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Impact of climate on Spot Blotch (*Bipolaris sorokiniana*) severity on wheat (*Triticum aestivum*) crop over Eastern Gangetic Plains (EGP) of India

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ABSTRACT

Spot blotch (SB) in wheat crop is caused by *Bipolaris sorokiniana*, become an epidemic in warm and humid regions. The climate influences the incidence and severity of the crop diseases. The present study is an attempt to assess the role of climatic parameters on the SB of wheat. The experiment was conducted on susceptible wheat varieties grown under timely and late sown conditions at Varanasi for three consecutive years (2014-15, 2015-16, and 2016-17). The Multi Liner Regression (MLR) model revealed that the R^2 for disease severity was 0.74 and 0.72, for timely and late sown conditions, respectively. Auto-regressive Integrated Moving Average (ARIMA) models were evaluated to predict the SB severity. Out of eight ARIMA models, ARIMA (1, 0, 1) was the best fit to predict the disease severity. The R^2 and RMSE were 0.88 and 7.61, respectively for the timely sown condition. For the late sown, R^2 was 0.86 and RMSE 5.48. It was noted that the disease incidence and severity increased rapidly during 8th to 13th SMW that follows after the heading. The risk of SB increased after heading in those areas characterized by average maximum temperature >30 ˚C with high relative humidity >50%. The outbreaks of SB were recorded during this period. This study will help wheat growers of the EGP for timely adaptation of management practices and breeder for the screening of SB resistant germplasms.

Key words: Spot blotch, wheat, heading, ARIMA model, MLR model.

Wheat (*Triticum aestivum* L.) is an important and widely grown crop which requires cool and moist weather during the vegetative phase, and warm and dry weather during reproductive phase (Dubey *et al.,* 2019). It is sensitive to weather, mainly temperature which may affect the growth and yield (Sonkar *et al.,* 2019; Pathania *et al.,* 2019; Vashisht and Jalota, 2018). Wheat being the second most important crop of South Asia, contributes nearly one-third of the total food grain production (Mall *et al.,* 2018). The area under wheat has steadily gone after the green revolution and its production and productivity have increased tremendously. The wheat area has increased from 12.83 million hectares in 1966-67 (Pant *et al.,* 2016) to 29.72 million hectares in 2017-18, with the record production of 98.61 million tonnes of wheat in 2017-18 (Anonymous, 2018).

Globally, an estimated 25 million hectares of wheat area is affected by SB and about 40% area falls under Indian subcontinent (Gupta *et al.,* 2018). Average annual crop losses are estimated to be 2-3 million tonnes. Several abiotic and biotic factors affect wheat yield in this region, which is mostly dominate in warm temperature and high humid at the late post-anthesis phase of the crop (Chatrath *et al.,* 2007). Among the biotic factors, spot blotch caused by *Bipolaris sorokiniana* has now emerged as a major threat (Chowdhury *et al.,* 2013). Out of 10 million hectares of wheat growing area in Indian sub-continent, 9 million hectares are in the Indo-Gangetic plains which are highly prone to SB (Mall *et al.,* 2011). Adequate grain yield decreases due to SB (Sharma *et al.,* 2007) and heat (Sharma *et al.,* 2007b) have been reported in South Asia. Both SB and heat are grievous during post anthesis period causing pre-mature senescence of leaves, reduced grain filling duration, and lower kernel weight (Joshi *et al.,* 2007). Delayed sown wheat faces terminal heat stress problems as temperature rises during grain filling (Sharma *et al.,* 2008), conditions that also increase the severity of SB (Sharma *et al.,* 2007a).

SB infection is known to be influenced by weather conditions particularly favourable temperature and relative humidity during critical growth stage of the crop (Mehta, 1998). Continuous rain for five to six days followed by warmer temperatures (day average temperature 20 to 30 ˚C) has been reported to be conducive for SB epidemics (Mehta, 1998). Infection was rapid and more grievous at 28 ˚C temperature. (Singh *et al.,* 1997). High humidity for 72 hours (h) was found to establish infection in adult plants and light infection was recorded when the temperature was more than 30 ˚C (Senthil, 2004). Outbreaks of spot blotch in Brazil were often shown to be associated with periods when the leaves remain wet for >18 h a day and mean air temperature stays at >18 ˚C (Reis, 1991). In the Indian subcontinent, the disease spreads when the temperature stays at >26 ˚C (Chaurasia *et al.,* 2000), which explains why late-sown wheat is particularly vulnerable to the disease (Gupta *et al.,* 2018).

North eastern plain zone (NEPZ) of India is the second highest wheat producer zone (Mall *et al.,* 2002; Mall *et al.,* 2000) which is characterized by high temperature and humidity at the late 'growth stage' of wheat, which provide the favorable conditions for SB progression (Pant *et al.,* 2016). Weather parameters contribute a major role in the development of different growth stages of crop and infestation of pest and diseases (Paul *et al.,* 2013).

In statistics, dependent variable, influenced by only one explanatory variable is generally unrealistic and it is often influenced by more than one independent variables. This relationship is at the core of the multi linear regression and has high explanatory power (Kumar *et al.,* 2019).

There are several studies which have applied model to estimate the disease severity of SB using the linear regression method, logistic regression and polynomial regression method. Auto-regressive integrated moving average model is one of the most widely used time series model (Han *et al.,* 2010). ARIMA model has various advantages for the forecasting compared with other methods, such as a moving average and exponential smoothing. In the present study, ARIMA model have been used for the forecasting of SB severity in wheat.

MATERIALS AND METHODS

Data used

SB susceptible wheat variety HUW 234 was sown at Agricultural Experimental Farm, BHU, Varanasi, India, during 2014-15 to 2016-17 seasons, under timely sown and late sown conditions. Weekly SB data, spinning 1st to 13th standard meteorological week, related to disease severity were collected for consecutive three years (2014-15, 2015-16 and 2016-17). In all three seasons, disease management practices were not applied. The timely sown condition crop was sown at 25th November and late sown at 25th December. The disease severity data were collected from 8th to 13th SMW for each year. The crops were harvested in mid of April of each year.

The meteorological data maximum temperature (Tmax in ˚C), minimum temperature (Tmin in ˚C), rainfall (mm), relative humidity (RH in %) and dew point (Temperature in ˚C) from the year 2015 to 2017 of experimental site (GPS coordinates 25° 16' 43" N and 82° 59' 25" E) were obtained from the Indian Meteorological Department (IMD), India. The analysis was performed for the wheat cropping seasons.

Measurement of disease

SB severity was recorded following double-digit scale (DD, 00-99) developed for the resistance screening (Saari and Prescott, 1975). The first digit (D_1) indicates the vertical disease progress in each plant and second (D_2) measured severity, which was based on affected leaf area and disease severity percentage (Sharma *et al.,* 2007). Disease severities for HUW 234 from 8th to 13th SMW in each year were calculated by using this following formula:

$$\text{Disease severity (\%)} = \frac{(D_1)}{9} \text{x} \frac{(D_2)}{9} \text{x} 100$$

Infection rate of disease

During the start of infection, disease use to be very low and change in infection rate is not possible to be measured. In mathematics *d* is short hand for a very little quantity. If the total amount *x* of disease increases at variable rate with time *t*, then *dt* means a very short interval of time, and *dx* is the very small bit that increase in that interval. That can be written as

$$dx = xrdt \quad (1)$$

During this point, the pathogen can spread practically unhindered due to susceptible tissue which it can infect. We can write this equation (Eq.) (Van der Plank, 1963), as

$$\frac{dx}{dt} = rx$$

The rate of increase of disease *dx /dt* is proportional to *x*. This increase is logarithmic and build this clear equation is *l* written as

$$\frac{dx}{dt} = r_l x \quad (2)$$

The subscript *l* denotes logarithmic increase. It is used only for increase at very small proportions of disease. We shall interpret this as x <0.05. This limit for logarithmic increase may appear certain high. But, there is nothing to stop one from using a lower limit, say x <0.005. The newly infected tissue takes a period p to exist infectious. One should therefore write an equation

$$\frac{dx_t}{dt} = Rx_{t-p}(1 - x_t) \quad (3)$$

Here x_t and x_{t-p} are x at times t and t-p, respectively. At time t, x_t is the total proportion of infected tissue and x_{t-p} is the proportion infected a period p earlier, i.e., x_{t-p} is the proportion of tissue that has reached, stage of being infectious. The period p is the latent period.

The rate R is the basic infection rate, if the rewrites equation with subscripts, one obtains

$$\frac{dx_t}{dt} = xr_t(1 - x_t)$$

Except at very small values of x, when 1-x is so nearer to 1 that it can be neglected, the increase of disease is no longer logarithmic, and r is written without a subscript. We call r the clear infection rate. Eq. (4) is only a definition. It defines r as $dx/[x(1-x)dt]$

To estimate r_l and r one estimates the proportion of disease in the field on two dates. If x_1 and x_2 are the proportions on dates t_1 and t_2, Eq. (2) becomes

$$rl = \frac{1}{t_2 - t_1} \log_e \frac{x_2}{x_1} \quad (5)$$

Similarly Eq. (1.4) becomes

$$r = \frac{1}{t_2 - t_1} \log_e \frac{x_2(1 - x_1)}{x_1(1 - x_2)}$$

More comfortably we use log $[x/(1-x)]$ and rewrite these equations as:

$$r = \frac{1}{t_2 - t_1} (\log_e \frac{x_2}{1 - x_2} - \log_e \frac{x_1}{1 - x_1}) \quad (6)$$

and

$$r = \frac{2.3}{t_2 - t_1} (\log_{10} \frac{x_2}{1 - x_2} - \log_{10} \frac{x_1}{1 - x_1}) \quad (7)$$

Stepwise multiple linear regression model

Stepwise multiple linear regressions was used according to Draper and Smith (1966) to determine the weather factors accounting for majority of entire variability in disease severity. Stepwise backward elimination method initiates with the present of perpetual model b_0 with a model that comprise all of the available predictor variables, namely

$$Y_d = b_0 + b_1X_1 + b_2X_2 + \cdots \ldots \ldots + b_kX_k$$

Which proceed by gradually eliminating one variable at a time from the model, such that in each step, the variable removed was the variable contributing the least to the prediction of Y at that step. Stepwise forward selection method start with the easiest function, namely, b_0 and successively one variable were being added at a time to the model in such a way that at each step a variable is added. At each step of the procedure, a present model was chosen a predictor variable that was included in the current model as the best candidate variable for adding to that model depending on whichever model selection criterion like R^2, C_p, $adj\ R^2$, C_p etc.

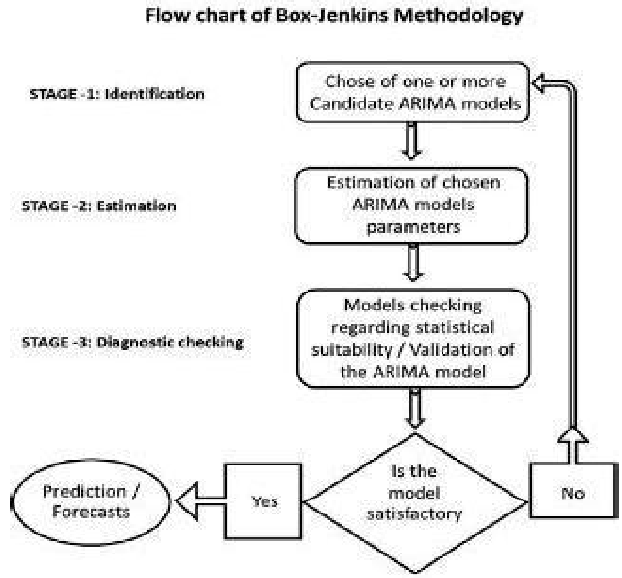

Fig. 1: Flow chart of Box-Jenkins methodology for time series ARIMA model

Auto-regressive Integrated Moving Average (ARIMA) model

In ARIMA models a non-stationary time series is made stationary by applying limited differencing of the data points. The standard statistical methodology to establish an ARIMA model includes three steps: identification, parameter estimation and diagnostic checking (Wang *et al.,* 2017). The model described in auto-regressive, integrated, moving average, called an ARIMA (p, d, q) model. The auto-regressive element, p, represents the lingering effects of preceding scores. The integrated element, d, represents trends in the data, and the moving average element, q, represents the lingering effects of preceding random shocks. ARIMA models can be estimated following the Box-Jenkins (Box and Jenkins, 1970) approach (Fig.1).

Accuracy measurement of the model

In the present study, the following statistics were used to test the forecasting model: the coefficient of determination between the observed value and predicted value (R^2), root mean square error (RMSE) and mean absolute error (MAE):

$$RMSE = \sqrt{\frac{\sum_{1=i}^{n}(O_i - P_i)^2}{N}}$$

Table 1: Disease infection growth rate (per day) of spot blotch of wheat for the susceptible genotype at timely and late sown conditions

Week No.	Average disease infection growth rate	
	Timely sown	Late sown
8	0.088	0.056
9	0.072	0.042
10	0.082	0.042
11	0.51	0.013
12	0.023	0.013

from 0.023 to 0.088 and 0.013 to 0.056 per day between 8th to 12th SMW at timely sown and late sown conditions, respectively. The growth rates were higher at the disease initiation weeks and slow after end weeks of infection (Table 1). The SB severity and infection rate increases when the hosts are more susceptible and aggressive pathogen under the favorable weather conditions. Every factor those influence the rate of increase of disease also affects the logarithmic and the apparent infection rates.

Multiple liner regression analysis

Multiple regression analysis used to characterize the variation in the dependent variable around the regression

Table 2: Stepwise multiple regression and subsets regression for disease severity versus temperature maximum (tmax in ˚C), temperature minimum (Tmin ˚C), rainfall (Rain in mm), relative humidity (RH %), and dew point temperature (DPT ˚C) of grown at timely and late sown conditions

Sl. No	Stepwise multiple Regression	Variables in significant* (Pr > F)						R-square	Mean square error (MSE)
		Intercept	Tmax	Tmin	Rain	RH	DPT		
1	Timely sown	0.8211	0.8180	0.8106	0.7936	0.8251	0.8183	0.7481	105.57
2		<0.0001	0.0009	<0.0001	0.7625	-	0.0045	0.7478	108.37
3		<0.0001	0.0002	<0.0001	-	-	0.0021	0.7471	105.56
4	Late sown	0.8989	0.9008	0.9109	0.8530	0.8950	0.9017	0.7289	54.98
5		0.0001	0.0068	-	0.8626	<0.0001	0.0008	0.7288	53.38
6		<0.0001	0.0032	-	-	<0.0001	0.0001	0.7285	51.90

* All variables left in the model are significant at the 0.01 level

Where, RMSE is the root mean square error between the observed value and predicted value; O_i is the observed value; P_i is the predicted value; N is the number of samples.

Statistical analysis

SAS software (SAS Institute Inc., Cary, NC, 2010) was used for data analysis in Proc REG model. In this model, a p-value ≤0.01 was considered statistically significant. SPSS statistical software (SPSS Inc., Chicago, IL, USA) were used for data analysis and to create the ARIMA model and make prediction. A p-value <0.05 was considered statistically significant.

RESULTS AND DISCUSSION

Disease infection growth rate

The disease infection average growth rates (r) ranged

function and also used to understand which among the independent variables are related to the dependent variable, and helps to be exploring these relationships. Multiple regressions were performed to test the combinations of factors that might result in a significantly better explanation of the variation observed in the field. MLR and partial coefficient of determination (R^2) were estimated for each disease resistant component (Snedecor and Cochran, 1989) in order to evaluate the relative contribution and to develop prediction model for the disease severity. The variables in timely sown (Tmax, Tmin and Dewpoint) and late sown condition (Tmax, RH, and Dewpoint) show its response on the disease severity (Fig. 2 and 3). The optimal number of variables used by stepwise regression procedure was 5, for the best prediction for SB of wheat. Different combinations among significance components which produced best fit linear model and explained the variation were 2 to 5 which contributed

Table 3: Goodness of fit statistics for plausible autoregressive integrated moving average (ARIMA) models for the prediction of spot blotch of wheat on timely sown

Sl. No.	Statistic	RMSE	MAE	BIC	R-square
1	ARIMA (1, 0, 0)	8.005	5.877	4.818	0.860
2	ARIMA (1, 0, 1)	7.617	5.510	4.812	0.877
3	ARIMA (1, 1, 0)	12.455	7.670	5.714	0.666
4	ARIMA (0, 1, 1)	12.508	7.273	5.723	0.664
5	ARIMA (1, 1, 1)	12.658	7.659	5.842	0.667
6	ARIMA (0, 0, 1)	7.973	5.930	4.810	0.861
7	ARIMA (0, 1, 0)	12.635	6.753	5.647	0.646
8	ARIMA (0, 0, 0)	10.567	7.801	5.279	0.748

RMSE= Root mean square error, MAE= Mean absolute error, BIC= Bayesian information criterion.

Table 4: Goodness of fit statistics for plausible autoregressive integrated moving average (ARIMA) models for the prediction of spot blotch of wheat on late sown

Sl. No.	Statistic	RMSE	MAE	BIC	R-square
1	ARIMA (1, 0, 0)	5.669	4.216	4.127	0.846
2	ARIMA (1, 0, 1)	5.486	3.937	4.156	0.861
3	ARIMA (1, 1, 0)	10.147	5.960	5.304	0.519
4	ARIMA (0, 1, 1)	10.102	6.182	5.295	0.523
5	ARIMA (1, 1, 1)	10.169	5.640	5.405	0.532
6	ARIMA (0, 0, 1)	5.607	4.091	4.106	0.850
7	ARIMA (0, 1, 0)	10.060	5.440	5.192	0.512
8	ARIMA (0, 0, 0)	7.416	5.508	4.571	0.729

RMSE= Root mean square error, MAE= Mean absolute error, BIC= Bayesian information criterion.

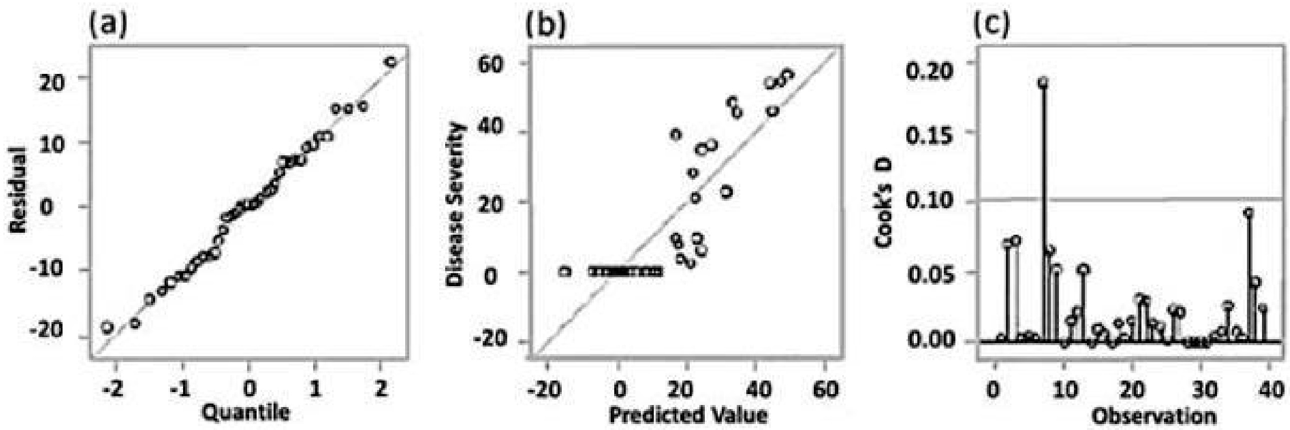

Fig. 2: Stepwise multiple regression backward elimination (a, b, c) of spot blotch of wheat grown at timely sown condition

approximately 75% (R^2 0.7478 to 0.7471 and 0.7288 to 0.7285 for the timely and late sown conditions, respectively) in the backward elimination regression (Table 2).

Autoregressive integrated moving average

The ARIMA (1, 0, 1) model developed in this study provide a simple tool to predict the disease severity based on the observed severity over the years. Out of various ARIMA models with different value of p, d and q, ARIMA (1, 0, 1) model were the best-fit. The Ljung-Box statistical test did not reject the null hypothesis of independence in the residuals time series (Q= 23.039, p= 0.113) and (Q= 31.521, p= 0.012) at timely and late sown conditions, respectively. Thus, the residual errors were considered to be white noise sequence and the selected models were confirmed to be appropriate. The coefficient of determination (R^2) of disease severity was 0.87 (with RMSE value 7.61) and 0.86 (with RMSE value 5.48) at timely and late sown conditions, respectively (Table 3 and 4). The actual data agreed with the predicted data from ARIMA model, which can provide better results for the forecasting of SB. However, the ARIMA model is generally used for short-term forecasts because the relative bias of prediction increases with time, resulting in poor long-term prediction.

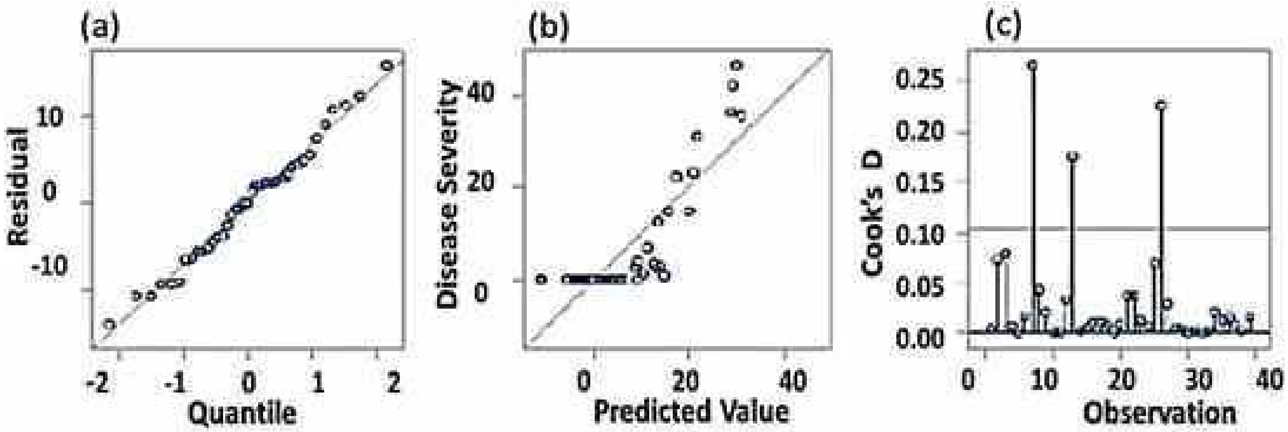

Fig. 3: Stepwise multiple regression backward elimination (a, b, c) of spot blotch of wheat grown at late sown condition

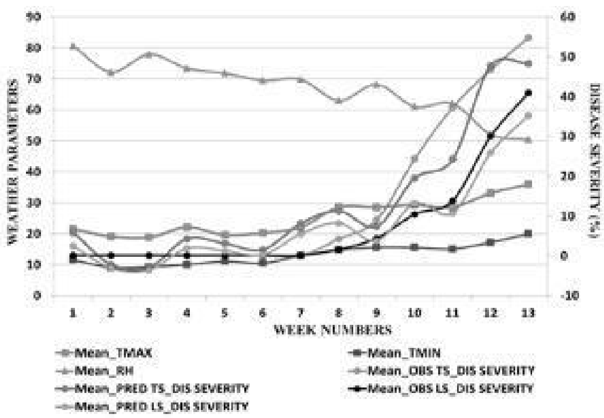

Fig. 4: Weekly average maximum temperature (TMAX in °C), weekly average minimum temperature (TMIN in °C), weekly average relative humidity (RH in %) on X-axis and weekly average spot blotch disease severity percent in observed (OBS) and predicted (PRED) on Y-axis at timely sown condition (TS) and late sown condition (LS) wheat crop for 2014-15 to 2016-17

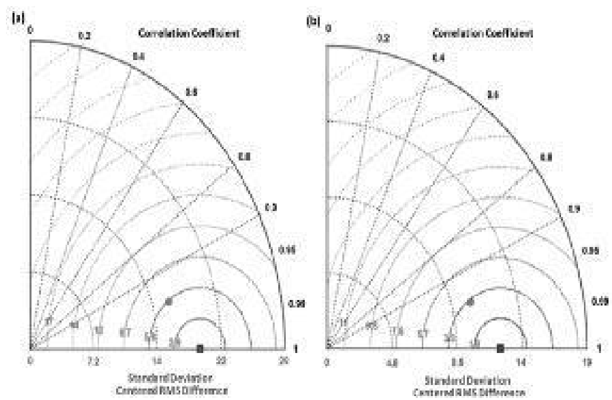

Fig. 5: Taylor diagram of disease severity of spot blotch of wheat grown at timely sown condition (a) and late sown condition (b) for 2014-15 to 2016-17. The green box represents observed disease severity data, and red dot represents the ARIMA (1, 0, 1) model predicted data

Weather parameters response on spot blotch severity

The time series data, during the crop season 2014-15 to 2016-17, of weekly average weather parameters and disease severity in mean observed (OBS) and mean predicted (PRED) at timely sown (TS) and late sown (LS) conditions was shown in Fig. 4. It was noted that the disease incidence and severity was comparatively higher in weekly average maximum temperature (ranged in 31.78-35.42 ˚C), while relative humidity (44.07-75.50%) showed decreasing trends during 8th to 13th SMW. The prediction model performance of disease severity was evaluated by Taylor Diagrams (Taylor, 2001) shown in Fig. 5. The disease severity predicts a significant correlation (r) with observed 0.81 and 0.82 at 95% confidence level for the timely sown and late sown conditions, respectively. The results show that the risk of SB increases when the maximum temperature >30 ˚C during heading, with high relative humidity (>50%), which are favorable conditions for the outbreak of SB epidemic in wheat crop.

CONCLUSION

The overall findings of the present study show significance influence of the disease incidence and severity percent increase mostly found during the 8th to 13th SMW. The average maximum temperature show increase and relative humidity percent show decrease at same duration. The study suggests that change in climate causes increase in the disease incidence and severity which in turn affect the growth and development of the wheat crop. The disease management strategies according to the changing climatic conditions with amalgamation of new strategies will be useful for the sustainable food production.

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