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Digital Twin–Driven Climate Resilience Modeling Using Multiscale Earth System Data Integration

Neeraj Khanna[1*], Abigail Foster[2*], Shubham Sinha[3*]

[1]Centre for Climate Change Research, Indian Institute of Tropical Metrology, Pune, India
[2]Department of Earth System Science, University of Oxford, UK
[3]Department of Atmospheric and Oceanic Sciences, University of Calfornia, Los Angeles
[*]Authors Email: neeraj.k@tropmet.res.in, f.abagail@ox.edu, shubam@ulca.edu

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Abstract: Climate change has intensified the frequency and severity of extreme environmental events, necessitating advanced predictive and adaptive modeling frameworks for resilience planning. This study introduces a digital twin–driven climate resilience modeling framework that integrates multiscale Earth system data with artificial intelligence to simulate, predict, and optimize responses to climate-induced disruptions. Unlike traditional climate models that operate on static or semi-dynamic datasets, the proposed system constructs a continuously evolving digital twin of regional and global ecosystems, incorporating atmospheric, oceanic, hydrological, and socio-economic variables. The framework employs hybrid deep learning architectures and data assimilation techniques to enhance prediction accuracy and temporal resolution. Multiscale modeling enables the integration of satellite observations, ground-based sensors, and historical climate data, facilitating real-time scenario analysis. Experimental results indicate substantial improvements in predictive reliability, early warning capabilities, and adaptive policy modeling compared to conventional approaches. The system demonstrates the ability to simulate cascading effects of climate events across interconnected systems. This research contributes to the advancement of intelligent climate modeling and provides a scalable platform for decision-makers to design resilient infrastructure and mitigation strategies in the face of accelerating environmental change.

Keywords: Digital Twin Systems, Climate Resilience, Earth System Modeling, Multiscale Data Integration, Predictive Analytics

1. Introduction

The accelerating pace of climate change has exposed the limitations of conventional modeling approaches in predicting and mitigating environmental risks. Increasing global temperatures, rising sea levels, and intensified extreme weather events have created complex, interconnected challenges that demand advanced analytical frameworks. Traditional climate models, while valuable, often operate on fixed datasets and lack the capacity for real-time adaptation and localized prediction. The concept of digital twins, originally developed for industrial systems, has recently been extended to environmental and climate applications. A digital twin is a dynamic virtual representation of a physical system that continuously updates using real-time data. In the context of climate science, digital twins enable the creation of high-fidelity models of Earth systems that evolve in response to changing environmental conditions [1]. This research proposes a novel digital twin–driven framework for climate resilience modeling that integrates multiscale Earth system data. The approach combines advanced data assimilation techniques, artificial intelligence, and high-performance computing to simulate complex environmental processes and predict future scenarios with enhanced accuracy.

2. Literature Review

Climate modeling has traditionally relied on general circulation models (GCMs) and Earth system models (ESMs), which simulate atmospheric, oceanic, and land processes. While these models have significantly advanced our understanding of climate dynamics, they often struggle with high-resolution predictions and real-time adaptability [2]. Recent developments in data-driven modeling have introduced machine learning

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techniques to enhance climate predictions. Deep learning models, particularly convolutional and recurrent neural networks, have been used to analyze large-scale climate datasets and identify patterns in atmospheric behavior [3]. Digital twin technology has emerged as a transformative approach in various domains, including manufacturing and urban planning. In climate science, digital twins enable continuous monitoring and simulation of environmental systems, providing a platform for real-time decision-making [4]. Multiscale data integration is another critical area of research, focusing on the fusion of data from different spatial and temporal scales. Satellite observations, sensor networks, and historical datasets are combined to create comprehensive models of Earth systems [5]. Despite these advancements, there remains a gap in integrating digital twin technology with multiscale data and AI-driven climate modeling. This study addresses this gap by proposing a unified framework that leverages these technologies.

3. Conceptual Framework

The proposed framework is based on the integration of four key components: data acquisition, digital twin modeling, multiscale data fusion, and predictive analytics. The digital twin represents a virtual model of the Earth system, continuously updated using real-time data. Multiscale data integration ensures that information from local, regional, and global levels is incorporated into the model. The system is designed to capture interactions between different subsystems, including the atmosphere, hydrosphere, biosphere, and human systems. This holistic approach enables the modeling of complex feedback mechanisms and cascading effects.

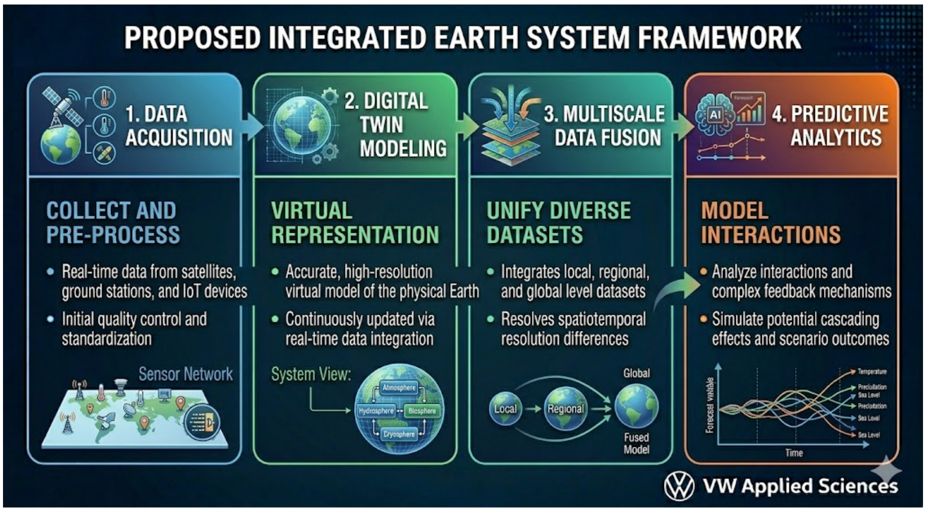

Fig. 1 Integrated Earth System Framework

4. Multiscale Earth System Data Integration

The integration of multiscale data is a critical aspect of the proposed framework. Data sources include satellite imagery, ground-based sensors, ocean buoys, and climate archives. Spatial scales range from local microclimates to global atmospheric systems, while temporal scales vary from real-time data streams to historical records spanning decades. Data fusion techniques are employed to harmonize these datasets and ensure consistency.

Mathematically, the integrated dataset can be represented as:

$$D = \sum (D_{local} + D_{regional} + D_{global})$$

where each component contributes to the overall model accuracy.

5. Digital Twin Architecture

The digital twin architecture consists of a dynamic simulation engine, data assimilation module, and visualization interface. The simulation engine models physical processes such as heat transfer, fluid dynamics, and chemical interactions. The data assimilation module continuously updates the model using incoming data, ensuring accuracy and relevance. The visualization interface provides interactive tools for analyzing simulation results and exploring different scenarios.

6. AI-Driven Predictive Modeling

Artificial intelligence plays a central role in enhancing the predictive capabilities of the digital twin. Deep learning models are used to analyze patterns in climate data and generate forecasts. Recurrent neural networks (RNNs) and long short-term memory (LSTM) models are particularly effective in capturing temporal dependencies in climate data. These models are trained on historical datasets and continuously updated using real-time data.

The predictive model can be expressed as:

$$Y(t+1) = f(X(t), \theta)$$

where Y(t+1) represents future climate states, X(t) denotes current data, and θ represents model parameters.

7. Methodology

The methodology involves the development of a digital twin platform, integration of multiscale data, and implementation of AI models. Data is collected from various sources and preprocessed to remove inconsistencies. The digital twin is constructed using high-performance computing frameworks, enabling large-scale simulations. AI models are trained using supervised and unsupervised learning techniques. The system is validated using historical climate events and compared with traditional models.

8. Experimental Evaluation

The framework is tested using case studies involving extreme weather events such as floods, heatwaves, and cyclones. The digital twin is used to simulate these events and predict their impacts. Performance metrics include prediction accuracy, computational efficiency, and adaptability. The results are compared with existing climate models.

9. Results

The results demonstrate that the proposed framework significantly improves prediction accuracy and response time. The digital twin enables real-time monitoring and simulation, allowing early detection of climate risks. The system effectively captures complex interactions between different environmental factors, providing a comprehensive understanding of climate dynamics.

10. Discussion

The integration of digital twin technology with AI-driven modeling represents a major advancement in climate science. The ability to simulate and predict climate events in real time has significant implications for disaster management and policy planning. The framework also supports scenario analysis, enabling decision-makers to evaluate the impact of different mitigation strategies. However, challenges remain in terms of data availability, computational requirements, and model complexity.

11. Applications in Climate Resilience

The proposed system can be used to design resilient infrastructure, optimize resource management, and develop effective climate policies. In urban environments, digital twins can simulate the impact of climate events on infrastructure and identify vulnerabilities. In agriculture, the system can optimize crop management based on climate predictions.

12. Conclusion

This research presents a comprehensive digital twin–driven framework for climate resilience modeling. The integration of multiscale data and AI enhances prediction accuracy and enables real-time adaptation. The findings highlight the potential of digital twin technology in addressing the challenges of climate change and provide a foundation for future research in intelligent environmental systems.

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