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e-Xtra

Applications of Geographic Information Systems and Geostatistics in Plant Disease Epidemiology and Management

Information management will be a key to improving farm practices in the coming decades. It makes sense to organize farm information in spatial databases because agricultural systems are inherently spatial. Biological and physical aspects of agricultural systems create spatial heterogeneity, and as a result, patchiness is the rule in the occurrence and distribution of plant pathogens and disease (3). Plant disease management practices can be improved by putting epidemiological information in the same format as other farm information using a geographic information system (GIS). A GIS is a computer system capable of assembling, storing, manipulating, and displaying data referenced by geographic coordinates (45). GIS can now be installed on any recent model desktop computer (e.g., a Pentium personal computer with at least 32 MB of RAM is adequate for most applications) and does not require an in-depth understanding of the statistical and mathematical basis of the technology. The large commercial push toward precision farming is based on combining GIS with sophisticated hardware for geographically referenced yield data and variable rate applications of fertilizers and other farm chemicals.

GIS can be adapted to any size operation, and data can be incorporated at any scale from a single field to an agricultural region. Many problems should be studied at more than one scale. Part of the art of GIS database development is to decide what scale to use and which kinds of information to include at each scale. The ability of government institutions, the nation's agricultural colleges and experiment stations, and private enterprise to provide spatially referenced information will open the way to farmers, pest control advisors, extension workers, and others to evaluate plant disease problems in a spatial context. New tools, including global positioning systems (GPS) and geostatistics, are available to use in connection with GIS. While these tools can be used at any scale, our efforts have been at the regional scale in generally arid irrigated agricultural areas. We focus on spatial relationships of landscape features that interact with the progress of an epidemic to refine cultural management strategies for plant disease control. Examples from this work will be used to illustrate the application of GPS, GIS, and geostatistics following a general introduction to the technologies.

GPS

GPS receivers determine location and are among the most important tools for spatially referencing agriculture data. GPS depends on a system of navigation satellites operated by the U.S. Department of Defense (the NAVSTAR system). These satellites broadcast signals containing time and position information. GPS receivers on the ground collect the satellite signals and determine position in a spherical coordinate system such as latitude and longitude or a planar coordinate system such as the Universal Transverse Mercator system common on terrestrial maps. An advantage of a planar coordinate system is that one can calculate distance and direction in a two-dimensional Euclidean system. Such calculations are required for geostatistical analyses. Elevation can be added if three-dimensional spatial considerations are important. GIS utilities are available to translate from one coordinate system to another.

At unannounced times, the Department of Defense degrades the freely available signal broadcast by GPS satellites according to a practice known as selective availability (SA). SA is important to the GPS user because both the precision and the accuracy of GPS readings are reduced unless corrections are made. Accuracy is "the closeness of a measured or computed value to its true value"; precision is "the closeness of repeated measurements of the same quantity" (43). Without adapters, corrections cannot be made on the inexpensive handheld GPS units, so these devices cannot be depended on for horizontal accuracy better than 100 m and vertical accuracy better than 156 m. The accuracy specifications represent two standard deviations of distance from the actual antenna position to a set of position estimates made under a specified set of satellite conditions (see http://www.utexas.edu/depts/grg/gcraft/notes/gps/gps.html). In practice, accuracy can be in the range of 15 to 25 m, because the signal is not always degraded. Differential GPS (DGPS) is used to improve accuracy to about 2 m. To achieve this accuracy, data from a receiver at a known position (base station) is combined with data from a receiver at the desired position (rover or remote station) to correct for SA and other sources of error. Precision farming equipment, such as yield monitors and variable rate applicators, depends on DGPS. DGPS can increase the cost and computer complication involved in obtaining point coordinates, so inexpensive handheld devices are preferable when DGPS accuracy is not required.

The regional applications described in this article are done with inexpensive handheld GPS units, because the interpretation of spatial patterns spanning more than 100 km does not require an accuracy of better than 100 m for point coordinates. Even in smaller areas where greater accu-

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racy is desired, a combination of tools can substitute for DGPS. Hand-drawn maps or USDA Farm Services Agency maps are frequently available. Handheld GPS units can be used to obtain coordinates of landmarks such as road intersections or irrigation wells, which can then be used as reference points to digitize the hand-drawn detailed map for display with other layers referenced to the same coordinate system. Similarly, greater precision can be achieved by staking out rectangular grids in a small area and then using a handheld GPS unit to relate the location of the grid as a whole to a wider area.

Between 1990 and 1994, we used maps with a spatially referenced grid, instead of GPS, to obtain coordinates for sample locations (33). We switched to GPS because it is easier to obtain the coordinate information from GPS than from a map unless you are intimately familiar with an area. Until about 1994, GPS units were too expensive for most projects. The rapid growth in availability and affordability of handheld GPS units is due in part to the mass market for navigation applications by small boat owners. Most mass-produced GPS units are designed for nautical applications and for the outdoorsman. Thus, most sources of handheld GPS units are marine or outdoor supply businesses.

GIS

GIS relates the data collected by GPS to other sources of geo-referenced information. GIS has the ability to integrate layers of spatial information and to uncover possible relationships that would not otherwise be obvious (16–18). The process of transforming one layer of spatial information to match a second layer is called registration (45). When a broad collection of data is registered to the same coordinate system, the possibilities for sharing data and creatively analyzing the spatial relationships increase dramatically. GIS applications for agriculture are developing rapidly and include generic commercial packages such as ArcView (ESRI, Redlands, CA) or MapInfo Desktop (MapInfo Corp., Troy, NY) as well as more specific applications derived from these packages (e.g., Site-Specific Technology Development Group, Inc., Stillwater, OK [ArcView] and Red Hen Systems, Fort Collins, CO [MapInfo]). As with other types of computer software, compatibility between competing systems can be a problem, but data transfer protocols and generic data formats have been developed to work around this problem.

There are two main forms of GIS data: vector and raster. Most GIS software can now handle both forms. In vector data sets, map features such as points, lines, and polygons are organized and manipulated in a database. In raster data sets, the data are organized as a matrix of numerical values and referenced spatially by row and column position. Header information or an associated computer file contains the spatial information that relates the rows and columns of the matrix to the GIS coordinate system. USGS digital elevation model data sets, satellite images, and some image files produced by scanners are examples of raster data sets.

GIS has been applied in agriculture for the spatial analysis of insect pests (2,7, 12,13,28,39,42,44), weeds (26,29,38,54), and plant diseases (33,35,36). Weltzien (50–53) introduced the term "Geophytopathology" to describe studies of spatial patterns of plant diseases, the causal understanding of these patterns, and the geographic aspects of disease control. He gave a detailed description of the use of maps to illustrate the spread of plant diseases over regional or even continental scales and classified the types of maps that can be used for these purposes (52). However, quantitative regional assessment requires analysis of large spatial databases. With development of powerful computers and better software, GIS is the appropriate technology to manage such spatial data (48).

A recent article on precision farming in the trade magazine *California Farmer* expressed concern about the accuracy of agricultural maps and that farmers could be misled by the "captivating, brightly colored images" produced by GIS (47). Users of GIS data can be misled because the degree of detail reported by the system can exceed the precision of the source data. Some GIS specialists suggest using "visualization," such as fading from color to gray with decreasing confidence, to communicate a sense of qualification to users of data (10,17). Since many users will depend on automated commercial software packages, the incorporation of easy-to-use tools for the display of uncertainty should be a goal of both consumers and producers of these products. Perhaps the best check on the validity of GIS maps is common sense. Although it might seem obvious, it is important to say that the user of a GIS analysis should always compare the conclusions with their general knowledge of the problem and recheck the methodology and data if there is a major variance with expectation.

Geostatistics

Geostatistics focuses on the analysis of spatially distributed variables and the prediction or estimation of values at unsampled locations. Cressie categorizes spatial analysis into three broad types: geostatistical, lattice, and point (8). He describes geostatistics as a statistical model appropriate for estimates across continuous areas (characterized as processes with a continuous spatial index). Trend surface and inverse distant weighting methods of interpolation preceded geostatistics, but geostatistical considerations, implicitly or

Table 1. World Wide Web sites about global positioning systems (GPS), geographic information systems (GIS), and geostatistics. Links to these sites and others can be found at http://ag.arizona.edu/PLP/GIS/gis.html

Category	Site title	Uniform resource locator
GIS	Geographic Information Systems	http://www.usgs.gov/research/gis/title.html
	The Geographic Information Systems FAQ!	http://www.census.gov/geo/gis/faq-index.html
	Geographic Information Science at the University of California, Santa Barbara	http://ncgia.ucsb.edu/research/ucgis/main.html
	GIS User Assistance	http://www.lib.berkeley.edu/UCBGIS/gisusers.html
	GIS WWW Resource List	http://www.geo.ed.ac.uk/home/giswww.html
GIS data	EROS Data Center, Sioux Falls, SD	http://edcwww.cr.usgs.gov/
	National Biological Information Infrastructure	http://www.nbii.gov/
GPS	Global Positioning System Overview	http://www.utexas.edu/depts/grg/gcraft/notes/gps/gps.html
Map datum	National Geodetic Survey Frequently Asked Questions	http://www.ngs.noaa.gov/
Geostatistics	AI-Geostatistics	http://curie.ei.jrc.it/ai-geostats.htm
	Geostatistics Frequently Asked Questions	http://curie.ei.jrc.it/faq/index.html
	What is Geostatistics?	http://www.u.arizona.edu/~donaldm/whatis.html
	Geostatistical Links	http://www.intera.com/link/lnkstat.html
	Stanford Center For Reservoir Forecasting	http://ekofisk.stanford.edu/SCRF.html

explicitly, underlie most attempts to create surface maps based on point samples or observations. A surface map is a map with an area shaded in a color or gray scale keyed to a variable. As with summary statistics (averages, medians, standard deviations) in nonspatial data analysis, when done well, surface maps allow the viewer to grasp the larger picture without being distracted by the noise and scatter of point data. Regional surface maps are appropriate when a variable (pathogen propagule density, disease incidence, insect vector abundance, etc.) exhibits positive spatial autocorrelation beyond the boundary of a single field. Spatial autocorrelation is the correlation of a variable with itself (auto) at various separation distances and directions (spatial). If adjacent fields are highly dissimilar with abrupt differences defined by field boundaries, surface maps that are interpolated without field boundary considerations can be misleading. Sometimes the absolute value of a variable is less important than whether it is above or below a biologically critical value. If a variable, such as pathogen propagule density, is uniformly above such a threshold, a surface map will not be helpful unless the uniformity is in contrast to patchiness at another place or time.

There are a number of excellent introductions to geostatistics (22,24,31,41) as well as an outstanding World Wide Web site and active list service that is friendly to those just beginning with the subject (Table 1). Geostatistics have been used in plant pathology to analyze the spatial distribution of plant disease epidemics, mainly at plot or field scales (4,21,25, 27,46,49). They have also been used in a regional risk assessment program for the management of plant virus diseases in Mexico (33). The difficulties of spatio-temporal analyses were explored in a geostatistical study of the development of cabbage downy mildew epidemics (46). Inoculum patterns at very small scales, such as along plant roots (9), have also been quantified using geostatistics.

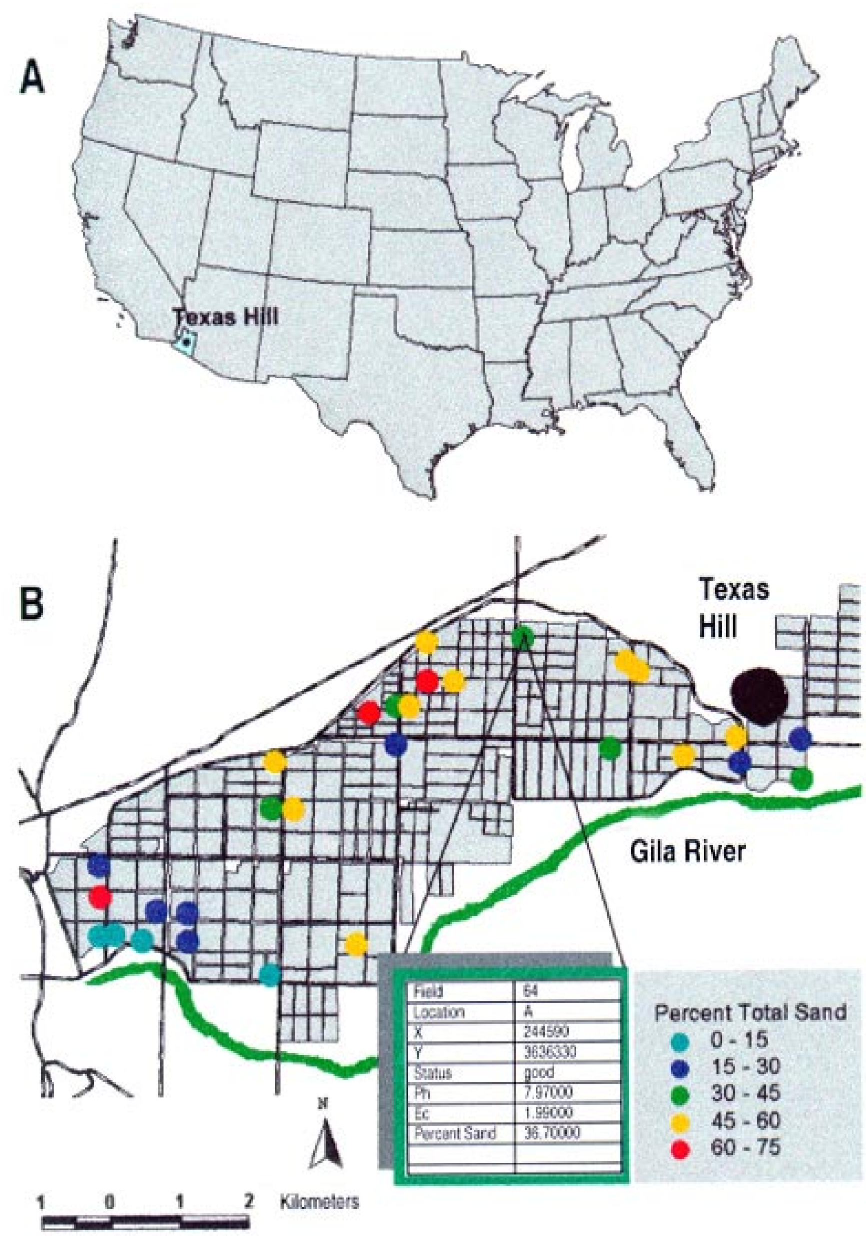

Fig. 1. (A) Location of Texas Hill in Yuma County, Arizona. (B) Map of Texas Hill data showing the simplest application of a geographic information system (GIS): data are linked to spatially referenced points so that the points can be overlaid on other map themes such as roads, field boundaries, and rivers. The inset shows data that are linked to one of the points.

A geostatistical analysis can be broken down into four phases: (i) exploratory data analysis; (ii) modeling of the spatial autocorrelation (characteristics of the spatial continuity); (iii) estimating at unsampled locations across a surface (surface maps); and (iv) evaluation of the reliability of the estimates. Isaaks and Srivastava (22) provide an easy-to-read explanation of geostatistics. In geostatistics, spatial autocorrelation is usually examined by variogram estimation and modeling. Procedures to develop experimental variograms and to fit model variograms are presented in several sources (8,11,22,24,31,37). The model variogram is incorporated into a procedure for surface interpolation known as "kriging" (22) (Table 1, Geostatistics). An advantage of kriging is that there are two outcomes, a surface map of the variable and a surface map of the kriging standard deviation (KSD), which provides a relative measure of confidence in the estimates. This combination is discussed later in the paper in an application involving a regional study of *Aspergillus flavus* strain composition.

The most sophisticated geostatistical tool is stochastic conditional simulation. This tool and its potential in crop protection have been explained in a regional study of corn rootworm in northwestern Iowa (40). Maps show where a minimum-loss strategy recommends the use of an insecticide for two different costs of the insecticide. The analysis can take into account not only the cost of acquiring and applying the insecticide but also an estimate of the environmental cost of applications (40). Because of the technical difficulties, few farmers, extension advisors, or regulators will apply stochastic conditional simulation in the near future. One might hope, however, that over time, conditional simulation will be incorporated into software extending geostatistics to plant disease situations.

Simple GIS maps of observed values overlaid on landmarks such as roads, rivers, towns, and district boundaries are sometimes sufficient to characterize a disease or pest problem. This can be done without geostatistics. Geostatistics adds the ability to model the range and directional-

ity of the spatial autocorrelation, which can provide clues to underlying disease processes involving spread, climate, and alternate hosts for pathogens and their vectors. Surface maps remove noise from point data and can improve communication. Geostatistics adds an assessment of confidence. It also provides tools to create probability maps from descriptive, categorical variables using indicator kriging (11,24; see Nonparametric Geostatistics in Geostatistics Frequently Asked Questions, http://curie.ei.jrc.it/faq/index.html [Table 1]). A reasonable stepwise approach to learning this technology is to start with GPS and simple GIS applications and move into geostatistical analyses as experience with GIS is developed. A criticism of the utility of geostatistics in agriculture is that the mathematical framework in which it is usually presented is beyond many potential users.

Integrating GPS, GIS, and Geostatistics

GPS, GIS, and geostatistics can be used to advantage at different levels of management and expertise. For example, an extension agent with a handheld GPS unit could relay the coordinates of a serious plant disease situation to a specialist at a land grant college, who could use GIS to place the observation in a broader context with similar observations coming in from elsewhere. One of the most helpful applications of this technology is simple: to store and query spatially referenced point data. The benefits of integration come from relating this simple format data to other data (roads, county boundaries, digital elevation models, hydrography, land ownership boundaries, and most importantly, other agricultural data) that are increasingly available from public and private sources via the World Wide Web (Table 1). Where appropriate, point data can be interpolated to produce surface maps using geostatistics.

GIS maps of plant diseases and risk of plant disease can be created in a number of ways. Experts, including farmers, can synthesize personal observations from memory and generate maps simply by sketching polygons over appropriately referenced backgrounds. For example, a risk map at the continental scale of gray leaf spot of corn based on observations of the NCR-25 technical committee on corn and sorghum diseases was presented as part of APSnet Feature, 1 through 31 May 1998 (http://www.scisoc.org/feature/grayleaf/top.html). Spatially located field observations of incidence combined with weather data can be used effectively for certain aerially dispersed fungal diseases. Continental-scale risk maps for blue mold of tobacco have been published on the World Wide Web 3 days a week during the tobacco growing season since 1996 by the

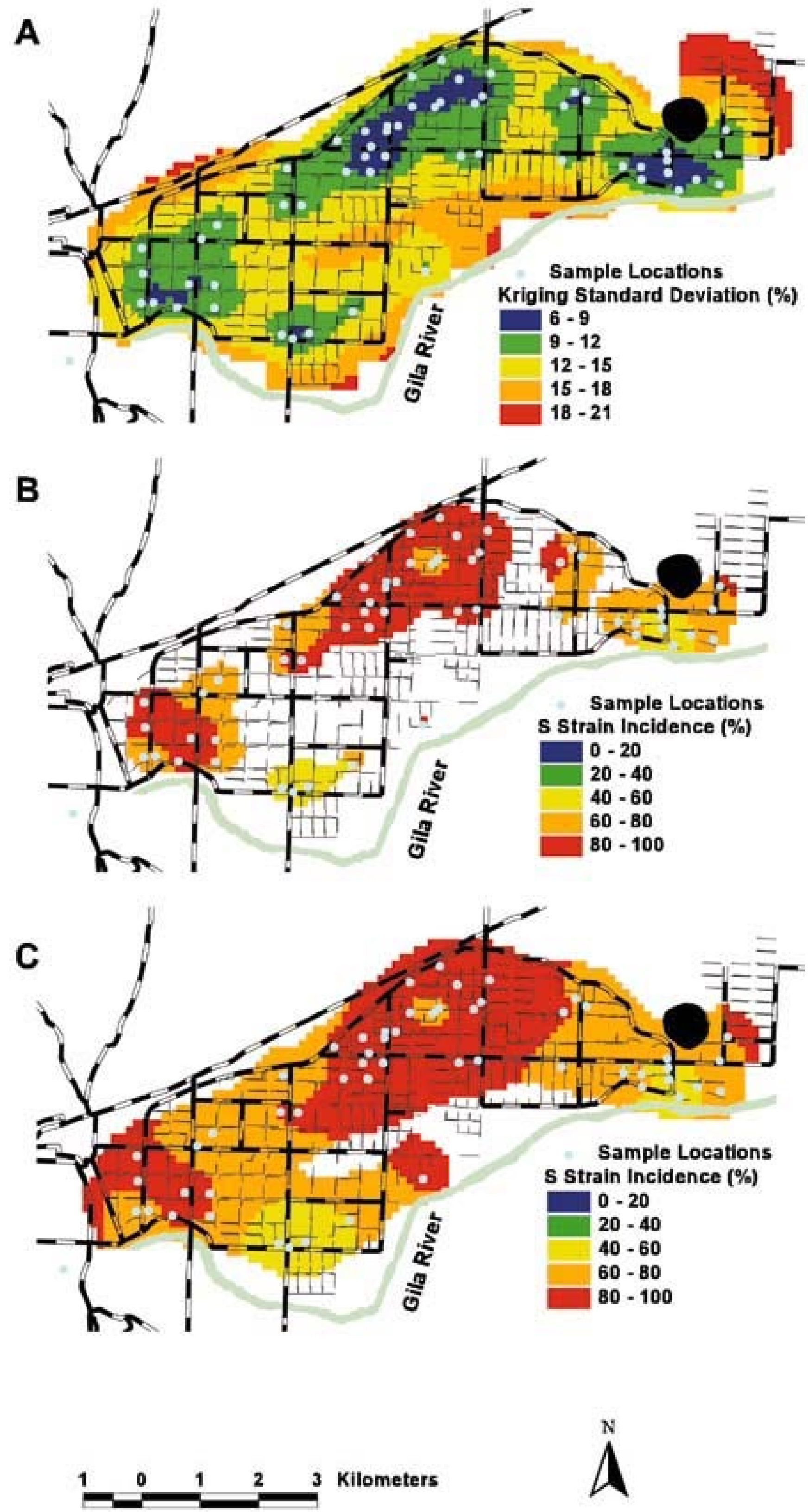

Fig. 2. Maps of the Texas Hill area, Yuma County, Arizona, illustrate the use of the kriging standard deviation (KSD) to measure confidence in the surface interpolation of *Aspergillus flavus* S strain incidence in July (data from 1995, 1996, and 1997 combined). The spatial pattern of the KSD of *A. flavus* S strain incidence shows that the KSD is lowest for grid cells near sample locations (A). A map of the *A. flavus* S strain incidence with KSD < 12% illustrates cells for which the confidence in the estimate is high (B). This view is contrasted with a less restrictive regional view (C) of the same surface including cells with higher KSDs (KSD < 15%).

Fig. 3. Representative field symptoms of virus diseases on tomato in the Del Fuerte Valley, Sinaloa, Mexico.

North American Blue Mold Forecast Center at North Carolina State University (http://www.ces.ncsu.edu/depts/pp/bluemold/). GIS risk assessment maps based on kriging of field observations were part of a tomato virus management program at the regional scale in the Del Fuerte Valley, Sinaloa, Mexico (33), discussed below. We predict that plant disease risk maps at a variety of scales will become increasingly available and helpful. Through an iterative process of comparing spatial data on risk with observed incidence, our understanding of the spatial and temporal aspects of disease processes should improve along with our ability to produce maps useful to farmers.

Applications

***Aspergillus flavus*, Yuma County, Arizona.** A series of examples will illustrate some of the ways in which GIS and geostatistics can be applied in an agricultural setting. In Figure 1, soil structure and chemistry information is linked to a point theme that is displayed as an overlay with field boundaries (polygon features) and roads (linear features) in the Texas Hill part of eastern Yuma County, Arizona. The points are color-coded according to the percent total sand in the soil. This is strictly a GIS illustration (no geostatistics). The important differences between GIS in this example and a hand-drawn map are the linkage of data to points and the use of a coordinate system. The x and y coordinates (determined from GPS readings in conjunction with digitized Farm Services Agency maps) are in the UTM coordinate system, which allows the points to be overlaid on similarly referenced polygon and linear features. Simple maps of observed values overlaid on spatial references such as roads and district boundaries are sometimes sufficient to characterize a disease or pest problem.

The point data on soil chemistry in the Texas Hill area of Yuma County are part of a study of *A. flavus* strain composition (36). *A. flavus* frequently produces aflatoxins, carcinogens that can contaminate cottonseed and other important seed crops such as peanuts, corn, and nuts. The toxins are highly regulated in order to reduce their level in the human food supply. *A. flavus* isolates can be divided into two strains based on sclerotial size (S strain [small] and L strain [large]) (5). The S strain isolates are very toxigenic. As part of a management program to control aflatoxin using naturally occurring atoxigenic strains (6), spatial patterns of the highly toxigenic S strain are being investigated. Understanding shifts in S strain incidence patterns in untreated areas will help in the interpretation of shifts observed in areas treated with atoxigenic L strain isolates. The two patches of lowest S strain incidence (Fig. 2B and C) are near the Gila River. This

coincidence, which is being investigated further, illustrates the GIS technique of overlaying one feature (the river) on another (S strain incidence) to uncover possible relationships that would not otherwise be obvious. The maps (Fig. 2) illustrate the use of the kriging standard deviation (KSD) to show relative confidence in surface maps of S strain incidence. A map of the KSD (Fig. 2A) shows, as one would expect with a spatially autocorrelated variable, that the KSD is lowest near the sample points. We have more confidence in the estimates where the KSD < 12% (Fig. 2B) than in estimates where the KSD is between 12 and 15% (area in Fig. 2C that was added to the area in Fig. 2B). Comparing such maps helps emphasize that estimates based on point sampling are not of equal value across a surface.

Tomato virus management in the Del Fuerte Valley, Sinaloa, Mexico. A regional plan for tomato virus disease management was implemented with the support of the tomato processing industry in the Del Fuerte Valley in Sinaloa, Mexico (1,33). The plan involved a risk assessment procedure and mitigation of risk based on observations of virus hazards immediately surrounding fields at the time of transplant. Mitigation of risk involved either destroying alternate host plants near fields or changing the time and location of planting. Observations of virus disease symptoms (Fig. 3) in fields were made each year from 1991 through 1996. GIS displays show that

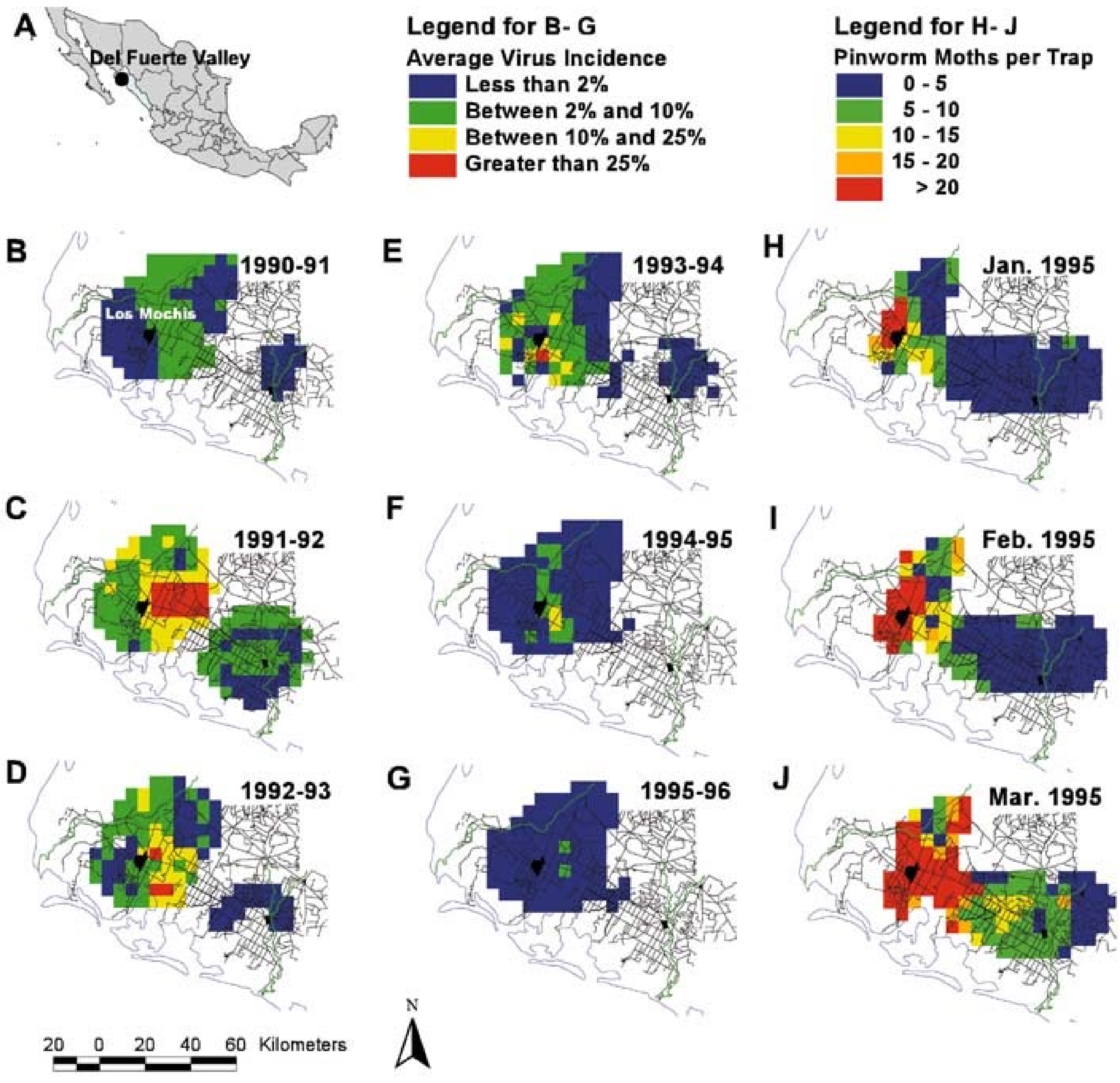

Fig. 4. A sequence of maps of the Del Fuerte Valley in Sinaloa, Mexico (A) showing the regional pattern of tomato virus disease incidence from the 1990-91 through the 1995-96 growing seasons (B to G) and tomato pinworm moth trap counts in the spring of 1995 (H to J). The average virus incidence was computed by the geostatistical technique of kriging point data of symptoms in more than 50 fields each year. There was a recurring pattern of higher virus incidence immediately east of Los Mochis, while the east-southeast part of the region was consistently lower in incidence. No data were taken in the east-southeast after the 1993-94 season because of the pattern of low incidence. The spatial patterns of tomato pinworm moths derived by kriging data from 110 pheromone traps in January, February, and March of 1995 show a pattern of lower counts in the east-southeast similar to the virus incidence pattern. The authors thank Ruben Felix-Gastelum and Rodolfo Trinidad-Acosta for the virus incidence data and Saul Alarcón for the tomato pinworm data.

there were recurring regional patterns (Fig. 4). Regardless of the overall virus incidence level, the highest incidence occurred each year east of Los Mochis. Displays of the patterns were used to encourage cultural management efforts in the areas of highest risk and incidence. We believe the encouragement of cooperation is a major value of GIS in a regional disease management program. Using GIS displays to avoid planting processing tomatoes in areas with a high risk of virus disease was part of an integrated pest management strategy that eliminated the use of pesticides for the control of insect vectors of tomato virus diseases by one producer (1). To complement the virus data, a study of tomato pinworm adults was conducted using a grid of 110 pheromone traps placed throughout the region. Pinworms were collected and counted every 14 days from November 1994 through April 1995. The spatial pattern of tomato pinworm adults (Fig. 4) was very similar to patterns of the virus risk and incidence. The higher-incidence areas contain a higher density of potato, tomato, and pepper fields than the lower-incidence areas. An abundance of alternate host plants during the summer off-growing season in unplowed tomato fields and among weeds along irrigation ditches and roadsides in certain areas of the valley was also identified as a source of the common pattern. The evidence helped put pressure on the irrigation district to control weeds along ditches and to establish plowdown requirements for tomato fields enforced by deposits tied to water contracts.

Late blight of tomatoes and potatoes, Del Fuerte Valley. Geostatistics and GIS were also used to analyze the spatial patterns of genotypes of *Phytophthora infestans* (Mont.) de Bary and their relationship to late blight disease (Fig. 5) in the mixed tomato and potato production area (23). Population genetic studies of *P. infestans* have intensified worldwide following the appearance of the A2 mating type and metalaxyl insensitive isolates of the pathogen outside central Mexico in the 1970s (14,15,19). The development of cellulose acetate techniques for rapid allozyme analyses (20) have created the opportunity to obtain enough data to characterize the pathogen spatially and incorporate this information into management programs at the scale of an agricultural region such as the Del Fuerte Valley. Maps displaying the probabilities of occurrence of mating types and genotypes of *P. infestans* and of disease severity on a regional scale were prepared (R. Jaime-Garcia, *unpublished data*). Probability maps of the GPI allozyme genotypes illustrate the results (Fig. 6). The probability of occurrence of allozyme genotypes was estimated by indicator kriging. Indicator variables can be used for nonnumerical data, such as the presence or absence of a particular genotype, to generate probability maps by kriging.

Fig. 5. Symptoms of late blight disease on tomato in the Del Fuerte Valley, Sinaloa, Mexico.

The maps of the probability of occurrence of *P. infestans* allozyme genotypes for the Del Fuerte Valley show that the epidemics of late blight are largely dominated by only one genotype each year (Fig. 6). This indicates strong clonal reproduction of the pathogen in the area. However, some other genotypes do occur in low frequencies and in restricted areas. Most genotype variables showed spatial autocorrelation in a range of 13,000 to 20,000 m in a valley that is 70,000 by 150,000 m. This suggests a restricted spread of some genotypes that can be visualized with the help of the probability maps generated by kriging (Fig. 6). The idea of creating pathogen genotype probability maps is new, and its applicability in a plant disease management system has not been tested commercially. We think it might be useful where environmental, worker safety, and economic concerns lead farmers to weigh a variety of new factors, including pathogen genotype, in the selection of plant disease control measures. For example, some genotypes have differential reactions to host or cultivar and to fungicides used for control of the disease. This type of information might be used to improve management practices. In the study of late blight in the Del Fuerte Valley, we found differential reactions to the fungicide metalaxyl and differential aggressiveness to tomato and potato among the genotypes of *P. infestans,* and these differences showed spatial continuity. Genotypes that were sensitive to metalaxyl or that were nonaggressive to either tomato or potato were found restricted to certain areas of the valley.

Cotton leaf curl disease, Punjab, Pakistan. A project with the same objec-

tives as the Del Fuerte Valley tomato virus project is underway with cotton leaf curl virus in Pakistan in a much larger agricultural region (over 400 km) than the Del Fuerte Valley. Cotton leaf curl has devastated cotton production in the Punjab province of Pakistan since it was first recognized as a major problem in 1991. The first report of cotton leaf curl in Sindh Province, southwest of Punjab, was in 1996, providing evidence that the affected area has been expanding. The cause of the disease is at least two whitefly-transmitted geminiviruses collectively named cotton leaf curl virus. Analysis of DNA sequences indicates that the cotton leaf crumple geminivirus of the southwestern United States is not closely related to the cotton leaf curl geminiviruses of Pakistan (32). The symptoms and economic impacts of cotton leaf curl in Pakistan (Fig. 7A) are much more severe than those of cotton leaf crumple in the United States (Fig. 7B). Because cotton is a major export crop and source of foreign exchange for Pakistan, the impact of the disease on the economy has been serious. A GIS database on incidence was established in 1996 using handheld GPS units to determine the coordinates of locations where incidence was assessed. Maps of Pakistan including major roads and district boundaries were digitized using handheld GPS coordinates taken at road intersections as reference points to put the digitized maps in the same coordinate system as the field observations.

Recent DNA analyses of virus collections from cotton plants exhibiting leaf curl symptoms suggest that the genetic composition of these viruses is very diverse (C. Fauquet, Scripps Institute, La Jolla, CA, *personal communication*). To the extent that GPS coordinates of tissue samples are recorded, probability maps of genetic variants of the virus characterized by DNA analysis can be created following the example of the late blight work in Sinaloa, Mexico. Such work is underway in Pakistan, and it is hoped that probability maps can help researchers evaluate the relationship of the genetic variants to disease progress and severity.

The project includes a spatial analysis of landscape characteristics associated with the risk of leaf curl disease. The University of Arizona, Tucson, and the Central Cotton Research Institute, Multan, Punjab, Pakistan, are analyzing landscape data from 229 locations referenced by GPS throughout Punjab and collected by the Pest Warning and Quality Control of Pesticides Department of the Punjab Department of Agriculture. Landscape data include the presence of alternate hosts, length of common watercourses, and virus hazards along common watercourses, roadways, farmhouses, and gardens. As an example of epidemiologically important factors, the presence of cotton resprouting from the previous season (called here "sprouting cotton") is a good indication of a mechanism for the virus to have overwintered. The additional presence of alternate hosts for the whitefly and the virus adds risk that the virus will be present in the new crop. These factors are shown graphically (Fig. 8) with point maps and a probability surface map as an illustration of the possibili-

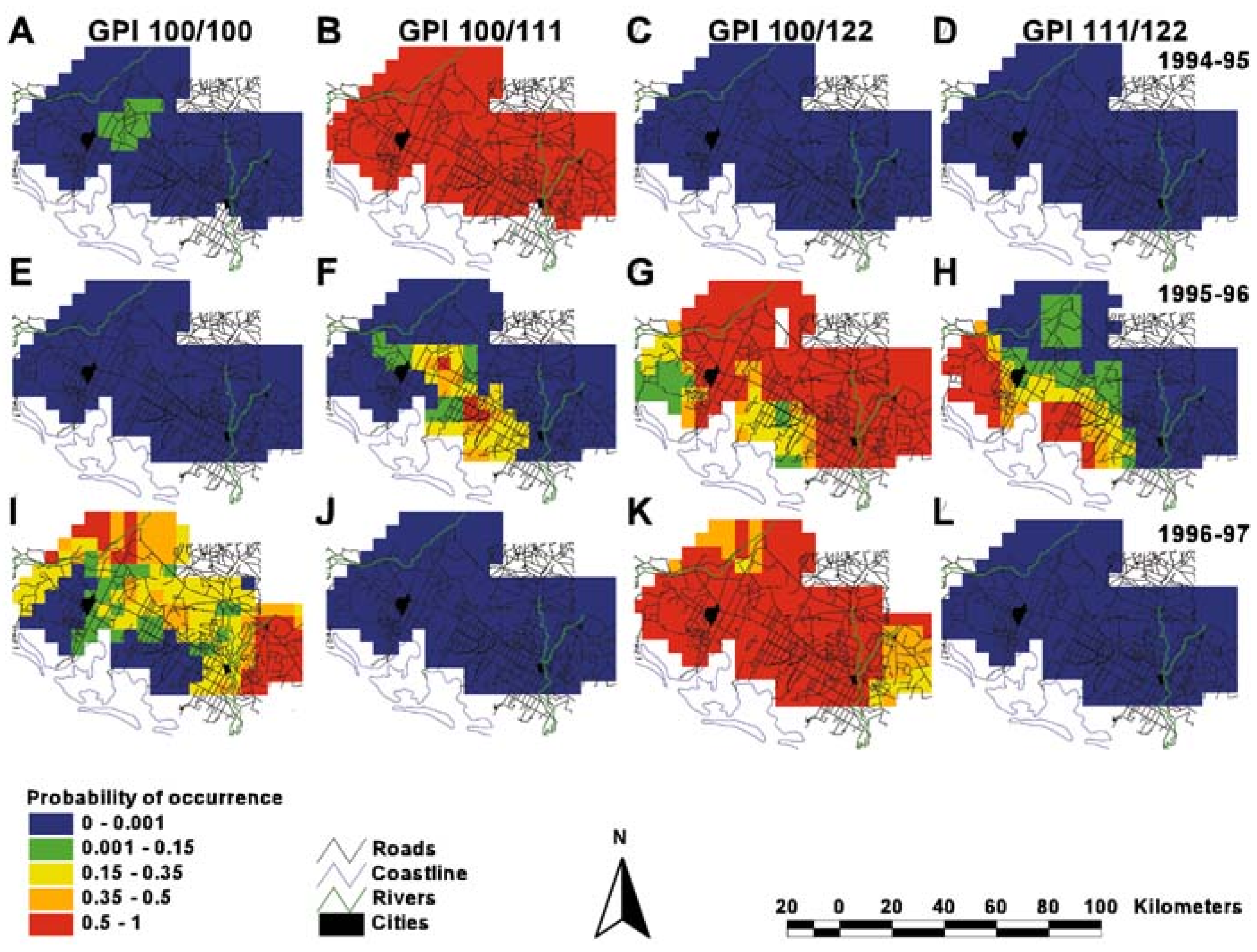

Fig. 6. Probability of occurrence of the *Phytophthora infestans* glucose-6-phosphate isomerase (GPI) loci 100/100 (A, E, and I), 100/111 (B, F, and J), 100/122 (C, G, and K), and 111/122 (D, H, and L) in the Del Fuerte Valley, Sinaloa, Mexico, during the seasons of 1994-95 (A, B, C, and D), 1995-96 (E, F, G, and H), and 1996-97 (I, J, K, and L). This illustrates the use of indicator kriging to create surface maps of the probability of occurrence of a categorical variable (the presence of particular genotypes).

ties for generating risk maps based on landscape observations. The geostatistical approach in this example is possible for categorical variables that have values at the same locations. An alternative approach, useful when categorical variables are from different locations within the same region, is to generate surface maps for each variable by indicator kriging and then use GIS overlays to combine the surfaces. The comparison of spatial patterns of risk and incidence of leaf curl in Pakistan will help focus the cultural management efforts needed to complement ongoing efforts to breed for resistance to the disease.

Cotton leaf crumple disease, Arizona. During 1992, populations of whitefly, *Bemisia tabaci*, were monitored with data collected weekly from over 900 traps across Arizona at a scale of hundreds of kilometers (34). At the same time, the presence or absence of symptoms of cotton leaf crumple disease was recorded at all trap locations. The virus disease was highly restricted spatially, with no apparent relationship to the abundance of whiteflies on a regional scale. The data on whiteflies and cotton leaf curl in the Pakistan project discussed above also indicate there is no obvious relationship between the overall abundance of the whitefly vector and the incidence of leaf curl disease. Early and unusually damaging infections of leaf crumple of cotton in Arizona may result from proximity of a cotton field to a good whitefly host, such as spring cantaloupes, and a virus host. The spatial relationship between hosts for vectors, alternate hosts for the virus, and the crop can be very important at the scale of a few kilometers. A geostatistical study of localized migration of whiteflies from a cantaloupe field showed that dispersal was largely wind directed and that whitefly distribution following dispersal was patchy up to 2.7 km from the field (2). The conclusion from work both in Arizona and in Pakistan is that beyond a good overall cultural management program for whitefly suppression, the chief focus for virus control should be action at the local level to reduce alternate hosts of the virus. The results of such activity can then be monitored regionally to detect hot spots for future intensified efforts.

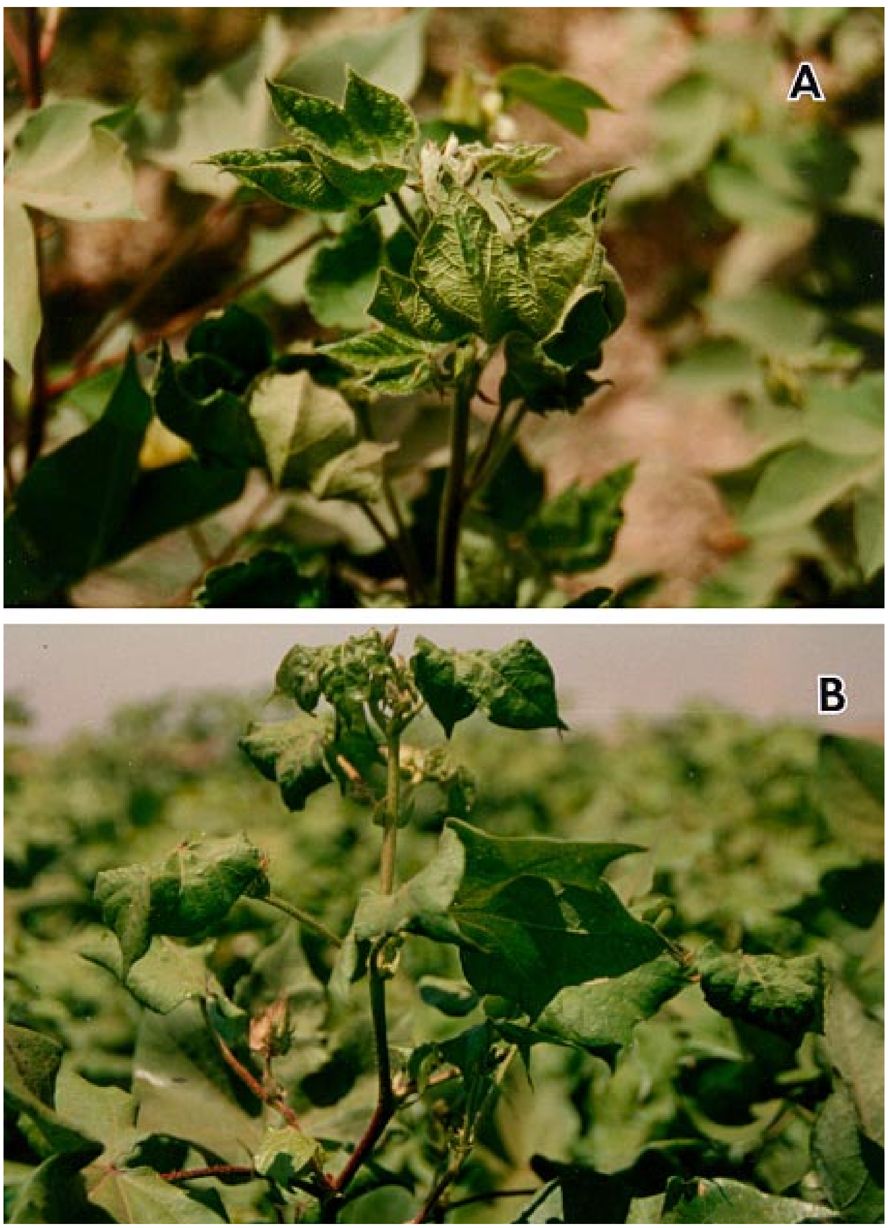

Fig. 7. Symptoms of cotton leaf curl disease in Pakistan (A) compared with symptoms of cotton leaf crumple disease in Arizona (B).

Summary and Conclusions

Despite our enthusiasm for this technology, we are not proposing that it is a solution to all plant disease management problems or that it is appropriate for every operation. A critical assessment of the technology can be summarized in terms of the practical, the theoretical, and the personal. Practically, the biggest drawback is the cost associated with the time needed to learn the software and to acquire the data. Research is needed on cost/benefit analyses of GIS applications in agriculture. GIS is of little practical value when a spatial pattern is uniform except perhaps in contrast to nonuniform patterns. On the other extreme, if the change in pattern is faster than data can be acquired, spatially referenced data might be skewed and misleading. There are theoretical limitations to the use of geostatistics, because the geostatistical model in which spatial analyses lead to surface maps does not always apply. Also, certain assumptions (30) may not be appropriate in some cases. A geostatistical analysis does not need to be a part of every spatial analysis or GIS. There is, we believe, a personal subjective component to the suitability of this technology in plant disease management. It is our informal observation that some people are more inclined than others to frame problems spatially. We suspect benefits from the communication possibilities of the technology will vary with individuals.

The current most successful applications of this technology involve teamwork. A good combination is a team that includes an experienced field person, an experienced computer user with some background in statistics, and a patient data entry person. Such a combination is not always available and is rare in a single individual. Larger farms, younger farmers, and better-funded extension programs are more likely to apply these tools. A characteristic of agricultural GIS is that it strongly favors operations that have computer resources and skills. On the other hand, it may not be practical to avoid a resource that is already in wide use in government and industry, including the agricultural industry.

We believe that the integration of GIS, GPS, and geostatistics provides a tool for the refined analysis of traditional and con-

temporary biological/ecological information on plant diseases. It will aid practitioners in the design of disease management in IPM programs, particularly on a regional scale. It will also provide a way of analyzing and communicating results of regional programs on a continuing basis. The availability of software capable of producing attractive maps provides an opportunity to visually communicate plant disease situations to a variety of audiences. We feel a major benefit of this technology is derived from a combination of many images, not just a single image (e.g., Figs. 4, 6, and 8). Such output can be used by decisionmakers to stimulate coordinated action allowing available resources to be focused on the most significant problems. GIS and geostatistics are particularly useful in identifying recurring patterns of plant disease, as well as other problems such as insect and weed infestations. The association of environmental factors, landscape features, and cropping patterns with the recurrence of disease or other problems can be readily communicated to key managers and decisionmakers.

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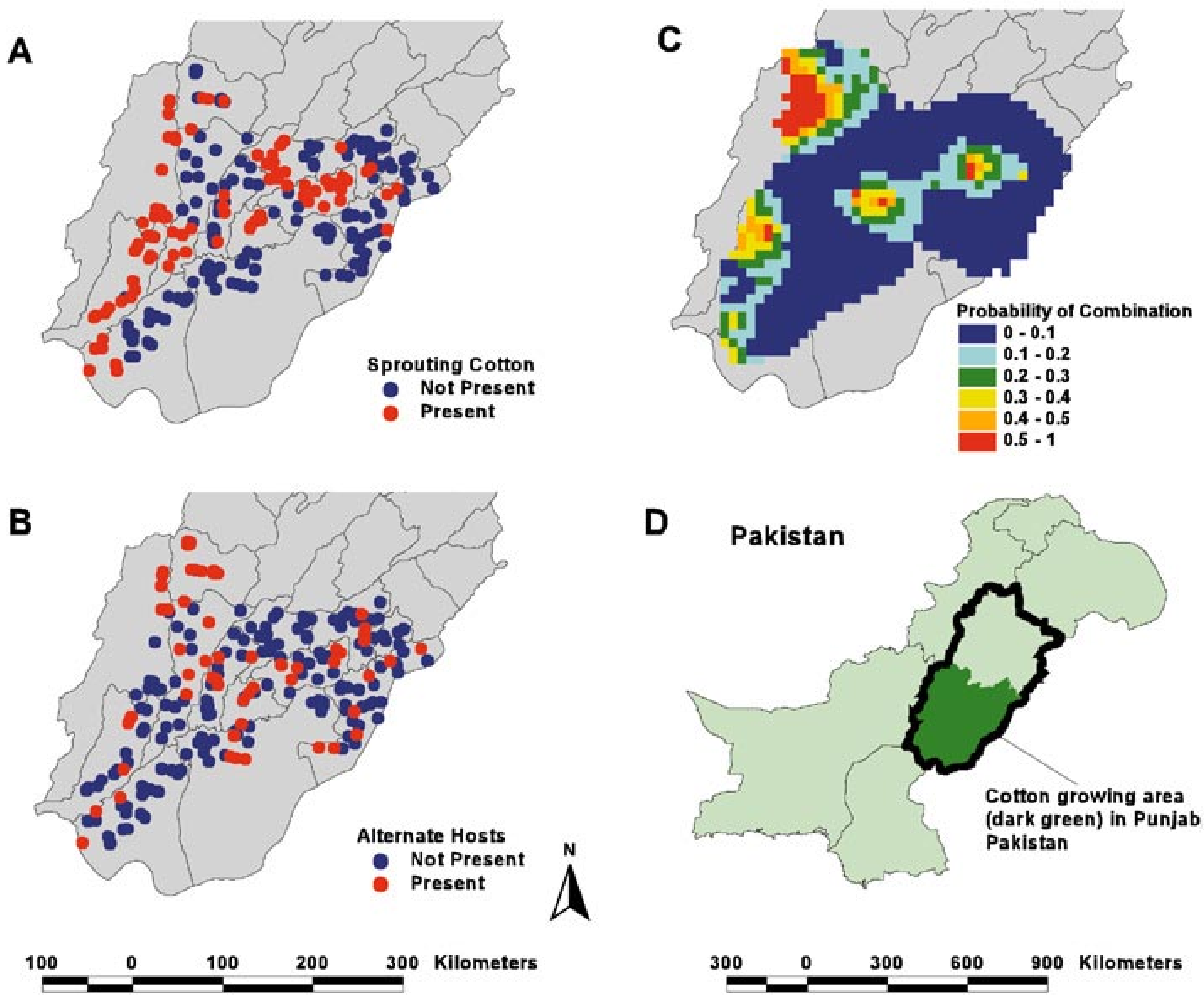
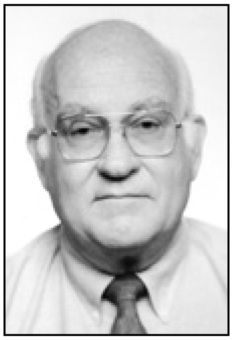


Fig. 8. An illustration of the use of indicator kriging to produce probability maps of virus hazards from categorical data on landscape features. Preseason observations around cotton fields in the spring of 1997 recorded the presence of sprouting cotton overwintering from the previous season (A) and the presence of alternate hosts of cotton leaf curl virus and/or its vector (*Bemisia tabaci*) (B). Indicator kriging was used on a combined variable (both sprouting cotton and alternate hosts present) to produce the probability map (C). The data are from a cotton growing area (dark green) in Punjab, Pakistan (D).



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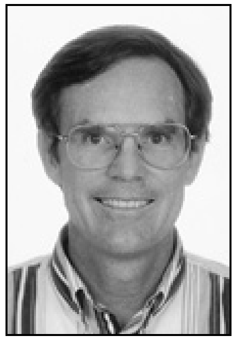

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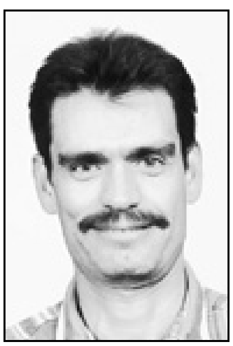

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