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Estimation of Landslide Damage Areas in Madenaadu Kodagu District using Minimum Distance Classifier

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***Abstract*—A landslide is the natural hazard that can result in environmental, economic or human losses. Detecting the landslide-prone areas is essential to ensure the safety of life and avoid impacts on regional as well as national economy. The lack of vegetation coverage allied with heavy rainy conditions can contribute to soil humidity, which increases the probability of landslides. This study focuses on determining the landslide dynamics of the Madenaadu region, north part of the Kodagu district. The Google Earth images considered for the study with a spatial resolution of 1.79m. This work tracts the landslides using image processing techniques by extracting the feature using Minimum distance classification and comparing the classified image to detect the landslides dynamics changes. The result showed that 67.16% of agriculture and plantation area had been damaged because of landslides.**

***Index Terms*— Landslide, Change detection, Minimum Distance Classifier, Kodagu.**

I. INTRODUCTION

A landslide is a disaster where an unexpected change occurs in the environmental conditions that causes significant loss in financial, environmental or human losses. It causes drastic changes in the landscape's morphology and damage natural and manmade structures. Detecting landslide-prone areas and generating landslide susceptibility maps is essential for the local admin and policymakers in disaster planning to mitigate landslides. Landslide susceptibility has been illustrated in versatile techniques in various case studies, yielding more or less reliable results depending on the complexity of the terrain and the suitability of the approach. Another considerable effect of the increase of land sliding is the steep slope that begins just from the shore. [16].
To decrease the losses, a study was conducted for mapping landslide susceptibility area with use of Head/Tail and Natural Breaks and later compared those classification results, in order to get the best landslide hazard map. Classification results achieved using both Head/Tail and Natural Breaks were validated using Pearson Chi-Square test. From the results, it is observed that 184.9166 of value was obtained for Natural Breaks which was higher than Head/tail Breaks (105.5885). Therefore, the author concluded that Natural Breaks were considered better in this case when compared to the Head/tail Breaks [2].
In this research paper, it intended to classify LSM using Landsat imagery, geological and DEM based derived attributes. 30m resolution terrain pixels were considered and were grouped into three factors: dormant, active

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landslide and stable ground. Support Vector Machine (SVM), Decision Trees (DT) and Logistic Regression (LR) learning techniques were compared which learns itself from the labelled data. κ index, area under ROC curve and false positive rate in stable ground class evaluation metrics were performed and achieved that the SVM classifier had been outperformed the AHP approach [10]. Spatial contraindication is what precisely LSM has been seeking. To detect such pattern, three commonly used machine learning approaches like Artificial Neural Network (ANN), maximum entropy (MaxEnt) and SVM were applied with their ensembles such as ANN-SVM, ANN-MaxEnt, ANN-MaxEnt, SVM and SVM-MaxEnt in the region of Wanyuan area, China [17]. Without a precise inventory map of slope instability, it is not probable to evaluate the controls on the temporal and spatial patterns of environment, geomorphic consequences of slides. Therefore, landslide inventory map is very tedious to compile and very difficult to process in vegetated terrain regions with use of conventional approaches and they tend to be subjective [8].

The current study planned an automatic finding of slope failures from use of multi-spectral ASTER DEM imagery based on the supervised classification approach like likelihood ratio functions (LRF) and ANN. From the experiment, it was identified that the major Earth flows can be suitably reconfigured, extracted and detected by demonstrating the probable application of this technique [6].

The present study aims to study both qualitatively and quantitatively, analysing and predicting the changes in environment. This project presents an overview of landslide susceptibility mapping using Minimum distance classifier and compares different methods from the view point of the algorithm used by each method. The main objective of current work is to examine the losses occurred by the landslide incident happened in 2018 at Madenaadu using supervised technique namely minimum distance classifier. The article is organized as follows, Section 1 includes the Introduction about Landslides and its applications, Section 2 include Materials and Methodology, Section 3 comprises of Result Analysis, Section 4 concludes the final work done on the research paper.

II. Materials and Methodology

A. Study Area

Madikeri is the hill station that lies in Karnataka. The Madennadu as shown in Figure 1 belongs to Madikeri District. It is located 9km towards west from Madikeri district and 255Km from Bangalore. The area under investigation is located with 120 250 43.03” N, 120 240 57.80” N latitude and 750 400 35.28” E, 750 400 35.28” E longitude with a height of nearly 728 m.

Figure 1. Google Earth image of Madenaadu (2017)

Figure 2. Google Earth image of Madenaadu (2019)

TABLE I. Details of the Data Products used for Change Detection

Sl. No	Data type	Data of Acquisition	Spectral Resolution	Spatial Resolution
1.	Multi-spectral (Unsigned 8-bit)	18 April 2017	Red(0.62-0.68μm); Green(0.52-0.59μm); Blue(0.45-0.51μm);	1.79m
		28 Jan 2019		

B. Proposed Methodology

Pre-Processing of Google Earth imagery

Two images are taken at two different times from Google Earth Pro version 7.32 i.e. 2017 and 2019 is downloaded using SmartGIS 2019. The downloaded images are geo corrected and pre-processed using ERDAS version 9.2. Figure 3 shows the methodology used for landslide area detection using Google Earth Images for two different years i.e., 2017 and 2019.

Minimum Distance Classifier

Change detection is defined as the process of identifying differences in the state of an object or phenomenon by observing it at different times. The overall aim of the classification process is to automatically classify all pixels an image into landslide area classes based on the pre-defined classification model. A supervised image classification technique, namely the minimum distance classifier, is used to identify the changes that occurred due to the landslide. In this method, the distance between the mean of the signature dataset and the pixel value is estimated band by band. Then, the total distance is estimated. This total distance estimation is repeated for all classes of signatures. The class that shows the minimum total distance is assigned to the pixel. This method is very fast and easy to understand.

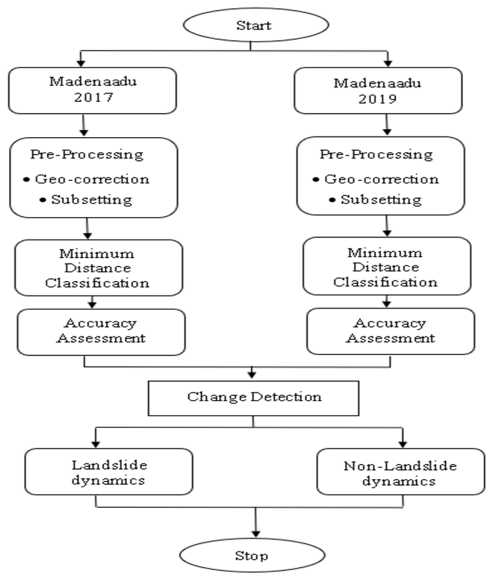


Figure 3. Methodology used for Landslide Area Detection

Accuracy assessment

Accuracy assessment shows how closely the results relate to actual values. An error matrix calculates the user's and producer's accuracy. The percentage of matched number of values to total number of values has been calculated using the following formula as represented in equation (1) called Overall Accuracy (OA).

$$\text{Overall Accuracy} = \sum \frac{Diagonal\ Value}{N} * 100 \qquad (1)$$

The user's accuracy is calculated as shown in equation (2). Whereas the producer's accuracy is calculated as shown in equation (3).

$$\text{Producer Accuracy (\%)} = \frac{Diagonal\ Value\ of\ Column}{Column\ Total} * 100 \qquad (2)$$

$$\text{Users Accuracy (\%)} = \frac{Diagonal\ Value\ of\ Row}{Row\ Total} * 100 \qquad (3)$$

III. Results and Analysis

A. Landslides change analysis for Data Madenaadu 2017 and 2019

Minimum distance is a supervised classification method has been used to show the changes of landslides over time. In this study the classification has been categorized into three classes Open Space, Agriculture, Plantation. To differentiate the three classes, different values of set of data were considered such as 150, 300, 450 and 600. For each class, 50 validation points are collected from the data 2017 and 2019. The landslide classification has been carried out for signature 150 is as shown in Fig 4. Confusion matrix and kappa values for three classes with 50 validation points are calculated as shown in Fig 5.

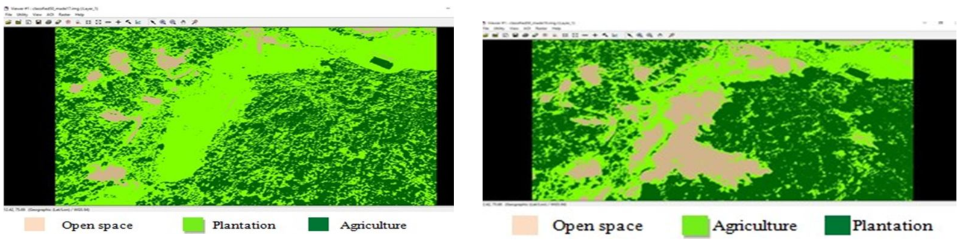


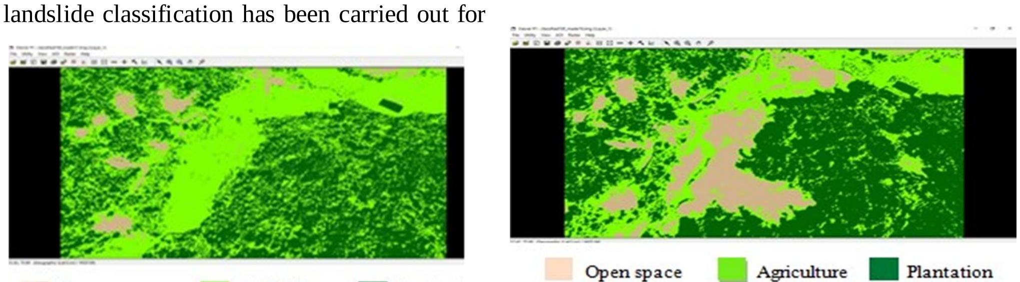
Figure 4. Classified image for training set of 150 pixel

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**2**	0	0	2	0.00%	100.00%
Agriculture	0	**19**	6	25	13.64%	86.36%
Plantation	0	3	**19**	22	24.00%	76.00%
Column total	2	22	25	**49**		
Omission error	0.00%	24.00%	13.64%			
PA%	100.00%	76.00%	86.36%			OCA:81.63%
Kappa	1.0000	0.7216	0.5644			OKS:0.6600

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**10**	0	1	11	0.00%	100.00%
Agriculture	0	**6**	6	12	40.00%	60.00%
Plantation	0	4	**23**	27	23.33%	76.67%
Column total	10	10	30	**50**		
Omission error	9.09%	50.00%	14.81%			
PA%	90.91%	50.00%	85.19%			OCA:78.00%
Kappa	1.0000	0.4737	0.4928			OKS:0.6233

Figure 5. Confusion matrix for 150 signatures with 50 validation points

Classification process is incomplete in the absence of accuracy in the assessment. Fig 6 shows the table of the confusion matrix and Kappa values obtained for three classes with 50 validation points for 2017 and 2019 data. 50 validation points of Madenaadu 2019 having overall classification accuracy (OCA) 78.00% and overall, Kappa statistics (OKS) 0.6233. For each class, 100 validation points are collected from the data 2017 and 2019. The landslide classification has been carried out for



signature 300 is as shown in Fig 6.

Figure 6. Classified image for training set of 300 pixels

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**2**	1	0	3	33.33%	66.67%
Agriculture	0	**38**	7	45	15.56%	84.44%
Plantation	0	7	**45**	52	13.46%	86.54%
Column total	2	46	52	**100**		
Omission error	0.00%	17.39%	13.46%			
PA%	100.00%	82.61%	86.54%			OCA:85.00%
Kappa	0.6599	0.7119	0.7196			OKS:0.7126

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**18**	2	2	22	5.26%	94.74%
Agriculture	1	**20**	11	32	20.00%	80.00%
Plantation	0	3	**43**	46	23.21%	76.79%
Column total	19	25	56	**100**		
Omission error	18.18%	37.5%	6.52%			
PA%	81.82%	62.50%	93.48%			OCA:81.00%
Kappa	0.9325	0.7059	0.5701			OKS:0.6938

Figure 7. Confusion matrix for 300 signatures with 100 validation points

Fig 7 shows the table of the confusion matrix and Kappa values obtained for three classes with 100 validation points for 2017 and 2019. 100 validation points of Madenaadu 2019 having overall classification accuracy (OCA) 81.00% and overall, Kappa statistics (OKS) 0.6938. For each class, 150 validation points are collected from the data 2017 and 2019. The landslide classificationhas been carried out for signature 450 as shown in Fig 8.

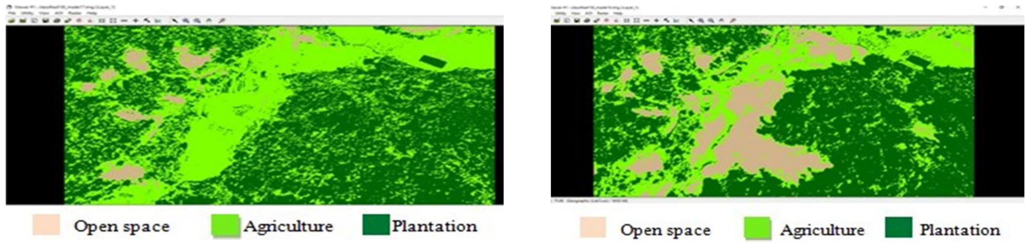


Figure 8. Classified image for training set of 450 pixels

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**7**	0	0	7	0.00%	100.00%
Agriculture	0	**53**	11	64	10.17%	89.83%
Plantation	0	6	**73**	79	13.10%	86.90%
Column total	7	59	84	**150**		
Omission error	0.00%	10.17%	7.59%			
PA%	100.00%	89.83%	92.41%			OCA:88.67%
Kappa	1.0000	0.8226	0.7233			OKS:0.7882

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**16**	2	2	20	5.88%	94.12%
Agriculture	1	**45**	13	59	10.00%	90.00%
Plantation	0	3	**68**	71	18.07%	81.93%
Column total	17	50	83	**150**		
Omission error	20.00%	23.73%	4.23%			
PA%	80.00%	76.27%	95.77%			OCA:86.00%
Kappa	0.9321	0.8352	0.6569			OKS:0.7635

Figure 9. Confusion matrix for 450 signatures with 150 validation points

Fig 9. shows the table of the confusion matrix and Kappa values obtained for three classes with 150 validation points for 2017 and 2019 data. 150 validation points of Madenaadu 2019 having overall classification accuracy (OCA) 86.00% and overall, Kappa statistics (OKS) 0.7635. For each class, 200 validation points are collected from the data 2017 and 2019. The landslide classification has been carried out for signature 600 is as shown in Fig 10.

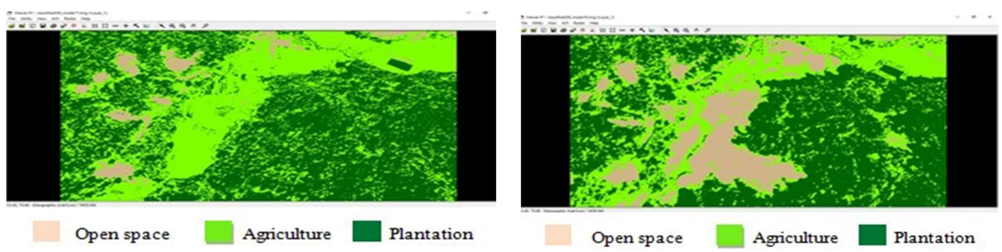


Figure 10. Classified image for training set 600 pixels

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**5**	0	0	5	16.67%	83.33%
Agriculture	1	**80**	7	88	11.11%	88.89%
Plantation	0	10	**97**	107	6.73%	93.27%
Column total	6	90	104	**200**		
Omission error	0.00%	9.09%	9.35%			
PA%	100.00%	90.91%	90.65%			OCA:91.00%
Kappa	0.8291	0.8016	0.8553			OKS:0.8279

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**31**	3	0	34	3.12%	96.88%
Agriculture	1	**47**	12	60	16.07%	83.93%
Plantation	0	6	**98**	104	10.91%	89.09%
Column total	32	56	110	**198**		
Omission error	8.82%	21.67%	5.77%			
PA%	91.18%	78.33%	94.23%			OCA:88.89%
Kappa	0.9623	0.7694	0.7702			OKS:0.8132

Figure 11. Confusion matrix for 600 signatures with 200 validation points

Fig 11 shows the table of the confusion matrix and Kappa values obtained for three classes with 200 validation points for 2017 and 2019 data. 200 validation points of Madenaadu 2019 having overall classification accuracy (OCA) 88.89% and overall, Kappa statistics (OKS) 0.8132. For each class, 250 validation points are collected from the data 2017 and 2019 data. The landslide classification has been carried out for signature 750 is as shown in figure 3.9. Confusion Matrix and Kappa Values for three classes with 250 validation points for 2017 and 2019 data are shown in Fig 12.

Fig 11 shows the table of the confusion matrix and Kappa values obtained for three classes with 250 validation points for 2017 and 2019 data. 250 validation points of Madenaadu 2019 having overall classification accuracy (OCA) 90.80% and overall, Kappa statistics (OKS) 0.8511.

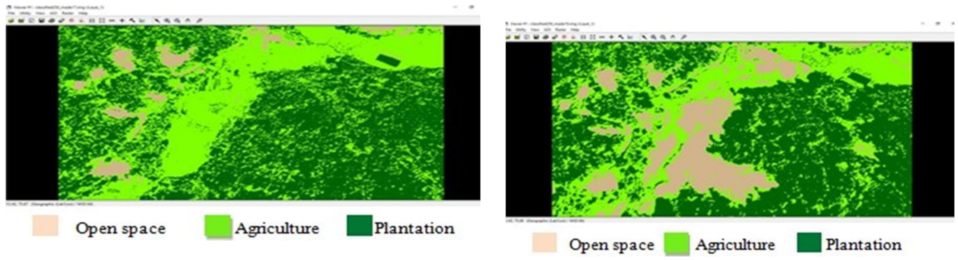


Figure 12. Classified image for training set of 750 pixels

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**6**	4	0	10	33.33%	66.67%
Agriculture	3	**95**	9	107	5.94%	94.06%
Plantation	0	2	**128**	130	6.57%	93.43%
Column total	9	101	137	**247**		
Omission error	40.00%	11.21%	1.54%			
PA%	60.00%	88.79%	98.46%			OCA:92.71%
Kappa	0.6526	0.8952	0.8613			OKS:0.8624

Classes	Open space	Agriculture	Plantation	Row total	Commission error	UA%
Open space	**37**	2	0	39	5.13%	94.87%
Agriculture	2	**87**	11	100	10.31%	89.69%
Plantation	0	8	**103**	111	9.65%	90.35%
Column total	39	97	114	**250**		
Omission error	5.13%	10.31%	9.65%			
PA%	94.87%	89.69%	90.35%			OCA:90.80%
Kappa	0.9392	0.8282	0.8265			OKS:0.8511

Figure 13. Confusion matrix for 750 signatures with 250 validation points

A Graph of Accuracy and Training Se

From the Fig 14, we can observe that the value of accuracy keeps on increasing with increase in the number of Training set, hence Accuracy depends on the number of training sets. Experiment conducted by taking a greater number of training sets, gives an accurate value.

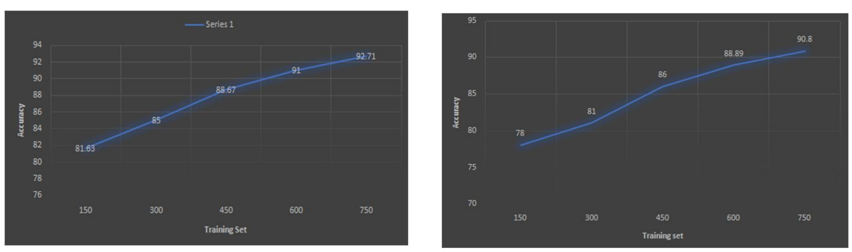


Figure 14. A Graph of Accuracy and Training Set for both 2017 and 2019 data

A Graph of Kappa statistics And Training Set

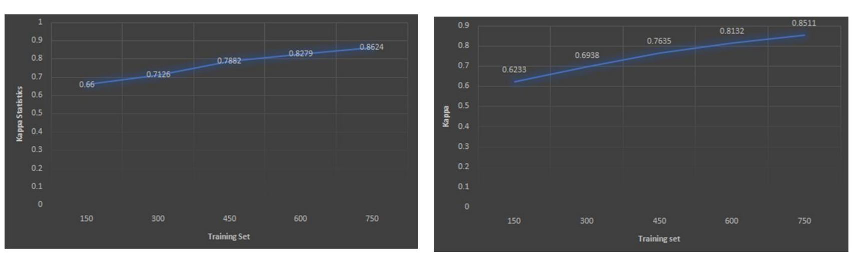


Figure 15. A Graph of Kappa Statistics and Training Set

From the Fig 15, we can observe that the value of Kappa value keeps on increasing with increase in the number of Training set, hence Kappa value depends on the number of training sets.

Pixels and Area changes from 2017 to 2019 in ha

Table II shows the changes in the pixels from data 2017 to 2019. There is a significant increase in pixels of Open space from 2017 to 2019. In the case of Agriculture and Plantation the pixels valueis gradually decreases. The area changes of landslides are as shown in Table III, there is a significant area increase of open space from 0.003938 ha to 0.020048 ha from 2017 to 2019. Agriculture from 0.051013 ha to 0.036695 ha and Plantation from 0.064793 ha to 0.059965 ha shown significant decrease from 2017 to 2019.

TABLE II. PIXELS CHANGES FROM 2017 TO 2019

Classes	2017						2019					
	50	100	150	200	250	**Total**	50	100	150	200	250	**Total**
Open space	2	2	7	5	6	**22**	10	18	16	31	37	**112**
Agriculture	19	38	53	80	95	**285**	6	20	45	47	87	**205**
Plantation	19	45	73	97	128	**362**	23	43	68	98	103	**335**

TABLE III. CHANGES IN AREA FROM 2017 TO 2019 IN HA

Classes	2017						2019					
	50	100	150	200	250	**Total**	50	100	150	200	250	**Total**
Open space	0.000358	0.000358	0.001253	0.000895	0.001074	**0.003938**	0.00179	0.003222	0.002864	0.005549	0.006623	**0.020048**
Agriculture	0.003401	0.00680	0.009487	0.01432	0.017005	**0.051013**	0.001074	0.00358	0.008055	0.008413	0.015573	**0.036695**
Plantation	0.003401	0.00805	0.013067	0.017363	0.022912	**0.064793**	0.004117	0.007697	0.012172	0.017542	0.018437	**0.059965**

Graph of Area in ha and Classes

TABLE IV. CHANGES IN PIXELS AND AREA FOR THREE CLASSES

Classes	Changes in Pixels	Changes in Area in ha	Percentage %
Open space	90	0.01611	67.16
Agriculture	80	0.014318	16.32
Plantation	27	0.004828	3.87

Figure 16. Graph of Area in ha and Classes

The Table IV shows the changes in pixels and area of Madenaadu 2017 and 2019. Graph in Fig 14 shows change detection, here Open space area is increased gradually but the area of Agriculture and Plantation is decreased in the year 2019 as compared to 2017, specifically in the year 2019 the Open space area increased by 0.020048 ha. Thus, it provides the amount of area affected by landslide.

IV. CONCLUSIONS

Minimum distance classifier is used for identifying the changes that has occurred after the landslide event in 2018 at Madenaadu region, Kodagu district. Result analysis showed that for before landslide data (2017) with 50, 100, 200, 250 validation points of OCA is 81.63%, 85.00%, 88.67%, 91.00%, 92.71% and OKS is 0.6600, 0.7126, 0.7882, 0.8279 and 0.8624. For data that is obtained after landslide with 50, 100, 200, 250 validation points have obtained the OCA of 78.00%, 81.00%,86.00%, 88.89% and 90.80% and OKS is 0.6233. 0.6938, 0.7635, 0.8132 and 0.8511. It is noticed that, 90 pixels were changed and area has changed by 0.01611 ha. Total 67.16% of area has been changed by landslide event that has occurred in 2018 at Madenaadu. The Google Earth Images was used in this work to detect the changes that occurred by landslide using Minimum distance classification method. The use of Classifier will ensembles the accuracy evaluation. Hence, It is recommended to use the Support Vector Machine (SVM) and Maximum Likelihood Classification (MLC) methods to obtain the best results for change detection landslide.

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