FOREST COVER CHANGE DETECTION IN MULLAITIVU DISTRICT, SRI LANKA USING LANDSAT MULTISPECTRAL IMAGERY

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ABSTRACT: *The estimation of forest cover and change detection is still a challenging task. Therefore, this study was carried out in a tropical forest, Mullaitivu district of Sri Lanka to assess the forest cover change detection using Landsat multispectral imagery from 1994 to 2022. The objectives of the study were to identify the forest type based on Normalized difference vegetation index (NDVI) and to detect the forest cover change based on supervised and unsupervised classifications. Landsat 8-9 OLI/TIRS C2 L2 (2022) and Landsat 4-5 TM C2 L2 (1994) were used for the change analysis by using ArcGIS Pro version 2.8. The cloud cover of the image was removed using masking and mosaic functions to increase the accuracy of the classification. Different band combination was used for NDVI calculation for Landsat 8 (NIR-5, Red-4 and Blue-3) and Landsat 4-5 (NIR-4, Red-3 and Blue-2) based on the spectral values. Iterative Self-Organized (ISO) Data Analysis Techniques and Support Vector Machine (SVM) learning algorithm were performed for the unsupervised and supervised classifications, respectively. The land use was categorized into four types namely forest, built-up & farmlands, water bodies and bare lands. The accuracy of the Landsat image was validated with Google Earth Pro timelapse images and field observations. Error matrix function was used to derive the Cohen's Kappa statistics with Overall accuracy (OA), Producer Accuracy (PA) and User Accuracy (UA) with 500 sampling points for accuracy assessment. NDVI value was ranged from -0.27 to 0.51 in 1994 and – 0.17 to 0.48 in 2022, and this represented that the forest was under category of dry zone lowland forest with dense vegetation. A trend of land use changes was the same from both supervised and unsupervised classifications. The total forest cover of the district was 58.70 % (157,372.31 ha) in 2022 and 63.33 % (169,798.75 ha) in 1994 with a decline of 4.63 % (12,426.44 ha) over 28 years period. The OA was ranged from 0.89 to 0.9 and K coefficient was ranged from 0.81 and 0.82, and this result indicated that the accuracy level was acceptable. Further study is needed to improve and validate the accuracy of the classifications using high-resolution multi and hyperspectral images with more land use categories.*

Keywords: Forest Cover, Change Detection, Satellite Images, Mullaitivu, Sri Lanka

1. INTRODUCTION

Sri Lanka is a tropical country, rich in forest cover, biodiversity, and other land uses. Due to the various climatic conditions, Sri Lanka is divided into dry zone, wet zone, and intermediate zone. The dry zone of Sri Lanka encompasses 59% of the total land area of the country and has the most extensive forest cover (Ranagalage et al., 2020). Sri Lanka's Forest cover statistics showed rapid deforestation from 1956 to 2010. In 1956, nearly half of the island (44.2%) had forest cover. However, rapid forest losses have been recorded in recent decades: 37.5% in 1983, 31.2% in 1992, 29.6% in 1999, and 28.7% in 2010 (Report on South-South Learning, 2018). During the recent decades since 1992, human resettlements, agricultural encroachments, and infrastructure development have driven substantial forest losses in the dry zone, while multiple dry-zone areas have been identified as deforestation hotspots (Marambe et al., 2015).

The Mullaitivu district is rich in forest cover in the northern province and has more than 50% of the total land area of the district (Department of Census and Statistics, 2022; Northern Provincial Council, 2021). The forest had a high aboveground carbon stock and species diversity (Thirukkumaran et al., 2017). However, the deforestation rate is high at an alarming rate due to the absence of proper implementation of forest policies and legislation. Therefore, assessing vegetation change detection is important for reducing emissions from forest degradation and deforestation (REDD+) implication in the study area (United Nations Development Programme, 2009). The detailed study of forest cover detection at the district level by using remote sensing techniques was very limited (Rajeevan et al., 2018). Landsat satellite images to obtain long-term forest cover data are required to overcome the aforementioned challenges at the subnational level (Vijitharan et al., 2022). Therefore, the assessment of land use and land cover change in the region by Geographic Information Systems (GIS) and Remote Sensing (RS) is highly important for forest management plans at the regional and national levels. In this study, we aimed to assess the forest cover change detection using Landsat multispectral imagery at GIS and remote sensing platform.

2. METHODOLOGY

2.1 Study Area

This study was carried out in Mullaitivu district, Northern Province, Sri Lanka. The district is bounded by Jaffna and Kilinochchi districts from the North, Sea from the East, Trincomalee and Vavuniya districts from the South, Mannar district from the West, and a small part of the South (Northern provincial council, 2022). Absolute Location of the district is longitude 090° 14’ N & latitude 80° 32’ E. (Figure 1). The total land area of the district is approximately 269,300 ha (Northern provincial council, 2021). This district accounts 3.87% of the country’s total land area. The district is located in the dry Zone of Sri Lanka. Average annual rainfall of the district varies from 1200mm to 1900mm and has a bimodal rainfall pattern. Temperature ranges from 23°C to 39°C. The district gets high rainfall and low temperature during North East Monsson from early October to January (Department of Census and Statistics, 2022).

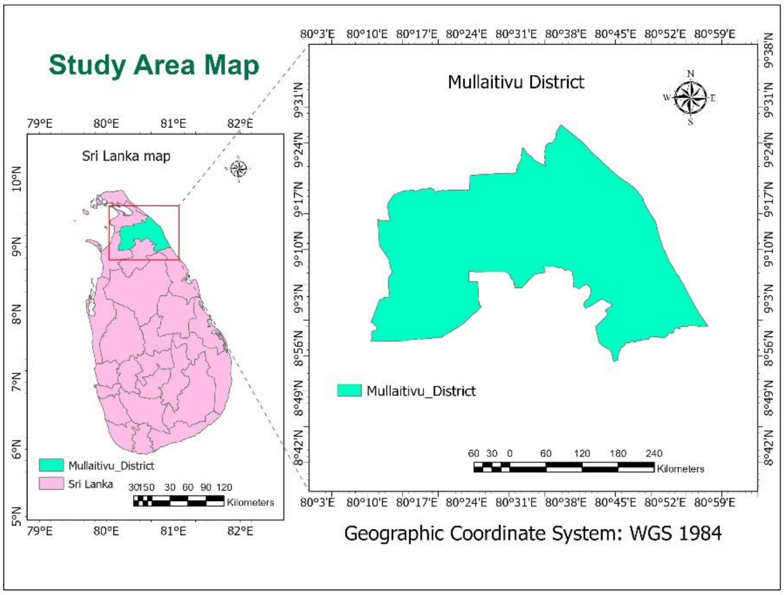

Figure 1: Study area map: left- study area district in Sri Lanka; right- study area, Mullaitivu district

2.2 Satellite imagery and processing

Landsat 8-9 OLI/TIRS C2 L2 and Landsat 4-5 TM C2 L2 were downloaded from the United States Geological Survey, Earth Explore (https://earthexplorer.usgs.gov/). Landsat 4-5 TM C2 L2 on 1994.09.11 was downloaded (LT05_L2SP_141054_19940911_20200913_02_T1) at 0 % land cloud cover and 1 % scene cloud cover L1. However, for 2022, two Landsat images were downloaded to composite the district boundary for the district change calculation. Therefore, Landsat 8-9 OLI/TIRS C2 L2 on 2022.02.04 at 0.69 % land cloud cover and 0.44 % scene cloud cover L1 (LC09_L2SP_141054_20220204_20220206_02_T1) and Landsat 8-9 OLI/TIRS C2 L2 on 2022.06.27 (LC08_L2SP_142054_20220627_20220706_02_T1) at 7.75 % land cloud cover and 2.74 % scene cloud cover L1 .

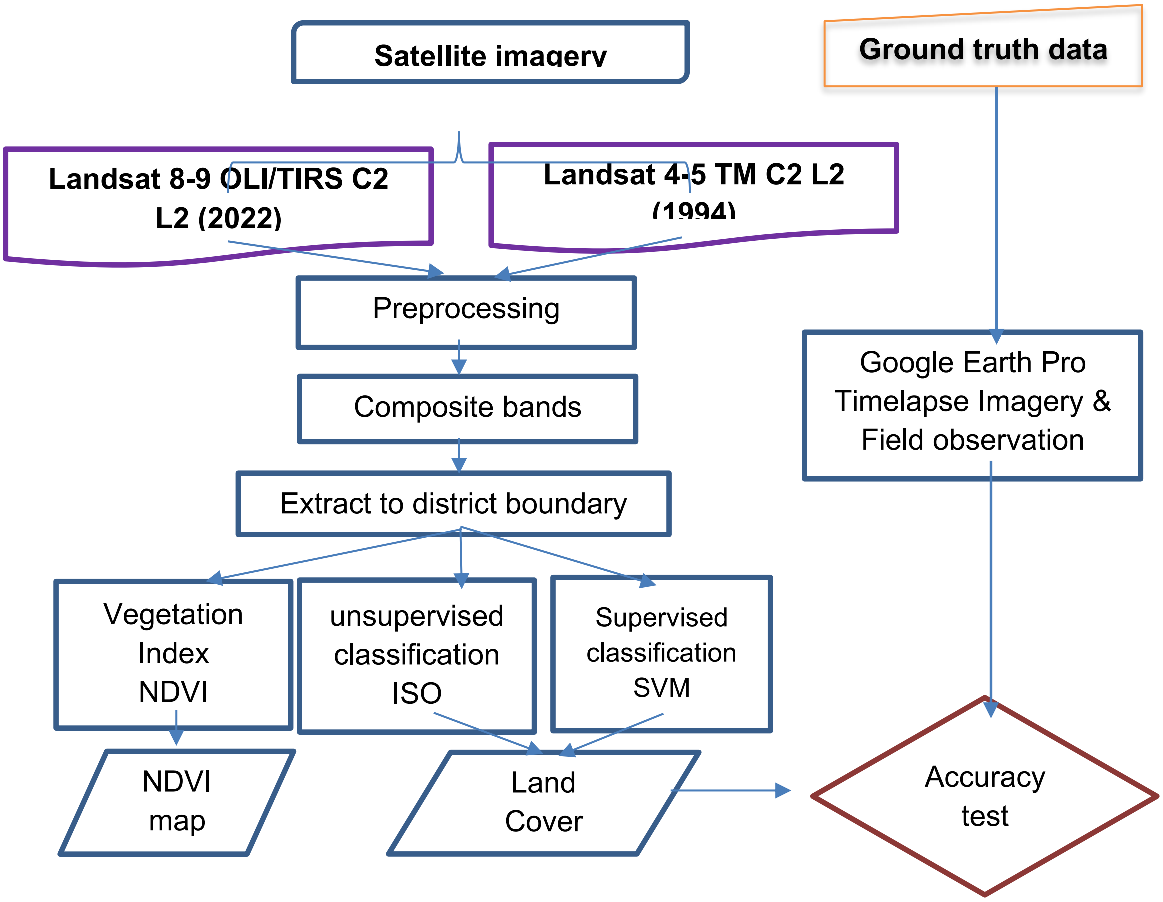

Figure 2: Work flow of forest cover change detection in Mullaitivu district

Processing and analysis were done using ArcGIS pro v.2.8. and Googe Earth Pro. First band 1-7 was composited using band composite function. Then, removal of cloud was done for Landsat 8 in 2022 which consists higher percentage of cloud cover. For this, pixel values of clouds were identified using pop-up menu by clicking the clouds in various locations at the raster map and values were recorded. Then, mask function was used in the raster function of the imagery tap. In the mask function menu, the composited band was selected as input and maximum values were filled with identified cloud pixel values. These steps were followed for second Landsat image. Then, mosaic function was used to combine the two raster composite bands to get the cloud-free Landsat raster image. Then, cloud-free Landsat image was extracted to region of interest (ROI) by using extract by mask function. This output image was used for NDVI calculation and land use classification (Figure 2).

2.3 NDVI assessment

NDVI is a simple graphical indicator that is often used to analyze RS measurements and assess whether the target being observed contains green health vegetation or not. The NDVI quantifies vegetation by measuring the difference between near-infrared (NIR) (which the vegetation strongly reflects) and red light (which the vegetation absorbs/has a low reflectance). The NDVI is calculated by the following method NDVI arithmetic function at the raster function which was used to calculate the NDVI value of the composite bands.

$$NDVI = \frac{NIR - RED}{NIR + RED} \times 100$$

Values of NDVI is ranged from -1 to +1, wherein -1 is generally water bodies and +1 is generally dense green–leafy vegetation. Hence one can say that NDVI is an index to measure healthy green vegetation. Negative values represent cloud, water and snow. Values closer to 0 represent rocks and ground surfaces. Values from 0 to 0.1 represent rocks, sand, barren land covered by snow. Values 0.2 to 0.3 indicates grassland and vegetation. Values from 0.6 to 0.8 represent temperate forest and tropical forest. For different bands are used for NDVI calculation for Landsat 8 (NIR-5, Red-4 and Blue-3) and Landsat 4-5 (NIR-4, Red-3 and Blue-2) (Zaitunah et al., 2018).

2.4 Unsupervised Classification

Iterative Self-Organized (ISO) Data Analysis Techniques is a tool that combines the functionalities of the ISO Cluster and Maximum Likelihood Classification tools (Lemenkova, 2021). Default setting was used the classification where number of classes was set to 5, minimum class size to 20, sample interval to 10 (Price, 2011). Based on the observation of the classified map, it was renamed into four categories such as bare lands, built-up & farmlands, forest and water bodies. The classified image was then converted into polygon data using raster to polygon function at the geoprocessing tool. Then, dissolve function was used to group the values into classified land use categories. Then, area of the respective category was calculated in ha using calculate geometric function in the attributed table.

2.5 Supervised Classification

For supervised classification, training the sample was done. It is significantly contributed to high classification accuracy. For this, training the sample manager was used at image classification wizard of the ArcGIS pro. For the identification of land use categories, high resolution image was derived from google earth pro. Four categories of land use were identified for the classification such as water bodies, forest, built-up & farmlands, and bare lands. Then, the trained sample was saved as a shape file for further processing. Then, classify option was used to classify the land use using support vector machine (SVM) learning algorithm where an already trained shape file was used (Lemenkova, 2021) as a training sample. The classified image was then converted into polygon data using the raster to polygon function at the geoprocessing tool. Then, the dissolve function was used to group the values into classified land use categories. Then, the area of the respective category was calculated in ha using calculate geometric function.

2.6 Accuracy Assessment

First, land use category was identified using google earth pro and field inspection (Table 1) (Potere, 2008; Vijitharan et al., 2022). Historical image of 1994 with a high-resolution option (8692 ×4699) was downloaded using Google Earth's timelapse function and it was validated with field observations (Olofsson et al., 2014; Tilahun, 2015). A total of 500 accuracy assessment points as a sampling were generated using create accuracy assessment points in ArcGIS Pro (Price, 2011). Then, these points data were converted kml (keyhole markup language file) (kml) file to visualize the points closer to the location on the Google Earth Pro. Time slider tap was used to load the 1994 and 2022 historical maps for accuracy validation. Error matrix function was used to derive the Cohen's Kappa statistics with Overall Accuracy (OA), Producer Accuracy (PA), and User Accuracy (UA) for validation (Foody et al., 2020)

$$PA = \frac{Number\ of\ accurately\ identified\ points}{Total\ reference\ points} \times 100$$

$$UA = \frac{Number\ of\ accurately\ identified\ points}{Total\ number\ of\ classified\ reference\ points} \times 100$$

$$OA = \frac{Total\ number\ of\ correctly\ classified\ land\ cover\ reference\ points}{Total\ number\ \ reference\ points} \times 100$$

$$Kappa\ (K) = \frac{OA - Probability\ of\ chance\ agreement}{100 -\ Probability\ of\ chance\ agreement} \times 100$$

Table 1. Land use category of training sample at Google Earh Pro and field with an accuracy assessment point

Land use category	Training sample	Field
Forest		
Built-up and Farmlands		
Bare lands		

ISBN: 978-955-627-013-6

Water bodies		

The kappa coefficient is a measurement used to determine the agreement between classification accuracy and the reference data. The parameter reflects the difference between actual agreement and the agreement expected by chance. Values of K range from 0 to 1, where 1 denotes perfect agreement, while 0 indicates poor or no agreement in the classification (Kaimaris et al., 2016).

3. DISCUSSION AND RESULTS

3.1 NDVI values

Figure 3 shows the resulted image of NDVI with ranged values. NDVI value was ranged from -0.27 to 0.51 in 1994 and – 0.17 to 0.48 in 2022. Dark green areas on the map indicated the vegetation cover in the district and light green resembled the other land uses.

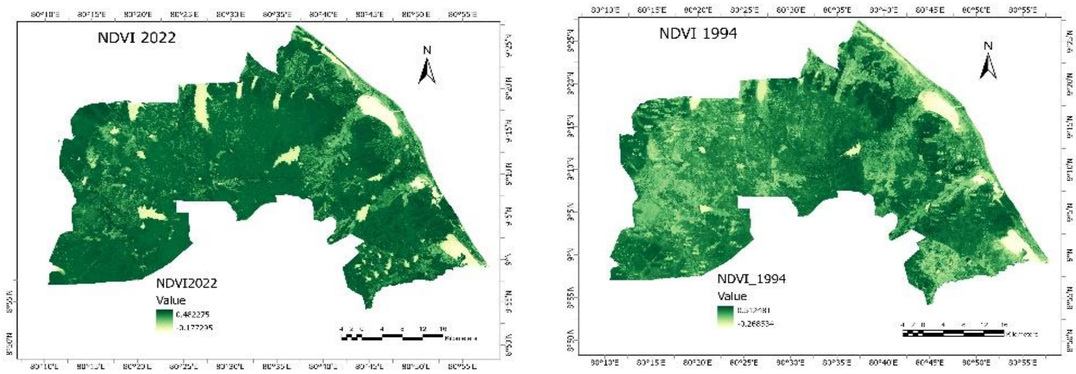

Figure 3: NDVI values in 2022 and 1994, Mullaitivu district

From the NDVI analysis, a comparatively lower value was obtained from our results. Even though our NDVI value represented the greener vegetation cover, but for wet evergreen rain forest, NDVI value should be more than 0.6. However, our NDVI value was comparable with other studies in the dry forest. Martinuzzi et al. (2008) obtained > 0.7 for semideciduous and evergreen forest, 0.56< NDVI >0.61 for the group of mix woodland, shrubland, and exposed lands, share with some shrubland, and the cactus forest in dry forest and less than 0.56 was the shrubland and the dwarf vegetation in the lowlands by using high-resolution imagery and these results were comparable with Cintrón and Rogers (1991). NDVI value ranges in the primary dry forest (0.513 to 0.57), then secondary dry forest (0.456 to 0.513) with dense vegetation density class (Zaitunah et al., 2018). John Weier and David Herring, (2000) reported that values greater than 0.6 indicate temperate and tropical rainforests. However, this value is based on the reflectance of the bands. Therefore, further study is required to use the high-resolution multispectral images for higher accuracy results and validation in study area.

3.2 Unsupervised classification

Figure 4 shows the results of the unsupervised classification map of 2022 and 1994 whereas table 2 shows the extent and percentage of the land uses. Forest cover was reduced from 61.5 % to 59.48 % similarly, built-up & farmlands were reduced from 19.32 % to 14.71 %. Bare lands and water bodies were increased from 15.59 % to 17.84 % and from 4.26 % to 7.79 %, respectively. Reduction of forest cover and built-up & farmlands was 1.28 % and 4.61 %, respectively. Similarly, bare lands and waterbodies were increased by 2.25 % and 3.53 %, respectively. Bare lands and water bodies were increased by 0.4 % and 2.4 %, respectively whereas forest cover and built-up & farmlands were reduced by 2 % and 0.9 %, respectively over 28 years period. Rajeevan et al. (2019) reported that areas under vegetation land use such as agriculture, sparse and plantation forest, and dense forest were decreased from 2013 to 2017, and changed area of agriculture land use, sparse and plantation forest, and dense forest was 2.3%, 3.6% and 5.2%, in 2013, 2014, 2016 and 2017, respectively. This changed values is higher than that our results in the classification method.

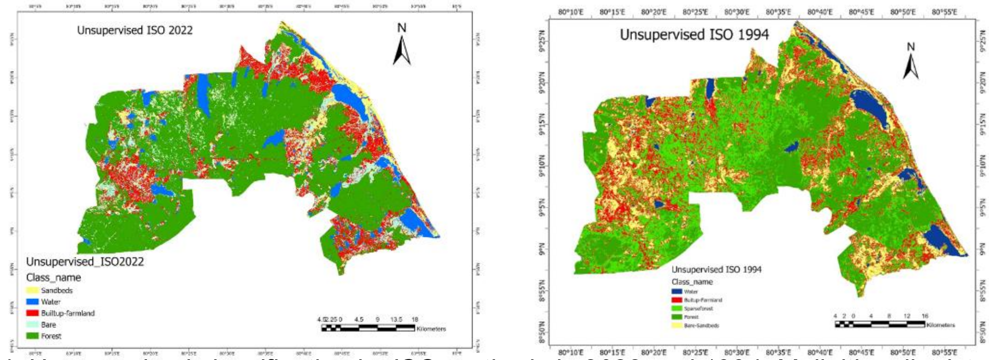

Figure 4: Unsupervised classification by ISO methods in 2022 and 1994, Mullaitivu district

Table 2. Extent and percentage of land use of Unsupervised classification in 2022 and 1994

SL.No	Land use	Extent in 2022 (ha)	%	Extent in 1994 (ha)	%
01	Bare	47,840.81	17.84	41,814.02	15.59
02	Buit-up & Farm land	39,437.78	14.71	51,789.95	19.32
03	Water	20,896.23	7.79	11,407.41	4.26
04	Forest	159,477.73	59.48	162,892.11	60.76
	Total (ha)				**268, 107.11**

3.3 Supervised classification

Figure 5 shows the results of the supervised classification map of 2022 and 1994 whereas table 3 shows the extent and percentage of the land uses. Forest cover was reduced from 63.33 % to 58.7 % over the period similarly built-up & farmlands were slightly reduced from 27.62 % to 26.31 %. Water bodies and bare lands increased from 4.13 % to 6.35 % and 4.85 % to 8.48 %, respectively. The reduction percentage of forest cover and built-up & farmlands was 4.63 % and 1.31 %, respectively, whereas water bodies and bare lands were increased by 2.22 % and 3.63 %, respectively. A total of 12,426.44 ha was degraded over 28 years period in the district.

Ranagalage et al. (2020) found that the dry zone had undergone rapid forest loss (246,958.4 ha) during the past 27 years, which accounts for 8.0% of the net forest

ISBN: 978-955-627-013-6

cover changes whereas 14,771.4 ha was lost over 10 years periods from 1999 to 2010. Pathmanandakumar (2020) reported that forest cover was reduced by 0.8 % in a Divisional secretariat division of the Mullaitivu district from 1997 to 2016 whereas agriculture and water bodies were increased by 0.65 % and 0.26 % in the same 20 years period except bare land was decreased by 0.12 %.

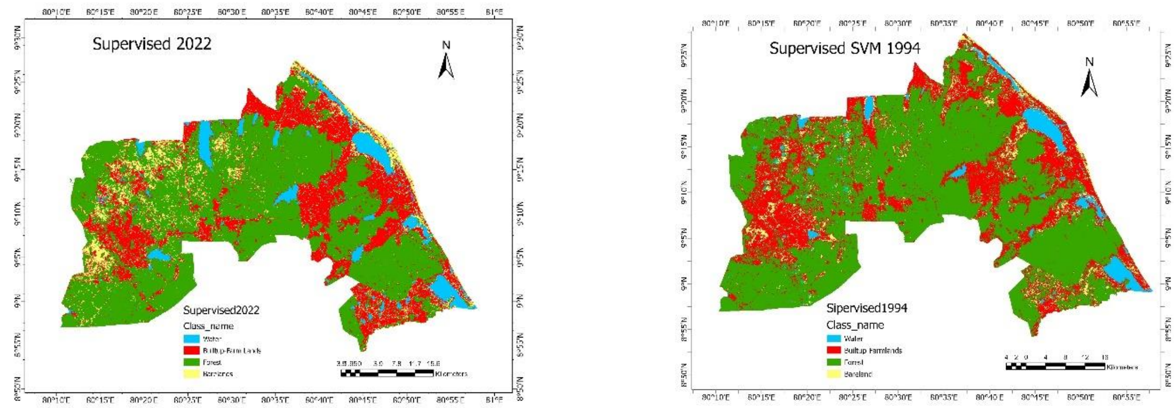

Figure 5: Supervised classification by SVM methods in 2022 and 1994, Mullaitivu district

Our forest cover result in 2022 was higher than that of the Department of Census and Statistics report of Sri Lanka (2022) that revealed forest cover percentage in the study area was 49.7 % in 2020 and it was less than that of 2010 which accounted 60.3 %, however, our result was consistent with the Department of Census and statistics which revealed that built-up & farmlands were reduced from 26.38 % to 17.7 % and bare land was increased from 4.73 % to 6.5 % from 2010 to 2020, respectively. But, water bodies were reduced from 7.7 % to 6.21 % in the study area (Department of Census and Statistics, 2011 and 2021).

Table 3. Extent and percentage of land use of supervised classification in 2022 and 1994

SL.No	Land use	Extent in 2022 (ha)	%	Extent in 1994 (ha)	%
01	Water	17,036.36	6.35	11,062.99	4.13
02	Built-up & Farmlands	70,546.40	26.31	74,059.21	27.62
03	Forest	157,372.31	58.70	169,798.75	63.33
04	Bare land	22,738.11	8.48	12,991.65	4.85
	Total (ha)	**268, 107.11**			

3.4 Accuracy and Validation

Table 4 shows the results of the Kappa statistics of the accuracy assessment. Acceptable accuracy was obtained by these classification methods. The OA was 0.89 and 0.9 in 2022 and 1994, respectively whereas the value of Kappa coefficient was 0.81 and 0.82 in 2022 and 1994, respectively. UA was high for water and forest classification whereas PA was high for water, built-up and farmlands and forest. Our result was consistent with Pathmanandakumar (2020) where Kappa coefficient and OA was ranged from 0.85 to 0.82 and from 0.86 to 0.88, respectively. Our result was also consistent with Vijitharan et al., 2022 reported that Kappa coefficient and OA were 0.83 and 0.87%, respectively in the forest cover of the Vavuniya district in the northern province.

Table 4. Accuracy assessment of supervised classification in 2022 and 1994

Land use	User Accuracy		Producer Accuracy		Overall Accuracy		Kappa statistics	
	2022	1994	2022	1994	2022	1994	2022	1994
Water	0.97	1	0.92	0.88	0.89	0.90	0.81	0.82
Built-up & Farmland	0.75	0.83	0.86	0.89				
Forest	0.97	0.94	0.92	0.97				
Bare land	0.72	0.76	0.72	0.44				

We obtained the acceptable Kappa coefficient and OA. However, the value was slightly lower PA and UA for bare lands and built-up & farmlands classification. Identification of bare lands from the farmlands was a challengeable task in the study area. It is mainly due to the give up or uncultivable lands scattered within the farmlands. Further, patch or open forest or scattered forest were identified as farmlands. Similarly bare lands within the dense forest identified as farmlands.

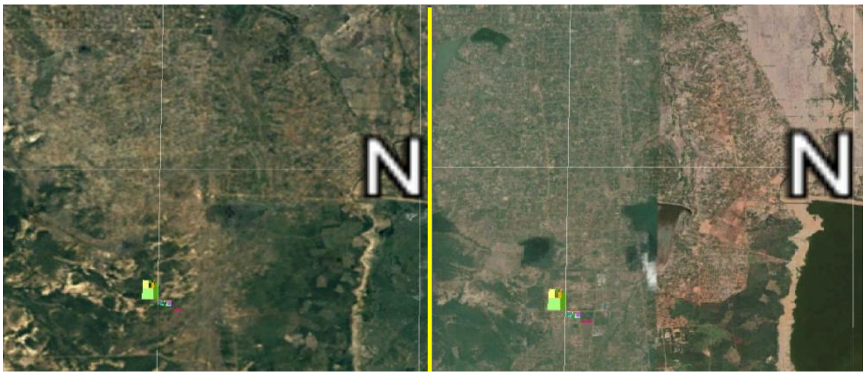

Figure 6: Same scale of Google Earth Pro images a) 1994 b) 2022

Figure 7: Same scale of Google Earth Pro images a) 1994 b) 2022

Figure 6 map clearly indicated that farmlands were converted into built-up areas. A total change deduction of built-up & farmlands was comparatively less than other land use changes from 1994 to 2022. Figure 7 map clearly shows that there was a huge encroachment held due to increased built-up areas. However, we could not come to a solid decision that which land use change majorly caused the forest cover reduction in the study area. It may be due to changes in the built-up, farmlands, bare land, and water body. From the district statistical information, built-up & farmlands areas together were decreased from 2011 to 2020 where built-up area was increased and agricultural land was decreased (Department of Census and Statistics, 2011 and 2022). In this study, we mainly focused on forest cover change assessment. However, further study is needed with more land use classification to assess causes for forest cover reduction such as farmlands, built-up, sparse forest, dense forest, and grasslands for precise land use change detection in the district.

4. CONCLUSIONS

The normalized difference vegetation index value was less than 0.51 and this value clearly indicated that the study area fell under the category of dry zone lowland forest. Area under forest cover and built-up & farmlands were decreased whereas water bodies and bare lands were increased over the 28 years periods. The total forest cover of the district was 58.70 % (157,372.31 ha) in 2022 and 63.33 % (169,798.75 ha) in 1994. Forest cover was reduced by 4.63 % (12,426.44 ha) in the study area. The accuracy of the classification was at an acceptable level for the land use and land cover classification in the district.

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