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Mapping Urban Transformation: The Random Forest Algorithm to Monitor Land Use and Land Cover Change in Bandar Lampung City

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ABSTRACT

Bandar Lampung City has substantially altered its land cover due to rapid urbanization in the past decade. Landsat 8 OLI is suitable for conducting land cover change research and offers current and precise data on the present land cover. This research aimed to monitor and analyze the changes in seven categories of land use and land cover (LULC): forest, agricultural land, rice field, settlement, water body, bare land and industrial area. The land use and land cover (LULC) in Bandar Lampung City were analyzed using Landsat 8 OLI satellite images from 2013 to 2023. The Random Forest Algorithm was employed for this analysis. The LULC model assessment was carried out with a confusion matrix, resulting in almost perfect agreement for the 2013 and 2023 LULC models. The LULC classes showed an area growth in settlement of 5,526.25 ha (29.12%) and agricultural land of 1,071.63 ha (5.30%) but opposite with forest class that experienced significant area loss that reached 2,012.35 ha (-26.02%) and waterbody and industrial area 285.64 (-6.15%) and 167.67 ha (-4.04%), respectively. The findings reveal significant shifts in forest and agricultural land, highlighting the region's rapid urbanization and deforestation patterns. These changes have practical implications for environmental management and urban planning, suggesting the need for sustainable LULC policies to prevent the impacts of rapid LULC transformations on ecosystem services and local communities.

1. Introduction

Changes in land use and land cover (LULC) have been a main focus of environmental research in the past few decades (Rahmat et al. 2022). LULC investigations have utilized a range of methods and strategies, with remote sensing essential for the capacity for comprehensive, reliable, and multi-time data (Putraditama et al. 2019; Yustika et al. 2019). Industrialization and urbanization have characterized the contemporary era, so the evaluation and monitoring of LULC have become crucial (Degife et al. 2019; Fatemi and Narangifard 2019; Li et al. 2020; Obodai et al. 2019). The alterations, encompassing the conversion of natural vegetation to urban regions or agricultural land, substantially influence the regional climate, biodiversity, water supplies, and human subsistence (Santoro et al. 2020; Si Salah et al. 2019). Consequently, understanding the LULC changes was essential for sustainable planning and environmental management (Chofreh et al. 2019; Panchal et al. 2021; Thamagasorn and Pharino 2019). The use of LULC-based planning can provide a robust basis for critical policy discussion since implementing appropriate policies is vital to promoting and improving the growth of forests. Therefore, evidence-based successful planning cannot be emphasized (Santoso et al. 2023).

Significant LULC changes in Bandar Lampung City have occurred over the last decade due to the city's rapid development of urbanization (Achmad et al. 2022; Meikatama et al. 2022). Bandar Lampung, an urban center in Lampung Province, Indonesia, has experienced increasing urbanization, significantly affecting changes in its LULC. The city's landscape has been changed due to increased built-up regions and decreased vegetated areas.

The urban expansion has led to the modification of the city's environment, resulting in the loss of green spaces and the increase of built areas A comprehensive and detailed research is essential in understanding the significance and implications of these changes (Cecchini et al. 2019; Pei et al. 2021; Shao et al. 2021). The Landsat satellites series has been widely utilized in LULC research because of their extensive data availability and optimal spatial and spectral resolution among remote sensing sensors (Chaves et al. 2020). Landsat 8 was equipped with enhanced features and capabilities, making it very suitable for monitoring alterations in LULC analysis (Pandey et al. 2022; Wulder et al. 2022). Landsat 8 OLI satellite can be employed for LULC analysis and offers current and precise data on the present LULC (Nedd et al. 2021; Sepuru and Dube 2018). Many studies have examined changes in LULC in various areas of Lampung Province, but there is a significant lack of comprehensive LULC research on Bandar Lampung City (Mukhlis and Perdana 2022; Octavia et al. 2022; Romli et al. 2019).

Land use and land cover (LULC) changes, especially in rapidly urbanizing areas such as Bandar Lampung, represent significant environmental difficulties. Monitoring these changes is essential for urban planning, environmental sustainability, and failure risk mitigation (Roccati et al. 2021; Roy et al. 2022). Remote sensing is a widely utilized instrument for land use and land cover (LULC) analysis, primarily because of its ability to acquire extensive spatial and temporal data (MohanRajan et al. 2020). However, implementing machine learning algorithms, such as Random Forest (RF), for land cover classification has demonstrated both potential and constraints across diverse geographical areas and environmental conditions (Bui and Mucsi 2021; Meng et al. 2021).

Numerous research studies have established the efficacy of Random Forest as a classifier for land cover alterations, which is attributed to its capacity to manage high-dimensional data and mitigate overfitting (Belgiu and Drăgu 2016). In densely populated regions, the diversity of land cover, such as the proximity of developed areas, vegetation, and aquatic environments, poses difficulties for precise categorization (Rodriguez-Galiano et al. 2012). These complications emphasize the necessity for increased refinement in the training and validation of RF models, particularly in regions such as Bandar Lampung, where fast urbanization exists with agricultural and forested landscapes.

Moreover, disagreements occur over the precision of remote sensing data in identifying subtle changes, especially in rural-urban borderline areas. Although higher-resolution data from Landsat 8 has enhanced the identification of land cover changes, concerns remain regarding the efficacy of the images in detecting detailed transitions across land cover categories (Fragou et al. 2020). Factors like cloud cover, shadowing, and seasonal fluctuations might hamper categorization efforts, resulting in misclassification and diminished model accuracy (Desjardins et al. 2023). Furthermore, the capacity of remote sensing to inspect small human changes, such as informal settlements or small-scale agricultural plots, remains an important challenge (Wulder et al. 2012).

This research improves the existing literature by concentrating on the region's distinct environmental and urban dynamics, improving the precision of the machine learning algorithm in LULC categorization, especially in mixed urban-rural environments. The research aimed to analyze and monitor land use and land cover (LULC) changes in Bandar Lampung City by employing Landsat 8 OLI satellite data and the Random Forest (RF) algorithm from 2013 to 2023.

2. Materials and Methods

2.1. Study Area

The research was located within Bandar Lampung City, Lampung Province, Indonesia (**Fig. 1**), Bandar Lampung City located between the coordinates 5°25'31" S latitude and 105°15'28" E longitude (Mukhlis and Perdana 2022). The study area presents the main socio-economic activities in urban areas. Most of the property consists of residential areas, economic centers, industrial area, agricultural land such as gardens and rice field, agroforestry, and forests that are part of the Wan Abdul Rachman Forest Park.

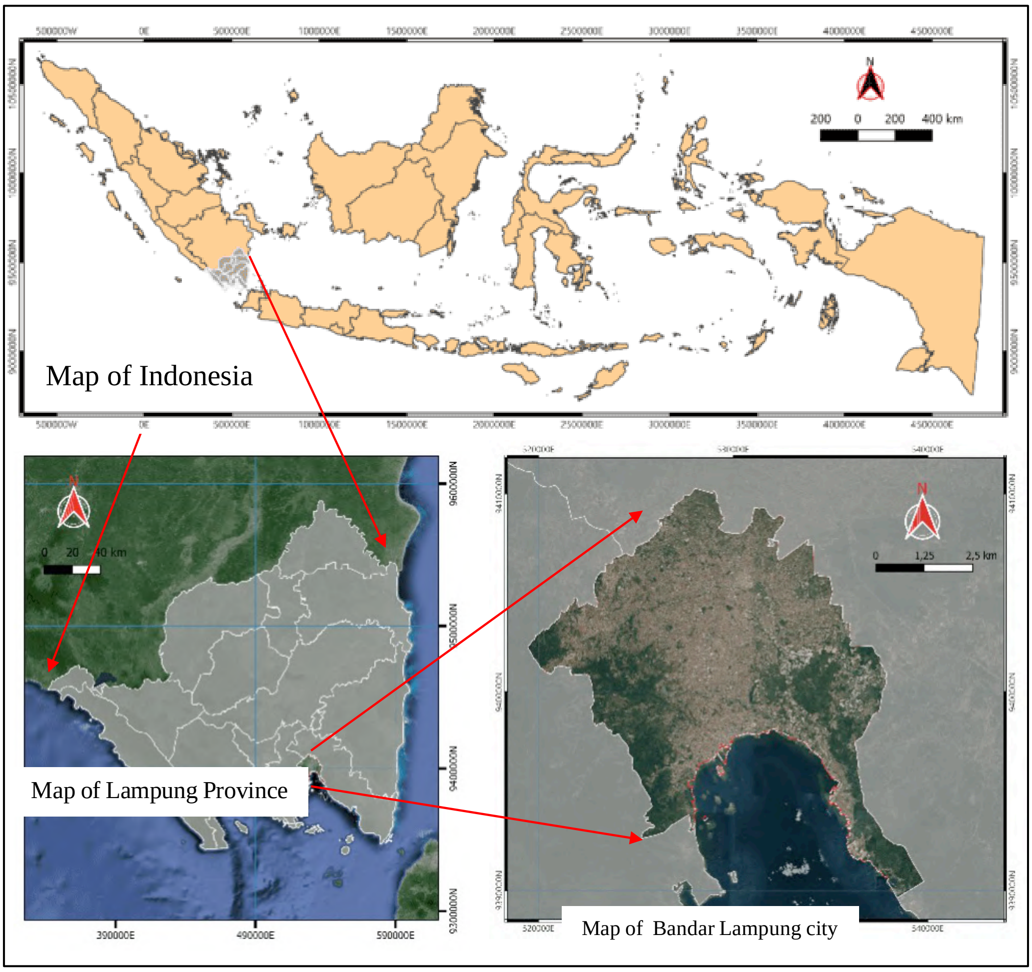

Fig. 1. Geographic map of Bandar Lampung City.

2.2. Landsat Data and Preprocessing

The Landsat 8 OLI image data used in this research were acquired from the official website of the United States Geographical Survey Agency (USGS), which provides data open access via the address https://earthexplorer.usgs.gov. Landsat 8 OLI/TIRS was launched on 11 February 2013 and carries two scientific instruments: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) (Markham et al. 2016; Masek et al. 2020). The two sensors offer comprehensive coverage of the Earth's terrestrial surface yearly. They capture data at a high level of detail has a spatial resolution of 30 m for visible, near-infrared, and shortwave infrared wavelengths; for thermal measurements, has 100 m spatial resolution, and for panchromatic images, 15 m spatial resolution (**Table 1**) (Wu et al. 2019). The Landsat 8 OLI data was selected to encompass the portion of Bandar Lampung City (Path 123 and Row 64). To minimize the effect of clouds and haze, we carefully selected Landsat 8 OLI imagery (**Table 1**).

Table 1. Landsat 8 OL Datasets Specification

Product ID	Path	Row	Acquisition Date
LC08_L1TP_123064_20131019_20200912_02_T1	123	64	19 October 2013
LC08_L1TP_123064_20230727_20230805_02_T1	123	64	27 July 2023

2.3. Land Use and Land Cover (LULC) Classes

In this research, 7 (seven) classes of LULC used (**Table 2**), namely: forest (Fr); agricultural land (Ag); rice field (Rc); settlement (St); bare land (Br); water body (Wt); and industrial area (In). To determine the training sample (**Fig. 2**), we used the reference of LULC map from the *Peta Potensi Desa* (PODES) of the year 2022 download from https://geoservices.big.go.id combined with visual interpretation using Google Earth and field survey. The number of sample points follows the principle of remote sensing research, which states that the number of samples in LULC classification was determined based on the number of pixels that can represent each LULC class, ranging from 10 N to 100 N, where N was the of LULC classes number (Dogru et al. 2020).

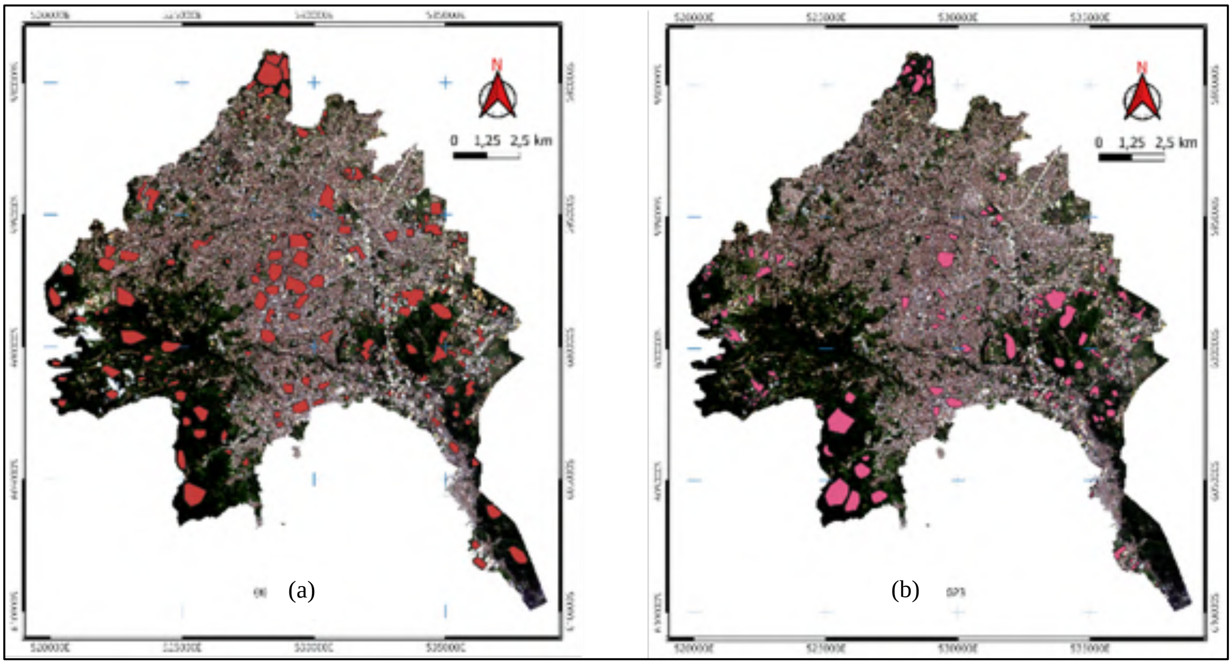

Fig. 2. Training samples for (a) 2013 and (b) 2023.

Table 2. The land cover classification specification

No.	Classes	Symbols	Descriptions	Training Samples (Pixel)	
				2013	2023
1	Forest	Fr	All types of Trees Cover	21,883.00	17,158.00
2	Agricultural land	Ag	Dryland farming mixed with shrubs	6,317.00	975.00
3	Rice field	Rc	Paddy fields in irrigated land area	10,484.00	6,760.00
4	Settlement	St	Built-up land for housing	26,982.00	8,932.00
5	Bare land	Br	All types of bare land or affected by humans	139.00	260.00
6	Water body	Wt	All types of water on the surface	6,255.00	7,424.00
7	Industrial area	In	Large industrial areas, factories, and warehouses	2,519.00	4,212.00

2.4. The Random Forest (RF) Algorithm

The Random Forest classifier is a machine-learning technique. Breiman initially introduced this strategy (Liang et al. 2021; Zounemat-Kermani et al. 2021). Random Forest (RF) runs by mixing many tree predictors (Gholizadeh et al. 2020; Huang et al. 2022; Sun et al. 2023). This study selected the RF algorithm due to its strong effectiveness in managing complicated LULC classifications (Tassi and Vizzari 2020). The fact that the ability of RF can handle non-linear relationships between input variables makes it ideal for classifying different types of land cover using spectral data from satellite images (Rana and Venkata Suryanarayana 2020). Its integrated feature importance method also improves interpretability by identifying the most relevant spectral bands, contributing to precise classification. This ensures that the model precisely and consistently captures large LULC shifts, including the growth of urbanization and deforestation (Rodriguez-Galiano et al. 2012).

2.5. LULC Model Validation

Evaluating the LULC classification was necessary to verify the temporal LULC changes (Tsendbazar et al. 2021; van Vliet et al. 2016). The assessment of LULC produced by RF was performed via a confusion matrix, with Overall Accuracy (OA) and Kappa Coefficient (KC) values (Shishir and Tsuyuzaki 2018). The confusion matrix comprehensively assesses individual object classes and the overall interpretation (Pahleviannur 2019).

Accuracy calculations compare the number of matches between sample area calculations derived from image interpretation data and the actual conditions observed in the field. A Confusion Matrix incorporates computations from various formulas, specifically User's Accuracy (UA), Procedural Accuracy (PA), and Overall Accuracy (OA). UA displays the classification outcomes for each category the user has participated in. The LULC items represented during classification were shown using the accuracy method. The number of LULC classes accurately classified each class was known as OA. UA, PA and OA were calculated in Equations 1, 2, and 3 (Li et al. 2019; Maxwell et al. 2021; Ridhayana et al. 2022; Sayyad et al. 2021).

$$UA = \frac{X_{ii}}{X_{+i}} \times 100\% \quad (1)$$

$$PA = \frac{X_{ii}}{X_{i+}} \times 100\% \quad (2)$$

$$OA = \frac{\sum_{i}^{r} X_{ii}}{N} \quad (3)$$

where Xii, X_{+i}, X_{i+}, and N consist of the contingency matrix i- row i-column value the diagonally, number of LULC classes in row i, number of LULC classes in column i and number of all observation points, respectively.

The Overall Accuracy (OA) number only includes correct data between classification results and field circumstances; in contrast, the Kappa Coefficient (KC) accounts for the error factor in the classification process, resulting in a lower Kappa Coefficient value. Suitability category of KC 0.81–0.99 (Almost perfect agreement), KC 0.61–0.80 (Substantial agreement), KC 0.41–0.60 (Moderate agreement), KC 0.21–0.40 (Fair agreement), KC 0.01–0.20 (Slight agreement) and KC < 0 (Less than chance agreement) (Viera and Garrett 2005). Equation 4 was used to compute the KC mathematically (Rwanga and Ndambuki 2017).

$$Kappa\ Coefficient\ (KC) = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+}.x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+}.x_{+i})} \quad (4)$$

where N, X_{i+}, X_{+i}, X_{ii} and r consist of the number of validated LULC points, the total number proven in validation, the number of validation results points on the LULC classes, the number of interpreted points for LULC classes, the number of LULC classes as a result of the interpretation of the diagonal row and the number of LULC classes, respectively.

2.6. Area Change and Transition Matrix

The QGIS 2.18 and MOLUSCE Plugins were used for LULC area change and to quantify the LULC Transition Matrix since the MOLUSCE Plugin was unavailable in the QGIS Version 3.0. Analysis of LULC results between first-year land cover and second-year land cover (Dinh et al. 2023; Suharyanto et al. 2023). The first land cover study was conducted in 2013, and the second in 20123. The transition matrix computes the probability and transition using data and variables driving the LULC (Khawaldah et al. 2020; Leta et al. 2021; Nath et al. 2020). The overall research workflow can be seen in **Fig. 3.**

3. Results and Discussion

3.1. LULC Model Validation

The highest PA was obtained for rice field (96.01%) and the lowest for industrial area (48.87%) (**Table 3**). The OA of the Landsat images for the year 2023 reached 89.40%, while the KC reached 85.72%, with the highest UA obtained for settlement (97.32%) and the lowest for agricultural land (46.54%) (**Table 3**). Since the Overall Accuracy (OA) and Kappa Coefficient (KC) values exceed the minimum requirements of 85%, LULC classification utilizing the RF algorithm has been considered acceptable with “Excellent” agreement. This value satisfies the minimum accuracy for map interpretation and field observation data outlined in the Geospatial Information Agency of the Republic of Indonesia Regulation Number 15 of 2014. The conformance interpretation indicates a value of 85.00%.

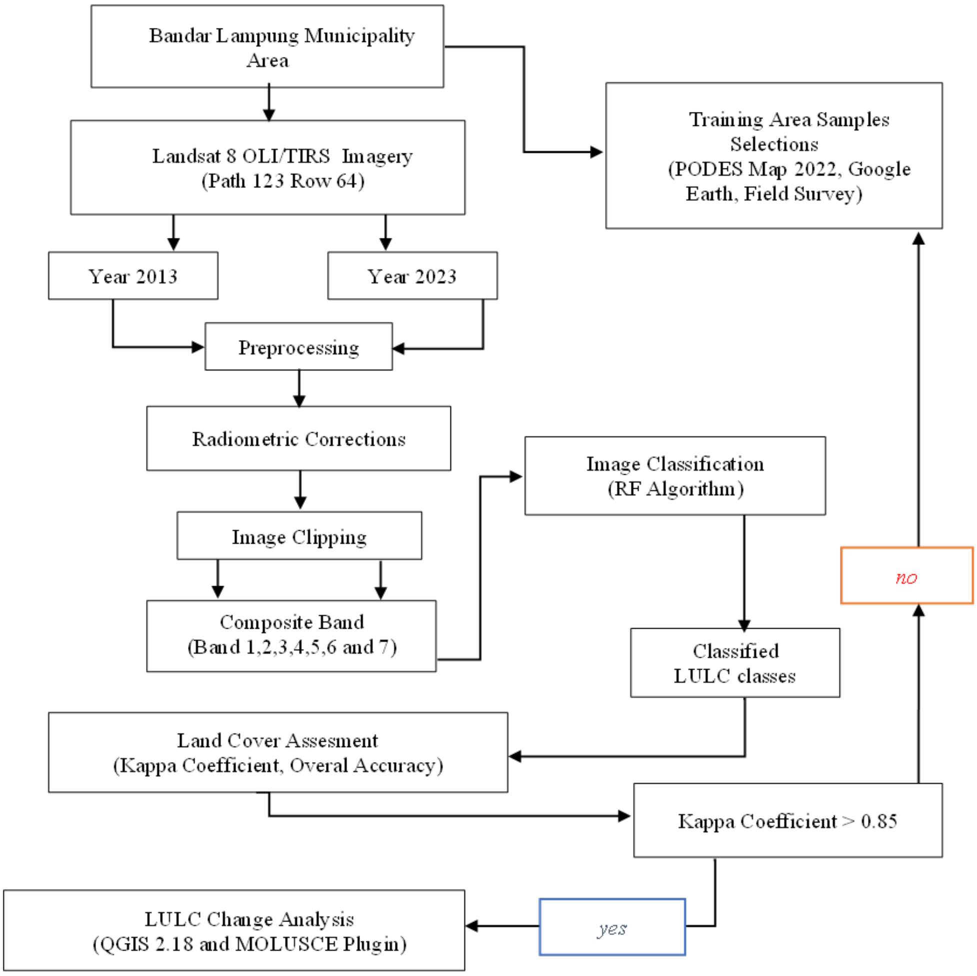

Fig. 3. Flowchart of the data inputs, procedures and processing for land cover change analysis mapping.

Table 3. Confusion matrix of the year 2013

LULC Classes	Fr	Ag	Rc	St	Br	Wt	In
Fr	20,981.00	384.00	75.00	31.00	11.00	4.00	397.00
Ag	2,193.00	2,940.00	494.00	136.00	5.00	16.00	533.00
Rc	84.00	462.00	9,730.00	2.00	10.00	4.00	192.00
St	6.00	59.00	9.00	26,260.00	8.00	521.00	119.00
Br	18.00	1.00	8.00	6.00	102.00	2.00	2.00
Wt	208.00	6.00	0.00	541.00	17.00	5,298.00	185.00
In	87.00	162.00	109.00	376.00	20.00	400.00	1,365.00
PA (%)	88.99	73.24	93.33	96.01	58.96	84.84	48.87
UA (%)	95.88	46.54	92.81	97.32	73.38	84.70	54.19
OA (%)	89.40						
KC (%)	85.72						

Recent studies have widely applied the RF algorithm for LULC classification, particularly in urbanizing regions. Recent research proved the efficacy of RF for LULC classification in urban environments in West Java, Indonesia, where it attained superior results compared to other classification methods (Gandharum et al. 2022). Also, using RF to identify the LULC method in another area highlights its effectiveness in locations experiencing rapid land cover changes, similar to Bandar Lampung City (Shahfahad et al. 2023; Zafar et al. 2024).

Geographically, studies conducted in the Mekong Delta, Vietnam, applied RF for LULC classification to investigate the impacts of agricultural expansion and urbanization on ecosystems (Nguyen et al. 2022). These findings are similar to our research, indicating substantial urban expansion and deforestation in Bandar Lampung City during the last decade. The LULC model validation using the RF algorithm has achieved a high OA of 89.40% and KC 85.72% for the year 2013 (**Table 3**) data and also a high OA of 89.96% and KC 86.82% for maps produced for the year 2023 (**Table 4**). The classification results could serve as a benchmark for calculating land changes in Bandar Lampung City.

Table 4. Confusion matrix of the year 2023

LULC Classes	Fr	Ag	Rc	St	Br	Wt	In
Fr	16,974.00	31.00	39.00	9.00	45.00	27.00	33.00
Ag	20.00	742.00	64.00	37.00	13.00	68.00	31.00
Rc	554.00	193.00	5,987.00	0.00	18.00	0.00	8.00
St	13.00	42.00	4.00	7,423.00	48.00	1,092.00	310.00
Br	11.00	0.00	0.00	4.00	229.00	16.00	0.00
Wt	433.00	4.00	0.00	319.00	17.00	6,031.00	620.00
In	47.00	30.00	1.00	163.00	18.00	209.00	3,744.00
PA (%)	94.03	71.21	98.23	93.31	59.02	81.03	78.89
UA (%)	95.88	46.54	92.81	97.32	73.38	84.70	54.19
OA (%)	89.96						
KC (%)	86.82						

The classification stage then continued to determine the area change and transition matrix of LULC for the Bandar Lampung City region for the Landsat 8 image for 2013 and 2023. Artificial Neural Network (ANN) resulted in the current validation KC was 0.88. This strengthens the legitimacy of the RF-based LULC map for further LULC change calculation. This study complements previous studies using RF, particularly in Bandar Lampung City. This region has not been thoroughly investigated using the method. We utilized Random Forest to classify satellite data from 2013 to 2023, offering a more recent and detailed assessment of LULC changes. The findings strengthen scientific understanding and social relevance by providing essential sources for policymakers and urban planners to plan sustainable development strategies.

3.2. LULC Area Changes

There has been a decrease in the area of land use and land cover (LULC) in the forest, bare land, and industrial area LULC classes, with respective reductions of 2,013.92 ha (10.96%), 285.64 ha (-6.15%), and 167.67 (-4.04%) ha, respectively. Simultaneously, there was an increase in land area in several LULC classes. Specifically, the areas that were designated for agricultural lands, rice field, settlement, and bare land increased to 1,072.46 ha (5.84%), 330.98 ha (1.80%), 821.89 ha (4.47%), and 242.24 ha (1.32%), respectively (**Table 5**).

The LULC forest class experienced the largest decrease in land area in the Bandar Lampung municipal area, caused by pressure to use other LULC classes. These findings were similar to previous research that claimed that vegetated and built-up areas were the type of land use with the most significant changes (Miswar et al. 2023).

The research findings indicate that using Landsat 8 OLI imagery in remote sensing technology enables monitoring LULC transformations within a specific region. The RF algorithm has consistently demonstrated excellent results in LULC categorization, as evidenced by numerous researches conducted in tropical settings. RF may address issues such as item overlap with other classes by identifying the optimal hyperplane and maximizing the inter-class distance (Lin and Doyog 2023; Ruiz et al. 2021; Shihab et al. 2020).

Table 5. LULC Classes Area Changes from year 2013 to 2023

LULC Classes	Area (ha)			Area (%)		
	2013	**2023**	**(2023–2013)**	**2013**	**2023**	**(2023–2013)**
Fr	8,030.17	6,016.25	-2,013.92	43.70	32.74	-10.96
Ag	287.71	1,360.17	1,072.46	1.57	7.40	5.84
Rc	617.9	948.89	330.98	3.36	5.16	1.80
St	5,231.43	6,053.32	821.89	28.47	32.94	4.47
Br	91.08	333.33	242.24	0.50	1.81	1.32
Wt	2,447.63	2,161.77	-285.86	13.32	11.76	-1.56
In	1,668.66	1,500.86	-167.8	9.08	8.17	-0.91

Although the RF algorithm is proficient at managing non-linear data, it may encounter difficulties in mixed LULC areas where class boundaries are unclear, resulting in classification inaccuracies, such as incorrectly identifying bare soil as non-vegetated areas (Xie and Niculescu 2021). Furthermore, the RF algorithm's need for substantial training data might render it less effective when high-quality labeled data is limited (Mesarcik et al. 2022).

The analysis of the LULC class changes for 2013 and 2023, as presented in **Table 3** and **Table 4**, reveals a significant expansion in the forest class LULC, with an increase of 505.94 hectares. Changes in agroforestry and agricultural land have primarily driven this growth. At the same time, there is a decrease in forest area due to land conversion for agricultural land and rice field. The LULC agroforestry transforms into a forest due to the heightened density and structure brought about by the natural growth of tree components (Ollinaho and Kröger 2021). The LULC Change in Bandar Lampung City from 2013 to 2023 can be seen in **Fig. 4**.

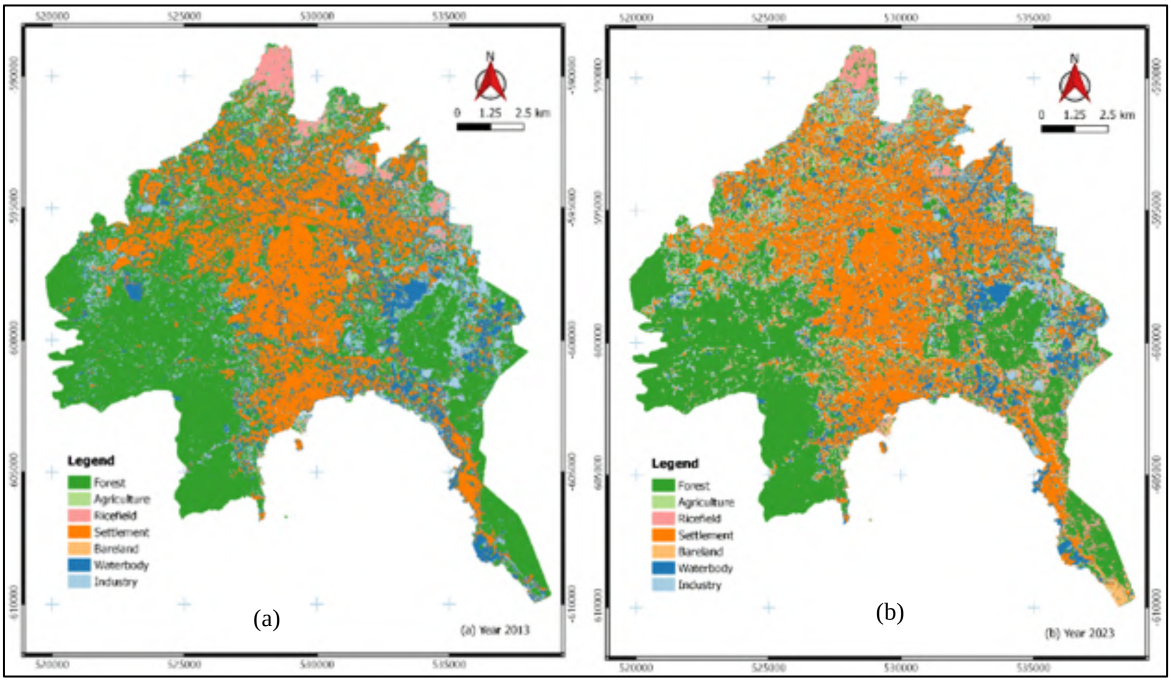

Fig. 4. LULC change detection map from 2013 (a) to 2023 (b) using Random Forest Algorithm.

Multiple factors, such as natural and anthropogenic factors, influence LULC in Bandar Lampung City. Anthropogenic factors impacting land cover changes include population growth, regional aspects, and social, cultural, economic, technical, and governmental influences. This urban area forms the center of all human activities, including the economy, business, residence, and education (Kim et al. 2020). Most of Bandar Lampung City's citizens and those from nearby cities participated in these activities. Population growth correlates with development, leading to heightened demand for land. The limited availability leads to a transformation of land cover from previously unused areas to those exploited by humans (Mahtta et al. 2022; Maja and Ayano 2021).

3.3. Transition of LULC Classes

The study findings indicate the most stable probability in the settlement LULC class (0.83) (**Table 5**) from 2013 to 2023. Meanwhile, the LULC classes were quite dynamic, namely forest to agricultural land (0.19), forest to bare land (0.27), agricultural land to bare land (0.14), rice field to agricultural land (0.14), settlement to wetland (0.14), settlement to industrial area (0.34), industrial area to bare land (0.15), bare land to agricultural land (0.15), and bare land to rice field (0.14). The LULC transition using the RF algorithm showed satisfactory results, with a KC level reaching 86.0%, thus strengthening the land change model (**Fig. 5**).

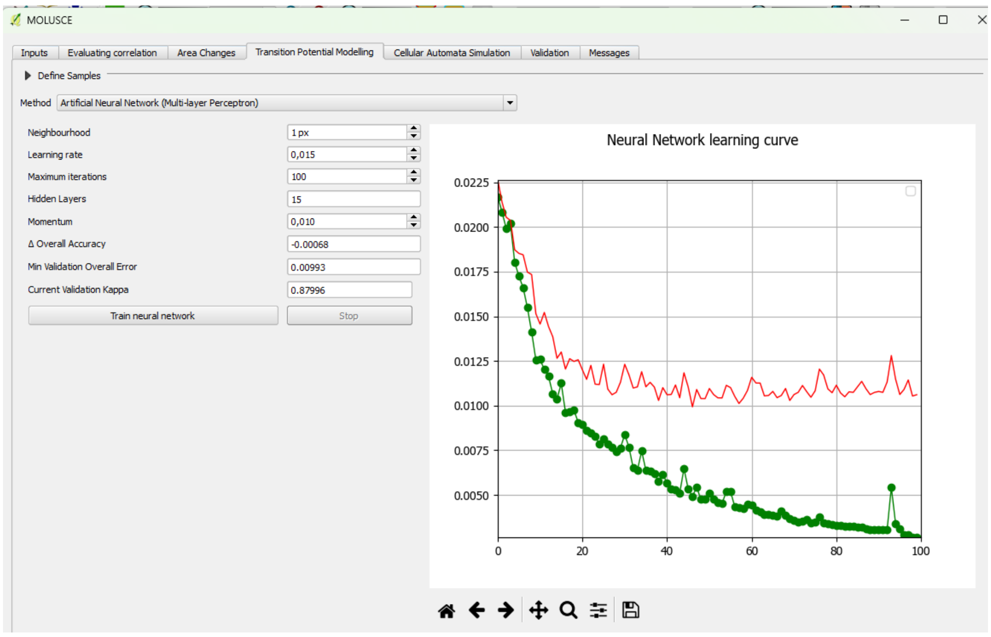

Fig. 5. LULC Transition potential model from 2013 to 2023 using Artificial Neural Network (ANN).

The forest class substantially reduced area during a decade, namely by 2,013.92 ha (-10.96%), due to alterations in other LULC classes. The reduction in forest class resulted from land utilization alterations, specifically towards agricultural land, rice field, waterbody, industrial area, and bare land classes. This phenomenon arises from many variables, including the necessity for food production, diminished soil fertility, local weather patterns and climate, and cultivation quality in forested areas.

The settlement class experienced a significant expansion (821.89 ha) due to changes in the other LULC classes. The settlement class experienced a considerable expansion (821.89 ha) due to changes in the other LULC classes. The demand for housing in the provincial capital is substantial, necessitating controlled residential growth. However, managing this growth carefully is crucial to mitigate future urban issues such as floods, droughts, and landslides (Jihad et al. 2020; Ni et al. 2021; Pôças et al. 2020; Priyono et al. 2020; Rahadiati et al. 2021; Wybieralski 2023). The image depicts areas with transition potential in the Bandar Lampung Municipal area (**Fig. 6**).

Table 6. Transition matrix of LULC from year 2013 to 2023

LULC Classes	Fr	Ag	Rc	St	Wt	In	Br
Fr	0.65	0.09	0.06	0.07	0.01	0.06	0.07
Ag	0.19	0.26	0.14	0.10	0.05	0.12	0.15
Rc	0.14	0.13	0.35	0.08	0.03	0.13	0.14
St	0.01	0.02	0.00	0.83	0.01	0.10	0.04
Wt	0.15	0.08	0.12	0.14	0.27	0.12	0.12
In	0.08	0.08	0.02	0.34	0.04	0.34	0.11
Br	0.27	0.14	0.06	0.12	0.03	0.15	0.22

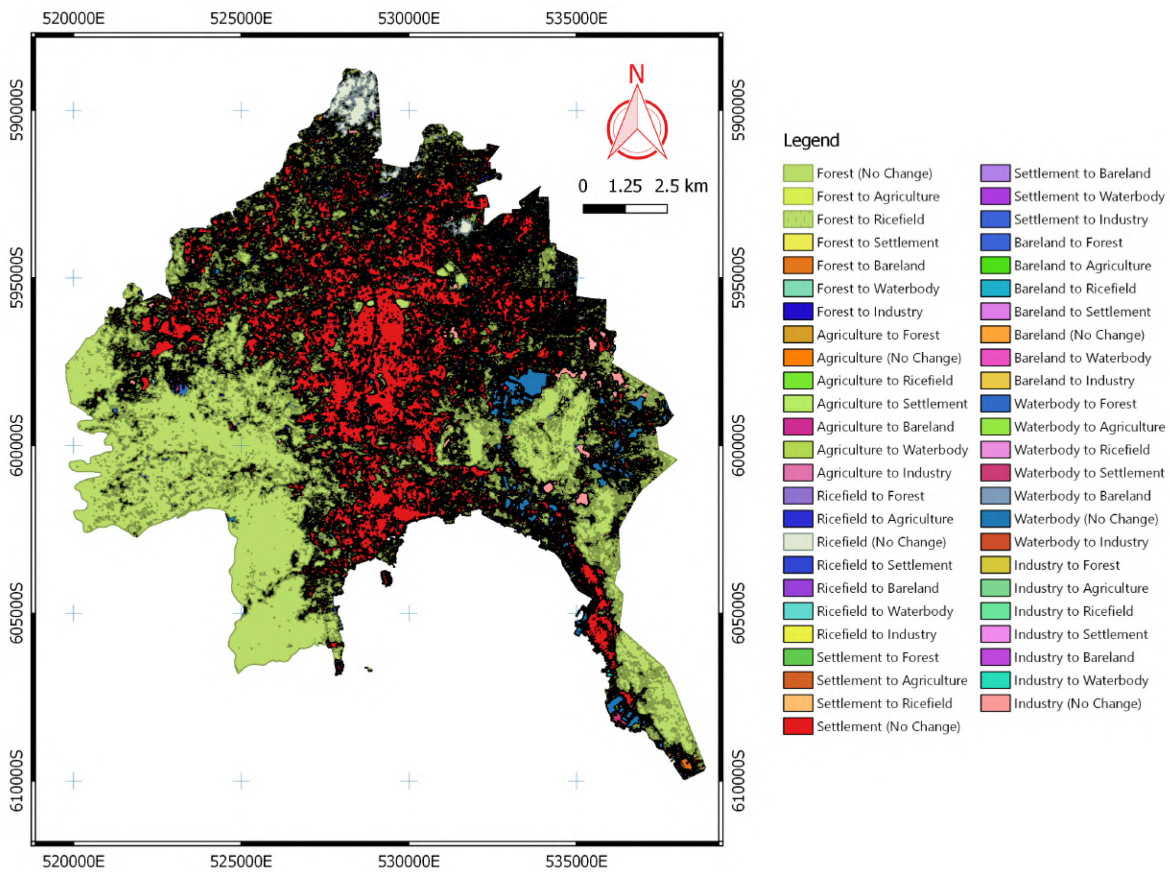

Fig. 6. Map of LULC transition from the year 2013 to 2023.

4. Conclusions

LULC in Bandar Lampung in 2013 and 2023 experienced dynamics. There has been a decrease in the forest, bare land, and industrial area LULC classes. Simultaneously, there was also an increase in agricultural land, rice field, settlement, and bare land in the LULC class area. The RF algorithm has consistently demonstrated excellent results in LULC categorization. The RF algorithm achieved a high Overall Accuracy and Kappa Accuracy of 89.40% and 85.72% for the 2013 maps produced, while it reached 89.96% and 86.82% for the 2023 maps produced, respectively. The classification results can be a benchmark for assessing LULC area changes and transitions. The LULC class that experienced the biggest area loss was the forest class. Meanwhile, agricultural land was the class that increased. Modeling the potential transition of LULC for 2013–2023 using ANN algorithms showed the Kappa coefficient of 88%, considered an excellent category. A significant decrease in LULC occurred in forest areas, which needs to be given great attention because forest areas in Bandar Lampung play an important role in water and soil conservation and other environmental service for residents in Bandar Lampung. In future research, we propose increasing the frequency of monitoring to enhance forest restoration's effectiveness. This can be achieved by utilizing vegetation indices and prioritizing the assessment of environmental concerns associated with land change.

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