

# Spatial Analysis of African Swine Fever Outbreak: A Basis for Developing a Web-Based Decision Support System using Business Analytics and Geospatial Technology

Roger S. Mission<sup>1</sup>, Alexis John M. Rubio<sup>2\*</sup>

**Abstract:** The Philippine hog industry, crucial to national food security and rural economies, is facing a major threat from African Swine Fever (ASF), a highly contagious disease that has devastated the domestic pig population since its emergence in 2019. The economic toll has been severe, with over 300,000 pigs culled to control outbreaks. Despite government efforts, including the declaration of a national state of calamity and various biosecurity measures, the response has been hindered by insufficient testing and weak monitoring mechanisms. This study proposes the development of a web-based decision support system (DSS) to enhance ASF management using Business Analytics, Geographic Information Systems (GIS) and Density-Based Spatial Clustering of Applications with Noise (DBSCAN). The system aims to map ASF outbreaks in real-time, identify disease hotspots, and provide actionable insights to various stakeholders, including veterinarians, farmers, and policymakers. It integrates descriptive, predictive, and prescriptive analytics to support informed decision-making, optimize resources, and guide targeted interventions. The research uses Region 6, Western Visayas, as a case study, known for its high ASF outbreak rate and significant role in the national hog industry. The DSS employs spatial and non-spatial data, including outbreak trends and biosecurity protocols, and is evaluated by ASF professionals, IT experts, and policymakers to ensure its effectiveness in real-world applications. The system's potential to improve outbreak forecasting and intervention planning is emphasized, with the goal of strengthening the resilience of the Philippine hog industry and contributing to global sustainability efforts. This study highlights the importance of integrating advanced technologies in managing ASF outbreaks, with a focus on data-driven decision-making to protect food security, promote public health, and support economic growth.

**Keywords:** African Swine Fever, Decision Support System, Business Analytics, GIS, DBSCAN

<sup>1</sup> College of Computer Studies, University of Antique, Sibalom, Antique, Philippines  
Email: [rsmmission@antiquespride.edu.ph](mailto:rsmmission@antiquespride.edu.ph)

<sup>2\*</sup> College of Engineering, University of the East-Caloocan, Caloocan, Metro Manila Philippines  
Email: [alexisjohn.rubio@ue.edu.ph](mailto:alexisjohn.rubio@ue.edu.ph)

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## **1. Introduction**

In the pursuit of sustainable development and resilient agricultural systems, the hog industry in the Philippines plays a vital role in ensuring national food security, supporting rural livelihoods, and driving economic growth. As a significant contributor to the nation's agricultural landscape, it is integral to both the domestic pork supply and the well-being of rural communities [1]. However, the industry faces a major threat in the form of African Swine Fever (ASF), a highly contagious and devastating viral disease for which no known cure or vaccine exists. First detected in the Philippines in 2019, ASF has rapidly spread across multiple provinces, causing widespread devastation and threatening the entire domestic pig population [2].

The economic toll of ASF has been severe, with the Philippine Statistics Authority reporting the culling of over 300,000 pigs in efforts to control the outbreak. This measure underscores the scale of the crisis, with far-reaching consequences not only for the hog industry but also for the country's food security, rural economies, and livelihoods [3]. ASF has emerged as a national concern, highlighting the urgent need for effective disease management strategies to safeguard both the agricultural sector and public health [4].

In response to the outbreak, the Philippine government declared a nationwide state of calamity, mobilizing local government units (LGUs) to take swift action. Initiatives like the Bantay ASF sa Barangay Program have been launched, focusing on biosecurity measures, public awareness campaigns, and providing financial assistance to affected farmers [5]. Despite these efforts, the effectiveness of the response has been limited by insufficient testing, inadequate biosecurity practices, and weak monitoring mechanisms. These challenges emphasize the necessity for a more robust and coordinated approach to managing ASF outbreaks, one that integrates modern technology and data-driven decision-making processes.

This study proposes the development of a web-based decision support system to enhance the management of ASF outbreaks in the Philippines. By leveraging Geographic Information Systems (GIS) and density-based spatial clustering algorithms such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), the system will enable real-time mapping of affected areas and identification of disease hotspots. These advanced tools are essential for providing stakeholders—ranging from veterinarians and farmers to policymakers—with actionable insights that facilitate effective decision-making. The proposed system will serve as a critical tool in monitoring and controlling ASF, improving the efficiency of response efforts, and reducing the spread of the disease.

The research aligns with the goals outlined in the Philippine Hog Industry Roadmap (2022-2026) and the United Nations Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being), SDG 8 (Decent Work and Economic Growth), and SDG 15 (Life on Land). By integrating sustainability principles into the management of ASF, this study contributes to broader global efforts aimed at ensuring food security, promoting public health, enhancing economic resilience [1], and preserving biodiversity.

Through the development of this web-based system, equipped with interactive dashboards and user-friendly visualizations, this research aims to improve ASF monitoring and management in the Philippines. The integration of choropleth mapping and spatial clustering algorithms will offer an innovative, data-driven approach to identifying ASF hotspots, assessing risks, and guiding strategic interventions. Ultimately, the goal is to strengthen the resilience of the Philippine hog industry against ASF while contributing to global sustainability initiatives.

The primary objective is to examine the African swine fever outbreak in the Western Visayas region of the Philippines as the basis for creating a web-based decision support system utilizing business analytics and geospatial technology.

Specifically, it will answer the following questions:

- (1) What are the stages undertaken in the development of a web-based decision support system for African Swine Fever based on choropleth mapping and density-based spatial clustering algorithms?
- (2) How do geographic information system methods and density-based spatial clustering algorithms identify ASF case clusters and distribution patterns?
- (3) How to design a dynamic web-based decision support system that can visualize interactive dashboards to help stakeholders understand ASF cases overtime and make data-driven decisions that reflect the three types of data analytics, specifically: (a) Descriptive; (b) Predictive; and (c) Prescriptive?

This study also seeks to address existing knowledge gaps in ASF response strategies, employing cutting-edge technologies and spatial analysis to mitigate the far-reaching impacts of this highly infectious disease. By collaborating with government agencies, civil society, and industry stakeholders, the research aims to provide practical solutions that promote a more sustainable, inclusive, and resilient hog industry in the Philippines, helping to safeguard the future of the sector and ensure long-term food security.

## 2. Research Methods

This study employs descriptive and developmental research approaches to create a web-based Decision Support System (DSS) for identifying African Swine Fever (ASF) hotspots. The descriptive approach analyzes ASF outbreak patterns from official sources, while the developmental approach focuses on designing and evaluating the DSS to meet technical and user needs. Using data from the Bureau of Animal Industry (BAI) and the World Organization for Animal Health (OIE), the system integrates spatial (geo-coordinates) and non-spatial (outbreak history, biosecurity protocols) data [6]. It visualizes ASF hotspots via GIS choropleth maps and identifies clusters using the DBSCAN algorithm, generating analytics for trend analysis, outbreak forecasting, and intervention planning.

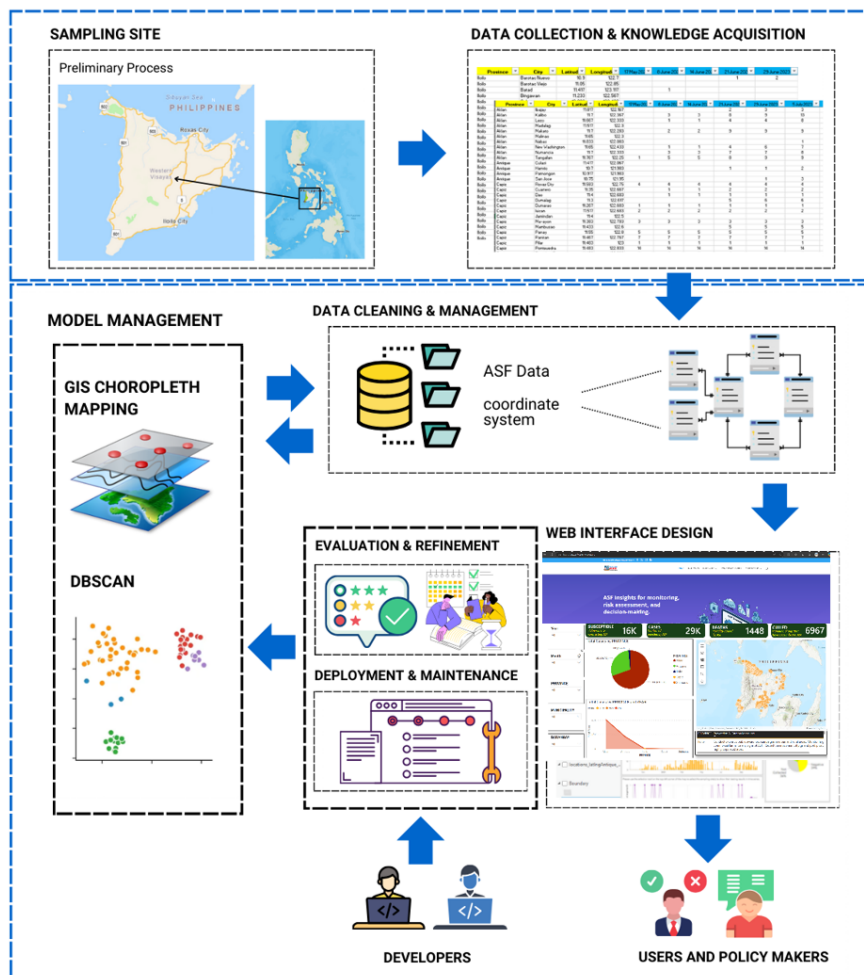
Region 6, Western Visayas, Philippines, was selected as the research site due to its high ASF outbreak rate, significant economic role in hog farming (12.1% of the national hog population), and diverse geography [7]. The DSS will provide real-time hotspot detection, enabling targeted interventions that can be scaled nationwide with support from local stakeholders and experts. The system's evaluation will involve 258 respondents, including 143 ASF professionals, 26 IT specialists, and 89 policymakers, who will assess its capacity to inform policy, optimize resources, and support ASF control measures.

The DSS development follows a process that includes data collection, integration, analysis, and presentation. Data from BAI and OIE (July 25, 2019, to present) was cleaned, standardized, and combined into a unified dataset. GIS mapping visualized ASF hotspots, while DBSCAN clustering identified ASF case clusters, guiding targeted interventions. Microsoft Power BI dashboards provided descriptive, predictive, and prescriptive analytics, offering stakeholders insights into past outbreaks, future forecasts, and recommended actions.

The development of the Decision Support System (DSS) was guided by a combination of research tools, including questionnaires, unstructured interviews, and document analysis. Qualitative insights were gathered through interviews with key stakeholders, while the review of ASF reports and GIS studies provided essential context for system design. Drawing on the triangulated approach, this method established a robust, data-driven, and user-centered foundation for creating a DSS aimed at managing ASF outbreaks [8][9].

### 3. Results and Discussion

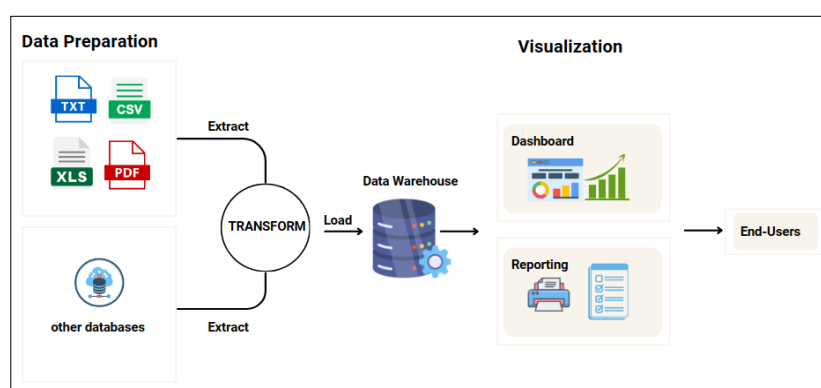
#### 3.1 What are the Stages Undertaken in the Development of a Web-based Decision Support System for African Swine Fever based on Choropleth Mapping and Density-based Spatial Clustering Algorithms?



**Figure 1.** Stages in the Development of a Web-based Decision Support System for African Swine Fever

Figure 1 outlines the different stages for developing the Decision Support System (DSS) for African Swine Fever (ASF) management. The process begins with data collection, which includes spatial data (geo-coordinates, ASF case records) and non-spatial data (outbreak trends, biosecurity protocols, and expert insights). This diverse dataset underpins the system’s analytical capabilities.

Collected data undergoes cleaning and integration to ensure accuracy, consistency, and usability. Issues like missing values and incompatible formats are addressed, enabling effective analysis. The next phase of the research process will involve utilizing Microsoft Power BI for data visualization. Power BI's powerful features enabled the researchers to create insightful and visually engaging dashboards and reports. The algorithmic stages of this process, as illustrated in Figure 2, were as follows: first, data was imported from various sources in multiple formats. Next, the data was integrated and securely stored in a designated repository, where preprocessing operations were carried out to clean the raw data, including tasks like removing redundant values. Finally, the processed data was transferred from the repository to Power BI platforms, such as Power BI Desktop, where tools within Power BI were used to generate reports, dashboards, and scorecards based on the refined data.



**Figure 2.** Workflow of Data Analytics Involves the Steps of Data Preparation, Transformation, and Visualization

The core analytical process uses business analytics software, Geographic Information Systems (GIS) and the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to provide critical insights for targeted disease control interventions.

A web-based platform is then developed to make these insights accessible to ASF-related professionals, policymakers, and hog farmers. The system features an interactive interface with GIS maps for hotspot detection and risk assessment tools to forecast outbreaks, supporting proactive decision-making.

Before deployment, the system will be evaluated against ISO 25010 quality standards, focusing on functionality, usability, reliability, and security. User testing with stakeholders identifies areas for improvement, prompting refinements to the interface, features, and algorithms.

Once finalized, the DSS is deployed through a secure online platform for government agencies and stakeholders. Continuous updates to ASF case data and health records are integrated to maintain system relevance. Ongoing technical support and user training ensure stakeholders can fully leverage the system's capabilities for effective ASF management and industry protection.

### 3.2 Geographic Information System Methods and Density-Based Spatial Clustering Algorithms in Identifying ASF Case Clusters and Distribution Patterns

Geographic Information System (GIS) methods, coupled with density-based spatial clustering algorithms, play a pivotal role in identifying African Swine Fever (ASF) case clusters and understanding their distribution patterns. These powerful tools allow for the spatial analysis of ASF data, enabling

stakeholders to visualize and analyze the geographic spread of the disease over time. GIS methods facilitate the mapping of ASF cases, highlighting areas with higher concentrations of infections, while density-based spatial clustering algorithms refine these patterns by grouping cases based on proximity and frequency.

**Table 1.** Summary of Responses on Familiarity, Usage, and Perceived Effectiveness of GIS and Clustering Algorithms in Managing ASF

Item No	Questions	Answers	ASF-related Professionals		IT-related Professionals		Policy Makers	
			N	%	N	%	N	%
1	What is your level of familiarity with Geographic Information Systems (GIS)?	None	0	0%	0	0%	3	3.37%
		Beginner	23	16%	10	38%	23	25.84%
		Intermediate	93	65%	12	46%	44	49.44%
		Advanced	27	19%	4	15%	19	21.35%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
2	What is your level of familiarity with business analytics tools?	None	0	0%	0	0%	2	2.25%
		Beginner	32	22%	8	31%	25	28.09%
		Intermediate	80	56%	13	50%	42	47.19%
		Advanced	31	22%	5	19%	20	22.47%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
3	Have you previously worked with clustering algorithms, specifically density-based methods, in analyzing disease outbreaks?	Yes	3	2%	14	54%	0	0%
		No	140	98%	12	46%	89	100%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
4	How effective do you believe GIS methods and business analytics tools are in visualizing ASF outbreaks and transmission patterns?	Very Effective	64	45%	13	50%	18	20.22%
		Effective	78	55%	13	50%	71	79.78%
		Ineffective	0	0%	0	0%	0	0%
		Very Ineffective	1	1%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
5	In your experience, how important is the use of Geographic Information Systems and business analytics for visualizing the density and spread of ASF cases?	Very Important	71	50%	16	62%	24	26.97%
		Important	71	50%	10	38%	65	73.03%
		Unimportant	1	1%	0	0%	0	0%
		Very Unimportant	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>

6	To what extent do GIS and business analytics tools help in identifying high-risk areas for ASF outbreaks?	Extremely Useful	86	60%	15	58%	33	37.08%
		Somewhat Useful	56	39%	11	42%	55	61.80%
		Not Very Useful	1	1%	0	0%	1	1.12%
		Not Useful at All	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
7	Have you used density-based spatial clustering algorithms in your work?	Yes	5	3%	17	65%	17	19.10%
		No	135	94%	9	35%	70	78.65%
		Not Applicable	3	2%	0	0%	2	2.25%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
8	If yes, which algorithm(s) have you found most effective in identifying ASF clusters?	DBSCAN	93	65%	10	38%	69	77.53%
		K-Means	10	7%	10	38%	2	2.25%
		Spatio-Temporal Clustering Algorithms	19	13%	0	0%	14	15.73%
		Kulldorff's Scan Statistic	11	8%	1	4%	2	2.25%
		Not Applicable	10	7%	5	19%	2	2.25%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
9	How accurately do you believe density-based clustering algorithms can identify ASF case clusters and predict potential future outbreaks?	Extremely Accurate	96	67%	8	31%	40	44.94%
		Somewhat Accurate	44	31%	18	69%	48	53.93%
		Inaccurate	3	2%	0	0%	1	1.12%
		Very Inaccurate	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
10	In your opinion, how useful would a web-based decision support system be for managing ASF outbreaks?	Very Useful	89	62%	11	42%	50	56.18%
		Useful	53	37%	15	58%	39	43.82%
		Not Very Useful	1	1%	0	0%	0	0%
		Not Useful at All	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
11	How important is real-time data visualization in such a system for managing ASF?	Extremely Important	80	56%	10	38%	21	23.60%
		Important	62	43%	16	62%	67	75.28%
		Not Important	1	1%	0	0%	1	1.12%
		Very Unimportant	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>

Table 1 highlights the familiarity, usage, and perceived effectiveness of Geographic Information Systems (GIS) and clustering algorithms among ASF-related professionals, IT professionals, and policy makers for identifying ASF case clusters and distribution patterns. ASF-related professionals demonstrated strong GIS proficiency, with 65.03% at an intermediate level and 18.88% at an advanced level, reflecting its integration into ASF outbreak tracking. IT professionals showed mixed familiarity, with 46.15% at an intermediate level and 38.46% as beginners, while policymakers had intermediate (49.44%) or beginner (25.84%) levels of familiarity. For business analytics tools, most ASF-related (55.94%) and IT professionals (50%) had intermediate familiarity, but IT professionals had a larger proportion of beginners (30.77%), highlighting the need for training. Policymakers also reported intermediate (47.19%) and beginner (28.09%) familiarity. Experience with clustering algorithms, particularly density-based methods like DBSCAN, was low among ASF-related professionals (97.90% had no experience) and policymakers (100% unfamiliar). IT professionals showed higher experience (53.85%), consistent with their technical background. This suggests a need for cross-sector training on clustering algorithms to support ASF case identification and distribution analysis.

The perceived effectiveness of GIS and analytics tools in visualizing ASF outbreaks was rated as effective by most ASF-related professionals (54.55%) and policymakers (79.78%), while 50% of IT professionals rated them as effective or very effective. All groups recognized the importance of these tools, with ASF-related and IT professionals rating them as "very important" and policy makers as "important." GIS and analytics tools were seen as "extremely useful" for identifying high-risk ASF areas by ASF-related (60.14%) and IT professionals (57.69%). Policymakers, however, were more cautious, with 61.80% finding them "somewhat useful." DBSCAN was the most preferred clustering algorithm for ASF management, with 65.03% of ASF-related professionals and 77.53% of policy makers selecting it. IT professionals favored both DBSCAN (38.46%) and K-Means, reflecting broader knowledge of clustering techniques. ASF-related professionals (67.13%) and policymakers (44.94%) considered clustering algorithms "extremely accurate," while IT professionals were more reserved, with 69.23% rating them "somewhat accurate."

All groups acknowledged the value of a web-based DSS for ASF management, with most rating it as "very useful" or "useful." Real-time data visualization was considered "extremely important" by ASF-related professionals (55.94%) and policymakers (75.28%), underscoring its role in timely decision-making during outbreaks.

### **3.3 Designing a Dynamic Web-Based Decision Support System: Visualizing Interactive Dashboards for Data-Driven Decision Making in ASF Management through Descriptive, Predictive, and Prescriptive Analytics**

In the context of managing African Swine Fever (ASF), the development of a dynamic web-based decision support system (DSS) is crucial for empowering stakeholders to make informed, data-driven decisions. This system must incorporate interactive dashboards that provide clear and concise visualizations, allowing users to track ASF cases over time and respond proactively. To ensure the effectiveness of the system, it must integrate three key types of data analytics: Descriptive Analytics, which offers insights into past and current trends; Predictive Analytics, which forecasts potential outbreaks and their impacts; and Prescriptive Analytics, which provides actionable recommendations for outbreak control. This section explores how a well-designed web-based DSS can harmonize these analytics to support stakeholders in making timely and effective decisions in the fight against ASF.



**Table 2.** Responses of respondents on the Use of the ASF Decision Support System in terms of Descriptive Analytics

Item No	Questions	Answers	ASF-related Professionals		IT-related Professionals		Policy Makers	
			N	%	N	%	N	%
1	How important is the inclusion of historical ASF case data (e.g., past outbreaks, affected areas) in the decision support system for managing future outbreaks?	Extremely Important	74	51.75%	10	38.46%	24	26.97%
		Important	68	47.55%	16	61.54%	65	73.03%
		Not Important	1	0.70%	0	0%	0	0%
		Very Unimportant	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
2	Which types of visualizations do you think are most effective in understanding ASF trends over time?	Area Chart	71	49.65%	12	46.15%	5	5.62%
		Pie Chart	50	34.97%	5	19.23%	24	26.97%
		Time Graph	21	14.69%	6	23.08%	60	67.42%
		Choropleth Maps	1	1%	3	11.54%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
3	What data would you consider critical to include in the descriptive dashboard (e.g., number of cases, mortality rate, geographical spread)?	Total Cases by Provinces	120	83.92%	25	96.15%	86	96.63%
		Total Number of Affected Municipality	117	81.82%	23	88.46%	88	98.88%
		Total Number of Affected Barangay	108	75.52%	24	92.31%	86	96.63%
		Susceptible Cases	65	45.45%	23	88.46%	8	8.99%
		Confirmed ASF Cases	74	51.75%	23	88.46%	17	19.10%
		Handling of Pigs that have succumbed to ASF	71	49.65%	22	84.62%	13	14.61%
		Maps	19	13.29%	19	73.08%	50	56.18%
		Prevention and Caution Measures	24	16.78%	20	76.92%	7	7.87%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
4	How frequently should the descriptive analytics dashboard update ASF case data to be most useful to stakeholders?	Real-time	87	60.84%	9	34.62%	21	23.60%
		Daily	33	23.08%	0	0.00%	43	48.31%
		Weekly	22	15.38%	17	65.38%	25	28.09%
		Monthly	0	0%	0	0%	0	0%
		On-demand	1	0.70%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>

5	Do you believe stakeholders (veterinarians, epidemiologists, hog farmers) need access to detailed descriptive analytics on ASF outbreaks for informed decision-making?	Yes	143	100%	26	100%	88	98.88%
		No	0	0%	0	0%	0	0%
		Not Sure	0	0%	0	0%	1	1.12%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>

Table 2 highlights responses on the use of descriptive analytics in the ASF Decision Support System. Most ASF-related professionals (51.75%) rated historical ASF case data as "Extremely Important," while 47.55% deemed it "Important." IT professionals shared similar views, with 38.46% marking it as "Extremely Important" and 61.54% as "Important." Policymakers placed less emphasis on historical data, with 73.03% rating it as "Important" and 26.97% as "Extremely Important."

For visualizing ASF trends, ASF-related and IT professionals preferred Area Charts (49.65% and 46.15%, respectively), valuing both geographical and temporal data. Policymakers, however, favored Time Graphs (67.42%) for tracking trends over time to support decision-making.

Regarding critical dashboard data, ASF-related professionals prioritized Total Cases by Provinces (83.92%) and Affected Municipalities (81.82%). IT professionals also emphasized Confirmed ASF Cases (88.46%) and Pig Disposal Data (84.62%). Policymakers prioritized Total Cases by Provinces (96.63%) and Affected Municipalities (98.88%), reflecting their need for broader geographic data for policy decisions.

On dashboard update frequency, ASF-related professionals preferred real-time updates (60.84%) to support immediate responses. IT professionals preferred weekly updates (65.38%), likely due to technical constraints, while policymakers leaned toward daily updates (48.31%) to balance strategic and immediate needs.

All stakeholders agreed on the need for access to descriptive analytics, with 100% of ASF-related and IT professionals and 98.88% of policymakers supporting it.

Descriptive analytics are crucial in managing ASF outbreaks. While ASF-related and IT professionals prioritize real-time, detailed data, policymakers emphasize broader geographic data with less frequent updates. This highlights the need for a decision support system that meets the distinct needs of all involved parties. The importance of descriptive analytics lies in its ability to provide real-time, detailed information to support informed decision-making during outbreaks [9] and underscores the need for thorough data analysis to comprehend the spread and impact of ASF, which is essential for policymakers focusing on larger geographic areas [10].

Table 3 presents responses on the use of predictive analytics in the ASF Decision Support System. Most ASF-related professionals (62.24%) rated predictive models as "Extremely Useful," highlighting their importance for outbreak forecasting. IT professionals were less emphatic, with 38.46% rating them as "Extremely Useful" and 61.54% as "Somewhat Useful." Policymakers were split, with 50.56% finding them "Extremely Useful" and 48.31% "Somewhat Useful," reflecting their supplementary role in decision-making.

**Table 3.** Responses of Respondents on the Use of the ASF Decision Support System in Terms of Predictive Analytics

Item No	Questions	Answers	ASF-related Professionals		IT-related Professionals		Policy Makers	
			N	%	N	N	%	N
1	How useful do you believe predictive models (e.g., predicted cases by year and month, and predicted deaths by year and month) would be in a web-based decision support system?	Extremely Useful	89	62.24%	10	38.46%	45	50.56%
		Somewhat Useful	54	37.76%	16	61.54%	43	48.31%
		Not Very Useful	0	0%	0	0%	1	1.12%
		Not Useful at All	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
2	Which factors do you think should be considered in predictive models to forecast ASF outbreaks?	Historical ASF Cases	87	60.84%	14	53.85%	35	39.33%
		Geographical Location	26	18.18%	8	30.77%	27	30.34%
		Geographic Coordinates (latitude and longitude)	30	20.98%	4	15.38%	27	30.34%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
3	What is your preferred visualization for predictive analytics in the decision support system?	Time-Series Graphs	122	85.31%	15	57.69%	79	88.76%
		Charts with Predictive Intervals	15	10.49%	4	15.38%	4	4.49%
		Trend Lines	2	1.40%	0	0.00%	5	5.62%
		Interactive Maps	4	2.80%	7	26.92%	1	1.12%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
4	How often should the predictive models in the decision support system be recalibrated based on new data to ensure accuracy and updated?	Daily	69	48.25%	4	15.38%	24	26.97%
		Weekly	51	35.66%	18	69.23%	63	70.79%
		Monthly	19	13.29%	4	15.38%	1	1.12%
		Quarterly	4	2.80%	0	0%	1	1.12%
		Annually	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
5	Do you believe predictive analytics could significantly improve ASF outbreak management by anticipating high-risk areas and future outbreaks?	Strongly Agree	78	54.55%	10	38.46%	44	49.44%
		Agree	65	45.45%	16	61.54%	44	49.44%
		Disagree	0	0%	0	0%	1	1.12%
		Strongly Disagree	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>178</b>	<b>100%</b>

For predictive model inputs, ASF-related professionals prioritized historical case data (60.84%), followed by geographical coordinates (20.98%) and location (18.18%). IT professionals similarly emphasized historical data (53.85%) but showed greater interest in location data (30.77%). Policymakers preferred a balanced approach, valuing both historical (39.33%) and geographical (30.34%) data.

Time-Series Graphs were the most preferred visualization method, selected by 85.31% of ASF-related professionals, 57.69% of IT professionals, and 88.76% of policymakers. IT professionals also showed interest in Interactive Maps (26.92%), but policymakers showed little interest in other visual formats.

Recalibration preferences varied, with 48.25% of ASF-related professionals favoring daily updates, while 69.23% of IT professionals and 70.79% of policymakers preferred weekly recalibration, reflecting differences in role-specific needs.

All groups acknowledged the value of predictive analytics for ASF management. A majority of ASF-related professionals (54.55%) strongly agreed on its potential to enhance proactive strategies, while 38.46% of IT professionals and 49.44% of policymakers shared this view, focusing on technical and strategic planning.

Predictive analytics play a crucial role in managing ASF outbreaks, allowing authorities to design targeted interventions and control the disease's spread [11][12]. Essential components like historical data, geographic information, time-series graphs, and recalibration schedules highlight the unique requirements and roles of ASF professionals, IT experts, and policymakers.

**Table 4.** Responses of Respondents on the Use of the ASF Decision Support System in Terms of Prescriptive Analytics

Item No	Questions	Answers	ASF-related Professionals		IT-related Professionals		Policy Makers	
			N	%	N	N	%	N
1	How valuable would actionable recommendations (e.g., quarantine measures, resource allocation) be in helping stakeholders control ASF outbreaks?	Extremely Valuable	83	58.04%	9	34.62%	35	39.33%
		Valuable	60	41.96%	17	65.38%	54	60.67%
		Not Valuable	0	0%	0	0%	0	0%
		Very Unnecessary	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
2	What kind of prescriptive recommendations would you expect from a decision support system to address ASF outbreaks?	Biosecurity	69	48.25%	20	76.92%	35	39.33%
		Surveillance	53	37.06%	3	11.54%	36	40.45%
		Quarantine Measures	14	9.79%	1	3.85%	14	15.73%
		Travel/Trade Restrictions	7	4.90%	2	7.69%	4	4.49%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>

3	How should the web-based decision support system communicate prescriptive recommendations?	Interactive Dashboards	106	74.13%	24	92.31%	14	15.73%
		Email Notifications	46	32.17%	21	80.77%	80	89.89%
		SMS Notifications	102	71.33%	22	84.62%	37	41.57%
		Chat Integrations	38	26.57%	20	76.92%	9	10.11%
4	How likely are you to follow the recommendations provided by a web-based decision support system for ASF management?	Very Likely	69	48.25%	11	42.31%	39	43.82%
		Likely	74	51.75%	15	57.69%	49	55.06%
		Unlikely	0	0%	0	0%	1	1.12%
		Very Unlikely	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>
5	How critical do you think prescriptive analytics is in ensuring timely and effective ASF outbreak control?	Extremely Critical	60	41.96%	10	38.46%	19	21.35%
		Important	80	55.94%	16	61.54%	70	78.65%
		Not Important	3	2.10%	0	0%	0	0%
		Not Critical at All	0	0%	0	0%	0	0%
<b>Total</b>			<b>143</b>	<b>100%</b>	<b>26</b>	<b>100%</b>	<b>89</b>	<b>100%</b>

Table 4 highlights responses on the use of the ASF Decision Support System for prescriptive analytics. Actionable recommendations, such as quarantine measures and resource allocation, were highly valued by all groups, with 58.04% of ASF-related professionals rating them as "Extremely Valuable" and 41.96% as "Valuable." IT professionals and policymakers also found these recommendations useful but to a lesser extent.

Biosecurity was the most widely recommended measure across all groups, with ASF-related professionals and policymakers also highlighting the importance of surveillance, while IT professionals underscored the focus on preventive strategies. The findings regarding the emphasis on biosecurity and surveillance among ASF-related professionals and policymakers are supported by a study titled "Biosecurity measures for the prevention of African swine fever on German pig farms: comparison of farmers' own appraisals and external veterinary experts' evaluations," which highlights the critical role of biosecurity in preventing ASF outbreaks and underscores the importance of surveillance measures in disease management [13]. Preferences for communication methods varied: ASF-related and IT professionals favored interactive dashboards and SMS notifications for real-time updates, whereas policymakers preferred email for formal communication. Adherence to system recommendations was high among ASF-related and IT professionals, with policymakers also showing a strong likelihood of compliance, albeit with greater caution, indicating significant trust in the system's guidance. The variation in communication preferences among different professional groups emphasizes the need for tailored communication strategies to effectively disseminate information during ASF outbreaks [14].

All groups acknowledged the importance of prescriptive analytics, with ASF-related professionals placing the highest emphasis on its role in outbreak control. IT professionals and policymakers also recognized its value, though with slightly less urgency. Overall, the responses highlight the essential

role of actionable recommendations, particularly for biosecurity, surveillance, and quarantine measures, in effective ASF outbreak management.

#### **4. Conclusion and Recommendations**

The African Swine Fever (ASF) outbreak presents a significant threat to the Philippine hog industry, adversely affecting food security, rural livelihoods, and economic stability. Despite concerted government efforts, the persistent spread of ASF reveals critical gaps in response strategies, particularly in biosecurity, monitoring, and resource allocation. Overcoming these challenges necessitates innovative and data-driven solutions to curb the disease's spread and mitigate its socioeconomic impact. This study highlights the potential of integrating Geographic Information Systems (GIS) and advanced spatial clustering algorithms into a web-based decision support system to enhance ASF outbreak management. By offering real-time mapping, interactive dashboards, and predictive analytics, the proposed system can provide stakeholders with actionable insights to implement targeted and efficient interventions. This approach not only aligns with national and global development goals but also underscores the importance of sustainability, resilience, and inclusivity in tackling the ASF crisis.

To address these issues, several recommendations are proposed. First, adopting data-driven decision-making through the implementation of the web-based system is crucial, as it equips policymakers and local government units with tools to monitor ASF trends, identify hotspots, and forecast outbreaks effectively. Second, biosecurity practices must be enhanced, with increased training and financial support for farmers to ensure adherence to protocols at farms, transportation hubs, and slaughterhouses. Third, investment in research and development should be prioritized, fostering collaboration with academic institutions and technology providers to develop and refine geospatial tools and machine learning models for ASF management. Fourth, strengthening public awareness campaigns is essential to educate farmers and rural communities about ASF transmission, prevention, and the importance of prompt case reporting. Fifth, fostering multi-stakeholder collaboration among government agencies, private sectors, and civil society organizations is key to improving resource mobilization, knowledge sharing, and coordinated actions. Finally, integrating sustainable practices, such as supporting income diversification for affected farmers, promoting alternative livestock industries, and implementing environmental safeguards, is necessary to reduce the ecological impact of ASF control measures. By adopting these strategies, the Philippines can bolster the resilience of its hog industry, mitigate the adverse effects of ASF, and contribute to sustainable agricultural development.

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