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Machine Learning Approach for Catastrophe Risk Assessment and Management Using Remote Sensing Data

Nita Nimbarte[1], Bharati Masram[1], Archana Tiwari, Sanjay Balamwar
[1]Department of Electronics & Telecommunication Engineering
Yeshwantrao Chavan College of Engineering, Nagpur
India
nitangp@gmail.com, bharatimasram@gmail.com
[2]Department of Electronics Engineering ,
Shri Ramdeobaba College of Enginering Nagpur,
India
e-mail: tiwariar@rknec.edu
[3]Maharashtra Remote Sensing and Applications Centre (MRSAC)
VNIT Campus,
Nagpur, India
Sanjay.balamwar@mrsac.maharashtra.gov.in

Abstract—With emergency programs for disaster preparedness and warning phases for earthquakes, landslides, and floods in recent years, remote sensing and geographic information systems have played a crucial role in Catastrophe Risk assessment and management. It has also been a key focus in the field of technology. Without the right tool for organizing massive volumes of data and gathering information from many sources, such maps or measurement channels, it would not be feasible to employ sensory data. In order to identify and assess areas affected by floods, earthquakes, avalanches, landslides, and wildfires, this study employs machine learning approaches. Following the application of filters to enhance image quality, the images are segmented through thresholding technique and classified using supervised and unsupervised classification methods. Images from before and after disasters are gathered from MRSAC Nagpur and processed using Python-based tools, ArcGIS, ERDAS, and QGIS for the purpose of analyzing devastation.

Keywords- Catastrophe Assessment, Remote Sensing, Earthquake, Flood, Landslide, Avalanche, Wildfire.

I. INTRODUCTION

Disasters cause various types of devastation to people and property all around the world. Higher population strain on the earth's resources has resulted in increased susceptibility of humans and their facilities to environmental hazards that have always existed. Earthquakes, floods, landslides, and forest fires that occur often must be examined using today's advance technology in order to identify efficient preventive methods. Better future scenario projections, identification of catastrophe-prone locations, location of protective measures and safe alternate routes, and other uses of space technology can aid disaster prevention. Satellite data collected after a disaster aids in disaster recovery and the damage claim procedure [1-2].

Binary Logistic Regression, K-Nearest Neighbor (KNN), Support Vector Classifier (SVC), and Decision Tree Classifier are presented by M. M. A. Syeed et al. [3]. A comparison research was conducted to ascertain the model that gives the maximum accuracy. T. Sharma et al. [4] reviewed several papers and find that there are algorithms like SVM, Regression, Random Forest techniques, Neural Networks, Bayesian Networks, and so on, with Random Forest and Neural Networks doing better than the others. There are several websites and sources that provide rainfall data for Indian states. This review report focused on three states: Uttar Pradesh, Bihar, and Kerala. According to B. Li et al. analysis [5], MODIS images with a 250 m resolution were utilized to monitor the area that was submerged and the dynamic changes that occurred in the flooding area between 2000 and 2010. The data showed that the area flooded by Poyang Lake in 2010 was more than in any other year. Between 2000 and 2010, Poyang Lake's inundated area grew, whereas the east and southwest Dongting Lakes exhibited a clear downward trend. Karamat Ali et al. [6] demonstrate the various parameters of flood risk assessment. Assessment steps are as area description, calculating intensity and hazard level, assessing vulnerability. Also reported advances in remote sensing, geographic information systems (GIS) and hydraulic modeling technology.

S. N. Ghate et al. [7] described machine learning approach for wildfire detection system for early prediction. Random Forest, Logistic Regression and kNN machine learning algorithms used for analysis using different features like

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pressure, temperature and vegetation. M. Rahul et al. [8] proposed image recognition system using Convolutional Neural Networks (CNN). Relu activation function was used with fine-tuned Resnet50 architecture by adding convolutional layers. Algorithm gives 89.57% accuracy for test data and 92.27% for training data set of forest fire. In the proposed system time scale base system apply for wildfire area detection. Adjusted Otsu algorithm used to segment the input images. Long Short Term (LSTM) and Deep Learning based approach used for current data prediction [9].

In order to develop a machine learning model for avalanche detection, Amirhosein Mosavi et al. [10] used alternating decision trees (ADT), logistic regression (LR), logistic model trees (LMT), functional trees (FT), and random subspaces (RS). The ROC curve is used to conduct the analysis, and the results are presented as follows: Sensitivity = 94.1%, Specificity = 92.4%, Accuracy = 93.3% and Kappa = 0.782. Bahram Choubin et al. [11] studied three parameters like terrain characteristics, meteorological factors and avalanche occurrence locations. Multivariate Discriminant Analysis (MDA) and support vector machine (SVM) based machine learning algorithms are proposed. Both algorithms performed excellent for avalanche area analysis with area under curve is more than 90%. Author reported SVM approach for high-dimensional data. For experimentation data collected from Lochaber, Scotland, UK area for avalanche forecasting. It gives better results as compared to Nearest-Neighbour (NN) method [12].

B. Bhargava and S. Pasari [13] proposed Artificial Neural Network (ANN) and long-short-term memory (LSTM) based models to detect earthquake and forecaster system. Both models give satisfactory results for small and medium sized earthquakes. B. Arunadevi et al. [14] proposed machine learning based approach. Also used instrument that records and measures earthquake information. In machine learning approach developed decision tree and geographic data mining techniques. X. Wang et al. [15] developed algorithm using LSTM neural networks, random forest and excel machine learning methods. For large scale database, random forest method performs better to classify large earthquake occurrences and magnitude identification carried out through LSTM method. Five case studies were provided for earthquake analysis by Essam Ghamryet al. [16]. Fast Fourier Transform (FFT) and Discrete Cosine Transform (DCT) methods are used to analyze magnetic data. Along with MODIS and MERRA-2, Swarm satellites gathered magnetic data in the upper side ionosphere. Multilevel feature augmentation network created in convolutional neural networks for landslide analysis. For the purpose of detecting changes in landslide areas, three models are described [17].

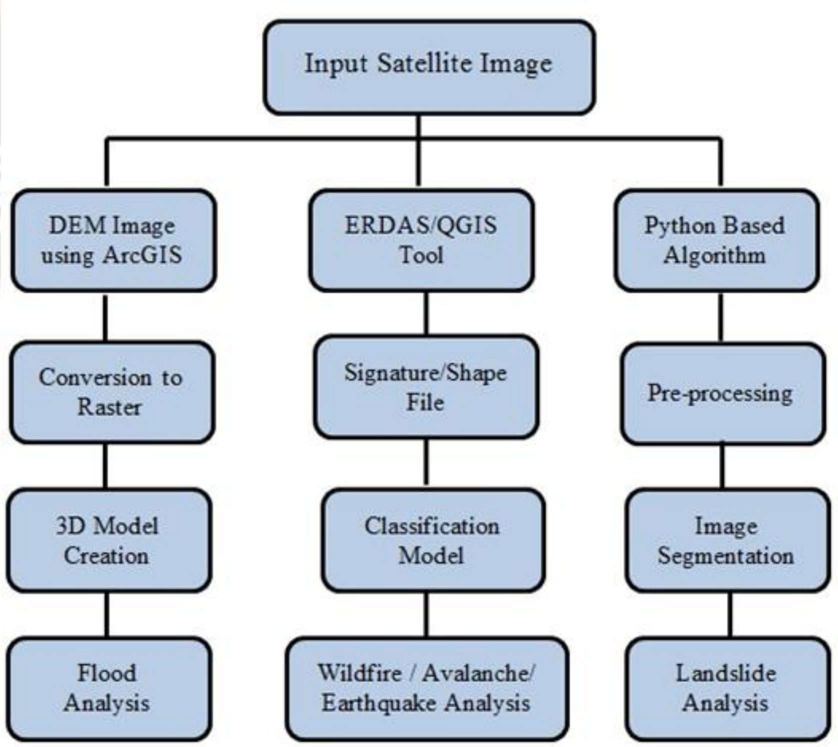


Figure 1. Flow Diagram of Catastrophe Assement System.

W. Zhang et al. [18] presented different approaches like Efficient Det, YOLOV5, SSD, Faster RCNN, and the improved YOLOV5 for landslide detection. 97.86% accuracy recorded for SSD algorithm with 57s training time for each epoch. Pixel-based segmentation approach with Mask R-CNN presented for landslide detection. Three steps as: increasing volume of training dataset; used limited sample with fine tuning; calculated measuring parameters recall, precision and F1 measure [19]. Machine learning and Deep learning approaches proposed in many research articles and reported challenges and solutions for disaster analysis [20]. Several disaster mechanisms were discussed in this article. Preprocessed input data was more accurately defined and improved in quality. The maximum likelihood method is a supervised machine learning approach used for categorization.

II. MATERIALS AND METHODS

The sample input images are collected from Dataset of USGS Earth Explorer and MRSAC Nagpur. These raw satellite images of before and after disasters are used for disaster prevention. Different conditions like floods, forest fires, earthquakes, landslides, avalanches are considered for disaster analysis.

The proposed disaster assessment algorithm is shown in Fig. 1. There are three approaches were used for analysis of satellite images. First approach based on 3D image analysis using ArcGIS. This approach used for flood analysis. Second approach used for Wildfire and Avalanche image analysis through ERDAS Imagine tool and Earthquake image analysis through QGIS tool. Third Python software based approach used for Landslide image analysis.

Stage 1:- In ArcGIS tool for simulation firstly create Digital Elevation Model (DEM). Input images contain 3D computer graphics like plain land, sea depths, and mountains, etc., in DEM images. Create polygon shape files for different features like water, land etc. For better visualization of Flood Modeling use ArcScene option. Also create 3D animation and change the color of different objects for further analysis.

Stage 2:- In ERDAS IMAGINE software through Raster tab select appropriate classification method. In supervised classification method, create signature files for different classes by selecting suitable geometric tool. Then signature files are used for further classification of objects. In unsupervised classification method need to enter number of classes for classification of objects.

In QGIS tool navigate the input data, and then it automatically identifies the longitude and latitude and shows them on the shape map of the required area. For accurate display in shape files, area of interest select manually for analysis.

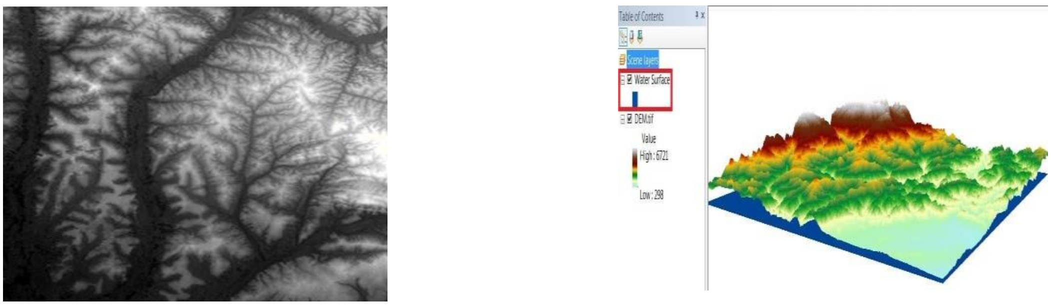
Stage 3:- In Python based approach input images are preprocessed for image enhancement. Thresholding technique is used for image segmentation. Finally analysis is carried out through pixel values.

A. Flood Risk Assessment

For doing flood risk assessment, firstly to get Digital Elevation Model (DEM) image of area of interest as shown in Fig. 2(a), then to convert that DEM image into raster and extract all the information stored in DEM image and generate shape file. Geographic features like attribute information and location of area of interest (AOI) are stored in the shape file. Fig. 2(b) depicts the 3D model of AOI created using shapefile. Identify the areas which can get submerged by changing elevation levels of land. It can identify high risk zones and decision makers can take necessary decision to reduce flood losses.

B. Wildfire Assessment

For wild fire assessment supervised and unsupervised classification methods are used. In ERDAS, signature file is created for different classes as shown in Fig. 3. This signature file further used for segmentation. Maximum Likelihood supervised Classification method is used for classification. Similarly, ISO cluster based classification method carried out for unsupervised classification. As shown in Fig. 4, examination of the burned area is done using images taken before and after the fire. After segmentation, the hue pink radish represents the scorched area.



(a) (b)

Figure 1. Flood Assessment: (a) Location: Mambili River, Congo Source: USGS Earth Explorer, (b) Simulation of 3D Model

Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order
1		Class 1		0.651	0.651	0.651	1	1
2		Class 2		0.650	0.650	0.650	2	2
3		Class 3		0.571	0.571	0.571	3	3
4		Class 4		0.276	0.276	0.276	4	4
5		Class 5		0.299	0.299	0.299	5	5
6		Class 6		0.385	0.385	0.385	6	6
7	▶	Class 7		0.558	0.558	0.558	7	7

Figure 2. Signature File Created for Different Classes

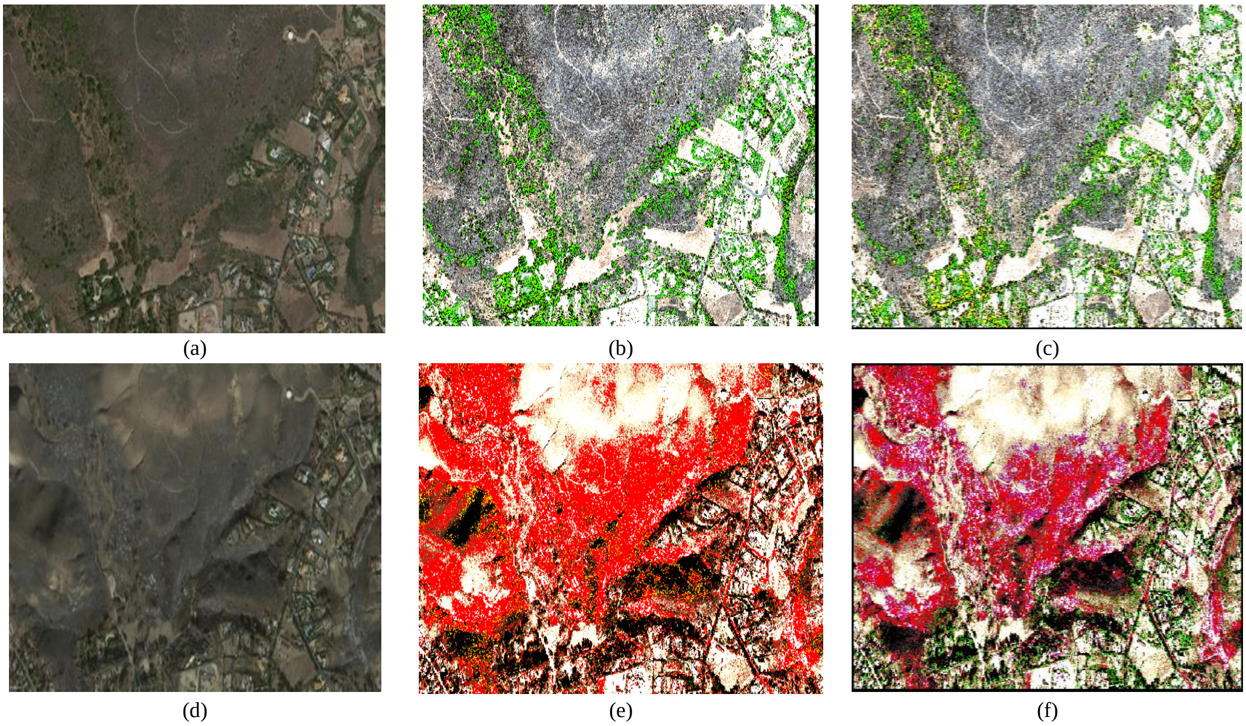


Figure 3. Wildfire Assessment: (a)Woosley, Texas, USA Year: July 2018 (Before Wildfire), (b) Supervised Classification Result, (c) Unsupervised Classification Result, (d) Woosley, Texas, USA Year: August 2018 (After Wildfire), (e) Supervised Classification Result, (f) Unsupervised Classification Result.

C. Avalanche Assessment

The ERDAS technology was used for the avalanche evaluation. As shown in Fig. 5, input images were subjected to both supervised and unsupervised classification in order to classify the damage area. The signature editor file defines various classes that are used to further classify objects. Avalanche images are compared before and after catastrophe, and change detection is noted for additional investigation.

D. Earthquakes Assessment

QGIS tool is used for earthquake hazard assessment. For doing earthquake assessment, firstly get a shape image of area of interest. After getting the shape image of required location, convert it into a raster.

Extract all the information stored in the raster file. Vector data generated using different shape like polygon, lines and points etc. Physical position of earthquake area with coordinate pairs present in the vector data form. Figure 6 illustrates the earthquake position of Japan area with green color points. Size of circular points defines the sensitivity of that area with respect to earthquake.

Firstly, we have to perform earth data visualization by collecting data from the USGS website record of earthquakes in the last 10 years, and then open both Shape Maps and collect data on QGIS software. Then select regions on the shape map. By selecting a feature, it becomes very easy to perform visualization on a selected region. For performing visualization, create a new shape file of the interesting area where earthquakes have happened in recent years.

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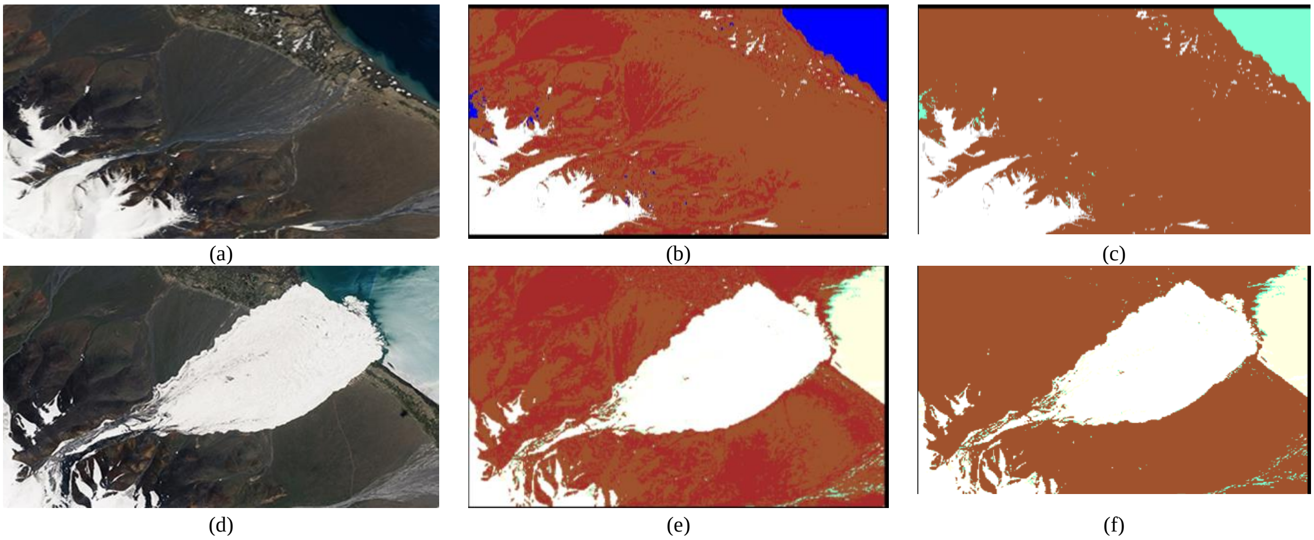

Figure 4. Avalanche Assessment: (a) Tibet's Aru Range Year: 24 June 2019 (Before Avalanche), (b) Supervised Classification Result, (c) Unsupervised Classification Result., (d) Tibet's Aru Range Year: 21 July 2019 (After Avalanche), (e) Supervised Classification Result, (f) Unsupervised Classification Result.

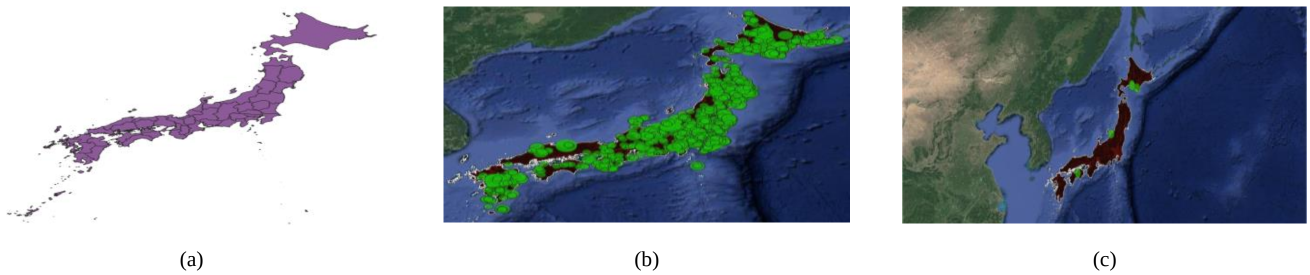

Figure 5. Earthquake Assessment: a) Location: Japan Source: USGS Earth Explorer, (b) Data Visualization Image Location: Japan, (c) Simulation of Earthquakes

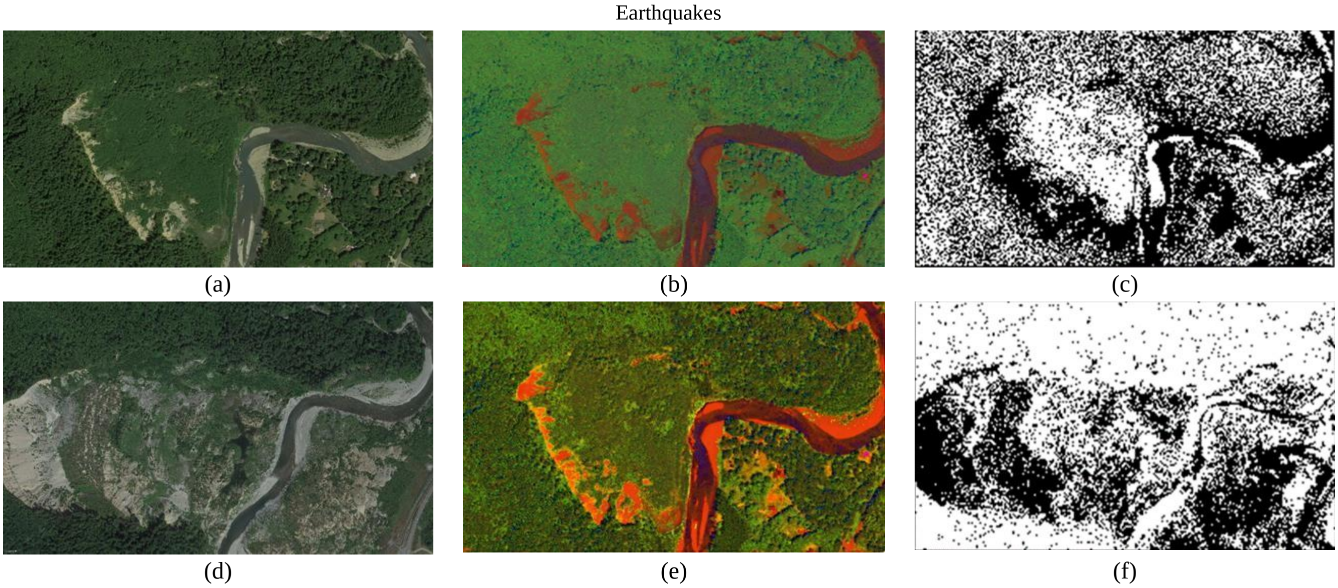

Figure 6. Landslide Assessment: (a) OSO, USA Year: May 2018 (Before Landslide) , (b) HSV Image Representation, (c) Binary Image Representation, (d) OSO, USA Year: July 2019 (After Landslide), (e) HSV Image Representation, (f) Binary Image Representation.

This data will refer to an earthquake of more than 2.5 magnitude. After merging both data and shape maps, users can see data like time, day, and months that the earthquake hit Japan.

E. Landslide Assessment

For landslide analysis, before landslide Oso USA July 2013 area and after landslide Oso USA July 2019 area images were collected from the MRSAC Nagpur with the help of Google

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earth pro Software, landset-8. These are used as RGB input images, Python based algorithm used for analysis of input images. In preprocessing stage RGB images converted into HSV (Hue Saturation Value) format. Then image segmentation carried out through thresholding technique, which results binary image representation as shown in Fig. 7.

III. RESULTS AND DISCUSSION

Fig, 2 (a) shows the 3D model of location Mambili River, Congo. The total area of the image is 119.55sq.km. The lowest elevation value is 304 and highest elevation value is 594, if we raise water level by the elevation level of 355 then the area below elevation level 355 will get completely submerged into water. The total area will get submerged in water is 19.42 sq.km and 100 sq.km area which is above the elevation level 355 will be safe from the flood as shown in Fig. 8. If we raise water level by the elevation level of 381 then the area below elevation level 381 will get completely submerged into water. The total area will get submerged into water is 30.40sq.km and 89.15 sq.km area which is above the elevation level 381 will be unaffected by flood. If we raise water level by the elevation level of 398 then the area below elevation level 398 will get completely submerged into water. The total area will get submerged into water will be 62.27 sq.km and 57.28 sq.km area which is above the elevation level 398 will not bear any losses from the flood.

Fig. 4 illustrates the results for supervised and unsupervised classification methods. Supervised algorithm gives better result for wildfire images. Table 1 represents the vegetation, land and burn land area parameters of before wildfire. In the green land class there are total 6892156 pixels, which cover around 43.63 sq. km. area. For land class there are total 8902518 pixels, which cover around 56.63 sq.km area. For burnt out land total pixel value is 0. Total pixel value of this image is 15794674 and the accuracy assessment of this image is 97%.

Similarly, Table 2 represents the vegetation, land and burn land area parameters of after wildfire. In the green land class there are total 3356481 pixels, which cover around 21.25 sq.km areas. For land class there are total 4160644 pixels, which cover around 26.34sq.km area. For burnt out land total pixel value is 8277579 of which burnt area cover around 52.40 sq.km. Total pixel value of this image is 15794674 and the accuracy assessment of this image is 98.03%. Fig. 9 shows that total green land pixel and land pixel value decreases due to wildfire. This analysis is carried out to assess the damage caused by wild fire.

TABLE I. BEFORE WILDFIRE ACCURACY ASSESSMENT

Sr. No.	Classification	Count of Pixels	Square kilometer	Accuracy Assessment
1	Vegetation	6892156	43.63	**97%**
2	land	8902518	56.63	
3	Burn land	0	0	
	Total Pixels	15794674	100.26	

TABLE II. AFTER WILDFIRE ACCURACY ASSESSMENT

Sr. No.	Classification	Count of Pixels	Square kilometer	Accuracy Assessment
1	Vegetation	3356481	21.25	**98.03%**
2	land	4160644	26.34	
3	Burn land	8277579	52.40	
	Total Pixels	15794674	99.99	

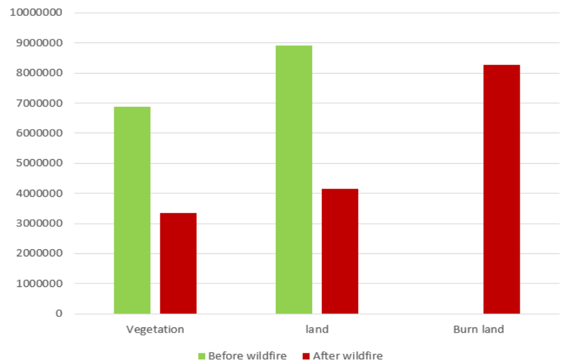
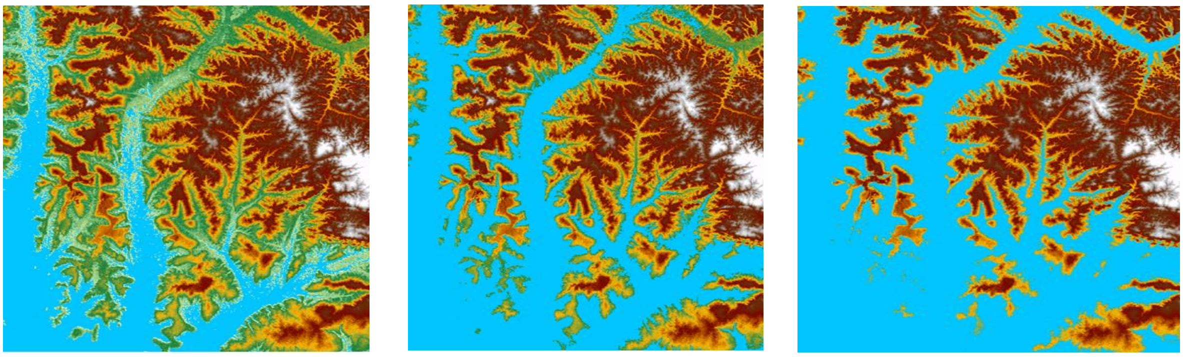


Figure 8. Analysis of Woolsey, USA Wildfire Disaster



Elevation: 355
Area: 19.42 sq km

Elevation: 381
Area: 30.40 sq km

Elevation: 398
Area: 62.27 sq km

Figure 7. Images Shows Area Covered by Water at Different Elevation Level

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Fig. 5 illustrates results for supervised and unsupervised classification methods. Supervised classification presents more details in the output image. Table 3 represents the snow, land and water area parameters of before avalanche. In the snow land class there are total 13037 pixels, which cover around 11.43 sq. km area. For land class there are total 94148 pixels, which cover around 82.55 sq.km area. For water total pixel value is 6863 pixels, which cover around 6.01sq. km area. Total pixel value of this image is 114048 and the accuracy assessment of this image is 97.54%.

Similarly, Table 4 represents the snow, land and water area parameters of after avalanche. In the snow land class there are total 35156 pixels, which cover around 30.96 sq.km area. For land class there are total 76929 pixels, which cover around 67.77 sq.km area. For water total pixel value is 1433 of which cover around 1.26 sq.km area. Total pixel value of this image is 113518 and the accuracy assessment of this image is 98.88%. Fig. 10 shows that total land area and water pixel value decreases due to avalanche. Change detection is carried out by comparing before and after avalanche images.

TABLE III. BEFORE AVALANCHE ACCURACY ASSESSMENT

Sr. No.	Classification	Count of pixels	Square kilometre	Accuracy
1	Snow	13037	11.43	**97.54%**
2	Land	94148	82.55	
3	Water	6863	6.01	
	Total pixels	114048	99.99	

TABLE IV. AFTYER AVALANCHE ACCURACY ASSESSMENT

Sr. No.	Classification	Count of pixels	Square kilometre	Accuracy
1	Snow	35156	30.96	**98.88%**
2	Land	76929	67.77	
3	Water	1433	1.26	
	Total pixels	113518	99.99	

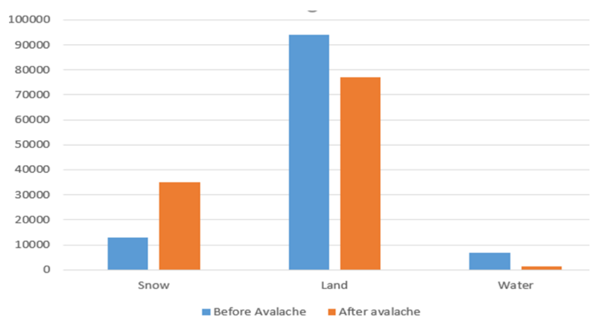


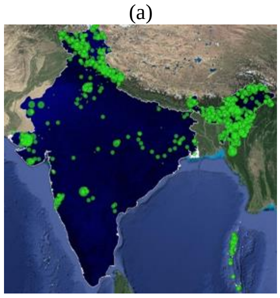
Figure 9. Analysis of Tibet's Aru Range Avalanche Disaster

Fig. 6 shows result of earthquakes on QGIS after performing data visualization process. There are 10 years of earthquakes data stored on maps out of which only select recent events of 5 or more than 5 magnitude as shown in Table 5. On February 13, 2021 Fukushima 7.01 magnitude an earthquake hit Japan at 23:07 JST, March 20, 2021 Miyagi 7.0 magnitude an earthquake hit Japan at 18:09:45, October 07, 2021 Chiba 5.09 magnitude an earthquake hit Japan at 22:41 and March 16, 2022 Fukushima 7.4 magnitude an earthquake hit Japan at 23:36. Similarly, area of India selected for earthquake analysis as shown in Table 6. This analysis can used to get information about earthquakes happen for better mitigation and better protocol.

TABLE V. EARTHQUAKE DETAILS OF JAPAN

Date/Time	Location	Magnitude
February 13, 2021 (23:07)	Fukushima	7.1 mag
March 20 ,2021 (18:09:45)	Miyagi	7.0 mag
October 7, 2021 (22:41)	Chiba	5.9 mag
March 16, 2022 (23:36)	Fukushima	7.4 mag

(a)



(b)

Figure 10. Location India: (a) Input Shape Maps, (b) QGIS Data Visualization Output

TABLE VI. EARTHQUAKE DETAILS OF INDIA

Date/Time	Location	Magnitude
January 04, 2016 (04:35)	Bangladesh	6.7 mag
January 03 ,2017 (02;40)	Bangladesh	5.7 mag
September 12, 2018 (10;12)	Assam	5.3 mag
April 28, 2021 (07:51)	Assam	6.0 mag

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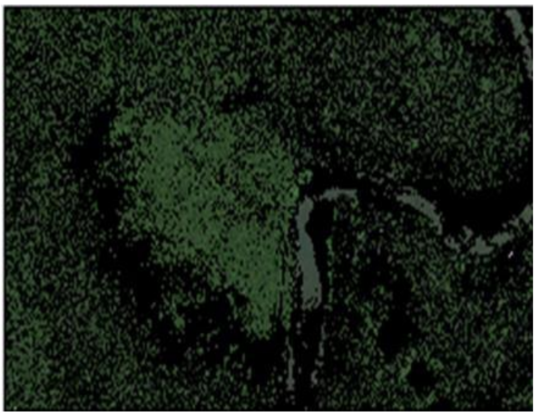
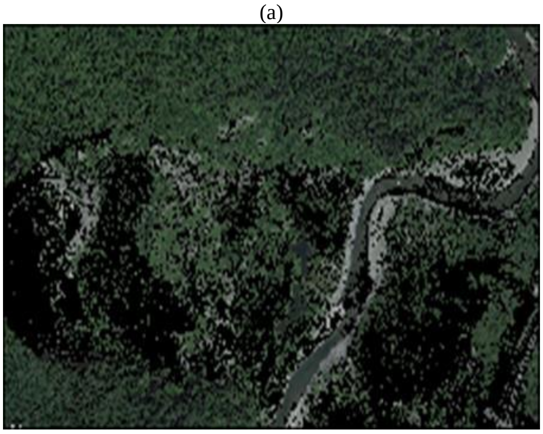
Landslide in the United States occurs in Oso, Washington, USA and other state. The primary region of landslide occurrence and potential are the coastal and mountains area Washington, therefore collected the input data images of Oso USA of the year of before landslide Fig 7 (a) and after landslide Fig 7 (d) images of July 2013 and July 2019 respectively. For change detection of deforestation, RGB image converted into HSV color space. An HSV is another type of color space in which H stand for Hue, S stands for Saturation and V stand for Value. In the images Fig 7 (b) and Fig 7 (e) over a time period, green color represents the vegetation area. Fig. 7 (c) and Fig. 7(f) are the binary representation of input image called as mask image. When a black and white image is used as a mask, the white region acts 100% transparent, is exposing the selective content of the original image. It generates a black and white image consisting of whites in place of the desired greens and unwanted region is replaced with black color. Add original image with binary image to get resultant image shown in Figure 12. The vegetation loss after the landslide disaster noted as 44.64%.



(a)



(b)

Figure 11. Resultant image (OSO, USA) for vegetation Analysis, a) Before Landslide Year: May 2018 , b) After landslide Year: July 2019

IV. CONCLUSION

This study discussed several catastrophe modalities that can be used in the future to concentrate on emergency situations. Remote sensing data used for forecasting, planning, and management of disaster condition. Using today's cutting edge technology, it is necessary to investigate the recurrent occurrences of earthquakes, floods, landslides, avalanches, and forest fires in order to identify practical preventive strategies. There are numerous effective pre- and post-disaster analysis examples provided. An algorithm based on Python, ERDAS, QGIS, and ArcGIS is described to identify and categorize the area of interest.

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AUTHORS PROFILE

Dr. Nita M. Nimbarte (Rehpade) is an Assistant Professor in the Department of Electronics and Telecommunication, Yeshwantrao Chavan College of Engineering, Nagpur, Maharashtra, INDIA. She specializes in the Digital Image Processing domain. She has presented her work in 13 Journals and 12 International Conferences. She is a life member of IETE and ISTE professional society.

Dr. Bharati Masram has received her Ph.D degree in the area of VLSI signal processing under the research centre of YCCE from RTM Nagpur University, India in 2020. She received her master degree and B.E degree in Electronics Engineering from Yeshwantrao Chavan College of Engineering (Autonomous) in 2010 and 2004 respectively. Her research interest is mainly in VLSI Signal Processing, Communication; 3D Image processing etc. With this she is also now working on machine learning for the analysis and prediction of weather of Nagpur city due to unpredictive nature of climatic change in current .She has published her total 20 research based papers in national, international conferences and also in International journal. She had on her name 3 published & 2 patent granted in National & Interbnational level

Prof. Archana Tiwari was born in 1983 in Nagpur, Maharashtra, India. She graduated from Nagpur University in Maharashtra with a B.E. in Electronics and Communication in 2004 and an M.Tech in VLSI Design in 2010,respectively. She is attending Nagpur University to complete her Ph.D. in antenna design.From 2005 to 2006, she was a lecturer in the Shri Ramdeobaba College of Engineering; Electronics Design Technology department is in Nagpur. She has been an assistant professor at Shri Ramdeobaba College of Engineering in Nagpur, Electronics Engineering Department since 2009. She is the author of one book chapter, filed one patent and has more than 10 research papers to her credit. Her research interests include Microwave Engineering, AntennaDesign, Electromagnetism, Waves and Propagation.

Dr. Sanjay Balamwar working as a Senior Scientist, Maharashtra Remote Sensing Applications Centre, Dept. Of Planning Govt. of Maharashtra, VNIT Campus, S.A. Road Nagpur -10 from last 21 Years. He had his Ph.D. in Investigations of Dielectric properties and related thermodynamics of some polar liquids at Microwave Frequency submitted to RTM, Nagpur University, Nagpur. Received various awards at state and central level including the AGI India Awards 2022 for prestigious project of MahaBHUMI which will going to transformvarious government schemes and infrastructure development programs in the State of Maharashtra.