

Reflections on the Application of Environmental Data Science in Environmental Systems Under the Background of Climate Risk

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Abstract: Global climate change grows increasingly severe, with compound climate risks repeatedly disrupting natural ecosystems and urban living environments. Applying targeted technologies to strengthen risk prevention mechanisms stands as a key priority in environmental governance. Drawing on the WMO 2024 Global Climate Report, key findings from the IPCC Sixth Assessment, and the ongoing operations of 33,000 national ecological monitoring stations, this paper explores the technical framework and practical applications of environmental data science. The article elaborates on the practical value of this discipline in the fields of watershed ecological governance, urban environmental operation and maintenance, and regional ecological protection, and identifies prominent practical problems such as data resource fragmentation and insufficient model regional adaptability in industry development. Based on the actual development of ecological governance in China, this article proposes feasible improvement ideas with targeted measures. These findings offer robust theoretical and practical insights for strengthening climate risk resilience, enhancing environmental systems' ecological carrying capacity, and advancing refined ecological governance based on environmental data science.

Keywords: Climate risk, Environmental data science, Environmental system, Intelligent modeling, Digital twins, Ecological resilience governance.

1. Introduction

Global climate change's cascading effects impact natural systems like atmospheric and hydrological cycles, and terrestrial ecosystems. The IPCC Sixth Assessment Report clearly states that climate change caused by human activities has affected various regions around the world. In the past fifty years, the frequency, scope, and destructive power of disasters such as extreme heat and short-term heavy rainfall have continued to rise, and the stability of the climate system has significantly declined [1]. Climate risks have surpassed the scope of pure meteorology and may also trigger secondary problems such as soil erosion, eutrophication of water bodies, degradation of biological habitats, and frequent urban waterlogging, posing a long-term threat to socioeconomic stability.

China's vast territory and diverse climate zones result in inherent ecosystem vulnerability. Against global warming, traditional manual monitoring and experience-driven management struggle with complex, sudden climate risks. The current governance mainly focuses on post-disaster remedial measures, lacking advance assessment and systematic simulation of risk evolution laws, and unable to achieve proactive protection of environmental systems [2].

To address this challenge, environmental data science merges environmental science with big data and geospatial tech. Harnessing the air-space-ground integrated monitoring network, we compile large-scale long-term datasets. Standardized processing, correlation analysis and simulation modeling then reveal inherent links between climate and environmental factors. China's ecological monitoring system features a robust data support framework, with over 33,000 national stations-underpinning practical technology rollout [3]. Against normalized climate risks, this paper examines environmental data science's value across diverse

environmental systems, identifies real-world barriers, and proposes context-specific optimizations to support climate-resilient environmental management.

2. The Technical Architecture of Environmental Data Science and the Logic of Climate Risk Response

Environmental data science operates on a well-established technical logic, linking data collection, standardization, correlation analysis and scenario application into a closed cycle. This system provides essential backing for environmental management to tackle ongoing climate risks, with tightly integrated components that dynamically sense and measure environmental system changes amid climate perturbations.

Data collection relies on space-air-ground integrated monitoring networks. The MODIS satellite of NASA is the core carrier of large-scale remote sensing, providing long-term and stable continuous observation data on surface temperature, vegetation coverage, land use types, etc. On the ground, China has established national-level air quality and surface water monitoring stations with full coverage, continuously collecting key indicators such as meteorology, hydrology, and pollutant concentration; Drones and coastal buoys fill monitoring gaps in mountainous, riparian, lacustrine and nearshore zones, forming a multi-dimensional complementary collection pattern [4].

Data processing tackles multi-source data heterogeneity, format inconsistencies and temporal misalignment. Meteorological, ecological and water conservancy departments adopt different monitoring standards, data formats and spatio-temporal resolutions, hindering direct joint analysis. The industry adopts data cleaning, normalization, and standardization, and time-series

interpolation to unify data specifications, and uses geographic information platforms for spatial matching, ensuring rigorous follow-up modeling [5].

Data analysis is centered around statistical models and intelligent algorithms. Traditional mathematical statistical methods can analyze the linear correlation between climate factors and environmental indicators, while machine learning and deep learning are more suitable for the nonlinear evolution characteristics of the climate system [6], and can explore potential risk patterns from long-term massive data. By combining the internationally recognized CMIP6 climate model, we can simulate climate trends under different emission scenarios, providing robust insights for medium- and long-term climate risk prediction [7].

The application layer focuses on the practical needs of environmental governance, relying on simulation, risk mapping [8, 9], and trend prediction to transform analysis results into actionable governance solutions. Climate risk response follows the process of risk identification, current situation assessment, trend prediction, emergency response, and long-term optimization [10], promoting environmental governance from passive post-disaster remediation to normalized early warning and proactive prevention and control, in line with the current needs of climate risk governance.

3. Multi-source Heterogeneous Data Integration: The Fundamental Support for Climate Risk Identification

Accurate identification of climate risks relies on complete and continuous environmental and climate basic data. Multi-source heterogeneous data fusion is a prerequisite for environmental data science to serve climate risk prevention and control [11]. Climate risk assessment involves multiple dimensions such as meteorology, hydrology, topography, ecology, and land development. The relevant data belongs to different administrative departments and covers forms such as monitoring reports, remote sensing images, and industry statistical texts, naturally possessing multi-source heterogeneous characteristics.

Siloed management across departments creates clear data fragmentation and inconsistent standards [12]. The meteorological, ecological environment, water conservancy, natural resources and other departments operate independently, but there is a lack of unified standards for monitoring indicators, sampling frequency, and storage formats, and the channels for inter-departmental data sharing are not perfect. Long-term data dispersion means single-factor analysis fails to capture cross-disciplinary climate risk linkages, which can easily lead to one-sided risk assessment.

Remote sensing technology provides core support for large-scale climate risk assessment [13]. The European Space Agency's Sentinel satellite stably outputs medium to high-resolution Earth observation data, which is often used for flood delineation, vegetation degradation tracking, drought identification, and other work, effectively filling the data gap in remote areas without ground monitoring. The global disaster monitoring platform built on remote sensing detects large-scale extreme weather events and offer data support for cross-regional climate risk coordination.

The ground intelligent monitoring network focuses on small-scale areas and conducts refined risk assessment.

Online devices installed in river and lake basins, urban areas, and ecological protection zones can collect high-frequency data round-the-clock, timely capturing water and atmospheric environmental fluctuations caused by climate anomalies. This type of time-series data fills the gap in remote sensing time resolution, achieving linkage between global macroscopic analysis and local location monitoring [14].

Climate risk assessment is not limited to the natural ecological dimension, population layout, infrastructure conditions, and regional economic carrying capacity also affect the degree of disaster hazard. Integrating population grids, land use, urban distribution and other data can build a comprehensive risk identification framework that integrates natural and social systems [15].

A unified data integration process and quality standards are key to ensuring the accuracy of risk identification. Referring to the industry guidelines for ecological environment monitoring, we will address issues such as data loss and numerical anomalies, improve the data fusion and sharing mechanism, and transform scattered multi-source data into reliable basis for risk identification [16], laying the foundation for subsequent modeling and governance decisions.

4. Machine Learning Driven Climate Risk Prediction and Assessment Model

Climate systems are nonlinear and stochastic; traditional linear statistics struggle to capture complex climate-environment relationships. Machine learning has powerful pattern recognition and nonlinear fitting capabilities, and has become a commonly used method for climate risk prediction and vulnerability assessment. Based on long-term observational data, it can summarize the evolution laws of extreme climate events and also quantify the sensitivity of environmental systems to climate disturbances [17].

At the level of extreme climate prediction, machine learning facilitates analysis of the development trends of high-frequency disasters such as high temperatures, heavy rainfall, and basin droughts. Traditional meteorological forecasts mostly focus on short-term weather changes, making it difficult to take into account the secondary environmental impacts caused by regional extreme events. Machine learning can integrate key factors such as temperature, precipitation, terrain, and vegetation [18], relying on training historical datasets to capture disaster precursors, improve the timeliness and accuracy of disaster prediction, and creates lead time for prevention and control work [19].

Machine learning delivers significant value in assessing climate risk vulnerability across watersheds and regions. Such evaluations incorporate multi-dimensional indicators including ecology, hydrology, terrain, and human activity. Algorithms like random forests and gradient boosting trees identify key drivers precisely, minimizing subjective bias from manual weighting, and generate grid-based risk zoning maps to inform ecological conservation and disaster planning [20].

Interpretability lies at the heart of any model's real-world deployment. While several deep learning models deliver strong fitting performance, their underlying reasoning mechanisms remain opaque and hard to parse. Public sector decision-makers are understandably hesitant to rely solely on

raw model outputs. Contemporary work prioritizes interpretable machine learning: it leverages techniques like factor contribution analysis and feature importance assessment to quantify how each indicator shapes risk outcomes. This ensures outputs are both interpretable and traceable, aligning with the rigor required for public sector decision-making [21].

Machine learning models built purely on data lack physical grounding, failing to align with the inherent dynamics of the climate system [22]. The mainstream academic approach now couples climate physics models with machine learning: leveraging CMIP6 outputs to establish a robust physical foundation [23], while using machine learning to refine downscaling accuracy and reconcile physical consistency with data fit. Such integrated models can not only deduce short-term extreme climate risks, but also predict the evolution trend of the environmental system under long-term climate warming. These integrated models deliver far greater practical value than single models.

5. Digital twins and Environmental System Simulation: A Virtual Test Field for Climate Risk Response

Digital twins can replicate the evolution process of climate risks, deduce future scenarios, and rehearse governance plans, which is an important support for environmental system management in climate risk governance [24]. This technology breaks through the constraints of physical system experiments and simulates the environmental response laws under different climate scenarios and prevention and control strategies in virtual space, providing scientific pre validation for governance decisions.

Watershed water environment is the most mature field for the implementation of digital twins. Integrating multiple sources of data such as hydrological monitoring, water quality stations, remote sensing images, and terrain elevation, a watershed simulation twin platform is built to reproduce the flow state of water systems, pollutant diffusion paths, and spatiotemporal evolution characteristics of water quality. By setting climate conditions such as extreme rainfall, low water and drought, it can simulate chain reactions such as sudden changes in water level, deterioration of water quality, and algal outbreaks, accurately identify vulnerable nodes in the watershed, and provides guidance for water resource scheduling and pollution prevention and control.

Urban digital twins focus on climate induced waterlogging, heat island effect, and air quality variability [25]. The urban underlying surface is complex, and heavy rainfall can easily cause drainage overload and local waterlogging. High temperatures worsen the heat island effect and degrade living conditions. Based on terrain, drainage network, green space, and building foundation data, the twin model can simulate different rainfall intensities and water accumulation ranges, quantify the mitigation effect of ecological space optimization on the heat island effect, and provide a basis for urban planning, disaster prevention infrastructure, and ecological restoration.

Digital twins serve the assessment of vegetation succession and ecosystem carrying capacity under climate change. Climate change changes the regional water and heat patterns, affecting vegetation growth rhythms and biological habitat distribution. A simulation model based on long-term remote sensing data can be used to deduce the changes in vegetation

cover and the migration patterns of ecologically fragile zones under different warming scenarios, providing a basis for the delineation of nature reserves and ecological restoration.

Digital twin deployment still faces hurdles: high computing demand, poor multi-model coupling and delayed real-time data sync [26]. The industry uses lightweight technologies such as model reduction and edge computing to reduce computing costs, open up the data link between monitoring and twin platforms, and achieve real-virtual dynamic linkage. Through scenario deduction, environmental governance has shifted from empirical analysis to data-driven decision-making, enhancing the resilience of ecosystems to withstand climate risks.

6. Limitations and Optimization Paths of Environmental Data Science Applications

The theoretical value of environmental data science in climate risk governance and ecosystem management has been widely recognized by both academia and practical fields. In practice, disciplinary application is limited by data, technology, management and talent gaps, restricting full technological potential [27]. Sorting out practical shortcomings and exploring improvement ideas that are suitable for industry development are the core prerequisites for promoting its deep implementation.

The imperfect construction of data system is the primary factor restricting the application of disciplines [28]. The data management systems of domestic departments such as ecology, meteorology, and water conservancy are independent and have not yet formed a unified and standardized sharing mechanism. A large number of monitoring resources have been closed and fragmented for a long time, which cannot support multidimensional integration analysis. remote zones such as plateau areas and mountains have sparse monitoring stations and limited long-term data, resulting in a lack of solid basis for local climate risk assessment and prone to evaluation bias.

In addition to the inherent shortcomings at the data level, the adaptability deficiencies of modeling techniques also urgently need to be addressed. The existing machine learning and environmental simulation models are mostly designed for single region and single type disaster training [29], and have weak cross-regional migration and adaptation capabilities [30]. Part of the modeling research focuses solely on numerical fitting accuracy and deviates from the physical operation mechanism of the climate system. Although the derived results conform to numerical characteristics, they lack practical ecological significance and are difficult to directly serve governance decisions [31]. Faced with the risk of compound climate risks, the existing coupling modeling technology is still immature and cannot accurately restore the linkage impact of multiple disasters.

The development of the industry cannot do without the support of composite talents, and the shortage of talent supply has become a common problem in the industry. Environmental data science requires practitioners to possess the abilities of ecological theory, big data processing, geographic information modeling, and intelligent algorithm application. Traditional university disciplines have significant barriers [32], and environmental majors lack data technology training. Data majors lack ecological accumulation, and there is a shortage of practical talents, which limits the large-scale

promotion of technology.

Based on the pain points in reality, it can be optimized from multiple dimensions. Improve cross-departmental data collaboration rules and establish a regional environmental data sharing base; Expand the monitoring network in ecologically vulnerable areas and supplement the full-length time-series observation data; Promote the integration of physical mechanisms and data-driven modeling to enhance the model's generalization ability and interpretability; Cross-disciplinary talent development via university-industry cooperation; Establish industry application standards and quality control standards to empower climate risk management through standardization [33].

7. Conclusion

The normalization of climate risks has become an unavoidable reality in global ecological governance. The natural and artificial environmental systems are continuously disturbed by climate factors, and traditional experiential and fragmented management models are no longer able to cope with complex and sudden risk prevention and control demands.

In this context, environmental data science provides a key technological path for solving governance dilemmas. Environmental data science relies on technological advantages such as integrated collection of air, space, and earth, multi-source data fusion, intelligent model prediction, and digital twin simulation. It deeply integrates into the entire process of environmental risk identification, trend prediction, scheme rehearsal, and governance decision-making, becoming a key support for strengthening ecological climate resilience and implementing refined governance.

In practice, data, algorithms and simulation work in tandem: multi-source data fusion breaks the limitations of single factor analysis and supports multidimensional analysis of climate and environmental information. Machine learning breaks through the limitations of traditional statistics, accurately depicts the nonlinear evolution laws of climate, and quantifies environmental vulnerability levels. Digital twins create virtual testbeds to simulate system responses, supporting governance plan optimization, and these technologies drive environmental governance from passive response to active warning, and from single point control to comprehensive system governance.

However, the implementation of technology is not smooth sailing, and there are still obvious shortcomings in industry applications. The problems of departmental data fragmentation, insufficient local monitoring points, weak model adaptability, and shortage of cross-disciplinary talent reserves are constraining the full potential of technological value.

Based on China's climate endowment and ecological pattern, in order to address the above shortcomings, it is necessary to deepen the integration and application of environmental data science and environmental management. Fill in the gaps in data sharing, monitoring layout, model optimization, and talent cultivation, and build a locally adapted data analysis and simulation system. By leveraging data foundations and modeling tools to serve scientific decision-making, this approach steadily enhances the environmental system's ability to resist risks, self-repair, and maintain stability, laying a solid technological and management foundation for regional ecological security and sustainable development.

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