2DCLASS, a Two-Dimensional Distance Class Analysis Software for the Personal Computer

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ABSTRACT

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2DCLASS is microcomputer software capable of performing Gray's two-dimensional distance class analysis of spatial pattern of plant disease. The program allows for rapid and concise analysis of the spatial pattern of binomial (presence/absence) data within a two-dimensional matrix (e.g., rows and columns of plants). The procedure is particularly useful for the detection and quantification of nonrandom spatial patterns, average cluster size, distance between or among clusters, relative cluster location within a lattice, within-row and across-row aggregation, and edge effects. The software also generates a map of observed spatial pattern and is tolerant of missing data points. Instructions (with examples) for use of 2DCLASS and guidelines and cautions for interpretation of program output are provided.

Information about spatial attributes of plant pathogens in the environment and of disease in plant populations provides insight into disease progress and the determinants of disease spread. Description and quantification of spatial aspects of pathogens and/or diseased plants enhance the performance of disease models and simulators as well as the efficiency of experimental and sampling designs in field experiments (1).

Diverse descriptive and analytical procedures exist to characterize and quantify spatial patterns. The procedures vary with regard to data requirements and their ability to determine whether diseased individuals are aggregated, the relative strength of aggregation (degree of departure from randomness), and directionality or two-dimensional orientation of aggregation. The techniques for analyzing spatial patterns of diseased plants or pathogen propagules fall into three general categories based on type of data required (1): position of healthy or diseased plants within a row or series of rows, quadrat or plot count data, and distance measurements. Much phytopathological research on spatial patterns has relied on grids of quadrats, whereby estimates of variance and means of count or proportion data are used to quantify spatial attributes.

Distance-based analyses have been used successfully to describe spatial patterns in ecological studies (7,8,11). These analyses consider distances between individuals of a population (e.g., of a particular species) within a continuous area. An underlying assumption is that members of the sampled population can occupy any location within the continuum. This assumption is not met for agronomic or horticultural row crops. Several distance-based or distance-class methods have been proposed, though seldom used, for describing two-dimensional spatial pattern of diseased/healthy plants arranged or demarcated on a lattice (6,9,10).

Gray et al (3) developed a two-dimensional distance class analysis for characterizing spatial relationships of virus-infected plants within row crops (which may be regarded as plant distribution lattices). The two-dimensional distance class method utilizes binomial data, collected as the presence or absence of symptomatic plant(s) in a particular quadrat or lattice position within a rectangular field plot. Gray's procedure has been applied to only two pathosystems (2,4). Adequate and accessible computer software could expand the application of this method of pattern analysis. This paper provides users of MS DOS-based personal computers with a description of software that will perform Gray's two-dimensional distance class analysis of spatial pattern.

Gray's method (3) uses a coordinate system with the location of plants described in terms of [*X*, *Y*] distance values. The distance relationship between plants, defined by the absolute differences between their [*X*] and [*Y*] values, is used to assign all pairs of diseased plants to [*X*, *Y*] distance classes. Because the total possible number of pairs varies among [*X*, *Y*] distance classes, the number of pairs of diseased plants in each [*X*, *Y*] distance class is standardized by dividing by the total number of pairs of living plants within the same [*X*, *Y*] distance class. This allows for direct comparison of standardized count frequency (SCF) values in any [*X*, *Y*] distance class. Comparison of observed and expected standardized counts in each [*X*, *Y*] distance class is used to define and quantify the randomness of diseased pairs of plants and their orientation within the lattice. Expected counts are generated by computer simulations (3) performed under the assumption of a random pattern of diseased plants. The procedure is particularly useful for the detection of nonrandom spatial pattern and for quantification of average cluster size, distance between/among clusters, relative cluster location within the lattice, within- and across-row aggregation, and edge effects.

Gray's two-dimensional distance class analysis program was written in FORTRAN for a mainframe computer (3). The program presented here, 2DCLASS, is an adaptation of Gray's program and is written and compiled in the Microsoft QuickBASIC language (Microsoft QuickBASIC Version 4.5., Microsoft Corporation, One Microsoft Way, Redmond, WA 98052-6399). The 2DCLASS program requires DOS 2.0 or higher. Data for use with 2DCLASS can be prepared with the aid of any word processor, spreadsheet, or database program that can output files in ASCII. Input data sets are arranged in columns. The first two columns contain *X* and *Y* coordinates or "cell" indicators of the spatial position associated with presence/absence of individuals of the population under study (e.g., diseased plants) in individual quadrats or at specific lattice points in a two-dimensional matrix. For plants, for example, each one is assigned a status code of 1, 2, or 3 that identifies it as healthy, diseased, or missing, respectively. Successive columns (columns 3 to *n*) can represent data from different replications or times of observations, data from different fields, etc. Data from an unlimited number of disease assessment dates can be stored in a single data file. Plot layouts with up to 16,000 quadrats or planting positions (number of rows × number of columns) may be analyzed.

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Examples. One actual and three hypothetical data sets are provided to demonstrate program output and to illustrate near-random spatial pattern and several types of aggregation amenable to analysis via 2DCLASS. The hypothetical data sets are provided to orient the reader's eye regarding interpretation of output for obvious patterns of aggregation and to facilitate interpretation of more subtle examples of aggregation. Each hypothetical set of data consists of plants arranged in a 10-column × 10-row matrix. The data could represent any type of pathogen or disease (soilborne or aerial) or any other binomially classified information (e.g., living vs. dead plants). The real data (a nearly random spatial pattern) are from an eight-column × eight-row lattice of white clover (*Trifolium repens* L.) plants in a clover/tall fescue (*Festuca arundinacea* Schreb.) pasture during a 1991 epidemic of foliar blight caused by *Rhizoctonia solani* Kühn (S. C. Nelson and C. L. Campbell, *unpublished*). Actual output produced by 2DCLASS is presented for the actual data (Table 1). Stylized summaries of the program output are presented to facilitate interpretation of the hypothetical data sets (Fig. 1). The stylized summaries represent the two components of program output produced by 2DCLASS (Table 1): a stylized map of observed data and a stylized representation of the distance class analysis matrix, showing significant distance classes detected by 2DCLASS. The stylized summaries should not be confused with actual program output.

In reality, spatial attributes of epidemics may be difficult to qualify and quantify through simple visual examination. For example, cluster shape and size, patterns of diseased plants, orientation and organization of clusters within a lattice, and edge effects may not be discernible without supporting quantitative or statistical evidence. Therefore, three additional data sets from actual epidemics are presented as more subtle illustrations of an edge effect (Fig. 2). The three examples vary regarding departure from randomness, magnitude of the edge effect, and size and shape of clusters of diseased plants.

In a case of nearly random spatial pattern of disease, 2DCLASS produced an output file consisting of: 1) a map of the input data set and 2) results of the two-dimensional $[X, Y]$ distance class analysis (Table 1). The following statistics are provided for each $[X, Y]$ distance class (based on $n = 400$ simulations): standardized number of observed infected pairs and standardized number of expected infected pairs in each distance class, the "level of significance" (computed directly by counting the number of times the simulated SCF exceeds the observed SCF during the 400 simulations) (3), and the 95% lower and upper

Table 1. 2DCLASS program output for Rhizoctonia leaf blight of white clover in Wake County, North Carolina

ROWS

COLUMNS	1	2	3	4	5	6	7	8
8	H	*	*	*	H	H	*	*
7	H	H	*	*	H	H	H	H
6	*	*	H	*	*	*	H	H
5	*	*	H	*	H	H	H	*
4	H	H	*	H	*	*	H	H
3	H	H	H	H	H	*	H	H
2	H	H	H	H	H	H	H	H
1	H	*	H	H	H	*	H	H

H = HEALTHY
* = INFECTED
. = VACANCY

Total number of positions in matrix	=	64
Number of vacancies	=	0
Number of infected plants	=	22
Number of healthy plants	=	42

LINE 1 STANDARDIZED NUMBER OF OBSERVED INFECTED PAIRS
LINE 2 STANDARDIZED NUMBER OF SIMULATED INFECTED PAIRS
LINE 3 SIGNIFICANCE LEVEL
LINE 4 LOWER CONFIDENCE LIMIT OF SIGNIFICANCE LEVEL
LINE 5 UPPER CONFIDENCE LIMIT OF SIGNIFICANCE LEVEL

Column		0	1	2	3	4	5	6	7
Row	0	0.0000	0.1250	0.1250	0.1500	0.0625	0.0833	0.0000	0.1250
Row	0	0.0000	0.1147	0.1143	0.1149	0.1128	0.1139	0.1116	0.1122
Row	0	0.0000	0.2750	0.2675	0.0975	0.8050	0.5775	0.9000	0.2275
Row	0	0.0000	0.2437	0.2365	0.0767	0.7773	0.5429	0.8790	0.1982
Row	0	0.0000	0.3063	0.2985	0.1183	0.8327	0.6121	0.9210	0.2568
Row	1	0.1607	0.1327	0.1429	0.1286	0.0893	0.0714	0.0357	0.1429
Row	1	0.1155	0.1133	0.1142	0.1150	0.1179	0.1158	0.1136	0.1116
Row	1	0.0475	0.1675	0.1175	0.2800	0.7350	0.7650	0.8350	0.2300
Row	1	0.0326	0.1414	0.0950	0.2486	0.7041	0.7353	0.8090	0.2005
Row	1	0.0624	0.1936	0.1400	0.3114	0.7659	0.7947	0.8610	0.2595
Row	2	0.1042	0.1429	0.194+	0.1000	0.1667	0.1111	0.0833	0.2500
Row	2	0.1134	0.1121	0.1149	0.1138	0.1171	0.1116	0.1139	0.1056
Row	2	0.4925	0.1100	0.0000	0.5525	0.0425	0.3950	0.5300	0.0450
Row	2	0.4575	0.0881	0.0000	0.5177	0.0284	0.3608	0.4951	0.0305
Row	2	0.5275	0.1319	0.0000	0.5873	0.0566	0.4292	0.5649	0.0595

(*continued on next page*)

Row	3	0.1250	0.1429	0.1333	0.1000	0.1000	0.0667	0.0500	0.1000
Row	3	0.1143	0.1150	0.1142	0.1128	0.1161	0.1188	0.1113	0.1140
Row	3	0.2875	0.1250	0.2000	0.5150	0.5375	0.7675	0.6850	0.3075
Row	3	0.2558	0.1018	0.1720	0.4800	0.5026	0.7379	0.6525	0.2752
Row	3	0.3192	0.1482	0.2280	0.5500	0.5724	0.7971	0.7175	0.3398
Row	4	0.188+	0.1250	0.1458	0.1000	0.0938	0.1250	0.0000	0.1250
Row	4	0.1141	0.1151	0.1158	0.1148	0.1178	0.1135	0.1188	0.1128
Row	4	0.0025	0.2750	0.1375	0.5275	0.5750	0.2675	0.9250	0.2225
Row	4	-.0010	0.2437	0.1134	0.4926	0.5404	0.2365	0.9066	0.1934
Row	4	0.0060	0.3063	0.1616	0.5624	0.6096	0.2985	0.9434	0.2516
Row	5	0.1250	0.0952	0.1111	0.1000	0.0833	0.0556	0.0000	0.1667
Row	5	0.1127	0.1146	0.1126	0.1145	0.1159	0.1163	0.1179	0.1125
Row	5	0.2500	0.5550	0.3800	0.4725	0.5950	0.6700	0.8200	0.1375
Row	5	0.2197	0.5202	0.3460	0.4376	0.5606	0.6371	0.7931	0.1134
Row	5	0.2803	0.5898	0.4140	0.5074	0.6294	0.7029	0.8469	0.1616
Row	6	0.1250	0.0357	0.0833	0.1500	0.0625	0.0000	0.0000	0.2500
Row	6	0.1163	0.1168	0.1178	0.1180	0.1167	0.1113	0.1181	0.1188
Row	6	0.2775	0.8600	0.5775	0.2100	0.6000	0.7875	0.6725	0.0675
Row	6	0.2462	0.8357	0.5429	0.1815	0.5657	0.7589	0.6396	0.0499
Row	6	0.3088	0.8843	0.6121	0.2385	0.6343	0.8161	0.7054	0.0851
Row	7	0.1250	0.0714	0.0833	0.1000	0.0000	0.0000	0.0000	0.0000
Row	7	0.1200	0.1113	0.1121	0.1100	0.1125	0.1204	0.1131	0.1338
Row	7	0.2300	0.4275	0.3850	0.3150	0.6450	0.5675	0.4150	0.2550
Row	7	0.2005	0.3929	0.3509	0.2825	0.6115	0.5328	0.3805	0.2245
Row	7	0.2595	0.4621	0.4191	0.3475	0.6785	0.6022	0.4495	0.2855

Number of Distance Classes With SCFs Greater Than Expected: 2
Number of Distance Classes With SCFs Fewer Than Expected: 0

Time required to perform the 400 simulations: .49 minutes

confidence limits on the significance level. In addition, the program calculates the number of [*X, Y*] distance classes with an observed SCF significantly higher (upper confidence limit on level of significance $\leq$0.05) than expected (indicated by a + in the body of the table) and significantly lower (lower confidence limit on level of significance $\geq$0.95) than expected (indicated by a $), and the time required to perform the $n = 400$ simulations. Examination of Table 1 reveals that only two [*X, Y*] distance classes, [2,2] and [4,0], have SCFs significantly higher, and no distance classes have SCFs significantly lower, than expected under a random spatial pattern of infected plants. Thus, the incidence of Rhizoctonia leaf blight on the day of observation was interpreted to be random.

Stylized representations of the program output for the hypothetical data sets illustrate: 1) an edge effect (Fig. 1A and B), common with diseases caused by insect-vectored pathogens (5) or with early-season foliar diseases in newly established field plots (S. C. Nelson and C. L. Campbell, *unpublished*); 2) clusters of diseased plants (Fig. 1C and D); and 3) within-row aggregation of diseased plants (Fig. 1E and F). In the example of edge effect, a departure from randomness is evinced by the relatively large number of distance classes with SCFs significantly higher and lower (31 and 13, respectively) than would be expected with a random pattern (Fig 1B). Vacancies are included to demonstrate the tolerance of two-dimensional distance class analysis for missing values. Scrutiny of the mapped data reveals a potential edge effect (Fig. 1A). Relevant to detection of an edge effect are the SCFs in [*X, Y*] distance classes [0-9,9] and [9,0-9]. Each of these classes has a significantly higher ($P \leq 0.05$) SCF than expected, which indicates that diseased pairs often occur at opposite edges and corners of the plot. Conversely, that fewer pairs of infected plants occur in or near midplot is evidenced by the group of significantly lower SCFs in those distance classes in the upper left-hand region of the two-dimensional distance class analysis matrix. Absence of significantly higher SCFs in the [*X, Y*] classes [0,1], [1,0], and [1,1] confirms the absence of discrete, relatively isodiametric clusters.

Figure 1C portrays a map of a hypothetical field plot with discrete, relatively isodiametric clusters of diseased plants. Nonrandom distribution of diseased pairs is indicated by those distance classes with significantly higher and lower (18 and 14, respectively) SCFs than expected (Fig. 1D). An attractive feature of Gray's two-dimensional distance class analysis is the potential identification of "average" cluster size and relative location within the lattice. If clusters of infected plants are found in the lattice, their dimensions will be evident from the distribution of the small distance classes (low [*X, Y*] values) that have SCFs significantly higher ($P\leq 0.05$) than expected. Four such classes —[0,1], [0,2], [1,0], and [1,1]—identify an average "core cluster size" of approximately five to nine plants (Fig. 1D). Resolution of the average core cluster size is limited to a range of values, because the significance level calculated for class [0,1], for example, is based on bidirectional comparison of plants within the matrix (i.e., each plant is compared with all other plants in that distance class, both to the "right" and the "left" of itself). Two other clusters of distance classes having SCFs significantly higher ($P \leq 0.05$) than expected, i.e., cluster [2,5-6], [3,5-7], [4,5-8], and [5,6-7] and cluster [6,1] and [7,0-1], represent the relative location of clusters within the lattice. The relative location and "average distance" (3) between clusters is determined by the position of these clusters in the lattice relative to the core cluster in the upper left-hand corner of the analysis lattice, in terms of [*X, Y*] direction and distance. For example, evidence for clusters of diseased individuals in the same column(s) of the matrix and separated by four rows is given by the two groups of [*X, Y*] distance classes with SCFs significantly higher than expected occurring in the [0-2] *Y*-value positions in the distance class analysis matrix (Fig. 1D).

The map for the third hypothetical situation (Fig. 1E) reveals evidence for within-row aggregation of infected plants. Significant, nonrandom distribution of infected pairs of plants is conspicuous in the two-dimensional distance class analysis. The number of SCFs is significantly higher ($P \leq 0.05$) than expected in 29 distance classes and significantly lower ($P \geq 0.95$) than expected in 17. Nonrandomness confirmed, the interpretive goal is to identify the manifestation (cluster size and orientation) of this nonrandomness. The 29 distance classes with a significantly higher number of standardized observed infected pairs are in classes [0,1-9], [3,0-9], and [6,0-9], which indicates significant, lengthy, within-row aggregation of infected pairs of plants (Fig. 1F).

Stylized representations of program output are provided for more subtle examples of edge effects of varying strength (Fig. 2). During an epidemic of Stagonospora leaf spot, caused by *Stagonospora meliloti* (Lasch) Petr., on white clover (S. C. Nelson and C. L. Campbell, *unpublished*) in an eight-column × eight-row matrix, only five of 63 distance classes ([0,0] is ignored) are significant (Fig. 2A and B). By itself, this is relatively weak evidence for a nonrandom spatial pattern of diseased plants. However, four of the distance classes form an L-shaped group (Fig. 2B), indicating at least two clusters in the matrix. The significant [*X, Y*] distance classes—[1,6], [2,6], and [3,6-7]—reveal elongate, roughly rectangular clusters that span several rows. The clusters have a minimum of four plants and are separated by one to three rows and by six or seven columns within the matrix, indicating a significant edge or near-edge effect. The two nonadjacent significant distance classes at matrix edge—[3,7] and [6,7]—offer relatively weak evidence for a significant edge effect for Stagonospora leaf spot.

A map of white clover plants infected with *Pseudomonas andropogonis* (Smith) Stapp in September 1991 (S. C. Nelson and C. L. Campbell, *unpublished*) (Fig. 2C) provides stronger evidence for across-row aggregation and a significant edge effect. The significant adjacent [*X, Y*] distance classes at the right-hand edge of the distance class analysis matrix are interpreted as indicating at least two lengthy (three to five plants) across-row (within-column) aggregates located at opposite edges of the plot (Fig. 2D). These [*X, Y*] distance classes are also associated with proximal significant distance classes—[0,6] and [1,6]—and provide evidence for the existence of at least two roughly rectangular clusters of five to 10 diseased plants. The significant [*X, Y*] distance classes [4,0], [5,0], and [7,0] indicate that diseased plants tend not to occur within the same column, especially at opposite edges.

An epidemic of summer blight, caused by *R. solani*, of white clover (S. C. Nelson and C. L. Campbell, *unpublished*) in an eight column × eight row matrix of plants was found to have a relatively

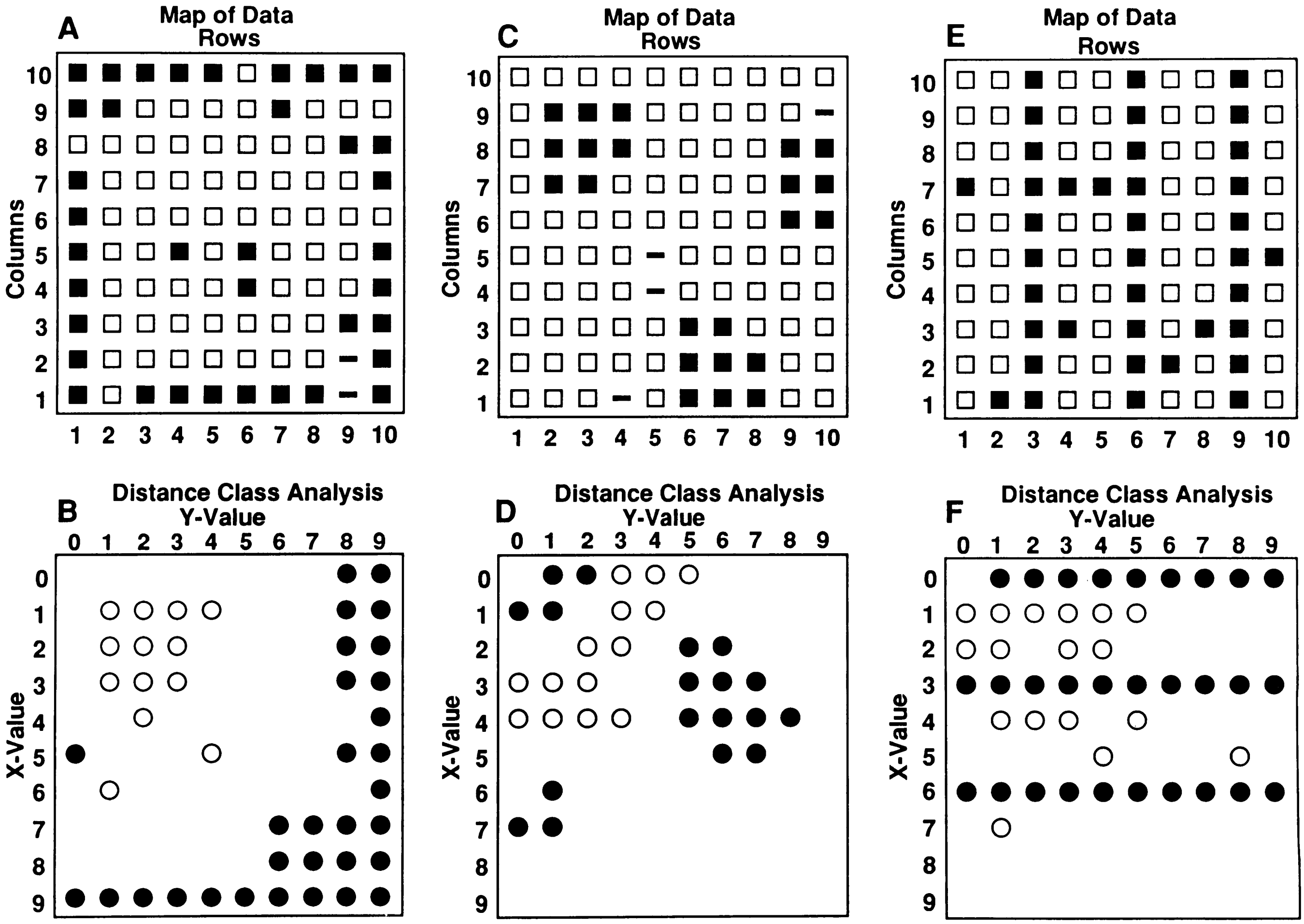

Fig. 1. (A, C, and E) Spatial patterns of diseased plants in hypothetical 10-column × 10-row lattices showing a pronounced edge effect in A, discrete clusters of diseased plants in C, and within-row aggregation of diseased plants in E. □ = Healthy plant, ■ = infected plant, dash = vacancy. **(B, D, and F)** Two-dimensional distance class analysis of the hypothetical data. ● = [*X, Y*] class with a standardized count frequency higher than expected ($P \leq 0.05$), ○ = [*X, Y*] class with a standardized count frequency lower than expected ($P \geq 0.95$).

strong edge effect (Fig. 2E and F). The magnitude of the relative strength of edge effect in Fig. 2E is not readily apparent when the map is compared with the spatial pattern map of diseased plants in Fig. 2C. 2DCLASS detected the relatively higher proportion of edge infections vs. interior infections (diseased plants not at plot edge) in Fig. 2E, resulting in a significantly stronger edge effect, at distance classes [0-6,7] (Fig. 2F). As in the previous two examples, the edge effect is across rows. The significant [*X, Y*] distance classes [5,5-7] and [6,5-7] illustrate a corner effect, wherein plants near the corners of the plot tend to be diseased.

Discussion and guidelines. Application of the two-dimensional distance class analysis has certain limitations. As with many spatial pattern analyses, interpretation may be meaningless without a concurrent examination of the mapped data. For example, although within-row and/or across-row clustering may be detected, significant edge effects may be missed if infected pairs aggregate at only one or two edges of the lattice. Furthermore, successive analyses of the same set of data may result in minor variability in results because of slight variations in the random placement of diseased plants during the simulations. This variability is a consequence of slight variability in confidence limits between runs (some "borderline" values for the confidence limits may rise above or fall below the significance levels we incorporated into 2DCLASS). A reason for performing the large number of simulations (at least 400) for each data set is to help stabilize the statistics generated by the analysis (e.g., confidence limits, significance levels, SCFs). We suggest that given an adequate number of simulations, minor variability in analytical results between analyses will lead to the same general interpretation, according to the criteria used for interpretation and the confidence level selected for significance. Thus, changes in significance for some distance classes should be interpreted with caution, ignored, or tested further with relaxed confidence limits.

Two-dimensional distance class analysis may be inappropriate when the number of infected plants is very small or very large in relation to the total number of plants in the lattice. For example, all relevant distance classes tend to yield significant SCFs when the proportion of infected plants is small (e.g., 0.05), even when the diseased plants are arranged randomly. The number of simulations needed and the number of SCFs that must be significant to claim nonrandomness depend on the size of the matrix and the proportion of plants infected. The minimum proportion of plants infected and the lattice shape and uniformity of planting within the lattice may also affect the sensitivity of the analysis and the interpretation of results. Finally, inherent in 2DCLASS is a tolerance for missing data points. The question of upper limits for the proportion of values missing remains unanswered and should be specified by the user.

Investigators using this analysis should specify the guidelines used in their interpretations of the results. At the present time, our analyses of epidemics of leaf spot on white clover in eight column × eight row plant lattices are guided by the following conservative criteria: 1) minimum proportion of diseased plants = 0.15–0.20; 2) maximum proportion of diseased plants = 0.80–0.85; 3) maximum proportion of missing values = 0.20; 4) minimum number of simulations = 400; and 5) minimum percentage of significant SCFs needed to indicate nonrandomness = 5–10% of total number of distance classes. The last guideline should be tempered by knowledge of the location of the significant SCFs,

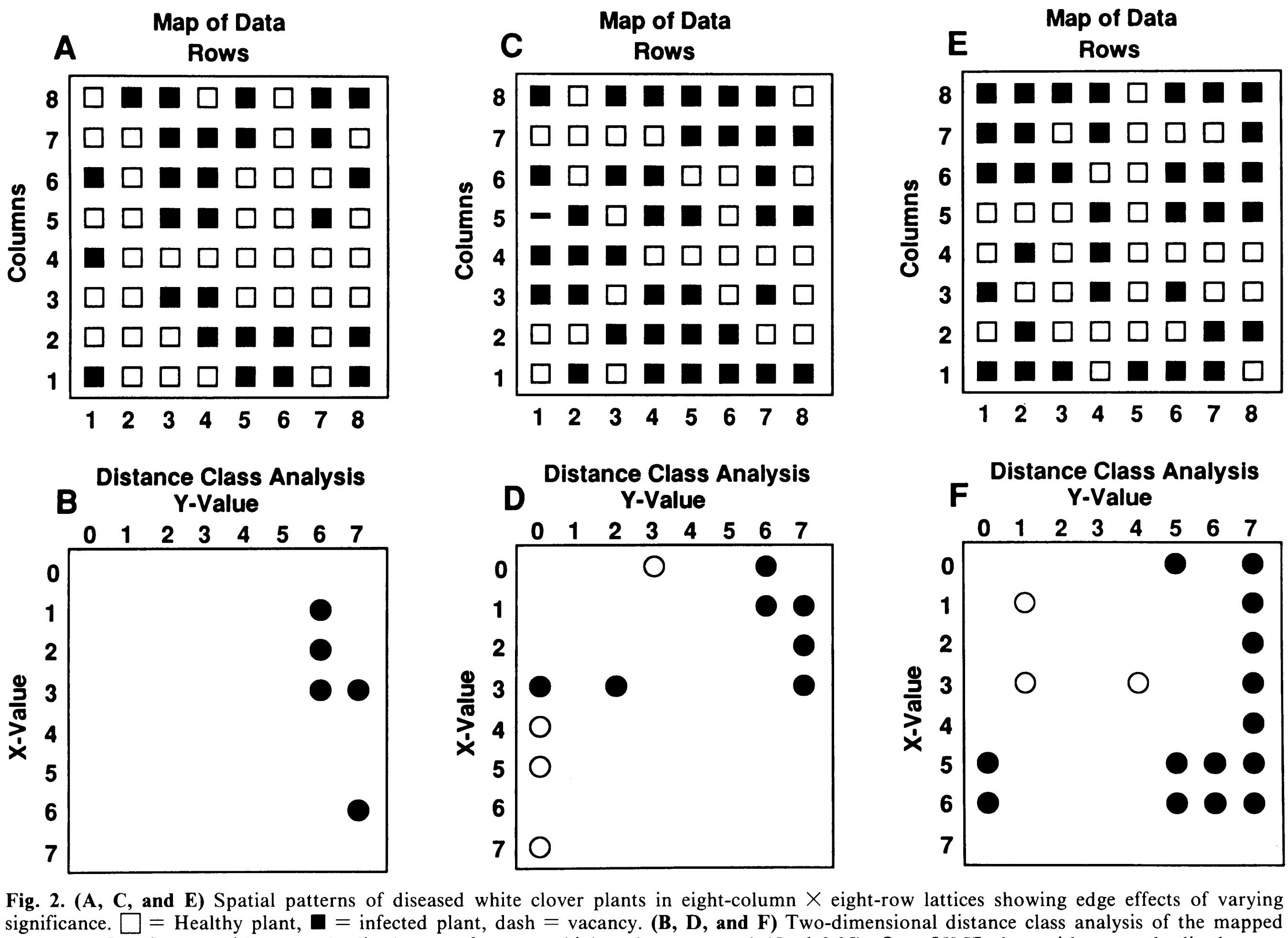

Fig. 2. (A, C, and E) Spatial patterns of diseased white clover plants in eight-column × eight-row lattices showing edge effects of varying significance. □ = Healthy plant, ■ = infected plant, dash = vacancy. **(B, D, and F)** Two-dimensional distance class analysis of the mapped data. ● = [*X, Y*] class with a standardized count frequency higher than expected ($P \leq 0.05$), ○ = [*X, Y*] class with a standardized count frequency lower than expected ($P \geq 0.95$).

with more weight being given to those grouped in patterns or in discrete clusters. In our work, edge effects are interpreted as being significant if 15–20% of the distance classes are significant in the outermost row and column (row 7 and column 7) of the matrix.

The 2DCLASS software has proved useful to us as a tool for analysis of spatial data of several pathogens of white clover. Improvements to the original FORTRAN programs have enhanced the utility of the 2DCLASS program. The new version provides a single flexible, interactive program, as opposed to two relatively inflexible, noninteractive programs, at reduced expense (personal computer vs. mainframe computer). Processing time required to perform two-dimensional distance class analysis with 2DCLASS depends on the number of simulations, the size of the lattice, the proportion of infected plants, and the speed of the computer. The data sets we used as examples require less than 1 min processing time each on a computer with an 80386 microprocessor and 20 MHz operation speed. The program is written in a relatively simple, widely used language for which software is not expensive. The 2DCLASS program source code, the compiled program, sample data sets, and a brief user guide can be obtained free of charge by contacting the third author.

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Salute to APS Sustaining Associates

This section is designed to help APS members understand more about APS Sustaining Associates. Information is supplied by company representatives. Each month features different companies. A complete listing appears in each issue of *Phytopathology*.

Rogers NK Seed Company. Contact: Wayne L. Wiebe, RR 1 Box 507, Woodland, CA 95695; 916/666-0986. On January 1, 1991, Rogers Brothers Seed Company and Northrup King Vegetable Division merged to form one company. Over the past 100 years each company has developed into a leader in its respective vegetable seed lines. Rogers NK Seed Co., which the combines the Rogers large seed line with the Northrup King small seed line, is one of the largest full-line vegetable seed companies in North America. Rogers NK Seed Co. has a strong commitment to research. The goal of its research is to develop, produce, and market improved agronomic and vegetable crop cultivars. To help achieve these goals, the company has research stations throughout the United States, as well as in Canada, Mexico, South America, and Europe. Plant pathology plays an important part in this research, both in the development of new cultivars with improved disease resistance and in the production and marketing of high-quality healthy seeds.

Rogers NK Seed Co. Contact: Paul Moser, Research Center, 6338 Highway 20-26, Nampa, ID 83687; 208/466-0319. On January 1, 1991, Rogers Brothers Seed Company and the vegetable seed division of Northrup King merged to form Rogers NK Seed Co., a full-line vegetable seed company that supplies seed to the processing, fresh market, and garden seed industries. The major research emphasis is development of new varieties and improvement of existing strains. Research at Rogers NK has top priority; its main goal is to increase the productivity, quality, and reliability of crops for the benefit of the consumer, farmer, and processor. Plant pathology and its application to disease control are important to its success. Rogers NK is a member of the Sandoz Seeds group.

Rohm & Haas Company. Contact: Stephen R. Connor, Independence Mall West, Philadelphia, PA 19105; 215/592-3051. Rohm & Haas has been involved with agricultural chemicals since 1929, when it introduced Lethane, the first synthetic organic insecticide. In the 1940s, the company developed Dithane fungicide, the most widely used organic agricultural fungicide in the world. Dithane fungicides (maneb and mancozeb formulations) are used to control more than 50 fungal diseases on more than 80 crops. In 1989, myclobutanil (Rally, Nova, Systhane) was introduced for disease control in apples and grapes. Current fungicide research efforts are on a wide variety of novel fungicides.

Rothamsted Experiment Station. Contact: Librarian, Harpenden, Herts. AL5 2JQ, England.

Sakata Seed America, Inc. Contact: Richard H. Morrison, 105 Boronda Road, Salinas, CA 93907; 408/758-0505.

Sandoz Crop Protection Corp. Contact: Louie T. Hargett, 1300 E. Touhy Ave., Des Plaines, IL 60018; 708/390-3806. Sandoz Crop Protection Corp. (SCPC) produces innovative biological and chemical products for North American agriculture. Products include chemical herbicides and fungicides and chemical and biological insecticides. Several major fungicide products in development will have uses in peanuts, turf, and wheat. SCPC's headquarters are in Des Plaines, IL. The research division is in Palo Alto, CA. Research and development farms are in Gilroy, CA, and Greenville, MS. SCPC was organized in 1986 and is a division of Sandoz Corporation, the U.S. subsidiary of Swiss-based Sandoz Ltd., an international producer of pharmaceutical, agricultural, nutritional, and chemical products.

O. M. Scott & Sons. Contact: J. Bell, D. G. Scott Research Center, Marysville, OH 43041; 513/644-0011. The O. M. Scott & Sons Co., with its title "First in Lawns," has been the recognized leader of the lawn products industry since 1870. Fertilizers, grass seed, and control products are sold to homeowners and professional users, such as golf course, park, industrial lawn, and commercial growers. Scott markets a complete line of fungicide products for turf.

Trical, Inc. Contact: Tom Duafala, P.O. Box 1327, Hollister, CA 95024; 408/637-0195. Trical, Inc., has been a leader in soil fumigation for more than 28 years, successfully controlling diseases, weeds, nematodes, and soilborne insects and improving the yield and quality of agricultural products.

Uniroyal Chemical Company. Contact: Allyn R. Bell, 74 Amity Road, Bethany, CT 06524; 203/393-2163. Uniroyal established an agricultural chemical company more than 45 years ago as a developer and supplier of fungicides, herbicides, miticides, and plant growth regulants. Emphasis was directed toward providing unique products in each of these areas. With the introduction of systemic fungicides for cereal/cotton disease control, the company began a solid commitment to seed treatment technology worldwide. Gustafson, Inc., an associate, has strengthened its efforts in this technology. Uniroyal also markets several soil fungicides for row crops, turf, and ornamentals. Its current spectrum of fungicide products consists of carboxin (Vitavax), etridiazole (Terrazole), oxycarboxin (Plantvax), PCNB (Terraclor), and thiram. Efforts are directed at foliar fungicides for fruit and field crops, including both systemic and nonsystemic active ingredients. The company has active programs with various universities, USDA pathologists, and extension people in the United States to evaluate these candidates in disease management programs.

Unocal Chemicals and Minerals Division. Contact: Sahag K. Garabedian, 3960 Industrial Blvd., Suite 600B, West Sacramento, CA 95691; 916/372-6050.

USDA Forest Service. Contact: Leon LaMadeleine, 324 25th Street, Ogden, UT 84401.