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Mintu Jana
Research Scholar, Coastal Environmental Studies, Egra S.S.B. College, West Bengal, India

Dipak Bisai
Associate Professor, Department of Geography, Egra S.S.B. College, West Bengal, India

Corresponding Author:
Mintu Jana
Research Scholar, Coastal Environmental Studies, Egra S.S.B. College, West Bengal, India

Kappa Coefficient accuracy estimation for assessing the major components of Mudbank formation through the temporal scale (24 years) of the Subarnarekha river estuary zone, Odisha, India.

Mintu Jana and Dipak Bisai

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Abstract
Remote sensing is an important tool and technique for the best assessment of LULC map preparation and satellite image classification. This study emphasizes the classification of LULC of the adjacent lower zone area of the Subarnarekha River. To complete this study, ten such parameters have been considered, like Water-Body, Vegetation, Settlement, agricultural land area, Point Bar, Sand Bar, Sand Bank, Sand Dunes, Fishery Zone, and Mud-Bank Area at estuarine part of this river. Availability of Landsat images six specific years are sampled like 1998, 2004,2009,2014,2018 and 2022 respectively. The several factors have been consider including availability of quality Landsat imagery data through precise classification steps and users experience and expertise of the procedures. The objective of this study has been completed using the geospatial techniques like RS and GIS applications, which have compiled distinct two sections. First phase is containing Land-use and Land-cover (LULC) classification and, second phase is containing accuracy assessment of considered parameters. The Non-parametric Kappa coefficient Khat Statistic rule has applied for esteemed supervised classification with Kappa coefficient scale. The study had an overall classification accuracy of 86.75% and Kappa coefficient (K) of 0.911, 0.908, 0.719, 0.803, 0.858, and 0.886 following the considered study year. Overall accuracy through Khat Statistic reveals that vegetation, settlement, agricultural land, fishery and mud-bank are dominant parameters for the considered random samples. The revealed results are considerable and helpful for sustainable plan in future for this area.

Keywords: LULC, Accuracy Assessment, Kappa Co-efficient, RS & GIS

Introduction
Baulies (1997) [2] suggested that, the land use and land cover change dynamically due to pressure of demographic activities and related human development activities. So that, land use and land cover change definitely be the result of natural process and human interference (Turner *et al*., 1994, Tucker *et al*., 1991) [21, 22]. Moreover, the technological advancement and expending population have put increasing trend of pressure on localized scarce resources and have compiled a variety of complex land use dilemmas that effects on individually or wholly at all levels of entire society (Sommers, 1981) [18]. Application of Land use and land cover (LULC) analysis is the very important steps for analysing the geomorphological characteristics of any geographical space. In every LULC studies are very crucial and effective for the estimating of physical characteristics of any place. Considering the selected parameters, this calculation have played vital role for environment planning and management. Many researchers tried to estimate the actual position of the geomorphological characteristics through the model building techniques in recent time. The LULC study and used for the input data of model which run in present time for calculating the changing nature of physical features. Moreover, LULC is the outcome of interdisciplinary considerable parameters, such as geo-morphological, geo-biophysical, socio-economic, systems behaviours and interaction to other related things. The updated application of hybrid classification contains combines the unsupervised and supervised techniques of LULC classification in two stages. An unsupervised method is used to achieve a number of naturally cloven categories in the first stage. After the segregated of each category, the

identification of considered parameters is confirmed through the aid of proper reference image. After that the tanning data has been generated with the help of these prior natural data. However, the selected classes that are ambiguous as well as may represent more than one LULC class or category can be discarded. This step helps to frame up a far crisper training dataset as an input for the supervised category. Sader, Ahi and Liou (1995) [19] have done a comparative analysis for the accuracy of various classification approaches and have revealed that the classification through the hybrid method supersedes the unsupervised and supervised methods by using the case study of Acadian wetlands. Similarly, hybrid classification of an unsupervised and supervised classification approaches are more applicable for the classification of complex ecosystem components (Ozesmi and Bauer, 2002) [14]. The application of remote sensing track out the changes occurred in LULC where the use of multi-date images analysed. A proper monitoring process has run thoroughly when this multi date image classification run. During the analysis of multi-date imageries the differences occurring in LULC values between the acquisition dates if considered images that are mainly due to temporally various natural conditions and human actions. O.R.Abd El- Kawy et, al., 2010, [15] ensuring that the prosperous use of satellite remote sensing for LULC change detection highly depends upon adequate understanding of considered land scape features, image system methodology used in relation to the aim of study. Accuracy assessment or validation of morphological change detection is a significant gradation in the processing of remote sensing data. That assessment emphasis on the information values of the resulting data to any user. Quantitative utilization of geo-data is only possible when the quality of considered data is known. Finally overall accuracy has to be calculated as per compare with the classified pixel versus definite land cover conditions which has obtained from corresponding ground truth data. This application has leads two types of error corresponding to producers and User accuracy but all classified pixels are checked by the ground truth. So, real locational and physical changes should be prominent through this assessment (Congalton, R.G.1991, Campbell, J.B. 2007, Jensen, J.R. 2005) [7, 3, 11].

Study area

The Subarnarekha estuary is situated at the Balasore district of Odisha state and its mouth shape width is 4.10 km. The considered lower course of Subarnarekha river estuary is about 35 km long from Paschimbar (upstream) to Bichitrapur (Estuary and confluence in the Bay of Bengal) within the states of West Bengal and Odisha. The geographical extension of this area is belongs to 21°28'45.99"N to 21°39'46.22"N and longitude 87°20'30.83"E to 87°31'49.20"E respectively. The entire river basin falls under the Chottonagpur plateau rim section. The origin of this river starts from Singhbhum plateau proper zone. After all, its flow direction has confirmed through the southern direction and meets with Bay of Bengal. As per the geological consequences, Subarnarekha River is designated as super- imposed river. The estuary of the Subarnerekha is having with beautiful large delta at its mouth point. The meso-tidal coastal plain of north-western Bay of Bengal is characterized by long sandy beaches, successive rows of many dunes, intertidal wetlands, tidal mudflats, sparse mangrove zones and long sand bars. The total considered study area is 467 km^2. The study area map was prepared with the help of LANDSAT 8 OLI/TIRS satellite map. The left bank of estuary contains broad mangrove and mud-banks area with major fishery zone and right bank of the estuaries contains broad sand beaches, Casuarina plantation area, mono-cropped farmland and small agricultural practices zones. The bank of Subarnarekha estuary characterized by wide mudflats, tidal creeks, mangrove patches, sporadic spits, Chenier plain, ridges, wetlands etc. Bichitrapur mangrove forest situated within the eastern part of this estuary.

Materials and Methods

This study comprises through two separate phases. To complete this work we have considered ten geomorphological components such as water-body, vegetation, settlement, agricultural land area, point bar, sand bar, sand bank, sand dunes, fishery zone and mud-bank. On the first phase Landuse/Landcover (LULC) classification has been done thoroughly. Accuracy assessment with comparable image pixel and ground truth verification has been completed on second phase.

1). Image Pre-Processing

The Landsat 5TM, Landsat 7 ETM, Landsat 8 OLI/TIRS , Landsat 9 OLI/TIRS are used for LULC map bearing different years 1999, 2004, 2009, 2014, 2018 and 2022. These images include; TM, ETM+ and OLI/TIRS (path 139, row 45) attribute and downloaded from United States Geological (USGS) Earth Explorer (https://earthexplorer.usgs.gov/). All considered images are downloaded through the low cloud cover and each Landsat image was geo-referenced to the WGS_84 datum and Universal Transverse Mercator Zone 45 North Coordinate system.

All images pre-processing has done such as geo-referencesing, mosaic and layer stacking processed through ARC GIS 10.8. The Images has extracted, composite, editing with different considered parameters selecting for this study area which have boundary delineation form Google Earth pro.

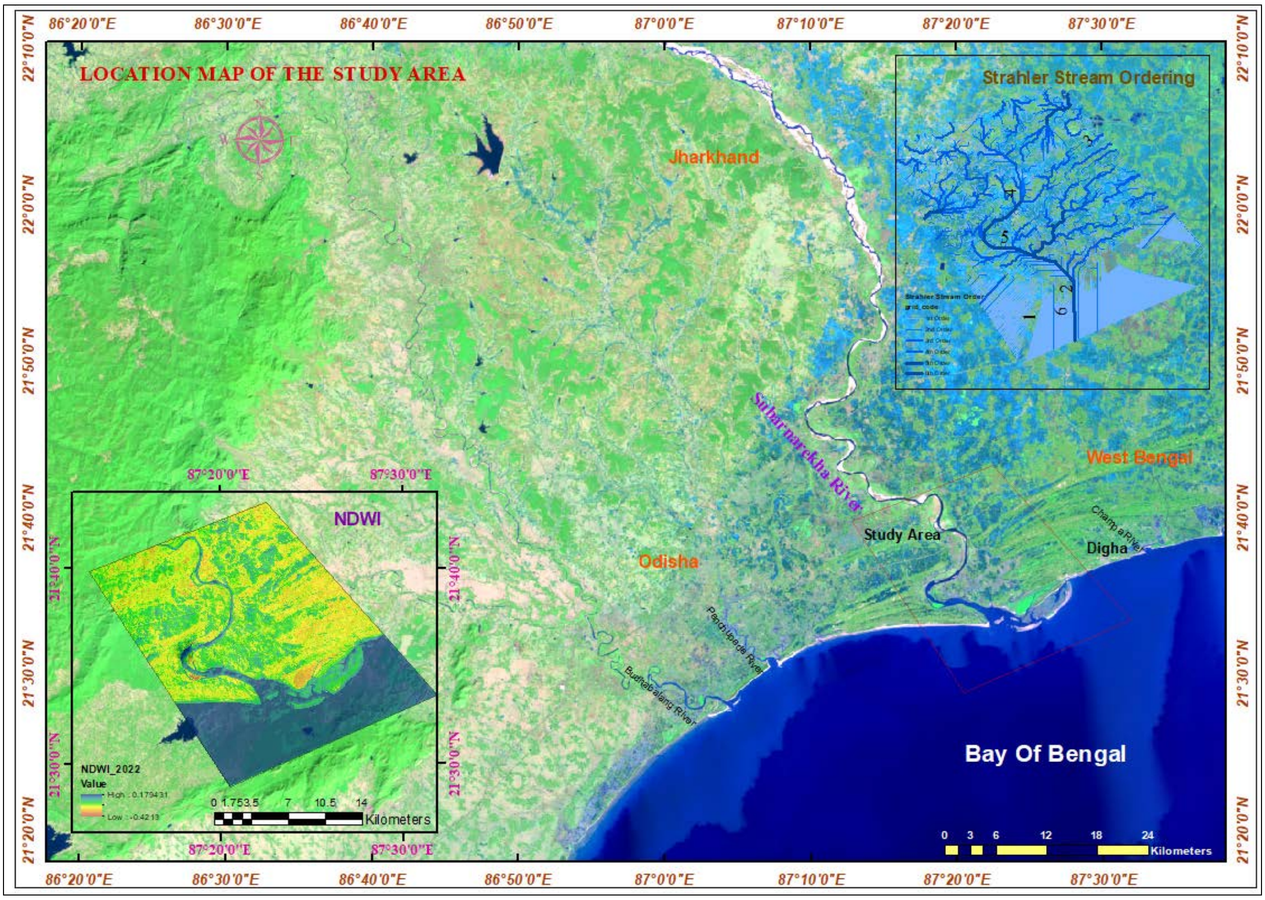

Fig 1: Location of the study area

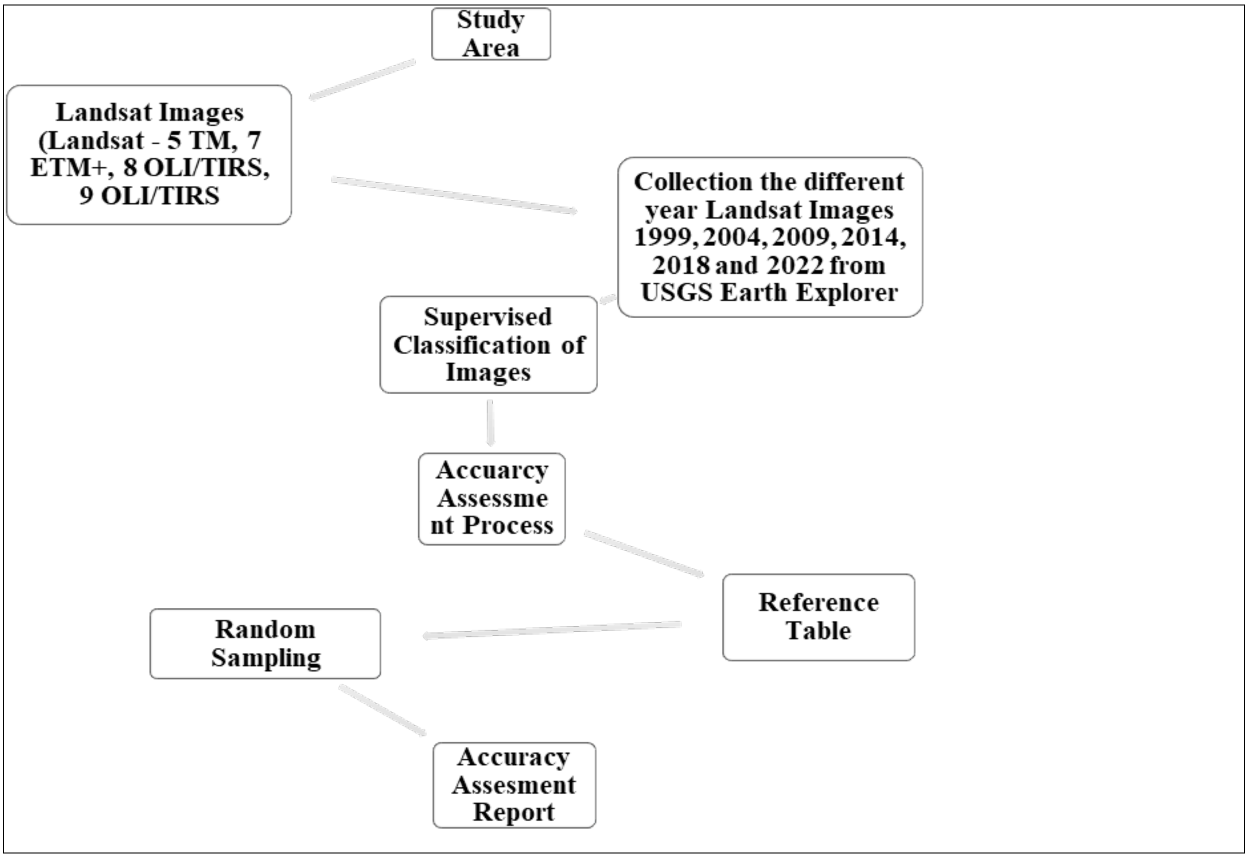

Fig 2 Flow diagramme for LULC and accuracy assessment of this study.

Table 1: Details of Landsat 8 OLI/TIS used for classification

Sl. No	Satellite	Sensor ID	WRS Path	WRS Row	Date of Acquisition	Grid cell size (m)
1	Landsat-7 ETM	LE71390451999342SGS01	139	045	1999-12-08	30
2	Landsat-5 TM	LT51390452004364BKT00	139	045	2004-12-29	
3	Landsat-5 TM	LT51390452009297KHC00	139	045	2009-10-24	
4	Landsat-8 OLI/TIRS	LC81390452014087LGN01	139	045	2014-03-28	
5	Landsat-8 OLI/TIRS	LC81390452018322LGN00	139	045	2018-11-18	
6	Landsat-9 OLI/TIRS	LC91390452022037LGN00	139	045	2022-02-06	

2). Landuse / landcover (LULC) Supervised Classification:

This study has been concentrated on supervised classification if considered images. This classification is most suitable for comparable of LULC classification through the spectral signatures of known and unknown categories (Eastman, J.R. 2003) [7]. Many researchers believe that, supervised classification when image processing is effective for quantitative analysis of remote sensing data (Richards, J. and Jia, X. 2006) [16]. The supervised classification is depending on training site data preparation along with LULC rectification, so we have executed the prior knowledge to utilize the supervised classification. As per suggestion of the renowned researchers it is necessary to collect spectral signatures from considered training sites during the execution of supervised classification which are used to "train" the classification algorithm (Chen and Stow, 2002; Jusoff *et al*., 2009) [5, 12].

1) Demarcation of training sites

After the confirmation of selected components area that will be used as training sites for each land cover class. Training sites for each considered LULC classes were collected by considering many training sites for the same class for their spatial distribution. The drawn up features are invocated Area of Interest (AOI). The identification of training sites was based on those areas evidently identified in all sources of considered images. In this work we have identified 40 training sites among all considered parameters. Based on the statistics of these considered training sites, each pixel in the classified image of LULC map was than assigned for these training sites. The LULC map was oriented based on the pixel by pixel supervised classification using Landsat 8 OLI images from six considered year such as 1998,2004,2009,2014,2018 and 2022 respectively.

2) Extraction of spectral signature: All the considered classes have been separated by selecting the spectral signatures of each class from different image sites, using the seed properties method through ERDAS imagine. The output from the seed properties were manually corrected by ARC GIS 10.8 along with 30 meter special resolution. Moreover, the image was improved and enhanced using digital image enhancement processing techniques to confirming each LULC classes before interpretation.

Comparative area coverage in percentage of considered six years extracted result is given in Table-2. In this study a supervised classification using maximum likelihood was applied based on the spectral differences between different classes. These differences were used to subdivide the LULC of the LZRB into separate classes. Prior knowledge is utilized to execute supervised classification, depending on previously collected training sites from certain areas of known LULC. In order to execute a supervised classification, it is necessary to collect spectral signatures from training areas, which are then used to "train" the classification algorithm (Chen and Stow 2002; Jusoff *et al*. 2009) [5, 12].

Several training sites were collected from different places of the study area depending on the collected ground control points, field observations and the auxiliary data. Training sites for each LULC class were collected by selecting many training sites for the same class considering their spatial distribution. Based on the statistics of these training sites, each pixel in the classified image of the LULC map was then assigned to these training sites.

The LULC map for the LZRB was generated based on the pixel-by-pixel supervised classification using Landsat 8 OLI images from September 2014. Classes have been separated by selecting the spectral signatures of each class from different image sites, using the seed properties method that is provided in ERDAS Imagine V.11 software.

The results were manually corrected by ArcGIS, using mainly OLI-8 images of 30-meter spatial resolution. The image was improved and enhanced using digital image enhancement processing techniques to highlight some LULC classes before interpretation. Image enhancement processes alter the impression of the image on the viewer.

In ERDAS software, different enhancement techniques are available: contrast enhancement, linear and nonlinear contrast stretching, density slicing, Gaussian stretching and so forth. Because the enhancement distorts digital pixel values, supervised classification was carried out on the original images.

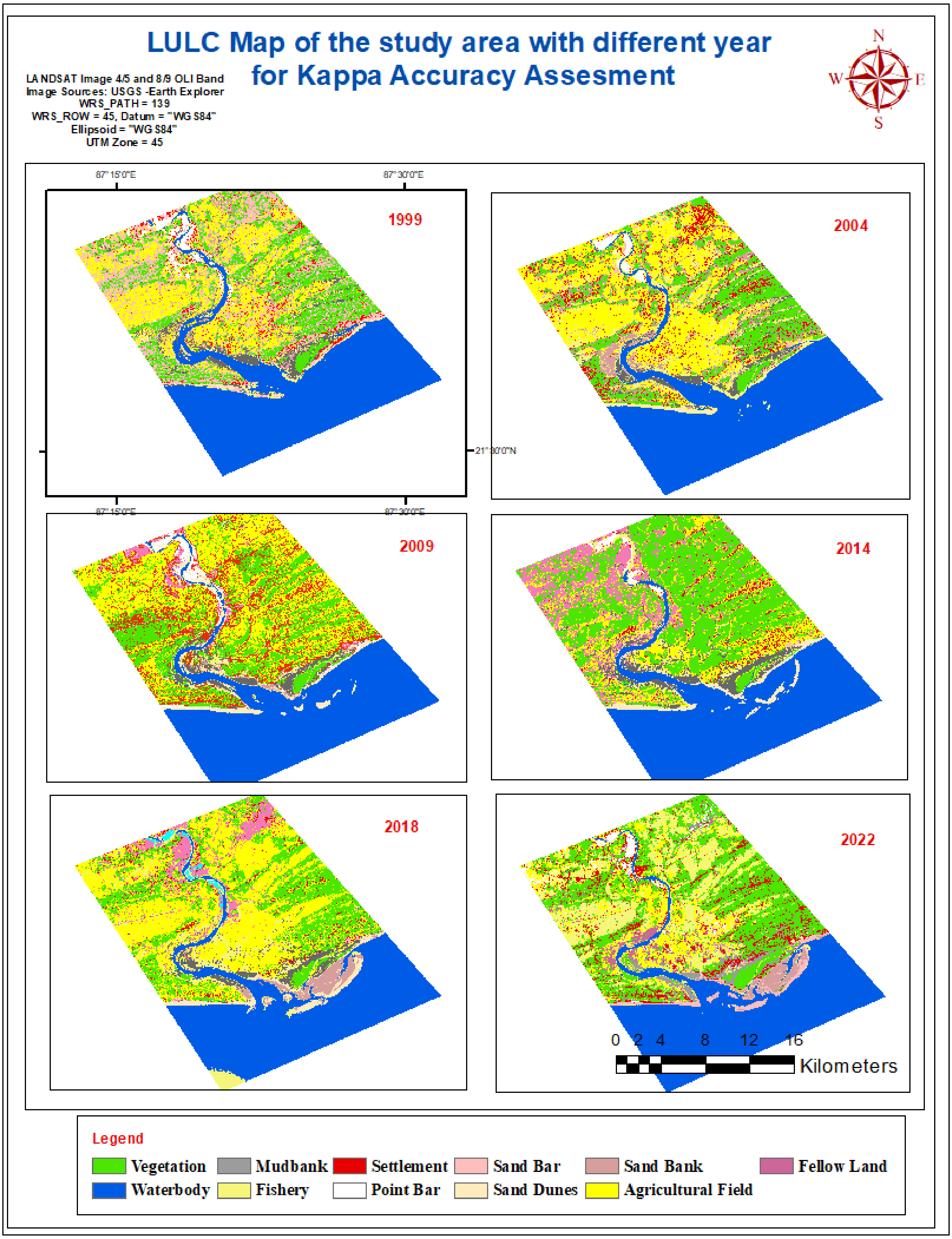

Fig 2: Land Use/Land Cover (LULC) maps of the study area for different years (1999, 2004, 2009, 2014, 2018 and 2022) used for Kappa accuracy assessment.

Table 2 Comparative results of area coverage for considered parameters in different years (% wise)

Land Parameter	Area coverage in different Year (% wise)					
	1999	2004	2009	2014	2018	2022
Water-body	34.2078	33.43527	33.11432	33.11024	29.39122	30.94201
Point Bar	2.33371	0.825586	1.807086	0.618996	0.545019	2.169203
Fishery	2.407663	9.056012	1.916983	1.059166	5.602802	14.726
Settlement	2.355886	6.031517	10.06284	10.137942	11.191143	11.118308
Sand Dunes	2.899551	0.423472	2.188231	0.17203	0.166981	0.078636
Sand Bar	15.55488	0.644431	2.697912	3.469714	2.611314	2.344144
Mud-bank	0.394805	3.02236	2.555007	4.769061	3.236717	3.351468
Sand Bank	4.092596	9.119504	0.589288	3.40734	2.359872	4.524803
Vegetation	11.652485	15.2382	20.29163	30.14108	19.056806	19.32256
Agricultural Land	24.10062	22.20365	24.77671	13.11443	25.83813	11.42287

3. Accuracy assessment

Accuracy assessment is the robust techniques in scientific field to detect the rectification of satellite data in recent time. Different scientific community have uses these data through the software application of image processing. This analysis provides faster and more powerful result in remote sensing field. The result obtained from the satellite image processing always accompanied with certain error probability during the analysis. Accuracy assessment id considered to be the metering of vicinity of the given results which values accepted as true. For estimation to evaluate of thematic maps produced from raster images the testing of accuracy of the classification and evaluating the agreement of the output man for the particular purpose is the main approach (Foody G.M, 2008) [8]. This assessment is emphasis on and comparing the classification results with known information. The minimum level of interpretation accuracy for the identification of considered LULC categories from remote sensor data should be at least 85 % in average (Wright and Morrice 1997; Anderson *et al.* 1976). [23, 1] Through the application of accuracy assessment the target value achieve as correct at 85% and typically should be standard for image classification. The attractiveness of the target values specified its accuracy as per its comparable factors (Foody, 2002) [9]. There are several factors which can directly effect on the accuracy values for indicating the characteristics of the satellite data, such as extension of the study area and considered LULC classes. Thematic maps extracted from the remote sensing data always follow a statistically intense accuracy assessment before being used for scientific investigations (Stehman and Czaplewski 1998) [17]. In this study, accuracy has been evaluated with an error matrix which is popularly known as confusion matrix. An error of confusion matrix is the most common steps used for calculating the accuracy of any thematic maps derived from multispectral imagery (Smits *et al.* 1999; Congalton and Green 2002; Liu *et al.* 2007) [20, 6, 13]. The estimated error matrix highlights the results from the comparison of references class corresponding to the LULC categories with the real results.

Confusion Matrix: The confusion matrix is considered as the standard steps to estimates the performance of collected data. This includes sensitivity and specificity, commission and omission error and positive and negative predictive power (Fielding and Bell, 1997) [10]. Computation is based on a “Confusion Matrix”, reflecting the four possible ways, as follows:

Table 3: Confusion Matrix.

	Actual Values		
Predicted value		+	-
	+	α	β
	-	ϒ	Δ

Table 4: Overall confusion Matrix.

	Actual Values		
Predicted value		+	-
	+	$\sum_{i=1}^{k} n_{ii}$	$\sum_{i=1}^{k}\sum_{j=1}^{k} n_{ij}$
	-	$\sum_{j=1}^{k}\sum_{i\neq j}^{k} n_{ij}$	$\sum_{i=1}^{k}\sum_{i\neq j}^{k} \quad \sum_{j\neq i}^{k}\sum_{j\neq i}^{k} n_{ij}$

α=Number of times a classification agreed with the observed value.

β = number of times a point was classified as X when it was observed to be X.

γ = Number of times a point was not classified as X when it was observed to be X.

α = Number of times a point was classified as X when it was observed to be not X.

as X when it was not observed to be X

Therefore,

Sensitivity = α / (α + γ), it is equivalent to Producer’s Accuracy.

Specificity = Δ / (β + Δ)

False Positive Rate (Commission Error) = β / (β + Δ) = (1 − Specificity)

False Negative Rate (Omission Error) = γ / (α + γ) = (1 − Sensitivity)

Positive Predictive Power = α / (α + β) (Equivalent to User’s Accuracy)

Negative Predictive Power = Δ / (Δ + γ)

Therefore, ten categories of error matrix have been calculated for this study (Table-3).

Now weighted average model statistics may be generated by combining those metrics over all classification as per following equations (Table-4).

Where,

$\sum_{i=1}^{k} n_{ii}$ = Sum of diagonal elements.

$\sum_{i=1}^{k} \sum_{j=1}^{k} n_{ij}$ = Sum of non-diagonal elements.

$\sum_{j=1}^{k} \sum_{i \neq j}^{k} n_{ij}$ = Sum of non-diagonal elements.

$\sum_{i=1}^{k} \sum_{i \neq j}^{k} \sum_{j \neq i}^{k} n_{ij}$ = Sum of non-row/column elements.

KAPPA co-efficient

Moreover KAPPA statistics has been applied for accuracy assessment for this study. KAPPA analysis is a discrete multivariate technique which used in accuracy assessment. KAPPA analysis yields a Khat statistic (an estimate of KAPPA) that is a measure of agreement or accuracy. The Khat statistic is computed as:

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+}\, x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+}\, x_{+i})}$$

Where:
r = Number of rows and columns in the error matrix.
N = Total number of observations.
x_{ii} = Observation in row *i* and column *i*.
x_{i+} = Marginal total of row *i*, and x_{+i} = Marginal total of column *i*.

The Kappa co-efficient equal to 1 means perfect agreement where as calculated value close to zero means the agreement is not better than would be expected by change. The categorization of Kappa statistic is widely referenced which is given in Table-5.

Table 5: Scale/Rating criteria of Kappa statistic.

Sl. No	Kappa Statistics	Strength of Agreement
1	<0.00	Poor
2	0.20	Slight
3	0.21 - 0.40	Fair
4	0.41 - 0.60	Moderate
5	0.61 - 0.80	Substantial
6	0.80 - 1.00	Almost Perfect

Result and Discussion

Following the step- wise assessment under supervised classification, the considered area has been derived such fruitful results for leading explanation. In this paper we have tried to understand the results of comparative analysis of LULC along with accuracy assessment through remote sensing application. Using the formulae furnished earlier, ten parameters were evaluated and analysed. After the allocation of each considered parameters, their area has been confirmed taking into account the pixel count in respect of total area. The considered parameters are water-body, vegetation, settlement, agricultural land, point bar, sand bar, sand bank, sand dunes, fisheries area, and mud-bank respectively. During the step-wise supervised classification, 40 training site have considered for six year-wise images such as 1998, 2004, 2009, 2014, 2018 and 2022 respectively. The aims of accuracy assessment were to quantitatively assess how effectively the pixels were sampled for the correct land-use and land-cover classes. Moreover the steps emphasis on accuracy assessment for pixel selection was on area that could be finally identified on considered land-sat high resolution image, Google Earth and Google Map respectively. The accuracy assessment cell array reference columns were computed accordingly on the best guess of each sampled reference points. Depends on the confusion matrix (error matrix), of LULC classification, the image pixel have been assigned into the ground truth. This computation helps to understand the proper results for true accuracy for both considered dataset. As per the results given in Table-6, Table-7, Table-8, Table-9, Table-10 and Table-11, for different considered years, sensitivity and specificity are exhibits almost similar results for all considered datasets. Minor some changes of numeric results for vegetation, settlement and agriculture also. Omission and commission errors are almost nil for 1998 and 2004 dataset, but there are some quite changes are found for rest considered four years.

Table 6: Category wise accuracy assessment of statistical parameters in 1998

Sl. No	Classified Data	Parameters						
		Sensitivity	Specificity	Prediction Power	Omission Error	Commission Error	UA	PA
1	Water-body	1.00	1.00	1.00	0.00	0.00	1.00	1.0
2	Vegetation	1.00	1.00	1.00	0.00	0.00	1.00	0.80
3	Settlement	1.00	0.944	1.00	0.00	0.055	0.667	1.0
4	Agricultural Land	1.00	0.967	1.00	0.00	0.033	0.91	1.0
5	Point Bar	1.00	1.00	1.00	0.00	0.00	1.0	1.0
6	Sand Bar	1.00	1.00	1.00	0.00	0.00	1.0	1.0
7	Sand Bank	0.00	1.00	1.00	0.00	0.00	0	0
8	Sand Dunes	1.00	1.00	1.00	0.00	0.00	1.0	1.0
9	Fishery	1.00	1.00	1.00	0.00	0.00	1.0	1.0
10	Mud-bank	1.00	1.00	1.00	0.00	0.00	1.0	0.80

Table 7: Category wise accuracy assessment of statistical parameters in 2004

Sl. No	Classified Data	Parameters						
		Sensitivity	Specificity	Prediction Power	Omission Error	Commission Error	UA	PA
1	Water-body	1.00	0.967	1.00	0	0.033	0.875	1.0
2	Vegetation	0.917	1.00	1.00	0.083	0.033	1.0	0.917
3	Settlement	1.00	1.00	1.00	0	0	1.0	1.0
4	Agricultural Land	1.00	0.969	1.0	0	0.031	0.889	1.0
5	Point Bar	0.714	1.00	0.943	0.286	0	1.0	0.714
6	Sand Bar	0	1.00	1.00	0	0	0	0
7	Sand Bank						0	0
8	Sand Dunes	0.50	1.00	0.974	0.50	0	0.50	1.0
9	Fishery	1.00	1.00	1.00	0	0	1.0	1.0
10	Mud-bank	1.0	1.0	1.0	0	0	1.0	1.0

Table 8: Category wise accuracy assessment of statistical parameters in 2009

Sl No	Classified Data	Parameters						
		Sensitivity	Specificity	Prediction Power	Omission Error	Commission Error	UA	PA
1	Water-body	0.583	1.00	1.00	0.417	0	1.0	0.583
2	Vegetation	1.00	1.00	1.00	0	0	1.0	1.0
3	Settlement	1.00	0.923	0.973	0	0.077	0.25	1.0
4	Agricultural Land	1.00	1.00	1.00	0	0	1.0	0.50
5	Point Bar	1.00	1.00	1.00	0	0.0811	0.40	1.0
6	Sand Bar	1.00	0.923	1.00	0.417	0.077	0.25	1.0
7	Sand Bank	0.50	1.00	0.974	0.50	0.00	1.0	0.50
8	Sand Dunes	0.666	0.973	0.973	0.333	0.27	0.667	0.667
9	Fishery	1.00	1.00	1.00	0	0	1.0	1.0
10	Mud-bank	1.00	1.00	1.00	0	0	1.0	1.0

Table 9: Category wise accuracy assessment of statistical parameters in 2014

Sl No	Classified Data	Parameters						
		Sensitivity	Specificity	Prediction Power	Omission Error	Commission Error	UA	PA
1	Water-body	0.50	1.0	0.943	0.50	0	1.0	0.50
2	Vegetation	1.00	1.00	1.00	0	0	1.0	1.0
3	Settlement	0.667	1.00	0.971	0.333	0	1.0	0.667
4	Agricultural Land	0.857	0.967	0.967	0.143	0.033	0.857	0.857
5	Point Bar	1.0	0.970	1.0	0	0.030	0.80	1.0
6	Sand Bar	1.00	1.00	1.00	0	0.028	0.50	1.0
7	Sand Bank	0	0	0	0	0	0	0
8	Sand Dunes	1.00	1.00	1.00	0	0	1.0	1.0
9	Fishery	1.00	0.971	1.00	0	0.03	0.75	1.0
10	Mud-bank	1.00	1.00	1.00	0	0	1.0	1.0

Table 10: Category wise accuracy assessment of statistical parameters in 2018

Sl No	Classified Data	Parameters						
		Sensitivity	Specificity	Prediction Power	Omission Error	Commission Error	UA	PA
1	Water body	1.0	1.0	1.0	0	0	1.0	1.0
2	Vegetation	0.857	0.939	0.969	0.143	0.06	0.75	0.857
3	Settlement	0.50	1.0	0.947	0.50	0	1.0	1.0
4	Agricultural Land	0.778	0.968	0.938	0.222	0.032	0.875	0.778
5	Point Bar	1.0	1.0	1.0	0	0	1.0	1.0
6	Sand Bar	1.0	0	1.0	0	0	1.0	1.0
7	Sand Bank	0	1.00	1.0	0	0	0	0
8	Sand Dunes	1.0	1.0	1.0	0	0	1.0	1.0
9	Fishery	1.0	0.947	1.0	0	0.0526	0.50	1.0
10	Mud-bank	1.0	1.0	1.0	0	0	1.0	1.0

Table 11: Category wise accuracy assessment of statistical parameters in 2022

Sl. No	Classified Data	Parameters						
		Sensitivity	Specificity	Prediction Power	Omission Error	Commission Error	UA	PA
1	Water-body	0.875	1.0	0.9697	0.125	0	1.0	0.875
2	Vegetation	1.00	1.00	1.00	0	0	1.0	1.00
3	Settlement	1.0	0.973	0	0	0.0270	0.75	1.00
4	Agricultural Land	0.75	0.969	0.939	0.25	0.031	0.857	0.75
5	Point Bar	1.0	1.0	1.0	0	0	1.0	1.00
6	Sand Bar	1.0	1.0	1.0	0	0	1.0	1.00
7	Sand Bank	1.0	1.0	1.0	0	0	0.50	1.00
8	Sand Dunes	1.0	0.974	1.0	0	0.026	1.0	1.00
9	Fishery						0.667	0.667
10	Mud-bank	1.0	1.0	1.0	0	0	1.00	1.00

The comparative results of User's (UA) and Producer's accuracy (PA) is shown in Table-12. The given result indicates that, the severer confusion of water-body, settlement, agricultural land and fishery land area in respect of other land cover classes. But the rest considered parameters indicates quasi change of numeric result values as their comparative assessment. Moreover, calculated User's accuracy reflects the reliability of the classification's where actual utility in the real field. The results of overall accuracy, Kappa co-efficient accuracy and their percentage are given in Table-13. The results from accuracy assessment have shown an overall accuracy obtained from the random sampling process for different years images are 93 % (1999), 92.5 % (2004), 75 % (2009), 82.5 % (2014), 87.5 % (2018) and 90 % (2022) respectively. The commission error reflects the points which are included in comparable categories while they really do not belong to considered categories. As per result shown, the commission errors are highest for vegetation, settlement, agriculture and mud-bank categories. On the other hand, omission errors reflects the numbers of points which are not included in the considered categories while they really belongs to the categories.

Table 12: Category Wise User's and producer's accuracy for considered Parameters

Classification Data	1998		2004		2009		2014		2018		2022	
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA
Water-body	1.00	1.00	0.875	1.00	1.00	0.583	1.00	0.666	1.00	1.00	1.00	0.875
Vegetation	1.00	0.80	1.00	0.917	1.00	1.00	1.00	1.00	0.75	0.857	1.00	1.00
Settlement	0.666	1.00	1.00	1.00	0.25	1.00	1.00	0.666	1.00	1.00	0.75	1.00
Agricultural Land	0.909	1.00	0.889	1.00	1.00	0.50	0.857	0.857	0.875	0.777	0.857	0.75
Point Bar	1.00	1.00	1.00	0.714	0.40	1.00	0.80	1.00	1.00	1.00	1.00	1.00
Sand Bar	1.00	1.00	0	0	0.25	1.00	0.50	1.00	1.00	1.00	1.00	1.00
Sand Bank	0.00	0.00	0	0	1.00	0.50	0.00	0.00	0.00	0.00	0.50	1.00
Sand Dunes	1.00	1.00	0.50	1.00	0.666	0.666	1.00	1.00	1.00	1.00	1.00	1.00
Fishery	1.00	1.00	1.00	1.00	1.00	1.00	0.75	1.00	0.50	1.00	0.666	0.666
Mud-bank	1.00	0.80	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 13: Kappa Co-efficient accuracy assessment result for six considered years

Sl. No	Year	Overall Accuracy	Kappa Co-efficient Accuracy Result	Kappa Co-efficient Accuracy result (%)	Result
1	1999	93 %	0.911	91%	Almost Perfect
2	2004	92.5 %	0.908	90%	Almost Perfect
3	2009	75 %	0.719	72%	Substantial
4	2014	82.5 %	0.803	80%	Almost Perfect
5	2018	87.5 %	0.858	86%	Almost Perfect
6	2022	90 %	0.886	89%	Almost Perfect

Table 14: Overall Weighted Average of Statistical Parameter of All Year

Parameter Type	1998	2004	2009	2014	2018	2022
Overall Weighted Average Sensitivity	0.949	0.902	0.811	0.892	0.875	0.878
Overall Weighted Average Specificity	0.860	0.994	0.972	0.988	0.887	0.989
Overall Weighted Average Omission Error	0.0526	0.09756	0.1892	0.108	0.125	0.122
Overall Weighted Average Commission Error	0.0082	0.0057	0.028	0.012	0.0125	0.0084

Conclusion

Image classification is a robust technical method for Land-use and land cover analysis using satellite images. Many researchers widely adopted this method during last recent decades for analysing the reliability of ground truth with the help of corresponding images. This study emphasis on adjacent river bank land use and land cover classification at lower part of Subarnarekha River. LULC maps production at considered kappa co-efficient scale for different yearly images have been completed in this study. Advancement of supervised classification through pixel to pixel rectification has revealed the accuracy results for considered parameters in different years. After the supervised classification applying non-parametric rules, the images were classified into six categorical classes as per their Kappa co-efficient accuracy magnitude (Table-13). The overall weighted average value also estimated for the concluding remark which given in Table-14. The result indicates less amount of error in respect of User's accuracy as well as Producer's accuracy and some dominant considered components are vegetation, settlement, agriculture, fishery and mud-bank coverage. The considered kappa coefficient is worth techniques as substantial and hence the classified images to be competent for further study.

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