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Assessment of Drivers Influencing Surface Water Temperature in Lake Gregory Using the General Lake Model (GLM) and Satellite Observation

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Abstract: Small and shallow lakes in tropical regions often lack reliable ground-based temperature data, making it challenging to fully understand their thermal dynamics, which are crucial as they directly influence water quality, ecosystem functioning, and the lake's response to climate variability. This study employed the General Lake Model (GLM) to simulate daily Lake Surface Water Temperature (LSWT) from 2017 to 2021, using NASA POWER reanalysis data as meteorological input. Landsat Level 2 Surface Temperature (LST-L2) data were used for calibration and validation, resulting in Root Mean Squared Error (RMSE) values of 2.15°C and 2.17°C, and correlation coefficients of 0.65 and 0.73, respectively. The research further examined the effects of climate variability on LSWT by analysing 625 climate scenarios that incorporated variations in air temperature, solar radiation, wind speed, and rainfall. Multiple independent methods, including linear regression, random forest, and ANOVA, were used in the analysis, consistently demonstrating that air temperature was the primary driver of LSWT, accounting for over 65% of the variance. Wind speed was the second most influential factor, describing over 31% of the variance. Shortwave radiation, although statistically significant, had a relatively minor contribution. Precipitation, although included in all scenarios, showed negligible explanatory power for LSWT under the simulated conditions. These findings suggest that, for Gregory Lake, future LSWT variations will be primarily influenced by atmospheric heating and wind-driven mixing. The study also demonstrates the effectiveness of combining satellite observations and reanalysis datasets with hydrodynamic modelling to estimate LSWT in ungauged lakes with limited climate records. Furthermore, this analytical framework can be applied to other lakes to identify their principal climatic drivers.

Keywords: Landsat Collection 2 Surface Temperature (LST-L2), Meteorological Forcing, NASA POWER Reanalysis Data, Small-Scale Lakes of Sri Lanka

1. Introduction

Lakes are dynamic ecosystems that respond sensitively to climate change, making them important indicators of environmental transformations. Among the parameters reflecting this sensitivity, Lake Surface Water Temperature (LSWT) plays a pivotal role in regulating aquatic ecosystems. It influences thermal stratification, mixing regimes, nutrient cycling, and biological productivity. Consequently, variations in LSWT provide insights into the effects of climate change on freshwater systems [1,2].

In recent decades, LSWT has exhibited a more rapid warming trend than air temperature in many regions, underscoring the heightened vulnerability of lakes to atmospheric forcing [3]. This makes LSWT not only a key ecological variable but also a potential alternative for monitoring regional climate trends. However, a critical barrier to LSWT monitoring, particularly in developing nations such as Sri Lanka, is the scarcity of long-term, high-resolution, in situ observational data.

Traditional water temperature monitoring methods, reliant on in situ instruments, are often constrained by logistical, financial, and human resource limitations. In regions with numerous small lakes, such as Sri Lanka, these challenges result in significant data gaps. Remote sensing, however, provides an alternative means of obtaining LSWT data with extensive spatial and temporal coverage [4,5].

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Sensors such as MODIS, AVHRR, ATSR, and Landsat have demonstrated varying degrees of success in capturing LSWT, though limitations in spatial or temporal resolution persist [4,5].

Of particular interest is Landsat, whose 30-meter spatial resolution enables the estimation of LSWT in small water bodies. However, a 16-day revisit cycle and exposure to cloud cover can hold back consistent data collection [6]. In contrast, NASA's POWER reanalysis dataset offers a continuous and easily accessible source of meteorological inputs essential for lake modelling [7]. This reanalysis data, although coarser in spatial resolution (0.5°), is particularly useful in data-scarce contexts due to its global coverage and availability.

To supplement or replace observational data, physically based hydrodynamic models like the General Lake Model (GLM) [8], have emerged as effective tools. GLM simulates lake temperature profiles and stratification patterns using meteorological drivers, enabling researchers to assess temporal trends in LSWT even where direct observations are scarce [4,8]. However, the successful application of GLM is dependent upon the availability of reliable meteorological inputs, often a significant challenge in regions with limited weather monitoring infrastructure.

Although Frassl et al. (2019) demonstrated the potential of reanalysis data for lake modelling in temperate climates [9], the application and assessment of such approaches in tropical, data-scarce small lakes—particularly using GLM—remain limited. These lakes are ecologically important but are often overlooked in modelling research.

This study addresses this gap by evaluating the suitability of NASA POWER reanalysis data and Landsat Level 2 thermal imagery for forcing and validating a daily GLM-based LSWT simulation for Lake Gregory, a high-altitude tropical lake in Nuwara Eliya, Sri Lanka.

The specific objectives of this study are to:

1. Assess the reliability of NASA POWER meteorological data for driving lake surface water temperature (LSWT) simulations.
2. Validate GLM-simulated LSWT against Landsat Level 2 thermal imagery.
3. Quantify the performance of the GLM model under tropical high-altitude conditions.
4. Investigate the sensitivity of LSWT to variations in key meteorological drivers using synthetic climate scenarios.

2. Materials and Methods

2.1 Study Area

Lake Gregory (Figure 1) is a man-made reservoir located in Nuwara Eliya, Sri Lanka, at an elevation of 1800 meters above mean sea level, with coordinates 06°53'.816N, 080°52'.536E. Constructed in 1874 by damming the Thalagala Oya, a tributary of the Nanu Oya (which ultimately joins the Mahaweli River), the lake initially served as a water source for a small hydropower plant [10]. Over time, its function shifted toward recreation, tourism, and sport fishing, contributing to the area's scenic and ecological value. Lake Gregory covers an area of 40 hectares and receives inflows from several streams originating in the Piduruthalagala mountain range, Kandapola and Magastota, as well as culverts from the Nuwara Eliya municipal area [10].

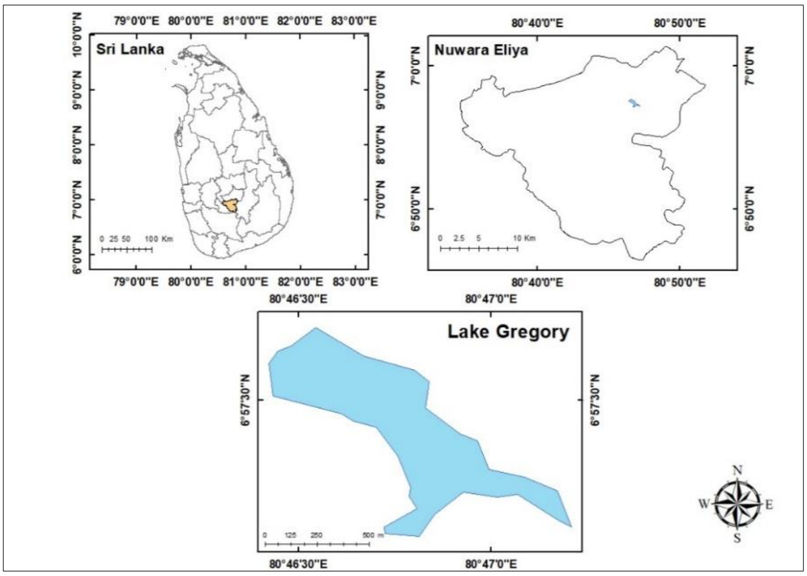

Figure 1 – Geographical Location of Lake Gregory

These diverse water sources enrich the lake's ecological diversity and support a variety of aquatic flora and fauna. The transformation of Lake Gregory from a utility infrastructure to a recreational and environmental asset highlights its historical, cultural, and ecological importance in the region [10].

2.2 Landsat Collection 2 Level 2 Surface Temperature Data Processing

The Landsat Collection 2 Level 2 Surface Temperature (ST) product was utilised to extract lake surface temperatures over Lake Gregory between 2017 and 2021. Data was downloaded from the USGS Earth Explorer platform, with cloud-free images manually selected to ensure data quality [11,12].

Three key bands were used in deriving Surface Temperature (ST): ST_B10 (Surface Temperature Band), ST_QA (Temperature Uncertainty Band), and QA_PIXEL (Pixel Quality Band). These bands were downloaded using the USGS Bulk Download tool and processed in the ArcMap Model Builder. The ST_B10 band was then converted to temperature values in Kelvin using the appropriate scaling factor, following the guidelines provided in the USGS user manual [12].

An unsupervised classification approach was used to delineate Lake Gregory from surrounding land cover by compositing Landsat Bands 4, 5, and 6. The water class was then reclassified and masked to isolate the lake area. The resulting water mask was converted into a vector polygon (shapefile), which was subsequently used to extract lake surface temperature values.

Temperature uncertainty values were extracted from ST_QA using a scaling factor (0.01), and both datasets were spatially joined at the pixel level for further analysis. QA_PIXEL bands were interpreted using bitwise operations to isolate high-confidence water pixels, ensuring only reliable surface temperature readings were considered. These values were further refined using pixel binary interpretation aligned with bit-level QA standards [13].

2.3 General Lake Model (GLM)

The General Lake Model (GLM) [8], is an open-source, one-dimensional hydrodynamic model designed to simulate vertical temperature stratification and mixing processes in lakes, reservoirs, and wetlands. Developed to meet the needs of the Global Lake Ecological Observatory Network (GLEON), GLM integrates meteorological data, site-specific bathymetry, inflows and outflows to model lake thermal dynamics with minimal calibration [8].

GLM operates using a flexible Lagrangian layer structure, which dynamically adjusts to inflows, outflows, and energy fluxes. It simulates heat exchange, density-driven mixing, and surface energy balance by incorporating radiative, sensible, and latent heat fluxes. The model also supports mass balance computations for water fluxes, allowing it to capture changes in lake volume and thermal structure over time. Given its physical basis and modular design, GLM is particularly well-suited for long-term simulations in data-scarce environments, requiring only meteorological input and basic lake geometry [8].

2.4 GLM Input Data

Meteorological data were obtained from the NASA POWER reanalysis platform (https://power.larc.nasa.gov), which offers freely accessible global climate datasets. For this study, daily data from 2017 to 2021 were retrieved for the Lake Gregory location, including key variables such as air temperature, wind speed, relative humidity, shortwave radiation, cloud cover, and precipitation. These parameters were selected via the NASA POWER API and downloaded in CSV format. Although Ravindu et al. [14] demonstrated the reliability of NASA POWER data for the Nuwara Eliya region, showing strong agreement with ground-based meteorological observations, a noticeable offset was identified in the average air temperature. This necessitated bias correction to improve accuracy, as also reported by them [14].

In addition to meteorological inputs, bathymetry data were essential for defining the lake's depth profile. For this purpose, a historical bathymetric survey conducted in 1988 by the Sri Lanka Land Development Corporation was used. The scanned drawings from this survey were scaled and processed using QGIS software to generate a digital hypsographic curve.

Furthermore, a dataset of observed lake water temperatures was obtained from the Department of Irrigation, Sri Lanka, consisting of eight measurements recorded between 2017 and 2021.

2.5 GLM Model Simulation

The simulation of Lake Gregory's thermal dynamics was conducted using the General

Lake Model (GLM) Version 3.0.5, implemented within the R Studio environment. The model setup involved preparing two key inputs: the configuration file (glm3.nml) and the time-series meteorological data file (met.csv). The configuration file controls simulation settings, including lake morphometry, mixing parameters, radiation settings, initial conditions, and output options [8].

Based on model performance testing, specific options were selected for radiation calculations: The shortwave radiation scheme employed daily solar radiation with sinusoidal sub-daily disaggregation, atmospheric longwave radiation was estimated using the cloud-corrected emissivity formulation of Brutseart (1975), and surface albedo was calculated using the solar-zenith-angle–based parameterisation of Briegleb et al. (1986) [15]. Bulk-transfer coefficients and atmospheric stability were held constant over the five-year simulation period due to the absence of high-resolution local data. Wind sheltering effects were omitted for the same reason. A closed-basin approach was used in the model due to the unavailability of measured inflow and outflow data.

The GLM was executed in R using the *GLM3r*, *glmtools*, and *rLakeAnalyzer* packages, with the *tidyverse* package used for data visualisation. Model outputs were saved in *NetCDF* format, allowing for flexible and multidimensional analysis.

Initial calibration carried out using a sensitivity analysis, where key parameters in the configuration file were adjusted by ±20% to evaluate their influence on the surface temperature Root Mean Square Error (RMSE) value. Parameters showing the highest sensitivity were then fine-tuned using GLM's automated calibration tool [16].

2.6 Synthetic Climate Scenarios

To evaluate the potential effect of meteorological factors on Lake Gregory's surface water temperature, a set of 625 synthetic climate scenarios was developed using the General Lake Model (GLM). Key meteorological drivers—air temperature, solar radiation, precipitation, and wind speed—were adjusted from baseline condition values. Air temperature scenarios ranged from +5°C (hot) to -5°C (cold) to reflect potential warming and cooling trends based on shifts in degree-day accumulation to identify effects on LSWT, as previously applied in agroclimatic studies [17]. Solar radiation, precipitation, and wind speed were also modified by ±25% and ±50%, representing conditions from very sunny to very cloudy, wet to dry, and high to low wind, respectively. Relative humidity was held constant to isolate the effects of other variables [17].

2.7 Statistical Evaluation of Climate Variable Effects on LSWT

To quantitatively assess the individual contributions of each climate variable to LSWT, a Multiple Linear Regression (MLR) analysis was first employed. This parametric method allowed for the estimation of both the direction (positive or negative) and magnitude of the main effects of air temperature, shortwave radiation, wind speed, and rainfall on LSWT. To complement the MLR results, an Analysis of Variance (ANOVA) was performed with eta-squared (η^2) to quantify the effect size of each factor, providing a measure of the relative importance of each variable in explaining LSWT variability [18].

In addition, a non-parametric Random Forest (RF) model was implemented to further evaluate the relative importance of each meteorological variable. This ensemble-based machine learning approach is well-suited for capturing nonlinear relationships and interactions between predictors, offering an alternative perspective on variable importance beyond the assumptions of parametric models [19].

3. Results and Discussion

3.1 Evaluating LST-L2 Product-Derived LSWT

A total of thirty-eight Landsat scenes were processed to extract Lake Surface Water Temperature (LSWT) values for Lake Gregory. The lake area comprises 488 pixels. As shown in Figure 2, twelve Landsat scenes were excluded from the analysis due to an insufficient number of valid water pixels, which compromised data quality. The remaining twenty-six Lake Surface Water Temperature (LSWT) observations, along with their associated uncertainty values, were used to calibrate and validate the GLM. In Figure 2, the size of each bubble corresponds to the number of valid water pixels available in each scene.

Cloud cover presents a major challenge in satellite-based remote sensing, as it can obscure the lake surface and produce underestimated temperature values. This occurs because clouds, particularly high-altitude clouds, are substantially cooler than the underlying surface and can bias the retrieved temperature. Moreover, even the presence of clouds near the target area, though not directly overhead, was found to bias LSWT estimates downward [20].

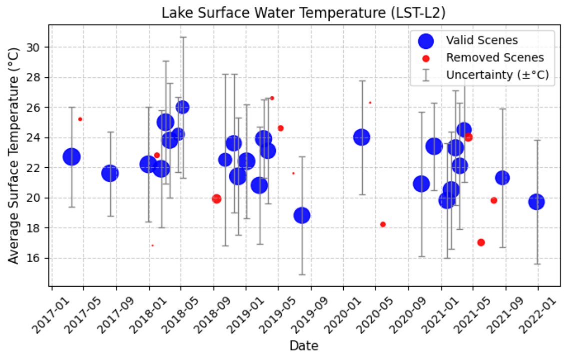

Figure 2 – LSWT with Uncertainty Values (LST-L2)

To account for these issues, erroneous or cloud-contaminated pixels were systematically excluded using cloud flags in the *QA_PIXEL* and *ST_QA* bands. The *ST_QA* uncertainty values, following the methodology outlined by Laraby et al. [20], were used to quantify and control for temperature retrieval errors. In the absence of in-situ temperature observations, this carefully filtered dataset was used as observed LSWT, with average uncertainty values.

3.2 Evaluation of LSWT Modelled by GLM

The calibration parameters, along with their corresponding lower and upper bounds, were determined based on the results of the initial sensitivity analysis. These values were then used as inputs for the GLM optimisation algorithm, as outlined in Table 1.

Table 1 – Calibration Parameters

Parameter	Lower Value	Upper Value	Initial Value
d_{T_z} at Z_1	60	130	130
d_{T_z} at Z_2	110	150	120
d_{T_z} at Z_3	100	140	110
C_E	0.001	0.0035	0.0035
K_W	0.3	2.9	2.9
C_H	0.003	0.005	0.003
Z_1	0.2	0.6	0.2
T_{Zmean} at Z_1	15	30	15
T_{Zmean} at Z_2	15	25	17
T_{Zmean} at Z_3	15	25	20
K_{soil}	1	2.9	2.9

In Table 1, K_{soil} denotes the soil–sediment thermal conductivity, Z refers to the sediment layer underlying the i^{th} water layer, T_{zmean} is the annual mean temperature of the sediment zone, and d_{T_Z} represents the day of the year when sediment temperature reaches its maximum. The bulk aerodynamic coefficients C_E and C_H correspond to latent and sensible heat transfer, respectively. The parameter K_w is the light extinction coefficient [8].

The sensitivity index (SI) was calculated using Equation 1.

$$\mathrm{SI} = \frac{\left(\frac{Output_{new} - Output_{original}}{Output_{original}}\right)}{\left(\frac{Parameter_{new} - Parameter_{original}}{Parameter_{original}}\right)} \quad \ldots (1)$$

The model calibration was carried out for the period from January 1, 2017, to December 31, 2018, while validation was performed using data from January 1, 2019, to December 31, 2021. Calibration involved the iterative minimisation of the Root Mean Square Error (RMSE) between simulated and observed LSWT values. This process utilised the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) optimisation algorithm, which was integrated into the automated calibration framework of the GLM (General Lake Model). A target RMSE of 2.0°C was defined as the calibration objective, and the optimisation procedure was run for 2,000 iterations to achieve the best possible model fit.

The final calibrated parameter values obtained through the optimisation process are summarised in Table 2.

Table 2 – Calibrated Final Parameters

Parameter	Calibrated Value
d_{T_z} at Z_1	60
d_{T_z} at Z_2	119.51
d_{T_z} at Z_3	140
C_E	0.0032
K_W	1.1653
C_H	0.005
Z_1	0.6
T_{Zmean} at Z_1	16.98
T_{Zmean} at Z_2	19.13
T_{Zmean} at Z_3	21.94
K_{soil}	1.28

The model surface temperature at 0 m depth was selected for calibration and validation against LST-L2 surface temperature products, as Landsat's thermal infrared sensors capture the skin temperature of the water surface (~top 1 mm) [12]. While the GLM model does not explicitly resolve the skin layer, its uppermost computational layer represents the bulk surface temperature (typically within the top 10 cm), making z = 0 m the best available approximation for comparison.

During the calibration phase, the model achieved an RMSE of 2.15 °C and a correlation coefficient (r) of 0.65. In the subsequent validation phase, the model maintained an RMSE of 2.17 °C with the same correlation coefficient. When evaluated across the full simulation period, considering both calibration and validation datasets, the model demonstrated an overall performance with an RMSE of 2.02 °C and a correlation coefficient of 0.73. The comparison between the GLM-simulated LSWT and the LST-L2 satellite-derived observations is illustrated in Figure 3. The additional dataset obtained from the Department of Irrigation was used exclusively for visual comparison with the validated model, as the limited number of sampling points did not permit robust statistical analysis. As shown in Figure 4, the comparison demonstrates a substantial level of agreement between most observed measurements and the model-simulated surface water temperatures.

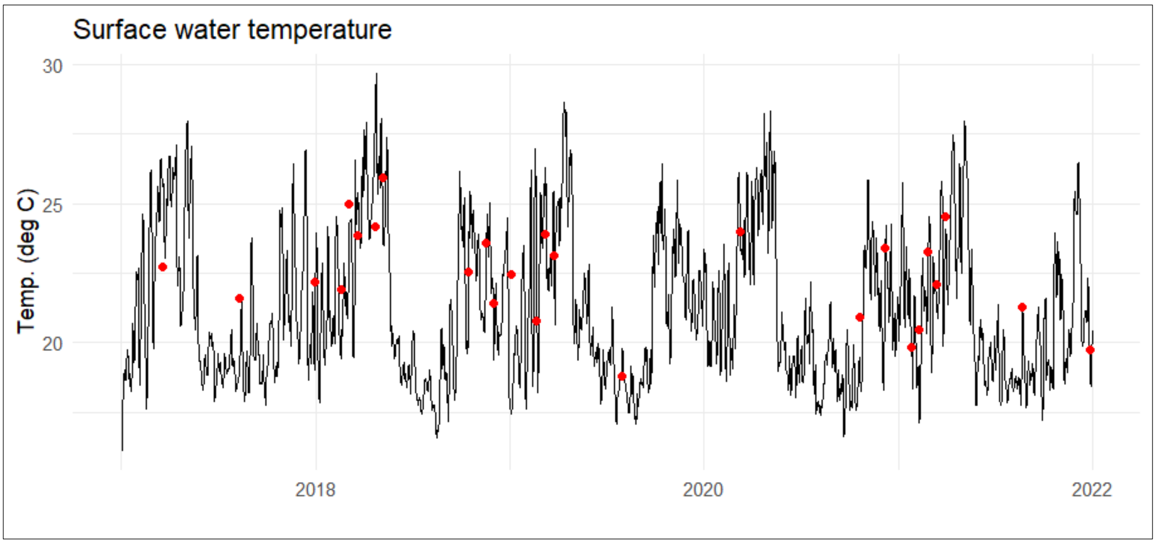

Figure 3 - Calibrated GLM Simulation (Black Line) of LSWT and Landsat LSWT (Red Dots)

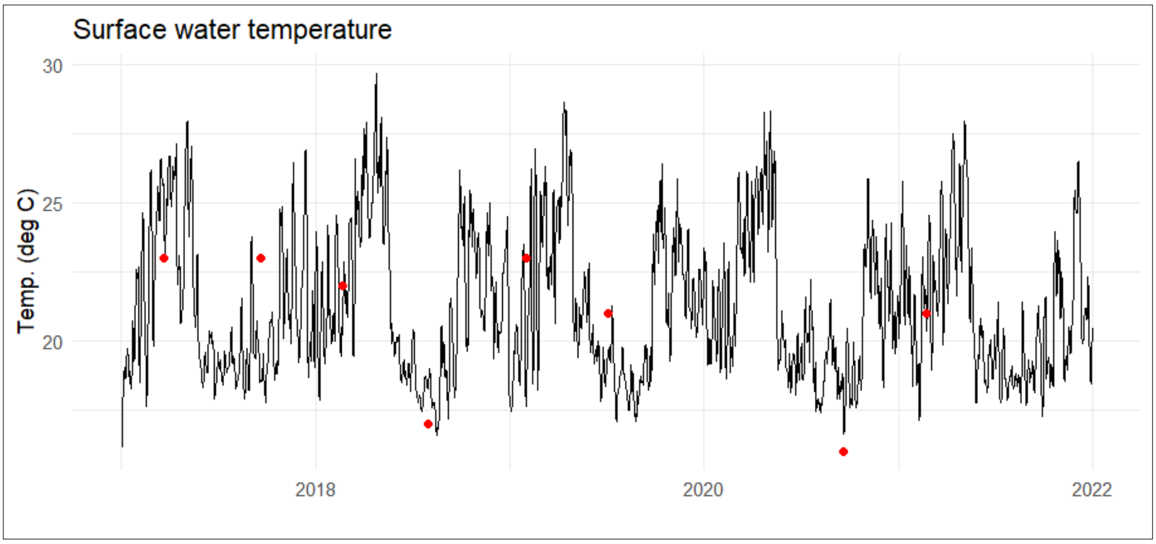

Figure 4 - Calibrated GLM Simulation (Black Line) of LSWT and Measured Water Temperatures by The Department of Irrigation (Red Dots)

3.3 Influence of Meteorological Variables on LSWT Dynamics

The results of the Multiple Linear Regression (MLR) analysis are shown in Table 3. Mean air temperature exhibited a positive slope of 0.82, indicating that increases in air temperature are associated with higher LSWT. In contrast, wind speed showed a strong negative slope of -1.58, indicating a substantial cooling effect on LSWT and underscoring its dominant influence among the meteorological variables considered.

Although the p-values for the predictors were below the 0.05 threshold, indicating statistical significance, the assumptions of the MLR model were not fully satisfied, as illustrated in Figure 5. The histogram of residuals displayed right-skewness, suggesting non-normality and the presence of biased residuals. As a result, the p-values may not be reliable indicators of true statistical significance in this context. Nevertheless, when considering the direction and magnitude of the main effects, air temperature exhibited a positive association with LSWT, while wind speed showed a strong negative impact.

The results of the ANOVA with eta-squared (η^2) are presented in Table 3. Air temperature accounted for approximately 65% of the variance in LSWT, while wind speed explained 31%. In comparison, shortwave radiation contributed only 3%, and rainfall less than 1%. All variables were found to be statistically significant ($p < 0.05$). As shown in Figure 6, the diagnostic plots indicate that the assumptions of the ANOVA model were met to an acceptable degree. The residuals exhibited an approximately normal distribution, and the Q-Q plot demonstrated a good alignment with the theoretical quantiles, supporting the validity of the model results.

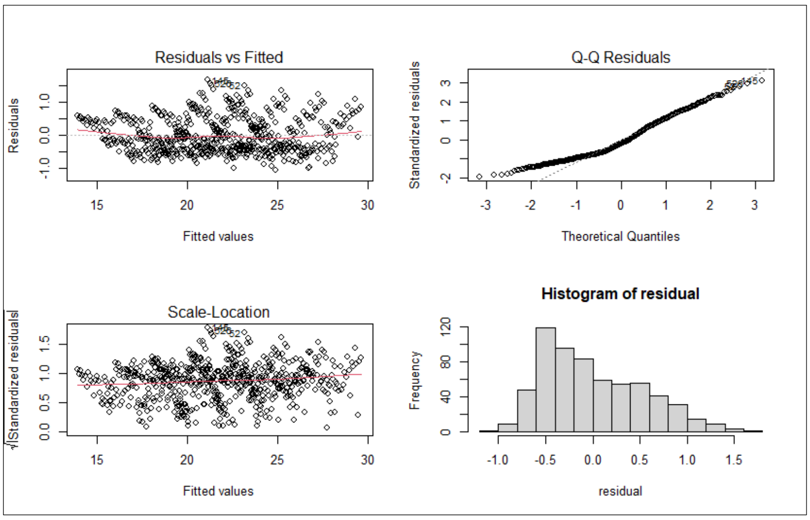

Figure 5 – Diagnostic Plots for the MLR, Including Residuals vs Fitted Values, Normal Q-Q Plot, Scale-Location Plot, and Histogram of Residuals

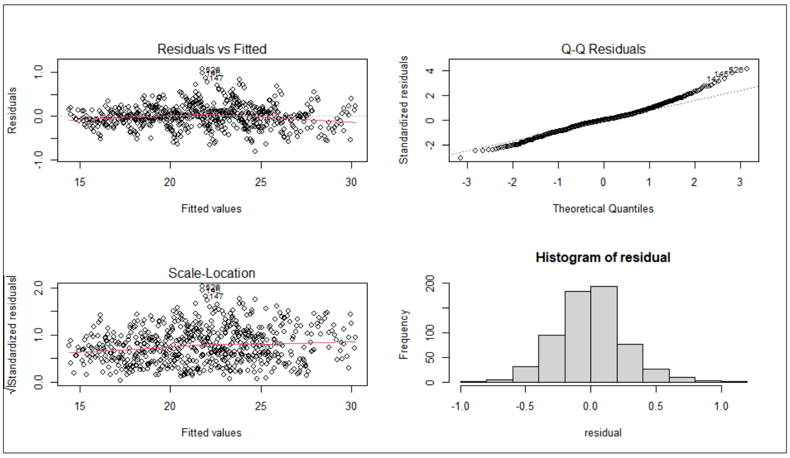

Figure 6 – Diagnostic Plots for the ANOVA, Including Residuals vs Fitted Values, Normal Q-Q Plot, Scale-Location Plot, and Histogram of Residuals

Table 3 – MLR and ANOVA Results

MLR				ANOVA +ETA²					
Parameter	Coefficients	Estimate Std. Error	P-Value	Sum Sq.	Mean Sq.	F value	P-Value	η^2	Df
(Intercept)	12.04	0.14	2×10^{-16}	-	-	-	-	-	-
Mean_AirTemp	0.82	0.006	2×10^{-16}	5246	1311.5	18614.50	2×10^{-16}	0.65	4
Mean_ShortWave	0.008	0.0003	2×10^{-16}	211	52.7	748.49	2×10^{-16}	0.03	4
Mean_WindSpeed	-1.58	0.017	2×10^{-16}	2506	626.6	8893.51	2×10^{-16}	0.31	4
Total_Rain	0.03	0.006	1.56×10^{-7}	11	2.8	40.31	2×10^{-16}	0.0001	4

To further evaluate the influence of climate variables on LSWT, a Random Forest (RF) algorithm was employed to rank the relative importance of the predictors and quantify their contributions. Variable importance was assessed using the percentage increase in mean squared error (*%IncMSE*), as shown in Figure 7. Among the predictors, air temperature emerged as the most influential variable, with the highest *%IncMSE*, indicating a substantial contribution to model accuracy.

Wind speed demonstrated a moderate effect, while rainfall had a negligible or even negative impact, suggesting it did not enhance the predictive performance of the model. These findings reinforce that air temperature is the dominant driver of lake surface water temperature in this study. The *IncNodePurity* metric further supported this ranking, with air temperature showing the largest reduction in node impurity across all trees in the forest.

4. Conclusion

The GLM model showed reasonable performance, with an RMSE of 2.15 °C and a correlation coefficient (r = 0.65) during calibration, and similar results in the validation phase (RMSE 2.17 °C, r = 0.65). When evaluated over the entire simulation period, the model achieved an improved RMSE of 2.02 °C and r = 0.73. Since the LST-L2 product was used directly as observed LSWT values, further research is recommended to evaluate its accuracy against ground-based measurements.

While the MLR model indicated statistically significant relationships, its assumptions were not fully met, suggesting caution in interpreting the p-values. Nonetheless, the direction and magnitude of the coefficients confirmed that air temperature has a strong positive effect, whereas wind speed exerts a strong cooling influence on LSWT.

The ANOVA with η^2 provided a more robust estimation of effect sizes, showing that air temperature accounted for 65% and wind speed for 31% of the variance in LSWT, while shortwave radiation and rainfall had minimal contributions. Diagnostic plots confirmed that ANOVA assumptions were reasonably satisfied.

The Random Forest model further reinforced these findings, identifying air temperature as the most important predictor, followed by wind speed. Rainfall showed negligible or even negative importance, indicating limited relevance in this context.

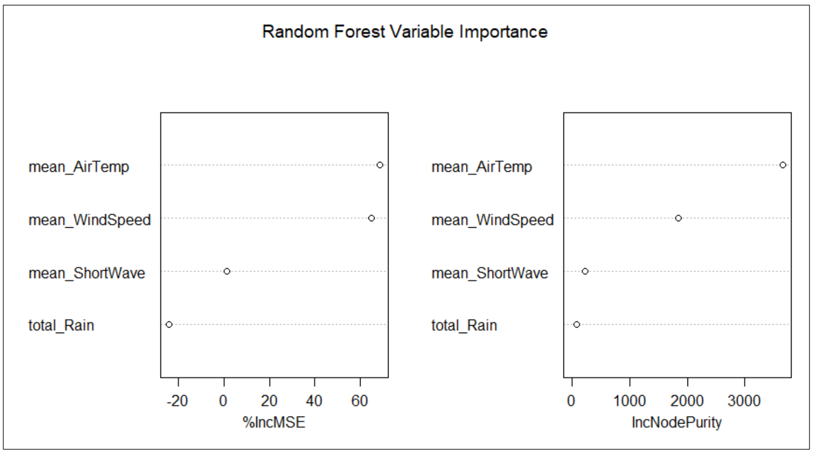

Figure 7– Random Forest Variable Importance Ranking

Both *%IncMSE* and *IncNodePurity* metrics consistently ranked air temperature highest in influencing LSWT.

This study focused solely on assessing the main effects of meteorological factors on LSWT. However, further research is needed to investigate potential interaction effects between these variables, which may also play a significant role in influencing lake thermal dynamics.

Data Availability Statement

The data supporting the findings of this study are publicly available on GitHub at https://github.com/Ishu93/Lake_Gregory

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