Integrating Artificial Intelligence with Physics Based Modeling for Enhanced Natural Disaster Prediction: A Hybrid Approach

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Abstract:
Natural disasters such as earthquakes, hurricanes, floods, and wildfires are escalating in frequency and intensity due to climate change. This paper explores the integration of artificial intelligence (AI) with physics-based models to improve natural disaster prediction. While physics-based models offer interpretability and adherence to fundamental laws, AI enhances pattern recognition and real-time analysis. The proposed AI-Physics hybrid model leverages the strengths of both methods to deliver timely, accurate, and physically consistent disaster forecasts. This approach has the potential to shift disaster management from reactive response to proactive prevention.

Keywords: Natural Disaster Prediction, Artificial Intelligence, Physics-Based Models, Hybrid Modeling, Early Warning Systems, Earthquake, Hurricane, Flood, Wildfire

1. INTRODUCTION

Natural disasters are among the most devastating global threats, costing billions in damages and thousands of lives each year. Traditional prediction systems relying on historical data and empirical models are limited in lead time, accuracy, and adaptability (Khandelwal et al., 2024). Two major approaches—physics-based simulations and AI—have emerged to address this. Physics-based models simulate environmental dynamics via conservation laws but often lack real-time responsiveness. AI models, especially deep learning, process large datasets efficiently but lack physical interpretability. A hybrid AI-Physics framework can potentially unify these strengths for better predictions and management (Scher & Messori, 2022).

2. Methodology

2.1 Data Integration Layer

A robust hybrid system begins with integrated data: satellite imagery, ground sensors, historical archives, and real-time feeds. This layer harmonizes spatial and temporal discrepancies using data fusion methods to create a cohesive environmental dataset (Chattopadhyay et al., 2024).

2.2 Physics-Based Simulation Module

Each disaster type is governed by specific physical principles:

- Earthquakes: Seismic wave propagation and fault rupture dynamics
- Hurricanes: Atmospheric and oceanic fluid dynamics
- Floods: Hydrological and hydraulic flow models

- Wildfires: Combustion and heat transfer simulations
  These simulations offer physically grounded insights but demand significant computational power and calibration (Rahmani et al., 2024).

2.3 AI Enhancement Layer

AI augments simulations in several ways:

- Pattern recognition: Learns precursors from historical data
- Anomaly detection: Flags real-time deviations
- Parameter optimization: Tunes physics model variables
- Computational acceleration: Neural networks as surrogate models reduce runtime by up to 90% (Abdollahian et al., 2024)

2.4 Prediction Integration System

Combining AI and physics outputs through Bayesian integration or ensemble models yields comprehensive predictions with uncertainty estimates, improving reliability and interpretability (Scher & Messori, 2022).

2.5 Validation and Feedback Loop

Continuous validation against real-world events refines the hybrid model. Performance metrics drive parameter updates, ensuring adaptability and resilience.

3. Results and Discussion

3.1 Improved Prediction Accuracy

Hybrid models leverage data-driven patterns and physical laws to outperform traditional methods. For instance, in earthquake prediction, AI identifies precursors while physics ensures physical plausibility (Khandelwal et al., 2024).

3.2 Reduced Computational Time

AI surrogate models reduce simulation time by 90–95%, enabling real-time predictions essential for evacuation and mitigation (Abdollahian et al., 2024).

3.3 Enhanced Interpretability

By embedding physical constraints in AI models, predictions become transparent and trustworthy—critical for stakeholder confidence (Scher & Messori, 2022).

3.4 Real-Time Adaptability

With continuous data assimilation, the system adapts to evolving disaster conditions, enhancing situational awareness during dynamic events like wildfires and hurricanes.

3.5 Uncertainty Quantification

Combining AI and physics enables better uncertainty estimation, guiding risk-based decisions and resource allocation during emergencies.

4. Conclusion

This paper presents a hybrid model integrating artificial intelligence with physics-based simulations for natural disaster prediction. By bridging data-driven learning with physical reasoning, the model enhances prediction accuracy, speed, and trustworthiness. It supports a shift from reactive disaster response to proactive risk mitigation. Future research should focus on refining physics-informed neural networks, exploring edge computing for local predictions, and incorporating community-driven data. As climate change intensifies, such interdisciplinary approaches are crucial for safeguarding communities and infrastructure.

References

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