

A Unified Agent-Based Simulation Framework for Epidemic and Wildfire Propagation in Complex Adaptive Systems

Natasha Stojkovikj, Aleksandra Stojanova Ilievska, Limonka Kocева Lazarova, Daniel Eftimov, Irena Eftimova
Faculty of Computer Science, Goce Delcev University, Stip, North Macedonia

Abstract—Spreading phenomena in complex adaptive systems often exhibit similar dynamic characteristics despite originating from different application domains. This study investigates heterogeneous spreading processes using a common agent-based modeling methodology implemented in the AnyLogic simulation platform. Two representative models were developed: influenza transmission within a university population and wildfire propagation in a forest environment. Both models employ statechart-based agents, stochastic state transitions, and local interactions while preserving domain-specific characteristics. The influenza model incorporates mask usage, vaccination, and isolation as intervention strategies. Simulation results show that the investigated intervention scenarios reduced epidemic intensity compared with the baseline under the specific parameter settings considered, with peak infectious populations ranging from 44 to 70 individuals compared with 104 in the baseline scenario. The wildfire model investigates the influence of vegetation density, wind conditions, and burning duration, with burned trees ranging from 1 to 1,035 depending on environmental conditions. Comparative analysis demonstrated that both systems exhibit marked changes in propagation dynamics across the investigated scenarios, together with strong dependence on local interactions and stochastic processes. The successful application of a common agent-based modeling methodology across two distinct spreading phenomena highlights its consistency and transferability while supporting decision-making in public health and environmental risk management.

Keywords—Agent-based modeling; AnyLogic; complex adaptive systems; influenza transmission; wildfire propagation

I. INTRODUCTION

Many natural and social systems are characterized by processes that spread through interactions among neighboring entities. Examples include infectious diseases, wildfires, information diffusion, and cascading failures in infrastructure systems. Although these phenomena belong to different scientific domains, they often exhibit similar propagation patterns influenced by local interactions, stochastic effects, threshold behavior, and nonlinear dynamics. Understanding these processes is important for improving prevention strategies, supporting decision-making, and reducing potential societal, environmental, and economic impacts. Despite differences in their physical mechanisms, many spreading phenomena exhibit comparable emergent behaviors that can be investigated using similar agent-based modeling concepts.

Agent-based modeling (ABM) has been widely used for studying complex systems because it allows individual entities,

their behavior, and interactions to be represented explicitly. In contrast to aggregate mathematical approaches, agent-based simulations enable researchers to investigate how relatively simple local rules may lead to complex system-level behavior. This capability has contributed to the increasing use of ABM in epidemiology, ecology, transportation systems, disaster management, and social sciences. In addition, modern simulation environments such as AnyLogic provide flexible mechanisms for implementing state-based agents, spatial interactions, and stochastic processes within a unified modeling framework. Such flexibility enables heterogeneous spreading phenomena to be investigated using a common modeling methodology, facilitating cross-domain comparisons while improving the transparency, interpretability, and reproducibility of simulation studies.

Seasonal influenza remains one of the most common infectious diseases worldwide and continues to place a considerable burden on healthcare systems and society. Educational institutions represent environments in which disease transmission can occur rapidly due to frequent interpersonal contacts, shared facilities, and high population densities. Investigating the dynamics of influenza outbreaks and evaluating the effects of protective measures are therefore important research topics in public health and epidemic modeling.

Wildfires represent another type of spreading phenomenon that has received substantial attention in recent years. Increasing temperatures, prolonged drought periods, and changing climatic conditions have contributed to more frequent and severe wildfire events in many regions of the world. Fire propagation depends on multiple factors, including vegetation density, wind conditions, burning duration, and local neighborhood interactions. Understanding how these factors influence wildfire dynamics is essential for improving prevention strategies, optimizing resource allocation, and supporting emergency response planning.

Most existing studies investigate epidemic transmission and wildfire propagation as separate research problems, primarily focusing on domain-specific models and applications. Consequently, relatively limited attention has been devoted to developing unified agent-based modeling frameworks that enable the systematic investigation of heterogeneous spreading phenomena using consistent modeling principles and comparable simulation structures. Although these phenomena share several fundamental propagation characteristics, including

local interactions, stochastic state transitions, and emergent behavior, their common modeling potential has received comparatively little attention. A cross-domain perspective may therefore provide a broader understanding of generic propagation mechanisms in complex adaptive systems while demonstrating the transferability of common agent-based modeling principles across different application domains.

Therefore, the objective of this study is to investigate whether different spreading phenomena can be consistently analyzed using a common agent-based modeling methodology implemented in the AnyLogic simulation environment. To achieve this objective, two agent-based models were developed. The first model represents influenza transmission within a higher education institution, while the second simulates wildfire propagation in a forest environment. Both models employ statechart-based agents, discrete spatial representations, and stochastic local interactions. Their comparative analysis enables the identification of common propagation characteristics while illustrating the applicability of agent-based simulation for studying heterogeneous spreading processes in complex adaptive systems.

The main contributions of this study are threefold. First, two comparable agent-based simulation models representing biological and environmental spreading phenomena are developed using a common statechart-based modeling methodology implemented in the AnyLogic platform. Second, the proposed models are comparatively evaluated under multiple intervention and environmental scenarios to investigate similarities and differences in propagation dynamics. Third, the study identifies common characteristics of spreading processes across heterogeneous complex adaptive systems, demonstrating the generalizability of agent-based simulation for cross-domain modeling of spreading phenomena.

The remainder of the study is organized as follows. Section II presents an overview of related studies in epidemic simulation, wildfire modeling, and agent-based methodologies. Section III introduces the theoretical concepts underlying the proposed models. Section IV describes the development and implementation of the influenza and wildfire simulations. Experimental results and comparative analyses are discussed in Section V, while Section VI summarizes the main findings and outlines potential directions for future research.

II. RELATED WORK

Agent-based modeling (ABM) has become one of the most widely adopted approaches for studying complex adaptive systems characterized by heterogeneous entities, decentralized interactions, and emergent behavior. Unlike aggregate mathematical models, ABM explicitly represents individual agents, their behavioral rules, and interactions within a dynamic environment, allowing researchers to investigate how local decisions and stochastic processes collectively shape system-level dynamics. The applicability of agent-based techniques has been demonstrated in numerous scientific disciplines, including epidemiology, social sciences, transportation systems, ecology, and disaster management [1]–[4]. The development of multimethod simulation environments has additionally facilitated the implementation of ABM by enabling the

integration of agent-based, discrete-event, and system dynamics paradigms within a common modeling framework [4].

The spread of infectious diseases has traditionally been investigated using compartmental epidemiological models. The classical SIR framework remains one of the most important theoretical foundations for epidemic modeling [5], while subsequent studies extended these concepts and demonstrated their usefulness for understanding disease dynamics and evaluating intervention strategies [6]. However, compartmental models generally assume homogeneous populations and often neglect heterogeneity in contact structures, mobility patterns, and individual behavior. To overcome these limitations, network-based and agent-based approaches have gained increasing attention [7]–[9].

Numerous studies have investigated influenza outbreaks and pandemic mitigation measures. Strategies for containing pandemic influenza at its source were investigated in [10], while targeted layered containment approaches were modeled in [11]. The role of herd immunity in infectious disease control was examined in [12]. School closure as a mitigation strategy was investigated in [13] and further evaluated in the context of the 2009 H1N1 pandemic in [14]. Factors affecting the controllability of infectious disease outbreaks were analyzed in [15], whereas a stochastic agent-based approach for epidemic simulation was developed in [16]. More recent research has expanded the methodological scope of epidemic modeling. An agent-based model incorporating non-pharmaceutical interventions and contact tracing was presented in [17]. A broader analysis of agent-based epidemic modeling approaches, applications, and future directions was provided in [18], while epidemic processes in complex networks were examined in [19].

Complex network theory has also played an important role in epidemic research. The influence of social network structures, connectivity patterns, and contact heterogeneity on disease transmission has been widely investigated [7], [20], [21]. These studies demonstrate that epidemic propagation is strongly influenced by local interactions among individuals as well as by the topology of the underlying contact network.

Wildfire propagation has been investigated through empirical, physical, and simulation-based approaches. Early studies demonstrated that simple local ignition mechanisms may generate self-organized critical behavior in forest-fire systems [22], [23]. Percolation theory has frequently been employed to explain the existence of critical vegetation density thresholds that significantly influence fire spread [24]. Cellular automata have also proven effective in modeling wildfire behavior, particularly when accounting for neighborhood interactions and environmental conditions [25]. More recent wildfire studies address different aspects of model realism. An efficient wildfire propagation approach using irregular grids was proposed in [26]. The effects of input-data variation and parameter adjustment were investigated in [27], while wildfire spread models addressing spotting phenomena were systematically reviewed in [28]. Together, these studies highlight complementary directions for improving spatial representation, parameterization, and the representation of complex fire-spread mechanisms. However, comparatively little attention has been devoted to investigating whether these modeling principles can

be generalized and consistently applied across different categories of spreading phenomena.

Although epidemic transmission and wildfire propagation are generally investigated within different scientific disciplines, both represent spreading phenomena governed by local interactions, stochastic state transitions, neighborhood effects, and nonlinear emergent dynamics. Consequently, both systems can be investigated using similar agent-based modeling concepts despite their fundamentally different physical mechanisms. Recent studies have additionally demonstrated the applicability of AnyLogic for modeling epidemic processes, educational environments, and other complex adaptive systems [29]–[32]. Nevertheless, these studies primarily focus on individual application domains rather than proposing a unified methodological framework for investigating heterogeneous spreading phenomena.

Building upon these observations, the present study adopts a common agent-based modeling methodology, implemented in the AnyLogic simulation environment, to investigate two different spreading phenomena. Rather than treating epidemic transmission and wildfire propagation as isolated case studies, the proposed approach explores their common propagation characteristics using comparable modeling principles, thereby providing a cross-domain perspective on the analysis of spreading dynamics in complex adaptive systems.

III. THEORETICAL BACKGROUND

Agent-based modeling (ABM) is a bottom-up simulation approach in which autonomous entities interact within a predefined environment according to specific behavioral rules. In contrast to aggregate mathematical models, agent-based simulations describe the state and behavior of individual entities explicitly, making it possible to investigate how local interactions and stochastic events contribute to the emergence of system-level dynamics [1]–[4]. The ability to incorporate heterogeneous populations, spatial relationships, and adaptive behavior has led to the widespread use of ABM in epidemiology, ecology, transportation systems, and disaster management.

The behavior of agents is commonly represented through statecharts, which define possible states and transitions among them. Statecharts provide a convenient mechanism for modeling event-driven and time-dependent processes, allowing agents to modify their states according to probabilistic rules, interactions with neighboring entities, or changes in environmental conditions [4]. This approach is particularly useful when studying spreading processes, where the state of one agent may directly affect the evolution of nearby agents.

Epidemic spread is traditionally described using compartmental models in which individuals transition between epidemiological states such as susceptible, infected, and recovered [5], [6]. Although these models provide valuable insights into disease dynamics, they generally assume homogeneous mixing within the population and often neglect variations in contact patterns, mobility, and individual behavior. Agent-based approaches address these limitations by explicitly representing social interactions and behavioral heterogeneity, enabling a more realistic description of disease transmission [7]–[9]. Recent studies have further demonstrated the

applicability of agent-based frameworks for incorporating intervention strategies, contact tracing mechanisms, and non-pharmaceutical mitigation measures [16]–[19].

Wildfire propagation can also be considered a spreading process governed by local interactions. In many simulation studies, trees are represented as discrete entities occupying cells within a spatial grid and may transition between states such as intact, burning, and burned. The likelihood that a tree ignites is influenced by several factors, including vegetation density, burning duration, wind conditions, and the characteristics of neighboring cells [21]–[27]. Previous investigations have shown that wildfire dynamics exhibit properties associated with self-organized criticality and percolation phenomena, where relatively small changes in vegetation density may substantially alter the probability of large-scale fire events [22]–[24].

Although epidemic transmission and wildfire propagation are generally investigated within different scientific disciplines, both can be formulated as spreading processes driven by interactions among autonomous agents evolving. From a simulation perspective, both systems share common modeling elements, including discrete agent states, stochastic state transitions, local neighborhood interactions, spatial environments, and scenario-dependent parameters. Consequently, similar agent-based modeling principles can be employed to investigate different spreading phenomena while maintaining a consistent simulation methodology.

Based on these common modeling principles, both simulation models presented in this study were implemented using the AnyLogic simulation platform [33], which provides integrated support for statechart-based agents, stochastic processes, spatial interactions, and scenario management [4]. Employing the same simulation environment and modeling methodology enables a consistent comparative investigation of biological and environmental spreading phenomena while preserving the specific characteristics of each application domain. This unified methodological perspective provides the basis for the comparative analyses presented in the following sections.

A. Common Agent-Based Modeling Methodology

The proposed models follow the same agent-based modeling methodology despite representing different application domains. In both models, the system is composed of autonomous agents situated within a discrete spatial environment. Each agent occupies one state at a given time and changes its state through statechart-based transitions triggered by local interactions, stochastic processes, or predefined simulation rules. The environment defines spatial relationships among neighboring agents, while scenario-specific parameters control interaction probabilities and propagation dynamics. Simulation outputs are obtained by observing the collective behavior emerging from numerous local interactions over time. The adoption of a common modeling methodology facilitates consistent comparative analysis, improves the interpretability of simulation outcomes, and demonstrates the transferability of agent-based modeling principles across different categories of spreading phenomena.

In this study, the term unified refers to the use of a common modeling methodology rather than to a shared mathematical formulation or identical parameter set. Both models follow the same sequence of agent specification, statechart design, local interaction modeling, scenario configuration, simulation execution, and comparative analysis, while their transition mechanisms and parameters remain domain-specific.

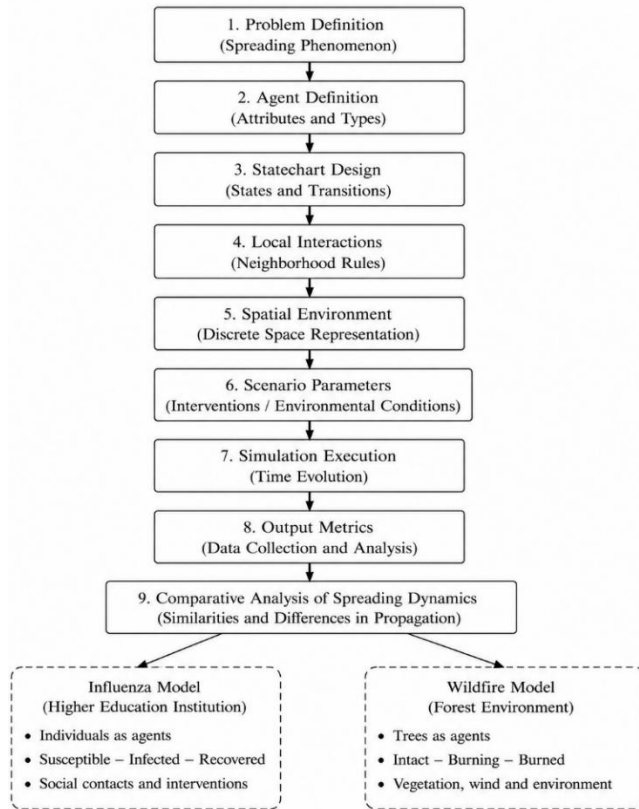


Fig. 1. General workflow of the common agent-based modeling methodology employed in both simulation models.

Fig. 1 summarizes the common agent-based modeling workflow adopted in this study. Although the influenza and wildfire models represent different application domains, both follow the same sequence of problem definition, agent specification, statechart design, local interaction modeling, scenario configuration, simulation execution, and comparative analysis. This workflow defines a reusable modeling procedure in which a new spreading domain can be represented by specifying its agents and states, defining domain-specific transition and local interaction rules, configuring relevant scenario parameters, executing the simulation, and analyzing the resulting system-level behavior. The following sections describe the implementation details of each application while maintaining this common methodological structure.

Although the influenza and wildfire models represent different application domains, they share several common modeling principles that ensure methodological consistency throughout the simulation process. Table I summarizes the principal modeling elements adopted in both agent-based models and highlights the similarities and domain-specific characteristics of each application.

TABLE I. COMPARISON OF THE COMMON MODELING ELEMENTS ADOPTED IN THE INFLUENZA AND WILDFIRE AGENT-BASED SIMULATION MODELS

Modeling Element	Influenza Model	Wildfire Model
Agents	Students	Trees
State representation	Susceptible, Exposed, Infectious, Recovered	Unburned, Burning, Burned
Environment	Higher education institution	Forest environment
Local interactions	Person-to-person contacts	Neighboring trees
State transitions	Infection, incubation, recovery	Ignition, burning, burnout
Scenario parameters	Vaccination, masks, isolation	Density, wind, burning duration
Output metrics	Epidemic dynamics	Fire propagation dynamics

As shown in Table I, both simulation models follow the same methodological structure despite representing different spreading phenomena. The primary differences relate to the definition of agents, state transitions, and domain-specific parameters, whereas the underlying agent-based modeling principles, statechart implementation, local interactions, and scenario-based experimentation remain consistent. This methodological consistency forms the basis for the detailed model descriptions presented in the following sections.

IV. METHODOLOGY AND SIMULATION SETUP

A. Influenza Transmission Model

Following the common agent-based modeling methodology described in Section III-A, the first application investigates influenza transmission within a higher education institution. The model was implemented in the AnyLogic simulation environment, where students are represented as autonomous agents interacting within a shared environment and transitioning among epidemiological states according to predefined behavioral rules (Fig. 2).

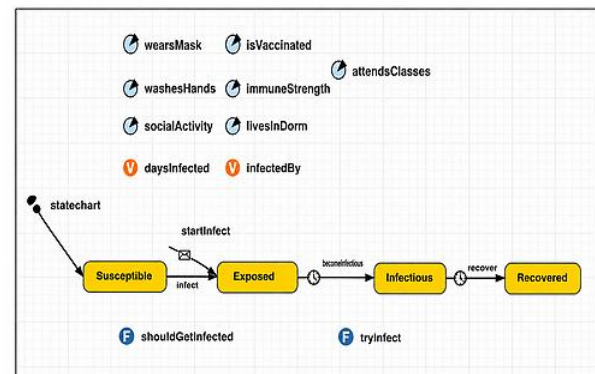


Fig. 2. Statechart of the influenza transmission model.

The implemented statechart consists of four epidemiological states, namely Susceptible, Exposed, Infectious, and Recovered, allowing the representation of an incubation period prior to the onset of infectiousness. State transitions are governed by probabilistic mechanisms describing disease transmission, progression, and recovery. The statechart implementation follows the common modeling workflow presented in Fig. 1,

where individual agent behavior emerges through state transitions triggered by local interactions and stochastic events.

At the beginning of each simulation run, a predefined percentage of students is initialized as infectious, whereas the remaining population is considered susceptible. Disease transmission occurs through interactions between susceptible and infectious individuals. The probability of infection depends on a transmission coefficient that can be adjusted to represent different outbreak conditions. Exposed individuals remain in the incubation state for a specified period before becoming infectious. After the infectious period, agents transition to the recovered state, where temporary immunity is assumed.

The simulation population consisted of 200 students, with three individuals initially infected. The incubation and recovery periods were configured within the ranges of 1–7 and 2–14 days, respectively. Disease transmission was governed by probabilistic interactions between susceptible and infectious agents, with the transmission coefficient controlling the likelihood of infection. The intervention scenarios considered 80% mask compliance, 75% vaccination coverage, and a 70% isolation probability. In the isolation scenario, students maintained an average of twelve daily contacts and could enter isolation only after at least two days in the infectious state.

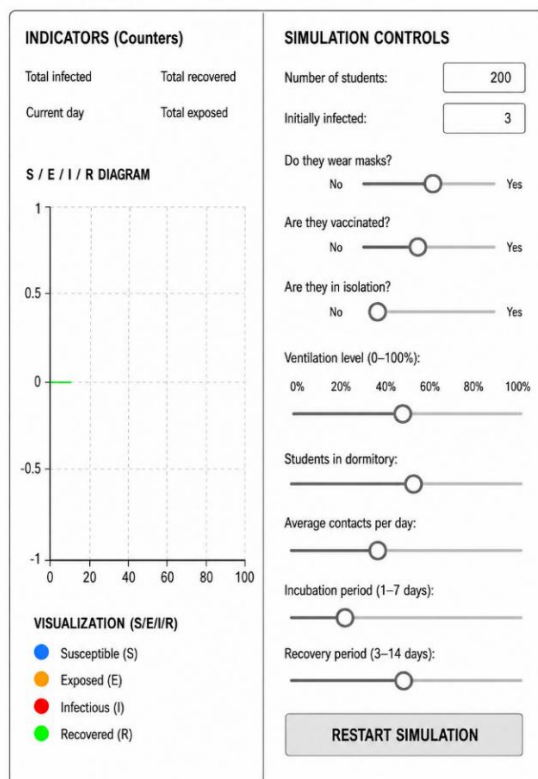


Fig. 3. Simulation environment of the influenza model.

To evaluate the influence of mitigation strategies on epidemic dynamics, several intervention mechanisms were incorporated into the model, including vaccination, mask usage, self-isolation, and reductions in contact frequency. These measures allow the investigation of their impact on epidemic dynamics and facilitate comparative analyses under different mitigation strategies. The simulation environment and the main

model parameters used to configure the influenza scenarios are shown in Fig. 3.

B. Wildfire Propagation Model

The second application follows the same agent-based modeling methodology and investigates wildfire propagation within a forest environment. Similar to the influenza model, the wildfire simulation was implemented using statechart-based agents in the AnyLogic platform. Individual trees occupy cells of a two-dimensional spatial grid and interact locally with neighboring trees according to predefined propagation rules (Fig. 4).

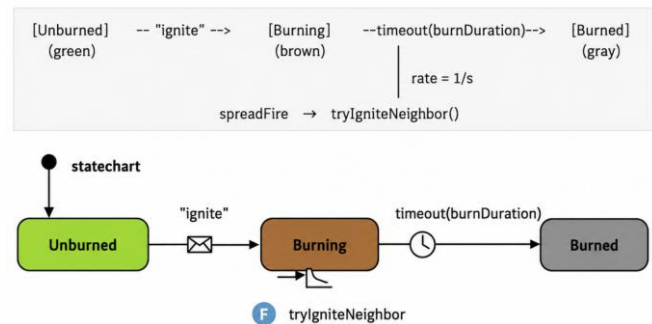


Fig. 4. Statechart of the wildfire propagation model.

Each tree may exist in one of three states: Unburned, Burning, and Burned. State transitions are implemented through an AnyLogic statechart. The wildfire statechart preserves the same state-based modeling philosophy adopted in the influenza model while incorporating domain-specific transition rules associated with fire propagation. A tree enters the burning state upon receiving an ignition message from a neighboring burning tree and remains active for a predefined burning duration before permanently transitioning to the burned state.

Fire propagation occurs locally through interactions among neighboring trees. The ignition probability depends on several factors, including forest density, burning duration, wind speed, and wind direction. Wind effects are incorporated by increasing ignition probabilities in the prevailing wind direction while simultaneously reducing propagation probabilities in the opposite direction.

Forest density, wind speed, wind direction, ignition probability, and burning duration were defined through adjustable simulation parameters accessible via the graphical user interface. These settings enabled the evaluation of wildfire propagation under different environmental conditions. The use of adjustable parameters enabled systematic scenario-based experimentation while maintaining consistency with the common simulation methodology described in Section III-A.

The wildfire environment was represented by a 50×50 spatial grid, with a base ignition probability of 0.3 in the illustrated configuration. The experimental scenarios considered forest densities of 0.3, 0.7, and 0.9, wind speeds of 0, 5, and 15 m/s, and burning durations of 2 and 5 simulation time units. Ignition depended on local interactions between neighboring trees, with wind direction modifying the likelihood of propagation along different directions. The complete scenario

configurations and corresponding simulation outcomes are summarized in Table III.

The initial forest configuration and the simulation environment used to configure the wildfire scenarios are shown in Fig. 5.

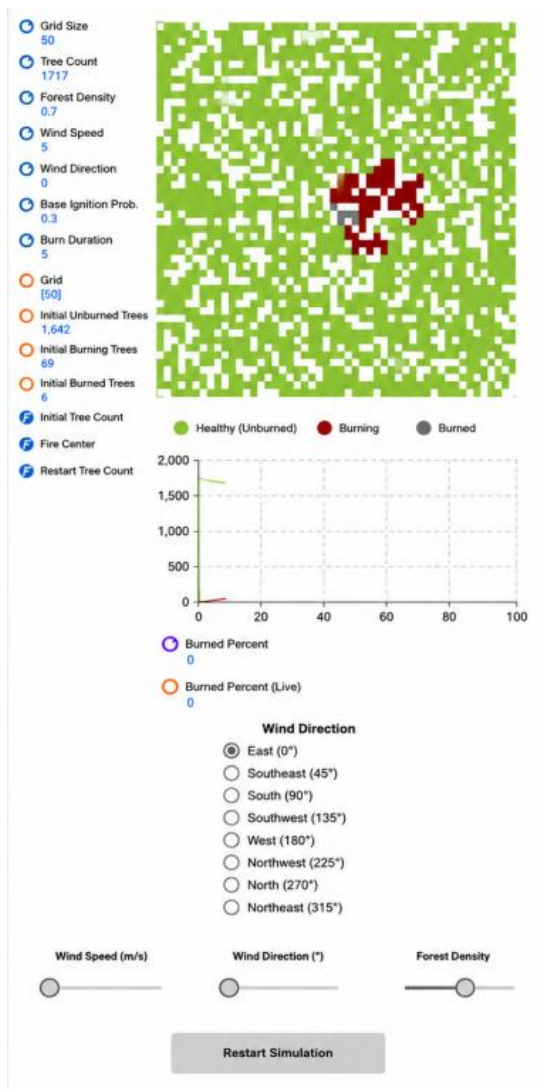


Fig. 5. Initial forest configuration and wildfire simulation environment.

V. RESULTS AND DISCUSSION

The results reported in this section correspond to representative simulation runs for each investigated scenario. Because the models include stochastic state transitions, individual runs may produce variations in peak magnitude, timing, and outcomes. Therefore, the reported values should be interpreted as illustrative scenario outcomes rather than statistical estimates of expected system behavior.

A. Epidemic Dynamics Under Different Intervention Strategies

The proposed agent-based influenza transmission model was evaluated under four intervention scenarios designed to investigate the impact of various mitigation measures on epidemic progression within a university environment. The

investigated scenarios included a baseline case without interventions, increased mask usage, vaccination, and isolation of infected individuals.

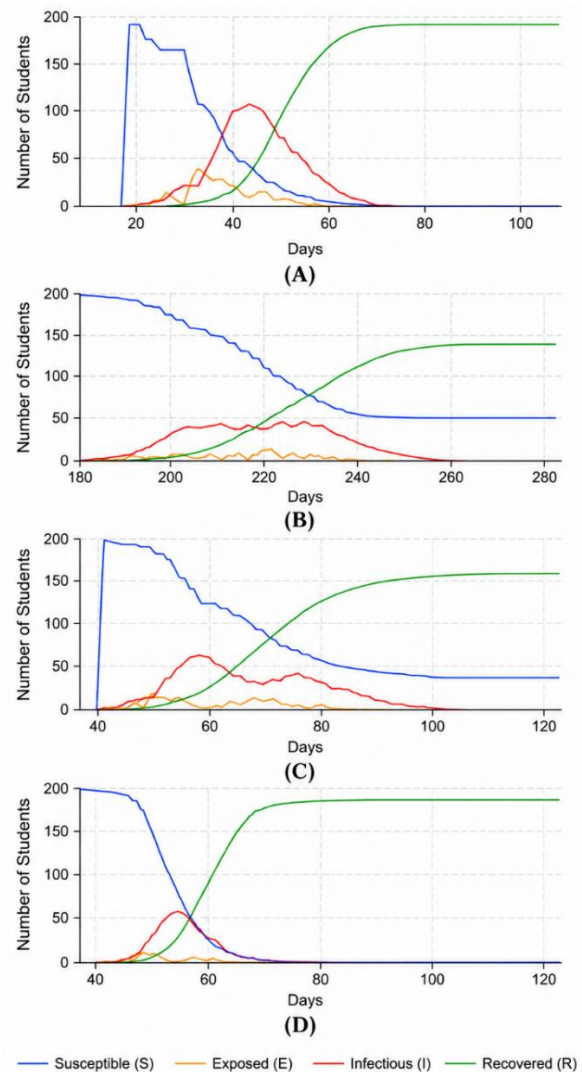


Fig. 6. Temporal evolution of Susceptible (S), Exposed (E), Infectious (I), and Recovered (R) Populations under four intervention scenarios: (A) Baseline scenario without interventions, (B) Mask usage, (C) Vaccination, and (D) Isolation of infected students.

Fig. 6 illustrates the temporal evolution of the SEIR compartments under the investigated intervention strategies. Significant differences in epidemic progression can be observed depending on the applied mitigation measure. The investigated scenarios were selected to evaluate the capability of the common agent-based modeling methodology to represent different intervention strategies using identical modeling principles while varying only domain-specific parameters.

The baseline scenario (Fig. 6A) represents disease transmission without preventive interventions. The epidemic spreads rapidly through the student population, reaching a maximum of approximately 104 simultaneously infectious students around day 15. By the end of the simulation, only six individuals remain susceptible, while 194 students recover from

the disease. These results indicate that approximately 97% of the population experiences infection in the absence of control measures.

The second scenario (Fig. 6B) investigates the effect of increased mask usage, assuming an 80% compliance rate among students. Compared with the baseline scenario, the epidemic peak is considerably reduced to approximately 45 infectious individuals and delayed until around day 50. The number of susceptible individuals at the end of the simulation increases to 52, while 148 students recover. The delayed epidemic peak and flatter epidemic curve suggest that mask usage effectively decreases transmission opportunities and slows disease propagation.

Vaccination was examined in the third scenario (Fig. 6C), assuming vaccination coverage of 75% of the student population. The number of infectious individuals reaches a maximum of approximately 44 students around day 15. Although vaccination substantially suppresses disease transmission, a smaller secondary increase in infectious cases can still be observed. At the end of the simulation, 34 students remain susceptible, while 166 recover from infection. These findings indicate that vaccination significantly improves epidemic control but may not eliminate disease spread among residual susceptible subgroups.

The fourth scenario (Fig. 6D) evaluates the impact of isolation as the sole intervention strategy. The isolation probability was set to 70%, whereas masks and vaccination remained disabled, and students maintained an average of twelve daily contacts. In contrast to masks and vaccination, isolation acts after infection has already occurred. Students may isolate only after being infectious for at least two days, allowing disease transmission during the initial infectious stage. The simulation results demonstrate a peak of approximately 70 infectious students around day 25. By the end of the simulation, 180 students recover, and only 20 remain susceptible. Under this scenario configuration, isolation reduced epidemic spread relative to the baseline, resulting in a peak of approximately 70 infectious students and an attack rate of 90%.

To facilitate comparison among the investigated intervention strategies, the principal epidemiological indicators extracted from the simulations are summarized in Table II.

As shown in Table II, all investigated intervention scenarios produced lower epidemic peaks and attack rates than the baseline scenario under the specific parameter settings considered. The mask scenario (80% compliance) resulted in a peak of 45 infectious individuals and an attack rate of 74%, while the vaccination scenario (75% coverage) produced a peak of 44 infectious individuals and an attack rate of 83%. The isolation scenario (70% isolation probability) resulted in a peak of 70 infectious individuals and an attack rate of 90%. Because these scenarios represent different intervention mechanisms and use different coverage or compliance levels, the results should not be interpreted as a normalized ranking of intervention effectiveness. Instead, they illustrate how the simulated epidemic dynamics changed under the specific intervention configurations investigated in this study.

TABLE II. COMPARATIVE EPIDEMIOLOGICAL INDICATORS OBTAINED FROM FOUR INTERVENTION SCENARIOS

	Interventi on Strategy	Peak Infectio us	Pea k Day	Susceptib le at End	Recove r at End	Attac k Rate
A	Baseline	104	15	6	194	97.0 %
B	Masks (80%)	45	50	52	148	74.0 %
C	Vaccinatio n (75%)	44	15	34	166	83.0 %
D	Isolation (70%)	70	25	20	180	90.0 %

B. Wildfire Propagation Analysis

To evaluate the proposed wildfire propagation model, four representative simulation scenarios were investigated by varying forest density, wind conditions, and burning duration. The resulting fire dynamics are illustrated in Fig. 7.

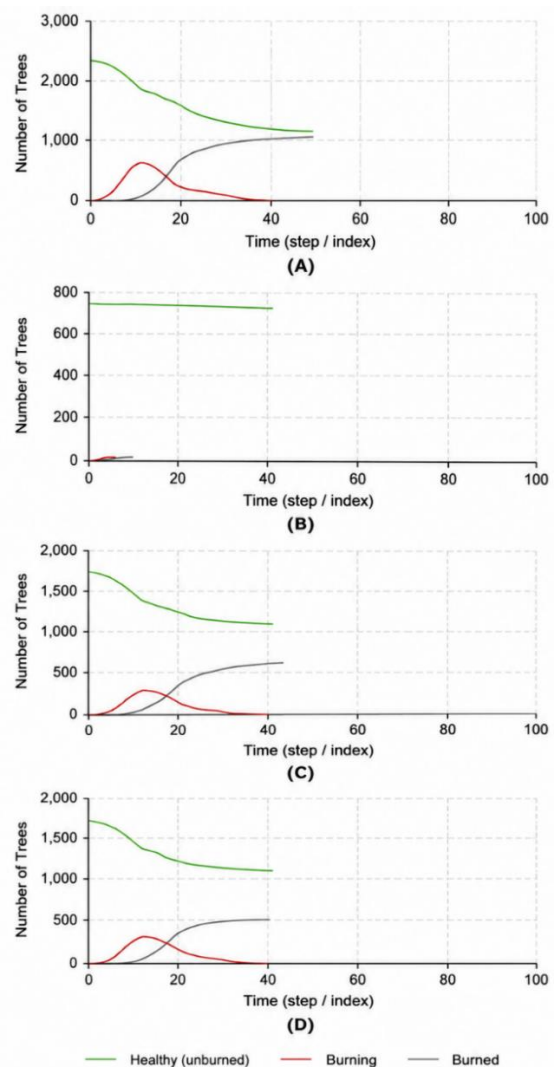


Fig. 7. Temporal evolution of healthy, burning, and burned trees under four representative wildfire propagation scenarios: (A) Dense forest without wind, (B) Sparse forest without wind, (C) Medium-density forest with strong wind, and (D) Reduced burning duration.

The investigated scenarios were selected to illustrate wildfire behavior under different combinations of the principal environmental parameters considered in the model. Consistent with the influenza case study, all wildfire scenarios preserve the same agent-based modeling methodology while using different application-specific environmental parameter settings. The scenarios were not designed as a factorial experiment to isolate the independent effect of each parameter. A summary of the considered configurations is presented in Table III.

TABLE III. COMPARATIVE SUMMARY OF WILDFIRE SIMULATION SCENARIOS

	Forest Density	Wind Speed	Burn Duration	Burned Trees	Peak Burning	Duration (steps)	Pattern
W1	0.9	0	5	1035	501	36	Circular
W2	0.3	0	5	1	3	6	Fragmented
W3	0.7	15 m/s East	5	617	239	46	Eastward
W4	0.7	5 m/s East	2	493	85	24	Reduced

The first scenario (Fig. 7A) represents a dense forest configuration with a vegetation density of 0.9 and no wind influence. Under these conditions, the fire spreads almost uniformly in all directions, producing a nearly circular propagation pattern. The fire spread rapidly through the highly connected vegetation, reaching a peak of approximately 501 simultaneously burning trees around simulation step 8. By the end of the simulation, 1,035 trees had burned, while 1,232 trees remained unaffected, indicating extensive fire damage under dense vegetation conditions. Since neighboring cells are highly connected, the fire rarely encounters natural barriers that would prevent further expansion.

The second scenario (Fig. 7B) investigates a sparse forest characterized by a density of only 0.3. In contrast to the previous case, numerous empty cells interrupt connectivity among trees, frequently leading to early fire extinction. The fire propagation remained highly localized. The maximum number of simultaneously burning trees did not exceed three, and only a single tree became permanently burned by the end of the simulation. These findings indicate that sparse vegetation acts as an effective natural barrier preventing large-scale fire spread.

The third scenario (Fig. 7C) considers a medium forest density of 0.7 and an eastward wind of 15 m/s. Under this parameter combination, the fire developed an elongated pattern directed along the wind axis. The simulation lasted 46 steps and resulted in 617 burned trees, while the maximum number of simultaneously burning trees reached approximately 239 around simulation step 13. Because this scenario differs from the no-wind scenarios in more than one parameter setting, the observed propagation pattern should be interpreted as specific to the investigated configuration rather than as an isolated estimate of the wind effect.

The final scenario (Fig. 7D) considers a forest density of 0.7, an eastward wind speed of 5 m/s, and a burning duration of 2

simulation time units. Under this parameter combination, 493 trees were burned, the maximum number of simultaneously burning trees was 85, and the propagation duration was 24 simulation steps. In comparison, Scenario W3 resulted in 617 burned trees, a peak of 239 simultaneously burning trees, and a duration of 46 simulation steps. Because W3 and W4 differ in both wind speed and burning duration, the observed differences cannot be attributed to burning duration alone.

Overall, the investigated scenarios produced substantial differences in fire extent, peak fire intensity, and propagation duration under different combinations of vegetation density, wind conditions, and burning duration. Because multiple parameters vary across the scenarios, these results describe scenario-specific propagation patterns rather than independent effects of individual environmental factors.

C. Comparative Discussion

The two developed simulation models demonstrate that different spreading phenomena can be investigated using a common agent-based modeling methodology while preserving their domain-specific characteristics. Although the biological and environmental processes considered in this study differ substantially in their underlying mechanisms, both follow identical modeling principles regarding autonomous agents, stochastic state transitions, local interactions, and scenario-based experimentation.

The influenza model considers students as individual agents interacting through social contacts and transitioning among susceptible, exposed, infectious, and recovered states. In contrast, the wildfire model represents trees as stationary agents whose states evolve from unburned to burning and eventually to burned. Despite these differences, both models employ statechart-based agent representations and incorporate probabilistic mechanisms governing state transitions.

To emphasize similarities and differences between the two simulation approaches, a comparative overview is presented in Table IV.

TABLE IV. COMPARATIVE CHARACTERISTICS OF THE DEVELOPED AGENT-BASED MODELS

Characteristic	Influenza Model	Wildfire Model
Simulation Platform	AnyLogic	AnyLogic
Modeling Approach	Agent-Based Modeling	Agent-Based Modeling
Agent Type	Student	Tree
State Representation	SEIR	Unburned–Burning–Burned
Statechart Implementation	Yes	Yes
Stochastic Components	Yes	Yes
Spatial Representation	Social interaction network	Two-dimensional grid
Main Influencing Factors	Masks, vaccination, isolation	Forest density, wind, burning duration
Main Performance Indicator	Peak infectious population	Percentage of burned trees
Intervention Strategies	Yes	No
Primary Objective	Epidemic mitigation	Wildfire propagation assessment

Table IV further demonstrates that, despite substantial differences in the modeled systems, the two simulation models preserve a consistent methodological structure. The principal distinctions arise from application-specific agents, states, and parameters, whereas the underlying simulation methodology remains identical.

The results obtained from both models indicate substantial differences in propagation dynamics across the investigated scenario settings. Similar observations have been reported in recent wildfire propagation studies employing calibrated simulation environments and irregular computational grids [26], [27]. In the epidemic simulations, preventive interventions substantially modify the magnitude and timing of epidemic peaks, while in the wildfire simulations relatively small variations in vegetation connectivity, wind conditions, and burning duration can lead to pronounced differences in fire extent and propagation patterns.

The comparison further demonstrates the flexibility of agent-based modeling for investigating complex dynamic systems characterized by heterogeneity, local interactions, and nonlinear behavior. By allowing individual entities to operate autonomously and interact according to predefined rules, agent-based models provide a flexible framework for studying spreading processes that are often difficult to analyze analytically or reproduce experimentally.

TABLE V. QUALITATIVE EFFECTS OF KEY PARAMETERS IN THE INVESTIGATED SIMULATION SCENARIOS

Model	Parameter	Observed Effect in the Investigated Scenario
Influenza	Mask Usage	Reduces transmission probability and delays epidemic peak
Influenza	Vaccination Coverage	Decreases the number of infectious individuals and increases population immunity
Influenza	Isolation Rate	Limits contacts after infection but acts with a delay
Wildfire	Forest Density	Determines connectivity among trees and extent of fire spread
Wildfire	Wind Speed	Accelerates directional fire propagation
Wildfire	Burning Duration	Influences secondary ignitions and final burned area

Table V summarizes the qualitative effects observed for the key parameters under the investigated simulation settings. In the epidemic model, the investigated mask, vaccination, and isolation scenarios produced different propagation outcomes under their respective parameter settings. Similarly, in the wildfire model, different combinations of forest density, wind conditions, and burning duration produced distinct fire propagation patterns. These observations are scenario-specific and should not be interpreted as a quantitative ranking of parameter influence. Nevertheless, they illustrate how agent-based simulation can support the comparative exploration of alternative parameter configurations in complex adaptive systems.

Several limitations should be acknowledged. The proposed models rely on simplified interaction mechanisms and do not incorporate empirical calibration, realistic mobility patterns, heterogeneous landscapes, or high-resolution meteorological datasets. Accordingly, the reported results should be interpreted

as simulation-based observations under the investigated parameter settings rather than as empirically validated predictions of real-world epidemic or wildfire behavior. In addition, the present analysis is based on representative simulation runs and does not quantify stochastic variability through repeated runs or confidence intervals. Future work should employ multiple replications for each scenario and report statistical measures of variability to assess the robustness of the observed propagation patterns. The study does not include quantitative benchmarking against conventional domain-specific approaches, such as compartmental epidemic models or cellular automata-based wildfire models; therefore, no claims are made regarding superior predictive accuracy, computational efficiency, or model fidelity. Furthermore, the study focuses on representative simulation scenarios rather than predictive forecasting. Further extensions may integrate real-world datasets and calibration procedures, employ systematic parameter sweeps, sensitivity analyses, and factorial experimental designs to quantify the individual and interaction effects of forest density, wind conditions, and burning duration, and extend the methodology to additional categories of spreading phenomena, including information diffusion and cascading infrastructure failures.

VI. CONCLUSION

This study presented a common agent-based modeling methodology, implemented in the AnyLogic simulation environment, for investigating different spreading phenomena in complex adaptive systems. The proposed methodology was demonstrated through two representative application domains: influenza transmission within a higher education institution and wildfire propagation in a forest environment. Although the underlying mechanisms of these processes differ substantially, both models were developed using consistent modeling principles based on autonomous agents, statechart-driven behavior, stochastic state transitions, local interactions, and scenario-based experimentation.

The influenza simulations demonstrated that the investigated mask, vaccination, and isolation scenarios reduced epidemic intensity compared with the baseline under the specific parameter settings considered. Because the interventions were implemented using different mechanisms and coverage levels, these results represent scenario-specific outcomes rather than a normalized comparison of intervention effectiveness. These findings illustrate the potential role of preventive measures in modifying epidemic dynamics within the simulated educational environment.

The wildfire simulations produced substantially different propagation patterns across the investigated combinations of vegetation density, wind conditions, and burning duration. Dense and sparse forest configurations showed markedly different fire-spread patterns, while the scenario including strong eastward wind exhibited directional propagation. Because multiple parameters varied across some scenarios, the observed differences should be interpreted as scenario-specific outcomes rather than as isolated effects of individual environmental factors.

The comparative analysis demonstrated that, despite representing different scientific domains, both models exhibit

common propagation characteristics arising from local interactions among autonomous agents operating under stochastic conditions. The successful application of the same modeling methodology to two substantially different spreading phenomena demonstrates its consistency and transferability across different application domains. This finding highlights the potential of agent-based modeling as a versatile simulation methodology for analyzing complex adaptive systems characterized by heterogeneous entities, nonlinear dynamics, and emergent behavior.

Future research may extend the proposed methodology by incorporating empirical calibration, realistic mobility patterns, heterogeneous landscapes, high-resolution environmental and meteorological datasets, and additional categories of spreading phenomena, such as information diffusion, cascading infrastructure failures, and ecological invasion processes. Such extensions would further improve the generality and practical applicability of the proposed modeling approach.

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