



Flood-Disease ABM: A Multi-Pathway Agent-Based Model for Simulating Flood Disruption and Post-Flood Health Impacts Across the Disaster Lifecycle

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Abstract.

Flood health burdens extend beyond inundation through displacement, service disruption, contaminated environments, and delayed disease. These processes are often modeled separately or as cause–effect relationships, limiting analysis of feedbacks among human behavior, institutions, and post-flood health. We present the Flood-Disease Agent-Based Model (Flood-Disease ABM), a spatially explicit, hourly modeling framework that integrates flood exposure, human mobility, worldview-informed decision-making, institutional response, economic activity, quality of life, and infectious, vector-borne, and mold-related respiratory disease pathways. Decision-making is differentiated across hierarchist, egalitarian, individualist, and fatalist worldview orientations. A browser-based interactive app enables users to configure scenarios, populations, hazards, service capacity, and policy assumptions and to observe spatial and temporal outcomes. Complementary batch runners support reproducible replications of the same configurations. The framework is implemented for the flood-prone Uvalde, Texas, region using representations of households, businesses, schools, shelters, healthcare facilities, and government. Under the selected assumptions, the compound scenario produces an early flood-related healthcare peak followed by sustained disease-related demand during recovery; mold emerges after floodwater recession; spatially uneven shelter demand exceeds capacity at peak demand; financial stress shifts among households and institutions; and quality-of-life losses are greatest among children and lower-income groups. Results are model-based outcomes and not calibrated forecasts for Uvalde.

1 Introduction

Flooding is among the most widespread natural hazards and creates health burdens that extend well beyond immediate mortality and injury (Shi, 2026; Liu et al., 2026). Intensifying precipitation extremes increase riverine and urban flood risk by overwhelming drainage systems, wastewater infrastructure, and emergency response capacity (Patz et al., 2008). As a result, flood impacts unfold through environmental contamination, displacement, infrastructure disruption, and delayed disease outcomes (Chowell et al., 2019; Collender et al., 2016).

The public health consequences of flooding are shaped by both physical exposure and social vulnerability. Wastewater failures, combined sewer overflows, and contaminated runoff can introduce microbial hazards into homes and streets. Displace-



ment to temporary shelters and damage to healthcare services can further amplify risk by concentrating exposed populations while reducing access to timely diagnosis and care (Gomez et al., 2021; Gallego, 2025). These disruptions produce several connected disease pathways. Flooding can alter vector-borne disease dynamics by changing aquatic habitats and ecological conditions. Heavy rainfall may initially flush mosquito habitats, but flood recession often leaves stagnant water that supports vector breeding and later transmission (Chowell et al., 2019; Adekunle et al., 2019). This delayed response is important for *Aedes*-borne diseases such as dengue, where outbreak peaks may occur weeks to months after flood events because of vector population recovery and pathogen incubation cycles (de Jesús Crespo et al., 2019; Molina-Guzmán et al., 2022).

Respiratory outcomes represent a third pathway that is often less visible during emergency response. Flood-induced dampness in residential structures promotes indoor mold growth, increasing exposure to fungal spores and microbial by-products that contribute to asthma, allergic reactions, and other respiratory conditions (Gatto et al., 2024; Hardeman et al., 2025). Together, these pathways show why flood health impacts should be treated as a dynamic process that changes across response and recovery phases, rather than as a single outcome measured at the flood peak.

Flooding can also alter contact-transmission conditions in several ways. Evacuation and temporary sheltering can increase crowding and contact rates, while displacement, school or workplace closure, and reduced access to routine care can change the timing and location of infectious contacts. We therefore include a contact-transmission pathway so that flood-driven changes in household, institutional, and shelter co-location can interact with the other health pathways.

1.1 Research Gap

Although these pathways are well documented, they are rarely represented together in a single framework. Hydrological and hydraulic models estimate inundation dynamics but generally do not include human mobility, sheltering, healthcare access, or downstream disease outcomes (Mark et al., 2018; Taillandier, 2021). Flood-health studies also tend to focus on one pathway at a time, such as cholera, dengue, diarrhea, or respiratory symptoms, while simplifying population behavior and institutional response (Mark et al., 2018; Mazzoleni et al., 2026).

The gap addressed in this study is therefore not the absence of flood models or disease models, but the limited availability of integrated frameworks that connect them across the disaster lifecycle. Existing studies often examine vector-borne, respiratory, or infectious disease processes separately, and flood-focused ABMs frequently model evacuation or risk perception with single or no explicit disease processes (Taillandier, 2021; Perez and Dragicevic, 2009; Hunter et al., 2018). As a result, feedbacks among flood exposure, evacuation decisions, shelter interactions, healthcare accessibility, government intervention, and post-flood disease emergence remain insufficiently understood.

1.2 Research Objectives and Contributions

To address this gap, this study develops the Flood-Disease Agent-Based Model (Flood-Disease ABM), an integrated simulation framework that couples flood hazards, human behavior, institutional response, and disease dynamics across preparedness, response, and recovery phases. The objectives and corresponding contributions of this study are as follows:



1. Develop an agent-based framework capable of representing flood impacts during the preparedness, response, and recovery phases of a flood disaster.
2. Integrate multiple health pathways, including infectious diseases, vector-borne diseases, and mold-related respiratory health outcomes, within a common modeling environment.
3. Represent the interactions among population mobility, evacuation behavior, shelter operations, healthcare services, and government interventions during flood events.
4. Provide a framework capable of evaluating how alternative preparedness, response, and recovery strategies influence flood impacts and health outcomes across the disaster lifecycle.
5. Provide a flexible platform for exploring coupled flood-health dynamics under different disaster scenarios and vulnerability conditions.

1.3 Related Work

The research base relevant to this study spans three areas: flood modeling, disease modeling, and agent-based simulation. The Flood-Disease ABM builds on these complementary modeling strengths and addresses the limited integration among them. Flood models provide the physical foundation for estimating inundation depth, duration, velocity, and spatial extent. Hydrological and hydraulic tools, often combined with GIS or remote sensing, are well suited for identifying flood-prone areas and physical exposure patterns (Addai et al., 2025; Mark et al., 2018; Shi, 2026). Their limitation for public health analysis is that people, institutions, and recovery processes are commonly treated as static exposure layers (Taillandier, 2021; Perez and Dragicevic, 2009).

Disease models provide a second foundation by representing transmission processes and outbreak dynamics. Equation-based and compartmental models are useful for population-level analysis. Statistical and machine learning approaches can also identify environmental predictors of disease incidence (Hunter et al., 2018, 2020; Molina-Guzmán et al., 2022). However, these models are often developed outside the context of flood events and therefore do not represent disaster-driven changes in spatial movement, shelter contacts, and exposure, making them difficult to apply directly to flood response and recovery settings.

Agent-based models offer a way to represent heterogeneous systems and events involving persons, movement, decision-making, and social contact, as well as infrastructure and institutions such as households, businesses, and governments with their policies. Prior ABMs such as the *Flood-ABM* (Addai et al., 2025) have been used in flood research to examine evacuation, risk perception, and decision making, whereas in epidemiology ABMs have been used to test transmission and intervention scenarios (Taillandier, 2021; Perez and Dragicevic, 2009; Willem et al., 2015). The present study draws on this modeling tradition, but applies it to the coupled flood-disease problem by linking environmental exposure, mobility, institutions, and multiple health pathways in one simulation framework.



2 The Flood-Disease ABM

The Flood-Disease ABM extends our earlier Flood-ABM work (Addai et al., 2025) into a spatially explicit case study of flood-related health disruption in Uvalde, Texas. It simulates how inundation changes where people live, travel, work, seek care, evacuate, and shelter, and how these disruptions interact with multiple disease pathways. The model represents infectious-
 90 disease transmission through person-to-person contacts in households, workplaces, schools, and shelters; vector-borne disease risk through stagnant water that forms as floodwater recedes; and mold-related respiratory illness through delayed dampness and mold growth in flood-damaged homes. These health processes interact with heterogeneous resident characteristics, household habitability, healthcare capacity, shelter operations, institutional support, and economic conditions at an hourly time step. The implementation therefore treats flooding as a physical hazard that interacts with distinct, spatially uneven health burdens
 95 during emergency response and recovery.

2.1 Model Overview

The Flood-Disease ABM is organized around the person agent, which is the most behaviorally developed unit in the model. Person agents represent individual residents whose attributes, locations, daily routines, health states, and decisions change over time. The model includes place-based and institutional agents that define the community context in which people live and
 100 respond.

For this study, the spatial environment is built from Uvalde-specific GIS layers for houses, businesses, schools, shelters, healthcare facilities, government facilities, and the flood footprint. Agents are placed in this processed spatial inventory and connected through household, employment, school, shelter, and healthcare relationships. Census-backed Uvalde demographic distributions and model defaults initialize age, ethnicity, income, wealth class, education, employment, vehicle access, and
 105 household context. Several person-level properties are then derived from these assigned attributes and the person's mapped household. This preserves heterogeneity while allowing vulnerability, health sensitivity, mobility, coping, and disease severity to emerge from correlated social, physical, and spatial context.

The model is scenario-based. It can be configured to isolate or combine major hazard and disease pathways. These include baseline, flood-only, infectious-disease-only, flood-and-mold, flood-and-vector-borne disease, flood-mold-and-vector-
 110 borne disease, and a full compound scenario that combines flood, infectious disease, vector-borne disease, and mold-related respiratory outcomes. This modular scenario design makes it possible to compare separate and combined effects of flood exposure, human movement, institutional response, and disease processes under a common simulation framework.

The model has two execution modes: the Solara interactive app and batch runners. The app provides controls for interactive exploration, and the batch runners execute repeated scenario replications with different random seeds, producing time series,
 115 summary statistics, and quantile summaries.

Figure 1 summarizes the model architecture from study-area initialization through person-centered interactions, hazard and disease pathways, response outcomes, and the hourly simulation timeline. It is a conceptual overview of how the spatial

inventory and population initialization feed the agent system, how flood and disease pathways interact, and how those pathways produce evacuation, healthcare, government-support, and recovery outcomes.

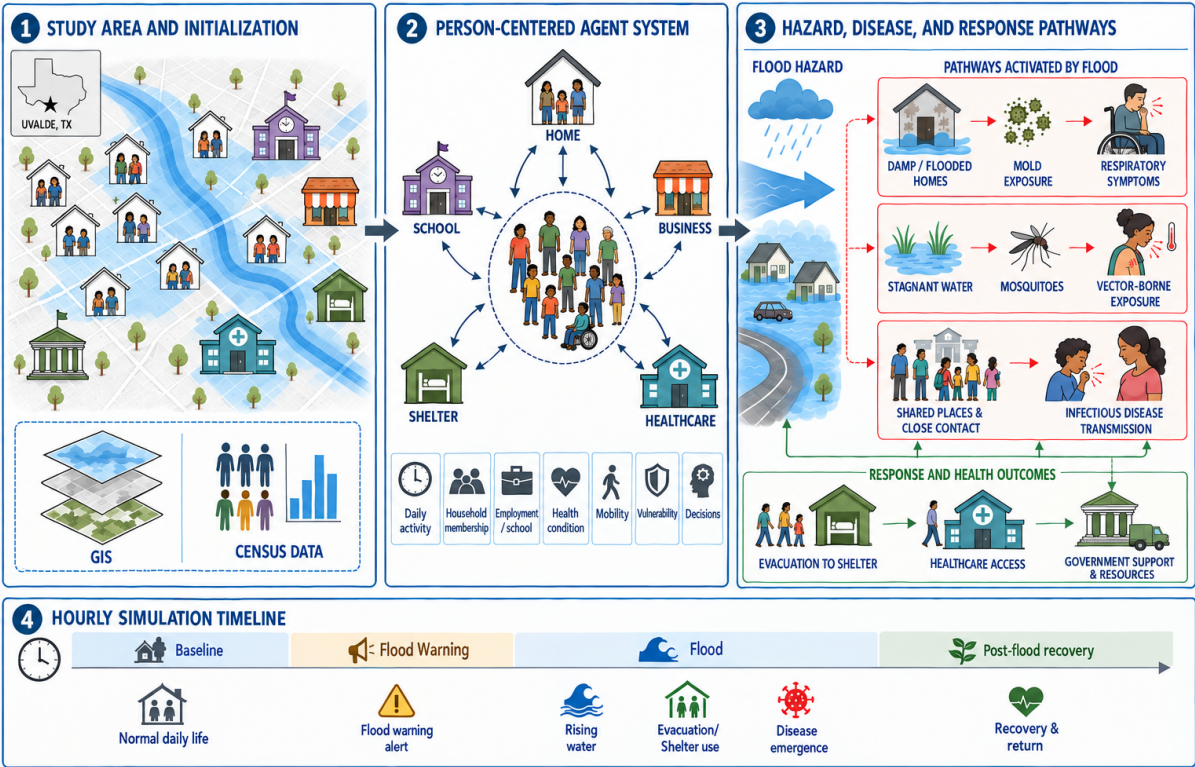


Figure 1. Architecture and temporal organization of the Flood-Disease ABM. (1) Illustration of Uvalde spatial layers and census-informed distributions that initialize the population and place-based agents. (2) Person agents move among homes, schools, businesses, shelters, and healthcare facilities according to their daily activities, household and institutional assignments, health, mobility, vulnerability, and decisions. (3) The model represents infectious, vector-borne, and mold-related respiratory health pathways together with evacuation, healthcare, and government-support responses. (4) The hourly simulation progresses through baseline, warning, flood, and post-flood recovery phases, allowing immediate physical impacts and delayed health outcomes to be represented within one model.

120 In the next sections, we discuss the different aspects of the model in detail together with its default parameters.

2.2 Study Area

Texas is exposed to recurrent flooding produced by several interacting hazards, including intense convective rainfall, tropical systems, riverine overflow, and rapid runoff across urbanizing watersheds. These events can occur in different parts of the state and on different timescales, but they commonly disrupt transportation, housing, public services, and access to healthcare.

125 State flood-planning products and stream-gage records consequently treat flood risk as a continuing planning and emergency-



management concern (Texas Water Development Board, 2026; U.S. Geological Survey, 2026b). This broader Texas context is especially relevant in south-central Texas, where short-duration rainfall can generate rapid rises in local waterways and where communities must manage both immediate inundation and the health and social consequences of recovery.

Uvalde provides a focused setting within this wider flood context. The city lies near the Nueces River and its tributary network, and its history of recurrent flood exposure illustrates why flood impacts should be examined beyond the moment of inundation. Severe storms and flooding affected the region in July 2026; the Texas Division of Emergency Management reported that the governor visited Uvalde County to receive updates on flood conditions, survey damage, and meet with state and local response officials (Texas Division of Emergency Management, 2026). This event further underscores the continuing relevance of evacuation, shelter access, healthcare continuity, household displacement, and post-flood environmental exposure.

The paper evaluates a compact urban–river corridor centered on Uvalde, Texas. The rectangular area of interest extends from approximately 29.16 to 29.26°N and 99.83 to 99.72°W, covers 118.5 km² (45.7 mi²), and measures approximately 10.8 km east–west by 11.2 km north–south. It contains the Uvalde urban core and adjacent low-density land toward the nearby Nueces River flood pathway. This footprint is large enough to capture flood exposure but compact enough to support repeated simulation experiments with a clear connection between inundation and agent interactions. The modeled study area is shown

in **Figure 2**.

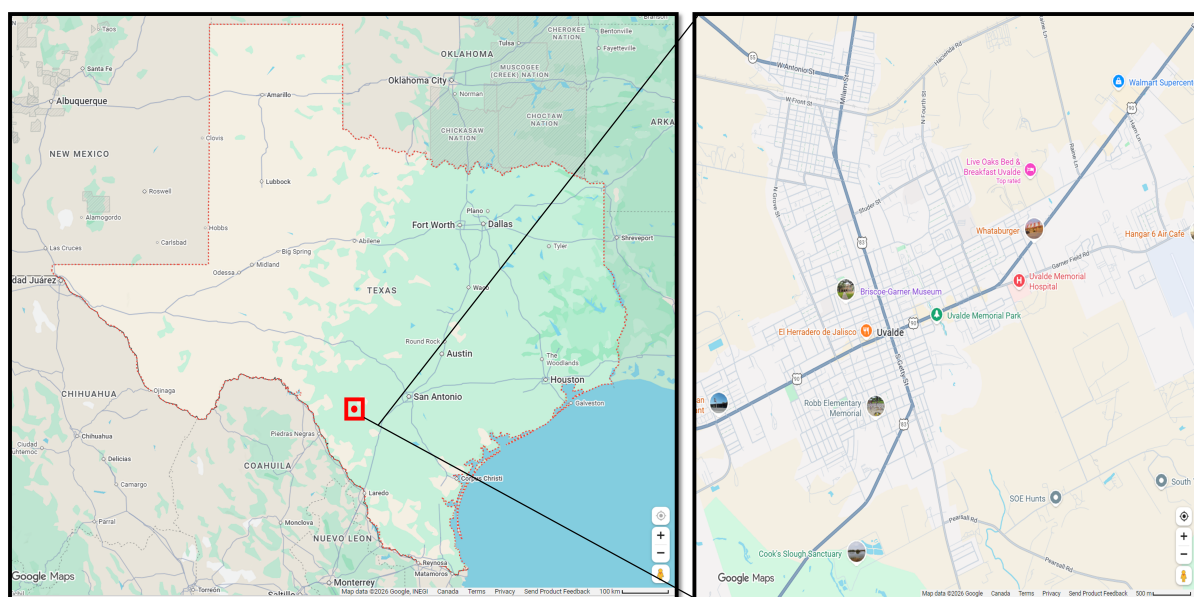


Figure 2. Location and extent of the Uvalde, Texas, study area used in the Flood-Disease ABM. The map shows the compact urban–river corridor and the modeled area of interest used to represent flood exposure and agent interactions. Map data: © 2026 Google, INEGI.

The area-of-interest boundary is a modeling extent and does not coincide exactly with a Census geography. We therefore use Uvalde city as the demographic reference because the corridor contains essentially all of the city, while the additional land is



predominantly a sparsely populated rural fringe. The U.S. Census Bureau estimated 15,455 residents in Uvalde city on 1 July 2025, compared with 24,963 residents in Uvalde County (U.S. Census Bureau, 2026). The Uvalde city profile is 51.1% male
145 and 48.9% female. The age groups comprise 22.0% children aged 0–14, 60.8% persons aged 15–64, and 17.2% persons aged 65 or older. For the model’s mutually exclusive race/ethnicity categories, 78.3% of residents are Hispanic or Latino, 17.5% are non-Hispanic White, 0.4% are Black, and 3.8% are assigned to an Other category as the remainder. Hispanic origin may overlap race in the underlying Census tables, so the non-Hispanic White measure and remainder were used to avoid double counting in agent assignment. In addition, 73.0% of residents aged 25 or older are high-school graduates or have higher educational
150 attainment (U.S. Census Bureau, 2026; Census Reporter, 2026).

2.3 Data Sources

The spatial data pipeline for the Uvalde application uses three main inputs. First, a Python-defined area-of-interest polygon was created to delimit a compact Uvalde study corridor around the city center and nearby flood-prone river pathway. Second, OpenStreetMap (OSM) building, point-of-interest, land-use, and local-road layers were downloaded for that study extent and
155 clipped to the boundary using OSMnx and GeoPandas (OpenStreetMap contributors, 2026). OSM data are © OpenStreetMap contributors and are available under the Open Database License (ODbL) 1.0; the applicable attribution and license information are provided at <https://www.openstreetmap.org/copyright>. Third, official flood-hazard data were obtained from the Texas Water Development Board (TWDB) Flood Planning Data Hub, which provides statewide flood-risk products intended to support regional flood-risk analysis and planning (Texas Water Development Board, 2026; Texas Water Development Board Flood
160 Planning Data Hub, 2025).

For the current Uvalde implementation, these source layers were further processed into a model-ready spatial inventory and a Uvalde-specific synthetic population baseline. Because raw OSM building coverage in the compact AOI underrepresented the residential stock, the residential layer was augmented with additional housing units placed along developed local roads so that the household inventory better matches the Uvalde city population and household counts reported by the U.S. Census
165 Bureau (U.S. Census Bureau, 2026; Census Reporter, 2026). The same processing step also normalized school buildings into campus-level school agents so that large school sites were not overcounted as separate institutions. The resulting Uvalde runtime inventory used in the present paper contains 5,461 houses, 298 businesses, 22 school campuses, 4 healthcare sites, 2 shelters, and 5 government sites. The full city population provides the demographic and household-scale reference but is not instantiated one-for-one. Study-area context and processed place counts are summarized in Table B1, while the synthetic-
170 population demographic composition is summarized separately in Table B2.

The model also relies on public hazard and health datasets for model construction and interpretation and to identify data sources for future calibration. TWDB flood-planning data provide the baseline inundation product used in this paper; USGS station 08195000 on the Frio River at Concan provides a nearby example of machine-readable discharge and gage-height observations; NOAA precipitation-frequency products provide a potential rainfall-forcing source; and CDC flood and mold
175 guidance supports the health-pathway logic for floodwater contact, reentry, and post-flood indoor exposure (Texas Water Development Board, 2026; Texas Water Development Board Flood Planning Data Hub, 2025; U.S. Geological Survey, 2026b, a;



NOAA National Weather Service Hydrometeorological Design Studies Center, 2026; Centers for Disease Control and Prevention, 2026, 2024). Together, these sources provide a reproducible basis for the compact Uvalde study extent, the flood layer, and the linked flood-health scenario design.

180 2.4 Agent Types and Initialization

2.4.1 Person Agents

Person agents are the primary behavioral units of the Flood-Disease ABM. Each person is implemented as a spatial agent with a point location, a household assignment, and, where applicable, a workplace or school assignment. Person agents are therefore the main mechanism through which flood exposure, mobility, evacuation, sheltering, healthcare demand, disease burden, and economic disruption are connected within the simulation. This person-centered structure follows established uses of ABMs for both flood evacuation behavior and infectious-disease transmission, where individual heterogeneity and location-specific interactions are central to the modeled outcomes (Taillandier, 2021; Perez and Dragicevic, 2009; Tonn and Guikema, 2018; Addai et al., 2025).

During initialization, attributes such as age, gender, ethnicity, wealth class, education, income, and vehicle access are drawn from configurable population mixes or class-based rules and assigned to person agents. Social variables such as worldview, social-capital, and trust attributes are randomly initialized and then used in the decision-making model. Person agents move in the spatial environment through a mobility function built from transport mode, age, household coordination, and current flood conditions. Mobility then informs how easily a person can commute, evacuate, or complete local errands. The mobility function $\mu_i(t)$ is the person's effective movement speed in meters per second and is defined as

$$195 \quad \mu_i(t) = v_i^{\text{mode}} J_i^{\text{age}} J_i^{\text{household}} J_i^{\text{depth}} J^{\text{flood}}(t), \quad (1)$$

where v_i^{mode} is the walking or driving speed, J_i^{age} is the age adjustment applied to older pedestrians, $J_i^{\text{household}}$ is the household-size coordination adjustment, J_i^{depth} is the local flood-depth adjustment, and $J^{\text{flood}}(t)$ is the global during-flood speed penalty. The person-specific stochastic mobility multiplier is included in v_i^{mode} . The corresponding distance-valued output is

$$200 \quad \mathcal{D}_i^{\text{reach}}(t) = [3600 \Delta t_h \mu_i(t)]_0^{R_{\text{max}}}, \quad (2)$$

where $\mathcal{D}_i^{\text{reach}}(t)$ is the distance reachable during a time step, Δt_h is the step length in hours, and the factor 3600 converts hours to seconds. The cap is $R_{\text{max}} = 400$ m in the reported configuration; it is the model's shared random-movement radius and limits the distance used for local random movement, rather than defining the person's underlying speed. Thus, $\mu_i(t)$ is the mobility function of interest, while $\mathcal{D}_i^{\text{reach}}(t)$ is its distance-valued output. Age, wealth, education, and social context affect these terms indirectly through transport access, activity capacity, and decision costs.

At each hourly time step, person agents move through a common update sequence. When conditions are normal, they follow routine activities such as staying home, going to work or school, shopping, or engaging in leisure travel. During disaster



periods, that routine can be interrupted by evacuation, shelter use, injury, illness, hospitalization, or return-home decisions. These disruptions reduce how much normal activity a person can perform in a given hour. We summarize that effect with an activity-capacity term,

$$A_i(t) = [M_i^{\text{inj}} M_i^{\text{resp}} M_i^{\text{vector}} M_i^{\text{inf}} M_i^{\text{shelter}}]_0^1, \quad (3)$$

where the M terms are multiplicative reduction factors associated with injury, respiratory illness, vector-borne illness, infectious illness, and sheltering or displacement. In simple terms, the more health or disaster burdens a person is carrying, the less able they are to maintain normal daily activity.

Injury progression is evaluated hourly. For a person stranded in floodwater, the injury probability increases with normalized local flood depth and person-level vulnerability and is scaled by the injury-risk multiplier. An injured person who remains flood-blocked is treated as requiring rescue; an injured person who is not flood-blocked can seek healthcare. Once local depth falls below the recovery threshold, injury resolves stochastically according to the person's recovery rate. Prolonged stranding under sufficiently hazardous conditions also creates mortality risk.

Person vulnerability is defined as a combination of social and physical components. The social component is derived from assigned demographic, socioeconomic, health, and behavioral context, while the physical component is derived from household habitability. The total vulnerability used by the model can be summarized as

$$V_i = \alpha V_i^{\text{soc}} + (1 - \alpha) V_i^{\text{phys}}, \quad (4)$$

where V_i^{soc} is the bounded social-context component derived during person assignment from demographic, socioeconomic, health, and behavioral context, and $V_i^{\text{phys}} = 1 - \mathcal{H}_{h(i)}$ is the household-derived physical component.

Person agents also store health and impact states such as injury, shelter use, hospitalization, infectious-disease status, mold-related respiratory symptoms, vector-borne symptoms, sick hours, and major categories of disaster-related expenses. These person-level states are later used to calculate outcomes. More detailed flood and disease processes are described in the next subsection; the active person and household initialization summary is reported in Table B2.

The implementation defines person-level quality of life as a weighted composite of current activity, health, safety, housing, and financial condition. For a living person, the score is

$$\text{QoL}_i(t) = 100 \left[0.35 A_i(t) + 0.25 H_i^{\text{health}}(t) + 0.20 S_i^{\text{safety}}(t) + 0.10 B_i(t) + 0.10 F_i(t) \right], \quad (5)$$

with $\text{QoL}_i(t) = 0$ for a deceased person. Here $A_i(t)$ is the activity component, equal to a context-dependent activity baseline multiplied by the person's activity capacity. The baseline is 0 for a stranded person, 1 for a person at home, work, or school, 0.35 for a person in a shelter or hospital, and 0.75 in other locations. Activity capacity is the health capacity further reduced by sheltering or stranding. $H_i^{\text{health}}(t)$ is health capacity: it starts at 1 and is reduced multiplicatively by injury, respiratory illness, vector-borne illness, infectious severity, and infectious-disease resting. $S_i^{\text{safety}}(t)$ is a safety component equal to 1 under normal conditions, reduced to 0.75 in a shelter and 0.65 in hospital, and set to 0 while stranded. $B_i(t)$ is household habitability. Finally, $F_i(t)$ is normally 1, but under event, health, displacement, or healthcare-debt pressure it equals the person's current-to-baseline income ratio divided by $1 + \delta_i^{\text{debt}}(t)$, where $\delta_i^{\text{debt}}(t)$ is healthcare debt divided by baseline income. The reported



QoL trajectories are means of $QoL_i(t)$ over living persons in each demographic group; this is an operational model index, not a validated clinical or survey instrument.

2.4.2 House, Business, and School Agents

House, business, and school agents are the main place-based counterparts to person agents. Each has a spatial location and operational state that can change during the simulation. During initialization, persons are assigned to these places according to age, household membership, schooling status, and employment status. Because these agents are built from the processed study-area inventory, the resulting person-place network reflects the local residential, educational, and economic structure. These agents are important because they connect hazard exposure to everyday life. Houses determine where people live and whether they can safely remain at home or return after flooding. Businesses and schools represent the main work and education destinations and therefore shape daily mobility as well as disruption during and after the event. All three building types can flood, recover, and experience operational interruption. Houses also carry the post-flood dampness and mold conditions that feed into later respiratory health effects.

2.4.3 Shelter Agents

Shelter agents represent capacity-limited emergency accommodation for displaced or stranded residents. Each shelter tracks who is currently sheltered, cumulative admissions and discharges, transfers to healthcare, operating costs, procurement spending, and received grants. Shelters also manage rescue requests by estimating when stranded person agents can be picked up. When a person requests rescue the shelter computes an estimated time-to-pickup, or estimated time of arrival (ETA), using network distance, a base vehicle speed, and local flood depth at the stranded person's location. The resulting ETA is queued in the shelter's pending-rescue map. To compute the ETA, let d be the round-trip distance to the stranded person, $u(d_f)$ the flood-adjusted speed multiplier, s the base rescue speed, τ the turnaround overhead, δ_f the local hazard delay, κ the funds factor, and η_q the queue factor. Then the waiting time can be represented as

$$ETA_i^{\text{shelter}} = \left\lceil \min(\tau_{\max}, (2d/(3600su(d_f)) + \tau + \delta_f) \kappa \eta_q) \right\rceil, \quad (6)$$

where the ceiling operator converts the estimated wait to an integer number of hours.

Admitted persons are marked as *in_shelter* and moved to the shelter location in the simulation. Shelters discharge residents when safe housing becomes available again, and they can request hospital admission for injured people when needed. During the disaster period, shelters also incur operating and procurement costs, linking emergency support to the local economy (Gomez et al., 2021; Gallego, 2025; Ahmed et al., 2024).

2.4.4 Healthcare Agents

Healthcare agents represent hospitals or clinics that manage admission queues, capacity-limited inpatient care, transfers from shelters, and self-presenting patients. Each healthcare agent tracks admitted patients, pending admissions, discharge status, operating costs, supplies spending, and received grants. As with shelters, the model computes an estimated time to admission



that depends on travel distance, flood conditions, and current service pressure. Let d be travel distance to the hospital, $u(d_h)$ the flood-adjusted speed multiplier around the hospital campus, s the base transfer speed, τ the turnaround overhead, κ the funds factor, and η_q the queue factor. Then the admission ETA is

$$\text{ETA}_i^{\text{hc}} = \lceil \min(\tau_{\max}, (\chi d / (3600 s u(d_h)) + \tau) \kappa \eta_q) \rceil, \quad (7)$$

where $\chi = 2$ for shelter transfers and $\chi = 1$ for self-presenting patients.

During hourly processing, healthcare facilities bill patients, spend part of their revenue on supplies, and retain the remainder as facility income. If patients cannot fully pay, the model records both patient debt and facility bad debt. Once patients are ready for discharge, the model attempts to place them back at home or, if needed, in shelter. This queue-and-capacity structure allows healthcare outcomes to depend not only on disease severity but also on access delays and post-disaster logistics (Ivers and Ryan, 2006; Baqir et al., 2012; Gallego, 2025).

2.5 Modeling Flood and Diseases

The following sections turn to the event processes that act on those agents. The implementation is modular: the flood process can be enabled independently, and the disease system can be activated in different combinations depending on the selected scenario.

2.5.1 Flood Inundation Map

The flood-hazard representation in the model is based on an inundation footprint for the Uvalde study area. The input is derived from the TWDB 2025 Existing Conditions Cursory Floodplain dataset, specifically the Scenario 5 product distributed through the TWDB Flood Planning Data Hub (Texas Water Development Board Flood Planning Data Hub, 2025; Texas Water Development Board, 2026). The source data are supplied as 3-meter raster tiles for multiple annual-chance flood frequencies. For Uvalde, the selected 1-in-100 annual-chance tile was clipped to the compact area of interest, cells with positive flood depth were polygonized, and the resulting footprint was stored as local flood-area polygons. The checked-in GeoJSON retains the source, scenario, tile, and return-period metadata but no per-feature depth attribute. It is therefore used as a planning-level spatial hazard footprint rather than as a time-resolved hydraulic input; the source does not provide observed arrival times, velocities, or a complete sequence of depth fields for the event.

At runtime, each person or place queries the local water depth from the active flood polygons. We summarize that as

$$d(x, t) = \lambda_f d_0(x) E(x, t), \quad (8)$$

where $d(x, t)$ is flood depth at location x and time t , $d_0(x)$ is the baseline depth assigned by the ABM to the inundation polygon containing x , λ_f is the runtime flood-depth multiplier, and $E(x, t) \in [0, 1]$ is the temporal-spatial flood envelope. Because the checked-in flood GeoJSON has no depth field, the reported runs use the configured model baseline depth together with the configured bounded spatial variation; the multiplier is then applied to the local depth before hazard queries are returned. The envelope is generated from a normalized position $q(x) \in [0, 1]$ along a configurable source-to-downstream direction. During



the rising limb, locations farther along the direction are activated later; during the falling limb, the same locations lose water according to the recession schedule. One representation is

$$E(x, t) = \begin{cases} 0, & t < t_0 + q(x)T_r, \\ \frac{t - [t_0 + q(x)T_r]}{T_p - [t_0 + q(x)T_r]}, & t_0 + q(x)T_r \leq t < T_p, \\ 1 - \frac{t - T_p}{T_f}, & T_p \leq t < T_p + T_f, \\ 0, & t \geq T_p + T_f, \end{cases} \quad (9)$$

where t_0 is flood onset, T_r is the rise duration, T_p is the modeled peak time, and T_f is the fall duration. The local depth value is used throughout the model to determine whether buildings flood, whether movement is still possible, and whether later health pathways are triggered. This construction preserves spatially explicit exposure while making the timing assumption explicit. A hydraulically calibrated implementation could replace $E(x, t)$ with time-indexed depth fields from HEC-RAS 2D or an equivalent model (U.S. Army Corps of Engineers Hydrologic Engineering Center, 2026).

2.5.2 Flood

At flood onset, local depth is initially zero or low in different parts of the footprint according to the directional envelope in Eq. 9. The modeled intensity then rises toward a peak and recedes before the flood footprint is removed at the end of the flood period. Once flooding begins, people respond to the changing conditions around them. Before the flood peaks, they may prepare or evacuate. During the flood, they may evacuate, shelter in place, or become stranded depending on local depth and travel feasibility. After the water recedes, they decide whether it is safe to return home.

Buildings respond to flood depth in a similar way. A house, business, or school is considered flooded when the local water depth exceeds a resilience-based threshold,

$$F_k(t) = \mathbf{1}\{d_k(t) > \theta_k\}, \quad (10)$$

where $F_k(t)$ is the flooded-state indicator for building k , $d_k(t)$ is the local flood depth at that building, and θ_k is the building-specific flood threshold. More resilient buildings have higher thresholds, so they can tolerate more water before being classified as flooded. For houses, flood damage also reduces habitability. We summarize household habitability as

$$\mathcal{H}_h(t) = [1 - \phi_h(t) - P_h^D(t) - P_h^M(t)]_0^1, \quad (11)$$

where $\mathcal{H}_h(t)$ ranges from 0 (uninhabitable) to 1 (fully habitable), $\phi_h(t)$ is the flood-damage penalty, $P_h^D(t)$ is the penalty from current dampness level, and $P_h^M(t)$ is the penalty from accumulated mold burden. The notation P_h^D and P_h^M avoids confusing these penalties with the mobility function $\mu_i(t)$. In the model, this quantity helps determine whether residents stay away from home, return home, or continue relying on shelter support. After the main flood event, the receding flood footprint can also leave behind stagnant-water areas, which are used to represent delayed mosquito-related risk.



2.5.3 Mold

330 Mold risk is modeled as a delayed post-flood household process. Mold appears after floodwater recedes, and a dampness episode begins. Once dampness begins, it gradually dries out over time. We represent that as

$$D_h(t+1) = \lambda_h D_h(t), \quad 0 < \lambda_h < 1, \quad (12)$$

where $D_h(t) \in [0, 1]$ is the current dampness level of house h and λ_h is the effective drying factor, which depends on building resilience and repair context. The associated dampness duration is denoted separately by $\tau_h(t)$ and measures the elapsed hours

335 since the dampness episode began:

$$\tau_h(t+1) = \tau_h(t) + 1 \quad (13)$$

with τ_h reset when a new dampness episode begins. More resilient houses dry faster, so dampness does not persist equally across all buildings. As long as a house remains damp, its mold burden can rise. We summarize this as

$$B_h(t+1) = [B_h(t) + g_h(t) - r_h(t)]_0^1, \quad (14)$$

340 where $B_h(t) \in [0, 1]$ is the accumulated mold burden, $g_h(t)$ is mold growth under damp indoor conditions, and $r_h(t)$ is repair- or drying-driven reduction. The episode-specific mold intensity, denoted ξ_h^{mold} , is a separate severity modifier sampled when the post-flood mold episode begins; it affects the target duration and repair-cost multiplier but is not the accumulated mold burden itself. Mold burden increases while indoor conditions remain wet and decreases when drying or repairs occur.

Respiratory illness is then generated at the person level. A resident can develop symptoms only when they are at home, the
 345 house has remained damp long enough, and mold has exceeded a minimum threshold. We express the idea simply as

$$P_i^{\text{mold}}(t) = \mathbf{1}\{\text{home}_i(t), \tau_{h(i)}(t) \geq \tau_{\min}, B_{h(i)}(t) > B_{\min}\} [\rho_M (1 + 1.8 B_{h(i)}(t)) \sigma_i^{\text{mold}} R(t) T_i(t)]_0^1, \quad (15)$$

where the indicator requires person i to be at home, dampness duration $\tau_{h(i)}(t)$ to exceed its onset threshold, and mold burden $B_{h(i)}(t)$ to exceed $B_{\min}$. The remaining factors represent the base onset probability, person-level mold sensitivity σ_i^{mold} , repair-subsidy reduction $R(t)$, and targeted-protection reduction $T_i(t)$. A household-level target set can further restrict which residents
 350 are exposed in a given episode. Mold symptoms are therefore a thresholded stochastic consequence of household conditions and person context. Once symptoms begin, the model allows them to persist for up to about two weeks unless recovery occurs earlier. This representation is supported by post-hurricane and post-flood evidence linking flood-damaged buildings, cleanup activities, damp indoor environments, mold exposure, and respiratory symptoms (Barbeau et al., 2010; Riggs et al., 2008; Gatto et al., 2024; Pakdehi, 2025, 2026; Hardeman et al., 2025; Johanning et al., 2014; Centers for Disease Control and Prevention,
 355 2024).

2.5.4 Vector-Borne Disease

Vector-borne disease is modeled as a localized risk that develops when floodwater leaves behind stagnant-water patches. These patches represent potential mosquito breeding sites. In the Uvalde implementation, they are selected from the usable flood



footprint, with preference given to patches near the modeled population. Their combined area is limited by

$$360 \quad \sum_{\ell=1}^L A_{\ell} \leq f_{\text{pool}} A_{\text{flood}}, \quad (16)$$

where A_{ℓ} is the area of patch ℓ , L is the number of patches, A_{flood} is the usable flood area, and f_{pool} is the fraction allowed for stagnant water. The default values are $f_{\text{pool}} = 0.005$ (0.5%) and $L = 7$.

Each patch has a formation time, an initial hazard, a finite lifetime, and an influence radius. Its hazard decreases over time according to

$$365 \quad H_{\ell}(t) = \mathbb{1}_{\ell}^{\text{active}}(t) H_{\ell,0} \exp \left[-\ln(2) \frac{t - t_{\ell,0}}{\tau_{1/2}} \right], \quad (17)$$

where $\mathbb{1}_{\ell}^{\text{active}}(t)$ indicates whether patch ℓ is active, $H_{\ell,0}$ is its initial hazard, $t_{\ell,0}$ is its formation time, and $\tau_{1/2}$ is the hazard half-life. The default half-life is 96 hours. For person i , the local vector-borne hazard is determined by the strongest nearby active patch and decreases with distance:

$$\mathcal{V}_i(t) = \max_{\ell \in \mathcal{A}(t)} H_{\ell}(t) K(d_{i\ell}), \quad K(d) = \left[1 - \frac{d}{R_V} \right]_0^1, \quad (18)$$

370 where $\mathcal{A}(t)$ is the set of active patches, $d_{i\ell}$ is the distance to patch ℓ , R_V is the influence radius, and $[\cdot]_0^1$ limits the distance effect to the range 0–1. The default influence radius is 125 m.

The probability that person i develops vector-borne illness increases with local stagnant-water hazard and individual vulnerability:

$$P_i^{\text{vec}}(t) = 1 - \exp \left[-\beta_V \mathcal{V}_i(t) (1 + 0.35U_i + 0.20V_i) S_i^{\text{sh}}(t) \right], \quad (19)$$

375 where β_V scales exposure risk, U_i and V_i represent health and general vulnerability, and $S_i^{\text{sh}}(t)$ represents the protection associated with sheltering. The probability is evaluated only when $\mathcal{V}_i(t)$ is positive.

After symptoms begin, illness may last for up to approximately two weeks unless recovery occurs earlier. Symptomatic people may seek healthcare, but admission is limited to a finite acute-care stay. This formulation captures a delayed, temporary, and localized post-flood pathway without assuming that all residents near floodwater become ill (Porphyre et al., 2005; Adekunle et al., 2019; Chowell et al., 2019; Coalson et al., 2021; Moya Quiroga Gomez et al., 2018; Tjaden, 2018; Leung et al., 2023).

2.5.5 Infectious Disease

The infectious-disease component is summarized from established epidemic and agent-based modeling approaches, including contact-based transmission, heterogeneous susceptibility, and intervention effects (Perez and Dragicevic, 2009; Hunter et al., 2018, 2020; Willem et al., 2015; Venkatramanan et al., 2018; Ivers and Ryan, 2006; Wilks et al., 2006; Liang and Messenger, 2018; Acosta-España et al., 2024; Gallego, 2025). We adapt these ideas to the Flood-Disease ABM as an agent-level, contact-driven, SIR-like process operating across households, workplaces, schools, and shelters. After the selected activation time, a



small share of the population is seeded into the infectious class, while the rest begin as susceptible. As the simulation proceeds, people move among the standard epidemic states of susceptible (S), infectious (I), and recovered (R), with death included for severe untreated cases.

The model assumes that infection becomes more likely when a person spends time around more infectious people. We summarize that idea as

$$\Lambda_i(t) = \beta_{\text{inf}} c_I [1 + 4.5 C_i^{\text{contact}}(t)] \Sigma_i(t), \quad (20)$$

where $C_i^{\text{contact}}(t)$ is the sum of infected shares in the person's household, workplace, school, and, when applicable, shelter; c_I is infectious contact intensity; and $\Sigma_i(t)$ is the single effective susceptibility multiplier. In the implementation,

$$\Sigma_i(t) = [1 + 0.35 V_i^H + 0.15 V_i] P_i^{\text{target}}(t), \quad (21)$$

where V_i^H is the normalized health-vulnerability proxy, V_i is general vulnerability, and $P_i^{\text{target}}(t)$ is the targeted-protection reduction. Shelter crowding and distancing modify the shelter contribution before it enters $C_i^{\text{contact}}(t)$. The nonlinear term captures the implementation's increase in transmission pressure as infected-group shares rise.

The probability that a susceptible person becomes infected is then written in simple form as

$$P_i^{S \rightarrow I}(t) = \min \{1, \Lambda_i(t)\}, \quad (22)$$

where $P_i^{S \rightarrow I}(t)$ is the probability that susceptible person i becomes infectious during hour t . Thus transmission depends on the contact environment and on the person's health, general vulnerability, and targeted protection.

Once infected, a person's illness severity changes over time and that course is represented as

$$I_i^{\text{severity}}(t) = I_i^{\text{severity}, \max} g_i(t), \quad 0 \leq g_i(t) \leq 1, \quad (23)$$

where $I_i^{\text{severity}}(t)$ is the current infectious illness severity for person i , $I_i^{\text{severity}, \max}$ is the case-specific peak severity implied by age, health, and vulnerability, and $g_i(t)$ is the within-case rise-and-decline trajectory. If symptoms become severe enough, the person may rest, seek hospital care, or in the worst case die if severe illness persists without treatment.

Recovery follows the usual SIR logic:

$$I \rightarrow R, \quad I \rightarrow D, \quad (24)$$

In the model, recovery or death can occur stochastically each hour or when the maximum illness duration is reached, with mortality depending on severity, vulnerability, and hospitalization.

2.6 Economic Activity

Economic activity is represented in a linked accounting system in which households, businesses, shelters, healthcare facilities, and government all exchange money during the simulation. Consequently, economic disruption emerges directly from evacuation, illness, service demand, workplace interruption, and post-flood repair. In this way, the model treats the economy as part of the disaster process.



At initialization, each person is assigned an income class and an initial cash stock derived from that class. During the simulation, household cash changes through wages, purchases, taxes, evacuation and preparation spending, repair spending, and healthcare payments. We summarize the household balance as

$$Y_i(t+1) = Y_i(t) + W_i(t) - C_i^{\text{cons}}(t) - E_i^{\text{evac}}(t) - R_i^{\text{repair}}(t) - H_i^{\text{care}}(t) - \tau_i^{\text{tax}}(t), \quad (25)$$

where $Y_i(t)$ is the available cash of person i , $W_i(t)$ is wage income, $C_i^{\text{cons}}(t)$ is ordinary consumption, $E_i^{\text{evac}}(t)$ is evacuation or preparation spending, $R_i^{\text{repair}}(t)$ is repair spending, $H_i^{\text{care}}(t)$ is healthcare spending, and $\tau_i^{\text{tax}}(t)$ is tax withholding. This equation is not intended as a full macroeconomic model; it simply expresses the bookkeeping logic used in the agent-based simulation.

Wages are earned only when employed persons can physically reach their workplaces and remain active enough to work. When a person works, the employer pays a wage, the worker's cash increases, and income tax is immediately transferred to government. Persons may also spend money at businesses during routine mobility, generating consumer-side demand. When evacuation occurs, households incur one-time spending for leaving or preparing, and those costs can also flow into the local business system.

Businesses are the main revenue-bearing agents. Their realized revenue depends not only on demand but also on whether they are open, unflooded, and adequately staffed. In the model, effective business revenue is

$$\Pi_b^{\text{net}}(t) = [1 - \tau_b] G_b(t) O_b(t) M_b(t) S_b(t) - W_b(t) - K_b(t), \quad (26)$$

where $G_b(t)$ is gross incoming spending, $O_b(t)$ is the open and operational indicator, $M_b(t)$ is the mold-related operating factor, $S_b(t)$ is the staffing factor, $W_b(t)$ is wage expense, and $K_b(t)$ is operating, closure, repair, and cleanup expense. Taxes are applied to retained business income. Revenue remains an ongoing accounting flow; flooding, closure, staffing, and mold reduce realized operations and wealth rather than replacing revenue with a phase-specific switch.

Shelter and healthcare agents provide two institutional spending channels. Shelters spend money on rescue pickups, operating costs, and procurement, with part of that spending routed to open businesses. Healthcare facilities admit patients, collect only a fraction of billed charges when people cannot fully pay, record the remainder as debt, and spend part of collected revenue on supplies. Because of this structure, the model can distinguish between care demand, collected revenue, and unpaid financial burden.

Government closes the loop by collecting sales tax, income-tax withholding, and corporate tax, then redistributing funds through baseline and event-triggered grants to shelters, healthcare facilities, and schools. In this way, disaster response in the model is both operational and fiscal: flooding and disease affect local income, service demand, and business continuity, while public transfers can partly stabilize stressed institutions during response and recovery (Tonn and Guikema, 2018; Addai et al., 2025).

Figure 3 provides a conceptual view of these linked flows. Flood and damp or mold conditions reduce movement, business operations, and sales; illness reduces workers' ability to earn wages and increases healthcare demand; households, businesses, shelters, and healthcare facilities exchange payments and services; and government collects taxes and distributes grants and emergency support.

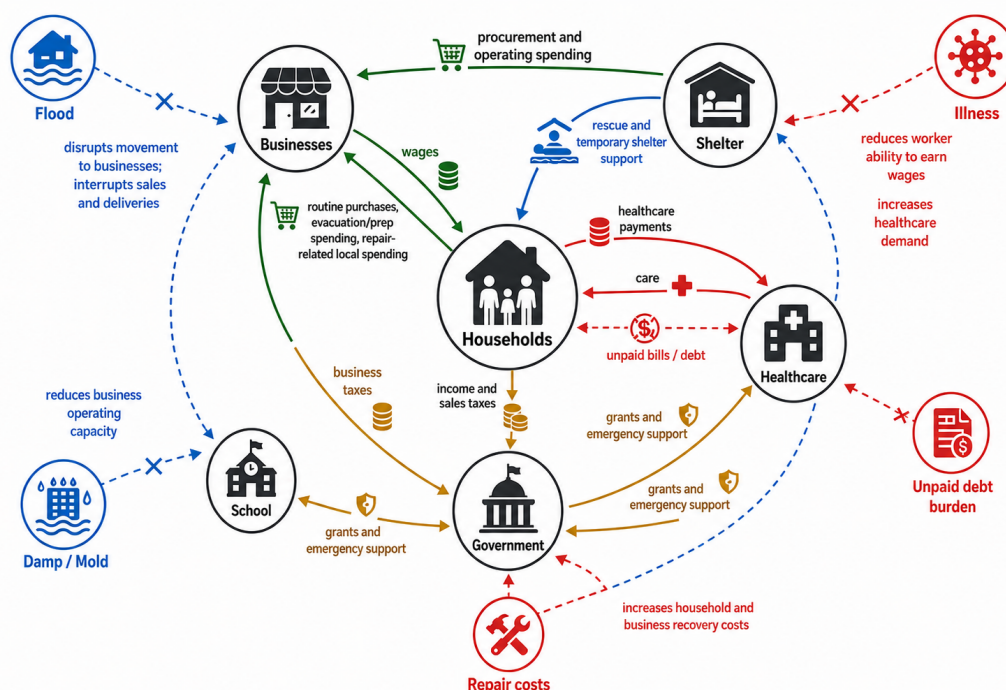


Figure 3. Economic and institutional accounting network in the Flood-Disease ABM. Households receive wages, make routine and event-related purchases, and pay for healthcare; businesses receive spending, pay wages and taxes, and incur operating and repair costs; shelters and healthcare facilities provide services and purchase supplies; and government collects taxes and distributes grants and emergency support. Flooding and dampness interrupt mobility and operations, while illness reduces earning capacity and increases care demand. Unpaid healthcare bills and repair costs remain recorded as financial burdens, allowing disaster impacts to propagate through the linked agent accounts.

2.7 Person-Agent Decision Making

Person-agent decision making in the Flood-Disease ABM is built around a phase-aware threat-and-coping kernel. The model does not assume that all residents react in the same way to the same hazard. Instead, each person periodically evaluates how threatening the situation appears and how capable they feel of responding. This evaluation is not performed continuously every hour. Rather, it occurs at decision intervals, with person-specific offsets that stagger responses across the population and avoid unrealistic synchronization.

In addition to demographic and socioeconomic differences, person agents also carry a simple worldview orientation. The model uses four categories. A *hierarchist* tends to emphasize rules, authority, and organized responses; an *egalitarian* emphasizes shared responsibility and collective action; an *individualist* emphasizes personal autonomy and self-reliance; and a *fatalist* tends to perceive less personal control over events. These categories are not intended to represent complete personality types. They provide a simple way to introduce differences in how people interpret risk and respond to warnings. The decision kernel uses four related ideas. *Threat* is how serious and immediate the person perceives the situation to be. *Coping* is the person's



overall perceived ability to take effective action. *Self-efficacy* is confidence in one's own ability to act, while *response efficacy* is confidence that the action itself will help. Thus, threat describes why action may be needed, whereas coping describes whether action seems possible and worthwhile. Worldview affects the interpretation of threat, while self-efficacy and response efficacy contribute to coping; these appraisals then influence decisions such as evacuation, preparation, sheltering, and return.

Threat combines environmental, social, and health signals, including local flood depth, flood imminence, official warnings, neighbors' evacuation behavior, flood memory, and disease pressure:

$$T_i(t) = [w_d d_i(t) + w_u U_i(t) + w_o O_i(t) + w_s S_i^{\text{social}}(t) + w_m F_i^{\text{memory}}(t) + w_p \Psi_i(t)]_0^1, \quad (27)$$

where $T_i(t)$ is the perceived threat for person i at time t ; $d_i(t)$ is normalized flood depth at the person's home; $U_i(t)$ is flood imminence; $O_i(t)$ is the official-warning signal; $S_i^{\text{social}}(t)$ is the social signal produced by nearby resident evacuation; $F_i^{\text{memory}}(t)$ is the person's flood memory; and $\Psi_i(t)$ is disease pressure. The parameters w_d , w_u , w_o , w_s , w_m , and w_p are the corresponding weights on depth, imminence, official warnings, social influence, memory, and disease pressure. The brackets $[\cdot]_0^1$ clip the score to the interval $[0, 1]$. The resulting score is modestly adjusted by worldview, so threat rises when flooding is deeper or more imminent, warnings are stronger, neighbors are leaving, prior experience is greater, or disease pressure is present. Coping reflects the perceived ability to act. It combines self-efficacy, response efficacy, and social support, while accounting for the cost of action:

$$C_i(t) = [a_e E_i(t) + a_r E_i^{\text{resp}}(t) + a_s S_i^*(t) - a_k K_i(t)]_0^1, \quad (28)$$

where $C_i(t)$ is coping capacity, $E_i(t)$ is self-efficacy, $E_i^{\text{resp}}(t)$ is response efficacy, $S_i^*(t)$ is social support, and $K_i(t)$ is perceived cost. Higher costs reflect expense, travel burden, health limitations, and household coordination difficulty; resources and protection can reduce these barriers. Threat and coping guide decisions across disaster phases. During the warning phase, agents may evacuate, prepare, or remain and monitor. The evacuation tendency follows a logistic rule:

$$P_i^{\text{evac}}(t) = \sigma(\beta_0 + \beta_T T_i(t) + \beta_C C_i(t)), \quad (29)$$

where β_0 , β_T , and β_C control baseline evacuation tendency and the effects of threat and coping. Higher threat and coping increase evacuation likelihood, but evacuation still requires a safe, available route. Otherwise, the person may prepare or remain in place. During flooding, physical constraints limit the available choices. A person may evacuate if the home is unsafe and a route is safe; otherwise, the person shelters in place, may become stranded, or carries out local coping actions.

After flooding, return depends mainly on home habitability and remaining coping capacity:

$$P_i^{\text{return}}(t) = \sigma(\gamma_0 + \gamma_H \mathcal{H}_{h(i)}(t) + \gamma_C C_i(t)), \quad (30)$$

where $P_i^{\text{return}}(t)$ is the return probability, $\mathcal{H}_{h(i)}(t)$ is the habitability of person i 's household, and the γ terms control baseline return tendency and the effects of habitability and coping. Return is less likely when homes remain damaged, damp, or mold-affected, or when households lack the resources to resume occupancy.



Figure 4 summarizes this process. Worldview shapes the interpretation of threat, while coping reflects resources, and
 495 perceived effectiveness. Periodic decisions then combine these appraisals with route safety, health status, and home habitability;
 the equations above give the corresponding reduced-form probabilities.

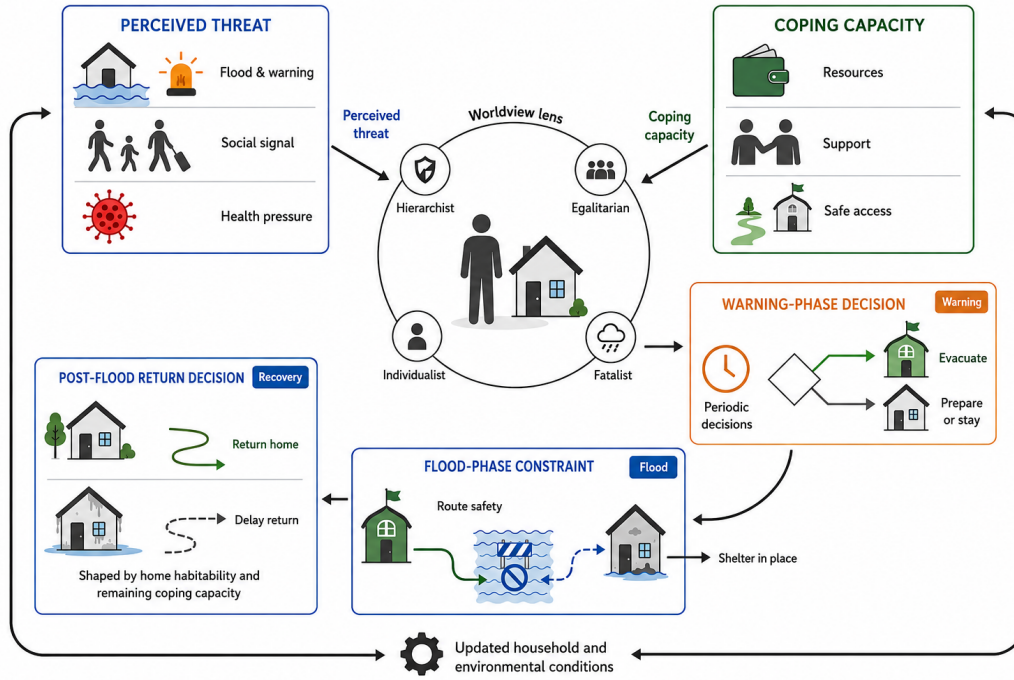


Figure 4. Phase-dependent decision process for person agents. Perceived threat combines flood and warning information, social signals, and health pressure; coping capacity combines resources, support, and safe access. A worldview-specific modifier alters the interpretation of these inputs. During warning, agents periodically choose whether to evacuate or prepare and stay; during flooding, route safety constrains movement and may lead to sheltering in place; during recovery, home habitability and residual coping capacity determine return or delayed return. Updated household and environmental conditions feed back into subsequent appraisals and decisions.

Notation has been qualified where the same base symbol previously represented different concepts. In particular, $\mathcal{V}_i$ denotes vector-borne hazard, H_i^{health} denotes health capacity, and $\mathcal{H}_{h(i)}$ denotes household habitability; C_i^{contact} is infectious contact pressure and C_i is coping capacity; D_i^{reach} is reachable distance and E_i^{resp} is response efficacy; S_i^{safety} , S_i^{social} , and σ_i^{mold} distinguish safety, social influence, and mold susceptibility; F_i^{memory} denotes flood memory; QoL_i is quality of life; I_i^{severity} is infectious illness severity; ξ_h^{mold} is episode-specific mold intensity; d_i is normalized flood depth; Ψ_i is disease pressure; and $\mathbb{1}_\ell^{\text{active}}$ is the active stagnant-pool indicator. The SIR state symbols S , I , R , and D remain reserved for susceptible, infectious, recovered, and deceased states.

500



3 Interactive App and Batch Runners

505 The Flood-Disease ABM is delivered through two complementary execution modes that share a single centralized configuration. The first is an interactive browser app intended for guided exploration, demonstration, and hypothesis generation. The second is a set of batch runners that execute repeated, reproducible scenario replications for the experiments reported in this paper. Both pathways read the same runtime defaults, so that anything observed interactively can be reproduced systematically in batch, and the two modes remain consistent with each other.

510 3.1 Interactive App

The interactive app is a web-based dashboard built with Solara on top of the Mesa and Mesa-Geo visualization stack. When launched, it opens in a browser and lets a user run the Flood-Disease ABM without editing code: the user chooses a scenario, adjusts model parameters through sliders, dropdowns, and toggles, selects which charts to display, and then plays, steps, or resets the simulation while watching outcomes evolve in real time. The app is therefore aimed at making the coupled flood-
 515 disease dynamics visible and interpretable to modelers, students, and decision makers who want to build intuition about how the system responds to different assumptions.

The overall layout of the application is shown in [Figure 5](#). A left-hand control column groups the run controls, including the play interval, the render interval, a threading option, and the reset, play, and step buttons, together with the model-parameter panel and an information panel that reports the current simulation step. The central panel shows the live simulation map of the
 520 Uvalde study area, and an adjacent legend explains the symbols used for persons and for place-based entities. This arrangement keeps the simulation controls, the spatial state, and the selected output charts visible together on a single screen.

The centerpiece of the application is the live simulation map, shown in [Figure 6](#). The map is rendered with an OpenStreetMap basemap of the Uvalde study corridor and is updated at every rendered step, so the user can watch agents move, flooding rise and recede, and health states change over the course of an event. Person agents are drawn as colored points whose color encodes
 525 their current state, distinguishing safe, infected, stranded, injured, and deceased residents, as well as vector-borne disease hotspots. Place-based entities, including houses, businesses, schools, healthcare facilities, shelters, and government buildings, are shown in their own colors, and the active flood footprint is overlaid as a cyan flood-extent layer. This spatially explicit view makes it possible to see, for example, where inundation intersects the residential fabric, which shelters and healthcare sites are reachable, and how the population redistributes during evacuation and return.

530 Model configuration is organized into grouped control panels, illustrated in [Figure 7](#). At the top, a scenario selector lets the user switch among the built-in scenarios: baseline, flood, infectious disease, flood and mold, flood and vector-borne disease, flood and infectious disease, and the full compound scenario that combines flood with all modeled diseases. Selecting a scenario enables the relevant hazard and disease pathways so that isolated and combined effects can be compared within the same interface. Below the scenario selector, the remaining parameters are grouped by theme. A population-composition panel controls
 535 the population size and the gender, age, ethnicity, and worldview mixes of the synthetic population. A capacity-and-services panel adjusts shelter and healthcare capacity and their funding levels. Additional panels expose the flood context, mold context,

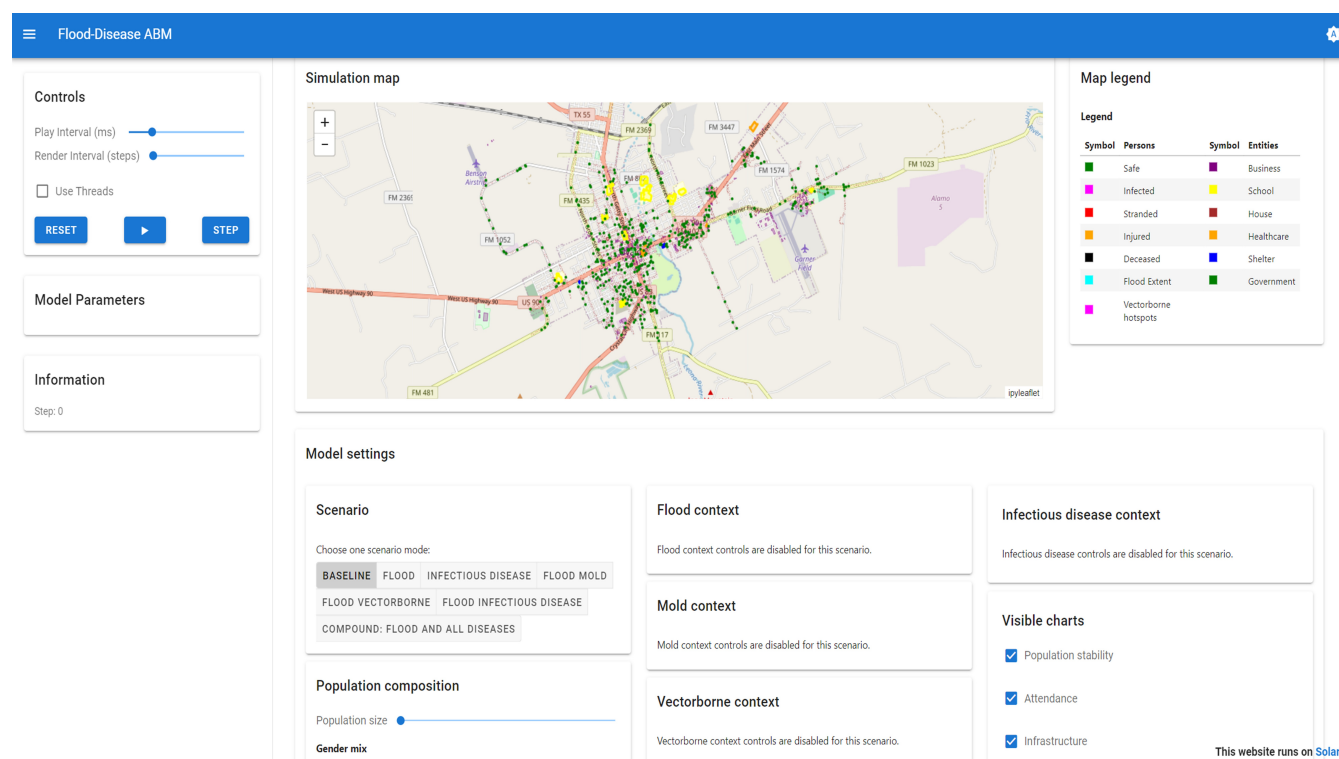


Figure 5. Interactive app for configuring and observing a Flood-Disease ABM simulation. The left panel contains playback and rendering controls, the map legend, grouped model parameters, and the current hourly step; the right panel displays the spatial state on an Open-StreetMap basemap. The app updates the map and selected charts as the simulation advances, supporting exploratory comparison of scenarios and parameter settings; the replicated results in this paper were generated with the separate batch runners. Basemap: © OpenStreetMap contributors, ODbL 1.0.

vector-borne context, and infectious-disease context, letting the user tune hazard timing, intensity, structural sensitivity, and the disease parameters relevant to each pathway. Each parameter is presented as a slider, dropdown, or toggle with sensible bounds, so that exploration stays within reasonable ranges. Consistent with the design of the application, the interactive controls emphasize scenario, population, capacity, hazard, and policy settings and do not expose every internal disease parameter as a direct outcome control.

Finally, the application includes a visible-charts selector that lets the user choose which output plots are displayed alongside the map. The available charts summarize model outcomes over time and include population stability, activity and attendance, infrastructure and structural impact, finance and impact expenses, routine activity by hour, healthcare and shelter load, the affected population, psychological state, and quality-of-life measures broken down by age, wealth, worldview, and ethnicity. Because the charts update as the simulation runs, the user can directly relate parameter choices and spatial dynamics to their downstream effects on health, service demand, and economic disruption.

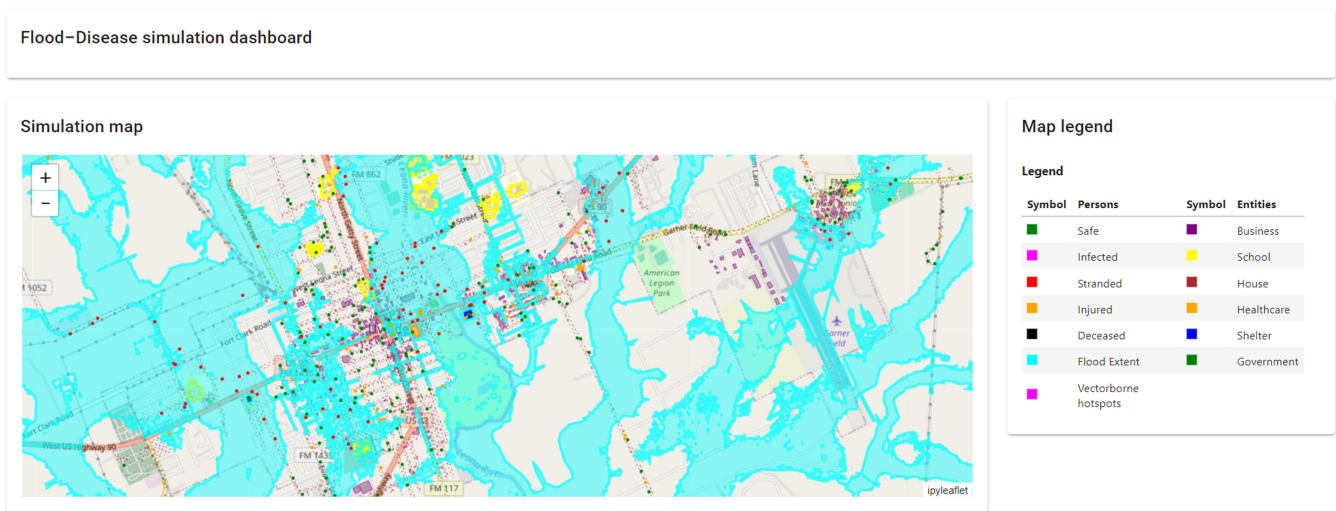


Figure 6. Spatial state of the Uvalde simulation during active flooding. The cyan overlay identifies the modeled inundation extent on the OpenStreetMap basemap. Point colors distinguish person states (safe, infectious, stranded, injured, or deceased), while colored place symbols identify businesses, schools, houses, healthcare facilities, shelters, and government sites; magenta symbols mark modeled vector-borne exposure hotspots. The display is an hourly model state used to inspect co-location, accessibility, and movement during an event, not an observed flood map. Basemap: © OpenStreetMap contributors, ODbL 1.0.

3.2 Batch Runners

The batch runners provide the reproducible counterpart to the interactive app. Rather than exposing a user interface, each runner
550 executes a chosen scenario for a specified number of replications. The batch pathway is designed for repeated experiments and
can be orchestrated across scenarios and dispatched to remote high-performance computing resources for larger replication
counts, while still reading the same parameter source as the app. The random seed changes across replications; the resulting
interquartile bands therefore describe stochastic variation under the selected configuration, not parameter uncertainty. The per-
run time series together with aggregated summary statistics and quantile summaries across replications form the basis for the
555 results reported in this paper. Parameter sweeps and uncertainty sampling are reserved for future sensitivity and calibration
experiments.

The figures presented here use only a subset of the data collection capabilities of the Flood-Disease ABM. Additional time
series could display repair progress, household displacement histories, and spatially resolved damage. Person-level health
records could be summarized by disease-specific healthcare use and overlapping conditions. Other outputs include return
560 actions, coping measures, and cause-specific expenses. These variables can also be cross-tabulated by age, sex, ethnicity,
income class, worldview, and household.

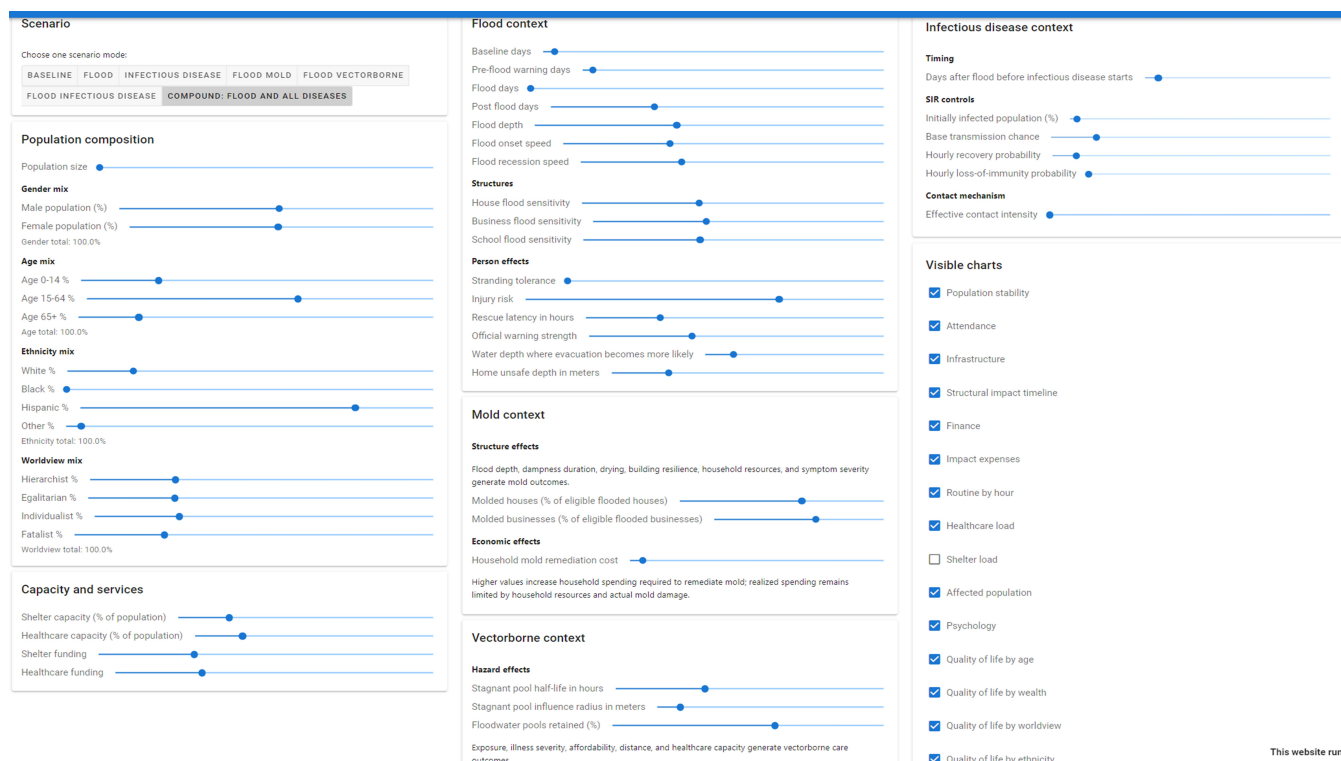


Figure 7. Scenario, parameter, and output controls in the interactive app. The scenario selector activates the relevant flood, infectious, mold, and vector-borne modules, including the compound configuration. Sliders specify simulation timing, population composition, service capacity and funding, flood intensity and structural sensitivity, and disease-process settings; the visible-charts checklist selects the time series shown beside the map. Controls that do not apply to the selected scenario are disabled, reducing the risk of combining incompatible settings during interactive exploration.

4 Results

The following results illustrate the coupled processes represented by the Flood-Disease ABM. They describe model behavior under a fixed set of assumptions and are not calibrated predictions for Uvalde. The reported experiments use a population of 5,000 persons and 30 replications per scenario, with four CPUs allocated to each scenario and a base random seed of 1500154 for reproducibility. Unless stated otherwise, each solid line is the median across replications and each shaded band spans the interquartile range; wider bands therefore indicate greater between-replication variability. We first establish the model's undisturbed behavior and then trace how flooding, disease, service demand, economic pressure, and welfare unfold once an event is introduced.



570 4.1 Baseline Population and Daily Activity

Figure 8 summarizes the model’s population used across all scenarios. The initialized cohort combines configured Uvalde demographic and income shares with an equal allocation among the four worldview categories. Hispanic residents and working-age adults form the largest demographic groups, while lower- and middle-income households account for most of the income-class distribution. This composition is fixed at initialization and is common to every scenario, so comparisons are not con-
 575 founded by changes in population composition.

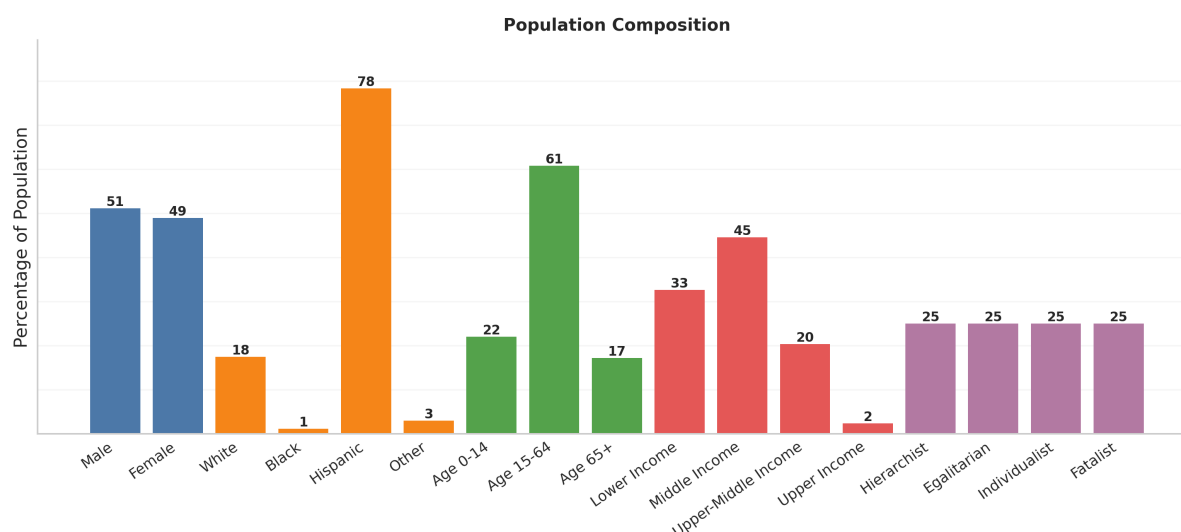


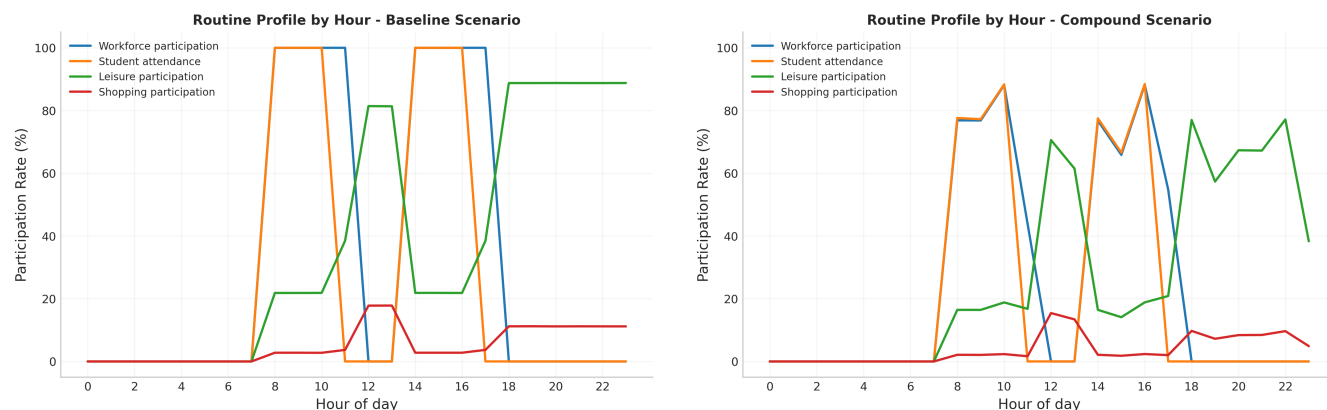
Figure 8. Composition of the 5,000-person synthetic population used in the reported experiments. Bars show the percentage of agents in each gender, ethnicity, age, income-class, and worldview category at initialization. Gender, ethnicity, age, and income shares follow the configured Uvalde population profile; the four worldview categories are assigned equal 25% shares by design. The same initialization targets are used across scenarios so that scenario comparisons are not confounded by different population compositions.

The hourly activity profiles in **Figure 9** compare a normal day with an average day from the compound scenario. In the baseline (**Figure 9a**), attendance among scheduled workers and students reaches 100% across the morning and afternoon activity blocks and falls to zero over the midday break and after the day ends. Leisure activity rises during the midday gap and evening, while shopping maintains a small, steady share. The flat profiles show that, without disruption, agents consistently
 580 complete their assigned schedules.

The compound profile (**Figure 9b**) shows the same schedule under event conditions, averaged over the full simulation. Work and school attendance no longer reach saturation; their peaks fall to approximately 78–89% and become more irregular as flooding, displacement, illness, and facility closures interrupt scheduled activity. Leisure participation rises during periods of reduced attendance and remains high into the evening, reaching approximately 77%, while shopping remains low and becomes



585 slightly more variable. Together, the panels show how the compound event reduces participation in scheduled activities and redistributes time toward leisure activity.



(a) No-event baseline activity.

(b) Activity under the compound flood-disease scenario.

Figure 9. Daily activity profiles in the baseline and compound scenarios. Curves show the median percentage participating at each hour of day, pooled across simulated days and 30 replications; work and school attendance are shown only during their scheduled activity blocks. (a) In the no-event baseline, scheduled work and school attendance reaches 100%, with leisure concentrated at midday and in the evening. (b) In the compound scenario, work and school peaks fall to approximately 78–89% and become more irregular, while leisure activity increases during disrupted periods. Because panel (b) pools all event phases, it summarizes average routine disruption across the simulation rather than the trajectory of a single event day.

4.2 Decision Psychology

The behavioral state of the population responds strongly to the presence of an event (Figure 10). In the no-event baseline, mean perceived threat and coping appraisal remain at zero, while the initialized self-efficacy and response-efficacy levels remain stable (Figure 10a). Once the warning and flood phases begin in the compound scenario, threat and coping appraisal rise together, and both efficacy measures increase as agents receive hazard information and update their assessments (Figure 10b). Threat peaks during the flood window and drops steeply as the water recedes near day 17, while coping and efficacy decline more gradually and remain above their initial levels during recovery. This persistence reflects the model's state-dependent appraisal process: evacuation and return decisions respond to accumulated perceptions of danger and response capacity in addition to current flood conditions.

4.3 Population Stability Across Scenarios

Figure 11 compares displacement, sheltering, service use, and mortality across four scenarios. The flood-only case (Figure 11a) is dominated by a rapidly oscillating stranded population that ranges from roughly 14% to 38% during the flood window. These oscillations coincide with the daily movement cycle, during which agents attempt routine trips and may become stranded when

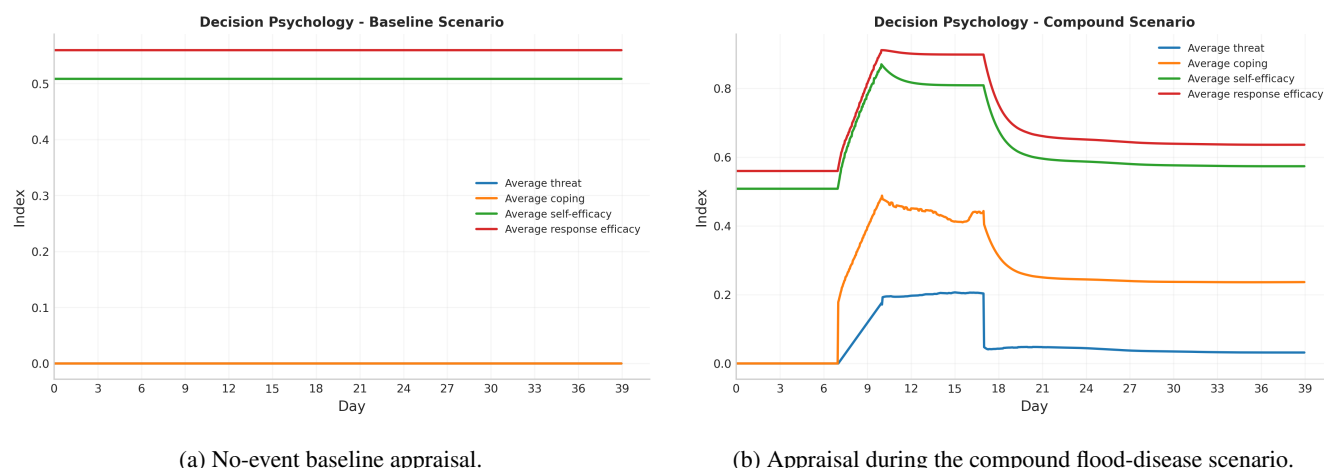


Figure 10. Population-mean decision-appraisal states in the baseline and compound scenarios. Solid curves are medians across 30 replications and shaded bands are interquartile ranges; all appraisal variables are bounded from 0 to 1. (a) Without an event, perceived threat and coping appraisal remain at zero and the initialized self-efficacy and response-efficacy levels remain stable. (b) Warning and flooding increase threat, coping, self-efficacy, and response efficacy; threat declines sharply after flood recession near day 17, while coping and efficacy decline more gradually during recovery.

600 flooded locations obstruct travel. Evacuation builds more gradually, reaching nearly 29% by day 17, then declines rapidly as the flood recedes and households begin returning. Shelter occupancy remains within a few percent of the population, and healthcare occupancy peaks near 4% around the middle of the flood before subsiding. By day 21 the acute displacement and service-use episode has largely resolved, while cumulative mortality remains near 1%.

Adding health pathways preserves this flood-driven displacement signature but changes what follows it (Figure 11b and 605 Figure 11d). In both the flood–mold and full compound runs, evacuation and stranding trace almost the same path as the flood-only case, yet healthcare occupancy no longer returns to zero once the water is gone. It instead remains elevated through the end of the 39-day horizon, while cumulative mortality rises gradually to about 2% in the compound run. The comparison isolates a specific model behavior: the physical hazard drives a short, intense displacement episode, while the active infectious, vector-borne, and mold-related respiratory pathways generate a slower health burden that persists throughout recovery.

610 The infectious-only scenario (Figure 11c) has a distinct shape. With no flooding there is no evacuation and no stranding; active infection fluctuates around 0.8–1.3% after seeding, healthcare occupancy remains near 0.3–0.6%, and cumulative mortality reaches approximately 1.5% by the end of the run. The interquartile bands remain proportionally wider than those of the dominant flood-displacement curves, showing that stochastic transmission still generates meaningful between-run variation even with 5,000 agents and 30 replications. Taken together, the four panels separate the acute, spatially concentrated disruption 615 of a flood from the diffuse, persistent burden of person-to-person transmission.

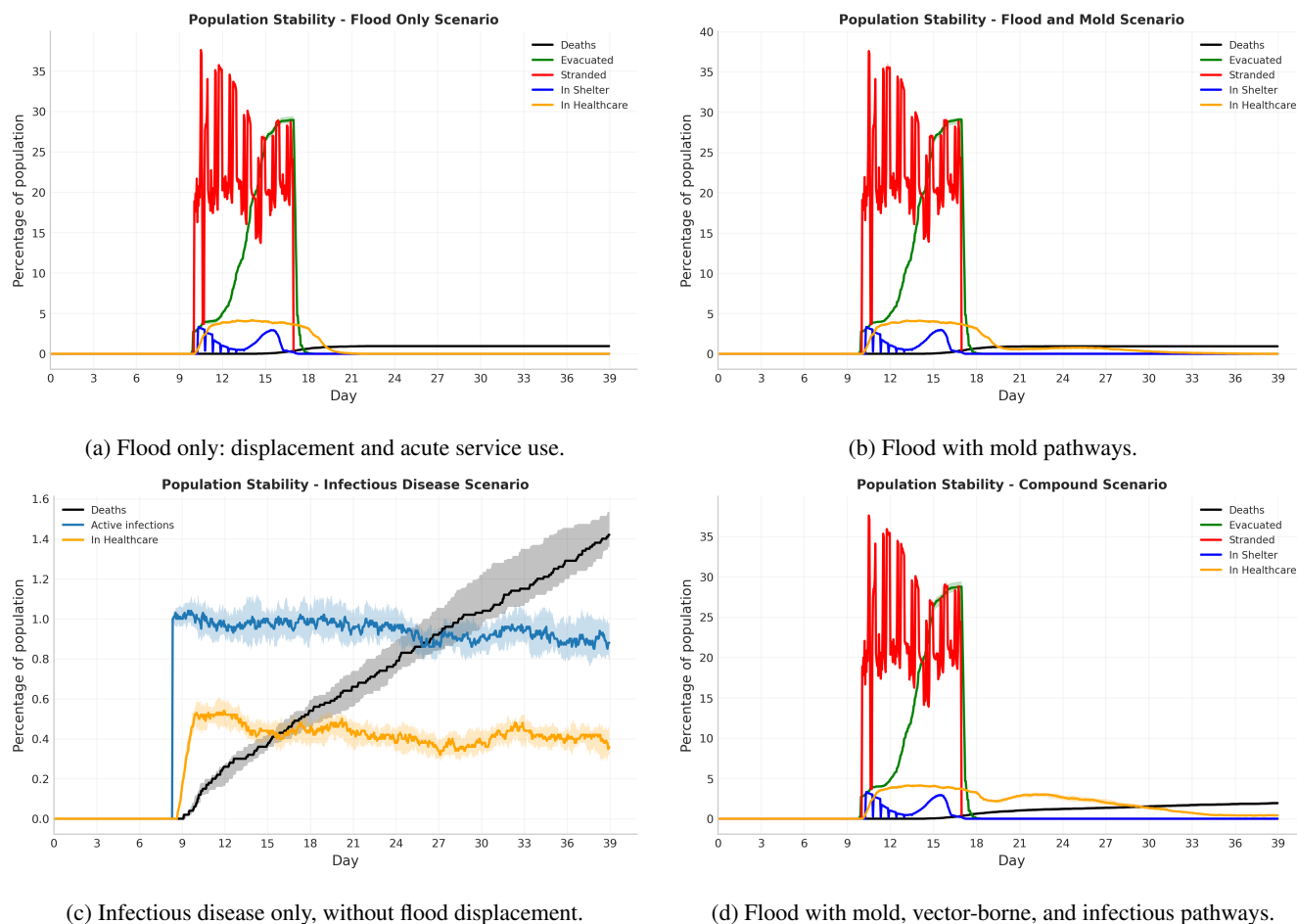


Figure 11. Population states across four hazard and disease configurations. Solid curves are medians across 30 replications and shaded bands are interquartile ranges for the 5,000-person simulations. Evacuated, stranded, sheltered, in-healthcare, and actively infectious curves represent current population shares; mortality is cumulative. (a) Flood-only runs produce rapid, daily variation in stranding, evacuation approaching 29%, and a short healthcare peak. (b,d) Adding health pathways leaves the displacement pattern largely unchanged but sustains healthcare use after recession and raises compound-scenario mortality to approximately 2%. (c) Infectious-only runs produce persistent infection, healthcare use, and cumulative mortality without evacuation or stranding.

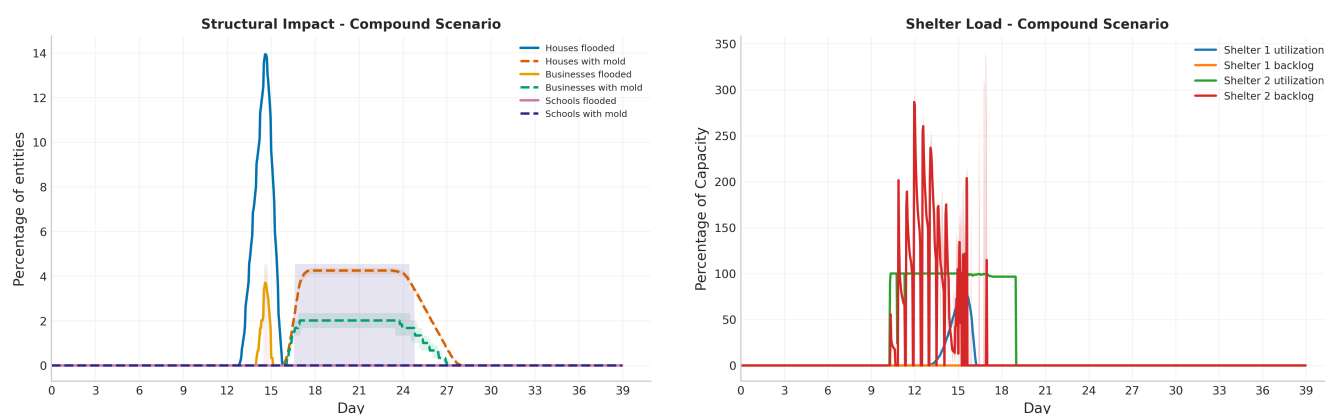
4.4 Structural Damage and Shelter Demand

Physical damage and its downstream service pressure appear in Figure 12. Flooded houses peak near 14% and flooded businesses near 4% during the inundation, then fall back to zero as the water recedes (Figure 12a). Mold builds up only after this recession, reaching about 4% of houses and 2% of businesses and persisting for several days into recovery. The clear temporal offset between the flooding curves and the mold curves reproduces the intended two-stage hazard: an immediate wetting phase



followed by a delayed indoor-air phase that keeps some buildings unusable well after visible flooding has ended. Schools register almost no impact in these runs, a direct consequence of where they sit relative to the selected flood footprint.

Shelter demand is markedly uneven between the two facilities (Figure 12b). Shelter 2 saturates for much of the flood period and accumulates a waiting list that repeatedly exceeds its capacity, while Shelter 1 fills later, remains below capacity, and carries little backlog. Values above 100% represent queued requests measured against facility capacity, not occupancy beyond the admission limit. The unused capacity at Shelter 1 is substantially smaller than the peak queue at Shelter 2, indicating that peak unmet demand reflects both an overall capacity shortfall and a spatial mismatch in access. Facility-level results therefore reveal an operational constraint that would be obscured by reporting only total shelter occupancy.



(a) Current flooding and mold prevalence among structures.

(b) Facility-specific shelter occupancy and queued demand.

Figure 12. Structural impacts and shelter demand in the compound scenario. Solid curves are replication medians and shaded bands are interquartile ranges. (a) Lines report the percentage of each structure type currently flooded or mold affected: flooding peaks near 14% of houses and 4% of businesses, while mold appears after recession and persists into recovery. (b) Occupancy and backlog are expressed as percentages of each shelter’s capacity; backlog above 100% denotes queued requests exceeding one facility-capacity equivalent, not occupancy above the admission limit. Shelter 2 saturates and develops a queue larger than Shelter 1’s unused capacity, indicating both spatially uneven access and insufficient total capacity at peak demand.

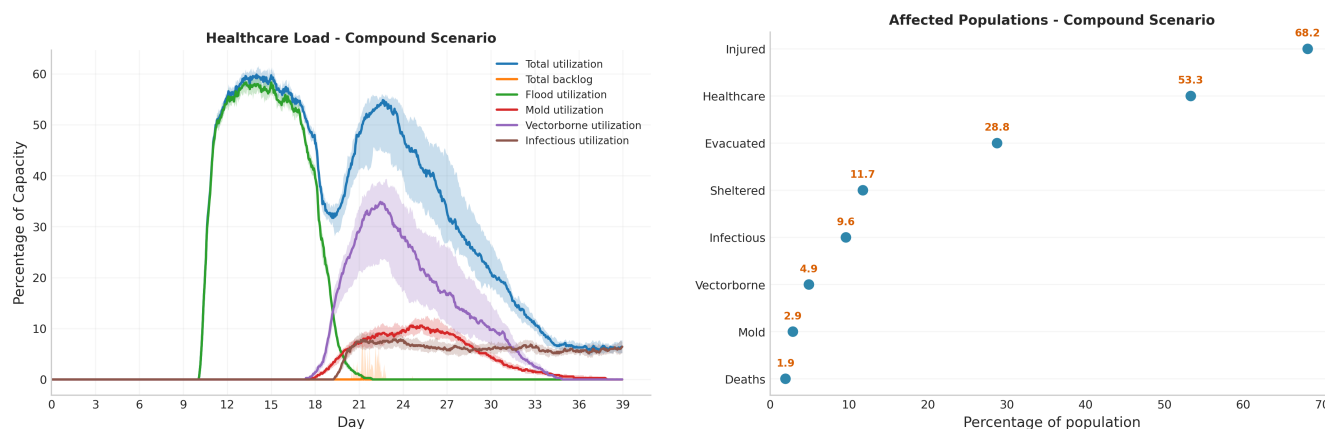
4.5 Healthcare Demand and Affected Population

The healthcare panel (Figure 13a) shows the health system absorbing two overlapping waves of demand with different causes. Flood-related utilization rises first, reaching approximately 58–60% of capacity during the flood window, then falls away as the water clears. Recovery-phase demand begins around day 18 and produces a second total-utilization peak near 54% around days 21–23. Vector-borne care is the largest component of this second wave, peaking near 32%, while mold and infectious care contribute peaks of approximately 14% and 10%, respectively. Their overlap keeps total utilization elevated even as each individual pathway begins to decline. Median backlog remains close to zero, with only short, isolated spikes, indicating that the configured healthcare capacity generally absorbs demand in these runs despite substantial occupancy.



The companion panel (Figure 13b) aggregates who was touched by the event over the whole run. About 68.0% of agents sustain an injury at some point, 53.2% use healthcare at least once, 29.0% evacuate, and 12.4% pass through a shelter. Infectious, vector-borne, and mold conditions reach approximately 9.6%, 5.2%, and 3.4% of the population, respectively, while cumulative mortality settles near 2.0%. These are cumulative, overlapping counts of ever-affected individuals: a single agent can be injured, evacuate, shelter, and be hospitalized, so the bars must not be added together. The panel's value is that it preserves each agent's full history, which lets a single simulation report both the headline injury and mortality totals and the specific service pathways that produced them.

These relatively large cumulative rates are possible under the selected illustrative configuration because stranding is evaluated during flood-blocked movement, injury risk is evaluated hourly while a person remains exposed, and the reported categories record whether an agent ever experienced the outcome. They should not be interpreted as empirical Uvalde rates. A formal sensitivity analysis of depth tolerance, rescue timing, injury risk, and mortality parameters is still required before these magnitudes can support substantive claims.



(a) Healthcare occupancy and backlog as percentages of capacity.

(b) Peak displacement and end-of-run cumulative impacts.

Figure 13. Healthcare demand and population impacts in the compound scenario. (a) Solid curves are median percentages of configured healthcare capacity across 30 replications and shaded bands are interquartile ranges. Flood-related care reaches approximately 58–60% of capacity during inundation; a second total-utilization peak near 54% during recovery combines vector-borne, mold, and infectious care. (b) Bars are replication medians and error bars span the interquartile range. Evacuated is the peak population share in each replication; stranded, sheltered, healthcare, injured, disease-affected, and deceased are end-of-run percentages of agents ever experiencing each outcome. These cumulative categories overlap at the person level and must not be summed.

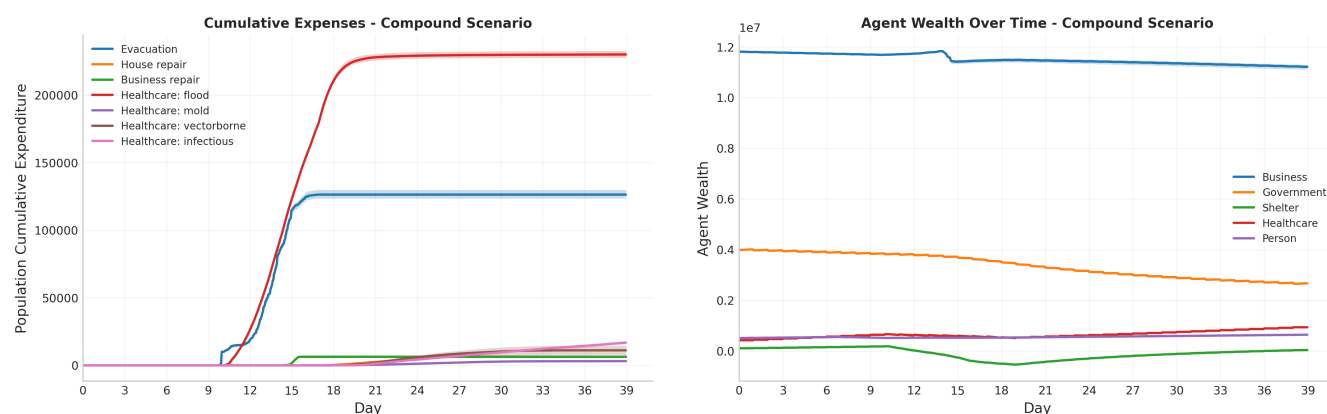
4.6 Financial and Economic Effects

Figure 14 shows the timing and distribution of modeled economic effects. Cumulative expenses (Figure 14a) accrue in a clear sequence: evacuation costs appear first and approach 39,000 model currency units, flood-related healthcare spending follows and becomes the largest category at approximately 70,000 units, and business-repair costs rise sharply as the flood



recedes. House-repair and disease-related healthcare costs accumulate later and more gradually. Infectious healthcare spending ultimately approaches the business-repair total, while vector-borne and mold-related expenditures remain smaller despite their contribution to sustained healthcare occupancy. This sequence is consistent with the event timeline: movement and acute-injury costs are concentrated during inundation, while repair and disease-related costs continue into recovery.

The institutional wealth panel (Figure 14b) shows distinct financial trajectories among agent types. Business wealth, the largest account in absolute terms, falls abruptly near the flood peak around day 14 and then stabilizes at a lower level, consistent with concentrated disruption and repair expenditure. Government wealth declines throughout the simulation as the modeled government funds transfers, grants, and services, ending approximately one-quarter below its initial balance. Shelter wealth becomes negative during peak demand and recovers only partially by the end of the run, indicating a temporary financing shortfall under the specified accounting rules. Healthcare and aggregate household wealth increase over time as service payments, wages, and other modeled transactions continue. Because these quantities are internal accounting units, they describe the direction and timing of financial pressure within the model and should not be interpreted as estimates of monetary losses in Uvalde.



(a) Cumulative evacuation, repair, and healthcare expenses.

(b) Institutional and aggregate household account balances.

Figure 14. Modeled financial effects of the compound scenario. Solid curves are medians across 30 replications and shaded bands are interquartile ranges; all values are internal model currency units and are not estimates of monetary losses in Uvalde. (a) Evacuation and flood-related healthcare expenses accrue first and dominate cumulative costs, while repair and disease-related healthcare expenses continue into recovery. (b) Business wealth falls near the flood peak, government wealth declines as transfers and services are funded, and shelter wealth becomes temporarily negative during peak demand; healthcare and aggregate household balances follow the payment, wage, and transfer rules of the model.

4.7 Quality of Life Across Population Groups

Quality of life (QoL) declines during the event across every population group, although the depth of the decline varies (Figure 15). All groups exhibit a regular daily oscillation associated with changes in activity and location, superimposed on a



pronounced event-period trough produced by the model's combined hazard, displacement, illness, and activity-loss components. By age (Figure 15a), children experience the deepest decline, adults the smallest, and seniors an intermediate decline. By wealth (Figure 15c), lower-income agents generally record the deepest event-period troughs and remain marginally below the other classes during recovery, while upper-income agents tend to retain the highest scores. The relatively narrow separation indicates that modeled resource differences moderate, but do not eliminate, the common flood-related decline.

The ethnicity and worldview panels show limited separation among groups. Ethnicity-specific trajectories overlap substantially (Figure 15b), although the Black subgroup has a wider event-period interquartile range and represents 0.4% of the synthetic population. The four equally represented worldview groups also follow nearly indistinguishable trajectories (Figure 15d). Worldview affects threat appraisal and decisions in the behavioral model, but under the selected assumptions these behavioral differences do not produce a consistent QoL ranking once hazard, displacement, and health pressures are combined. The absence of clear separation should be interpreted as a result of the current model specification, not as evidence that ethnicity or worldview is unrelated to disaster outcomes in observed populations.

5 Discussion

At the framework level, the experiments show that flood exposure can propagate through mobility, shelter and healthcare access, institutional finances, and delayed disease pathways rather than producing a single instantaneous health outcome. The compound scenario therefore illustrates the value of representing these processes together, while the uncalibrated configuration limits the interpretation to internal model behavior.

5.1 Potential Policy Applications

The simulated patterns illustrate several policy questions that could be investigated after calibration. First, a calibrated model could examine how long healthcare capacity should be maintained during recovery when flood-related, vector-borne, mold-related, and infectious demand overlap. Second, it could compare how shelter siting, capacity, transport access, and allocation affect occupancy and unmet demand. Third, it could test how alternative forms of targeted household assistance affect welfare trajectories across age and income groups. Finally, it could examine how pre-arranged financing or reserve arrangements affect the continuity of front-line institutions during peak demand. These are candidate applications for future calibrated analysis, not policy findings or prescriptions from the present uncalibrated experiments.

5.2 Verification, Validation, and Limitations

Internal consistency checks confirmed that the modeled mechanisms respond in the expected directions to changes in key inputs. For example, greater shelter or healthcare capacity reduces unmet demand and stranding, safer or faster rescue reduces the duration of stranding, and hazard, mobility, disease, and service constraints produce the intended changes in agent states and activity. These checks provide evidence that the implementation behaves consistently with its specified mechanisms, but they do not constitute comprehensive verification or empirical validation. The experiments use an illustrative, uncalibrated

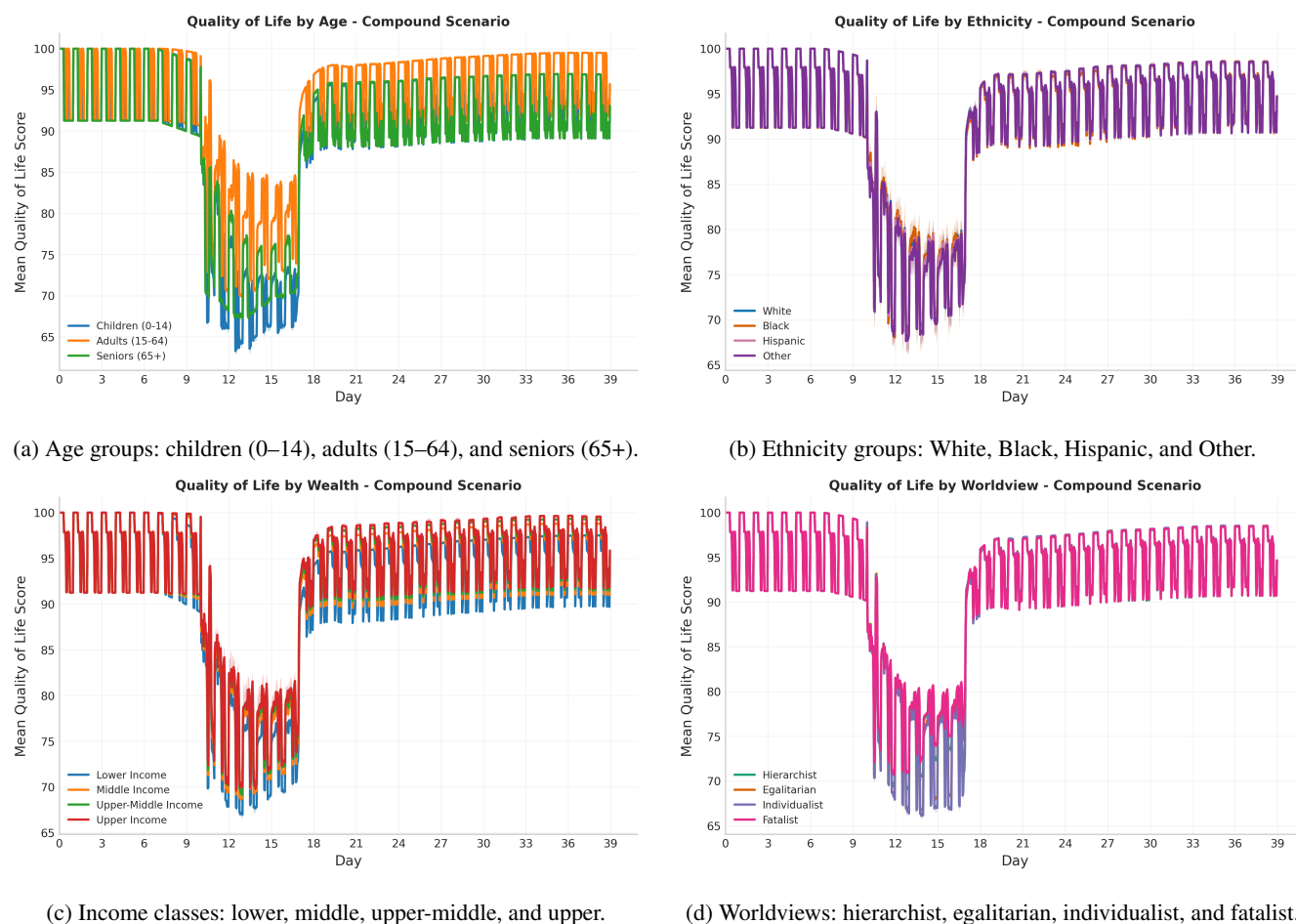


Figure 15. Quality of life (QoL) across population groups in the compound scenario. Each curve is the median across 30 replications of the within-group mean QoL score (0–100), and shaded bands are interquartile ranges. All groups show daily oscillation superimposed on a pronounced flood-period decline and subsequent recovery. (a) Children experience the deepest decline and adults the smallest. (b) Ethnicity trajectories overlap substantially, with greater uncertainty for the Black subgroup because it comprises 0.4% of the synthetic population. (c) Lower-income agents generally have the deepest troughs, while upper-income agents retain the highest scores. (d) Worldview trajectories are nearly coincident, indicating no consistent worldview-based QoL ranking under the current model specification; this result should not be interpreted as evidence of absent disparities in observed populations.

700 configuration, and detailed Uvalde-specific observations of evacuation, shelter use, healthcare demand, disease incidence, infrastructure damage, and household decision-making are not available in a form sufficient for direct comparison. The reported trajectories should therefore be interpreted as scenario-based model results rather than validated forecasts or estimates of observed magnitudes. Accordingly, neither the reported magnitudes nor the qualitative patterns should be interpreted as empirically established or robust to parameter uncertainty. Empirical calibration, comparison with available administrative and



705 event data, formal sensitivity analysis, and expert review are needed to assess predictive performance and quantify uncertainty before the model is used for operational or policy decisions.

5.3 Future Work

Several extensions follow directly from the limitations of the present study. The most immediate is empirical calibration and validation against Uvalde-specific data, including health service records, shelter logs, and economic indicators, so that the
 710 model's currently illustrative magnitudes can be tied to observed outcomes. Further scaling beyond the 5,000-person population used here would reduce sampling noise in the smallest demographic subgroup, particularly the 0.4% Black population represented in the ethnicity-stratified welfare results, and would support finer distributional analysis.

Building on the current framework, we are preparing a companion policy paper that uses the Flood-Disease ABM as a scenario testbed to evaluate specific flood-and-disease policies for the Uvalde, Texas area, comparing preparedness, response,
 715 and recovery strategies under a common set of assumptions before any real-world implementation.

A further line of work situates the model within a broader forecasting-to-adaptation pipeline, developed as part of a proposed Cooperative Institute for Research to Operations in Hydrology (CIROH) effort, *From Forecasts to Adaptation: Linking Hydrologic Predictions, Human Decisions, and Post-Flood Health in Seasonal and Compound Flood Modeling*. The aim of that effort is to couple hydrologic forecasts, inundation products, and real-time observations with the agent-based framework so that flood
 720 forcing is dynamic and seasonally or compound-driven, replacing the single static inundation footprint used here. The coupling is intended to serve three goals: to improve understanding of how effectively flood forecasts are communicated and acted upon, to develop frameworks that integrate post-flood health adaptation into resilience planning, and to deliver open-source agent-based tools aligned with the priorities of the NOAA Office of Water Prediction, the NOAA National Ocean Service, and the U.S. Geological Survey. Realizing this pipeline will require assimilating real-time hydrologic data, representing seasonal and
 725 repeated flood forcing, and expanding the behavioral and health components so that forecast information, human decisions, and downstream health outcomes are modeled as a continuous, adaptive loop.

6 Conclusions

This study introduced the Flood-Disease ABM, a spatially explicit agent-based model that couples flood hazard, human mobility and decision-making, institutional response, and three disease pathways—infectious, vector-borne, and mold-related
 730 respiratory—within a single Uvalde, Texas case study spanning the preparedness, response, and recovery phases of a flood disaster. Across a set of baseline, single-hazard, and compound scenarios, the model generated a stable no-event population and daily routine, the disruption of that routine under stress, and a sequence of coupled impacts: displacement and stranding during inundation, a delayed and longer-lived disease burden during recovery, uneven shelter access, redistribution of financial pressure across institutions, and distributional welfare effects that varied most clearly with age and wealth while remaining
 735 similar across ethnicity and worldview groups. Taken together, these results demonstrate that the integrated framework can represent feedbacks among flooding, behavior, services, and health that are difficult to represent with single-pathway or single-



domain approaches. While the present magnitudes are illustrative and await empirical calibration, the model provides a flexible foundation for the calibrated policy analysis and the forecast-coupled, adaptation-focused extensions outlined above.

Code and data availability. The source code and data-processing materials for this study are openly available at https://github.com/uofs-simlab/floodDisease_abm. The repository contains the model implementation, scenario runners, spatial-processing scripts, and documentation needed to reproduce the reported experiments.

Appendix A: Model Parameters

This appendix reports a subset of application-level values needed to reproduce the current Uvalde experiments. Internal timers, queue bookkeeping, and disease-specific care probabilities are omitted but can be found in the repository, https://github.com/uofs-simlab/floodDisease_abm. Unless identified as an experiment-specific setting, runtime defaults are read from the centralized configuration used by both the interactive app and the batch runners. The reported results use 5,000 persons and 30 replications per scenario.

Table A1. Hazard and disease-process values retained as application-level controls.

Process	Baseline	Mechanistic interpretation
Flood timing	7 baseline days, 3 pre-flood days, 7 flood days, 22 post-flood days	Applies a progressive spatial rise and recession to the single flood footprint.
Flood depth	Synthetic baseline 0.60 m with bounded local variation of 0.15 m, scaled by multiplier 2.5	The checked-in footprint supplies the spatial inundation geometry but no per-feature depth field. The model assigns the baseline depth, adds deterministic local variation, applies the temporal flood envelope, and then multiplies the queried depth by 2.5 before building flooding, movement constraints, injury, and displacement are evaluated.
Mold	Dampness half-life 20 h; resilience effect 0.8; symptom threshold 0.15	Mold emerges after flood recession from damp, damaged homes and is reduced by drying and repair.
Household mold remediation	Cost scale 0.10; attempt scale 0.25	Converts actual mold damage and household resources into repair spending and mold reduction.
Vector-borne pathway	Up to 7 compact stagnant patches; 96-h hazard half-life; 125-m influence radius; 0.5% area cap; exposure hazard 0.05	Creates localized, temporary exposure after recession rather than treating the full flood footprint as vector habitat.
Infectious pathway	$\beta = 0.008$, contact intensity 0.02, severity scale 1.20, $\gamma = 0.0167$, initial share 0.01	Contact-driven SIR-like transmission across households, work, school, and shelters.



Table A2. Economic and institutional parameters retained for interpretation and intervention experiments.

Parameter	Baseline	Role in the model
Tax rates	Sales 0.05; corporate 0.16; income 0.12	Link household, business, and government accounts.
Business revenue	Multiplier 3.80; staffing floor 0.20; staffing elasticity 1.6	Makes revenue respond to demand, closure, flooding, and worker availability.
House repair cost scale	0.10	Scales damage-driven household mold remediation spending; resources limit realized spending.
Business and school repair	Relative cost multipliers 0.75 and 0.50	Represents place-level cleanup and repair burden after flooding.
Mold business penalty	0.05 per active operating period	Carries unresolved mold into business continuity and wealth.
Service capacity and funding	Healthcare and shelter capacity each 7% of population; initial funding 100,000 and 50,000, respectively	Makes access, rescue, care, and displacement outcomes depend on congestion and resources.



Appendix B: Spatial Inventory and Baseline Population

Table B1. Compact Uvalde spatial and population baseline.

Quantity	Value	Use in the model
Study area	Compact Uvalde urban–river corridor	Defines the spatial extent of the case study.
AOI area and dimensions	118.5 km ² (45.7 mi ²); approximately 10.8 by 11.2 km	Computed from the model’s area-of-interest polygon in UTM Zone 14N.
Reference city population	15,455 (1 July 2025 estimate)	Demographic benchmark; the custom AOI also includes a sparsely populated rural fringe.
Flood layer	TWDB Scenario 5, Existing Conditions, 1-in-100 annual chance	Provides the single clipped inundation footprint.
Synthetic population	5,000 persons	Computationally controlled population used in the reported 30-replication batch experiments.
Houses	5,461	Residential inventory used for household placement.
Businesses / schools	298 / 22 campuses	Employment, spending, attendance, and exposure.
Healthcare / shelters / government	4 / 2 / 5 sites	Capacity-limited support systems and public transfers.

Table B2. Person and household heterogeneity used to initialize the Uvalde synthetic population.

Attribute	Baseline	Mechanistic role
Sex	Male 51.1%; female 48.9%	Shapes the person-agent composition.
Age	0–14: 22.0%; 15–64: 60.8%; 65+: 17.2%	Shapes household assignment, activity, health sensitivity, and exposure.
Race/ethnicity	Non-Hispanic White 17.5%; Black 0.4%; Hispanic or Latino 78.3%; Other 3.8%	Creates mutually exclusive model categories from Census race and Hispanic-origin measures.
Education	73.0% high-school graduate or higher among residents aged 25+	Initializes the adult education parameter.
Wealth and income	Uvalde with class-specific income bands	Affect cash, mobility, evacuation and repair affordability.
Vehicle access and movement	Class- and age-dependent access; one shared movement-radius control	Constrain travel, evacuation, routine activity, and access to services.
Household physical context	Mapped house resilience, flood depth, habitability, dampness, and mold	Generates physical vulnerability and return-home constraints.
Social and behavioral traits	Derived from assigned demographic, health, household, and resource context with bounded stochastic variation	Produces heterogeneous threat appraisal, coping, mobility, and protection without an independent phenotype generator.



Author contributions. Obeng A. Addai developed the model, performed the simulations and analysis, and prepared the original manuscript.
750 Raymond J. Spiteri contributed to the conceptualization, supervision, resources, funding acquisition, and review and editing of the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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755 Artificial intelligence tools were used to assist with selected software-development tasks, to generate initial versions of some graphical assets, and to support a targeted proofreading and consistency review of the manuscript under author-defined instructions. The authors reviewed, tested, edited, and integrated all AI-assisted code, graphics, and textual revisions, and take full responsibility for the final software, figures, analyses, interpretations, and conclusions presented in this manuscript.



References

- 760 Acosta-España, J. D., Romero-Alvarez, D., Luna, C., and Rodriguez-Morales, A. J.: Infectious disease outbreaks in the wake of natural flood disasters: global patterns and local implications, *Le Infezioni in Medicina*, 32, 451, 2024.
- Addai, O. A., Soares, C. P., Dhawale, R. S., Clark, M., Schuster-Wallace, C. J., and Spiteri, R. J.: Flood-ABM: An agent-based model of differential flood effects on population groups and their decision-making processes, *International Journal of Disaster Risk Reduction*, p. 105698, 2025.
- 765 Adekunle, A. I., Adegboye, O. A., and Rahman, K. M.: Flooding in Townsville, North Queensland, Australia, in February 2019 and its effects on mosquito-borne diseases, *International Journal of Environmental Research and Public Health*, 16, 1393, <https://doi.org/10.3390/ijerph16081393>, 2019.
- Ahmed, S. H., Shaikh, T. G., Waseem, S., Zahid, M., Mohamed Ahmed, K. A. H., Irfan, U., and Hasibuzzaman, M. A.: Water-related diseases following flooding in South Asian countries—a healthcare crisis, *European Journal of Clinical and Experimental Medicine*, 22, 232–242, 770 2024.
- Baqir, M., Sobani, Z. A., Bhamani, A., Bham, N. S., Abid, S., Farook, J., and Beg, M. A.: Infectious diseases in the aftermath of monsoon flooding in Pakistan, *Asian Pacific Journal of Tropical Biomedicine*, 2, 76–79, 2012.
- Barbeau, D. N., Grimsley, L. F., White, L. E., El-Dahr, J. M., and Lichtveld, M.: Mold exposure and health effects following hurricanes Katrina and Rita, *Annu. Rev. Public Health*, <https://doi.org/10.1146/annurev.publhealth.012809.103643>, 2010.
- 775 Census Reporter: Census Reporter Profile: Uvalde, Texas, <https://censusreporter.org/profiles/16000US4874588-uvalde-tx/>, aCS 2024 5-year estimates; accessed 16 July 2026, 2026.
- Centers for Disease Control and Prevention: Mold, <https://www.cdc.gov/mold-health/about/index.html>, accessed 30 June 2026, 2024.
- Centers for Disease Control and Prevention: Floods and Your Safety, <https://www.cdc.gov/floods/about/index.html>, accessed 30 June 2026, 2026.
- 780 Chowell, G., Mizumoto, K., Banda, J. M., Poccia, S., and Perrings, C.: Assessing the potential impact of vector-borne disease transmission following heavy rainfall events: a mathematical framework, *Philosophical Transactions of the Royal Society B: Biological Sciences*, 374, 20180272, <https://doi.org/10.1098/rstb.2018.0272>, 2019.
- Coalson, J. E., Anderson, E. J., Santos, E. M., Madera Garcia, V., Romine, J. K., Luzingu, J. K., Dominguez, B., Richard, D. M., Little, A. C., Hayden, M. H., et al.: The complex epidemiological relationship between flooding events and human outbreaks of mosquito-borne 785 diseases: a scoping review, *Environmental Health Perspectives*, 129, 2021.
- Collender, P. A., Cooke, O. C., Bryant, L. D., Kjeldsen, T. R., and Remais, J. V.: Estimating the microbiological risks associated with inland flood events: Bridging theory and models of pathogen transport, *Critical Reviews in Environmental Science and Technology*, 46, 1787–1833, 2016.
- de Jesús Crespo, R., Méndez Lázaro, P., and Yee, S. H.: Linking wetland ecosystem services to vector-borne disease: dengue fever in the San 790 Juan Bay Estuary, Puerto Rico, *Wetlands*, 39, 1281–1293, 2019.
- Gallego, B. C.: Most common flood-associated infectious diseases in children, *Anales de Pediatría (English Edition)*, <https://doi.org/10.1016/j.anpede.2025.503777>, 2025.
- Gatto, M. R., Mansour, A., Li, A., and Bentley, R.: A state-of-the-science review of the effect of damp-and mold-affected housing on mental health, *Environmental Health Perspectives*, 132, 086001, 2024.



- 795 Gomez, J., Prieto, J., Leon, E., and Rodríguez, A.: INFEKTA—An agent-based model for transmission of infectious diseases: The COVID-19 case in Bogotá, Colombia, *PLOS ONE*, 16, e0245 787, 2021.
- Hardeman, A., Lindgren, E. C., and Carlson, J. C.: Mold remediation in homes after flooding, *The Journal of Allergy and Clinical Immunology in Practice*, <https://doi.org/10.1016/j.jaip.2024.12.018>, 2025.
- Hunter, E., Mac Namee, B., and Kelleher, J. D.: A comparison of agent-based models and equation based models for infectious disease
800 epidemiology, *CEUR Workshop Proceedings*, <https://doi.org/10.21427/rtq2-hs52>, 2018.
- Hunter, E., Mac Namee, B., and Kelleher, J. D.: A hybrid agent-based and equation based model for the spread of infectious diseases, *Journal of Artificial Societies and Social Simulation*, <https://doi.org/10.18564/jasss.4421>, 2020.
- Ivers, L. C. and Ryan, E. T.: Infectious diseases of severe weather-related and flood-related natural disasters, *Current Opinion in Infectious Diseases*, 19, 408–414, 2006.
- 805 Johanning, E., Auger, P., Morey, P. R., Yang, C. S., and Olmsted, E.: Review of health hazards and prevention measures for response and recovery workers and volunteers after natural disasters, flooding, and water damage: mold and dampness, *Environmental Health and Preventive Medicine*, 19, 93–99, 2014.
- Leung, X. Y., Islam, R. M., Adhami, M., Ilic, D., McDonald, L., Palawaththa, S., Diug, B., Munshi, S. U., and Karim, M. N.: A systematic review of dengue outbreak prediction models: Current scenario and future directions, *PLOS Neglected Tropical Diseases*, 17, e0010 631,
810 2023.
- Liang, S. Y. and Messenger, N.: Infectious diseases after hydrologic disasters, *Emergency Medicine Clinics of North America*, 36, 835–851, <https://doi.org/10.1016/j.emc.2018.07.002>, 2018.
- Liu, Q., Zhang, S., Liu, M., and Liu, J.: Assessing the impact of flood duration on dengue burden across 108 countries, *iScience*, 29, 2026.
- Mark, O., Jørgensen, C., Hammond, M., Khan, D., Tjener, R., Erichsen, A., and Helwich, B.: A new methodology for modelling of health
815 risk from urban flooding exemplified by cholera-case Dhaka, Bangladesh, *J Flood Risk Management*, <https://doi.org/10.1111/jfr3.12182>, 2018.
- Mazzoleni, M., Defilippo, F., Torti, C., Quiros-Roldan, E., and Raffetti, E.: A socio-hydro-epidemiological model for simulating trade-off between dengue infections, water shortages, and adaptive behavior, *iScience*, 29, 2026.
- Molina-Guzmán, L. P., Gutiérrez-Builes, L. A., and Ríos-Osorio, L. A.: Models of spatial analysis for vector-borne diseases studies: A
820 systematic review, *Veterinary World*, 15, 1975, 2022.
- Moya Quiroga Gomez, V., Kure, S., Udo, K., and Mano, A.: Analysis of exposure to vector-borne diseases due to flood duration, for a more complete flood hazard assessment: Llanos de Moxos, Bolivia, *Ribagua*, 5, 48–62, 2018.
- NOAA National Weather Service Hydrometeorological Design Studies Center: NOAA Atlas 14 precipitation-frequency estimates, <https://hdsc.nws.noaa.gov/hdsc/pfds/>, accessed 22 July 2026, 2026.
- 825 OpenStreetMap contributors: OpenStreetMap, <https://www.openstreetmap.org/>, accessed 30 June 2026, 2026.
- Pakdehi, M.: Modeling the latent impacts of extreme floods on indoor mold spores in residential buildings Application of machine learning algorithms, *Environment International*, <https://doi.org/10.1016/j.envint.2025.109319>, 2025.
- Pakdehi, M.: Impacts of major floods on new human respiratory health symptoms in indoor environments, *Journal of Cleaner Production*, <https://doi.org/10.1016/j.jclepro.2026.148247>, 2026.
- 830 Patz, J. A., Vavrus, S. J., Uejio, C. K., and McLellan, S. L.: Climate change and waterborne disease risk in the Great Lakes region of the US, *American Journal of Preventive Medicine*, 35, 451–458, 2008.



- Perez, L. and Dragicevic, S.: An agent-based approach for modeling dynamics of contagious disease spread, *International Journal of Health Geographics*, 8, 50, 2009.
- Porphyre, T., Bicout, D., and Sabatier, P.: Modelling the abundance of mosquito vectors versus flooding dynamics, *Ecological Modelling*, 183, 173–181, 2005.
- Riggs, M. A., Rao, C. Y., Brown, C. M., Van Sickle, D., Cummings, K. J., Dunn, K. H., Deddens, J. A., Ferdinands, J., Callahan, D., Moolenaar, R. L., et al.: Resident cleanup activities, characteristics of flood-damaged homes and airborne microbial concentrations in New Orleans, Louisiana, October 2005, *Environmental Research*, 106, 401–409, 2008.
- Shi, K.: Assessing global flood-induced occurrence and transmission risks of biological contaminants, *Water Research*, <https://doi.org/10.1016/j.watres.2026.126264>, 2026.
- Taillandier, F.: An agent-based model to simulate inhabitants' behavior during a flood event, *International Journal of Disaster Risk Reduction*, <https://doi.org/10.1016/j.ijdr.2021.102503>, 2021.
- Texas Division of Emergency Management: Governor Abbott Signs Major Disaster Declaration After Severe Weather and Flooding, Texas Division of Emergency Management press release, <https://www.tdem.texas.gov/press-release/7-17-26>, accessed 1 September 2026, 2026.
- Texas Water Development Board: Flood Planning Data, <https://www.twdb.texas.gov/flood/planning/data.asp>, accessed 16 July 2026, 2026.
- Texas Water Development Board Flood Planning Data Hub: Cursory Floodplain Dataset – Existing Conditions, <https://twdb-flood-planning-resources-twdb.hub.arcgis.com/pages/cursory-floodplain-data-2025>, accessed 16 July 2026, 2025.
- Tjaden, N. B.: Mosquito-borne diseases advances in modelling climate-change impacts, *Trends in Parasitology*, <https://doi.org/10.1016/j.pt.2017.11.006>, 2018.
- Tonn, G. L. and Guikema, S. D.: An agent-based model of evolving community flood risk, *Risk Analysis*, <https://doi.org/10.1111/risa.12939>, 2018.
- U.S. Army Corps of Engineers Hydrologic Engineering Center: HEC-RAS: River Analysis System, <https://www.hec.usace.army.mil/software/hec-ras/>, accessed 22 July 2026, 2026.
- U.S. Census Bureau: QuickFacts: Uvalde city, Texas; Uvalde County, Texas, <https://www.census.gov/quickfacts/fact/table/uvaldecitytexas,uvaldecountytexas/PST045224>, accessed 16 July 2026, 2026.
- U.S. Geological Survey: USGS 08195000 Frio River at Concan, Texas: instantaneous discharge and gage height, <https://waterservices.usgs.gov/nwis/iv/?format=json&sites=08195000¶meterCd=00065,00060>, accessed 22 July 2026, 2026a.
- U.S. Geological Survey: USGS Water Data for the Nation, <https://waterdata.usgs.gov/nwis>, accessed 30 June 2026, 2026b.
- Venkatramanan, S., Lewis, B., Chen, J., Higdon, D., Vullikanti, A., and Marathe, M.: Using data-driven agent-based models for forecasting emerging infectious diseases, *Epidemics*, 22, 43–49, 2018.
- Wilks, C. R., Turner, A. J., and Azuolas, J.: Effect of flooding on the occurrence of infectious disease, *Advances in Ecological Research*, 39, 107–124, [https://doi.org/10.1016/S0065-2504\(06\)39006-X](https://doi.org/10.1016/S0065-2504(06)39006-X), 2006.
- Willem, L., Stijven, S., Tijssens, E., Beutels, P., Hens, N., and Broeckhove, J.: Optimizing agent-based transmission models for infectious diseases, *BMC Bioinformatics*, 16, 183, 2015.