The effect of Pare-Pare City’s development on land use/land cover change in Karajae Watershed

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Abstract Pare-Pare City is one of the centers of industry, trade and sea transportation in Eastern Indonesia. It also continues to be developed marked by changes in land use/land cover (LULC) now and in the future. Pare-Pare city’s development will greatly affect the Karajae watershed as a boundary of the hydrological ecosystem. The purpose of the study was to analyze the effect of the development of Pare-Pare City on the LULC of the Karajae watershed. Analysis of LULC change with the approach of Geographic Information Systems (GIS), remote sensing, Cellular Automata Markov Chain (CA-markov) for LULC projection, and Binary Logistic Regression for the impact of City development. Change in LULC in the actual period (2004-2018) indicates a significant increasing of settlement and dryland agriculture area, while secondary dryland forest, grassland and shrub have been reducing. However, the LULC projection in 2032 shows a huge change than the actual period. Settlement experienced an increasing in area twice than the actual period (2004-2018), this was followed by an increasing in deforestation as well. However, it is different from agriculture which has extensive decreasing, and shrub has increasing of area. So that it shows the pattern of shifting cultivation conducted by the farming community. The changes in LULC in the future are influenced by the settlement and the road network.

1. Introduction

Urban areas continue to develop from all directions at a much faster pace from time to time. Population growth is unprecedented, rapid urbanization, infrastructure expansion, land use conversion will have an impact on the urban environment [1]. Today’s world population reaches 55% in urban areas and is projected to increase to 68% by 2050 [2]. The trend of urbanization causes populations in urban areas to be faster, especially in developing countries [3–6]. Urban characteristics are not only in the human population but also economic activities and macro-scale land use management which will have a large impact on the formation and characteristics of dynamic urban spatial patterns [7,8]. Developments also occur inside and outside the city limits in the form of roads, housing development, commercial enhancement and industrial expansion [9]. Even urban development can cause expansion of built-up areas outside urban areas which will have an impact on environmental degradation [10].

Urban expansion and increase of population growth have a major effect on continuous depletion of natural resources and LULC change [11]. LULC change is one of the main characteristics in urban development [12]. Urban areas to the upper watershed areas there has been an increase in residential areas [13,14]. Furthermore, urban areas will eliminate green spaces and agricultural cultivation lands inside and around cities [13,15–17]. Temporal and spatial LULC changes in urban areas and certain
ecosystem boundaries are analyzed by integrating a remote sensing approach, and a more efficient and inexpensive geographical information system (GIS) [18–22].

Future LULC predictions or projections can be done by using the CA-Markov model [23–28]. The CA-Markov model is the integration of cellular automata and Markov chain analysis to predict future land use trends based on past LULC change results [28–30]. The CA-Markov model is very good and accurate for predicting future land use change scenarios with a level of accuracy higher than 80% [28,30–33]. Factors that influence LULC change can be known in urban areas and certain ecosystem boundaries with logistic regression analysis [34,35].

The dynamics of LULC change are very sensitive to hydrological responses. Urbanization activities that cause an increase in areas built and settlements have quite an impact on hydrological conditions in a watershed [36]. In more detail LULC change will have an impact on surface runoff, discharge and sedimentation results [37]. The condition of urban areas is very much influenced by current and future watershed conditions.

The National Planning Agency of the Republic of Indonesia states that in 2045 it is projected that the population of Indonesia is predicted to experience a very high population growth, which is as much as 24.7 percent which will reach 318 million people. Specifically, in urban areas is expected to increase from 53.1 percent in 2015 to 67.1 percent. Based on this, around 73 percent of Indonesia's population will live in cities. Urban issues will become national issues and become very important to be addressed immediately. Cities and population in Indonesia are mostly concentrated on the island of Java. Indonesia also must pay attention to other cities outside Java. One of the Largest Cities outside Palu Java is on Sulawesi Island, namely Makassar City, South Sulawesi Province. Besides Makassar City, there is also Pare-Pare City which is one of the centers of industry, trade and sea transportation in Indonesia. The Municipality of Pare-Pare City strongly supports the economic activities of Makassar City which greatly affect the eastern region of Indonesia. Determination of the Ministry of Forestry’s Director General of Land Rehabilitation and Social Forestry (RLPS) in 2009, Pare-Pare City is topographically included in the Karajae watershed [38]. Almost the entire area of the City of Pare-Pare is included in the Karajae watershed.

The Pare-Pare City which continues to experience current and future developments will greatly affect the Karajae watershed. Based on this, analysis of LULC change in the Karajae watershed by using remote sensing approach, GIS, and CA-Markov model. The impact of the development of the City of Pare-Pare includes aspects of population, settlement, roads, and strategic areas to changes in land use / closure using Binary Logistic Regression.

2. Materials and methods
The Karajae watershed boundary is the outer boundary of all types of data used for the purposes of analyzing research sites. It is based on the Determination of the Directorate General of Land and Social Forestry Rehabilitation (RLPS) of the Ministry of Forestry in 2009. Administratively, the Karajae watershed boundary consists of two municipal/regency areas, those are Pare-Pare City and Sidenreng Rappang Regency, South Sulawesi Province. It has an area around 18,000 hectares which shown in Figure 1.
2.1. Data preparation
The study began with the determination of the Karaja watershed boundary based on the Determination of the Directorate General of Land and Social Forestry Rehabilitation (RLPS) of the Ministry of Forestry in 2009. The general data covers are the main rivers, creeks, roads, and district/city administrative boundaries in the Indonesian Geospatial Portal with Scale 1:50.000 (tanahair.indonesia.go.id). Other general data is the National Digital Elevation Model (DEM) 8 m resolution at tides.big.go.id.

Analysis of LULC change with the remote sensing approach and GIS by using Landsat 8 OLI path data path 114 row 64 records in 2004, 2011 and 2018 downloaded earthexplorer.usgs.gov. Data of settlements, roads and Strategic Areas based on the Regional Spatial Planning (RTRW) of Pare-Pare City and Sidenreng Rappang Regency Scale 1: 50.000 and population data of each village in the Pare-Pare City Civil Registry Office and Sidenreng Rappang Regency for factor analysis which affects LULC change.

2.2. The processing and analyzing research data land use/land cover change
LULC change were analyzed by using remote sensing data, those are Landsat 8 with 30-meter resolution path 114 row 64 records in 2004, 2011 and 2018 which can be downloaded at earthexplorer.usgs.gov [39]. Landsat images that are repeated every 16 days can be used to detect LULC changes [40]. Furthermore, interpreting the Landsat image begins with a composite band (merging of color bands), cutting the image according to the boundary, and digitizing with a visual delineation method. The classification of LULC is determined based on patterns and characteristics, called hue, color and texture in the image by the Directorate General of Planology and Environmental Management of the Ministry of Environment and Forestry. Land use/land cover annually will result in LULC change starting from the pattern of distribution, area and land use / land cover that has changed.

Image classification validation was conducted to test the accuracy of image interpretation. Validation or accuracy testing is a comparison between the results of image classification with existing conditions in the field [41]. The accuracy level of image interpretation that can be accepted is 85% [42]. Image classification validation was done by setting the coordinates of the points that represent each LULC classification. The determination of coordinates was conducted by marking the actual LULC map (2018) which has been interpreted. The selected sample points, the coordinate data are recorded and a ground check is conducted in the field. The validation process is a proportional measurement [43]. The validation process is called overall accuracy by using a Confusion Matrix table. The overall accuracy equation is as follows:

\[ OA = \frac{X}{N} \times 100\% \]  

(1)
Where:
\[ X = \text{The sample points that match the interpretation results with the results of ground check} \]
\[ N = \text{Total number of sample points} \]

### Table 1. Confusion matrixs

| Reference Data (ground) | Column Total |
|-------------------------|--------------|
|                         | A \(X_{ii}\) | \(X_{k+}\) |
| Image Classification Result Data | A \(X_{i+}\) | \(X_{kk}\) |
|                         | B \(X_{i+}\) | \(X_{kk}\) |
|                         | C \(X_{i+}\) | \(X_{kk}\) |
| Line Total              | \(X_{+k}\)  | \(N\)    |

Source: [44]

#### 2.3. Projected Land Use / Land Cover (LULC) in 2032

LULC projection was conducted by using the Cellular Automata Markov Chain (CA Markov) method. CA Markov method by comparing the changes between 2004 and 2018. This Cellular Automata simulation model is a combination of Markov Chain and Multi Objective Land Allocation (MOLA). Changes in land use are based on previous period land use and neighboring land use [28,30,45].

The Markov Chain model will produce a transitional/probability area matrix which is a transition matrix of changes from the previous year to the projected year. The Markov equation is constructed using a land use distribution at the beginning and end of the observation that is represented in a vector (one column matrix), as well as a transition matrix [28,45]. \(U_t\) presents the opportunity of each point clarified as class U at time t, \(LC_{ua}\) shows the probability of a class U being another class over a certain period of time. The relationships of the three matrices are as follows:

\[
M_{LC} \cdot M_t = M_{t+1} \\
\begin{pmatrix}
LC_{iuu} & LC_{iua} & LC_{iuw} \\
LC_{auu} & LC_{aau} & LC_{aw} \\
LC_{wuu} & LC_{wa} & LC_{ww}
\end{pmatrix}
\begin{pmatrix}
U_t \\
A_t \\
W_t
\end{pmatrix}
= 
\begin{pmatrix}
U_{t+1} \\
A_{t+1} \\
W_{t+1}
\end{pmatrix}
\]

(2)

Cellular Automata model to get LULC prediction in 2032. The data entered in the form of a transition matrix, land use in 2018 and land suitability (suitability of previous settlement land has been validated). Model validation is also conducted to determine the accuracy of the projection. So also do projections in the actual year (2018) based on data from 2004 and 2011. Validation will then be conducted by comparing the simulated land use results (2018) with the field observations (2014) based on kappa values [28,46]. The kappa value equation is as follows [46,47]:

\[
K = \frac{N \times \sigma_{x_i}^2 + \sigma_{x_i}^2 \times x_{i+1} \times x_{i+1}}{N^2 \times \sigma_{x_i}^2 \times x_{i+1} \times x_{i+1}} \times 100\%
\]

(3)

Where:
- \(K\) : Kappa Value
- \(X_{ii}\) : area of type i land use simulation results that corresponds to area of type i of land use observations results
- \(X_{i+}\) : area of type i land use simulation results
- \(X_{+i}\) : area of land use type i observation results
- \(N\) : the total area of all types of land use
- \(Z\) : Total land use types
Kappa value calculation was done by using the validation tool. If the calculation results obtained kappa value (K), for example 0.9 or 90%, it means that the land use results of the simulation and the results of observations correspond to 90%, both in terms of area and spatial distribution.

2.4. Binary logistic regression model

Logistic regression was used to identify how much a parameter is in determining the presence and/or absence of phenomena [48–50]. Binary logistic regression model is a formula that connects the probability of a LULC change in 2032 as a dependent variable with an independent variable with the last derivative equation [49–51].

\[
\text{Logit} \left( p_i \right) = \beta + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k
\]  

(4)

Where:

- Logit \( p_i \): Probability of change / expansion
- \( \beta \): Constants of linear regression equations
- \( \beta_2 \): The coefficient of the predictor variable
- \( X \): Predictor variable

The independent variables chosen are physical factors that develop an urban area, called population density, settlement, road, and strategic areas which can be seen in Table 2.

| Variables | Analysis | Unit | Analysis |
|-----------|----------|------|----------|
| \( X_1 \) = population density | Grid map | Soul/km\(^2\) | Grid cell pixel 30 m |
| \( X_2 \) = settlement plans | Grid map | m\(^2\) | Grid cell pixel 30 m |
| \( X_3 \) = road plans | Euclidean distance | M | Kontinu pixel 30 m |
| \( X_4 \) = strategic areas | Grid map | m\(^2\) | Grid cell pixel 30 m |

LULC change is mainly due to high population growth rates [28,52]. The increasing in population in urban areas is strongly influenced by urbanization activities. That urbanization continues to experience an upward trend to date [6,11]. Population density is the ratio of the population to the area. Most urban areas where LULC changes occur are mainly influenced by population density [46].

In addition, houses that continues to grow in urban areas has converted most of the agricultural land [53]. House developments also exert pressure outside the urban areas to protected areas [54]. Roads also provide urban developments that occur in almost all directions, especially regional roads [53]. Land use planning has been identified as a regional/city policy instrument [55]. So that the strategic area of the city has a different impact on LULC outside the urban areas.

Binary logistic regression analysis by using GIS software produces several calculation values. The calculation value is a history of the process of the regression equation, those are:

a. Pseudo Square

Pseudo square is an index that states whether or not the relationship between the dependent and independent variables in a binary logistic regression equation. This pseudo square value ranges from 0 to 1. A value of 0 states that there is no relationship between the independent variable and the dependent variable, while value 1 indicates the relationship between the two variables perfectly.

b. Odd Ratio & Kappa index

Odd ratio is the ratio between the true occurrence of a projection and the incorrectness of a projection. The probability value in calculating the odd ratio is 0.5. Probabilities below 0.5 are considered 0 (predicted no change) while probabilities above 0.5 are considered 1 (predicted changes occur). If the odd ratio number> 1 means the equation produced from binary logistic regression analysis can be applied to make projections.
The kappa index represents the optimal accuracy that can be achieved by the probability model of the binary logistic regression projection. Whether or not the dependent variable changes seen from the comparison of the kappa index value with the threshold value. If the kappa index value or probability number is above the threshold value is considered as 1 (change), while the number below the threshold is considered 0 (unchanged). The dependent variable is a binary event, if it produces a number 1 then it is considered to be a change, and angk indicates no change [51].

c. Regression coefficient
Regression coefficient shows the size of the effect of each independent variable on the dependent variable. The greater the regression coefficient, the greater the influence of the independent variables on the changes that occur in the dependent variable. Positive and negative values on the regression coefficient have a special meaning, that the value of the positive regression coefficient indicates that the greater the value of the independent variable, the greater the probability of land use change at that location. Conversely, if the regression coefficient is negative, it indicates that the smaller the value of the independent variable the greater the probability of land use change at that location.

3. Results and discussion
3.1. Actual changes to LULC for the period 2004-2018
LULC spatial data based on the interpretation of Landsat imagery 8 of 2004, 2011 and 2018 in the Karajae watershed shown in Figure 2. The LULC class consists of secondary dryland forest, settlements, dryland agriculture, grasslands, paddy fields, shrubs and body of water. It is based on data from the Directorate General of Environmental Planning and Planning, Ministry of Environment and Forestry. The spatial data of LULC changes in the Karajae watershed shown in Tables 3 & 4.

![Figure 2. LULC in Kelara Watershed (a) 2004, (b) 2011, and (c) 2018](image-url)
The Karajae watershed LULC was dominated by Dryland agriculture with an area of almost half of the watershed area. Dryland agriculture, settlement, and paddy fields have increased in area. Improvement of agricultural and urban land is a community choice for meeting the necessities of life as a result of food demand and increasing population [56,57]. Secondary dryland forests, grasslands, and shrubs area were decreased. Decreased area of secondary dryland forest by 0.64 percent. The average rate of decreasing of forest area (deforestation) on the island of Sulawesi, especially South Sulawesi Province is less than two percent [58]. Table 4 shows every LULC change in the Karajae watershed in the 2004-2018 period.

### Table 3. LULC on 2004, 2011, dan 2032 in Karajae Watershed

| No. | LULC                     | 2004 (ha) | 2011 (ha) | 2018 (ha) | Area of Change 2004 -2018 (%) | Percentage of Change 2004-2018 (%) |
|-----|--------------------------|-----------|-----------|-----------|-------------------------------|-----------------------------------|
| 1   | Secondary dryland forest | 2,785.67  | 2,773.36  | 2,767.78  | -17.89                        | -0.64                             |
| 2   | Settlement               | 776.60    | 869.69    | 1,004.90  | 228.30                        | 29.40                             |
| 3   | Dryland Agriculture      | 8,016.70  | 8,420.14  | 8,495.83  | 79.13                         | 5.98                              |
| 4   | Grassland                | 2,870.59  | 2,490.07  | 2,332.54  | -538.05                       | -18.74                            |
| 5   | Paddy Fields             | 1,044.54  | 1,074.04  | 1,090.04  | 45.50                         | 4.36                              |
| 6   | Shrub                    | 2,072.48  | 1,939.28  | 1,875.48  | -197.00                       | -9.51                             |
| 7   | Water Bodies             | 63.52     | 63.52     | 63.52     | 0.00                          | 0.00                              |
|     | Total                    | 17,630.09 | 17,630.09 | 17,630.09 | -                             | -                                 |

### Table 4. LULC change matrix for 2014-2018 in the Karajae watershed

| LULC          | 2018 (ha) |
|---------------|-----------|
|               | P1        | P2        | P3        | P4        | P5        | P6        | P7        |
| 2004 (ha)     | 2,767.78  | -         | 7.06      | -         | -         | 10.83     | -         | 2,785.67  |
|               | -         | 776.60    | 0.00      | -         | -         | -         | -         | 776.60    |
| P3            | -         | 191.71    | 7,602.76  | -         | 46.89     | 175.33    | -         | 8,016.70  |
| P4            | -         | 1.73      | 361.03    | 2,332.54  | -         | 175.28    | -         | 2,870.59  |
| P5            | -         | 1.39      | -         | 1,043.15  | -         | -         | -         | 1,044.54  |
| P6            | -         | 33.47     | 524.97    | -         | 1,514.04  | -         | -         | 2,072.48  |
| P7            | -         | -         | -         | -         | -         | 63.52     | -         | 63.52     |
| Total         | 2,767.78  | 1,044.90  | 8,495.83  | 2,332.54  | 1,090.04  | 1,875.48  | 63.52     | 17,630.09 |

Where: P1 (Secondary dryland forest); P2 (Settlement); P3 (Dryland Agriculture); P4 (Grassland); P5 (Paddy Fields); P6 (Shrub); P7 (Water Bodies).

Dryland agriculture, grassland, and shrub farming has increased and decreased in size among the three forms of land use/cover. This indicates that farmers in the Karajae watershed are carrying out shifting cultivation. Paddy fields are converted only from 47 hectares of agricultural land. The change from LULC to Settlement came mainly from dry land agriculture and shrubs. Dryland agriculture is mostly converted to settlements in urban areas [13,53,59]. Secondary dryland forests are converted to dryland agriculture and shrubs. Deforestation occurs due to food demand which causes conversion to agricultural land use [60,61].

The results of the 2018 LULC classification were then tested for accuracy. Accuracy testing is very important in the classification of LULC to determine the level of correctness of the LULC classification data [62,63]. Accuracy test is performed to determine the percentage of confidence level of data from the interpretation of Landsat 8 images obtained based on the overall accuracy equation. Input data in this test include predetermined sample points (Figure 4) juxtaposed with the results of field observations related to these sample points shown in the Confusion matrix table. The number of
sample points in accordance with the actual situation in the field is then divided by the total number of sample points. The results will show the percentage level of accuracy of image interpretation performed.

The number of sample points observed in the field were 10 samples for each LULC class. Secondary dryland forests, settlements and bodies of water have the highest degree of accuracy without error resulting from image interpretation. LULC's classification of forests, settlements, and body of water has a high to perfect accuracy without error [46,64]. Shrubs and grasslands have the lowest accuracy, that 2 out of 10 sample points turned out to be the other LULC.

Accuracy test results with overall accuracy based on the confusion matrix table show 64 points corresponding between sample points and conditions in the field, while 6 points do not correspond. These results in the accuracy of the results of image interpretation which is 65/70 = 91.42 percent. This shows that the results of image interpretation conducted can be accepted accordingly, that the image classification that can be accepted is a minimum accuracy level of 85 percent [31,47].

Table 5. Confusion matrix of the 2018 LULC classification sample points in the Karajae watershed

| LULC          | Field Data in 2019 |
|---------------|---------------------|
|               | P1  | P2  | P3  | P4  | P5  | P6  | P7  | Total |
| Classificatio Data in 2018 | 10  | 0   | 0   | 0   | 0   | 0   | 0   | 10    |
| P1            | 0   | 10  | 0   | 0   | 0   | 0   | 0   | 10    |
| P2            | 0   | 0   | 8   | 0   | 0   | 1   | 0   | 10    |
| P3            | 0   | 0   | 0   | 9   | 0   | 1   | 0   | 10    |
| P4            | 0   | 1   | 0   | 0   | 9   | 0   | 0   | 10    |
| P5            | 0   | 0   | 1   | 1   | 0   | 8   | 0   | 10    |
| P6            | 0   | 0   | 0   | 0   | 0   | 0   | 10  | 10    |
| P7            | 0   | 0   | 0   | 0   | 0   | 0   | 10  | 10    |
| Total         | 10  | 11  | 9   | 11  | 9   | 10  | 10  | 70    |

Where: P1 (Secondary dryland forest); P2 (Settlement); P3 (Dryland agriculture); P4 (Grassland); P5 (Paddy fields); P6 (Shrub); P7 (Water bodies).

Figure 3. Ground check LULC 2018 in Kelara Watershed
The accuracy of the 2018 image interpretation provides legitimacy that the results of the 2004 and 2011 image interpretations should also have the same accuracy. The accuracy of image interpretation in 2004 and 2011 is based on 2018 because it is no longer possible to carry out field observations at these times. The results of the interpretation meet the accuracy standards, then all three are valid for further use in conducting LULC projections.

3.2. Projected land use/land cover in 2032

LULC Projection in 2032 uses LULC data in 2004 and 2018. While LULC data in 2011 is used for validation of the LULC Projection. Validation was done first by projecting LULC 2018 using LULC in 2004 and 2011 as well as transition probabilities resulting from the markov process between 2004 and 2018. The results of the 2018 projection are then adjusted to the results of the 2018 interpretation based on the suitability of the area and spatial distribution. The results of the 2018 projections validation of the 2018 interpretations show a Kappa value of 0.89 (Appendix 1). This means that the projection results with LULC actually have good compatibility in terms of spatial and spatial distribution up to 89%. This shows that LULC in 2004 and 2018 can be used to make LULC projections in 2032. The results of LULC projections in 2032 shown in Figures 4, Tables 6 and 7.

![Figure 4. LULC projection in 2032 in the Karajae watershed](image)

| No. | LULC                        | 2018 (ha) | 2018 (%) | 2032 (ha) | 2032 (%) | Change LULC (ha) | Change LULC (%) |
|-----|-----------------------------|-----------|----------|-----------|----------|------------------|-----------------|
| 1   | Secondary dryland forest    | 2,767.78  | 15.70    | 2,361.61  | 13.40    | -406.16          | -14.67          |
| 2   | Settlement                  | 1,004.90  | 5.70     | 1,620.50  | 9.19     | 615.60           | 61.26           |
| 3   | Dryland Agriculture         | 8,495.83  | 48.19    | 7,669.80  | 43.50    | -826.03          | -9.72           |
| 4   | Grassland                   | 2,332.54  | 13.23    | 2,142.85  | 12.15    | -189.69          | -8.13           |
| 5   | Paddy Fields                | 1,090.04  | 6.18     | 1,096.38  | 6.22     | 6.34             | 0.58            |
| 6   | Shrub                       | 1,875.48  | 10.64    | 2,675.43  | 15.18    | 799.95           | 42.65           |
| 7   | Water Bodies                | 63.52     | 0.36     | 63.52     | 0.36     | 0.00             | 0.00            |
|     | Total                       | 17,630.09 | 100.00   | 17,630.09 | 100.00   | 0.00             | 0.00            |
LULC projections show huge changes in LULC land in the 2018-2032 period compared to the previous period in 2004-2018. The area of LULC change is almost double the comparison of the time period. This shows that LULC will change much larger in the future based on the current change trend.

Shrub is a large land which has an additional area of almost 800 hectares. Most shrubs are converted from dry land agriculture, and forests. Conversion of shrubs into dry agricultural land around 415 hectares or more than half the additional area. This pattern is different that occurs in most regions, that an increase in agricultural area converted from shrubs [31,46,65]. This shows, that the agricultural pattern of the community is still doing shifting cultivation in the Karajae watershed.

Agriculture Dry land is a broad class of LULC that has experienced a reduction in area. Dryland agriculture is at the center of land use change [31]. Dry land agriculture has decreased significantly to reach 826 hectares. This is very different in the previous period (2004-2018), that dryland agriculture experienced an increase in area. Projections also differ in some non-urban areas, that dryland agriculture continues to experience extensive expansion [31,46,57,65]. Reducing agricultural land will also threaten food security [59].

Most of the agricultural land is converted into built land in the form of settlements. Dry land agriculture is converted into settlements reaching an area of 516 hectares or around 80 percent of the additional settlement area. Most dry land agriculture is converted to developed land including settlements that occur in urban areas [13,17,28,53,66,67]. So that the settlement experienced an increase in area that reached 615 hectares. This figure shows that the addition of residential area more than doubled from the previous period (2004-2018). Urban areas are developing at a much faster pace than before [53].

The City of Pare-Pare, the increasing population as a center of economic activity will encourage the development of land use that has an impact on changing the vegetation area to be awakened. Urbanization and economic activities are highly correlated with changes in land use in urban areas [8]. The population of urban areas is expected to continue to increase rapidly and more than 70 percent of the population will live in cities [68]. In addition to increasing population, there have been developments inside and outside the city limits in the form of roads, housing development, commercial and industrial improvements [53]. An increasing in residential area as a form of land use change in urban areas will have an impact on urban expansion [17,66]. The increase in settlements and built-up land has the most significant effect on life processes in urban and surrounding areas [59].

The important thing in a watershed ecosystem is the existence of forests. Secondary dryland forest has decreased by more than 400 hectares. The last few centuries, that forests continue to experience extensive decline [39]. The reduction in the area of secondary dryland forest is very large, when compared to the reduction in the area of the previous period (2004-2018). It is estimated that in the future there will be a dramatic decline in forest area [30,33]. The reduction in the area of secondary

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**Table 7. LULC change matrix for 2018-2032 in the Karajae watershed**

| LULC     | 2018 (ha) | 2032 (ha) |
|----------|-----------|-----------|
|          | P1        | P2        | P3        | P4        | P5        | P6        | P7        | Total     |
| P1       | 2,345.94  | -         | 116.21    | 12.01     | -         | 293.62    | -         | 2,767.78  |
| P2       | -         | 978.29    | 3.36      | 1.51      | 0.04      | 21.71     | -         | 1,004.90  |
| P3       | 3.74      | 516.20    | 7,355.86  | 61.86     | 143.10    | 415.06    | -         | 8,495.83  |
| P4       | 11.93     | -         | 178.43    | 2,055.38  | 0.83      | 85.98     | -         | 2,332.54  |
| P5       | -         | 125.27    | 9.16      | 0.95      | 952.05    | 2.60      | -         | 1,090.04  |
| P6       | 0.01      | 0.74      | 6.78      | 11.14     | 0.35      | 1,856.47  | -         | 1,875.48  |
| P7       | -         | -         | -         | -         | -         | -         | -         | 63.52     |
| Total    | 2,361.61  | 1,620.50  | 7,669.80  | 2,142.85  | 1,096.38  | 2,675.43  | 63.52     | 17,630.09 |

Where: P1 (Secondary dryland forest); P2 (Settlement); P3 (Dryland Agriculture); P4 (Grassland); P5 (Paddy Fields); P6 (Shrub); P7 (Water Bodies).
Dryland forests was 22 times that of the previous period. So that the deforestation rate will reach 14 percent in the future.

Urban areas also have an impact on deforestation or reduction in forest area. Settlements provide a pressure in the form of community visiting activities to a protected location [69]. As a result of the conversion of dry land agriculture into settlements and flooded areas, the community encroached on the forest to be used as agricultural land. Most of the forest is converted to agricultural land [31]. In addition, the increasing demand for food in line with the increasing number of human populations causes greater forest encroachment [56].

Land use projections are an initial source of information about estimates of deforestation events. Future maps of deforestation projections can be used as an early warning system for developing protected forest areas [70]. The LULC projection map in the form of deforestation can help forest area managers, conservation efforts and forest management. Deforestation prediction can help sustainable forest management in the long term [51]. It can even help in the field of natural resource management [32]. So, we need a policy and fast steps from forestry stakeholders including local government. An institutional arrangement was conducted starting from the government, coordination, and the Institution in compiling the components of the regulatory framework, procedures for collaboration between stakeholders and specific activities of land use planning practices [71].

3.3. Factors influencing land use/land cover of Karajae Watershed

Determination of factors that led to the development of the City of Pare-pare against LULC in 2032 using binary logistic regression analysis with the help of the GIS approach. Logistic regression is useful to explain quantitatively the relationship between changes in LULC and its driving factors [50]. GIS becomes an approach that will help logistic regression in mapping LULC changes [49]. Analysis of the phenomenon of LULC change in 2032 as the dependent variable and the factors that affect the occurrence of change as an independent variable (Figure 5), produced the following equation (Appendix 2).

Some indexes that are considered important and state the level of validation of the binary logistic regression analysis model are starting from the pseudo square value, odd ratio, kappa index, and threshold. The pseudo square value of the binary logistic regression equation in this study is 0.1340 and is quite strong causing changes. Odd ratio value in the binary logistic regression equation is 2.9263 that shows the number of odd ratios> 1 means the equation generated from binary logistics can be applied to make projections. Kappa index value is based on the results of binary logistic regression that is 0.8075 and the resulting threshold value is 0.1945. This value is included in the very possibility of change. The probability number above the threshold value is considered as 1 (change) while the number below the threshold is considered 0 (unchanged). So that the Regression coefficient on the independent variable can be used.

\[ \logit (p_i) = 1.1948 - 0.102927(X1) - 20.215886(2) - 3.676704(X3) - 0.803281(X4) \]
Figure 5. The driving force behind LULC change in the Karajae watershed: (a) Population density, (b) Settlement, (c) Roads, and (d) Strategic region

Table 8. Regression coefficient values for each independent variable

| Driving Force (Variabel Independen) | Regression coefficient |
|------------------------------------|------------------------|
| Population density                 | -0.102927              |
| Settlements                        | -20.215886             |
| Roads                              | -3.676704              |
| Strategic areas                    | -0.803281              |

Regression coefficient values indicate all independent variables or driving factors have negative values. The driving factor which has the smallest negative coefficient shows a great influence on the phenomenon. Based on this, settlement has a large impact on the occurrence of changes in LULC in the Karajae watershed. Settlements are more dominant in determining LULC changes than other motivating factors. Faster land use changes occur in the environment around human settlements [14]. Even settlements put pressure on protected areas [69]. Aside from settlements, roads are a significant driving factor causing LULC changes. Developments that occur within and outside urban areas due to the road network [53].

A very large increase in settlement area cannot be separated from increasing population and urbanization. An increase in population will shape urban conditions one of which is housing development [53]. Population growth or urbanization is the factor that most influences the changing conditions of urban areas [59,67]. Urbanization occurs because cities have a better place regarding...
settlement scenarios [11]. But the increase in settlement area must certainly be a particular concern for the city government and local governments around it. The addition and expansion of built areas including settlements will have an impact on consumption patterns, cause urban sprawl, change urban urban patterns and lead to depletion of natural resources [17,59,66,72].

4. Conclusions
Changes in LULC in the actual period (2004-2018) are only around 5 percent of the total area of the Karajae watershed. These changes indicate the addition of a large area of settlement and dry land agriculture. Secondary dryland forests, grasslands and shrubs have been reduced. The decrease in the area of secondary dryland forest is quite small with a percentage not reaching one percent of the area of secondary dryland forest. LULC Projection in 2032 shows a greater change than the actual period. Settlements experienced an increase in area twice the actual period. This was followed by a very large deforestation event that reached 14 percent of the forest area. This is different from agriculture that has experienced a large reduction, while shrubs have a fairly large increase in area. This shows the pattern of shifting cultivation conducted by the farming community in the Karajae watershed. The changes in LULC in the future are very much influenced by the settlement and the road network.

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References
[1] Mukherjee S, Bebermeier W and Schütt B 2018 An Overview of the Impacts of Land Use Land Cover Changes (1980–2014) on Urban Water Security of Kolkata Land 7 1–25
[2] United Nations 2019 Revision of World Urbanization Prospects 2018 (New York)
[3] Bhalii M N, Ghaffar A, Shirazi S A, Parveen N and Anwar M M 2012 Change Detection Analysis of Land Use by Using Geospatial Techniques: A Case Study of Faisalabad-Pakistan. Science International (Lahore) 24 539–46
[4] Minallah M N, Ghaffar A, Rafique M and Mohsin M 2016 Urban Growth And Socio-Economic Development In Gujranwala, Pakistan: A Geographical Analysis Pakistan Journal of Science 68 176–83
[5] Yang Q, Duan X and Wang L 2017 Spatial–Temporal Patterns and Driving Factors of Rapid Urban Land Development in Provincial China: A Case Study of Jiangsu Sustainability 9 2371
[6] United Nations 2019 Revision of World Urbanization Prospects 2018 (New York)
[7] Qian M, Pu L, Zhang J and Zhang M 2013 Urban Spatial Expansion Characteristics in China’s Rapid Urbanization Region—A Case Study of SXC Region International Journal of Geosciences 4 1–11
[8] Yang Q, Duan X and Wang L 2017 Spatial–Temporal Patterns and Driving Factors of Rapid Urban Land Development in Provincial China: A Case Study of Jiangsu Sustainability 9 2371
[9] Khan A A, Arshad S and Mohsin M 2014 Population Growth and Its Impact on Urban Expansion: A Case Study of Bahawalpur, Pakistan Universal Journal of Geoscience 2 229–41
[10] Patra S, Sahoo S, Mishra P and Mahapatra S C 2018 Impacts of Urbanization on Land Use/Cover Changes and Its Probable Implications on Local Climate and Groundwater Level Journal of urban management 7 70–84
[11] Minallah M N, Ghaffar A, Rafique M and Mohsin M 2016 Urban Growth And Socio-Economic Development In Gujranwala, Pakistan: A Geographical Analysis Pakistan Journal of Science 68 176–83
[12] Dadras M, Mohd Shafri H Z, Ahmad N, Pradhan B and Safarpour S 2014 Land Use/Cover Change Detection and Urban Sprawl Analysis in Bandar Abbas City, Iran The Scientific World Journal 2014 1–12
[13] Rahimi A 2016 A methodological approach to urban land-use change modeling using infill development pattern—a case study in Tabriz, Iran Ecological Processes 5 1
[14] Yang J, Wang Y C, Guo L and Xue D 2015 Patterns and structures of land use change in the Three Rivers Headwaters Region of China PloS one 10
[15] Khawaldah H A, Farhan I and Alzboun N M 2020 Simulation and Prediction of Land Use and Land Cover Change Using GIS, Remote Sensing and CA-Markov Model Global Journal of Environmental Science and Management 6 215–32
[16] Wang Z, Chai J and Li B 2016 The Impacts of Land Use Change on Residents’ Living Based on Urban Metabolism: A Case Study in Yangzhou City of Jiangsu Province, China Sustainability 8 1–17
[17] Patra S, Sahoo S, Mishra P and Mahapatra S C 2018 Impacts of Urbanization on Land Use/Cover Changes and Its Probable Implications on Local Climate and Groundwater Level Journal of urban management 7 70–84
[18] Arekhi M 2011 Modeling Spatial Pattern of Deforestation Using GIS and Logistic Regression: A Case Study of Northern I lam Forests, I lam Province, Iran African journal of biotechnology 10 16236–49
[19] Galiniene J, Dailidiene I and Bishop S R 2019 Forest Management and Sustainable Urban Development in The Curonian Spit European Journal of Remote Sensing 52 42–57
[20] Hamad R, Balzter H and Kolo K 2018 Predicting Land Use/Land Cover Changes Using a CA-Markov Model Under Two Different Scenarios Sustainability 10 1–23
[21] Hyandye C, Mandara C G and Safari J 2015 GIS and Logit Regression Model Applications in Land Use/Land Cover Change and Distribution in Usangu Catchment American Journal of Remote Sensing 3 6–16
[22] Liping C, Yujun S and Saeed S 2018 Monitoring and Predicting Land Use and Land Cover Changes Using Remote Sensing and GIS Techniques—A Case Study of a Hilly Area, Jiangle, China PloS one 13 1–23
[23] Azizi A, Malakmohamadi B and Jafari H R 2016 Land Use and Land Cover Spatiotemporal Dynamic Pattern and Predicting Changes Using Integrated CA-Markov Model Global Journal of Environmental Science and Management 2 223–34
[24] Hishe S, Bewket W, Nyssen J and Lyimo J 2020 Analysing Past Land Use Land Cover Change and CA-Markov-Based Future Modelling in The Middle Suluh Valley, Northern Ethiopia Geocarto International 35 225–55
[25] Hua A K 2017 Application of Ca-Markov Model and Land Use/Land Cover Changes in Malacca River Watershed, Malaysia Applied Ecology and Environmental Research 15 605–22
[26] Nguyen T T H and Ngo T T P 2018 Land Use/Land Cover Change Prediction in Dak Nong Province Based on Remote Sensing and Markov Chain Model and Cellular Automata Journal of Vietnamese Environment 9 132–40
[27] Yulianto F, Maulana T and Khomarudin M R 2018 Analysis of The Dynamics of Land Use Change and Its Prediction Based on The Integration of Remotely Sensed Data and CA-Markov Model, in The Upstream Citarum Watershed, West Java, Indonesia International Journal of Digital Earth 12 1151–76
[28] Khawaldah H A, Farhan I and Alzboun N M 2020 Simulation and Prediction of Land Use and Land Cover Change Using GIS, Remote Sensing and CA-Markov Model Global Journal of Environmental Science and Management 6 215–32
[29] Yulianto F, Suwarsono S and Sulma S 2019 Improving The Accuracy and Reliability of Land Use/Land Cover Simulation by The Integration of Markov Cellular Automata and Landform-Based Models _ A Case Study in The Upstream Citarum Watershed, West Java, Indonesia Journal of Degraded and Mining Lands Management 6 1675–96
[30] Liping C, Yujun S and Saeed S 2018 Monitoring and Predicting Land Use and Land Cover Changes Using Remote Sensing and GIS Techniques—A Case Study of a Hilly Area, Jiangle, China PloS one 13 1–23
[31] Azizi A, Malakmohamadi B and Jafari H R 2016 Land Use and Land Cover Spatiotemporal Dynamic Pattern and Predicting Changes Using Integrated CA-Markov Model Global Journal of Environmental Science and Management 2 223–34

[32] Hamad R, Balzter H and Kolo K 2018 Predicting Land Use/Land Cover Changes Using a CA-Markov Model Under Two Different Scenarios Sustainability 10 1–23

[33] Nguyen T T H and Ngo T T P 2018 Land Use/Land Cover Change Prediction in Dak Nong Province Based on Remote Sensing and Markov Chain Model and Cellular Automata Journal of Vietnamese Environment 9 132–40

[34] Achmad A, Hasyim S, Dahlan B and Aulia D N 2015 Modeling of Urban Growth in Tsunami-Prone City Using Logistic Regression: Analysis of Banda Aceh, Indonesia Applied geography 62 237–46

[35] Arsanjani J J, Helbich M, Kainz W and Boloorani A D 2013 Integration of Logistic Regression, Markov Chain and Cellular Automata Models to Simulate Urban Expansion International Journal of Applied Earth Observation and Geoinformation 21 265–75

[36] Aboelnour M, Gitau M W and Engel B A 2020 A Comparison of Streamflow and Baseflow Responses to Land-Use Change and the Variation in Climate Parameters Using SWAT Water 12 1–29

[37] Welde K and Gebremariam B 2017 Effect of Land Use Land Cover Dynamics on Hydrological Response of Watershed: Case Study of Tekeze Dam Watershed, Northern Ethiopia International Soil and Water Conservation Research 5 1–16

[38] Ministry of Forestry R of I 2009 Minister of Forestry Regulation Number: P. 32/MENHUT-II/2009. Concerning the Procedure for Formulating a Forest Rehabilitation Engineering Plan and Watershed Land (RTKRL-DAS) (Indonesia)

[39] Yulianto F, Maulana T and Khomarudin M R 2018 Analysis of The Dynamics of Land Use Change and Its Prediction Based on The Integration of Remotely Sensed Data and CA-Markov Model, in The Upstream Citarum Watershed, West Java, Indonesia International Journal of Digital Earth 12 1151–76

[40] Galiniene J, Dailidiene I and Bishop S R 2019 Forest Management and Sustainable Urban Development in The Curonian Spit European Journal of Remote Sensing 52 42–57

[41] Foody G M 2002 Status of Land Cover Classification Accuracy Assessment Remote sensing of environment 80 185–201

[42] Lillesand T M, Kiefer R W, Sutarto, Dulbahri, Suharsono P, Hartono and Suharyadi 1997 Penginderaan Jauh dan Interpretasi Citra (Yogyakarta: Gadjah Mada University Press)

[43] Estoque R C and Murayama Y 2012 Introducing New Measures of Accuracy for Land-Use/Cover Change Modeling Tsukuba geoenvironmental sciences 8 3–8

[44] Sutanto S 1994 Penginderaan Jauh Jilid I (Yogyakarta: Gadjah Mada University Press)

[45] Yulianto F, Suwarsono S and Sulma S 2019 Improving The Accuracy and Reliability of Land Use/Land Cover Simulation by The Integration of Markov Cellular Automata and Landform-Based Models _ A Case Study in The Upstream Citarum Watershed, West Java, Indonesia Journal of Degraded and Mining Lands Management 6 1675–96

[46] Hyandye C, Mandara C G and Safari J 2015 GIS and Logit Regression Model Applications in Land Use/Land Cover Change and Distribution in Usangu Catchment American Journal of Remote Sensing 3 6–16

[47] Lillesand T M, Kiefer R W, Sutarto, Dulbahri, Suharsono P, Hartono and Suharyadi 1997 Penginderaan Jauh dan Interpretasi Citra (Yogyakarta: Gadjah Mada University Press)

[48] Das P and Pandey V 2019 Use of Logistic Regression in Land-Cover Classification with Moderate-Resolution Multispectral Data Journal of the Indian Society of Remote Sensing 47 1443–54

[49] Achmad A, Hasyim S, Dahlan B and Aulia D N 2015 Modeling of Urban Growth in Tsunami-Prone City Using Logistic Regression: Analysis of Banda Aceh, Indonesia Applied geography 62 237–46
[50] Arsanjani J J, Helbich M, Kainz W and Boloorani A D 2013 Integration of Logistic Regression, Markov Chain and Cellular Automata Models to Simulate Urban Expansion International Journal of Applied Earth Observation and Geoinformation 21 265–75

[51] Arekhi M 2011 Modeling Spatial Pattern of Deforestation Using GIS and Logistic Regression: A Case Study of Northern Ilam Forests, Ilam Province, Iran African journal of biotechnology 10 16236–49

[52] Bhalli M N, Ghaffar A, Shirazi S A, Parveen N and Anwar M M 2012 Change Detection Analysis of Land Use by Using Geospatial Techniques: A Case Study of Faisalabad-Pakistan. Science International (Lahore) 24 539–46

[53] Khan A A, Arshad S and Mohsin M 2014 Population Growth and Its Impact on Urban Expansion: A Case Study of Bahawalpur, Pakistan Universal Journal of Geoscience 2 229–41

[54] Weitowitz D C, Panter C, Hoskin R and Liley D 2019 The Effect of Urban Development on Visitor Numbers to Nearby Protected Nature Conservation Sites Journal of Urban Ecology 5 1–12

[55] Maruna M, Crnčević T and Milojević M P 2019 The Institutional Structure of Land Use Planning for Urban Forest Protection in the Post-Socialist Transition Environment: Serbian Experiences Forests 10 1–28

[56] Norris K, Potts S G and Mortimer S R 2010 Ecosystem services and food production Ecosystem Services (Issues in Environmental science and technology, RSC Cambridge) pp 52–69

[57] Wilson T S, Sleeter B M and Cameron D R 2017 Mediterranean California’s water use future under multiple scenarios of developed and agricultural land use change PloS one 12

[58] Rijal S, Barkey R A, Nasri N and Nursaputra M 2019 Profile, Level of Vulnerability and Spatial Pattern of Deforestation in Sulawesi Period of 1990 to 2018 Forests 10 1–14

[59] Wang Z, Chai J and Li B 2016 The Impacts of Land Use Change on Residents’ Living Based on Urban Metabolism: A Case Study in Yangzhou City of Jiangsu Province, China Sustainability 8 1–17

[60] Margono B A, Turubanova S, Zhuravleva I, Potapov P, Tyukavina A, Baccini A, Goetz S and Hansen M C 2012 Mapping and Monitoring Deforestation and Forest Degradation in Sumatra (Indonesia) Using Landsat Time Series Data Sets from 1990 to 2010 Environmental Research Letters 7 1–16

[61] Prasetyo L B, Kartodihardjo H, Adiwibowo S, Okarda B and Setiawan Y 2009 Spatial Model Approach for Deforestation: Case Study in Java Island, Indonesia Journal of Integrated Field Science 6 37–44

[62] Estoque R C and Murayama Y 2012 Introducing New Measures of Accuracy for Land-Use/Cover Change Modeling Tsukuba geoenvironmental sciences 8 3–8

[63] Foody G M 2002 Status of Land Cover Classification Accuracy Assessment Remote sensing of environment 80 185–201

[64] Das P and Pandey V 2019 Use of Logistic Regression in Land-Cover Classification with Moderate-Resolution Multispectral Data Journal of the Indian Society of Remote Sensing 47 1443–54

[65] Hishe S, Bewket W, Nyssen J and Lyimo J 2020 Analysing Past Land Use Land Cover Change and CA-Markov-Based Future Modelling in The Middle Suluh Valley, Northern Ethiopia Geocarto International 35 225–55

[66] Dadras M, Mohd Shafri H Z, Ahmad N, Pradhan B and Safarpour S 2014 Land Use/Cover Change Detection and Urban Sprawl Analysis in Bandar Abbas City, Iran The Scientific World Journal 2014 1–12

[67] Mukherjee S, Bebermeier W and Schütt B 2018 An Overview of the Impacts of Land Use Land Cover Changes (1980–2014) on Urban Water Security of Kolkata Land 7 1–25

[68] Bappenas 2018 Peluncuran Buku Proyeksi Penduduk Indonesia 2015-2045 untuk Pengambilan Kebijakan Berbasis Data Akurat Badan Perencanaan Pembangunan Nasional Republik Indonesia, Jakarta
[69] Weitowitz D C, Panter C, Hoskin R and Liley D 2019 The Effect of Urban Development on Visitor Numbers to Nearby Protected Nature Conservation Sites Journal of Urban Ecology 5 1–12
[70] Hua A K 2017 Application of Ca-Markov Model and Land Use/Land Cover Changes in Malacca River Watershed, Malaysia Applied Ecology and Environmental Research 15 605–22
[71] Maruna M, Crnčević T and Milojević M P 2019 The Institutional Structure of Land Use Planning for Urban Forest Protection in the Post-Socialist Transition Environment: Serbian Experiences Forests 10 1–28
[72] Qian M, Pu L, Zhang J and Zhang M 2013 Urban Spatial Expansion Characteristics in China’s Rapid Urbanization Region—A Case Study of SXC Region International Journal of Geosciences 4 1–11