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Dynamic epidemiological modeling of fractional order SEICD for the control of spread of the classical swine fever virus

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Abstract

A fractional order dynamic model (SEICD) was designed to describe the transmission dynamics of classical swine fever virus (CSFV) under certain intervention scenarios in a population of 667 pigs present on farms in the Ecuadorian Sierra. The model was used to describe the impact on mortality caused by the implementation of control strategies (vaccination and quarantine). We determined a function that explains the decrease in spread through the use of quarantine and vaccination measures, incorporating a reduction in the transmission rate. The model predicts that 40% of pig deaths due to CSFV infections can be avoided by implementing quarantine measures within 14 days of the onset of the epidemic; meanwhile, vaccination strategies implemented before day 14 of the epidemic provide 61% immunity, and only 39% lead to avoided pig deaths. When control measures are combined with quarantine and vaccination, the model predicts that 65% of pigs would be saved. However, if interventions are delayed, these life expectancy indicators for pigs with the possible presence of CSFV tend to decline, leading to increased infection and mortality rates. Early detection and management of CSFV epidemics with reinforced control measures mitigate the negative effects on the pig population in the Sierra region of Ecuador.

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Introduction

Classical swine fever virus (CSFV) is a devastating disease in domestic pigs, promoted by a causal agent, an RNA virus of the Flaviviridae family, of the Pestivirus genus, known as Pestivirus C (CSFV) (1,2). This disease represents a significant limitation in pig production since it causes economic losses in the farms where the breeding activity is carried out and represents a threat to food security (3). Classical swine fever is viral in nature and has a high prevalence as a contagious disease in domestic and wild pigs in most of Ecuador (4,5). This infectious disease, with a high speed of contagion, makes it an animal health problem, both globally and locally, that must be addressed urgently (6,7). It causes acute hemorrhagic fever in animals, with high disease severity and high mortality rates, with manifestations in subacute, chronic, and infrequent versions. Where the transmission rate occurs through direct contact with infected animals or contagious substances present in the surroundings (8,9). Understanding morbidity and mortality is fundamental to research aimed at managing CSFV outbreaks. Quantifying the degree of virulence of the strains causing the infection is influenced by the age and strain of the host and the environment in which they develop, whether domestic or wild, factors that determine the probability of morbidity and mortality (10). Regarding the presentation of the disease, several symptoms have been observed that appear nonspecifically in pigs: fever, loss of appetite, and mortality two or three months after infection, caused by the chronic type of the causal agent. The prevalence in piglets infected with PPCV occurs through vertical transmission, observing cases of piglets between birth and three weeks of age with persistent postnatal infection with moderately virulent strains of PPCV (11,12). In general, these infections caused by highly virulent strains in highly vulnerable host animals cause considerable mortality; the case fatality rate in young and adult domestic pigs is between 80% and 100% (13,14). This case fatality rate can be determined by the number of deaths per infection among infected animals. Mathematical models help us understand the spread of swine disease and containment tactics, identifying vital thresholds, measuring disease frequency, and assessing the effects of interventions such as quarantine or immunization. These models' ability to manage variability, traditionally restricted by limited data, poor observations, or experimental records, is crucial for understanding infection behavior in domestic and wild animals (15-17). With the exception of transmission experiments with controlled environments (18,19), estimating key parameters for transmission dynamics has been difficult, primarily due to the lack of time-series data on population density before and after the introduction of CSF. The key to a study is the sampling of domestic or wild pigs, which is often hampered by certain contexts (20,21) and the behavior of the animals themselves (22). Therefore, the objective of this study was to develop and validate a SEICD model that allows simulating the dynamics of the spread of the classical swine fever virus, based on the effectiveness of the implementation of different control and prevention strategies within the management of public health and pig production in the Sierra region of Ecuador. In this sense, it is necessary to estimate essential parameters for the construction of a SEICD model (23), with data on the dynamic behavior of the pig population present in the territory.

Materials and methods

Ethical approval

This study was conducted with the approval of ESPOCH Institute, under protocol number EC060155.

Type and design of research

This study is exploratory and descriptive in nature, seeking to understand the behavioral dynamics of classical swine fever virus (CSFV) using SEICD modeling, based on historical records of disease incidence in the provinces of the Ecuadorian Sierra. Furthermore, it is prospective and non-experimental, as it anticipates disease behavior based on the characterization, description, and functioning of the model. Finally, it is non-experimental, as it involves the exploration and evaluation of previously collected data to feed the mathematical model.

Research methods

In this research, deductive and analytical methods were applied to construct the SEICD model. Documentary content and data were also analyzed to predict the resulting dynamics of CSF control through effective interventions in the highlands of Ecuador.

Research approach

This research focuses on quantitative research for a precise assessment of the dynamics of control measures in the presence of classical swine fever on farms in the Sierra region of Ecuador.

Study population

The study, conducted from 2017 to 2020, used a population of 667 pigs present on farms in the Ecuadorian Sierra. These pigs underwent intervention measures after the presence of CPPV was detected. These data are from the official entity responsible for the Animal Health Surveillance Office (SIZSE), which uses the real-time reverse transcription polymerase chain reaction (RT-PCR) method. This method allows for rapid and accurate detection of CPPV.

Data collection techniques and instruments

The Agrocalidad Ecuador system was used, which served as a data source for the epidemiological modeling of the SEICD model for CFPV outbreaks in the Ecuadorian Sierra.

Model definition

The SEICD model consists of five compartments that classify pigs according to their inherent pathological state (24). Therefore, the mathematical model considers the demographic profile (25,26). of the population of 667 pigs studied in the Sierra of Ecuador. This SEICD model is proposed as a system of ordinary differential equations defined for a total population, which is expressed by the following equation:

$$N = S + E + I + C + D \quad (1)$$
$$\frac{dS}{dt} = -\beta S(I + \varepsilon C) + \mu N - \mu S \quad (2)$$
$$\frac{dE}{dt} = \beta S(I + \varepsilon C) - (\sigma + \mu)E \quad (3)$$
$$\frac{dI}{dt} = \sigma E + \kappa C - \gamma\rho I - \gamma(1-\rho)I - \mu I \quad (4)$$
$$\frac{dC}{dt} = \gamma(1-\rho)I - (\kappa + \mu)C \quad (5)$$
$$\frac{dD}{dt} = \gamma\rho I \quad (6)$$

The model structure is illustrated in Figure 1 with the respective events, parameter definitions, data sources, and presented estimates described in Table 1 and Table 2. According to Figure 1, the interpretation of the dynamics in the parameters is given by: The transition from state (S) to state (E) was governed by the transmission rate (β), while the transition from state (E) to state (I) depended on the latency period (σ). Infectious animals die at a rate (γρ) and enter state

(D) or enter the carrier state but asymptomatic animals (C) at a rate of γ(1−ρ). Asymptomatic carriers also transmit the virus at a small rate (εβ) and can reactivate the infection at a rate (κ). Therefore, there is a level of natural mortality that occurs in the infectious class at a rate of μ. Identified cases tend to enter the susceptible state S at a rate of μN.

Model parameters

Table 2 presents the estimates for the model parameters, based on data recorded by the Ecuadorian Animal Health Surveillance Office (SIZSE) and with the formulas present in the literature. Non-specific mortality (μ) was estimated as the reciprocal of the average lifespan of pigs in the study region (i.e., 280–500 days). The transmission rate parameter β(t) has been estimated from the literature (27), taking into account the difference in pig interactions between those under experimental conditions and those in a natural environment. The reduction factor (ε) of the transmission rate from carrier animals and the reactivation rate of carriers (κ) to the infectious state are defined by calculations with the available data. These parameters have been standardized to have values between 0 and 1 for comparative purposes.

Table 2 shows the estimated parameters based on records provided by the Ecuadorian Animal Health Surveillance Office (SIZSE). The interpretation of these parameters focuses on the fact that all new pigs are in a susceptible state (S), so the per capita birth rate is defined as an indirect indicator of the natural mortality rate μ. This is necessary to adjust the dynamics of the model to be built around the disease burden of interest. The transition state of pigs from susceptible (S) to latently exposed (E) is defined by the parameter β (transmission rate). After a latency period of σ -1 days, exposed pigs transition to the infected state (I). Consequently, there is a probability ρ that infected pigs die from the disease, while those surviving beyond the infectious period (γ -1 days) are assumed to become carrier pigs at a rate γ(1 −ρ) (20,21). Carrier pigs are also assumed to contribute to the spread of the infection, albeit at a lower rate (βε), and may occasionally reactivate and return to the infectious class (I) at a rate κ (28). Natural mortality occurs in all classes, and additional disease-specific mortality occurs in the infectious class at a rate (γρ). In this context, transmission is assumed to depend on the population density of pigs per specific area; this is based on the fact that pigs in a given territory interact freely, becoming infectious agents through contact.

Intervention scenario modeling

In the context analysis, the effect and interaction of the interventions (vaccination and quarantine) against CSFV present in pigs belonging to the Sierra region of Ecuador must be evaluated, which quantifies records concerning 1460 days during the annual period 2017-2020. As a reference point to evaluate the impact of the interventions, the description of the dynamic behavior of the disease in a population of 667 pigs in the modalities (without intervention, under intervention with vaccination measures, and another intervention category corresponds to implementation) begins with quarantine and combined measures as an intervention option. Each intervention option was considered at different points in time after the detection of possible positive cases of CSFV. The first categorical state of the study consisted of the moment of applying the control measures in the spread, represented by the changes that were determined in the parameter of transmission speed of the disease per unit of time $\beta(t)$, according to the place τ(province, canton, and specific parish) where the control with intervention measures began. The parameter is adjusted $\beta(t)$with gradual reduction with exponential decay (29).

$$\beta(t) = \begin{cases} \beta_1 \; si \; t < \tau \\ \beta_0 + (\beta_1 - \beta_0)e^{-(t-\tau)} \; si \; t \geq \tau \end{cases}$$

For modeling purposes, the parameter can be considered insignificant or equal to zero when control measures have an effect on mitigating any future disease transmission process. Considering the dynamic parameter of the time in which the intervention is carried out, defined in the present study within the first 14 days after the detection of positive cases on family farms in the Sierra of Ecuador, the nature of the state of uncertainty is described, identifying the intervention scenarios where the intervention with vaccines occurs within the first 14 days after the onset of the epidemic and the application of quarantine as an intervention measure within the first 14 days after the detection of positive cases. Considering a free intervention scenario, a combined action with quarantine and vaccination is defined as a control measure within the first 14 days.

Designing the SEIR model in Python

To develop the SEICD model, the parameters to be used must be calculated (Table 2). These are obtained from infection records submitted on farms in the Ecuadorian Sierra. This data is presented in command lines as follows (Figure 2). After defining the system of differential equations, an algorithm is designed to determine a numerical and graphical solution in Python 3.11, using the integrated development platform PyCharm 2024.1. This is achieved through the use of appropriate libraries for the functions required for program development and compilation.

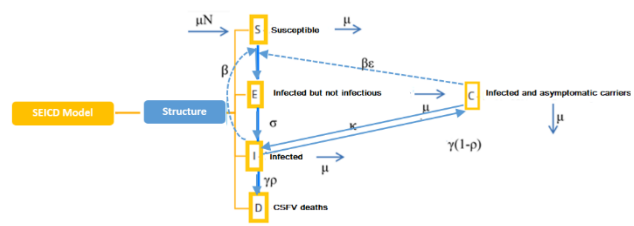

Figure 1: State transition structure of the SEICD model.

Table 1: States according to the transition effects and speed between compartments

State	Effect	Transition rate
Exposure	(S, E, I, C) → (S-1, E+1, I, C)	$\beta S(I+\varepsilon C)$
Infection	(S, E, I, C) → (S, E-1, I+1, C)	σE
Mortality due to illness	(S, E, I, C) → (S, E, I-1, C)	$\mu\rho I$
Reactivation	(S, E, I, C) → (S+1, E, I, C)	μN
Asymptomatic pigs carrying the virus	(S, E, I, C) → (S, E, I-1, C+1)	$\gamma(1-\rho)I$
Virus reactivation in pigs	(S, E, I, C) → (S, E, I+1, C-1)	κC
Natural death in a susceptible state	(S, E, I, C) → (S-1, E, I, C)	μS
Natural death in a state of exposure	(S, E, I, C) → (S, E-1, I, C)	μE
Natural death without infections	(S, E, I, C) → (S, E, I-1, C)	μI
Death of pigs in handling asymptomatic infected animals	(S, E, I, C) → (S, E, I, C-1)	μC

Table 2: Numerical estimates of the parameters in the SEICD model

	Definition	Vaccination strategies	Combined control strategy	Without intervention
$\boldsymbol{\mu}$	Non-specific mortality/crude birth rate	0.0012	0.0019	0.0045
$\boldsymbol{\beta}$	Transmission rate	0.38	0.53625	0.613
$\boldsymbol{\gamma}$	Specific mortality rate due to classical swine fever	0.067	0.200	0.350
$\boldsymbol{\rho}$	Proportion of infected people who die	0.033	0.059	0.0683
$\boldsymbol{\sigma}$	Transition rate from exposed class to infectious state	0.8	0.85	0.9
$\boldsymbol{\kappa}$	Operator reactivation rate	0.031	0.039	0.041
$\boldsymbol{\varepsilon}$	Effective contact rate reduction factor for carrier animals	0.150	0.2000	0.250

Note data-driven calculations and research approach.

```
def differential_VPPC(d, t):
    mu = 0.0019
    beta = 0.53635
    gamma = 0.200
    rho = 0.059
    sigma = 0.85
    kappa = 0.039
    epsilon = 0.200
    betai = 0.05
    if intervention:
        if t >= intervention:
            beta = (betai + (beta - betai) * exp(-(t - intervention)))
    N= max(d[0] + d[1] + d[2] + d[4], 1)
    dS_dt =  -(beta * d[0] * (d[2] + epsilon * d[4])/N) + mu * N - mu *d[0]
    dE_dt = (beta * d[0] * (d[2] + epsilon * d[4]) / N) - ( sigma + mu) * d[1]
    dI_dt = sigma * d[1] +  kappa * d[4] - gamma * rho *d[2] - gamma * (1-rho) *d[2]- mu * d[2]
    dC_dt = gamma * (1-rho) * d[2] - (kappa +mu) *d[4]
    dD_dt = gamma * rho * d[2]
    return dS_dt, dE_dt, dI_dt, dD_dt, dC_dt
```

Figure 2: Command lines.

Results

Description of the behavior of the classical swine influenza virus in the highland region of Ecuador

Regarding the behavior of the spread of classical swine fever virus (CSFV) in pigs, shown in Figure 3, the number of infected pigs starts low and then increases rapidly, indicating a rapidly spreading outbreak around the fourth (04) day, suggesting a rapid progression of the disease. After the peak, the number of infected pigs gradually decreases following the implementation of biosecurity measures (vaccination or quarantine) but remains at a relatively high level even at the end of the 8-day period shown in the graph (Figure 3). This graph represents the increase in the disease burden during the first 14 days. This allows us to infer that, once the presence of an infection has been detected in the pigs on a farm, a specific control measure must be implemented to prevent the increase in the spread of the classical swine fever virus.

According to Figure 4, with a low start and a rapid increase, CSFV carrier pigs reach a peak around the fourth (04) day. The number of carrier pigs decreases steadily after the peak but remains quite high even at the end of the eight-day period shown in the graph (Figure 4). Although there tends to be a recovery from the infection, carrier pigs (in stage C+D) can still maintain a margin in the spread of the virus. Even after the existence of the first outbreak has ceased, the dynamics of these carrier pigs are essential to understand in order to infer possible persistence and long-term effects of CSFV in the affected pig population. Among the feasible scenarios in the parameters in the transition from the infectious state (I), it is presented with a natural mortality rate due to vaccination of 0.0012, as well as, due to the effect of combined control (vaccination and quarantine) at 0.0019 and without any intervention mechanism at 0.0045 The parameter defining the transition from the stage of asymptomatic pigs infected with CSFV to vaccinated pigs $\gamma(1-\rho)=0{,}064789$or pigs with combined control measures $\gamma(1-\rho)=0{,}1882$ and no intervention is also described $\gamma(1-\rho)=0{,}326095$. This indicates that asymptomatic pigs carrying CSFV without the application of control measures tend to cause a higher number of pig deaths compared to contexts where interventions (vaccination, quarantine, or both control measures) are applied to the disease burden.

The number of susceptible pigs starts at a very high level, around 660. As implied throughout the 8-day period (Figure 5), the number of susceptible pigs rapidly declines following the overall progression of the CSFV outbreak. This decline in the number of susceptible pigs is very pronounced, indicating a rapidly spreading outbreak affecting a large portion of the swine population. By the end of the 8-day period, the number of susceptible pigs has significantly decreased, suggesting that a large number of pigs have been infected or eliminated from the susceptible population through the implementation of effective strategies to control and contain the CSFV outbreak, such as biosecurity measures, vaccination programs, and culling of infected animals. Figure 5 tends to depict the disease burden when implementing combined actions, where 65% of at-risk animals are protected by the vaccine 14 days after the intervention, mitigating the consequences of the epidemic. In this sense, the intensification of control measures in the respective vaccination and quarantine before eight (08) days allows improvements by reducing the burden of the disease in pigs from the different farms in the Sierra of Ecuador.

Impacts on the implementation of measures to control swine morbidity in the Sierra region of Ecuador

This section presents the results obtained by numerically solving the optimization of the system of ordinary equations proposed in this study. According to the results obtained in Table 3, in the highland region of Ecuador, if no intervention measures are applied in the first 14 days, when the spread of the CSF virus should be controlled, the SEICD model predicts a 60% life expectancy in pigs, representing a 40% mortality rate. Conversely, if farms choose to apply control measures defined by vaccination, a 61% increase in pig immunization is observed, leading to a 39% decrease in deaths from the virus. Therefore, if combined control measures (vaccination combined with quarantine) can be defined, pig life expectancy increases to 65%, a decisive situation for controlling the spread and managing pig mortality within a 35% margin due to the disease burden. Therefore, if these control measures are implemented late, these life expectancy indicators in pigs in the presence of the possible CSF virus tend to decrease, which implicitly increases the infection and mortality rate.

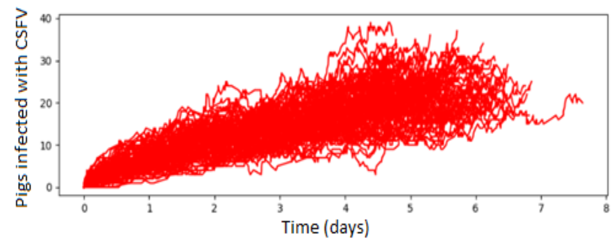

Figure 3: Description of the behavior of classical swine fever virus infections in pigs in the Sierra region of Ecuador.

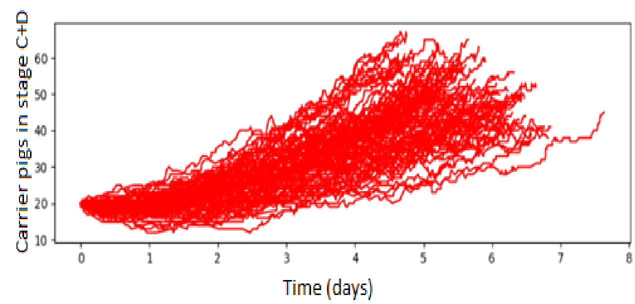

Figure 4: Behavior of pigs carrying asymptomatic infections by classical swine fever virus (CSFV) and deaths in the Sierra region of Ecuador.

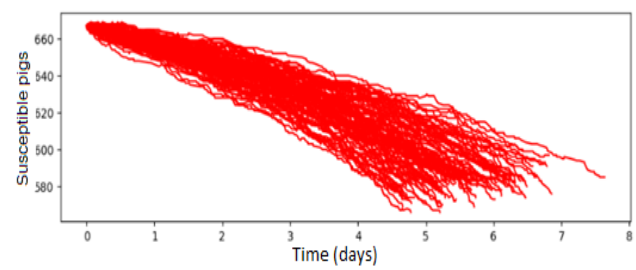

Figure 5: Description of the behavior of classical swine fever virus in pigs when implementing combined control measures.

Table 3: Description of the results in the SEICD modeling

Control Strategies	VPCC (%)	Deaths (%)	Description
Combination	65%	35%	The longer the life expectancy, the lower the mortality rate
Vaccination	61%	39%	Moderate life expectancy implies an intermediate mortality rate
Without intervention	60%	40%	The lower the life expectancy, the higher the mortality rate

Discussion

Although the application of fractional order SEICD models for describing CSFV dynamics may be relatively new, there is a growing body of research focused on developing fractional order models in veterinary epidemiology to capture the complexity of disease transmission and assess the impact of control strategies such as vaccination (30,31). and tick-borne parasitic infection (32,33) These models offer a powerful tool for understanding, monitoring, and controlling the system for the spread of infectious diseases in animal populations (34,35). and even more so if the epidemic spread is monitored in real time (36,37). In this scenario, recent contributions on the comparative analysis of different strategies for the control of classical swine fever in the Republic of Serbia through Monte Carlo simulation determined that integrating control strategies such as vaccination, quarantine, and culling in the model allows obtaining efficient parameters and simulations of different intervention scenarios and predicting their impact on key epidemiological indicators. Where depopulation of affected animals with early diagnosis and vaccination in the protection and surveillance zone proved to be the most effective measures to stop the spread with eradication of the disease and the establishment of a stable epizootiological situation (38,39).

As reported by modeling the effects of quarantine and vaccination on the dynamics of CSFV transmission in a pig population, the findings showed that vaccination and quarantine together significantly reduced incidence and mortality, outperforming either control measure alone (40,41). Or alternatively, they evaluated it in the implementation of a mass vaccination program for the control of the classical swine fever virus in Germany. To eradicate the virus within a year, they found that it was essential to vaccinate at least 80% of the pig population (42,43). Another contribution reviewed highlighted that CSFV control measures in several countries, such as immunization, quarantine, and stamping out, and concluded that the most successful method to control and eliminate CSFV has been the combination of vaccination and quarantine (44,45).

Modeling disease transmission between wild and domestic species is a complex task that has been accomplished by multiple methods, but only for a few disease scenarios (46,47). Indeed, of the 118 diseases at the wildlife-livestock interface represented in the literature, only 14 have been explored using mathematical models (48,49). From selecting model frameworks and host representations to determining which transmission factors to include in models, distinct populations, often with drastically different population dynamics, have been situations that must be accurately represented. These methodological decisions reflect the skills of the researcher; the problem formulation aligns with the model definition and data availability.

According to the results obtained with this model, intervention strategies have been able to reduce the incidence of swine mortality from 40% to 35% in the Ecuadorian Sierra. These findings validate previous approaches on the effectiveness of using the SEICR and SEICD models that describe the behavior in response to CSF vaccination, predicting a 30% to 40% reduction in the number of sick pigs (50,51). Similar findings were obtained in the present study.

The validation of a new compartmental epidemiological model to model the transmission dynamics of classical swine fever represents an essential option to analyze the rate of disease transmission with real data from reported cases in Ecuador, which facilitates the estimation of unknown biological parameters, as was done by (52,53). The simulated model shows that increasing the rate of burial or cremation of dead pigs infected by CSFV significantly reduces monthly and cumulative cases of the referred virus. This is associated with the findings of (54,55), when establishing a 30% increase in said rate can result in a 38% reduction in monthly cases at its peak. Control measures, such as confinement and slaughter of pigs, along with proper management of dead pigs, are essential to contain CSFV outbreaks.

The proposed model is simulated to evaluate the impact of presymptomatic, symptomatic, and asymptomatic detection on CSFV dynamics. In this context, the results are similar to those obtained by (56), who stated that a symptomatic infection detection rate of 60% and 80% increases the maximum number of confirmed cases by 7% and 13%, respectively. This has suggested that early detection and control strategies can minimize the spread of the virus in the community, facilitating the development of new, informed disease control strategies that contribute to economic stability, public health, swine productivity, and optimizing food security in the Sierra region of Ecuador.

Epidemiological models, such as SEICD (Susceptible, Exposed, Infected, Quarantine, and Death), have proven to be valuable tools for predicting the spread of CSFV and evaluating the effectiveness of interventions. According to a study by Shuvo *et al.* (57), simulation of different intervention scenarios showed that vaccination combined with quarantine could significantly reduce the disease burden in pig populations, improving life expectancy and reducing mortality. Recent research has highlighted the importance of vaccination strategies in controlling CSFV. A study by Ukita *et al.* (58). evaluated different vaccination protocols and found that early vaccination and periodic booster vaccination are crucial for maintaining high levels of immunity in pigs, which in turn reduces mortality and virus spread.

The economic impact of CSFV is significant, and the implementation of effective control measures not only improves animal health but also has positive implications for the agricultural economy. These impacts have been widely discussed to elucidate how appropriate interventions can reduce the costs associated with CSFV outbreaks, highlighting the need for public policies that support vaccination and disease control (59).

The evolution of the CSFV virus and its ability to adapt to new environments is an area of growing concern. Research such as that of Liu *et al.* (60). has identified mutations in the virus genome that could affect the effectiveness of current vaccines, underscoring the need for continued monitoring and the development of new vaccine formulations.

Recent scientific contributions provide a solid foundation for the implementation of effective strategies for CSF control. A combination of predictive models, vaccination strategies, economic analysis, and monitoring of viral evolution represents essential components for addressing this disease.

Conclusions

The cattle vaccination control strategy as an intervention measure to mitigate potential adverse effects was considered by evaluating the parameters that describe the efficiency of the vaccination process, allowing for the generation of antibodies and an acquired immune response against CSF. This alternative presents optimal efficiency over time. In this sense, the combined vaccination and quarantine strategy is the most effective, achieving a 65% life expectancy in pigs before CSFV and reducing deaths to 35%. Vaccination alone also shows an improvement, with a life expectancy of 61% and a mortality rate of 39%. Without any intervention, life expectancy is the lowest 60%, and the mortality rate is the highest 40%. Previous studies have defined a 75% probability of protection days after vaccination, which seeks to confirm that piglets manage to develop antibodies after vaccination. In this context, due to the fragility of contagion, it is useful to complement vaccination control with control derived from quarantine. It is important to consider the balance between complexity, comprehension, and underlying assumptions when selecting a paradigm to describe modeling using a system of differential equations. Since model selection involves determining the level of realism required and considering that models are only artificial representations of phenomena, although a model should be a realistic representation, it is necessary to specifically remember the concept of parsimony, especially when addressing wildlife scenarios in pig farm management, where parameters are difficult to record, extensive information is required to draw conclusions, or data are extremely variable due to the interaction between various factors. The severity of CSF disease varies depending on the virus strain, the age and immune status of the pig, as well as other factors such as the animal's overall health and viral load. Despite intensive studies, diagnosis, and subsequent eradication efforts, the virus persists and re-emerges, threatening the food supply in affected areas. The immunopathogenesis of the disease, the complex virus-host interactions, and the virulence factors of the CSF virus remain poorly understood. Furthermore, further research is needed to understand the causes of CSF's limited host range, as well as the genetic factors that drive host vulnerability to the virus. Another line of future research is highlighted by the importance of evaluating the effectiveness of implementing different types of vaccines in controlling the disease and comparatively considering the cost-benefit implications of implementing different intervention measures for disease eradication on pig farms in the Ecuadorian Sierra.

Conflict of interest

The authors declare that there are no conflicts of interest with respect to the publication and/or funding of this manuscript.

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النموذج الوبائي الديناميكي لـ SEICD للسيطرة على انتشار فيروس حمى الخنازير الكلاسيكية

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الخلاصة

تم تصميم نموذج ديناميكي من الدرجة الكسرية لوصف ديناميكيات انتقال فيروس حمى الخنازير الكلاسيكي (كسف) في ظل سيناريوهات تدخل معينة في مجموعة من الخنازير ٦٦٧ موجودة في المزارع في سييرا الإكوادورية. تم استخدام النموذج لوصف التأثير على النفوق الناجم عن تنفيذ استراتيجيات المكافحة (التطعيم والحجر الصحي). لقد حددنا وظيفة تفسر الانخفاض في الانتشار من خلال استخدام تدابير الحجر الصحي والتطعيم، بما في ذلك انخفاض معدل انتقال العدوى. يتوقع النموذج أنه يمكن تجنب ٤٠ ٪ من نفوق الخنازير بسبب عدوى الفيروس الدماغي النخاعي عن طريق تنفيذ تدابير الحجر الصحي في غضون ١٤ يوما من ظهور الوباء؛ وفي الوقت نفسه، توفر استراتيجيات التطعيم التي تم تنفيذها قبل اليوم ١٤ من الوباء ٦١٪ مناعة، و ٣٩٪ فقط تؤدي إلى تجنب نفوق الخنازير. عندما يتم الجمع بين تدابير المكافحة والحجر الصحي والتطعيم، يتوقع النموذج أنه سيتم إنقاذ ٦٥٪ من الخنازير. ومع ذلك، إذا تأخرت التدخلات، فإن مؤشرات العمر المتوقع للخنازير مع احتمال وجود فيروس الورم الحليمي البشري تميل إلى الانخفاض، مما يؤدي إلى زيادة معدلات العدوى والنفوق. إن الكشف المبكر عن أوبئة فيروس الورم الحليمي البشري وإدارتها مع تدابير المكافحة المعززة تخفف من الآثار السلبية على أعداد الخنازير في منطقة سييرا في إكوادور.