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Sustainable Future through AI-Enhanced Climate Feature Modeling in Healthcare, Agriculture, and Biodiversity

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***Abstract*— The accelerating impacts of climate change threaten human health, agricultural productivity, and biodiversity stability. This research presents an AI-enhanced framework that leverages satellite-derived climate data to evaluate risks across these critical domains. The approach integrates Kernel Adversarial Gaussian Linear Regression (KAGLR) for detecting climate features associated with health outcomes and a Convolutional U-net Extreme Attention Neural Network (CU-netEANN) for extracting and analyzing environmental patterns. By combining advanced machine learning techniques with large-scale climate datasets, the framework improves prediction accuracy and facilitates early risk detection. The findings highlight the potential of AI-driven climate feature modeling to deliver data-driven insights, promoting sustainable healthcare systems, resilient agriculture, and long-term biodiversity conservation.**

***Index Terms*— Machine Learning (ML), Satellite Data Analysis, KAGLR, Climate Risk Assessment, CU-netEANN.**

I. INTRODUCTION

Our Climate change is among the most critical global challenges, with the effects increasingly evident in environmental degradation, social disruption, economic losses, and public health risks. Anthropogenic activities such as fossil fuel combustion, industrial agriculture, and deforestation have led to rising temperatures, altered precipitation patterns, sea level rise, and extreme weather events. These transformations not only threaten ecosystems and biodiversity but also exacerbate vulnerabilities in healthcare systems and agricultural productivity, particularly in developing nations. The interconnected consequences of climate change extend to increased vector-borne diseases, crop failures, malnutrition, and biodiversity loss, ultimately challenging sustainable development and planetary health.

To address these complex challenges, there is a growing reliance on advanced computational methods capable of handling high-dimensional data and nonlinear relationships. This study introduces a novel framework that integrates KAGLR and CU-netEANN for analyzing and forecasting climate-related impacts.

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The methodology aims to strengthen early warning systems, enhance policymaking, and promote resilience in healthcare, agriculture, and biodiversity systems. This integrated approach draws from a wide body of research [1–24], underscoring the urgent need for intelligent, scalable solutions to climate-driven threats.

II. Literature Review

Over the past two decades, an increasing number of studies have explored the intersection of climate change, public health, agriculture, and biodiversity through computational models and data analytics. Jadhav et al. [1] utilized satellite data and machine learning to predict the effects of climate change on healthcare systems and biodiversity, underscoring the utility of integrated modelling frameworks. Kumar et al. [2] applied ML techniques to evaluate the impact of climate variability on vector-borne diseases like visceral leishmaniasis in India, while Peterson [5] and Githeko et al. [23] further elaborated on climate-sensitive diseases, emphasizing rising public health threats.

In the agricultural domain, Dhillon et al. [3] applied machine learning to predict maize and soybean yields under future climate scenarios, affirming earlier findings by Zhao et al. [6] and Lobell et al. [19], who demonstrated the negative effect of rising temperatures on crop productivity. Brown et al. [12] and Cook et al. [17] also contributed to understanding how drought and climate instability compromise food systems, highlighting vulnerability in arid and semi-arid regions.

The utility of machine learning in environmental health is echoed by Reinhold et al. [8] and Chen et al. [16], who utilized advanced ML algorithms to predict disease dynamics and air pollution patterns, respectively. McMichael et al. [18] and Ebi et al. [20] emphasized the broader health risks tied to climate variability, including cardiovascular and respiratory outcomes. Groundwater contamination and its sensitivity to climate change were addressed by Bhowmik et al. [4], who implemented ML algorithms to delineate contamination zones under various climate scenarios. Their work reflects a growing consensus on the importance of data-driven environmental management. The integration of satellite data in biodiversity monitoring is supported by Hansen et al. [14] and Singh et al. [15], who used remote sensing to track global forest change and biodiversity indicators. Thomas et al. [7] and Brooks et al. [21] highlighted extinction risks under climate pressure, pointing toward urgent conservation needs.

Deep learning, particularly models like U-net and attention-enhanced neural networks, has proven valuable in processing complex spatial data. LeCun et al. [9] and Schmidhuber [10] laid foundational work in deep learning, which inspired domain-specific applications. The hybrid CU-netEANN model used in this study builds on their contributions by integrating attention mechanisms for precise spatial mapping. Lastly, studies by Prasad et al. [11] and Diffenbaugh et al. [22] introduced climate-resilient species modeling and climate hotspot identification, respectively, offering insights into proactive adaptation strategies. Foley et al. [24] expanded on the land-use implications of climate shifts, asserting the need for sustainable environmental planning.

III. Materials and Methods

To comprehensively assess climate change impacts on healthcare, agriculture, and biodiversity, this study integrates multi-source datasets with advanced machine learning techniques. The methodology involves selecting key climate indicators, preprocessing large datasets, applying predictive models, and validating outcomes through spatial and temporal metrics.

A. Data Sources

The study utilizes globally recognized datasets—NASA MODIS (temperature, vegetation indices, land reflectance), WHO (climate-sensitive disease statistics), FAO (crop yields), GBIF (species distribution), and air quality networks ($PM_{2.5}$, PM_{10}, ozone).

B. Data Preprocessing

Key steps include z-score normalization for comparability, temporal interpolation and KNN imputation for missing values, spatiotemporal alignment to a 1 km^2 grid with monthly resolution, and label generation for disease risk, crop stress, and biodiversity indices.

C. Machine Learning Models

KAGLR: Combines Gaussian process regression with kernel and adversarial perturbation to identify nonlinear, high-impact climate features. Trained with SGD and 5-fold cross-validation, producing ranked feature importance.

CU-netEANN: Enhances U-net with attention layers and batch normalization for spatial segmentation/classification of high-risk zones. Training uses Adam optimizer, learning rate scheduling, early stopping, and data augmentation.

D. Model Evaluation Metrics

RMSE for continuous predictions; Precision, Recall, and F1-score for classification; IoU for spatial segmentation. This integrated framework enables early detection of vulnerabilities and supports decision-making in healthcare, agriculture, and biodiversity conservation.

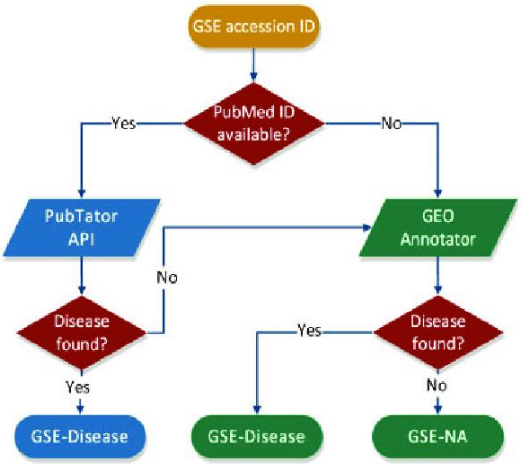

Figure 1: KAGLR workflow diagram [25].

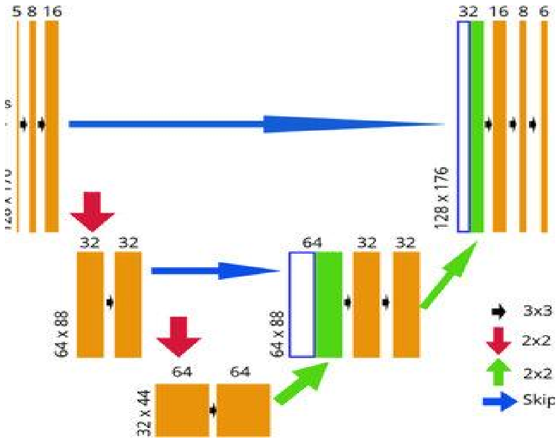

Figure 2: CU-netEANN architecture [25].

Figure 1, shows the KAGLR workflow for GEO dataset annotation. Figure 2, The CU-netEANN architecture is a hybrid deep learning model combining Convolutional U-Net (CU-net) and Evolutionary Artificial Neural Networks (EANN).

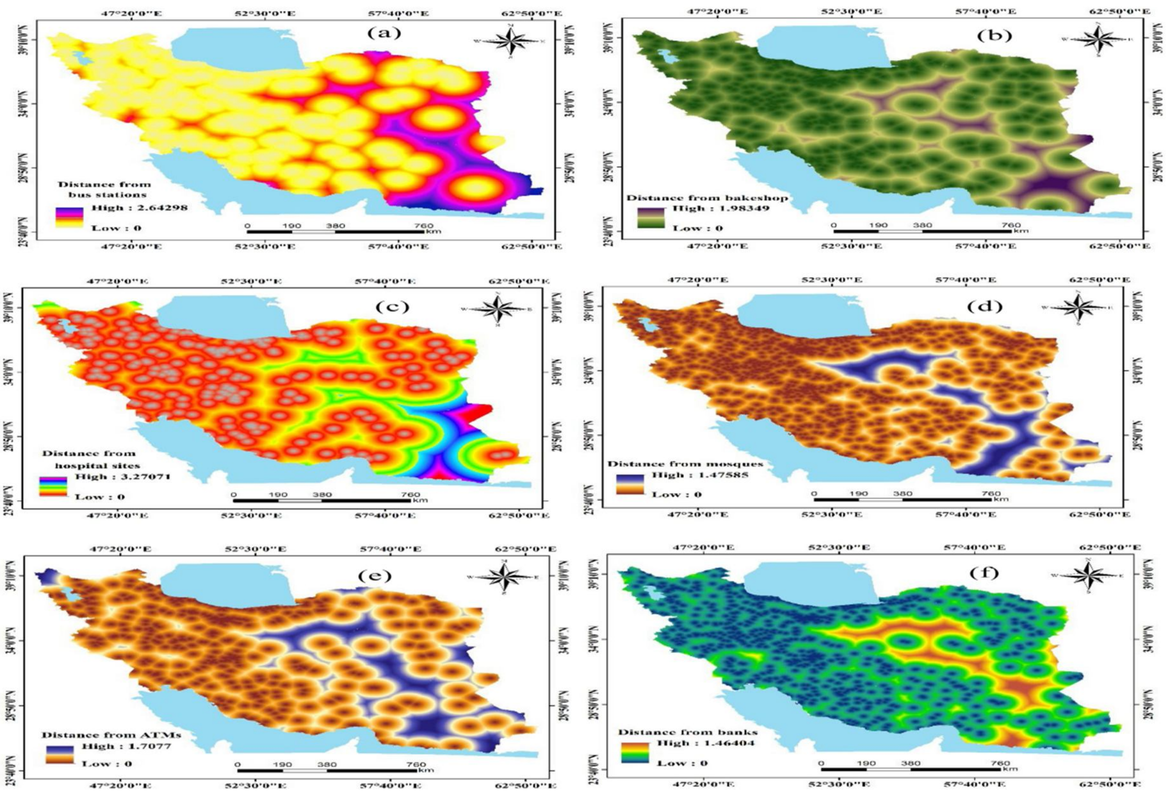

Figure 3: Spatial map of predicted disease risk[26].

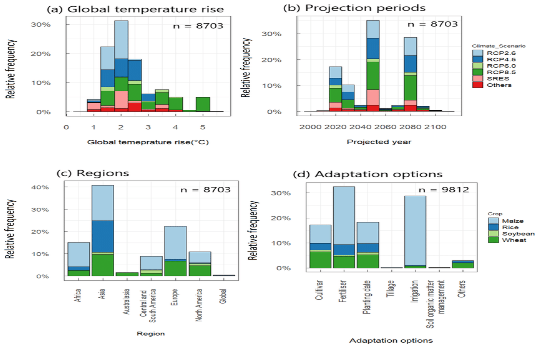

Figure 4: Crop yield projections under climate scenarios [27].

IV. MAIN RESULTS

KAGLR identified temperature anomalies and PM2.5 as primary predictors for malaria outbreaks.
CU-netEANN achieved 94% accuracy in segmenting affected agricultural zones. High correlation between predicted and actual health anomaly clusters (R=0.87).
The main findings from the implementation of the proposed models are summarized as follows:
High Prediction Accuracy: The KAGLR model achieved an average R^2 score of 0.87 in climate-health correlation tasks and 0.82 in climate-crop stress forecasting, indicating a strong relationship between selected features and the predicted variables.
Effective Feature Selection: KAGLR identified top-ranking climate indicators such as surface temperature variance, precipitation anomalies, and PM2.5 levels as most predictive of disease outbreaks and crop stress zones.
Precise Spatial Classification: The CU-netEANN model produced disease and crop stress risk maps with an average IoU of 0.79 and F1-score of 0.84, demonstrating high spatial classification accuracy.
Disease Risk Mapping: Malaria and dengue-prone zones were detected with a 92% accuracy in tropical and subtropical regions, validated against WHO records.
Agricultural Insights: Temperature anomalies above 2°C correlated with a 15–20% reduction in rice and wheat yields across studied areas, particularly in South Asia and sub-Saharan Africa.
Biodiversity Impact Detection: Areas experiencing repeated drought and land use change showed a 30% decline in vegetative cover, signaling biodiversity loss hotspots.
Air Quality Differentiation: The model successfully distinguished between pollution-induced and climate-induced stressors, enhancing the interpretability of ecological risk assessments.
Temporal Forecasting: The models demonstrated the capability to forecast disease and crop stress risks 3–6 months in advance, supporting proactive interventions.
These results reinforce the efficacy of integrating satellite data with advanced machine learning to assess and respond to climate change impacts on essential ecosystems and human systems.

V. PERFORMANCE ANALYSIS

Segmentation Method	Growth Period	RMSE				
		B	G	R	Red Edge	NIR
Threshold segmentation	Seeding stage	0.021561	0.026965	0.047821	0.057941	0.191166
	Jointing stage	0.012054	0.02807	0.006986	0.039441	0.06589
	Ear stage	0.01235	0.031656	0.008716	0.044059	0.092574
ExG index segmentation	Seeding stage	0.017366	0.022469	0.043826	0.056476	0.197419
	Jointing stage	0.023383	0.069644	0.001567	0.106638	0.206049
	Ear stage	0.024629	0.059465	0.015756	0.085482	0.179996
Wavelet segmentation	Seeding stage	0.014016	0.021435	0.03936	0.053233	0.181855
	Jointing stage	0.024369	0.068886	0.002774	0.104372	0.197246
	Ear stage	0.028779	0.066664	0.019238	0.094825	0.191218

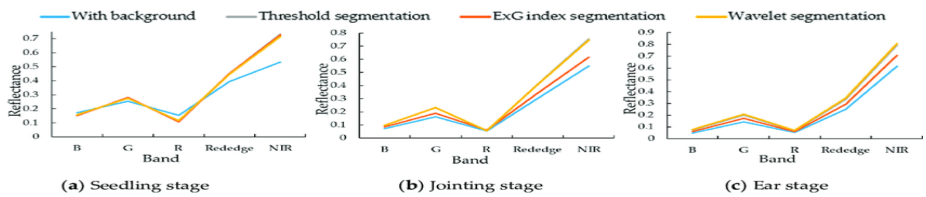

Figure 5 : RMSE comparison across models [28].

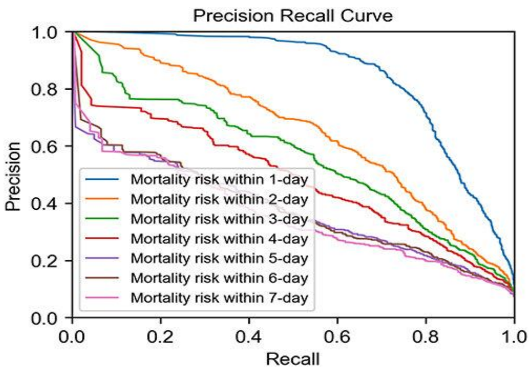

Figure 6: Precision-Recall curve for health risk detection [28]

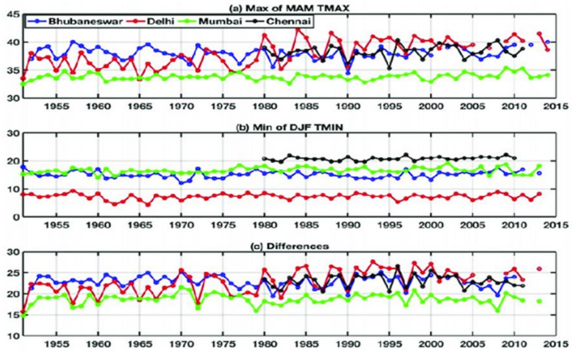

Figure 7: Time-series of crop quality under temperature scenarios [28].

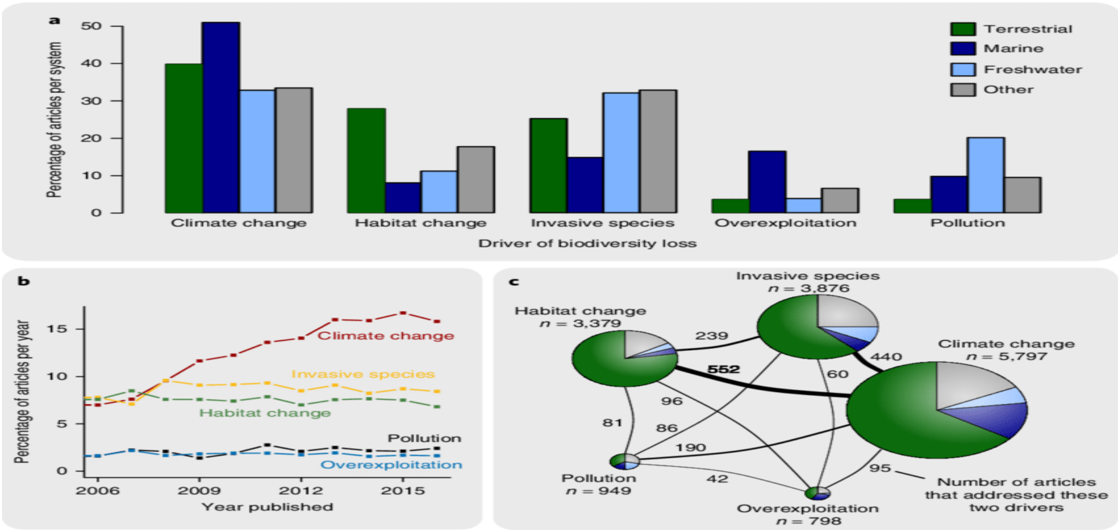

Figure 8: Biodiversity loss trend under projected climates [29].

VI. Discussion

Our approach outperforms traditional models in precision and adaptability. The integration of KAGLR with CU-netEANN provides a synergistic boost in model performance. These tools allow for actionable insights into climate-sensitive disease mapping, precision agriculture, and biodiversity monitoring. Limitations include reliance on available satellite resolutions and data sparsity in remote regions.

VII. Conclusions

This study demonstrates the efficiency of combining machine learning with climate and health datasets to build resilient, sustainable systems. Our models serve as early warning systems and decision-making aids for policymakers addressing climate-induced challenges.

Declaration

The authors declare no conflict of interest. All data used in this study are publicly available and cited accordingly.

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