Plant Health

https://doi.org/10.71252/2177-34912025720009
ISSN: 2177-3491

Temporal analysis of *Phoma* leaf spot of coffee plants at different altitudes[1]

Humberson Rocha Silva[2], *Edson Ampélio Pozza*[3*], *Aurivan Soares de Freitas*[4], *Marcelo Loran de Oliveira Freitas*[5], *Mauro Peraro Barbosa Junior*[3], *Marcelo Angelo Cirillo*[6]

[1] The article was extracted from the thesis of the first author

[2] Departamento de Agronomia, Universidade Federal Rural de Pernambuco, Recife, Pernambuco, Brazil. humbersonrs@gmail.com

[3] Departamento de Fitopatologia, Universidade Federal de Lavras, Lavras, Minas Gerais, Brazil. edsonpozza@gmail.com; mjrperaro@gmail.com

[4] Departamento de Entomologia e Fitopatologia, Universidade Federal Rural do Rio de Janeiro, Seropédica, Rio de Janeiro, Brazil. aurivan.soares@hotmail.com

[5] Instituto Federal de Minas Gerais, Bambuí, Minas Gerais, Brazil. marcelo.freitas@ifmg.edu.br

[6] Departamento de Estatística, Universidade Federal de Lavras, Lavras, Minas Gerais, Brazil. macufla@ufla.br

*Corresponding author: edsonpozza@gmail.com

Editors:
Danielle Fabíola Pereira da Silva
Valdir Lourenço Junior

Submitted: October 1st, 2024.
Accepted: February 2nd, 2025.

ABSTRACT

Phoma leaf spot (*Phoma* spp.) of coffee causes losses of between 15 and 43%, and presents significant variability over time and space, especially in mountain coffee production. Thus, the objective of this study was to evaluate the behavior of this disease at different altitudes and to use time series techniques and regression models to explain disease behavior. The experiment was conducted over two years (from September 2013 to August 2015) with monthly evaluations in a *Coffea arabica* L. plantation. The incidence and severity progress curves showed irregular behavior most of the time, typical of the disease. Higher altitudes provided higher disease incidence and severity values. Only the incidence and severity progress curves at the altitude of 1143.2 m showed significant autocorrelation over time. Thus, the first-order autocorrelation structure, AR(1), was incorporated in the estimates of the parameters of the linear and nonlinear models. Only the months from February to June/July 2014 were considered, when the disease progressed regularly. The rates obtained for the incidence, overall mean of the 85 points and mean altitude of 1143.2 m, were 5.2 and 4.6%, respectively, while the estimated rates for the severity data under the same conditions were 0.3 and 0.1%, respectively. These values represent the expected increase in incidence and severity each month. The Phoma leaf spot presents complex temporal dynamics, influenced by microclimatic variables associated with altitude.

Keywords: Epidemiology; *Coffea arabica* L.; Phoma spp.; autoregressive models; regression models

INTRODUCTION

Coffee is one of the most consumed beverages in the world, and is also one of the most traded commodities both for immediate consumption and for speculation on stock exchanges and futures markets. To support this demand, high production volume is required. Brazil stands out in the international coffee market as the largest producer and exporter worldwide, whereas the main importers are the European Union and United States.[(1)] More than 38.9 million 60-kg bags of *Coffea arabica* L were produced in Brazil in a total planted area of 1.48 million hectares in 2023.[(2)] Even at this level of production, highlighting the susceptibility of the planted cultivars to the various diseases that limit productivity gains and compromise the quality of the beverage is important.

Among these diseases, Phoma leaf spot (*Phoma* spp.) stands out because it causes losses of between 15 and 43% from damage such as stem drying, flower necrosis, pinhead mummification and leaf spot.[(3)] Fungus penetration is facilitated by mechanical damage to the plant tissues that is produced by insects or by friction between leaves due to intense winds in cold months.[(4)] Plantations located at higher altitudes are more prone to the occurrence of cold winds because they are more exposed, favoring temporal and/or spatial disease progress. However, this information lacks scientific data because the hypothesis has been stated without scientific verification of altitudinal variation and of the influence of this variation on environmental variables and disease intensity.

Another important aspect is to understand the dynamics of plant diseases over time to help define control strategies for the reduction of fungicide applications and, consequently, to minimize environmental costs and impacts.[(5)] Phoma leaf spot of coffee has no pattern of occurrence throughout the growing season of the crop, thus hindering its management.[(6)] In this context, time series techniques associated with regression models can be useful to describe disease dynamics (Box et al.)[7], and thus, they are helpful when determining the appropriate periods for spraying fungicides.

Therefore, the objectives of this study were to analyst the influence of altitude on the incidence and severity of Phoma leaf spot of coffee and to model the disease progress curves.

MATERIALS AND METHODS

The experiment was conducted for two years, from September 2013 to August 2015, in a commercial plantation of NKG Fazendas Brasileiras Ltda., located in the municipality of Santo Antônio do Amparo, Minas Gerais state, Brazil. The geographical coordinates of the reference point were 20°53’23.7” S, 44°52’56.9” W and an altitude of 1145.9 m. The area used in the study encompassed 7.65 ha, cultivated with *Coffea arabica* L. cultivar Catucaí amarelo 2 SL[(8)], planted at a spacing of 3.7 x 0.7 m. The plants were four years old at the beginning of the study. A regular grid of 7.6 ha with 85 points was demarcated in this area, with a spacing of 30 x 30 m between points (Figure 1).

The points were georeferenced with a Topcon® Hiper Lite L1/L2 GNSS receiver. Data were collected using the post-processing kinematic (PPK) method. Each georeferenced sampling point of the grid consisted of five coffee plants, with three plants in the same row-one above the central plant and the other below it.

The management of fertility, pests and other diseases in the study area was performed homogeneously and according to crop requirements.

To study the Phoma leaf spot progress curve over time, 24 monthly assessments of disease incidence and severity were conducted over the study period. In each plant, the first pair of fully expanded leaves was randomly evaluated for four branches in the upper third of the canopy, with two branches on each exposure face, for a total of eight leaves per plant and 40 leaves per georeferenced point. The disease was evaluated on the first pair of leaves because they are most predisposed to infection. Furthermore, due to the short incubation period, symptoms are often noticed on the first or second pair of leaves. The disease incidence data at each georeferenced point were obtained dividing the number of diseased leaves by the total number of leaves, multiplied by 100. Severity was assessed using the diagrammatic scale developed by Salgado et al.[(9)]

To construct the progress curves of incidence and severity over time, the mean of the 85 points in each month evaluated was used. In addition, progress curves were constructed with these same data, considering the direction with the highest terrain slope, to analyze the effect of altitude on disease progress (Table 1 and Figure 1). Two automatic stations (Datalogger CR10X and CR1000, Campbell Scientific Inc.®) were installed at 1130.9 m (lower altitude) and 1145.0 m (lower altitude), to study the hypothesis of microclimatic differences within the crop. Although the amplitude between 1130.9 and 1145.0 m is short, it was previously observed that it was sufficient to cause variations in disease intensity in the studied area. This could be

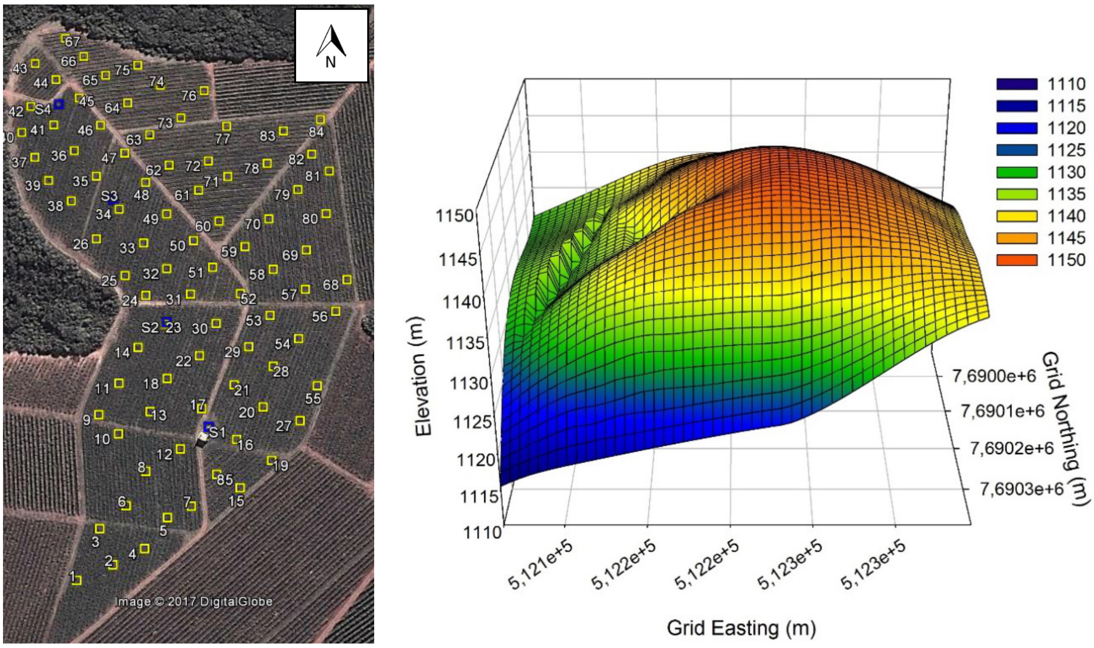

Figure 1: Satellite image of the experimental area (left) and plani-altimetric representation of the relief (right). Values in the legend (right) indicate altitude (m). NKG Fazendas Brasileiras Ltda., Santo Antônio do Amparo, Minas Gerais, 2014 (Google Earth, 2014), and grid of georeferenced points. S1 and S4 (in blue) indicate, respectively, the positions of the Datalogger CR1000 and CR10X automatic stations (Campbell Scientific Inc.®) installed at the area.

related to the local topography and native vegetation in the surrounding area, interfering with wind direction and speed (Figure 1).

Each curve was plotted with the mean disease intensities of 10 georeferenced points over the 24 months. The progress curves of 1130.5 and 1143.4 m altitude were constructed with the means of the sampling points closest to the automatic stations. The other two curves were constructed with data from plants located at altitudes intermediate to these two (Table 1 and Figure 1). The stations provided mean air temperature and wind speed and direction data, whose values corresponded to the weekly means, which showed a lag of two weeks.

Table 1: Mean altitude of the georeferenced points used to construct each Phoma leaf spot of coffee progress curve, considering the unevenness of the plantation terrain

Mean Altitude (m)	Georeferenced points corresponding to each curve
1130.5	36, 37, 40, 41, 42, 44, 45, 46, 65, 66
1140.6	26, 33, 34, 35, 38, 47, 48, 49, 61, 62
1143.2	14, 18, 22, 23, 24, 25, 30, 31, 32, 52
1143.4	07, 08, 12, 13, 15, 16, 17, 19, 20, 21

The disease progress curve will be called time series, or simply, series. When the assumption of temporal independence of data is not met, it is necessary to consider the autocorrelation structure in regression models. Therefore, it is necessary to use time series techniques. If it is designated by Z, its value at time t can be written as Z_t (t = 1, 2, ..., n). These observations (Z_t, t = 1, 2, ..., n) can be broken down into the following additive model: $Z_t = T_t + S_t + \varepsilon_t$, where T_t and S_t represent trend and seasonality, respectively, and ε_t is a random component with zero mean and constant variance. The trend can be understood as the gradual increase or reduction of observations over time.[10] Seasonality represents fluctuations occurring in periods less than or equal to twelve months.[10] The analyzed series must be stationary; that is, free of the T_t and S_t components. The stationary quality of the incidence and severity progress curves was checked by autocorrelogram analysis.

The ε_t component represents the residuals of the data, and if it is correlated, the present moment data, that is, the incidence or severity, influence the behavior of the future (or past) data in t instants of time.[10] Thus, the existence of autocorrelation in the ε_t component is an essential condition for applying time series techniques. This criterion was evaluated using the Q test, applied to the partial autocorrelation function (PACF), and the autocorrelation function (ACF).

The determination of the mean altitude considered to estimate the progress curves with regression models was performed using descriptive statistics. Adjustments were made considering only the months with regular disease progression for at least four subsequent evaluations, that is, when there is an increase or stabilization of the disease over time, with the data divided by 100. Subsequently, data adjustments were made, considering the maximum disease intensity in each curve equal to 1. This was necessary due to the use of nonlinear models with two parameters. Subsequently, linear and nonlinear regression models were proposed in two approaches, defined by the presence and absence of the first-order autocorrelation structure, AR(1), in order to contemplate the temporal effect of the model. For this purpose, the models of interest are listed below (Equations 1 to 5).

$$y_i = y_0 + rt_i + \varepsilon_i \ (i=1,...,n) \quad (Linear\ model) \qquad (1)$$

$$y_i = y_0 e^{rt_i} + \varepsilon_i \quad (i=1,\ldots,n) \quad (\mathit{Exponential}) \qquad (2)$$

$$y_i = 1-(1-y_0)\,e^{-rt_i} + \varepsilon_i (i=1,\ldots,n)(\mathit{Monomolecular}) \qquad (3)$$

$$y_i = \frac{1}{1+e^{\left(-\frac{\ln y_0}{1-y_0}+rt_i\right)}} + \varepsilon_i (i=1,\ldots,n)(\mathit{Logistic}) \qquad (4)$$

$$y_i = e^{\left(\ln y_0 e^{(-rt_i)}\right)} + \varepsilon_i (i=1,\ldots,n)(\mathit{Gompertz}) \qquad (5)$$

Where
y_i = the amount of disease at time t_i;
y_0 = the initial amount of disease;
r_i = the disease progress rate;
t_i = the time;
In the above models,

$$\varepsilon_i = \mu_i\, \varepsilon_{i-1} + \varepsilon_t, \text{ where} \qquad (6)$$

ε_t is the white noise, that is, $E[\varepsilon_t] = 0$, $E[\varepsilon_t^2] = \sigma_\varepsilon^2$, $E[\varepsilon_t\ \varepsilon_{t-n}] = 0$, if $h \neq 0$. Under these conditions, the incorporation of the AR(1) structure in the parameter estimates was carried out by the iterative method, in order to consider the weight matrix W defined by

$$W = \frac{\sigma_\varepsilon^2}{1-\rho_1}\begin{pmatrix} 1 & \rho_1 & \rho_1^{\,2} & \cdots \rho_1^{\,n-1} \\ \rho_1 & 1 & \rho_1 & \cdots \rho_1^{\,n-2} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_1^{\,n-1} & \rho_1^{\,n-2} & \rho_1^{\,n-3} & \cdots 1 \end{pmatrix} \qquad (7)$$

In the absence of this correlation structure, models (1) to (5) followed the same definition, however, $\varepsilon_i \sim N\,(0, \sigma^2)$.

The estimation of the predicted values in the models was performed using information from the confidence bands, obtained through equation (8) for the models presented in equations 1 to 5.

$$f_i\,(x_0, \hat{y}_0, \hat{r}) \pm Z_{\alpha/2}\sqrt{F_{i0}}V_i\,(\hat{y}_0, \hat{r})\,F_{i0}{}^T \qquad (8)$$

Where the subscript i corresponds to the Linear, Exponential, Monomolecular, Logistic or Gompertz regression model. x_0 represents the values to be predicted, corresponds to the gradient matrix evaluated in x_0, and $_i\,(\hat{y}_0, \hat{r})$, to the covariance matrices of the estimates of the parameters of the regression models. Finally, $Z_{\alpha/2}$ indicates the quantile of the standard normal distribution for the 95% confidence interval.

The selection of models was carried out considering the interval amplitude of the confidence intervals for the parameter estimates. The smaller the amplitude, the greater the accuracy of the estimates of the values associated with the response variable. In addition, the criteria of least mean square of residues (MSR) and highest coefficient of determination (R^2) were used to evaluate adjustments.

Finally, the disease incidence and severity rates at time t_i were obtained using a simple linear regression model, assuming the original data (divided by 100), and the linearized data using the monomolecular (y), exponential (y), logistic (y) and Gompertz (y) methods (Equations 9 to 12). Then, the simple linear regression model was fitted to these data as follows:

$$y_e = ln\ (y) \qquad (9)$$

$$y_m = ln[1/(1-y)] \qquad (10)$$

$$y_l = ln[y/(1-y)] \qquad (11)$$

$$y_g = -ln[-ln(y)] \qquad (12)$$

Where

y_i = the disease incidence or severity observed in the evaluated plot, and the subscript i corresponds to the exponential (e), monomolecular (m), logistic (l) and Gompertz (g) transformations.

The analyzes of the linear and nonlinear models were performed using the R software version 3.4.0, with the aid of the NLME package.[11]

RESULTS

In the descriptive analysis of the data, the Phoma leaf spot incidence and severity progress curves showed several peaks within each 12-month period, albeit on different dates in the two years of study (Figures 2a and 2b). That is, this pathosystem exhibited variable behavior over time. For the first 12-month period, between September 2013 and August 2014, four peaks were observed in the disease incidence progress curve, corresponding to the months of October and December 2013 and June and August 2014 (Figure 2a). In the second 12-month period (September 2014 to August 2015), incidence peaks were recorded in September and November 2014 and in February and May 2015 (Figure 2a). The disease severity progress curve showed a pattern similar to that of the incidence curve, with the exception of the occurrence of peaks in March and June 2015, instead of in February and May 2015, approximately one month after the high incidences were recorded (Figure 2b).

When all 24 months were considered, the only period with regular disease incidence and severity progress was between February and June 2014 (Figures 2a and 2b). That is, only this interval was appropriate for subsequent regression modeling, as it showed an increase and/or stabilization of the disease over time, for five months.

The progress curves located at the highest altitude points of the plantation showed, in general, higher disease incidence and severity values over the 24 months of the study (Figures 3a and 3b). Thus, the progress curve at 1143.4 m of altitude was the one with the highest mean disease intensity, whereas the one at 1130.5 m showed the lowest disease incidence and severity values (Figures 3a and 3b).

Thus, the t-test was applied within each month to compare the incidence and severity values between the 1130.5 and 1143.4 m curves. The incidence at the 1143.4 m altitude was significantly higher in 15 of the 24 months, and in nine months, there was no significant difference (Figure 3). The severity at the 1143.4 m altitude was higher in 13 of the 24 months; in ten months, there was no significant difference, and only in June/2014, there was greater severity at the lower altitude (Figure 1).

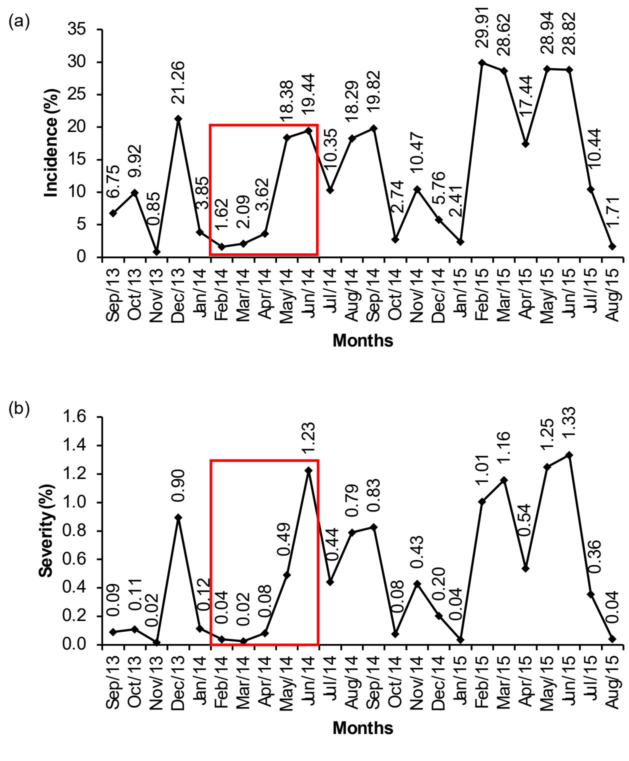

Figure 2: Progress curves for (a) incidence and (b) severity of Phoma leaf spot of coffee (mean of 85 georeferenced points) recorded at the experimental area from September 2013 to August 2015. The highlighted months (February to June of 214) correspond to the period of regular disease progress.

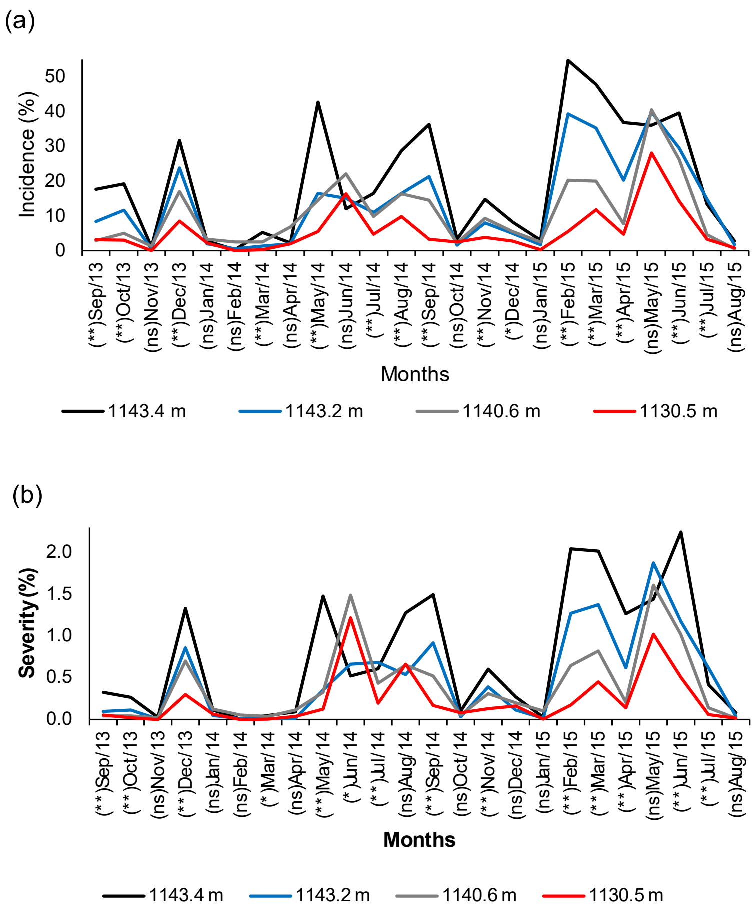

Figure 3: Progress curves of (a) incidence and (b) severity of Phoma leaf spot of coffee plants at different altitudes (1143.4, 1143.2, 1140.6 and 1130.5 m) recorded at the experimental area from September 2013 to August 2015. ns: not significant; * and ** indicate significant difference at 5 and 1%, respectively, by the t-test, between the means of the 1130.5 and 1143.4 m progress curves.

In general, higher disease values were observed when the temperature remained between 15 and 20 °C over time (Figure 4a). For periods with higher wind speed, a higher occurrence of Phoma leaf spot was observed, with the wind direction being a variable clearly associated with this pathosystem (Figures 4b and 4c). Regarding altitude, the mean temperature difference between the automatic stations was 0.1 °C, with a predominance of lower temperatures at the highest altitude in most months (data not shown). The mean difference in wind speed between the automatic stations was 0.2 $m.s^{-1}$, with no predominance of values associated with altitude. Regarding wind direction, the mean difference over the months was 19° (azimuth), with the southernmost winds being recorded at the highest altitude (Figure 4c).

According to time series techniques, the residuals ε_t of the incidence and severity progress curves constructed with the means of the 85 points were only white noise, i.e., uncorrelated random variables. When the analysis was performed at different altitudes, the incidence and severity progress curves at 1130.5, 1140.6 and 1143.4 m showed the same behavior. The progress curve at 1143.2 m for these two variables showed significant autocorrelation when the Q test ($p \leq 0.05$) (Table 2) was used.

The stationary conditions of these series were checked by analysis of the correlograms, which showed an absence of both trend and seasonality (data not shown). For the incidence and severity progress curves at 1143.2 m, according to the partial autocorrelation function (PACF), the data showed a first-order autoregressive structure, AR(1), and likewise, for the autocorrelation function (ACF), there was a significant structure of moving averages for the first lag, MA(1).

To adjust the regression models, the results of descriptive analyses and time series techniques were considered. The models were adjusted without autocorrelation structure for the incidence and severity progress curves of the means of the 85 points, from February to June 2014. No adjustments

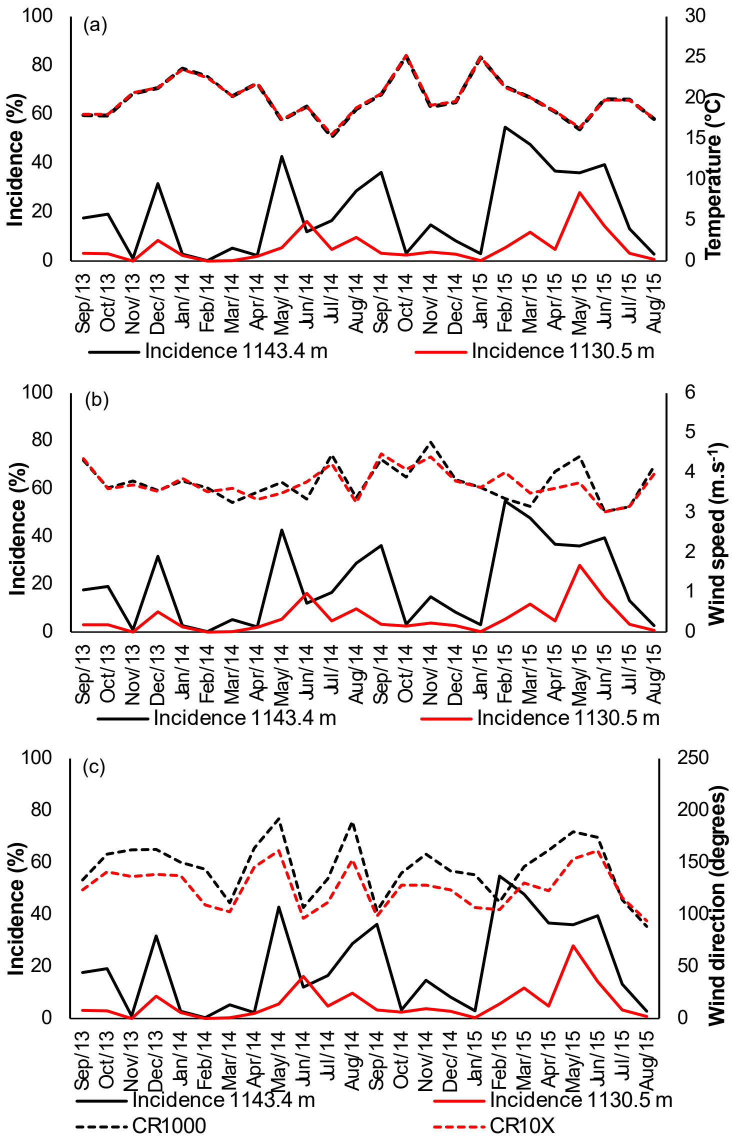

Figure 4: Phoma leaf spot incidence progress curves at altitudes of 1143.4 and 1130.5 m and weekly mean air temperature (°C), wind speed ($m.s^{-1}$) and wind direction (°) with a two-week lag, recorded with the CR1000 and CR10X stations.

Table 2: Results of the autocorrelation function (ACF), partial autocorrelation function (PACF) and Q (k) statistic for the significant lags ($p \leq 0.05$) of the incidence and severity progress curves at 1143.2 m altitude

Progress curve	Significant lag	ACF	PACF	Q(*k*)	p-value
Incidence 1143.2 m	1	0.3691	0.3691	3.6951	0.055
Severity 1143.2 m	1	0.3775	0.3775	3.8656	0.049

were made for the curves of 1130.5, 1140.6 and 1143.4 m, as they presented similar results to the means of the 85 points, in relation to time series techniques. In addition, the regression models were also adjusted to data from the incidence and severity series at the mean altitude of 1143.2 m, considering the same period for incidence, and from February to July 2014 for severity, as this variable extended the regular behavior by one month. For the incidence and severity progress curves at 1143.2 m, as well as for the rate estimates, the AR(1) structure was incorporated into the parameter estimates, as the Q test was significant (Table 2).

For the adjustments of the models to the disease incidence and severity progress curves, the models with smaller interval amplitudes of the confidence interval (CI) for the initial amount of disease (y_0) did not present the smallest interval amplitudes of the CI for the parameter of rate (r), and vice versa. Thus, the criteria of least mean square of residues (MSR) and highest coefficient of determination (R^2) were used for selection. The Logistic model was selected both for the incidence progress curve, mean of 85 points, and for the mean altitude progress curve of 1143.2 m, as it presented a lower CI interval amplitude for y_0, lower MSR and higher R^2 (Table 3).

For the disease severity progress curves, mean of 85 points, and mean altitude of 1143.2 m, the Exponential and Logistic models were selected, respectively, which presented better indicators of quality of adjustments (Table 4). It is important to highlight that the Gompertz model was not adjusted because it did not converge to the analyzed data.

Regarding the estimates of incidence and severity progress rates using the simple linear regression model, both for the mean of the 85 points and for the mean altitude of 1143.2 m, the original data were more promising in relation to the linearized ones, because in all situations they presented lower CI interval amplitude, both for y_0 and for r, in addition to lower MSR values (Tables 5 and 6). The estimated rates for the incidence data, mean of the 85 points and mean altitude of 1143.2 m, were 5.2 and 4.6% (Table 5), and for the severity of 0.3 and 0.1% (Table 6) per month, respectively.

DISCUSSION

The incidence and severity progress curves showed several peaks or maximum points throughout the 24 months of evaluation. This variability, and even the lack of reproducibility between years, are expected for this disease, influenced by microclimatic changes. There was regular progress, or typical exponential form only between February and June 2014. This finding can be explained by the occurrence of environmental conditions favorable to the progress of the disease during this period, with a gradual reduction in air temperature and occurrence of higher wind speeds from the south. These winds, with mean speeds reaching up to 4.7 $m.s^{-1}$ may have provided even lower temperatures on the leaf surface, in addition to cuticle injuries, facilitating pathogen penetration.

The findings are consistent with prior studies, such as those by Santos et al. [6], which reported the highest incidences of this coffee disease in periods with lower mean temperatures, ranging between 16 and 19 °C. Another study reported higher growth of the germination tubes of the conidia of this pathogen when subjected to low temperatures between 15 and 20 °C.[12] Temperatures in this range increase the chances of pathogen infection because when they grow more, the germination tubes are more likely to find gateways for penetration. Furthermore, fungal penetration is facilitated by mechanical damage to plant tissues, which can be produced by intense winds during the cold period Carvalho et al. [4].

The progress curves located at the highest plantation altitudes showed, in general, higher incidence and severity values and evident association with the more southerly winds, suggesting the absence of obstacles diverting the

Table 3: Linear and nonlinear regression models fitted to the monthly incidence data (February to June 2014) of Phoma leaf spot of coffee, and fit quality indicators

Coefficients and fit quality indicators (progress curve) – INCIDENCE						
Model[1]	**y_0**	**Interval Amplitude y_0**	**r**	**Interval Amplitude r**	**MSR**	**R^2**
Data from mean of the 85 points						
Linear	-0.604 ^{ns}	1.194	0.267 *	0.281	0.052	0.82
Monomolecular	-1.353 ^{ns}	5.763	0.398 ^{ns}	0.842	0.094	0.67
Exponential	0.038 ^{ns}	0.177	0.561 ^{ns}	0.832	0.050	0.83
Logistic	1.32×10^{-8} ^{ns}	2.97×10^{-7}	4.176 *	5.620	0.006	0.98
Gompertz	NA[2]	NA	NA	NA	NA	NA
Data from altitude of 1143.2 m						
Linear	-0.759 ^{ns}	0.983	0.295 *	0.235	0.072	0.76
Monomolecular	-1.517 ^{ns}	5.800	0.397 ^{ns}	0.778	0.106	0.65
Exponential	0.014 ^{ns}	0.054	0.751 *	0.693	0.106	0.65
Logistic	1×10^{-7} ^{ns}	1.38×10^{-6}	3.668 *	3.060	0.009	0.97
Gompertz	NA	NA	NA	NA	NA	NA

[1]To adjust the models, the data were divided by 100 and adequate for the highest observed incidence to be equal to 1; [2]Not available. * $p \leq 0.05$; ** $p < 0.01$.

Table 4: Linear and nonlinear regression models fitted to the monthly severity data (February to June/July 2014) of Phoma leaf spot of coffee and fit quality indicators

Coefficients and fit quality indicators (progress curve) – SEVERITY						
Model[1]	**y_0**	**Interval Amplitude y_0**	**r**	**Interval Amplitude r**	**MSR**	**R^2**
Data from mean of the 85 points						
Linear	-0.623 ^{ns}	1.243	0.232 *	0.293	0.056	0.76
Monomolecular	-0.916 ^{ns}	3.662	0.266 ^{ns}	0.584	0.090	0.61
Exponential	0.002 ^{ns}	0.005	1.050 **	0.416	0.002	0.99
Logistic	1.60 x10$^{-9\ ns}$	1.39 x10^{-8}	3.974 ^{ns}	5.643	0.002	0.99
Gompertz	NA[2]	NA	NA	NA	NA	NA
Data from elevation of 1143.2 m						
Linear	-0.633 *	0.905	0.235 **	0.188	0.051	0.86
Monomolecular	-0.916 *	3.792	0.291 ^{ns}	0.641	0.114	0.70
Exponential	0.034 ^{ns}	0.153	0.497 *	0.679	0.062	0.84
Logistic	1.71 x10$^{-8\ ns}$	9.49 x10^{-8}	3.586 **	1.108	0.0001	0.99
Gompertz	NA	NA	NA	NA	NA	NA

[1]To adjust the models, the data were divided by 100 and adequate for the highest observed incidence to be equal to 1; [2]Not available. * $p \leq 0.05$; ** $p < 0.01$.

Table 5: Fitting of simple linear regression models to the original and linearized data on the incidence (February to June 2014) of Phoma leaf spot of coffee to estimate disease progress rates

Coefficients and fit quality indicators (rates) – INCIDENCE						
Linearized form[1]	**y_0**	**Interval Amplitude y_0**	**r**	**Interval Amplitude r**	**MSR**	**R^2**
Data from mean of the 85 points						
Original data	-0.117 ^{ns}	0.232	0.052 *	0.055	0.002	0.82
Monit	-0.134 ^{ns}	0.263	0.058 *	0.062	0.002	0.82
Exponit	-5.788 **	2.248	0.715 *	0.530	0.183	0.90
Logit	-5.922 **	2.497	0.773 *	0.588	0.225	0.90
Gompit	-2.067 **	0.980	0.267 *	0.231	0.035	0.87
Data from elevation of 1143.2 m						
Original data	-0.113 ^{ns}	0.169	0.046 *	0.040	0.002	0.77
Monit	-0.136 ^{ns}	0.180	0.053 *	0.043	0.002	0.76
Exponit	-7.474 **	1.194	1.011 **	0.287	0.294	0.91
Logit	-7.615 **	1.363	1.065 **	0.327	0.345	0.90
Gompit	-2.426 **	0.639	0.320 **	0.153	0.045	0.86

[1]Data divided by 100; * $p \leq 0.05$; ** $p < 0.01$.

mass of cold air from its origin, thus favoring disease progress. These results are in accordance with Carvalho et al. [4], who reported this disease in regions with crops facing south, southeast, and east and exposed to strong and cold winds.

Species of the genus *Phoma* can penetrate their hosts through different mechanisms, such as natural openings[13], injuries[14] and directly[15], breaking the epidermis and establishing infectious processes. [12]

Using scanning electron microscopy, Lorenzetti et al. [12] observed early events in the establishment of pathogen-host relationships, such as the separation of the cuticle from the leaf tissue. Firman[16] studied this same pathosystem and observed the development of symptoms of Phoma leaf spot only in artificially injured young leaves. According to the author, uninjured leaves and even injured mature leaves did not develop symptoms when inoculated with conidial suspension. These findings agree with field observations, as the symptoms of this disease usually occur in the first and second pairs of leaves, most likely because these leaves are the youngest and predisposed to mechanical damage. Consequently, the wounds generated are used as gateways for pathogen penetration.

Table 6: Fitting of simple linear regression models to the original and linearized data on the severity (February to June/July 2014) of Phoma leaf spot of coffee to estimate disease progress rates

Coefficients and fit quality indicators (rates) – SEVERITY						
Linearized form[1]	**y_0**	**Interval Amplitude y_0**	**r**	**Interval Amplitude r**	**MSR**	**R^2**
Data from mean of the 85 points						
Original data	-0.008 ^{ns}	0.015	0.003 *	0.004	8.39 x10^{-6}	0.76
Monit	-0.008 ^{ns}	0.015	0.003 *	0.004	8.53 x10^{-6}	0.76
Exponit	-10.549 **	3.631	0.989 *	0.856	4.77 x10^{-1}	0.87
Logit	-10.556 **	3.641	0.991 *	0.858	4.79 x10^{-1}	0.87
Gompit	-2.499 **	0.591	0.160 *	0.139	1.26 x10^{-2}	0.87
Data from elevation of 1143.2 m						
Original data	-0.003 ^{ns}	0.008	0.001 *	0.002	2.5 x10^{-6}	0.81
Monit	-0.003 ^{ns}	0.008	0.001 *	0.002	2.5 x10^{-6}	0.81
Exponit	-12.149 **	3.575	1.107 **	0.748	8.39 x10^{-1}	0.87
Logit	-12.153 **	3.580	1.109 **	0.749	8.41 x10^{-1}	0.87
Gompit	-2.645 **	0.515	0.159 **	0.108	1.68 x10^{-2}	0.87

[1]Data divided by 100; * $p \leq 0.05$; ** $p < 0.01$.

When the temporal autocorrelation of the residuals ε_t of the progress curves (means of the 85 georeferenced points and altitudes of 1130.5, 1140.6 and 1143.4 m) were analyzed, the values were not significant; that is, the residuals ε_t were independent. As for the incidence and severity progress curves at 1143.2 m, these residues showed a significant autocorrelation. This is due to the short incubation and latent period of this disease. Consequently, significant autocorrelations will be observed more frequently for field evaluations carried out at fortnightly and weekly intervals, justifying the adoption of time series techniques and the incorporation of the autocorrelation structure in the estimates of model parameters. However, for assessments of the progress of this disease at monthly intervals or longer timescales, this approach may be unnecessary, and thus, classical analysis for fitting regression models will be satisfactory for parameter estimates.

Souza et al.(17) also used an autoregressive structure to estimate the parameters of the nonlinear regression models to model the progress curves for the incidence and severity of brown eye spot of coffee plants, obtaining R^2 values of 0.79 and 0.75 for the incidence and for severity, respectively. Other authors have also been successful in modeling their data considering time series techniques, although they have not used nonlinear regression models.[18-21]

The Logistic and Exponential models were the ones with the best fit to the analyzed data set, satisfactorily explaining the temporal progress of the disease between February and June/July 2014. The disease progress during these months may be associated with the increase of inoculum in the area, favored by the occurrence of microclimatic conditions favorable to the pathogen. In subsequent months, the values of incidence and severity reduced significantly, due to the fall of infected leaves or the vegetative growth of the host under environmental conditions unfavorable to the disease, with the formation of healthy young leaves at the time of the evaluations.

It is important to highlight that for the same period of the following year, linear or nonlinear models were not adjusted due to the irregular behavior of the disease. That is, generalizing the fit of a model for different seasons is not possible due to the temporal dynamics of this disease, which is strongly influenced by both climatic and edaphic variables.

CONCLUSIONS

The progress curves of the incidence and severity of Phoma leaf spot of coffee showed a random pattern throughout each year of the study. Higher disease intensities were observed at a mean altitude of 1143.4 m.

Time series techniques were used in association with linear and nonlinear regression models to fit the 1143.2 m mean altitude progress curve, with a first-order autoregressive effect.

The Logistic model satisfactorily adjusted to the incidence data in the period of regular epidemic progression, considering the mean values of the 85 points and the mean altitude of 1143.2 m. Regarding severity, this model was also the best fit for the 1142.2 m data, while the Exponential was the most suitable for the 85 point mean data.

AUTHOR CONTRIBUTION

Conceptualization: Humberson Rocha Silva; Edson Ampélio Pozza.

Formal analysis: Humberson Rocha Silva; Marcelo Angelo Cirillo.

Funding acquisition: Edson Ampélio Pozza.

Investigation: Humberson Rocha Silva; Aurivan Soares de Freitas; Marcelo Loran de Oliveira Freitas; Mauro Peraro Barbosa Junior.

Methodology: Humberson Rocha Silva; Edson Ampélio Pozza

Project administration: Humberson Rocha Silva.

Software: Humberson Rocha Silva; Marcelo Angelo Cirillo.

Resources: Edson Ampélio Pozza.

Supervision: Humberson Rocha Silva.

Validation: Humberson Rocha Silva; Edson Ampélio Pozza; Marcelo Angelo Cirillo.

Writing: Humberson Rocha Silva; Edson Ampélio Pozza.

Revision: Humberson Rocha Silva; Edson Ampélio Pozza; Aurivan Soares de Freitas; Marcelo Loran de Oliveira Freitas; Mauro Peraro Barbosa Junior; Marcelo Angelo Cirillo.

REFERENCES

1. United States Department of Agriculture. Coffee: world markets and trade. Washington (DC): USDA; 2023 [cited 2023 Feb 26]. Available from: https://www.fas.usda.gov/data/coffee-world-markets-and-trade

2. Companhia Nacional de Abastecimento. Boletim café janeiro 2024. Brasília: CONAB; 2024 [cited 2024 Feb 26]. Available from: https://www.conab.gov.br/info-agro/safras/cafe/boletim-da-safra-de-cafe

3. Pozza EA, Carvalho VL, Chalfoun SM. Sintomas de injúrias causadas por doenças em cafeeiro. In: Guimarães RJ, Mendes AN, Baliza DP, editors. Semiologia do cafeeiro: sintomas de desordens nutricionais, fitossanitárias e fisiológicas. Lavras/MG; 2010. p. 69-101.

4. Carvalho VL, Chalfoun SM, Cunha RL. Doenças do cafeeiro: diagnose e controle. Belo Horizonte: EPAMIG; 2013.

5. Campbell CL, Madden LV. Introduction to plant disease epidemiology. New York: John Wiley & Sons; 1990.

6. Santos LS, Pozza EA, Faria MA, Silva ML, Custódio AA, Vasco GB. Incidence of the phoma leaf blight in drip irrigated coffee trees under different irrigation managements. Coffee Sci. 2014;9(1):77-89.

7. Box GP, Jenkins GM, Reinsel GC. Time series analysis: forecasting and control. San Francisco (CA): Holden-Day; 1994.

8. Procafé Foundation. Catucaí Amarelo 2SL: ficha técnica da cultivar. [place unknown]: Procafé Foundation; 2000 [cited 2024 Dec 27]. Available from: https://www.fundacaoprocafe.com.br/cultivares-1/catuca%C3%AD-amarelo--2sl

9. Salgado M, Pozza EA, Lima LM, Pereira RT, Pfenning LH. Diagrammatic scale to evaluate severity of phoma leaf blight of coffee trees. Trop Plant Pathol. 2009;34(6):422-7.

10. Morettin PA, Toloi CM. Análise de séries temporais. 2. ed. São Paulo: Blucher; 2006.

11. R Development Core Team. R: a language and environment for statistical computing. Vienna: R Foundation for Statistical Computing; 2018.

12. Lorenzetti ER, Pozza EA, Souza PE, Santos LA, Alves E, Silva AC, et al. Effect of temperature and leaf wetness on *Phoma tarda* and *Phoma* leaf spot in coffee seedlings. Coffee Sci. 2015;10(1):1-9.

13. Roustaee A, Dechamp-Guillaume G, Gelie B, Savy C, Dargent R, Barrault G. Ultrastructural studies of the mode of penetration by *Phoma macdonaldii* in sunflower seedlings. Phytopathology. 2000;90(8):915-20.

14. Zucker WV, Catara A. Observations in the scanning electron microscope on the foliar penetration of *Phoma tracheiphila*. Inf Fitopatol. 1985;35(4):33-35.

15. Graaf PV, Joseph ME, Chartier-Hollis JM, O'Neill TM. Prepenetration stages in infection of clematis by *Phoma clematidina*. Plant Pathol. 2002;51(3):331-337.

16. Firman ID. Some investigations on a disease of *Coffea arabica* caused by *Ascochyta tarda*. Trans Br Mycol Soc. 1965;48(2):161-166.

17. Souza AG, Maffia LA, Silva FF, Mizubuti ES, Teixeira H. A time series analysis of brown eye spot progress in conventional and organic coffee production systems. Plant Pathol. 2015;64(1):157-166.

18. Yang XB, Zeng SM. Detecting patterns of wheat stripe rust pandemics in time space. Phytopathology. 1992;82(5):571-576.

19. Scherm H, Yang XB. Interannual variations in wheat rust development in China and United States in relation to the El Niño/Southern Oscillation. Phytopathology. 1995;85:970-976.

20. Workneh F, Rush CM. Evaluation of relationships between weather patterns and prevalence of sorghum ergot in the Texas Panhandle. Phytopathology. 2002;92(6):659-666.

21. Holb IJ. Monitoring conidial density of *Monilinia fructigena* in the air in relation to brown rot development in integrated and organic apple orchards. Eur J Plant Pathol. 2008;120:397-408.