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Satellite-Ground Temperature Correlation for Solar Energy: Insights from Oman

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Abstract:
As Oman shifts towards renewable energy to meet growing electricity demands, solar power has become a cornerstone of its energy strategy. However, the efficiency of photovoltaic (PV) systems is sensitive to temperature, with higher temperatures reducing their performance. This study investigates the relationship between ground-based temperature measurements and satellite-derived temperature data from Landsat 8 in Seeb, Muscat, Oman. By comparing ground temperatures with satellite data, the study aims to enhance the accuracy of temperature predictions, improving energy yield forecasts for solar farms and off-grid systems. A linear regression analysis between ground temperatures and Landsat 8 data resulted in a high correlation R^2=0.9189, with a trend line equation of $y=1.0811x-0.5489$, suggesting that satellite readings are slightly higher than ground temperatures, particularly in summer months. The seasonal variation between the datasets shows convergence during cooler months (January and October) and divergence in peak summer (July), where satellite data reports temperatures up to 2°C higher than ground-based measurements. The study provides insights into the potential of using satellite data to model temperature variations and optimize solar power generation in Oman, where direct ground measurements may not always be feasible.

Keywords: *Solar energy, Temperature correlation, Satellite data, Photovoltaic*

1 Introduction

As the global demand for energy continues to rise, the transition to renewable energy sources has become critical (Chen et al., 2025). To addressing both environmental and energy security concerns, solar power in particular, stands out as a promising and sustainable solution, especially in regions with high solar irradiation such as Oman (Danbatta et al., 2024b). With its abundant sunshine, Oman is well positioned to capitalize on solar energy to meet its growing electricity demands and to reduce its reliance on fossil fuels (Danbatta et al., 2024a). However, despite the favourable solar conditions, maximizing the efficiency of photovoltaic (PV) systems requires precise environmental monitoring and data-driven insights.
One of the key factors that influences the performance of solar power systems is temperature (Ammari et al., 2022). PV system efficiency decreases as temperature increases, meaning that accurate temperature data is crucial for optimizing energy output. Traditionally, ground-based temperature measurements is used to assess the conditions of solar farm sites. However, these measurements can be sparse and limited in scope, especially in remote areas where solar farms and off-grid systems are often located.
Additionally, by correlating satellite and ground temperature data, the research in Oman contributes to enhancing the accuracy and reliability of these datasets, which is crucial for generating TMYs. Improved TMYs, based on accurate correlations, enable more precise simulations of solar power generation and ensure that PV systems are designed to operate efficiently under real-world climatic conditions (N. Al-Azri et al., 2013).
Furthermore, ground and satellite temperature correlation is often used as a proxy to estimate solar radiation. Since temperature variations influence the amount of incoming solar radiation, correlating satellite and ground-based temperature measurements provides valuable insights into solar radiation predictions on various surfaces. By extending this method to non-horizontal surfaces, it allows for more accurate predictions for tilted PV panels, which are

often installed at non-horizontal angles to maximize energy absorption (N.Z.Al-Rawahi et al., 2011).
Solar energy production is influenced by the angle of incidence of solar radiation on a surface. Non-horizontal surfaces, such as tilted PV panels, are strategically placed to capture the most radiation based on geographic location. The correlation between satellite and ground data helps in refining the estimation of the solar irradiance that these surfaces will receive, making predictions more accurate and improving the efficiency of PV systems in locations like Oman (Alwadei et al., 2022).
Satellite technology offers a powerful complement to ground-based observations. With the ability to capture large-scale temperature data across vast geographic areas, satellite imagery provides continuous and comprehensive insights into surface conditions (Zhang et al., 2019). The integration of satellite-derived temperature data with ground truth measurements can significantly improve the accuracy of environmental assessments for solar energy projects.
The objective of this research is to leverage satellite data for temperature forecasting in solar energy studies by firstly Quantifying the relationship between ground and satellite temperatures to create a predictive model for temperature impacts on solar farm efficiency. Identifying seasonal patterns and environmental factors that contribute to temperature discrepancies, especially in high-temperature conditions. The findings aim to contribute to accurate temperature modelling, supporting the optimization of solar power systems in Oman.

2 Theoretical Framework

Recent studies have highlighted the importance of accurate temperature prediction in solar energy applications. Temperature variations can affect PV efficiency (Abdel-Aziz & ElBahloul, 2025). Traditional ground-based measurements, while accurate, fail to capture spatial variations effectively. Subsequently, satellite-based temperature monitoring has evolved significantly over the past decade. Machine learning approaches for temperature prediction can achieve accuracy improvements (Hedar et al., 2021).
The fundamental relationship between satellite-derived and ground temperatures requires a comprehensive theoretical framework that accounts for the complex interactions between atmospheric, surface, and environmental factors. Land surface [1]temeperature (LST) approach that can be expressed in equation (1) from (Li et al., 2023), where the radiometric temperature is T_s, the viewing zenith angle is θ_v ,the azimuth angle as φ_v, the effective channel wavelength λ , the Planck's law inverse B_λ^{-1}, at sensor radiance, upward, downward atmospheric radiance respectively, R_λ, $R_{ay\lambda}\uparrow$, $R_{at\lambda}\downarrow$. The atmospheric transmittance as τ_λ. the land surface emissivity denoted as ε_λ. The atmospheric interaction correction in equation (2) from (Wan et al., 2025) utilizes the the radiative transfer equation. L_λ is the sensor apparent radiance. $L_{atm,i}\downarrow$ and $L_{atm,i}\uparrow$ is the downward and upward radiance, τ is the thermal band transmittance, ε is the emissivity and $B\ (T_S)$ is the black body thermal infrared. This formulation significantly improves upon previous models by incorporating multiple environmental factors and their interactions.

$$T_s(\theta_v,\varphi_v) = B_\lambda^{-1}\left[\frac{R_\lambda(\theta\_v,\varphi\_v) - R_{ay\lambda}\uparrow(\theta_v,\varphi_v) - \tau_{\lambda(\theta_v,\varphi_v)}\,[1-\varepsilon_\lambda(\theta_v,\varphi_v)\ ]\,R_{at\lambda}\downarrow)}{\tau_\lambda(\theta_v,\varphi_v)\,\varepsilon_\lambda(\theta_v,\varphi_v\ )}\right] \quad (1)$$

$$L_\lambda = [\varepsilon\ B\ (T_S)+(1-\varepsilon)\ L_{atm,i}\downarrow]\ \tau + L_{atm,i}\uparrow \quad (2)$$

Urban heat island effects are modeled through building density and impervious surface percentage, while coastal effects are captured through an exponential decay function based on distance from the coastline. This approach ensures that all major environmental factors affecting temperature are properly accounted for in the model. Additionally, temporal evolution plays a crucial role in temperature prediction. (Pande et al., 2024) employs a modified Fourier series model that captures both annual and diurnal temperature variations. This approach allows for the representation of multiple temporal scales, from daily fluctuations to seasonal patterns.

3 Study Region

Seeb illustrated in Fig. 1, located in the northern part of Muscat, the capital city of Oman, is a coastal area that plays a critical role in the country's socio-economic development. Seeb has rapidly urbanized over recent decades, transitioning from a small fishing village to a bustling suburban region. It is strategically positioned along the Gulf of Oman, with a combination of coastal plains, low-lying terrain, and

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nearby mountainous areas. The region experiences a hot desert climate, characterized by long, extremely hot summers and mild winters. The summer months, from May to September, are particularly harsh, with average daily temperatures exceeding 40°C, while winters see more moderate temperatures, ranging between 18°C and 25°C. This region receives minimal annual rainfall, typically around 100 mm, primarily concentrated in short bursts during the winter months. The arid environment, combined with intense solar irradiation throughout most of the year, makes Seeb an ideal location for solar energy studies, but also introduces challenges related to high temperatures, which can affect PV efficiency. The proximity to the sea adds a layer of complexity to temperature dynamics, as coastal winds and humidity levels vary significantly from inland locations.

Fig. 1. Seeb, Muscat Oman

This geographical diversity provides a unique environment for studying solar energy production, particularly in relation to temperature variations that affect PV performance.

4 Methodology

The overview methodology is illustrated in Fig. 2. The data collected for the land surface temperature comparison utilized Landsat 8 TIR bands and ground temperature reading of Seeb, Muscat obtained from NOAA Database(National Centers for Environmental Information (NCEI), 2019).

Landsat 8(U.S. Geological Survey, 2021), launched by NASA and the USGS in 2013, is a vital Earth observation satellite that provides high-resolution multispectral and thermal imagery for environmental monitoring, land use analysis, and climate studies.

It features the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), which enable accurate surface temperature measurements critical for applications such as urban heat mapping, agriculture, and water resource management. While Landsat 8 offers reliable long-term temperature data, its accuracy can be influenced by atmospheric conditions, sensor calibration, and spatial resolution limitations compared to ground-based measurements.

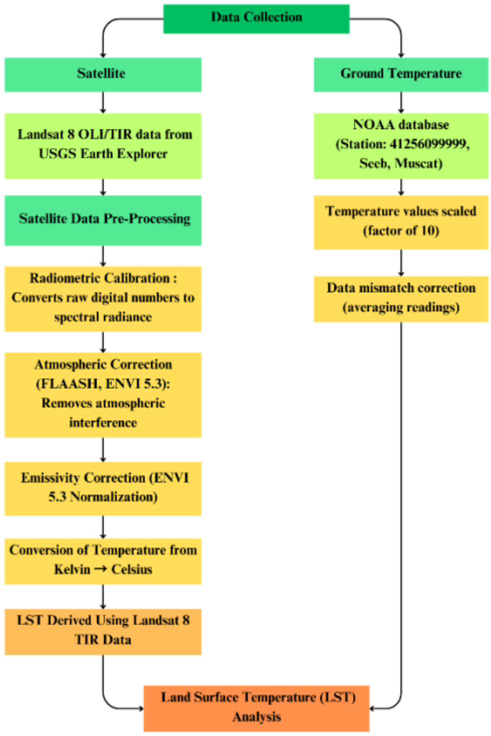

Fig. 2 Overview Methodology

4.1 Ground Temperature Data Collection

The details of the ground parameters are shown in Table 1, from the NOAA dataset the average temperature that corresponded to the Landsat 8 TIR images are downloaded based on date and time, ISD (integrated surface database) data was retrieved. The average is taken, due to the challenge that the satellite path time and the ground station time reading does not match exactly.

Table 1. Location description of ground temperature measurement

Station	Latitude	Longitude
41256099999	23.59328	58.284444
Elevation	Name	Quality Control
14.63	Seeb international, mu	V020

The NOAA ISD format is processed. The ISD data type values are scaled by a factor of 10. Table. 2 shows the post processed average temperature of the ground station. The average was chosen because the flight time of the satellite over the scene is at 06:34:43 and the hourly reading is at 06:00 and 06:50, the ground truth temperature doesn't coincide with the exact minutes of the satellite flight times.

Table 2. Post processed average temperature measurement

Date (yyyy/mm/dd-time)	Average temperature (Celsius)
2019-01-10T06:00:00	26.25
2019-01-10T06:50:00	
2019-04-16T06:00:00	31
2019-04-16T06:50:00	
2019-07-05T06:00:00	37.1
2019-07-05T06:50:00	
2019-10-09T06:00:00	34.75
2019-10-09T06:50:00	

4.2 Satellite Imagery Data Collection

The dataset utilized in this research, is derived from satellite imagery captured by the Landsat 8 Thermal Infrared Sensor (TIR). These images were acquired through the U.S. Geological Survey's Earth Explorer platform. The Landsat 8 OLI/TIR dataset possesses unique spatial, spectral, and temporal attributes, enabling a thorough analysis of the study area.

From a spatial perspective, the Landsat 8 OLI/TIR system delivers a resolution of 30 meters for its multispectral bands, allowing for a detailed examination of land surface characteristics. The sensor records data across multiple spectral bands, offering critical insights into diverse surface attributes. The multispectral range spans from visible to shortwave infrared, supporting the extraction of key environmental indicators such as vegetation conditions, land use patterns, and thermal variations.

Regarding spectral coverage, the Landsat 8 OLI/TIR sensor captures an extensive range of electromagnetic wavelengths, providing both multispectral and thermal imaging capabilities for Earth surface analysis. In terms of temporal resolution, the sensor revisits the same location every 16 days, ensuring consistent data acquisition to monitor seasonal changes and detect long-term environmental shifts. The specific satellite scenes utilized in this research are detailed in Table 3.

Table 3. Landsat 8 OLI/TIR satellite scenes

Scene Time	WRS
06:35:01.2220310Z	
06:34:33.9627430Z	(158,44)
06:34:10.2046779Z	
06:34:43.5675189Z	

4.3 Satellite Data Pre-Processing

As part of the analysis, radiometric calibration and atmospheric correction were applied to all acquired images. Radiometric calibration serves to transform the raw digital values recorded by satellite sensors into physically interpretable units, thereby ensuring uniformity and comparability across multiple datasets. This process follows the methodology outlined in (Eq.3) from (Sholihah & Shibata, 2019). Where L_λ is the Spectral radiance. ML is the radiance multiplicative factor. Qcal is the quantized pixel values. Al is the radiance additive factor

$$L_\lambda = ML \times Qcal + AL \qquad \text{-(Eq.3)}$$

The atmospheric correction for this study was conducted using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubus (FLAASH) method within ENVI 5.3. This step significantly improves the precision and dependability of data extracted from Landsat 8 TIR imagery. By accounting for variables such as water vapor, aerosols, and atmospheric gases, this correction reduces their influence on the thermal radiation emitted from the Earth's surface. The FLAASH algorithm utilizes radiative transfer equations to simulate interactions between atmospheric components and both incoming solar and emitted thermal radiation, ensuring the retrieval of atmospherically corrected values.

Radiometric calibration and FLAASH atmospheric correction are critical in maintaining the accuracy of reflectance values, especially in areas with varying atmospheric conditions, such as coastal environments. Applying these corrections strengthens the reliability of the extracted data, facilitating precise surface analyses and fostering a deeper understanding of environmental dynamics.

Land Surface Temperature (LST) plays a key role in evaluating Earth's surface energy balance and is extensively applied in various environmental studies.

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LST measures the temperature of the land's surface while excluding atmospheric influences. Its accurate estimation is crucial for assessing climate patterns, agricultural conditions, and urban heat island effects. It is worth noting that LST is affected by several factors, including surface emissivity and atmospheric variations, which may necessitate further adjustments depending on the specific application. Lastly, thermal emissivity correction is executed using the ENVI 5.3 Emissivity Normalization tool, followed by converting temperature values from Kelvin to Celsius.

4.4 Results and Discussion

As obtained from the processed satellite images, Fig. 3 depicts the LST of Seeb Muscat and the reading scale of the temperature in Celsius on the left.

The illustration in Fig. 3 shows the corresponding temperature of ground station temperature and the satellite thermal image temperature corresponding to the longitude and latitude of the exact same location respectively. Comparing the ground temperature data with Landsat 8 TIR satellite temperature readings. From Fig. 4, consisting of four time points throughout the year (January, April, July, and October), showing the trends in temperature across these months for satellite and ground measurements. Reflecting a typical seasonal temperature variation for Seeb, with temperatures steadily rising from January to July, followed by a decline toward October. This pattern is characteristic of the hot desert climate in the region, where temperatures peak during the summer months (July) and are lowest in the winter (January). Both ground and satellite temperature datasets follow this seasonal trend.

The satellite-derived temperature readings are consistently higher than the ground temperature measurements for most of the year. This difference is most notable in July, where the satellite records the highest temperatures (around 40°C), while the ground temperature is slightly lower. The ground temperature readings show a similar seasonal trend but remain slightly lower than the satellite readings in April and July. The temperature difference between satellite and ground data is most pronounced in the hotter months, particularly in summer (July).

Interestingly, the ground and satellite temperatures converge in the cooler months (January and October) as schematised in Fig. 4. In January, both data sources show nearly identical readings around 27°C, indicating minimal discrepancies between the two datasets when temperatures are lower.
In October, the gap between ground and satellite temperatures also narrows, suggesting that the satellite data may be more accurate in cooler conditions.

Additionally, satellite measurements might reflect the surface heat radiated by buildings, pavements, or even soil, leading to higher readings than ground-based thermometers, which measure the ambient air temperature.

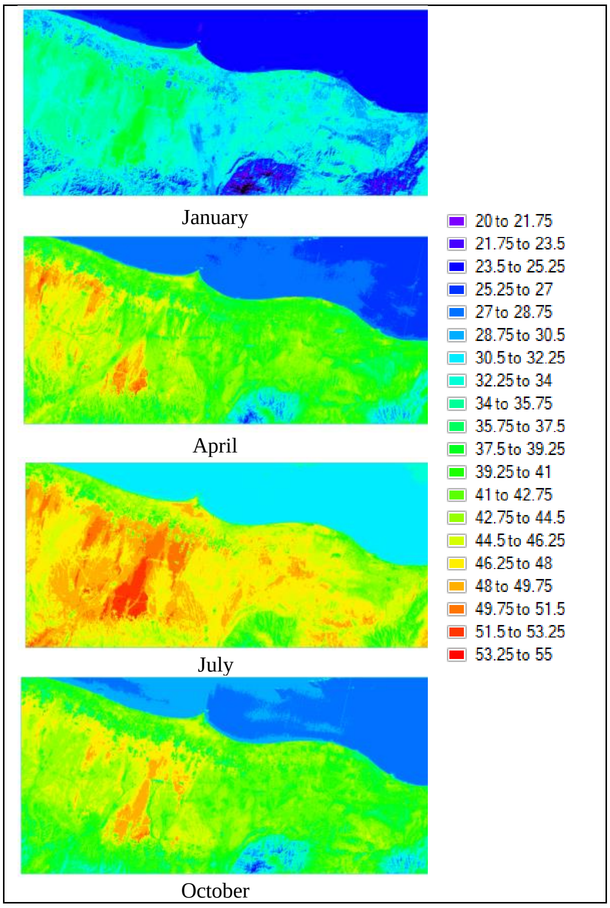

Fig. 3 Thermal Images

The higher temperatures recorded by Landsat 8 are likely due to several factors inherent in satellite-based thermal infrared measurements. Satellites often detect surface temperatures, which can be influenced by factors such as heat retention in urban areas or the presence of vegetation, which may not always match ground-level air.

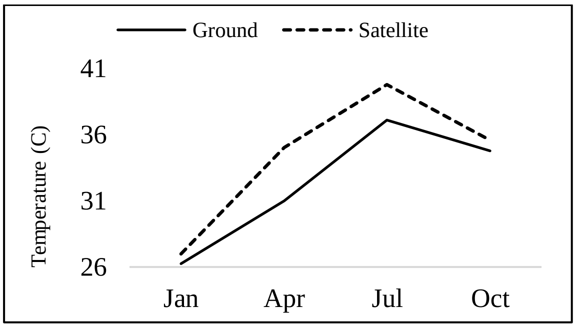

Fig. 4 Ground Temperature vs LANDSAT 8 TIR Temperature

In densely populated areas like Seeb, urban heat islands (UHIs) could explain the elevated satellite temperature readings. UHIs occur when built environments such as roads and buildings absorb and retain heat, causing localized temperature increases. Satellite sensors are more likely to capture these heat variations, which could explain the larger discrepancy between satellite and ground temperatures during the hottest months (July), when UHIs are at their peak.

Understanding the differences between ground and satellite temperature measurements is crucial for solar energy production studies. Since PV systems are sensitive to temperature, using accurate temperature data to predict energy yield is important. This plot suggests that satellite data, while useful for large-scale monitoring, may require ground-based calibration, especially during the hottest months. Using both data sources in conjunction could provide a more reliable understanding of temperature impacts on solar farm performance. The consistent pattern in temperature differences between ground and satellite readings suggests the potential for developing a correction model. By understanding how the temperature gap varies seasonally, researchers can create an adjustment factor to better align satellite-derived temperatures with ground-based data, improving the accuracy of energy production models for solar farms. Fig. 5 illustrates the steps and procedure for obtaining the R^2 value.

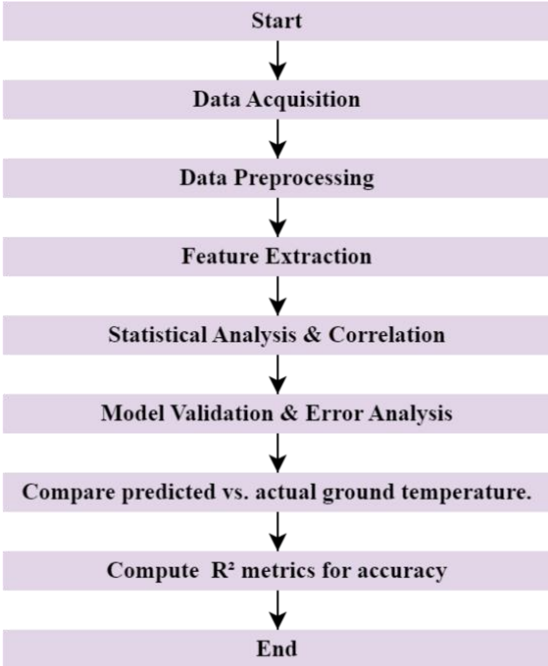

Fig. 5 R-squared computation flowchart

Fig. 6 showcases linear correlation of the ground temperature and the satellite temperature readings. This plot presents the relationship between ground temperature (°C) and Landsat 8 satellite temperature. The scatter plot shows a positive linear relationship between ground temperature and the satellite temperature values recorded by the Landsat 8 satellite. As the ground temperature increases, the satellite temperature also increases. The slope of the trend line (1.0811) indicates that for every 1°C increase in ground temperature, the satellite temperature increases by approximately 1.08°C.

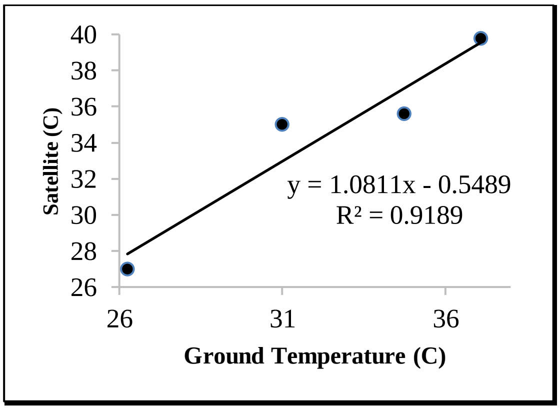

Fig. 6 linear correlation of the ground temperature and Satellite.

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The equation of the trend line is given as y=1.0811x−0.5489; where y represents the Landsat 8 temperature and x represents the ground temperature. The R^2 value is 0.9189, which indicates a very strong correlation between the two temperature datasets. An R^2 value close to 1 suggests that the linear model explains approximately 91.89% of the variance in the Landsat 8 temperature data based on the ground temperature measurements. This high value implies that the satellite data closely follows the ground temperature trends, with minimal variation.

This strong correlation between satellite-derived and ground temperature data has significant implications for solar energy production forecasting. Since temperature influences the efficiency of photovoltaic systems, being able to predict ground temperatures using satellite data allows for better operational planning, especially for regions where real-time ground temperature measurements may not always be available. The high R^2 value suggests that satellite data from Landsat 8 can be reliably used as a proxy for ground temperature in this region. This accuracy is particularly important for remote areas where installing ground-based sensors might be difficult or costly. With this linear model, temperature forecasts can be made with confidence, allowing for more efficient solar farm management and energy yield predictions. Despite the strong correlation, there could be factors causing slight deviations between satellite and ground temperatures. For instance, localized weather effects such as humidity or cloud cover, time of day, or the physical characteristics of the ground surface (e.g., urban heat islands or vegetation) may cause discrepancies. These factors could be explored in further studies to refine the model. (White-Newsome et al., 2013) validated satellite derived surface temperature with in situ measurement and obtained a high correlation with R^2 of 0.98.

Overall, this analysis highlights the potential of satellite data to improve solar energy management by accurately reflecting ground conditions, supporting the optimization of renewable energy systems, particularly in regions like Oman, where this study is focused.

5 Implementation Guidelines

6.1 Practical Application

To effectively implement satellite-ground temperature correlation, for solar energy optimization, it is crucial to establish a comprehensive data collection protocol. The ground station placement optimization involves strategically positioning ground sensors to ensure representative data capture, minimizing environmental biases and capturing temperature variations across different terrains. This approach ensures that collected data accurately reflect the temperature conditions relevant to the area of interest. Measurement frequency guidelines specify the need for high-resolution data collection at consistent intervals to align with satellite overpasses, enhancing data reliability and enabling meaningful comparisons between satellite and ground observations.

To maintain data accuracy, quality control procedures should be established, including periodic equipment calibration, validation checks, and cross-referencing against known standards to filter out anomalies or outliers. For real-time implementation, a robust data processing workflow should be developed, encompassing automated data collection, satellite-ground data integration, and immediate analysis to facilitate ongoing solar energy optimization. Efficient error handling procedures are essential to identify and address discrepancies promptly, ensuring continuous data reliability. The application of correction factors—such as adjustments for seasonal temperature variances or local environmental influences—further enhances the accuracy of temperature predictions and strengthens the reliability of the model for practical use.

6.2 Integration with PV Systems

Integrating accurate temperature predictions with PV systems is pivotal for enhancing energy production. Temperature prediction integration involves developing models that can input real-time satellite and ground temperature data into PV performance algorithms, thereby refining the estimation of energy output. These models help anticipate fluctuations due to temperature impacts, allowing for better scheduling and resource allocation. For performance optimization guidelines, it is recommended to apply predictive analytics to adjust operating parameters of PV systems dynamically, maximizing efficiency under varying temperature conditions. This can involve fine-tuning panel orientation or cooling mechanisms based on temperature forecasts.

Lastly, establishing robust monitoring system requirements ensures continuous oversight and adaptation of the integrated system. This includes setting up automated alerts for significant temperature deviations that might affect PV output and ensuring the infrastructure supports real-time data visualization and analysis for informed decision-making. Through these measures, solar farm operators can leverage temperature data more effectively to optimize energy yield and maintain operational resilience.

6 Conclusions

This study concludes the strong correlation between satellite-derived temperatures and ground measurements in Seeb, Muscat, Oman, with a significant quantitative match during cooler months and slight deviations during the hotter months. The high correlation R^2=0.9189 supports the use of Landsat 8 data as a reliable method for ground temperature, though adjustments may be necessary to account for seasonal discrepancies, particularly during peak summer when satellite temperatures tend to overestimate by 1–2°C. The qualitative analysis suggests that urban heat islands and surface-level heating may contribute to the elevated satellite temperatures, especially in densely populated or built-up areas like Seeb. The convergence of data in the cooler months reinforces the utility of satellite data in predicting ground temperatures under milder climatic conditions, making it a useful tool for forecasting solar energy production year-round.

For practical applications in solar farm performance modeling, this study provides a foundational framework for integrating satellite data with ground observations, allowing for more accurate predictions of energy yields in Seeb, Muscat Oman. However, a key challenge faced is, the average of the satellite path time and ground station time reading was taken to account for the discrepancy between the two values. Future enhancements could involve incorporating localized factors such as humidity and wind to refine accuracy, developing real-time correction systems, expanding to different climatic zones, and integrating findings with machine learning models and smart grid systems for broader applications in arid and semi-arid regions. This approach can be utilized for an estimation, though further investigation into atmospheric conditions, which can enhance the accuracy of the results.

REFERENCES

Abdel-Aziz, M. M., & ElBahloul, A. A. (2025). Innovations in improving photovoltaic efficiency: A review of performance enhancement techniques. *Energy Conversion and Management*, *327*, 119589. https://doi.org/https://doi.org/10.1016/j.enconman.2025.119589

Alwadei, S., Farahat, A., Ahmed, M., & Kambezidis, H. D. (2022). Prediction of Solar Irradiance over the Arabian Peninsula: Satellite Data, Radiative Transfer Model, and Machine Learning Integration Approach. *Applied Sciences (Switzerland)*, *12*(2). https://doi.org/10.3390/app12020717

Ammari, N., Mehdi, M., Alami Merrouni, A., El Gallassi, H., Chaabelasri, E., & Ghennioui, A. (2022). Experimental study on the impact of soiling on the modules temperature and performance of two different PV technologies under hot arid climate. *Heliyon*, *8*(11), e11395. https://doi.org/https://doi.org/10.1016/j.heliyon.2022.e11395

Chen, H., Zhang, L., Pinzon, S., Chen, H., & Chen, B. (2025). Decarbonizing the G7: Renewable Energy, Economic Growth, Globalization, and Policy Pathways to Sustainability. *Renewable Energy*, 122671. https://doi.org/https://doi.org/10.1016/j.renene.2025.122671

Danbatta, M. B., Al-Azri, N., & Al-Rawahi, N. (2024a). Analysis of Solar Radiation and Remote Sensing Indices for Coastal Management in Oman. *European Journal of Engineering and Natural Sciences*, *9*(1), 6–14.

Danbatta, M. B., Al-Azri, N., & Al-Rawahi, N. (2024b). Exploring the Impact of Solar Radiation on Environmental Dynamics in Oman Normalized Difference Vegetation Index (NDVI). *European Journal of Engineering and Natural Sciences*, *9*(1), 15–19.

Hedar, A.-R., Almaraashi, M., Abdel-Hakim, A. E., & Abdulrahim, M. (2021). Hybrid machine learning for solar radiation prediction in reduced feature spaces. *Energies*, *14*(23). https://doi.org/10.3390/en14237970

Li, Z.-L., Wu, H., Duan, S.-B., Zhao, W., Ren, H., Liu, X., Leng, P., Tang, R., Ye, X., Zhu, J., Sun, Y., Si, M., Liu, M., Li, J., Zhang, X., Shang, G., Tang, B.-H., Yan, G., & Zhou, C. (2023). Satellite Remote Sensing of Global Land Surface Temperature: Definition, Methods, Products, and Applications. *Reviews of Geophysics*, *61*(1), e2022RG000777.

Corresponding author: Mohammadu Bello Danbatta , *143273@student.squ.edu.om*

https://doi.org/https://doi.org/10.1029/2022RG000777
N. Al-Azri, Y. H. Zurigat, & N. Al-Rawahi. (2013). Selection and assessment of passive cooling techniques for residential buildings in oman using a bioclimatic approach. *Journal of Engineering Research*, *10(2)*, 52–68.
National Centers for Environmental Information (NCEI). (2019). *Climate Data Online: Daily Summaries*. NOAA National Centers for Environmental Information. https://www.ncei.noaa.gov/
N.Z.Al-Rawahi, Y.H.Zurigat, & N.A Al-Azri. (2011). Prediction of hourly solar radiation on horizontal and inclined surfaces for Muscat/Oman. *Journal of Engineering Research*, *8(2)*, 19–31.
Pande, C. B., Egbueri, J. C., Costache, R., Sidek, L. M., Wang, Q., Alshehri, F., Din, N. M., Gautam, V. K., & Chandra Pal, S. (2024). Predictive modeling of land surface temperature (LST) based on Landsat-8 satellite data and machine learning models for sustainable development. *Journal of Cleaner Production*, *444*, 141035. https://doi.org/https://doi.org/10.1016/j.jclepro.2024.141035
Sholihah, R. I., & Shibata, S. (2019). Retrieving Spatial Variation of Land Surface Temperature Based on Landsat OLI/TIRS: A Case of Southern part of Jember, Java, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *362*(1), 12125. https://doi.org/10.1088/1755-1315/362/1/012125
U.S. Geological Survey. (2021). *Landsat 8 OLI/TIRS Data*. https://www.usgs.gov/landsat
Wan, Y., Du, H., Xie, X., Xu, X., Tang, H., Chai, X., & Yuan, L. (2025). Spatial heterogeneity in effects of horizontal and vertical environmental features of blocks on land surface temperature: A case study of Shenzhen, China. *Building and Environment*, *272*, 112670. https://doi.org/https://doi.org/10.1016/j.buildenv.2025.112670
White-Newsome, J. L., Brines, S. J., Brown, D. G., Dvonch, J. T., Gronlund, C. J., Zhang, K., Oswald, E. M., & O'Neill, M. S. (2013). Validating satellite-derived land surface temperature with in situ measurements: A public health perspective. *Environmental Health Perspectives*, *121*(8), 925–931. https://doi.org/10.1289/ehp.1206176
Zhang, B., Zhang, M., Kang, J., Hong, D., Xu, J., & Zhu, X. (2019). Estimation of pmx concentrations from landsat 8 oli images based on a multilayer perceptron neural network. *Remote Sensing*, *11*(6). https://doi.org/10.3390/RS11060646

BIOGRAPHY

Mohammadu Bello Danbatta: a Ph.D. candidate at Sultan Qaboos University, specializing in carbon capture technology. His research focuses on the application of Rotating Packed Bed (RPB) systems, an innovative approach for enhancing mass transfer efficiency in CO_2 absorption processes. With a strong background in Artificial Intelligence and renewable energy.

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Nasser Al-Azri: an Associate Professor in the Department of Mechanical and Industrial Engineering. He holds a Ph.D. and a Master of Science in Chemical Engineering from Texas A&M University, along with a Master of Engineering in Industrial Engineering from the same institution. His expertise spans multiple disciplines, including mechanical, chemical, and industrial engineering, with a strong focus on energy and process optimization.