availability of free satellite data and platforms for analysis made experts easy. This study is mainly focused on flood mapping and damage assessment in Google Earth Engine which is a cloud-based analysis platform. Flood inundated map was generated using pre and post flood images of SAR i.e., sentinel-1 which provides data by continuous observation during flood, as it has capacity to penetrate through the cloud. Land use/ land cover map was generated using pre-flood cloud free sentinel-2 datasets, the overall accuracy and kappa coefficient was 83.42% and 0.79 respectively. Finally, assessment of damage was done by overlaying flood inundated map on land use/ land cover map. A total area of 377.95 km^2 was flooded out of which 302.03 km^2, 4.1 km^2 of cropland, built up were flooded respectively. Therefore, this study concludes that by combining microwave and optical data for flood mapping and damage assessment in Google Earth Engine platform is more advantageous and cost efficient.

1. INTRODUCTION

1.1 Background

Flood is defined as flow of water in abnormal condition or above standard water surface which inundates higher ground (Rahman Rejaur, 2014). It is a natural disaster and occurs frequently due to excessive rainfall and causes loss to human life, property, wide area of agriculture and forest/ vegetation, which in turn impacts the country by economically, environmentally and socially (Zhang, S L and Zhou W C, 2017). Therefore, for efficient management, it has created interest for the researchers, policy makers and governmental organizations to assess the information related to flood accurately. In general management of disaster can be divided into three phases: the preparatory phase which is applied before disaster by identifying threat zones; the mitigation phase in which activities such as emergency evacuation, tracking and execution of contingency plans are conducted only before or during the disaster; finally, response phase which includes activities such as damage estimation, recovery measures are conducted shortly after the damage (Jeyaseelan, 2014).

Recent developments in space technology enables the researchers and agencies in utilizing the satellite images, it can also provide flooding period and extent approximately (Peter, Matjaž, & Krištof, 2013) and mapping of flooded areas is a key practice for understanding the affected land use/ cover (Addabbo etal., 2018). The use of optical data is very difficult due to cloud cover and accessibility of free Synthetic Aperture Radar (SAR) data by European Space Agency's (ESA) i.e., sentinel-1 created an advantage for monitoring the flood extent because the radar sensor does not depend on solar illumination and has capacity to penetrate through the clouds (Uddin, Matin, & Meyer, 2019). Madagascar is a flood prone zone, most of them were occurred due to excessive rainfall, a report from National Office for Risk and Disaster Management (BNGRC), Madagascar stated that during January 2020 almost 116,675 people were affected from 7 regions i.e., Alaotra Mangoro, Analamanga, Betsiboka, Boeny, Diana, Melaky and Sofia.

1.2 Objectives of the study

This study includes following goals where the processing and analysis is performed in GEE:

1. Analyzing and generating flood inundation map using SAR i.e., sentinel-1 datasets.
2. Estimating land use land cover using optical dataset i.e., sentinel-2 satellite imagery.
3. Flood damage assessment using flood inundated and LULC maps.

2. STUDY AREA

Port Berge and Mampikony districts lies between -15.5645° south, 47.6685° east i.e., south central and -16.05105° south, -47.606163° east i.e., south western respectively of Sofia region. These districts have a sub type climate characterized by two distinct seasons, dry from May to October and humid from November to April. The temperatures in the region are quite favorable for agriculture and varies according to the altitude, where the average annual temperature reaches in Sofia region is 26°C.

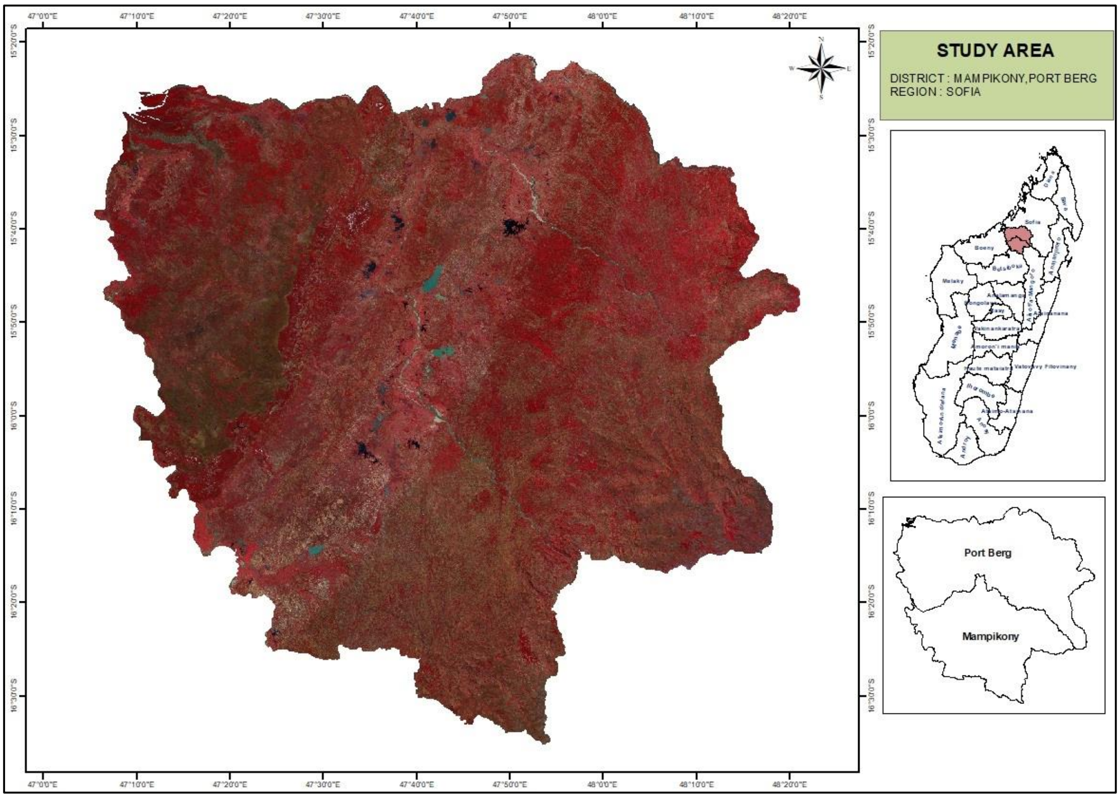

Figure 1: Location of Study area

The annual average temperature recorded at Mampikony was 22.2°C. Port-Berge is a coastal zone having a mean annual temperature above 25°C. Rainfall in this region is characterized by a high degree of irregularity, wet season usually begins from December and is mainly concentrated over 4 months of a year (December to April). There can be heavy rainfall of a few hours during the day.

3. DATA USED AND METHODOLOGY

3.1 Data used

In this study sentinel-1, sentinel-2 and SRTM satellite datasets were used. For estimating flooded areas, a mosaic of sentinel-1 level-1 Ground Range Detected (GRD) having Interferometric Wide Swath (IW) and 'VH' polarized products were acquired for the dates of pre-flood event between 5 to 16 January 2020 and post flood event between 17 to 27 January 2020. In addition to SAR data, for assessing damage a mosaic of pre-flood cloud free sentinel-2 satellite data collection between 1 January 2019 to 14 November 2019 were utilized for land use/land cover mapping. Google Earth Engine is used for image processing, analysis and ArcMap 10.5 is used for map generation.

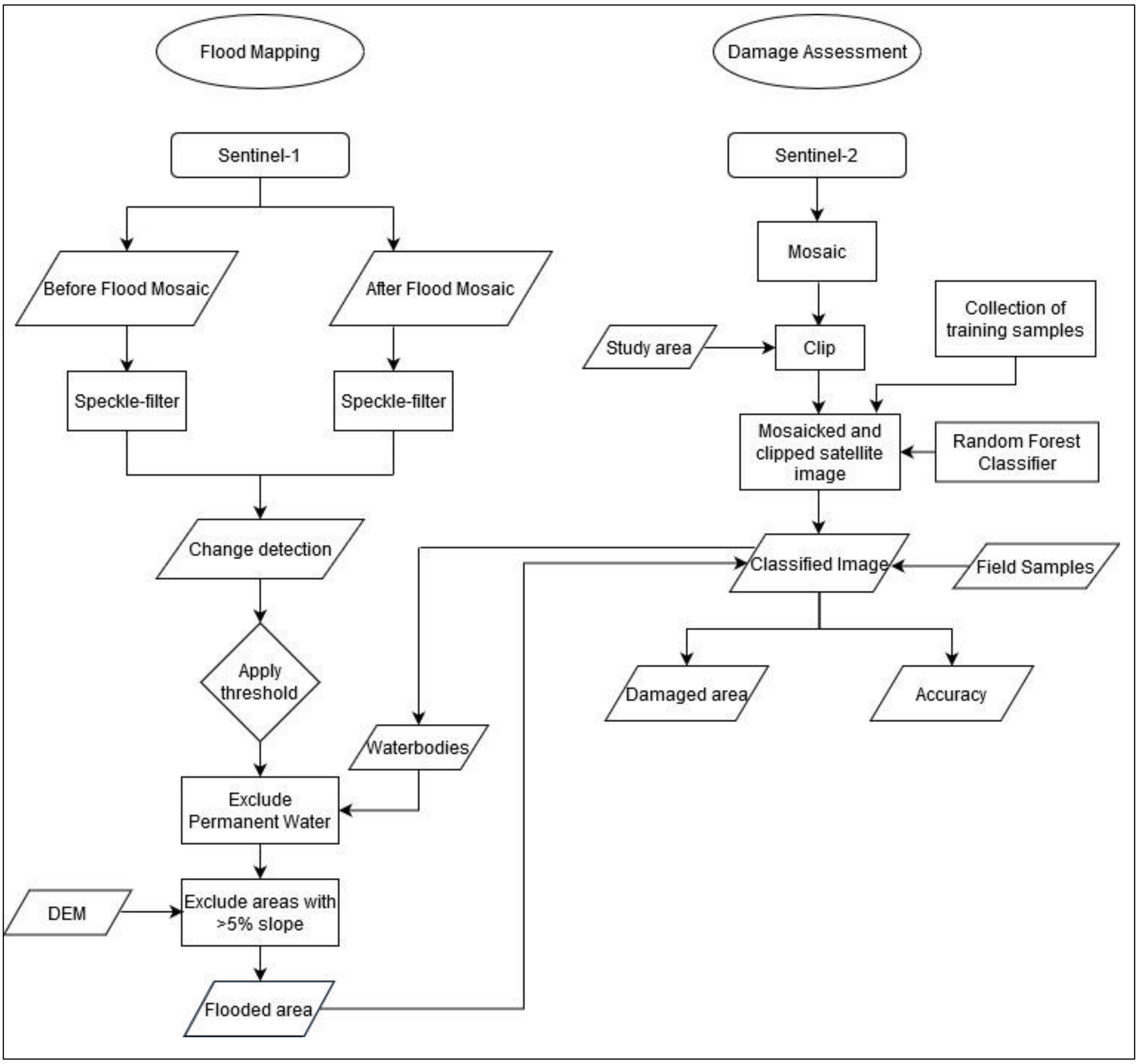

Figure 2: Flow diagram indicating methodology of the study

3.2 Methodology

The detailed method utilized for the study is shown in figure 2. Precisely, sentinel-1 data is used for identifying flooded areas with initial processing of speckle filter, change detection, exclusion of permanent water bodies and using sentinel-2 data LULC is created for estimating damage occurred due to the flood.

Flood Mapping: Google Earth Engine provides Ground Range Detected (GRD) products consists of SAR focused data that has been detected, multi-looked and projected to ground range using an earth ellipsoid model. Using height of terrain, the ellipsoid projection of GRD products were rectified. Speckle filter is applied to the GRD products of pre and post flood events, generally speckle noise is occurred within one resolution cell due to irregular interference of several elementary reflectors and has a great effect on radiometric resolution (Moreira, Prats-iraola, & Younis, 2013). Speckles were removed by using either two techniques multi-look processing and filtering techniques, for this study filtering techniques were used and mean filter is applied with a smoothing radius of 50 meters, circle kernel is used for this purpose. Pre (R) and post (F) flood images were selected, for change detection technique(Long et al., 2014) image ratio is applied to extract the flooded areas (CD).

$$CD = F/R \qquad (1)$$

Permanent or natural water bodies (e.g. ponds, river, lake etc.) were masked from the extracted flooded areas (CD) using classified image which is derived from sentinel-2 satellite imagery in order to differentiate the actual flooded region. Areas having slope >5% were excluded using HydroSHEDS data it provides information of hydrographic, in regional and global-scale which has been developed by World Wildlife Fund (WWF) based on SRTM Digital Elevation Model (DEM).

Land use/ land cover map generation: Supervised classification technique is applied on an FCC (False Color Composite) image for generating LULC map, 586 training samples were collected for each LULC class. According to level-1 classification (Lillesand and Keifer, 2002) a total of six classes were identified i.e., barren land, built up, cropland, sand, forest/vegetation and waterbody. Finally, in Google Earth Engine Random Forest algorithm is applied using the training samples. The RF classifier is a collection of tree-structured classifier which is an advanced form of Bagging and creates randomness. Rather than dividing each node using the optimal split of all the variables, RF divides each node using the best of a subset of randomly chosen predictors at that node. A new set of training data is created with replacement from original dataset, then a tree is grown using random feature selection, grown trees are not pruned (Akar & Güngör, 2012). The technique makes RF outstanding in precision and can form many trees depending on user requirements, it is very fast and strong against overfitting (Breiman and Cutler 2005). Finally, overall, producer and user accuracies were estimated for the obtained LULC result using another set of 255 samples i.e., 45 barren land, 39 built up, 43 cropland, 41 sand, 45 forest/ vegetation, 42 waterbody samples which were collected from publicly open earth observation and online map tools such as open street map and google earth. Kappa coefficient is also calculated for testing the interrater reliability.

Flood Damage Assessment: Flood damage is characterized as the probability that a loss will happen (Kefi et al., 2018). Therefore, flooded areas which was extracted from sentinel-1 image is overlaid on LULC map which was generated from sentinel-2, to estimate damage occurred due to flood and finally, the area of each inundated land use/ land cover class is calculated.

4. RESULTS AND DISCUSSIONS

4.1 Flood Inundation Map

The cause of flood is due to excessive and continuous rainfall in the month of January from 18th to 24th which is obtained from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data as shown in figure 3. Based on the rainfall data pre and post flood datasets were selected from sentinel-1. Therefore, flood inundated map was prepared and total area of 377.95 km^2 i.e., 3.19% was flooded which is shown in figure 4.

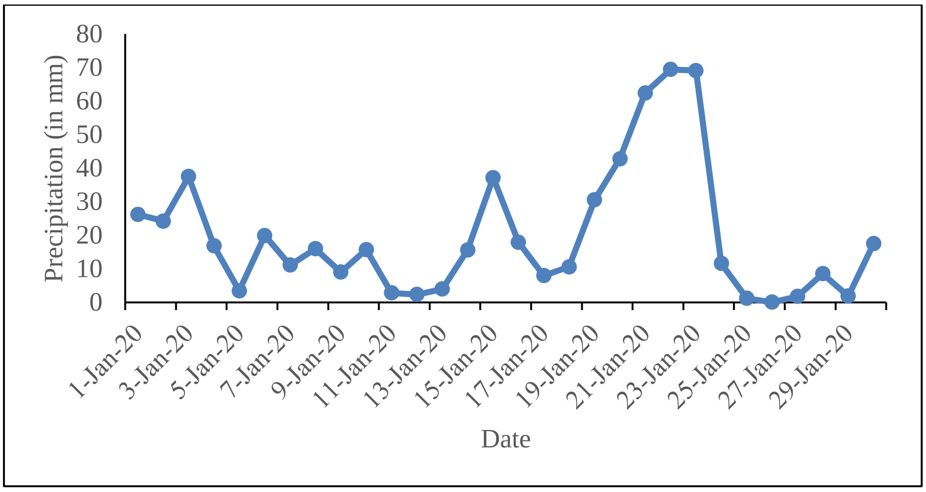

Figure 3: Rainfall data during January 2020, CHIRPS data

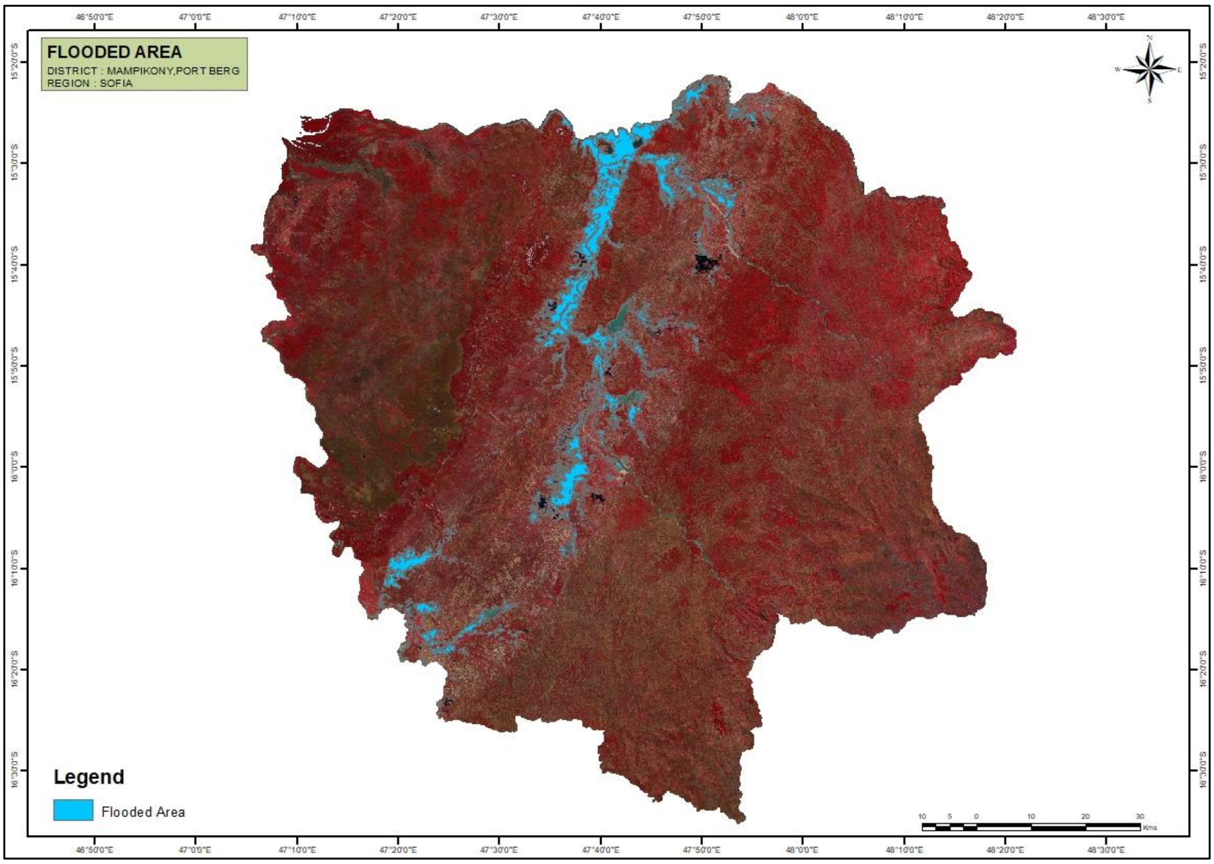

Figure 4: Flood inundated map

4.2 Land use/ land cover map

In order to estimate damage initially LULC map was prepared using a mosaic of sentinel-2 pre-flood datasets which is shown in figure 5. The total area of both districts is 11,860.43 km^2 where cropland occupies most and sand occupies least i.e., 39.34%, 0.48% of total area respectively and detailed statistics of each LULC classes were shown in table 1.

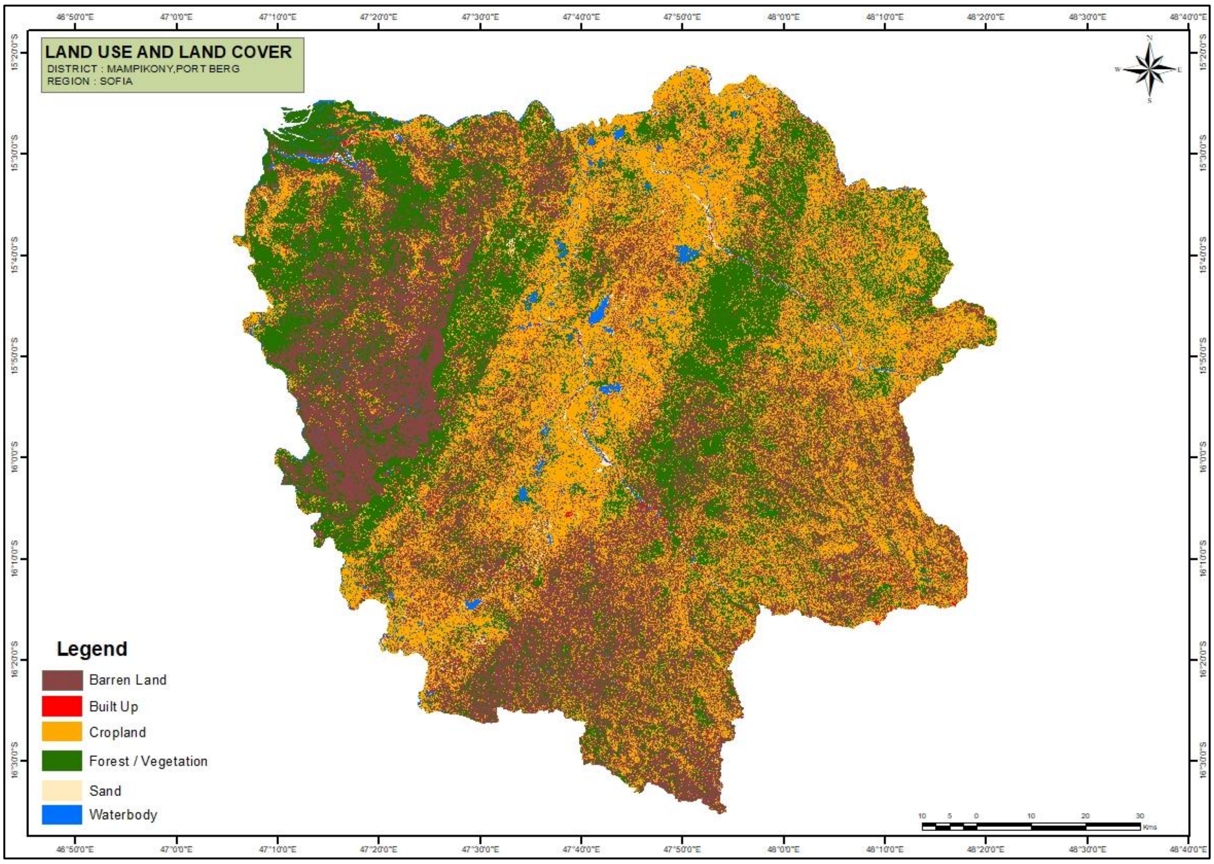

Figure 5: Land use/ land cover map of Port Berge and Mampikony

The overall accuracy estimated using 255 training samples for 2019 sentinel-2 derived land use/ land cover map was found to be 83.42%, the kappa coefficient is 0.79 which indicates the level of agreement is moderate. The detailed error matrix is shown in table 2, which includes user and producer accuracies also.

Table 1: Statistics of land use/ land cover classes

LULC classes	area in km^2	% of total area
Barren Land	4,140.21	34.91
Built up	63.61	0.54
Cropland	4,665.6	39.34
Forest/ Vegetation	2,815.86	23.74
Sand	56.76	0.48
Waterbody	118.39	1.00
Total	11,860.43	100

Table 2: Error matrix of LULC map for 2019

LULC Classes	Barren land	Built up	Cropland	Sand	Forest/ Vegetation	Waterbody	Total	Producer Accuracy (%)
Barren land	71	0	9	1	0	2	83	85.54
Built up	0	11	5	6	0	0	22	50.00
Cropland	6	1	68	0	10	0	85	80.00
Sand	2	0	0	42	0	1	45	93.33
Forest/ Vegetation	0	0	0	0	88	2	90	97.78
Waterbody	0	0	1	15	2	37	55	67.27
Total	79	12	83	64	100	42	380	n.a.
User Accuracy (%)	89.87	91.67	81.93	65.63	88.00	88.10	n.a.	n.a.

4.3 Flood Damage Assessment

As discussed in methodology the affected LULC classes were extracted from the flood map which was derived from sentinel-1 dataset. The affected classes were shown in figure 6, cropland is most affected whereas sand is least affected and the detailed statistics were shown in table 3.

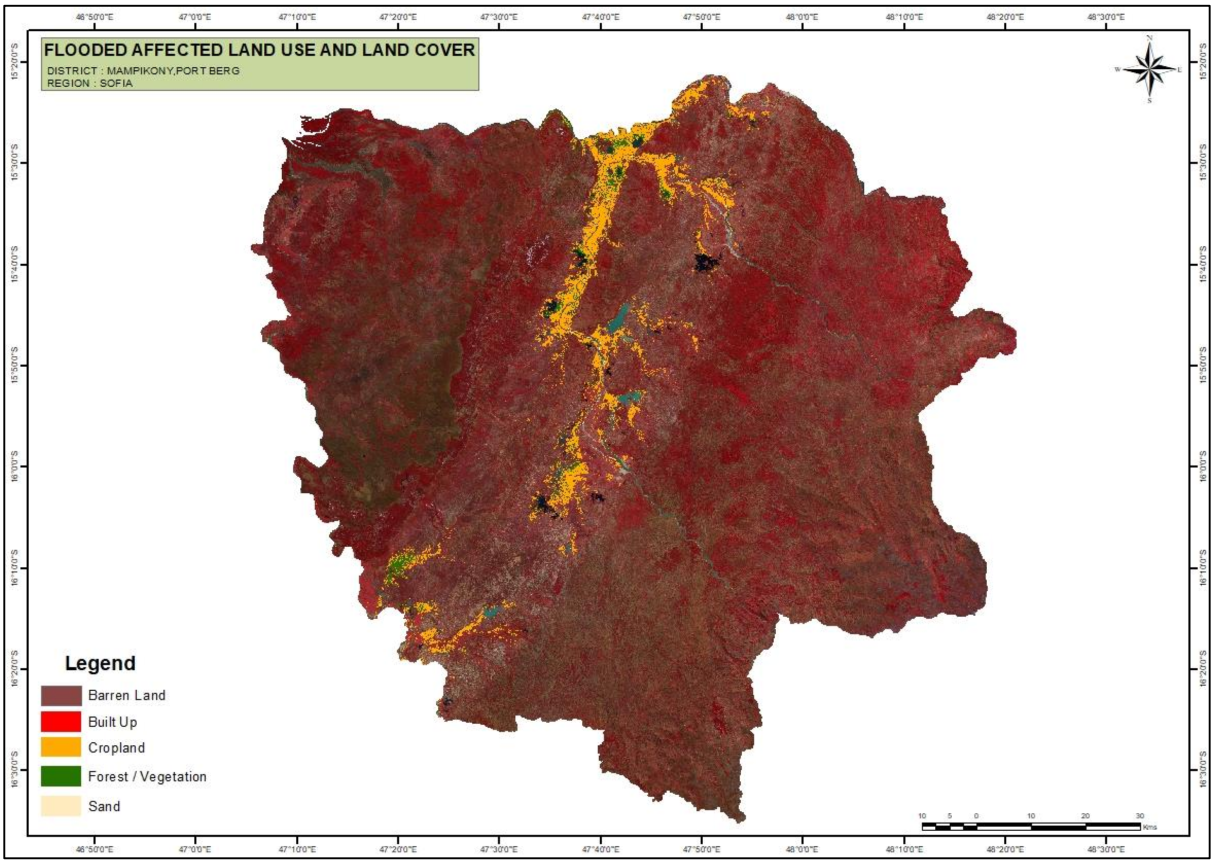

Figure 6: Affected land use land cover map

Table 3: Statistics of affected land use/ land cover classes

LULC classes	affected area in km^2	% of total affected area
Barren Land	31.69	8.27
Built up	4.1	0.93
Cropland	302.03	80.44
Forest/ Vegetation	35.97	9.47
Sand	4.17	0.89
Total	377.95	100

The entire analysis was performed in Google Earth Engine which is a cloud based interactive development environment (IDE) platform and code was written using JavaScript, the code link of the analyzed work and results.
https://code.earthengine.google.com/cf43f25ffa4ab5f79fc2f2f14bdd3b04.

5. CONCLUSIONS

Depending on the findings of the study, an area of 377.95 km^2 was affected due to the flood, when compared with the areas of each class of the entire study area 0.77% of barren land, 6.45% of built up, 6.47% of cropland, 7.35% of sand, 1.28% of forest/ vegetation were affected and overall accuracy of the estimated LULC was 83.42%, therefore we can infer that the geospatial and earth observation technologies furnish timely data for efficient decisions and detailed management of flood disasters. Due to the weather conditions during flooding the availability of cloud free optical data is not so easy and SAR data can be utilized for estimating the flooded area. Cloud based platform i.e., GEE has been shown to be very useful for the users in preparing an emergency response related to flood and evaluating the damaged area by generating land use land cover map. This approach was developed by utilizing freely available data and analysis platform i.e., GEE, which can be particularly useful for under developed countries.

5.1 References and/or Selected Bibliography

References from Journals:

Addabbo, A. D., Re, A., Lovergine, F. P., & Pasquariello, G. (2018). Computers and Geosciences DAFNE : A Matlab toolbox for Bayesian multi-source remote sensing and ancillary data fusion , with application to fl ood mapping. *Computers and Geosciences*, *112*(December 2017), 64–75. https://doi.org/10.1016/j.cageo.2017.12.005.

Akar, Ö., & Güngör, O. (2012). Classification of Multispectral Images Using Random Forest Algorithm Classification of multispectral images using Random Forest algorithm. *Journal of Geodesy and Geoinformation*, (August 2015). https://doi.org/10.9733/jgg.241212.1.

Jeyaseelan, A. T. (2014). Droughts & Floods Assessment and Monitoring using Remote sensing and GIS, (March).

Kefi, M., Mishra, B. K., & Kumar, P. (2018). Assessment of Tangible Direct Flood Damage Using a Spatial Analysis Approach under the Effects of Climate Change : Case Study in an Urban Watershed in Hanoi , Vietnam. *International Journal of Geo-Information*. https://doi.org/10.3390/ijgi7010029.

Long, S., Fatoyinbo, T. E., & Policelli, F. (2014). Flood extent mapping for Namibia using change detection and thresholding with SAR. *Environmental Research Letters*, *9*(2014). https://doi.org/10.1088/1748-9326/9/3/035002.

Md, R. R. (2014). Flood Inundation Mapping and Damage Assessment Using Multi-temporal RADARSAT and IRS 1C. *Asian Journal of Geoinformatics*, (January 2006).

Moreira, A., Prats-iraola, P., & Younis, M. (2013). A Tutorial on Synthetic Aperture Radar. *IEEE Geoscience and Remote Sensing Magazine*, (May 2014).

Peter, L., Matjaž, M., & Krištof, O. (2013). Detection of Flooded Areas using Machine Learning Techniques : Case Study of the Ljubljana Moor Floods in 2010. *Disaster Advances*, (June 2014).

Uddin, K., Matin, M. A., & Meyer, F. J. (2019). Operational Flood Mapping Using Multi-Temporal Sentinel-1 SAR Images : A Case Study from Bangladesh, 1–19. https://doi.org/10.3390/rs11131581.

Xie, S., Liu, L., Zhang, X., Yang, J., & Chen, X. (2019). Automatic Land-Cover Mapping using Landsat Time-Series Data based on Google Earth Engine, (Cdl).

Zhang, S L and Zhou, W. C. (2017). Flood monitoring and damage assessment in Thailand using multi-temporal HJ-1A / 1B and MODIS images Flood monitoring and damage assessment in Thailand using multi-temporal HJ-1A / 1B and MODIS images. *Earth and Environmental Science*. https://doi.org/10.1088/1742-6596/755/1/011001.

References from Books:
Lillesand, T. M & Kiefer, R. W., (2002). *Remote Sensing and Image Interpretation*, New York: John Wiley & Sons, Inc.

References from websites:
Breiman L., Cutler A., (2011). Random forest. Retrieved from https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm.