Transforming climate adaptation with artificial intelligence

Case studies in hydroclimatology and agriculture

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Abstract

The Asia-Pacific region faces urgent challenges due to climate change, including rising temperatures, unpredictable precipitation patterns, and extreme weather events, necessitating the transformation of climate adaptation strategies with Artificial Intelligence (AI). This article investigates the transformative potential of AI, Machine Learning (ML), and Deep Learning (DL) technologies in hydroclimatology to provide innovative solutions for these pressing issues. Through three different case studies in India – a hybrid DL-based approach for multi-step ahead prediction of temperature and heatwave, a DL-based assessment of future streamflow variability, and AI for soil moisture monitoring and intelligent irrigation—our primary exploration reveals significant advancements in predictive accuracy and resource management efficiency. These cases highlight AI's ability to enhance climate models and optimize agricultural practices. Policy recommendations emphasize fostering innovation, regional knowledge-sharing cooperation, and capacity building. Leveraging AI-driven solutions can substantially boost adaptive capacity, mitigate adverse impacts, and ensure sustainable development in the Asia-Pacific region.

Introduction

Climate change poses urgent global challenges with rising temperatures, shifting precipitation patterns, and increased extreme weather events (IPCC, 2023; Sarkar et al, 2023; Sarkar & Maity, 2024). Human activities, particularly greenhouse gas emissions, have indisputably driven global warming, pushing temperatures 1.1°C above 1850–1900 levels by 2011–2020. Persistent emissions from unsustainable energy use, land practices, and consumption patterns contribute unequally across regions and within societies, threatening global ecosystems, health, and socio-economic stability. Agriculture and water sectors face heightened vulnerability, endangering food security and water resources (IPCC, 2023; Srivastava et al., 2022b; 2024). The Asia-Pacific region, with diverse climates and extensive coastlines, is no longer an exemption from amplified risks. According to the Asian Development Bank, the region is home to 60% of the world's population. It is highly vulnerable to climate change, with projections indicating a potential increase in temperature by 1.5°C to 3.9 (with an average of 2.7°C by 2050 under the worst climate change conditions (ADB, 2017). Extreme weather events' frequency and intensity have increased, leading to economic losses estimated at $675 billion annually (Hallegatte et al., 2016). Given the dense population and reliance on climate-sensitive sectors, addressing climate change here is paramount in this region.

Climate change generally poses profound challenges in hydroclimatology and agriculture, where the complexity and non-linear relationships in hydroclimatic data present significant hurdles. This vast volume and heterogeneity of the data, encompassing various meteorological, hydrological, and agricultural parameters, further complicate efforts to analyze and interpret the trends and underlying processes. Moreover, there is an increasing demand for precise and real-time predictions and recommendations to manage water resources, forecast extreme weather events, and optimize agricultural practices. Traditional methods often struggle to meet these requirements (Baker et al., 2020), highlighting the need for advanced, data-driven approaches. In this context, Artificial Intelligence (AI), particularly its subsets such as Machine Learning (ML) and Deep Learning (DL) offers promising solutions. These technologies can process large datasets, identify hidden patterns, and provide accurate forecasts, thus enhancing our ability to adapt to and mitigate the impacts of climate change. Therefore, AI may be considered as one of the ways forward to combating climate change issues.

Applying AI, ML, and DL in hydroclimatology and agriculture is not merely theoretical but has shown practical benefits across various case studies and real-world implementations. For instance, AI-driven models have been employed to accurately predict streamflow variations, aiding water resource management and planning (Khan et al., 2023). In agriculture, ML algorithms are being used to optimize irrigation schedules, reducing water wastage while ensuring crop health (Srivastava et al., 2022a). DL techniques, particularly hybrid models, have proven effective in forecasting extreme weather events such as heatwaves, providing critical lead time for preparedness and response (Khan &

Maity, 2022). These applications underscore the potential of AI, ML, and DL in addressing the multifaceted challenges posed by climate change, from ensuring water security to enhancing agricultural productivity and sustainability. By leveraging these advanced technologies, we can develop more resilient systems capable of adapting to the evolving climate dynamics.

This article thus presents the transformative utilization of AI, ML, and DL in addressing climate change impacts in hydroclimatology and agriculture. The focus is to showcase how AI techniques can be applied to complex hydroclimatic data for future streamflow assessments under climate change scenarios, to illustrate the effectiveness of a hybrid deep learning approach for multi-step-ahead predictions of daily maximum temperatures and heatwaves, and to present an AI-based intelligent system for soil moisture monitoring and irrigation management designed for marginal farmers, demonstrating its potential to enhance agricultural productivity and sustainability. By harnessing the power of these advanced technologies, we can better understand and predict complex climate phenomena, optimize resource management, and enhance decision-making processes.

AI-ML-DL techniques in hydroclimatology and agriculture

Overview

The journey of AI began in the mid-20th century with John McCarthy's introduction of 'artificial intelligence' in 1956 (McCarthy et al., 2006). Early AI focused on symbolic methods and problem-solving. ML emerged in the 1980s, shifting to data-driven approaches with advancements in decision trees (Breiman et al., 1984). The rise of the internet in the 1990s led to more data and boosted algorithms, such as Support Vector Machines (SVM) (Cortes & Vapnik, 1995) and Random Forests (RF) (Breiman, 2001). In the 21st century, DL saw a resurgence with deep neural networks advancing tasks such as image and speech recognition (LeCun et al., 1998). Table 1 details essential AI, ML, and DL concepts, defining AI's replication of human cognitive functions, ML's focus on predictive accuracy through data exposure, and DL's use of deep networks for complex data patterns. These technologies are crucial in diverse fields like natural language processing, image analysis, and decision support systems, shaping modern computational paradigms and technological progress.

Table 1: Outlining definitions and classifications of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL)

Concept	Definition	Types
AI	Any technique enabling computers to mimic human intelligence, performing tasks that typically require human intellect, such as natural language understanding, pattern recognition, and decision-making.	**Narrow AI:** Designed for specific tasks (e.g., virtual assistants).
		General AI: Hypothetical AI capable of performing any intellectual task a human can.
		Superintelligent AI: A theoretical concept surpassing human intelligence across all fields.
ML	A subset of AI focused on developing algorithms that learn from and make predictions or decisions based on data, improving performance over time with more data exposure.	**Supervised Learning:** Algorithms are trained on labeled data for tasks like classification and regression
		Unsupervised Learning: Finds patterns in data without labels, used in clustering and association tasks.
		Reinforcement Learning: Algorithms learn by interacting with an environment and receiving rewards or penalties to maximize cumulative rewards.
DL	A subset of ML utilizing neural networks with many layers to model complex patterns in large datasets, excelling in tasks requiring high-level feature extraction from raw data.	**Feedforward Neural Networks (FNNs):** The simplest form, lacking cycles between nodes.
		Convolutional Neural Networks (CNNs): Excel at processing image data through convolutional layers that learn spatial hierarchies.
		Recurrent Neural Networks (RNNs): Designed for sequential data, used in time series analysis and Natural Language Processing (NLP).
		Long Short-Term Memory (LSTM): Advanced RNN variant effectively managing long-term dependencies.

Specific algorithms used in hydroclimate and agricultural studies

Applying AI, ML, and DL in hydroclimatology and agriculture uses various algorithms (Table 2) designed for specific challenges. AI algorithms often involve expert systems and knowledge-based approaches, aiding drought monitoring and early warning systems (Elbeltagi et al., 2022; Kumar et al., 2023). Knowledge-based systems integrate qualitative reasoning with quantitative data for actionable insights into hydrological processes. ML algorithms are used for pattern recognition and predictive modeling. Techniques such as SVM and RF predict precipitation patterns and drought severity (Maity et al., 2010; Tulla et al., 2024; Vishwakarma et al., 2024). Clustering algorithms help identify hidden patterns in meteorological and hydrological datasets. DL algorithms excel in handling complex data relationships. CNNs effectively analyze satellite data. RNNs and LSTM networks are used in time-series forecasting for streamflow dynamics and temperature variations (Khan & Maity, 2020; 2023; Maity et al., 2021). These models capture temporal dependencies and nonlinear relationships, enhancing predictive accuracy in dynamic environments.

Case studies from India

This section delves into three detailed case studies that showcase the significant impact of AI technologies in tackling major challenges in hydroclimatology and agriculture. By examining these examples, we highlight the practical advantages of integrating AI into these fieles. These case studies also offer insights into how AI can promote sustainable development and enhance climate adaptation efforts in Asia-Pacific and beyond.

Case study 1: Hybrid DL for multi-step-ahead temperature and heatwaves prediction

Accurate prediction of daily maximum temperatures and heatwaves is crucial for mitigating the adverse effects of extreme weather events. Traditional methods often fail to capture the complex relationships between meteorological precursors and temperature variations, especially when dealing with large and heterogeneous datasets. This limitation hampers the

Table 2: Overviewing AI (Artificial Intelligence), ML (Machine Learning), and DL (Deep Learning) algorithms applied in hydroclimatology and agriculture.

Algorithm Type	Algorithm	General Application	Key Features
AI Algorithms	Expert Systems	Drought monitoring and early warning systems	Rule-based inference, domain-specific knowledge integration
	Knowledge-based Systems	Qualitative and quantitative reasoning in hydrological and climate processes	Integration of expert knowledge with data-driven insights
ML Algorithms	Support Vector Machines (SVM)	Precipitation pattern recognition, drought severity prediction	Effective in high-dimensional spaces, kernel methods for non-linear decision boundaries
	Random Forest	Forecasting hydrological variables, land cover classification	Ensemble decision trees handle large datasets and complex relationships
	Clustering Algorithms	Identifying spatial and temporal patterns in meteorological and hydrological data	Unsupervised learning groups similar data points based on defined similarity metrics
DL Algorithms	Convolutional Neural Networks (CNN)	Satellite imagery analysis for land cover classification, cloud pattern recognition	Hierarchical feature extraction, effective in spatial data analysis
	Recurrent Neural Networks (RNN)	Time-series forecasting of streamflow dynamics, climate data analysis	Captures temporal dependencies, sequential data processing
	Long Short-Term Memory (LSTM)	Daily temperature prediction, hydrological forecasting	Memory cells for long-range dependencies, suitable for time-series prediction

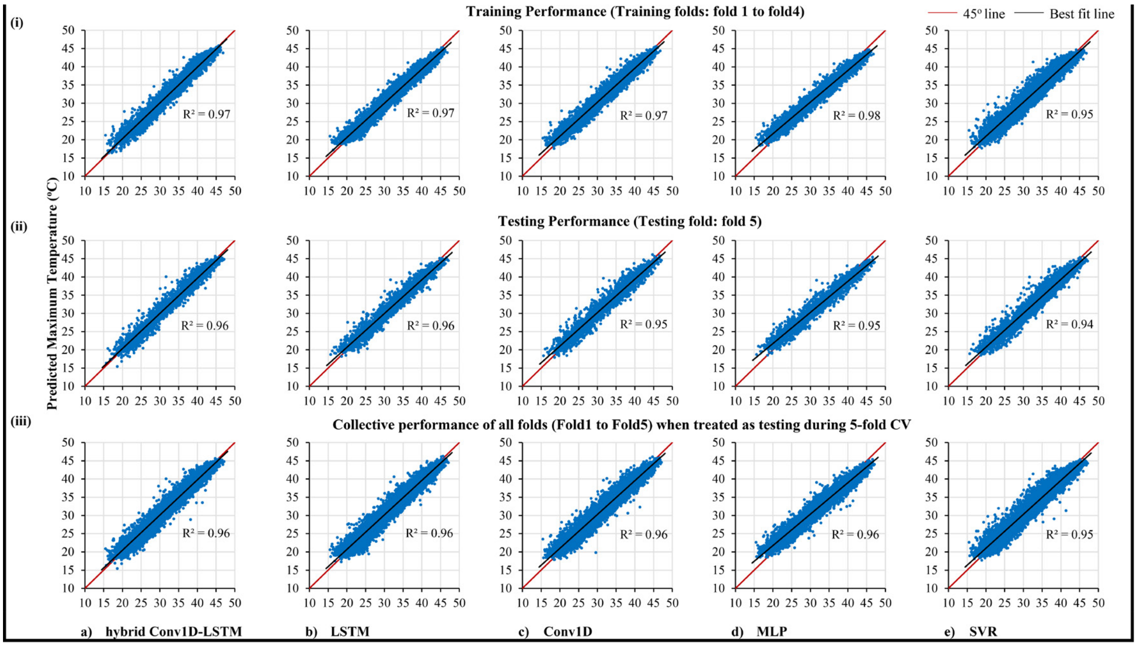

Figure 1: Comparative scatter plots between the observed and 1-day ahead predicted maximum temperature obtained during the (i) training period (i.e. by considering fold1 to fold 4 as training dataset), (ii) testing period (i.e. by considering fold5 as a testing dataset) and (iii) testing period of all 5 folds (i.e., fold1+fold2+fold3+fold4+fold5, when each fold is treated as a testing dataset during 5 fold CV), for a traditionally hot weather city (Jaipur), of a) hybrid Conv1D-LSTM, b) LSTM, c) Conv1D, d) MLP and e) SVR model run respectively (Reproduced from Khan and Maity, 2022).

effectiveness of early warning systems and preparedness measures, particularly in India, which has diverse climatic regions.

To address these challenges, Khan and Maity (2022) propose a hybrid deep learning approach combining a one-dimensional convolutional neural network (Conv1D) and an LSTM neural network, leveraging their strengths to enhance the predictive accuracy of daily maximum temperatures and heatwave events. Historical daily maximum temperature data and relevant meteorological precursors were collected for 28 major cities in India. The Conv1D component extracted local patterns from the data, providing a detailed understanding of spatial hierarchies. In contrast, the LSTM component captured temporal dependencies, enabling the model to learn from sequential data. The hybrid Conv1D-LSTM model was trained on the collected historical data, and its performance was validated using a separate dataset over the observational period to ensure robustness. Finally, the model performance was benchmarked against other conventional ML/DL models and three popular weather applications, namely AccuWeather, real-time weather system, and Weather Underground, to evaluate its predictive capabilities.

The hybrid Conv1D-LSTM model significantly improved over traditional approaches (Fig. 1) and popular weather applications (Khan & Maity, 2022) in predicting daily maximum temperatures and detecting heatwave events. Applied to 28 major cities in India, this model achieved superior accuracy in temperature forecasts and a 20-30% higher success rate in predicting heatwaves. The model's efficacy stems from its ability to capture intricate relationships between meteorological precursors and temperature variations. Conv1D layers excelled in extracting local features, while LSTM layers comprehensively represented temporal dynamics. This combination allowed the model to generalize effectively across diverse climatic conditions, enhancing its reliability for meteorological forecasting. This approach represents a promising pathway for developing sophisticated and reliable early warning systems, ultimately contributing to enhanced disaster preparedness and climate adaptation strategies in Asia-Pacific and beyond.

Case study 2: Deep learning for streamflow assessment Accurate streamflow prediction is vital for effective water resource management, particularly in climate change, which alters precipitation patterns and hydrological cycles. Traditional prediction models often struggle with the non-linear and complex interactions between climatic variables and hydrological responses. Khan et al. (2023) address these challenges by employing DL techniques, specifically LSTM networks, to model monthly-scale streamflow and project it for the future over the Bhadra River Basin (BRB) – a rain-fed river basin in the southern part of India. Historical streamflow data and various meteorological variables were used to train and validate the LSTM model. The K-fold cross-validation technique was also employed to ensure the robustness of the proposed model. Next, its performance was benchmarked against two traditional statistical and ML tools, Multiple Linear Regression (MLR) and Support Vector Regression (SVR), to evaluate its effectiveness in capturing complex patterns and improving modeling accuracy.

The results (Fig. 2) demonstrated that the proposed LSTM model

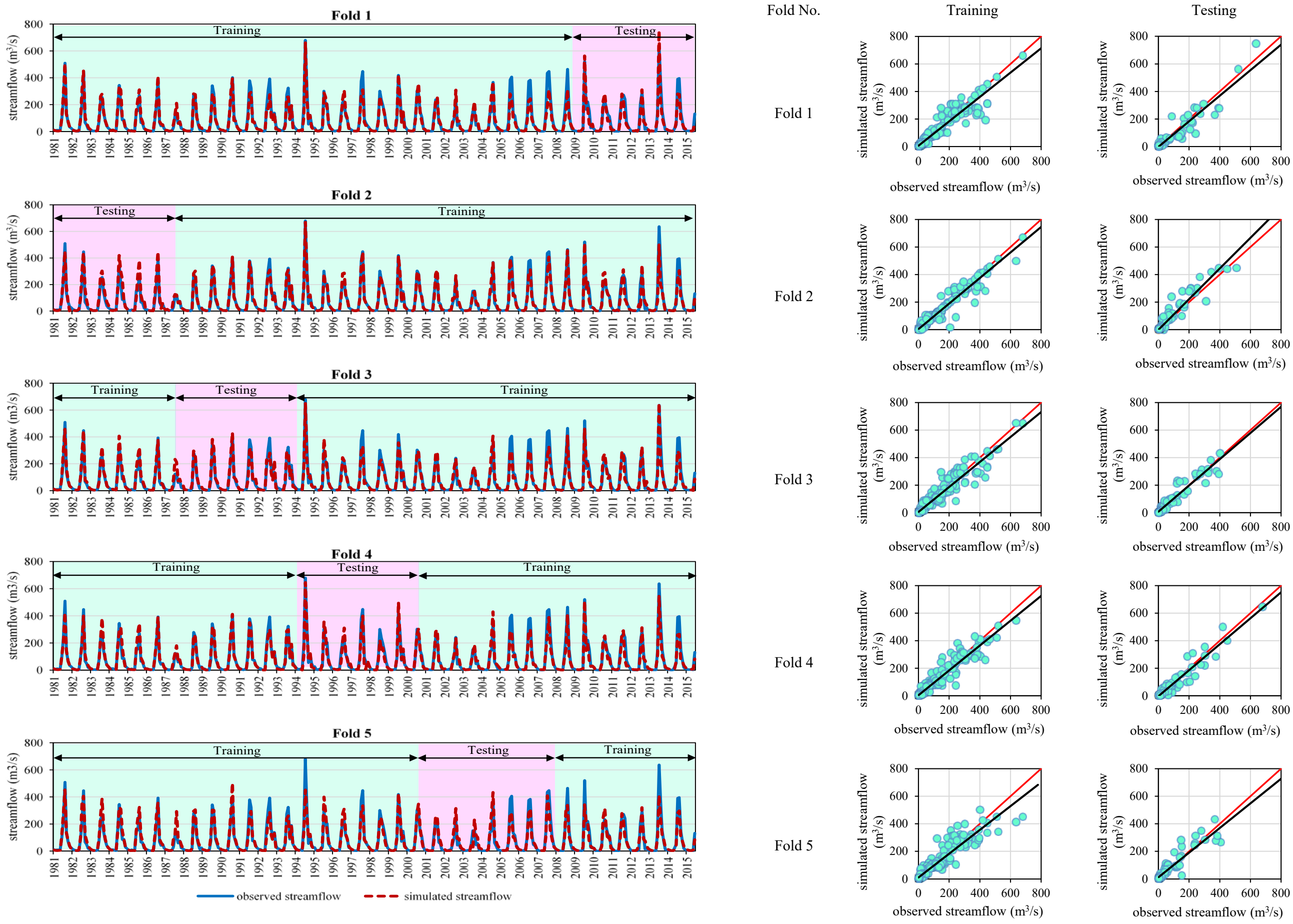

Figure 2: Fold-wise performance of the proposed LSTM model in simulating streamflow over BRB. Observed and simulated streamflow values are shown through time series (left) and scatter plots (right) for all five folds. In the scatter plots, the solid red lines show the 45° line (line of perfect simulation), and the black line shows the best-fit lines for the scatter plots. (Reproduced from Khan et al. (2023)).

successfully simulated the monthly distribution of streamflow over BRB, capturing both high-flow and low-flow regions with reasonable accuracy (with a correlation coefficient of 0.95 and Nash Sutcliff error of 0.89 over the testing period). Moreover, the proposed model significantly outperforms the benchmark models like MLR and SVR models in simulating the streamflow patterns. The superior performance of the proposed model can be attributed to its memory cell structures, which can capture the long-term dependencies and remember the complex non-linear causal relationships over a long period. Additionally, the developed LSTM model was utilized for long-term future projections over BRB after ensuring the model's stability. Simulations from six General Circulation Models (GCMs) under different climate change scenarios were considered for this purpose. The results reveal some critical insights into potential changes in hydrological patterns, highlighting the river basin's experience of increased and decreased streamflow over the high-flow and low-flow months, respectively, enhancing the risk of flood and drought simultaneously.

This case study underscores the immense potential of DL techniques, particularly LSTM networks, in hydroclimatology and streamflow prediction. These important findings are crucial for developing adaptive water management strategies to mitigate the adverse effects of climate change on water resources in the Asia-Pacific region and beyond.

AI-driven intelligent system for marginal farmers

Marginal farmers face significant challenges in managing irrigation water effectively, leading to water scarcity, soil degradation, increased salinity, pest outbreaks, and financial strain. Current soil moisture monitoring systems are often costly and complex, making them inaccessible to these farmers (Dutta et al., 2022a; Srivastava et al., 2022a). A promising area for future research is developing an AI-driven intelligent system for real-time soil moisture monitoring to address these issues.

The proposed future case study aims to leverage sensor technology and a user-friendly mobile app to empower marginal farmers in India with precise irrigation management tools, ultimately enhancing crop yields, reducing water waste, and alleviating financial stress. This project would integrate sensor-based soil moisture monitoring with advanced AI algorithms for data analysis. The initial steps include developing a mobile app that spatially displays soil moisture depth and values at various profile depths. Further stages would focus on refining sensor technology to measure soil moisture in electronic pulses, converting these pulses into readable formats, and validating the data through physical measurements. AI algorithms would be applied using observed data for model calibration and validation to ensure accurate predictions, allowing for continuous improvement and optimization of the system.

The future roadmap includes iterative development and field testing of the prototype. Extensive soil moisture data collection, AI-driven predictive analysis, and incorporation of historical data and

Table 3: Integration of AI, ML, and DL in climate change adaptation strategies: Applications, benefits, and challenges

Integration Area	AI/ML/DL Applications	Expected Benefits	Potential Challenges
Hydrological Modeling	▪ Streamflow prediction ▪ Flood forecasting	✓ Improved accuracy in water resource management ✓ Enhanced early warning systems	1. High data requirements 2. Complex model calibration and validation
Agricultural Management	▪ Crop yield prediction ▪ Soil moisture monitoring ▪ Pest and disease detection	✓ Increased agricultural productivity ✓ Efficient irrigation management ✓ Reduced crop losses	3. Integration with existing farming practices 4. Dependence on high-quality, real-time data
Urban Planning and Infrastructure	▪ Heatwave prediction ▪ Urban heat island effect modeling	✓ Enhanced resilience of urban areas ✓ Improved public health outcomes	5. Coordination between multiple stakeholders 6. Scalability of models to different urban settings
Disaster Risk Management	▪ Wildfire risk assessment ▪ Landslide susceptibility mapping	✓ Reduced human and economic losses ✓ Improved resource allocation for disaster response	7. Real-time data integration 8. Uncertainty in predictions due to changing climate patterns
Water Resource Management	▪ Drought forecasting ▪ Groundwater recharge estimation	✓ Sustainable water use ✓ Improved drought preparedness and mitigation strategies	9. Data sparsity in remote areas 10. Incorporation of socio-economic factors
Renewable Energy Planning	▪ Solar and wind power prediction ▪ Optimization of energy grids	✓ Increased efficiency and reliability of renewable energy sources ✓ Better planning and resource allocation	11. Variability in weather patterns 12. Integration with existing energy systems
Biodiversity and Ecosystem Services	▪ Habitat suitability modeling ▪ Species distribution prediction	✓ Conservation of endangered species ✓ Maintenance of ecosystem services	13. Complexity of ecological data 14. High computational requirements
Public Health	▪ Disease outbreak prediction ▪ Climate-related health impact assessment	✓ Proactive healthcare responses ✓ Reduced morbidity and mortality related to climate extremes	15. Integration with public health infrastructure 16. Addressing privacy and ethical concerns

simulation models would be critical components. Expected outcomes include a cost-effective and user-friendly mobile app for real-time soil moisture monitoring, optimized irrigation practices, enhanced crop yields, and improved financial stability for marginal farmers. This case study could demonstrate the potential of AI-driven solutions in addressing critical agricultural challenges, paving the way for broader adoption and innovation in the sector.

Advancing applications and future directions

Integration of AI/ML/DL in climate change adaptation strategies

The integration of AI, ML, and DL into climate change adaptation strategies offers transformative potential across various sectors (Table 3). These advanced technologies enable the development of sophisticated models that can predict the impacts of climate change with unprecedented accuracy and timeliness. By harnessing vast datasets and leveraging complex algorithms, AI-driven solutions can provide insights into water resource management, agricultural productivity, urban resilience, and disaster preparedness (Khan & Maity, 2024; Pande et al., 2022). For instance, ML algorithms can

Table 4: Policy recommendations with expected outcome and challenges for enhancing AI technologies in the Asia-pacific region

Recommendation	Expected outcome	Challenges
Invest in high-speed internet, data centers, and cloud resources.	Enhanced computational capacity for AI research.	High initial costs and need for ongoing upgrades.
Foster innovation through collaboration between governments, the private sector, and academia.	Faster AI technology development and deployment.	Aligning interests and equitable benefit distribution.
Implement programs to build AI skills, focusing on technical and ethical aspects.	Larger talent pool and informed citizens engaging with AI.	Overcoming educational disparities and integrating AI in curriculums.
Promote policies for sharing public sector data in open, standardized formats.	Better data availability for training diverse AI models.	Ensuring data privacy and security with transparency.
Develop regulations addressing AI's ethical implications, like data privacy and transparency.	Responsible AI development and increased public trust.	Balancing innovation with regulation to avoid stifling progress.
Fund AI R&D for climate change, healthcare, agriculture, and critical sectors.	Innovative AI applications for region-specific challenges.	Securing sustained funding and prioritizing research.
Encourage regional collaboration in AI projects to leverage strengths and share practices.	Strengthened regional cooperation on AI issues.	Navigating geopolitical tensions and aligning national policies.
Create a supportive environment for AI start-ups with incentives and mentorship.	Thriving AI start-up ecosystem boosting local innovation.	Mitigating market saturation risks and supporting SMEs.
Educate the public on AI benefits, risks, and opportunities, encouraging community involvement.	Greater public support and informed AI discourse.	Combating misinformation and fostering inclusive dialogue.
Deploy pilot AI projects in disaster management, urban planning, and environmental monitoring.	Real-world validation and strategies for broader AI implementation.	Managing pilot project scalability and transferability.

enhance drought forecasting, optimize irrigation systems, and predict El Niño-Southern Oscillation, while DL models can predict heatwave occurrences and their effects on urban environments (Pal et al., 2020). Additionally, AI applications in renewable energy can forecast solar and wind power availability, thus aiding in the efficient planning and integration of these resources into existing energy grids (Dutta et al., 2022b). These innovations not only improve predictive capabilities but also facilitate proactive measures, thereby enhancing the resilience of communities and ecosystems to climate change. As we advance, the key challenge lies in ensuring the scalability and integration of these AI solutions across different regions and sectors, considering local socio-economic and environmental contexts.

Policy recommendations and practice for enhancing AI technologies in the Asia-Pacific region

A multifaceted approach is essential to enhance the adoption and effectiveness of AI technologies in the Asia-Pacific region (Table 4). Emphasizing the importance of a robust policy framework, governments should focus on fostering innovation ecosystems conducive to AI development and deployment (Jobin et al., 2019). This includes creating incentives for research and development, promoting the exchange of knowledge and resources among countries, and facilitating the integration of AI into various sectors such as agriculture, healthcare, and environmental management (Agarwal et al., 2024). Additionally, it is crucial to address ethical considerations and establish guidelines that ensure responsible AI usage, protecting citizens' privacy and preventing misuse (Jobin et al., 2019). By aligning national strategies with regional goals, leveraging public-private partnerships, and investing in education and skill-building initiatives, the Asia-Pacific region can harness the full potential of AI to drive sustainable development and resilience against climate change (Gasser & Almeida, 2017; Agarwal et al., 2024). These efforts must be supported by continuous dialogue and collaboration among stakeholders to adapt to evolving technological landscapes and ensure inclusive growth (IPCC, 2023).

Concluding remarks

This article explores the transformative potential of AI technologies in addressing climate change challenges, particularly in the Asia-Pacific region. Detailed case studies demonstrate the efficacy of advanced AI techniques in improving climate prediction models, optimizing resource management, and enhancing disaster preparedness. Hybrid deep learning approaches for temperature prediction, heatwave forecasting, and streamflow assessment highlight significant strides in environmental modeling accuracy and reliability. AI technologies integrated into climate change adaptation strategies revolutionize traditional practices, exemplified by AI-driven models in agriculture for soil moisture monitoring and intelligent irrigation, improving water management and crop yields. Policy recommendations emphasize a collaborative approach to AI adoption. The Asia-Pacific region can lead AI-driven climate action by fostering innovation, addressing ethics, and promoting regional cooperation through public-private partnerships, education investment, and supportive policies. In conclusion, the synergistic application of AI holds immense promise for climate change mitigation and adaptation. By leveraging these technologies, we can achieve more precise climate predictions, optimize resource utilization, and enhance our capacity to respond to environmental challenges.

Acknowledgment. Support from my students Subharthi Sarkar, Aman Srivastava, and Mohd Imran Khan in preparing this article is duly acknowledged.

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