Review

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A Decision-Support Agent-Based Framework for Evacuation Planning Under Compound Hazards

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Abstract

Evacuation planning is increasingly challenged by compound hazards in which interacting threats degrade infrastructure, influence human behavior, and destabilize transportation systems. Although agent-based models and dynamic traffic simulations have advanced substantially, much of the evacuation literature remains hazard-specific, case-bound, or difficult to transfer across regions. In parallel, transportation resilience research shows that multi-hazard effects are often non-additive and that cascading infrastructure failures can amplify disruption beyond directly affected areas. These realities motivate the development of evacuation modeling frameworks that are modular, adaptable, and able to represent co-evolving behavioral and network processes under compound conditions. This review synthesizes advances in evacuation agent-based modeling, dynamic traffic assignment, hazard-induced network degradation, and compound disaster research to propose an adaptable compound-hazard evacuation framework integrating three interdependent layers: hazard processes, transportation network dynamics, and agent decision-making. The proposed framework is organized around four principles: (1) modular hazard representation, (2) decoupling behavioral decision logic from hazard physics, (3) dynamic network state evolution, and (4) neighborhood-scale performance metrics. The framework prioritizes planning-relevant, spatially resolved outputs, including neighborhood clearance time, isolation probability, and shelter demand imbalance. By prioritizing modularity, configurability, and policy-aligned metrics, this review bridges the gap between methodological advances in evacuation modeling and the operational needs of local multi-hazard planning.

Keywords: agent-based modeling; evacuation simulation; infrastructure resilience; disaster response; compound hazards; local planning

1. Introduction

Extreme events are increasingly characterized not by isolated hazards, but by overlapping and interacting disruptions that strain physical infrastructure, social systems, and emergency management capacity [1–3]. Hurricanes, for example, combine wind, storm surge, and inland flooding and can generate non-additive impacts on transportation and power systems [4,5]. Wildfires can coincide with smoke-induced visibility loss, roadway blockages, and power shutoffs, producing rapidly evolving constraints on mobility and situational awareness [6,7]. Earthquakes can similarly trigger debris accumulation, bridge damage, and cascading utility failures that alter network accessibility during evacuation [8–10]. Under these compound conditions, planning approaches that treat hazards independently or assume static infrastructure availability are increasingly misaligned with contemporary risk realities [11,12].

Evacuation remains one of the most consequential protective actions available to emergency managers when implemented in a timely manner, reducing mortality, injury, and exposure [13,14] However, evacuation outcomes emerge from interacting behavioral and infrastructural processes. Decisions to leave depend on risk perception, trust in authorities, household constraints, prior experience, and social influence [15–17]. Once departures begin, transportation networks experience

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sharp demand surges that may exceed capacity, particularly when infrastructure is simultaneously degraded by hazard impacts [18–20]. In hurricane contexts, variation in compliance and route choice can substantially alter congestion formation and clearance times [21,22], while wildfire studies show that limited vehicle access, delayed awareness, and fast-changing hazard conditions can produce critical bottlenecks [23]. These findings highlight the need for evacuation models that capture feedback among household decisions, network dynamics, and hazard-driven disruption.

Over the past two decades, evacuation modeling has advanced substantially [24–26]. Agent-based models (ABMs) support representation of heterogeneous households [27], probabilistic departure timing [17], adaptive rerouting [28], and congestion feedback mechanisms [3]. Dynamic traffic assignment approaches further capture time-varying demand and spillback effects that static clearance calculations cannot reproduce [29,30]. In parallel, hazard modeling has improved representations of inundation extents, debris blockages, fire spread, and network fragility, while transportation resilience research has shown that multi-hazard effects are often not additive and may differ qualitatively from single-hazard analyses [1,2,31].

Despite this progress, three structural gaps remain. First, many evacuation models are designed for specific hazards or case studies, with hazard physics embedded directly into scenario assumptions and network representations (e.g., hard-coded flood rasters, wildfire perimeters, or debris ratios), limiting usability across hazards/regions with minimal re-engineering. Second, behavioral decision logic and hazard representation are frequently intertwined, making it difficult to adapt models across contexts without substantial recalibration or redesign. Third, performance is commonly summarized with aggregate measures such as total clearance time or average travel duration, which can obscure localized vulnerabilities and distributional inequities. These limitations are amplified under compound hazards, where interacting disruptions and cascading service failures can reshape accessibility beyond directly damaged zones [11,32–34] and degrade travel time reliability disproportionately relative to simple connectivity metrics [35,36]. Simultaneously, municipal decision environments demand tools that are transparent, configurable, and aligned with operational questions such as evacuation order timing, shelter placement, route prioritization, and contingency planning across plausible scenarios. Decision support systems have been developed to support routing and shelter allocation [37–39], yet many remain tailored to specific contexts or require specialized expertise that can limit routine use.

This review proposes an adaptable, modular compound-hazard evacuation framework that synthesizes existing methodological strands into a coherent architecture organized around four principles: (1) modular hazard representation, (2) decoupling of behavioral decision logic from hazard physics, (3) dynamic network state evolution, and (4) neighborhood-scale performance metrics. The framework is intentionally hazard-agnostic, allowing wind, flood, wildfire, seismic debris, or other disruptions to be incorporated as interchangeable modules that affect capacity, speed, or accessibility through scenario-based or probabilistic processes, while preserving consistent behavioral structures for departure timing, destination choice, and rerouting. The review has two objectives: (O_1) to synthesize advances in evacuation ABMs, shelter system modeling, dynamic traffic assignment, compound disaster research, and transportation network resilience to identify design requirements for adaptable modeling; and (O_2) to articulate how a modular architecture can support multi-hazard evacuation planning across regions with differing risk profiles. The contribution is a conceptual structure that improves methodological coherence while supporting policy relevance of evacuation modeling under compound impacts.

2. Behavioral and Network Mechanisms in Evacuation ABMs

Agent-based models (ABMs) conceptualize evacuation not as an aggregate flow problem but as an emergent outcome of interacting decision-makers whose behavior evolves with changing environmental conditions and network performance. This perspective has become a dominant paradigm for representing evacuation as a decentralized, adaptive process embedded within dynamic infrastructure systems. Over the past decade, ABM-based evacuation research has matured substantially, incorporating richer behavioral adaptation, congestion formation, and hazard exposure mechanisms [3,25,28]. However, the increasing sophistication of individual components has not always been matched by system-level architectural coherence [30]. As behavioral, traffic, shelter, and hazard modules advance in parallel, integration, transferability, and consistency become central design concerns. This section reviews the behavioral and network foundations of evacuation ABMs and emphasizes how these elements can be organized in a unified, modular structure capable of supporting compound-hazard analysis.

A defining contribution of evacuation ABMs is their ability to represent behavioral heterogeneity within system-level simulations [40,41]. Across hazard contexts, evidence consistently shows that evacuation outcomes are highly sensitive to departure timing, risk perception, information exchange, compliance dynamics, and mobility constraints [42,43]. Evacuees are not passive users of infrastructure; staggered departures, adaptive rerouting, and socially mediated compliance reshape congestion and accessibility in ways that feed back into subsequent decisions. Wildfire simulations illustrate how delayed awareness and limited vehicle access can amplify exposure [23,44], while integrated fire-traffic models demonstrate how hazard propagation can alter route viability in real time [45,46]. Similar sensitivities occur in tsunami, landslide, and technological hazards, where small changes in participation or departure timing can generate disproportionate shifts in congestion and survival outcomes [47–49]. Architecturally, these findings imply that behavioral modules must remain flexible under uncertainty while avoiding hazard-specific assumptions that reduce adaptability [50].

Recent modeling developments extend beyond simple decision rules to represent cognitive, physiological, and strategic dimensions of evacuation behavior. Agents are increasingly treated as adaptive entities whose movement speed, spacing, and route choice evolve under perceived threat, social contagion, and stress amplification [51,52]. Motion dynamics increasingly incorporate acceleration variability, collision avoidance, and density-dependent interactions, enabling crowd behavior to emerge from micro-scale heterogeneity rather than imposed flow assumptions [53,54]. Demographic diversity further recognizes systematic variation in mobility, response delay, and assistance needs across age groups and physical abilities, with nontrivial consequences for system performance [27]. In parallel, strategic modeling introduces probabilistic learning and game-theoretic reasoning, enabling agents to anticipate congestion, revise expectations, and adapt to evolving network states [55,56]. From an adaptable framework perspective, the key challenge is not simply adding behavioral realism, but organizing behavioral submodules so that complexity is extensible without sacrificing clarity or cross-context portability.

Model structure also matters in how uncertainty is represented. Systematic reviews report a shift away from deterministic “if–then” rules toward probabilistic decision structures that better reflect uncertainty in hazard forecasts, infrastructure availability, and social influence [25,57–60]. Behavioral research on compound emergencies further indicates that risk perception under multiple threats may diverge from single-hazard assumptions, particularly when public health, flood, or wildfire risks coincide [61,62]. This reinforces the need for behavioral architectures that can accommodate multiple concurrent signals and evolving credibility without hard-wiring hazard-specific logic into the core decision engine.

Despite advances in behavioral representation, a persistent gap remains between behavioral sophistication and empirical grounding. Many hurricane-focused ABMs reproduce large-scale traffic patterns and evacuation orders by integrating road networks, forecast cones, and evacuation zones to simulate congestion, contraflow, and demand surges [21,63,64]. Microsimulation-based optimization frameworks further enhance temporal realism by coupling dynamic programming with traffic simulation [65]. Yet behavioral inputs such as participation rates, destination splits, and departure timing, are often indirectly calibrated through socioeconomic predictors or machine-learning models [66,67], with fewer studies anchoring agent decisions directly to survey-reported evacuation probabilities at meaningful spatial strata. In addition, evacuees are frequently introduced at zonal centroids rather than realistic household-to-road access points, which can mask localized bottlenecks and distort neighborhood-scale performance assessment. Thus, while ABMs capture heterogeneity conceptually, empirical and spatial specificity remains uneven across applications.

Parallel progress has occurred in representing traffic dynamics and congestion feedback. Whereas clearance-time approaches typically rely on deterministic flow assumptions and static assignments, dynamic traffic assignment frameworks incorporate time-varying demand, background traffic, rerouting behavior, and spillback [29,30]. Mesoscopic and microscopic approaches can capture queue formation, spillback, and adaptive detouring [27,68]. Research shows that communication-induced surges can intensify congestion [69] while locally rational detours may degrade system-level performance [24]. Wildfire evacuation simulations further confirm that route switching, and phased strategies can substantially alter exposure and clearance times [14,70]. These findings underscore the importance of congestion feedback mechanisms and endogenous route adaptation within evacuation models. However, many applications still report system-wide clearance time as the primary performance metric, giving less attention to spatially uneven impacts across origins or to localized isolation risks under network disruptions. This limitation is especially consequential under compound hazards, which can degrade accessibility nonuniformly across space.

Shelter modeling has also progressed from simple capacity accounting toward spatially and behaviorally informed allocation frameworks. Recent work incorporates geographic distribution, capacity constraints, and optimization routines to improve allocation efficiency and reduce exposure [71,72]. Moreover, evidence indicates that increasing shelter supply alone does not guarantee improved performance without attention to placement and accessibility [73], and evacuees' destination choices reflect social ties, logistics, and perceived safety rather than strict proximity [74–76]. In system terms, shelters function as dynamic sinks whose effectiveness depends on how origin-specific demand propagates through constrained infrastructure and how behavioral decisions interact with capacity thresholds. When analyses rely primarily on system-wide occupancy totals, they risk obscuring the spatial origin of imbalances and the feedback mechanisms that generate them. Shelter modules must therefore be designed to interact explicitly with origin-resolved demand and evolving network states, enabling localized deficits to be identified without embedding hazard-specific assumptions.

Destination modeling has similarly shifted from static aggregate designs toward adaptive, context-sensitive decision structures. Early models treated destination choice as probabilistic selection among predefined alternatives conditioned on socioeconomic attributes and travel impedance [77,78], generally assuming stable hazard conditions and infrastructure availability. Subsequent work introduced temporal dynamics so preferences could evolve with changing trajectories, congestion, and accommodation constraints [79]. More recent approaches incorporate strategic anticipation and collective effects [80] and use data-driven predictors to refine spatial allocation patterns [81]. Empirical findings consistently show that income, housing tenure, and social capital shape accommodation outcomes: lower-income households and renters are more likely to rely on public shelters, while higher-income households more often evacuate to hotels or friends and relatives [16,82,83]. Structural inequality also shapes shelter reliance and post-evacuation hardship [84,85], while social networks influence both destination choice and response timing [83,86]. Prior experience, perceived shelter safety, and information credibility further mediate these patterns [15,87,88]. These results motivate destination modules that can represent both resource constraints and network-mediated social options.

Departure-time modeling has moved beyond static assumptions to incorporate adaptive learning, social influence, vulnerability, and warning system dynamics. Early work emphasized that evacuees may not optimize timing but learn and adjust based on evolving information and perceived congestion [89]. Later studies highlighted the interdependence of departure time and destination/route choices, especially in rapidly evolving hazards, motivating integrated choice structures [90,91]. Information credibility and dissemination delays have been shown to meaningfully affect participation timing [17,92]. Social vulnerability indicators have also been linked to evacuation decision latency, suggesting resource constraints and risk perception interact to delay or accelerate departure [3,93]. Although these models increasingly represent nuanced determinants of timing, socioeconomic variables are still more often used to parameterize decisions than to assess disparities in outcomes such as isolation probability, clearance time, or unmet shelter demand [94]. For compound-hazard planning, this gap is consequential because layered disruptions can differentially constrain departure feasibility across neighborhoods.

Modeling scale, validation, and usability remain central challenges. Microscopic models capture fine-grained interactions shaping evacuation time [53,95,96], while mesoscopic approaches emphasize scalability for system-level flow [97,98]. Appropriately, hybrid frameworks attempt to bridge these strengths [52,99]. Early spatial decision support systems (DSS) highlighted the value of integrating simulation with geographic information systems (GIS) for practical planning [100–103]. More recent resilience-oriented DSS work continues to stress interoperability and usability across hazards [104,105]. Methodologically, verification and validation remain challenging given behavioral uncertainty and data scarcity during extremes. Emerging approaches include virtual reality (VR)-based behavioral calibration [106], machine-learning-assisted parameter tuning [107], and structured verification/validation protocols emphasizing documentation, consistency testing, sensitivity analysis, and reproducibility [108,109]. Yet for municipal planners, sophisticated engines can still appear opaque, and outputs are often reported in aggregate technical metrics rather than neighborhood-scale indicators directly usable for shelter planning, mitigation prioritization, or routine preparedness.

Overall, the literature discussed herein demonstrates that evacuation ABMs can represent heterogeneous behavior, congestion feedback, shelter allocation, and adaptive routing under hazardous conditions. However, persistent limitations remain in empirical grounding, spatial specificity, compound-hazard integration, and practitioner-facing usability. These gaps motivate modular evacuation architectures in which behavioral, network, shelter, and hazard components can be flexibly composed while producing origin-resolved, decision-ready metrics suitable for compound-hazard planning.

3. Dynamic Traffic, Network Degradation, and Evacuation Reliability

Evacuation performance emerges from the interaction between individual decision-making and transportation network dynamics. Even when behavioral rules are specified with high fidelity, evacuation outcomes depend on how departures and route choices propagate through constrained, time-varying road systems [17,24,26]. Empirical and simulation-based studies show that route switching, congestion awareness, and information exchange can either improve or degrade system performance depending on network conditions and coordination mechanisms [27,69,110]. This interaction has motivated a long-term shift in evacuation modeling away from deterministic clearance-time calculations and toward dynamic traffic assignment and agent-based traffic representations that can capture congestion formation, spillback, rerouting, and capacity constraints under evolving conditions [29,30,111,112]. Compared with aggregate clearance approaches, these models improve realism by allowing demand to vary over time, incorporating background traffic, and representing adaptive routing in response to changing network states [30,47,113,114].

Traditional clearance models estimate evacuation time primarily as a function of demand and network capacity under fixed roadway availability [39,64,115]. While useful for preliminary planning, they typically assume stable infrastructure, uniform exposure, and predictable demand patterns [47,116]. Dynamic models relax these assumptions by representing time-dependent demand, route switching, multimodal travel, and congestion feedback loops [29,30]. Agent-based or mesoscopic simulations further capture localized density effects, queue spillback, and nonlinear system responses to small behavioral shifts [27,68]. The broader modeling shift exposes a structural limitation that becomes critical under compound hazards: network availability is still often treated as exogenous and predetermined, rather than evolving probabilistically during the evacuation as hazard intensity changes [1,117]. Multi-hazard resilience research shows that infrastructure functionality can evolve nonlinearly under sequential or interacting hazards, producing outcomes that differ substantially from single-hazard estimates [10,118].

Congestion also actively reshapes decision-making, creating feedback cycles between perception, route selection, and network loading [17,26]. Information dissemination can trigger synchronized departure surges that intensify early bottlenecks [69], and locally rational detours can degrade overall system performance when agents act independently [24]. Reviews of group evacuation dynamics similarly emphasize that collective movement patterns and coordination failures can amplify congestion waves in high-stress environments [119]. These findings reinforce that evacuation networks function as adaptive socio-technical systems, where behavioral responses and traffic dynamics co-produce accessibility outcomes.

A parallel line of research emphasizes that infrastructure functionality often changes during the event itself and should be represented explicitly. Monitoring and assessment frameworks for transport infrastructure exposed to multiple hazards highlight the importance of real-time damage detection and dynamic functional evaluation [120]. Road closures, contraflow strategies, and rerouting under disrupted conditions can substantially alter clearance outcomes [121,122]. In wildfire contexts, reduced visibility, debris, and roadway temperature changes measurably affect speeds and route viability [123,124]. Foundational work argues that roadway capacity constraints and occupancy thresholds should be incorporated explicitly into community planning [125]. Hurricane evacuation studies similarly show that network performance is sensitive to dynamic shelter allocation and background traffic conditions [29]. These contributions move beyond demand–capacity calculations under fixed assumptions and motivate time-evolving representations of accessibility.

Infrastructure interdependencies further complicate this evolution. Integrated network models demonstrate that transportation systems are tightly coupled with power, communication, and water infrastructure, such that failure in one subsystem can propagate across others [126,127]. Transportation has been identified as an underestimated backbone of community resilience because disruptions in mobility constrain access to healthcare, shelter, and emergency services even when other systems remain partially functional [128]. Policy-based recovery models show that restoration sequencing and infrastructure prioritization significantly influence overall system resilience under uncertainty [129]. However, evacuation traffic models rarely integrate such interdependent restoration dynamics into simulations of ongoing population movement.

These gaps become more consequential under compound hazards. Emerging literature demonstrates that multi-hazard effects are often non-additive and that the timing and interaction of concurrent events can produce outcomes that differ substantially from single-hazard estimates [1,2]. Spatial hazard configuration also matters because resilience depends on how hazard intensity overlaps with network topology [130]. For example, flood-related road loss combined with wind-driven debris may isolate neighborhoods even when each hazard alone would not [117,131–133]. Transportation resilience studies further show that travel-time reliability can deteriorate disproportionately under multi-hazard stress relative to simple connectivity metrics [36], yet these insights are still rarely embedded within evacuation simulations that couple demand, routing, and disruption processes.

Cascading failures introduce additional pathways through which evacuation outcomes can diverge from single-system assumptions. Behavioral responses to evacuation orders can overload communication networks and induce flash congestion, generating nonlinear stress patterns [18,134]. Power outages may disable traffic signals and reduce effective roadway capacity precisely when evacuation demand peaks [20]. These interdependencies can expand impacts beyond the direct hazard footprint and reshape accessibility gradients across neighborhoods, yet they remain underrepresented in many operational ABMs and traffic-based evacuation models.

Taken together, the literature demonstrates substantial progress in modeling traffic dynamics, congestion feedback, rerouting, and infrastructure constraints. However, current approaches remain fragmented: behavioral models, traffic assignment models, hazard impact models, and infrastructure resilience frameworks are often developed in parallel rather than within unified architectures. As a result, many evacuation simulations remain hazard-specific, region-specific, and difficult to adapt across contexts.

This fragmentation motivates the development of a modular, adaptable compound-hazard evacuation framework. Such a framework must (1) represent hazard impacts as stochastic, time-varying processes affecting network links; (2) couple behavioral adaptation with evolving infrastructure functionality; (3) quantify neighborhood-scale performance metrics rather than only aggregate clearance times; and (4) remain adaptable to different hazard combinations, from wind–surge systems to wildfire–smoke scenarios or earthquake–landslide interactions.

In this context, evacuation modeling should move beyond reproducing historical traffic patterns toward constructing configurable socio-technical systems capable of simulating interacting hazards, adaptive agents, and evolving infrastructure states within a unified structure. The next section, therefore, synthesizes emerging work on compound hazards and infrastructure interdependencies, highlighting the conceptual foundations necessary for such an adaptable framework.

4. Proposed Conceptual Framework

4.1. Micro-Scale Compound-Hazard Evacuation

Existing evacuation models have achieved substantial sophistication in representing behavioral heterogeneity, congestion dynamics, shelter allocation, and hazard-specific disruptions. However, much of the literature remains hazard-specific, geographically tailored, or structurally rigid. Models developed for hurricanes often assume surge-based road closures; wildfire models focus on fire spread and smoke-induced visibility reduction; earthquake simulations emphasize debris and structural collapse [135]. While each of these approaches advances hazard-specific realism, they are rarely structured for cross-hazard transferability or modular adaptation across regions. This fragmentation presents a fundamental limitation for emergency planning in an era of compound and cascading risks. Climate-driven hazard intensification, urban expansion into high-risk zones, and increasing infrastructure interdependencies require evacuation models that are not only behaviorally realistic but also structurally adaptable [1,11,119]. Sequential or interacting hazards produce non-additive impacts on transportation networks, shelter demand, and evacuation timing [2,36].

Accordingly, Figure 1 presents an overview of an adaptable evacuation modeling framework organized around four foundational pillars and their associated structural components. Each pillar reflects a core requirement for scalable compound-hazard evacuation modeling: modular hazard representation, behavioral parameterization that can be recalibrated across settings, dynamic network-state evolution, and neighborhood-scale performance assessment. The figure serves as a roadmap showing how these elements interact while preserving flexibility to accommodate different hazard processes, data availability, and geographic contexts.

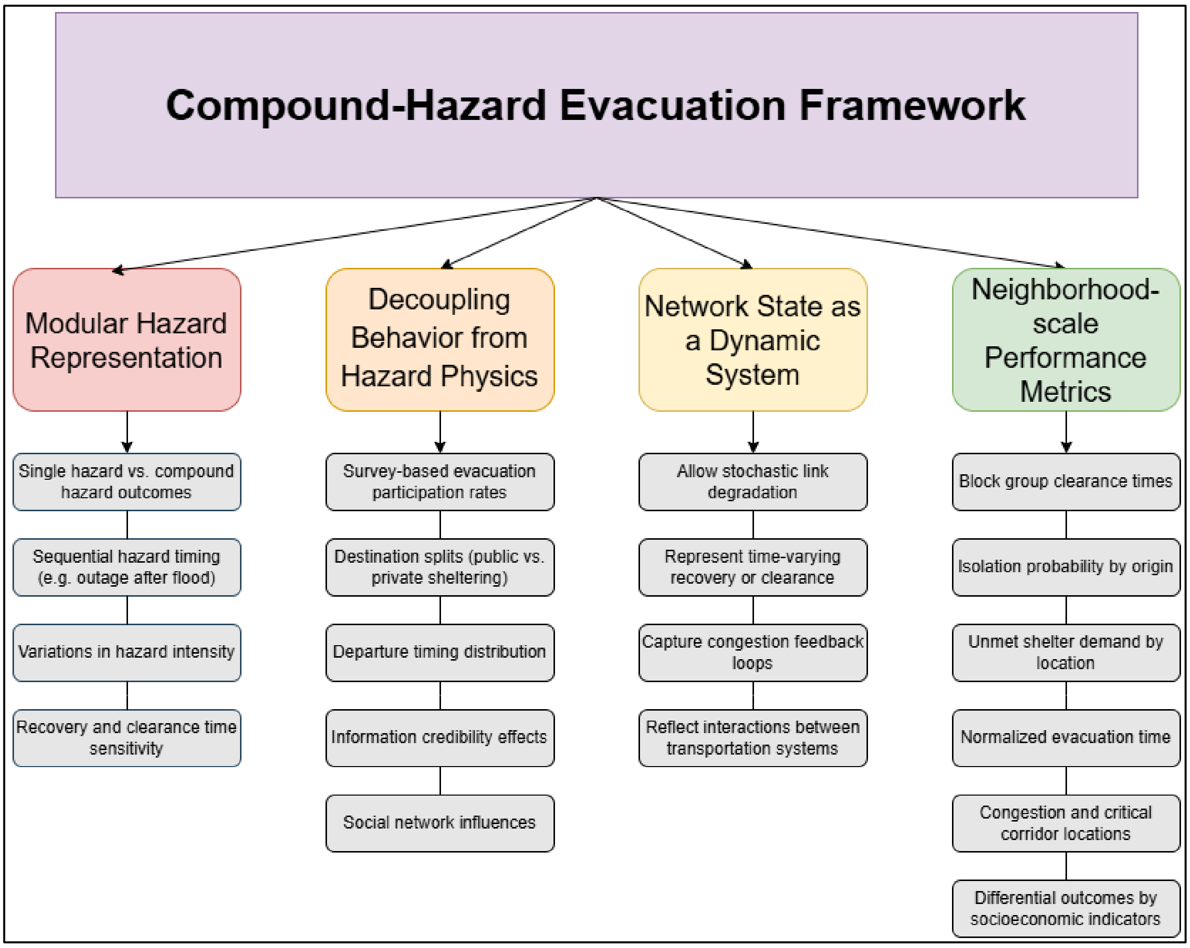

Figure 1. Foundational components of a comprehensive and adaptable micro-scale compound hazard evacuation framework.

4.1.1. Modular Hazard Representation

Hazards should be represented as modular processes that affect network availability, travel speed, and departure behavior through probabilistic link degradation and time-varying disruption states rather than through hard-coded scenario assumptions. Instead of embedding a specific hazard directly into routing logic (e.g., “storm surge closes these roads”), the hazard layer should operate as an independent module that modifies network attributes dynamically. This modular approach allows wind, flood, wildfire, earthquake, landslide, or cascading infrastructure failure processes to be incorporated as interchangeable components without altering the behavioral core of the model. Such modularization aligns with emerging multi-paradigm and meta-model approaches that separate agents, environment, and events into reusable structures [136]. Modular representation enables scenario-based compound simulations, where multiple hazards can be activated independently or jointly. For example, a single-hazard flood scenario may produce specific patterns of link closures and reduced speeds, while a wind–flood compound scenario may introduce both inundation-based closures and debris-induced stochastic failures. A wildfire–heatwave scenario may combine fire spread constraints with increased departure rates driven by risk perception.

In this framework, compound hazards are not treated as exceptional cases but as configurable combinations within a standardized simulation environment. Each scenario yields distinct performance metrics such clearance time, isolation probability, congestion duration, shelter overflow, or exposure time allowing comparison across hazard combinations rather than relying on a single deterministic “worst-case” assumption. This scenario-based architecture supports uncertainty analysis and stress-testing of evacuation plans under evolving risk landscapes [2,11].

4.1.2. Decoupling Behavior from Hazard Physics

Behavioral decision rules such as departure timing, destination choice, compliance with evacuation orders, and rerouting should be parameterized independently of specific hazard types. Whether agents respond to wildfire proximity, rising water, seismic debris, or chemical plumes, the underlying processes governing risk perception, social influence, and congestion adaptation can be represented with a common behavioral architecture, while hazard inputs enter as context-specific signals that shape perceived risk and feasible routes.

For this decoupling to be meaningful, behavioral rules must be grounded in empirical evidence rather than synthetic assumptions. A persistent limitation in evacuation modeling is reliance on assumed participation rates or socioeconomic proxies without direct calibration to observed or survey-reported behavior. Empirical datasets such as post-event evacuation surveys, stated-preference studies, and behavioral experiments provide more realistic depictions of how households respond to warnings and infrastructure constraints [3,16,17]. Embedding empirically estimated probabilities into agent decision rules improves realism and portability because parameters can be swapped or recalibrated across regions without restructuring hazard or traffic modules. By separating hazard physics from behavioral logic and anchoring behavior in observed decision-making, the framework avoids conflating infrastructure disruption with assumed compliance patterns and enables consistent comparison of how the same population responds under wildfire, flood, hurricane, or compound scenarios.

4.1.3. Network State as a Dynamic System

Transportation infrastructure should be modeled as a time-evolving system whose effective capacity changes in response to hazard intensity, cascading failures, and adaptive loading from evacuees. Instead of assuming static road closures or fixed capacity reductions, the framework represents network links as dynamic entities whose operational states transition probabilistically over time.

Hazard impacts can reduce speeds, lower capacity, or trigger link failure, while evacuation-induced congestion can amplify disruption through spillback, queue propagation, and overload of adjacent corridors. Research on cascading infrastructure failures further shows that evacuation behavior can create nonlinear stress on interdependent systems, including power grids and communication networks [18,34]. Infrastructure vulnerability is therefore not purely exogenous but can emerge partly from feedback between behavioral responses and evolving network conditions. This representation shifts evacuation modeling from static routing to a co-evolving system simulation in which behavior and infrastructure jointly shape accessibility and performance.

4.1.4. Neighborhood-Scale Performance Metrics

Most evacuation studies report aggregate system-level metrics such as total clearance time or overall evacuation rate. Although useful for high-level benchmarking, these metrics can mask spatial disparities and localized vulnerability. In contrast, spatially disaggregated outputs enable planners to identify neighborhoods that repeatedly experience elevated delay, isolation, or unmet shelter demand across scenarios, and to determine which hazard combinations amplify these localized deficits. In addition, this supports targeted interventions, such as corridor reinforcement, phased messaging and information campaigns, or shelter redistribution, based on origin-specific performance rather than uniform mitigation. Crucially, neighborhood-scale metrics also create the analytical foundation for examining differential outcomes across socioeconomic groups. When evacuation performance is resolved at fine spatial scales, it becomes possible to stratify results by income, renter share, age distribution, disability prevalence, or vehicle access, thereby revealing whether certain populations face systematically longer clearance times or higher exposure to network disruption. Rather than using socioeconomic indicators solely to parameterize behavior, this approach enables their use in post-simulation equity assessment, distinguishing between behavioral assumptions and outcome disparities.

To make these principles operational within a usable and adaptable modeling approach, the framework is implemented through three interacting layers. First, the agent layer represents heterogeneous households and individuals using probabilistic decision rules grounded in empirical evidence. Second, the network layer represents transportation infrastructure with dynamic capacity, congestion propagation, and hazard-induced degradation. Third, the hazard layer represents one or more hazards as time-varying disruption processes that probabilistically affect network links and, where appropriate, departure conditions. Separating these layers allows future applications to incorporate wildfire spread, storm surge, seismic debris, or floodplain inundation without restructuring the core evacuation engine. The hazard layer updates network states, the agent layer governs decision-making, and the network layer governs traffic flow propagation. This architecture directly addresses limitations identified in prior literature, including hazard-specific rigidity, limited compound-hazard integration, and weak adaptability across regions [11,25].

4.2. Agent-Based Modeling Methodology

Figure 2 presents the overall conceptual flowchart of the proposed agent-based modeling (ABM) framework. Unlike hazard-specific implementations, this diagram illustrates a high-level, adaptable architecture that separates core components into modular layers: hazard modules, behavioral decision processes, dynamic network states, and performance evaluation outputs. The flowchart emphasizes how scenario-based hazard inputs (i.e., single or compound) modify network conditions and perceived risk, which in turn influence agent-level decisions regarding departure timing, destination selection, and rerouting. These individual decisions propagate through the transportation network, generating congestion dynamics and potential cascading effects that feed back into subsequent agent behavior. By structuring the framework in this layered manner, the figure demonstrates how different hazards can be interchanged without altering the behavioral core, enabling application across diverse geographic regions and risk contexts. The modular flow also clarifies the distinction between exogenous hazard processes and endogenous congestion dynamics, reinforcing the framework's flexibility for scenario testing and decision support.

Although the framework is presented conceptually, it is compatible with a wide range of existing ABM platforms. General-purpose environments such as NetLogo, Repast, and GAMA have been widely used to construct evacuation simulations with heterogeneous agents and spatially explicit networks [84,137–140]. More scalable or hybrid modeling environments, including AnyLogic and Unity-based simulation ecosystems, support integration with dynamic traffic assignment, 3D visualization, and complex decision logic [55,141]. Specialized evacuation platforms such as ESCAPE, CrowdEgress, and PRISM further enable detailed social-force modeling and immersive or virtual-reality–enhanced experimentation [142–144]. Table 1 summarizes commonly used platforms and their relative strengths and limitations for evacuation and infrastructure modeling [145–151]. The layered architecture outlined in Figure 2 is intentionally software-agnostic, allowing implementation within any platform capable of representing agent-level decision rules, network dynamics, and scenario-driven hazard inputs. This ensures that the methodological contribution lies in structural organization rather than dependence on a particular computational tool.

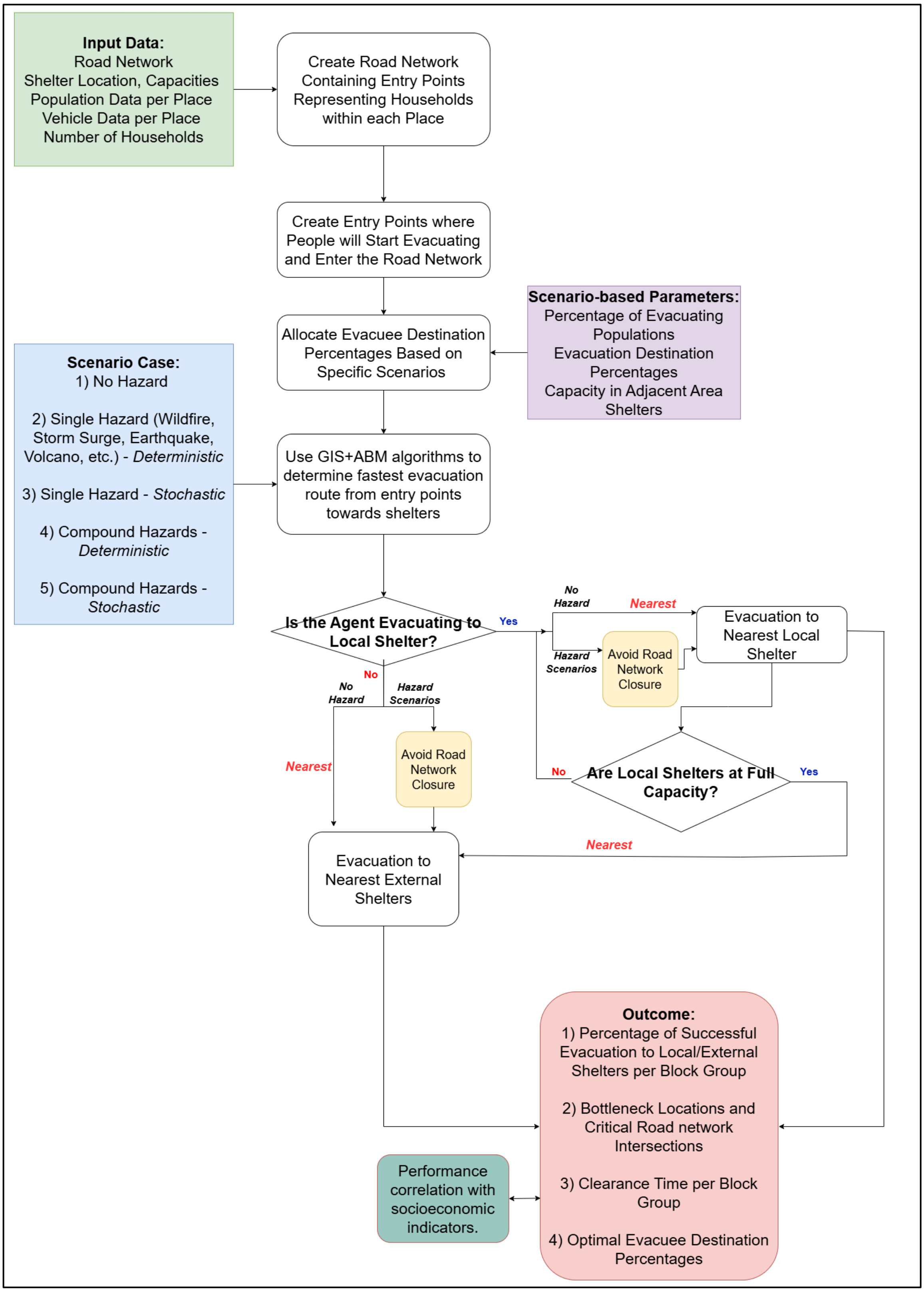

Figure 2. Flowchart of the overall ABM methodology.

Table 1. Comparison of Common Agent-Based Modeling Platforms for Evacuation and Infrastructure Simulation.

Platform	Typical Scale	Programming Language	Strengths	Limitations	Typical Use Context
AnyLogic	Large-scale, hybrid	Java	Multi-paradigm (ABM + system dynamics + discrete event); strong GIS integration;	Proprietary license; limited low-level	Urban evacuation, transportation,

		(with visual modeling interface)	2D/3D visualization; built-in traffic libraries; commercial support	control compared to pure-code frameworks	infrastructure systems
NetLogo	Small–medium scale	NetLogo	Highly intuitive; rapid prototyping; strong educational use; extensive model libraries; good visualization	Performance constraints for large-scale simulations; limited scalability; less suitable for high-resolution traffic modeling	Social science, crowd modeling, conceptual evacuation models
MASON	Large-scale	Java	High performance; discrete-event scheduler; strong for distributed simulation; scalable	Minimal built-in visualization; requires strong programming expertise	Large computational experiments, urban systems
Swarm	Medium-scale	Objective-C / Java	Early ABM framework; object-oriented; reusable components	Limited modern support; dated ecosystem	Historical ABM research
Repast	Large-scale	Java, Python, C++	Flexible architecture; good data logging; supports GIS; strong academic use	Steeper learning curve; less plug-and-play than visual tools	General-purpose social and infrastructure modeling
MATSim	Large-scale	Java	Activity-based transport simulation; dynamic traffic assignment; iterative replanning; strong for evacuation traffic	Focused primarily on transport; less flexible for non-transport agent logic	Transportation systems, evacuation traffic
TRANSIMS	Large-scale	C++, Python	Detailed traffic microsimulation; activity-based demand; queue-based traffic models	Complex setup; less intuitive for behavioral modeling	Regional traffic and evacuation planning
GAMA	Medium–large scale	GAML	Intuitive modeling language; strong GIS integration; data-driven modeling; 2D/3D visualization	Smaller user base than Java platforms; scalability depends on model structure	Urban planning, environmental and evacuation modeling
OpenAMOS	Regional-scale	R	Activity-based travel demand; econometric modeling integration	Limited real-time traffic detail; smaller development community	Travel forecasting and planning analysis
SACSIM	Regional-scale	C#	Activity-based travel forecasting; integrated traffic assignment	Specialized for travel demand; less general-purpose ABM flexibility	Regional travel demand modeling

5. Discussion & Policy Relevance

Evacuation modeling has matured considerably over the past two decades, yet the translation of modeling advances into operational municipal planning remains uneven. Sophisticated agent-based simulations now incorporate behavioral heterogeneity, probabilistic decision rules, congestion feedback, and dynamic routing. However, many implementations remain hazard-specific, data-intensive, or optimized for academic validation rather than for iterative use by local planners. Thus, the gap is not primarily technical; it is structural. Academic models often prioritize validation, algorithmic sophistication, or hazard-specific realism, while municipal agencies require adaptable, scenario-driven tools that can be updated, interpreted, and deployed under evolving risk conditions. Policy implications and relevance are built around two components: (1) methodological implications for compound-hazard modeling and multi-layer system integration, and (2) practical implications for municipal planning, shelter management, and infrastructure prioritization.

5.1. Compound-Hazard Preparedness in Municipal Planning

For local governments, evacuation planning is not an abstract modeling problem; it is an operational responsibility that must function under uncertainty, resource constraints, and changing hazard profiles. Effective evacuation performance emerges from the interaction of three interdependent systems: individual decision-making, transportation network dynamics, and evolving hazard processes. Although prior research has significantly advanced each of these components, implementation in planning practice often remains fragmented. Behavioral realism may be incorporated without dynamic infrastructure representation. Hazard overlays may be added without endogenous congestion modeling. As a result, many evacuation plans implicitly assume that disruptions are predictable, isolated, or static.

Operational planning requires a different approach. Instead of embedding hazard impacts within case-specific assumptions, municipal models must be structured to accommodate uncertainty across multiple interacting drivers. A modular hazard architecture provides this flexibility. In practical terms, this means representing hazard effects not as fixed closures derived from a single flood raster or wildfire perimeter, but as probabilistic and time-varying degradation processes that influence link capacity, accessibility, and travel speed. Wind damage, storm surge, wildfire spread, seismic debris, or landslide obstructions can then be introduced as interchangeable modules without altering the behavioral decision core of the model. Guo et al. [136] emphasize the value of separating agents, environment, and event processes to enhance reusability; within evacuation planning, this separation enables towns in different hazard contexts to apply a common structural framework while customizing local hazard inputs.

This modularization has direct policy implications. Many municipal evacuation studies remain hazard-specific, developed in response to a recent event or regulatory requirement. Flood closures may be hard-coded from a single storm scenario. Wildfire impacts may rely on one historical fire footprint. Earthquake disruptions may be simulated using assumed blockage ratios. While such approaches can improve realism for a single case study, they limit adaptability. When a new hazard profile emerges, or when climate-driven intensification alters exposure patterns, planners must often reconstruct models from scratch. An adaptable compound-hazard structure reduces this institutional friction by allowing scenario substitution rather than model redesign.

Equally important is the representation of infrastructure as a dynamic system rather than a static background condition. Traditional clearance models treat network capacity as fixed throughout the evacuation window. Even some dynamic simulations introduce closures exogenously and maintain them for the duration of the run. However, research on cascading infrastructure failures demonstrates that evacuation demand itself can destabilize system performance. Barrett et al. [18] show that compliance levels can trigger nonlinear congestion and communication overloads. Mühlhofer et al. [34] further demonstrate that cascading disruptions often account for most service impacts during compound events. From a municipal planning perspective, this means that evacuation-induced loading and hazard-induced degradation must be modeled as co-evolving processes rather than sequential inputs.

A dynamic network-state representation therefore becomes central to operational planning. Instead of binary open-or-closed road segments, links may experience probabilistic failure, partial capacity reduction, delayed clearance, or staged recovery. Congestion feedback influences travel time, which then reshapes departure decisions and route selection. Spillback effects can propagate disruptions beyond initially affected corridors, amplifying localized impacts. Smyrnakis and Galla [26] and Firdausyi et al. [27] demonstrate how individually rational routing decisions can degrade overall system performance, reinforcing the importance of endogenous feedback modeling. For planners, this translates into a clearer understanding of where congestion hotspots may emerge under compound conditions and how network fragility varies across neighborhoods.

Compound hazards further emphasize the need for scenario-based evaluation. Multi-hazard resilience research indicates that hazard interactions are rarely additive. Argyroudis et al. [1] show that sequential or simultaneous hazard exposures can produce markedly different system performance trajectories compared to isolated events. In evacuation planning, this implies that wind damage preceding storm surge, wildfire smoke preceding traffic surges, or seismic debris combined with infrastructure outages may generate qualitatively distinct clearance patterns. Rather than relying on a single deterministic clearance estimate, planners benefit from evaluating performance distributions across hazard combinations, intensity levels, and compliance assumptions. Scenario-based simulation enables municipalities to assess robustness, identify thresholds of system instability, and compare intervention strategies under varied compound-risk conditions.

Importantly, the framework does not prescribe hazard-specific parameters. Its value lies in defining structural requirements that support adaptability: probabilistic link degradation, time-varying capacity, endogenous congestion feedback, and configurable scenarios. This structure allows coastal towns, wildfire-prone communities, seismic regions, or multi-risk metropolitan areas to implement the same methodological backbone while tailoring hazard modules to local conditions. The result is not a model tied to one geography, but an institutional planning tool that can evolve alongside changing hazard landscapes.

Embedding neighborhood-scale performance metrics into planning practice addresses a persistent blind spot in evacuation assessment. Aggregate clearance time remains a dominant indicator across many studies [47,64]. While useful for benchmarking overall performance, system-wide averages can obscure spatial inequities. Certain communities may experience prolonged isolation, limited shelter accessibility, or disproportionate congestion even when total clearance appears acceptable. For municipal decision-makers, these localized disparities are often more relevant than aggregate efficiency. Incorporating origin-based metrics such as block-group clearance time, isolation probability, normalized evacuation duration, and unmet shelter demand enables targeted mitigation strategies rather than uniform system-wide prescriptions.

Operationalizing compound risk, therefore, requires more than improved simulation fidelity. It demands structural reconfiguration of evacuation modeling to support adaptability, scenario comparison, dynamic infrastructure interaction, and spatially resolved outputs. The methodological implications of this planning-oriented shift are summarized in Table 2.

Table 2. Methodological Implications for Compound-Hazard Evacuation Modeling.

Modeling Dimension	Common Limitation in Literature	Framework Advancement	Policy Relevance
Hazard Representation	Hazard-specific, case-bound implementation [117]	Modular, interchangeable hazard processes [127,136]	Enables cross-regional adaptability [120,128]
Infrastructure State	Static closures or fixed capacity [39]	Stochastic degradation and recovery [10,118]	Captures cascading and nonlinear effects [18,36]
Behavioral Coupling	Behavior embedded in hazard assumptions [57]	Decoupled behavioral core [42,60]	Supports and reuse across hazard types [50,119]
Performance Metrics	Aggregate clearance focus [47,152]	Micro/Neighborhood-scale outputs [27,51]	Reveals spatial inequities [3,88]
Scenario Testing	Single scenario evaluation [29,153]	Configurable compound scenarios [133]	Supports comparative planning analysis [38,104]

5.2. Decision Support for Shelter, Infrastructure, and Evacuation Timing

Even the most sophisticated evacuation model has limited value if it cannot inform real decisions under real constraints. Municipal emergency managers operate within budget cycles, staffing limits, political oversight, and public scrutiny. Tools that require extensive recalibration, advanced programming expertise, or opaque optimization routines are unlikely to be integrated into routine planning practice. What local governments need are systems that translate simulation outputs into interpretable, scenario-sensitive insights that directly support timing, shelter, and infrastructure decisions. To synthesize these planning implications, Table 3 organizes the framework’s operational contributions across key municipal decision domains, including evacuation timing, shelter allocation, infrastructure prioritization, and communication strategy. Rather than presenting abstract methodological features, the table translates simulation capabilities into concrete planning actions, associated metrics, and potential implementation pathways.

Table 3. Planning Applications of the Proposed Adaptable Evacuation Framework.

Planning Domain	Key Question	Model Output	Practical Action
Evacuation Orders	When should evacuation begin under compound hazards?	Scenario-based clearance time ranges	Adjust order timing and phasing
Shelter Management	Where will unmet demand occur?	Neighborhood-level shelter deficits	Expand or redistribute capacity
Infrastructure Hardening	Which links repeatedly fail or congest?	Bottleneck frequency and isolation probability	Prioritize reinforcement and backup systems
Communication Strategy	How does compliance affect network overload?	Participation sensitivity analysis	Improve warning dissemination
Hazard Mitigation Funding	Where are compounding risks highest?	Multi-scenario vulnerability mapping	Target investments strategically

Scenario-based simulation plays a central role in this translation. Instead of producing a single evacuation time estimate tied to one assumed hazard condition, planners can examine performance variability across alternative compound configurations. A coastal municipality may compare wind-only impacts, surge-only inundation, and combined wind-surge degradation to determine how road fragility shifts under each configuration. A wildfire-exposed jurisdiction might test smoke-induced speed reduction together with phased evacuation compliance levels to identify when visibility constraints begin to destabilize network flow. In seismic regions, debris-related link failures can be layered with congestion surges to evaluate secondary isolation risk. The objective is not prediction of a single outcome, but stress-testing of the system across plausible hazard combinations. This approach shifts evacuation planning from reactive estimation toward anticipatory resilience design. Rather than asking how long evacuation would take under one assumed scenario, planners can ask which hazard combinations generate persistent bottlenecks, which compliance ranges trigger network overload, and which neighborhoods repeatedly experience delayed clearance. Such insight directly informs evacuation order timing, staged departure policies, and pre-event infrastructure reinforcement.

Shelter system evaluation similarly benefits from origin-resolved analytics. Traditional shelter planning often emphasizes total capacity or optimized allocation, yet system-wide adequacy does not guarantee spatial equity. Du et al. [73] demonstrate that adding shelters without strategic siting does not necessarily improve performance. Milburn et al. [76] further show that evacuees do not consistently select the nearest shelter, undermining simplified proximity assumptions. When shelter demand is traced back to specific origins, planners can detect which neighborhoods generate overflow under varied scenarios, whether imbalances stem from capacity constraints or routing congestion, and how alternative shelter activation strategies redistribute flows. This transforms shelter planning from aggregate capacity accounting into spatial demand management.

Departure timing represents another actionable layer. Empirical research highlights the importance of information dissemination and behavioral responsiveness in shaping congestion dynamics. Siam et al. [92] show that warning delays materially alter evacuation curves, while studies such as Roy et al. [17] and Sun et al. [3] illustrate how compliance and risk perception influence participation rates. Incorporating behavioral sensitivity testing into scenario runs enables planners to evaluate how earlier orders, staggered departure windows, or targeted communication campaigns affect peak loading. Rather than assuming fixed participation rates, municipalities can identify threshold conditions where marginal increases in compliance begin to overwhelm infrastructure capacity. This supports more nuanced communication strategies that balance urgency with network stability.

Infrastructure prioritization also becomes more defensible when informed by repeated scenario performance. Road segments or intersections that consistently exhibit high congestion, extended spillback, or elevated isolation probability across multiple hazard combinations represent structural weaknesses. These recurrent bottlenecks provide empirical justification for targeted capital

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improvements such as signal backup systems, lane widening, contraflow planning, debris clearance prioritization, or culvert reinforcement. Aligning such findings with hazard mitigation funding mechanisms strengthens grant applications by grounding proposals in simulation-based evidence rather than anecdotal observation.

Beyond technical optimization, transparency remains critical. Municipal decision environments require metrics that can be communicated clearly to elected officials, grant reviewers, and community stakeholders. Aggregate optimization outputs or abstract efficiency scores rarely translate into actionable policy language. In contrast, neighborhood-level indicators such as clearance time distribution, evacuee percentage-normalized evacuation duration, isolation probability, and shelter deficit mapping align more directly with planning discourse. These metrics allow stakeholders to visualize disparities, compare alternatives, and justify interventions without requiring familiarity with simulation algorithms.

Importantly, the framework also allows planners to examine equity implications without embedding deterministic demographic assumptions directly into agent behavior. Instead of prescribing behavior based on socioeconomic proxies, post-simulation analysis can evaluate performance disparities across neighborhoods. If certain areas consistently exhibit longer clearance times, higher isolation probability, or elevated shelter overflow under comparable hazard exposure, planners can investigate structural causes such as limited egress routes, constrained vehicle access, or communication gaps. This approach aligns with vulnerability-informed planning perspectives while avoiding reductionist behavioral modeling.

Ultimately, the policy relevance of this framework lies in its ability to integrate multiple planning dimensions within a single, adaptable architecture. It supports evacuation order evaluation, shelter strategy refinement, communication timing analysis, and infrastructure prioritization without requiring hazard-specific reconstruction. By linking modular hazard representation with dynamic network interaction and spatially resolved outputs, the framework transforms evacuation modeling from an academic exercise into a practical decision-support instrument. The result is not simply improved simulation fidelity, but improved institutional capacity to plan under uncertainty, justify investments, and communicate risk transparently across communities.

6. Conclusions

Evacuation modeling is entering a phase in which the central challenge is no longer behavioral realism or traffic representation in isolation, but the integration of interacting hazards, adaptive agents, and evolving infrastructure within coherent and reusable system architectures. While substantial methodological progress has been achieved across behavioral, traffic, and hazard modeling domains, these advances often remain compartmentalized within hazard-specific or region-specific implementations. The contribution of this review lies in articulating an adaptable compound-hazard framework that organizes these advances into a modular and adaptable structure, positioning evacuation simulation as a configurable planning instrument rather than a single-case analytical exercise.

The proposed architecture provides a foundation for comparative, scenario-driven analysis under uncertainty. By supporting interchangeable hazard modules, dynamic network evolution, and spatially resolved performance outputs, the framework enables systematic exploration of how compound drivers alter evacuation outcomes across varying intensities, compliance conditions, and infrastructure stress states. This shift from deterministic clearance estimation toward variability-based performance assessment aligns evacuation modeling with contemporary resilience thinking and risk-informed planning.

Future work should focus on operationalizing this architecture across diverse geographic contexts and hazard portfolios to test its transferability in practice. Applied case studies can evaluate how the modular structure performs under coastal wind–surge systems, wildfire–smoke interactions, seismic–landslide coupling, or other region-specific compound risks. Empirical calibration of behavioral processes, probabilistic infrastructure degradation functions, and recovery dynamics remains a priority for strengthening predictive validity. In parallel, deeper integration of cascading infrastructure interdependencies and communication system effects will enhance the representation of nonlinear disruption patterns.

Ultimately, advancing compound-hazard evacuation modeling requires moving beyond isolated methodological refinement toward integrative, cross-disciplinary development. By structuring behavioral, network, and hazard processes within a unified yet adaptable framework, evacuation simulation can better support comparative planning, institutional learning, and equitable resilience strategies under increasingly complex risk environments.

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