IJE | INDONESIAN JOURNAL OF ENERGY
P-ISSN: 2549-1016 | E-ISSN: 2549-760X
available online at www.ije-pyc.org

Published by:
The Purnomo Yusgiantoro Center

Illuminating Energy Efficiency: Satellite-Guided Insights for Optimizing Urban Street Lighting Across Indonesian Cities

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Article History

Received 25 June 2024
Accepted 06 January 2025
Available 27 February 2025

Abstract

Our study introduces an innovative method for enhancing urban energy management by integrating high-resolution nighttime satellite imagery from SDGSAT-1 with detailed ground-truth verification of street lighting in major cities across Central Java and the Special Region of Yogyakarta. Utilizing the Glimmer Imager for Urbanization (GIU) with 10-meter resolution, our research precisely identifies various urban streetlamp types and evaluates their impact on energy consumption. As urban expansion increases the demand for public street lighting, there is a pressing need for efficient energy management to support urban development and reduce environmental footprints. This study focuses on Semarang, Yogyakarta, and Solo, aiming to assess energy efficiency by examining the impact of different street lighting on energy usage across various road network types. We discover significant correlations, especially in the red spectral band by employing pan sharpening techniques to enhance image resolution and zonal statistics for in-depth analysis. These correlations suggest the potential of using SDGSAT-1 data to estimate energy consumed by street lighting where direct measurements are unavailable. The findings also reveal significant variations in energy consumption across different road types, attributed to varying traffic and lighting needs. By highlighting these disparities, we underscore the potential of transitioning to Light-Emitting Diode (LED) lighting, which can reduce energy consumption by up to 69%. Our research not only demonstrates the capabilities of satellite imagery in urban energy management but also offers practical insights for cities looking to improve lighting efficiency, reduce costs, and promote sustainability in urban planning.

Keywords:
energy efficiency, energy management, nighttime satellite imagery, street lighting

1. Introduction

As urbanization continues to shape the world, an increasing portion of the population is concentrated in cities (Jain, 2021). This urban shift places significant strain on infrastructure, particularly in terms of energy demands for public lighting. Local governments bear the financial responsibility of providing adequate street lighting to ensure public safety and urban functionality. However, the rising energy costs present a challenge to sustainable urban development. Effective energy management is essential for cities to optimize their lighting systems, reduce operational expenses, and minimize their environmental footprint (Guittet, 2012; Radulovic et al., 2011).

Public street lighting plays a crucial role in ensuring vibrant and safe urban life during nighttime hours (van Bommel, 2015; Morrow et al., 2000). It enhances visibility and safety for motorists and pedestrians, allowing them to navigate roads and sidewalks with greater ease and confidence (Mohamed et al., 2018). This, in turn, reduces the risk of accidents and instils a sense of security among the populace. Furthermore, adequate street lighting fosters a thriving nighttime economy by illuminating commercial areas, encouraging pedestrian traffic, and extending business hours. This not only supports local businesses but also contributes to a more vibrant and dynamic urban atmosphere. Given the numerous benefits of public street lighting, it is increasingly important to strive for their energy efficiency in alignment with sustainability goals.

A critical factor influencing energy consumption in street lighting is the intensity of illumination (Ergüzel, 2019; Khade et al., 2017; Wojnicki & Kotulski, 2018). By analyzing the intensity of light emitted from streets, city planners and utility managers can gain crucial insights into energy consumption patterns and identify areas for energy efficiency improvements. Streets with exceptionally high light intensity can be examined to determine the type of lighting fixtures in use. If conventional, energy-inefficient lamps are employed, these areas should be prioritized for Light-Emitting Diodes (LED) lamp retrofits. Transitioning to energy-efficient LED lighting can significantly reduce energy consumption and associated costs.

Recognizing this, local governments have increasingly adopted LED lighting technology as a sustainable solution for public street lighting. LED lights offer a significant advantage by providing equivalent lighting intensity while consuming much less energy compared to conventional lamps (Srivatsa et al., 2013). This energy efficiency stems from their design, which converts electrical energy directly into light, minimizing energy loss in the form of heat. Additionally, LED lights boast exceptional durability, extending their lifespan and reducing the frequency of lamp replacements (Casamayor et al., 2015; Curran & Keeney, 2006; Masara, 2019). This combination of energy efficiency and longevity translates into substantial cost savings and environmental benefits for municipalities.

Satellite imagery of nighttime lights offers a valuable tool for evaluating and optimizing street lighting infrastructure in urban areas (Arellano & Roca, 2020; de Meester & Storch, 2020). Several prior studies have explored the potential of satellite imagery to extract streetlight information and evaluate energy consumption patterns. Cheng et al. (2020) utilized JL1-3B Nighttime Light Data to estimate energy savings achievable through lamp replacements, demonstrating the promise of this approach. However, the commercial nature of JL1-3B data poses a barrier to widespread adoption. Recognizing this limitation, Yin et al. (2024) developed a method to identify streetlights from SDGSAT-1 imagery, leveraging the freely available nature of this data source.

Our research aims to refine the methodology further and apply it to three Indonesian cities: Semarang, Yogyakarta, and Solo. The novelty of this research lies in introducing a groundbreaking framework that combines high-resolution nighttime satellite imagery from SDGSAT-1 with rigorous ground-truth verification of street lighting types across various road segments in Indonesian cities. The objectives of this study include calculating the streetlight wattage at the research sites. This data is subsequently utilized to simulate energy savings from the replacement of non-LED lamps. A comparison is then conducted across the three cities, taking into account road functions. As a contribution, this study endeavours to offer insightful findings and suggestions to local authorities, utility companies, and urban designers who aspire to enhance street lighting infrastructures, reduce energy usage, and foster sustainable urban growth.

2. Methods and Materials

Figure 1 illustrates the research framework, encompassing data sources, processing steps, and the ultimate goal of supporting strategic decision-making in urban energy management. Initially, nighttime satellite imagery is processed using pan-sharpening, a technique that fuses panchromatic with multispectral imagery data. This process results in high-resolution imagery with retained multispectral data (González-Audícana et al., 2006). The multispectral red, green, and blue (RGB) data is then filtered, with low-value data removed due to insufficient light intensity. There is no existing research that definitively determines the threshold value for excluding low-light data in street lighting studies. Astronomy-based research typically uses a threshold value of 6 or lower to classify low light, while nighttime photography research uses a threshold value of 8 light (Zhao et al., 2023). Consequently, this research adopts a cut-off value of 7 to classify low light in street lighting.

The data in Table 1 was collected from several secondary sources and validated through field review results. SDGSAT-1 nighttime satellite imagery data, collected in raster form, was processed using programs such as ArcGIS or QGIS. Data on street light usage is essential. Public street lighting was chosen due to the significant noise in residential area lighting, which is sourced from various types of lights and is difficult to identify. Data about public street lighting must include the location point, the type of lamp used, the number of lights at each point, and the power required. Data completeness is a challenge in this research. Therefore, Semarang City was chosen because its data on public street lighting points is much more complete than that of other locations. The total number of public street lighting points in Semarang is 64,354 street lights. After filtering and removing incomplete data, 48,995 street lighting points remained. The street lighting data in Semarang City serves as a reference for the next stage.

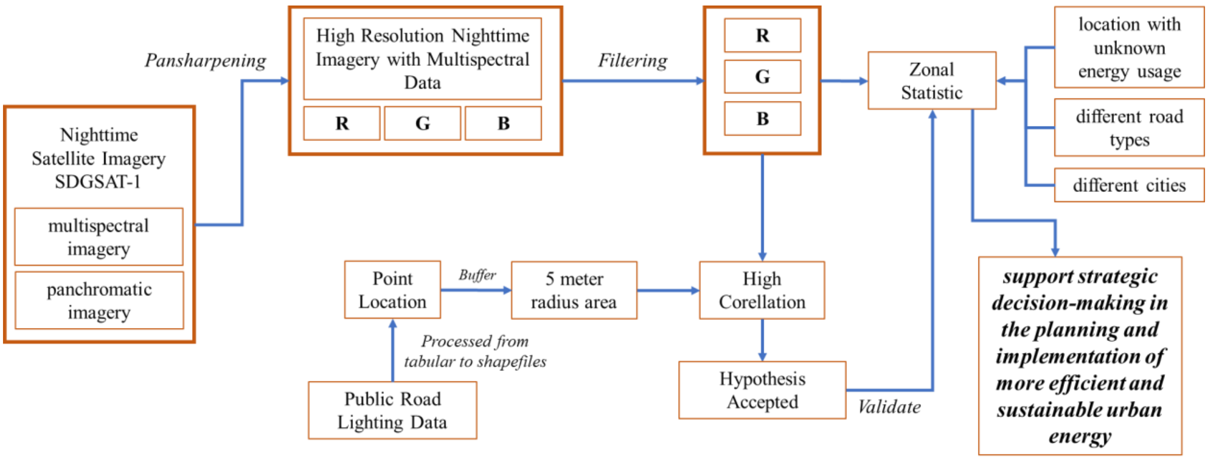

Figure 1. Research frameworks.

The road lighting data is processed from tabular format to shapefile format, a suitable format for Geographic Information System (GIS) management, represented as point locations. Verification of street lighting types across various roads is conducted using random sampling methods. Each point location is buffered within a 5-meter radius and processed using zonal statistics to determine the RGB values at those points. Correlation is established by comparing the RGB values at specific points with the lamp type, average power usage, and total power usage per point.

Data from Semarang City's public street lightings indicates a variety of lamp types. Correlating the energy usage of all lamp types with nighttime satellite imagery using the Pearson method yielded a maximum correlation of 40%. This relatively low correlation is insufficient for accurately simulating energy usage. The low correlation results from the wide range of energy usage within a single lamp type, which can vary from 15 watts to 1000 watts. To address this, the research focuses on the type of lamp and uses the average energy usage per type and the total average energy usage at each point location (Ozadowicz & Grela, 2014).

The strong correlation value in one of the multispectral image bands supports the hypothesis that SDGSAT-1 satellite data can accurately simulate power usage at specific locations. Further simulations are conducted to compare power consumption in unknown locations, as well as to observe varying energy usage across different types of roads or cities. To perform these simulations, the filtered nighttime satellite image data is processed using zonal statistical methods to determine specific RGB values at those locations.

Table 1. Research dataset.

No.	Data Type	Data Sources	Data acquisition
1	Administrative Boundary	Indonesian Base map (Ina-Geoportal) (Indonesian Geospatial Information Agency)	March 2024
2	Road Lighting • Lamp Type, • Energy usage, • Number of Lamps, • Coordinates	https://sigpju.semarangkota.go.id/	March 2024
3	SDGSAT-1 nighttime satellite imagery • Panchromatic imagery • multispectral imagery	https://data.SDGSAT-1.ac.cn/dataQuery	March 2024
4	Road Data	Open Street Map Downloader Plugin in QGIS	March 2024

3. Results and Discussions

3.1 Nighttime Satellite Data Processing

SDGSAT-1 is a newly developed satellite launched in 2021 by the International Research Center of Big Data for Sustainable Development Goals (CBAS). The innovative design of RGB bands was applied to the Glimmer Imager, resulting in a spatial resolution of 10 meters for the panchromatic band and 40 meters for the RGB bands (Li et al., 2024). Figure 2 shows the pan-sharpening process of a 40-meter resolution multispectral night image of Semarang with a 10-meter resolution panchromatic image, resulting in a 10-meter resolution image that retains the multispectral information. For further analysis, multispectral data with values below seven were deleted because they were deemed to have no light or too low intensity.

3.2 Road Lighting Data Processing

Figure 3 shows a detailed map of street lighting lamp types in Semarang. The public street lighting data indicates a variety of lamp types, including floodlights, mercury lamps, sodium lamps, light-emitting diodes (LED), solar-powered lamps, and fluorescent lamps. The distribution of lamp types is as follows: Straight Line Fluorescent Lamps (SL) make up 46.49% of the filtered data, High-Pressure Sodium Tubular Lamps (HPST) account for 23.52%, and LED lamps constitute 9.89%, among others.

Table 2 presents the average power and total average power for each type of lamp. The total average power is calculated because a single street lighting pole may have more than one lamp. The data shows that the FLOOD type lamp has the highest average power, while the TL type has the lowest. Similarly, the total average power is highest for FLOOD lamps at 5,000 watts and lowest for TL lamps at 28 watts. Floodlights have a high power value because they are typically used for illuminating large areas such as parks, sports fields, or buildings, providing bright and even light. In contrast, TL lamps use gas and phosphor coatings to produce light and are more common in commercial, industrial, and household lighting.

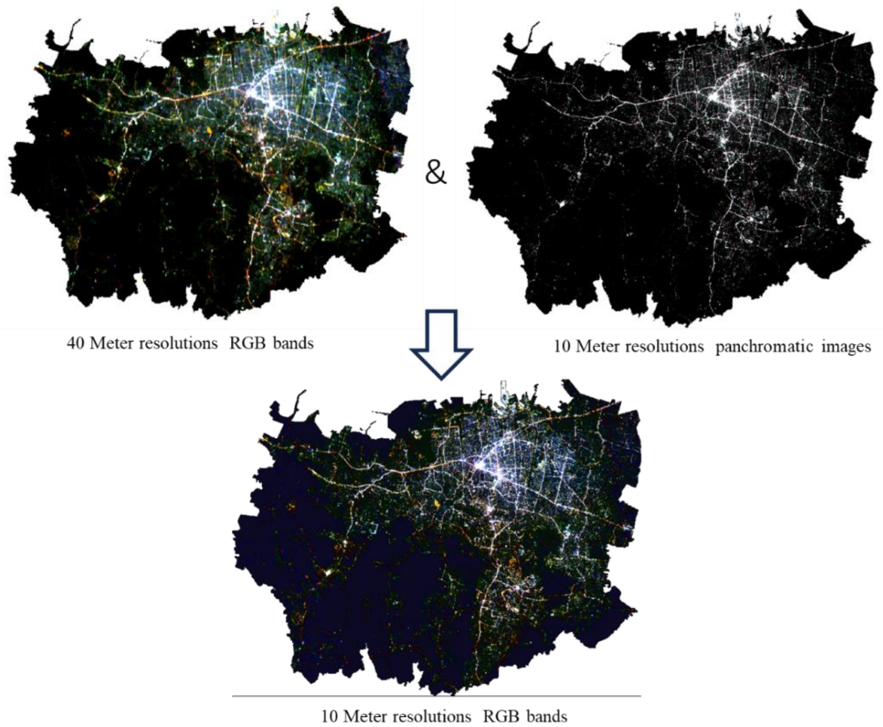

Figure 2. Pan-sharpening process on night satellite image of Semarang City.

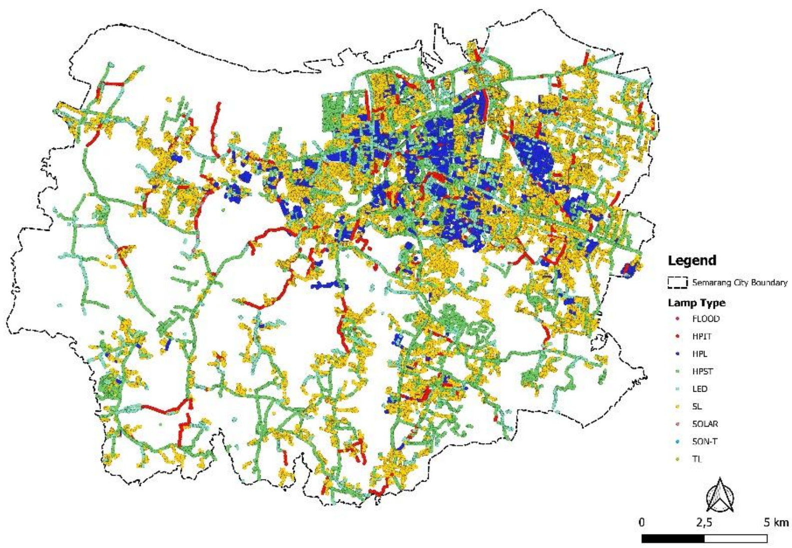

Figure 3. Street lighting lamp type in Semarang City.

Figure 4 provides an intriguing observation on the variation of power across different types of lamps. It highlights a significant range, with the highest recorded power peaking at 1000 watts, while the lowest dips below 30 watts. The breakdown by lamp type reveals that FLOOD lamps dominate in terms of power output, achieving the highest wattage. This is followed by HPIT and HIPST types, with TL lamps recording the lowest wattage among them. Such a distribution suggests distinct functional or design differences among these lamp types, influencing their power consumption and output levels. Additionally, the total power data for FLOOD lamps exhibit a noticeable jump, indicating that the typical installation of FLOOD lamps at a single location includes about five lamps. This contrasts with other lamp types, which generally have just one lamp per location on average. This difference significantly impacts the total average power values, with the total for FLOOD lamps being much higher. Such a setup for FLOOD lamps suggests they are used in locations requiring higher illumination, thus accounting for the higher total average power compared to other types, where the power figures are more consistent with individual lamp output.

Table 2. Streetlight type and average power usage data.

Lamp Type	Description	Average power (watt)	Total average power (Average power * average number)
FLOOD	Floodlight	1,000	5,000
HPIT	High-Pressure Mercury Vapor Lamp	155	180
HPL	High-Pressure Sodium Lamp	113	113
HPST	High-Pressure Sodium Tubular Lamp	147	169
LED	Light Emitting Diode	97	120
SL	Straight Line (Fluorescent)	41	41
SOLAR	Solar-Powered Lamp	80	80
SON-T	Sodium Lamp - Tubular	40	40
TL	Tubular Lamp (Fluorescent)	28	28

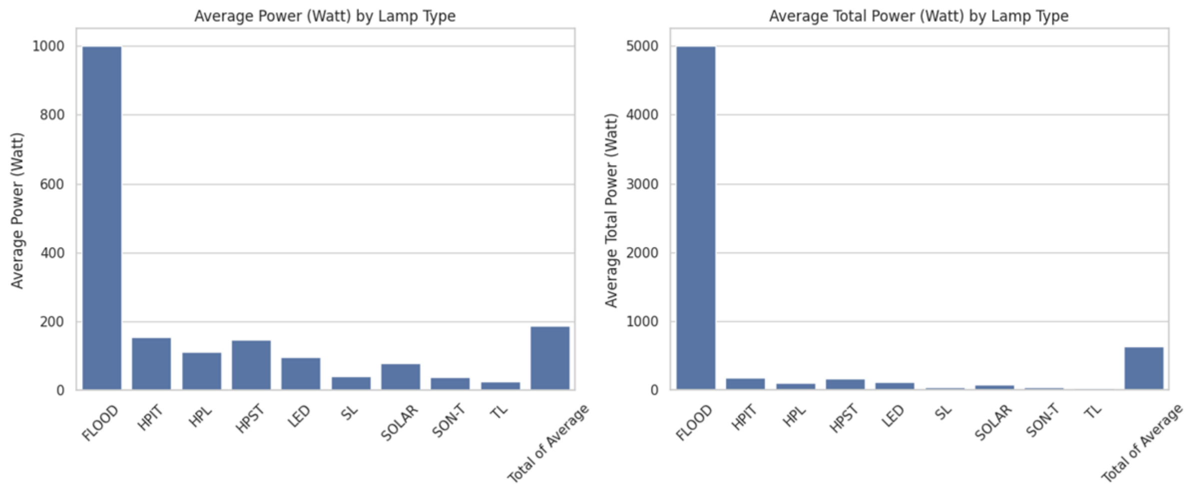

Figure 4. Average power and total average power of lamp type.

3.3 The Correlation of Road Lighting Lamp Types and Nighttime Satellite

To establish a correlation between road lighting and nighttime satellite RGB data, point-shaped street lighting data is initially processed using a buffering technique that expands each point into a 5-meter radius, transforming it into area-shaped data. This method broadens the scope of analysis by creating a larger spatial footprint for each light point, enabling more accurate comparisons with satellite imagery data. This expanded area data allows for a more comprehensive interaction between the localized lighting data and the broader spectral data captured by satellites at night.

Following the buffering process, zonal statistics are employed to calculate the average RGB values of nighttime lighting within these newly defined areas. This statistical method aggregates the RGB values within each buffered zone to produce a representative average for that specific area, facilitating detailed analysis of light intensity and color characteristics across different zones. The results of these zonal statistics are compiled into Table 3, providing a structured and accessible format to analyze and interpret the relationship between street lighting configurations and the corresponding satellite-detected RGB night light data.

In the analysis of average band values for Red (gray), Green, and Blue, a clear pattern emerges in relation to different types of street lighting lamps. The FLOOD lamp type consistently shows the highest average values across all three color bands—Red (gray), Green, and Blue. This suggests that FLOOD lamps emit a stronger light across the entire visible spectrum, indicative of their broader and more intense illumination capabilities, often employed in areas requiring significant lighting.

On the other hand, the SL type exhibits the lowest average values in the red and green bands, highlighting its relatively weaker light output in these color spectra. Interestingly, the blue band also identifies SL-type lamps as one of the lowest, alongside another unspecified type, demonstrating a consistent trend of lower intensity across these spectral bands. This pattern may reflect the specific usage and design of SL-type lamps, which are typically optimized for more subdued and energy-efficient urban street lighting.

Table 3. The average red (gray), green, blue band data based on lamp type.

Lamp Type	Average of Red (gray)	Average of Green	Average of Blue
FLOOD	55	47	17
HPIT	18	19	5
HPL	6	9	3
HPST	16	18	5
LED	15	19	6
SL	4	6	2
SOLAR	17	13	3
SON-T	22	32	15
TL	5	8	2

The average red band intensity depicted in Figure 5 shows significant differences among various types of lamps. The data indicates noticeable variations in the average intensities of the green and blue bands among different lamp types as well. Specifically, the FLOOD lamp type has the highest average red band intensity, while the SL lamp type has the lowest. These differences may reflect the characteristics of each lamp type. Therefore, understanding the disparities in light intensities and the correlation of different bands with lamp types is essential.

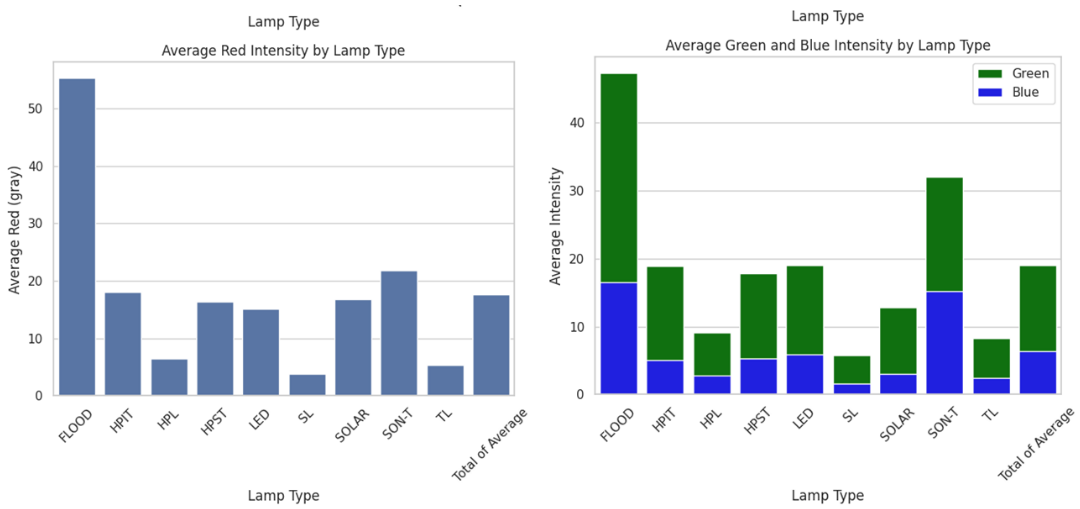

Figure 5. Average power and total average power of lamp type.

Figure 6 is the correlation matrix between the energy usage of each lamp type and nighttime satellite RGB data. The data shows that the red band has the highest correlation values, with a correlation value of 0.92 for both average power (watt) and total average power (watt). The green band ranks second, with correlation values of 0.80 for average power (watt) and 0.81 for total average power (watt). The blue band has the lowest correlation values, at 0.66 for average power (watt) and 0.68 for total average power (watt). All RGB bands in the nighttime satellite imagery data exhibit a high positive correlation with the average power usage of each lamp type, with the red band showing the highest correlation values.

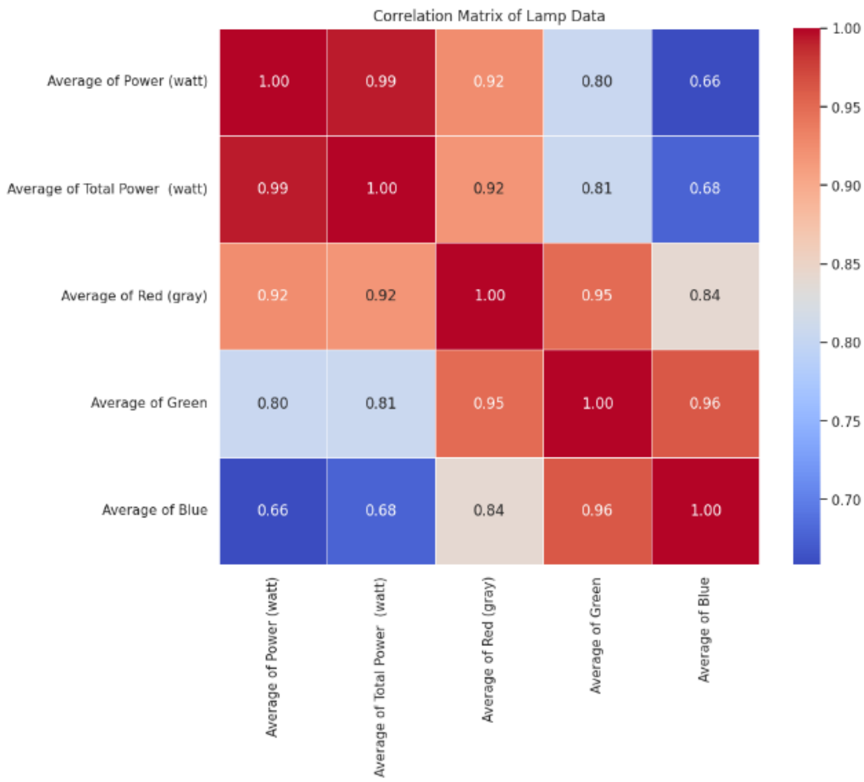

Figure 6. Correlation matrix of energy usage for different lamp types and nighttime satellite RGB.

Table 4 describes the correlation between total average power and variables such as average power and average red, green, and blue bands on SDGSAT-1 nighttime multispectral data. The red band has the highest correlation value of 0.92, with a p-value of only 0.00018, indicating highly significant correlation results between the two variables. Several studies have explained how RGB values can be used to determine the type of lighting or the level of luminosity (Elvidge et al., 2010; Yin et al., 2024). Additionally, some studies have discussed the relationship between luminosity levels and energy usage (Itasari et al., 2023; Kostic & Djokic, 2009). However, no research has directly linked RGB values with energy levels. The high correlation of the red band in night satellite imagery with energy usage levels, both average power usage and total average power usage, supports the hypothesis that SDGSAT-1 satellite night satellite imagery can illustrate energy usage. Red band correlation values reaching 0.92 indicate that the red band can be used as a proxy to calculate power usage in unknown locations. This result enables us to extrapolate energy usage in locations lacking data, compare energy usage among specific street classes, or juxtapose energy usage between cities.

Table 4. Correlations and P-value of total average power to other variables.

Variables	Pearson Correlations	P-Value
Average of Power (watt)	0.9931	9.4059e-09
Average of Red	0.9175	0.00018
Average of Green	0.8056	0.00491
Average of Blue	0.6773	0.03142

3.4 The Correlation of Road Types and Energy Usages

After identifying that the red band has the highest correlation with total average power and average power, the red band data could be used as a proxy to estimate the total average power in locations lacking data. However, our research is based on data points within a 5-meter radius, which may not be accurate enough for application in other locations due to the lack of known street lighting points to take the 5-meter radius area. To address this issue, a broader sampling area is required. Consequently, the road network was selected according to its classification as a larger sample area.

The road data is derived from OpenStreetMap, an open-source data. The road network is classified into primary, secondary, and tertiary roads based on their importance in urban areas. Each type of road includes connecting roads, typically represented by the word "link" in the classification. Detailed road types in Semarang City are presented in Figure 7.

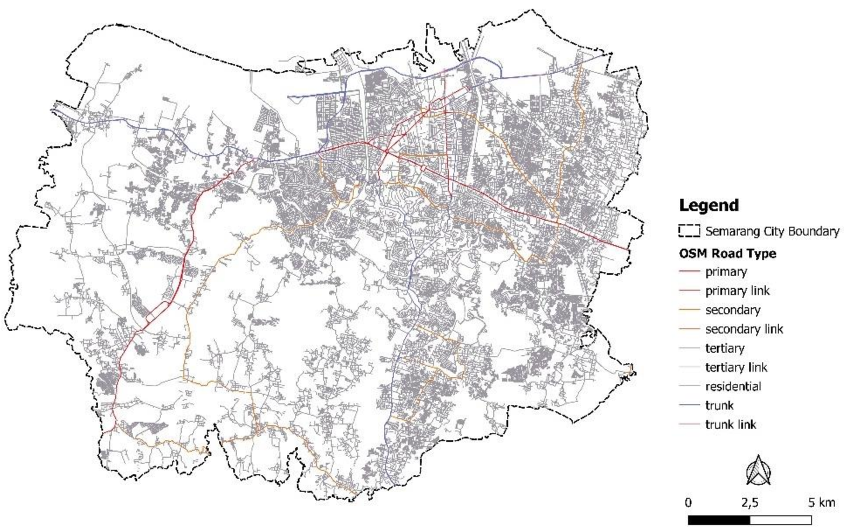

Figure 7. Road types in Semarang City.

Roads with different classifications should exhibit different energy usage patterns (Vidyarthi et al., 2023). More important roads, with higher hierarchy and frequent traffic, generally have better lighting compared to quieter roads, leading to higher energy consumption. Thus, the road class influences the amount of energy used for street lighting. By analyzing the complete street lighting data in Semarang City, energy usage for each classification was calculated and illustrated in Figure 8.

Figure 9 shows the average power consumption for each road type, revealing varied values. The highest power consumption is observed in the tertiary link road type. Tertiary links, or slip roads/ramps, connect tertiary roads to each other. These roads require higher illumination due to their quieter nature, necessitating increased lighting at intersections to enhance driving safety. Conversely, the residential road type has the lowest consumption, attributed to lower population density, slower vehicle speeds, and considerations for cost and energy efficiency.

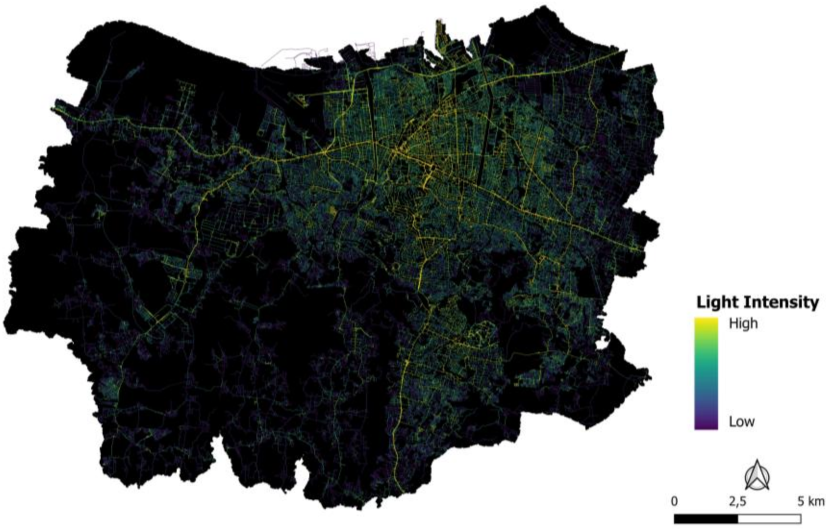

Figure 8. Light intensity in different road types in Semarang City.

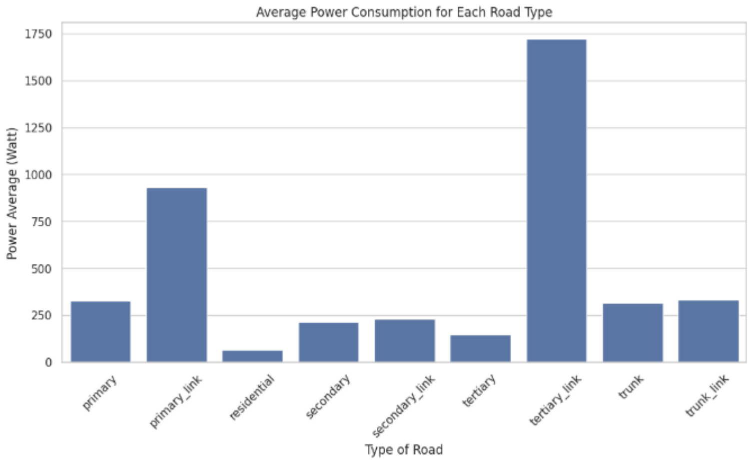

Figure 9. Average power consumption for each road type.

The road data correlation matrix in Figure 10 shows varied values, but the differences among bands are not substantial. The red band has a correlation value of 0.86 with average power (watts) and 0.79 with total average power (watts). The green band has a correlation of 0.87 with average power (watts) and 0.85 with total average power (watts). The blue band shows a correlation of 0.81 with average power (watts) and 0.80 with total average power (watts). While the correlation values between the red, green, and blue bands vary, they are not significantly different. Nonetheless, all bands exhibit a strong relationship with average power and total power. Based on the results, although the accuracy is lower than the 5-meter radius at the street lighting location point, the road network class can still be used to estimate energy usage levels.

3.5 Potential Energy Saving

The data analysis of Semarang's lighting infrastructure reveals a significant potential for energy savings through the adoption of LED lamps. The current utilization of fluorescent and sodium lamps, which are prevalent across the city, offers an opportunity for energy efficiency improvements. Replacing these traditional lighting options with LED lights could result in a substantial reduction in energy consumption—up to 69% compared to existing conditions (Kurniawan & Kurniawan, 2022). This transition not only supports environmental sustainability but also reduces the economic burden associated with high energy costs.

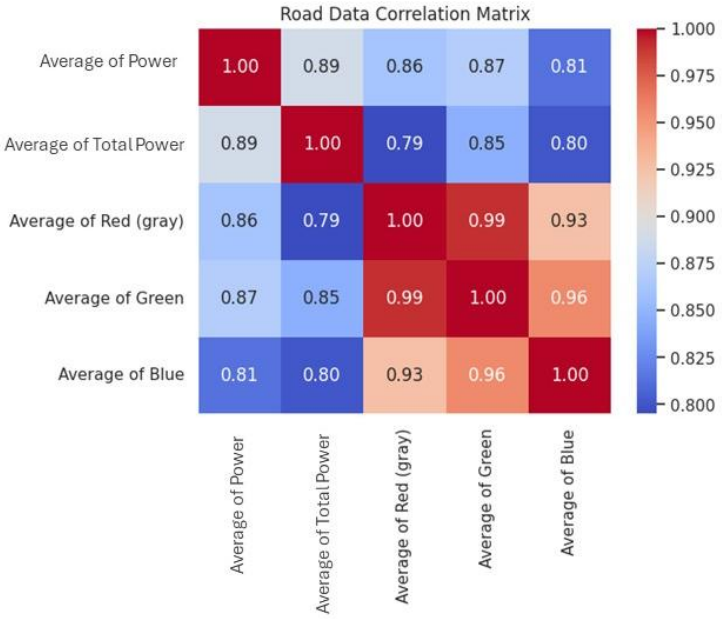

Figure 10. Correlation matrix of energy usage on different road class and nighttime satellite RGB.

If switching to LED lighting can reduce 50% of energy consumption in the street lighting in Semarang City, the impact on the energy profile would be significant. As shown in Figure 11, this reduction would markedly decrease the average power consumption. This scenario underscores the practical benefits of upgrading to LED technology, highlighting both immediate energy savings and long-term advantages in terms of sustainability and cost-effectiveness. The proportion of LED lights in Semarang accounts for only 9.89% of the total data used in the study. Thus, achieving a 50% power saving should be relatively easy. Tertiary links have the highest potential for electricity savings, with an average power usage reduction of 800 watts. Residential roads have a lower power-saving potential due to factors such as high traffic volume, mixed-use areas, irregular activities, and possibly poor road conditions, making them less efficient in terms of energy use compared to other road types.

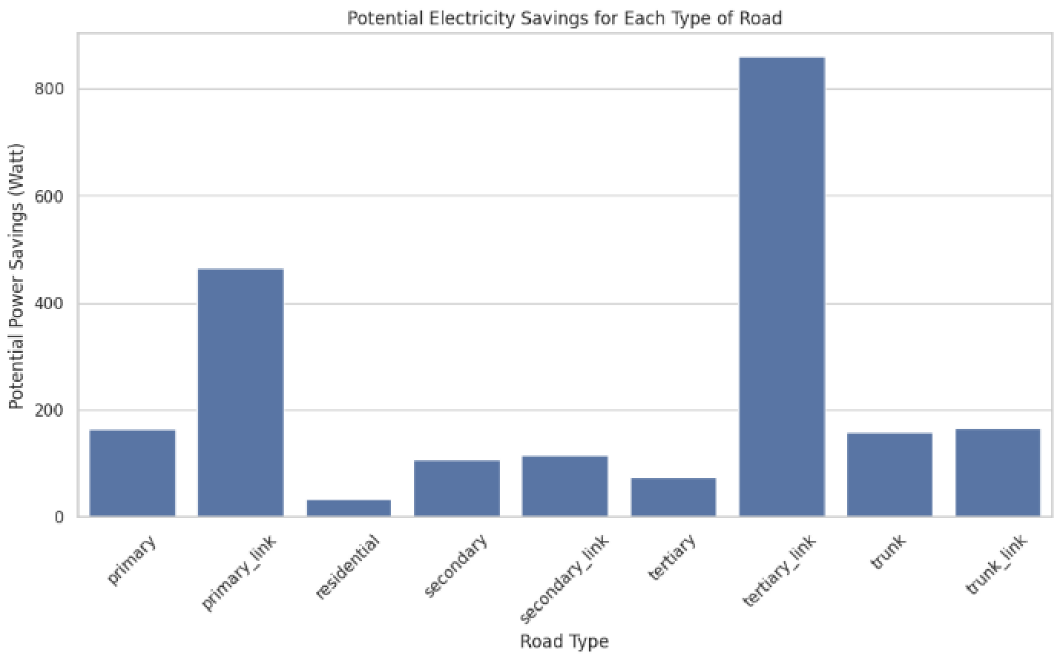

Figure 11. Potential electricity saving for each road type.

3.6 Modelling Energy Usage in Different Cities

Energy usage modelling was conducted in two different cities, Yogyakarta and Solo. Data from Solo, Yogyakarta, and Semarang were compared to analyze energy management across the three cities. Street data from Yogyakarta and Solo, obtained using OpenStreetMap data, is illustrated in Figures 12a and 12b. SDGSAT-1 nighttime multispectral data was collected at locations in Solo and Yogyakarta and processed using the Pan sharpening method. The results of Pan sharpening RGB data in Solo and Yogyakarta are illustrated in Figures 13a and 13b.

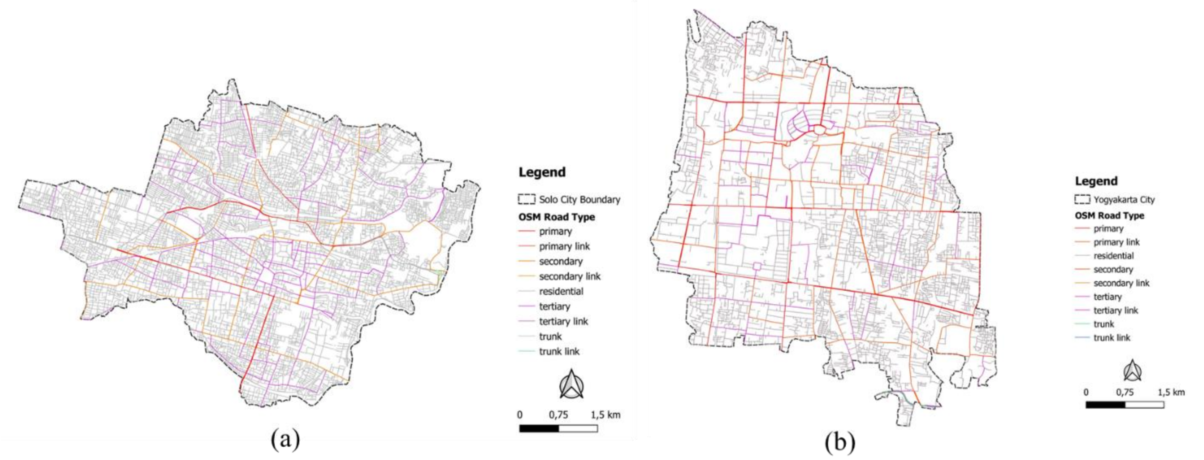

Figure 12. Road network (a) Solo and (b) Yogyakarta**.**

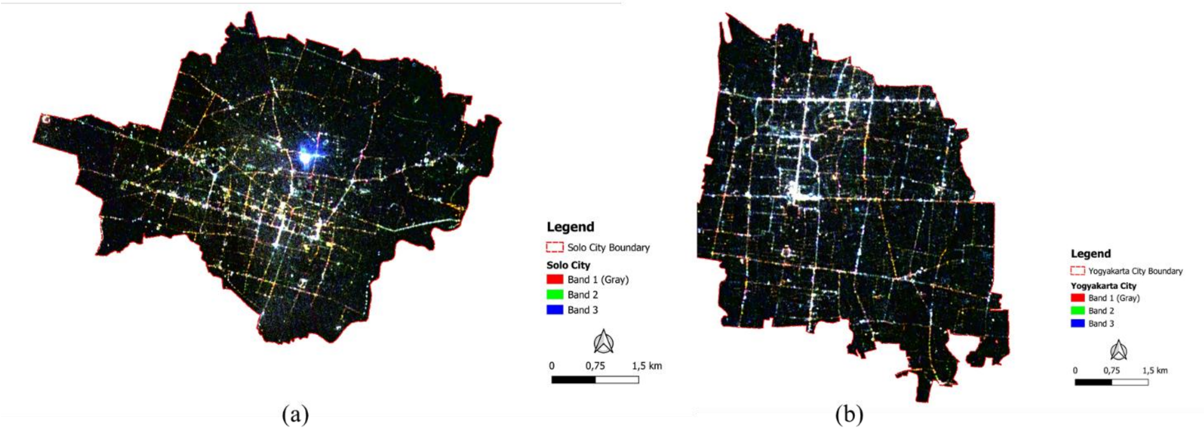

Figure 13. Night satellite image light results in (a) Solo and (b) Yogyakarta.

The road network, represented as line data, is subjected to a buffering process with a radius of 5 meters. This technique extends the area of analysis around the existing roads, enabling more accurate assessments of the road network's impact on its surroundings. The resulting buffered road area data is then utilized for more detailed area representation. Thereafter, the road area data is statistically zoned to determine the average value from the SDGSAT-1 nighttime multispectral data. This statistical analysis is vital to identify variations in light intensity recorded in the data, which may indicate different characteristics of the area, such as population density or economic activity levels. In the final stages, the red band from the SDGSAT-1 data serves as the primary reference in calculating the average light power for each road network class. The light intensity based on the red band values is then visually presented for Solo and Yogyakarta, as seen in Figures 14a and 14b, respectively. This visualization not only clarifies the light distribution in both cities but also facilitates the comparison of various road network classes in terms of nighttime light intensity.

Table 5 shows a comparison of the average zonal statistics for each type of road in each city. In Semarang City, the highest power (watts) is observed in the red band for the secondary link road type, with street lightings on these roads averaging 41.40 watts. This is influenced by the characteristics of the roads in Semarang City. In Yogyakarta City, the highest red band value is found in the primary link road type, with an average of 58.22 watts. This value is influenced by the fact that Yogyakarta City has more primary link roads than Semarang and Solo. In Solo City, the highest red band value is on secondary link roads, with an average of 35.69 watts. This is due to urban growth, the diversion of traffic from main roads, and increased accessibility to various city areas aimed at improving mobility and better accommodating the transportation needs of residents.

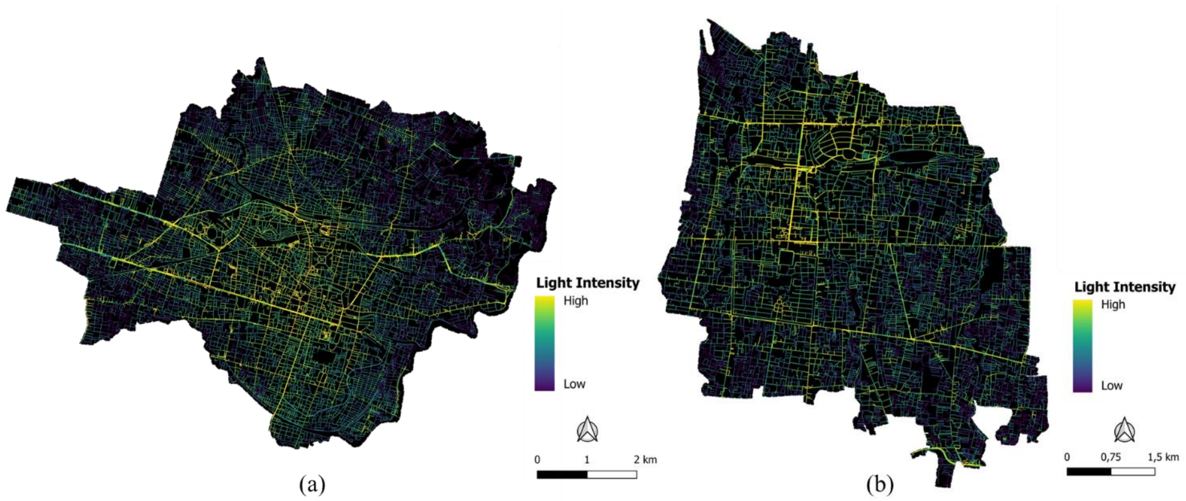

Figure 14. Light intensity in different road types in (a) Solo and (b) Yogyakarta.

Table 5 shows different road lighting configurations. In the three cities, it was found that link roads, on average, have better street lighting than their equivalent road networks. This configuration is shared among different cities to increase road safety at intersections. This pattern is found in all road types in all cities except for trunk-level roads in Solo City, which do not have significant trunk roads. Trunk roads are one of the most important roads in a city's system that are not freeways/tolls and have a higher hierarchy than primary roads.

Yogyakarta City has brighter street lightings in locations with higher road classifications. This is also true for Solo, except at the trunk road level, which is rare in Solo. However, Semarang City has a different configuration, with the highest light intensity appearing on the link type of tertiary road. It is suspected that this arrangement ensures quieter road types have better security through better lighting. We believe that lighting level does not need to be raised to the level of trunk or primary roads. Improving energy efficiency in Semarang City could lower the lighting level in these locations to the lighting level on secondary roads but keep it brighter than comparable road types. The lighting level on tertiary roads tends to be closer to residential areas, so lowering the very high lighting level to a reasonably bright level can improve the comfort of residents.

Table 5. Average red band value in different street type.

Road Type	Semarang City	Yogyakarta City	Solo City
Trunk	38,99	45,93	14,11
Trunk_Link	33,57	18,30	12,25
Primary	39,22	43,69	30,82
Primary_Link	38,66	**58,22**	30,27
Secondary	26,73	17,97	27,89
Secondary_Link	**41,40**	23,78	**35,69**
Tertiary	20,20	15,06	15,93
Tertiary_Link	40,40	18,43	17,23
Residential	4,99	4,51	4,66

4. Conclusions

We hypothesize that SDGSAT-1 satellite data, particularly the nighttime light multispectral data, can illustrate energy usage at specific locations. To substantiate this hypothesis, quantitative methods were employed to determine the high correlation between SDGSAT-1 RGB multispectral data, lamp types, and average energy usage. We then estimate energy usage in locations lacking direct data, compare energy usage among different street classes, and contrast energy usage between cities. Integrating satellite imagery with empirical field data not only provides new dimensions of understanding in urban energy management but also establishes a scalable and adaptable framework for enhancing street lighting infrastructure across various municipalities. Ultimately, the research findings can support strategic decision-making in planning and implementing more efficient and sustainable urban energy solutions.

We thoroughly analyze the correlation between nighttime satellite imagery and urban lighting, utilizing SDGSAT-1's multispectral capabilities to link energy usage with specific types of street lamps in Semarang. We integrate pan-sharpened images that enhance spatial resolution to 10 meters while preserving multispectral data, facilitating detailed urban lighting analysis. Various lamp types, such as floodlights, mercury, sodium, LED, solar-powered, and fluorescent lamps, are evaluated for their power usage and light emission characteristics. It was found that the FLOOD lamp type, generally used for illuminating extensive areas, exhibited the highest average and total power consumption, confirming its high energy intensity. A significant discovery of this study is the robust correlation between the red spectral band of the satellite images and the power usage of different lamp types, with a correlation coefficient of 0.92. This high correlation suggests the feasibility of using red band data as a proxy for estimating unknown power consumption across various urban settings. Further, we explore the impact of road classification on energy consumption in street lighting, demonstrating that higher-traffic roads typically consume more energy due to enhanced lighting requirements. This pattern is evident across different cities, including Yogyakarta and Solo, with variations in road lighting configurations reflecting urban planning and road hierarchy. We also point towards potential energy savings, highlighting the significant reduction in energy consumption achievable by replacing less efficient lamps with LEDs, resulting in up to a 69% energy saving (Kurniawan & Kurniawan, 2022).

Relying on open-source data highlights the need for more comprehensive ground truth data to refine satellite image calibration and verification. Increasing the dataset's granularity would improve the accuracy of light intensity identification and energy usage estimations, ensuring the analysis more accurately reflects actual conditions. Future research should integrate advanced artificial intelligence and machine learning technologies to analyze large datasets more efficiently, uncovering patterns not readily visible through manual methods. This could enhance the precision of energy usage estimation and aid in better urban planning and environmental monitoring.

Additionally, exploring the actual impact of lamp-type replacements, such as switching to LED lighting, could provide insights into the cost-benefit ratios of such initiatives on a larger scale. Collaborative multidisciplinary approaches involving engineering, urban planning, and environmental science are recommended to tackle the complexities of urban lighting and energy consumption comprehensively. Such collaborations could lead to more innovative and sustainable solutions, improving urban environments globally. Overall, while our research marks a significant step forward, its conclusions underscore the need for more detailed studies across varied urban landscapes. This would not only confirm the reliability of using satellite imagery for urban energy assessments but also enhance global urban lighting strategies, promoting sustainability and safety in city planning.

Acknowledgments

We would like to extend our heartfelt thanks to PT Sagamartha Ultima Indonesia for not only funding this research but also providing a fertile ground for its inception. This study originated from a series of insightful discussions within the UrbanLab at PT Sagamartha Ultima Indonesia, which blossomed into the comprehensive analysis presented here. Their generous support has been crucial in enabling us to delve deeper into energy efficiency modelling in Indonesia and to bring these important findings to light. Additionally, our gratitude goes out to all the individuals and organizations whose expertise and assistance have been invaluable throughout this research process. Their contributions have not only enriched our work but have also been instrumental in advancing our collective understanding of sustainable energy solutions. We are deeply appreciative of their continued support and collaboration.

References

Arellano, B., & Roca, J. (2020). The extraction of urbanized areas through images of high resolution nighttime lights. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLIII-B3-2020*, 649–655. https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-649-2020

Casamayor, J., Su, D., & Sarshar, M. (2015). Extending the lifespan of LED-lighting products. *Architectural Engineering and Design Management*, *11*(2), 105–122. https://doi.org/10.1080/17452007.2013.834813

Cheng, B., Chen, Z., Yu, B., Li, Q., Wang, C., Li, B., Wu, B., Li, Y., & Wu, J. (2020). Automated extraction of street lights from JL1-3b nighttime light data and assessment of their solar energy potential. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 675–684. https://doi.org/10.1109/JSTARS.2020.2971266

Curran, J. W., & Keeney, S. P. (2006). *Replacement of fluorescent lamps with high-brightness LEDs in a bridge lighting application* (I. T. Ferguson, N. Narendran, T. Taguchi, & I. E. Ashdown, Eds.; p. 633719). https://doi.org/10.1117/12.682727

de Meester, J., & Storch, T. (2020). Optimized performance parameters for nighttime multispectral satellite imagery to analyze lightings in urban areas. *Sensors*, *20*(11), 3313. https://doi.org/10.3390/s20113313

Elvidge, C. D., Keith, D. M., Tuttle, B. T., & Baugh, K. E. (2010). Spectral identification of lighting type and character. *Sensors*, *10*(4), 3961–3988. https://doi.org/10.3390/s100403961

Ergüzel, A. T. (2019). A study on the implementation of dimmable street lighting according to vehicle traffic density. *Optik*, *184*, 142–152. https://doi.org/10.1016/j.ijleo.2018.12.183

González-Audícana, M., Otazu, X., Fors, O., & Alvarez-Mozos, J. (2006). A low computational-cost method to fuse IKONOS images using the spectral response function of its sensors. *IEEE Transactions on Geoscience and Remote Sensing*, *44*(6), 1683–1690. https://doi.org/10.1109/TGRS.2005.863299

Guittet, M. (2012). Management of urban energy systems. In *Network Industries Quarterly* | (Vol. 14). http://www.revedavenir.org/

Itasari, M., Samman, F. A., & Salam, A. E. U. (2023). Comparative study of the interconnected street light luminance levels control for energy efficiency. *ICMSA*.

Jain, R. (2021). The Urban Transformation: issues and challenges. In *urban growth and environmental issues in India* (pp. 17–34). Springer Singapore. https://doi.org/10.1007/978-981-16-4273-9_2

Khade, D. R., Gajane, N. V., Gawade, S. N., & Metri, R. A. (2017). Intensity controller of LED street lights. *2017 International Conference on Circuit ,Power and Computing Technologies (ICCPCT)*, 1–4. https://doi.org/10.1109/ICCPCT.2017.8074171

Kostic, M., & Djokic, L. (2009). Recommendations for energy efficient and visually acceptable street lighting. *Energy*, *34*(10), 1565–1572. https://doi.org/https://doi.org/10.1016/j.energy.2009.06.056

Kurniawan, I. W., & Kurniawan, R. (2022). Fostering energy efficiency through street lighting system improvement: a case study of city-level in indonesia. *Indonesian Journal of Energy*, *5*(2). https://doi.org/10.33116/ije.v5i2.146

Li, H., Jing, L., Dou, C., & Ding, H. (2024). A comprehensive assessment of the pan-sharpening of the nighttime light imagery of the glimmer imager of the sustainable development science satellite 1. *Remote Sensing*, *16*(2), 245. https://doi.org/10.3390/rs16020245

Masara, V. M. (2019). The replacement of tradiocional lamps by LED in Brazil: a case of environmental and economic sustainability (short review). *MOJ Civil Engineering*, *5*(1), 31–33. https://doi.org/10.15406/mojce.2019.05.00146

Mohamed, R. R., Mohamed, M. A., Ahmad, A., & Abd Halim, M. A. H. (2018). Provisioning of street lighting based on ambience intensity for smart city. *Indonesian Journal of Electrical Engineering and Computer Science*, *12*(3), 1401. https://doi.org/10.11591/ijeecs.v12.i3.pp1401-1406

Morrow, E. N., Hutton, S. A., Ryan, G. H., Bensinger, P. B., & Kane, C. M. (2000). *The Chicago Alley Lighting Project: Final Evaluation Report Prepared by*.

Ozadowicz, A., & Grela, J. (2014). The street lighting integrated system case study, control scenarios, energy efficiency. *Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA)*, 1–4. https://doi.org/10.1109/ETFA.2014.7005345

Radulovic, D., Skok, S., & Kirincic, V. (2011). Energy efficiency public lighting management in the cities. *Energy*, *36*(4), 1908–1915. https://doi.org/10.1016/j.energy.2010.10.016

Srivatsa, D. K., Preethi, B., Parinitha, R., Sumana, G., & Kumar, A. (2013). Smart street lights. *2013 Texas Instruments India Educators' Conference*, 103–106. https://doi.org/10.1109/TIIEC.2013.25

van Bommel, W. (2015). Purpose and benefits of road lighting. In *Road Lighting* (pp. 3–6). Springer International Publishing. https://doi.org/10.1007/978-3-319-11466-8_1

Vidyarthi, A., Coxon, S., Napper, R., & Gusheh, M. (2023). *A proposed hierarchy of smart roads: assisting future technological developments* (pp. 455–466). https://doi.org/10.1007/978-981-99-0264-4_38

Wojnicki, I., & Kotulski, L. (2018). Empirical study of how traffic intensity detector parameters influence dynamic street lighting energy consumption: a case study in Krakow, Poland. *Sustainability*, *10*(4), 1221. https://doi.org/10.3390/su10041221

Yin, Z., Chen, F., Dou, C., Wu, M., Niu, Z., Wang, L., & Xu, S. (2024). Identification of illumination source types using nighttime light images from SDGSAT-1. *International Journal of Digital Earth*, *17*(1). https://doi.org/10.1080/17538947.2023.2297013

Zhao, Z., Qiu, S., Chen, F., Chen, Y., Qian, Y., Cui, H., Zhang, Y., Khoramshahi, E., & Qiu, Y. (2023). Vessel detection with SDGSAT-1 nighttime light images. *Remote Sensing*, *15*(17), 4354. https://doi.org/10.3390/rs15174354

Appendix

Appendix A

Data Sample

Types	Description	Sample Location	%
FLOOD	Floodlight	4	0,01%
HPIT	High-Pressure Mercury Vapor Lamp	2.439	4,98%
HPL	High-Pressure Sodium Lamp	7.183	14,66%
HPST	High-Pressure Sodium Tubular Lamp	11.525	23,52%
LED	Light Emitting Diode	4.844	9,89%
SL	Straight Line (Fluorescent)	22.780	46,49%
SOLAR	Solar-Powered Lamp	15	0,03%
SON-T	Sodium Lamp - Tubular	8	0,02%
TL	Tubular Lamp (Fluorescent)	197	0,40%
Total		48.995	100,00%

Data Sample by Road Types

highway	Lamp Types	Count of Types	Average Power	Average Lamp in single point	Total Average Power
trunk	FLOOD	4,00	1.000,00	5,00	5.000,00
	HPIT	84,00	249,64	1,32	329,89
	HPL	18,00	234,44	1,00	234,44
	HPST	1.101,00	244,81	1,25	307,07
	LED	508,00	184,08	1,42	260,55
	SL	7,00	44,29	1,00	44,29
trunk Total		1.722,00	227,96	1,31	298,66
trunk_link	HPIT	4,00	147,50	2,25	331,88
	HPL	3,00	208,33	1,00	208,33
	HPST	43,00	250,58	1,21	303,03
	LED	27,00	171,48	1,11	190,53
trunk_link Total		77,00	215,84	1,22	263,50
primary	HPIT	68,00	197,35	1,57	310,54
	HPST	688,00	224,81	1,19	266,96
	LED	299,00	191,89	1,47	282,38
	SL	2,00	40,00	1,00	40,00
	SOLAR	12,00	80,00	1,00	80,00
primary Total		1.069,00	211,88	1,29	273,13
	HPIT	4,00	175,00	1,00	175,00
	HPST	10,00	320,00	2,00	640,00
primary_link	LED	2,00	200,00	2,50	500,00
primary_link Total		16,00	268,75	1,81	487,11
secondary	HPIT	361,00	194,46	1,23	238,63
	HPL	8,00	111,25	1,00	111,25
	HPST	906,00	178,78	1,10	197,53
	LED	354,00	181,36	1,31	236,68
	SL	11,00	60,00	1,00	60,00
secondary Total		1.640,00	181,66	1,17	213,23
secondary_link	HPIT	3,00	208,33	1,00	208,33
	HPST	3,00	216,67	1,33	288,89
	LED	1,00	80,00	1,00	80,00

highway	Lamp Types	Count of Types	Average Power	Average Lamp in single point	Total Average Power
secondary_link Total		7,00	193,57	1,14	221,22
tertiary	HPIT	836,00	160,46	1,10	176,20
	HPL	96,00	100,94	1,00	100,94
	HPST	2.635,00	145,00	1,02	148,47
	LED	943,00	119,01	1,15	137,06
	SL	186,00	41,18	1,00	41,18
	TL	1,00	15,00	2,00	30,00
tertiary Total		4.697,00	137,50	1,06	145,96
tertiary_link	HPST	6,00	406,67	3,00	1.220,00
	LED	1,00	120,00	2,00	240,00
tertiary_link Total		7,00	365,71	2,86	1.044,90
	HPIT	1.079,00	131,66	1,03	136,05
	HPL	7.058,00	112,97	1,00	113,30
	HPST	6.133,00	118,87	1,02	121,31
	LED	2.709,00	54,88	1,01	55,61
	SL	22.574,00	40,84	1,00	40,97
	SOLAR	3,00	80,00	1,00	80,00
	SON-T	8,00	40,00	1,00	40,00
residential	TL	196,00	28,21	1,00	28,21
residential Total		39.760,00	69,04	1,01	69,55

Appendix B

```
# -*- coding: utf-8 -*-
"""PJU dan SDGSAT-1.ipynb

**DATA LAMPU**
"""

import pandas as pd

# Load the Excel file to see the sheet names and preview the data
file_path = '/content/Data per lampu.xlsx'
excel_data = pd.ExcelFile(file_path)

# Show sheet names and preview the first sheet
sheet_names = excel_data.sheet_names
first_sheet_preview = pd.read_excel(excel_data, sheet_name=sheet_names[0], nrows=5)

sheet_names, first_sheet_preview

# Load the full data
lamp_data = pd.read_excel(excel_data, sheet_name=sheet_names[0])

# Calculate basic statistics for each relevant column
basic_stats = lamp_data.describe()
basic_stats

import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Setting the aesthetic style of the plots
sns.set(style="whitegrid")

# Creating subplots
fig, axes = plt.subplots(2, 2, figsize=(14, 12))

# Plotting Average Power
sns.barplot(ax=axes[0, 0], x='Lamp Type', y='Average of Power (watt)', data=lamp_data)
axes[0, 0].set_title('Average Power (Watt) by Lamp Type')
axes[0, 0].set_xticklabels(axes[0, 0].get_xticklabels(), rotation=45)
axes[0, 0].set_ylabel('Average Power (Watt)')

# Plotting Total Power
sns.barplot(ax=axes[0, 1], x='Lamp Type', y='Average of Total Power  (watt)', data=lamp_data)
axes[0, 1].set_title('Average Total Power (Watt) by Lamp Type')
axes[0, 1].set_xticklabels(axes[0, 1].get_xticklabels(), rotation=45)
axes[0, 1].set_ylabel('Average Total Power (Watt)')

# Plotting Red Intensity
sns.barplot(ax=axes[1, 0], x='Lamp Type', y='Average of Red (gray)', data=lamp_data)
axes[1, 0].set_title('Average Red Intensity by Lamp Type')
axes[1, 0].set_xticklabels(axes[1, 0].get_xticklabels(), rotation=45)
axes[1, 0].set_ylabel('Average Red (gray)')

# Plotting Green and Blue Intensity
sns.barplot(ax=axes[1, 1], x='Lamp Type', y='Average of Green', data=lamp_data, color='green',
label='Green')
sns.barplot(ax=axes[1, 1], x='Lamp Type', y='Average of Blue', data=lamp_data, color='blue',
label='Blue')
axes[1, 1].set_title('Average Green and Blue Intensity by Lamp Type')
axes[1, 1].set_xticklabels(axes[1, 1].get_xticklabels(), rotation=45)
axes[1, 1].set_ylabel('Average Intensity')
axes[1, 1].legend()

plt.tight_layout()
plt.show()

import numpy as np  # Make sure to import numpy

# Calculate the correlation matrix excluding non-numeric columns
numeric_data = lamp_data.select_dtypes(include=[np.number])  # This ensures only numeric columns
are included
correlation_matrix = numeric_data.corr()

# Plotting the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Correlation Matrix of Lamp Data')
plt.show()

from scipy.stats import pearsonr  # Importing the pearsonr function

# Extracting correlations and p-values between 'Average of Total Power  (watt)' and other variables
total_power_correlations = {}
variables = ['Average of Power (watt)', 'Average of Red (gray)', 'Average of Green', 'Average of Blue']
```

```
for var in variables:
    corr, p_value = pearsonr(lamp_data['Average of Total Power  (watt)'], lamp_data[var])
    total_power_correlations[var] = {'Correlation': corr, 'P-value': p_value}

total_power_correlations

"""**DATA JALAN**"""

import pandas as pd

# Memuat data
data = pd.read_excel('/content/Data per jalan.xlsx')

# Mencetak nama-nama kolom untuk memeriksa adanya spasi atau typo
print(data.columns)

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Memuat data
data = pd.read_excel('/content/Data per jalan.xlsx')

# Mengonversi data dictionary ke DataFrame
road_data = pd.DataFrame(data)

# Menghitung statistik deskriptif
statistik_deskriptif = road_data.describe()

# Membuat visualisasi
plt.figure(figsize=(12, 6))
sns.barplot(x='Road Type', y='Average of Total  (watt)', data=road_data)
plt.title('Rata-rata Konsumsi Daya per Jenis Jalan')
plt.ylabel('Rata-rata Daya (Watt)')
plt.xlabel('Jenis Jalan')
plt.xticks(rotation=45)
plt.show()

# Korelasi - Hanya kolom numerik
numeric_data = road_data.select_dtypes(include=[np.number])
korelasi = numeric_data.corr()

# Plotting matriks korelasi
sns.heatmap(korelasi, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Matriks Korelasi Data Jalan')
plt.show()

# Analisis penghematan
# Asumsi: Lampu LED menggunakan 50% daya dari jenis lampu konvensional
road_data['Savings Potential (Watt)'] = road_data['Average of Total  (watt)'] * 0.5
total_savings = road_data['Savings Potential (Watt)'].sum()

print("Total Potensi Penghematan Daya (Watt):", total_savings)
```

```
# Visualisasi potensi penghematan
plt.figure(figsize=(12, 6))
sns.barplot(x='Road Type', y='Savings Potential (Watt)', data=road_data)
plt.title('Potensi Penghematan Daya per Jenis Jalan')
plt.ylabel('Potensi Penghematan Daya (Watt)')
plt.xlabel('Jenis Jalan')
plt.xticks(rotation=45)
plt.show()
```