



Forecasting of Wheat Diseases: Insights, Methods and Challenges

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2.1 Introduction

On the global level the plant diseases are known to cause huge losses in terms of quality and quantity (Agrios 2005; Strange and Scott 2005; Chakraborty and Newton 2011; Savary et al. 2012). Plant pathologists are making their best efforts to reduce these losses by using the different strategies of plant disease management singly or in combination. But each one has its own advantages and disadvantages in different host-pathogen interaction systems. E.g. in some crops the resistance sources are not available, in some crops good number of resistance sources is available but due to continuous evolution of the pathogen(s) that does not last long. In some diseases especially seed and soil borne diseases, the seed or soil treatment with biocontrol agents or biofungicides are effective (Akhmedovich et al. 2020) but in some biological control is restricted to laboratory. Fungicides are giving good management of plant diseases but in case of soil borne diseases it is not possible to use large amount of fungicides to treat the soil due to problem of persistence and harmful effects on non-target soil borne organisms. In some diseases due to polycyclic nature of the pathogen or fast multiplication, the chances of fungicide resistance development will increase (Lucas et al. 2015). Moreover due to increased public awareness and environmental issues etc. the application of

If “technology transfer tool” can be defined as a way to get information into the hands of as many people as possible, weather-based disease forecasting models are the perfect example of how this works in practice.: Julianne Isaacs.

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fungicides is restricted although their application has given a boom to the yield in almost all the crops. Above all the irrational or non-optimal use of the fungicides/pesticides leads to an economic loss to farmers, as well as crop and land quality. Most recently a draft on the banning of 27 pesticides has been released by the Indian Government due to their ill effects on humans, animals and environment etc. (The Economic Times 2020). So the efforts of the plant pathologists are targeted towards the integrated disease management to minimize the use of fungicides. Wherever other management practices don't work properly, and use of fungicides is the only option; in that case judicious use of fungicides i.e. application at proper time with exact dose, spray volume and right kind of spray pumps and nozzle is desirable. Timely application of fungicides based on the epidemiology of the particular disease results in effective management of that particular disease otherwise the application goes waste. Both in case of monocyclic (Head Blight, Septoria Blight) and polycyclic diseases (Rusts) several epidemiological models have been developed in different crops for timely plant protection measures. In simple words the plant disease forecasting is the prediction of the occurrence or changes in severity levels of plant diseases in relation to weather, crop, or pathogen. The process of forecasting involves all the activities like ascertaining and notifying the growers of community that conditions are sufficiently favorable for certain diseases, the timely application of control measures will result in economic gain. Different reviews on the various aspects of disease epidemiology and modeling of plant diseases (Zadoks and Rabbinget 1985; Teng 1985; Madden 2006; Savary et al. 2018) has been published which clearly described the types of modeling approaches starting from initial equations to linked differential equation models (Madden 1980; Madden 2006; Madden et al. 2007).

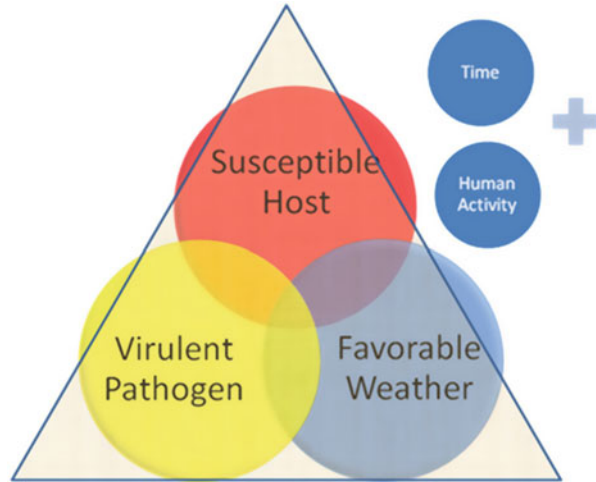
The principle behind plant disease forecasting systems is to determine the risk that a disease will pose, or the the intensity of the disease will increase (Campbell and Madden 1990). Norton et al. (1993) stated the possible objectives for modelling in fungal epidemiology include (1) Predicting the timing of an event i.e. when disease infection is likely to occur; (2) Predicting the scale of an event; such as the severity of disease infection or crop loss; (3) Estimating the frequency or the probability of an event, such as monocyclic (Karnal Bunt) or polycyclic epidemics (Rusts); (4) Assessing and comparing the performance of different management strategies. So, basically the epidemiologists are detectives which watch the each and every activity of the pathogen and each step of the disease development critically. Wade Hampton Frost, the dean of American epidemiologists in 1927 stated that "The nature and spread of a disease may often be established quite firmly by circumstantial evidence well in advance of experimental confirmation" (Stolley and Lasky 1995).

The predictive systems are of two different types i.e. the one that predict disease and the other that predicts infection (Bourke 1955). All the prediction models can be further categorized on the basis of their development i.e. empirical or fundamental. The empirical predictive systems are developed by studying and comparing historical records of disease occurrence and concurrent weather conditions in the same or approximate locality. Such systems usually result in the formulation of "rules" or

specific meteorological conditions that must be fulfilled before disease development can take place. The fundamental predictive systems are developed based on the data obtained experimentally in the laboratory or field regarding the relationships of biological and environmental conditions governing host-pathogen interactions. The utility of the predictive systems can be assessed by three different overlapping criteria i.e. conceptual utility, developmental utility, and the output utility (usefulness of the model to the farmer).

The success of forecasting system depends upon its reliability i.e. it should be based on the sound biological and environmental data, simple, developed for the disease of economic importance with risk of spreading on the larger area if not controlled at initial stages. The necessary information about the components of the models should be available, should be of multipurpose applicability, and above all it should be cost effective. Most of the disease forecasting systems available till date are based on reducing the initial inoculum (soil borne diseases/monocyclic diseases) and in polycyclic diseases with large amount of initial inoculum and lesser number of secondary cycles) or controlling the apparent infection rate (in polycyclic diseases with low initial inoculums and more number of secondary cycles/inoculums) and hence provide information on how a grower's management decisions can help to avoid initial inoculum or to slow down the rate of an epidemic. These two concepts are of utmost importance as they are able to differentiate the risk for a monocyclic disease (having only one cycle of infection) versus polycyclic disease, where there are multiple infection cycles, and a forecasting system can be used to time appropriate management tactics. (Madden et al. 2007). Some forecasting models focus both on avoiding primary inoculum and also on reducing the rate of the epidemic development during the season especially in case of diseases in which more initial inoculum is present and also they multiply rapidly with more number of secondary generations. (Agrios 2005; Campbell and Madden 1990). Better understanding of the host, and environment and its influence on the pathogen and disease development, available detection technology for that particular disease/pathogen and in depth knowledge about the disease and pathogen dynamics helps in the development of a successful forecasting model with sufficient accuracy. After the development of the forecasting model the proper validation is the key criterion for its wider adoption. There is increased interest among plant disease modelers and researchers to improve cost benefit ratio through validation based on quantifying the cost of a model making false predictions (positive and/or negative). An economic validation of a plant disease forecasting system requires the examination of two false predictions (a) false positive predictions, in which a forecast was made for a disease when in fact no disease was found in a location, and (b) false negative predictions, in which a forecast was made for a disease not to occur when in fact the disease was found. These two have different economic effects for producers (Madden 2006). Flexibility of the model, its accuracy, statistical representation of interaction and contact assumptions, defining the critical threshold of transmissibility, methods followed to model disease dynamics in case of pathogens which can travel long distances with the help of air and identification of natural scale to track movement and interaction with host are the key challenges for advancing the models (Newbery et al. 2016).

Fig. 2.1 Components for the development of plant disease epidemic



Since the focus of the chapter is on forecasting of wheat diseases and crop is known to be affected by different diseases among them the important ones are rusts (stripe, stem and leaf) foliar blights, smuts and bunts, Fusarium head blight and Blast. These diseases are known to cause huge losses annually at global level (Reis et al. 2000; Hovmøller 2001; Kohli et al. 2011; Savary et al. 2012; Newbery et al. 2016; Jindal et al. 2012). In wheat diseases especially in case of rusts the main goal of the wheat breeding always remains to increase host resistance by deploying variety of resistance genes which decrease the chances of resistance breakdown by the pathogens (Ojiambo et al. 2017). But development of new races with more virulence, aggressiveness and better adaptability to high/low temperature gives a new direction to the crop breeding programme. In the absence of the effective resistance cultivars the role of fungicides becomes prominent for the management of the quick spreading diseases like rusts. In such cases decisive system is needed for the timely application of fungicides to reduce economic cost, environmental impacts and yield losses. Under these situations the importance of epidemiologists increases to have good and effective disease forecasting models applicable for single disease or multiple diseases in same crop or different crops. The discipline of epidemiology gained its status after the publication of book, *Plant Diseases: Epidemiology and Control* in 1963 by Vander Plank. In this period of around 57 years the concept of disease pyramid (Disease triangle+Time + human activity) has evolved from disease triangle (Host, pathogen and Environment) (Fig. 2.1) and the discipline has gained much application in terms of technological advancements for the development of disease prediction models. The computer based systems has increased the speed and accuracy of the forecasting models.

This book chapter will focus on the various forecasting models designed by various researchers for different wheat diseases (Fig. 2.2), insights into those models and challenges before the epidemiologists to develop more accurate, reliable and cost effective forecasting models in wheat crop under different agro-climatic zones

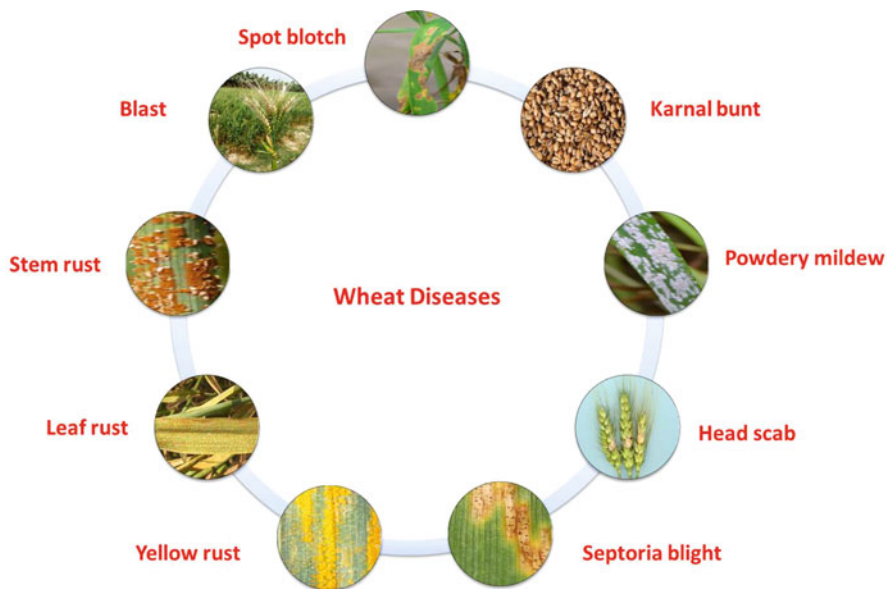


Fig. 2.2 Main wheat diseases for which forecasting models have been discussed

for a single disease or for prediction of multiple wheat diseases. Like all other crops three different types of disease prediction models i.e. Empirical (based on field observations); Simulation models (based on theoretical relationships) and general circulation models (based on fixed changes in temperature or precipitation to predict disease expansion range) are used for wheat disease forecasting.

2.2 Rusts

Rusts are the known to cause the significant economic damage in cereals worldwide. All the stages of rust development starting from landing of the uredospores, followed by their germination, penetration into host, reproduction, colonization, symptom development, disease severity and secondary spread of the pathogen all are affected by the weather parameters such as temperature, relative humidity, wind speed and direction etc. Rust diseases develop and spread rapidly under favourable conditions. Three different types of rusts; stem rust/black rust (*Puccinia graminis tritici*) leaf/brown rust (*Puccinia recondita*), yellow/stripe rust (*Puccinia striiformis tritici*) affect wheat crop from seedling stage to maturity (Bhardwaj et al. 2016; Kaur et al. 2018). Each *Puccinia* species has particular environmental requirements that include presence of free film of water on the leaf surface (due to intermittent rains or heavy dews) and temperatures optimum for the germination and growth of the fungus (Marsalis and Goldber 2017). *Puccinia* spp. causing rust diseases in wheat are polymorphic in nature and produce five different types of spores namely,

picniospores/spermatia, aeciospores, uredospores, teliospores and basidiospores. Vast number of spores is produced by the rust fungi which travel long distances with the help of wind (Visser et al. 2019) and in the presence of susceptible host and favorable weather conditions can cause huge losses or can lead to epidemic like situation in very short period of time (Leonard 2001). For the rust diseases the top priority of the wheat breeder is always to have a cultivar(s) with good yield and rust resistance to achieve sustainable crop yield. Owing to fast multiplication of the pathogen and continuous evolution the new races of the fungus with enhanced virulence, aggressiveness and better adaptation develop which most of the times overcome the resistance. Moreover the effectiveness or performance of some of the resistance genes is also affected by the environmental conditions but the basis for which is poorly understood (Bryant et al. 2014). Many epidemics have been reported globally due to the wheat rusts which resulted in big yield losses. Best approach in the absence of resistance is the timely application of fungicides. In case of rusts the fungicide application must generally occur during the early stages of epidemics, and at sufficient rates. Over-application is costly and creates added selection pressure for more fungicidal tolerant strains; while under-application may also be cost-prohibitive in regions where expected yield is lower (Chen 2007). In such cases the disease prediction models help to take the decision that when to apply the fungicide and where to apply i.e. targeted application of fungicides. In case of wheat rusts most of the disease prediction models are based on environmental conditions as numerous environmental factors are there and their affect on disease development vary with growth stages, season to season and region to region. So the identification of the critical factors involved in the initiation of disease and development at different growth stages of the crop in different regions help to predict the disease accurately by working out the correlation coefficients between each environmental variable and the observed “target variable” i.e. disease severity level (Gouache et al. 2015). These results serve to improve the understanding of the studied pathosystem and provide useful knowledge for managing the disease (Gouache et al. 2015). For wheat rusts till date many disease prediction models have been developed in different countries by using the different parameters and different approaches which included simple regression analysis (Eversmeyer et al. 1973), discrimination analysis (Chen et al. 2006), principal component analysis (Naseri and Sharifi 2019), grey model forecast method (Pu 1998), neural networks (Wang and Ma 2012), support vector machine (Wang and Ma 2011), Markov forecast method (Qiang 1999) etc.

2.2.1 Stripe Rust of Wheat

A number of studies have been conducted throughout the world for predicting stripe rust of wheat early in the season (Zeng 1962; Coakley et al. 1982; Murray et al. 1994; Hu et al. 2000; Fan et al. 2008; Wang et al. 2016; Mulatu et al. 2020). Each study has its own data requirements and complexities which are summarized in the Table 2.1 and only a few are discussed below. The prediction of stripe rust of wheat

Table 2.1 Disease prediction models developed globally for stripe rust of wheat caused by *Puccinia striiformis tritici*

Year	Parameters taken into considerations/ Methods used	Area/Country	References
1962	Number of rainy days, precipitation and mean temperature of 10 days from 11 March to 20 April.	China	Zeng (1962)
1981	Temperature (January, April and June), precipitation in June and positive as well as negative degree days	Pullman	Coakley and Line (1981)
1982	Standardized degree days positive and negative (PDD& NDD)	US Pacific northwest	Coakley et al. (1982)
1983, 1984	PDD, NDD, Julian day of spring	US Pacific northwest	Coakley et al. (1983, 1984)
1983	Disease development data to calculate yield loss due to rust attack at soft dough stage	Victoria	Brown and Holmes (1983)
1987	Temperature and wet period	Australia	Dennis (1987)
1988	PDD, NDD, Julian day of spring, mean max. Temperature, total precipitation, precipitation frequency, number of days with temperature more than 25 °C and number of days with temperature less than 0 °C	US Pacific northwest	Coakley et al. (1988)
1994	Affected area at early milk stage, time and daily maximum temperature (seven days before to one days after early milk stage)	Australia	Murray et al. (1994)
1995	Temperature, dew duration & wetness	France	De Vallavieille-Pope et al. (1995)
2000	Amount of pathogen inoculum in autumn of the last year, amount of pathogen inoculum in spring, average temperature & precipitation in April and area under susceptible variety	Hanzhong in Shaanxi Province/China	Hu et al. (2000)
2003	Disease on lower canopy of plants	UK	Young et al. (2003)
2007	Temperature, dew formation, cultivar resistance rating, frost, seed treatments and foliar fungicide applications	England	Gladders et al. (2007)
2007	Diseased fields (%) in autumn in preceding year, area under susceptible variety, average tem. In January and maximum temperature in march	Longman mountainous area in southern Gansu/China	Xiao et al. (2007)
2007	Precipitation in middle 10 days of April and last 10 days of may, precipitation in middle and last 10 days of may & average relative humidity in may	Shanxi Province	Fan et al. (2007)

(continued)

Table 2.1 (continued)

Year	Parameters taken into considerations/ Methods used	Area/Country	References
2008	Average temperature in march, precipitation in march–may and area under susceptible varieties.	Gangu, Gansu/ China	Fan et al. (2008)
2008	Temperature from February to June and rainy days	UK	Beest et al. (2008)
2008	Weather correlations with disease severity and predictions were made using BP neural network with its network structure simplified through PCA and with its initial weights and threshold optimized by GA.	China	Zeng and Luo (2008)
2009	Incidence is correlated to temperature in Feb. & march and severity is correlated to precipitation in Jan & Feb and temperature in June	S. Sweden	Wiik and Ewaldz (2009)
	Disease prevalence in spring, amount of over-summering pathogen, total precipitation in September-october	Pingliang region in eastern Gansu	
2010	Precipitation in last 10 days of July in the preceding year, sunlight in the first 10 days of November and march in the preceding year., average temperature in the middle 10 days of April and precipitation in the last 10 days period of April.	Jincheng region in Shanxi Province	Cheng et al. (2010)
2013	Web based geographical information system (WeBGIS)	China	Kuang et al. (2013)
1994	Assessment yield losses due to stripe rust at different growth stages from end of heading to late milk in relation to temperature	Australia	Murray et al. (1994)
2006	Discrimination analysis for the forecast of wheat stripe rust based on the occurrence data of this disease and the climate data	China	Chen (2007)
2011	Neural networks	China	Wang and Ma (2011)
2014	Hyperspectral reflectance data	India	Krishnaa et al. (2014)
2016	Hyper spectral data acquired using a black-paper-based measuring method	China	Wang et al. (2016)
2017	Stepwise regression analysis showed existing of low temperature (10–12 °C), high relative humidity (90%) along with intermittent rainfall was conducive for disease onset. Thermic variables (atmospheric, canopy and soil temperature) along with age of crop in the selected varieties showed significant positive correlation with disease severity	India	Gupta et al. (2017)

(continued)

Table 2.1 (continued)

Year	Parameters taken into considerations/ Methods used	Area/Country	References
2019	Air temperature, icy and rainy days, relative humidity	Iran	Naseri and Sharifi (2019)
2020	Rainfall, relative humidity, and air temperature conditions	Morocco	El Jarroudi et al. (2020)
2020	Rainfall, relative humidity and temperature were by machine learning tools	Ethopia	Mulatu et al. (2020)
2020	Non linear prediction model (classification regression tree (CART) using night temperature, dew point temperature, relative humidity data	Mexico	Rodriguez Moreno et al. (2020)

based on weather variables is as old as the science of epidemiology is (Zeng 1962). During the year 1978 a disease prediction model EPIPRED (EPidemics PREdiction and PREvention) for stripe rust of wheat was launched in Netherland and Belgium promoted after the heavy epidemics of yellow rust in 1975 and 1977 in Netherland and is a kind of simulation model which works on field-by-field basis (Rabbinge and Rijdsdijk 1983). EPIPRED is a system of supervised control of diseases and pests in winter wheat. In this system the participating farmers do their own monitoring of diseases and pests and send that information related to field, crop stage and disease/pest to the data bank which then fed into the computer based model. Field data updated daily and by simple simulation models expected damage/loss were calculated and used in making decision i.e. to spray or not to spray. Initially this model was operational in Netherland and Belgium for stripe rust only later on it was used for making decisions related to leaf rust, powdery mildew, septoria blight, glume blotch and aphid during the successive years (Smeets et al. 1994). Shtienberg et al. (1990) developed a threshold level forecasting model and finally on the basis of the pathological parameters and weather forecasts developed a Wheat disease control advisory (WDCA), a computerized decision support system for septoria blotch, leaf rust, and yellow rust, under the semi-arid conditions of Israel. In the decision making process, the system take into consideration the economic, agronomic, phytopathological and both recorded and forecasted weather. It provides a recommendation for fungicidal action to reduce the diseases efficiently in time after analyzing the effects of thevarious factors on the benefits of disease control. The advisory system was tested over 4 years in 81 field experiments by the developers and commercial growers. In managed fields as per advisories of WDCA, a significant increase of 0.78 t/ha in yield, or US \$ 92.70 per ha in net profit, was obtained relative to the common management policy. El Jarroudi et al. (2017a) in Luxembourg developed a threshold-based weather model for predicting stripe rust. In this model first, by using the Monte Carlo simulation method based on the Dennis model, the range of favorable weather conditions were characterized. Then, the optimum combined favorable weather variables (air temperature, relative humidity, and rainfall) during

the most critical period of infection (May–June) were identified and then were used to develop the model. Uninterrupted hours with such favorable weather conditions over 10-day period during the months of May–June were also considered while building the model. A combination of relative humidity $>92\%$ and $4\text{ }^{\circ}\text{C} < \text{temperature} < 16\text{ }^{\circ}\text{C}$ for a minimum of 4 continuous hours, associated with rainfall $\leq 0.1\text{ mm}$ (with the dekad having these conditions for 5–20% of the time), were optimum to the development of a wheat stripe rust epidemic. The model accurately predicted infection events: probabilities of detection were ≥ 0.90 and false alarm ratios were ≤ 0.38 on average, and critical success indexes ranged from 0.63 to 1. Naseri and Sharifi (2019) used Principal component analysis (PCA) to identify climatic variables associated with occurrence and intensity of stripe rust epiphytotics in Iran. They found that disease epidemic intensity was linked to the number of rainy days, the number of days with minimum temperatures within the range of $7\text{--}8\text{ }^{\circ}\text{C}$ and relative humidity (RH) above 60%, and the number of periods involving consecutive days with minimum temperature within the range of $6\text{--}9\text{ }^{\circ}\text{C}$ and $\text{RH}\% > 60\%$ during a 240-day period, from September 23 to May 21. Sadar et al. (2019) firstly developed wheat rust (stripe and stem rust) early warning system (EWS) in which near real-time field survey observations and advanced numerical weather prediction (NWP) meteorological forecast data, Lagrangian spore dispersion forecasts along with detailed environmental suitability model forecasts, and wide-ranging communication methods were used collectively to predict near real-time risks of disease occurrence in Ethiopia.

El Jaroudi et al. (2020) made efforts to couple the use of artificial intelligence algorithms with weather based models for predicting in season development of stripe rust of wheat. They used machine learning techniques such as random forest, naïve bayes algorithms and multivariate adaptive regression splines for stripe rust prediction in Morocco. A combined effect of relative humidity $>90\%$, rainfall $\leq 0.1\text{ mm}$, and temperature ranging from $8\text{ to }16\text{ }^{\circ}\text{C}$ for a minimum of 4 continuous hours (with the week having these conditions for 5–10% of the time) during March–May were optimum to the development of WSR epidemics. Dong et al. (2020) developed an automatic system for Crop Pest and Disease Dynamic Monitoring and Early Forecasting of stripe rust of wheat and locust based on web GIS platform. Wheat rust index (WRI) was constructed based on plant senescence reflectance index (PSRI) and red-edge vegetation stress index (RVSI) to monitor wheat yellow rust, for which WRI could consider wheat growth, chlorophyll content and their variation characteristics. Then, integrated with disease habitat information including land surface temperature (LST, MODIS product), rainfall and wind (meteorological data), also historical data, Disease Index (DI) was constructed for wheat yellow rust habitat monitoring based on previous work. Rodríguez-Moreno (2020) in Mexico explored the use of the classification and regression tree (CART), a type of nonlinear prediction model, to know the key weather–disease links in case of stripe and leaf rust of wheat.

Comparisons of different types of models for their efficacy, accuracy were done by various workers in. Nei et al. (2014) did the comparison of methods for forecasting yellow rust in winter wheat at regional scale. They compared the

Bayesian network (BNT), BP neural network (BP), support vector machine (SVM), and fisher liner discriminant analysis (FLDA) used to develop YR forecasting models and found that three methods of BNT, BP neural networks and SVM are of great potential in development of disease forecasting model at a regional scale. Gouache et al. (2015) used Window Pane analysis for identifying synthetic weather variables over overlapping time frames for eachgrowing season. The correlation coefficients between each variable and the observed “target variable”i.e. the disease level at the end of a season were calculated and critical periods were identified during which the variation in specific environmental variable(s) lead to variations in level of disease expression. Newlands (2018) evaluated the two models; CLR model, which is a simple, site-specific model, and hhh4 model; a complex and spatially-explicit transmission model. The ability of these models to reproduce an observed infection pattern is tested using two climate datasets with different spatial resolution-a reanalysis dataset (~55 km) and weather station network township-aggregated data (~10 km). Thehhh model using weather station network data had the highest forecast accuracy and reliability under heterogeneous modeling assumptions.

Many prediction models have been developed for forecasting of stripe rust of wheat. However, each model has its own advantages and shortcomings and certain application conditions. According to the region or actual conditions suitable model should be selected for application. Prediction model system for yellow/stripe rust of wheat could be built to collect the prediction models into one computer system through programming the models. It could make easier to choose suitable model. Integrated prediction model could be established using different models and methods according to the needs in the future.

2.2.2 Leaf Rust

For the forecasting of leaf rust two different approaches have been used by many researchers throughout the world; firstly considering the influence of weather parameters on the disease (regression equations/disease indicies/flow charts etc) and secondly forecasting disease severity on the basis of epidemic dynamics i.e. from growth rate of the disease. Like stripe rust, again the temperature, relative humidity and rain fall are the key weatherparameters, which are known to influence the disease development and forms the basis for predicting WLR by various disease modelers (Table 2.2) starting from 1969 by Eversmeyer and Burleigh to 2020 by Rodrigues Moreno, a few has been discussed below.

In India during 1980, Nagarajan et al. gave a biclimatic model for prediction of leaf rust in northwestern India. They reported that the following criteria need to be satisfied if an epidemic is to occur. 1. During the period of January 15 to January 20, a wheat disease survey in UP and North Bihar should detect infections in at least five or six sites, separated by a minimum of 25 ± 5 km. 2. The number of rainy days from January to mid April over northwestern India should be at least double the normal of 12 days. 3. Over northwestern India the weekly mean maximum temperature during March to mid April should be ± 1 °C of normal (26 °C).

Table 2.2 Disease prediction models developed globally for Leaf rust of wheat caused by *Puccinia triticina*

Year	Parameters taken into considerations	Area/ Country	Reference(s)
1969	Weekly uredospore number,commulative uredospore numbers, temperature, hours of free moisture as dew or rain/day and precipitation	USA	Eversmeyer and Burleigh (1969)
1972	Developed stepwise linear equation using number of spores trapped, temperature, wheat growth stage, fungal growth function, infection function, hours of free moisture and precipitation	USA	Burleigh et al. (1972)
1981	Linear equation model for predicting rust severity	India	Srivastava (1981)
1983	EPIPPE (EPIdemic PREdiction and PREvention)	Netherland	Rabbinge and Rijsdijk (1983)
1983	Higher temperature results in shorter latent and infectious perid	USA	Tomerlin et al. (1983)
1989	AUDPC, incubation period, Commulative degree days,hours of leaf wetness per day	USA	Suba Rao et al. (1989)
1990	Date of inoculation, weather variables, host susceptibility	USA	Rao et al. (1990)
1997	Meteorological conditions and uredospore cycles (RUSTDEP)	Italy	Rossi et al. (1997a)
1997	Weekly and monthly air temperature and rainfall.	Mississippi	Khan and Trevathan (1997)
1997	Step wise regression using weekly maximum and minimum temperatures, rainfall, relative humidity, wind speed and 24 hr. wind movement leaf rust severity.	Pakistan	Khan (1997)
1998	Daily deviations from the 10-year average maximum and minimum temperature, fungal temperature equivalence function, cumulative fungal temperature function, precipitation, cumulative precipitation, and snow cover averaged for 10-day periods prior to date of inoculum forecast	USA	Eversmeyer and Kramer (1998)
1999	Weather parameters & resistance level of the variety	Argentina	Moschini and Pérez (1999)
2007	PUCTRI : Air temperature, relative humidity and precipitation.	Netherland	Rader et al. (2007)
2008	Weather parameters(temperature, RH, precipitation)	Pakistan	Umer et al. (2008)
2014	Night weather conditions i.e. temperature, RH & Rainfall	Europe	El Jarroudi et al. (2014)
2014	Humid thermal ratio (HTR), maximum temperature (MXT) and special humid thermal ratio (SHTR)	India	Kumar (2014)
2015	EPIWHEAT, a generic simulation model based on weather variables, healthy, latent, infectious, and removed sites, and lesion expansion etc	France & Europe	Savary et al. (2015)

(continued)

Table 2.2 (continued)

Year	Parameters taken into considerations	Area/ Country	Reference(s)
2020	Solar radiation, total precipitation, average wind speed, maximum wind speed, minimum air temperature, maximum air temperature, minimum relative humidity and maximum relative humidity	Egypt	El-Orabey and Elkot (2020)
2020	Non linear prediction model (classification regression tree (CART) using night temperature, dew point temperature, relative humidity data	Mexico	Rodriguez-Moreno et al. (2020)

A simulation model was developed for the prediction of brown rust on winter wheat by Rosii et al. (1996) based on the uredospore cycle. The interaction between the host, weather, and infection process were transformed into model parameters by curve fitting, corrections and empirical assumptions. The model was validated by a backward method and the model outputs were compared with actual data collected at eight sites in Italy over 4 years. The model gave a good simulation of the establishment of primary infections of leaf rust and showed 93% accuracy. Air temperature and leaf wetness were identified as the critical factors for infection establishment. Rosii et al. (1997a) developed a simulation model for the development of leaf rust epidemics which blends the two earlier approaches i.e. RUSTDEP (RUST Development of EPidemics) model and WHEGROSIM (WHEat GROwth SIMulation) model. The model simulates the progress of disease severity level, expressed as a percentage of rusted leaf area on individual leaves, over the course of a growing season, with a time step of one day, as a result of the increase in the diseased area caused by each infection cycle. Information about the interactions between stages of disease cycles, weather variables and host characteristics are incorporated into a system dynamic model. The variables used in this model are leaf area with latent infections, infectious leaf area, no longer infectious leaf area, total rusted leaf area, daily increase of RLA, infection efficiency of uredospores (0–1), failure rate of latent infections (0–1), eruption rate of uredia (0–1) and exhaustion rate of uredia along with Auxiliary and intermediate variables namely germination of uredospores on leaves (0–1), appressorium formation (0–1), penetration into leaves (0–1), leaf area (green leaf area), affectable leaf area, leaf area no longer vulnerable to infection, latent period (days), infectious period (days), leaf wetness, wheat growth phase Constants and parameters like maximum leaf area, host effect on DRLA (number < 1), daily mean temperature, hourly temperature, hourly relative humidity and hourly amount of rainfall. This model allows simulating the progress of rust severity well in a wide range of conditions. The hold out method was used for validation and resulted in 80 per cent of the simulated disease severity which fall into the confidence interval of the observed data.

Rosii et al. (1997b) designed an advisory system for the control of leaf rust on winter wheat by combining three simulation models previously elaborated and validated with the networks of weather station, spore collection and field monitoring by combining the three models. The presence of weather conditions conducive to

infection establishment is then checked by RUSTPRI (RUST PRimary Infection) model, especially when uredospores could be washed onto the ground by rainfall from the cloud of spores in the air. When the infection might be established, the days when uredia could appear in the field are determined and the technicians take action: they intensify surveys in the pilot-fields to note rust appearance. With disease onset they assess disease severity, as an input for RUSTDEP together with the meteorological data and the simulation from WHEGROSIM. The outputs of epidemic simulation are then used in order to advise growers.

El Jarroudi et al. (2014) made predictions of wheat brown rust infection and progress of the disease based on night weather variables (i.e., air temperature, relative humidity, and rainfall) and a mechanistic model for leaf emergence and development simulation (i.e., PROCULTURE) and used this information to develop a decision support system. They also reported that even a single fungicidal application based on the DSS gave a good protection of the upper three leaves in case of susceptible cultivars under field conditions with predominant leaf rust occurrences and the grain yield was not significantly different from that of the plots sprayed twice or thrice with fungicides. Gouache et al. (2015) studied the impact of weather variables on the severity of brown rust in wheat using data from unsprayed plots during 1980–2011. They calculated logistic regressions between the weather parameters derived from the temperature, precipitation, solar radiation and evapotranspiration. They followed the window pane analysis for selecting the weather parameters. The window algorithm was developed by Coakley et al. (1988) to predict stripe rust severity on winter wheat using weather parameters. The window pane algorithm helps in automatically selecting the weather variables of different overlapping time windows and searches for multiple linear regressions of the variables and the disease severity. With this approach they received a root-mean-squared-error of 0.29 representing 22.4% of occurred disease severity values and a ROC Area Under the Curve value of 0.85. Savary et al. (2015) developed a model known as EPIWHEAT for mapping the epidemics of leaf rust and spot blotch of wheat. This model chiefly included the parameters namely lesion size, lesion expansion, number of infectious sites, temperature, duration of wetness, rainfall and area under disease progress curve for predicting the wheat diseases. Chai et al. (2016) discussed about the use of CLIMEX model to know the global climate suitability for *P.triticina* causing leaf rust of wheat. The distribution of leaf rust is strongly influenced by land use in terms of host availability and irrigation. In this CLIMEX model the parameters were fitted based on the biology of leaf rust pathogen and adjusted according to its known distribution using natural rainfall scenario/irrigation schedule. Garin et al. (2018) made an effort for modeling interaction dynamics between two foliar pathogens of wheat i.e. Septoria blight and leaf rust because both the fungi have contrasting traits in terms of colonization of leaf tissues and of spore dispersal. This modeling framework comprised of three sub-models: 1. geometric model of lesion growth and interactions at the leaf scale; 2. model of lesion growth with global interactions at leaf scale 3: epidemiological model with interactions at canopy scale. They found that the simulated epidemics of brown rust were greatly affected by the presence of septoria, but the reverse was not

the case. A weather based approach to predict leaf and stripe rust in winter wheat has been deployed by Rodríguez-Moreno et al. (2020). They used Classification and regression trees (CARTs) for data analysis, in which an hourly weather variables data, and a 3 year field disease data of winter wheat rust were integrated to forecast the presence/absence of pathogens. They observed the association of leaf rust severity with a night temperature of <14.25 °C and global radiation of <521.67 Wm⁻², while the estimated dataset showed that its severity is better explained by the dew point temperature of <13.7 °C and a mean temperature of <19.06 °C. The analysis indicated the pathogen's preference for non-dry ambient conditions and the preference of stripe rust pathogen for humid and warmer temperatures than leaf rust.

2.2.3 Stem Rust of Wheat

Eversmeyer et al. (1973) predicted the severity of stem rust by weekly and cumulative number of uredospores deposited per cm², cultivar, growth stage of the crop, minimum and maximum temperature, fungal temperature growth function and fungal infection function. They used the stepwise multiple regression analysis to find out the meteorological and biological factors responsible for variation in stem rust severities. In India, detailed studies have been conducted by Nagarajan and his co-workers for the prediction of stem rust of wheat. The important ones like "Indian stem rust rules"; a set of synoptic conditions for prediction of stem rust was given by Nagarajan and Singh (1975) as described under:

1. A storm/depression should be formed either in the Bay of Bengal or in the Arabian Sea between 65°--85°E and 10°--15°N and should dissipate over central India.
2. A persistent high-pressure cell must be present over south-central India (not far from the Nilgiris).
3. A deep trough extending up to south India and caused by the onward movement of a western disturbance should occur. If one or a combination of these conditions is satisfied, it is likely that uredospores will be transported to central India and deposited there in rain.

For predicting infections of wheat stem rust 20–25 days before the appearance of the disease on the crop a method was also described by Nagarajan and Singh (1976) in which the application of linear equations aided in the local decision making for successive disease management operations in the likely areas and times of disease appearance are known. Based on field epiphytotic studies, a linear model for prediction of stem rust severity 7 days in advance was developed by Nagarajan and Joshi (1978):

$$Y = -29.373 + 1.820 X_1 + 1.7735 X_2 + 0.2516 X_3.$$

where Y = expected disease severity after 1 week,

X₁ = mean disease severity for the past week,

X₂ = mean weekly minimum temperature (°C) expected for the next week,

X_3 = mean maximum relative humidity expected in the next week and -29.3733 is a constant.

This model was further tested by multilocation test (Karki et al. 1979). Hernandez Nopsa and Pfender (2014) developed a latent period duration model for stem rust of wheat. They formulated a mathematical model to predict latent period duration based on temperature, the model can be applied to data consisting of varying temperature readings measured at any desired time increment and can help in estimating epidemic development, and also in improving understanding epidemiology of stem rust. Recently many modelers have tracked the spore transport events and spread probabilities in case of stem rust in different parts of the world (Meyer et al. 2017; Visser et al. 2019). Prank et al. (2019) made certain attempts to study the impact of climate change on spread potential of stem rust and reported that warmer climate with lower relative humidity and enhanced turbulence will lead to ~40% increase in the urediniospore emitting potential of an infected field as global average. Allen Sader et al. (2019) developed an early forewarning system for mitigation of stripe and stem rust of wheat in Ethiopia. The EWS comprised of a sophisticated framework which integrates field and surveillance data, spore dispersal and disease environmental suitability forecasting and further communicates the information to policy-makers, advisors and smallholder farmers. The system involves daily automated data flow between two continents during the wheat season in Ethiopia. The system works on an interdisciplinary approach (biology, agronomy, meteorology, computer science and telecommunications). This EWS is the first system which combines near real-time field survey observations, advanced numerical weather prediction (NWP) meteorological forecast data, Lagrangian spore dispersion forecasts along with detailed environmental suitability model forecasts, and wide-ranging communication methods to predict near real-time risks of disease occurrence in a developing country context.

Mulatu et al. (2020) developed a nonlinear model for prediction of stripe and stem rust based on historical weather and disease data during 2010 to 2019. The weather variable such as daily rainfall, temperature (minimum & maximum) and humidity were used. The initial disease incidence and severity were assessed at 3 days interval and the data was combined with mean values of weather parameters and correlation was worked out. The presence or absence of the disease was predicted using WEKA software machine learning tool with J48 decision tree algorithm for data analysis. J48 un-pruned decision tree algorithm and J48 pruned decision tree algorithm were used respectively to develop stripe rust and stem rust prediction model.

2.3 Karnal Bunt

Karnal bunt (KB) is an important disease of wheat caused by a fungal species *Tilletia indica* Mitra. Even though Karnal bunt is a minor disease but it is always significant with respect to its quarantine importance worldwide. Besides, soil, seed as well as air borne nature of the fungus makes its management quite difficult (Mitra 1937; Mundkur 1943; Bedi et al. 1949). In India, the germination of teliospores took

place from the middle of February to the middle of March under optimum temperature (18–25 °C) and relative humidity (>70%) to produce primary sporidia (Mitra 1937; Mundkur 1940; Holton 1949; Krishna and Singh 1981). The secondary sporidia are produced by primary sporidia which are air borne and lodge onto plant surfaces by air currents and rain splash or monkey jumping of sporidia from the soil surface to the ear heads. They may germinate and produce additional generations of secondary sporidia on the wheat heads and cause infection (Bedi 1989; Bains and Dhaliwal 1989; Dhaliwal and Singh 1989; Gill et al. 1993; Nagarajan et al. 1997). Wheat spikes are susceptible from early head emergence to late anthesis (Duran and Cromarty 1977; Warham 1986; Bondeet et al. 1997). Sporidial germ tubes penetrate through stomata of glumes, lemmas and palea. In some cases, there may be direct penetration of immature seed (Aujla et al. 1988; Dhaliwal et al. 1988; Goates 1988; Salazar-Huerta et al. 1990). The various stages of the life cycle of the fungus right from the initiation till the development is highly dependent on suitable weather conditions during flowering which is most susceptible stage to infection. There are number of studies which proved the effect of weather parameters on different stages of life cycle of the fungus *Tilletia indica* (Purdy and Kendrick 1957; Munjal 1975; Bains (1992); Bansal et al. 1983; Zhang et al. 1984; Smilanick et al. 1985; Aujla et al. 1986; Singh 1986; Dhaliwal and Singh 1989; Smilanick et al. 1989; Aujla et al. 1990; Bedi et al. 1990; Schall 1991, Ratan and Aujla 1992; Gill et al. 1993; Singh and Aujla 1994; Nagarajan et al. 1997; Kaur et al. 2002a; Sharma and Nanda 2002; Sharma and Nanda 2003; Murray 2004, Goates and Jackson 2006; Sansford et al. 2008; Bedi 1989; Dhaliwal and Singh 1989; Bains and Dhaliwal 1989; Siddhartha et al. 1995).

If we know the exact weather parameters, the disease can be easily controlled by chemicals (Sharma et al. 2004). Various studies have been conducted in this regard (Table 2.3) and most of them are from India. Initially, the role of high humidity, low temperature, continuous rainy/foggy and cloudy weather from ear emergence to anthesis have been reported to be responsible for disease epiphytotic in different years at many places (Munjal 1971; Aujla et al. 1977; Singh and Prasad 1978).

In a comparative study of KB epiphytotic years and KB free years it was indicated that more number of foggy days, reduced sunshine hours and rainfall during flowering stage were the characteristics of epidemic years. On the basis of this analysis, thumb rule to forecast the disease in endemic areas was postulated by Aujla et al. (1991) as described in Table 2.3. Number of rainy days at flowering stage in February at Mexico was found to be positively correlated while the amount of rainfall showed weak positive relation and temperature had negative correlation with Karnal bunt incidence (Nagarajan 1991). Multiregression Model based on different weather parameters was developed and Karnal bunt infection can be predicted using multiple regression models with reasonable reliability (Mavi et al. 1992; Singh et al. 1996). Jhorar et al. developed a disease prediction model for Karnal bunt disease on the basis of 20 year data. In their study HTI (Humid Thermal Index) was generated as a single compound variable for more than 90% disease variation fitting a quadratic function. Smiley (1997) stressed the importance of suitable rain and humidity events and defined conditions for Karnal bunt occurrence. Both the models

Table 2.3 Weather parameters/models for development of Karnal bunt over the years

Parameters/Models	Specific Conditions/ Equations	Year	Country	References
Relative humidity (RH), temperature, continuous rainy / foggy and cloudy weather from ear emergence to anthesis	Humidity more than 70% low temperature (19–23 °C), continuous rainy / foggy and cloudy weather for >13 days	1971–1978	India	Munjal (1971), Aujla et al. (1977), Singh and Prasad (1978)
Cloudy weather, temperature, relative humidity and rains during last week of February	At heading satge, 1) sky remained overcast, 2) temperature was 15–22 °C, 3) RH >40% and up to 80% and high showering	1991	India	Aujla et al. (1991)
Number of rainy days, amount of rainfall and high temperature in February	–	1991	Mexico	Nagarajan (1991)
Humid thermal index (HTI) Evening relative humidity (ERH) Maximum temperature (TMX)	HTI = ERH/ TMX Disease incidence (DI) = $-0.85 + 1.5 \text{ HTI}$	1992	India	Jhorar et al. (1992)
Multiregression model based on maximum temperature (Tmax), sunshine duration (SSD), evening relative humidity (RHe) and rainy days (RD)	Plant disease incidence (PDI) = $4.12 - 0.10 * \text{Tmax} + 0.10 * \text{RHe} - 0.115 * \text{SSD} + 0.076 * \text{RD}$	1992	India	Mavi et al. (1992)
Multiple regression model using different weather parameters	–	1996	India	Singh et al. (1996)
Suitable rain and humidity events	1) more than 3 mm rain on each of two or more successive days, 2) at least 10 mm being collected within the 2 days interval and 3) more than 70% average daily RH during both rainy day	1997	USA	Smiley (1997)
Humid thermal index (HTI) and suitable rains events (SRE)	–	2002	Australia	Stansbury and McKridy (2012)
Temperature, rainfall amount and frequency	$Z = 6.6X1 - 9.45X2 - 1.12X3$, X1 is average maximum temperature, X2 is	2008	Texas	Workneh et al. (2008)

(continued)

Table 2.3 (continued)

Parameters/Models	Specific Conditions/ Equations	Year	Country	References
	average rainfall amount, and X3 is average rainfall frequency for the 18-day period			
GeoPhytopathology model (GPMTI) based on HTI	$HTI = ERH/TMX$ ($5 \leq T \leq 35$ and $60\% \leq RH \leq 95\%$), $HTI = 0$ ($T < 5$ or $T > 35$ or $RH < 60\%$ or $RH > 95\%$)	2010	China	Wei-chuan and Gui-ming (2010)
Total rainfall in the month of march and evening relative humidity of February	$DI = 6.873(0.0962(FmT) - 0.132(FmxT) - 0.34(Frhm) - 0.056((Frhe) + 0.040(Mtrf) + 0.065(MmxT) - 0.132(MRd))$	2015	India	Bala et al. (2015)
Rainfall frequency, total rainfall and HTI during susceptibility period i.e. ear head emergence to anthesis stage	$LogitY = -5.245 + 0.0279total\ rainfall = 0.0449\ rainfall\ frequency/rainy\ days + 0.239\ heat\ thermal\ index$	2016	India	Singh and Karwasra (2016)

developed by Jhorar et al. (1992) and Smiley (1997) were compared by Stansbury and McKridy (2012). They suggested that data on HTI and SRE (Suitable Rains Events) during the susceptible period every year may be more suitable in determining climatic suitability for Karnal bunt in comparison to long term, average data. Workneh et al. (2008) again used temperature, rainfall amount and frequency to predict the disease in Texas. An HTI based GeoPhytopathology Model was developed by Wei-chuan and Gui-ming (2010) in China. Recently, total rainfall, evening relative humidity was defined as the most critical factors for KB development. The model resulted in a coefficient of determination of 0.88 and D. W value of 1.54 (Bala et al. 2015). Singh and Karwasra (2016) established a significant correlation between KB infection and rainfall frequency (0.71), total rainfall and HTI for identifying the KB positive and KB negative crop seasons during susceptibility period i.e. ear head emergence to anthesis stage.

All these studies indicated that there is an unexplained variation in Karnal bunt incidence over the periods. Variable environmental conditions over the periods at the susceptible stage of host may result in such variations in Karnal bunt incidence. However, such variation has also been observed under artificially epiphytotic conditions created for screening of germplasm. This suggests that several other aspects of pathogen biology i.e. inoculum threshold level, pathogen fitness at every stage and probability of encounters between compatible sporidia may also contribute to disease escape or variation in Karnal bunt incidence over the period.

2.4 Fusarium Head Blight

Fusarium head blight is an important disease of cereals which mainly affects wheat, barley, corn and oats (Schmale and Bergstrom 2003). It is the second biggest disease problem in USA, Canada and parts of South America (Savary et al. 2019) and is also known by names such as wheat scab, head scab or simply scab. It affects floral ear heads and is primarily caused by *Fusarium graminearum* Schwabe [teleomorph *Gibberella zeae* (Schwein.) Petch] (Parry et al. 1995). Around 17 species of *Fusarium*, are known to be associated with FHB; *Fusarium culmorum*, *Fusarium avenaceum* (*Gibberella avenacea*), *Fusarium poae*, *F. oxysporum*, *F. pallidoroseum* and *Microdochium nivale* (*Monographella nivalis*) being the predominant ones (Parry et al. 1995; Kaur 1998; Saharan and Sharma 2009; Panwar et al. 2016).

The disease was first described by Smith (1884) in U.K. Its epidemic was reported in the same year in U.K. and *Fusisporium culmorum* now known as *Fusarium culmorum* was found associated with it (Ghimire et al. 2020). In later years, the epidemics also occurred in USA where heavy losses were observed in 1917, 1919, 1928, 1932 and 1935 (Stack 2003). It caused havoc in Paraguay in 1972 and 1975 (Viedma 1989); south-eastern region of Argentina in 1963, 1976, 1978 and 1985 (Moschini et al. 2004) and several states of USA and Canada in 1993 (Nganje et al. 2004). Later on severe outbreaks of the disease occurred all around the world where high rainfall and humidity persists during the wheat season. It was reported to occur in moderate to severe intensity in China (Zhuang and Li 1993) and India (Roy 1974; Singh and Auja 1994). The disease is favoured by wide range of temperatures depending upon the species involved. *Microdochium* sp. is common in temperate climate while *F. graminearum* require comparatively higher temperatures (25–30 °C) along with persistent high moisture and rains (Teli et al. 2016). *F. culmorum*, *F. avenaceum*, *F. poae* thrive more in cool temperatures of around 20 °C (Parry et al. 1995; Kaur et al. 1999).

Fusarium head blight of wheat is a minor disease in India. But, since nineties it has started appearing in Punjab, where it is more severe on durum wheat as compared to bread wheat. Epidemic of the disease occurred in 1995–96 and 2004–05 in sub-mountainous districts of Punjab due to frequent rains resulting in more than 90 per cent infected heads in PDW 274 (Bagga and Saharan 2005). Most of the wheat varieties have limited resistance to FHB (Kharbikar et al. 2019).

It can result in crop losses as high as 70 per cent under epidemics (Moschini et al. 2004). In North America, it resulted in loss of 7.7 billion US dollars from 1993–2001 (Nganje et al. 2004). Under artificial epiphytotic conditions, FHB can result in yield losses of up to 21.6% in PBW 222 wheat variety (Kaur et al. 2002b). Besides yield loss, it results in food and feed contamination due to production of mycotoxins. Deoxynivalenol (DON) is the most common associated mycotoxin present in grains infected with this fungus (McMullen et al. 1997; Desjardins 2006; Dweba et al. 2017), the MRLs for which have been fixed at 1 ppm in finished products and 5–10 ppm for livestock feed (FDA 2010). Thus, it has become the biggest cause of concern associated with this disease.

Epidemiological parameters affecting FHB have been described by several workers (Kaur et al. 1999; Osborne and Stein 2007; Molineros 2007; Bolanos-Carriel 2018). The disease in the field is favoured by 48–72 h of high relative humidity (90%) along with temperatures between 15–30 °C. Infection efficiency reduces significantly when these conditions are not met. Perithecia can develop between 9–29 °C, with an optimal temperature around 22 °C. Sexual reproduction is limited at temperatures of more than 30 °C. Relative humidity is a crucial component for development and maturation of perithecia (Dufault et al. 2006). It required an optimal barometric pressure of less than –50 bars (–5Mpa) (Sung and Cook, 1981), rainfall of more than 5 mm for its development (Inch 2001). Perithecia bear 3-septate ascospores which are hyaline and $19\text{--}24 \times 3\text{--}4 \mu\text{m}$ in size (Booth 1971). Ascospores are produced at a temperature of 25–28 °C under ultraviolet light (Sutton 1982). Macroconidia of *F. graminearum* are produced in a temperature range of 28–32 °C (Keller et al. 2013), while temperatures below 16 °C or above 36 °C are detrimental. Under dry conditions, *F. graminearum* produces perithecia while macroconidia is produced under wet conditions (Sung and Cook 1981).

Extensive work has been carried all over the world to develop and test weather-based forecasting models of FHB (Table 2.4). A sizeable amount of information has been generated to predict mycotoxin associated with FHB (DON) in wheat grains. The models are generally formulated considering the relative importance of components of disease triangle in a manner which gives best fit for disease risk assessment (McCown 2002). Estimation of a disease in any moment of time is essential to predict the outcome in a crop production program. It helps us to cover our weak points in the crop growth season, which could be due to any living or non-living reasons. The corrective actions integrate into a decision support system. The principle involved here is that life cycles of diseases proceed in certain well defined manner which can be predicted with great accuracy if long term disease and weather data is available. Based on predicted critical points in disease development, a farmer can go for management practices with optimal fungicide doses (Landschoot et al. 2013). Timely and accurate identification of plant diseases is another aspect of decision support system which can counter disease in environment friendly and cost effective way (Thandapani et al. 2019).

For fusarium head blight, there can be two lines for developing models, first based on predicting disease or presence of scabbed grains at harvesting and the second is predicting the mycotoxin (DON) in mature grain at/after harvesting. Several weather based models have been developed all around the world for predicting FHB, but most of these are site and year specific. Because of their specificity to region for which they have been developed, only few FHB models could be used in other regions. Italian, Argentinean, and Canadian models have been adjusted for other crop conditions and even used in countries outside their region of origin (Moschini et al. 2004; Del Ponte et al. 2005; Schaafsma and Hooker 2007).

Forecast models have been developed and validated in United States (De Wolf et al. 2003; De Wolf and Isard 2007; McMullen et al. 2012; Shah et al. 2013; Shah et al. 2014), Canada (Hooker et al. 2002; Schaafsma and Hooker 2007; Giroux et al. 2016), Belgium (Landschoot et al. 2013; Hellin et al. 2018), Netherlands (Franz et al.

Table 2.4 Disease prediction models developed globally for Fusarium Head Blight and Septoria blight of wheat

Year	Equation	Parameters taken into considerations	Area/ Country	References
Fusarium head blight				
2002	$DON = \exp[-2.15 + 2.21RAIN_A - 0.61 (RAIN_A)^2 + 0.85RAIN_B + 0.52RAIN_C - 0.30TMIN - 1.10TMAX] - 0.1$	Rainy days (>5 mm), temperature (< 12 °C or > 32 °C) 7–10 days before and after heading	Canada	Hooker et al. (2002)
2003	$TRH9010 = \text{Logit}(p^*) - \beta_0/\beta_1$ Model A	Temperature (15–30 °C) and humidity (hrs. Of >90%) after flowering	USA	De Wolf et al. (2003)
	$TRH9010 = \text{Logit}(p^*) - \beta_0/\beta_1, T15307$ Model B	Temperature and humidity variables 7 days prior to flowering		
	Where, $T15307 = \text{Logit}(p^*) - \beta_0 - \beta_1 DPPTT / \beta_2$			
2003	Risk of DON presence in kernels $R_{toX} = -6.915 + X_{1,n} + X_{2,n} + X_{3,n} + X_{4,n} + X_{5,n} + X_{6,n}$	Temperature, rainfall, leaf wetness duration and relative humidity Different crop management practices	Italy	Rossi et al. (2003)
2004	$PI\% = 20.37 + 8.63 NP - 0.49 nDD$ $R^2 = 0.86$	Rainfall (>0.2 mm), humidity (>81%), 8 days before heading till accumulation of 530 degree days nDD = daily residuals obtained by subtracting 9 to the minimum temperature and the exceeding amount of maximum temperature from 26 °C	Argentina	Moschini et al. (2004)
2005	DONcast	Rainfall and minimum temperature 4–7 days before and 3–10 days after heading	Canada	Schaafsma and Hooker (2007)
2013	Base.0: $\text{Logit}(\mu) = \beta_0 + \beta_1 \text{res1} + \beta_2 \text{res2} + \beta_3 \text{res3}$ Base.1: $\text{Logit}(\mu) = \beta_0 + \beta_1 \text{res1} + \beta_2 \text{res2} + \beta_3 \text{res3} + \beta_4 \text{wc2} + \beta_5 \text{wc3}$ Base.2: $\text{Logit}(\mu) = \beta_0 + \beta_1 \text{res1} + \beta_2 \text{res2} + \beta_3 \text{res3} + \beta_4 \text{TYPE}$	Temperature and relative humidity	USA	Shah et al. (2013)
Septoria blotch of wheat				
2003	$S_{GS75} = 4.37(1.01)W_{\text{etNodISO}}[62,17] + 3.12(1.48)T_{\text{minChodf7+}}[145,70] + 2.78(1.26)$	Average wind speed [78,25], average leaf Wetness [57,22], number of days with minimum	U.K.	Pietravalle et al. (2003)

2009	$Rain_{NoD:9}[81.61]-6.4(2.7)$ $Adj.R^2 = 0.77$ $S_{GS75} = 13.8(1.5)Rain_{NoD:9}[60,37] + 6.1(2.8) Adj.R^2 = 0.86$ $Model^e: 0.046 \times Rain + 0.042 \times T_{min} - 6.69 > 0$ $Model^l: p = 1/\sqrt{e^{4.38-0.22 \times Rain-0.032 \times T_{min}}}$	temperature less Or equal to 7 °C [190, 70], and number of consecutive days with minimum temperature less or equal to 7 °C [190, 70] Rainfall and temperature	England	Beest et al. (2009)
2016	$CRI Y = 20.00 + 8.90Z1,1 + 3.11Z2,1 + .005Z12,1$ $.004Z12,1$ $Jointing Y = 97.45 + 0.58Z1,1 + 2.87Z2,1 - .029Z12,1$ $Flowering Y = 100.8 + 2.29Z1,1 + 0.87Z2,1 - .008Z12,1$ $Milking Y = 37.41 + 0.87Z1,1 + 0.34Z2,1 + .014Z12,1$ $Dough Y = 101.0 + 1.21Z1,1 + 0.78Z2,1 - .002Z12,1$ $Y = [(36-T)/7] \times [(T-16)/13]^{1.8571} \times [1-(0.8114)^{P-m}]$	Maximum temperature, maximum relative humidity and their interaction	India	Pant et al. (2016)
2017		Minimum relative humidity duration (m) of 9 h produced lesions Temperature (T) and RH-duration (D) affected Daily infection index (Y)	India	Viani et al. (2017)
2019	Model B $TPC(T) = \frac{1}{LP_{min} + C_{lrv} \times (T - T_{opt})^2}$	Temperature and latent period LP_{min} = minimum latent period, T = mean canopy temperature, T_{opt} = optimal mean leaf temperature	U.K.	Chaloner et al. (2019)

2009; Van Der Fels-Klerx et al. 2010), Switzerland (Musa et al. 2007), Italy (Rossi et al. 2003; Prandini et al. 2009), China (Zhao and Yao 1989), Argentina (Moschini et al. 2004) and Brazil (Del Ponte et al. 2005).

In United States, five weather based logistic regression models for FHB were developed which could predict *Fusarium* head blight epidemics with accuracy of 62–85 per cent using predictor variables in narrow time periods around crop anthesis (De Wolf et al. 2003; Haran et al. 2010; Peel et al. 2007; Shah et al. 2013; Shah et al. 2014). The models used precipitation hours, time duration of temperature remaining between 15–30 °C, pertaining to period of 7 days prior to anthesis (Z65) and the duration when temperature remained between 15–30 °C along with relative humidity of 90 per cent.

De Wolf et al. (2003) were associated with development of 10 regression models which could predict epidemics. Models A (TRH9010) requires temperature and humidity combination variables in post flowering phase. Models B, C and D required the interactions of weather parameters during pre and post flowering phase of the crop to predict FHB. Models C and D had high prediction accuracy of more than 90 per cent under, when FHB severity remained low (<10%) but, in epidemics (>10% severity) the accuracy dipped to less than 73%. The authors however emphasized three models A, B and I (DPPT7). The first model set (DPPT7: I) utilized rainfall hours during 7 days to flowering, the second set of models (T15307: B and I) used hours when temperature remained between 15–30 °C, in 7 days period before flowering while the third set of models (TRH9010: A and B) required hours with both relative humidity of more than 90 per cent and temperature between 15–30 °C 10 days post flowering. These models can forecast an epidemic if critical predicted probability reaches or exceeds 0.5, as per the algebraic equations (Table 2.4). Molineros (2007) redefined the De Wolf et al. (2003) by using only average relative humidity of 7 days prior to flowering and four levels of varietal susceptibility.

Shah et al. (2013, 2014) in their three logistic regression models (Base 0, Base.1 and Base.2) which included resistance predictor besides weather-based variables like temperature, rainfall and relative humidity values within 15 days around flowering. Relative humidity was found better at characterizing moisture effects on FHB than rainfall in these models and therefore except one RHR.RHG90nR.PRE7.24H, rest all used only temperature and relative humidity predictors. The predictors were the combinations of *t* and *rh* in different observation periods, pre- or post-flowering. Unlike previous models, they considered 24-h day period from 08:00 to 08:00 instead of midnight to midnight cycle. All models we developed contained four or fewer weather-based predictors. Fifteen model sets based on both logistic and additive logistic regression models were selected by the authors when model selection protocols were applied different combinations of base models and weather parameter periods. Five models were developed from base.0, four from base.1 and six from base.2. Seven models out of fifteen were based on pre-flowering weather predictors (7, 10, 14 and 15-day window) while remaining used post-flowering (5, 7 and 10 days) data. These models made fewer misclassification errors than models deployed in US.

In Canada, a weather based prediction model was developed by Hooker et al. (2002) to access DON content (ppm) in grains based on weather parameters existing in three time zones near to heading i.e. Z58 stage of wheat crop, represented in three equations. This empirical model was based on predicting DON content (in ppm) at harvest with different equations related to three time periods around heading (Z58). Rainfall and temperature were identified as crucial meteorological parameters in three time zones (1) 4–7 days before heading (2) 3–6 days and (3) 7–10 days after harvesting. Time period, 4–7 days before and 3–10 days after heading, were found to contribute maximum in predicting DON in grains. Before heading period helped in inoculum build up and DON content was positively correlated with rainy days (>5 mm rainfall) and inversely related to daily minimum air temperatures (<10 °C). Post heading period influenced flower infection. Here, DON was positively correlated with number of rainy days and days with relative humidity of over 75 per cent at 11:00 h while it negatively correlated with maximum daily temperature (>32 °C) and average temperature (<12 °C). Number of rainy days exceeding 5 mm per day and temperature below 10 °C, 4–7 days before heading could determine DON in 55 per cent of fields as per following equation.

$$1. \text{DON} = \exp.[-0.30 + 1.84\text{RAIN}_A - 0.43 (\text{RAIN}_A)^2 - 0.56\text{TMIN}] - 0.1.$$

Where, DON = concentration of DON ($\mu\text{g g}^{-1}$),

RAIN_A is the number of days of rain >5 mm day⁻¹ 4–7 days to heading.

TMIN is the number of days of temperatures <10 °C 4 and 7 days before heading.

Weather variables observed from 7 days before heading to 10 days after harvesting could justify DON content in 63–79 per cent of events. The prediction equations involved additional variables of RAIN_B (no. of days of rain >3 mm per day, 3–6 days after heading), RAIN_C (no. of days of more than 3 mm per day 7–10 days after heading) and TMAX (days with more than 32 °C temperature).

If RAIN_B is positive value, then model mentioned in Table 2.4 explains the DON content but, when RAIN_B is 0, then

$$2. \text{DON} = \exp.(-0.84 + 0.78\text{RAIN}_A + 0.40\text{RAIN}_C - 0.42\text{TMIN}) - 0.1.$$

These models could predict with high accuracy in case the DON content remain low to moderate. However, it failed to predict in case of epidemics.

Modification in continuation to above model came as DONcast which was released commercially in Canada (Schaafsma and Hooker 2007). It predicted DON in harvested grains using meteorological variables in five distinct time zones around heading (Z58) instead of three in Hooker et al. (2002). In addition, it also worked in maize for DON and fumonisins. Total rainfall (mm); daily average, minimum, and maximum temperature (°C); and relative humidity are used singly or in combination to make predictions in this model. Wheat variety, crop rotation and tillage were found to influence DONcast predictions. Robustness of this model lied in the fact that it could predict DON across diverse environments. Accuracy of prediction of DON content was as high as 72 and 83 per cent in case the content stayed around 1.0 mg/kg and 2.0 mg/kg, respectively in France, while the corresponding figure for

prediction accuracy in Uruguay were 68.3 and 74.8 per cent, respectively. In Netherlands, DONcast regression equations could predict DON content with an accuracy of 44.7 per cent for the threshold value of 1250 $\mu\text{g}/\text{kg}$ (Franz et al. 2009). Overall, this model could explain DON content with an accuracy of 72 per cent in case the content stayed around 1.0 mg/kg in more than 1000 fields of wheat from four countries over a period of 10 years.

Giroux et al. (2016) in Canada reported two American (De Wolf et al. 2003) and one the Argentinean (Moschini et al. 2001) forecasting models to work accurately, with high sensitivity and specificity under Quebec conditions when the thresholds were adjusted using the results for the ROC curve analyses. Weather-based models predicting FHB incidence and DON in Italy did not work in Canada. DON content (1 ppm) was best crop damage indicator to differentiate epidemics and non-epidemics. The models which captured pre- and post-flowering weather attributes (De Wolf et al. 2003) worked well as compared to ones which used only pre-flowering weather data (Molineros 2007). Thus, flowering stage is the critical point, which if missed can lead to decreased effectiveness of a model (Giroux et al. 2016). All these empirical models predict the infection risks with simple polynomial equations, which are easy to develop and can be used for predicting FHB with adequate accuracy. Higher complexity models means more accuracy but at the cost of difficulty in adaptation to new regions other than for which it has been developed (Prandini et al. 2009; Rossi et al. 2010). DONcast and Hooker prediction models from Canada and Rossi inf and Rossi tox from Italy with prediction sensitivity of 60, 60, 53, and 40 per cent, respectively were not much effective as they would not advocate FHB control even if the weather is favourable for the disease. De Wolf I model from the United States gave sensitivity and specificity of 6.7 and 64.9 per cent, which meant that disease management warnings will be absent despite high risk conditions or control strategies, may be recommended in the absence of disease.

In Belgium, Landschoot et al. (2013) extensively evaluated the performance of five regression techniques (multiple linear regression, ridge regression, regression trees, gradient boosting and support vector machines) and four cross-validation strategies (random K -fold cross-validation, cross-year cross location, cross-year validation, and cross-location validation) to predict *Fusarium* head blight (FHB) in winter wheat. The authors developed procedures to obtain an unbiased performance of the model during its development phase itself, before its actual release thus paving way for robust models which can work in new locations and different years from the years and locations based on which it has been developed. Furthermore, advanced predictive models developed in areas like data mining and machine learning were able to outperform traditional multiple linear regression models to a great extent. In subsequent years, models were developed which correlated air-borne inoculum (macroconidia and ascospores) quantified with TaqMan qPCR assay with FHB infection ($R = 0.84$) and DON content ($R = 0.9$) in the grains (Hellin et al. 2018).

DONcast model developed by Hooker et al. (2002) could not give accurate prediction in most of the cases, when applied in Netherlands. Franz et al. (2009) formulated two prediction models 1 and 2 for DON content for Netherlands agro-climatic conditions by considering 24 days pre- and post-heading dataset in formal

and 6 days around heading in later model. Both the models predicted DON content in mature Dutch winter wheat with high accuracy. Higher DON content was observed when temperature increased from 15 to 25 °C, increase in precipitation from normal and high relative humidity. The disease and DON content in grains reduced if temperature went above 25 °C. Model 1 with coefficient of determination of 0.59 between observed and predicted values and sensitivity of 63 per cent performed better than model 2. The authors also observed high disparity in DON levels in different regions of Netherlands although there was no significant difference in meteorological variables or infection pressure.

A neural network model for prediction of Deoxynivalenol was designed in Czech Republic taking continuous variables of average temperature and total precipitation in April, average temperature and total precipitation 5 days prior to flowering and categorical variable of the preceding crop (Klem et al. 2007). This neural network model gave high correlation ($R^2 = 0.87$) between observed and predicted data.

Weather based mechanistic model for FHB (*F. graminearum* and *F. culmorum*) infection and mycotoxin contamination was developed in Italy, which was applied successfully over a commercial scale as a decision support system (Rossi et al. 2015). The model is based on calculation of daily infection index (FHB-inf) and daily mycotoxin accumulation index in wheat kernels (FHB-tox). The index of infection risk varies between 5 and 35 and the index of accumulation of toxins is generally between 0 and 2. The infection prediction model uses average temperature, number of hours where relative humidity stayed above 80 per cent, total precipitation (in millimeters), and the intensity of rainfall from heading (Z58) until harvest. The model retains cumulative daily FHB-inf and FHB-tox index for each *Fusarium* species till harvesting of the crop. The model was validated in Italy (Rossi et al. 2006) and Netherlands (Camardo Leggieri et al. 2013) with 90 per cent accurate DON predictions, while in Egypt, U. K., Mexico, Hungary and Russia, the prediction accuracy was around 60 per cent (Battilani et al. 2013; Camardo Leggieri 2012; Camardo Leggieri et al. 2011). This FHB model was later included in a Decision support system granoduro.net[®] (Ruggeri 2014), which provides outputs in real time to farmers via a web-based user interface.

In Argentina, *Fusarium graminearum* is the main pathogen associated with fusarium head blight (Carranza et al. 2002). Moschini et al. (2013) reported an empirical model forecasting head blight/deoxynivalenol and its spatial distribution, supported by land and remote sensing data in the Pampas region. The model considered thermal amplitude instead of relative humidity took into comparison the past (1961–1990) and future (2071–2100) climate to train their model.

Two-day periods when rainfall exceeded 0.2 mm and relative humidity remained above 81 per cent on first and 78 per cent on second day, showed high relation with disease incidence ($R^2 = 0.81$). Weather variables and FHB incidence had high correlation starting from 8 days before heading till accumulation of 530 degree days (DD) (Table 2.4).

$$PI\% = 20.37 + 8.63 NP - 0.49 nDD$$

$$R^2 = 0.86$$

With the same data another model was developed that required only maximum and minimum temperature and rainfall.

$$PI\% = -9.15 + 6.47 ND + 0.35 pDD$$

$$R^2 = 0.81$$

Where, *ND* is number of consecutive days with rainfall and thermal amplitude (difference in maximum and minimum temperature) should be less than 7 °C; *pDD* is accumulating residuals of more than 9 °C in minimum temperature, on days when maximum and minimum temperature is less than 25 °C and more than 9 °C, respectively.

Predicted Fusarium index (PFI %) was obtained from (a) and (b)

(a) being observed daily progress of anthesis (% of wheat heads with exposed anthers).

(Anther, values from 0 to 1) and the time in degree days (DD_{12} : daily accumulation of average daily temperature above 12 °C)

$$\text{LogitAnther} = -6.765052912 + 0.136395967 DD_{12} - 0.000694621 DD_{12}^2 + 0.000001384 DD_{12}^3 - 0.000000001 DD_{12}^4$$

(b) Predicted severity (PS %): in controlled environment with conidia exposed to different wetness period and temperature during wetness period.

$$\text{LogitS} = 38.77166158 - 0.53815698 W - 6.02985565 T_W + 26,849,793 T_W^2 - 0.00396097 T_W^3 + 0.04990941 I_1 - 0.00092343 I_2$$

A day with rainfall of at least 0.2 mm and relative humidity of at least 81 per cent is considered for assigning the value of *W*. A single day is represented as $W = 24$ h, while two or three consecutive days means $W = 48$ and 72 h, respectively. T_W depicted temperature during wet day. Final *PFI* % was obtained by adding the partial products between (a) and (b) divided by 100.

As the crop response to FHB varies with genotypes having different ear head characteristics and even the same genotype may respond differently over years under prevailing weather conditions (McMullen et al. 1997). Therefore, availability of regular and precise weather data is the absolute requirement for any model to work accurately (Solis and Flores 2003). Moschini et al. (2013) could successfully use the model for locations lacking meteorological data by substituting the missing weather inputs from satellite and remaining from interpolated weather station data. Rainfall and temperature data, respectively were sourced from Tropical Rainfall Measurement Mission (TRMM, 3B42 product) and climatic zoning based on NOAA-AVHRR images to predict FHB with adequate accuracy.

Nicolau and Fernandes (2012) in Brazil devised a Hierarchical Autoregressive Binary Data Model (HARBDM) to predict daily inoculum levels (spore density), deposition probability of airborne spores of *Gibberella zeae* and probable incidence of FHB. Rainfall and relative humidity positively correlated while sunshine hours were associated negatively with spore prevalence in air. Temperature had weak association with spore incidence.

Several other models have been put to use for farmers through online interactive systems such as Fusarium Risk Tool in USA available at <http://www.wheatscab.psu.edu/>; FusaProg in Switzerland available at <https://www.fusaprog.ch/> (Musa et al. 2007) and [granoduro.net](http://www.horta-srl.com) available through <http://www.horta-srl.com> at <https://www.horta-srl.it/sito/portfolio-item/granoduro-net/> (Rossi et al. 2015).

There are certain inherent shortcomings in modelling data such as variation of DON content in different regions despite having same varietal or weather setup. Since, these cannot be captured while modelling with agronomic and climatic variables, their validation over large areas is non-consistent (Franz et al. 2009).

2.5 Septoria Blight

There are two main pathogens associated with Septoria blotch disease in wheat. *Zymoseptoria tritici* (formerly known as *Mycosphaerella graminicola* or *Septoria tritici*) (*Zt*) is the causal agent of septoria tritici blotch (STB), the primary leaf disease of wheat in temperate wheat growing regions and *Septoria nodorum* (teleomorph: *Leptosphaeria nodorum*) causing septoria nodorum blotch (SNB). This disease has become a major constraint to wheat production, especially in high-rainfall areas. Under high disease pressure, the disease infects upper leaves and ear heads and causes shrivelling of kernels and deteriorates grain quality. Cool temperatures associated with frequent rains favours epidemic development in susceptible cultivars of wheat (Thomas et al. 1989). The optimum temperature for infection is 16 to 21 °C with at least 6 hours of leaf wetness. Latent period of infection for the fungus is 21 to 28 days. The spores are dispersed by rain splashes as they are trapped in sticky masses.

The fungus *Septoria tritici* survives through the summer on residues of a previous wheat crop, other grassy hosts and even wheat seed. The disease process in case of *Zymoseptoria tritici* is more complex due to its latent period and is a relatively less understood pathogen (Orton et al. 2011; Steinberg 2015). It can be as long as 14 days in spring to 28 days in cold weather. In this phase, there are no visible symptoms on plant, despite a compatible reaction between pathogen and host (Orton et al. 2011). The curative azole fungicides used in the blotch management are under constant threat due to resistance development in the pathogen. *Z. tritici* has a high gene flow rate and thus lot of sexual recombinations occur within a planting season in a field (Eriksen et al. 2001).

Alternate host in the vicinity of the crop plays a crucial role in disease development. *Z. tritici* has been reported on 26 grasses Suffer et al. (2011) and one non-graminaceous chickweed. So far, risk associated with presence of alternate hosts is not very clear (Fones and Gurr 2015).

STB cause yield losses ranging from 31% to 53% (Eyal et al. 1987; Polley and Thomas 1991). The incidence of septoria leaf blotch is on the rise for last three decades and they damage around 50 million ha of wheat around the world. STB has been reported to cause EU €280–1200 million losses per annum in Europe (Fones and Gurr 2015) and around AU\$ 100 million, in Australia (Murray and Brennan

2009). The disease is fast spreading in recent years (Milgate et al. 2014). SNB has been reported from France and the Scandinavian countries, but in United Kingdom, SNB has been fully replaced by STB in the 1980s (Bearchell et al. 2005). In Mediterranean region of Tunisia, septoria leaf blotch has been responsible for decreasing yields especially in durum wheat since last four decades (Berraies et al. 2014). Actual losses associated with STB are less clear in other growing regions.

In Nordic-Baltic region, septoria tritici blotch (*Zymoseptoria tritici*) and stagonospora nodorum blotch (*Parastagonospora nodorum*) are present with variable incidence and severity in spring as well as winter wheat. STB dominated winter wheat in Denmark, southern Sweden and Lithuania. SNB dominated spring wheat in Norway with a grain yield loss of 10–11 q/ha (Jalli et al. 2020).

Based on the importance of septoria blotch, several disease prediction models have been formulated which are based on different weather variables (Coakley et al. 1985; Shaw and Royle 1993; Gladders et al. 2001; Pietravalle et al. 2003). The blotch pathogens require free water on leaves to cause infection and frequent rains for disease spread to adjoining plants. Days with rainfall of more than 10 mm or continuous wet days (3 days with at least 1 mm rain) during early growth stages of crop are the main factors which can be used to predicting disease outbreaks (Thomas et al. 1989). Sub zero temperatures has been found to decrease the risk of STB in winter wheats. Since last three decades, decision support systems have been in use which converts complex agro meteorological information relating to disease production in a crop in an easy to understand way.

DSS has been used to reduce pesticide load using Danish system PC-Plant Protection (Secher 1991), available with Danish farmers since 1993. A web based decision support system available as crop protection online (CPO) Rydahl (2003) has been in use in Denmark since 2002. The model uses rainfall data and gives decision on spray requirement based on varietal resistance (Henriksen et al. 2000). Four rainy days with rainfall of 1 mm or more during wheat growth stage 32 in susceptible cultivars and 5 days during GS 37 in resistant cultivars will require spraying to control septoria blotch. SeptoriaSim along with humidity models were refined by Axelsen et al. (2020) which could reduce number of sprays to control septoria blight in farmers' fields along with marginal edge in yield.

Most of the septoria blotch models are weather based but rarely consider the role of crop canopy in development of epidemics. Since, the disease progression in time and space occur through rain splashed pycnidiospores, the crop architecture i.e. distance between leaves (Audsley et al. 2005), plant height (Bannon and Cooke 1998) and resulting microclimate inside the plant canopy should be a key feature of any model that predict disease progression from lower leaves to upper ones during crop growth. Robert et al. (2008) were successful in combining virtual 3D wheat architecture crop model ADEL (Evers et al. 2005) with septoria disease model (Rapilly and Jolivet. 1976) with little modification. This model describes the disease dispersal with lesion development based on spatial advance of crop canopy. The model considered dispersal unit (DU) i.e. spores splashed with rain droplets as the most important factor responsible for disease lesion production and further spore production on this diseased tissue. In ADEL crop simulation model, Phyllochron

proved the major contributor followed by leaf size, stem elongation rate and the internodal length. Three year climate scenario used in this study predicted favourable, intermediate and un-favourable disease development scenario which matched the ground results of disease in Grignon, France. Therefore, this model can efficiently predict blotch disease in case crop ideotype is known.

Beest et al. (2009) in England developed an early warning prediction model to contain septoria blotch at wheat GS 31. They used Window-Pane approach (Pietravalle et al. 2003) to work out the most appropriate relationships between disease and weather at a stage where it is difficult to access the disease physically. The authors took into account the pathogen build up period that will ultimately correlate to disease when weather and crop stage are ideal. Out of three models formulated while taking into account rain and minimum temperature, rain and wind run and vapour pressure and wind run; the former gave the strongest relationship between disease and weather. The total rainfall occurring 80 days prior to GS 31 and minimum temperature above 0 °C in 50 days (Jan-Feb) and maximum temperature below 4 °C (Feb-March) starting from 120 days before GS 31 were found to give accurate disease predictions. The rain and minimum temperature model has two parts Model^e and Model^f as mentioned in Table 2.4.

If Model^e is satisfied then, regression model equation Model^f will give the epidemic prediction, where $p > 0.5$ means epidemic development. For different resistance categories of cultivars, the model was re-structured for resistant cultivar:

$$Model^f : 0.053 \times Rain^d + 0.038 \times T min^e - 6.80 > 0$$

Intermediate cultivar:

$$Model^f : 0.027 \times Rain^d + 0.023 \times T min^e - 3.88 > 0$$

Susceptible cultivar:

$$Model^f : 0.046 \times T min^e - 4.20 > 0$$

^eis the equation of the model to predict an epidemic if the statement is true.

^dis daily rain accumulated is more than 3 mm in an 80 day window preceding GS 31.

^eis daily minimum temperature accumulated >0 °C in a 50-day period starting from 120 days preceding GS 31.

Two Weather based mechanistic models Model A and Model B developed in UK predicted the germination and growth of *Z. tritici* spores on wheat leaves to predict the final disease severity. One spore materialising to one lesion was the underlying principle used for prediction. Model A could differentiate areas with different disease incidence but could not predict severity due to limitations associated with the observed disease and climate data and plant growth parameters including host resistance (Chaloner et al. 2019). This model required high resolution data for climate-derived parameters, such as temperature, rainfall and leaf wetness to predict

accurately. These models could not capture high spore density situations and the following pycniospore infections.

Model B has two further limitations, firstly model B, is parameterized using an experimentally derived thermal performance curve for *Z. tritici*, but the experimental data is restricted to the range 10–22 °C. As this does not cover the entire range of conditions experienced in UK wheat-growing areas, the curve for model B had to be extrapolated. In contrast, the data used to parameterize model A was in the range of 0–30 °C and required less extrapolation. Secondly, the equation in model B did not incorporate the death of spores over time. So, all the spores landing on the leaf remains in the model until it grow and infect the leaf, thereby giving false prediction information. The authors emphasized the inclusion of pathogen biology to increase the fit of the models.

Another mechanistic model, PROCULTURE after GS32 (second node detectable), was developed in Belgium to predict the progress of Septoria leaf blotch on winter wheat in western Europe (Luxembourg). The model could accurately predicted SLB in 2000 and 2002 on susceptible and semi-susceptible varieties with a probability of detection (POD) of more than 0.90 (El Jarroudi et al. 2009). During 2001, the false alarm ratio (FAR) in the model remained high. So, actual disease based on prediction could not be validated although the POD never fell below 0.90. The model however overestimated disease periods by 50 per cent in weakly susceptible cultivars especially on leaves close to flag leaf. Under worst-case scenario or with 7 day forecasted weather data (Global Forecast System, National Centers for Environmental Prediction) the model yielded promising results for predicting disease progress and yield loss even without actual weather data. Junk et al. (2008) got a continuous spatial coverage of the country through amalgamation of PROCULTURE in offline mode to 12-hourly operational weather forecasts from an implementation of the Weather Research and Forecasting (WRF) model for Luxembourg at 1 km resolution. As the WRF model did not provide leaf wetness directly, an artificial neural network (ANN) was used to model this parameter. El Jarroudi et al. (2017b) later modified the model by including Fourier transform method (FTM) for frequency domain analysis of three intra-day meteorological variations of air temperature, humidity and rainfall from 2006 to 2009. The authors found contrasting differences in intraday meteorological variations among two sites which otherwise behaved similarly when compared at diurnal, dekadal and intra-seasonal scales. Fourier-transformed data/methods approach was found to specify the microclimate conditions prevailing at a given site which could help in improving the prediction accuracy of disease forecast models involved in regional warning systems and decision support systems.

In India, Pant et al. (2016) developed models to forecasting spot blotch severity in susceptible and resistant cultivars of wheat under irrigated timely sown (ITS), irrigated late sown (ILS) and rainfed timely sown condition (RFTS) based on maximum temperature, relative humidity and their combination. Lower RMSE value of MLR models at jointing and flowering stage was found to predict disease more accurately than other stages. The significance of maximum spot blotch infection index (asymptote) and minimum time lag (m) has been shown to be influenced

byinteraction between temperature and relative humidity (Viani et al. 2017). Their model depicted decreased dependence of relative humidity duration on spot blotch infection with increase in temperature upto 29 °C while it increases above till 34 °C (Table 2.4).

2.6 Powdery Mildew (PM)

Powdery mildew affects the wheat yield and cause significant economic loss worldwide (Sharma et al. 2004; Strange and Scott 2005). To effectively manage the disease and reduce the dose of chemicals, there is urgent need to forecast the disease in wheat fields accurately. Various prediction models based on weatherfor PM forecasting has been developedby various workers (Daamen and Jorritsma 1990; Holb and Füzi 2016). Some of the important models have been listed in Table 2.5 which indicated that there are several tools to model one or several steps of the *Blumeria graminis* f. sp. *Tritici* (*Bgt*) life cycle. Liu and Shao (1998) demonstrated a strong relationship of temperature, sunshine duration and rainy days the occurrence of disease, and rainfall was the mostcritical factor related to the disease epidemic. A simple approach in this regard was introduced with the disease severity threshold by Kasbohrer et al. (1988). A disease incidence threshold of 70% was identified by Klink (1997) to avoid yield damage. A similar but more complex method based on threshold systems like PC-Plant Protection was developed by Secher et al. (1995).

A local model following the role of temperature and RH for the conidial production and wind speed for the release of conidia of Powdery mildew fungus was developed. An hourly development value of the infection is computed, which adds up for every hour until an exceedance of the value “1” which indicated a successful infection. The similar method is used to calculate incubation (Friedrich 1994; Friedrich 1995a; Friedrich 1995b; Friedrich 1995c).

A decision support system baesd model MIDAS was developed by Jensen and Jensen (1996) for the management of PM in winter wheat. Temperature, humidity and wind are usedin the MIDAS model. In the subsystems, they used deterministic model which further used thermal weeks to show the temporal progression during a wheat growth period. Each thermal week derived from the sums of daily mean air temperature and it represents one timestep. The calculations both for the host’s treatment as well as pathogen development are made for every time step resulting in a disease-level where disease prediction comes close to the observation. Bruns (1996) developed the MEVA-PLUS on the basis of the model MEVA which aimed at the prognosis of the damage due to PM on winter wheat. Bruns (1996) referred to the GEMETA model of Hau (1985). The daily maximum and minimum temperature and the precipitation sum represent the weather in the MEVA-PLUS model. By using the information of monitoring intial infectionthe model run, the implemented GEMETA model and calculates a prognosis of the infestation and calculated the possible damage that can be caused due to the infection and thus developed different crop loss functions. The validation of MEVA-PLUS was done by comparing observed and predicted disease severity values at different plant growth stages. In

Table 2.5 Important models developed for the prediction of powdery mildew

Parameters/models	Specific conditions/ equations	Year	Country	References
Decision support system MIDAS	Temperature, humidity and wind	–	DenMark	Viani et al. (2017)
MEVA-PLUS	Coefficients of determination (R ²) between 0.00002 and 0.796.-	–	–	Chaloner et al. (2019)
WHEat GROwth SIMulation (WHEGROSIM)	$PLA_{Lj} = PLA_{L(j-1)} + (DPLA_{Lj}) \cdot CV \cdot LL_L$ where PLALj is the infected leaf area, PLAL (j-) is the infected leaf area of the foregone timestep, DPLALj is the daily increase of infection, CV is a parameter for the wheat variety and LL _L is the leaf layer	1991–98	Italy	Viani et al. (2017)
Mechanistic simulation model WHEATPEST	Daily temperature and radiation	2008	Europe	Chaloner et al. (2019)
Precipitation, temperature, sun radiation, humidity, and two remotely sensed features including reflectance of red band (Rr)	Spatial distribution and temporal dynamics of the disease	2010–2012	China	Viani et al. (2017)
Wheat growth situation (NDVI), habitat factors (land surface temperature, LST) and meteorological conditions (rainfall and air temperature)	A decision tree was constructed to identify four infection severities (healthy, mild, moderate and severe) R ² = 0.999 with 83.33% forecasting accuracy	2010–11	Michigan, US	Chaloner et al. (2019)
Forecasting models based on meteorological factors and spore concentration	Spore concentration was the most important of all of the variables studied, including weather	2009–2012	China	Cao et al. (2015)
Moderate resolution imaging Spectroradiometer (MODIS) time-series data products	In this model, the wheat areas were identified using 8-day interval normalized difference vegetation index (NDVI) dataset at 250 m resolution	2015	China	Zhao et al. (2018)
Average temperature, average maximum temperature and positive degree days, rainfall and mean wind velocity	Accumulated spore concentration and weather variables	2015	China	Gu et al. (2020)

the start of the season, (Bruns 1996) coefficients of determination (R^2) between 0.00002 and 0.796 was achieved by using this model which decreased with time.

Rossi and Giosuffe (2003) developed a model to predict PM on winter wheat using infection chain. Like the model of Friedrich (1994) this model also requires data on temperature, vapour pressure deficit, rainfall and wind. The disease progress can be predicted by using the following formula based on logistic function:

$$PLAL_j = PLAL_{(j-1)} + (DPLAL_j) \cdot CV \cdot LL_L$$

where $PLAL_j$ (infected leaf area), $PLAL_{(j-1)}$ (infected leaf area of the foregone timestep), $DPLAL_j$ = daily increase of infection, CV = parameter for the wheat variety and LL_L = leaf layer. The daily increase in disease was calculated by a submodel, based on infection chain. They used the model given by Friedrich (1994) as well as WHEat GROwth SIMulation (WHEGROSIM) (Rossi et al. 1997b). The model simulated the disease with a R^2 of 0.89.

The mechanistic simulation model known as WHEATPEST was developed by Willocquet et al. (2008) to know the effects of various pests and pathogens infestations on winter wheat. It needs data on daily temperature and radiation as well as drivers for production situation and for injury profiles. An injury profile was generated from the combined effects of various pests such as fungi, aphids and weeds etc. Like the model InfoCrop given by Aggarwal et al. (2006), the crop yield assessment simulation models needs the actual data on infestation events to calculate the potential crop damage. The model's outputs are the development stage of the crop, the dry biomass, the leaf area index and the expected yield.

Recently many studies are using multispectral and hyperspectral remote sensing data at the leaf or canopy level for the field-based identification investigation of wheat PM, (Zhang et al. 2012; Zhao et al. 2012; Cao et al. 2015).

The meteorological and phenological data are used to predict the disease most of the studies. But the prediction accuracy and timeliness have usually been affected due to lack of sufficient number of weather stations, especially for a large-scale region. The satellite remote sensing technology can help in this regard to quickly acquire wide field and time series images (Dutta et al. 2008). It can facilitate the monitoring and forecasting of the plant diseases over the inefficient, labour-intensive and time-consuming traditional methods. (Nilsson 1995; Franke and Menz 2007; Huang et al. 2007; Bock et al. 2010; Huang et al. 2012). Zhang et al. (2014) integrated meteorological and remote sensing data with crop characters and habitat traits for predicting PM. They constructed a disease-forecasting model using four meteorological factors (precipitation, temperature, radiation and humidity) and remote sensing data [reflectance of red band (R_r) and land surface temperature (LST)] to predict dynamics of the disease over space and time. This integrated model gave a accuracy ranging from 69% to 78% for disease forecasting. Similarly, Zhang et al. (2014) used 9 different remotely sensed variables to develop the powdery mildew forecasting model and Ma et al. (2016) used L and sat 8 remote sensing image and meteorological data to develop the model for predicting PM at filling stage.

So it can be interpreted that there is a great potential for predicting the PM occurrence probability by combining the meteorological and remote sensing data.

Zhao et al. (2018) predicted the disease by using the Moderate Resolution Imaging Spectroradiometer (MODIS) time-series data. The wheat areas were identified using 8-day interval Normalized Difference Vegetation Index (NDVI) dataset at 250 m resolution. A decision tree was constructed to identify four infection severities (healthy, mild, moderate and severe) using three kinds of forecasting factors (wheat growth situation), habitat factors (LST) and meteorological factors (rainfall and temperature). The coefficient of determination (R^2) was 0.999 between the remote sensing based and the statistical data and the overall forecasting accuracy was 83.33%.

Apart from all these, some of the forecasting studies in PM occurrence are based on the dispersal and deposition of conidia, which are further affected by meteorological factors (Granke et al. 2014). Significant correlations were observed between spore concentration and many weather factors (Troutt and Levetin 2001; Burch and Levetin 2002), which are useful in predicting the number of conidia in the air (Bruno et al. 2007). Pakpour et al. (2015) reported a negative correlation between the conidia concentration in the air and rainfall. Cao et al. (2012) monitored air borne conidia of Bgt and analyzed relationships between airborne inoculum with weather variables and disease index. A forecasting model was developed by them in the year 2015 (Cao et al. 2015). They monitored the spore concentrations in air using spore samplers and RT PCR. A positive correlation was found between the temperature, solar radiation and rainfall with conidial concentrations and hence disease development. Although there was a negative correlation between relative humidity and spore concentration, but it was positively related with disease development. Stepwise regression models were obtained for predicting the dynamics of airborne conidia based on the PDD and accumulation of rainfall ($R^2 = 0.31$, $P < 0.01$), the positive degree days ($R^2 = 0.16$, $P = 0.04$) and mean temperatures ($R^2 = 0.24$, $P = 0.01$) at three locations, respectively (Cao et al. 2015).

Recently Gu et al. (2020) also showed that accumulated spore concentration and 10-day temperature variables (average temperature, maximum temperature and PDD) along with rainfall and mean wind velocity. In this model they reported that conidial concentration and weather factors are playing equal role for predicting the development of PM. Disease development is highly influenced by the prevailing microclimate, and hence a crucial factor for disease prediction. It is well known that the regional conditions significantly influence the disease severity (Junk et al. 2016). Therefore, monitoring the dynamics of airborne conidia and meteorological variables are of help to predict the disease and give recommendations for the management of disease.

There have been reports about the negative effect of solar radiation on the development of PM (Liu and Shao 1998; Zahavi et al. 2001; Austin and Wilcox 2012).

2.7 Wheat Blast

Wheat blast is known to be caused by the *Triticum* pathotype of *Magnaporthe oryzae* (MoT). It was first reported in 1985 in Paraná State of Brazil (Igarashi et al. 1986) and further moved into other areas of Brazil and South America from where erratic epidemics have been reported (Urashima et al. 2004; Kohli et al. 2011, Cruz and Valent 2017). Most recently, it has been appeared in Bangladesh demonstrating the threat of global spread via the movement of infected seed or grain. The fungal pathogen affects wheat earheads, with symptoms closely resembling FHB. Wheat blast can cause yield losses as high as 64% and may lead to total crop failure (Goulart et al. 2007). Fungicides are not effective under very severe conditions but can manage the disease when disease levels are low to moderate. Till date no effective source of durable resistance have been found (Cruz and Valent 2017). So disease management requires identification of new resistance sources and a complete understanding of pathogen ecology and disease epidemiology.

As wheat blast is an emerging disease of wheat, hence not many epidemiological studies have been conducted. There are several studies establishing that blast severity varies greatly with weather conditions, cultivar, and plant organ infected (Goulart et al. 2007; Urashima et al. 2009). Continuous rainy and warm weather is necessary for pathogen survival during spring and summer seasons. The production of conidia of *M. grisea* is known to be favored by the combination of high relative humidity ($\geq 90\%$) and temperature around 28 °C (Alves and Fernandes 2006). High temperatures coupled with excessive rain, long and frequent leaf wetness, and poor fungicide efficacy are the major factors favouring the occurrence of disease in severe form (Goulart et al. 2007). Environmental conditions that favour the disease development are similar for MoT, MoO and MoL strains (Anderson et al. 1947; Uddin et al. 2003; Cardoso et al. 2008).

P. oryzae grows better at 21–27 °C and 10–14 h of spike wetness (Ou 1972) hence the temperature and spike wetness are the most important environmental factors affecting the disease development in different hosts.

Cardoso et al. (2008) predicted wheat blast intensity based on the temperatures and the durations of wheat spike wetness under artificial epiphytic conditions using standard methods. The study indicated that temperature (25 and 30 °C) with spike wetness (25 and 40 h alone) can favor wheat blast intensity. The wetting-period data fitted the Gompertz model, and combining the temperature and wetting-period equations as:

$$Z = 0.00108 * (T - 10.0)^{1.8} * ((35.0 - T)^{0.762}) * (0.847 / (1 + \exp(6.498 - 0.348 * HW)))$$

The interaction between the leaf wetness and the average temperature forms the bases of many disease forecasting systems (Zadoks and Schein 1979). The effect of the interactions between temperature and the duration of the wetting-period on infection occurring under our controlled conditions can cause distortions when applied to the field and the accurate prediction under field conditions is difficult (Sutton. 1988). To partially overcome such issue divide the data on the response to infection (daily probability of infection; DPI) values following the procedure of

those models developed by Krause and Massie (1975) and Madden et al. (1978) predicted the disease using a climatic model to develop a table of critical periods containing four arbitrary selected categories of infection efficiency, denominated daily severity values (DSV). A computer program was developed to automatically combine mean temperature values and wetting-period values collected in the field by weather stations and calculates both daily probability of infection (DPI) values and the sum of the DPI (DDPI) values over a specific period. The main limitation of infection-based models as that of Cardoso et al. (2008) lies in the assuming the presence of abundant inoculum during the susceptible period. However, in temperate regions freezing temperatures affect the inoculum production (Farman et al. 2017). Contrastingly, under tropical climatic conditions, inoculum production is limited more by moisture than temperature. So, a model that can predict both inoculum potential (IP) and favorability for infection would have a wider application for predicting wheat blast.

Fernandes et al. (2017) developed a prediction model by using the historical data analysis of epidemics and weather series in Brazil for the period of 10 years. A specific database management application (agroDb) helped to visualize and identify patterns in weather variables during two major outbreaks (2004 and 2009). An IP and a spore cloud (SPOR) variable were estimated to predict inoculum build-up and availability. A day favoring infection (DFI) was conditioned to rules relating temperature and relative humidity for the day derived from the epidemic analysis. Successful daily infection (INF) during a DFI was conditioned to $IP > 30$ and $SPOR > 0.4$. The model was tested at heading date for 10 planting dates, spaced 5 days apart, within a year, totaling 320 simulations. The model described well epidemic and non-epidemics conditions for the historical dataset, and was able to correctly predict.. The CSM-CROPSIM model included in DSSAT 4.6 (Decision Support System for Agrotechnology Transfer) was used to simulate growth and development of spring wheat (cultivar BRS Louro). The model was coded in R statistical and programming language (R CoreTeam2017) and uses Shiny (Chang et al. 2017) for visualizing model outputs (<http://gpca.passofundo.ifsul.edu.br/agroweb>). The model starts by the time of emergence of the first cohort of heads, which is predicted by the wheat model. Three variables are predicted: IP and SPOR are continuous variables and DFI is binary (0, 1).

In the erratic diseases like wheat blast model development and validation is complicated due to the lack of detailed field disease data. Some models have been developed by using the data under controlled conditions. Further refinements and evaluations will require long-term field data. Concludingly high humidity and warm temperatures are more relevant for predicting observed wheat blast outbreaks.

2.8 Conclusions

To prevent the losses in ecofriendly manner in the absence of host plant resistance, the limited and timely application of fungicides as guided by the disease forecasting models plays an important role. In case of wheat various disease forecasting models

have been developed globally by following different methods and using different weather variables along with crop growth stages to predict the disease over space and time. EPIPRE, RUSTDEP, EPIWHEAT, DONCAST, and WHEATPEST etc. are a few. Most of these models are focused on one disease or two and moreover they are designed with regional specificity. So there is a dire need to develop a kind of forecasting system by using the recent advances in information technology or by adopting multi-disciplinary approach, which can deal with multiple diseases of a wheat and should be applicable globally. Based on these prediction models decision support system should be developed for our ultimate beneficiaries i.e. farmers by guiding them when and where to apply the fungicides for successful management of the wheat diseases.

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