Evaluation Land Use Cover Changes Over 29 Years in Papua Province of Indonesia Using Remote Sensing Data

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Evaluation Land Use Cover Changes Over 29 Years in Papua Province of Indonesia Using Remote Sensing Data

Sri Murniani Angelina Letsoin[1,2,a], David Herak[1], Ratna Chrismiari Purwestri[3,4]
[1]Department of Mechanical Engineering, Faculty of Engineering, Czech University of Life Sciences Prague, Kamycka 129, 16500 Praha-Suchdol, Czech Republic
[2]Faculty of Engineering, University of Musamus, Merauke Regency, Papua 99611, Indonesia
[3]Faculty of Forestry and Wood Sciences, Czech University of Life Sciences Prague, Kamycka 129, 16500 Praha-Suchdol, Czech Republic
[4]Institute of Nutritional Sciences, University of Hohenheim, Garbenstrasse 28, 70599 Stuttgart, Germany

[a] Corresponding author: letsoin@tf.czu.cz

Abstract. Land use/cover change (LUCC) observation and determination have been extensively discussed in natural resources management, biodiversity and ecosystem preservation, land management also climate changes studies. An evaluation of the LUCC in Merauke, the easternmost city of Indonesia, was conducted to gain relevant information in agriculture and forestry based on historical data from remotely sensed land cover data. To obtain the historical dynamics of the LUCC, a supervised classification algorithm was implemented to the Landsat images of 1990, 1996, 2009, 2015, and 2019 as well as statistical analysis Wilcoxon signed-rank. This study aims to investigate and analyze the LUCC over a period of 29 years. The results show a significant decline in the forest area by around 7% in 2019. As compared to the LUCC in 1990, agriculture sectors such as dry-land agriculture, shrub-mixed dry land and paddy field gained an area higher than 50%, while the area of the water body is a declined by 0.61 % over the period. The evaluation of LUCC will help government development plans in the protection of commodities in this Province and the promotion for biomass and bioenergy resources.

***Keywords*:** Land use cover change (LUCC), Remotely, Wilcoxon Signed-Rank test

1 Introduction

Indonesia has a huge number of islands, around 17.000 in an area of 1.904.569 km^2, of which 1.811.569 km^2 is covered by land area, and the rest, i.e., is occupied by water (about 93.000 km^2). Indonesia nowadays is known as the world's largest island country and the fourteenth-largest country by land area. As an archipelago country with a population of approximately 270 million people, Indonesia today become the world's fourth-most populous country, which is spread into 34 provinces. The wealth of the archipelago provides a prominent number of biomass and bioenergy resources. Papua Province is the easternmost province of Indonesia, within Jayapura city as the capital city has an area of about 315.091,62 km^2. The province encompasses twenty-eight regencies, and one city has tremendous potential in natural resources, such as gold, nickel, copper, petroleum, etc. Other significant commodities are agriculture, horticulture and food crops products, forestry, livestock, and fishery. For instance, Merauke Regency has become the largest paddy production in Papua Province, about 91.47%. In the past decade, the population growth in this Province was about 18.28 percent and around 1.20

million people are working in the agricultural sector [1]. Nevertheless, the dramatic expansion of population might have caused the enlargement of land-use land cover changes due to urbanization or the extension of settlement areas [2]. In general speaking, Land Use Cover Changes (LUCC) can be resulted from firstly, natural driving forces such as climate, soil, topography; and secondly, human driving forces for instance population, urbanization, deforestation, etc [3] or other aspects for example regulation and social or economic condition. The driving forces by humans, nonetheless, may lead to deterioration in natural resources, biodiversity loss, and degradation of ecosystem services [4,5]. Therefore, LUCC monitoring, and evaluation will help to sustain natural resources, and development planning of a certain area.

Numerous studies through satellite imagery and geographical information systems (GIS) have been undertaken for many years to detect or monitor, thus evaluate, and analyse the LUCC of sites. For instance, in the Siberian Baikal Region, the observation was arranged using remote sensing imagery to monitor the forest land cover area, since the site is also controlled by the local policy and various land use purposes [6]. Furthermore, Sentinel 2A and 2B were applied to detect and analyse the long-term dynamics of shrublands around the site [7]. Also, in the Colombian Caribbean, the high resolution of satellite imagery was taken by QuickBird-2, WorldView-2, GeoEye-1, within the ArcGIS to analyse land-use changes in the community [8]. In the same way, the study of Mangrove cover change in Malaysia was identified by using various kinds of remote sensing tools for example Landsat, Sentinel, Google Earth, and Moderate Resolution Imaging Spectroradiometer (MODIS), and the QGIS software to analyse the mangrove loss in this area [9]. Likewise, in Southwest China were used Advanced Land Observing Satellite (ALOS) SAR (Synthetic Aperture Radar) data was used to provide dataset LUCC in a particular area such as a foggy cliff [10]. Thus, several classifiers methods have been used in a simulation of LUCC for instance, Support Vector Machine, Artificial Neural Network, Maximum Likelihood Classification, Minimum Distance, Random Forest, K-Means Cluster, Minimum distance, Supervised Classification that already been integrated in various computer-aided software specifically SNAP (Sentinel Application Platform), ENVI (the Environment for Visualizing Images), QGIS (Quantum Geographic Information System), ArcGIS, SAGA (System for Automated Geoscientific Analyses) [11–17]. Even though different studies have been concerned with LUCC observation in Indonesia, the implementation of the remote sensing imagery in Papua Province is rarely done. Therefore, in the previous study, we were done to produce land use land cover maps in this Regency and the impact on the Sago palm was produced [18]. Hence, in present work we used Landsat imagery and supervised classification to evaluate the changes in land use types in the easternmost city in Indonesia. The goal of this study was, firstly, to quantify historical LUCC in Merauke Regency, secondly, to evaluate the LUCC, and thirdly, to analyse the significant changes in the forested area and agriculture sector. Hence, we applied the Wilcoxon Signed-Rank test to estimate the coverage area over a period of 29 years based on their LUCC.

2 Materials and Methods

2.1 Study Area

The region of Merauke Regency is located between Mappi and Boven Digoel Regency at the North, the Arafuru Ocean at the South and West, and Papua New Guinea to the East (Figure 1). Merauke is known as the east-most city in Indonesia with the largest area, i.e., around 46.074,63 Km^2 over Papua Province. This Regency is also considered as the largest paddy contributor in Papua Province of Indonesia, with the number of paddy~~'s~~ production ~~was~~ around 215.266,16 Tons in 2019 or approximately 91% over Papua Province. Merauke Regency consists of 20 districts that is, Kimaam, Ilwayab, Tabonji, Waan, Okaba, Tubang, Ngguti, Kurik, Malind, Animha, Semangga, Tanah Miring, Naukenjerai, Sota, Muting, Jagebob, Elikobel, Ulilin, Kaptel and Merauke as the capital city of the Regency. The region's climate is humid with about 80.5%, and the air temperature oscillates in the range of 22.40-32.06 ℃. These conditions are favoured for the growth of agricultural crops, such as horticulture, estate, and food crops, as well as forestries such as swamp forests or mangrove forests.

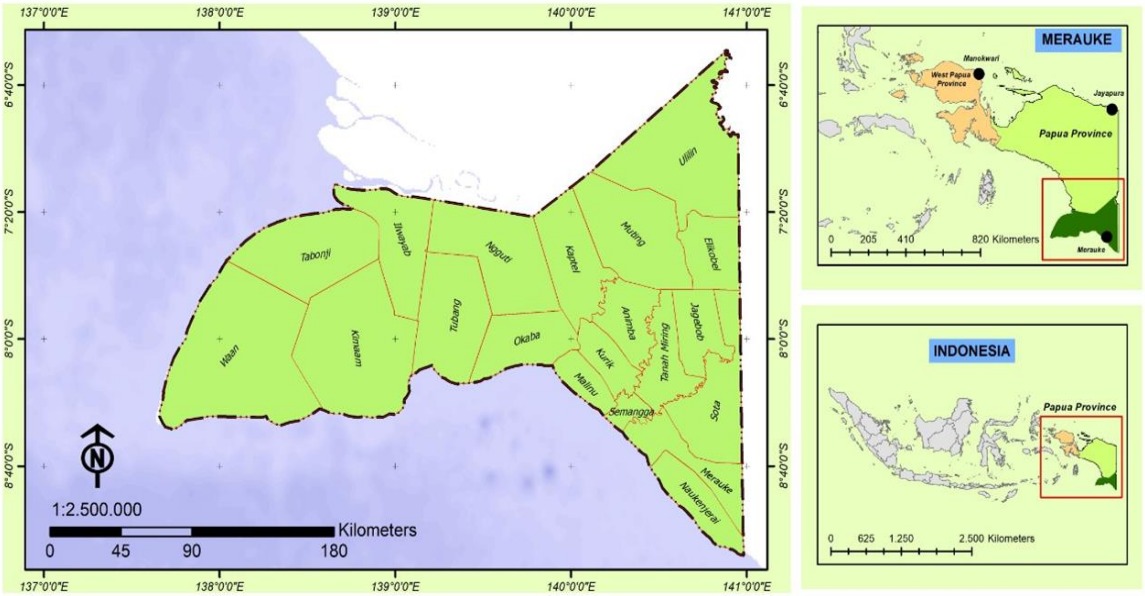

Figure 1. Location of the study area, Merauke Regency, Papua Province of Indonesia (137°38'52.9692"E - 141°0'13.3233"E and 6°27'50.1456"S - 9°10'1.2253"S)

2.2 Data Sources

Satellite imagery acquirement was executed to examine the cloud cover, resolution, altitude, and seasonality. Remote sensing data were used, based on supervised classification of multi-temporal Landsat data (Thematic Mapper (TM) / Enhanced Thematic Mapper (ETM+)/operational land imager (OLI) at a 30 m resolution, a 705 km of altitude and lower than 50% of cloud cover. Thus, we adopted the land use land cover (LULC) approach described by the Indonesian National Standard, which uses twenty-three classes Land use Land Cover. The LULC in this scheme is consists of six classes of forests, one plantation forest and the rest classes of the non-forests area [19]. Further, we also used definitions of land use land cover classes described by the Intergovernmental Panel on Climate Change (IPCC). The LUCC classification was represented in the Quantum Geographic Information System (QGIS) software, which allowed the observable images' positions from remote sensing to be received according to the study area, EPSG: 23894, UTM World Geodetic System (WGS) 84, in zone 54S. Other data sets include existing land cover maps from 1990 to 2014, were provided by the Ministry of Environment and Forestry (MoEF). All remote sensing data from the US Geological Survey (USGS) archives were downloaded (). Additionally, field data location was recorded using a hand-held global positioning system.

2.3 Data Processing and Analysis

The research workflows approach was divided into five stages, i.e., (1) image downloading and pre-processing data, (2) image processing and classification, (3) validation, (4) LUCC classification, and (5) LUCC analysis. Image processing and classification were conducted in SAGA and QGIS, including geometric and radiometric correction, visual interpretation, and region of interest. This study implemented supervised classification [20], a pixel-based classification that categorized images based on the homogeneity of image pixel spectral information. The input bands were used in this work to produce false colour composite maps consisting of bands 4,3,2 for Landsat TM and 7 ETM+ and bands 5,4,3, for Landsat 8 OLI. After requiring remote sensing and field data, the shapefiles were downloaded in the GIS software and covered on the categorized image selected as a candidate area to establish a representative sample of points to be used for accuracy evaluation. A total of 450 ground truth of GPS were used to detect and line distinct land cover classes in the study area. Besides synchronous with the GPS points, the Google Earth engine was also used to help interpret the classified images and land cover validation.

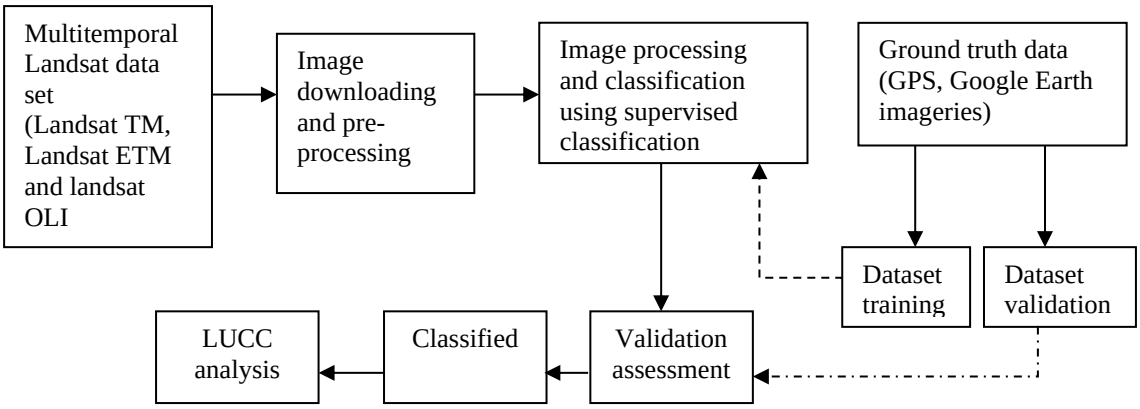

Figure 2. Methodological workflows.

And at the final step, we applied data analysis to evaluate the LUCC, namely Wilcoxon Signed Rank within the statistical significance of less than 0.05. Moreover, the gain and losses, also the rate of LUCC were estimated through the following way (Equation (1)[21,22].

$$Cr = \frac{A_{b-A_f}}{A_f} x \frac{1}{T} x100\% \quad (1)$$

Where Cr states the dynamic rate of change of land use land cover, also connotes the annual change rate of the LUCC type in the area of study. Thus, $A_b$and A_f are the areas of a specific LUCC type in the beginning and at the final of study period, while Tdenotes the study period.

Table 1. Spectral bands of the satellite data used in this study.

	Landsat 7	Landsat 8 OLI
Spatial resolution	30m for visible and Infrared (I.R.), 15m for panchromatic (Pan) and 60mfor thermal	30 m for visible and I.R. 15m for (Pan) and 100 m for thermal
Spectral resolution	8 band (visible, I.R., Pan And Thermal band)	11 bands (visible, I.R., Pan and thermal)
Radiometric resolution	8 bits	16 bits
Temporal resolution	16 days	16 days
Details spectral resolution	Band 1: blue (0.45-0.51) Band 2: green (0.52-0.60) Band 3: red (0.630-0.60) Band 4: N.I.R. (0.76-0.90) Band 5: SWIR-1 (1.55-1.75) Band 6: thermal (10.4-12.5) Band 7: SWIR-2 (2.09-2.35) Band 8: Pan (0.52-0.92)	Band 1: blue (0.43-0.45) Band 2: blue green (0.45-051) Band 3: green (0.53-0.59) Band 4: red (0.64-0.67 Band 5: N.I.R. (0.85-0.88) Band 6: SWIR-1 (1.57-1.65) Band 7: SWIR-2 (2.11-2.29) Band 8: Pan (0.59-0.68) Band 9: cirrus (1.36-1.38) Band 10: thermal I.R. (10.60-11.19) Band 11: thermal I.R. (11.50-12.51)

3 Results

3.1 Land Use Cover Changes (LUCC) in Merauke Regency

By using a supervised classification of remotely sensed imagery, it is possible to get the resultant area estimates that occurred over 29 years in the Regency. Five LUCC consisting of land cover maps in 1990, 1996, 2009, 2015 and 2019 were produced (Figure 3). As a result, twenty-one land cover classes were detected: (1) 6 classes of natural forest, i.e. primary dry land forest, secondary dry land forest, primary mangrove forest, primary swamp forest, secondary mangrove forest, secondary swamp forest; (2) 15 classes of the non-forested area include swamp shrub, swamp, bush/rub, estate crop plantation, settlement area, barren land, clouds, grassland, water body, dry land agriculture, shrub mixed dry land, paddy field, fishpond, airport, transmigration area.

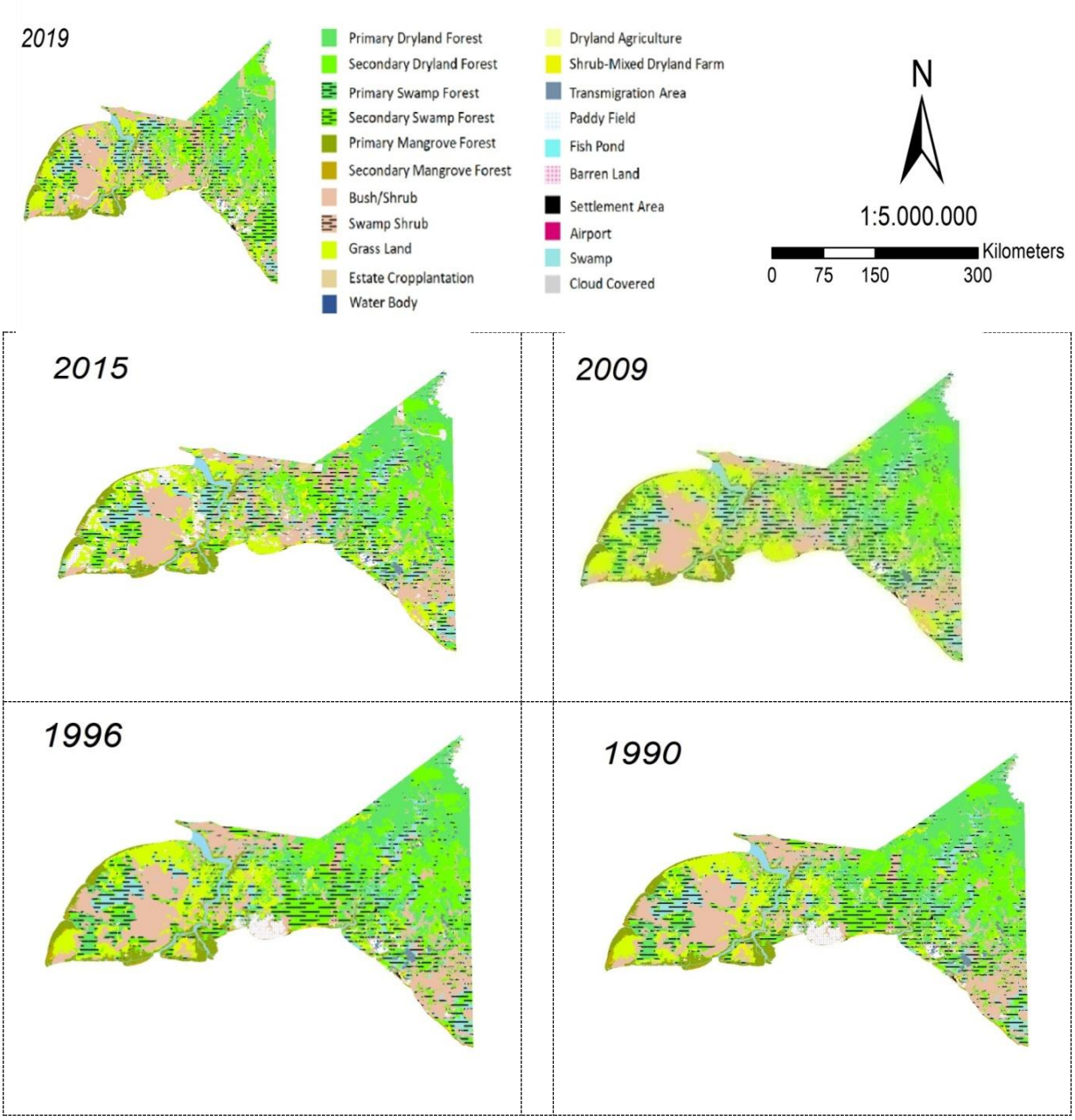

Figure 3. LUCC in Merauke Regency.

Table 2. Quantitative Distribution of LUCC in 1990 and 1996.

Land Use Land Cover Classes	Area (ha)	Area (%)	Area (ha)	Area (%)
	1990		**1996**	
Primary mangrove forest	208.727	4,30	207.345	4,27
Secondary mangrove forest	25.345	0,52	24.209	0,50
Primary swamp forest	342.429	7,06	329.304	6,79
Secondary swamp forest	531.109	10,95	419.213	8,64
Primary dryland forest	697.737	14,38	664.757	13,70
Secondary dryland forest	638.049	13,15	620.773	12,79
Dryland agriculture	14.377	0,30	15.368	0,32
Shrub-mixed dryland farm	43.462	0,90	49.013	1,01
Paddy field	10.932	0,23	10.932	0,23
Water body	352.031	7,26	352.012	7,26
Settlement area	3.160	0,07	3.366	0,07
Transmigration area	36.638	0,76	41.430	0,85

Table 3. Quantitative Distribution of LUCC in 2009, 2015, and 2019.

Land Use Land Cover Classes	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (ha)
	2009		**2015**		**2019**	
Primary mangrove forest	196,510	4,05	196.758	406	195.384	4,03
Secondary mangrove forest	23.574	0,49	23.521	0,48	24.060	0,50
Primary swamp forest	205.343	4,23	202.799	4,18	202.193	4,17
Secondary swamp forest	371.810	7,66	359.399	7,41	531.266	10,95
Primary dry land forest	553.728	11,41	529.715	10,92	500.359	10,31
Secondary dry land forest	672.086	13,85	664.888	13,70	631.259	13,01
Dry land agriculture	16.880	0,35	16.396	0,34	21.671	0,45
Shrub-mixed dry land farm	65.379	1,35	62.139	1,28	68.600	1,41
Paddy field	10.974	0,23	11.459	0,24	45.505	0,94
Water body	351.994	7,26	322.282	6,64	349.884	7,21
Settlement area	3.891	0,08	3.653	0,08	7.090	0,15
Transmigration area	46.221	0,95	46.440	0,96	25.575	0,53

According to the land cover classes of Indonesia [18], the forested area consists of primary and secondary dry land forest, primary and secondary mangrove, primary and secondary swamp forest. Further, cropland's classes are contained of estate cropland, pure and mixed dry agriculture, paddy field. Thus, settlement area divided into transmigration area and settlement areas, nonetheless, barren land with no vegetation spread yet or open exposure areas and area post-fire that has not shown rebuild yet. Other classes such as grasslands, wetlands, port and harbour or water bodies. This study focuses on the

dynamic changes based on land use land cover information, specifically in crops and agriculture areas as well as forested sites. About 50% of Merauke Regency had clothed by natural forest area approximately 50.3 % in 1990, however in the next 6 years, the forest site tends to lose the area by at least 3,6% (Table 2). The same pattern happened also in 2009 and 2015 (Table 3); where the areas lost were around ŧ 5 % and 0.94% respectively. Nonetheless, the forested area was slightly extended up to 2.2% in 2019. Although the forest area revealed an increasing trend in 2019, over 29 years, the site had experienced a decrease which is around 7 % compared to 1990. Another sector, i.e., agriculture area, that consists of dry land agriculture, shrub mix dry land and paddy field were increased up to 8.5% in 2019. The settlement area was also increased from 3.160 ha in 1990 to 7.090 ha in 2019, also the transmigration area tends to be increased from 1990 to 2015, however in 2019, and the area was decreased by around 0.4% compared to 2015.The water body area in this regency also went down slowly by approximately 0.05% over 29 years.

3.2 LUCC over 29 years of Merauke Regency

LUCC losses and gains in this Regency were also evaluated as shown in Table 4; the result indicates that six classes in the natural forest category were generally decreased; only secondary swamp forest gained the area around 0.03%. In contrast, the agriculture sector, namely dry land agriculture, shrubs mixed dry land, paddy field were gained in terms of total changed area higher than 50%. Others class such as settlement area was gained the area around 124,38%, nevertheless, the transmigration area was decreased over 29 years. Furthermore, from 1990 to 2019 the water body area seems lost the area of about 0.61%.

Table 4. LUCC of each class in Merauke Regency over 29 years.

Land cover Class	Changed rate (ha/yr)	Total changed area	
	Net (±)	Ha	%
Primary dryland forest	-16.198,17	-194.378,00	-27,98
Secondary dryland forest	-562,83	-6.754,00	-1,06
Primary mangrove forest	-1.111,92	-13.343,00	-6,39
Secondary mangrove forest	-107,14	-1.285,70	-5,07
Primary swamp forest	-11.686,33	-140.236,00	-40,95
Secondary swamp forest	13,08	157,00	0,03
Settlement area	327,52	3.930,23	124,38
Transmigration area	-921,92	-11.063,00	-30,20
Barren land	602,71	7.232,50	8,85
Water body	-178,93	-2.147,15	-0,61
Dryland agriculture	607,82	7.293,80	50,73
Shrub mixed dryland	2.094,78	25.137,40	57,84
Paddy field	2.881,08	34.572,90	316,26

We also examined the LUCC of Merauke Regency using the Wilcoxon Signed-Rank test to analyse data derived from supervised classification-based restricted by remote sensing imagery of the study area. Therefore, as demonstrates in Table 5, the result of the analysis during the study period.

Table 5. LUCC in Merauke Regency over 29 years (in ha)[1]

Land cover Class	Land cover Class		
	1990	**2019**	*p*-Value
Forested area	2,441,256.56 (1.02; 315,511.00)	2,172,113.451(1.02; 229,220.00)	0000
Crops and agriculture	68,771.00(28.10; 12,616.00)	122,078.93(15.08; 15,025.40)	0.001
Settlement area	39,797.74 (17.85; 8,696.00)	33,365.07 (19.82;5,700.00)	0.642
Water body	351,903.03(335.36; 58,824.67)	290,824.02 (802.50;51,772.81)	0.182
Barren land	80,942.58(18.07; 52,844.40)	77,527.85(608.75;20,717.90)	0.031

[1] Data are presented in total (minimum,maximum)

From 1990 to 2019, the forested areas were significantly decreased (*p*-value = 0.000), while the crops and agriculture region were increased undoubtedly (*p*-value = 0.001). Additionally, the barren land had also decreased during the observed year. Other categories were greater than 0.05, namely settlement area and water body.

4 Discussion

Descriptive results of the dynamic of LUCC in this Regency were given in table 2 and table 3. Furthermore, the changes of the land use land cover of each category are presented in table 5. From the year 1990 to the year 2019, it has been observed that the land use categories such as forested areas have slightly reduced in their respective areas. For example, primary swamp forest had lost an area of -140.236,00 ha or about 40.9% during the study period, and only one subclass of the site has shown a considerable positive rate, namely secondary swamp forest. In contrast, the agriculture sectors including crops, horticulture had seen a steep ascent from 68.771 ha in 1990 to 135.776 ha in 2019 or enlarged higher than 50%, specifically paddy field area was reached approximately 300% increment than other subclasses. This circumstance also explains why Merauke Regency is today becoming the most significant contributor of paddy commodity over Papua Province [1]. Moreover, the settlement area had also considered an increase in its area from 3.165 ha in 1990 and jumped to 7.090 ha in 2019. However, another class of the categories, i.e., transmigration areas went down approximately 30.20% in term of the total changed area for 29 years. Since the enforcement of the Special Autonomy Law by Indonesia Government in 2001, the transmigration program has been falling off and has not been further continued by the Local Government [23].

To add this, we analysed the LUCC statistically of total of five categories in this Regency by using Wilcoxon signed-rank test; as classified as forested area, crops and agriculture, settlement area, and barren land (Table 5). Crops and agriculture showed a substantial increase in area during the study period with *p-value* lower than 0.05. The forested area showed a dramatic decrease statistically in its area by *p*-value = 0,000. Therefore, the result reveals that forest area and agriculture sector were experienced statistically significant changes over the past 29-years period. Nonetheless, the forested area is beneficial to support ecological service as well as the sustainability of biodiversity habitat as experienced in Western Rwanda that lost the forested area about 19% from 1986 and 2006 [24]. Thus, the local government should concentrate more to the regeneration of the forest and forest management should pay more attention to the environmental and social impact. Nevertheless, the increment of urban growth and built-up areas without proper guidelines can lead to a reduction of ecosystem services such as water bodies and increase the effect of climate change [25]. On the other side, Indonesia has been actively promoting the use of indigenous renewable energy (RE) since 2009. Hence, Government in Presidential Decree No. 5/2006 defines the goal at 17% of RE and sets the target at 25% share of RE by 2021 [26]. However, in 2011 the portion of renewable energy is only about 3%. Furthermore, one of the programs is to support biomass for low households and encouraging the potential of other biomass resources from the plantation, agriculture, and forestry. Likewise, as experimented on the previous study about bio-briquette fuel in Indonesia [27]. Besides the main production of forest and agriculture/plantation, which are directly used for income-generating or achieving household food security, the waste of the raw materials is potentially used for biomass sources. The mapping of LUCC, especially forested and agriculture regions could also give a proxy indication of the potential biomass in the Merauke Regency.

Therefore, annual evaluation of LUCC is highly required to support the Government or other relevant stakeholders in their development plans.

5 Conclusions

We accustomed the Landsat satellite imagery and supervised classification to gain historical dynamics LUCC of Merauke Regency in almost three last decades. The result from this study showed that these days, the Regency majority covered by non-forested area which is around 57%, moreover, the forested area was declined about 7% from 1990 to 2019. Concerning the significant changes of each category, we applied statistical analysis Wilcoxon signed-rank test of five categories namely, forested area, crops and agriculture, settlement area and barren land. As the result, the Forested area, as well as barren land and the agriculture sector were significantly changed from 1990 to 2019, throughout their *p*-values, i.e., 0.000;0.001; and 0.031 respectively. Even though other classes were not statistically changing, for example, the settlement area within *p*-value = 0,121, but the area tends to be enlarged. On the other side, the *p*-value of the water body class was 0,1182 but based on the rate of change, this area seems to be declined, approximately 0.61%. Nevertheless, the findings should be integrated within decision makers' policy to establish Government plans, specifically in controlling and protecting the potential of biomass and bioenergy resources.

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