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Factors Driving Rice Land Change 1989–2018 in the Deli Serdang Regency, Indonesia

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Abstract: The Deli Serdang Regency produces amongst the highest amounts of rice in the province of North Sumatera in Indonesia. Due to land use change and stagnant productivity, the total rice land area and its production have gradually decreased over the years. Hence, understanding this issue is crucial, especially to ensure the sustainability of rice production in the future. The objectives of this study were to identify the trends in land use change (especially regarding rice land) and to investigate the factors affecting rice land change. We classified the satellite images acquired for the years 1989, 1994, 2003, 2009, and 2018 to determine the total area of various land uses. The factors driving rice land change were analyzed using biophysical and socio-economic factors identified from the collected primary and secondary data. The primary data were derived from field surveys, soil analysis, and household surveys, and the secondary data were derived from the Statistical Institution of the Deli Serdang Regency. Correlation analysis, principle component analysis, binary logistic regression, normalization, and weighted index were used to investigate the factors driving rice land change. The results show that forest and rice land have continuously decreased, while plantations and urban areas have continuously increased over this period. We found that the majority of rice land has been converted to plantation expansion and urban development, especially from 2009 to 2018. The factors most affecting rice land change were the distance of rice land to the district capital, the distance of rice land to the provincial capital, population density, slope, and the distance of farmers' rice land to a road. A suitability map for rice land was generated. All the outputs could help with making appropriate strategic decisions to achieve sustainable land use management, especially for rice land.

Keywords: spatial-temporal change; rice land change; policy; biophysical and socio-economic factors; sustainable land use management; Indonesia

1. Introduction

Land use change is a natural and anthropogenic phenomenon that may occur directly and indirectly at the local, regional, and global levels [1,2]. Land uses changes are categorized as natural phenomena when they are the result of a natural hazard, such as a typhoon or earthquake [3]. The changes are considered anthropogenic when any kind of change in land use is influenced by human activities. Influential factors include socio-economic, urbanization, industrialization, population, and policy changes [4,5]. Today, globalization is a particular issue that drives land use change [6,7].

As globalization increases, urbanization and industrialization tend to increase as well. Some drivers behind these two issues are population growth, rural to urban migration, increased wealth, international trade, and policy changes [8]. These issues have been paid less attention in the literature with respect to large-scale land use change assessment. A total of 271 Mha (2.06%) of the Earth's surface was categorized as urban in 2000, which was expected to increase to 621 Mha (4.72%) in 2040, implying that majority of agricultural land be converted for urban land use [9].

Urbanization, one of the significant factors affecting land use change, has been occurring in the Deli Serdang Regency in the province of North Sumatera in Indonesia. Population growth, increasing wealth, industrialization, and new policies are the factors driving this urbanization development. The urbanization policy in the Deli Serdang Regency is the land use planning (LUP) of Mebidangro (2008), which is the acronym for Medan-Binjai-Deli Serdang-Karo [10]. The LUP was included in the Presidential Role No. 62 in 2011. The focus of this plan was to help the Indonesia-Malaysia-Thailand Growth Triangle (IMT-GT) program succeed. Unfortunately, this policy adversely affected agricultural land use, especially rice land.

The expansion of plantation areas is another factor influencing land use change. Oil palm, rubber, and cacao are three plantation commodities that have led to changes in rice land. The increase in oil palm production is supported by international trade, for which globalization is the causal source. Crude palm oil (CPO) from Indonesia is mainly exported to India, China, and The Netherlands, and the amount exported increases every year. In 2014, Indonesia exported 25.3 Mton (48% of world CPO exports), while India alone imported palm oil amounting to US $3.73 billion (60% of Indonesia's CPO exports) from Indonesia [11,12].

The evidence for the land use change issue in Indonesia is the existence of forest cover and agricultural land. Illegal logging, transmigration programs, estate crop expansion, and spontaneous settlement are the main factors contributing to deforestation in Indonesia. Approximately 6 million hectares of primary forest was lost from 2000 to 2012, mostly in the Sumatera and Kalimantan Islands [13]. Thousands of hectares of irrigated and prime agricultural lands have been converted to other uses in Indonesia, and these changes have been extremely uncontrolled. In Java, approximately 30% (480,000 ha) of existing rice land was converted from 1981 to 1999 [14]. In the Deli Serdang Regency, approximately 3735 ha of rice land was converted from 2010 to 2016, which amounts to 533 ha/year [15].

The increases in globalization, deforestation, urbanization, and industrialization, as well as plantation expansion will produce more greenhouse gases (GHGs) through the many activities in these sectors [16–18]. The cumulative GHGs lead to climate change that will continue to increase temperature and the frequency of extreme events, such as drought and flooding [19]. These negative impacts will further lead declining rice productivity [20,21] and income. The consequence of declining income has persuaded farmers to sell their rice land and/or to switch to growing other commodities. In other words, the climatic issue may change the rice land both directly and indirectly.

Investigating the factors driving land use change requires comprehensive understanding of the issues behind. Land use change is influenced by many factors that can be categorized as either biophysical (i.e., slope, elevation, etc.) or socio-economic (i.e., number of populations, income, etc.) [22,23]. These factors, which work in isolation or in combination, can have different effects on land use [24]. In the case of rice land conversion, due to low income, farmers change their rice land to other land uses. The rice land located in lowlands and flat areas can easily be converted via urbanization and the expansion of plantations. Investigating what factors drive rice land change can help land use planners in Deli Serdang Regency select the appropriate strategic actions for addressing the issue of continuous rice land decline.

Maintaining agricultural land is necessary, especially for rice, maize, and wheat, to meet the food needs of the world's population, which is projected to reach around 9.1 billion in 2050. The population of Indonesia, together with those of India, China, Pakistan, Nigeria, and Bangladesh, is expected to make up half that number [25]. To meet the demand for food at that time, the global food production level has to double [26,27] to minimize food insufficiency. However, increasing the rate of global food production is no simple task. Indonesia is facing challenges including climate change [28,29] and plantation expansion [30,31], creating barriers to increasing food production.

Given the lack of reliable and quantified information in the Deli Serdang Regency of Indonesia, we aimed to identify the trend in land use changes, especially the rice land trend from 1989 to 2019, and investigate the factors affecting these changes. We integrated geographic information system (GIS) and remote sensing technology with field and household-based surveys. This provides information for policy makers to generate new strategic actions and to strengthen existing policies to achieve sustainable land use management specifically for rice land.

2. Materials and Methods

2.1. Study Area

The Deli Serdang Regency is located at 2°57′–3°16′ N, 98°33′–99°27′ E. The Deli Serdang Regency is bordered by Medan city and Malacca Strait to the north, Karo and Simalungun Regencies to the south, Binjai city and Langkat Regency to the west, and Serdang Bedagai Regency to the east. Deli Serdang Regency is divided into 22 districts and 394 villages (Figure 1). The Hamparan Perak, Sinembah Tanjung Muda Hulu, and Sinembah Tanjung Muda Hilir Districts are the largest districts at 230.15 km^2, 223.38 km^2, and 190.50 km^2, respectively. The population density of the Deli Serdang Regency is 847 people/km^2. The highest population density is in Deli Tua District, followed by Sunggal and Lubuk Pakam at 7672, 3109, and 3079 people/km^2, respectively. The Deli Serdang Regency has only two seasons: the dry season occurs from June to September and the rainy season from November to March [15].

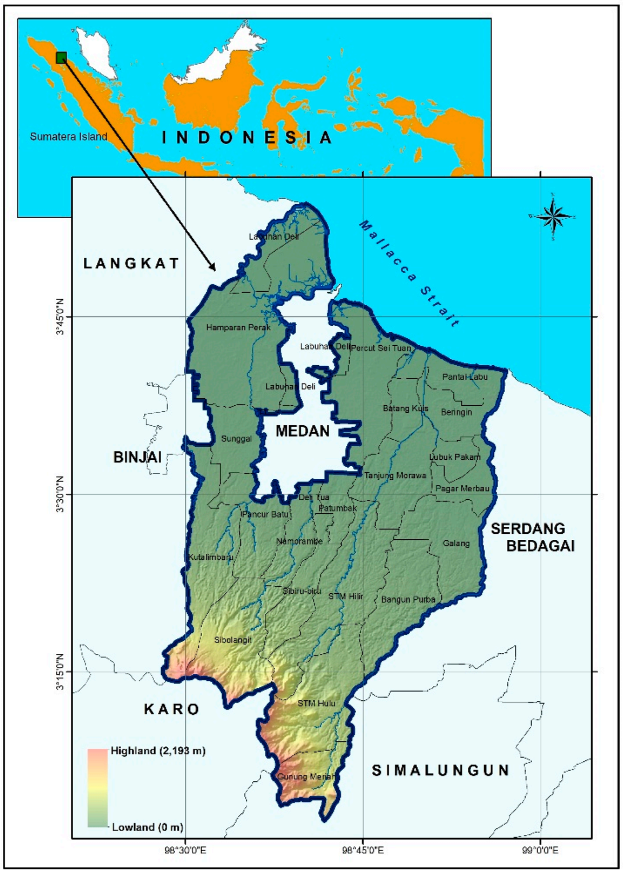

Figure 1. Location map of the study area.

The elevation of Deli Serdang Regency ranges from 0 to 2200 m above sea level. It has diverse topography; the southern part is characterized by undulating and mountainous areas, and the northern part is characterized by flat topography. Hence, various crops, such as food crops (rice and maize), horticulture crops (vegetables and fruits), and estate crops (oil palm, rubber, and cacao) are produced in this area [15]. Three major types of soil are found in this study area according to the Centre for Agricultural Land Resources Research and Development (Agricultural Ministry, Bogor city, West Java, Indonesia): Inceptisol, Entisol, and Oxisol (according to United States Department of Agriculture (USDA) Soil Taxonomy).

2.2. Data Preparation and Processing

The primary and secondary data were acquired to investigate the factors affecting rice land change. Satellite imageries from Landsat 4, 5, 7, and 8 of Path 129/Rows 57–58 for the years 1989, 1994, 2003, 2009 and 2018 were downloaded from the Earth Explore website [32]. By considering two rice growing seasons in the study area May–August, November– February), we used the images accordingly to delineate rice growing areas. The Shuttle Radar Topography Mission Digital Elevation Model (SRTM-DEM) data, with 30 m resolution downloaded from http://srtm.csi.cgiar.org, were used to generate contour, slope, and elevation data. Several thematic layers in shapefile format, such as administrative boundaries, roads, rivers, forests, and agro-ecological zones, were obtained from the Development Planning Agency of North Sumatera Province and Centre for Agricultural Land Resources Research and Development at Bogor, West Java.

The primary data were collected through field surveys, soil analysis, and household surveys; the secondary data, such as the total population, population density, and total rice land area, were collected from the Statistical Institution of Deli Serdang Regency. The field survey was conducted to measure the soil depth and collected soil samples. The soil depth was measured until 60–80 cm, given the ability of rice roots to penetrate the soil. The total number of sampling points was decided by the number of land mapping units in the study area, which have different characteristics related to soil type, slope, and elevation. A total of 26 soil samples were collected and sent to the laboratory for soil texture analysis using the hydrometer method, pH using a pH meter, C-org using the spectrophotometric method, total N using the Kjeldahl method, P_2O_5 using the atomic absorption spectroscopy method, and K_2O using the atomic absorption spectroscopy method. The soil analysis result together with slope, elevation, and soil depth data were used in the rice suitability analysis due to the absence of a rice suitability map in the study area. Based on the rice suitability classification result, the areas with potential (highly suitable, moderately suitable, and low suitable) and without potential (unsuitable) for rice growth were generated. We further investigated these potential and non-potential areas as the biophysical driving factor of rice land change. We conducted a household survey to collect socio-economic data like age, household numbers, education level, total income/expenditure, and frequency and occurrence rate of flood and drought in the area.

2.3. Methodology

The research framework of this study is presented in Figure 2, which included three main parts: landsat image analysis, biophysical variables analysis, and socio-economic variables analysis.

Since two Landsat image scenes were required to cover the whole study area in each period, the scenes were accordingly mosaiced to form a continuous image. The mosaic images from 1989, 1994, 2003, 2009, and 2018 were subset to the same extent as the study boundary. Unsupervised classification, using the iterative self-organizing data analysis technique (ISO-DATA) method, was used to produce a land use map for each period. This classification technique relies on a computed algorithm that clusters pixels based on their inherent spectral similarities [33]. Despite its weakness that is related to the limited control of the classifier over the classes chosen during the classification processing [30], this technique still selected due to its abilities [34,35] to discriminate the features of the area for the analysts with little or no knowledge about the area, to identify and solve errors easily, and to recognize the unique classes that might be overlooked when using supervised classification techniques. In unsupervised classification, a total of 180, 179, 193, 190, and 199 clusters were derived from the images for 1989, 1994, 2003, 2009, and 2018, respectively. Some RGB-composite imageries were used to aid in the visual interpretation and image classification processes. The observation of the color, size, shape, pattern, site, and association that were generated by the RGB-composite imageries guided us in relating the clusters with the real-world classes. Ground truth data from the field survey were also used for identifying the land use classes. In the end, these clusters were classified into seven land uses: forest, plantation, mixed vegetation, rice land, urban, waterbody, and barren land, as shown in Table 1.

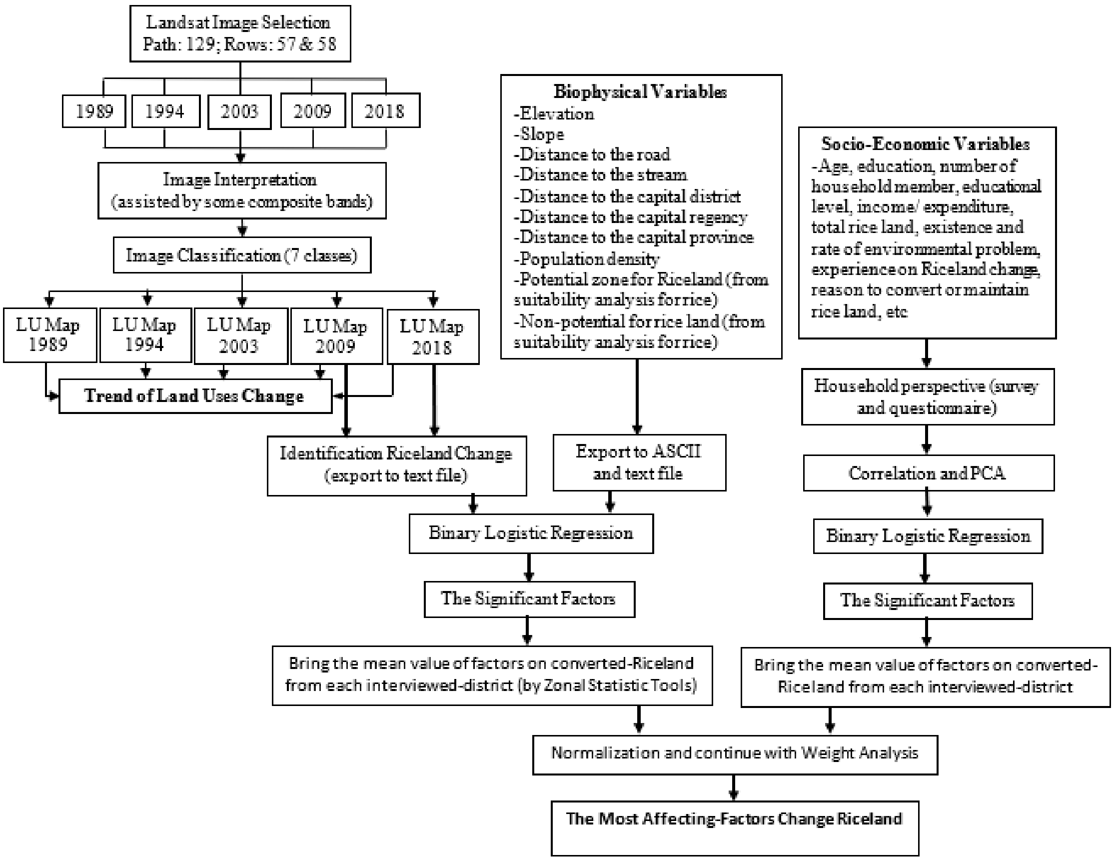

Figure 2. The research framework, where LU for Land Use, ASCII for American Standard Code for Information Interchange, and PCA for Principle Component Analysis.

Table 1. Characterization of land use types for image classification.

Land Use Type	Characterization
Forest	Land covered by forest, mangrove, and highly dense vegetation
Plantation	Land covered by oil palm, rubber, cacao, and sugarcane
Mixed Vegetation	Land covered by a mixture of trees and the others of low dense-covered vegetation
Rice land	Land covered by rice, distributed on low and high land
Urban	Land covered by the high and low density of buildings, roads, housing, or others infrastructure
Waterbody	Land covered by water, e.g., river, seashore, lake, dam, and fishpond
Barren	Land covered by nothing: no vegetation and no infrastructure

Accuracy assessments were used to test the accuracy of the land use classification in terms of the accuracy of image classification in relation to the ground reality [36]. Different approaches are available for conducting accuracy assessments [37]: (1) ground truthing using a global positioning system (GPS) and observing the research area, (2) comparing our land use classification with the image that is thought to be correct like Google Earth image (Google LLC, Mountain View, CA, USA), and (3) obtaining the information from someone with trusted experience or trusted information. There are two methods for collecting ground truth points: by conducting a field survey and identifying ground truth points with GPS assistance and recording the land use, and by creating additional ground truth points randomly in ArcGIS ver. 10.2 (ESRI, Redlands, CA, USA) and overlaying using Google Earth (Google LLC, Mountain View, CA, USA) and then recording the land use. Both recorded-ground truth points were validated with classified-image then. All data were summarized using the error matrix. Then, Cohen's Kappa coefficient (κ), as a standard measurement, was used to quantify the classification accuracy [38,39] using this equation:

$$\kappa = \frac{observed\ accuracy\ -\ change\ agreement}{1\ -\ change\ agreement}. \tag{1}$$

The evaluation of land use change requires the comparison of two specific classified land use images from different time periods. Thus, we needed to generate images of the four time periods of land use conversion: 1989–1994, 1994–2003, 2003–2009, and 2009–2018.

We investigated some plausible factors of land use change in this study, especially for rice land change. We used two approaches conducted to identify these factors, from which the most influential factors were determined. The first approach, a biophysical (pixel data analysis) approach, involved the use of binary logistic regression with dependent and independent variables derived from raster data. The rice land change compared with the other land uses from 2009 to 2018 was designated as the dependent variable. The 'extract by value' command in ArcGIS (ESRI, Redlands, CA, USA) generated this raster data, where "1" denotes a changed pixel and "0" denotes an unchanged pixel. Ten variables were designated as independent variables: elevation, slope, distance to the main road, distance to the stream, distance to the district capital, distance to the regency capital, distance to the provincial capital, population density, potential for rice land, and non-potential for rice land. These independent variables were transformed into raster data. Both dependent and independent variables were converted into ASCII (*.asc) format and exported into a text file (*.txt). DynaCLUE package ver. 2.0 (Institute for Environmental Study, VU University Amsterdam, Amsterdam, The Netherlands) was used to process this conversion [24]. Binary logistic regression analysis was applied to identify which variables have a high probability of influencing rice land change. The logistic model is

$$\ln\left[\frac{p}{1-p}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n \tag{2}$$

where the dependent variable is an odds is ratio of probability (p) of change to the probability ($1 - p$) of no change; β_0 is the intercept; and $\beta_1, \beta_2, \beta_3, \ldots, \beta_\mathrm{n}$ are the coefficients of the independent variables of $x_1, x_2, x_3, \ldots$, and x_n, respectively [40].

The potential and non-potential areas for rice procued were derived from land suitability classification for rice (Table 2). The System of Land Suitability Evaluation was used to assist with this classification measurement [41]. The S1 (highly suitable), S2 (moderately suitable), and S3 (low suitable) suitability level were grouped and labeled as potential rice production zones, and N (unsuitable) was grouped as the non-potential zones. These outputs were transferred into ArcGIS to generate the maps of potential and non-potential zones and were used as two biophysical variables.

Table 2. The rice land suitability classification [42].

Characteristic	Rice land Classification			
	S1	S2	S3	N
Slope (%)	0–3	3–8	8–15	>15
Elevation (m)	0–400	400–700	700–1200	>1200
Soil Texture	Moderately Fine	Medium	Moderately Coarse	Coarse
Soil Depth (cm)	>50	40–50	25–40	<25
pH	5.9–7.5	5.4–5.9	4.5–5.4	<4.5; >7.5
Organic C (%)	>3	1.2–3	0.8–1.2	<0.8
Total N (%)	>0.5	0.2–0.5	0.1–0.2	<0.8
C/N	<8	8–10	10–15	>15
P_2O_5 (mg/100 g)	>40	20–40	15–20	<15
K_2O (mg/100 g)	>60	30–60	16–30	<16

Note: S1 = highly suitable; S2 = moderately suitable; S3 = low suitable; N = unsuitable.

The second approach used to investigate the socio-economic variables that affect rice land change were identified by conducting a household-based survey. Purposive sampling was implemented to choose particular districts and respondents. Based on the recent total area of rice land, the particular districts with the highest, medium, and lowest total rice land area were identified. Then, two representative districts for each level were selected. We determined the sample size using [43]:

$$n = \frac{N}{1 + Nd^2} \tag{3}$$

where n denotes the sample size, N denotes the population of rice farmers in the selected area, and d denotes the margin of error (0.05).

We conducted structured interviews using closed- and open-ended questions to collect in-depth information from respondents' perspective on the issue. The questionnaire was prepared to be as comprehensive as possible to gather all variables. All variables were analyzed using Spearman correlation and descriptive statistical analysis was used to summarize the significant variables. Then, principal components analysis (PCA) was performed. PCA is a multivariate analysis commonly used to compress a large number of original variables into a smaller number of new composite variables, while minimizing the loss of information [44]. Binary logistic regression was then applied to identify the significant factors affecting rice land change. The decision of respondents to change their rice land was selected as the dependent variable, where "0" denoted no experience and "1" denoted experience with rice land conversion. The most significant variable from each component was set as the independent variable.

Finally, the most influential biophysical and socio-economic factors were determined by normalization and weight analysis. The values of biophysical factors were calculated from the mean values from each significant factor for each interviewed district (as the similar districts where the socio-economic variables were taken as well). The zonal statistic tool in spatial analyst of the ArcGIS toolbox (ESRI, Redlands, CA, USA) was used to calculate the mean values [45]. Normalization was used to ensure all factors were both unitless and scaleless using the min-max approach. Before normalizing the factors' values, we determined the functional relationship of each factor with the probability of changing rice land, which was observed from sign of their coefficient value (positive (+) or negative (–)). This is related to implementing the min-max equation.

$$(X_i - \text{Min } X_j)/(\text{Max } X_j - \text{Min } X_j) \tag{4}$$

was applied when increasing the factors value increased the probability of rice land changing, and

$$(\text{Max } X_j - X_i)/(\text{Max } X_j - \text{Min } X_j) \tag{5}$$

was applied when increasing the factor value decreased the probability of rice land changing, where X_i is the actual value of the factor with respect to district (i), Min X_j and Max X_j are the minimum and maximum values, respectively, of factor (j) among all the districts.

After obtaining the normalized value for each factor, the weight was measured using the following equation. The weight value from each factor indicated the degree of its influence on rice land change [46]:

$$W_j = \frac{1}{(SD_j \times \sum_{j=1}^{n}(\frac{1}{SD_j}))}. \tag{6}$$

where W_j is the weight of the factor of j and SD_j is the standard deviation of the factor j.

3. Results and Discussion

3.1. Land Use Change

The classification accuracy is important when generating a new classified image to identify the correctness of the image. A total of 176, 156, 161, 102, and 96 ground truth points were evenly distributed in the study area for the images for 2018, 2009, 2003, 1994, and 1989, respectively. These points were gathered to obtain the overall accuracy (OA), κ coefficient, user's accuracy (UA), and producer's accuracy (PA) values, as listed in Table 3. UA is the proportion of pixels that were precisely classified based on the classified image; PA is the proportion of pixels that were precisely classified based on the reference map.

Table 3. Accuracy assessment of the land use classification.

Land Use	1989		1994		2003		2009		2018	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Forest	91.7	88	95.7	81.5	94.9	86.1	90.7	82.9	96.3	86.7
Plantation	90	90	92.3	85.7	79.2	86.4	78.1	89.3	86.7	86.7
Mixed Veg	70	100	69.6	94.1	76.9	83.3	83.3	71.4	77.3	80.9
Rice	91.3	84	87.5	82.4	88.9	80	86.1	88.1	86.1	83.8
Urban	84.6	91.7	78.6	84.6	78.1	89.3	85.7	82.8	91.7	94.3
Waterbody	100	83.3	75	75	81.3	86.7	76.9	83.3	81.3	92.8
Barren	83.3	100	100	83.3	100	100	100	66.7	88.8	88.8
OA (%)	88.5		84.3		85.1		84.6		87.5	
κ Coef.	0.86		0.81		0.82		0.81		0.85	

Note: PA = producer's accuracy; UA = user's accuracy; OA = overall accuracy.

Among all land uses, the most user accurate classes were forest, plantation, rice, and urban, which were greater than 80% in all classified images. The other three classes, mixed vegetation, waterbody, and barren, had UA values below 80%: 71.4%, 75%, and 66.7%, respectively. The reason for misclassifying the images was the similarity of range land between two or more land uses classes that creating an overlap. The OA for all classified images was more than 84.3% and the κ coefficient was greater than 0.81, indicating that a high proportion of pixels were classified correctly, which is categorized as good performance. A κ coefficient greater than 0.8 is categorized as good classification performance, 0.4–0.8 is categorized as moderate, and less than 0.4 is categorized as poor classification performance [38,47].

By following the procedures in the methodology, a land use image for each year (1989, 1994, 2003, 2009, and 2018) was generated. The seven land uses that were generated (the forest, plantation, mixed vegetation, rice land, urban, waterbody and barren) had their own characterization. The land uses images are presented in Figure 3, depicting the changes in forest, plantation, rice land, and urban.

Forest and rice land were the predominant land uses from 1989 to 2003 (Table 4), representing 35% and 34% of the total area in the Deli Serdang Regency, respectively, in 1989. In 2003, these two land uses were still dominant: rice land area (31%) was the highest, followed by forest (30%). A different trend in land uses changes occurred in 2018, where plantation became the dominant land use as forest and rice land had continuously decreased. Plantations covered 32% of the total area while rice land and forest were 26% and 25%, respectively. In line with the plantation trend, urban areas gradually increased. In 1989, urban areas only covered 3% and continuously increased to 8% in 2018, a nearly three-fold increase in area.

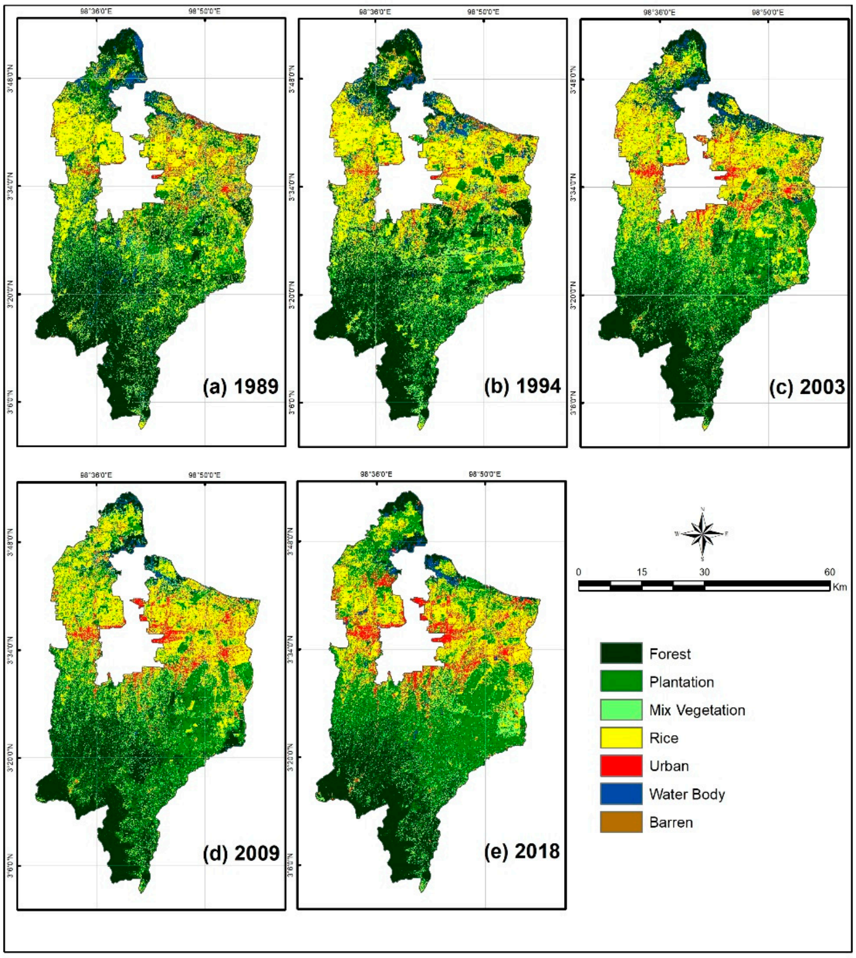

Figure 3. Land uses images of (**a**) 1989, (**b**) 1994, (**c**) 2003, (**d**) 2009, and (**e**) 2018.

Table 4. The total area of land use in 1989, 1994, 2003, 2009, and 2018.

Land Use	**Total Area (ha)**				
	1989	**1994**	**2003**	**2009**	**2018**
Forest	91,300	89,524	77,141	72,961	63,393
Plantation	37,611	39,752	53,584	66,130	82,137
Mixed Vegetation	14,090	24,697	23,772	17,659	17,174
Rice	88,000	80,836	79,406	75,863	66,009
Urban	6504	9317	13,755	14,609	20,834
Waterbody	18,613	11,572	8743	9482	6888
Barren	1409	1831	1127	824	793
Total	257,528	257,528	257,528	257,528	257,528

Figure 4 shows that forest and rice land decreased consistently from 1989 to 2018. The highest percentage of forest change occurred in during 1994–2003 and 2009–2018 at 14% and 13%, respectively, rice land decreased during 1989–1994 and 2009–2018 by 8% and 13%, respectively. While forest and rice area decreased, plantations and urban areas continuously increased. The highest plantation increases occurred during 1994–2003 and 2009–2018, at 35% and 24%, respectively, and those for urban development occurred during 1989–1994 and 1994–2003, at 43% and 48%, respectively.

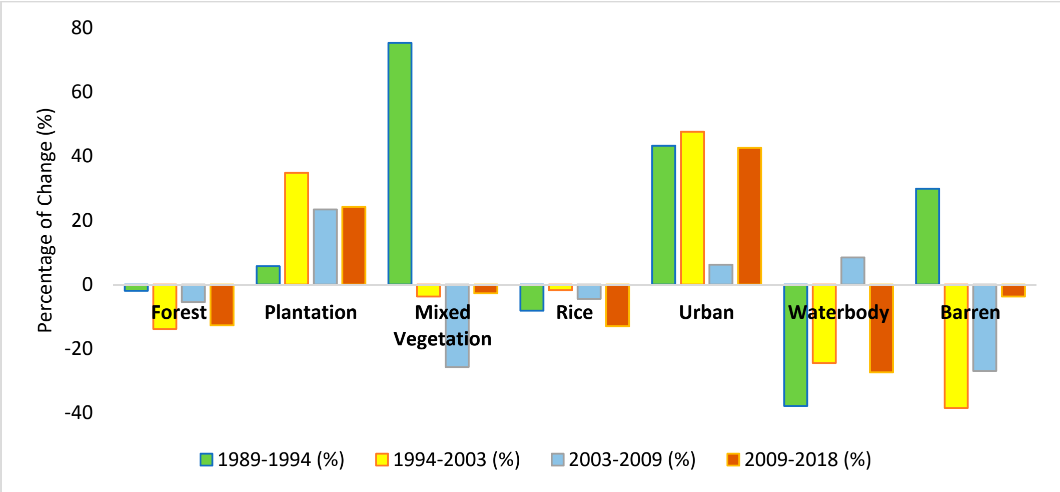

Figure 4. The percentage of land uses change (1989–2018).

Our land use change analysis result is supported by Food and Agriculture Organization (FAO) data [48], which reported that about 246,000 ha of rice land in Indonesia were converted to other land uses during 1981–1985 and 1998–1999. A total of 187,720 ha of rice land was converted in Indonesia from 2000 to 2002 [49]. Through the Green Revolution, Indonesia, including the Deli Serdang Regency, has achieved food self-sufficiency using technology, high-yielding varieties, fertilizer application, and pest and disease control with pesticides along with a large rice land area, as rice is a staple food in Indonesia.

Higher forest conversion (12,382 ha) was observed from 1994 to 2003 due to one of the national Indonesian government programs called the Transmigration Program (Law No. 15, 1997). The purpose of this program was to move people from densely populated to less populous provinces. The government allowed transmigrated-people to convert forest to plantations to provide a livelihood. Deli Serdang Regency was one of destinations for trans-migrants from Java, Madura, and Bali Island. Hence, many intentional forest fire incidents occurred to clear land to build large-scale plantations [50].

During 2003–2018, rice land was still one of the highest converted-land use types. The high profit from oil palm farming encouraged farmers to change their rice land to plantations. During 2009–2018, the urban area increased significantly (6225 ha). The reason for this increase was the new Kuala Namu Airport development, which required a large space to build the supporting infrastructure (i.e., roads, hotels, warehouse, etc.). Also, the nationally-owned plantation and rice land had to be converted. Land use planning related to Mebidangro started in 2008, which was supported by Presidential Role No. 62 in 2011 to ensure the success of the Indonesia-Malaysia-Thailand-Growth Triangle (IMT-GT) in this region. This policy resulted in the faster growth of urbanization and industrialization [10].

3.2. Land Suitability Classification for Rice

Land suitability classification information provides detailed knowledge about the potential and non-potential land that can be used for rice production. Two variables, potential and non-potential land, were applied further to be parts of biophysical factors, which is discussed in Section 3.3.

Land suitability for rice was classified to identify where the locations suitable and unsuitable zones for rice. Then, policymakers would understand what land is suitable for rice, which could then be retained and prevented from being converted. The main purpose for protecting this rice land from conversion is to maintain rice production [51]. In this study, the suitability rice land was classified into four classes: S1, S2, S3, and N. Based on the field survey and soil laboratory results, only three classes were used (Figure 5). Some limiting factors such as slope, elevation, status of soil fertility, were used as parameters for classification measurement. A large area in the south was grouped as unsuitable because the majority of this area has a high degree of slope (in the highlands).

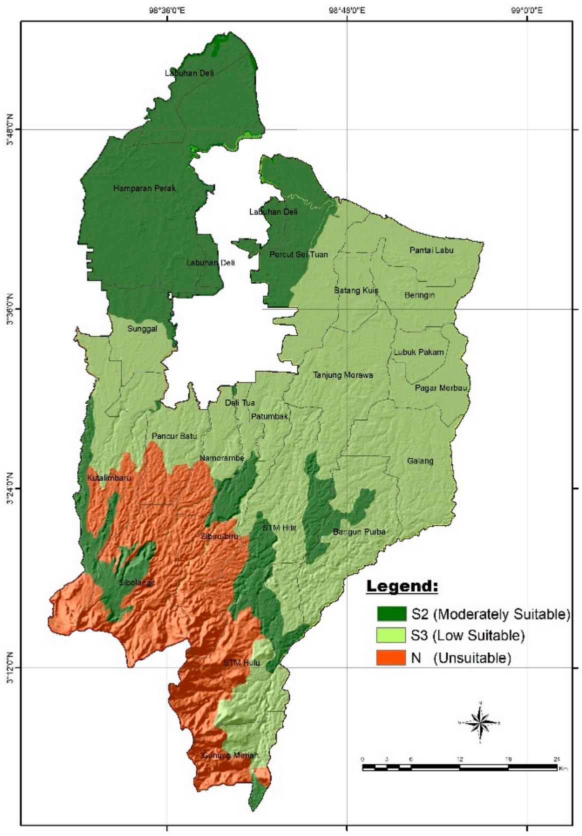

Figure 5. The land suitability map for rice in 2018.

Table 5 shows the total of rice land where located according to the suitability level of rice land in 1989 and 2018. The total rice land area in 1989 and 2018 can be differentiated by considering the same level of rice land suitability classification. We used the overlay raster technique in GIS between rice land and the suitability level to obtain the output. The highest rice land decrease occurred in low suitable areas, followed by moderately suitable and unsuitable areas by 394, 258, and 106 ha/year, respectively.

Table 5. The coverage area of rice land according to the suitability level for rice land in 1989 and 2018.

Suitability Level	1989	2018	Change from 1989 to 2018	
	(ha)	(ha)	(ha)	(ha/year)
Moderately Suitable	32,126	24,641	−7485	−258
Low Suitable	51,946	40,518	−11,428	−394
Unsuitable	3928	850	−3078	−106
Total	88,000	66,009	−21,991	

Table 6 presents the total area of each land use that were classified as different levels of suitability for rice in 1989 and 2018. Rice land still covered a larger part of the suitable area (84,072 ha) in 1989. The majority of land suitable for rice was replaced by plantations (73,813 ha) by 2018. Urban development on the land suitable for rice production increased significantly over the 30-year period. In 1989, urban areas covered only 6497 ha, and increased to 20,546 ha in 2018.

Table 6. The coverage area of land use types in each suitability level for rice land in 1989 and 2018.

Land Use	Total Area in 1989 (ha)			Total Area in 2018 (ha)		
	S2	S3	N	S2	S3	N
Forest	22,117	32,042	37,140	14,239	13,369	36,086
Plantation	10,657	24,104	2851	23,649	50,164	8324
Mixed Vegetation	3015	8068	3007	3273	10,426	3475
Rice land	32,126	51,946	3928	24,641	40,158	850
Urban	1909	4588	8	7826	12,720	288
Waterbody	7886	8488	2239	4452	2318	118
Barren	574	818	17	204	539	50
Total	78,284	130,054	49,190	78,284	130,054	49,190

3.3. Factors Affecting Rice land Change

Two approaches were used to identify the factors driving rice land change in this study. For the first approach, 10 biophysical factors derived from secondary data and field surveys were investigated (Figure 6).

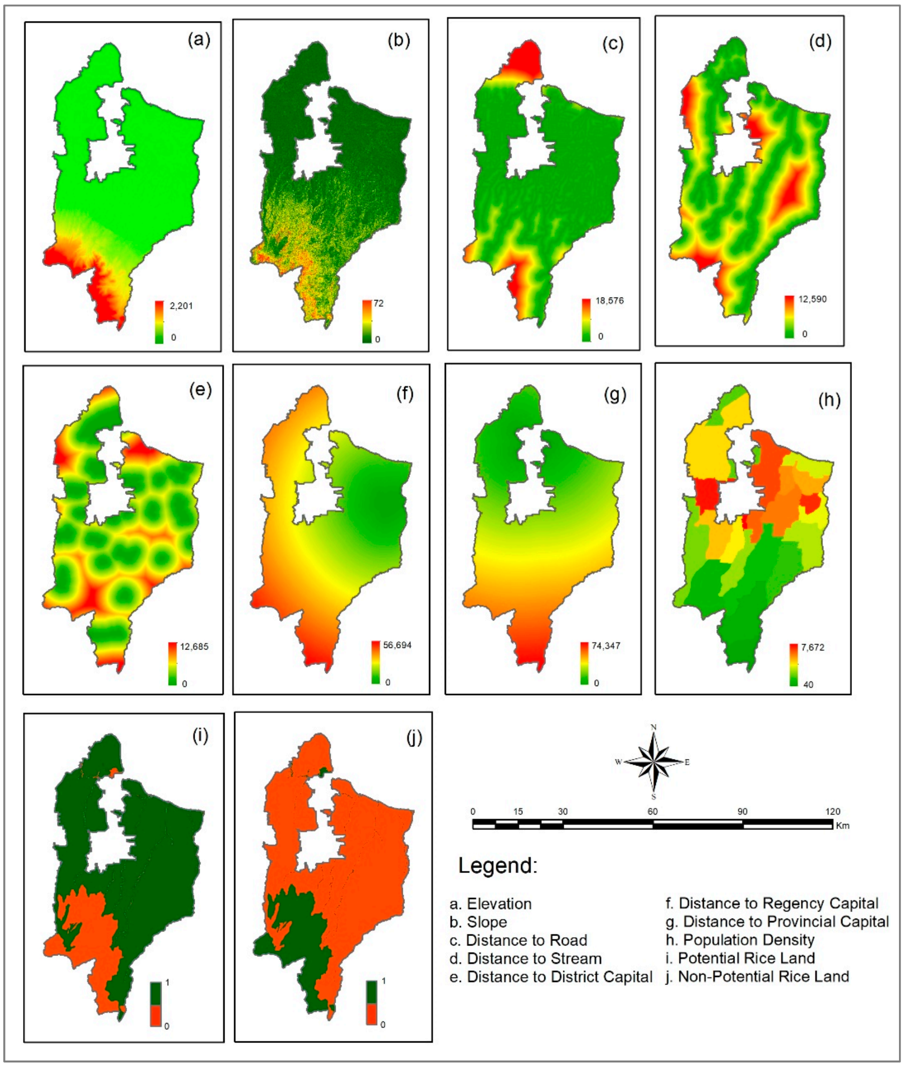

Figure 6. Biophysical factors affecting rice land change (elevation (**a**), slope (**b**), distance to road (**c**), distance to stream (**d**), distance to district capital (**e**), distance regency capital (**f**), distance to provincial capital (**g**), population density (**h**), potential for rice land (**i**), and non-potential for rice land (**j**)).

All level measurements of the biophysical variables used the scale format, except potential and non-potential, which are presented in nominal format. The values 0 and 2201 for the elevation variable for pixels denote lowland and highland, respectively. The values 0 and 72 for slope for the pixels represent flat and steep areas, respectively. The values 0 and 7672 for population density for the pixels denote the least-densely and most-densely populated areas, respectively. For distances variables (meters), a smaller value (0) indicates pixels closer to the variable (road, stream, district capital, regency capital, and provincial capital); conversely, a higher value means the pixels are farther from the variable. The descriptive statistic of each biophysical variables is given at Table 7.

Table 7. Descriptive statistics of each biophysical variable.

Variable	Min	Max	Mean	SD
Elevation (m)	0	2201	155	287
Slope (degree)	0	72	5	5
Distance to road (m)	0	18,576	1403	2696
Distance to stream (m)	0	12,590	2740	2201
Distance to district capital (m)	0	12,685	3309	2321
Distance to regency capital (m)	0	56,694	24,489	13,609
Distance to provincial capital (m)	0	74,347	26,702	16,461
Population density (people/km^2)	0	7672	925	957
Variable	**Min**	**Max**	**Mode**	
Potential for rice land	0	1	1	
Non-potential for rice land	0	1	0	

Table 8 shows the result of the binary logistic regression analysis of rice land conversion to other land uses from 2009 to 2018. The elevation, slope, distance to the road, distance to the stream, distance to the district capital, distance to the provincial capital, population density, and potential for rice land significantly influenced the probability of rice land conversion. Distance to regency capital and non-potential land insignificantly influenced the probability of rice land conversion.

Table 8. Binary logistic regression of the probability of rice land conversion 2009 to 2018.

Variable	β	SE	Sig.	Exp (β)
Elevation	−0.000653	0.000019	0.001	0.999347
Slope	−0.045154	0.000711	0.001	0.955850
Distance to road	−0.000024	9.7345×10^{-7}	0.001	0.999976
Distance to stream	0.000004	0.000001	0.001	1.000004
Distance to district capital	−0.000013	0.000001	0.001	0.999987
Distance to regency capital			ns	
Distance to provincial capital	−0.000015	2.5389×10^{-7}	0.001	0.999985
Population density	0.000014	0.000003	0.001	1.000014
Potential for rice land	0.438468	0.009334	0.001	1.550331
Non-potential for rice land			ns	
Constant	0.352	0.013		1.42
Overall Percentage				63.3
ROC				0.66

Note: β = regression coefficient; SE = standard error; Sig. = the significance level, Exp (β) = the odds ratio, ns = not significant at 0.05 level, and ROC = relative operating characteristics.

The odds ratio, exp (β), expresses the relative contribution of independent variables (driving factors) in rice land change. An odds ratio greater than one means that an increase in the variable by one unit of standard deviation will result in an increase in the chance of rice land change equal to exp (β). An odds ratio less than one means that an increase in the variable by one unit of standard deviation will result in a decrease in the chance of rice land change equal to exp (β). An odds ratio of one means rice land change has no probability to increase or decrease caused by the independent variable. We used relative operating characteristics (ROC) applied to figure out the goodness of fit for the models. The ROC value of this model is 0.66, which is [52] found that a model was considered to have skill when its value is above 0.5.

Table 8 shows the probability of rice land change was significantly affected by elevation and slope. This negative relationship means that the higher the elevation and slope, the lower the probability of rice land changing. This makes sense because the majority of rice land that was located on lowland and flat areas tend was replaced by population growth, urbanization, and plantation expansion. This table also shows that the probability of rice land change increases by factors of 0.99 and 0.95 for every 287 m and 5 degrees of elevation and slope, respectively.

The probability of rice land change was affected significantly by driving factors of distance to the main road, distance to the district capital and distance to the provincial capital. The relationship means that closer these distances to the rice land area will increase the probability of rice land to change. It is a plausible relationship because urbanization growth is in line with the existence of road [53] and with the distance to the district capital/provincial capital. This table also indicates the probability of rice land change will increase by a factor of 0.99 for every 2696 m, 2321 m and 13,609 m of distance to the road, to the district capital and to the provincial capital, respectively.

The distance to a stream and the potential for rice land, together with the population density also significantly affected the probability of rice land change. Contrary to the other driving factors, these three factors have a positive relationship; a closer distance to a stream, the potential for rice land and lower population density decrease the probability of rice land changing. Supporting water from a stream and fertile land will maintain high productivity, so farmers will avoid converting their rice land. In line with distance to a stream and potential for rice land, a lower population density will reduce rice land conversion.

For the second approach, a survey was administered to investigate the main factors affecting rice land conversion from the household perspective. Six districts were grouped into three levels of total rice land area: large (Percut Sei Tuan and Hamparan Perak districts), medium (Beringin and Sunggal districts), and small (Tanjung Morawa and STM Hilir districts). There were 180 household respondents and the purposive sampling method was used to select the proper respondents. Among all respondents, 105 respondents (58%) had no experience and 75 (42%) had experience with rice land changes.

Some specific reasons for converting and maintaining their rice land were recorded. Multiple responses analysis was used to determine the reasons distribution. As presented in Table 9, the top three reasons for changing the land to the production of another commodity were: following the lead of other farmers, increasing income, and weather conditions, accounting for 29%, 23%, and 13% of the responses, respectively. The respondents' reasons for maintaining their rice land included food provision, high productivity, and providing an inheritance asset for their children, accounting for 30%, 21%, and 18% of the responses, respectively.

The household-based survey was used to in-depth explore the socio-economic reasons why respondents changed their rice land and issue of environmental change. The first step was setting explanatory variables that were hypothesized as the factors affecting rice land conversion. Table 10 presents the descriptive statistics of 26 significant variables resulting from Spearman correlation analysis.

After identify the significant variables, PCA was conducted as the second step. The purpose of this analysis was to condense the large number of significant variables to a small number of significant variables. This extraction was processed by grouping the significant variables into eight specific components based on the initial eigenvalue (>1), with 73.218% of the cumulative variance for this analysis. The pattern matrix table from PCA provided meaningful information about the most significant variables for each component. The criterion for factor loading >0.5 was used to group every variable into a specific component. This PCA had a 63.4% Kaiser–Meyer–Olkin (KMO) value, and Bartless's Test explained that our PCA performed well [54]. Table 11 presents the pattern matrix that showed which variable in each component highly contributed to rice land conversion.

Table 9. Respondents' reasons to convert and maintain their rice land (n = 180).

Reasons to Convert	%
Sell rice land to support family needs	2
Change to another commodity due to weather conditions	13
Change to another commodity to increase income	23
Change to another commodity due to costly rice land inputs	5
Change to another commodity due to the difficulty accessing agricultural inputs	2
Change to another commodity due to the availability/cost of labor	11
Change to another commodity due to technical cultivation	12
Change to another commodity due to pest and disease	3
Change to another commodity due to following other farmers' lead	29
Total	100
Reasons to Maintain	**%**
Cannot be sold due to the inheritance land status	15
High productivity	21
Children will inherit	18
Food provision	30
Located in a strategic area	16
Total	100

Table 10. Descriptive statistic of significant variables for rice land conversion.

No.	Variable	Label	Min	Max	Mean
1	The changing of planting pattern	Patern_Change	0	1	−8.14
2	Number of planting season	Indx_Plant	0	3	1.67
3	The availability of agricultural organization benefit	Org_Ben	0	1	0.92
4	Kind of land tenure	Land_Tenur	1	3	2.04
5	Distance of irrigation network to the rice land	Dis_Irrig	10	8000	625.57
6	Existence of inadequate water occurrence	Inad_Water Occur	0	1	0.5
7	Frequency of inadequate water	Inad_Water Freq	0	3	0.57
8	Frequency of drought	Drought_Freq	0	3	1.01
9	Existence of drought occurrence	Drought_Occur	0	1	0.84
10	Frequency of flood	Flood_Freq	0	3	0.62
11	Existence of flood occurrence	Flood_Occur	0	1	0.48
12	Number of environmental problems	No_Env Prob	0	5	2.29
13	Level of farmer's understanding on the sustainable agriculture policy	Underst_Policy	1	2	1.86
14	Total household member	HH_Member	0	7	3.36
15	Total household member stay-in the same district	HH_Memb Stayin	0	7	3.04
16	Age	Age	25	71	45.66
17	Distance of road network to the rice land	Dis_Road	30	2500	883
18	Distance of housing to the rice land	Dis_Housing	15	2000	668.25
19	Strategic action to anticipate land degradation through the usage of high-quality seed	Strat_Seed	1	5	3.96
20	Number of strategic activities applied to anticipate land degradation	No_Strat	2	7	4.3
21	Level of agricultural organization involvement	Org_Involv	2	5	4.36
22	Total income from non-agriculture sector	Incom_Non-Agri	0	8571.43	815.01
23	Strategic action to anticipate land degradation through water efficiency	Strat_Water Eff	1	5	1.84
24	Frequency of delayed planting season	Delay Plant_Freq	0	2	0.48
25	Strategic action to anticipate land degradation through using water-pump	Strat_Wat Pump	1	5	2.19
26	Distance of plantation to the rice land	Dis_Plantation	50	7500	2552.78

Table 11. Distributed variables for each component as output from the principle component analysis (PCA) pattern matrix.

Variable	Component							
	1	2	3	4	5	6	7	8
Patern_Chang	−0.838							
Indx_Plant	−0.818							
Org_Ben	−0.655							
Land_Tenur	−0.599							
Inad_Water Occur		0.937						
Inad_Water Freq		0.916						
Drought_Freq		0.507						
Flood_Freq			0.908					
Flood_Occur			0.884					
No_Env Prob		0.534	0.587					

Table 11. Distributed variables for each component as output from the principle component analysis (PCA) pattern matrix.

Variable	Component							
	1	2	3	4	5	6	7	8
HH_Member				0.959				
HH_Memb Stayin				0.911				
Age				0.539				
Dis_Road					0.832			
Dis_Housing					0.806			
Strat_Seed						0.840		
No_Strat						0.748		
Org_Involv						0.640		
Incom_Non-Agri							0.747	
Strat_Water Eff							0.505	
Strat_Wat Pump								0.731
Dis_Plantation								0.651
Initial Eigenvalues								
% of Variance	20.874	14.406	9.948	7.612	5.989	5.131	4.862	4.395
Cumulative %	20.874	35.280	45.229	52.840	58.829	63.960	68.822	73.218

The name and information of each component from PCA is presented in Table 12.

Table 12. The name and information of each component.

Component	Name and Information
1	Cultivation Management: The changing planting patterns, number of planting seasons, the benefit to the agricultural organization, and kind of land tenure.
2	Drought Issue: The existence of inadequate water occurrence and its frequency per year together with drought frequency.
3	Flood Issue: The frequency and occurrence of flood and number of environmental problems
4	Socio-economic: The number of household members and their ages.
5	Distance: The distance of rice land to the road network and housing.
6	Strategic Farming: The strategy to address land degradation using high-quality seeds, number of strategic farming methods applied, and the level of agricultural organization involvement.
7	Income Non-Agriculture: The total income from the non-agriculture sector and the strategic action of water efficiency.
8	Water Efficiency Strategy: The strategic action used to anticipate land degradation using water pumps and distance to the plantations.

Table 13 presents the result of the binary logistic regression, with the respondent's decision to change or maintain their rice land as the dependent variable and the eight most significant variables from each component as independent variables. Among the eight variables, seven variables were identified as significant factors affecting rice land change: total number of household members (HH_Member), the existence of inadequate water occurrences (Inad_Water Occur), the distance of the road network to the rice land (Dis_Road), the changing planting patterns (Patern_Change), the frequency of flood (Flood_Freq), the strategic actions used to anticipate land degradation using water pumps (Strat_Wat Pump), and the total income from non-agriculture sector (Incom_Non-Agri). The regression analysis showed that the model explained 83.9% of the variance in the data.

Table 13. The output of the binary logistic regression analysis.

Variable	β	SE	Sig.	Exp (β)
Total number of household members	0.912	0.209	0.001	2.489
Inadequate water occurrences	1.551	0.477	0.001	4.716
Distance of road network to rice land	−0.002	0	0.001	0.998
The changing planting patterns	1.902	0.586	0.001	6.697
Frequency of floods	1.708	0.425	0.001	5.518
The strategic action to anticipate land degradation using a water pump	−0.851	0.218	0.001	0.427
Total income from the non-agriculture sector	−0.001	0	0.004	0.999
Constant	−1.615	0.92	0.79	0.199

Note: β = regression coefficient; SE = standard error; Sig. = the significance level, and Exp (β) = the odds ratio.

The binary logistic regression analysis showed the relationship of each variable to the probability of respondents changing their rice land (Table 13). The number of household members contributes significantly to the farmers' decision to change their rice land. This issue was frequently encountered in farmers' lives. A higher number of household members provides more motivation for farmers to change their rice land, includes: sell the rice land to support their income and share a portion of their rice land with their children as an inheritance. A higher number of children increases the cost/expenditure for their education and health.

The existence of inadequate water occurrence and frequency of floods are the real negative impact of climate change perceived by farmers in the Deli Serdang Regency. The more environmental problems occur and the more their frequencies increase, the greater the probability of farmers changing their rice land. During the survey, many respondents stated they have many experiences with environmental issues, including inadequate water, drought, flooding, and erosion. These environmental problems have encouraged farmers to use water pumps for irrigating their rice land as one of strategic actions to mitigate the problems caused by issues. We observed a negative relationship of this variable with farmer decision to change their rice land. Without the use of a water pump, both rice production and income are low. This is also why some farmers changed the commodity produced (such as oil palm plantations) to one more tolerant of drought and flooding.

The changing planting pattern was investigated as one of the significant factors affecting rice land use change. The farmers formerly had a fixed schedule for planting their rice, but climate change has posed challenges to determining an appropriate planting date. Sometimes they postpone their planting time or plant corn, soybean, etc. instead. This could be one of the reasons why farmers tend to change their rice land.

The distance of a road network to rice land had a negative relationship with rice land change. The shorter this distance, the higher possibility of rice land change to other land uses. The existence of a road increases the fragmentation of the landscape pattern through urbanization and industrialization growth [55]. The large-scale construction of new highways has been underway to support socio-economic improvement, with the addition of a new airport in Deli Serdang Regency.

The total income from the non-agriculture sector was no less important in influencing farmers to change their rice land. This factor was negatively related with rice land conversion. The more income farmers earn from the non-agricultural sector, the lower the possibility of rice land change. Additional income from the non-agricultural sector supports basic family needs, such as water, food, health, and education. This supporting income prevents farmers from changing or selling their rice land.

Normalization and weight-based analysis was used to identify the factors most influencing rice land change among all significant biophysical and socio-economic factors. Table 14 presents the mean, normalized, and weight values of all significant factors derived from the previous equations. As the weight value of the factors indicates the degree to which they influence rice land change [46], the distance of rice land to the district capital, distance of rice land to the provincial capital, population density, slope, and distance of farmers' rice land to the road were the factors most influencing the change of the rice land in the Deli Serdang Regency.

Table 14. The mean, normalized, and weighted values of the factors significantly influencing rice land change.

District	Mean Values														
	Biophysical Factor								Socio-Economic Factor						
	Elevation	**Slope**	**Distance Road**	**Distance District**	**Distance Province**	**Distance Stream**	**Pop Density**	**Potent Land**	**Dis_ Road**	**Strat_Wat Pump**	**Incom_ Non-Agri**	**HH_ Member**	**Inad_ Water Occur**	**Pattern_ Chang**	**Flood_ Freq**
STM Hilir	144.5	6.12	934.67	3252.49	36,642.84	1902.32	191	0.8578	1219.64	1.14	684.84	2.96	0.43	0.15	0.71
T. Morawa	26.01	2.75	185.7	2800.13	23,089.64	2000.02	1723	0.9855	707.14	3.14	1201.12	2.93	0.71	0.07	0.14
Sunggal	32.74	1.66	198.02	1782.75	15,844.05	3008.91	3109	0.9909	822	1.63	615	3.93	0.85	0	0.15
H. Perak	7.59	1.44	2565.69	3172.2	7581.25	2644.27	770	0.9907	979.41	2.53	1101.63	2.88	0.35	0.18	1.12
P.S. Tuan	8.30	1.73	483.48	4687.54	9461.9	3974.72	2381	0.9926	1214.06	1.34	777.5	3.28	0.25	0.03	1.09
Beringin	9.46	2.02	166.13	2307.13	20,932.09	1830.26	1179	0.9784	308.13	3.91	742.94	3.78	0.44	0.25	0.31
District	**Normalized Values**														
	Biophysical Factor								**Socio-Economic Factor**						
	Elevation	**Slope**	**Distance Road**	**Distance District**	**Distance Province**	**Distance Stream**	**Pop Density**	**Potent Land**	**Dis_ Road**	**Strat_Wat Pump**	**Incom_ Non-Agri**	**HH_ Member**	**Inad_ Water Occur**	**Pattern_ Chang**	**Flood_ Freq**
STM Hilir	0	0	0.68	0.494	0	0.034	0	0	0	1	0.881	0.076	0.3	0.6	0.582
T. Morawa	0.865	0.72	0.992	0.65	0.466	0.079	0.525	0.947	0.562	0.278	0	0.048	0.767	0.28	0
Sunggal	0.816	0.953	0.987	1	0.716	0.55	1	0.987	0.436	0.823	1	1	1	0	0.01
H. Perak	1	1	0	0.522	1	0.38	0.198	0.986	0.264	0.498	0.17	0	0.167	0.72	1
P.S. Tuan	0.995	0.938	0.868	0	0.935	1	0.751	1	0.006	0.928	0.723	0.381	0	0.12	0.969
Beringin	0.986	0.876	1	0.819	0.541	0	0.339	0.895	1	0	0.782	0.857	0.317	1	0.173
	Elevation	**Slope**	**Distance Road**	**Distance District**	**Distance Province**	**Distance Stream**	**Pop Density**	**Potent Land**	**Dis_ Road**	**Strat_Water Pump**	**Incom_ Non-Agri**	**HH_ Member**	**Inad_ Water Occur**	**Pattern_ Chang**	**Flood_ Freq**
SD	0.388	0.379	0.389	0.342	0.365	0.39	0.367	0.395	0.379	0.398	0.408	0.438	0.38	0.384	0.461
1/SD	2.575	2.638	2.568	2.922	2.739	2.567	2.723	2.531	2.638	2.515	2.452	2.284	2.631	2.603	2.17
Weight	0.0668	0.0684	0.0666	0.0758	0.071	0.0666	0.0706	0.0657	0.0684	0.0652	0.0636	0.0592	0.0682	0.068	0.056
Rank	8	4	9	1	2	10	3	11	5	12	13	14	6	7	15

4. Conclusions

In this study, we investigated the trend in land uses change for three decades, 1989–2018, and the factors affecting land use change, especially for rice land in the Deli Serdang Regency in Indonesia by integrating GIS and remote sensing with field and household surveys. The trends in land use changes showed that the majority of forest and rice land decreased due to plantation expansion and urban development, especially in 2009–2018. Population growth, socio-economic factors, industrialization and urbanization, airport-building, and specific policies (such as the transmigration program and Mebidangro policy) generally contributed to those changes. We also found that the distance of rice land to the district capital, the distance of rice land to the provincial capital, the distance of rice land to a road, the population density, and the slope were the most influential biophysical and socio-economic factors affecting the change of rice land.

The information about the total decrease in rice land over time together with the factors most affecting change the rice land could be used as basic data for local and upper governments to create and implement strategic and precise policies to anticipate the continuous rice land conversion. Hence, the results of this study can be used to help meet the human food demand in the future to meet the sustainable rice production goal. The information about rice land suitability, which was one of biophysical factors, would highly benefit policy makers, providing exact data that can be used to prevent any land with the potential for rice farming from being used for other purposes.

Based on the results, we provide some recommendations for farmers and the policy makers including practicing integrating crop management (ICP), good agricultural practices (GAPs), and climate smart agriculture (CSA) [56], planting a high yield-rice variety that is tolerant to drought or flood [57], constructing and developing irrigation systems and water catchments on potential rice land areas [58], providing insurance for rice cultivation especially from climate change and environmental issues [59], providing a map of the zones with the potential for rice land, creating and implementing a precise and strict policy related to forest and rice land protections, and ensuring land use management is sustainable by considering soil biodiversity, water resources, forests, and agricultural and human sectors. All these recommendations could increase rice production and prevent rice land conversion in the future. This research was limited by resources, time, and financing. The specific limitation for this research was the difficulty to find the clear satellite images at a particular time because the study area located in the equatorial zone, where cloud existence unavoidable. Hence, finding the appropriate acquisition date of satellite images is needed for the next research.

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