Models for Predicting Potential Yield Loss of Wheat Caused by Stripe Rust in the U.S. Pacific Northwest

D. Sharma-Poudyal and X. M. Chen

First and second authors: Department of Plant Pathology, Washington State University, Pullman 99164-6430; and second author: U.S. Department of Agriculture-Agricultural Research Service, Wheat Genetics, Quality, Physiology, and Disease Research Unit, Pullman 99164-6430.

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ABSTRACT

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Climatic variation in the U.S. Pacific Northwest (PNW) affects epidemics of wheat stripe rust caused by *Puccinia striiformis* f. sp. *tritici*. Previous models only estimated disease severity at the flowering stage, which may not predict the actual yield loss. To identify weather factors correlated to stripe rust epidemics and develop models for predicting potential yield loss, correlation and regression analyses were conducted using weather parameters and historical yield loss data from 1993 to 2007 for winter wheat and 1995 to 2007 for spring wheat. Among 1,376 weather variables, 54 were correlated to yield loss of winter wheat and 18 to yield loss of spring wheat. Among the seasons, winter temperature

variables were more highly correlated to wheat yield loss than the other seasons. The sum of daily temperatures and accumulated negative degree days of February were more highly correlated to winter wheat yield loss than the other monthly winter variables. In addition, the number of winter rainfall days was found correlated with yield loss. Six yield loss models were selected for each of winter and spring wheats based on their better correlation coefficients, time of weather data availability during the crop season, and better performance in validation tests. Compared with previous models, the new system of using a series of the selected models has advantages that should make it more suitable for forecasting and managing stripe rust in the major wheat growing areas in the U.S. PNW, where the weather conditions have become more favorable to stripe rust.

Additional keywords: *Triticum aestivum*, yellow rust.

Stripe rust of wheat (*Triticum aestivum* L.) is caused by *Puccinia striiformis* Westend. f. sp. *tritici* Eriks. The disease can cause severe yield loss in many wheat growing areas of the world including the United States (3–5,7,23,32). Stripe rust epidemics are more frequent in the western United States, especially the Pacific Northwest (PNW), which includes Washington (WA), Oregon (OR), and Idaho (ID).

Yield loss caused by stripe rust depends on several factors, including the degree of cultivar susceptibility, infection time, rate of disease development, and duration of disease (3). These crop and disease factors are influenced by environmental factors, among which temperature and moisture are the most important in determining disease severity and yield loss (4,17,28,35). Because temperature and moisture conditions vary significantly from year to year in most wheat producing regions, they are the major limiting factors for the development of stripe rust epidemics and therefore have been used to develop descriptive and forecasting models for the disease.

Forecasting models have been developed and used in management of many plant diseases (2,12–14,18,19,27,29,30,34,36) including stripe rust (10,11,23). Because temperature has the most profound effect on the *P. striiformis* f. sp. *tritici* life cycle, influencing pathogen survival, infection, latent period, and sporulation, it has been used to develop forecasting models for stripe rust (9–11,23). Coakley (8) initially studied the relationship between climatic variables and stripe rust epidemics in Pendleton,

Oregon and found epidemics were favored by winter temperatures that are higher than normal (the mean winter temperature from 1961 to 1975). In a subsequent study, Coakley et al. (9) quantified the relationships between temperature and stripe rust epidemics on winter wheat using disease data from Pullman, WA from 1963 to 1979. Negative and positive degree days were used to determine the effect of cumulative temperatures on disease development using 7°C as a base temperature. This base temperature was selected because it was found to be the most optimum for urediniospore germination and infection (31). Coakley et al. (9) found that the mean temperature for January was positively correlated with stripe rust intensity recorded on susceptible cultivars. However, the cumulative negative (1 December to 31 January) and positive degree days (1 April to 30 June) had higher negative correlations to disease intensity than the January mean temperature. Therefore, simple linear regression models for predicting stripe rust severity were developed using the positive and negative degree days as descriptors. Later, Coakley and Line (10) extended their stripe rust forecasting models developed for Pullman to other locations in the PNW using standardized negative degree days accumulated during December and January. Additional predictive models were developed by Coakley et al. (11) using disease index, temperature, and other meteorological factors such as the amount and frequency of precipitation from 1968 to 1986 at Pullman, WA using multiple regression analysis. However, the simpler models based on negative and positive degree days have been mostly used in forecasting for stripe rust management in the PNW (3,23).

The previous models can generally predict disease intensity in a 0 to 9 scale at the flowering stage of wheat growth (9–11). Though these models have been used successfully to predict stripe rust in most years, they could not accurately predict the epidemic levels in some years when the weather conditions did

Corresponding author: X. M. Chen; E-mail address: xianming@wsu.edu

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not follow the normal pattern. It is possible that the weather pattern in the PNW may have changed after the period used for developing the previous forecast models, which might make the models less suitable for stripe rust forecasting in the recent years. The major limitation of these models using negative and positive degree days is the lumping of the temperature during December and January, which usually are coldest months. If temperatures increase dramatically in this period, they negate the effect of the colder period. For example, the mean monthly temperature in December 2005 was significantly lower than normal and that of January 2006 was much higher than normal. Using these models, stripe rust was predicted in 2006 to be as severe as in 2005, the most severe year of stripe rust since the early 1980s (4), however, the actual damage in 2006 was much less than in 2005 (6). Furthermore, the highest stripe rust intensity index (9 in the 0 to 9 scale) or severity (>95% of the foliage infected) at the flowering stage, which was used in the previous models (10), occurred in the experimental fields at the Pullman location in 2004, 2005, and 2006, but yield loss varied considerably with 40% in 2004, 74% in 2005, and 30% in 2006 for susceptible winter wheat (X. M. Chen, *unpublished data*). The difference in yield loss was caused by variation in duration of epidemic. The previous models do not consider the duration factor and thus, cannot give a fine scale estimation of epidemic severity or yield loss when disease reaches the highest severity level by the flowering stage. This highlights the need for prediction models that provide information on potential yield loss rather than disease severity. Because the previous models require experts' help on translation of predicted disease index to yield loss, growers have relied on experts to do forecasting and interpretation. Prediction models requiring simple calculations may be directly used by growers, extension agents, and farm consultants. Therefore, the major objective of this study was to identify weather variables correlated to yield loss and to develop a series of models for early prediction of potential yield loss caused by stripe rust in the PNW.

MATERIALS AND METHODS

Meteorological data. Data of daily minimum and maximum temperature and precipitation for Pullman, WA from 1975 to 2007 were obtained from the National Oceanic and Atmospheric Administration (NOAA) National Data Centers (NNDC) Climatic Data Online service (<http://cdo.ncdc.noaa.gov/CDO/dataproduct>). The Pullman meteorological station is at the 46°45'N latitude, 117°12'W longitude, and 775 m elevation. A year was divided into four seasons based on *P. striiformis* f. sp. *tritici* biology and wheat crop seasons applicable to the Pullman situation: winter (1 November to 28 February), spring (1 March to 30 May), summer (1 June to 31 August), and fall (1 September to 31 October). The relatively long winter season was used to insure that all cold periods were included. Daily mean temperatures were calculated based on the daily maximum and minimum temperatures. If the maximum, minimum, and average temperatures of 1 day were missing, they were calculated by averaging the previous and following day temperatures. Any year with two or more continuous days of missing daily temperature was excluded from analysis. The minimum, maximum, and mean temperatures for a period were calculated based on daily minimum, maximum, and mean temperatures in that period, respectively. In addition, minimum and maximum moving average temperatures (MAT) were calculated based on daily minimum and maximum mean temperatures for 10-, 20-, 30-, and 60-day periods of 1, 2, 3, and 4 months in each season wherever applicable. The sum of accumulated positive degree days (APDD) and the sum of accumulated negative degree days (ANDD) were calculated using a previously described method (10). Instead of the sum of degree days, the sum of temperatures (ST) was calculated due to the easiness of computation. The amounts of rainfall and snowfall, rainfall days,

snow depth, and snow ground cover days (>2.54 cm) were also used. Thus, a total of 1,376 weather variables were tested in this study.

Disease data. Historical data of stripe rust yield loss for winter and spring wheat were from the fungicide and cultivar yield loss tests conducted in Pullman, WA over the years in our program, some of which were published in *Fungicide and Nematicide Tests Reports* and *Plant Disease Management Reports* (<http://www.plantmanagementnetwork.org/pub/trial/pdmr/>). In the fungicide tests, the standard susceptible wheat genotypes PS 279 and Lemhi were used for winter wheat and spring wheat, respectively. A completed randomized block design was used with four replications for each of nonsprayed check and various fungicide-sprayed treatments. Percentage yield loss caused by stripe rust was obtained using the following formula: $Y(\%) = (Y_1 - Y_2)/Y_1 \cdot 100\%$, where Y_1 was the mean grain yield of a fungicide treatment providing the complete or best control of stripe rust and Y_2 was the mean grain yield of the nonsprayed check treatment. In the cultivar tests, PS 279 or Lemhi was tested together with 23 winter or 15 spring wheat cultivars grown in that year using a randomized split-block design with four replications for each of sprayed and nonsprayed treatments of each cultivar. A fungicide, the most popularly used in any particular period (e.g., Tilt at 4 fl oz/A used from 2000 to 2007), was sprayed before stripe rust reached 5% severity and when plants were usually at boot to heading stages. Percentage of yield loss was calculated using the above formula with Y_1 as the mean grain yield of the sprayed treatment and Y_2 as the nonsprayed treatment of PS 279 or Lemhi. In both fungicide and cultivar tests, the length (about 5 m) and width (about 1.5 m) were measured for each plot. The tests were conducted under natural infection, without artificial inoculation, of stripe rust and fields were managed using the standard cultural practice of commercial fields in the region. Stripe rust severity for each plot was recorded 1 day before or on the same day of fungicide application and two to four times after application. Stripe rust yield loss data confounded by other diseases (in most cases, leaf rust) >5% were excluded from analysis. Yield loss data were available for winter and spring wheat from 1993 to 2007 and 1995 to 2007, respectively.

Data analyses. The variables included in this study were yield loss percentage of winter wheat or spring wheat due to stripe rust (Y) and temperature- and precipitation-based variables (X). Pearson's correlation coefficients were calculated between yield loss percentage and temperature-based variables (minimum, maximum, mean, minimum MAT, maximum MAT, ANDD, APDD, and ST) as well as precipitation variables (total rainfall, total rainfall days [RFD], snow depth [SD], and snow ground cover days [SCD]) for different periods. Separate but similar analyses were performed to develop yield loss models for winter and spring wheat.

Simple linear regression models were developed for each variable that was significantly correlated with yield loss. Models for different months within a season were selected based on the coefficient of determination (R^2) and prediction sum of squares (PRESS) value (22). Stepwise regression was used to select the explanatory variables for different winter periods: 1, 2, 3, and 4 months. Selected independent variables were subjected again for stepwise regression to select the descriptors for the entire winter season. Stepwise regression identified variables that explained the maximum variation in yield loss. Explanatory variables identified by stepwise regression were subjected for the best subset regression algorithm for model selection (22). Mallows' C_p , which is an indication of goodness of fit of the regression equations with different numbers of independent variables, was used to select models. In addition, the adjusted coefficient of multiple determination (R^2_{adj}), which accounts for the number of independent variables, was used to identify the total variation in a response variable associated with the multiple descriptors (12,22).

A multicollinearity test was performed as indicated by variance inflation factors (VIFs) (15,22,26). After the stepwise regression analysis, all explanatory variables from each season were used for the yearly model development. Descriptors for yearly models were identified by stepwise regression analysis. Correlated independent variables with a small regression sum of square were excluded from further model development in multiple regressions. The best subset regression algorithm was used to identify different models in the seasonal and yearly multiple regressions. Principal component analysis was also used to select explanatory variables for the most information (1,20,21). Principal component analysis addresses the problem of multicollinearity transforming the variables into a set of orthogonal or uncorrelated variables (15,16).

Model validation. Model validation was done based on the PRESS value, which is equivalent to the leave-one out cross validation method (25,33). The best fitting models should have the lowest PRESS value. Models with small PRESS values fit well because these models have small prediction errors (15,22, 26). Additionally, prediction accuracy percentage for selected models was calculated using contingency tables (11). In addition to data used for model development, yield loss data from 2008 and 2009 of winter and spring wheat, Pullman, WA were included

to compute prediction accuracy percentage, chi-squared test, and predicted R^2 . Because stripe rust was able to cause yield loss ranging from 3 to 86% during the period of 1975 to 2007 on susceptible cultivars in the PNW, yield loss of 20% or less was generally considered light, more than 20 to 50% moderate, and more than 50% severe. The probability of chi-squared test was used to compare the observed and expected frequency of yield loss categories for different selected models. Furthermore, predicted R^2 values were determined to find out the predictive ability of the selected models (11).

RESULTS

Winter temperature variables correlated with winter wheat yield loss. None of the November based variables were significantly correlated with yield loss percentage. Out of seven significantly correlated December variables, accumulated negative degree days based on daily maximum [DecANDD(Max), X_2] had the highest correlation coefficient ($r = -0.72$, $P = 0.02$). In January, only one variable, accumulated positive degree days based on 10 days MAT using daily maximum temperature [JanAPDD10D-MAT(Max), X_9], had a significant correlation coefficient ($r = 0.66$, $P = 0.03$) (Table 1). Among the monthly winter

TABLE 1. Correlation coefficients obtained between weather variables and yield loss percentage of winter wheat (1993 to 2007) and spring wheat (1995 to 2007) caused by stripe rust in Pullman, Washington

Period	Variable no.	Weather variable ^a	Winter wheat		Spring wheat	
			<i>r</i> ^b	<i>P</i> ^c	<i>r</i> ^b	<i>P</i> ^c
Winter						
Temperature						
One-month						
Dec	X ₁	Dec10D-MaxMAT(Mean)	0.27	0.45	0.68	0.02
Dec	X ₂	DecANDD(Max)	-0.72	0.02	-0.41	0.21
Dec	X ₃	DecANDD10D-MAT(Max)	-0.64	0.04	-0.29	0.37
Dec	X ₄	DecANDD20D-MAT(Max)	-0.65	0.04	-0.33	0.32
Dec	X ₅	DecAPDD(Min)	0.70	0.02	0.65	0.03
Dec	X ₆	DecAPDD10D-MAT(Max)	0.26	0.46	0.63	0.04
Dec	X ₇	DecST(Max)	0.71	0.02	0.45	0.16
Dec	X ₈	DecST10D-MAT(Max)	0.65	0.03	0.32	0.32
Jan	X ₉	JanAPDD10D-MAT(Max)	0.66	0.03	0.60	0.03
Feb	X ₁₀	Feb10D-MinMAT(Max)	0.35	0.31	0.73	0.01
Feb	X ₁₁	FebANDD(Max)	-0.84	0.002	-0.63	0.04
Feb	X ₁₂	FebANDD(Mean)	-0.78	0.008	-0.43	0.18
Feb	X ₁₃	FebANDD10D-MAT(Max)	-0.80	0.005	-0.45	0.15
Feb	X ₁₄	FebANDD20D-MAT(Max)	-0.76	0.01	-0.32	0.32
Feb	X ₁₅	FebAPDD(Max)	0.82	0.004	0.15	0.65
Feb	X ₁₆	FebAPDD(Mean)	0.71	0.02	0.23	0.48
Feb	X ₁₇	FebAPDD20D-MAT(Max)	0.51	0.13	0.70	0.02
Feb	X ₁₈	FebST(Max)	0.94	0.0001	0.42	0.19
Feb	X ₁₉	FebST(Mean)	0.79	0.007	0.42	0.19
Feb	X ₂₀	FebST10D-MAT(Max)	0.79	0.007	-0.20	0.54
Feb	X ₂₁	FebST20D-MAT(Max)	0.81	0.005	-0.21	0.53
Two-month						
Nov-Dec	X ₂₂	NovDecANDD(Max)	-0.73	0.01	0.31	0.32
Nov-Dec	X ₂₃	NovDecAPDD10D-MAT(Max)	0.03	0.92	0.64	0.03
Dec-Jan	X ₂₄	DecJanAPDD(Min)	0.70	0.02	-0.36	0.26
Jan-Feb	X ₂₅	JanFeb10D-MaxMAT(Max)	0.71	0.02	0.10	0.70
Jan-Feb	X ₂₆	JanFeb10D-MaxMAT(Mean)	0.74	0.01	0.05	0.86
Jan-Feb	X ₂₇	JanFeb20D-MaxMAT(Max)	0.85	0.002	0.44	0.17
Jan-Feb	X ₂₈	JanFeb20D-MaxMAT(Mean)	0.82	0.003	0.44	0.17
Jan-Feb	X ₂₉	JanFeb30D-MaxMAT(Max)	0.80	0.005	0.37	0.34
Jan-Feb	X ₃₀	JanFeb30D-MaxMAT(Mean)	0.66	0.03	0.31	0.34
Jan-Feb	X ₃₁	JanFebAPDD(Max)	0.77	0.009	0.31	0.34
Jan-Feb	X ₃₂	JanFebAPDD(Mean)	0.67	0.03	0.20	0.57
Jan-Feb	X ₃₃	JanFebAPDD20D-MAT(Max)	0.25	0.28	0.68	0.02
Jan-Feb	X ₃₄	JanFebAPDD30D-MAT(Max)	0.13	0.31	0.63	0.04

(Continued on following page)

^a D = days, Max = maximum, MAT = moving average temperature, (Min) = based on daily minimum temperature, (Mean) = based on daily mean temperature, (Max) = based on daily maximum temperature, ST = sum of temperatures, ANDD = accumulated negative degree days, APDD = accumulated positive degree days, SD = snow depth, and RFD = rain fall days.

^b r = correlation coefficient. Significant r values are highlighted in bold.

^c P = probability. Significant P values (< 0.05) are highlighted in bold.

temperature variables, February variables had relatively higher correlation coefficient than the others. February sum of temperatures based on daily maximum temperature [(FebST(Max), X_{18})] had the highest correlation coefficient ($r = 0.94$, $P = 0.0001$).

Among significantly correlated bi-monthly variables, January to February 20 days maximum MAT based on daily maximum temperature [(JanFeb20D-MaxMAT(Max), X_{27})] had the highest correlation coefficient ($r = 0.85$, $P = 0.002$). However, all correlated bi-monthly variables had lower correlation coefficients than the single month variable, [FebST(Max), X_{18}].

None of the 3-month period temperature-based variables from November to January were significantly correlated to yield loss of winter wheat. All significant temperature variables were from December to February periods. None of the significantly correlated tri-monthly variables had a higher correlation coefficient than the 1 month [FebST(Max), X_{18}] and bi-monthly variable [(JanFeb20D-MaxMAT(Max), X_{27})].

Only two variables based on entire winter season (November to February) were significantly correlated to yield loss of winter wheat, but these variables had a lower correlation coefficient than most of the significant variables for 1-, 2-, and 3-month periods (Table 1). All variables were positively correlated to yield loss of winter wheat, except for ANDD variables that were negatively correlated. These results indicated that higher temperatures during

the winter season were likely to result in greater yield loss due to stripe rust.

Winter precipitation variables correlated with winter wheat yield loss. Among different precipitation variables, total rainfall days (RFD) of different winter periods were significantly correlated to yield loss of winter wheat (Table 1). January RFD ($r = -0.76$, $P = 0.01$) had a higher correlation coefficient than the December RFD ($r = -0.64$, $P = 0.04$), however, the highest correlation coefficient ($r = -0.92$, $P = 0.001$) was associated with the three-month precipitation variable, December to February RFD (DecFeb-RFD, X_{56}). Except for monthly precipitation variables, correlation coefficients obtained for 2-, 3-, and 4-month winter periods had higher values than the temperature variables for the same periods of winter. The snow depth and snow cover days were not significantly correlated to yield loss. All of the RFD variables were negatively correlated with yield loss of winter wheat. These results indicate that a higher number of rainfall days in the winter season is associated with less yield loss caused by stripe rust.

Spring and summer weather variables correlated with winter wheat yield loss. Only three and four temperature variables of the spring and summer seasons were significantly correlated with winter and spring wheat yield loss, respectively (Table 1). None of the significantly correlated variables had

TABLE 1. (Continued from previous page)

Period	Variable no.	Weather variable ^a	Winter wheat		Spring wheat	
			r^b	P^c	r^b	P^c
Three-month						
Dec–Feb	X ₃₅	DecFeb10D-MaxMAT(Max)	0.70	0.02	0.05	0.86
Dec–Feb	X ₃₆	DecFeb20D-MaxMAT(Max)	0.80	0.005	0.47	0.14
Dec–Feb	X ₃₇	DecFeb30D-MaxMAT(Max)	0.76	0.01	0.35	0.28
Dec–Feb	X ₃₈	DecFeb60D-MaxMAT(Mean)	0.69	0.02	0.33	0.31
Dec–Feb	X ₃₉	DecFebAPDD(Max)	0.73	0.01	0.37	0.26
Dec–Feb	X ₄₀	DecFebAPDD(Min)	0.70	0.02	−0.09	0.79
Dec–Feb	X ₄₁	DecFebAPDD10D-MAT(Max)	0.74	0.01	0.42	0.19
Dec–Feb	X ₄₂	DecFebAPDD20D-MAT(Max)	0.75	0.01	0.67	0.02
Dec–Feb	X ₄₃	DecFebAPDD30D-MAT(Max)	0.73	0.01	0.62	0.04
Dec–Feb	X ₄₄	DecFebST(Max)	0.70	0.02	0.45	0.17
Dec–Feb	X ₄₅	DecFebST10D-MAT(Max)	0.67	0.03	0.41	0.21
Four-month						
Nov–Feb	X ₄₆	NovFebAPDD(Max)	0.68	0.03	0.42	0.19
Nov–Feb	X ₄₇	NovFebST(Max)	0.68	0.03	0.52	0.10
Nov–Feb	X ₄₈	NovFebAPPD30D-MAT(Max)	0.48	0.15	0.63	0.04
Precipitation						
One-month						
Dec	X ₄₉	Dec-RFD	−0.64	0.04	−0.50	0.11
Jan	X ₅₀	Jan-RFD	−0.76	0.01	−0.42	0.20
Two-month						
Dec–Jan	X ₅₁	DecJan-RFD	−0.90	0.001	−0.64	0.03
Dec–Jan	X ₅₂	DecJan-SD	−0.43	0.21	−0.72	0.01
Jan–Feb	X ₅₃	JanFeb-RFD	−0.82	0.004	−0.31	0.35
Three-month						
Nov–Jan	X ₅₄	NovJan-RFD	−0.87	0.001	−0.48	0.15
Nov–Jan	X ₅₅	NovJan-SD	−0.38	0.28	−0.71	0.01
Dec–Feb	X ₅₆	DecFeb-RFD	−0.92	0.001	−0.51	0.11
Dec–Feb	X ₅₇	DecFeb-SD	−0.51	0.12	−0.64	0.03
Four-month						
Nov–Feb	X ₅₈	NovFeb-RFD	−0.82	0.004	−0.38	0.14
Nov–Feb	X ₅₉	NovFeb-SD	−0.46	0.17	−0.64	0.03
Spring						
Mar	X ₆₀	Mar20D-MaxMAT(Max)	0.67	0.04	0.21	0.53
Apr	X ₆₁	Apr10D-MaxMAT(Mean)	0.74	0.02	0.01	0.97
May	X ₆₂	MayANDD(Max)	−0.27	0.48	−0.60	0.05
Mar–Apr	X ₆₃	MarApr10D-MaxMAT(Mean)	0.74	0.02	−0.03	0.93
Summer						
Jul	X ₆₄	Jul10D-MinMAT(Min)	0.70	0.02	0.006	0.99
Jul	X ₆₅	Jul10D-MinMAT(Mean)	0.64	0.04	0.002	0.99
Jul–Aug	X ₆₆	JulAug30D-MaxMAT(Max)	0.70	0.02	0.33	0.31
Jun–Aug	X ₆₇	JunAug30D-MaxMAT(Max)	0.70	0.02	0.18	0.58

higher correlation coefficients than the best winter temperature and precipitation variables. Precipitation variables of both seasons were not significantly correlated with yield loss.

Simple linear models developed for winter wheat yield loss.

Simple linear regression models developed based on temperature variables explained different amounts of variation in yield loss. Because not all of the models were equally important, models with relatively high R^2 values, and low PRESS values were selected from different periods within a season (Table 2). Different prediction models were developed using the different temperature variables during the winter period (Models 1 to 5, Table 2). Yield loss could be predicted using the temperature data as early as December, but the total variation explained was relatively low (Model 1, Table 2). Among the simple linear models, a model with 1-month explanatory variable, Model 2 (Table 2), described the highest yield loss variation. Model 3 (Table 2), developed with the 2-month variables, explained more variation in yield loss than the best early single month model (Model 1, Table 2). Model 8 had the highest R^2 among the precipitation-based models; however, it explained less variation than the temperature-based Model 2. Models 9 to 11, based on spring and summer variables, had lower R^2 values and higher PRESS values than did most of the simple linear models based on winter weather variables. Therefore, models based on winter weather variables are more predictive than the other seasons. Since none of the bi-monthly, tri-monthly, and winter season models explained more variation in yield loss than the monthly Model 2, the latter was considered the best for predicting yield loss due to stripe rust.

Multiple linear models developed for winter wheat yield loss. All of the 54 significantly correlated variables were subjected to a stepwise regression for selection of variables that could explain most of the variation in yield loss. After stepwise regression, five independent variables were identified (Model 12, Table 2). All selected explanatory variables were winter temperature variables. Multicollinearity as indicated by the VIF values was found among weather variables. Therefore, explanatory variables

with a high VIF value and a low regression sum of squares were excluded for model refinement. Another set of yield loss prediction models (Models 13 to 17, Table 2) was developed for different numbers of descriptors through the best subset algorithm. These multiple regression models explained more yield loss variation (6 to 11.4% more) than the best simple linear model (Model 2, Table 2). Multiple regression models (Models 18 and 19, Table 2) based on spring and summer variables had lower adjusted R^2 and higher PRESS values than did Models 13 to 17. Therefore, multiple regression models based on winter weather variables explained the most variation in yield loss among all multiple-variable models. Model 12 with the highest predicted R^2 was the best predicted model followed by Model 14 among the multiple regression models (Table 2).

Weather variables correlated with spring wheat yield loss.

Twelve temperature and six precipitation variables were significantly correlated with yield loss (Table 1). Among the 12 winter temperature variables, X_{10} [Feb10D-MinMAT(Max)] had the highest correlation coefficient ($r = 0.73$, $P = 0.01$). Of the earlier variables, the best correlation was with Dec10D-MaxMAT(Mean), X_1 ($r = 0.68$, $P = 0.02$). Among the precipitation variables, December to January snow depth (DecJan-SD, X_{52}) had the highest correlation coefficient ($r = -0.72$, $P = 0.01$), which is the second highest coefficient after Feb10D-MinMAT(Max), X_{10} . Only one spring variable, [MayANDD(Max), X_{62}], was significantly correlated with yield loss ($r = -0.60$, $P = 0.01$). None of the summer weather variables were correlated with spring wheat yield loss.

Prediction models for yield loss of spring wheat. Five models were developed using temperature and precipitation variables (Models 1 to 5, Table 3). Winter temperature (Models 1 and 2) and precipitation (Models 3 and 4) explained more variation in yield loss than a spring temperature-based model (Model 5). In general, models developed for predicting yield loss of spring wheat, including multiple regression models, were not as good as those for winter wheat. A simple linear model (Model 1, Table 3) with Dec10D-MaxMAT(Mean) (X_1) as a descriptor allows for

TABLE 2. Single-variable and multiple-variable models obtained through stepwise and the best subset regression analyses for predicting winter wheat yield loss caused by stripe rust

No.	Models ^a	P^b	R^2/R^2_{adj} (%) ^c	PRESS ^d	Mallows' C_p	VIF ^e
Single-variable models						
1	$Y = 84.3 - 0.323 X_2$	0.001	51.1	2,255.8		
2	$Y = -6.22 + 0.312 X_{18}$	0.0001	88.1	605.6		
3	$Y = 89.1 - 0.274 X_{22}$	0.01	53.3	2,139.7		
4	$Y = -17.2 + 8.34 X_{27}$	0.002	73.0	1,147.5		
5	$Y = -16.0 + 7.96 X_{36}$	0.005	64.4	1,533.7		
6	$Y = 84.7 - 3.64 X_{49}$	0.04	41.5	2,510.1		
7	$Y = 112 - 2.56 X_{51}$	0.0001	80.0	732.3		
8	$Y = 116 - 2.01 X_{56}$	0.0001	85.4	1,343.7		
9	$Y = -139 + 17.3 X_{61}$	0.023	54.8	1,985.6		
10	$Y = -139 + 17.3 X_{63}$	0.023	54.8	1,985.6		
11	$Y = -19.1 + 6.74 X_{64}$	0.025	48.5	1,934.3		
Multiple-variable models						
<i>Based on yearly/winter weather variables</i>						
12	$Y = 68.6 + 0.448 X_{18} - 0.0502 X_{47} - 0.390 X_3 - 0.368 X_7 + 0.265 X_{43}$	0.0001	99.4	119.5	6.0	5.7 X_{18} , 5.2 X_{47} , 38 X_3 , 55.6 X_7 , 3.4 X_{43}
13	$Y = 17.3 + 0.444 X_{18} - 0.0640 X_{47} - 0.0840 X_3 - 0.021 X_{43}$	0.0001	96.8	7,316.8	25.4	5.7 X_{18} , 4.2 X_{47} , 1.6 X_3 , 2.3 X_{43}
14	$Y = 52.2 + 0.469 X_{18} - 0.0569 X_{47} - 0.304 X_3 - 0.255 X_7$	0.0001	98.7	110.7	10.1	4.8 X_{18} , 4.4 X_{47} , 27.9 X_3 , 37.1 X_7
15	$Y = 17.3 + 0.441 X_{18} - 0.0637 X_{47} - 0.0831 X_3$	0.0001	97.3	125.7	23.4	4.2 X_{18} , 4.0 X_{47} , 1.5 X_3
16	$Y = 4.00 + 0.438 X_{18} - 0.0649 X_{47} + 0.0769 X_7$	0.0001	96.0	197.4	35.6	4.4 X_{18} , 4.1 X_{47} , 2 X_7
17	$Y = 3.16 + 0.467 X_{18} - 0.0592 X_{47}$	0.001	94.0	238.3	59.4	4 X_{18} , 4 X_{47}
<i>Based on spring weather variables</i>						
18	$Y = -148 + 3.57 X_{60} + 14.2 X_{61}$	0.008	73.4	1,206.9	3.0	1.1 X_{60} , 1.1 X_{61}
<i>Based on summer weather variables</i>						
19	$Y = -132 + 4.36 X_{64} + 4.29 X_{66}$	0.03	52.7	1,974.4	3.0	1.4 X_{64} , 1.4 X_{66}

^a X_n , explanatory variables as described in Table 1.

^b P = probability.

^c R^2 = coefficient of determination for single-variable variable models, R^2_{adj} = adjusted coefficient of multiple determination for multiple-variable models.

^d PRESS = prediction sum of squares.

^e VIF = variance inflation factor.

prediction of spring yield loss in early January. However, the temperature-based Model 2 [Feb10D-MinMAT(Max)] and the precipitation-based Model 3 (DecJan-SD) explained the highest amounts of variation of yield loss and can predict the yield loss in the end of the winter season. Four multiple regression models were developed with one temperature- and three precipitation-based variables (Models 6 to 9, Table 3). Due to presence of multicollinearity among the precipitation variables, other multiple regression models with different numbers of descriptors (Models 7 to 9) were developed through the best subset of algorithm.

Model validation. Six models each for winter and spring wheat were chosen for model validation. In addition to PRESS values, validations were done by the chi-squared test using yield loss categories (Table 4) and by regressing prediction and actual values of yield loss for selected models (Figs. 1 and 2). For winter wheat, all selected multiple regression models had a prediction accuracy (based on categories) of 92% and were superior to the two single-variable models (Table 4). The same pattern was evident with regression analysis of the percent yield loss; multiple-variable models had higher R^2 values than single-variable models, although in this case the multiple-variable models had different R^2 values, with Model 12 (Table 2) having the highest.

Predictions were generally better with both validation approaches for winter wheat than for spring wheat. In the case of the latter, there was less of a clear superiority of multiple-variable models although one model (Model 9, Table 3) had a prediction accuracy of 92%, which was the highest. However, the R^2 of Model 9 was slightly lower than that of Model 6 (58.9 and 64%, respectively) and overall, R^2 values were lower for spring wheat (34.9 to 64%) than for winter wheat (55.9 to 87.6%) (Figs. 1 and 2).

A partial comparison of a new model and an older model was made for winter wheat. Model 12 (Table 2) predicted yield loss similar to that observed in all 3 years (Fig. 3), while the older

model based on disease index predicted the actual index accurately in only 2 of the 3 years.

DISCUSSION

From a total of 1,376 weather variables, 54 (40 temperature and 14 precipitation variables) were identified to be correlated to yield loss of winter wheat and 18 (12 temperature and 6 precipitation variables) to yield loss of spring wheat caused by stripe rust (Table 1). Using these correlated variables, 19 models with single or multiple variables were developed for predicting yield loss of winter wheat and nine for spring wheat (Tables 2 and 3). Based on their greater practicality, six models each (Table 4) were selected for both winter and spring wheat crops to be validated, and eventually to be used in disease management. Use of the series of the selected models will allow prediction of yield loss as early as just after December and also more accurate predictions as the season progresses and more weather data become available.

Compared with previous models (9–12), the new system of prediction using the series of models has several advantages. First, the new models directly predict yield loss rather than disease severity at the flowering stage, which can make predictions more meaningful. Second, the new model system makes prediction 1 month earlier than the old models (December versus January). Growers in the PNW would benefit from knowing the potential level of a stripe rust epidemic in the following crop season as early as possible to select spring cultivars to plant and prepare for early management of winter wheat crops. Third, the new system uses a series of models, which allows refinement of prediction as weather condition changes and the crop growth progresses. Fourth, several selected models, which use simple weather factor values without complicated calculation and conversion of negative or positive degree days, should be easy to understand by growers. Finally, the new models, which were

TABLE 3. Single-variable and multiple-variable models obtained through stepwise and the best subset regression analyses for predicting spring wheat yield loss caused by stripe rust

No.	Models ^a	P^b	$R^2/R^2_{adj}(\%)^c$	PRESS ^d	Mallows' C_p	VIF ^e
Single-variable models						
1	$Y = 13.9 + 6.35 X_1$	0.02	46.8	2,156.0		
2	$Y = 15.0 + 5.60 X_{10}$	0.01	52.7	1,845.9		
3	$Y = 50.3 - 0.357 X_{52}$	0.01	52.7	1,843.6		
4	$Y = 50.4 - 0.306 X_{55}$	0.01	50.5	1,935.1		
5	$Y = 35.2 - 15.0 X_{62}$	0.04	36.4	2,256.7		
Multiple-variable models						
<i>Based on winter weather variables</i>						
6	$Y = 56.9 + 2.82 X_{17} - 0.731 X_{51} - 0.905 X_{52} + 0.679 X_{57}$	0.004	83.5	1,251.4	4.3	3.3 X_{17} , 2.8 X_{51} , 13.9 X_{52} , 15.0 X_{57}
7	$Y = 68.0 + 0.37 X_{10} + 1.28 X_{17} - 0.902 X_{51} - 0.268 X_{52}$	0.03	62.1	1,985.1	11.1	3.5 X_{10} , 4.3 X_{17} , 2.7 X_{51} , 1.7 X_{52}
8	$Y = 34.3 + 4.42 X_{17} - 0.925 X_{52} + 0.712 X_{57}$	0.002	82.1	645.7	3.7	1.3 X_{17} , 13.8 X_{17} , 14.9 X_{57}
9	$Y = 83.8 - 1.33 X_{51} - 0.299 X_{52}$	0.003	69.7	1,092.1	7.9	1.1 X_{51} , 1.1 X_{52}

^a X_n , explanatory variables as described in Table 1.

^b P = probability.

^c R^2 = coefficient of determination for single-variable models, R^2_{adj} = adjusted coefficient of multiple determination for multiple-variable models.

^d PRESS = prediction sum of squares.

^e VIF = variance inflation factor.

TABLE 4. Prediction accuracies and probabilities of χ^2 tests for selected stripe rust yield loss models for winter and spring wheat based on predicted and actual yield loss data of winter wheat (1993 to 2009) and spring wheat (1995 to 2009) at Pullman, Washington

Model for winter wheat	Prediction accuracy (%) ^a	χ^2 test P^b	Model for spring wheat	Prediction accuracy (%) ^a	χ^2 test P^b
Model 1, Table 2	75	0.21	Model 1, Table 3	83	0.57
Model 2, Table 2	83	0.49	Model 2, Table 3	85	0.41
Model 12, Table 2	92	0.49	Model 3, Table 3	69	0.57
Model 15, Table 2	92	0.49	Model 6, Table 3	85	0.80
Model 16, Table 2	92	0.49	Model 8, Table 3	84	0.41
Model 17, Table 2	92	0.49	Model 9, Table 3	92	0.80

^a The accuracy values were calculated as frequency (%) of predicted and actual values in the same yield loss categories.

^b P = chi-squared test probability.

developed using weather and disease data from 1993 to 2007, should be more suitable than the old models, which were based on data from 1963 to 1979 (9) for reasons discussed below.

In the present study, two different periods of weather data were analyzed: 1975 to 2007 and 1993 to 2007 for winter wheat and

1979 to 2007 and 1995 to 2007 for spring wheat. In addition to the data in the 1960s and 1970s used in previous studies (9,10), the yield loss data since 1975 were used in this study. The variables that had the highest correlation to stripe rust yield loss were not the same for the periods 1975 to 2007 and 1993 to 2007.

Fig. 1. Relationship between actual yield loss and predicted yield loss (%) obtained using six models selected for winter wheat; data represent trials from 1993 to 2009 at Pullman, Washington.

A number of weather variables from 1993 to 2007 had higher correlation coefficients with yield loss percentage than the weather variables from 1975 to 2007 (data not shown). For example, the highest correlation coefficient obtained for the 1975 to 2007

period was for the entire winter season, NovFebST(Max), ($r = 0.71$, $P = 0.0001$), while the highest correlation coefficient obtained for variables of the 1993 to 2007 period was with FebST(Max) ($r = 0.94$, $P = 0.0001$). Since the weather variables

Fig. 2. Relationship between actual yield loss and predicted yield loss (%) obtained through selected models on spring wheat; data represent trials from 1995 to 2009 at Pullman, Washington.

of 1993 to 2007 had higher correlation coefficients than those of 1975 to 2007, the new models were developed using weather variables of 1993 to 2007. Within the winter season, December temperatures were found more highly correlated with winter and spring yield loss than the January temperatures in the present study. However, January temperatures were previously thought to be a more limiting factor (9). This difference may indicate changes in weather patterns between the periods.

Comparison between the normal winter temperatures for the period of 1963 to 1979 used in a previous study (9) and that of 1993 to 2007 revealed increases and pattern changes in winter temperature during the winter period (November to February) in the PNW except for December mean and February minimum temperatures (Fig. 4). The coldest month for the period of 1963 to 1979 was January, while December was the coldest month for the

period of 1993 to 2007, although overall winter temperatures have risen. Therefore, the more recent winter temperature probably had less limiting effect on the pathogen winter survival and thus in stripe rust development compared with the previous period, 1963 to 1979 (Fig. 4).

The monthly mean minimum temperature for April was significantly correlated with stripe rust intensity during the period of 1963 to 1979 (9). In the present study, none of the spring weather variables based on minimum temperature correlated with yield loss. These results indicate that spring temperature in the period of 1993 to 2007 was not as critical for stripe rust development as in 1963 to 1979. For example, April and spring season mean maximum, minimum, and mean temperatures were 13.74, 1.94, and 7.84°C; and 14.00, 2.53, and 8.26°C, respectively, for the period of 1993 to 2007. In contrast, during the period of 1963

Fig. 3. Comparison of actual and predicted yield loss percentages, and disease severity indices for 2005 to 2007 for Pullman, Washington.

Fig. 4. Comparison of monthly winter normal (long-term mean) temperatures for the periods of 1963 to 1979 and 1993 to 2007 for Pullman, Washington.

to 1979, these temperatures were 8.03, -1.03, and 3.5°C; and 12.66, 1.68, and 7.17°C, respectively. Normal mean temperatures of April and spring season of 1993 to 2007 were closer to the basal temperature, 7°C, for *P. striiformis* f. sp. *tritici* than during the 1963 to 1969 period. The 1993 to 2007 April temperatures were more favorable for stripe rust development and therefore the spring-season temperatures were more favorable to stripe rust and might no longer be a critical limiting factor for stripe rust development in the PNW. The changes in winter and spring temperatures in the periods compared here demonstrate the necessity of periodically updating forecasting models based on these weather variables. The disease-favorable temperature changes in the spring, together with the changes in the winter season toward conditions less detrimental for pathogen survival, could partially explain the more frequent severe epidemics that have occurred in the region in the recent years (3–7).

A number of approaches are available to develop crop loss models (19,24,28,29). We relied on the commonly used least squares regression analysis to develop yield loss prediction models using weather variables (24). Absolute yield loss may provide direct information for wheat growers; however, relative yield loss can be expressed in different forms (24). Relative yield loss should be interpreted cautiously in accordance with wheat productivity of a locality. For example, 10% yield loss represents different actual yield losses in Whitman and Benton counties (WA) because of different productivities, 4.7 and 2.4 t ha⁻¹, respectively. However, yield loss percentage gives a good indication of absolute loss for a particular cultivar in a given region. Our program annually conducts yield loss experiments for major wheat cultivars grown in the PNW to estimate percentage and absolute value of yield loss for each cultivar and uses this information to guide disease management on the basis of individual cultivars (X. M. Chen, unpublished data).

Simple linear models developed using an independent variable of different months/periods can be used for long-term, mid-term, and short-term yield loss predictions. Prediction models such as Model 1 (Table 2) based on December temperature would be applicable for very early forecasting of yield loss. Model 2 (Table 2) with FebST(Max) as a descriptor is the best simple linear model because this model has the least PRESS and the highest predicted R^2 and prediction accuracy percentage among the simple regression models. Model 7 (Table 2) with DecJan-RFD can predict yield loss in early February, earlier than Model 2 (Table 2). Without measuring other weather parameters, just counting raining days during December to January, this model can be used to predict potential yield loss.

Relatively few weather variables were significantly correlated with spring wheat yield loss compared with winter wheat yield loss. Among the simple linear models developed for spring wheat, Model 1 (Table 3) can be used for yield loss prediction in early January. Models 2 and 3 (Table 3) can be used for yield loss prediction in early February and March, respectively. Better prediction can be obtained with multiple regression Model 6 (Table 3) or Model 8 (Table 3).

Since the winter wheat and spring wheat yield loss due to stripe rust is highly correlated ($r = 0.91$, $P = 0.001$), yield loss prediction models developed for winter wheat are practically useful for managing stripe rust of spring wheat. In the PNW, winter wheat is generally planted in September and October and harvested in July and August; and spring wheat is planted in March and April and harvested in August and September. Urediniospores produced on winter crops provide inoculum for spring wheat. Any control measures for stripe rust management of winter wheat, such as growing resistant cultivars and timely use of fungicides should reduce the disease pressure for spring wheat. However, it is also important to grow resistant spring wheat cultivars because stripe rust only varies in the inoculum level from year to year, but never disappears in the PNW, and also because the

summer weather conditions allow stripe rust to develop on spring wheat.

Although the selected models were developed with yield loss and weather data at Pullman, WA, they can be useful for other areas in the PNW with the exceptions of western Oregon, western Washington, and possibly southern Idaho. However, the stripe rust epidemic levels in the Pullman region (southeastern Washington and north-central Idaho) give indications of severe, moderate, and light damage levels for the whole PNW even though damage can vary among different areas in the region. The prediction models can be directly used for stripe rust management in the PNW. Based on our observations, if stripe rust is predicted to be light (1 to 20% yield loss) on susceptible cultivars, fungicide application is not necessary for most of the currently grown cultivars that are resistant to moderately susceptible. Moderately susceptible to susceptible cultivars should be sprayed and moderately resistant to resistant cultivars may not need to be sprayed with fungicides if stripe rust is predicted to be moderate (>20 to 50% yield loss). If stripe rust is predicted to be severe (>50% yield loss), all cultivars except those highly resistant should be sprayed with fungicides one or two times.

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