

M. H. Royer

USDA-ARS Foreign Disease-Weed Science Research, Fort Detrick, Frederick, MD

J. M. Russo and J. G. W. Kelley

The Pennsylvania State University, University Park

Plant Disease Prediction Using a Mesoscale Weather Forecasting Technique

The coincidence of an “outbreak” of a plant disease and certain weather conditions undoubtedly was recognized by astute farmers of the past. With the gradual understanding of the nature of disease, how disease spreads in plant populations, and how chemicals could control it, the weather conditions necessary for a disease outbreak were perceived in a different way. Attention gradually shifted from generalizations of weather conditions, such as cloudy, damp, and warm, to specific variables thought to govern disease. Where the relationships have been well defined, weather forecasts frequently have been used to predict disease development so that growers could initiate timely and efficient controls.

Contribution No. 143, Department of Horticulture, The Pennsylvania State University. Authorized for publication as paper No. 8161 in the journal series of the Pennsylvania Agricultural Experiment Station.

This study and the third author were supported by the USDA-ARS Foreign Disease-Weed Science Research under Research Support Agreement No. 58-3615-7-006.

Mention of a trademark or proprietary product does not constitute a guarantee or warranty of the product by the U.S. Department of Agriculture and does not imply its approval to the exclusion of other products that may also be suitable.

Present address of second author: ZedX, Inc., P.O. Box 404, Boalsburg, PA 16827.

This article is in the public domain and not copyrightable. It may be freely reprinted with customary crediting of the source. The American Phytopathological Society, 1989.

This paper presents an application of a new forecasting technique, called Model Output Enhancement (MOE), to mesoscale disease prediction. We report on the feasibility of using mesoscale weather forecasts to derive disease forecasts 24 hours into the future for areas as small as 1-km² (1-km resolution). We chose potato late blight, caused by *Phytophthora infestans* (Mont.) de Bary, to illustrate how the MOE technique could be applied to generate a mesoscale disease forecast. This disease is particularly responsive to weather, and its epidemiology has been studied extensively.

Mesoscale Forecasts

Mesoscale forecasts are weather predictions made for areas having a spatial resolution between the synoptic scale (popularly known as the weather-map scale) and the microscale. Depending on which international or national definition is used, the mesoscale could range from hundreds of square meters on its lower end to a few thousand square kilometers at its upper limit. On a time scale, the mesoscale could range from several minutes to a few days. Mesoscale weather systems are probably the least understood of the predictable meteorological phenomena. They cannot be adequately resolved by current synoptic scale monitoring networks and they are too large to be investigated properly using microscale data. Seem and Russo (11) graphically depicted this time and space disparity between weather data networks used to define weather

systems and some disease forecasting methods in their scale presentation of past, present, and future weather states.

Meteorologists commonly use the term “numerical” in front of “models” or “forecasts” to indicate they are based on a set of mathematical equations that describe atmospheric motions. Because the solutions to these equations require numerous computations, large computers have been used to run the models and generate forecasts. Since the inception of numerical weather prediction over three decades ago, operational models have steadily improved in spatial and temporal resolution, in forecast accuracy, and in the number of weather variables generated in forecasts.

In 1985, the U.S. National Meteorological Center's (NMC) Nested Grid Model (NGM) replaced the Limited-Area Fine Mesh (LFM) model for hemispheric, continental, and sub-continental numerical synoptic forecasts. The NGM produces horizontal spatial resolutions as small as 91.5 km, compared with a previous limit of 190.5 km. It also has greatly increased the vertical resolution. The NGM, like the LFM, provides gridded analyses and predictions of standard weather variables and indices up to 48 hours in the future at 6-hour intervals for various pressure levels. As with all previous operational models, NGM numerical output is interpretable at the synoptic scale.

There is currently a strong research effort to provide numerical simulations and forecasts at a subsynoptic resolution. This effort has been directed at both mesoscale phenomena and the interac-

tion of terrain-induced airflows with larger-scale weather systems. The books by Pielke (6) and Ray (7) are excellent sources of information on recent analyses and models of sea breezes, mountain-valley winds, convective clouds, thunderstorms, fronts, hurricanes, and other complex regional-scale weather processes. In each study, the research requires an appreciation of changes in spatial and temporal scales, atmospheric processes, energy transformations and transports, observation networks to obtain data for simulations, and computational stability. To date, nearly all mesoscale investigations have been experimental and short-term and have covered a limited area.

In contrast to mesoscale modeling that requires an in-depth understanding of mesoscale processes, Russo (9) proposed an alternative approach for deriving weather data at a higher resolution than traditionally available. He suggested that smaller-scale forecasts could be generated from synoptic scale numerical models by interpolating their output to a higher spatial resolution and "enhancing" it with geophysical data. This approach is based on the knowledge that topography and other surface features exert a strong influence on mesoscale weather systems and, hence, could be used indirectly to predict smaller-scale, short-term conditions close to the farm level. Russo (9) suggested that such a generated "local" forecast data base could be used as input to pest, plant, and management models to aid decisionmakers. He further saw the value of presenting a forecast or pest data base on a perspective plot of terrain to "give the user a three-dimensional feel" for the data field."

Kelley (1) and Kelley et al (2,3), in a demonstration of the approach advocated by Russo (9), developed the Model Output Enhancement (MOE) technique. The technique operates by: 1) interpolating numerical model output to approximately 1-km resolution, 2) extrapolating the interpolated data to the surface using theoretical and observed atmospheric processes, and 3) adjusting the extrapolated surface values with digital terrain data. The output is a high-resolution forecast that accounts for the influence of elevation on the prediction of a weather variable that can be verified with station observations.

In an initial study limited to two weather variables (maximum and minimum temperatures) for clear-sky conditions, objective mesoscale temperature forecasts were generated from the LFM model using the MOE technique. Temperature forecasts out to 48 hours, using daily time steps, were made for over 215,000 rectangular areas of approximately 1-km² each throughout Pennsylvania. These temperature forecasts were displayed as two-dimensional

grayscale maps, as color-class maps, and as color-class maps overlaid on perspective plots of terrain. With the aid of a state map showing county boundaries, the displayed temperature forecast field could be easily interpreted for relatively warm and cool areas generated by topography and for thermal gradients caused by synoptic conditions across the state. Although verification was limited to a few case-study days, the temperature forecasts generated by the MOE technique showed a potential to be competitive with existing operational techniques (3). Since Kelley's original work with clear skies, the MOE technique has been used to forecast temperatures for all sky conditions (12) and has been modified to make predictions of relative humidity and precipitation.

Model Output Enhancement Technique for Disease Prediction

With the MOE technique, weather variables can be forecast up to 2 days in advance at about a "farm-level" resolution over a large region such as the northeastern United States. As compared with the synoptic scale, this resolution is considerably closer to the level where disease prediction methods were developed and tested. By using forecast data generated by the MOE technique as input to a disease prediction scheme, one could have a geographic projection of expected disease incidence and severity. Furthermore, as in the case of meteorological applications, disease forecasts can be displayed as two- or three-dimensional maps for easy interpretation.

A first attempt at using high-resolution forecast data as input to a disease prediction scheme was reported by Russo

et al (10). Potato late blight was chosen as a "test" disease because the epidemiology and biology have been studied intensively. The Wallin system, as presented by MacKenzie (5) (Fig. 1), was used to define the meteorological conditions for late blight development in Pennsylvania. It was assumed that a susceptible crop and infective propagules were present everywhere in the forecast domain.

Maximum and minimum temperatures and relative humidities were generated from the 850- and 700-mb output of the NGM using the MOE technique for one case-study day in late summer of 1986. A mean temperature was calculated from maximum and minimum values, and hours of relative humidity greater than 90% were summed over the 6-hour prediction intervals of the NGM. These data were input to the Wallin system to give accumulative severity values for potato late blight at a spatial resolution of about 1 km and a temporal resolution of 1 day. The prediction of daily severity values for Pennsylvania was graphically displayed as a grayscale planar map (10).

This first attempt, as a necessary step in learning how to make a disease prediction based on a forecast, revealed serious shortcomings. Whereas the temperature data were acceptable, the relative humidity forecasts were crude, because they were directly extrapolated from upper-air model output. The resulting severity values for the case-study day were limited to two categories: 0, indicating no possibility for most of Pennsylvania, and 1, indicating a low possibility for six counties along the state's southern border. The validity of those predictions was not evaluated with field data.

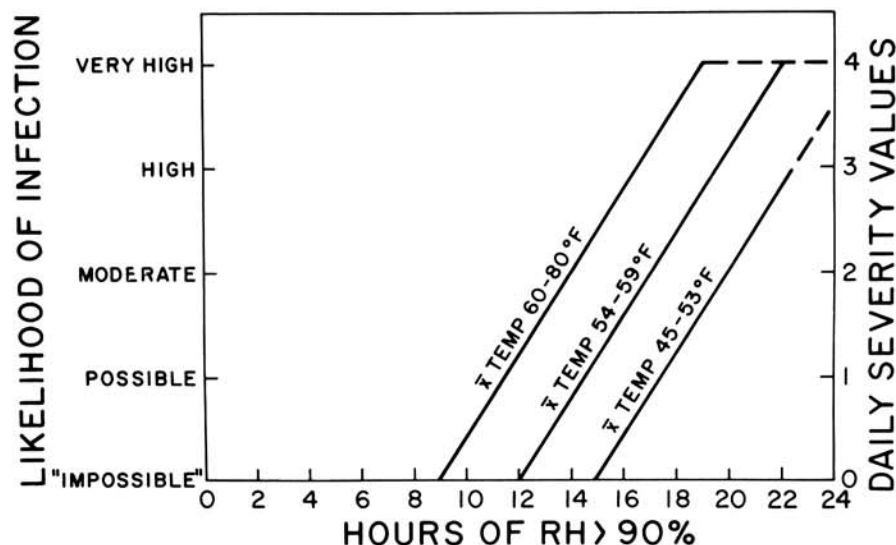


Fig. 1. Relationship of the duration of high relative humidity and the average temperature (45-53 F = 7.2-11.9 C, 54-59 F = 12.0-15.2 C, 60-80 F = 15.3-26.7 C) during that period to the likelihood of infection and the corresponding severity value. (From MacKenzie [5])

A Recent Study

In a second attempt at making 24-hour predictions of the likelihood of potato late blight development, the MOE technique was again applied to the 850- and 700-mb output from the NGM, but with some improvements. A more accurate algorithm for relative humidity and a higher temporal resolution were used, and the relative humidity threshold of the Wallin system was modified slightly. Instead of extrapolating surface relative humidities directly from model output, upper-air dew points were first computed from relative humidity values and then adjusted for the surface, using the appropriate vertical gradient for the synoptic situation. Relative humidities were calculated from the extrapolated dew points and temperatures.

The 6-hour prediction intervals used in the earlier study were reduced to 2 hours by interpolation, thus mimicking the 2-hour data intervals that are typically extracted from hygrothermograph charts. In addition, the relative humidity threshold was changed from greater than 90% (Fig. 1) to greater than or equal to 90%. This lower threshold (the original one proposed by Wallin [15]) results in a small increase in the computed severity values when relative humidities hover near 90%.

The second attempt was conducted over an 8-day period (19–26 August

1988) for 1-km resolution areas in Pennsylvania. Each 24-hour forecast of this investigation began at 8:00 a.m. eastern daylight time.

The daily blight severity predictions computed from the 2-hour forecast temperatures and relative humidities were compared with values calculated from observations of the same weather variables recorded at nine selected stations across Pennsylvania. Two of the stations were situated in open, agricultural settings. The other seven stations were part of the National Weather Service's climatological network and were located in the vicinities of airports. Hygrothermograph data were available from the two agrometeorological stations, whereas only 3-hour summaries of temperature and relative humidity were available from the climatological stations. These summaries are part of the local climate data distributed by the National Climatic Data Center in Asheville, North Carolina. The 3-hour summaries had to be interpolated to derive matching 2-hour values for comparison with forecast data.

Grayscale planar maps for hourly mean temperatures, total hours of relative humidity greater than or equal to 90%, and late blight severity values computed using the Wallin system are depicted for Pennsylvania in Figures 2, 3, and 4. The ability of the MOE

technique to create mesoscale forecast data is evident from the pattern of gray shades. The high severity values (4.0) indicated for some areas (Fig. 4) reflect the relatively warm and moist conditions (especially at night) resulting from the prevailing synoptic weather systems in combination with the local terrain.

The amount of information in a mesoscale forecast for blight severity is more striking in the color-class map overlaid on a perspective plot of terrain (Fig. 5). The three-dimensional appearance of the color map facilitates the topographic and geographic interpretation of a late blight forecast. As in the earlier study, 215,000 predictions are being displayed in one generated map product.

Table 1 shows the average differences between daily late blight severity values computed from forecasted and from observed weather data for the nine selected station sites. Most differences were due to the variable performance of the technique in providing forecasts for local settings, but a few were due to poor station observations. To cite one example, during the 24-hour period spanning 21–22 August 1986, nine contiguous hours of 87% relative humidity were reported for Pittsburgh while fog was being observed; the relative humidity was probably underestimated, either because of a miscalibrated instrument or because

of human error.

The size of the confidence intervals for the differences between forecast-generated and observation-computed values at a given site is not surprising, given the 1-km spatial scale of the MOE forecast and the microscale resolution of the weather stations. Whereas an *individual* severity value in a prediction map may have a high level of uncertainty, the *pattern* of values depicted may give a reasonable indication where late blight is more likely to occur and at what relative intensity.

Conclusion

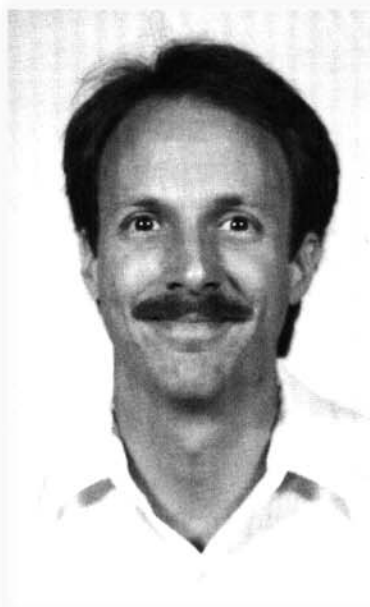
The late blight predictions depicted in Figure 5 are useful because of the ease with which one can interpret an area where a disease outbreak is likely. A decisionmaker can locate geographic areas that need further disease surveillance. In this respect, the mesoscale disease forecasts provide guidance in much the same way as numerical pre-

diction models do for meteorologists. A plant pathologist trained in the use of the mesoscale forecasts can recommend appropriate action based on a local interpretation of the forecast product.

This guidance is useful to plant pathologists outside the scope of local disease prediction. Future geographic predictions of the expected establishment or dispersal of exotic diseases can be made if: 1) the pathogens' environmental requirements are known and 2) the weather variables defining these requirements could be accurately forecasted. Royer and Dowler (8) foresaw this application of high-resolution forecast weather data to pest risk assessment in the linkage of weather forecasts to disease prediction models. They stated that such models could "make the analyses of the probability of establishment of exotic pests possible on a daily basis."

With improved meteorological and plant pathological models describing weather conditions and their relation to

disease development, mesoscale disease predictions will improve over the years. Experimental mesoscale numerical models will probably become operational within the next decade, providing weather forecasts at scales on the order of 10 km. But it is clear from previous station and field observations (14,16) that there is a limit to any improvement in local disease prediction using weather forecasts. With temperature variations of several degrees within a plant canopy, there is little likelihood that one could consistently extract accurate weather predictions from mesoscale forecasts for a particular potato field. If one understands the different mesoscale situations and their effect on disease development, however, it seems possible that mesoscale forecasts could give reasonable estimates of local conditions. There is evidence for such a possibility in the analogy of meteorologists following synoptic events and using map analysis to predict future disease outbreaks.



Matthew H. Royer

Dr. Royer is a research plant pathologist at the USDA-ARS Foreign Disease-Weed Science Research in Fort Detrick, Frederick, Maryland. He received his Ph.D. degree in plant pathology from The Pennsylvania State University in 1982. Since 1983 he has conducted research on foreign plant diseases in a quarantine facility to determine their threat to U.S. agriculture and has cooperated internationally with scientists on certain threatening plant diseases. He is particularly interested in the use of computerized data bases to manage foreign plant disease and crop data and in the integration of these data bases with certain crop and pest models for pest risk analysis.



Joseph M. Russo

Dr. Russo is an agricultural meteorologist and private consultant with an information technology company. He is currently developing data base structures and algorithms to assist decisionmakers using expert systems in agricultural and environmental industries. Dr. Russo holds a Ph.D. degree in agricultural meteorology from Cornell University and an M.S. degree in meteorology from McGill University.



John G. W. Kelley

Mr. Kelley is an agricultural meteorologist and expert system programmer now with the integrated pest management program in the Department of Entomology at The Pennsylvania State University. He is a member of a research team developing expert systems for fruit and field crop management in Pennsylvania. Mr. Kelley holds an M.S. degree in meteorology and an M.P.A. in public administration from The Pennsylvania State University.

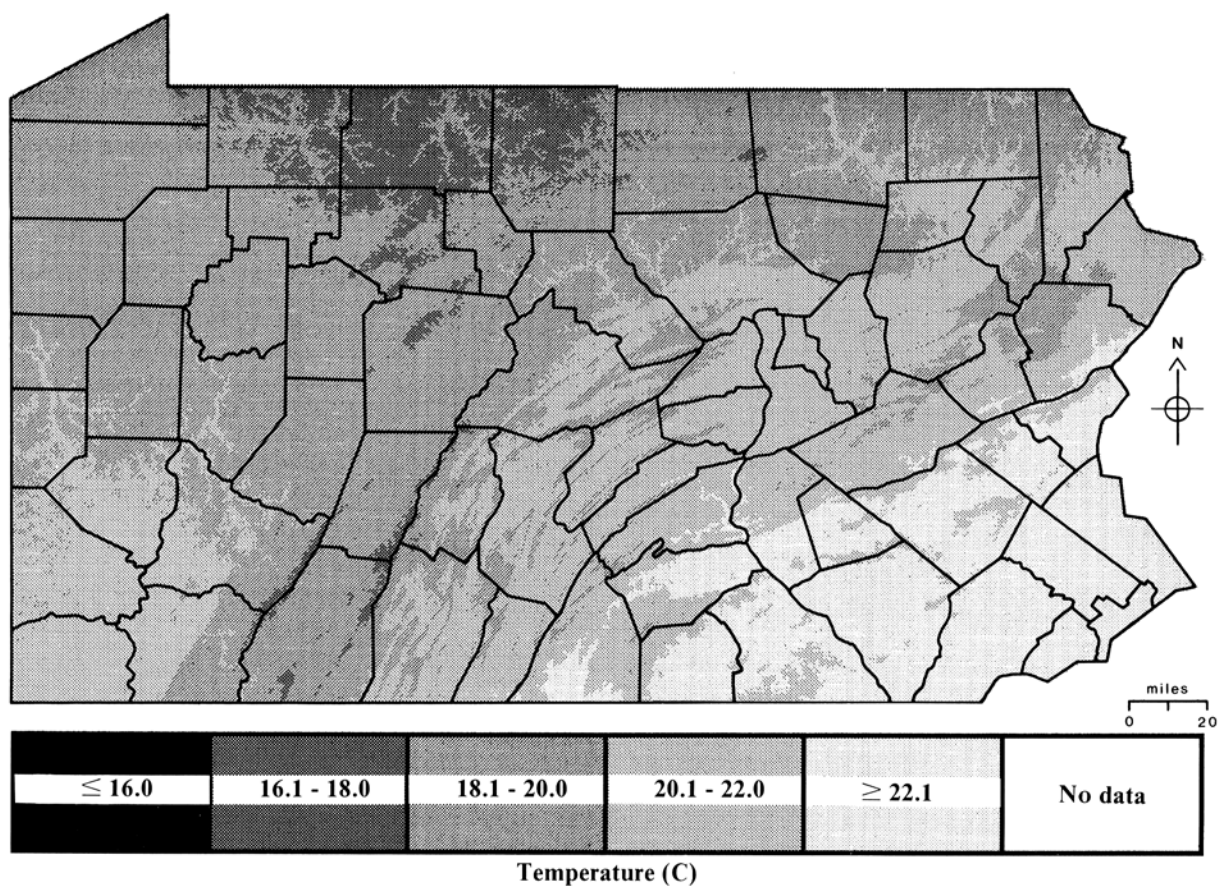


Fig. 2. Grayscale planar map of daily mean temperature forecast for Pennsylvania. Forecast made 24 hours in advance for 21 August 1986 (8:00 a.m. 21 August to 8:00 a.m. 22 August).

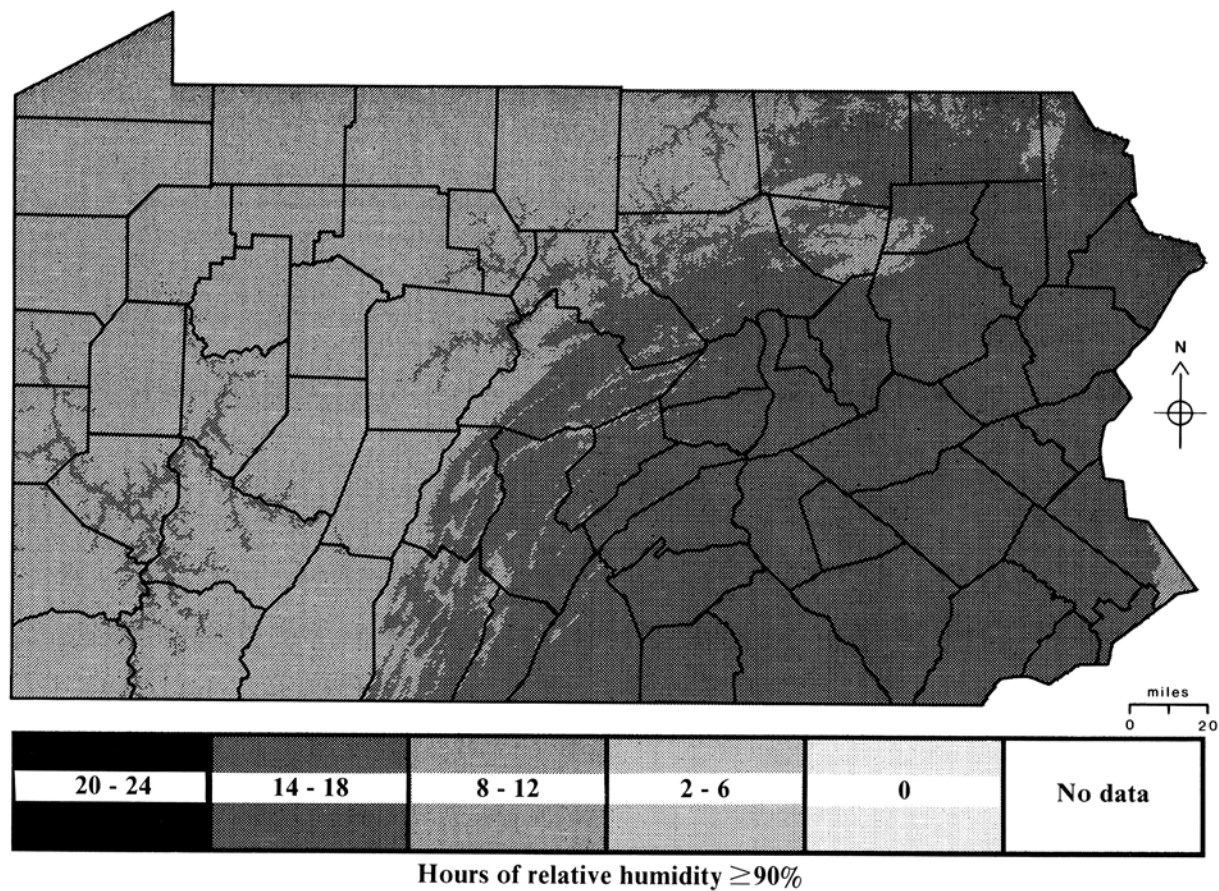


Fig. 3. Grayscale planar map of daily hours of relative humidity greater than or equal to 90% forecast for Pennsylvania. Forecast made 24 hours in advance for 21 August 1986 (8:00 a.m. 21 August to 8:00 a.m. 22 August).

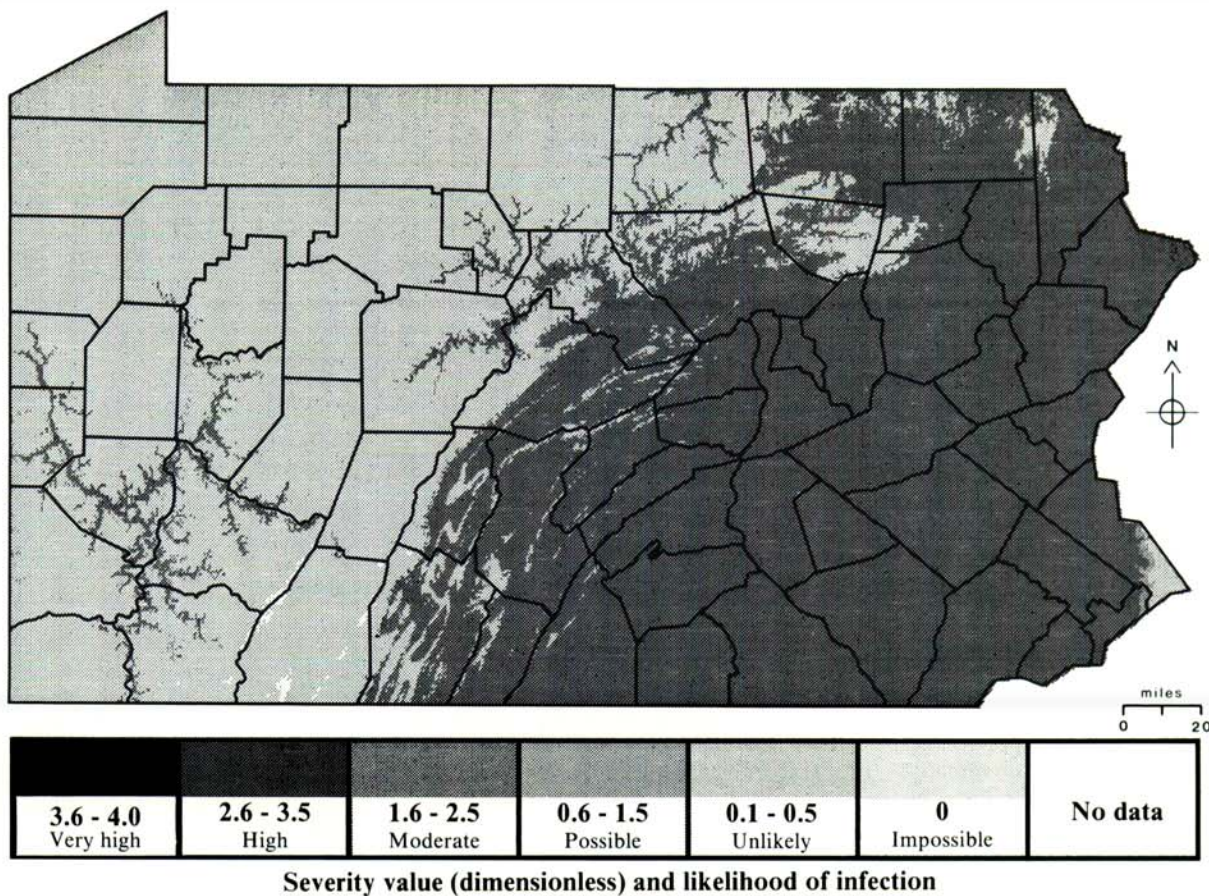
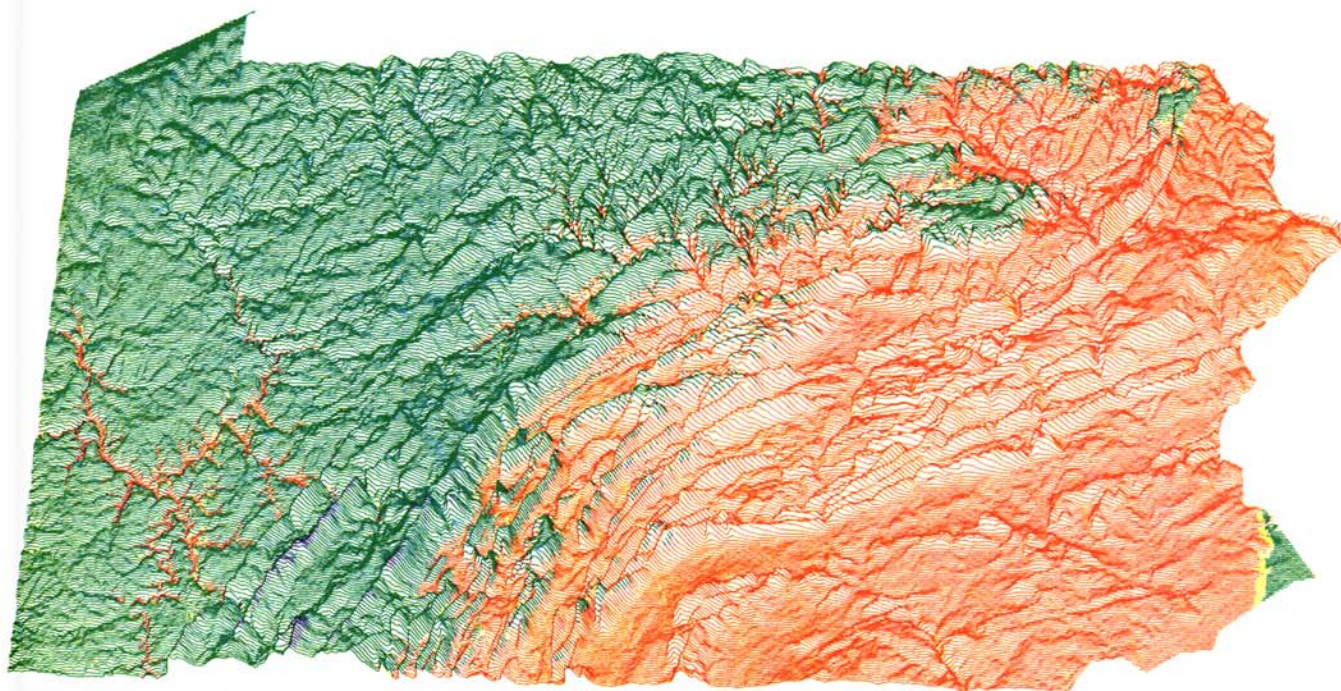


Fig. 4. Grayscale planar map of daily severity values and likelihood of late blight infection forecast for Pennsylvania (severity values 0.1–0.5 and 3.6–4.0 were not predicted). Forecast made 24 hours in advance for 21 August 1986 (8:00 a.m. 21 August to 8:00 a.m. 22 August).



KEY:	Color class	Magenta	Red	Yellow	Green	Cyan	Purple
	Severity value	3.6-4.0	2.6-3.5	1.6-2.5	0.6-1.5	0.1-0.5	0
	Likelihood of infection	Very high	High	Moderate	Possible	Unlikely	Impossible

Fig. 5. Color-class map of daily severity values overlaid on a perspective map of terrain to forecast the likelihood of late blight infection for Pennsylvania (severity values 0.1–0.5 and 3.6–4.0 were not predicted). Forecast made 24 hours in advance for 21 August 1986 (8:00 a.m. 21 August to 8:00 a.m. 22 August).

Table 1. Differences between daily late blight severity values derived from forecasted and from observed weather for nine locations in Pennsylvania

Location	Date (August 1988)								CI*
	19	20	21	22	23	24	25	26	
Allentown	1.2	1.2	1.6	0.0	0.0	0.0	0.0	1.2	±0.83
Avoca	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.2	±1.08
Erie	0.0	1.2	1.2	0.0	0.0	0.0	0.0	0.0	±0.42
Harrisburg	0.8	1.2	-1.2	0.0	1.2	0.0	0.0	1.2	±1.29
Mountainview	-0.4	1.2	0.0	-1.2	1.2	0.0	-0.4	0.0	±1.49
Philadelphia	1.2	1.2	1.6	0.0	0.0	0.0	0.0	1.2	±0.83
Pittsburgh	0.0	2.8	2.8	0.0	0.0	0.0	0.0	0.0	±0.99
Rocksprings	-1.2	1.2	0.0	0.0	1.2	0.0	0.0	0.0	±1.73
Williamsport	0.0	1.2	0.8	...	1.2	0.0	0.0	1.2	±0.93

*CI = 95% confidence interval of the difference between the mean late blight severity values derived from forecasted and observed weather data.

^bData missing.

One example of the use of synoptic analysis was Large's time-line displays of late blight outbreaks at locations scattered throughout England (4). These displays depicted a relatively uniform appearance of blight in a "blight year" as compared with a spread-out incidence in a "no-blight year." The blight years were characterized by dull and cool weather, with significant rainfall in all parts of the country during much of the growing season. Under such a cool and moist environment, local conditions tended to mimic the synoptic conditions, which were dominated by large-scale weather systems affecting the whole country. In no-blight years, the weather was characterized as hot, dry, and sunny. Under these synoptic conditions, smaller-scale weather systems such as thunderstorms dominate, and their effects were felt only regionally. It is during such no-blight years that mesoscale forecast maps could provide a better picture of areas that are more likely to experience a disease outbreak.

The use of mesoscale forecasts as input to local disease prediction schemes can provide a powerful prognostic tool for decision making, provided an individual is trained in its interpretation and understands its limitations. However, such a "man-machine mix," as the meteorologists like to call a forecaster's use of computerized products, requires a slow and tortuous process of learning

and relearning daily routine assessments and interpretations in different ways. As a historical comparison, it took about 10 years before the first numerical upper-air model moved from an idea to an operational reality. During the latter part of that period, it was recognized that further development of numerical weather prediction would be "a necessary, slow, and generally unspectacular process, and that it should go hand-in-hand with the daily routine of numerical weather forecasting" (13).

Mesoscale forecasting and disease prediction is a long-term enterprise like numerical weather prediction itself. Its success rests on the continued cooperation of plant pathologists and agricultural meteorologists and their focused goal of providing better disease prediction through the use of advances in weather forecasting.

Literature Cited

1. Kelley, J. G. W. 1986. Model Output Enhancement technique. M.S. thesis. The Pennsylvania State University, University Park. 195 pp.
2. Kelley, J. G. W., Russo, J. M., Eyton, J. R., and Carlson, T. N. 1985. Enhancement of numerical weather prediction output for operational agricultural programs. Pages 101-104 in: Repr. Conf. Agric. For. Meteorol. 17th.
3. Kelley, J. G. W., Russo, J. M., Eyton, J. R., and Carlson, T. N. 1988. Mesoscale

forecasts generated from operational numerical weather prediction model output. Bull. Am. Meteorol. Soc. 69:7-15.

4. Large, E. C. 1956. Potato blight forecasting and survey work in England and Wales, 1953-55. Plant Pathol. 5:39-52.
5. MacKenzie, D. R. 1981. Scheduling fungicide applications for potato late blight with BLITECAST. Plant Dis. 65:394-399.
6. Pielke, R. A. 1984. Mesoscale Meteorological Modeling. Academic Press, New York. 612 pp.
7. Ray, P. S., ed. 1986. Mesoscale Meteorology and Forecasting. American Meteorological Society, Boston, MA. 793 pp.
8. Royer, M. H., and Dowler, W. M. 1984. Assessing the threat of foreign plant pathogens after entry. Pages 583-592 in: The Movement and Dispersal of Agriculturally Important Biotic Agents. D. R. MacKenzie, C. S. Barfield, G. G. Kennedy, R. D. Berger, and D. J. Taranto, eds. Claitor's Publishing Division, Baton Rouge, LA.
9. Russo, J. M. 1985. Planning for a high resolution data base for agricultural programs. Pages 98-100 in: Repr. Conf. Agric. For. Meteorol. 17th.
10. Russo, J. M., Kelley, J. G. W., and Royer, M. H. 1987. High resolution weather forecast data as input into a plant disease model. Pages 54-57 in: Conf. Agric. For. Meteorol. 18th.
11. Seem, R. C., and Russo, J. M. 1983. Predicting the environment. Pages 226-238 in: Challenging Problems in Plant Health. T. Kommedahl and P. H. Williams, eds. American Phytopathological Society, St. Paul, MN.
12. Sullivan, D. J. 1988. Objective temperature prediction by cloudiness using the Model Output Enhancement technique. M.S. thesis. The Pennsylvania State University, University Park. 134 pp.
13. Thompson, P. D. 1983. A history of numerical weather prediction in the United States. Bull. Am. Meteorol. Soc. 64:755-769.
14. Waggoner, P. E., and Shaw, R. H. 1951. Plant part temperature influencing the epiphytology of potato and tomato late blight. (Abstr.) Phytopathology 41:36-37.
15. Wallin, J. R. 1962. Summary of recent progress in predicting late blight epidemics in United States and Canada. Am. Potato J. 39:306-312.
16. Wallin, J. R., and Waggoner, P. E. 1950. The influence of climate on the development and spread of *Phytophthora infestans* in artificially inoculated potato plots. Plant Dis. Rep. Suppl. 190:19-33.