Original Article

Spatiotemporal Clustering and Hotspot Detection of Reported African Swine Fever Cases in the Cordillera Administrative Region, Philippines, January 2023–February 2025

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ABSTRACT

Background: African swine fever (ASF) remains a major threat to swine production in the Philippines. In the Cordillera Administrative Region (CAR), understanding the spatial and temporal distribution of reported ASF cases is important for improving local disease surveillance and control.

Objectives: This study examined the spatiotemporal clustering and hotspots of laboratory-confirmed ASF cases recorded and validated by the DA—CAR Animal Health Unit in CAR from January 2023 to February 2025.

Methods: The ASF cases were summarized by year, month, and province. Standard deviational ellipse (SDE) analysis was applied to examine changes in geographic center and directional distribution. Global Moran's I, local indicators of spatial association, Getis-Ord Gi*, and SaTScan space-time cluster analysis were used to assess spatial and space-time clustering. The Prophet time-series model was applied to weekly cases to examine temporal trends.

Results: Most reported ASF cases occurred in 2024 and were temporally concentrated from August to October. At the provincial level, Apayao recorded the highest number of cases, followed by Abra, Ifugao, and Kalinga. SDE results indicated a shift in the geographic center and orientation of reported cases between 2023 and 2024. Global Moran's III showed weak but statistically significant positive spatial autocorrelation in 2023 (I=0.0593, P=0.0005), 2024 (I=0.0942, P=0.0001), and the complete study period (I=0.0898, P=0.0001). Local Moran's III identified localized clusters and spatial outliers. Meanwhile, Getis–Ord Gi* detected significant hotspots and cold spots. SaTScan identified significant high- and low-rate space-time clusters. The Prophet model showed an upward trend and suggested a possible yearly pattern with higher values around September to October.

Conclusion: Reported ASF patterns in CAR varied across locations and periods. The findings supported flexible surveillance, prioritized field monitoring, and targeted biosecurity activities in repeatedly affected and emerging areas. Coordination among neighboring local government units may strengthen outbreak detection and response.

Keywords: African swine fever (ASF), Spatial clustering, Hotspot detection, Space-time cluster analysis, Cordillera administrative region (CAR)

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1. Introduction

African swine fever (ASF) is a contagious viral disease affecting domestic pigs and wild boars, with up to 100% mortality in outbreaks (FAO, 2026). It is known to be transmissible to pigs but not to humans. The disease has limited cure or effective means of disease control (Ligue-Sabio et al., 2025). It has spread beyond endemic areas to multiple countries and regions worldwide (Kawaguchi et al., 2025). This then creates significant challenges to swine production systems worldwide (Abao et al., 2026). The disease raises concerns for global food security and market stability (Ceruti et al., 2025). The impact of ASF is not limited to animal health but also affects rural economies and livelihoods.

The disease continues to affect the swine industry in the Philippines since its detection in 2019 (Abao & Sabiniano, 2026). Smallholder farmers are particularly vulnerable because they may lack the financial capacity to implement biosecurity measures, restock animals, and absorb prolonged production losses (Portugaliza, 2025). Reported cases and persistence are not uniform across regions. While some have periodic outbreaks, others experience relatively few reported cases or short periods of outbreak activity. Moreover, the progression of outbreaks in different regions can be influenced by a variety of factors and may vary from one place to another. Therefore, it is essential to examine the spatiotemporal distribution and clustering of reported ASF cases at the regional level. Understanding these dynamics requires regional-level data in order to develop effective disease control policy that is tailored to the specific risk in each location.

In the Cordillera Administrative Region (CAR), ASF poses substantial risks to communities that depend on swine production for food and livelihood. CAR has been reported to have the highest per capita pork consumption in the Philippines, at approximately 15 kilograms per person annually (Agoot, 2024). Hence, maintaining a stable regional swine industry and pork supply is important. Outbreak control measures also require considerable institutional and financial support (Portugaliza, 2025). The effective allocation of these limited resources therefore requires evidence on where and when reported cases have been concentrated. Identifying historical areas and periods of elevated case activity can help local government unit (LGU) authorities prioritize surveillance and implement locally targeted interventions.

Although previous Philippine studies have examined ASF transmission at the national level, evidence on the spatial and temporal clustering of reported ASF cases within the CAR remains limited. National-level findings may not fully reflect conditions in CAR because regions differ in geography, swine movement networks, production systems, market linkages, farming practices, biosecurity measures, and local response capacity. Consequently, the specific locations and periods in which ASF cases were concentrated or formed significant clusters in CAR have not been sufficiently documented. Identifying these historical clusters can help determine areas and periods that may require closer surveillance and strengthened preventive measures. This study addressed this knowledge gap by describing the spatial and temporal distribution of reported ASF cases and assessing changes in case concentration and clustering across the region.

This study analyzed the spatiotemporal patterns of ASF cases in CAR from January 2023 to February 2025 to generate information that could guide local disease-control strategies. Specifically, it aimed to describe the annual and monthly distribution of reported ASF cases; examine their spatial distribution across provinces, municipalities, and barangays; identify changes in their geographic center and directional distribution; assess global, local, and space-time clustering; and model temporal trends and possible seasonal patterns using the Prophet method.

Materials and Methods

Study area

As shown in Figure 1, the CAR is a landlocked region located in the Northern Philippines comprising six provinces: Abra, Apayao, Benguet, Ifugao, Kalinga, and Mountain. These provinces are further divided into two cities (Baguio City and Tabuk City), 75 municipalities, and 1,178 barangays. For this study, however, Baguio City was treated as a separate entity from Benguet since administrative and political control is separate from the said province and reports of cases from the city were not included in the reports for Benguet Province.

Most residents (66.7%) live in rural areas and depend on agriculture. Swine production is both a major source of livelihood in the livestock sector and a culturally significant practice among Indigenous communities (Agoot, 2024). Moreover, hog production declined by 13.4% in the third quarter of 2024 compared with 2023 (PSA, 2024). This decline puts the livelihoods of farmers and other industry stakeholders at risk, as swine production is part of Filipino culture and heritage.

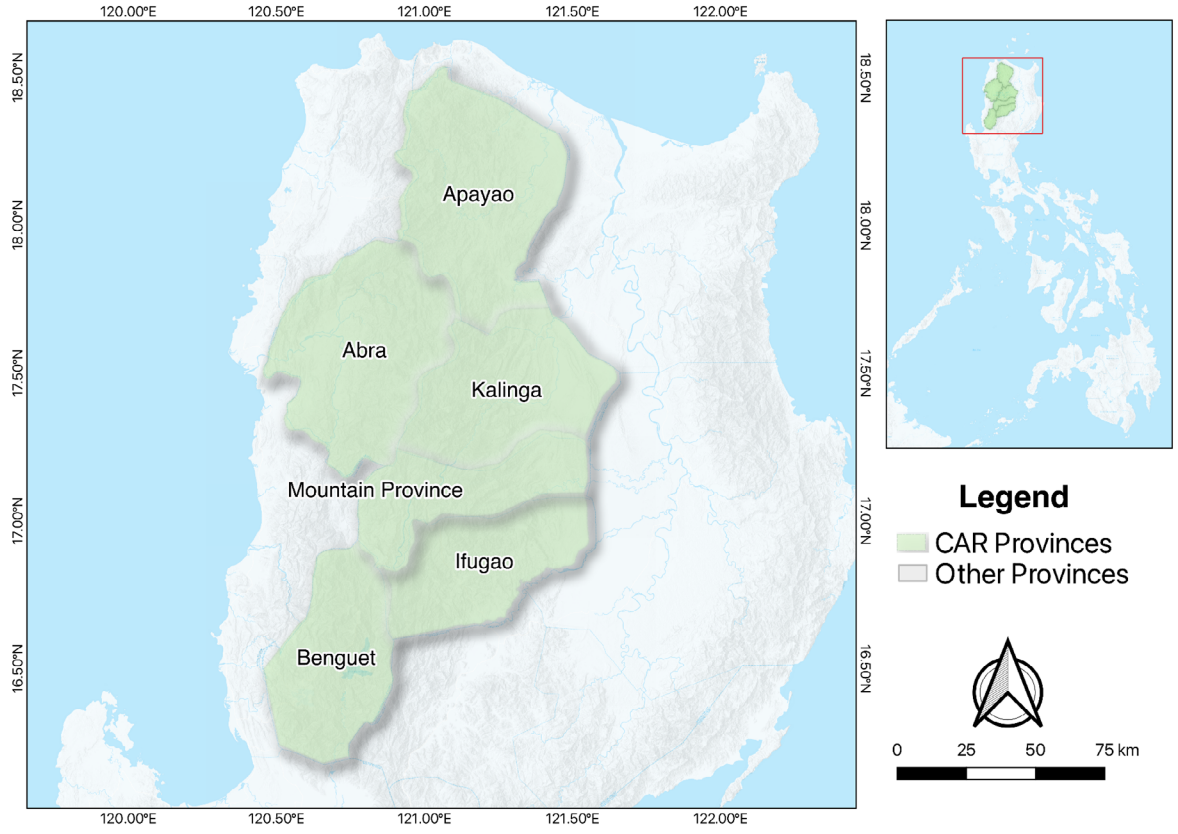


Figure 1. Location map of the CAR, Philippines

Spatiotemporal analysis

This study conducted a retrospective analysis of the official ASF surveillance dataset obtained from the Animal Health Unit of the Department of Agriculture–Cordillera Administrative Region (DA-CAR). An officially reported ASF case was defined as a laboratory-confirmed occurrence recorded and validated by DA-CAR. The dataset covered the period from January 2023 to February 2025. The study began in January 2023 to provide a baseline for comparison with 2024, when a marked increase in ASF cases and outbreak activity was observed. The study period ended in February 2025 because these were the latest official records available at the time of data extraction. Consequently, the data in 2025 were excluded from full-year comparisons. Each record included the date of occurrence and the corresponding geographic location at the barangay, municipality, or city and provincial levels. Because swine population data were not available for the entire study period, the analyses were based on case counts rather than prevalence or incidence rates.

Before the dataset was released to the researcher, it had undergone DA-CAR's routine data-cleaning and validation procedures to verify case status and ensure the completeness and consistency of the recorded information. The validated dataset was analyzed as provided and did not independently reclassify the cases. Because the study relied solely on secondary surveillance records, no direct animal handling or experimentation was conducted. However, the possibility of underreporting or incomplete case detection could not be independently assessed.

Temporal analyses used weekly, monthly, and annual case counts. Provincial totals were used for descriptive comparisons, while geocoded case locations were used for the standard deviational ellipse (SDE) and SaTScan analyses. Barangays, the smallest units of local government in the Philippines, served as the spatial units for Global Moran's I, LISA, and Getis–Ord Gi*. Data were processed and analyzed using scripts written in Python. In addition, QGIS and Python were used for map visualization. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

The analysis began with descriptive statistics to characterize the patterns of ASF outbreaks. This involved examining annual and monthly case counts to identify temporal trends and periods of elevated case occurrence. The spatial distribution was assessed by tabulating outbreaks per province to highlight areas of high incidence counts.

To examine changes in the geographic center, dispersion, and directional orientation of reported ASF case locations and to assess whether this trend changed over time, a SDE method was applied to the geocoded outbreak locations for the region and selected provinces. It summarizes the spatial characteristics of a point distribution by identifying its geographic mean center, the extent of its dispersion, and its primary directional orientation. The analysis was performed on the WGS 84 geographic coordinates of the reported ASF case locations. Therefore, the resulting ellipse dimensions are expressed in decimal degrees. To compare changes in the spatial distribution of reported cases between 2023 and 2024, separate ellipses were calculated for the 2023 and 2024 outbreak data.

Spatial autocorrelation was assessed at the barangay level using Global Moran's I for 2023, 2024, and the cumulative January 2023-February 2025 period. The variable analyzed was the number of reported ASF cases per barangay. Spatial neighbors were defined using a whole-CAR symmetric K-nearest-neighbor (KNN) matrix with k=10, based on centroid-to-centroid distances in WGS 84/UTM Zone 51N. The matrix was row-standardized, and statistical significance was evaluated using 9,999 permutations. Global Moran's I was calculated as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \quad \sum_{j=1}^{n} \quad w_{ij}(x_i - \underline{x})(x_j - \underline{x})}{\sum_{i=1}^{n} \quad (x_i - \underline{x})^2},$$

Where, n is the number of barangays, x_i and x_j are the reported ASF cases in barangays i and j, $\underline{x}$ is the mean case count, w_{ij} is the spatial weight between barangays i and j, and $S_{0=} \sum_i \sum_j w_{ij}$. Positive values indicate clustering of similar counts, negative values indicate spatial dispersion, and values near the expected value suggest spatial randomness. Local indicators of spatial association (LISA) were calculated using the same k=10 neighborhood structure to identify high-high and low-low clusters and high-low and low-high spatial outliers (Anselin, 1995). Getis-Ord Gi* was then applied using binary weights with the same neighbor topology to identify statistically significant hotspots and coldspots (Getis & Ord, 1992). Sensitivity analyses were conducted using K=2 to K=20 for Global Moran's I and K=8 to K=12 for LISA.

A focused retrospective space–time cluster analysis was conducted on reported ASF cases from 2024 using SaTScan™ v10.3.2 under the space–time permutation model. The analysis was limited to 2024 because it accounted for 283 of the 339 reported cases (83.48%), which provided the greatest case concentration for detecting localized clusters. The case-only model used day-level data and cylindrical scanning windows to identify locations and periods with significantly higher or lower case counts than expected. The maximum spatial and temporal cluster sizes were each set at 50%, and statistical significance was assessed using 999 Monte Carlo replications. Secondary clusters with no geographical overlap were reported. Clusters were classified as high-rate or low-rate according to whether the observed counts were higher or lower than expected. The cluster radius represents the distance from the cluster center to its boundary, while the span represents the maximum distance between any two locations within the cluster. SaTScan™ is a trademark of Martin Kulldorff and was developed under the joint auspices of Martin Kulldorff, the National Cancer Institute, and the New York City Department of Health and Mental Hygiene.

For the temporal trends, the study forecasted future ASF outbreak trajectories by modeling weekly case data using the Prophet time-series procedure. This approach allowed stable short-term projections while accommodating structural changes in transmission dynamics (Ahmad et al., 2025). The Prophet model decomposes ASF incidence into trend, seasonal, and irregular components. An indicator for a special event was included for the week beginning August 5, 2024, when the highest weekly case count was recorded. This indicator was entered through Prophet's holiday-function framework to account for the unusually large outbreak spike during that week. The model was fitted to the regional time series and separately to five key provinces to generate short-term forecasts with 95% prediction intervals. Model fit was evaluated using mean absolute error (MAE), root mean square error (RMSE), Nash–Sutcliffe efficiency (NSE), and the coefficient of determination (R^2). MAE and RMSE quantified error magnitude, whereas R^2 assessed goodness of fit.

Ethics and administrative considerations

This study used secondary ASF surveillance records and did not involve direct animal handling or experimentation. Administrative authorization to access and use the dataset was obtained from the Department of Agriculture–CAR Animal Health Unit. The records were used solely for research purposes and did not contain personally identifiable information.

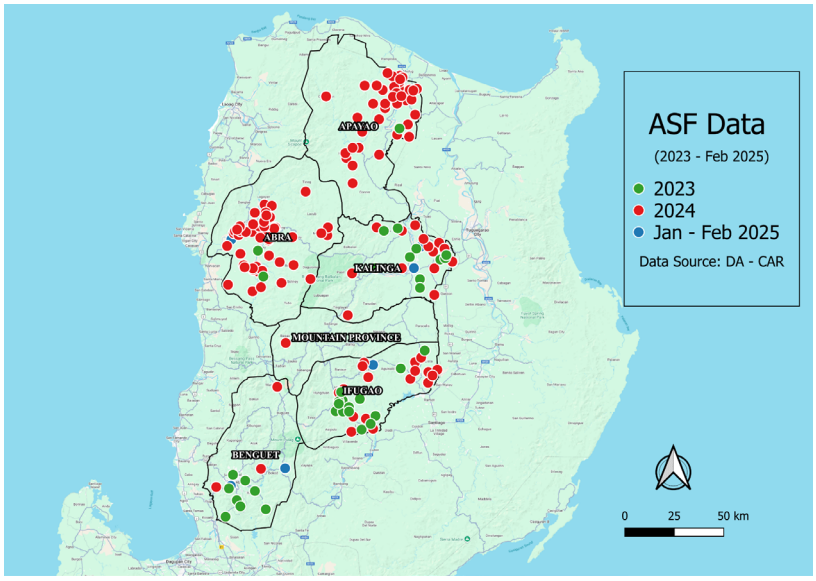


Figure 2. Annual distribution of officially reported ASF cases in the CAR from January 2023 to February 2025

Note: The dots represent the geocoded locations of reported cases.

Results

Descriptive epidemiology of reported ASF cases

From January 2023 to February 2025, a total of 339 officially reported ASF cases occurred in the CAR. Of these, 49 cases (14.45%) were reported in 2023, 283 cases (83.48%) were reported in 2024, and 7 cases (2.06%) were reported from January to February 2025. Figure 2 illustrates the distribution of reported ASF cases during the study period.

Figure 3 presents the monthly distribution of officially reported ASF cases in CAR. October 2024 recorded the highest count at 96 cases, followed by September 2024 with 78 and August 2024 with 44. Together, these months accounted for 218 cases, or 64.31% of the study total.

At the provincial level presented in Table 1, the highest number of reported ASF cases was recorded in Apayao, with 120 cases, or 35.4% of the regional total. This was followed by Abra with 98 cases, or 28.91%; Ifugao with 50 cases, or 14.75%; and Kalinga with 47 cases, or 13.86%. Lower numbers were reported in Benguet, with 20 cases, or 5.9%, while Mountain Province and Baguio City recorded 2 cases each, or 0.59%. Moreover, Apayao and Abra accounted for a total of 218 cases, representing 64.31% of all reported ASF cases during the study period.

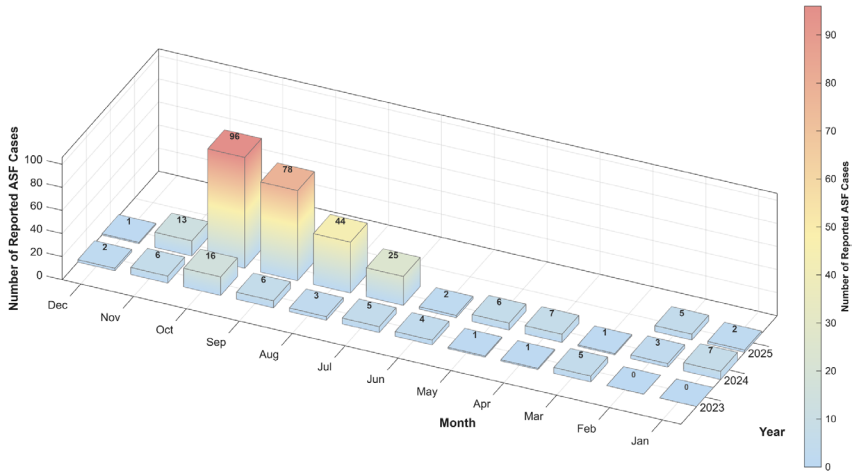


Figure 3. Monthly distribution of officially reported ASF cases in the CAR from 2023 to February 2025

Table 1. Distribution of officially reported African swine fever cases by province in the CAR from 2023 to February 2025

Province/Area	2023	2024	Jan–Feb 2025	Total	%
Apayao	1	119	0	120	35.40
Abra	4	93	1	98	28.91
Ifugao	17	32	1	50	14.75
Kalinga	13	31	3	47	13.86
Benguet	13	6	1	20	5.90
Mountain Province	0	2	0	2	0.59
Baguio City	1	0	1	2	0.59
Entire Region	49	283	7	339	100.00

Geographic shift

Table 2 presents the SDE parameters for the CAR and selected provinces, while Figures 5 to 6 show the corresponding ellipses. Based on the ellipse angles, the recorded orientations were northeast to southwest in the CAR in 2023 and north-northeast to south-southwest in 2024 in Figure 4. In the provinces reflected in Figure 5, the shifts were as follows: north-northwest to south-southeast in Abra in 2023 and northwest to southeast in 2024; north-northeast to south-southwest in Apayao in 2024; northwest to southeast in Benguet in 2023 and east to west in 2024; northeast to southwest in Ifugao in 2023 and northwest to southeast in 2024; and northwest to southeast in Kalinga in 2023 and east to west in 2024. Among the provinces with comparable SDE values in both years, Kalinga showed the smallest shift in outbreak centers. Meanwhile, Benguet showed the largest shift in outbreak centers. In terms of directional tendency, Ifugao showed the greatest change in orientation, while Kalinga showed the least change in geographic center and directional distribution.

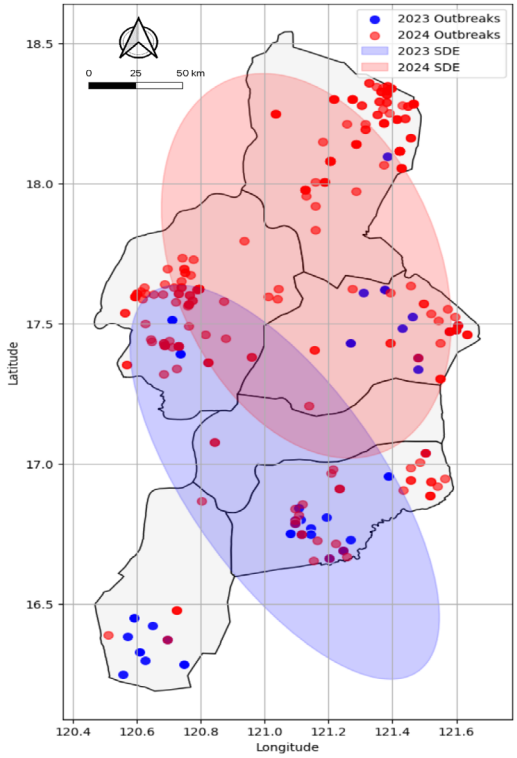


Figure 4. Standard deviational ellipses of reported ASF case locations in the CAR for 2023 and 2024

Table 2. SDE parameters of ASF cases in the CAR and selected provinces for 2023 and 2024

Area	Year	Mean Center		Width (◦)	Height (◦)	Angle (◦)
		Longitude	Latitude			
CAR	2023	121.06	16.93	0.62	1.59	59.59
	2024	120.97	17.61	0.64	1.27	69.59
Abra	2023	120.72	17.45	0.00	0.18	-78.15
	2024	120.77	17.53	0.33	0.45	-12.17
Apayao	2023	–	–	–	–	–
	2024	121.19	18.04	0.03	0.19	75.28
Benguet	2023	120.63	16.34	0.14	0.19	-49.08
	2024	120.72	16.48	0.00	0.00	0.00
Ifugao	2023	121.20	16.80	0.18	0.41	35.85
	2024	121.10	16.77	0.00	0.06	-61.83
Kalinga	2023	121.43	17.50	0.24	0.33	-25.27
	2024	121.47	17.44	0.00	0.32	7.47

Note: Dashes indicate that no SDE was computed due to insufficient distinct reported ASF case locations.

Global and local spatial clustering

Global Moran's I was computed at the barangay level for 2023, 2024, and the entire study period using a whole-region symmetric KNN spatial weights matrix with and 9,999 permutations. The results presented in Table 3 show weak but statistically significant positive spatial autocorrelation across all periods.

The LISA and Getis–Ord Gi* analyses provided more detailed information about where localized clusters and spatial outliers occurred, as shown in Figure 6. The 2023 LISA map identified localized high–high and low–low clusters, as well as high–low and low–high outliers, with the most visible significant configurations concentrated in portions of southern CAR and selected eastern and northern barangays. In 2024, significant local configurations became more extensive, particularly in the northern part of the region, while additional local clusters and outliers appeared in central and southern areas. The cumulative LISA pattern was similar to the 2024 pattern, consistent with the predominance of 2024 cases in the complete dataset.

The Getis–Ord Gi* results showed statistically significant concentrations of relatively high and low reported cases. In 2023, hotspot areas were localized mainly in the southern and eastern portions of the region, while broad areas were classified as coldspots. In 2024, hotspots became more apparent in northern and selected eastern areas, whereas significant coldspots were concentrated across many central and southern barangays. The whole-period Gi* map closely followed the 2024 pattern.

Table 3. Global Moran's I results for reported ASF cases in the CAR

Time	Cases	Barangays with Cases	n	k	Moran's I	Expected I	Permutation z	P
2023	49	33	1172	10	0.0593	-0.0009	5.3728	0.0005
2024	283	133	1172	10	0.0942	-0.0009	8.4484	0.0001
January 2023–February 2025	339	162	1172	10	0.0898	-0.0009	8.1424	0.0001

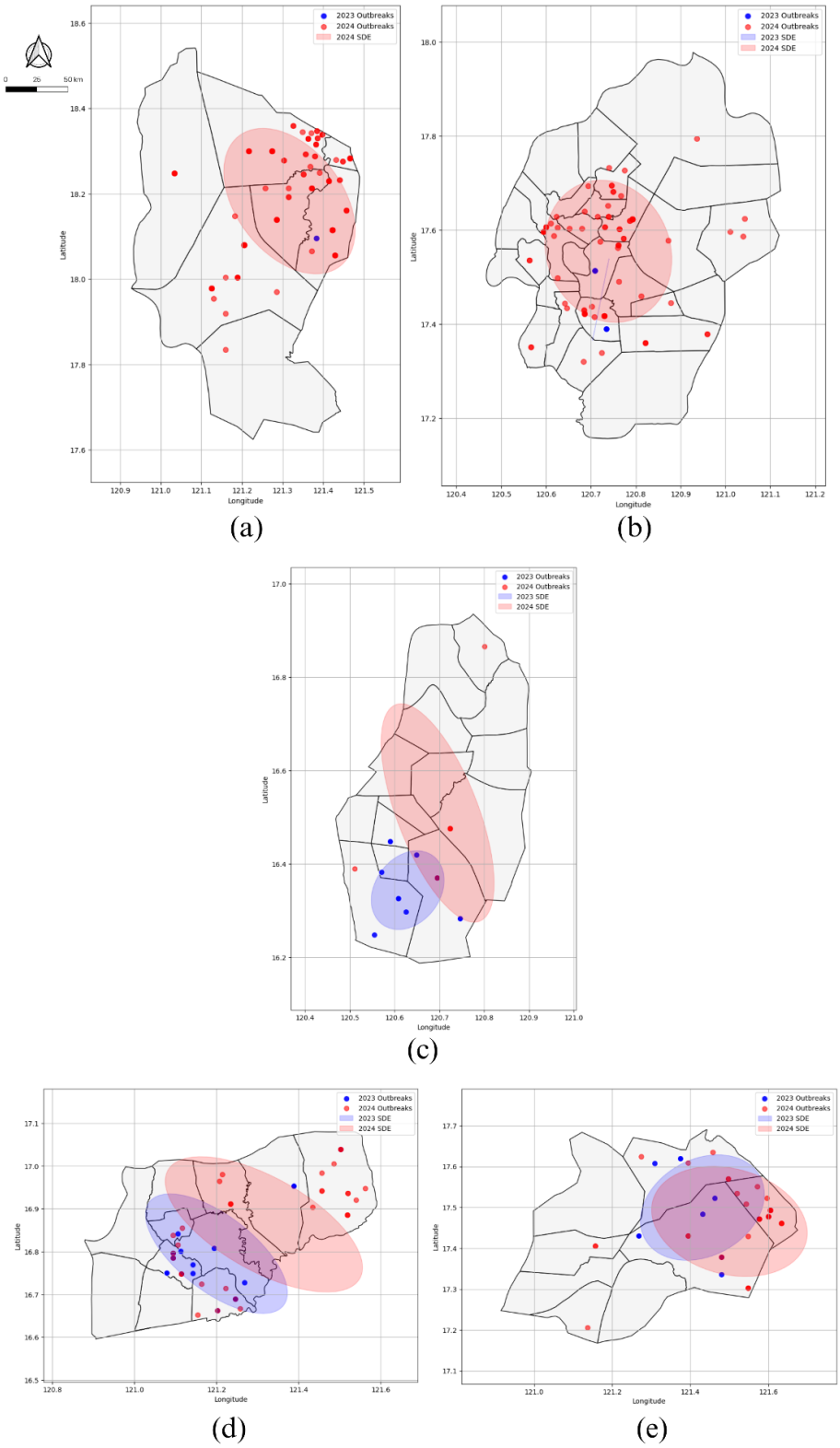


Figure 5. SDE of reported ASF case locations in (a) Apayao, (b) Abra, (c) Benguet, (d) Ifugao, and (e) Kalinga for 2023 and 2024

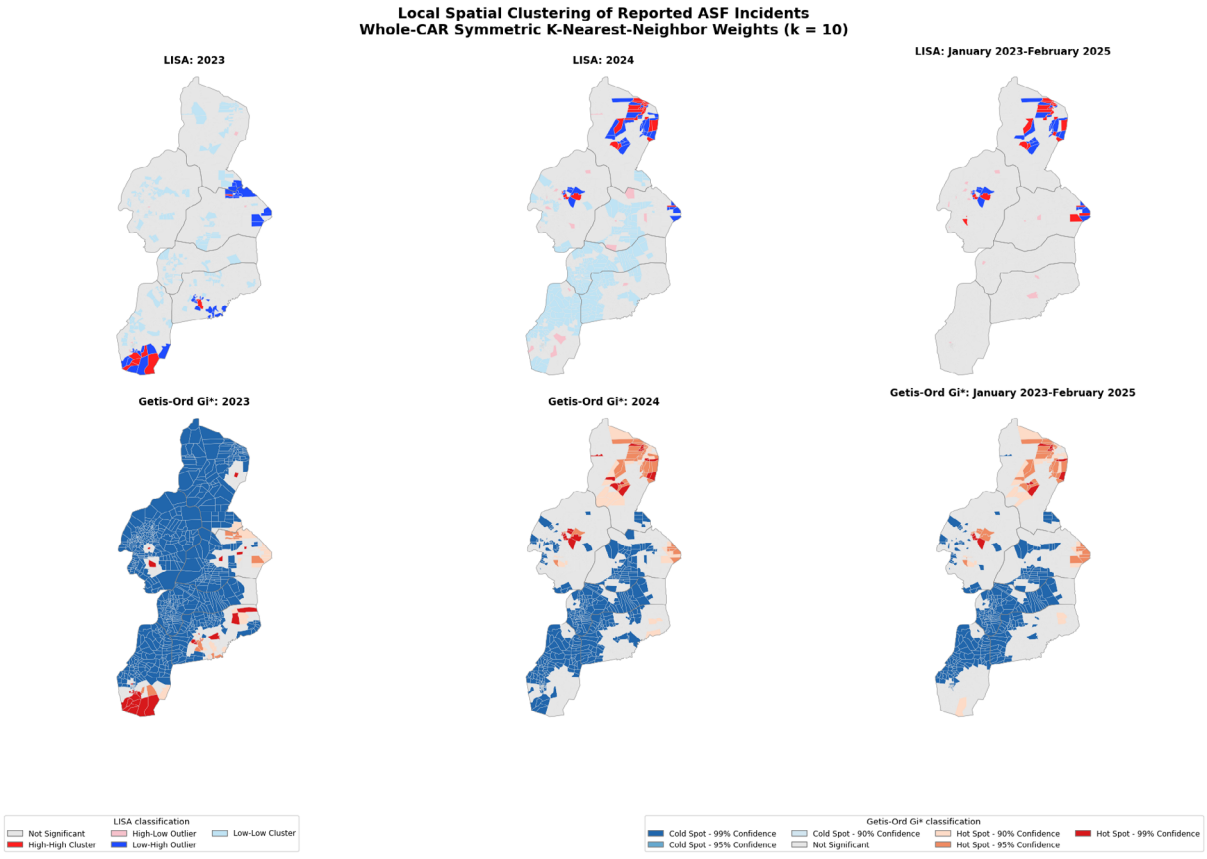


Figure 6. Local spatial clustering of reported ASF case counts at the barangay level in the CAR

Note: The first row presents LISA classifications for 2023, 2024, and the complete January 2023–February 2025 period. High–high and low–low categories represent local clusters of similar values, whereas high–low and low–high categories represent spatial outliers. The second row presents Getis–Ord Gi* classifications for the same periods. Red shades indicate statistically significant hotspots, blue shades indicate statistically significant cold spots, and gray barangays were not statistically significant.

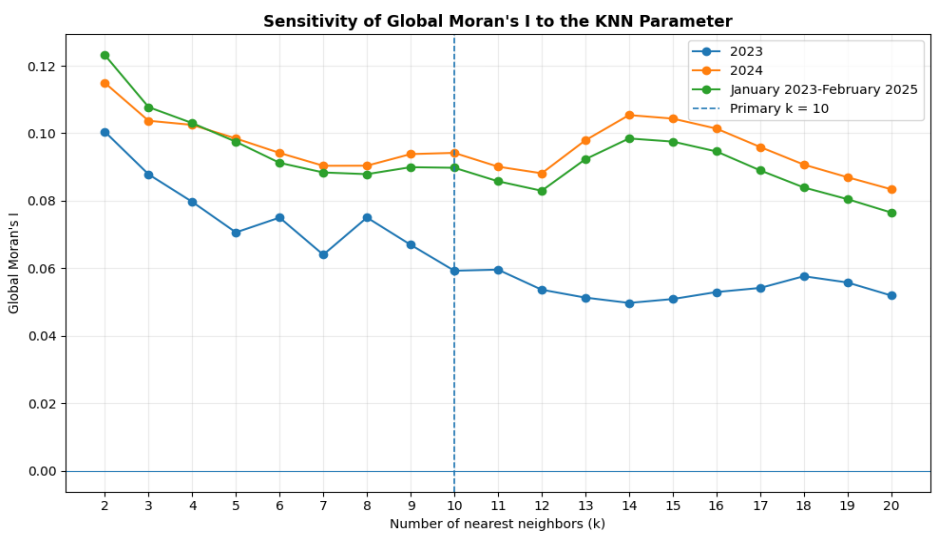


Figure 7. Sensitivity of Global Moran's I across KNN values (k=2–20)

Note: The dashed line marks k=10.

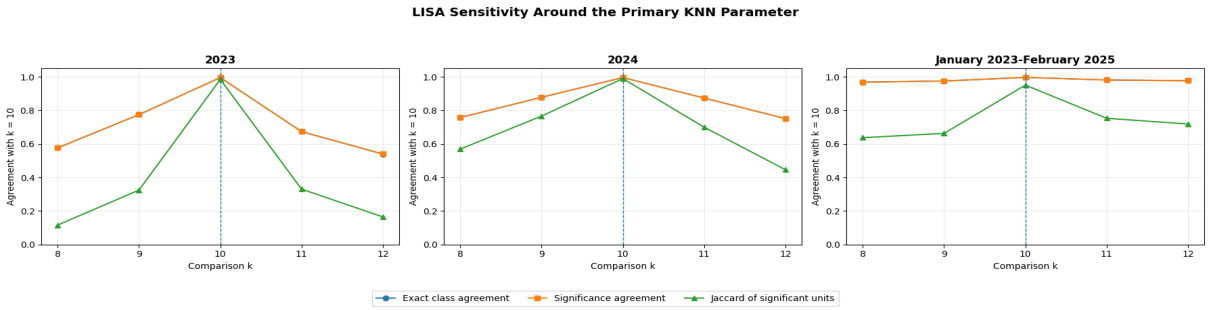


Figure 8. Agreement of LISA classifications across nearby KNN values (k=8–12), using k=10 as the reference

Sensitivity of the spatial weights specification

Sensitivity analysis showed that k=10 produced a single connected regional network with no isolated barangays. As seen in Figure 7, Global Moran's I remained positive and statistically significant across nearby specifications, (k=8 to k=12). Thus, the global pattern remained consistent across nearby values of k.

The cumulative LISA results were stable, while the annual results, particularly for 2023, were more sensitive to changes in the number of neighbors as observed in Figure 8. Therefore, k=10 was retained.

Space-time cluster detection

Table 4 and Figure 9 present the significant high-rate and low-rate space–time clusters detected in 2024. Eighteen significant clusters were identified, including point-based clusters with a radius of 0 km and spatially extended clusters covering broader areas. Clusters with a radius of 0 km represent point-based clusters detected at a single barangay centroid, as they were used as the geographic reference locations for the analysis. The mean cluster radius was 12.74 km when all detected clusters were included, although this value was influenced by several point-based clusters with zero radius; when only spatially extended clusters were considered, the mean radius increased to 25.48 km. Many of the high-rate clusters were highly localized, while only a few broader clusters covered multiple municipalities.

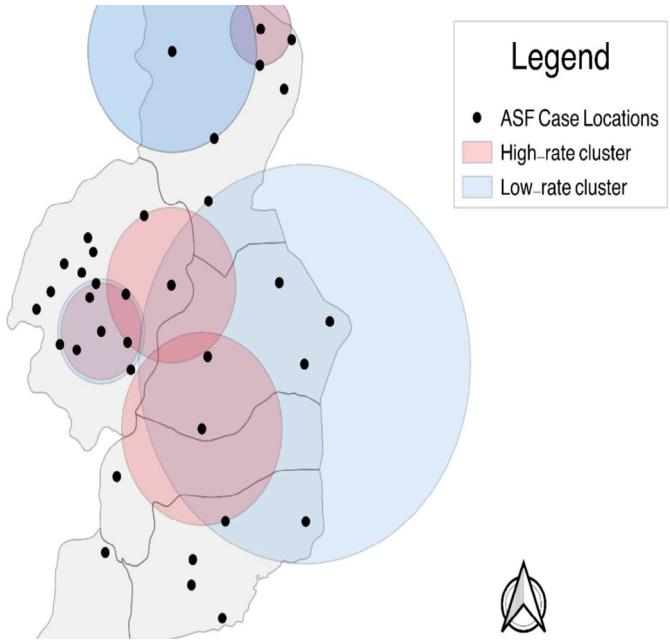


Figure 9. Significant space-time clusters of ASF outbreaks in the CAR, Philippines

Note: Black dots denote reported ASF case locations, and shaded circles represent detected high-rate (red) and low-rate (blue) cluster zones.

Table 4. Significant high-rate and low-rate spatiotemporal clusters of ASF outbreaks in the CAR, Philippines

Cluster	Radius (km)	Span (km)	Time Frame	Observed	Expected	O/E Ratio	Test Statistic	P	Cluster Type
1	14.8	24.89	August 2, 2024 - August 9, 2024	35	6.78	5.16	30.702317	0.001	High-rate
2	16	29.33	September 24, 2024 - December 2, 2024	1	29.35	0.034	26.49509	0.001	Low-rate
3	0	0	July 29, 2024 - July 29, 2024	13	1.24	10.48	19.034106	0.001	High-rate
4	0	0	July 10, 2024 - July 16, 2024	8	0.34	23.58	17.728308	0.001	High-rate
5	11.16	11.16	June 20, 2024 - September 7, 2024	0	14.66	0	15.057901	0.001	Low-rate
6	0	0	April 29, 2024 - May 21, 2024	5	0.12	40.43	13.663632	0.001	High-rate
7	61.13	104.48	June 7, 2024 - August 9, 2024	0	12.78	0	13.082222	0.001	Low-rate
8	0	0	November 11, 2024 - November 21, 2024	7	0.45	15.72	12.80738	0.001	High-rate
9	23.77	39.27	January 17, 2024 - April 4, 2024	5	0.15	33.69	12.776334	0.001	High-rate
10	0	0	September 6, 2024 - September 6, 2024	5	0.16	31.44	12.441789	0.001	High-rate
11	11.16	11.16	October 10, 2024 - October 28, 2024	32	12.19	2.62	11.815362	0.001	High-rate
12	0	0	September 27, 2024 - October 18, 2024	28	9.89	2.83	11.635646	0.001	High-rate
13	29.55	50.8	October 22, 2024 - October 30, 2024	7	0.62	11.26	10.640599	0.001	High-rate
14	0	0	October 11, 2024 - October 14, 2024	5	0.25	20.21	10.319466	0.004	High-rate
15	30.89	30.89	October 6, 2024 - December 2, 2024	0	9.97	0	10.147989	0.006	Low-rate
16	0	0	January 5, 2024 - January 16, 2024	3	0.042	70.75	9.835372	0.007	High-rate
17	30.89	30.89	August 2, 2024 - September 26, 2024	0	9.64	0	9.807574	0.008	Low-rate
18	0	0	September 30, 2024 - September 30, 2024	6	0.51	11.79	9.366911	0.013	High-rate

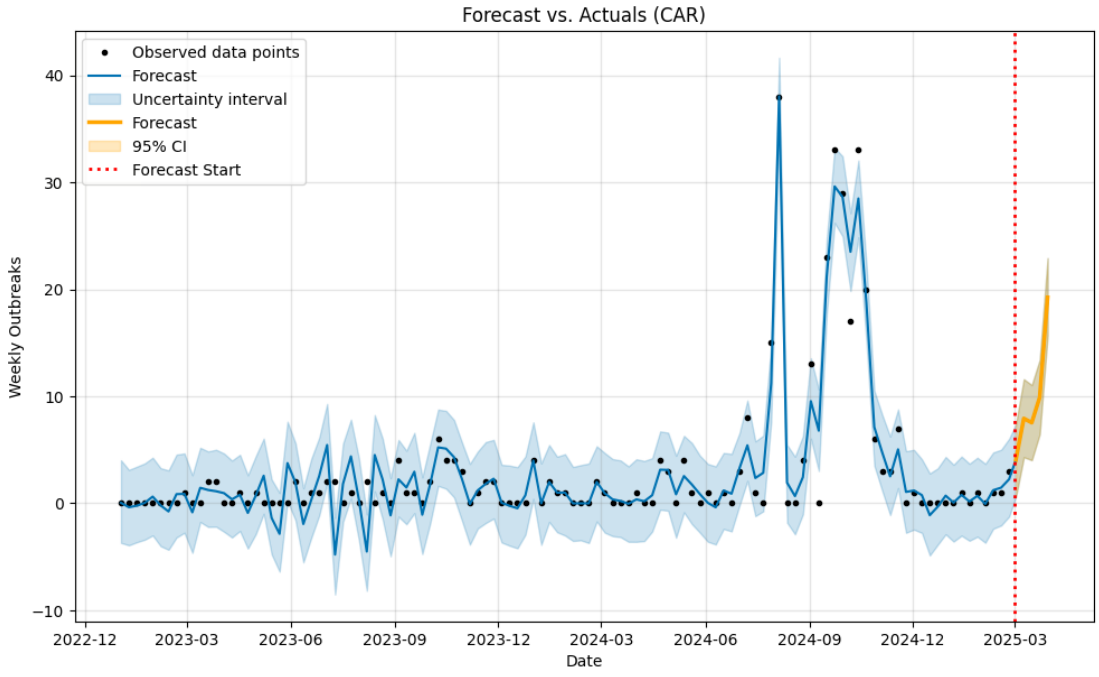


Figure 10. Prophet time-series model for weekly ASF cases in the CAR

Note: Black dots represent the observed counts, the blue line represents the fitted historical values, and the orange line represents the five-week forecast. The shaded areas indicate the corresponding 95% uncertainty intervals.

Time-series analysis

Figure 10 shows the observed weekly outbreak counts, the model forecast, and the 95% uncertainty interval. Weekly outbreaks generally ranged from 0 to 5 cases from 2023 to mid-2024. Counts increased from July to August 2024, with weekly values reaching nearly 40 cases. Forecast values for early 2025 were approximately 5 to 10 cases.

Figure 11 presents the Prophet components. The model showed an upward trend and suggested a possible yearly pattern with higher values around September–October. The monthly component showed within-month oscillations.

The Prophet model yielded an MAE of 1.14, an RMSE of 1.86, an score of 0.9286, and an NSE of 0.9286. Provincial-level performance metrics are summarized in Table 5. The table presents MAE, RMSE, R^2, and NSE values for Abra, Apayao, Benguet, Ifugao, and Kalinga. Variation in model fit was observed across provinces.

Figure 12 shows the time-series forecasts for Abra and Apayao. In Abra, weekly outbreaks remained low for extended periods, with an increase observed in August 2024. The early 2025 forecast remained near zero and was accompanied by a wide uncertainty interval. In Apayao, the time series showed an upward long-term trend and an increase in cases in early 2025.

Table 5. Prophet model performance Metrics by province

Province	MAE	RMSE	R^2 Score	NSE
Abra	0.47	0.78	0.9574	0.9574
Apayao	0.69	1.25	0.8967	0.8967
Benguet	0.19	0.30	0.7311	0.7311
Ifugao	0.25	0.43	0.8585	0.8585
Kalinga	0.32	0.50	0.8145	0.8145

Abbreviations: MAE: Mean absolute error; RMSE: Root mean square error; NSE: Nash–Sutcliffe efficiency.

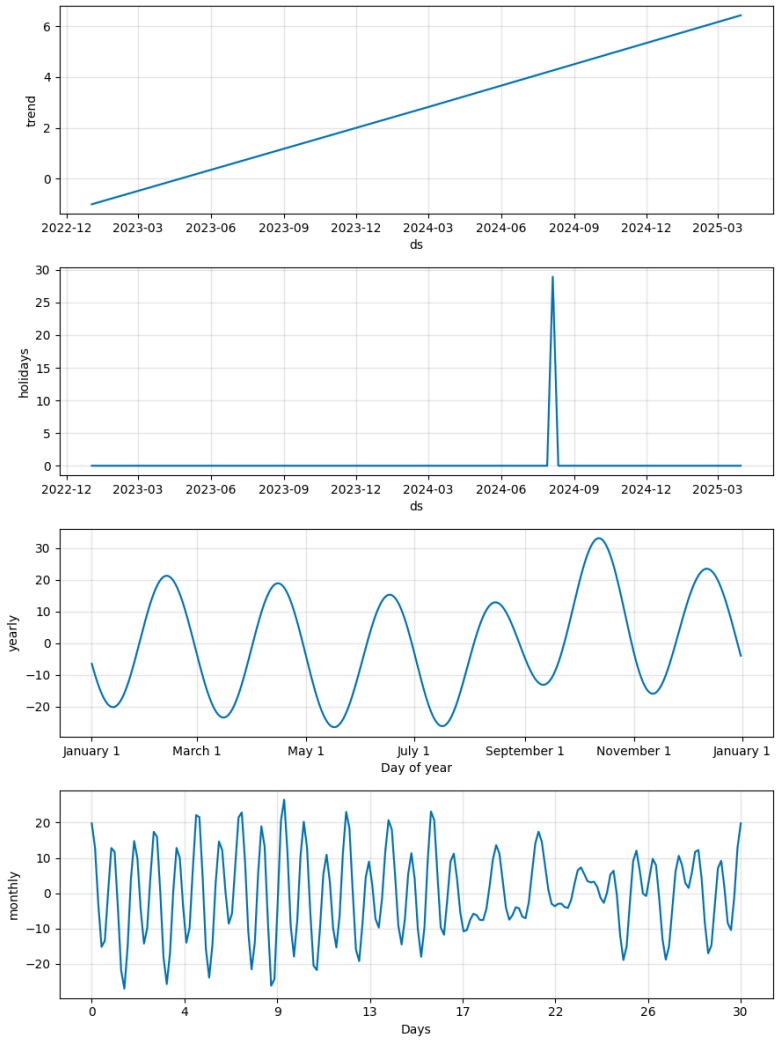


Figure 11. Prophet model components for reported ASF cases, including the overall trend, special-event effect, possible yearly pattern, and monthly component

Figure 13 shows the time-series forecast for Benguet. Weekly outbreaks remained low, and the forecast for early 2025 remained close to zero. The figure shows the forecast line and uncertainty interval together with the observed weekly counts. No large weekly peaks were observed in the projected period.

Figure 14 shows the time-series forecasts for Ifugao (a) and Kalinga (b). In Ifugao, the series showed an upward trend with continued weekly outbreaks in early 2025. In Kalinga, the forecast also showed continued weekly outbreaks during the same period.

Discussion

Reported ASF cases in the CAR varied across provinces and months. The strongest temporal concentration occurred from August to October 2024. This concentration supports the presence of a late-year seasonal pattern in the region. It was consistent with Hsu et al. (2023), who reported greater ASF activity in the Philippines during the second half of the year, with the highest seasonal indices in August and September. Hsu et al. (2025) likewise identified recurring national peaks from August to October as reported by the Bureau of Animal Industry (2025). The agreement between the regional and national findings indicates that the late-year increase in the CAR was not an isolated event. The timing may also reflect seasonal changes in social activity. The latter part of the year includes preparations for Christmas and other gatherings, when demand for pigs and pork products may increase (Abao & Sabiniano, 2026). Increased demand, movement, slaughtering, sales, and distribution of pork products would provide opportunities for disease transmission when there are poor movement control and biosecurity measures (Thakur et al., 2026; Portugaliza, 2025).

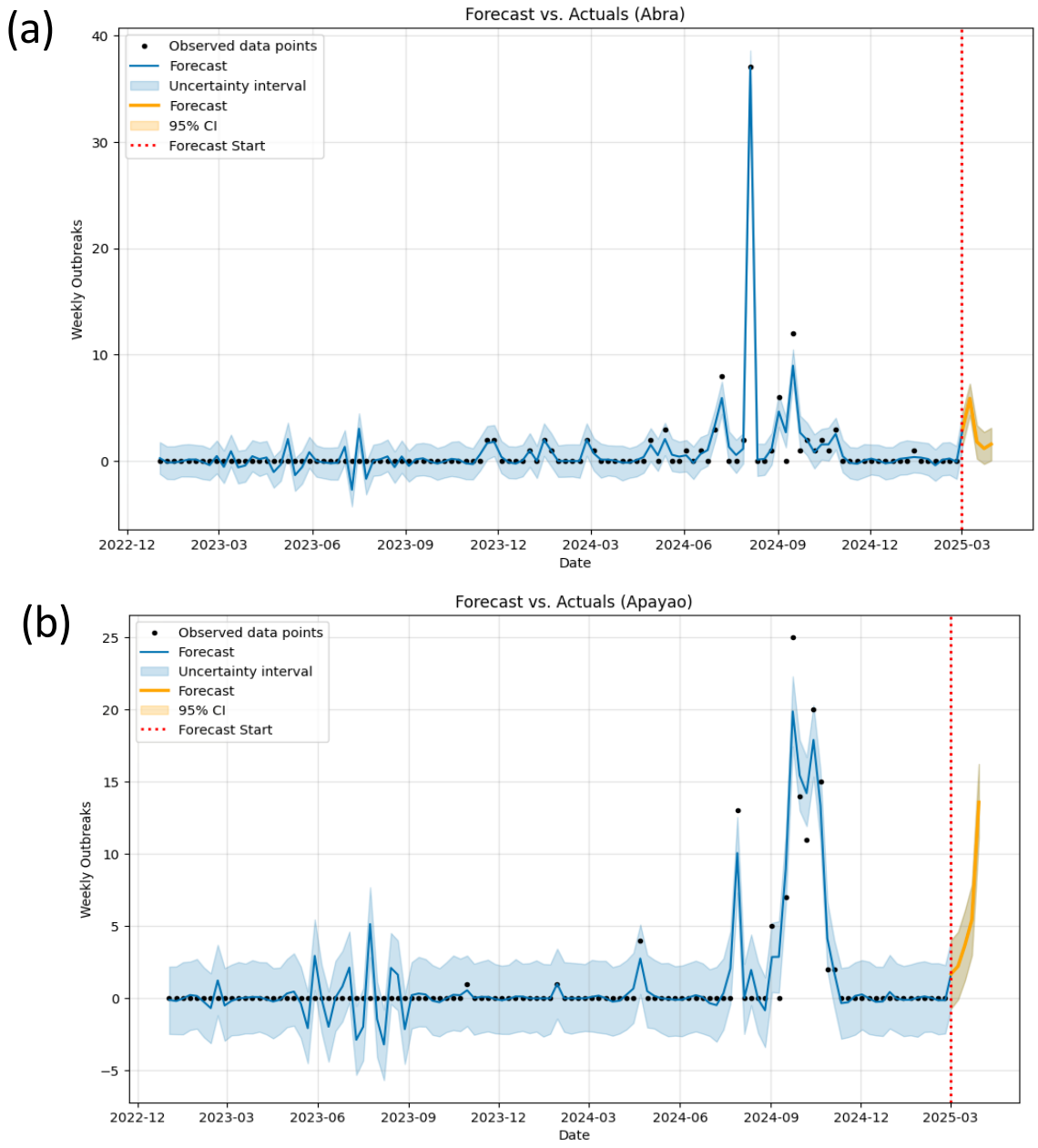


Figure 12. Prophet time-series models for weekly ASF cases in Abra (a) and Apayao (b)

Note: Black dots represent the observed counts, the blue lines represent the fitted historical values, and the orange lines represent the five-week forecasts. The shaded areas indicate the corresponding 95% uncertainty intervals.

Time series results showed three different temporal patterns. First, Apayao, Ifugao, and Kalinga had an upward trend with yearly late increases. Therefore, these provinces need intensive monitoring prior to the expected peak and biosecurity measures, despite few reported cases. Secondly, despite being the region with the highest pig population based on DA-CAR records, Benguet demonstrated a low trend. Thus, the fewer reported cases of ASF cases could not be attributed to a relatively small swine population in Benguet. Benguet was characterized by higher animal checkpoints and stringent monitoring of animal movements, since it is the region surrounding Baguio City, a densely populated urban center with substantial demand for pork. Thirdly, prolonged periods of fewer reported cases and sudden increases were evident in Abra Province. This is indicative of an intermittent occurrence followed by abrupt increases in reported cases. Early detection and prompt control of animal movements are critical in the case of outbreaks in the province. In summary, the different patterns of incidence in

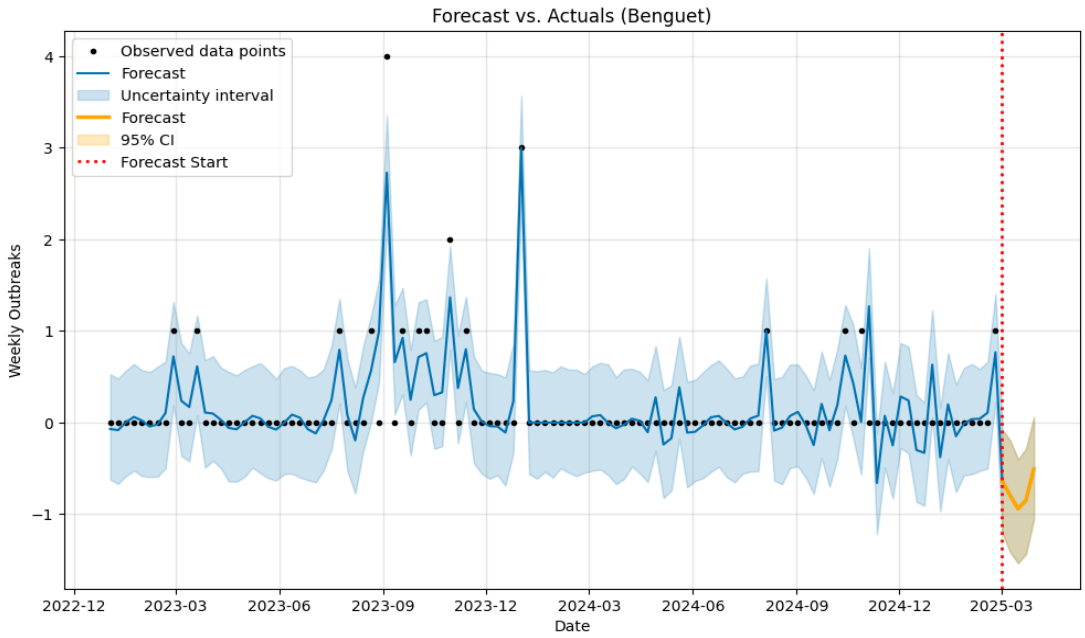


Figure 13. Prophet time-series model for weekly ASF cases in Benguet

Note: Black dots represent the observed counts, the blue line represents the fitted historical values, and the orange line represents the five-week forecast. The shaded areas indicate the corresponding 95% uncertainty intervals.

provinces in CAR show that there should not be a "one size fits all" approach in the epidemiology of ASF in the region.

Further proof for geographical change was found in the SDE method. From 2023 to 2024, there had been an observable northward shift of the mean center regionally and a change in the main orientation. Hence, apart from the higher number of reported cases in 2024, there is also a redistribution of ASF activity toward the northern CAR. The observed changes in CAR were similar to those found by Hsu et al. (2023) at the national level. Their analysis identified consecutive clusters in Luzon, including a later resurgence in Northern Luzon, where CAR is located. The cluster radii also increased over time, which implies that ASF activity expanded geographically and re-emerged in previously affected areas. Within the CAR, the observed northward shift implies that the priority areas need to be constantly reassessed.

Global Moran's I confirmed this finding. Reported cases were found in certain barangays, especially those in the northern parts of CAR, but not in one single continuous cluster. High-high and low-low clusters pointed out regions where there was similar case occurrence, while high-low and low-high clusters revealed differences between neighboring barangays. The hot spots and cold spots were also present in specific locations. Patchy clustering implies that ASF had not moved from one neighboring barangay to another in a steady manner. The occurrence of the disease may have been determined by other factors that were not part of the analysis. This is substantiated by Ligue-Sabio et al. (2025), who noted that the hotspots have moved toward the northeast provinces of the Davao Region. The researchers stated that even with strict controls, the persistence of the spread of ASF indicates that transboundary movement via trade and other human activity is an essential element in its transmission. Thus, the movement of infected pigs, pork products, vehicles, or other contaminated materials along trade routes may be a plausible explanation for the patchy and non-adjacent distribution observed in the CAR.

These spatial patterns may also be a result of differential reporting and disease diagnosis capabilities of the provinces. According to Portugaliza (2025), the silent transmission of ASF is possible due to the lack of surveillance, delayed or non-existent reporting, lack of laboratory confirmation, inconsistency in quarantine implementation, logistic difficulties, and lack of local veterinarians. In a similar manner, Hsu et al. (2025) identified difficulties in collecting samples from backyard farms, underreporting caused by inadequate incentives, limited data sharing, shortages of diagnostic and field personnel, and inconsistent implementation of ASF protocols across LGUs. These findings then support a province-specific, risk-based surveillance system tailored to CAR's local conditions. As recommended by Ceruti et al. (2025), pas-

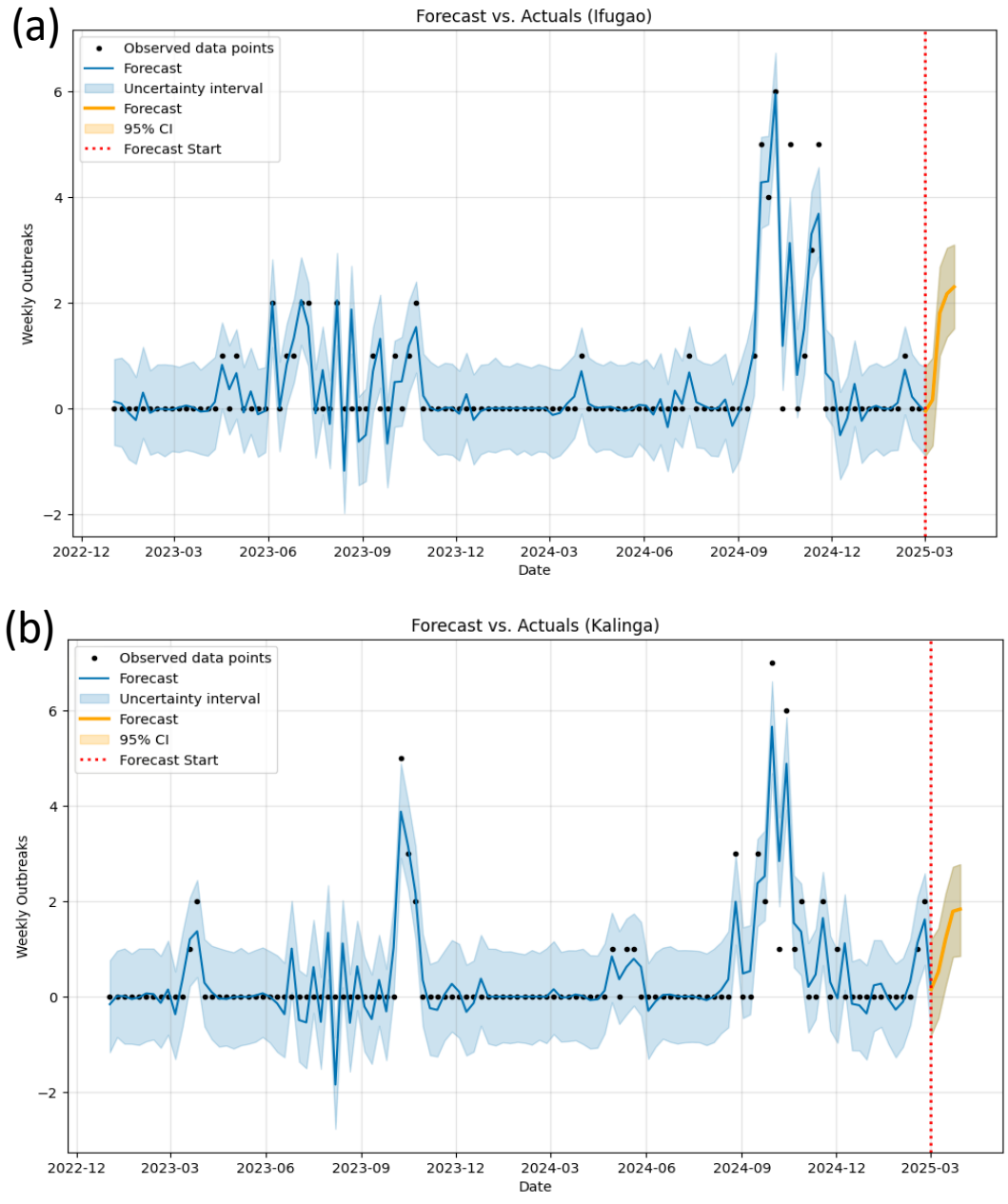


Figure 14. Prophet time-series models for weekly ASF cases in Ifugao (a) and Kalinga (b)

Black dots represent the observed counts, the blue lines represent the fitted historical values, and the orange lines represent the five-week forecasts. The shaded areas indicate the corresponding 95% uncertainty intervals.

sive surveillance should strengthen farmer awareness, timely reporting, community participation, and rapid investigation, while active surveillance should target previously affected barangays, northern hotspots, markets, entry points, and areas with limited diagnostic access. The 2024 increase, marked by late-year concentration, localized clustering, and northward redistribution, also calls for stronger preparedness before August, improved movement biosecurity, and coordination across LGUs.

Study limitations

This study relied on officially reported ASF cases. Therefore, unreported or undiagnosed cases were not accounted for. The analyses were also based on reported case counts rather than prevalence or incidence rates because swine population denominator data at the required spatial and temporal resolution were not available for the entire study period. Consequently, differences in case counts may part-

ly reflect variations in the underlying swine population across locations. Thus, the identified spatial and temporal patterns should be interpreted as patterns of reported ASF occurrence rather than direct measures of disease risk. Administrative boundaries and barangay centroids may not accurately represent the exact locations of ASF occurrence at the farm level. Moreover, differences in reporting intensity, access to veterinary and diagnostic services, surveillance coverage, sample submission, and outbreak-detection efficiency across provinces may have influenced the observed distribution of cases. The study also did not account for epidemiological links between cases, road networks, livestock market locations, movements of pigs and pork products, biosecurity practices, farm type, environmental conditions, or enforcement capacity.

Conclusion

The results show that there were variations in the presence of ASF reported within the CAR both over time and space, where some periods and locations experienced a higher reported case occurrence of the disease than others. The variations in ASF presence imply that an average figure from different regions may mask local and temporal risks, thereby making a uniform plan of control measures less effective. Therefore, surveillance and response efforts must be adaptable and tailored to each province, where more surveillance will be undertaken before the late-year surge of the disease and emphasis on re-emerging, emerging, and geographically clustered barangays. Allocation of funds and capacity for investigation, diagnostic testing, movement controls, and implementation of biosecurity measures needs to be done in the periods and places where risks are high, while those places with a lower incidence will still be monitored for potential emergence of the disease. Moreover, better coordination between adjacent LGUs is required since changes in ASF occurrences can be beyond administrative boundaries.

Ethical Considerations

Compliance with ethical guidelines

This research analyzed secondary ASF surveillance data and did not involve live animals, direct experimentation, or collection of biological samples. Administrative authorization to access and use the dataset was obtained from the Department of Agriculture–Cordillera Administrative Region Animal Health Unit. The records contained no personally identifiable information and were used solely for research purposes. All data were handled confidentially, and the reported locations represented administrative areas rather than exact farm or household locations.

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Conflict of interest

The author declared no conflict of interest.

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