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Temporal changes in Land Use and Land Cover (LULC) and local climate in the Krueng Peusangan Watershed (KPW) area, Aceh, Indonesia

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Abstract. Watersheds are important sources of various ecosystem services. The Krueng Peusangan Watershed (KPW), one of the watersheds in Aceh Province, is expected to become the "lungs" of the ecology of the north-central part of Aceh. Currently, the KPW is one of the watersheds that suffers from severe or critical damage, especially that caused by changes in forest cover. Spatiotemporal monitoring of changes in landscape patterns (composition and configuration) is needed to inform policy and support planning for sustainable watershed management. This study aims to: 1) determine the pattern of changes in LULC in KPW in two decades (1999–2009 and 2009–2019, and 2) determine the impact of changes in the LULC pattern on the local climate. Landsat Satellite Imagery for three years (1999, 2009, and 2019) is used to classify LULC. Geographic Information System (GIS) technology and remote sensing are used to analyze it. Each satellite image is classified into six categories: built-up area, forest, agriculture, bare land, wetland, and water body. This classification resulted in LULC maps for 1999, 2009, and 2019 with kappa coefficients of 0.84, 0.88, and 0.84. It is found that between 1999–2009 and 2009–2019, there has been a consistent decrease in forest cover area and an increase in built-up area. Local climate change is also occurring in this KPW. Continuous monitoring of LULC changes in KPW is also necessary to keep management planning up to date.

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Contents:

1. Introduction

Changes in land use and land cover (LULC) patterns are one of the main factors for global change (Turner II et al. , 2007) and harm to the natural environment (Allen & Lu, 2003). These changes directly affect the community's welfare through changes in environmental conditions, such as land degradation (Sánchez-Cuervo et al., 2012), decreased ecosystem services value, and local climate change (Haberl et al., 2007). This change in LULC is also continuously being studied so that different effects can be known at the local, regional and global levels. It continues to occur rapidly in various places. Accurate mapping of LULC changes will make an essential contribution to the study of LULC worldwide. The causes of changes in LULC are generally related to human activities, such as increasing population, urbanization, deforestation, and agricultural intensification.

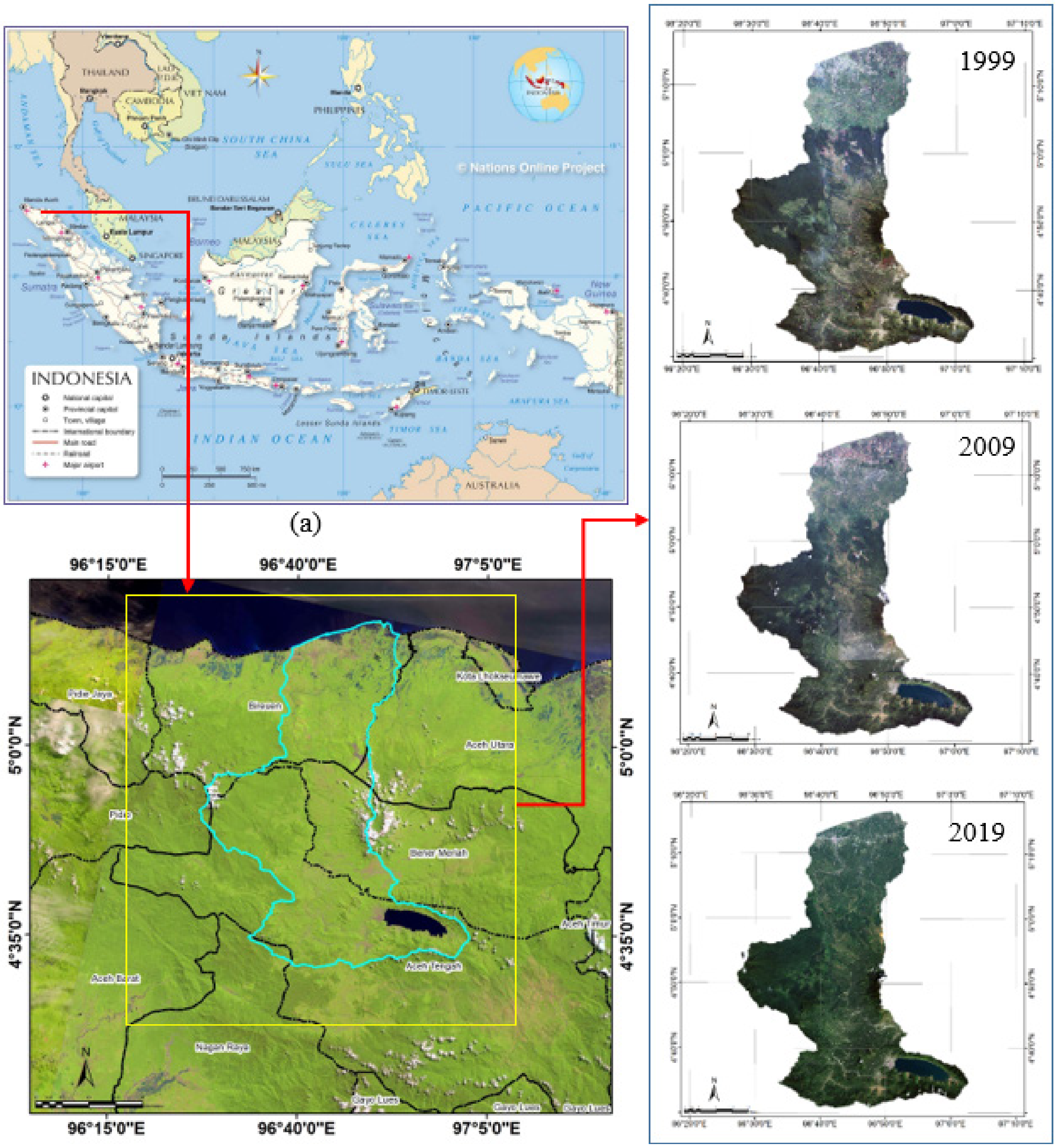
Currently, the study of changes in LULC is mostly carried out in areas with rapid population growth, large cities, or metropolitan areas. There is a lack of focused studies on watershed areas. Watershed areas are important sources with various benefits that humans derive from ecosystems, including provisioning, support, regulatory, and cultural services (Estoque et al., 2018). Planners can use the watershed assessment results for landscape planning and natural resource management; these include biological, physical, social, and economic processes. Watersheds are also vulnerable to drastic landscape changes due to deforestation (Maina et al., 2013; Estoque et al., 2018; Yang et al., 2018). Deforestation affects landscape patterns or structures because it can change landscape composition (e.g., loss or reduction of forest cover) and landscape configuration (i.e., spatial connectivity and fragmentation of landscape elements, e.g., forests) (Haddad et al., 2015; Taubert et al., 2018). In LULC change assessment and many studies related to environmental monitoring and its impacts, remote-sensing technology is still an important data source. We can obtain information stored in satellite images and aerial photographs with this technology. Satellite images provide valuable information about LULC and changes in regional landscape patterns and spatial configurations to study LULC in watershed areas (Estoque et al., 2018).

Deforestation in Indonesia is high, and the governance system is still unsatisfactory. The inconsistency between regional planning and forest management are fundamental problems related to the environment (Barri et al., 2018). In 2015, forests in Indonesia reached 128 million ha, which subsequently decreased to 126 million ha by 2017 (Barri et al., 2018). In 2018, the forest cover figure in Aceh Province was reduced by 15,071 ha. The high rate of deforestation has severe impacts on the environment; many natural disasters have occurred in Aceh, such as floods and droughts. The deforestation that occurred in the Krueng Peusangan Watershed (KPW) made decision-makers prioritize the management of KPW to stop the damage (Ramli et al., 2019).

KPW is considered as the "lungs" and ecological frontier in the central region of Aceh, Indonesia. This KPW is one of many watersheds in the country that are experiencing deforestation. Spatial-temporal monitoring of the LULC pattern is needed to inform policymakers and to support spatial management planning towards future sustainability. Changes in LULC in KPW, including the extent of forest cover loss and gain in recent years, have not been quantified. In making regional development policies, information on the effects of landscape patterns and climate changes on ecosystem services is essential. Therefore, the development of knowledge about this relationship still needs to be deepened.

To help the decision-makers and development planners who use the KPW area not to exacerbate the damage, this study aims to:

1. determine the pattern of changes in LULC in KPW in two decades (1999–2009 and 2009–2019),
2. determine the local climate impact of changes in the LULC pattern.



(c)

Fig. 1. Study location, the Krueng Peusangan Watershed (KPW). (a) Map of Indonesia; (b) Landsat 8 image of Districts of KPW; and (c) Landsat imagery used in this study
Source: www.nationsonline.org; https://glovis.usgs.gov/

2. Materials and methods

2.1. Study location

This research was conducted in KPW, which is located at 5°16'34"N–96°27'12"E and 4°30'38"N–97°02'40"E. The KPW has an area of 2,557.8 km^2. It consists of six districts in Aceh, namely Central Aceh Regency, Bener Meriah Regency, Bireuen Regency, North Aceh Regency, Pidie Regency, and Nagan Raya Regency (Fig. 1). The length of the main river from the seafront of Bireuen to Lake Lut Tawar reaches 128 kilometers. Around 107 rivers empty into "Krueng Peusangan" of which 12 are sub-KPW. These are Krueng Peusangan Downstream, Ulee Gle, Teupin Mane, Krueng Keueh, Krueng Simpo, Wih

Genengan, Timang Gajah, Wih Bruksah, Onion Elephant, Wih Balek, Krueng Ceulala, and Laut Tawar. The watershed's condition is now critical, even in the national critical category. This is due to the mining of construction materials, encroachment for plantations, and illegal logging.

Based on the *Decree of the Minister of Forestry of the Republic of Indonesia No. 170 of 2000 concerning Designation of Forest and Water Areas*, approximately 167,443 hectares or 65% of the KPW area is a Cultivation Area or other use area. A total of 47,816 hectares (18%) are Protection Forests; 24,383 hectares (9.5%) are Production Forest; the rest is in Limited Production Forests, Nature Reserves, and Waters. The forest categories in KPW are changing very quickly, including to oil palm plantations, coffee plantations, areca nut plantations, potato plantations, and others.

Visually, KPW can be categorized into watersheds that are elongated in shape with a north–south orientation. The roundness of the watershed as determined using the circularity ratio (Rc) method is 0.31, which is due to the presence of the main river, which receives flow from tributaries on the left and right and flows into the sea. Sub KPW is not round in shape, indicating a relatively small centralized discharge and speed. This condition causes the travel time of water from tributaries to the center of the flow to vary depending on the shape of the watershed, slope, land use, rainfall, and river density (Ramli et al., 2019). Rainfall is trapped on the plants (interception) then evaporates before reaching the ground (evapotranspiration), running off and infiltrating.

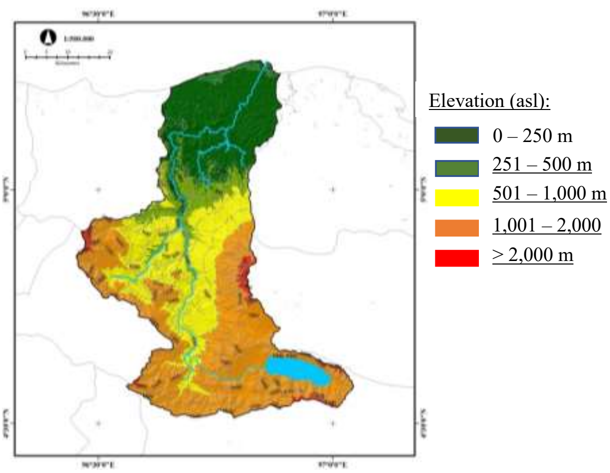


Fig. 2. Elevation of study location
Source: https://www.indonesia-geospasial.com/

Physiographically, KPW is dominated by hilly and mountainous areas in the upstream and middle parts (Fig. 2). Some parts are dominated by undulating plains located downstream (Fig. 3). The middle and downstream part of the KPW has the lowest altitude of 43 s.d. 750 m above sea level (a.s.l.). Meanwhile, the highest point of ~800–3000 m a.s.l. is located upstream or around Mount Peutsagoe, Geureundong, and the Gayo mountains (Ramli et al., 2019).

2.2. Data collection

In this study, the data collected were Landsat satellite image data for 1999, 2009, and 2019, obtained through https://glovis.usgs.gov/ (Table 1), with 30 m × 30 m spatial resolution. Meanwhile, climate data were obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG) (Pegasing Station and Malikussaleh Station).

2.3. Change in LULC

We used Landsat satellite imagery to create the LULC map. In this first stage, each of these images was classified to produce the LULC maps for 1999, 2009, and 2019. This classification uses the supervised classification with the maximum likelihood classification (MLC) algorithm method, using ArcGIS®10.1. There are six categories of LULC classified in this study, namely 1) built-up area, 2) forest, 3) agriculture, 4) bareland, 5) wetland, and 6) water body. Each of these categories is described in detail in Table 2.

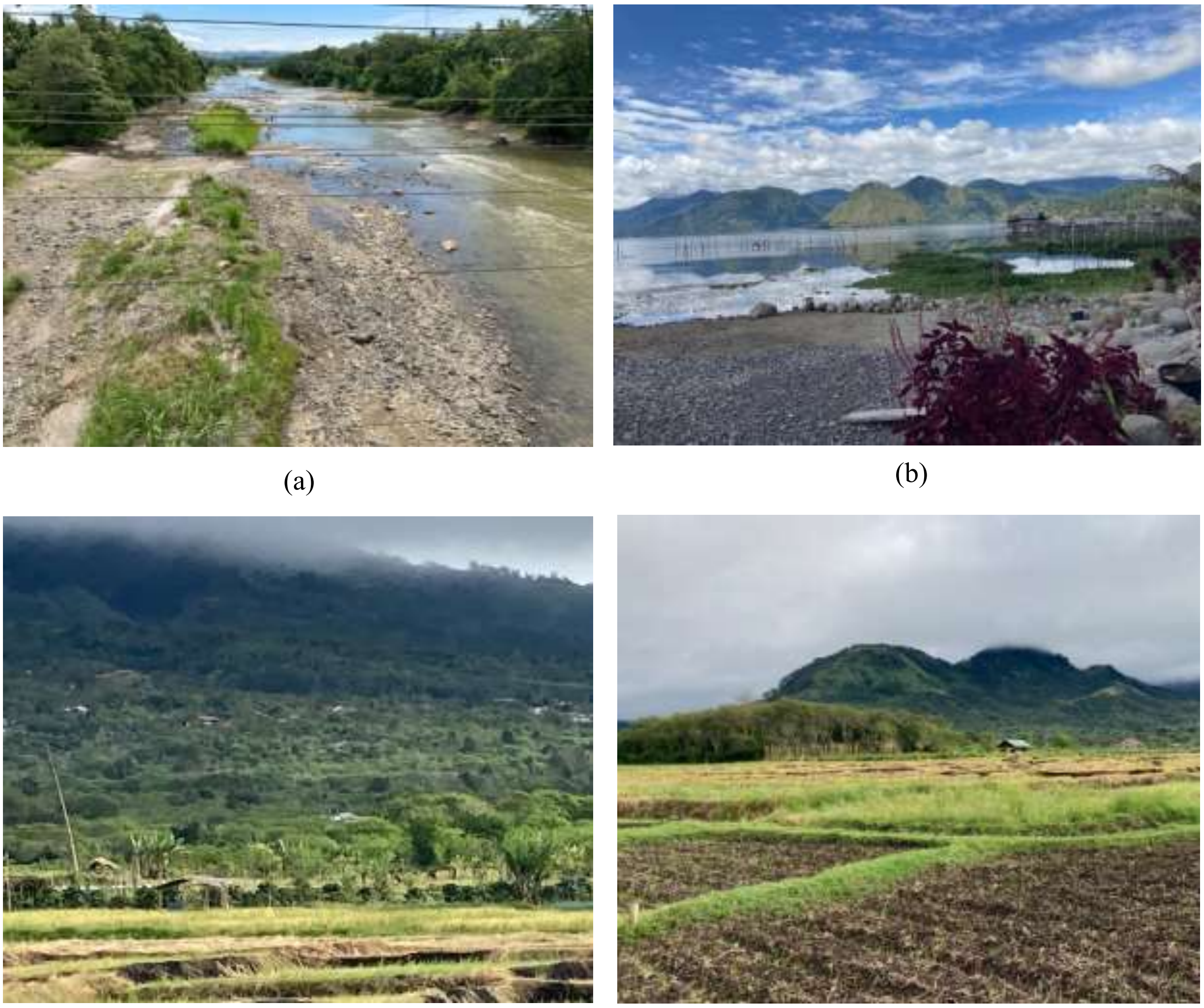
The accuracy of each classified LULC map was measured by reviewing 1,200 reference points using stratified random sampling. The ERRMAT module is contained in TerrSet®, a geospatial monitoring and modeling software. It is used to assist in this accuracy testing process. Furthermore, Google Earth and pan-sharpened are used as a reference in the assessment. Determination of the number of reference points is also based on previous research by Estoque and Murayama (2013) for a land area of 5,700 ha with four LULC categories, using 312 reference points. For a watershed with 1.47 ha Zhou & Chen (2018) used 256 reference points.

The resulting generated matrix calculates user accuracy, producer accuracy, overall accuracy, and kappa coefficient (Table 3). This study adopted Table 3 and equations (1) and (2) to calculate the overall accuracy and kappa coefficient (Ramadhani

Table 1. Description of Landsat satellite imagery

Sensor	Scene ID	Acquisition date	Time (GMT)	Season
Landsat 5 TM	LT51300571999175BKT00	24/06/1998	03:24:23	dry
Landsat 5 TM	LT51300572009330BKT00	26/11/2009	03:36:56	dry
Landsat 8 OLI/TIRS	LC81300572019006LGN00	06/01/2019	03:46:20	dry

Source: own elaboration



(a) (b) (c) (d)

Fig. 3. KPW condition: (a) situation in Krueng Peusangan, where water discharge is decreasing; (b) the lake water has shrunk; (c) and (d) land conversion into plantations
Source: Authors"

et al., 2020). Detection of changes in each LULC category in 1999, 2009, and 2019 was carried out by calculating the area of each LULC category. We created a tabulation to determine the area in each LULC category for each year: 1999, 2009, and 2019. Accuracy was assessed using the following equation:

$$\text{Overall accuracy} = \frac{N_{AA} + N_{BB} + N_{CC}}{N} \text{ x } 100\%$$

$$\text{Kappa} = \frac{N\ \sum_{j=1}^{k} N_{jj} - \sum_{j=1}^{k} N_{jR} N_{Pj}}{N^2 - \sum_{j=1}^{k} N_{jR} N_{Pj}}$$

Where: *N* is total points, *k* is number of classes, *R* is test classes, and *P* is classified class.

Table 2. Description of LULC category

Category	Description
Built-up area	Areas used mainly as structures and pavements, such as high-density residential, commercial, industrial, and transportation, attached to urban activities
Forest	Tree-covered land with tree-cover density greater than 10%
Agriculture	Agricultural land or grazing land in either vegetated or non-vegetated state used for food production (rice, fruit, coffee plants, rubber, etc.)
Bareland	Vacant land that has not been used for certain activities, consisting of soil, sand, rocks, with less than 10% of vegetation in the area
Wetland	Water-saturated land, or land consisting of water and plants, such as fishponds
Water body	Areas always covered with water, such as rivers, lakes, reservoirs, or oceans

Source: own elaboration

2.4. Local climate change

The climate elements studied in this study are rainfall, temperature, humidity, and wind speed (Elmhagen, Maina et al., 2013; Eriksson & Lindborg, 2015; Ashfa Achmad et al., 2019). This climate assessment uses trend analysis (Minitab 16.2.1), and it is selected based on the smallest accuracy value of the Mean Absolute Percentage Error/MAPE. The measure of accuracy is matched with time-series data (percentage). Mean Absolute Deviation/MAD is the average of the absolute values of deviation, Mean Squared Deviation/MSD is the average of the squared values of data deviations.

The change analysis uses the Mann–Kendall Test method by calculating the *Z* value. In the initial stage, the relative *R* ranking of the data is carried out in order of rank. The values of *P* and *M* are determined by comparing the ranking each time (R_i) with the rankings of the next time (R_j) (where $i = 1$ to $N - 1$, and $j = i + 1$ to N). A value of 1 is added for *P* if $R_j > R_i$ and a value of 1 is added for *M* if $R_j < R_i$. Statistical value $S = P - M$. Then the Z statistic value can be used using equation (5) (Tabari et al., 2011; Diress & Bedada, 2021):

$$Z = \begin{cases} \frac{(S-1)}{\sqrt{var(S)}} & \text{if } S < 0 \\ 0 & \text{if } S = 0 \\ \frac{(S+1)}{\sqrt{var(S)}} & \text{if } S > 0 \end{cases} \quad (1)$$

$$Var(S) = N(N+1)(2N+5)/18 \quad (2)$$

Where: N = number of years of rain; data S = trend statistic test; P = number of events where $R_j > R_i$; M = number of events where $R_j < R_i$; Var(S) = variance of S; i = data sequence 1 to N-1; and j = data sequence i + 1 to N.

2.5. Relationship between LULC change and local climate

To determine the relationship between LULC change and local climate, a simple linear regression formula is used with the formula:

Table 3. Example confusion matrix

		Test Data				
		A	B	C	Σ	User's accuracy (%)
Classified Data	A	N_{AA}	N_{AB}	N_{AC}	Σ_{AR}	N_{AA} / Σ_{AR} x 100%
	B	N_{BA}	N_{BB}	N_{AC}	Σ_{BR}	N_{BB} / Σ_{BR} x 100%
	C	N_{CA}	N_{CB}	N_{CC}	Σ_{CR}	N_{CC} / Σ_{CR} x 100%
	Σ	Σ_{PA}	Σ_{PB}	Σ_{PC}	N	
	Producer's Accuracy (PA)x100%	N_{AA}/Σ_{PA} x100%	N_{AA}/Σ_{PA} x100%	N_{AA}/Σ_{PA} x100%		

Source: Ramadhani et al. (2020)

$$y = \beta_0 + \beta_1 X + \epsilon$$

Where:

y is the predicted value of the dependent variable (*y*) for any given value of the independent variable;.

B_0 is the intercept, the predicted value of y when the x is 0; .

B_1 is the regression coefficient – how much we expect y to change as x increases;.

X is the independent variable (the variable we expect is influencing y);.

e is the error of the estimate, or how much variation there is in our regression coefficient estimate.

3. Research results

3.1. Accuracy assessment

Figure 3 can be seen from the 1999, 2009, and 2019 LULC classifications results, while the accuracy assessment is shown in the confusion matrix in Table 4. The confusion matrix is the basis for calculating the Kappa (*K*) coefficient, which describes how the LULC categories are distributed in the simulation map and how they are different from the actual map.

In Table 3, the producer accuracy row shows the probability of the reference pixels being correctly classified. The user accuracy column indicates the probability that the pixels classified on the actual

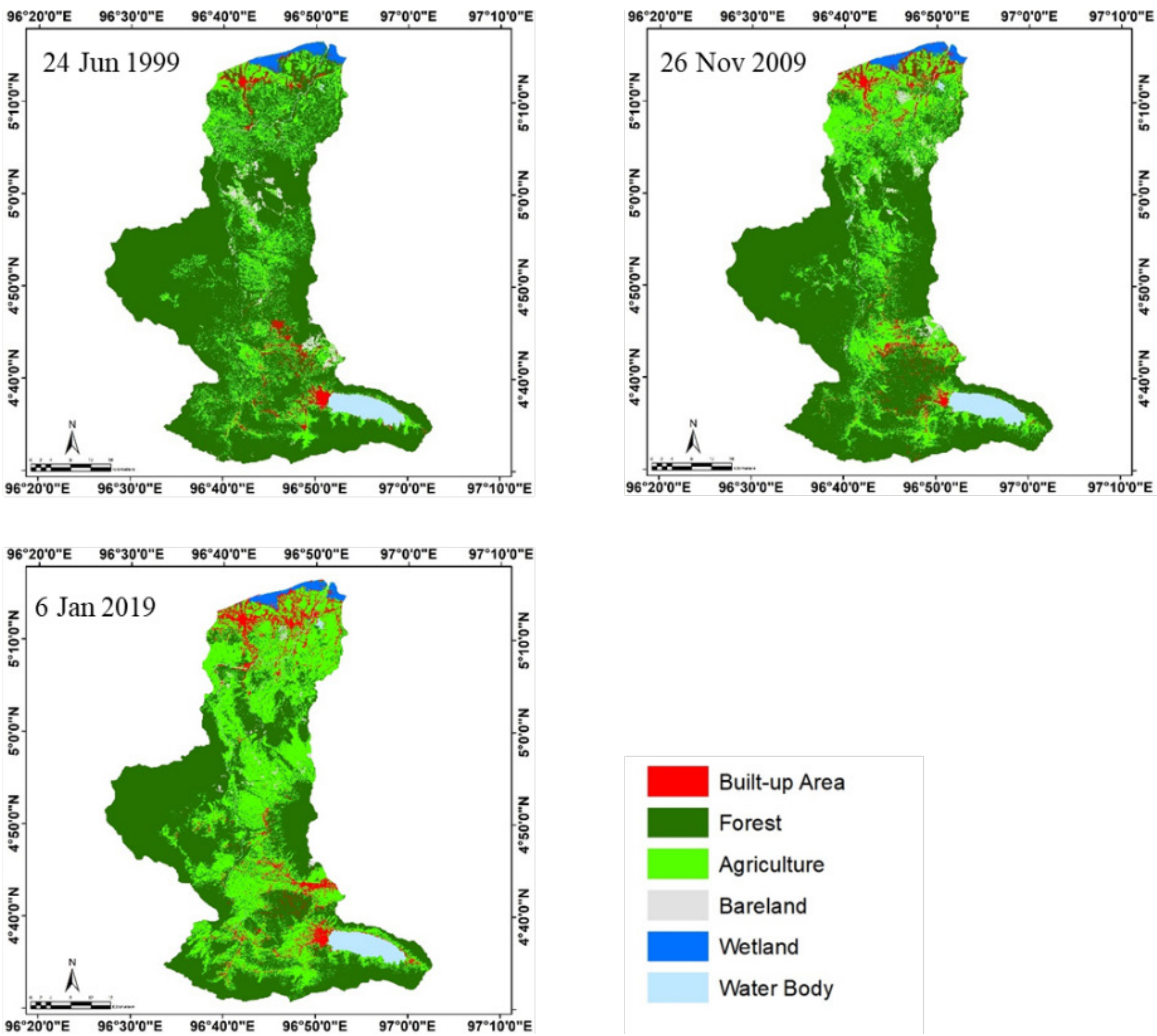


Fig. 4. LULC maps of KPW
Source: Authors'

Table 4. Confusion matrix of LULC

Classified Data	Reference Data							
	Built-up Area	Forest	Agriculture	Bareland	Wetland	Water Body	Total	User's accuracy (%)
(a) 1999								
Built-up Area	24	1	4	0	0	0	29	82.76
Forest	4	750	119	0	0	0	873	85.91
Agriculture	10	4	208	6	0	3	231	90.04
Bareland	0	1	2	15	0	0	18	83.33
Wetland	0	0	2	0	14	0	16	87.50
Water Body	0	1	1	0	0	31	33	93.94
Total	38	757	336	21	14	34	1,200	
Producer's accuracy (%)	63.16	99.08	61.90	71.43	100.00	91.18		
Overall accuracy (%) = 86.83; K coefficient = 0.84								
(b) 2009								
Built-up Area	41	2	2	0	0	0	45	91.11
Forest	12	688	91	0	0	0	791	86.98
Agriculture	6	25	271	2	0	0	304	89.14
Bareland	0	2	0	12	0	0	14	85.71
Wetland	0	0	0	1	14	0	15	93.33
Water Body	0	1	1	0	0	29	31	93.55
Total	59	718	365	15	14	29	1,200	
Producer's accuracy (%)	69.49	95.82	74.25	80.00	100.00	100.00		
Overall accuracy (%) = 89.83; K coefficient = 0.88								
(c) 2019								
Built-up Area	58	1	11	1	0	1	72	80.56
Forest	3	548	61	0	0	0	612	89.54
Agriculture	19	46	391	2	0	5	463	84.45
Bareland	0	0	2	12	0	0	14	85.71
Wetland	1	0	0	0	5	0	6	83.33
Water Body	0	1	0	0	0	32	33	96.97
Total	81	596	465	15	5	38	1,200	
Producer's accuracy (%)	71.60	91.95	84.09	80.00	100.00	84.29		
Overall accuracy (%) = 87.00; K coefficient= 0.84								

Source: own elaboration

map represent the actual category in the field, and it is considered a commission error measurement. As an illustration, in the 2019 confusion matrix (Table 3), there are 612 forest reference pixels. From 612 pixels, 64 pixels were misclassified or not correctly classified as forest, while 548 pixels were correct.

Most of the confusion occurs between forest, agriculture, and built-up areas in this classification. In addition, there is also confusion between the built-up area, agriculture, and bare land. The accuracy results obtained from the LULC classification of these three images are still above 80%, while the Kappa (K) coefficient is above 0.8. Of the three LULC maps produced, the minimum overall accuracy is 86.83, and the minimum K coefficient is 0.84, which indicates a strong agreement or accuracy between the two maps (Landis & Koch, 1977; Zheng et al., 2015). This accuracy is influenced by several factors, such as the scale of the study area, the characteristics of the satellite data, and the details of the LULC class (Al-Saady et al., 2015).

3.2. LULC change

LULC change in KPW over the two decades (1999–2019) has been dramatic (Fig. 4). The LULC forest category experienced a decline, from 72.76% in 1999 to 65.95% in 2009, and fell again to 51.00% in 2019. This decrease was due to a loss in the LULC forest category of 3,216 ha (1999–2009). In the period 2009–19, the loss in forest increased to 5,876 ha. This condition is the same as our previous research for the City of Sabang (Achmad et al., 2019).

The results of the analysis also show that the built-up area increased rapidly. On average, the increase in the built-up area was 455 ha per year (1999–2019). The built-up area increased from 2.46% in 1999 to 3.71% in 2009. This increase continues, from 6.01% in 2019 (Fig. 5). Drastic changes also occurred in other LULC categories, such as agriculture, which experienced many changes away from forest cover. The area of agricultural land increased rapidly, doubling between 1999 and 2019. This increase continues until the analysis results show that, in 2019, agriculture was 38.58% of the KPW area, or 98,668 ha.

The bareland and wetland classes experienced an extensive decline in the two reviewed decades. Bareland decreased to 1.18% of the total area of KPW in 2009 and had fallen again by 2019. Previously, in 1999, bareland had accounted for 1.47% of the area of KPW, or 3,758 ha. Meanwhile, wetlands decreased from 1.3% in 1999 to 1.24% in 2009. The wetland area decreased again to 0.50% in 2019 (Fig. 5). Wetland currently remains only in the northern part of KPW. There is a uniqueness in the water body category, where there is a decrease and then an increase. A broad decline occurred in the 1999–2009 decade, from 2.77% to 2.61% of the area of KPW, then increased in the 2009–2019 decade from 2.61% to 2.77% (Fig. 5). However, on average, waterbodies have increased their percentage, by 0.82 ha per year. The waterbody area in KPW in 2019 was 7,092 ha.

3.3. Local climate changes

Trends in climate conditions were analyzed using Minitab software on climate data from 1981–2020 to estimate or forecast for the future. Trend analysis commonly uses a linear trend model, quadratic trend model, exponential growth model, and S-Curve model. The appropriate trend is selected by the criteria of the smallest accuracy value of MAPE (Mean Absolute Percentage Error) and the average of the overall percentage error (difference) between actual and forecasted data. Accuracy measures are matched against time-series data and are expressed as percentages. MAD (Mean Absolute Deviation) is the average of the absolute values of deviation, MSD (Mean Squared Deviation) is the average of the squared values of data deviation. By comparing the values of MAPE, MAD, and MSD, it is possible to determine the appropriate or best model, namely the model with the best accuracy measures (Box & Jenkins, 1994).

Rainfall based on the Schmidt-Ferguson climate classification in the upstream location of the KPW from the Bebesan station data is classified as climate type B (wet) with a ratio of dry to wet months of 28.86%. There has been a shift in the climate type C to the slightly wet category (34.25%). The equation obtained for the trend of rainfall changes (Fig. 6A) based on time follows the quadratic equation $y = 155.2 + 0.433t - 0.001117t^2$. The air temperature trend is a quadratic model because the trend has the smallest accuracy measure. The equation obtained for the pattern of changes in air temperature in the KPW follows a linear trend, namely $y = 26.5441 + 0.001117t$, with an average temperature of 26.51°C.

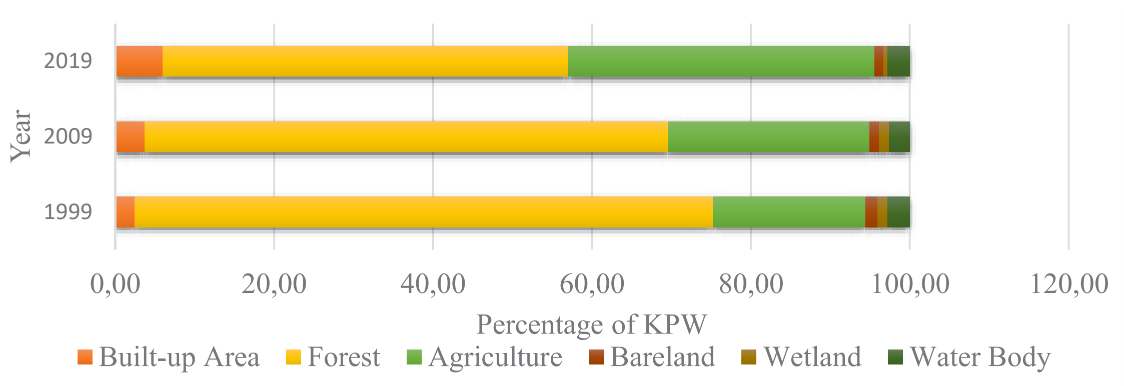


Fig. 5. LUC changes in KPW
Source: Authors'

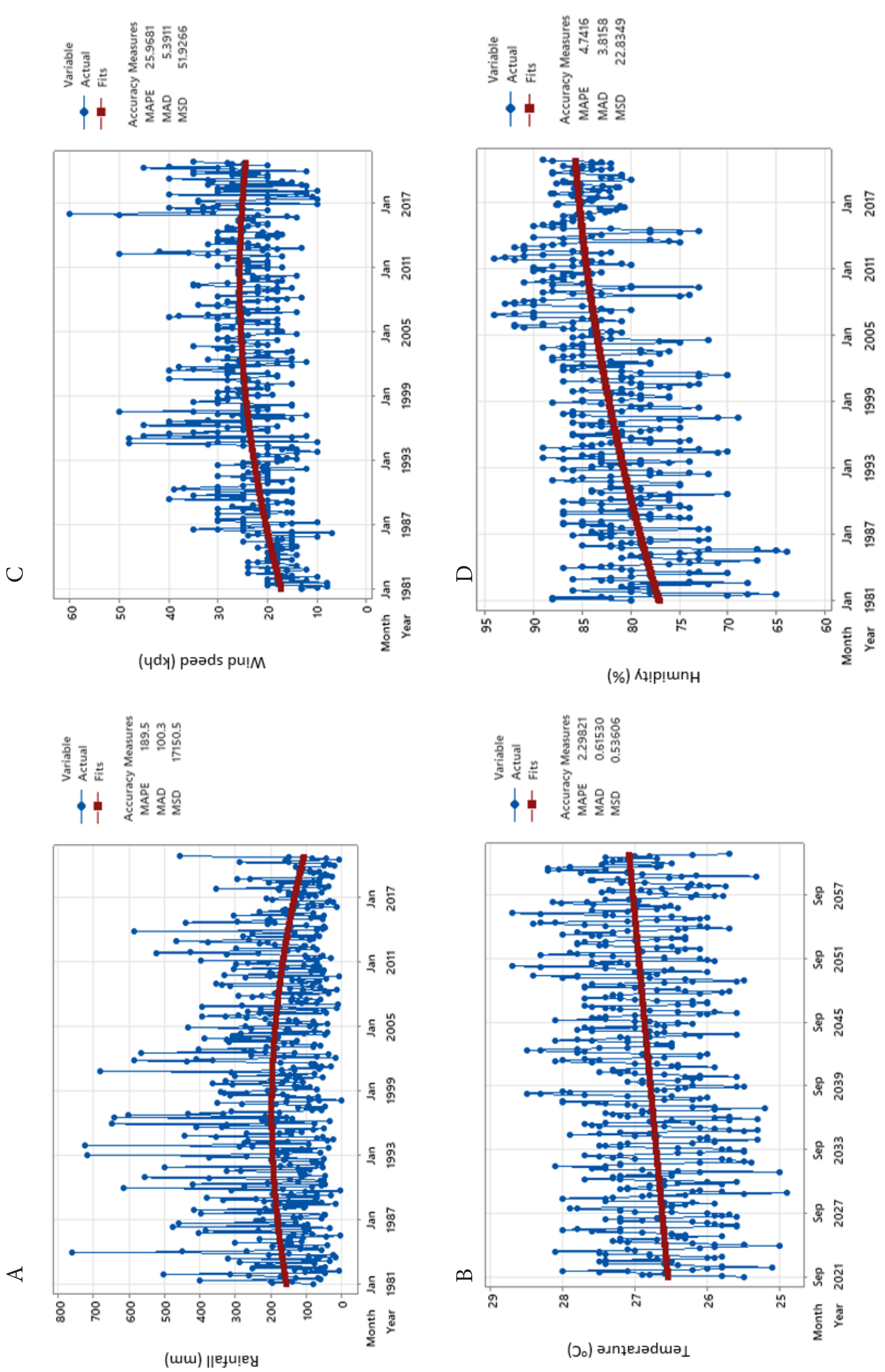


Fig. 6. Trend analysis plot for: (A) rainfall, (B) temperature, (C) wind speed, and (D) humidity
Source: Authors'

A decrease in humidity value indicates an increase in temperature, as the relationship between these two parameters is inversely proportional . The average humidity in the Krueng Peusangan Hulu watershed is 81.773%. The corresponding humidity trend is the trend of the quadratic model (as shown in Fig. 6B). The equation obtained for the humidity trend is $y = 77.082t + 0.02859t - 0.000022t^2$.

The highest monthly wind speed is in December–January, and the lowest is in September–October. The appropriate model for wind speed in the KPW is quadratic with the equation $y = 17.144 + 0.04881t - 0.000070t^2$, with an average speed of 23.02 km/day.

Figure 6 also shows an increasing trend in the variables of humidity, wind speed, and temperature. Climate change based on the Mann–Kendall test obtained Kendall's tau values of 0.326 (humidity), 0.186 (wind speed), 0.135 (temperature), and 0.018 (rainfall). Compared with the critical value of Z0.05, there is no change trend for rainfall. Meanwhile, the climatic elements of temperature, humidity, and wind speed experienced a significant change trend.

3.4. Relationship between LULC change and local climate

Data for 1999 to 2019 were analyzed to determine the impact of changes in LULC on the local climate (rainfall, temperature, humidity, and wind speed). The coefficient of determination was tested to measure the model's ability to explain the influence of the independent climate variables simultaneously influencing the dependent variable, which can be indicated by the adjusted *R*-sq value (Ghozali, 2016). *R*-sq shows the value of the contribution of the independent variable in the regression model that can explain the variation of the dependent variable. The coefficient of determination can be seen through the value of having the ability to provide all the information needed to predict the dependent variable (*R*-sq(pred)). Analysis of humidity provides the equation.

Humidity = 210,216 + 2.71 Forest – 60 Waterbody – 18 Bareland – 67 Wetland

The regression equation shows that if other variables are constant, the rainfall value will change by itself at a constant value of 210.216 (Table 5). If other variables are constant, the forest value will change to 2.71 per unit, and the same applies to the following variable. i.e., a change of −60 per unit in water body value, a change of −18 per unit in bareland value, and a −67 change per unit in wetland value. This indicates that the independent variable influences the dependent variable or that changes in LULC significantly affect humidity.

4. Discussion

Based on the analysis results, it can be seen that forest cover in KPW is decreasing in area, followed by bareland and wetland. At the same time, the water body is in a state that is not much changed over two decades, although there are fluctuations in each decade. In contrast, built-up areas and agriculture are experiencing a rapid increase. Continuous conversion of forest cover will reduce the services of environmental ecosystems that are critical to the sustainability of human life and nature (Indarto & Hakim, 2021; Zbierska, 2022). These LULC changes are dynamic and non-linear, which can be seen based on the changes that occur in each decade. They can occur due to natural factors, policy changes, rapid population growth, and declining land productivity (Dessie & Kleman, 2007; de Groot et al., 2010). Agricultural and residential activities drive this lack of ecosystem services. These results are consistent with several other studies (de Groot et al., 2010; Estoque et al., 2018; Achmad et al., 2020.

There are many changes in land cover. In this case, land-cover changes are due to community activities around the areas, in the form of illegal logging. The purpose of this logging is usually to

Table 5. Regression analysis for each climate variable

No	Climate	S	R-sq	R-sq(adj)	R-sq(pred)
1	Rainfall	304.425	51.40%	39.25%	20.97%
2	Temperature	0.244364	21.28%	1.60%	0.00%
3	Humidity	191.802	56.88%	46.10%	20.82%
4	Wind velocity	0.0000041	49.84%	37.30%	20.79%

Source: authors'

use tree wood and to clear land for plantation areas. These activities are due to the economic needs of the community. However, it is compulsory for the public to have ecological understanding. It is necessary to reforest so that the watershed can carry out its primary function.

The surrounding areas upstream of the KPW are the areas of Aceh Tengah and Bener Meriah. Forests in those areas generally consist of Pine, Areca, Neem, Dragon blood, Palm, and Parkia trees. Over time, the condition of this land cover continues to decrease, especially since pine trees are becoming fewer and fewer. This land cover is essential for the upstream KPW. If this land cover decreases, there will be an increase in surface flow, which will cause landslides and sedimentation of river banks. In the upstream KPW, the largest critical areas are Krueng Ceulala Sub-watershed (75.56%) and Laut Tawar Watershed (77.35%) (Syafjanuar et al., 2021) (T.E. Syafjanuar et al., 2021). Low infiltration indicates a high surface run off because the rainfall cannot be absorbed by the soil. Soil particles will be very easily transported and settle into sedimentation (Muntazar et al., 2021).

A large amount of illegal logging for wood and for clearing large areas of new land to make farms for the community is causing the KPW to lose its main trees as land cover. The loss of these main trees is crucial and critical for the KPW. The main impact is decreased water discharge, low water quality, and sedimentation upstream. Meanwhile, downstream will be impacted by river abrasion, and flooding is the main problem. The decrease in the area of forest cover is a severe threat in the KPW, and if this continues to happen, it is feared that it will continue to exacerbate the damage that is occurring. Appropriate policies must be prepared immediately by the Local Government to protect forest cover resources from damage.

The water body category in KPW includes lakes and rivers. Lake Lut Tawar, located in the southern part of KPW, is a raw water source for the surrounding communities. Changes in the landscape around the lake can affect the availability of raw water. This category of water bodies experienced a vast decrease in 1999–2009, while 2009–2019 experienced a vast increase.

In the two decades reviewed, built-up area continues to increase. The overall increase in the 2009–2019 decade was more rapid than in 1999–2009. The increase in population and their activities is still the main factor in increasing the built-up area (Łowicki, 2008; Lix et al., 2013; Zbierska, 2022). Our results are consistent with studies that have been conducted (Estoque et al., 2018; Achmad et al., 2019). With an increase in population, there is also an increase in demand for housing, waste, and more buildings for public services and facilities.

The rapid growth in built-up area occurred at the northern end of the KPW adjacent to the beach and the area around Lake Lut Tawar. The driving forces for the growth of this built-up area, apart from rapid population growth, are thought to be its proximity to existing growth centers, for example, in urban areas (Lhokseumawe, Bireuen and Takengon cities) and the development of regional infrastructure networks, such as roads, energy, etc. Growth is closely related to the location's distance from the economic center and the city center (Achmad et al., 2015).

Agriculture is also experiencing rapid growth. The industrial sector, which is still very lacking in the Aceh region, makes people choose farming and agriculture. The increase in land for agricultural activities mostly comes from forests. This is in line with previous studies by other researchers (de Groot et al., 2010; Estoque et al., 2018).

The results of the air temperature analysis based on MAPE, MSD, and MAD values resulted in the equation y = 26.5441 + 0.001117t, which describes the occurrence of temperature increases in the two decades reviewed in this study. Natural and anthropogenic factors can influence this temperature change, especially CO2. This substance is produced from human activities that increase the concentration of greenhouse gases (Rizki et al., 2016). In addition, an increase in temperature can also occur due to heat stored in building materials and radiated back, and reduced vegetation (Meng et al., 2018; W. Zhou et al., 2019).

The results of the air temperature analysis based on MAPE, MSD, and MAD values resulted in the equation y = 26.5441 + 0.001117t, which describes the occurrence of temperature increases in the two decades reviewed in this study. Natural and anthropogenic factors can influence this temperature change, especially CO_2. This substance is produced from human activities that increase the concentration of greenhouse gases (Rizki et al., 2016). In addition, an increase in temperature can also occur due to heat stored in building materials and radiated back, and reduced vegetation (Meng et al., 2018; W. Zhou et al., 2019).

The relationship between the wind and air temperature distribution is because the wind is critical in spreading the air temperature. In general, the local climate change that occurred in the past two decades is in line with previous studies (Achmad et al., 2019). Climate change causes changes in rainfall patterns, although the rainfall patterns did not change significantly in this study. Climate change is affecting livelihoods and is a challenge for future upland development. The air temperature and humidity increased, as seen in the trend that occurred and changed significantly with the Mann–Kendall test.

Based on Table 4, it was found that the *R*-Square value indicates a correlation between the dependent and independent variables. The variables of rainfall, humidity, and wind speed are moderately correlated with land use because they are 49% to 56%. In comparison, the temperature variable shows low correlations ranging from 9% to 25%. This means that one of the capabilities of the independent variable (humidity) in this study affects the dependent variable by 56.88%. In comparison, the remaining 43.12% is explained by variables other than the independent variables in the study.

5. Conclusion

This study quantifies losses and gains in six LULC categories over twenty years (1999–2019) using Landsat satellite imagery data and analyzes them using remote-sensing technology. It can be seen that there have been changes in LULC in KPW in the last two decades, 1999–2009 and 2009–2019. Changes in LULC occur in each category. The most significant change was in the forest category, which experienced a significant decrease from 1999 to 2019, with a total loss percentage of 21.76%. Deforestation in KPW, mainly due to the increase and expansion of agricultural activities, especially plantations and cultivation, has resulted in landscape fragmentation. In contrast, forest restoration activities have not been carried out optimally. Rapid urbanization has been the main factor driving the LULC changes in KPW. Forest conservation and rehabilitation need to be improved to ameliorate environmental quality in KPW. Local climate change is also occurring in this KPW. Continuous monitoring of LULC changes in KPW is also necessary to keep management planning up to date. This study has only been conducted for the KPW area. The results of this study can be used as a reference for other similar studies and future monitoring of LULC changes using remote sensing. In the study location, the temperature slightly increased compared to the global average temperature, while the rainfall decreased. This will shorten the length of the growing period. Rainfall irregularities also occur. This can be seen from the existing trends, so an adaptation strategy for agricultural systems is needed based on the prevailing climatic conditions.

The results of LULC analysis provide a relationship of 56.88% to humidity and other elements. This shows that, if land use is not regulated and maintained in accordance with its land use, it will have an effect on the KPW. The impact of LULC changes has the effect of changing the hydrological function of the watershed originating from the decline in regional rainfall and followed by watershed yields, so LULC protection must be established (land management strategy).

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