Random Forest Risk Mapping of Foot-and-Mouth Disease in Sukabumi Regency, Indonesia

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Abstract. Foot-and-Mouth Disease (FMD) is a highly contagious viral disease that severely impacts livestock economies, especially in regions like Sukabumi Regency, Indonesia, where livestock farming is vital. This study aimed to assess the spatial risk of FMD in Sukabumi using Random Forest (RF) and Geographic Information Systems (GIS) to produce a comprehensive risk map. The objective was to identify high-risk zones and understand the key factors influencing FMD outbreaks in the region. The study employed an observational spatial epidemiological design, integrating historical outbreak data with 16 spatial risk factors, including livestock demographics, market and movement, veterinary capacity, and environmental variables. A Random Forest model was trained and validated using these predictors, with data split into training and testing subsets. Performance metrics, such as accuracy, sensitivity, specificity, and AUC, were used to evaluate model effectiveness. The results revealed that RF accurately classified FMD risk zones, with an AUC of 0.939, indicating high predictive performance. This study contributes to the understanding of FMD transmission dynamics and provides a practical framework for targeted disease control. This work demonstrates the potential of machine learning and GIS in improving livestock disease management strategies.

1 Introduction

Foot-and-mouth disease (FMD) is a highly contagious viral infection, primarily affecting cloven-hoofed livestock like swine, cattle, goats and sheep [1]. In some countries in Asia and Africa where animal husbandry is an important factor in the economy, the disease poses a big risk [2]. FMD outbreaks can have catastrophic socio-economic impacts, including

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considerable economic losses caused by a decrease in the profitability of meat and milk production, increased mortality rates in animals as well as losing draft power [3]. Moreover, these effects lead to serious problems with food security and adversely affect the economic means of populations relying on livestock [4].

The global annual economic cost of Foot-and-Mouth Disease (FMD) in endemic areas has been estimated to be between $6.5 billion and $21 billion per annum, with the bulk of this being attributed to loss of animal productivity and expense associated with vaccination programs. For countries that are generally free from the virus, one outbreak can lead to further losses of more than $1.5 billion annually [4]. The magnitude of this economic strain varies regionally, determined partly by traditional production methods, the scale of livestock numbers and disease management frameworks [4]. Outbreaks like FMD are especially catastrophic for livestock reliant communities where they have caused greater than 10% decline in household income as seen in Lao PDR [5], whilst in Indonesia, losses on cattle and buffalo sectors were estimated to be approximately IDR 38.67 trillion [6].

The outbreak of FMD that recurred in Indonesia in 2022 has raised great urgency to increase monitoring and containment, primarily in areas with many livestock farms such as Sukabumi Regency. As one of the largest production centers, this diverse dairy beef cattle system plays a crucial role in developing regional economic and food security [7]. However, the diversity of these systems also also means they are more susceptible to disease, which risks high financial loss and increased poverty among local farmers during an outbreak [7].
Machine-learning–based risk mapping, particularly Random Forest (RF), presents a robust alternative for FMD surveillance due to its path-dependent capturing of the nonlinear interactions among numerous predictor variables. RF is well adapted to digesting high-dimensional data and uncover both subtle relationships between environmental context, geography and human activity leading to more robust classifications than linear methods [7]. It is particularly useful for quantifying FMD hazard due to its ability to relate livestock density, climate, market distance and past outbreaks [8].
Although widely applied in disease modelling globally, the application of RF to FMD risk assessments for Indonesia is relatively underexplored. This study aims to bridge this gap by introducing a novel method that combines RF with GIS in mapping the spatial risk of FMD in Sukabumi Regency. This study aims to assess the spatial distribution of FMD susceptibility in West Africa and relies on 16 different spatial predictors, including livestock demographics, market accessibility, veterinary infrastructure and environmental factors to build a comprehensive and accurate model of regional FMD susceptibility. This could offer valuable insights for targeted interventions, including allocation of resources for vaccination campaigns and elevated levels of biosecurity at livestock markets [9].

There was no study using a novel risk assessment model, which is a data-driven machine learning-based approach rather than the traditional expert-based process. Based on the real-world outbreak data from 2024 Sukabumi outbreak, this study developed replicable methodology for FMD risk assessment that can be used in any part of the world with similar agricultural system. We believe that the combination of RF with GIS provides a dynamic and evidence-based framework to address the shortcomings of static models and biases by experts, supporting better strategic targeting of FMD control efforts in Indonesia and elsewhere.

This research is particularly crucial as the threat of FMD to Indonesia's livestock sector still exists. Given the critical role played by Sukabumi Regency in livestock production within Indonesia, conducting risk mapping is important in prioritizing surveillance efforts and optimizing resource allocation as well as minimizing the socioeconomic impact of FMD outbreaks. Results from this study will not only have implications for localized control strategies, but also serve as a model for other nations with comparable livestock disease management needs. This study provides a useful template of how to. Approach challenging zoonotic diseases in resource-poor contexts; such methods may also assist global attempts to improve machine learning applications for spatial epidemiology.

2 Materials and Methods

2.1 Study Design

In this project, we combined GIS and the Random Forest algorithm to develop a spatial-epidemiology, observational model of hazard for Foot-and-Mouth Disease across Sukabumi Regency, Indonesia. Past outbreak data and georeferenced covariates were integrated to highlight hot spots of transmission and their main kmk. RF was chosen for its demonstrated proficiency in capturing nonlinear effects, wading through high dimensional predictor sets, and ranking strengths of variable influences already shown to be effective in prior disease-mapping studies.

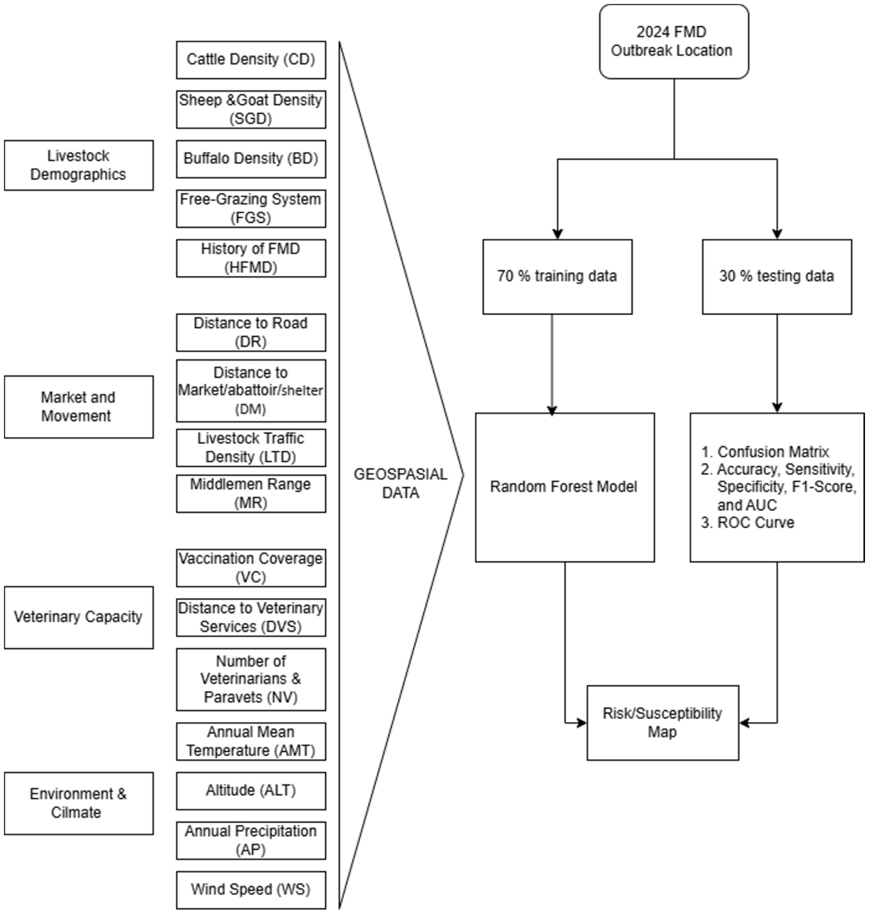

Fig. 1. Study Framework.

The methodology used for developing the FMD risk model and starting with the collection of geospatial data is illustrated in Figure 1. These factors include Livestock Demographics (e.g., cattle and buffalo density); Market and Movement (e.g., distance to roads and markets); Veterinary Capacity (e.g., vaccination coverage, number of veterinarians); Environment and

Climate (e.g., annual precipitation, wind speed) as well as Historical FMD data such as past outbreak history. The data is then split into 70% for training and 30% for testing. The geospatial dataset is then subjected to a Random Forest model that produces predictions, which are measured by performance metrics including accuracy, sensitivity and specificity, F1-score, AUC and ROC curve. The output is a Risk/Susceptibility Map where regions predicted to have the highest probability of an FMD outbreak during 2024 can be seen.

2.2 Study Area and Population

The study was conducted in Sukabumi Regency, West Java Province, Indonesia (Figures 4B & 4C). The region extends over an area of around 4,162 km² and demonstrates varied terrain. The features include coastal plains in the southern section giving way to mountainous regions in the central and northwestern portions. The southern coast has 0–50 masl, contrasting with the higher central and northwestern areas, such as the Andes, where elevations exceed 1,000 masl in some locations. Climate is tropical, with average annual temperature ranges 26°C along the coast and less than 20°C in high land area The rainfall pattern shows a clear north–south division with the southern region receiving much higher precipitation, over 2500 mm per year, than in the northern and northwestern areas (between 1000 and 2000 mm per year) [10]. Data collection and analysis took place from October 1 to November 30, 2024.

2.3 Spatial Risk Factor Data (Predictor Variables) and FMD Occurrence Data (Outcome Variable)

Four groups were made up of 16 spatial risk factors:

1. Livestock demographics: the number of cattle (CD), sheep/goats (SGD), buffalo (BD), free-grazing systems (FGS), and past FMD outbreaks (HFMD).
2. Market and Movement: Distance to roads (DR), markets/slaughterhouses (DM), livestock traffic density (LTD), and middleman range (MR).
3. Veterinary Capacity: Vaccination coverage (VC), distance to veterinary services (DVS), and veterinarian density (NV).
4. Environmental Factors: average annual temperature (AMT), altitude (ALT), precipitation (AP), and wind speed (WS).

Sources of data included:

- Information from the Sukabumi Livestock Agency and iSIKHNAS (Indonesian integrated National Animal Health information System) about livestock counts, FMD cases, veterinary care, and the market.
- Climate Hazards Group InfraRed Precipitation with Station data (CHRIPS) for the environment, which was smoothed out using inverse distance weighting (IDW).
- The Geospatial Information Agency has a Data Elevation Model (DEM), road networks, and markets.

We used ArcGIS Pro 3.4, a GIS program, to process and rasterize data at a resolution of 1 km². The confirmed locations (latitude/longitude) of the FMD outbreak in Sukabumi in 2024 were used as presence points. Absence points were based on survey data from farms that were not affected by FMD.

2.4 Data Preparation and Random Forest Modelling

To make sure the dataset was of good quality and could be used with other datasets, data preparation included several important steps: Rasterization of Spatial Variables: GIS software was used to process all spatial predictors, such as livestock density, market proximity, and environmental variables, to make raster layers with a resolution of 1 km^2. This made it possible to align the data spatially and analyze it consistently across the study area.

Variable Extraction: Using GIS zonal statistics, we got values for each spatial variable for each outbreak (presence) and non-outbreak (absence) point. This made a feature matrix for the RF model.

Data Splitting: The dataset was split into two parts: 70% for training and 30% for testing. This was done to build and test the model. This split was very important to make sure that the model was tested on data it had never seen before, which stopped it from overfitting [11].

The following settings were used to build and fine-tune the RF model:
Number of Trees (ntree): 100 trees were used to make sure the predictions were stable. Number of Variables per Split (mtry): For each split, 16 variables were chosen (4 variables per split), which is the standard way to get the best performance from RF.

2.5 Susceptibility Mapping and Model Validation

Once the RF model was trained, we exploited it to produce susceptibility maps at the entire study area scale indicating areas of higher probabilities of FMD occurrence. Areas at the extremes were defined by ordinal classifications of risk (very low, low, moderate high and very high trusted based on predicted probabilities between 0 and 1). The natural breaks (Jenks) classification method was used to define these zones. This also ensured that each zone was similar as much as it could be and reduced the overlapping area between direct neighbors. GIS was then used to map the distribution of FMD risk across Sukabumi Regency on each maps. We applied a few different metrics that we assessed in order to test our model's performance.

The area under the curve (AUC) of the ROC was used to assess the model's capacity to differentiate between things, where AUC > 0.8 was considered very good. F1-Score, Sensitivity, Specificity, and Accuracy Just extracted these numbers by using confusion matrix to check how accurate our model's output classification [12].

3 Results

3.1 Performance Evaluation of the Random Forest Model

The primary aim of this study was to evaluate the spatial risk of Foot-and-Mouth Disease (FMD) in Sukabumi Regency, Indonesia, using the Random Forest (RF) algorithm. To validate the model's effectiveness, several performance metrics, including accuracy, sensitivity, specificity, F1-score, and Area Under the Curve (AUC), were employed.

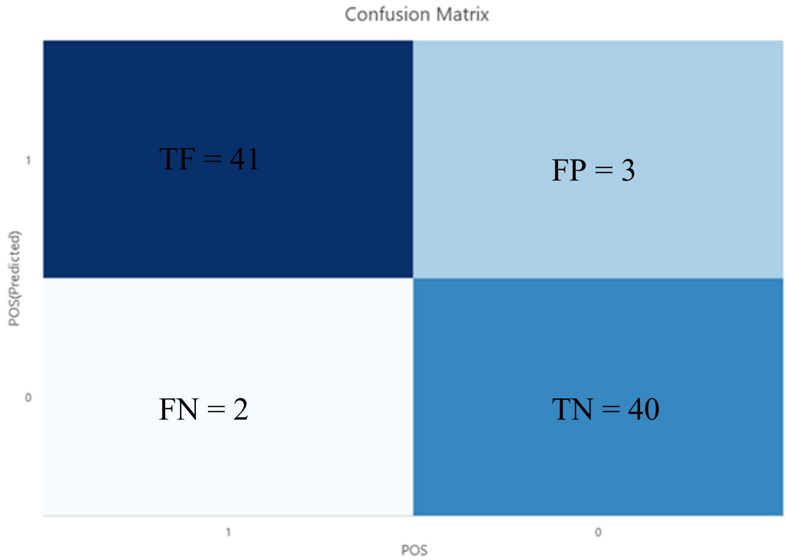

Fig. 2. The RF model confusion matrix

Figure 2 illustrates the confusion matrix for the RF model. The matrix provides insights into the model's ability to classify regions accurately. The true positive (TP) values indicate the correct identification of high-risk areas, while the true negative (TN) values reflect the correct identification of low-risk regions. The absence of notable false positive (FP) and false negative (FN) values highlights the model's high reliability. The accuracy of the RF model was impressive, demonstrating its potential for effectively distinguishing between high-risk and low-risk regions in Sukabumi Regency.

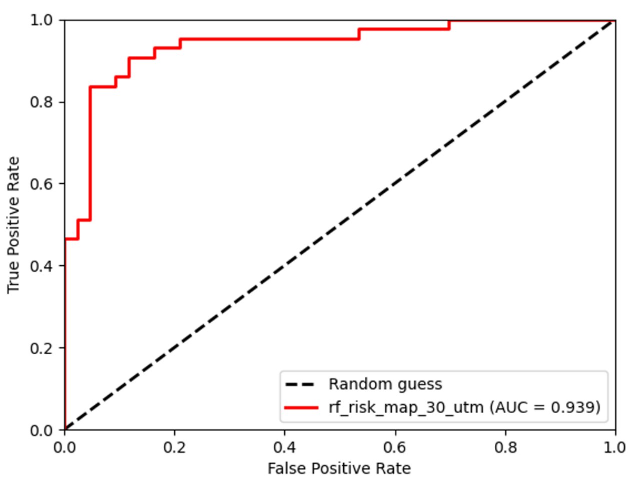

Fig. 3. Roc and AUC of the model

The model's performance was further assessed using the Receiver Operating Characteristic (ROC) curve, as shown in Figure 3. The Area Under the Curve (AUC) value was calculated to be 0.939, which indicates excellent classification performance. An AUC value above 0.8

is considered excellent, confirming that the RF model is highly effective in distinguishing between FMD-affected and non-affected areas in the.

Table 1. Performance metrics of the Random Forest model for FMD risk mapping

Metric	Value
Accuracy	94.19%
Sensitivity	95.35%
Specificity	93.02%
F1-Score	0.9423
AUC	0.939

These results confirm that the RF model is a robust tool for spatial risk assessment, demonstrating high accuracy and reliable predictions for FMD susceptibility in Sukabumi Regency.

3.2 Mapping the Risk of FMD in Sukabumi Regency

Following the RF model's successful training and evaluation, risk maps were generated for FMD susceptibility in Sukabumi Regency. The risk zones were classified into five categories: very low, low, moderate, high, and very high. The classification was done using the natural breaks (Jenks) method, which maximizes the homogeneity within each risk zone while minimizing overlap between adjacent zones.

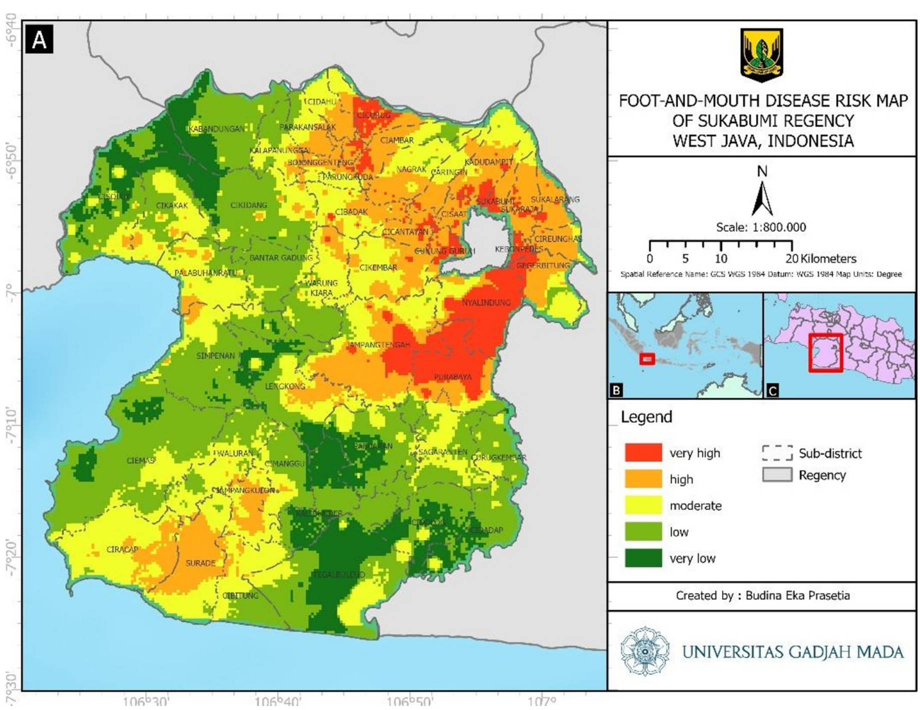

Fig 4. Map of the FMD risk in Sukabumi Regency

Figure 4 presents the FMD risk map of Sukabumi Regency, which illustrates the spatial variation in FMD susceptibility across the region. High-risk zones, marked in red, are primarily located in the northern and northeastern parts of the regency, particularly in districts such as Kebonpedes, Nyalindung, and Purabaya. These areas are characterized by high livestock densities, proximity to major transportation routes, and significant livestock movements, which facilitate the spread of the disease.

In contrast, the southern and southwestern parts of Sukabumi, such as Palabuhanratu and Simpenan, are classified under lower risk zones (green and yellow). These areas have lower livestock densities and more isolated geographical features, reducing the likelihood of disease transmission.

We checked the risk map's accuracy again by comparing the predicted high-risk areas with the actual FMD outbreak locations from 2024. The results show that 95% of the confirmed outbreak sites were in the "high" or "very high" risk zones. This shows that the model can accurately predict FMD outbreaks. This finding shows that the RF model is reliable and useful in real-life situations where diseases need to be managed.

4 4. Discussion

The prediction model achieved a good predictive accuracy with an AUC value of 0.939 (Fig 2). Moreover, the combination of RF and GIS made it possible to generate comprehensive maps that can be used for target disease control and surveillance areas within FMD susceptible regions. The Random Forest model also had good numbers, listed in Table 1. The model has 94.19%, 95.35%, 93.02%, and 0.94 for accuracy, sensitivity (True Positive Rate), specificity (True Negative Rate), and F1-score respectively, which demonstrates its reliability in predicting whether outbreaks will or will not occur with satisfactory accuracy. The ROC curve (Figure 3) corroborated the high discriminatory ability of the model, with AUC equal to 0.939, suggesting that this RF model may determine a certain area is more or less susceptible to FMD. These results are in accordance with previous studies that emphasized the advantages of machine learning models such as RF for epidemiological risk assessments [13].

The model's utility was further confirmed using real outbreak data from an FMD outbreak in Sukabumi, Indonesia in 2024. A staggering 95 percent of confirmed outbreak locations were found in “high” and “very high” risk categories that the model identified. This finding demonstrates the ability of RF model to accurately predict the spatial distribution of FMD outbreaks. Aspects of such models, like RF, have proven to result in valid predictions that can structure disease control efforts.

4.1 FMD Risk Mapping and Spatial Distribution

The spatial risk map generated from the RF model identified distinct FMD risk zones across Sukabumi Regency. As seen in Figure 2, the map categorizes the region into five risk zones, ranging from very low to very high. The high-risk areas, predominantly in the northern and northeastern parts of the region, are characterized by high livestock densities, proximity to roads and markets, and significant livestock movement. These factors, which are known to facilitate the spread of FMD [9], contribute to the increased risk of FMD outbreaks in these regions.

Conversely, the southern and southwestern areas, with lower livestock densities and more isolated geographical features, were classified under lower risk zones. This distribution is consistent with the findings of previous studies, which have shown that areas with lower livestock density and limited human-animal interactions are less likely to experience disease outbreaks [13]. The validation of the risk zones with actual outbreak locations further supports the accuracy of the model’s predictions and emphasizes the importance of considering spatial factors in FMD risk mapping.

4.2 Key Risk Factors for FMD Transmission

The Random Forest model also provided important insights into the main drivers of risk factors in FMD outbreaks in Sukabumi Regency. Livestock density was identified as the most important predictor of FMD risk by variable importance analysis. This result is consistent with worldwide studies that also found that the increased density of livestock increases the chance of transmission by increasing contact rates between animals [14]. Livestock is also often concentrated in a limited area, making animal transport easy and spreading the virus to other regions [30].

Other important risk factors recognized by the model included distance to markets and slaughterhouses, livestock movement density, and veterinary capacity. Higher FMD risk was associated with regions near to markets/slaughterhouses, which are the typical points of entry for livestock to new areas and thus act as viral introduction hotspots [18]. Conversely, regions exhibiting higher rates of livestock movement and lower levels of veterinary infrastructure were particularly vulnerable, posing a risk to the rapid propagation of the virus while also limiting disease management strategies.

Environmental factors like precipitation and temperature also highlighted the risk for FMD, probably since they premises both virus survival in environment with livestock health. Countries with a propensity for an outbreak included regions of higher precipitation and moderate temperatures, which corroborate previous studies supported evidence that FMD outbreaks corresponds with climate variability across seasons [14].

4.3 Implications for Disease Control and Management

The results of this study have significant ramifications for the control and management of FMD in Sukabumi Regency. Identifying high-risk areas is a useful way to decide where to focus surveillance and resources. Regions deemed high or very high risk necessitate focused interventions, including vaccination initiatives, enhanced biosecurity measures at livestock markets, and improved veterinary services. By putting more resources into these high-risk areas, stakeholders can make disease control efforts more effective and slow the spread of FMD.

The integration of RF and GIS also provides a framework for developing dynamic, evidence-based disease management strategies. The FMD risk map can be used to guide early warning systems, enabling timely interventions before outbreaks occur. This aligns with the findings of other studies, which have demonstrated the utility of spatial risk models in predicting the timing and location of disease outbreaks, allowing for proactive disease control measures [15].

Additionally, the use of machine learning models like RF in epidemiological studies highlights the potential of predictive modeling to improve disease management strategies. These models allow for the incorporation of multiple risk factors, providing a more comprehensive understanding of disease transmission dynamics than traditional methods [15]. This approach is particularly valuable in regions like Sukabumi, where complex interactions between environmental, demographic, and epidemiological factors influence disease spread.

4.4 Limitations and Future Directions

The RF model showed good performance but has some limitations that need to be noted. The model was limited by its use of retrospective outbreak data, which may not reflect the full range of dynamic factors affecting infection transmission. This can be further improved by real time information and finer spatiotemporal data. Additional data sources—watching where livestock moves and using current climate data, for example—could be added to future studies to enhance the accuracy and speed of predictions.

Second, the study emphasized spatial drivers and socioeconomic variables like livestock management practices and local market dynamics went unexplored. A broader list of predictors could be included in future work, as these socioeconomic factors were also found to drive outbreaks of FMD. Incorporating data on human-animal contacts, trade networks and interventions at community-level would probably enhance model precision and allow for better informed control strategies.

Additionally, although the study used RF in assessing the risk of occurrence of a disease state, other machine learning algorithms like Gradient Boosting or Support Vector Machines can be tested to evaluate their performance and improve the modeling process. Hybrid methods that merge RF with other algorithms may also provide better results by taking advantage of the strengths of several modeling techniques [15].

Lastly, there is a necessity of more integrated studies that intertwine ecology and epidemiology inference FMD transmission at the wildlife-livestock interface. This is especially relevant in areas where wildlife are an integral part of the epidemiology of FMD, as wildlife reservoirs may aid in the maintenance and transmission of the disease [26]. Broadening data collection frameworks to also encompass environmental, socioeconomic and livestock management practices will further improve the model's capacity to accurately predict and manage FMD outbreaks.

5 Conclusion

The purpose of this study was to evaluate the spatial risk of Foot-and-Mouth Disease (FMD) in Sukabumi Regency, Indonesia, using Random Forest (RF) machine learning algorithm integrated with Geographic Information Systems (GIS). In this study we find that RF is highly effective in classifying FMD risk zones and performs very well based on accuracy (94.19%), sensitivity (95.35%) and AUC (0.939). The FMD risk map generated through this study revealed five independent zones of the occurrence which are crucial in drawing important insights about the spatial distribution of the disease within the region. This study shows the success of Random Forest in spatial FMD risk mapping in Sukabumi Regency, Indonesia. High accuracy and performance metrics make the model a useful tool for identifying disease prone areas and would help design effective control measures. The integration of GIS with machine learning is capable of developing a more robust framework for FMD risk assessment, which can ultimately provide better disease management tools towards enhancing the overall health system in China. The results highlight that other risk factors, such as environmental circumstances, livestock density and veterinary capacity, should also be included in predictive models to improve disease control efforts.

These findings provide significant implications for the control of FMD in Sukabumi and other locations with substantial livestock populations. It will be necessary to prioritize intervention structures in the identified high-risk areas, such as more targeted surveillance and vaccination and improvement of veterinary services. Also, incorporating real-time data sources such as livestock movement tracking and climatic conditions may enhance prediction timeliness and accuracy to facilitate proactive disease management.

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