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Strategic risk factor selection in disease risk mapping applied to the African swine fever outbreak in Sweden

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A R T I C L E I N F O

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A B S T R A C T

Risk mapping in epidemiology is a strategic tool that identifies high-risk areas for disease outbreaks, guiding preventive, surveillance, and control measures. In this study, we investigated how the selection of risk factors in ASF risk mapping affected the output of risk maps using the outbreak in Fagersta, Sweden as a study area. We identified ASFV risk factors by considering the sequence of introduction, release, and spread. Introduction was linked to pathways through which the virus could enter new areas, while release was associated with human activities and infrastructure that may lead to environmental contamination. Spread was then examined in relation to wild boar populations and environmental conditions that influence virus transmission. We demonstrated how previously overlooked human activities, such as the management of residual waste in areas accessible to wild boar, contributed to the risk of ASF in Fagersta, an area classified as low risk, and how this affected the calculation of disease risk. This study emphasizes the need for robust risk assessment frameworks that take into account ecological and socio-demographic factors, as well as emerging research findings. In addition, the existence of region-specific threats or vulnerabilities point out the necessity of frequent revisions of risk maps by incorporating new threats or vulnerabilities and adapting regional features to environmental changes. These findings are meant to improve preparedness and response strategies for ASF and other infectious disease events, ultimately contributing to animal as well as public health protection.

1. Introduction

Risk mapping is a powerful tool in epidemiology that offers a systematic approach to understanding and managing the risk of introduction and spread of infectious diseases (De Smith et al., 2007; Maceachren et al., 2004). By identifying geographical areas at higher risk for disease outbreaks, risk maps serve as prioritization tools for preventive measures and preparedness and for guiding the implementation of surveillance- and control measures. This approach is particularly important for managing diseases in wildlife due to the complexities associated with the movement and behaviour of wild animals. Unlike domestic animals, which are usually confined to controlled environments, wildlife moves freely across diverse habitats, which presents significant challenges for disease monitoring and control. Our inability to predict such movements, often spanning national borders, complicates coordinated efforts to manage disease spread through movement control and surveillance (De la Torre et al., 2015). African swine fever (ASF) is a contagious viral disease that affects both domestic pigs and wild boar populations, causing severe illness and high mortality. The challenges of managing ASF are particularly relevant in wild boar populations due to their mobility and interactions with the environment. ASF causes severe economic losses in the pig industry due to its high mortality rates, imposition of trade restrictions, and the absence of effective vaccines or treatments (Blome et al., 2020; Dixon et al., 2020). During the last 10 years, ASF has affected large parts of the EU, where the disease has predominantly spread through wild boar populations, underscoring the importance of targeted risk mapping strategies to address the risk of ASF introduction and spread into new areas.

Several experiences have shown that long-distance translocations of ASF virus (ASFV) can occur unexpectedly, driven by human activities such as the transport of contaminated materials, regardless of geographic barriers. ASFV exhibits considerable persistence in the tissues of infected animals, particularly when protected by a protein rich matrix such as meat or blood. During viremia, the virus is distributed

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throughout the body, rendering non heat-treated contaminated meat and food waste infectious. ASFV remains stable in raw, frozen, and even cured meat products, allowing it to survive in food waste originating from infected animals (Davies et al., 2017; Sánchez-Vizcaíno et al., 2012). The risk of ASFV spread through food waste is strongly influenced by human practices, particularly when food waste is improperly disposed of or when biosecurity measures are insufficient in waste management systems. This has contributed to outbreaks in ASF-free areas when contaminated food waste or items are transported, whether intentionally or accidentally, from affected regions (Mazur-Panasiuk et al., 2019). Wild boar frequently scavenge exposed food waste, especially in areas with inadequate disposal practices. Discarded food waste containing ASFV poses a risk of infection to both wild boar and domestic pigs (Gavier-Widén et al., 2020; Guinat et al., 2016; Olesen et al., 2020). This highlights the important role that human-mediated factors may play in the introduction of the virus into new areas (De la Torre et al., 2015).

Risk mapping may serve as a valuable tool for identifying high-risk regions for the introduction and spread of ASF, enabling guided prevention and surveillance efforts. This approach reduces the risk of introduction, enhances the likelihood of early detection, limits the spread of the disease, and mitigates the negative impacts of outbreaks on both wildlife and domestic animal populations. Such risk mapping relies on the careful selection of risk factors, which in the case of ASF in wild boar are related to the wild boar population, its habitat and ecology as well as factor related to human-related activities. Precise selection of these factors to suit the characteristics of the target area, species, and epidemiological situation improves the predictive capacity of risk maps, enabling risk-based, and thus more effective, contingency planning, surveillance activities and prevention measures (Mur et al., 2012). However, selecting inappropriate or incomplete risk factors may increase uncertainty in the mapping results, leading to less effective disease control measures, including surveillance and preventive actions.

In Sweden, wild boar populations are primarily concentrated in the southern parts of the country where they overlap with areas that have relatively high densities of domestic pig herds, see Fig. 1 in Ernholm et al. (2022). Sweden's geographical location, lacking land borders with ASF-affected countries and surrounded largely by sea, prevents ASFV introduction via contact between infected and naïve wild boar populations (Acevedo et al., 2022; Croft et al., 2024; More et al., 2018). Therefore, since the introduction of ASF into the EU in 2014, previous risk assessments have suggested that focal introduction via human activities is the most likely pathway for ASFV to enter Sweden (Swedish Veterinary Agency, 2021). Several of the outbreaks in the current global epidemic show that such human-mediated spread can occur at any time and to any country, regardless of the distance to ongoing transmission in wild boar populations (Chenais et al., 2019; Licoppe et al., 2023). Such a scenario was therefore used in the risk assessment, and the distribution and density of wild boar populations, human population density, traffic volumes, vehicle capacity at rest areas, and international trade volumes at seaports were considered key risk factors. In multiple scenarios with varying weightings assigned to these factors, regions with high wild boar densities, particularly in the southern parts of the country, consistently emerged as high-risk areas for the introduction and spread of ASFV (Swedish Veterinary Agency, 2021). However, in 2023, an ASF outbreak occurred in Fagersta municipality, an area initially classified as low-risk due to its low wild boar density and its location in inland Sweden. As expected, the virus was most likely introduced through human activities, such as disposing of contaminated food leftovers in the environment, exposing wild boar to the virus (Chenais et al., 2024). Various

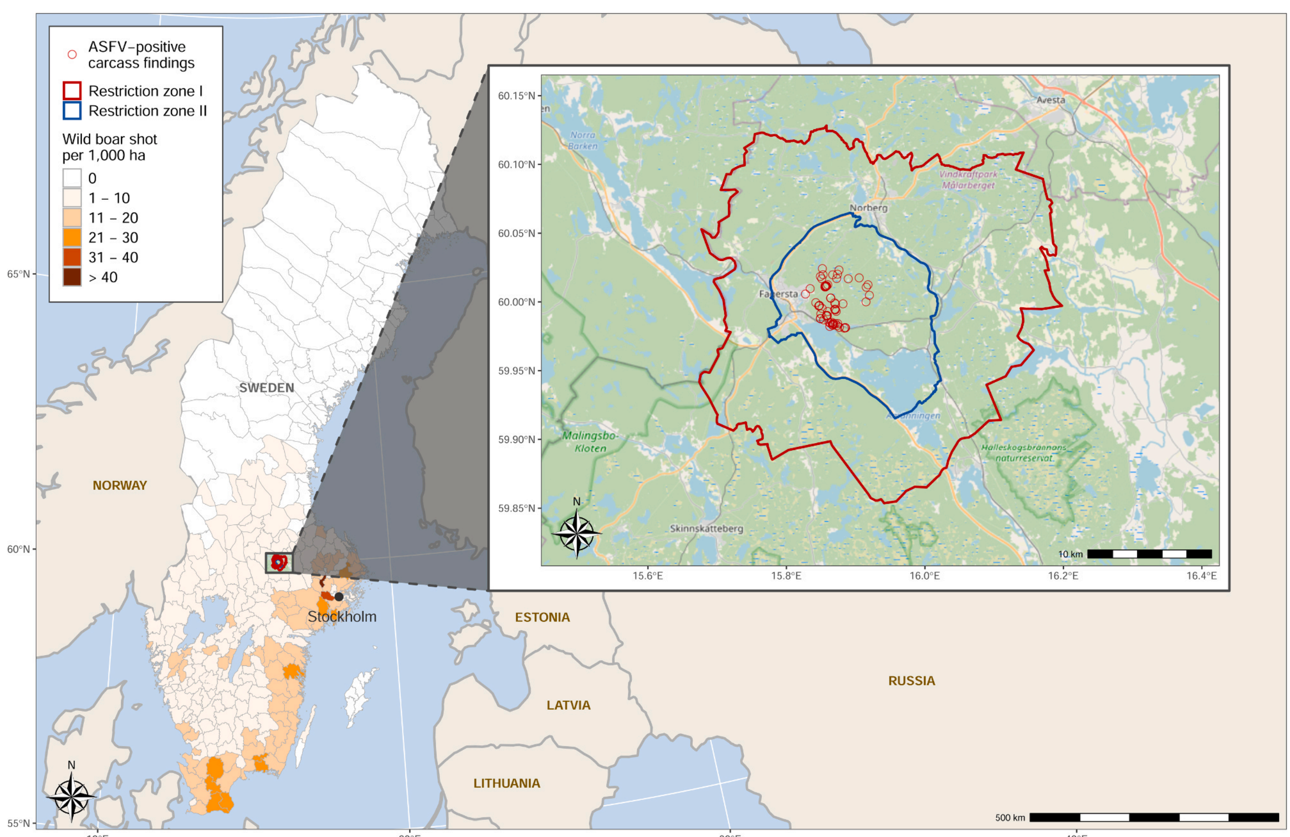

Fig. 1. A map showing the location of the ASF outbreak and the wild boar hunting bag in Sweden for 2022. Red points indicate the locations where infected carcasses were found. The red line represents Restricted Zone I, while the blue line marks Restricted Zone II and the fenced-off area, both established by the European Commission on 30 November 2023. The wild boar hunting bag is expressed as the number of wild boar shot per 1000 ha, with darker colours indicating higher hunting intensity.

human-related risk factors were incorporated into the risk mapping, including vehicle capacity at rest areas to account for potential transmission through contaminated food waste discarded in bins at campsites or roadside locations. However, municipal waste collection centres, later identified as potentially contributing to ASFV spread in the Fagersta outbreak (Chenais et al., 2024), were not included due to insufficient prior information regarding the structure and complexity of the of the Swedish waste management systems.

This study examines how the selection and spatial resolution of risk factors affect the calculation of the risk of ASFV introduction, release, and spread, with the Fagersta outbreak serving as the primary study area for model application. Additionally, we aim to assess the impact of spatial units and scales on identifying high-risk areas.

2. Background

In September 2023, Sweden confirmed its first case of ASF in wild boar near Fagersta, Västmanland County, approximately 170 km northwest of Stockholm (Fig. 1). This detection led to the implementation of strict control measures within a defined infected zone. Over 10 months, 125 wild boar carcasses were discovered, with 70 testing positive for ASFV. All positive cases were confined to a core area around the initial outbreak site.

Investigations suggest that the virus was introduced between early May and late June 2023, with spread peaking between mid-August and mid-September and the last death occurring in late September 2023. It was concluded that the introduction resulted from human activities, possibly linked to a municipal waste collection centre near the epicentre of the outbreak that lacked wild boar-proof fencing, attracting local wild boar and thus facilitating virus spread (Chenais et al., 2024). Following rigorous surveillance and eradication strategies, Sweden was declared free from ASF on September 25, 2024.

The general waste management system in Sweden is designed to prioritize recycling, waste reduction, and energy recovery. Municipalities are responsible for managing household waste and ensuring that waste is separated into categories such as recyclables (paper, plastics, metal, glass) and non-recyclable materials. Municipal waste collection centres play a central role in the system, providing residents with accessible locations to dispose of a wide range of waste, including recyclables, electronics, hazardous materials, and bulky items (Avfall Sverige, 2022).

3. Materials and methods

We identified risk factors by considering a sequence of events that includes introduction, release, and spread. For the introduction of ASFV, traffic and international trade were identified as major pathways through which the virus could enter new areas. The release of ASFV into the environment was associated with human activities and infrastructure such as roadside rest areas, waste disposal centres, human population density, and land cover characteristics, all of which may increase the likelihood of contaminated materials being deposited in wild or rural settings. The subsequent spread of ASFV was then considered in relation to the local wild boar population, which serves as a reservoir and amplifier host, allowing the virus to prevail and move through the landscape. In addition, environmental factors such as temperature and precipitation were included, as they influence virus survival in the environment, wild boar movement patterns, and the overall suitability of habitats for ASFV transmission (Aguilar-Vega et al., 2024; Bergmann et al., 2021, 2022; ENETWILD-consortium et al., 2024; Sauter-Louis et al., 2021; Viltrop et al., 2021). The selection of these risk factors was based on a review of the literature, Swedish environmental conditions, expert opinions (Swedish Veterinary Agency, 2021), and data availability. All data cleaning, data processing, analysis, risk calculations, and visualizations were performed using R version 4.4.1 (R Core Team, 2024).

3.1. Data

An overview of the risk factors, along with data sources and formats, is presented in Table 1. To incorporate a risk factor for ASFV entry into the country from ASF-affected countries through international trade, we used data on trade volumes at seaports from Transport Analysis and the annual average traffic volumes of the road network from the Swedish Transport Administration (Jurado et al., 2019; Patterson et al., 2021; Transport Analysis, 2024; Swedish Transport Administration, 2024).

Human-related activities can be estimated through human presence, which can be effectively measured by population density (Bergmann et al., 2021). We obtained the population density, aggregated at the municipality level from Statistics Sweden (Statistics Sweden, 2024). We used vehicle capacity at rest areas as a proxy for food waste, from the Swedish Transport Administration (Swedish Transport Administration, 2024), and included municipal waste collection centres, which were identified as a potential risk factor for the release and spread of ASFV in the Fagersta outbreak (Chenais et al., 2024), based on data from Swedish Waste Management (Swedish Waste Management, 2023). Information on the waste collection capacity of each collection centre as well as biosecurity measures in place (e.g. perimeter fences) was unavailable; therefore, a value of 1 was assigned for presence and 0 for absence. We also utilized CORINE Land Cover data (Copernicus Land Monitoring Service, 2018) to identify suitable wild boar habitats. Using GPS collar records of wild boar visits (Augustsson et al., 2024), we assigned values to five land cover types: artificial surfaces, agricultural areas, forests and seminatural areas, wetlands, and water bodies, based on the proportion of visits recorded in each land cover type.

For wild boar population data, we obtained the national hunting bag statistics from the 2021–22 hunting season, provided by Swedish Association for Hunting and Wildlife Management, Game Monitoring. Hunting bag statistics are commonly used as a proxy for estimating the relative abundance of wildlife species (Aubry et al., 2020; Lindström and Bergqvist, 2022), though this method has recognized limitations

Table 1
Risk factors used in the model, including data sources and format.

Risk factor	Data type	Temporal unit	Spatial unit	Data source
Traffic volumes	Vector - line	2021	Road network (link)	Swedish Transport Administration
Trade volumes	Text	2021	Point	Transport Analysis
Human population	Text	2021	Municipality (pop/km^2)	Statistics Sweden
Vehicle capacity at rest areas	Vector - point	2021	Point	Swedish Transport Administration
Municipal waste collection centres	Text	2021	Point	Swedish Waste Management
Land cover	Raster	2018	100 m^2 grid cell	Copernicus Land Monitoring Service
Hunting bag	Vector - polygon	2021–2022	Hunting bag	Swedish Association for Hunting and Wildlife Management
Wild boar-vehicle collision records	Vector - line	2016–2020	Road network (link)	Swedish Transport Administration
Temperature	Text	2021	Point	Swedish Meteorological and Hydrological Institute
Precipitation	Text	2021	Point	Swedish Meteorological and Hydrological Institute

(Focardi et al., 2020). To enhance reliability, we incorporated accident statistics from the Swedish Transport Administration, documenting wild boar-vehicle collisions across the road network over a five-year period (Augustsson et al., 2024; Seiler et al., 2019; Swedish Transport Administration, 2024). Temperature and precipitation data were collected from all monitoring stations across Sweden (Swedish Meteorological and Hydrological Institute, 2025). Using daily mean temperature and daily mean precipitation records, we calculated the annual average values to represent the overall climatic conditions.

3.2. Data processing

The collected data came in various formats, including text, raster, and vector (point and line). To use these data in risk calculations, we standardized them into a uniform format: raster with a 1 km^2 resolution. A raster file consists of equally sized cells, each assigned an attribute value. For example, in the population raster data, all cells within a municipality share the same value, representing the population density for that area. Data collected as points or lines, such as wild boar-vehicle collision records, rest areas, traffic volumes, and municipal waste collection centres, were used to create buffered areas with a 5 km radius around both points and lines. In cases where two buffered areas overlapped, the overlapping area was assigned the mean value of the two buffers. This radius was determined based on the home range size derived from movement data analysis of Swedish wild boar (Augustsson et al., 2024). Each buffered area was assigned an attribute value corresponding to the original data source, such as the number of vehicles a rest area can accommodate. Temperature and precipitation were interpolated from weather station data using inverse distance weighted interpolation with a power value (p) of 2. After data cleaning and conversion, all raster files were rescaled to have attribute values between 0 and 1, where 0 represents the lowest risk and 1 the highest (Fig. 2). This standardization ensured a common scale across all datasets, enabling direct risk comparison (Fig. 3).

3.3. Multicollinearity assessment of risk factors

An assessment of multicollinearity among the risk factors was conducted to ensure the robustness of the model. Multicollinearity occurs when predictor variables are highly correlated, potentially leading to instability in regression estimates and affecting the reliability of the results (Dormann et al., 2013). To evaluate multicollinearity, Pearson correlation coefficients were computed for each pair of risk factors. Pairs of variables with correlation coefficients greater than 0.7 were considered highly correlated (Vatcheva et al., 2016).

3.4. Risk weighting based on expert assessments

To assess the relative importance of various risk factors, we employed the paired comparison method, a structured decision-making technique used in multi-criteria analysis (Saaty, 1987). This method enables the derivation of relative weights among a set of factors based on expert judgments by systematically comparing them in pairs. A questionnaire was distributed to a panel of eight experts, including epidemiologists, disease spread modelers, veterinarians, and risk assessors, all with extensive knowledge of the Swedish context, ASF, and wild boar behaviour. Six of the eight experts provided responses. The experts were asked to evaluate the importance of 10 risk factors (listed in Table 1) that could affect the introduction, release, and spread of ASF in wild boar populations. For each pair of factors, respondents indicated which was more important, using a predefined scale ranging from "much less important" (1/4) to "much more important" (4), with "equal importance" assigned a value of 1 (Saaty, 1987; Vargas, 1990). To minimize group influence and bias, all responses were provided independently. The individual matrices were subsequently analysed to produce an aggregated ranking of the risk factors. The expert panel later reconvened to review the aggregated results, discuss inconsistencies, and make final adjustments. This collaborative process led to a consensus-based set of final weights for each risk factor, which were subsequently used as inputs for the risk mapping and analysis. Details of the expert assessments are available in the Supplementary Information (Table S1 and Table S2).

3.5. Calculation of expert-assessed risk of ASFV introduction, release, and spread in wild boar

The risk of ASFV introduction, release, and spread in wild boar was calculated using Eq. (1), which was designed to incorporate expert opinion, emphasizing that there is no such risk in areas without wild boar. Risk factors were assigned weights ranging from 0 to 1, where a weight of 0 indicates that the factor has no impact on the risk of introduction, release, and spread, while a weight of 1 signifies that the factor is assumed to fully influence these risks.

$$Risk_i = \begin{cases} 0, \ \text{if} P_{WB_i} = 0 \\ \sum_{k=1}^{K} \left(r_{IN_k i} \bullet w_{IN_k} \right) + \sum_{m=1}^{M} \left(r_{RE_m i} \bullet w_{RE_m} \right) + \sum_{n=1}^{N} \left(r_{SP_n i} \bullet w_{SP_n} \right), \ \text{if} P_{WB_i} > 0 \end{cases}, \quad (1)$$

where r_{IN} represents risk factors related to human-mediated virus introduction (e.g., traffic volumes, trade volumes), r_{RE} represents risk factors associated with virus release into the environment (e.g., population density, waste disposal, land cover), and r_{SP} represents factors influencing the spread of the virus in wild boar populations and their habitats (e.g., hunting bag, wild boar-vehicle collisions, temperature, precipitation). The variable w denotes the weights assigned by experts. The index i refers to the raster cell, while k, m, and n index the risk factors related to Introduction ($k = 1$ to K), Release ($m = 1$ to M), and Establishment and Spread ($n = 1$ to N), respectively. P_{WB} is a binary indicator that denotes the presence or absence of wild boar.

The output results were rescaled from 0–1 to ensure a consistent scale across all scenarios (Fig. 4) and are intended to assess relative, not absolute, risk. This allows for cross-regional comparisons to determine which regions are more vulnerable to ASF.

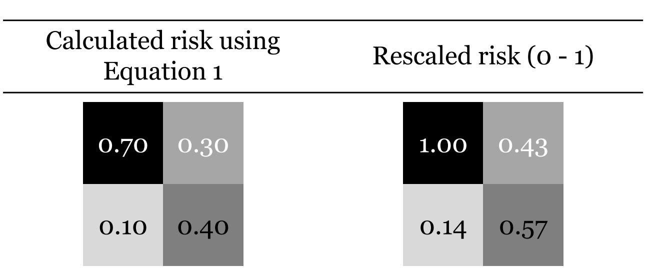

Fig. 2. An illustration of the raster (risk factor) rescaling process. On the left, the original rasters display varying ranges of cell values. On the right, the rescaled rasters are normalised to a value range of 0–1.

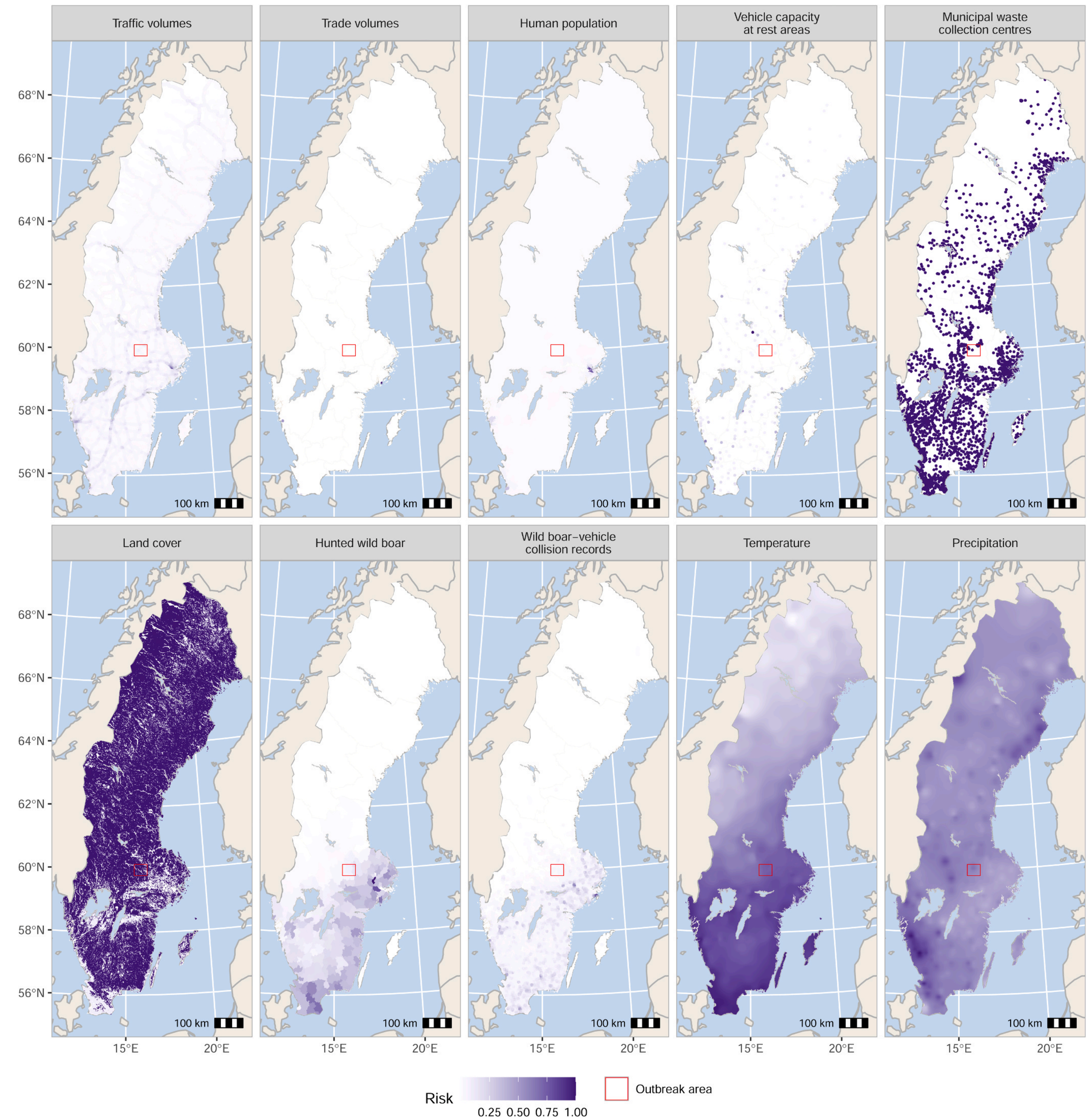

Fig. 3. Maps displaying each risk factor at a 1 km^2 resolution, with a scale ranging from 0 to 1. Darker colours represent higher intensity levels, and the red rectangle marks the outbreak area.

3.6. Sensitivity analysis

We conducted a sensitivity analysis to evaluate the impact of each risk factor. Since our model calculated a relative rather than an absolute risk, direct comparison of numerical risk values was inappropriate. Instead, we assessed the sensitivity of the results by examining how the ranking of risk for each spatial unit (specifically, grid cells and municipalities) changed when individual risk factors were excluded from the model. All 10 risk factors were initially incorporated with weights derived from expert assessments to establish a baseline risk. In this baseline model, each factor contributed according to its relative importance as determined through the paired comparison method. Following this, a series of 10 iterations was conducted. In each iteration, a single risk factor was removed, and the remaining nine factors, each weighted according to the expert assessments, were used to recalculate the relative risk. Each iteration, therefore, produced an alternative risk scenario where the influence of one particular risk factor was excluded. Calculations for risk were first made for each 1 km^2 grid cell, and then the average risk per municipality was computed from these grid cell values. If a grid cell is located on the boundary between municipalities, it is included in the municipality where the majority of the area of that cell lies, and the risk calculation is assigned accordingly.

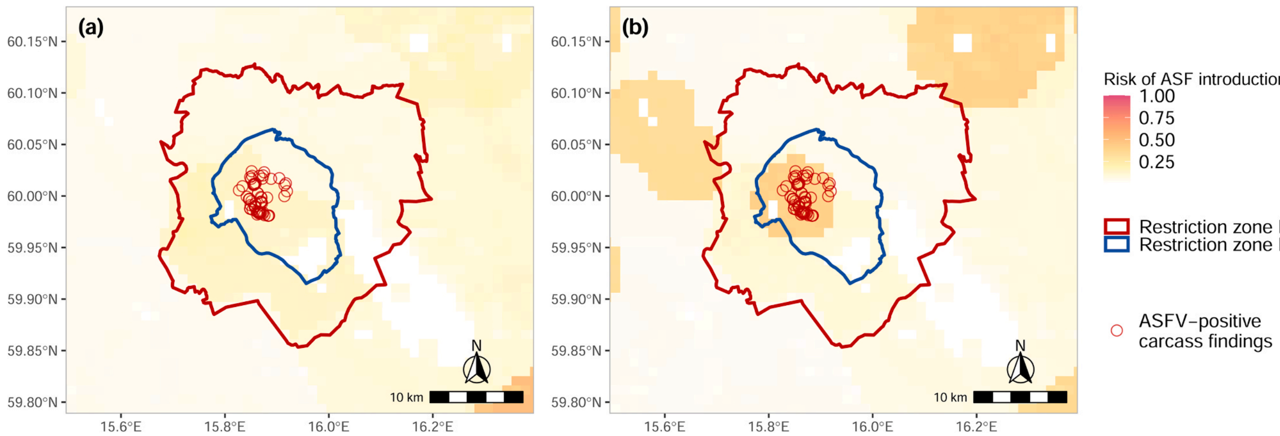

Fig. 4. An illustration of the risk raster rescaling process. On the left, the calculated risk raster, based on Eq. (1), has a certain range of cell values. On the right, the rescaled risk raster is normalised to a value range of 0–1.

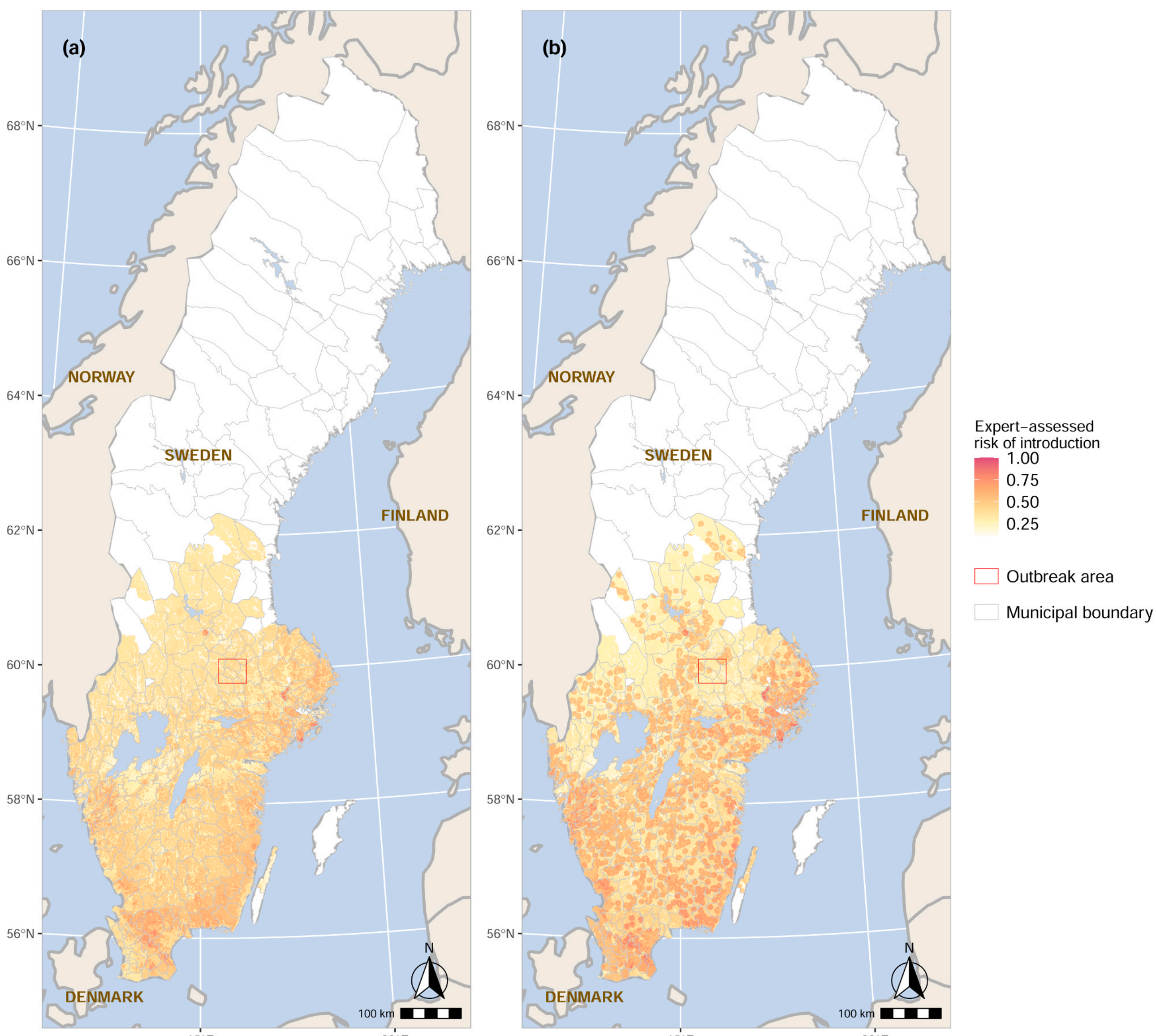

Fig. 5. Maps showing the risk of ASFV introduction, release, and spread at a 1 km² resolution, with darker colours indicating relatively higher risk. (a) includes traffic volumes, trade volumes, human population, vehicle capacity, land cover, hunted wild boar, wild boar-vehicle collision records, temperature, and precipitation as risk factors. (b) incorporates the same risk factors as (a), with the addition of municipal waste collection centres.

For the global sensitivity test, which evaluates risk sensitivity across the entire country, we assessed whether the ranking of municipalities by ASF risk was stable when individual risk factors were removed. We generated a total of 11 ranking sets, each representing a unique model configuration: one for the baseline model and 10 for models where one risk factor was excluded. The municipality rankings for each of these 10 alternative scenarios were then compared to the baseline ranking using the Wilcoxon signed-rank test (Wilcoxon, 1992). This non-parametric test allowed us to statistically evaluate if excluding a single risk factor produced a significant shift in the spatial pattern of risk. A local sensitivity analysis was also conducted for five regions of equal size (in terms of the number of grid cells), including the outbreak area in Fagersta municipality (Supplementary Fig. 1). These regions were selected based on varying levels of human and wild boar populations: high, moderate, and low. Within each of these areas, a total of 1840 grid cells were ranked according to their calculated risk values under both baseline and modified scenarios. To assess the impact of excluding individual risk factors, we applied the Wilcoxon signed-rank test to determine whether significant ranking changes occurred.

4. Results

The calculation of Pearson correlation coefficients between all pairs of risk factors revealed no significant correlations among the variables, indicating that the risk factors are independent of one another (Table S3). As a result, all 10 risk factors were included in the risk calculation. Based on this, the risk was then calculated for the entire country of Sweden. Fig. 5(a) and Fig. 6(a) display the results based on risk factors identified by SVA prior to the 2023 ASF outbreak. These factors include traffic volumes, trade volumes, human population, vehicle capacity, land cover, hunted wild boar, wild boar-vehicle collision records, temperature, and precipitation. At the national level, the outbreak area in Fagersta municipality was considered a relatively low risk (Fig. 5(a)). Out of 290 municipalities in Sweden, Fagersta municipality was ranked 147th for the risk of ASFV introduction, release, and spread. This is a relatively low position, especially considering that 50 municipalities with no wild boar populations have a risk of 0. Additionally, the risk values in the grid cells where positive cases were detected in the outbreak were also low, ranging from 0.24 to 0.46 (Fig. 6 (a)).

After including municipal waste collection centres as an additional risk factor, Fagersta municipality was ranked 179th out of 290 municipalities (Fig. 5(b) and Fig. 6(b)). However, the risk values for the grid cells where positive cases were located were notably higher than the municipal average, ranging from 0.43 to 0.59 (Fig. 6(b)).

In the global sensitivity analysis, we calculated the average risk for each municipality. Based on these averages, the municipalities were ranked (from 1 to 290), and the Wilcoxon signed-rank test was applied. Subsequently, the municipalities were grouped into six distinct risk levels for the purpose of visually assessing the risk of ASFV introduction, release, and spread. Fig. 7 illustrates the spatial pattern of ASF risk. The baseline panel shows risk levels calculated with all risk factors included, while the other panels show risk levels calculated after removing the factor indicated by each panel title. For example, in the “Without traffic volumes” panel, risk levels reflect the exclusion of only that factor while including the remaining nine risk factors. Results of the Wilcoxon signed-rank test confirmed excluding traffic volumes, human population, and vehicle capacity at rest areas from the risk calculation led to changes in the ranking of municipalities compared to the baseline scenario. However, the overall spatial pattern remained consistent (Table 2). By contrast, the local sensitivity analysis for the outbreak area reveals a notable difference as illustrated in Fig. 8. Specifically, the inclusion or exclusion of municipal waste collection centres significantly affects the spatial pattern of the risk of ASFV introduction, release, and spread. When municipal waste collection centres are excluded as a risk factor, grid cells in the outbreak area show consistently low risk values. However, when municipal waste collection centres are included, areas with substantially higher risks emerge. The Wilcoxon signed-rank test showed that, except for precipitation and trade volumes, all other risk factors significantly influence the ranking of risk values for each grid cell (Table 2). For the other regions, the sensitivity analysis showed distinct patterns of influence (Supplementary Fig. 2). In Region 1, traffic volumes, human population, vehicle capacity at rest areas, and municipal waste collection centres significantly influenced risk rankings. Region 2 was significantly affected by all risk factors except trade volumes and precipitation. Region 3 was influenced by all risk factors, while Region 4 showed significant sensitivity to all except trade volumes and temperature (Table S4).

5. Discussion

This study demonstrates how careful selection of relevant risk factors influences the confidence of disease risk assessments. Since risk factor selection is inherently incomplete, omitting critical factors can introduce substantial biases and uncertainty, potentially causing deviations in predictive scenarios.

Food waste is widely recognized as a significant factor in the introduction and spread of ASFV through human-mediated activities

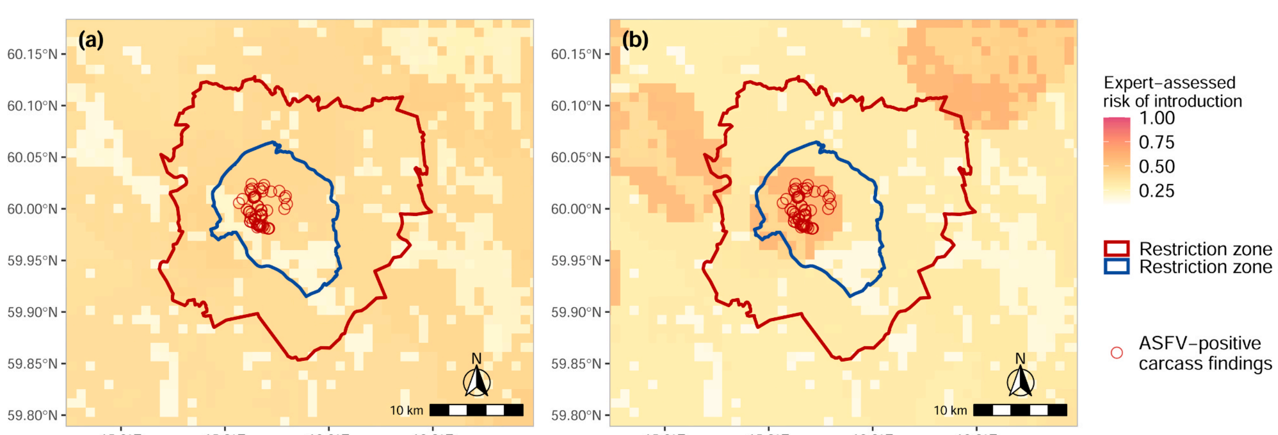

Fig. 6. Zoomed-in maps around Fagersta showing the risk of ASFV introduction, release, and spread at a resolution of 1 km^2, with darker colours indicating relatively higher risk. The red and blue lines delineate the zones established by the European Commission on 30 November 2023 (red line = restricted zone I, blue line = restricted zone II). Red dots indicate the locations where infected carcasses were found. (a) includes traffic volumes, trade volumes, human population, vehicle capacity, land cover, hunted wild boar, wild boar-vehicle collision records, temperature, and precipitation as risk factors. (b) incorporates the same risk factors as (a), with the addition of municipal waste collection centres.

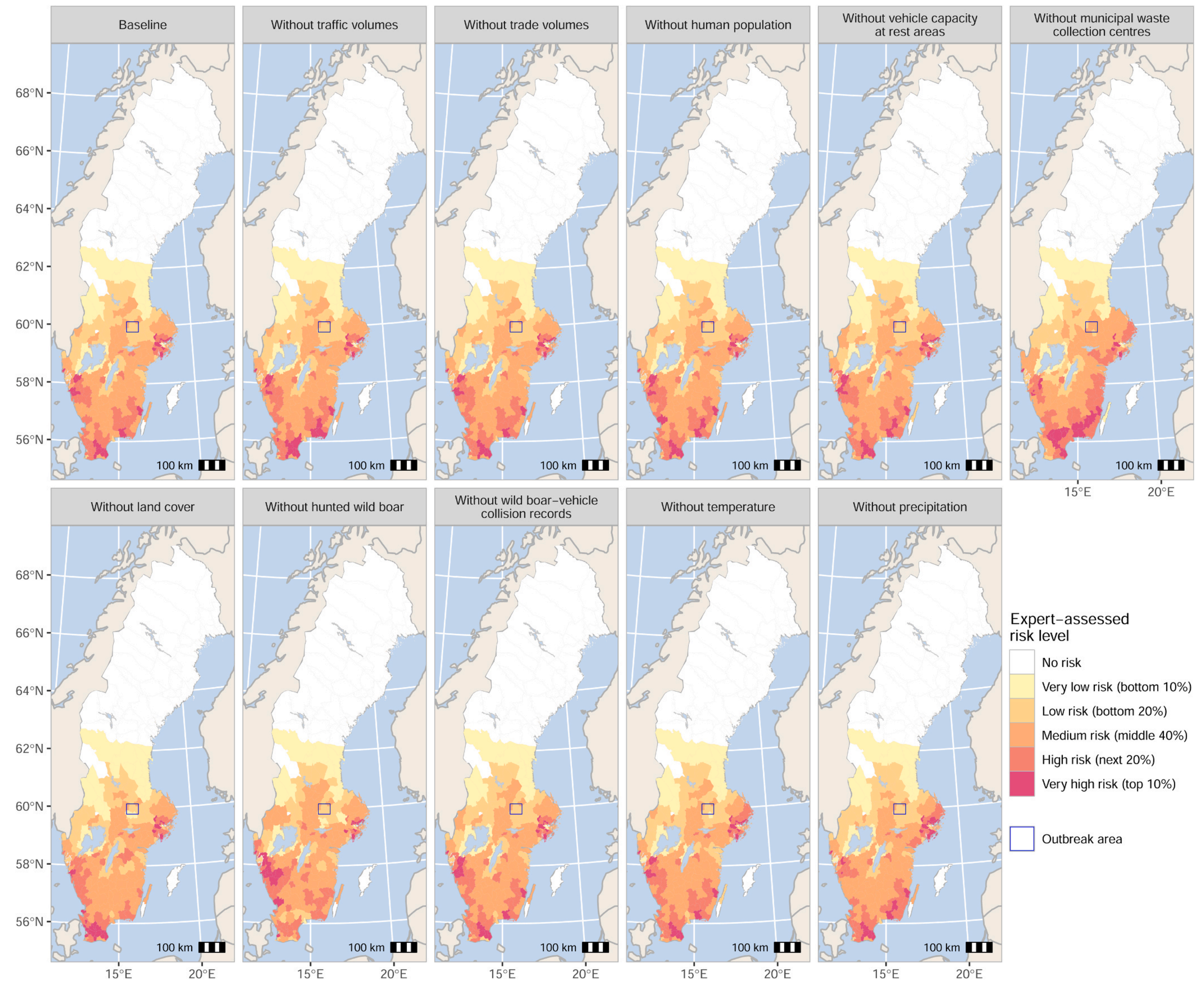

Fig. 7. The results showing the sensitivity analyses at the municipality level. The baseline panel displays the results when all 10 risk factors are included, while the other panels show the recalculated risk after excluding the specific risk factor indicated in the panel title. For instance, the 'Without traffic volumes' panel illustrates the risk calculated using only the remaining nine risk factors, excluding traffic volumes. Darker colours represent higher risk values.

(Gavier-Widén et al., 2020; Guinat et al., 2016; Olesen et al., 2020) and it has been identified as a potential risk for spreading ASFV to the Swedish wild boar population. As a result, it was included in the risk mapping prior to the Fagersta outbreak (Swedish Veterinary Agency, 2021). However, due to insufficient prior information concerning the Swedish waste management chain, the risk of virus introduction and spread through food waste was not fully addressed. A simplified view of the system's complexity led to potential biosecurity concerns, particularly since the risk at municipal waste collection centres was not adequately considered. Consequently, confidence in the assessment was hindered by a lack of comprehensive consideration of risk distribution across multiple dimensions.

In addition to selecting relevant risk factors, it is essential to assign proper weight to each factor to reflect its true impact on disease introduction (Gierak et al., 2019; Stiles et al., 2024). Our analysis, which covered five regions with varying characteristics (Fig. 8 and Supplementary Fig. 2), revealed that each region is influenced by different risk factors, emphasizing the importance of accounting for regional variation when assessing disease dynamics. Regional characteristics, such as geographical environment, climate conditions, and local wild boar population behaviours, played a significant role in shaping these differences. This variability suggests that a one-size-fits-all approach may not be effective, and region-specific adjustments are necessary to improve prediction accuracy and control measures (Heymann, 2005).

When assessing the risk of ASF across Sweden at the municipality level, the highest-risk areas remain in the southern part of the country (Fig. 5 and Fig. 7). This variation in risk levels is mainly attributed to the higher concentration of wild boar populations, greater human population density, and increased human activity in southern parts of Sweden (Fig. 3). However, despite Fagersta being ranked as a lower-risk area at the national scale, it is important to recognize that it still carries a probability of ASFV introduction, release, and spread due to the presence of wild boar habitats and ongoing human activity. This underscores the need for continued vigilance even in areas classified as low risk, as local conditions can still facilitate disease introduction under certain circumstances. As shown in Fig. 6 and Fig. 8, when the risk is analysed at the grid cell level, all positive cases in the Fagersta outbreak are concentrated in high-risk areas. These findings highlight the importance of using high-resolution maps to capture local environmental, ecological, and human factors influencing disease introduction and spread. Such maps allow stakeholders to pinpoint high-risk areas within larger regions, enabling targeted, effective interventions. Consequently,

Table 2
Wilcoxon signed-rank test results comparing baseline risk (calculated with all risk factors included) to recalculated risk scenarios with each risk factor individually excluded.

Risk factor	Region	Wilcoxon signed-rank test	
		Test statistic ***W***	***p*-value**
Traffic volumes	Sweden	11621.0	0.002
Trade volumes		2045.0	0.852
Human population		9407.5	< 0.001
Vehicle capacity at rest areas		7976.5	0.062
Municipal waste collection centres		12523.5	0.596
Land cover		12148.0	0.182
Hunted wild boar		13079.0	0.708
Wild boar-vehicle collision records		10664.0	0.454
Temperature		11311.5	0.744
Precipitation		11441.5	< 0.001
Traffic volumes	Outbreak area	856305.5	0.007
Trade volumes		330993.5	0.489
Human population		491777.0	0.003
Vehicle capacity at rest areas		757391.5	< 0.001
Municipal waste collection centres		1235842.5	< 0.001
Land cover		505188.0	< 0.001
Hunted wild boar		962135.0	< 0.001
Wild boar-vehicle collision records		847536.0	< 0.001
Temperature		657300.5	0.001
Precipitation		737488.5	0.977

distinguishing between national and regional scales is essential when calculating the risk and formulating a disease prevention plan to ensure effective implementation (Plavšic et al., 2019).

Limited or poor-quality data on specific risk factors can hinder their effective inclusion in models, ultimately diminishing the reliability of risk assessments. Inaccurate or incomplete data may misrepresent the relationships between risk factors and disease occurrence, resulting in incorrect predictions and potentially flawed prevention plans. For instance, the hunting bag and wild boar-vehicle collision records utilized in our study to estimate the density and distribution of wild boar are valuable for national-scale risk analysis. However, when examined at a regional scale, the information derived from hunting bag data becomes overly generalized. This is due to the average hunting bag area being 1477.40 km^2 (SD = 2476.82 km^2), which closely resembles the average area of a Swedish municipality at 1545.83 km^2 (SD = 2657.09 km^2). As a result, a municipality may be assigned the same wild boar density value despite variations in actual conditions. More accurate predictions of wild boar abundance and density could be achieved through a combination of habitat analysis and regional measurements, with camera traps providing reliable estimates at a reasonable scale. While GPS collaring may not be as scalable, it can still offer valuable insights into individual movement patterns and behaviour, contributing to a more comprehensive understanding of wild boar dynamics (Acevedo et al., 2022; Augustsson et al., 2024; Thurfjell et al., 2014, 2009). Similarly, the risk mapping strategy for waste collection centres relies on binomial attribute values, primarily due to limited data availability. In this approach, areas associated with waste collection centres are classified as either a risk or non-risk factor. This binary classification may lead to disproportionately high-risk values in these areas, as the presence or absence of a waste collection centre is treated as a simple yes/no attribute. Consequently, waste collection centre areas may be assigned high-risk values regardless of specific management practices or waste accumulation levels. This oversimplification can distort risk estimates, as it does not account for the variability in how waste is stored or handled across different locations. To improve the accuracy of risk assessments, a more nuanced approach, which incorporates the intensity and biosecurity measures at waste collection centres, would provide a more reliable representation of the actual risk they pose.

Over time, changes in the activity patterns of wildlife and human populations can have a significant impact on disease transmission dynamics. Additionally, climate change leads to alterations in landscapes and habitats, further complicating risk assessments. For example, changes in temperature and precipitation patterns can lead to changes in land cover, which can affect the distribution of species, such as wild boar, and their interactions with human populations, thereby affecting the spread of diseases (Buttke et al., 2021; Cohen et al., 2020). As such, periodic updates and detailed seasonal risk maps are essential for accurately reflecting these changes (Stiles et al., 2024). These maps enable researchers and policymakers to plan and prepare for potential outbreaks and implement timely interventions based on the current ecological and epidemiological landscape (Beauvais et al., 2019).

6. Conclusion

In conclusion, this study highlights the importance of careful selection and appropriate resolution of risk factors in risk mapping. Applying the model to the Fagersta outbreak highlights the importance of a comprehensive, multi-dimensional approach to risk assessment, with thorough evaluation at both national and regional scales to capture local conditions and to support targeted interventions. Additionally, as environmental and ecological conditions shift, regularly updating risk assessments is essential to maintain their accuracy over time. Enhancing the spatial resolution of risk factors and adapting them to regional

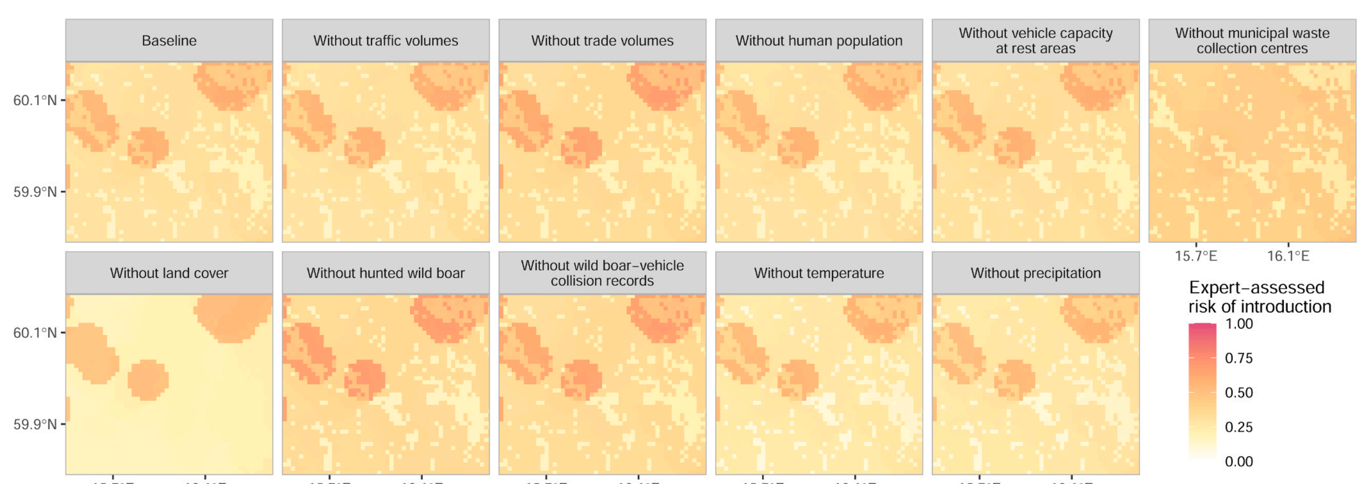

Fig. 8. The results showing the sensitivity analyses at a 1 km^2 resolution for the outbreak area. The baseline panel displays the results when all 10 risk factors are included, while the other panels show the recalculated risk after excluding the specific risk factor indicated in the panel title. For instance, the 'Without traffic volumes' panel illustrates the risk calculated using only the remaining nine risk factors, excluding traffic volumes. Darker colours represent higher risk values.

characteristics can make risk mapping a more effective tool for prioritizing resources, strengthening biosecurity, and ultimately reducing the economic and ecological impact of disease outbreaks in host species.

CRediT authorship contribution statement

Erika Chenais: Writing – review & editing, Methodology, Conceptualization. **Hyeyoung Kim:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Stefan Widgren:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Karl Ståhl:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Cecilia Hultén:** Writing – review & editing, Methodology, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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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.2025.106576.

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