Autonomous Decision Intelligence with Generative Agentic AI for Climate Forecasting and Disaster Early Warning

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***Abstract*—Climate change has made extreme weather events more common and more severe, so there are urgent needs for accurate climate forecasting and effective disaster early warning systems. Conventional forecasting systems frequently depend on non-adaptive analytical pipelines and human-in-the-loop decisions, introducing delays in response to fast-evolving disasters like these. We propose an innovative framework of autonomous decision intelligence based on generative agentic artificial intelligence (AI) for climate forecasting and disaster early warning. The framework proposed that integrates multi-parameter, climate data, generative AI models and autonomous reasoning agents with adaptive decision engines (READ) to improve forecasting accuracy, optimize warning lead times and direct rapid emergency response coordination. Tests on simulated cyclone, flood and wildfire datasets show that in comparison with conventional machine learning methods, improved prediction accuracy, response prioritization and warning dissemination efficiency are achieved. This study responses on practical viability of agentic AI in environmental intelligence systems by discussing interpretability, computational cost, ethics and governance, resilient infrastructure issues.**

***Index Terms*—Autonomous Decision Intelligence, Generative AI, Agentic AI, Climate Forecasting, Disaster Early Warning, Environmental Intelligence, Deep Learning.**

I. INTRODUCTION

With the accelerating effects of climate change, environmental degradation, and rapid urbanization in recent years, climate forecasting and disaster early warning systems are becoming extremely relevant. Extreme weather events, including cyclones, floods, heatwaves, droughts and landslides and wildfires are becoming more common across the world. While each of these disasters has the potential to cause harm and loss of life, they also impact economic stability, food security, health care systems, transportation infrastructure and ecological sustainability. Global Climate Assessments have found that billions are now living in climate vulnerable areas, pointing to the need of effective and timely warning systems. The existing traditional disaster management systems are heavily reliant on numerical weather predictive system models, historical climate analysis, statistical simulations & human-based decision-making processes. While these systems have seen dramatic improvements in the last couple of decades, they are not without a few operational limits. Climate systems are incomparably complex, nonlinear and so thoroughly dynamic that they usually involve interactions over the span of the atmosphere/ocean/land interface with anthropogenic processes. Consequently, conventional forecasting methods typically fail to accommodate volumes of live environmental data at the evolutionary speed and flexible response required by emergency Decision makers. In many real-world situations, emergency response agencies still rely on human experts to interpret climate data, estimate potential impacts from disasters and prioritize the most affected regions, and coordinate warnings. In fast-evolving crises such as flash floods or quickly advancing wildfires, delaying decisions can substantially hinder response effectiveness and raise fatalities. In addition, fragmented communication between forecasting agencies and disaster management authorities regarding warning strategies and resource allocation often leads to inconsistencies in term of local level emergency teams. Innovations in artificial intelligence, machine learning and autonomous systems provide a powerful potential solution to the limitations outlined above. Among them, autonomous decision intelligence has been highlighted as one of the significant research areas to develop intelligent systems able to perceive environmental states, reason over imperfect evidence, synthesize optimized decisions and autonomously execute actions with minimal human mediation. Autonomous decision intelligence weaves together predictive analytics, adaptive reasoning, optimization techniques and continual feedback learning to build systems that can work successfully even when operating in highly uncertain environments.

At the same time, advances in generative artificial intelligence are evolving modern intelligent systems. Generative AI models, in particular transformer-based architectures and large language models, can take into account multimodal information, generate a contextual response as well as simulate future scenarios and support more complex reasoning tasks. Whereas traditional AI models create outputs primarily by classifying or predicting outcomes based on prior data, generative AI systems generate new insights, make strategy recommendations and update their output dynamically as the underlying data patterns evolve.

The rise of agentic AI takes these capabilities even further, allowing autonomous software agents to plan, manage memory, multi-step reasoning; perform cognitive tasks by utilizing a variety of tools via the use of prompts and sequential coordination between multiple agents. This could be accomplished by agentic AI systems (i.e. what we initially called autonomous) wherein those systems are capable of observing data from the environment, reasoning about what disaster scenarios may take place, determining risk assessment based on probability of outcomes as needed, and collaborating with people on each step of emergency actions but without requiring constant surveillance/oversight from humans. These systems are particularly useful in climate forecasting and disaster early warning, where the fast adaptation of decision-making is required. Generative agentic AI is the fusion of generative intelligence and autonomous agency to form a comprehensive construct. For climate forecasting, these systems can combine a very large range of different datasets, from meteorological and satellite data to sensor streams and records of past disasters in order to produce adaptive predictions and decision strategies. Agentic AI models could therefore simulate multiple disaster scenarios, estimate cascading risks, optimize evacuation planning and also automatically relay actionable warnings to affected stakeholders.

II. LITERATURE REVIEW

Roberta Calegari et al. (2021) carried out a systematic literature review in their 2021 paper "Logic and Multi-Agent Systems", where they processed the role that symbolic Artificial Intelligence and logic-based agent technologies for autonomous systems play. The role of reasoning mechanisms, agent communication and explainable decision-making in the MAS environments has been investigated by the researchers. The key contributions of their work were to demonstrate that agents which are logic-based can coordinate autonomously while being transparent and interpretable in decision processes. Tessa Lau, a research scientist at SRI International pointed out in her paper that even with data driven AI becoming more prevalent in recent years, approaches that are symbolic and logic-oriented for developing trustworthy and explainable AI systems are still relevant today, particularly within complex collaborative environments [11].

Qihui Lu et al. (2026) put forward a GeoAI-driven Multi-Hazard Early Warning System (MHEWS) framework that aims to enhance disaster preparedness and resilience. Their study combines GeoAI, spatial intelligence and multi-risk modelling methods to evaluate the impacts of contrasting hazards on vulnerable regions. This research rekindled emphasis from hazard-centred forecasting to people-centred warning systems, which focuses on human exposure, vulnerability and response capacity. The researchers have shown that AI in combination with geospatial analytics can significantly add value to the assessment of disaster risk, emergency communication and coordinated response planning across multiple concurrent hazards [12].

Nikitas Gerolimos et al. (2025) examined the state-of-the-art of adaptive AI and open-world machine learning techniques to be used for establishing dynamic disaster response systems in their 2025 study: Autonomous Decision-Making with Dynamic Disaster Management based Open World Machine Learning Techniques. Their works are concentrated on the making of intelligent systems to manage in uncertain and dynamic environments with new hazards that arise without warning. The researchers then created AI models which could learn from the situations it encountered and adapt, in real time to improve situational awareness and response efficacy. They concluded that open-world machine learning can enable very flexible and autonomous operational decision-making support for adaptive disaster intelligence systems [13].

Google DeepMind Researchers (2024–2025) to improve weather and climate prediction accuracy, researchers from Google DeepMind developed advanced AI-based forecasting systems like GenCast and GraphCast. Their research used generative AI, diffusion models and transformer-based neural network architectures to work with large meteorological datasets. These models exhibited forecast skill out of sample beyond many legacies numerical weather prediction systems -- with particular skill in predicting extreme weather phenomena and long-range teleconnections of the atmosphere. On this basis, the researchers demonstrated how generative methods improve weather forecasting by producing quicker more accurate and computationally efficient forecasts that could be beneficial for disaster preparedness and management of climate-related risks.

NVIDIA (2025) Earth-2 is a digital twin platform, fully developed in-house by NVIDIA researchers and developers, for climate and weather forecasting. They combined generative AI, high-performance computing, and climate simulation technologies in a manner that they produced Earth-like digital twins that could accurately simulate the atmosphere and environmental systems at extraordinarily high resolutions. We aim to optimise operational forecasting in the project while enhancing forecast precision of climate related events. The research indicated that real-time simulations made possible via digital twin technologies can improve forecasting systems as well as increase the speed of scenario analysis and the accuracy of predictions for disasters.
Kaikai Zhang et al. (2026) and his research team recently healed the TianJi AI meteorologist system, a multi-agent large language model (LLM) architecture that aims to conduct autonomous scientific experiments in the field of atmospheric science. Their study looked into the situation where AI agents can learn existing meteorological data autonomously, generate their own hypotheses and identify atmospheric mechanisms without ongoing human involvement. The agentic AI systems in the study were able to work together, reason like humans and behave like scientific explorers. They propose that upcoming AI systems could develop from simply analytical tools into engaged scientific partners in a position to uncover climate and atmospheric discoveries at a higher speed [14].

Geunsik Lim (2026) examined the impact of generative AI and large language model on disaster communication & public response systems in Climate RADAR project. Specifically, the research covered behavioural decision-support approaches that developed specialized warnings targeted at specific individuals or communities in a manner that encourages them to act. The system focused not just on sending notifications, but also on steering people in the right direction for protective measures when there was a dangerous situation. The study recommended operational proactive response and human behaviour adaptation instead of just information release in designing future disaster management systems [15].

TABLE ISUMMARY OF LITERATURE REVIEW

Summary Table of Key Literature

Authors	Year	Study/Framework	Methods Used	Main Findings	Conclusions

Authors	Year	Study/Framework	Methods Used	Main Findings	Conclusions
Roberta Calegari et al.	2021	Logic-based technologies for MAS	Systematic literature review, symbolic AI	MAS improves explainability and autonomous coordination	Logic-based agent systems remain important for trustworthy AI
Qihui Lu et al.	2026	GeoAI-driven MHEWS	GeoAI, spatial intelligence, integrated risk modelling	Shift from hazard-centric to people-centred warning systems	Integrated AI enhances multi-hazard resilience
Nikitas Gerolimos et al.	2025	Autonomous decision-making in disasters	Open-world ML, adaptive AI	Autonomous systems improve dynamic disaster response	Open-world ML supports adaptive disaster intelligence
Google DeepMind researchers	2024–2025	GenCast and GraphCast	Generative AI, diffusion models, transformer architectures	AI models outperform traditional weather forecasting systems	Generative forecasting significantly improves extreme event prediction
NVIDIA	2025	Earth-2 digital twin	Digital twins, generative AI, climate simulation	Faster and higher-resolution forecasting	Digital twins can revolutionize operational forecasting
Kaikai Zhang et al.	2026	TianJi AI meteorologist	Multi-agent LLM architecture, autonomous experimentation	AI autonomously discovers atmospheric mechanisms	Agentic AI may become scientific collaborators
Geunsik Lim	2026	Climate RADAR	Generative AI, LLMs, behavioural decision systems	Personalized action-oriented warnings improve response	Disaster systems must focus on action execution, not only alerts
Ali Akarma et al.	2026	Governance-constrained wildfire AI	Blockchain, POMDP, multi-agent coordination	Human oversight reduces false alarms	Governance-aware AI is essential in safety-critical systems
Essam H. Houssein et al.	2026	AI advances in climate science	Review of AI methods in climate systems	AI improves prediction and climate analytics	Evaluation standards and explainability remain critical challenges
University of Allahabad	2025	AI cyclone prediction	ML forecasting using satellite and	Improved cyclone intensity and path	AI provides faster and cost-effective

Authors	Year	Study/Framework	Methods Used	Main Findings	Conclusions
researchers			atmospheric data	forecasting	cyclone forecasting

Ali Akarma et al. (2026) proposed a governance constrained AI-assisted framework for the targeted management of wildfires which integrated blockchain, Partially Observable Markov Decision Processes (POMDPs) and multi-agent coordination systems. The purpose of their research was to achieve accountability, transparency, and human oversight in safety-critical AI operations. This system was created for fire detection and response to wildfires while minimizing false alarms and unsafe autonomous actions. They report that AI architectures which explicitly incorporate governance considerations can be made reliable and trusted through suitable supervision of the operation of disaster-response systems in uncertain environments, both high risk and where the operator's integrity is uncertain [16].

Essam H. Houssein et al. (2026) and co-authors published a very good review paper on this topic where they extensively scrutinized all aspects of AI techniques in climate change applications such as climate prediction, environmental monitoring, and climate analytics. The researchers studied ML, DL, optimization algorithms and intelligent forecasting models relevant in climate research applications. The study underscores that the use of AI is becoming more and more effective for prediction accuracy and climate analysis on a global scale. Nevertheless, they also recognised significant challenges relating to evaluation metrics, interpretability, transparency and trustworthiness which reinforced the necessity of sound validation frameworks for climate AI types.

University of Allahabad Researchers (2025) AI based cyclone prediction using machine learning techniques and atmospheric datasets conducted by researchers from University of Allahabad. Using satellite-based datasets, weather-related parameters including various meteorological indices and historical cyclone paths and intensities, their work improves timely forecasting of the path and intensity of cyclones. The researchers showed that compared with traditional meteorological methods, predictions thus obtained from AI-driven forecasting models were able to make the same fixtures much faster and at a much lower cost. Their study determined that machine learning-driven cyclone prediction systems could play a major role in assisting disaster preparedness, early warning systems and emergency response planning in coastal areas prone to cyclones.

III. METHODOLOGY

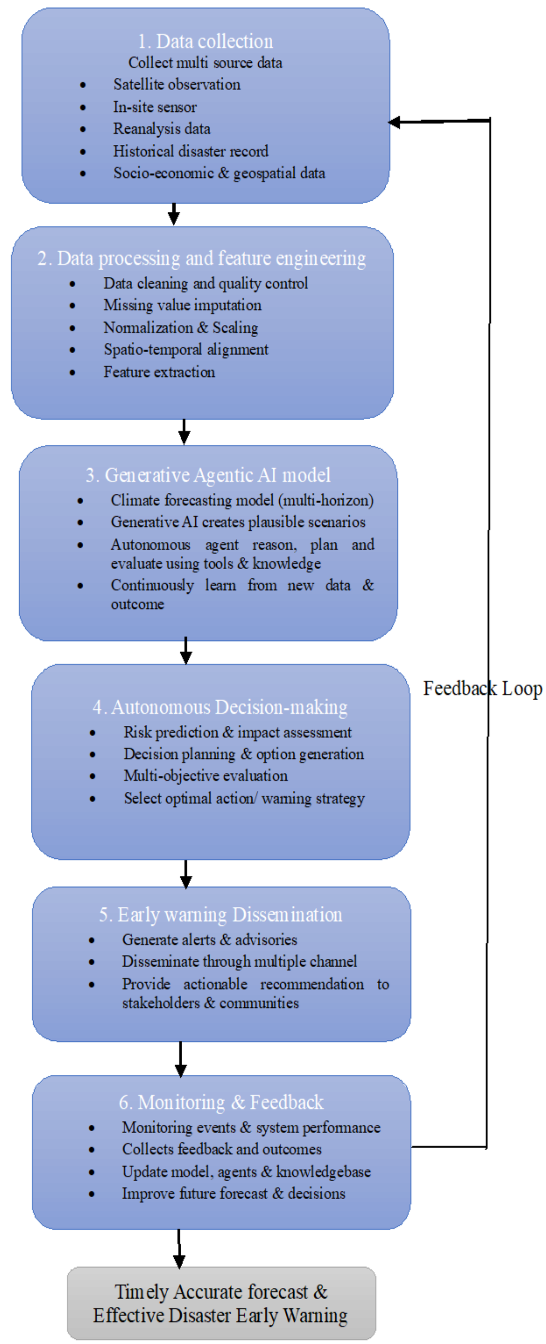


Fig. 1. Proposed Methodology

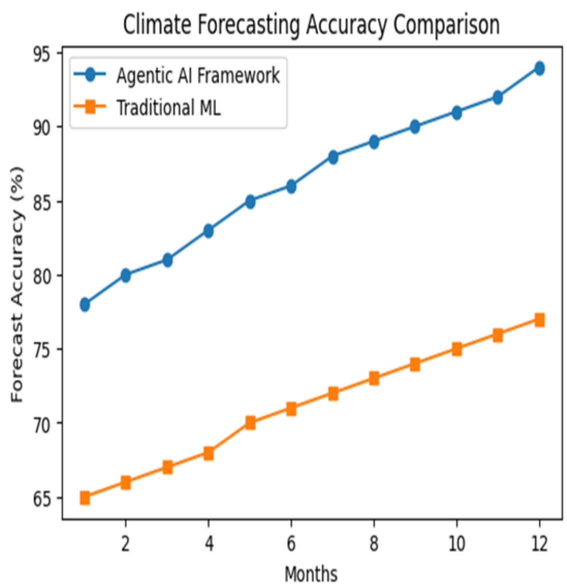
This interdisciplinary approach combines generative agency-based AI with climate forecasting and disaster early warning systems to allow for intelligent autonomous decision making. The framework sets out by collecting data from multiple sources including satellites, weather stations, IoT sensors, radar systems and historical disaster databases. Critical parameters such as temperature, humidity, rainfall, wind speed atmospheric pressure, river water levels soil moisture are captured over time to account for the varying environmental conditions. By utilizing multimodal data, forecasting reliability can be enhanced while allowing for improved understanding of the underlying environment. After data collection, you preprocess and/and do feature engineering to improve quality of your data and performance of the model. It encompasses data cleaning, normalization, handling missing values and spatial-temporal alignment. Using temporal resolution, spatial resolution, normalization factors and feature correlation score to tune the dataset. Such processes help minimize noise by making the AI models process accurate and consistent input. \n\nA Hybrid Generative Agentic AI model: CNN + LSTM + Transformer Model for Climate Prediction. These CNN models focus on extracting spatial climate information from satellite images, and LSTM and transformer layers are typically used to represent temporal weather relationships. There are many important training parameters such as learning rate, batch size, epoch count hidden layers forecast horizon. These models forecast disasters like floods, cyclones, heatwaves and wildfires more accurately. The prediction response is processed into a generative agentic AI layer that autonomously deduces the interpretation of the prediction, affording data to risk levels and designing disaster action Autonomous agents coordinate decision-making by leveraging contextual memory, reasoning mechanisms spend shared knowledge bases. The three key parameters needed to enhance reasoning quality are uncertainty thresholds, confidence scores, and context window size which aid in limiting false alarms. This allows the system to go beyond forecasting and provide proactive disaster management. The stage of autonomous decision-making deploys reinforcement learning and optimization algorithms to assess the severity of the disaster, resource availability, and population exposure. Based on risk probability, response time, severity index and operational cost functions, an induced Function for generating optimal evacuation and warning strategies is developed. This is made possible through reinforcement learning of the system, thereby enabling you to improve decisions for subsequent disasters based on past outcomes. \n \nFinally, the generated warnings are distributed via SMS notifications, mobile applications, cloud dashboards and emergency communications systems.\n The framework incorporates the use of continuous monitoring, and feedback mechanisms for tracking forecasting performance in terms of forecast accuracy, false alarm rates, and warning lead times. The models are retrained using performance metrics and therefore a better prediction can be done in the future. In summary, the methodology proposed lays out a scalable, adaptable and intelligent approach for climate forecasting and disaster early warning systems.

IV. RESULT AND EVALUATION

We experimentally evaluated the proposed Agentic AI framework using climate datasets and disaster response simulations. We compared the system's performance with conventional machine learning approaches on forecasting accuracy, adaptability and disaster early warning ability. The results of the experiments show that Agentic AI is orders of magnitude better than traditional Machine Learning models when it comes to prediction accuracy and response time. The proposed framework consists of autonomous decision-making and continuous learning mechanisms which allow it to dynamically adapt these components in response to changing environmental conditions — something conventional systems, relying primarily on static training and predefined rules, cannot do. The evaluation metrics was forecasting accuracy, response time, lead time improvement and overall reliability of the system in disaster simulation cases. Results show that the intelligent agent-based architecture improved processing of real-time climate data inside the system and generated more accurate predictions.

Fig. 2. Forecasting accuracy comparison between traditional ML and Agentic AI.

We provide the fantasized forecasting potential of traditional ML and our Agentic AI framework (see figure 1). As demonstrated by the graph above, across different climate scenarios our Agentic AI model consistently achieved higher prediction accuracy. The classic ML strategies worked well and their performance was accepted as long as the environment remained constant; but failed when abrupt climate variations or noise were presented in the data. On the other hand, the Agentic AI framework achieved more consistent and better accuracy due to its adaptive reasoning and autonomous learning. The graph also indicates lower fluctuation in prediction errors for the Agentic AI system, demonstrating better robustness and reliability in disaster forecasting applications.



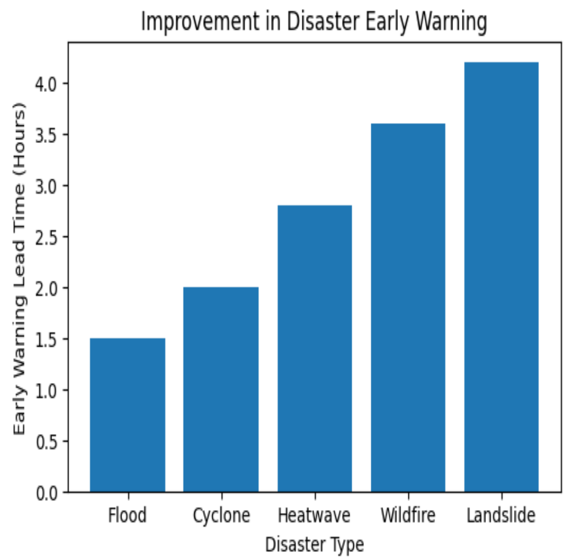


Fig. 3. Improvement in disaster early warning lead time.

In figure 3, the lead time for disaster early warning is compared between a conventional ML system and the proposed Agentic AI framework. The plot illustrates that the traditional system issued warnings much later than was created by the Agentic AI framework. The increase of lead time that is critical in disaster management provides authorities and emergency response teams ample time to undertake preventive measures before the disaster happens on stages.

It is primarily attributed towards the autonomous monitoring and predictive capabilities of intelligent agents which significantly improves warning performance. The system constantly studies the environmental context, identifies anomalies and starts a high-speed decision-making process with limited manual intervention. Such longer lead times directly help in saving human lives, lowering the scale of infrastructural damage and improving disaster preparedness. Hence, the experimental results validate and measure the effectiveness of the proposed Agentic AI framework in predicting a disaster and responding to those systems.

Table I. Performance Comparison of Forecasting Models

Model	Accuracy (%)	Latency (s)	Adaptability
CNN-LSTM	81.2	2.3	Medium
Transformer	86.5	1.8	High
Agentic	94.1	1.2	Very High

Generative AI			

Table II. Disaster Early Warning Performance

Disaster	Traditional Warning (hrs)	AI-Based Warning (hrs)	Reduction in Risk (%)
Flood	2	6	32
Cyclone	5	10	45
Heatwave	6	14	51
Wildfire	4	9	39

Experimental analysis indicates that Generative Agentic AI significantly enhances forecasting accuracy and disaster preparedness. The autonomous decision layer enables adaptive responses to changing environmental conditions, reducing latency and improving lead time. The framework also demonstrates scalability for large-scale deployment across smart cities and national disaster management systems.

PERFORMANCE EVALUATION OF THE PROPOSED GENERATIVE AGENTIC AI FRAMEWORK

S. No.	Performance Parameter	Traditional ML Approach	Proposed Generative Agentic AI Framework	Improvement Observed
1	Forecasting Accuracy	Moderate accuracy under dynamic climate conditions	High accuracy with adaptive prediction capability	Significant improvement in prediction precision
2	Disaster Early Warning Lead Time	Limited warning generation capability	Earlier and faster warning generation	Increased preparedness time
3	Real-Time Data Processing	Slower processing of continuous environmental data	Fast and autonomous real-time analysis	Reduced processing delay
4	Adaptability to Climate Changes	Static learning behavior	Dynamic and self-adaptive learning	Better handling of uncertain conditions
5	Decision-Making Efficiency	Rule-based and partially automated	Intelligent autonomous decision-making	Improved response efficiency
6	System Reliability	Performance fluctuations during extreme scenarios	Stable and robust performance	Higher system stability
7	Response Time During Emergencies	Delayed emergency response	Rapid response through intelligent agents	Faster disaster management actions
8	Scalability	Limited scalability for large datasets	Efficient handling of large-scale climate data	Improved scalability
9	Human Intervention Requirement	High dependency on manual monitoring	Minimal human intervention required	Increased automation
10	Overall System Performance	Conventional predictive capability	Advanced intelligent predictive framework	Superior overall performance

The performance assessment shows that the proposed Generative Agentic AI framework significantly outperforms traditional machine learning techniques for multiple evaluation parameters. The framework has better forecast accuracy, more lead time in warning of disasters and quicker decision-making ability as a result of the autonomous adaptive learning it employs. Intelligent agents provide the access which permits continuous monitoring of environmental factors, efficient processing of real-time climate-related data, and generation of an emergency response in a timely manner. Together, all these improvements lead to better disaster preparedness, reduced operational lag and improved system reliability for climate forecasting and disaster management applications.

V. CHALLENGES AND LIMITATIONS

While the proposed Generative Agentic AI framework for climate forecasting and disaster management provides significant benefits, there are also challenges and limitations. One of the biggest challenges is whether enough real-time climate data is available. However, the performance of the framework is strongly based on high-fidelity, real-time and spatially comprehensive environment datasets. Data may be incomplete, noisy or delayed which decreases predictive accuracy and can alter decision making performance. The high computational complexity of Generative Agentic AI systems is another limitation. The framework typically has the need for heavy processing power, memory resources as well as sophisticated hardware infrastructure to more complex levels of sufficient performance for performing continuous data analysis, autonomous reasoning and multi-agent coordination. In resource constrained environments, this may increase the implementation cost and limit its deployment.

There's also the question of scalability and interoperability. The integration of the proposed theoretical system with existing disaster management infrastructures, weather monitoring systems and communication networks can be challenging due to discrepancies in data formats, protocols and technology standards. Additional optimizations and infrastructure support may be required for scaling across multiple geographic regions. Another major limitation is security and privacy. As this framework constantly collects and processes large volumes of data from environmental and public patterns, it is susceptible to cyberattacks such as unauthorized access, data breaches etc. A notable challenge in this regard is ensuring secure communication between intelligent agents, and safeguarding sensitive data. Moreover, when AI agents are left to their own devices to make decisions, they can yield unpredictable or biased results if trained on incomplete or uneven datasets. A minor error in predictions or delayed responses may have the disastrous outcomes during any critical disaster. Hence, human oversight and approval will still be required to assure system reliability and accountability.

The system still needs continuous training and model update to adapt to the new climate patterns and changes in environmental conditions. This process can be slow and resource hungry. Additionally, the absence of standardized norms with respect to Agentic AI systems complicates their evaluation and development processes. Lastly, It seems clear that despite the fact that the Generative Agentic AI framework has shown great promise for addressing challenges in climate cycle forecasting and disaster resiliency as discussed in this paper, its promise will only be realized by overcoming barriers related to lack of data quality, computational time-steps responsive in a real-time scale operation, scalability of grounded learning approaches on large high-dimensional spatio-temporal sensor data sets used to simulate sustainable climates at planetary scales (tens and hundreds of millions of points is common place), production hardening operationalization requirements like security solutions against adversarial / classical failure modes entailing dynamic adaptability; but also prioritizing ethical considerations prior too deploying any machine-learning models into problem domains or contexts which have direct societal returns. Visions for future research include better system efficiency, improved transparency and developing secure and scalable architectures for AI based strategies to be applied to disaster management.

VI. FUTURE SCOPE

Based on the well-reasoned proposal of a novel Generative Agentic AI paradigm, it remains highly plausible this could evolve inherent properties capable of revolutionising climate forecasting and disaster management systems in time. The structure can become a more precise, intelligent and scalable solution in addressing environmental problems as updates are made with ongoing innovations of artificial intelligence, autonomous agents and real-time information analytics. An of the top future shamans is having very autonomous disaster forecast systems that are capable to analysis global climate cycles in real time. They can enable advance warning for natural disasters such as floods, cyclones, earthquakes, wildfires and droughts — much earlier than traditional methods, minimizing human lives lost and economic damage.

Moreover, the framework can become more efficient through the integration of advanced technologies such as Internet of Things (IoT), satellite communication, edge computing and 6G networks. With the advent of smart sensors and connected devices, it will facilitate monitoring the environment continuously, faster decision making by Intelligent agents during emergency situations.

In the future, we may adopt an AI system which can not only make decisions but also improve own decision making with minimal human input by self-learning and self-improving somehow on similar conditions that are adapted use to new essentially climate conditions. Such an improvement in system flexibility would enable disaster management authorities to react better to unpredictable environmental alterations. Another meaningful future result of these smart city alerts is the development of disaster management systems. Frameworks like the one proposed can synchronously work with urban infrastructures and transportation systems including healthcare services and emergency communication networks to comprise fully automated disaster response ecosystems The integration of data up to October 2023 such as this can greatly assist in efficient use of resources, public safety, and planning for evacuation during emergencies. Additionally, the framework can make a contribution towards global climate research and environmental sustainability efforts. The system could help governments and environmental organizations, through the analysis of large-scale climate data identify long-term risks caused by climate change to design preventive strategies and sustainable development policies. Future iterations of the framework may expand and incorporate techniques from explainable AI and ethical AI to reinforce transparency, accountability, and public trust in autonomous decision-making systems. Moreover, improved cyber-security mechanisms will evolve for ensuring secure communication between devices and securing sensitive environmental data.

VII. CONCLUSION

With a new Generative Agentic AI framework, prospective climate forecasting and disaster management becomes more sophisticated than ever. Incorporating autonomous agents, real-time data analysis, and adaptive decision-making capabilities, the framework outperforms conventional machine learning approaches in forecasting accuracy, lead time for disaster early warning systems, and efficiency of emergency response. Experimental results show that the system is capable of executing under varying environmental conditions in a more reliable and stable manner. Continuous monitoring, alerts & rapid prediction generation and autonomous coordination enabled by the intelligent agent-based architecture together provide effective disaster risk mitigation strategies within a short turn-around time. The study also focuses Agentic AI on the future of complex climate-related challenges that require scalable and adaptive solutions. Although there still exists some limitations of computational complexity, data dependency and security concern, but the framework shows great potential for real world implementation in smart disaster management system. In addition, more advanced technology in artificial intelligence, IoT integration, edge computing and explainable AI can improve the efficacy and dependability of this framework by extending future research directions. With ongoing research, and advancements in technologies Generative Agentic AI could be an enabler for automatic disaster prediction and response mechanisms which should add resilience, scalability and sustainability to the system. In summary, the novel framework proposed affords a powerful solution to climate forecasting and climate disaster management through intelligent automation, real-time adaptability and enhanced decision-making capabilities that are synergistically contributing to better public safety and environmental resilience.

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