Ecology and Epidemiology

Model for Predicting Severity of Septoria tritici Blotch on Winter Wheat

Stella Melugin Coakley, Larry R. McDaniel, and Gregory Shaner

First and second authors: associate research professor and research associate, Department of Biological Sciences, University of Denver (mail address: NCAR, P.O. Box 3000, Boulder, CO 80307); and third author: professor, Department of Botany and Plant Pathology, Purdue University, West Lafayette, IN 47907.

This research was supported by the Climate Dynamics Program, Division of Atmospheric Sciences, National Science Foundation Grants ATM 80-17604 and 82-11253.

Acknowledgement is made to the National Center for Atmospheric Research, Boulder, CO 80307, which is supported by the National Science Foundation, for supplying computer time used in this research and for research space provided by the Advanced Study Program and Acid Deposition Modeling Project.

Disease nomenclature in this article follows the recommendations of the International Workshop on the Septoria Diseases of Cereals, 1–4 August 1983, at Bozeman, MT.

Accepted for publication 15 May 1985 (submitted for electronic processing).

ABSTRACT

Coakley, S. M., McDaniel, L. R., and Shaner, G. 1985. Model for predicting severity of Septoria tritici blotch on winter wheat. Phytopathology 1245-1251.

A statistical model was developed to predict severity of septoria tritici blotch (pathogen teleomorph: *Mycosphaerella graminicola*) on susceptible Monon winter wheat at the Purdue Agronomy Farm. Disease severity at adjusted Julian day 170 (which on the average was 17 June, 26 days after the average heading date of 22 May) was significantly correlated ($P<0.05$) with nine meteorological variables for the period between 2 March and 13 May. An equation was developed for predicting percent disease severity ($\hat{y}$) at adjusted Julian date 170 based on 1973-1984 data. The equation is $\hat{y} = 147.480 - 3.025\ X_1 - 2.093\ X_2$ ($R^2 = 0.86$), in which X_1 is the total consecutive days (8–19 days) without precipitation between 26 March and 4 May, and X_2 is the total consecutive days (12–24 days) between 4 April and 3 May that minimum temperature was equal to or less than 7 C. Model selection and validation were based on the use of different regression analysis techniques, including Mallow's *Cp* statistic, Allen's PRESS statistic, and the variance inflation factor.

Additional key words: data splitting, linear regression, multicollinearity, quantitative epidemiology, *Septoria tritici*, Septoria leaf blotch.

Research on the relationship between climate and stripe rust on winter wheat resulted in the development of a methodology for quantifying the relationship between climatic factors and disease severity that was intended to be applicable to other diseases (4,5). To test the applicability of this methodology to a different disease, Septoria tritici blotch was selected because of its increasing importance and its apparent dependence on weather factors for the development of epidemics (15).

Septoria tritici blotch of wheat (*Triticum aestivum* L. em Thell), formerly called Septoria leaf blotch, is caused by *Mycosphaerella graminicola* (Fuckel) Schroeter (2) (anamorph: *Septoria tritici* Rob. ex Desm.) and is a major disease in many areas of the world including the United States (7,9,13,15,16). Annual average reduction in potential wheat yield due to Septoria tritici blotch and Septoria nodorum blotch (caused by *Leptosphaeria nodorum* Muller) was estimated at 1% for the United States (1). In the more humid areas east of the Mississippi, average constraint to yield due to these diseases is probably higher. Susceptible cultivars may have yield potentials reduced 30–50% after severe epidemics (20).

Because of the increase in the importance of Septoria tritici blotch in Indiana, Shaner and Finney (15) reviewed the literature on the relationship of this disease to temperature and moisture. They concluded that although moisture was important at all stages of the infection cycle, little quantification of the moisture or temperature requirements for disease development in the field was available. Renfro and Young (12) report that infection failed to develop when free moisture was available for less than 15 hr or when minimum temperature was 7 C or less for a 2-day

---

postinoculation period. In subsequent work, Bahat et al (3) developed functions to analyze the net contribution of climatological factors to the vertical progress and disease severity of Septoria tritici blotch on short-statured wheats. In their method, factors were summed for 7-day intervals, and the temperature range used for developing the indices was 12–25 C. Disease severity was correlated with number of days with dew and temperature indices summed for the 7- to 21-day period prior to disease observation. Eyal (7) found that frequent rains and temperatures from 12–25 C favored Septoria tritici blotch, whereas rain-free intervals and higher temperatures interfered with disease development.

Because weather conditions favorable to Septoria tritici blotch epidemics had never been precisely defined, Shaner and Finney (15) compared rainfall and temperature data with the severity of Septoria tritici blotch on winter wheat at Lafayette, IN, for 1955 to 1974. The 3 yr with "very severe" epidemics had a minimum of 40 days of rain from 1 April to 14 June, whereas a "severe" epidemic required 34 days of rain (average for period was 32 days of rain). Shaner and Finney hypothesize that 34 or more 2-day periods between 1 April and 14 June with minimum temperatures of 7 C or less will prevent an epidemic regardless of rainfall frequency. They discuss the possibility of forecasting severe epidemics at the time that flag leaves emerge (~10 May) on the basis of weather data from 1 April to 10 May, observations of disease in the field, and a weather prediction for 11 May to 14 June. That forecast system was limited by the lack of a dependable weather prediction for those 35 days.

In recent years there has been an increase in the use of control measures for Septoria tritici blotch. A predictive system was developed in the United Kingdom (9) to improve control of this disease; however, none is available in the United States.

The objectives of this research were: to quantify the relationship between the severity of Septoria tritici blotch and the climatic data from 1973 to 1984 at Lafayette, IN, to develop a model for prediction of disease severity that could be applied early enough (ideally before heading) to allow chemical control of the disease, and to further develop the general method for quantifying the relationship between climatic factors and disease occurrence.

MATERIALS AND METHODS

Disease severity data were collected for the highly susceptible winter wheat cultivar Monon (CI 13278) at the Purdue University Agronomy Farm near West Lafayette, IN, for 12 yr from 1973 to 1984. Average planting date for these plots was 4 October. Severity was recorded for a minimum of 20 plants in each of four replicate plots from three to nine times each season (average 6.2 times) as the percent of area of the upper four leaves that was necrotic from natural infection by *M. graminicola*. A mean percent disease severity was calculated from these data for each observation date. Growth stage was also recorded each time by using the two-digit code described by Zadoks et al (19). The average heading date was 22 May and the average harvest date was 10 July for the 12-yr period.

Because variation in planting dates and other factors such as meteorological conditions resulted in different harvest dates for each year, it is desirable to have disease severity recorded on a phenological time scale to facilitate comparisons between years. In the first year of the study, heading occurred on 24 May 1973 (Julian date 144). For all subsequent years, heading was recorded as occurring on Julian date 144, and all observations were recorded relative to this adjusted Julian date (AJD). For example, in 1975, heading was on 23 May (AJD 144) and the next observation was made on 30 May (AJD 151); in 1976, heading was on 14 May (AJD 144) and the next observation was on 21 May (AJD 151). Disease observations were recorded over the range of AJD 117 to 182; the average first date was AJD 134 and the average last date was AJD 173. For our analysis, we selected percent disease severity at AJD 170 (26 days after heading or average actual date of 17 June) for two reasons. First, it was late enough in the growing season that any subsequent increase in disease would have little effect on the wheat yield. Shaner and Finney (15) stated that infections after 14 June are not likely to contribute to yield loss because by then flag leaves are senescing naturally and the grain is in the soft dough stage. The second reason was to minimize extrapolation of the disease progress curve in this study. Final observation of disease severity was made after AJD 170 in all years except 1975, 1978, 1979, and 1984. In those years, final dates for observation were AJD 167, 167, 168, and 167, respectively. Disease severity at AJD 170 was estimated for 1978, 1979, and 1984 by extrapolation of the disease progress curve by maintaining the slope of the line connecting the last two observations. For 1975, the estimate was made by extrapolation of the lines connecting observations made on AJD 158 and 165 and on AJD 165 and 167 and taking the midpoint between these lines at AJD 170. This was considered a more reliable estimate than one based on the last two points because of a sharp change in slope caused by the observation at AJD 165.

A National Oceanic and Atmospheric Administration weather station (latitude 40°28′ N, longitude 87°00′ W, elevation 216 m) was within 0.25 km of the plots where disease assessments were made. The daily data collected for 1955 to 1981 were available on tape at the National Center for Atmospheric Research (NCAR) from the National Climatic Center (NCC), Asheville, NC. Data for 1982–1984 were taken from monthly copies of Climatological Data for Indiana published by NCC. Data include daily maximum and minimum temperatures, total precipitation, snowfall, and depth of snow on the ground. Time of data observation has been the same at this station since 1953.

Correlation coefficients between disease severity at AJD 170 for each year from 1973 to 1984 and monthly mean and cumulative totals for maximum, minimum, and average temperature, total precipitation, frequency of precipitation, snowfall, snow depth, and negative and positive degree days (5) were calculated. Correlation coefficients were also calculated for these factors on a seasonal basis. Cumulative totals for the meteorological variables were calculated by summing the mean or total counts for each month during the growing season (through August), first starting with September, then using successive months thereafter as the starting month. For example, average temperature would be calculated for September through August, then for October through August, then for November through August until it ended with average temperature for August.

The results of the above calculations showed that it was necessary to develop a method to identify the meteorological variables that were most highly correlated with disease. The WINDOW program was written in Fortran to identify the length of time for each variable that was most highly correlated with disease severity at AJD 170. A flow chart for WINDOW (Fig. 1) shows how the program works; each step has a reference letter to aid in the description of the program. Meteorological variables (independent variables) were selected as described in the next paragraph. In Step B, Window lengths used were 75, 60, 50, 40, 30, and 21 days. The procedure always started with the larger windows (e.g., 75 or 60 days) and subsequently considered the smaller windows. In Step C, dates were given as Julian dates (JD) with JD 1 representing 1 January. In Step D, the window was advanced in 10-, 5-, 3-, or 1-day increments, and the larger increments were always used first. In Step E, the data for the first window were read, and in Step F the value for each of the variables was calculated. In Step G, the total, average, and standard deviation of each variable were calculated. The correlation coefficient (and its significance) between each variable and disease severity at AJD 170 was calculated. After Step H, the Window START was advanced according to the increment specified in Step D, and the analysis continued until the Window END (which had been set in Step C) was reached. Printouts were examined for steady increases and decreases in correlation coefficients as the WINDOW program moved forward in time. Time periods with the highest coefficients were further analyzed by selecting shorter window lengths (Step B), setting the Window START and END closer to the time period of interest (Step C), and decreasing the window increment (Step D). In the last run of the program, increments of 1 day were used.

Selection of the meteorological variables for evaluation by the WINDOW program was based in part on the research described in the introduction of this paper. The eleven variables selected were precipitation frequency, total precipitation, mean maximum and mean minimum temperatures, total consecutive days (TCD) with minimum temperature less than or equal to 7 C (TCD ≤7 C), TCD with minimum temperature greater than 7 C, TCD with maximum temperature greater than 25 C, TCD with precipitation, TCD without precipitation (TCD w/o P), and accumulation of positive and negative degree days from a 14 C base. The selection of TCD ≤7 C and the method of counting consecutive days were based on the methods and results of Shaner and Finney (15). Since a minimum of two consecutive days was necessary to inhibit infection (12), only sequences of two or more days were considered, i.e., two such consecutive days counted as one period, three consecutive days counted as two periods, etc. These periods were then summed for the Window. For example, in a Window of 15 days with sequences of 4, 3, and 2 days with minimum temperature ≤7 C, the consecutive days would be counted as 3, 2, and 1, respectively, for a sum of 6 TCD ≤ 7 C.

Linear regression analysis was used to determine the relationship between the important meteorological variables identified by the WINDOW program and disease severity at AJD 170. The Statistical Analysis System (SAS) programs used for the analysis of our data were REG, RSQUARE, STEPWISE, and GLM (14). Only variables from windows that ended before date of heading (22 May) were used in the analysis so that the equations would predict disease early enough in the growing season to allow some form of disease control. The dependent variable (y) is disease severity at AJD 170 and the independent variables are the meteorological variables.

Mallow's Cp was used as a criterion for goodness of fit of regression equations with different numbers of independent variables. A model is less subject to bias, as discussed by Neter et al (11), when the Cp value is closest to the number of x-variables plus one (number of parameters [p]) in the model (17). Draper and Smith (6) used the guideline of looking for a regression with a low Cp value about equal to p.

The variance inflation factor (VIF) measures the effect of multicollinearity between variables on the variances of estimated coefficients and is another measure of model stability. If a VIF > 5, experience shows that the associated regression coefficients are poorly estimated (6,10,18).

Allen's PRESS (Predicted Error Sum of Squares) technique was used in model selection and validation (6,10,18). This statistic was calculated by the GLM (General Linear Models) procedure from SAS (14). PRESS is calculated in the following way. The first observation (i) of n data points is deleted and the regression model is fitted to the remaining $n - 1$ data points. This model is used to predict the withheld observation y_i which is then called the predicted $\hat{y}_{(i)}$. The prediction error for this point i is $e_{(i)} = y_i - \hat{y}_{(i)}$. The first observation is returned and the procedure is repeated for each observation $i = 1, 2, \ldots n$ resulting in a set of n deleted residuals $e_{(1)}, e_{(2)}, \ldots, e_{(n)}$. The PRESS statistic is thus defined by Montgomery and Peck (10) as the sum of squares of the n deleted residuals as in

$$\text{PRESS} = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} [y_i - \hat{y}_{(i)}]^2 \qquad (1)$$

The PRESS statistic was calculated for each regression model evaluated in Results. The best fitting models have the lowest value of PRESS.

RESULTS

Disease progress curves relating average disease severity to the adjusted Julian date for each year from 1973 to 1984 are shown in Fig. 2.

The analysis of correlation between disease severity at AJD 170 and monthly mean and cumulative totals of meteorological variables identified significant correlation ($P < 0.05$, df = 10) between disease severity and total precipitation from 1 March to 31 May ($r = 0.793$) and frequency of precipitation from 1 February to 31 May ($r = 0.789$).

Model development. Results from the Window analysis are given in Table 1 for the meteorological variables with the highest correlations with disease severity at AJD 170. These nine meteorological variables were used as independent variables in regression analysis. The SAS procedure RSQUARE (14) was used to evaluate all possible models up to a maximum of three independent variables. RSQUARE provided the R^2 and Mallow's Cp statistic for each of the 129 models evaluated (84 three-variable, 36 two-variable, and nine one-variable models).

There were no one-variable models having $Cp < p$ ($p = 2$ in a model with one variable). There were four two-variable models which had $R^2 \geq 0.83$ and $Cp < 3$ (Table 2). Each of these models used variable A (TCD ≤7 C) and either variable B (precipitation frequency) or C, D, or E which were measures of TCD w/o P. These models are subsequently referred to as Models BA, CA, DA, and EA. There were 20 three-variable models with R^2 between 0.86 and 0.89 and $Cp < 4$. However, in each three-variable model there were at least two variables highly correlated with each other and hence none of those models was considered further.

A low PRESS statistic was used to select the best model; this eliminated Model BA because its PRESS statistic was 958 as compared to 779, 795, and 793 for Models CA, DA, and EA, respectively.

The STEPWISE procedure from SAS (14) was used to independently evaluate the nine variables. Using the stepwise option, the one-variable model with the largest F-statistic was selected. Two- and three-variable models were subsequently evaluated. Each time a new variable was added, all previously entered variables were reevaluated on the basis of their partial F-statistics (10). If a partial F-statistic for a variable was significant at $P \leq 0.15$, then the variable was retained. For the nine variables, Model E was the best one-variable model. Model EA best met this criterion for two-variable models. No three-variable models met this criterion. Model E did not meet the criteria of appropriate Cp

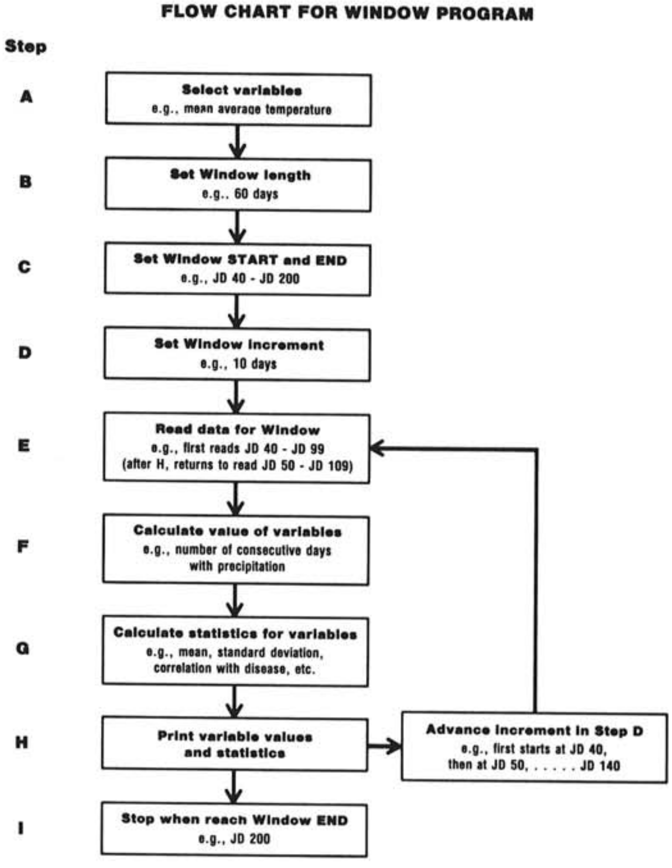

Fig. 1. Prediction of Septoria tritici blotch on winter wheat. Description of how the WINDOW program is used to identify the meteorological variables most highly correlated with severities of Septoria tritici blotch at adjusted Julian date 170. All variables are considered at the same time for a given Window.

and PRESS statistics described earlier. Model EA was also identified by the RSQUARE procedure. The linear equation that describes this model is:

$$\hat{y} = 147.480 - 3.025X_1 - 2.093X_2 \qquad (2)$$

in which $\hat{y}$ = predicted disease severity at AJD 170, X_1 = TCD w/o P from 26 March to 4 May and X_2 = TCD $\leqslant$7 C between 4 April and 3 May. This equation is proposed as best describing the relationship between disease severity at AJD 170 and the meteorological variables analyzed. Values of actual disease severity (y), predicted disease severity ($\hat{y}$), and the variables X_1 and X_2 for 1973 to 1984 are given in Table 3. The unadjusted R^2 indicated that Model EA explained 86% of the variation in disease severity at AJD 170, and if the PRESS is used to adjust the R^2, the adjusted R^2 is 0.78. The observed disease severity was within one standard error of the predicted severity in 10 of 12 yr (83%).

Model validation. In addition to being used as a tool for model selection, Allen's PRESS statistic was used for model validation. It is a form of data splitting (6). For the 12 yr of observations (n), each observation was removed in turn and the remaining observations ($n - 1$) were used to formulate a "model" which would predict the deleted observation. The result was twelve different model equations, each based on 11 yr of data ($n - 1$), which are given in Table 4. For example, the equation used to predict disease severity ($\hat{y}$) in 1973 was based on the regression equation developed from the 1974 to 1984 observations of disease (y) and meteorological variables (X_1 and X_2); the equation for 1974 was based on the observations for 1973, and 1975 to 1984. Actual disease severity (y), predicted disease severity ($\hat{y}$), prediction error ($y - \hat{y}$), and the prediction error squared $(y - \hat{y})^2$ for each year are given in Table 4. The sum of squares of the prediction error is the PRESS statistic for the model. Examination of the β_0, β_1, and β_2 regression coefficients indicate that their magnitudes and signs were very

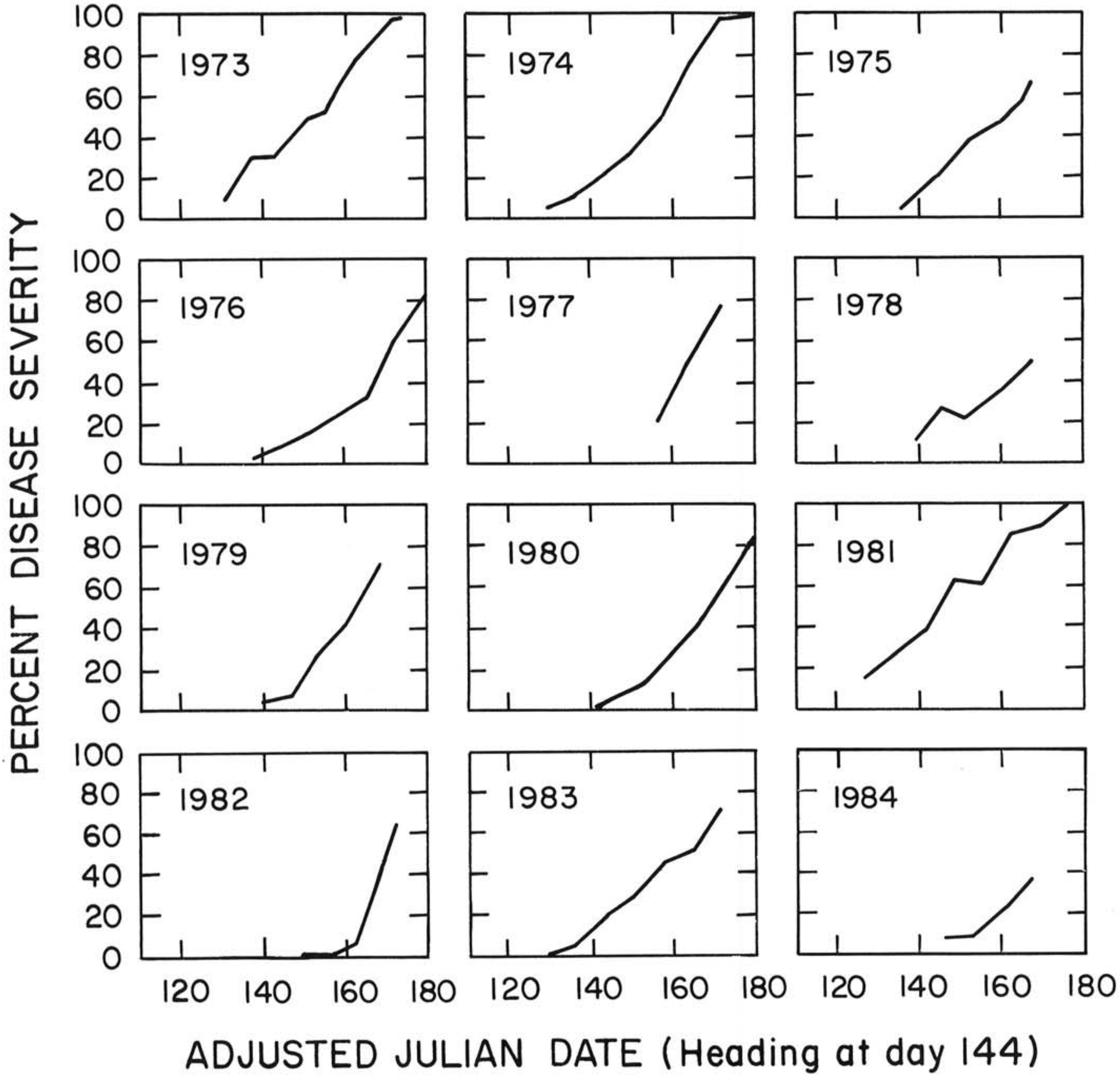

Fig. 2. Average percent severity of Septoria tritici blotch in winter wheat for four plots recorded on adjusted Julian dates such that heading occurred on day 144. Plots were of winter wheat cultivar Monon located on the Purdue Agronomy Farm.

stable for all models. Examination of the prediction error for each year shows how well the model based on 11 yr of data predicts for that year. The largest prediction errors occur in 1975 and 1982; the standardized residuals in the full model were 1.81 for 1975 and −1.38 for 1982.

To determine how much the 1975 and 1982 observations affected the proposed model (equation 2), the data for 1975 and 1982 were omitted and a model based on the remaining 10 yr of data was formulated as:

$$\hat{y} = 147.199 - 3.008X_1 - 2.107X_2 \quad (3)$$

Even though observations in 1975 and 1982 contribute a large amount to the PRESS statistic (and are thus considered high-leverage observations), in the full model they balance each other and do not affect the estimation of β_0, β_1, and β_2.

The VIF's of all two-variable models were close to 1 (Table 3) which indicates the coefficients were properly estimated and stable. The standard errors of the coefficients are given in Table 3.

To further check the usefulness of the model, predictions were made for 1957 and 1970; these years were ranked qualitatively by Shaner and Finney (15) as having very severe and severe disease. Our model (equation 2) predicted disease severities for 1957 and 1970 of 93 and 91%, respectively, which confirms the accuracy of the model's predictions for years outside the original data base.

DISCUSSION

We propose equation 2 as a model for predicting the severity of Septoria tritici blotch on a susceptible wheat cultivar, typified by Monon. The model is simple because it depends on two variables which are easily calculated for relatively short time periods. The frequency of consecutive days without precipitation from 26 March to 4 May (X_1) is comparable to the number of days with rain from 1 April to 14 June used by Shaner and Finney (15). The frequency of consecutive days with minimum temperature equal to or less than 7 C from 4 April to 3 May (X_2) is the same variable identified by Shaner and Finney (15) as being important from 1 April to 14 June.

TABLE 1. Correlation between meteorological variables and severity of Septoria tritici blotch on winter wheat cultivar Monon at 26 days after heading (adjusted Julian date 170) and the statistical significance (P) of the correlation coefficient

Meterological variable	Window length	Time period	Correlation coefficient[a]	P (df = 10)
Total consecutive days with minimum temperature ≤7 C	60[b]	5 March–3 May	−0.70	0.05
	30	4 April–3 May	−0.71	0.01
Negative degree days	60	2 March–30 April	−0.65	0.05
Mean minimum temperature	60	2 March–30 April	0.64	0.05
Total consecutive days without precipitation	50	24 March–13 May	−0.75	0.01
	40	26 March–4 May	−0.82	0.001
	30	5 April–4 May	−0.75	0.01
Precipitation frequency	40	29 March–7 May	0.67	0.05
	21	10 April–30 April	0.70	0.05

[a] Based on data collected at Purdue University Agronomy Farm from 1973 to 1984 and analyzed by the WINDOW program as described in the text.

[b] For a window length 60, the variable was summed for 60 days beginning on 5 March and ending 3 May.

TABLE 2. Meteorological variables, R^2, R_a^2 (adjusted R^2), Mallow's Cp, Allen's PRESS statistic, R_p^2 (adjusted PRESS), Variation Inflation Factor (VIF), regression coefficients ($\beta_0 - \beta_2$) and standard errors of $\beta_0 - \beta_2$ ($s\beta_0 - s\beta_2$) for predicting Septoria tritici blotch on Monon winter wheat at Purdue University Farm

Model	Variable	R^2	R_a^2	Cp	PRESS	R_p^2	VIF	β_0	s(β_0)	β_1	s(β_1)	β_2	s(β_2)
A	TCD ≤7 C[a] 4 April–3 May	0.51	0.46	17.5	2,372	0.35	1.000	128.282	18.691	−3.360	1.035	···	···
B	Precipitation frequency 29 March–7 May	0.48	0.43	19.15	2,464	0.32	1.000	16.133	17.783	2.946	0.968	···	···
C	TCD w/o P 5 April–4 May	0.60	0.56	13.10	2,035	0.43	1.000	115.123	12.506	−4.107	1.067	···	···
D	TCD w/o P 24 March–13 May	0.61	0.57	12.65	1,848	0.49	1.000	128.655	15.637	−3.144	0.803	···	···
E	TCD w/o P 26 March–4 May	0.70	0.67	7.95	1,559	0.57	1.000	122.449	11.614	−3.893	0.815	···	···
BA	†[b]	0.83	0.79	2.97	958	0.74	1.042	75.151	17.518	2.436	0.598	−2.823	0.661
CA	†	0.86	0.83	1.46	779	0.79	1.096	149.961	11.630	−3.267	0.701	−2.507	0.618
DA	†	0.86	0.83	1.36	795	0.78	1.101	160.173	12.569	−2.496	0.530	−2.481	0.616
EA	†	0.86	0.83	1.35	793	0.78	1.211	147.480	11.338	−3.025	0.642	−2.093	0.645

[a] TCD w/o P = total consecutive days without precipitation; TCD ≤7 C = total consecutive days with minimum temperature less than or equal to 7 C; R^2 = variability fit by the model. Equations based on 12 yr of disease data at adjusted Julian date 170 for 1973–1984 at Purdue University Agronomy Farm.

[b] These models (†) use combinations of two variables taken from the corresponding single-variable models. β_1 is the regression coefficient for variables B, C, D, or E and β_2 is the coefficient for variable A.

Our results were consistent with those of Bahat et al (3) and Eyal (7) in finding that rain-free intervals interfered with disease development. The model predictions had a standard error of 8–9% which was comparable to the estimated error of the actual disease recordings. The model can be used on 5 May (when the wheat is in the boot stage) to predict disease severity for 22 days after heading. Since the average heading date is 22 May, at least 2 wk are available for application of chemical control before heading if severe disease (80% severity or above on the upper four leaves) is predicted. According to other research reviewed by King et al (9), application of chemical fungicides during this time should give good disease control.

We assumed that the potential for an epidemic on susceptible cultivars existed equally each year and that its development depended on favorable meteorological conditions. Summer conditions are unfavorable for the survival of the fungus in its pycnidial state. Spore trapping over the last two summers indicated essentially no pycnidiospores after wheat harvest (G. Shaner, *unpublished*). In Indiana, the presence of asci of *M. graminicola* on leaf blade residue collected from plant stubble in late October has been confirmed by F. R. Sanderson (*personal communication*). This is the probable source of primary inoculum for fall infection of winter wheat. Pycnidia are the most important source of inoculum in subsequent disease increase in the spring.

TABLE 3. Comparison of actual and predicted severity of Septoria tritici blotch on Monon winter wheat at 26 days after heading at Purdue Agronomy Farm

Year	Severity (%) at AJD 170[a]	Predicted disease ± standard error[b]	Meteorological variables[b]	
			X_1	X_2
1973	94	92 ± 9	8	15
1974	94	90 ± 9	10	13
1975	75[c]	61 ± 8[d]	16	18
1976	53	54 ± 9	19	17
1977	72	75 ± 9	15	13
1978	56[c]	49 ± 9	16	24
1979	80[c]	86 ± 9	8	18
1980	54	50 ± 8	17	22
1981	91	89 ± 9	11	12
1982	48	58 ± 8[d]	17	18
1983	66	70 ± 8	11	21
1984	44[c]	52 ± 8	17	21
$\bar{X}$	68.9 ± 18	68.8 ± 17	13.8 ± 3.9	17.7 ± 3.9

[a] AJD 170 is an adjusted Julian date on a time scale where heading always occurs on AJD 144.

[b] Prediction equation is $\hat{y} = 147.480 - 3.025X_1 - 2.093X_2$ in which $\hat{y}$ = predicted disease severity as percent of area of the upper four leaves that was necrotic from Septoria tritici blotch. X_1 = total consecutive days without precipitation from 26 March to 4 May, and X_2 = total consecutive days with minimum temperature $\leqslant 7$ C for 4 April–3 May. Equation was based on 1973–1984 data.

[c] Estimated value. Final dates of observations for 1975, 1978, 1979, and 1984 were AJD 167, 167, 168, and 167, respectively.

[d] Predicted severity is more than one standard error from observed disease severity.

Although any mathematical model with an adjusted R^2 of 0.86 would be expected to explain only 86% of the variability in $\hat{y}$, it is important to look at the 2 yr when the predictions were too low (1975) and too high (1982) and consider the implications if our model had been used to predict disease in those years. Underprediction of disease may be more serious than overprediction, particularly if chemical control is withheld because of the prediction. However, although chemical control for Septoria tritici blotch is available, it is not routinely applied in the United States because of the lack of an adequate forecast for the disease and the high cost of application of fungicides to large acreages of wheat. The review by King et al (9) summarizes reports on an increased use of chemical control for this disease in other countries. Our experience with *Septoria* suggests that chemical control on susceptible cultivars be used only when predictions of disease severity on the upper four leaves of 80% or greater are made. In 1975, when the predicted disease was 61 ± 8% and the actual disease was 75%, the prediction would have resulted in the recommendation that no chemical control be used, and since the final disease was less than 80%, no control would have been necessary. In 1982, when the predicted disease was 58 ± 8%, the actual disease was 48% and again no control would have been recommended. We were unable to identify what meteorological variables caused the higher than expected disease in 1975 or unusually low disease severity in 1982. Both fall and winter conditions were examined. It is possible that the excessive winter killing in the winter of 1981–1982 eliminated much fall-infected tissue and thereby reduced the level of inoculum to begin the epidemic in the spring.

The model presented is based on all 12 yr of data to maximize the range of meteorological conditions included in its development. On the basis of available statistical techniques, we believe our model validation is sufficient. This model can be used to accurately predict *Septoria tritici* in the future if certain limits are applied. The model was developed as an interpolation equation for conditions when TCD w/o P between 26 March and 4 May (X_1) ranged from 8 to 19 days and TCD with minimum temperature at or below 7 C between 4 April and 3 May (X_2) ranged from 12 to 24 days. Under simultaneously wetter ($X_1<8$) and warmer ($X_2<12$) conditions, this model would predict disease severity greater than 100%. Under extremely dry and cold conditions less than 0% disease could be predicted. However, the correlation between X_1 and X_2 is low (r = 0.417) and such simultaneously extreme conditions are unlikely.

TABLE 4. Calculation of Allen's PRESS static for the model $\hat{y} = 147.480 - 3.025\,X_1 - 2.093\,X_2$ for prediction of Septoria tritici blotch severity ($\hat{y}$) at 26 days after heading (adjusted Julian date 170) where X_1 = total consecutive days without precipitation from 26 March to 4 May and X_2 = total consecutive days with minimum temperature $\leqslant 7$ C; y = observed disease severity

Year	y	$\hat{y}$	$(y-\hat{y})$	$(y-\hat{y})^2$	$\hat{y} = \beta_0 - \beta_1(X_1) - \beta_2(X_2)$[a]
1973	94	91.06	2.94	8.64	$145.763 - 2.925(8) - 2.087(15)$
1974	94	88.78	5.22	27.25	$143.997 - 2.956(10) - 1.974(13)$
1975	75	59.62	15.38	237.16	$148.248 - 3.261(16) - 2.025(18)$
1976	53	55.07	−2.07	4.28	$147.271 - 2.941(19) - 2.136(17)$
1977	72	76.09	−4.09	16.73	$149.263 - 2.929(15) - 2.249(13)$
1978	56	45.37	10.70	114.49	$153.620 - 2.993(16) - 2.515(24)$
1979	80	88.46	−8.46	71.57	$150.184 - 3.387(8) - 1.924(18)$
1980	54	48.94	5.06	25.60	$149.744 - 3.077(17) - 2.204(22)$
1981	91	88.36	2.70	7.29	$145.606 - 3.017(11) - 2.005(12)$
1982	48	60.29	−12.29	151.04	$146.298 - 2.746(17) - 2.185(18)$
1983	66	71.88	−5.88	34.57	$146.994 - 3.202(11) - 1.899(21)$
1984	44	53.84	−9.84	96.83	$143.938 - 2.892(17) - 1.949(21)$

PRESS = 795.45

[a] β coefficients are estimated for each year based on n-1 observations (11 yr). For example, in 1973, observations for 1974 to 1984 were used to estimate the coefficients and the resulting equation was used to predict disease severity ($\hat{y}$) for 1973.

From 1950 to 1972, X_1 ranged from 4 to 23 days and X_2 ranged from 4 to 24 days, but disease predictions for those years were from 34 to 97% (S. M. Coakley, *unpublished*).

Model EA was selected over CA and DA (Table 3) because it was identified by two separate regression analysis techniques as best fitting the data. The differences between these models are small and should not be considered significant.

We limited the models considered to three variables because there were only five different types of variables (Table 1) and some were highly correlated with each other, e.g., TCD without precipitation is highly correlated with precipitation frequency ($r = -0.87$).

We intend to test these models in other geographical areas and to evaluate other cultivars in a similar manner. The WINDOW program should be readily applicable for investigating the relationships between other plant diseases and meteorological variables. A similar analysis procedure is described by Goldwin (8) for studying the association between weather components and horticultural parameters.

We believe that we have established that our model can be useful in prediction of Septoria tritici blotch and hence as a tool for control of this disease. However, the final requirement for this model is to set up a procedure for maintaining it. This will be done by validation of the model on new observations as they become available. The model will be reformulated if new data indicate that it is appropriate.

LITERATURE CITED

1. Anonymous. 1965. Losses in Agriculture. U.S. Dep. Agric. Handb. 291. U.S. Government Printing Office, Washington, DC. 120 pp.
2. Anonymous. 1983. Nomenclature—Septoria Diseases of Cereals. Phytopathol. News 17(11):77.
3. Bahat, A., Gelernter, I., Brown, M. B., and Eyal, Z. 1980. Factors affecting the vertical progression of Septoria leaf blotch in short-statured wheats. Phytopathology 70:179-184.
4. Coakley, S. M., Boyd, W. S., and Line, R. F. 1984. Development of regional models that use meteorological variables for predicting stripe rust disease on winter wheat. J. Climate Appl. Meteorol. 23:1234-1240.
5. Coakley, S. M., and Line, R. F. 1981. Quantitative relationships between climatic variables and stripe rust epidemics on winter wheat. Phytopathology 71:461-467.
6. Draper, N. R., and Smith, H. 1981. Applied Regression Analysis. (Pages 419-422) John Wiley & Sons, New York.
7. Eyal, Z. 1981. Integrated control of Septoria diseases of wheat. Plant Dis. 65:763-768.
8. Goldwin, G. K. 1982. A technique for studying the association between components of the weather and horiticultural parameters. Sci. Hortic. 16:101-107.
9. King, J. E., Cook, R. J., and Melville, S. C. 1983. A review of Septoria diseases of wheat and barley. Ann. Appl. Biol. 103:345-373.
10. Montgomery, D. C., and Peck, E. A. 1982. Introduction to Linear Regression Analysis. (Pages 424-446) John Wiley & Sons, New York.
11. Neter, J. W., Wasserman, W., and Kutner, M. H. 1983. Applied Linear Regression Models. (Pages 426-429) R. D. Irwin, Inc., Homewood, IL.
12. Renfro, B. L., and Young, H. C. 1956. Techniques for studying varietal response to Septoria leaf blotch of wheat. (Abstr.) Phytopathology 46:23-24.
13. Saari, E. E., and Wilcoxson, R. D. 1974. Plant disease situation of high-yielding dwarf wheats in Asia and Africa. Annu. Rev. Phytopathol. 12:49-68.
14. SAS Institute Inc. 1982. SAS User's Guide: Statistics. 1982 Edition. Cary, NC. 584 pp.
15. Shaner, G., and Finney, R. E. 1976. Weather and epidemics of Septoria leaf blotch of wheat. Phytopathology 66:781-785.
16. Shipton, W. A., Boyd, W. R. J., Rosielle, A. A., and Shearer, B. I. 1971. The common Septoria diseases of wheat. Bot. Rev. 37:231-262.
17. Snedecor, G. W., and Cochran, W. G. 1980. Statistical Methods. Iowa State University Press, Ames. 507 pp.
18. Snee, R. D. 1977. Validation of regression models: Methods and examples. Technometrics 19:415-428.
19. Zadoks, J. C., Chang, T. T., and Konzak, C. F. 1974. A decimal code for the growth stages of cereals. Weed Res. 14:415-421.
20. Ziv, O., and Eyal, Z. 1978. Assessment of yield component losses caused in plants of spring wheat cultivars by selected isolates of *Septoria tritici*. Phytopathology 68:791-796.