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EMERGING TECHNOLOGIES FOR CLIMATE CHANGE MONITORING: PROSPECTS AND CHALLENGES OF AI, IOT, AND UNMANNED SYSTEMS APPLICATION

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This paper examines the increasing importance of artificial intelligence (AI), Internet of Things (IoT) technologies, and unmanned systems in modern environmental monitoring, with particular attention to climate change and the growing likelihood of natural and technogenic emergencies. As conventional monitoring practices often lack the spatial density and temporal resolution required for timely detection of hazardous developments, the combined use of intelligent analytical tools and distributed sensing devices offers a more reliable basis for observing dynamic environmental conditions. The study outlines the functional capabilities of these technologies, emphasizing their contributions to data accuracy, operational continuity, and predictive assessment. Building on this analysis, the work proposes a generalized architecture for an integrated environmental monitoring system intended to support both long-term observations and rapid identification of emergency scenarios. The proposed structure reflects the coordinated operation of heterogeneous IoT sensors, communication channels, and AI-driven analytical modules deployed on remote computational nodes. Particular attention is given to the mechanisms that ensure stable data transmission, fault tolerance, and timely interpretation of sensor signals under variable environmental and infrastructural constraints. The study also discusses several practical challenges associated with implementing such systems, including the reliability of sensor networks, the adaptability of AI models to changing environmental regimes, and the necessity of maintaining transparent and accountable analytical processes. The conclusions highlight the advantages of integrating AI and IoT within a unified monitoring framework and identify promising directions for further research aimed at enhancing system resilience, analytical robustness, and scalability across different categories of industrial and environmental facilities.
Key words: climate change, man-made and natural emergencies, environmental monitoring system, artificial intelligence, Internet of Things, unmanned systems.

Нові технології для моніторингу зміни клімату: перспективи та проблеми застосування ШІ, IoT та безпілотних систем. Алексєєва А. О., Білоконь А. О.

У роботі розглядається зростаюча важливість застосування технологій штучного інтелекту (ШІ), Інтернету речей (IoT) та безпілотних систем у сучасному моніторингу навколишнього середовища, з особливою увагою до процесів зміни клімату та зростаючої ймовірності природних та техногенних надзвичайних ситуацій. Оскільки традиційні методи моніторингу часто не мають просторової щільності та часової роздільної здатності, необхідних для своєчасного виявлення небезпечних подій, комбіноване використання інтелектуальних аналітичних інструментів та розподілених зондувальних пристроїв пропонує більш надійну основу для спостереження за динамічними умовами навколишнього середовища. У дослідженні окреслено функціональні можливості цих технологій, підкреслюючи їхній внесок у точність даних, безперервність роботи та прогнозну оцінку. Спираючись на цей аналіз, у роботі пропонується узагальнена архітектура інтегрованої системи моніторингу навколишнього середовища, призначеної для підтримки як довгострокових спостережень, так і швидкої ідентифікації сценаріїв надзвичайних ситуацій. Запропонована структура відображає скоординовану роботу гетерогенних датчиків IoT, каналів зв'язку та аналітичних модулів на основі ШІ, розгорнутих на віддалених обчислювальних вузлах. Особлива увага приділяється механізмам, що забезпечують стабільну передачу даних, відмовостійкість та своєчасну інтерпретацію сигналів датчиків за змінних екологічних та інфраструктурних обмежень. У дослідженні також обговорюється кілька практичних проблем, пов'язаних із впровадженням таких систем, включаючи надійність сенсорних мереж, адаптивність моделей штучного інтелекту до змінних режимів навколишнього середовища та необхідність підтримки прозорих та підзвітних аналітичних процесів. Висновки підкреслюють переваги інтеграції ШІ та IoT в єдину систему моніторингу та визначають перспективні напрямки подальших досліджень, спрямованих на підвищення стійкості системи, аналітичної надійності та масштабованості в різних категоріях промислових та екологічних об'єктів. *Ключові слова:* зміна клімату, техногенні та природні надзвичайні ситуації, система моніторингу навколишнього середовища, штучний інтелект, Інтернет речей, безпілотні системи.

Introduction. The growing severity of climate change continues to reshape ecological systems, socio-economic structures, and global security landscapes [1]. Addressing this multifaceted phenomenon requires not only effective policy and mitigation strategies but also robust, scalable, and adaptive environmental monitoring systems. Traditional observation methods, such as satellite imagery and ground-based meteorological stationsm, have played a critical role in climate assessment. Yet, they often lack sufficient spatial granularity, suffer from delays in data acquisition, and face limitations in remote or inaccessible areas.

Recent technological advancements offer new possibilities for real-time, data-driven environmental surveillance. Artificial intelligence, the Internet of Things, and unmanned systems, particularly drones and autonomous sensor platforms, are gaining attention as key components of next-generation climate observation infrastructures. These technologies enable the collection of high-resolution environmental data, dynamic interpretation of complex patterns, and early detection of anomalous climate-related behaviors.

This study investigates the emerging role of AI, IoT, and unmanned systems (aerial, land, underwater and surface) in environmental monitoring of climate change, natural and man-made emergencies. It highlights the potential contributions of these technologies to environmental data collection and interpretation, explores practical and ethical limitations of their deployment, and identifies critical challenges associated with their integration. Through this analysis, we aim to outline a future-oriented framework that supports more responsive, granular, and intelligent climate monitoring solutions.

Literature review and problem statement. A broad spectrum of methods, tools, and integrated technological systems has been developed for now to enhance the monitoring of climate change, natural and man-made disasters, as well as to improve early detection of both natural and anthropogenic hazards [2–4]. Traditional approaches to monitoring climate change and environmental hazards have relied primarily on systematic field observations and classical geophysical and meteorological instruments [5]. Ground-based weather stations, ocean buoys, hydrological gauges, and seismic detectors provided long-term records of temperature, precipitation, ocean dynamics, and tectonic activity, forming the backbone of early environmental monitoring [6–8]. These data sources were complemented by standardized sampling in climatology and ecology, as well as historical archives, such as station logs, maritime records, and paleoclimatic evidence from tree rings or ice cores, that helped trace environmental shifts over extended timescales. Although limited in spatial coverage and resolution, these traditional methods established the essential empirical foundation for understanding climatic variability and natural disaster dynamics.

Recent years have witnessed the rapid emergence of advanced technological approaches for environmental and climate monitoring, driven by the expanding capabilities of the Internet of Things, artificial intelligence, and unmanned systems [9–11]. IoT-based sensor networks enable continuous, high-resolution observation of atmospheric, hydrological, and ecological parameters across vast and previously inaccessible regions [12]. These interconnected devices generate streams of real-time data, significantly improving the timeliness and precision of environmental assessments. Complementing these systems, AI methods, including machine learning, deep learning, and advanced data assimilation techniques, allow for the automated processing of massive heterogeneous datasets, enabling early detection of anomalies, improved prediction of extreme events, and more reliable interpretation of complex environmental dynamics [13]. Unmanned aerial, terrestrial, and maritime platforms further enhance monitoring capabilities by providing flexible, rapid-deployment tools for surveying hazardous or remote locations, capturing detailed imagery, and performing measurements that ground-based systems cannot easily obtain [6].

Despite these advances, most modern monitoring tools are still implemented as isolated solutions designed for specific, narrow tasks rather than as components of a unified global system. This fragmentation limits the broader analytical potential that could be achieved through their coordinated use. The challenge of integrating IoT infrastructures, AI-driven analytics, and unmanned systems into cohesive, interoperable monitoring architectures remains largely unresolved.

Therefore, the *aim of this paper* is to examine and analyze the distinctive features, strengths, and limitations of each of these technologies when applied individually, and to explore the prospective benefits and expanded analytical capabilities that might arise from their combined use in addressing large-scale environmental and climate-related challenges.

Emerging technologies for climate change and emergencies monitoring systems. The integration of cutting-edge technologies into environmental monitoring frameworks is redefining the capabilities of climate observation systems. Among the most impactful innovations are artificial intelligence, the Internet of Things, and unmanned systems. Each contributes uniquely to enhancing the spatial resolution, temporal responsiveness, and analytical depth of environmental data acquisition and interpretation.

Artificial Intelligence. AI serves as the analytical core of modern climate monitoring infrastructures, enabling systems to process massive volumes of heterogeneous data, detect subtle environmental changes, and generate actionable insights [13]. Central to this functionality is the use of artificial neural networks (ANNs) and their specialized architectures. For spatiotemporal pattern recognition in satellite and drone imagery, convolutional neural networks (CNNs) are employed to classify land cover, identify vegetation loss, and detect glacial retreat. When dealing with sequential environmental data such as temperature or gas concentration trends, recurrent neural networks (RNNs) and more advanced long short-term memory (LSTM) models are applied to forecast climate variables and identify anomalies [9, 14]. Autoencoders are useful in unsupervised learning contexts, allowing systems to compress and reconstruct environmental datasets for anomaly detection or dimensionality reduction. Furthermore, graph neural networks (GNNs) are gaining relevance for modeling climate impacts across interconnected geographic regions and ecosystems. These models collectively support high-resolution environmental diagnostics and predictive analytics far beyond the capacity of conventional tools.

Internet of Things. IoT technologies enable the deployment of extensive sensor networks that continuously collect environmental data across diverse terrains and climate zones [10]. These interconnected devices measure microclimatic variables such as ambient temperature, relative humidity, soil moisture, solar radiation, wind velocity, and concentrations of greenhouse gases like CO_2, CH_4, and NO_x [15]. LoRaWAN and NB-IoT protocols allow for long-range, low-power communication between sensors and central data hubs, facilitating monitoring even in remote or infrastructure-sparse regions. The distributed nature of IoT systems supports real-time observation of environmental conditions and enhances the granularity of climate data at both local and regional scales. The combination of low-cost sensor nodes with edge computing capabilities further enables local data preprocessing and intelligent event filtering prior to cloud-based analysis.

Unmanned Systems. Unmanned platforms extend the reach and precision of environmental data collection by accessing areas that are either hazardous or logistically impractical for human observers [6, 16, 17]. These systems can be classified based on their operational domains.

Aerial unmanned vehicles (UAV), such as fixed-wing and multirotor drones, are employed for high-resolution mapping of land surface temperature, vegetation indices (e.g., NDVI), and snow cover extent. They can also carry gas analyzers and spectrometers to detect emissions and surface pollution.

Unmanned ground-based vehicles (UGVs) are utilized in harsh or contaminated terrains to deploy sensors, collect soil samples, and track land degradation. Equipped with machine vision and robotic arms, UGVs are increasingly used in precision agriculture and desertification studies.

Unmanned surface aquatic systems (USVs) operate on rivers, lakes, and oceans to monitor water temperature, pH, turbidity, and pollutant levels. These platforms are especially effective in assessing eutrophication, harmful algal blooms, and thermal pollution. In turn, underwater unmanned vehicles (UUVs) are critical for exploring submerged ecosystems, mapping coral bleaching zones, and measuring ocean acidification. They often rely on sonar, chemical sensors, and fluorometers to capture data in real time.

Integration Scenarios. The combined deployment of AI, IoT, and unmanned systems yields synergistic benefits for climate monitoring. For example, an IoT-enabled sensor network can detect rising ground temperatures in a vulnerable region, then this anomaly triggers a drone flight to collect high-resolution thermal and spectral imagery. Subsequently, AI models analyze the data to identify early signs of drought stress or fire risk. Similarly, coordinated fleets of drones and autonomous boats, guided by AI-driven navigation systems, can be used to assess glacial meltwater contributions to sea-level rise in polar regions. Through such integrative frameworks, emerging technologies provide not only richer and more accurate data, but also the ability to respond adaptively to dynamic environmental conditions.

Moreover, smart sensors, distributed across critical infrastructure within an industrial enterprise, can be effectively employed to monitor operational conditions and prevent man-made accidents. By continuously transmitting real-time data on the status of key equipment and signaling when operational parameters exceed predefined thresholds, these sensors supply intelligent control and decision support systems with the information needed for rapid situation assessment and the formulation of appropriate managerial responses. Such analytical platforms may include, for example, fuzzy-logic-based decision support systems, as demonstrated in study [18]. The connection between distributed sensors and higher-level analytical modules is enabled by Internet of Things technologies, which ensure reliable communication and seamless data integration. Moreover, various intelligent methods can be applied not only for monitoring but also for the synthesis and optimization of control systems themselves, as illustrated in papers [19] and [20].

Opportunities and benefits. The integration of artificial intelligence, Internet of Things technologies, and unmanned systems into climate change and natural and man-made emergencies monitoring presents transformative opportunities across multiple dimensions. These technologies enhance both the technical precision and operational flexibility of environmental observation frameworks, enabling a shift from reactive assessments to proactive, predictive, and geographically extensive surveillance.

The first important advantage is the enhanced spatiotemporal resolution. Conventional monitoring networks often operate at coarse spatial and temporal resolutions, limiting the granularity of climate impact assessments. Unmanned aerial and aquatic systems, equipped with multispectral cameras and environmental sensors, provide centimeter-level resolution data with customizable flight schedules. In parallel, IoT sensor networks deliver continuous data streams from fixed or mobile stations, filling observational gaps and supporting near-real-time updates. These capabilities are particularly valuable in regions with fragmented infrastructure, such as mountainous terrain, wetlands, or polar zones.

The second benefit is the intelligent data interpretation and forecasting of such systems. AI-powered models facilitate the extraction of actionable insights from vast and heterogeneous environmental datasets. Rather than relying solely on manual interpretation or statistical analysis, neural networks can recognize complex nonlinear relationships among climate variables. This enables more accurate forecasting of temperature fluctuations, precipitation anomalies, or extreme weather events. Furthermore, AI systems support change detection algorithms that can autonomously identify environmental degradation, land cover shifts, or urban heat island formation, empowering early warning mechanisms and timely intervention.

The next no less important advantage is the scalability and modularity. One of the key advantages of emerging technologies is their scalability. Sensor nodes can be incrementally deployed across regions without the need for major infrastructure investment. Unmanned systems are modular in design, allowing mission-specific payloads (e.g., gas analyzers, thermal imagers, hyperspectral sensors) to be integrated based on operational objectives. This modularity ensures adaptability to evolving monitoring needs and facilitates tailored deployments in urban, rural, or coastal contexts.

Another benefit that can be gained is the cost efficiency and operational accessibility. Compared to satellite launches or large-scale ground-based monitoring stations, IoT devices and UAVs offer more affordable and accessible solutions, especially for developing countries. Off-the-shelf drones and open-source sensor platforms enable localized climate observation programs with minimal technical overhead. Their autonomous or semi-autonomous nature reduces labor requirements and enhances safety when operating in hazardous environments.

And the last advantage is the support for climate-smart decision making. By combining real-time observations with predictive analytics, these technologies empower data-driven climate governance. Urban planners can use AI-interpreted heat maps for designing climate-resilient infrastructure; agricultural stakeholders can monitor drought risks through UAV-enabled NDVI analysis; coastal authorities can predict storm surge threats using sensor-driven early warning models. This information supports not only adaptation and mitigation planning but also public awareness and education.

Drawing upon the analysis presented above, it becomes possible to outline the structure of a generalized monitoring system designed for observing climate change as well as detecting natural and man-made emergencies. The conceptual architecture of this system, proposed by the authors, is illustrated in Fig. 1, where the corresponding notation is provided: UML – upper monitoring level; LML – lower monitoring level; SMS (L/S/U) – stationary measuring station (land/surface/underwater); LUV – land unmanned vehicle; UAV – unmanned aerial vehicle; UWC (S/U) – unmanned watercraft (surface/underwater); X_{EVi} – vector of environmental variables measured using the i-th measuring station (stationary or mobile), $i = 1, 2, \dots, n$; U_{Si} – vector of sensor output signals transmitted to data recording and storage devices, $i = 1, 2, \dots, n$; U_{PIi} – vector of signals of processed information transmitted to wireless data transmission devices, $i = 1, 2, \dots, n$; U_{CPIi} – vector of signals of compressed and processed information from measuring stations, transmitted via the Internet to the upper level of the monitoring system, $i = 1, 2, \dots, n$; U_{EV} – vector of signals of all environmental information transmitted via the Internet from measuring stations to the upper level of the monitoring system; U_{AERS} – vector of output signals of the intelligent anomaly and emergency recognition system; U_{DSS} – vector of output signals of the intelligent decision support system; Y_{AERS} – vector of adjustable parameters for the intelligent anomaly and emergency recognition system; Y_{DSS} – vector of adjustable parameters for the intelligent decision support system.

The system follows a hierarchical organization comprising two principal monitoring levels: a lower (data acquisition) level and an upper (analytical and management) level.

The lower level is formed by a distributed network of stationary and mobile measuring stations equipped with an array of sensors that capture critical environmental parameters indicative of ongoing or emerging climatic shifts and potential emergency conditions. These parameters may include atmospheric temperature, humidity, barometric pressure, wind characteristics, soil moisture, water pH and conductivity, radiation background levels, CO_2, CH_4, and NO_x and other physical or chemical indicators essential for assessing environmental stability. Each station incorporates modules for local data storage, preliminary processing, and event logging, along with a communication interface for wireless transmission of measurements through internet-based channels to the upper-level monitoring system. Stationary measuring stations may be deployed on land, positioned on surface platforms, or anchored underwater to ensure comprehensive spatial coverage. Mobile stations, in turn, are mounted on ground-based unmanned vehicles or robotic platforms, aerial unmanned systems, and autonomous or remotely operated surface and underwater vessels, thereby enabling flexible, adaptive monitoring in dynamic or inaccessible environments.

The upper level of the proposed monitoring architecture incorporates a suite of intelligent components responsible for the interpretation of incoming data, the recognition of hazardous conditions, and the support of informed human decision-making. At its core lies

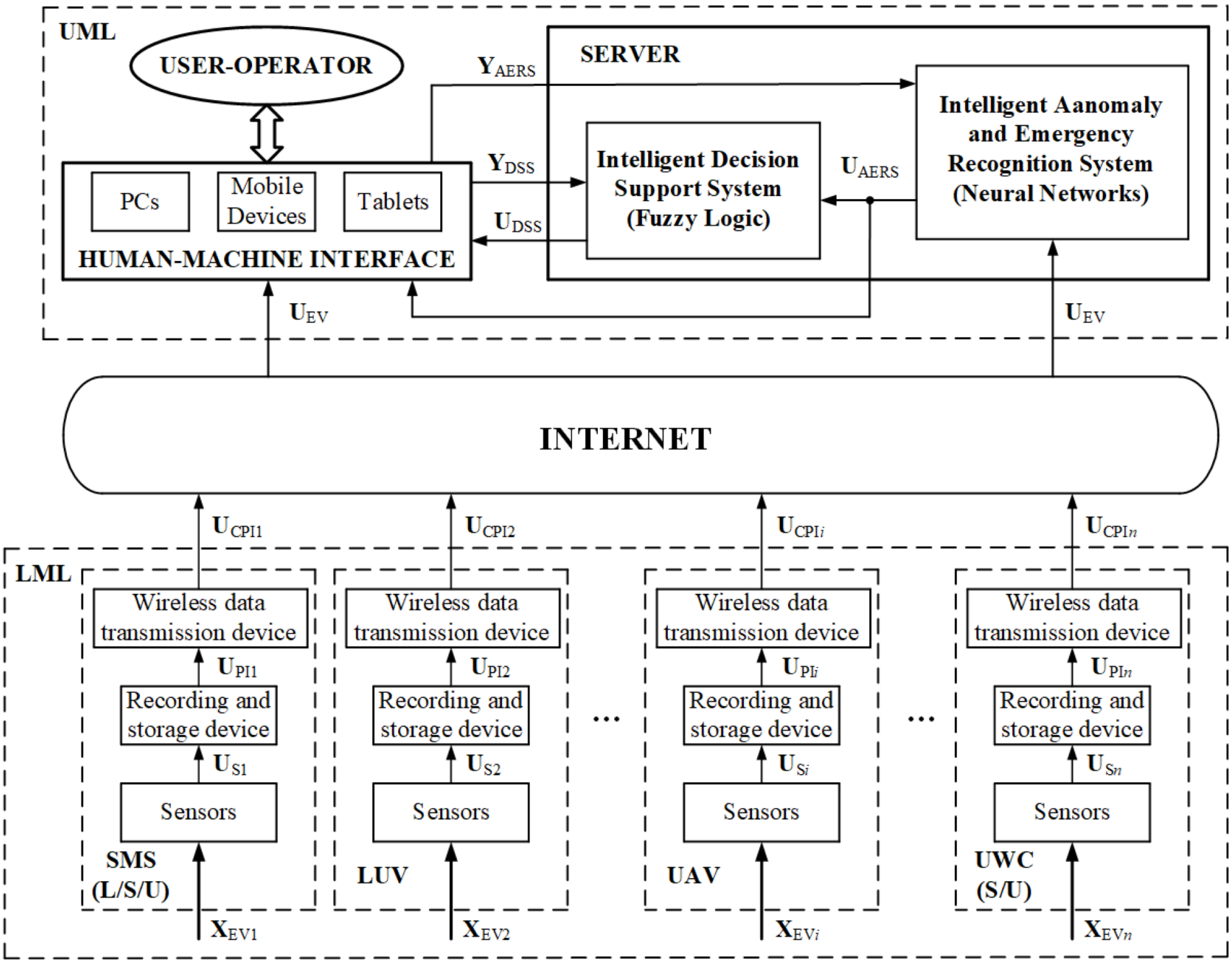

Fig. 1. Functional structure of the generalized hierarchical system for environmental monitoring of climate change and emergencies based on AI, IoT and unmanned vehicles

an intelligent system for detecting anomalies and identifying potential or ongoing emergency situations. This subsystem may be implemented using various neural network models trained on extensive datasets that reflect a wide range of environmental states and emergency scenarios. By processing multidimensional vectors of signals originating from heterogeneous sensors at the lower level, the recognition module is capable of distinguishing normal environmental dynamics from signatures indicative of approaching or existing natural or man-made disasters. Upon detecting such conditions, it generates corresponding alerts and transmits them to the intelligent decision support system for further analysis.

The intelligent decision support system, also hosted at the upper tier, provides the human operator with analytically grounded recommendations tailored to the current operational context. Drawing on expert rules, implemented based on fuzzy logic methods, this subsystem assists in selecting appropriate response strategies, thereby increasing the accuracy, timeliness, and reliability of human decisions. The interaction between the operator and the entire monitoring infrastructure is facilitated by a human-machine interface that presents processed information in a clear and accessible form. This interface can be deployed on various remote devices connected to the internet, including personal computers, tablets, and mobile devices, enabling flexible and convenient supervision of environmental conditions regardless of the operator's location. In turn, the anomaly-recognition and decision-making modules are situated on a high-performance remote server, ensuring adequate computational resources for real-time data processing and analysis.

A system built upon such a generalized architecture can be effectively adapted for a wide spectrum of applications. Its modularity and scalability allow it to function with equal efficiency when deployed within a single industrial enterprise for internal emergency monitoring and ecological assessment, as well as across larger territorial units such as districts, cities, or other administrative or geographic regions.

Next, we will consider the limitations and the inherent challenges that may arise when employing AI technologies, IoT infrastructures, and unmanned systems in advanced environmental monitoring applications.

Challenges and Limitations. Despite their transformative potential, the integration of AI, IoT, and unmanned systems into climate monitoring frameworks presents a number of practical, technical, and ethical challenges. These limitations must be critically addressed to ensure reliability, scalability, and responsible deployment of such technologies in diverse environmental and socio-political contexts.

Infrastructure and connectivity constraints. Many of the regions most vulnerable to climate change, such as remote islands, mountainous zones, or politically unstable territories, lack the digital infrastructure required to support dense IoT networks or consistent operation of unmanned systems. Limited access to stable electricity, mobile networks, or satellite communications restricts real-time data transmission and sensor coordination. In addition, poor maintenance and harsh environmental conditions can lead to frequent hardware failures or data loss in the field.

Energy dependence and hardware limitations. The autonomous operation of drones, surface vehicles, and sensor nodes heavily depends on battery life and energy efficiency. Extended missions in isolated areas often require complex logistical planning, such as solar-powered charging systems or swappable batteries. Sensor payloads may also face limitations in size, sensitivity, or calibration accuracy, affecting the consistency and reliability of collected data, particularly in extreme temperature or humidity conditions.

Data management and computational load. The integration of multimodal data streams, imagery, telemetry, time-series sensor logs, poses challenges for storage, transmission, and analysis. Real-time processing of high-frequency data, especially from video feeds or hyperspectral sensors, demands significant computational resources, often beyond the capabilities of local edge devices. Although cloud computing offers scalability, data latency, cost, and privacy considerations must be balanced. Moreover, heterogeneous data formats and a lack of standardized protocols can hinder interoperability between devices and systems.

Algorithmic transparency and model bias. While AI models offer unprecedented predictive capabilities, their “black-box” nature often reduces interpretability. Climate policy decisions based on AI-generated insights may face scrutiny if model logic is not transparent or explainable. Additionally, biases in training data, stemming from geographic or temporal gaps, can result in skewed outputs or inaccurate forecasts. In high-stakes applications, such as disaster response or emissions regulation, such biases may lead to misinformed decisions or resource misallocation.

Ethical and legal considerations. The use of unmanned aerial or ground systems for environmental surveillance raises ethical questions about data ownership, privacy, and sovereignty. In regions with indigenous communities or contested territories, climate monitoring may unintentionally infringe upon local rights or be perceived as external intrusion. Furthermore, regulatory ambiguity in the deployment of drones or data collection sensors complicates cross-border collaboration and long-term monitoring efforts.

Conclusions. The convergence of artificial intelligence, Internet of Things, and unmanned systems is reshaping the landscape of environmental monitoring of climate change, natural and man-made emergencies by enabling more dynamic, precise, and intelligent observation of environmental systems. These technologies offer a multidimensional advantage over conventional methods by extending spatial coverage, improving temporal resolution, and unlocking data-driven insights through automated analysis and forecasting. Their application enhances the ability to detect early signals of ecological degradation, assess regional vulnerabilities, and inform climate-responsive decision-making.

However, the deployment of these technologies is not without limitations. Challenges related to infrastructure, energy consumption, data integration, algorithmic transparency, and regulatory ambiguity continue to hinder their full-scale adoption. Addressing these issues requires coordinated efforts from engineers, data scientists, environmental experts, policymakers, and local communities to ensure equitable, ethical, and sustainable implementation. Looking ahead, future research should focus on improving the robustness and interoperability of sensor networks, developing energy-efficient AI algorithms suitable for edge computing, and establishing international frameworks for data governance and system standardization. Advances in neuromorphic computing, federated learning, and autonomous swarm coordination among unmanned systems hold particular promise for expanding the scalability and responsiveness of climate monitoring operations. Ultimately, the integration of emerging technologies into environmental observation is not merely a technical innovation, it represents a paradigm shift toward more proactive, adaptive, and collaborative approaches to understanding and confronting the complex realities of global climate change as well as natural and man-made emergencies.

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