

AN AGENT-BASED MODEL TO ASSESS INTERVENTIONS FOR CONTINUOUS CARE OF CARDIOVASCULAR DISEASES AFTER NATURAL DISASTERS

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ABSTRACT

Cardiovascular disease (CVD) is contributing significantly to rising death rates in the U.S. Furthermore, areas susceptible to natural disasters face more challenges. When a disaster strikes, a part of the population seeks refuge in shelters where access to essential treatments is limited. The limitation of treatments results in a higher mortality rate among individuals with CVD. In response, this research presents an agent-based model to explore the repercussions of CVD patients lacking access to essential treatment. The model is built to represent the potential impact on health outcomes of individuals with CVD conditions that might be relocated to shelters during a hurricane event. The simulation results show an average 14% rise in CVD mortality after hurricane occurrences which approximately represent the rates observed from hurricane events in Texas. The model is an instrument to forecast long-term health outcomes and to plan for public health interventions associated with disaster relief.

1 INTRODUCTION

Population groups with debilitating chronic, noncommunicable diseases (NCDs) are among those at risk after natural disasters. Natural disasters are indeed responsible for the increment in mortality rates in affected areas, however, the major impact due to the destruction of infrastructure (e.g., homes, businesses, and care facilities) is the internal displacement of residents. The recent examples of Hurricanes Harvey, Irma, and Maria destroyed large areas of the United States and US territories. In 2005, Hurricane Katrina flooded approximately 80% of New Orleans, Louisiana, and decimated the health infrastructure, destroying hospitals, clinics, dialysis centers, and other critical health infrastructure for weeks. The lack of planning for shelter during Hurricane Katrina led to limited access to healthy food options and inadequate access to medication (Mizelle Jr 2020). The Centers for Disease Control and Prevention (CDC) reported that chronic NCDs accounted for five of the six most reported conditions after Hurricane Katrina (Mensah et al. 2005). The number of individuals with 1 or more chronic illness diagnoses in Houston shelters after Hurricane Katrina was 41% (Brodie et al. 2006). More than 45% of evacuees did not bring their daily medications with them, and more than two thirds of all medications provided during the response were for the treatment of chronic diseases (Jhung et al. 2007).

In the situation of emergencies like natural disasters, the vulnerability due to noncommunicable diseases becomes more significant due to the acute stress of such events. Hayman et al. (2015) reported 17 observations on cardiovascular events and reported a variety of cardiovascular outcomes following a natural disaster. Life-threatening cardiovascular events such as stroke and myocardial infarction often occur among the survivors after a disaster. A disaster can trigger cardiovascular diseases (CVD) through sympathetic nervous activation and potentiation of acute risk factors. Specifically, blood pressure increases due to sympathetic activation from fear and increment of salt sensitivity from insomnia and disrupted circadian rhythm (Kario et al. 2011). Providing continuation of medication for the population having noncommunicable diseases is important to reduce the impact of CVD. Nonadherence to medication remains a major problem for the cardiovascular population which results in poor clinical outcomes and hospitalization. Baroletti and Dell'Orfano (2010) concluded that primary nonadherence (i.e., not following

the written prescription) increases 1-year mortality after hospitalization for myocardial infarction. Secondary nonadherence (i.e., failure to follow instructions or refill prescriptions) has also been observed to increase mortality, hospitalization, and cost. Wu et al. (2009) claimed that adherence to medication reduces 80% of death risk. For 135 heart failure patients, the study shows that if a patient takes the medication according to the prescription the survival of that patient without an event becomes more than 88 percent.

Providing continuity of care for chronic diseases to affected and displaced individuals is a major challenge after a natural disaster. Underscoring the strong links between natural disasters and public health can result in elevated risks for complications, emergency room visits, hospitalizations, and reduction in the life expectancy for individuals with chronic diseases (Arrieta et al. 2008). Unfortunately, the 2017 hurricane season showed that significant gaps exist in disaster planning and preparedness for chronic NCDs. Interviews of first responders in Texas, during the 2017 hurricane season, revealed that better planning is still needed (Horn and Kirsch 2018). The interviews narrated how life-threatening needs were often addressed on real time, including (1) long-term acute care for assisted living patients requiring nonurgent but life-sustaining interventions such as chronic oxygen therapy, (2) the needs of patients with end-stage renal disease and those who would need to be transported out for dialysis, and (3) triage and care for the more than 10,000 people that arrived at the George R. Brown Convention Center—a shelter that was meant to hold roughly 5,000. In an attempt to manage the health-related needs of the victims, the first responders had to create census and medical records; track prevalence of diseases and treatments; catalogue medication needs and resources; treat with few resources; and, at the same time, seek more staff, equipment, and resources (Horn and Kirsch 2018).

The goal of this research is to create decision-making models that can inform the development of public health interventions aimed at mitigating adverse cardiovascular health effects following natural disasters. *This paper studies the use of agent-based simulation (ABS) to forecast the impact on healthcare outcomes of individuals suffering from CVD after a natural disaster.* This work is based on the model presented in Li et al. (2014) and considers the effects on individuals who must evacuate their homes and may experience restricted access to their medications due to a natural disaster. The ABS model predicts population health outcomes by analyzing people's behavior after a natural disaster while also considering demographics, existing health conditions, physical activity, smoking habits, and dietary patterns. The ABS allows for decision-making in terms of resource allocation and planning that can be used to decide where new investments should be directed to achieve better community health outcomes. The rest of the paper is organized as follows. In Section 2, a review of closely related work is presented. The methodology, including a detailed description of the problem situation is presented in Section 3. Section 4 discusses the computational results and experiments to be conducted using the model and Section 5 provides a discussion of the findings of this research. The paper ends with future research opportunities in Section 6.

2 LITERATURE REVIEW

Agent-based simulation models have been employed across various sectors in healthcare, including oncology (Wang et al. 2015; Pérez et al. 2010; Alvarado et al. 2018; Huggins et al. 2014; Pérez et al. 2013; Pérez et al. 2011), CVD (Li et al. 2014), stress testing (Pickett 2014), radiological emergency (Hwang and Heo 2021; Pérez 2022), orthopedic department (Kittipittayakorn and Ying 2016), among others.

Several simulation studies have attempted to model and forecast CVD outcomes in communities, however none of them have study the impact of potential natural disaster on CVD health outcomes. Li et al. (2014) developed a study where they created an agent-based model focusing on CVD. The model aimed to assess the effects of hypothetical lifestyle programs on incidences of diabetes, myocardial infarction (MI), and stroke. The model's parameters were derived from published evidence, and simulated populations were generated using nationally representative survey data. The findings indicate that improving various behaviors and health factors can have varying impacts on health outcomes. Luo et al. (2019) develop an agent-based model for the Chinese population to simulate the diabetes epidemic, capturing individual health

progression, peer influence, and projecting population health outcomes. By simulating interventions and comparing them with external data, it was found that improving physical activity has the greatest impact on reducing diabetes prevalence. Correa et al. (2019) created an agent-based model to simulate diabetes and its complications, using data from health surveys, cohort studies, and trials for parameterization and validation. The model focused on a simulated cohort of patients with diabetes in San Antonio, TX. Pérez et al. (2021) proposed a decision-making model that complements an ABS by offering optimized program selection without the need for a traditional trial-and-error approach. Garney et al. (2022) used an agent-based model to assess the long-term impacts of a comprehensive smoke-free policy implemented in Arlington and Mesquite, Texas, on CVD outcomes. The model predicted reductions in the percentage of the population with myocardial infarction, stroke, and diabetes over a span of 10- and 20-years following policy adoption. The results proved statistically significant decreases in these conditions in both communities, supporting the use of agent-based modeling as an evaluation strategy for estimating the potential long-term effects of policies and gaining intervention support for implementation.

Chan and Sondorp (2007) reviewed the impact of natural disasters on individuals with chronic medical needs and highlights challenges in disaster response. They suggested strategies to overcome these barriers, such as increasing awareness and sensitivity among stakeholders, developing assessment tools for identifying chronic medical needs, and promoting community partnerships for sustainable services. Debacker et al. (2016) stated that the field of disaster medical response (DMR) lacks evidence-based literature, relying on descriptive studies and expert opinions when developing interventions. Experimental studies on DMR interventions and health outcomes are lacking. Traditional analytic methods are inadequate for capturing the complexity of DMR systems. Therefore, new models are needed that enable testing of interventional factors and have potential for experimental research, contributing to evidence-based disaster medical management.

3 METHODOLOGY

3.1 Model Structure

To investigate the impact of natural disasters on individuals' health outcomes, particularly those with CVD, we developed an agent-based simulation model utilizing AnyLogic Simulation software (Grigoryev 2021). The system under study includes diverse agents with distinctive characteristics, behaviors, and decision-making rules. ABS is used to capture this diversity and its impact on system dynamics. The model simulates hurricane events and the consequent behavioral responses, including medication management and relocation, with each agent being an individual characterized by specific attributes (i.e., health behavior and factors), states, and state transition probabilities as illustrated in Figure 1. The model is an extension of the research presented by (Li et al. 2014) which predict CVD outcomes considering three health behaviors (i.e., smoking state, physical activity, and diet) and four health factors (i.e., body weight, cholesterol, blood pressure, blood glucose). In the new model, health outcomes are interconnected through a CVD state chart (Figure 1d), designed to evaluate the cumulative impact of natural disaster and health factors and behaviors on the cardiovascular mortality rate, accounting for myocardial infarction (MI) and stroke. The simulated population is defined by age, gender, and health history. Parameters for the new extended version of the ABS model were obtained from historical data and recent published studies.

Within our model, a specific state transition diagram is employed to simulate the occurrence of a hurricane annually, based on historical data. A probability model was developed to decide the occurrence of a hurricane per year. If a hurricane event occurs, a signal is dispatched to all agents within the simulation, indicating the transition from a no-hurricane to a hurricane state, as defined in the hurricane state chart presented in Figure 1a. For example, when a hurricane occurs, all agents enter the "hurricane state," with some transitioning to the "relocation state" based on probabilities obtained from literature. Agents in the "relocation state" may then move to the "no medication state" with a given probability. Agents in the "no medication state" face an increased risk of cardiovascular disease (CVD) and stroke, potentially leading to

death. The equations related to the no medication state are detailed in Section 3.2.3. Within this hurricane state, we have further incorporated a composite state to assess agents' decision-making processes on relocation in response to the hurricane threat. This assessment allows agents to adopt one of two possible actions: deciding to relocate or choosing to remain in place, each dictated by their corresponding probabilities. For those agents opting for relocation, a later division occurs, categorizing them into two distinct states based on the availability of their medications: those with medication and those without. These states, integral to the hurricane state chart, operate in conjunction with the pre-existing state charts from the (Li et al. 2014) model, facilitating a comprehensive analysis of each individual's health outcomes. This parallel operation enables the model to aggregate outputs for each agent, thereby assessing the impact of hurricane-induced relocation and medication availability on their health status.

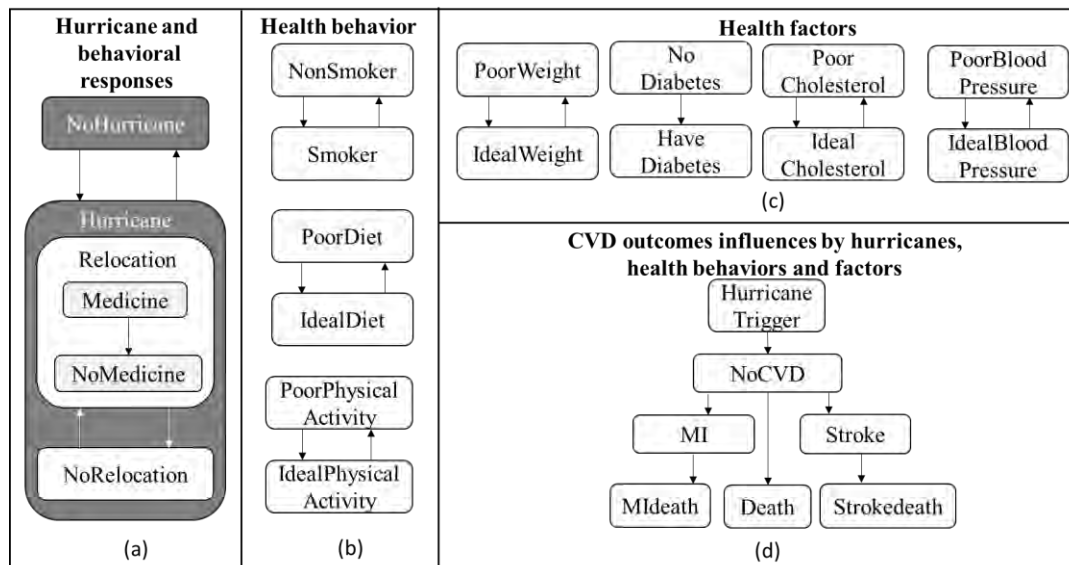


Figure 1: State charts capturing agents' behavior in simulation model, (a) hurricane, (b) health behavior, (c) health factors, and (d) CVD outcomes.

In addition to its core simulation features, our model is equipped with a user-friendly interface designed to ease the customization of simulation parameters. Figure 2 depicts the user interface.

Health Profile and Disaster Probability	
Total population:	10000
Age:	45.55 15.23 20.0 79.0 (Mean, Standard Deviation, Minimum, Maximum)
Female	0.511
No current smoking	0.8
Normal BMI	0.342
Physically active	0.369
Have healthy diet	0.244
No history of diabetes	0.917
No history of hypertension	0.731
No history of high cholesterol	0.705
No history of MI	0.963
No history of Stroke	0.977
Hurricane Probability	0.16
Prediction for <input type="text"/> Years	<input type="button" value="RUN"/>

Figure 2: AnyLogic user interface.

This interface enables users to specify the size of the population under study, the simulation's time horizon, a group of basic demographic and health characteristics and hurricane probability. Upon setting up the initial population parameters, the interface offers users the capability to monitor, track, and visually represent the health outcomes and mortality rates over the selected period. This functionality is critical for evaluating and comparing the potential effectiveness of various intervention strategies tailored to the population in focus. Later the execution of the simulation model, the interface provides a comprehensive visual representation of the simulation's progression. This visualization not only allows for an immediate visual assessment of the entire simulation run but also offers the flexibility to adjust simulation parameters dynamically. Such interactive features enhance the model's utility as a tool for hypothesis testing and scenario analysis, offering insights into the complex dynamics between hurricane events, population behavior, and health outcomes.

3.2 Parameter Estimation

Table 1 presents the new parameters incorporated into the simulation model. Among these, certain transitions are predicated on assumptions—for instance, it is assumed that the effects of a hurricane will not exceed one year, thereby causing a return to the “No Hurricane” state within this period. The parameter values for the state transitions have been sourced from recent published literature. Six of the sources are listed in Table 1. Given that our model builds upon the framework presented in (Li et al. 2014), we have elected to retain their original parameters, thereby maintaining both continuity and accuracy in the simulation of transitions.

Table 1: Source of parameters used for ABS model extension.

Parameters	Data Sources
Hurricane probability in Texas	(Research, 2020)
% of people relocated in Texas after a hurricane event	(Kever, 2020)
% of people postpone their medication during hurricane, Texas	(KFF, 2023)
Increase rate of MI due to non-persistence of antihypertensive drug use	(Breekveldt-Postma et al., 2008)
Increase rate of stroke due to non-persistence of antihypertensive drug use	(Breekveldt-Postma et al., 2008)
Medication discontinuation survival rate	(Ho et al., 2006)

3.2.1 Parameter Estimation for Hurricane Events and Associated Behavioral Responses

The hurricane occurrence probabilities were derived from the “CSU Tropical Cyclone Impact Probabilities” dataset (Research 2020), which utilizes NOAA's historical data from 1880-2020 to analyze tropical cyclone impacts near specific areas. The probability of being affected by a hurricane year by year is independent. By applying a Poisson distribution, this methodology correlates the frequency of tropical cyclone events with the Atlantic's Accumulated Cyclone Energy (ACE), demonstrating that more active hurricane seasons are associated with increased chances of landfall in the U.S. Focusing specifically on Houston, located in Harris County, our model integrates an average hurricane impact probability of 16%, thereby setting this figure (0.16) as the default parameter for the probability of hurricane occurrences in Houston. Annually, the model might generate a hurricane event based on this probability. When such an event is simulated, a signal is dispatched to the entire population within the model, prompting a state transition from “NoHurricane” to “Hurricane”. Immediately upon this transition, the population separates into two distinct groups: those who choose to move (i.e., “Relocation” state) and those who do not (i.e., “NoRelocation” state). The probabilities of transitioning to “Relocation” state were obtained from a University of Houston survey (Kever 2020), which indicates that approximately 20% of individuals displaced by storms remain in temporary housing. Among those relocating, individuals are then categorized based on whether they have access to their medications. Data from (KFF 2023) reveal that 59% of those affected by storms alter their

healthcare routines which include delaying or avoidance of necessary care, reduced medication adherence, or difficulties accessing mental health services.

3.2.2 Estimation of Parameters Related to Previous Model

In the original model (Li et al. 2014), health behavior state charts (i.e., Figure 1b) for smoking, diet, and physical activity operate independently. Smoking behavior state transitions are based on age-specific initiation and cessation rates. Diet and physical state transitions have fixed annual probabilities. There is a 3% probability transitioning from “PoorDiet” to “IdealDiet” and a 4.9% probability of transitioning from “PoorPhysicalActivity” to “IdealPhysicalActivity”. Health factor state charts (i.e., Figure 1c) for body weight, blood glucose, blood pressure, and cholesterol are influenced by those behaviors. Changes in body weight are influenced by the positive effects of healthy diets and physical activity, adjusting obesity risk accordingly. Similarly, transitions for blood glucose, blood pressure, and cholesterol are adjusted for the obesity-related risks, using age-specific incidence rates.

3.2.3 Hurricane Impact when Estimating Cardiovascular Disease Risk and Mortality

In the new extended version of the ABS model, the user sets the distribution of the population across the CVD state chart, specifying the proportions of individuals with prior myocardial infarction (MI), stroke, and those without any history of CVD. These individuals are categorized into corresponding states: “NoCVD”, “MI”, and “Stroke”, as illustrated in Figure 1d. In addition, the entire agent population is now responsive to hurricane events. The influence of hurricanes on cardiovascular disease (CVD) outcomes is analyzed by modeling population behavior concerning relocation and adherence to medication. State transition probabilities now account for the impact of hurricane events. Two binary variables are defined to show hurricane activity and individuals’ medication adherence during the potential event. Variable *hurricane* equals 1 if a hurricane event happened during the observed time-period and variable *nomed* equals 1 if individuals do not have access to their medications. The “NoCVD” state utilizes the Framingham CVD Risk Calculator (Anderson et al. 1991) and the probability of medication adherence given a hurricane event to compute the probability of transitioning to “MI” or “Stroke” states. The model now considers an increased risk when transitioning to the “MI” state. The potential medication nonadherence given a hurricane event is set to 15%, resulting in a base impact factor of 1.15 (Breekveldt-Postma et al. 2008). The probability of transitioning to the “MI” state (p_{MI}) is given as follows:

$$p_{MI} = \text{Framingham CVD Risk Calculator} \times 1.15^{\text{hurricane} * \text{nomed}}$$

Similarly, probability of transitioning from the “NoCVD” to the “Stroke” state (p_{Stroke}) is given as follows. The p_{Stroke} transition probability incorporates a base impact factor of 1.28 to reflect a 28% increase in stroke risk due to medication nonadherence (Breekveldt-Postma et al., 2008).

$$p_{Stroke} = \text{Framingham CVD Risk Calculator} \times 1.28^{\text{hurricane} * \text{nomed}}$$

Upon reaching the “MI” or “Stroke” states, individuals could progress to the “Mideath” and “Strokedeath” states. The ABS model considers an added risk associated with medication nonadherence when transitioning to the “Mideath” and “Strokedeath” states. An 11.5% increased mortality risk due to medication nonadherence was reported by Ho et al. (2006) and was used as a scalar for the transition probabilities reported by (Li et al., 2014) for MI deaths ($p_{Mideath}$) and stroke deaths ($p_{Strokedeath}$). The updated probabilities are presented as follows.

$$p_{Mideath}^* = 1.115^{\text{hurricane} * \text{nomed}} \times p_{Mideath};$$

$$p_{Strokedeath}^* = 1.115^{\text{hurricane} * \text{nomed}} \times p_{Strokedeath};$$

3.3 Model Validation

The original model was validated through the study conducted by (Li et al. 2014). Given that our model is specifically designed to predict the effects of hurricanes and medication adherence extension on the CVD outcomes, a further validation process was needed. We utilized mortality data from Hurricane Ike in Texas (Zane et al. 2011) as a case study, where it was determined that CVD accounted for 16% of the deaths, marking it as a predominant cause of illness-related fatalities. This percentage served as a key benchmark for the validation of the model. Hurricane occurrence probabilities were derived from the "CSU Tropical Cyclone Impact Probabilities" dataset, which analyzes historical data from 1880-2020 (Research 2020). The methodology employs a Poisson distribution to correlate the frequency of tropical cyclone events with the Atlantic's Accumulated Cyclone Energy (ACE), showing that more active hurricane seasons increase the likelihood of landfall in the U.S. The computational results for validation are presented in the next section.

4 COMPUTATIONAL RESULTS

4.1 Model Inputs

Table 2 provides a summary of the new input parameters incorporated into the new ABS model. These inputs are related to hurricane scenarios and the resulting behavioral reactions of the population. The data is a core part of the user input framework in the agent-based simulation model, facilitated by AnyLogic software. The adaptability of input parameters enables custom adjustments suited to different model experiments.

Table 2: Added input parameter for new ABS model.

Parameter	Definition
$P_{hurricane}$	% of experiencing hurricane per year
$P_{relocation}$	% of people relocated in Texas after a hurricane event
$P_{nomedication}$	% of people postpone their medication during hurricane, Texas

The model's population profiles were generated following the 2007 Behavioral Risk Factor Surveillance System (BRFSS) data. This dataset supplied comprehensive individual attributes such as age, gender, smoking habits, dietary patterns, physical activity levels, BMI, and medical histories of conditions like myocardial infarction (MI), diabetes, stroke, cholesterol, and hypertension, which were inputted into the agent-based simulation model.

4.2 Computational Results

The computational study considers a population of 10,000 individuals over a span of 25 years. The first part of the experimentation compares two scenarios. The first scenario assumes the absence of hurricane events ($P_{hurricane} = 0$) throughout the 25-year period, while the second introduces a 16% *probability of experiencing a hurricane* ($P_{hurricane} = 16\%$) in any given year within the same timeframe. The goal of this part of the computational study is to understand the impact of hurricane events on the studied population and to validate the ABS model. It is assumed that no more than one hurricane event can occur per year.

Evaluation and Validation of the Integrated Model Table 3 reports the number of CVD deaths for both scenarios, Scenario-1: $P_{hurricane} = 0$ and Scenario-2: $P_{hurricane} = 16\%$, for the years in which hurricane events were observed for Scenario 2 (i.e., years 13, 23, and 25). Zane et al. (2011) reports a 16% increase in the number of CVD-related deaths for the state of Texas in years when hurricane impact the state. The simulation model approximates this with an average increase in the CVD death rate of 14%, aligning closely

with the published findings. This correlation validates the ABS model's capacity to predict the impact of hurricanes on CVD mortality rates accurately.

Table 3: CVD deaths reported for $P_{hurricane} = 0$ and $P_{hurricane} = 16\%$.

Year	$P_{hurricane} = 0$	$P_{hurricane} = 16\%$	Increase %of CVD Deaths
13	56	66	18%
23	148	161	9%
25	165	188	14%
Average			14%

4.2.1 Projecting CVD Mortality Post-Hurricane Using the Model

The study conducted by (Research 2020) indicates that in 2023, Texas had a 41% probability of experiencing hurricane events, with an average annual probability of 36%. Therefore, the computational study now considers those scenarios to understand the potential implications on CVD outcomes over a 25-year period; Scenario-3: $P_{hurricane} = 36\%$ and Scenario-4: $P_{hurricane} = 41\%$. The computational results were contrasted with Scenario-2 ($P_{hurricane} = 16\%$). A total of ten replications were run per experiment.

Figure 3 presents a comparative analysis of the results. At the outset, or the 5-year mark, all scenarios recorded a relatively small number of CVD-related deaths, suggesting that hurricane impacts on CVD mortality may not be immediately evident. However, as time progressed to the 25-year threshold, the model predicted a significant escalation in CVD deaths correlating with increased hurricane probabilities, peaking notably at the 41% probability level. The observed trend—a rise in CVD mortality with higher hurricane probabilities—highlights the substantial health risks associated with hurricanes. Specifically, the simulation revealed that over 25 years, Scenario 2 saw four hurricane events in 25 years, Scenario-3 observed seven hurricane events in 25 years and Scenario-4 nine hurricane occurrences in 25 years. Ultimately, after 25 years, Scenario-3 accounted for a 20% increase in CVD deaths, and Scenario-4 resulted in a 40% increase, illustrating the critical impact that such weather events can have on cardiovascular health outcomes.

The decrease seen for the 36% probability scenario (i.e., Scenario 3) in years ten and fifteen is due to the random distribution of population cohort within the 25-year span. This randomness affects the agents' health factors and behaviors, leading to different outcomes in each run. After the first 10 years, the number of deaths for the 16% hurricane probability scenario is 52, while for the 36% scenario, it is 42. This difference is not significant and is within a short time span. The health factors and behaviors result in deaths over a longer period, causing an anomaly between the 16% and 36% hurricane probabilities. The model's rationality becomes apparent after a 20-year span, indicating that the impact of hurricane probability is more accurately reflected after 15 years. In summary, the model shows the significant impact of hurricane probability only after a longer period.

4.2.2 Estimating Post-Hurricane CVD Mortality with Intervention Strategies

Figure 4 presents a bar chart illustrating the impact of increased medication adherence and supply on CVD mortality over a 25-year period, with data points recorded every five years. The chart benchmarks against a scenario with a 16% annual hurricane probability without any interventions. Three intervention scenarios are compared: the first shows the effect of a 10% increase in both medication adherence and added medicine supply in shelters; the second scenario accounts for a 15% increase in these parameters; and the third demonstrates the outcomes of a 20% increase. These interventions reveal a decreasing trend in CVD mortality over time.

Ten years into the simulation, the interventions yield an average CVD death reduction of 23%. At the 15-year mark, the average reduction drops to 10%. By year 20, the improvement is more modest, averaging at 3%, yet still proves a continued benefit in reducing mortality. Notably, at the 25-year point, there is a significant average reduction in the CVD death rate of 10%. The trend suggests that while the most

substantial impact of the interventions is seen in the earlier years, sustained efforts continue to provide meaningful reductions in mortality. This graph underscores the significant potential of targeted health interventions to reduce CVD mortality, which is influenced by individual health profiles and the effectiveness of intervention strategies over time.

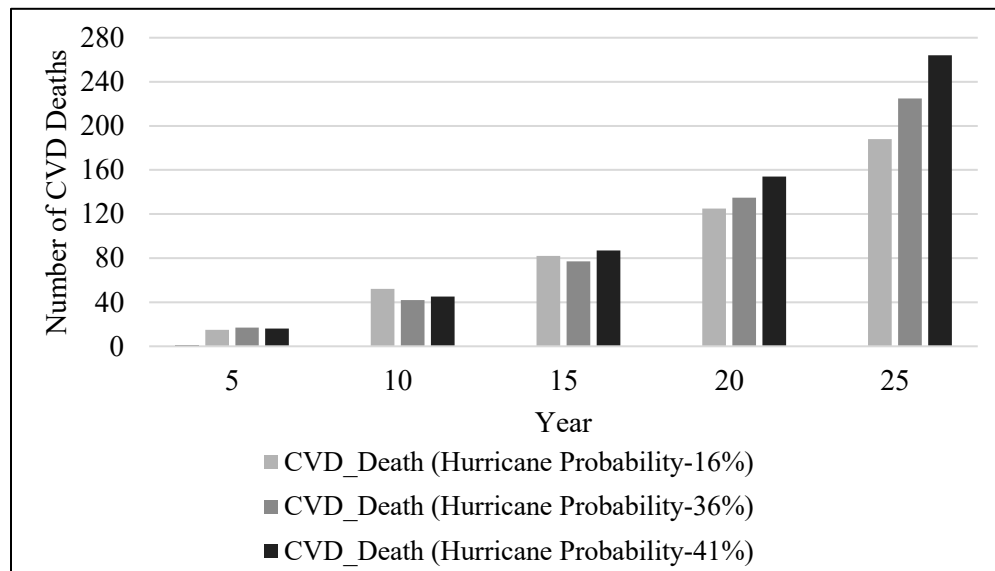


Figure 3: Impact of annual hurricane probabilities on CVD mortality over 25 years.

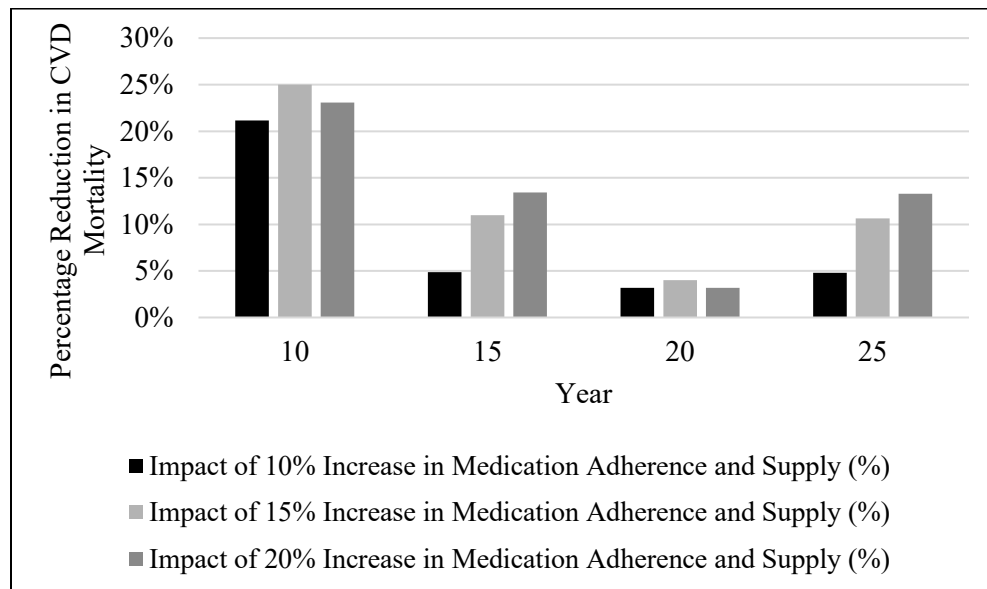


Figure 4: Impact of medication interventions on CVD mortality in hurricane scenarios.

5 DISCUSSION

The agent-based simulation model developed in this study offers a decision-making mechanism to plan for health interventions during hurricane events. The validated ABS model forecasts health outcomes for people with CVD's based on their behavior in terms of their willingness to relocate and potential adherence to medication after a natural disaster. The computational results show that a rise in CVD mortality is

expected after hurricane occurrences and that potential interventions can be successful in reducing the number of deaths. The model's intervention scenarios, particularly the increases in medication supply and adherence, point to a potentially useful tactic for lowering post-hurricane rates of CVD mortality. Interestingly, over a 25-year period, there is a significant correlation between a 15% increase in medication adherence and supply and a marked decline in CVD deaths. However, the findings also draw attention to a crucial part of public health preparedness: the requirement for ongoing advancements in medication administration in times of emergency. Our results highlight how difficult it is to respond to disasters and how short and long-term strategies must work together to reduce negative health effects. Our model also shows that improving medication adherence and supply can significantly lower the mortality from CVD and that hurricanes have a major impact on this mortality. Based on available data, public health initiatives should incorporate comprehensive plans for medication distribution and adherence support before and after hurricane events. Even in case of a natural disaster, these actions can significantly improve the health outcomes for those with CVD.

The ABS model presented in this paper is a powerful tool for supporting decision-making in complex systems, such as the allocation of medications after a natural disaster. The model simulates the affected geographical area by considering the potential impact of damaged infrastructure and models how natural disasters disrupt supply chains and how these disruptions affect medication availability. The model also represents individuals in need of medication based on their health progression over the years and simulates sudden increases in medication demand due to potential shelter relocations. The model could be used to support decision-making. In particular, the decision makers can assess different strategies for allocating limited medication supplies, such as prioritizing by severity of need, geographic location, or first-come-first-served basis. Finally, allows the user to compare the outcomes of different allocation strategies based on a defined criterion.

6 FUTURE RESEARCH

The results of this study are expected to guide future research. For instance, coordinated longitudinal research involving healthcare providers would be helpful in tracking the long-term consequences of hurricanes on people with CVD and assessing different approaches to intervention. Additionally, a greater range of interventions, such as those focused on public health communication and disaster preparedness and response, need to be evaluated using the model. An even more thorough understanding of the effects of disasters on health could be obtained by expanding the model to incorporate other chronic diseases affected by disaster scenarios, such as diabetes or respiratory conditions. Finally, researching how policy choices affect healthcare delivery and disaster management will be essential to creating well-informed, evidence-based plans to enhance patient outcomes both during and after disasters.

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