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Spatial distribution of fatal yellowing cases in oil palm plantations in the Eastern Amazon

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Abstract
Fatal yellowing (FY) is a lethal and poorly understood disease that threatens the sustainability of oil palm (*Elaeis guineensis* Jacq.) cultivation in the Amazon region. Despite decades of research, its etiology remains unknown, and its spatial dynamics are still unclear, particularly under different cultivation systems. This study aimed to characterize and compare the spatial distribution of FY cases in oil palm plantations under organic and conventional cultivation systems in the Eastern Amazon. Field data were collected monthly from December 2012 to March 2014 in four plots located in Acará, Pará State, Brazil. Each plant was evaluated for the presence or absence of FY symptoms, and geostatistical analyses were applied to assess spatial dependence and disease aggregation patterns using spherical, exponential, and Gaussian models. The results indicated a predominance of aggregated spatial distribution in both cultivation systems, with stronger spatial dependence observed in plots with higher FY incidence. The disease tended to cluster within a radius of up to 220 m, with hotspot formation often near access roads. These findings suggest the possibility of a biotic dissemination mechanism and support the development of targeted surveillance strategies. By quantifying the spatial behavior of FY, this study provides a technical basis for implementing localized monitoring and management practices in oil palm plantations, contributing to early detection and more effective disease control.

Keywords *Elaeis guineenses* · Variogram · Plant disease · Epidemiology

1 Introduction

Elaeis guineensis (Jacq.) is an oilseed crop with significant potential for oil and biomass production, noted for its economic and social importance in various countries [1, 6]. It is an excellent alternative for renewable energy generation.

According to the USDA [20], global palm oil production in the 2023 season reached approximately 74.3 million tons, surpassing soybean oil production, which was 62.4 million tons. In this context, the leading producers were Indonesia, Malaysia, and Thailand, with outputs of 47.0 million tons, 19.0 million tons, and 3.2 million tons respectively. Brazil

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produced 585,000 tons, ranking tenth among global producers, also behind Colombia (1.9 million tons), Nigeria (1.5 million tons), Guatemala (920,000 tons), Papua New Guinea (820,000 tons), Ivory Coast (600,000 tons), and Honduras (595,000 tons).

In Brazil, 200,527 hectares of oil palm were cultivated, with most of these areas located in the eastern Amazon region. Pará, the Brazilian state highlighted in this research, is the largest producer in the country, accounting for about 98% of national production, with significant contributions from the municipalities of Tailândia, Tomé-Açu, and Bonito. The study area for this research is within the municipality of Acará, the seventh-largest producer in the state [11].

Fatal Yellowing (FY) is a plant disease [14, 21] and the most severe phytosanitary problem faced by oil palm cultivation in Latin American countries [5, 19]. In Brazil, the disease was detected in Pará in 1980, eradicating over two thousand hectares of oil palm plantations [15]. FY is the main obstacle to the expansion of oil palm cultivation in Pará and poses significant risks to the investments being made in Brazil's oil palm production chain.

The main characteristic of Fatal Yellowing (FY) is the yellowing of the basal leaflets of the intermediate leaves (3, 4, 5, and 6), which necrotize at the leaflet tips and progress to total leaf desiccation. The disease can present different symptoms and conditions at any stage of plant development. The expression of FY and the development of its symptoms can follow different stages, depending on the environmental, spatial, and temporal conditions of the cultivation [7, 9].

One of the first steps for effective pest control is understanding the dispersion process. Studies by Bergamin Filho et al. (1998) and Laranjeira et al. [15] attribute the origin of the problem to abiotic factors. Clarifying the mode of FY dissemination is crucial for developing effective combat and control strategies.

Although some previous studies have applied geostatistical analyses to assess FY spatial patterns (e.g., [15, 16, 18]), these efforts were often limited to isolated plantations or did not compare different cultivation systems. This study is innovative in combining geostatistical modeling with a comparative approach between organic and conventional oil palm plantations over a two-year monitoring period in the Eastern Amazon.

Therefore, this study fills a critical gap by applying geostatistical models to compare the spatial distribution of FY cases in both organic and conventional oil palm plantations. The findings aim to advance current knowledge on FY epidemiology and support the development of targeted monitoring and control strategies based on spatial dependence metrics.

We hypothesized that the spatial distribution of Fatal Yellowing (FY) in oil palm plantations follows an aggregated pattern that varies depending on the cultivation system (organic vs. conventional). Therefore, the objective of this study was to apply geostatistical models to characterize and compare the spatial patterns of FY in both systems, providing insights into potential mechanisms of disease spread and management implications.

2 Materials and methods

Field data were collected monthly over a 16-month period, from December 2012 to March 2014, in four plots located on the Companhia Palmares da Amazônia (CPA) farm, owned by the Agropalma Group, in the municipality of Acará, Pará State, Brazil. The collection period encompassed both the rainy season (typically from January to May) and the dry season (from August to November), allowing the assessment of FY behavior under varying climatic conditions. The study area was selected based on the presence of early-stage FY cases and its representativeness for oil palm cultivation in the Eastern Amazon.

Two plots from conventional planting systems (J25 and J26) and two from organic planting systems (H13 and H14) were selected. Plots J25 and J26, with central geographic coordinates of 02°18′13″ S; 48°40′03″ W and an average altitude of 21 m (AMSL), are bordered by forest to the north and west, and by oil palm plantations in other directions. Plots H13 and H14, with central geographic coordinates of 02°15′51″ S; 48°39′23″ W and an average altitude of 26 m (AMSL), are bordered by forest to the west and by oil palm plantations in other directions (Fig. 1). The plot sizes are 36.49 ha (H13), 36.06 ha (H14), 41.71 ha (J25), and 35.86 ha (J26).

The cultivation area contains a variety of genetic material, with a spacing of 9 m between plants arranged in an equilateral triangle configuration. The plots were planted in 1996 for the conventional system and in 2000 for the organic system.

The climate is classified as Ami according to the Köppen [13] classification, with higher precipitation from January to May and lower precipitation from August to November, averaging 2,430.4 mm annually. The average annual temperature is approximately 26 °C, with a relative humidity of 80%. The predominant soil type in the study area is Yellow Latosol, with a medium-clay texture [10].

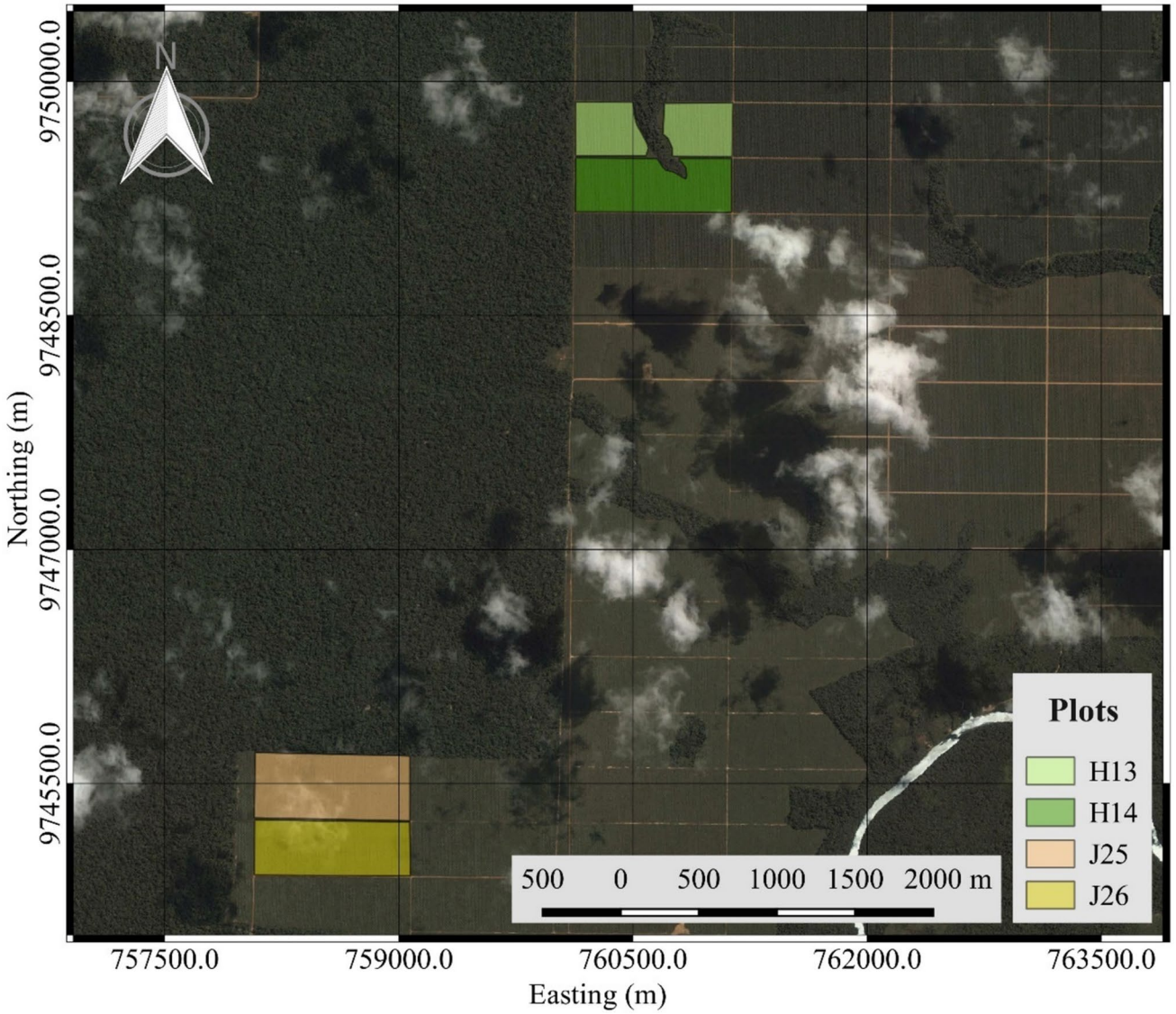


Fig. 1 Geographical location of the evaluated oil palm plots (organic and conventional) in the municipality of Acará, Pará State, Eastern Amazon. The map shows the spatial arrangement and environmental context of the experimental areas used for data collection

The property was chosen due to the presence of early-stage FY cases (between 4 and 10%). The plants in each plot were georeferenced, and information on the disease occurrence was collected monthly by observing each plant for typical FY symptoms, using a presence (1) or absence (0) method.

All data collectors received prior training, based on standardized, symptom identification protocols developed in collaboration with phytopathology experts. The training included field demonstrations and calibration exercises to ensure consistency in symptom recognition. Inter-observer variability was minimized by assigning the same observers to specific plots throughout the study period, and periodic cross-evaluations were conducted to ensure uniformity in diagnoses.

At the end of the survey, a total count of diseased plants was conducted to define the dispersion pattern in each plot over time. The data were subjected to geostatistical analysis to verify the existence of spatial dependence through the experimental variogram, described by (Eq. 1):

$$y^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z\left(x_i + h\right)\right]^2 \quad (1)$$

where N(h) is the total number of plant pairs separated by a distance h. The plot of γ*(h) versus the corresponding values of h is called a variogram, which depends on the magnitude and direction of the distance. In cases of spatially dependent variables, the difference [Z(xi)—Z(xi + h)] is expected to increase with distance until it stabilizes at a threshold, symbolized by C, which numerically approximates the variance of the data. The coefficient of determination (R^2) was used for fitting and selecting the best model.

In geostatistics, spatial dependence refers to the degree to which the values of a variable (in this case, FY incidence) at nearby locations are correlated. When a variable exhibits spatial dependence, it means that nearby observations tend to have similar values, and this relationship can be quantified using a variogram.

The experimental variogram is a graphical tool that shows how the similarity between data points changes with distance. It plots the average squared difference between pairs of observations as a function of the distance separating them. The shape of the variogram provides insight into the spatial structure of the data.

A pure nugget effect (PNE) occurs when the variogram shows no spatial structure — that is, the variability between points is essentially random and does not depend on distance. This typically indicates a lack of spatial dependence, or that the sampling scale is too coarse to detect it.

Variogram fitting involves adjusting theoretical models (such as spherical, exponential, or Gaussian) to the experimental variogram to mathematically represent the spatial structure. This process allows the estimation of key parameters: the nugget effect (C_0), the sill ($C_0 + C_1$), and the range (a) — the distance over which spatial dependence exists. These parameters are critical for subsequent interpretation and spatial predictions (e.g., via kriging).

The strength of spatial dependence was classified using the Spatial Dependence Index (SDI) proposed by Seidel and Oliveira [17], which quantifies the proportion of total variance explained by the spatial component. Using the parameters defined in the variogram fitting (C_0, C_1, and a), the portion of variability due to spatial dependence was calculated and classified according to the SDI thresholds.

The spherical, exponential, and Gaussian models were selected because they are the most commonly used and widely recommended theoretical models for analyzing plant disease spatial patterns, particularly when working with presence-absence data and aggregated distributions. These models offer flexibility in capturing different spatial structures: the spherical model is often used to describe phenomena with a defined range beyond which spatial dependence no longer exists; the exponential model captures shorter-range correlations with a gradual decrease in similarity; and the Gaussian model is suitable for smoother spatial gradients and high continuity. The use of multiple models allowed for better fitting to the empirical variograms, with model selection based on the coefficient of determination (R^2) and visual assessment of residuals.

The methods adopted have been widely used in spatial epidemiology of plant diseases and are particularly effective for detecting aggregation patterns in presence/absence data, which are common in large-scale field studies such as this one.

Although soil parameters and bioclimatic variables are known to influence disease dynamics, they were not incorporated into the present geostatistical analysis. The primary objective of this study was to assess the spatial distribution of FY cases based solely on field-observed presence/absence data. This approach allows for the identification of aggregation patterns without the influence of covariates, serving as a baseline for understanding the spatial behavior of the disease. However, future studies should consider incorporating environmental covariates such as soil moisture, temperature, elevation, and organic matter content to evaluate their potential role in FY dissemination and severity.

3 Results and discussion

The incidence of FY over the evaluation months in the four experimental plots is shown in Fig. 2. The first cases of FY in the conventional planting were identified only in the first half of 2013, about five months after the experiment began. In the second half of the evaluation period, a significant increase in incidence was observed in all plots. During this period, the incidence of FY in the conventional planting plots increased by an average of 304%, while the organic planting plots showed an average growth rate of 131%.

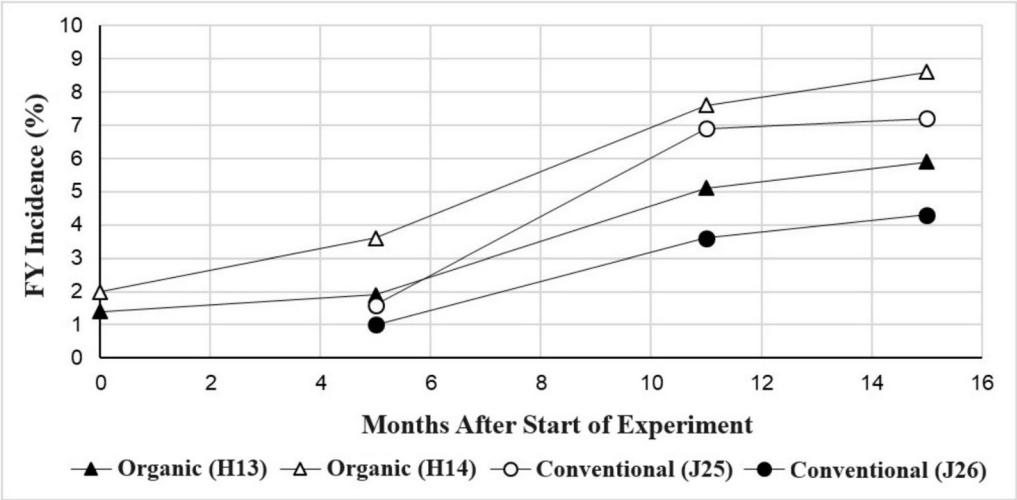


Fig. 2 Monthly incidence of Fatal Yellowing (FY) cases in oil palm plots under organic and conventional cultivation systems from December 2012 to March 2014. The figure illustrates the temporal dynamics and contrasting progression rates of the disease across different management systems

The spatial pattern of FY was described by spherical and Gaussian models for organic cultivation, and by spherical and exponential models for conventional cultivation (Table 1). Additionally, for organic cultivation, a lack of spatial dependence (pure nugget effect) was observed in the first two evaluations of plot H14.

It is noteworthy that the occurrence of a pure nugget effect at the onset of FY incidence may indicate that the initial incidence is random. However, as the disease progresses, its pattern evolves into spatially dependent forms, characterized by the fit of Gaussian models. Additionally, even with a low incidence of FY (1.4%), it is possible to observe the aggregation of cases in plot H13 under the same type of cultivation.

The fitting of data to Gaussian, spherical, and exponential models confirms field observations by revealing clusters of plants (hotspots) affected by FY. These findings are consistent with those of Sales [16], who also identified the occurrence of plant clusters with FY in plots with low incidence levels. However, Sales [16] asserts that incidences greater than 15% make it difficult to identify the spatial distribution pattern of FY.

Table 1 Parameters and models of variograms fitted to data on plants affected by FY in the municipality of Acará, Pará, in organic and conventional cultivation plots (2012–2014)

Plot	Period	C_0	C_1	$a(m)$	Model	R^2	SDI (%)	Degree of Dependence
Organic cultivation								
H13	Dec/12	0.009	0.001	20.700	Spherical	0.920	0.270	Weak
	Jun/13	0.012	0.001	21.000	Spherical	0.810	0210	Weak
	Dec/13	0.042	0.005	150.000	Gaussian	0.990	2.820	Weak
	Mar/14	0.047	0.008	170.000	Gaussian	0.980	4.360	Weak
H14	Dez/12	–	–	–	PNE	–		–
	Jun/13	–	–	–	PNE	–		–
	Dec/13	0.062	0.008	210.000	Gaussian	0.900	2.260	Weak
	Mar/14	0.070	0.010	220.000	Gaussian	0.920	2.590	Weak
Conventional cultivation								
J25	Jun/13	0.015	0.001	42.300	Spherical	0.920	0.180	Weak
	Dec/13	0.075	0.017	76.000	Exponential	0.970	0.800	Weak
	Mar/14	0.078	0.017	78.500	Exponential	0.980	0.800	Weak
J26	Jun/13	0.007	0.002	19.200	Spherical	0.910	0.300	Weak
	Dec/13	0.030	0.004	22.000	Spherical	0.980	0.180	Weak
	Mar/14	0.035	0.005	24.400	Spherical	0.930	0.210	Weak

SDI spatial dependence index, *PNE* pure nugget effect

The presence of spatial aggregation observed in this study corroborates the findings of Sales [16], who reported FY clustering in early stages of disease development. Similarly, Silva et al. [18] identified non-random patterns of FY in organic plantations, though using different spatial analysis techniques. Our study advances these findings by applying geostatistical models, which not only confirmed the aggregation pattern but also quantified the spatial range of dependence. Interestingly, the increasing range observed with higher incidence levels suggests a dynamic spread behavior, possibly indicating a shift from localized infection to a more widespread dissemination. This pattern is consistent with the two-stage epidemic progression described by Drenth et al. [9] and observed in other pathosystems, where initial random cases evolve into structured foci, reinforcing the hypothesis of a biotic agent associated with the disease.

The spatial dependence index of FY incidence was considered weak, according to the classification proposed by Seidel and Oliveira [17], for all evaluated situations. However, the fitting of variograms (Table 1) with coefficients of determination (R^2) greater than 0.80 is an excellent indication of the good fit of the models in the disease dispersion process in the evaluated plots.

The range of spatial dependence is a fundamental parameter in interpreting the variogram, indicating the distance over which sample points are correlated with each other. Thus, points located within a radius are more similar to each other than those separated by greater distances.

The smallest range of the variogram in organic planting plots was 20.70 m (H13) at twelve months from the beginning of the study, and the largest was 220.00 m (H14) at the end of the study. In conventional planting, the range (a) ranged from 19.20 (J26) to 78.50 m (J25). In the case of studying the spatial distribution of diseases, the range can be an excellent tool for identifying the distance for possible control measures.

It is worth noting that in both planting systems (organic and conventional), the range (reach) was always less than 220 m (Table 1). Furthermore, it is observed that with the increase in FY incidence (Fig. 2), the range also increases, showing a positive linear correlation ($r = 0.797$; $p = 0.002$) between them.

It is observed that the highest numbers of diseased plants are located near the access roads (Fig. 3). The proximity to the access road may have contributed to the higher occurrence of FY due to the dispersal process. The increased circulation of winds, animals, and greater light penetration may have somehow contributed to the advancement of the disease.

It was also noted that groups of affected plants were located near the edges of the plots. These areas likely have conditions that are more favorable for the occurrence of FY.

The emergence of new diseased plants near those with FY may indicate abiotic origin of the disease, as plants with FY influence the condition of immediately adjacent plants.

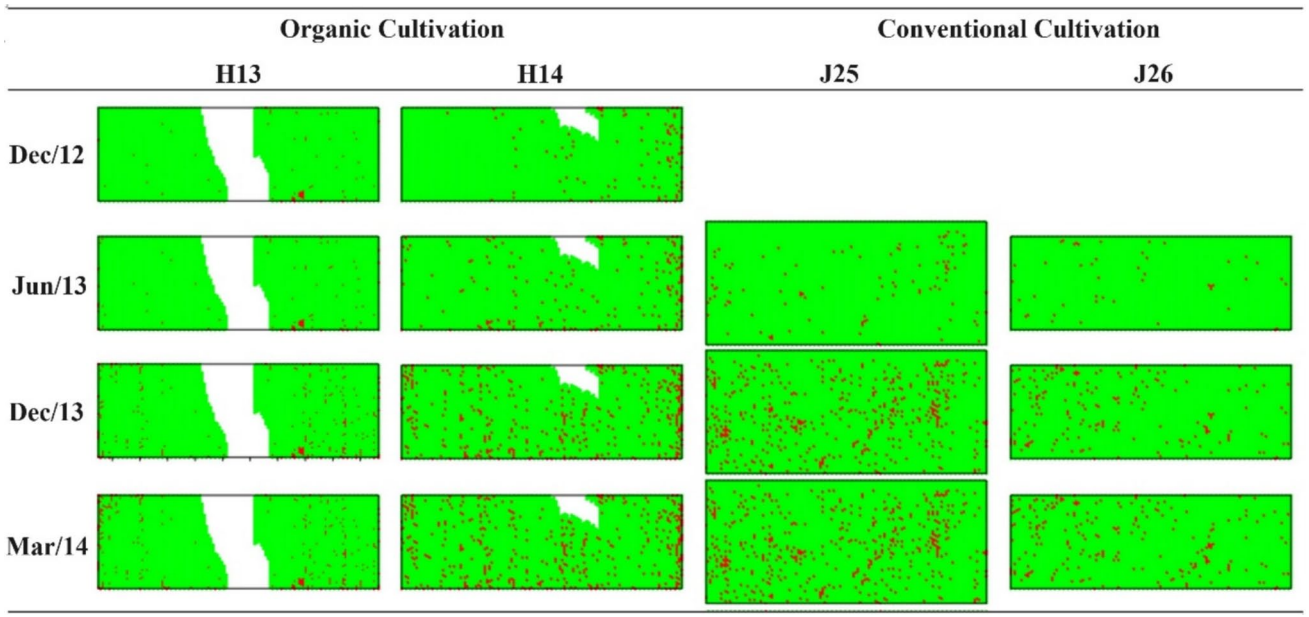


Fig. 3 Spatial distribution of fatal yellowing (FY) cases (red) and healthy plants (green) in organic and conventional oil palm plots. Areas with a higher concentration of red points represent "hotspots" of disease incidence, suggesting spatial aggregation potentially linked to biotic spread. Note the proximity of several hotspots to access roads, which may indicate environmental or management-related factors influencing disease dissemination

The fact that more cases are found near access roads and away from streams supports the findings of Sales [16].

Environmental factors may also play a key role in shaping the observed spatial patterns. For instance, Anhê et al. [4] observed a higher FY incidence in areas near watercourses, suggesting that soil moisture could predispose plants to the disease. Although our study identified more FY cases near access roads, where moisture is not necessarily higher, both scenarios reinforce the multifactorial nature of FY. These spatial trends could reflect complex interactions between plant susceptibility, pathogen behavior, and environmental conditions, as previously hypothesized by Joaquín et al. [12] and Alvarez et al. [2].

The difficulty in identifying the primary cause of FY occurrence may be related to the presence of factors that predispose plants to the disease. Poor soil drainage at certain times of the year can weaken plants. Thus, abiotic factors, such as waterlogged soil, may facilitate or even be essential in making oil palms more susceptible.

Anhê et al. [3] also concluded that AF may have been caused by biotic factors, emphasizing that regions near a river in the study area had a higher incidence of the disease, likely due to increased soil moisture. The possible biotic origin has also been suggested by Silva et al. [18]. Regarding the moisture in the area, Anhê et al. [4] also highlighted the high incidence of the disease in sections near the watercourse, suggesting that this factor also influences the greater spread of the disease.

The observed spatial clustering of FY cases may be influenced by a combination of environmental and agronomic factors. Areas near access roads, for example, may experience greater exposure to wind, light, and mechanical disturbance, potentially creating microclimatic conditions that favor disease development. The circulation of vehicles, machinery, and personnel in these areas could also contribute to the mechanical dissemination of a biotic agent, if one is present. In addition, localized differences in soil characteristics — such as drainage, compaction, and nutrient availability — may affect plant vigor and susceptibility. Poorly drained soils, common in parts of the Eastern Amazon, may predispose oil palms to stress conditions that exacerbate disease expression. The presence of shaded edges or areas adjacent to forest fragments may also create variable humidity and temperature regimes, further influencing the spatial pattern of disease incidence.

The emergence and severity of FY cannot be separated from a series of conditions that stress the plant due to the continuous imbalance between soil, plant, and environment. These conditions can induce a morphophysiological syndrome that results in the disease [2, 12].

Additionally, the disease exhibits behavior similar to an infectious process, as plantings in areas with a history of the disease tend to be more aggressively affected compared to plantings in previously unused areas [16].

FY does not occur uniformly and continuously around the first affected plant; instead, its pattern is similar to that caused by an infectious agent transmitted by a vector.

Biotic and abiotic factors can contribute to aggregated dispersal [8]. In the case of biotic diseases, contagion causes the formation of infection foci, whereas for abiotic diseases, the microclimate is responsible for the aggregated expression of symptoms [15]. Plots H13 and H14 are bordered by denser forests on the west side, yet there is a focus of diseased plants on the east side, which is bordered by an access road.

It is important to acknowledge potential sources of bias in the dataset. Although efforts were made to standardize disease identification through training and consistent field protocols, some degree of subjectivity in symptom recognition may have persisted, particularly in early-stage FY cases. Additionally, environmental heterogeneity across the plots — such as variations in soil moisture, microclimate, and proximity to roads or forest edges — may have influenced disease development and visibility, potentially affecting reporting accuracy. These factors may also have contributed to the observed spatial patterns. While these limitations do not invalidate the findings, they highlight the importance of integrating environmental and physiological data in future studies to improve the interpretation of spatial disease dynamics.

Moreover, the geostatistical modeling approach adopted in this study also presents inherent limitations. The use of presence/absence data, while effective for detecting overall patterns, does not account for disease severity or symptom progression, which may influence spatial relationships. The models applied assume stationarity and isotropy, meaning that spatial dependence is constant across the study area and does not vary by direction—an assumption that may oversimplify the complex environmental and agronomic conditions of the Amazon. Additionally, the analysis did not include potential explanatory variables, such as soil properties, topography, or plant genotype, which could help explain the observed aggregation. Future studies should consider incorporating these factors and exploring alternative spatial models, such as anisotropic or spatially varying coefficient models, to enhance understanding of FY dynamics.

The results of this study have direct implications for disease monitoring and management in oil palm plantations. The identification of spatial aggregation and range of dependence for FY cases provides a scientific basis for implementing site-specific disease surveillance strategies, allowing for early detection and localized intervention in high-risk zones. For example, the knowledge that FY clusters tend to form within a range of up to 220 m suggests that buffer zones or

targeted phytosanitary inspections can be established around initial infection foci. In addition, recognizing the influence of landscape features such as access roads on disease occurrence can inform land-use planning and agronomic practices, such as traffic flow restrictions or differentiated planting layouts. These insights are particularly valuable for producers, extension agents, and policymakers seeking to minimize losses and improve the sustainability of oil palm cultivation in the Amazon.

4 Conclusions

This study revealed that Fatal Yellowing (FY) in oil palm plantations exhibits a clear spatial aggregation pattern, with varying degrees of spatial dependence between organic and conventional systems. Using geostatistical modeling, we quantified the spatial range of aggregation and demonstrated that disease clusters tend to form within distances of up to 220 m, often near access roads. These findings support the hypothesis of a biotic dissemination mechanism and suggest that landscape and management features may influence disease spread.

Scientifically, the study advances our understanding of FY epidemiology by providing robust spatial metrics that characterize the disease's distribution across different cultivation systems — an approach not previously addressed with this level of detail.

Practically, the results offer a technical foundation for developing targeted monitoring and control strategies. Knowing where and how FY tends to cluster enables the design of site-specific management interventions, such as intensified inspections in hotspot areas, implementation of buffer zones, or adjustments to traffic and planting layouts. These insights can help producers and policymakers minimize economic losses and improve phytosanitary decision-making in oil palm cultivation.

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Author's contributions JNS conducted the experiment, performed data collection and discussed the results. PRSF and AGS provided general guidance for the work. FJO, RST, AVFS, LASC and LHFM contributed to the discussion and performed the final review of the manuscript before submission.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Ethical approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish Not applicable.

Competing interest The authors declared that they have no competing interest.

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