RESPOND: Realistic Environment Simulation of Population and Natural Disasters with LLM-Driven Agents (Student Abstract)

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Abstract

Climate change is driving more frequent and severe disasters, putting people and infrastructure at risk. Protecting communities requires models that capture both natural disasters dynamics and how people behave under extreme conditions. This demo presents RESPOND, a multi-agent LLM-enhanced platform that jointly simulates natural hazards and human response. RESPOND couples high-fidelity flood AI forecasting an agent-based model of human behavior. LLM modules improve each agent decision-making, enabling context-aware reasoning over alerts, road closures, social signals, and changing water levels. The system simulates evacuation flows, resource seeking, and communication patterns producing actionable outputs for emergency management, urban planning, and policy. In the live demo one can run what-if or predicted scenarios, adjust assumptions, and observe emergent population behavior and risk hot spots in real time. By tightly coupling dynamic hazards with LLM-driven multi-agent behavior, RESPOND moves beyond fragmented tools and offers a practical, integrated platform for disaster preparedness and response.

Introduction

The frequency and intensity of natural disasters are rising, demanding robust and adaptive management strategies to protect people and infrastructure (Shevchenko et al. 2024; Taniushkina et al. 2024). Current simulation approaches often limited as using simplified models of human behavior and lacking real-time environmental data integration, which restrict their predictive power in complex, evolving scenarios (Martin et al. 2016). Multi-Agent Systems (MAS) can model complex disaster settings by representing individuals (agents) with distinct attributes, decisions, and interactions capturing emergent behaviors (Dorri, Kanhere, and Jurdak 2018).

This paper presents RESPOND, a demo system that combines MAS, LLMs, and advanced flood forecasting to jointly simulate hazards and human response. RESPOND provides high-fidelity, near real-time flood dynamics prediction and uses LLM-driven agent cognition to produce realistic, context-aware decisions at population scale

Related Work

Research in multi-agent systems has long supported disaster management by simulating evacuation dynamics, coordination, and communication during crises (Massaguer, Balasubramanian, and Mehrotra 2006). More recently, the integration of LLMs into agent-based modeling has enabled agents to reason and communicate in more human-like ways (Gao 2024). Emerging work showcases LLM-driven agents in large-scale simulations for understanding behavior and social dynamics (Piao 2025), as well as for decision support in disaster contexts. These systems advance realism by allowing agents to demonstrate sophisticated cognition and emergent collective behaviors.

In parallel, natural disasters and flood forecasting models have advanced dramatically, producing high-resolution, real-time flood depth maps critical for preparedness and response (Floodbase 2025). Recent innovations include Large Multimodal Models (LMMs) for flood-depth estimation from images (DeepFlood 2025) and LLM–GIS integration for geospatial analysis.

Unfortunately, a key state-of-the-art gap remains: while MAS and LLM research improves agent realism, it rarely integrates dynamic, high-fidelity hazard forecasts into simulations. Conversely, natural disasters forecasting systems generate rich predictions but lack mechanisms to translate them into real-time, agent-level behavioral responses that capture human decision-making under stress (Ma et al. 2025).

RESPOND closes this gap by combining real-time flood maps with LLM-driven agents to simulate physical, social, and logistical disaster impacts in a unified testbed.

System Description

RESPOND is a modular platform that simulates the interaction between floods dynamics and human responses through three core modules.

Flood forecasting and mapping module generates high-resolution flood-depth maps as the main environmental in-

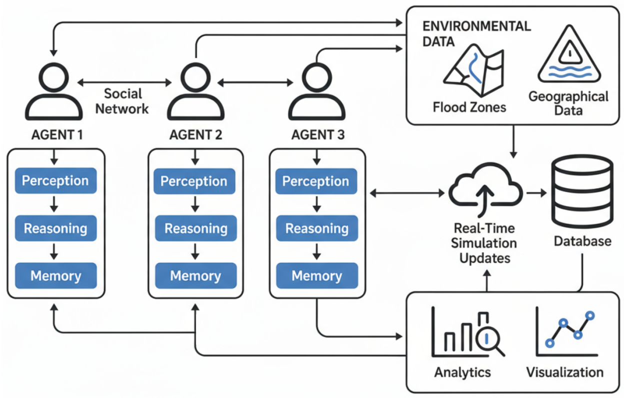

Figure 1: RESPOND architecture: interacting agents enhanced by LLMs and real-time flood data, produce population-scale simulations and predictions

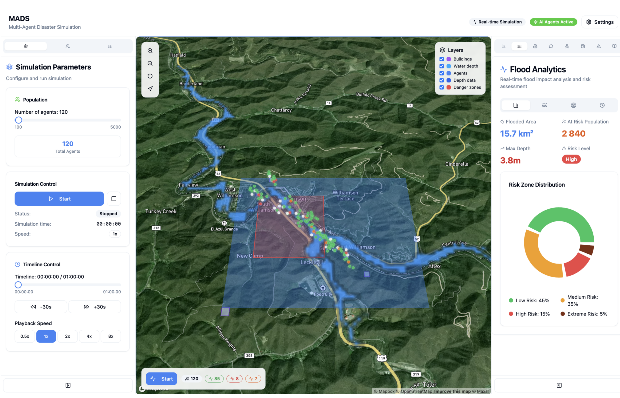

Figure 2: RESPOND user interface, simultaneously demonstrating agents behavior and natural disaster impact.

put. It combines real-time meteorological, river gauge, and topographic data with hydrological and machine learning models to simulate water flow and inundation (Okeukwu-Ogbonnaya et al. 2025).

Multi-agent simulation module represents individuals as agents, each with unique attributes, goals, and decision-making processes.

LLM-enhanced agent cognition module equips agents with advanced reasoning capabilities using LLMs. Unlike rule-based systems, LLMs let agents interpret unstructured inputs such as road-closure reports, social media updates, or official alerts.

Together, these modules create a powerful simulation where real-time environmental dynamics directly shape adaptive, human-like population behaviors.

Discussion and Conclusion

Our platform substantially advances disaster preparedness by integrating dynamic environmental models with realistic human behavior. Unlike traditional simulators, it establishes a continuous feedback loop between flood forecasting, multi-agent simulation, and LLM-driven cognition, enabling adaptive responses to evolving threats (Guo et al. 2024). This interplay is critical for understanding cascading disaster effects.

RESPOND delivers actionable insights for emergency managers, urban planners, and policymakers. It can improve evacuation planning, resource allocation, and communication strategies, while also supporting resilience planning and policy evaluation (Ma et al. 2025).

Future directions optimizing scalability and LLM performance, expanding multimodal data integration, and exploring human-in-the-loop simulation (Lyu 2025). Thanks to its modular design, RESPOND can also be extended to other disaster types.

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References

DeepFlood. 2025. DeepFlood for Inundated Vegetation High-Resolution Dataset for Accurate Flood Mapping and Segmentation. *Scientific Data*. Nature Scientific Data.

Dorri, A.; Kanhere, S. S.; and Jurdak, R. 2018. Multi-agent systems: A survey. *IEEE Access*, 6: 28573–28593.

Floodbase. 2025. Global Flood Database. https://global-flood-database.floodbase.com/.

Gao, C. 2024. LLMs empowered agent-based modeling and simulation: a survey and perspectives. *Nature*.

Guo, T.; et al. 2024. Large Language Model Based Multi-agents: A Survey of Progress and Challenges.

Lyu, H. 2025. Assessing Large Multimodal Models for Urban Floodwater Depth Estimation. *Water Resources Research*, 61(2): e2024WR039494.

Ma, J.; et al. 2025. Large-language-model-driven agents for fire evacuation simulation. *Safety Science*.

Martin, T.; Hofman, J. M.; Sharma, A.; Anderson, A.; and Watts, D. J. 2016. Exploring limits to prediction in complex social systems. *Proceedings of the 25th ACM WWW Conference*.

Massaguer, D.; Balasubramanian, V.; and Mehrotra, S. 2006. Multi-agent simulation of disaster response. In *Proceedings of the ATDM Workshop at AAAI*.

Okeukwu-Ogbonnaya, A.; et al. 2025. LLM-Based Community Surveys for Operational Decision Making in Interconnected Utility Infrastructures. arXiv:2507.13577.

Piao, J. 2025. AgentSociety: Large-Scale Simulation of LLM-Driven Generative Agents Advances Understanding of Human Behaviors and Society. arXiv:2502.08691.

Shevchenko, V.; et al. 2024. Climate change impact on agricultural land suitability: An interpretable machine learning-based Eurasia case study. *IEEE Access*, 12: 15748–15763.

Taniushkina, D.; et al. 2024. Case study on climate change effects and food security in Southeast Asia. *Scientific Reports*, 14(1): 16150.