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SAPTIO-TEMPORAL STUDY OF FOREST COVER CHANGE IN AIZAWL DISTRICT, MIZORAM

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Abstract: **The Assessment of forest cover change is important for the urban development and making the policy for forest management policy. Forest depletion is a common topic in the North-east India, especially in Mizoram as most of the agricultural practices are based on shifting cultivation. So, it is very important to have knowledge about the changing pattern of forest. In this paper, it shows the changing pattern of forest in Aizawl District, Mizoram. This forest has been declining at an alarming rate as a result of land use and land cover change (LULCC). For supporting decision-making processes, identifying LULCC and comprehending the underlying forces are crucial. We examined and analyze the changing variation of forest cover during the period of 2000 to 2018 using Landsat Thematic Mapper (TM) 4-5 C1 level-1 satellite imagery for 2000 and Landsat 8 OLI/TIRS C1 level-1 imagery for 2018. The methodologies are Transitional Probability Matrix (TPM), Kappa coefficient, post-classification change (PCC) detection approach and simple statistical techniques. Detecting the Land Use Land Cover (LULC) showed that in 2000 dense forest cover an area of 827.59 sq.km which was 36.67 per cent of the total study area while in 2018 forest cover changed drastically with an area of only 284.22 sq.km which was 12.59 per cent of the total study area. On the other hand, open forest during 2000 was 51.25 sq.km and in 2018 it increased to 107.76 sq.km. The results showed that settlement, light vegetation and barren land were increasing, while forest cover was declining. The loss of forest cover could lead to an unpleasant environment and have an impact on people's wellbeing.**

Keywords: **Land Use Land Cover Change, approach, management, Aizawl.**

1. INTRODUCTION

Modern society is concerned about changing forest cover. Mizoram, in the north-eastern state of India, is experiencing a lot of forest cover loss. For the analysis of land cover change over time, it is necessary to detect land use changes. Identifying the traits, scope, and patterns of land use and land cover change (LULCC) is crucial for decision-making (Armenteras et al., 2019; Abebe et al., 2019; Yan et al., 2018; Tolessa et al., 2017). Monitoring land use changes has become an important element of environmental management (Kiswanto & Mardiany, 2018; Mensah et al., 2019). A marmalade culture, which means cutting and burning, has been practiced by the Mizo people of India for several centuries (Leblhuber S.K & Vanlalhruaia H, 2012). For the purposes of subsistence, small holder farmers collect fuel wood, construction materials, wild foods, and other forest products (Nerfa et al., 2020; Salghuna et al., 2018; Pellikkaa et al., 2018). Forests play an important role in regulating climate change by sequestering atmospheric carbon dioxide and mitigating global climate change (Negassa M. D. et al., 2020). Extensive studies have been conducted to examine the extent of land use land cover change (LULC) in several countries at different times (Deng et al., 2013; Geng et al., 2015; Lark et al., 2017). A recent study indicates that Mizoram is the second most vulnerable state to climate change (IHCAP, 2019) because forest areas are expected to continue to decline at alarming rates in some regions (d'Annunzioin et al. 2015). According to FSI (2017; Sahoo et al., 2018), Mizoram has experienced net decreases in forest cover, fragmentation and degradation of forests, and an

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increase in forest fires and pest outbreaks. Forest ecosystem degradation, soil erosion and biodiversity loss are all consequences of habitat loss and fragmented forests (Wilson et al., 2016). These losses threaten a substantial portion of the population, especially those who rely on climate-sensitive sectors like rainfed agriculture, short cycle shifting cultivation (jhum), and regular gathering of forest produce for sustenance. Due to a limited development of industries, as well as a lack of access to physical infrastructure (roads, transport, markets, electricity, and communication), the population in the state is heavily dependent on natural resources. These constraints make the population more vulnerable to the fast-changing climate. Considering that forests are so important to Mizoram's people, it is imperative that questions are answered regarding how climate change and future development may affect the forests and the services they provide, and how best to manage them for future resilience. According to Forest Survey of India (FSI) data 2017-2018, the total forest cover in Mizoram was 18005.51 sq. km in which Aizawl district forest cover was 3078.91 sq. km. There are two types of drivers based on the causes, which are proximate/direct drivers, and underlying/indirect drivers. Among the primary drivers of deforestation are anthropogenic activities that directly influence the loss of forests, which can be classified into several categories, including agricultural expansions, infrastructure expansions, and wood extraction (Geist & Lambin, 2001).) The expansion of agriculture has been identified as a major contributor to deforestation in the tropics (Gibbs et al., 2010), though the factors vary by region and time (Rudel et al., 2009; Boucher et al., 2011). In order to conserve forests, it is important to develop and implement policies that address livelihood issues for forest dependent communities and environmental protection.

Study Area

Aizawl is located at latitudes 23°21' N to 24°24' N and longitudes 92°39' E and 93°03' E. The district is located in the northernmost portion of the state. Mamit is surrounded by the west, Serchhip and Lunglei districts in the south, the State of Manipur in the north, and Champhai district in the east. The district shares a significant portion of its north-western border with Kolasib. The district is 1,132 meters above sea level on average. With 3,576 square kilometers, it is the second-largest district in the state. Across the district, there are 128.7 kilometers north and 72.4 kilometers east. Aizawl is the most industrialized district in Mizoram, with sericulture, handloom, handcraft, and furniture workshops all present in small scales. The Köppen-Geiger system describes Aizawl as a humid sub-tropical climate with cool summers and cold winters, with winter temperatures varying between 11ºC and 13ºC and summer temperatures around 30ºC. It has tropical semi-evergreen and sub-montane forests, with the dominant species being Michelia champaca, Emblica officinales, Bombax ceiba, Terminilia myriocarpa, Mesua ferrea, Toona ciliata, Acrocarpus fraxinifolius, Gmelina arborea, Albizzia chinensis, Schima wallichii, etc. (Department of EF&CC, 2017). The district also contains bamboos and canes. Melocanna baccifera is the predominant bamboo species followed by Dendrocalamus hamiltonii.

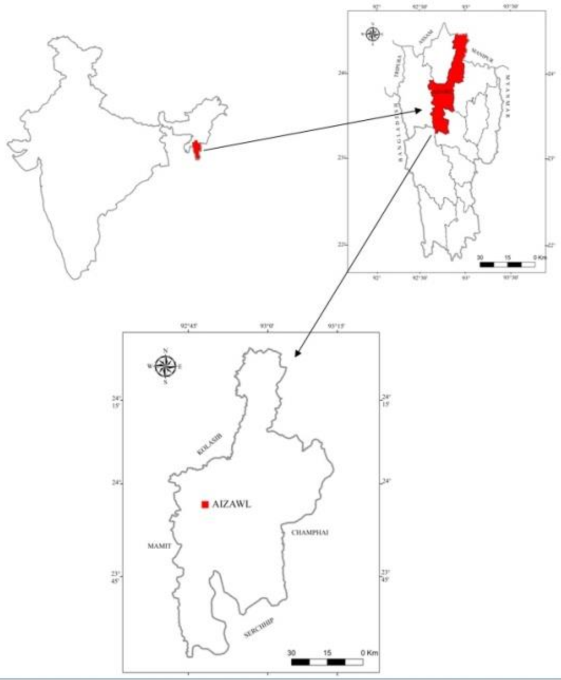

Figure 1. Location map of the study area

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2. DATABASE AND METHODOLOGY

For this study, three Landsat Thematic Mapper (TM) 4-5 C1 level-1 satellite images were used, including image from 2000, 2009 as well as images from Landsat 8 OLI/TIRS C1 level-1 for 2018. Landsat archive (https://glovis.usgs.gov/) and Earth Explorer (https://earthexplorer.usgs.gov/) provide free access to satellite data. The classification of land use and land cover was based on satellite images (Tucker et al., 1985). Landsat sensor data and a multi-sector supervised classification method were used to produce three land cover maps for the selected years in the process, which are based on supervised classification and a maximum likelihood algorithm. The data from Landsat was analyzed and the land cover maps were computed (Lucas et al., 2007).

Two Forest cover maps were produced using supervised classification method. Forest cover maps for the selected years were produced using Landsat sensor data and a multi-sector supervised classification method. ArcMap 10.4® was used for the entire process. An overlay approach in combination with the GIS technique was used to determine the geographical distribution of forest cover and change dynamics within the research area. The change analysis was used to determine whether forest cover has changed over time.

3. RESULT AND DISCUSSION

Accuracy Assessment

An accuracy assessment determines how many pixels are in a classified image that correspond to reality - that is, how many pixels have been correctly classified by the algorithm. Understanding the accuracy of the results and implementing different policies is dependent on them (Lu et al., 2007). Various logical measurements have been used to assess the accuracy of grouping based on the information gathered from the possibility table, including overall accuracy, producer's accuracy, and user's accuracy (Richards, 1996). The producer's accuracy represents the map of accuracy from the perspective of the map maker (the producer). Basically, this is the frequency with which real features on the ground are shown correctly on the classified map or the probability that a certain land cover on the ground is classified accordingly. In addition, it is the number of reference sites classified accurately divided by the total number of reference sites for that class (Eq. 1).

$$\text{Producer Accuracy} = \frac{\text{Total numbers of pixel in category}}{\text{Total number of pixels of that category derived from the reference data (i.e., row total)}} \quad (1)$$

The User's accuracy is defined as the accuracy from the perspective of a map user. Based on the accuracy of the user, we are able to determine how often the class depicted on the map will actually occur. User accuracy is the complement of commission error, meaning that User accuracy equals 100% commission error. In order to calculate the User's accuracy, we divide the total number of correct classifications by the number of rows for each class (Eq. 2)

$$\text{User's Accuracy} = \frac{\text{Total numbers of pixel in category}}{\text{Total number of pixels of that category derived from the reference data (i.e., column total)}} \quad (2)$$

A measure of overall accuracy was calculated in order to assess the overall accuracy of the classified image across all classes (Eq. 3). It is possible to measure the collective accuracy of the map for all classes by calculating overall accuracy, which calculates the proportion of pixels correctly classified for each class.

$$\text{Overall Accuracy} = \frac{\text{Sum of diagonal elements}}{\text{Total number of accuracy sites pixels (column total)}} \quad (3)$$

A kappa statistic measures the degree of agreement between classifications and references (Wang et al. 2012; Mishra et al. 2019). Landis and Koch (1977) ranked the kappa values, ranging from −1 to 1, into three groups: (1) greater than 0.80 represented strong agreement (2) between 0.40 and 0.80 represented moderate agreement, and (3) less than 0.40 represented poor agreement between the classification and reference data. For the years 2000, 2009 and 2018, the land use/land cover maps were classified using supervised maximum likelihood classification. Table 1 reveals that the kappa coefficients and overall accuracy of forest cover maps classified between 2000 and 2018 were over 70% and 0.76, respectively.

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Table 1. Accuracy Assessment

	2000		2018	
	User	**Producer**	**User**	**Producer**
Dense Forest	100.0	77.8	100.0	87.5
Open Forest	66.7	44.4	78.6	91.7
Scrub Land	66.7	66.7	75.0	31.6
Overall Accuracy	**74.14**		**74.14**	
Kappa Coeffiecient	**69.44**		**68.70**	

Source: *Analysing Satellite image*

Status of Forest Cover

Multi spectral images of 2000 and 2018 were used to evaluate Forest cover change in the study area. Between 2000 and 2018, there was a significant change in forest cover in Aizawl district. Fig. 2 illustrates the spatial distribution of each forest cover in 2000 and 2018. This quantitative outcome is presented in Table 3, which provides statistics on forest cover change, and Table 4, which illustrates the dynamics of the forest cover during the two-time nodes.

As a result, between 2000 and 2018, the district's forest cover declined. In 2000, dense forest, open forest, scrub land covers an area of 827.59 sq.km, 51.25 sq.km, 306.44 sq.km respectively while in 2018 dense forest declined extensively with 284.22 sq.km, open forest extended around 107.76 sq.km and scrub land increases with a huge number of 644.20 sq.km.

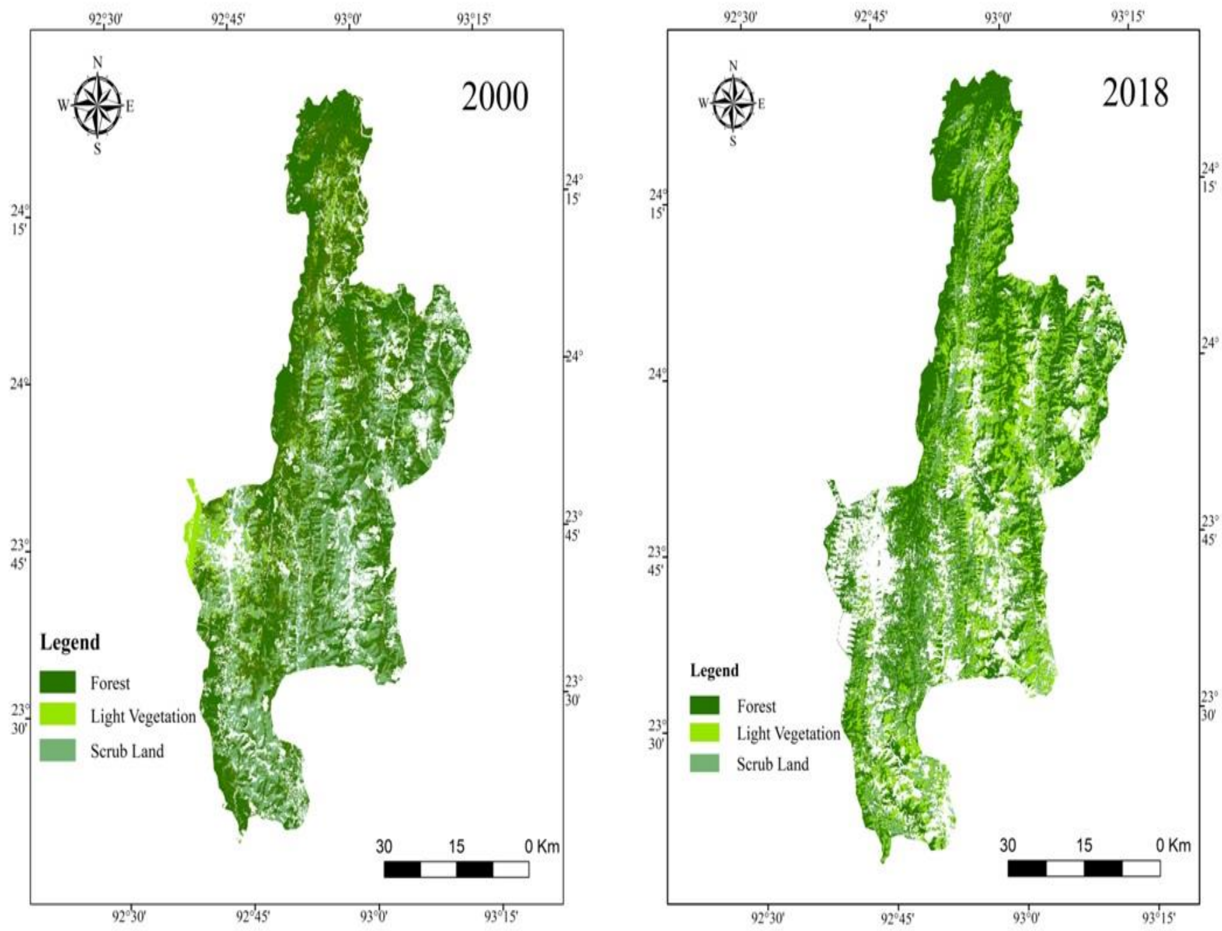

Figure 2. Forest cover maps of 2000 and 2018

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Table 2. Land use land cover areas in 2000, 2009 and 2018

LULC Classes	2000 (in sq.km)	2009 (in sq.km)	2018 (in sq.km)
Agricultural Land	289.71	155.52	91.48
Barren Land	51.35	71.47	159.43
Built-Up	511.63	857.59	957.26
Dense Forest	827.59	511.41	284.22
Open Forest	51.25	74.68	107.76
Scrub Land	306.44	532.80	644.20
Water Body	218.94	53.44	12.56
Total	2256.91	2256.91	2256.91

Source: *Analysing Satellite image*

Table 3. Forest cover changes during 2000-2018

	2000		**2018 (in sq.km)**	
	Area (in sq.km)	Area (%)	Area (in sq.km)	Area (%)
Dense Forest	827.59	36.67	284.22	12.59
Open Forest	51.25	2.27	107.76	4.77
Scrub Land	306.44	13.58	644.20	28.54

Source: *Analysing Satellite image*

Table 4. Dynamics of Forest Cover Changes During 2000-2018

	Area Changed	Changed in %
Dense Forest	-543.37	-24.07
Open Forest	56.51	2.50
Scrub Land	337.76	14.96

Source: *Analysing Satellite image*

The outcome shows that there was a decreasing of dense forest cover, during 2000 to 2018 it declined with -543.37 sq.km, on the other hand both open forest and scrub land increases with 56.51 sq.km and 337.76 sq.km respectively during the same time frame.

The rapid population growth brought on by rural-to-urban migration causes the depletion of forest, during the study period there was an enormous increase of settlement, especially in Aizawl city which causes an infrastructure development and results in the depletion of forest cover. Figure 4 shows graphically the historical forest cover change results for 2000 and 2018

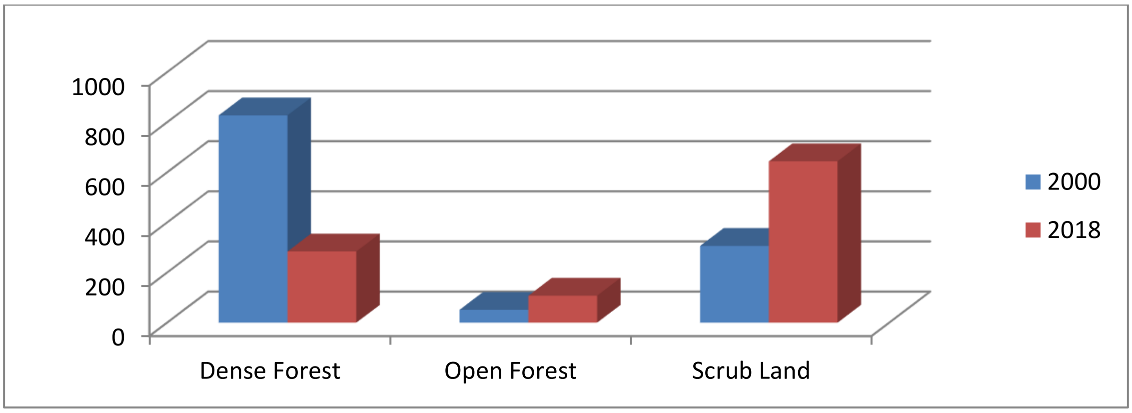

Figure 3. Forest cover change between 2000 and 2018

Source: *Analysing Satellite image*

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Transition Probability Matrix:

Using the analysis of the transition probability matrix (TPM), which was produced between 2000 and 2009 and 2009 and 2018, it was possible to identify the changing dynamics of the forest cover in the study area. In Table 5, the TPM is displayed and the likelihood of a change in land use/land cover class from horizontal to vertical increases as value increases. The diagonal value of each land use and land cover class in the transition matrix represents the likelihood of persistence in that land use and land cover class for that era. The values off the diagonal show the likelihood that one land cover class will change into another in the long term.

Table 5. Transitional Probability Matrix

	LULC Classes	**Agricultural Land**	**Barren Land**	**Built-Up**	**Dense Forest**	**Open Forest**	**Scrub Land**	**Water Body**
2000-2009	Agricultural Land	**2.89**	1.38	0.28	37.34	46.11	10.98	1.02
	Barren Land	12.7	**8.02**	4.92	20.75	28.06	3.12	22.43
	Built-Up	13.79	13.69	**2.44**	2.69	30.56	36.7	0.11
	Dense Forest	12.69	4.83	1.67	**6.85**	40.11	32.25	1.58
	Open Forest	14.24	1.68	81.53	0.05	**1.06**	1.00	0.44
	Scrub Land	18.12	7.42	2.16	3.69	33.78	**34.78**	0.04
	Water Body	20.14	33.2	6.75	5.52	17.06	17.07	**0.25**
2009-2018	**LULC Classes**	**Agricultural Land**	**Barren Land**	**Built-Up**	**Dense Forest**	**Open Forest**	**Scrub Land**	**Water Body**
	Agricultural Land	**15.45**	21.3	18.97	4.27	5.91	33.37	0.74
	Barren Land	17.43	**14.17**	23.15	2.21	13.75	28.93	0.36
	Built-Up	14.53	13.01	**11.76**	31.89	7.56	20.2	1.05
	Dense Forest	0.38	68.17	27.47	**0.11**	1.61	2.01	0.25
	Open Forest	1.58	53.9	31.33	0.2	**3.26**	9.59	0.14
	Scrub Land	5.42	35.66	23.61	0.49	4.29	**30.44**	0.1
	Water Body	0.83	41.63	26.37	2.87	8.72	2.6	**16.98**

Source: *Analysing Satellite image*

In the transition probability matrix, potential LULC change trajectories were displayed for periods 1 and 2. The matrix shows that the chance of future conversion of Dense Forest into agricultural land is 37.34 percent during 2000-2009 to 4.27 percent during 2009-2018. Considering the extent of settlements in the study area, there has been a high rate of conversion of dense forest into built-up areas during 2009-2018, with 31.89 percent being converted into built-up areas. As a result of the changed probability between the two periods, urbanization has been rapid and forest areas have been decreased.

4. CONCLUSIONS

In the present study, an analysis of spatio-temporal forest cover change in Aizawl district was carried out using geospatial techniques using two sets of landsat images. A significant amount of forest cover area has been lost over the last 20 years as a result of this study. In 2000, dense forest covers 36.67%, which was declined to 12.59% in 2018. Open forest showed an increasing trend, i.e., 2.27% in 2000 and 4.77% by the year 2018. Scrub land also showed an remarble increasing trend, in 2000 scrub land covers 13.58% and was increased to 28.54%. Surprisingly, there was a decrease in the agricultural land during 2000 and 2018, while there was an enormous increase in the built-up area during the study period. The main reasons for the declining of forest cover area especially dense forest was due to the increasing of built-up area. The built-up area increased from 22.67% in 2000 to 42.41% in 2018. Since, Aizawl district is the capital district of Mizoram and it resulted in the migration from rural to urban and increased the infrastructures. Developing a forest conservation strategy requires knowledge of changing patterns of forest cover and their key drivers. It was necessary to monitor forest change so that deforestation and development could be planned and the ecosystem's balance could be maintained.

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