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**Angaben zur Veröffentlichung / Publication details:**

Malekela, Asnath Alberto, Sifuni Lusiru, Harison K. Kipkulei, Prisca Kimaro, Michel Kabirigi, Stefan Sieber, and Masahiro Ryo. 2026. "Generative artificial intelligence for climate information services." *Discover Applied Sciences* 8 (6): 684. https://doi.org/10.1007/s42452-026-08943-0.

Discover Applied Sciences

REVIEW

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# Generative artificial intelligence for climate information services

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**Abstract**

The escalating global climate crisis, marked by rising temperatures and extreme weather events, demands a fundamental shift in how Climate Information Services (CIS) are delivered to enhance climate resilience. Around the world, many local communities lack access to relevant climate information due to ineffective communication and integration channels. Most research and efforts related to CIS focus on enhancing scientific prediction and observation systems, rather than making these systems user-friendly by involving communities as end users. Generative Artificial Intelligence (GenAI), especially its large language models (LLMs), has emerged as a transformative technology with promising applications in CIS. While individual studies show potential, their findings are fragmented. We conduct a systematic literature review (2022–2025) following PRISMA guidelines to identify relevant studies on GenAI, particularly LLMs such as ChatGPT, in climate-related contexts. The chosen timeframe is based on ChatGPT's 2022 release. After a thorough search, we found 281 articles; after screening, 19 were chosen for detailed analysis. The results indicate that implementing GenAI in CIS is vital for improving early warning systems, fostering community engagement, generating climate data, enhancing weather forecasts, and mapping local climate vulnerabilities. However, few studies examine user experience, which is essential for building trust and encouraging widespread adoption. Therefore, inclusive, bottom-up approaches should be adopted to promote community participation in deploying GenAI technologies for CIS in local settings. Despite its promising potential, GenAI also poses challenges, including a lack of transparency (black-box systems), misinformation, and digital accessibility issues. Therefore, the initiation and deployment of GenAI models should also consider their associated challenges.

**Keywords** Generative artificial intelligence (GenAI), Large language models (LLMs), ChatGPT, Climate change (CC), Climate information services (CIS)

## 1 Introduction

The world is witnessing unprecedented advancements in generative artificial intelligence (GenAI). GenAI technology can create unstructured data, including text, image, audio, and video files. Although the field of GenAI has been developing for decades, a wave of critical innovation occurred in 2022 when OpenAI released ChatGPT. GenAI complements emerging algorithms and transformative technologies with unique capabilities among artificial intelligence technologies [15, 40, 56]. For instance, GenAI is expected to generate novel, realistic data that simulate the characteristics of real data, thereby constituting a novel form of simulation study [12, 47]. GenAI, particularly its large language models (LLMs) such as ChatGPT, can play a vital role across various scientific domains [15]. LLMs can generate human-like text, engage in conversations, write code, translate between languages, and produce creative writing from natural language.

The rise of GenAI as a powerful tool supports efforts to address climate-related challenges by enabling the development of innovative adaptation strategies and early warning systems [8, 22, 26]. Given current environmental uncertainties, involving communities in GenAI technologies is essential. Climate change and variability threaten humanity, with ongoing impacts on the planet and its inhabitants [19–21, 45]. Therefore, this underscores the importance of incorporating digital technologies—such as GenAI models—into climate mitigation and adaptation strategies, including CIS.

CIS are the processes and practices for establishing and using climate data, information, and knowledge to support decision-making. The launch of the Global Framework for Climate Services (GFCS) in 2009 marked the beginning of increased demand for the dissemination of climate information to communities [49, 50]. CIS provides early warning and timely information that can be harnessed to improve management and mitigation of climate risks. The systems are essential across various livelihood domains,for example, agricultural communities can better anticipate and manage hazards associated with a changing, unpredictable climate [11, 57]. CIS are designed to provide timely, accurate, and user-tailored climate information essential for decision-making on climate change adaptation, mitigation, and disaster risk reduction [17].

CIS can operate across multiple scales, ranging from short-term weather forecasts to long-term climate projections, and includes sectors such as agriculture, water management, public health, and infrastructure planning [59]. They involve a complex interplay of data collection, processing, analysis, product development, and dissemination. Often, emphasis is placed on the co-creation of knowledge and the co-production of services with end users to ensure relevance and usability [55]. Providing CIS requires effective mechanisms between the recipient and its provider [13]. Although Chavula and Kayusi [13] address the role of GenAI in climate communication, empirical evaluation involving local communities remains limited. Most local communities lack effective channels for communication and integration with CIS. Meanwhile, most studies and efforts on CIS focus on improving scientific prediction and observation systems rather than enhancing usability mechanisms to support appropriate decision-making. There is a need to develop mechanisms that engage communities as end users of climate information to enhance resilience [10, 25, 48]. GenAI can improve CIS, similar to its applications in health services [14, 23, 43], teaching and learning [6, 29, 41], business operations [32, 33], and agriculture [27, 35]. GenAI is already used in climate change research, from studies of global warming [9] and climate impacts [38] to climate mitigation strategies [35, 40].

Recent applications of GenAI in CIS highlight its increasing importance and emphasize the need for a systematic review. Previous research shows that GenAI can translate complex climate forecasts into clear, localized narratives for farmers and vulnerable groups, helping to overcome ongoing communication and language barriers [8, 13, 22, 26]. Likewise, GenAI-based systems have been used to integrate diverse climate datasets for disaster response and early warning, aiming to enhance the speed and relevance of decision-making [9, 36, 39]. Despite these advances, the literature remains fragmented, mainly technology-focused, and inconsistent in addressing user trust, usability, and real-world effects. Therefore, a systematic review is needed to synthesize the evidence, compare research approaches, and identify key gaps for future study and application. While GenAI encompasses a wide range of models, this work focuses primarily on LLMs, particularly ChatGPT, given their current prominence and rapid adoption across CIS-related domains. Other GenAI models, such as diffusion models and generative adversarial networks (GANs), are referenced selectively to provide contextual grounding, but are not the primary analytical focus of this study. Several LLMs have emerged recently, but this review focuses on ChatGPT because of its early 2022 release and its dominant role in both academic and practical contexts. Consequently, ChatGPT currently represents the most empirically and conceptually documented LLM within the GenAI literature compared to other LLMs such as Gemini, DeepSeek, and Bard. The study focuses on two specific goals, which include:

i. Assessing the potential of GenAI for CIS; and
ii. Examining the limitations of deploying GenAI for CIS.

## 2 Methodology

This study adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [30]. The search approach was conducted using the Scopus database. Scopus was selected as a primary database because it offers comprehensive multidisciplinary coverage, robust indexing standards, and advanced filtering tools that are well aligned with established guidelines for conducting systematic reviews. Despite the potential contributions of other databases, such as ArXiv, Web of Science, and IEEE Xplore, to GenAI research, they were excluded to maintain consistency in the inclusion of peer-reviewed, quality-controlled literature. This choice may limit coverage of emerging GenAI studies, particularly those shared through preprint repositories. However, excluding these databases did not diminish the review's analytical rigor, as the selected sources sufficiently capture the main conceptual and empirical trends relevant to GenAI in this field. Therefore, this limitation is acknowledged as a methodological constraint, and future research is encouraged to incorporate multiple databases to provide a broader, more comprehensive view of the GenAI landscape. The keywords used in the search for data were ("generative artificial intelligence" OR "generative AI" OR "GenAI" OR "large language models “OR "ChatGPT") AND ("climate change" OR "climate information services"). The search initially identified 281 results. After removing duplicates and non-relevant titles/abstracts, 132 articles were screened in full, of which 19 met all inclusion criteria, as shown in Fig. 1. This review examines studies published between 2022 and 2025, a period characterized by rapid growth in LLM-based applications following the release of ChatGPT. While GenAI approaches relevant to CIS predate 2022, this timeframe was selected to capture recent, consolidated research reflecting contemporary GenAI capabilities and use cases. Earlier generative approaches are therefore not fully covered, and future reviews may extend this temporal scope to provide a more comprehensive historical perspective. Additionally, the search was limited to

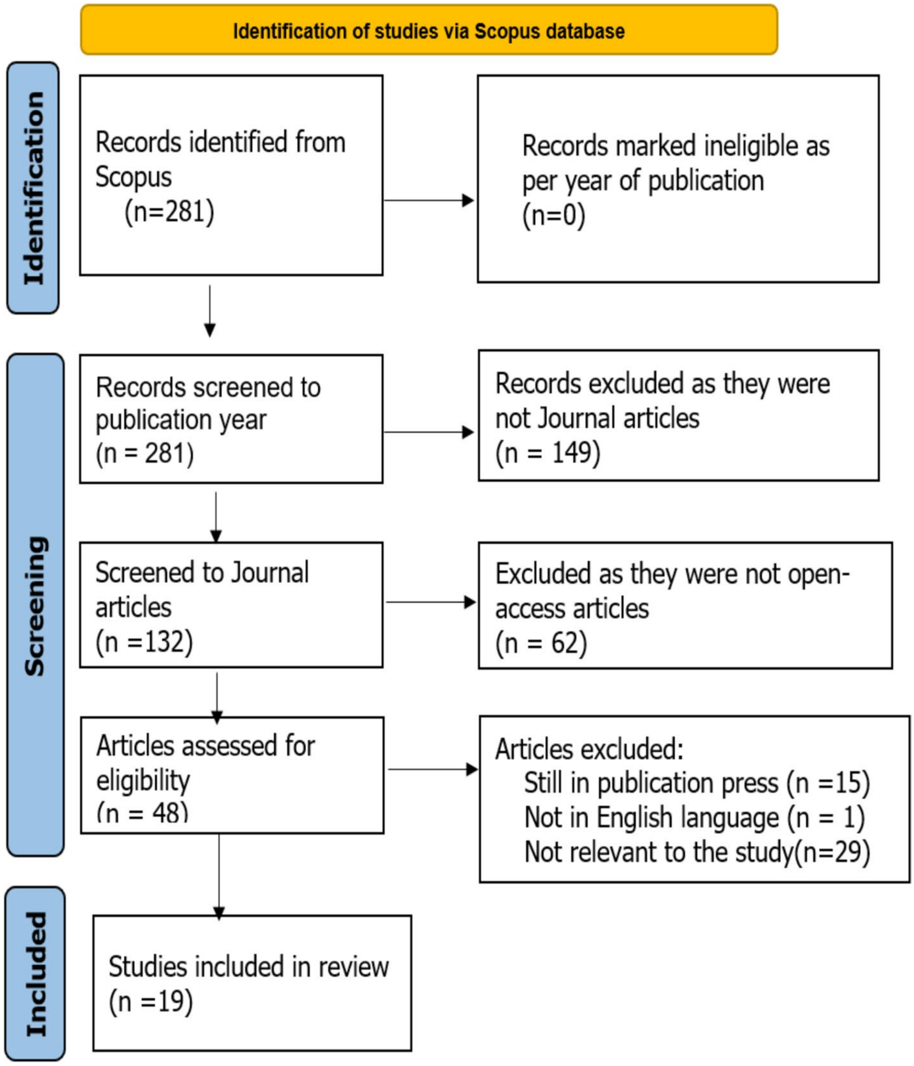


**Fig. 1** Prisma selection of included and excluded studies. Source: Adopted from Page et al. [30]

**Table 1** Inclusion and exclusion criteria

| Criteria | Inclusion | Exclusion |
|---|---|---|
| Focus of the articles | Articles focusing on GenAI, LLM, climate change, CIS and ChatGPT | Articles not focusing on GenAI, LLM, climate change, CIS and ChatGPT |
| Year of publication | Articles published between 2022 and 2025 | Articles published before 2022 |
| Publication type | Articles that are peer-reviewed | Conference proceedings, books, monographs |
| Publication stage | Articles with completely published information | Articles in press |
| Language | Articles written in English | Articles written in other languages |
| Accessibility | Articles that are open access only | Articles with limited accessibility |

open-access articles. This enabled researchers to retrieve full articles rather than relying on abstracts, as with non-open-access articles. Table 1 details our predefined inclusion and exclusion criteria, which were applied to peer-reviewed journal articles published between 2022 and 2025, written in English, and available as open access. The screening process for the selected articles adhered to the PRISMA 2020 flowchart, comprising three stages: identification, screening, and application of inclusion and exclusion criteria.

**Table 2** Applications of GenAI on CIS enhancements

| Author(s) | GenAI used | Focus | Key findings |
|---|---|---|---|
| Storey et al. [47] | LLM (ChatGPT) | GenAI and LLMs in information systems | ChatGPT enables human-like interaction and predictive support but also raises risks of bias and misinformation |
| Biswas [9] | LLM (ChatGPT) | Climate projection | LLMs support climate data analysis, interpretation, and scenario generation |
| Chavula and Kayusi [13] | NLP-based AI/LLMs | CIS dissemination | AI and NLP reduce language and accessibility barriers in CIS dissemination |
| Raj et al. [34] | Multi-modal GenAI (LLMs, CNNs) | Disaster assessment and management | GenAI enables multi-modal damage assessment across text, image, audio, and video |
| Rao and Ranganath [36] | LLMs | Agricultural climate adaptation | LLMs enhance data processing and communication in agriculture |
| Rane et al. [35] | LLMs (ChatGPT, Bard) | Climate mitigation | LLMs enhance communication, policy optimization, and decision-making |
| Sai et al. [42] | LLM-based chatbots (e.g., KissanGPT) | Agricultural advisory services | GenAI supports prediction, disease identification, and knowledge dissemination |
| Hsu et al. [18] | AI systems (human-centered AI) | Community-engaged AI design | Emphasizes participatory AI development with local communities |
| Keim et al. [24] | Not GenAI-specific | Extreme weather vulnerability | Links socio-economic status with exposure to extreme events |
| Schulte et al. [44] | Not GenAI-specific | Climate hazards and health | Highlights health impacts of extreme weather events |
| Zhuang and Duraisamy [62] | Diffusion model (LaDCast) | Weather forecasting | LaDCast outperforms traditional NWP for rare extreme events |
| Asperti et al. [5] | Diffusion models (GED) | Precipitation nowcasting | Diffusion models generate diverse short-term scenarios |
| Alet et al. [2] | Forecast Generative Network (FGN) | Probabilistic weather forecasting | FGN improves efficiency and CRPS performance |
| Bhattacharjee and Gugliani [7] | GANs | Climate prediction | GANs effectively impute missing wind data |
| Price and Rasp [31] | GAN (CorrectorGAN) | Weather forecasting | Improves reliability of extreme rainfall prediction |
| Toplic [51] | LLM-based chatbots | Climate adaptation | Chatbots support adaptation among vulnerable communities |
| Reichstein et al. [39] | Integrated AI systems | Early warning systems | AI enhances early warning capabilities for climate hazards |

The 19 scrutinized articles examine various aspects of GenAI and climate-related issues, as summarized in Table 2.

We performed a qualitative content analysis of the selected articles. Key information extracted included the GenAI application domain, the climate service context, and any reported benefits or challenges. We then clustered the findings into major themes corresponding to different CIS enhancement areas. This formed the basis for identifying GenAI applications in micro-level climatic vulnerability mapping, community integration, extreme weather event forecasting, climate data generation, and early warning system enhancement, as described in Sect. 3 of this paper.

The studies summarized in Table 2 reveal a clear predominance of technology-centered approaches in GenAI research on CIS, with a strong focus on LLMs, diffusion models, and GAN-based applications for climate forecasting, disaster assessment, and data generation. This stream of work primarily emphasizes model performance, computational efficiency, and automated climate data processing, frequently with limited attention to end-user engagement or contextual use [2, 5, 31, 34, 62]. By contrast, community-centered studies, though comparatively scarce, foreground user needs, contextual relevance, and the socio-institutional processes through which climate information is interpreted and acted upon, particularly within local and agricultural settings [13, 18, 35, 42, 51]. From a methodological perspective, conceptual and framework-oriented contributions dominate the literature, while empirically grounded studies involving real-world deployment, participatory design, or systematic user evaluation remain limited [9, 24, 39, 47]. Consequently, substantive evidence gaps persist regarding user trust, usability, and impact assessment, constraining the robust evaluation of how GenAI-enabled CIS functions in practice. Addressing these limitations necessitates a more deliberate integration of technical innovation with rigorous, user-centered empirical validation.

## 3 Usefulness of GenAI on climate information services to the local communities

Developments in the domain of GenAI have led to substantial innovations that are applicable and useful across various human spheres. The application of GenAI and its subfield of LLMs specifically ChatGPT, since its emergence in 2022 has largely focused on various aspects, including health services, business operations, as well as teaching and learning processes [6, 14, 29, 32, 43]. LLMs are expected to bring positive changes by enabling local communities to obtain timely climate information, processed in plain language and tailored to their locations. Over the years, communities have been depending on climate information provided by meteorological agencies. However, climate service providers are mostly located in urban areas, limiting access for rural communities. With the development of ChatGPT and its ability to generate text using natural language processing (NLP), communities can access information through chatbots. This can enhance communities' resilience to climate change [9, 35, 53]. Based on the present study, GenAI is identified as having the potential to contribute to multiple aspects related to CIS, as discussed in the subsequent sections.

### 3.1 Micro-level climate vulnerability mapping

Micro-level vulnerability assessment encompasses identifying significant exposures, sensitivities, and adaptive capacities to recognize the likely consequences of climate change [21]. Mapping vulnerability status to inform decisions is essential for enhancing climate resilience. Micro-level mapping is often hindered by a lack of context-based climate data from the local areas, especially in developing countries [13]. GenAI can synthesize realistic, high-resolution climate data, including temperature, precipitation, sea-level rise, floods, and wildfires, at local scales [34, 36]. This is especially important for regions where critical information needed to advance development and sustainability remains scarce at the local level.

GenAI applications, such as Chatbots, can integrate with the intimate knowledge and life experiences through a co-creation approach. This can bridge the gap between scientific data and the local contexts of the most vulnerable communities affected by climate change, thereby facilitating the dissemination of climate information [35]. Instead of simply providing generic, top-down information, Chatbots can be trained on a combination of scientific data and qualitative, lived-experience data collected directly from communities [18, 34]. Conventional climate vulnerability assessments rely primarily on comprehensive models and large datasets, which are often unable to capture the micro-level experiences of diverse populations, particularly those representing marginalized communities [34]. GenAI incorporates techniques from machine learning, deep neural networks, and natural language processing (NLP) to learn patterns and traits from large-scale datasets. These generate outputs that closely resemble human-generated content [12, 42]. The output can be generated in different modalities, such as text, audio, and video, each tailored to specific user requirements and prompts, thereby enhancing community decision-making at the local level [42, 47]. While Storey et al. [47] provide a comprehensive socio-technical framework that effectively bridges technical perspectives on GenAI, it lacks empirical grounding and case examples to demonstrate the real-world application of GenAI. Some practical examples can be drawn from countries such as India, where various GenAI Chatbots, such as "Farmer. CHAT" and "JugalBandi", have reportedly contributed positively to local communities [42]. Such applications can enhance local communities' resilience to climate uncertainties. Although Sai et al. [42] present illustrative examples of GenAI tools tailored to farming communities, their analysis is limited by the absence of a systematic, rigorous impact evaluation.

### 3.2 Enhancing community integration

Over the years, climate information has been produced centrally by scientific research centers and meteorological authorities located in urban areas with effective communication networks. In most instances, local communities have poor linkages with climate scientists, which often complicates the retrieval and use of climate information [13]. In developing effective GenAI tools for CIS, communities must be engaged to ensure that the tools are trusted, transferable, and usable, and that they meet local needs [18, 34]. To enhance climate resilience among vulnerable communities, the digital divide between scientists and local communities should be reduced through a human-in-the-loop (user-involving) mechanism [18]. This bottom-up, top-down approach blends technology into practice and in scientific discourse to discover solutions to real-world problems. The top-down strategy employs large-scale, general-purpose models to process and analyze large volumes of climate data. However, this approach often lacks locally specific details [4]. Therefore, a bottom-up approach is essential, as it focuses on gathering and incorporating local knowledge from stakeholders, including farmers, community leaders, and local meteorological services. Combining the two methods, i.e., using top-down data for a big-picture perspective and bottom-up information for localized relevance, allows for the creation of a comprehensive, robust, and trustworthy system of CIS. Communities should be involved in different stages of GeAI tool development, including data collection that incorporates indigenous knowledge and local observations as well as model training and testing [18]. While Hsu et al. [18] emphasize participatory GenAI development with local communities, the study offers a limited assessment of CIS performance outcomes. LLMs can facilitate community involvement by enhancing communication platforms and providing data-visualization tools tailored to local contexts, using plain language. The developed tools, such as Chatbots and voice assistants, can help to disseminate climate advisories in local languages [35, 60]. NLP can help bridge the gap in climate information between climate experts and communities by translating climate concepts into simple, easily understood language [13, 42].

### 3.3 Extreme weather events forecasting

Extreme weather events are severe climatic conditions that can occur at a particular location and time of year. Such events can be characterized by unusual magnitude, location, timing, or extent; they also frequently cause significant damage to the natural environment and human society. Changes in climate systems have led to increased frequency of extreme weather events, including droughts, tropical cyclones, heavy precipitation, floods, and heat waves [24, 44]. Accurate prediction of extreme weather events is vital for early warning systems and enhancing the community resilience to weather uncertainties. GenAI models, such as the latent diffusion model (LaDCast), can improve extreme precipitation forecasts by enabling larger ensemble sizes and enhancing spatial and temporal consistency in predictions. LadCast is a latent-space diffusion framework designed to generate high-dimensional data with an emphasis on forecasting or conditional generation. The model can generate medium-range forecasts for periods of one to fifteen days, thereby improving short-term weather prediction [54, 62]. The model incorporates geometric rotary position embedding (GeoRoPE), enabling it to overcome the challenges of traditional numerical weather prediction (NWP). Despite its potential, the LaDCast model requires improved reconstruction metrics and transformer-based autoencoders to enhance multimodal weather-pattern forecasting [62]. Furthermore, the generative ensemble diffusion (GED) model was developed and tested for its ability to forecast precipitation in Central Europe from 2016 to 2021. GED is a generative modelling framework that combines diffusion-based generative models with ensemble learning to improve robustness, diversity, and uncertainty estimation in generated data. The model was compared with the weather fusion unet (WF-UNet) model in terms of performance and reported to outperform traditional U-Net models in accuracy [5]. Additionally, other GenAI models capable of climate forecasting have been developed, such as the forecast generative network (FGN), which is suitable for probabilistic modelling. FGN is a neural generative model that produces future scenarios by learning from past observations. The model is reported to have been trained on the European Center for Medium-Range Weather Forecasts (ECMWF) and ERA5 reanalysis data to optimize the continuous ranked probability score (CRPS), a popular top-line metric for probabilistic weather forecasts [2]. The models can generate and predict various climate scenarios, therefore, they can automate the interpretation of complex forecasts into community advisories. For instance, a GenAI system might automatically issue a warning about the likelihood of certain events, such as floods, based on the forecast model's output. This can enable local communities to take the necessary actions, as they are well informed prior to the climatic event. A practical example can be drawn from Los Angeles, where researchers examined how ChatGPT could help residents make informed decisions before climate hazards such as hurricanes occur [27].

### 3.4 Climate data generation

Climate information services require access to climate data from multiple sources. Traditionally, meteorological authorities have been the central source of climate data. This approach has significant gaps in observational networks, particularly in data-scarce regions, hindering comprehensive climate monitoring. Additionally, there have been challenges in maintaining high-quality observational data and ensuring data consistency over time. This can affect the development of robust climate models [59]. generative adversarial networks (GANs) and variational autoencoders (VAEs) can learn complex climate data and generate new, realistic data that simulate the patterns and characteristics of a given training dataset. VAEs are generative models that learn continuous latent representations of data by combining neural networks with variational Bayesian inference [3, 28]. GANs consist of two neural networks: a generator (G) that synthesizes climate data and a discriminator (D) that distinguishes between real and generated data. VAEs can address data scarcity, particularly for rare events, by generating synthetic samples that improve model generalization and reduce the need for extensive real-world data collection [7, 31]. This can fill observational gaps in vulnerable regions, thereby improving information available for planning and enabling more comprehensive training of predictive models. A practical example can be drawn from India, where a developed GAN was used to impute missing wind data [31]. Advancements in GenAI enable the development of tools that help reach diverse groups of people and data users and provide accurate climate information for a specific locality [13]. An example in Colombia is the Melisa Chatbot, which was developed to provide climate information via WhatsApp, Facebook, and Telegram. Studies report that Melisa Chatbot obtains information from meteorological authorities, specifically the Aclimate Colombia service, and uses this information to answer farmers' questions in simple language [9, 51]. With such tools, farmers become well-informed about weather changes and can make operational decisions across various aspects of farming. As communities become better informed, necessary measures can be implemented, thereby enhancing their climate resilience.

### 3.5 Advancing early warning systems

Early warning systems provide communities with information about the occurrence of risky situations, thereby empowering them to implement effective measures to reduce risk [52]. However, these systems do not always reach everyone in society. As such, early warning systems based on improved communication channels are key for climate resilience among vulnerable communities [13]. The deployment of GenAI technologies capable of integrating traditional and scientific knowledge is necessary [18]. Instead of relying on traditional approaches, GenAI, through its LLMs, can process and synthesize complex, multi-source data, which is key for early warning for all (EW4A) initiatives [39]. EW4ALL was launched in 2022 with the aim of ensuring that everyone on earth is protected from threatening weather, water, or climate events through life-saving early warning systems by 2027 [60]. This need can be readily met by integrating various methods, including the deployment of GenAI models. This can facilitate the dissemination of climate information, ensuring that communities are informed about climate uncertainties and can prepare for them [13]. Advances in climate modelling using GenAI tools can facilitate more accurate predictions. The models can determine the current and past status of climate systems, their drivers and impacts, therefore, enhancing the value of CIS in local communities [39]. In India, ChatGPT has been reported to translate weather warnings into regional languages, such as Malayalam, thereby making extreme weather alerts more accessible to local populations and facilitating timely action. In Bangladesh, a country highly vulnerable to floods and cyclones, ChatGPT has been used to explore climate-hazard adaptation and early-warning needs [58].

## 4 Limitations in deploying generative artificial intelligence for climate information services

While GenAI, specifically LLMs such as ChatGPT, holds immense potential for CIS, it is essential to acknowledge and address challenges associated with its use. The challenges include, among others, a lack of transparency, given that many sophisticated GenAI models operate as "black boxes," making it difficult for human experts and policymakers to understand how decisions or outputs are reached [16, 35]. A lack of trust can affect the dissemination of climate information to end users.

Secondly, misinformation and manipulation, some GenAI responses can be incorrect or lack local context, which could be problematic for critical climate advisories. The ability to generate fake images and videos is a genuine threat to the reliability of GenAI-based assessments [34, 47]. Thirdly, due to digital accessibility barriers, the benefits of GenAI are not readily accessible to a wide range of users, owing to location disparities. Rural communities require internet or mobile connectivity, which may be limited, to access GenAI-driven services [46]. While Chavula and Kayusi [13] compellingly outline the potential of GenAI to improve the dissemination of CIS across Africa, they discuss practical barriers to GenAI adoption among vulnerable rural populations only minimally. Several models, specifically developed for climate-related applications, require continued advancement to better serve community needs by providing trusted climate information. For example, ClimateGPT, which was developed for climate-related tasks, has been reported to provide accurate responses to community prompts due to ongoing improvements [61]. However, in the reviewed literature, critical concerns surrounding GenAI, such as data privacy, high energy consumption of large models, and ethical issues, were discussed little. Biases embedded in model design, data sovereignty (who owns, controls, and governs data), and informed consent need to be considered. This indicates that, despite the positive contributions of GenAI in CIS, researchers, scientists, academics, and other stakeholders must verify information from other sources rather than rely entirely on GenAI models, as such systems can sometimes generate misleading information.

## 5 Discussion and future research directions

This review demonstrates that Generative Artificial Intelligence (GenAI), particularly large language models (LLMs), is emerging as a potentially transformative tool for Climate Information Services (CIS). Across the reviewed studies, GenAI applications were associated with improvements in climate communication, localized advisory services, early warning systems, vulnerability mapping, weather forecasting, and synthetic climate data generation [9, 36, 39]. These findings suggest that GenAI can enhance the accessibility, timeliness, and interpretability of climate information, especially where conventional CIS delivery mechanisms remain centralized or difficult for end users to access. Natural-language interfaces such as chatbots may help translate complex forecasts into practical guidance for farmers, vulnerable households, and local decision-makers [42, 51].

The review reveals a disparity between rapid technological advances and comparatively limited attention to user-centered design. Much of the existing literature remains technology-focused, emphasizing model accuracy, forecasting skill, automation, and computational efficiency [2, 31, 62]. By contrast, fewer studies examine how communities interpret, trust, and integrate GenAI-enabled CIS into everyday decision-making [13, 18]. Given that CIS effectiveness depends not only on technical quality but also on relevance, usability, and legitimacy, future innovation should integrate advances in GenAI with participatory design, co-production approaches, and human-in-the-loop governance structures. Such integration is particularly important in rural and climate-vulnerable contexts, where local knowledge remains essential.

Several obstacles to broader adoption are apparent, including limitations in digital infrastructure, inconsistent internet access, language barriers, low levels of AI literacy, gaps in institutional capacity, and concerns about data quality [1, 37, 46]. For many rural areas, accessing GenAI-enabled CIS may be challenging without affordable connectivity, mobile-friendly platforms, and interfaces in local languages. Adoption may also be hindered when outputs are not aligned with existing advisory systems or if users lack confidence in automated recommendations. To overcome these barriers, efforts should focus on targeted capacity building, multilingual design, partnerships with meteorological agencies, and hybrid models that combine AI outputs with trusted human intermediaries such as extension officers, community leaders, and local forecasters.

Transparency, misinformation, and accessibility are critical governance concerns. Many advanced GenAI systems operate as opaque "black boxes," making it difficult for users or policymakers to understand how outputs are generated [16, 35]. In climate-risk contexts, inaccurate or hallucinated responses may undermine trust or lead to poor decisions, while synthetic media may pose additional misinformation risks [34, 47]. At the same time, GenAI offers important opportunities to access climate knowledge through conversational interfaces, translation tools, and low-cost digital advisory services. Realizing these benefits will require safeguards such as source verification, explainability measures, human oversight, and context-specific quality assurance mechanisms. Finally, several urgent research gaps remain, as empirical evidence on user experience, adoption behavior, trust formation, and long-term development outcomes is still limited. Future studies should therefore move beyond conceptual promise and technical benchmarking toward field-based evaluations, participatory pilots, living labs, and co-design experiments. Comparative research across regions, sectors, and user groups would also help identify where GenAI creates the greatest value for CIS and where conventional approaches remain preferable.

## 6 Conclusion

The study examines the potential of Generative artificial intelligence (GenAI) to enhance climate information services (CIS) for local communities. Most communities, especially those vulnerable to climate hazards, have little access to climate information. This is attributed to a lack of effective communication and integration channels. By deploying generative GenAI technologies, such as ChatGPT, communities can be informed about climate uncertainties through applications that use plain language. The application of GenAI can enhance community integration, as effective GenAI technologies for CIS require community engagement to ensure that the proposed tools are trusted, usable, transferable, and meet local needs. Furthermore, GenAI has potential for climate prediction and for advancing early warning systems, as it can integrate traditional and scientific knowledge, thereby informing communities about likely uncertainties and preparing them to address them. GenAI offers digital opportunities to enhance the dissemination of climate information. However, despite the promising potentialities of GenAI, it is worth noting the challenges associated with its use. Such limitations include the lack of transparency, misinformation, and digital accessibility. Therefore, the initiation and deployment of GenAI models should also account for the likelihood of associated challenges. Furthermore, there is a need to investigate the suitability of GenAI models across localities within the community. When initiating certain GenAI projects, environmental heterogeneity should also be considered. Despite growing interest in GenAI applications, the review reveals a significant lack of empirical studies systematically examining user experience, a key research gap. Existing work largely prioritizes technical performance or conceptual frameworks, with limited attention to how users interact with, perceive, and trust GenAI-enabled systems in practice. This gap constrains understanding of usability, adoption, and real-world impact. Future research should therefore emphasize empirical, user-centered approaches, including participatory pilot studies, living-lab deployments, and co-design experiments, to generate robust evidence on user experience and to inform more effective and responsible GenAI integration.

**Acknowledgements**
The authors thank the Alexander von Humboldt Foundation-Germany, through the Georg Forster Research Fellowship for Postdocs for the sponsorship given to the corresponding author.

**Author contributions**
AAM was involved in the study conception and design, as well as writing the draft of this paper. MR contributed to the study conception, design, and writing, as well as to the modification of the paper. SS worked on study conception and editing. SL worked on study conception and editing. HKK worked on study conception and editing. PK worked on study conception and editing. MK worked on study conception and editing. All authors read and approved the final manuscript.

**Funding**
Open Access funding enabled and organized by Projekt DEAL. This work was supported by the Alexander von Humboldt Foundation under a Georg Forster Research Fellowship for Postdocs.

**Data availability**
No datasets were generated or analysed during the current study.

**Code availability**
Not applicable.

## Declarations

**Ethics approval and consent to participate**
Not applicable.

**Consent for publication**
Not applicable.

**Competing interests**
The authors declare no competing interests.

Received: 29 September 2025 / Accepted: 29 May 2026
Published online: 10 June 2026

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