Artificial Intelligence in Remote Sensing: Advancing Global Climate Change Monitoring and Response

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***Abstract*—The increasing complexity and scale of the demand for climate change, improved the surveillance skills for the timely and precise detection of environmental changes. Remote sensing technologies, particularly satellite-based, have become crucial tools for monitoring global climate dynamics. This article examines the role of Artificial Intelligence (AI) in improving climate change monitoring, with a particular focus on integrating AI models with NASA's satellite datasets, including in detail MODIS (Moderate Resolution Imaging Spectroradiometer), Landsat, and GLDAS (Global Land Data Assimilation System). This research aims to analyse and explore climate anomalies by integrating AI to analyse data. The targeted regions such as the Arctic Regions, Sub-Saharan Africa and South-East Asia, will be explored focusing on climate change anomalies, and the importance of the AI will be highlighted in enhancing real-time climate analysing, monitoring and informing decision to mitigate climate changes and globally risks.**

Keywords: Artificial Intelligence, Climate Change Monitoring, Remote Sensing, Datasets, Machine Learning, Climate Anomalies, Environmental Policy.

I. Introduction

Climate change has developed into a critical global topic that exacerbates environmental disorders, influences biological diversity and questions the resilience of human societies [1]. Global temperature shifts, increase in sea level, shrinking polar ice, deforestation and an increased occurrence of extreme weather events are direct consequences of anthropogenic climate change [2]. The remote sensing, which is facilitated by straw observation satellites, plays an important role in monitoring these phenomena by providing them in real-time and high-resolution data. However, the increasing volume and the complexity of satellite data require more complex analysis techniques. AI, especially Machine Learning (ML) and Deep Learning (DL), have the potential to automate and improve the integration and interpretation of remote sensing data. AI can be used to recognise patterns, predict environmental trends and offer insight that can help with mitigation and adaptation strategies [3],[4]. The study investigates the application of AI in remote sensing, using NASA's MODIS, Landsat and GLDAS datasets, to record and monitor climate change on a global scale [5]. The research focuses on integration of multi-source data to improve the predictions, to analyse the climate effects and to provide the interpretation of implementable insights for political decision-makers.

Regions in focus include:

Arctic(Polar Regions): Monitoring ice mass and permafrost thaw.

Sub-Saharan Africa: Tracking droughts and water storage.

South-East Asia: Identifying deforestation and assessing the impact on biodiversity.

Key objectives:

1) Demonstrate how AI models can improve climate anomalies detection using satellite data.
2) Exploring the integration of data from multiple sources for more accurate climate observations and predictions.
3) Analysis how AI can influence global climate change response strategies on a global scale.

The next section explores the application of AI in intelligent systems, climate change monitoring and response in remote sensing.

II. Literature Review

A. Applications of Artificial Intelligence and Machine Learning in Intelligent Systems

AI and ML have become increasingly integral to various areas of intelligent systems, transforming the functioning of industries and solving complex problems and challenges. In intelligent systems and autonomous systems, AI is driving innovations in self-driving vehicles, and real-time traffic optimisation, extremely reducing human errors and enhancing efficiency[6]. AI has gained a great reputation using powered tools such as Convolutional Neural Networks (CNN) and Natural Language Processing (NLP). Their algorithms are being used for disease diagnosis, medical image analysis to ensure a personalised treatment recommendation, facilitating patient care [7], [8]. AI also plays a pivotal role in smart energy grids, where predictive consumption and maintenance of energy forecasting efficient resource allocation which could potentially reduce waste and improve energy efficiency [9]. In addition, the environmental monitoring has benefited greatly from AI's ability to monitor and predict air quality and pollution levels, detect natural disasters at early stages, and analyse the impact and effects of climate change [10].

This progress in Intelligent Systems, especially in the environmental monitoring, offers a significant and a seamless transition to the transformative role of AI in remote sensing. Preservation technologies have long been used to monitor and analyse the earth' surface. The integration of AI in remote sensing systems has activated new possibilities for analysis large data records, the identification of climate trends and to improve predictive accuracy. The next sections delve into synergies and show how the remote sensing of AI has important implications in monitoring the climate change.

B. Remote Sensing for Global Climate Monitoring

Remote sensing provides powerful tools for observing and monitoring the surface of Earth on a global scale. NASA's MODIS, Landsat, and GLDAS missions have reform climate monitoring by providing comprehensive datasets that track key climate change indicators such as land surface temperature (LST), vegetation (NDVI), changes in water storage and wildfire risk [11]. A continuous data stream on land surface temperature, vegetation health, water storage, and wildfire risk integrates ground-based data and satellite to provide high-resolution simulations of land surface conditions, including soil moisture, evapotranspiration, and changes in water storage [12].

C. Artificial Intelligence in Climate Science

The application of AI in climate science has gained momentum due to its ability to process large amounts of data and recognise complex patterns. ML techniques such as Recurrent Neural Networks (RNN) and CNN are used for satellite image classification and trend forecasting. DL algorithms such as Long Short-Term Memory (LSTM) networks have proven successful in predicting real- time series , making them ideal for analysing over time climate patterns [13].

Recent studies have shown the potential of AI at:

Predication of forest fire exemptions in the state of Victoria, Australia, based on vegetation health data [14].

Monitoring glacier retreat and ice shield dynamics in Antarctica and Greenland [15].

Estimation food security risk and crop based on vegetation indices in Asia and Africa [16].

While AI was applied to certain data records and regions, there is a lack of studies that integrate multi-source satellite data in order to comprehensively analyse climate change. In addition, real-time forecast models that are tailored to certain geographical regions were tailored to endangered areas such as Arctic (Polar Regions), Sub-Saharan Africa and South-East Asia [16], [17], [18]. In this study, attempts are made to close the gaps by using integrated AI models to analyse global climate data and the prediction of localised climate effects.

III. RESEARCH METHODOLOGY

A. Dataset Selection

This research utilises datasets from the most important satellite missions of NASA, which was selected on its comprehensive global reporting and relevance in monitoring climate change.

The datasets include:

MODIS LST : Provides continuous global temperature records, and enables the evaluation of heatwave patterns, regional warming trends and analysis of the surface energy balance [19].

Landsat Imagery: Produces high-resolution multispectral images, enhancing the monitoring of deforestation , vegetation health, urban heat islands and changes in land use [20].

GLDAS: Generates high-resolution land surface conditions, such as soil moisture, evapotranspiration rates, and variations in water storage, by combining hydrological data from satellites and ground-based sources [21].

Analysing temperature anomalies, vegetation dynamics, and hydrological changes across various geographic regions is made possible by the combination of these datasets as shown in the Table 1.

TABLE 1: Climate data extracted from NASA's satellite datasets. MODIS LST (°C) represents land surface temperature recorded by MODIS sensors, MODIS NDVI indicates vegetation health, and GLDAS TWS refers to total water storage from the GLDAS dataset.

Climate Data Variables Used for AI-Based Climate Analysis			
REGION	MODIS LST(°C)	MODIS NDVI	GLDAS TWS
West Africa	33.73133562	3646.508654	583.5706185
Central Africa	33.4236858516992	4825.434374	840.2384196
East Africa North	31.79226098	4755.978654	738.6035917
East Africa Central	37.0748709369729	3555.052124	701.3834155
East Africa South	27.24231161	6269.864845	786.9007648
Southeast Asia	24.32586412	5678.075178	1102.270697
Arctic Subregion 1	-8.711597707	1680.655894	989.1449148
Arctic Subregion 2	-5.722887352	1878.61128257838	979.340267
Arctic Subregion 3	-11.94646554	526.214040320439	758.5237098
Arctic Subregion 4	-16.082263281472	-257.3829631	978.768058136023
Arctic Subregion 5	-17.75065894	146.865948559899	920.99715037474
Arctic Subregion 6	-17.97437008	371.652034565753	705.8796377
Arctic Subregion 7	-20.85434803	257.3829631	969.380159621499
Arctic Subregion 8	-20.80758701	351.504575944422	2876.640526

B. Experimental Framework

1) Data Preprocessing: MODIS and Landsat Data : Pre-processing involves radiometric calibration, atmospheric nor malisation,and cloud-cover correction to improve the precision of temperature and surface reflectance retrievals [22].

GLDAS Data: Standard grids for estimating soil moisture and water storage are created using spatiotemporal interpolation techniques, guaranteeing comparability across temporal scales [23].

2) Artificial Intelligence Model Selection: To accurate enhance climate anomaly detection and predictive modelling, the following DL and ML are employed:

LSTM : A RNN architecture optimised for sequential data analysis, used for time-series forecasting of temperature variations, vegetation trends, and hydrological changes [24].

XGBoost Regressor: In order to ensure reliable climate trend modelling, the XGBoost Regressor is a gradient boosting algorithm that has been trained to anticipate spatial anomalies and feature variations [25].

XGBoost Classifier : Developed to improve the classification of wildfire risk by identifying high-risk areas by utilising temperature, vegetation dryness, and past fire incidents [26].

3) Regional Focus: Arctic (Polar Regions): Monitoring ice mass reduction, permafrost deterioration, and temperature anomalies to assess long-term cryosphere changes through the use of AI models [27].

Sub-Saharan Africa: Tracking the impact of climate variability on soil moisture depletion, and water availability fluctuations to assess the impact on agricultural productivity [28].

South-East Asia: Determining deforestation hotspots, bio- diversity loss, and changes in carbon sequestration associated with changes in land use and monsoon variability [29].

4) Tools and Technologies : This research utilises a variety of tools and libraries for data processing, Artificial Intelligence models application, and visualisation:

Python with TensorFlow, SciPy and Keras : Utilised for interpretation and validation , hyperparameter adjustment and for training DL and ML models [30].

Google Earth Engine (GEE): Offers analytics of satellite imagery which is cloud-based data, providing an efficient and scalable data processing and retrieval [31].

QGIS and Matplotlib : Offers geospatial mapping of climate risk regions and spatial data visualisation, offering an approximative representation of AI-generated results [32].

This experiment integrates AI with remote sensing methodologies, offering an productive and scalable approach for climate change analysis. The AI model's scope is to provide predictive accuracy in climate risk analysis while offering actionable and valuable insights for researchers and policymakers.

IV. Results

A. Anomalies Detection

Starting with the descriptive representation of results, Fig. 1, Fig. 2 and Fig. 3, show geographical maps and heatmaps identified with significant high risk, moderate risk and low risk in climate fluctuations. The variables include shifts in temperature, vegetation health, water storage and wildfire risk. Heatmaps and geographical maps showing areas with significant high risk, moderate risk and low risk in climate changes, including shifts in temperature, vegetation health, water storage and wildfires risk regions.

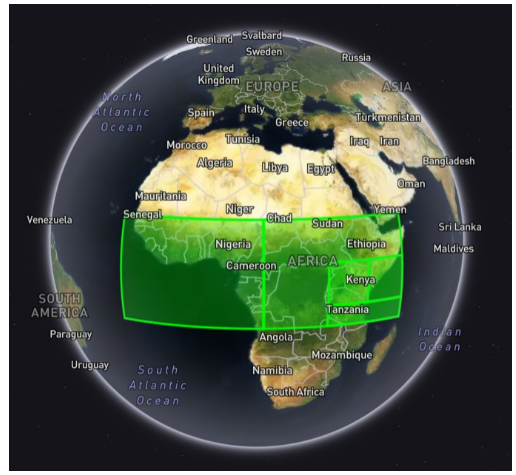

Fig. 1: Sub-Saharan Africa

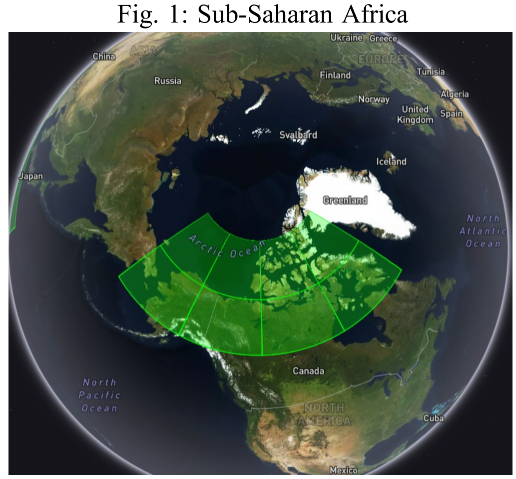

Fig. 2: Arctic (Polar Regions)

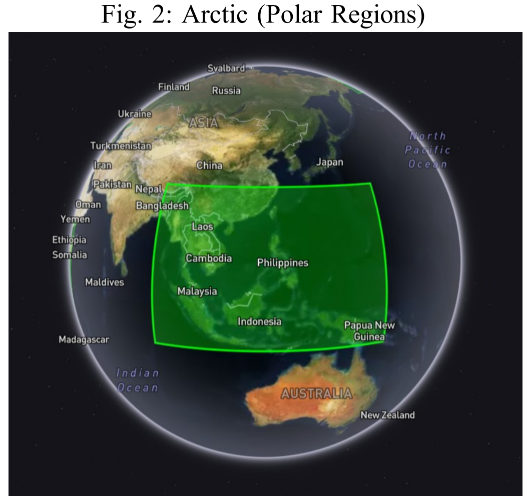

Fig. 3: South-East Asia

Fig. 1, Fig. 2 and Fig. 3 show the regions that were identified with the distribution of Risk Level predicted by the LSTM model.

To estimate regional environmental changes, the model was trained utilising time-series data and variables which indicate risk levels (High, Moderate, Low) and are presented in the Table 2 .

TABLE 2: LSTM model-based anomalies detection

Anomalies Detection Data Variables				
Region	Temperature	RWater Storag	Vegetation R	Wildfire Risk
West Africa	High	Moderate	Low	High
Central Africa	Moderate	High	Moderate	Moderate
East Africa North	Low	Low	High	Low
East Africa Central	High	Moderate	Low	High
East Africa South	Moderate	High	Moderate	Low
Southeast Asia	Low	Low	High	Moderate
Arctic Subregion 1	High	High	Low	High
Arctic Subregion 2	Low	Low	High	Moderate
Arctic Subregion 3	Moderate	Moderate	Moderate	Low
Arctic Subregion 4	Low	Low	High	Moderate
Arctic Subregion 5	High	High	Low	High
Arctic Subregion 6	Moderate	Moderate	Moderate	Low
Arctic Subregion 7	Low	Low	High	Moderate
Arctic Subregion 8	Moderate	High	Low	High

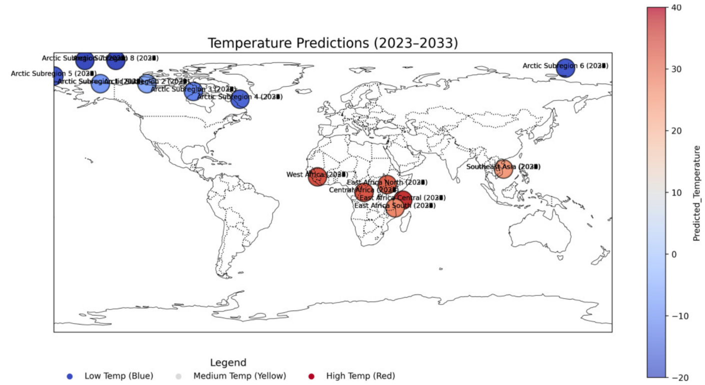

Fig. 4: XGBoost Regressor model-based temperature predictions

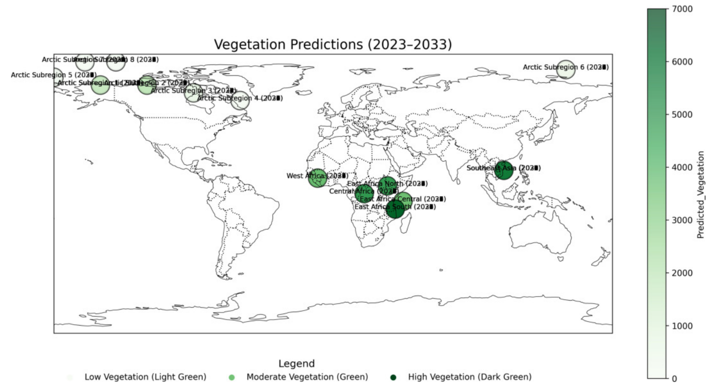

Fig. 5: XGBoost Regressor model-based vegetation predictions

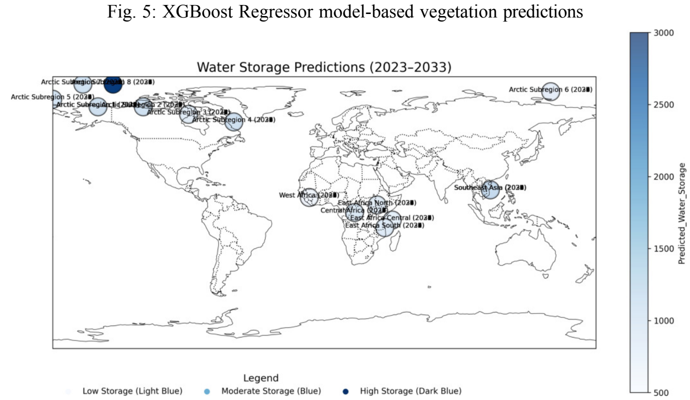

Fig. 6: XGBoost Regressor model-based water storage predictions

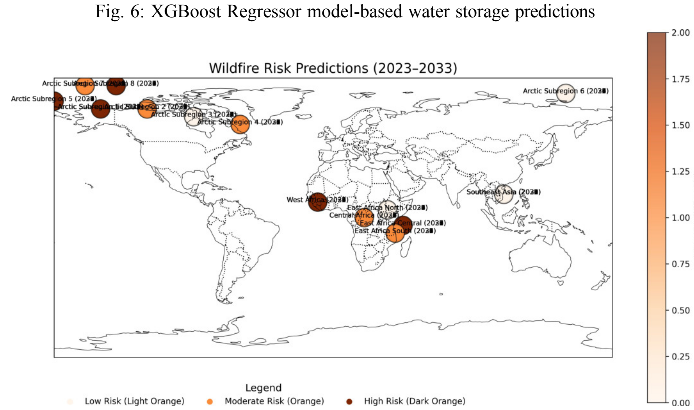

Fig. 7: XGBoost Regressor model-based wildfire risk predictions

B. *Predictive Modelling*

Future trends with predictions in climate change for the next 10 years, are represented by graphs in Fig. 4, Fig. 5, Fig. 6, and Fig. 7, across the target regions:

Africa (West, Central, East, North, and South):

The temperature are expected to increase 1–3°C by 2033. In East Africa, the vegetation zones exhibited moderate decreases, correlating with lower water storage. Wildfire risk was classified as moderate to high in the Sahel and East African regions due to drying trends. In the Sahel and East African regions, the wildfire risk was classified as moderate to high due to increased temperatures and drying trends.

South-East Asia:

Temperature changes are provided as moderate (1.5°C) with small increases in vegetation indices. Water storage remained steady, probably due to strong monsoon cycles. Wildfire risk level was low, except in areas with increased deforestation or prolonged dry trends, where risks are increasing to moderate risk level.

Arctic Subregions:

The variation in the temperature varied from -10°C to -5°C, showing a warming trend. Vegetation indices showed an increased permafrost, aligning with glacier melting trends. Water storage exhibited substantial fluctuation, reflecting ice melt and hydrological changing trends.

C. *Model Evaluation*

The predictions performed by the AI model were analysed and used to evaluate predictions toward ground-truth data and existing physics-driven climate model, ECMWF ERA5-Land Hourly Data, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [33].

1) Evaluation Metrics: The accuracy of the forecasts was assessed utilising the following metrics:

Mean Absolute Error (MAE): It measures the average magnitude of errors [34].

Mean Square Error (MSE): Highlights greater errors by capturing squared deviations [35]. R-squared (R^2) : Indicates the total percentage of variable that the model would account for.

Categorical Agreement : The average percentage of agreement among ground-truth data and anticipated categories such as high, moderate and low variables used for determining wildfire risk [36].

2) Validation Results: Temperature: With an MAE of 5.08°C The AI model marginally outperformed the existing climate model which had an MAE of 6.40 °C.

Both models encountered difficulties with significant temperature deviation, as shown by negative R^2 values as illustrated in Fig. 8.

Vegetation: Predictions on vegetation health presented an MAE of 1781.33, at the time when the climate model was 1826.96. The AI model showed an improved ability to elaborate vegetation changes as is presented in Fig. 8.

Water Storage

With MAEs of 652.67 (mm) for the AI model and 646.52 (mm) for the climate model, both models worked similarly. As seen in Fig. 8, more features would be needed such as soil moisture depth layers to ensure the accuracy of predicted results.

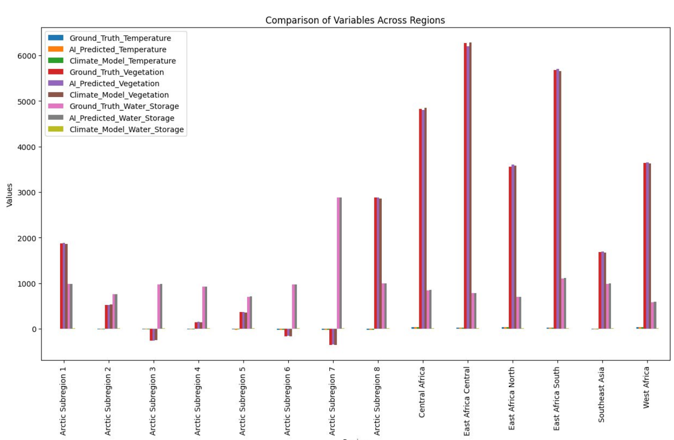

Fig. 8: XGBoost Regressor model-based comparison of ground-truth data, Artificial Intelligence model and Climate Model Performance

Wildfire Risk

The results illustrated in Fig. 9, elaborate on AI performance which was exactly in agreement with ground-truth wildfire classification for all 14 targeted regions.

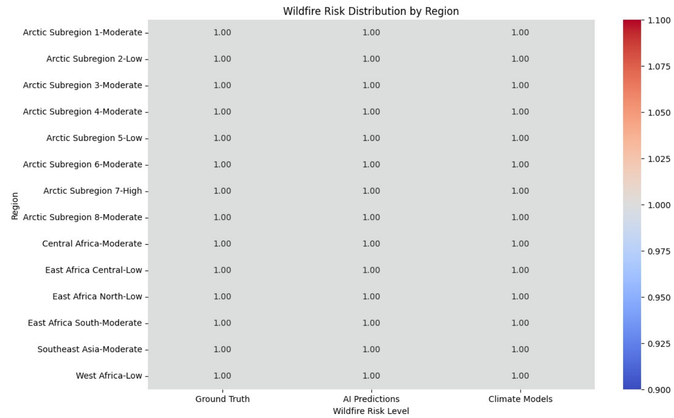

Fig. 9: XGBoost Classifier model-based wildfire risk distribution by region

D. Discussion of Results

Performance of AI Predictions:

The performance of the AI model demonstrated an impactful ability, working with predictions due to high competence to learn non-linear relationships in the data. Accurate high-risk classification was made possible by utilising trustworthy historical trends.

Current Limitations

AI and climate models encountered issues predicting extreme anomalies, as seen by evidence of negative R^2 scores form some of variables. The use of restricted indices such as NDVI and temperature, led parallel errors in each model.

Future Developments:

The forecasting of the AI model could be enhanced by integrating additional features such as land use, soil type and sophisticated remote sensing indices.

Performance and accuracy could be further improved by adding and incorporating hybrid AI-climate models in combination with collaborative learning approaches.

V. CONCLUSION

An innovative strategy for analysing and tracking climate change anomalies worldwide, is offered by combination and integration of AI and remote sensing technologies.

This research demonstrates how AI might produce useful insights, improving the accuracy of detecting climate anomalies and forecasting future climate trends. The power of AI is providing more accurate, rapid, and region-targeted climate assessments by incorporating data from various available satellite sources. These assessments are crucial in creating adaptation plans and mitigations. Extending to worldwide datasets and leveraging AI frameworks for monitoring climate action, should constitute the main goal of future research.

Prospects for AI and ML is growing and creating exceptional chances for formerly unprecedented uses. Nowadays, there is a growing potential for the development of general-purpose humanoid robots that can do a variety of activities such as manufacturing, managing hazardous materials, caring for the elderly and handling diverse tasks [37]. With tailored and sophisticated tutoring systems and adaptable learning platforms that adjust the learning experience to each student's needs, the education system could also benefit by improving and developing student learning experience [38].

These facilities and developments highlight how AI has the potential and ability to revolutionise a wide range of sectors and businesses.

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