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The Generative Logic and Implementation Pathways of AI-Empowered Precision Enhancement in Disaster Monitoring and Forecasting

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Abstract. The increasing frequency of extreme weather events and compound disasters has rendered traditional disaster monitoring and forecasting models inadequate for meeting complex operational demands. Artificial intelligence (AI) has emerged as a critical tool for enhancing the precision of disaster forecasting. To elucidate the mechanisms through which AI empowers forecasting precision and to propose feasible optimization pathways, this paper integrates existing research with domestic practical cases. It deconstructs the rich connotations of forecasting precision across three dimensions—spatiotemporal, intensity, and impact—and analyzes the generative logic of AI empowerment from value, technological, and institutional perspectives, while also examining its practical boundaries. The study reveals that AI-driven improvements in forecasting effectiveness do not rely solely on technological upgrades, but rather constitute a governance process involving the synergistic coupling of technology, institutions, and grassroots capacity. Accordingly, this paper proposes countermeasures including the establishment of unified data platforms, the construction of human-AI interactive systems, the localization of AI models, and the refinement of a“peacetime-wartime integrated”emergency technology support system, thereby providing theoretical underpinnings for the modernization of emergency management with Chinese characteristics.

Keywords: Artificial intelligence; disaster forecasting; precision early warning; governance limitations; modernization of emergency management.

1. Introduction

On July 10, 2026, the State Council held an executive meeting to further coordinate flood prevention and disaster relief efforts. The meeting underscored the need to“further improve the precision of monitoring and forecasting,”activate timely warning and response protocols, and decisively organize population evacuations when dangers are identified, so as to minimize casualties. This directive positions“monitoring and forecasting precision”as central to flood prevention and disaster relief operations. It also reflects that, under the realistic conditions of intensifying global climate change and increasingly frequent extreme weather events, enhancing monitoring and forecasting precision has become an imperative for advancing the modernization of China’s emergency management system and capacity.

Although China’s emergency management has progressively transitioned from a“post-disaster relief”paradigm to a“pre-disaster prevention”approach, and the theoretical and practical frameworks for flood control and drought relief have matured considerably, the complexity of disasters continues to escalate under the influence of extreme weather conditions. The chain effects triggered by a single hazard often result in the coupling and superimposition of multiple disaster types, leading to simultaneous outbreaks. Traditional monitoring and forecasting models, built upon linear causal logic, struggle to adequately address complex scenarios characterized by multi-hazard superposition and abrupt disaster evolution induced by extreme weather. They commonly exhibit deficiencies in spatiotemporal precision, intensity accuracy, and impact assessment. In the July 2023 extreme rainstorm event in North China (“7·30”), conventional numerical forecasting models failed to capture

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the coupling effects of multiple factors, producing significant deviations between predicted rainfall amounts/precipitation zones and actual observations. In the August 2025 flash flood disaster in Yuzhong, Gansu (“8·7”), the traditional model, relying on linear extrapolation of historical rainfall records, overlooked the rainfall-amplifying effects of mountainous terrain and other compounding factors, resulting in a more than threefold underestimation of actual precipitation. The conventional forecasting paradigm, dependent on historical empirical extrapolation, can no longer satisfy the precision requirements of contemporary complex disaster prevention and control. This misalignment between technological limitations and practical disaster response needs has become a critical bottleneck constraining the efficacy of emergency management decision-making.

In recent years, the deep integration of artificial intelligence (AI) with meteorological and hydrological forecasting has opened new avenues for overcoming the linear constraints of traditional monitoring and forecasting models. China’s domestically developed meteorological large models, such as“Pangu”“Fenglei”and“Fengqing”have demonstrated robust comprehensive capabilities.“Fenglei”can generate high-resolution short-term severe convection forecasts within three minutes, while“Fengqing”fundamentally addresses the inherent deficiencies of linear extrapolation through novel algorithmic architectures. Numerous operational applications have validated the effectiveness of AI empowerment: in Shanghai, the“Yushi”and“Fuyao”AI models for severe convection achieved a heavy rain forecast accuracy of 89.7%, with warnings issued an average of 4 hours and 20 minutes in advance. In Chongqing, the“Tianzi·12h”AI model accurately predicted 29 rounds of heavy rainfall, enabling the early evacuation of 6,793 residents during the June 18 storm with zero casualties. These practices demonstrate that AI has become a pivotal factor in reshaping monitoring and forecasting systems and enhancing forecasting precision.

Existing studies provide a theoretical foundation for AI-empowered precision forecasting. Zhong Kaibin emphasizes the critical importance of timely and accurate information for emergency decision-making and advocates for the adoption of predictive simulation tools to address increasingly complex emergencies [1].Together with Xue Lan, he further contends that the application of AI technologies in emergency governance can effectively enhance the scientific rigor and refinement of emergency management [2].Ma Baocheng, from the perspective of Chinese-style modernization, explicitly identifies technological empowerment as the key to translating institutional strengths into governance effectiveness [3]. Zhan Chengyu argues that emergencies are inherently scenario-dependent, and that the improvement of emergency management systems should be oriented toward“addressing the system’s own vulnerabilities” [4].However, existing research predominantly concentrates on“scenario applications”and general macro-level recommendations, lacking a systematic analysis of the mechanisms through which AI empowers forecasting precision. In light of this research gap, this paper addresses the following questions: What is the intrinsic mechanism by which AI enhances forecasting precision? How should institutional frameworks be designed to ensure the effective implementation of AI-based forecasting technologies? By systematically analyzing the deep connotations and internal logic of AI empowerment in precision forecasting, this study aims to fill the existing research void and provide theoretical guidance for precision disaster governance in the contemporary era.

2. The Deep Connotations of“Precision”from the Perspective of Emergency Management

2.1. A Three-Dimensional Deconstruction of "Precision"

“Precision”is not merely a matter of data error, but a complex and multidimensional concept. Drawing upon modern emergency management systems and practices, this paper decomposes forecasting precision into three progressive dimensions: spatiotemporal precision, intensity precision, and impact precision.

2.1.1. Spatiotemporal Precision

Spatiotemporal precision refers to determining when and where a disaster will occur. It is the primary and most foundational dimension, as well as the prerequisite for subsequent intensity assessment and disaster evaluation. It comprises two components—temporal precision and spatial precision—which together enable very short-range nowcasting and the precise identification of townships and other specific localities [5].

In the temporal dimension, spatiotemporal precision entails two core requirements: forecast lead time and temporal resolution. Zhong Kaibin introduced the concept of"decision time lag,"defined as the interval from the"event occurrence point"to the"correct decision point"[1] Emergency decision-making involves coordination across multiple departments and administrative levels; every step—from receiving forecast information to executing population evacuation—requires buffer time. Insufficient lead time compresses the response window, even if decisions are made immediately, potentially causing the loss of the optimal rescue opportunity. Traditional forecasts are typically issued at 24-hour intervals, yet the critical time scale for flash floods and mountain torrents is measured in hours or even minutes. In response to this operational need, short-term precipitation nowcasting has emerged, aiming to provide hourly-scale rainfall forecasts at fine temporal resolution that can directly inform evacuation planning.

In the spatial dimension, spatiotemporal precision requires forecasts to move beyond coarse administrative units such as counties and districts, refining risk identification to the level of villages, ravines, and low-lying areas, and clearly distinguishing high-risk zones from safe areas. Through techniques such as radar precipitation retrieval and multi-source data fusion, forecast products can be refined to kilometer-scale or even hectometer-scale grids, enabling targeted early warning [6]. The core value of spatial precision lies in directing emergency resources precisely toward high-risk areas, thereby fundamentally avoiding resource waste caused by uniform regional prevention and control measures.

2.1.2. Intensity Precision

Intensity precision refers to the magnitude and destructive power of a disaster, advancing the inquiry from the"positioning"question addressed by spatiotemporal precision to the "quantification"of disaster intensity. It encompasses three layers of meaning: initial magnitude assessment, full-cycle dynamic projection, and graded response support.

The first layer concerns the multi-indicator integrated measurement of initial disaster magnitude. Taking rainstorm-induced flooding as an example, short-duration extreme rainfall and prolonged persistent rainfall produce different damage patterns and thus require distinct prevention priorities, placing high demands on forecast refinement and timeliness[7]. More importantly, intensity precision cannot rely on static threshold comparisons; rather, it must incorporate real-time watershed hydrological conditions and dynamically update critical rainfall thresholds[8]. Zhan Chengyu also noted that the impact of emergencies unfolds within dynamically evolving scenarios, and that assessments based solely on static initial values cannot accurately predict the extent of damage under extreme scenarios [4].

The second layer involves the dynamic probabilistic projection of disaster evolution intensity. The "butterfly effect"of modern disasters is increasingly pronounced, as ordinary events can easily trigger disaster chains that escalate into major catastrophes. However, the causal relationships within disaster chain evolution are merely logical associations; the occurrence of a preceding disaster does not guarantee that a subsequent one will follow [9]. This means intensity precision cannot stop at assessing current disaster severity, but must extend to projecting subsequent risk trajectories based on real-time data, quantifying the probabilities of various secondary risks at different stages of the disaster chain. This captures the core essence of intensity precision: addressing both present and future risk assessments.

The third layer consists of providing scientific evidence for graded emergency response. Different disaster intensities correspond to different response levels and resource allocation schemes [10]. The central function of intensity precision is to supply the scientific basis for determining“which response level to activate.”Zhong Kaibin pointed out that pre-disaster prevention represents the lowest-cost, highest-benefit phase of the full-cycle disaster management [11], and that disaster prevention governance must balance risk control effectiveness with resource investment, finding the equilibrium between over-defense and under-defense. The prevalent conservative tendency in grassroots emergency assessment is precisely a coping strategy forced by the absence of precise intensity forecasts, which indirectly demonstrates the necessity of intensity precision as a foundation for graded response.

2.1.3. Impact precision

Impact precision refers to the distribution of hazard-affected body vulnerability and the targeted prediction of disaster impacts. While spatiotemporal and intensity precision focus on natural hazards themselves, impact precision shifts the perspective to hazard-affected bodies, elevating disaster forecasting from the physical-natural dimension to the social governance dimension—constituting the highest level of the precision system.

Impact precision first requires breaking through the traditional limitation of focusing solely on hazard factors and incorporating the vulnerability of hazard-affected bodies into the forecasting framework. Studies have shown that traditional geological disaster meteorological risk warning methods neglect the vulnerability of hazard-affected bodies, leading to high false alarm rates in high-risk zones [12]. Shi Peijun pointed out that complete disaster risk is the result of the coupling of multiple elements, and that disasters of the same intensity produce differentiated losses depending on the affected bodies [13]. For instance, a short-duration heavy rain of the same magnitude causes almost no damage in uninhabited mountainous areas, but in densely populated urban areas it can readily trigger widespread entrapment and structural damage.

Second, impact precision requires the translation of disaster intensity into social loss estimates. Comprehensive vulnerability assessment of hazard-affected bodies encompasses three core dimensions: exposure, sensitivity, and adaptive capacity [14]. Moreover, vulnerability is not static; the degree of damage to affected bodies exhibits a nonlinear relationship with hazard intensity. The key to impact precision lies in establishing a projection chain of“hazard intensity–vulnerability level–estimated loss”feeding physical forecast outputs into quantitative models to project, under different scenarios, the likely scope of population entrapment and the scale of infrastructure damage.

Ultimately, impact precision serves emergency management practice. By delineating risk levels and identifying vulnerable populations and critical facilities, it provides a quantitative basis for evacuation decisions and resource allocation. Traditional“blanket”dissemination of early warnings through broadcast channels severely undermines disaster mitigation effectiveness [15]. Only by specifying whom and where the disaster will affect can warnings be translated into concrete actions for population evacuation and infrastructure protection.

These three dimensions form a progressive sequence—from disaster positioning to quantification and finally to social impact assessment. They are mutually indispensable and together explain the full connotation of“precision”within the emergency management context.

2.2. The Paradigm Shift from“Empirical Forecasting”to“Digital Twin Projection”

The empowerment of monitoring and forecasting precision by artificial intelligence is not merely about faster and more accurate measurements; more fundamentally, it drives a paradigm shift in disaster forecasting—from“empirical extrapolation”to“digital twin projection.”

Traditional monitoring and forecasting relies on historical disaster data, using statistical patterns to project future events—a fundamentally static approach. Faced with the realities of frequent extreme weather and coupled disaster superposition, its predictive capability degrades substantially. Zhong

Kaibin, analyzing the July 2021 extreme rainstorm in Zhengzhou, noted that linear extrapolation based solely on historical data is prone to significant errors when confronting unconventional, multi-factor coupled extreme events[16]. Furthermore, traditional forecasting models assume mutual independence among influencing factors, failing to capture the complex interactions among multiple variables and proving inadequate for projecting disaster chain evolution—compromising the reliability of their outputs.

Artificial intelligence, by contrast, transforms forecasting from“empirical extrapolation”to“dynamic projection.”AI systems can ingest real-time observational data, continuously capturing the interplay among multiple elements, and, combined with dynamically updated information, perform iterative computations. This means forecasting is no longer static but evolves continuously with incoming real-time data. This embodies the“scenario dependence”emphasized by Zhan Chengyu in the context of forecasting: the forecast becomes a dynamically constructed real-time scenario, rather than a static extrapolation based on historical data.

2.3. The Role of the Forecasting Link in the Full Emergency Management Cycle

This paper argues that monitoring and forecasting occupies a pivotal position in the full emergency management cycle, serving as the nexus between“risk identification”and“emergency response.”This argument is elaborated from three perspectives.

First, risk identification marks the beginning of emergency management. Raw data from risk identification can be transformed into actionable disaster forecasts only through the integration and synthesis performed by forecasting models. Second, spatiotemporal precision determines whether and where to activate emergency response; intensity precision determines the scale of resources required; and impact precision determines how those resources should be allocated. Any deviation in forecast information will propagate through the response system, potentially exacerbating disaster losses. Third, forecast precision directly affects the length of the“decision window.”The lead time of forecasts determines the starting point of the window, while the credibility of forecasts—built on historical accuracy—determines whether decision-makers act decisively. Higher precision enables decision-makers to respond immediately upon receiving information, thereby enhancing overall emergency effectiveness.

In summary, forecasting precision is not merely a technical indicator but a critical factor affecting the governance effectiveness of the entire emergency management chain. The paradigm shift in forecasting—from static to dynamic—transforms risk governance from a static assessment to a dynamic response process. Improving monitoring and forecasting precision therefore represents not only technological optimization but also a structural enhancement of the entire emergency management system's response effectiveness.

3. The Generative Logic of Artificial Intelligence-Enabled Disaster Monitoring and Forecasting

3.1. Value Logic: Goal Reshaping Anchored in People’s Lives and Safety

Research on artificial intelligence-enabled disaster early warning risks a biased perspective if it prioritizes model architecture and algorithm accuracy above all else. The fundamental nature of the technology is determined by who it serves and what problems it solves. General Secretary Xi Jinping has repeatedly emphasized putting people first and prioritizing human lives [17]. In July 2024, the Standing Committee of the Political Bureau of the CPC Central Committee held a special meeting to study and arrange flood control, disaster relief and rescue work, reiterating the requirement to“always put protecting people’s lives and safety first, evacuate residents in hazard-prone areas early and decisively, and minimize casualties” [18]. The two key words“early”and“decisively”precisely capture the core essence of disaster early warning: no matter how thorough post-disaster review and

summary may be, they can never replace the critical action of organizing mass evacuation from danger zones before disasters strike.

Traditional disaster early warning systems have long been plagued by a structural contradiction: warning messages can be released effectively, yet there is often no valid tracking or verification of whether information reaches target populations and whether relevant actors can take prompt risk-avoidance actions. This is the so-called“last-mile”challenge in early warning implementation.

The core value of artificial intelligence-enabled disaster monitoring and forecasting lies not merely in improving the computational efficiency of early warning models, but more importantly in forming a traceable and accountable closed loop of early warning response. Deputy Director Xie Yunshi from the Miyun Branch of Beijing Municipal Commission of Planning and Natural Resources developed a geological hazard“call-and-response”mini-program independently with large model interactive tools at a computing cost of less than 30 RMB. The system incorporates information of residents exposed to risks at more than 2,000 geological hazard sites across the district into a dynamic database, automatically marks subjects with incomplete responses and triggers secondary notifications, and completes risk-evacuation verification for each individual at the final stage of evacuation. It realizes effective linkage between notification procedures and accountability mechanisms[19]. The profound transformative implication of AI-enabled disaster monitoring and forecasting is that it translates the macro political requirement of“putting people first and prioritizing human lives”——which was previously hard to quantify—into a standardized operational mechanism with full traceability, reversible accountability and verifiable outcomes. General Secretary Xi Jinping pointed out that“when it comes to protecting people’s lives and safety, we must spare no expense.”[17] Applied to disaster early warning work, this means sparing no technical cost to remove transmission bottlenecks, ensure warning information accurately reaches every resident, and truly convert the arrival of warning messages into effective risk-evacuation actions.

3.2. Technical Logic: Qualitative Breakthrough from Data Silos to Multi-source Fusion

China’s traditional disaster forecasting system has long adopted departmental governance. Meteorological, water conservancy, natural resources and other authorities operate separate systems and run independent models. Such a system can cope with single-hazard disasters, yet when compound disasters occur, data from a single department is insufficient to support comprehensive risk assessment. Disaster evolution follows a chained pattern, while early warning platforms of different departments remain isolated with poor information flow, creating a long-standing structural mismatch.

The introduction of artificial intelligence provides technical support to break this deadlock. An AI collaborative architecture centered on large language models, graph neural networks and time-series forecasting models thoroughly overturns conventional paradigms and builds an integrated panoramic risk assessment framework with multi-factor and full-dimensional coverage. This architecture can effectively integrate heterogeneous monitoring data from meteorology, hydrology, geology, urban lifeline systems and other sources. Meanwhile, it incorporates the coupling logic of environmental change, infrastructure stress and disaster evolution into a unified analytical system [20]. Specifically, large models possess powerful capabilities for unified representation and semantic parsing of multi-modal data, which can deeply mine implicit coupling correlations of cross-industry disaster data, break data barriers in traditional risk assessment, and provide underlying support for full-domain heterogeneous data fusion and chained disaster correlation reasoning [21]. Leveraging the advantages of spatial topological modeling, graph neural networks can precisely characterize risk transmission patterns within geographic spaces and urban infrastructure networks, compensating for the drawback that conventional methods ignore the coupling effects of spatial networks and improving the identification accuracy of disaster spatial spread [22]. Time-series forecasting models can dynamically capture temporal evolution characteristics such as geological deformation, hydrometeorology and infrastructure load, achieving continuous iterative updates of risk status and effectively addressing the strong lag of traditional static risk assessment [23].

Deep learning models are inherently suited to processing multi-source heterogeneous data. Meteorological, geological, urban pipeline, satellite remote sensing and even social media data can all be incorporated into a unified analytical framework. Instead of predefining functional relationships between different types of data, the model autonomously identifies feature correlations from massive samples[24]. This nonlinear fitting capability carries special methodological significance in disaster early warning. Extreme disasters often fall outside the scope of historical experience; black swan events refer to extreme scenarios rarely or never observed in existing records. Traditional statistical models have limitations when handling such events and tend to produce severely distorted predictions. Deep learning models can overcome this limitation at the principle level: multi-layer neural networks can capture weak combined precursor signals from seemingly unrelated variables. Once abnormal patterns formed by superposition of multiple signals are identified, warnings can be issued, which provides technical support to extend forecast lead time [25] [26]. The Jiu'an large model, jointly developed by the Ministry of Emergency Management and Baidu, can automatically identify waterlogging sites from tens of thousands of video streams within 30 seconds. The time required for fire prevention dispatch has been reduced from manual assessment to mere seconds. Such time compression reflects structural shortening of the decision-making chain [27].

3.3. Institutional Logic: Collaborative Catalysis of Government-Industry-University-Research Partnership under the New System for Mobilizing Resources Nationwide

Technical effectiveness cannot be achieved without institutional guarantees. For an AI disaster early warning model to move from code to practical application, it requires at minimum high-quality training data, large-scale computing power and institutional channels for embedding into business workflows. None of these can be accomplished by technological research alone.

Zhong Kaibin notes that the centralized and unified leadership of the CPC can rapidly translate national strategic intentions into cross-departmental, cross-level and cross-domain collaborative actions [27]. Cross-departmental disaster data sharing remains a prevalent challenge in most countries. In China, however, an organizational system featuring top-level coordination and grassroots implementation provides institutional channels for data aggregation. Ma Baocheng summarizes the nationwide coordination and capacity to pool resources for major tasks as one of the institutional strengths of China's emergency management system with Chinese characteristics [3]. This judgment gains new implications in the field of AI-enabled disaster monitoring and forecasting: the predictive performance of large models improves with larger datasets and broader scenario coverage. China's territorial space covering nearly all climate zones and geological types, alongside the world's largest IoT sensor network, makes super-large-scale data resources possible. Yet scale cannot automatically translate into advantages; the key lies in institutions that integrate data into usable training resources. The National Data Bureau promotes the construction of a national integrated computing power network, aiming to shape computing power into public infrastructure similar to water, electricity, heating and gas [28]. This supply approach substantially lowers the threshold for grassroots institutions to carry out AI research and development.

The government-industry-university-research collaboration has formed a recognizable practical model. The Ministry of Emergency Management and Baidu jointly developed the Jiu'an large model: the government provides application scenarios and data, enterprises deliver technical implementation, universities and research institutes undertake basic algorithm research, and grassroots users drive system iteration in practice. This collaboration is neither purely market-driven nor implemented through traditional administrative orders; rather, it represents a distinctive hybrid model under the new system for mobilizing resources nationwide [27]. Zhan Chenyu's analytical framework of institutional-governance dynamic evolution helps us understand this process. The advancement of AI-enabled disaster monitoring and forecasting itself forces emergency management institutions to shift from departmental fragmentation to integrated collaboration, and from experience-driven to data-driven governance [30].

What AI-enabled disaster monitoring and forecasting requires is not one-off emergency resource mobilization after disasters, but capacity building for long-term and continuous iteration. The Third Plenary Session of the 20th Central Committee of the CPC dedicated a chapter to modernizing the national security system, incorporating emergency management and disaster prevention, mitigation and relief into the holistic national security outlook. It explicitly takes constructing a major security and emergency response framework and improving the full-domain risk monitoring and early warning system as long-term reform tasks. Consistent and stable top-level policy guarantees lay a solid institutional foundation for government-industry-university-research collaborative innovation, continuously converting China's institutional strengths in coordination into technical reserves for disaster risk assessment and governance effectiveness at the grassroots level.

4. Practical Examination: Boundaries and Constraints of AI-Enhanced Forecasting Accuracy

Against the backdrop of digitally empowered emergency governance, artificial intelligence leverages its technical strengths including data fitting, dynamic simulation, full-domain perception and rapid dispatching to overcome the limitations of conventional meteorological and hydrological forecasting that relies on empirical models and linear deduction. Satellite remote sensing, ground-based radars and clusters of unmanned systems form a space-ground integrated monitoring infrastructure. AI algorithms can fuse multi-source monitoring data and compensate for the deficiencies of traditional numerical models in simulating compound disasters[31]. At present, China's emergency management is gradually advancing toward digitalization and intelligence. Data from the Data Center of the Ministry of Emergency Management indicates that the coverage rate of digital platforms within the national emergency management system reached 89% in 2023. Nevertheless, delayed emergency responses and unsatisfactory practical governance performance remain evident amid certain disaster events. The discrepancy between technological advancement and practical effectiveness reveals that social emergency management is currently in a transitional phase of technological empowerment and institutional innovation[32]. A prevalent misconception of "technological omnipotence" persists in the sector, assuming that AI can completely break through bottlenecks in forecasting accuracy and realize precise prevention and control of disaster risks. In fact, technological empowerment has clear boundaries and scope of application. AI technologies decoupled from governance systems, grassroots contexts and decision-making logic often fail to deliver expected benefits. Governance performance enabled by technology cannot be fully unleashed under multiple constraints. Therefore, improvements in early warning capacity cannot rely solely on hardware and system upgrades.

4.1. Cross-departmental Data Silos: Fundamental Data Constraints for Model Training

Data constitutes the core element of AI forecasting and serves as the fuel for training AI models. Iterative optimization of models is essentially deep learning and pattern extraction from multi-scenario datasets. Larger data volume, richer multi-source dimensions and stronger temporal continuity contribute to higher model accuracy, whereas data fragmentation directly undermines algorithm training. Widely deployed emergency management platforms across regions commonly suffer from isolated systems and overlapping functions. Sectors including meteorology, water conservancy, geology and natural resources have established separate monitoring systems. Inconsistencies exist in data collection standards, storage formats and update frequencies across departments, alongside the absence of unified sharing interfaces. As a result, real-time sharing of core information is difficult to achieve. Resource allocation instructions frequently experience transmission interruptions and response lags, severely impairing the efficiency and accuracy of emergency response. The coexistence of "functional silos"and "information silos" has long persisted [30]. Furthermore, national general large models currently face critical limitations in training samples: samples are concentrated in plain areas while disaster records from mountains, plateaus and similar terrain remain scarce, leading to an immature sample structure.

4.2. Logical Conflicts between Algorithm Black Boxes and Emergency Decision-Making: Boundaries of Trust and Implementation

Whether natural disasters or various anthropogenic accidents, each hazard type carries unique characteristics and response requirements. In real-world operational contexts, emergency management confronts complex, volatile and unpredictable challenges. AI forecasting outputs cannot be directly translated into definitive operational orders such as school closures or public evacuation, which creates a dilemma where high model accuracy coexists with delayed decision-making. Digital twins and simulation improve visualization, yet the underlying algorithmic logic is untraceable. In cases of false or missed alerts, liability becomes difficult to define, further reducing decision-makers' willingness to adopt AI forecasts. Professor Zhan Chengyu argues that emergency response constitutes high-accountability and high-risk situational decision-making. Administrative decision-makers have rigid requirements for certainty, traceability and explainability of analytical evidence; decisions must be underpinned by clear physical mechanisms and linear deduction processes [32]. Unlike the transparent inference logic of conventional forecasting models, deep learning AI algorithms are typically black-box systems that mostly produce probabilistic interval outputs and fail to explicitly interpret disaster triggering mechanisms. This creates tensions between technical logic and administrative decision-making.

4.3. Structural Gaps in Grassroots Absorptive Capacity:"Last-Mile"Frictions in Forecasting Dissemination

Challenges remain in the allocation and integration of technological resources. First-tier cities and economically developed regions are equipped with abundant high-end intelligent sensing devices and processing platforms. In contrast, central and western regions and grassroots institutions generally suffer from insufficient investment, difficult technical maintenance and inadequate talent reserves, widening regional disparities in emergency response capacity[17]. County and township governments face dual shortages of hardware and skilled personnel: low-performance computing terminals cannot support computation for minute-scale and kilometer-scale refined forecasting datasets. Most grassroots staff lack professional capabilities for algorithm interpretation and platform operation and maintenance, making it hard for them to parse and apply sophisticated forecasting products. Accurate data generated at higher administrative levels often suffers information degradation during transmission to grassroots units, resulting in a paradox: accurate forecasts yet ineffective on-the-ground implementation. This further exacerbates vulnerabilities in awareness, capacity and communication when multiple stakeholders participate in community emergency management. A focus on rural communities reveals a pervasive cognitive bias of "prioritizing development while neglecting emergency preparedness"in China's rural and grassroots governance, manifested mainly in weak crisis awareness, inadequate emergency capacity and poor communication and coordination[33]. Cumulative structural gaps in grassroots absorptive capacity prevent AI forecasting products from bridging the delivery channel from platforms to frontline responders. The technical advantages in prediction accuracy cannot be translated into tangible disaster prevention outcomes at the grassroots level, thereby generating last-mile frictions.

5. Implementation Paths for Enhancing the Accuracy of AI-Empowered Disaster Monitoring and Forecasting

General Secretary Xi Jinping has pointed out that meteorological work bears on the safety of life, the development of production, the prosperity of people's livelihood, and the soundness of the ecological environment; it is therefore necessary to accelerate scientific and technological innovation and achieve precise monitoring, accurate forecasting, and fine-grained services. Adhering to a systems perspective, planning and advancing the high-quality development of meteorology necessarily requires promoting the high-quality development of integrated meteorological observation. Based on the practical constraints identified above, this paper proposes optimization paths from four

dimensions, with the aim of deeply integrating artificial intelligence technology into the entire process of modernized emergency governance and fully unleashing its potential.

5.1. Path One: Strengthening Top-Level Design and Building a Unified Disaster Data Platform

To address the underlying data constraints, this path improves the comprehensive data supply system from three aspects.

First, it is necessary to build a national-level integrated disaster monitoring and forecasting data platform. Improving forecasting accuracy relies on the real-time integration and analysis of multi-source data. By connecting the data obtained from monitoring across multiple industries into a unified data platform, performing centralized storage and management, forming a unified catalogue, and realizing the principle of "one source for each dataset,"it is possible to provide a comprehensive and accurate data foundation for AI-based forecasting.

Second, it is necessary to unify the technical standards and regulatory framework for disaster monitoring data. At present, different departments use different monitoring equipment, and their operational systems may also be incompatible; differences in the data formats of some core indicators prevent the effective integration of data across departments and reduce the efficiency and accuracy of forecasting. It is therefore necessary to introduce nationally applicable technical data standards, establish data audit mechanisms, and use artificial intelligence to clean anomalous data in advance, thereby improving the reliability of datasets and reducing the interference of noisy data with accuracy.

Third, it is necessary to improve the data security system. Breaking down "data silos" does not mean that all data can be freely shared among different departments. It is essential to balance the relationship between data openness and security control, distinguish among different categories of data such as classified data, public data, and sensitive data, define tiered sharing permissions, and—on the premise of ensuring the confidentiality of critical security data—open standardized training datasets so as to consolidate the data foundation.

5.2. Path Two: Building a Human–Machine Interaction System

In August 2023, when studying flood prevention and disaster relief work, General Secretary Xi Jinping pointed out at a meeting of the Standing Committee of the Political Bureau of the CPC Central Committee:"It is necessary to achieve precise early-warning response, further strengthen the linkage between meteorological warning and disaster forecasting, highlight imminent-disaster warning, deliver point-to-point accurate forecasting and rolling updates, enhance the targeting of warnings, implement the imminent-disaster 'call-and-response' mechanism that reaches flood-prevention responsible persons at the grassroots level directly, strengthen the linkage between early warning and emergency response, implement the action measures of emergency plans, and grasp the initiative in the work."Therefore, the introduction of artificial intelligence cannot be confined to algorithm tuning. In emergency management, a highly complex and context-dependent field, it is necessary to strengthen the dynamic interaction between AI systems and actors from two aspects: "technology-side decision-making" and "reception-side response."

The first is technology-side decision-making, which is the beginning of the chain of forecast-information dissemination. The outputs generated by artificial intelligence through algorithms are often probabilistic—that is, probability information about the occurrence of disasters and extreme scenarios—whereas what emergency management issues are necessarily deterministic instructions (whether to act and what to do). There is thus a tension between the two. It is therefore necessary to establish a human–machine collaborative and complementary forecasting mechanism that incorporates the practical experience of forecasting experts and balances the advantages of computational power with professional expertise. This workflow can be broken down into three stages: in the first stage, AI models complete real-time computation of massive monitoring data, output preliminary forecasting results, automatically identify high-risk areas, and carry out

spatiotemporal and intensity prediction; in the second stage, experts from various fields are organized to conduct manual verification of the AI-generated forecast; in the third stage, AI is used to deduce the evolution paths of disasters and estimate the affected scope of people and property under different warning levels, thereby providing a quantitative basis for tiered emergency response.

Next is reception-side response, which is likewise an important link in emergency management. It is necessary to improve the tiered, categorized, and precise early-warning“call-and-response” mechanism, replace the traditional mode of uniformly broadcasting warnings to a broad audience, and deliver targeted messages to different population groups so as to embody the flexible advantage of“human–machine interaction.”First, for responsible persons at all levels, differentiated evacuation instructions should be pushed according to risk areas and disaster types to improve response efficiency. Second, for the general public, low-cost AI forecasting terminals should be developed, with attention paid to the design of information presentation and feedback mechanisms. From the perspective of human–computer interaction theory, system effectiveness depends not only on its level of intelligence but also on whether the logic of technological interaction fits users' cognitive models [34]. Different departments interpret the same set of probability data with different emphases: for example, water-resource departments focus on “the probability of flood-peak discharge,”transportation departments on “the probability of waterlogging depth exceeding the threshold,”and the public on “the window period for evacuation behavior.”It is therefore necessary to enhance users' perception of risk states and their initiative to respond, and to increase public participation in emergency management.

When users participate in the work of emergency management, they become the densest “mobile sensors” during an actual disaster, transmitting real-time data back from the field to continuously calibrate and correct short-term forecasts for the coming hours, thereby improving short-term forecasting accuracy. Moreover, users' actual responses can help the AI system conduct post-event review: for example, when the forecasted physical quantities are accurate, but the social side shows no response or over-response, this indicates that the AI has miscalculated the vulnerability of hazard-bearing bodies at different locations. Such social response data can promote model correction and improve subsequent forecasting accuracy.

5.3. Path Three: Advancing Lightweight AI Models and Localized Adaptation

At present, China has built national-level meteorological foundation models such as Fenglei (“Wind-Thunder”) and Fengqing (“Wind-Clear”) and has achieved unified deployment across the four levels of meteorological operations nationwide, outputting forecast products supported by the national supercomputing cluster to provide basic analytical support for national disaster monitoring. However, in addition to the limitation of cloud computing power, these foundation models also have shortcomings such as sample limitations and insufficient resolution. Trained on national datasets, they can capture the evolution patterns of large-scale disasters, but there is an upper limit to grid resolution, so that small-scale, local phenomena can only be treated through smoothing statistics; forecasters still need to combine weather patterns, surface conditions, and other factors to issue more accurate forecasts in advance [35]. The General Secretary has repeatedly emphasized that different regions differ greatly in terrain, climate, and disaster types, and that it is necessary to ground responses in local risk characteristics and refine monitoring, early-warning, and disaster-prevention measures according to local conditions. The meteorological bureaus of Tibet and Guizhou have also pointed out that general-purpose national AI models produce significant errors in plateau and mountainous areas, and that supporting regional lightweight models is necessary to meet grassroots disaster-prevention needs. It is therefore necessary to focus on regional differences and adapt the AI models accordingly.

First, it is necessary to promote lightweight pruning and grassroots deployment of foundation models. Foundation models have a large number of parameters and a high computational-power threshold, making them difficult to run on township-level servers; grassroots units can only passively receive finished products from the cloud and cannot connect local data in real time for immediate correction,

while network latency weakens the timeliness and accuracy of forecasts—if extreme disasters cause network outages, forecasting capability may even be lost entirely. Therefore, through model pruning, the core predictive capability should be retained to obtain a lightweight model that can be deployed locally at the grassroots level, no longer relying on cloud servers throughout the entire process, thereby improving the accuracy of local disaster prediction.

Second, it is necessary to localize the AI models. Nationally applicable training data can hardly encompass the disaster characteristics unique to each locality, which limits the effectiveness of general-purpose models in recognizing local disasters. Therefore, relying on the unified disaster data platform, region-specific disaster sample sets should be established and the AI models fine-tuned to correct parameter deviations that do not match local disaster-causing patterns, enabling AI to accurately capture the risk-evolution characteristics unique to each region and improve the accuracy of local disaster forecasting.

5.4. Path Four: Improving the "Peacetime–Wartime Integration"Science and Technology Support System for Emergencies

General Secretary Xi Jinping has repeatedly stressed that disaster prevention and mitigation work must firmly establish bottom-line thinking and extreme-scenario thinking, be prepared for major floods and major disasters, and carry out all risk-prevention work well. Regarding the construction of the disaster prevention, mitigation, and relief system, the General Secretary has put forward the core principle of"adhering to prevention first and combining prevention, resistance, and relief, and uniting routine disaster mitigation with extraordinary disaster relief."Based on this logic, it is necessary to build an emergency system that integrates peacetime and wartime operations, and to improve the dual safeguards of long-term operation and maintenance and emergency backstop.

First, wartime computational-power reserves should serve as a backstop. AI forecasting computing power should be incorporated into the national emergency-material reserve system. Distinguished from routine computing-power scheduling, in the conventional stage without disasters computing resources are kept on standby without occupying resources for daily business operations; when extreme disasters cause a surge in monitoring data and computational overload, the reserved computing power is activated to guarantee the supply of computing power and solve the practical problems of forecast failure and delay under extreme conditions.

Second, routine iterative updates should continuously optimize forecasting accuracy. In the routine stage without flood season or disasters, historical disaster samples, grassroots feedback, and other data should be used to continuously iterate and optimize model parameters, improving the model's ability to recognize local disaster patterns and realizing a closed loop of "peacetime–wartime integration"in which accumulation and optimization in peacetime yield effectiveness in wartime.

6. Conclusion

In summary, this paper first clarifies the multi-dimensional connotation of disaster forecasting accuracy within emergency management contexts. It identifies the paradigm shift of AI-driven forecasting from empirical extrapolation to digital-twin simulation and defines the pivotal role of forecasting across the full emergency lifecycle. The paper further analyzes the internal generative logic of AI-enabled disaster monitoring and forecasting from three dimensions: value, technology and institution. Meanwhile, it acknowledges practical boundaries stemming from data silos, algorithmic black boxes and deficiencies in grassroots absorptive capacity. To address these dilemmas, actionable pathways are proposed in four respects: data platform development, human-machine collaborative assessment, model localization, and science and technology support integrating routine preparedness and emergency response. This study argues that the performance of intelligent forecasting hinges on the coordinated alignment of technology, institutions and grassroots capacity, rather than unilateral technological innovation. The findings offer insights for improving the practical implementation of intelligent disaster early warning in China. The empowering effect of

artificial intelligence on disaster monitoring and forecasting cannot be simply attributed to advances in algorithms and computing power. Fundamentally, continuous improvements in intelligent forecasting accuracy represent a process through which China's emergency governance system with Chinese characteristics translates its institutional strengths of coordinated planning and nationwide mobilization into grassroots disaster prevention practices.

Future modernization of disaster prevention and mitigation requires moving beyond narrow technological determinism and adhering to a holistic approach to national security. Technological innovation, institutional development and grassroots capacity building should be advanced in tandem. A national integrated disaster data coordination platform can break sectoral information silos; human-machine interactive mechanisms can align forecasting simulations with administrative responses; localized adaptive modifications enable region-specific precise forecasting. Technology upgrades remedy forecasting weaknesses, institutional improvements remove coordination barriers, and capacity building consolidates grassroots foundations. The mutually supportive triad of"technology–institution–capacity"works synergistically to transform disaster forecasting from computational precision at the data level into implementable precision at the governance level. This will continuously refine a scientific, refined and modern disaster forecasting governance system and provide solid support for advancing the modernization of China's emergency management and safeguarding public security and stability.

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