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Spatiotemporal analysis and deep-learning based forecasting of land surface temperature in the UNESCO world heritage sinharaja rainforest

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ABSTRACT

Currently, climate change is a global issue receiving significant attention and it leads to unpredictable temperature patterns that threaten the biodiversity and ecological stability of forests. While accurate temperature prediction in such ecosystems is challenging due to sparse ground observations and strong spatial heterogeneity. To fill this gap, this study develops and compares multiple deep learning architectures for land surface temperature (LST) prediction in the Sinharaja Forest Reserve, Sri Lanka's last remaining major tropical rainforest and a UNESCO World Heritage Site. Monthly MODIS LST data from 2001 to 2021 were used to analyze historical temperature dynamics and develop spatiotemporal forecasting models. The nonparametric Mann-Kendall test did not indicate a statistically significant trend. However, the time series decomposition method revealed a subtle long-term warming signal in the region. Three deep learning architectures, including ConvLSTM, CNN-LSTM, and PredRNN, were evaluated using a hindcast validation framework, where models were trained using historical observations and tested against independent satellite observations from the later years. The ConvLSTM model demonstrated the highest predictive accuracy, achieving a root mean square error (RMSE) of 1.55 °C, a mean absolute error (MAE) of 1.14 °C, a coefficient of determination (R^2) of 0.45, and a mean absolute percentage error (MAPE) of 4.36%, demonstrating improved capability in capturing nonlinear spatiotemporal temperature patterns compared to CNN-LSTM and PredRNN models. The findings provide valuable insights to support future climate adaptation and conservation policy decisions for the globally significant Sinharaja Forest Reserve.

1. Introduction

Tropical rainforests are among the most biodiverse and ecologically important ecosystems on Earth, and they play a central role in regulating the global climate system through carbon sequestration, evapotranspiration, and hydrological recycling (Sanjeewani et al., 2024; Bonan, 2008; Gallery, 2014). However, these ecosystems are increasingly vulnerable to climate change. The global temperature has increased over 1.4 °C since the pre-industrial period (1850–1900) due to rising concentrations of greenhouse gases in the atmosphere, together with other forces (Intergovernmental Panel on Climate Change (IPCC), 2021). Many studies show that temperatures have risen across tropical regions over the past several decades (Abatzoglou et. al., 2025). Recent research highlights that local temperature responses to land-cover changes are significantly asymmetrical across latitudes, with tropical zones showing high sensitivity to forest dynamics (Liu et al., 2023). Furthermore, the use of satellite remote sensing has become a foundational method for monitoring these global Land Surface Temperature (LST) trends, providing essential data for climatological applications (Liu et al., 2023). Importantly, tropical forests exhibit limited seasonal temperature variability; therefore, even small increases in temperature may push ecosystems beyond physiological thresholds, affecting photosynthesis,

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respiration, and biodiversity (Doughty et al., 2023; Sullivan et al., 2020).

The Sinharaja Forest Reserve in Sri Lanka, a UNESCO World Heritage Site, is the country's last extensive patch of primary lowland rainforest (Munidasa et al., 2002; UNESCO World Heritage Centre, 1987). Despite this apparent stability, emerging evidence suggests subtle but important climatic changes within the forest margins (Samarasinghe et al., 2022). Forest microclimates, shaped by dense canopy structure, are sensitive to both external warming and localized land-use change, making accurate temperature monitoring and prediction essential for long-term conservation planning (Braziunas et al., 2025).

It is challenging to characterize climatic patterns accurately in dense tropical forests due to the limited availability of ground-based meteorological stations across ecologically diverse regions (Ismaeel et al., 2024). Traditional numerical climate models, such as General Circulation Models (GCMs) and Regional Climate Models (RCMs) succeeded in simulating large-scale climate processes; however, they often struggle to capture fine-scale microclimatic variability in complex ecosystems like rainforests (McGuffie and Henderson-Sellers, 2005; Ruosteenoja and Räisänen, 2024). The situation in Sri Lanka is no different, where a very limited meteorological station coverage across ecologically diverse regions further constrains localized climate analysis (Kottawa-Arachchi and Wijeratne, 2017).

Despite the availability of satellite-derived LST products, accurate temperature monitoring and forecasting in tropical rainforest regions remain challenging. Persistent cloud cover leads to frequent data gaps, while sparse ground-based observations limit validation. Moreover, relatively few studies have explored spatiotemporal LST prediction in tropical rainforest ecosystems using advanced deep learning approaches (Chen et al., 2022; Gong et al., 2023).

On the other hand, satellite-based remote sensing approaches provide an effective means of monitoring land surface temperature across large and inaccessible forest regions. Beyond forest dynamics, remote sensing has been widely applied in diverse environmental fields. Recent studies have applied remote sensing to monitor cryospheric variability and snow cover extent in high-altitude basins (Abbas et al., 2026), model large-scale soil erosion using remotely sensed data on Google Earth Engine (GEE) (Fahd et al., 2025), and evaluate groundwater sustainability (Nadeem et al., 2023) and developing high-resolution land surface temperature models for diverse terrains (Shen et al., 2025). While products such as MODIS offer consistent spatial coverage (Z. Li et al., 2023) and long-term records are suitable for climate studies, and are used to monitor ecosystem productivity, such as in the Amazon rainforest (Maeda et al., 2014). However, traditional land surface temperature (LST) retrieval and statistical forecasting methods primarily support retrospective analysis (J.-H. Li et al., 2023) and often fail to capture the nonlinear, spatiotemporal dynamics required for accurate future prediction (Cheng et al., 2025).

Nevertheless, recent advances in deep learning approaches have transformed climate and environmental forecasting into a different era. Long Short-Term Memory (LSTM) networks have demonstrated excellent performance in modeling nonlinear and sequential climate data by effectively capturing long-term temporal dependencies (Bilgili et al., 2025; Elshewey et al., 2025; Vo et al., 2023; Xiong and Su, 2025). Recent studies have further demonstrated the versatility of LSTMs in capturing the impact of urbanization on vegetation disparities, providing a robust tool for long-term ecological sustainability and forecasting (Zafar et al., 2023). Hybrid deep learning approaches, including CNN-LSTM ConvLSTM and PredRNN architectures, extend this capability by integrating spatial feature extraction with temporal learning (Gong et al., 2024; Shen et al., 2025; Hou et al., 2022; Wang et al., 2023). Furthermore, the integration of signal processing techniques, such as wavelet transformations with machine learning, has emerged as a powerful hybrid framework for accurately forecasting complex environmental phenomena like agricultural drought (Zafar et al., 2026). These models have been successfully applied to temperature, precipitation, and air-quality forecasting in many studies, often surpassing traditional statistical approaches such as ARIMA and SARIMA.

In Sri Lanka, prior studies have used LSTM-based models for rainfall forecasting, urban temperature prediction, and hydrological simulations for catchment and agricultural areas (Saubhagya et al., 2024). However, existing research is largely limited to urban environments, river basins, or agricultural regions, with no documented application of LSTM or ConvLSTM models for temperature forecasting within a tropical rainforest ecosystem in Sri Lanka. The unique microclimatic dynamics of dense rainforests, such as the Sinharaja Rainforest, driven by canopy buffering, high humidity, and spatial heterogeneity, have not been explored with deep learning-based temperature-prediction approaches.

Therefore, the aim of this study is to address the research gap in tropical thermal forecasting by evaluating and comparing the performance of multiple deep learning-based architectures, specifically ConvLSTM, PredRNN, and a hybrid CNN-LSTM model in predicting spatiotemporal temperature patterns within the Sinharaja rainforest. By employing the strengths of remote sensing and advanced deep learning architectures, this research aims to provide accurate, spatially explicit temperature predictions for a data-scarce yet ecologically significant tropical rainforest. This framework contributes to both regional climate research and global rainforest monitoring efforts, offering a replicable methodology for similar ecosystems worldwide.

2. Study area

The Sinharaja Rainforest is the last major tropical lowland rainforest in Sri Lanka. It is in the South-Western wet zone of the country as shown in Fig. 1 (the study area was defined by a rectangular region of interest (ROI) bounded by the coordinates 6.25°N to 6.50°N latitude and 80.30°E to 80.60°E longitude). This area covers the geographical boundary of the Sinharaja Rainforest, approximately 1015 km^2. The region experiences high rainfall year-round, influenced by both the southwest and northeast monsoons, and is an important biodiversity hotspot. The Sinharaja Rainforest harbors exceptionally high levels of endemism in both its flora and fauna (Ediriweera et al., 2024). Climatically, it is rated as a "wet" lowland rainforest according to the Per Humidity Index, with high annual rainfall and relatively stable temperature conditions. Historical records indicate mean annual rainfall exceeding 5000 mm, while temperatures are usually within the range of 22 °C and 28 °C, with the warmest months being April–May and the coolest month, December (Samarasinghe et al., 2022).

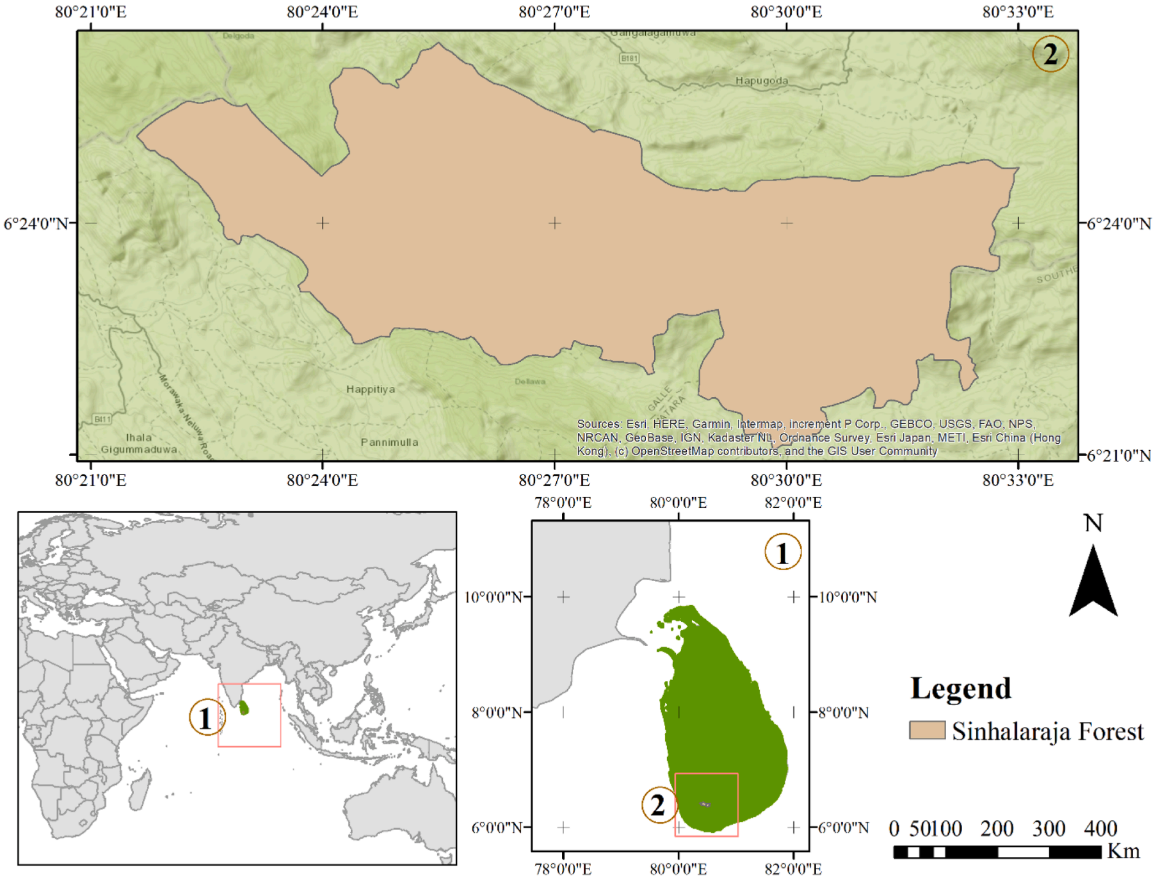
However, Samarasinghe et al. (2022) found an increase in built up areas in the vicinity of the declared forest over the past decade. Therefore, this indicates growing human influence. In addition, LST showcased some interesting patterns with variabilities with six internal clearing areas. Therefore, the case area in this analysis showcases a high research potential.

3. Materials and methodology

3.1. Data sources and collection

This study utilized satellite-based and ground-observed temperature datasets to analyze land surface temperature variations in the Sinharaja Rainforest. Land Surface Temperature (LST) data were obtained from the MODIS MOD11A1 Version 6.1 Terra product at a spatial resolution of 1 km, accessed via the Google Earth Engine data catalog (accessed on 31 January 2025). The data set spans from 2nd February 2000 to 2nd February 2021.

MOD11A1 was selected over the MOD11A2 (8-day composite) product due to its higher temporal resolution (Lu et al., 2018). While MOD11A2 provides temporally aggregated LST suitable for long-term and SUHI analyses (Shen et al., 2025b), it smooths short-term variability. In contrast, the daily MOD11A1 data preserve high-frequency temporal dynamics, which are essential for spatio-temporal based



Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community

Fig. 1. Study area, sinharaja rainforest.

forecasting. Therefore, MOD11A1 was considered more appropriate for this study.

Although the spatial resolution of MODIS (1 km) is relatively coarse for a study area of 1015 km^2, it is well suited for this research due to several factors. Primarily, it provides high temporal resolution. MODIS provides near-daily observations, enabling the construction of continuous time series required for deep learning models. In contrast, higher-resolution datasets often suffer from low temporal frequency. Furthermore, the study area is represented by multiple MODIS pixels, allowing the capture of regional temperature patterns. Therefore, MODIS data offers an effective balance between spatial coverage and temporal continuity for temperature analysis and forecasting.

Ground-based air temperature data were collected from the Sri Lankan Department of Meteorology, specifically from the Deniyaya Meteorological Station, which is one of the official weather monitoring stations located near the Sinharaja Rainforest. The monthly temperature data, including monthly minimum temperature (°C) and monthly maximum temperature (°C) were collected. The ground data spans a significant historical period; however, includes a notable gap. The data were available from 2000 to 2022, except for the period between 2008 and 2012, where no records were available. The average temperature (T_{avg}) was calculated using the T_{min} and T_{max} and shown in Fig. 2a.

It is important to note that ground-based air temperature and satellite-derived LST are physically distinct variables. LST is governed by surface radiative properties, vegetation cover, and soil moisture, whereas air temperature reflects atmospheric conditions influenced by boundary-layer processes. Therefore, ground observations are used only as a proxy to assess the consistency of temporal variability and in satellite-derived thermal patterns, rather than to directly validate LST accuracy.

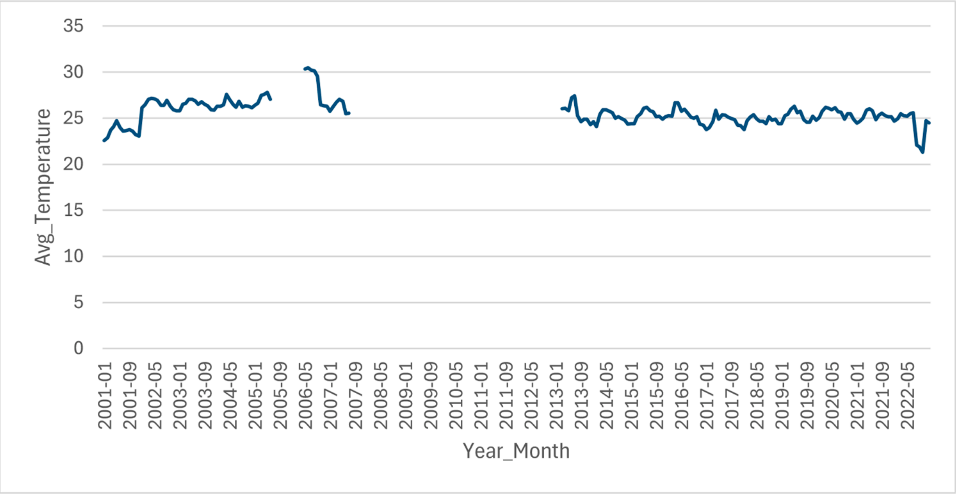
Data preprocessing, analysis, and model development were carried out using Python, with spatial processing performed in ArcGIS, Google Earth Engine, and Google Earth Pro platforms.

3.2. *Data preprocessing*

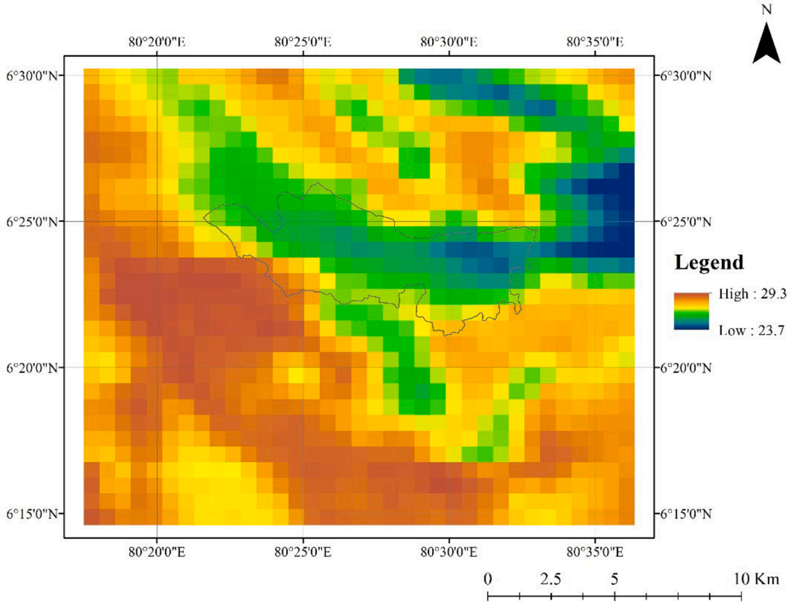
The MODIS dataset was originally stored as a multi-band GeoTIFF format. Each band represented the average LST for a specific month. In total, the dataset contained 252 monthly bands (21 years × 12 months). Each monthly band was extracted and saved as a separate single-band GeoTIFF file to facilitate temporal analysis.

In GeoTIFF files, missing values were identified in 36,309 out of 255,780 pixels, representing a missing data proportion of 14.2%. These gaps were addressed using a combination pf linear interpolation (estimates a missing value by creating a linear function between two known points) and nearest-neighbor interpolation (which assigns the closest valid pixel value to missing entries). Interpolated based approaches, including spatial and temporal methods, are commonly used to reconstruct such gaps in remote sensing datasets (Inglada et al., 2017; Defourny et al. 2019; Neteler 2010). However, they rely on assumptions of spatial and temporal continuity, which many do not fully hold under persistent cloud cover conditions.

These data were stored in 1 km x 1 km pixels, meaning each pixel represents a 1 km^2 area on the Earth's surface. The monthly average temperature data were processed by computing the mean land surface temperature (LST) for each month from daily values. After processing, the dataset was compiled into a collection of images, with each image representing the average LST for a specific month. These monthly images were combined into a single multi-band image, where each band corresponds to a different month from the time series. Each band within the multi-band image is 1 km x 1 km in spatial resolution and contains 1015 pixels. The processed data was exported as a GeoTIFF file, as



(a) Data from the Department of Meteorology, Sri Lanka



(b) Multi-band GeoTIFF file view in the ArcMap software

Fig. 2. Temperature data processing.

shown in Fig. 2b The exported GeoTIFF files were then visualized in the ArcMap Software to ensure the pixel alignment matched with the Sinharaja boundaries and no unintended rotation in the raster.

3.3. *Trend and correlation analysis*

To analyze the long-term trend of average ground temperature in the Sinharaja Rainforest region, the Mann-Kendall test (Mann, 1945) was applied to the satellite-derived LST dataset to detect monotonic trends. Additionally, Pearson's correlation was used to evaluate linear relationships between satellite LST and ground-based measurements, while Spearman's correlation was used to assess monotonic associations across two continuous periods (2001–2007 and 2013–2021).

3.4. *Time series decomposition*

The monthly LST time series was decomposed into trend, seasonal, and residual components using an additive decomposition model. A linear regression was applied to the trend component to estimate a straight-line trend.

3.5. *Spatio-Temporal deep learning model development*

To identify the most robust architecture for LST forecasting in the Sinharaja Rainforest, a comparative analysis was conducted between three spatio-temporal deep learning models: ConvLSTM, hybrid CNN-LSTM, and PredRNN. Based on final validation, the ConvLSTM was identified as the primary architecture due to its superior ability to preserve spatial structures and temporal dependencies simultaneously.

All models were developed using TensorFlow/Keras (open-source machine learning framework), while NumPy (for numerical computing), Pandas (for data manipulation), Matplotlib and Seaborn (for powerful data visualization) were employed for data handling and visualization.

The ConvLSTM architecture extends the traditional LSTM by replacing fully connected operations with convolutional operations, enabling the preservation of spatial structures within sequential image data. The primary architecture utilizes a deep, three-layer stacked configuration. This primary architecture utilizes a deep, three-layer stacked configuration. This hierarchy begins with a high-capacity layer of 128 filters to extract fine-grained spatial features, followed by two subsequent layers of 32 and 16 filters to refine spatiotemporal representations. To preserve the spatial metadata of the Sinharaja rainforest, the final output is generated through a TimeDistributed Conv2D layer, which maps the internal states back to the original 29 × 35 pixel grid.

To rigorously verify the performance of the architecture of the ConvLSTM, two additional architectures were developed as benchmarks:

1. CNN-LSTM: architecture combines convolutional neural networks (CNNs) for spatial feature extraction with LSTM layers for temporal sequence learning. In this framework, CNN layers extracted spatial temperature features from monthly LST maps before temporal dependencies were learned through LSTM units.
2. PredRNN: advanced recurrent architecture designed for predictive learning, which are capable of modelling spatiotemporal evolution through recurrent memory transitions.

All models were trained on the same MODIS MOD11A1 LST dataset, with an identical chronological train/test split (2001–2018 for training, 2019–2021 for hindcast validation). Common preprocessing steps were applied across all models. All models were optimized using the Adam optimizer with early stopping and learning rate on plateau.

3.6. Model training and hyperparameter tuning

The ConvLSTM architecture was optimized using Bayesian optimization via Optuna framework. A total of 30 trials were conducted to sample the sample the search space, including sequence length (12–24 months), layer depth (2–3), filter sizes, and regularization parameters. The best-performing configuration was then retrained for 200 epochs using Early Stopping and a learning rate scheduler to prevent overfitting. The final optimized hyperparameters, which provided the best balance between convergence stability and predictive accuracy, are summarized in Table 1.

3.7. Independent (Hindcast) validation

To address the requirement for rigorous validation, hindcast validation strategy was employed. The model was trained exclusively on MODIS LST observations from January 2001 to December 2018, with no data from the validation or forecast periods used during training or hyperparameter optimization. The trained model was then applied to predict monthly LST for the period January 2019 to December 2021, for which actual MODIS satellite observations were withheld. Predicted values were compared against these withheld observations using RMSE, MAE, MAPE, R^2, and Bias metrics computed pixel-wise across the entire spatial domain. This chronological holdout design ensures strict temporal independence between training and evaluation, providing unbiased evidence of the model's predictive performance on unseen data.

The trained models were then used to forecast temperature for the next 12 months, which were denormalized and saved as GeoTIFFs, preserving spatial metadata. The predictions were analyzed for seasonal variation and spatial distribution across the Sinharaja Rainforest. Additionally, long-term projections (2022–2027) were examined to evaluate gradual warming trends. The Deep Learning model development is shown in Fig. 3.

Table 1
Optimized hyperparameters for convLSTM model.

Hyperparameter	Optimized value
Sequence Length	18 months
Number of ConvLSTM2D layers	3
Filter Configuration	128 (L1), 32 (L2), 16 (L3)
Dropout Rate	0.4 (L1), 0.3 (L2)
L2 Regularization Penalty	0.0007
Learning Rate	0.0016
Loss Function	Huber Loss
Batch Size	4

4. Results and discussion

4.1. Pearson correlation analysis

Before model development, it was essential to examine the degree of association between satellite-derived LST and ground-based air temperature data for representing near-surface thermal conditions in the Sinharaja Rainforest. The Pearson correlation coefficient between ground-based temperature data and satellite-derived LST was 0.5571 for the period 2001–2007. As shown in Fig. 4a, the scatter plot indicates a moderate positive correlation with an upward trend. It was very similar for the period from 2013 to 2022 and found to be 0.5147 (refer to Fig. 4b). This again indicates a moderate positive correlation, suggesting a consistent linear association between the two datasets in recent years. As shown in the scatter plot and its corresponding regression line (Fig. 4b), the satellite LST data shows a moderate level of co-variation with ground-based air temperature during this period.

4.2. Spearman correlation analysis

Complementary to the Pearson correlation, the Spearman correlation coefficient (ρ) for the period from 2001 to 2007 was found to be 0.6333, indicating a strong and statistically significant monotonic relationship between ground-based temperature data and satellite-derived LST measurements. After the data gap, for the period from 2013 to 2022, the Spearman correlation coefficient was 0.4077. This indicates a moderate but statistically significant monotonic correlation between the two temperature datasets.

4.3. Temperature trend analysis

The non-parametric Mann-Kendall test was applied to the satellite-derived LST dataset extracted from the GeoTIFF files for the Deniyaya meteorological station. No significant trend was detected from the data series. Fig. 5a shows the yearly average satellite-derived LST trend. While minor fluctuations are presented across years, no clear or consistent directional trend is visible, which aligns with the Mann-Kendall test's statistical outcome.

4.4. Time series decomposition of land surface temperature

The time series decomposition of monthly average LST values over the Sinharaja Rainforest region revealed a unique trend, seasonal, and residual components. The trend component showed a long-term increase in LST, suggesting a potential warming trend in the region. A linear regression applied to the trend values yielded a positive gradient of 0.0004, indicating a subtle but persistent warming pattern (refer to Fig. 5b). The residual component appeared as random noise, with a non-identified pattern, indicating that most of the systematic variation was captured by the trend and seasonal components.

4.5. Predicted LST for 2022

The ConvLSTM model, trained with Optuna-optimized hyperparameters, was used to forecast LST maps for all 12 moths of 2022 using a recursive month-by-month prediction strategy with an 18-month input sequence. Fig. 6 presents the predicted spatial distribution of monthly LST across the Sinharaja rainforest for 2022. Cooler conditions dominated from July to February, where this part of Sri Lanka experiences milder temperatures. However, a progressive warming trend can be observed since March. As expected, peak temperatures were observed

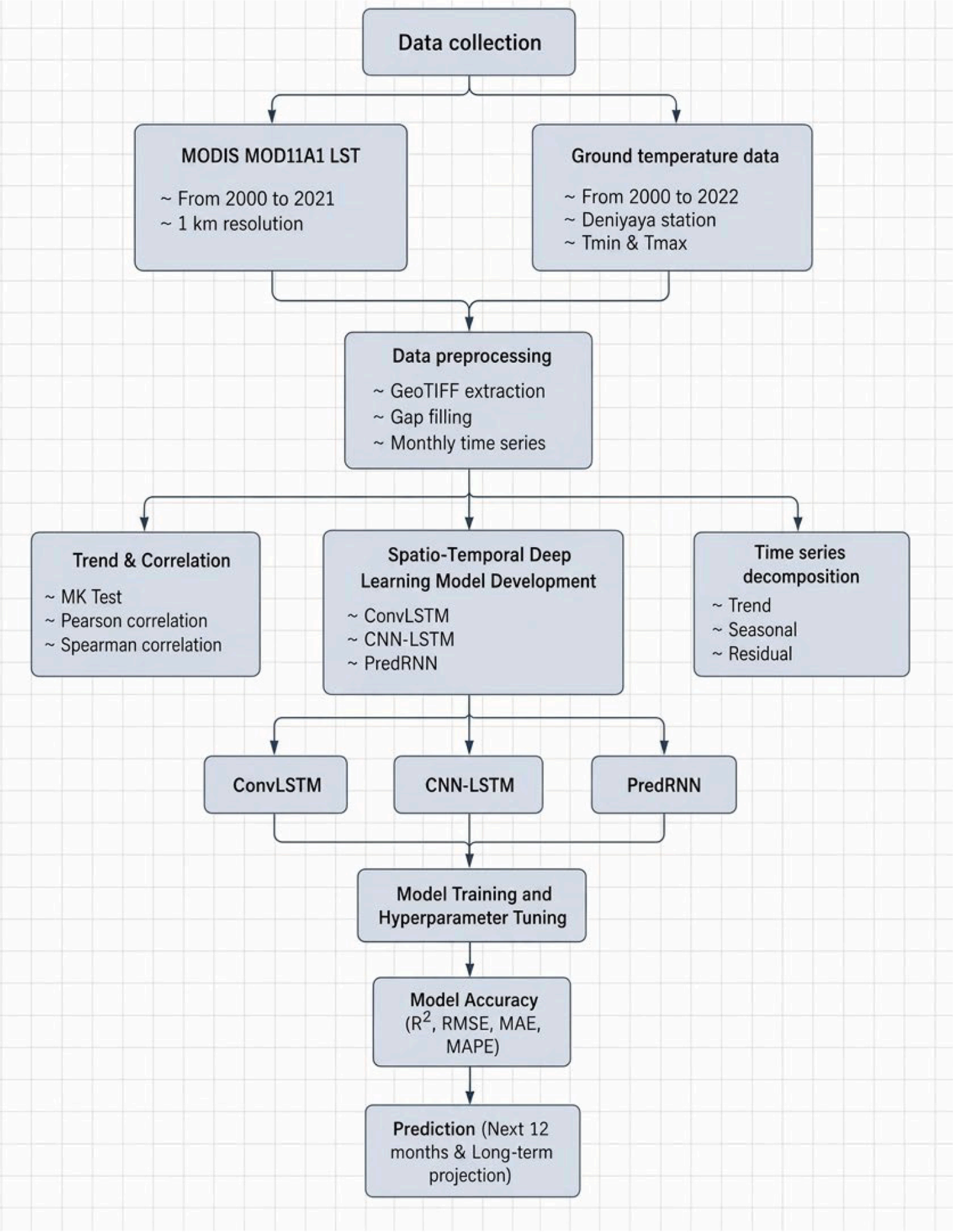


Fig. 3. Flowchart of LSTM model development.

during mid months (April to June). Interestingly, spatial variation showcases the warmer patches are consistently concentrated in specific regions. This could be due to land use changes, topography, localized climatic conditions, etc. Overall, the figure demonstrates a pronounced seasonal cycle in LST, with distinct spatial patterns that persist across months, underscoring the effectiveness of the model in capturing both temporal and spatial temperature dynamics.

Fig. 7 presents the monthly variation of LST with respect to the monsoonal seasons experienced in a year in Sri Lanka. The LST level reached its highest in April, as indicated by the average temperatures, and then began to decrease during the southwest monsoon, when the area receives its highest rainfall of the year (May to September). However, the lowest average LST was predicted for the month of August. Overall, the figure illustrates the strong influence of monsoon transitions on monthly temperature variability, with warmer conditions during inter-monsoon periods and cooler conditions during peak monsoon months.

The 2022–2027 projections are produced using a recursive forecasting strategy in which each predicted monthly LST map serves as input for subsequent predictions. Uncertainty is expected to accumulate with increasing forecast horizon as prediction errors propagate forward. Near-term projections (2022–2023) are therefore considered more reliable than longer-horizon projections (2024–2027), which should be interpreted as indicative trends rather than deterministic forecasts. The 2019–2021 hindcast validation results (ConvLSTM2D: $R^2 = 0.4551$, RMSE = 1.5513 °C) provide the empirical basis for assessing the credibility of these projections. Direct validation against future satellite observations, as they become available, is recommended as a priority for subsequent work.

4.6. Comparative performance of deep learning architectures

To validate the selection of the ConvLSTM, its performance was compared against two benchmark models (CNN-LSTM and PredRNN) using the independent hindcast period (2019–2021). As shown in Table 2, the optimized ConvLSTM demonstrated superior predictive

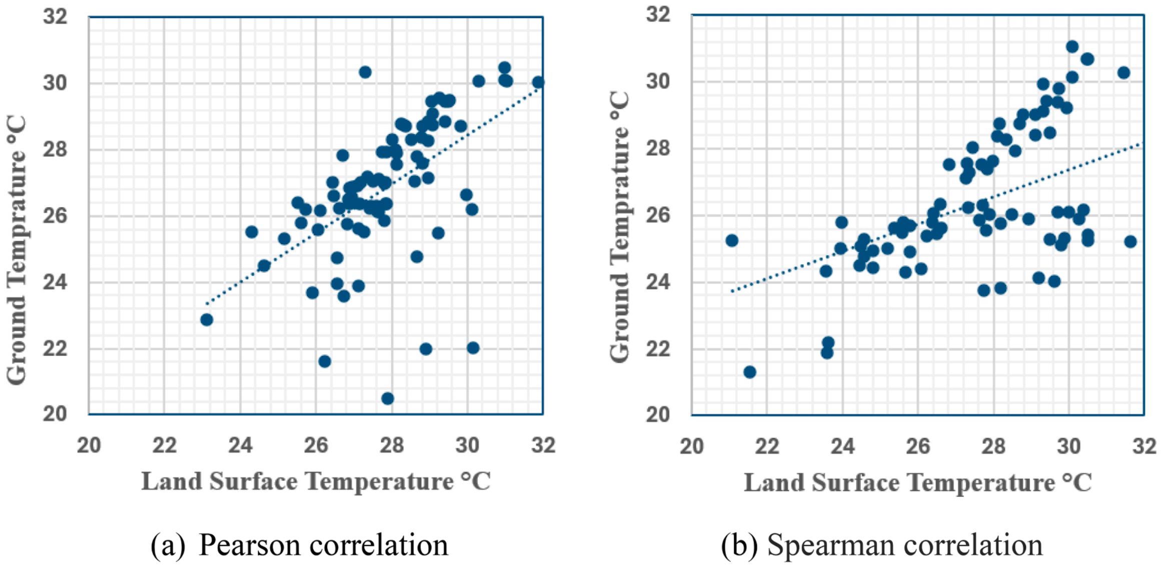


Fig. 4. Correlation coefficients.

accuracy across all evaluation metrics.

Among the evaluated architectures, the ConvLSTM model achieved the best predictive performance. This indicates that ConvLSTM was more effective in learning the complex spatiotemporal relationships within the MODIS-derived LST dataset compared to CNN-LSTM and PredRNN approaches.

4.7. *Training convergence and stability*

The final ConvLSTM model was retrained using the optimized parameters for 200 epochs. The learning curves (Fig. 8) show that both training and validation losses (Huber) stabilized around epoch 60. The close tracking of the training and validation MAE and RMSE confirms that the integrated Dropout and L2 regularization effectively prevented overfitting, satisfying the requirement for a generalized forecasting model.

4.8. *Independent hindcast validation (2019–2021)*

The relationship between the observed MODIS LST and the ConvLSTM predictions is illustrated through two primary diagnostic plots. The scatter plot (Fig. 9a) compares the predicted vs actual pixel-wise LST. The data points generally cluster around the 1:1 line, indicating a reasonable agreement between predicted vs actual LST across Sinharaja rainforest region. Although some dispersion is evident due to the inherent variability and noise associated with satellite-derived LST in tropical environments, the model captures the overall spatial and temporal patterns effectively. The obtained R^2 value of 0.4551 suggests a moderate predictive capability with no substantial systematic bias observed in the predictions.

To evaluate the model's forecasting consistency, a hindcast validation was performed for the 2019–2021 period. As illustrated in Fig. 9b, the optimized ConvLSTM successfully captures the seasonal thermal trajectory, with the predicted spatial mean (dashed orange line) closely tracking the observed values (solid blue line) across all three validation years. The pixel-level uncertainty clouds indicate that the model reproduces the general spread of spatial LST variability, though the predicted distribution is somewhat narrower than the observed, particularly at the lower temperature extremes, suggesting a degree of spatial smoothing of cold anomalies. The residual panel confirms that most monthly prediction errors remain within ±1 °C, with isolated exceedances reaching up to approximately 2.5 °C during anomalous months such as August 2020. A mild tendency toward negative residuals in early 2019 transitioning to positive residuals from mid-2020 onward warrants cautious interpretation, though no systematic long-term error drift is evident across the full 36-month window.

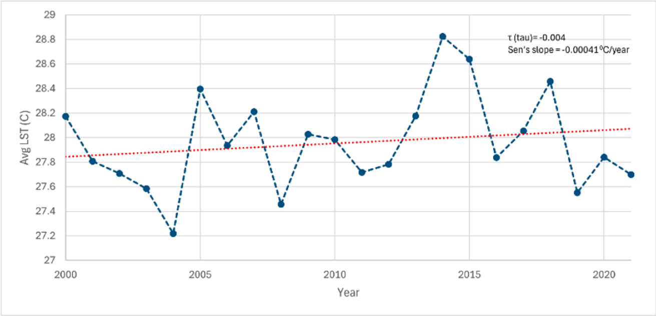
4.9. *Discussion of results*

Results of the study present distinct spatiotemporal characteristics in the variability of LST within the Sinharaja Rainforest, showing seasonal stability with subtle long-term warming signals. Regional climatic conditions, dense forest canopy structure, and inherent microclimatic heterogeneity can influence temperature dynamics within tropical rainforests. In contrast to urban or agricultural landscapes, temperature variations in Sinharaja Rainforest are moderated through vegetation cover, evapotranspiration, and topography, which complicates the detection and prediction of thermal trends.

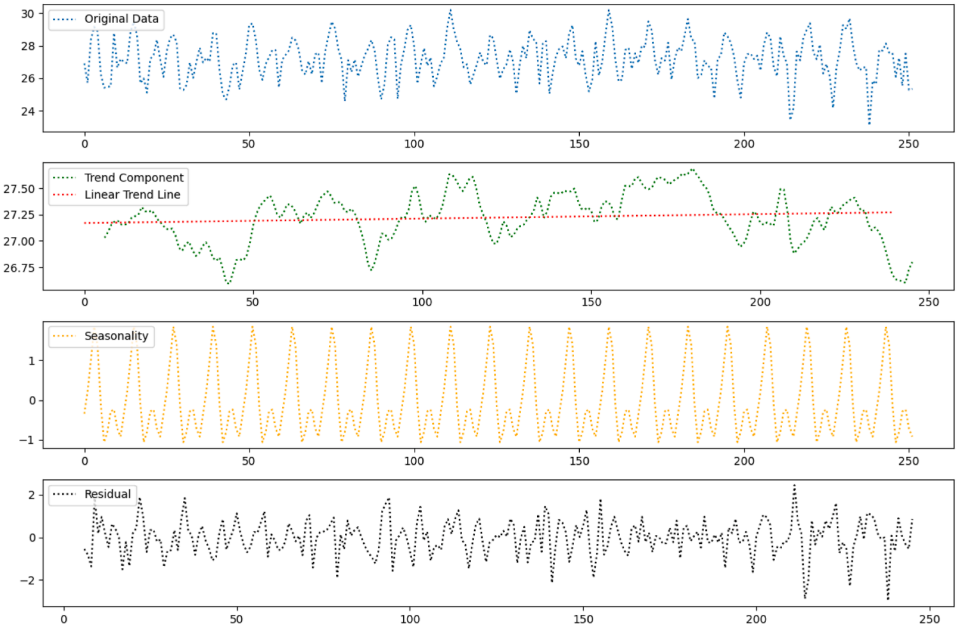
Previous studies in tropical regions have primarily relied on retrospective satellite analysis or ground-based observations to assess temperature variability (Samarasinghe et al., 2022), while statistical trend detection methods such as the Mann–Kendall test have often failed to identify significant monotonic warming trends due to high interannual variability. Consistent with these findings, the Mann–Kendall test applied in this study did not detect a statistically significant trend in satellite-derived temperature records. By decomposing the time series into trend and seasonal components, this study identified a weak but persistent warming signal, suggesting that conventional statistical approaches alone may underestimate gradual climatic changes in complex rainforest environments.

Furthermore, it is important to acknowledge the physical discrepancy between the MODIS derived LST and ground-station air temperature used in this study. The ground measurements represent near-surface air temperature rather than true LST, and these variables are not physically equivalent. LST is primarily controlled by surface radiative properties, vegetation cover, and soil moisture. In the Sinharaja rainforest, dense canopy cover, high humidity, and complex land atmosphere interactions can further weaken the coupling between surface and air temperatures. Accordingly, ground-based observations serve as a consistency check rather than a direct validation of absolute LST accuracy.

In contrast to earlier studies that focused solely on historical analysis (Samarasinghe et al., 2022) this research extends the examination of temperature dynamics by integrating deep learning–based forecasting.



(a) Yearly average LST trend



(b) Time series decomposition of monthly average LST, trend with linear fit (slope = 0.00042), seasonal pattern, and residuals

Fig. 5. Trend analysis results.

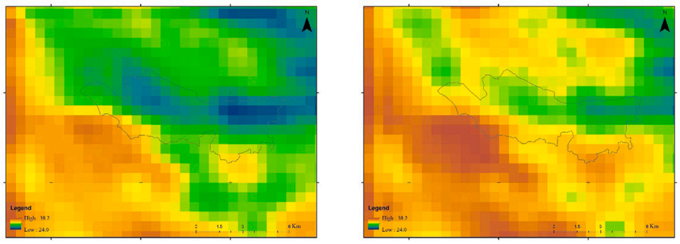
While recent studies in diverse landscapes have demonstrated that ensemble learners like Random Forest (RF) can achieve high accuracy ($R^2 = 0.796$) multiple biophysical predictors such as NDVI, IBI, and moisture-related indices (Zafar et al., 2026), these models often rely on the availability of high-quality datasets. In contrast, our ConvLSTM framework achieves a robust representation of the Sinharaja rainforest by strictly utilizing spatiotemporal LST sequences. By using integrated convolutional gates, our modek automatically captures the necessary spatial and temporal patterns from the temperature data itself, reducing the need for external indices while maintaining high predictive accuracy in complex forest environments.

The ConvLSTM model demonstrated a strong ability to capture both seasonal cycles and long-term temperature evolution, preserving known climatic rhythms of the Sinharaja region. Warmer periods during March–June and cooler conditions during August to February were consistently reproduced, reflecting the influence of monsoonal circulation patterns. Similar studies have been reported in ConvLSTM applications for environmental forecasting using MODIS datasets (Kartal et al., 2024), reinforcing the suitability of this architecture for spatiotemporal climate modeling.

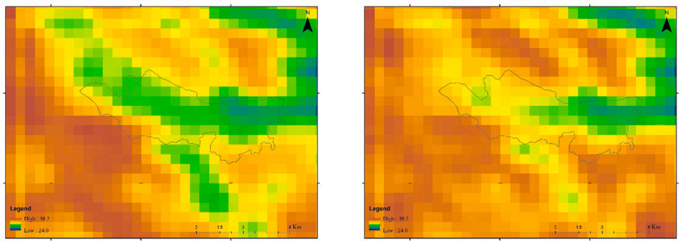
The predictive performance achieved in this study is comparable to, and in some cases exceeds, that reported in similar deep learning–based temperature forecasting studies. Previous research employing CNN–LSTM or hybrid architectures for temperature prediction reported RMSE values ranging from approximately 1.8 °C (Li and Qian, 2024), whereas this study achieved an RMSE of 1.55 °C. This improvement can be attributed to the explicit modeling of spatiotemporal dependencies using ConvLSTM.

Compared with traditional statistical and machine learning approaches, such as ARIMA, linear regression, and Random Forest models (Tektaş, 2010), the ConvLSTM framework offers a distinct advantage by explicitly modeling spatial dependencies alongside temporal dynamics (Shi et al., 2015). Studies applying ConvLSTM to rainfall and vegetation forecasting have reported substantial improvements in predictive accuracy over linear models (Kim et al., 2017; Shi et al., 2015).

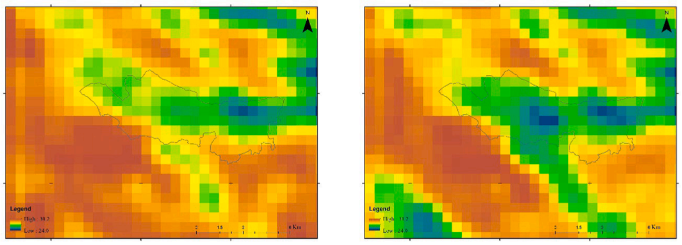
This study differs from earlier Sri Lankan climate modeling efforts, which largely focused on urban areas, agricultural regions, or point-based meteorological stations (De Silva et al., 2007). By employing spatially continuous satellite-derived LST data and a deep spatiotemporal learning model, this research provides a more comprehensive representation of temperature dynamics across an entire forested landscape. The results support recent calls for integrating remote sensing and



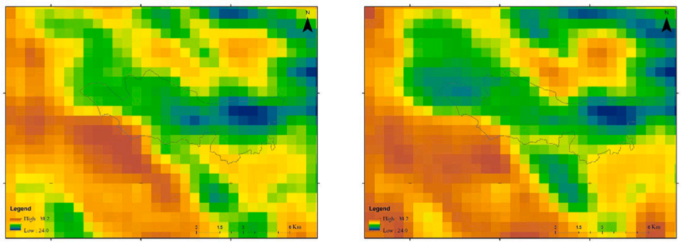
(a) For January (b) For February



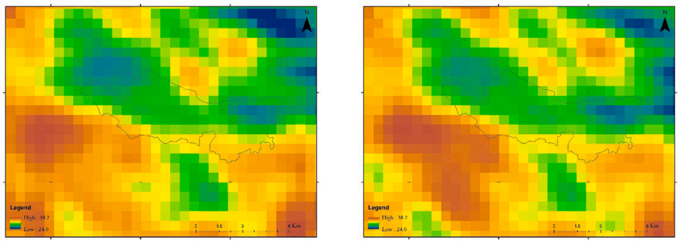
(c) For March (d) For April



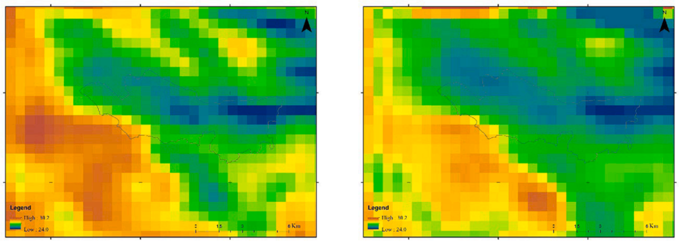
(e) For May (f) For June



(g) For July (h) For August



(i) For September (j) For October



(k) For November (l) For December

Fig. 6. Spatial distribution of predicted monthly average LST for 2022.

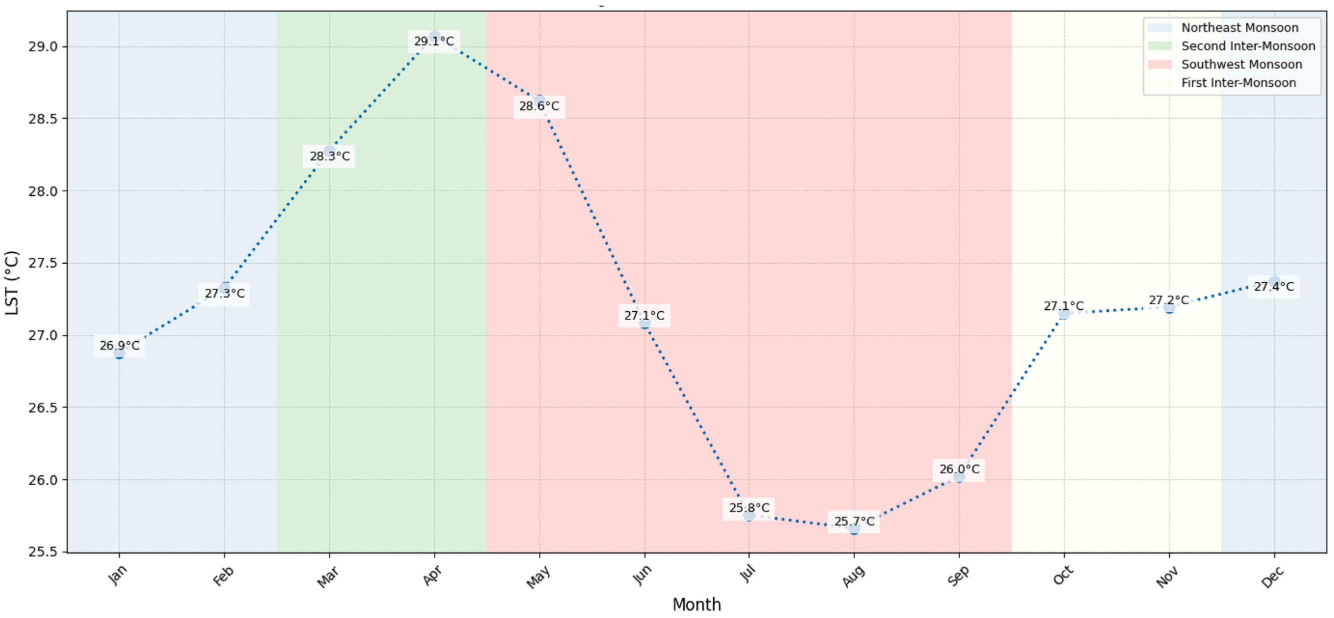


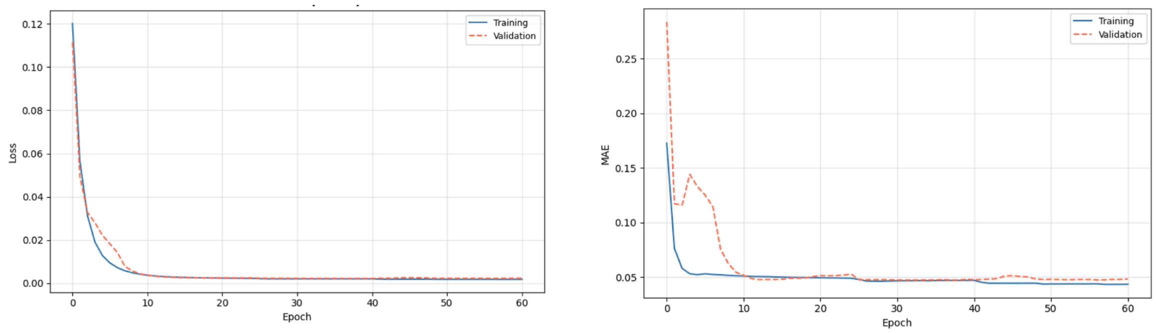
Fig. 7. Seasonal pattern of the predicted LST for 2022.

artificial intelligence in environmental monitoring and ecosystem management (Ball et al., 2022).

Overall, this study demonstrates that ConvLSTM-based spatiotemporal modeling provides a robust and scalable approach for temperature forecasting in complex tropical rainforest ecosystems. By bridging retrospective analysis and future projections, the findings contribute to a deeper understanding of rainforest climate dynamics and offer valuable insights for climate resilience and conservation policy.

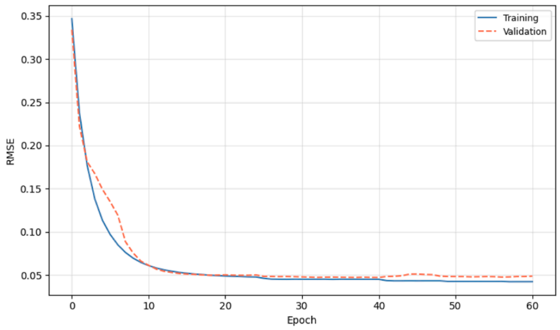
Table 2
Comparative performance metrics (Independent Test Set: 2019–2021).

Model	Period	RMSE (°C)	MAE (°C)	R^2	MAPE
ConvLSTM	2019–2021	1.5513	1.1401	0.4551	4.36
CNN-LSTM	2019–2021	1.5739	1.1618	0.4391	4.44
PredRNN	2019–2021	1.5688	1.1300	0.4427	4.32



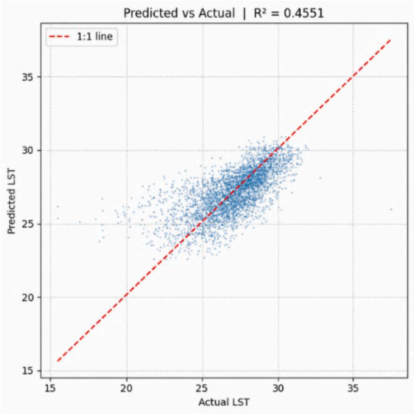
(a) Model Loss Convergence over Epochs

(b) Mean Absolute Error (MAE) Learning Curve

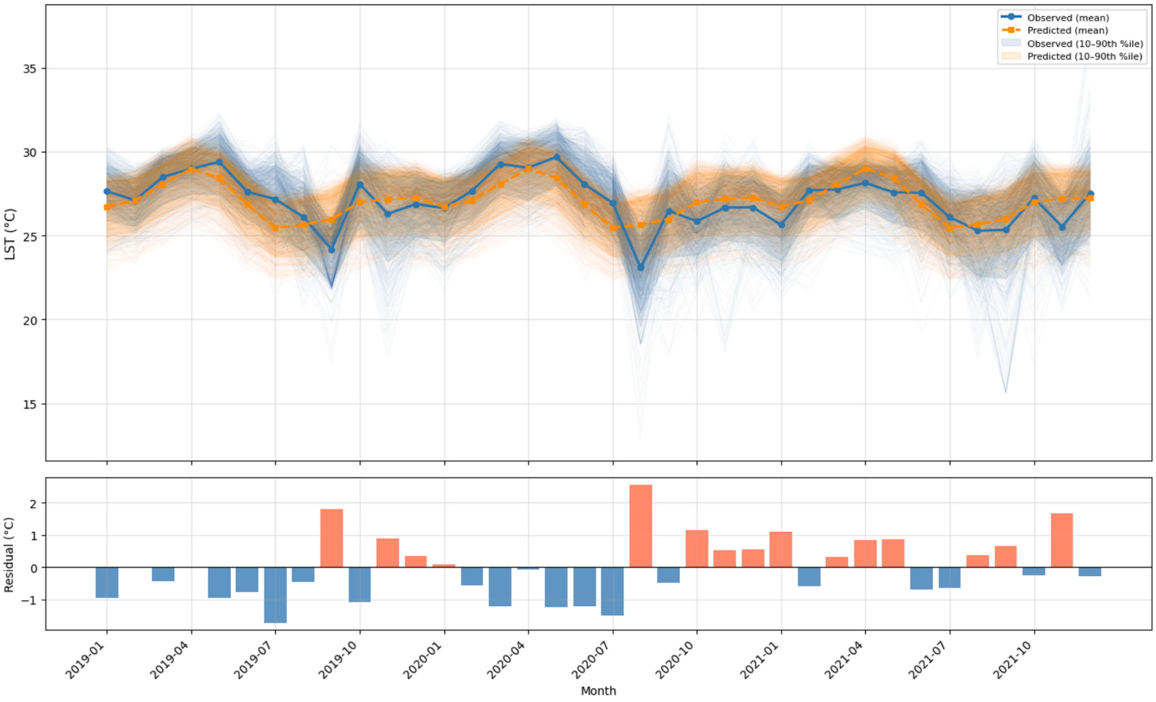


(c) Root Mean Square Error (RMSE) Convergence

Fig. 8. Model performance and error analysis across training epochs.



(a) Scatter plot of Observed vs. Predicted LST for the independent hindcast period (2019–2021).



(b) Hindcast Validation Time Series and Residual Analysis (2019–2021)

Fig. 9. Independent hindcast validation (2019–2021).

4.10. Limitations of the study

Despite the performance of the optimized ConvLSTM framework, several limitations must be acknowledged. First, a primary constraint relates to the validation of satellite-derived LST. Due to the absence of ground-based LST sensors within the Sinharaja Rainforest, meteorological station air temperature was utilized as a comparative proxy. As LST and air temperature are physically distinct variables governed by different energy exchange processes with LST being more sensitive to surface radiative properties and canopy structure, this comparison served to assess the consistency of temporal and seasonal patterns rather than to provide a direct validation of absolute LST accuracy.

Although the 14.2% missing data proportion was addressed using systematic interpolation, persistent cloud cover in tropical regions remains a challenge. Therefore, these methods provide a practical solution for generating continuous datasets, they may introduce uncertainty and potentially smooth variability, which could influence the magnitude and derived trends.

Finally, while the ConvLSTM demonstrated high proficiency in capturing seasonal cycles, its ability to predict extreme temperature anomalies remains limited. This suggests that the model primarily learns the dominant climatic rhythms rather than stochastic weather events. Future research should look to enhance predictive sensitivity by incorporating higher temporal resolution data and additional climatic drivers such as precipitation and vegetation indices (e.g., NDVI), which have been shown to significantly influence LST variability in diverse landscapes. Expanding this optimized framework to other tropical forest regions would further validate its generalizability and its utility for global forest conservation and climate resilience policies.

The 2022–2027 LST projections are generated using a recursive forecasting strategy in which each predicted monthly map was fed forward as input for the subsequent prediction. This approach is necessitated by the absence of future observational data but introduces the risk of error accumulation over successive forecast steps. Uncertainty in the projections is therefore expected to increase with forecast horizon, and the longer-range projections (2024–2027) should be interpreted as indicative trends rather than deterministic forecasts. Direct validation against future MODIS observations, as they become available, is recommended.

5. Conclusions

This study developed and validated spatiotemporal deep learning framework to forecast land surface temperature (LST) variations in the world heritage Sinharaja Rainforest, a critical biodiversity hotspot in Sri Lanka. Using 21 years of MODIS satellite-derived LST data, this research transitioned from traditional statistical analysis to an automated, deep-learning based forecasting approach.

The comparative evaluation of multiple architectures demonstrated that the ConvLSTM model is superior to both hybrid CNN-LSTM and PredRNN models for tropical rainforest environments. During the independent hindcast validation (2019–2021), the model achieved a robust RMSE of 1.55 °C and an MAE of 1.14 °C. While the R^2 of 0.4551 reflects the inherent noise and high variability of cloud-impacted satellite data in the tropics, the low absolute error confirms the model's reliability for ecological monitoring.

Although the Mann–Kendall test did not indicate a statistically significant monotonic trend, time series decomposition revealed a subtle but persistent warming signal, highlighting the importance of advanced analytical techniques for detecting complex climatic changes.

Direct ground-based temperature measurements across the entire rainforest are logistically challenging and spatially limited. In contrast, satellite remote sensing enables comprehensive coverage of the forest and, when combined with deep learning, provides a powerful approach for predicting future thermal trajectories, providing essential data to support climate impact assessments, biodiversity conservation planning, and sustainable management strategies for the Sinharaja Rainforest and similar tropical ecosystems globally.

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CRediT authorship contribution statement

Kushani I. Silva: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Panchali U. Fonseka:** Writing – original draft, Validation, Supervision, Methodology, Investigation. **Shantha Gamage:** Writing – review & editing, Validation. **Komali Kantamaneni:** Writing – review & editing. **Upaka Rathnayake:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Some of the data and material will be made available on reasonable request.

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