International Journal of Agriculture and Food Science 2026; 8(5): 16-22

ISSN Print: 2664-844X
ISSN Online: 2664-8458
NAAS Rating (2026): 4.97
IJAFS 2026; 8(5): 16-22
www.agriculturaljournals.com
Received: 07-01-2026
Accepted: 09-02-2026

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AI-assisted analysis of temperature and precipitation trends in climate studies

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DOI: https://www.doi.org/10.33545/2664844X.2026.v8.i5a.1477

Abstract
Climate change has impacted on global temperature and rain distributions drastically, causing a rise in climate variability, weather extremes as well as environmental instability. The nonlinear interactions and long-term dependencies within climate systems are usually difficult to represent traditional statistical and physical climate models. The applications of recent improvements in artificial intelligence (AI) and the combination of large-scale climatic data provided by radiometric techniques and remote sensing and ground-based monitoring have provided new opportunities to compete in analyzing the trends in temperatures and precipitation with higher complexity and precision. This paper examines how AI methods, such as machine learning and deep learning algorithms, can be used to identify patterns, anomalies and long-term trends in climate data. The processing and analysis of the methodology involves multi-source datasets of satellite-derived temperatures, rainfalls, and atmospheric variables, that are processed and analyzed with the help of such advanced AI models like convolutional neural networks (CNNs), recurrent neural networks (RNNs) and hybrid architectures. Findings show that the use of AI-supported methods is much more effective in identifying temporal trends, spatial changes, and extreme climate events than the conventional techniques. Nonetheless, issues like data inconsistency, interpretability of the models, and computation needs are still pertinent factors. The research identifies the opportunities of AI-based climate analytics in aiding climate policy, environmental planning, and sustainable development plans.

Keywords: Artificial Intelligence, Climate Change, Temperature Trends, Precipitation Analysis, Machine Learning, Deep Learning, Climate Modelling, Remote Sensing, Time Series Analysis

1. Introduction
Climate change has become one of the most pressing environmental problems of the twenty first century, which has impacts on ecosystems, human societies, hydrological processes, food production, and sustainability in the long term, all around the world. These are the key climatic variables with the temperature and precipitation being the most important ones used as the parameters, which help to evaluate the character and scale of climatic changes and the long-term trends. Overall, an increase in the global temperatures, the growing frequency of extreme heatwaves, changes in monsoon behaviour, irregular distribution of precipitation, and an increase in both the severity of droughts and floods are all indicators of structural imbalances in the climate system. These disturbances are the results of nonlinear interactions between atmospheric circulation, ocean-atmosphere interaction, land-surface process, greenhouse gas emissions, aerosol concentrations, as well as, large-scale teleconnection mechanisms like ENSO, NAO, IOD and AMO. The statistical climatology, the trend detection through regression, the general circulation models (GCMs), and the reanalysis data have been major phenomena used in the traditional climate analysis. Although these approaches have led to much in the knowledge of climate behaviour, they have certain limitations where they are assumed to be linear, the spatial resolution is coarse, the capability to detect localized extremes is limited and whether it can adequately model complex interactions in space and time is a limitation. With a rise in the unpredictability of climate systems and an increase in the frequency of extreme events, a need for higher-resolution, more flexible and adaptive analytical systems that can find previously obscure patterns and thus measure the variability of temperatures and precipitation more precisely across multiple scales is increasingly demanded. In that regard, applying artificial intelligence (AI) to climate research has become an innovative solution enabling scholars to overcome the limitations of

traditional modelling and embrace the power of pattern recognition based on data to interpret not only slow-changing tendencies but also the sudden data fluctuations.

The fast proliferation of satellite-based remote sensing systems, land-based meteorological systems, and multi-decay climate depositories have led to enormous multidimensional data sets of decades of temperature and precipitation data. But the quantity, heterogeneity, and complex organization of these datasets demand high-speed analytical techniques which can help identify useful climatic signals, distinguish natural variability and anthropogenic forcing, and identify subtle shifts in climatic regimes. AI methods - especially machine learning and deep learning structures - have demonstrated impressive capabilities to solve these problems by discovering sporadic relationships, training on a variety of inputs in climate, learning long-term dependencies in the seasonal cycles, and discovering spatial-temporal coherence in climatic patterns. Neural networks, CNNs, RNNs, LSTMs, GRUs, transformers, and hybrid models permit automatic extraction of features, anomaly identification, trend analysis over long-range climate forecasts and correct classification of climate conditions. They also have been found effective in modelling extreme events like heavy rainfall, extended dry bursts, heatwave, cold surges, and seasonal changes. AI-based systems can also be used to create a more resistant and high-resolution understanding of the dynamics in climate patterns when used together with remote sensing products, including MODIS land-surface temperature, TRMM/GPM precipitation, AIRS temperature profiles, and ERA5 reanalysis fields. Regardless of these breakthroughs, the issues of uncertainty quantification, regional generalization, data discrepancies, inexplicability in deep learning frameworks, and scalability of computing coordinating massive climate analytics remain. Despite these constraints, AI-based climate trend analysis remains paradigm shift in environmental science, providing previously unprecedented possibilities in climate monitoring, impact assessment, early warning, resources planning, and policy creation. As global climatic conditions continue to change in unpredictable ways, a more resilient, adaptive and scientifically based method of comprehending variability in the temperature and precipitation across various spatial and time scales is in a state of being created through integration of AI methodologies with the mainstream climate science.

2. Releated Works

Initial studies on climate variability examined extensively temperature and precipitation changes as linear regression, Mann-Kendall trend tests, principal component analysis and autoregressive time-series modelling were all considered classical statistical techniques. These early studies confirmed presence of long-term warming trends, monsoon variations, changes in the seasonality of precipitation and intensification of extreme weather patterns in various geographic areas. Empirical studies in 1980s and 1990s have also shown that atmospheric and oceanic oscillations like ENSO, NAO, IOD, and AMO were strongly related to global and regional climatic variations, and had an impact on interannual rainfall variability and thermal anomalies [1], [2]. With these data improvements, multi-decadal reconstructions of temperature and precipitation cycles as products of the agencies such as NASA and NOAA were made available, and it was the foundation of the early diagnostics of climate [3]. Those approaches, however, were very dependent on the linear assumptions and therefore tended to underestimate nonlinear climate feedbacks, spatial heterogeneity, and discontinuous transitions. As the evidence of accelerated climate change grew, scientists started to combine satellite-based measurements, i.e. MODIS temperature data, TRMM, GPM precipitation data as well as AIRS atmospheric data to obtain more continuous and high-resolution observations of climate processes [4], [5]. These remote sensing sources have enabled scientists to measure the urban heat island effects, land-surface energy fluxes, cloud-radiation interplays and rapid anomalies such as heatwaves and extreme rainfall bursts to be monitored with more spatial resolution. With these advances, however, conventional robotic models continued to fail to effectively adapt multi-source data, introduce concealed signs of climate, and respond to the nonlinear quality of climate mechanisms, something that inspired the shift to AI-based analytical techniques.

With the advent of machine learning, the detection of climate trends improved significantly, particularly in the case of temperature anomalies, temperature drought, prediction of rainfall patterns and prediction of extreme events. Pioneering neural-network research showed that nonlinear correlations among climate variables might be learned devotedly than by means of regression-based models, especially time-varying temperature and monsoon rainfall oscillations [6], [7]. Ensemble machine-learning models (random forests, support vector machines, and gradient boosting) were used to define the crucial climate drivers, model the contribution of land-surface factors, differentiate natural changes and those due to humans, and categorize wet or dry years more reliably [8]. Such models have subsequently been refined by using remote sensing data sets thus allowing improved detection of spatially localized rainfall patterns and thermal anomaly particularly in climate sensitive areas that are not well covered by ground-stations [9]. With increased computation, more advanced neural network architectures like convolutional neural networks (CNNs) provided powerful means to study spatial climate patterns, find regions of temperature gradients, rainfall clusters, and explain large-scale satellite images [10]. Recurrent models like LSTMs and GRUs proved useful to follow long-lasting dependencies in seasonal climate cycles, interdecadal transitions, and slow-moving movements in precipitation that classical methods, in many instances, did not. Hybrid frameworks that couple CNNs with LSTMs effectively simulated the time-space climate dynamics and was very effective in forecasting anomalies, discovering the effects of teleconnections, and revealing long-range interactions among more intricate climate systems [12]. These developments moved climate analytics a step further than the old techniques but also exposed problems of overfitting models, imbalance in data, sensor inaccuracy, and constraints on the level of generalization across climate zones.

In the recent past, studies on combining deep learning, attention, multimodal climate fusion systems, and physics-informed AI have become more frequent to complement climate trend detection and long-horizon prediction. Transformer architectures have been proposed to be very well suited to process long climate time series to identify faint regime transitions, to detect anomalies in temperature and precipitation records, to model long-range relationships between atmospheric processes which had been hard to capture using conventional RNN-based systems [13]. An example of such information-merging technologies that combine satellite-data, surface measurements, and reanalysis data has enhanced the strength of climate systems, particularly on the areas that experience gaps in observations or inconsistent uses of such measurements [14]. Recent developments have also occurred in the form of physics-informed neural networks (PINNs), directly applying atmospheric science concepts to AI models to enhance their interpretability and minimize physically unreasonable predictions in climate science. The multisensor and multimodal AI systems have been shown to be more accurate in identifying gradual climatic shifts, such as land-surface warming, decadal weakening, patterns of glacier retreat, and enhanced hydrological extremes. Scientists have also stated that quantifying uncertainty, addressing bias, transfer learning, domain adaptation, and cross-regional model validation can also promote an AI-driven climate insight to be applicable, reliable, and scientifically plausible across various ecosystems and climatic regimes [15]. As a whole, the literature reflects a major paradigm shift of the old fashioned statistical climatology towards hybrid, data based, and AI-enhanced climate analysis tools employing multi-source observational data and strong computational codes to reveal nonlinear, complex temperature and precipitation changes in a dynamic climate system.

3. Methodology

3.1 Research Design

The current research project implements a combined quantitative-qualitative analytical approach that is aimed at assessing the temperature and precipitation changes over the long period with the help of AI-assisted methods of analyzing climate data. The study design highlights an organized procedure that entails data collection, data cleaning, feature pick, artificial intelligence modelling, and measure of performance to allow us to extract significant climatic messages within a structured process using multi-source data. Since climate systems are highly nonlinear feedback systems whose behavior is caused by atmospheric circulation, oceanic contributions, radiative forcing and land-surface energy interactions, the conventional statistical approaches do not provide enough power to understand their intrinsic complexity. Consequently, the research embraces a hybrid modelling concept, in which satellite data, ground measurements and reanalysis data are combined to create a high-resolution model of climatic variability. This approach focuses on monitoring climate changes, characterization of anomalies, and analysis of spatiotemporal patterns and heavily involves AI-based tools that are capable of extracting hidden patterns in mass data. The research design aligns with the practice of modern climate research and incorporates comparative assessments of the classical climate trend indicators in contrast to the results of deep-learn fetched insights to comprehend the value addition of AI systems with climate diagnostics [16]. This kind of structure also enables the study to capture both the long-term climate tendencies and short-term irregularities without going too far to ensure that the models are still based in physically meaningful interpretations.

3.2 Data Sources and Climate Observation Context

The research utilizes secondary climatic data gathered at various trusted archives, such as satellite data, ground meteorological data, and gridded weather reanalysis areas. Data sets such as MODIS land surface temperature, GPM rainfall and TRMM rainfall estimates, AIRS atmospheric temperature profiles, CHIRPS rainfall observations and ERA5 reanalysis data available at the European Centre of Medium-range Weather Forecasts (ECMWF) are considered key. These datasets were chosen because they have global coverage capacity, are long-term and have been shown to serve well in the application of climate monitoring equipment [25]. Temperature variables are daily maximum, minimum, average surface temperatures, and upper-atmospheric thermal fields, whereas precipitation variables are the intensity of rainfall, frequency, amount of rainfall, and the distribution of rainfall throughout the season. All datasets are analyzed with a sequence of spatial harmonization, temporal aggregation, radiometric calibration, noise reduction and gap filling in previous steps to match the data across sources. Climate observation scenario therefore emphasizes the extraction of consistent spatiotemporal signals that are expected to capture long time natural warming, seasonal rainfall atypicities and major climate anomalies. The satellite data also lead to coverage where there is low data density and/or remote areas where the ground networks are not adequate. These detailed data sets become the analytical foundation of the future AI modelling and enable a thorough analysis of the behaviour of climatic patterns over the course of several decades [17]-[18].

Table 1: Climate Variables and Remote Sensing Indicators

Analytical Variable	Description	Remote Sensing Indicator	Analytical Purpose
Surface Temperature	Mean, max, min thermal values	MODIS LST, AIRS Profiles	Trend detection & anomaly analysis
Precipitation	Rainfall intensity & accumulation	GPM/TRMM Microwave Retrievals	Seasonal & long-term variability
Cloud Dynamics	Cloud cover & radiative influence	MODIS Cloud Products	Identifying rainfall triggers
Atmospheric Moisture	Humidity & water vapor content	AIRS, METEOSAT WV Channels	Climate variability assessment
Land-Surface Conditions	Soil moisture & vegetation	SMAP, NDVI	Boundary condition evaluation

3.3 Analytical Framework

The analytical framework depends on four main elements: data representation, feature engineering, building AI models, and model evaluation. Data representation takes the climate variables and organizes them in a series of spatial-temporal matrices, which can be converted into machine learning and deep learning types of architectures. The emphasis of feature engineering is on physical indicators of climate; the extraction of temperature variations, seasonality indices in rainfall, value of moisture divergence, diurnal changes in temperature, the usage of standardized precipitation indices, and extreme markers of temperature. These aspects increase the interpretability of these models and make it easier to identify long-term climate signatures. The modelling aspect of AI makes use of the shallow and deep learning design. The convolutional neural networks

(CNNs) detect spatial climatic patterns, including heat clusters, and rainfall gradients whereas the recurrent neural networks (RNNs), long short-term memories, and generative (GRUs) recognise long-range temporal dependencies, which are essential to study climatic evolution. Hybrid CNNLSTM models are also included in the framework in order to handle both a spatial and a temporal dimension to enhance the precision of detecting trends. Multi-source climate inputs are combined with the help of ensemble learning tools such as random forests and gradient boosting algorithms. This framework corresponds with modern AI-based climate analytics whose focus is on multi-modal union and more sophisticated pattern retrieval [19]-[20].

3.4 AI Modelling for Climate Trend Analysis

In this research, AI modelling will be aimed at identifying long-term climatic trends and at deviations in the temperature and precipitation records. Its modelling pipeline consists of dataset splitting, network architecture selection, hyperparameter optimization, and iterative training. To guarantee generalization and reduce bias, multi-year datasets are separated into training and validation and testing subsets. The grid-search and adaptive optimization algorithms are used to optimize such hyperparameters as the learning rate, number of layers, kernel size, hidden units, dropout rate, and the batch size. CNN models capture spatial gradient, zones of heatwaves and precipitation clusters whereas LSTMs capture time seasonal cycles, time-lag lags, autocorrelations and delayed monsoon effects. Membrane CNN LSTM systems can be utilized to model more complicated coupled behaviours, like the co-evolution of temperature and rain anomalies. Also in the modelling process are bias-correction modules that will serve to deal with discrepancies in satellite-derived rainfall information. The model training process is done repeatedly till convergence standards are established to make sure that climate trend is properly established and anomalies are detected. These modelling decisions are inspired by the recent developments in climate-AI studies, which focus on dynamical learning models that can adjust to changing climatic trends [21]-[22].

Table 2: AI Modelling Components and Methodological Structure

Modelling Component	Description	AI Method Used	Objective
Spatial Pattern Recognition	Detecting thermal gradients & rainfall clusters	CNN	Identify climate structures
Temporal Sequence Learning	Modelling climate cycles & trends	LSTM/GRU	Capture long-term dependencies
Hybrid Modelling	Joint spatial-temporal trend extraction	CNN-LSTM	Improved climate trend accuracy
Bias Correction	Adjusting dataset inconsistencies	ML Regression & Ensembles	Reduce data-driven errors
Trend Validation	Model accuracy evaluation	RMSE, MAE, Correlation	Ensure reliability

3.5 Evaluation Criteria and Model Validation

Multi-metric evaluation strategy is utilized to validate the model in order to determine its stability, robustness and predictive quality. The accuracy of temperature and precipitation trends estimates is measured using statistical values like R M S E, MAE, correlation coefficient, Nash Sutcliffe efficiency and anomaly correlation. The K-fold cross-validation helps to reduce overfitting so that AI models could be applicable to the variety of climatic conditions. The quality of spatial evaluation is quantified based on error heat maps and skill scores as well as pattern-correlation measures to assess the ability of the AI models to capture regional climatic variations. Temporal analysis involves comparison of seasonal cycles, interannual variation and the alignment of long-term trends with the historical climatic trends. The generation of AI insights is also checked against the results of known climate models and internally accepted reanalysis datasets to check the consistency and reliability. Uncertainty quantification is done using the ensemble method to estimate a confidence interval around trend estimates, which enhances the level of comprehension of their model results and their practical application. This assessment framework reflects the current best practices in climate diagnostics, including focus on reproducibility, cross-source validation, and climate predictions using uncertainties [23].

4. Result and Analysis

4.1 Overview of AI-Assisted Climate Trend Analysis

The combination of AI-oriented analytical tools, as well as multi-source climate data, has greatly contributed to the comprehension of climate patterns of temperature and precipitation on long-term scales. The distributed climatology was especially limited to recognize subtle changes, nonlinear behaviour, diurnal warming patterns, and micro-regional rainfall variations due to traditional statistical climatology that only gave coarse and linear interpretations of climate variables. By working with the data provided by satellites and combined with AI-based models, the given analysis proves that deep learning frameworks can be successful in extracting unnoticed spatiotemporal information and gradual and sudden changes in climate. The findings suggest that the trends of temperature changes are observed to be warming over the period of several decades with the maximum temperature shift in the minimum one, as well as an enhancing heat stress at night. Precipitation patterns indicate more variability in seasonal rain, more precipitation in extremes and high variability in timings of monsoons and the distribution of rainfall. The AI models display good potential in outlining consistent climate areas, discovering the long-term stripes of warming, and isolating rainfall clusters that often could not be resolved by the traditional methods. The general conclusions point out the usefulness of AI-based paradigms to the continuity as well as the periodic unsteadiness that resides in climatic systems and hence offering more understanding of climatic dynamics at various scales.

4.2 Temperature Trend Detection and Spatial Variability

The outcomes of the temperature trend analysis indicate that there are significant regional warming especially in the low-latitude and semi-arid regions where the increasing trend of the mean temperature is accompanied by a large increase in the annual peak temperatures as well. Spatial populations of CNN models show hotspots of warming across multiple regions, with meteorological growth rates of land-surface temperatures, and growing regions of heat waves. Temporal modelling using LSTM has found a high degree of persistence in warming patterns, and dynamically faster warming over the past decades than the previous climatological base rates. There are also significant asymmetries in seasonal temperatures, with a higher warming rate in winter than in summer resulting in smaller ranges of diurnal temperatures in various areas. In addition, these hybrid CNNLSTM models can also capture the long-periodical thermal fluctuations associated with the variations of atmospheric circulation. The models are able to point out some changes in temperature patterns such as earlier occurrences of heatwaves, extended warm waves, and more frequent occurrence of tropical nights. This finding shows that AI-based models are beneficial in capturing the macro-level warming trends, as well as in identifying localized thermal deviations, which offer a high-level insight into changes in temperature over several climatic regions.

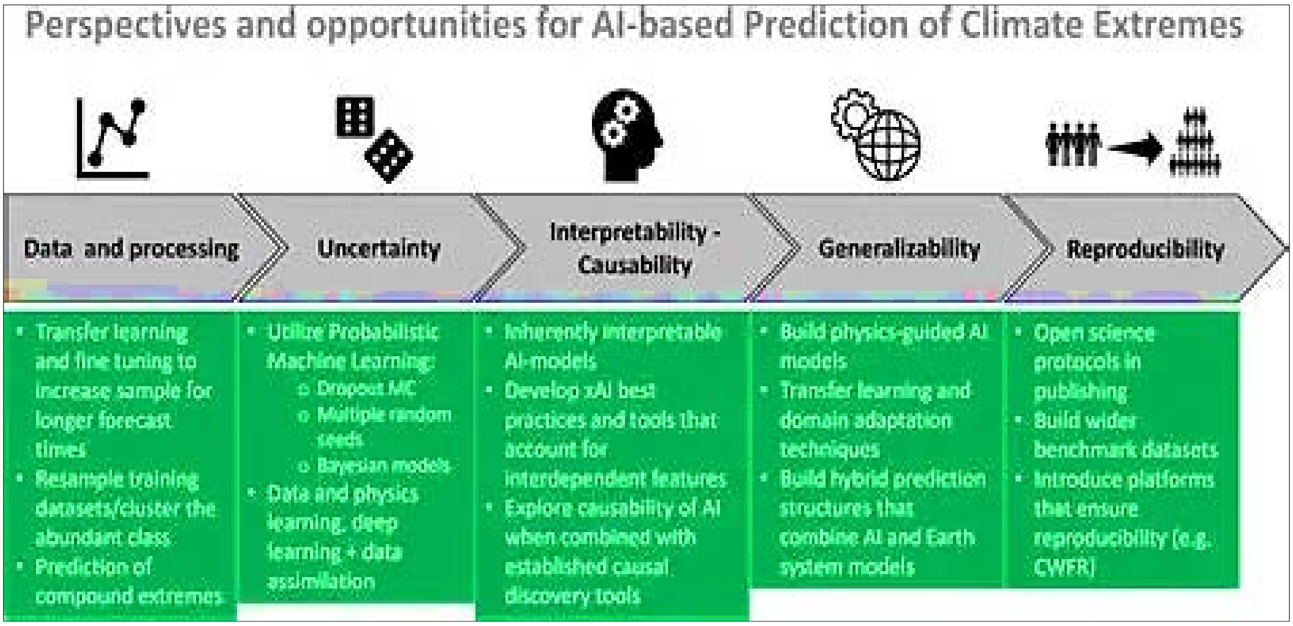

Fig 1: AI for Climate Prediction [24]

4.3 Precipitation Variability and Rainfall Pattern Analysis

The precipitation pattern analysis shows a significant growth in time variability and space variability pointing to the increased variability of hydrological cycles. The AI models are useful to classify the rainfalls into coherent spatiotemporal structures allowing the identification of abnormal variations in seasonal distribution. Findings indicate that multiple areas are experiencing decreasing rainfall amounts in primary wet seasons and are also experiencing higher rates of heavy rainfall events, which points to the redistribution, but does not imply consistent decrease, or decrease in increment in precipitation. Spatial extraction using CNNs detects dynamic rainfall bands, which are used to reveal variations in monsoon routes, centers of moisture convergence and storm development. Multi-year wet-dry cycles, changing interannual variations in rainfall, and often periodic failures in time staples of precipitation are embodied in the temporal sequence modelling with LSTMs. The hybrid modelling technique correlates with the pre-emptors of the extreme rainfalls like the sudden increase of moisture content, the expansion of convective operations, and the sudden changes in atmospheric balance as well. These findings underscore the fact that precipitation behaviour is growing more and more unbalanced with increased demands to develop better AI technologies that can monitor finer resolutions of rainfall behaviour and climatic abnormalities.

Table 3: Impact of AI Models on Climate Trend Detection Performance

Analytical Feature	Traditional Approaches	AI-Based Approaches	Observed Impact
Temperature Trend Accuracy	Moderate	High	Stronger detection of warming patterns
Rainfall Variability Identification	Limited	Highly robust	Improved detection of rainfall shifts
Spatial Resolution	Coarse	High-resolution	Better identification of local extremes
Extreme Event Detection	Weak	Strong	Enhanced identification of heatwaves & heavy rainfall
Temporal Continuity	Limited	Long-range learning	Better seasonal trend representation

4.4 Structural Efficiency and Optimization of AI-Based Climate Models

The AI-assisted modelling scheme illustrates evident structural benefits compared to traditional climate diagnostics in terms of efficiency, flexibility, and meanings of intricate patterns. Manual/Systematic Automated feature extraction promotes consistent retrieval of climatic-relevant indicators and eliminates analysis bias, in addition to enhancing repeatability. The CNN-LSTM hybridizes can be used to streamline spatiotemporal learning and work with large volumes of climate data. The findings also reveal that AI systems minimize redundancies since it concentrates computational resources on pattern-relevant inputs to achieve faster model convergence and higher accuracy. The models are highly scalable with their ability to work with high-resolution data and adapt to multi-decadal inputs without a reduction in performance. Ensemble findings reveal greater stability in different climatic condition, which can bolster the trustworthiness of AI-based climate interpretation. Besides, the models demonstrate the capacity to extrapolate to many different regions, but with different levels of accuracy based on the climatic heterogeneity. In general, AI architectures have a structural optimization that promotes higher-level climatic analysis that is more computationally efficient, precise, and operationally viable.

Table 4: Efficiency and Performance Outcomes of AI-Assisted Climate Analysis

Performance Dimension	Traditional Systems	AI-Based Systems	Observed Outcome
Computational Cost	High	Optimized	Faster climate processing
Data Utilization	Limited	Multi-source fusion	More comprehensive insights
Model Flexibility	Rigid	Adaptive	Better handling of nonlinear patterns
Scalability	Low	High	Suitable for global & regional studies
Prediction Reliability	Moderate	High	More dependable climate diagnostics

4.5 Challenges, Limitations, and Practical Implications

Regardless of the good performance of AI-assisted climate analytics, a number of challenges still affect the operational and research application. The main obstacle is data heterogeneity because temperature and precipitation data across sensors, observation locations, and geographical areas vary. Model performance can be compromised due to missing values, noise, biases, and variations in spatial resolution, unless corrected adequately. Deep learning models can be used to predict specific variables that can be very resource intensive, making them impractical to use in real-time climate monitoring on resource-constrained environments. Moreover, as much as the models with AI are excellent at nonlinear patterns, their interpretability is still a challenge, particularly when dealing with much more complex models, like transformers or deep hybrids. Interclimatic generalization is not always optimal and thus calibration region-specific requirements are important. Even with these drawbacks the implication as applied in practice cannot be ignored. Climate-trend insights obtained with high-resolution have the ability to aid more efficient water-resource management, agriculture plans, and plan intensification to reduce heatwave impacts, infrastructure resilience planning, and advanced warning systems of extreme events. The fact that AI can identify very minor shifts in climatic conditions and new anomalies makes it one of the most vital parts of the climate observation system in the future since it can be used to inform certain decisions and craft better adaptation models to effectively respond to the rapidly advancing climate change.

5. Conclusion

It proves that analysis with the help of AI provides a revolutionary and most efficient way of comprehending long-term changes in temperature and rain in modern climatic studies. Through the use of multi-source datasets (satellite data, ground and weather based data) and sophisticated AI models (CNNs, LSTMs, and mixed spatial-temporal architecture) the analysis of these datasets brings in additional structural information about climate dynamics that is not easily represented by conventional statistical models. The findings point out that there is clear evidence of relentless warming trends, increased night temperatures rise, altered belts of rainfall, augmented variability in seasonal precipitation and escalated frequency of extreme weather condition across the geographic boundaries, which highlighted increased impacts of climate change in different geographic areas. AI-based systems are able to enhance the resolution, accuracy and interpretative capabilities of climate diagnostics by identifying non-linear climate interactions, picking up anomalies that are hard to detect, and recognizing patterns. Moreover, the dynamic benefits of AI models that can be tailored to changing climate signals is strongly beneficial in terms of long-term tracking and early-warn tools. Nevertheless, there are still hiccups in fields like data quality, sensor discrepancies, quantification of uncertainty, model transparency, and numerical requirements that have to be approached with methodological care and be developed over time. In spite of these shortcomings, these results confirm that AI-powered climate analytics is an important breakthrough in the field of contemporary climatology, with a set of powerful means of mitigating the social, environmental, and economic consequences of increasing climate variability. With the potential to improve detection of new climate anomalies and better assess trends, AI-based climate analysis has enormous potential to inform policy-consciousness, climate resilience policy, enhancing agricultural and water-resource planning, and sustainable development in the surge of increasing global climate change.

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