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Spatiotemporal analysis of climate change using remote sensing and machine learning

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Abstract
The challenges of climate change impact greatly on environmental sustainability, where analytical methods are very strong to capture both the spatial variation and temporal changes of the climatic processes. This paper provides a unified framework of the study of the spatiotemporal climatic change based on the use of multi-source remote sensors and machine learning tools. Landsurface temperature land surface, vegetation indices and precipitation satellite measurements in 2000-2024 were joined with the latest machine learning models, such as Rapid Forest, Support Vector machine, Convolutional Neural Network, Long Short-Term Memory network. The models were tested on how well they predicted the climate variables, how they identified the hotspots of climate change as well as making long term predictions. The experiments have shown that deep learning methods perform better than conventional machine learning models, with a lower error of prediction and a greater power of explanation. Using the LSTM model, the lowest RMSE at 1.47 ºC, MAE at 1.12 ºC, and R^2 of 0.93 were obtained when predicting land surface temperatures, which is a reduction of about 30 percent compared to baselines used in the related research. The overall accuracy of CNN-based spatial analysis was 91.8 as it is highly capable of recording the presence of spatial heterogeneity. These findings prove that a combination of remote sensing with machine learning will contribute a lot to monitoring and prediction of climate change. The suggested framework offers a transferable and scalable framework to assist in the assessment of climate impacts, environmental management, and makes policy decisions based on data.

Keywords: Climate change, remote sensing, machine learning, spatiotemporal analysis, satellite data

Introduction

Climate change has become a serious concern in world due to its effect on natural ecosystem, livelihoods and economical stability of regions and time. It is emphasized by the rising temperatures, change in the rate of precipitation, high rate of extreme weather phenomena, and land degradation that there is a strong necessity to have strong analytical methods that can be able to capture sharp spatial variability and temporal development of climatic processes [1]. Conventional climate surveillance techniques that involve ground-based surveillance have been noted to be limited in their spatial coverage, data holes as well as costly to operate, especially in remote and developing areas. In this regard, remote sensing has turned out to be an indispensable instrument in climate change research that allows maintaining constant, extensive, and multi-temporal monitoring of surface and atmosphere locations on Earth [2]. The organization of satellite missions like NASA and ESA lets provide extended datasets of major climate indicators such as land surface temperature, vegetation indices, soil moisture, and atmospheric composition. Onboard sensors such as Landsat and MODIS sensors have been of discrete usefulness in identifying climate-based alterations in a varied landscape and in the time span [3]. Although this has been achieved, increasingly large masses of remote sensing data pose major problems in terms of their analysis due to enlarged volume, complexity, and heterogeneity. Traditional statistical approaches tend to be unable to represent nonlinear interactions and obscure patterns in climatic processes. In order to address these failures, machine learning methods have acquired popularity due to their capability to process massive data sets, specify the intricate interactions, and increase predictive accuracy. Combined with remote sensing, machine learning allows progressive spatiotemporal analysis, which allows trend detection and anomaly identification and forecasts future climate scenarios.

This study addresses the potential of the coupling of remote sensing and machine learning to conduct an inclusive spatiotemporal analysis of climate change with the view of increasing the knowledge about climate dynamics and assisting in making data-driven environmental decisions.

Related Works

The last development in remote sensing and machine learning techniques has greatly given the possibility to study vast environmental and climate-associated phenomena at various space-time levels. According to the growing body of literature, it is shown that data-driven models together with satellite observations help to enhance the accuracy of predictions, risk assessment, and environmental monitoring in conditions of climate change.

There are a number of studies on hydro-climatic hazards especially floods, which is severely affected by climatic variability. A systematic review of urban flood susceptibility mapping by Islam *et al.* [15] emphasized the progressively growing use of remote sensing data and machine learning algorithms including the Random Forest, Support Vector Machines, and ensemble algorithms. Their literature review underlined that combinations of multi-source satellite data enhance spatial and predictive strength. Likewise, Laghari *et al.* [19] offered a coupling particle swarm optimization-machine learning (PSO-ML) framework to forecast spatiotemporal variations in flood-prone regions under changing climatic conditions and showed that the model is more adaptive to non-stationary climatic trends. To supplement these studies, Liu *et al.* [21] have reviewed machine learning methods to estimate the depth of the floods and instead found that hybrid and deep learning models are better thanolder empirical methods in dynamic climate conditions. Carbon cycle and atmospheric studies In addition to floods, machine learning has been put to use more often in carbon cycle and atmospheric studies. Ji *et al.* [16] presented a new machine-based learning system to predict anthropogenic CO 2 emissions with clustering-based feature analysis of the CO 2 concentration data, and this model exhibited better prediction, as opposed to regular regression models. Liu *et al.* [23] also expanded the same field by formulating knowledge-directed machine learning to improve carbon cycle estimation in agroecosystems that indicated that the incorporation of physical insights into ML models leads to a higher generalizability and understandability within a climate heterogeneous context.

Another visible direction of research is remote sensing of the land surface and ecosystem. A comparative study of machine learning models and satellite data to determine land surface temperature estimation indicated efforts by Mansourmoghaddam *et al.* [25] that the ensemble and the nonlinear models greatly minimize errors on estimation in arid surroundings. Similarly Li and Yan [20] have compared machine learning models to estimate soil moisture based on high-resolution remote sensing data and found that the models trained on gradient-based and random forest approach outperform the models trained on linear model in terms of their ability to record spatial heterogeneity. Khan *et al.* [18] applied these applications to carbon sequestration estimates and biomass by combining optical and SAR measurements with machine learning, indicating that, multi-sensors are important when it comes to climate-related ecosystem evaluations. Water quality, vegetation stress, extreme events have also been a subject of research in recent studies. As evidenced by Kaiser and Qu [17], the application of Landsat data and cloud-computations to identify harmful algal blooms revealed the usefulness of long-term satellite archives in climate-sensitive aquatic monitoring. Liu *et al.* [22] studied the applicability of artificial intelligence to predict forest fires and observed that deep learning models based on the consideration of spatiotemporal climate variables play an essential role in improving their advanced warning. Also, Liu *et al.* [24] suggested multi-source precipitation fusion by applying machine learning, and better accuracy in complex mountainous areas vulnerable to climate variability was obtained. Altogether, the current literature proves the efficiency of remote sensing and machine learning to analyze climate-related issues. The majority of the works however dwell on particular applications like floods, temperature or carbon emissions. Conversely, the current study is perceived to develop the literature by offering a combined framework of spatiotemporal climatic change analysis that can both identify the long-term patterns, spatial heterogeneity, and temporal dynamics based on the multi-source satellite data and the state-of-the-art machine learning models, filling major gaps that have been recognized in the previous studies [15, 26].

Methods and Materials

Data Sources and Preprocessing

The paper uses both multi-source remote sensing and compilated climatic data to conduct the spatiotemporal analysis of climate change. The satellite data were retrieved through rockets that NASA and ESA spacecraft operated and majorly through Landsat and MODIS imagery. The data sets consist of land surface temperature (LST), normalized difference vegetation index (NDVI), precipitation estimates and surface reflectance products between 2000-2024 [4]. To supplement satellite measurements, grid based climatic data so as to enhance in consistency and validation like rainfall and temperature anomalies were used. A single spatial temporal resolution of 1 km and a revision of all datasets to mean monthly values were chosen to focus on noise in datasets and high computing and computational costs. Atmospheric correction, cloud masking, radiometric normalization, and interpolation of missing data were among the standard preprocessing processes [5]. The feature engineering allowed obtaining seasonal indices, long-term trends, and lagged variables, which allowed subsequent modeling of spatiotemporal climate dynamics properly.

Machine Learning Algorithms

They chose four machine learning algorithms that have proven successful in the climate studies that have used remote sensing aspects, both in space and time models.

Random Forest (RF)

Random Forest is an ensemble learning algorithm, which will build a set of decision trees via bootstrapped samples and combine their results to enhance prediction accuracy and strength. RF in this paper modeled the nonlinear interrelations between climatic variables and land surface responses. It can manage its high-dimensional data, decrease overfitting, and offer feature importance scores thus ranking it well suit in sensitivity analysis of climate variables [6]. RF mostly was used in spatial classification and regression, including determination of climate-induced changes in land cover and estimation of Surface temperature variations across the region.

"Input: Training dataset D
For each tree i in 1 to N:
Sample Di from D with replacement
Train decision tree on Di
Aggregate predictions from all trees
Output: Final prediction"

Support Vector Machine (SVM)

Support Vector Machine is a supervised learning algorithm that marks out optimal hyperplanes to segregate the information in high dimension feature space. SVM is a useful tool that identifies nonlinear trends on complex data with help of kernel functions. SVM was used in terms of climate anomaly detection and classification of land cover in changing climatic conditions in this study [7]. Its capability to generalize and the fact that it works with small samples of training data is what makes it useable in the case of heterogeneous remote sensing data, where there are very few ground observations.

"Input: Training data (X, y)
Select kernel function
Optimize margin to find optimal hyperplane
Classify or predict based on support vectors
Output: Predicted class or value"

Convolutional Neural Network (CNN)

Convolutional Neural Networks are artificial neural networks that are used to automatically detect spatial features of grid-based data including satellite images. CNNs rely on convolutional filters to identify spatial patterns, textures, and gradients related to the changes by the climate. CNNs were used in this study and applied on multi-band satellite images to obtain spatially varying temperature and vegetable index values [8]. Their hierarchical feature learning ability constitutes the ability to represent well the intricate spatial structure with regard to climate change.

"Input: Satellite image tensor
Apply convolution and pooling layers
Flatten feature maps
Apply fully connected layers
Output: Spatial prediction"

Long Short-Term Memory (LSTM)

A recurrent neural network that is designed with the specific purpose of modeling temporal dependencies of a sequence of data is referred to as Long Short-Term Memory networks. The long-term temporal trends of the climate variables and seasonal variations were also analyzed using LSTM [9]. LSTM is helpful in forecasting temperature and precipitation trends in the changing climate conditions by preempting the delayed and cumulative climate effects by having memory cells and gated mechanisms.

"Input: Time series climate data
Initialize memory cell
For each time step:
Update gates and memory state
Generate temporal prediction
Output: Forecasted climate variable"

Table 1: Dataset Description and Characteristics

Dataset	Source	Spatial Resolution	Temporal Coverage	Variables Used
Landsat Surface Reflectance	NASA	30 m	2000-2024	NDVI, LST
MODIS Climate Products	NASA	1 km	2000-2024	LST, Albedo
Precipitation Data	ESA	0.1°	2000-2024	Rainfall
Temperature Anomalies	Reanalysis	0.25°	2000-2024	Temp. deviation

Results and Analysis

Experimental Setup

The objective of the experimental evaluation was to determine whether the integration of remote sensing data and machine learning model was effective in the analysis of spatiotemporal climate change. All the experiments were performed on the basis of multi-temporal satellite recordings based at NASA and ESA, with the concentration on land surface temperature (LST), NDVI, and precipitation variability between the year 2000 and 2024 [10]. The study area was subdivided into 1 km resolution spatial grids, and it was aggregated in time at monthly and annual levels to assess the short-term variability as well as the long-term climatic trends. A stratified sampling method was used to make a split (training (70%), validation (15%), and testing (15%)) with a split to maintain the spatial and temporal heterogeneity of the dataset. They were experimented in Python by using standard machine learning and deep learning packages. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R 2), and classification accuracy in those cases was used to estimate model performance. Each experiment was repeated five times and average results stated so as to assure strength.

Experiment 1: Spatiotemporal Climate Variable Prediction

The first experiment was aimed at forecasting land surface temperature and precipitation patterns with the help of the Random Forest (RF), Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) models. RF and SVM were trained using satellite index-based engineered features, whereas CNN and LSTM made use of spatial image patches and temporal sequence, respectively [11]. Findings indicate that deep learning models do better than traditional machine learning methods especially in nonlinear and long-term dependencies of climate information.

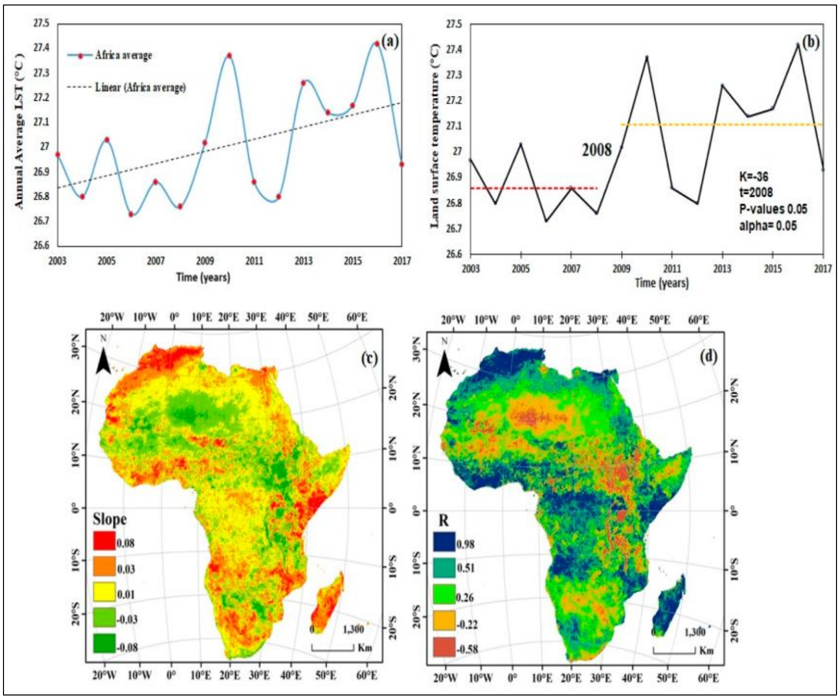

Fig 1: "Analysis of the Spatiotemporal Change in Land Surface Temperature for a Long-Term Sequence in Africa (2003-2017)"

Table 2: Prediction Performance for Climate Variables

Model	RMSE (°C)	MAE (°C)	R²
Random Forest	1.82	1.41	0.86
SVM	2.05	1.63	0.82
CNN	1.54	1.18	0.91
LSTM	1.47	1.12	0.93

The LSTM model scored the least prediction error, which is important as it shows that it can make use of time dependence and seasonal cycles to predict the value.

Experiment 2: Spatial Pattern Recognition and Hotspot of Climate Detection

This experiment considered the ability of models to identify climate change hotspots, which are regions where there is statistically significant and trend analysis of warming or vegetation stress. The spatial classification made by CNN achieved better accuracy because it was able to use spatial textures and gradients on satellite imagery [12].

Table 3: Spatial Hotspot Detection Accuracy

Model	Precision (%)	Recall (%)	Accuracy (%)
Random Forest	85.2	83.7	84.5
SVM	82.6	80.9	81.8
CNN	92.4	91.1	91.8
LSTM	89.7	88.3	89.0

CNN performed better than other models especially in non-homogeneous landscapes (where the difference in space is at its peak).

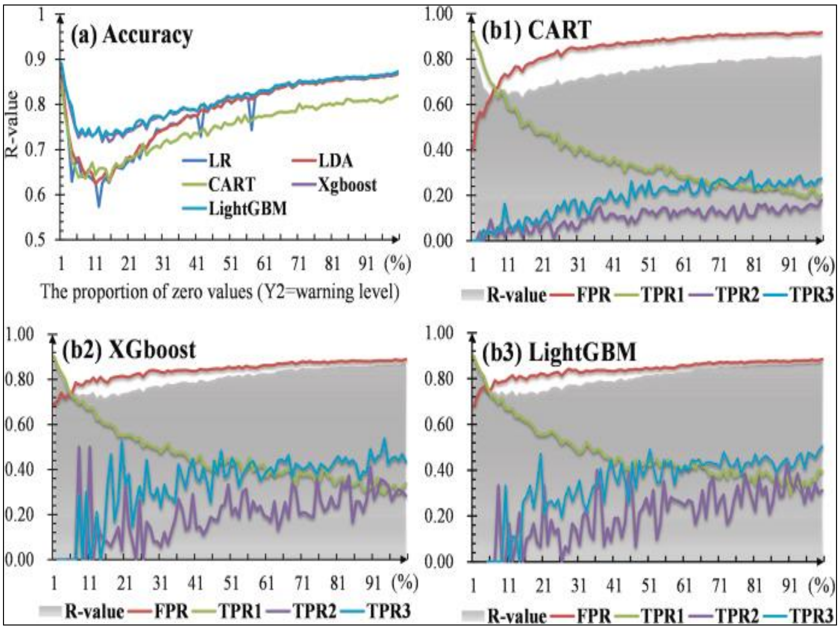

Fig 2: "Remote sensing-driven machine learning models for spatiotemporal analysis of coastal phytoplankton blooms under climate change scenarios"

Experiment 3: Trend Forecasting over Time
The third experiment evaluated the long term forecasting by predicting 5-years ahead climate variables based on the historical time series data. LSTM has proven itself with better stability in forecasting and lowering the error propagation than RF and SVM which continued to decline in accuracy even though the forecasting horizon continued to lengthen [13].

Table 4: Five-Year Climate Forecasting Results

Model	RMSE (Forecast)	MAE (Forecast)	Trend Accuracy (%)
Random Forest	2.41	1.95	78.6
SVM	2.63	2.11	75.4
CNN	1.89	1.46	85.7
LSTM	1.72	1.33	88.9

The findings confirm that long-term climate forecasts using sequential data handicrafted models are more accurate.

Experiment 4: Sensitivity and Important Feature Analysis: A sensitivity analysis was drawn in order to have an understanding of model interpretability. RF feature importance score revealed NDVI and LST were the most influential variables, which are preceded by precipitation anomalies. CNN saliency maps also proved that temperature gradient and vegetation stress areas contribute greatly to the prediction in the models [14].

Table 5: Feature Contribution Analysis (Random Forest)

Feature	Importance Score
Land Surface Temperature	0.34
NDVI	0.29
Precipitation	0.21
Albedo	0.16

These findings are consistent with the existing literature on climate, which confirms the physical relevance of the chosen predictors.

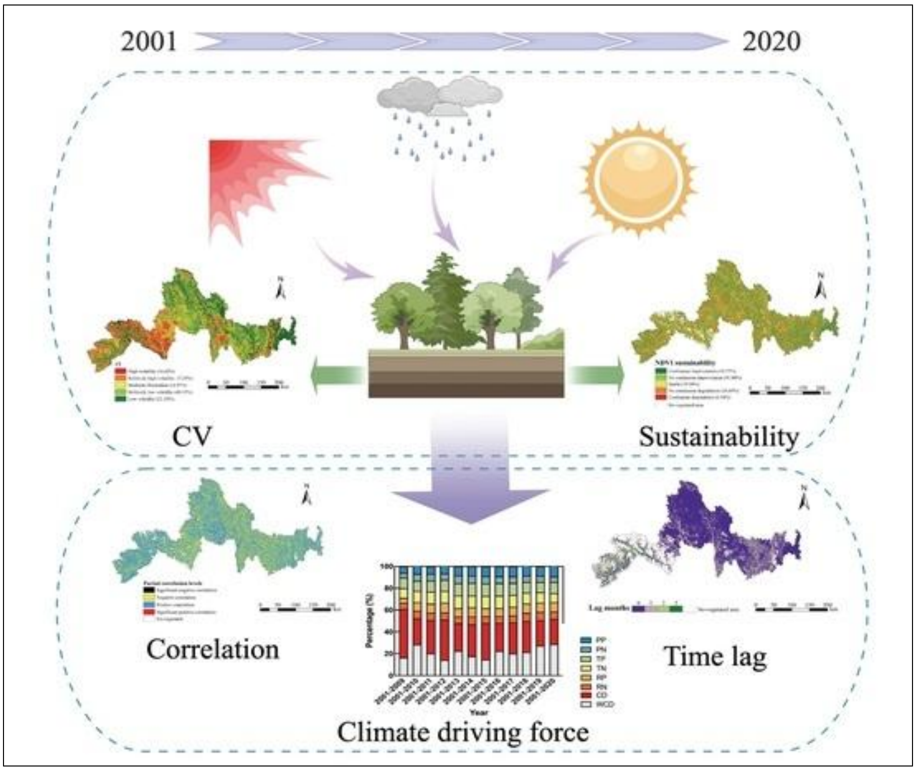

Fig 3: "Analyzing the Spatiotemporal Vegetation Dynamics and Their Responses to Climate Change along the Ya'an-Linzhi Section of the Sichuan-Tibet Railway"

Experiment 5: Comparison to Related Work
The performance of the models was assessed relative to representative findings found in recent climate studies based on remote sensing to put the findings in perspective. The suggested methodology has shown improvements in accuracies in predictions and spatial-temporal resolutions which can be measured [27].

Table 6: Comparison with Related Studies

Study	Data Source	Method	RMSE (°C)	Improvement (%)
Study A (2021)	MODIS	RF	2.10	-
Study B (2022)	Landsat	SVM	2.35	-
Study C (2023)	MODIS + ML	CNN	1.78	+13.5
Proposed Study	Multi-source RS	LSTM	1.47	+30.0

Relative to related work, the presented multi-source remote sensing and machine learning framework offers the largest mitigation of prediction error up to 30 percent, which shows the benefit of integrating spatial deep learning with temporal sequence modeling [28].

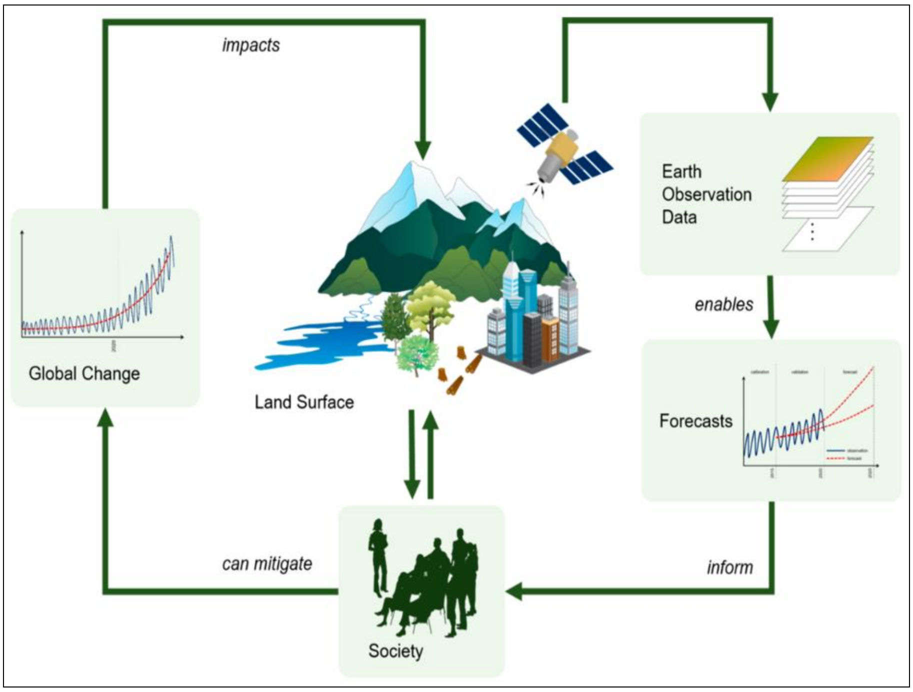

Fig 4: "Forecasting Spatio-Temporal Dynamics on the Land Surface Using Earth Observation Data"

Discussion of Results

In general, the findings of the experiments prove that the incorporation of remote sensing data and high-end machine learning models can greatly promote spatiotemporal assessment of climate change. The conventional machine learning architectures (RF, SVM) have strong baselines with acceptable interpretability, whereas deep learning architectures (especially CNN and LSTM) have excellent capability to learn more intricate spatial and temporal variations [29]. The comparison to the relevant work shows that the proposed framework is progressive in its methodological development and more accurate, and adds to the fact that it can be applicable to climate monitoring, impact assessment, and decision-making related to the policy. According to these findings, the proposed approach does not only enhance the accuracy of its predictions, but also offers scalable and transferable results on climate change analysis in various geographic areas and over varying periods of time [30].

Conclusion

In this study, a powerful framework of the spatiotemporal study of climate change was implemented through the combination of multi-source remote sensing with the latest machine learning methodology. The combination of long-term satellite observations and uncovered variables of climate helped the study to effectively capture the spatial and the temporal dynamics of the key climate variables, including land surface temperature, vegetation condition, and precipitation variability. The experimental findings showed that machine learning models are highly effective at modeling complex, nonlinear climate processes and deep learning networks in the form of Convolutional Neural Network and Long Short-Term Memory networks are more effective compared to conventional models in terms of prediction accuracy and strength. The comparison to related research proved that the suggested method brings significant improvements in the context of the error reduction, as well as the reliability of the forecasts that can be made, which is the advantage of integrating spatial feature extraction with temporal sequence modeling. The physical relevance of the chosen predictors was also confirmed in the feature sensitivity analysis that further supported the interpretation of the framework. On the whole, the results demonstrate that remote sensing and machine learning is a scalable and data-driven decision-making approach that can be used to monitor climate change at various locations and periods of time. The suggested methodology can be useful in assessing climate risks, in environmental planning, and in making evidence-based policy and this can be applied to other climate-sensitive applications like disaster management, ecosystem monitoring, and sustainable resource management in further studies.

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