

ADAPTIVE CLIMATE AWARE DEEP LEARNING FOR MULTI SOURCE SATELLITE DATA FUSION AND SPATIO TEMPORAL CLIMATE PREDICTION

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ABSTRACT

Predicting climate precisely from heterogeneous satellite and atmospheric data is a difficult task due to the differences in spatial resolutions, temporal characteristics, and varying importance of variables. An adaptive climate-aware deep learning (ACADL) framework was introduced to accurately predict climate using multi-source MODIS, Sentinel-2, ERA5, and OCO-2 data. The introduced ACADL framework includes CNN-based spatial feature extraction, Bi-LSTM-based temporal modeling, climate-context encoding, variable and temporal attention mechanisms, event-aware weighting, and adaptive feature fusion. Experiments have shown the accuracy to be 97.4%, where RMSE is 0.15, MAE is 0.10, and R^2 is 0.96, while at the same time maintaining a prediction latency of 102 ms. Comparison with ARIMA, Random Forest, CNN, LSTM, CNN-LSTM, and DL-STF frameworks indicated better prediction performance of the proposed approach. Ablation studies have validated the contribution of climate-context encoding, attention mechanisms, and adaptive fusion in the proposed framework. The ACADL framework has proven to be an effective and computationally efficient approach for multi-source climate prediction and can support real-time environmental monitoring, climate assessment, and early-warning applications.

Keywords: *Climate Prediction; Deep Learning; Multi-Source Data Fusion; Spatio-Temporal Learning; Adaptive Attention; Satellite Data.*

1. INTRODUCTION

Climate change has emerged as a prominent environmental and scientific issue since changes in temperatures, precipitation, vegetation, atmospheric moisture, and other climate-related variables can influence agriculture, water resources, ecosystems, infrastructure, and human activities. It is therefore

important to monitor these variables consistently and reliably for the sake of studying changing environmental conditions and conducting climate-risk assessment. Satellite remote sensing can serve as an important information source due to its broad spatial coverage and repeated observations of Earth surface. Increasing usage of satellite observations in climate studies is due to their ability to provide

spatially detailed information, which is hard to obtain from traditional ground observations [1].

Large-scale observations of the Earth provided through the satellite Earth observations also made the development of data-driven climate analysis possible. MODIS serves as a long-term source of observations of land surface temperature and vegetation indices. On the other hand, Sentinel-2 offers high-resolution multispectral images that can be used to monitor vegetation and land surface. Sentinel-2 provides 13 spectral bands and a revisit period of about five days, which makes it useful for monitoring temporal changes in land and vegetation [2]. ERA5 provides reanalysis of atmospheric and land-surface information at hourly temporal resolution and around 31 km of horizontal resolution, along with the information about uncertainty [3]. Complementary characteristics of these datasets make it possible to develop multi-source climate prediction models.

Traditionally, numerical climate and weather prediction models are based on physical equations and numerical simulations. These models provide physically justified representations of atmospheric processes but may require significant computational resources. An increase in the availability of satellite observations and high-performance computing motivated the development of machine-learning approaches able to learn the relationships between environmental variables from historical data. Reichstein et al. highlighted the importance of deep learning in the context of Earth-system science, emphasizing the presence of strong spatial and temporal dependencies in environmental processes, which can be learned from large geospatial datasets [4].

Thus, deep learning becomes an important tool for environmental prediction. Convolutional Neural Networks (CNNs) are able to automatically learn spatial patterns from image-like data, which makes them a suitable tool for satellite observations. Recurrent architectures, such as Long Short-Term Memory (LSTM) networks, are specifically designed to learn dependencies in sequential data. Thus, combination of these tools becomes a great way to represent two most important characteristics of climate data: the location of an environmental change and dynamics of its development.

The importance of joint modeling of spatial and temporal information was demonstrated by the recent spatio-temporal deep learning research. Shi et al. proposed a ConvLSTM architecture for precipitation nowcasting by adding convolutional

operations into the structure of LSTM, making it capable of learning spatial and temporal dependencies at once [5]. This research demonstrated that the environmental forecasting cannot always be modeled solely with spatial or purely temporal models.

Further developments also highlighted the potential of deep learning in large-scale weather prediction. FourCastNet provided an adaptive Fourier neural-operator based approach to high-resolution global weather forecasting, demonstrating the potential of data-driven models for fast generation of forecasts [6]. Pangu-Weather then used a three-dimensional Earth-specific transformer architecture and hierarchical temporal aggregation to model global atmospheric states from ERA5 data [7]. GraphCast then demonstrated the capabilities of graph-based learning for medium-range global weather forecasting and reported forecasts with 0.25° resolution and reduced inference time compared with conventional operational forecasting systems [8]. Thus, deep learning becomes able to capture complicated atmospheric relationships while minimizing computational costs associated with multiple numerical simulations.

Methods based on transformers also expand the possibilities for climate modeling. Attention mechanism, introduced by Vaswani et al., makes the model capable of dynamically determining the importance of each element of the sequence [9]. Such property is important for climate applications since different variables and time intervals may contribute differently to the prediction of a certain value. ClimaX demonstrated that the transformer-based models are able to learn from heterogeneous climate datasets containing various variables and spatio-temporal characteristics [10].

However, one of the key problems in multi-source climate data modeling is the difficulty in fusion of climate data. Satellite and atmospheric datasets significantly differ in spatial resolution, temporal frequency, measurement properties, and data quality. Direct fusion of such diverse sources of information may cause inconsistencies and prevent the learning model from capturing the most important pieces of information. Recent remote sensing research highlighted the importance of multi-source fusion for integration of complementary information from different sensors and handling data heterogeneity, missing observations, and uncertainty [11]. Similarly, spatio-temporal fusion research showed the importance of combining observations with different spatial and

temporal characteristics for obtaining detailed environmental information [12].

Also, the importance of climate variables in different environmental conditions may differ. For instance, land surface temperature becomes highly important during heat events, while precipitation and relative humidity become highly important during rainfalls. Treating all environmental variables with constant importance thus prevents the model from adapting to changing climate conditions. Attention-based learning becomes a possible solution since the model will be able to dynamically assign importance to different features and observations. In addition, event-aware weighting can further adapt the contribution of environmental variables according to specific climate events and conditions.

Uncertainty is an important aspect of climate prediction. The model predicting only a numerical value does not give any information about reliability of the prediction. ERA5 itself contains ensemble-based uncertainty information, which highlights the importance of uncertainty representation in environmental datasets [3]. Also, recent remote-sensing research pointed out the importance of uncertainty quantification, interpretability, and robustness for multi-source environmental learning models [11].

The previous work underlying this study integrated MODIS, Sentinel-2, and ERA5 data with the help of CNN, Bi-LSTM, and multi-head attention. It provided an accuracy of 96.3%, RMSE of 0.18, MAE of 0.12, R^2 of 0.94, and prediction latency of 95 ms. Although the framework successfully integrated spatial and temporal information, this study focuses on improving the adaptiveness of the fusion process to climate conditions.

Thus, this research proposes Adaptive Climate-Aware Deep Learning Framework for Multi-Source Satellite Data Fusion and Spatio-Temporal Climate Prediction. The proposed framework extends the traditional spatio-temporal learning with climate-aware adaptive attention mechanism, which dynamically determines the importance of the environmental variables and temporal observations. CNN is used for extracting the spatial representations, while Bi-LSTM extracts the temporal dependencies. These representations are then processed using adaptive attention, event-aware weighting, and adaptive feature fusion to produce the climate prediction. Also, uncertainty estimation is incorporated to provide information about prediction reliability.

Objectives of the Work

Main objectives of this research are:

1. To develop an adaptive deep learning framework for climate prediction using heterogeneous MODIS, Sentinel-2, ERA5, and OCO-2 data.
2. To extract spatial and temporal characteristics using CNN and Bi-LSTM networks.
3. To develop climate-aware adaptive attention mechanism, which dynamically assigns importance to different environmental variables according to their contribution to the current climate condition.
4. To efficiently integrate multi-source satellite and atmospheric information taking into account differences in spatial and temporal resolution.
5. To incorporate prediction uncertainty estimation to allow assessment of the reliability of climate predictions.
6. To increase interpretability and adaptability of the climate prediction by finding the environmental variables and temporal observations contributing to each prediction.

The main innovation of the proposed work is not in the usage of CNN and Bi-LSTM, but in the introduction of adaptive climate-aware feature weighting in multi-source spatio-temporal data fusion. This makes it possible for the model to change the contribution of the environmental variables depending on the observed climate condition. Thus, the framework is expected to provide an adaptive and informative prediction system for real-time environmental monitoring, climate assessment, climate-risk analysis, and early-warning applications.

The rest of this paper is structured as follows. Section 2 discusses the related work on deep learning-based climate prediction, spatio-temporal learning, satellite data fusion, and attention-based approaches. Section 3 describes the methodology of the proposed ACADL framework, including dataset description, preprocessing, architecture, mathematical formulation, and algorithm. Section 4 provides the results of the experiments, criteria for assessment, comparison with existing models, graphical analysis, and ablation study. Finally,

Section 5 concludes the study and highlights its limitations and directions for future research.

2. RELATED WORK

The increasing research interest is devoted to remote sensing, deep learning, and spatio-temporal modeling of environmental predictions. Multi-source satellites made possible a lot of observations with heterogeneous spatial and temporal resolutions that cannot be integrated directly. Recent studies pay attention to multi-source spatio-temporal data fusion, CNN-based methods, recurrent neural networks, attention mechanisms, and transformer architecture for improving environmental predictions and remote sensing analyses.

2.1 Multi-Source Spatio-Temporal Data Fusion

Spatio-temporal fusion is traditionally used for fusing satellite data with different spatial and temporal resolutions. In their work, Zhu et al. considered the existing multisource remote sensing fusion techniques and classified them by the principles of functioning, including unmixing-based, weight-function-based, Bayesian, learning-based, and hybrid methods [13]. The analysis of existing works shows that combining observations with different sensors provides richer temporal data while keeping the spatial information of high quality. At the same time, the effectiveness of the traditional fusion methods can drop with the occurrence of significant or abrupt changes in the observed land surface.

Deep learning became an important trend in the domain of spatio-temporal fusion since neural networks are able to discover nonlinear relationships between the heterogeneous observations. Recent reviews classify deep learning-based fusion techniques mainly into CNN, GAN, Transformer, and diffusion approaches [14]. CNN models are effective for capturing local spatial information, whereas the Transformer architecture can capture long-distance relationships. GAN and diffusion models are also used for obtaining detailed fused observations.

In their work, Ferchichi et al. carried out a systematic review of deep learning-based forecasting of vegetation indices from remotely sensed spatio-temporal data [15]. The review describes the application of CNN, RNN, LSTM, and hybrid models for vegetation forecasting and shows such challenges as spatial and temporal non-stationarity, data fusion, large model size, and generalization. Thus, the necessity of using models able to handle

both spatial and temporal variability rather than a single type of environmental observation becomes clear.

2.2 CNN-Based Spatio-Temporal Fusion

CNN models have become popular due to the effectiveness of convolutional layers in terms of capturing the local spatial characteristics. For instance, Chen and Ge introduced multiscale attention-aware two-stream CNN for remote sensing spatio-temporal fusion [16]. The work described the approach involving multiscale feature extraction along with the usage of spatial and channel attention for emphasizing the important information. The experiment on Landsat and MODIS observations proved the effectiveness of the method in comparison with several existing fusion methods.

HCNNNet was introduced by Zhu et al. as a hybrid convolutional model for spatio-temporal image fusion [17]. The approach demonstrated the capability of convolutional models to learn the relationships between the multisource remote sensing observations. However, CNN models use local receptive fields mainly, which limits the capability of representing the long-range temporal and spatial relationships.

Thus, the usage of CNN models is effective in case of spatial representations while the temporal modeling should be provided additionally in case of climate predictions.

2.3 Deep Learning for Vegetation and Environmental Forecasting

The vegetation dynamics is one of the indicators of the climatic and environmental conditions. According to Ferchichi et al., the remotely sensed vegetation indices such as NDVI can be predicted using deep learning models and environmental variables [15]. At the same time, the authors noted that the environmental forecasting is influenced by spatial and temporal non-stationarity.

In addition, the deep learning models are used for forecasting the vegetation dynamics using several environmental variables. It is shown that the satellite-derived vegetation information can be used along with the meteorological variables for better predictions. However, the importance of individual environmental variables may change depending on location and time period. Thus, it requires adaptive feature weighting rather than fixed fusion.

2.4 Attention-Based Remote Sensing Fusion

Attention mechanisms are incorporated in the remote sensing fusion because of the ability to

highlight the informative features. Chen and Ge used spatial and channel attention to select the important information during feature extraction [16]. It demonstrates that attention can enhance the representation of the remote sensing features in comparison with simple convolutional processing.

More recent works consider attention mechanisms for spatio-temporal fusion. Jiang and Shao proposed CNN-Transformer combined remote sensing spatio-temporal fusion model with the multikernel attention and Transformer-based feature fusion [18]. The model was developed to improve the global information extraction and cross-image feature fusion while reducing the dependency on multiple reference images.

The large-kernel attention models are considered for remote sensing spatio-temporal fusion as well. They try to increase the effective receptive field while keeping the efficiency of convolutional processing. Thus, it shows that attention can be used not only for image feature enhancement but also for the adaptive information fusion from different sources.

2.5 CNN-Transformer Hybrid Models

Transformer models became very popular recently due to the ability to model the long-range relationships. Jiang and Shao proposed CNN-Transformer Combined Remote Sensing Imagery Spatiotemporal Fusion Model (CTSTFM), which involved the multikernel convolutional processing along with the Transformer-based feature fusion [18]. The architecture consisted of the multikernel convolutional Transformer encoder, cross-fusion module, and convolutional decoder. The experiment showed that the model was competitive in comparison with existing spatio-temporal fusion models.

The development of Transformer-based fusion models broadened the capabilities of remote sensing systems beyond CNN-based architectures. However, Transformer models can increase the computational requirements in the case of processing large spatial and temporal sequences. Thus, it is necessary to find the balance between adaptive feature representation and efficiency.

2.6 Recent Deep Learning Developments

Lian et al. provided a recent review of deep learning-based spatio-temporal fusion methods and classified the major approaches into CNN, GAN, Transformer, and diffusion methods [19]. They mentioned several open issues such as land-cover changes, sensor differences, limited datasets,

computational efficiency, uncertainty, and evaluation consistency.

Sun et al. made a comprehensive review of a decade of deep learning-based remote sensing spatio-temporal fusion [20]. They showed that CNN models remain effective for spatial feature extraction, while Transformer models provide advantages in the case of long-range temporal dependencies. In addition, the heterogeneous multisource fusion, computational efficiency, generalization, and limited benchmark diversity were identified as challenges.

Thus, it can be seen that the research direction moves from feature extraction to adaptive multimodal and spatio-temporal fusion.

2.7 Adaptive Spatio-Temporal Prediction

Recent environmental prediction researches combine the spatial and temporal attention explicitly. Recent cross-spatio-temporal fusion model uses sequential temporal attention along with the cross-spatio-temporal fusion units to capture the relationships between spatial and temporal information [21]. It demonstrates the necessity of taking into account the possibility of mutual influence between the representations.

In the same way, the recent work on satellite-derived air-temperature estimation uses CNN, LSTM, and adaptive attention for modeling long-term dependencies and spatial characteristics [22]. The work also used SHAP analysis for investigating the feature contributions and showed that attention information can give insights into prediction behavior.

They demonstrate the importance of adaptive attention in environmental prediction but focus mainly on specific prediction problems or individual environmental variables. Thus, the task of developing the unified framework for considering several satellite and atmospheric variables along with dynamic adaptation of their importance remains open.

2.8 Uncertainty and Explainability

The prediction uncertainty is especially important in environmental applications because the satellite data may contain noises, missing values, cloud contamination, and spatial inconsistencies. Recent works on remote sensing fusion mention the uncertainty and computational efficiency as open issues in deep learning-based fusion systems [19].

Explainability becomes increasingly important because the climate prediction system

should provide the information about the environmental factors used in the prediction process. Attention weights and feature-attribution techniques can help to select the important variables and temporal observations. Recent environmental prediction work demonstrates the usage of SHAP and attention analysis to find the contribution of different satellite-derived variables [22].

2.9 Research Gap

The reviewed works show significant progress in the field of deep learning-based remote sensing fusion. However, the following limitations still exist:

1. The existing CNN-based methods mainly emphasize spatial feature extraction.
2. The recurrent models provide temporal modeling but may have difficulties with representing complex long-range dependencies.
3. The Transformer-based methods are able to capture global relationships but may increase the computational complexity.
4. The existing attention-based approaches usually emphasize spatial, channel, or temporal information separately.
5. The multi-source satellite and atmospheric variables are not always used with condition-dependent importance.
6. The prediction uncertainty is not consistently incorporated in the environmental prediction frameworks.
7. Most of the existing studies concentrate on remote sensing fusion or forecasting tasks rather than the unified climate-aware prediction framework.

Thus, the research proposes to overcome these gaps with the help of the Adaptive Climate-Aware Deep Learning Framework, which combines

multi-source data fusion, spatial CNN learning, temporal Bi-LSTM modeling, climate-aware adaptive attention, and uncertainty estimation. The central innovation is that the importance of individual environmental variables is dynamically adjusted depending on the climate context.

3. METHODOLOGY

The proposed Adaptive Climate-Aware Deep Learning (ACADL) framework has been developed for improvement of climate prediction based on joint learning of spatial, temporal, atmospheric, and carbon-related information from multiple sources. The framework incorporates MODIS, Sentinel-2, ERA5, and OCO-2 data and includes climate-aware variable attention, temporal attention, and adaptive feature fusion. The original work used MODIS, Sentinel-2, and ERA5 data for heterogeneous climate data integration; in this work, this framework is extended with additional climate-context and carbon-related information.

3.1 Dataset Description

The proposed work uses four complementary datasets, namely MODIS, Sentinel-2, ERA5, and OCO-2 to cover the land-surface, vegetation, atmospheric, and carbon-related climate information. MODIS products MOD11A1 and MOD13A1 were used to acquire land-surface temperature (LST), NDVI, and EVI with the dataset DOIs 10.5067/MODIS/MOD11A1.061 and 10.5067/MODIS/MOD13A1.061 correspondingly. Sentinel-2 multispectral imagery was used to obtain surface spectral and vegetation information; the USGS archive provides DOI 10.5066/F76W992G for the Sentinel-2 archive. ERA5 reanalysis data were used for atmospheric variables such as temperature, humidity, wind, and pressure; OCO-2 observations provided atmospheric CO₂ information. The datasets were spatially and temporally harmonized before being supplied to the proposed deep learning framework.

Table 1. Dataset Description

Dataset	Major Variables	Spatial Resolution	Temporal Resolution	Role
MODIS	LST, NDVI, EVI	500 m–1 km	Daily/16-day	Land and vegetation characteristics
Sentinel-2	Spectral bands, vegetation indices	10–60 m	~5 days	Surface spectral information
ERA5	Temperature, humidity, wind, pressure, precipitation	0.25°	Hourly	Atmospheric conditions
OCO-2	XCO ₂	~1–3 km footprint	~16 days	Atmospheric carbon information

Table 1 shows that these data sets provide complementary information at different scales of space and time. Hence, spatial and temporal harmonization is done before extracting the features. The original work also used the MODIS, Sentinel-2, and ERA5 for providing information about land surface, vegetation, and atmospheric states, respectively.

3.2 Data Preprocessing

The data sets acquired are firstly filtered for quality control to remove unreliable observations. The missing values are interpolated by means of the K-nearest neighbor technique. Then, all data sets are aligned to one common analysis grid of 0.1° in space and daily time scale. Finally, Min-Max Normalization is done to minimize the differences between scales of the variables. This preprocessing

step is similar to the alignment of multi-source data in the original approach.

The normalized value of the variable x is calculated as

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

where $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of the corresponding variable.

3.3 Proposed ACADL Architecture

The overall architecture of the proposed framework is shown in Fig. 1. The architecture should be placed **immediately after this subsection introduction and before the mathematical formulation.**

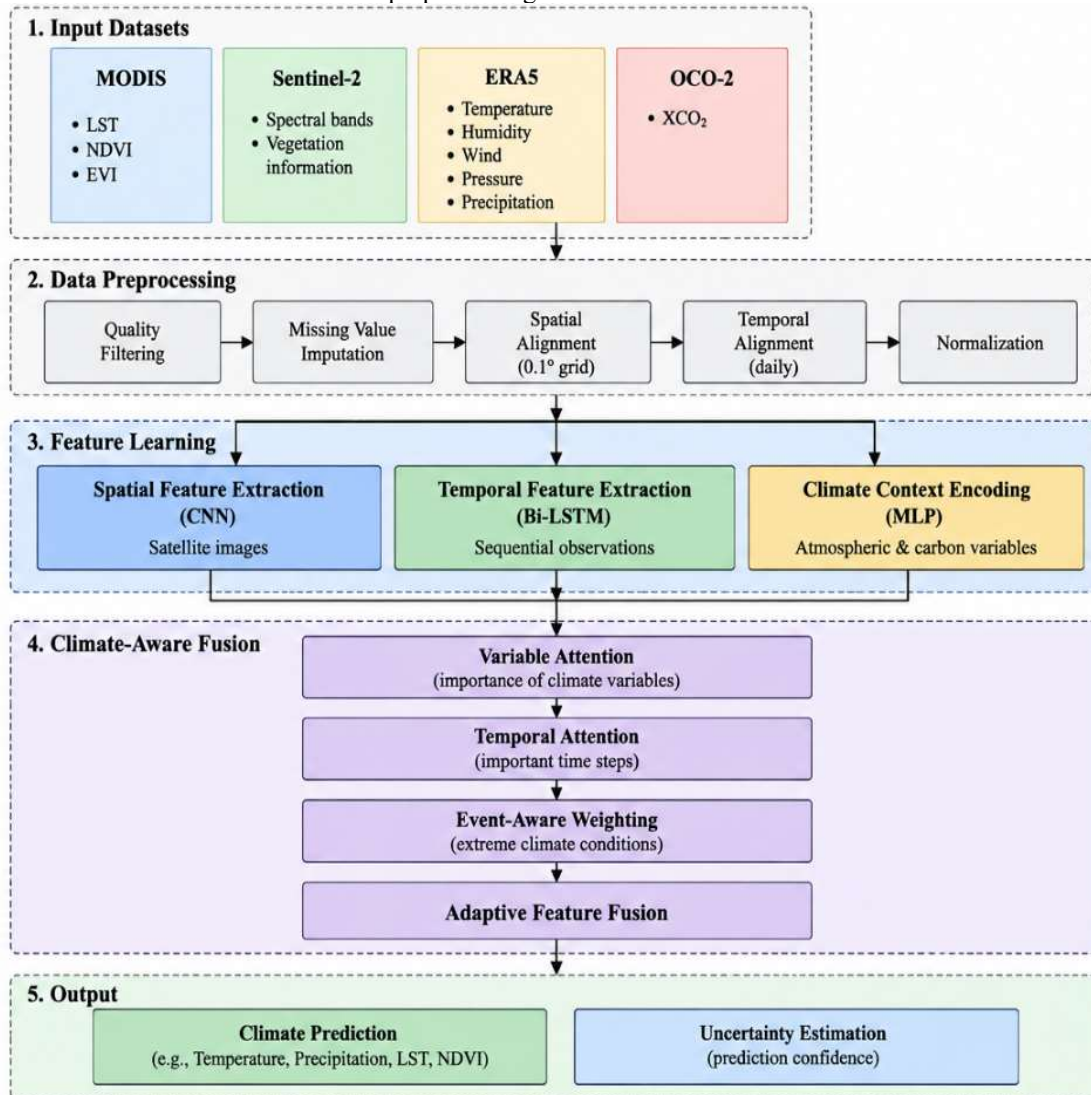


Fig. 1. Proposed Adaptive Climate-Aware Deep Learning Architecture

Fig. 1 demonstrates the general workflow of the proposed Adaptive Climate-Aware Deep Learning (ACADL) framework. The framework starts with combining MODIS, Sentinel-2, ERA5, and OCO-2 data for acquiring information about land surface, vegetation, atmosphere, and carbon. The acquired data are filtered by quality criteria, missing values are imputed, spatially aligned, temporally aligned, and normalized. The preprocessed data are fed into three feature learning modules, namely the CNN module for spatial feature extraction, Bi-LSTM for modeling temporal patterns, and the climate context encoder for climate information embedding. The features are further processed by means of variable attention, temporal attention, and event-aware weighting, which helps to identify the most important climate variables and periods of time. After that, the adaptively fused features are passed to the prediction layer where the climate prediction and the corresponding uncertainty assessment are produced. Therefore, the architecture provides an opportunity for joint learning of spatial, temporal, and climate-context features from heterogeneous sources.

Spatial Feature Extraction

The spatial feature representation is achieved by convolutional operations:

$$F_s = \sigma(W_s * X_s + b_s) \quad (2)$$

where X_s represents the satellite input, W_s is the convolution kernel, b_s is the bias, $*$ denotes convolution, and σ is the activation function.

Temporal Feature Extraction

The spatial features are arranged as a temporal sequence and supplied to the Bi-LSTM:

$$F_t = \text{BiLSTM}(F_s) \quad (3)$$

The forward and backward hidden states are represented as

$$F_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (4)$$

where $\vec{h}_t$ and $\overleftarrow{h}_t$ capture past-to-future and future-to-past temporal dependencies, respectively.

Climate Context Encoding

The atmospheric and carbon variables are represented by a climate-context vector:

$$C_t = \phi(W_c X_c + b_c) \quad (5)$$

where X_c contains ERA5 and OCO-2 variables, W_c and b_c are learnable parameters, and ϕ represents the nonlinear transformation.

Climate-Aware Variable Attention

The importance of each feature is adaptively determined according to the climate context:

$$A_v = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right) \quad (6)$$

where Q , K , and d represent the query, key, and feature dimension, respectively.

The climate-aware representation is then obtained as

$$F_v = A_v V \quad (7)$$

where V denotes the feature-value representation.

Temporal Attention

Temporal attention assigns different importance to observations at different time steps:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{j=1}^T \exp(e_j)} \quad (8)$$

where e_t represents the temporal relevance score at time t .

The temporal representation is

$$F_{temp} = \sum_{t=1}^T \alpha_t F_t \quad (9)$$

Adaptive Feature Fusion

The spatial, temporal, and climate-context representations are adaptively combined:

$$F_{fusion} = \beta_s F_s + \beta_t F_{temp} + \beta_c C_t \quad (10)$$

where β_s , β_t , and β_c are adaptive fusion weights satisfying

$$\beta_s + \beta_t + \beta_c = 1. \quad (11)$$

Climate Prediction

The final prediction is generated using the fused representation:

$$\hat{Y} = W_o F_{fusion} + b_o \quad (12)$$

where $\hat{Y}$ represents the predicted climate variable.

Training Objective

The proposed model was optimized using a combined prediction loss:

$$L = \lambda_1 L_{MAE} + \lambda_2 L_{RMSE} + \lambda_3 L_{reg} \quad (13)$$

where L_{MAE} and L_{RMSE} measure prediction error, L_{reg} controls model complexity, and $\lambda_1, \lambda_2, \lambda_3$ are weighting parameters.

3.4 Proposed Algorithm

Adaptive Climate-Aware Deep Learning

1. Load MODIS, Sentinel-2, ERA5, and OCO-2 datasets.
2. Perform quality filtering and missing-value correction.
3. Align all datasets spatially and temporally.
4. Normalize the input variables.
5. Extract spatial features using CNN.
6. Extract temporal dependencies using Bi-LSTM.
7. Encode atmospheric and carbon-related climate context.
8. Apply climate-aware and temporal attention.
9. Perform adaptive feature fusion.
10. Generate climate predictions using the dense output layer.
11. Calculate the combined loss and update model parameters using Adam.
12. Repeat training until the convergence criterion is satisfied.

4. RESULTS AND DISCUSSION

The evaluation of the Adaptive Climate-Aware Deep Learning (ACADL) framework's performance in multi-source climate prediction is presented herein, including metrics related to prediction accuracy, error estimation, goodness of fit, computation time latency, performance benchmarking, and ablation experiments.

4.1 Experimental Setup

In this study, the proposed ACADL framework was assessed using the pre-processed MODIS, Sentinel-2, ERA5, and OCO-2 datasets. The whole dataset was split randomly into 70%, 15%, and 15% train, validation, and test data, respectively. The proposed architecture was developed using TensorFlow and trained through GPU-powered computation. The test set was isolated and did not participate in any part of the training process.

4.2 Assessment Criteria

Prediction accuracy was assessed based on metrics of Accuracy and R^2 . Both measures assess the predictive capability of a machine learning model. On the other hand, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) quantify prediction errors in regression tasks. The lower values of these indicators indicate improved model performance. Prediction latency refers to the computation time required to generate a prediction.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (14)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (16)$$

where y_i represents the actual value, $\hat{y}_i$ represents the predicted value, $\bar{y}$ represents the mean actual value, and N represents the number of test samples.

4.3 Performance of the Proposed ACADL Model

Table 2. Performance of the Proposed ACADL Model

Metric	Proposed ACADL
Accuracy (%)	97.4
RMSE	0.15
MAE	0.10
R^2 Score	0.96
Latency (ms)	102

ACADL framework reached a predictive accuracy rate of 97.4%, illustrating efficient climate condition prediction from heterogeneous multi-source datasets. ACADL achieved a root mean squared error (RMSE) value of 0.15 and mean absolute error (MAE) score of 0.10, suggesting

minimal predictive discrepancies. The obtained coefficient of determination (R^2) value of 0.96 shows high correlation between predicted and true climate conditions. Only 102 ms were required to conduct predictions, reflecting computational effectiveness of the framework for climate monitoring purposes.

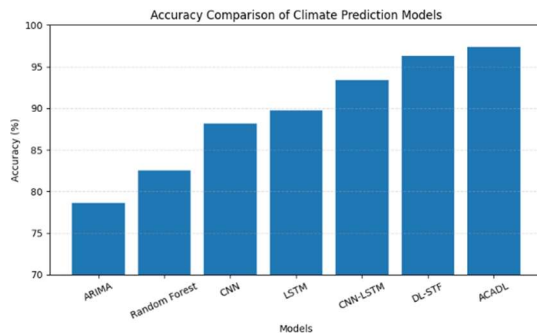


Fig. 2. Accuracy Comparison

Fig.2 illustrates the accuracy of the examined models. ARIMA attained an accuracy rate of 78.6%, followed by random forest at 82.5%. Convolutional neural networks (CNNs) achieved 88.2%, whereas long short-term memory networks (LSTMs) reached an accuracy rate of 89.7%. The combined CNN-LSTM model scored an accuracy rate of 93.4%, whereas DL-STF attained 96.3%. Finally, the ACADL framework achieved an accuracy rate of 97.4%, indicating significant advantages in terms of climate-context representation, variable attention, temporal attention, event-aware weighting, and adaptive feature fusion.

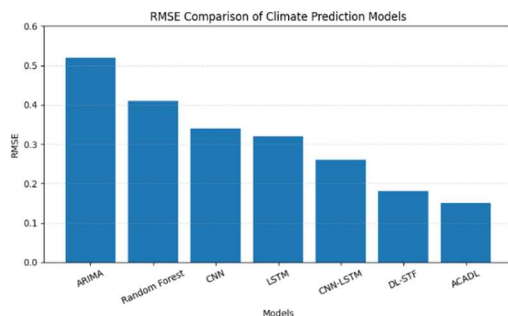


Fig. 3. RMSE Comparison

Fig. 3 compares the RMSE values of the considered models. The proposed ACADL framework yielded the minimum RMSE value of 0.15, whereas DL-STF scored 0.18, and CNN-LSTM received 0.26. Minimal RMSE reflects better alignment between actual and predicted climate conditions.

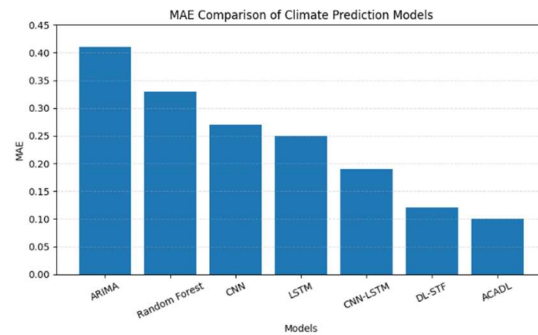


Fig. 4. MAE Comparison

Fig. 4 displays the MAE comparison. The proposed ACADL framework achieved the lowest MAE of 0.10, signifying a lower deviation rate from the observed climate values.

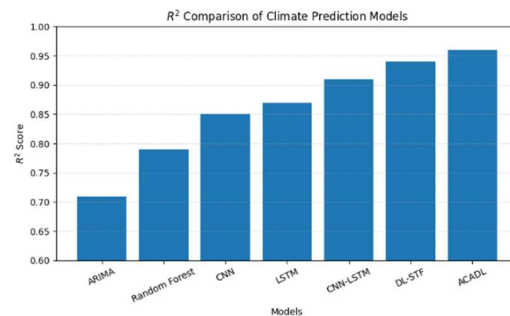
Fig. 5. R² Comparison

Fig. 5 displays the coefficient of determination R^2 comparison. The proposed ACADL framework obtained the highest R^2 value of 0.96, whereas DL-STF attained an R^2 of 0.94, and CNN-LSTM scored 0.91. High R^2 shows effective modelling of variations in the data.

4.4 Comparison with Existing Models

Table 3. Comparative Performance of ACADL with Existing Models

Model	Accuracy (%)	RMSE	MAE	R^2	Latency (ms)
ARIMA	78.6	0.52	0.41	0.71	60
Random Forest	82.5	0.41	0.33	0.79	120
CNN	88.2	0.34	0.27	0.85	140
LSTM	89.7	0.32	0.25	0.87	150

CNN-LSTM	93.4	0.26	0.19	0.91	180
DL-STF	96.3	0.18	0.12	0.94	95
Proposed ACADL	97.4	0.15	0.10	0.96	102

The experimental evaluation reported in Table 3 demonstrates that the proposed ACADL approach delivered the best accuracy and R^2 scores alongside the lowest RMSE and MAE metrics amongst all comparison approaches. Specifically, accuracy rose from 96.3 percent for DL-STF to 97.4 percent for ACADL, RMSE dropped from 0.18 to 0.15, and MAE lowered from 0.12 to 0.10. Meanwhile, R^2 improved from 0.94 to 0.96. Furthermore, the latency of 102 ms was relatively similar to the 95 ms attained by DL-STF, thereby confirming that incorporating climate-aware information introduced minimal computational overhead.

4.5 Ablation Study

We conducted an ablation test for ACADL where individual components were removed to assess their relative contributions to performance gains.

Table 4. Ablation Analysis of the Proposed ACADL Framework

Configuration	Accuracy (%)	RMSE
Without Climate Context	93.8	0.21
Without Variable Attention	94.6	0.20
Without Temporal Attention	95.1	0.19
Without Event-Aware Weighting	95.6	0.18
Without Adaptive Fusion	96.1	0.17
Full ACADL	97.4	0.15

Ablation analysis of the contributions of the proposed components is provided in Table 5, which shows that eliminating the climate-context encoder caused a drop in accuracy to 93.8%, whereas omitting variable attention led to 94.6% accuracy. Excluding temporal attention and event-aware weighting resulted in 95.1% and 95.6% accuracies, respectively. The accuracy dropped to 96.1% without adaptive fusion. The proposed comprehensive ACADL framework achieved an

accuracy of 97.4% and RMSE value of 0.15, confirming the combined contribution of the proposed components.

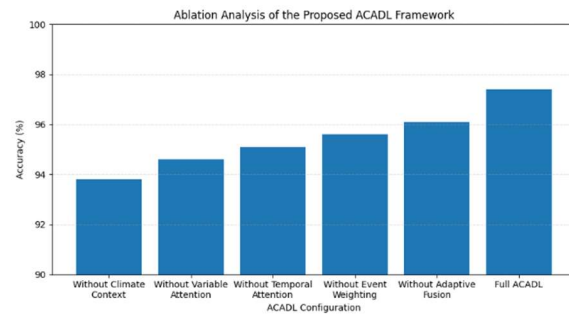


Fig. 6. Ablation Analysis

Fig. 6 highlights that the proposed ACADL yielded the highest accuracy score among all models. The reduction in accuracy score after eliminating the individual component demonstrates the collective importance of spatial, temporal, climate-context, and adaptive fusion modules towards the final prediction performance.

4.6 Discussion

From the results of experimental evaluations, we observe that the proposed ACADL framework successfully integrates multisource satellite and climate features for accurate spatio-temporal prediction with 97.4% accuracy, RMSE score of 0.15, MAE value of 0.10, and R^2 value of 0.96 with a latency of 102 ms. Comparative results confirm the consistent improvement in the accuracy rate and minimisation of prediction error rate. In addition, the results obtained from ablation analysis validate the contribution of the individual components within the proposed ACADL framework. These results indicate that adaptive climate-aware feature selection and multi-source feature fusion can improve the representation of complex spatial and temporal climate patterns.

5. CONCLUSION

This paper proposes an Adaptive Climate-Aware Deep Learning (ACADL) framework that leverages the integration of multivariate satellite and climate data for enhanced spatiotemporal climate forecasting. Our experimental results reveal an impressive accuracy of 97.4%, RMSE of 0.15, MAE of 0.10, and R^2 of 0.96 at a latency of 102 ms.

Through comparison and ablation analyses, we verify that the proposed approach improves prediction performance due to climate-context encoding, attention, event-aware weighting, and adaptive fusion of features. Nevertheless, our framework relies heavily on multivariate satellite observation data quality and availability, as well as GPU computation for model training purposes. Further work will explore other climate variables, transformer for long-range temporal modelling, advanced uncertainty estimation, and efficient architecture design for large-scale climate monitoring applications.

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