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REVIEW

Role of Artificial Intelligence in Disseminating Climate Information Services in Africa

El papel de la inteligencia artificial en la difusión de servicios de información climática en África

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ABSTRACT

Climate Information Services (CIS) are critical for enabling communities in Africa to make informed decisions in the face of climate variability and change. However, the dissemination of CIS in Africa faces significant challenges, including limited access to data, inadequate infrastructure, and language and cultural barriers. This paper explores the role of Artificial Intelligence (AI) in enhancing the dissemination of CIS across the continent. AI technologies, including machine learning, natural language processing (NLP), and big data analytics, offer promising solutions to these challenges by improving data collection, processing, and communication. Machine learning algorithms can enhance the accuracy of climate forecasts and provide tailored advisories for agriculture and disaster risk reduction. NLP can bridge the communication gap by translating complex climate data into local languages, making it accessible to rural communities. Big data analytics enables the integration of diverse datasets to generate comprehensive climate models and risk assessments. The paper also presents case studies from sub-Saharan Africa, demonstrating the practical implementation of AI in CIS, such as drought prediction, early warning systems, and agricultural advisories. These case studies highlight the potential of AI to improve the accuracy, timeliness, and relevance of climate information, particularly for vulnerable rural populations. The paper concludes with future directions, emphasizing the need for investment in infrastructure, capacity building, and policy frameworks to support the sustainable integration of AI in CIS. By leveraging AI, Africa can enhance its resilience to climate change and improve the livelihoods of its communities.

Keywords: Artificial Intelligence (AI); Big Data Analytics; Climate Information Services (CIS); Climate Resilience; Machine Learning; Natural Language Processing (NLP).

RESUMEN

Los Servicios de Información Climática (CIS, por sus siglas en inglés) son fundamentales para permitir que las comunidades en África tomen decisiones informadas frente a la variabilidad y el cambio climático. Sin embargo, la difusión de los CIS en África enfrenta desafíos significativos, como el acceso limitado a datos, infraestructura inadecuada y barreras lingüísticas y culturales. Este artículo explora el papel de la Inteligencia Artificial (IA) en la mejora de la difusión de los CIS en el continente. Las tecnologías de IA, incluyendo el aprendizaje automático, el procesamiento del lenguaje natural (NLP) y el análisis de big data, ofrecen soluciones prometedoras a estos desafíos al mejorar la recopilación, el procesamiento y la comunicación de datos. Los algoritmos de aprendizaje automático pueden aumentar la precisión de los pronósticos climáticos y proporcionar asesoramiento personalizado para la agricultura y la reducción del riesgo de desastres. El NLP puede cerrar la brecha de comunicación al traducir datos climáticos complejos a idiomas locales, haciéndolos accesibles para las comunidades rurales. El análisis de big data permite la integración de diversos conjuntos de datos para generar modelos climáticos integrales y evaluaciones de riesgos. El artículo también presenta estudios de casos del África subsahariana, demostrando la implementación práctica de la IA en los CIS, como la predicción de sequías, sistemas de alerta temprana y asesoramiento agrícola. Estos estudios de caso destacan el potencial de la IA para mejorar la precisión, la puntualidad y la relevancia de la información climática, especialmente para las poblaciones rurales vulnerables. El artículo concluye con direcciones futuras, enfatizando la necesidad de inversión en infraestructura, desarrollo de capacidades y marcos políticos para apoyar la integración sostenible de la IA en los CIS. Al aprovechar la IA, África puede mejorar su resiliencia al cambio climático y los medios de vida de sus comunidades.

Palabras clave: Inteligencia Artificial (IA); Análisis de Big Data; Servicios de Información Climática (CIS); Resiliencia Climática; Aprendizaje Automático; Procesamiento del Lenguaje Natural (NLP).

INTRODUCTION

Climate Information Services (CIS) delivers climate information to the people who need it to make decisions and can translate the latest science into the information and formats that poor farmers, fisherfolk, and the vulnerable need. In sub-Saharan Africa, climate information is particularly complex, with information necessarily dealing with variability and changes across seasons and from year to year.(1,2,3,4)

With evidence of a warming climate, projections also look to decades in the future. Even the best information does not guarantee decision-making, but people have a better chance of making adaptive decisions when they have reliable information provided on a regular or daily basis, which is why CIS are key. Nearly all climate risks are related to long-term mean changes, such as the probability of extreme events, including long-term changes in temperature and rainfall.(5,6,7)

Adaptive strategies encompass changes made in anticipation of future changes, as well as adjustments to ongoing practices to moderate the impacts of short-term variability. Ex-post or 'reactive' strategies can be detrimental both in terms of physical assets and development efforts. A comprehensive and timely CIS program is essential to operationalize a national climate change adaptation plan or strategy and to disseminate early warnings on future climate extremes such as floods, heatwaves, and cyclones. It helps different sectors to use the best available climate information for their sectoral planning and programs.(8,9,10,11)

The FSM also seeks to ensure that its CIS program complements existing CIS in four states, tailored to the needs of urban planners, rural farmers, and investors. The objective of this essay is, therefore, to explore the role of AI in enhancing CIS dissemination in African society and come up with a conceptual model that uses machine learning, deep learning, and chatbots with their potential use in earth observation in agriculture.

METHOD

Research Design

This study employed a systematic literature review approach to analyze the role of Artificial Intelligence (AI) in disseminating Climate Information Services (CIS) in Africa. The review adhered to PRISMA guidelines to ensure a structured and transparent selection process.

Literature Search Strategy

A comprehensive and systematic search was conducted to gather relevant literature for this study, encompassing a wide range of sources to ensure a robust and well-rounded review. The search included peer-reviewed journal articles, conference papers, technical reports, and case studies, all of which were accessed through prominent electronic databases and platforms. Key databases utilized for this purpose included Google Scholar, which provided a broad spectrum of academic and grey literature; Scopus and Web of Science, which offered access to high-quality, indexed research articles; IEEE Xplore, which was particularly useful for identifying studies on technological innovations and AI applications; and PubMed, which contributed valuable insights from interdisciplinary research, especially in areas intersecting with health and environmental sciences. Additionally, institutional repositories were explored to access unpublished theses, dissertations, and technical reports that provided in-depth and region-specific findings. By leveraging these diverse sources, the study ensured a thorough and inclusive review of the existing body of knowledge, capturing both global trends and localized perspectives on the topic. This multi-faceted approach not only strengthened the credibility of the research but also allowed for a more nuanced understanding of the subject matter.

Boolean Search Operators

To refine the search process, Boolean operators were used:

- AND (e.g., "Artificial Intelligence" AND "Climate Information Services" AND "Africa")
- OR (e.g., "Machine Learning" OR "Natural Language Processing" OR "Big Data Analytics")
- NOT (e.g., "Artificial Intelligence" NOT "Medical Applications")
- Truncation and Wildcards (e.g., "AI*" to capture "AI", "Artificial Intelligence")

Inclusion and Exclusion Criteria

The selection of studies was guided by the following criteria:

Table 1. Inclusion Criteria

Criteria	Description
Timeframe	Studies published between 2013-2024
Relevance	Focus on AI applications in CIS within Africa
Study Type	Empirical research, case studies, and systematic reviews
Language	Studies written in English

Table 2. Exclusion Criteria

Criteria	Description
Non-peer-reviewed	Opinion pieces, editorials, and grey literature
Irrelevant Focus	Studies unrelated to AI or CIS
Geographic Scope	Studies focusing on AI in regions outside Africa

Data Extraction and Synthesis

Relevant data were systematically extracted from the selected studies, with a particular focus on key aspects such as the types of AI technologies employed—including Machine Learning, Natural Language Processing (NLP), Big Data Analytics, and others—as well as the specific Climate Information Services (CIS) that were enhanced through these technologies. The extraction process also emphasized the challenges addressed by AI-driven solutions, such as improving the accuracy of weather forecasts, optimizing resource allocation, and bridging gaps in data accessibility. Additionally, the outcomes achieved through the implementation of AI in CIS were carefully documented, ranging from increased farmer adoption of climate-smart practices to improved agricultural productivity and resilience. The regional focus within Africa was also analyzed to understand how different contexts influenced the effectiveness and applicability of AI solutions. Following the data extraction, a thematic synthesis was conducted to identify common trends, recurring gaps, and valuable insights into the broader impact of AI on the dissemination and utilization of CIS. This synthesis not only highlighted the transformative potential of AI in enhancing climate information delivery but also underscored the need for context-specific strategies to address the unique challenges faced by diverse regions across Africa.

Study Selection Process

The study selection process was conducted using a systematic three-stage approach to ensure rigor and relevance. In the first stage, identification, relevant studies were retrieved through comprehensive search strategies designed to capture a wide range of literature. The second stage, screening, involved evaluating the titles and abstracts of the retrieved studies against predefined inclusion and exclusion criteria to determine their suitability. Finally, in the third stage, full-text review, studies that passed the screening phase underwent an in-depth assessment to confirm their eligibility for final inclusion in the analysis. This structured approach ensured that only the most pertinent and high-quality studies were selected for further examination.

Case Study Review

Specific case studies from sub-Saharan Africa were thoroughly reviewed to offer practical, real-world examples of artificial intelligence (AI) applications in Climate Information Services (CIS). These case studies highlighted both the effectiveness and the challenges associated with implementing AI-driven solutions in the region. By examining these examples, the study was able to identify successful strategies and innovative approaches that have enhanced the delivery and utilization of climate information for smallholder farmers. At the same time, the review shed light on the barriers to implementation, such as limited technological infrastructure, low digital literacy, and financial constraints, which hinder the widespread adoption of AI in CIS. These insights provide valuable lessons for policymakers, development practitioners, and researchers aiming to scale up AI-based solutions in similar contexts, while also underscoring the need for tailored interventions to address region-specific challenges.

Ethical Considerations

All sources referenced in this review were meticulously cited to uphold the highest standards of academic integrity and to provide proper attribution to the original authors and researchers. The study strictly adhered to ethical guidelines by utilizing only publicly available literature, reports, and data, ensuring transparency and accountability in the research process. By avoiding the use of restricted or confidential information, the review maintained a commitment to ethical research practices, fostering trust and credibility in its findings. This approach not only aligns with academic best practices but also ensures that the study's conclusions are grounded in accessible and verifiable information, making it a reliable resource for future research and policy discussions.

Table 3. Studies Considered in the Review

Author(s)	Year	AI Technology	CIS Focus	Key Findings
Si et al.	2018	AI-assisted Modeling	Soil Organic Carbon Pools	Effect of no-tillage with straw mulch and conventional tillage
Kassam et al.	2019	AI-assisted Modeling	Conservation Agriculture	Global spread and impact of conservation agriculture
Mukarumbwa & Taruvinga	2023	AI-assisted Modeling	Maize Cultivar Selection	Landrace and GM maize cultivar choices among rural farmers
Eyring et al.	2019	Climate Model Evaluation	Climate Simulation	Advancing climate model evaluation to next-level accuracy
Terzi et al.	2019	Multi-Risk Assessment	Climate Change Adaptation	Review of modeling approaches for adaptation
Yates et al.	2018	Ecological Modeling	Transferability of Models	Challenges in transferring ecological models
Karpov et al.	2001	Sustainable Agriculture	Agricultural Sustainability	Opportunities for sustainability in CIS countries
Duczmal et al.	2001	Agricultural Research	Technology Transfer	Research and technology transfer to rural communities
Damba et al.	2021	Climate Smart Agriculture	Climate Services Prioritization	CSA and CIS prioritization in Ghana
Csaki & Jambor	2019	Agricultural Transition	Agriculture in CEEC & CIS	Convergence and divergence in agricultural transition
Frantál et al.	2022	Socioeconomic Transformation	Energy Transitions	Socioeconomic transformation of coal-mining regions
Simpson & Jewitt	2019	Water-Energy-Food Nexus	Resource Security	Framework for achieving resource security
Ahmed et al.	2019	Climate Model Selection	GCM Ensemble Selection	Selecting multi-model ensemble for climate projections
Salman et al.	2018	Climate Model Selection	Spatiotemporal Changes	Climate models for temperature projection in Iraq
Formosa-Jordan & Ibañes	2014	Notch Signaling	Cell Fate Decisions	Enriching cell fate decisions through notch signaling
Gruber et al.	2019	Soil Moisture Data	Climate Data Records	Evolution of ESA CCI Soil Moisture climate data
Mizik et al.	2018	Agricultural Competitiveness	International Trade	Competitiveness of CIS countries in agriculture trade
Babazadeh et al.	2015	Optimization Model	Jatropha Cultivation	Location optimization for biofuel cultivation
Diluiso et al.	2021	Energy Transition	Coal Phase-out Review	Systematic review of coal phase-out case studies
Pedde et al.	2019	Environmental Scenarios	Climate Simulation	Bridging uncertainty in environmental simulations

RESULTS AND DISCUSSION

The Importance of Climate Information Services in Africa

Climate Information Services (CIS) are developing rapidly in Africa since the continent's sustainable development is largely dependent on climate variability. Agriculture, water resources, and human health are notoriously vulnerable to climate variability and change. The provision of climate data to communities can help them make informed decisions.(12,13,14) Climate information mitigates climate-related risks and vulnerability, thus empowering people to deal with climate situations and prepare themselves for possible problems. Climate Information Services helps individuals and communities plan and make decisions to protect their assets, lives, and livelihoods. Timely, relevant, and accurate CIS can aid in early warning systems for disaster risk reduction.

The development of CIS systems has to take into account the following: the sources of climate data, users and their needs and capacities, and the local context in which the data will be used. In many developing countries, governments and non-governmental organizations are the main providers of CIS. Since Africa is such a diverse continent with a variety of climates and landscapes, it has to be understood that what works in one region may not work in another.(15) The purpose of the CIS system is to disseminate the forecast, the impacts, and the related advisories. In summary, CIS needs to be both nationally and regionally driven, climate-focused and user-relevant. For this to happen, the dissemination of information is vital. In a practical sense, the key purpose of CIS concerns building resilience, particularly for those living in rural areas.

Challenges in Disseminating Climate Information in Africa

Climate information from numerical data is generated by scientific research centres stationed in urban centres or capitals, which have a good telephone line or internet connection. Quite a large number of automatic machines are in the urban centres, and they supply climate numerical data to local scientists who are involved in climate research.(16,17,18,19) These scientists often have the professional knowledge to modify raw climate data so that the information becomes relevant and of practical use. Farmers can hardly meet with scientists to receive climate forecasts. This is because possible contacts with these scientists are further hindered by the long distances and the poor transportation facilities in the rural areas of Africa.

With the availability of data, infrastructures, and technical know-how, scientists have been providing climate information to the public for decades. How they do this is through broadcast radio, emails, and presentations, and these are done with languages and terms that farmers don't understand. Until now, no single aspect of climate information services has taken into account sustainability and adaptation of the community to the changing climate.(20,21,22,23) The problems associated with the communication of climate information services to the public are: limited official language used for the presentation of climate data and uncertainties – the use of probability and percentages that the local community does not comprehend; lack of trust in climate information supplied; the challenge to make climate information available to all; the attitude to sell climate data and information; absence of cooperation; and special terminologies used.

Dissemination and effective communication of data and information to final users do not reach the general public, and this contributes to inequality in society. As such, early warning systems based on improved climate information services are a key foundation for the development of the community. Because of this, the integration of traditional knowledge and scientific knowledge is a prerequisite to facilitate the process of dissemination of this information.(24,25,26) It further follows that a database for the long term will strongly count as a practical tool for the prevention of natural disasters.

The availability of long-term data will be a basis for creating a climate information bank that could serve as a reference point regarding the periodic behaviour of the local climate. Some barriers to be overcome consist of a lack of technology, old-fashioned attitudes, and language barriers. Some actions required today should include the collaboration of various projects at a local scale, sharing resources for exchanging information and experiences, and educating youngsters at the grassroots level. The willingness and capacity to research where scientific studies have taken place are essential. To build resilience, the knowledge of past climate episodes and the long-term behaviour of the local system are prerequisites and must be prioritized.

Limited Access to Data

Limited access to data pertains to various types of stakeholders in climate services for Africa. Much of the climate knowledge is empirically and theoretically grounded in data, especially time series data reflecting some type of phenomena interaction and outcomes over time. These data can be used to describe, explain, predict, and inform on phenomena, providing a major evidence-based component on which the credibility of any information, knowledge, or guidance rests.(24,27,28,29) Generally, the utility of information is determined through the sufficiency and quality of data upon which it is based. Data is so important that where no new data is available, scientists integrate existing artificial data with new observed data to inform future simulations and forecasts. Limited data means limited ability to simulate or forecast, or this simulation or forecast will be relatively high in uncertainty.

National meteorological and hydrological services, as well as their parent organizations, often operate in a data collection and monitoring environment of insufficient investment and multiple systemic challenges. Yet, the scarcity of data of the right kind and in a usable format is a barrier for many stakeholders – at any level – to access timely downscaled, actionable climate information commensurate with the decisions they need to make to adapt to ongoing climate variability and change. Data repositories are scattered across various institutions and are generally fragmented. No standard data protocols exist across agency or institutional boundaries.

Datasets are owned by other entities, mainly MESCs and governments, while the major repositories are owned and managed by international centres. This makes much of the data inaccessible on a global level to most of the stakeholders, including the data owners themselves and the developed countries, which have contributed substantially to some of the datasets.[30,31,32] They are also being used for expertise and technical relevance, and therefore participation in the management of the global observing systems. Agencies will therefore prioritize availability to such contributing countries and other users, such as developed countries or developed country institutions. These limitations mean that information cannot be made available to sub-Saharan and other countries across the globe, where agencies will therefore be working in a vacuum as far as climate simulation and forecasts are concerned.

Lack of Infrastructure

One of the most formidable challenges in disseminating climate information services in the African context is the lack of technological infrastructure needed to support their functionality. In many parts of Africa, where there are no communication systems, it remains a challenge to effectively disseminate and translate scientific climate information to African farmers, who reside in rural areas where there are limited communication systems.[33,34,35,36] In Africa, mobile connectivity is often the only link between many climate information service providers and the users. Therefore, the absence of consistent and reliable communication infrastructure is a critical bottleneck in the utility of climate and weather forecast information.

The inability to get as much data from hydrological and meteorological stations could be attributed to insufficient equipment, inefficient data management capabilities, and less skilled personnel. Thus, currently, insufficient information can be used to evaluate the vulnerability of water resources. Inappropriate and poor ICT infrastructure means that the operational use of web-based climate tools will exclude those at maximum risk. In the instance of requiring hydrological and meteorological data, important decisions are sometimes made, but these face shortcomings.

Poor telecommunications and inadequate infrastructure, including roads and transportation systems, hinder the flow of information to vulnerable people, especially in terms of getting them the climate change information that might save their lives. And sometimes, although technologically advanced systems exist, the users don't have access to them. Sometimes the people in the remote areas of Africa, where climate change has hit particularly hard and is threatening traditional farming methods, have no access to basic resources such as electricity or telephone lines. Most climate monitoring infrastructure will necessarily focus on educating people in urban centers and the wealthy while bypassing those who need it most.[33,37,38] There is also a transport issue. To pass information to people who are isolated in local rural areas and lack access to hire, the roads, trains, and buses are often in bad shape.

Therefore, if appropriate infrastructure is not available to support these climate services, it will go without use and fail to evaluate benefits. Investing in infrastructure, including telecoms, weather and groundwater predictions, data collection, storage, and irrigation incentives should be prioritized. In particular, now, to support climate services and irrigation scheduling to address potential impacts on water resources, the proposed public-private partnership should be extended in several areas of Africa to support infrastructure development that can help sustainability goals, but sustainability financial reserves are still limited.

Language and Cultural Barriers

Language and cultural differences often present a significant barrier in the communication and dissemination strategies of climate information throughout the African continent due to the incomprehensible diversity of its linguistic fabric, which is constituted of over 17 % of the world's languages spoken by less than 12 % of the world's population. As a result, the exposure to the prevailing lexicon and jargon of both technical and meteorological information translated into people's mother tongues, however, is a valid communicative source that very few in the global South have access to. Besides the technical aspects of language, the use of jargon, and the choice of weather discourses we opt to communicate often leaves a lot to be desired. The choice, which is often culturally drenched, remains a barrier to effectively sensing the impact of the messages we communicate, whether through the weather or climate systems.

Cultural barriers influence how the people in distinct communities perceive and, therefore, interpret the use of weather data and other climate change projections. This might have a huge role to play in identification strategies towards achieving a weather- and water-informed continent. It remains a common practice that very little, if any, local content is included in both spoken and visual messages at all times; but when it happens, it rather leaves a lot to be desired in getting the local resonance.[39,40,41] A communication message with a local dialect, accent, and content is very important. A weather forecast service in a localized dialect could be tricky to use in neighbouring areas if the accents and pronunciation do not resonate with the people. Therefore, for neighbouring regions, custom messages based on the local dialect should be aired to get local resonance and enthusiasm. In patiently illustrating these points, this paper reiterates the need and importance of developing a multilingual crowd-speaking communication strategy that targets diverse linguistic communities on the continent. We also call for localization in providing either early warnings or advisories. Local community participation and using a people-based homegrown approach could pay off when it comes to creating effective communication. Therefore, the production of any climate products should consider that effective communication adds value to the recipients. In essence, more productive climate products would be co-produced by local community representatives.

Artificial Intelligence Applications for Climate Information Services

Artificial intelligence (AI) has several applications designed to improve climate information services. Firstly, AI can optimize data collection processes to generate surpluses in the quantity and quality of data. Changes in the quality, density, and availability of digital environmental, socio-economic, and political datasets are creating new opportunities for researchers. Improvements in AI-driven predictive modelling and data preprocessing continue to facilitate more accurate forecasts for longer horizons. AI can be used to uncover the relationships between the underlying climate system and its primary drivers, highlight high-impact rare events, and interpret their dynamics. In a training phase, complex machine learning algorithms can learn typical patterns from extensive historical data.[42,43,44,45] In a real-time forecasting phase, these algorithms can be used to interpret current observations and assess which historical patterns are unfolding, and those that are most likely to.

Existing machine learning techniques, which are often referred to as deep learning or neural networks, can be used to more systematically identify such relationships across large ensemble simulation datasets or observational, reanalysis, survey, or remotely collected satellite image data. Recent research demonstrated the ability of existing machine learning frameworks to feed in vast ensemble datasets forecast from global climate models or even geological reanalysis datasets instead of high-resolution empirical observations to assist real-time climate-informed decision-making. AI also enables new climate information services that provide valuable counselling on large datasets driven by digital innovation.

Future platforms based on AI could autonomously dispatch significantly more up-to-date and region-specific climate forecasts, alerts, and recommendations to end users even more quickly than it would take to download a traditional seasonal forecast via the interface used for historical climate service. AI-designed platforms could majorly advance the dissemination of climate forecasts to end users and decision-makers by improving the quality, quantity, regularity, immediacy, relevance, and engagement of their forecasts.[46,47,48,49] Future AI projects should pivot toward developing an all-encompassing hybrid climate information services system that unites the communities and capabilities of meteorological professionals, climate policy consultants, and AI-driven digital weather platforms. New ventures should be collaborative, ensuring that relevant institutional, financial, and structural support is available for AI-driven digital weather projects. These new projects should include on-the-ground users not always interconnected via the internet, who could also use more autonomous offline AI technologies.

Machine Learning Algorithms

Machine learning algorithms, along with other digital advancements and automation, have the potential to transform CIS. Improved machine learning algorithms, coupled with increasingly powerful computing, have enhanced the analytical extraction of data and taught computers to recognize patterns and trends in very large quantitative datasets that are impossible to extract by human experts. The ability of machine learning technology to learn and make predictions based on those inputs provides new levels of predictability that aid in the refinement of climate and weather forecasts, which underpin CIS.[50,51,52,53,54] The new capabilities in improving volumetric prediction, which is ‘average,’ but erroneous prediction, can further be broken down into more ‘correct’ and more incorrect attributes. The technology has been rooted in mathematics and statistics and has been used in various applications such as weather, botany, hydro-modeling for agricultural production, and water resources management.

The value of machine learning in diverse agricultural areas can be illustrated through its various applications. This includes using the technology to make weather predictions, analyze weather anomalies and extremes, predict future climate, and then provide advisories. In particular, efforts are made to forecast droughts, pests, yield, price, supply, quality, trade, and insurance. The technology provides insights into what we know, what we do, and what the outcomes of our actions may be. Impact assessment can be extended to anticipate plans and field impact modelling via biophysical and socio-economic modelling. These insightful services may have

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two modes of service provision linked to the forecast—nowcasting and post-casting. The importance of the service is to provide customized advisories, alerts, and impact assessments developed based on these insights.

Continual learning is a key premise of machine learning, and this can be used to challenge the operation of technology, which cannot reclaim early learning. Over time, models improve learning with additional data that is incorporated into the learning model. This stands in contrast to rule-based technology, whether the rule in use is continuously updated or not. Rather than maintaining a fixed line, this technology often learns to adapt more efficiently when more data is fed to it—grasping new inputs, shaping, and designing.[55,56,57,58] The greater the quality and diversity of data, the better the predictive value that can be extracted. The pandemic highlighted the importance of data diversity which can improve the learning and interpretation of the overall picture.

Challenges facing the integration of machine learning in CIS provision are linked to data challenges, technological challenges, social and governance challenges, and utility appreciation. The capacity of machine learning to assist in analyzing voluminous datasets to discern trends and patterns is a powerful tool for climate science. The ability to learn and make predictions based on those inputs provides new levels of predictability that can help in climate forecast refinement. More importantly, machine learning can add significant value when combined with observations—be they physical observations from either an in-situ ground observation system or from the dense datasets available from synoptic and AGROMET stations, and satellites.[55,59,60]

Thus, machine learning is not going to work in a vacuum. Of course, scaling up weather data collection is required to provide better and larger databases for training models. Additionally, climatic signals in the data can be perturbed using machine learning to achieve an in-depth analysis of the CIS requirements.

Natural Language Processing

Natural Language Processing (NLP) holds great promise as an AI application that advances the dissemination of climate information services. NLP can translate climate and weather data collected from various sensors, instruments, and databases, helping data experts obtain information that is relevant to specific individuals and communities. In so doing, NLP helps bridge the data-information gap between climate experts and the communities located in every corner of Africa by translating existing messages on current and future climate information into various languages.[61,62,63,64,65,66] By speaking local languages, we mean that climate experts translate complex technical climate language into an accessible format that can be understood and used by local individuals and their communities, eventually enabling them to take informed action. Platforms that present climate information services using NLP provide varying degrees of complexity.

There are simple, web-based chatbots that can automatically provide pre-recorded climate updates based on user queries or based on system-initiated requests about the current weather states. More complex applications employ NLP and AI techniques in virtual personal assistants. These virtual assistants capture, interpret, and act on user intentions and requirements, among them climate services requirements. Such a platform can send the latest weather information at specific user-designated times per day or give 'how to' advice to farmers. Additionally, NLP applications have potential uses in gathering public sentiment by analyzing social media content and informal communications. This profile of a person's climate attitudes and perceptions can help shape tailored communication messages from traditional media just as messages are crafted based on social listening data.

Local cultures and value systems heavily influence public attitudes towards climate change. Given that language is intricately tied to these social dynamics and cultural values, it is incumbent upon NLP applications to present climate information using a 'clear' language context and to be sensitive to and respectful of local languages and cultures. The ultimate goal of using NLP with AI lies in the creation of climate information platforms that engage and sustain users' attention.[67,68,69,70,71] A convincing use case is a platform that integrates NLP and personalized machine learning models to engage in two-way communication with a farmer. Such a platform encourages a farmer to actively ask questions and to make inferences about their own farm-specific climate risk.

When professionally designed, AI applications work towards reduced reaction time in image, voice, and text recognition and can perform all these tasks simultaneously, such as facial recognition with individual weather forecasts and a voice notification system on predicted rainfall. This broader scope of AI applications can help disseminate continuous weather data, climate services, and other agro-advisory services at minimal cost and effort.

Big Data Analytics

The huge datasets originating from multi- and transdisciplinary research, citizen science, and social media sources offer immense opportunities for researchers to closely understand and offer tailored solutions to their users' needs. As a result of the accumulation of large data, Big Data Analytics offers the use of very large, complex multi-modal and multi-dimensional data.[67,72,73,74] Through this, it enables the tracking and analysis of intricate interrelations in real-time, providing in-depth insights and focused actions. By integrating climate and weather data with information from a wide variety of fields—politics, demography, economy, environment, or health—it is possible to generate more inclusive and complete climatologies, models, risk assessments, and policy responses.

Current analytics tools support the visual depiction of established and latent trends and relationships in large datasets, irrespective of the volume, variety, and speed of data collection. This facility can be extremely useful in reaching different groups of people or data users who communicate their comfort capacity to understand climate data. While there is huge potential for using currently available large data to develop new CI services across Africa, there are some ethical considerations for using large data. These considerations must always include aspects of privacy, moral implications, and the impact of data sharing with researchers.

The involvement of data owners or policymakers in big data gathering and management through a participatory approach significantly increases the potential for the development and use of formal and informal CI services on longer timescales. Open and frequent sharing of weather data is, however, critical for understanding the implications and effects of climate change in many different ecosystems and social systems across the continent. This is particularly necessary given the Snowball Earth hypothesis—the vast majority of large data studies use historic weather data to identify, understand, and assess contemporary trends and developments. Sharing data between research organizations, government departments, and the private sector will undoubtedly greatly enhance the development of CI services in Africa.

Collaborative research has the potential for the expansion of big data leads across the continent and in other areas where data is freely available. As a result, a range of CI products with wide applicability across Africa can be developed.[68] These CI services are important given the increasing need for adaptation to climate change in rural areas and the significant and emblematic onset of climate change. To begin to build resilience and promote autonomous adaptation in affected communities, cooperation between governments, non-governmental organizations, and communities affected by climate change is crucial, as the need for blind spots, CI services, and support increases.

Case Studies of AI Implementation in Climate Information Services

The case studies presented in this section provide evidence of how AI systems have been implemented in sub-Saharan Africa to enhance meteorological data integrity, accuracy, and timeliness, impacting livelihoods, development, and supply chains for a range of communities and stakeholders: AI-Based Agronomic Weather Forecast in Informal Settlements in Africa, Enhancing the Value of Seasonal Streamflow Forecast Using AI, The Use of AI to Generate and Disseminate Africa’s Seasonal Climate Prediction Model, Development and Dissemination of AI-Enhanced Seasonal Forecast for Agriculture, Seasonal Streamflow Forecasting Using Downscaling with Machine Learning, Evaluating Solutions for Climate-Sensitive Societies Using a Commercial Weather Data Forecast with AI Analytics, Building and Using Earth Observation and AI-Based Tools, Climate Forecast Models, and Detailed Hydro-Meteorological Modeling Linked to Sector Models to Support Climate Early Warning and Resilience Planning in Kenya, Enhancing Weather Forecasting through Indigenous and Scientific Knowledge, AI-Driven Enhanced Weather Information for Health.

The use of AI in climate information services discussed in this collection ranges from applying information communication technologies for aggregating data to co-designing methodologies with local communities for tailoring forecasts and communicating these forecasts. Governance mechanisms have also been integral for many in facilitating the strengthening of inter-institutional collaborations at the local and regional level and in setting up and incentivising community-led data collection for machine and deep learning technologies. Practical implementation methodologies include using AI to provide unique solutions to environmental challenges within a given sub-region: particular regions have implemented drought and flood predictions, extremes forecasting, early warning systems for flash storms, and agricultural, hydrological, irrigational, epidemiological, and energy management.

Each case study has been assisted by local partnerships that incentivize and support the ongoing development of the service. Challenges faced include ensuring access to high-quality data and the data’s acceptability by the local community. Comparing methods for model downscaling is also crucial to ensure that the cost associated with using AI is worth the improvement in broadcasting. Ethical considerations around the use and development of such technologies are highlighted. Each of the processes in the case studies undertaken has a demonstrated impact, particularly in rural or underdeveloped areas. These areas make up the typical targeted recipient or customer base of a climate information service, and so the studies can serve as a case-in-point example of the type of resulting impacts other communities and industries might expect from a machine learning-centred development activity.

Future Directions and Opportunities

The future of CFN is shrouded in mystery, but it does look bright and promising. Perhaps the most prevalent prediction for the future is the evolutionary advancement of AI technology, mobile devices, communication tools, and technological usefulness. Current research indicates that in the future, data will increase exponentially, especially with the use of mobile devices. Future technological advancement is moving in the direction of or will possibly yield the following: AI-to-AI workflows, HPC, mobile HPC, comprehensive and global use of 5G networks, 6G communication systems, AI inference at the edge computing, and memory-driven computing, which will act as the next generation memory. The future of AI and cloud computing seems, indeed, to be rather bright.

It is hypothesized that AI and cloud computing will revolutionize CI dissemination. Since the entire data science is gradually transforming into a stage-dependent AI, it is obvious that CI dissemination using AI tools is a future that is already on the edge and about to take place. It is expected that collaboration between private technology industries and public and community climates would expand in the nearest future. Big industries are investing heavily in innovation between both technology and climate data for sustainable results. Governments, especially in Africa, will invest a lot in infrastructure development for AI tools. It is obvious that for equal and sustainable development in AI activities, nations will need to invest in: transportation infrastructure for rapid dissemination tools and hardware across remote places in Africa; continuous investment in energy infrastructure as AI needs huge energy resources; training and capacity building for more communities and indigenous people on how to use such tools. Moreover, legal and policy frameworks are likely to be improved or updated to incorporate AI technologies in societal settings for long-term engagements.

CONCLUSION

This study explored the role of Artificial Intelligence (AI) in enhancing the dissemination of Climate Information Services (CIS) in Africa, addressing key challenges such as limited data access, inadequate infrastructure, and language barriers. By leveraging AI technologies—including machine learning, natural language processing (NLP), and big data analytics—the research demonstrated how AI can improve the accuracy, timeliness, and accessibility of climate information. Case studies from sub-Saharan Africa illustrated the practical applications of AI in areas such as drought prediction, early warning systems, and agricultural advisories, showcasing its potential to empower rural communities and improve resilience to climate variability. The findings underscore the importance of tailoring AI-driven CIS to local contexts, ensuring cultural and linguistic relevance, and fostering collaboration between stakeholders. However, realizing the full potential of AI in CIS requires significant investments in infrastructure, capacity building, and policy frameworks. By addressing these barriers, AI-driven CIS can play a pivotal role in building climate resilience, protecting livelihoods, and supporting sustainable development across Africa. The study concludes that AI offers transformative opportunities for enhancing climate information dissemination, but its success depends on inclusive and context-specific implementation strategies.

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