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Utilizing Remote Sensing for Land Change and Night Lights in Urbanization: Correlation between Built-Up Area Expansion in Berau City and Changes in Climate Parameters

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Abstract: This study explores the relationship between population growth and urban expansion as well as their impacts on climate and environmental parameters in Berau Regency, Indonesia. Using night-light data and land use/land cover (LULC) analysis from 2019 through 2023, the research identified significant urban growth, with night-lit areas doubling and a population increase from 232,290 to 280,990. Urban expansion led to notable land conversion, reducing vegetated areas by 18,202.38 ha, while built-up and open land grew by 11,768.6 ha and 5,989.74 ha, respectively. These changes impacted environmental conditions, with non-vegetated areas experiencing higher land-surface temperatures (31–34°C) and lower rainfall (5,000–6,000 mm/year) compared to the cooler and wetter vegetated areas (20–21°C; 7,000–8,000 mm/year). The findings emphasized vegetation's role in regulating temperature and rainfall, highlighting the environmental risks of urbanization and the need for sustainable land management to mitigate climate impacts in growing cities.

Keywords: remote sensing, urban expansion, land use/land cover, land-surface temperature

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1. Introduction

Urbanization is a global process that significantly reshapes physical landscapes, ecosystems, and local climate systems [1]. In Indonesia, this trend has become increasingly evident – particularly in secondary urban areas and developing regions such as Berau Regency in East Kalimantan Province. Although Berau is classified as a 3T region (disadvantaged, frontier, and outermost), it is currently undergoing rapid development – especially in line with the planned relocation of Indonesia's capital city to Nusantara in East Kalimantan. The trend is especially evident in secondary urban regions, including Berau Regency in East Kalimantan. Despite its classification as a 3T region, Berau has undergone accelerated development, largely influenced by the planned relocation of Indonesia's capital to Nusantara.

The relocation of the national capital has been shown to stimulate regional economic activity, infrastructure growth, and employment expansion across Kalimantan [2]. This transformation makes Berau an interesting case study, as regional development is expected to directly influence the pace of the urbanization and spatial transformation in the surrounding areas [3]. Furthermore, the establishment of IKN Nusantara has triggered extensive land-use transitions and internal migration to nearby regions such as Balikpapan, Penajam Paser Utara, and Samarinda; this can potentially extend to Berau's administrative region [4].

The BPS-Statistics Indonesia (Berau Regency) [5] reported that the population rose from 232,287 in 2019 to 280,998 in 2023, thus reflecting the rapid pace of urban expansion. This growth has triggered notable changes in land use and land cover (LULC) – particularly through the conversion of agricultural and forested areas into urban built-up zones [6, 7]. These changes have affected various environmental aspects, including increased land-surface temperatures (LSTs) and shifts in local precipitation patterns. The urban-heat-island (UHI) effect (which is primarily caused by the reduction of vegetated land) has been observed in many rapidly growing tropical cities; it has contributed to elevated surface temperatures and microclimatic instability [8]. Unplanned land conversion such as the transformation of natural or agricultural areas into residential or industrial zones can damage local ecosystems and increase environmental risks such as flooding and land degradation [9].

To date, urban-area monitoring has generally focused on LULC dynamics without comprehensively linking them to environmental aspects. In fact, LULC changes have had significant implications for environmental quality, such as rising surface temperatures, altered water flow patterns, vegetation degradation, and declining air quality.

From a theoretical perspective, urban ecology and landscape change theories explain that land conversion from vegetated and permeable surfaces to built-up and impervious ones directly affects the urban microclimate and ecological balance. The UHI theory posits that increasing impervious surfaces enhances heat storage, reduces evapotranspiration, and alters the surface albedo, thus leading to higher land surface temperatures and deteriorating environmental comfort [10, 11]. Similarly, landscape ecology emphasizes the role of spatial structure and fragmentation in influencing ecosystem functions, including vegetation covers, biodiversity, and hydrological regulation.

In hydrological theory, the modification of natural land cover alters runoff, infiltration rates, and water-retention capacity; these can exacerbate flood risks, reduce water quality, and disturb groundwater recharge processes [12]. The coupling of land transformation and urban climatic response therefore represents a core dimension of sustainable urban studies – especially in rapidly developing regions.

In Berau Regency, the use of remote-sensing technology to monitor urban development remains limited; yet, this technology holds great potential for providing accurate and sustainable spatiotemporal data for analyzing regional transformations and their environmental impacts. This study utilized multi-resolution satellite imagery, including night-time light (NTL) data as a valuable indicator of urbanization and human activity. Advances in remote sensing have enabled the monitoring of built-up areas and the spatial distribution of artificial lighting, which reflects patterns of population growth and infrastructure development [13]. NTL serves as a crucial tool for analyzing the spatial and environmental implications of urban growth. Increased night-time light intensity often correlates with higher economic activity and rising infrastructure demands [14].

In this study, the NTL data was not only employed as an indicator of human activity but was also systematically integrated with LULC classifications, annual temperatures, annual rainfall, and population density data to analyze their interrelationships. This integration allowed for an examination of how urban expansion (reflected through increased light intensity) corresponded with changes in land cover and climatic parameters. Previous studies [13, 15] have demonstrated the growing utility of NTL data in urban research – particularly when combined with Landsat imagery – to examine land use trends and their socioeconomic impacts. Additionally, a meta-analysis by [16] confirmed the effectiveness of DMSP/OLS night-light imagery in capturing urban landscape changes and their environmental consequences [17].

Through this integrated approach, the study seeks to develop a comprehensive understanding of the correlation between land-change dynamics, variations in NTL intensity, and fluctuations in climatic parameters. The integration of multi-source data enables a more nuanced interpretation of urbanization processes – particularly how the spatial expansions of built-up areas and increasing light emissions at night reflect anthropogenic pressures on the local environments. By correlating land-use transitions with NTL-derived indicators of human activity and annual climatic variables such as temperature and rainfall, the study aims to identify potential linkages between urban growth, microclimatic modification, and environmental sustainability.

To support the analysis, various multi-resolution data sets were employed, including NTL data from the Visible Infrared Imaging Radiometer Suite (VIIRS) (at a 500-meter spatial resolution), Sentinel-2 imagery (at a 10-meter resolution) for LULC classification, and Landsat 8/9 imagery (as complementary spatial references). The climate variables were obtained from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) data, which provides precipitation data at a spatial resolution of 5.5 km.

The primary objectives of this study were as follows:
- To detect urban-development patterns NTL data from 2019 through 2023 and examine its relationship with population growth.
- To map and quantify changes in LULC over the period of 2019 through 2023.
- To analyze the relationship between LULC changes and climate variables – particularly LST and precipitation.

By integrating multi-sensor data and time-series analysis, this study offers new insights into the interactions between urban growth and environmental changes in ecologically sensitive regions. The findings are expected to support sustainable urban planning and environmental policymaking by providing a clearer understanding of how human activities influence regional climate variability.

2. Data and Methodology

2.1. Study Area

This study focused on Berau Regency, which is located in East Kalimantan Province, Indonesia (as illustrated in Figure 1). Classified as a 3T region (underdeveloped, frontier, and outermost), Berau is currently experiencing significant development; this is being driven by population growth and expanding economic activities – particularly in the mining and plantation sectors. The regency also holds considerable potential for ecotourism – especially in its coastal and island regions (including Derawan Island, Maratua Island, and the Sangkulirang-Mangkalihat Karst landscape, which are recognized as key natural tourism destinations in East Kalimantan).

The physical landscape of Berau is characterized by a heterogeneous mix of dense tropical forests, agricultural plantations, mining zones, and rapidly expanding built-up areas. This ecological and socio-economic diversity renders Berau a strategic case study for analyzing urban-growth patterns and their associated environmental transformations.

2.2. Data Sources

This study utilized both spatial and non-spatial data for the years of 2019, 2021, and 2023. This research used both vector and raster format geospatial data that was sourced from various providers (as detailed in Table 1).

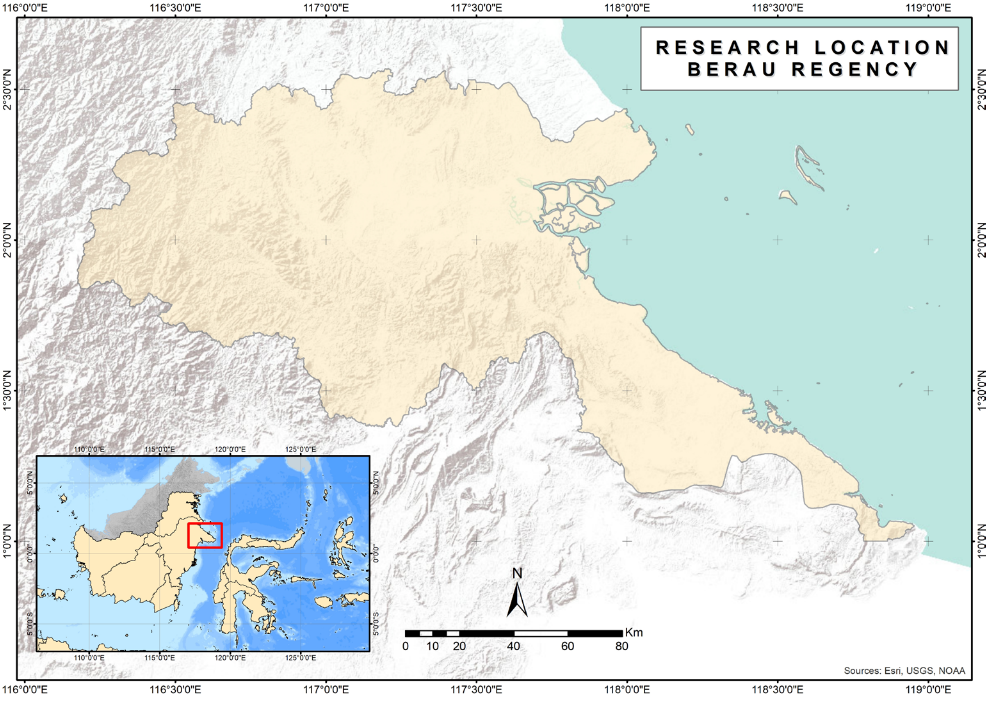

Fig. 1. Study area
Source: Data Processing, 2024

Table 1. Research spatial data

Data Type	Format Data	Year	Indicator Observed	Source
Sentinel-2	raster	2019, 2021, and 2023	land-cover classification and change detection	Google Earth Engine
Landsat-8	raster	2019, 2021, and 2023	land-surface temperatures	Google Earth Engine
Night-time light data	raster	2019, 2021, and 2023	Night-time light intensity (urbanization proxy)	Google Earth Engine
Precipitation data	raster	2019, 2021, and 2023	total annual precipitation [mm/year]	Google Earth Engine
Spatial data: boundary shapefiles	vector	–	administrative boundaries (district/sub-district level)	Indonesia Geospatial Information Agency

Source: Data Processing, 2024

The primary spatial data sets included the following:
- Sentinel-2 imagery (10-meter resolution) for LULC classification;
- VIIRS NTL data for urban illumination intensity (500-meter resolution);
- Landsat 8/9 (Band 10) for LSTs;
- CHIRPS precipitation data for annual rainfall trends.

Non-spatial data (including population density statistics) were sourced from the BPS-Statistics Indonesia to analyze demographic trends and their relationships with urban expansion. The NPP-VIIRS data set covered the years of 2019, 2021, and 2023, with a spatial resolution of 500 m by 500 m. This data set captured artificial lighting at night, thus allowing for assessments of urbanization trends. The potential applications of this data are vast, including urban planning, environmental monitoring, and socioeconomic research [17].

2.3. Methodology

This research utilized cloud computing technology (specifically, Google Earth Engine) for processing geospatial data. Google Earth Engine is used to process satellite images and data that are related to land changes, surface temperatures, and night-time lighting. Additionally, the research enhanced the analysis by examining the correlation between population density and the expansions of built-up areas using statistical techniques, thus providing a more comprehensive understanding of the relationship between urbanization and environmental factors within the study area. The research methodology is illustrated in Figure 2.

Figure 2 provides an overview of the research process by outlining the various stages and their interconnections. The research data consisted of both spatial and non-spatial data; the spatial data was obtained from remote-sensing satellite imagery, while the non-spatial data was derived from annual population density information. The research process was outlined as follows:

Data Pre-Processing. Effective data pre-processing was a critical step for ensuring accurate classification and analysis LULC, NTL, LSTs, and annual precipitation. This process involved the filtering of data sets by acquisition dates, the selection of appropriate spectral bands, and the application of techniques such as cloud masking to eliminate data noise. These steps were essential for improving the data quality and ensuring the reliability and validity of the subsequent analytical results.

Classification. This study conducted classification across four key variables: LULC, NTL intensity, LST, and annual rainfall. The LULC classification followed the SNI 7645-2010 standard [18], encompassing nine distinct categories: built-up areas, open lands, fields, mixed plantations, plantations, shrubs, dryland forests, mangroves, and water bodies. A similar classification scheme was used as defined by [19], covering fields, mixed plantations, plantations, dryland forests, mangrove forests, shrubs, settlements, open lands, and water. Multi-spectral satellite imagery supported the classification, with each class identified based on unique spectral characteristics [20].

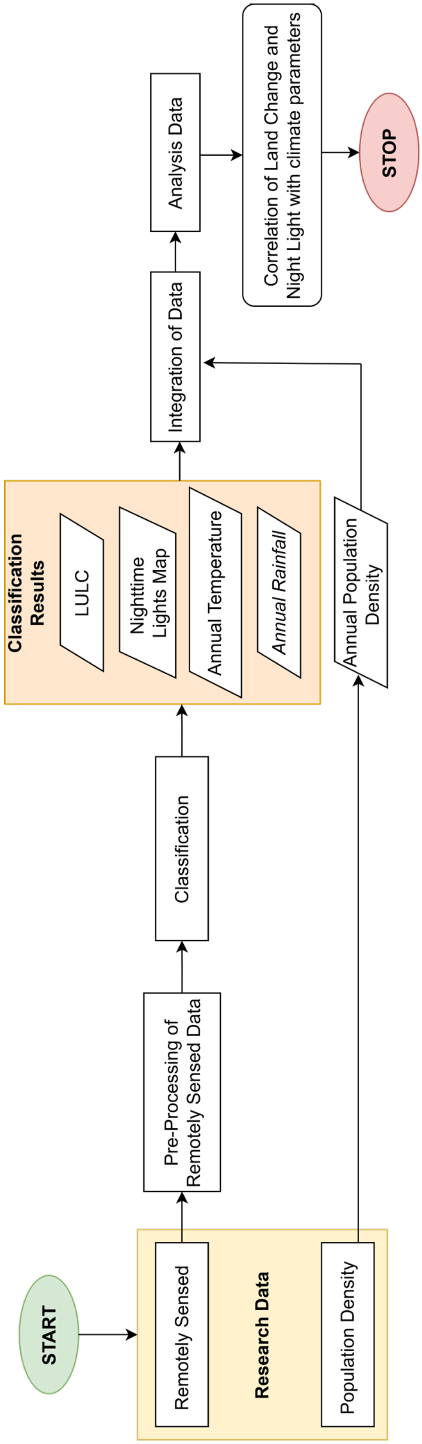

Fig. 2. Research flow chart

Source: Data Processing, 2024

The random forest algorithm, a supervised machine-learning method, was used for classification. Training samples were obtained from high-resolution satellite imagery and validated through visual inspection to ensure classification accuracy.

NTL data from the VIIRS satellite was used to assess light intensity in urban and residential areas during the night-time. The NTL classification process divided radiance (brightness) values into classes based on specific threshold values, thus reflecting the level of economic activity and urbanization in a given region [21].

The LST data was derived from the thermal bands of Landsat-8, which capture the radiant temperature of the Earth's surface. This classification identified temperature variations across different land-cover types such as forests, plantations, and urban zones. The annual precipitation data was sourced from satellite-based measurements and meteorological station records. Rainfall classification aimed to analyze the spatial distribution and intensity of precipitation and examine its interaction with LULC types and surface temperature variations.

Data Integration and Analysis. This process represents an advanced stage of data integration for spatial analysis. The key parameters that were utilized in this study included NTL, annual population density, LULC, and environmental variables such as LST and annual precipitation.

To analyze the relationship between population growth and the expansions of urbanized areas, a simple linear regression analysis was conducted by comparing the spatial distribution of illuminated areas (NTL) with annual population data. The NTL data was obtained from VIIRS-DNB satellite imagery, with illuminated areas being identified by using a specific radiance threshold to classify bright and dark zones. The extent of the illuminated areas (calculated in hectares) was used as a proxy for built-up-area expansion. The simple linear regression approach was applied to quantify the relationship between annual population figures and the extent of illuminated areas, allowing for a statistical interpretation of urban-growth patterns in relation to population dynamics.

As part of the data-integration process, this study also applied simple linear regression analysis to evaluate the statistical relationships between LULC classes and two key climate variables: LSTs and annual precipitation.

LULC classification was derived from Sentinel-2 imagery and categorized into several land cover types, including settlements (1), open lands (2), shrubs (3), fields (4), mixed plantations (5), plantations (6), dryland forests (7), mangrove forests (8), and water (9). The LST values were extracted from the Landsat 8/9 imagery, while the annual precipitation data was obtained from the CHIRPS data set.

Simple linear regression analyses were conducted to accomplish the following:

- assess linear relationship between LULC classes and LSTs;
- assess linear relationship between LULC classes and annual precipitation;
- quantify strengths of these relationships using R^2 values and evaluate influence of each LULC class on environmental variables through regression coefficients.

3. Results and Discussion

The integration of remote-sensing (RS) and geographic information system (GIS) data over time is essential for monitoring urban growth and land changes. It is also important to consider the broader context of these changes – especially in those cases where land transformation is linked to climate parameters [22, 23]. Technological advancements enable a comprehensive analysis of the temporal evolutions of urban areas and their environmental impacts. These technologies also facilitate assessments of how climate-induced changes affect urban development and land cover [24]. Furthermore, the spatial resolution of remote sensing is crucial for the rapid and accurate identification of urban expansion, which may encroach upon ecologically sensitive areas or worsen vulnerabilities that are related to climate phenomena.

3.1. Night-Time Light and Population Growth

This section used the 2019–2023 period, as population growth data from the BPS was only available up to 2023. Based on the analysis, population increases were observed in 2019, 2021, and 2023. This growth was accompanied by urban development, as was indicated by night-time activity that was monitored using the VIIRS satellite imagery. These night-time activities reflected the spatial distribution of built-up areas as were captured during nights in 2019, 2021, and 2023. This growth was accompanied by urban development, as was evidenced by the capture of night-time activities through the use of the VIIRS satellite imagery.

The activity was based on the distribution patterns of buildings that were recorded during nights in 2019, 2021, and 2023. A two-year interval was selected under the assumption that the area had experienced changes in its spatial pattern over time. Additionally, the choices of these years were due to the availability of the population growth data, which was only accessible from 2019 through 2023.

The relationship between the extent of NTL and population size was analyzed using simple linear regression, with the NTL area as the independent variable (X), and the population (in thousands) as the dependent variable (Y). The R^2 value of 0.8692 indicated that approximately 87% of the variation in population could be explained by changes in the illuminated area (NTL). This suggested that NTL could be effectively used as a spatial indicator for the mapping and modeling of population density or distribution dynamics in those regions that experienced urban growth.

Figure 3 illustrates the correlation between the expansions of night-lit areas and population growth over two-year intervals. The analysis of the NTL data from 2019 to 2023 revealed a consistent spatial expansion of illuminated areas, which reflected increased human activity and infrastructure development [13, 25]. The lit area grew from 3,410.16 ha in 2019 to 7,119.01 ha in 2023; during the same period, Berau's population increased from 232,287 to 280,998 residents. This positive trend indicated a strong correlation between population growth and night-time illumination, thus supporting the use of NTL as a proxy for urban development [26].

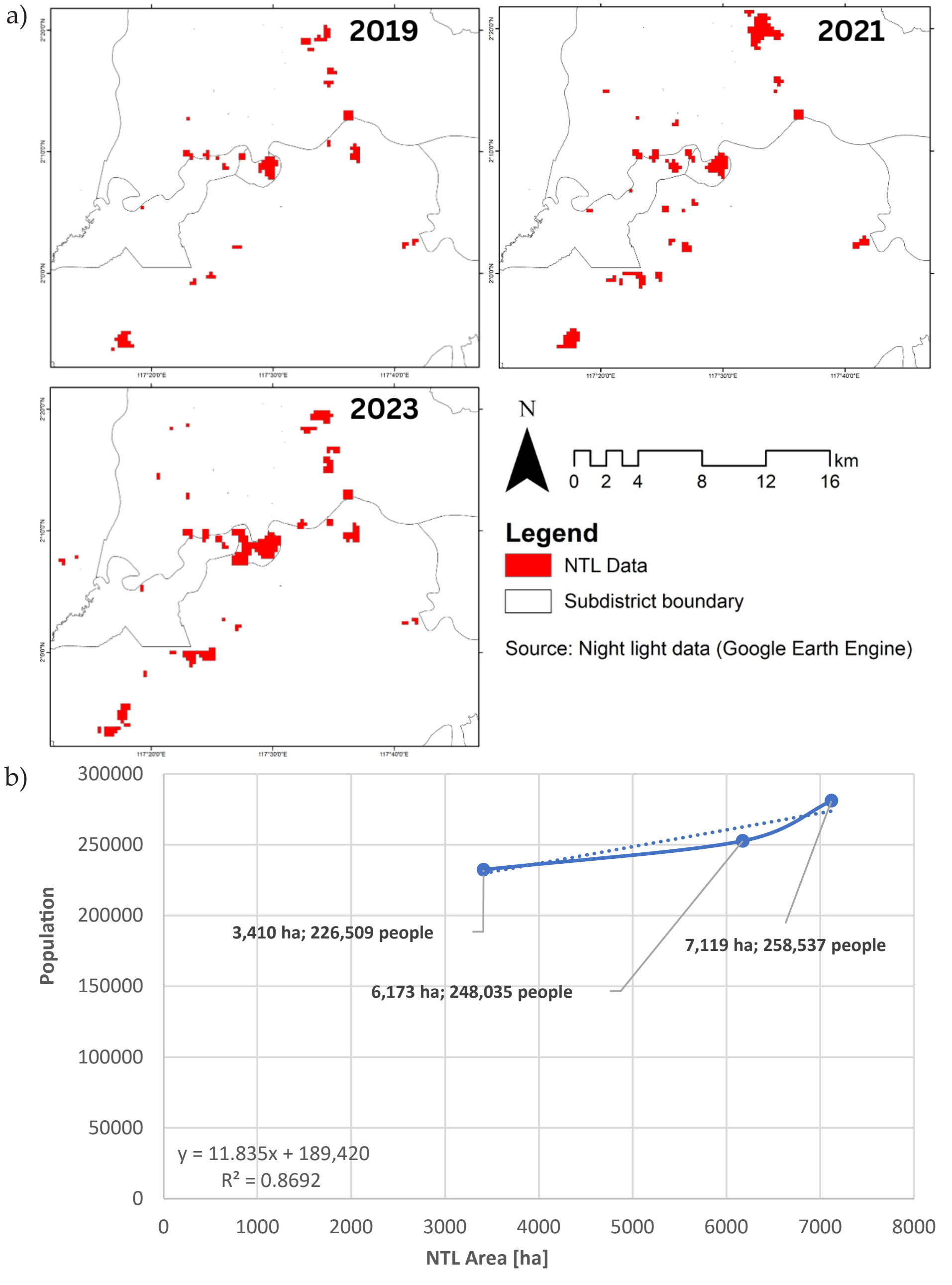

Fig. 3. Latest edition including expanded night light coverage encompassing years 2019, 2021, and 2023 (a);
comparison between expansion of night-time light coverage and population growth during years 2019 (represented by first dot), 2021 (second dot), and 2023 (third dot) (b)

Source: Data Processing, 2024

This aligned with recent studies that showed that night-time lights had a moderate to strong correlation with population size or density at the regional level [20]. A meta-analysis that was conducted by [27, 28] confirmed the growing trend of NTL-based urban studies and their effectiveness in capturing urban dynamics.

3.2. Land-Use/Land-Cover Change over Berau Regency

Figure 4 presents the spatial distribution of the LULC changes in the study area for the years of 2019, 2021, and 2023.

a)

b)

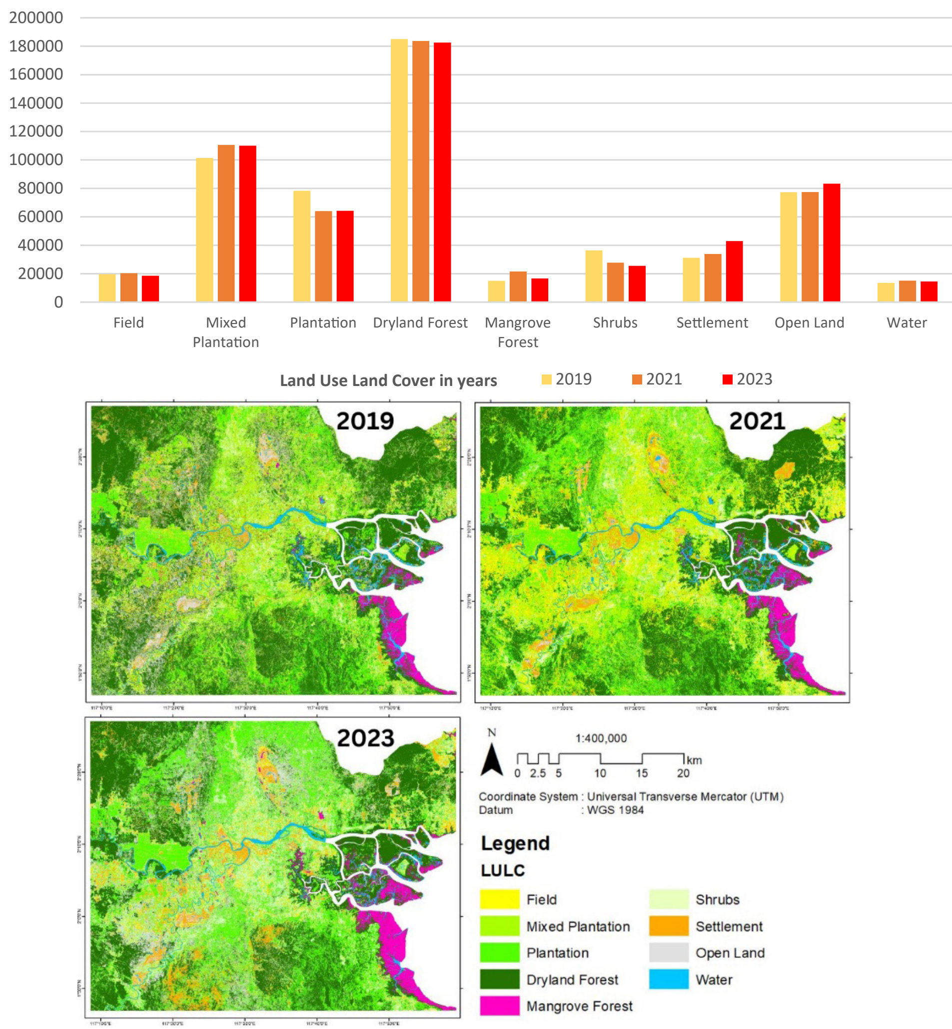

Fig. 4. Area changes in each LULC class expressed in hectars (a);
LULC maps for 2019, 2020, and 2023 (ordered from top to bottom) using nine classes (b)

Source: Data Processing, 2024

The analysis revealed significant dynamics in several land-use categories. The settlement class showed a consistent increase in area throughout the period, thus indicating a trend of urbanization and the expansions of built-up areas [29]. This was accompanied by increases in the open-land category, which suggested new land-clearing activities that were likely associated with infrastructure development or other land-conversion processes [30].

The dryland forest class remained relatively stable, with a slight increase observed in 2023; this was possibly linked to conservation policies or natural reforestation processes. Meanwhile, the mangrove forest and water body categories did not exhibit significant changes, thus indicating that these ecosystems remained relatively stable during the observation period.

Conversely, there was a noticeable decline in the plantation, mixed plantation, and shrub classes. This decline could be interpreted as a result of land-use conversion toward more-intensive uses such as settlement and development activities. The field class also showed a slight decrease, potentially reflecting a shift in agricultural land-use orientation. Urbanization and infrastructure development (particularly in the city's central, northern, and southern regions) have driven the expansions of built-up areas. In contrast, the southern and eastern regions experienced deforestation and the conversions of forest lands into open lands.

3.3. LULC Dynamics for Study Periods of 2019, 2020, and 2023

Information on the extent and percentage of LULC changes that were generated from the Sentinel-2 imagery is presented in Table 2. This table outlines the various LULC classes that have experienced changes from 2019 through 2023. Spatiotemporal and spatial analyses indicated a growing trend in LULC – particularly within the settlement and open-land classes.

The results of the calculations revealed that the settlement class experienced the highest change trend during the 2021–2023 period, encompassing an area of 9,192.33 ha (which represented a 21.39% increase). Furthermore, the most significant change in the settlement class also occurred between 2019 and 2023, with a total area of 11,768.61 ha and a percentage change of 27.39%.

Another LULC category that witnessed an increase in area was open land, which showed the highest change during the biennial period from 2021 to 2023 (with an area of 5,878.19 ha – translating to a 7.05% increase). Conversely, dryland forests and shrubs exhibited declining trends in area. The decrease in the dryland forest area was recorded at 1,139.49 ha, reflecting a 0.7% reduction; meanwhile, shrubs experienced a substantial decline over the two years from 2019 to 2021, with a percentage decrease of 31.55% (equivalent to approximately 8,742.07 ha). In conclusion, the identified LULC changes highlighted a pattern of rapid urbanization that was characterized by the expansions of settlements and open land, while the areas of forests and shrubs diminished.

Table 2. Area and annual percentage of LULC changes

LULC Class	Change					
	Area [ha]			Annual Percentage [%]		
	2019–2021	2021–2023	2019–2023	2019–2021	2021–2023	2019–2023
Field	684.10	−1,834.87	−1,150.78	3.36	−9.92	−6.22
Mixed Plantation	9,227.84	−583.38	8,644.45	8.34	−0.53	7.86
Plantation	−14,309.15	259.83	−14,049.33	−22.36	0.40	−21.87
Dryland Forest	−1,282.90	−1,139.49	−2,422.40	−0.70	−0.62	−1.33
Mangrove Forest	6,571.32	−4,872.87	1,698.46	30.54	−29.27	10.20
Shrubs	−8,742.07	−2,180.73	−10,922.79	−31.55	−8.54	−42.79
Settlement	2,576.27	9,192.33	11,768.61	7.63	21.39	27.39
Open Land	111.55	5,878.19	5,989.74	0.14	7.05	7.19
Water	1,563.03	−596.10	966.94	10.35	−4.11	6.66

Source: Data Processing, 2024

3.4. Area Change and Annual Percentage of Change

A comparative analysis was conducted on key parameters, including NTL, LULC, and environmental factors such as rainfall and surface temperatures across the years of 2019, 2021, and 2023. Within the LULC classification, residential areas represent the built-up zones, while open lands indicate those areas that have been converted from vegetated to non-vegetated cover. Vegetation includes various types, such as dryland forests, shrubs, plantations, mixed plantations, and mangrove forests.

The considered environmental parameters included climatic variables such as precipitation and surface temperature. As shown in Table 3, the period from 2019 to 2023 witnessed a significant increase in the area that was exposed to night-time illumination. The findings revealed a substantial increase in those areas that were exposed to night-time illumination – from 3,410.16 ha in 2019 to 7,119.01 ha in 2023. This growth reflected the expansion of urban development, infrastructure, and night-time economic activities. Similarly, residential areas expanded significantly – from 31,203.29 ha in 2019 to 42,971.89 ha in 2023. This change likely resulted from accelerated urbanization, population migration, and land conversion, which were driven by economic development and demographic shifts from rural to urban areas.

Table 3. Temporal changes in land-use and environmental parameters (2019–2023)

Year	Nightlights [ha]	Settlement [ha]	Open Land [ha]	Vegetation [ha]	Rainfall [mm]	Temperature [°C]
2019	3,410.16	31,203.29	77,370.33	435,725.54	6,710.5	28.5
2021	6,173.13	33,779.56	77,481.88	427,874.68	6,931.5	29.5
2023	7,119.01	42,971.89	83,360.07	417,523.16	7,512.0	30.5

Source: Data Processing, 2024

Open land also increased from 77,370.33 ha in 2019 to 83,360.07 ha in 2023, thus indicating a potential rise in deforestation, land clearing for construction, or reduced agricultural activity. In contrast, vegetation cover declined from 435,725.54 ha to 417,523.16 ha over the same period. This decrease suggested the conversions of natural landscapes into settlements or open lands, which could have led to negative environmental impacts such as reduced air quality, disruptions of the water cycle, and losses of biodiversity habitats [31].

Environmental variables also experienced changes. Rainfall rose from 6,710.5 mm in 2019 to 7,512.0 mm in 2023, which may reflect shifts in climate patterns or increased seasonal variability associated with climate change. Similarly, the average temperature increased from 28.5°C to 30.5°C. This gradual rise suggested the influence of global warming and may have intensified the urban-heat-island effect, particularly as urbanization accelerated and vegetative cover diminished [32]. The rising temperatures could have adversely impacted human health, agricultural productivity, and local climate regulations.

In summary, the region has undergone substantial transformations due to urbanization and potential climate change. The expansions of residential areas and increased nightlight exposure have reflected rapid development, while the reductions in vegetation and increases in open land have signaled a shift from natural to constructed or undeveloped landscapes. Environmental indicators have further reinforced this trend, with rising temperatures and rainfall variability suggesting broader climatic impacts. These changes highlight the need for integrated land-use planning and environmental management to mitigate adverse effects on ecosystems and human well-being.

3.5. Rainfall and Temperature Distribution over Berau Regency

The following image depicts the distributions of rainfall and temperatures in Berau Regency. The most notable changes that could be observed during the analysis period included reductions in precipitation levels and increases in temperatures. These alterations could be attributed to the phenomenon of urban sprawl [33]. The persistent decline in rainfall may have indicated a shift in climate patterns, which could have had potentially negative impacts on local ecosystems and agricultural productivity.

Figure 5 shows the spatiotemporal variation of LST and rainfall from 2019 through 2023.

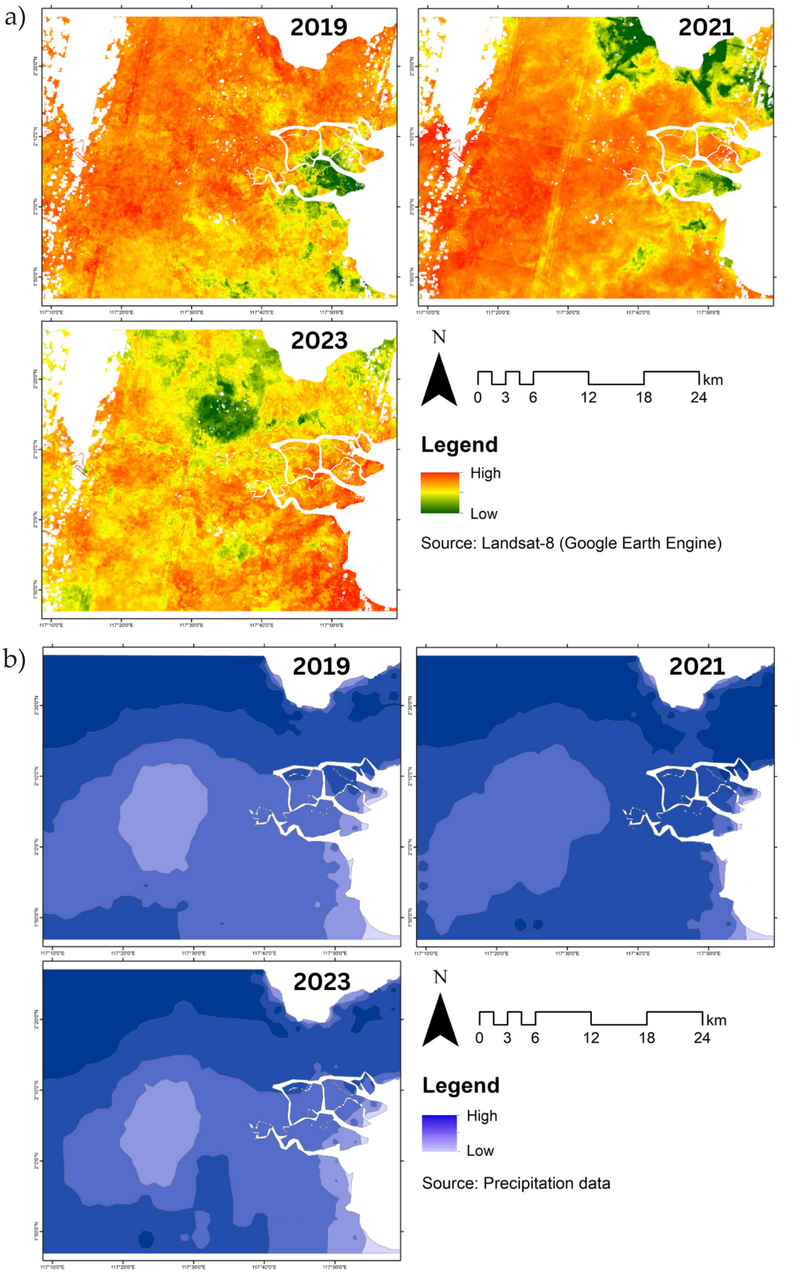

Fig. 5. Annual rainfall (a) and temperature (b) trends for 2019, 2021, and 2023

Source: Data Processing, 2024

The built-up and open-land areas recorded the highest LST values (31–34°C), while the forested and mangrove zones maintained cooler profiles (20–21°C). This supported the hypothesis that vegetation played a key role in surface cooling through evapotranspiration. Meanwhile, rainfall remained at the highest levels (7,000–8,000 mm/year) in the densely vegetated zones, whereas urban and open areas received lower precipitation (5,000–6,000 mm/year).

3.6. Correlation of LULC with Rainfall and LST

A comparative analysis was conducted on the key parameters, including NTL, LULC, and environmental factors such as rainfall and LSTs for the years of 2019, 2021, and 2023. In the LULC classification, settlement areas represented built-up zones, while open land indicated those areas that had been converted from vegetated to non-vegetated surfaces. Vegetation in this context included various land cover types such as dryland forests, shrubs, plantations, mixed plantations, and mangrove forests.

The environmental parameters that were analyzed included rainfall and LSTs. As shown in Table 3, there was a significant increase in the extents of those areas that were exposed to night-time lighting from 2019 to 2023 (3,410.16–7,119.01 ha). This finding reflected the expansions of built-up areas, increased infrastructures, and intensified night-time economic activities. Similarly, settlement areas increased from 31,203.29 ha to 42,971.89 ha; this growth was most likely due to accelerated urbanization, population growth, and the conversions of natural vegetation into built-up zones.

The expansion of open land from 77,370.33 ha to 83,360.07 ha indicated ongoing deforestation, land clearing for construction, or unsustainable agricultural land conversion. Conversely, the extents of vegetated areas decreased from 435,725.54 ha in 2019 to 417,523.16 ha in 2023. This shift from natural to built-up landscapes has had serious environmental impacts, including reduced air quality, disrupted hydrological cycles, and losses of biodiversity habitats.

In terms of environmental variables, rainfall increased from 6,710.5 mm in 2019 to 7,512 mm in 2023; this indicated a shift in climate patterns or increased seasonal variabilities that were linked to global climate change. Similarly, the average temperature rose from 28.5°C to 30.5°C; this temperature increase aligned with the expansions of built-up areas and reductions in vegetation cover, reflecting the impacts of global warming (which exacerbated the urban-heat-island effect). This phenomenon could have negatively affected public health, agricultural productivity, and local climate regulations.

The relationships among LULC, LST, and rainfall were further analyzed to understand the interconnections among these variables, as illustrated in Figure 6. The figure presents the relationships between LULC classes and LST for 2019, 2021, and 2023 (Fig. 6a–c), as well as the relationships between LULC classes and rainfall for the same years (Fig. 6d–f).

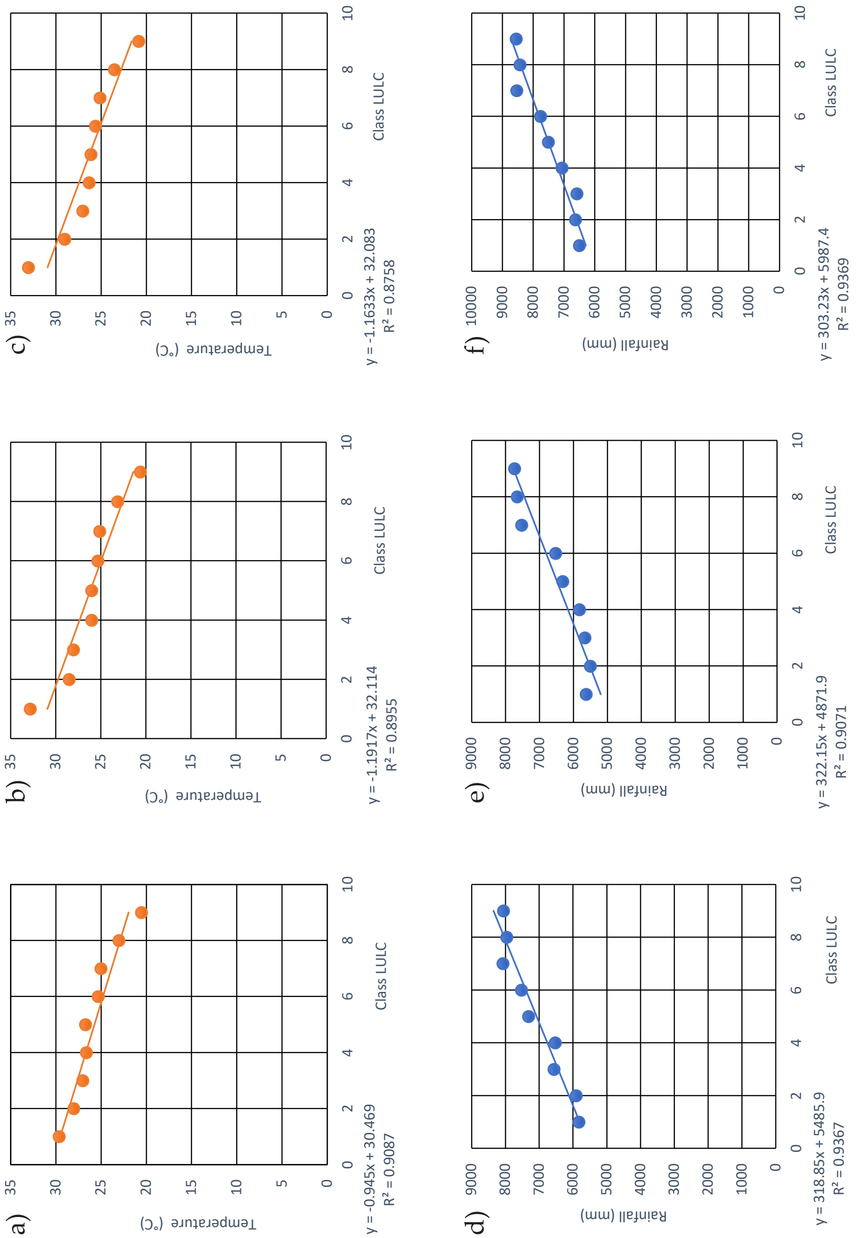

Fig. 6. Relationships among LULC classes, LST, and precipitation: relationships between LULC and LST for 2019, 2021, and 2023 (a, b, and c, respectively); relationships between LULC and rainfall for 2019, 2021, and 2023 (d, e, and f, respectively)

Source: Data Processing, 2024

The LULC classes were numerically labeled from 1 to 9, with the following categories: settlements (1), open lands (2), shrubs (3), fields (4), mixed plantations (5), plantations (6), dryland forests (7), mangrove forests (8), and water bodies (9). The analysis showed a significant correlation between the LULC classes and LST. In the settlement and open-land classes, LST temperatures tended to be higher (31–34°C). This was consistent with the previous findings that showed that low-vegetation areas absorbed more heat and intensified the urban-heat-island effect [34, 35].

In contrast, those areas with vegetative covers such as dryland forests and mangrove forests showed lower LST values (20–21°C). The vegetation acted as a natural cooling system through the process of evapotranspiration, which released latent heat and lowered surface temperatures. Additionally, a pattern was found between LULC and rainfall distribution. Non-vegetated areas such as settlements and open lands tended to receive lower rainfall levels (ca. 5,000–6,000 mm/year), whereas forested and highly vegetated areas received higher levels of rainfall (ca. 7,000–8,000 mm/year). This indicated the critical role of vegetation in maintaining humidity, strengthening the hydrological cycle, and enhancing cloud formation [36, 37].

Ecologically, vegetation contributes significantly to temperature and rainfall patterns through physical-biological interactions with the atmosphere. The evapotranspiration process not only reduces surface temperatures but also increases cloud formations and local rainfall. Vegetation also influences energy distribution by balancing latent and sensible heat fluxes, thus supporting micro- to regional-scale cooling [38]. On a larger scale, dense vegetation such as tropical forests plays a vital role in dampening heatwaves and increasing moisture retention. Recent studies have revealed that the presence of vegetation also mitigates the severity of climate-related disasters such as droughts and enhances ecosystem resilience to climate change [39].

4. Conclusion

This study demonstrates the strong interplay among urban expansion, vegetation loss, and environmental changes in Berau Regency between 2019 and 2023. Using integrated remote-sensing data including night-time lights (NTL), land use/land cover (LULC), land surface temperatures (LSTs), and precipitation, our findings confirmed that built-up area expansion correlated with increased NTL intensity, rising temperatures, and reduced vegetated cover. Our key findings included the following:

1. The significant increase in built-up areas (11,768.6 ha) and NTL-lit regions (3,410.16–7,119.01 ha) indicated rapid urban growth.
2. The decline in vegetated land (−18,202.38 ha) mainly occurred in plantation and shrub areas, thus contributing to higher surface temperatures.
3. Surface temperatures rose by 2°C in built-up areas over the four years, thus confirming the urban-heat-island effect.
4. Vegetated areas consistently maintained lower temperatures (20–21°C) and received higher levels of precipitation (7,000–8,000 mm/year), thus underscoring their role in local climate regulation.

This study affirmed that the integration of NTL, LULC, and climatic variables constitutes an effective and scalable approach for monitoring urban growth and assessing its environmental implications – particularly in the secondary cities of Indonesia. The findings demonstrated that such an integration enables a comprehensive spatial understanding of the complex interactions among urban expansion, vegetation loss, and climate variability. Nonetheless, certain limitations must be acknowledged. The spatial resolution of the NTL data that was used (500 m) may have obscured finer spatial variations – especially in those areas with dense or small-scale settlements. Moreover, the reliance on annual temporal snapshots restricted the ability to capture intra-annual or seasonal climate dynamics, thus limiting a more nuanced interpretation of the temporal variability and short-term anomalies.

To overcome these constraints, future research is encouraged to utilize higher-resolution spatial data sets such as PlanetScope or VIIRS-DNB and adopt multi-temporal analyses that incorporate monthly or seasonal observations. Additionally, the application of advanced modeling techniques, including spatiotemporal regression or land-use-change-forecasting models, could further elucidate causal relationships and provide robust projections of urban-environmental dynamics over time.

From a policy perspective, the results underscored the urgent need to integrate urban-development planning with environmental-management frameworks. Key actions include regulating uncontrolled land conversion, conserving existing vegetative covers, and promoting green infrastructures to mitigate the adverse effects of rising surface temperatures and hydrological imbalances. In the broader national context, the methodological framework that was adopted in this research holds significant potential for replication in other rapidly urbanizing regions of Indonesia. It provides a scientific data-driven foundation to support spatial planning, inform sustainable land-use policies, and guide climate-adaptation efforts, thereby aligning with national objectives for resilient and environmentally sustainable urban development.

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CRediT Author Contribution

S. M. P.: conceptualization, methodology, formal analysis, writing – review and editing, supervision, validation, funding acquisition, visualization.

L. A. K.: methodology, original draft preparation, writing – review and editing, formal analysis, validation, data curation, project administration.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work that is reported in this paper.

Data Availability

No data.

Use of Generative AI and AI-Assisted Technologies

No generative AI or AI-assisted technologies were used in the writing, editing, data analysis, or preparation of this manuscript.

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References

[1] Irawan H., Hartono D.: *Impact of urbanization on energy intensity in Indonesia: Spatial analysis*. Jurnal Perencanaan Pembangunan – The Indonesian Journal of Development Planning (JPP), vol. 6(2), 2022, pp. 202–215. https://doi.org/10.36574/jpp.v6i2.309.

[2] Hotswadi, Rarasati I., Nuzulia N.: *Investigation of the impact of the development of the Nusantara Capital City (IKN): Economic growth, output and employment*. Jurnal Ilmu Ekonomi, vol. 9(3), 2025, pp. 295–314. https://doi.org/10.22219/jie.v9i03.41926.

[3] Forbes V.L., Hamzah B.A.: *Relocating capital city to Nusantara will enhance regional shipping*. Indonesian Quarterly, vol. 51(1), 2023, pp. 6–27. https://journals.csis.or.id/index.php/iq/article/view/1884.

[4] Syaban A.S.N., Appiah-Opoku S.: *Unveiling the complexities of land use transition in Indonesia's New Capital City IKN Nusantara: A multidimensional conflict analysis*. Land, vol. 13(5), 2024, 606. https://doi.org/10.3390/land13050606.

[5] BPS Kabupaten Berau [Statistics Indonesia of Berau]: *Kabupaten Berau dalam Angka 2021* [Berau Regency in Figures 2021]. Berau 2021. https://beraukab.bps.go.id/id/publication/2021/02/26/f44b8329451b580830f5ed0e/kabupaten-berau-dalam-angka-2021.html [access: October 4, 2024].

[6] Fan C., Tian L., Zhou L.: *Examining the impacts of urban form on air pollutant emissions: Evidence from China*. Journal of Environmental Management, vol. 212, 2018, pp. 405–414. https://doi.org/10.1016/j.jenvman.2018.02.001.

[7] Pierri Daunt A.B., Sanna Freire Silva T., Bürgi M., Hersperger A.M.: *Urban expansion and forest reserves: Drivers of change and persistence on the coast of São Paulo State (Brazil)*. Land Use Policy, vol. 101, 2021, 105189. https://doi.org/10.1016/j.landusepol.2020.105189.

[8] Dai X., Wang L., Huang C.: *Spatio-temporal variations of ecosystem services in the urban agglomerations in the middle reaches of the Yangtze River*. Science of The Total Environment, vol. 747, 2020, 141541. https://doi.org/10.1016/j.scitotenv.2020.141541.

[9] Dupras J., Alam M.: *Urban sprawl and ecosystem services: A half-century perspective in the Montreal area (Quebec, Canada)*. Journal of Environmental Policy & Planning, vol. 17(2), 2015, pp. 180–200. https://doi.org/10.1080/1523908X.2014.927755.

[10] Halefom A., He Y., Nemoto T., Feng L., Li R., Raghavan V., Jing G., Song X., Duan Z.: *The impact of urbanization-induced land use change on land surface temperature*. Remote Sensing, vol. 16(23), 2024, 4502. https://doi.org/10.3390/rs16234502.

[11] Rendana M., Idris W.M.R., Abdul Rahim S., Abdo H.G., Almohamad H., Al Dughairi A.A., Al-Mutiry M.: *Relationships between land use types and urban heat island intensity in Hulu Langat district, Selangor, Malaysia*. Ecological Processes, vol. 12(1), 2023, 33. https://doi.org/10.1186/s13717-023-00446-9.

[12] Zhao L., Fan X., Hong T.: *Urban heat island effect: Remote sensing monitoring and assessment – methods, applications, and future directions*. Atmosphere, vol. 16(7), 2025, 791. https://doi.org/10.3390/atmos16070791.

[13] Zheng Q., Seto K.C., Zhou Y., You S., Weng Q.: *Nighttime light remote sensing for urban applications: Progress, challenges, and prospects*. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 202, 2023, pp. 125–141. https://doi.org/10.1016/j.isprsjprs.2023.05.028.

[14] Elvidge C.D., Baugh K., Zhizhin M., Hsu F.C., Ghosh T.: *VIIRS night-time lights*. International Journal of Remote Sensing, vol. 38(21), 2017, pp. 5860–5879. https://doi.org/10.1080/01431161.2017.1342050.

[15] Hasan S., Shi W., Zhu X., Abbas S.: *Monitoring of land use/land cover and socioeconomic changes in South China over the last three decades using Landsat and nighttime light data*. Remote Sensing, vol. 11(14), 2019, 1658. https://doi.org/10.3390/rs11141658.

[16] Huang Q., Yang X., Gao B., Yang Y., Zhao Y.: *Application of DMSP/OLS nighttime light images: A meta-analysis and a systematic literature review*. Remote Sensing, vol. 6(8), 2014, pp. 6844–6866. https://doi.org/10.3390/rs6086844.

[17] Shi K., Ma J., Chen Z., Cui Y., Yu B.: *Nighttime light remote sensing in characterizing urban spatial structure*. The Innovation Geoscience, vol. 1(3), 2023, 100043. https://doi.org/10.59717/j.xinn-geo.2023.100043.

[18] Badan Standardisasi Nasional (BSN): *Klasifikasi Penutup Lahan* [Land Cover Classification]. Standard Nasional Indonesia (SNI) 7645-2010, Jakarta 2010.

[19] Jensen J.R.: *Remote Sensing of the Environment: An Earth Resource Perspective* (2nd ed.). Prentice Hall (Pearson), Upper Saddle River 2007.

[20] Townshend J.R.G., Huang C., Kalluri S.N.V., Defries R.S., Liang S., Yang K.: *Beware of per-pixel characterization of land cover*. International Journal of Remote Sensing, vol. 21(4), 2000, pp. 839–843. https://doi.org/10.1080/014311600210641.

[21] Elvidge C.D., Baugh K., Zhizhin M., Hsu F.C., Ghosh T.: *VIIRS night-time lights*. International Journal of Remote Sensing, vol. 38(21), 2017, pp. 5860–5879. https://doi.org/10.1080/01431161.2017.1342050.

[22] Zhuang Q., Shao Z., Li D.: *Impact of global urban expansion on the terrestrial vegetation carbon sequestration capacity*. Science of The Total Environment, vol. 879, 2023, 163074. https://doi.org/10.1016/j.scitotenv.2023.163074.

[23] Wei X., Zhang W., Zhang Z., Huang H., Meng L.: *Urban land use land cover classification based on GF-6 satellite imagery and multi-feature optimization*. Geocarto International, vol. 38(1), 2023, 2236579. https://doi.org/10.1080/10106049.2023.2236579.

[24] Dissanayake D., Morimoto T., Murayama Y., Ranagalage M., Handayani H.H.: *Impact of urban surface characteristics and socio-economic variables on the spatial variation of land surface temperature in Lagos City, Nigeria*. Sustainability, vol. 11(1), 2018, 25. https://doi.org/10.3390/su11010025.

[25] Kii M., Matsumoto K., Sugita S.: *Future scenarios of urban nighttime lights: A method for global cities and its application to urban expansion and carbon emission estimation*. Remote Sensing, vol. 16(6), 2024, 1018. https://doi.org/10.3390/rs16061018.

[26] Bruederle A., Hodler R.: *Nighttime lights as a proxy for human development at the local level*. PLOS One, vol. 13(9), 2018, e0202231. https://doi.org/10.1371/journal.pone.0202231.

[27] Chen X.: *Nighttime lights and population migration: Revisiting classic demographic perspectives with an analysis of recent European data*. Remote Sensing, vol. 12(1), 2020, 169. https://doi.org/10.3390/rs12010169.

[28] Dong B., Zhang R., Li S., Ye Y., Huang C.: *A meta-analysis for the nighttime light remote sensing data applied in urban research: Key topics, hotspot study areas and new trends*. Science of Remote Sensing, vol. 11, 2025, 100186. https://doi.org/10.1016/j.srs.2024.100186.

[29] Aji A., Husna V.N., Purnama S.M.: *Multi-temporal data for land use change analysis using a machine learning approach (Google Earth Engine)*. International Journal of Geoinformatics, vol. 20(4), 2024, 3145. https://doi.org/10.52939/ijg.v20i4.3145.

[30] Gandharum L., Hartono D.M., Karsidi A., Ahmad M.: *Monitoring urban expansion and loss of agriculture on the north coast of West Java Province, Indonesia, using Google Earth Engine and intensity analysis*. The Scientific World Journal, vol. 2022, 2022, 3123788. https://doi.org/10.1155/2022/3123788.

[31] Danniswari D., Honjo T., Furuya K.: *Land cover change impacts on land surface temperature in Jakarta and its satellite cities*. IOP Conference Series: Earth and Environmental Science, vol. 501(1), 2020, 012031. https://doi.org/10.1088/1755-1315/501/1/012031.

[32] Ariska M., Suhadi, Supari, Irfan M., Iskandar I.: *Spatio-temporal variations of Indonesian rainfall and their links to Indo-Pacific modes*. Atmosphere, vol. 15(9), 2024, 1036. https://doi.org/10.3390/atmos15091036.

[33] Dissanayake D., Morimoto T., Murayama Y., Ranagalage M., Handayani H.H.: *Impact of urban surface characteristics and socio-economic variables on the spatial variation of land surface temperature in Lagos City, Nigeria*. Sustainability, vol. 11(1), 2018, 25. https://doi.org/10.3390/su11010025.

[34] Huang B., Huang Y., Wu D., Bao X., Wu Y.: *The influence of vegetation on climate elements in Northwestern China*. Atmosphere, vol. 15(3), 2024, 325. https://doi.org/10.3390/atmos15030325.

[35] Patel S., Indraganti M., Jawarneh R.: *Land surface temperature response to land use dynamics in urban areas of Doha, Qatar*. Sustainable Cities and Society, vol. 104, 2024, 105273. https://doi.org/10.1016/j.scs.2024.105273.

[36] Ren H., Wen Z., Liu Y., Lin Z.: *Vegetation response to changes in climate across different climate zones in China*. Ecological Indicators, vol. 155, 2023, 110996. https://doi.org/10.1016/j.ecolind.2023.110932.

[37] Derdouri A., Wang R., Murayama Y., Osaragi T.: *Understanding the links between LULC changes and SUHI in cities: Insights from two-decadal studies (2001–2020)*. Remote Sensing, vol. 13(18), 2021, 3654. https://doi.org/10.3390/rs13183654.

[38] Miralles D.G., Vilà-Guerau de Arellano J., McVicar T.R., Mahecha M.D.: *Vegetation-climate feedbacks across scales*. Annals of the New York Academy of Sciences, vol. 1544(1), 2025, pp. 27–41. https://doi.org/10.1111/nyas.15286.

[39] Martinuzzi F., Mahecha M., Camps-Valls G., Montero D.: *Learning extreme vegetation response to climate drivers with recurrent neural networks*. Nonlinear Processes in Geophysics, vol. 31(4), 2024, pp. 535–557. https://doi.org/10.5194/npg-31-535-2024.