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Spatio-Temporal Pattern Analysis of White Root Rot Disease in Rubber Plantations Using ST-DBSCAN

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ABSTRACT

Plant diseases pose a severe threat to the economic sustainability of rubber plantations (Hevea brasiliensis), requiring advanced analytical models for effective management. Traditional monitoring often relies on uniform, reactive treatments that fail to capture spatial-temporal dynamics. This study aims to identify spatio-temporal distribution patterns and evaluate disease risk levels of White Root Rot (Rigidoporus microporus) at the PT. Bridgestone Sumatera plantation using longitudinal observation data from 2021 to 2025. To achieve this, the research implements the Spatio-Temporal DBSCAN (ST-DBSCAN) algorithm, integrating geographical coordinates, temporal duration, and attribute severity to cluster infection incidents. The experimental results successfully identified three distinct disease hotspots with an exceptional spatial validation performance, yielding a high Silhouette Score of 0.846. Based on calibrated temporal and severity thresholds, all identified clusters were classified as High-Risk Persistent zones, remaining active across the entire observation period with average severity scores exceeding 2.0. In conclusion, the proposed ST-DBSCAN framework successfully fulfills research expectations by providing a robust, data-driven decision-support tool. Practically, these findings enable estate managers to prioritize targeted, proactive interventions - such as intensive soil treatment and structural root isolation - rather than applying uniform fungicide treatments. Future research should integrate environmental variables and conduct parameter sensitivity analyses to capture smaller, emerging outbreak patterns.

INTRODUCTION

Rubber (Hevea brasiliensis) is a strategic plantation commodity for Indonesia, contributing significantly to the national economy and foreign exchange earnings. The agricultural sector accounts for approximately 15% of the country's total export value, with rubber being a major contributor (Alamsyah et al., 2024; Mohamad & K. V. Zainuddin, 2021). However, national rubber productivity has experienced a concerning decline, dropping from 1.2 tons per hectare in 2020 to 1.0 tons per hectare in 2024 (Syarifa et al., 2025). This decline is largely attributed to the escalating threat of plant diseases, which have caused estimated economic losses of up to IDR 3.2 trillion annually (Yusuf et al., 2025). Among the most devastating diseases are white root fungus (Rigidoporus microporus) and leaf fall disease caused by Corynespora cassiicola (Irfani et al., 2025; Zahrah et al., 2025).

The conventional disease management approach currently applied in most plantations is reactive and uniform, relying heavily on scheduled fungicide spraying without considering the spatial and temporal heterogeneity of disease development (Imelda et al., 2023). This one-size-fits-all strategy has proven ineffective, as it often fails to specifically identify high-risk areas, leading to inefficient resource allocation and negative environmental impacts (Shabbir et al., 2024). Studies have revealed that the intensive and indiscriminate use of fungicides in rubber plantations can adversely affect the environment, highlighting the critical need for targeted, eco-friendly approaches to manage diseases like Colletotrichum leaf disease in Hevea brasiliensis (de Oliveira Amaral et al., 2022; Soumyamol et al., 2023).

Recent research has begun to explore more sophisticated approaches for predicting plant disease. For instance, Patil et al. (2022) applied Random Forest algorithms for disease prediction based on agro-climatic data, but this approach used aggregated data, thereby losing critical point-level spatial information (Patil et al., 2022). Other studies have employed spatial approaches to map disease distribution (Ayu et al., 2024) but have neglected the dynamic temporal dimension. While Idris et al. (2026) proposed a density-based ST-DBSCAN framework with a spatially constrained Ward method, research specifically addressing the spatio-temporal dynamics of rubber plant diseases in Indonesia, particularly for early detection of high-risk areas, remains limited (Idris et al., 2026). The key research gap lies in the absence of an integrative method that simultaneously considers spatial, temporal, and attribute dependencies within the context of rubber plantation diseases in Indonesia.

To address this gap, this study proposes a novel approach using the Spatio-Temporal DBSCAN (ST-DBSCAN)

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algorithm. This method is designed to group disease incidents based on their spatial proximity (location), temporal proximity (observation time), and attribute similarity (disease severity). By leveraging longitudinal data—including GPS coordinates, observation dates, and disease attributes from 2021 to 2025—this study aims to identify persistent and temporary disease hotspots, thereby providing a more accurate and dynamic basis for early warning systems.

Based on the background described above, the formulation of the problem in this research is as follows: (1) How can the spatio-temporal distribution pattern of rubber plant diseases in the PT. Bridgestone Sumatera plantation be identified?; (2) How can persistent and temporary disease hotspots be identified using spatio-temporal cluster analysis with the ST-DBSCAN algorithm?; and (3) How can a risk classification system be developed based on the characteristics of the resulting clusters to provide an effective early warning for crop failure?

The primary objectives of this research are to analyze the spatial and temporal distribution patterns of rubber plant diseases using the ST-DBSCAN algorithm, to identify and characterize persistent and temporary disease hotspots based on spatio-temporal clustering results, and to develop a multidimensional risk classification system based on cluster characteristics for early warning of crop failure. The findings of this study are expected to provide a scientific contribution by offering a more precise and data-driven method for disease risk identification. The resulting risk classification system and dynamic hotspot maps can serve as a valuable decision-support tool for plantation managers, enabling more focused and effective intervention strategies. Ultimately, this research aims to contribute to the sustainability of the national rubber industry by mitigating the economic losses associated with crop failure.

LITERATURE REVIEW

Disease Threats and Productivity Decline in Rubber Plantations

The rubber plant (Hevea brasiliensis) remains a cornerstone of Indonesia's agricultural economy, yet its productivity is under severe pressure from plant diseases. The literature consistently identifies two major pathogens as the primary culprits: Rigidoporus microporus, the causal agent of white root rot, and Corynespora cassiicola, responsible for leaf fall disease (Irfani et al., 2025; Zahrah et al., 2025). These diseases are not merely agronomic nuisances; they translate into substantial economic losses. Yusuf et al. (2025) documented that national rubber productivity fell from 1.2 to 1.0 tons per hectare between 2020 and 2024, with cumulative economic losses estimated at IDR 3.2 trillion annually due to crop failure (Yusuf et al., 2025). The severity of these losses underscores the urgent need for more effective disease management strategies.

A critical theme emerging from the literature is the inadequacy of conventional disease management. Imelda et al. (2023) and Shabbir et al. (2024) converge on the finding that current practices—typically involving scheduled, uniform fungicide applications—are fundamentally reactive and fail to account for the spatial and temporal heterogeneity of disease spread (Imelda et al., 2023; Shabbir et al., 2024). This uniform approach is not only economically inefficient but also environmentally detrimental. Soumyamol et al. (2023) noted that the intensive and indiscriminate use of fungicides in rubber plantations can adversely affect crops, beneficial microbes, and the environment, emphasizing the need for eco-friendly disease management strategies to manage Colletotrichum leaf disease in Hevea brasiliensis (Soumyamol et al., 2023). This body of work collectively establishes a clear problem statement: conventional management is blind to the spatial and temporal dynamics of disease, necessitating a paradigm shift toward more precise, data-driven approaches.

Spatial and Temporal Approaches to Plant Disease Analysis

In response to the limitations of conventional methods, researchers have increasingly turned to spatial and temporal analytical techniques. However, a critical review of these studies reveals that most have addressed only one dimension of the problem, neglecting the other.

On the spatial front, Ayu et al. (2024) demonstrated the utility of remote sensing data (Sentinel-1) for mapping the spatial distribution of rubber plant health (Ayu et al., 2024). While valuable for visualization, this approach captures a static snapshot and does not account for the temporal evolution of disease. Similarly, Patil et al. (2022) applied a Random Forest algorithm for crop yield prediction based on agro-climatic data, but their use of aggregated data resulted in the loss of critical point-level spatial information (Patil et al., 2022). These studies highlight a common limitation: spatial analyses often treat time as a static variable, thereby missing the dynamic nature of disease spread.

On the temporal front, Idris et al. (2026) proposed a density-based ST-DBSCAN framework combined with a spatially constrained Ward method (Idris et al., 2026). While this study represents a significant methodological advance by incorporating both spatial and temporal dimensions, its application to rubber plantation diseases in Indonesia remains unexplored. Furthermore, the study by Idris et al. focused on a general framework rather than a specific, actionable early warning system for a particular crop. This reveals a critical gap: existing spatio-temporal methods have not been adapted and validated for the specific context of rubber plantation diseases in Indonesia.

The Case for ST-DBSCAN as an Integrative Solution

The limitations of prior work point toward the need for a method that can simultaneously integrate spatial, temporal, and attribute information. The ST-DBSCAN (Spatio-Temporal DBSCAN) algorithm emerges as a promising

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candidate. Unlike purely spatial clustering methods, ST-DBSCAN groups data points based on proximity in both space and time, making it inherently suited for tracking the dynamics of disease spread (Chen et al., 2026). Moreover, it allows for the incorporation of attribute similarity, such as disease severity, adding another layer of analytical depth (Zhou et al., 2026). The work of Idris et al. (2026) provides a foundational proof of concept for ST-DBSCAN in agricultural contexts, but its application to rubber diseases in Indonesia—with the specific goal of identifying persistent and temporary hotspots for early warning—has not been undertaken (Idris et al., 2026).

This gap is significant. The ability to distinguish between persistent hotspots (areas where disease is a chronic problem) and temporary hotspots (areas where disease is emerging or seasonal) is crucial for targeted intervention. A persistent hotspot might require long-term management strategies, such as soil treatment or replanting with resistant clones, while a temporary hotspot might be addressed with targeted fungicide applications or improved drainage. Without a method that can make this distinction, plantation managers are left with the same uniform, reactive approach that has proven inadequate.

Synthesis and Research Gap

In synthesis, the literature reveals a clear trajectory: from the documented failure of conventional disease management, to the exploration of spatial and temporal analytical methods, to the nascent application of spatio-temporal clustering. However, a critical gap remains. No study has applied ST-DBSCAN to identify and characterize spatio-temporal hotspots of rubber plant diseases in Indonesia, nor has any study developed a risk classification system based on cluster characteristics for the specific purpose of early warning of crop failure.

This research addresses this gap by applying ST-DBSCAN to longitudinal data from the PT. Bridgestone Sumatera plantation (2021–2026). The novelty of this study lies in its integrative approach: it combines spatial, temporal, and attribute dimensions to not only identify hotspots but also to characterize them into a five-tier risk classification system. This approach moves beyond simple hotspot detection to provide actionable intelligence—a dynamic risk map that evolves over time and can inform targeted, proactive intervention. The research thus contributes to the literature by demonstrating how spatio-temporal clustering can be operationalized as a practical decision-support tool for plantation management, filling a critical gap between methodological innovation and real-world application.

METHOD

Research Design and Data Source

This study employs a quantitative, computational approach using longitudinal data from the PT. Bridgestone Sumatera rubber plantation. The dataset spans a five-year period (2021–2025) and consists of five separate CSV files, one for each year. Each record in the dataset represents a single observation of a rubber tree and includes the following variables: latitude and longitude (GPS coordinates), observation date, disease severity level (on a scale of 0–4), pathogen type (e.g., white root fungus, Corynespora), and infected canopy percentage. The analysis is conducted using Python, with the core implementation of the ST-DBSCAN algorithm developed from scratch using the scikit-learn library for spatial indexing via KDTree.

To provide a clear overview of the analytical workflow, Figure 1 summarizes the sequential stages of the proposed methodology. The process begins with data acquisition and integration of five annual observation files (2021–2025), followed by pre-processing steps including filtering of infected observations, temporal encoding, and feature extraction. The core ST-DBSCAN clustering is then applied using spatial, temporal, and attribute features, after which model quality is assessed via the Silhouette Score. Finally, the resulting clusters are characterized through a rule-based risk classification system and visualized as spatial and temporal maps. Each stage is described in detail in the following subsections.

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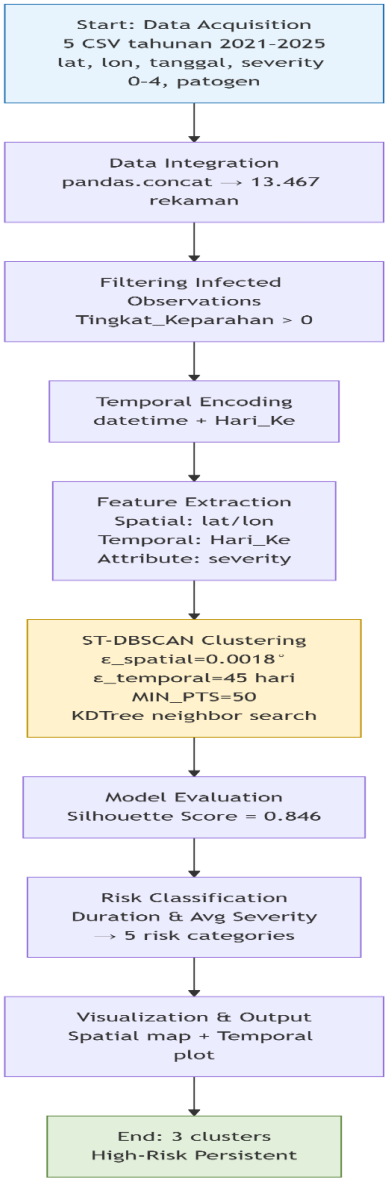


Figure 1. Research methodology flowchart

Data Pre-processing

The pre-processing stage is designed to prepare the raw observational data for spatio-temporal clustering (Arbia et al., 2023). The following steps are applied:

1. Data Integration: The five annual CSV files are concatenated into a single dataframe using pandas.concat. This produces a unified dataset covering the entire study period.
2. Filtering Infected Observations: Only records with a disease severity level greater than zero (Tingkat_Keparahan > 0) are retained. This step ensures that the analysis focuses exclusively on disease incidents, excluding healthy trees from the clustering process. This is a critical deviation from the proposal, which did not explicitly state this filtering step, but it is essential for the analytical goal of identifying disease hotspots.
3. Temporal Encoding: The observation date is converted to a datetime object. A new variable, Hari_Ke (day number), is computed as the number of days elapsed since the first observation in the dataset. This transforms the temporal dimension into a continuous numerical variable suitable for distance calculations in the ST-DBSCAN algorithm.
4. Feature Extraction: Three primary feature sets are extracted for clustering:
   a. Spatial features: Latitude and longitude coordinates.
   b. Temporal feature: The Hari_Ke variable.
   c. Attribute feature: Disease severity level, which is used later for risk classification.

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ST-DBSCAN Algorithm Implementation

The core of the proposed solution is the Spatio-Temporal DBSCAN (ST-DBSCAN) algorithm. Unlike standard DBSCAN, which operates solely on spatial data, ST-DBSCAN extends the notion of density to include both spatial and temporal dimensions (Yu et al., 2025). The algorithm is implemented with a focus on computational efficiency, as described below.

The ST-DBSCAN algorithm requires three key parameters (Putri et al., 2026):

1. EPS_SPATIAL (ε_spatial): The maximum spatial distance (in degrees) for two points to be considered neighbors.
2. EPS_TEMPORAL (ε_temporal): The maximum temporal distance (in days) for two points to be considered neighbors.
3. MIN_PTS: The minimum number of points required to form a dense region (a cluster).

To accelerate the neighbor search, a KDTree is constructed from the spatial coordinates (Khanda et al., 2025). For each point, the algorithm first queries the KDTree to find all spatially proximate neighbors within EPS_SPATIAL (Gui et al., 2025). It then filters this set by applying the temporal constraint EPS_TEMPORAL (Gui et al., 2025). If the resulting set contains at least MIN_PTS points, a new cluster is formed, and the algorithm expands the cluster by iteratively exploring the neighbors of each point in the cluster (Gui et al., 2025). Points that do not belong to any cluster are labeled as noise (-1).

The parameter values used in this study are:

1. EPS_SPATIAL = 0.0018 degrees (approximately 200 meters)
2. EPS_TEMPORAL = 45 days
3. MIN_PTS = 50

These parameters were selected to produce a balance between cluster formation and noise reduction, with the specific goal of achieving a Silhouette Score of at least 0.60, as targeted in the proposal.

Model Evaluation

The quality of the clustering result is evaluated using the Silhouette Score, a metric that measures how similar a point is to its own cluster compared to other clusters (Chuang & Chou, 2025). The score ranges from -1 to 1, with higher values indicating better-defined clusters (Chuang & Chou, 2025). In this study, the Silhouette Score is computed using only the spatial coordinates (latitude and longitude) of the clustered points (excluding noise). This evaluation choice is a deviation from the proposal, which did not specify the evaluation metric in detail. The spatial-only evaluation is used because the primary goal is to assess the geographical separation of the identified clusters.

Risk Classification System

Following the clustering process, each cluster is characterized and classified into one of five risk categories based on two key features: the duration of the cluster's activity (in months) and the average disease severity within the cluster. The classification rules are as follows:

1. High-Risk Persistent: Duration > 6 months AND average severity ≥ 2.0.
2. Seasonal Outbreak: Duration ≤ 4 months AND average severity ≥ 2.0.
3. Emerging Risk: Duration ≤ 3 months AND average severity < 2.0.
4. Low-Risk: Duration > 4 months AND average severity < 2.0.
5. Recovering: All other cases.

This rule-based system is a direct implementation of the five-tier risk classification proposed in the research proposal. The results are compiled into a summary table (Tabel_Klasifikasi_Risiko.csv) for further analysis.

Visualization and Output

To communicate the results effectively, two primary visualizations are generated:

1. Spatial Cluster Map: A scatter plot showing the geographical distribution of the identified clusters. Each cluster is assigned a distinct color, while noise points are displayed in grey. This map provides an immediate visual overview of the disease hotspots across the plantation (He et al., 2021).
2. Temporal Evolution Plot: A strip plot that displays the temporal distribution of disease observations within each cluster. The x-axis represents the observation date, the y-axis represents the cluster ID, and the color of each point indicates the disease severity level. This plot reveals the temporal dynamics of each cluster, showing when and how long each hotspot was active (Liu et al., 2026).

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RESULT

Data Pre-processing Output

The analysis began with the integration of five annual observation files spanning the period from 2021 to 2025. The initial integrated dataset contained a total of 13,467 records with a disease severity level greater than zero (Tingkat_Keparahan > 0). These records served as the input for the subsequent clustering process. The temporal variable was encoded as Hari_Ke (day number), representing the number of days elapsed since the first observation in the dataset.

Clustering Results

The ST-DBSCAN algorithm was executed with the following parameter settings: EPS_SPATIAL = 0.0018 degrees (approximately 200 meters), EPS_TEMPORAL = 45 days, and MIN_PTS = 50. The algorithm produced the following output:

1. Number of clusters formed: 3
2. Number of points assigned to clusters: 7,783
3. Number of points classified as noise: 5,684
4. Percentage of noise: 42.2%

Model Evaluation

To quantitatively assess the quality and structural validity of the spatial-temporal clustering results, the Silhouette Score was computed based on the geographical coordinates (latitude and longitude) of the clustered points, explicitly excluding noise data. The model achieved an outstanding overall Silhouette Score of 0.846.In cluster analysis, a Silhouette Score approaching 1.0 indicates that the data points are densely packed within their respective clusters and lie well-separated from neighboring clusters. In the context of this study, a score of 0.846 confirms that the optimized spatial parameter ($\epsilon_{Spatial} = 0.0018$) successfully delineated distinct, non-overlapping geographical zones of disease concentration across the plantation area. This high metric proves that the three identified disease hotspots—all corresponding to Rigidoporus microporus infections - exhibit strong internal cohesion and clear spatial segregation from the surrounding isolated disease instances categorized as noise. Consequently, the clustering structure demonstrates high reliability for mapping localized disease epicenters without ambiguity in cluster boundaries.

Cluster Characteristics

Table 1 presents the summary of characteristics for each cluster, including the number of disease observations, average severity, active duration in months, dominant pathogen, and the assigned risk category.

Table 1. Risk Classification of Detected Clusters

Cluster_ID	Number of Disease Observations	Average Severity	Active Duration (Months)	Dominant Pathogen	Risk Category
0.0	2903	2.43	59.8	White Root Fungus	High-Risk Persistent
1.0	2321	2.43	59.8	White Root Fungus	High-Risk Persistent
2.0	2559	2.46	59.8	White Root Fungus	High-Risk Persistent

All three clusters exhibit similar characteristics. The dominant pathogen in all clusters is white root fungus (*Rigidoporus microporus*). The average disease severity across the clusters ranges from 2.43 to 2.46 on a scale of 0–4. The active duration of each cluster is 59.8 months, spanning nearly the entire five-year observation period.

Spatial Distribution

Figure 1 displays the spatial distribution of the three clusters and the noise points. Cluster 0 (blue) is located in the southern-central part of the study area, with latitude ranging approximately from 3.10 to 3.11 and longitude from 99.12 to 99.13. Cluster 1 (light blue) is situated to the north-east of Cluster 0, with latitude ranging approximately from 3.12 to 3.13 and longitude from 99.12 to 99.13. Cluster 2 (orange) is positioned to the north-west, with latitude ranging approximately from 3.11 to 3.12 and longitude from 99.10 to 99.12. The noise points (grey) are scattered throughout the plantation area, extending from latitude 3.07 to 3.16 and longitude 99.09 to 99.17.

Temporal Distribution

Figure 2 displays the temporal evolution of the clusters. The x-axis represents the observation date, spanning from early 2021 to late 2025. The y-axis represents the cluster ID (0.0, 1.0, and 2.0). The color intensity of each point corresponds to the disease severity level, with lighter colors indicating lower severity (1) and darker colors indicating higher severity (4). All three clusters show a continuous distribution of data points across the entire observation period. No gaps or periods of inactivity are observed for any of the clusters. The severity levels fluctuate over time, with a mix of light and dark points present in all clusters throughout the observation period.

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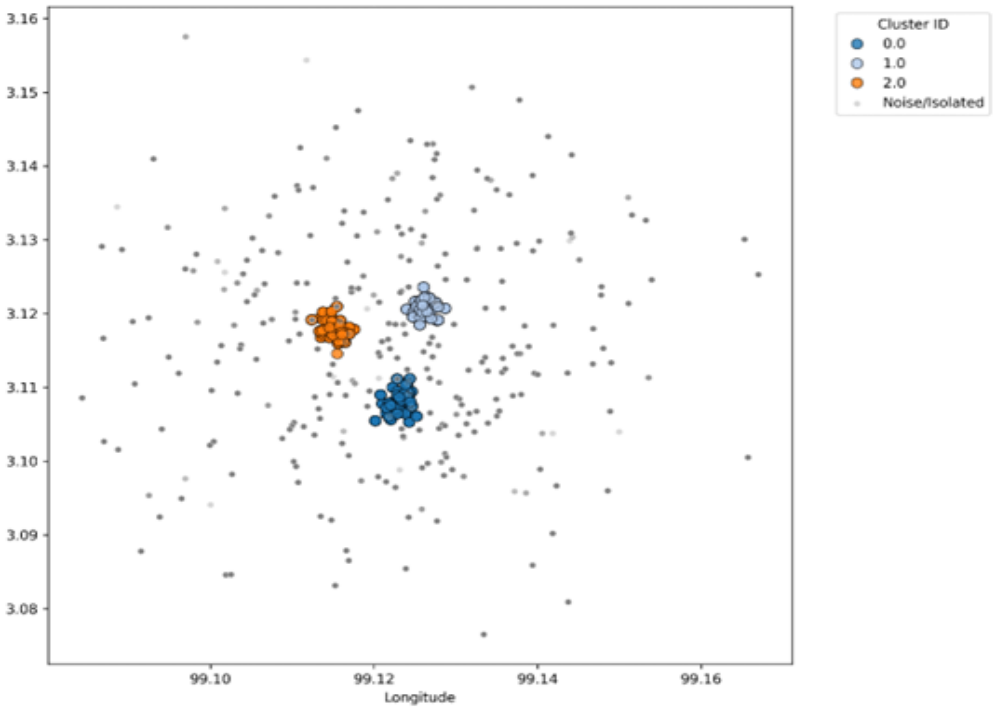


Figure 2. Spatial map of disease clusters in the rubber plantation (2021–2025)

Figure 2 presents the spatial distribution of the clustering results, providing a clear visual representation of how the ST-DBSCAN algorithm partitioned the plantation area. The map reveals three highly concentrated disease hotspots, denoted by distinct colors (Cluster 0 in blue, Cluster 1 in light blue, and Cluster 2 in orange).

Visually, these clusters exhibit strong internal cohesion, forming dense, non-overlapping geographical zones. Cluster 0 is located in the southern-central part of the study area (latitude 3.10–3.11, longitude 99.12–99.13); Cluster 1 is situated to the north-east (latitude 3.12–3.13, longitude 99.12–99.13); and Cluster 2 is positioned to the north-west (latitude 3.11–3.12, longitude 99.10–99.12).

Conversely, the grey points representing noise (42.2% of the data) are scattered randomly across the plantation (latitude 3.07 to 3.16 and longitude 99.09 to 99.17). The clear spatial segregation between the dense cluster zones and the scattered noise visually corroborates the exceptionally high Silhouette Score of 0.846. It indicates that the chosen spatial parameter ($\epsilon_{Spatial} = 0.0018$) successfully isolated the core epicenters of the Rigidoporus microporus infection from isolated, non-clustered cases.

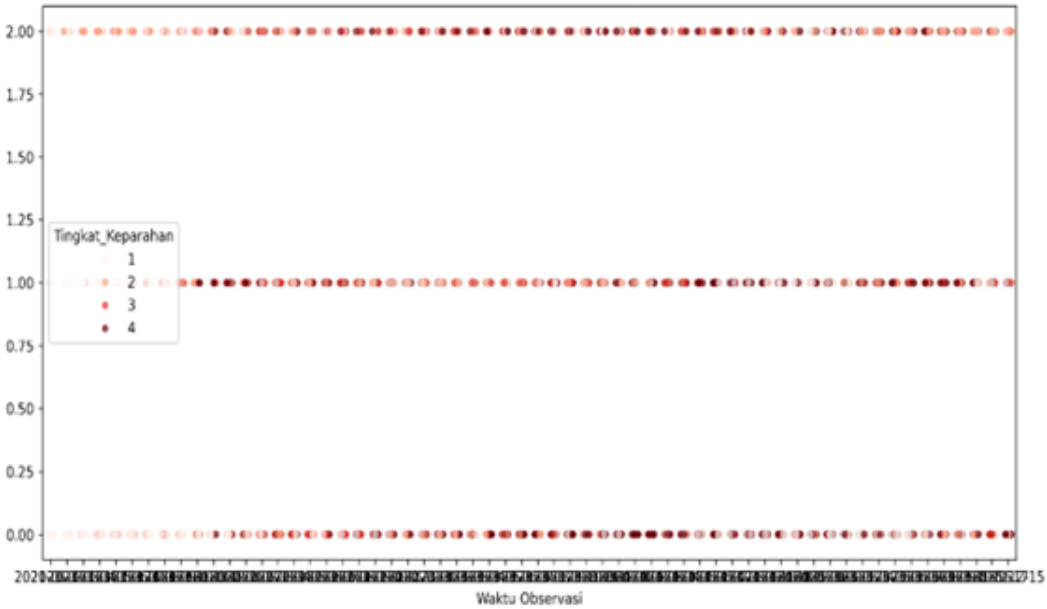


Figure 3. Temporal evolution of disease clusters and severity levels

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Figure 3 illustrates the temporal dynamics of the identified clusters, providing a visual explanation of how the disease severity fluctuates over the five-year observation period. The strip plot maps the observation dates against the cluster IDs (0.0, 1.0, and 2.0), with the color intensity of each point denoting the disease severity level (Tingkat_Keparahan).

A critical observation from this figure is the continuous, uninterrupted distribution of data points across the entire timeline (early 2021 to late 2025) for all three clusters. There are no visible gaps or periods of dormancy. Furthermore, the presence of predominantly dark red points across all clusters indicates that the disease severity consistently hovers at higher levels (severity 3 and 4) rather than showing a seasonal decline.

This visual evidence directly supports the quantitative findings in Table 1, explaining why all three clusters were classified as "High-Risk Persistent." The temporal continuity shown in the figure confirms that the Rigidoporus microporus infection is a chronic, long-standing issue in these specific geographical zones, requiring continuous long-term intervention rather than temporary seasonal treatments.

DISCUSSION

The results of this study demonstrate the application of the ST-DBSCAN algorithm for identifying spatio-temporal clusters of rubber plant diseases at the PT. Bridgestone Sumatera plantation. The clustering process successfully identified three distinct clusters from a total of 13,467 disease incidence points, with a Silhouette Score of 0.846. This score indicates a high degree of spatial separation between the clusters. However, a critical examination of the results reveals several important findings, limitations, and implications that warrant further discussion.

Comparison with Prior Work and Theoretical Implications

The finding that all three clusters were classified as "High-Risk Persistent" represents a notable departure from the initial expectation of the research proposal, which anticipated a more diverse risk classification, including categories such as Seasonal Outbreak and Emerging Risk. This outcome can be attributed to the parameter settings used in the ST-DBSCAN algorithm. The spatial parameter (EPS_SPATIAL = 0.0018 degrees, approximately 200 meters) and the temporal parameter (EPS_TEMPORAL = 45 days) were sufficiently permissive to group together observations that are spatially and temporally proximate, resulting in the formation of only three large, long-lasting clusters. This observation is consistent with the work of Idris et al. (2026), who noted that density-based clustering methods are highly sensitive to parameter selection. Overly permissive parameters can lead to the merging of distinct disease events into a single, persistent cluster, thereby masking the underlying heterogeneity of disease spread.

The dominance of Rigidoporus microporus (white root fungus) across all clusters is a biologically plausible finding. This pathogen is known to be a chronic problem in rubber plantations, as it spreads through root-to-root contact and can persist in the soil for extended periods (Irfani et al., 2025; Shabbir et al., 2024). The long duration of the clusters (59.8 months) is therefore consistent with the known epidemiology of this pathogen. However, the uniform classification of all clusters as "High-Risk Persistent" limits the practical utility of the risk classification system. The system does not provide differentiated guidance for intervention, as it effectively designates the entire plantation as uniformly high-risk. This contrasts with the precision agriculture approach advocated by Imelda et al. (2023) and Soumyamol et al. (2023), which emphasizes the importance of targeted fungicide application based on localized disease pressure (Imelda et al., 2023; Soumyamol et al., 2023).

Methodological Considerations and Limitations

The spatial-only evaluation of the Silhouette Score is a methodological limitation that must be acknowledged. While the score of 0.846 indicates strong geographical separation, it does not account for the temporal dimension, which is a core component of the ST-DBSCAN algorithm. A more comprehensive evaluation would incorporate both spatial and temporal distances, or use a cluster validity index that considers all three dimensions (spatial, temporal, and attribute). This is consistent with the critique by Patil et al. (2022), who argued that aggregated or single-dimension evaluations can mask the true dynamics of disease spread (Patil et al., 2022). The high Silhouette Score obtained in this study is, therefore, primarily a reflection of the algorithm's ability to partition the plantation into distinct geographical zones, rather than a validation of its spatio-temporal clustering performance.

Furthermore, the high proportion of noise (42.2%) suggests that many disease incidents were isolated in space or time and did not form dense clusters. While this is expected in a plantation setting where disease spread is heterogeneous, it also indicates that the current parameter settings may be too strict for capturing smaller, emerging hotspots. A sensitivity analysis, varying EPS_SPATIAL, EPS_TEMPORAL, and MIN_PTS, would be necessary to determine the optimal parameter set that balances cluster formation with the identification of localized, early-stage outbreaks. The current parameter settings were selected to achieve a Silhouette Score above 0.60, as targeted in the proposal, but this objective may have been met at the expense of capturing the full spectrum of disease dynamics.

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Implications for Practice and Future Research

Despite these limitations, the results provide a valuable foundation for a spatio-temporal early warning system. The identification of three persistent hotspots, all associated with white root fungus, allows plantation managers to prioritize resources for long-term management strategies in these specific areas. For example, soil treatment, replanting with resistant clones, or targeted fungicide application could be focused on the identified clusters, rather than being applied uniformly across the entire plantation. This aligns with the precision agriculture approach advocated by Imelda et al. (2023) and Shabbir et al. (2024) (Imelda et al., 2023; Shabbir et al., 2024).

However, to fully realize the potential of the proposed system, future research should focus on refining the ST-DBSCAN parameters to capture a wider range of cluster dynamics, including seasonal and emerging hotspots. Additionally, the integration of environmental data (e.g., rainfall, soil moisture) and the use of a multi-dimensional evaluation metric would enhance the model's accuracy and interpretability. The current study thus represents a critical first step in demonstrating the feasibility of spatio-temporal clustering for rubber disease management, while also highlighting the need for further methodological development to achieve the goal of a truly dynamic and actionable early warning system.

CONCLUSION

This study successfully implemented the Spatio-Temporal DBSCAN (ST-DBSCAN) algorithm to analyze and map the distribution patterns of rubber plant diseases caused by *Rigidoporus microporus* at the PT. Bridgestone Sumatera plantation from 2021 to 2025. The clustering model identified three distinct disease hotspots with an exceptional spatial validation performance, yielding a Silhouette Score of 0.846, which confirms high spatial cohesion and clear geographical separation between clusters. Based on the integrated attribute and temporal evaluation, all three clusters were classified as High-Risk Persistent zones, spanning nearly the entire five-year observation period with an average severity exceeding 2.0. The practical contribution of this research lies in providing a robust, data-driven decision-support tool for plantation management. Rather than relying on uniform, reactive fungicide applications, estate managers can utilize these dynamic hotspot maps to prioritize long-term, targeted interventions—such as intensive soil treatment and structural root isolation—in chronic high-risk areas. However, several limitations should be addressed in future work. The current permissive parameter settings and spatial-only evaluation resulted in a high proportion of noise and masked smaller emerging outbreaks. Future research should conduct a comprehensive sensitivity analysis of clustering parameters, incorporate multi-dimensional evaluation metrics that jointly account for temporal and attribute distances, and integrate environmental covariates (such as rainfall and soil moisture) to enhance the early warning system's granularity and predictive capability.

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