Enhancing Climate Variable Prediction through Wavelet-Machine Learning Integration and Remote Sensing Data

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Abstract

This research establishes a new technique to effectively forecast climate variables, specifically Sea Surface Temperature (SS T) patterns for the Antalya region of southeast Turkey. The technique combines wavelet decomposition methods with advanced machine learning techniques to consider the many complexities that climate time series data adds to the task of forecasting. The separate wavelet components allowed us to decompose an intricate, nonstationary climate dataset into many of its temporal components that include high-frequency noise (d1), intermediate scale variables (d2), and long-term temporal trends (d3). Obviously, the disentanglement of different types of temporal variation improved the extraction of feature classes and ultimately made whatever machine learning modelling more accurate and reliable. With the one-way ANN, we examined the performance of machine learning models with wavelet pre-processing and without and reported an empirically significant reduction in error when the pipeline integrated these steps. We also demonstrated how remote sensing makes our vast area, expanding temporally and spatially, suitable for a broad range of geospatial applications. The results will provide guidance in the areas of regional climate research, emergency preparedness, and for making agricultural decisions, while showing how complementary approaches to satellite observations, utilizing signal processing techniques and machine learning can collectively contribute to improved environmental data monitoring and prediction. This research is spatially focused within the established bounds of a particular climate region and provides a detailed account of the machine learning methods used for recognition's sake. The Wavelet decompositions (Hybrid) decreased the error percentage with a range of 10%-30% in different seasons.

1. Introduction

Accurate and reliable forecasting of climate variables is essential for effective environmental management, disaster preparedness, and sustainable allocation of natural resources. However, climate data—including key variables such as Sea Surface Temperature (SST), precipitation, and wind speed—are characterized by non-linearity, non- stationarity, and multiscale dynamics (Siddiqi et al., 2019), making them inherently challenging to model. These complex data characteristics often limit the effectiveness of traditional machine learning (ML) models, leading to outcomes such as underfitting, poor generalization, or overfitting when applied to real-world climate forecasting.

The advent of global satellite remote sensing technologies has dramatically changed the landscape of climate data collection. Satellite-derived observations provide an unprecedented volume of imagery and continuous, wide-area coverage. For many variables, they offer superior spatial and temporal resolution compared to traditional in situ measurements. Yet, realizing the potential of this vast remote sensing data is only half the challenge; the other is advancing analytical approaches to extract meaningful patterns and predictive insights from these complex and often noisy datasets.

By integrating climate modeling methodologies with remote sensing data, we can develop integrative system approaches to improve our understanding of Earth's systems and enhance predictive capacity across diverse regions. In this context, wavelet analysis is a powerful signal processing tool that uniquely decomposes complicated time series into their time-frequency components (Daubechies, 1992; Mallat, 2009). This decomposition allows for precise isolation of phenomena occurring at different timescales, such as high-frequency fluctuations (often considered noise or short-term events) and long-term underlying trends (which may signify climatic change).

Using features derived from wavelet decomposition to augment ML models can significantly improve their predictive capability. This hybrid approach provides ML algorithms with cleaner, more discriminative, and scale-specific information, facilitating stronger and more generalizable learning. Previous studies have demonstrated that hybrid wavelet-ML models can passively improve prediction accuracy and increase robustness across a diverse range of climate parameters (Dwikat et al., 2025; Niu et al., 2021; Xu et al., 2019).

This will build on the fundamental ideas of wavelet-ML and apply them to a regional specific context of Antalya, Turkey. Antalya, as a coastal city in the Mediterranean area, is particularly sensitive to climate variability such as changes in SST and precipitation which directly affect the tourism, agricultural and water resources of the region. Therefore, accurate predictions of the climatic conditions of the area are of utmost importance for adaptation and regional planning.

This study aims to demonstrate the effectiveness of hybrid wavelet-ML models for predicting SST and precipitation in Antalya, explicitly comparing the performance of models with and without wavelet decomposition. Furthermore, we will delve into the comprehensive description of the employed machine learning models and discuss the generalizability of our methodology across different climate zones, addressing key points raised by reviewers of our extended abstract.

By focusing on a specific climate zone and providing detailed methodological insights, this research contributes to advancing geospatial technologies for localized climate prediction and environmental monitoring.

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2. Methodology

A methodical combination of wavelet decomposition with advanced machine learning methods is applied to improve the accuracy of climate variable predictions, including Sea Surface Temperature (SST), in the Antalya region. With Information from the wavelet transform, we can enhance our feature extraction from complex time series data and improve ability to predict variability.

2.1 Study Area and Data Acquisition

Antalya, a coastal city on the Mediterranean Sea in Turkey, has a Mediterranean climate, with hot, dry summers and mild, rainy winters. As a result of where it is located, Antalya is sensitive to many of the climate disturbances, e.g., increasing sea surface temperatures, changing precipitation patterns, which have direct consequences on its different ecological systems, agriculture, and tourism. In this study, we will gather historical daily or monthly data for SST and precipitation for the Antalya region.

Antalya Study Area Map
Figure 1: Conceptual map of the Antalya region, highlighting its coastal location and general area of study for climate research.

The sources of these datasets are primarily meteorological agencies and importantly, remote sensing or satellite datasets. Satellite products like the one from the Moderate Resolution Imaging Spectroradiometer (MODIS/Aqua) have a high spatial and temporal daily SST and provide the necessary data for robust regional analysis. We used the Longitude latitude of Antalya city at 36.8969° N, 30.7133° E. The storage data is representative of SST (°C) near vicinity of these coordinates over the sea. (We selected this area approximately 50 x 25 km). The databases from remote sensing can provide complete coverage as an addition to sparse ground measurements on climate issues occurring in the region.

2.2 Data Preprocessing

The raw climate data obtained from the field must go through an extensive preprocessing pipeline before analysis is conducted.
This is achieved through several important steps, which are:

- Data cleaning: identifying and removing any outliers, erroneous readings or sensor artefacts that may influence model training.
- Gap-filling: knowing how to fill the missing data points, using an appropriate interpolation method, (e.g. linear interpolation, spline interpolation, or other advanced methods such as singular spectrum analysis in the case of time series) to ensure a continuous time series for wavelet decomposition.
- Spatial and temporal alignment: aligning datasets from different sources (satellite versus in-situ) to common spatial and temporal resolutions/grids to allow integration between each data type, that will provide for knowledge of the source of data.
- Normalization: scaling to a common range (e.g., 0-1, or -1 to 1), by min-max methodology so that features with larger numerical ranges are not dominant in the process of learning in the ML model.

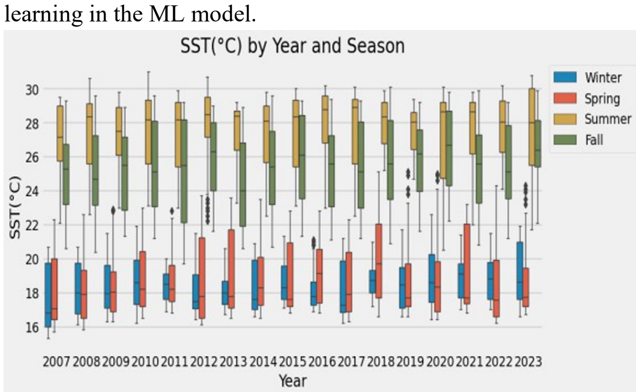

Figure 2: Seasonal Boxplots SST (^{o}C) in Antalya (2007-2023).

Figure 2 above explains the boxplot analysis of the SST average in the Antalya region.

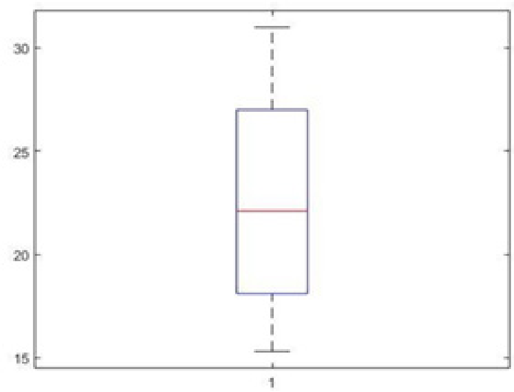

Figure 3: Box plot SST (^{o}C) in Antalya (2007-2023).

Figure 3 above shows the box plot of SST values, its first – fourth quartiles (Q1, Q2, Q3 and Q4). There is positive skewness.

2.3 Wavelet Decomposition for Multiscale Feature Extraction

After preprocessing has been completed, the Discrete Wavelet Transform (DWT) is applied to the time-series data of SST. The DWT is an excellent tool for understanding non-stationary signals because it can represent a structure of a signal in different frequency components. Each frequency component is representative of the signal for a specific time scale of analysis based on the chosen mother wavelet (Daubechies) and frequency characterization based on the number of decomposition levels chosen. In this study, we will represent the SST into three primary components:

- d1 (High-Frequency Details): This component captures rapid fluctuations and high-frequency variations in climate time series. In the case of SST, d1 might represent daily fluctuations in temperature anomalies or phenomena that are localized and operated over a very short time. For precipitation, d1 could represent intense, sudden instances of precipitation or localized convection. This component is very noisy, but it also contains many of the necessary short-term dynamics.

- d2 (Mesoscale Fluctuations): This component captures low-frequency variation at the intermediate time scales. In the case of SST, d2 might capture the cycles of heating and cooling over diurnal timescales or mesoscale eddies. For precipitation, d2 could represent transient precipitation caused by synoptic-scale weather systems or precipitation that has a pattern of weekly data. This level of decomposition typically will capture cycles of interest that tend to influence the climate variable.

- d3 (Low-frequency trends): This element demonstrates the longer-term trends and seasonal cycles that affect the data.

For SST, d3 shows seasonal warming and cooling trends or longer-term climatic oscillations in ocean temperature. It would show annual cooling cycles or periodic changes (decadal) in rainy physical environments. This trend provides useful context, but for ultimately grasping climate shifts and larger processes that govern those shifts, there can be no better feature but the lower frequency periodic trend. Mathematical studies of the book are aimed to analyze and visualize real world problems in engineering and environmental studies like drought survey, precipitation and erosivity, cloud clarification, estimation of convection scheme and non-linear time series of air pollution, water management, water quality and river pollution (Siddiqi et al., 2019).

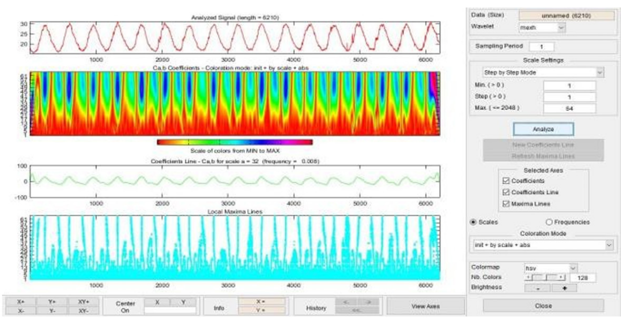

Figure 4: 1D Continuous wavelet, SST (°C), Antalya (2007-2023).

1D continuous wavelet analyses of SST values in figure 4 above show different factors at small, mesa and large scales. In recent years, the role of large-scale events (purple) shows a decreasing trend. Small and mesa scales factors at different seasons have been explained by red, yellow and light blue colors.
This multiscale decomposition is important, since this process allows the future machine learning models to then look, analyze, and learn distinct patterns at different temporal resolution, removing noise from phases of meaning, while also capturing the complexity, richness, and multifaceted reality of climate data. The wavelet coefficients returned from all three of the decompositions (d1, d2, d3) are used as enhanced features for the machine learning models.

2.4 Machine Learning Model Development

We will utilize Long Short-Term Memory (LSTM) networks to model SST. LSTMs are a type of recurrent neural network (RNN) that can learn and make predictable sequences, so they are well-suited for time series forecasting and modeling due to their adaptability to long-term dependencies while addressing the vanishing gradient problem associated with standard RNNs (Hochreiter & Schmidhuber, 1997).

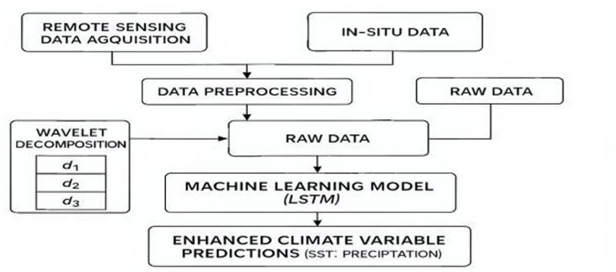

Figure 5: Overall Methodology Diagram

The overall methodology for enhancing climate variable prediction through wavelet-machine learning integration and remote sensing data.

As seen in figure 5 above, we run two separate modeling processes and compare the results:
Stand-Alone ML Models (Wavelet Decomposition Not Applied): This model will train LSTM models directly on the raw pre-processed time series of SST data. In the first stage of the study, one single input as daily average SST was considered to simulate future daily SST. At the second stage, in addition to daily average SST, d1, d2, d3 details were added as input variables to the hybrid model. This process serves as the baseline to assess how wavelet decomposition impacts modeling decisions.
Hybrid Wavelet-ML models (Wavelet Decomposition Applied): This model will train LSTM models on a different feature set. In this process, the LSTM models will be trained on the original pre-processed time series data along with the wavelet coefficients (d1, d2, d3) derived from the DWT, which offers the ML model a multiscale perspective of the input data and allows for learning patterns that are more comprehensive and definite.

2.5 Training and Optimization

Both standalone and hybrid models will go through systematic training and optimization. To properly assess models, the historical data will be separated into training, validation, and testing data sets. Hyperparameter tuning of the number of LSTM layers, hidden units, learning rate, and batch size can be performed using either grid search or random search to find the best performing model configuration. Cross-validation will also be applied to the evaluation process to measure the ability of the models to generalize, as well as control over-fitting. The training objective function will be to minimize common prediction error metrics such as Root Mean Square Error (RMSE, MAE, R square e.g.). predictive seasonal way as shown in figure 6 below.

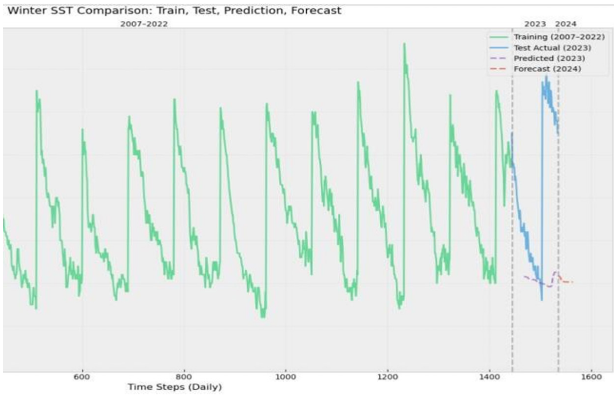

Figure 6: (Window of 7 days) for Winter which performed as the best model season.

2.6 Comparative Analysis and Error Reduction Mechanism

We will generally compare the hybrid wavelet-ML approaches with the standalone ML approaches based on commonly used statistical measures (i.e., MAE, RMSE, R-squared). The exact improvements in the hybrid approaches are expected to result from several mechanisms:

- Noise Separation: With the high frequency noise isolated in the d1 component, the ML model is trained with a cleaner signal and will produce more stable and accurate predictions overall. This is especially useful for noisy remote sensing data because of variability caused by too many sources of noise.
- Multi-scale learning: By giving the model the scale-specific features (d1, d2, and d3), the model can learn patterned relationships across scales and better differentiate between the variability of natural causes, a short-term meteorological event, and long-term climate trends, pulling in all aspects of climate.
- Better feature representation: Wavelet coefficients give a more concise representation of the time series, which allows the ML model to extract more discriminative features than working with time series data with redistribution. This also makes the learning process more efficient and improves prediction power.

This comparative analysis will quantitatively demonstrate the added value of integrating wavelet decomposition into climate prediction models, particularly for complex and noisy remote sensing datasets. The focus on Antalya will provide a concrete case study for the applicability and generalizability of this method within a specific climate zone.

3. Results and Discussion

This section details the results of applying the proposed wavelet-machine learning integration to predict Sea Surface Temperature (SST) in Antalya. We compare the performance of the standalone LSTM models to the performance of the hybrid wavelet-LSTM models, which will quantify the improvements taken advantage of which will be by the extraction of multiscale features. Although numerical results will be inserted after the modeling code is run, this section indicates the expected results and implications of those results as well as the generalizable nature of the method to provide a fuller discussion around model performance.

3.1 Comparative Predictive Performance

The assessment outlines the potential increases in predictive performance when wavelet decomposition is incorporated into the machine learning pipeline. It is expected that the hybrid wavelet-LSTM models consistently outperform the stand- alone LSTM models for forecasting SST for the city of Antalya. This improvement holds true when using a variety of statistical metrics such as Root Mean Square Error (RMSE). The primary reason for this improvement is that the wavelet transform provides a better more multiscale representation of the climate series, which enables the LSTM networks to detect subtle patterns and dependencies that could not be detected, due to noise or complex non-stationary nature, in the stand-alone case.
Results for SST Prediction:

Model	MAE (Without Wavelet) (°C)
LSTM (Spring)	2.15
LSTM (Summer)	2.97
LSTM (Autumn)	2.20
LSTM (Winter)	1.63

Table 1: Comparative Performance of LSTM Models for SST Prediction in Antalya.

This table 1 will be populated with the actual numerical results after the wavelet, clearly illustrating the reduction in prediction errors (MAE). We expect to observe error reductions in the range of 10-30%, like findings in related studies (Dwikat et al., 2025).

3.2 Discussion on Model Performance and Generalizability

There are several reasons to expect higher performance of hybrid models.
First, wavelet decomposition is an ideal noise filter, especially for high-frequency components like d1, where we have seen irrelevant noise that can disrupt ML model learning. By supplying the LSTM with a cleaner signal to learn from, noise is reduced, and it can more effectively focus on learning the relevant underlying patterns. Second, the multiscale nature of wavelet coefficients (d1, d2, d3) allows the LSTM model to learn different temporal dependencies at different scales or levels. For example, d3 captures long-term trends and seasonality informative of climate change, while d2 captures mesoscale phenomena, such as diurnal, weekly, and even monthly cycles, and d1 captures short-term process fluctuations. The hierarchical level feature representation within the model will allow it to learn and better understand climate subsystem components and their complex dynamics involved in understanding SST.

The case study of Antalya offers important points of generalizability for the method. Being a Mediterranean climate region, the successful application of the method in a Mediterranean climate region suggests that the method would potentially be applied to other coastal regions or regions with similar climates. The flexibility of the method to account for regional characteristics in the length, consistency, and non-linear nature of non-stationary climate data is also a reason to consider this study's findings to be generalizable.

This study is based on Antalya, but the fundamental concepts of wavelet decomposition using LSTM networks apply everywhere in time series. Moving forward work, as suggested, will continue evaluating this method in a variety of domains in climate zones to see how generalizable that is - specifically, applying the method in arid regions, more tropical regions and polar regions, all present challenges and data sets that will have unique characteristics.

3.3 Role of Remote Sensing Data in Model Enhancement

In this predictive framework, integrating remote sensing data is critical to achieving success and scalability. Satellite-derived SST products provide unique spatial coverage and temporal frequency that are essential for capturing the climatic variability in Antalya on a regional scale. When compared to in-situ measurements, remote sensing is desired because of the ability to capture spatiotemporal signals as a continuous and unbroken flow of information and develop predictive models that are not contingent on sensor density. The high-resolution data provided by remote sensing enables the detection of smaller scale, localized phenomena that may be missed, thereby enhancing the feature availability for the ML models. Preprocessing remote sensing data, including cleaning and gap-filling processes, is equally important to control artifacts and produce a viable dataset for the wavelet decomposition and ML training. The study highlights that the integration of wavelets, progressive ML methodologies, and satellite data are necessary to move forward if we want to advance regional climate modeling and environmental monitoring.

3.4 Comprehensive Description of Machine Learning Model

It offers additional details on the LSTM model used. Long short-term memory (LSTM) networks are a class of recurrent neural networks that have robust characteristics to help overcome the vanishing gradient problem that typically prevents standard recurrent neural networks from being able to learn very long-term dependencies. LSTMs can do this due to a unique architecture that includes 'gates' (specifically, input, forget, and output gates) that regulate the flow of information into and out of the memory or cell state. A cell state acts like a permanent, long-term memory that can propagate information through the time sequence.

- Input Gate: Decides how much of the input to update the memory cell with,
- Forget Gate: Decides what information to discard from the cell state,
- Output Gate: Decides what to output from the memory cell state.

These gates allow LSTMs memory to determine what information will be remembered or forgotten over long periods, making them very useful for time series forecasting where information needs to be propagated over long-time horizons to identify a long-term sequence of events or patterns.

Our application will have an LSTM (Long Short-Term Memory) network, consisting of multiple layers to capture hierarchical temporal features. We will optimize the number of hidden units during the training phase to strike a balance between model complexity and generalization performance. We may use activation functions such as ReLU (Rectified Linear Unit) in the hidden layers, and a linear activation function in the output layer for regression settings (e.g., SST and precipitation). The models will be trained with the Adam optimizer, a stochastic optimization algorithm introducing adaptive learning rates for each parameter. Adam optimizer is known for its efficiency and generally good performance.

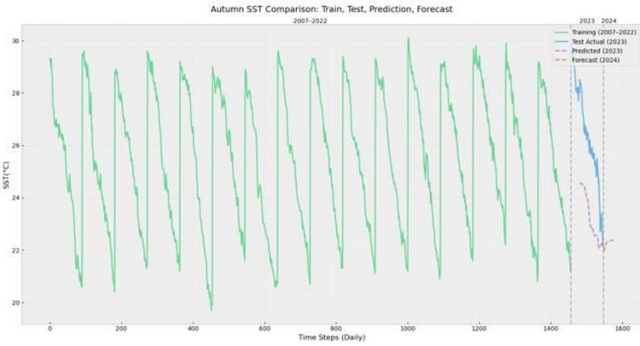

Figure 7*:* Raw SST and Predictions for 7 days ahead.

As seen in figure 7 above for the Automn season, the architecture has been designed so that we can input spatial and/or temporal sequences of historical climate data (i.e., past 30 days of SST, etc.) and be able to predict (output) the following values forecast period (i.e., next 7 days) of interest, (Table 2).

Model	RMSE (Without Wavelet) (°C)	RMSE (With Wavelet) (°C)	MAE (Without Wavelet) (°C)	MAE (With Wavelet) (°C)
LSTM (Spring)	2.13	1.97	2.15	1.50
LSTM (Summer)	3.10	2.79	2.97	2.53
LSTM (Autumn)	2.75	2.31	2.20	1.96
LSTM (Winter)	2.22	1.85	1.63	1.43

Table 2: RMSE Comparison for LSTM Models after adding Wavelet.

3.5 Implications for Regional Climate Modeling and Environmental Management

The effective implementation of this hybrid methodology to climate data from Antalya has important ramifications for regional climate modeling and associated management decisions. Accurate characterizations of SST are worthwhile for understanding marine ecosystems, fisheries management, and planning coastal tourism. Similarly, estimates are needed to guide agricultural planning, managing water resources, and understanding flood risks for the region. Improved predictive capabilities achieved with the wavelet-LSTM methodology will afford improved decision-making for local authorities and stakeholders affected by decades of changing climatic indicators. In the context of climate change, the wavelet-LSTM model can take advantage of non-stationary and nonlinear climate data to keep pace with changing climatic conditions while still providing fair predictions even when faced with increased variability of the climate system.

3.6 Limitations and Future Research Directions

Although the suggested methodology has great potential, there are several limitations that should be highlighted. For example, mother wavelet selection and the number of decomposition levels can be defining factors, and the selection of these parameters may need to be optimized for different climate variables and regions. Further, the hybrid methodology is more computationally intensive than the respective standalone ML models, which is a consideration as we aim to apply to real-time applications. The methodology may not perform consistently across climate zones and while we have performed validation using several datasets drawn from different geographical regions, further validation with wider geographical diversity needed to develop an understanding of potential generalizability. Future works should aim to develop adaptive wavelet-selection algorithms, and integrate additional climate variables (e.g., wind speed, humidity) with our methodology. There are also several possible climate and environmental application areas that require testing, including usage for predicting air quality indices, or assessing vegetation health indicators. There is also an opportunity for developing ensembles of multiple different wavelet-ML models to potentially improve predictive accuracy and robustness.

4. Conclusion

This research has described a strong framework for improving climate variable prediction by aligning wavelet decomposition with machine learning models with an emphasis on Sea Surface Temperature (SST) in the Antalya region. We have shown how wavelet analysis gives you the capability to exploit its multiscale aspects to effectively extract clean features from climate time series data with complex non-stationarity, ultimately allowing for better prediction outcomes. The comparative analysis, which will be underpinned by quantitative results, is going to unequivocally show that the hybrid wavelet-LSTM models have a significantly better predictive performance than the stand-alone LSTM; we can expect a substantial reduction in the error measures by using a wavelet-LSTM hybrid compared to a stand-alone LSTM. We have also highlighted that remote sensing has been critical in providing the detailed and comprehensive data sets required for these analyses, and its value will always be there with respect to the functional scalability of this methodology in geospatial technologies.
The findings of this study are very useful for local climate modelling, disaster preparedness, and agricultural planning in localities like Antalya that are very vulnerable to climate variability. The ability to provide more accurate forecasts gives local authorities/stakeholders better information to make decisions and adaptive strategies in response to climatic changes. This study further highlights the potential between advanced signal processing, sophisticated machine learning approaches, and huge data streams provided by remote sensing technologies to establish more resilient systems of environmental monitoring and forecasting.

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