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Estimating Tree Canopy Cover and Identifying Deforestation Patterns in Meghalaya (1990-2021) through ML Classifiers

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Abstract

This study utilizes ML classifiers to estimate canopy density based on three decades of data (1990-2021). The Support Vector Machine (SVM) classifier outperformed other classifiers, such as Random Tree and Maximum Likelihood. Satellite data from Landsat and Sentinel 2 was classified using a developed python model, providing an economical and time-saving approach. The accuracy of the classification was evaluated through a confusion matrix and area computation. The findings indicate a negative trend in the overall decadal change, with significant tree loss attributed to jhum cultivation, mining, and quarry activities. However, positive changes were observed in recent years due to the ban on illegal mining. The study highlights the dynamic nature of tree cover and emphasizes the need for biennial assessments using at least five time-series data. Micro-level analysis in Shallang, West Khasi hills, revealed a concerning trend of shortening jhum cycles. Automation in canopy change analysis is crucial for effective forest monitoring, providing timely information for law enforcement proposals and involving forest managers, stakeholders, and watchdog organizations.

Keywords

Meghalaya, Forest Cover, ML, SVM, Python Script, Decadal Change, Biennial Change

1. Introduction

Land cover and land use are often used interchangeably, but their original denotations are very distinctive [1] [2]. The Meghalaya state of northeastern India was studied for its forest cover. The tropical forest is the worst sufferer of shifting cultivation and is the utmost significant land use practice by indigenous [3]. In India, shifting cultivation is also known as slash-and-burn agriculture or jhum cultivation; jhum is performed considerably in the Northeastern states of India [4].

[5] stated that in North Eastern India, above 100 tribal ethnic minorities follow slash and burn, and, in several parts, the landless people and lowland migrants even practice it. In Meghalaya, nearly 52,290 families depend on jhum cultivation [6] [7]. The entire NE India lost 8771.62 sq km under shifting cultivation in 2005-2006, which was 3.5% of the entire geographical area of the region and the total shifting cultivation area of the country is about 86% [8]. In Meghalaya annually 530 sq. km of land is slashed and burned for cultivation. Almost 2650 sq. km of the state was under jhum cultivation [9] [10] observed that in Meghalaya, the jhum cycle of 5 to 10 years is more vulnerable to weed aggression compared to 15 years of the jhum cycle. Additionally, the jhumias were forced to reduce the fallow time to 2 - 3 years due to rising population pressure on forests [11] [12]. Jhum-affiliated forests lose about 77 square kilometres of coverage per year. Every year, over 20 sq. km. of jhum are returned to the natural forest [6] [13].

Remote sensing technology makes keeping an eye on the planet's natural resources simply because it helps manage, evaluate, discover, identify changes in features, and describe the planet's natural resources [14]. In satellite remote sensing, the changes can be identified where spectral signatures are commensurate with the change in land cover [15]. Scholars [14] [16] [17] [18] observed that remote sensing is very helpful, efficient, time-saving and economical in forest cover monitoring and change detection. Several studies witnessed a pattern of deforestation, and the rate of forest cover changes was mapped using Remote Sensing [19] [20]. The main potency of remote sensing is that it empowers spatially exhaustive, wall-to-wall coverage of the study area. Satellite imageries with various sensors have also been used in the case of multiple Normalize Difference Vegetation Index and Forest Canopy Density studies of the world [21] [22].

Compared with outdated classification methods, Machine Learning (ML) efficiently utilizes more elements. It has the supremacy of simple function, fast processing and robustness in various data sizes and classification types [23]. ML is a technique to study the computer's ability to simulate new human learning behaviours, acquire new human skills, and reorganize existing structures to expand a computer's performance [24]. Artificial neural networks, Support Vector Machines (SVMs), and Random forests are a few standard ML classifiers in Remote Sensing [23].

When identifying changes in satellite data, factors including scale, classification method, classification accuracy, and mapping techniques must be taken into account [25]. The medium resolution (10 - 30 m) satellite data are essential to capture small-scale canopy-cover loss, which accounts for abundant changes in tropical forest regions [26] [27]. However, the strength of remote sensing as it empowers them to prepare, monitor, and analyze wall-to-wall coverage of the study area. As might be anticipated with any mapping procedure, the results could be better [28].

The present study intends to assess canopy cover, examine classification accuracy, and monitor the decadal and biennial change in the canopy cover, which is imperative in the present scenario, as forest cover is shrinking daily. This may cause harmful outcomes like a rise in temperature, pollution, soil erosion, drought, flood etc.

2. Study Area

The state of Meghalaya has been chosen for this study. 26˚05'27.20"N, 89˚47'47.80"E, and 25˚01'28.51"N, 92˚48'22.13"E are the state's geographic coordinates. The state's total area is 22,429 square kilometres. Assam state borders the state to the east and north, and Bangladesh borders the state to the west and south (see Figure 1).

The Garo, Khasi, and Jaintia hills are Meghalaya's three geographical subregions. In terms of the variety of its forests and richness in flora, orchids, and angiosperms, the state ranks among the wealthiest in India [6]. Due to the region's frequent discovery of new species of amphibians, orchids, butterflies, and other plants, taxonomists from a variety of fields frequently treat it as a gold mine. Meghalaya is one of the four bio-diversity hotspots in India and a part of the global "Indo-Burma" biodiversity hotspot, according to different studies [6] [29].

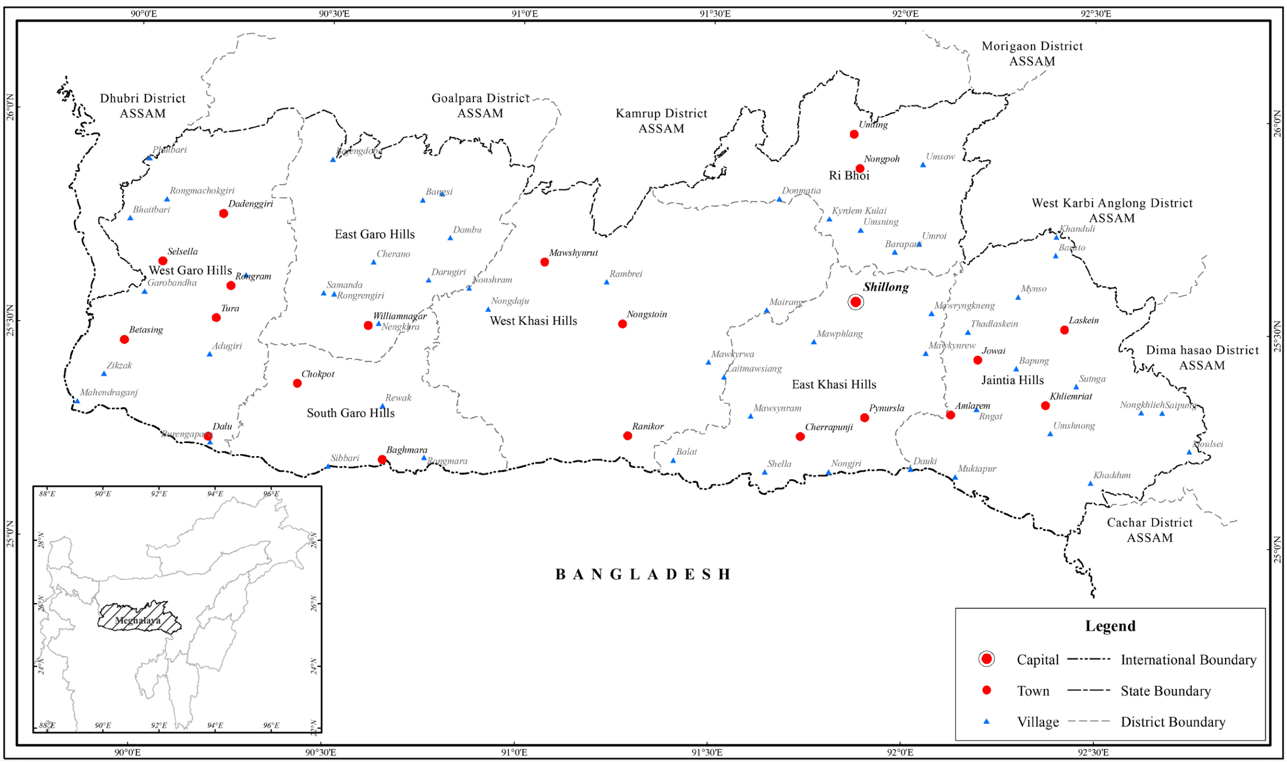

Figure 1. Study area, Meghalaya.

3. Data

3.1. Dataset

Satellite imageries of Landsat TM were acquired from the USGS portal, and Sentinel-2 MSI data were downloaded from ESA's Copernicus portal. The time series data for 1990, 2000, 2010, 2017, 2019, and 2021 were downloaded (see Table 1). The state of Meghalaya is covered by five Landsat scenes and six Sentinel-2 MSI scenes. Image composite was formed for six-time series, the initial three-time series were of Landsat 5 TM data, and the remaining were of imagery of Sentinel-2 Multispectral Instrument (Figure 2). The acquisition of imagery was challenging as the study area is mostly covered with clouds throughout the year. All the image composites were created with minimum or no cloud coverage.

3.2. Image Pre-Processing

Imageries were atmospherically and topographically corrected to extract detailed information (Figure 3). The importance of these corrections was already discussed in different articles [30] [31]. For topographic correction Digital elevation model of the region is required. That is why the SRTM DEM of 1 arc-second (~30 meters) has been downloaded, pre-processed, and reprojected to UTM Zone-46 to create a seamless mosaic.

4. Methods

The composite satellite data of the study area was classified using three different machine learning (ML) algorithms for six-time series data. The algorithms are Maximum Likelihood classifier (parametric), Random Tree Classifier, and Support vector machine (non-parametric).

Table 1. Satellite data used in this study.

Time Series	Spacecraft and Sensor	WRS Path Row/Scene Number	Date Acquired	Spectral Bands	Pixel Size (in mtr)	Radiometry
TS 1 (1990)	LANDSAT 5, TM	136-42, 136-43, 137-42, 137-43, 138-42	27-11-1989 To 16-01-1990	7	30	8bit
TS 2 (2000)	LANDSAT 5, TM	136-42, 136-43, 137-42, 137-43, 138-43	12-01-2000 To 27-02-2000	7	30	8bit
TS 3 (2010)	LANDSAT 5, TM	136-42, 136-43, 137-42, 137-43, 138-44	21-01-2010 To 30-01-2010	7	30	8bit
TS 4 (2017)	Sentinel-2B, MSI	T45RYJ, T45RZJ, T46RCN, T46RCP, T46RDN, T46RDP	03-11-2017 To 30-12-2017	13	10, 20 and 60	16bit
TS 5 (2019)	Sentinel-2B, MSI	T45RYJ, T45RZH, T46RBP, T46RCN, T46RCP, T46RDN, T46DRP	08-11-2018 To 07-01-2019	13	10, 20 and 60	16bit
TS 6 (2021)	Sentinel-2B, MSI	T45RYJ, T45RYJ, T45RZJ, T46RBN, T46RCN, T46RCP, T46RDN, T46RDP	01-01-2021 To 23-02-2021	13	10, 20 and 60	16bit

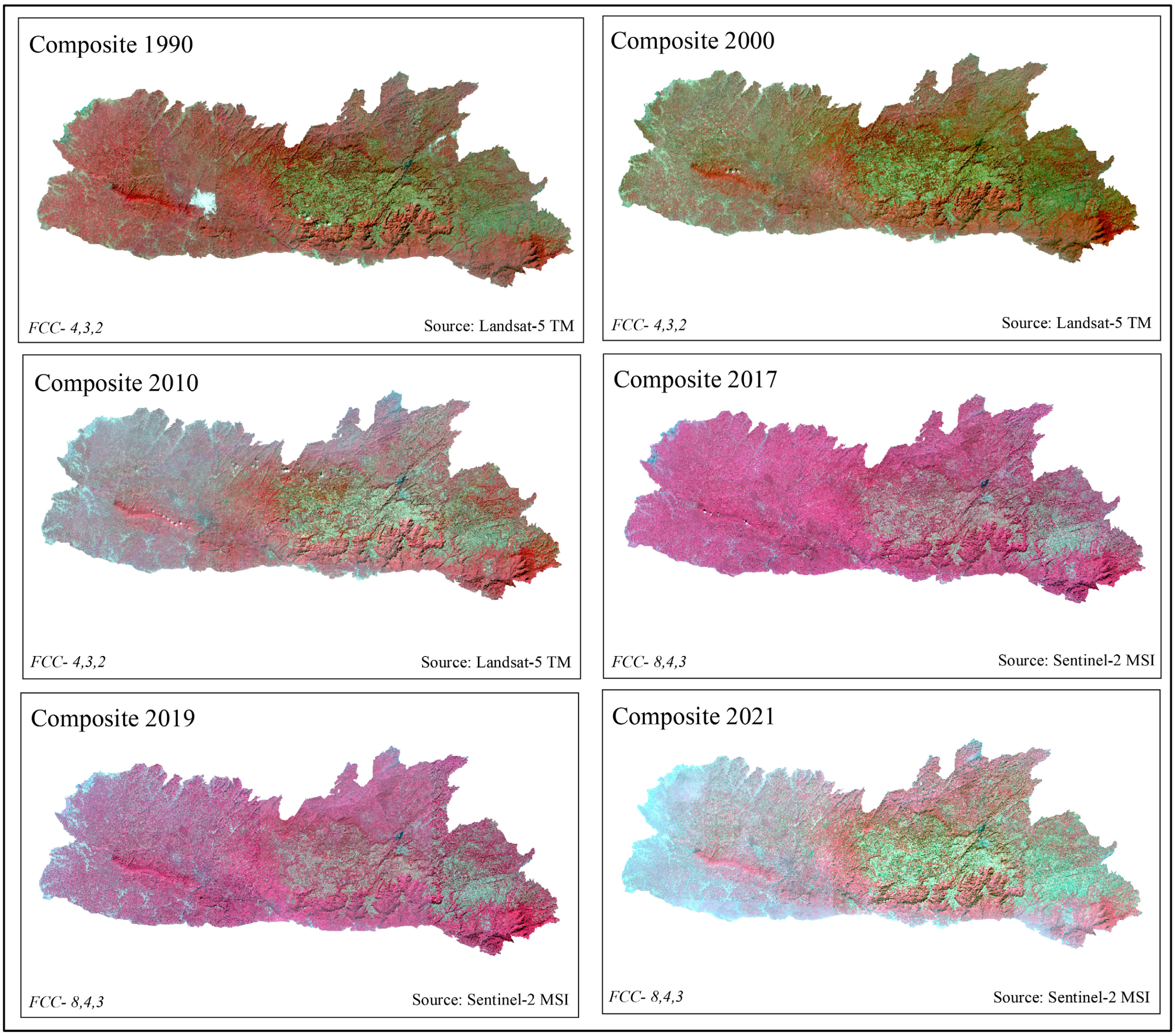

Figure 2. Image composite of different time interval.

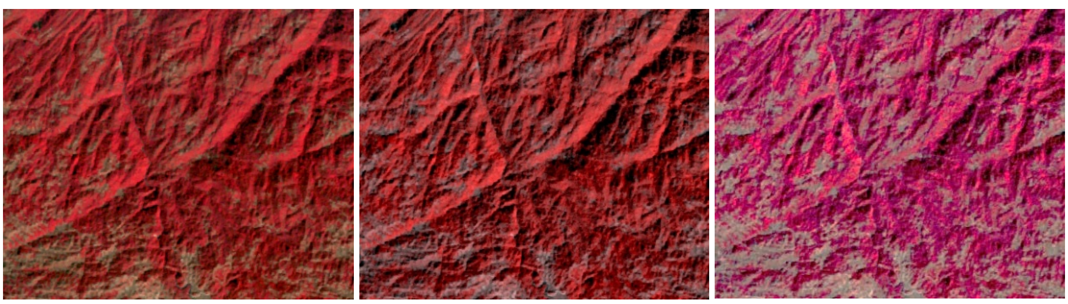

Figure 3. (a) Raw satellite imagery, (b) Atmospherically corrected imagery, (c) Topographically and atmospherically corrected imagery respectively.

4.1. Parametric Classification

Maximum Likelihood Classification (MLC)

A computer-based classification method relying mostly on parametric methods is called maximum likelihood classification [32] [33]. This classification determines the probability that a given pixel belongs to a specific class by assuming that the statistics for each class in each band are normally distributed. All pixels are categorised unless a probability threshold is reached. Each pixel is given the class with the highest chance. If the highest likelihood is less than the threshold has been set, the pixel is left unclassified [34].

4.2. Non-Parametric Classification

The non-Parametric approach has proved to be more beneficial as they do not base on the classification of statistical parameters or a normality [35]. Thus, SVM and RTC were considered in this study.

1) *Support Vector Machine* (SVM) is an effective supervised classification technique is the SVM classifier. It can handle both standard images and segmented raster inputs. With time, this classifier was developed by [36] and gained popularity among researchers. Using SVM, if two sample classes (Tree Cover and Non-Tree Cover) are not separable linearly in a two-dimensional space, they could be distinguishable in a higher-dimensional space called hyperplanes [37]. The SVM classifier uses the kernel, a statistical function, to translate the support vectors generated from the training samples into a higher-dimensional space.

2) The *Random Forests Classifier* (RTC) is a framework that was introduced by [38] which is enormously influential as a general-purpose classification and regression approach [39]. A supervised machine-learning classifier called Random Trees constructs numerous decision trees, opting a random subset of variables for each tree and using the most common tree output to determine the classification as a whole.

There are three principal decisions to be considered when developing a random tree. These are 1) the method for separating the leaf, 2) the type of interpreter to use in each leaf, and 3) the method for introducing randomness into the trees [39].

The study consists of six time-series data, and there are multiple scenes in each time-series. Single time series data has three classified outputs of different classifiers, all stored in a geodatabase. Hence, a model has been prepared for quicker assessment and precise classification (**Figure 4**).

The model requires input 1) Training sample (polygon layer), 2) Satellite imagery (multiband Raster), and 3) District File (polygon administrative boundary) of the state. The model will analyze these inputs to classify the study area as per three machine learning algorithms. The output will be a classified state mosaic and a table consisting area of the respective classifier. The classified output has tree cover and non-tree cover as two classes. The classified data needs to be tested for its correctness.

4.3. Accuracy Assessment

The accuracy refers to the degree of "correctness" of a classified map which has

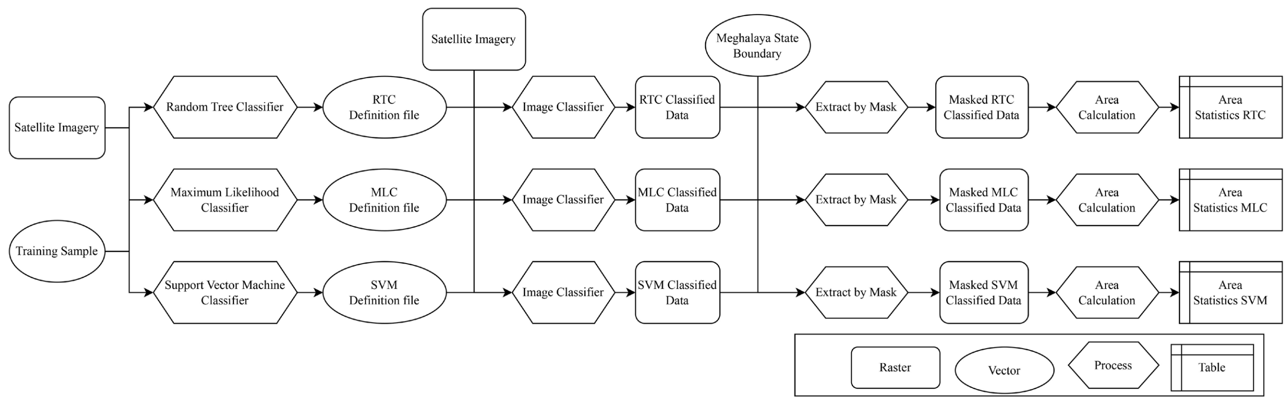

Figure 4. ML classification model.

been prepared by satellite imageries [40]. For accuracy assessment, the classified data and the reference data are prerequisites; the reference data must go through accuracy assessment and essentially be recognized. The classified data (SVM ML classified data) needs to be verified using reference data or ground-verified data.

4.3.1. Classified Data

In this research, Landsat and Sentinel 2 MSI data were classified using Support Vector Machine classifier for the year 1990, 2000, 2010, and 2021 for studying decadal change and for probing drastic change, classification of 2017, 2019 and 2021 were made.

4.3.2. Reference Data

Reference Data 1—One of the NASA Research Environment Programs, the Land Processing Distributed Active Archive Center (LP DAAC) stores and disseminates Global Forest Cover Change (GFCC) data beginning in 2000 with a 5-year time series gap [41]. The dataset was prepared using Landsat 5 TM and ETM+ sensors at 30-meter spatial resolution. The data provide tree cover information and the change in forest cover worldwide. This study used the GFCC 2000 and 2010 datasets as reference data.

Reference Data 2—Japan Aerospace Exploration Agency (JAXA) prepared the Global Forest/Non-Forest Map (FNF), where “forest” refers to a tree-covered land with 0.5ha of the area or larger and above 10 per cent of canopy cover. The data was prepared by Random Forest ML algorithm with a re-processed 25-meter ALOS-2 PALSAR-2 global mosaic dataset. The dataset is available from 2015 onward with a 1˚ × 1˚ tile and one year of the time interval. The study area is mostly covered with cloud; hence, the “L” band SAR data of PALSAR-2 can access tree cover accurately. The dataset from 2017, 2019, and 2020 were utilized in this research.

Reference Data 3—Forest Cover Map (FCM) is published biennially in India in the Indian State of Forest Report (ISFR) by the Forest Survey of India. The FCM is prepared by classifying IRS, LISS III data on a pan-India basis. The FCM data of the Forest Survey of India has an accuracy of more than 80 per cent [42].

The FCM data for 2017 and 2019 were utilized, along with JAXA data.

Ground coverage photograph—The ground verification of Meghalaya has been accomplished several times, starting from 2015 onwards; likewise, all the districts were visited to investigate canopy cover and canopy cover changes. Almost half of the geographical extent of the state was covered during the field visit, based on available road connectivity. The change in forest cover was observed due to shifting cultivation, rubber plantation, mining activities, forest fire, and regeneration from scrubland (**Figure 5**).

4.3.3. Technique Adopted

In this research, data were classified from 1990 to 2021; hence, the reference data was carefully selected for accuracy assessment. For accuracy assessment entire Meghalaya state has been segregated in to sample plot of 400-meter diameter. The Food and Agriculture Organization, UN, recommended a Stratified Random sample for the land cover classified map [43] [44]. The Stratified random sampling will choose the randomly distributed sample plots within each class, where each class has a number of points proportional to its relative area. Using Stratified Random sampling, 1000 sample plots were selected for accuracy assessment, as represented in **Figure 6**.

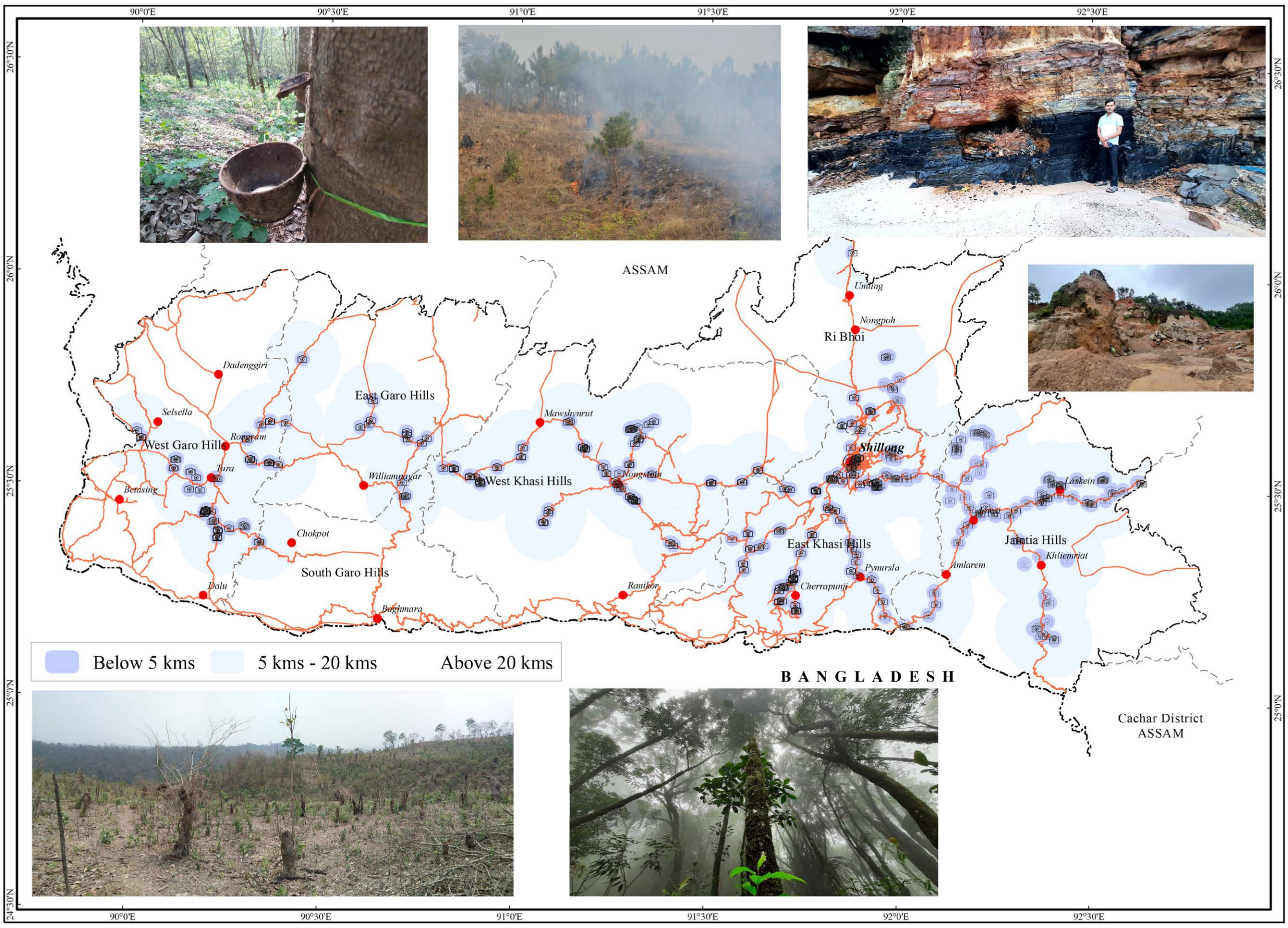

Figure 5. Ground verified places (black dots) and respective few photographs.

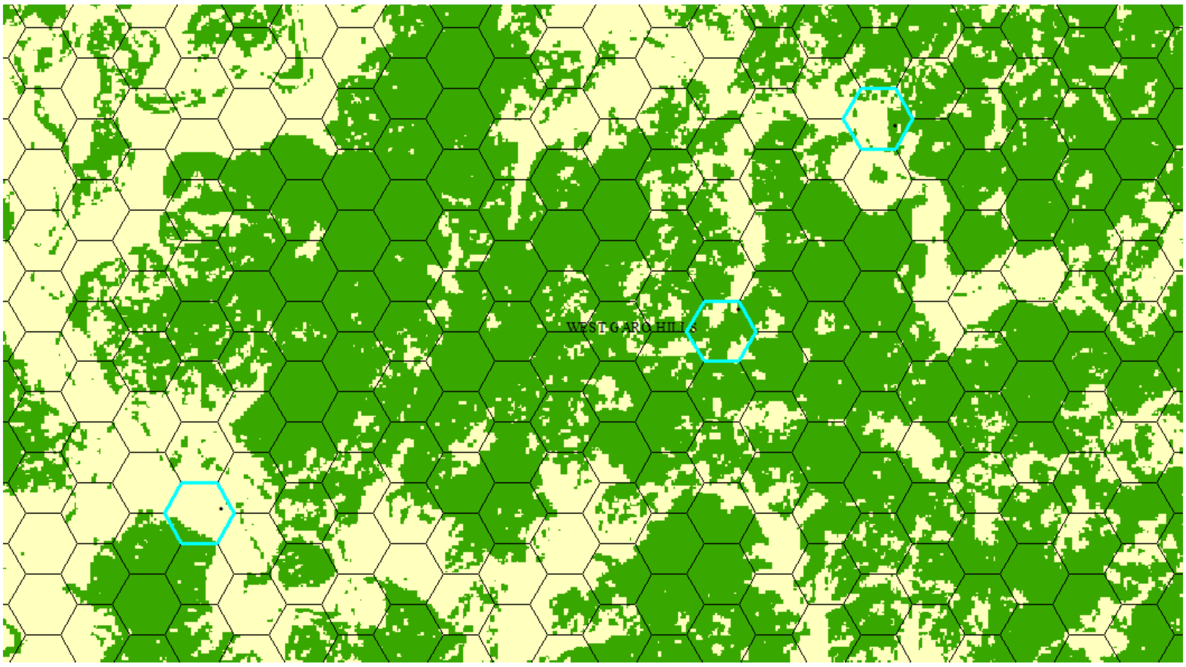

Figure 6. Selected hexagon based on stratified random sampling.

Polygon geometry sample plots were more correct than the point-based approach; the sample plot layout in the study area was based on the tessellation of the Earth's surface into hexagons of equal in the area [44]. The hexagons are 10.39 ha in area, as described in **Figure 7**.

In this research, there are a total six classified datasets to check for accuracy, and the individual steps followed for accuracy assessment consist of several steps, as described in **Figure 8**. Hence, a python script has been employed for quick and precise assessment. The script required one input of classified data and another of reference data; based on the input, the majority of statistics will be calculated for reference and classified data of each plot and stored them. The majority of information was then joined with hexagonal plots. For calculation of accuracy assessment, point geometry is required in GIS Software; thus polygon plot is converted to point geometry. The required attribute field name was assigned, and missing values (zero values in rows) were removed from attribute information; then confusion matrix was calculated and kept in separate CSV files. The confusion matrix may be useful in refining estimations of the boundary of classes in the region. [40] [45] [46] have enlightened that the confusion matrix is presently at the soul of accuracy assessment.

The accuracy evaluated for the time series data, mentioned in **Table 2**, represents that the land cover classification performed using ML algorithms has an impressive correlation with reference data. The user's accuracy of the Tree cover class has more than 91 percent, and the Producer's accuracy is over 88 percent in all classified data. The classified data has an overall accuracy ranging from 86.65 percent to 92.01 percent. In Remote Sensing, if the accuracy of land cover data is below 80 percent, the classification is not acceptable [46] [47]. Researchers [48]

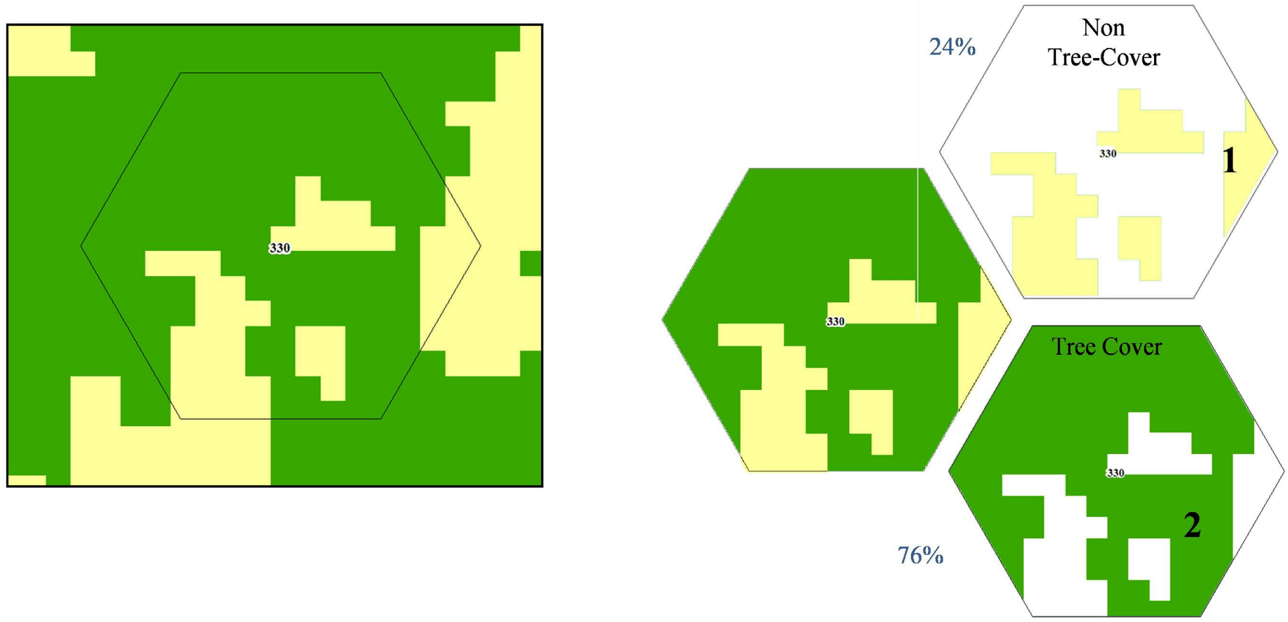

Figure 7. Hexagonal sample plot with calculated majority of land cover. The plot has majority of tree cover class, as it extends almost 76% of hexagon area.

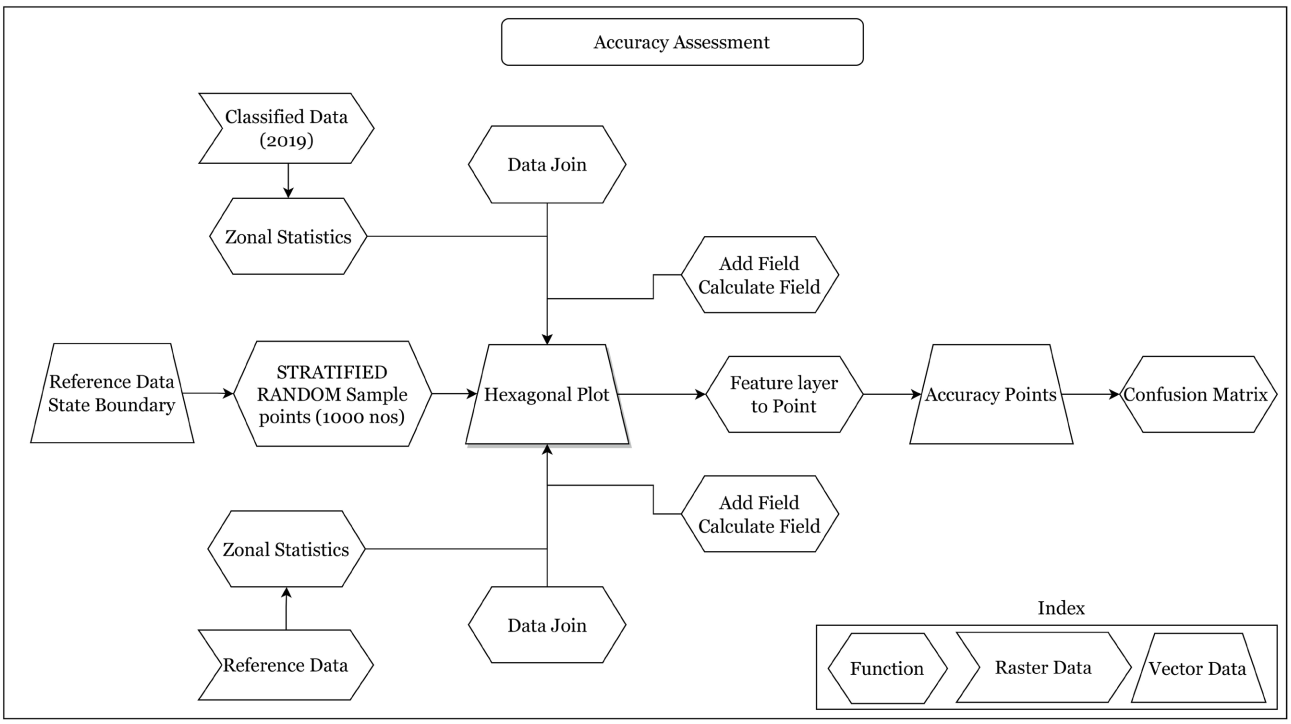

Figure 8. Methodology adopted for accuracy assessment.

[49] explained that the classified land cover map needs to be accurately checked to be used suitably and efficiently.

The rating criteria of the kappa coefficient (Table 3) depict that the classification done by the user has a substantial strength of agreement; hence the data can be exercised for further work.

Table 2. Summary of confusion matrix.

Data used	Class	User's Accuracy	Producer's Accuracy	Overall Accuracy	Kappa coefficient
Classified 2000 Reference LP DAAC 2000	No Tree-Cover	0.737968	0.821429	0.920121	0.728959
	Tree Cover	0.962594	0.940317		
Classified 2010 Reference LP DAAC 2010	No Tree-Cover	0.619247	0.783069	0.866532	0.607905
	Tree Cover	0.945333	0.88625		
Classified 2017 Reference JAXA 2017	No Tree-Cover	0.782828	0.704545	0.890688	0.672551
	Tree Cover	0.917722	0.94401		
Classified 2017 Reference ISFR 19	No Tree-Cover	0.767677	0.795812	0.913968	0.727952
	Tree Cover	0.950633	0.942284		
Classified 2019 Reference JAXA 2019	No Tree-Cover	0.815789	0.691964	0.894843	0.682862
	Tree Cover	0.913642	0.954248		
Classified 2019 Reference ISFR 2021	No Tree-Cover	0.8	0.783505	0.91911	0.741485
	Tree Cover	0.947434	0.952201		
Classified 2021 Reference JAXA 2020	No Tree-Cover	0.792746	0.711628	0.896866	0.68527
	Tree Cover	0.922111	0.94832		

Table 3. Rating criteria of Kappa coefficient.

Sl. No.	Kappa Coefficient	Agreement
1	0.80 - 1.00	Almost perfect
2	0.60 - 0.80	Substantial
3	0.40 - 0.60	Moderate
4	0.20 - 0.40	Fair
5	0.00 - 0.20	Minor
6	<0	Poor

5. Results and Discussion

The output of these Machine Learning classifiers has tabularized in **Table 4**, where a non-parametric classifier's output is significantly superior to a parametric classifier (**Figure 9**). Furthermore, the output area figure of MLC is inconsistent compared to SVM and RTC, although a consistent training sample for each classifier has been adopted during classification. The turnout of the SVM classifier is much more reliable. Hence, for further study, the output of the SVM classifier will only be considered.

The output computed area of the model (**Figure 4**) is further normalized using the normalizing factor (nf).

$$nf = \frac{\text{Geographical Area}}{\text{Digital Area}}$$

The nf is a bit disarrayed in the hilly region compared to the plain region. Hence the variance in area computed using nf, and without-nf was observed.

Table 4. Area comparison in different ML classifier.

Area is sq. km.					
Sl. No.	Data Source	Year	Classifier		
			SVM	RTC	MLC
1	Landsat 5	1990	16,756	16,636	14,970
2	Landsat 5	2000	16,981	13,886	12,792
3	Landsat 5	2010	16,534	14,649	14,511
4	Sentinel-2	2017	16,461	15,304	13,867
5	Sentinel-2	2019	16,557	13,816	15,945
6	Sentinel-2	2021	16,698	17,008	11,731

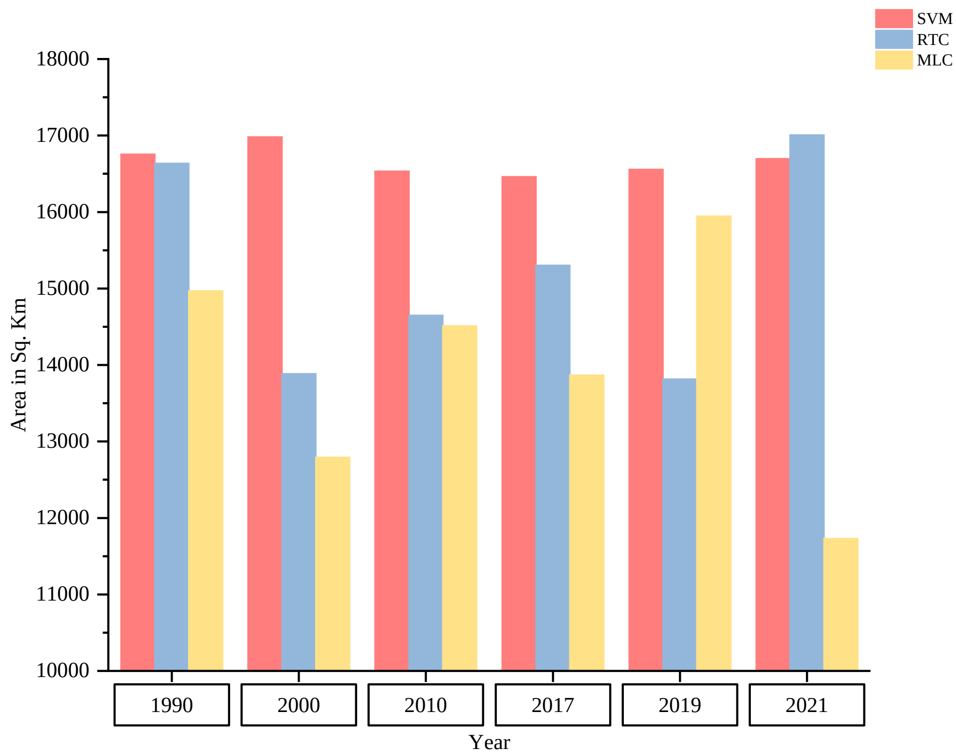

Figure 9. Area comparison in different ML classifiers.

The observed *nf* varies from 0.918023564 to 1.049603814 for the different districts in the classified data of 1990. The normalized area was further computed for all seven districts of Meghalaya to evaluate district-wise canopy cover and its transformation with time (**Table 5**).

The normalised tree cover area of Meghalaya in 1990 was 16,824 sq. km. which increased to 17,002 sq. km. in 2000. In the year 2010, the tree-cover of the state decreased to 16,566 sq. km. which was probed and realized that in Jaintia hills, the mining activity has initiated in full tempo, which further compounded with time by 2021, the district has lost more than 35% of its forest cover. West Khasi hills is another district which losing its tree cover steadily with time.

Table 5. Tree cover in different districts of Meghalaya.

Area in sq. km.									
Sl. No.	District Name	District Area	Tree Cover 1990	Tree Cover 2000	Tree Cover 2010	Tree Cover 2017	Tree Cover 2019	Tree Cover 2021
1	RI BHOI	2448	1931	2079	2016	1936	2037	2079
2	WEST GARO HILLS	3677	2917	2644	2647	2454	2506	2806
3	EAST GARO HILLS	2603	2176	2101	2039	2119	2000	2093
4	WEST KHASI HILLS	5247	4012	3960	3926	4175	4005	3898
5	JAINTIA HILLS	3819	2334	2795	2551	2229	2469	2352
6	EAST KHASI HILLS	2748	1778	1867	1718	1927	1899	1821
7	SOUTH GARO HILLS	1887	1676	1556	1669	1628	1663	1677
	TOTAL	**22,429**	**16,824**	**17,002**	**16,566**	**16,468**	**16,579**	**16,726**

While analysing district-wise tree cover of 2021, it was observed that in the district of West Khasi hills, the canopy cover is 3898 sq. km.; That is 23.30 percent of total tree cover and 17.38 percent of the geographical area in the state. Henceforth the tree cover is utmost when compared to other districts. The minimum tree cover observed in the South Garo hills district is 1677 sq. km. moreover, it is 10.02 percent of the total tree cover and 7.48 percent of the geographical area of the state, over and above it is 88.87 percent of the district area.

Presently (2021), the forest cover in the state is 16,726 sq. km. Hence, the assessment of decadal change and biennial change requisites to accomplish.

5.1. Decadal Change

Since the state's forest cover deteriorates for a variety of reasons, it is necessary to investigate the decadal change. According to [50] shifting farming, clear-cutting trees for timber, quarrying, and mining have all significantly altered the natural landscape of Meghalaya. Researchers like [51] [52] [53] and many others have researched the decadal change in vegetation cover with the aid of a remote sensing technique. Numerous academics have studied the issue of urban sprawl expansion, including [54] [55]. The decadal change in the tree cover of Meghalaya is presented in **Table 6**.

1) T1 Change—Change in canopy cover from 1990 onward in Meghalaya was studied, decadal changes were probed district-wise, and it was observed in T1 (1990 to 2000) a slight increase in overall canopy cover in the state (**Figure 10**). There were numerous negative along with positive changes in the state. The canopy cover was lost mostly in Garo hills and West Khasi hills, although in Jaintia hills, the canopy cover increased substantively, followed by Ri Bhoi and East Khasi hills.

2) In T2 (2000 to 2010), the state lost more than 400 sq. km. of tree cover is due to drastic forest cover change in Jaintia hills and East Khasi hills. During this period, all districts lost tree cover except the South and West Garo hills. Jaintia hills lost most tree cover during this period because of the district's accelerated

Table 6. Decadal change in tree cover in different districts of Meghalaya.

Sl. No.	District Name	Change (T1)	Change (T2)	Change (T3)	Overall Change
		Area in sq. km.			
		1990 to 2000	2000 to 2010	2010 to 2021	1990 to 2021
1	RI BHOI	148	−63	63	148
2	WEST GARO HILLS	−273	3	159	−111
3	EAST GARO HILLS	−75	−62	54	−83
4	WEST KHASI HILLS	−52	−34	−28	−114
5	JAINTIA HILLS	461	−244	−199	18
6	EAST KHASI HILLS	89	−149	103	43
7	SOUTH GARO HILLS	−120	113	8	1
	TOTAL	178	−436	160	−98

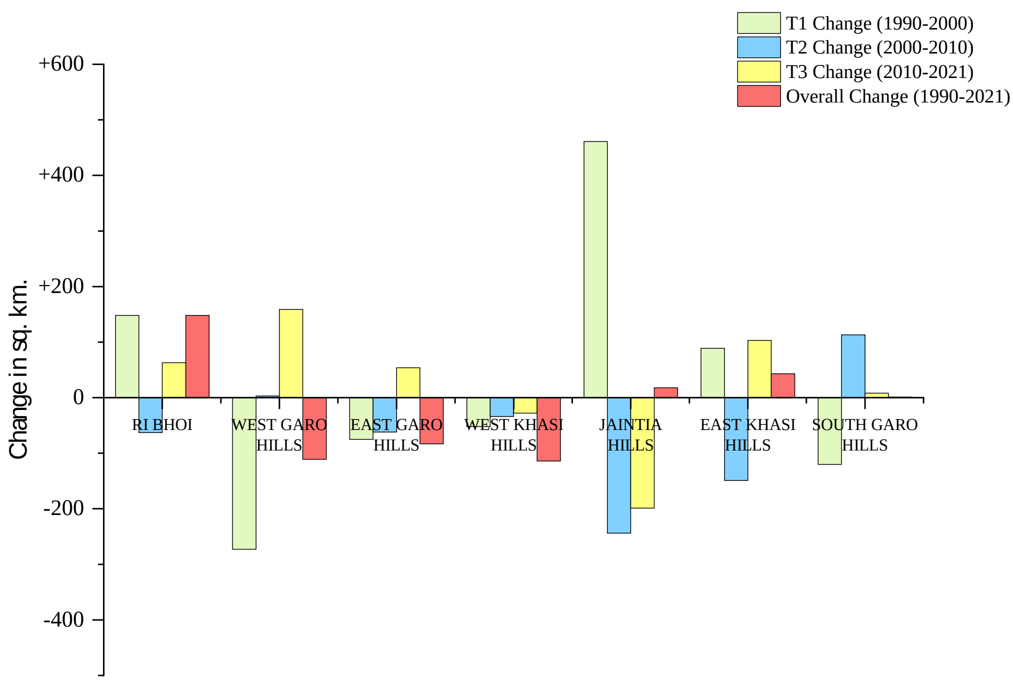

Figure 10. Decadal change and overall change during 1990 to 2021.

mining activities. Places like Umbadoh, Lumsnang, and Umlaper region lost the most canopy cover (**Figure 11**); in those regions, different cement factories became operational from 2000 onwards.

3) T3 (2010 to 2021)—The overall tree cover has increased during this period; the state grew its tree cover from 16,566 to 16,726 sq. km. which aggregates 160 sq. km. of positive change. This is due to impose a ban on illegal mining in different places in Meghalaya as directed in National Mining Policy (2003) [6]. The Districts like West Khasi hills (**Figure 12**) and Jaintia hills (**Figure 13**) continue losing forest cover because of shifting cultivation and mining activities.

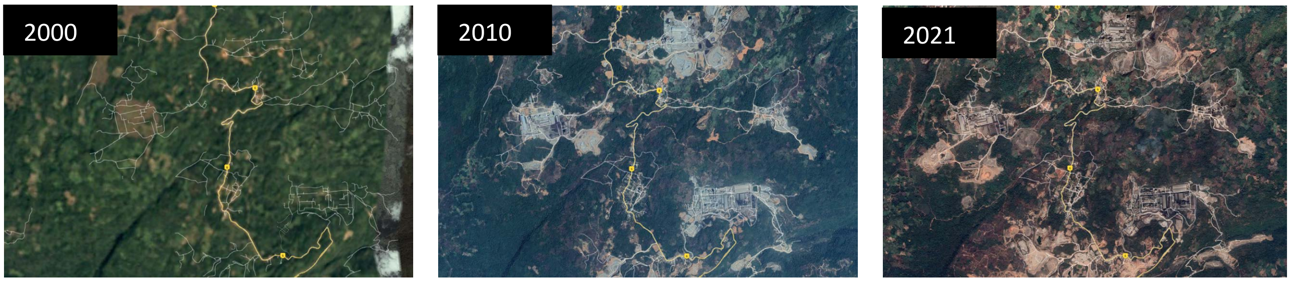

Figure 11. Change in canopy cover in Umbadoh, Lumsnang and Umlaper places of Jaintia hills district from 2000 to 2021.

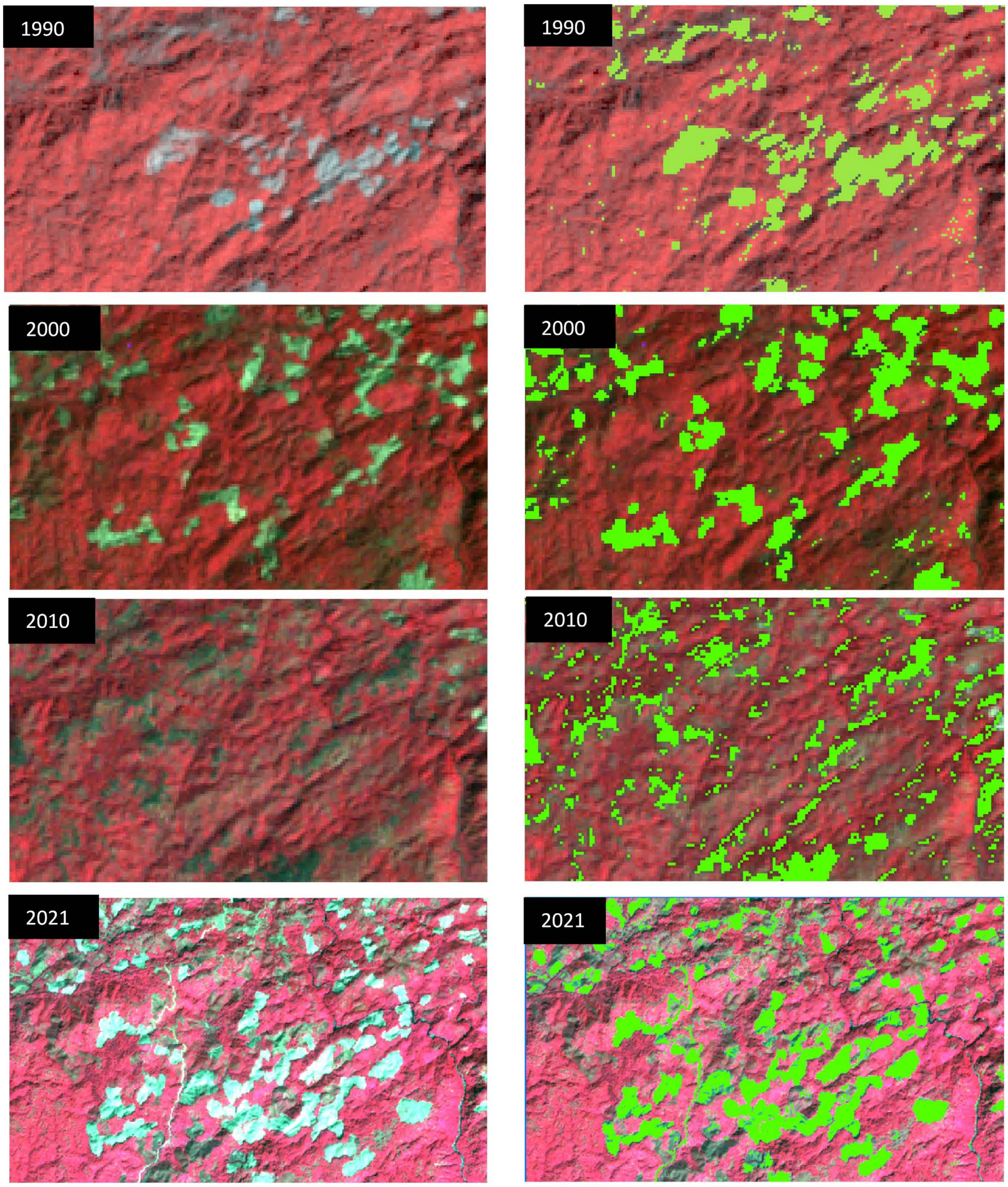

Figure 12. Three decadal (1990-2021) satellite data were compared for tree cover loss due to jhum cultivation in West Khasi hills. The bare land is highlighted in green colour.

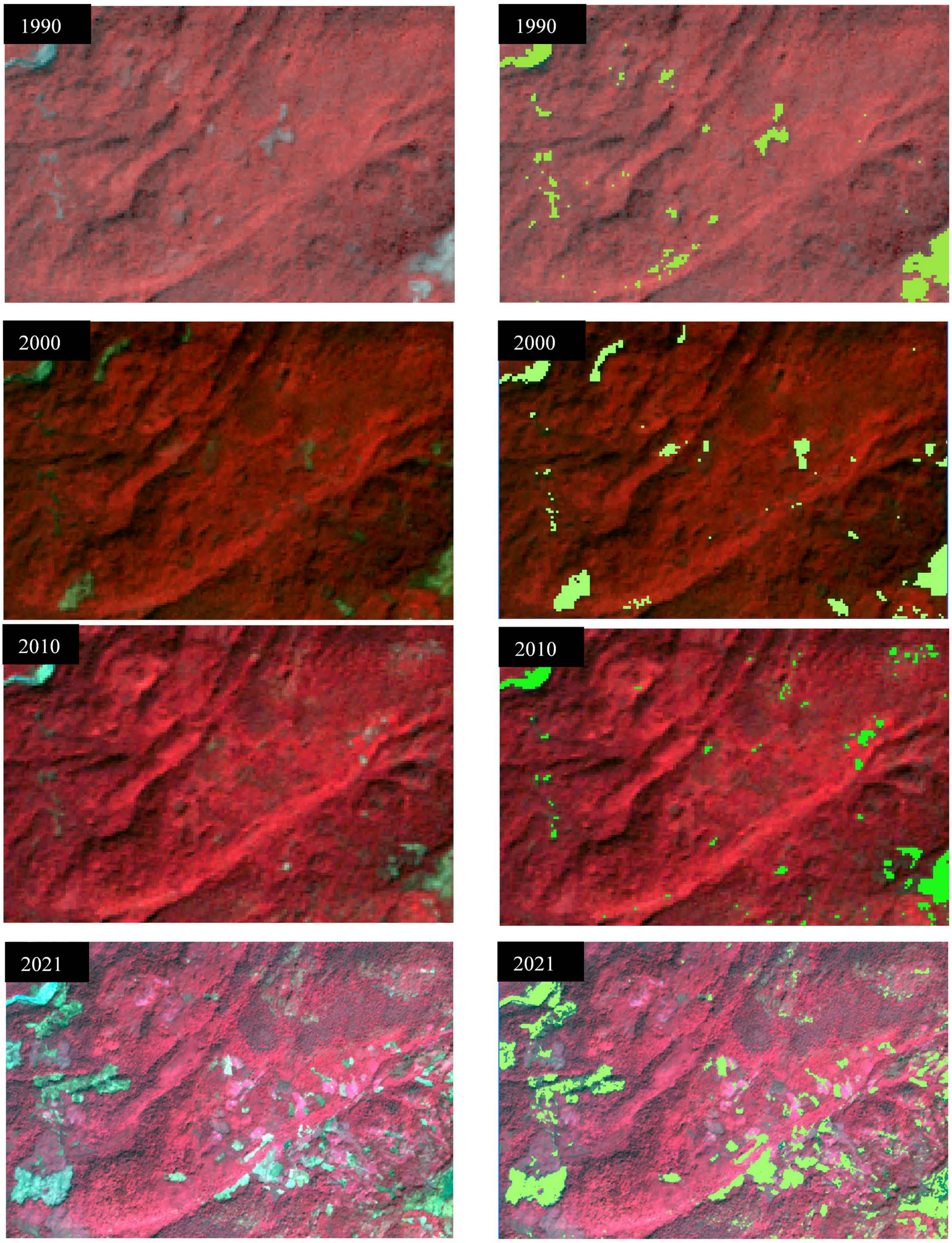

Figure 13. Three decadal (1990-2021) satellite data were compared for tree cover loss due to jhum cultivation in Jaintia hills. The bare land is highlighted in green colour.

Following an investigation of the decadal change from 1990 to 2021, it has been observed that the tree cover of the state is inconsistent. The major cause is jhum cultivation and mining activity. Forest managers need to monitor tree cover regularly for better management of tree cover in the state. Thus, to understand the vibrant nature of tree cover, the forest has been classified biennially (2017, 2019, and 2021). The biennial forest assessment was done on a regular basis by the Forest Survey of India from 1987 onward. The assessment was initially based on visual interpretation and later shifted to digital interpretation, as presented in **Table 7**. The forest cover mapping (FCM) is being done biennially at the pan India level at the 50,000 scale. ISFR, 2021 states that Meghalaya has 17,046 sq. km of forest cover, 76% of the state's geographical area, whereas India's forest cover is 713,789 sq. km, which is 21.71% of GA. Consequently, Meghalaya state contributes 2.39% of tree cover.

5.2. Biennial Change

In this study, biennial analysis was done using Sentinel 2 MSI data, which has 10 meters of spatial resolution. Hence a superior data is expected when compared to FCM data of ISFR, which use LISS III data. The tree cover is changing drastically. Today tree cover; tomorrow, it may become agriculture, stone quarry, or else mining field. [56] described that burning the jungle is most easier approach to clear the land for agriculture. The jhum is practiced almost in each and every district of Meghalaya. **Table 8** represents the biennial change of two time periods, T5 (2017 to 2019) and T6 (2019 to 2021).

Table 7. Forest cover area of Meghalaya State and India, ISFR, FSI.

Area in Sq. Km.						
Interpretation	ISFR Year	Assessment	Meghalaya	% of GA*	India	% of GA*
Visual	1987	Forest Cover	16,466	73.41	640,819	19.49
	1989	Forest Cover	15,645	69.75	638,804	19.43
	1991	Forest Cover	15,875	70.78	639,364	19.45
	1993	Forest Cover	15,769	70.31	639,386	19.45
Visual and Digital	1995	Forest Cover	15,714	70.06	638,879	19.43
	1997	Forest Cover	15,657	69.81	633,397	19.27
	1999	Forest Cover	15,633	69.70	637,293	19.39
Digital	2001	Forest and Tree cover	15,724	70.11	757,009	23.03
	2003	Forest and Tree cover	16,925	75.46	677,816	20.62
	2005	Forest and Tree cover	16,988	75.74	677,088	20.60
	2007	Forest and Tree cover	17,321	77.23	690,899	21.02
	2011	Forest and Tree cover	17,275	77.02	692,027	21.05
	2013	Forest and Tree cover	17,288	77.08	697,898	21.23
	2015	Forest and Tree cover	17,217	76.76	701,673	21.35
	2017	Forest and Tree cover	17,146	76.45	708,273	21.55
	2019	Forest and Tree cover	17,119	76.33	712,249	21.67
	2021	Forest and Tree cover	17,046	76.00	713,789	21.71

*Percentage of GA = (Total Forest/Geographical Area) × 100.

Table 8. The detected biennial change from 2017 onwards.

Sl. No.	District Name	Change (T4)	Change (T5)	Change (T6)
		2010 to 2017	2017 to 2019	2019 to 2021
1	RI BHOI	−80	101	42
2	WEST GARO HILLS	−193	52	300
3	EAST GARO HILLS	80	−119	93
4	WEST KHASI HILLS	249	−170	−107
5	JAINTIA HILLS	−322	240	−117
6	EAST KHASI HILLS	209	−28	−78
7	SOUTH GARO HILLS	−41	35	14
	TOTAL	−98	111	147

Every jhum year, an ample number of trees were lost. After doing agriculture for a few years, the nomads leave the land to regain fertility, and this cycle continues. The jhum cycle has apparently been reduced from 8 - 10 years to 3 - 5 years [11] [12] [57] and even lesser. Hence continuous mapping and monitoring of forest resources are essential.

Compared 2019 classified with 2017, it has been observed that the tree cover of the state has increased. The growing pattern persists in T6 (2021-2019). The biennial change in T5 and T6 are positive, but these changes are due to the regeneration of tree cover that nomads have left after exploitation for 4-5 years. Hence the tree cover changes during the studied period only depict a biased version. To understand tree cover changes, researchers need to study biennial changes for at least 4 - 5 time series data. To understand the temporal frequency of jhum in Meghalaya, a jhum-affected region has been selected for in-depth research.

5.3. Micro-Level Change Analysis

A micro-level study was done near the Shallang region falling in Meghalaya's West Khasi hills district (**Figure 14**). The district has the most tree cover, and almost all tree-covered region is experiencing shifting cultivation. Hence a study was done on a six sq. km. zone of tree cover based on the availability of high-resolution data.

The available Google earth imagery of 2013, 2017, 2020, and 2022 were analysed. The shifting cultivation patch count in 2013, 2017, and 2020 was 19, 36, and 34 numbers, respectively, but recently (in the year 2022), the patch count increased to 65 numbers. The jhum patch size varies from 0.04 ha to 9.67 ha in the area within the spatiotemporal study (**Figure 15**).

These reflect the dynamic nature of tree cover; furthermore, the jhum cycle was investigated, and if truth be told, the jhum cycle cut down from 8 - 10 years to 2 - 3 years. In this six sq. km. zone, it has been observed that six number of

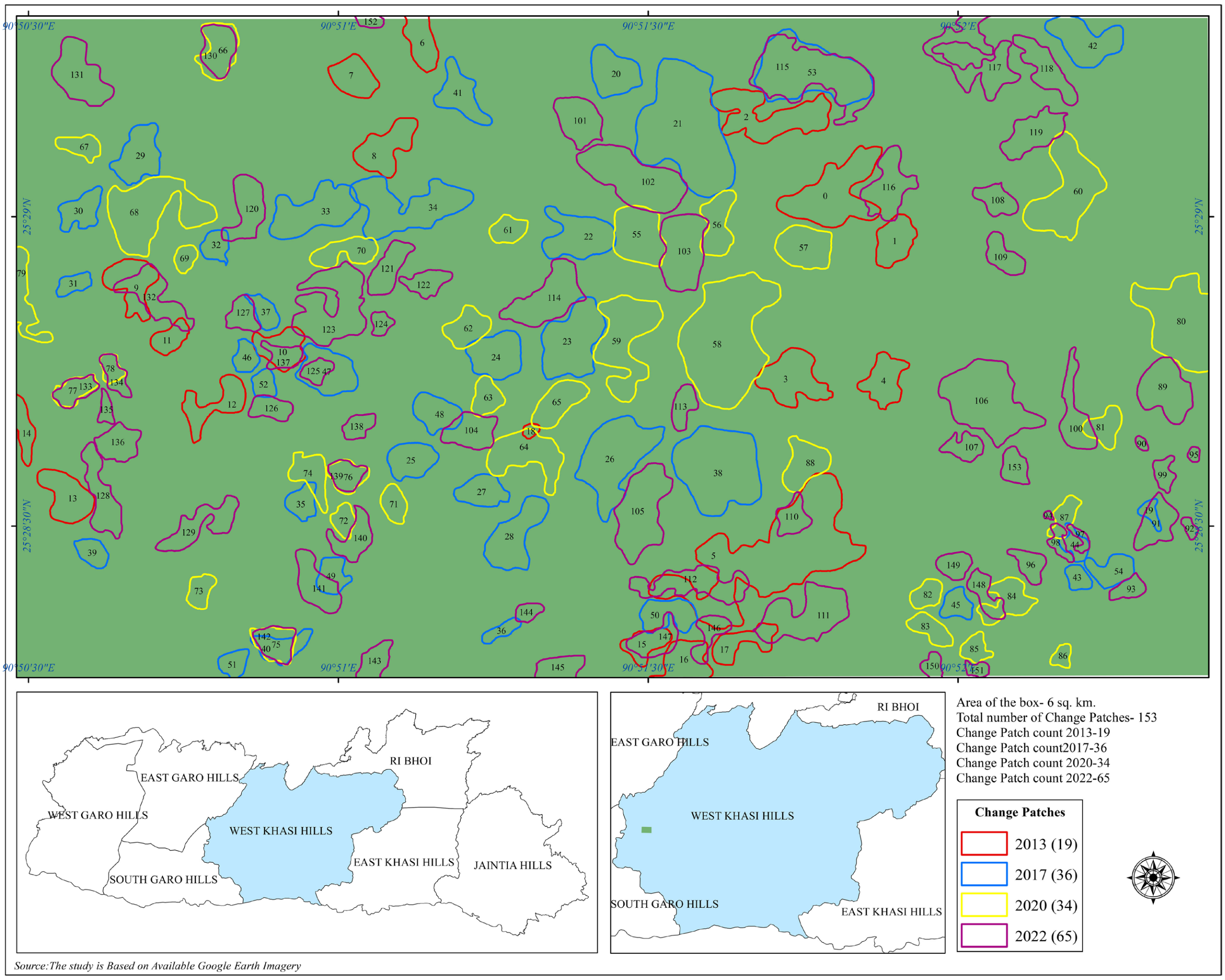

Figure 14. Micro level jhum cycle study in a part Shallang region of West Khasi hills.

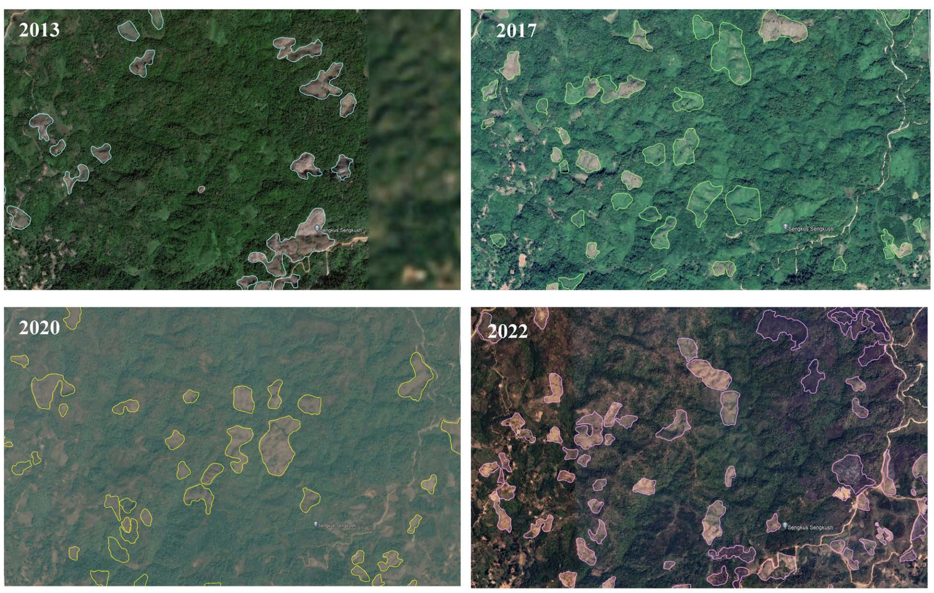

Figure 15. Year wise shift in jhum patch in 6 sq. km. of micro level study area.

patches with 2 - 3 year of jhum cycle, and the average jhum cycle is 4 - 5 years. It can be anticipated that the number of jhum patches will intensify in the studied spatial extent in the near future.

6. Conclusions

Tree canopy estimated using remote sensing technology for six-time series data from 1990 to 2021. The machine learning classifiers were employed to classify the study area efficiently. A python model was developed, where based on user inputs (multispectral satellite data, training samples, and administrative layer), the output (Classified layer of three classifiers and corresponding area figure) will be generated. Support vector machine, the ML algorithm has more correctly classified the study area into tree cover and non-tree cover zone. The python model made the classification accurate and time-saving. Using the model, the satellite images were classified effortlessly and accurately.

The classified output needs to be tested for accuracy; hence a python script has been developed. For accuracy assessment, the classified data needs to be tested based on reference data. A careful selection of reference data is a prerequisite. The selected reference data of Global Forest Cover offered by LP DAAC of 2000 and 2010, JAXA FNF data from 2017, 2019 and 2020, and ISFR 2019 and 2021 data of FCM were utilized. The python script for accuracy assessment was executed for six-time series data to get the user's accuracy, producer's accuracy, overall accuracy, and kappa coefficient. The overall classification accuracy is more than 86%, and the kappa coefficient is substantial.

The classification accuracy is higher in SVM classified data; hence for further study, the output of the SVM classifier has been taken. The district-wise canopy cover area was calculated by applying the normalized factor (*nf*) for six-time series data. The decadal change was extracted from 1990 to 2021. The examined overall change is negative (−98) throughout the studied period. Biennial changes were identified using classified data from 2017, 2019, and 2021 to understand deforestation frequency. It has been observed that the biennial changes during the studied period displayed a positive inclination but this is only a one-sided story. As a result, a study of at least five-time series data for biennial change detection is required. Although in the current study, it has been observed that the canopy cover is removed due to shifting cultivation, and they regain the canopy after being left over by nomads. To understand the cycle of jhum, a microlevel study has been done in a six sq. km. zone near Shallang in West Khasi hills. The study reveals that the cycle of jhum is shortened to 2 - 3 years which was previously 8 - 10 years, this trend is really worrisome as it prevents the canopy from regaining, and a permanent non-tree cover patch will take place.

The succeeding work is to develop a python model where the changes will be sensed automatically, and the deforestation alert will be sent on near real-time to the forest managers with all relevant information. Hence, by using the automation, the canopy cover can be monitored efficiently at regular intervals.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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