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Analysis of Changes in Agricultural Land Area in Central Lombok Regency Using Google Earth Engine

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ABSTRACT

Agricultural land plays a vital role in supporting food security and the regional economy; however, rapid development often leads to land-use conversion. This study aims to analyze changes in agricultural land in Central Lombok Regency over the past ten years (2014–2023) using the Google Earth Engine (GEE) platform. The research utilized Landsat satellite imagery to classify land cover types and identify agricultural areas through supervised classification and change detection techniques. The analysis results show a significant decline in agricultural land area, from 29% in 2014 to 26% in 2023. This decrease indicates a conversion of agricultural land to other more economically profitable uses, such as infrastructure development and plantation expansion. The accuracy assessment yielded an overall accuracy of 99%, which is categorized as *very good*, demonstrating the reliability of the model in mapping land-use changes. The findings of this study are expected to provide useful insights for policymakers in promoting sustainable land-use planning and mitigating the negative impacts of land conversion on the agricultural sector in Central Lombok Regency.

Keywords : Google Earth Engine, Kappa Accuracy, Agriculture, Overall Accuracy

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1. Introduction

Central Lombok Regency is one of the district in the province of West Nusa Tenggara which is known as a farm granary with its fertile land so that support various commodity featured. As The district that occupies position second in agricultural area matters the largest in NTB, Central Lombok has agricultural area amounting to 52 thousand hectares . Central Lombok Regency has great potential to sector agriculture. However , there are transfer function land non-agricultural like sector tourist or land settlements, threatening sustainability land productive. Currently, Central Lombok Regency is selected become area economy creative (KEK) which is currently prioritize development around circuit Mandalika. Transformation This reflect dilemma between maintain potential agrarian or support growth tourist as well as urbanization . Although so , the challenge this also opens opportunity For apply innovation agriculture sustainable for productivity still awake in the middle development rapid development of the region. Central

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Lombok is now become symbol changes that demand balance between tradition agrarian and modernization (Walidaroyani & Kadir, 2023).

Change of function land fertile agriculture become a development area for hotels, restaurants and housing often happen For support need sector tourism and growth population. Condition This threaten sustainability land agriculture productive, which becomes source main eye livelihood public local. If not controlled, reduction land agriculture. It can lower resilience food local and result in the disappearance inheritance agricultural (Yusradi et all, 2022). For overcome problem this, is required policy protection land agriculture sustainable development (LP2B), strict spatial planning supervision , and synergy between development economy creative and protective sector agriculture so that both can walk balanced . In addition to the threat transfer function land, other problems faced sector agriculture in Central Lombok is low access farmer to modern technology and market information. Many farmers Still use method less traditional efficient , so that productivity land not optimal, plus Again with difficulty sell results harvest in a way direct Because chain Long distribution (Fariz & Sultan, 2021). For overcome problem this , the government and other parties related need give training technology modern agriculture , providing subsidy or help tools agriculture , as well as to form cooperative farmer For strengthen position bargain and make it easy access direct to the market or consumers . With solution this, it is expected sector agriculture can Keep going survive and thrive although face various challenges (Faisal et all, 2023). With existence study about analysis change land agriculture in Central Lombok using Google Earth Engine (GEE) which implements Random Forest algorithm, can aiming For know How change the extent of agricultural areas that occur , so that can become base taking policy (Dewi & Rudiarto, 2013).

The research problem addressed in this study is the lack of detailed, long-term spatial information on agricultural land conversion in Central Lombok Regency, which hampers efforts to plan and implement sustainable land-use management. Therefore, the purpose of this study is to analyze the spatial and temporal changes in agricultural land over the last ten years (2014–2023) using Google Earth Engine (GEE). By employing satellite imagery and supervised classification techniques, this research seeks to quantify the extent of agricultural land conversion and identify patterns of change that can inform policymakers in developing sustainable agricultural and land-use strategies for Central Lombok Regency.

2. Research methods

2.1 Data collection

Activity study implemented in Central Lombok Regency, NTB Province during the period 10 years time final namely 2014 - 2023. In general geographical Central Lombok Regency is located between 116° 10' – 116° 30' East Longitude and 82° 7' – 8° 30' South Latitude. Central Lombok Regency borders on the north with Mountain Rinjani , to the south with the Indian Ocean, to the west with West Lombok Regency , to the east with East Lombok Regency. The tools used in study This is the GEE platform (https://code.earthengine.google.com/). Data used in research This in the form of Landsat 8 C02 surface reflectance imagery with resolution spatial 30 meters per pixel. Point sample field includes (1) Classification class built up land represented with color red, (2) Classification class of water body represented with color blue, (3) Classification class agriculture represented with color yellow, (4) Classification class plantation represented with color orange, (5) Classification class open land represented with color gray.

2.2 Data Analysis Techniques

2.2.1. Preprocessing Data

Masking clouds on Landsat imagery using Quality Assurance (QA) information and data clipping based on Area of Interest (AOI). Cloud masking aiming For remove pixels affected by clouds or shadow cloud, because can bother spectral analysis (Fuady & Jauhary, 2019). AOI is defined as an area that becomes focus research , in matter This Central Lombok Regency. AOI was created with take administrative area features from collection geographic (Novianti et all, 2024). After the AOI is determined, the Landsat image is cropped in accordance with the boundaries of Central Lombok. After the cloud masking and AOI clipping process, only free pixels clouds and is within the boundaries of Central Lombok Regency which are maintained (Fariz et all, 2021). Script for know cloud masking percentage can seen below This.

```
// Defines the cloud mask as binary image
var cloudMask = landsat2018.map(function(image) {
var qa = image.select ('QA_PIXEL');
return qa.bitwiseAnd (1 << 3). neq (0).rename('cloud'); // 1 = cloud , 0 = no There is cloud
});
// Counting the pixel
var cloudPixelCount = cloudMask.map(function(image) {
  return image.reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: LombokTengah.geometry(),
    scale: 30,
    maxPixels: 1e13
  }).get('cloud');
}).reduce(ee.Reducer.sum());
// Menghitung total piksel dalam AOI
var totalPixelCount = cloudMask.map(function(image) {
  return ee.Image.constant(1).reduceRegion({
    reducer: ee.Reducer.count(),
    geometry: LombokTengah.geometry(),
    scale: 30,
    maxPixels: 1e13
  }).get('constant');
}).reduce(ee.Reducer.sum());
// Count cloud masking percentage
var cloudPercentage = ee.Number(cloudPixelCount).divide(ee.Number(totalPixelCount)).multiply(100);
print(' Amount Cloud Pixels :', cloudPixelCount );
print(' Total Pixel Count :', totalPixelCount );
print(' Cloud Masking Percentage :', cloudPercentage );
```

2.2.2. Training Data Creation

Study This use population sample of 4374 with sample Class classification 1 : 870, Class classification 2 : 873, Class classification 3 : 874, Class classification 4 : 879, and Class classification 5 : 878. Sampling area based on dot, dot, dot sample with a buffer of 500 m for define class land containing 28 pixels in each direction .

2.2.3. Classification

Random Forest is algorithm very strong classification in handle diverse and large data like image satellite (Lapian et all, 2023). Landsat 8 imagery with reflectance data clean and comprehensive surface give enough features for *Random Forest* For building an accurate classification model . In this research this , is used branch tree decision as many as 25. Total 25 trees decision in Random Forest often chosen as point a good start For experiment , because can give balance between accuracy and efficiency computing . This number can represent data with good , but No always optimal for every case . Usage Random Forest algorithm works For train the classification model on the relevant spectral bands (SR_B1 to SR_B7) (Nawangwulan , 2013). In the context of image Landsat satellites , every picture consists of from several spectral bands , which are representation from reflection light in various long waves . Each band has different information and different relevance in detect feature certain (Novianti , 2021) on the surface earth with information as following :

SR_B1 : Reflect reflection light blue . Useful For detect elements like water and some vegetation
SR_B2 : Contains information about vegetation , forests , and plants .
SR_B3 : Detect vegetation , but also more sensitive to other elements such as land woke up .
SR_B4 : Identify vegetation , because plant absorb Lots light red and reflective Lots light infrared near .
SR_B5 : Detect humidity land , water, and vegetation .
SR_B6 : Detect humidity soil and vegetation as well as variation temperature surface .
SR_B7 : Detecting elements specific in soil and vegetation .

Script used in the research with data filters in 2018 , presented below This

```
// Case Study: Central Lombok, West Nusa Tenggara ( 2018 Data )
// Defines the Area of Interest (AOI) for Central Lombok Regency
var Central Lombok = ee.FeatureCollection ("FAO/GAUL_SIMPLIFIED_500m/2015/level2")
.filter( ee.Filter.eq ('ADM2_NAME', 'Central Lombok'));
print('AOI:', Central Lombok );
// Function for masking clouds on collections Landsat imagery
var maskLS = function(image) {
var qa = image.select ('QA_PIXEL'); // Use QA_PIXEL for C02 dataset
var mask = qa.bitwiseAnd (1 << 3).eq(0); // Cloud masking for Landsat C02
return image.updateMask (mask);
};
// Use Landsat C02 surface reflectance collection for 2018
var landsat2018 = ee.ImageCollection ('LANDSAT/LC08/C02/T1_L2')
. filterDate ('2018-01-01', '2018-12-31') // Change range time to 2018
.map( maskLS )
. filterBounds ( Central Lombok )
.median()
.clip( Central Lombok );

// Define AOI class for land awake and kind other land as training data
var aoi = ee.FeatureCollection ([
  ee.Feature ( ee.Geometry.Point ([116.3, -8.65]).buffer(500), {'lc': 1}), // Class 1: Built-up land
  ee.Feature(ee.Geometry.Point([116.4, -8.65]).buffer(500), {'lc': 2}),  // Kelas 2: Badan air
  ee.Feature(ee.Geometry.Point([116.3, -8.7]).buffer(500), {'lc': 3}),   // Kelas 3: Pertanian
  ee.Feature(ee.Geometry.Point([116.4, -8.7]).buffer(500), {'lc': 4}),   // Kelas 4: Perkebunan
  ee.Feature ( ee.Geometry.Point ([116.35, -8.68]).buffer(500), {'lc': 5}), // Class 5: Open Land]);
print(' AOI Class :', aoi );
// Defines the band for classification
var bands = ['SR_B1', 'SR_B2', 'SR_B3', 'SR_B4', 'SR_B5', 'SR_B6', 'SR_B7'];
Sampling area for training data in 2018
var training = landsat2018.select(bands).sampleRegions({
  collection: aoi,
  properties: ['lc'],
  scale: 30
});
print('Data Pelatihan:', training);
// Melatih classifier untuk tahun 2018
var classifier = ee.Classifier.smileRandomForest(25).train({
  features: training,
  classProperty: 'lc',
  inputProperties: bands
});
// Classify image For 2018
var classified2018 = landsat2018.select(bands).classify(classifier);
Map.addLayer (classified2018, {
min: 1,
```

```
max: 6,
palette: [
'FF0000', // Class 1: Built-up land - Red
'008000', // Class 2: Water body - Blue
'0000FF', // Class 3: Agriculture - Yellow
'FFFF00', // Class 4: Plantation - Orange
'FFA500', // Class 5: Open Land - Grey ]
}, ' 2018 Classification ');
// Evaluation accuracy with random data separation
var withRandom = training.randomColumn ();
var split = 0.7;
var trainingPartition = withRandom.filter(ee.Filter.lt('random', split));
var testingPartition = withRandom.filter(ee.Filter.gte('random', split));
print('Training Partition:', trainingPartition);
print('Testing Partition:', testingPartition);
// Melatih classifier pada training partition
var trainedClassifier = ee.Classifier.smileRandomForest(25).train({
  features: trainingPartition,
  classProperty: 'lc',
  inputProperties: bands
});
// Menguji classifier pada testing partition
var test = testingPartition.classify(trainedClassifier);
var confMatrix = test.errorMatrix('lc', 'classification');
print('Confusion Matrix:', confMatrix);
print('Overall Accuracy:', confMatrix.accuracy());
print('Kappa:', confMatrix.kappa ());
// Count area per class with reduceRegions
var areaImage = ee.Image.pixelArea (). addBands (classified2018);
var areas = areaImage.reduceRegions ({
collection: Central Lombok ,
reducer: ee.Reducer.sum ().group({
    groupField : 1,
    groupName : 'class'
}),
scale: 30,
  tileScale : 2
});
// Convert wide to km² and calculate percentage
var areaResults = areas.map (function(feature) {
var groups = ee.List ( feature.get ('groups'));
  var totalArea = ee.Number(groups.map(function(f) {
   return ee.Number(ee.Dictionary(f).get('sum'));
  }).reduce(ee.Reducer.sum())).divide(1e6);
  var classAreas = groups.map(function(f) {
    var classNumber = ee.Dictionary(f).get('class');
    var areaKm2 = ee.Number(ee.Dictionary(f).get('sum')).divide(1e6);
    var percentage = areaKm2.divide(totalArea).multiply(100);
    return ee.Feature(null, {
     'Class': classNumber,
     'Area_km2': areaKm2,
     'Percentage': percentage
    });
  });
  return ee.FeatureCollection(classAreas);
}).flatten();
print('Luas dan persentase tiap kelas:', areaResults);
// Count amount sample per class
var numberofSamplesPerClass = training.reduceColumns ({
reducer: ee.Reducer.frequencyHistogram (),
selectors: ['lc']
}).get('histogram');
print(' Amount samples per class :', numberofSamplesPerClass );
// Exporting results area and percentage each class to Google Drive as a CSV file
Export.table.toDrive ({
collection: areaResults ,
description: 'Area_and_Percentage_of_Central_Lombok_Class_2018',
  fileFormat : 'CSV'
});
// Exporting results classification to Google Drive
Export.image.toDrive ({
image: classified2018,
description: 'LombokCentral_Classification_2018',
scale: 30,
```

```
region: Central Lombok.geometry ().bounds(),
   maxPixels : 1e13
});
```

2.2.4. Accuracy Evaluation

Sharing training data become training (70%) and testing (30%) partitions . The model is trained use training section , and then tested in the testing section (Novrianti et all, 2023). Furthermore evaluation accuracy done with measure matrix confusion matrix, accuracy overall , and kappa value (Putri et all, 2023).

Table 1. Confusion Matrix

Usage / Coverage Yield land Interpretation		Use	Land	References		Amount
	P_{i+}	P_{i+}			P_{r+}	
P_{+i}	Xii					X_{i+}
P_{+i}		Xii				X_{i+}
…			Xii			X_{i+}
…				Xii		X_{i+}
P_{+r}					Xii	X_{i+}
Amount	X_{i+}	X_{i+}	X_{i+}	X_{i+}	Xii	N

Overall Value *Accuracy* can counted use formula below This :

$$OA = \frac{\sum X_{ii}}{N} \times 100 \quad (2.1)$$

Kappa *Accuracy Value* can counted use formula below This :

$$P_o = \frac{X_{ii}}{N} \quad (2.2)$$

$$P_e = \frac{\sum(X_{i+} \times X_{+i})}{N^2} \quad (2.3)$$

$$K = \frac{P_o - P_e}{1 - P_e} \quad (2.4)$$

where,

X_{i+} : Total rows
X_{+i} : Total columns
X_{ii} : Number of Diagonals
P_o : Proportion of observation error
P_e : Proportion of random error
K : Kappa *accuracy*
OA : Overall *accuracy*
N : Total sample
P_{+i} : Type of land use/land cover resulting from interpretation
P_{i+} : Type of land use/land cover resulting from validation

Table 2. Accuracy Evaluation Value Categories

Category	Overall Accuracy	Kappa Accuracy
Very bad	≤ 0	$\leq 50\%$
Bad	$0.01 - 0.20$	$51\% - 60\%$
Enough	$0.21 - 0.40$	$61\% - 70\%$
Currently	$0.41 - 0.60$	$71\% - 80\%$
Good	$0.61 - 0.80$	$81\% - 90\%$
Very good	$0.81 - 1.00$	$> 90\%$

2.2.5. Area Calculation

Use method *reduceRegions* For count wide each class in km^2 units and their percentages to the total area (Rakuasa , 2022)..

2.2.6. Final Results & Data Export

Classification results in the form of area of each class land in $km^2$and its percentage.

2.3 Research Procedures

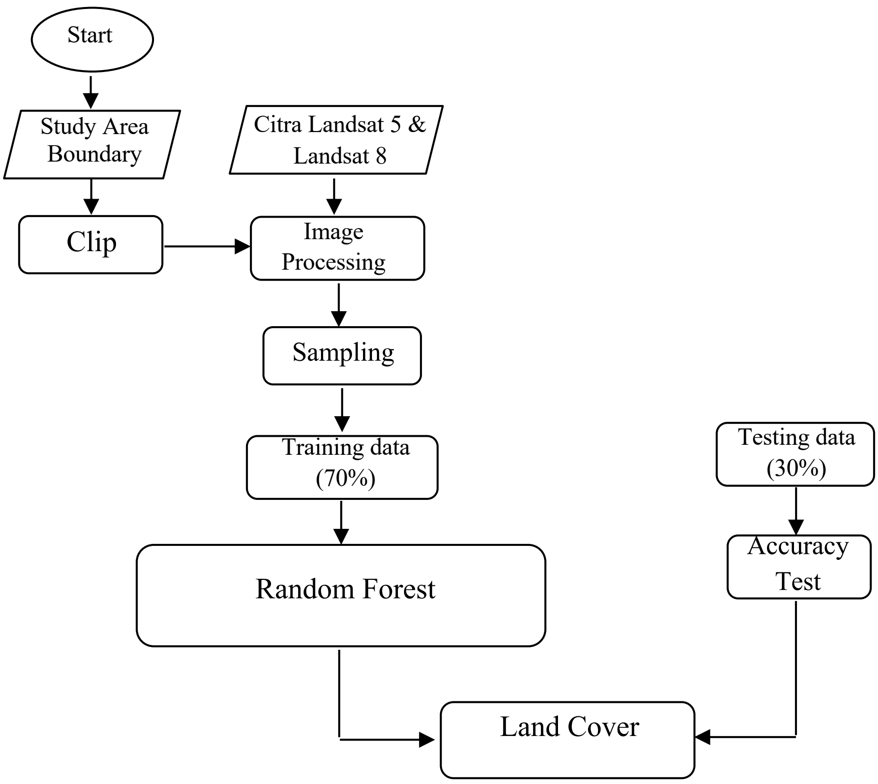

Figure 1. flowchart research

3. Results and Discussion

3.1 Data Acquisition

The data obtained is data for the Central Lombok district area with a geographical map which can be seen in Figure 2.

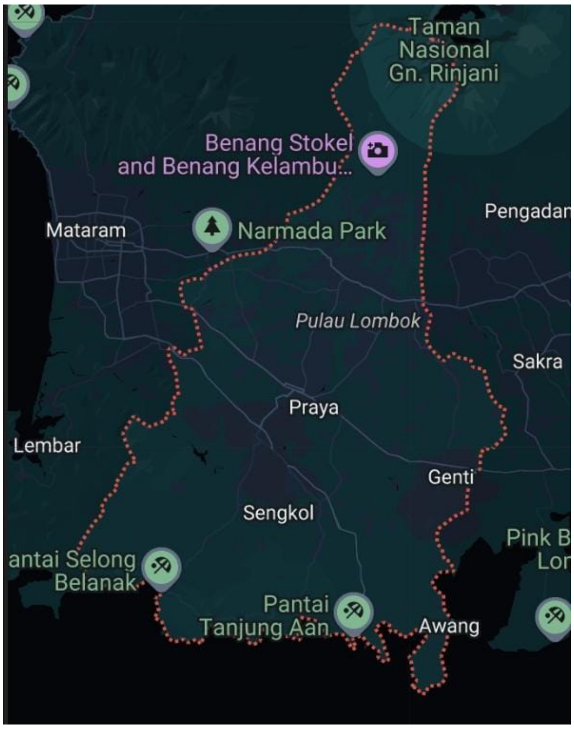

Figure 2. map of Central Lombok Regency

3.2 Land Area Classification Class

Table 3 Land Changes in Central Lombok Regency (km2)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Built up land	384	261	261	310	228	170	138	130	189	119
Water Body	136	152	152	200	129	107	117	129	130	147
Agriculture	344	334	334	310	357	334	301	310	292	304
Plantation	112	209	209	192	230	199	2205	170	158	180
Open Land	225	245	245	188	255	159	230	236	227	254

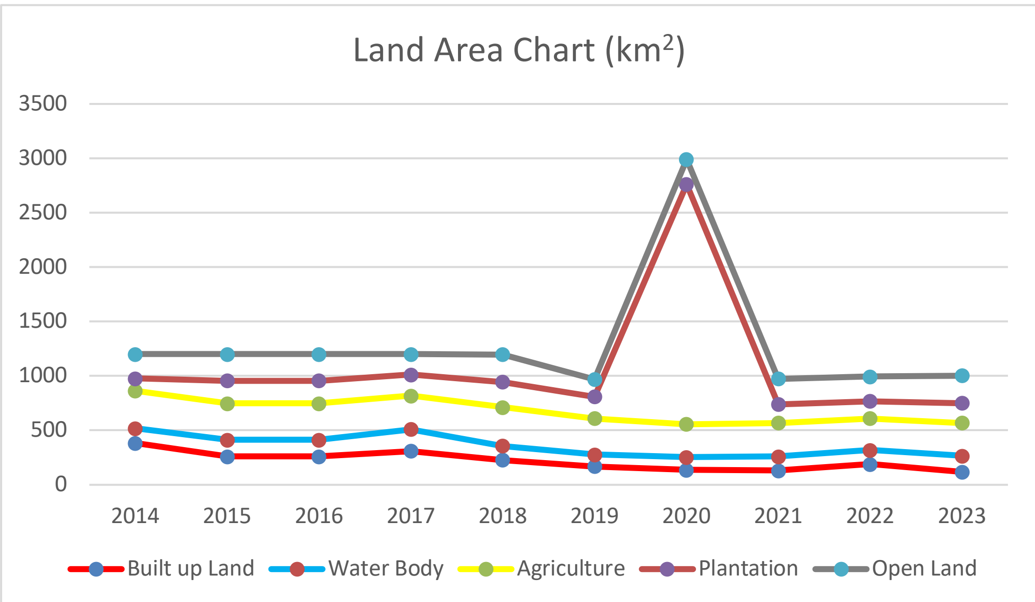

Figure 3. Graph of Land Change in Central Lombok Regency (km ^{2})

3.3 Class Classification Percentage

Table 4 Percentage of Land in Central Lombok Regency (%)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Built-up Land	32	32	22	25.77	19	17.5	14	13.3	19	13.1
Water Body	11	9	13	16,87	11	11	11,8	13,3	13,1	13,1
Agriculture	29	29	28	25,77	30	34.5	30,4	31.8	29,3	26,3
Plantation	9	18	17	15,8	19	20,6	20,7	17,4	15,4	19,2
Open Land	19	12	20	15.8	21	16.4	23.27	24.2	22.8	28.3

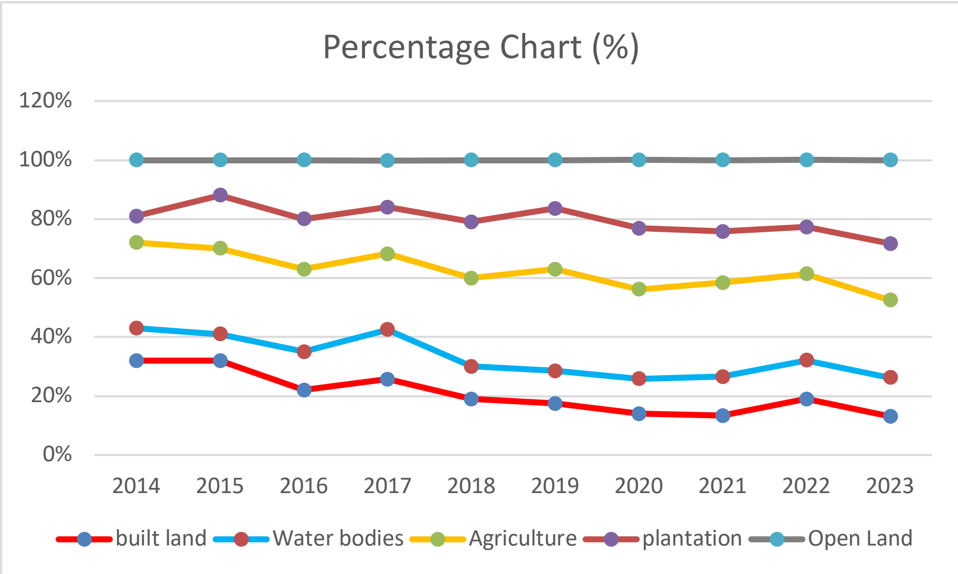

Figure 4 graph of land percentage in Central Lombok Regency (%)

3.4 Comparison of Area and Percentage of Land in 2014 to 2023

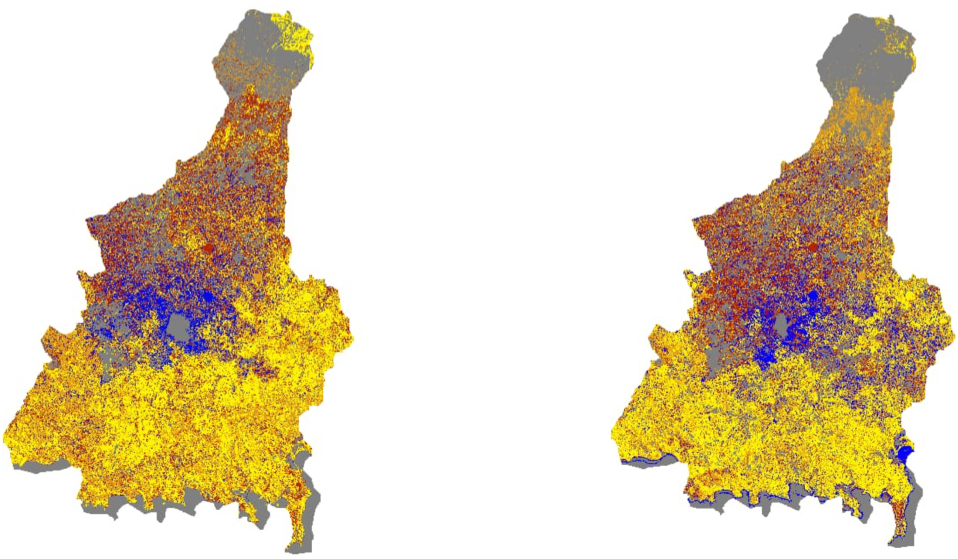

Figure 5 GEE Results of Land Area for Each Classification in 2014 & 2023

Analysis results show of 971.57 pixels beginning . That is means that amount detected pixels as cloud masking in the analyzed area . Percentage from the cloud masking obtained 0.0023% which gives information that just a small part from the analyzed area closed cloud . This also shows that almost the entire area No closed cloud or image data used own A little disturbance from cloud , which allows For more analysis clear and accurate .

Table 5 Comparison of Land in Central Lombok Regency

Classification	Land Area 2014 (km^2)	(%)	Land Area 2023 (km^2)	(%)	Total Area Change (km^2)	Total Change (%)	Caption
Built-up Land	383.620364	32	154.0696017	13	229.5507623	19	Down
Water Body	136.3974327	11	156.0421666	13	19.6447339	2	Go on
Agriculture	343.5170415	29	317.5947323	27	25.9223092	2	Down
Plantation	111.7765888	9	230.7868381	19	119.0102493	10	Go on
Open Land	224.941123	19	341.7592113	28	116.8180883	9	Go on

Analysis results show use Land in Central Lombok Regency is dominated by agricultural land vegetation that includes land plantation and agriculture Then followed by the use of land open, land built, and water bodies. In Table 4 it can be seen that percentage use land agriculture experience increase and decrease in each year. When it happened increase wide land agriculture in the Central Lombok area , this the in line with government programs Central Lombok area, namely Planting Area Expansion (PAT). This program aiming For increase planting area rice, especially on land accessible by the system irrigation pumping . However , if happen decline wide land agriculture in Central Lombok, things the can caused by several factors. Based on results research obtained, occurred increase land open later will put into operation For non-agricultural land. Plus Again moment This, Central Lombok is prioritize sector economy and tourism especially around Circuit Mandalika. In 10 years Lastly, land agriculture show trend decrease from 29% in 2014 to 26.3% in 2023. Built -up land also experienced decline from 32% in 2014 to 13.1 % in 2023. Different with the area of the water body experiencing increase from 11% in 2014 to 13.1 % in 2023. Then , the land vegetation in the form of land plantations also experienced improvement from 9% in 2014 to 19.2% in 2023. And finally , land woke up in Central Lombok experiencing improvement from 19% in 2014 to 28.3% in 2023.

3.5 Accuracy Evaluation Value

Based on Table 1 in this study, manual calculations on 2014 data obtained the following confusion matrix.

Table 5 Comparison of Land Areas in Central Lombok Regency

Prediction / Reference	Built-up Land	Water Body	Agriculture	Plantation	Open Land	Amount (Pred)
Built-up Land	380	1	1	1	1	384
Water Body	1	135	0	0	0	136
Agriculture	1	0	341	1	1	344
Plantation	0	0	1	111	0	112
Open Land	1	1	1	0	223	225
Amount (Pred)	383	137	344	113	225	1201

Based on Equation (2.1) in this study, manual calculations on 2014 data obtained the following Overall Accuracy value:

$$\boldsymbol{OA} = \frac{\sum \boldsymbol{X_{ii}}}{\boldsymbol{N}} \times \mathbf{100} = \frac{\mathbf{1190}}{\mathbf{1201}} \times \mathbf{100} \approx \mathbf{99}\%$$

The manual calculation using the 2014 data produced an Overall Accuracy (OA) value of approximately 99%**.** This indicates that 99% of the classified pixels were correctly identified when compared with the reference data. In other words, the classification model demonstrates **a** very high level of accuracy, meaning that the land-cover classification results for 2014 are highly reliable and consistent with the actual land-use conditions observed in the field or reference dataset.

Based on Eequation (2.4) in this study, manual calculations on 2014 data obtained the Kappa Accuracy value as follows:

$$P_o = \frac{1201}{1201} = 1{,}0$$
$$P_e = \frac{1201 \times 1201}{1202^2} = \frac{1442401}{1442401} = 1{,}0$$
$$K = \frac{1{,}0 - 1{,}0}{1 - 1{,}0} = \frac{0}{0}$$

Overall, the accuracy evaluation values for each classification class are presented in Table 6.

Table 6 Accuracy Evaluation Value Obtained

Year	Overall Accuracy	Kappa Accuracy
2014	99%	99%
2015	99%	99%
2016	99%	99%
2017	99%	99%
2018	99%	99%
2019	99%	99%
2020	99%	99%
2021	99%	99%
2022	99%	99%
2023	99%	99%

The results obtained by manual calculations and calculations with the help of GEE *software* produce the same value. In the process of calculating the Kappa accuracy value, it produces a division by zero, which means that Kappa Accuracy is undefined in this case because the results show perfect agreement, which makes the calculation impossible. Based on the calculations that produce an undefined Kappa Accuracy (due to division by zero), this shows that the model obtained is very good in terms of agreement between predictions and observations. A very high Kappa value (close to 1 or even perfect agreement) indicates that the model is very accurate in classifying data (Siska et all, 2023). Likewise, the acquisition of the Overall accuracy value produces a model with a very good category when the number of diagonals is divided by the number of samples used.

4. Conclusion

In the last 10 years (2014-2023), agricultural land in Central Lombok Regency has decreased by 7.54% from 343,517 km2 to 317,595 km2 . This decrease indicates a significant change in land use, possibly due to urbanization or conversion of non-agricultural land. With an Overall Accuracy (OA) value of 99% and Kappa 0.99 indicating the reliability of the data and the consistency of the results of the land change analysis.

For future research, it is recommended to integrate socioeconomic and environmental variable such as population growth, economic development, and rainfall patterns into the analysis to better understand the driving factors behind agricultural land conversion. Additionally, applying predictive modeling or machine learning approaches could help forecast future land-use changes and support the formulation of sustainable land management policies in Central Lombok Regency.

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