


Article

# Change Detection and Land Suitability Analysis for Extension of Potential Forest Areas in Indonesia Using Satellite Remote Sensing and GIS

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**Abstract:** The objective of this research was to detect changes in forest areas and, subsequently, the potential forest area that can be extended in the South Sumatra province of Indonesia, according to the Indonesian forest resilience classification zones. At first, multispectral satellite remote sensing datasets from Landsat 7 ETM+ and Landsat 8 OLI were classified into four classes, namely urban, vegetation, forest and waterbody to develop Land Use/Land Cover (LULC) maps for the year 2003 and 2018. Secondly, criteria, namely distance from rivers, distance from roads, elevation, LULC and settlements were selected and the reclassified maps were produced from each of the criteria for the land suitability analysis for forest extension. Thirdly, the Analytical Hierarchy Process (AHP) was incorporated to add expert opinions to prioritize the criteria referring to potential areas for forest extension. In the change detection analysis, Tourism Recreation Forest (TRF), Convertible Protection Forest (CPF) and Permanent Production Forest (PPF) forest zones had a decrease of 20%, 13% and 40% in area, respectively, in the forest class from 2003 to 2018. The Limited Production Forest (LPF) zone had large changes and decreased by 72% according to the LULC map. In the AHP method, the influential criteria had higher weights and ranked as settlements, elevation, distance from roads and distance from rivers. CPF, PPF and LPF have an opportunity for extension in the highly suitable classification (30%) and moderately suitable classification (41%) areas, to increase coverage of production forests. Wildlife Reserve Forests (WRFs) have potential for expansion in the highly suitable classification (30%) and moderately suitable classification (52%) areas, to keep biodiversity and ecosystems for wildlife resources. Nature Reserve Forests (NRFs) have an opportunity for extension in the highly suitable classification (39%) and moderately suitable classification (48%) areas, to keep the forests for nature and biodiversity. In case of TRF, there is limited scope to propose a further extension and is required to be managed with collaboration between the government and the community.

**Keywords:** change detection; Land Use/Land Cover; forest classification; land suitability analysis; GIS; remote sensing

## 1. Introduction

Indonesia has been losing up to 2 million hectares of land annually, mainly due to illegal cutting and land conversion [1]. Due to a faster growing population, the land conversion takes place to support the infrastructure expansion investment in agriculture and the establishment of cash-crop plantations [2]. Indonesia's urbanization and growth are covered for economic security through conversion of millions

of hectares of forest to palm oil plantations [3]. Deforestation rates have increased throughout Indonesia due to urbanization and palm oil plantations covering 5,418,413 ha [4]. In addition, forest fires, poor forest management practices and an increasing demand for forest products and agriculture contribute to the damage of forests, which are more severe in the South Sumatra province of Indonesia. Many forests in South Sumatra have recently experienced high rates of deforestation due to human migration and the expansion of agriculture or industry. Land-use planning has not taken place over time to align the changes in forest resources according to the Indonesian forest resilience classification. It is also necessary to increase the growth of the economy and, on the other hand, the sustainability of forests through improving the resilience of forest coverage. Forest coverage must be estimated periodically to detect these changes. The change detection analysis has the advantage to visualize the dynamics of changes in forest and deforestation processes. Though the forest is a gift of nature, to maintain the carbon cycle, stocking and sequestration processes in vulnerable areas, further expansion of forest areas needs to be extended by locating such potential areas in time. Production and convertible type forests have the opportunity to expand into these potential areas, which can support the Indonesian forest management system through community support [5]. In Indonesia, there are six types of forest classification zones, defined by the Indonesian forest resilience system: Tourism Recreation Forest (TRF), Convertible Protection Forest (CPF), Permanent Production Forest (PPF), Limited Production Forest (LPF), Wildlife Reserve Forest (WRF) and Nature Reserve Forest (NRF) [6]. A TRF is a forest used for tourism, research, education and cultural activities. CPFs are spatially reserved for use in the development of transmigration, agricultural and plantation settlements. A PPF is a forest exploited for the treatment of selective logging or by clear-cutting. An LPF is allocated to produce wood on a small scale and is located in mountainous areas. A WRF is the natural reserve zone for wild animals and other natural ecosystems. In turn, an NRF consists of natural forest and has the function of protecting the forest, controlling soil erosion, preventing seawater intrusion and maintaining soil fertility. In each type of forest change detection could help to project the changes in the ecosystem, carbon stocking and sequestration.

The change detection analysis can be mapped using satellite remote sensing datasets for the coverage and changes in the spatial and time scales. Remote sensing techniques provide a source of data that updates land cover information to monitor ecosystem changes over time [7–9]. The change detection analysis has the advantages of determining the nature, biodiversity, extent, and rate of land-cover changes, as well as aiding future planning and land management, such as plantation, urbanization, water management and extending the land [10–12]. Monitoring and analysis for change detection is the most adopted application of the satellite data [13–15]. Among them, Landsat satellite datasets have been used for change detection analysis [11,14,16,17]. Change detection analysis can enhance the land-use planning within a framework of laws and policies to guide forest zone allocation. The change detection assessment has become central to diverse facets of the natural environment [18–20]. The changed information is highly needed to encourage forest management and to inform appropriate expansion. It is thus important to detect when, where and why change occurs, as well as study the patterns of the changes for the future [21].

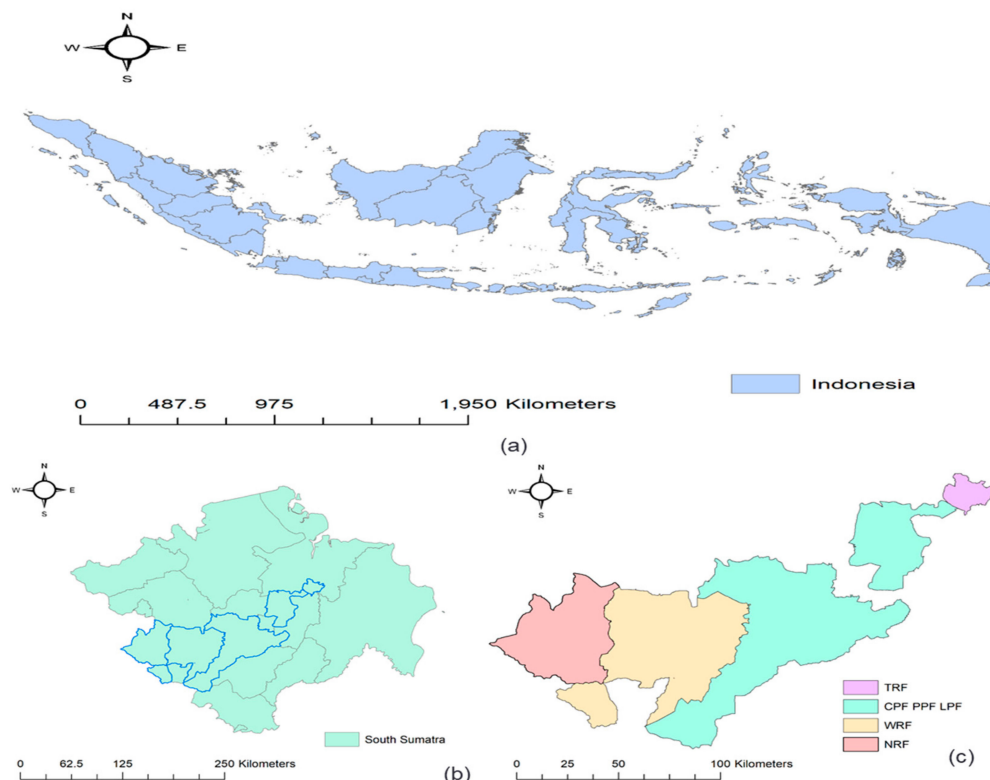
In the change detection analysis, remote sensing and GIS help to drive and integrate the present land-use planning criteria, including important factors such as elevation, settlements, distance from roads and distance from rivers. These factors govern the possibility of expansion. However, land encroachment for forest expansion is a critical problem in many countries. Land encroachment and conversion need the opinions of the government and local stakeholders [22]. In the stakeholder opinion, the population and settlement factors are very much significant when considering the potential expansion of production forests. Both expert opinion and government policy maker participation are very important to enable successful forest expansion. Analytical Hierarchy Process (AHP) has the potential to include expert opinion into GIS and remote sensing datasets [23–25]. Expert opinion and stakeholder participation are required to minimize the adverse effect due to deforestation, and to confirm the change detection for the classified forest areas. Once the classified forest changes are

largely identified, it is necessary to propose further extended areas that have the potential to extend new plantations as production forest. Therefore, the objective of this research is to perform a change detection analysis for the classified forest zones and a suitability analysis to locate potential areas for extension.

## 2. Materials and Methods

### 2.1. Geographical Extent and Forest Coverage in Study Area

The study area is located in South Sumatra covered with TRF, CPF, PPF, LPF, WRF and NRF declared by the local government in the forest management system (Figure 1). The six forest zones are located in the four different locations were taken spatially to analyze the changes in those zones. Three types of forest zones are located in the same area of South Sumatra (Figure 1c). TRF is located in the Palembang city, the capital of the province of South Sumatra with an area of 40 ha, inside the city area of 3,585,500 ha. CPF, PPF and LPF are located in the agricultural area covered with 81,581,400 ha in the middle of South Sumatra. CPF covers only 819.84 ha of land, which is used for the production of forest products and reserved for the development of transmigration, agriculture and plantations. PPF has an area of 172.75 ha and can be used through selective logging or clear-cutting of wood products. LPF covers 312.33 ha of forest land that is allocated for the production of wood on a small scale. WRF covers 989 ha with a total area of 407,600 ha as a reserve zone for wild animals and other natural ecosystems. NRF covers 305 ha with a total area of 22,565,100 ha [6]. NRF has the function of protecting the forest, controlling soil erosion, preventing seawater intrusion and maintaining soil fertility (Figure 1).



**Figure 1.** Geographical extent and forest zones in the South Sumatra province of Indonesia. (a) Indonesia, (b) South Sumatra and (c) the forest zones: Tourism Recreation Forest (TRF), Convertible Protection Forest (CPF), Permanent Production Forest (PPF), Limited Production Forest (LPF), Wildlife Reserve Forest (WRF) and Nature Reserve Forest (NRF).

## 2.2. Change Detection Analysis

Change detection of forest land is important to understand the trends of changes in the past, currently and projections for the future. This study considered the time scale of 2003 to 2018 to assess the trend of changes over the last 15 years. The post-classification method was employed for change detection to provide the matrix table of “from-to” change for the two date images on the base pixel comparison [26]. The change area is the area of the target vegetation cover type at the beginning (2003) and the end (2018) of the study period, respectively. Since it is a large forest area, the continuing years of change may not have as much of a significant difference compared to the highly urbanized areas where land-use changes are very frequent and yearly reporting is very important.

### 2.2.1. Data Acquisition and Sources

The change detection analysis was conducted using two-year series of multispectral datasets for South Sumatra, using Landsat 7 for 2003 and Landsat 8 OLI for 2018. Data were collected from the USGS satellite remote sensing datasets resources and Indonesia Geospatial Agency (BIG). Selected criteria were taken into account in the GIS analysis to map the potential areas for further extension of forests (Table 1).

**Table 1.** Satellite and GIS datasets for land suitability analysis for extension of potential forest areas.

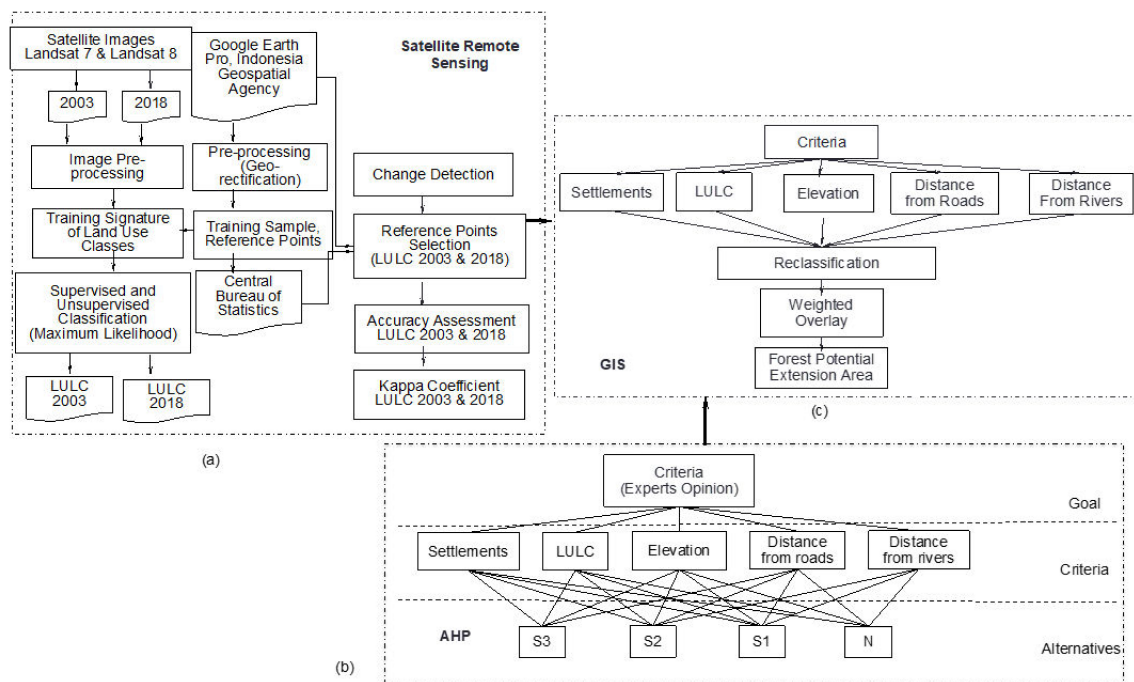
No	Data and Map	Description	Source
1	LULC	Extracted from 30 m resolution	2018, Landsat 8 OLI, Landsat 7 ETM+
2	River	Scale 1:25.000	2005, Indonesia Geospatial Agency
3	Road	Scale 1:25.000	2005, Indonesia Geospatial Agency
4	Elevation	Extracted 90 m from Data Elevation Model National SRTM	2015, USGS
5	Settlements	Extracted from 30 m resolution	2018, Landsat 8

### 2.2.2. Image Processing for Land Use/Land Cover (LULC)

Satellite datasets from Landsat 7 ETM+(2003) and Landsat 8 OLI (2018) were used to develop the LULCs. The imagery was visually interpreted to prepare the change detection maps using a knowledge-based supervised and maximum likelihood classification in the ArcMap environment. The maximum-likelihood classifier was adopted from a parametric classification algorithm [27–30] and divided into four classes: urban, vegetation, forest and waterbodies (Table 2). The classes that were involved in the selection of the training sites were used as a reference in the user-guided approach [17,31–34]. For each of the predetermined change detection types, training samples were selected by delimiting the polygons in the study area. Spectral signatures from the satellite imagery were chosen by pixels. A satisfactory spectral signature was ensured for the land cover map [35] (Figure 2a).

**Table 2.** Selected features for supervised classification in Land Use/Land Cover (LULC) analysis.

Class Name	Description
Urban	Areas designated as urban zone
Waterbodies	River, lakes, waterlogged and swamp areas
Vegetation	Areas covered by trees, both agriculture and planted
Forest	Areas covered by forest



**Figure 2.** Research framework for land suitability analysis to propose the extension of potential forest area. (a) Land use and land cover for change detection analysis from Landsat 7 and Landsat 8 OLI datasets; (b) Analytical Hierarchy Process (AHP) to integrate the expert opinion’s weight in the suitability analysis; and (c) the land suitability analysis.

### 2.2.3. Accuracy Assessment

The accuracy assessment was conducted using reference data points from the base map used to validate the LULC. A stratified random sampling method was employed for selecting 200 points on the map with each class of 50 points (Figure 2a). The accuracy was evaluated using the Producer’s Accuracy (PA), User’s Accuracy (UA) and Overall Accuracy (OA) [36–38] for consideration of the nearest results to accept as true. PA is the map accuracy from the point of the mapmaker (the producer) to represent how well the reference pixels of the ground cover type are classified. The PA refers to the number of correctly classified pixels in each category (on the major diagonal) by the number of reference pixels “known” to be of that category (the column total). While, the UA was computed by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category (the row total). The UA represents the probability that a pixel classified into a given category actually represents that category on the ground, referred to as reliability. In addition, to measure the agreement, we used the Kappa coefficient (Figure 2a). Kappa measures the percentage of data values in the main diagonal of the table and then adjusts these values for the amount of agreement that could be expected due to chance alone. The Kappa needs to calculate the observed level of agreement and then compares it to the value that is expected. The value of Kappa is defined as

$$\hat{K} = \frac{N \sum_{i=1}^r X_{ii} - (\sum_{i=1}^r (X_{ij} * X_{ji}))}{N^2 - \sum_{i=1}^r (X_{ij} * X_{ji})} \tag{1}$$

where  $\hat{K}$  is the Kappa coefficient;  $r$  is the number of rows in error matrix;  $N$  is the total number of observations (pixels) in the matrix;  $X_{ii}$  is the number of observations in row  $i$ , column  $i$ ;  $X_{ij}$  is the total number of observations in row  $i$ ; and  $X_{ji}$  is the total number of observations in column  $i$ . To interpret the Kappa coefficient following the formula is more useful:

$$\hat{K} = \frac{p_o - p_e}{1 - p_e} \tag{2}$$

where  $po$  is the accuracy of the observed agreement,  $\frac{\sum X_{ij}}{N}$ ; and  $pe$  is the estimate of chance agreement,  $\frac{\sum_{i=1}^r (X_{ij} * X_{ji})}{N^2}$ . The coefficient of agreement Kappa is  $-1 \leq k \leq 1$ . Interpretation of Kappa is referred to as a poor agreement if it is less than 0.20; a fair agreement is from 0.20 to 0.40; a moderate agreement ranges between 0.40 and 0.60; a good agreement ranges from 0.60 to 0.80; and a very good agreement ranges from 0.80 to 1.00. An accuracy assessment provides the information for estimating the uncertainty of map classes and the construction of confidence intervals. Accuracy assessment is performed by comparing the map created by remote sensing analysis to a reference map based on a different information source. Both of the maps were evaluated and registered geometrically to each other.

### 2.3. Suitability Analysis for Extension of Potential Forest Area

The suitable potential area refers to the lands that have the opportunity for conversion of forest with economic return over a period of time. In the forest extension planning process, it is important to understand the problem of finding suitable locations for the potential areas. The vegetation land was considered with the timeframe for coverage. Basic land-use change focuses on the land use covered by humans and their habitats (such as agriculture, settlements, industry, etc.), apart from natural disaster factors. The suitable areas for forest potential extension was computed using the weighted overlay procedure in ArcGIS® (ESRI, Redlands, NY, USA). In this research, five criteria were selected: settlements, LULC, elevation, rivers and roads. The description of the criteria and reclassification are described in the following section.

#### 2.3.1. Criteria for Suitability Analysis

The criteria for suitability analysis were settlements, LULC, elevation, distance from rivers and distance from roads (Table 3 and Figure 3).

##### Settlements

Settlements include buildings for residences or for industrial activity that has that land-use component [39,40]. Settlements are areas of human habitation with buildings, civil facilities (hospitals, schools, places of worship and sports areas). The forest loss corresponded with an increase in human settlement. Settlements are driven to overexploit natural resources in forest areas and accelerate land degradation [41]. A settlements map was produced from Landsat 8 OLI satellite images that were verified using Google Earth Pro and confirmed with an overlay process using Indonesian geospatial datasets (Figure 3a).

##### LULC

LULC was built using satellite remote sensing from Landsat 7 ETM+ and Landsat 8 OLI. Landsat 7 was used to develop the classifier for the study area in 2003 and Landsat 8 OLI was used for the classifier in 2018. Both Landsat images were processed using supervised maximum likelihood classification. Land-cover classes were defined by a string of classifiers with the aim of achieving a logical and functional hierarchical arrangement of the classifiers; certain criteria were applied. The four categories urban, waterbody, vegetation and forest were used in the LULC for 2018 (Figure 3b).

##### Elevation

The study area is comprised of lowlands, although there were no peatlands in the forest zones. However, South Sumatra had deforestation due to plantation potential and agriculture. In addition, this area has a tropical rainforest heritage. Tropical elevation areas have high biodiversity and rich ecosystem services [42,43] (Figure 3c).

### Distance from Rivers

The unavailability of water strongly constrains the distribution of plants on the Earth's surface [44,45], ecosystems and forests [46–49]. Therefore, rivers are a source of water to get potential area for extensions. The data for distance from rivers were collected from the Indonesian geospatial agency (Figure 3d). It is worth mentioning that the rivers are important in supporting regional biodiversity and provides important services for people, such as food, fodder, shelter, construction materials and medicine [50]. The ecology in forests refers to the relationships that living organisms have with each other and with their environment. In that case, access to water sources (rivers) is required for new forestation. Consider supporting potential forest areas: The distance to a river has a direct impact on the importance of the relationship between forests and water: The location of the rivers needs to be close to the vegetation and the dependent animal life. To protect a variety of forest ecological processes, distance from rivers is one of the factors. There are several types of forest ecological processes that depend on dry areas (distance from rivers is far) or wet areas (distance from rivers is close) [51]. The rivers have been highlighted as a priority for scientists, policymakers and managers [52].

### Distance from Roads

The availability of roads in forest areas was considered in order to increase the forest plantation area to facilitate the extension of some plantation forest. The potential extension might be difficult when the road is unavailable in forest zones (except, of course, the roads that were built for the plantation system) (Figure 3e).

Furthermore, the masking of areas in each forest type was done to understand the changes that occurred in each forest (Figure 4).

**Table 3.** Criteria of the land suitability analysis for the extension of forest areas.

Criteria	Suitability Class	Sub-criteria	Reference
Settlements	S1	<214	[52]
	S2	264–365	[52]
	S3	365–414	[52]
	N	>414	[52]
LULC	S1	Forest	[53]
	S2	Vegetation	[53]
	S3	Urban	[53]
	N	Waterbodies	[53]
Elevation	S1	<350 m	[15]
	S2	350–900 m	[15]
	S3	900–1600 m	[15]
	N	>1600 m	[15]
Distance from roads	S1	<10 m	[54]
	S2	10–23 m	[54]
	S3	23–45 m	[54]
	N	>45 m	[54]
Distance from rivers	S1	<6 m	[55]
	S2	6–13 m	[55]
	S3	13–21 m	[55]
	N	> 29 m	[55]

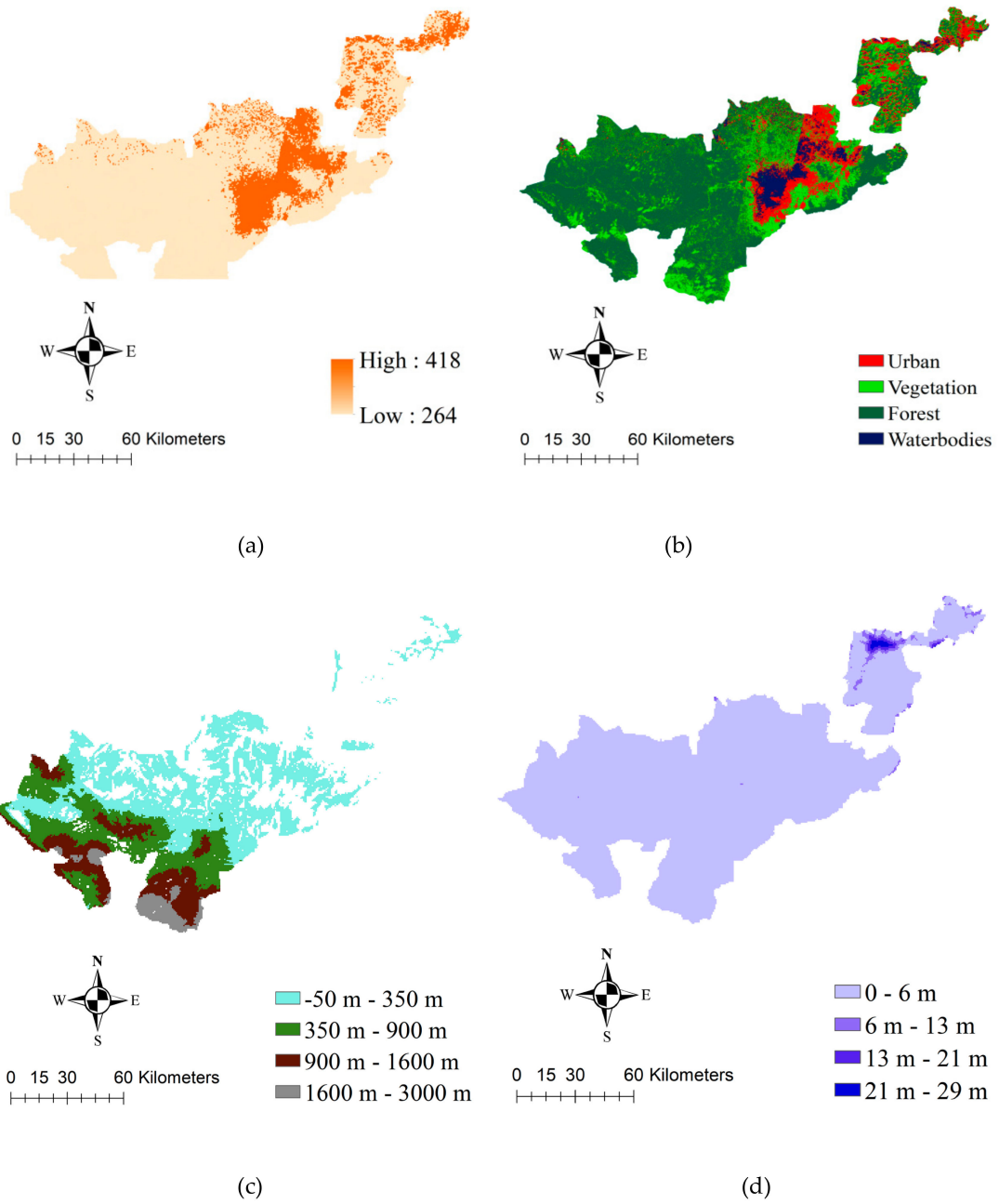
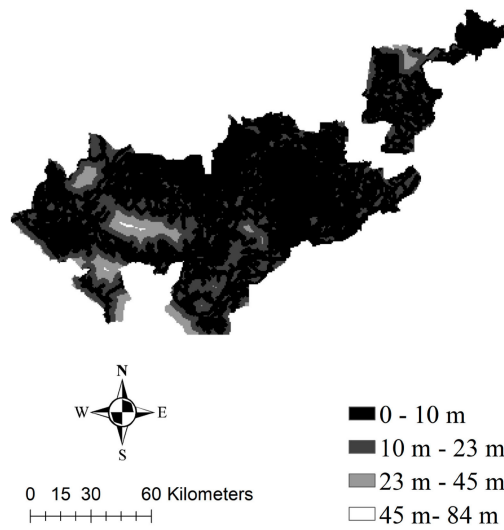


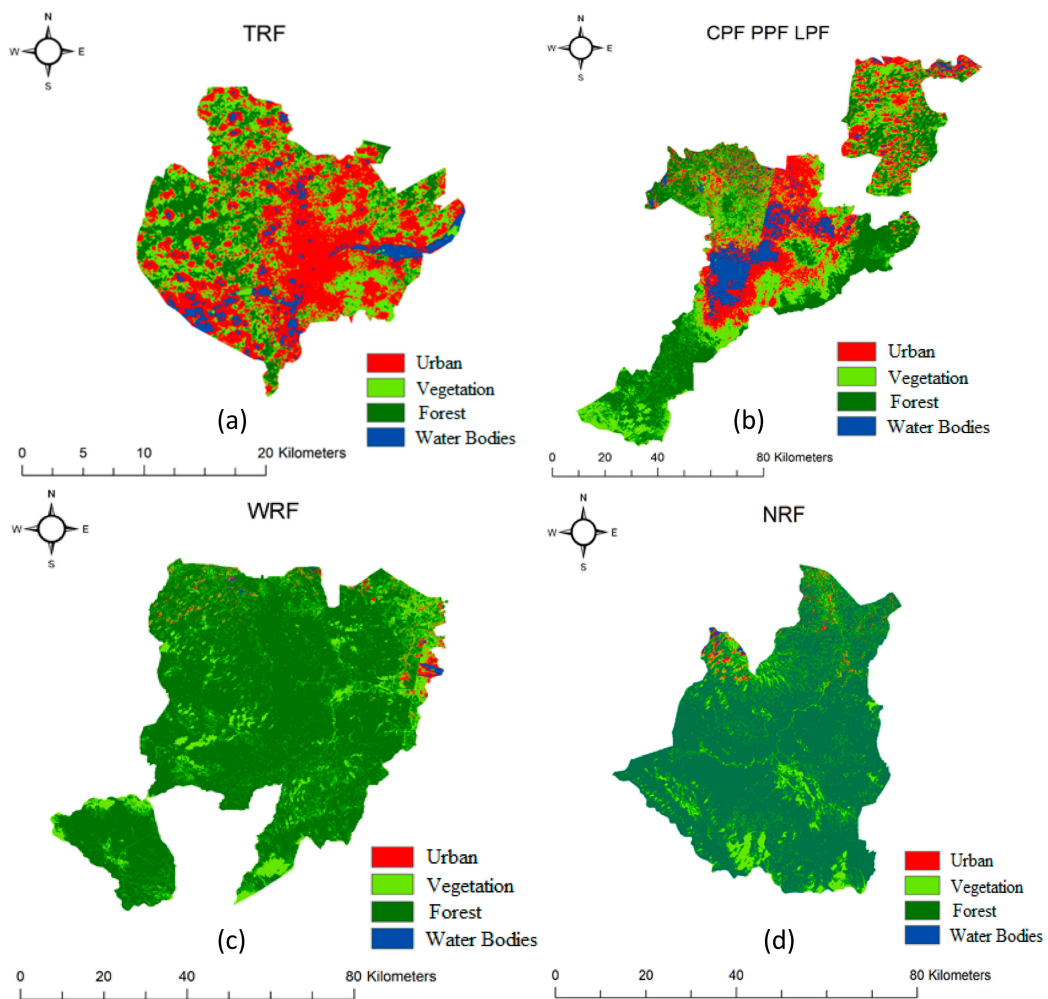
Figure 3. Cont.





(e)

**Figure 3.** Criteria for the land suitability analysis for extension of potential forest areas. (a) Settlements, (b) LULC, (c) elevation, (d) distance from rivers and (e) distance from roads.



**Figure 4.** LULC for each type of forest: (a) TRF; (b) CPF, PPF and LPF; (c) WRF; and (d) NRF.

### 2.3.2. Reclassification of Criteria

The selected criteria were reclassified to understand the importance of each of the criteria and their suitability assessment. The reclassification was performed using the criteria to classify the vector and raster data by replacing a new value in the four classifications based on FAO recommendations. The classification was suggested based on the following levels of suitability: highly suitable (S1), moderately suitable (S2), marginally suitable (S3) and not suitable (N). The classification of the spatial data, such as vector datasets, were translated into raster layers and were processed using ArcGIS®10.4 (Table 4).

**Table 4.** Reclassification of the criteria of land suitability for forest extension areas.

Criteria	Suitability Class	Suitability Range	Percentage Area (%)	Area (Ha)
Settlements	S1	<214	57.47	1310
	S2	264–365	23.48	535
	S3	365–414	13.72	313
	N	>414	5.33	121
LULC	S1	Forest	57.6	790,712
	S2	Vegetation	24.2	333,020
	S3	Urban	13.2	180,615
	N	Waterbodies	5	68,806
Elevation	S1	<350	53.28	495,989
	S2	350–900	25.56	237,940
	S3	900–1600	15.82	147,314
	N	>1600	5.34	49,681
Distance from roads	S1	<10	85.77	1,163,759
	S2	10–23	9.77	132,494
	S3	23–45	3.73	50,577
	N	>45	0.74	9985
Distance from rivers	S1	<6	97.96	1,339,701
	S2	6–13	1.38	18,856
	S3	13–21	0.44	6032
	N	>29	0.22	2994

### 2.4. AHP

AHP is a mathematical method that uses several criteria to analyze complex decisions [56,57]. This method has been successfully applied to forestry applications [57–62]. In this AHP analysis, weighting of several criteria was used to conduct the pairwise comparison of two criteria at a time. Each weight was determined by experts to choose for the pairwise comparison matrix. In our research framework, the top class was to determine the potential forest extension areas (goal), the middle class being the criteria and bottom class the alternative. The middle class of the hierarchy was considered the rules or criteria of the goal. The bottom class was considered alternative decisions (Figure 5). Questionnaires were used to gather expert opinions on the relative importance of the criteria and factors. Comparative results (for each factor pair) were described as integer values of 1 (equal value) to 9 (extremely different), where a higher number indicated that the chosen factor was more important than the other factors to which it was compared (Table 5). In the AHP analysis, first, five criteria were selected based on a literature review and expert opinion. All scores were assembled in a pairwise comparison matrix, with diagonal and reciprocal scores located in the lower left-hand triangle. Reciprocal values (1/3, 1/5, 1/7 and 1/9) were used where the row criterion was found to be less important than the column criterion. Secondly, scoring was involved in the criteria via pairwise comparisons and scales of relative importance. The random indices of Saaty [63] are listed for the observation from 3 to 9 (Table 6). Thirdly, the matrix was calculated and ensured the consistency of

the pairwise comparison criteria. The pairwise matrix was calculated with the comparison results, creating a matrix form C with dimensions of  $m \times n$  by the following expression:

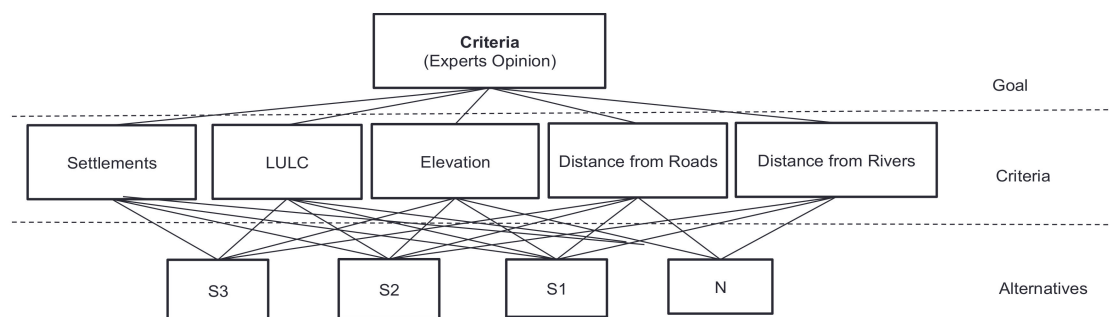
$$\begin{bmatrix} C_{11} & C_{12} & C_{13} & \cdots & C_{1n} \\ C_{21} & C_{22} & C_{23} & \cdots & C_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ C_{m1} & C_{m2} & C_{m3} & \cdots & C_{mn} \end{bmatrix} \tag{3}$$

**Table 5.** Saaty scale for pairwise comparison between the criteria in the AHP.

Index	Definition	Index	Definition
1	Equally important	1/1	Equally important
2	Equally or slightly more important	1/2	Equally or slightly less important
3	Slightly more important	1/3	Slightly less important
4	Slightly to much more important	1/4	Slightly to way less important
5	Much more important	1/5	Way less important
6	Much to far more important	1/6	Way to far less important
7	Far more important	1/7	Far less important
8	Far more important to extremely more important	1/8	Far less important to extremely less important
9	Extremely more important	1/9	Extremely less important

**Table 6.** Random indices in the AHP.

n	3	4	5	6	7	8	9	10
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49



**Figure 5.** The AHP framework to incorporate expert opinion into the land suitability analysis for extension of potential forest areas.

The sum of each column of the pairwise matrix was denoted as follows:

$$C_{ij} = \sum_{i=1}^n C_{ij} \tag{4}$$

Then the element of the matrix was divided by its column total to generate a normalized pairwise matrix:

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^n C_{ij}} = \begin{bmatrix} X_{11} & X_{12} & X_{13} & \cdots & X_{1n} \\ X_{21} & X_{22} & X_{23} & \cdots & X_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ X_{m1} & X_{m2} & X_{m3} & \cdots & X_{mn} \end{bmatrix} \tag{5}$$

The AHP generates a weight for each evaluation criterion according to the expert’s pairwise comparisons of the criteria. The higher weight is more important than the corresponding criteria. Then the AHP combines the weights and the scores to determine the total score for each option and a consequent ranking was used (n) to generate the weighted matrix of the priority criteria (W):

$$W_{ij} = \frac{\sum_{j=1}^n X_{ij}}{n} \begin{bmatrix} W_{11} \\ W_{12} \\ \vdots \\ W_{1n} \end{bmatrix} \tag{6}$$

To compute an estimate of the eigenvector for a pairwise comparison matrix, we multiplied the normalized matrix with the priorities vector (principal eigenvector of the matrix). Then we divided the elements in the resulting vector of priorities and took the average. The initial consistency vectors were derived by multiplying the pairwise matrix by the vector of weights:

$$\begin{bmatrix} C_{11}C_{12}C_{13} & \dots & C_{1n} \\ C_{21}C_{22}C_{23} & \dots & C_{2n} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ C_{m1}C_{m2}C_{m3} & \dots & C_{mn} \end{bmatrix} \times \begin{bmatrix} W_{11} \\ W_{12} \\ \vdots \\ W_{1n} \end{bmatrix} = \begin{bmatrix} C_{11}W_{11} & C_{12}W_{12} & \dots & C_{1n}W_{1n} \\ C_{21}W_{21} & C_{22}W_{22} & \dots & C_{2n}W_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ C_{m1}W_{m1} & C_{m2}W_{m2} & \dots & C_{mn}W_{mn} \end{bmatrix} = \begin{bmatrix} V_{11} \\ V_{12} \\ \vdots \\ V_{1n} \end{bmatrix} \tag{7}$$

The number of objectives and alternatives should not exceed seven, respectively, to make the decision process manageable [64]. The principal eigenvector ( $\lambda_{max}$ ) was calculated by averaging the values of the consistency vector:

$$\lambda_{max} = \sum_i^n CV_{ij} \tag{8}$$

Eigenvalues were calculated by averaging the rows of each matrix. Eigenvalues were also referred to as relative weights. The largest eigenvalue was equal to the number of criteria, and when  $\lambda_{max} = n$ , judgments were consistent. Normalized eigenvalues were generated as the weights of the priority criteria. The consistency index (CI) was calculated following [56], where the deviation  $\lambda_{max}$  from n is a measure of inconsistency:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{9}$$

The evaluation is considered acceptable if the consistency ratio (CR) < 0.1 [56]. The evaluation is considered as moderately consistent and acceptable if 0.1 < CR < 0.2 [65] or CR < 0.2 [66]. CR is calculated as follows:

$$CR = \frac{CI}{RI} \tag{10}$$

### 2.5. Land Suitability for Forest Extension Areas

The land suitability analysis for potential forest extension areas was carried out using various classification categories suggested by the FAO. The reclassified criteria were selected to perform the weighted overlay to develop the land suitability map for forest extension. In the weighted overlay, the AHP weights were used and can be expressed as

$$Weighted\ Overlay = \sum_{i=1}^n C_i * W_n \tag{11}$$

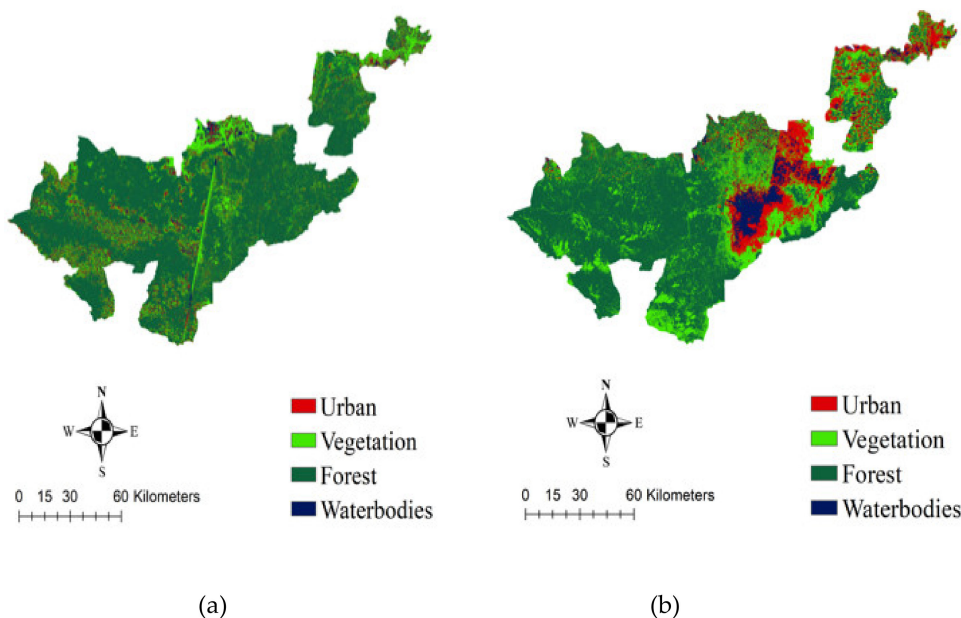
where  $C_i$  is the criteria ( $i$ ) that was reclassified, and  $W_n$  is the amount of weighted data ( $n$ ). The classes are noted as highly suitable (S1), moderately suitable (S2), marginally suitable (S3) or not suitable (N)

within the FAO land assessment framework. Then these suitability classes can be subdivided further as needed. These three classes, S1, S2 and S3, were used to identify highly suitable, moderately suitable and marginally suitable lands for potential forest extension areas. In the GIS environment, suitability analysis was conducted to find the potential areas for extension of forests.

### 3. Results

#### 3.1. Change Detection Analysis

Based on the landscape of the study area, change detection analysis was done in four categories: urban, waterbody, vegetation and forest for six types of forest zones (Figure 6 and Table 7). A negative value is presented to show a decrease in change detection while a positive value indicates an increase in the change detection class. In the study area, TRF was observed as an increasing trend in the urban class by 37.03% (14.78 ha). A decreasing trend was observed in the vegetation and forest classes by 21.47% (8.61 ha) and 20.09% (8.06 ha), respectively. CPF, PPF and LPF had an increased rate in the urban land-use class. The highest percentage of increased area was observed in the LPF area of 48.75% (1514.34 ha). The CPF and PPF were 4.56% (372.16 ha) and 9.52% (163.72 ha). An increasing trend was observed in the vegetation class with the highest percentage in the PPF area of 31.16% (535.7 ha). In the case of the LPF and CPF, vegetation class was increased by 23.63% (733.92 ha) and 10.09% (823.49 ha), respectively. CPF, PPF and LPF had a decreasing trend in the percentage of forest classes by 72% (2236.62 ha), 40.21% (691.12 ha) and 13.56% (1105.72 ha). Waterbodies were decreased by 1.09% (88.66 ha) for CPF and 0.37% (11.65 ha) for LPF. WRF was increased in urban and forest classes by 3% (29.56 ha) and 33.44% (329.7 ha). Waterbody classes were decreased by 6.2% (61.15 ha). NRF had an increasing trend in the forest class by 33.05% (92.26 ha). However, the declining trend was also observed in urban and waterbody classes by 19.78% (55.22 ha) and 0.99% (2.75 ha), respectively (Table 7).



**Figure 6.** Change detection in the LULC for classified forest areas in South Sumatra. (a) LULC, 2003; and (b) LULC, 2018.

**Table 7.** Change detection of forest classes from 2003 until 2018.

Forest Zone	Changing Area (Urban Class)		Changing Area (Vegetation Class)		Changing Area (Forest Class)		Changing Area (Waterbody Class)	
	(%)	(ha)	(%)	(ha)	(%)	(ha)	(%)	(ha)
TRF	37.03	14.78	−21.47	−8.61	−20.09	−8.06	−	−
NRF	−19.78	−55.22	−	−	33.05	92.26	−0.99	−2.75
WRF	3	29.56	−	−	33.44	329.7	−6.2	−61.15
CPF	4.56	372.16	10.09	823.49	−13.56	−1105.72	−1.09	−88.66
PPF	9.52	163.72	31.16	535.7	−40.21	−691.12	−	−
LPF	48.75	1514.34	23.63	733.92	−72	−2236.62	−0.37	−11.65

### 3.2. Accuracy Assessment

The accuracy assessment was referred to by the producer's accuracy of 86% and 96% for the urban class in 2003 and 2018 in the six types of forest zones. The vegetation class had a producer's accuracy of 86% and 100% for both the years in 2003 and 2018. The forest class also had a producer's accuracy of 90% and 96% in 2003 and 2018. The waterbody class had a producer's accuracy of 80%–96%. The Kappa coefficient of agreement was more than 0.60 (Table 8). The interpretation of Kappa showed a good agreement for all types of forests.

**Table 8.** Accuracy assessments for LULC in 2003 and 2018.

Accuracy Assessment	Class	TRF		CPF, PPF and LPF		WRF		NRF	
		Class		Class		Class		Class	
		(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Producers Accuracy	Urban	96	90	92	92	88	94	92	86
	Vegetation	90	96	88	100	94	96	86	86
	Forest	92	96	92	90	96	94	96	96
	Waterbody	92	80	88	84	96	96	96	90
User Accuracy	Urban	96	82	92	85	100	98	90	86
	Vegetation	90	96	88	85	87	87	91	86
	Forest	92	100	92	100	89	96	96	96
	Waterbody	92	85	88	100	100	100	92	90
Overall Accuracy		93	91	90	92	94	95	93	90
Kappa Coefficient		0.84	0.79	0.80	0.82	0.86	0.89	0.83	0.78

### 3.3. Land Suitability Analysis for Extension of Potential Forest Area

#### Reclassification of Criteria

The reclassifications of criteria were categorized into four classifications, namely highly suitable, moderately suitable, marginally suitable and not suitable, according to a land suitability analysis (FAO 1976). The settlements criteria showed that 57.47% of the areas were highly suitable (1310 ha) and 23.48% of the areas were moderately suitable (535 ha). In the case of the LULC reclassification, 57.6% of the areas had forest and were highly suitable (790,712 ha). On the other hand, 24.2% of the areas were observed as vegetation and were reported as moderately suitable (333,020 ha). From the reclassification of elevation criteria, 53.28% of the areas were noted as highly suitable (495,989 ha) and 25.56% were moderately suitable (237,940 ha). The roads were measured using the Euclidean distance and a reclassification of this criteria showed that 85.77% of the areas were highly suitable (1,163,759 ha) and 9.77% were moderately suitable (132,494 ha). Evaluating the distance from rivers in a similar way, the reclassification referred that 97.96% of the areas were highly suitable (1,339,701 ha) and 1.38% were moderately suitable (18,856 ha) (Table 4, Figure 7).

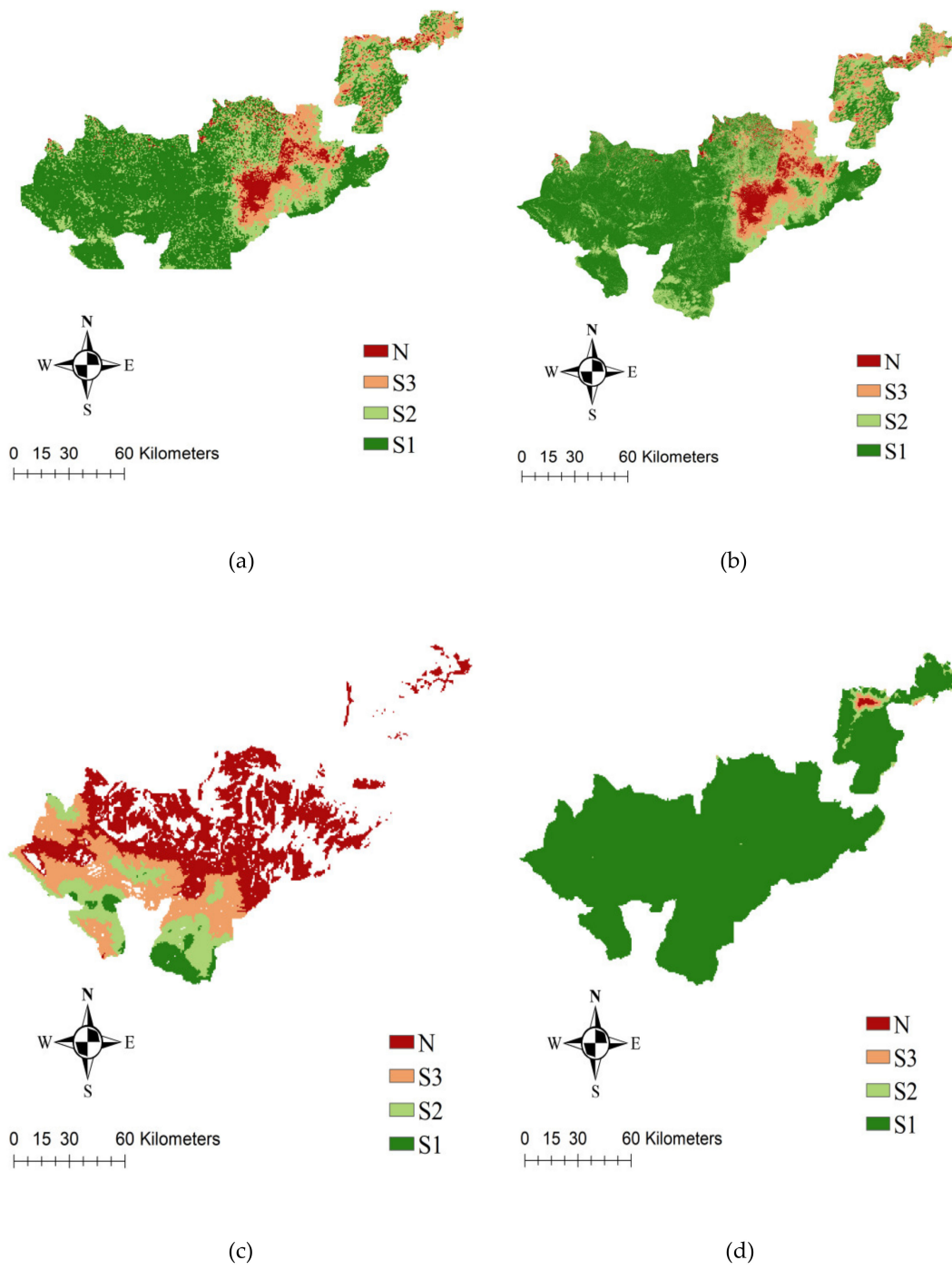
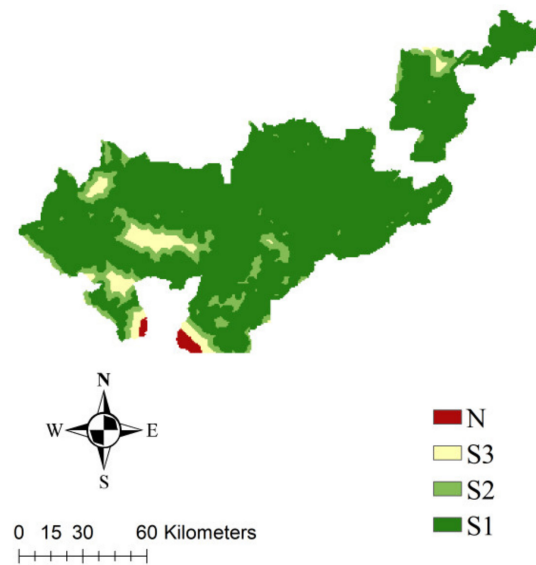


Figure 7. Cont.



(e)

**Figure 7.** Reclassification of the criteria for the land suitability analysis to propose extension of potential forest areas. (a) Settlements, (b) LULC, (c) elevation, (d) distance from rivers, and (e) distance from roads.

### 3.4. AHP

In the AHP, the expert’s opinions were considered using a comparison of the scale matrix for each criterion, whose expert judgment for the ranking of the criteria affected the area of land suitability. A pairwise matrix was used in the AHP for the expert opinion using five criteria. The AHP weight results indicated that the settlements weight was scored first, LULC second, elevation third, distance from road fourth and distance from a river fifth (Table 9). In ArcGIS®, the criteria were reclassified as raster-based data layers and integrated with a weighted overlay according to the weight rank given by the experts. The rank was given to prioritize the influence of the criteria for the extension of potential areas of forest in the land suitability analysis.

**Table 9.** Expert opinion weights for prioritizing the criteria in AHP.

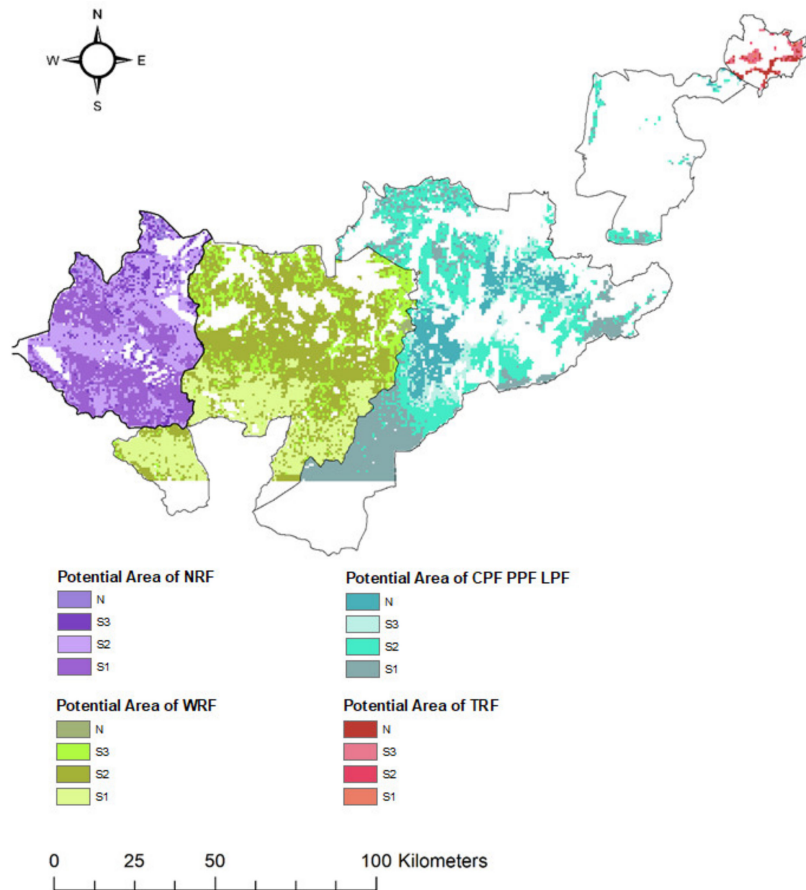
Criteria	Expert A	Expert B	Expert C	Expert D	Expert E	Average Weight	Weight (%)
Settlements	0.190	0.354	0.160	0.245	0.102	0.210	29
LULC	0.214	0.222	0.102	0.143	0.379	0.212	29
Elevation	0.086	0.066	0.379	0.119	0.160	0.162	23
Distance from roads	0.092	0.097	0.065	0.100	0.065	0.084	12
Distance from rivers	0.074	0.049	0.043	0.033	0.043	0.048	7

### 3.5. Land Suitability Analysis for Extension of Potential Forest Area

Change detection analysis was performed not only to detect changes that occurred in the forest but also to identify the potential areas for further extension of production forest. In the land suitability analysis, five criteria were used in the TRF, CPF, LPF, PPF, WRF and NRF zones to find out the potential areas for forest extension (Figure 8). In these types of forest zones, a highly suitable classification had the highest preferences followed by the moderately suitable classification. In the TRF, forest extension could possible in 7% and 8% of the limited areas belonging to the highly suitable class and moderately suitable class (Table 10). There were highly and moderately suitable classes in the CPF, LPF and PPF



areas of 30% (81,663.91 ha) and 41% (112,191.20 ha), respectively. In the case of a WRF, there is the possibility of extension in 30% (98,133.18 ha) in highly suitable areas and 52% in areas (167,012.93 ha) in the moderately suitable class. The potential areas for an NRF forest zone was 39% (79,798.61 ha) in the highly suitable class and 48% of areas (99,498.03 ha) in the moderately suitable class (Table 10).



**Figure 8.** Land suitability analysis for the extension of potential areas in NRF, CPF, LPF, PPF, WRF and TRF forest zones.

**Table 10.** Land suitability analysis for extension of potential forest areas in the forest zones.

Land Suitability Classes	TRF		CPF, PPF and LPF		WRF		NRF	
	(%)	(ha)	(%)	(ha)	(%)	(ha)	(%)	(ha)
N	45	3730.61	16	44,994.77	1	2638.72	2	4913.48
S3	40	3275.66	13	37,215.08	17	54,503.27	11	22,793.10
S2	8	682.43	41	112,191.20	52	167,012.93	48	99,498.03
S1	7	591.44	30	81,663.91	30	98,133.18	39	79,798.61
Total	100	8280.13	100	276,064.96	100	322,288.09	100	207,003.22

#### 4. Discussion

South Sumatra is one of the most important provinces for conservation of biodiversity and forest resources in Indonesia. The stewardship and use of forest land must be managed for their biological diversity, productivity, regeneration capacity, vitality and potential to fulfil the current and future needs relevant to ecological, economic and social functions at the local, national and global levels [67]. Potential forests area extension strategies can be targeted with creating sustainable forestry market opportunities, such as oil palm plantations and agricultural lands [68–70]. In this research, CPF, PPF and LPF are referred to as community forestry [6]. Potential land can be set up for new

forest generation to promote plantations that bring benefits to the environment and surrounding communities [70–73]. Protecting and restoring forests could provide the best decision with the local communities to get the benefit and restore the environmental and economic functions of the forests [74]. The challenges in achieving sustainable forest management and forest conservation need to develop with collaborative solutions between stakeholders and communities [75,76]. CPF, PPF and LPF entail forest production, providing support and opportunities for enhancing the economic benefits through wood and palm oil. In the demographic shift, TRF can play an important role in supporting efforts of urban forestry and urban landscapes to provide ecosystem and natural infrastructure [77,78] and NRF have an important role in maintaining and protecting the biodiversity of wildlife habitat and natural land [75,79]. The proposed potential areas can be extended by forest classifications to balance the deforestation with production forests, such as plantations. Therefore, the change detection analysis and periodic determination of potential forest extension areas could help to create a new policy space for plantation forests and ecosystems to be present in designing national and sub-national policies.

## 5. Conclusions

In this research, remotely sensed data were used to monitor the changes in the LULC and quantify the differences in the forest classes in the South Sumatra province of Indonesia from 2003 to 2018. In the LULC analysis, six types of forest zones: CPF, PPF, LPF, WRF, TRF and NRF were focused upon to find out their changes and locate potential areas for extension of forest. In the change detection analysis, we have observed that the TRF, CPF and PPF forest zones had a decrease of their forest class by 20%, 13% and 40%, respectively, from 2003 to 2018. LPF regions had large changes and decreased by 72% in LULC for its forest class. Palm oil plantations had a significant impact on the LPF forest classification areas. For the extension of forest types that decreased over the time period, the AHP analysis incorporated selected criteria using weights from experts. The weights were used in the GIS analysis to propose the potential areas for extension. The influential criteria had higher weights and ranked as settlements, elevation, distance from roads and rivers. We found CPF, PPF and LPF had an opportunity of extension in the highly suitable classification (30%) and moderately suitable classification (41%) areas, in order to increase coverage of production forests. WRF had a forest potential area in the highly suitable classification of 30% and moderately suitable classification of 52% to keep biodiversity ecosystems for wildlife resources. The potential areas for NRF was 39% (79,798.61 ha) in the highly suitable class and 48% of areas (99,498.03 ha) in the moderately suitable class, to keep the natural ecosystem. TRFs had a very limited scope to propose a further extension and is required to be managed with collaboration between the government and the community.

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