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Land Cover Changes from 1990 to 2019 in Papua, Indonesia: Results of the Remote Sensing Imagery

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Abstract: Long-term land cover changes play a significant driver of ecosystem and function of natural biodiversity. Hence, their analysis can be used for evaluating and supporting government plans, especially conservation and management of natural habitats such as sago palm. In Papua Province of Indonesia, sago palm has been stated as one of the priority plants in the Medium-Term Development Plan (R.P.J.M.). However, limited studies have examined this palm in one of the Regencies of Papua Province, namely, Merauke Regency. In this study, we performed remotely sensed data imagery and supervised classification to produce land cover maps from 1990 to 2019. During the study period, twenty-one land cover classes were identified. The six classes of the natural forest consist of primary dryland forest, secondary dryland forest, primary mangrove forest, secondary mangrove forest, primary swamp forest, and secondary swamp forest; thus, fifteen classes of non-forested area. Concerning the sago palm habitat, our study evaluated two different categories (1) based on the land cover scheme from the Ministry of Environment and Forestry and (2) according to the peatland land cover ecosystem in Papua. Based on paired samples *t*-test, the result indicated statistically significant changes specifically at primary dryland (p-value = 0.015), grassland (p-value = 0.002) and swamp (p-value = 0.007). Twelve from 20 districts of Merauke Regency tend to lose the forecasted natural habitat of the sago palm. Therefore, this study suggests the further need to recognize and estimate the yield of sago palm area in these various ecosystems.

Keywords: land cover; Merauke Regency; sago palm

1. Introduction

The land cover indicates the physical land class covered by swamp forests, mining areas, and other land cover classes. In contrast, land use refers to the purpose land serves, for example, recreation and wildlife habitat. Land cover and land use are often used reciprocally, but both of them can be performed to support various purposes, for instance, identification and change detection [1,2]. Land cover changes information is useful to achieve a better perspective of landscape dynamics and is also proper for evaluating the sustainability of natural resources [3,4]. Thus, ground cover monitoring and mapping are required to investigate spatial planning and environmental examination [5,6]. Additionally, land cover and land use analysis will help in the reliable prediction of future circumstances. For example, future changes in forest cover can be predicted using the substance gained from historical datasets and remote sensing observations [7].

Numerous studies have been conducted on the measurement of land cover change at a national as well as a global scale because of its tremendous impact on various aspects such as urban development, water supplies, or environmental studies [8,9]. Long-term monitoring of land cover changes is significantly needed to estimate carbon stock, ecosystem service, and biodiversity losses [10–12]. Generally, the main focus on developing countries such as Indonesia is related to the conversion of forest areas for supporting agriculture expansion, urban or infrastructure planning [13–15]. However, the loss of forest cover changes can rigidly decrease the natural sustainability of the site, including the loss of biodiversity, which leads to a reduction in ecosystem functioning and an increase in the climate change factor. To handle this, some strategic ways have been set up, for instance, the Indonesian Government in Presidential Instruction Number 3 of 2020 has mentioned about the mitigation of forest and land fires prevention, monitoring, and forest evaluation. Also, Presidential Decree Number 1 of 2016 established The Peat Restoration Agency or Badan Restorasi Gambut (B.R.G.) to coordinate and facilitate efforts to restore peat lands in several provinces, including in Papua [16,17].

In Papua, forest areas play an essential role as a natural habitat of sago palm that grows in the moist upland rainforest, freshwater, peat lands, swamps, or salty areas of tropical lowlands up to 700 m above sea level. The favorable preconditions date temperatures of above 25 °C and relative air humidity of around 70%; at the time of vegetative just before flowering, the plant transforms its saved nutrition towards starch, which fills the trunk. Thus, at the mature phase, it occupies a huge trunk and may reach a height of 6–10 m. Sago palm reaches commercial maturity at 9–12 years of age, when fruits start to develop and starch growth in the trunk reaches its highest level [18]. In comparison to other starches, sago produces an amount of approximately 400kg dry starch for each tree, while cassava or potato produces just around 40 kg [19]. Sago palm is also a part of indigenous costumes and, as a staple food, it will be cooked traditionally using burnt stones while the sago waste is used as livestock feed. Today, sago palm is said to be one of the priority plants in the Medium-Term Development Plan, or Rencana Pembangunan Jangka Menengah (R.P.J.M.), of Papua Province, because it provides many benefits in various sectors such as food security, the agro-industry, and environmental issues [20,21].

At the moment, current satellite imagery has been explored extensively for mapping and monitoring land cover changes using Landsat [22], Sentinel [23], Moderate Resolution Imaging Spectroradiometer (MODIS) [24], Synthetic Aperture Radar (SAR) [25], Satellite Pour I 'Observation de la Terre (SPOT) [26], Pleiades [27], and other openness of data satellites. Furthermore, a broad range of suitable spectral bands with a very high resolution and accessibility with various computer-aided software has improved the use of remotely sensed data. For instance, the System for Automated Geoscientific Analyses (SAGA) [28], Quantum Geographic Information System (QGIS) [29], Sentinel Application Platform (SNAP) [30], eCognition [31], Earth Resources Data Analysis System (ERDAS) [32], and other platforms such as Google Earth [33] have improved the use of remotely sensed data. The long-term series of Landsat has been demonstrated successively to monitor land cover changes because of land degradation [34], to investigate land cover changes as a result of some variables such as urban expansion [35], flooding [36], deforestation [37], coastal abrasion [38], and vegetation spreads [39]. It continues to measure forest carbon stock [40], climate [41], biodiversity [42], and other land cover changes.

Although some studies have focused on monitoring land cover changes of Indonesia in general, we found studies applying remote sensing to evaluate changes in swamp forest land cover, and its impact on the natural habitat in this location are still unreported [43]. Therefore, this paper aims (1) to provide the current land cover maps for the Merauke Regency in Papua Province of Indonesia, (2) to evaluate land cover changes, and (3) to estimate the potential area forthe natural habitat ofthe sago palm. To deal with these objectives, we combined existing land cover maps that we obtained from the Ministry of Environment and Forestry (MoEF) and Landsat imagery to create new land cover maps.

Thus, we calculated the rate of land cover change throughout the study. Regarding the sago palm habitat, this study examined the natural ecosystem of sago palm habitat based on two categories, i.e., (1) based on MoEF land cover scheme [44], and (2) peatland land cover in Papua [45]. We also applied statistical analysis to investigate the significant change of sago palm habitat based on their land cover. Our findings provide current land cover maps and the evaluation of land cover map changes over time, which can be used to support decision-making of the local Government for managing and conserving natural resources.

2. Materials and Methods

2.1. Study Area

The study was carried out in Merauke Regency (137°38′52.9692′′ E–141°0′13.3233′′ E and 6°27′50.1456′′ S–9°10′1.2253′′ S; Figure 1), which is located on the southern part of Papua Province. Papua Province is one of the thirty-four provinces of Indonesia, with a total area of about 31,509.162 ha and is noticed as a province with the most significant area. Papua and West Papua contribute to approximately 10% of the world mangrove area within various ecosystems [46]. In this study, the selected sago palm tree is scientifically known as *Metroxylon sagu Rottb*. The palm tree is one of the ecological tree species that grows in Indonesia, particularly in Papua and West Papua [21]. The palm has tremendous advantages to support the food sector, bioethanol [47,48], as a raw material for the agro-industry, and other aspects of sago [20]. This palm rises well in freshwater such as in Jayapura and swamps or salty areas of tropical lowlands, for example, in Merauke Regency.

Merauke Regency encompasses twenty districts, namely, Ulilin, Muting, Kaptel, Ngguti, Ilwayab, Tabonji, Waan, Kimaam, Tubang, Okaba, Malind, Kurik, Animha, Elikobel, Jagebob, Tanah miring, Semangga, Sota, Naukenjerai, and Merauke). The capital of Regency is located in Merauke. This Regency occupies an area of around 4,851,715 ha and is well known as the largest Regency in Papua Province. Merauke Regency is also a leader of the top three paddies providers, with about 91.47% of paddy production over Papua Province [49].The site Regency is bordered directly with Papua New Guinea and Australia, with an average temperature of around 27 °C, while the humidity is about 81%. The type of forest in this regency consists of primary forest and secondary forest, including mangrove, swamp, and dryland [49,50].

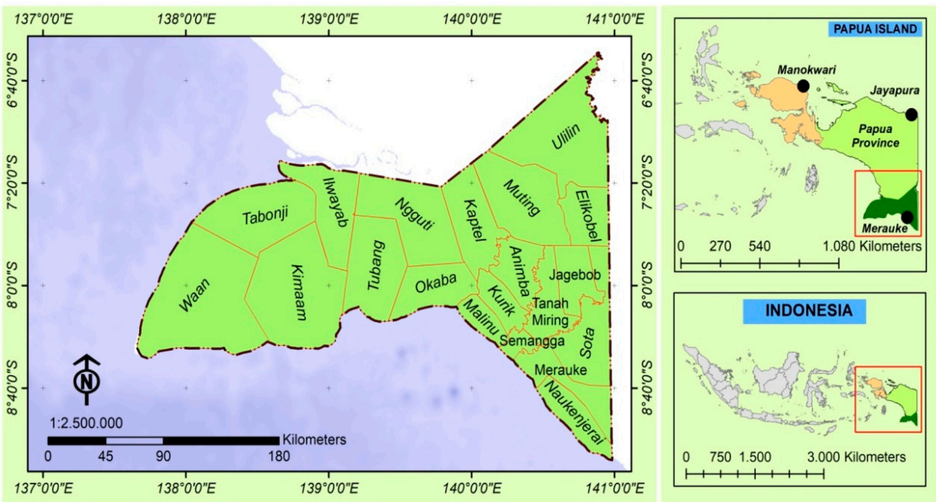

Figure 1. Geographical position of study area. The study area has boundaries with Mappi and BovenDigoel Regency to the north, the Arafuru Ocean to the south and west, Papua New Guinea to the east.

2.2. Data Acquisition and Preprocessing

In this study, two types of data from remotely sensed and secondary data were analyzed. Several secondary data such as the type of forest, area of forest by function, were contributed by Government agencies, i.e., Plantation and Forestry, and statistics agencies through their catalogues: Papua Province in figure 2020 (Number of catalogue: 1102002.94) [49], and Merauke in figure 2020 (Number of catalogue: 1102002.9401) [50]. Existing land cover maps for 1990, 1996, 2003, 2006, 2011, and 2014 were published on www.webgis.menlhk.go.id. The provincial boundary spatial data were acquired from the Regional Development Planning Agency or Badan Perencanaan Pembangunan Daerah (BAPPEDA) of Papua Province that we used as supporting data. Land cover classes of Indonesia and the description are referred to the Ministry of Environment and Forestry (MoEF), which includes the Standardization Agency of Indonesia or Badan Standardisasi Nasional (B.S.N.), specifically, the Indonesian National Standard or Standard Nasional Indonesia (S.N.I. 8033:2014). The land cover is classified into twenty-three classes that consist of six classes of forests, one plantation of the forest, 16 classes of non-forests (Table 1).

Table 1. Land cover classes of Indonesia [1].

No.	Class	Abbreviation	Definition	Category	IPCC [1]
1.	Primary dryland forest	P.D.F.	The natural tropical forest grows on dryland habitat including lowland, upland, and mountain forests, with no signs of human or logging activities.	Natural forest	Forest
2.	Secondary dryland forest	S.D.F.	The natural tropical forest grows on dryland habitat including lowland, upland, and spotting of logging.	Natural forest	Forest
3.	Primary mangrove forest	P.M.F.	Inundated forest with access to sea/brackish water and dominated by species of mangrove and nipa that has no signs of logging activities.	Natural forest	Forest
4.	Secondary mangrove forest	S.M.F.	Inundated forest with access to sea/brackish water and dominated by species of mangrove and nipa that exhibit signs of logging activities, indicated by patterns and spotting of logging.	Natural forest	Forest
5.	Primary swamp forest	P.S.F.	The natural tropical forest grows in wet habitat including brackish swamp, sago, and peat swamp.	Natural forest	Forest
6.	Secondary swamp forest	S.S.F.	The natural tropical forest grows in wet habitat including brackish swamp, sago, and peat swamp, with signs of human intervention or logging activities.	Natural forest	Forest
7.	Plantation forest	P.F.	Planted forest including areas of reforestation, industrial plantation forest, and community plantation forest.	Plantation forest	Forest
8.	Estate cropland	E.C.	Estate areas that have been planted, mostly with perennial crops or other agriculture trees commodities.	Non-forest	Cropland
9.	Pure dry agriculture	P.D.A.	All land cover associated with agriculture activities on dry/nonwet land such as moors, mixed garden, and agriculture fields.	Non-forest	Cropland
10	Mixed dry agriculture	M.D.A.	All land cover associated with agriculture activities on dry land that is mixed with shrubs, thickets, and logs over the forest. This cover type often results in shifting cultivation and its rotation, including on carts.	Non-forest	Cropland
11	Dry shrub	D.S.	Highly degraded log over areas on dryland habitat that is undergoing succession but have not yet hit a stable forest ecosystem, having natural scattered trees or shrubs.	Non-forest	Grassland
12	Paddy field	P.F.	Agriculture areas on nondry habitats, especially for paddies that typically exhibit dyke patterns, rained, seasonal, and irrigated paddy fields.	Non-forest	Cropland
13	Wet shrub	W.S.	Highly degraded log over areas on nondryland habitat of wet habitat that have not yet reached a stable forest ecosystem, having natural separated trees or shrubs.	Non-forest	Grassland
14	Savanna and grasses	S.G.	Areas with grasses and scattered trees and shrubs, could be in wet or nonwet habitats. Typical of the natural ecosystem on Sulawesi Tenggara, NTT, and the south part of Papua.	Non-forest	Grassland
15	Open swamp	O.S	Open swamp with less vegetation.	Non-forest	Wetland
16	Open water	O.W.	Water body including ocean, rivers, lakes, ponds.	Non-forest	Wetland
17	Fishpond	F.P.	Areas exhibiting aquaculture activities such as fish, shrimp, or salt ponds.	Non-forest	Wetland
18	Port and harbor	P.H.	Ports and harbors big enough to be independently delineated as independent objects.	Non-forest	Other land
19	Transmigration areas	T.A	Unique settlement, association with houses, agroforestry, and garden in and around.	Non-forest	Settlement
20	Settlement areas	S.A.	Including rural, urban, industrial, and other typical appearances of settlement.	Non-forest	Settlement
21	Mining areas	M.A	Mining areas such as open-pit mining, tailing ground.	Non-forest	Other land
22	Bare ground	B.G	Barren land with no vegetation cover yet, open exposure areas, craters, sandbanks, sediments, and area post-fire that has not shown regrowth yet.	Non-forest	Other land
23	Clouds and no-data	C.Oo	Clouds, cloud shadows with size up to 4 cm^2 at 100.000 scales.	Non-forest	No data

[1] [44] (pp. 5–6 and 49–51); [2] Intergovernmental Panel on Climate Change (IPCC).

To achieve remotely sensed data (Table 2), we used Landsat multispectral images that, since 1972, have provided sensor Multispectral Scanner Systems (MSS)/Return Beam Vidicon (RBV) (1972/1978), MSS/Thematic Mapper (TM) (1982/1984), Enhanced Thematic Mapper (ETM+) (1993/1999) and Operational Land Imager/Thermal Infrared Scanner (OLI/TIRS) (2013). In this study, we applied Landsat 7 ETM + and Landsat 8 OLI/TIRS (L1T) multispectral images covering the study area. The L-1Terrain (L1T) product will automatically correct their geometrics and radiometric based on inputs from the sensors as well as the Ground Control Point (G.C.P.) and Digital Elevation Models (D.E.M.). We obtained data freely for the years 2000, 2009, 2015, 2016, 2017, 2018, and 2019 (E.T.M. + and OLI/TIRS), with 30 m of the resolution, 705 km of altitude, and less than 50% cloud cover. To reduce this cloud cover, we combined multitemporal Landsat images from two seasons of Papua, which were appropriately selected from Figure 2.

Table 2. Characteristics of the satellite data used in this study.

Property	Landsat 5	Landsat 7	Landsat 8
Spatial resolution	30 m for visible and I.R.,	30 m for visible and Infrared (I.R.)	30 m for visible and I.R.
	120 m for thermal	15 m for Panchromatic (Pan) and 60 m for thermal	15 m for (Pan) and 100 m for thermal
Spectral resolution	7 bands (visible, I.R., thermal band)	8 bands (visible, I.R., Pan, and thermal band)	11 bands (visible, I.R., Pan, and thermal)
Radiometric resolution	8 bit	8 bit	16 bit
Temporal resolution	16 day	16 day	16 day
Details of spectral resolutions (µm)	Band 1: (blue) 0.450–0.515	Band 1: (blue) 0.450–0.515	Band 1: (blue) 0.43–0.45
	Band 2: (green) 0.525-0.605	Band 2: (green) 0.525–0.605	Band 2: (blue-green) 0.45–0.51
	Band 3: (red) 0.63-0.69	Band 3: (red) 0.63–0.69	Band 3: (green) 0.53–0.59
	Band 4: Near-Infrared (N.I.R.) 0.76–0.90	Band 4: (N.I.R.) 0.76–0.90	Band 4: (red) 0.64–0.67
	Band 5: Short-Wave Infrared (SWIR-1) 1.55–1.75	Band 5: (SWIR-1) 1.55–1.75	Band 5: (N.I.R.) 0.85–0.88
	Band 6: (thermal) 10.4–12.5	Band 6: (thermal) 10.4–12.5	Band 6: (SWIR-1) 1.57–1.65
	Band 7: (SWIR-2) 2.09–2.35	Band 7: (SWIR-2) 2.09–2.35	Band 7: (SWIR-2) 2.11–2.29
		Band 8: (Pan) 0.52–0.92	Band 8: (Pan) 0.50–0.68
			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

All remote sensing data were downloaded from the archives of the United States Geological Survey (USGS), available on https://earthexplorer.usgs.gov/. We also recorded field data location using a hand-held global positioning system (G.P.S.).

After extracting the images, we carried out preprocessing steps consisting of radiometric calibration to remove the effect of atmospheric, illumination angles, and seasonal variation across the image [51]. Then, we projected the image according to our study area (European Petroleum Survey Group/EPSG: 23894), which is Universal Transverse Mercator (U.T.M.) World Geodetic System (W.G.S.) 84, in zone 54S local projection type. Preliminary image based on the area of interest was conducted using false color composites of red, green, and blue. To add these, we also did image enhancement and mosaicking to merge the image frame; all the preprocessing tasks here were carried out using the System for Automated Geoscientific Analyses (SAGA) Geographic Information System (GIS) that was included in the Quantum GIS (QGIS) software.

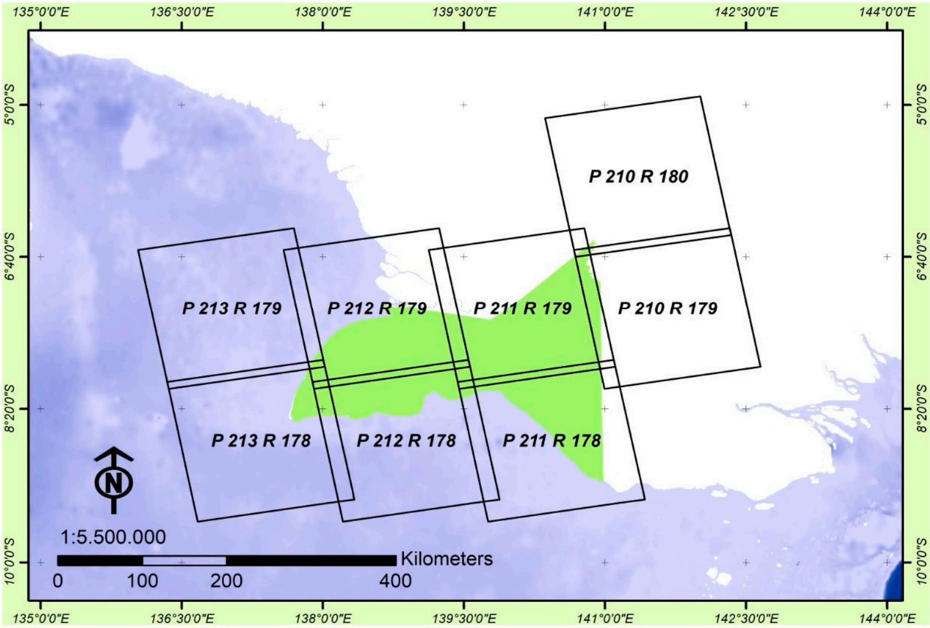

Figure 2. The study area: Landsat imagery path and row scenes.

2.3. Data Processing

For image classification, firstly, the actual land cover maps from MoEF (1990, 1996, 2003, 2006, 2011, 2014, and 2017) were clipped and overlaid on Landsat imagery in the same year. During this process, we looked at the entire map and made corrections wherever it was needed. Afterwards, supervised classification was applied [52]; training samples were selected by delineating polygons at characteristics sites. We chose 15 of each class as the training data; at this step of the procedure, we also compared each class that was collected in the fields using G.P.S. The accuracy assessments of the image classification were done as an integral part of the image classification process using QGIS. Next, we developed land cover maps for other years (2000, 2009, 2015, 2016, 2018, 2019) by analyzing the supervised classification result and the existing land cover maps. Since the visual interpretation should be more standardized, we therefore complied with the Ministry of Environment and Forestry scheme [44], which included the Indonesian National Standard (S.N.I.), particularly SNI 8033:2014, that allows us to recognize the image through structure, texture, shape, pattern and color; at the same time, grants land cover classification in Indonesia (Table 1). According to that scheme, there were twenty-three land cover classes in total, consisting of 6 classes of natural forests, 1 class of plantation forest, 16 classes of non-forest. Following the natural habitat of sago palm, there were two sites, i.e., primary swamp forest and secondary swamp forest. At the final step, we validated the land cover maps by using a geographic browser, which is Google Earth Pro [53], that provides a higher resolution of satellite imagery. We ensured that checkpoints were spread throughout the study area and expressed all land cover classes; nonetheless, these numbers were selected in a different amount due to the possibility of high resolution images.

2.4. Data Analysis

The land area for general characteristics of the study site were presented in mean and standard deviation (minimum, maximum). Land area changes over time were analyzed using the paired *t*-test [54,55] for the years 1990 and 2019. To designate the statistical significance in all analyses, a *p*-value of less than 0.05 was used. Statistical analysis was performed using IBM SPSS statistics version 25 (IBM Corp., Armonk, NY, USA). In this study, a *t*-test was performed to examine the means of land cover for the general characteristics of the site and whether or not the natural habitat of sago palm has significantly changed throughout the study.

Moreover, we also calculated gain and losses [56], the rate of land cover change, in the following way (Equation (1)) [57,58].

$$the\ change\ rate\ of\ land\ (C) = \frac{Area(f) - Area(i)}{Area(i)} \quad (1)$$

Area(*f*) and *Area*(*i*) are the areas of a certain land type at the final area or at the end, while *Area*(*i*) represents an initial or at the beginning of the research period, respectively. The negative rate number of the land cover shows a decreasing trend during the period of study, while in contrast, the positive number indicates an increasing area of each class or category.

3. Results

3.1. Land Cover Changes in Merauke Regency

Recent land cover maps from 1990 to 2019 are presented in Figure 3; we made 13 years of land cover maps in this Regency, consisting of land cover maps in 1990, 1996, 2000, 2003, 2006, 2009, 2011, and from 2014 to 2019. Twenty-one land cover categories were identified: (1) 6 classes of the natural forest included primary dryland forest, secondary dryland forest, primary mangrove forest, primary swamp forest, secondary mangroves forest, secondary swamp forest; (2) 15 classes of non-forest consisting of swamp shrub, swamp, bush/shrub, estate crop plantation, settlement area, barren land, clouds, grassland, water body, dryland agriculture, shrub-mixed dryland, paddy field, fishpond, airport, transmigration area (Figure 3). By using supervised classification [1] of remotely sensed imagery, it is possible to get the resultant area estimates that occurred in this Regency, as shown by Tables 3–5.

Table 3. Land cover area (ha) and the percentage of change from 1990 to 2003.

LC Class	1990 (ha)	1996 (ha)	2000 (ha)	2003 (ha)
Natural Forest				
Primary dryland forest	694,737	664,757	634,776	619,004
Secondary dryland forest	638,049	620,773	603,496	618,381
Primary mangrove forest	208,727	207,345	205,963	201,768
Secondary mangrove forest	25,345	24,209	23,073	25,776
Primary swamp forest	342,429	329,304	316,179	292,789
Secondary swamp forest	531,109	419,213	307,317	313,173
Total area (ha)	2,440,396	2,265,600	2,090,804	2,070,891
Percentage of change (%)	50.30	46.70	43.09	42.68
Change rate (ha/yr)	=	−7.1626	−7.715	−0.952
Non-Forest				
Bush/shrub	71,946	24,194	176,443	177,229
Estate crop plantation	-	-	-	101
Settlement area	3160	3366	3571	3667
Barren land	81,714	51,759	21,805	21,805
Cloud covered	764	764	764	764
Savanna/grassland	471,693	549,087	626,480	646,258
Water body	352,031	352,012	351.993	351,992
Swamp shrub	930,069	931,438	932,806	929,360
Dryland agriculture	14,377	15,368	16,358	16,772
Shrub-mixed dryland farm	43,462	49,013	54,563	54,563
Paddy field	10,932	10,932	10,932	10,974
Fishpond	-	-	-	-
Airport/harbor	159	159	159	159
Transmigration area	36,638	41,430	46.221	46,221
Swamp	394,375	456,596	518,816	521,051
Total area (ha)	2,411,319	2,586,115	2,760,912	2,780,824
Percentage of change (%)	49.70	53.30	56.91	57.32
Change rate (ha/yr)	=	7249	6759	0.721

Table 4. Land cover area (ha) and the percentage of change in two categories from 2006 to 2014.

LC Class	2006 (ha)	2009 (ha)	2011 (ha)	2014 (ha)
Natural Forest				
Primary dryland forest	598,828	553,728	553,098	543,670
Secondary dryland forest	627,494	672,086	672,425	678,803
Primary mangrove forest	196,510	196,510	196,510	197,808
Secondary mangrove forest	23,678	23,574	23,574	23,675
Primary swamp forest	238,249	205,343	205,343	206,530
Secondary swamp forest	338,909	371,810	371,810	374,446
Total area (ha)	2,023,668	2,023,051	2,022,760	2,024,932
Percentage of change (%)	41.71	41.70	41.69	41.74
Change rate (ha/yr)	−2280	−0.030	−0.014	−0.107
Non-Forest				
Bush/shrub	178,032	178,463	177,262	174,273
Estate crop plantation	101	101	1533	16,535
Settlement area	3891	3891	3891	3917
Barren land	21,853	21,853	21,913	23,501
Cloud covered	764	764	764	-
Savanna/grassland	655,175	704,034	704,044	708,703
Water body	351,995	351,994	351,994	322,264
Swamp shrub	949,786	900,908	900,838	906,111
Dryland agriculture	16,803	16,880	16,880	17,184
Shrub-mixed dryland farm	65,250	65,379	65,379	65,760
Paddy field	10,974	10,974	11,044	11,463
Fishpond	-	-	-	-
Airport/harbor	159	159	159	159
Transmigration area	46,221	46,221	46,221	46,440
Swamp	527,044	527,044	527,034	530,472
Total area (ha)	2,828,047	2,828,664	2,828,955	2,826,783
Percentage of change (%)	58.29	58.30	58.31	58.26
Change rate (ha/yr)	1698	0.022	0.010	−0.077

Table 5. Land cover area (ha) and the percentage of change in two categories from 2015 to 2019.

LC Class	2015 (ha)	2016 (ha)	2017 (ha)	2018 (ha)	2019 (ha)
Natural Forest					
Primary dryland forest	529,715	522,977	519,144	401,879	500,359
Secondary dryland forest	664,888	654,663	652,518	732,934	631,295
Primary mangrove forest	196,758	195,162	195,007	195,660	195,384
Secondary mangrove forest	23,521	23,876	23,829	23,932	24,060
Primary swamp forest	202,799	200,958	200,400	202,694	202,193
Secondary swamp forest	359,399	356,270	358,089	357,151	531,266
Total changed area (ha)	1,977,080	1,953,906	1,948,987	1,914,250	2,084,557
Percentage of change (%)	40.75	40.27	40.17	39.46	42.97
Change rate (ha/yr)	−2363	−1172	−0.252	−1782	8897
Non-Forest					
Bush/shrub	169,262	166,111	170,801	169,656	29,465
Estate crop plantation	19,885	27,397	53,857	80,231	4359
Settlement area	3653	3878	3480	7216	7090
Barren land	263,859	75,081	56,539	77,994	88,946
Cloud covered	-	-	-	-	-
Savanna/grassland	568,723	700,156	603,422	576,528	555,274
Water body	322,282	351,749	351,734	349,816	349,884
Swamp shrub	860,813	917,482	969,770	978,818	942,998
Dryland agriculture	16,396	17,072	16,377	18,278	21,671
Shrub-mixed dryland farm	62,139	65,071	65,344	70,692	8600
Paddy field	11,459	11,388	11,388	48,795	45,505
Fishpond	-	-	-	448	80
Airport/harbor	159	159	159	175	175
Transmigration area	46,440	46,152	45,504	26,526	25,575
Swamp	529,565	516,113	554,354	532,291	37,538
Total area (ha)	2,874,635	2,897,809	2,902,728	2,937,465	2,767,158
Percentage of change (%)	59.25	59.73	59.83	60.54	57.03
Change rate (ha/yr)	1693	0.806	0.170	1197	-5798

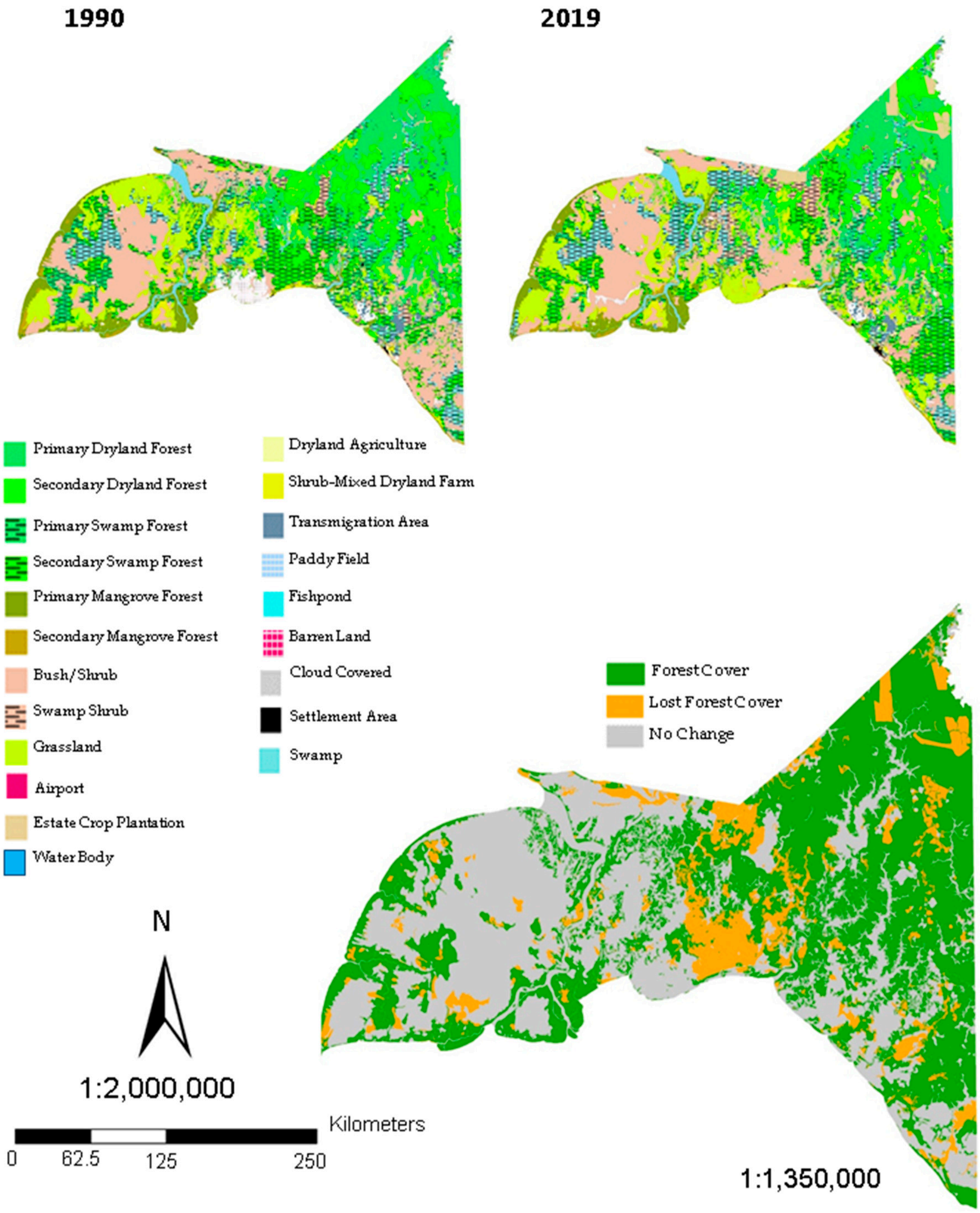

Figure 3. Merauke Regency land cover maps in 1990, 2019, and land use changes map.

In 1990, Merauke Regency was covered by the natural forest of around 2,440,396 ha, or approximately 50.3% (Figure 4), compared to the non-forest area of about 2,411,319 ha, or 49.70% of total area (Table 3). Although this Regency was dominated by natural forest, the area cropped highest by swamp shrub and was followed by three classes of natural forest area, namely, primary dryland, secondary dryland and secondary swamp forest, around 19.17%, 14.32%, 13.15%, and 10.95%, with areas of 930,069 ha, 694,737 ha, 638,049 ha, and 531,109 ha, respectively. Also in 1990, the land cover map did not include estate crop plantation and fishpond. Conversely in 2003, this site was mostly covered by non-forest area for about 2,780,824 ha (Table 3), or approximately 57.32% of the total area, while the natural forest had an area of 2,070,891 ha, or about 42.68%.

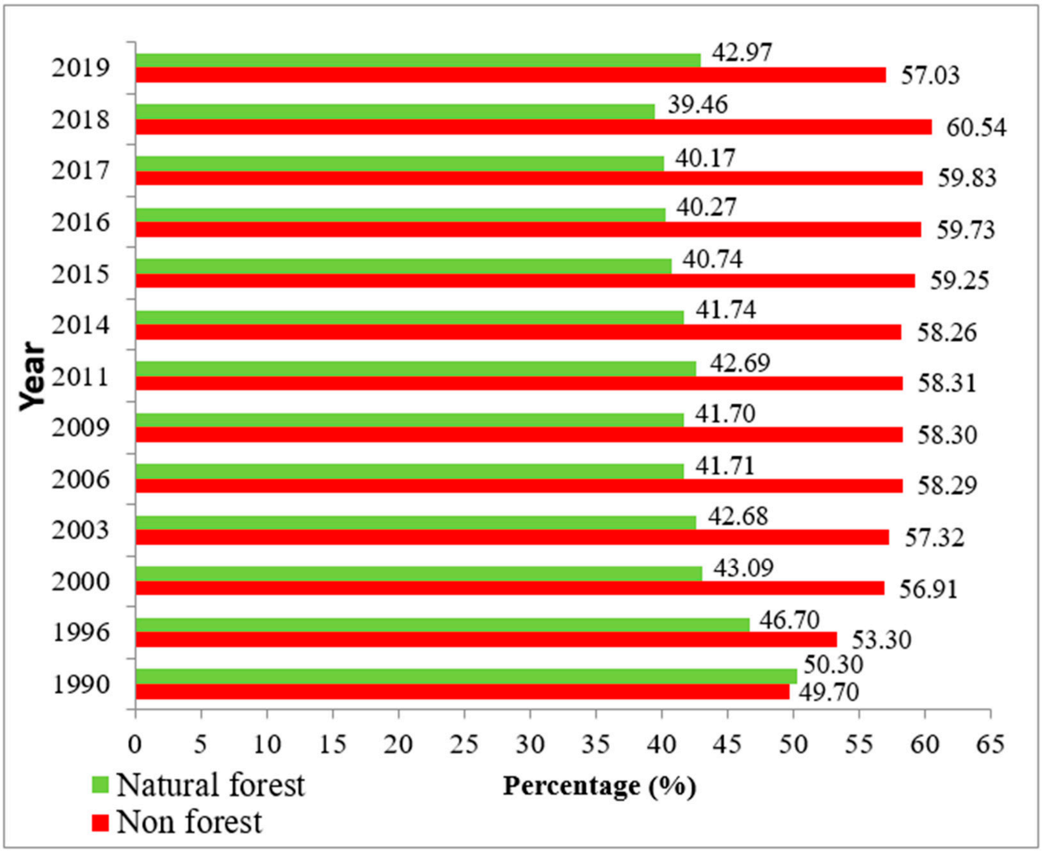

Figure 4. Percentage of non-forest and natural forest land cover changes during 29 years.

In 2006, the Regency was also coated by a non-forested area of 2,828,047 ha, or 58.29%, while the natural forest was decreased to 41.71% (Table 4). The most typical land cover of this Regency was swamp shrub with the area of 949,786 ha, followed by two other land cover types, i.e., grassland about 655,175 ha, and secondary dryland forest with the area around 627,494 ha. The pattern of land cover changes continued in 2014; this Regency was also mostly covered by the non-forest area, which is swamp shrub, grassland, and another class of natural forest, namely secondary dryland forest. The total area change in 2014 was about 906,111 ha, 708,703 ha, and 678,803 ha, respectively.

In 2015 (Table 5), it is shown that the natural forests were 1,977,080 ha, or approximately 40.75%, of the total area. Thus, the non-forest occupied 2,874,635 ha or near to 59.25%. This percentage explained why, in 2015, the non-forest category revealed an increasing trend which was about 18.5% higher than the natural forest. The area was still wrapped highest by swamp shrub for about 860,813 ha and was followed by the secondary dryland forest (664,888 ha). The grassland seems to decrease compared to the previous year. In 2018, the non-forest area reached the highest percentage of change: a loss of about 60.54% more than the natural forest, which tended to lose space for around 39.46% of the total Regency area. The dominant land cover in 2018 was swamp shrub, secondary dryland forest, and then grassland. Even though in 2019 the Regency was still covered by non-forested area (for about 2,767,158 ha or 57.03% of the entire site), the area of natural forest slightly increased about 3.51% compared to 2018 (Figure 4).

3.2. Land Cover Losses and Gains from 1990 to 2019

Land cover category losses and gains were also examined in this study. The total changed areas for each class are shown in Table 6. The result indicates that five classes of natural forests were generally decreasing; only one class of it, that has a small number, was increasing. Primary swamp forest was reduced by around 40.95%, followed by primary dryland forest, that also decreased by about 27.98% during this period. Likewise, primary mangrove, secondary mangrove, and thus, the secondary dryland forest were also reduced by around 6.39%, 5.07%, and 1.06% respectively, while only secondary swamp forest had gained not up to 0.03% in terms of the total area and the percentage of change. In contrast, in the non-forest category, the paddy field was the significantly increased area with an overall percentage of change of about 316.26%. Thus, an expansion of about 124.38% in the settlement area was observed. On the other hand, we could not examine the percentage of the changed estate crop plantation and fishpond due to the lack of initial value in 1990. Furthermore, the transmigration area and water body lost their aerial extent around 30.20% and 0.61%. Other non-forest categories gained less than 80%, i.e., bush/shrub, shrub-mixed dryland, dryland agriculture, grassland swamp, airport, barren land, and swamp shrub subsequently around 79.95%, 57.84%, 50.73%, 17.72%, 10.94%, 10.27%, 8.85%, and 1.39%, respectively. Although the transmigration and water body lost their areas, the overall non-forest gained an increasing trend in the 1990–2019 change period.

Table 6. Land cover changes of each class in Merauke Regency, Papua, Indonesia, from 1990 to 2019.

L.C. Class	Changed Rate (ha/yr)			Total Changed Area	
	Gain(+)	Loss(−)	Net(±)	Ha	%
Primary dryland forest	8206.67	24,404.83	−16,198.17	−194,378.00	−27.98
Secondary dryland forest	12,976.92	13,539.75	−562,83	−6754.00	−1.06
Primary mangrove forest	162.58	1274.50	−1111.92	−13,343.00	−6.39
Secondary mangrove forest	282.60	389.74	−107,14	−1285.70	−5.07
Primary swamp forest	290.08	11,976.42	−11,686.33	−140,236.00	−40.95
Secondary swamp forest	20,255.25	20,242.17	13.08	157.00	0.03
Bush/shrub	9267.26	4474.00	4793.26	57,519.10	79.95
Estate crop plantation	7863.22	-	7863.22	94,358.60	-
Settlement area	393.19	65.68	327.52	3930.23	124.38
Barren land	22,871.75	22,269.04	602.71	7232.50	8.85
Cloud covered	-	63.64	−63.64	−763.65	−100
Grassland	30,703.58	23,738.50	6965.08	83,581.00	17.72
Water body	2462.99	2641.91	−178.93	−2147.15	−0.61
Swamp shrub	12,203.42	11,126.00	1077.42	12,929.00	1.39
Dryland agriculture	731.42	123.60	607.82	7293.80	50.73
Shrub-mixed dryland	2570.88	476.09	2094.78	25,137.40	57.84
Paddy field	3161.55	280.48	2881.08	34,572.90	316.26
Fishpond	37.35	30.71	6.64	79.67	-
Airport	1.38	0.02	1.36	16.30	10.27
Transmigration area	816.87	1738.78	−921.92	−11,063.00	−30.20
Swamp	14,529.00	10,932.08	3596.92	43,163.00	10.94

3.3. Land Cover Changes and Their Impact on the Prediction of the Natural Habitat of the Sago Palm

We evaluated the natural habitat of sago palm based on the land cover changes of the Regency. We used two different categories, i.e., (1) based on the Ministry of Environment and Forestry land cover schemes (Table 1) and (2) the peatland land cover ecosystem of Papua [45]. In [44] (Table 1), as mentioned previously, it predicts two typical habitats of the sago palm, namely, primary swamp forest and secondary swamp forest. Other natural ecosystems were forecasted, i.e., dryland forest, bush/shrub, swamp, swamp shrub, and savanna/grassland [45]; the local community usually utilizes this peat ecosystem to find fish, or to plant and harvest sago palm [45]. Here, we assessed statistically twenty districts of Merauke Regency, by including eight classes of the potential habitat of the sago palm(primary dryland forest, secondary dryland forest, primary swamp forest, secondary swamp forest, bush/shrub, grassland, swamp shrub, swamp), as shown by Tables 7 and 8 using the paired samples *t*-test for the years 1990 and 2019. We used this result to examine the significant changes of the various natural sago palm ecosystems in Merauke Regency as well as to support our third aim of this study.

Table 7 presents that, in 1990, Semangga, Malind, Kurik, and Naukenjerai did not have a possible area of sago of more than 11 ha, while Waan, Ulilin, Kimaam, and Ngguti had a larger potential area of sago habitat compared to other districts, with the mean value of the land area of 60,482.52 ha, 56,469.20 ha, 45,414.98 ha, and 39,547.46 ha, respectively. In the year 2019, it is observed that those districts still had a large area in comparison to other districts based on their mean values, i.e., Waan, Ulilin, Kimaam, and Muting. However, Ulilin, Kimaam, and Muting gradually decreased the land area by around 1.69 ha to 451.68 ha throughout the study. In contrast, Waan district extended the area by approximately 899.53 ha. Semangga, Malind, Kurik, and Naukenjerai still had an inadequate site according to their mean value, and overall, the area progressively declined during the study period.

Table 7. General characteristics of the prediction of sago palm habitat in Merauke Regency (N = 8).

District	1990	2019
Animha	16,975.06 ± 12,669.66 (125.05, 36,055.10)	16,983.27 ± 13,440.54 (437.21, 43,225.50)
Elikobel	18,216.17 ± 33,037.63 (0.00, 96,199.60)	17,495.36 ± 34,366.44 (0.00, 96,199.60)
Ilwayab	21,715.66 ± 27,109.94 (0,00, 80,960.40)	21,900.72 ± 21,947.41 (0.00, 80,960.40)
Jagebob	15,381.23 ± 21,832.78 (841.02, 6,459.20)	15,082.23 ± 23,852.07 (841.02, 64,359.20)
Kurik	8312.54 ± 7576.85 (482.92, 20,296.30)	7971.55 ± 6519.25 (482.92, 20,296.30)
Kaptel	27,868.15 ± 22,683.46 (2305.88, 63,204.40)	27,699.84 ± 20,332.62 (5649.91, 63,317.30)
Kimaam	45,414.98 ± 63,137.85 (434.43, 181,539.00)	45,413,29 ± 64,595.09 (20.49, 1,9042.00)
Malind	4975.18 ± 3897.71 (0.00, 10,343.10)	4883.73 ± 4361.10 (0.00, 11,261.90)
Merauke	15,106.11 ± 22,450.10 (0.00, 60,288.60)	15,126.20 ± 18,966.08 (0.00, 60,228.60)
Muting	39,547.46 ± 46,345.29 (3699.06, 118,800.00)	39,489.52 ± 41,776.44 (3954.98, 112,000.00)
Naukenjerai	10,682.42 ± 16,181.12 (0.00, 46,611.40)	9737.45 ± 10,263.51 (0.00, 50,872.70)
Ngguti	40,029 ± 24,706.78 (11,205.70, 70,419.90)	38,816.99 ± 28,004.91 (11,293.40, 89,504.20)
Okaba	17,481.54 ± 32,317.97 (37.903, 94,925.10)	18,900.30 ± 25,688,46 (505.92, 76,309.70)
Semangga	2702.08 ± 3717.96 (0.00, 10,013.90)	2702.08 ± 3978.13 (0.00, 11,292.90)
Sota	31,005.28 ± 35,952.15 (1608.15, 110,369.00)	30,931.49 ± 29,605.80 (6158.29, 99,919.30)
Tanah Miring	16,414.01 ± 9013.24 (4923.28, 28,562.60)	16,359.38 ± 11,134.00 (347.94, 30,763.80)
Tabonji	33,038.64 ± 40,211.73 (0.00, 111,643.00)	33,030.82 ± 42,503.87 (0.00, 120,527.00)
Tubang	26,192.51 ± 108,655.74 (1027.90, 73,437.70)	32,655.19 ± 42,503.87 (8534.63, 89,472.00)
Ulilin	56,469.20 ± 108,655.74 (1409.11, 315,111.00)	56,017.52 ± 103,832.79 (742.51, 299,073.00)
Waan	60,482.52 ± 60,071.43 (0.00, 165,196.00)	61,382.05 ± 64,152.86 (742.51, 29,9073.00)

Statistical analyses using paired *t*-test were carried out on data generated from supervised classification-based restricted by remote sensing images of the study area. Specifically, the potential habitat of the sago palm is shown in Table 8. The result of the paired samples *t*-test (Table 8) demonstrates that the *p*-value is less than 0.05 for primary dryland (*p*-value = 0.015), grassland (*p*-value = 0.002) and swamp (*p*-value = 0.007). Other categories are greater than 0.05, namely, secondary dryland, primary swamp forest, secondary swamp forest, bush/shrub, and swamp shrub. Therefore, the result reveals that primary dryland forest, grassland, and swamp experienced a statistically significant change from 1990 to 2019.

Table 8. Land cover changes from the natural habitat of sago in 1990 and 2019.

LC	1990	2019	*p*-Value
Primary dryland	34,736.82 ± 71,532.46 (0.00, 315,111.00)	27,686.42 ± 67,227.85 (0, 299,073.00)	0.015
Secondary dryland	31,902.33 ± 38,007.26 (1.02, 118,800.00)	33,604.22 ± 39,934.11 (0, 112,000.00)	0.313
Primary swamp forest	17,126.28 ± 23,169.16 (1276.23, 107,615)	10,271.99 ± 8519.85 (531.72, 24,711.10)	0.107
Secondary swamp forest	26,555.19 ± 24,072.41 (4668.14, 94,925.10)	18,590.47 ± 23,439.27 (949.07, 105.92)	0.152
Bush/shrub	3597.31 ± 6055.62 (0, 24,048.80)	8923.07 ± 16,655.05 (0, 63,317.30)	0.081
Grassland	23,585.31 ± 36,748.43 (0, 111,643.00)	35,202.67 ± 42,540.96 (0, 152,745.00)	0.002
Swamp shrub	46,503 ± 52,913.31 (51.08, 181,539.00)	45,045.15 ± 50,975.60 (51.08, 190.427)	0.723
Swamp	19,197.62 ± 16,473.24 (79.92, 62,207.50)	25,707.58 ± 17,481.00 (34.41, 68,235.40)	0.007

4. Discussion

We used the Landsat satellite imagery and supervised classification to develop recent land cover changes in Merauke Regency over the past 29-year period (Figure 3). The land cover of this Regency today consists of six classes of the natural forest and fifteen classes of non-forested areas. The result from this study showed that a land cover map of Merauke Regency is now generally dominated by non-forested regions, followed by natural forests. Concerning the proportion of natural versus non-forest regions (Figure 4), it is shown that, in 1990, the percentage of the natural forested landscape was 49.70%; however, in 2019, it declined by 7.33%. In the opposite category, the non-forested area was about 49.70% in 1990 and then expanded in 2019, approximately by 57.03%. During this study period, we found two classes of non-forest land cover that extended to up to 100% in terms of total area and the percentage of change, i.e., settlement area and paddy field; 124%, 316.26%, respectively (Table 6). The land area changes also explain why Merauke Regency nowadays is the largest producer of paddy commodities by around 91.47% over Papua Province [49,50]. The settlement area was naturally expanding, expressing population growth in this Regency. Inversely, two other classes of non-forest, for instance water body and transmigration area, had slightly decreased around 0.61% and 30.20% (Table 6). The increment of built-up areas can bea result of migration or urban growth and may lead to environmental problems such as degradation in vegetation and water bodies [59].

In this study, the natural forest cover consists of primary dryland, secondary dryland, primary mangrove, secondary mangrove, primary swamp, and secondary swamp forest. Our evidence confirmed that primary swamp forest and primary dryland forest had higher area losses compared to other forest types, such as primary mangrove, or secondary mangrove. As shown in Table 6, the primary dryland forest lost about 27.98%. Meanwhile, secondary dryland forest, primary mangrove forest, and secondary mangrove forest lost around 1.06%, 6.39%, and 5.07%, respectively. Only the secondary swamp forest gained about 0.03% during the study period. Decrement of the forested landscape was also experienced by some European countries due to increased temperatures caused by climate change. In the Czech Republic, the forest area is currently diminished because of the bark beetle attack [60,61]. Most of the Czech forests are productive forests with less-diverse trees [62]. Therefore, to restore the forested landscape, it is suggested to cultivate various plants with different ages of trees and appropriate width stands of the trees in the Czech forests to provide a natural interconnection in the food chain or food web, to reduce the damage caused by insect attacks [63,64]. The challenge can be taken as a lesson learned, and the recommendations can also be adopted for forest management and restoration in Merauke Regency.

In contrast, the agricultural sector, such as dryland agriculture, mix dryland farms, gained from around 50% to 57% of the land cover area in Merauke Regency (Table 6), which is in agreement with the previous notion that agricultural development can be a threat to the sustainability of mangrove forest in Papua [46].Nevertheless, the mangrove environment can support ecological and economic services to neighborhood, society, and also in the country [65]. Another class of natural forest that suffered in terms of the percentage of change was primary swamp forest; this class lost area by around 40.95% during the study period. This phenomenon can lead directly to a decreased forest quality such as loss of plants that live ecologically in this area, for instance, sago palm *(Metroxylon sago Rottb)* (Table 1) [45]. It also refers to previous studies that found sago palm raising well in particular ecosystems, for example, swamp forest, peat soil, saline [19].

Moreover, sago forests have the opportunity of excellent carbon sinks for carbon absorption, reducing the greenhouse impact and global warming [66]. The wetlands changes and the effect on biodiversity are also acquainted by East African countries such as Tanzania [12]; the number of native species, for instance, woody plant species, bird species, have declined due to some reasons such as deforestation, agricultural expansion, and the extension of the settlement area. Deforestation in peat swamp areas is also experienced by Malaysia [67]; it mentioned that swamp forests declined mostly as the result of the transformation to other non-forested regions such as the agriculture sector. In Papua, sago is believed to be one of the natural resources which can enhance the needs of communities such as to support households' low energy consumption [47] and to strengthen food security as a staple food [68]. Therefore, more preventive approaches, such as regulation or desertification programs from the local government or relevant stakeholders, are highly required.

Other natural ecosystems of sago palm, as estimated in the peatland ecosystem [45], were dryland, bush/shrub, grassland, swamp shrub, and swamp. We analyzed these areas in twenty districts of Merauke Regency by using paired t-test (Tables 7 and 8). Based on the mean values, our findings confirmed that 12 districts from 20 districts of Merauke Regency lost the natural habitat of sago palm, namely, Elikobel (mean = 17,495.36), Jagebob (mean = 15,082.23), Kurik (mean = 7971.55), Kaptel (mean = 27,699.84), Kimaam (mean = 45,413.29), Malind (mean = 4883.73), Muting (mean = 39,489.52), Naukenjerai (mean = 9737.45), Ngguti (mean = 38,816.99), Tanah Miring (mean = 16,359.38), Tabonji (mean = 33,030.82), and Ulilin (mean = 56,017.52) (Table 7). Only one district remained unchanged, i.e., Semangga, thus, seven districts increased slightly, specifically Animha (mean = 16,983.27), Ilwayab (mean = 21,900.72), Merauke (mean = 15,126.20), Okaba (mean = 18,900.30), Sota (mean = 30,931.49), Tubang (mean = 32,655.19) and Waan (mean = 61,382.05). Waan had the largest potential of sago palm area in Merauke Regency.

To add to this, we analyzed the natural habitat of sago palm in eight possible ecosystems from land cover changes in 20 districts of Merauke Regency, especially primary dryland, secondary dryland, primary swamp forest, secondary swamp forest, bush/shrub, grassland, swam shrub, and swamp. Based on land cover losses and gains (Table 6), the peatland ecosystem gained in the area of bush/shrub (+79.95%), swamp shrub (+1.39%), swamp (+10.94%), savanna/grassland (+17.72%), and secondary swamp forest (+0.03%). However, this regency lost the peatland area mostly at primary swamp (−40.95%), primary dryland (−27.98%), and secondary dryland (−1.06%) from 1990 to 2019. Nevertheless, the decreasing trend of the natural forest seems to be broke out in 2019. It can be seen in Figure 4 that the area of natural forest has increased by around 3.5% compared to the previous year. This circumstance could be achieved through support by some strategic plans from the Indonesian Government such as the Peat Restoration Agency or Badan Restorasi Gambut (B.R.G.), the mitigation of forest, land fires, and forest evaluation. The Peat Restoration Agency takes a responsibility to restore peat lands ecosystem in several provinces including Papua [16,17]. The forest restoration is expected to be continued in the coming years. In this respect, the annual land cover maps on this site are required by the region, as well as on a national scale, to monitor and to evaluate particular habitat; since the habitat is damaged overtime, Indonesia will suffer from the loss of various natural plants [43,69]. Moreover, the outcomes of the paired sample t-test as presented in Table 8 reports that primary dryland (p-value = 0.015), grassland (p-value = 0.002) and swamp (p-value = 0.007) significantly changed statistically. The area of primary dryland seems to have decreased; however, swamp and grassland have increased in the statistical term.

On the other hand, this study has not compared the trend of sago palm over time, due to the lack of supporting data, especially the area of sago palm in this site. Therefore, the yield estimation or calculation of this plant in this particular area should be considered annually produced. This study recommends further research in terms of detecting and recognizing the sago palm in this specific area of Merauke Regency.

5. Conclusions

The study has produced recent land cover maps and examined the spatial temporal patterns and rate of land cover changes in Merauke Regency from 1990 to 2019 using remote sensing techniques and supervised classification. Merauke land cover consists of twenty-one classes, which are classified into six classes of natural forest and fifteen classes of non-forested areas. Our analysis of the land cover map presented that the largest declines mostly occurred in the natural forest, namely primary dryland forest, secondary dryland forest, primary mangrove, secondary mangrove, primary swamp forest, for about −81.45% altogether, and only secondary swamp forest has slightly increased by about 0.03% over time. According to the natural habitat of the sago palm, we evaluated eight possible ecosystems, namely, dryland, bush/shrub, grassland, swamp shrub, swamp, and swamp forest, using paired sample *t*-test. The result indicated statistically significant changes specifically at primary dryland (p-value = 0.015), grassland (p-value = 0.002), and swamp (p-value = 0.007). We also analyzed these areas in twenty districts of Merauke Regency. Our findings confirmed that 12 districts from 20 districts of Merauke Regency tend to lose the natural habitat of the sago palm, while only one district remains unchanged. Nonetheless, these particular ecosystems are beneficial to support local community life; for example, planting and harvesting sago palm. Therefore, these outcomes could be integrated within decision-makers and stakeholders to evaluate and to establish government development plans.

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