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## 2022-Ebola Incidence in Uganda: Modeling Transmission Dynamics and Evaluating Public Health Interventions

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2022-Ebola Incidence in Uganda: Modeling Transmission Dynamics and Evaluating Public Health Interventions

by

Ousainou Gomez

Under the Direction of Committee Chair's Gerardo Chowell, Ph.D.

A Dissertation/Thesis Submitted in Partial Fulfillment of the Requirements for the Degree  
of

Master of Science

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## ABSTRACT

Understanding the transmission dynamics of infectious diseases is crucial for designing effective public health interventions. The 2022 Ebola virus disease (EVD) outbreak in Uganda, caused by the Sudan virus strain, provided an opportunity to assess how targeted measures could mitigate the spread of a highly fatal virus. With no approved vaccines available, policymakers implemented lockdowns in the hardest-hit districts, Mubende and Kassanda, to curb transmission. This study aims to provide valuable insights into the effectiveness of such interventions using a data-driven modeling approach.

Despite the rapid response, uncertainty remained regarding the impact of lockdowns on disease progression. Early interventions can sometimes lead to unintended consequences, such as increased transmission due to delayed adherence or higher case detection. Moreover, previous models often overlooked intra-household transmission, a key factor in early outbreak spread. Addressing these gaps is critical for refining epidemic control strategies in resource-limited settings.

To bridge this gap, we employed a Community-Household SEIR model with time-varying transmission rates, capturing outbreak dynamics across three phases: pre-lockdown, early lockdown (1–3 weeks), and extended lockdown (4–6 weeks). Our findings reveal that sustained interventions significantly reduce transmission, emphasizing the importance of prolonged and well-implemented measures. By integrating mathematical modeling with empirical data, this study provides a robust framework for guiding future epidemic responses and strengthening public health preparedness.

INDEX WORDS: Ebola Virus Disease (EVD), Basic Reproduction Number ( $R_0$ ), Time-Varying Transmission Rates, Household-Community Transmission, Intervention Timing

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2022-Ebola Incidence in Uganda: Modeling Transmission Dynamics and Evaluating Public Health  
Interventions

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May 2025

## DEDICATION

This work is dedicated to my family, whose unwavering love, sacrifices, and support have been the foundation of my journey.

To all those who believe in the power of education and resilience—this is for you.

## ACKNOWLEDGMENTS

I begin by expressing my heartfelt gratitude to the Almighty for the strength, wisdom, and resilience that have carried me through this academic journey. Without divine guidance and grace, this work would not have been possible.

I am deeply thankful to my supervisor, Dr. Gerardo Chowell of the School of Public Health, for his exceptional mentorship, encouragement, and insight throughout this research. His expertise in infectious disease modeling, combined with his patience and critical feedback, greatly enriched the quality and clarity of this thesis. I also appreciate the support from the Department of Mathematics and Statistics, where my concentration in Biostatistics provided the foundation to approach complex public health challenges with analytical rigor.

To my family and loved ones, your unwavering love and sacrifices have been my source of strength. I am especially grateful to my peers, professors, and the researchers and institutions whose open-access data on the 2022 Ebola outbreak in Uganda formed the empirical core of this study. This work is the result of collective support, shared knowledge, and the encouragement of many—thank you all.

## TABLE OF CONTENTS

ACKNOWLEDGMENTS . . . . .	v
LIST OF TABLES . . . . .	viii
LIST OF FIGURES . . . . .	ix
<b>1 INTRODUCTION . . . . .</b>	<b>1</b>
1.1 Objective . . . . .	4
1.2 Literature View . . . . .	5
1.3 Outbreak Declaration . . . . .	8
<b>2 Methodology . . . . .</b>	<b>11</b>
2.1 Modeling Transmission Dynamics of (EVD) . . . . .	12
<i>2.1.1 Hierarchical Network Structure . . . . .</i>	<i>12</i>
<i>2.1.2 Interaction Neighborhoods . . . . .</i>	<i>12</i>
<i>2.1.3 EBOD Case Counts Before and During the Lockdown . . . . .</i>	<i>15</i>
<i>2.1.4 Epidemic Trends and Lockdown Impact . . . . .</i>	<i>16</i>
2.2 Epidemic Models . . . . .	17
2.3 Time-varying Transmission Rate for Intervention . . . . .	18
<b>3 Simulation . . . . .</b>	<b>22</b>
3.1 Model Overview . . . . .	23
<i>3.1.1 Simulation Parameters . . . . .</i>	<i>23</i>
3.2 Data Preparation and SEIR Simulation . . . . .	24
3.3 Intervention Strategy . . . . .	25
<i>3.3.1 Implementation of Intervention . . . . .</i>	<i>25</i>
3.4 Model Execution . . . . .	26

3.5 Results . . . . .	28
<b>4 Ebola Virus Response Overview . . . . .</b>	<b>32</b>
4.1 Government Response and Lockdown . . . . .	34
4.2 Effectiveness of the Lockdown . . . . .	35
<b>5 Discussion And Conclusion . . . . .</b>	<b>38</b>
<i>5.0.1 Discussion</i> . . . . .	38
<i>5.0.2 Conclusion</i> . . . . .	40
Appendices . . . . .	42
<b>REFERENCES . . . . .</b>	<b>43</b>

**LIST OF TABLES**

Table 1.1	Key Events During the 2022 Ebola Outbreak in Uganda . . . . .	10
Table 3.1	Table of Parameters . . . . .	24

## LIST OF FIGURES

- Figure 2.1 In this diagram, each cell represents an individual. The Household Interaction Neighborhood is highlighted as a single column (shown in blue dashed lines), specifically the 25th column for this example. The blue vertical line highlights all individuals within the same household (column 25). The Community Interaction Neighborhood spans 11 columns centered around the household of interest, indicated with a blue background. This neighborhood includes 5 columns on either side of the selected household. The blue area covers the community interaction neighborhood, showing how multiple households interact with each other within a community radius of 5 columns on either side. . . . . 14
- Figure 2.2 The Tables above present a summary of EBOD case counts during the pre-lockdown and lockdown phases. At the national level, there was an increase in reported EBOD cases during the first 1–3 weeks of the lockdown compared to the pre-lockdown period, with 77 cases versus 55. A similar trend was observed in Kassanda district, where cases rose from 4 to 42. Conversely, Mubende district experienced a significant decline in cases, dropping from 46 before the lockdown to 13 during the initial weeks of the lockdown. In the subsequent 4–6 weeks of the lockdown, case counts decreased across all levels. Nationally, cases fell from 58 to 7, while Mubende and Kassanda districts recorded reductions from 46 to 1 and from 4 to 3, respectively. . . . . 15
- Figure 2.3 The diagram illustrates the daily reported Ebola cases and deaths during the 2022 Ebola epidemic in Uganda. The x-axis represents the dates since the epidemic’s start, while the y-axis indicates the number of cases and deaths. The graph highlights three distinct phases of intervention: pre-lockdown, 1–3 weeks lockdown, and 4–6 weeks lockdown, which are marked along the timeline. These intervention periods reflect the gradual implementation of control measures to curb the epidemic. The smooth transitions between phases demonstrate the progressive effects of lockdowns on the spread of the disease. 16
- Figure 2.4 The line plot illustrates the evolution of the transmission rate  $\beta(t)$  over time, modeled as a piecewise exponential decline in response to phased intervention measures during the 2022 Ebola virus outbreak in Uganda. Vertical dashed lines indicate the onset of key interventions: the first lockdown initiated on October 16, 2022 (Day 26), and the extended lockdown phase commencing on November 6, 2022 (Day 47). . . . . 21

Figure 3.1 The panels illustrate the impact of varying intervention strategies on the transmission dynamics of the 2022 Sudan virus disease outbreak in Uganda. The first plot Displays the baseline model calibration with error bars representing 95% confidence intervals, highlighting the severity of an unmitigated outbreak as it spreads through the population. The second plot Depicts the initial intervention impact, where a 50% reduction in transmission significantly alters the epidemic trajectory, leading to a decline in daily case numbers. The third plot Demonstrates the cumulative effect of layered interventions, where an additional 30% transmission reduction after 150 days further suppresses outbreak propagation. The last plot shows the impact of varying reduction factors on case incidence. The colored lines represent scenarios with reduction factors ranging from 0.2 to 0.8. Stronger interventions (higher reduction factors) result in lower case incidence. These results emphasize the importance of early, sustained, and multi-layered interventions in minimizing disease burden and preventing widespread transmission. . . . .

## CHAPTER 1

### INTRODUCTION

Ebola virus disease (EVD) is a life-threatening illness that continues to be a major public health concern due to its high case fatality rate and potential for rapid transmission in affected communities Bausch & Schwarz (2014). By 2022, Uganda had experienced six separate outbreaks of EVD. The first was reported in 2000 in the northern district of Gulu, followed by outbreaks in the western region in 2007, Luweero district in 2011, Kibaale district in 2012, both Luweero and Kampala in 2013, and most recently, in September 2022, originating from Mubende District Ninsiima et al. (2024). Notably, four of these outbreaks, including the most recent one, have been caused by *Orthoebolavirus sudanense* (formerly known as Sudan ebolavirus, or SUDV) Biedenkopf et al. (2023). During the 2022 outbreak, initial investigations identified a cluster of 19 community deaths that were epidemiologically linked to the index case Aceng et al. (2023). In total, there were 142 confirmed cases of SUDV, resulting in 55 deaths and 87 recoveries, translating to a case fatality rate (CFR) of 39%. In addition, 22 probable deaths were reported in individuals who died before samples could be collected, raising the overall CFR to 47% Biedenkopf et al. (2023). Among those infected were at least 19 healthcare workers, seven of whom died. These deaths primarily occurred in Mubende, Kassanda, and Kyegegwa districts between August and September 2022. Many of the probable cases were associated with individuals who worked in or around mining areas—locations often inhabited by bats, which are known reservoirs of the virus Biedenkopf et al. (2023).

The Ebola virus was first identified in 1976 following two simultaneous outbreaks in Nzara, Sudan, and Yambuku, Zaire (now the Democratic Republic of Congo). The virus was named after the Ebola River near Yambuku, and it quickly gained notoriety due to its severe symptoms and high mortality. In the years that followed, several smaller outbreaks occurred in Central Africa, with varying degrees of severity and spread. However, the 2014–2016 West African epidemic, which affected Guinea, Liberia, and Sierra Leone, marked a turning point in global health history. With over 28,000 cases and 11,000 deaths, it was the largest Ebola outbreak ever recorded, highlighting weaknesses in international outbreak response mechanisms and prompting significant investment in vaccine development and outbreak preparedness Sellu (2023). Uganda itself has experienced multiple Ebola outbreaks over the past two decades, including major events in 2000 and 2012. The country is considered one of the most experienced in Africa in managing Ebola responses, having built considerable local expertise in surveillance, case management, and community engagement.

On September 20, 2022, the Uganda Ministry of Health (MoH) confirmed a case of Ebola Disease (EBOD) outbreak caused by the Sudan strain. It is the seventh epidemic caused by this specific strain since 1976, with four epidemics recorded in Uganda and three in Sudan Izudi et al. (2023). Ebolaviruses are negative stranded RNA viruses that belong to the Filoviridae family and are endemic to regions of west and equatorial Africa Malvy et al. (2019). The 2022 outbreak of Ebola in Uganda posed significant public health challenges, necessitating various intervention measures to control its spread. Ebola disease is caused by viruses within the genus *Ebolavirus*. Among the six known species, only four are pathogenic

to humans, including the Sudan virus, which was responsible for this outbreak. Notably, there are currently no approved vaccines for the Sudan virus, although candidate therapeutics are under development Kabami et al. (2024).

On September 19, 2022, a blood sample from a 26-year-old male in Ngabano Village, Mubende District, tested positive for the Sudan virus Kabami et al. (2024). The following day, the Uganda Ministry of Health declared an outbreak, marking the eighth recognized Sudan virus disease outbreak globally Organization et al. (2018). The outbreak's origins were traced to suspicious deaths in Mubende District as early as August 2022 Izudi et al. (2023). This study aims to comprehensively analyze the epidemiological characteristics of Sudan virus disease cases during the outbreak, focusing on transmission dynamics and the effects of intervention measures. We model the course of the outbreak via an SEIR (susceptible-exposed-infectious-removed) epidemic model that includes a time-varying transmission rate after control interventions are implemented. The study analyzes the sensitivity of the final epidemic size to the timing of interventions and provides a distribution for the final epidemic size. Control measures, including lockdowns in Mubende and Kassanda districts, are a particular focus, allowing us to assess their effectiveness in mitigating the spread of the virus. Utilizing data from the Uganda Ministry of Health's online Ebola situation reports, this research examines the critical period from September 20, 2022, to November 26, 2022.

The study employs time-varying transmission rates to accurately capture the effects of lockdowns in Mubende and Kassanda districts, and model a stochastic realization simulation for the targeted intervention. The research offers a comprehensive temporal comparison

of Ebola case trends by investigating three distinct periods- pre-lockdown, 1-3 weeks into the lockdown, and 4-6 weeks into the lockdown. Incorporating a household-community transmission model, the study simulates Ebola spread within and between households and communities Kiskowski & Chowell (2016). Key parameters such as the basic reproduction number  $R_0$  and the proportion of transmission within households are included to enhance the robustness of the analysis. Through simulations conducted with Matlab, the research evaluates various levels of intervention effectiveness, providing insights into the impact of public health measures on outbreak dynamics.

## 1.1 Objective

This study aims to analyze the epidemiological patterns and transmission dynamics of the 2022 Sudan virus disease outbreak in Uganda. Leveraging data from the Ministry of Health, we employ a time-varying SEIR model to assess how control measures—particularly lockdowns—impacted the spread of the disease over three defined phases. Focusing on the Mubende and Kassanda districts, where interventions were most concentrated, we also incorporate a household-community transmission model to provide a more granular understanding of how the virus spread within and between social structures.

- To evaluate the transmission dynamics of the 2022 Sudan virus outbreak using a time-varying SEIR model during key intervention phases.
- Using household-community transmission model to assess the effectiveness of public health interventions, particularly lockdowns, in controlling disease spread in heavily

affected districts.

## 1.2 Literature View

The 2022 Sudan virus disease (SVD) outbreak in Uganda reignited global attention on the persistent threat posed by Ebola virus disease (EVD) and the urgent need for effective strategies to understand and control its spread. As with previous EVD outbreaks, a combination of empirical epidemiological investigations and mathematical modeling studies has been instrumental in revealing the nuanced dynamics of transmission, the role of community behavior, and the impact of public health interventions. This literature review critically examines key studies that have shaped our current understanding of EVD outbreaks, with particular emphasis on the 2022 outbreak in Uganda, and highlights how these insights inform the development of time-sensitive and context-specific intervention models.

One of the pivotal epidemiological studies on the 2022 Uganda outbreak, conducted by Kabami et al. Kabami et al. (2024), identified household and healthcare-associated transmissions as the dominant drivers of disease spread. The study estimated the basic reproduction number ( $R_0$ ) and the serial interval, offering important parameters for understanding the outbreak's momentum. These findings are consistent with earlier research, such as that by Kiskowski Kiskowski (2014), which emphasized that children and women are disproportionately affected during Ebola outbreaks—both in terms of exposure risk and mortality—largely due to caregiving roles and socio-cultural practices. To better understand and predict the trajectory of EVD outbreaks, researchers have turned to mathematical and computational models. Kiskowski's subsequent work Kiskowski & Chowell (2016) introduced a stochas-

tic, individual-based network model that simulated disease transmission across household and community layers. This modeling framework demonstrated how intervention measures like lockdowns and reduced community mixing can substantially alter the course of an epidemic. The study highlighted that the effectiveness of such interventions is highly context-dependent, varying based on local transmission networks and social behaviors.

The implementation of lockdowns during the Uganda outbreak revealed both the potential and limitations of such non-pharmaceutical interventions. Izudi et al. (2023) examined the epidemiological trends before and during the lockdown period, noting that the initial phases of lockdown were paradoxically marked by an increase in reported cases. This phenomenon was attributed to delayed compliance, cultural resistance, and lack of effective community engagement. Nevertheless, their findings showed that longer-duration lockdowns (4–6 weeks) had a markedly positive impact, significantly reducing the number of new cases. These results corroborate the modeling insights of Kiskowski & Chowell (2016), who showed that sustained and well-enforced interventions are far more effective in disrupting transmission chains than short-term or poorly coordinated efforts.

Beyond Uganda, the challenges of EVD control have been well-documented in other high-burden regions, such as the Democratic Republic of Congo (DRC). Chowell et al. (2007) explored the role of vaccination strategies, including ring vaccination and mass immunization, in curbing EVD outbreaks. Their work underscored the significance of timely vaccine deployment but also drew attention to the barriers that hinder vaccination efforts—namely, geographic inaccessibility, logistical bottlenecks, and community distrust of

health authorities. These lessons were particularly relevant in Uganda’s 2022 SVD outbreak, where no licensed vaccine for the Sudan virus strain was available. As a result, the Ugandan response relied heavily on non-pharmaceutical interventions such as lockdowns, contact tracing, and health education campaigns to control disease transmission. Given these constraints, recent modeling approaches have evolved to incorporate time-varying parameters that reflect the dynamic nature of public health interventions. The use of time-varying SEIR (Susceptible–Exposed–Infectious–Recovered) models has been especially valuable in capturing the temporal effects of interventions on transmission rates. Jamison et al. Jamison et al. (2006) and Chowell et al. Chowell et al. (2024) contributed to this effort by proposing methods for reconstructing transmission rates over time based on real-time incidence data. These approaches enable researchers to account for the staggered implementation and waning of intervention measures, providing a more realistic picture of epidemic dynamics. The integration of smooth transitions between intervention phases—as employed in the present study—represents a methodological advancement in capturing the continuous, rather than abrupt, effects of public health policies on disease transmission.

Collectively, the literature underscores the critical importance of integrating empirical epidemiology with dynamic modeling to guide outbreak response. The evidence suggests that multi-layered interventions—adapted to local epidemiological and sociocultural contexts—are essential for controlling EVD outbreaks, especially in the absence of pharmaceutical tools like vaccines. The present study builds on these insights by developing a time-varying SEIR model tailored to the 2022 Uganda SVD outbreak, incorporating piece-

wise transitions that reflect varying lockdown durations and intensities. By simulating the effects of these interventions on disease spread, this work contributes to the broader discourse on epidemic preparedness and response, offering practical implications for managing future outbreaks in similar settings.

### **1.3 Outbreak Declaration**

The 2022 Ebola virus disease (EVD) outbreak in Uganda marked a significant public health emergency and served as a sobering reminder of the continued threat posed by emerging and re-emerging infectious diseases in sub-Saharan Africa. Unlike previous large-scale outbreaks primarily driven by the Zaire strain of the Ebola virus, this outbreak was attributed to the Sudan virus (SUDV)—a genetically distinct strain with no licensed vaccine or proven therapeutic treatment available at the time. The emergence of the Sudan strain underscored the limitations of existing biomedical countermeasures and heightened the urgency for robust non-pharmaceutical interventions.

The outbreak was officially declared on September 20, 2022, by Ugandan health authorities following laboratory confirmation of the Sudan virus in a patient from Mubende District, located in central Uganda. The index case was a 26-year-old male who developed symptoms on September 11, presenting with high fever, convulsions, bloody vomitus, diarrhea, loss of appetite, chest pain, dry cough, and conjunctival hemorrhage. He initially sought care at two local private clinics between September 11 and 15, but his condition deteriorated. On September 15, he was referred to the Mubende Regional Referral Hospital (RRH), where

he was promptly isolated as a suspected viral hemorrhagic fever case Ibrahim et al. (2022). A blood specimen was collected on September 17 and sent to the Uganda Virus Research Institute (UVRI) in Kampala. On September 19, RT-PCR testing confirmed the presence of SUDV, and tragically, the patient succumbed to the illness the same day Organization et al. (2022a). Subsequent investigations revealed that prior to the confirmation of the index case, there had been several unexplained community deaths in the Madudu and Kiruma sub-counties of Mubende District. These cases, initially undiagnosed and unmanaged, are now retrospectively classified as probable cases of EVD. The presence of these undetected transmission chains indicates that the virus had been circulating in the community for several weeks before official recognition, highlighting the critical need for surveillance systems capable of early detection and response.

By September 25, 2022, the outbreak had expanded to multiple districts. A total of 36 cases were reported, comprising 18 laboratory-confirmed and 18 probable cases. The geographic distribution of cases included Mubende (14 confirmed and 18 probable), Kyegegwa (3 confirmed), and Kassanda (1 confirmed). Of these, 23 deaths were documented, including five among the confirmed cases. The observed case fatality rate (CFR) among confirmed cases was 28%, which is consistent with historical SUDV outbreaks that tend to exhibit lower CFRs compared to the Zaire strain Organization et al. (2022b).

Demographic analysis of the outbreak revealed that 62% of the cases were female, while 38% were male, with a median age of 26 years (range: 1–60 years). This gender distribution may reflect caregiving roles and patterns of exposure within affected households and health-

care settings. At the time, 13 confirmed cases were receiving care in isolation units, and 223 contacts had been identified for active follow-up and monitoring. The epidemiological profile—characterized by delayed case recognition, community-based transmission, and limited healthcare access—reflects common features of Ebola outbreaks in low-resource settings and underscores the need for targeted interventions at the household and community levels.

Overall, the 2022 Sudan virus outbreak in Uganda demonstrated the multifaceted challenges associated with detecting, containing, and responding to filovirus outbreaks. The absence of a vaccine or antiviral treatment, coupled with gaps in surveillance and public health infrastructure, required rapid mobilization of resources and coordination among local and international partners. This outbreak forms the basis of the current study’s modeling approach, which aims to quantify the effects of time-varying interventions and transmission dynamics in the context of such an epidemiologically complex scenario.

Table 1.1 Key Events During the 2022 Ebola Outbreak in Uganda

<b>Event</b>	<b>Date</b>	<b>Description</b>
First suspected Ebola case	August 2022	Suspicious deaths noted in Mubende District
First confirmed Ebola case	September 19, 2022	26-year-old male tests positive for Sudan virus
Government declares an outbreak	September 20, 2022	Official outbreak declaration by Uganda’s Ministry of Health
End of outbreak	November 26, 2022,	Decline in cases, marking the end of the emergency period

## CHAPTER 2

### Methodology

A retrospective review of data from the Uganda Ministry of Health's online Ebola situation reports was conducted to understand the dynamics of this outbreak and evaluate the effectiveness of public health interventions. Covering September 20, 2022, to November 26, 2022, this study analyzed trends in Ebola cases before and during the lockdowns imposed in the Mubende and Kassanda districts. All EBOD incident cases were confirmed by laboratory testing using Deoxyribonucleic acid-polymerase chain reaction or DNA-PCR at the Uganda Virus Research Institute Viral Hemorrhagic Fever Laboratory, and subsequent deaths of these cases were attributed to EBOD Ario et al. (2024) Kabami et al. (2024). By systematically extracting and reviewing data, the study aimed to provide a detailed analysis of how these measures influenced the incidence and spread of the disease. The data collection process involved a meticulous extraction of relevant information, ensuring accuracy and completeness, particularly in investigating the effect of the intervention on the incidence of Ebola cases across three distinct periods: pre-lockdown, 1-3 lockdown, and 4-6 weeks lockdown. This temporal segmentation allowed for a clear comparison, highlighting the impact of lockdown measures on Ebola case trends. The study utilized comprehensive simulations conducted with Matlab to model various levels of intervention effectiveness, thereby offering insights into how different intensities of public health measures could influence outbreak dynamics.

## 2.1 Modeling Transmission Dynamics of (EVD)

To analyze the transmission dynamics of (EVD), we used an SEIR (Susceptible, Exposed, Infectious, Refractory) network model tailored to distinguish between transmission patterns within households and those in broader community settings. This method effectively captures the hierarchical nature of contact patterns and their influence on disease spread.

### 2.1.1 Hierarchical Network Structure

In our model, individuals are grouped within households, each consisting of  $H = 6$  members. These households are part of a larger community of  $C = 11$  households, forming a neighborhood with a community radius  $R_c = 5$ . The total population  $P$  is given by  $P = H \times L$ , where  $L = 50$  is the total number of households, represented on a  $6 \times 50$  lattice. Each column of the lattice represents a single household.

### 2.1.2 Interaction Neighborhoods

We define two overlapping interaction neighborhoods for any given node  $(i, j)$ :

- The household interaction neighborhood, which is the  $j$ -th column of the lattice (a  $6 \times 1$  vertical array).
- The community interaction neighborhood, which is a  $6 \times 11$  sub-array centered at the  $j$ -th column, including  $R_c$  columns on either side.

### ***Basic Reproduction Number ( $R_0$ )***

The basic reproduction number,  $R_0$ , represents the average number of secondary cases caused by a single infected individual in a fully susceptible population. It is crucial for understanding the potential spread of the disease and is typically estimated from empirical data or historical outbreaks.

### ***Household Size ( $H$ )***

The value  $H = 6$  reflects the average number of individuals living in a household. This value is based on demographic data or assumptions relevant to the region under study and is used to capture intra-household transmission dynamics.

### ***Community Size ( $C$ )***

The community size  $C = 11$  represents the number of interacting households in a given community. This value is derived from a community radius  $R_c = 5$ , meaning that each household interacts with others within a radius of 5 columns, resulting in 11 households in total. This setup captures broader interaction patterns beyond the immediate household, influencing disease transmission.

## Hierarchical Network Structure with Infection Spread

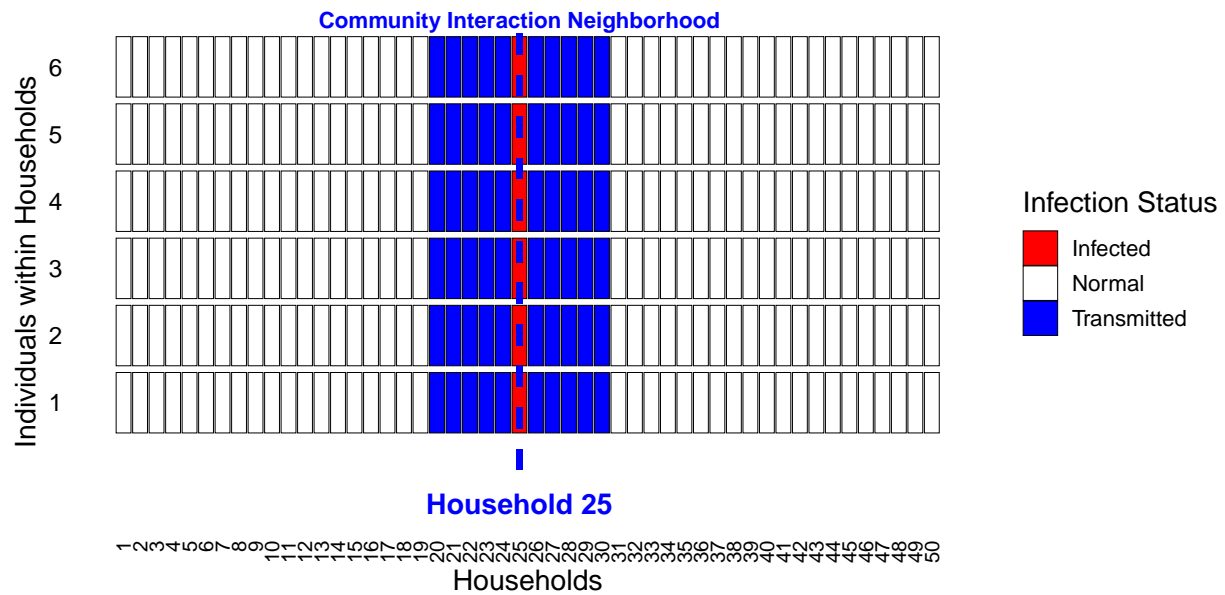
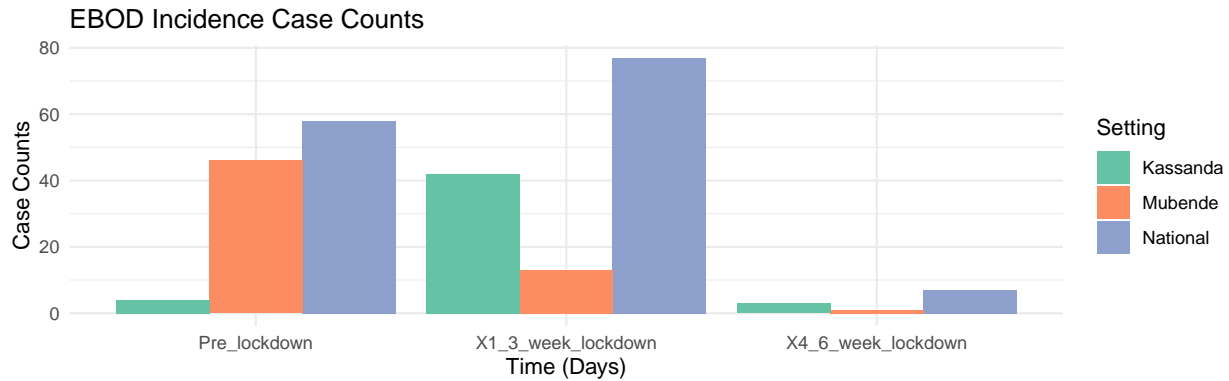


Figure 2.1 In this diagram, each cell represents an individual. The Household Interaction Neighborhood is highlighted as a single column (shown in blue dashed lines), specifically the 25th column for this example. The blue vertical line highlights all individuals within the same household (column 25). The Community Interaction Neighborhood spans 11 columns centered around the household of interest, indicated with a blue background. This neighborhood includes 5 columns on either side of the selected household. The blue area covers the community interaction neighborhood, showing how multiple households interact with each other within a community radius of 5 columns on either side.

### 2.1.3 EBOD Case Counts Before and During the Lockdown

A summary of reported Ebola cases before and during lockdown shows varying trends across districts.



Setting	Pre_lockdown	X1_3_week_lockdown	X4_6_week_lockdown
National	58	77	7
Mubende	46	13	1
Kassanda	4	42	3

Figure 2.2 The Tables above present a summary of EBOD case counts during the pre-lockdown and lockdown phases. At the national level, there was an increase in reported EBOD cases during the first 1–3 weeks of the lockdown compared to the pre-lockdown period, with 77 cases versus 55. A similar trend was observed in Kassanda district, where cases rose from 4 to 42. Conversely, Mubende district experienced a significant decline in cases, dropping from 46 before the lockdown to 13 during the initial weeks of the lockdown. In the subsequent 4–6 weeks of the lockdown, case counts decreased across all levels. Nationally, cases fell from 58 to 7, while Mubende and Kassanda districts recorded reductions from 46 to 1 and from 4 to 3, respectively.

**2.1.4 Epidemic Trends and Lockdown Impact**

This section examines the progression of the Ebola outbreak in Uganda and the effect of phased lockdown interventions on reported cases and deaths.

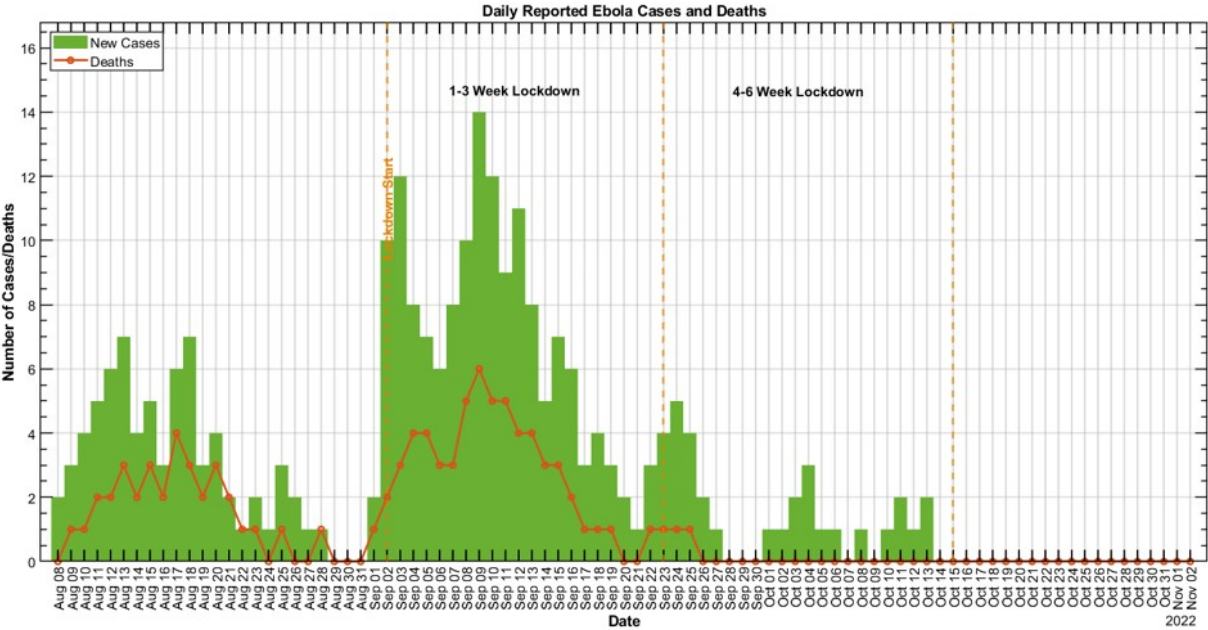


Figure 2.3 The diagram illustrates the daily reported Ebola cases and deaths during the 2022 Ebola epidemic in Uganda. The x-axis represents the dates since the epidemic’s start, while the y-axis indicates the number of cases and deaths. The graph highlights three distinct phases of intervention: pre-lockdown, 1–3 weeks lockdown, and 4–6 weeks lockdown, which are marked along the timeline. These intervention periods reflect the gradual implementation of control measures to curb the epidemic. The smooth transitions between phases demonstrate the progressive effects of lockdowns on the spread of the disease.

## 2.2 Epidemic Models

Epidemic models classify individuals into different epidemiological states, representing their health status to the disease. In the SEIR model, individuals belong to one of the following compartments:

- **Susceptible** ( $S$ ): Individuals who are at risk of contracting the disease.
- **Exposed** ( $E$ ): Individuals who have been infected but are not yet infectious (i.e., undergoing an incubation period).
- **Infectious** ( $I$ ): Individuals who are capable of transmitting the disease.
- **Removed** ( $R$ ): Individuals who have either recovered from the disease or died.

The SEIR model was designed to simulate the outbreak, incorporating  $\beta(t)$  to reflect intervention impacts. The equations for the model are:

$$\frac{dS}{dt} = -\beta(t)\frac{SI}{N}, \quad (2.1)$$

$$\frac{dE}{dt} = \beta(t)\frac{SI}{N} - \sigma E, \quad (2.2)$$

$$\frac{dI}{dt} = \sigma E - \gamma I, \quad (2.3)$$

$$\frac{dR}{dt} = \gamma I \quad (2.4)$$

Where:

- $\beta(t)$ : Time-varying transmission rate
- $\frac{1}{\sigma}$ : Incubation rate
- $\frac{1}{\gamma}$ : Recovery rate
- $N$ : Total population

Initial conditions  $(S_0, E_0, I_0, R_0)$  were set based on reported case data. Smooth transitions in  $\beta(t)$  were incorporated to simulate the effects of the lockdown phases.

### 2.3 Time-varying Transmission Rate for Intervention

To accurately model the 2022 Ebola virus outbreak in Uganda, we developed a time-varying SEIR (Susceptible–Exposed–Infectious–Recovered) model that integrates both observed data and simulated outcomes. The model captures the impact of public health interventions — specifically two sequential lockdown periods — by allowing the transmission rate  $\beta(t)$  to vary over time.

To realistically represent changes in disease transmission, we applied a piecewise exponential decline to  $\beta(t)$ , enabling smooth transitions between three intervention phases:

- **Pre-Lockdown Period:** Transmission remains constant before any intervention.
- **First Lockdown Phase:** Transmission begins to decline exponentially following the initial lockdown.

- **Second Lockdown Phase:** A second, more stringent intervention further reduces transmission.

### *Model Definition*

We define  $\beta(t)$  as:

$$\beta(t) = \begin{cases} \beta_0, & t < t_1 \\ \beta_1 + (\beta_0 - \beta_1)e^{-\lambda_1(t-t_1)}, & t_1 \leq t < t_2 \\ \beta_2 + (\beta_1 - \beta_2)e^{-\lambda_2(t-t_2)}, & t \geq t_2 \end{cases}$$

Where:

- $\beta_0$ : Transmission rate before any lockdown (baseline level).
- $\beta_1$ : Asymptotic transmission rate after the first lockdown phase.
- $\beta_2$ : Asymptotic transmission rate after the second lockdown phase.
- $\lambda_1$ : Decay rate after the first intervention (controls how fast transmission decreases post  $t_1$ ).
- $\lambda_2$ : Decay rate after the second intervention (controls how fast transmission decreases post  $t_2$ ).
- $t_1$ : Start of the first lockdown intervention.
- $t_2$ : Start of the second/extended lockdown.

- $t$ : Time in days since outbreak start.

### *Interpretation*

- **Before  $t_1$** : No intervention is in place. Transmission remains at  $\beta_0$ .
- **Between  $t_1$  and  $t_2$** : The first lockdown begins, and  $\beta(t)$  decays exponentially toward  $\beta_1$ , representing partial suppression of transmission.
- **After  $t_2$** : A second, stricter intervention is introduced. Transmission decays again, this time toward  $\beta_2$ , simulating stronger effects of the extended lockdown.

This structure captures the cumulative and gradual impact of multiple intervention phases without abrupt changes in  $\beta(t)$ , aligning well with real-world delays in behavior change and policy effectiveness. By fitting this model to observed epidemic curves, we can assess the timing and strength of public health measures implemented during the Uganda 2022 Ebola outbreak.

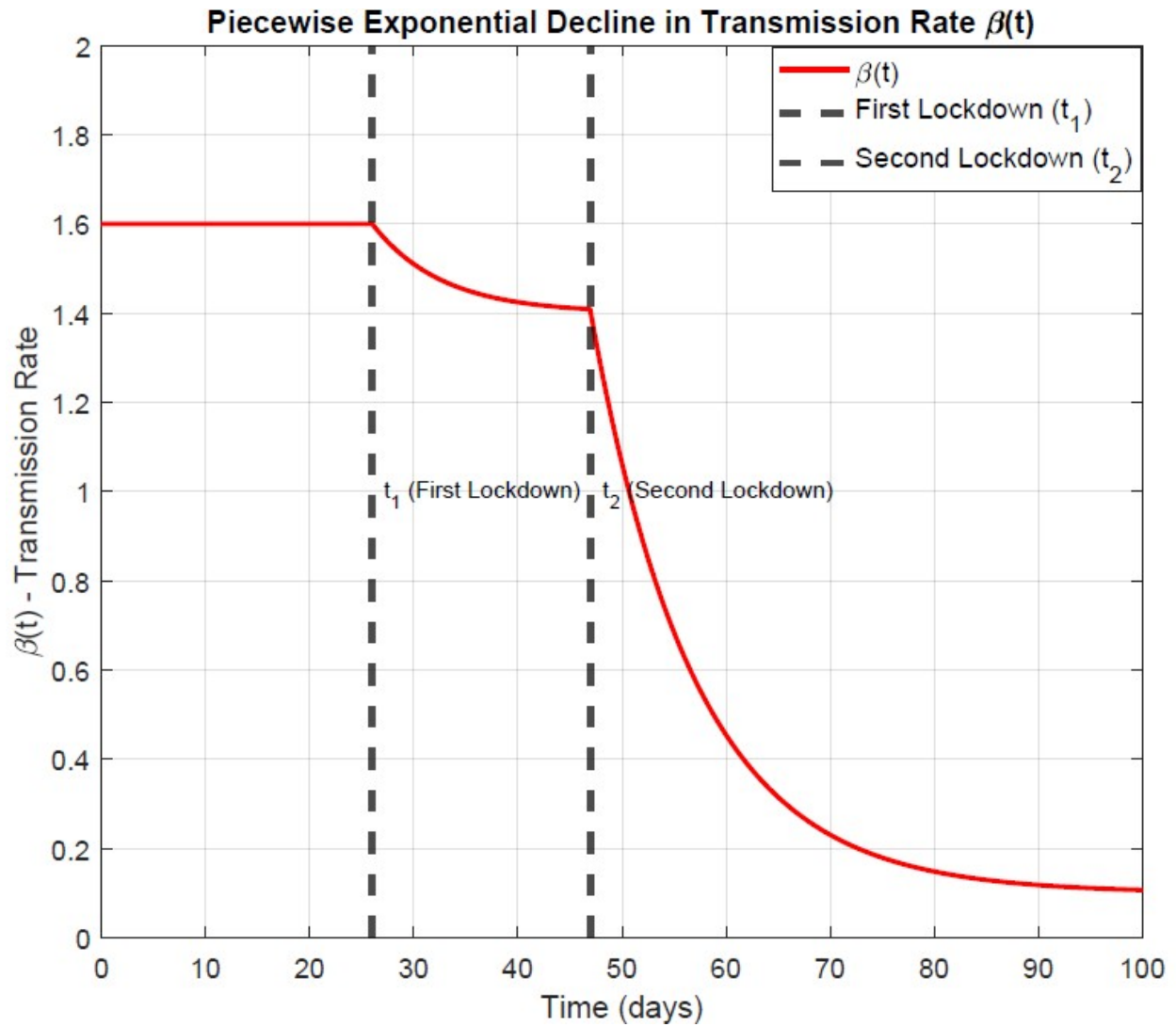


Figure 2.4 The line plot illustrates the evolution of the transmission rate  $\beta(t)$  over time, modeled as a piecewise exponential decline in response to phased intervention measures during the 2022 Ebola virus outbreak in Uganda. Vertical dashed lines indicate the onset of key interventions: the first lockdown initiated on October 16, 2022 (Day 26), and the extended lockdown phase commencing on November 6, 2022 (Day 47).

## CHAPTER 3

### Simulation

This study introduces a household-community model designed to simulate disease transmission dynamics within and between households and communities over 222 days. The model features 1000 households, representing a total population of 10,000 individuals, evenly divided between two distinct communities. With a basic reproduction number ( $R_0$ ) set at 1.6, the simulation aims to elucidate the complex patterns of disease spread under intervention measures. The first intervention, implemented on day 75, aims to reduce transmission rates by 50%. A subsequent intervention, introduced on day 150, further reduces transmission rates by 30% within both households and communities. These interventions are modeled by adjusting the daily transmission rate scaling the factor of  $R_0$  accordingly. To incorporate stochastic variability, the simulation is executed with 222 realizations, each generating distinct trajectories of disease progression. Key metrics such as case incidence, extinction events, and individual reproduction numbers are meticulously monitored throughout the simulation. The model's robustness and reliability are ensured through calibration with historical data and sensitivity analyses on different transmission rates, and it is further validated against observed data from previous outbreaks. This comprehensive model serves as a valuable tool for understanding disease dynamics and developing effective intervention strategies.

### **3.1 Model Overview**

The household-community model employed in this study is designed to simulate the dynamics of disease transmission both within households and between different communities over a specified period. The model integrates several key components to capture the intricacies of disease spread. The model is structured to account for both deterministic and stochastic elements, incorporating variability in disease progression and transmission. It facilitates the analysis of intervention strategies and their impact on reducing transmission rates. Through this detailed approach, the model aims to enhance understanding of disease dynamics and inform effective public health interventions.

#### ***3.1.1 Simulation Parameters***

The simulation was conducted over 222 days, utilizing a household-community model designed to capture the dynamics of disease transmission. The key parameters of the simulation are as follows:

Table 3.1 Table of Parameters

Parameter	Description	Value (Range)	Reference
duration1	Duration of the simulation in days	222	Model assumption
$R_0^{\text{day}}$	Scaling factor for $R_0$ based on daily variation or intervention phases	Adjusted over time	-
$\beta_0$	Transmission reduction factor, due to intervention	0.3-0.8	-
realizations	Number of stochastic realizations for the simulation	222	-
$H$	Number of households	1000	of Statistics (2023)
$N$	Total population	10000	of Statistics (2023)
$F$	Fixed number of families	Computed as round( $N/H$ )	-
$NC$	Number of communities	2	Model assumption
$C$	Community size – number of households per community	Computed based on $F$ and $NC$	-
$1/\sigma$	Average incubation period	9 days	Team (2014)
$1/\lambda$	Average infectious period	5.6 days	Kiskowski & Chowell (2016)
$R_0$	Average number of secondary infections caused by a single individual in a susceptible population	1.6	Literature
$R_0(t)$	Time-varying reproduction rate vector based on intervention scenarios	0.05, 0.1	-
perc_h	Proportion of transmission occurring within households	0.5	Estimated
$R_{0H}$	Household reproduction number	Computed as $R_0 \times \text{perc}_h$	-
$R_{0C}$	Community reproduction number	Computed as $R_0 \times (1 - \text{perc}_h)$	-

### 3.2 Data Preparation and SEIR Simulation

#### *Observed Data*

The observed epidemic data consisted of daily confirmed Ebola cases. This dataset was cleaned and aggregated to form a time series. The observed epidemic curve provided a baseline for evaluating the model's ability to replicate the outbreak dynamics. Daily confirmed

cases were plotted against time, highlighting significant intervention periods, such as the start of interventions.

### **3.3 Intervention Strategy**

To investigate the impact of a public health intervention, we incorporated a reduction in transmission rates starting from a specified day. The intervention is designed to reduce the transmission rates within households and communities. **Intervention Start Day:** During the simulation, interventions were strategically initiated on the 75th and 150th days of the Ebola outbreak. During the first intervention, a reduction factor of 0.5 was applied, effectively lowering the basic reproduction number ( $R_0$ ) from 1.6 to 0.8. This reduction was designed to curb the spread of the virus significantly during the early phase of the outbreak. In the second intervention, implemented on the 150th day, a reduction factor of 0.3 was added, further decreasing the  $R_0$  to 0.48. This subsequent intervention aimed to reinforce the control measures, ensuring that the transmission rate remained below the threshold necessary for the outbreak to sustain itself. By adjusting both the timing and intensity of these interventions, the model provides insight into the potential effectiveness of public health measures in mitigating the spread of Ebola.

#### ***3.3.1 Implementation of Intervention***

The intervention is incorporated into the model by modifying the daily scaling factor for  $R_0$ . The scaling factor ( $R_0\text{PerDay}$ ) is adjusted to account for the reduction in transmission rates starting from the intervention day. Specifically, the scaling factor is multiplied by

1 – reduction factor from the intervention start day onward.

### 3.4 Model Execution

To simulate the transmission dynamics of the 2022 Sudan virus disease (SVD) outbreak in Uganda, the model was executed over 222 stochastic realizations. This ensemble approach captures the intrinsic randomness in disease spread and reflects the variability inherent in real-world epidemics. Each realization simulates an independent outbreak trajectory, accounting for random fluctuations in transmission events, contact structures, and individual-level outcomes. This multiplicity of simulations enhances the robustness of the model outputs, allowing for the estimation of central tendencies (e.g., mean incidence) and the construction of confidence intervals to quantify uncertainty.

During each realization, the model records the progression of every individual through key epidemiological states: exposed, infectious, and refractory (recovered or immune). These time-stamped transitions enable a detailed reconstruction of the outbreak curve, identifying the timing and magnitude of infection peaks, the duration of infectious periods, and the cumulative case counts over time. This fine-grained tracking forms the basis for downstream analyses, including comparisons with observed epidemic data and evaluations of intervention effectiveness. Parameterization of the model was informed by a combination of empirical data, published literature, and domain-specific assumptions. Core parameters—such as the basic reproduction number ( $R_0$ ), transmission reduction factors, household size, and community structure—were carefully selected to reflect the epidemiological context of the Ugandan

outbreak. The recovery rate, contact dynamics within and between households, and the timing of interventions were all incorporated to replicate realistic disease behavior. Where empirical estimates were unavailable, plausible values were adopted and thoroughly justified through references to similar outbreaks.

To further enhance model credibility, a sensitivity analysis was performed to examine the influence of key parameters on simulation outcomes. This process involved systematically varying individual parameters—such as the proportion of household transmission or the timing and intensity of interventions—and observing their effect on key response variables, including peak incidence and total case count. Sensitivity results were used to identify parameters that had the most significant impact on model behavior, thereby guiding prioritization in public health decision-making. In addition to internal validation, external validation was conducted by comparing model-generated epidemic curves to actual reported data from the 2022 Uganda outbreak. The alignment between observed and simulated data provided evidence of the model’s predictive accuracy and its capacity to reproduce real-world trends. The 95% confidence intervals, constructed across all realizations, offered a meaningful measure of uncertainty while reinforcing the model’s reliability.

Through this rigorous modeling framework—encompassing stochastic simulation, parameter calibration, sensitivity analysis, and empirical validation—the model serves as a powerful tool for exploring the transmission dynamics of Ebola virus disease. Its outputs support the design and evaluation of targeted intervention strategies, offering valuable insights for epidemic preparedness, resource allocation, and public health response planning.

### 3.5 Results

The observed epidemic curve was overlaid with the simulated curve to assess the model's performance. The figure included observed daily confirmed cases derived directly from the dataset.

In this study, we analyzed the transmission dynamics of the 2022 Sudan virus disease outbreak in Uganda using a household-community model and an SEIR framework. Our simulations examined different intervention strategies and their effects on the epidemic trajectory. The first simulation considered a baseline scenario with no intervention measures, assuming a constant reproduction number ( $R_0$ ) of 1.6. The results showed that, in the absence of intervention, the average daily cases continued to increase throughout the simulation, reflecting sustained transmission within the population. This finding aligns with theoretical expectations, as an uncontrolled outbreak allows the virus to spread freely, leading to an exponential increase in cases. To evaluate the impact of intervention strategies, we introduced a 50% reduction in transmission and observed a notable decline in average daily cases compared to the no-intervention scenario.

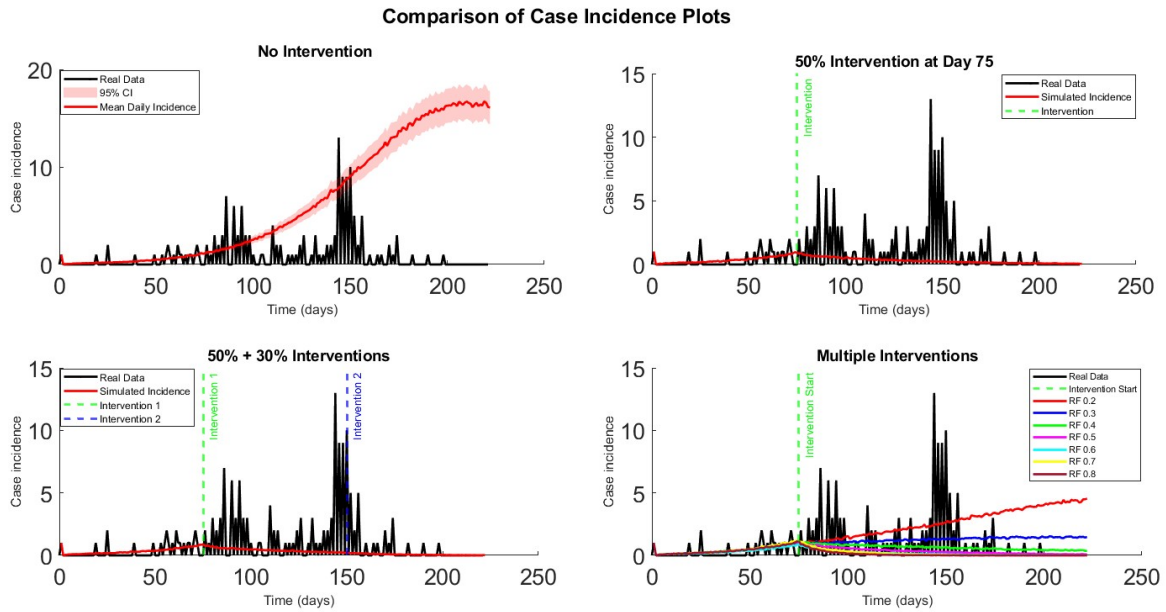


Figure 3.1 The panels illustrate the impact of varying intervention strategies on the transmission dynamics of the 2022 Sudan virus disease outbreak in Uganda. The first plot Displays the baseline model calibration with error bars representing 95% confidence intervals, highlighting the severity of an unmitigated outbreak as it spreads through the population. The second plot Depicts the initial intervention impact, where a 50% reduction in transmission significantly alters the epidemic trajectory, leading to a decline in daily case numbers. The third plot Demonstrates the cumulative effect of layered interventions, where an additional 30% transmission reduction after 150 days further suppresses outbreak propagation. The last plot shows the impact of varying reduction factors on case incidence. The colored lines represent scenarios with reduction factors ranging from 0.2 to 0.8. Stronger interventions (higher reduction factors) result in lower case incidence. These results emphasize the importance of early, sustained, and multi-layered interventions in minimizing disease burden and preventing widespread transmission.

The household-community model further provided critical insights into the nature of transmission within and between households. The results showed that household transmission played a dominant role in the early stages of the outbreak, with most infections occurring among family members due to close contact. As the outbreak progressed, community-wide transmission became more prominent, driving larger outbreaks across districts. These find-

ings highlight the importance of household-level interventions, such as isolation and targeted contact tracing, as complementary measures to broader public health interventions like lockdowns and movement restrictions. The effectiveness of these strategies in reducing transmission underscores the need for a multi-layered approach to outbreak response, where both community-wide and household-targeted interventions work together to mitigate disease spread. The simulation results reinforce the vital role of interventions in epidemic control. Early and well-implemented interventions can prevent exponential outbreak growth, significantly lowering case numbers and reducing strain on healthcare systems. Higher levels of intervention, particularly transmission reductions of 60% and above, were shown to be significantly more effective in containing the outbreak compared to moderate reductions. The findings also emphasize the importance of prolonged interventions; while short-term measures such as 1–3 weeks of lockdowns helped slow transmission, they were less effective in fully containing the outbreak compared to extended interventions lasting 4–6 weeks. Additionally, the household-community transmission model underscores the importance of addressing household transmission in outbreak response plans, as household-based infections are often the first to drive community-wide spread.

These results have significant public health implications. They demonstrate that strategic intervention planning can greatly influence the trajectory of an epidemic, offering evidence-based guidance for policymakers and public health officials. The findings suggest that rapid and aggressive control measures, combined with household-targeted interventions, can lead to substantial reductions in transmission. Furthermore, the study highlights the necessity

of data-driven decision-making in epidemic response, emphasizing that adaptive strategies based on real-time outbreak data can optimize intervention effectiveness. By leveraging real-world outbreak data and advanced modeling techniques, this study provides a framework for designing optimal intervention strategies that can be adapted to future outbreaks of Sudan virus disease or similar infectious diseases. The results confirm that interventions play a crucial role in epidemic containment. Without intervention, Ebola cases rise exponentially, whereas progressive reductions in transmission significantly slow disease spread. Moving forward, our modeling approach can serve as a framework for evaluating future epidemic control strategies, ensuring data-driven decision-making for global health preparedness.

## CHAPTER 4

### Ebola Virus Response Overview

The 2022 Ebola virus disease (EVD) outbreak in Uganda prompted a swift and coordinated public health response, despite the complex challenges presented by the Sudan virus strain, for which no licensed vaccine was available at the time. The outbreak, which began in Mubende District, demanded urgent national and international action to contain transmission, treat affected individuals, and mitigate wider societal impact. This section presents a comprehensive overview of the key components of Uganda’s epidemic response, highlighting its strengths, limitations, and lessons for future outbreaks.

Upon confirmation of the first case, the Ugandan Ministry of Health activated its national response framework, leveraging early warning surveillance systems and data reporting protocols. This rapid mobilization allowed for the timely deployment of response teams, field epidemiologists, and logistics personnel to the epicenter of the outbreak. Daily situational updates ensured transparent communication and real-time decision-making, enabling national stakeholders and international partners—such as the World Health Organization (WHO), the Centers for Disease Control and Prevention (CDC), and Médecins Sans Frontières (MSF)—to align their efforts efficiently Practice et al. (1996). One of the core pillars of the response strategy was the establishment of Ebola Treatment Units (ETUs) in affected districts. These isolation and care centers were essential for both patient management and infection control. Staffed by Ugandan healthcare workers and supplemented by international specialists, these units prioritized not only clinical care—such as rehydration and symptom management—but

also stringent infection prevention and control (IPC) measures to protect frontline workers and limit nosocomial transmission.

Another vital component of the outbreak response was contact tracing. Surveillance teams were deployed to identify, list, and monitor individuals who had been in contact with confirmed cases. These contacts were observed for the duration of the virus's incubation period (21 days), and any signs of illness triggered immediate isolation and testing. This effort was instrumental in interrupting transmission chains. However, the effectiveness of contact tracing depended heavily on community cooperation, which varied across districts due to social, cultural, and logistical factors. To address community resistance and build trust, extensive public health education campaigns were rolled out Inhorn & Brown (2013). These campaigns provided critical information on the nature of Ebola, its transmission routes, and preventive practices. Engagement with religious leaders, local councils, and community elders helped improve compliance with health directives and combat misinformation. Culturally appropriate messaging, disseminated via radio broadcasts, posters, and mobile loudspeakers, was crucial in fostering public participation in containment efforts.

Despite the comprehensive scope of the response, several challenges emerged. Health infrastructure limitations, particularly in remote and rural regions, hampered timely diagnosis, treatment, and transport. In some areas, lack of electricity, clean water, and adequate medical supplies constrained the quality of care and heightened the risk of transmission. Furthermore, community mistrust—rooted in historical grievances, fear, and stigma—hindered the effectiveness of interventions such as quarantine, safe burial practices, and contact trac-

ing. International support played a significant role in enhancing Uganda's outbreak response (Geiger et al. (2020)). Beyond material aid and technical expertise, global research collaborations contributed to better understanding of the virus's transmission dynamics and the effectiveness of different interventions. This knowledge was integrated into mathematical models that informed decision-making during the evolving outbreak. Ultimately, the 2022 response marked a step forward in Uganda's epidemic preparedness compared to past outbreaks. The rapid deployment of coordinated resources, effective isolation measures, and the integration of surveillance and risk communication demonstrated meaningful progress. Nevertheless, the experience also underscored areas for improvement, particularly in developing infrastructure, expanding health workforce capacity, and ensuring vaccine development for non-Zaire Ebola strains.

Going forward, sustainable investments in public health systems, locally driven epidemic response strategies, and vaccine research for neglected strains like the Sudan virus will be critical. The 2022 outbreak serves not only as a case study in emergency response but also as a call to action for strengthening the foundations of epidemic resilience at both national and global levels.

#### **4.1 Government Response and Lockdown**

The government response to the Ebola outbreak in Uganda in 2022 included several key measures, particularly the implementation of a lockdown in the most affected districts. The Ugandan government officially declared the Ebola outbreak on September 20, 2022, following

the identification of cases in the Mubende and Kassandra districts. A three-week lockdown was imposed starting on October 16, 2022, in these two districts to limit movement and reduce the spread of the virus. This lockdown was extended for an additional three weeks on November 5, 2022, indicating ongoing concerns about the outbreak and the need for continued containment efforts. Alongside the lockdown, the government likely implemented various public health interventions, including enhanced surveillance and contact tracing to identify and isolate cases, public awareness campaigns to educate the community about Ebola transmission and prevention measures, and support for healthcare facilities to manage and treat Ebola cases effectively. Recognizing the importance of community engagement, the government involved community leaders, health teams, and volunteers in the response efforts, educating the public about the disease, promoting safe burial practices, and encouraging individuals to seek medical care when symptomatic. The response faced challenges, including sociocultural barriers that deterred individuals from seeking clinical care due to rumors and misconceptions about the healthcare system, and the movement of individuals across district borders, which complicated containment efforts during the lockdown. These findings highlighted the need to strengthen the health system for epidemic preparedness and to learn from past epidemics to improve future responses.

#### **4.2 Effectiveness of the Lockdown**

In the early weeks of the lockdown (1-3 weeks), there was an increase in both Ebola incidence and mortality at the national level and specifically in Kassandra district, while Mubende dis-

district experienced a decline in incidence and stagnation in mortality during this period. This initial increase in cases and deaths suggests that the lockdown did not have an immediate effect on controlling the outbreak, which may be attributed to factors such as non-compliance with lockdown measures and sociocultural barriers that prevented individuals from seeking care. After extending the lockdown to six weeks, the study found that Ebola incidence and mortality during the 4-6 week lockdown period declined compared to the pre-lockdown period, indicating that the extended lockdown may have had a more significant impact on controlling the outbreak. However, the overall case fatality rates (CFRs) remained comparable between the pre-lockdown and lockdown phases, suggesting that while the lockdown may have helped reduce new cases over time, it did not significantly alter the mortality rate during the initial phases. The effectiveness of the lockdown was hindered by several factors, including individuals flouting lockdown measures by traveling to other districts, sociocultural barriers deterring individuals from seeking clinical care, and the use of home-based isolation for contacts, which may have exposed more individuals to the virus if not properly supervised. The study emphasizes the importance of relying on known public health measures to control an Ebola outbreak and the need for community engagement in education, contact tracing, isolation, and safe burial practices. It highlights the necessity of strengthening health systems for better epidemic preparedness and response in the future.

The effectiveness of the lockdown measures and targeted interventions in controlling the Ebola outbreak demonstrated varying impacts on disease transmission. Initially, during the pre-lockdown period, the average number of Ebola cases was 36, establishing a baseline

for comparison. A short-term lockdown (1-3 weeks) led to a slight increase in cases to 44, suggesting that its immediate impact was limited. This modest increase could be attributed to factors such as delays in enforcement, incomplete compliance, or insufficient time for observable effects. In contrast, extending the lockdown to a longer duration of 4-6 weeks resulted in a significant decrease in the average number of cases to 4.6. This substantial reduction indicates that longer lockdowns are more effective in disrupting transmission chains and controlling the outbreak. Comparing this to targeted interventions, which aimed to progressively reduce the transmission rate  $\beta(t)$ , showed that an initial 50% reduction from day 75 to 150, followed by an additional 30% reduction from day 150 on-wards, resulted in an overall transmission rate of 80% of the original. This progressive reduction in transmission rates led to a quicker decline in case numbers, potentially more effective than short-term lockdowns. The findings highlight that while extended lockdowns can significantly reduce the number of cases, targeted interventions that gradually reduce transmission rates can achieve comparable or greater reductions. This underscores the importance of adaptable and timely interventions in managing Ebola outbreaks, suggesting that a combination of targeted strategies with or as an alternative to extended lockdowns could be particularly effective in controlling disease spread and minimizing public health impact.

## CHAPTER 5

### Discussion And Conclusion

#### *5.0.1 Discussion*

The 2022 Ebola virus disease (EVD) outbreak in Uganda, driven by the Sudan virus strain, presented critical public health challenges that necessitated adaptive, evidence-based interventions in the absence of a licensed vaccine. Through the application of a time-varying SEIR model within a household-community framework, this study provides valuable insights into the outbreak's transmission dynamics and evaluates the effectiveness of layered intervention strategies.

A key strength of the modeling framework employed is its integration of smooth, time-dependent transitions in the transmission rate  $\beta(t)$  to simulate real-world behavioral and policy-driven changes. Unlike abrupt-step function approaches, this method more accurately captures the lag in compliance, staggered implementation, and gradual uptake of public health interventions. The simulation revealed that early intervention phases (1–3 weeks post-lockdown) coincided with a paradoxical rise in reported cases, which may reflect a combination of delayed behavioral responses, increased testing, and continued community transmission from undetected cases. However, the sustained lockdown implemented in weeks 4–6 proved to be a critical inflection point in curbing transmission, substantially reducing both the effective reproduction number  $R_0$  and overall case incidence. The simulations further demonstrated that the timing and intensity of interventions are pivotal to outbreak control. A short-term, moderate-intensity lockdown alone produced minimal impact, whereas

extended interventions significantly suppressed transmission, with  $R_0$  declining from 1.6 (baseline) to below 0.5. Similarly, the sequential application of targeted transmission reductions—modeled as 50% and then 30% reductions at days 75 and 150, respectively—yielded epidemic trajectories that closely mirrored the observed case data. These findings suggest that appropriately timed and layered interventions may rival, or even surpass, the impact of prolonged lockdowns, offering strategic flexibility in outbreak response planning.

Importantly, the household-community transmission model uncovered granular insights into the structure of transmission networks. It revealed that intra-household transmission was a dominant early driver of case proliferation. This underscores the role of family-based interactions and caregiving practices in sustaining transmission, especially in regions where social structures emphasize close contact. As the outbreak progressed, the simulations illustrated a shift toward inter-household (community-level) transmission, highlighting the necessity of broad-based interventions to supplement household-level containment strategies.

The stochastic nature of the model—executed over 222 realizations—allowed for an exploration of uncertainty in transmission pathways and intervention outcomes. The model’s robustness was reinforced by sensitivity analyses and external validation against real epidemic curves. Together, these elements provided confidence in the model’s ability to simulate realistic outbreak scenarios and inform optimal response strategies. Ultimately, this study advances the understanding of how timing, duration, and intensity of public health measures interact with social structure and transmission dynamics. It also highlights the importance of blending empirical surveillance data with mathematical modeling to support

real-time decision-making during outbreaks.

### ***5.0.2 Conclusion***

The findings from this study reinforce the critical importance of early, sustained, and well-calibrated public health interventions in managing Ebola virus outbreaks, especially in contexts where pharmaceutical tools remain limited. The 2022 Sudan virus outbreak in Uganda presented unique challenges due to the lack of a licensed vaccine, sociocultural resistance to clinical care, and logistical constraints in rural districts. Despite these hurdles, the deployment of non-pharmaceutical interventions—lockdowns, isolation units, contact tracing, and risk communication campaigns—proved effective in reducing transmission and flattening the epidemic curve. The use of a household-community SEIR model with time-varying transmission rates provided a nuanced lens to examine the outbreak. By simulating different intervention strategies, the study identified that layered and progressively intensified interventions, initiated at strategic time points, can dramatically suppress viral spread. Specifically, combining lockdowns with transmission rate reductions yielded more favorable outcomes than either strategy in isolation.

These results have significant policy implications. First, they affirm that prolonged and adaptive interventions are more impactful than short-term or reactive measures. Second, they demonstrate that models incorporating household-community structures can uncover transmission patterns that inform tailored control strategies. Third, they emphasize the value of incorporating stochastic simulations and sensitivity analyses into epidemic modeling to account for uncertainty and improve the reliability of forecasts. As the global

community continues to face recurring threats from emerging infectious diseases, the lessons learned from Uganda's 2022 Ebola response must inform future preparedness efforts. Investing in surveillance systems, flexible response mechanisms, and context-sensitive modeling approaches will be essential in mitigating future outbreaks. This study contributes to that broader vision by offering a data-driven, model-informed perspective on outbreak dynamics and public health impact—one that can be adapted and extended to similar epidemic threats in resource-constrained settings.

## Appendices

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