

Comparative Forecasting of Land Surface Temperature in Kathmandu Using Univariate and Multivariate Time Series Models

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Article

Comparative Forecasting of Land Surface Temperature in Kathmandu Using Univariate and Multivariate Time Series Models

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Abstract: Rapid growth and domestic migration to capital city, Kathmandu Metropolitan City (KMC), Nepal have amplified land-use transition to unmanaged and unplanned urbanization have exacerbated problems of Urban Heat Island (UHI) Effect. Increasing built up surfaces, means of transport and industrial activities are major results for increasing temperature in the city area as compared to other areas. This study focuses on forecasting Land Surface Temperature (LST) using both univariate and multivariate time series models. The primary goal is to predict the impact of climatic factors on the UHI effect, utilizing data from 1981 to 2019 and understand which model best serves as key to prediction for LST. We analyzed key factors including - (i) relative humidity, (ii) surface pressure, (iii) specific humidity, and (iv) wind speed sourced from the MEERA-2 dataset. This study aims provides valuable information via prediction for sustainable urban planning and landscape design in KMC.

Keywords: machine learning (ML); urban heat island (UHI); land surface temperature (LST); remote sensing; univariate time series; multivariate time series; Kathmandu Metropolitan City (KMC); Climatic Factors Forecasting; sustainable urban planning

1. Introduction

Urbanization and Land Use in Kathmandu

Figure 1 illustrates the capital city, Kathmandu Metropolitan City - the focal point of the study.

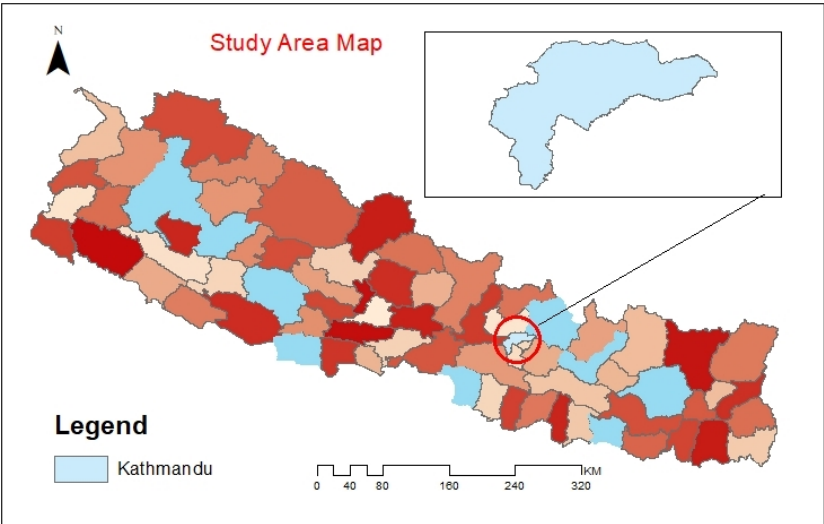


Figure 1. Nepal, Kathmandu Metropolitan City

Various land use and land cover (LULC) studies in Kathmandu Metropolitan City (KMC) (see Figure 2) have highlighted the negative impacts of rapid urbanization and population growth. These studies point to environmental challenges such as the Urban Heat Island (UHI) effect [1,2], where urban areas exhibit significantly higher temperatures than surrounding rural areas [3].

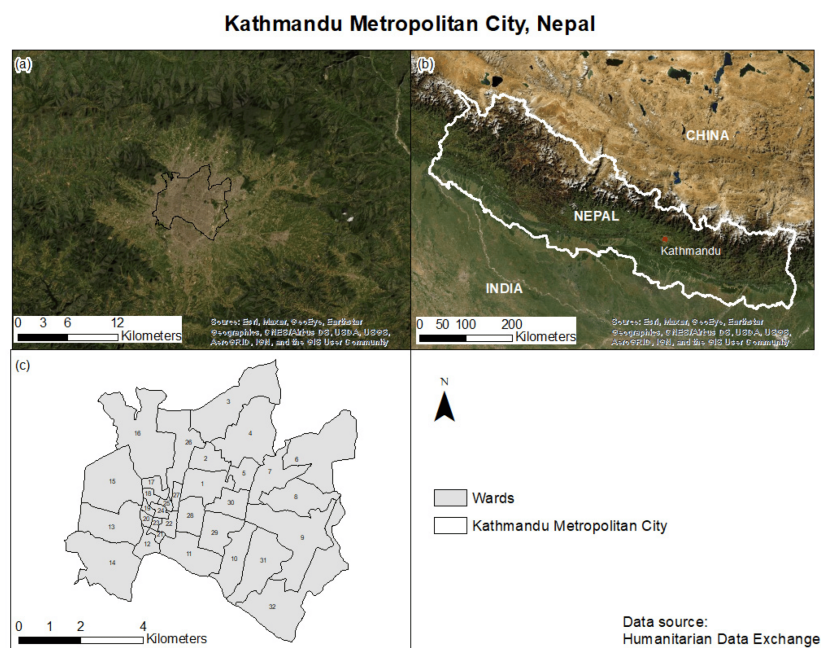


Figure 2. Kathmandu Metropolitan City, Nepal; (a) Geographic location of KMC; (b) Land cover comparison between KMC and its surroundings; (c) Administrative wards in KMC.

Impact of Land Use Change on UHI

Changes in land cover properties alter the thermal properties, surface radiation (energy emitted from the Earth's surface), and humidity of urban areas, which contributes to the UHI effect [4]. Evaluating UHI in rapidly urbanizing cities like Kathmandu is crucial to understand changes in surface albedo (reflectivity), emissivity (radiation efficiency), and evapotranspiration (water transfer from land to the atmosphere) [5]. The rise in UHI affects natural and human systems by altering rainfall patterns, worsening air quality, and increasing risks of floods and water contamination [6,7].

Global Evidence and Land Surface Temperature (LST) Studies

Globally, extensive evidence shows the link between urbanization and rising land surface temperatures (LST) [8–10]. LST is a critical factor in quantifying UHI effects [11]. Monitoring LST through remote sensing (RS) technologies provides insights into how land use changes impact surface temperatures.

Remote Sensing in UHI Studies

There is a growing body of literature demonstrating the benefits of satellite remote sensing for monitoring urban LULC patterns and LST [12,13,15]. Studies such as those by Estoque et al. [13] examined LST patterns in Southeast Asian megacities, while Athukorala and Murayama [15] analyzed spatial variations in land use and surface heat islands in Accra, Ghana. Jiang et al. [16] explored how urbanization in the U.S. Midwest influenced LST and surface moisture, while Yan et al. [4] assessed the warming effects of urbanization in Chinese urban areas. These studies provide essential insights into UHI mitigation strategies and contribute to urban planning aimed at reducing the UHI effect [4,10,16].

Urbanization and Thermal Comfort in KMC

Kathmandu, as one of the most developed cities in Nepal in terms of population and economic growth, has seen rapid increases in built-up areas. Thermal comfort (the perception of temperature as comfortable or uncomfortable) has become a significant issue in Kathmandu [1], with recent studies by Maharjan et al. [17] addressing this problem. This paper aims to forecast LST in Kathmandu, contributing to strategies that could enhance thermal comfort and mitigate UHI effects.

2. Materials and Methods

2.1. Dataset Information

The dataset used for this study was sourced from the Open Data Nepal platform, titled “Climate Data”. It is available in CSV format and contains daily time-series data related to climate variables such as temperature, relative humidity, precipitation levels, surface pressure, specific humidity, and wind speed. The dataset covers the period from 1981 to 2019 and includes records for 62 districts in Nepal. However, the model was primarily trained and evaluated on data from the Kathmandu Metropolitan City (KMC). No additional datasets or external data sources were used in this project.

2.2. Study Area

While we have recorded data of skin temperature for 62 districts provided by Open Data Nepal as shown in the figure, we focused on the capital city, KMC for the reasons of immediate study and assumption of quick implementation of action based on the research.

Figures showcasing recorded LST against Districts:

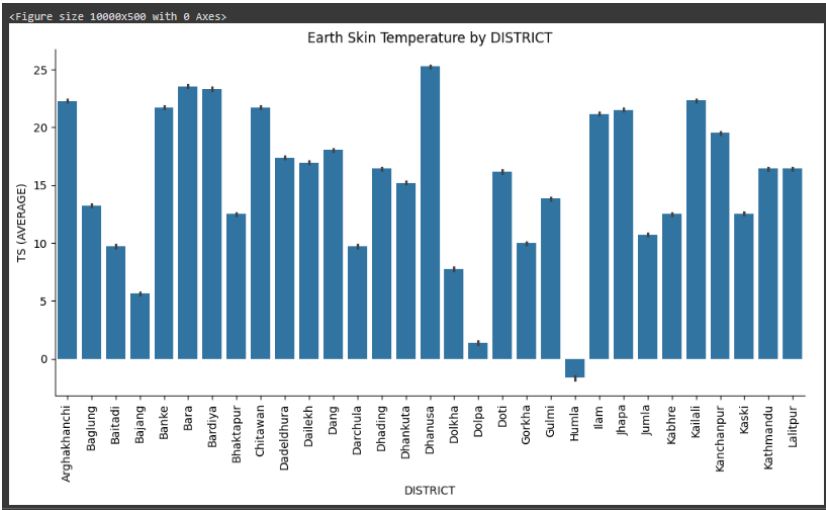


Figure 3. District VS TS 1

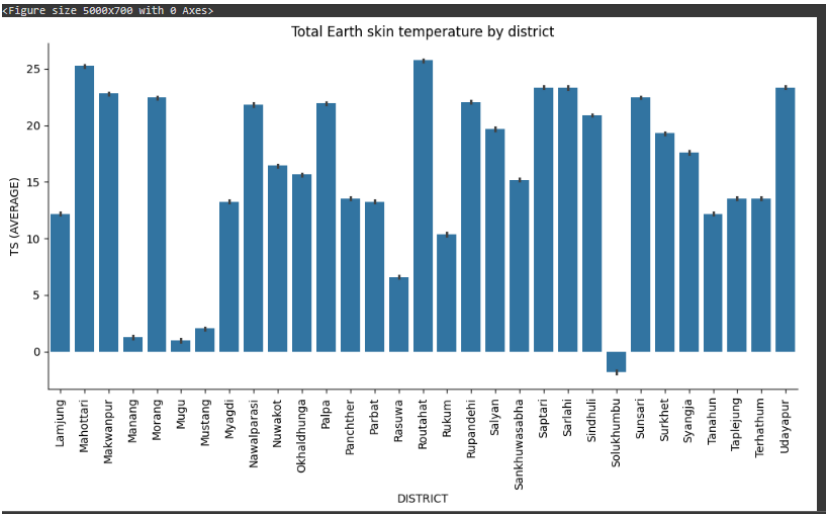


Figure 4. District VS TS 2

The study area is limited to the Kathmandu Metropolitan City (KMC), located in the central region of Nepal. Although the dataset includes data for 62 districts, this research focuses solely on forecasting for Kathmandu. The data provides insights into the urban climate patterns within KMC, which is rapidly urbanizing.

2.3. Tools and Software

The following tools and libraries were used for data processing and analysis:

- **Pandas** for data manipulation and analysis.
- **NumPy** for numerical computations.
- **Matplotlib** and **Seaborn** for data visualization.
- **Prophet** for time series forecasting, which is an open-source software designed for time series analysis.
- The entire development and model training was carried out using **Google Colab**, a cloud-based environment suitable for machine learning projects.

2.4. Model Information

The machine learning models used in this study include:

- **Exponential Smoothing (ES)**: This method was used for univariate time series forecasting. It is well-suited for short-term forecasting with a single variable.
- **Prophet**: This model was used for multivariate forecasting, incorporating multiple climate variables such as temperature, humidity, and precipitation. The default hyperparameters of the Prophet model were utilized for this study.

2.5. Data Preprocessing

To prepare the dataset for analysis:

- **Handling Missing Data**: Missing values in the dataset were handled using interpolation methods to ensure continuity of the time series data.
- **Data Normalization**: The dataset was normalized using the **Min-Max Scaler** to transform all variables into a common range (typically between 0 and 1). This ensured that features with larger ranges did not dominate the model's predictions.

2.6. Evaluation Metrics

The following metrics were used to evaluate the performance of the models:

- **Mean Absolute Error (MAE)**: Measures the average magnitude of errors in the predictions.
- **R² Score**: Measures the proportion of variance in the dependent variable that is predictable from the independent variables.

2.7. Experimental Setup

The entire process of training and testing the models was conducted in **Google Colab**, an online platform offering a cloud-based Python environment. Although Google Colab supports GPU acceleration, no specific hardware configurations or GPU setups were used for this study.

2.8. Methodology

- **Exponential Smoothing (ES)** was employed for univariate analysis, forecasting the temperature time series data for Kathmandu.
- **Prophet Model** was applied for multivariate time series forecasting, using multiple climatic variables such as temperature, humidity, and precipitation.

The dataset was divided into training and testing subsets to evaluate the model's performance. Cross-validation was not explicitly performed, but the split ensured robust model validation.

2.9. Deployment

After model training, the resulting forecasting model was deployed using **Django**, a Python web framework. This deployment enabled users to interact with the model and obtain forecasts for Land Surface Temperature (LST). However, the deployed model is not publicly available, and specific configurations for deployment have been made available in the github repository [14].

3. Results

3.1. Models

Exponential Smooth Forecast

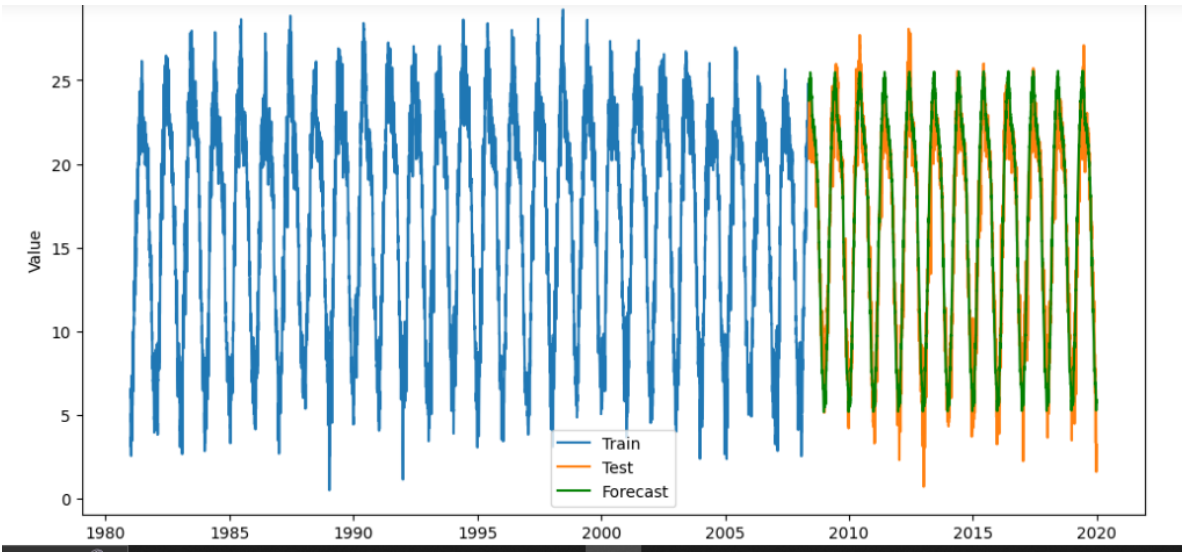


Figure 5. Exponential Smoothing Model Forecast

Mean Absolute Error (MAE): 1.2082659975428822

R-squared (R²) Score: 0.9425295902006932

FB Prophet

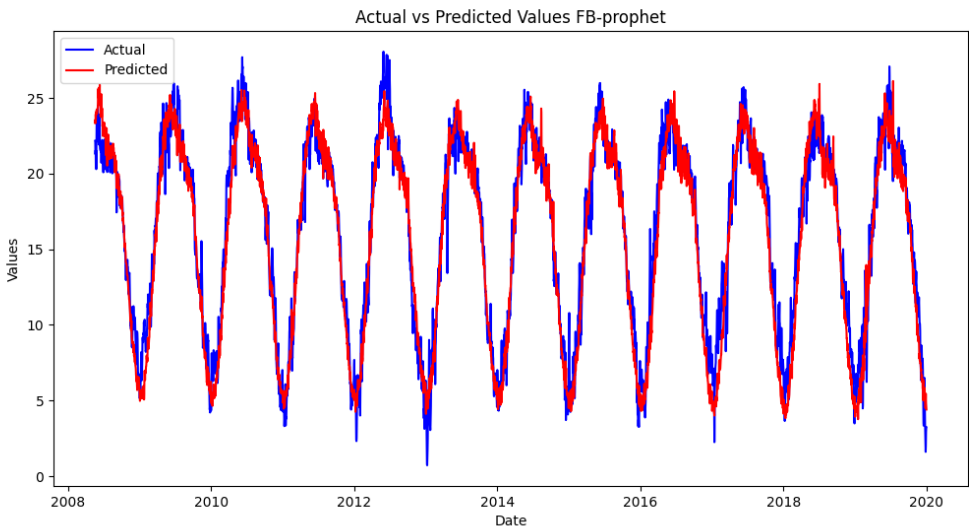


Figure 6. FB Prophet Model Forecast

Mean Absolute Error (MAE): 1.1958573696229469
R-squared (R²) Score: 0.9404890481566638

3.2. User Interface

The user interface to use the model has been made minimalist. The requirements for the prediction to be made are: (i) Date, (ii)PS, (iii)QV2M and (iv)WS10M. The model works in the backend with these features to showcase the output in the range of minimum to maximum as well as the average forecast.

Earth Skin Temperature Prediction Kathmandu

Input the Date

Date: 09/30/2019

PS: 83.95

QV2M: 15.53

WS10M: 1.73

Forecast

Figure 7. Input Area

Earth Skin Temperature Prediction Kathmandu

Type	Value
Average Forecast	17.93
Minimum Forecast	15.27
Maximum Forecast	20.77

Figure 8. Output Area

Overall, these results indicate that the Prophet model provides more accurate forecasts of temperature, humidity, and precipitation levels in KMC, contributing valuable insights for climate studies and urban planning. Future research could explore the integration of additional variables or alternative modeling techniques to enhance forecasting accuracy further.

4. Discussion

As a researcher working on the Climate Analysis Nepal project, the goal is to identify the most accurate model for climate forecasting, which can inform policy-making and urban planning in KMC. Satellite imagerys provide an appropriate data of different data scale to evaluate LST, UHI and such observations.

4.1. Impact of ML Model in LST Forecasting

Machine Learning(ML) has revolutionized in various field of study specially in research through integration of vast, multi-dimensional datasets. Hence two of such models - Exponential Smoothing (ES) and Prophet have been used for Earth Skin Temperature accounting seasonal patterns, trends, and other climatic factors.

The impact of ML models leads to improved accuracy in predicting temperature variations and UHI effects. This accuracy is critical for policy-making, urban planning, and disaster management, particularly in rapidly urbanizing cities like Kathmandu, where the consequences of climate change and urban heat can be profound.

In this model, both univariate (Exponential Series) and multivariate model (Prophet model) have been applied for foreceasting LST trends.

4.2. Implications and Future Research Directions

These findings have significant implications for climate studies, urban planning, and policy-making in KMC. The Prophet model’s ability to provide more accurate forecasts can inform disaster

management, water resource planning, and climate-resilient infrastructure development. Future research could explore the integration of additional variables, such as urban heat island effects or land use changes, as well as alternative modeling techniques to enhance forecasting accuracy. Additionally, assessing the long-term impacts of climate variability on urban infrastructure and public health in KMC could yield valuable insights for creating more resilient urban environments.

5. Conclusion

Through our prediction model, we have demonstrated Prophet model outperforms the Exponential models because of prophet model’s ability to capture both maximum and mean values of the dataset. This characteristics enhances the accuracy of predictions.

These results underscore the Prophet model’s effectiveness in capturing climate variability, providing valuable insights for urban planning, disaster management, and resource allocation in KMC. Future research should explore additional variables and methodologies to enhance predictive accuracy and address climate challenges in urban settings.

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Data Availability Statement: We used data from the Open Data Nepal platform, specifically the dataset titled "District-wise Daily Climate Data for Nepal," which can be accessed at <https://opendatanepal.com/dataset/district-wise-daily-climate-data-for-nepal>. We encourage all authors of articles published in MDPI journals to share their research data. For this study, the dataset supporting the reported results is publicly available at the provided link. Where no new data were created, or where data is unavailable due to privacy or ethical restrictions, a statement is still required. Suggested Data Availability Statements are available in section “MDPI Research Data Policies” at <https://www.mdpi.com/ethics>.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

KMC	Kathmandu Metropolitan City
UHI	Urban Heat Island
LST	Land Surface Temperature
RS	Remote Sensing
LULC	Land Use and Land Cover
MEERA-2	Modern-Era Retrospective analysis for Research and Applications, Version 2
MAE	Mean Absolute Error
ML	Machine Learning
R ²	Coefficient of Determination
RMSE	Root Mean Squared Error
MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	Directory of open access journals
TLA	Three letter acronym
LD	Linear dichroism

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