Estimating the effectiveness of control actions on African swine fever transmission in commercial swine populations in the United States

Abagael L. Sykes[1φ], Jason A. Galvis[1φ], Kathleen C. O'Hara[2], Cesar Corzo[3], Gustavo Machado[1*]

Running title: The effectiveness of African swine fever control strategies

[1]Department of Population Health and Pathobiology, College of Veterinary Medicine, North Carolina State University, Raleigh, NC, USA.

[2]U.S. Department of Agriculture, Animal and Plant Health Inspection Service, Veterinary Services, Strategy and Policy, Center for Epidemiology and Animal Health, Fort Collins, CO, USA.

[3]Veterinary Population Medicine Department, College of Veterinary Medicine, University of Minnesota, St. Paul, MN, USA.

[φ]**share first author**

***Corresponding author:** gmachad@ncsu.edu

Abstract

Given the proximity of African swine fever (ASF) to the U.S., there is an urgent need to better understand the possible dissemination pathways of the virus within the U.S. swine industry and to evaluate mitigation strategies. Here, we extended *PigSpread*, a farm-level spatially-explicit stochastic compartmental transmission model incorporating six transmission routes including between-farm swine movements, vehicle movements, and local spread, to model the

dissemination of ASF. We then examined the effectiveness of control actions similar to the ASF national response plan. The average number of secondary infections during the first 60 days of the outbreak was 49 finisher farms, 17 nursery farms, 5 sow farms, and less than one farm in other production types. The between-farm movements of swine were the predominant route of ASF transmission with an average contribution of 71.1%, while local spread and movement of vehicles were less critical with average contributions of 14.6% and 14.4%. We demonstrated that the combination of quarantine, depopulation, movement restrictions, contact tracing, and enhanced surveillance, was the most effective mitigation strategy, resulting in an average reduction of 79.0% of secondary cases by day 140 of the outbreak. Implementing these control actions led to a median of 495,619 depopulated animals, 357,789 diagnostic tests, and 54,522 movement permits. Our results suggest that the successful elimination of an ASF outbreak is likely to require the deployment of all control actions listed in the ASF national response plan for more than 140 days, as well as estimating the resources needed for depopulation, testing, and movement permits under these controls.

Keywords: ASF dynamics, elimination of transmission, vehicle movements, disease preparedness, outbreak response.

1. Introduction

In July 2021, African swine fever (ASF) was identified in the North American continent for the first time since 1984 (Costard et al., 2009), with outbreaks now reported in domestic swine farms of both the Dominican Republic (Gonzales et al., 2021) and Haiti (OIE, 2021). This occurred alongside ongoing outbreaks across Europe and Asia in both domestic and feral swine (Mighell and Ward, 2021; You et al., 2021; de la Torre et al., 2022; Iscaro et al., 2022; Penrith and Kivaria, 2022) which have been characterized, in most cases, by high mortality and morbidity

(EFSA Panel on Animal Health and Welfare (AHAW), 2010, 2014; Gallardo et al., 2017). The transmission of ASF between domestic swine farms is primarily driven by direct transmission via contact with infected swine, often introduced to commercial farms via swine movements, while close contact with feral swine has been associated with spillover events (Vergne et al., 2015; Miller et al., 2017; Podgórski and Śmietanka, 2018; Ferdousi et al., 2019; Gebhardt et al., 2021; Yoo et al., 2021). ASF dissemination is also positively correlated with the spatial proximity between farms, which facilitates the local spread of ASF over short distances and the possible formation of spatial clusters (Vergne et al., 2015; Yoo et al., 2021). In particular, the movement of contaminated personnel and/or equipment between farms at short distances has been previously associated with local spread (Bellini et al., 2016; Zani et al., 2019; Gao et al., 2021; Chuchard et al., 2022). Additionally, the potential for ASF to survive on contaminated surfaces, such as transportation vehicles, for several days could lead to transmission via indirect contact (Y. Li et al., 2020; Yoo et al., 2021; Adedeji et al., 2022; Galli et al., 2022), another important route in ASF dissemination (Kim et al., 2021; Yoo et al., 2021; Cheng and Ward, 2022; Galli et al., 2022).

With heavy economical losses associated with ASF evident across the globe (Mason-D'Croz et al., 2020; Niemi, 2020; Weaver and Habib, 2020; Nguyen-Thi et al., 2021; You et al., 2021), mathematical-based modeling approaches have been utilized to estimate and forecast ASF epidemic trajectories, as well as to assess the effectiveness and cost of control actions (Nigsch et al., 2013; Korennoy et al., 2014; Halasa, Bøtner et al., 2016; Mur et al., 2018; Andraud et al., 2021; EFSA et al., 2021; Hayes et al., 2021; Machado et al., 2021; Yoo et al., 2021; Ezanno et al., 2022). In countries with previous ASF outbreaks, transmission models can be directly calibrated with outbreak data, allowing for the estimation of transmission parameters (e.g., the

transmission coefficient for between-farm animal movements) (Mur et al., 2018; Akhmetzhanov et al., 2020; Hayes et al., 2021; Yoo et al., 2021) however, ASF-free countries lack the disease-related data necessary for model calibration. In such cases, simulation-based approaches can be used to examine the possible transmission and dissemination dynamics of an ASF introduction.

Epidemiological parameters and knowledge regarding the structure of the swine industry are pivotal in the characterization of disease dissemination and the evaluation of control actions (Halasa et al., 2020; Hayes et al., 2021). In this study, we have collected detailed data on domestic swine populations including farm-level demographics, and between-farm swine and vehicle movement data to develop a stochastic, farm-level, compartmental ASF transmission model for the southeastern U.S.. To address the lack of epidemiological parameters regarding ASF dissemination dynamics and outbreaks in the U.S., we calibrated the transmission rates and surveillance effectiveness parameters using historical porcine epidemic diarrhea virus (PEDV) data from the first recorded outbreak in the study population (Machado et al., 2019). From our model, we estimated the volume of secondary infections, quantified the contribution of six transmission routes, measured the spatial distance from seeded to secondary infections, and assessed the impact of between-company dissemination of ASF. Importantly, we also examined the effectiveness of control actions based on the response strategy detailed in the U.S. Department of Agriculture (USDA) ASF response plan (The Red Book) (USDA, 2020), but with key differences, such as stricter movement controls and depopulation strategies, and estimated the resources required under the most effective control strategy, including the number and relative compensation cost of depopulated animals, the quantity of diagnostic tests performed, and the volume of movement permits required for swine and vehicle movements. With the

88 outputs of this model we address the lack of real-data driven transmission models of ASF spread
89 within the U.S..
90
91 **2. Material and Methods**
92 In the following sections we describe the farm-level population data, the construction of the
93 between-farm swine and vehicle movement networks, the modification of our previous stochastic
94 transmission model *PigSpread* (Galvis, Corzo and Machado, 2021; Galvis, Corzo et al., 2022;
95 Galvis, Jones et al., 2022) to accommodate ASF epidemiological parameters, and the evaluation
96 of ASF control actions listed in The Red Book (USDA, 2020).
97
98 *2.1 Data source*
99 The data used in this model was collected from the Morrison Swine Health Monitoring Project
100 (MSHMP) (MSHMP, 2022), and included a total of 2,294 farms from three swine production
101 companies in the southeastern U.S., identified as A (n = 1,745), B (n = 228), and C (n = 321) for
102 confidentiality purposes. The data consisted of: i) geolocation; ii) the unique premises
103 identification number; iii) production type (sow[1], nursery, finisher[2], gilt isolation unit[3], and boar
104 stud); and iv) swine capacity, which accounted for animals at the nursery age and older. In total
105 the data included 1,459 (63.6%) finisher farms, 468 (20.4%) nursery farms, 328 (14.3%) sow
106 farms, 33 (1.4%) gilt isolation units and six (0.3%) boar studs. The median swine capacity across
107 all production types was 3,200 (IQR: 2,201-5,135). In addition, between-farm swine movement
108 records from January 1st, 2020, to December 31st, 2020, were provided for each company and

[1]Sow farms included: farrow, farrow-to-wean and farrow-to-feeder farms.
[2]Finisher farms included: wean-to-feeder, wean-to-finish, feeder-to-finish farms.
[3]Gilt development and isolation: farms that could either be a finisher or sow farm depending upon the production company.

included information on: i) movement dates, ii) origin and destination farms, iii) the number of swine moved, and iv) the movement purpose (e.g., weaning, replacement gilts). Company A also provided global positioning system (GPS) data of four types of transportation vehicles from January 1st, 2020, to December 31st, 2020, described in more detail in section 2.2.

2.2 Swine movement and transportation vehicle networks

Using the between-farm swine movement data, we created a daily contact network with directed edges from the origin farm(s) to the destination farm(s). In total 731 (1.7%) movements were removed from the network due to missing data regarding either of the following: i) the farm location, ii) premises identification number, iii) the number of swine moved, or iv) the movement purpose.

Using the GPS data of 398 individual vehicles from company A, which included 76% of the farms in the study area, we constructed four daily directed contact networks to capture the potential for indirect transmission via vehicles moving swine between farms (swine vehicles, n=118), vehicles moving swine from farms to slaughterhouses (market vehicles, n= 89), vehicles delivering feed to farms (feed vehicles, n=159), and vehicles moving loading crews between farms (crew vehicles, n=32). Here we used an approach proposed by Galvis et al., 2022 to reconstruct daily networks. A more detailed description is provided in Supplementary Material Section A. In total there were 3,182,144 edges in the feed vehicle network, 386,730 edges in the pig vehicle network, 35,854 edges in the market vehicle network, and 109,675 edges in the crew vehicle networks (Galvis, Corzo et al., 2022). Further summary metrics for the networks are provided in Galvis, Corzo et al., (2022).

2.3 Model calibration

As the U.S. remains free of ASF at the time of writing, there was no outbreak data available to calibrate ASF transmission dynamic parameters. Instead, we used PEDV outbreak data from the first introduction of the virus in the study region in 2013, as a proxy (USDA, 2014; Machado et al., 2019), which allowed for the evaluation and reproduction of the transmission dynamics of a novel pathogen introduced into a susceptible population.

Using an Approximate Bayesian Computation (ABC) rejection algorithm (Hartig *et al.*, 2011; Minter and Retkute, 2019), we identified particles (sets of transmission parameters produced by the model) that reproduced the temporal distribution of PEDV cases according to a tolerance acceptance error (Supplementary Material Section B, Table S1) (Sisson et al., 2007). We drew posterior probabilities for selected parameters from these particles, including transmission rate parameters (β_n, β_s, β_p, β_m, β_f, β_c and β_l); and the effectiveness of passive surveillance for each production type (L_{sow}, $L_{nursery}$ and $L_{finisher}$), the results of which are presented in Supplementary Material Section B Figures S1-S5 and Table S3. An in-depth description of the PEDV calibration is presented in Supplementary Material Section B.

2.4 Baseline transmission model (No control scenario)

Here we modified *PigSpread* (Galvis, Corzo et al., 2022) to accommodate an ASF compartmental model which included the following four mutually exclusive farm-level health states, Susceptible (S), Exposed (E), Infected (I), and Detected (D) (SEID) (Figure 1) and six transmission routes: i) swine movements; ii) swine vehicles; iii) market vehicles; iv) feed vehicles; v) crew vehicles; and vi) local spread, which accounts for mechanical transmission via personnel, equipment and wildlife/pests. The swine and vehicle movements were incorporated as

directed temporal networks while the local spread was incorporated using a gravity model with a varied cutoff from one km to 25 km. Further details about the transmission routes including local spread are available in Supplementary Material Section C.

To account for the variation of between-farm movements we varied the start date and initial seed infection for each simulation. Start dates were sampled between January 1st, 2020, to December 31st, 2020, while each farm in the study population was the initial seeded infection for 100 simulations, resulting in 229,400 repeats in total. To mimic long-duration outbreaks, we ran each simulation for 140 days and collected information at each time step t, where $t \rightarrow t+1$ is one day (Supplementary Material Section C, Figure S6). As our model was implemented at the farm level, we assumed that animal populations within farms remained constant unless purposefully depopulated within the control scenarios (section 2.5). Additionally, as no control actions were implemented in the no control scenario, it was assumed that farms in this scenario could move swine freely regardless of the compartment in which the farm resides. Further details of the model dynamics and sensitivity analyses, including the comparison of sensitivity results are available in Supplementary Material Section C.

[Figure 1]

2.5 Control scenarios

We assessed the impact of five ASF control scenarios (Table 1), which incorporated combinations of the control actions based on the USDA's ASF response plan, The Red Book (USDA, 2020), detailed below. These control actions were implemented once the first ASF case was detected in a domestic swine farm (USDA, 2020). Below we describe each strategy and note differences between the strategy modeled and the current USDA response plan. Additionally,

Supplementary Material Section D Table S4 describes the interaction between the control actions and the transmission routes.

Standstill: The 72-hour movement standstill was defined as a "stop" in all between-farm swine and vehicle movements[4] (USDA, 2020).

Depopulation: Once a domestic swine farm was detected, the farm, including all swine present on the premises, was scheduled for depopulation immediately. To reflect the limited resources available during an outbreak, it was assumed that a maximum of four farms could be depopulated per day (state animal health official, personal communication, 2022), introducing a delay in depopulation whose length was relative to the number of farms awaiting depopulation. Once depopulated, farms were moved to a Removed (R) compartment for 30 days (USDA-APHIS-VS 2022, personal communication, 2022) to simulate a necessary period of cleaning and disinfection prior to repopulation of the farm. After the end of the 30 days, we assumed that all farms had been repopulated and moved back to the S compartment. In control scenarios four and five (Table 1), depopulation was also implemented on direct contacts of the detected farms[5] regardless of their infection status and these direct contacts were subject to the same depopulation delay as the detected farms.

Contact tracing: Contact tracing was defined as identifying farms that were in direct contact with a detected farm in the previous 30 days and indirect contact with the detected farm in the previous 15 days. Both swine and vehicle networks were traced back one step in the contact chain. Farms identified as contacts were then tested three times at six-day intervals (USDA, 2020) starting the day after they were identified as contacts. As direct contact farms are

[4]While current USDA plans for a movement standstill will only cover live swine movements and related vehicles, we have modeled stricter controls.

[5] We assumed that all direct contacts were considered high risk and therefore were depopulated, however an automatic depopulation of direct contacts without a known ASF disease status is not included in the USDA's current ASF response. This current plan would also quarantine direct and indirect contacts

depopulated in control scenarios four and five (Table 1) only the indirect contacts were subjected to testing under the contact tracing control action.

Control area and surveillance zones: The control areas (CA) and surveillance zones were defined as areas of increased surveillance and movement permitting around detected farms. The CA consisted of a 3 km infected zone (IZ) and a 2 km buffer zone (BZ), which was then surrounded by a 5 km surveillance zone (SZ) (USDA, 2020). Both the CA and SZ were in place for 30 days after the detection of an infected domestic swine farm. All farms within the IZ were tested every three days for the first two tests, and then every six days, while all farms within the BZ were tested every six days. In contrast, only a sample of the farms in the SZ were tested; see Supplementary Material D for the sampling design utilized to sample farms in the SZ (Cannon, 2001), and the selected farms were tested every 15 days (USDA, 2020). In our model assumptions, it was possible for farms to be within two or more zones (i.e., IZ, BZ or SZ) during the same period. These farms would be tested under the testing schedule for the highest priority zone they were situated within. From highest to lowest, the priority of testing was as follows: IZ, BZ, indirect contacts, and SZ. Farms in multiple zones would only be released from restrictions once the last CA or SZ they were in was lifted. Movement permits were required for any movement of swine or vehicles to and from farms within the IZ and BZ, as well as farms identified as indirect contacts, for 30 days and 15 days, respectively.

It is pertinent to note that the start date and particle sampled for each simulation in the no control scenario were also used for the respective simulation number in the control scenarios to ensure the difference in cases observed was as a result of the control action rather than differences in animal movements by day or transmission parameters.

221 *2.6 Model outputs*

222 To capture the dynamics of an ASF outbreak, our model outputs reflect only the simulations
223 which resulted in secondary infections. All results are shown for up to day 60 and day 140 post-
224 ASF introduction, providing a short-term and a long-term perspective of ASF dissemination and
225 control. Model outputs were generated to characterize ASF outbreak dynamics including: i) the
226 number of secondary cases; ii) the contribution of the six transmission routes to ASF
227 dissemination; iii) between-company dissemination of ASF; and iv) the distance between
228 initially seeded farms and secondary infections. The accumulated number of secondary cases
229 was calculated using the time point at which farms transitioned out of the S compartment,
230 regardless of which compartment they transitioned to. The between-company dissemination and
231 distance between seeded and secondary cases were built upon this result. To assess the
232 contribution of the different transmission routes to the dissemination of ASF, we calculated the
233 daily proportional force of infection of the transmission routes for each farm that became
234 exposed, infected, or detected (i.e., moved into the E, I, or D compartment after exposure).

235 The effectiveness of the five control scenarios was presented via the following outputs: i)
236 number of secondary cases; and ii) the number of animals depopulated and the associated
237 compensation cost under each control scenario. The number of diagnostic tests and volume of
238 movement permits required under the most effective control scenario was also presented. Briefly,
239 the compensation cost of depopulation was calculated using the number of depopulated animals
240 in each production stage and their respective current market-value (USDA, 2022a). The number
241 of diagnostic tests required was calculated assuming a within-farm sampling methodology
242 detailed in The Red Book (USDA, 2020) and Cannon (2001), and pooling the samples by groups
243 of five. We additionally calculated the number of tests required if animals were tested

244 individually. Lastly, the number of permits required was calculated assuming that each
245 movement to or from farms in the IZ and BZ, or movements to or from indirect contact farms,
246 required an individual single-day permit.
247
248 **3. Results**
249 *3.1 ASF dissemination*
250 From the 229,400 simulations generated by the no control scenario, 91.9% (210,727) resulted in
251 secondary infections. 133,629 of these simulations were seeded in finisher farms, 46,297 in
252 nursery farms, 29,056 in sow farms, and 1,745 were seeded in other production types (gilt
253 isolation and boar stud). In 60 days of ASF dissemination, the average number of secondary
254 infections was 72 (±100, with a lower bound of zero) farms of which 49 (±69, with a lower
255 bound of zero) were in finisher farms, 17 (±24, with a lower bound of zero) were in nursery
256 farms, 5 (±9, with a lower bound of zero) were in sow farms, and 0.07 (±0.57, with a lower
257 bound of zero) were in other production types. The number of secondarily infected farms over
258 140 days of ASF dissemination was, on average, 810 (±523), which included 543 (±347)
259 infected finisher farms, 191 (±123) infected nursery farms, 74 (±53) infected sow farms, 2 (±3)
260 infected gilt isolation units and 0.2 (±0.5) infected boar studs (Supplementary Material Section
261 E, Figure S8). Sensitivity analyses comparing the mean number of secondary cases were
262 particularly influenced by the date of initial infection; the length of the ASF latent period; the
263 maximum distance for local spread; and the transmission rates for local spread, swine vehicles,
264 feed vehicles and crew vehicles. Results of the sensitivity analyses can be found in
265 Supplementary Material Section E, Figures S9 to S12.
266 **[Figure 2]**
267 *3.2 Contribution of transmission routes for baseline model (no control scenario)*

Over the first 60 days of ASF dissemination, the dominant transmission route was the between-farm movement of infected swine, whose contribution to dissemination varied from 65.5% on day two of the outbreak to 37.5% on day 60 (Figure 3), with an overall average of 47.7%. The movement of exposed but undetected swine was the second most relevant transmission route, going from no contribution on day two to 23.8% on day 60, with an overall average of 23.3%. The local spread was particularly important during the first days of the outbreak, contributing to 31.7% of ASF dissemination on day two, which decreased to 9.8% by day ten, but increased to 17.3% by day 60, with overall average of 14.6%. Individually, transportation vehicles had limited contributions to ASF dissemination, but the combined contributions varied from 3.3% on day two to 21.3% on day 60 (Figure 3), with a combined overall average of 14.4%. Lastly, the lowest contribution was from the movement of detected swine, which had no contribution on day two and a contribution of 0.1% on day 60, with an overall average of 0.1%.

Over 140 days, the movements of infected swine, the movements of exposed swine, and local spread continued to lead to transmission with average contributions of 44.7%, 21.2%, and 16.4% at day 140, respectively, while the combined average contribution of the four vehicle movement types was 18.2% (Supplementary Material Section E Figure S13). Details about the average contribution by production type for both 60 and 140 days are available in Supplementary Material Table Section E S5 and S6.

[Figure 3]

Additional results concerning the average distance between seeded and secondary infections, and the between-company dissemination of ASF are presented in Supplementary Material Section E Figures S14 and S17.

3.5 Control scenarios

291 *3.5.1 Effectiveness of control scenarios*

292 To assess the effectiveness of the control actions, the results from each control scenario were
293 benchmarked against the baseline model where no control actions were applied, also referred to
294 as the no control scenario (Figure 4 and Supplementary Material Section E, Table S7). The
295 results of scenario one, which considers quarantine and depopulation of detected farms,
296 demonstrate a median overall reduction in secondary cases of 11.1% by day 60, halting 20% of
297 secondary infections in sow farms, 16.1% of infections in nursery farms and 10.0% of secondary
298 cases in finisher farms. When the 72-hour standstill was added to the quarantine and
299 depopulation of detected farms in scenario two, a median of 14.5% of secondary infections were
300 reduced when compared with the no control scenario, with reductions of 23.5% in sow farms,
301 20.0% in nursery farms, and 13.6% in finisher farms (Supplementary Material Section E, Table
302 S7).

303 Scenarios three to five showed a substantial reduction in secondary infections compared
304 to scenarios one and two (Figure 5 and Supplementary Material Section E, Table S7). In scenario
305 three, which included contact tracing of direct contacts (from swine movements) and indirect
306 contacts (from vehicle movements) in addition to the actions described in scenarios one and two,
307 the number of secondary infections was reduced by a median of 34.4%. By farm type, scenario
308 three reduced sow infections by a median of 43.2%, nursery infections by a median of 39.4%,
309 and finisher infections by a median of 33.3%. Scenario four, in which the depopulation of direct
310 contacts is considered, showed very similar overall performance as scenario three with a median
311 decrease in the number of secondary cases of 33.5%, compared to the no control scenario. Here
312 the number of cases in sow farms decreased by a median of 43.8%, in nursery farms decreased
313 by a median of 40.0%, and in finisher farms decreased by a median of 32.1%. Scenario five,

where all the control actions including control areas and surveillance zones were implemented, showed the best performance compared to all previous scenarios, with a median decrease of 47.4% in the number of secondary cases compared to the no control scenario. The number of cases in sow farms decreased by a median of 50.0%, nursery farms decreased by a median of 50.0%, and finisher farms decreased by a median of 45.1% (Table S7). In Supplementary Material Figure S18 we show the reduction in the number of secondary cases for each scenario at 140 days. Briefly, for scenario five, the median decrease in total secondary infections at 140 days was 79.0% compared to the no control scenario, with a median decrease in infected sow farms of 82.1%, a median decrease in infected nursery farms of 79.3%, and a median decrease in infected finisher farms of 76.6%. However, while there was a substantial decrease in the number of secondary cases under scenario five, only 29.0% of simulations were controlled by day 140 (i.e. no cases after day 135). Visualization of the total secondary cases at 60 and 140 days across the simulations for each control scenario is available in Supplementary Material Section E, Figures S19 and S20. **[Figure 4]**

3.5.2 Depopulation

Across all control scenarios, we investigated the number of depopulated swine considering farm capacity and production type (Figure 5). Scenario one showed a median of 8,800 (IQR: 2,448-25,440) depopulated swine, while scenario two demonstrated the lowest number of depopulated swine with a median of 8,700 (IQR: 2,448-24,929) (Figure 6). In scenarios three to five, the median number of swine depopulated increased substantially with a median of 20,380 (IQR: 3,350-94,100) swine depopulated in scenario three, a median of 27,177 (IQR: 4,000-126,560) swine depopulated in scenario four and a median of 50,208 (IQR: 5,280-217,283) swine depopulated in scenario five, representing the highest number of swine depopulated. Over 140

337 days of outbreak, the highest number of swine depopulated was under scenario four with an
338 average of 699,887 swine (Supplementary Material Section E, Figure S21). This was followed
339 by scenario three with 526,675 swine depopulated, scenario five with 488,531 swine
340 depopulated, scenario one with 342,923 swine depopulated and scenario two with 332,398 swine
341 depopulated. Additionally, as a result of enhanced surveillance, we observed the depopulation of
342 swine in nursery farms in scenarios three, four, and five, which was not present in scenarios one
343 and two due to the low effectiveness of surveillance assumed in this production type (Figure 5).
344 Estimations on the financial compensation required under each scenario is given in
345 Supplementary Material Section E, Tables S9 and S10.

346 **[Figure 5]**

347 *3.5.3 Diagnostic testing*

348 In section 3.5.1 we demonstrated that scenario five was the most effective in decreasing ASF
349 secondary infection. Therefore, we selected only scenario five for further analysis. Over the first
350 60 days of the outbreak, the median cumulative number of tests required under scenario five,
351 assuming samples were pooled into groups of five, was 11,974 (IQR: 0-68,337). Regardless of
352 farm type, the testing of farms in the IZ required the most tests with a cumulative median of
353 2,609 (IQR: 0-14,409) (Figure 6) followed by the SZ, which had a cumulative median number of
354 tests of 2,602 (IQR: 0-13,006). The number of tests required for farms in the BZ and indirect
355 contact farms was slightly lower with a cumulative median of 2,473 (IQR: 0-11,626) and 2,513
356 (IQR: 0-28,074), respectively. Consistently, across the IZ, BZ, SZ and indirect contacts, more
357 tests were required for finisher farms with the median number of tests ranging from 1,512 (IQR:
358 0-7,665) in the BZ to 1,759 (IQR: 0-19,173) for the indirect contacts. Nursery had lower
359 numbers of the tests required, with median numbers of tests ranging from 364 (IQR: 0-5,188) for

360 indirect contacts to 540 (IQR: 0-2,661) for the BZ. Sow farms had the lowest numbers of tests
361 required, with a median number of tests ranging from 236 (IQR: 0-1,265) in the BZ to 296 (IQR:
362 0-3,517) for the indirect contacts.

363 By 140 days of the outbreak, a median of 357,789 (IQR: 24,429-840,126) diagnostic tests
364 were required. Over this time frame, the largest volume of tests was for farms that were
365 identified as indirect contacts, with a median of 115,729 (IQR: 2,798-255,948) tests required.
366 More details regarding the number of tests required for 140 days of outbreaks are presented in
367 Supplementary Material Section E, Figure S22.

368 **[Figure 6]**

369 *3.5.4 Movement permits required*

370 Figure 7 presents the distribution of the required movement permits under scenario five. Daily
371 permits were required for movements to and from farms within IZ and BZ, and movements to
372 and from farms indirectly connected (via the transportation vehicles network) with ASF-positive
373 farms. Over the first 60 days of outbreaks, a median of 1,808 (IQR: 0-9,737) permits was
374 required. The majority of these permits were for movements of feed vehicles which had a median
375 of 1,323 (IQR: 0-6,695) permits. The movement of swine vehicles had the second highest
376 requirement for permits with a median of 240 (IQR: 0-1,641) permits, while the crew vehicles,
377 market vehicles, and the movement of swine required substantially fewer permits with medians
378 of 85 (IQR: 0-759), 43 (IQR: 0-274) and 58 (IQR: 0-291) permits, respectively.

379 When considering the production type of the movement destination, we observed that
380 movements into finisher farms consistently required more permits ranging from a median of 21
381 (IQR: 0-103) permits for movements of swine to a median of 994 (IQR: 0-4,933) permits
382 required for movements of feed vehicles over 60 days. For nursery farms, the lowest number of

383 permits was required for the movement of market vehicles with a median of 3 (IQR: 0-24)
384 permits, while the movement of feed vehicles required the most with a median of 161 (IQR:0-
385 976) permits. Lastly, movements to sow farms required the least amount of permits, ranging
386 from a median of 0 (IQR: 0-9) permits for the movement of market vehicles to 145 (IQR: 0-796)
387 permits for the movement of feed vehicles.

388 The number of permits required over the 140 days of simulated outbreaks was a median
389 of 54,522 (IQR: 4,950-207,912) permits. The highest number of permits required was, once
390 again, for the movement of feed vehicles, with a median of 37,741 (IQR: 3,554-73,339) permits,
391 while the lowest number of permits was required for the movement of market vehicles, with a
392 median of 1,518 (IQR: 154-2,967) permits. The full results of the permit requirements for 140
393 days of the outbreak are available in Supplementary Material Section E, Figures S23.

394 **[Figure 7]**

395 **4. Discussion**

396 In this study, we extended the previously developed farm-level stochastic transmission model
397 *PigSpread* (Galvis, Corzo et al., 2022) to simulate ASF dissemination within the domestic swine
398 population of the southeastern U.S.. This is the first published study to estimate the
399 dissemination of ASF among a commercial swine population in the U.S. using real population
400 and multiple contact networks, incorporating most of the known direct and indirect transmission
401 routes for the virus (Hayes et al., 2021; Lee et al., 2021; Galli et al., 2022). Our data-driven
402 modeling results elucidate the contribution of six transmission routes to ASF dissemination and
403 evaluate the impact of control actions based on the Red Book (USDA, 2020), with a few key
404 differences, while also estimating the numbers of depopulated animals, diagnostic tests, and
405 movement permits required under the most effective combination of control actions.

4.1. ASF transmission

From our model simulations, we demonstrated that, on average, 72 farms could become infected in the first 60 days of dissemination, with finisher farms being the most affected, likely due, in part, to the larger number of finisher farms in the study population. We also identified between-farm movements of infected and exposed swine as the main routes of ASF transmission while also confirming the contribution of local spread and vehicle movement, particularly in the infection of finisher farms. Our results also showed long-distance spread between seeded and secondary infections as far as 474 km during the first 60 days and demonstrated ASF dissemination among farms not commercially related, which can be attributed to the spatial proximity between farms.

While the population structure of swine production and the pattern of between-farm contact networks is considerably different across countries, we observed similar epidemic trajectories in our model as seen in ASF transmission models from France and Australia (Bradhurst et al., 2021; Andraud et al., 2022). In the Australian model, 28 days of silent ASF dissemination within moderate to large commercial farms led to, on average, 4.3 to 6.3 infected farms (Bradhurst et al., 2021). This is particularly close to the eight infected farms that we observed over the same time frame. The incidence of infection observed in the French model was slightly lower with a median of 12 farms infected over 40 days (Andraud et al., 2022), whereas our model estimated 20 infections. These discrepancies could be attributed to differences in the population structure or model assumptions between the studies. Indeed, both studies (Bradhurst et al., 2021; Andraud et al., 2022) limited their local spread to 2 km compared to our less restrictive range of one km to 25 km, which coupled with the high density of farms in our study population (Galvis, Corzo, Prada et al., 2021; Jara et al., 2021), led to a more effective spread

429 between farms. Similar ASF spread dynamics have been observed in outbreaks in Vietnam
430 (Nguyen-Thi et al., 2021) and the Dominican Republic (Gonzales et al., 2021) where a
431 substantial number of cases were observed in a short time frame.

432 The prominent route of ASF transmission in our study was the movement of infected and
433 exposed swine, whose contribution to ASF dissemination varied from a minimum of 59.9% to a
434 maximum of 86.7% over 140 days (Supplementary Material Section E, Figure S13). Recent
435 mathematical simulation studies have demonstrated a similar dominance of between-farm swine
436 movement in ASF dissemination (Halasa, Boklund et al., 2016; Andraud et al., 2019, 2022). An
437 ASF transmission model in Denmark (Halasa, Bøtner et al., 2016), associated 99% of
438 transmission with the movement of swine, while a French transmission model (Andraud et al.,
439 2022) observed contributions between 68% and 85% for the movement of swine between farms.
440 The contrast of the Danish model with the results observed in our model and the French model
441 could be attributed to the structure of the models, the model assumptions and the pig population
442 dynamics. Both our model and the French model, used detailed between-farm movement data
443 including daily movements, while the Danish model approximated the daily frequency of
444 movements from annual data, which may not accurately represent the contribution of swine
445 movements. Additionally, in our study, each farm is under a swine production contract, only
446 moving swine between farms of the same company which reduces the mixing of swine of
447 different health statuses and subsequently lowers the probability of disease transmission
448 (Passafaro et al., 2020; Galvis, Corzo, Prada et al., 2021).

449 We also observed a significant contribution of local spread and transportation vehicles to
450 ASF dissemination, highlighting the role that such transmission routes may play in an ASF
451 outbreak in the U.S. (Gao et al., 2021; Cheng and Ward, 2022; Galli et al., 2022). Local spread

452 was particularly important in finisher farms where it contributed to nearly 20% of ASF
453 dissemination, likely due to the high farm density in our study area. While previous literature has
454 associated local spread with ASF transmission, there is no consensus on the maximum distance
455 that ASF can spread via this route. To account for both short and long-distance transmission
456 scenarios, such as those observed in ASF outbreaks in Africa, Asia and Europe (Okoth et al.,
457 2013; Vergne et al., 2015; Boklund et al., 2020; Nguyen-Thi et al., 2021), we allowed our local
458 spread to vary between one km and 25km. The contribution of swine vehicles was also important
459 in finisher and nursery farms, most likely due to the vertical structure of the U.S. swine industry
460 resulting in numerous swine vehicle movements to these production types. Similar to local
461 spread, transportation vehicles have previously been recognized for their influence on ASF
462 outbreaks in China and Korea (Yoo et al., 2021; Cheng and Ward, 2022), supporting the
463 necessity to include such transmission routes in future ASF transmission models.

464 We also demonstrated long distance spread of ASF and dissemination between farms of
465 unrelated production companies. Long distance spread in ASF has been observed before in
466 outbreaks in the Republic of China (Akhmetzhanov et al., 2020) as well as a transmission model
467 from France (Andraud et al., 2019, 2022). Interestingly our results diverge from those of the
468 Danish transmission model (Halasa, Bøtner et al., 2016), where most secondary infections were
469 at short distances (under ten km), which could be attributed to several variables including the
470 geographical distribution of the study populations, model assumptions and the transmission route
471 parameters (Boklund et al., 2009; Nigsch et al., 2013; Halasa, Boklund et al., 2016). In contrast
472 to the long-distance spread of ASF, this study is the first description of between-company
473 dissemination in ASF. As there are no recorded movements of swine or vehicles between
474 companies, our results suggest that local spread was the most likely transmission route between

475 companies. Indeed, 88.9% of farms in our study population were within 25 km (the maximum
476 distance for ASF spread in the model) of a farm of another company. However, we cannot rule
477 out the contribution of other transmission routes, such as rendering vehicles, which are managed
478 by third-party companies and may serve multiple farms of different companies.
479
480 *4.2. ASF control and elimination*
481 When considering the effectiveness of the control actions included in this paper, we
482 observed a reduction of ASF cases in all control scenarios compared to the no control scenario.
483 With the addition of each control action, we demonstrated an increase in the efficacy of ASF
484 control, with scenario five, which implements all the control actions, being the most successful,
485 reducing secondary cases by 79% over 140 days of outbreaks. In particular, we observed
486 substantial reductions in cases when adding control actions which enhanced ASF surveillance,
487 such as contact tracing of direct contacts (contacts from swine movements) and indirect contacts
488 (contacts from vehicle movements), and the implementation of control areas and surveillance
489 zones which included frequent testing of farms. Similar reductions in cases have been observed
490 in the French model (Andraud et al., 2022) and a model of ASF spread in the Rio Grande do Sul,
491 Brazil (Machado et al., 2021), where the detection of ASF was increased by lowering the
492 mortality threshold in farms. However, despite the increased effectiveness of scenario five, it was
493 not capable of successfully eliminating the disease spread in all simulations by day 140, with
494 only 29% of simulations being controlled. Thus, we demonstrated that with the current proposed
495 control actions, an ASF outbreak duration in the southeastern U.S. will go beyond four months.
496 This could be due to a number of factors including delayed detection of ASF, limited
497 depopulation resources, and high connectivity of the swine industry in our study area.

To provide an estimate of the resources needed under scenario five, we estimated the quantity of swine depopulated, the number of diagnostic tests, and the volume of movement permits required Over the first 60 days of outbreaks, we observed a higher number of swine depopulated under scenario five, compared to the other scenarios, equating to a compensation cost of USD $3.8 million. However, when we consider 140 days of simulation, the compensation cost of depopulation in scenario five was lower than the cost estimated for scenarios three and four, with a maximum compensation cost of $79.2 million in scenario five compared to a maximum cost of $115.2 million in scenario four (Supplementary Material Section E, Table S11). Therefore, while the compensation cost of depopulation in scenario five is high during the first two months of the outbreaks, depopulation in the scenario becomes more cost effective as the outbreaks continue.

Over the simulated 140 days of the outbreak, we observed high numbers of diagnostic tests required for farms identified as indirect contacts of detected farms compared to the IZ, BZ or SZ, attributed to the high connectivity of the vehicle networks. Interestingly we noted a large number of tests required for the surveillance zones, which we attribute to the larger geographic area covered by the SZ compared to the CA, given the SZ surrounds the CA. Similarly, the density of farms in the region and their capacity will influence the number of diagnostic tests that would be required.

We also observed a large number of permits required for vehicles transporting feed, with a median of 37,741 permits required over 140 days, compared to the other movements of vehicles and swine. This substantial difference is due to the size of the feed vehicle network, which consisted of a median of 1,258 (IQR: 257-1,877) farms visited per day (Supplementary Material Section F, Table S9). Despite the decrease in cases associated with scenario five, which

521 will reduce the resources required, the compensation cost of depopulation and quantities of
522 movement permits are significant. By considering permits that cover movement for a 30-day
523 time period for select movement types within the model, such as the movement of feed vehicles,
524 between the same farms, we may reduce the resources needed. Nevertheless, the estimation of
525 resources is pivotal to gauge the feasibility of strategies and help animal health officials
526 anticipate the workload needed in the event of an ASF introduction.
527

528 **5. Limitations and further remarks**

529 While our ASF stochastic transmission model is the first to model ASF between-farm
530 dissemination in the southeastern U.S. using real population and multiple contact networks
531 (swine and vehicles), the lack of ASF outbreak data limited our ability to calibrate transmission
532 parameters. As a novel alternative, we used the first waves of the 2013 PEDV epidemic in the
533 study region (Machado et al., 2019), to reflect the dynamics of a novel virus spreading in a
534 completely susceptible population. Yet, we cannot be certain that ASF dissemination would
535 follow the same transmission dynamics as PEDV, as each virus has a different fitness and
536 transmission capability (Pensaert and de Bouck, 1978; Alonso et al., 2014). An example is
537 differences in transmission rates, which are similar but not equal, as the basic reproduction
538 number R_0 of PEDV has been estimated to be 1.87 (95% CI: 1.52-2.34) (Greer et al., 2017)
539 while ASF R_0 in Vietnam has been estimated to be at 1.49 (95%CI: 1.05–2.21) (Mai et al.,
540 2022). Despite the limitations of using PEDV data to calibrate the ASF model discussed above,
541 we believe that they do not outweigh the benefit of using real outbreak data from our study
542 population to capture the parameters of epidemic disease spread within this region. Similarly, we
543 chose to use PEDV over other swine diseases such as porcine reproductive and respiratory

544 syndrome virus (PRRSV), as we do not have epidemic outbreak data for PRRSV in our study
545 region.

546 Another limiting factor of our model is the paucity of data regarding additional
547 transmission routes, such as the movements of rendering vehicles, the distribution of independent
548 backyard producers, and the density of feral swine (Yoo et al., 2021; Galli et al., 2022; Pepin et
549 al., 2022). As the access to such data becomes available in the future, subsequent iterations of
550 this model should take into consideration the influence that these transmission routes and
551 population dynamics may have on ASF dissemination (Neumann et al., 2021; Cheng and Ward,
552 2022). In particular, the introduction of ASF into feral swine populations is greatly important, as
553 it has the potential for spillover into domestic populations (Hayes et al., 2021) due to their wide
554 geographic range (Fodor et al., 2015; Iglesias et al., 2016; Boklund et al., 2020). It should also be
555 noted that without the relevant data from the other U.S. states, the results of this model cannot be
556 generalized outside of the southeastern U.S..

557 Limited data also may have impacted the transmission routes already considered in the
558 model, as we were unable to collect transportation vehicle movement data from 24% of farms in
559 the study. Additionally, farms were identified as a node in the vehicle networks if a vehicle was
560 stationary within 1.5 km of the farm, however, due to the high density of the farms in our study,
561 a vehicle could have been in 1.5 km of multiple farms at the same time, over-estimating the
562 number of vehicle contacts (Galvis, Corzo et al., 2022). In the future, we expect to improve the
563 reconstruction of the vehicle movement networks, to include these missing vehicle movements
564 and incorporate the movement of additional third-party vehicles, such as rendering vehicles and
565 maintenance crews which are documented as having an important role in the dissemination of
566 ASF in Asia (Neumann et al., 2021; Cheng and Ward, 2022). There is also a myriad of factors

such as presence of other pathogens within the population which could influence the impact of an ASF outbreak, however, without comprehensive data or evidence we are not able to simulate this in our model.In future iterations of this model, we will include biosecurity practices present on the farms to account for the direct impact they can have on the pathogens' forces of infection, such as the presence of on-farm cleaning and disinfection stations which has been shown to reduce the risk of pathogen introduction (Bellini et al., 2016; De Lorenzi et al., 2020; Juszkiewicz et al., 2020; Jiang et al., 2021) and the use of open-sided barns which increases the chance of direct nose-to-nose contact between feral swine and domestic pigs (Yoo et al., 2021; N. T. Mai et al., 2022). It may also be pertinent to model the level of compliance regarding the control actions implemented, which has been associated with ASF persistence in Sardinia (Cappai et al., 2018), and incorporate varying effectiveness of cleaning and disinfection practices, which our current model assumes to be 100%. Additionally, outbreaks of ASF within Europe have identified the spread of less virulent strains of ASF, which has been suggested to lengthen the delay in detection of the initial case, increasing the duration of silent dissemination. Currently the results of this model only apply to an outbreak of highly pathogenic ASF.

Along with the above additions to the model, we also plan to explore the implementation of quarantine to premises in the CA and those identified as contacts, as well as removing the depopulation of direct contacts, in an effort to model realistic scenarios included in the USDA's current ASF response plan. Thus, future modeling efforts will unlock our capacity to understand ASF propagation at multiple levels and test the effectiveness of disease control strategies under different conditions.

6. Conclusion

590 In this study we have demonstrated that an introduction of ASF into the southeastern U.S. could
591 result in 72 infected farms in the first two months of an outbreak, with the potential for between-
592 company dissemination. Transmission of ASF via between-farm movements of swine was
593 identified as the predominant route of ASF dissemination, however, local spread and the
594 movement of vehicles also contributed significantly to ASF spread, resulting in long-distance
595 spread of ASF as far as 474km away from the index case. However, with the implementation of
596 the control actions similar to what is described in the national response plan, secondary cases
597 could be reduced by 79% by day 140. Despite this reduction in cases, the above control strategy
598 was not able to stamp-out the epidemic in all simulations by day 140 and required a substantial
599 amount of diagnostic testing, movement permits, and depopulation resources. Nevertheless, the
600 critical evaluation of ASF response and control activities provided, along with estimations of the
601 resources needed under the most effective scenario, can guide further research and preparations
602 to ensure we can effectively limit a future outbreak.
603

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609 **Conflict of interest**

610 All authors confirm that there are no conflicts of interest to declare

611 **Ethical statement**

612 The authors confirm the ethical policies of the journal, as noted on the journal's author guidelines page.
613 Since this work did not involve animal sampling nor questionnaire data collection by the researchers,
614 there was no need for ethics permits.

Data Availability Statement

The data that support the findings of this study are not publicly available and are protected by confidential agreements, therefore, are not available. A preprint has previously been published Abagael L. Sykes et.al 2022 and code examples can be found at https://github.com/machado-lab/PigSpread-ASF.

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911

912 **List of tables**

913

914 **Table 1. Control scenarios applied to an ASF outbreak in the U.S.**

Scenario	Depopulation of infected farms	Standstill	Contact tracing	Depopulation of direct contacts	Control areas and surveillance zones
1	Yes	No	No	No	No
2	Yes	Yes	No	No	No
3	Yes	Yes	Yes	No	No
4	Yes	Yes	Yes	Yes	No
5	Yes	Yes	Yes	Yes	Yes

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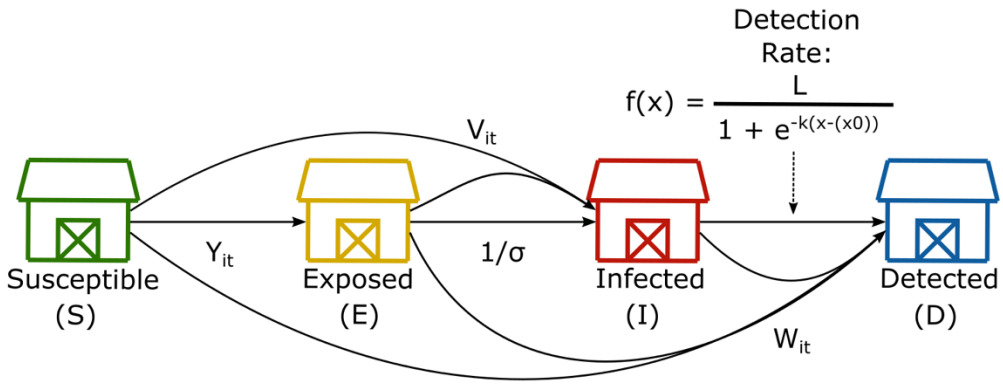


Probability of transition:

$Y_{it} = 1 - e^{-(\lambda_{nit} + \lambda_{lit} + \lambda_{fit} + \lambda_{pit} + \lambda_{mit})}$

$V_{it} = 1 - e^{-(\lambda_{sit})}$

$W_{it} = 1 - e^{-(\lambda_{ait})}$

Conditions for transition:

$Y_{it} > X \sim U(0,1)$

$V_{it} > X \sim U(0,1)$

$W_{it} > X \sim U(0,1)$

Transmission routes:

Movement of exposed pigs ------→ $\lambda_{nit} = \beta_n * N_{nit}$

Movement of infected pigs ------→ $\lambda_{sit} = \beta_s * N_{sit}$

Movement of detected pigs ------→ $\lambda_{ait} = \beta_s * N_{ait}$

Pig vehicles ------→ $\lambda_{pit} = \beta_p * M_{ijt} * Z_{it}$

Market vehicles ------→ $\lambda_{mit} = \beta_m * M_{ijt} * Z_{it}$

Crew vehicles ------→ $\lambda_{cit} = \beta_c * M_{ijt} * Z_{it}$

Feed vehicles ------→ $\lambda_{fit} = \beta_f * M_{ijt} * Z_{it}$

Local ------→ $\lambda_{lit} = \beta_l * \Sigma^2_{(j=1)} g_{ijt}$

Figure 1. Schematic representation of the SEID ASF model. The schematic demonstrates the transition of farms through the four compartments: Susceptible (S), Exposed (E), Infected (I), and Detected (D). Y_{it} represents the probability of a farm moving from the susceptible compartment into the exposed compartment; V_{it} represents the probability of a farm moving from the susceptible or exposed to the infected compartment, and W_{it} represents the probability of a farm moving from either the susceptible, exposed or infected compartment to the detected compartment. λ represents the force of infection for each transmission route and β represents the transmission rate for each route.

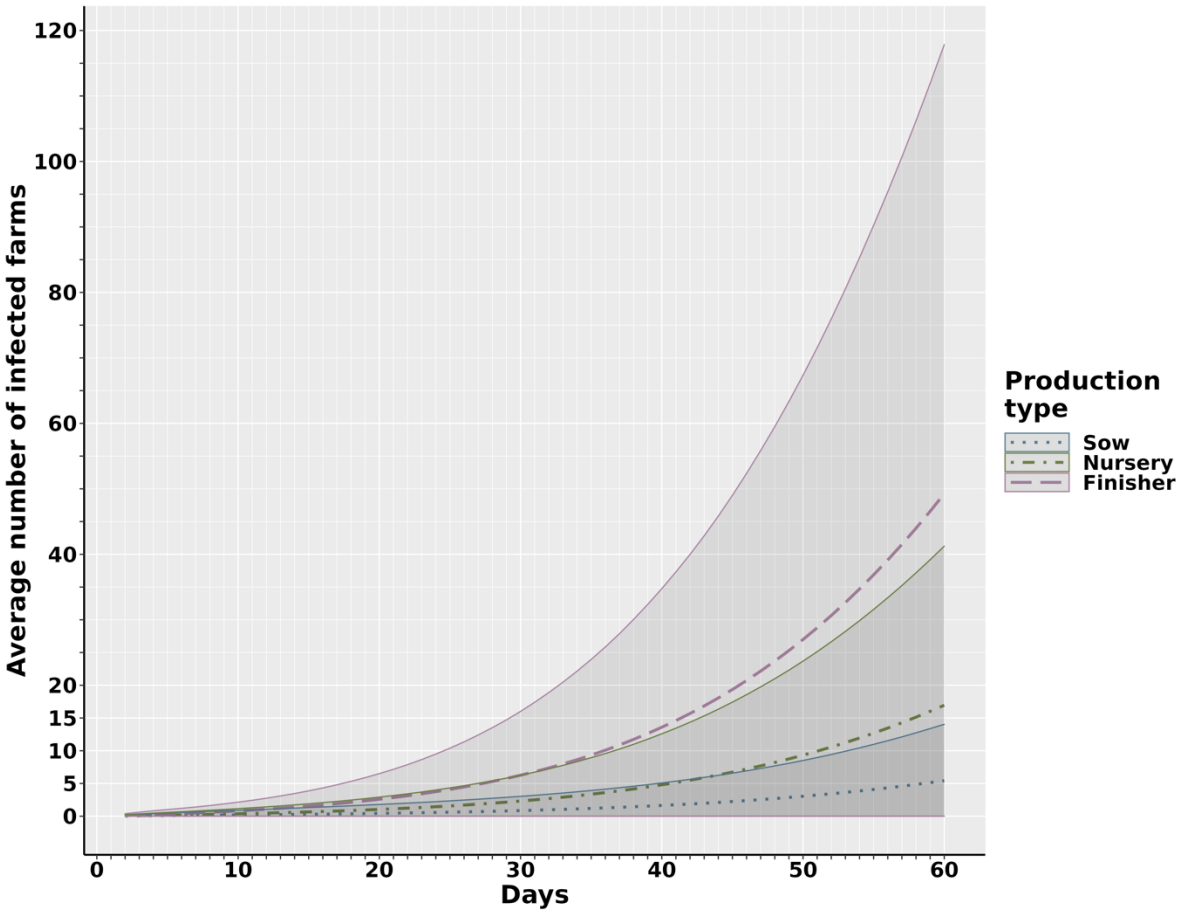
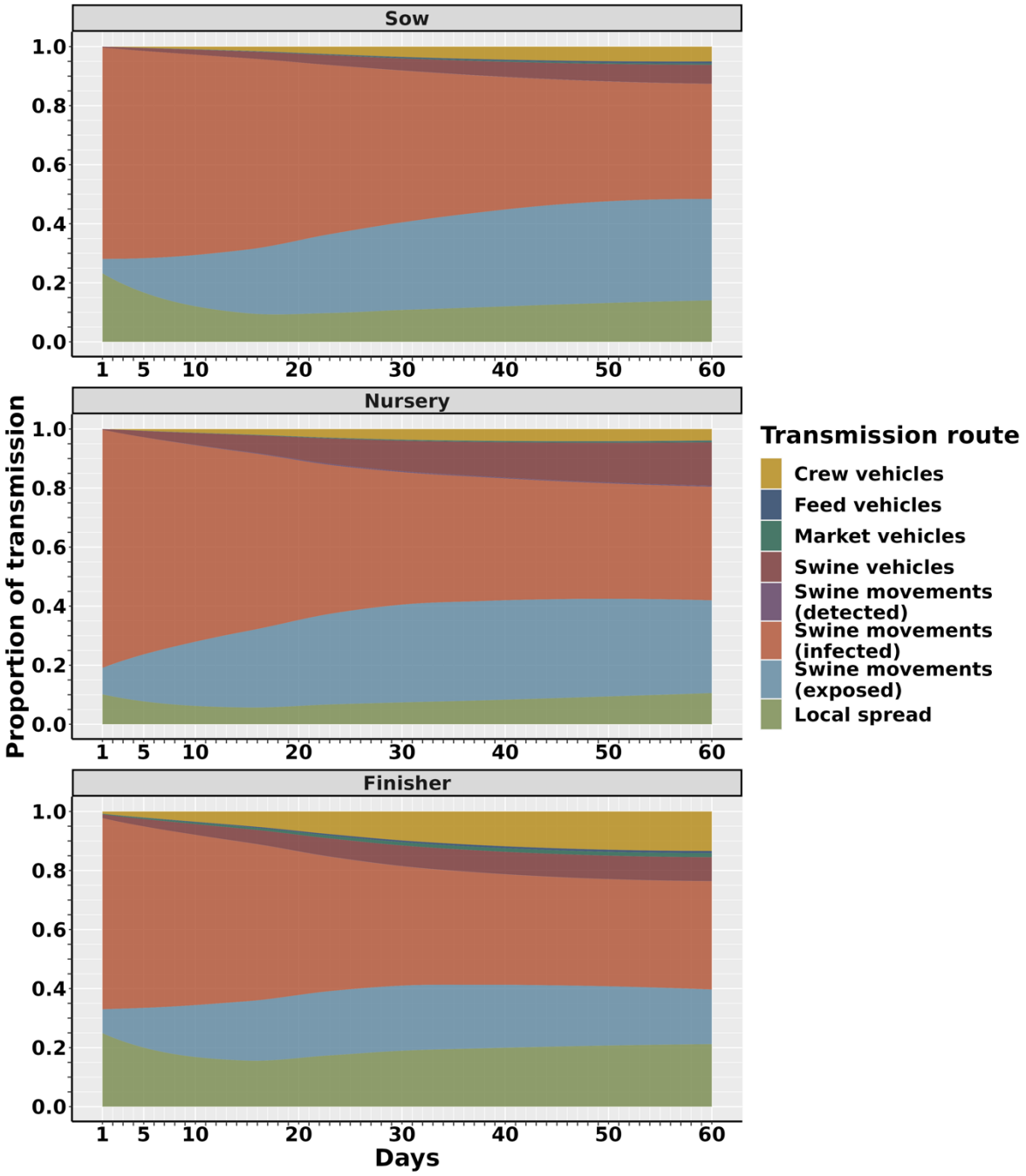


Figure 2. The average number of secondary ASF infections by farm type, accumulated over 60 days of simulated outbreaks. The y-axis represents the average number of secondary infections (farms). The dashed and dotted lines represent the mean at time *t* (days) for each swine production type while the solid lines and shaded areas represent the standard deviation at time *t*.



933

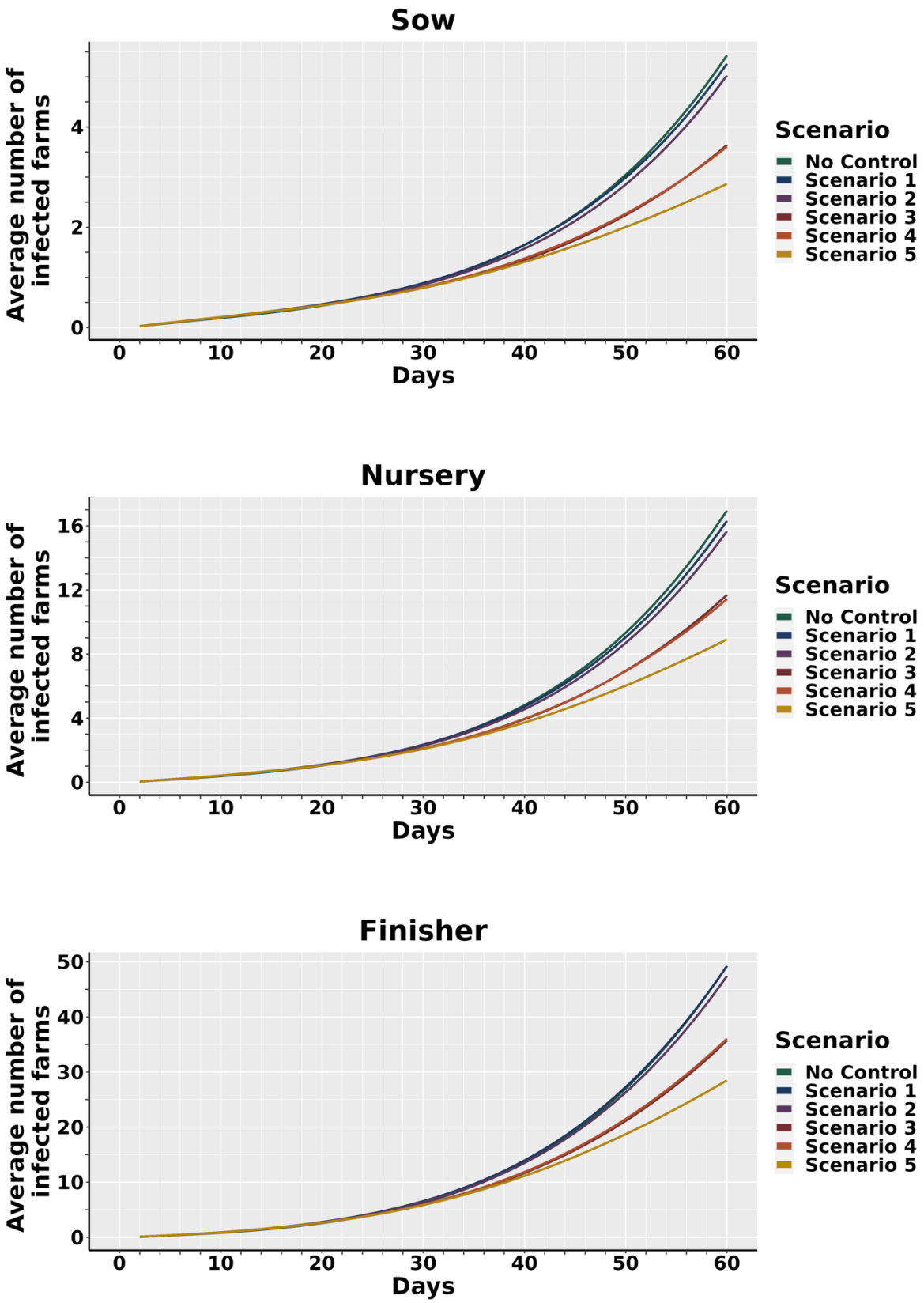
934 **Figure 3. The average contribution of six transmission routes of ASF dissemination in each farm**

935 **type over 60 days of outbreaks.** The y-axis represents the mean proportion of each transmission route on

936 a given day for each production type, which was averaged at each time point and smoothed using a

937 generalized linear model. Transmission of ASF through the movement of swine has been separated into

938 the movement of exposed, infected, and detected swine to reflect the influence of these compartments of
939 ASF transmission. Transmission starts on day two as day one was the time step at which the initial seeded
940 infections were introduced.


Sow
Average number of infected farms
0
2
4
0
10
20
30
40
50
60
Days
Scenario
No Control
Scenario 1
Scenario 2
Scenario 3
Scenario 4
Scenario 5
Nursery
Average number of infected farms
0
4
8
12
16
0
10
20
30
40
50
60
Days
Scenario
No Control
Scenario 1
Scenario 2
Scenario 3
Scenario 4
Scenario 5
Finisher
Average number of infected farms
0
10
20
30
40
50
0
10
20
30
40
50
60
Days
Scenario
No Control
Scenario 1
Scenario 2
Scenario 3
Scenario 4
Scenario 5

941

Figure 4. The average number of cumulative infections over 60 days of an outbreak under five different control scenarios. The colored lines represent the mean prevalence after *t* days, under each control scenario. Control scenarios were implemented upon detection of the first ASF case and are described in detail in Table 1.

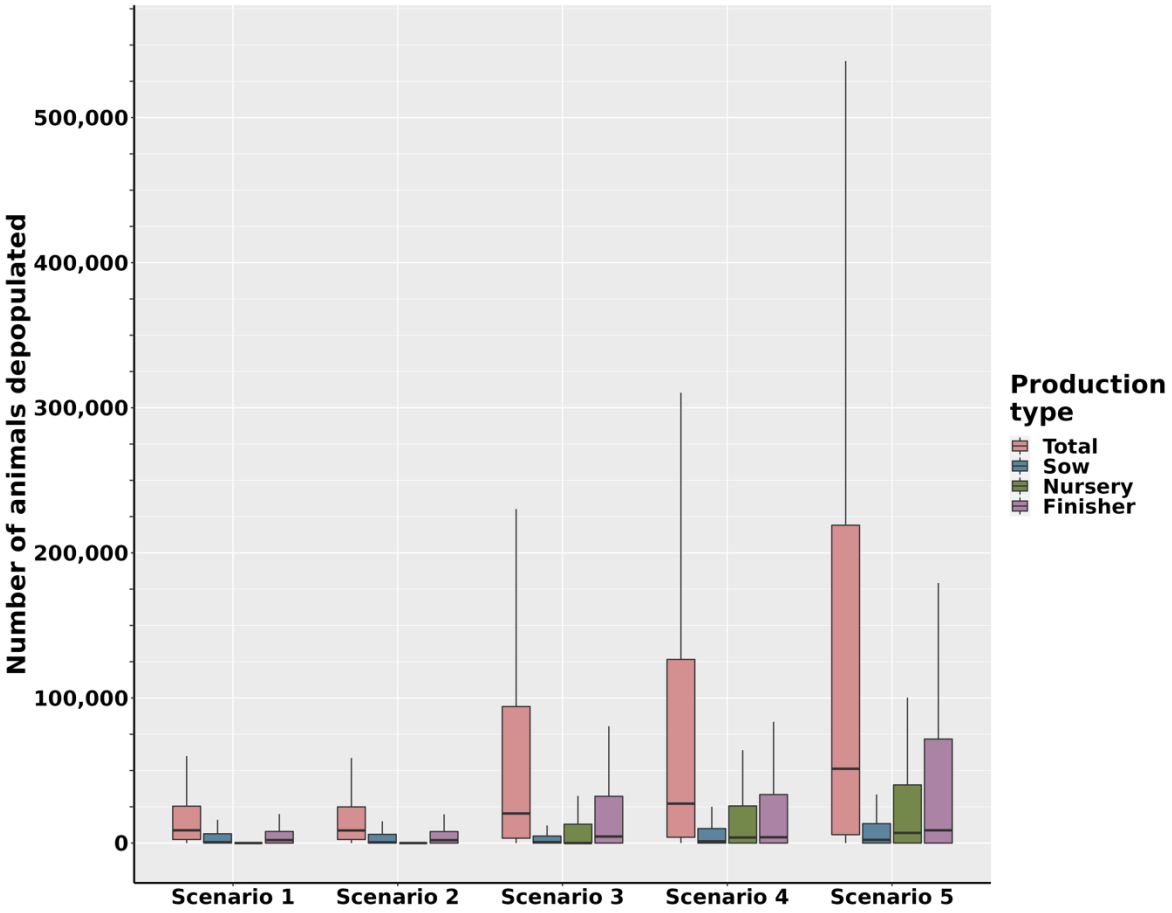


Figure 5. Box and whisker plots showing the number of animals depopulated under the five ASF control and eradication scenarios for each farm type at 60 days post seeded infection.

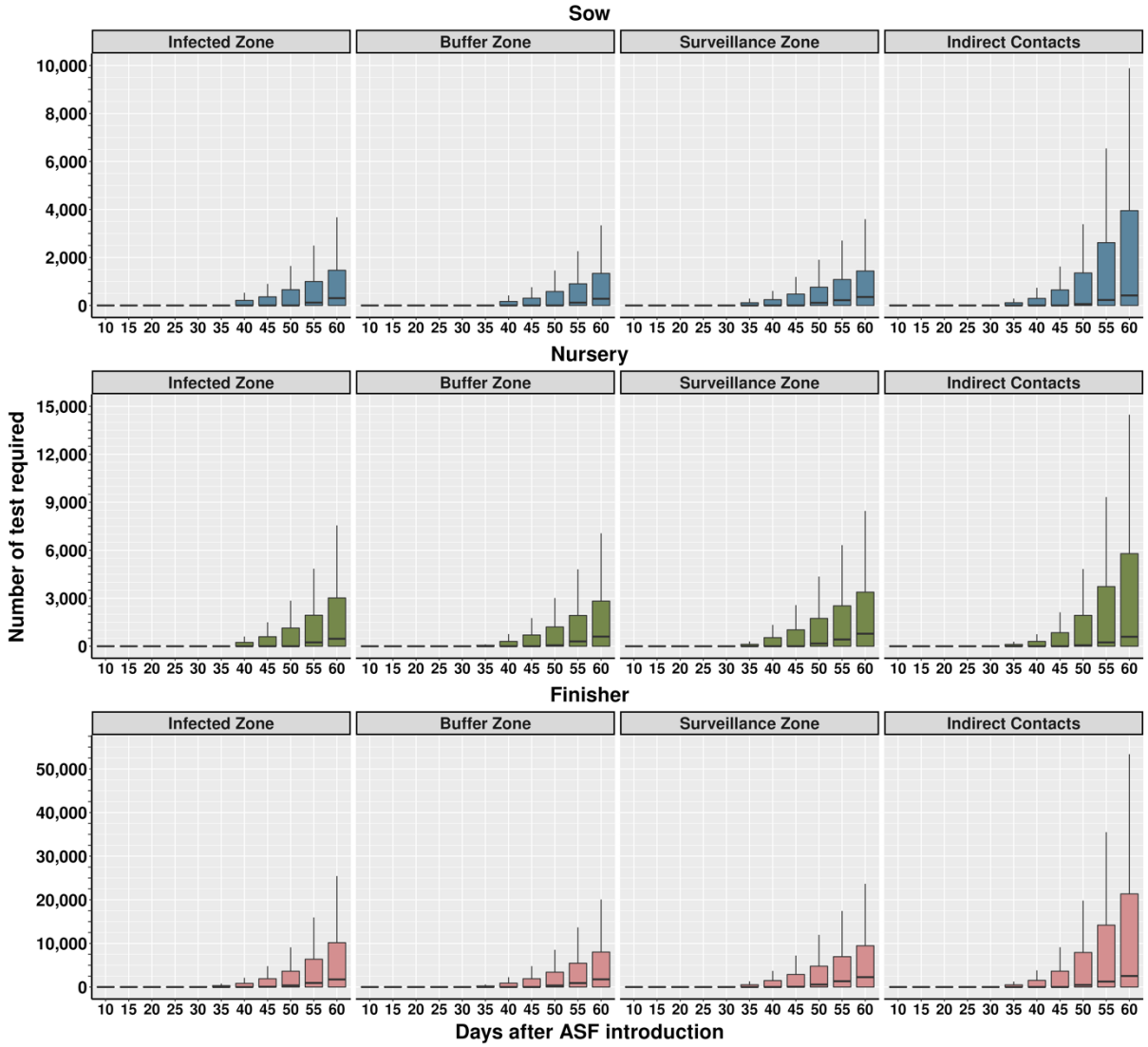
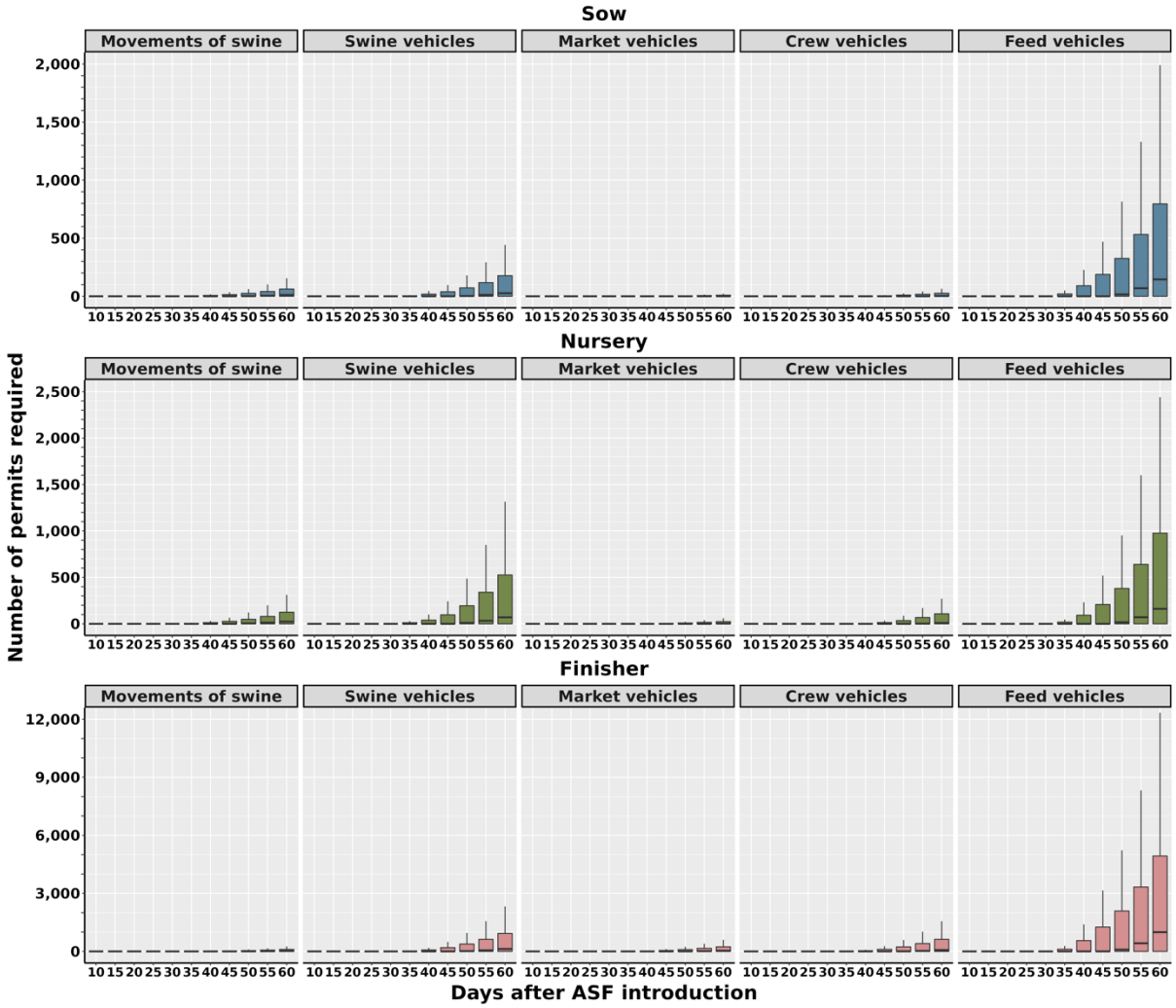


Figure 6. The cumulative number of diagnostic tests required for indirect contacts, infected zones, buffer zones and surveillance zones during control scenario five across 60 days of outbreaks, when samples are pooled in groups of five. Due to the delay in detection implemented in the model, testing was not required earlier than day 13 of the outbreak. Further details are available in section 2.5.



954

955 **Figure 7. Median daily number of permits required for movements to or from infected zones,**

956 **buffer zones and indirect contacts, during control scenario five across 60 days of outbreaks.** Due to

957 the delay in detection implemented in the model, the earliest date that permits were required was day 13

958 of the outbreak.