Spatial Pattern of Southern Stem Rot Caused by *Sclerotium rolfsii* in Six North Carolina Peanut Fields

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ABSTRACT

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Frequency distributions of southern stem rot lesions in five of six data sets from North Carolina peanut fields sampled in 1980–1982 were fitted ($P = 0.13$ to 0.75) by a negative binomial distribution, which indicated that disease occurred in a clustered pattern. Disease incidence ranged from 5.4 to 32.3% in the six fields sampled. Estimates of the parameter k of the negative binomial distribution ranged from 0.87 to 6.49 and generally increased with plot size and with the population mean. Incidence of southern stem rot lesions in three fields was positively correlated with soil bulk density ($r = 0.47^{**}$). Spatial correlations calculated from data from three fields indicated different patterns of disease in each field.

Additional key words: *Arachis hypogaea*, groundnut.

Sclerotium rolfsii Sacc. infects more than 500 species of plants in about 100 families, and causes economically important diseases in warm, moist climates throughout the world (1). In the United States, *S. rolfsii* causes southern stem rot of peanut (*Arachis hypogaea* L.), but relatively little is known about population dynamics of the pathogen or environmental effects on this disease.

Sampling programs, experimental designs, and analytical procedures used in epidemiological and management studies require some knowledge of disease pattern. For example, use of Gregory's (10) multiple-infection correction in analyses of epidemics assumes a random distribution of infections, but infections caused by many soilborne plant pathogens probably occur in clusters (5). Stem rot apparently occurs nonrandomly on peanut (16). Heterogeneous soil types and inoculum densities, and nonuniform cultural practices could cause nonrandom patterns of stem rot occurrence.

Statistical methods that may be used to characterize spatial patterns include use of indices of dispersion (8), fitting of discrete frequency distributions to disease frequency data (20), and use of quadrat variance methods (15). Indices of dispersion are usually modifications of the variance-to-mean ratio, which has an expected value of one when the population parameters being analyzed fit a

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Poisson distribution. Modifications of the variance-to-mean ratio have been introduced to reduce dependence of the index on population or sample size.

Block size and the method of grouping data into frequency categories influence the statistical fit of discrete frequency distributions to frequency data as well as the parameter estimates obtained in fitting these distributions. Describing the spatial relationships of a population with a fitted frequency distribution partially obscures the pattern because many qualitatively different patterns can be fitted by the same frequency distribution.

In quadrat variance methods, scale and pattern of clustering are studied by plotting the variance against plot size as adjacent unit plots are combined to create larger plots. Unless the population is randomly distributed, however, combining adjacent plots leads to dependent estimates of variance because adjacent plots are correlated.

Underlying spatial correlations in data from plots in homogeneity trials may be studied by using an extension of Smith's analysis of heterogeneity (13,19). Spatial correlation analysis could be useful in characterizing patterns of stem rot on peanut.

The purpose of this research was to describe the spatial pattern of southern stem rot in affected portions of several North Carolina peanut fields. A preliminary report on a portion of the research has been published (4).

MATERIALS AND METHODS

A total of six peanut fields in which stem rot was present was sampled in late September or October of 1980, 1981, or 1982. Fields were located as follows: 1980, field A in Northampton County; 1981, field B in Bertie County and field C in Columbus County; 1982, field D in Bertie County, field E in Edgecombe County, and field F on the Peanut Belt Research Station in Bertie County. Fields A and B were divided into a 7 × 14 grid of 98 contiguous quadrats (Fig. 1). Each quadrat measured six rows (0.9-m row spacing) × 6 m. Field C was a 6 × 14 grid of 84 quadrats, and fields D, E, and F were 7 × 7 grids of 49 quadrats each (Fig. 1). Quadrats in fields A, D, E, and F were subdivided into one-row × 6-m plots to give frequency data for grids of 588 (field A) or 294 (fields D, E, and F) plots. Total dimensions and areas of each field were: fields A and B, 42 rows × 84 m for an area of 0.32 ha; field C, 36 rows × 84 m for an area of 0.27 ha; and fields D, E, and F, 42 rows × 42 m for an area of 0.16 ha.

Stem rot lesion counts were obtained by inspecting all the peanut plants growing in each quadrat. Stem rot lesions were characteristically brown-to-black regions that penetrated stems or crowns of plants, causing a stringy, dry rot (1). Superficial growth of *S. rolfsii* on pegs or leaflets, but not extending into a limb or the crown, was not recorded as a lesion. A maximum of one lesion per 30-cm section of row was recorded; therefore, lesion counts actually reflected disease incidence per 30 cm of row.

TABLE 1. Soil physical properties and stem rot incidence caused by *Sclerotium rolfsii* in three North Carolina peanut fields[a]

Variable	Field D		Field E		Field F	
	Mean	Range	Mean	Range	Mean	Range
% Sand	74	71–79	72	62–77	55	27–82
% Silt	16	12–19	17	11–26	28	8–47
% Clay	10	8–13	11	10–13	17	8–29
Particle density[b]	2.59	2.36–2.86	2.54	2.50–2.68	2.51	2.36–2.68
Bulk density[c]	1.33	1.25–1.42	1.48	1.37–1.68	1.42	1.30–1.55
Disease incidence[d]	0.7	0–3	2.8	0–7	1.8	0–6

[a] Twenty 7.5-cm-diameter × 7.5-cm-deep soil samples were taken in a diagonal path across each field.
[b] Units g/cm^3.
[c] Units g/cm^3.
[d] Number of stem rot lesions in the 6-m plot from which the soil sample was taken. A maximum of one lesion per 30 cm of row was counted.

The frequency distribution of sclerotia of *S. rolfsii* in soil samples was determined for field A in June 1980. Forty 2.5-cm-diameter soil cores were taken from each quadrat by sampling at two depth ranges (0–7.5 cm and 7.5–15 cm) at 10 sites on each of two opposite diagonals within each quadrat. Samples from a given depth class were pooled, air-dried, mixed, and assayed by using the aqueous-methanol method (17). A 660-g (air-dried) soil sample was assayed from each quadrat.

Soil physical properties were assessed at 20 intersections of alternate rows with a diagonal path constructed across each 42-row × 42-m sampling area in fields D, E, and F. Intact 7.5-cm-diameter soil cores, taken to a depth of 7.5 cm, were oven-dried and weighed for bulk density determinations (mass of dried soil per unit bulk volume including air space, in grams per cubic centimeter). Particle density (mass of soil particles per unit volume, in grams per cubic centimeter) was found by displacement (3), and soil particle analysis (percent sand, clay, and silt) was performed by using the hydrometer method (3). Simple correlation coefficients were calculated for soil physical properties (bulk density, particle density, percent sand, silt, and clay) and lesion number in the one-row × 6-m plot from which a given soil sample was taken. Data from the three fields were combined and correlations between the same variables and fields (coded 1, 2, or 3) were calculated.

The number of lesions in six-row × 6-m quadrats in all fields was mapped, and the mean and variance of number of lesions per quadrat or plot, and the variance to mean ratio were calculated. Count data from individual six-row × 6-m quadrats or one-row × 6-m plots were arranged in frequency categories, and a FORTRAN program (9) was used to estimate parameters of discrete frequency distributions from counts of lesions and to calculate a chi-square statistic for goodness-of-fit of the data to Poisson (8), Poisson-with-zeros (6), negative binomial (8), Thomas double Poisson (21), Neyman A (14), and Poisson-binomial (12)

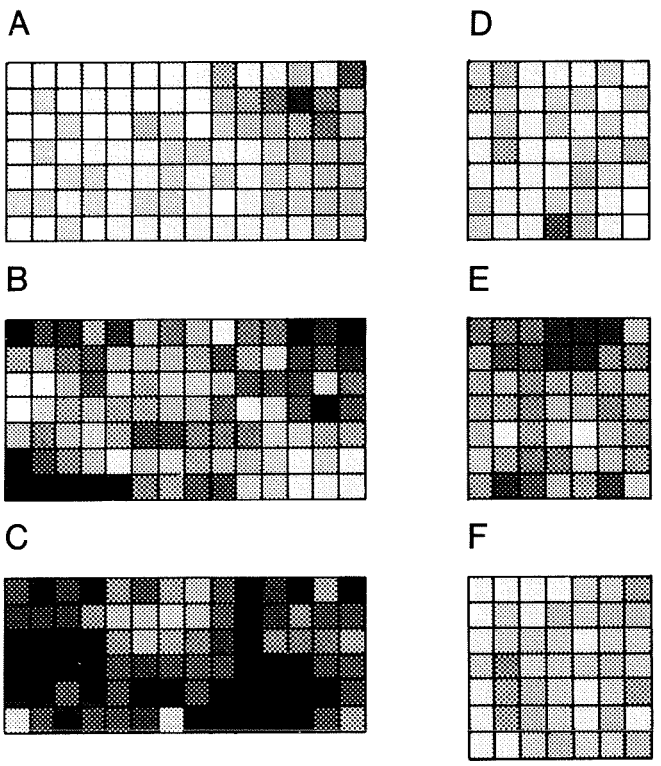

Fig. 1. Maps of incidence of lesions of southern stem rot caused by *Sclerotium rolfsii* in six peanut fields in North Carolina. One square represents a six-row × 6-m quadrat, and intensity of shading indicates increasing numbers of lesions. Shading categories were: 1 (not shaded), 0–5 lesions; 2, 6–10 lesions; 3, 11–15 lesions; 4, 16–20 lesions; 5, 21–25 lesions; 6, 26–30 lesions; 7, 31–35 lesions; 8, 36–40 lesions; 9, 41–45 lesions; and 10 (most heavily shaded), >45 lesions. Field A was located in Northampton County, field B in Bertie County, field C in Columbus County, field D in Bertie County, field E in Edgecombe County, and field F in Bertie County.

distributions. Only data in tail classes were combined in fitting frequency distributions.

Spatial correlations were used to analyze pattern of lesions in fields D, E, and F (13). In this method, spatial correlations between one-row plots and their nearest, next nearest, and ...*n*th nearest neighbors were calculated.

The matrix of disease data from fields of dimensions $R \times S$ plots was defined as $Y = \{Y_{ij}\}$, in which the subscripts denote the position of the *ij*th elements in Y and the coordinates of the plots on the grid; $i = 0,1,...R$, $j = 0,1,...S$, in which R = number of rows and S = number of 6-m sections of row that were sampled. Counts of lesions in plots could be correlated with counts from plots $l = 0,1,...R$ rows and $k = 0,1,...S$ sections distant. l and k Designate the two-dimensional distance, or lag, across rows and sections, respectively, from the *ij*th plot. All such correlations between plots up to a distance of $l = 6$ rows and $k = 32$ sections were calculated by the following formula to give a $l = 6 \times k = 32$ matrix of correlations:

$$\widehat{\mathrm{Cor}}^{+}(l,k) = \left\{\sum_{i,j}\sum Y_{ij}\,Y_{i+l,j+k} - \left[\left(\sum_{i,j}\sum Y_{ij}\right)\left(\sum_{i,j}\sum Y_{i+l,j+k}\right)\right]/(R-l)(S-k)\right\} \Big/ \left\{\left[\sum_{i,j}\sum Y_{ij}^{2} - \left(\sum_{i,j}\sum Y_{ij}\right)^{2}/(R-l)(S-k)\right]\left[\sum_{i,j}\sum Y_{i+l,j+k}^{2} - \left(\sum_{i,j}\sum Y_{i+l,j+k}\right)^{2}/(R-l)(S-k)\right]\right\}^{1/2}.$$

Similarly, lesion counts in the *ij*th plot could be correlated with counts in plots $l,-k$ or $-l,k$ rows distant by

$$\widehat{\mathrm{Cor}}^{-}(l,k) = \left\{\sum_{i,j}\sum Y_{i,j-k}\,Y_{i-l,j} - \left[\left(\sum_{i,j}\sum Y_{i,j-k}\right)\left(\sum_{i,j}\sum Y_{i-l,j}\right)\right]/(R-l)(S-k)\right\} \Big/ \left\{\left[\sum_{i,j}\sum Y_{i,j-k}^{2} - \left(\sum_{i,j}\sum Y_{i,j-k}\right)^{2}/(R-l)(S-k)\right]\left[\sum_{i,j}\sum Y_{i-lj}^{2} - \left(\sum\sum Y_{i-l,j}\right)^{2}/(R-l)(S-k)\right]\right\}^{1/2}.$$

The first row and first column ($l = 0$ or $k = 0$) of $\widehat{\mathrm{Cor}}^{+}$ and $\widehat{\mathrm{Cor}}^{-}$ were identical. For $l,k > 0$, $\widehat{\mathrm{Cor}}^{+}$ and $\widehat{\mathrm{Cor}}^{-}$ contain spatial correlations along different diagonals. It was assumed that plots having the same spatial relationships (for example, l,k with $-l,-k$ and $-l,-k$ with l,k) had the same spatial correlations.

Correlation matrices ($\widehat{\mathrm{Cor}}^{+}$ and $\widehat{\mathrm{Cor}}^{-}$) were inspected for patterns in spatial correlations; the $l,0$ row and $0,k$ column were graphed to illustrate correlation changes. No correlation between plots would be expected if lesions were uniformly distributed, but with random errors. If lesions occurred in the field in a regular pattern, spatial correlations would cycle between +1 and −1 at a frequency corresponding to the lesion pattern. If the axes of the pattern cycle coincided with the axes of the field, positive and negative correlation matrices would be similar. If axes of disease pattern were not oriented in the same direction as the axes of the field, $\widehat{\mathrm{Cor}}^{+}$ and $\widehat{\mathrm{Cor}}^{-}$ would differ.

TABLE 2. Means and variances of number of southern stem rot lesions caused by *Sclerotium rolfsii* per 6 m of row or per six 6-m rows sampled in six peanut fields in North Carolina

Field and county	Sample size[a]	Mean ($\bar{x}$)	Variance (s^2)	$s^2/\bar{x}$	Disease incidence[b]
One-row plots:					
A. Northampton	588	1.2	2.4	2.0	6.1
D. Bertie	294	1.1	2.3	2.2	5.4
E. Edgecomb	294	3.4	7.6	2.3	17.1
F. Bertie	294	1.5	2.6	1.8	7.4
Six-row quadrats:					
A. Northampton	98	7.7	43.1	6.0	6.1
B. Bertie	98	21.2	219.6	10.4	17.9
C. Columbus	84	38.2	287.8	7.5	32.3
D. Bertie	49	6.3	27.0	4.2	5.4
E. Edgecomb	49	20.2	88.2	4.4	17.1
F. Bertie	49	8.8	26.3	3.0	7.4

[a] Number of plots or quadrats sampled.
[b] Incidence in fields = (number of lesions counted in field/number of 30-cm sections of row counted in field) × 100.

Maximum variance among plots should occur when plot size and shape correspond to disease cluster size and shape; therefore, the matrix of variances among plots of all possible dimensions up to $R/2 \times S/2$ was computed. Variances were calculated from the mean of the numerators of $\widehat{\mathrm{Cor}}^{+}$ and $\widehat{\mathrm{Cor}}^{-}$ above, and were divided by the variances among unit plots (variance among unit plots equalled one after standardization). By analogy with quadrat variance techniques (15), a single peak in variance at a given plot size indicated clusters of disease of the corresponding size, with the clusters themselves being distributed at random. Other possible patterns in variances included a small peak followed by a larger peak or peaks, indicating that clusters were themselves distributed in larger clusters, or no or slight change in the variance once the maximum was reached, indicating a regular pattern of cluster distribution.

RESULTS

An average of 0.2 sclerotia of *S. rolfsii* per kilogram of air-dried soil was detected in samples from field A, and sclerotia were found in only 10 of the 98 quadrats sampled. Of the 14 sclerotia found, 13 were present in the upper 7.5 cm of soil sampled. These observations suggest a random distribution of sclerotia in our samples. Stem rot lesions were found in 97 of 98 quadrats when field A was sampled for disease in October 1980. Counts of sclerotia per one-quadrat sample (660 g of air-dried soil) and of lesions per quadrat were significantly ($P = 0.05$), but not highly, correlated, with $r = 0.24$.

Means and ranges of measured soil physical properties and stem rot incidence from fields D, E, and F are listed in Table 1. Number of lesions per plot was negatively correlated with percent sand ($r = -0.53$*) and positively correlated with percent silt ($r = 0.54$*) in field E. In a combined analysis of data from fields D, E, and F, number of lesions per plot was correlated with the field sampled and with soil bulk density ($r = 0.47$**), and bulk density was highly correlated with the field sampled ($r = 0.68$**).

Approximate incidence of stem rot (calculated as number of lesions per number of 30-cm sections of row counted) varied in the six fields from 5.4% in field D to 32.3% in field C (Table 2, Fig. 1). Size of block (six-row × 6-m quadrat or one-row × 6-m plot) influenced variance, variance/mean ratio ($s^2/\bar{x}$), fit of frequency data to distributions, and estimates of the parameter k of the negative binomial calculated from the data. Variance in lesion number per quadrat ranged from 26.25 in field F to 287.84 in field C. In one-row plots, variances ranged from 2.32 to 7.63.

TABLE 3. Probability of a chi-square statistic greater than calculated for fit of four discrete frequency distributions to six sets of frequency data. Data were counts of lesions caused by *Sclerotium rolfsii* in six peanut fields in North Carolina[a]

Field[b]	Negative binomial	Thomas Poisson	Neyman A	Poisson binomial	k
One-row plots:					
A	<0.01	<0.01	<0.01	<0.01	...
D	0.52	<0.01	0.05	<0.01	0.87
E	0.75	0.29	0.49	0.08	2.63
F	0.47	0.57	0.59	0.50	1.76
Six-row quadrats:					
A	0.16	<0.01	0.01	<0.01	3.17
B	0.20	...[c]	...	...	3.32
C	0.13	...	...	...	6.49
D	0.68	0.63	0.64	0.59	3.25
E	...	...	...	...	...
F	0.49	<0.01	0.47	0.46	5.34

[a] None of the data were well described by the Poisson or Poisson-with-zeros distributions ($P < 0.01$).
[b] Fields were located as follows: A, Northampton County; B, Bertie County; C, Columbus County; D, Bertie County; E, Edgecomb County; and F, Bertie County.
[c] Computer program could not fit distribution data in these plots without combining frequency categories.

Variance/mean ratio was greatest for quadrats in field B and least for one-row plots in field F (Table 2). All variance/mean ratios were significantly different from one, the expected value under a random (Poisson) distribution, according to χ^2 tests.

Except for data from one-row plots in field A, all frequency data for either block size were well described by the negative binomial distribution, and estimates of k ranged from 0.87 for one-row plots in field D to 6.49 for quadrats in field C (Table 3). The negative binomial could not be fitted to disease data from one-row plots from field E without combining frequency categories. None of the frequency distribution data were well described by the Poisson or Poisson-with-zeros distributions. Thomas double Poisson, Neyman A, and Poisson-binomial distributions each fitted more than one set of frequency data (Table 3).

Correlations between plots decreased rapidly to independence (r not significantly different from zero) with increasing distance for l,0 lags (Fig. 2). The l,0 lags were for correlations between plots and their nearest, next nearest,...nth nearest neighbors within the same 6-m section of row up to a distance of 32 of the 42 rows sampled in each field. The 0,k lags were for correlations between plots and their neighbors within the same row down six of the seven 6-m sections of row sampled. In field D, l,0 correlations became negative at lags 9,0 and 11,0, returned to independence, and became positive again at lags 27–28,0 (Fig. 2). A similar pattern in correlations was seen for lags l,1 and l,−1 (where plots were correlated with their neighbors one 6-m section of row over and up to 32 rows distant) in field D. Stem rot lesions within rows were correlated with disease in nearest and fourth nearest sections in field D (Fig. 3), and there was some skewness towards the negative distances or lags (ie, l,−k values increased faster than l,k) for this field. Apparently, clusters of plants with stem rot occurred in irregular cycles and the axes of the pattern cycles were oriented at an angle with the peanut rows.

Correlations for l,0 lags in field F were somewhat similar to those in field D, but they never became significantly negative (Fig. 2). Sections within rows were only similar to their nearest neighbors.

Correlations for l,0 in field E alternated between positive and zero values between lags of 0 and 6 (Fig. 2), indicating greater similarity between alternate rows up to lag 6. This may have been related to cultural practices, specifically driving of equipment down rows, which affected adjacent rows dissimilarly. From lags 7 to 19, plots were independent, then negatively correlated at lag 21, indicating a greater distance between clusters than in fields D and F. Similar patterns were seen in l,−1 and l,1 lags. Sections within rows were correlated with their nearest and third nearest neighbors. There was a slight skewness towards small positive values of l,k in this field.

Inspection of matrices of standardized error mean squares (variances among plots of all sizes and shapes up to $R/2 \times S/2$) revealed maximum variance for field D = 2.54 at a plot size of four sections × eight rows. After reaching the maximum, variances decreased steadily for plots of greater dimensions up to four sections × 21 rows. In field F, a maximum variance of 2.80 at four sections × seven rows was followed by lower peaks in variance at three sections × 10 rows (s^2 = 2.74) and two sections × 11 rows (s^2 = 2.43). Variances decreased very slowly up to the maximum plot size of four sections × 21 rows. No peak in variance occurred for field E; rather, variances increased with increasing plot size up to the maximum of four sections × 21 rows.

DISCUSSION

Frequency counts of sclerotia of *S. rolfsii* per quadrat should be described by a Poisson distribution because sclerotial populations were very low. A Poisson distribution commonly describes occurrence of rare events (8).

The inoculum density of 0.2 sclerotia per kilogram of soil found in field A was much lower than the 15–460 sclerotia per kilogram of soil found in sugar beet fields in California (11), and was also lower than the 3.9 sclerotia per 250 cm^3 of soil found in an Alabama peanut field (16). The inoculum density we found for *S. rolfsii* on peanut was, however, very similar to that found for *Sclerotium cepivorum* on garlic and onion (7). Recovery of any sclerotia from a sampled garlic or onion field indicated a risk of disease loss from *S. cepivorum*.

The observed shallow occurrence of sclerotia of *S. rolfsii* would add to sampling problems caused by low inoculum densities. Large

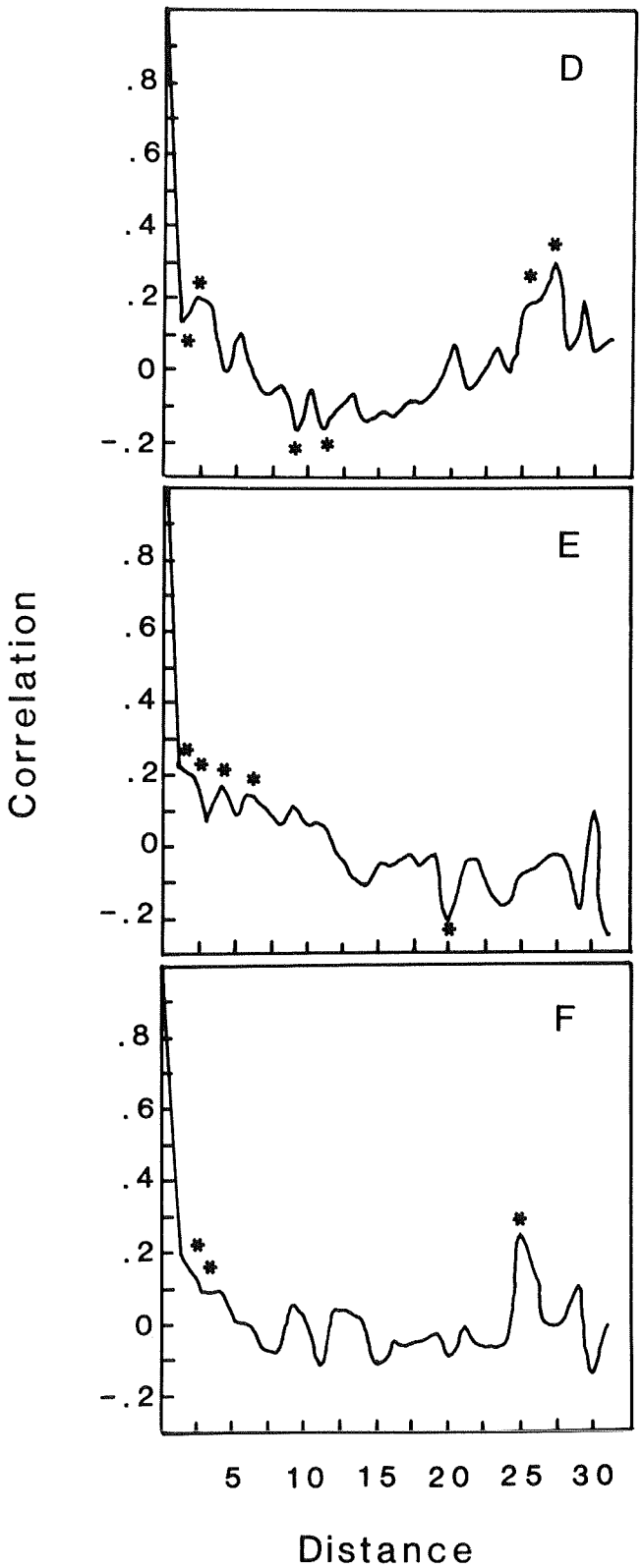

Fig. 2. Correlations of southern stem rot lesion numbers in 6-m long × one-row wide plots of peanut with plots l rows distant within the same section of rows. Correlations significantly different (P = 0.05) from zero are indicated by an asterisk (*). Letters designate different fields located as follows: D, Bertie County; E, Edgecombe County; F, Bertie County.

volumes of soil sampled at relatively shallow depths would be necessary to precisely estimate sclerotial populations and relate inoculum density to amount of stem rot on peanut. The value of inoculum density estimates for predicting disease incidence would be further limited by the modifying effects of field microenvironments on development of stem rot (18).

Drainage and fertilization influenced the degree of correlation between inoculum density and disease incidence for *S. rolfsii* on sugar beet (11). On other crops, either heavy or light soils may favor development of diseases caused by *S. rolfsii* (1). In field E, the most-affected field for which soil physical properties were analyzed, significant correlations occurred among soil fractions (sand and silt) and numbers of lesions. As percent sand increased (percent silt decreased), numbers of lesions decreased, suggesting an inoculum density- or environmentally dependent relationship between soil moisture (sandier soils generally drain faster) and stem rot on peanut. Sources of much of the variation in lesion numbers were unidentified, but factors such as rainfall and canopy microclimate may have been involved (18).

Distribution data at block sizes equal to one or six rows from most fields were fitted by more than one of the models which characteristically describe clustered distributions. Distribution data are commonly fitted by multiple models arising from many and sometimes opposing mechanisms, so fit to a given model does not necessarily imply a given mechanism of clustering. Of the models examined, the negative binomial is the most general and can arise from many different mechanisms (20).

The k parameter of the negative binomial distribution has been used as an index of clustering (low ks indicate extreme clustering). Estimates of k tend to increase with the population mean (20). In general, our k-values increased with increasing amounts of disease, especially in one-row plots. The k-values calculated for one-row plots were low (except in field E, which had the greatest disease incidence), but larger k-values were calculated when data from one-row plots were combined into six-row quadrats. Because estimates of k are affected by sample size, published k-values should be interpreted in light of the scale of sampling used and the density of the target population, particularly if the entire population was not sampled.

Fit of the negative binomial distribution to the data gave little information on spatial pattern of stem rot occurrence. Spatial correlation analysis, however, provided detailed information on disease pattern. Using spatial correlations, we detected differences between fields in cluster size and distribution. These differences suggest that pattern of southern stem rot on peanut is more strongly influenced by external or environmental factors than by intrinsic properties of the pathogen or host. The tendency for lesion counts in rows to be more similar to counts in alternate than in adjacent rows in field E suggests that cultural practices (row operations) could be one group of factors influencing pattern in some fields.

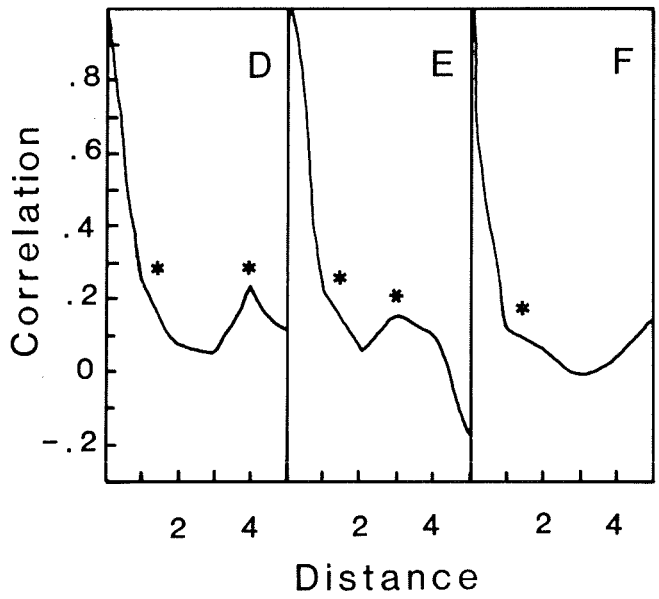

Fig. 3. Correlations of numbers of southern stem rot lesions in 6-m long × one-row wide plots with plots k 6-m sections distant within the same row of peanut plants. Correlations significantly different from zero ($P = 0.05$) are indicated by an asterisk (*). Letters designate different fields located as follows: D, Bertie County; E, Edgecombe County; and F, Bertie County.

Because *S. rolfsii* normally has no airborne spore stage (1), spread of stem rot is limited to adjacent peanut plants (by contact of infected parts or by single-row cultural operations) during the growing season. Digging and harvesting of peanuts probably makes the inoculum pattern more random, as do subsequent plowings, rotations to nonhost crops, and field preparations. The ability of *S. rolfsii* to produce sclerotia on organic debris (2) and the apparent importance of microclimates in favoring or suppressing disease (18) would tend to favor clustering of stem rot infections. In a given field, therefore, factors that tend to favor random and clustered spatial patterns occur together. Different factors probably dominate within different fields and with changing inoculum densities, which results in varying degrees and patterns of clustering. Completely random patterns of disease, however, would still be very rare.

Lack of randomness should be anticipated in epidemiological studies of southern stem rot on peanut. At the same time, a better understanding of environmental influences on disease and of dynamics of disease should help explain observed distribution patterns. The further understanding of spatial pattern and the biological and environmental factors which influence pattern should ultimately lead to better management of stem rot and similar diseases.

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