Monitoring Electrical Substations Using Landsat Surface Temperature Derived from Time-Series Landsat Satellite Imagery with Google Earth Engine

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***Abstract*:** *Monitoring electrical substations is essential for maintaining the reliability and efficiency of the power grid. Continuous monitoring helps detect faults, prevent equipment malfunctions, and ensure a stable electricity supply. In this research, the thermal conditions of the Gunsan substation, located on a mountain, were monitored using Land Surface Temperature (LST) data generated from the multispectral bands of time-series Landsat-8/9 satellite images, processed through Google Earth Engine. The study followed a systematic approach, where in the first step, daily LST was derived from a single Landsat-8/9 satellite image acquired over the Gunsan substation. Subsequently, a time-series analysis of the LST was conducted, and the differences between the LST and corresponding air temperature were calculated. The statistical results indicated that the LST at the Gunsan substation was consistently higher than the air temperature, with differences ranging from 3°C to 18°C, and the difference between the LST and air temperature was higher in the spring than in the summer, autumn, and winter seasons. Several factors likely contribute to this variation, including the increased solar radiation in spring, unique surface characteristics of the Gunsan substation, Urban Heat Island (UHI) effect and etc. In future research, we aim to generate daily LST data over the long term to gather sufficient samples for more accurate trend analysis and continuous monitoring of thermal conditions at the Gunsan substation. Additionally, the LST of the surrounding areas will be calculated to assess spatial temperature variations and understand thermal interactions between the substation and its environment, which may impact equipment performance and operational stability. Finally, we plan to extend the study to other industrial facilities, such as fossil fuel and nuclear power plants, to monitor thermal conditions and ensure the sustainable inspection and safety of these critical infrastructures. This comprehensive approach will enhance our understanding of thermal dynamics in industrial settings.*

Keywords: Electrical Substation, Land Surface Temperature, Landsat-8/9 satellite image, Google Earth Engine

Introduction

An electrical substation is a vital component of the electric power infrastructure, playing a key role in the transmission and distribution of electricity (Brown, 2009). It acts as an intermediary between high-voltage transmission lines, which transport electricity over long distances, and lower-voltage distribution lines, which deliver power to end-users, such as households, businesses, and industries (Momoh, 2012). The primary function of a substation is to regulate voltage levels by using transformers, stepping up voltage for efficient long-distance transmission or stepping it down for safe distribution (Glover *et al*., 2012). In addition to voltage regulation, substations are equipped with various control devices like switchgear, circuit breakers, and protective relays, which safeguard the system from electrical faults and ensure the continuous, stable operation of the power grid (Brown, 2009). Moreover, electrical substations play a crucial role in the integration of renewable energy sources, such as solar and wind, into the grid by managing the variable input of these sources (Momoh, 2012). By facilitating power flow control, voltage regulation, and protection, substations help maintain grid stability and reliability (Stevenson & Grainger, 1994). Figure 1 illustrates a photograph of a large-scale substation, highlighting its complexity and significance in modern electrical systems.

Figure 1. Photograph of a large-scale substation, highlighting its complexity and significance in modern electrical systems (Captured from a figure in Energy Education, 2024).

Monitoring electrical substations is essential for maintaining the stability, efficiency, and safety of power systems, ensuring the reliable flow of electricity across the grid. Substations are responsible for key functions such as voltage regulation, power transformation, and distribution, making them critical nodes within the power network (Jenkins *et al*., 2010). Any malfunction or failure in a substation can result in widespread disruptions, including power outages, equipment damage, and safety risks to both workers and the public. Effective monitoring helps prevent such failures by allowing for early detection of potential issues, enabling timely interventions (Terzija *et al*., 2011). Real-time monitoring of critical substation components, such as transformers, circuit breakers, and protective relays, is crucial for detecting signs of wear or malfunction before they lead to significant failures (Farinaccio *et al*., 2020). Additionally, continuous monitoring allows for more efficient load management and helps optimize maintenance schedules, reducing the risk of unexpected breakdowns and minimizing downtime (Momoh, 2012). Advanced monitoring systems can also facilitate the integration of renewable energy sources, which introduces variability into the grid, by ensuring substations can handle fluctuations in supply and demand (Hasan *et al*., 2016). This proactive approach enhances the overall reliability and safety of the power grid.

Land Surface Temperature (LST) serves as an essential tool for ensuring the safety and operational integrity of electrical substations by enabling the detection of unusual heat signatures, which may indicate overheating of critical equipment. Transformers and other substation components naturally produce heat during operation, but when cooling systems malfunction or equipment becomes overloaded, surface temperatures can rise significantly, leading to potential failures or even fires if not addressed promptly (Miettinen & Holappa, 2006). Continuous LST monitoring allows operators to identify early signs of excessive heating and take preventive measures before a more serious issue arises. In addition to equipment-specific monitoring, LST plays a crucial role in assessing external environmental factors, particularly the Urban Heat Island (UHI) effect, which can exacerbate thermal stress in substations located in urban or industrial areas. Urban areas typically experience higher surface temperatures compared to rural zones due to the prevalence of heat-absorbing materials such as concrete and asphalt (Voogt & Oke, 2003). In such cases, substations situated in urban environments may face elevated risks of overheating due to UHI effects, especially during heatwaves. The combination of UHI and localized equipment heat can result in excessive thermal loads, making LST monitoring even more essential for identifying potential risks. LST data can also be instrumental in evaluating how UHI effects interact with other environmental risks. For example, high LST values combined with dry conditions can signal increased wildfire risks in vegetation near substations, which could further compromise the safety and stability of power infrastructure (Kalantar *et al*., 2020). As urban areas continue to expand and temperatures rise due to climate change, the integration of LST in substation monitoring not only helps in detecting equipment overheating but also provides insights into the broader thermal dynamics affecting these facilities. This dual capability makes LST a valuable tool for both operational maintenance and environmental management. Moreover, LST monitoring can help utility companies optimize substation locations and designs in urban environments by identifying UHI hotspots and recommending mitigation strategies, such as increasing green spaces around substations to reduce localized heat build-up (Santamouris, 2014; Li *et al*., 2017; Zhou *et al*., 2014). By incorporating LST into routine monitoring practices, operators can manage thermal stresses more effectively and ensure the long-term safety and efficiency of electrical infrastructure.

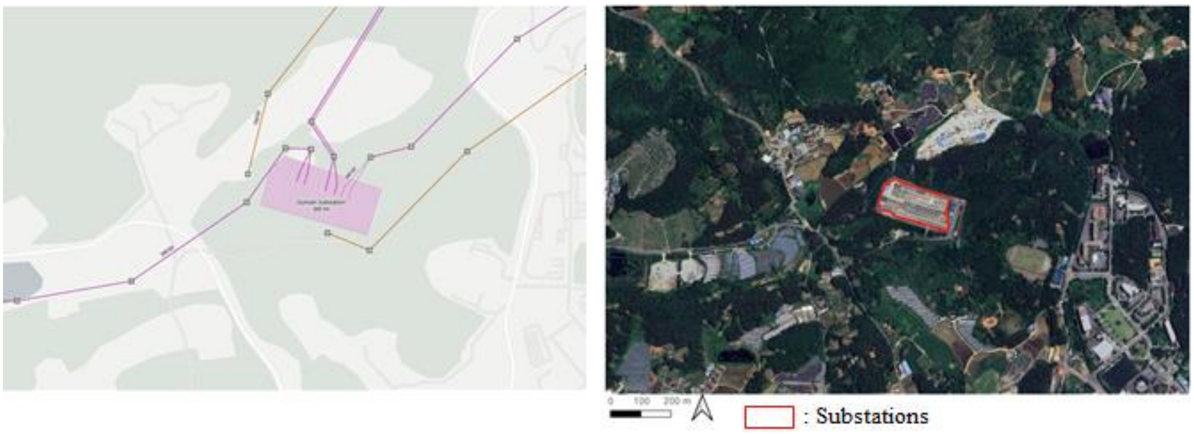
Previous studies have extensively investigated the application of satellite-based LST in enhancing the safety and efficiency of electrical substations. Miettinen and Holappa (2006) highlighted the importance of monitoring thermal conditions in substations, focusing on the use of technologies such as infrared thermography and LST derived from satellite data. Their research demonstrated that LST can be an effective early warning system, capable of detecting overheating in key substation components, such as transformers, which are susceptible to excessive heat due to factors like insulation deterioration or poor cooling performance. Early identification of these issues through LST allows for timely maintenance and reduces the risk of equipment failure and potential power outages. Further exploration by Kalantar *et al*. (2020) underscored the benefits of integrating LST data from remote sensing platforms, such as Landsat, with real-time monitoring systems to improve substation reliability. They demonstrated that LST data could be used to track thermal anomalies, enabling operators to manage thermal stress and prevent substation malfunctions. Additionally, LST monitoring provides insights into environmental hazards such as extreme heat events and nearby wildfire risks that could further endanger substation functionality. The integration of satellite-based LST with other monitoring technologies thus offers a comprehensive approach to improving the operational efficiency and safety of electrical substations (Voogt & Oke, 2003).

Google Earth Engine (GEE) is a cloud-based platform developed by Google that facilitates large-scale analysis of satellite imagery and geospatial data. Its core functionality is to provide researchers, scientists, and developers with access to vast geospatial data archives and powerful computing resources, allowing for real-time environmental monitoring, historical trend analysis, and other advanced applications (Amani *et al*., 2020; Gorelick *et al*., 2017). GEE integrates a wide range of remote sensing datasets, including imagery from the Landsat, MODIS, and Sentinel missions, as well as climate and topographic data, making it a versatile tool for analyzing the Earth's surface and environmental changes (Kumar and Mutanga, 2018; Tamiminia *et al*., 2020). One of GEE's primary advantages is its cloud-based architecture, which allows users to process massive datasets without the need for local computing resources. This makes it possible to perform complex analyses on global datasets quickly and efficiently. GEE supports a user-friendly interface through its JavaScript and Python APIs, enabling the creation of custom algorithms and data processing workflows (GEE, 2024). The platform also accommodates the integration of multiple data types, such as raster and vector data, facilitating diverse spatial analyses (Kumar & Mutanga, 2018). GEE has been applied in numerous research fields, including land cover classification, deforestation monitoring, climate change assessment, and urban studies. For example, Hansen *et al*. (2013) used GEE to generate a global map of forest cover change, processing over a decade of Landsat data to monitor deforestation trends. Similarly, Tamiminia *et al*. (2020) employed GEE in agricultural monitoring, applying remote sensing techniques to assess crop yields and monitor agricultural practices across large regions. Furthermore, GEE's built-in machine learning capabilities enable users to apply algorithms for classification, change detection, and time-series analysis (GEE, 2024). These features have made GEE an invaluable tool for applications ranging from disaster response to environmental conservation and urban planning (Sidhu *et al*., 2018). Its capacity to handle global-scale geospatial data with ease has positioned GEE as a vital resource for researchers working on environmental and geospatial challenges.

In this research, the thermal conditions of the selected electrical substation were assessed using LST data obtained from the multispectral bands of time-series Landsat-8/9 satellite images, processed via Google Earth Engine. The research adopted a systematic approach, beginning with the extraction of daily LST from individual Landsat-8/9 satellite images over the selected substation area. This was followed by a time-series analysis of the LST data, which was used to calculate and analyze the differences between LST and the corresponding air temperature.

Study Area and Datasets

In this study, the Gunsan Substation located in Gunsan City of Republic of Korea, was selected as the study area. Figure 2(a) shows the Gunsan Substation shown in Open Infrastructure Map, while Figure 2(b) shows the Gunsan Substation shown in Google Satellite Map.



(a) (b)

Figure 2. Location of the Gunsan Substation shown in Open Infrastructure Map (a) and Google Satellite Map (b).

The 28 scenes of the Landsat-8/9 satellite images acquired in 2022 with cloud cover less than 50% were used to generate the daily LST of the Gunsan substation area.

Methodology

In the first step of the proposed methodology, Land Surface Temperature (LST) was generated from a single Landsat-8/9 satellite image following several computational stages. Initially, the spectral radiance (L_λ) was calculated using the radiance multiplicative scaling factor (ML), the radiance additive scaling factor (AL), and the digital number (DN) of the thermal band (Band 10) of the Landsat image, as shown in Equation 1 (United States Geological Survey (USGS), 2019).

$$L_\lambda = ML \times DN + AL \tag{1}$$

Where L_λ represents the spectral radiance, ML is the radiance multiplicative scaling factor, AL is the radiance additive scaling factor, and DN is the digital number from Band 10. Next, the spectral radiance was converted into brightness temperature (Tb) in Kelvin by applying the inverse of Planck's Law, as described in Equation 2 (Chander *et al.*, 2009).

$$T_b = \frac{K_2}{\ln(\frac{K_1}{L_\lambda}+1)} \tag{2}$$

In this equation, Tb is the brightness temperature in Kelvin, K_1 and K_2 are constants specific to the Landsat thermal band, and L_λ is the spectral radiance. The surface emissivity (ϵ) was corrected using the Normalized Difference Vegetation Index (NDVI), which relates vegetation cover to emissivity. The emissivity was calculated using Equation 3 (Sobrino *et al.*, 2004).

$$\epsilon = 0.004 \times NDVI + 0.986 \tag{3}$$

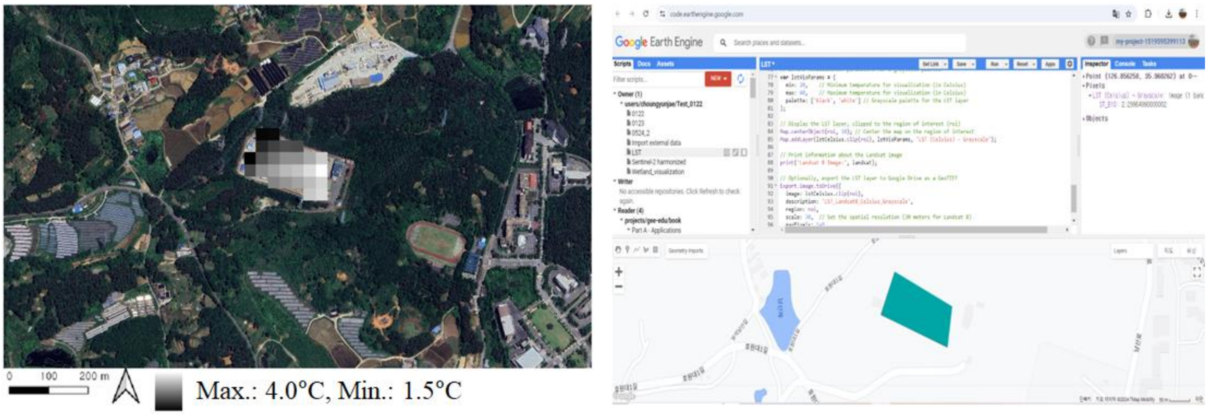
Subsequently, the LST in Kelvin was derived from brightness temperature (T_b), with emissivity correction, using Equation 4, based on the relationship between brightness temperature, wavelength, and surface emissivity (Jiménez-Muñoz *et al.*, 2014).

$$LST_{Kelvin} = \frac{T_b}{1+\left(\lambda \cdot \frac{T_b}{\rho}\right)\ln(\epsilon)} \tag{4}$$

Here, λ is the wavelength of the thermal band (10.9 μm for Band 10), and ρ is the ratio of Planck's constant to Boltzmann's constant, with a value of 1.438×10^{-2} mK. Finally, the LST was converted from Kelvin to Celsius using Equation 5.

$$LST_{Celsius} = LST_{Kelvin} - 273.15 \quad (5)$$

We generated the daily LST in Celsius from the Landsat-8/9 satellite image using the Google Earth Engine, and Figure 3 shows the generated daily land surface temperature (a) derived from the Landsat-8/9 satellite image acquired in the Gunsan station area generated by using the Google Earth Engine (b).



(a) (b)

Figure 3. Example of the daily land surface temperature derived from the Landsat-8/9 satellite image acquired in the Gunsan station area generated by using the Google Earth Engine (b).

After generating the daily LST in Celsius, time-series LSTs for the Gunsan electrical substation area in 2022 were produced using Landsat-8/9 satellite imagery with a cloud cover of 50% or less, processed through Google Earth Engine. The calculated daily LST of the Gunsan substation was then compared with the daily air temperature of Gunsan City to analyze the thermal characteristics of the electrical substation.

Table 1: Difference between the daily LST of the Gunsan substation area and the daily air temperature of Gunsan City.

Date	**Daily LST of Gunsan substation (°C)**	**Daily air temperature of Gunsan City (°C)**	**Difference (°C)**
2022-01-04	5.6	0.3	5.3
2022-01-13	-0.3	-3.5	3.2
2022-01-20	1.1	-3.5	4.6
2022-01-21	3.0	-1.2	4.2
2022-01-28	4.5	-0.6	5.1

2022-01-29	4.5	-0.8	5.3
2022-02-14	9.3	3.9	5.4
2022-02-21	5.9	-0.2	6.1
2022-02-22	6.3	-1.3	7.6
2022-03-02	11.6	2.6	9.0
2022-03-09	16.9	4.5	12.4
2022-04-02	20.1	5.8	14.3
2022-04-03	21.0	7.0	14.0
2022-04-10	21.3	17.1	4.2
2022-04-11	28.5	19.1	9.4
2022-05-04	30.1	15.3	14.8
2022-05-05	31.0	16.7	14.3
2022-05-21	30.3	18.1	12.2
2022-06-22	41.9	24.2	17.7
2022-09-09	32.7	23.6	9.1
2022-10-11	20.5	13.0	7.5
2022-10-12	21.2	12.8	8.4
2022-10-19	19.6	9.9	9.7
2022-10-20	20.9	11.5	9.4
2022-10-27	20.9	13.1	7.8
2022-10-28	20.2	11.8	8.4
2022-11-04	15.3	6.9	8.4
2022-11-05	15.8	6.9	8.9
		Total difference	8.8

Results and Discussion

Table 1 shows the following results. First, the LST is higher than the corresponding air temperature, with the difference fluctuating around several degrees Celsius. For example, on January 4th, 2022, the LST was 5.6°C, while the air temperature was 0.3°C, creating a difference of 5.3°C. This consistent pattern is due to how the Earth's surface absorbs heat and releases it more quickly than the surrounding air. Second, the differences between LST and air temperature may also reflect seasonal changes. During the colder months (e.g., January), the differences tend to be smaller, possibly because both the surface and the air are colder, and heat retention in the land is lower. Conversely, as we approach warmer periods (spring and summer), the surface retains and releases more heat, leading to a larger discrepancy. Third, despite the general trend of LST being higher than air temperature, the difference is not constant. The statistical results showed that the LST at the Gunsan substation was consistently higher than the air temperature, with differences ranging from 3°C to 18°C, and the difference between the LST and air temperature was generally higher in the spring than in the summer, autumn, and winter seasons. These variations could be driven by several factors, including weather patterns, cloud cover, and surface characteristics of the Gunsan substation.

Based on the derived results shown in Table 1, we could derive the multiple discussions as follows. First, the urban or industrial facilities such as the Gunsan substation, likely contributes to the Urban Heat Island (UHI) effect, occurring when urbanized areas experience significantly higher temperatures than their rural surroundings, due to the modification of land surfaces and human activities (Voogt & Oke, 2003). As can be seen in Figure 1, the Gunsan substation is located in built-up areas with impervious surfaces like asphalt and concrete, which absorb more heat and release it slower than natural landscapes. Second, the nature of land cover in the area of Gunsan substation could play a significant role in this temperature difference. In general, vegetation absorbs solar radiation for photosynthesis and releases water vapor, effectively cooling the surface and moderating LST (Bonan, 2019). In contrast, the Gunsan substation's surfaces, which are impervious and devoid of significant plant cover, lack this cooling mechanism, leading to higher LST values. Third, the concept of thermal inertia also plays a role in the observed difference. Surfaces with high thermal inertia, like concrete and metal, retain heat longer and cool more slowly after sunset compared to natural surfaces like soil or grass (Stull, 1988). This means that the Gunsan substation's surfaces remain warmer throughout the day, resulting in elevated LST measurements compared to the surrounding air. Air temperature, in contrast, fluctuates more rapidly, as the lower atmosphere has less capacity to store heat.

Conclusion and Recommendation

Electrical substations are fundamental to the efficient operation of power systems. Their ability to manage voltage, protect the grid, integrate renewable energy, and facilitate continuous monitoring makes them indispensable in modern electrical networks (Glover *et al*., 2012). In this research, daily Land Surface Temperature (LST) was generated to monitor the thermal conditions of the Gunsan substation. This study demonstrated the potential of satellite imagery and multispectral data for evaluating the safety and operational efficiency of industrial facilities, particularly electrical substations. However, several technical limitations were identified that impact the ability to fully assess substation safety. First, the dataset was limited to only 28 daily LST measurements due to significant cloud cover and data availability, which reduces the reliability of the findings, particularly in evaluating seasonal LST changes. Insufficient sample size limits the ability to capture the full range of seasonal temperature variations, which are critical for understanding long-term thermal trends (Zhang *et al*., 2014). Second, LST was only calculated for the Gunsan substation itself, which prevented a broader analysis of the surrounding environment. Understanding how local topography, land use, and vegetation affect the temperature differences between LST and air temperature requires a more comprehensive spatial analysis. Third, key atmospheric conditions, such as wind speed, humidity, and atmospheric pressure, were not considered in the analysis. These factors can significantly affect the LST-air temperature relationship and should be included in future work to provide a more robust understanding of thermal conditions (Voogt & Oke, 2003). Lastly, the exclusive reliance on Landsat-8/9 imagery, which is only available at 8 to 9-day intervals, introduced further limitations. Continuous monitoring at shorter intervals is necessary to identify potential overheating issues in real-time (Hansen *et al*., 2013). To address these limitations, future research should focus on generating long-term LST datasets to obtain sufficient samples for more accurate trend analysis and continuous monitoring of the Gunsan substation. Furthermore, expanding the analysis to include the surrounding areas will allow for an evaluation of spatial temperature variations, enabling a better understanding of thermal interactions between the substation and its environment, which may affect equipment performance and operational stability. Additionally, future studies should include other industrial facilities, such as fossil fuel power plants and nuclear power plants, to monitor thermal conditions and ensure the sustainable safety of these facilities. Incorporating atmospheric conditions and utilizing higher-frequency satellite imagery, or complementing satellite data with ground-based measurements, will enhance the accuracy and practicality of thermal monitoring (Jiménez-Muñoz *et al*., 2014).

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