LAND USE AND LAND COVER CHANGE DETECTION USING REMOTE SENSING AND GIS TECHNIQUES: A CASE STUDY OF YEBYU TOWNSHIP IN DAWEI DISTRICT*

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Abstract

Remote sensing is one of the tools which is very important for the production of Land use and land cover maps through a process called image classification. For the image classification process to be successfully, several factors should be considered including availability of quality Landsat imagery and secondary data, a precise classification process and user's experiences and expertise of the procedures. The objective of this research was to classify and map land-use/land-cover of the study area using remote sensing and Geospatial Information System (GIS) techniques. Nowadays, land use and land cover (LULC) changes due to both human beings and natural environment. Consequently, LULC changes impact on water resources such as forestry, water bodies, agriculture land, wetland, urbanization, industrialization and so on. The aim of this research is To classify and map land use and land cover changes in the study area using remote sensing and GIS, and to assess the accuracy and usefulness of the classification results. ArcGIS 10.4.1 has been used to analyze the images processing and classification. LULC conditions of this area for the time periods 2009 and 2023 have been considered and downloaded from Landsat ETM and Landsat 8 OLI satellites images. Maximum likelihood method has been conducted in supervised image classification technique. The ground truth data or reference points are used to classify the image classification applying Google Earth Pro. Moreover, water bodies, Dense vegetation (forest), light Vegetation (garden land), bare soil, settlement (Built-up), and agriculture land of six LULC classes are identified in this study. Bare soil, light Vegetation and settlement are significantly changed during two periods. Further, dense vegetation (forest) area was decreased to approximately 8.02 % between 2009 and 2023. However, the water bodies of this study area were decreased slightly. LULC by agriculture land was decreased between 2009 and 2023. The study area had an overall classification accuracy of 81.03% and kappa coefficient (K) of 0.67 in 2009 and an overall classification accuracy of 87.33% and kappa coefficient (K) of 0.72 in 2023 respectability. The results of this research paper can contribute effectively about LULC change detection and help decision makers to develop plan in this study area.

Keywords: LULC, Change detection, Image classification, overall classification accuracy, Kappa coefficient

Introduction

Land use and land cover information plays a vital role in policy-making, business, and administrative planning. These data are essential for environmental conservation and spatial planning due to their detailed spatial attributes. Land use classification is particularly significant as it provides valuable input for environmental modeling, including those addressing climate change and policy developments [1]. By combining land use and land cover (LULC) data, a more comprehensive understanding of interactions within geo-biophysical and socioeconomic systems can be achieved [2].

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Remote Sensing is frequently integrated with Geographic Information System (GIS) technology to offer deeper insights into land cover information. Remote sensing serves as the primary source for various thematic data crucial to GIS analysis, including characteristics of land use and land cover. Aerial and Landsat satellite imagery is commonly used to analyze land cover distribution and update existing geospatial data. With advancements in remote sensing systems and image processing software, the role of remote sensing in GIS has expanded considerably [3]. The rapid growth of remote sensing data and techniques has made geospatial analysis more efficient and powerful, although this complexity also increases the potential for errors. In earlier studies, accuracy assessment was not a key concern in image classification. However, due to higher risks of errors in digital imagery, accuracy assessment has become essential.

Accuracy assessment, or validation, is a crucial step in processing remote sensing data as it determines the reliability of the resulting data for users. The overall accuracy of a classified image is assessed by comparing each pixel classification against ground truth data representing actual land cover. Producer's accuracy measures omission errors, indicating how well real-world land cover types are classified. User's accuracy measures commission errors, showing the probability of a classified pixel matching its real-world land cover type. Error matrices and the kappa coefficient have become standard methods for evaluating classification accuracy, frequently employed in numerous land classification studies, including this research.

The objective of this research is to classify and map the land use/land cover change detection of the study area using remote sensing and GIS techniques and to perform accuracy assessments to evaluate classification effectiveness and interpret the classification's utility

Yebyu Township is located within Dawei District in the Tanintharyi Region of southern Myanmar. The area falls under latitude 14˚9'40.713"N, 15˚11'44.421"E and longitude 97˚43'54.898"N and 98˚27'53. 482"E. The total study area is 6170.454 km2.The township is characterized by a tropical climate, dense forests, and mountainous terrain, with coastal areas along the Andaman Sea. This region has diverse ecosystems, including mangrove forests, freshwater rivers, and rich marine resources. The local economy is largely dependent on agriculture, fishing, and natural resource extraction, with rubber plantations, rice cultivation as the main activities.

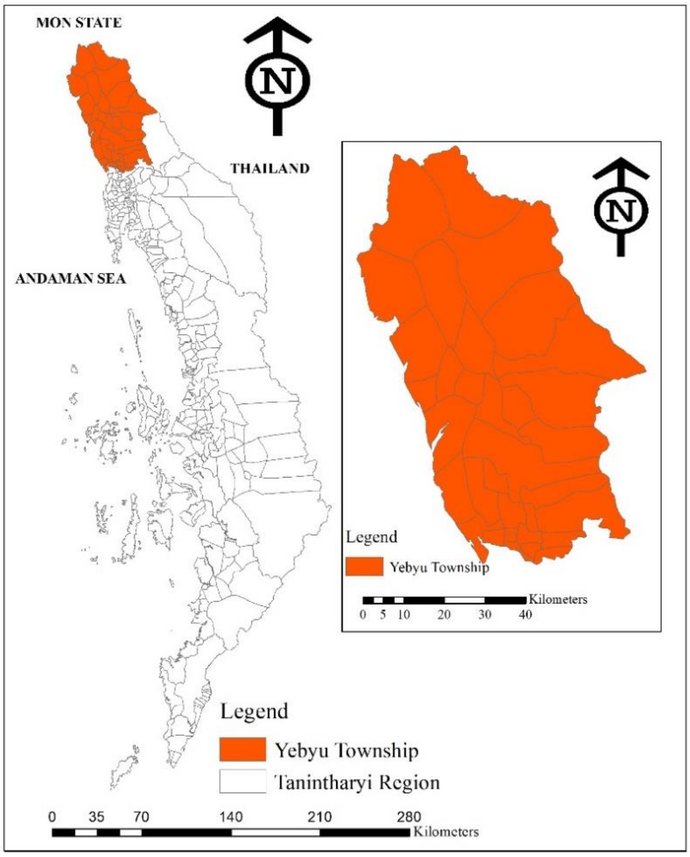

Figure 1 Location of study area.
Source: Myanmar Information Management Unit (MIMU)

. Materials and Methods

This paper focuses on three key components: (1) land use/land cover (LULC) classification, (2) LULC change detection, and (3) accuracy assessment. These analyses were conducted following the methodology illustrated in Figure 2.

The map and other data were obtained from the Government Administrative Department as the secondary data for this study. The Google Earth Pro was used to navigate the location for the ground truth samples. A total of 200 random sample points were collected with their land cover. An error matrix or contingency matrix used showed the information between the actual and prediction that had been classified through the classification for accuracy assessment. Overall accuracy shows the accuracy of the map. The individual classes' accuracy is calculated using the user's accuracy and producer's accuracy. For the user's accuracy, the number of corrected classified pixels was divided by the total number of pixels classified in that class. It measures the probability of the correct classified pixel with the actual class on the ground. While for producer's accuracy is calculated by the number of correctly classified pixels divide with the total number of pixels as the reference data (ground truth point) in the class. It indicates the accuracy of the classifier. Kappa coefficient measures the classifier performance derived from the error matrix without any bias from the chance agreement between the reference data and the classifier output.

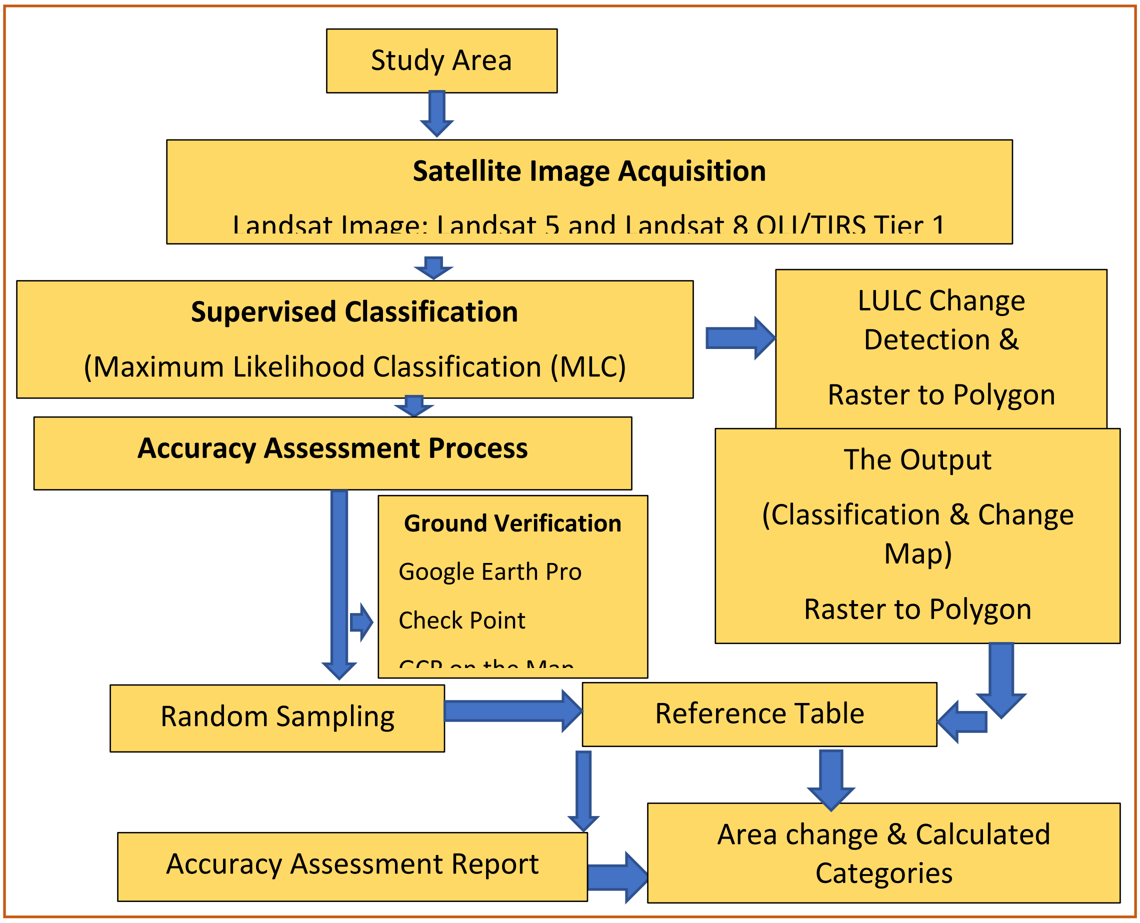

Figure 2 Schematic of work flow for LULC Change Detection and accuracy assessment.

Results and Finding

Land Use/ Land Cover Classification:Image Pre-Processing

Classification process and analysis of the different LULC classes were done using two Landsat satellite images covering the Landsat 8 OLI/TIS acquired on 3 March 2023. These images include; LC8 OLI/TIRS (path 131, rows 50) and LC5 OLI/TIRS (path 131, rows 50) (Table 1). The Landsat images were downloaded from United States Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov/). The selection of the Landsat satellite images dates was influenced by the quality of the image especially for those with limited or low cloud cover. Each Landsat was georeferenced to the WGS_84 datum and Universal Transverse Mercator Zone 47 North coordinate system. An intensive pre-processing such as geo-referencing, mosaic, and layer stacking were carried out in order to Ortho-rectify the satellite images. The image was then processed; the satellite image of each band was stacked within interpreter main icon utilities with layer stacked function. Then, from the stacked satellite image, the study area image was extracted by clipping the study area using ArcGIS 10.4.1 software.

Table 1 Details of Landsat Data from USGS Earth Explorer

Satellite	Sensor _ID	Path/row	Layers	Date of acquisition	Grid cell size (m)
Landsat 8 OLI/TIS	LC0813105020220309GN00	131/50	11	3 March 2023	30
Landsat 5 TM	LC0513105020100309GN00	131/50	7	3 March 2009	30

The yearly downloaded Landsat images were preprocessed radiometric corrections, haze, and mosaicking the two satellites of the study area and extracting them. Layer stacking, images composition activities had done by using ArcGIS 10.4.1. Results of Images were also converted into Universal Transverse Mercator (UTM Zone 47 N) projection. Extraction of Yebyu map was made vector shape file MIMU in ArcGIS 10.4.1. In this study, land use and land cover (LULC) datasets for the years 2009 and 2023 were generated to analyze changes over a 14-year period. Six classifications of land use and land cover such as water bodies, Dense Vegetation (forest), Light Vegetation (Garden Land), built-up, bare soil and agriculture land for this area were considered. Land use and land cover changes were analyzed to identify spatial and temporal patterns in the study area. The following classification scheme was used to check the change detection in this study. Table 2 shows land use and land cover classification scheme.

Land use/Land cover (LULC) Classification: Supervised

For this study, only supervised classification was performed. Supervised classification according to Tso and Mather (2009) is where “the user develops the spectral signatures of known categories, such as urban and forest, and then the software assigns each pixel in the image to the cover type to which its signature is most comparable”. “Supervised classification is the process most frequently used for quantitative analyses of remote sensing image data” [Jensen (2015)]. The supervised classification was applied after defined region of interest (ROI) which is called training classes. More than one training area was used to represent a particular class. The training sites were selected in agreement with the Landsat Image, Google Earth and Google Map(Figure 3). The basic sequence operation followed on supervised classification was;

Defining of Training Sites: The first step in undertaking a supervised classification is to define the areas that will be used as training sites for each land cover class. This is usually done by using the on-screen digitized features. The created features are called Region of Interest (ROI). The selection of the training sites was based on those areas clearly identified in all sources of images. In this study, one hundreds training sites were been identified.

• Extraction of Signatures: After the training site (ROI) being digitized, the next step was to create statistical characterizations of each information. These are called signatures editors in ArcGIS. In this step, the goal was to create a signal (SIG) file for every informational class. The SIG files contain a variety of information about the land cover classes described. After the entire signature has been created, then the SIG file saved as dialog box (Table 2).

• Classification of the Image (Supervised classification): The supervised classification has been applied after defined training classes. One or more than one training area was used to represent a particular class. During the supervised classification process, the entire signature editor was selected in order to be used on the classification process. Then the classify was selected from the Editor Menu bar, classify/supervised. Non-Parametric Rule was used in this classification. The Image was classified into six classes namely; Waterbody, Built-up areas, Barren/bare land, light vegetation, dense vegetation and Agricultural land (Table 3)

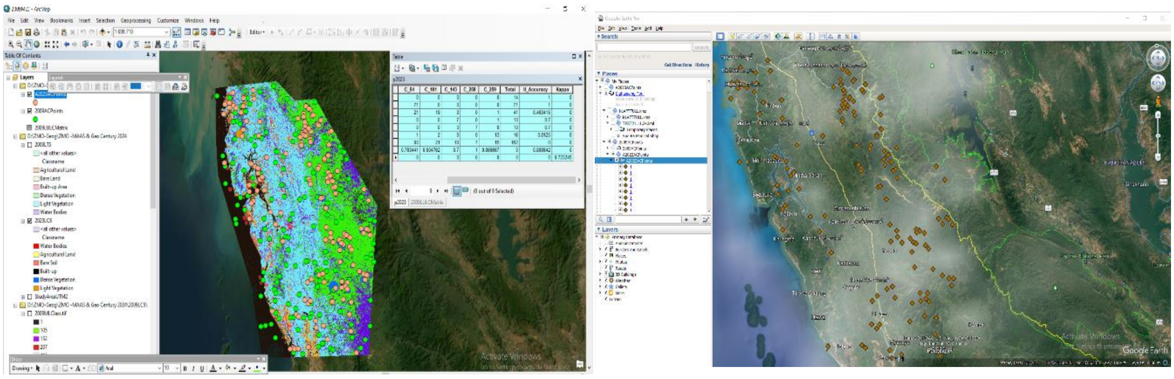

Figure 3 Identification of training sites using Landsat image (ArcGIS 10.4.1 software) and Google earth Pro and Google map

Source: calculated by author

Table 2 Signature editor table for classified image

Class value (2023)	Class name	RED	GREEN	BLUE	Count	Class value (2009)	Class name	RED	GREEN	BLUE	Count
1	Water Bodies	0	92	230	26213	1	Water Bodies	224	176	107	28368
2	Dense Vegetation	56	168	0	134613	2	Dense Vegetation	186	76	229	178381
3	Light Vegetation	170	255	0	77991	3	Light Vegetation	206	252	147	18029
4	Bare Soil	255	235	190	11695	4	Bare Soil	99	83	128	6513
5	Built-up	241	135	222	4325	5	Built-up Area	49	80	136	3239
6	Agricultural Land	255	255	0	29424	6	Agricultural Land	12	200	143	44218

Source: calculated by author

Table 3 Land Use and Land Cover Classification Scheme

Land Use / Land cover	Description
Dense Vegetation (Forest)	Areas covered with dense natural forest
Light Vegetation (Garden Land)	Lands dominated by trees with a percent cover >60% and height exceeding 2 meters, Perennial Tree such as Rubber, Cashew, Betel nut, and Durian land etc
Agriculture	Lands covered with temporary crops followed by harvest period, Crop fields and pastures
Bare soil or Bare soil	Lands with exposed soil, sand or rocks, and never has more than 10% vegetated cover during any time of the year. Bare ground, bare exposed rocks, and gravel pits
Water body	Sea, Lakes, reservoirs, stream, rivers,
Settlement (Built-up)	Land covered by buildings and other man-made structures. Mixed urban or built-up lands

Lulc Classification Results and Discussion

Supervised classification was carried out at study area in 2009 and 2023. The area of each class was calculated taking into account the pixel count and total area (study area). This, allocations of each classified area (percentage) are tabulated in Table 4 Figure 4.

The percentage of areas as classified are; Agriculture (35.51%) and (27.16%), water body (12.94%) and (12.96%), built up areas (4.56%) and (9.83%), Dense Vegetation (31.05%) and (21.03%), Light Vegetation (13.71%) and (22.93%), and Barren/bare land (2.23%) and (4.38%) of 2009 and 2023 in Figure 5. Agriculture was found to be the dominant type of land use classified which covers about (35.51%) and (27.16%) of the total study area, followed by Built-up areas while the least classified was Barren/bare soil which accounts for (2.23%) and (4.38%).

Table 4. Land Use and Land Cover Classification and LULC Changes.

Class Value	LULC	Area_Sq_KM (2009)	Area_Sq_KM (2023)	2009 (%)	2023 (%)
1	Water Bodies	798.28	809.258	12.94	12.66
2	Dense Vegetation	1916.17	1472.104	31.05	23.03
3	Light Vegetation	845.92	1465.860	13.71	22.93
4	Bare Soil	137.47	280.187	2.23	4.38
5	Built-up	281.52	628.555	4.56	9.83
6	Agricultural Land	2191.54	1736.480	35.51	27.16
Total		**6170.89**	**6392.44**	**100.00**	**100.00**

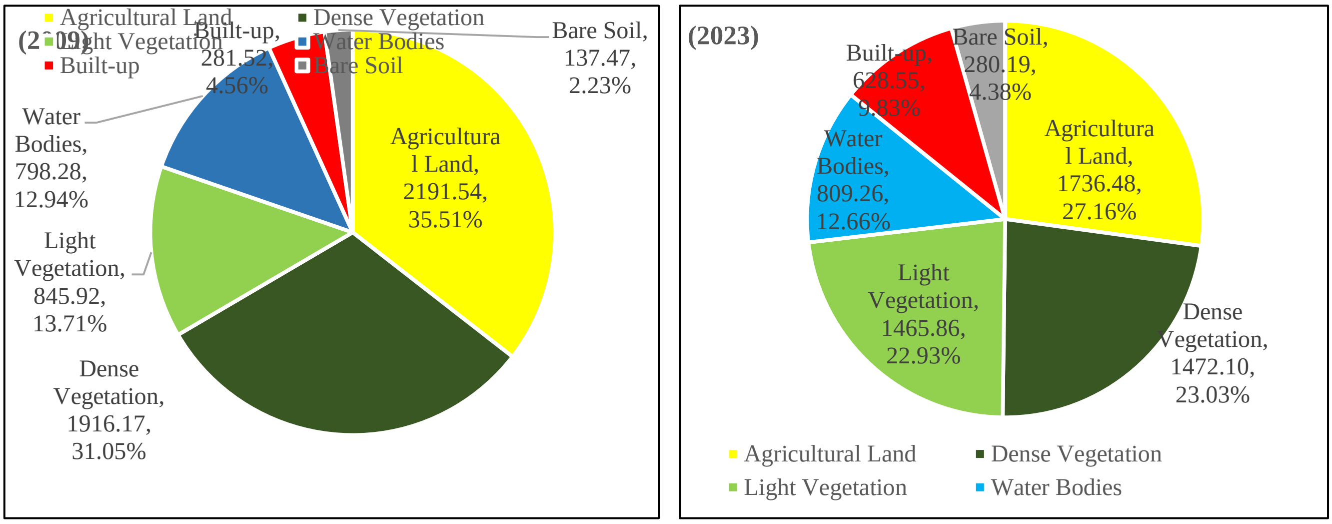

Figure 4 Land Use and Land Cover Classification of 2009 and 2023

Area Changes

In this study, Landsat 5 and 8 satellite images of 2009, and 2023 were used for GIS and RS image analysis. Based on remote sensing and GIS techniques, the images are classified as water bodies, vegetation, settlement, agricultural land and bare land. Temporal land use maps of (2009, and 2023) are shown in figures 4 and table 4.

Change detection was carried out using ArcGIS software. Raster calculator in ArcGIS was used in this process. For the existing study five different LULC classes were involved and 6 LULC change categories were created as the change. In the final analysis, it was reduced into six change categories as agricultural change, water Change, dense vegetation change, light vegetation change, bare soil change and Built-up change (Table 4 and figure 4). Fundamental change categories are defined from one class to another because it is convenient in final assessment in change detection and smooth visual interpretation (Example: vegetation to settlement). The spatial and temporal land use maps of (2009, and 2023) are shown in figures 8.

According to the classification, dense vegetation coverage on 2009 was 1916.17 km^2 and decreased to it was 1472.10 km^2 by total area extent. According to the study period, 107.66 km^2 contributes to Agriculture decrease and the settlement area was increased from 2009 to 2023.

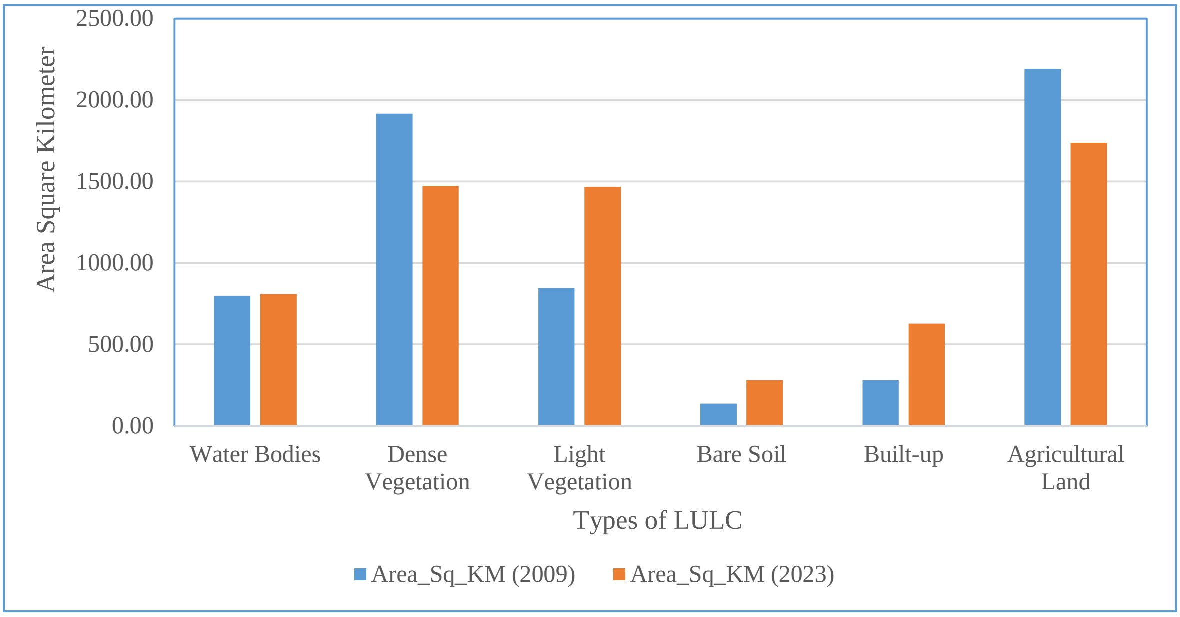

Figure 5 Changes of LULC in 2009 and 2023.
Source: Calculated by author

Classification Accuracy Assessment

One of the most important final steps at classification process is accuracy assessment. The aim of accuracy assessment is to quantitatively assess how effectively the pixels were sampled into the correct land cover classes. Accuracy assessment focused on selecting pixels from areas clearly identifiable in high-resolution Landsat imagery, Google Earth, and Google Maps. A total of 200 points (locations) were created in the classified image of the study area. The Accuracy Assessment Cell Array Reference column was filled according to the best guess of each reference point. Topographic map, and Google earth pro and Google Map were used as reference source to classify the selected points. Table 5 and 6 show the relationship between ground truth data and the corresponding classified data obtained through error matrix report.

Table 5 Category wise accuracy assessment statistical parameters and confusion matrix of the supervised classification in 2009

Class Value (2009)	Class Name	C_1	C_2	C_3	C_6	C_4	C_5	Total	User Accuracy	Kappa	Correct Sample
C_1	Water bodies	16	0	0	0	0	0	16	1.000	0	16
C_2	Dense Vegetation	0	43	2	0	2	0	47	0.910	0	43
C_3	Light Vegetation	0	2	20	1	0	0	23	0.870	0	20
C_6	Agricultura l Land	0	2	20	27	0	0	49	0.550	0	37
C_4	Bare Soil	0	0	2	2	5	0	9	0.560	0	5
C_5	Built-up	0	0	2	3	0	1	6	0.170	0	1
Total		**16**	**47**	**46**	**33**	**7**	**1**	**150**		0	**122**

Class Value (2009)	**Class Name**	**C_1**	**C_2**	**C_3**	**C_6**	**C_4**	**C_5**	**Total**	**User Accuracy**	**Kappa**	**Correct Sample**
Producer Accuracy		1.00	0.91	0.43	0.82	0.71	1.000	0	0.75	0	
Kappa		0	0	0	0	0	0	0	0	**0.67**	
		The Overall Classification Accuracy						0.8133			

Accuracy assessment is one of the most important final steps in the classification process. The purpose of accuracy assessment is to quantitatively evaluate due to have efficiently pixels are sampled in the correct land cover classes. In addition, the main focus for the accuracy evaluation pixel selection is the Landsat image, which is clearly distinguishable in both Google Earth and Google Maps. A total of 150 and 162 training sites of 2009 and 2023 were created on the classified image of the study area. The best estimate of each reference was entered in the reference column of the accuracy assessment cell array. UTM map series of topographic map, Google Earth and Google Map were used as a reference source to classify training samples.

Table 6 Category wise accuracy assessment statistical parameters and confusion matrix of the supervised classification in 2023

Class Value (2023)	**Class Name**	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**Total**	**User Accuracy**	**Kappa**	**Correct Sample**
C_1	Water bodies	14	0	0	0	0	0	14	1.0000	0	14
C_2	Dense Vegetation	0	71	0	0	0	0	71	1.0000	0	71
C_3	Light Vegetation	0	21	19	0	0	1	41	0.4634	0	29
C_4	Bare Soil	2	0	0	7	0	1	10	0.7000	0	7
C_5	Built-up	0	0	0	3	7	0	10	0.7000	0	7
C_6	Agricultural Land	0	1	2	0	0	13	16	0.8125	0	13
Total		16	93	21	10	7	15	**162**		0	**141**
Producer Accuracy		0.88	0.76	0.9	0.7	1	0.87	0	0.81	0	
Kappa		0	0	0	0	0	0	0	0	**0.72**	
		The Overall Classification Accuracy						**0.87037**			

Table 5 and 6 show the relationship between ground truth data and the corresponding classified data obtained through error matrix report.

The overall classification accuracy = $\dfrac{No.of\ correct\ (actual)\ locations}{total\ number\ of\ training\ sites}$

The overall classification accuracy is 81.33% and 87.04% in 2009 and 2023. It measures the almost perfect level of a pixel being correctly classified with the actual class on the ground.

Table 5 and 6 show a theoretical confusion matrix (error matrix) of a LULC classification. The used error matrix or contingency matrix showed the information between actual and prediction separated through classification for accuracy evaluation. Overall accuracy shows the accuracy of the map. The accuracy of each class is calculated using the user's accuracy and the producer's accuracy. For user accuracy, the number of corrected classification pixels is divided by the total number of pixels classified in that class. It measures the probability of a pixel being correctly classified with the actual class on the ground.

Table 8 and 9 show a theoretical confusion matrix (error matrix) of a LULC classification. The columns of the confusion matrix show to which classes the pixels are in the validation set belong (ground truth) and the rows show to which classes the image pixels have been assigned to in the image. The diagonal shows the pixels that are classified correctly. Pixels that are not assigned to the proper class do not occur in the diagonal and give an indication of the confusion between the different land-cover classes in the class assignment. Furthermore, the off-diagonal elements in the rows of the confusion matrix, divided by the total number of pixels assigned to the Landsat image class corresponding to the row, represent the commission errors and describe the confusion between that image class and describes the other land-cover classes. The commission errors describe the chance that a pixel that has been assigned to a particular class actually belongs to one of the other classes. Moreover, this study considered other metrics derived from the error matrix to further describe accuracy assessments including; commission and omission error, sensitivity and specificity, positive and negative predictive power and Kappa statistics. For thorough information of these concepts.

In this research, various statistics related with classification accuracy as well as overall Kappa statistic are computed based on formulation.

The Kappa coefficient measures the classification ability obtained from the error matrix without bias from chance agreement between the reference data and the classification. The Kappa coefficient measures the classification ability obtained from the error matrix without bias from chance agreement between the reference data and the classification.

According to Table 7, the range of the kappa statistic is between 1 and 0, with higher values, is the better the classification performance; 0.59 show (weak), value of Kappa below 0.60-0.79 (moderate) and >0.80 show (strong) level of agreement. The two years result show 0.67 of 2009 and 0.72 of 2023, it means that the almost perfect level of LULC classification.

Table 7. Rating criteria of Kappa statistics

Sr. No	Kappa statistics	Strength of agreement
1	< 0.00	Poor
2	0.00 - 0.20	Slight
3	0.21 - 0.40	Fair
4	0.41 - 0.60	Moderate
5	0.61 - 0.80	Substantial
6	0.81 - 1.00	Almost perfect

Using the formulae furnished on the above section, various accuracy evaluating parameters were computed and tabulated in Table 8 and Table 9. The results from accuracy assessment showed an overall accuracy obtained from the random sampling process for the image of 81.7%. User's accuracy ranged from 57.1% to 97.1% while producer's accuracy ranged from 26.7% to 93.6%. The broad range of accuracy indicates a severe confusion of Barren/bare land with other land cover classes. Moreover, the measure of producer's accuracy (Sensitivity) reflects the accuracy of prediction of the particular category.

Table 8 Category wise accuracy assessment statistical parameters

Parameters (2009)						
Classified Data	**Sensitivity**	**Specificity**	**Commission error**	**Omission error**	**User Accuracy**	**Producer Accuracy**
Water bodies	1.0000	1.00000	0.000	0.0000	1.0000	1.0000
Dense Vegetation	0.9149	0.91489	0.085	0.0851	0.9149	0.9149
Light Vegetation	0.4348	0.86957	0.130	0.5652	0.8696	0.4348
Bare Soil	0.7143	0.55556	0.444	0.2857	0.5556	0.7143
Built-up	1.0000	0.16667	0.833	0.0000	0.1667	1.0000
Agricultural Land	0.8182	0.55102	0.449	0.1818	0.5510	0.8182

Commission error refers to instances where pixels are incorrectly assigned to a category they do not truly belong to. In this study, the highest commission error was observed in the light vegetation class, where 21 pixels were misclassified as dense vegetation in the 2023 map. Conversely, omission error indicates the number of pixels that genuinely belong to a category but were not classified under it. The barren/bare land class exhibited a relatively high omission error of 0.3000, with three pixels that should have been included in this category left unclassified. The overall classification yielded a Kappa coefficient of 0.722, indicating substantial agreement. Beyond overall accuracy, these class-specific metrics provide a more nuanced understanding of the model's performance across individual land cover types, offering valuable insights for researchers working within this domain.

Table 9 Category wise accuracy assessment statistical parameters

Parameters (2023)						
Classified Data	**Sensitivity**	**Specificity**	**Commission error**	**Omission error**	**User Accuracy**	**Producer Accuracy**
Water bodies	0.8750	1.00000	0.000	0.1250	1.000	0.8750
Dense Vegetation	0.7634	1.00000	0.000	0.2366	1.000	0.7634
Light Vegetation	0.9048	0.46342	0.537	0.0952	0.463	0.9048
Bare soil	0.7000	0.70000	0.300	0.3000	0.700	0.7000
Built-up	1.0000	0.70000	0.300	0.0000	0.700	1.0000
Agricultural Land	0.8667	0.81250	0.188	0.1333	0.813	0.8667

Commission error refers to pixels incorrectly assigned to a category they do not truly belong to. In this study, the highest commission error occurred in the bare land class, where four pixels were misclassified as light vegetation and agricultural land in the 2009 dataset. Conversely, omission error indicates pixels that genuinely belong to a category but were not classified under it. The light vegetation class showed a higher omission error of 0.5652, with three pixels excluded from their correct category. The overall classification yielded a Kappa coefficient of 0.67, indicating substantial agreement. Beyond overall accuracy, these class-specific metrics offer deeper insight into the model's performance across individual land cover types, supporting more informed analysis within the study's domain.

User's accuracy measures the reliability of classification from the perspective of the end user and is considered a key indicator of its practical utility in the field. In this study, water bodies and dense vegetation classes demonstrated the highest reliability, each achieving a user's accuracy of 1.00. Commission error refers to points incorrectly assigned to a category they do not truly belong to. The highest commission error was observed in the dense vegetation class, where 31 pixels were misclassified as built-up areas. Omission error, conversely, indicates points that genuinely belong to a category but were not classified under it. The barren/bare land class showed the highest omission error of 0.7333, with 33 pixels excluded from their correct category. An overall Kappa coefficient of 0.722 was obtained, indicating substantial agreement. In addition to overall classification accuracy, these class-specific metrics provide a more detailed evaluation of model performance, offering valuable insights for researchers working with specific land cover categories.

Change Detection Result and Discussion

In this study, Landsat 5 and 8 satellite images of 2009, and 2023 were used for GIS and RS image analysis. Based on remote sensing and GIS techniques, the images are classified as water bodies, dense vegetation, light vegetation, built-up (settlement), bare land and agricultural land. Temporal land use maps of (2009, and 2023) are shown in figures 6 to 8.

Change detection was carried out using ArcGIS software. Raster calculator in ArcGIS was used in this process. For the existing study six different LULC classes were involved and 36 LULC change categories were created as the change. In the final analysis, it was reduced into five change categories as agriculture change, water bodies change, vegetation change, bare soil change and settlement Change (Table 10). Fundamental change categories are defined from one class to another because it is convenient in final assessment in change detection and smooth visual interpretation (Ex: Vegetation to settlement). The spatial and temporal land use maps of (2009, and 2023) are shown in figures 8.

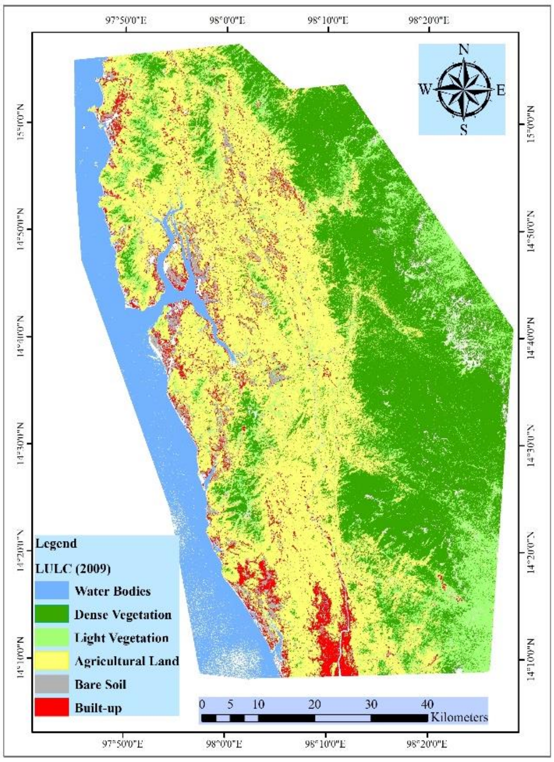

Figure 6. LULC of Yebyu Township in 2009

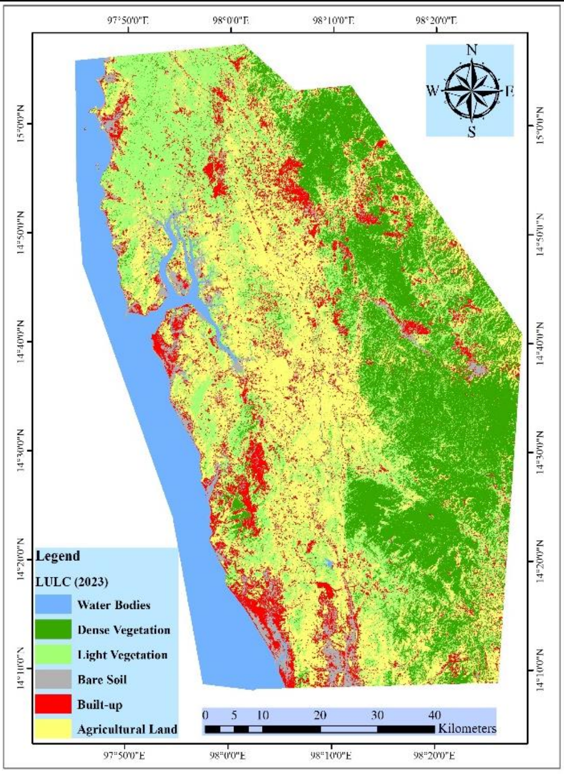

Figure 7. LULC of Yebyu Township in 2023

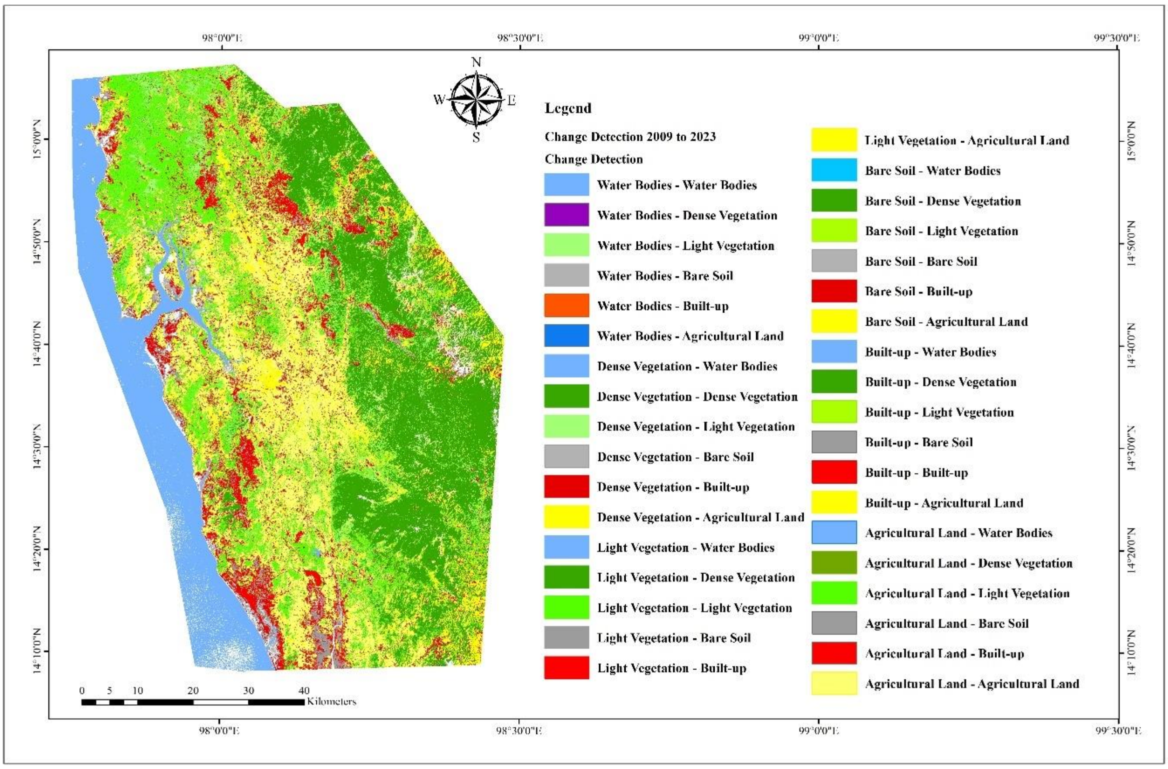

Figure 8 Spatial changes Analysis from 2009 to 2023

Table 10 Change Detection Analysis 2009 and 2023

Change Detection Analysis	**Area Change (Sq-km)**	**Change Detection Analysis**	**Area Change (Sq-km)**
Agricultural Land - Agricultural Land	1126.33	Dense Vegetation - Agricultural Land	132.843429
Agricultural Land - Bare Soil	45.72	Dense Vegetation - Bare Soil	11.324401
Agricultural Land - Built-up	234.16	Dense Vegetation - Built-up	71.580191
Agricultural Land - Dense Vegetation	49.97	Dense Vegetation - Dense Vegetation	1275.862367
Agricultural Land - Light Vegetation	734.12	Dense Vegetation - Light Vegetation	424.378883
Agricultural Land - Water Bodies	1.17	Dense Vegetation - Water Bodies	0.016566
Bare Soil - Agricultural Land	48.23	Light Vegetation - Agricultural Land	326.066685
Bare Soil - Bare Soil	28.02	Light Vegetation - Bare Soil	24.313664
Bare Soil - Built-up	53.31	Light Vegetation - Built-up	122.462434
Bare Soil - Dense Vegetation	0.07	Light Vegetation - Dense Vegetation	129.259688
Bare Soil - Light Vegetation	7.66	Light Vegetation - Light Vegetation	243.642854
Bare Soil - Water Bodies	0.18	Light Vegetation - Water Bodies	0.050203
Built-up - Agricultural Land	68.33	Water Bodies - Agricultural Land	0.03324
Built-up - Bare Soil	76.14	Water Bodies - Bare Soil	30.801202
Built-up - Built-up	105.02	Water Bodies - Built-up	0.482638
Built-up - Dense Vegetation	0.87	Water Bodies - Dense Vegetation	0.010959
Built-up - Light Vegetation	30.91	Water Bodies - Light Vegetation	0.135079
Built-up - Water Bodies	0.25	Water Bodies - Water Bodies	766.739539

Based on the classification results, agricultural land is more prevalent in the northern region, whereas settlement areas are predominantly concentrated in the western part. Dense vegetation coverage on 2009 was 1332.46 km^2. It is occupied by the eastern part of the study area. During the study period, an expansion of 107.66 km² in agricultural land was recorded, primarily occurring around settlement zones and forested areas.

Conclusions

Remote sensing is essential for producing Land Use and Land Cover (LULC) maps, primarily through image classification techniques that have evolved significantly over recent decades. Key advancements include the ability to generate maps at multiple spatial scales, the use of sophisticated methods such as pre-field analysis and sub-pixel classification, the adoption of knowledge-based classification systems, and the integration of auxiliary datasets like Digital Elevation Models (DEM), road networks, soil profiles, land use records, and census data. However, achieving accurate and reliable LULC information from Landsat imagery remains challenging due to factors such as the type and quality of imagery selected, the complexity of the landscape, the image processing techniques applied, and the classification approach used.

The accelerated usage of remote sensing data and techniques has made geospatial process faster and powerful, although the increased complexity also creates increased possibilities for error. The objective of this paper was to classify and map the land use/land cover change detection of the study area using remote sensing and GIS techniques and to perform accuracy assessments to evaluate classification effectiveness and interpret the classification's utility.

The supervised classification was performed using Non-Parametric Rule. The image was classified into six classes; water body (283 km^2), dense vegetation (372 km^2), light vegetation (499 km^2), built-up areas (1309 km^2), Barren/bare land (37 km^2) and Agriculture (4638 km^2). Agriculture was the dominant type of Land use classified which covers about 35.51% of the study area.

In this study, accuracy assessment was performed using error matrix. The study had an overall classification accuracy is 87.03% and kappa coefficient is 0.722 of 2023 and overall classification accuracy is 81.33% and kappa coefficient is 0.67 of 2009. The kappa coefficient is rated as substantial and almost perfect hence the classified image found to be fit for further research.

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