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The role of vehicle movement in swine disease dissemination: Novel method accounting for pathogen stability and vehicle cleaning effectiveness uncertainties

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ABSTRACT

Summary: Several propagation routes drive animal disease dissemination, and among these routes, contaminated vehicles traveling between farms have been associated with indirect disease transmission. In this study, we used near-real-time vehicle movement data and vehicle cleaning efficacy to reconstruct the between-farm dissemination of the African swine fever virus (ASFV). We collected one year of Global Positioning System data of 823 vehicles transporting feed, pigs, and people to 6363 swine production farms in two regions in the U.S. Without cleaning, vehicles connected up to 2157 farms in region one and 437 farms in region two. Individually, in region one vehicles transporting feed connected 2151 farms, pigs to farms 2089 farms, pigs to market 1507 farms, undefined vehicles 1760 farm, and personnel three farms. The simulation results indicated that the contact networks were reduced the most for crew transport vehicles with a 66% reduction, followed by vehicles carrying pigs to market and farms, with reductions of 43% and 26%, respectively, when 100% cleaning efficacy was achieved. The results of this study showed that even when vehicle cleaning and disinfection are 100% effective, vehicles are still connected to numerous farms. This emphasizes the importance of better understanding transmission risks posed by vehicles to the swine industry and regulatory agencies.

1. Introduction

Similar to the movement of live animals known to dominate between-farm pathogen dissemination (Galvis et al., 2022a; Green et al., 2006), transportation of vehicle movements is of great concern as an indirect dissemination route (Galvis et al., 2022a, 2022b; Smith et al., 2013; Thakur et al., 2016). Recent studies investigated the role of vehicles as the pathway of porcine epidemic diarrhea virus (PEDV) outbreaks (Boniotti et al., 2018; Garrido-Mantilla et al., 2022; Lowe et al., 2014); African swine fever (ASF) (Adedeji et al., 2022; Cheng and Ward, 2022; Li et al., 2020; Nigsch et al., 2013; Yoo et al., 2021b); and avian influenza virus (Huneau-Salaün et al., 2020; Yoo et al., 2021a). In addition, (Boniotti et al., 2018; Dee et al., 2004; Gebhardt et al., 2022; Greiner, 2016; Mannion et al., 2008) demonstrated that infectious pathogens are found on vehicle surfaces, while others estimated the contribution of vehicles in PEDV and porcine reproductive and respiratory syndrome virus (PRRSV) (Dee et al., 2002; Galvis et al., 2022a; Thakur et al., 2017; VanderWaal et al., 2018). That said, the underlying mechanisms of vehicles as disease dissemination routes remain to be examined in large-scale studies (Galvis et al., 2022a; Neumann et al., 2021). Thus, without access to actual vehicle movement data along with pathogen stability in vehicle environments at field conditions; and the effects of vehicle cleaning and disinfection in reducing vehicle contamination, are still challenges highlighted in better understanding the indirect contribution of vehicles in disease dissemination (Bernini et al., 2019; Galvis et al., 2022a; Gao et al., 2023b; Neumann et al., 2021).

The complexity and the dynamics of animal and vehicle between farm movement networks present a formidable challenge for decision-makers and producers who need to implement disease control measures, often not knowing when a new load of animals will arrive and if the farm or origin has been recently infected or not, or if a feed truck is delivering feed after being at an infected farm (Galvis et al., 2022a, 2022b; Lee et al., 2019; Yoo et al., 2021b). Some studies in North America and Europe utilized actual animal and vehicle movement data to reconstruct the between-farm transmission dynamics of infectious diseases (Andraud et al., 2022; Bernini et al., 2019; Galvis et al., 2022a, 2022b) while considering pathogen stability at the environment and the

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effects of cleaning and disinfection. Even though previous studies enhanced our understanding of indirect swine disease dissemination through vehicle movements, authors identified uncertainties about the association between i) the efficacy of vehicle cleaning and disinfection and ii) factors affecting pathogen stability over their contribution in disseminating disease from farm-to-farm (Andraud et al., 2022; Bernini et al., 2019; Galvis et al., 2022a, 2022b). Vehicle cleaning and disinfection may not effectively eliminate infectious pathogens, especially in difficult access areas, such as behind windows or gates (Boniotti et al., 2018; Li et al., 2020; Mannion et al., 2008). Therefore, it is essential to consider that several factors modulate the impact of vehicle cleaning and disinfection effectiveness, including using different disinfectants associated or not with heat, which is directly associated with the time needed for a complete truck wash (De Lorenzi et al., 2020; Porphyre et al., 2020). Similarly, the better pathogen that survives in the environment is more likely to be disseminated among farms by vehicles (Jacobs et al., 2010; Mazur-Panasiuk and Woźniakowski, 2020). Temperature, pH, humidity, and ultraviolet (UV) radiation are associated with pathogen stability (Carlson et al., 2020; Cutler et al., 2012; Espinosa et al., 2020; Hijnen et al., 2006). For example, the high temperature reduces ASF, PRRSV, PEDV, and foot-and-mouth disease stability outside the host over time (Bøtner and Belsham, 2012; Jacobs et al., 2010; Kim et al., 2018; Mazur-Panasiuk and Woźniakowski, 2020).

The scarcity of vehicle movement data and the lack of network methods capable of combining contact networks, variables associated with pathogens' stability, and uncertainty of cleaning and disinfection limit our ability to understand the contribution of vehicles in disease transmission. Here, we collected GPS data of 567 vehicles transporting feed, pigs, and people to 6363 farms. We developed a novel vehicle contact network method that considers environmental variables and vehicle cleaning and disinfection effectiveness. Thus, our goal was to reconstruct a vehicle contact network of swine companies in the U.S. while using ASFV pathogen stability profile.

2. Materials and methods

2.1. Database

In this study, we used information from two U.S. regions. Region one with 1974 commercial swine farms managed by six swine production companies (coded hereafter A, B, C, D, E, and F), and region two with 4389 commercial swine farms managed by 13 swine companies (coded here as G, H, I, J, K, L, M, N, O, P, Q, R, and S). Farm data includes a unique premise identification, animal capacity stratified by age, latitude, and longitude representing the farm's centroid and associated management company. In addition, enhanced on-farm Secure Pork Supply (SPS) biosecurity plans (Center for Food Security and Public Health, 2017) were used to identify the exact farm geolocations and were available for 95.8% and 29.5% of farms located in regions one and two, respectively (subsection 2.2). Furthermore, farms were classified into 24 types based on the swine production phase or how each production company classified them. Briefly, in North American swine production, a site may have more than one production phase (i.e. farrow-to-finisher). Thus, farms are categorized based on the farm capacity of each production phase present per site. Swine companies usually have their farm classification but present inconsistencies by multiple formats among the companies. Because of this inconsistency, we simplified farm-type classification. For example, a farm with breeding-age animals was classified as a sow farm, while a farm that reported space for breeding animals and finishers was considered a sow-finisher farm (Supplementary Material Table S1 for the complete list of farm types). In regions one and two, 16% and 20% of farms, respectively, lacked pig capacity information for each production phase. For those farms as an alternative, we used farm types provided by participating companies (Supplementary Material Table S1).

Data on the vehicles used by companies A, B, and G for 2020 (from January 01 to December 31) was collected. A total of five types of vehicles were included in the study. Company A operated with 654 vehicles which included: (i) 230 trucks delivering feed to farms, named hereafter "feed-vehicle"; (ii) 169 vehicles utilized in the transportation of live pigs between farms, named hereafter "pig-farm-vehicle;" (iii) 127 vehicles used in the transportation of pigs to markets (a.k.a. slaughterhouse, packing plants) named hereafter "pig-market-vehicle"; (iv) 44 vehicles used in the transportation of crew members named hereafter "crew-vehicle," which correspond to the movement of personnel performing a wide range of farm tasks: vaccination, power washing at closeouts, pig loading, and unloading; and (v) 84 vehicles without a defined role, which are used for multiple tasks such as delivering feed and pigs, were named hereafter "undefined-vehicle." For company B, 105 vehicles were tracked, including 41 feed vehicles, 19 pig-farm-vehicles, 30 pig-market-vehicles, and 15 crew-vehicles. Company G 64 vehicles were monitored, and all were classified as undefined-vehicles roles. From each vehicle, 12 months of daily GPS tracker records were collected, which comprised geographic coordinates for every five seconds of any vehicle in movement. In addition, each vehicle movement included a unique identification number, speed (in km/h), date, and time. We also gathered information on 14, 3, and 15 "company-owned cleaning stations" (CCS) from companies A, B, and G, respectively. Each CCS included centroid coordinates (latitude and longitude), address, and name.

2.2. On-farm biosecurity data

We extracted enhanced SPS biosecurity plans data from the Rapid Access Biosecurity (RAB) application (RABapp™) database (Machado et al., 2023). Briefly, the RABapp™ serves as a platform for standardizing the approval of SPS-enhanced biosecurity plans while storing and analyzing animal and semen movement data. SPS biosecurity plans are part of a USDA and Pork Checkoff initiative (https://www.securepork.org/) to enhance business continuity by helping swine producers implement enhanced on-farm biosecurity measures on individual farms. An SPS biosecurity plan encompasses 169 unique biosecurity measures (written component) and farm maps (Center for Food Security and Public Health, 2017; Machado et al., 2023). Each farm map (Supplementary Material Figure S1) is formed of twelve biosecurity features, one of which is the Perimeter Buffer Area (PBA) is an outer control boundary around the line of separation to limit possible contamination near animal housing. It is not rare for farms to have more than one PBA because of how swine barns are distributed at a premise (Supplementary Material Figure S1). Therefore, because our methodology measures vehicle contacts to a group of barns within PBA in farms with more than one PBA, we created a unique "farm unit" identification to measure vehicle contact to each group of barns (Supplementary Material Figure S1). Our final farm population database for region one consisted of 2519 farm units, of which 2437 (96.7%) used PBA's geolocation, while 82 (3.3%) farms did not have an on-farm biosecurity plan, we used farm's centroid geolocation provided by the companies as an alternative. Region two consisted of 4619 farm units with 1523 (33%) PBA's geolocation and 3096 (67%) farms in which we used farm centroid geolocation due to the lack of on-farm biosecurity plans.

2.3. Vehicle movement network

2.3.1. Vehicle farm visit

We defined a farm visit as a risk event in which vehicles pose a significant risk of disease introduction (Galvis et al., 2022a; Guinat et al., 2016; Li et al., 2020; Neumann et al., 2021). Thus, a vehicle visit was registered when a vehicle stopped within a defined distance from a "farm unit," named hereafter as "vehicle buffer distance" (VBD). In this study, we used three VBD sizes 50, 100, and 300 m. The VBD sizes were defined based on the average length of transportation vehicles used in swine production, which ranges from 12.5 m to 53.5 m (Walton et al., 2009). In addition, we also tracked the time vehicles spent at VBD and conditioned a vehicle visit according to a minimum elapsed time inside that area. This time was named "vehicle visit time" (VVT) (Fig. 1). It is worth noting that in some regions, third-party vehicles will deliver, for example, feed to farms of different companies. Because we were informed that vehicles may visit farms from different companies, and such movements could be associated with disease dissemination among companies (Smith et al., 2013), we also computed the contacts between companies A, B, and G to farm units from companies C, D, E, and F in region one and H, I, J, K, L, M, N, O, P, Q, R, and S in region two.

2.3.2. Farm-to-farm contact network

We assumed a vehicle is contaminated after visiting a farm unit (Bernini et al., 2019; Dee et al., 2002), with the potential to transmit pathogens to the subsequently visited farm units. Thus, in chronological order, we computed the contacts among farm units visited by each vehicle and referred to these contacts as edges (*E*) (Fig. 1). While we considered a range of VBD and VVT values to identify a vehicle visiting a farm unit (Section 2.3.1*),* to compute the direct contacts among farm units and reconstruct the contact network, we only evaluated the results of a VBD of 50 m and a VVT of five minutes due to limited computational resources.

2.3.3 Pathogen stability: For most pathogens, the stability outside the host (a.k.a. environment) decreases as temperature increases (Espinosa et al., 2020). This phenomenon has been demonstrated for PEDV (Kim et al., 2018), PRRSV (Jacobs et al., 2010), and ASFV (Carlson et al., 2020; Mazur-Panasiuk and Woźniakowski, 2020; Nuanualsuwan et al., 2022). Here, we model pathogen stability decay as a function of time and pathogen exposure to environmental temperature. Thus, vehicle network edges are weighted by pathogen decay over time, as shown in Fig. 1 (Nuanualsuwan et al., 2022). Briefly, edge weight between two farm units is modulated by two variables: i) the number of minutes a vehicle takes to go from one farm unit to another (Γ); and ii) the average environmental temperature the vehicle was exposed to along the route between these two farm units (ω) (Fig. 1 and Supplementary Material Figure S2). We downloaded daily temperature raster layers with 1 km^2 resolution from Daily Surface Weather and Climatological Summaries (*daynet)* (Thornton et al., 2022). Here, the GPS geolocation of each truck was matched with the respective daily temperature raster along its route between farm units (Fig. 1). In addition, we assumed that pathogens' stability decay obeys an exponential distribution, a function of the environmental temperature decay rate and cumulative time that the pathogen was exposed to the environment modulated by λ_ω and Γ, respectively (Fig. 1). The edge weight values range between 1 and 0, with one a high pathogen stability and 0 a low pathogen stability. To avoid edges with extremely low weights, we assumed weights <0.0006 were zero. Here, we evaluated edge weights frequency by grouping it into five categories: ">0.8 - 1", ">0.6 - ≤ 0.8", ">0.4 - ≤ 0.6", ">0.2 - ≤ 0.4," and ">0 - ≤ 0.2".

2.3.3. Vehicle disinfection

An effective farm vehicle visit to a CCS was when a vehicle came to a complete stop (0 km/h) within 500 m of a CCS for at least 60 minutes (60 minutes was based on personal communication from the standard operating procedures for a large swine producing company) (Fig. 1). We remark that eliminating 100% of organisms in vehicle surfaces via cleaning and disinfection is an optimistic assumption (Deason et al., 2020; Dee et al., 2004; Mannion et al., 2008). For example, 18% to 6% of disinfected vehicles tested positive for salmonella (Mannion et al., 2008), which could be translated to cleaning effectiveness of 82% and 94%, respectively. Similarly, in a PEDV study, 46% of disinfected vehicles were positive for PEDV via swab (Boniotti et al., 2018), cleaning effectiveness of 54%. Thus, here we simulated cleaning effectiveness (*d*), defined as a standard proportion of vehicles successfully disinfected after a CCS visit, with all possible values ranging from 0% to 100%.

2.4. African swine fever network scenario

We utilized the new network methodology developed in subsection 2.3 to simulate between-farm ASFV dissemination. The between-farm indirect dissemination of ASFV via contaminated vehicles has been described elsewhere (Neumann et al., 2021; Gebhardt et al., 2022), while recent studies evaluated ASFV stability under different temperatures (Supplementary Material Table S2) from which we extracted ASFV stability information used in our model. We used an exponential decay curve with different decay rates λ for each temperature (see subsection 2.3.3 and Supplementary Material, Figure S2). The results of Mazur-Panasiuk et. al., 2020 were used for ASFV stability because it provided several stability metrics at different points in time that allowed us to reconstruct a robust decay stability curve (Supplementary Material

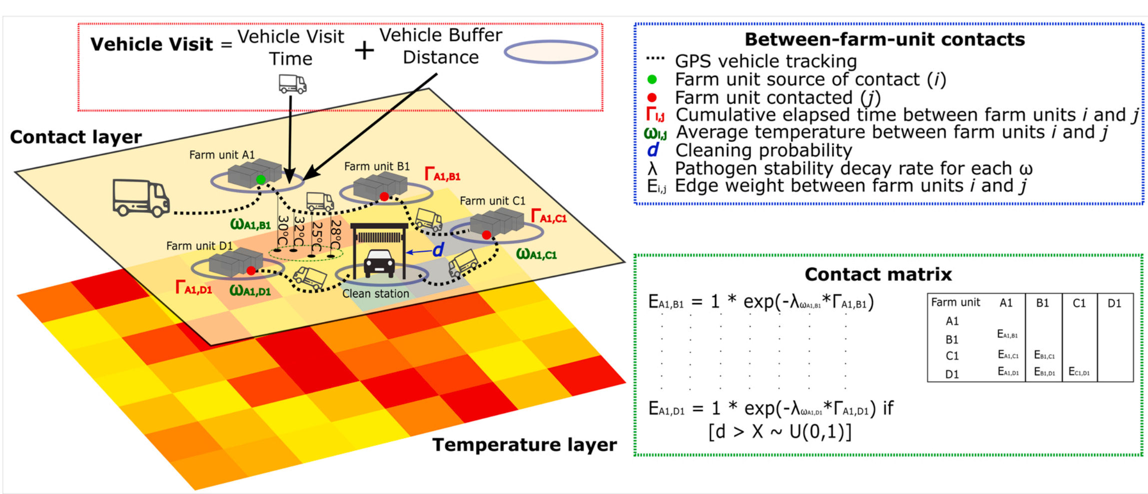

Fig. 1. Network reconstruction framework. A vehicle visited a farm if the vehicle's latitude and longitude were inside a buffer distance and for a minimum time specified by the visit time (red box, top-left panel). An edge connecting different farms is recorded if all farms were visited by the exact vehicle in decreasing chronological order and if the edge weight (E), which represents our pathogen stability, is higher than 0 (green box, bottom-right panel). In the example, a vehicle visited four different farms, creating edges from A1→ B1 and A1→C1, and B1→ C1, while no edges were recorded from A1, B1, and C1 to D1 because the vehicle stopped at a C&D before visiting D1 and the cleaning probability *d* was effective. The weight edges among the farms are calculated through an exponential distribution, where λ is the decay rate for each average temperature (ω) from the source of the contact (e.g., farm A1, green dot) until the destination (e.g., farms B1 and C1, red dots). Similarly, Γ is the cumulative time from the source of the contact (e.g., farm A1, green dot) until the destination (e.g., farms B1 and C1, red dots).

Figure S2). Mazur-Panasiuk et. al., 2020 suggested that ASFV remains stable in soil for up to 9 days at 23 °C and 32 days at 4 °C, half-time was 0.44 days at 23 °C and 1.88 days at 4 °C, and 90% decay of 1.48 days at 23 °C and 6.26 days at 4 °C (Mazur-Panasiuk and Woźniakowski, 2020). We used a range of temperatures from 4 °C to 23 °C and assumed ASFV stability decay rate λ was 0.001 at 4 °C and this rate increased by $4.48*10^{-05}$ for each temperature degree increase. Given that ASFV stability on temperatures lower than 4 °C and higher than 23 °C was not available, we assumed that environmental temperatures lower than 4 °C use the same decay rate as 4 °C, and temperatures higher than 23 °C use the same decay rate as 23 °C. Even though cleaning and disinfection procedures have been investigated in ASFV (De Lorenzi et al., 2020), the contributions of cleaning and disinfection procedures in eliminating the virus from vehicle surfaces are still to be fully demonstrated (Gao et al., 2023b; Li et al., 2020; Neumann et al., 2021). Because of that, we decided to simulate a range of pathogen reductions (*d*) from 0, 10%, 50%, 80%, 90%, and 100%.

2.5. Vehicle network outputs

We evaluated nine vehicle visit scenarios, which included a factorial combination of three VBDs (50, 100, and 300 m) and three VVTs (5, 20, and 60 minutes). We evaluated the ratio of farm unit visits, and cumulative time vehicles spent within farm units and at cleaning stations. The ratio of farm unit visits was calculated as the number of times each vehicle visited a farm divided by the number of times each vehicle visited a cleaning station. The vehicle contact network was reconstructed following the steps and conditions described in Sections 2.3 and 2.4 with the aid of the R programming language (R Core Team, 2023). Briefly, this network is represented by direct and weighted edges between farms. Additionally, we ran ten simulations for each cleaning effectiveness scenario to estimate the edges among farms. We used eight metrics to compare networks: network density, number of edges in the static and temporal networks, in-degree, out-degree, degree and betweenness centralization, and outgoing contact chains (Supplementary Material Table S3), evaluated via the R package igraph (Csardi and Nepusz, 2006; R Core Team, 2023). In addition, for region one, we combined all vehicle movements and referred to this group as the combined-vehicle type. Results are presented by vehicle types and for each region.

3. Results

3.1. Number of farm visits

Table 1 shows that increasing the buffer distance around farm units leads to more vehicle visits while lengthening the minimum duration for a visit to count from 5 minutes to 20 or 60 minutes decreases the number of visits. These findings suggest a trade-off between buffer distance and visit frequency. In region one, the total number of vehicle visits varied between a minimum of 47,847 and a maximum of 301,774 visits (Supplementary Material Table S4), while the median by vehicle varied between 59 and 432 visits (Table 1). For region two, the total number of vehicle visits ranged from a minimum of 6951 to a maximum of 15,094 (Supplementary Material Table S4), while the median by vehicle varied between 112 and 231 (Table 1).

The number of visits among vehicle types was found to vary significantly with variations in VBD (50, 100, and 300 m) and VVT (5 and 20 minutes). The median number of visits by vehicle varied from 474 to 827 for feed-vehicles; 388 and 522 for pig-farm-vehicle; 277 and 360 pig-market-vehicle; 210 and 309 for undefined-vehicles; 2 and 8 for crew-vehicles, while undefined-vehicles in region two the median of visits was 205 and 231 farm units. Conversely, we observed a marked decrease in the number of visits across all vehicle types, particularly for feed-vehicles, when the minimum duration required for a visit to be considered a farm visit was extended to 60 minutes. Supplementary Material Figure S3 shows that the median number of feed-vehicle visits ranged from 22 to 29 farm units. We also demonstrated that vehicles visited farm units under the management of different companies. Company A owned vehicle visited a maximum of 19 farm units across different companies in region one, whereas, in region two, vehicles serving multiple companies visited a maximum of 12 farm units (Supplementary Material Table S5).

Regarding different farm types visited with VBD of 50 m and VVT of five minutes, finisher farm units were the most visited, with 33% of visits associated with feed-vehicles and less than 1% with crew-vehicles (Supplementary Material Figure S4). Pig-farm-vehicles made up 8.9% of all visits to nursery farm units, as shown in Supplementary Material Figure S4. Sow farm units were visited mainly by feed-vehicles (7.5%), followed by pig-farm-vehicles (7.2%), as shown in Supplementary Material Figure S4.

3.2. Frequency of visits to clean stations

In the scenario of 500 m and at least 60 minutes within a truck wash in region one, the vehicles with the most visits to cleaning stations were pigs-market-vehicles and pigs-farm-vehicles (as shown in Table 2 and Supplementary Material Figure S13). The ratio of visits between clean stations and farm units showed that for each clean station visited, undefined-vehicles visited, on average, 4.4 (IQR 2.2–27.8) farm units. This was followed by feed-vehicles (2.9, IQR 2.9–10.6), pig-farm-vehicles (2.4, IQR 1.8–2.9), crew-vehicles (1.6, IQR 1.6–1.6) and pig-market-vehicles (1.3, IQR 1.2–1.5). Similar results were observed in region two, where undefined-vehicles visited, on average, 1.6 (IQR 1.3–2.1) farm units per clean station visit. Additional scenarios can be found in Supplementary Material Table S6-S10 and Figures S14-S15.

3.3. The relationship between vehicle movement, the effectiveness of vehicle cleaning, and the stability of ASFV in the environment

Our findings indicated slight fluctuation in network metrics across ten different cleaning and disinfection simulations in both study locations (Figs. 2 and 3, and Supplementary Material Tables S11-S14). With a 100% cleaning efficacy, the maximum reduction of nodes was 14% of the crew-vehicle networks (Tables 3 and 4). On the other hand, the network constructed from vehicles transporting pigs to market displayed

Table 1
Show the median and the interquartile range (IQR) of farm units visited by each vehicle for one year.

	VVT		
VBD	5 minutes	20 minutes	60 minutes
50 m	364 (170-680) (R1)	326 (141-540) (R1)	59 (23,150) (R1)
	205 (148-278) (R2)	196 (143-274) (R2)	112 (83-147) (R2)
100 m	374 (175-703) (R1)	338 (147-552) (R1)	62 (25-157) (R1)
	215 (152-293) (R2)	207 (146-285) (R2)	118 (88-156) (R2)
300 m	432 (202-820) (R1)	378 (162-651) (R1)	70 (28-183) (R1)
	231 (158-319) (R2)	218 (147-309) (R2)	127 (97-166) (R2)

(R1) = region 1; (R2) = region 2

Table 2
Show the median and the interquartile range (IQR) number of clean stations visited by each vehicle for one year.

Transportation role	Median (IQR)
Vehicle transporting feed (R1)	136 (21-359)
Vehicle transporting pigs to farms (R1)	188 (99-238)
Vehicle transporting pigs to market (R1)	206 (95-300)
Vehicle transporting crew (R1)	5 (5-5)
Vehicle undefined (R1)	39 (7-78)
Vehicle undefined (R2)	138 (62-166)

(R1) = region 1; (R2) = region 2

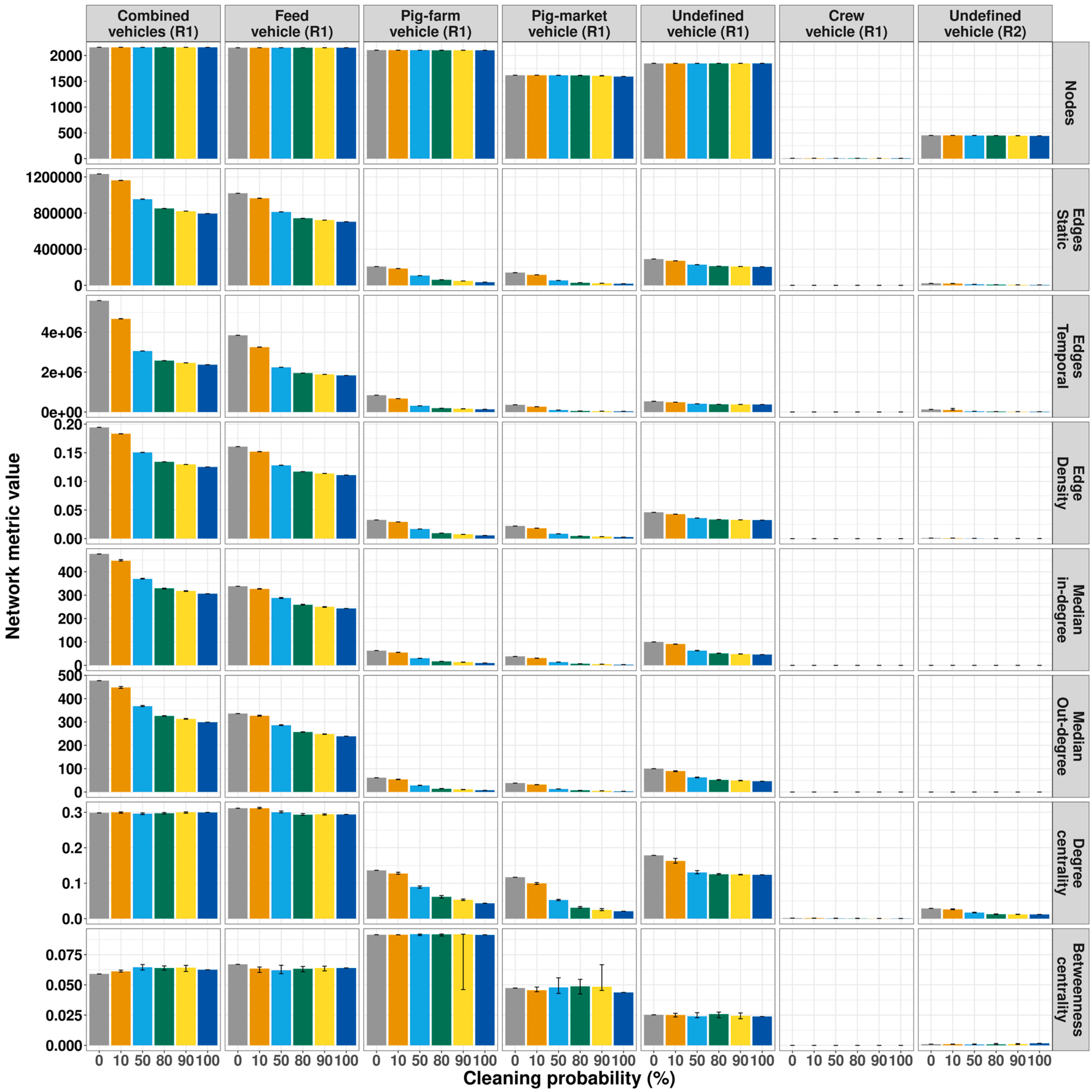

Fig. 2. Distribution of network metrics from ten different reconstructed vehicle contact networks using a VBD of 50 m and a VVT of five minutes and six cleaning probabilities. Bar graphs represent the median values for each clean probability, and the error line is the minimum and maximum ranges for each distribution.

the most significant reduction in static and temporal views, with 88% and 91% fewer edges, respectively. Furthermore, vehicles transporting pigs to market exhibited the most significant reduction of in-degree and out-degree, with 92% fewer adjacent neighbors in the network. Finally, for region two, undefined vehicles showed the most substantial decrease in the number of farm units in the outgoing contact chains, with a reduction of 76% in the total number of farm units that could be potentially exposed to indirect contact through vehicle movements (Tables 3 and 4).

Fig. 2 and Supplementary material Table S11 indicate that the level of centralization remained relatively constant across the simulated cleaning effectiveness (*d*) for the combined and crew vehicle networks without any significant variation. On the contrary, as *d* increased, a slight decrease in degree centralization was observed in vehicles transporting feed, while a more evident reduction was observed for all the other vehicle types (Fig. 2). On the other hand, the betweenness centralization was mainly the same across simulated *ds* for all vehicle types.

The edge weight distribution of the combined vehicles network had 6–13% of edges with ASFV stability between 0.8–1 and 61–72% of ASFV stability between 0–0.2 (Tables 3 and 4, and Supplementary Material Table S13). In the feed vehicles network, 5% and 10% of all edges were in scenarios with ASFV stability of 0.8 to 1, while stability between 0 and 0.2, the median number of edges varied between 63% and 73%. The

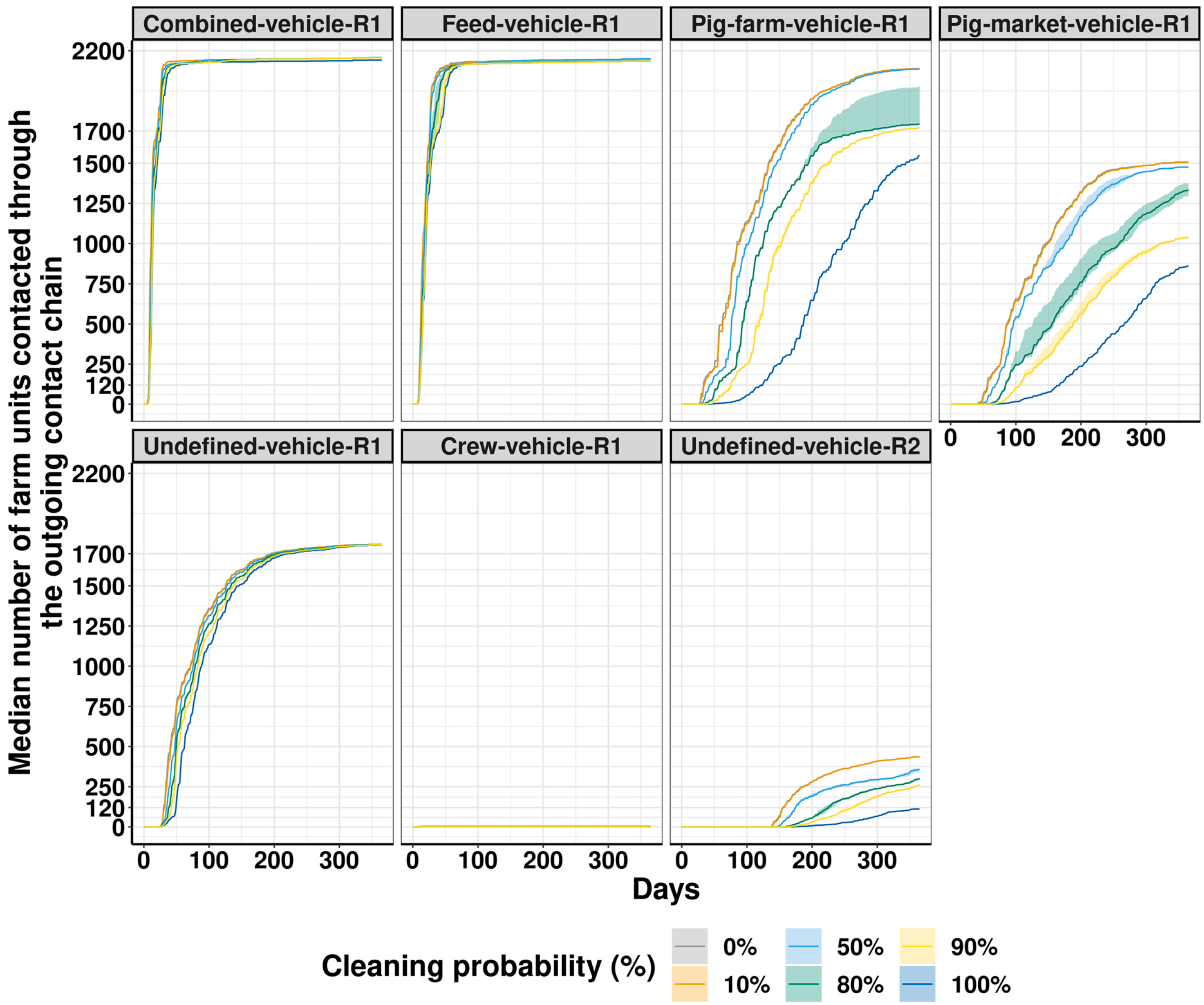

Fig. 3. The number of farm units contacted through the outgoing contact chain from vehicle movements. Solid lines represent the median, while shadow areas represent the interquartile ranges. (R1) = region 1; (R2) = region 2.

Table 3
Summary of network metrics. Values represent the median of ten stochastic simulations for each *d* evaluated; all *d* values and IQR are available in Supplementary Material Tables S11-S12 and S14.

Network metric	Combined-vehicles-R1		Feed-vehicles-R1		Pig-farm-vehicles-R1		Pig-market-vehicles-R1	
Cleaning scenarios	Values with $d = 0\%$	% Decreased with $d = 100\%$	Values with $d = 0\%$	% Decreased with $d = 100\%$	Values with $d = 0\%$	% Decreased with $d = 100\%$	Values with $d = 0\%$	% Decreased with $d = 100\%$
Summary network metrics								
Nodes	2159	.05%	2151	0%	2103	0.1%	1618	1.6%
Edges static network	1232,684	36%	1018,941	31%	207,232	83%	139,786	88%
Density	0.19	36%	0.16	31%	0.03	83%	0.02	88%
In-degree	476	36%	338	28%	63	84%	38	92%
Out-degree	477	37%	336	29%	61	88%	38	92%
Edges temporal network	5583,703	57%	3846,333	52%	841,987	84%	359,796	91%
Outgoing contact chain	2157	1%	2159	1%	2089	26%	1507	43%
Summary of edge weight metrics								
Edges of ASFV stability >0.8-1	339,490	6%	198,947	8%	87,603	1%	20,226	16%
Edges of ASFV stability >0-<0.2	4031,537	64%	2799,520	58%	582,593	96%	261,215	98%

(R1) = region 1

Table 4
Summary of network metrics. Values represent the median of 10 stochastic simulations for each *d* evaluated; all *d* values and IQR are available in Supplementary Material Tables S11-S12 and S14.

Network metric	Crew-vehicles-R1		Undefined-Vehicles-R1		Undefined-Vehicles-R2	
Cleaning scenario	Values with d = 0%	% Decreased with d = 100%	Values with d = 0%	% Decreased with d = 100%	Values with d = 0%	% Decreased with d = 100%
Summary network metrics						
Nodes	7	14%	1848	0.1%	450	2%
Edges static network	23	69%	290,960	30%	21,385	82%
Density	0.000004	69%	0.05	30%	0.001	82%
In-degree	0	0%	100	54%	0	0%
Out-degree	0	0%	100	54%	0	0%
Edges temporal network	24	71%	535,563	30%	128,483	89%
Outgoing contact chain	3	66%	1760	0.2%	437	76%
Summary edge weight metrics						
Edges of ASFV stability >0.8-1	7	0%	32,707	3%	6973	3%
Edges of ASFV stability >0-<0.2	13	100%	388,136	34%	95,888	97%

(R1) = region 1; (R2) = region 2

edges of vehicles transporting pigs with an ASFV stability >0.8 - 1 ranged from 10% to 64% and >0 - ≤0.2 from 15% to 69%. The vehicles transporting pigs to market edges ranged between 6% and 51% for ASFV stability >0.8 - 1, while the number of edges with stability between 0 and 0.2 varied between 15% and 73%. For the crew vehicle network, the median number of edges with an ASFV stability >0.8 - 1 varied between 29% and 100%, while the edges with an ASFV stability >0 - ≤0.2 varied between 0% and 54%. The undefined vehicles network in region one exhibited a median number of edges with an ASFV stability >0.8 - 1 varied between 6% and 8%, while the edges with an ASFV stability >0 - ≤0.2 varied between 68% and 72%. Finally, the network of undefined vehicles in region two showed that the median number of edges with an ASFV stability >0.8 - 1 varied between 5% and 47%, and edges with an ASFV stability >0 - ≤0.2 varied between 20% and 75%.

4. Discussion

In this study, we developed a novel transportation vehicle contact network methodology that explicitly considers environmental pathogen stability and vehicle cleaning effectiveness uncertainties. We demonstrated that when cleaning and disinfection were either not performed in between farm visits or were simulated to be not effective ($d = 0\%$), the vehicle's contact networks had 5583,703 edges in region one and 128,483 in region two. This means that 88% of 2519 farm units in region one and 9% of 4619 farm units in region two were connected and potentially exposed to infected vehicles. When cleaning and disinfection were simulated at 100% effective in region one, the number of edges was reduced by 57%, yet 87% of farm units were still connected. In region two, the number of edges was reduced by 89%, and the farm units connected decreased from 9% to 2%. Additionally, for our simulated pathogen stability scenarios, with $d = 100\%$, up to 13% and 47% of edges in regions one and two, respectively, were highly contaminated (ASFV stability range of 0.8 to 1), thus posing significant disease spread risk. Ultimately, we demonstrated that cleaning and disinfection reduced the number of edges in the vehicle to farm units' movement network. Nevertheless, it was not sufficient to eliminate the risk of vehicles in disease dissemination, but it disrupted the underlying structure of the vehicle network.

The frequency of visits by pig-farm-vehicles and pig-market-vehicles to cleaning stations was directly related to how cleaning and disinfection disrupted their networks. This suggests that cleaning and disinfection had a significant effect on disconnecting networks. We demonstrated that pig-market-vehicles visit cleaning stations for every other farm visit, and pig-farm-vehicles after three farm visits. On the other hand, feed-vehicles were disinfected after two and 12 farm units, and undefined-vehicles between three and 80 farm units (Supplementary Material Figure S15). The few cleaning feed vehicles are probably because of the perceived risk of contamination from these vehicles, which do not have direct contact with animals (Boniotti et al., 2018; Henry et al., 2018). Undoubtedly, pig-farm and pig-market vehicles transporting animals in direct contact with infected organic material are usually recognized as high risk of disease dissemination (Alarcón et al., 2021; Mannion et al., 2008). However, recent studies in Vietnam and Mexico demonstrated the association between feed vehicles and ASFV dissemination (Gebhardt et al., 2022) and PEDV (Garrido-Mantilla et al., 2022). Therefore, regardless of the vehicle's transportation function, we emphasize the significance of increasing the frequency of disinfecting vehicles between farm visits to reduce the number of indirect contacts between farms. It is essential to mention that if cleaning and disinfecting are prohibited due to cost or logistic challenges (e.g., freezing weather), as described elsewhere (Denver et al., 2016; Weng et al., 2016), it is recommended that efforts be made to prioritize the disinfection of vehicles used for transporting animals after each farm visit at a minimum (Porphyre et al., 2020). In addition to the challenges of cleaning and disinfecting, alternative strategies to minimize indirect contact between farms could involve redirecting vehicles based on factors such as the health status of farms and distance, as proposed in Sweden (Nöremark et al., 2009).

As described in recent studies (Büttner and Krieter, 2020; Galvis et al., 2022a), transportation vehicles and animal movement network configurations differ significantly. It has been demonstrated that the vehicle transportation network links up to 100 times more farms than the animal movement network (Büttner and Krieter, 2020; Galvis et al., 2022a), which directly impacts the effectiveness of network risk-based farm ranking often proposed in disease control programs (Büttner and Krieter, 2020). Our results show that vehicle transportation networks are not as pyramidal as the pig movement networks, in which breeding farms are on the top of the pyramid and finisher farms are at the bottom (Lee et al., 2017; Schulz et al., 2017) (Supplementary Material Figures S17-S30). As such, because vehicle movement network configuration is more chaotic, it poses an increased risk of disease dissemination, making target control strategies more challenging to implement (Galvis et al., 2022a; VanderWaal et al., 2018).

Despite our simulated cleaning effectiveness scenarios, we uncover highly connected vehicle networks, except crew vehicle networks, which connected fewer farm units. Interestingly, we observed through the degree of centralization that the number of farms heavily interconnected (a.k.a. hubs) by vehicles transporting pigs and undefined vehicle networks was less frequent when cleaning efficacy was 100%. Given that contact networks with fewer hubs have been associated with slow disease propagation (Kiss et al., 2006; Martínez-López et al., 2009), increasing cleaning efficacy is indeed expected to impact disease dissemination through vehicle movements (Porphyre et al., 2020).

Measuring the outgoing contact chain, we demonstrated that 88% of the farms were interconnected. Büttner and Krieter, 2020 reported similar results in which 70% to 97% of the farms became infected via transportation network. Galvis et. al., 2022, demonstrated that vehicles transporting feed significantly contributed to PRRSV dissemination to breeding sites, and VanderWall et al., 2018, demonstrated that feed vehicles have a high potential to introduce PEDV into new geographical areas. Although contamination and disease transmission through feed vehicles are less likely than through vehicles transporting animals, they still pose a significant risk (Büttner and Krieter, 2020; Galvis et al., 2022a,b; Sykes et al., 2023). On the contrary, pig-farm-vehicles, pig--market-vehicles, and undefined-vehicles interconnected fewer farm units. Importantly, we observed that 100% cleaning efficacy reduced by 26% and 43% the potential number of infected farm units via vehicles transporting pigs to farms and markets, respectively. It is worth mentioning that we observed significant variability in the effectiveness of reducing the number of farm units in the contact chain of pig and market vehicle networks when we simulated a cleaning efficacy of less than 100% (Fig. 3). As previously discussed, these two types of vehicles are more prone to become contaminated while visiting farms. Hence, attaining a cleaning efficacy of nearly 100% is critical to mitigating the spread of diseases among swine production through contaminated vehicles that transport pigs (Boniotti et al., 2018; Mannion et al., 2008). It is worth highlighting that our findings revealed an unexpected behavior of the contact chain of the unidentified vehicle network in region two after 120 days. That was because GPS data of company G vehicles started to be collected in its entirety in May 2020 (as per personal communication).

We demonstrated that vehicles connect farm units of various swine-producing companies, thus posing a potential risk for between-company dissemination. Pathogen dissemination among swine companies is plausible and described earlier (Jara et al., 2020; Smith et al., 2013). Jara, et. al., 2020 identified distance from farms to roads as a risk for transmission, and Seedorf and Schmidt, 2017 suggested that vehicle movements may disseminate bioaerosols in the surrounding area, creating a potential infection risk for farms situated close to roads. At least in densely swine-populated regions in which the traffic of swine production related vehicles is elevated, it is likely that infectious pathogens may be circulating among swine companies, even in the absence of farm visits (Seedorf and Schmidt, 2017). Future transmission models should formally account for this novel indirect route of intercompany transmission to investigate its potential contributions to disease spread.

The outcomes of our study indicated that the majority of farm-to-farm network connections had low ASFV stability, with less than 0.2 quantity of viable virus, thereby posing a low risk of disease transmission (Carlson et al., 2020; Mazur-Panasiuk and Woźniakowski, 2020; Nuanualsuwan et al., 2022). Due to our analysis that considers the decline of ASFV stability to 90% within a maximum of 6.26 days of exposure to the environment, we expected a significant number of movements with low ASFV stability (Mazur-Panasiuk and Woźniakowski, 2020). It is noteworthy that cleaning and disinfection had a significant impact on reducing the number of contacts between farm units. When disinfection efficacy was at 100%, the edges in the combined-vehicle network with ASFV $\leq$0.2 reduced by 64%, whereas in the pig-market-vehicle network, this reduction was even more substantial, at 98%. Conversely, cleaning and disinfection efficacy did not substantially impact the reduction of contacts between farm units where ASFV stability exceeded 0.8. The highest reduction, with 16% fewer edges with 100% disinfection, was observed in the pig-market-vehicle network. Feed-vehicles and pig-farm-vehicles had the highest number of movements and ASFV stability greater than 0.8, even with 100% disinfection, in which pig-farm-vehicles pose an exceptionally high risk of disease dissemination due to their direct contact with animals (Alarcón et al., 2021). In conclusion, our findings suggest that enhancing the effectiveness of cleaning protocols has a limited impact on decreasing the number of inter-farm contacts for vehicles, particularly in this simulation with elevated ASFV stability values. However, it may influence the disease propagation by disrupting the underlying structure of the vehicle movement network.

5. Limitations and further remarks

We recognize the limitations of the novel methodology for the proposed vehicle movement network and the available vehicle movement data. It is worth noting that the absence of data from vehicles serving most, but not all, premises in both regions underestimated the outcomes concerning indirect contact between companies and networks metrics evaluated at the regional level. Likewise, we were unaware of third-party vehicle washing locations; this limitation likely impacted significantly the crew and undefined vehicle networks, since smaller vehicles are more prone to be clean at drive-throughs at gas stations. In addition, information about the biosecurity measures implemented at CCS and premises was unavailable. These measures, which may include disinfection products, methods, and frequency (e.g., before/after farm visits), are likely to have a significant association with effective cleaning (De Lorenzi et al., 2020). Therefore, incorporating these biosecurity protocols into future studies is expected to enhance the reliability of our findings. The assumption of 60 minutes being adequate to fully clean and disinfect a vehicle may not hold in regions with freezing temperatures (Gao et al., 2023a). Additionally, it should be noted that our novel network methodology utilizes GPS data from the vehicle cab and does not monitor trailers. This is because most swine companies do not track trailers via GPS; some trace trailers based on plate identification. This is a critical data limitation; however, because our methodology only requires GPS data, it can be used to reconstruct trailer networks when the data becomes available. Similarly, truck drivers with contaminated boots have been associated with disease dissemination (Dee et al., 2002). Also, Perri, et al., (2020), showed that drivers might step out of the truck at farms (Perri et al., 2020); thus, in future studies, between-farm driver movement networks should be further investigated.

Due to the imminent risk of ASFV introduction into the U.S., its remarkable stability in the environment (Mazur-Panasiuk and Woźniakowski, 2020), high transmissibility, and the significant economic losses (You et al., 2021), it is imperative to enhance our understanding of the potential dissemination routes, to prepare better and to formulate and revise effective control strategies (Sykes et al., 2023). As for the assumptions about the stability of pathogens, our primary limitation was that we used soil as the reference material for ASFV stability, as indicated by Mazur-Panasiuk and Woźniakowski (2020). While studies examined ASFV stability in different materials (Nuanualsuwan et al., 2022), we opted to streamline our approach by considering the data from ASFV in soil. This choice was made due to the extensive viral stability measurements investigated by Mazur-Panasiuk and Woźniakowski (2020), which enabled us to construct a more sophisticated ASFV decay curve. Similarly, we simplified the temperature effects on the ASFV stability curve due to prior evaluations of only extreme temperature ranges, including cold and warm scenarios such as 4 °C and 23 °C (Carlson et al., 2020; Mazur-Panasiuk and Woźniakowski, 2020; Nuanualsuwan et al., 2022). Not considering temperatures below 4 °C might have underestimated the connections between farms given the ASFV stability in low temperatures (Mazur-Panasiuk and Woźniakowski, 2020; Gao et al., 2023a). Consequently, the interpretation of this study is more suitable for U.S. regions with warmer climates. Despite the limitations, this study is the first to recreate the between-farm networks using actual vehicle movement data of commercial swine companies in North America. This is also the first study that combined vehicle GPS data with pathogen environmental stability and vehicle cleaning and disinfection effectiveness. We demonstrated the potential role of vehicles in the spread of between-farm swine diseases, providing the swine industry and regulatory agencies with the necessary information to develop effective control strategies against future threats.

6. Conclusion

In this study, we extended a previously developed methodology for vehicle contact networks, which is commonly employed in disease transmission models (Galvis et al., 2022a,b; Sykes et al., 2023). In this updated approach, we have considered the uncertainty related to the processes of vehicle cleaning and disinfection, as well as the decay of ASFV stability in the environment. Our study revealed that although efficient cleaning and disinfection measures affected the number of farms connected through vehicle movements, simulations with 100% cleaning and disinfection still resulted in 88% of farms being in contact over one year. Importantly, achieving 100% cleaning effectiveness reduced the risk of between-farm contacts only when the ASFV stability was low ($\leq$0.2). Conversely, there was an insignificant reduction in the number of between-farm contacts when the ASFV stability was still high ($>$0.8). We noted that farms of different swine production companies were visited by vehicles that also visited farms under other production companies, enhancing the potential for between-company dissemination. This study enhances our understanding of the role of transportation vehicles in spreading diseases between farms and the risks involved. The new methodology introduced in this study can be used to develop novel disease control strategies, including rerouting vehicles based on their infection status.

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CRediT authorship contribution statement

Jason A. Galvis: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gustavo Machado:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

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

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.prevetmed.2024.106168.

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