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Climate Change Mitigation Towards the Lens of Urban Heat Island under Urban Forest Development

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ABSTRACT

Rapid urbanization and land-use change in Indonesian cities have led to urban heat islands, exacerbating air pollution. This situation elevates sensible heat, thereby compromising human thermal comfort. Palu City, situated in Central Sulawesi Province, Indonesia, has experienced significant urban heat island effects in recent decades. To mitigate this issue, increased development of green open spaces is necessary. This study prioritizes urban forest development in urban areas using a spatial analysis approach. We employ a weighting and scoring system based on vegetation indices, land cover, and air temperature parameters. Our study identified three priority areas with total areas of approximately 6,741 ha, 2,746 ha, and 20,695 ha for priorities 1, 2, and 3, respectively. This study prioritizes areas with high temperatures, low vegetation cover, and bare land for urban forest development. To effectively implement the proposed urban forest development plan, this study also highlights recommendations to create a more sustainable, resilient, and livable urban environment.

1. Introduction

Climate change, a significant challenge of the Anthropocene epoch, has far-reaching implications across diverse sectors. The increasing concentration of greenhouse gases in the atmosphere is a primary driver of global temperature rise (Brum et al. 2024; Zargari et al. 2024). Rising temperatures also influence other climate parameters, such as precipitation, increasing climate variability and uncertainty (Pendergrass 2017). Anthropogenic activities, including transportation, industry, and land use/land cover change, are major sources of greenhouse gas emissions (Barlow et al. 2016; Jiao et al. 2015). These intensive activities, concentrated in urban areas, contribute to the urban heat island effect, leading to higher air temperatures in urban areas compared to surrounding rural areas (Zargari et al. 2024).

Urban forest development is a key strategy for mitigating the urban heat island effect (Almeida et al. 2021). Urban forests can also help reduce greenhouse gas emissions, such as CO_2, through photosynthesis (Muslih et al. 2022). Additionally, urban forests can improve air quality by removing atmospheric pollutants. Urban forests can also intercept solar radiation, helping to regulate local climate conditions (Steenberg et al. 2023). Thus, urban forest development is crucial to create a better micro-climate situation in the cities.

The advent of satellite technology has revolutionized the landscape of urban planning and development. Integrating satellite data into urban planning has become increasingly sophisticated and indispensable (Almeida et al. 2021). From monitoring urban growth patterns to assessing environmental impacts, satellite technology offers a powerful tool for informed decision-making (Diem et al. 2024).

Palu City, situated in a tropical coastal region of Indonesia, faces a confluence of factors that heighten its vulnerability to climate change impacts, particularly concerning heat stress. The city's rapid urbanization contributes significantly to the expansion of impervious surfaces and the subsequent intensification of the urban heat island (UHI) effect. This phenomenon, wherein urban temperatures exceed those of surrounding areas, is further compounded by the broader context of global climate change (Sanjaya et al. 2022). Here, we provide a comprehensive study on determining the priority of green open-space development towards spatial perspectives by weighting and scoring through vegetation index, land cover, and air temperature parameters. The objectives of this research were: i) To estimate spatial air temperature in Palu City, ii) To identify current land cover in Palu City, iii) To determine priority locations for developing urban forest in Palu City, and iv) To provide recommendations for urban forest development in Palu City. In this research, we genuinely develop urban forest priority locations regarding the urban heat islands phenomenon in Palu City by using the coupled vegetation and temperature dimensional approach.

2. Materials and Methods

2.1. Study Area

This study was conducted in Palu City, Central Sulawesi, Indonesia, from September 2023 to April 2024 (**Fig. 1**). This city has been identified as a priority location for climate action and resilience initiatives in Indonesia (Bappenas 2021).

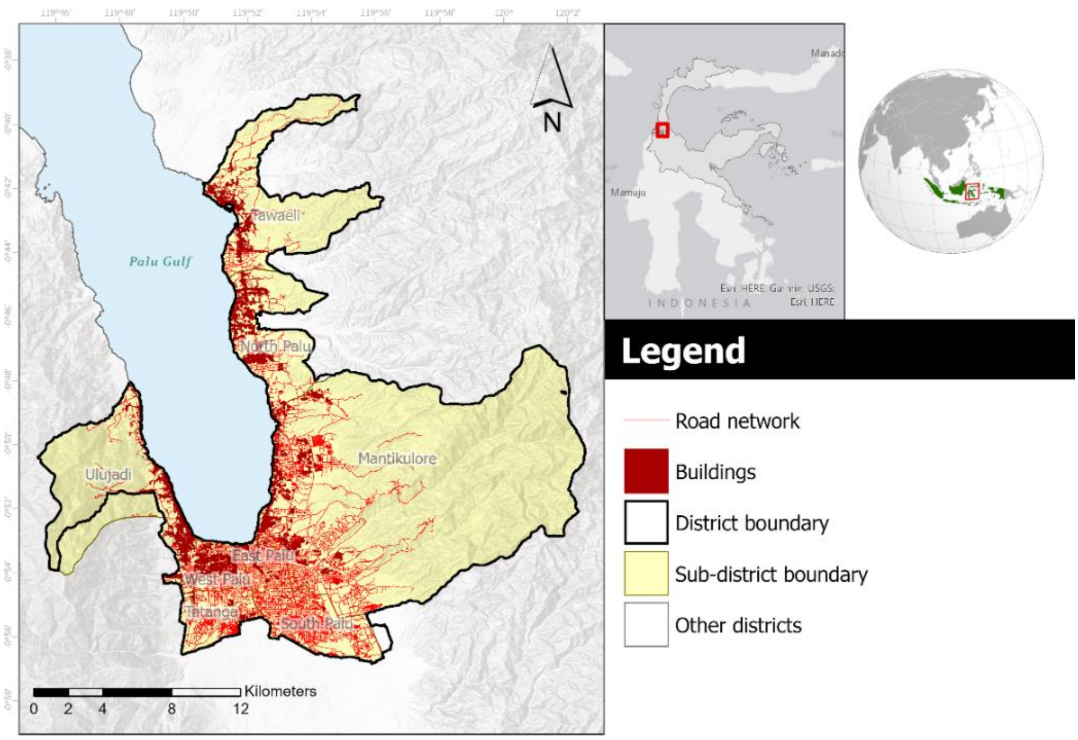

Fig. 1. Research location in Palu City, Central Sulawesi, Indonesia.

2.2. Data and Tools

This study employed Landsat 8 OLI/TIRS satellite imagery with a 30-meter spatial resolution to acquire data for Path/Row 114/61 (acquired on August 29, 2023 and September 14, 2023) and Path/Row 115/60 (acquired on August 20, 2023 and September 10, 2023), available from https://earthexplorer.usgs.gov/. Additional datasets were utilized to complement the satellite data, including the Palu City Spatial Plan 2021–2041, land cover reference data, administrative boundaries, and demographic data provided by the Palu City government. Data analysis and processing were conducted using ArcGIS Desktop 10.5, Google Earth Pro, Microsoft Word, and Microsoft Excel.

2.3. Research Flow

This study comprised several phases: i) Image composite: combining all available band imageries by using ArcGIS Desktop 10.5 with Composite Bands tool; ii) Image projection: the coordinate system of the provided images was adjusted to the UTM 50S zone; iii) Cloud removal: cloud and cloud shadow removal was implemented using the BQA band of Landsat 8 imagery, addressing the challenges outlined in Braaten et al. (2015); iv) Scene mosaic: adjacent scenes were combined to create a single mosaic covering the study area; v) Masking: the mosaicked image was clipped to the administrative boundaries of the study area; vi) Normalised difference vegetation index (NDVI) analysis; vii) Land cover identification; viii) Air temperature estimation; ix) Weighting and scoring analysis; x) NDVI, land cover, and air temperature maps overlay; and xi) Urban forest development priority identification. The flowchart of this study is provided in the **Fig. 2**.

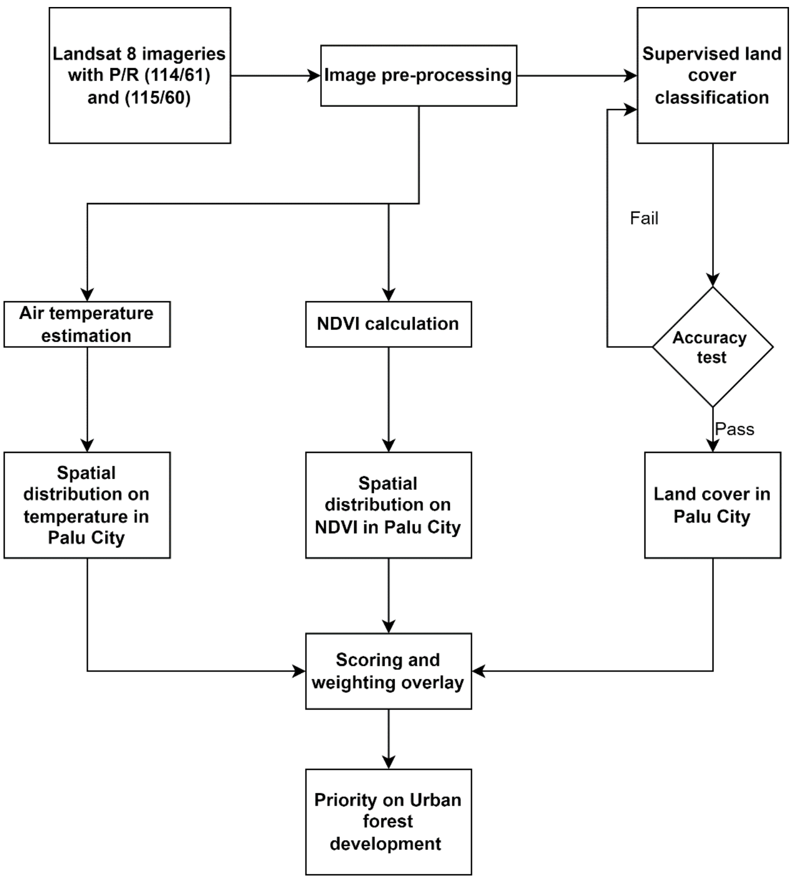

Fig. 2. Main flowchart of the study.

2.4. Data Analysis

ArcGIS Desktop 10.5 was employed to process the image data and derive land cover, vegetation index, and air temperature information. These derived datasets and the Palu City Spatial Plan were integrated through overlay analysis to identify priority areas for urban forest development. The prioritization process considered factors such as air temperature distribution, land cover characteristics, and vegetation index values. The resulting priority map delineated potential locations suitable for urban forest establishment, aligning with the city's spatial planning objectives.

2.4.1. Land cover identification

The land cover classification was conducted using a supervised maximum likelihood classification technique. Training areas, representing distinct land cover classes, were delineated based on spectral similarities and visual interpretation. The classification system employed in this study adhered to the guidelines of BSN (2014) and Bickel et al. (2006). The identified land cover classes included water bodies, built-up land, open land, tree vegetation, and non-tree vegetation.

To assess the accuracy of the land cover classification, a stratified random sampling approach was employed to select 200 sample points across each land cover class. A confusion matrix was used to compare the classified land cover with reference data collected in the field, following the methodology outlined by Congalton and Green (2008). According to Lillesand and Kiefer (2008), a classification accuracy of at least 85% is acceptable for remote sensing applications.

2.4.2. Vegetation index calculation

This satellite provides high-resolution data across multiple spectral bands, including the red and near-infrared bands, which are crucial for calculating the Normalized Difference Vegetation Index (NDVI). The NDVI, a widely recognized vegetation index (Rouse Jr. 1973), is derived from the following formula:

$$NDVI = \frac{NIR\text{-}Red}{NIR+Red} \quad (1)$$

where *NIR* is Near-Infrared Reflectance, and *Red* is red reflectance. Higher NDVI values indicate healthier and denser vegetation, while lower values suggest sparse or stressed vegetation. By analyzing the spatial and temporal patterns of NDVI, we can gain valuable insights into vegetation dynamics, land use changes, and the overall ecological health of the study area.

2.4.3. Air temperature calculation

According to (BSN 2001), thermal comfort in tropical regions is categorized into three levels: cool, optimal, comfortable, and warm. For this study, we focused on the warm and comfortable category, representing the upper limit of thermal tolerance for individuals in tropical environments. This temperature range falls between 25.8°C and 27.1°C. Consequently, areas exceeding 27.1°C were identified as priority zones for urban forest development. The analysis of air temperature distribution was calculated based on the surface energy balance model, following Mkhwanazi et al. (2015).

Spectral radiance

Spectral radiance was calculated by converting a digital number of Band 10 and 11 to spectral radiances (L_λ) as follows:

$$L_\lambda = M_L * Q_{cal} + A_L \tag{2}$$

where L_λ is spectral radiance (watt/(m^2 × srad × µm)), M_L is radiance multiplicative band conversion factor from metadata, A_L is radiance additive band conversion factor from metadata, and Q_{cal} is quantized and calibrated standard product pixel values (digital number).

Brightness temperature

Brightness temperature (TB) was calculated spectral radiance (Lλ) into brightness temperature (Tb) as follows:

$$TB = \frac{K2}{ln(\frac{K1}{L_\lambda} + 1)} \tag{3}$$

where TB is brightness temperature (Kelvin), L_λ is spectral radiance (watt/(m^2 × srad × µm)), $K2$ and $K1$ are constants band from metadata.

Vegetation proportion

Vegetation proportion (Pv) was calculated by deriving it from the Normalized Difference Vegetation Index (NDVI) using a mathematical equation as follows:

$$Pv = (\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}})^2 \tag{4}$$

where Pv is the proportion of vegetation, $NDVI_{max}$ is the maximum value of NDVI, and $NDVI_{min}$ is the minimum value of NDVI.

Emissivity

Emissivity (ε) was calculated by deriving it from the vegetation proportion (Pv) using an empirical equation as follows:

$$\varepsilon = (0.004 \times Pv) + 0.986 \tag{5}$$

where Pv is the proportion of vegetation.

Land surface temperature

Land surface temperature (Ts) was calculated by applying the brightness temperature (TB) and surface emissivity (ε) using the radiative transfer equation as follows:

$$Ts = \frac{TB}{1 + \left(\frac{\lambda * TB}{\sigma}\right) * ln(\varepsilon)} \tag{6}$$

where TB is brightness temperature (Kelvin), ε is emissivity, λ is the wavelength of the band (µm), and σ is the Stefan-Boltzmann constant.

Net radiation calculation

Net radiation (Rn) was calculated by combining incoming and outgoing shortwave and longwave radiation using the surface energy balance equation as follows:

$$Rn = RSin - (RSout + RLout) \quad (7)$$

where Rn is net radiation (Wm^{-2}), $RSin$ is incoming shortwave radiation (Wm^{-2}), $RSout$ is outgoing shortwave radiation (Wm^{-2}), and $RLout$ is outgoing longwave radiation (Wm^{-2}).

Shortwave outgoing radiation

Shortwave outgoing radiation (RSout) was calculated by summing the contributions of spectral radiance from multiple bands, considering the solar distance and wavelength, as follows:

$$RSout = \pi \times L_{\lambda n} \times d^2 \times \frac{1}{band\ n} \quad (8)$$

where $RSout$ is outgoing shortwave radiation (Wm^{-2}), n is band number, L_λ is spectral radiance (watt/(m^2 × srad × µm)), d is the distance from solar to earth (from metadata), *1/band* is the mean of wavelength value for each band.

Albedo calculation

Albedo calculation (α) is calculated with the following equation:

$$\alpha = \frac{L_{\lambda n} \times Maximum\ reflectance}{Minimum\ radiance \times Cos(\theta)} \quad (9)$$

where θ is the zenith solar angle.

Incoming shortwave solar radiation

Incoming shortwave solar radiation (*RSin*) was calculated by relating it to outgoing shortwave radiation (RSout) and surface albedo (α) as follows:

$$RSin = \frac{RSout}{\alpha} \quad (10)$$

where $RSout$ is the outgoing shortwave radiation (Wm^{-2}), and α is albedo.

Outgoing longwave radiation

Outgoing longwave radiation (RLout) was calculated by applying the Stefan-Boltzmann law, which relates surface temperature to radiative energy emission, as follows:

$$RLout = \varepsilon \times \sigma \times Ts^4 \quad (11)$$

where Ts is the surface temperature (Kelvin), and σ is Stefan Boltzmann constant (5.67×10^{-8} $Wm^{-2}K^{-4}$).

Soil heat flux

Soil heat flux (G) was calculated by relating it to emissivity (ε) and net radiation (Rn) using an empirical equation as follows:

$$G = \varepsilon \times Rn \quad (12)$$

where ε is emissivity and Rn is net radiation ($W\ m^{-2}$).

Sensible heat flux

Sensible heat flux (H) was calculated by using the Bowen ratio (β) to partition the available energy between sensible and latent heat fluxes, as follows:

$$H = \frac{\beta(Rn - G)}{1 + \beta} \quad (13)$$

where β is the Bowen ratio, Rn is net radiation (W m^{-2}), and G is soil heat flux (W m^{-2}).

Air temperature calculation

Air temperature (Ta) was calculated by incorporating aerodynamic resistance, air density, and specific heat capacity under constant pressure as follows:

$$Ta = Ts - \left(\frac{H \times raH}{\rho air \times Cp}\right) \quad (14)$$

where raH is aerodynamic resistance (sm^{-1}), ρair is air density (1.27 kg m^{-3}), and Cp is air-specific heat conductivity under constant pressure (1004 $Jkg^{-1}K^{-1}$). Subsequently, the temperature values were converted from Kelvin to Celsius by subtracting 273.15.

2.4.4. Air temperature calculation

A scoring and weighting approach was employed to prioritize areas for urban forest development. This method assigns scores to each criterion or parameter to assess land potential. Additionally, weighting is applied to prioritize parameters based on their relative importance. **Table 1** presents the assigned scores and weights for each parameter. Air temperature receives the highest weight (55%), indicating it is the most critical factor in prioritizing urban forest development. This aligns with the primary function of urban forests in mitigating the urban heat island effect. Numerous studies emphasize the correlation between tree canopy cover and temperature reduction (Giraldo-Charria et al. 2025; Simonson et al. 2021). Weighting land cover at 25% acknowledges its importance in determining the feasibility and impact of urban forest development. Prioritizing bare land and non-tree vegetation suggests focusing on areas where tree planting is most achievable and can greatly improve ecological conditions. Research supports targeting impervious surfaces and barren areas for green infrastructure interventions (Ahern et al. 2014). NDVI is given the lowest weight as a measure of existing vegetation. This is consistent with the development of new urban forests. The scoring system appropriately assigns the highest scores to areas with the lowest NDVI, as these areas need the most vegetation. Research has used NDVI to assess vegetation cover and its relationship with urban heat islands (Zhao et al. 2020).

Air temperature, land cover, and NDVI data were reclassified into predefined classes to prioritize areas for urban forest development. These reclassified datasets were then integrated through an overlay analysis. Subsequently, a scoring and weighting system was applied to assign values to each parameter, reflecting its relative importance. A priority value was calculated for each area by summing the weighted scores. Finally, these priority values were categorized into specific intervals to determine the corresponding priority level, as detailed in **Table 2**.

The priority map for urban forest development was overlaid with the Palu City Spatial Plan to identify areas aligned with the existing land use plan. This integrated analysis ensures that the proposed urban forest development is compatible with the city's overall spatial planning objectives.

Table 1. Parameters used in scoring and weighting analysis

No	Parameter	Class	Score	Weight
1	Air temperature	> 27.1°C	3	55%
		25.8°C – 27.1°C	2	
		< 25.8°C	1	
2	Land cover	Bareland	3	25%
		Non-tree vegetation	2	
		Tree vegetation	1	
		Waterbodies	-	
		Built-up area	-	
3	NDVI	0 – 0.2	4	20%
		0.21 – 0.4	3	
		0.41 – 0.6	2	
		0.61 – 1	1	
		< 0	-	

Table 2. Urban forest development priority value

Priority class	Probability value
1	2.47 – 3.2
2	1.74 – 2.46
3	1 – 1.73

3. Results and Discussion

3.1. General Conditions

Palu City, located in Central Sulawesi, Indonesia, has been experiencing a significant rise in air temperatures. This trend is exacerbated by a growing population, necessitating increased urbanization and subsequent loss of green open spaces. The combination of urban expansion and air pollution has intensified the urban heat island effect, leading to higher temperatures within the city than surrounding areas.

Between 2000 and 2023, Palu City's population surged from 269,083 to 387,493 (BPS 2024). This rapid population growth has directly impacted land use patterns, with increasing demands for built-up areas and a corresponding decline in green open spaces. These changes in land cover have contributed to the intensification of the urban heat island effect.

3.2. Vegetation Conditions

Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), are widely utilized in remote sensing to assess vegetation health, density, and biomass (Zeng et al. 2022). Healthy vegetation exhibits high near-infrared (NIR) reflectance and low red reflectance, while sparse vegetation demonstrates the opposite pattern. The NDVI, calculated as the difference between NIR and red reflectance divided by their sum, quantifies this spectral contrast. Higher NDVI values indicate denser and healthier vegetation, whereas lower values signify lower vegetation cover or stress (Wei and Fang 2024). Landsat 8, with its high-resolution multispectral imagery, provides valuable data for NDVI calculations, enabling accurate monitoring of vegetation dynamics and ecosystem health (Ke et al. 2015).

Landsat 8 bands 4 and 5 analysis revealed an NDVI range of -0.202 to 0.622 across Palu City. The dominant NDVI values, ranging from 0.4 to 0.6, covered approximately 19,918 hectares, constituting 56% of the city's total area. **Fig. 3** visually depicts the spatial distribution of NDVI values within Palu City.

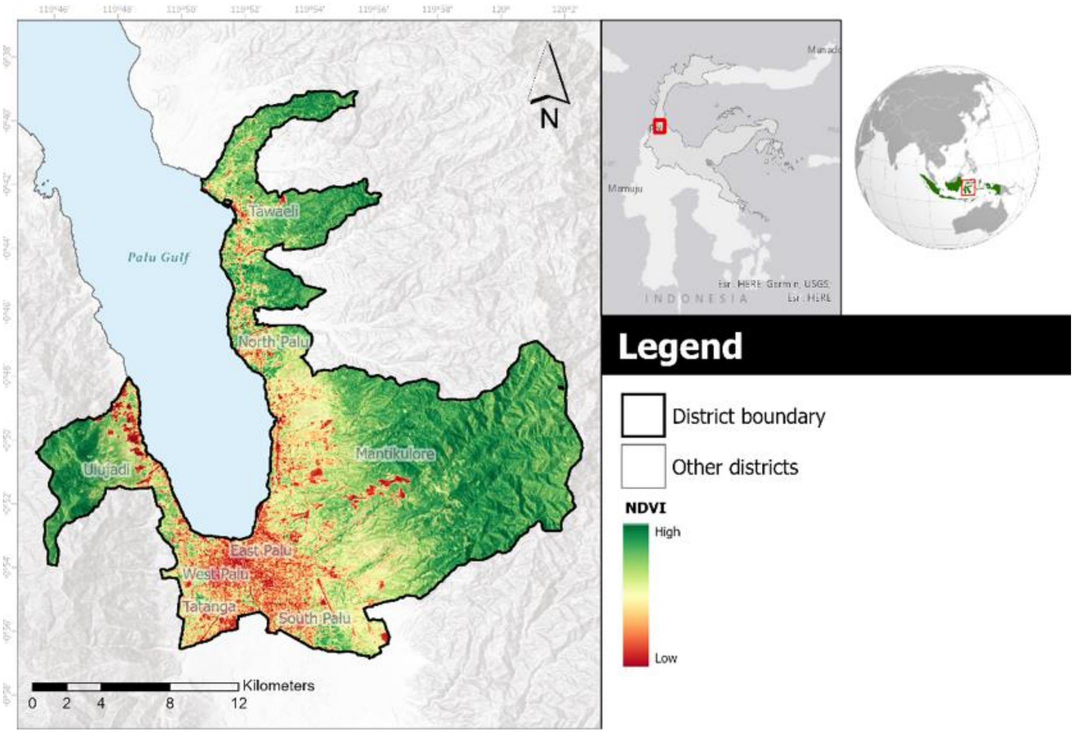

Fig. 3. NDVI map of Palu City, Indonesia.

3.3. Land Cover Situations

The land cover classification process yielded a promising overall accuracy of 90.70%, accompanied by a substantial Kappa coefficient of 86.18%. These metrics indicate a high degree of agreement between the classified land cover map and the ground truth data used for validation. Critically, the overall accuracy and the Kappa coefficient comfortably exceed the 85% benchmark recommended by Lillesand and Kiefer (2008) for reliable land cover classification. This signifies the robustness of the classification methodology and underscores the high quality and reliability of the resulting land cover type map.

Dominating the land cover of Palu City is non-tree vegetation, accounting for 48% (17,153 ha) of the total area. Tree vegetation follows, covering 35% (12,389 ha). Built-up land constitutes 15% (5,426 ha), while open land and water bodies comprise 2% (717 ha) and 0.04% (14 ha), respectively. **Fig. 4** illustrates the spatial distribution of these land cover classes. Notably, vegetated land is predominantly concentrated in suburban and rural areas.

3.4. Air Temperature Conditions

The urban heat island effect, characterized by elevated temperatures within urban areas, is evident in Palu City. Spatial analysis of Landsat 8 satellite imagery revealed that air temperatures in Palu City range from a low of 11.4°C in Taweli District to a high of 33.9°C in Tatanga District. Districts with air temperatures exceeding 27.1°C, indicative of high thermal stress, include Mantikulore (3,925 ha), South Palu (1,740 ha), Ulujadi (1,194 ha), Tatanga (1,156 ha), North Palu (1,016 ha), West Palu (644 ha), East Palu (554 ha), and Tawaeli (506 ha), in descending order of area (**Fig. 5**).

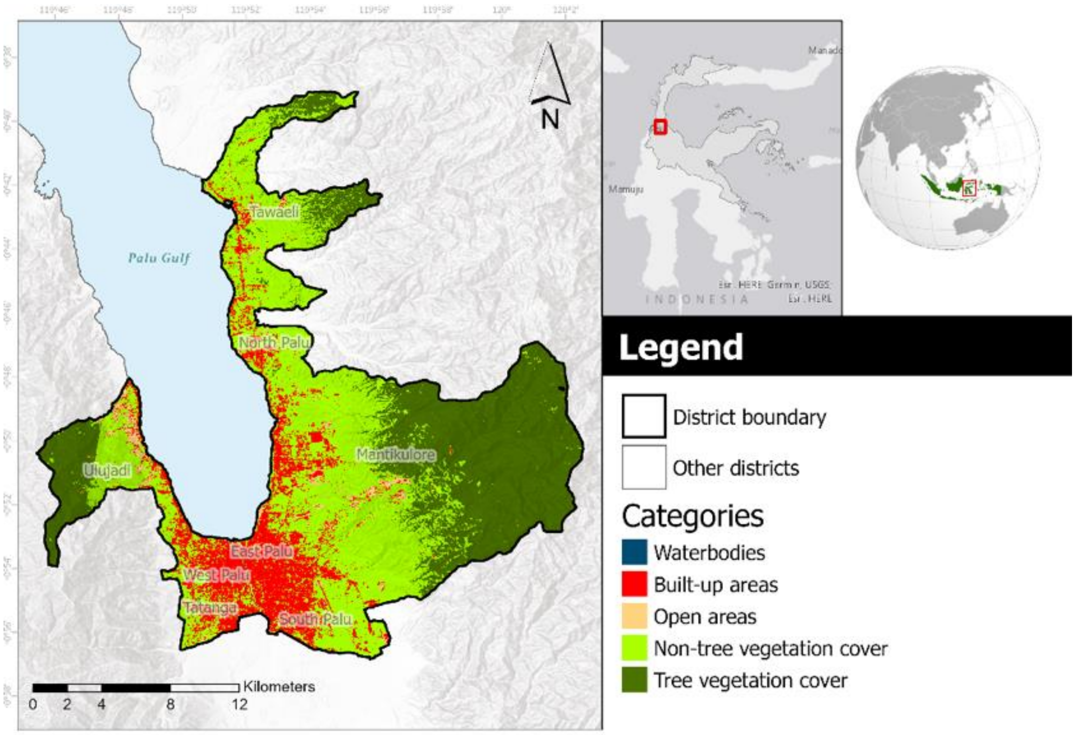

Fig. 4. Current land cover map of Palu City, Indonesia.

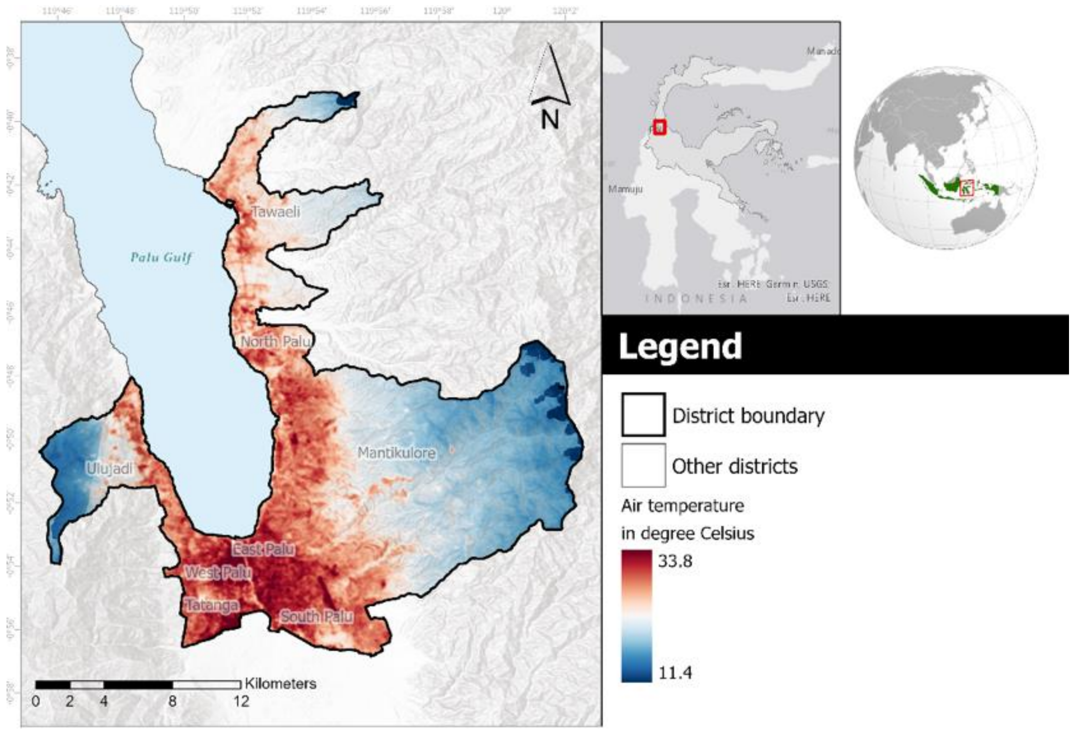

Fig. 5. Spatial air temperature distribution of Palu City, Indonesia.

3.5. Priority of Urban Forest Development

The prioritization of urban forest development was determined through a comprehensive analysis integrating air temperature distribution, land cover, and NDVI data. A scoring and weighting methodology was employed to assess the relative importance of these factors. The resulting priority levels for urban forest development are presented in **Table 3**.

Table 3. Priority of urban forest development in Palu City, Indonesia

Subdistrict	Total area (ha)			Total
	Priority 1	Priority 2	Priority 3	
Mantikulore	2,949	1,080	14,162	18,190
West Palu	149	27	1	176
South Palu	830	138	88	1,056
East Palu	62	1	0	62
North Palu	870	470	1,040	2
Tatanga	590	25	11	625
Tawaeli	429	734	2,935	4,098
Ulujadi	862	271	2,458	3,591
Total	**6,741**	**2,746**	**20,695**	**27,800**

Priority 1, encompassing 6,741 ha, is the highest priority for urban forest development across all sub-districts of Palu City. This area predominantly comprises non-tree vegetation (90%) and open land (10%). Prioritizing this area for urban forest development would significantly mitigate the urban heat island effect and create a more favorable microclimate. Priority 2, covering 2746 hectares, is largely dominated by non-tree vegetation (98%), with minor proportions of open land (1.6%) and tree vegetation (0.4%). Developing urban forests in this area would also help alleviate the urban heat island effect and improve local climate conditions. Priority 3, spanning 20,695 hectares, is characterized by a significant proportion of tree vegetation (60%) and non-tree vegetation (40%). While this area already possesses a substantial amount of green cover, formal designation as a city forest through legal procedures would ensure its protection and sustainable management.

Fig. 6 visually represents the prioritized areas for urban forest development in Palu City. By strategically implementing urban forest initiatives in these identified priority areas, Palu City can significantly enhance its ecological resilience, improve air quality, and create a more sustainable urban environment.

Landsat 8 thermal imagery analysis revealed a distinct urban heat island effect in Palu City. Land surface temperature (LST) analysis showed that areas classified as Priority 1, characterized by predominantly non-tree vegetation (90%) and open land (10%), had an average LST of 32°C. This was significantly higher than the average LST of 28°C observed in Priority 3 areas, which have a substantial amount of tree vegetation (60%). This 4°C difference highlights the strong influence of vegetation cover on urban temperatures. Priority 2 areas, mostly non-tree vegetation (98%), exhibited an average LST of 31°C. These findings demonstrate a clear correlation between lower vegetation cover and higher LST, supporting the prioritization of these areas for urban forest development to mitigate the urban heat island effect.

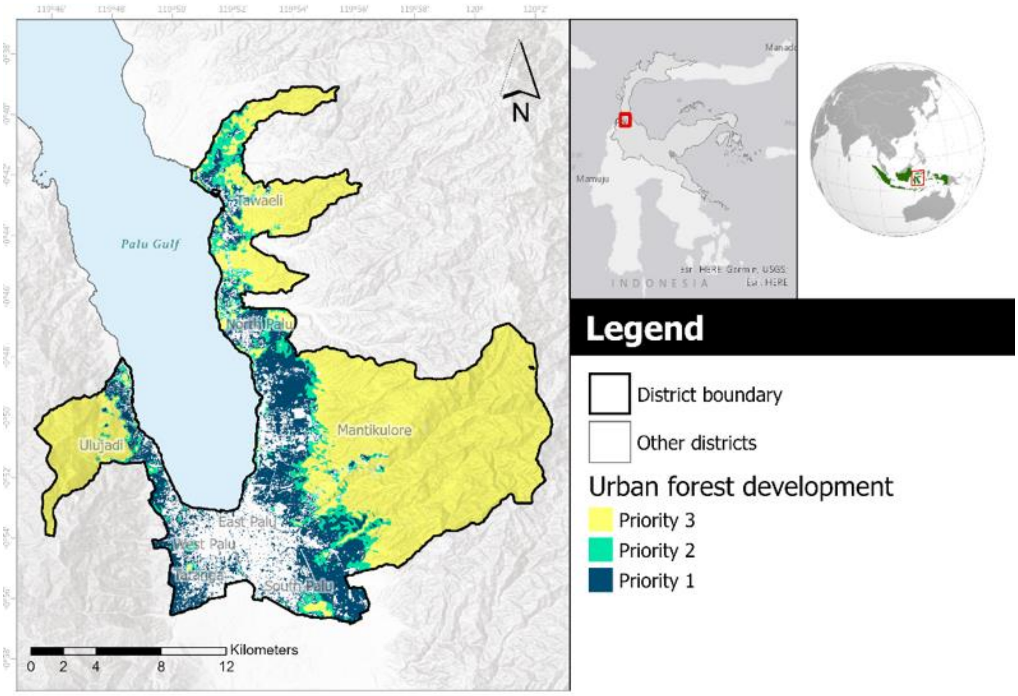

Fig. 6. Priority of urban forest development in Palu City, Indonesia.

The following recommendations are suggested for implementing the proposed urban forest development plan: i) Conduct comprehensive site assessments to identify specific locations within the prioritized areas suitable for planting trees. Consider factors such as soil quality, topography, and existing infrastructure (Scharenbroch et al. 2017; Vasenev et al. 2021); ii) Involve local communities in planning and implementing urban forest projects. This can be achieved through workshops, public consultations, and collaborative decision-making processes (Almulhim et al. 2024); iii) Prioritize the use of native plant species that are well-adapted to local climatic conditions and soil types (Kandari et al. 2024). This approach can enhance biodiversity, reduce maintenance costs, and improve the overall ecological value of urban forests (Toledo-Garibaldi et al. 2023); iv) Establish a long-term monitoring program to assess the effectiveness of urban forest initiatives in mitigating the urban heat island effect, improving air quality, and enhancing biodiversity (Darmawan and Santoso 2024). This monitoring program should include regular assessments of tree growth, mortality rates, and ecosystem services provided by urban forests; v) Strong policy and institutional frameworks are essential for the successful implementation and maintenance of urban forests. Develop clear guidelines and regulations for urban forest planning, management, and funding (Bürgi et al. 2017; Freeman et al. 2015; Riggs et al. 2021).

4. Conclusions

This study demonstrates the effectiveness of multispectral and thermal satellite imagery in identifying priority areas for urban forest development in Palu City. Three priority areas were delineated, totaling approximately 6,741 ha, 2,746 ha, and 20,695 ha for priorities 1, 2, and 3, respectively. Priority 1 areas, spanning 6,741 hectares, are distributed across all sub-districts of Palu City. These areas, characterized by high temperatures, low vegetation cover, and bare land, represent optimal locations for urban forest development to mitigate the urban heat island effect and enhance local climatic conditions. While this study provides valuable insights into urban forest prioritization, it is important to acknowledge certain limitations. The accuracy of the land cover classification and temperature mapping is influenced by factors such as cloud cover, atmospheric conditions, and the spatial resolution of the satellite imagery. Additionally, the study primarily focuses on biophysical factors and may not fully account for socio-economic and institutional constraints that could impact the implementation of urban forest projects. To maximize the effectiveness of urban forest development, several key recommendations are proposed: i) site-specific planning, ii) community engagement, iii) native species prioritization, iv) long-term monitoring, and v) a strong policy framework.

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Author Contributions

S.B.R.: Conceptualization, Methodology, Software, Validation; N.N.A.: Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft Preparation; A.A.C. and Y.S.: Writing – Review and Editing, Visualization, Supervision, Project Administration, Funding Acquisition.

Conflict of Interest

The authors declare no conflict of interest.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation

During the preparation of this work, the authors used Grammarly and Gemini AI to enhance the clarity, readability, and ensure alignment with the scope and interests of this journal. After using these tools, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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