Ciencia e Investigación AGRARIA

Cien. Inv. Agr. 39(3):459-471. 2012
www.rcia.uc.cl
CROP PROTECTION

RESEARCH PAPER

Determination of spatiotemporal stability of corn head smut (*Sporisorium reilianum*) by SADIE

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Abstract

J.F. Ramírez-Dávila, J.R. Sánchez-Pale, E. Porcayo-Camargo, and C. de León. 2012. Determination of spatiotemporal stability of corn head smut (*Sporisorium reilianum*) by SADIE. Cien. Inv. Agr. 39(3): 459-471. Recently, *S. reilianum* has caused significant ecological and economic damage in the maize-producing areas of Mexico and other countries. Knowledge about the spatiotemporal stability and distribution of the disease is important for the development of integrated management programs. The present study was performed to model the spatial distribution of *S. reilianum* from 2006 to 2009 using geostatistic techniques and to determine the spatiotemporal stability of corn head smut via a spatial analysis by distance indices (SADIE) and the Cramer-von Mises test. The incidence of the disease was determined in 100 corn parcels located in Santa Magdalena Valle de Bravo Municipality, and the parcel locations were determined with dGPS. The spatial distribution analysis was performed using spatial statistics (Geostatistic and SADIE). Aggregation maps were developed; and the long term spatiotemporal stability was determined with the Cramer-von Mises test and the SADIE association index. The results showed that geostatistics were able to establish *S. reilianum* spatial patterns, visualizing its centers of aggregation through elaborated maps. Such aggregation enables adequate management actions in terms of points or specific sites. The association index of SADIE (I_m) and the bi-variable Cramer-von Mises (Ψ) proof make it possible to determine the spatiotemporal stability of the disease over the four years of the study.

Key words: Geostatistics, SADIE, spatial distribution, Spatiotemporal stability, *Sphacelotheca*, *Zea mays*.

Introduction

White Maize (*Zea mays*) is the main food crop in Mexico, produced between 1,800 and 2,200 m.a.s.l., and it is affected by corn head smut (*Sporisorium reilianum* (Kuhn) Langdon and Fullerton *(=Sphacelotheca reiliana)* (Kühn) Clinton). Corn head smut is a quarantine disease favored by a transition climate, a temperate sub-humid climate with summer rains (García, 1988). Head smut prevalence is estimated between 0.2 and 15.0%. It causes significant economic and ecological damage (CESAVEM, 2005). A yield

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Received May 5, 2011. Accepted July 3, 2011.
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reduction of up to 15% in susceptible cultivars and hybrids has been estimated in the State of Mexico. Prevalence between 0.1 and 40% has been reported in other regions of Mexico (SARH, 1992). Pataky (1999) mentions prevalences of up to 80% in other regions of the world.

Head smut survives as a teliospore in the soil, where it germinates to infect growing seedlings. The mycelium develops systematically toward the floral tissues and the tissue adjacent to the meristem. The symptoms are evident upon flowering in both male and female inflorescences. Black masses of spores develop instead of ears and corncobs. When the soros break, teliospores are released, fall to the ground, and persist into the following cultivation cycle (CIMMYT, 2004).

Determination of the spatiotemporal disease stability is very important to enable more efficient management of infested areas. Obtaining spatial patterns (arrangements) may provide valuable information about the nature and sources of inoculate for the development of epidemics (Navas-Cortés *et al*., 2008). Geostatistics has been used to analyze and characterize the spatial patterns of diseases in plants (Wu *et al*., 2001) and to characterize pathogen populations through time (Stein *et al*., 1994). Franke *et al*. (2009) consider the technique of spatial analysis by distance indices (SADIE) to be appropriate for the analysis of spatial patterns of some diseases, as well as for the evaluation of relationships among spatial patterns within a field at different periods of time (Scott *et al*., 2003). Recently, head smut has infested creole maize crops, which threatens the genetic diversity of maize in Mexico, which is considered a primary center of maize diversity. Teosinte (*Z. mays* subsp. *mexicana*), the closest relative of maize, has also been affected by head smut.

Geostatistics provide a direct measure of spatial dependence because they consider the bidimensional nature of organism distribution, allowing for the elaboration of useful maps (Sciarretta *et al*., 2001; Blom and Fleischer, 2001) that show gradients of disease intensity (Nava-Díaz, 2009). Campbell and Benson (1994) consider a correct control strongly linked to the knowledge of spatial distribution, specifically for radical diseases. It is possible to establish maps of spatial disease distribution and the infection percentage using geostatistics, thus providing economic and environmental savings, as alternatives to controlling to specific points where the disease is present.

Sánchez *et al*. (2011) determined the spatial distribution of aggregation presented by *S. reilianum* in hybrids and maize cultivars in different regions of Mexico in 2007. However, no information is available about the spatiotemporal stability of *S. reilianum*. This knowledge would allow the selection of efficient and sustainable alternatives for integral management. Therefore, the generation of information about spatiotemporal stability using an integrated cluster of programs and computer applications for managing data organized and referenced spatially is important. This information should be visualized by maps, including all of the agroclimatic information available, which might help in the implementation of integrated management of maize cultivation (Schemale *et al*., 2005). These elements must enable the precise use of technology for the benefit of farmers. Thus, the aims of this study were as follows: a. Model the spatial distribution of *S. reilianum* between 2006 and 2009 using geostatistic techniques, and b. Determine the spatiotemporal stability of head smut using the SADIE index and the Cramér-von Mises technique.

Materials and methods

Samples were collected when the commercial cultivars and hybrids of maize were at 50% of stage R3 (Ritchie y Hanway, 1982). One hundred plots with a history of head smut in Santa Magdalena, Valle de Bravo, Mexico, were sampled, and their coordinates were determined with a dGPS (Model SPS351, Trimble, EUA). The determination of the incidence involved dividing each lot into five sectors and counting 100 consecutive plants in the same transect in each sector. The number of plants showing head smut symptoms between 2006 and 2009 were recorded. The area of the plots varied between 0.56 and 0.83 ha.

Spatial statistics and geostatistics. We followed the methodology described by Sánchez *et al*., 2011; Ramírez-Dávila and Porcayo-Camargo (2008, 2009a, 2009b). The geostatistic analysis consisted of the following steps: 1) estimation of the semivariogram, 2) estimation of the parameters of the semivariogram model, and 3) estimation of the surface (maps) using points (estimates) from kriging. The semivariogram estimation was made with data collected in the sampling sites of the disease; the experimental value of the semivariogram was calculated with the following expression (Journel and Huijbregts, 1978; Isaaks and Srivastava, 1989):

$$\gamma^{*}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(H)} [z(x_i + h) - z(x_i)]^2$$

where $\gamma^{*}(h)$ is the experimental value of the semivariogram for the distance interval h, $N(h)$ is the number of pairs of sampling points separated by the distance interval h, $z(x_i)$ is the value of the variable of interest in the sampling point x_i, and $z(x_i+h)$ is the value of the variable of interest in the sampling point x_i+h.

The validation of the models fitted to the experimental semivariograms was performed using a crossed validation procedure (Isaaks and Srivastava, 1989). A sampling value was eliminated, and the method of geostatistic interpolation (kriging) was used, along with the semivariogram model for validation, in order to estimate the value of the variable of interest in that sampling point from the other sampling values. This procedure was carried out successively for all sampling points, and the differences between the experimental values and the estimates are summarized in the crossed validation statistics (Isaaks and Srivastava, 1989; Hevesi *et al*., 1992). The parameters for validation were the Nugget effect, the plateau, and the scope, which were modified by trial and error until the following crossed validation statistics were obtained:

a) Mean estimation errors (MEE):

$$\mathrm{MEE} = \frac{1}{n} \sum_{i=1}^{n} [z^{*}(x_i) - z(x_i)]$$

where $z^{*}(x_i)$ is the estimated value of the variable of interest in the point x_i, $z(x_i)$ is the value measured from the value of interest in the point $x_{i,}$ and n is the number of sampling points used in the interpolation.

The MEE should not be significantly different from 0 (t Test), which would indicate that the semivariogram model allows for the calculation of unbiased estimates values.

b) Mean squared error (ECM):

$$\mathrm{ECM} = \frac{1}{n} \sum_{i=1}^{n} [z^{*}(x_i) - z(x_i)]^2.$$

A semivariogram model is considered appropriate if, as a rule of thumb, the statistical value is close to zero (Hevesi *et al*., 1992).

c) Dimensionless mean square error (DMSE):

$$\mathrm{ECMA} = \frac{1}{n} \sum_{i=1}^{n} \frac{[z^{*}(x_i) - z(x_i)]}{\sigma k}$$

where σk is the standard deviation of the error expected in the estimation by kriging.

The model is valid if ECMA is between the values $1 \pm 2\,(2/N)^{0.5}$ (Hevesi *et al*., 1992).

d) Another statistical value for validation of model fit consisted of a variance value lower than the sampling variance.

The level of spatial dependence was calculated to determine the aggregation strength among the disease populations. This value was obtained by dividing the Nugget effect by the plateau and expressing the value as a percentage, with values considered high if they are less than 25%, moderate if they are between 26 and 75%, and low if higher than 76% (Cambardella *et al*., 1994; López-Granados *et al*., 2002).

Calculation and graphic representation of the infested surface based on density maps. After the semivariogram models were validated, the kriging was used to estimate the unbiased values of unsampled points to elaborate the density maps of the disease. The estimations of the spatial distribution on the incidence of corn head smut in different years in the locality studied were made using the program VarioWin 2.2., and the real infested surface was estimated with the program Surfer 9.0.

Spatial analysis by distance indices (*SADIE*). The SADIE analysis was performed according to the method of Perry and Hewitt (1991), Perry (1995a,b) and Alston (1996). The use of this tool to determine the spatial distribution of plant diseases is novel. In this work, the index based on the distance for regularity I_a and the index J_a, based on the clustering distance Perry (1995a,b), were used to establish the distribution model of the *S. reilianum* populations.

Estimation of the indices I_a and J_a. The data collected in the pre-designed grid (made up by sampling units) were assumed to be a system of individual counts, where i =1,...,n sampling units. Additionally, the bidimensional position of each sampling unit (x_i,y_i) and its associated count, N_i, were assumed to be known. The regularity distance, *D*, is the minimum value of the total distance where the sampled individuals apparently moved from one sampling unit to another; therefore, all the sampling units had an identical number of individuals. The solution refers to the optimal form in which the individuals might move from each sampling unit with an initial count higher than the media towards other sampling units lower than the media. If the counts observed are randomly interchanged among the sampling units, to obtain a sample that is a simple change or a refitting of the original, then P_a (aggregation of probability) represents the proportion of samples selected at random with a distance for regularity as high or higher than the observed value *D*. Intuitively, an aggregation or clustering might be expected with a value higher than *D* (for example, a heterogeneous spatial pattern, and inversely); a lower *D* value would involve a regularity (for example, a uniform spatial pattern). A P_a value derived from a sufficiently large number of randomizations provides a formal test of randomness. The null hypothesis of spatial randomness might be rejected if $P_a < 0.025$ (in favor of an alternative aggregation hypothesis), or it may be rejected if $P_a > 0.975$ (in favor of the regularity alternative) providing the usual 5% probability for rejecting the null hypothesis when true. If the mean arithmetic distance for the regularity of the random samples are called E_a, then the aggregation index is defined as $I_a = D/E_a$. Usually, a sample is called aggregated if $I_a > 1$, the sample is spatially random if $I_a = 1$, and the sample is regular if $I_a < 1$. A total of 2,000 randomizations are sufficient to derive the values of the corresponding indices (Perry, 1998).

The term *C* indicates the distance for the clustering, which is the minimum value of the total distance that the sampled individuals should move to congregate in one unit. This value occurs sooner than *D*, using a simple direct search on all the sampling units; the sampling unit with the minimum value is called the “focus” of the clustering. Random permutations of the observed counts lead to a proportion called Q_a (clustering probability) with a very small distance for the clustering, or smaller than the value observed, *C*. Intuitively, for data comprising an individual clustering, a low *C* value might indicate an aggregate spatial pattern; inversely, a high *C* value might involve a regular spatial pattern. Analogously, the null randomness hypothesis might be rejected if $Q_a < 0.025$ (in favor of the aggregation alternative) or if $Q_a > 0.975$ (in favor of the regularity alternative). If the mean distance for the clustering of random samples is called

F_a, then the aggregation index is defined as $J_a = F_a/C$. As in the case of the index I_a, values of $J_a > 1$ usually indicate an aggregate sample, $J_a = 1$ represent data especially random, and $J_a < 1$ indicate regular samples. Therefore, the values of the index J_a help to corroborate the results obtained with the index I_a. Additionally, this index is used to discriminate between spatial patterns in which there is only one important clustering, patterns in which the values are significantly higher than the unit, and patterns in which there are two or more clusterings where the value is very similar to, or even lower than, the unit. The respective probability is used to determine the significance in relation to the unit (Q_a) (Perry, 1998). The I_a and J_a values for random counts are not correlated, so 2,000 randomizations may also be used in the software to obtain the respective values. SADIE 1.22 was the program used in this work to determine the values and probabilities for both indices (program provided by Dr. Perry). Density maps made before by Geostatistic Analysis with an Ordinary Kriging were used to corroborate the results obtained by the SADIE indices.

Long-term spatiotemporal stability.

The maps developed with the Ordinary Kriging method for different years were compared to determine the spatiotemporal stability of S. reilianum populations by the non-parametric test of Cramér-von Mises (Ψ), modified by Syrjala (1996), as advised by Liebhold *et al.* (1993). It is worth mentioning that the comparisons were made with results from dates close to each other, as indicated by Rossi *et al.* (1992). In parallel, the association SADIE index, called I_m, was used (Perry and Klukowsky, 1997 and Korie *et al.*, 2000). An I_m value greater than zero indicates an association or a spatiotemporal stability among the maps if there is a significance level of $P_m < 0.025$. The determination of the stability was performed with the program SADIE 1.22.

Results

The incidence of *S. reilianum* ranged between 0.2 and 3.0% during the four years of study. The highest incidence was observed in 2006 (Table 1). A continuous increase in the infested surface, from 4.5 ha in 2006 to 10.12 ha in 2009, was detected year after year in the locality of Santa Magdalena, Valle de Bravo, Mexico (Table 1).

Geostatistics

It was determined that the spatial distribution of corn head smut presents an aggregate spatial arrangement in the locality analyzed in the four years of study. The statistical analysis and cross validation indicated that the experimental semivariograms fit well with a theoretical spherical model for the four years analyzed (Table 2). These results indicate an aggregate spatial structure of corn head smut in the locality of Santa Magdalena. A Nugget effect equal to zero was determined in all of the semivariograms of the models obtained (Table 2 and Figure 1a), which means that 100% of the variation in disease distribution is explained by the spatial structure determined in the respective semivariograms. In the plateau, the values varied between 0.02893 and 0.11285. The range

Table 1. Surface, incidence, value of Ia and Ja indices and their respective probabilities Pa and Qa in the populations of corn head smut during the years 2006 to 2009.

Year	Surface (ha)	Incidence (%)	I_a	P_a	J_a	Q_a
2006	4.5	0.2-3.0	1.46	0.011s	1.12	0.212ns
2007	9.43	0.2-1.0	1.57	0.008s	1.11	0.143ns
2008	9.93	0.2-1.8	1.51	0.016s	1.14	0.265ns
2009	10.12	0.2-1.0	1.60	0.013s	1.16	0.258ns

ns: do not differ significantly (P=0.05), s: significant difference (P=0.05) Test SADIE (Perry, 1998).

Table 2. Parameters (nugget, sill and range) in the adjusted models of corn head smut semivariograms obtained from 2006 to 2009.

Year	Model	Nugget	Sill	Range	Nugget/Sill (%)	Level of space dependence
2006	Spherical	0	0.11285	376.6	0.00	High
2007	Spherical	0	0.02893	134.5	0.00	High
2008	Spherical	0	0.02958	689.3	0.00	High
2009	Spherical	0	0.03563	422.3	0.00	High

Table 3. Cross-validation statistics for the aggregation model of corn head smut obtained from 2006 to 2009.

Year	Sample Size	Sample Average	Variance Sample	MEE	Variance of the errors	MSE	SMSE
2006	100	0.101	0.25390	0.11ns	0.20522	0.09	1.10
2007	100	0.074	0.03892	0.11ns	0.0277	0.11	1.13
2008	100	0.062	0.05096	0.07ns	0.03711	0.05	1.05
2009	100	0.066	0.03844	0.09ns	0.02105	0.07	1.08

$1 \pm 2 (2/N)^{0.5} = 1 \pm 0.45$, ns: do not differ significantly (P=0.05).
MEE: Mean estimation error.
MSE: Mean squared error.
SMSE: Standardized mean squared error.

or scope values varied between 134.5 and 689.3 m (Table 2). The level of spatial dependence found for all cases was high. The values obtained within the appropriate range of the statistics of cross validation (Table 3) allow for the validation of the theoretical fitted models. The fitted semivariogram models for each observed year are presented in Figure 1a.

Infested surface based on density maps.

Aggregation maps of corn head smut were determined by using the obtained models (Figure 1b) and disease gradients. Aggregations of the *S. reilianum* populations in maize were obtained for the four years, with specific zones where the disease is expressed with respect to the sampled points, with incidence lower than 3.0%. A relationship between disease incidence and aggregation centers was not observed. Such a relationship was observed in the 2007 map (Figure 1b), with a lower incidence of the disease in the largest estimated uninfested area (Table 4). The aggregation centers are located in the upper right margins in the four maps (Figure 1b).

The estimated area without head smut was between 17.0% and 81.0% of the total sampled area for 2008 and 2007, respectively. In 2006, the estimated infested area was 28%, and for 2009 it was 26%. The largest estimated infested surface was observed in (83%), allowing for the identification of both infested areas, with management, and areas free from disease. The smallest infested area (17%) was observed in 2007, whereas infested areas of 72% and 74% were estimated for 2006 and 2009, respectively.

Table 4. Density maps comparing the bivariate test of Cramér-von Mises (Ψ) and the spatial association index (I_m) of SADIE during the years 2006 to 2009.

Compared Dates	ψ	P Value	Difference (P=0.05)	I_m
2006 *vs.* 2007	0.38	0.49	Not Significant	0.88
2007 *vs.* 2008	0.91	0.38	Not Significant	1.76
2008 *vs.* 2009	1.01	0.62	Not Significant	1.13

I_m: values › 0 indicate spatial association (P=0.05). Test SADIE (Perry, 1998).

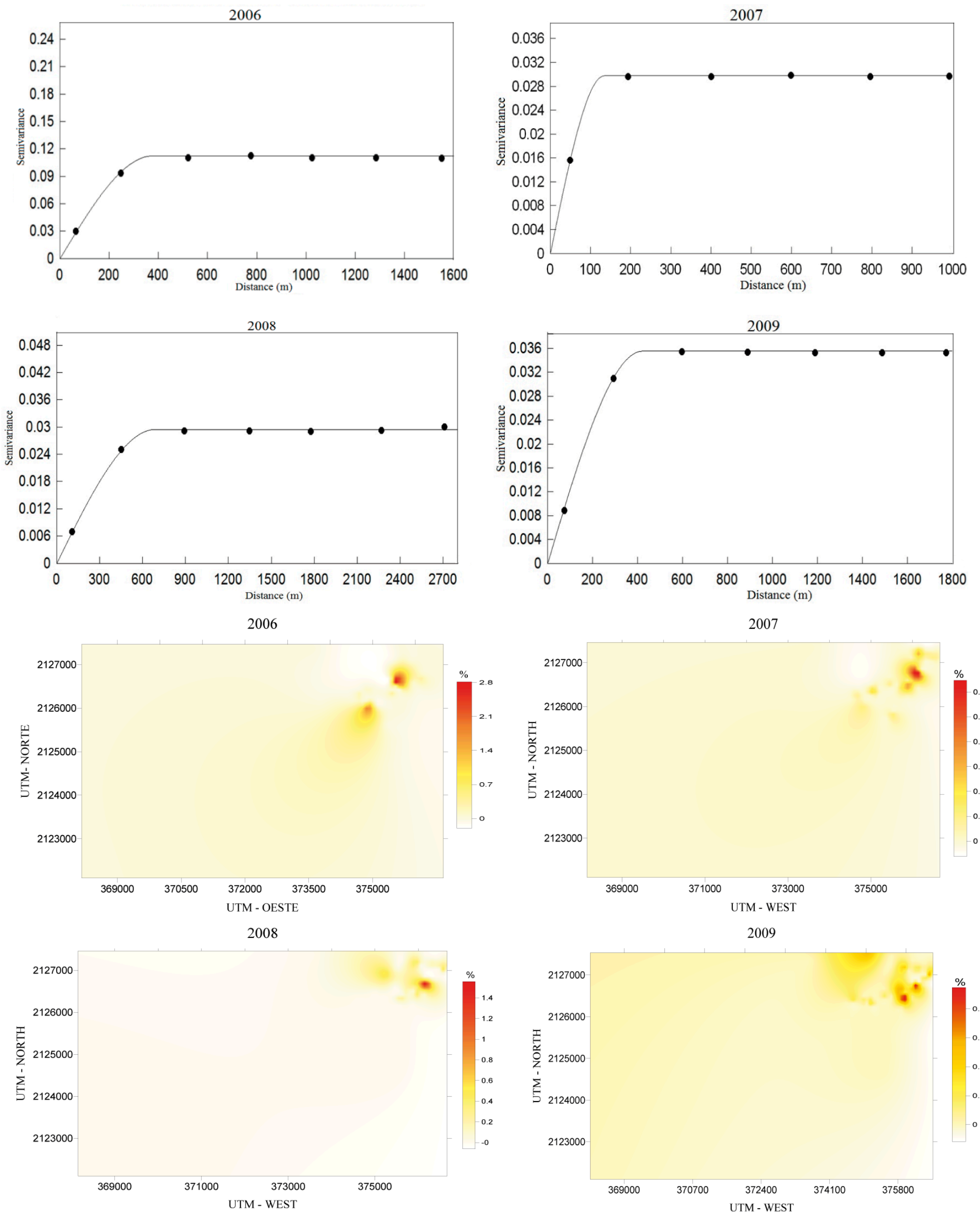

Figure 1. Semivariogram (a) and density maps (b) of corn head smut obtained from 2006 to 2009. % disease incidence; UTM: Coordinate System Universal Transverse Mercator in meters.Table 1. Surface, incidence, value of *Ia* and *Ja* indices and their respective probabilities *Pa* and *Qa* in the populations of corn head smut during the years 2006 to 2009.

SADIE and the estimation of indices I_a and J_a.

The spatial analysis per distance indices (SADIE) determined that the highest I_a value (1.60) was obtained in 2009, and the lowest value (1.46) was obtained in 2006. In all years, the I_a value was significantly higher than one (Table 1), which indicates an aggregate spatial distribution of corn head smut in the four years of study. The highest J_a value (1.16) was obtained in 2009, whereas the lowest value (1.11) was found in 2007. The fact that the values are higher indicates that the distribution of head smut populations presents aggregation, which supports the results for index I_a. The spatial distribution of the disease showed concentrations in several aggregation centers within the locality of Santa Magdalena because the probability value (Q_a) of the index J_a was not significantly different from one, which indicates that the I_a and J_a indices support the existence of an aggregate distribution of corn head smut in the four years of study.

Long-term spatiotemporal stability.

It was determined that there was no significant difference between the years 2006 and 2007, 2007 and 2008, and 2008 and 2009. The bivariate test of Cramér-von Mises (Ψ) was used to compare the different estimates of the spatial distribution of corn head smut with kriging. This test indicates the spatiotemporal stability of the head smut disease. Similar results were found with the association index of spatial distribution (I_m) of the SADIE analysis (Table 4).

Discussion

The aggregated spatial distribution of corn head smut, presented in specific geographic points within Santa Magdalena, is coherent with the results of Xu and Madden (2004), who indicated that the SADIE technique is appropriate for determining the spatial patterns of plant diseases. Although SADIE is virtually new in the phytopathological field, it has proven to be useful for determining the spatial patterns of several diseases, insects and vectors (Bassanezi and Laranjeira, 2007; Navas-Cortés *et al*., 2008; Ramírez and Porcayo, 2004a, 2004b, 2008, 2009a,b; Pethybridge *et al*., 2005; Schmale *et al*., 2005; Sciarretta *et al*., 2008; Scott *et al*., 2003; Shah *et al*., 2001).

The geostatistics analysis was appropriate for obtaining the spatial patterns and for the generation of spatial distribution maps of corn head smut. The high level of spatial dependence observed and the validation of the experimental semivariograms in the four years of study indicated that the distribution of *S. reilianum* is added for the locality of Santa Magdalena. Additionally, the fit of the experimental semivariograms to theoretical models was appropriate, assuming that a value of zero in the Nugget effect indicates that the sampling error was minimal and that the sampling scale used was adequate (Rossi *et al*., 1992). The similarities in both the incidences of head smut and the geographical locations of the lots with disease may explain why we observed the same type of spatial distribution of the disease.

The spatial distribution fitted to the spherical model indicates that there are zones in which *S. reilianum* has a larger manifestation within the analyzed locality in comparison to the sampled plots. That is, there are foci of the disease advancing from an initial source, and such foci are surrounded by maize plots presenting the disease, which extend within the locality of Santa Magdalena. This observation is consistent with the observations of Van de Landea and Zadoks (1999), who determined that the spherical model assumes that the infection of unknown etiological origin in oil palm (*Elaeis guineensis*) comes from a specific source. On the other hand, Jaime-Garcia *et al.* (2003) consider the fact that the spherical model indicates an irregular distribution of the disease within the analyzed area. Similarly, Roberto *et al.* (2002) indicate that the irregular foci of infestation within the locality allow the assumption that the disease originates from contaminated seeds, although Webster and Oliver (2000) mention that the exponential model also indicates an irregular distribution. The irregular distribution of the infection foci of *S. reilianum* could be associated with favorable environmental conditions, contaminated seeds, or genotypes susceptible to maize, which would favor the expression of the disease within the locality of Santa Magdalena. The existence of specific points of the disease within the locality makes it possible to focus monitoring efforts and direct control measures to specific points or sites.

The geostatistic spatial modeling of *S. reilianum* in maize agrees with the spatial distribution of maize ear obtained by Sánchez-Pale *et al.* (2011) in 2007 in different localities of the State of Mexico. These results also agree with the reports by Allen *et al.* (2008) regarding wheat, with *Tilletia indica*. Additionally, this modeling agrees with other studies, such as those of Johnson *et al.* (2007), who determined the patterns of spatial distribution of *Puccinia melanocephala* with spherical models, and Larkin *et al.* (1995), who modeled the epidemic caused by *Phytophthora capsici* in Chile.

Geostatistic techniques allow for the elaboration of maps leading to accurate plague and disease management (Fleischer *et al*., 1997). The aggregations of corn head smut in the maps obtained in this study enable management actions that affect specific points or sites. This precise management makes it possible to reduce pesticide use (Weisz *et al*., 1996) and delay the onset of pesticide resistance by creating temporary dynamic shelters (Fleischer *et al*., 1999), thus allowing for economic savings. Carvalho and Ampélio (2010) indicate that the maps obtained by kriging are appropriate for disease monitoring and management and useful for detecting changes in spatial disease patterns through time (Lecoustre *et al*., 1989). The results of this study, in which spatial distribution of *S. reilianum* are represented in the study maps, were non-uniform in 100% of the area of the sampled locality, which is consistent with the distribution of *Colletotrichum kahawae* in coffee, as obtained by Mouen-Bedimo *et al*. (2007), and in olive trees (*Verticillium dahlia*), as studied by Rodríguez *et al*. (2009). In contrast, the highest percentages of estimated infested surface were associated with the spherical model. It was observed that the higher incidence percentages of the disease determined in field in 2006 and 2008 are associated with the highest percentages of estimated infested areas.

Fleischer *et al*. (1999) report that a plague normally presents variable densities in the total infested area and that such infestation rarely reaches 100%, which suggests that control tactics should be targeted to the infested areas, especially those tactics for which the population overcomes the economic threshold if such a threshold is known. The results obtained in this work suggest the use of different methods for disease control, and they suggest a focus on sampling activities within the locality of Santa Magdalena, particularly in areas where head smut is present, in order to obtain significant economic and environmental savings. The use of maize seeds treated with fungicides and the elimination of diseased plants, as well as the directed samplings of population incidence, are alternatives directed to specific sites or foci where the disease is present. These actions justify the use of precision agriculture techniques for controlling the damage caused by *S. reilianum*.

The association index of the spatial distribution of the SADIE analysis (I_m) and the bivariate test of Cramér-von Mises (Ψ) made it possible to identify the spatiotemporal stability of the *S. reilianum* distribution in the locality of Santa Magdalena. The spatiotemporal stability obtained in the comparisons made in the four years of study indicate a strong association of the spatial patterns from one year to another, which suggests that, regardless of the increased infested surface in field, new infection foci did not form within the locality or were less important relative to the points of the disease established the year before (Scott *et al*., 2003). This situation enables prediction and makes it possible to use direct control or sampling efforts in zones of future infestation. These results are in agreement with the findings of Scott *et al*. (2003), who determined the spatiotemporal stability of *Peronospora arborescens*, and the reports by Navas-Cortés *et al*. (2008), who studied *Verticillium dahliaev*in olive trees. The results are also consistent with the reports of Oveisi *et al*. (2010), who determined the spatiotemporal stability of *Orobanche crenata* in broad bean using SADIE. The spatiotemporal stability determined in this work enables the direction of control tactics to specific sites requiring precise management based on the presence of head smut within the locality of Santa Magdalena; therefore, our results enable precision agriculture techniques to target this disease. This finding is similar to the results obtained in other organisms (Ramírez-Dávila *et al*., 2004a, 2004b; Ramírez and Porcayo, 2008; Sciarretta *et al*., 2008), which have represented the initial bases of vegetal protection in specific sites toward a precision agriculture, achieving economic savings and a lower ecological impact through management. Additional research is required to explore the ecological and economic implications of spatiotemporal stability and the spatial arrangements detected in this study in order to include these findings in the control of head smut within the integrated management of maize cultivation.

Resumen

J.F. Ramírez-Dávila, J.R. Sánchez-Pale, E. Porcayo-Camargo y C. de León. 2012. Determinación de la estabilidad espacio temporal del carbón de la espiga del maíz (*Sporisorium reilianum*), por medio de SADIE. Cien. Inv. Agr. 39(3): 459-471. *S. reilianum* causa daños económicos y ecológicos importantes en regiones productoras de maíz en México y otros países. El conocimiento de la distribución y estabilidad espacio temporal de la enfermedad es indispensable para la elaboración de programas de manejo integrado. El presente estudio se realizó para determinar la spatiotemporal stability del carbón de la espiga con el índice de SADIE y la prueba de Cramér-von Mises, así como la de modelizar la distribución espacial de *S. reilianum* en los años 2006 a 2009 con técnicas geoestadística. La incidencia de la enfermedad se determinó en 100 parcelas de maíz de la localidad de Santa Magdalena del municipio de Valle de Bravo, ubicándolas geográficamente con un dGPS. La determinación de la distribución espacial se realizó con el uso de la estadística espacial (SADIE y geoestadístico). Se elaboraron mapas de agregación y se determinó la estabilidad espacio temporal a largo plazo con las pruebas de Cramér-von Mises (Ψ) y con el índice de asociación del SADIE (I_m). Los resultados mostraron que la geoestadística y SADIE lograron establecer los patrones espaciales de *S. reilianum*, visualizando sus centros de agregación a través de los mapas elaborados. Dicha agregación permite adecuar las acciones de manejo hacia determinados puntos o sitios específicos del campo. El índice de asociación del análisis SADIE (I_m) y la prueba bivariable de Cramér-von Mises (Ψ) permitieron determinar la estabilidad espacio temporal de la enfermedad en los cuatro años de estudio.

Palabras clave: Distribución espacial, estabilidad espacio-temporal, geoestadística, SADIE, *Zea mays*.

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