Journal of Sylva Indonesiana
Journal homepage: https://talenta.usu.ac.id/jsi

Land Cover and Land Surface Temperature Dynamics in West Kotawaringin (2005-2025) Based on Remote Sensing and Random Forest Classification

Nazla Paradisa[1], Beni Iskandar[1*], Sari Marlina[1], Ahmad Jauhari[2]

[1]*Department of Forestry, Faculty of Agriculture and Forestry, Universitas Muhammadiyah Palangka Raya, Palangka Raya, 74874, Indonesia*

[2]*Forestry Study Program, Faculty of Forestry, Universitas Lambung Mangkurat, Banjarbaru, 70714, Indonesia*

[*]Corresponding Author: beniiskandar@umpr.ac.id

ARTICLE INFO

Article history:
Received May 9th, 2026
Revised August 23rd, 2026
Accepted August 27th, 2026
Available online August 31st, 2026

E-ISSN: 2622-5093
P-ISSN: 2622-5158

How to cite (IEEE):
N. Paradisa, B. Iskandar, S. Marlina, and A. Jauhari, "Land Cover and Land Surface Temperature Dynamics in West Kotawaringin (2005-2025) Based on Remote Sensing and Random Forest Classification", *Journal of Sylva Indonesiana*, Vol. 09, No. 02, pp. 221-231, Aug. 2026, doi: 10.32734/jsi.v9i02.25534.

http://doi.org/10.32734/jsi.v9i02.25534

ABSTRACT

Land cover changes can influence surface temperatures and environmental conditions; therefore, spatial and temporal monitoring is crucial for regional management and climate-change mitigation. This study analyzes land-cover and Land Surface Temperature (LST) dynamics in West Kotawaringin Regency in 2005, 2015, and 2025 using Google Earth Engine, Landsat 7, Landsat 8, and Landsat 9 imagery, Random Forest classification, accuracy assessment, and LST extraction. Forest area decreased by 228,930 ha, from 598,649 ha (63.37%) in 2005 to 369,719 ha (39.14%) in 2025, while agricultural land increased by 172,131 ha, from 207,659 ha (21.98%) to 379,790 ha (40.20%). The classification yielded an Overall Accuracy of 0.93 and Kappa coefficients of 0.89-0.90. Mean LST increased from 19.50°C to 22.31°C in forest areas and from 24.58°C to 26.20°C in settlements. The spatial pattern consistently shows lower mean LST in forested areas than in built-up and other non-forest surfaces. Scientifically, the study integrates multi-temporal land-cover and LST analysis at the regency scale to support spatial planning, environmental management, and climate-change mitigation.

Keyword: Climate Change, Land Cover, Land Surface Temperature, Remote Sensing, West Kotawaringin

1. Introduction

Changes in land cover are a dynamic process resulting from both natural causes and human activities [1]. Population growth increases demand for residential and infrastructure development and can contribute to urban expansion and land-use/land-cover change [2], [3] Unplanned land-use and land-cover changes can degrade environmental quality, reduce biodiversity, and increase ecological risks in terrestrial ecosystems [4]. Therefore, continuous monitoring is necessary to maintain a balance between development needs and environmental conservation.

Land-cover conversion also alters surface thermal conditions. Replacing vegetated cover with built-up or other non-vegetated surfaces is generally associated with higher land surface temperatures and lower thermal comfort [5], [6]. Higher temperatures may place organisms under stress, disturb life cycles, and contribute to habitat degradation. Studies [6], [7] have reported clear differences in land surface temperature where vegetation has been replaced by built-up or sparsely vegetated land. This change reduces evapotranspiration and modifies the exchange of energy at the surface. Monitoring both land cover and land surface temperature can therefore provide evidence for environmental management, spatial planning, and land-use policy.

Remote sensing data has been widely used to analyze vegetation because it is more cost-effective, faster, and more accurate. This data can measure changes in land cover over time across a wide area and over long periods [8]. It demonstrates a clear relationship between land cover and land surface temperature, whereby changes in land cover can substantially influence surface temperature patterns across a region [9].This data enables the monitoring of land cover and surface temperature to support the rapid and accurate management of natural resources.

Remote sensing data hold great potential for analyzing changes in land cover and variations in land surface temperature in West Kotawaringin Regency. The Regency is located in Central Kalimantan Province, Indonesia, and has a total administrative area of approximately 10,759 km^2. In fact, this regency experiences year-round land-cover dynamics due to the expansion of agriculture and plantations, as well as forest and land fires. Previous research indicates a deforestation rate of 24,975 hectares per year, or 1.9 % annually, during 2000-2021 [10], as well as recurring forest and land fires, particularly in peatland and plantation areas [11]. Earlier studies were concentrated in Arut Utara Subdistrict or Pangkalan Bun and did not provide a regency-wide, multi-temporal comparison of land-cover classes and Land Surface Temperature (LST) using one consistent framework [8], [10], [12]. Therefore, this study evaluates land-cover and LST dynamics across West Kotawaringin Regency in 2005, 2015, and 2025 using Landsat imagery, Random Forest classification, LST analysis, and Google Earth Engine. The research question is how land-cover composition and LST patterns changed across the three observation years and how LST differed among land-cover classes. The novelty of this study lies in integrating regency-scale multi-temporal land-cover classification and class-based LST comparison within the same remote-sensing workflow to support sustainable natural-resource management and climate-change mitigation.

2. Method

2.1 Time and Location

The research was carried out over approximately seven months, from November 2025 to May 2026. During this period, the authors prepared the data, processed the satellite images, classified land cover, assessed classification accuracy, extracted LST, and interpreted the results. The study area was West Kotawaringin Regency in Central Kalimantan Province, located at approximately 2°24'0" S and 111°43'59.99" E (Figure 1).

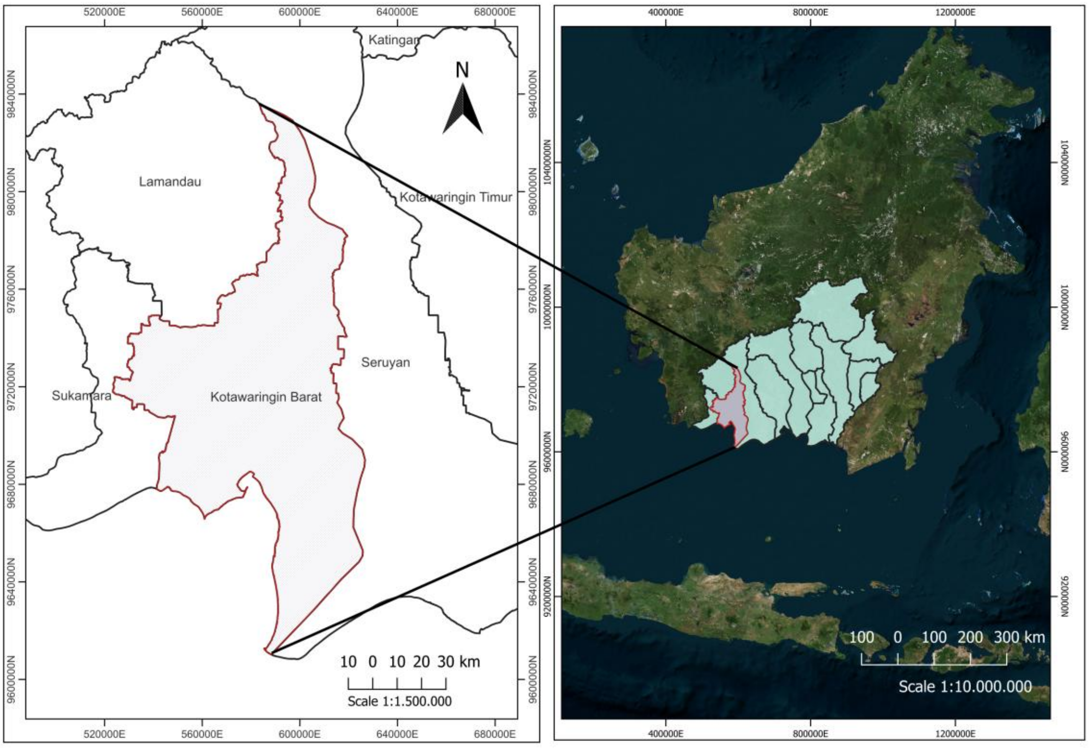


Figure 1. Research Location

2.2 Data and Software

The analysis used the administrative boundary of West Kotawaringin Regency and Landsat imagery for three observation years. Landsat 7 represented 2005, Landsat 8 represented 2015, and Landsat 9 represented 2025 (Table 1). Thermal information from these images was used to derive land surface temperature. Image processing and analysis were conducted in Quantum GIS and Google Earth Engine (GEE).

Table 1. Research data

No	Data	Scale/Resolution	Source
1.	Administrative data for West Kotawaringin Regency	1:50,000	Geospatial Information Agency (BIG) of the Republic of Indonesian
2.	Landsat 7 imagery for 2005, Landsat 8 imagery for 2015, and Landsat 9 imagery for 2025	30 m	https://earthexplorer.usgs.gov/

2.3 Data Collection and Analysis Procedures

Figure 2 shows the framework of this research method. The research methodology framework is generally divided into three stages. The first is the classification of land cover using Landsat-7 imagery from 2005, Landsat-8 imagery from 2015, and Landsat-9 imagery from 2025. Land cover classification using the Random Forest algorithm. Followed by accuracy testing and analysis of changes in land cover. The second step involved analysing land surface temperature using Landsat-7 imagery from 2005, Landsat-8 imagery from 2015, and Landsat-9 imagery from 2025. This stage was followed by an analysis of changes in land surface temperature. Finally, this study analysis trends in land surface temperature for each land cover class in 2005, 2015 and 2025.

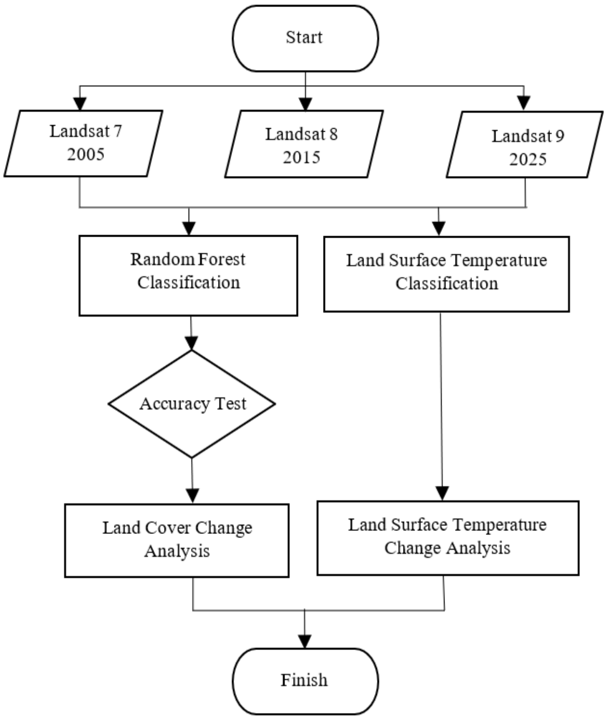


Figure 2. Methodological framework

2.3.1 Random forest classification

Image preprocessing included atmospheric correction, cloud masking, and median compositing. Land cover was then classified with Random Forest, which combines decisions from multiple trees. In Google Earth Engine, the classifier was specified as ee.Classifier.smileRandomForest (10, 5), corresponding to 10 trees and 5 variables at each split. Land cover classification variables using the coastal/aerosol, blue, green, red, nearinfrared, and shortwave infrared-2 bands from Landsat imagery. Classification sample points were placed at 1 x 1 km intervals within the study area, resulting in a total of 9,460 sample points. These points are divided into two sets: 80% training data and 20% test data. This data partitioning aims to achieve representative classification accuracy [13]. The same procedure was applied to the Landsat 7, 8, and 9 images to map seven classes: forest, agricultural land, grassland, wetland, settlement, other land, and water bodies. The classified maps for 2005, 2015, and 2025 were compared, and LST was summarized for each class. Random Forest was selected because its ensemble structure can represent nonlinear class boundaries and is less sensitive to overfitting than a single decision tree [14].

2.3.2 Accuracy test

The land cover classification results obtained were tested for accuracy using a confusion matrix (Table 2). A confusion matrix is useful for comparing machine learning classification results with training data to determine the accuracy of the classification results [15]. Subsequently, the Overall Accuracy (OA) and Kappa Accuracy (KA) were calculated. The land cover classification results are considered good and accurate if the accuracy value exceeds 85% [16].

Table 2. Confusion matrix

Reference data	**Classified into classes**							**Total**	**Producer's Accuracy**
	A	B	C	D	E	F	G		
A	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{1+}	X_{11}/X_{1+}
B	X_{21}	X_{22}	X_{23}	X_{24}	X_{25}	X_{26}	X_{27}	X_{2+}	X_{22}/X_{2+}
C	X_{31}	X_{32}	X_{33}	X_{34}	X_{35}	X_{36}	X_{37}	X_{3+}	X_{33}/X_{3+}
D	X_{41}	X_{42}	X_{43}	X_{44}	X_{45}	X_{46}	X_{47}	X_{4+}	X_{44}/X_{4+}
E	X_{51}	X_{52}	X_{53}	X_{54}	X_{55}	X_{56}	X_{57}	X_{5+}	X_{55}/X_{5+}
F	X_{61}	X_{62}	X_{63}	X_{64}	X_{65}	X_{66}	X_{67}	X_{6+}	X_{66}/X_{6+}
G	X_{71}	X_{72}	X_{73}	X_{74}	X_{75}	X_{76}	X_{77}	X_{7+}	X_{77}/X_{7+}
Total	X_{+1}	X_{+2}	X_{+3}	X_{+4}	X_{+5}	X_{+6}	X_{+7}	N	

Class codes: A forest; B agricultural land; C grassland; D wetland; E settlement; F other land; G water bodies. $UA_j = X_{jj}/X_{+j}$.

$$OA = (\Sigma_{i=1}^{r} X_{ii} / N) \times 100 \quad (1)$$

$$KA = [N\Sigma_{i=1}^{r}X_{ii} - \Sigma_{i=1}^{r}(X_{i+}X_{+i})] / [N^2 - \Sigma_{i=1}^{r}(X_{i+}X_{+i})] \times 100\% \quad (2)$$

Where OA is Overall Accuracy, KA is the Kappa coefficient, X_{ii} is the diagonal value of row i and column i, X_{i+} and X_{+i} are the corresponding marginal totals, and N is the total number of reference observations.

2.3.3 Land surface temperature classification

Land surface temperature was calculated from the Landsat thermal data using Equation [17]. The calculation converted digital numbers to spectral radiance, radiance to brightness temperature in Kelvin, and Kelvin to degrees Celsius, as summarized in Table 3.

Table 3. Land surface temperature calculation

No	**Description**	**Formula**
1	Radiance	$L\lambda = ML \times Qcal + AL$
2	Radiance to Surface Temperature (Kelvin)	$T = K2 / \ln(K1 / L\lambda)$
3	Conversion from Kelvin to Celsius	$T2 = T - 273.15$

In Table 3, Lλ denotes spectral radiance; ML and AL are the multiplicative and additive rescaling factors; Qcal is the digital number; K1 and K2 are the thermal calibration constants; T is temperature in Kelvin; and T2 is temperature in degrees Celsius.

For mapping, the LST values were arranged into the operational classes proposed by Fahwari et al. [18] (Table 4). This classification is a simplified version designed to be easy to understand and to facilitate data analysis.

Table 4. Land surface temperature class

No	**Temperature (°C)**	**Description**
1.	26-35	High
2.	24-25	Medium
3.	21-23	Low

2.3.4 Analysis of land cover changes

Land-cover change analysis was conducted to identify temporal dynamics by comparing the mapped areas in 2005, 2015, and 2025. Changes were calculated for 2005-2015 and 2015-2025 as the later-year area minus the earlier-year area (Table 5). Therefore, positive values indicate expansion and negative values indicate reduction. The analysis reports area, percentage, and inter-period change for each land-cover class. Table 5 is adapted from the analytical format used in study [19].

Table 5. Land cover class

No	Land Cover Class Classification	Year									
		2005		2015		2025		Δ2005-2015		Δ2015-2025	
		Ha	%	Ha	%	Ha	%	Ha	%	Ha	%
1.	Forests	...	...	...	...	...	...	...	...	...	...
2.	Agricultural Land	...	...	...	...	...	...	...	...	...	...
3.	Grasslands	...	...	...	...	...	...	...	...	...	...
4.	Wetlands	...	...	...	...	...	...	...	...	...	...
5.	Settlements	...	...	...	...	...	...	...	...	...	...
6.	Other Land	...	...	...	...	...	...	...	...	...	...
7.	Water Bodies	...	...	...	...	...	...	...	...	...	...

2.3.5 Analysis of changes in land surface temperature

Land surface temperature analysis was conducted to describe temperature variation among land-cover classes. The analysis summarized minimum, maximum, mean, and standard deviation values for each class [19]. These descriptive statistics were used to compare thermal patterns among forest, agricultural land, grassland, wetland, settlement, other land, and water bodies. Because the analysis is descriptive and does not include Pearson correlation, regression, or another inferential test, the results are interpreted as spatial-temporal associations rather than proof of a causal statistical relationship between land cover and LST (Table 6).

Table 6. Relationship between land cover and land surface temperature in year X

No	Land Cover Class Classification	Year X			
		Min(°C)	Max(°C)	Average(°C)	Stdev(°C)
1.	Forests	…	…	…	…
2.	Forests	…	…	…	…
3.	Agricultural Land	…	…	…	…
4.	Grasslands	…	…	…	…
5.	Wetlands	…	…	…	…
6.	Settlements	…	…	…	…
7.	Other Land	…	…	…	…
8.	Water Bodies	…	…	…	…

3. Results and Discussions

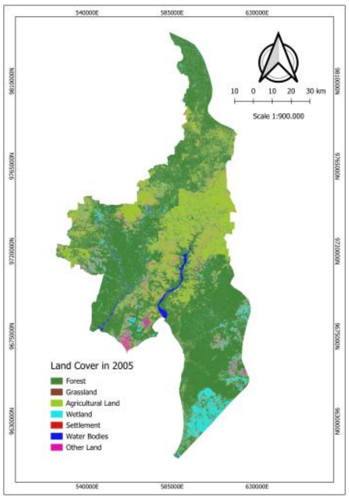
3.1 Analysis of Land Cover Changes

Table 7 and Figure 3 summarize land-cover changes in West Kotawaringin from 2005 to 2025. Between 2005 and 2015, forest area declined by 176,627 ha, whereas agricultural land increased by 149,610 ha. The findings of this study demonstrate that changes to forests resulting from the conversion of land to agricultural use. [20] The findings of this study indicate that there was a strong trend towards the expansion of oil palm plantations during the period 2009–2016. The key drivers of this expansion were smallholders and companies. The trend towards the expansion of oil palm plantations is driven by their high economic value compared with other agricultural commodities [21]. The period 2015–2025 shows a trend of a 52,302 ha reduction in forest area, whilst the same period shows a trend of a 30,473 ha increase in grasslands area. Consequently, the main changes that have occurred are a reduction in forest area and an increase in agricultural area. This change is linked to the growing demand for palm oil products for food, cosmetics and biodiesel [22]. The conversion of forest to oil palm plantations is heavily influenced by economic factors [22-23]. To ensure that this conversion does not occur too rapidly in the future, an environmentally friendly oil palm plantation strategy is required, involving the increase in crude oil production through fertilisation techniques and the selection of high-quality seedlings. In addition, spatial planning that takes into account the carrying capacity and environmental capacity of West Kotawaringin Regency.

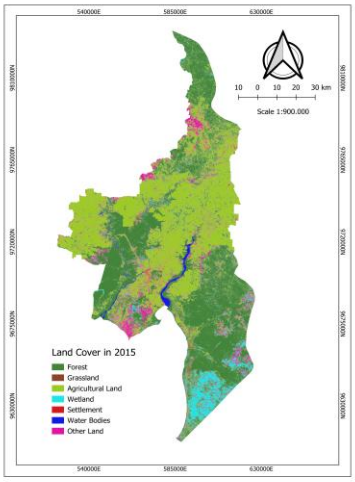
The conversion of forest to non-forest land results in a reduction in tree canopy cover on the Earth's surface. This reduction in tree canopy cover has the potential to increase Land surface temperature (LST). This phenomenon is clearly evident during the dry season, when LST on bare land and agricultural land are higher, whilst forested areas have lower LST. Consequently, rapid and massive deforestation increases the risk of a significant rise in LST [24]. The best strategy is to preserve existing forests and increase the area of urban forests in order to keep temperatures stable.

Table 7. Land cover 2005, 2015, and 2025

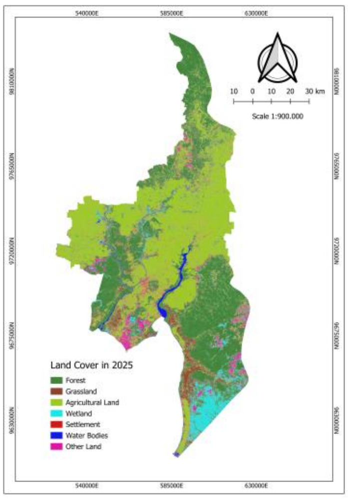
No	Land Cover	2005		2015		2025		2005-2015	2015-2025
		Ha	%	Ha	%	Ha	%	Ha	Ha
1.	Forests	598,649	63.37	422,022	44.67	369,719	39.14	-176,627	-52,303
2.	Agricultural Land	207,659	21.98	357,269	37.82	379,790	40.20	149,610	22,521
3.	Grasslands	41,700	4.41	40,506	4.28	70,980	7.51	-1,194	30,474
4.	Wetlands	62,617	6.62	52,009	5.50	53,229	5.63	10,607	-1,219
5.	Settlements	3,790	0.40	5,473	0.57	4,005	0.42	1,683	-1,468
6.	Other Land	20,789	2.20	58,034	6.14	56,916	6.02	-37,245	1,118
7.	Water Bodies	9,374	0.99	9,267	0.98	9,934	1.05	-107	667
	Total	**944.580**	**100.00**	**944.580**	**100.00**	**944.580**	**100.00**		



(a)



(b)



(c)

Figure 3. (a) Land Cover 2005; (b) Land Cover 2015; (c) Land Cover 2025

3.2 Accuracy of Land Cover

Table 8 reports an Overall Accuracy (OA) of 0.93 for each of the three classified maps. Kappa values were 0.89 in 2005 and 0.90 in 2015 and 2025. These estimates were obtained by comparing the test samples with the assigned land-cover classes. All three OA values exceed the 85% criterion adopted in this study [16], indicating a high level of agreement at the map level between the classification and the reference labels. The result is also consistent with the use of an ensemble classifier: Random Forest combines multiple trees to accommodate complex spectral patterns in remote-sensing data [25].

Table 8. Accuracy of land cover

No	Year	Accuracy (%)	
		OA	**KA**
1	2005	0.93	0.89
2	2015	0.93	0.90
3	2025	0.93	0.90
	Average	**0.93**	**0.93**

3.3 Analysis of Soil Surface Temperature

Figure 4 shows mean LST trends for forest and non-forest areas in West Kotawaringin Regency for 2005, 2015, and 2025. Mean LST in forest areas increased from 19.50°C in 2005 to 21.34°C in 2015 and 22.31°C in 2025. Mean non-forest LST increased from 21.87°C to 23.55°C and 23.73°C over the same years. Thus, non-forest areas remained warmer than forest areas in all three observations. This pattern is consistent with earlier studies showing that reduced vegetation and increased built or exposed surfaces are associated with higher LST [26]. The thermal contrast can be explained by vegetation shading and evapotranspiration, which dissipate energy as latent heat, whereas built-up and less-vegetated surfaces tend to store and reradiate a larger proportion of incoming energy [27], [28]. These results show a consistent descriptive association, but no inferential statistical test was performed to establish the strength or causality of the land-cover-LST relationship.

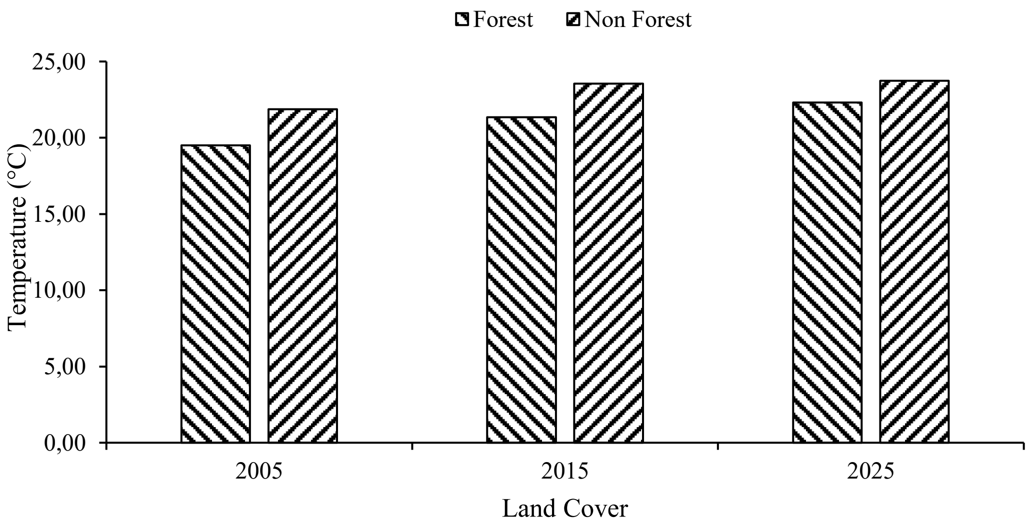


Figure 4. Mean Land Surface Temperature of forest and non-forest areas, 2005-2025

According to Table 9, mean LST in 2005 varied among land-cover classes. LST data were obtained for January, June, and September; these months were selected based on the availability of images with relatively low cloud cover and good image quality. Settlements recorded the highest mean value at 24.58°C, followed by other land at 23.68°C, agricultural land at 21.41°C, grasslands at 21.21°C, water bodies at 20.21°C, wetlands at 20.14°C, and forest at 19.50°C. The settlement class also reached a maximum LST of 28.38°C, whereas the forest maximum was 21.99°C. The lower mean LST in forest and wetland classes is consistent with the cooling role of denser vegetation and moist surfaces [19]. The spatial distribution of LST in 2005 is shown in Figure 5a.

In 2015, LST data were obtained for June, October, and November, other land recorded the highest mean LST at 27.14°C and the highest maximum value at 33.32°C, followed by settlements with a mean of 25.99°C and a maximum of 30.10°C. Agricultural land and grasslands had mean LST values of 23.13°C and 22.75°C, respectively. Lower means were found in water bodies 21.48°C, forest 21.34°C, and wetlands 20.77°C. The lower LST of vegetated classes relative to built or exposed surfaces is consistent with the role of evapotranspiration and canopy shading in dissipating heat [28]. The spatial distribution of LST in 2015 is shown in Figure 5b.

For 2025, the available images were acquired in May, September, and October. Settlements had the highest mean LST (26.20°C) and a maximum of 28.14°C. Other land followed, with a mean of 25.36°C and a maximum of 28.11°C. Mean values were 23.33°C for agricultural land and 22.98°C for grassland. Water bodies, wetlands, and forest had means of 22.25°C, 22.23°C, and 22.31°C, respectively. The warmer settlement surfaces are consistent with the heat-storage properties of materials such as concrete and asphalt [29]. Figure 5c presents the spatial distribution for 2025. These class differences also point to the value of retaining vegetation when local surface heating is considered in land-use decisions.

The analysis was descriptive. No correlation, regression, or other inferential test was used to quantify the relationship between land cover and LST. The reported differences should therefore be read as thermal contrasts among mapped classes, not as evidence of statistical significance or causation. The satellite-derived LST values were not checked against measurements collected on the ground and describe the land surface rather than near-surface air temperature. Acquisition dates also differed among the three observation years: January, June, and September in 2005; June, October, and November in 2015; and May, September, and October in 2025. Differences in solar radiation, rainfall, and surface moisture at those times may have affected the LST estimates. For this reason, comparisons across years require caution

Table 9. Land surface temperature trends from 2005 to 2025

No	Land Cover	2005			2015			2025		
		Min (°C)	Max (°C)	Average (°C)	Min (°C)	Max (°C)	Average (°C)	Min (°C)	Max (°C)	Average (°C)
1.	Forest	16.44	21.99	19.50	19.80	22.49	21.34	20.96	23.38	22.31
2.	Agricultural Land	19.97	22.84	21.41	21.37	26.30	23.13	21.41	25.89	23.33
3.	Grasslands	20.26	22.27	21.21	21.13	26.47	22.75	21.28	25.38	22.98
4.	Wetlands	17.04	22.27	20.14	18.41	23.82	20.77	18.56	26.76	22.23
5.	Settlements	23.40	28.38	24.58	23.11	30.10	25.99	24.11	28.14	26.20
6.	Other Land	21.70	24.81	23.68	22.41	33.32	27.14	23.15	28.11	25.36
7.	Water Bodies	18.81	21.99	20.21	18.04	24.59	21.48	21.30	24.30	22.25

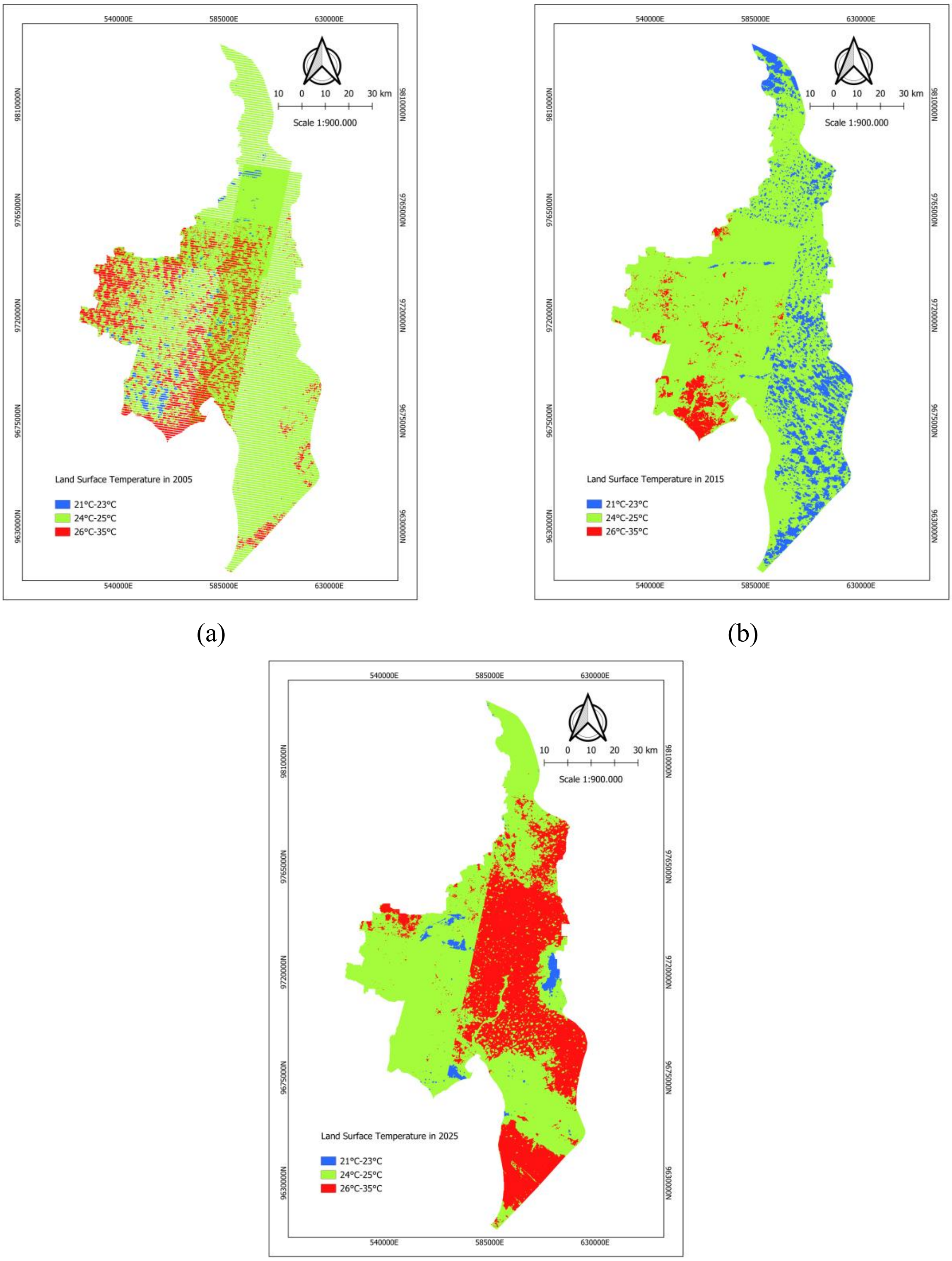


Figure 5. (a) Land Surface Temperature 2005; (b) Land Surface Temperature 2015; (c) Land Surface Temperature 2025

4. Conclusion

Research has concluded that significant changes in land cover have occurred, and it has also identified trends in LST changes during the period from 2005 to 2025. Forest cover decreased from 598.649 ha to 369.719 ha, while non-forest cover showed an increase in grassland cover of 29.270 ha and other land cover of 36.127 ha. The random forest algorithm produces excellent classification accuracy, and thus has the potential to be implemented in other areas. The average LST indicates that urban areas had higher temperatures ranging from

28.38 to 26.20°C compared to other land cover classes such as agricultural land, grasslands, wetlands, other lands, and water bodies during the period from 2005 to 2025. The average LST for forest cover ranged from 19.50 to 22.31°C from 2005 to 2025. This research successfully characterized land cover and LST on a spatial basis. The results of this analysis were used as a reference for LST-based land cover planning in West Kotawaringin Regency. The researchers recommend further research comparing LST data with field data and conducting inferential statistical analyses of forest cover data and LST data.

References

[1] O. Setiawan, A. A. D. Rahayu, G. Samawandana, H. L. Tata, I. W. S. Dharmawan, H. H. Rachmat, and H. Khotimah, “Unraveling land use land cover change, their driving factors, and implication on carbon storage through an integrated modelling approach,” *The Egyptian Journal of Remote Sensing and Space Sciences*, vol. 27, no. 4, hlm. 615–627, 2024, doi: https://doi.org/10.1016/j.ejrs.2024.08.002.

[2] R. Mahtta, M. Fragkias, B. Güneralp, A. Mahendra, M. Reba, E. A. Wentz, and K. C. Seto, “Urban land expansion: the role of population and economic growth for 300+ cities,” *npj Urban Sustainability*, vol. 2, no. 1, Des 2022, doi: 10.1038/s42949-022-00048-y.

[3] S. Fahad, W. Li, A. H. Lashari, A. Islam, L. H. Khattak, and U. Rasool, “Evaluation of land use and land cover Spatio-temporal change during rapid Urban sprawl from Lahore, Pakistan,” *Urban Clim.*, vol. 39, hlm. 100931, 2021, doi: https://doi.org/10.1016/j.uclim.2021.100931.

[4] P. C. Latue and H. Rakuasa, “Analisis Spaisal Perubahan Tutupan Lahan di DAS Wae Batugantong, Kota Ambon,” *Jurnal Tanah* and *Sumberdaya Lahan*, vol. 10, no. 1, hlm. 149–155, Jan 2023, doi: 10.21776/ub.jtsl.2023.010.1.17.

[5] G. Mohiuddin and J. P. Mund, “Spatiotemporal Analysis of Land Surface Temperature in Response to Land Use and Land Cover Changes: A Remote Sensing Approach,” *Remote Sens. (Basel).*, vol. 16, no. 7, Apr 2024, doi: 10.3390/rs16071286.

[6] S. Hussain and S. Karuppannan, “Land use/land cover changes and their impact on land surface temperature using remote sensing technique in district Khanewal, Punjab Pakistan,” *Geology, Ecology, and Landscapes*, vol. 7, no. 1, hlm. 46–58, Jan 2023, doi: 10.1080/24749508.2021.1923272.

[7] G. F. Akomolafe and R. Rosazlina, “Land use and land cover changes influence the land surface temperature and vegetation in Penang Island, Peninsular Malaysia,” *Sci. Rep.*, vol. 12, no. 1, Des 2022, doi: 10.1038/s41598-022-25560-0.

[8] B. Iskandar, N. Hanafi, and R. Anshari, “Kajian Pemantauan Perubahan Penutupan Lahan Berbasis Penginderaan Jauh Di Kotawaringin Barat,” *Jurnal Belantara*, vol. 5, no. 2, Agu 2022, doi: 10.29303/jbl.v5i2.866.

[9] S. Singh, P. Kumar, R. Parijat, B. Gonengcil, and A. Rai, “Establishing the relationship between land use land cover, normalized difference vegetation index and land surface temperature: A case of Lower Son River Basin, India,” *Geography and Sustainability*, vol. 5, no. 2, hlm. 265–275, 2024, doi: https://doi.org/10.1016/j.geosus.2023.11.006.

[10] B. Iskandar and N. Hanafi, “Algoritma machine learning deteksi deforestasi hutan hujan tropis di kabupaten kotawaringin barat,” *Jurnal Teknologi Informasi, Komputer,* and *Aplikasinya (JTIKA)*, vol. 4, no. 2, hlm. 194–201, 2022.

[11] E. I. Purnawan, H. Chotimah, H. R. Effendi, A. Delmi, and R. Jemi, “Evaluasi Program Dalkarhutla Untuk Menekan Kebakaran Hutan dan Lahan di DI UPT KPHP Kotawaringin Barat,” *Jurnal Hutan Tropis*, vol. 13, no. 1, hlm. 63–73, 2025, doi: doi.org/10.20527/jht.v13i1.22180.

[12] R. Anshari, A. Jauhari, and M. Mufidah, “Menganalisis Tutupan Lahan dan Urban Heat Index (UHI) Yang Ada di Kota Pangkalan Bun,” *Jurnal Hutan Tropis*, vol. 12, no. 3, hlm. 327–335, 2024, doi: http://dx.doi.org/10.20527/jht.v12i3.20550.

[13] L. De Simone and P. Gennari, “Earth observations for official crop statistics in the context of scarcity of in-situ data,” *Stat. J. IAOS*, vol. 38, no. 3, hlm. 1009–1019, 2022, doi: 10.3233/SJI-220054.

[14] T. Kattenborn, F. Schiefer, J. Frey, H. Feilhauer, M. D. Mahecha, and C. F. Dormann, “Spatially autocorrelated training and validation samples inflate performance assessment of convolutional neural networks,” *ISPRS Open Journal of Photogrammetry and Remote Sensing*, vol. 5, Agu 2022, doi: 10.1016/j.ophoto.2022.100018.

[15] Z. Li, X. Chen, J. Qi, C. Xu, J. An, and J. Chen, "Accuracy assessment of land cover products in China from 2000 to 2020," *Sci. Rep.*, vol. 13, no. 1, Des 2023, doi: 10.1038/s41598-023-39963-0.

[16] M. D. A. As *dkk.*, "Perbandingan Hasil Klasifikasi Tutupan Lahan dan Penggunaan Lahan Menggunakan Citra Satelit Landsat, Sentinel, and Pleiades," *Jurnal Pendidikan Geografi Undiksha*, vol. 13, no. 1, hlm. 60–67, Apr 2025, doi: 10.23887/jjpg.v13i1.83872.

[17] D. P. D. Putri, "Analisis Variasi Suhu Permukaan Tanah dan Gas Nitrogen Dioksida di Masa Pandemi Covid–19 (Studi Kasus: Kota Semarang)," *Jurnal Ilmiah Geomatika*, vol. 1, no. 1, 2021.

[18] N. Fahwari, I. Yanuarsyah, and S. Hudjimartsu, "Hubungan Suhu Permukaan Tanah Dengan Zona Rawan Longsor Menggunakan Land Surface Temperature," dalam *Seminar Nasional Teknologi Informasi*, 2019, hlm. 366–371.

[19] R. Limehuwey *dkk.*, "Analisis Hubungan Suhu Permukaan Tanah, Tutupan Lahan dan Indeks Kerapatan Vegetasi Menggunakan Data Citra Landsat 8 Di Kota Ambon," *Jurnal Penelitian Geografi (GeoJPG)*, vol. 4, hlm. 57–69, 2025, doi: 10.37905/geojpg.v3i2.31418.

[20] R. Amalia, A. H. Dharmawan, L. B. Prasetyo, and P. Pacheco, "Perubahan Tutupan Lahan Akibat Ekspansi Perkebunan Kelapa Sawit: Dampak Sosial, Ekonomi dan Ekologi," *Jurnal Ilmu Lingkungan*, vol. 17, no. 1, hlm. 130, Mei 2019, doi: 10.14710/jil.17.1.130-139.

[21] L. C. Ginting, F. U. Ritonga, and R. P. K. Sinaga, "Survival Strategy Of Farmworkers "Oil Palm Harvesters " Of Bakti Makmur Hamlet, Riau Using SWOT Analysis," *Journal of Peasants' Rights*, vol. 3, no. 1, hlm. 24–44, Mar 2024, doi: 10.32734/jpr.v3i1.16660.

[22] G. Bausano, M. Masiero, M. Migliavacca, D. Pettenella, and P. Rougieux, "Food, biofuels or cosmetics? Land-use, deforestation and CO2 emissions embodied in the palm oil consumption of four European countries: a biophysical accounting approach," *Agricultural and Food Economics*, vol. 11, no. 1, Des 2023, doi: 10.1186/s40100-023-00268-5.

[23] Diharyo and A. imam Santoso, "Perubahan Lahan and Erosi Tanah akibat Ekspansi Perkebunan Kelapa Sawit: kajian Lingkungan di Kalimantan Tengah," 2024.

[24] P. C. Latue, J. S. I. Septory, and H. Rakuasa, "Perubahan Tutupan Lahan Kota Ambon Tahun 2015, 2019 dan 2023," *JPG (Jurnal Pendidikan Geografi)*, vol. 10, no. 1, Mar 2023, doi: 10.20527/jpg.v10i1.15472.

[25] N. Sulistiyono, C. P. Tarigan, A. F. Daulay, S. A. Hudjimartsu, and Y. U. Putri, "Identification of mangrove forests using Sentinel-1 Synthetic Aperture Radar (SAR) satellite imagery in Meand Belawan District, Meand City," dalam *IOP Conference Series: Earth and Environmental Science*, Institute of Physics, 2024. doi: 10.1088/1755-1315/1352/1/012051.

[26] H. Rakuasa and S. Pertuack, "Pola Perubahan Suhu Permukaan Daratan di Kecamatan Ternate Tengah, Kota Ternate Tahun 2013 and 2023 Menggunakan Google Earth Engine," *sudo Jurnal Teknik Informatika*, vol. 2, no. 2, hlm. 78–85, Jun 2023, doi: 10.56211/sudo.v2i2.271.

[27] R. Safitri, M. Vonnisa, and M. Marzuki, "Analisis Dampak Perubahan Tutupan Lahan di Kalimantan Terhadap Temperatur Permukaan," *Jurnal Fisika Unand*, vol. 11, no. 2, hlm. 173–179, Apr 2022, doi: 10.25077/jfu.11.2.173-179.2022.

[28] X. Li, Y. Li, S. Di, Y. Niu, and C. Zhang, "Evapotranspiration and land surface temperature of typical urban green spaces in a semi-humid region: Implications for green management," *Front. Environ. Sci.*, vol. 10, Agu 2022, doi: 10.3389/fenvs.2022.977084.

[29] Z. D. Calhoun, F. Willard, C. Ge, C. Rodriguez, M. Bergin, and D. Carlson, "Estimating the effects of vegetation and increased albedo on the urban heat island effect with spatial causal inference," *Sci. Rep.*, vol. 14, no. 1, Des 2024, doi: 10.1038/s41598-023-50981-w.