

Chapter 3

Satellite Image Classification

3.1 Introduction

As per the inference drawn from the existing literature references, image classification can be broadly classified into three identifiable categories, namely unsupervised, semi-supervised, and supervised, based on the availability of the knowledge/labeled dataset that serves as a basis for classification. This research initiative has considered a candidate from each of these categories for classifying the satellite image. ISODATA, Hybrid, and MLC techniques have been selected as representative for unsupervised, semi-supervised, and supervised approaches respectively for classifying the temporal satellite imageries. A cross-sectional analysis has also been conducted to determine the strengths and weaknesses of each approach to identify the most effective one.

3.2 Objectives

With respect to the research motivation, the objectives for this research initiative are:

- a) classification of temporal satellite images using supervised, unsupervised, and hybrid techniques
- b) perform accuracy assessment of the various classification techniques
- c) suggest a favorable approach based on the results of the accuracy assessment.

3.3 Selection of remotely sensed temporal data and the seed points

Satellite data from five reference years has been utilized to ascertain the degree of sprawl. Landsat 7 TM+ETM+ data from the year 2000 has been utilized. Landsat 8

OLI-TIRS data has been utilized for the years 2013, 2015, and 2018. Similarly, data from Landsat 9 OLI-2 and TIRS-2 has been utilized for the year 2023.

3.4 Methodology pursued

The research initiatives have been strategized as per the schematic representation presented in figure 3.1,

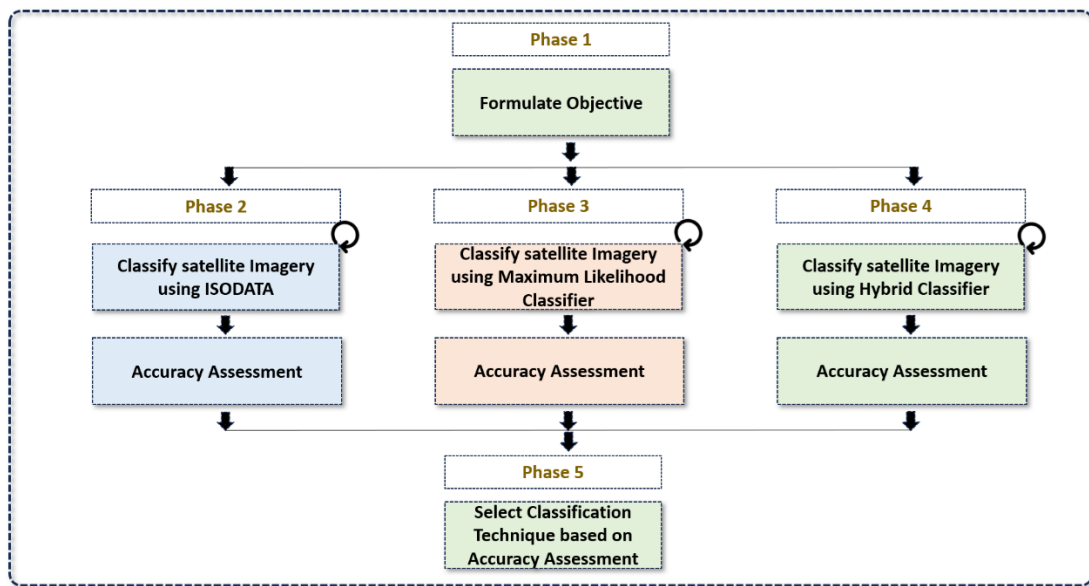


Figure 3.1: Schematic representation of the research initiative

This research initiative adheres to the following sequence of phases represented hereunder,

Phase 1: in this phase the objectives were established

Phase 2: temporal satellite images for the years 2000, 2013, 2015, 2018, and 2023

Phase 3: apply unsupervised classification ISODATA

Phase 4: apply supervised classification Maximum Likelihood

Phase 5: apply Hybrid classification

Phase 6: Accuracy Assessment

3.5 Unsupervised classification using ISODATA

3.5.1 Process Description

ISODATA classification is an unsupervised classification technique. In this case, it is unnecessary to ascertain the initial quantity of clusters present in the image. The ISODATA classification algorithm can either partition the data picture into distinct clusters or amalgamate existing clusters into new ones during its iterative process. The cluster points will be arbitrarily positioned during this process, and the pixels in the relevant data imagery will be allocated to one of the clusters based on the distance that is closest between each of the pixels and the centers of the clusters. The average standard deviation of the clustering and the associated distances between numerous cluster centers will also be measured during iterations. The clusters shall be divided into new groups if the standard deviations exceed the threshold established by the analyst. Merging of clusters occurs when the distance between their respective centers is minimal relative to the threshold established by the analyst. The process of dividing and consolidating the clusters will persist until the predetermined maximum number of iterations set by the analyst is attained. The graphic illustrating the formation of the clusters is given in figure 3.2 below.

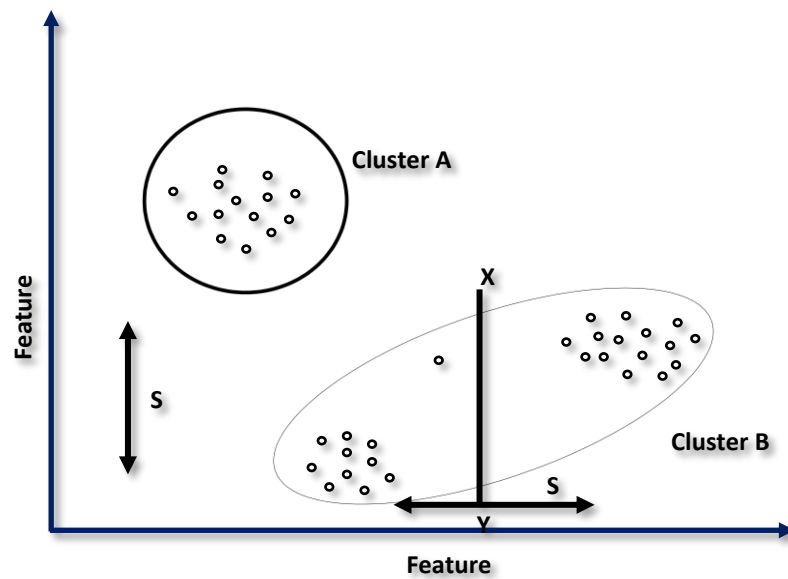


Figure 3.2: Cluster formations using ISODATA

The steps involved in the classification of data are:

- In this classification, the centers of the cluster are initially positioned randomly, and each pixel in the data images is allocated to the clusters based on the shortest distance.
- The standard deviation among the clusters and the distances between the various centers are computed. When the standard deviation exceeds the threshold level, the clusters are divided into new clusters. Likewise, when the distance amongst the clusters is minimal relative to the threshold value, the clusters are amalgamated.
- Subsequent iterations were conducted.
- The procedure was reiterated until the mean inter-center distance fell below the designated threshold.

3.5.2 Algorithm Description

Algorithm 3.1: ISODATA

Input:

- a) cluster centers (random or based on knowledge)
- b) specify parameters such as maximum and minimum number of clusters, maximum standard deviation, minimum inter cluster distance and maximum number of iterations
- c) temporal satellite dataset

Output:

- a) clusters representing classes dense forest, vegetation, barren land and urban spaces

Step 1: Start

Step 2: Assign the pixels to the nearest cluster based on the distance matrix (preferably Euclidean Distance)

Step 3: Recompute mean based on the assigned pixels and decide on the new cluster head

Step 4: In situation if the inter cluster head distance is less than that of the specified inter cluster head distance then perform **merge**

Step 5: In situation if the standard deviation of the cluster is greater than the maximum standard deviation specified and number of clusters is less than the maximum number of clusters specified then perform **split**

Step 6: terminate in situation

if (the maximum iteration has reached or the clusters stabilizes)

goto **step 7**

Step 6: goto **step 2**

Algorithm 3.1: ISODATA

3.5.3 Advantages and disadvantages

- The algorithm is highly adaptive as it determines ideal number of clusters and is generally preferred for complex dataset such as remotely sensed data. In contrast, this algorithm is computational complex because of the uncertainty in the number of executions.

3.5.4 Experimental Run

The Landsat images from the years 2000, 2013, 2015, 2018, and 2023 were set as input to the classification algorithm. The maximum number of clusters was set to 100, the maximum number of iterations was set to 10, and the convergence criterion was set to 0.95 (i.e., terminating the procedure when a minimum of 95% of the pixels remain in an identical cluster). Upon concluding the clustering procedure, the algorithm consolidated 100 specified clusters into 4-5 clusters, aligning with the number of LULC classes. Thereafter, utilizing field expertise and supplementary data, including Google Maps as a base map, ground truthing was performed. The unsupervised algorithm ultimately generated the classified thematic maps.

Table 3.1: Land cover classification system used for this study

SI No	Classes	Description
1	Vegetation	Forest, Grassland, woody vegetation, sparse vegetation area, Agriculture lands and irrigated lands
2	Urban Space	Built up areas like: residential, industrial, transportation, commercial complexes, mixed urban or built-up land, road etc

3	Barren land	Open land, rock etc
4	Dense forest	Steep slope mountains/hills with trees
5	Snow	Snow covered mountains
6	Clouds	Cloud covered areas

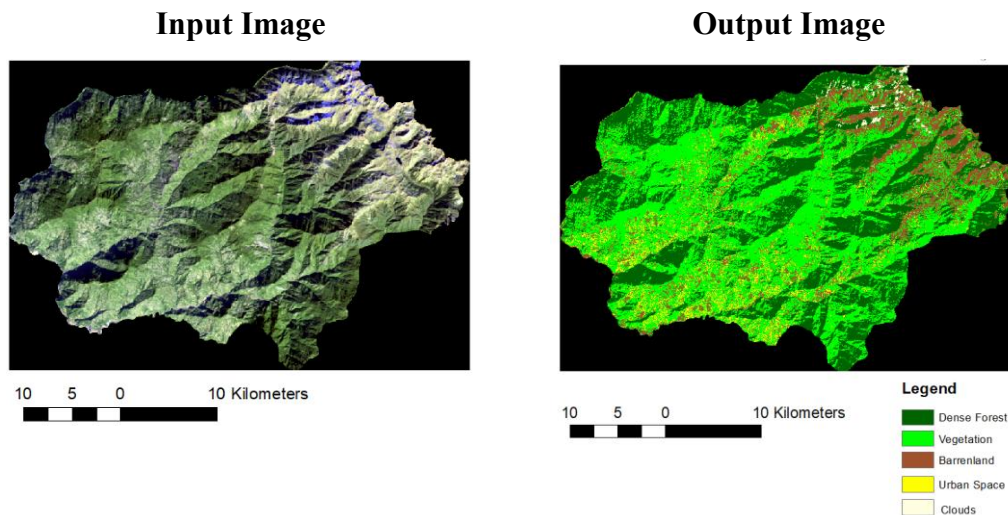
3.5.5 Results

3.5.5.1 Classification Results

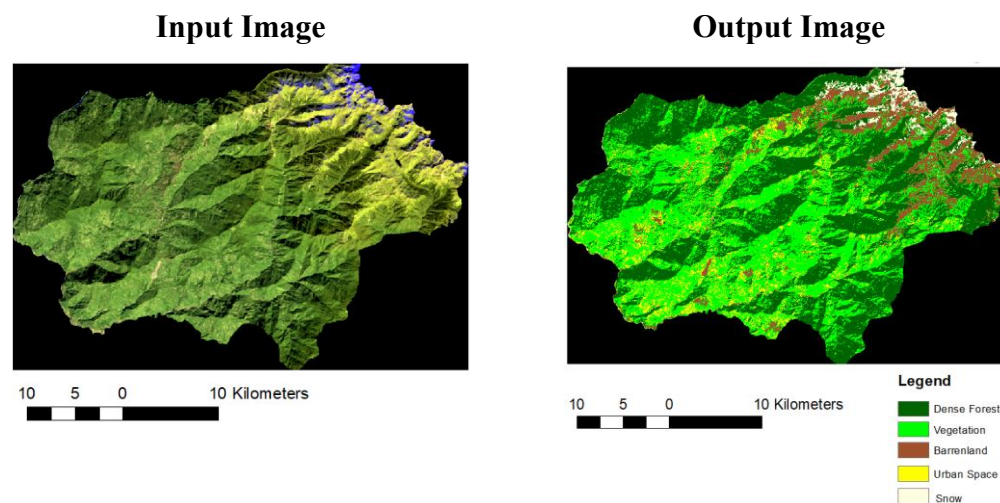
Table 3.2 represents year wise results obtained from the classification process.

Table 3.2: ISODATA classifier outputs

Year 2000

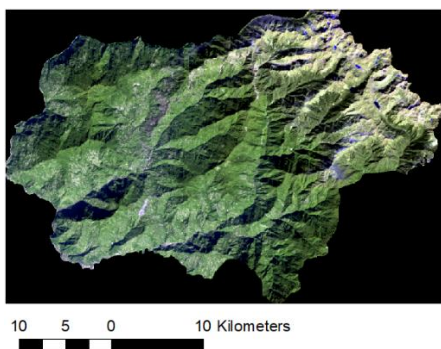


Year 2013

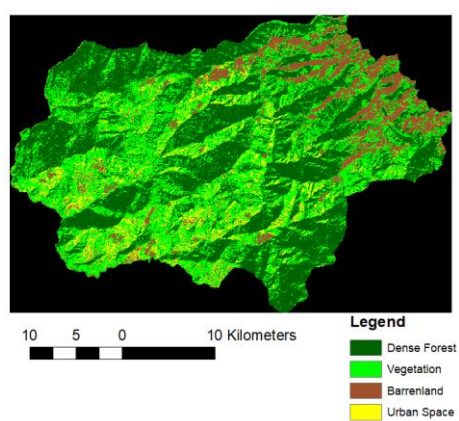


Year 2015

Input Image

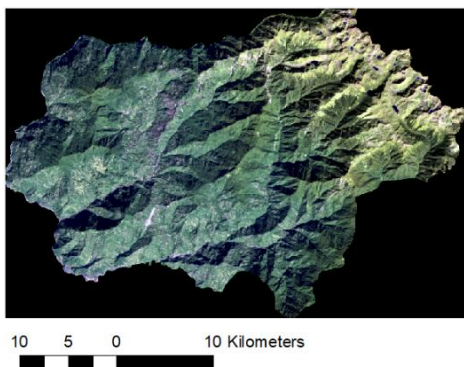


Output Image

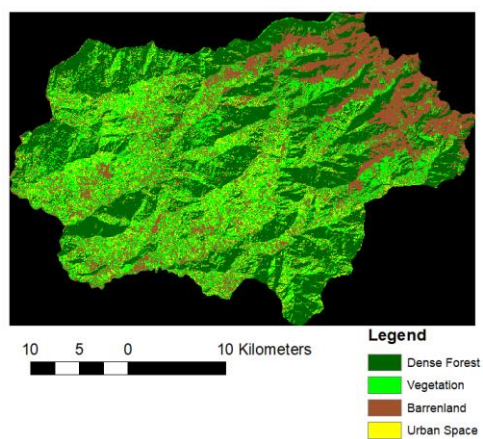


Year 2018

Input Image

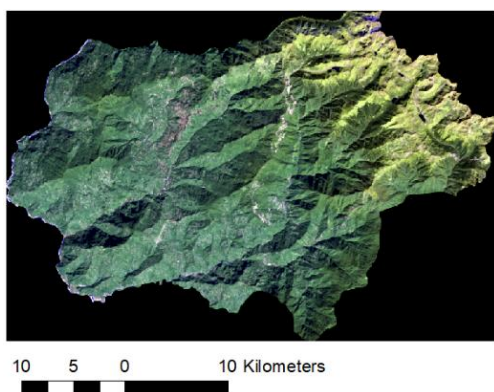


Output Image

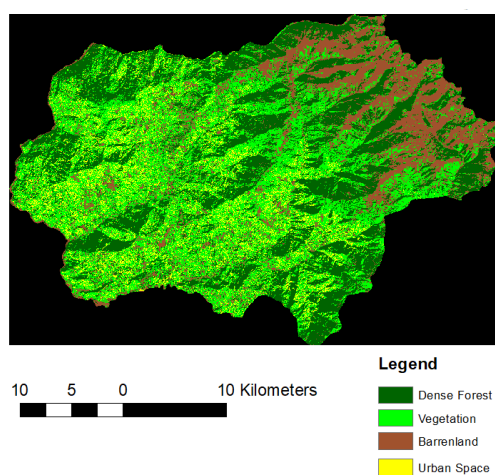


Year 2023

Input Image



Output Image



All five satellite images from different years: 2000, 2013, 2015, 2018 and 2023 were analysed and categorized into multiple classes namely dense forest, vegetation, barren land, urban areas, snow, and clouds, respectively.

3.5.5.2 Estimation of coverage of various classes

i) Pixel Coverage

Table 3.3 illustrates the total amount of pixels classified into the distinct recognizable groupings (graphically represented in figure 3.3) depicted in table 3.2 by ISODATA classifier.

Table 3.3: Pixel coverage by various classes (ISODATA)

Year	Dense Forest	Vegetation	Barren Land	Urban spaces
2000	439528	414008	140673	64775
2013	443293	410442	123909	80313
2015	436077	417689	122403	89749
2018	435097	418578	121134	91109
2023	433774	412589	120996	98559

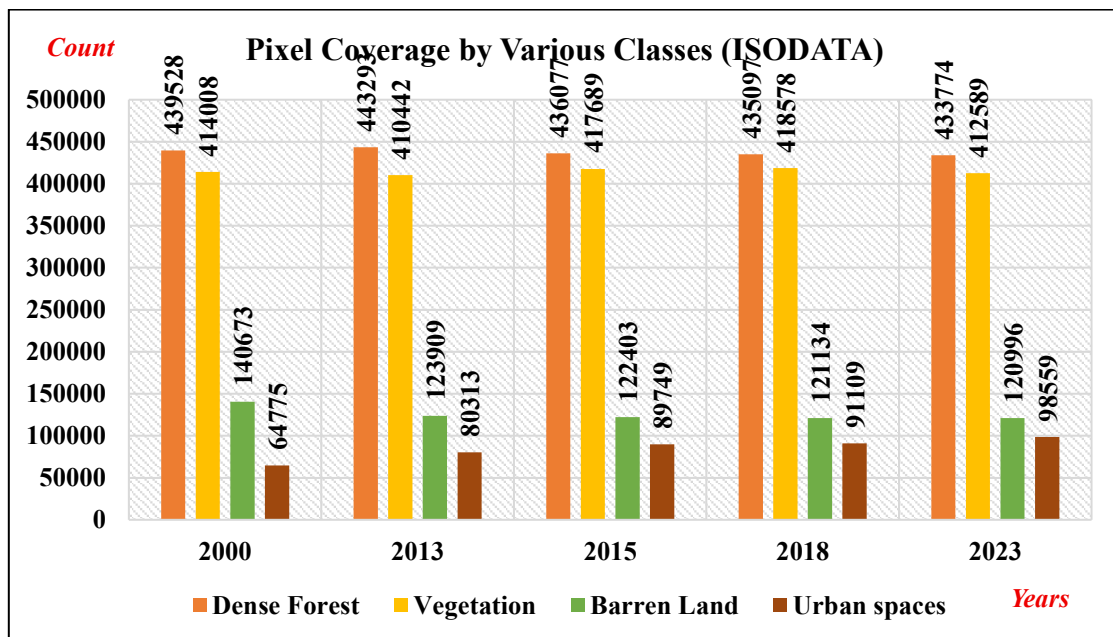


Figure 3.3: Graphical representation for pixel coverage (ISODATA)

ii) Area Coverage

Table 3.4 represents the total area covered by the identified classes (graphically represented in figure 3.4). This was estimated by multiplying the pixel coverage with resolution of the reference data.

Table 3.4: Representation of area coverage in sq km

Year	Dense Forest	Vegetation	Barren Land	Urban spaces
2000	395.58	372.61	126.61	58.30
2013	398.96	369.40	111.52	72.28
2015	392.47	375.92	110.16	80.77
2018	391.59	376.72	109.02	82.00
2023	390.40	371.33	108.90	88.70

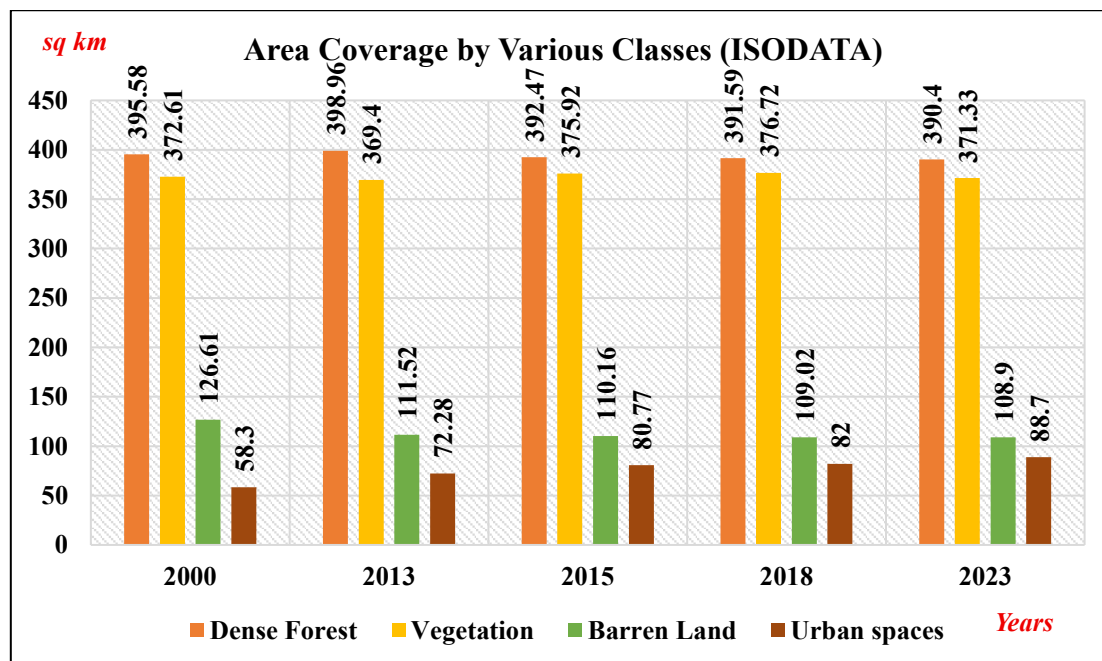


Figure 3.4: Graphical representation for area coverage in sq km (ISODATA)

3.6 Supervised classification using Maximum Likelihood

3.6.1 Process Description

Maximum likelihood (MaxLi) is a widely utilized parametric classifier in land use and land cover (LULC) classification, employed globally over time. This classic method is frequently selected by researchers to evaluate the accuracy of alternative algorithms. The classifier evaluates the Gaussian distribution for each spectral class with a covariance matrix derived from the input data. The matrix of covariance is employed to assign weights to the disparities among spectral clusters and picture pixels [227]. MaxLi computes the probability distribution of categories associated with Bayes' theorem.

Where, the likelihood L_k is defined as the posterior probability of a pixel belonging to a LULC class k [228].

$$L_k = P(k/X) = \frac{P(k) * P(X/k)}{\sum_1^m P(i) * P(X/i)} \dots \text{equation 1}$$

Here,

- $P(k/X)$ is the posterior probability that a pixel belongs to class k given X (observed feature)
- $P(k)$ is the prior probability of the pixel belonging to class k
- $P(X/k)$ is the likelihood of observing the feature X provided that the pixel belongs to class k
- Implies that L_k depends on $P(X/k)$

Were,

$$P(X/k) = \frac{1}{\sqrt{(2\pi)^d |\Sigma_k|}} \exp\left(-\frac{1}{2}(X - \mu_k)^T \Sigma_k^{-1} (X - \mu_k)\right) \dots \text{equation 2}$$

Here,

- μ_k is the mean vector of class k
- Σ_k is the covariance matrix of class k
- D is the dimensionality of the feature vector X

The steps involved in the classification of data are:

- An individualized preprocessing procedure has been implemented to rectify data issues stemming from sensor input, image alignment, and atmospheric correction. Satellite pictures were geometrically adjusted to the UTM projection (zone 40 north, datum WGS 1984). A multiband image is generated in this step using the composite band tool. Then a subset of multiband is created for classification.
- In supervised classification, samples for training are utilized to discern classes and compute their signatures. Training samples are easily generated interactively utilizing the sample for training drawing tools included on the classification of images toolbar. New classes are generated by themselves when samples of training are displayed. Furthermore, the classes can be renamed or renumbered, modified in display color, divided, deleted, and training samples can be saved and loaded, among other functionalities.
- Upon the identification of training samples that are typical of the target classes and identifiable from other samples, a signature file will be created.
- This initiative employs a maximum likelihood algorithm due to its probabilistic nature, robustness, efficiency in managing multispectral data, capability to incorporate variability, facilitation of performance metric quantization, accuracy evaluation, and effective handling of miscalculation probability.

- In instances where the classifier erroneously incorporates a pixel into a class or mistakenly omits a pixel from a class owing to the significant impact of the physical environment, auxiliary data may be utilized to amend the classification outcomes, hence enhancing the accuracy of the results achieved. Satellite data about mountainous regions is significantly affected by the presence of geomorphological landforms and their interactions, particularly in relation to the position of the sensor and the light origin. Consequently, two pixels of the same class may appear markedly dissimilar due to the impact of the physical surroundings. The accuracy of the classified image is evaluated by comparing the classified output with the ground truth data.

3.6.2 Algorithm Description

Algorithm 3.2: Maximum Likelihood

Input:

- a) probability distribution function
 - b) temporal satellite data
-

Output:

- a) classes representing classes dense forest, vegetation, barren land and urban spaces
-

Step 1: Start

Step 2: Compute probability distribution for each data point based on identified distribution function.

Step 3: Invoke the likelihood function to represent probability based on the parameters under study

Step 4: Find the parameter value that maximizes likelihood function

Step 5: Apply optimization technique to find best parameter values that maximizes likelihood function

Step 6: Display the parameter values and interpret

Step 7: Stop

Algorithm 3.2: MLC

3.6.3 Advantages and disadvantages:

- Its probabilistic approach helps to deal with uncertainty effectively; it is computationally simple and proves efficient for data with lower dimensions. In situation if the data follows normal distribution than maximum likelihood proves to be an effective classifier. On the contrary, maximum likelihood turns ineffective in situation there is insufficient training data, further its performance decreases with increase in the dimension and heterogeneity of data.

3.6.4 Experimental Run

The Landsat images from the years 2000, 2013, 2015, 2018, and 2023 were set as input for the classification algorithm. Upon concluding the classification procedure, the algorithm consolidated into 4-5 classes, aligning with the number of LULC classes. Thereafter, utilizing field expertise and supplementary data, including Google Maps as a base map, ground truthing was performed. The unsupervised algorithm ultimately generated the classified thematic maps.

Table 3.5: Land covers classification system used for this study

Sl No	Classes	Description
1	Vegetation	Forest, Grassland, woody vegetation, sparse vegetation area, Agriculture lands and irrigated lands

2	Urban Space	Built up areas like: residential, industrial, transportation, commercial complexes, mixed urban or built-up land, road etc
3	Barren land	Open land, rock etc
4	Dense forest	Steep slope mountains/hills with trees
5	Snow	Snow covered mountains
6	Clouds	Cloud covered areas

3.6.5 Results

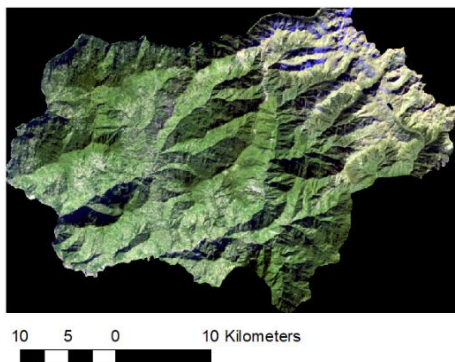
3.6.5.1 Classification Results

Table 3.6 represents year wise results obtained from the classification process.

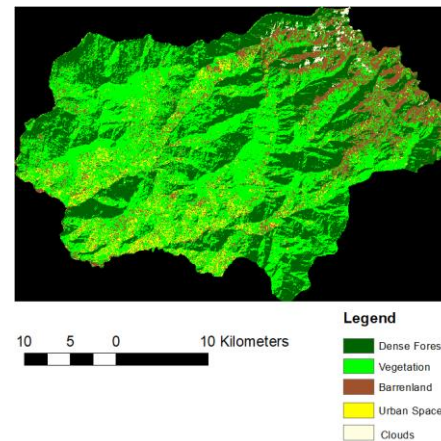
Table 3.6: Output from Maximum Likelihood classifier

Year 2000

Input Image

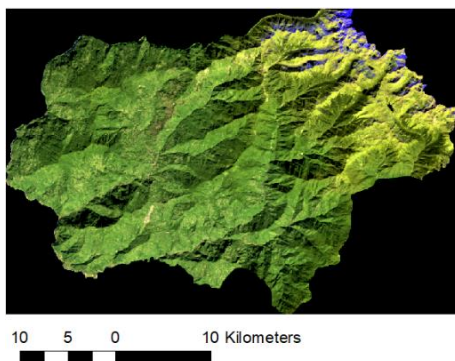


Output Image

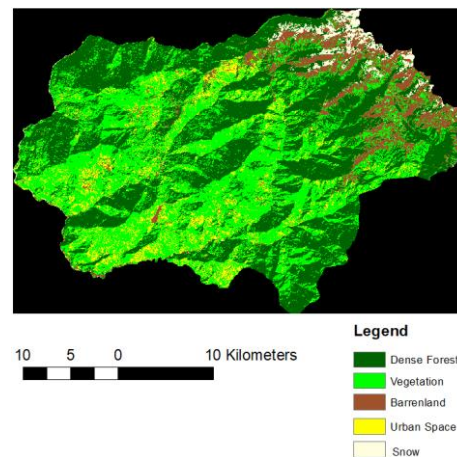


Year 2013

Input Image



Output Image



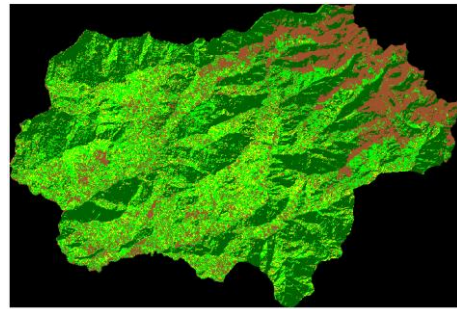
Year 2015

Input Image



10 5 0 10 Kilometers

Output Image



10 5 0 10 Kilometers

Legend

- Dense Forest
- Vegetation
- Barrenland
- Urban Space

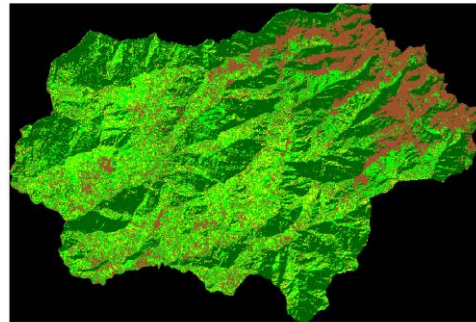
Year 2018

Input Image



10 5 0 10 Kilometers

Output Image



10 5 0 10 Kilometers

Legend

- Dense Forest
- Vegetation
- Barrenland
- Urban Space

Year 2023

Input Image



10 5 0 10 Kilometers

Output Image



10 5 0 10 Kilometers

Legend

- Dense Forest
- Vegetation
- Barrenland
- Urban Space

The aforementioned outputs are the outcomes of the maximum likelihood classification method. All five satellite photos from different years: 2000, 2013,

2015, 2018 and 2023 were analysed and categorized into multiple classes including dense forest, vegetation, barren land, urban areas, snow, and cloud.

3.6.5.2 Estimation of Coverage of various classes

i) Pixel Coverage

Table 3.7 illustrates the total amount of pixels classified into the distinct recognizable groupings (graphically represented in figure 3.5) depicted in table 3.6 by Maximum Likelihood classifier.

Table 3.7: Pixel coverage by various classes (Max. Likelihood)

Year	Dense Forest	Vegetation	Barren Land	Urban spaces
2000	439528	414008	140673	64775
2013	443293	410442	123909	80313
2015	436077	417689	122403	89749
2018	435097	418578	121134	91109
2023	433774	412589	120996	98559

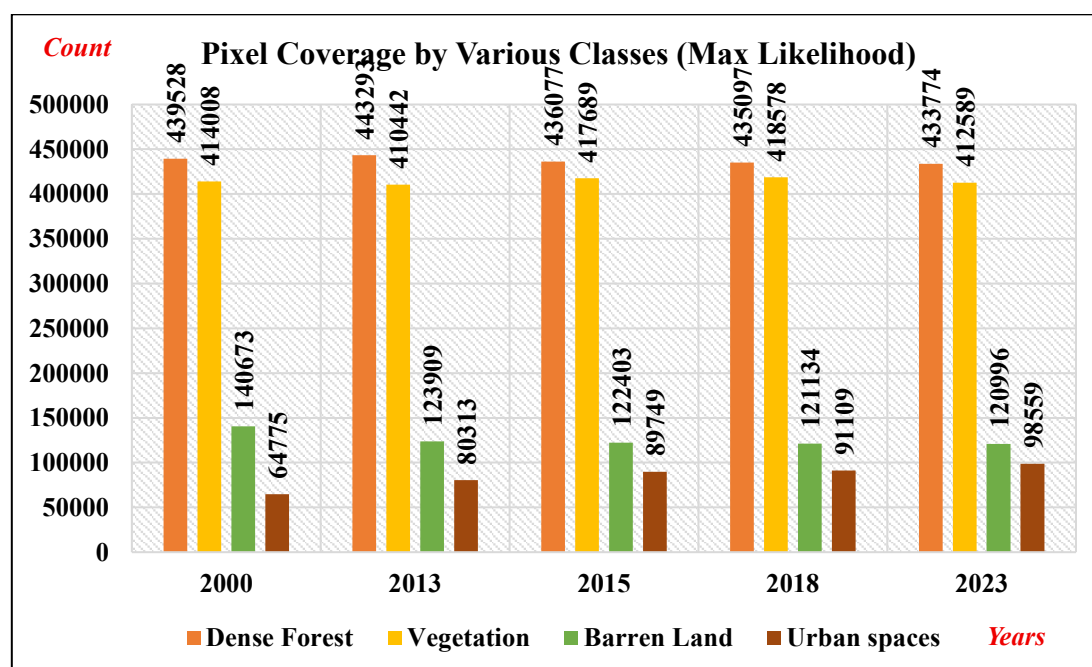


Figure 3.5: Graphical representation for pixel coverage (Max. Likelihood)

ii) Area Coverage

Table 3.8 represents the total area covered by the identified classes (graphically represented in figure 3.6). This was estimated by multiplying the pixel coverage with resolution of the reference data.

Table 3.8: Represents the area coverage in sq km (Max. Likelihood)

Year	Dense Forest	Vegetation	Barren Land	Urban spaces
2000	395.58	372.61	126.61	58.30
2013	398.96	369.40	111.52	72.28
2015	392.47	375.92	110.16	80.77
2018	391.59	376.72	109.02	82.00
2023	390.40	371.33	108.90	88.70

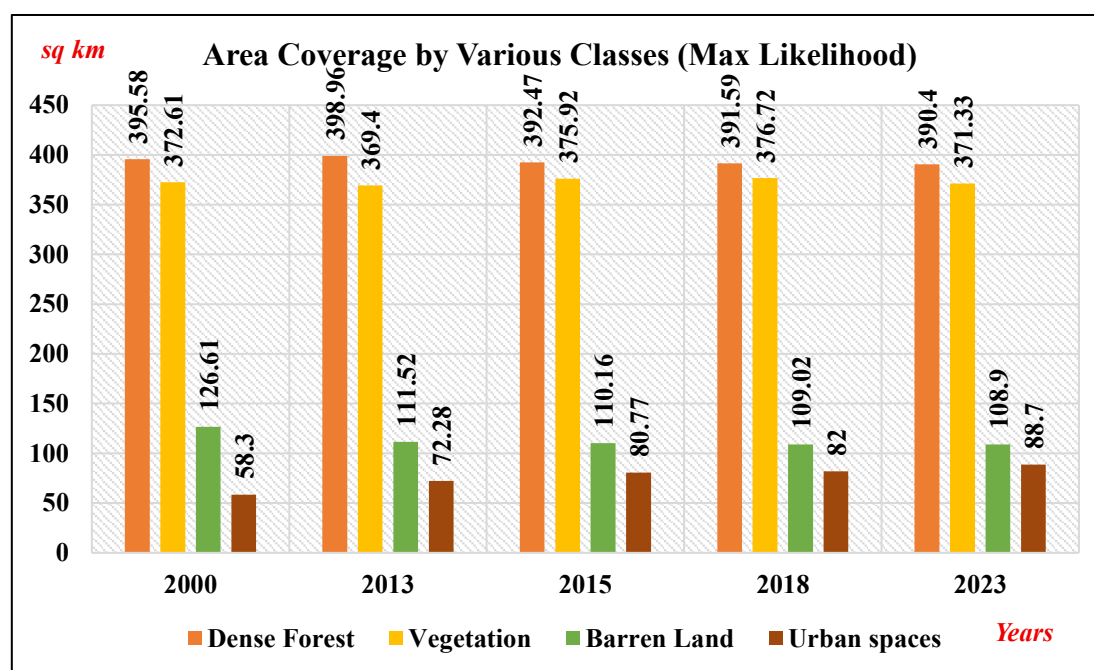


Figure 3.6: Graphical representation for area coverage in sq km (Max. Likelihood)

3.7 Hybrid classification methodology

3.7.1 Process Description

The hybrid classification method comprises of supervised and unsupervised classification methods. All five satellite images were used as input for this method.

The images were first classified with ISODATA clustering method to reduce the

number of classes for further classification as detailed in section 3.2. The total amount of clusters for classification was established at 5000, with a maximum of ten iterations permitted. The convergence criterion was set at 0.95, terminating the procedure when a minimum of 95% of the pixels remain in an identical cluster throughout two iterations. Due to the huge number of pixels and classes the time taken for classification was considerable higher than two previous methods when compared. Once the images are classified, training samples are selected to implement the supervised method. The detailed method for supervised classification using maximum likelihood classifier as detailed in section 3.3. Following the same methodology the classified images are further classified in to 4-5 classes respectively. If the images classified meet the expectation, then the images are processed further for correction else the classification steps are repeated. Then the classified images are ready for accuracy assessment and analysis, which is explained in the section 3.4. Table 3.10 highlights the description of the classes used for classification of images.

3.7.2 Algorithm Description

Algorithm 3.3: Hybrid Classification
Input: a) temporal satellite data
Output: a) classes representing classes dense forest, vegetation, barren land and urban spaces
Step 1: Start
Step 2: Perform ISODATA clustering using algorithm 3.1
Step 3: Identify class labels.
Step 4: Use class labels and perform classification using algorithm 3.2

Step 5: Stop

Algorithm 3.3: Hybrid Classification

3.7.3 Advantages and disadvantages:

- It is capable of identifying ideal number of class labels for facilitating proper and complete classification. On the contrary, the hybrid approach takes considerable time due to its greater complexity.

3.7.4 Experimental Run

The Landsat images from the years 2000, 2013, 2015, 2018, and 2023 were set as input for the classification algorithm. Upon concluding the classification procedure, the algorithm consolidated into 4-5 classes, aligning with the number of LULC classes. Thereafter, utilizing field expertise and supplementary data, including Google Maps as a base map, ground truthing was performed. The unsupervised algorithm ultimately generated the classified thematic maps.

Table 3.9: Land cover classification system used for this study

Sl No	Classes	Description
1	Vegetation	Forest, Grassland, woody vegetation, sparse vegetation area, Agriculture lands and irrigated lands
2	Urban Space	Built up areas like: residential, industrial, transportation, commercial complexes, mixed urban or built-up land, road etc
3	Barren land	Open land, rock etc
4	Dense forest	Steep slope mountains/hills with trees
5	Snow	Snow covered mountains
76	Clouds	Cloud covered areas

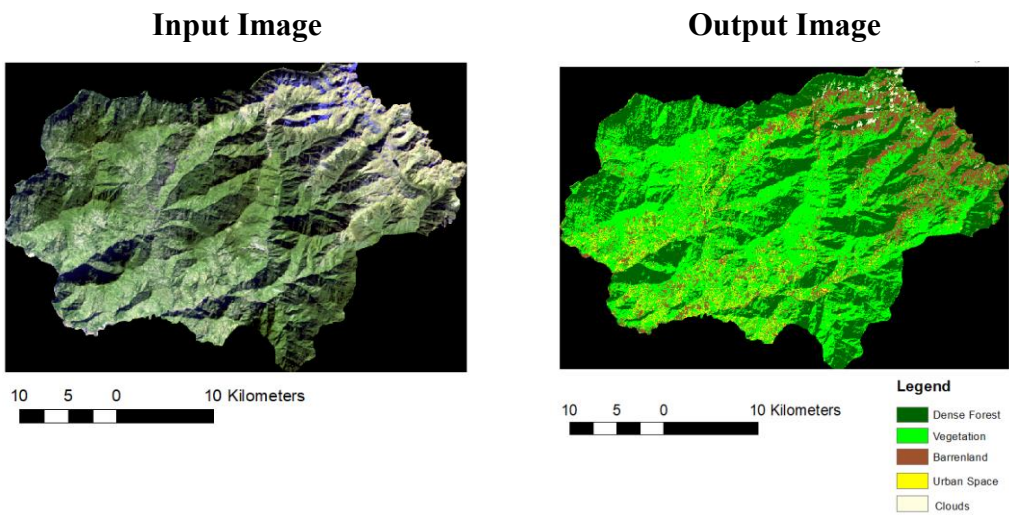
3.7.5 Results

3.3.5.1 Classification Results

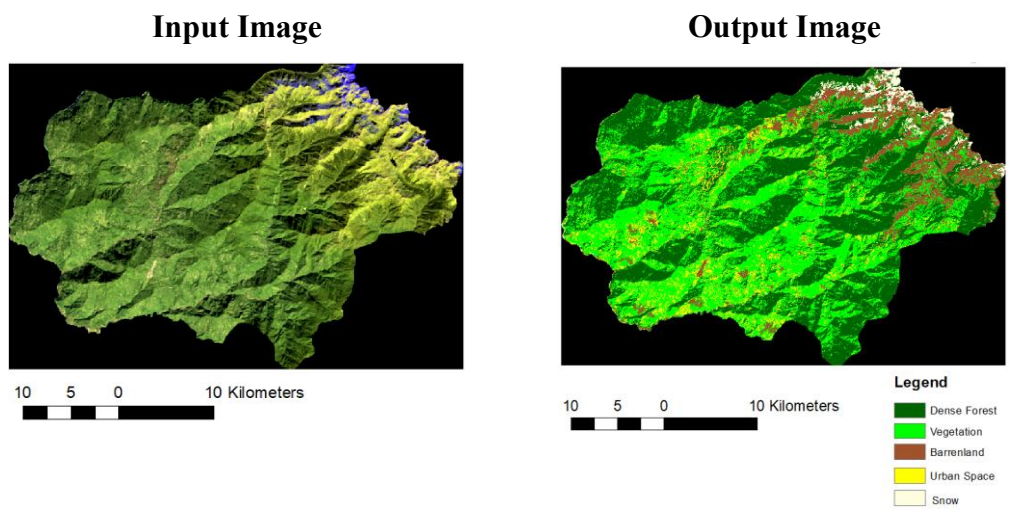
Table 3.10 represents year wise results obtained from the classification process.

Table 3.10: Output from Hybrid classifier

Year 2000



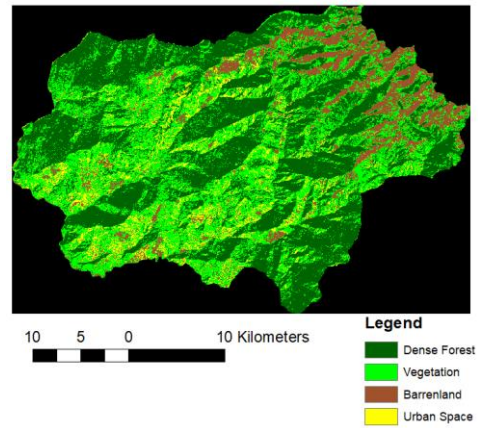
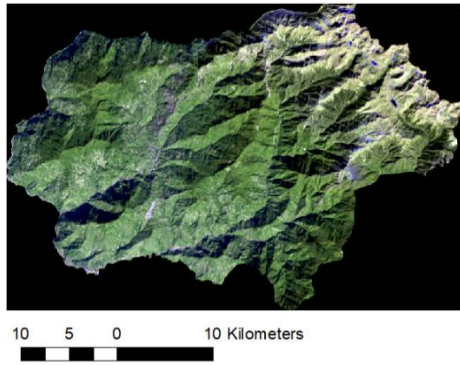
Year 2013



Year 2015

Input Image

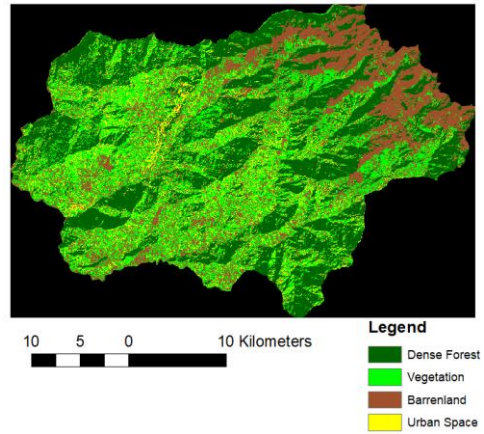
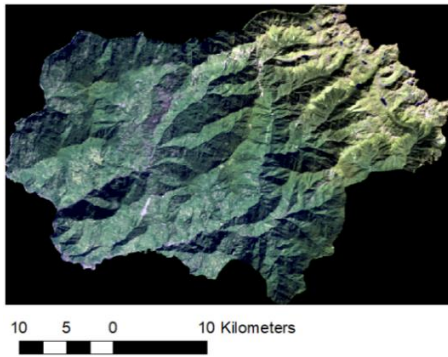
Output Image



Year 2018

Input Image

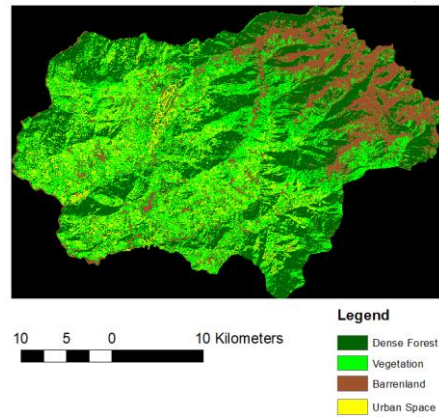
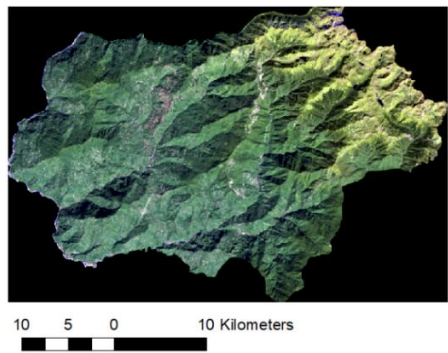
Output Image



Year 2023

Input Image

Output Image



The above listed outputs are the outcomes of the hybrid classification method. All five satellite images from the years 2000, 2013, 2015, 2018, and 2023 were analyzed and classified into several categories such as dense forest, vegetation, barren land, urban areas, snow, and clouds.

3.7.5.2 Estimation of coverage of various classes

i) Pixel Coverage

Table 3.11 illustrates the total amount of pixels classified into the distinct recognizable groupings (graphically represented in figure 3.7) depicted in table 3.10 by Hybrid classifier.

Table 3.11: Pixel coverage by various classes (Hybrid)

Year	Dense Forest	Vegetation	Barren Land	Urban spaces
2000	446984	412380	137679	61941
2013	441293	412442	122989	81233
2015	436950	417723	122938	88307
2018	436167	417613	121267	90871
2023	433981	413189	119996	98752

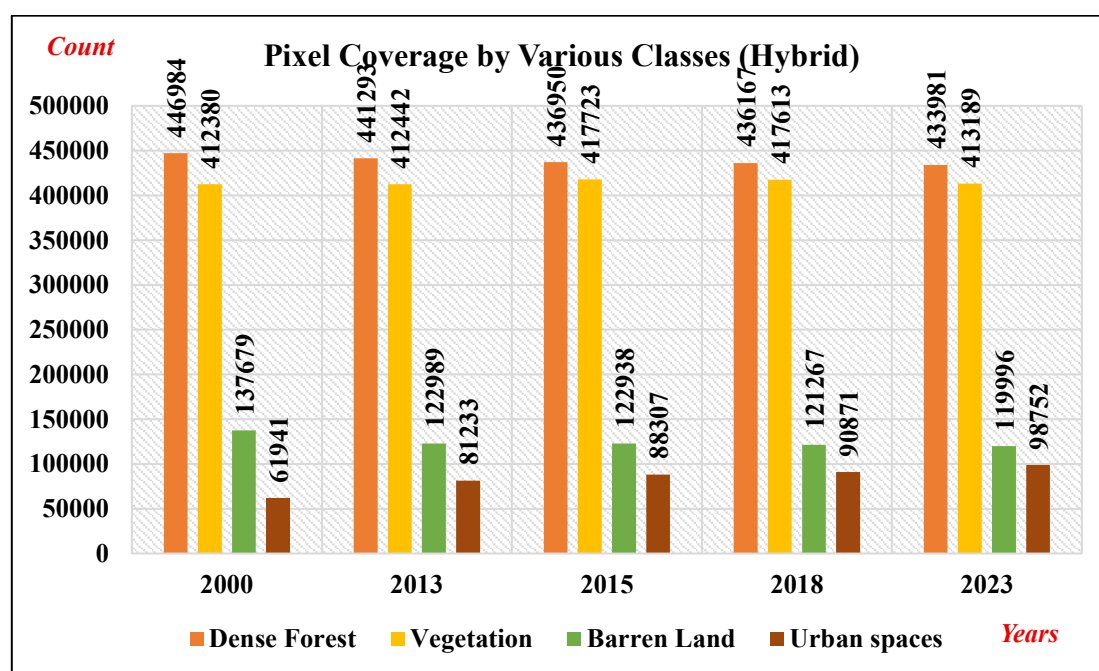


Figure 3.7: Graphical representation of pixel coverage (Hybrid)

ii) Area Coverage

Table 3.12 represents the total area covered by the identified classes (graphically represented in figure 3.8). This was estimated by multiplying the pixel coverage with resolution of the reference data.

Table 3.12: Representation of area coverage in sq km (Hybrid)

Year	Dense Forest	Vegetation	Barren Land	Urban spaces
2000	402.29	371.14	123.91	55.75
2013	397.16	371.20	110.69	73.11
2015	393.26	375.95	110.64	79.48
2018	392.55	375.85	109.14	81.78
2023	390.58	371.87	108.00	88.88

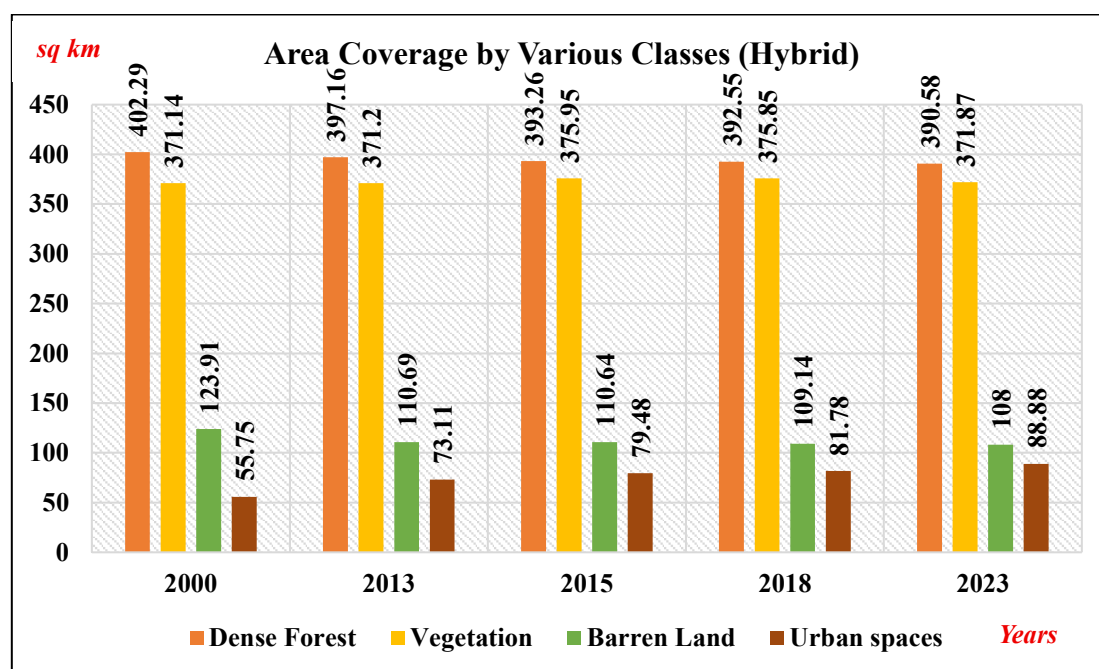


Figure 3.8: Graphical representation of area coverage in sq km (Hybrid)

3.8 Brief of the results achieved

The five Landsat images from the years 2000, 2013, 2015, 2018, and 2023 were pre-processed and classified utilizing the supervised Maximum Likelihood Classifier, the

unsupervised ISODATA classifier, and a hybrid approach that integrates both methods. The classes were categorized into four to five groups: dense forest, vegetation, barren land, urban spaces, snow and clouds. Only two images featured snow and clouds; the remainder were clear. A number of similarities in area coverage were noted in the data obtained from the maximum likelihood classifier and hybrid classifiers. The unsupervised method required an extended duration for classification owing to the substantial data size. The classified images were subsequently utilized for accuracy assessment.

3.9 Accuracy Assessment

This section provides a detailed examination of the accuracy evaluation conducted on all classed images. The images were classified using ISODATA classifier, Maximum Likelihood Classifier, and Hybrid classifier. The outcomes of all classifications can be compared subsequent to calculating the accuracy and verifying the accuracy percentage. This strategy assists in identifying the optimal classification technique for subsequent observation and analysis.

The accuracy assessment was conducted utilizing the ERDAS Imagine 14 module. Random points were chosen for classification according to distribution parameters, employing stratified sampling. A total of 400 random points were selected, ensuring a minimum of 60 points per class. The image classification for each sample point was recorded automatically. The viewer was employed to ascertain the reference class for each location. Upon entering the reference class for each sample point, Imagine was employed to generate the error matrix and compute accuracy estimates. The reference

data utilized for this evaluation was the Google Earth map, with the categories examined being Vegetation, Barren land, and Urban space.

An error matrix or a confusion matrix is a compilation of data regarding actual and expected classifications produced by a classification system. The pixel indicated in the snapshot was correlated with the matching location in the field utilizing Google Maps as the reference. The accuracy assessment findings enable users to determine the overall precision of the map as well as the precision of each class within it.

3.9.1 Calculating Error Matrix or Confusion Matrix

A popular method for expressing classification accuracy is the construction of a classification error matrix (confusion matrix or contingency table) [229]. The initial stage in preparing an error matrix is to identify ground reference sample pixels or gather samples, which serve as the basis for constructing the error matrix. The precision of the classification outcomes is assessed using an error matrix. It encompasses Overall Accuracy (OA), User's Accuracy (UA), Producer's Accuracy (PA), Commission Error (EC), Omission Error (EO), and Kappa Coefficient (KC).

i) User's Accuracy (UA)

UA is the proportion of pixels correctly classified by the classifier into a LULC class to all the pixels that are classified into a LULC class. UA for a given LULC class k is estimated as:

$$UA(k) = \frac{TP(k)}{TP(k) + FP(k)} \dots \text{equation 3}$$

Here,

- UA(k) is the Users Accuracy for a given LULC class k

- TP(k) is the representation for true positive i.e. number of pixels of LULC class k classified in LULC class k
- FP(k) is the representation for false positive i.e. number of pixels not belonging to LULC class k classified in LULC class k.

Lower value of UA indicates inability of the classifier to correctly identify pixels into a given LULC class leading to increased misinterpretation, therefore higher value of UA is desired.

ii) Producer's Accuracy (PA)

PA is the proportion of pixels correctly classified by the classifier into a LULC class to all the pixels that actually belongs to the LULC class. PA for a given LULC class k is estimated as

$$PA(k) = \frac{TP(k)}{TP(k) + FN(k)} \dots \text{equation 4}$$

Here,

- PA(k) is the Producers Accuracy for a given LULC class k
- TP(k) is the representation for true positive i.e. number of pixels of LULC class k classified in LULC class k
- FN(k) is the representation for false negative i.e. number of pixels belonging to LULC class k not classified in LULC class k

Lower value of PA indicates inability of the classifier to correctly identify pixels into a given LULC class leading to exclusions. Higher value of PA indicates increased credibility of the classifier.

iii) Error of Omission (EO)

EO is the proportion of correct pixels excluded by the classifier from a LULC class to all the pixels that actually belongs to the LULC class. EO for a given LULC class k is estimated as

$$EO(k) = \frac{FN(k)}{TP(k) + FN(k)} \dots \text{equation 5}$$

Here,

- EO(k) is the Error of Omission for a given LULC class k
- TP(k) is the representation for true positive i.e. number of pixels of LULC class k placed in LULC class k
- FN(k) is the representation for false negative i.e. number of pixels belonging to LULC class k not classified in LULC class k

Lower value of EO indicates ability the classifier to correctly identify pixels into a given LULC class.

iv) Error of Commission (EC)

EC is the proportion of wrong pixels included by the classifier into a LULC class to all the pixels that are classified into the LULC class. EC for a given LULC class k is estimated as

$$EC(k) = \frac{FP(k)}{TP(k) + FP(k)} \dots \text{equation 6}$$

Here,

- EO(k) is the Error of Omission for a given LULC class k
- TP(k) is the representation for true positive i.e. number of pixels of LULC class k placed in LULC class k

- FN(k) is the representation for false positive i.e. number of pixels not belonging to LULC class k classified in LULC class k

Lower value of EO indicates ability the classifier to correctly identify pixels into a given LULC class.

v) Kappa Coefficient (κ) (Cohen's Kappa)

It is a finite multivariate technique employed in accuracy evaluation. In the classification process, randomly assigning pixels to classes will yield a percentage of correct classifications [229]. Pixels are not allocated arbitrarily in image classification; rather, statistical methods are employed to consider the influence of random chance while assessing classification accuracy. The resultant Kappa statistic accounts for chance agreement in classification and quantifies the extent to which the classification outperforms the likelihood of randomly assigning pixels to their appropriate groups. In this research initiative Kappa Coefficient is a use to determine the agreement between a classifier and ground truth. 1, 0, and -1 indicates perfect, random, and worst agreement.

$$\kappa = \frac{P_o - P_e}{1 - P_e} \dots \text{equation 7}$$

Here,

- P_o is the observed agreement, were

$$P_o = \frac{\sum TP_i}{\text{Total number of instances}} \dots \text{equation 8}$$

- P_e is the expected agreement, were

$$P_e = \sum_i \frac{\text{Row Total}_i * \text{Column Total}_i}{\text{Total number of instances}^2} \dots \text{equation 9}$$

vi) Overall Classification Accuracy

It denotes the overall classification accuracy. It is derived by dividing the total number of accurately categorized pixels by the total number of reference pixels. This measure's limitation is the fact it does not provide information regarding the classification accuracy of particular classes. Producer and user accuracy are two often utilized metrics of class accuracy, contingent upon omission and commission accuracy, respectively.

Classification accuracy may be estimated as

$$EC(k) = \frac{TP(k) + TN(k)}{TP(k) + TN(k) + FP(k) + FN(k)} \dots \text{equation 10}$$

vii) Classification Accuracy sample collection

Minimum sample size required per category for an estimated classification accuracy of 95% with a $\pm 10\%$ error margin is shown in the table below [227].

Table 3.13: Classification Accuracy minimum sample collection (Source: [228])

Classification accuracy	Sample size
0.95	60
0.90	30
0.85	20
0.80	15
0.60	10
0.50	5

3.9.2 Accuracy Assessment Results

The aforementioned formulas were employed to compute the error matrix table. The attained results are presented below.

3.9.2.1 Error matrix table for results of unsupervised classifier (ISODATA classifier)

Table 3.14: Notations used

Term	Notation	Term	Notation
Classified Data	CD	Urban Space	US
Dense Forest	DF	Classified Totals	CT
Vegetation	V	User's Accuracy	UA
Barren land	BL	Producer's Accuracy	PA

Table 3.15: Error Matrix Year 2000 (ISODATA)						
ISODATA Classifier			Reference Data			
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	16	175	14	10	215	85%
BL	0	15	74	19	108	72%
US		15	15	47	77	62%
Reference	16	205	103	76	Overall Classification Accuracy = 74%	
Totals						
UA	-	81%	69%	61%	Overall, Kappa Statistics = .6878	

In the error matrix table 3.15, the maximum producer accuracy recorded is 85% for Vegetation, while the lowest is 62% for Urban space. The maximum user accuracy attained is 81% for Vegetation, while the lowest is 61% for Urban areas. The overall classification accuracy attained is 74%, with Kappa statistics of .6878.

Table 3.16: Error Matrix Year 2013 (ISODATA)						
ISODATA Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	15	171	17	12	215	84%
BL	0	16	72	20	108	69%
US		17	15	45	77	58%
Reference	15	204	104	77	Overall Classification Accuracy = 72%	
Totals						
UA	-	80%	67%	58%	Overall Kappa Statistics = .6698	

In the error matrix presented in Table 3.16, the highest producer accuracy documented is 84% for Vegetation, whilst the lowest is 58% for Urban space. The highest user accuracy achieved is 80% for Vegetation, and the lowest is 58% for Urban areas. The achieved total classification accuracy is 72%, accompanied by Kappa statistics of 0.6698.

Table 3.17: Error Matrix Year 2015 (ISODATA)						
ISODATA Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	10	169	20	16	215	84%
BL	0	15	73	20	108	67%
US	0	18	16	43	77	54%
Reference	10	202	109	79	Overall Classification Accuracy = 71.25%	
Totals						
UA	-	79%	68%	56%	Overall Kappa Statistics = .6613	

The highest producer accuracy documented is 84% for Vegetation in the error matrix depicted in Table 3.17, while the lowest is 54% for Urban space. Vegetation exhibits

the maximum user accuracy at 79%, while urban areas exhibit the lowest at 56%. The total classification accuracy obtained is 71.25%, and the Kappa statistics are 0.6613.

Table 3.18: Error Matrix Year 2018 (ISODATA)						
ISODATA Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	12	169	24	20	225	87%
BL	0	10	70	20	100	63%
US	0	15	18	42	75	51%
Reference	12	194	112	82	Overall Classification Accuracy = 70.25%	
Totals						
UA	-	75%	70%	56%	Overall Kappa Statistics = .6591	

In the error matrix illustrated in Table 3.18, the highest producer accuracy ever documented is 87% for Vegetation, while the lowest is 51% for Urban space. Urban areas demonstrate the lowest user accuracy at 56%, while vegetation demonstrates the highest at 75%. The Kappa statistics are 0.6591, and the total classification accuracy is 70.25%.

Table 3.19: Error Matrix Year 2023 (ISODATA)						
ISODATA Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	9	173	20	16	218	89%
BL	0	10	76	21	107	67%
US	0	11	18	46	75	55%
Reference	9	194	114	83	Overall Classification Accuracy = 73.75%	
Totals						
UA	-	79%	71%	61%	Overall Kappa Statistics = .6791	

The error matrix presented in Table 3.19 indicates that the highest recorded producer accuracy is 89% for Vegetation, whilst the lowest is 55% for Urban environment. Urban regions exhibit the lowest user accuracy at 61%, whilst vegetation displays the greatest at 79%. The Kappa statistic is 0.6791, and the overall classification accuracy is 73.75%.

3.9.2.2 Error matrix table for results of supervised classifier (Maximum Likelihood classifier)

Table 3.20: Error Matrix Year 2000 (Max. Likelihood)						
Maximum Likelihood Classifier Reference Data						
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	11	183	1	4	199	96.32%
BL	0	7	100	4	111	91.74%
US	0	0	8	82	90	91.11%
Reference Totals	11	190	109	90	Overall Classification Accuracy = 91.25%	
UA	-	91.96%	90.09%	91.11%	Overall Kappa Statistics = 0.8627	

The error matrix presented in Table 3.20 indicates that the highest recorded producer accuracy is 96.32% for Vegetation, whilst the lowest is 91.11% for Urban environment. Barren Land exhibit the lowest user accuracy at 90.09%, whilst vegetation displays the greatest at 91.96%. The Kappa statistic is 0.8627, and the overall classification accuracy is 91.25%.

Table 3.21: Error Matrix Year 2013 (Max. Likelihood)						
Maximum Likelihood Classifier Reference Data						
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	6	254	6	2	268	97.69%
BL	1	6	64	1	72	83.12%

US	0	0	7	53	60	94.64%
Reference Totals	7	260	77	56	Overall Classification Accuracy = 92.75%	
UA	-	94.78%	88.89%	88.33%	Overall Kappa Statistics = 0.8575	

Table 3.21 reveals that the maximum producer accuracy observed is 97.69% for Vegetation, whereas the lowest is 83.12% for the Barren Land. Urban space demonstrate the lowest user accuracy at 88.33%, whilst vegetation exhibits the highest at 94.78%. The Kappa statistic is 0.8575, and the overall classification accuracy is 92.75%.

Table 3.22: Error Matrix Year 2015 (Max. Likelihood)						
Maximum Likelihood Classifier Reference Data						
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	10	208	2	6	226	96.30%
BL	0	5	102	5	112	93.58%
US	0	3	5	54	62	83.08%
Reference Totals	10	216	109	65	Overall Classification Accuracy = 91.00%	
UA	-	92.04%	91.07%	87.10%	Overall Kappa Statistics = 0.8483	

The maximum producer accuracy recorded is 96.30% for Vegetation in the error matrix shown in Table 3.22, and the minimum is 83.08% for Urban space. Vegetation demonstrates the highest user accuracy at 92.04%, whereas urban areas display the lowest at 87.10%. The overall classification accuracy achieved is 91%, with Kappa statistics of 0.8483.

Table 3.23: Error Matrix Year 2018 (Max. Likelihood)						
Maximum Likelihood Classifier Reference Data						
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	8	245	1	0	254	96.84%
BL	0	5	65	4	74	90.28%
US	0	3	6	63	72	94.03%
Reference Totals	8	253	72	67	Overall Classification Accuracy = 93.25%	
UA	-	96.46%	87.84%	87.50%	Overall Kappa Statistics = 0.8738	

The highest producer accuracy documented is 96.84% for Vegetation in the error matrix presented in Table 3.23, while the lowest is 90.28% for Barren Land. Vegetation exhibits the highest user accuracy at 96.46%, while urban areas reveal the lowest at 87.50%. The attained classification accuracy is 93.25%, accompanied by Kappa statistics of 0.8738.

Table 3.24: Error Matrix Year 2023 (Max. Likelihood)						
Maximum Likelihood Classifier Reference Data						
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	10	208	2	6	226	96.30%
BL	0	5	102	5	112	93.58%
US	0	3	5	54	62	83.08%
Reference Totals	10	216	109	65	Overall Classification Accuracy = 91.00%	
UA	-	92.04%	91.07%	87.10%	Overall Kappa Statistics = 0.8483	

The maximum producer accuracy recorded is 96.30% for Vegetation in the error matrix shown in Table 3.24, and the minimum is 83.08 for urban space. Vegetation demonstrates the highest user accuracy at 92.04%, whereas urban areas have the lowest

at 87.10%. The achieved classification accuracy is 91.00%, with Kappa statistics of 0.8483.

3.9.2.3 Error matrix table for results of hybrid classifier

Table 3.25: Error Matrix Year 2000 (Hybrid)						
Hybrid Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	10	180	2	5	197	93%
BL	0	8	90	7	105	87%
US		6	12	80	98	87%
Reference Totals	10	194	104	92	Overall Classification Accuracy = 87.5%	
UA	-	91%	86%	82%	Overall Kappa Statistics = .8121	

The highest producer accuracy documented is 93% for vegetation in the error matrix presented in Table 3.25, while the lowest is 87% for urban areas and barren land. Vegetation exhibits the highest user accuracy at 91%, while urban spaces display the lowest at 82%. The attained classification accuracy is 87.5%, accompanied by Kappa statistics of 0.8121.

Table 3.26: Error Matrix Year 2013 (Hybrid)						
Hybrid Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	10	181	2	4	197	93%
BL	0	7	91	6	104	88.01%
US		6	11	82	99	89%
Reference Totals	10	194	104	92	Overall Classification Accuracy = 88.5%	

UA	-	92.02%	88%	83%	Overall Kappa Statistics = .8276
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The maximum producer accuracy recorded is 93% for vegetation in the error matrix shown in Table 3.26, whereas the minimum is 88.01% for bare land. Vegetation demonstrates the highest user accuracy at 92.02%, whereas urban areas have the lowest at 83%. The achieved classification accuracy is 88.5%, with Kappa statistics of 0.8276.

Table 3.27: Error Matrix Year 2015 (Hybrid)						
Hybrid Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	10	182	2	4	198	93%
BL	0	7	93	3	103	89%
US		6	9	84	99	92.01%
Reference Totals	10	195	104	91	Overall Classification Accuracy = 89.75%	
UA	-	92%	90%	85.02%	Overall Kappa Statistics = .8345	

The highest producer accuracy documented is 93% for vegetation in the error matrix presented in Table 3.27, while the lowest is 89% for bare land. Vegetation exhibits the highest user accuracy at 92%, while urban spaces display the lowest at 85.02%. The attained classification accuracy is 89.75%, accompanied by Kappa statistics of 0.8345.

Table 3.28: Error Matrix Year 2018 (Hybrid)						
Hybrid Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	9	180	2	4	195	95%
BL	0	5	96	5	106	91%
US		5	8	86	99	91%

Reference Totals	9	190	106	95	Overall Classification Accuracy = 90.50%
UA	-	92%	91%	87%	Overall Kappa Statistics = .8379

The maximum producer accuracy recorded is 95% for vegetation in the error matrix shown in Table 3.28, whereas the minimum is 91% for bare land and urban areas. Vegetation demonstrates the highest user accuracy at 92%, whereas urban areas have the lowest at 87%. The achieved classification accuracy is 90.50%, with Kappa statistics of 0.8379.

Table 3.29: Error Matrix Year 2023 (Hybrid)						
Hybrid Classifier		Reference Data				
CD	DF	V	BL	US	CT	PA
DF	0	0	0	0	0	-
V	9	178	2	3	192	93%
BL	0	7	94	7	108	90%
US		6	9	85	100	89%
Reference Totals	9	191	105	95	Overall Classification Accuracy = 89.25%	
UA	-	93%	87%	85%	Overall Kappa Statistics = .8307	

The highest producer accuracy documented is 93% for vegetation in the error matrix presented in Table 3.29, while the lowest is 89% for urban regions. Vegetation exhibits the highest user accuracy at 93%, while urban spaces display the lowest at 85%. The attained classification accuracy is 89.25%, accompanied by Kappa statistics of 0.8307.

The accuracy assessment has been conducted on all classified images. A total of fifteen images were assessed for accuracy. The photos were classified utilizing ISODATA classifier, maximum likelihood classifier and hybrid classifier. For each classified

image, 400 reference points were utilized for ground truthing and for the generation of an error matrix. The reference material utilized for ground truthing comprised Google Earth maps and GPS data collected from several significant locations. The accuracy assessment was conducted using ERDAS Imagine 14 software using the tool Classification Accuracy Assessment tool. The overall classification accuracy and overall Kappa statistics generated are compiled in the Table 3.30 for further comparison.

Table 3.30: Overall classification accuracy and Kappa statistics

Year	Unsupervised classification		Supervised classification		Hybrid classifier	
	Overall classification accuracy (%)	Overall Kappa statistics	Overall classification accuracy (%)	Overall Kappa statistics	Overall classification accuracy (%)	Overall Kappa statistics
2000	74	.6878	91.25	.8627	87.5	.8121
2013	72	.6698	92.75	.8575	88.5	.8276
2015	71.25	.6623	91.00	.8483	89.75	.8345
2018	70.25	.6591	93.25	.8738	90.50	.8379
2023	73.75	.6791	91.00	.8483	89.25	.8307

3.10 Conclusion

In this section of the research initiative, Maximum Likelihood, ISODATA and their combination were selected as representatives for supervised, unsupervised, and hybrid classification approaches and applied to the sample satellite images to determine its effectiveness with which it identifies various classes. User accuracy, producer accuracy, error of omission, error of commission, kappa, and overall accuracy were evaluated for determining the performance. Based on the observations, Maximum likelihood classifier was found to be the most suitable candidate. There after

the same was applied to the temporal satellite images for identifying the various classes. The results obtained have been suitably discussed and represented in Section 3.7.5.

Considering the results from the accuracy evaluation (Ref: Table 3.30), it has been noted that the maximum likelihood classifier produced the highest overall accuracy in comparison to the other two approaches. While the average overall accuracy does not determine the optimal accuracy, Tables 3.20, 3.21, 3.22, 3.23, and 3.24 present the specific classification accuracy for each class, indicating that the maximum likelihood classifier achieved the highest accuracy overall. The maximum likelihood classifier attained a best accuracy average of 93.25%, with a minimum of 91.00%. In contrast, the ISODATA classifier achieved a best accuracy average of 74%, with a minimum of 70.25%. The hybrid classifier recorded a best accuracy average of 90.50%, with a minimum of 87.5%. Correspondingly, the optimal Kappa statistics produced by the maximum likelihood classifier is .8738, the ISODATA classifier is .6878, and the Hybrid classifier is .8379, respectively.

In light of the results obtained, the decision was made to utilize the outcomes from the maximum likelihood classifier for further research and analysis of the classified images. The classified images will be subsequently compared with the demographic data. The results obtained from this chapter are utilized for further analysis in subsequent chapters.