ORIGINAL PAPER

Modeling spatial variability and pattern of rust and brown eye spot in coffee agroecosystem

**Marcelo de Carvalho Alves · Fábio Moreira da Silva ·
Edson Ampélio Pozza · Marcelo Silva de Oliveira**

Abstract The advent of Precision Agriculture has made possible the analysis of complex spatial patterns of plant disease epidemiology considering statements of integrated disease management. The objective of this work was to use geostatistics, statistics and geographical information systems to characterize the structure and magnitude of spatial dependency of rust (*Hemileia vastatrix*) and brown eye spot (*Cercospora coffeicola*) incidence and severity in coffee agroecosystem cultivated with Catuai Vermelho IAC-99 (*Coffea arabica* L.). Evaluations of incidence and severity of rust and brown eye spot were accomplished at 67 georeferenced points arranged in 6.6202 ha of coffee crop, in the years of 2005, 2006 and 2007. Exponential models of covariance enabled the characterization of the magnitude and structure of rust and brown eye spot spatial variability in the evaluated dates. Ordinary block kriging presented satisfactory performance to map rust and brown eye spot outbreaks based on kriging error coefficients. Kriged maps enabled the visualization of intensity of rust and brown eye spot in each evaluation date. Assessments of incidence and severity presented highly statistical correlation based on linear regression models, also confirmed by the spatial variability of kriging maps. Kriging maps of rust and brown eye spot enabled to observe that intensity of disease was dispersed in foci patterns along the coffee plantation, indicating that the current strategy of disease control based in total area may be replaced by site specific disease management, with less environmental impact and sustainability of coffee crop, according to statements of integrated disease management and precision agriculture.

Keywords *Cercospora coffeicola* · Disease ·
Hemileia vastatrix · Ordinary kriging ·
Precision agriculture · Plant protection

M. de Carvalho Alves (✉)
Department of Soil and Rural Engineering,
Faculty of Agronomy and Veterinary Medicine,
Federal University of Mato Grosso, Av. Fernando Correa da
Costa S/N, Coxipo District, Cuiabá, MT 78060-900, Brazil
e-mail: mdecalves@ufmt.br; marcelocarvalhoalves@gmail.com

F. M. da Silva
Engineering Department, Campus of Federal University of
Lavras (UFLA), cx. 3037, Lavras, MG cep 37200-000, Brazil
e-mail: famsilva@ufla.br

E. A. Pozza
Department of Phytopathology, UFLA,
cx. 3037, Lavras, MG cep 37200-000, Brazil
e-mail: eapozza@ufla.br

M. S. de Oliveira
Department of Exact Sciences, UFLA,
cx. 3037, Lavras, MG cep 37200-000, Brazil
e-mail: marcelo.oliveira@ufla.br

Introduction

Ecological and epidemiological aspects of diseases, and the factors that influence its spatial variability in coffee crop (*Coffea arabica* L.), could be useful in the establishment of more effective and less environmental impact strategies and tactics for sustainable management. Knowledge about these aspects can be obtained through the study of diseases spatial patterns, which vary according to the interaction of processes and sub process of primary and secondary cycles of host–pathogen relationships, influenced by physical, chemical and biological factors as well as the overall crop management system (Madden 1989; Campbell and Madden 1990; Agrios 2004).

Descriptive statistics, data frequency distribution, indices and rates of dispersion have been used to study spatial patterns of diseases (Nicot et al. 1984; Campbell and Madden 1990). However, these methods lead to losses of spatial information when geographical location, spatial distance between samples and its neighbourhood relationship degree are not considered in the data analysis. Statistical methods that take account of this dependency, as geostatistics, are key techniques in the analysis of spatial variability and pattern of environmental variables (Isaaks and Srivastava 1989; Cressie 1993; Burrough and Mc-Donnell 1998).

Geostatistical methodology of analysis has being applied in modern epidemiology to examine spatial patterns and to generate hypotheses about ecological and epidemiological aspects of plant diseases, impossible or difficult to be studied in the past (Nelson et al. 1999; Agrios 2004). Regarding coffee crop, Mouen Bedimo et al. (2007) studied the spatial and temporal dynamics of coffee berry disease (Colletotrichum kahawae, J. M. Waller and P. B. Bridge) through geostatistics. According to the authors, based on semivariograms and kriging maps, it was possible to observe the dynamics of infection in neighbouring plants from the original diseased focus.

Considering rust (Hemileia vastatrix Berk. and Br.) and brown eye spot (Cercospora coffeicola Berk. and Cke.) epidemiology, the variability of nutrients over soil profile, the climate, shade trees, the host spacing and the result of this interaction, can influence disease intensity (Echandi 1959; Fernandez-Borrero et al. 1966; Silva-Acuña et al. 1992; Carvalho et al. 2001; Soto-Pinto et al. 2002; Avelino et al. 2004, 2006; Salgado et al. 2007). Nevertheless, techniques of spatial analyses have not yet been applied as a method to characterize the spatial variability and pattern of rust and brown eye spot in the field.

Based on the hypothesis that precision agriculture can be useful as a decision support tool for coffee crop sustainable management, providing information about the location of high levels of disease intensity, the objective of this work was to use geostatistics and geographical information system as methodology to characterize spatial variability and pattern of rust and brown eye spot in a coffee agroecosystem.

Materials and methods

The experiment was conducted in the years of 2005, 2006 and 2007 at Cafua farm, located in Ijaci municipal district, south of Minas Gerais, Brazil, in an area of about 6.6202 ha of coffee crop (C. arabica L.), Catuaí Vermelho IAC-99 cultivar, susceptible to coffee rust and brown eye spot attack, with 16 years old in 2007, grown in spacing of

4 m between rows and 1 m between plants, given a plant population of 2,500 plants per ha. The geographical coordinates are 21°10′11″ of south latitude and 44°58′37″ of west longitude of Greenwich, with mean altitude of 934 m.a.s.l. and 0.84% of slope towards north-south direction and 12% towards east–west direction.

The climatic variables monthly average values of maximum, mean and minimum air temperature (°C), monthly total rainfall (mm), monthly mean relative humidity (%) and monthly mean insolation (hours) from August 2004 to August 2007 were obtained at principal INMET climatological station of Lavras, Minas Gerais, located 5.09 km away from the experimental area.

A sample grid was demarcated in the area with distances of 25 × 25 and 50 × 50 m, in a total of 67 sampling points (Fig. 1).

The sample point's georeferencing was carried out with GPS TRIMBLE 4600 LS® and Electronic Station Leica TC600®, based on correction of coordinates based marks of Brazilian Institute of Geography (IBGE), located in Federal University of Lavras. The crop fertilization was held in November 2004, 2005, 2006, January 2005, 2006, 2007, February 2005, 2006, 2007 and September 2006 (Table 1).

The chemical control of pest-organisms in crop was conducted in November 2004, April 2005, November 2005, February 2005, 2006, December 2006 and February 2007 (Table 2).
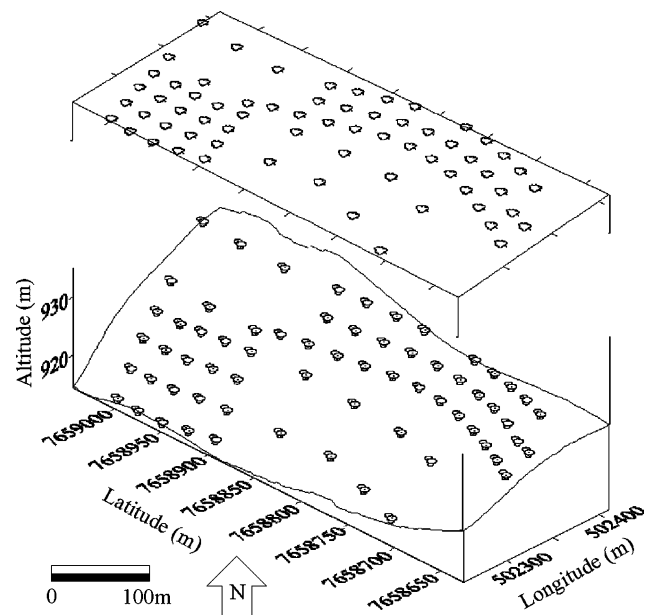
Fig. 1 Sample arrangement used to monitor intensity of rust (Hemileia vastatrix) and brown eye spot (Cercospora coffeicola) in coffee (Coffea arabica L.) agroecosystem, where each point in the map represents five sampled coffee trees

Table 1 Coffee crop fertilization in Cafua farm, Ijaci, MG

	Fertilization in soil (kg per ha)				Aqueous solution in leaves (kg per ha)		
	N	P	K	Lime	Zn	B	KCL
Jan 2005	148	37	148				
Jan 2006	148	37	148				
Jan 2007	148	37	148				
Feb 2005					0.086	0.052	0.086
Feb 2006					0.086	0.052	0.086
Feb 2007					0.086	0.052	0.086
Sep 2006				1,700			
Nov 2004	42	10	42		0.24	0.14	0.24
Nov 2005	42	10	42				
Nov 2006	42	10	42				

Table 2 Chemical control of pest-organisms in coffee crop at Cafua farm, Ijaci, MG

Fungicide/insecticide/herbicide/spreader sticker	Feb 2005 (per ha)	Feb 2006 (per ha)	Feb 2007 (per ha)	Apr 2005 (per ha)	Nov 2004 (per ha)	Nov 2005 (per ha)	Dec 2006 (per ha)
Epoxiconazol 125 g per L (Opus®)	0.9 L	0.9 L		0.4 L	0.6 L		
Azoxystrobin 500 g per kg (Amistar®)				0.01 kg			0.045 kg
Endosulfan 350 g per L (endosulfan AG®)			1.4 L	2.0 L			
Paraffinic mineral oil 42.8% (Nimbus®)				2.0 L			0.9 L
Tiametoxam 300 g per kg and ciproconazol 300 g per kg (Verdadero 600WG®)						0.12 kg	
Glifosato 792.5 g per kg (Roundap WG®)	0.4 kg	0.4 kg					
Tiametoxam 250 g per kg (Actara 250 WG®)							0.69 kg
Azoxistrobin 250 g per L (Priori®)			0.5 L				

The crop fertilization was held with Kamak® implement and the pulverization with Jacto Arbus 400 Airblast Sprayer Tractor Mount® implement. Both implements were traction by a VALTRA VALMET BF75® tractor, 72 hp. The pulverization was realized during the morning and afternoon under conditions of minor insolation and velocity of wind. The regulation of implements and operational speed was the same during the application of fertilizer and pesticides in order to minimize the effects of those applications in the spatial distribution of diseases in the field. It is worth emphasizing that the applied dose often did not follow the recommendation of the pesticides, according to the rural entrepreneur decision, based on his cost-benefit analysis.

Evaluations of intensity of rust (H. vastatrix Berk. and Br.) and brown eye spot (C. coffeicola Berk. and Cke.) in coffee leaves were realized looking up signs of disease incidence in the dates of 06/15/2005, 05/29/2006, 05/30/2007 and severity of diseased leaf area in the dates of 05/29/2006 and 06/30/2007. The evaluation period was determined according to the harvest peak, when the attack intensity was greatest in the region, according to reports of Talamini et al. (2001) and Santos et al. (2008).

Disease assessment was conducted in 100 leaves collected at each georeferenced point in the field ($n = 100$). Each sampled point consisted of five plants. The samples were collected randomly from each side of the planting row, corresponding to the west and east cardinal points, in the middle third of the plants, with ten sampled leaves per plant on each side of the planting row, from the third and fourth pair of leaves, counted from the end of the plagiotropic branch, totaling 6,700 leaves in each evaluation date, according to Huerta (1963) and Boldini (2001) recommendations. The leaves were detached from the plants and analyzed in the Laboratory of Epidemiology and Management of Federal University of Lavras. A leaf was considered to be diseased when there was at least one visible pustule of rust or necrotic spot, considered as 1% of incidence of rust and brown eye spot, respectively. The severity of rust was estimated as proportion of leaf area infected, using a diagrammatic scale proposed by Kushalappa and Chaves (1980). The scale consists of a 50 cm²

leaf illustrating 1, 3, 5 and 7% of foliar area infected by individual or coalesced lesions of rust giving a cumulative area of 25%. The severity of brown eye spot in leaves was estimated as percentage of infected area using an adaptation of the diagrammatic scale proposed by Oliveira et al. (2001). Five ranked categories were established as follows: healthy leaf,]0, 3],]3, 6],]6, 12],]12, 25]. There was no case over 25%. Evaluations of incidence and severity of brown eye spot in coffee fruits were conducted in dates of 05/20/2005, 05/28/2006 and 05/30/2007. A total of 100 cherry fruits were collected at each georeferenced point in the field ($n = 100$), according to the same principle as for leaves. The fruits were detached from plants and analyzed in the laboratory. A fruit was considered to be diseased when there was at least one visible dark spot, depressed, considered as 1% of incidence of brown eye spot. The structure of the pathogen was analyzed under stereoscopic microscope under doubts situations. The severity of brown eye spot in fruits was estimated as percentage of infected area using an adaptation of the diagrammatic scale proposed by Boldini (2001). Four ranked categories were established as follows: healthy fruit,]0, 25],]25, 50],]50, 100]. The sampling procedure was similar to the adopted in Talamini et al. (2001) and Santos et al. (2008) methodology, and the same method was adopted for all evaluated points in the field.

The estimated severity values were calculated based on weighted arithmetic mean of rust and brown eye spot S_p, referring to a set of leaves or fruits $x_1,…,x_n$, classified in severity levels $w_1,…,w_n$, according to the following equation:

$$S_p = \frac{x_1 w_1 + x_2 w_2 + x_3 w_3 + \cdots + x_n w_n}{w_1 + w_2 + w_3 + \cdots + w_n} = \frac{\sum_{i=1}^{n} (x_i w_i)}{\sum_{i=1}^{n} w_i}$$

The variability and pattern of the spatial dependency of incidence and severity of rust and brown eye spot was analyzed by geostatistics, based on the methodology of ordinary kriging system.

Field observations were considered as achievements of a random function $Z(x)$, where x denotes the spatial location with expected values $E[Z(x_i)] = m(x_i)$ and $E[Z(x_i + h)] = m(x_i + h)$, where m is a constant mean and h is a vector distance in the sampled space. In geostatistics, covariance analysis is an important step since the chosen model is the interpretation of the structure of spatial correlation to be used in the kriging inferential procedures (Burrough and McDonnell 1998). This analysis includes first the estimation of the experimental covariance, and later, the adjustment of theoretical models. The adjusted model must represent the trend of $C(h)$ in relation to h, in order to achieve more accurate and reliable kriging estimates (Olea 1999; Webster and Oliver 2001). The covariance between data

values separated by a vector h is computed by the experimental function of covariance as follows (Goovaerts 1997; Soares 2000):

$$C(h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} Z(x_i)Z(x_i + h) - m(x_i)m(x_i + h),$$

where

$$m(h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} Z(x_i)$$

$$m(x_i + h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} Z(x_i + h),$$

$N(h)$ is the number of data pairs within the class of distance and direction, and $m(h)$, $m(x_i + h)$ are the means of the corresponding lag means, referent to tail and head values. The covariance can be computed for different lags, h_1, h_2,…,h_n, and the ordered set of covariances $C(h_1)$, $C(h_2)$,…,$C(h_n)$, is the experimental function of autocovariance or experimental function of covariance. The theoretical models of covariance were adjusted by Chilès and Delfiner (1999):

$$C(h) = \exp\left(-\frac{h}{a}\right),$$

where C is a covariance in $\mathbb{R}^n$ for any n, a is the range and h is the distance. The exponential model reaches its sill ($Co + C$) only asymptotically when $r \to \infty$, and its practical range is about $3a$. Like the spherical model, the exponential model is linear at very short distances near the origin; however, it rises more steeply and then flattens out more gradually (Isaaks and Srivastava 1989; Chilès and Delfiner 1999).

The weighted least square method was used for the adjustment of theoretical models of covariance according to the methodology of Cressie (1985). Models were chosen considering results of cross-validation (Cressie 1993; Chilès and Delfiner 1999). In ordinary kriging, the local variation of the mean is limited by the field of stationary of the mean to the local neighborhood $V(x)$ centered on the location x to be estimated. The linear estimator is therefore a linear combination of the n random variables $Z(x_i)$ plus the constant local mean $m(x)$.(Goovaerts 1997):

$$\hat{Z}(x) = \sum_{i=1}^{n} \lambda_i Z(x_i) + \left[1 - \sum_{i=1}^{n} \lambda_i\right] m(x),$$

In this case, the unknown local mean $m(x)$ is filtered from the linear estimator $\hat{Z}(x_i)$ by forcing that the sum of kriging weights λ_i is 1. Thus, the estimator of ordinary kriging is written as a linear combination of n random variables $Z(x)$:

$$\hat{Z}(x) = \sum_{i=1}^{n} \lambda_i \bar{Z}(x_i), \text{ where } \sum_{i=1}^{n} \lambda_i = 1,$$

In block kriging interpolation, the Z value should be estimated inside a block B, which may be a line, an area or a volume, considering that the variable occurs in one, two or three spatial dimensions, respectively (Burrough and McDonnell 1998).

$$\hat{Z}(B) = \sum_{i=1}^{n} \lambda_i Z(x_i),$$

And the expected error is $E\left[\{\hat{Z}(B) - Z(B)\}^2\right] = 0$. The estimation variance is:

$$\text{var}[\hat{Z}(B)] = E[\{\hat{Z}(B) - \hat{Z}(B)\}^2]$$
$$= 2\sum_{i=1}^{n} \lambda_i \bar{C}(x_i, B) - \sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i \lambda_j C(x_i, x_j) - \bar{C}(B, B)$$

where $\bar{C}(x_i, B)$ is the covariance of Z between the data points x_i and x_j, $\bar{C}(B, B)$ is the mean covariance between the ith sampled point and the target block B, defined by the integral (Webster and Oliver 2001):

$$\bar{C}(x_i, B) = \frac{1}{|B|} \int_B C(x_i, x) \mathrm{d}x,$$

where $C(x_i, x)$ is the semivariance between the sampled point x_i and the point x used for description of the block. The term $\bar{C}(B, B)$ is the double integral:

$$\bar{C}(B, B) = \frac{1}{|B|^2} \int_B \int_B C(x, x') \mathrm{d}x \mathrm{d}x',$$

where $C(x, x')$ is the covariance between the points x and x' that sweep independently over B.

The next step consists in find the weights that minimize these variances, subject to the constraint that weights sum to 1. This is achieved using a function $f(\lambda_i, \phi)$ containing the variance to be minimized and an additional term containing the multiplier of lagrange ϕ:

$$(\lambda_i, \phi) = \text{var}[\hat{Z}(B) - Z(B)] - 2\phi\left\{\sum_{i=1}^{n} \lambda_i - 1\right\},$$

According to the partial derivatives of the function with respect to 0, the weights of the ordinary block kriging system are obtained by:

$$\begin{cases} \sum_{i=1}^{n} \lambda_i C(x_i, x_j) + \phi(B) = \bar{C}(x_j, B), & \text{for all } j \\ \sum_{i=1}^{n} \lambda_i = 1, \end{cases}$$

The block kriging variance is obtained by $\sigma^2(B)$ (Burrough and McDonnell 1998):

$$\sigma^2(B) = \sum_{i=1}^{N} \lambda_i \bar{C}(x_i, B) + \phi(B) - \bar{C}(B, B),$$

The kriging equations represented in matrix form is (Burrough and McDonnell 1998; Webster and Oliver 2001):

$$A\lambda = b \approx \lambda = A^{-1}b,$$

where A is the matrix of covariances between pairs of data points, b is the vector of semivariances between each data point and the block to be predicted, λ is the vector of weights and ϕ is a lagrangian for solving the equations:

$$A = \begin{bmatrix} C(x_1, x_1) & C(x_1, x_2) & \cdots & C(x_1, x_n) & 1 \\ C(x_2, x_1) & C(x_2, x_2) & \cdots & C(x_2, x_n) & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ C(x_n, x_1) & C(x_n, x_2) & \cdots & C(x_n, x_n) & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix},$$

$$\lambda = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \varphi \end{bmatrix}, \quad b = \begin{bmatrix} \bar{C}(x_1, B) \\ \bar{C}(x_2, B) \\ \vdots \\ \bar{C}(x_n, B) \\ 1 \end{bmatrix}.$$

The kriging variance is given by: $\sigma^2(B) = b^{\mathrm{T}}\lambda - \bar{C}(B, B)$.

Ordinary block kriging was chosen considering the large amplitude of short-range variation of natural phenomena like plant diseases, where ordinary point kriging may result in maps that have many sharp spikes or pits. When ordinary block kriging is used, the resulting smoothed interpolated surface is free from the pits and spikes (Burrough and McDonnell 1998). There were delineated blocks of 4×4 m, considering two points in the horizontal cell and four points in the vertical cell, in order to represent the size of the sampled parcels in the field.

Using this method, plant disease spatial variability could be represented according to coffee crop spacing in the field. The number of neighbours was chosen based on cross-validation results.

Ordinary block kriging estimates were evaluated using cross-validation analyses. Cross-validation is a powerful validation technique used to check the performance of the kriging model. It consists of removing data on at a time, and then trying to predict it. Thus, the predicted values can be compared to the observed values in order to assess how well the prediction is working according to its self-consistency and lack of bias (Isaaks and Srivastava 1989; Cressie 1993; Goovaerts 1997; Chilès and Delfiner 1999; Burrough and McDonnell 1998). The mean standardized prediction errors were defined by:

Fig. 2 Monthly average values of maximum, mean and minimum air temperature (max$T$, T, min$T$) (°C), monthly total rainfall (mm), monthly average relative humidity (%) and monthly average insolation (hours) from August 2004 to August 2007 at principal INMET climatological station of Lavras, Minas Gerais
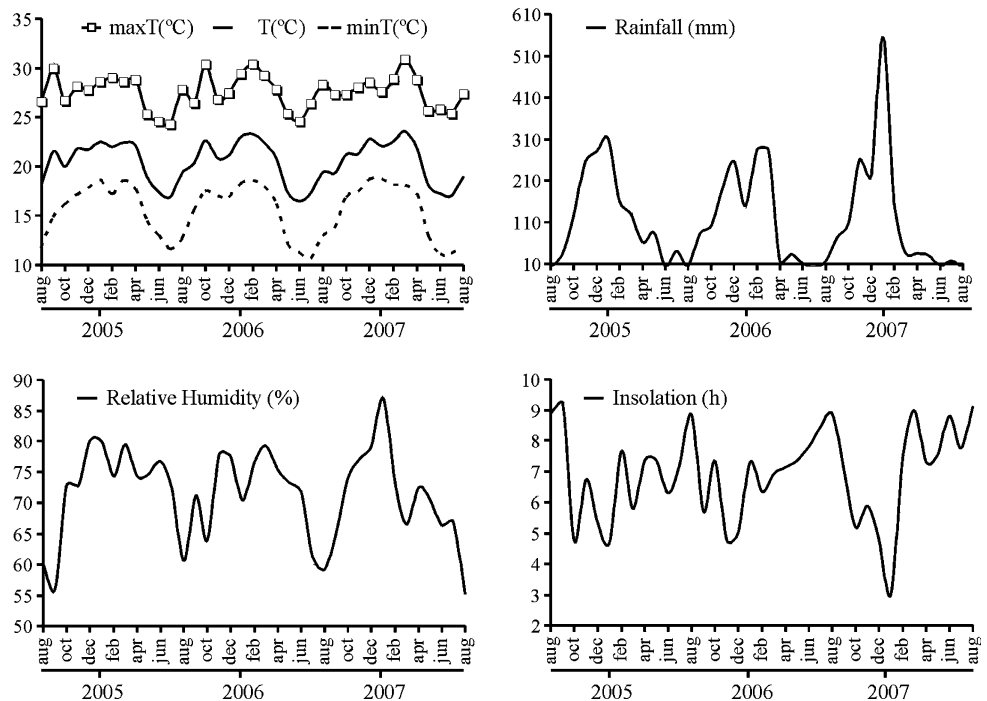
$$\frac{\sum_{i=1}^{n}\left(\hat{Z}(x_i) - Z(x_i)\right)\big/\hat{\sigma}(x_i)}{n}, \text{ and}$$

The root-mean square standardized prediction errors were defined by:

$$\sqrt{\frac{\sum_{i=1}^{n}\left[\left(\hat{Z}(x_i) - Z(x_i)\right)\big/\hat{\sigma}(x_i)\right]^2}{n}},$$

where $\hat{Z}(x_i)$ is the kriging estimation, $Z(x_i)$ is the observed value, $\hat{\sigma}(x_i)$ is the prediction standard error for the location x_i. Considering an ideal performance, mean standardized prediction errors should be 0 and root-mean square standardized prediction errors should be 1 (Cressie 1993).

The relationship between incidence and severity of rust and brown eye spot in each evaluated date was quantified through linear regression (Pimentel-Gomes and Garcia 2002). The least squares criterion was used for polynomial function adjustment:

$$y = a_0 + a_1 x + a_2 x^2 = \text{Parabol},$$

where y is the leaf area with lesions, a_0 is the intercept or linear coefficient and $a_1, a_2,\ldots,a_n$, the parameters of the model or angular coefficients. The R-square coefficient (R^2) was used to measure the quality of models fit, based on the diagram of dispersion between disease incidence (x) and severity (y) data.

Results

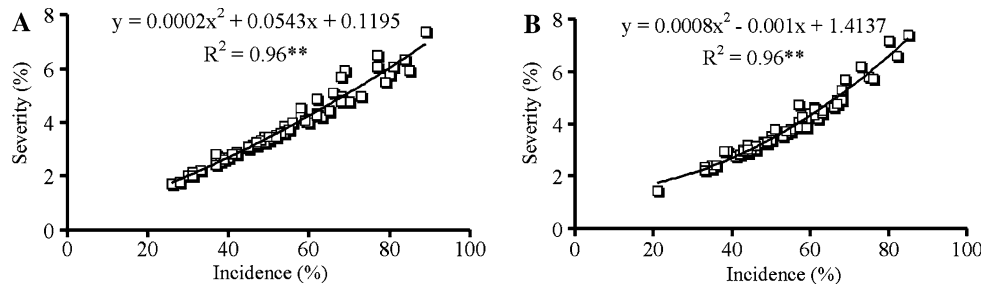The climatic conditions of the studied region presented suitability conditions for the epidemiology of rust and brown eye spot, mainly in the rainy period, from October to March (Fig. 2). The optimum mean air temperature for spore germination and infection of *H. vastatrix* is situated between 22 and 24°C, with lower limit of 15°C and above 28°C. Periods of leaf wetness above 6 h until 48 h were considered as great for the disease progress (Kushalappa et al. 1983). Considering *C. coffeicola*, the mean air temperature of 24°C led to the increase of mycelial growth and sporulation, with higher germination of conidia in vitro between 24 and 30°C. Temperatures under 12°C and above 30°C provided smaller diameter of colonies (Echandi 1959). Leaf wetness above 6 h until 48 h resulted in greater cumulative proportion of leaves with injury (Fernandes 1988).

Rust and brown eye spot incidence and severity assessments presented strongly statistical correlation based on R^2 coefficients. Linear regression models were significant ($P < 0.001^{**}$) to describe the interaction between assessments of incidence and severity through second order polynomial adjustment, with R^2 values ranging from 0.75 to 0.99 (Figs. 3, 4 and 5).
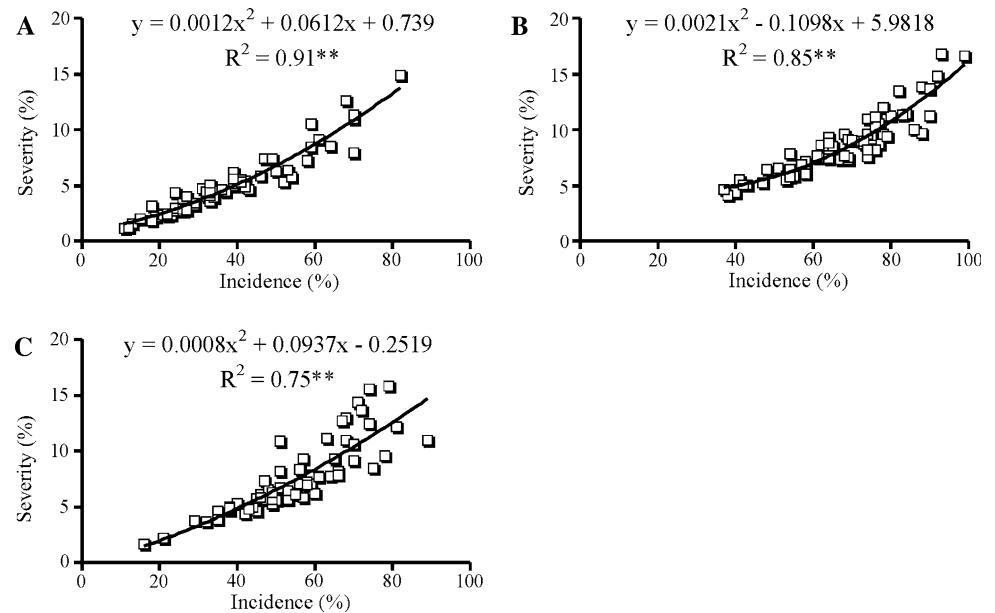
Based on the methodology of geostatistical analysis, it was possible to quantify the magnitude and structure of spatial dependency of intensity of rust and brown eye spot in the field (Tables 3, 4).

Theoretical exponential models were fitted to the experimental functions of covariance. The structural analysis enabled to observe the existence of spatial dependency of rust and brown eye spot in the evaluated dates, considering the tendency of decrease of covariance with the increase of distance, culminating in the stability of the
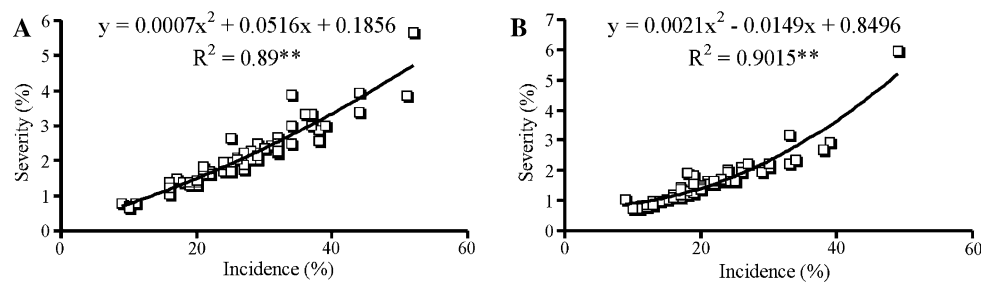
Fig. 3 Linear regression relationship (*line*) between incidence and severity assessments (*open square*) of 67 sampled points with rust (*Hemileia vastatrix*) on coffee (*Coffea arabica* L.) leaves in the dates of 05/29/2006 (**a**) and 06/30/2007 (**b**)

A $y = 0.0002x^2 + 0.0543x + 0.1195$
$R^2 = 0.96^{**}$

B $y = 0.0008x^2 - 0.001x + 1.4137$
$R^2 = 0.96^{**}$

Fig. 4 Linear regression relationship (*line*) between incidence and severity assessments of 67 sampled points with brown eye spot (*Cercospora coffeicola*) on coffee (*Coffea arabica* L.) fruits in the dates of 05/20/2005 (**a**), 05/28/2006 (**b**), 05/30/2007 (**c**)

A $y = 0.0012x^2 + 0.0612x + 0.739$
$R^2 = 0.91^{**}$

B $y = 0.0021x^2 - 0.1098x + 5.9818$
$R^2 = 0.85^{**}$

C $y = 0.0008x^2 + 0.0937x - 0.2519$
$R^2 = 0.75^{**}$

Fig. 5 Linear regression relationship (*line*) between incidence and severity assessments of 67 sampled points with brown eye spot (*Cercospora coffeicola*) on coffee (*Coffea arabica* L.) leaves in the dates of 05/29/2006 (**a**) and 06/30/2007 (**b**)

A $y = 0.0007x^2 + 0.0516x + 0.1856$
$R^2 = 0.89^{**}$

B $y = 0.0021x^2 - 0.0149x + 0.8496$
$R^2 = 0.9015^{**}$

Table 3 Theoretical parameters of functions of covariance and quality coefficients of estimates of ordinary kriging used to characterize the spatial variability and pattern of intensity of rust (*Hemileia vastatrix*) in coffee leaves (*Coffea arabica* L.)

Evaluation type	Evaluation date	Nugget effect (Co)	Sill (Co + C)	Effective range (a)	Mean standardized prediction errors	Root-mean-square standardized prediction errors
Incidence	06/15/2005	11.6761	70.6171	38.4850	0.0045	1.0900
	05/29/2006	58.2538	209.9413	56.4536	−0.0025	1.2610
	06/30/2007	32.2414	123.2190	84.4900	0.0178	1.3040
Severity	05/29/2006	0.3839	1.3814	56.4536	−0.0017	1.2530
	06/30/2007	0.2409	1.0740	76.4983	0.0156	1.2650

models in the distance that separates the structured and random universe, satisfying the hypothesis of stationarity. The relationship between evaluations of incidence and severity of rust and brown eye spot was represented by the range values of the exponential models in the evaluated dates (Tables 3, 4).

Table 4 Theoretical parameters of functions of covariance and quality coefficients of estimates of ordinary kriging used to characterize the spatial variability and pattern of intensity of brown eye spot (*Cercospora coffeicola*) in coffee fruits and leaves (*Coffea arabica* L.)

Coffee organ	Evaluation type	Evaluation date	Nugget effect (Co)	Sill (Co + C)	Effective range (a)	Mean standardized prediction errors	Root-mean-square standardized prediction errors
Fruit	Incidence	05/20/2005	77.8738	192.1658	63.2373	0.0020	0.9243
Fruit	Incidence	05/28/2006	15.6365	192.4277	40.0820	0.0098	0.9860
Fruit	Incidence	05/30/2007	75.4612	147.5693	46.4819	0.0258	1.4660
Fruit	Severity	05/20/2005	0.6174	6.8447	74.2597	0.0003	0.9172
Fruit	Severity	05/28/2006	0.3824	7.0768	41.6473	0.0125	1.2720
Fruit	Severity	05/30/2007	3.8715	5.9438	46.4819	0.0115	1.5090
Leaf	Incidence	06/15/2005	23.6896	91.4990	57.1567	0.0141	1.0860
Leaf	Incidence	05/29/2006	19.4412	61.9261	46.4819	0.0166	1.2460
Leaf	Incidence	06/30/2007	20.0533	36.0166	46.4819	0.0197	1.4710
Leaf	Severity	05/29/2006	0.1847	0.5728	46.4819	0.0125	1.2720
Leaf	Severity	06/30/2007	0.1870	0.3807	46.4819	0.0079	1.4160

According to the range values, rust disease presented distribution in aggregated pattern, with effective ranges of 38.4 m in 06/15/2005, 56.4 m in 05/29/2006 and 76.4–84.4 m in 06/30/2007. Based on values of range and sill, there was higher disease severity in evaluations performed in 05/29/2006 and 06/30/2007, when compared to 06/15/2005 (Table 3).

Considering theoretical exponential models of covariance, intensity of brown eye spot in leaves presented aggregated pattern, with effective ranges varying in distances between 46 and 57 m. Regarding assessments of brown eye spot in fruits, the range of intensity varied in distances between 40 and 63 m, depending on the evaluated date (Table 4). There was observed minor range and sill values in 05/30/2007 and 06/30/2007, when compared to the other dates.

Using theoretical exponential models of covariance, rust and brown eye spot incidence and severity values where interpolated in the studied area without bias and with minimal variance, by the method of ordinary block kriging (Goovaerts 1997; Webster and Oliver 2001). The ordinary kriging system presented satisfactory performance to estimate intensity of coffee rust and brown eye spot based on kriging error coefficients, considering that mean standardized prediction errors and root-mean square standardized prediction errors presented values near 0 and 1, respectively (Cressie 1993) (Tables 3, 4).

Through maps of ordinary block kriging, it was observed the spread of epidemics, according to the range of spatial variability, in the evaluated dates. Disease incidence and severity maps presented spatial variability with patterns of correspondence in 05/29/2006 and 06/30/2007, however, severity maps highlighted areas with higher disease intensity when compared to incidence maps (Figs. 6, 7 and 8). Kriging maps of rust and brown eye spot enabled to observe that intensity of disease was dispersed in foci patterns along the coffee plantation. Considering maps of brown eye spot, it was observed some correspondences and differences between areas with disease in fruits and leaves in May and June 2005, May 2006, May and June 2007 (Figs. 7, 8).

Discussion

Considering the observed correlation between rust and brown eye spot incidence and severity evaluations, Silva-Acuña et al. (1999) also verified strong correlation between assessments of incidence and severity of coffee rusted leaves through linear regression models, using second order polynomial adjustment, with R^2 values ranging from 0.89 to 0.99, in municipal district of Teixeiras and Patrocínio of Minas Gerais state, along three consecutive years. Rengifo-Guzmán et al. (2006), studying the intensity of brown eye spot in relation to mineral nutrition of coffee seedlings submitted to Hoagland solution, also verified statistic relationship between incidence and severity evaluations, related to the mean percentage of infected leaves and the number of spots per leaf, under concentrations of 0, 25, 50, 75 and 100%. Considering the statistical and geostatistical correlation between incidence and severity measurements, if a choice had to be made between the two kinds of maps, it could be chosen to keep the more informative map and not necessarily the map built with the easiest variable to assess. However, the information about both variables is important to confirm the results about disease distribution in the field and to emphasize the areas that deserve greater concern with regard to disease control.

Based on geostatistical analysis, it was also possible to observe the correspondence between rust and brown eye

Fig. 6 Ordinary kriging maps used to characterize the spatial variability incidence (**a**, **b**, **c**), and severity (**d**, **e**), of rust (*Hemileia vastatrix*) in coffee leaves (*Coffea arabica* L.) in the dates of 06/15/2005 (**a**), 05/29/2006 (**b**, **d**) and 06/30/2007 (**c**, **e**)
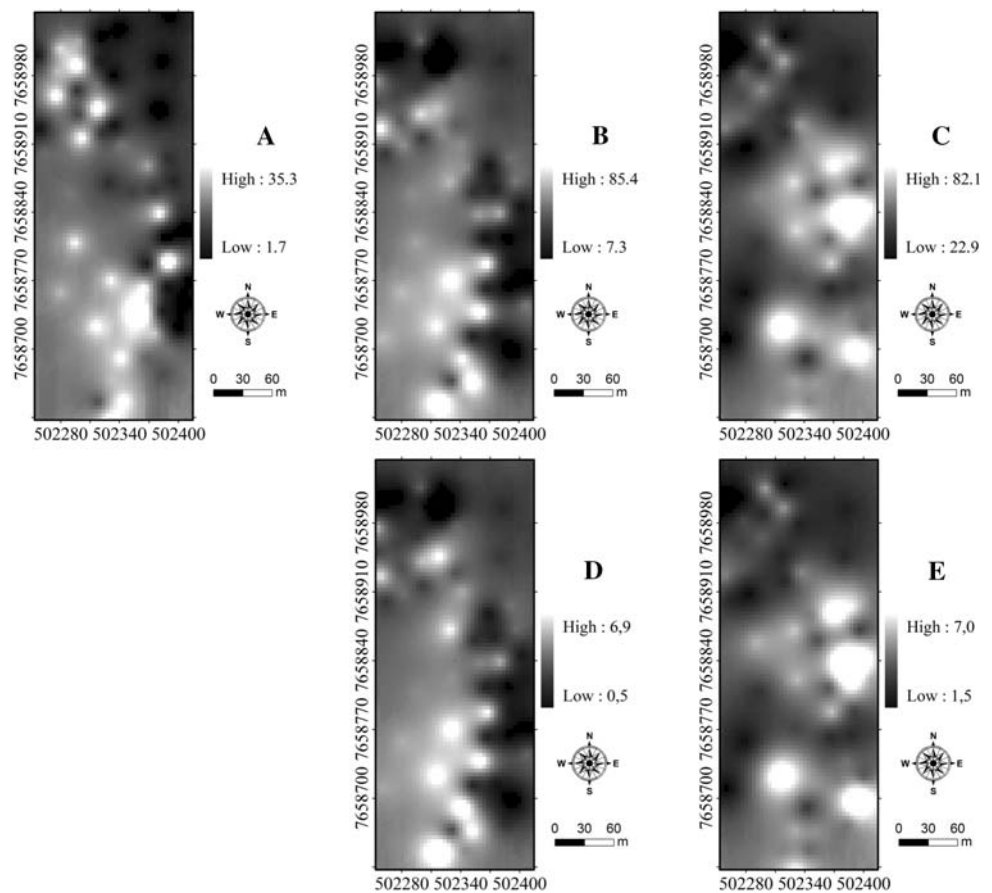
spot incidence and severity evaluations, considering the range of functions of covariance and spatial variability of kriging maps. The minor values of range and sill of rust observed in the date of 06/15/2005 can be explained by the chemical control of epoxiconazol realized in April 2005. The highest range and sill values observed in the subsequently evaluated dates can be related to the reduction of the residual effect of the chemical control realized in February 2006 and 2007. The spatial pattern of rust in the field may have been influenced by suitability of climatic conditions, the spatial variability of the mineral nutrition of coffee trees, as well as due to the bienality of coffee yield. The positive correlation between rust, mineral nutrition and coffee yield during the harvest period was related by Avelino et al. (2006) and Carvalho et al. (2001). According to Carvalho et al. (2001) and Silva-Acuña et al. (1992), the abundant yield promotes nutritional imbalance of plants caused by the drain of fotoassimilates from leaves to fruits, affecting the energy supply for rust defense. It is worth emphasizing that *Cercospora* and *Hemileia* are very different and do not have the same requirements. One of the main differences is that *Hemileia* is a biotrophic fungus whereas *Cercospora* is a necrotrophic one. A correlation between *Cercospora* and *Hemileia* may exist, but the presence of the two diseases together probably involves

different mechanisms. However, according to the studies of Scott and Smillie (1966), after infection of the host tissue by a pathogen, there is increase in the respiratory rate, resulting in an increase of biosynthetic activity, carbon flow through Embden–Meyerhoff and pentose phosphate pathways, division of secondary metabolites and formation of compounds such as lignin and other isoflavones, as phytoalexins (Kossuge and Kimpel 1981), which probably help in defending coffee trees against both brown eye spot and rust (Silva-Acuña 1985).

In the case of brown eye spot, the minor range and sill values observed in 05/30/2007 and 06/30/2007, when compared to the other evaluated dates, can be related to the azoxistrobin chemical control realized in December 2006 and February 2007, as well as due to the spatial variability of mineral nutrition in plants, as related by Fernandez-Borrero et al. (1966).

Ordinary block kriging maps enabled to observe the pattern of distribution of rust and brown eye spot in foci along the coffee plantation, indicating that the current strategy of disease control based in total area may be replaced by site specific disease management, according to rust and brown eye spot action threshold levels. The various correspondence between brown eye spot maps in fruits and leaves, suggested that similar factors related to the

Fig. 7 Ordinary kriging maps used to characterize the spatial variability of incidence (**a**, **b**, **c**), and severity (**d**, **e**) of brown eye spot (*Cercospora coffeicola*) in coffee leaves (*Coffea arabica* L.) in the dates of 06/15/2005 (**a**), 05/29/2006 (**b**, **d**) and 06/30/2007 (**c**, **e**)
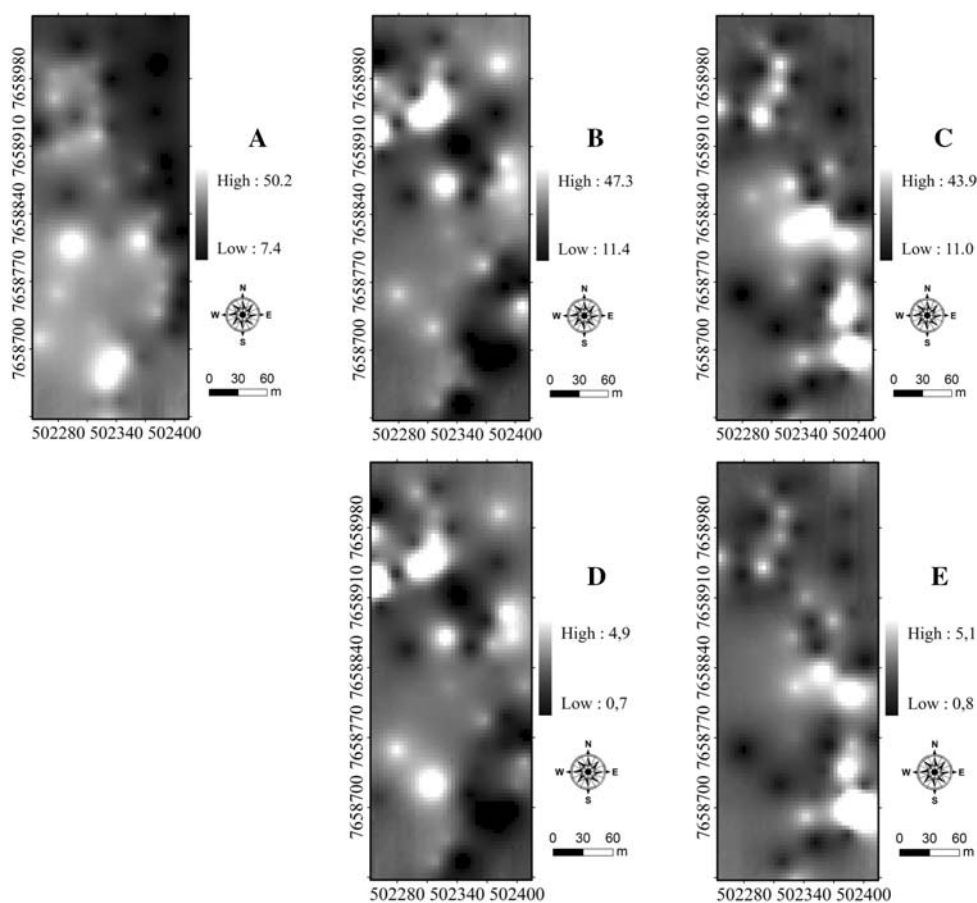
disease distribution are influencing the location of outbreaks in fruits and leaves in the field. This fact also suggested that infected leaves with brown eye spot could be the primary source of disease inoculum for the infection of neighbouring coffee trees, considering the presence of leaves in the host throughout all the months of the year, promoting the pathogen survival. The differences in the spatial distribution of the brown eye spot in the leaf and fruits could be related to coffee tree architecture, because Echandi (1959) observed that water drops facilitates the spread of the fungus within short distances and the wind facilitates spread over long distances. In this case, the infection of fruits by conidia could have been more effected by water drops dissemination inside the canopy of trees, with reduced effect of wind. Otherwise, the infection of leaves by conidia could have been not only influenced by water, but also in major scale by the wind, considering the major surface of contact of leaves around the canopy of trees when compared to the fruits. In the same way, there is an accumulation of water around the fruits that may promote the infection process. Additionally, the contacts between fruits of the same glomerule may favour the contamination of healthy fruits at different scale when compared to the scale of leaves infection. Sentelhas et al. (2005) observed differences of leaf wetness duration at the top and the lower part of coffee canopy, indicating spatial variability of humidity according to coffee canopy architecture, supporting this hypothesis.

Mouen Bedimo et al. (2007) also used ordinary kriging to study spatial-temporal dynamics of *C. kahawae* in the field. According to the authors, the geostatistical method reveled the primary foci of disease and suggested that inoculum from previous epidemics survives at points in the initial foci in a coffee plantation.

Despite Bowden et al. (1971) and Nagarajan and Singh (1990) stated about the long-distance dispersion of rust pathogens, the short distance had not been studied yet. The present work demonstrated that coffee rust and brown eye spot presented spatial structure on a plantation scale, so that, it could be possible to consider that spatial structure for the implementation of control tactics in relation to coffee diseases.

Thus, based on the methodology of spatial analysis adopted in this study, ordinary kriging system and regression analysis were useful to characterize the pattern and spatial variability of rust and brown eye spot patosystems.

Fig. 8 Ordinary kriging maps used to characterize the spatial variability of incidence (**a**, **b**, **c**) and severity (**d**, **e**, **f**), of brown eye spot (*Cercospora coffeicola*) in coffee fruits (*Coffea arabica* L.) in the dates of 05/20/2005 (**a**, **d**), 05/28/2006 (**b**, **e**), 05/30/2007 (**c**, **f**)
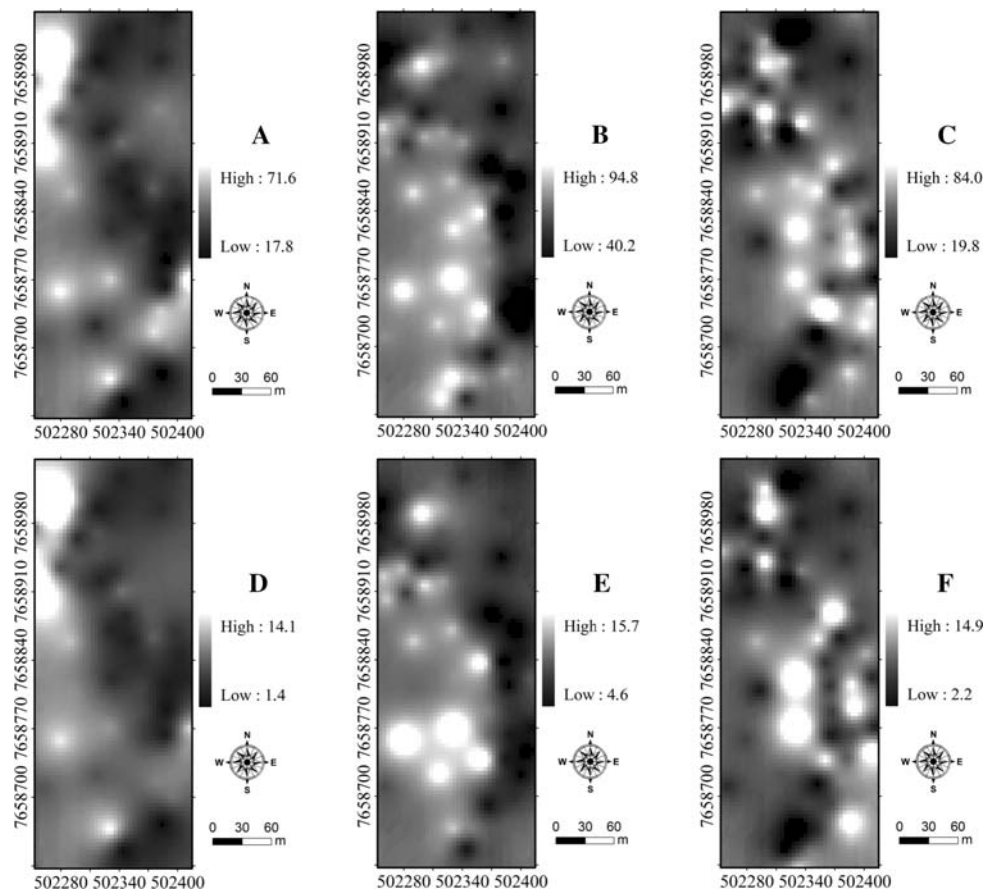
Conclusions

Disease incidence and severity assessments presented strongly statistical correlation modeled with linear regression in each evaluation date.

Exponential models of covariance and ordinary block kriging maps enabled the characterization of spatial pattern and variability of rust and brown eye spot in coffee agroecosystem.

Kriging maps of rust and brown eye spot enabled to observe that intensity of disease was dispersed in foci patterns along the coffee plantation, indicating that the current strategy of disease control based in total area may be replaced by site specific disease management.

References

Agrios GN (2004) Plant pathology. Academic Press, San Diego

Avelino J, Willocquet L, Savary S (2004) Effects of crop management patterns on coffee rust epidemics. Plant Pathol 53:541–547

Avelino J, Zelaya H, Merlo A, Pineda A, Ordõnez M, Savary S (2006) The intensity of a coffee rust epidemic is dependent on production situations. Ecol Model 197:431–447

Boldini JM (2001) Epidemiologia da ferrugem e da cercosporiose em cafeeiro irrigado e fertirrigado (Epidemiology of rust and brown eye spot in irrigated and fertirrigated coffee). Master's dissertation in phytopathology, Federal University of Lavras

Bowden J, Gregory PH, Johnson CG (1971) Possible wind transport of coffee leaf rust across the Atlantic. Nature 229:500–501

Burrough PA, McDonnell RA (1998) Principles of geographical information systems. Oxford University Press, Oxford

Campbell CL, Madden LV (1990) Introduction to plant disease epidemiology. Wiley, New York

Carvalho VL, Chalfoun SM, Castro HA, Carvalho VD (2001) Influence of different yield levels on coffee rust evolution and on phenolic compounds on leaves. Cienc Agrotech 25:49–59

Chilès JP, Delfiner P (1999) Geostatistics: modeling spatial uncertainty. Wiley, New York

Cressie N (1985) Fitting variogram models by weighted least squares. J Int Assoc Math Geol 17:653–702

Cressie N (1993) Statistics for spatial data. Wiley, New York

Echandi E (1959) La chasparria de los cafetos causada por el hongo *Cercospora coffeicola* Berk. and Cooke (the brown eye spot caused by the fungus *Cercospora coffeicola* Berk. and Cooke). Turrialba 9:54–67

Fernandes, CD (1988) Efeito de fatores do ambiente e da concentração de inóculo sobre a cercosporiose do cafeeiro. Master's dissertation in phytopathology, Federal University of Viçosa

Fernandez-Borrero O, Mestre AM, Duque SIL (1966) Efecto de la fertilización en la incidência de la mancha de hierro (*Cercospora coffeicola*) en frutos de café. (fertilization effect on the incidence

of brown eye spot (*Cercospora coffeicola*) in coffee fruits. Cenicafe 17:5–6

Goovaerts P (1997) Geostatistics for natural resources evaluation. Oxford University Press, New York

Huerta SA (1963) Par de folhas representativo del estado nutricional del cafeto (pair leaves representative of the nutritional status of coffee). Cenicafe 14:111–127

Isaaks EH, Srivastava RM (1989) Applied geostatistics. Oxford University Press, New York

Kossuge T, Kimpel JA (1981) Energy use and metabolic regulation in plant pathogen interaction. In: Ayres PG (ed) Effects of disease on the physiology of the growing plant. Cambridge University Press, London, pp 29–45

Kushalappa AC, Chaves GM (1980) An analysis of the development of coffee rust in the Field. Fitopatol Bras 5:95–103

Kushalappa AC, Akutsu M, Ludwig A (1983) Application of survival ratio for monocyclic process of *Hemileia vastatrix* in predicting coffee rust infection rates. Phytopathology 73:96–103

Madden LV (1989) Dynamic nature of within field diseases and pathogen distributions. In: Jeger MJ (ed) Spatial components of plant disease epidemics. Prentice-Hall, USA, pp 96–126

Mouen Bedimo JA, Bieysse D, Cilas C, Nottéghem JL (2007) Spatio-temporal dynamics of arabica coffee berry disease caused by *Colletotrichum kahawae* on a plot scale. Plant Dis 91:1229–1236

Nagarajan S, Singh DV (1990) Long-distance dispersion of rust pathogens. Annu Rev Phytopathol 28:139–153

Nelson MR, Orum TV, Jaime-Garcia R, Nadeem A (1999) Applications of geographic information systems and geostatistics in plant disease epidemiology and management. Plant Dis 83:308–319

Nicot PC, Rouse DI, Yandell BS (1984) Comparison of statistical methods for studying spatial patterns of soilborne plant pathogens in the field. Phytopathology 74:1399–1402

Olea RA (1999) Geostatistics for engineers and earth scientists. Kluwer, Norwell

Oliveira CA, Pozza EA, Oliveira VB, Santos EC, Chaves ZM (2001) Escala diagramática para avaliação da severidade de cercosporiose em folhas de cafeeiro (diagrammatic scale to evaluate the severity of brown eye spot in coffee leaves). (Abstract), 2° Simpósio dos Cafés do Brasil (2nd symposium of coffee in Brazil), Vitória, pp 80

Pimentel-Gomes F, Garcia CH (2002) Estatística aplicada a experimentos agronômicos e florestais (statistics applied to agronomic and forest experiments). FEALQ, Piracicaba

Rengifo-Guzmán HG, Lequizamón-Caycedo JE, Riaño-Herrera NM (2006) Incidencia Y Severidad de La mancha de hierro em plântulas de *Coffea arabica* em diferentes condiciones de nutrición. Cenicafe 73:232–242

Salgado BG, Macedo RLG, Carvalho VL, Salgado M, Venturin N (2007) Progress of rust and coffee plant cercosporiose mixed with grevílea, with ingazeiro and in the full sunshine in Lavras MG. Cienc Agrotech 31:1067–1074

Santos FS, Souza PE, Pozza EA, Miranda JC, Barreto SS, Theodoro VC (2008) Progress of brown eye spot (*Cercospora coffeicola* Berkeley and Cooke) in coffee trees in organic and conventional systems. Summa Phytopathol 34:48–54

Scott KT, Smillie RM (1966) Metabolic regulation in diseased leaves. I. The respiration rise in barley leaves infected with powdery mildew. Plant Physiol 41:289–297

Sentelhas PC, Gillespie TJ, Batzer JC, Gleason ML, Monteiro JEBA, Pezzopane JRM, Pedro MJ Jr (2005) Spatial variability of leaf wetness duration in different crop canopies. Int J Biometeorol 49:363–370

Silva-Acuña, R (1985) Fatores que influenciam o progresso da ferrugem do cafeeiro (*Hemileia vastatrix* Berk. and Br.). Master's dissertation in phytopathology, Federal University of Viçosa

Silva-Acuña R, Zambolim L, Venegas VHA, Chaves GM (1992) Relation between coffee beans yields, levels of foliar macronutrients and the severity of coffee leaf rust. Revista Ceres 39:365–377

Silva-Acuña R, Maffia LA, Zambolim L, Berger RD (1999) Incidence–severity relationships in the pathosystem *Coffea arabica–Hemileira vastatrix*. Plant Dis 83:186–188

Soares A (2000) Geoestatística para as ciências da terra e do ambiente (geostatistics for Earth and environmental sciences). IST Press, Lisboa

Soto-Pinto L, Perfecto I, Caballero-Nieto J (2002) Shade over coffee: its effects on berry borer, leaf rust and spontaneous herbs in Chiapas, Mexico. Agrofor Syst 55:37–45

Talamini V, Souza PE, Pozza EA, Silva AM, Bueno Filho JSS (2001) Progress of the rust and of the brown eye spot of the coffee trees (*Coffea arabica* L.) in different irrigation depths and different fertilizer parcelaments. Ciênc agrotec 25:55–62

Webster R, Oliver M (2001) Geostatistics for environmental scientists. Wiley, England