PLOS Complex Systems

RESEARCH ARTICLE

Integrating epidemiological and economic dynamics to assess Rift Valley fever vaccination strategies: A system dynamics model from Kenya

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OPEN ACCESS

Citation: Bahta S, Wanyoike F, Bett B, Rich KM (2026) Integrating epidemiological and economic dynamics to assess Rift Valley fever vaccination strategies: A system dynamics model from Kenya. PLOS Complex Syst 3(6): e0000101. https://doi.org/10.1371/journal.pcsy.0000101

Editor: Alexander Petersen, University of California Merced, UNITED STATES OF AMERICA

Received: August 20, 2025

Accepted: March 18, 2026

Published: June 11, 2026

Data availability statement: All data used in this study are derived from a combination of primary household survey data collected in Ijara County, Kenya, and secondary sources including published literature and publicly

Abstract

Livestock diseases such as Rift Valley Fever (RVF) present systemic threats to animal health, rural livelihoods, and national economies in endemic regions. However, conventional impact assessments often fail to capture the nonlinear feedbacks, time lags, and cross-sectoral interactions involved. This study develops a dynamic, multi-component system dynamics (SD) model to simulate the Epidemiological and Economic impacts of RVF outbreaks in Ijara County, Kenya, under alternative vaccination strategies. The model integrates biologically detailed Susceptible Exposed Infectious (SEI) dynamics for *Aedes* and *Culex* mosquito vectors, Susceptible Exposed Infectious Recovered (SEIR) livestock infection dynamics, herd demography, and end-market processes, incorporating demand-side shocks and behavioral feedback. Using a 10-year simulation with a daily time-step, parameterized with primary and secondary data, including El Niño associated rainfall patterns and producer survey results, the model reproduces key outbreak features consistent with historical RVF events and enables ex-ante comparison of policy responses. Findings indicate that the business-as-usual (BAU) strategy, involving delayed reactionary vaccination, yields only marginal improvements in herd recovery and producer income relative to no intervention. In contrast, annual preventive vaccination with sufficient coverage of susceptible animals prevents simulated outbreaks within the model horizon, while biannual and triennial strategies reduce outbreak severity but do not fully eliminate risk. Shortening the delay between outbreak onset and vaccination initiation substantially reduces livestock losses and improves income recovery trajectories. These results highlight the value of system dynamics modeling for evaluating intervention strategies under uncertainty. The model offers a decision-support tool for livestock health policy, demonstrating that proactive vaccination and rapid response outperform delayed, reactive approaches in both disease control and economic resilience in RVF-prone pastoral systems.

available datasets. Aggregated data and parameter values used in the model are reported in the manuscript and supplementary materials.

Funding: The author(s) received no specific funding for this work.

Competing interests: The authors have declared that no competing interests exist.

Author summary

Rift Valley fever (RVF) is a mosquito-borne disease that causes substantial losses to livestock producers in East Africa and poses risks to human health. While vaccination is an effective control measure, its economic benefits depend critically on timing, coverage, and implementation strategy. In this study, we develop a system dynamics model that integrates RVF transmission, cattle herd demography, livestock markets, and producer income to assess the impacts of alternative vaccination strategies in Ijara County, Kenya, a region with recurrent RVF outbreaks. Using simulated outbreak scenarios, we compare BAU reactive vaccination, regular preventive vaccination programs, and improved response timing. The results show that delayed, reactive vaccination yields limited economic benefits, whereas preventive vaccination and rapid response substantially reduce livestock losses, stabilize incomes, and shorten recovery periods. By explicitly linking disease dynamics and economic outcomes, the model provides a decision-support tool for evaluating RVF control strategies and highlights the importance of proactive vaccination in enhancing livestock-based livelihoods in RVF-prone pastoral systems.

1. Introduction

Livestock diseases constitute one of the most significant constraints to realizing the full potential of livestock systems as a pathway out of poverty for millions of smallholder producers and value chain actors across developing countries. These diseases adversely affect productivity, market access, and asset security, particularly in arid and semi-arid regions where livestock are central to household welfare. Rigorous assessments of their economic impacts are essential for setting priorities and guiding efficient allocation of scarce veterinary and public health resources [1].

Rich and Hamza [2] emphasize that traditional impact studies often overlook the multiple functions livestock serve, ranging from food and income to draught power and social capital. Beyond direct losses in animal health and productivity, disease outbreaks cause ripple effects across value chains, affecting traders, processors, consumers, and public institutions. Zoonotic and transboundary diseases like RVF have especially wide-ranging impacts, influencing trade, public health, and national economies.

To better understand RVF, researchers have employed various modeling approaches. For instance, Gachohi et al. [3] developed a compartmental SEIR (Susceptible–Exposed–Infected–Recovered) model to explore RVF transmission dynamics between livestock and mosquitoes, focusing on the impact of temperature variations. In contrast, Tennant et al. [4] used a spatially explicit metapopulation model to examine how ecological connectivity and landscape heterogeneity influence RVF persistence across island regions. More recently, Sulaimon et al. [5] applied a network-based modeling approach to assess how imperfect livestock movement data can still guide effective targeted vaccination strategies. These models are powerful in elucidating epidemiological patterns and environmental drivers but often treat economic consequences as external outcomes rather than as integral system feedbacks.

To address these gaps, Rich and Hamza advocate the use of systems-based approaches such as system dynamics (SD) modeling. SD models enable the simulation of feedback relationships, time lags, and behavioral adaptations over time. They support scenario-based evaluation of interventions, making them well-suited for ex-ante policy assessment in complex systems.

Our study builds directly on this methodology and addresses the limitations of the epidemiological models by employing a System Dynamics (SD) methodology that allows for the endogenous coupling of epidemiological processes (vector-host SEIR/SEI dynamics), livestock herd demographics, and local market economics. The novelty of this work lies in the explicit integration of these three components into a single, comprehensive framework that captures the complex, non-linear feedbacks characteristic of RVF outbreaks. Furthermore, this modeling framework extends earlier working paper concepts developed at the International Livestock Research Institute (ILRI) by rigorously validating the model against historical outbreak data (the 2006/2007 El Niño-associated epidemic) and transforming the approach into a generalizable, validated tool for scenario analysis.

Despite decades of research, a clear research gap remains in providing policy-makers with a robust, integrated tool that quantifies the trade-offs between proactive and reactive RVF interventions, accounting for both public health and economic outcomes. The primary objective of this study is therefore to develop a validated System Dynamics model to evaluate the long-term economic efficacy and disease control thresholds of various vaccination strategies in Ijara County, Kenya, thereby providing evidence-based guidance for regional RVF preparedness and policy.

Rift Valley fever virus (RVFV) transmission is fundamentally driven by mosquito vectors, with *Aedes and Culex* genera playing distinct and complementary epidemiological roles in endemic regions of East Africa. Primary RVFV maintenance occurs through *Aedes* mosquitoes, which are capable of transovarial transmission, allowing infected females to lay eggs that retain the virus across dry seasons. These infected eggs can hatch following periods of heavy rainfall, triggering sudden amplification of infectious adult mosquito populations and initiating outbreaks among susceptible livestock. *Culex* mosquitoes, in contrast, do not transmit the virus vertically but act as highly efficient secondary amplifiers, becoming infected through feeding on viremic animals and rapidly increasing transmission intensity once an outbreak has begun [6,7].

This vector-driven ecology creates a strong linkage between climatic conditions, particularly anomalous rainfall events such as those associated with El Niño, and RVF emergence. Because infection risk depends not only on livestock density but also on vector population dynamics, infection status, and biting behavior, explicitly modeling mosquito populations is essential to capture the nonlinear feedbacks, time delays, and threshold effects that characterize RVF outbreaks. Models that omit vector dynamics or treat transmission as exogenous shocks risk underestimating outbreak timing, intensity, and persistence. For these reasons, the present study explicitly represents mosquito population and infection dynamics as endogenous components of the system, allowing rainfall-driven vector emergence, vector–host transmission, and subsequent economic impacts to co-evolve within a unified modeling framework.

2. Methodology

2.1. Overview of the system dynamics model

To assess the Epidemiological and Economic impacts of Rift Valley Fever (RVF) in Ijara County, a dynamic simulation model was developed using a system dynamics (SD) approach. The model integrates biological transmission mechanisms, herd demographic processes, and livestock market dynamics within a single time-evolving framework. Built using the STELLA modeling platform, the simulation runs with a daily time step over a ten-year horizon (3,650 days), allowing for the analysis of both disease progression and economic consequences.

The ten-year simulation horizon was chosen to capture both the immediate impacts of an RVF outbreak, such as mortality shocks and short-term market disruptions, and the longer-term recovery dynamics of livestock herds. These recovery processes include natural herd growth through births and maturation, as well as gradual stabilization of livestock markets and producer income following a major disease event.

The model consists of two interconnected domains (Fig 1) that jointly represent the biological and economic dimensions of RVF outbreaks.

Epidemiological domain: This domain represents RVF transmission dynamics and includes mosquito vector dynamics (*Aedes* and *Culex*) and livestock infection dynamics.

Socioeconomic domain: This domain represents livestock production and economic responses, including herd demographic processes and livestock market dynamics.

Interactions between these domains allow the model to simulate how RVF outbreaks influence herd size, livestock sales, market prices, and producer income over time.

2.2. Model architecture and core modules

Building on the two-domain structure described above, the system dynamics model is organized into three integrated modules that capture the key biological and economic processes of RVF.

2.2.1. Epidemiological module. This module captures the dynamics of mosquito vector populations (*Aedes* and *Culex*) and their interactions with livestock infection processes. The structure is based on the RVF transmission model of Lo Iacono et al. [6].

2.2.3. Herd dynamics module. This module represents livestock demographic processes and is based on the DynMod herd modeling framework developed by Lesnoff et al. [8]. It tracks age- and sex-specific population flows, including births, natural mortality, and RVF-induced mortality.

2.2.3. Market and income module. This module represents livestock market dynamics and economic outcomes. It is based on the supply and demand framework of Whelan and Msefer [9] and simulates animal sales, price formation, and producer income under different outbreak and vaccination scenarios.

Fig 2 illustrates the schematic structure of the livestock infection dynamics module, showing the SEIR framework and the transmission pathways between vectors and livestock. Detailed diagrams of the model components are provided in the appendix (see S1 Fig). The following sections describe the main epidemiological and economic components of the model in greater detail.

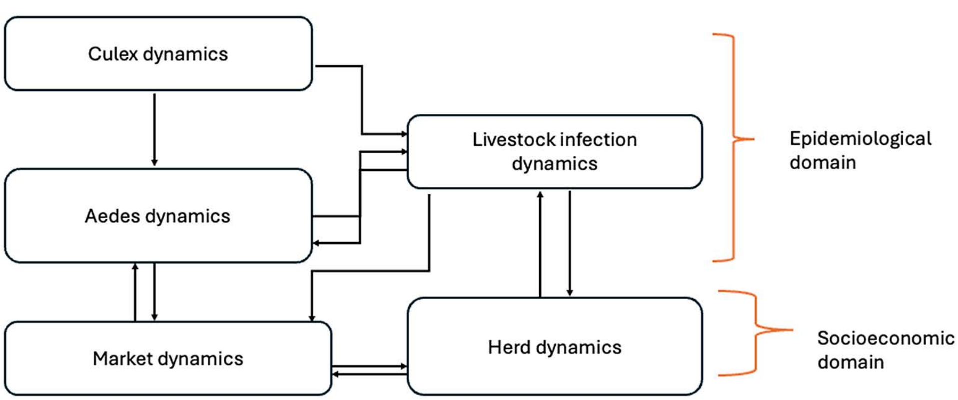

Fig 1. Conceptual structure of the integrated system dynamics model of Rift Valley fever (RVF).

https://doi.org/10.1371/journal.pcsy.0000101.g001

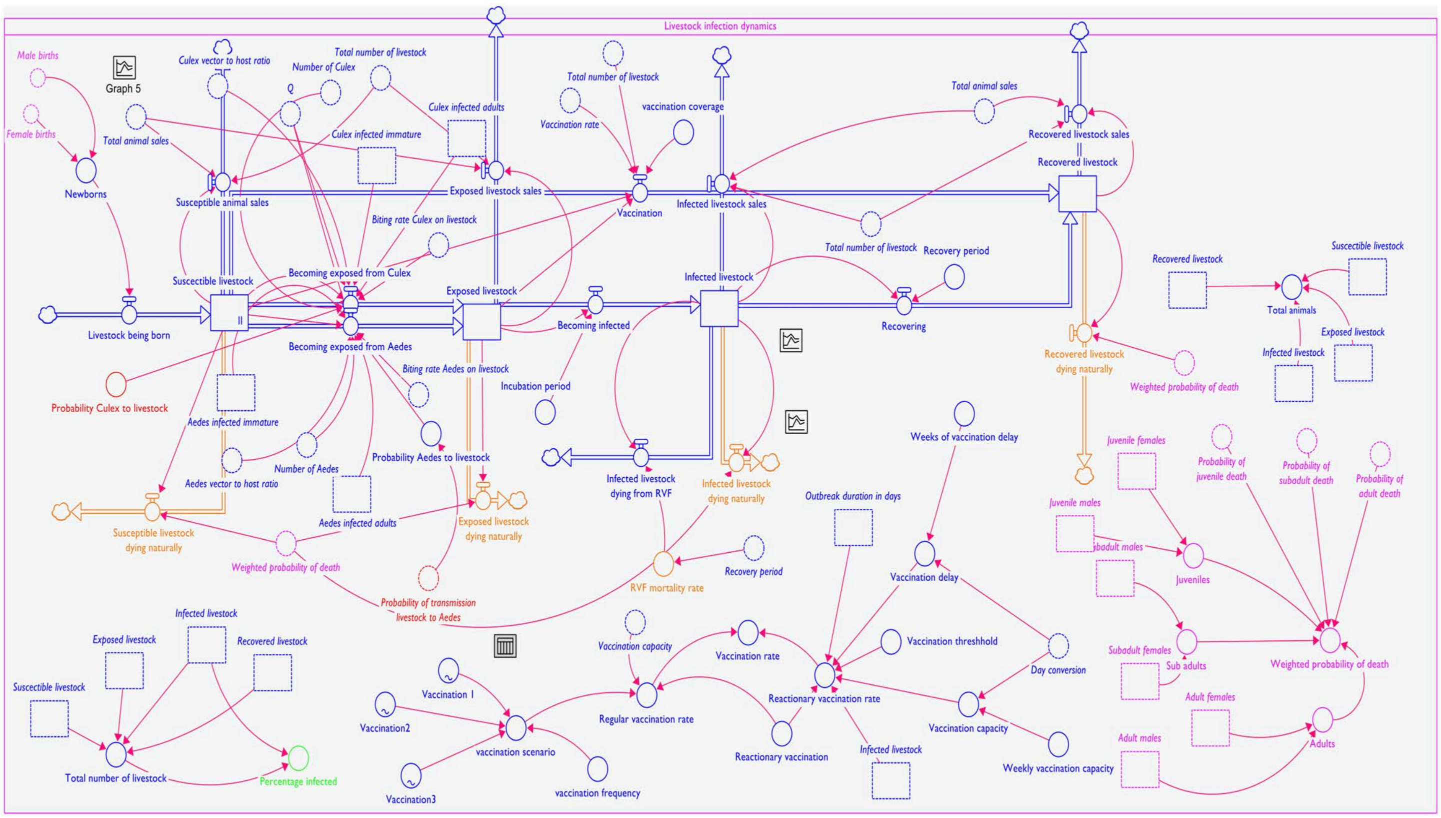

Fig 2. Schematic representation of the livestock infection dynamics module, illustrating the susceptible–exposed–infectious–recovered (SEIR) structure, vector-to-host transmission pathways, vaccination processes, and herd demographic flows.

https://doi.org/10.1371/journal.pcsy.0000101.g002

2.3. Epidemiological structure

2.3.1. Mosquito vector dynamics. The model includes two mosquito genera, mosquito vectors, *Aedes* and *Culex*, that are known to be the primary vectors of Rift Valley Fever Virus (RVFV) in East Africa. Each genus is modeled with its own population structure and infection dynamics to reflect their distinct ecological roles and disease transmission pathways [6,7].

Aedes Mosquitoes are modeled with a complete life cycle that includes eggs, larvae, pupae, and adults. They are unique in their ability to transmit RVFV transovarially, meaning infected adult females lay eggs that can hatch into infected adults following rainfall events. This transovarial mechanism allows the virus to persist in the environment during inter-epidemic periods (see S2 Fig).

The development of *Aedes* through pre-adult stages is represented using aging chain dynamics. The transition between stages i is modeled as:

$$\frac{dS_i}{dt} = \propto_{i-1} .S_{i-1} - \left(\propto_i + \mu_i\right) .S_i$$

where:

- S_i: Population in stage i
- α_i: Transition rate to the next stage
- μ_i: Mortality rate in stage i

The infection dynamics for adult *Aedes* mosquitoes follow an SEI structure, defined as:

$$\frac{dS_\nu}{dt} = b_\upsilon E_\upsilon - \lambda_\upsilon S_\upsilon - \mu_\upsilon S_\upsilon$$

$$\frac{dE_\upsilon}{dt} = b_\upsilon E_\upsilon - \sigma_\upsilon E_\upsilon - \mu_\upsilon E_\upsilon$$

$$\frac{dI_\upsilon}{dt} = \sigma_\upsilon E_\upsilon - \alpha_E E^I - \mu_\upsilon I_\upsilon$$

where:

b_υ: Recruitment rate of adults from pupae

λ_υ: Force of infection from livestock to vector

σ_υ: Extrinsic incubation rate, i.e., the rate at which exposed mosquitoes become infectious

μ_υ: natural Mortality rate of adult mosquitos

E^I: Infected egg population

α_E: Egg hatching rate of infected eggs into infectious adults

S_υ: Number of susceptible adult mosquitoes

E_υ Number of exposed (infected but not yet infectious) adult mosquitoes

I_υ: Number of infectious adult mosquitoes

Culex mosquitoes do not transmit RVFV vertically. Their breeding is strongly influenced by surface water availability, making their population size responsive to rainfall. They become infected through horizontal transmission when feeding on viremic livestock (see S3 Fig). The force of infection from livestock to mosquitoes is modeled as:

$$\lambda_\upsilon = b.\beta_{\upsilon h}.\frac{I_h}{N_h} \tag{2}$$

Where:

- b: biting rate,
- $\beta_{\upsilon h}$: transmission probability from host to vector,
- I_h: number of infectious cattle,
- N_h: total cattle population

Rainfall is used in the model to trigger emergence of both genera, simulating outbreaks consistent with historical events such as the 2006 El Niño episode.

2.3.2. Livestock infection dynamics (SEIR). As illustrated in Fig 2, the transmission dynamics in livestock are modeled using a SEIR framework. The stock of susceptible animals increases through calf births and decreases as animals become exposed to the virus through mosquito bites (from both Culex and Aedes species) or die from other causes.

The rate at which susceptible animals become exposed depends on several factors, including the mosquito biting rate on livestock, the vector–host ratio, the prevalence of infection within mosquito populations, the probability of virus transmission from infected mosquitoes to livestock, and the size of the susceptible livestock population. Animals that become exposed enter a latent stage during which the virus incubates but clinical infection has not yet developed.

The transition from the exposed to the infectious state is governed by the viral incubation period. Following infection, animals either die due to RVF-induced mortality or recover after the recovery period.

Livestock are categorized as susceptible S_h, exposed E_h, infectious I_h and recovered R_h. The force of infection from mosquito vectors is:

$$\lambda_h = b.\beta_{h\upsilon}.(\frac{I_v^{Cx}}{N_v^{Cx}} + \frac{I_v^{Ae}}{N_v^{Ae}}) \tag{3}$$

Where:

- $\beta_{h\upsilon}$ transmission probability from mosquito to cattle,
- I_v^{Cx}, I_v^{Ae} infected *Culex* and *Aedes* vectors respectively.

Transition equations:

$$\frac{dS_h}{dt} = births - \lambda_h S_h - \mu S_h \tag{4}$$

$$\frac{dE_h}{dt} = \lambda_h S_h - \sigma E_h - \mu_d I_h \tag{5}$$

$$\frac{dE_h}{dt} = \sigma E_h - \gamma I_h - \mu_d I_h \tag{6}$$

$$\frac{dE_h}{dt} = \gamma I_h - \mu R_h \tag{7}$$

Where:

- σ: incubation rate,
- γ: recovery rate,
- μ: natural mortality,
- μ_d: RVF-induced mortality.

All epidemiological state variables are expressed in number of animals (head), and all transition rates are defined on a daily basis, consistent with the model's daily simulation time step.

2.4. Economic modules

2.4.1. Herd demographic dynamics. Adapted from the DynMod herd model [8], this component tracks the evolution of herd composition over time. Livestock are grouped into sex- and age-specific categories: juveniles, sub-adults, and adults. Flows between these groups occur through, births (based on parturition and prolificacy rates), maturation and aging transitions, purchases and sales and deaths due to natural causes or predation.

Animal stock $H_j$changes via:

$$\frac{dH_j}{dt} = Inflow_j - Outflow_j \tag{8}$$

Where inflows include births and purchases, and outflows include deaths, sales, and aging transitions.

All herd stocks are measured in number of animals (head), and flows are expressed in head/day.

Fractional inflow through purchases:

$$PF_j = \frac{P_j}{I_j + S_j + D_j + B_j} \pi r^2 \tag{9}$$

Where:

- P_j animals purchased,
- I_j animals held,
- S_j animals sold,
- D_j deaths (including predation),
- B_j slaughtered animals.

Parturition rate and prolificacy determine births:

$$Births = \rho * H_{adult\ females} * \pi \tag{10}$$

Where:

ρ = parturition rate,

π = prolificacy (offspring per birth).

The demographic module reflects management practices and reproductive behavior typical of pastoral systems in northeastern Kenya.

2.4.2. Market and income module. This module simulates the supply and demand for meat, linking animal offtake rates to consumer behavior and price formation. Built on the framework of Whelan and Msefer [9], it reflects:

- Demand drivers: human population (baseline 4.5 million, 4% annual growth), per capita meat consumption, and income elasticity.
- Supply-side variables: offtake volumes, carcass weights, and disease-induced constraints on market supply.
- Price adjustment: driven by supply-demand imbalances and market disruptions caused by RVF-related shocks (e.g., movement restrictions, demand suppression).

Market supply is determined by offtake volumes and carcass weights. Demand is modeled as:

$$Q_d = C.PoP.\left(\frac{P}{Po}\right)^{\varepsilon}.\left(\frac{Y}{Y_0}\right)^{\eta} \tag{11}$$

Where:

- Q_d = total meat demand (kg/day)
- C = baseline per capita consumption at the reference point (kg/person/day)
- PoP = population (persons)
- P = current meat price (USD/KG)
- P_0 = reference (baseline) meat price (USD/Kg)

- ε = price elasticity of demand
- Y = current per capita income (USD/person/day)
- Y_0 = reference (baseline) per-capita income (USD/person/day)
- η = income elasticity of demand

Price and income enter as dimensionless indices relative to baseline values (P_0, Y_0), so demand remains expressed in physical quantity units (kg/day).

Producer income is calculated as the product of carcass-weight-adjusted sales and farmgate prices.

$$Income– = \sum_j Sales_j.CarcassWeight_j.Price \tag{12}$$

$Income_t$ = total producer income at time t (USD/day);
$ISales_t$ = number of cattle sold at time t (head/day);
Carcass Weight = average carcass weight per animal (kg/head);
$Price_t$ =farmgate beef price (USD/kg)
Sales represent physical offtake volumes (number of animals sold), such that income is generated by the interaction of quantities sold and price per unit of carcass weight.
Outbreaks induce a demand shock:

$$P = P_0.(1 - \delta) \text{ during outbreak period} \tag{13}$$

Where δ = proportional reduction in meat demand during an RVF outbreak, expressed as a fraction (e.g., δ = 0.10 corresponds to a 10% reduction in demand).

During outbreak periods, the demand shock is implemented as a proportional downward shift in the demand function rather than as a direct price shock, with prices adjusting endogenously through market-clearing dynamics.

The economic module is intentionally stylized and designed to capture first-order market responses to RVF shocks rather than to reproduce detailed market equilibrium outcomes. Livestock prices adjust endogenously through supply–demand interactions, while outbreak-related demand reductions are implemented as temporary proportional shifts in demand. Producer income is calculated from physical offtake volumes and farmgate prices, ensuring that epidemiological effects (mortality, offtake) and market effects (prices) enter income through distinct channels without double counting.

All scenarios analyzed in the Results section are defined within the model structure described above, and no additional assumptions or interventions are introduced outside this framework.

2.5. Model validation and consistency checks

Model validation focused on assessing structural consistency, behavioral plausibility, and coherence with established Epidemiological and Economic knowledge rather than on statistical prediction. The livestock infection dynamics reproduce expected SEIR patterns for RVF, including rapid amplification following favorable climatic conditions, peak infection shortly after outbreak onset, and subsequent decline as susceptible animals are depleted. Herd demographic responses, including post-outbreak recovery through births and longer-term rebuilding of susceptible populations, are consistent with observed dynamics in pastoral cattle systems.

The timing of the simulated outbreak was anchored to daily rainfall data from 2006, corresponding to a documented El Niño–associated RVF epidemic in Kenya, providing an external reference for outbreak triggering. Economic outcomes generated by the model, including temporary declines in livestock sales, short-term price volatility under demand shocks, and gradual income recovery, are consistent with empirical observations and findings from previous RVF studies. Sensitivity checks on key parameters (e.g., vaccination timing, coverage levels, and demand shock magnitude) confirmed that qualitative model behavior and policy conclusions remain robust across plausible parameter ranges.

2.6. Simulation scenarios

To evaluate the epidemiological and economic impacts of RVF, simulation experiments were conducted using a ten-year time horizon. An outbreak was triggered in year six of the simulation using daily rainfall data from 2006, a year associated with a major El Niño event and widespread RVF outbreaks across Kenya, including in Ijara [6]. At the time of the simulated outbreak, the cattle population was assumed to have no pre-existing immunity to RVF. Reactionary vaccination campaigns were introduced in response to the outbreak with a four-week lag following disease detection, reflecting observed delays in vaccination response.

Two baseline scenarios were considered in the simulations: (i) a no-vaccination scenario, representing the absence of any vaccination intervention, and (ii) a business-as-usual (BAU) vaccination scenario, reflecting the current reactive vaccination practice implemented after the detection of an outbreak. In addition, three preventive vaccination strategies were evaluated: annual vaccination of susceptible animals, biannual vaccination, and vaccination once every three years. These scenarios were used to assess how different vaccination strategies influence outbreak dynamics, herd size, livestock sales, and producer earnings over the simulation horizon.

3. Data and descriptive statistics

The system dynamics model was parameterized using a combination of primary data collected through household surveys and secondary data from national statistics and scientific literature.

3.1. Primary data collection

Primary data were collected through a structured household survey conducted in 2018 covering 200 livestock-keeping households in Ijara County, Kenya. The questionnaire used for data collection is provided in S1 Questionnaire, and the dataset used for model parameterization and analysis is available in S1 Data.

The survey targeted households in the Kotile and Ijara divisions, which were purposively selected to capture heterogeneity in market access and production orientation. Kotile, located closer to major livestock markets, represents relatively market-integrated production systems, while Ijara division typifies more remote pastoral systems with limited market connectivity. Both areas have experienced repeated RVF outbreaks, including the severe 2006–2007 epidemic, making them particularly relevant for policy-oriented scenario analysis.

Households within each division were selected using purposive sampling, guided by local administrative records and community leaders, to ensure inclusion of active cattle-keeping households with recent experience of RVF-related shocks. While the sampling strategy does not aim to provide statistically representative estimates at the county or national level, it was designed to capture behaviorally and structurally relevant production systems for model parameterization.

Potential sources of sampling bias were mitigated by cross-checking key herd demographic parameters and marketing behaviors against secondary data from national statistics and published studies [10,11]. The primary data were used primarily to calibrate model parameters (e.g., herd structure, offtake rates, reproductive performance, and marketing behavior) rather than to generate population-level estimates, consistent with the objectives of system dynamics modeling.

3.2. Secondary data sources

Complementary parameters were sourced from authoritative secondary references to ensure biological, epidemiological, and economic consistency in model calibration. These included:

- National livestock census data from the Kenya National Bureau of Statistics [12],
- Epidemiological and mosquito vector parameters from Lo Iacono et al. [6] and Xue et al. [13],
- Livestock demographic rates from Otte and Chilonda [4] and Ejlertsen et al. [14],
- Economic parameters, including prices and elasticities, from ILRI & MLFD [15] and Elisabeth and Mbwika (2012).

The initial herd population for simulation was set at 352,617 cattle, based on the 2009 livestock census data for Ijara. Daily rainfall data corresponding to the 2006 El Niño event, which triggered widespread RVF outbreaks, were used to initiate outbreak dynamics within the model, providing a historically validated scenario for disease emergence.

3.3. Ethics statement

Primary data collection involving livestock producers was conducted in accordance with institutional ethical guidelines. Participation in the household survey was voluntary, and informed consent was obtained from all respondents prior to the interviews. The survey collected information on livestock production and marketing practices, and no personal identifiers are included in the dataset used for analysis.

3.4. Descriptive statistics from the survey

Table 1 presents summary statistics for key herd-level parameters derived from the primary survey. Livestock were grouped into juvenile, sub-adult, and adult age categories, with further disaggregation by sex. The reproductive performance of adult females showed a parturition rate of 0.56 and a prolificacy rate of 0.96. Reflecting localized breeding practices, no purchases of juvenile or sub-adult males were reported during the recall period.

These statistics were critical for initializing herd population structures and calibrating life-cycle transition and demographic rates in the system dynamics model.

Additional model constants (Table 2) included equal birth ratios for male and female calves, abortion rate during RVF outbreaks (assumed at 47%), and age-specific transitions: juvenile (48 weeks), sub-adult (104 weeks), and adult (up to 624 weeks for females).

Market dynamics were informed by assumptions of a 4.5 million target consumer population (Nairobi, Thika, and Mombasa urban zones), 4% annual population growth, and baseline beef prices of USD 4.20/kg. Demand elasticity was set at –1, consistent with previous livestock marketing studies in Kenya [12,16].

Table 1. Herd Composition and Key Parameters (Cattle).

Animal Category	Share of Herd	Parturition Rate	Prolificacy Rate	Purchase Rate	Death Rate	Offtake Rate
Juvenile	22%	–	0.96	0.00	0.16	0.001
Sub-adult Males	15%	–	–	0.06	0.13	0.06
Sub-adult Females	07%	–	–	0.29	0.11	0.44
Adult Males	11%	–	–	0.00	0.12	0.07
Adult Females	45%	0.56	–	0.01	0.10	0.03

https://doi.org/10.1371/journal.pcsy.0000101.t001

Table 2. Selected Constants and Parameters for Herd Dynamics.

Parameter	Value
Initial cattle population	352,617
Proportion of female births	0.50
RVF-related abortion rate	47%
Age (weeks): Juvenile	0–48
Age (weeks): Sub-adult	49–104
Age (weeks): Adult (M/F)	105–364 (M), 105–624 (F)

https://doi.org/10.1371/journal.pcsy.0000101.t002

4. Results

4.1. Baseline simulation and outbreak dynamics

Fig 3 presents the simulated dynamics of an RVF outbreak triggered by an extreme rainfall event. The upper panel shows the daily rainfall pattern used to initiate the outbreak, while the lower panel illustrates the trajectories of the susceptible, exposed, infected, recovered, and total livestock populations over the simulation period.

When the outbreak occurs, the number of susceptible animals declines rapidly as infections spread through the herd. At the same time, the number of exposed animals increases sharply, followed by a rise in the number of infectious animals after the incubation period. This progression reflects the typical epidemic transition from exposure to active infection in livestock.

Following the peak of the outbreak, the number of infected animals declines as animals either recover or die due to RVF-induced mortality. The number of recovered animals increases during this period as surviving animals acquire immunity. Consequently, the susceptible population decreases during the outbreak but gradually rebuilds over time through births.

The simulation also shows a decline in total herd size during and after the outbreak, reflecting disease-induced mortality and other demographic processes. Over the longer term, herd recovery occurs gradually as new animals enter the susceptible population through natural herd growth.

4.2. Economic impact of RVF outbreaks on producer earnings

This section presents simulation results on cattle producer earnings following RVF outbreaks under alternative demand and vaccination scenarios.

Fig 4 illustrates the projected livestock prices (USD/kg of carcass weight) under two scenarios: with and without the assumed 10% decline in demand (Runs 1 and 2, respectively). The demand reduction is introduced to represent potential market disruptions during RVF outbreaks, such as reduced consumer demand, movement restrictions, and temporary market closures. Because reliable quantitative estimates of demand reductions during RVF outbreaks are limited, the 10% reduction is used as a plausible representation of short-term market contraction during outbreak periods. When demand is reduced, the model projects greater price volatility during the outbreak period, which gradually stabilizes over time. In contrast, stable prices are projected in the scenario where demand remains unaffected.

The assumed 10% demand reduction does not influence the number of animals sold (Fig 5). However, the occurrence of an RVF outbreak, irrespective of the demand assumption, leads to a sharp, temporary decline in animal sales, followed by a rapid recovery once the outbreak subsides.

The impact of RVF on producer income reflects these combined effects on price and volume. In the absence of demand disruption, income levels mirror sales trends in the short term (Fig 6), but show a long-term upward trend as prices recover. When a 10% demand shock is assumed, income exhibits greater short-term fluctuations during the outbreak, but the overall long-term trajectory remains positive.

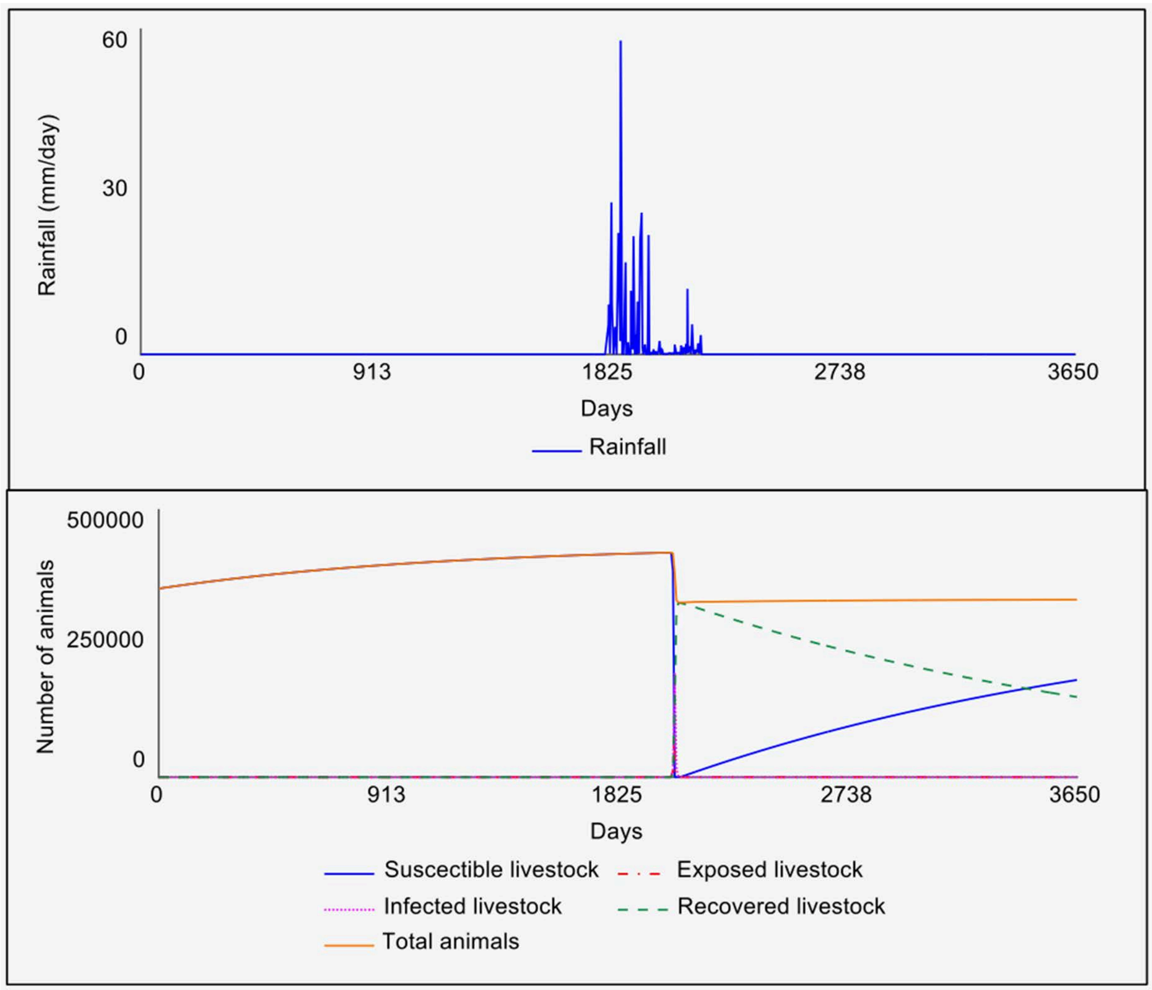

Fig 3. Simulated RVF outbreak dynamics triggered by extreme rainfall. The upper panel shows the daily rainfall series (mm/day) used in the model to trigger mosquito population increases and the onset of an RVF outbreak. The lower panel presents the simulated trajectories of susceptible, exposed, infected, recovered, and total livestock populations (number of animals, head) over the simulation period.

https://doi.org/10.1371/journal.pcsy.0000101.g003

4.3. Impacts of persistent RVF outbreaks under different vaccination strategies

This section presents an ex-ante analysis of vaccination strategies and their effects on herd dynamics, animal sales, and producer income following RVF outbreaks. The analysis begins by comparing two baseline scenarios: (i) no vaccination, representing the absence of vaccination interventions, and (ii) the business-as-usual (BAU) reactive vaccination strategy, reflecting the current practice in which vaccination is initiated approximately 3–4 weeks after outbreak detection in response to an outbreak.

In addition to the baseline comparison, two further policy scenarios are considered. The first explores routine preventive vaccination programs, designed to reduce the probability of outbreaks or limit their impacts when outbreaks occur. The second evaluates improved outbreak response timing, examining the potential benefits of shortening the delay between outbreak detection and the initiation of vaccination campaigns targeting susceptible and exposed animals.

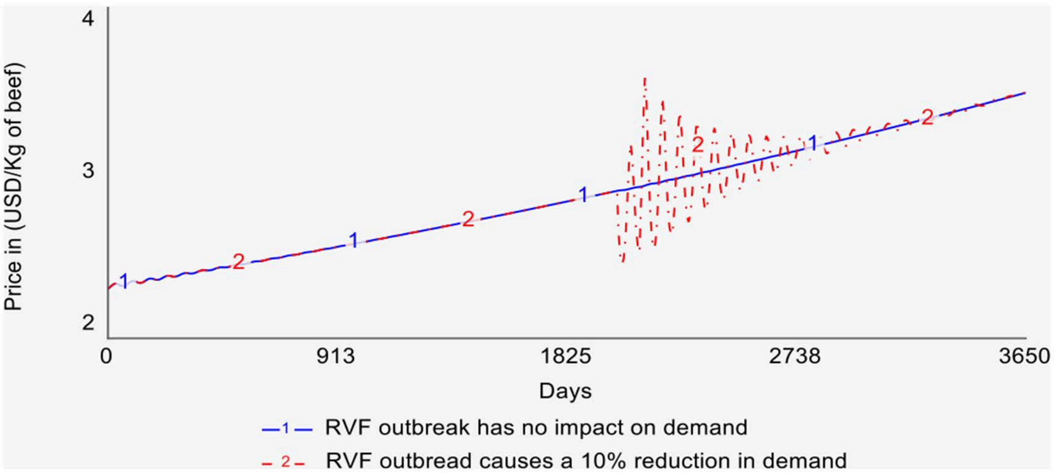

Fig 4. Simulated producer prices for cattle (USD/kg carcass weight) under RVF outbreak scenarios with and without a temporary demand shock. The Fig compares price trajectories across two simulation runs, highlighting increased price volatility during the outbreak period when demand is reduced.

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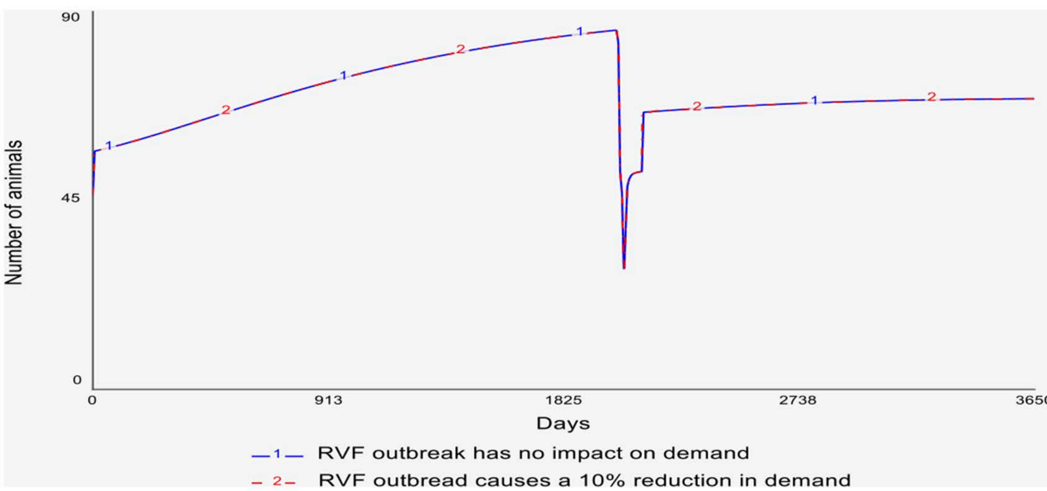

Fig 5. Total number of animals sold (head/day) over time under RVF outbreak scenarios with and without a temporary demand shock, showing a sharp but temporary decline in sales during the outbreak period followed by recovery. Run 1 = Outbreak assumed to have no impact on Demand Run 2 = Outbreak assumed to have a 10% reduction in demand.

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Across all scenarios, a vaccination trigger threshold of 200 infected animals is assumed to activate a vaccination response. In addition, a weekly vaccination capacity of 150,000 animals is assumed for the study area, reflecting plausible operational constraints for large-scale vaccination campaigns.

Figs 7 and 8 present simulation results comparing the baseline scenarios of no vaccination and the BAU reactive vaccination strategy. Fig 7 illustrates the projected number of animals sold before and after an RVF outbreak. In both scenarios, the outbreak results in a sharp temporary decline in animal sales, reflecting the immediate effects of disease-induced mortality and disruptions in livestock marketing. Animal sales gradually recover as herd dynamics stabilize and the cattle

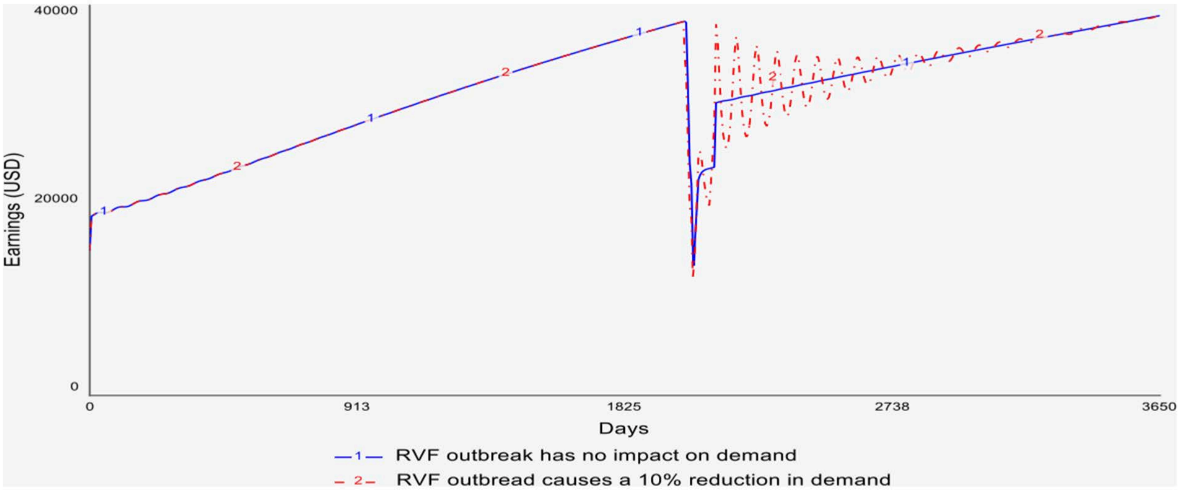

Fig 6. Producer earnings from cattle sales (USD/day) under RVF outbreak scenarios with and without a temporary demand shock, illustrating short-term income volatility during the outbreak period followed by recovery as herd size and market conditions stabilize. Run 1 = Outbreak assumed to have no impact on Demand Run 2 = Outbreak assumed to have a 10% reduction in demand.

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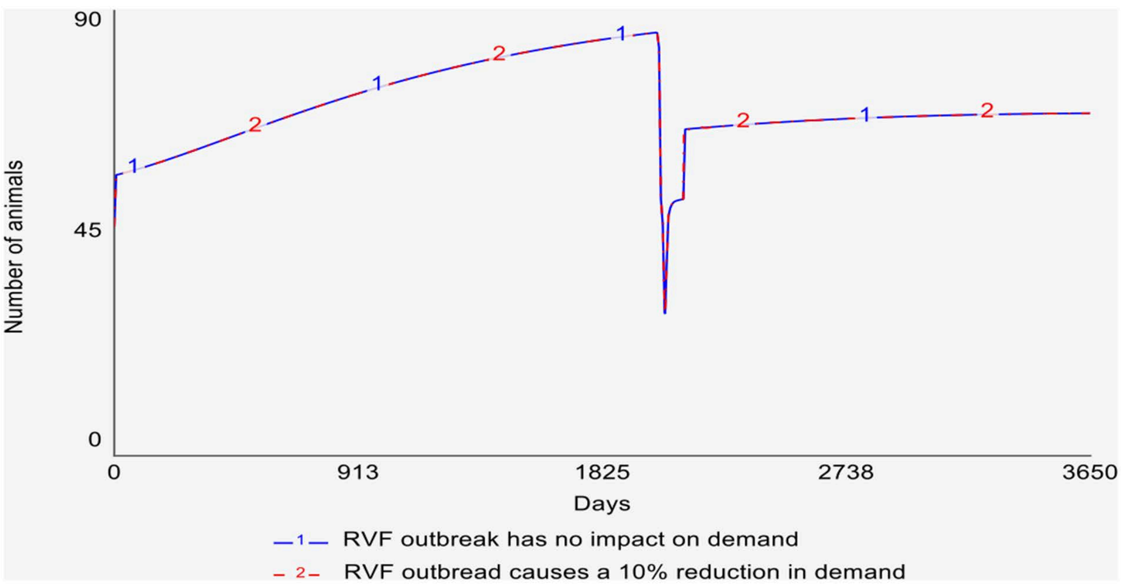

Fig 7. Total number of animals sold (head/day) before and after an RVF outbreak under two baseline scenarios: no vaccination and business-as-usual (BAU) reactive vaccination.

https://doi.org/10.1371/journal.pcsy.0000101.g007

population rebuilds. The BAU reactive vaccination strategy slightly moderates the magnitude of the decline, although the overall differences relative to the no-vaccination scenario remain modest.

Fig 8 shows the corresponding dynamics of herd size under the same scenarios. The outbreak leads to a noticeable reduction in herd size due to RVF-induced mortality. Over time, the herd gradually rebuilds through births and normal herd demographic processes. The BAU vaccination strategy results in slightly lower herd losses compared with the no-vaccination scenario, although the overall herd recovery trajectories remain broadly similar.

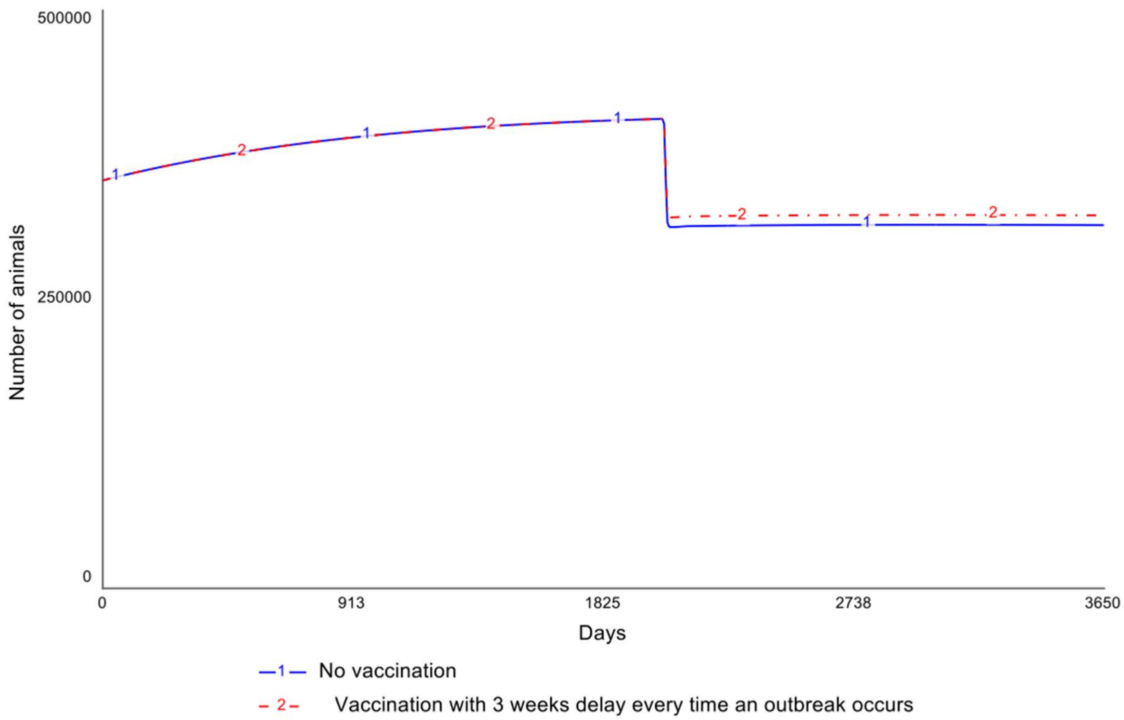

Fig 8. Herd size dynamics (number of animals, head) under alternative vaccination scenarios, comparing no vaccination and BAU reactive vaccination following an RVF outbreak.

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Fig 9 presents the projected producer income before and after an RVF outbreak under the two baseline scenarios. Consistent with the patterns observed for herd size and animal sales, producer income declines during the outbreak period due to reduced livestock sales and market disruptions. Income gradually recovers as herd size and sales increase over time. The BAU vaccination strategy results in only marginally higher income levels compared with the no-vaccination scenario.

The results suggest that reactive vaccination implemented several weeks after outbreak detection provides only limited mitigation of the economic impacts of RVF outbreaks. These findings highlight the potential importance of preventive vaccination strategies, which are examined in the following section.

4.4. Regular vaccination programs

Preventive vaccination of livestock is widely recognized as an important strategy for reducing the risk and impact of Rift Valley fever (RVF) outbreaks. International guidelines emphasize that vaccination can increase herd immunity and reduce the proportion of susceptible animals in livestock populations, thereby limiting the potential for large-scale transmission when ecological conditions favor mosquito population growth. In contrast, vaccination campaigns implemented during outbreaks are often difficult to deploy effectively due to the rapid progression of the disease and logistical constraints in vaccine availability and distribution. For this reason, international organizations recommend sustained preventive vaccination programs in high-risk areas as a key component of RVF control strategies [17,18].

In this study, the evaluation of vaccination frequency is based on the simulated herd dynamics generated by the system dynamics model. Following an initial vaccination, the susceptible livestock population gradually increases over time due to births and other herd demographic processes. Additional vaccination rounds therefore reduce the number of susceptible

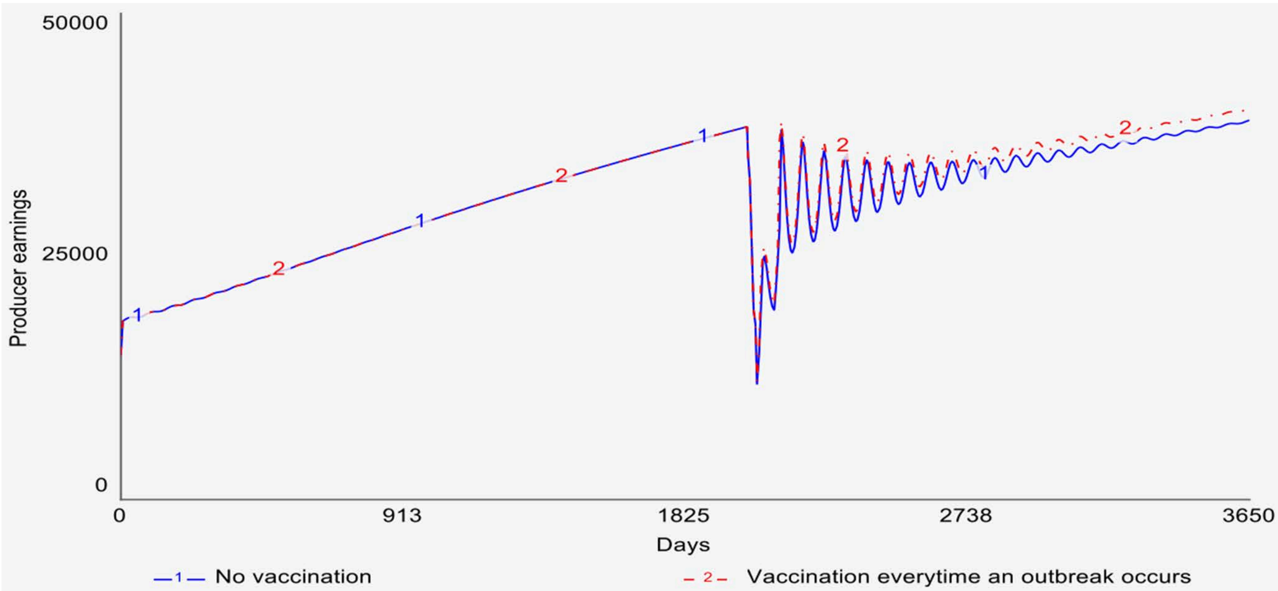

Fig 9. Producer earnings from cattle sales (USD/day) under alternative vaccination scenarios, comparing no vaccination and business-as-usual (BAU) reactive vaccination following an RVF outbreak.

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animals and consequently lower the number of animals exposed and infected during an outbreak. The simulation results allow assessment of how successive vaccination rounds, such as annual vaccination, biannual vaccination, or vaccination every three years, affect the number of cattle affected by RVF and the resulting economic outcomes.

For each strategy, different levels of vaccination coverage among susceptible animals were simulated. Fig 10 presents the simulation results showing the occurrence of RVF outbreaks together with projections of total herd size, animal sales, and producer income under the three vaccination frequencies.

The results indicate that an annual vaccination strategy covering at least 60% of susceptible animals is sufficient to completely prevent RVF outbreaks within the 10-year simulation period. In contrast, outbreaks are projected to occur under both biannual and triennial vaccination strategies, even when 100% of susceptible animals are vaccinated during each campaign.

The duration and severity of RVF outbreaks, reflected in their impacts on herd size, animal sales, and producer income, are lower under the biannual strategy than under the triennial strategy at comparable coverage levels. Under the triennial vaccination strategy, higher coverage levels reduce the magnitude of these impacts but do not fully prevent outbreaks.

4.5. Vaccination delay

To assess the effect of vaccination timing, the system dynamics (SD) model was run under multiple scenarios with vaccination delays ranging from 1 week to 4 weeks after outbreak onset.

Fig 11 illustrates the projected effects of these delays on cattle population dynamics. Shorter vaccination delays are associated with smaller reductions in herd size, while longer delays result in progressively larger declines.

A vaccination delay of 4 weeks produces outcomes similar to the no-vaccination scenario, with substantial losses in animal numbers following the outbreak.

Fig 12 presents the projected impact of different vaccination delay periods on the volume of slaughter animals sold by cattle producers. Across all five scenarios, animal sales decline sharply immediately after the outbreak, followed by a rapid recovery once the outbreak subsides.

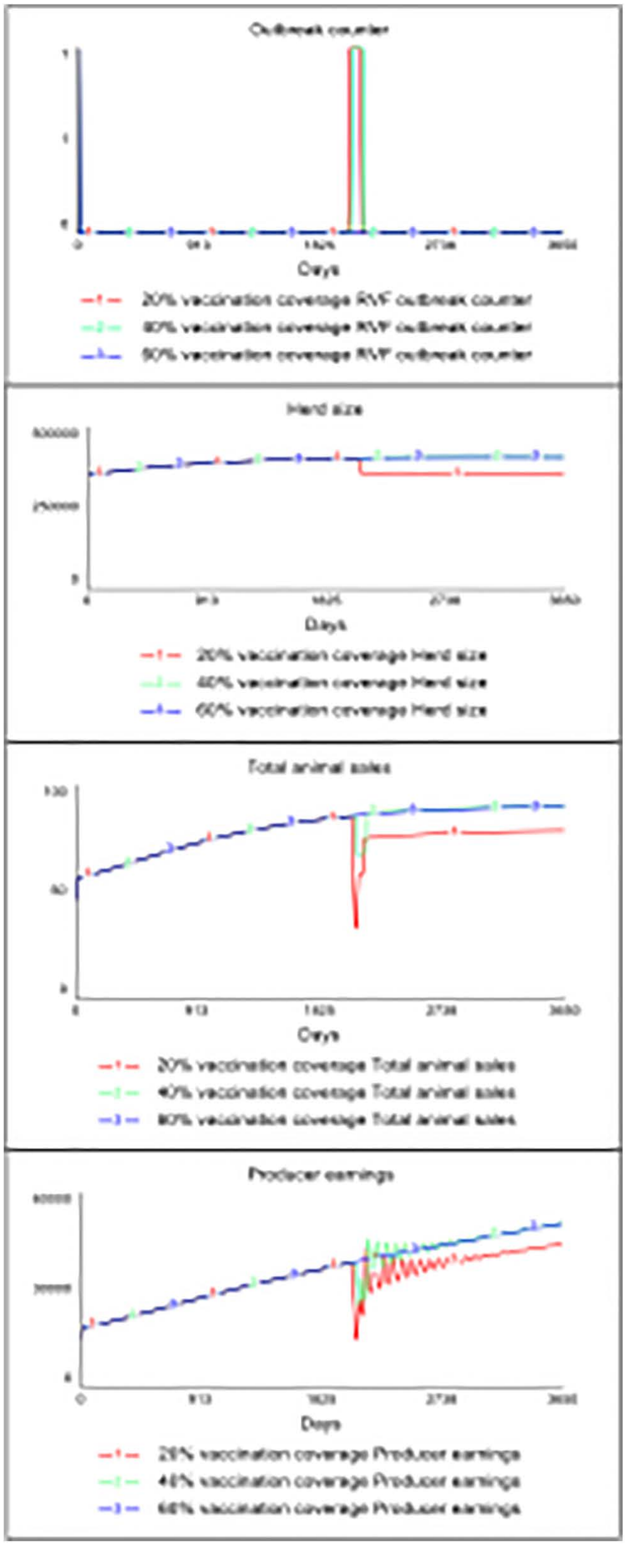

Fig 10. Impacts of regular preventive vaccination programs under alternative vaccination frequencies and coverage levels. The Fig compares (i) annual vaccination of susceptible animals, (ii) biannual vaccination of susceptible animals, and (iii) triennial vaccination (once every three years). For annual vaccination, simulation runs represent 20%, 40%, and 60% coverage of susceptible animals. For biannual vaccination, runs represent 40%, 60%,

80%, and 100% coverage. For triennial vaccination, runs represent 60%, 80%, and 100% coverage. Outcomes shown include RVF outbreak occurrence, herd size, animal sales, and producer income.

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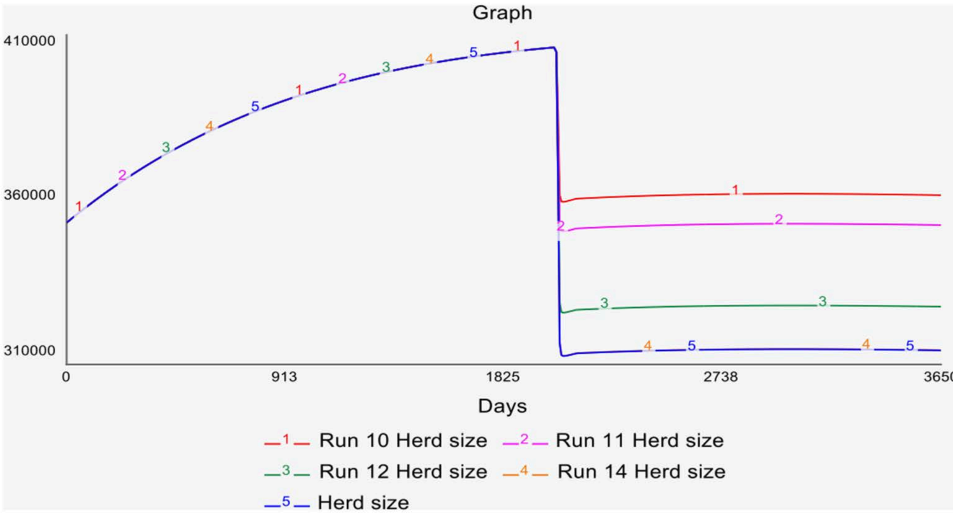

Fig 11. Cattle population dynamics (number of animals, head) under alternative delays between RVF outbreak onset and the initiation of vaccination campaigns, comparing response delays ranging from one to four weeks and a no-vaccination baseline. Ran 1 = 1 week delay; Run 2 = 2 weeks delay; Ran 3 = 3 weeks delay; Run 4 = 4-week delay; Run 5 = No vaccination.

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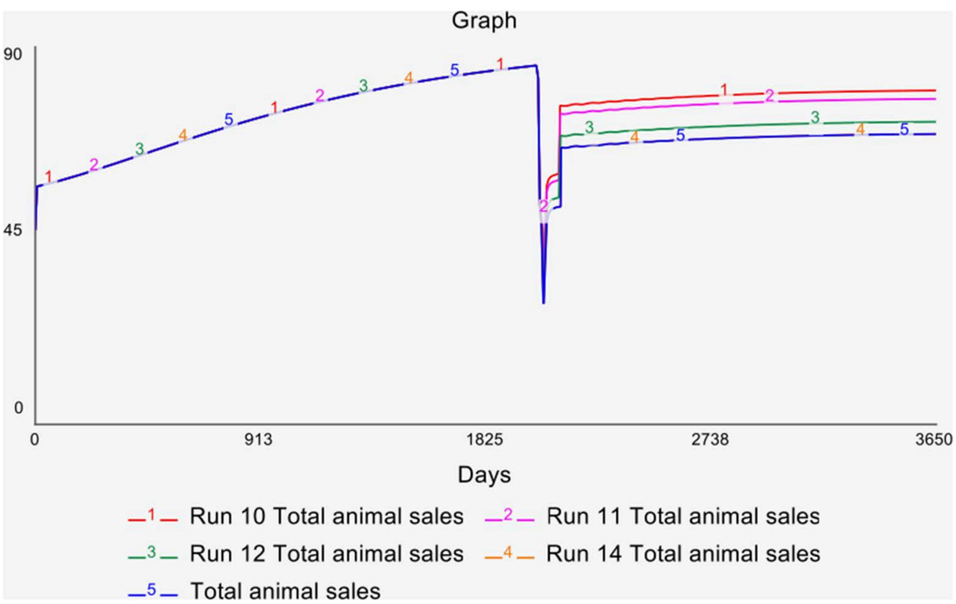

Fig 12. Total number of animals sold (head per day) under alternative delays between RVF outbreak onset and vaccination initiation, comparing response delays of one to four weeks and a no-vaccination baseline. Ran 1 = 1 week delay; Run 2 = 2 weeks delay; Ran 3 = 3 weeks delay; Run 4 = 4-week delay; Run 5 = No vaccination.

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However, the long-term trajectory of animal sales varies significantly depending on the length of the vaccination delay. The lowest sales volumes occur when vaccination is delayed by four weeks or not conducted, while the highest sales volumes are observed when vaccination is initiated one week after outbreak onset.

Fig 13 illustrates the projected impact of repeated RVF outbreaks on producer income from cattle sales under different vaccination delay scenarios (Runs 1–4) and a no-vaccination baseline (Run 5). In all cases, income from livestock sales experiences a sharp decline immediately after outbreak onset, followed by a recovery period once the outbreak subsides.

Income also exhibits short termvolatility during outbreak periods, with fluctuations that gradually diminish over time.

Across scenarios, the lowest projected income levels occur when vaccination is delayed by four weeks or not conducted, while the highest income levels are observed when vaccination is initiated one week after outbreak onset.

5. Discussion

This study demonstrates the value of an integrated system dynamics modeling approach for assessing the Epidemiological and Economic impacts of Rift Valley fever (RVF) and evaluating alternative vaccination strategies under conditions of uncertainty. By explicitly linking livestock infection dynamics, herd demography, and market outcomes, the model captures feedback mechanisms and time delays that shape both disease transmission and producer income trajectories. This integrated structure allows the analysis to move beyond short-term outbreak impacts and assess longer-term economic consequences and recovery pathways associated with different control strategies.

The simulation results also highlight the dynamic nature of herd immunity following an RVF outbreak. Although the initial outbreak leads to a rapid decline in susceptible animals and a temporary increase in recovered or vaccinated individuals, this protection erodes over time as susceptible animals are replenished through births. In the absence of sustained

Fig 13. Producer earnings from cattle sales (USD/day) under alternative delays between RVF outbreak onset and vaccination initiation, comparing response delays of one to four weeks and a no-vaccination baseline sales. Ran 1 = 1 week delay; Run 2 = 2 weeks delay; Ran 3 = 3 weeks delay; Run 4 = 4-week delay; Run 5 = No vaccination.

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immunity, this gradual rebuilding of the susceptible population increases herd-level vulnerability to future outbreaks, particularly under conditions of recurring heavy rainfall that favor vector proliferation. These dynamics underscore the limitations of one-off or delayed interventions and illustrate how short-term outbreak control does not necessarily translate into long-term risk reduction.

In this study, the BAU scenario represents the current practice in Kenya, in which RVF control relies on reactive vaccination campaigns initiated several weeks after outbreak detection rather than on routine preventive vaccination. The comparison between BAU reactive vaccination and no vaccination illustrates the limitations of delayed response strategies. Although reactive vaccination reduces losses relative to a no-intervention baseline, the model results indicate that these gains are modest when vaccination is initiated three to four weeks after outbreak onset. By the time vaccination campaigns are implemented, a substantial proportion of transmission and associated livestock losses have already occurred, limiting the scope for meaningful epidemiological or economic mitigation. As a result, BAU strategies tend to dampen peak impacts without fundamentally altering longer-term recovery trajectories for herd size, sales, or producer income.

The analysis of regular preventive vaccination strategies highlights the importance of both vaccination frequency and coverage in reducing RVF risk and associated economic losses. Annual vaccination programs that maintain sufficient coverage among susceptible animals are particularly effective because they limit the accumulation of susceptible individuals between campaigns, thereby preventing the conditions necessary for large-scale outbreaks. In contrast, less frequent vaccination schedules, such as biannual or triennial programs, allow susceptible animals to rebuild more rapidly, increasing the likelihood and severity of outbreaks even when coverage during each campaign is high. These findings illustrate that vaccination frequency plays a critical role alongside coverage levels in shaping long-term disease dynamics and economic outcomes.

The analysis of vaccination delay scenarios further emphasizes the critical role of timing in RVF control. Shortening the interval between outbreak onset and the initiation of vaccination campaigns substantially reduces livestock losses and stabilizes producer income by curtailing transmission before infection reaches its peak. Conversely, prolonged delays result in outcomes that closely resemble those observed under no vaccination, as disease spread and associated mortality largely occur before control measures take effect. These results highlight that even modest improvements in response time can yield disproportionate Epidemiological and Economic benefits, reinforcing the importance of timely detection and rapid mobilization of vaccination campaigns in RVF-prone systems.

Beyond direct production losses, the model highlights the importance of demand-side responses in shaping the economic impacts of RVF outbreaks. Temporary reductions in meat demand, driven by consumer risk perceptions, trade restrictions, and downstream income shocks, amplify price volatility during outbreak periods even when livestock supply dynamics remain unchanged. While these demand disruptions do not substantially alter the number of animals sold, they contribute to short-term income instability through fluctuating prices. However, the results also suggest that such demand-induced effects are transitory, with producer income recovering over time as market confidence is restored and prices stabilize. This interaction between epidemiological shocks and market dynamics underscores the need to consider both supply- and demand-side mechanisms when evaluating the economic consequences of zoonotic disease outbreaks.

Building on this foundation, the present study extends the existing literature by embedding market outcomes and producer income dynamics directly within the RVF transmission framework, allowing simultaneous assessment of epidemiological control and economic recovery trajectories over time. While earlier modeling studies in Kenya and the region have demonstrated the importance of vaccination timing and coverage for controlling RVF outbreaks (e.g. [3,14]), these analyses primarily focus on infection dynamics and outbreak suppression. By contrast, the integrated system dynamics approach used here explicitly links herd immunity and disease progression to livestock sales behavior, price responses, and producer income. This enables the model to show, for example, that BAU reactive vaccination, consistent with current practice in Kenya, reduces peak infection but delivers only modest economic gains due to delayed intervention, whereas preventive vaccination strategies not only lower outbreak incidence but also reduce price volatility and shorten income recovery periods. In doing so, the study complements and extends prior epidemiological and network-based vaccination analyses (e.g. [7,4]) by demonstrating how alternative RVF control strategies translate into longer-term livelihood and economic resilience outcomes for livestock producers.

These findings are consistent with previous RVF modeling studies that emphasize the importance of vaccination timing, coverage, and strategic targeting in controlling outbreaks under environmental conditions favorable to vector amplification. For Kenya, Gachohi et al. [3] demonstrated that delayed or low-coverage vaccination substantially limits achievable disease control, while mechanistic eco-epidemiological models have highlighted how rainfall and environmental constraints shape RVF emergence and persistence [6]. Related work also supports the value of pre-emptive or targeted vaccination approaches; for example, network-based simulations show that strategically targeted pre-emptive vaccination can substantially reduce outbreak size even when livestock movement information is imperfect [19]. Broader spatially explicit models further emphasize how persistence and control depend on landscape heterogeneity and the timing of interventions [20]. Building on this foundation, the present study extends the literature by embedding market outcomes and producer income dynamics directly within the disease transmission framework, allowing simultaneous assessment of epidemiological control and economic recovery trajectories over time. By explicitly linking herd immunity dynamics, livestock sales behavior, price responses, and income recovery, the model demonstrates how alternative RVF control strategies translate into longer-term livelihood and economic resilience outcomes for cattle producers.

Three key limitations of this study should be acknowledged. First, the analysis focuses on cattle and does not explicitly model RVF impacts on small ruminants or human health outcomes, which may lead to an underestimation of total societal losses associated with outbreaks. Second, the demand-side response to RVF outbreaks is represented using an assumed proportional reduction in meat demand due to limited empirical evidence on consumer behavior during zoonotic disease events in Kenya. While this assumption allows exploration of market-mediated effects, improved empirical data on demand responses and trade restrictions would enhance future analyses. Third, RVF outbreaks are triggered in the model using a single extreme rainfall event, and recurrent or stochastic climatic shocks are not explicitly represented, potentially understating longer-term variability in outbreak risk. Future research could extend this framework by incorporating multi-species dynamics, explicit public health outcomes, stochastic climate drivers, and targeted vaccination strategies informed by livestock movement networks. Such extensions would further strengthen the model's value as a decision-support tool for integrated animal health and livelihood resilience planning in RVF-prone systems.

6. Conclusion and recommendations

This study contributes to the assessment of livestock disease impacts by developing and applying a system dynamics (SD) model that captures the interactions between RVF epidemiology and the economic behavior of cattle producers. Conducted in Ijara County, Kenya, a high-risk area with a history of RVF outbreaks, the analysis integrates disease transmission dynamics, herd demographic processes, market responses, and producer income outcomes to evaluate the effectiveness of alternative vaccination strategies.

The SD model consists of two core components. The first is an epidemiological module that simulates RVF transmission between livestock and mosquito vectors (Aedes and Culex), adapted from the framework of Lo Iacono et al. [6]. The second is an economic module that incorporates herd demographic dynamics, livestock marketing behavior, and income generation. Primary data collected from 200 livestock producers, together with secondary sources, were used to parameterize the model.

Using this framework, the model was applied to simulate and compare three broad vaccination strategies: (i) the business-as-usual (BAU) approach involving delayed or absent reactive vaccination following outbreaks; (ii) routine preventive vaccination programs implemented at annual, biannual, or triennial intervals with varying levels of coverage; and (iii) improved outbreak response timing, in which the delay between outbreak detection and vaccination is progressively reduced.

The simulation results indicate that reactive vaccination implemented several weeks after outbreak detection provides only limited mitigation of the epidemiological and economic impacts of RVF outbreaks. Under the BAU scenario, vaccination yields only marginal improvements in herd recovery, animal sales, and producer income due to delays in response and incomplete immunization coverage.

In contrast, preventive vaccination strategies significantly improve outcomes. Annual preventive vaccination programs with adequate coverage of susceptible animals prevent simulated RVF outbreaks within the model horizon and provide substantial benefits in terms of herd preservation and producer income. Biannual and triennial vaccination strategies, while less effective in preventing outbreaks, still reduce the severity of their impacts when implemented with high vaccination coverage. In addition, reducing the delay between outbreak detection and vaccination substantially mitigates livestock losses and accelerates income recovery trajectories.

These findings highlight the importance of preventive vaccination strategies and timely response mechanisms in managing RVF outbreaks in pastoral livestock systems. The study also demonstrates the usefulness of system dynamics modeling as a decision-support tool for evaluating alternative disease control strategies and their economic implications.

While the analysis is grounded in data and conditions specific to Ijara County, Kenya, the results are intended to inform strategic comparisons of reactive versus preventive vaccination approaches in similar RVF-prone pastoral systems rather than to imply direct quantitative transferability across contexts. The modeling framework presented in this study can be adapted to other regions and livestock disease contexts to support scenario analysis and evidence-based policy planning.

Based on the results of this study, the following policy implications emerge:

1. Promote preventive vaccination programs in high-risk RVF areas

The simulation results show that regular preventive vaccination, particularly annual vaccination with adequate coverage of susceptible animals, can effectively prevent RVF outbreaks within the modeled time horizon and substantially reduce livestock losses and economic impacts.

2. Improve the timeliness of vaccination responses following outbreak detection

The analysis indicates that delays in reactive vaccination significantly reduce its effectiveness in mitigating disease impacts. Strengthening mechanisms for rapid vaccination deployment after outbreak detection could therefore improve livestock health outcomes and producer income recovery.

3. Utilize economic modeling tools to support livestock disease policy planning

Economic modeling approaches, such as the integrated epidemiological–economic framework developed in this study, can assist policymakers in evaluating alternative disease control strategies, anticipating economic consequences, and designing more effective intervention programs under different epidemiological and operational conditions.

Model availability. The system dynamics model was developed using standard SD software. The full model structure, equations, and parameter values are described in the manuscript to allow replication and adaptation for other settings. The model can be made available upon reasonable request to the authors.

Supporting information

S1 Fig. A schematic representation of the aedes mosquito dynamics module.
(TIFF)

S2 Fig. A schematic representation of the culex mosquito dynamics module.
(TIFF)

S3 Fig. The herd dynamics.
(TIFF)

S1 Questionnaire. Household survey questionnaire used for primary data collection from livestock producers in Ijara County, Kenya.
(DOCX)

S1 Data. Dataset used for descriptive statistics and parameterization of the system dynamics model.
(DOCX)

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Resources: Sirak Bahta.

Supervision: Sirak Bahta.

Validation: Francis Wanyoike, Bernard Bett.

Writing – original draft: Sirak Bahta.

Writing – review & editing: Sirak Bahta, Francis Wanyoike, Bernard Bett, Karl M. Rich.

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