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Original Article

# Agent-based Modeling the Spread of African Swine Fever on a Regional Scale and Evaluating Its Control Measures using a Cloud-based Simulator

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**Abstract:** African Swine Fever (ASF) is a highly contagious disease affecting pigs, with mortality rates varying based on host, viral dose, and transmission route. Since its first detection in Vietnam in 2019, ASF has spread rapidly, particularly among small-scale farms with limited biosecurity, causing severe economic losses. While pig movement studies have explored disease transmission, there is limited research on ASF control strategies using cloud-based multi-agent simulations. This study develops a novel multi-agent ASF spread model on the GAMA simulation platform, focusing on Hanoi, Vietnam's second-largest pig-producing region. The model allows for scenario analysis by adjusting direct and indirect transmission factors. By deploying simulations of six control measures, such as movement restriction and culling, with an intuitively interactive map interface, the unseen behaviors and interactions of agents are revealed. Results highlight its potential in aiding policymakers to design effective ASF outbreak control strategies.
*Keywords:* African Swine Fever, Cloud Computing, Disease Control Strategy, GAMA Platform, Multi-Agent Simulation.

## 1. Introduction

African Swine Fever (ASF) is commonly known worldwide, not only in Vietnam, was first detected by the Vietnamese government in February 2019 in the two provinces of Hung Yen and Thai Binh [1], and spread rapidly to all Vietnam's provinces. ASF, despite proactive prevention measures and early awareness of the disease, was discovered for the first time in Hanoi on 31 May 2019. ASF cases were reported in Hanoi's 24 districts, towns, and villages with pig-farming in that same year. The total number of pigs killed was nearly 550,000, with a weight of approximately 37,100 tons [2]. ASF returned to Hanoi in April 2020, four months after it had

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been declared eradicated. This time, the Department of Agriculture and Rural Development reported that the disease affected 43 families in 25 communes in the 12 Hanoi districts on November 15, 2020. This led to 506 pigs being killed and culled, with a combined weight of 31,342 kg. In 2024, ASF once again returned and broke out strongly in Vietnam even though Vietnam had developed an ASF vaccine since 2023. From the beginning of 2024 to July 2024, the country had more than 630 outbreaks of ASF in 44 provinces and cities, forcing the destruction of more than 40,500 pigs [1].

According to research by Sykes et al., conventional ways of controlling pig diseases have been successful in the past [3]. These include killing any pigs that show signs of infection, limiting the movement of pigs and pig products, and improving agricultural biosecurity. However, its effectiveness is limited by how long it takes to completely contain the disease, which can range from 6-10 months. In addition, the methods used only account for human factors, such as care, transportation, and handling, whereas the characteristics of the pigs and their movements play a major role in transmitting infectious diseases. It is also not practical to conduct real-life experiments in a large population such as a whole region [3]. Besides, to efficiently allocate resources for surveillance in the event of personnel shortages, it is important that disease control directives are timely and accurate. Therefore, it is necessary to develop a simulation model of ASF spread, taking into account multiple influencing factors, to help policymakers not only understand how disease outbreaks affect a large geographical area but also make informed and precise decisions about cost-effective controls such as vaccinations and movement restrictions. In veterinary epidemiology, social network analyses are also commonly used to determine the role of animal movement in disease transmission. Some studies were conducted using social network analyses to determine the impact of contact networks between farms [4, 5]. These studies provided new insights on the influence of network properties on disease spread within a community.

Meanwhile, cloud computing is a paradigm for delivering computing resources via the Internet, enabling consumers and businesses to access and utilize hardware, software, and services through a cloud infrastructure without the necessity of investing in physical infrastructure. This concept enables enterprises and individuals to reduce initial investment and maintenance expenses while offering flexible scalability and convenient access from any location and device with an Internet connection. Cloud computing offers unlimited computational resources, yet integration with ABM frameworks remains underexplored. Running simulation models on the cloud enables researchers to tap into unlimited resources as well as to perform and share their experimental results in an intuitive, user-friendly, and easy way.

Recently, in Vietnam, studies of pig movement patterns provided more in-depth information on how farm systems can affect the spread of infectious diseases in pigs [4, 6, 7]. Vietnam's livestock statistics for 2020 show that there were 19.6 million pigs. Hanoi was the second largest province when it came to pig farming with almost 1 million. Therefore, data collection for the Hanoi pig farming industry will become easier. To the best of our knowledge, there are no studies evaluating the effectiveness of ASF epidemic control strategies using multi-agent cloud simulation in a specific geographical area such as Hanoi. The purpose of this study is to create a cloud-based simulator implementing ASF spread models, which will allow us to assess the effectiveness of disease control measures to reduce the impact of ASF on Vietnam. It is functionally tested using the ASF disease spread model in Hanoi. The results of simulations with different scenarios will also be presented and discussed in terms of their epidemiological implications for the community.

This paper is organized into six sections. Section 2 provides a summary of the relevant literature. The multi-agent model for ASF spreading to Hanoi farms is described in Section 3. In Section 4, we present the implementation of this model on our cloud platform using GAMA (GIS Agent-based Modeling Architecture), a powerful agent-based simulation (ABS) platform. Section 5 discusses numerous findings from running simulations with various control measures. Finally, we conclude the paper in Section 6.

## 2. Literature Review

Harvey et al. [8] collected and classified studies on the ASF spread model in three categories, which are methodology, objectives, and framework work. If they are classified by method, then there are three different types: experimental, observational, and simulation. Four types can be classified according to the objectives of the model. Estimate parameter type determines how quickly the virus spreads in pig farming, within herds of pigs, and under other conditions. The type that evaluates alternative strategies for disease control, pig reproductive strategies, and other measures is Assess Alternative Control Strategies. Type Assess Transmission Determinants focuses on the transmission dynamics, ecological aspects of the virus causing the illness, etc. Type Assess the consequences of hypothetical outbreak analyzes how the size and duration of control areas affect the outcome of an epidemic. It also assesses whether the virus poses a threat to the livestock sector.

According to the frameworks, the classification includes models based on population, on meta-population, and solely on individuals. Population-based modeling is one where organisms are defined as belonging to a species. Each population has characteristics such as density, increase in natural rate, death rate, age distribution, dispersal, growth rate, etc. [9]. Models that consider a single population are the simplest. To determine the interactions between populations, growth rates and death rates are taken into account. It can depend on the size of the population but not on other populations. A metapopulation can be defined as an ensemble of disjunct spatial groups with some genetic or demographic connection. As a result, any specific group of populations could be considered a metapopulation. If they are not connected genetically or in a demographic sense, the groups can function separately and as different populations. Last, the agent-based or individual-based is known. These models provide feedback through the modeling framework [10]. Every individual has unique characteristics, which allows greater variations in behavior. The individual, the interactions among individuals, and the environment are three important aspects to take into account when creating an individual-based simulation. The development of traits with adaptive properties that mimic the behavior of real-organisms is the key to a successful model. Indirect interactions can take place through the modification of an environment. For example, a chemical or physical mark is placed in a particular area to signal future individuals. The environment is the physical landscape in which organisms can move and interact. Changes in the environment are frequent enough that individuals can adapt to them.

There are several studies on the spread of ASF in the world and in Vietnam. In the study by Tiwari et al., the authors utilized the Minimum Convex Polygon (MCP) model combined with the logistic diffusion model to analyze the spatial growth rate of ASFV on a weekly, monthly, and yearly basis. This approach provides a better understanding of the disease spread trends, thereby supporting the adjustment of management measures and the effective establishment of buffer zones [11]. In another study, Hsu et al. developed an integrated spatiotemporal model to provide an in-depth analysis of ASF spread [12]. The research team estimated outbreak clusters based on both temporal and spatial factors, thereby identifying seasonal indices and the disease's transmission direction. The results revealed a distinct seasonal distribution of outbreaks, with the highest frequency occurring from August to October and the lowest from April to May. This model suggests that, at least in part, the seasonal trends of ASF can be explained by the interaction between environmental factors, such as rainfall, and cultural practices that contribute to the disease's spread. Lee et al.'s model [13] uses the North American Animal Disease Spread Model (NAADSM) to evaluate control strategies and simulate various scenarios for ASF transmission among farms. The authors used real data from Vietnamese pig farms in the Red River Delta region. The author's scenarios included both direct and indirect contact scenarios, and then movement restrictions were implemented. The restriction of movement led to a significant decrease in the number of affected farms. In another work by Lee et al. [5], an SIR model is used to determine the effect of eliminating contaminated farms on disease outbreaks. The primary limitation of this study is its inability to consider all possible risk factors. They also point out the uncertainty of estimated parameters associated with disease transmission.

Our study uses an individual-based simulation modeling method to evaluate different control strategies, the transmission of disease, and its consequences. ASF outbreaks are the subject of similar studies such as [5, 11-13], but they differ from ours by the geographical scope applied (ours involves Hanoi), the platform technology used (we utilize a cloud-based multi-agent simulation platform, GAMA [14-16]), or even the methodology used (agent-based modeling).

## 3. Model of the ASF Spread

### *3.1. Main Components of the Simulation Process*

The NAADSM (North American Animal Disease Spread Model) is a simulation model used to study the spread of animal diseases, including the simulation of ASF spread [8]. Since it focuses on the goal of measures to control disease spread, the model has omitted some components such as infectious states: exposed, subclinical infected, and recovered. Thus, the built model studies only two states: susceptible and infected (i.e., SI model). The object of the model is to develop pig farms with the assumption that when one pig is infected, the whole herd is considered infected. The model also disregards vaccination mechanisms because it takes time to assess the effectiveness of the new ASF vaccine developed in Vietnam. The research focuses on models aimed at evaluating alternative control strategies and belongs to the category of individual-based models (or agent-based models). Instead of applying population-based models and metapopulation models, which are unsuitable due to the absence of geographical attributes for each studied entity, this approach provides a more precise representation. The equations describing the dynamics of the simulation system are differential equations or probabilistic rules that depict the state transitions of individuals from susceptible (S) to infected (I). The infection rate based on pig population density is calculated using Equation 1.

$$\rho = \frac{N}{A} \quad (1)$$

Where N is the number of pigs in a farm or area, and A is the area of that farm or region.

The main parameters of the model are referenced from the model of Lee et al. [13], including the probability of infection when a farm comes into contact with another infected farm and the frequency of contact between farms. At the same time, the model has added a number of parameters to simulate additional scenarios, such as the waiting time for destruction or the number of farms taken from reality.

The model is simulated using the GAMA platform [14] with components of the simulation process, as shown in Fig. 1. QGIS is used as a preprocessing tool to filter out unnecessary map information for simulation, utilizing the .shp (shapefile) format [17], which is supported in GAMA. Data on the number of farms and the total pig population in each district is processed in Excel and stored in .csv format. The GAMA platform is employed to construct and execute simulations based on the disease spread model, incorporating two input data sources from the preprocessed .shp and .csv files. The entire simulation code is stored in .gaml files [14]. During the simulation process, the Parameter Setting feature allows users to customize scenarios to validate different outbreak situations. Simulation also allows users to influence the parameters to set up simulation scenarios. The simulation is capable of displaying the spread of the ASF epidemic on a map of Hanoi, and is also capable of extracting parameters used to test and verify the model. Simulation also allows the extraction of parameters used to evaluate the impact of epidemic control methods.

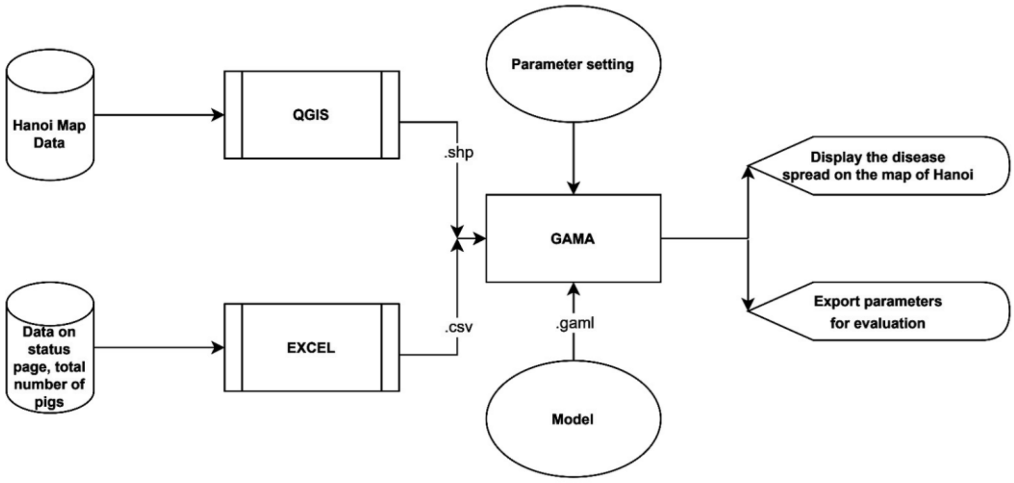



Fig. 1. The main components of the simulation process: QGIS is used as a preprocessing tool to filter out unnecessary map information, data on the number of farms and the total pig population in each district is processed in Excel, the GAMA platform is employed to construct and execute simulations based on the disease spread model, incorporating two input data sources from the QGIS and Excel files.

### *3.2. Simulation Data*

General Statistics Office of Vietnam provided information on the number of large and medium pig farms and small households that raise pigs. They also provided data on the total number of pigs in Hanoi's communes and districts [18]. To classify livestock operations, they were divided into three different categories: small farms (less than or equal 100 pigs), medium farms (100 to 1,000 pigs), and large farms (more than 1,000 pigs). These data show that while the number of large and medium farms (226) is very low compared to the number of smallholdings that raise animals (44,429), they represent a substantial proportion of total pigs (27.27%).

It is worth noting that, while the General Statistics Office (GSO) provides official statistics on farm structures and pig populations at the commune and district levels, detailed time-stamped, farm-resolved ASF outbreak and culling records are not publicly available in Vietnam. In practice, available outbreak statistics are often aggregated at administrative levels, reported using different definitions (e.g., "culled" versus "dead and culled"), and maintained across multiple agencies, which makes it difficult to construct a consistent ground-truth dataset for rigorous quantitative validation at the farm level. Therefore, in this work, we focus on calibrating the baseline livestock system using official population statistics and use the model primarily for large-scale scenario comparisons while acknowledging this validation constraint.

The map data was downloaded from Vietnam Map [19]. These map data were processed using QGIS, keeping only the necessary information to simulate. We retained two specific layers that were related to the boundaries and centers of the commune and district. At the same time, we deleted any data from outside of Hanoi.

*3.3. Multi-agent Model*

Model input is the total number of pig farms in Hanoi, classified by size. Randomly, a farm is chosen as the source of infection. From there, the model simulates the spread of disease using random probabilities. Every simulation cycle is equivalent to a day in real time and the model will run for 364 cycles. This is equivalent to 52 weeks. A predetermined list of trading relations will determine how the farms interact. In each case, the probability of the recipient farm becoming infected is high if the farm source is also infected. ASF spreads in Vietnam mostly through indirect contacts (such as vehicles or people moving around, feeding, etc.). For medium- and small-scale farms, the direct and indirect probabilities of transmission are both 0.6 or 60% (according to [6, 20]). The biosecurity level of large farms is usually high, resulting in lower probabilities of indirect transmission. Following consultation with experts in the area, a probability of 0.006 (0.6%) of indirect transmission was determined for this type of farm.

The main suppliers of pigs in Vietnam are medium and large farms. The number of pigs transported from smaller to larger farms is very low [20]. Lee et al. (2020), suggest that the weekly trading rate is determined by considering the distribution [5]. To determine direct contact, they looked at statistics such as the frequency with which farmers catch pigs on farms for the purpose of sale and the frequency in which boars are shared between breeding facilities. They used a number of factors to evaluate the possibility and frequency of direct contact. These included the frequency and duration of vehicle visits to the farm within a six-month period, the number and duration of time veterinarians, veterinary technicians, or other residents visited the farm and how they interacted with the farm. The statistical process showed that the Poisson probability was the most appropriate. It is possible to use this probability for different parameter models. The distributions for the contact rate are calculated weekly.

Because ASF spreads quickly, if one pig becomes infected, almost 100% of animals in a herd will also become infected. We ignore transmission within a herd when we study ASF and assume that all animals are infected. Our model visualizes the infected farm as a change from green to red, and it disappears once destroyed.

*3.4. Design of the Model in GAMA*

Our study utilizes GAMA, a desktop simulation platform, to create explicit agent-based simulations. GAMA was chosen over other simulation tools such as Matlab, Dymola, and SciPy due to its specialized design, which enables the development of complex models with multiple interacting entities. Its powerful spatial processing capabilities, with built-in GIS integration, allow GAMA to simulate real-world environments more effectively than Matlab and SciPy, which require additional libraries. GAMA's intuitive interface enables users to easily observe, adjust, and analyze simulations without the need for complex programming, unlike Matlab or Dymola. Additionally, GAMA supports high-performance computing with parallel execution across multiple CPU cores, whereas Matlab and SciPy are not optimized for large-scale multi-agent simulations. With its dedicated GAML language, GAMA simplifies agent behavior modeling compared to the more complex coding approaches required in Matlab and SciPy. Furthermore, GAMA offers strong integration with various data formats and web services, while other tools often require additional configurations.

GAMA provides a comprehensive agent-based modeling (ABM) and simulation environment. In this research, it is applied to model the spread of ASF in pig farm environments in the Hanoi region. GAMA has a simulation interface that consists primarily of a screen that shows the Hanoi map, the districts, and the communities in Hanoi as well as the pig farms with the option to track the facilities. To make GAMA more accessible to epidemiology researchers, we have created a cloud-ready version [15]. It is based on the services and key principles of Parlavantzas et al. [21] for developing and implementing high performance cloud-based epidemic simulation applications.

In terms of appearance, each farm has a circle that represents it. Its radius is based on the number of pigs in the facility. ASF infection is indicated by the color of the circles. We designed a species (a GAMA data class representing a species or object) to represent the pig farms, which includes attributes such as the number of pig individuals in each farm, whether the farm has been infected or not, the number of days since the farm detected an infected pig, and a list of other small-/medium-/large-scale farms that can trade with this farm. Pig farms can also be designed to have certain behaviors, such as "infect". When the farm is infected, there is a probability that it will spread the disease randomly to other farms listed in the contact list.

GAMA represents district shapes as species in its simulation environment. The species in GAMA include attributes like whether a district has been infected or not. They also contain the number of farms and pigs that are located there, including the number of farms with pigs. The parameters of this species are updated as well when drawing it. For the display of district shapes and coordinates, the Shapefile format [17] and other data are imported into the software.

The model presents statistics such as the number of farms, infected individuals, and non-infected individuals, along with displaying color changes for each district and farm on the map. The intensity of the red color in the RGB system increases as the number of infected farms rises. It also displays line charts showing the percentages and numbers of infected and uninfected farms. Each stage will generate shapefiles for display on the front-end of the web-based graphical interface on the cloud. Fig. 2 shows an illustration of the distribution of farms displayed by the front-end of the GAMA cloud-based simulator, which will be discussed in detail in the next section.

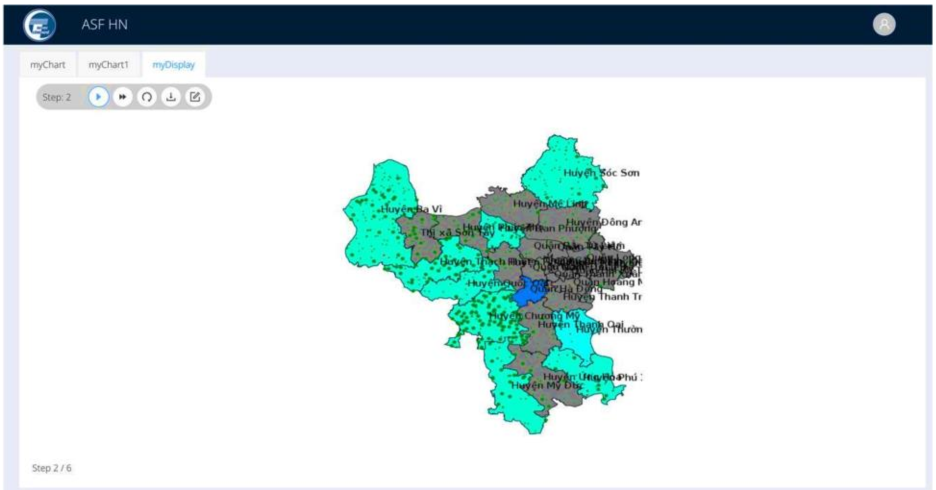



Fig. 2. The design of the graphical interface that implements the ASF spread model on the GAMA cloud-based simulator: The main screen shows the Hanoi map, the districts, and the communities in Hanoi as well as the distribution of pig farms (green dots).

## 4. Implementation of the Simulation Application in the Cloud

### *4.1. Implementation of the Simulation Application*

Using the agent-based ASF spread model developed on the GAMA platform, we simulated the spread of ASF in Hanoi. The simulations were divided into six scenarios: the base scenario and those that employ disease control strategies. In each scenario, the simulation is run 100 times, and the average values of key metrics such as the number of infected farms and the number of farms requiring pig culling are calculated for each farm type. During the initialization phase of each scenario, the simulation reads farm data and geographic data of Hanoi. Then, farms are initialized with their random locations and sizes across districts by the GAMA program. The program maintains the locations and sizes of the farms, as well as the randomly initial infected farm, until it executes all simulation runs of the scenario. In each simulation run, the spread of ASF in Hanoi is simulated over 52 weeks, a period long enough to cover a full pig production cycle in Vietnam (typically 6 to 8 months).

Fig. 2 depicts a map showing pig farm locations in Hanoi. In this figure, districts are divided by a black border with little yellow spots indicating their centers. Small, medium and large farms are denoted by different sized dots. The green dots on the map represent unaffected farms, while the red dots signify farms that are infected by ASF. The spread of ASF is also indicated by the colors of districts. Red areas have an extremely high spread rate. Depending on the settings, this could be greater than 75% of affected pigs and/or farms. Orange, yellow, and green indicate infection rates that are below 75%, 50%, 25%, respectively. The grey zones indicate areas without disease. In the inner districts of Hanoi, there are no pig-farming areas, so these appear naturally gray. This application displays not only the geographical distribution but also various charts to track statistical data. Line charts illustrate the evolution of both the farms involved and the number of pigs infected during an outbreak. The software allows us to understand trends and predict whether the outbreak is likely to escalate quickly or slowly. This software also includes pie charts showing the number of infected farms and how many infected pigs are in each district.

### *4.2. Architecture of the Simulation Application on the Cloud*

Regarding the architecture of the simulation application deployment system, we use the Client - Server architecture pattern to design the system as described in Fig. 3. This system runs on the OpenStack private cloud deployed at the Center for Digital University of our university [22]. On the client side, the ReactJS framework is used to build a user interface that displays the simulation for the user. On the server side, Laravel [23] is used as the backend, using the Restful API to communicate with the front end, and the server side also needs to preinstall GAMA Desktop. When the client side runs the simulation API, Laravel will run GAMA through Headless mode. The resulting information will be saved in the MySQL database and files, and folders (e.g., projects, simulation images) will be managed by AWS cloud [24]. All user management operations are performed on the standard client-side interface. The back-end system source code has been openly published by the research team [16]. It can be seen that interacting through the cloud-based interface provides ease of use for users and experts. Additionally, availability is always ensured, allowing policymakers without deep technical expertise to use the system without requiring complex configurations, unlike the GAMA Desktop version. Another important aspect is that cloud infrastructure solutions offer high computational performance and flexible scalability, enabling simulations to run faster and expand more efficiently [7].

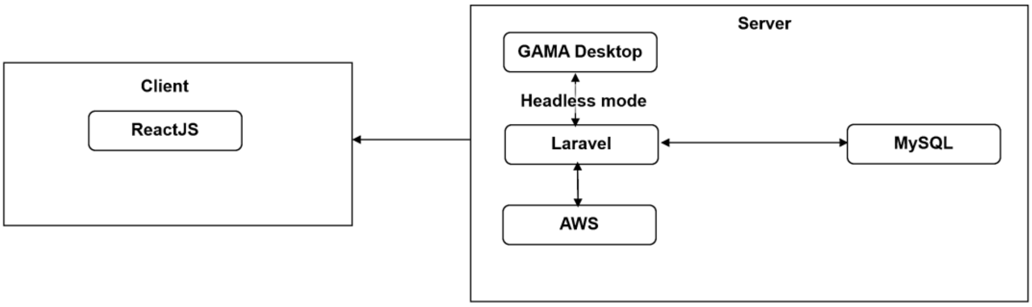



Fig. 3. The architecture of the GAMA-based cloud simulation application with ReactJS at the client side and GAMA Desktop, Laravel, MySQL at the server side.

## 5. Results and Discussion

In this section, we perform simulations with the multi-agent model mentioned in Section 3 on the cloud system described in Section 4. To be able to evaluate the effectiveness of strategies to control the spread of ASF, many different scenarios have been designed that correspond to these strategies. The parameters used for each scenario are shown in Table 1. These parameters can also be customized right on the graphical interface of the cloud simulation application

Table 1. The parameters used for the scenarios

| Parameter / Scenario | Direct contact | The contact of large farms | Movement restriction (%) | The duration of the restriction (weeks) | Movement restriction (%) | Reduce the probability of transmission through indirect contact (%) | The destruction of pigs | The duration of destruction delay (weeks) |
|---|---|---|---|---|---|---|---|---|
| Base Scenario | True | True | 0 | 4 | 0 | 0 | False | 2 |
| Culling all pigs from infected farms | True | True | 0 | 4 | 0 | 0 | True | 3 |
| Elimination of direct contact and contact of large farms | False | False | 0 | 4 | 0 | 0 | False | 2 |
| Limitation of movement of infected farms | True | True | 75 | 4 | 0 | 0 | False | 2 |
| Restriction of movement of all farms | True | True | 0 | 4 | 75 | 0 | False | 2 |
| Improving biosecurity for small and medium farms | True | True | 0 | 4 | 0 | 50 | False | 2 |

### *5.1. Base Scenario*

In this scenario, no measures are applied to prevent disease spread. The simulation results of the base scenario in Fig. 4 show that most farms were infected at the end of the third quarter, consistent with the model results of Lee et al. [13]. The remaining uninfected farms are mostly large farms with high levels of biosecurity. Fig. 4 also depicts the states of the ASF model in each of the four quarters when the spread of ASF is simulated without applying any controls. In the graphs, it is clear that 99% of the farms were infected within a year. Regardless of this extreme high, as we can see from the figure, the infected number of pigs only represents approximately 30% of the total population of pigs in Hanoi. In other words, large farms tend to have lower rates of infection. It is easy to explain by the biosecurity standards and hygiene measures implemented on larger farms. It is clear from these charts that ASF's severity and spread will be increased if control measures are not implemented. In one year, most of the areas in the region have become red zones because there are so many facilities that are affected.

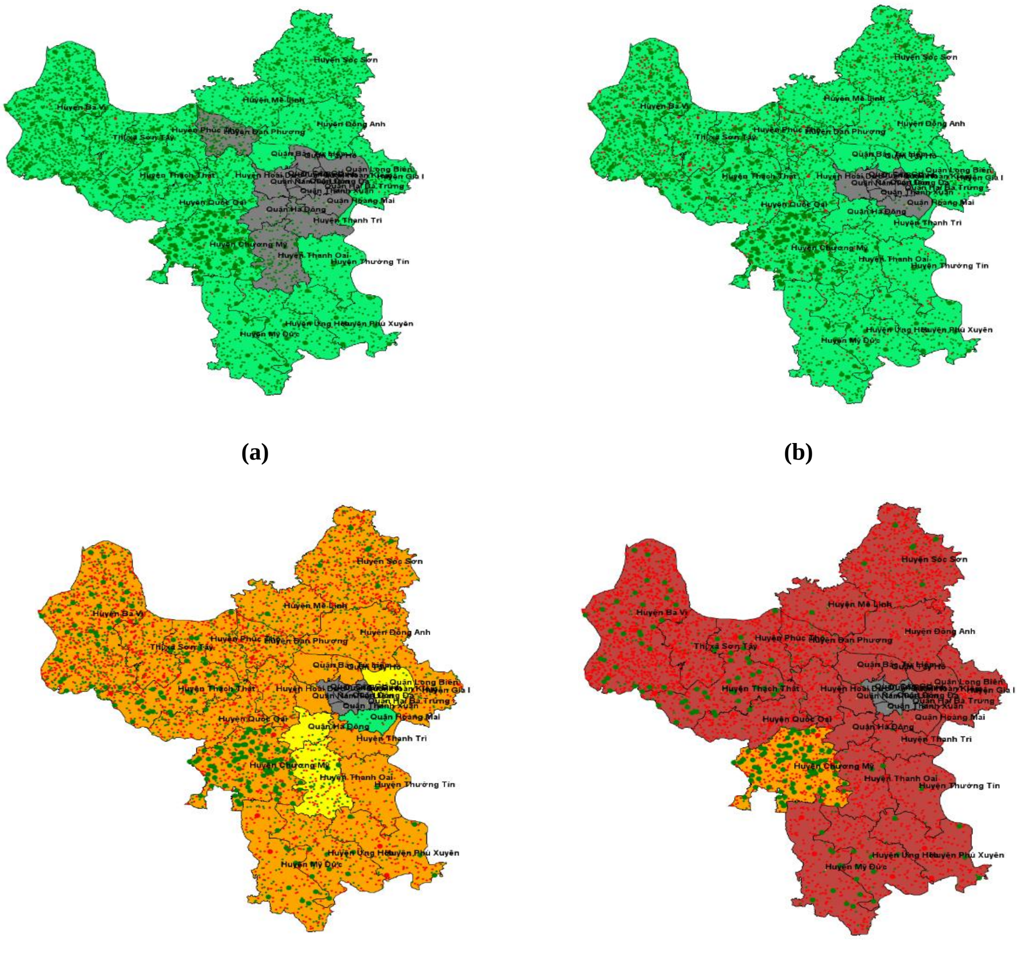


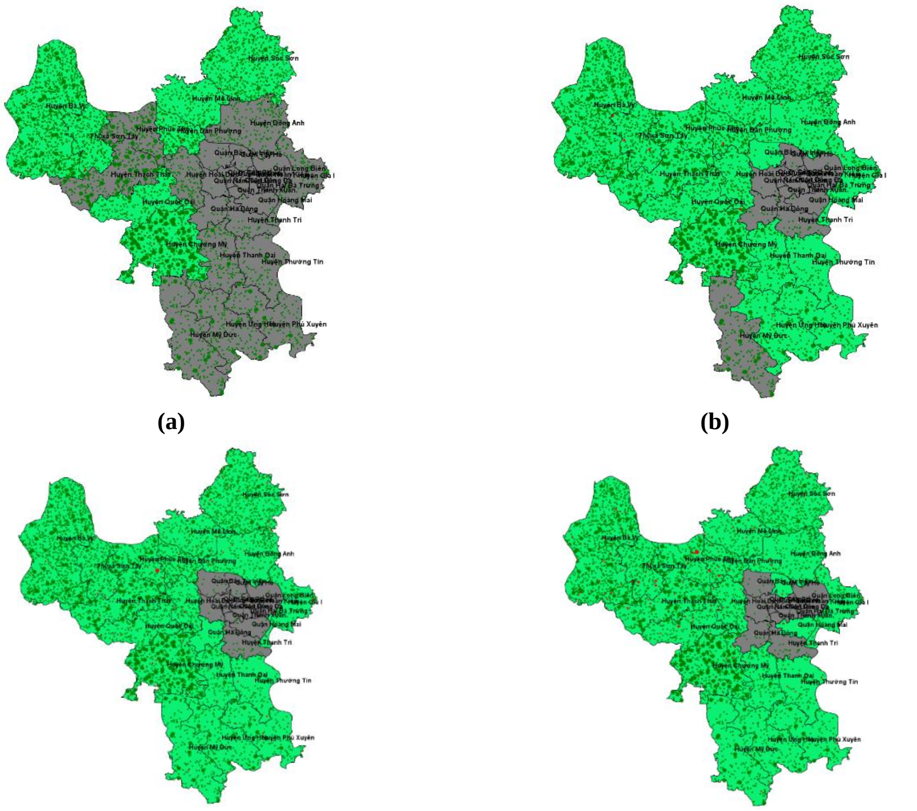

Fig. 4. The ASF states spread at the end of a) the first, b) the second, c) the third and d) the fourth quarters when no control strategy was applied: most farms were infected at the end of the third quarter and the remaining uninfected farms are mostly large farms with high levels of biosecurity.

### *5.2. Culling All Pigs from Infected Farms*

The scenario of culling pigs from infected farms allows us to assess the role of culling measures on the rate of spread of ASF. By adjusting the delay time parameter before culling, we can create different scenarios such as culling pigs after 2/3/4/6 weeks after the farm is infected.

Fig. 5 depicts different model states at the ends of four quarters when the ASF is spread by implementing a strategy culling pigs with at least one infected animal on the farm, but with a six-week delay. Pigs are culled six weeks after determining a farm of infected pigs. We can see from the figure that, after 1 year, the risk has been significantly reduced. Specifically, the number of infected pigs is now only 2% (a 15-fold reduction compared to the base scenario). The number of infected farms has also dropped dramatically to about 3% (an 87% decrease), excluding culled farms and pigs. The infected and culled pigs make up approximately one-third of the infected ones in the base scenario (approximately 8% compared to 30% infected without control).

This number is very impressive. After the implementation of the culling measures, only a little more than 10% of the farms were infected. Failing control measures, the non-infected farms would only be around 9%, mainly large farms. When the culling approach is applied, this number of farms that are safe and noninfected increases 10 fold. By comparing maps for culling infected animals and those without intervention, we can clearly see the decrease in infected farms during the third quarter. As shown in Fig. 5d, we see that most areas only have a small number of infected farms.



(a) (b) (c) (d)

Fig. 5. States of the ASF spreading model at the end of a) the first, b) the second, c) the third, and d) the fourth quarters when applying the strategy of culling all pigs on farms with infected pigs with a delay time of 6 weeks. Consequently, little more than 10% of farms were infected, with a notable decline recorded in the third quarter relative to the base scenario.

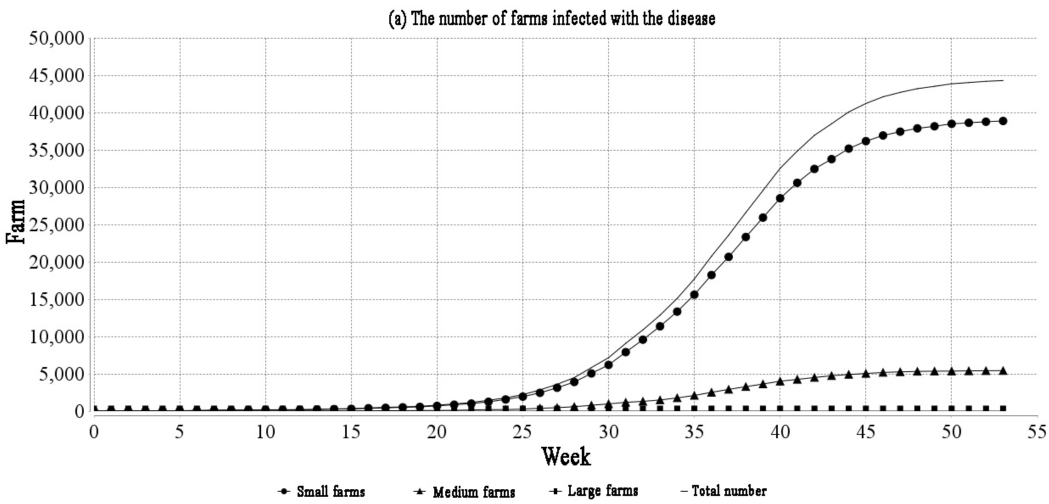
Due to space restrictions, we are only able to provide maps for the scenario in which infected pigs would be killed after a 6-week delay. However, the results obtained by applying the culling strategy with different time delays show that by reducing the culling time to under 3 weeks, we will be able to prevent the ASF epidemic from spreading. The use of this measure is one of the most effective disease control strategies, especially in the absence of an ASF vaccine. Culling has a significant impact on epidemic control and is crucial to preventing ASF. However, it is necessary to consider the economic consequences it brings to farmers and society.

### *5.3. Eliminating Direct Contacts of All Farms and Contacts of Large Farms Only*

The scenario of elimination of direct and large farm contact allows us to assess the role of direct and indirect contact in the spread rate of the ASF. By changing the two parameters involved in the elimination of direct contact and the contact of large farms, we can create two scenarios for evaluation: the elimination of direct contact scenario and the removing contact of large farms scenario. These two scenarios are compared and assessed with the base scenario, where there is direct contact and contact of large farms. The average number of farms infected with the elimination of direct contact and contact of large farms is described in Table 2.

Table 2. Results when eliminating direct contact and contact of large farms. The indirect contact has a huge influence on the spread of the disease, but large farm contact does not have much impact on results

| Contact Type | Total | Small Farm | Medium Farm | Large Farm |
|---|---|---|---|---|
| Both direct and indirect contact | 44645 | 39444 | 5201 | 139 |
| Indirect contact only | 44615 (-0.07 %) | 39443 (-0.02%) | 5172 (-0.56%) | 127 (-9.45%) |
| Eliminate contact of large farms | 44134 (-1.16 %) | 39340 (-0.27%) | 5169 (-0.62%) | 0 (-100%) |



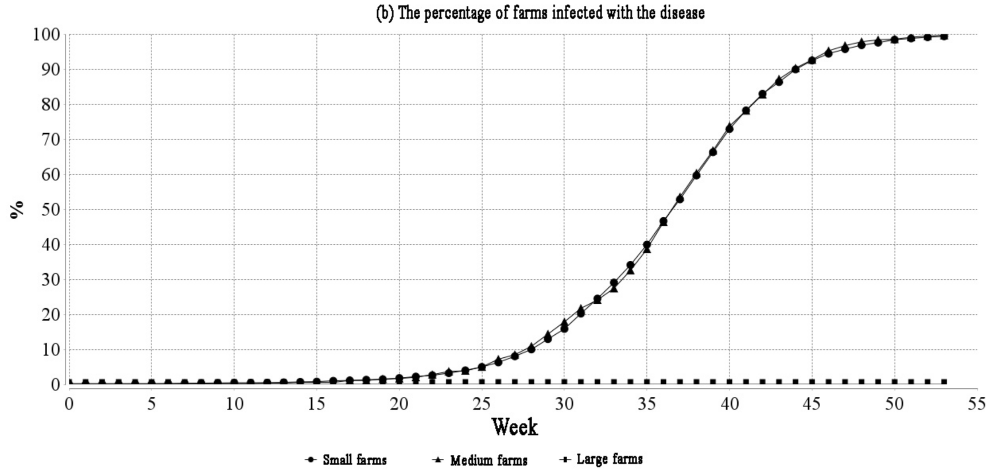



Fig. 6. Results of simulations for scenarios involving the elimination of large farm contacts and direct contacts: (a) Number of infected farms and (b) Percentage of infected farms.

Based on the results, we can see that indirect contact has a huge influence on the spread of the disease. If we ignore direct contact, the results do not change much. Large farms are highly biosafe, making it more difficult to get infected. So ignoring large farm contacts does not have much to do with the outcome. Fig. 6 shows the results when eliminating direct and large farm contact.

### *5.4. Limiting the Movement of Infected Farms*

The movement limit of the infected farm scenario allows one to assess the role of movement restrictions on the ASF spread rate. By changing the parameters related to the movement limitation coefficient and the duration of limitation applied, we can create many different scenarios, such as limiting 25/50/75/100% of the movement of infected farms after 2/4/6/8 weeks. On the simulation side, restriction of movement is represented by a reduction in the Poisson distribution coefficient when calculating the average number of contacts an infected farm has had in a week [25]. For example, a large farm with 50% movement restrictions would have: the average number of direct contacts to medium-sized farms per week is Poisson(0.073/2); the mean number of indirect contacts from medium-scale farms for a week is Poisson(3.5/2) (instead of Poisson(0.073) and Poisson(3.5)). Subsequently, a contact list is created, selecting target farms within a 30 km radius that match the appropriate farm type.

The results of the simulation for the movement limit scenarios are presented in Table 3. Restricting the movement of infected farms only yields the expected results when the restriction of movement is greater than 75%. If the movement restrictions are too low, the rate of spread remains very high. Restricting 100% of movement to infected farms will reduce the infection rate by 99.72%, but it seems that this scenario is not practical. Fig. 7 also shows that the result of restricting movement by 75% has significantly reduced the number of infected farms.

### *5.5. Restricting the Movement of All Farms*

The restraint scenario for all farms is similar to the limiting scenario of infected farms. The difference here is to apply the movement restriction to all the farms and apply it right from the start of the simulation when the epidemic appears. By changing the coefficient of limitation of movement, we can create other scenarios like limiting 25/50/75% of movement of all farms. The results of these scenarios are presented in Table 4.

Table 3. Result when restricting movement of infected farms. Restricting the movement of infected farms only yields significant results when the movement restriction percentage is greater than 75%

| Movement restriction percentage | Average number of infected farms | | | | % change in average number of infected farms |
|---|---|---|---|---|---|
| | Total | Small | Medium | Large | |
| Base scenario | 44645 | 39444 | 5201 | 139 | N/A |
| 25% | 44565 | 39236 | 5329 | 71 | 0.18 |
| 50% | 44163 | 39049 | 5114 | 55 | 1.08 |
| 75% | 26206 | 23112 | 3094 | 9 | 41.30 |
| 100% | 126 | 112 | 14 | 0 | 99.72 |

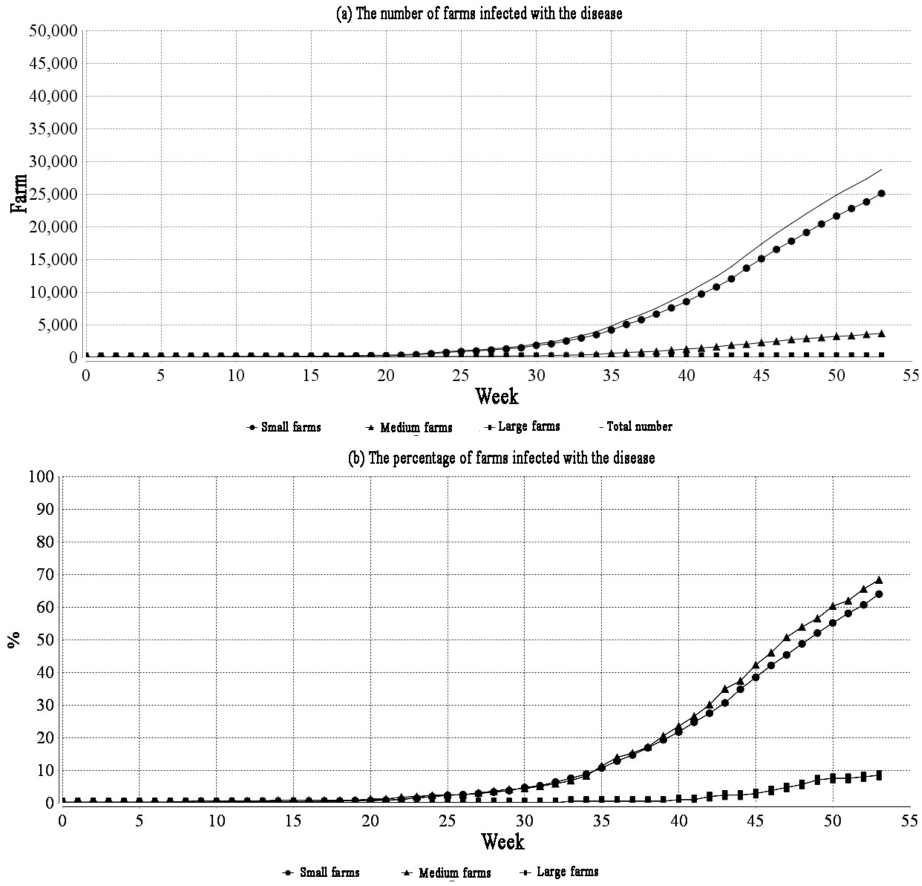



Fig. 7. Results when restricting 75% of infected farm movements: (a) Number of infected farms and (b) Percentage of infected farms.

Restricting the movement of all farms is effective in preventing disease spread quite quickly when the restriction is greater than 50% (see Fig. 8). However, restricting the movement of all farms will have a negative economic impact.

### *5.6. Improving Biosecurity for Small and Medium Farms*

The biosafety improvement scenario for small and medium-sized farms enables the assessment of the role of biosecurity improvement measures in the spread rate of ASF. Improved biosafety for small and medium farms helps reduce the risk of infection from indirect contact with these farms. By changing the parameter that reduces the probability of infection from indirect contact of small and medium farms, we created other scenarios, such as a 25/50/75% decrease in the probability of infection via indirect contact. These scenarios were compared and evaluated with the base scenario when there is no change in the probability of infection. The simulation results for the scenarios are presented in Table 5.

Table 4. The result when restricting the movement of all farms. Restricting the movement of all farms is effective in preventing disease spread when the restriction is greater than 50%

| Movement restriction percentage | Average number of infected farms | | | | % change in average number of infected farms |
|---|---|---|---|---|---|
| | Total | Small | Medium | Large | |
| Base scenario | 44645 | 39444 | 5201 | 139 | N/A |
| 25% | 44354 | 38873 | 5481 | 71 | 0.65 |
| 50% | 26655 | 23745 | 2912 | 6 | 40.30 |
| 75% | 621 | 570 | 51 | 0 | 98.61 |

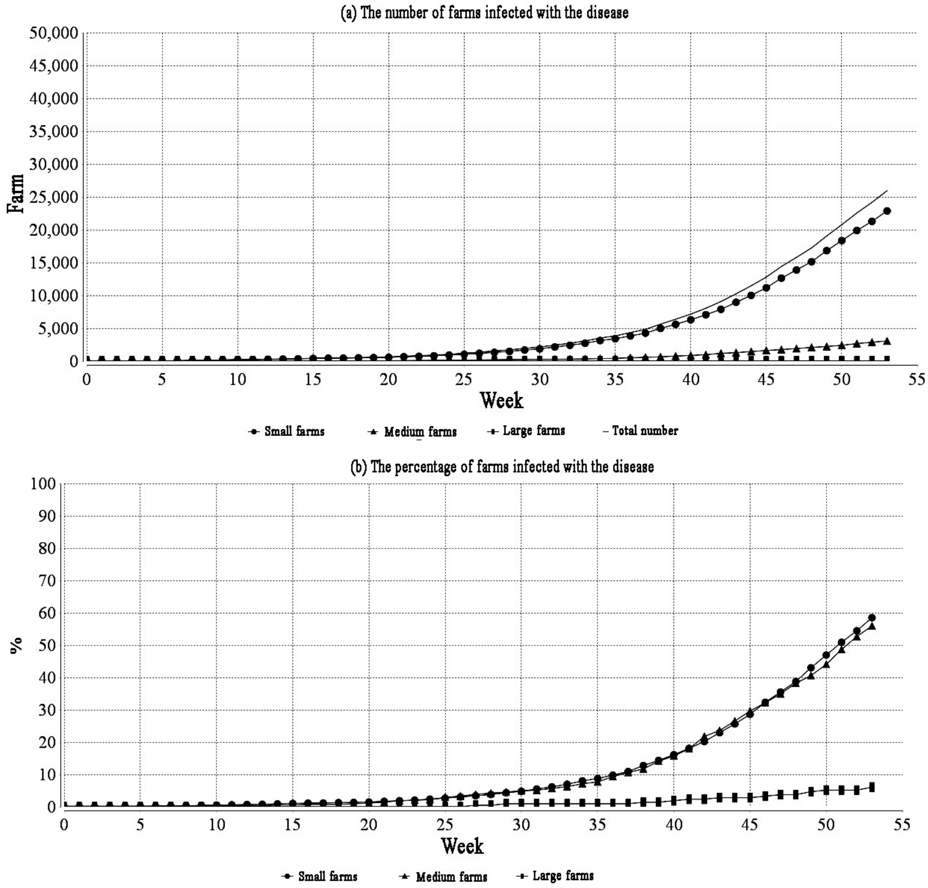



Fig. 8. Result when restricting movement of all farms by 50%: (a) Number of farms infected and (b) Percentage of farms infected.

We can see that improved biosafety measures for small and medium farms start to work when the probability of infection through indirect contact is reduced by more than 50%. Fig. 9 describes in more detail the outcome of this scenario.

Table 5. Results in improving biosecurity for small and medium farms. The measure starts to work when the probability of infection through indirect contact is reduced by more than 50%

| Parameters (Probability of infection) | | % change of parameters (Probability of infection) | | Average epidemic scale | % change in average results compared to the baseline scenario |
|---|---|---|---|---|---|
| Direct Contact | Indirect Contact | Direct Contact | Indirect Contact | | |
| 0.6 | 0.6 | N/A | N/A | 44645 | N/A |
| 0.6 | 0.45 | N/A | −25% | 44605 | 0.09 |
| 0.6 | 0.3 | N/A | −50% | 34105 | 23.61 |
| 0.6 | 0.15 | N/A | −75% | 24646 | 44.80 |

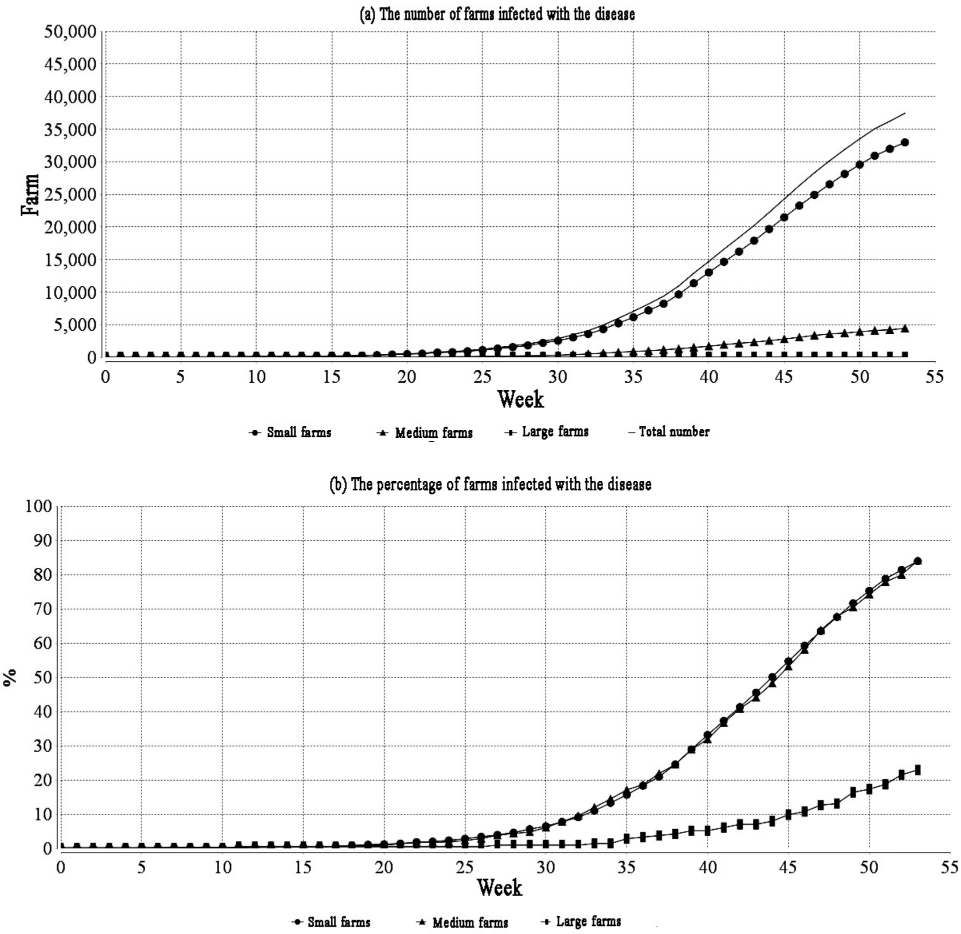



Fig. 9. Results when improving biosecurity by 50% for small and medium farms: (a) Number of infected farms and (b) Percentage of infected farms.

### *5.7. Limitations and Future Work*

In this study, the disease dynamics were intentionally simplified to support large-scale scenario experimentation. Specifically, the model adopts an SI formulation and omits additional epidemiological states such as exposed, subclinical, and recovered. While this abstraction is adequate for comparative evaluation of control strategies, it may not capture delays due to incubation or heterogeneous progression at the individual level, potentially affecting the timing and magnitude of simulated outbreaks.

Moreover, the model operates at the farm (herd) level and assumes that once infection is introduced into a farm, the whole herd is considered infected. In addition, within-herd transmission is not explicitly modeled. This assumption can accelerate the apparent transition of farms to the infected state and may overestimate outbreak severity when compared with real-world within-herd dynamics and detection delays. Consequently, the results should be interpreted primarily as a basis for relative comparison across intervention scenarios at the farm level, rather than as a precise prediction of within-farm infection trajectories.

Vaccination effects are excluded because the manuscript disregards vaccination mechanisms. Therefore, the simulated outcomes correspond to a no-vaccination setting, and the reported effectiveness of non-pharmaceutical interventions should be interpreted under this assumption. Future work will incorporate vaccination-related parameters (e.g., coverage, efficacy, and time-to-immunity) to assess vaccination and hybrid control strategies once more reliable field evidence becomes available.

Finally, the contact process is constrained by a spatial selection rule that considers connected farms within a 30 km radius, and the current implementation does not consider restocking after infection due to performance constraints at larger simulation scales. These constraints may limit long-term realism, especially for scenarios involving prolonged epidemic periods and supply-chain recovery. In future work, we plan to extend the model with restocking behavior and more flexible movement/contact mechanisms, leveraging distributed execution to maintain computational efficiency at scale.

## 6. Conclusions

According to the situation of ASF and the prevention policies implemented in Vietnam in recent years, the Vietnamese government is constantly making efforts to publish directives and develop support plans that aim to minimize damage to the pig herds and society. Contributions from this paper can help local authorities predict the spread of the disease and give timely, decisive instructions in order to reduce the damage. Our GAMA simulation platform on the cloud is user-friendly and open source. It can be used to develop and execute multi-agent models to predict the spread of ASF. Some key conclusions of interest can be drawn from the results of multi-agent simulations with different control measures, some of which have not been implemented in practice in Vietnam for various reasons. Using Hanoi as a case study, the simulation results indicate that (i) indirect contact plays a critical role in ASF transmission; (ii) small and medium farms contribute substantially to disease spread; (iii) movement restrictions can slow down transmission, although restricting all farms involves trade-offs with economic impacts; and (iv) improving biosecurity for small and medium farms is an effective mitigation strategy. Finally, in the absence of vaccination, early culling remains the most effective measure to control the epidemic. Future work will address the current modeling limitations (e.g., vaccination, restocking, and contact modeling) as discussed in Section 5.7.

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