COMPARATIVE STUDY OF FORECASTING MODELS FOR STRIPE RUST OF WHEAT

By

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(J-16-D-289-A)

Thesis submitted to Faculty of Postgraduate Studies
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

IN

PLANT PATHOLOGY

Division of Plant Pathology

Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu
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2021

CERTIFICATE-I

This is to certify that the thesis entitled **"Comparative study of forecasting models for stripe rust of wheat"** submitted in partial fulfilment of the requirements for the degree of **Doctor of Philosophy in Agriculture (Plant Pathology)** to the Faculty of Post-Graduate Studies, Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu, is a record of bonafide research carried out by **Ms. Sheikh Saima Khushboo,** Registration No. **J-16-D-289-A** under my supervision and guidance. No part of the thesis has been submitted for any other degree or diploma. It is further certified that such help and assistance received during the course of investigation have been duly acknowledged.

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Acknowledgements

ACKNOWLEDGEMENTS

"In the name of Allah, the most gracious and the most merciful"

All praises to ALLAH and his blessing for the completion of this thesis. I thank ALLAH for all the opportunities, trials and strength that have been showered on me to finish writing the thesis. I experienced so much during this process, not only from the academics aspect but also from the aspect of personality. My humble gratitude to the holy Prophet Muhammad (peace and blessings be upon him) whose way of life has been a continuous guidance for me.

I express my profound gratitude to my honorable guide, ***Dr. Vishal Gupta****, Assistant Professor, Division of Plant Pathology, Sher-e-Kashmir University of Agricultural Sciences and Technology – Jammu. I am very much thankful to him for picking me up as a student in Ph.D. I have been amazingly fortunate to have an advisor who gave me the freedom to explore on my own and at the same time for his unique way of guidance, inspiring help, sustained encouragement, keen interest and care throughout the course of present investigation as well as in the preparation of this manuscript. I could not have imagined having a better advisor and mentor for my Ph.D. study.*

Words are insufficient to express my deep sense of gratitude and sincere thanks to the worthy members of my advisory committee, ***Dr. S.K. Singh****, Associate Professor and Head, Division of Plant Pathology,* ***Dr. Susheel sharma****, Assistant Professor, School of Biotechnology,* ***Dr. P.K. Rai****, Associate Professor, Scientist ACHR and* ***Prof. Hafeez Ahmad****, Professor and Head, Division of Entomology and Dean's Nominee for their constant support, thoughtful guidance and valuable suggestions during the work.*

My sincere thanks to all the teachers of Division of Plant Pathology, ***Prof. Anil Gupta (Retd.)****,* ***Dr. Ranbir Singh Sodhi****,* ***Dr. Sachin Gupta****,* ***Dr. A.K. Singh****. I am also indebted to* ***Prof. V. K. Razdan (Retd.)*** *for his sustained and insightful guidance, constructive suggestions, continuous support and most importantly, he has provided positive encouragement and a warm spirit to finish this thesis.*

I shall fail in my duty if I don't thank the non-teaching staff ***Mr. Mangat Ram****,* ***Mr. Rakesh****,* ***Mrs. Arpana****,* ***Mr. Varun****,* ***Mrs. Sukhbir*** *and* ***Mr. Tilak*** *in Division of Plant Pathology, so their help is duly acknowledged.*

I owe my deepest gratitude towards **Mr. Albasit Mohammad Khalid** *for his eternal support, endless inspiration and for being a continuous source of encouragement in achieving my goals and aspirations. I am grateful for his infallible affection and moral support which has always been my strength during the entire course of work.*

No work can be turned as one man show. It needs the close co-operation of friends. I can hardly overlook the co-operation, timely help, moral support extended by my friends, especially **Mrs. Devanshi, Ms. Aaminah, Ms. Sonali, Ms. Dechan, Mr. Sardar** *for always being around me with a smile and helping hand. I also take this opportunity to thank my Seniors,* **Dr. Kausar, Dr. Saima, Dr. Varsha, Dr. Devendar, Mr. Jagdish** *and my Juniors,* **Ms. Tabasia, Ms. Sonali, Ms. Sneha, Ms. Diskit, Ms. Roohi, Ms. Ramsha, Ms. Dyutima, Ms. Saloni, Mr. Rafakat, Mr. Mohsin, Mr. Amrit, Mr. Jitender** *for their whole hearted support.*

Emotions cannot be verbalized in words to express my love, heartfull reverence, indebtness and deep sense of gratitude to my family. I admire the confidence bestowed on me by my parents, **Mr. Sheikh Ghulam Mohammad** *and* **Mrs. Atiqa Bano**. *This thesis of mine is dedicated to my parents who have been a constant source of love, concern, support and strength all these years. They selflessly encouraged me to explore new directions in life and seek my own destiny. Also I express my special thanks to my loving brothers,* **Mr. Sheikh Sohail Arafat, Mr. Sheikh Suhaib Murtaza, Mr. Sheikh Qayser Rizwan** *and* **Mr. Sheikh Babar Jahanzeb**, *my caring sisters,* **Mrs. Rehana Naaz, Mrs. Rukhsana Naaz, Ms. Sheikh Heena Mursaleen** *and* **Ms. Sheikh Iram Kehkashan**, *my brother-in-laws,* **Mr. Showkat Ahmad** *and* **Syed Asif Iqbal**, *my sister-in-law,* **Mrs. Fehmeeda Akhter** *for their affection and moral advocacy during the periods of distress. I am also thankful to my nephews,* **Syed Khurram Sohrab, Mr. Khushroo Muntaha, Mr. Shehwar Hanan** *and my nieces,* **Ms. Toiba-un-Nissa** *and* **Ms. Shehla Zainab** *for giving me happiness during the course of my studies. Last but not the least, I wish to offer my sincere gratitude towards my Aunty* **Mrs. Muneera Begum**, *who has nourished me with her unconditional love during these years.*

End is inevitable for any kind of work. Though acknowledging is an endless task, I end by saying infinite thanks to all those whom I am able to recall here and also to those whom I might have left unknowingly.

Place : Jammu

Dated: 18.03.2021

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ABSTRACT

Title of Thesis	:	**Comparative study of forecasting models for stripe rust of wheat**
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Name and designation of Major advisor	:	Dr. Vishal Gupta Assistant Professor
Degree to be awarded	:	Ph.D. in Agriculture (Plant Pathology)
Year of award of Degree	:	2021
Name of University	:	Sher-e-Kashmir University of Agricultural Sciences & and Technology, Jammu (J&K)

The investigations were conducted to predict the spatial and temporal changes in the latent period and number of generations of *Puccinia striiformis* f. sp. *tritici* across different prefectures, under four representative concentration pathway emissions scenarios (RCPs) *viz.*, 2.6, 4.5, 6.0 and 8.5 in the three future periods (2020, 2050 and 2080) by using Growing Degree Days (GDD) approach. Daily maximum and minimum temperatures for 2020, 2050 and 2080 were generated from MarkSim® DSSAT weather file generator, whereas, baseline data for the year 1975 of the selected locations were downloaded from Indian Meteorological Department (IMD), Govt. of India. Under the influence of climate change, model outputs exhibited an increase in maximum and minimum temperatures at Jammu, Hisar, Ludhiana, Dhaulakuan and Meerut except for Leh, where maximum and minimum temperatures decreased by ±5.60°C and ±5.85°C, respectively. Maximum reduction of 110, 49, 36, 35 and 40 per cent was observed in the duration of latent period (days) of *Puccinia striiformis* f. sp. *tritici* in Jammu, Hisar, Ludhiana, Dhaulakuan and Meerut, respectively, during 2080 under RCP 8.5 scenario. However, 25 per cent increase was observed in the latent period in Leh. Maximum increase in the number of infection cycles with 49, 27, 20, 21, 24 and 20 per cent were recorded by RCP 6.0 scenario in Jammu, Hisar, Ludhiana, Dhaulakuan, Meerut and Leh, respectively, in three future time periods over the baseline period.

Relationship of meteorological parameters with the onset and progress of stripe rust of wheat was investigated to develop forewarning models by the time series and multiple linear regression. ARIMA $(2,1,1)(1,1,1)_7$ with minimum temperature (°C) and rainfall (mm) with lag 1, adjusted best having maximum accuracy of 96.00 per cent in predicting stripe rust of wheat for short-term period. Severity of stripe rust had highly significant positive correlation (0.89 and 0.91; 0.91 and 0.75) with the maximum and minimum temperatures, whereas, morning relative humidity had significantly negative correlation (-0.84 and -0.80) in 2005-17 and 2017-2019, respectively. Rainfall had non-significant correction with the disease during 2005-17 and 2017-19, respectively. Model *viz.*, $Y = -502.1392 + 0.6373X_1 + 8.5741X_2 + 3.0402X_3 + 1.4227X_4 + 0.5764X_5$ and $Y = 322.5683 + 9.4103X_1 - 4.1446X_2 - 2.5589X_3 - 0.7089 + 0.2609X_5$ were developed by multiple regression for 2005-17 and 2017-2019, and were highly significant in the prediction of stripe rust of wheat. Both the models exhibited that 91 and 89 per cent variation in the disease severity was influenced by the maximum and minimum temperatures, maximum and minimum relative humidity and rainfall. Eighty four per cent increase in spore concentration of *Puccinia striiformis* f. sp. *tritici* was recorded from 51st to 7th SMW (Standard Meteorological Week) during 2017-2019.

Keywords: climate change, prediction, *Puccinia striiformis* f. sp. *tritici*, stripe rust, wheat

Vishal Gupta
Signature of Major Advisor

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Signature of the Student

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Introduction

CHAPTER-1

INTRODUCTION

Stripe (yellow) rust of wheat, caused by *Puccinia striiformis* f. sp. *tritici* is one of the most important disease occurring in most wheat-growing areas of the world with cool and moist weather conditions during the growing season (Tomar *et al*., 2014; Chai *et al*., 2015). This disease has been most widely distributed in cooler wheat growing regions comprising more than 60 countries in the world and has caused severe damage in Central Eastern and Western Asia, Europe, Uganda, Ethopia, Kenya, Australia, New Zealand, North and South America, Mexico and Chile (Wellings, 2011; Chen, 2020). Early infection of the disease on susceptible varieties has resulted in yield losses of up to 100 per cent, whereas it may vary from 10-70 per cent during the epidemics (Chen, 2005; Ali *et al*., 2017). Stripe rust poses a major threat to the farming communities throughout the world because majority of winter wheat cultivars are either susceptible or possess low level of resistance against the disease (Sharma *et al*., 2016). Wheat infection at the seedling stage usually results in reduced root growth, plant height, dry matter production, size and number of flowering spikes and shriveled grains (Wellings, 2011).

In India, during last decades, stripe rust has become more severe and has posed serious menace in the wheat production areas particularly that of northern west plains zone (NWPZ), northern and southern hills zones (NHZ & SHZ) (Prashar *et al*., 2007; Saharan *et al.*, 2013; Bhardwaj *et al*., 2019), covering more than 12.0 million ha, annually. Stripe rust has appeared in severe form in plain areas in Jammu and Kashmir, foot hills of Punjab and Himachal Pradesh, parts of Haryana, *Tarai* region of Uttarakhand (Sharma and Saharan, 2011). During 2007-08, epidemics of stripe rust in northern plains and hills zones was responsible for 25 per cent yield losses with monetary loss of rupees ten thousand million, because the commonly grown mega-cultivar PBW343 succumbed to this disease, signifying the importance of the disease in food security of the nation (Jindal *et al*., 2012).

Epidemics of the stripe rust mainly depend on geographic location, cultivar response, prevailing virulent pathotypes and environmental conditions in the area (Zadoks 1985; Jindal *et al*., 2012). Weather plays a major role in the disease initiation, multiplication and dispersal of the *P*. *striiformis* f. sp. *tritici*. Severe epidemics have usually resulted due to quick and successive five to six disease cycles in a season, during conducive environmental conditions. Under Indian conditions, in the absence of alternate host, the primary inoculum of *P. striiformis* f. sp. *tritici* survives in the form of urediospores, on volunteer plants, summer wheat crop or some other grasses/plants grown on the Himalayan hills and subsequently causes infection to the wheat crop of the northern west plains zone and Indo-Gangetic plains every year.

Change in climate resulting in increased temperature which has acute consequences on plant diseases through exotic incursions of plant pathogens, modification of host phenology, change in geographical distribution of plant pathogens, out-break of aggressive and virulent races, increased over summering and overwintering of plant pathogens, faster dissemination, increased severities, rate of invasion, adaptations, and growth and reproduction of plant pathogens (Luck *et al*., 2011). On an average twenty per cent of yield losses have been reported due to the plant diseases from sowing to post harvest stages which aggravate more (9-16%), due to climate change driven impacts in the important crops such as maize, rice, wheat, barley, potato, soybean, cotton and coffee (Oerke *et al.*, 1994).

Weather based forecasting models are known to reduce the cost of production by optimizing the adequate planning, proper timing and frequency of fungicide applications, which ensures the sustainable production and environmental safety. Quantitative relationship between disease severity and prevailing environmental conditions, temporal distribution and load of inoculums help in predicting the epidemics. Further, short- and long-term changes in prevailing climatic conditions significantly influence the growth and development of rust pathogens (biotropic) which ultimately increase in number of reproductive cycles. Quantification of air-borne inoculum using a weather-based predictive model can be useful for interpreting disease severity models and avoiding over-estimates of disease risk. Keeping in view the importance of the crop, losses caused to it by stripe rust and scanty literature available on the various aspect of disease, especially with reference to Jammu region, it was considered imperative to study the disease with the following objectives:

1. Prediction of *Puccinia striiformis* f. sp. *tritici* under future climate change scenario.

2. Development of weather forecasting model for stripe rust of wheat.

3. To study the quantification and temporal distribution of *Puccinia striiformis* f. sp. *tritici* inoculum.

Chapter-2

Review of Literature

CHAPTER-2

REVIEW OF LITERATURE

History

Although the existence of stripe rust or yellow rust has been there long before human beings started to grow wheat as a staple food, yet the first report on the disease was documented by Gadd in Europe in 1777. In 1794, the epidemic of the stripe rust appeared on rye in Sweden (Singh *et al*., 2002). Severe epidemics of stripe rust all around the world with immense limiting potential of wheat yield, marked with profound economic importance makes it a global disease (Roelfs *et al*., 1992). The first record of yellow rust in the USA was in 1915, but there were no potentially serious outbreaks until 1960s (Line, 2002). Yellow rust first appeared in Eastern Australia in 1979 and then it spread to New Zealand in 1980 (Wellings *et al*., 1987). Yellow rust was reported in South Africa in 1996 and after eight years in Western Australia, a new isolate of the pathogen suggested that it may have been derived from East Africa (Boyd, 2005).

Stripe rust has been more important in areas with cool and wet environmental conditions therefore, it occurs regularly in Northern Europe, the Mediterranean region, Middle East, Western United States, Australia, East African highlands, China, the Indian subcontinent, New Zealand and South America (Danial, 1994; Mamluk *et al*., 1996). However, recent disease outbreaks, in countries closer to the equator, suggested a new level of adaptation of the pathogen (Khanfri *et al*., 2018).

Stripe rust is widely distributed across all continents except Antarctica. Its epidemics have become more frequent in the USA (particularly the Pacific Northwest region of North America), South America, North Africa (Morocco, Algeria and Tunisia), East Africa (Ethiopia and Kenya), East Asia (Northwest and Southwest China), South Asia (India, Pakistan and Nepal), Oceania (Australia and New Zealand), the Nile Valley and Red Sea (Egypt and Yemen), West Asia (Lebanon, Syria, Turkey, Iran, Iraq and Afghanistan), Central Asia (Kazakistan, Uzbekistan, Tajikistan and Turkmenistan), Caucasus (Georgia, Armenia and Azerbaijan) and Europe (UK, Northern and Southern

France, Netherlands, Northern Germany, Denmark, Spain and Sweden) (Solh *et al*., 2012; Sanders, 2018; Waqar *et al.*, 2018). Stripe rust has been reported to be more prevalent in tropical areas of higher altitudes of North Africa, Mexico, Himalayan foothills of India and Pakistan, due to the favourable environmental conditions and cultivation of mega-varieties (McIntosh, 1980).

Transcaucasia is considered as the center of origin for *Puccinia striiformis* f. sp. *tritici* (Hassebrauk, 1965; Stubbs, 1985). Recent studies of *P. striiformis* f. sp. *tritici* populations reported highest levels of genetic diversity and recombinant population structure in Himalayan and near-Himalayan regions which demonstrated the center of origin and diversity for *P. striiformis* f. sp. *tritici* (Ali *et al*., 2014; Thach *et al*., 2016).

India has witnessed several rust epidemics in past several years resulting in heavy yield losses (Barclay, 1892). Mehta (1950) estimated the loss of about ₹ 200 million due to rust of the wheat every year. Nayar *et al*. (1997) reported that both leaf rust and stripe rust occurred each year from 1967 to 1974. Stripe rust is destructive and important in the northern areas of India specially in Punjab, Haryana, Western Uttar Pradesh and Jammu & Kashmir, where frequent epidemics occurred since 1982 (Nagrajan *et al*., 1984). Sporadic high incidence of stripe rust was recorded in some parts of Punjab and in north-western areas (Gangwar *et al*., 2013, 2017).

Losses

Stripe rust of wheat is the most important disease of wheat worldwide and if the disease appeared very early in the growing season, plants usually remain stunted and weakened, causing severe yield losses up to 70 per cent (Khanfri *et al*., 2018). Yield losses caused by stripe rust depends on several factors such as cultivar susceptibility, infection time, rate of disease development, duration of the disease and weather conditions (Chen, 2005). About 90-100 per cent grain yield losses was reported on the occurrence of infection on susceptible cultivars during an early growth stage of the crop which remained for a long time under favourable conditions (Afzal *et al*., 2007). Losses of up to 20 and 75 per cent in wheat were reported in the USA (Doling and Doodson, 1968; Roelfs, 1978). Epidemics of wheat stripe rust occurred in North Africa and the

Middle East in the 1970s (Saari and Prescott, 1985). In Asia, about 46 per cent yield losses were caused due to the epidemics of stripe rust (Singh *et al*., 2004). Epidemics in China (Wan *et al.*, 2004), Pakistan and Iran (Bimb and Johnson, 1997) caused serious yield losses across different wheat growing seasons. Khan and Mumtaz (2004) reported yellow rust epidemic during 1995 on wheat varieties, Pak 81 and Pirsabak 85 and on Inquilab 91 during 2003 in Pakistan. Afzal *et al*. (2007) reported the yield losses of 5.77, 6.63 and 14.90 per cent caused by stripe rust on Inqlab-91, Wafaq-2001 and Bakhtawar, respectively, in Pakistan. Syria and Turkey were most affected countries due to the disease and half of their wheat harvest was lost in 2010, followed by Ethiopia (45%), Morocco and Uzbekistan (35%) (Yahyaoui and Rajaram, 2012).

Losses of ₹ 2 billion were reported during 1997 and 1998 in Pakistan due to progressive increase of virulent pathotypes of *P. striiformis* f. sp. *tritici* (Hussain *et al*., 2004). Losses of nearly $2.25 million were estimated in the 1998 in South Africa (Pretorius, 2004). Ahmed *et al*. (1991) reported $8 million losses in three districts of Baluchistan. In China, a widespread stripe rust epidemic affected about 6.6 million hectares of wheat in 11 provinces during 2001-2002, causing yield loss of 13 million tonnes (Wan *et al*., 2004). Substantial losses were reported between 1999 and 2000 in Central Asia with yield losses from 20 to 40 per cent (Morgounov *et al*., 2004). In Australia, $40 million of fungicides, in 2003, were used to manage the disease (Wellings and Kandel, 2004). The most severe yield losses of 9 million bushels of wheat were recorded in at least 20 states of USA in 2000 (Markell and Milus, 2008). Several yellow rust epidemics have occurred in Turkey in the last decades resulting in more than 10-30 per cent crop losses with an estimated grain loss of 1-2 million tonnes (Aktas and Zencirci, 2016).

Wheat rust epidemics in India have significant impact on the wheat production (Nagarajan and Joshi, 1975). Rust epidemics have occurred during 1843 in Delhi and in 1884 and 1895 at Allahabad, Banaras and Jhansi. Later on, in 1905 rust epidemic was reported in Punjab and sub-mountainous regions of Gorakhpur (Gupta *et al*., 2017a). India has witnessed significant losses of grain yield, generally in northwestern regions, northern foothills and adjacent plains and in the Nilgiri and Pulney hills in the south, due to the cultivation of susceptible cultivars (Joshi, 1976) which are generally attributed to several factors, such as early appearance of the disease, congenial environmental conditions, inoculum load and the grown cultivars (Srivastava *et al*., 1984). Wide spread occurrence of stripe rust was observed during 2008-09 in sub-mountainous districts of Punjab on the widely cultivated wheat variety PBW-343 with disease severity of 60S-80S, resulting in drastic reduction in yield (Jindal *et al.*, 2012).

Present status

Puccinia striiformis f. sp. *tritici* has remained a noteworthy threat in most of the global wheat growing areas, with possibility to impose consistent regional crop damages. It has been an important biotic constraint to winter bread wheat production in Central Asia over the last 15 years (Nazari *et al*., 2008; Ziyaev *et al*., 2011; Sharma *et al*., 2013). Morgounov *et al.* (2012) reported substantial increases in the severity of stripe rust between 2001 and 2010 in Central and West Asia which was responsible for the epidemics in different parts of Central Asia during 2009-2014 (Ziyaev *et al*., 2011; Sharma *et al*., 2013, 2014).

In 2014, the Central Research Institute for Field Crops (CRIFC) in Ankara and the Regional Cereal Rust Research Center (RCRRC) in Izmir reported a new *P. striiformis* f. sp. *tritici* race, “Warrior” in Turkey which was previously identified in the United Kingdom in 2011. Turkish commercial cultivars known to be resistant to the previously characterized races of *P. striiformis* f. sp. *tritici* succumbed to this new race (Khanfri *et al*., 2018). The “Warrior” was present in high frequencies in most European countries and North Africa (Mert *et al*., 2016) and also in Morocco in 2013 and Algeria in 2014, with relatively higher genetic diversity than other previously documented races of *P. striiformis* f. sp. *tritici* (Hovmoller *et al*., 2016).

Life Cycle

Puccinia striiformis f. sp. *tritici* belongs to the family Pucciniaceae within the order Pucciniales (Hibbett *et al*., 2007), obligate biotrophic fungi (Voegele *et al*., 2009) highly diverse with respect to host preference and number of spore stages within the life cycle (Vander *et al*., 2007; Liu and Hambleton, 2010). Life cycle of *P. striiformis* f. sp.

tritici has remained a mystery for more than a hundred years, it requires two taxonomically unrelated hosts and it alternates between a graminaceous host for asexual reproduction and barberry where sexual reproduction may occur (Jin *et al*., 2010; Berlin *et al*., 2017) and includes five types of different spores (Schwessinger, 2017). Urediniospores and teliospores of the fungus are dikaryotic, whereas, teliospores produce haploid basidiospores (Chen, 2005). The diakaryotic phase of the life cycle is confined to the primary host (wheat), upon which urediniospores, teliospores and basidiospores are produced. As the nutrient supply in the infected tissues declines, the telial stage is initiated. Teliospores overwinter on residual senesced tissues and germinate on the following spring to produce four haploid basidiospores. The fungus does not have any known alternate hosts for the basidiospores to infect, and thus, it does not have any known pycnial and aecial stages (Stubbs, 1985). However, recently, pycnial and aecial spore stages of the fungus has been identified on *Berberis* spp. (*B. chinensis*, *B. holstii*, *B. koreana* and *B. vulgaris*), that serve as alternate hosts for the *P. striiformis* f. sp. *tritici* (Jin *et al*., 2010).

Infection process

An accurate description of how stripe rust fungus infects its hosts has been given by Cartwright and Russell (1981) by using the fluorescence microscopy. They observed the entering of urediniospores of the *P. striiformis* f. sp. *tritici* in the leaf through stomata. Urediniospores are mainly responsible for the initiation and spread of the disease (Chen, 2005; Bux *et al*., 2012). After urediniospores adhere to the surface of wheat leaf with optimum temperature and humidity condition, germ tube is produced which grows towards stoma initiating primary infection in the stomatal cavity (Ma and Shang, 2009; Sorensen, 2012). After the germ tube produces an appressorium, the plant is invaded through the stomata and the fungus differentiates a series of infection structures, the substomatal vesicle, primary infection hypha, haustorial mother cell, and finally a haustorium. In the secondary infection, excessive network of mycelium is formed in the mesophyll layer within the mesophyll tissue and form nutrient-absorbing haustoria, which are localized between the host cell wall and the plasma membrane. Taking up nutrients from its host through haustoria, the fungus forms sporogenic tissue, the uredinium, near the surface of the leaf and produces urediniospores, completing the asexual life cycle (Voegele *et al*., 2001; Kang *et al*., 2002; Wang *et al*., 2010; Zhang *et al*., 2012; Jiao *et al*., 2017). Approximately one week after the infection, chlorotic spots appear at the leaf surface, sporulation starts and the distinctive yellow streaks appear on leaf (Chen, 2005; Sorensen, 2012). Optimum temperature for germination of the spores is 10-12°C. High temperature inhibits sporulation or forces the fungus to enter into dormancy. Under optimum conditions, the time between inoculation and sporulation is 12-13 days (Line, 2002).

Symptoms

All growth stages of the wheat crop are susceptible to the infection by *P. striiformis* f. sp. *tritici* (Line, 2002). Initial symptoms of stripe rust appear about one week after infection, as small, yellow spots or flecks on the leaf sheaths. These spots develop into long and narrow stripes on leaf sheaths, glumes and awns. Mature pustule break open and release yellow-orange masses of urediniospores (Khanfri *et al*., 2018). The infected tissues may become brown and dry when plants begin to senescence or become stressed. These spores have the ability of rapid germination in presence of moisture along with optimum temperature of 7 to 12°C (Waqar *et al*., 2018). The pathogen reduces plant vigour by confiscating plant nutrients and water and results in desiccation of leaves. Severe early infection can result in stunted plant (Line, 2002; Chen, 2005; Singh *et al*., 2017). With an increase in temperature or through the late growth phases of the host, urediniospore production is usually followed by two-celled, dark brown, thick walled black teliospores which infect barberry (*Berberis* spp.) leaves and produce pycnia on the upper surface and aecia on the lower surface. Oregon grape (*Mahonia aquifolium*), also act as alternate host for *P. striiformis* f. sp. *tritici* in which pycnia and aecia are produced on the upper and lower side of leaves, respectively (Wang and Chen, 2013; Khanfri *et al*., 2018).

Weather Conditions for disease development

With the presence of pathogen inoculum and susceptible host, the development of stripe rust depends on weather conditions such as moisture, temperature and wind (Chen, 2005). Spore germination, infection, dispersal and survival of *P. striiformis* f. sp. *tritici*, are directly affected by moisture. Continuous moisture for three hours is required for urediniospores germination and infection (Rapilly, 1979). A relative humidity near to saturation before inoculation increases rates of spore germination considerably (Line, 2002). Precipitation, especially light rains provide encouraging conditions for infection. However, high moisture affects viability of spores which lack the ability to cause and spread of the disease. Individual or cluster dispersal of urediniospores also depends on the relative humidity (Chen, 2005).

Temperature also influences the germination, infection and survival of spores. Temperature range of 2.8-21.7°C is capable of *P. striiformis* f. sp. *tritici* germination, however, 10-12°C is suitable for their faster germination (Line, 2002), although the minimum and maximum temperature requirements for the growth of the pathogen are 3 and 20°C, respectively (Sharp, 1965; Tollenaar and Houston, 1966; Stubbs, 1967; Roelfs *et al*., 1992; Line, 2002). The latent period varies among isolates and can be 11 days at optimum conditions and 180 days at near freezing (Sharp and Hehn, 1963; Roelfs *et al*., 1992; Bux *et al*., 2012). Lower temperatures adversely affect survival of the pathogen and further development could be stopped below at -10°C (Chen, 2005). Temperatures above 30°C limit pathogen development and survival. Infections are more likely to occur at night, where both dew formation and cool temperatures occur together (Sorensen, 2012; Khanfri *et al*., 2018).

Quantification and distribution of inoculum

Molecular methods, especially the polymerase chain reaction (PCR), have been developed in the last decades for specific, sensitive and rapid detection of several plant pathogenic fungi such as *Phytophthora nicotianae* (Lacourt and Duncan, 1997; Grote *et al*., 2002; Ippolito *et al*., 2002), *Phytophthora infestans* (Judelson and Tooley, 2000), *Phytophthora parasitica* (Goodwin *et al*., 1990), *Fusarium solani* (Li and Hartman, 2003), *Phakopsora pachyrhizi* (Frederick *et al*., 2002), *Colletotrichum gloeosporioides* (Mills *et al*., 1992) and *Leptosphaeria korrae* (Tisserat *et al*., 1991).

Puccinia striiformis f. sp. *tritici* causes stripe rust of wheat, a devastating disease with worldwide distribution (Zadoks, 1961; O'Brien *et al*., 1980; Li and Zeng, 2002; Line, 2002; Viljanen-Rollinson *et al*., 2002). At the end of the growing season, large numbers of urediniospores can be produced and blown away from contaminated fields. Although most urediniospores are deposited near their source (Roelfs and Martell, 1984), some can be dispersed over considerable distances by the wind (Hirst and Hurst, 1967). *P. striiformis* f. sp. *tritici* being an obligate biotroph, is difficult to culture on artificial media, therefore, a PCR-based technique would be very useful for its detection in host tissues (Aggarwal *et al*., 2018). Molecular methods, especially real-time PCR with species-specific primers, offer several advantages over microscopic spore counting, (West *et al*., 2008; West and Kimber, 2015).

Dispersal of airborne inoculum from the source and after deposition on a crop is a complex process which is influenced by wind direction and turbulence (McCartney and Fitt, 1998; Aylor, 1999, 2003; McCartney and West, 2007). Recent developments in molecular biology, however, have made it easier to estimate spore concentration above the canopy of wheat fields which could help in predicting epidemics more accurately, where disease severity is influenced by timing or amount of inoculum (West *et al*., 2008). Spore traps, combined with inoculum detection and real-time PCR assays, are being increasingly used to quantify the airborne inoculum of plant pathogens and to improve precision in disease risk management and fungicide applications (Luo *et al*., 2007; Rogers *et al*., 2009; Dedeurwaerder *et al*., 2011; Duvivier *et al*., 2013, 2016; Wieczorek and Jørgensen, 2013; Almquist and Wallenhammar, 2014; Chandelier *et al*., 2014)

Pan *et al*. (2010) established a real-time polymerase chain reaction (PCR) assay to quantify the inoculum level of *P. striiformis* f. sp. *tritici* in leaves by quantifying the latent infection levels and estimating potential disease intensity in the field. By targeting latent infection foci with fungicide applications, the initial inoculum could be effectively lessened, reducing the build-up of rust epidemic (Yan *et al*., 2012).

Air-sampling devices, such as the Burkard 7-day volumetric trap (Hirst-type) have been routinely used to collect airborne particles such as pollen and fungal spores. The particles adhere onto a wax coating on a transparent plastic film attached to a supporting surface. Traditionally, the wax-coated film is mounted as a microscope slide and particles of interest attached identified and counted (Sutton and Jones, 1979; Xu *et al*., 1995; Trapero-Casas *et al*., 1996; Blanco *et al*., 2004; Khan *et al*., 2009; Cao *et al*., 2012). These air samplers, combined with inoculums detection using PCR assays or microscopy observations, have been used to study the density of airborne inoculums of various plant pathogens (Calderon *et al*., 2002; Holb *et al*., 2004; Luo *et al*., 2007; Rogers *et al*., 2009; Fountaine *et al*., 2010). The accuracy and sensitivity of the real-time PCR method compared with that of microscopy observation to investigate the development of epidemics in crops had already been demonstrated by Fraaije *et al*. (2005); Luo *et al*. (2007); Rogers *et al*. (2009) and Fountaine *et al*. (2010). Fraaije *et al*. (2005) used a specific real-time PCR assay to study the role of ascospores in the spread of quinine-outside inhibitors (QoI) resistance strains in *Mycosphaerella graminicola*. They observed that the frequency of R-allele increased from 35-80 per cent in first spray and up to 95 per cent in second spray in QoI treated fields.

Schweigkofler *et al*. (2004) studied Real-time PCR to detect the presence of *Fusarium circinatum* inoculum in the air causing pine pitch canker in *Pinus radiata* (Monterey pine). They observed that the liners correlation between threshold cycle (Ct) and DNA concentration from 10^1 to 10^4 pg and 10^2 to 10^5 spores/100 µl, and the lower reliable detection threshold was 10 pg or 10^2 spores/100 µl for *F. circinatum* which demonstrated that species-specific real-time PCR amplification can improve spore detection significantly compared to more traditional approaches.

Real-Time qPCR assay was conducted to quantify the inoculum of *Verticillium dahlia*, causal organism of Verticillium wilt in olive, a serious disease in the Mediterranean countries and worldwide. Defoliating D and non-defoliating ND strains of *V. dahlia* were present at a significantly higher level in Amfissis (susceptible cultivar) than in Kalamon and Koroneiki (tolerant cultivars). Relative amount of the pathogen in roots was lower than in stems and shoots which further declined in plant tissues over time (Markakis *et al*., 2009).

The airborne inoculum of *Sclerotinia sclerotiorum* responsible for Sclerotinia stem rot (SSR) was quantified for disease-forecasting at Rothamsted in England by a

SYBR-green quantitative PCR (qPCR). A linear relationship was found between ascospore numbers and *S. sclerotiorum* DNA ($R^2 = 0{\cdot}76$, $P < 0{\cdot}001$) with mean 0·35 pg DNA per spore, whereas, no relationship between rainfall and numbers of airborne ascospores of *S. sclerotiorum* were observed during the severe period of infection in 2007 as large numbers of airborne ascospores were detected when the recorded daily rainfall was < 0·2 mm (Rogers *et al*., 2009)

Carisse *et al*. (2009) demonstrated that qPCR assay was reliable for quantifying *Botrytis squamosa*, airborne inoculum in commercial onion fields and molecular conidia quantification could be used as a component of a risk management system for Botrytis leaf blight. A linear relationship was observed between numbers of conidia counted with a compound microscope and those determined with the qPCR assay by using receiver operating characteristic curve (ROC) analysis. The results further showed that the area under curves (AUCs) were significantly higher for the TaqMan qPCR assay with AUC = 0.94 and 0.95 than for the microscope counts with AUC = 0.85 and 0.84 with $P = 0.0029$ and 0.0016 for damage threshold (Dth) = 5 and 10 lesions/leaf, respectively.

A real-time polymerase chain reaction (PCR) assay was applied to quantify the level of latent infection of stripe rust of wheat in Gangu and Shangzhuang, China (Yan *et al*., 2012). The computer software SURFER showed that the spatial distribution patterns of molecular disease index (MDX) had a linear relationship with disease indices (DX) in field plots (P=0.01). Application of triadimefon fungicide on the detected latent infection foci reduced both the initial inoculum and disease development, resulting in an average reduction of disease area (73-81 per cent).

Mean daily quantities of airborne inoculum of *Mycosphaerella graminicola*, causative agent of spot blotch in wheat was up to 60.7 cDNA by real-time PCR during the stem elongation and flowering stages, which contribute to the infection of upper leaves later in the season (Duivier *et al*., 2013).

Klosterman *et al*. (2014) performed real-time quantitative polymerase chain reaction (qPCR) assay for detection of airborne inoculum of *Peronospora effuse*, causing downy mildew of spinach (*Spinacia oleracea*) in California. Significant correlation (R^2 =

0.7603) was observed between DNA copy number of *P. effuse* derived from a standard curve of the amplification of rDNA and counts of spores obtained from light microscopy.

Meitz-Hopkins *et al*. (2014) studied molecular detection and quantification of ascospore discharge of *Venturia inaequalis* and the use of this method for orchard sanitation treatments by using volumetric spore traps (VSTs). Primary inoculum was estimated to be 51 per cent lower in the orchard sections where leaves had been removed using the *CYP51A1* primer pair for amplification of genomic regions of the mitochondrial *CYP51A1* gene which indicated that this method could be used to evaluate the efficacy of alternative control strategies such as leaf removal to reduce potential ascospore dose.

Quantification of inoculum of Canola seedling blight caused by *Rhizoctonia solani* and *Fusarium* spp. which resulted in large yield losses to canola (*Brassica napus*) was studied by Zhou *et al.* (2014). They found that from a conventional PCR amplification, an 88-bp product was amplified from all isolates classified as AG-2-1 with the primers Rs21F and Rs21R and no product was amplified with DNA from isolates belonging to other anastomosis groups of *R. solani*. A high correlation for both *R. solani* AG-2-1 and *F. avenaceum* ($R^2 = 0.93$ and $R^2 = 0.92$, respectively) was observed between the quantity of DNA from soil samples with different inoculum densities estimated using qPCR and the number of colony-forming units (cfu) obtained from the same soil samples.

Cao *et al.* (2016) quantified the air-borne inoculum of *Blumeria graminis* f. sp. *Tritici* (*Bgt*) using Burkard 7-day spore traps in Langfang City, Hebei Province, China. They found significant correlation ($R^2 = 0.99$) in air with $P < 0.01$ between spore concentrations of *Bgt* by compound microscope and the real-time PCR assay.

Duvivier *et al.* (2016) studied the real-time PCR quantification and spatio-temporal distribution of airborne inoculum of *Puccinia triticina* in Belgium and observed that the mean daily quantities of airborne inoculum were 0–131.4 spores/day during the stem elongation (GS30) to the flag leaf stage (GS39). Rainfall in late summer and autumn, whereas, mean minimum temperature in winter positively influence ($R^2 = 0.73$) the spore density.

Lastra *et al*. (2018) developed a new TaqMan real-time polymerase chain reaction (qPCR) to detect and quantify the soil-borne fungus *Fusarium solani*, in plant and soil samples of strawberry. They observed a linear relationship (R^2=0.994) between DNA concentration of *F. solani* in plants and quantification cycles (Ct) in the qPCR reactions using the designed primers and TaqMan probe. They also found a significant correlation (P=0.0002) between the amount of genomic DNA of *F. solani* detected by qPCR and the number of fungal propagules present in artificially inoculated soils. Based on the results and observations, this novel qPCR assay represented a useful tool for rapid assessment of pre-planting soils and nursery plants to prevent *F. solani* infection and production losses.

TaqMan PCR assays for quantification of *Neofabraea* spp. (*N. alba* and *N. perennans*) and *Cadophora* spp. (*C. malorum* and *C. luteo-olivacea*), causing post-harvest diseases of apple and pear, were developed by Kohl *et al*. (2018). They found that *N. alba* was detected in 73 per cent samples of apple orchards and 48 per cent from pear orchards. On the other hand, *C. luteo-olivacea* was detected in 99 per cent from apple orchards and 93 per cent from pear orchards. *N. perennans* was present in a few samples and *C. malorum* was not detected in any sample. They further observed that in apple orchards the colonization by pathogens decreased from April until August and increased from September until December, but this pattern was less pronounced in pear. Therefore, knowledge on population dynamics is essential for the development of preventative measures to reduce risks of fruit infections during the growing season.

Both conventional and quantitative PCR techniques (cPCR and qPCR) were used by Gadaga *et al.* (2018) for the detection and quantification of *Colletotrichum lindemuthianum*, causal agent of anthracnose in common bean seeds. They observed that the efficiency of the qPCR was of 1.03, as determined by the linear regression equation, with the mean values of the corresponding amplifications (r^2 = 0.99). Therefore, it was found that the qPCR technique was more sensitive than the cPCR one.

Moein *et al*. (2019) quantified oomycete of apple pathogens by real-time quantitative PCR (qPCR). *Pythium sylvaticum*, *Pythium irregulare*, *Pythium ultimum*, *P. vexans* and *Phytophthora cactorum* were quantified in artificially (glasshouse) inoculated apple seedlings roots and *P. irregulare* from naturally (nursery) infected nursery tree roots. They correlated the relative and absolute pathogen DNA quantities in infected glasshouse seedling roots and nursery tree roots with percent roots infect and found that both trials significantly negatively correlated (r = -0.569 to -0.684; P = 0.001 to 0.009 and r = -0.589 to -0.701; P = 0.0001 to 0.006, respectively) with the increase in seedling length for *P. sylvaticum*, *P. vexans* and *P. ultimum* infected seedlings, however, this was not true for *P. cactorum* (r = -0.057 and 0.067; P = 0.812 and 0.780) and *P. irregulare* (r = -0.443 and -0.415; P = 0.058 and 0.078). The percent infected roots also had a significantly negative correlation (r = -0.515 to -0.725; P = < 0.0001 to 0.010) with increase in seedling length for *P. sylvaticum*, *P. vexans* and *P. ultimum* and *P. irregulare*, but not for *P. cactorum* (r = -0.398; P = 0.054).

Development of weather forecasting models

Among the different abiotic factors, temperature and moisture are the major limiting factors for the development of stripe rust epidemics and have been used to develop forecasting models for the disease (Sharma-Poudyal and Chen, 2011). Various weather forecasting models have been developed for the management of many plant diseases (James, 1974; Zadoks, 1984; Coakley *et al*., 1985; Hardwick, 1998; Xu, 1999; Audsley *et al*., 2005; De Wolf *et al*., 2003; Savary *et al*., 2006; De Wolf and Isard, 2007) including stripe rust (Coakley and Line, 1981; Coakley *et al*., 1988; Line, 2002).

Prediction model is based on the relationship between the environmental conditions and the severity of the disease (Kaundal *et al*. 2006). Forecasting systems for the plant diseases have been developed to reduce uses of fungicide or make its judicious use. An accurate prediction is crucial for properly application of disease control measures in order to avoid crop losses and over application of fungicide. Such system not only reduces the cost of production but also promote the environmental safety for the operator and consumers by reducing chemical usage (Malicdem and Fernandez, 2015).

Temperature has the most profound effect on the life cycle of *P. striiformis* f. sp. *tritici*, influencing its survival, dispersal, infection, latent period and sporulation, therefore, has been used to develop forecasting models for stripe rust (Coakley and Line, 1981, 1982, 1988; Madden *et al*., 2007). Time series models have long been of interest as they are used to predict epidemiological behaviours of the plant diseases by modeling historical surveillance data (Zhang *et al*., 2014).

The multiple regression models, autoregressive integrated moving average (ARIMA) model and artificial neural network (ANN) architecture have been widely used for forecasting yield as well as pests of different crops (Agarawal and Mehta, 2007; Kumari *et al*., 2013, 2014, 2016, 2017). Multiple linear regressions (MLR) are explanatory model and more suitable to short term or intermediate term forecasting (Varmola *et al*., 2004; Chauhan *et al*., 2009). ARIMA model (Box and Jenkins, 1970) is a forecasting technique that projects the future values of a series based entirely on its own inertia and work best when data exhibits a stable or consistent pattern overtime with a minimum amount of outliers (Gorantiwar *et al*., 2011; Kumar *et al*., 2013; Kumari *et al*., 2017)

Stepwise multiple regression computer programme was performed to generate epidemic prediction model for wheat leaf rust caused by *P. triticina* by incorporating weekly urediospores numbers, cumulative urediospore numbers, average maximum and minimum temperatures and hours of free moisture (dew, rain per day and days of precipitation). The developed multiple regression model observed a variation of over 70 per cent in actual and predicted disease severity. Minimum temperature was responsible for the variation in severity and inclusion of precipitation increased the accuracy (Eversmeyer and Burleigh, 1969).

Khan and Trevathan (1999) developed multiple regression models used for forecasting leaf rust caused by *Puccinia triticina* in wheat and found a linear relationship between minimum temperature (12 to 18^{o}C) and relative humidity (70 to 85%) having coefficient of determination (R^2) of more than 0.90 for the development of disease.

Forecasting models have also been developed for prediction of stripe rust of wheat (Coakley and Line, 1981; Coakley *et al*., 1988; Line, 2002). The relationships between temperature and stripe rust epidemics on winter wheat were quantified by Coakley and Line (1981) during 1963 to 1979 and found significant correlation between stripe rust disease index and cumulative negative (December 1 to January 31) and positive degree days (April 1 to June 30). Coakley *et al*. (1982) used these weather descriptors to develop simple linear regression models for predicting stripe rust disease severity for the Pullman area which were further extended to other locations in the Pacific Northwest (PNW). Predictive models with multiple regression approach were developed to estimate disease intensity by analyzing temperature and other meteorological factors such as the amount and frequency of precipitation from 1968 to 1986 at Pullman, Washington (Coakley *et al*. 1988). However, the simple linear models based on negative and positive degree days have been used mostly in forecasting for stripe rust in the PNW (Line, 2002; Chen, 2005). Another forecasting models for stripe rust disease severity with logistic regression approach was developed by Eddy (2009) based on relative humidity (>87%), leaf wetness duration and mean relative humidity that predicted infection with 93, 80 and 76 per cent accuracy, respectively.

The roles of ascospores and condia are very crucial for the life cycle and forecasting the severity of leaf spot in rape seed oil crop (*Brassica napus*) caused by *Pyrenopeziza brassicae* (Gilles *et al*., 2000). They noticed that epidemics was initiated primarily by ascospores produced from apothecia that survived on the infected debris during summer, while in winters the epidemic was commenced by rain splashed conidia that spread the disease from foci to the main crop.

Uddin *et al.* (2003) developed a prediction model for gray leaf spot caused by *Pyricularia grisea* of perennial ryegrass turf based on four different temperatures (20, 24, 28 and 30^{o}C) and leaf wetness duration (3 to 36h at 3h interval), and observed that disease severity increased with the increase in leaf wetness duration at each selected temperature. Low disease incidence was observed at 20^{o}C with leaf wetness duration of 3 to 9h which increased with 12 to 18 hours wetness duration and attained maximum severity (57%) at 36 hours of wetness duration at 28^{o}C. Thus, they found that increase in temperature from 20 to 32^{o}C with leaf wetness duration of 3 to 6h resulted in an increase in disease incidence but decreased with increase in leaf wetness duration (> 21h).

Paul and Munkvold (2005) combined regression and artificial neural network (ANN) modeling approaches to develop models to predict the severity of gray leaf spot of maize, caused by *Cercospora zeae-maydis*. They revealed that the best ANN models (A1, A2, A3, A5, A6, and A10) had R^2 ranging from 0.70 to 0.75 and MSE ranging from 174.7 to 202.8. The daily temperatures between 22 and 30°C (85.50 to 230.50h) and hours of nightly relative humidity ≥90 per cent (122 to 330h) were found to be the most valuable predictors for forecasting the onset of the grey leaf spot disease.

Kaundal *et al*. (2006) developed the prediction of disease severity of rice blast by support vector machine (SVM) which was better than multiple regression (REG), back-propagation neural network (BPNN) and generalized regression neural network (GRNN).Conventional multiple regression (REG) approach exhibited correlation coefficient (*r*) of 0.50 and per cent mean absolute error (per cent MAE) of 65.42 for the relationship between disease severity and its associated environmental conditions (minimum temperature, maximum temperature minimum relative humidity, maximum relative humidity and rainfall), whereas, back-propagation neural network (BPNN) showed better correlation coefficient (*r*) of 0.60 and per cent mean absolute error (per cent MAE) of 52.24. With generalized regression neural network (GRNN), the *r* increased to 0.70 and per cent MAE also improved to 46.30, which further increased by support vector machine (SVM) based method having $r = 0.77$ and per cent MAE = 36.66. Similarly, in cross-location validation of rice blast severity, correlation coefficient (*r*) of 0.48, 0.56 and 0.66 were recorded for REG, BPNN and GRNN, respectively, with their corresponding per cent MAE as 77.54, 66.11 and 58.26. The SVM-based method out performed all the three approaches by further increasing *r* to 0.74 with improvement in per cent MAE to 44.12.

Statistical methods like multiple stepwise regression, principal component analysis and partial least-square regression were explored to calculate and estimate the disease severity of rice brown spot caused by *Bipolaris oryzae* (Zhan-yu *et al*., 2007). The root mean square errors (RMSEs) for training ($n = 210$) and testing ($n = 53$) dataset were 6.5 and 5.8 per cent, respectively. The partial least-square regression with seven extracted factors could most effectively predict disease severity compared with other statistical methods with RMSEs of 4.1 per cent and 2.0 per cent for the training and testing dataset, respectively, where as principal component analysis showed approximately 80 per cent of the variance of the original hyperspectral reflectance.

The multiple correlation and regression analyses of the weather data during 1991-2001 in Coimbatore was conducted with the downy mildew of pearl millet caused by *Sclerospora graminicola* (Krishaveni *et al*., 2008). They observed a positive correlation value of 0.7566 and regression value of 0.73 (at 5% level of significance) between average rainfall (55.3 mm) and average minimum temperature (21.4^{o}C). They further inferred that rainfall (avg. 45.3 mm) and minimum temperature (20.8^{o}C) during the vegetative phase (30 days after the sowing) were favourable for the maximum incidence of the disease.

Various meteorological variables were assessed to develop regression equations for predictions of wheat leaf rust caused by *Puccinia triticina* at Bahawalpur and Faislabad during 2002 to 2007 (Jamshed *et al.,* 2008). They reported that relative humidity along with total precipitation were critical for the onset of leaf rust having coefficient of determination (R^2) of more than 0.75. Further, comparison of different models revealed that regression model with maximum temperature (15-22^{o}C) and average relative humidity (>60%), was best suited for forecasting the leaf rust severity.

Te Beest *et al*. (2009) developed early warning weather-based prediction model for Septoria leaf blotch of wheat caused by *Mycospharella graminicola* in which the accumulated rainfall of more than 3 mm in 80-day period along with minimum base temperature (0^{o}C) in 50-day period preceding growth stage (GS31) extremely favoured the development of disease. The developed disease model had a run-length of 3 window-pane with low misclassification value (<0.20), a positive proportion value of 0.61, specificity of 0.18 along with sensitivity value of 0.83 which indicated its good predictive value.

The 14 years of meteorological data (1991 to 2004) was analyzed by Sharma *et al*. (2010) to study the epidemiology of Kernel smut caused by *Tilletia barclayana* of rice. They found positive correlation of 0.24 and 0.22 for maximum temperature (33.5^{o}C) and sunshine duration (7.5h) respectively, with the disease intensity during 33rd standard meteorological week. They further revealed that high temperature during day time coupled with bright sunshine hours favoured the formation and multiplication of sporidia, whereas, other weather variables *viz*., rainfall and number of rainy days showed least impact on the development of the disease.

Maximum (34°C) and minimum temperatures (26°C) along with maximum relative humidity (>90%) were favourable for the spread of rice sheath blight caused by *Rizoctonia solani*. High coefficient of determination (R^2) of 0.80 per cent significantly validated the model (Biswas *et al*., 2011).

Sharma-Poudyal and Chen (2011) developed models for predicting potential yield loss by conducting correlation and regression analyses of weather parameters and yield loss data from 1993 to 2007 for winter wheat and 1995 to 2007 for spring wheat. They observed that in winter wheat the sum of daily temperatures and accumulated negative degree days were significantly correlated to yield loss (55.9 to 87.6%), whereas, in spring wheat, it was 34.9 to 64 per cent to rainfall days.

Fernández-González *et al*. (2012) forecasted ARIMA models for atmospheric vineyard pathogens, *Botrytis cinerea* spores in two vineyards, one located in Cenlle (Spain) and other in Amares (Portugal), from 2005-2007. During the grapevine cycle the highest total spore concentrations were recorded in 2007 in both locations i.e.16, 145 spores in Cenlle and 1,858 spores in Amares, and the lowest, in 2005 in Cenlle (1,700 spores) and in Amares (800 spores) in 2006. The best adjusted model was an ARIMA (0,2,2) in Cenlle while in Amares there was an ARIMA (1,2,3).

Kumar (2014) selected humid thermal ratio, maximum temperature and special humid thermal ratio as predictor variables to develop weather based prediction models of wheat leaf rust and observed that weather during 7-9th standard meteorological weeks at Ludhiana, Faizabad and Sabour and 10-12th SMW at Kanpur had the highest correlation coefficient of 0.53 with minimum temperature, 0.64 with relative humidity, 0.85 with humid thermal ratio and 0.77 with special humid thermal ratio in Indo-Gangetic plains of India. He further reported that in all four locations, highest average seasonal humid thermal ratio coincided with the highest disease severity which established it as a critical predictor variable for disease development model.

The partial least squares (PLS) and multiple linear regression (MLR) were used to identify suitable bands and develop spectral models for assessing severity of yellow rust disease caused by *Puccinia striiformis* f. sp. *tritici* in winter wheat (Krishna *et al.,* 2014). MLR model yielded acceptable results in the form of r^2 as 0.89 for calibration and 0.90 for validation with SEP of 3.90 and RMSEP of 3.70. The result showed that the developed model had a great potential for precise delineation for detection of yellow rust disease in winter wheat crop.

Ahmed *et al.* (2015) developed a disease predictive model using stepwise multiple regression analysis for potato late blight (PLB) caused by *Phytophthora infestans* (Mont.) de Bary. The model showed 80 per cent disease variability under favorable environmental conditions of maximum and minimum temperatures, relative humidity, rainfall and wind speed. The coefficient of determination R^2 (maximum value) and mean square error MSE (minimum value) of MLR model were found to be 0.80 and 0.55 at $P<0.05$ respectively.

Chen *et al*. (2015) analyzed an auto-regressive integrated moving average (ARIMA) model to predict daily chlorophyll a (Chl a) concentrations, for algal bloom forecasting and its management in China. ARIMA (1, 1, 2) model was observed to be the best model with respect to the absolute error of peak value, root mean square error and index of agreement. ARIMA model needs only one input variable therefore it shows greater applicability as an algal bloom early warning system using online sensors of Chl a.

Linear regression model for assessing the yield loss of mustard due to Alternaria leaf blight disease was analyzed by Mahapatra and Das (2016). The correlation co-efficients (r) of avoidable seed yield loss for the two years and the pooled mean were observed to be r = -0.973, r = -0.973, and r = -0.969, respectively. Further, the co-efficient of determination (R^2) were R^2 = 0.947, R^2 = 0.946, and R^2 = 0.939, respectively.

Bhardwaj *et al*. (2016) analyzed the yield of gram by using Auto-regressive Integrated Moving Average (ARIMA), structural time series models from 2009-10 to 2014-15 of promising varieties (Vijay, JG-6, JG-11, JG-14, JG-16, JG-63, JG-74, JG-

130, JG-226, Vaibhav and JAKI-9218), and observed that maximum yield (27.95q/ha) was obtained for Vaibhav variety for the year 2017-18 with upper and lower limits of 41.16 and 14.75 q/ha, respectively. The minimum yield was obtained for JG-6 (7.82 q/ha) with upper and lower of limit 1.37 and 14.28 q/ha, respectively.

Ilić *et al.* (2016) studied the forecasting of future trends in corn production in Serbia from 1947 to 2014, and 100 models with different combinations of AR and MA variables were examined. The most acceptable model was AR (1) MA (1) MA (2), i.e. (1,1,1,2) model according to the values of the Akaike and Schwarz tests.

Hossain *et al*. (2016) made an attempt to identify the Auto-Regressive Integrated Moving Average (ARIMA) model from 1972 to 2013, to forecast the production of banana in Bangladesh. ARIMA (0,2,1) was found to be the best to forecast the banana productions in Bangladesh. The graphical comparison between the observed and forecasted banana production indicated the fitted model behaved statistically well during and beyond the estimation period.

Fernández-González *et al*. (2016) used ARIMA models as a tool for Integrated Pest Management protocols to forecast the spore concentrations of powdery mildew caused by *Uncinula necator* and downy mildew produced by *Plasmopara viticola* in the North-West Spain vineyards during the grapevine active period 2004–2012. It was found that the annual total *U. necator* spore amount ranged from the 578 spores in 2007 to 4,145 spores sampled during 2008, whereas, the highest annual total *P. viticola* spores quantity was observed in 2010 (1,548 spores) and the lowest in 2005 (210 spores). The most accurate models were an ARIMA (3.1.3) for *U. necator* and (1.0.3) for *P. viticola.*

Kumari *et al*. (2017) conducted comparison of different time series statistical models like autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) with explanatory multiple linear regression model for predicting pod damage in pigeon-pea caused by pod borer in Varanasi region of Uttar Pradesh during 1985-86 to 2011-12. Based on their empirical studies, ANN was found to be best suited model with lowest RMSE, MSE and R^2 of 1.97, 3.89 and 0.77, respectively.

Osman *et al.* (2017) studied on Auto-Regressive Integrated Moving Average (ARIMA) model to forecast the tomato production in Bangladesh over the period of 1971 to 2013. The best model was found to be ARIMA (0,2,1) as this model forecasts well during and beyond the estimation period.

Vennila *et al*. (2018) studied abundance, infestation and disease transmission by thrips on groundnut at Kadiri of Anantapur (Andhra Pradesh) during 2011-16 through multiple linear regression (MLR) models. The prediction models showed that peanut bud necrosis disease (PBND) incidence combining weather and thrips abundance (R^2:0.39) and weather and infestation (R^2:0.53) was dependent on relative humidity and prevalent wind. They observed significantly higher abundance of thrips in 2016 over 2011 to 2015 and also minimum temperature had a positive effect on the incidence of PBND, whereas, rainfall had a negative effect on thrips infestation.

Aswathi and Duraisamy (2018) compared the prediction accuracy of Multiple Linear Regression, ARIMA and ARIMAX model for pest incidence of cotton with weather factors, rainfall, maximum temperature, minimum temperature, morning humidity and evening humidity on weekly basis for aphid, thrips, jassid and whitefly at the TNAU region, Coimbatore. The results showed that for all pests ARIMAX model possessed lowest RMSE value compared to ARIMA and MLR. Thus, ARIMAX was considered the best fit model for prediction of pest incidence.

Ajetomobia and Olaleye (2019) attempted to forecast Nigerian cocoa (*Theobroma cacao* L.) production between 2018 and 2025 using the ARIMA. It was found that ARIMA (1,1,0) was the most appropriate for forecasting from the automated analytical procedure implemented in R software. It was revealed from the results that cocoa production would fall by more than 20 per cent in 2025 in comparison with the 2017 figure.

Singh *et al.* (2019) studied the impact of climate on spot blotch severity on wheat crop over Eastern Gangetic Plains of India for three consecutive years (2014-15, 2015-16, and 2016-17), under both timely and late sown conditions. R^2 for disease severity in Mutiple Linear Regression (MLR) was found to be 0.74 and 0.72 for timely and late sown conditions, respectively. Out of eight ARIMA models, ARIMA (1,0,1) was found to be the best to predict disease severity. R^2 and RMSE were found to be 0.88 and 7.61, respectively, for timely sown conditions; and 0.86 and 5.48, respectively, for late sown conditions. Thus it was found that the risk of spot blotch increased after heading in those areas where average maximum temperature was above 30^{o}C with high relative humidity (>50%).

Chiu *et al*. (2019) performed modelling and forecasting of greenhouse whitefly incidence using time-series and ARIMAX analysis to provide a more efficient way for applying pesticides by predicting the possible increase in whitefly population in greenhouses. The ARIMA and ARIMAX models were compared by setting different combinations of input data for around 60 days to 90 days. ARIMA included only the whitefly count while ARIMAX included the whitefly count and environmental data. ARIMAX was found to be the best model with input data including the increase in whitefly counts, temperature and humidity. The RMSE for 7-day forecasting was found to be around 1.30. Thus, four levels of increase in whitefly count were defined such as Normal, Moderate, High and Critical to assist farmers in decision-making for pesticide application scheduling.

Prediction of disease under future climate change scenario

Temperature is an important weather variable affecting the production and productivity of various cultivated crops. The last three decades have witnessed a sharp rise in mean annual temperature throughout the country. Annual mean temperature has risen by 0.51°C over the period of 1901–2005. This rise in temperature is primarily due to rise in maximum temperature (Mathukumalli *et al*., 2016). However, since 1990, minimum temperature is steadily rising and rate of its rise is slightly more than that of maximum temperature (Arora *et al*., 2005). In every 1°C rise in temperature throughout the growing period of wheat, losses of 4 - 5 million tonnes was reported (Aggarwal, 2008). Zacharias *et al*. (2014) and Sandhu *et al*. (2016) have studied the climate change impacts on the productivity of Indian wheat yields. The unusual warming trends during grain filling stage are causing yield declines, especially in eastern and central India (Chatrath *et al*., 2007). Bapuji Rao *et al.* (2015) identified exposure to continual minimum temperature (Tmin) exceeding 12°C for 6 days and terminal heat stress with maximum temperature (Tmax) exceeding 34°C for 7 days during the post-anthesis period as thermal constraints in realizing potential productivity.

Stripe rust principally attacks wheat grown in cooler climate. The minimum of 3°C and maximum of 20°C temperatures have been observed for the growth of pathogen (Line, 2002). The recent attack of some species on the wheat grown in dry areas demonstrated its adaptation to high temperature. Therefore, the knowledge of temperature at a specific location can give information to predict the presence or absence of stripe rust (Chen, 2005).

Numerous weather generators such as Climate weather generator (Climgen), Weather Generator (WGEN), Long Aston Research Station (LARS-WG), Mark-Sim are available for synthetic generation of data on weather variables such as temperature and precipitation. Utilization of weather generators has become essential for climate change studies as the GCM output is often given in terms of anomalies at monthly interval under future climate change scenarios. Representative concentration pathways (RCP), the latest generation of scenarios that provide input to climate models consist of four climate change scenarios *viz*., RCP8.5, RCP 6, RCP 4.5 and RCP 2.6 (previously called as A2, A1B and B1 emission scenarios) describe four possible future climates, (Garg *et al*., 2015). In order to make use of the datasets for crop, pest and disease modeling or prediction of disease, it is essential that the information be temporally downscaled using weather generators. Mark-Sim GCM was developed to simulate weather from known sources of monthly climate data. It combines the spatial downscaling of weather data of selected GCMs to the point of interest and temporal downscaling to daily level (Rao *et al*. 2015).

He *et al*. (2012) predicted the early seeding dates of spring wheat (*Triticum aestivum* L.) in the Canadian Prairies under four climate databases that included a baseline (1961–1990) and three climate change scenarios (2040–2069), generated by the Canadian global climate model (GCM) with the forcing of three greenhouse gas (GHG) emission scenarios (A2, A1B and B1). They observed that compared to the baseline conditions, there was no reduction in grain yield because precipitation increased during sensitive growth stages of wheat, suggesting that there was potential to shift seeding to an earlier date. The average advancement of seeding dates varied among sites and chosen scenarios. The Swift Current (south-west) site had the highest potential for earlier seeding (7 to 11 days), whereas, such advancement was small in the Melfort (north-east, 2 to 4 days) region. The results may be used for adaptation assessments of seeding dates under possible climate change to mitigate the impact of potential warming.

The prediction of carbon dioxide (CO_2) concentration in the atmosphere is going to change in the future and its influence on crops and insect pests was studied by Rao *et al*. (2012). Substantial influence of elevated CO_2 on *Spodoptera litura* was observed which was reared on peanut (*Arachis hypogea* L.) foliage grown under elevated CO_2 concentrations (550 ppm and 700 ppm). They noticed that there was increased consumption of peanut foliage by *S. litura* larvae under elevated CO_2.

Manimanjari *et al*. (2014) also studied the prediction of increase in temperature and atmospheric CO_2 concentration and its influence on the growth of crop plants and phytophagous insects. It was found that finite (k), intrinsic rates of increase (rm), net reproductive rate (Ro), mean generation time, (T) and doubling time (DT) of *S. litura* increased significantly with temperature up to 27–30^{o}C and declined with further increase in temperature. It was predicted that increased 'rm', 'k', and 'Ro' and reduced 'T' would occur during near future NF and distant future DF scenario over present period at all locations. Therefore, the results indicated that temperature and CO_2 were vital in influencing the population growth of *S. litura* and pest incidence may possibly be higher in the future.

Rao *et al.* (2015) predicted more generations of *S. litura.* Fab. (peanut pest) would occur during the three future climate periods i.e., Near future (NF)-2020, Distant future (DF)-2050 and Very Distant future (VDF)-2080, with significant variation among scenarios (A2, A1B and B1) and models. They predicted that, 1–2 additional generations would occur during DF and VDF due to higher maximum and minimum temperatures. They further observed that generation time would decrease by 18–22 per cent over baseline (1975) due to future temperature projections of these models. With the increase in temperature the incidence of *S. litura* may increase in future climate change periods due to increase in number of generations and reduction of generation time across the six peanut growing locations of India, *viz*., Bhubaneswar, Jalgaon, Junagadh, Raichur, Tirupathi and Vridhachalam.

The weather data of future daily maximum and minimum temperatures was simulated from seven General Circulation Models (GCM) *viz*., BCCR-BCM2.0, CNRM-CM3, CSIRO-Mk3.5, ECHams5, INCM-CM3.0 and MIROC3.2 along with Ensemble AVERAGE-AVG for three emission scenarios (A2, A1B & B1) using MarkSim (Mathukumalli *et al*., 2016). They found more (one to two) generations of *Helicoverpa armigera* with reduced generation time (15%) would occur with CSIRO-Mk3.5 and ECHams5 models due to higher temperatures during all the three future climate periods viz., 2020, 2050 and 2080, which indicated that the incidence on pigeon pea could be higher due to the increase in temperature.

Pramod *et al.* (2017) observed the wheat yield responses to three future climatic periods (2025, 2050 and 2075), with daily weather from three CMIP-5 climate models' (GFDL-ESM2M, MIROC5, and NorESM1-M) at four sites (Ludhiana, Raipur, Akola and New Delhi). They observed that day temperatures were projected to rise conspicuously at Ludhiana, representing northwest parts of the country, and moderately over central parts of India (Akola and Raipur). Further, positive rainfall anomalies at Ludhiana (+76%) and negative anomalies at Raipur (-15%) were projected in future. Therefore, with these climate changes, wheat was likely to experience warmer days (+1.1°C) at Ludhiana and nights at Raipur (+2.8°C) and more seasonal moisture availability at Ludhiana in future. Therefore, it could be inferred that wheat yields in future are likely to decline in absence of adaptation options for major wheat growing regions.

The prediction of generations and generation time of Oriental fruit fly, *Bactrocera dorsalis* which is a major pest of mango crop in India was studied for baseline (1961 to 1990), present (1969 to 2005), near future (2021 to 2050) and distant future (2071 to 2098) periods using A1B emission scenario data by Providing Regional Climates for Impacts Studies (PRECIS) model. It was estimated that faster accumulation of degree days would make possible for occurrence of one or two additional generations with shortened mean life cycle (5 to 7 days less) in near and distant future climate change periods compared to baseline and present periods at majority of selected locations. Increased number of generations and reduction of generation time at majority of mango growing locations of India suggested that the incidence of *B. dorsalis* was likely to increase due to the projected increase in temperatures during future climate change scenarios (Choudhary *et al*., 2017).

Alkishe *et al*. (2017) assessed the potential distribution of *Ixodes ricinus* under current and future climate conditions to understand the effect of climate change over a continental extent that included Europe, North Africa, and the Middle East, based on future projections of climate data from 17 general circulation models (GCMs) under 2 representative concentration pathway emissions scenarios (RCPs), for the years 2050 and 2070.The results showed that present and future potential distributions of *I. ricinus* overlapped across most of the western and central Europe, and in more narrow zones in eastern and northern Europe, and North Africa. These results indicate that *I. ricinus* populations could emerge in areas in which they were currently lacking, posing increased risks to human health in those areas.

Artificial Neural Network (ANN) and Least Square Support Vector Machine (LSSVM) were used by Nourani *et al*. (2018) to statistically downscale and project rainfall data from CMIP5 (GCM) for Tabriz and Ardabil stations in north-west Iran. They performed the calibration, validation and projection of the proposed downscaling models over the periods of Jan. 1951 to Dec. 1991, Jan. 1992 to Dec. 2005 and Jan. 2017 to Dec. 2100. They used the ANN, LSSVM and Multiple Linear Regression (MLR) models to capture relationship between the large-scale climate data and the stations' observed rainfall values. It was found that the projection of rainfall for near and distant future (2017-2050 and 2050-2100) by the proposed multi-GCM ensemble framework yielded to rainfall alteration pattern; 40 per cent - 41per cent and 35 per cent- 42 per cent decrease at Tabriz station and 6 per cent-12 per cent and 5 per cent-13 per cent increase at Ardabil station under RCPs 4.5 and 8.5, respectively.

He *et al*. (2018) obtained data across the rice belt in southern China from Coupled Model Inter comparison Project phase 5 (CMIP5) with two emissions scenarios (RCP 4.5 for current emissions and RCP 8.5 for increasing emissions) to calculate the heat stress indices. They observed that multi-model projections over the historical period (1960–2010), and found that the frequency of heat stress events was projected to increase by 2061–2100 in both scenarios (up to 185 and 319% for RCP 4.5 and RCP 8.5, respectively). Thus, the increasing risk of exposure to heat stress above 30°C during flowering and grain filling was predicted to impact rice production and therefore it was suggested to adapt or mitigate strategies, such as selection of heat-tolerant cultivars and adjustment of planting date in a warmer future world.

ALRahahleh *et al*. (2018) studied the use of certain tree species in forest regeneration and their effect on volume growth, timber yield, and carbon stock of boreal forests in Finland under the current climate (1981–2010) and recent-generation global climate model (GCM) predictions using the representative concentration pathways RCP 4.5 and RCP 8.5, over the period of 2010–2099. They observed that the volume growth increased in the south from 5.8 to 7.0 m3 $ha^{-1}a^{-1}$, and in the north from 2.8 to 3.3 m^3 ha^{-1} a^{-1}; the mean annual timber yield range in the south was 4.2–4.3 m^3 ha^{-1} a^{-1} and, in the north, 1.5–1.8 m^3 ha^{-1} a^{-1}; and the carbon stock (in trees and soil) of forests increased from 79 to 87 Mg ha^{-1} in the south, and from 72 to 88 Mg ha^{-1} in the north. Therefore, the magnitude of the climate change impacts depended largely on the geographical region and the severity of the climate projection.

Shahsavari *et al*. (2019) predicted the spatial and temporal non-uniformity of water availability in the climate change projections in five climatic zones of Iran, based on the future projections (2041–2070), under four emission scenarios, including RCP 2.6, RCP 4.5, RCP 6.5, and RCP 8.5. The results indicated that in hyper-arid region global warming projections there was a positive increase of 0.3–146.2 per cent in green water availability and a reduction of 5.1–266.4 per cent in drought severity in future climate. Hence, sustainable dryland agriculture, highly depends on regionally prioritizing susceptible area for dry farming was required, since the criteria indices showed an extreme spatial and temporal variability over the mid twenty-first century.

Most of the optimal and medium suitability areas of tea (*Camellia sinensis*) habitat in Sri Lanka in the low elevation areas would be lost to a greater extent in comparison to the high elevation areas for all tested RCPs by 2050 and 2070 under both

GCMs of MIROC5 and CCSM4, in response to the current and future climate change scenarios (Jayasinghe and Kumar, 2019). They found that in relation to the current time, areas of 6090 km^2 (9.3%), 5769 km^2 (8.8%), and 5086 km^2 were projected as potential areas of having optimal, medium and marginal climate suitability for tea, respectively, using the correlative habitat suitability model MaxEnt. On comparison of the current and future distributions of suitable tea growing areas a decline of approximately 10.5, 17 and 8 per cent in total 'optimal', 'medium', and 'marginal' suitability areas, respectively, was observed, which implied that climate would have a negative effect on the habitat suitability of tea in Sri Lanka by 2050 and 2070.

Choudhary *et al*. (2019) observed significant variation of future temperature (MaxT. and MinT.) projected by eight models i.e., BCC-CSM1-1(BC), CSIRO-Mk3-6-0(CS), FIO-ESM (FI), GFDL-ESM2M (GF), HadGEM2-ES (Had), IPSL-CM5A-MR (IP), MIROC-ESM-CHEM (MI) including Ensemble. It was inferred that the maximum and minimum temperatures would fluctuate by ±0.47 to ±4.02^{o}C and ±0.43 to ±6.78^{o}C, respectively, during three future climate periods (2020, 2050 and 2080) over Baseline period (1969–2005) of four scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) at ten locations of India *viz*., Lucknow, Mohanpur, Paria, Ranchi, Rewa, Rupnagar, Bengaluru, Vengurle, Sangareddy and Dharampuri. They further indicated that there will be addition of 1-2 generations during 2050 and 2080 due to higher temperature projected in CS and Had models. The temperature projections of these models also indicated that the generation time of *Bactrocera dorsalis* (19.31 to 25.38 days), *Bactrocera zonata* (20.74 to 25.97 days) and *Bactrocera correcta* (47.66 to 61.69 days) on mango will decrease by 15-24 per cent during future climate change periods over baseline which will lead to increase in voltinism and infestation of mango fruits and will have significant impacts on mango protection and production.

Chapter-3

Materials and Methods

CHAPTER-3

MATERIALS AND METHODS

The present investigation titled **‘Comparative study of forecasting models for stripe rust of wheat’** was carried out during the years 2017-2019, at the Research Farm, Faculty of Agriculture, Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu, Chatha. The research materials used and the methodologies followed to conduct the study have been described under the following headings:

3.1 Prediction of stripe (yellow) rust under future climate change scenario

Six location *viz*., Jammu (Jammu and Kashmir), Ludhiana (Punjab), Dhaulakuan (Himachal Pradesh), Hisar (Haryana), Meerut (Uttar Pradesh) and Leh (Ladakh), representing the northern western plains zone and northern hills zones of wheat growing regions of India, were selected based on the occurrence of stripe rust epidemics in past. Future projected temperatures (maximum and minimum) at selected study prefectures were downloaded from MarkSim® DSSAT weather file generator (http://gisweb.ciat. cgiar.org/MarkSimGCM/) for the six General Circulation models (GCMs) under the four greenhouse gas concentration trajectories scenarios, RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 (Van Vuuren *et al*., 2011) with 20 replicates of each (Jones and Tornton, 2013). The details of the six GCMs used in present study were the Chinese Beijing Climate Centre, China Meteorological Administration and Analysis model BCC-CSM1-1 (BCC); the Australian Commonwealth Scientific and Industrial Research Organization model CSIRO-Mk3-6-0 (CSIRO); the US National Oceanic and Atmospheric Administration’s Geophysical Fluid Dynamics Laboratory model GFDL-ESM2M (GFDL); the French Institute Pierre-Simon Laplace model IPSL-CM5A-MR (IPSL); the Japan’s Atmosphere and Ocean Research Institute, National Institute for Environmental Studies and Agency for Marine Earth Science and Technology model MIROC-ESM-CHEM (MIROC) and the National Aeronautics and Space Administration, Goddard Institute for Space Studies (GISS).

Baseline data was considered of the year 1975, where the daily temperatures (maximum and minimum) of all the selected locations were obtained from Indian Meteorological Department (IMD) grid temperature data available at 1×1 degree resolution. Climate projections were studied over four time periods, *viz*., 2020 (near future), 2050 (distant future) and 2080 (very distant future) and compared with Baseline (BL) (1975) periods from each GCM for six prefectures. The projected maximum and minimum temperature data were collected for four climate change periods (1975, 2020, 2050 and 2080), across six models with four different Representative Concentration Pathways (RCPs; RCP2.6, 132 RCP4.5, and RCP8.5) for each model and at six wheat growing locations of India to estimate duration of latent period (days per generation) and number of infection cycles for *Puccinia striiformis* f. sp. *tritici*, the causal organism of stripe/yellow rust of wheat.

3.2 Estimation of growing degree-days of *Puccinia striiformis* f. sp. *tritici*

Growing degree-days (GDD) were calculated to predict the duration of latent period of *P. striiformis* f. sp. *tritici* under future climate scenarios (Danelli and Reis, 2016). The lower threshold temperature of 4°C (LTT) for of *Puccinia striiformis* f. sp. *tritici* was considered for the study (Chai *et al.*, 2015). Software ***'ingen'*** (Insect Generations) available at www.nicra.in was employed to calculate the GDD (Rao *et al.*, 2015). Wheat is mainly growing during *rabi* season (November to April) in Jammu, Ludhiana, Meerut, Dhaulakuan and Hisar, whereas, in Leh it is grown during *kharif* season (April to September). By considering the previous reports of appearance of stripe rust in these locations, daily temperature data (maximum and minimum) with respect to Standard Meteorological Weeks (SMW) of each location were generated for predicting the variation in generations and duration of latent period of *P. striiformis* f. sp. *tritici*.

3.3 Development of forecasting models

3.3.1 Time series models

Time series is a set of numbers that measures the status of some activity over equally spaced time interval. Time series models, Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Integrated Moving Average with Exogenous

Variables (ARIMAX) were computed for the prediction of stripe rust of wheat based upon weekly data of meteorological factors *viz.*, maximum and minimum temperatures (^{o}C), maximum and minimum relative humidity (%) and rainfall (mm) and per cent severity of stripe rust during the period 2005-2019. Disease severity during 2005-2017 was considered as training data sets, and were collected from secondary data source, whereas, severity during 2017-2019 (test data sets) were generated by sowing wheat crop in *rabi* season of 2017-18 and 2018-2019. Weekly data of five different meteorological factors *viz.*, maximum and minimum temperatures (^{o}C), morning and evening relative humidity (%) and rainfall (mm) during 2005-2019 were collected from Agro-meteorological section of SKUAST-Jammu.

3.3.2 Layout of experiment

Susceptible wheat variety, PBW 343, was sown in experimental plots at Research Farm, Chatha, on 15th November, 2017 and 11th November, 2018, under randomized block design (RBD), with four replications, having row to row distance of 22.5 cm, in a plot size of 2x4m.

3.3.3 Disease severity

During 2017-2019, severity of stripe rust was recorded on labelled plants (5 plants/plot), starting from the time of disease initiation till the harvesting of the crop, at weekly intervals (January to April) using modified Cobb's scale (Peterson *et al.*, 1948).

3.3.4 Descriptive statistics of meteorological factors and stripe rust of wheat

The weekly data of meteorological factors *viz.*, maximum temperature (^{0}C), minimum temperature (^{0}C), morning relative humidity (%), evening relative humidity (%), rainfall (mm) and severity of stripe rust of wheat (%) during *rabi* seasons from 2005 to 2019 were investigated to study the distribution pattern and quantitative description of these data sets for 180 observations. Computation of the descriptive statistics resulted in mean, median, standard deviation, skewness and kurtosis for all the selected parameters.

3.3.5 Autoregressive Integrated Moving Average (ARIMA) Modeling

The equally spaced univariate time series data was analyzed and forecasted using the Autoregressive Integrated Moving-Average (ARIMA). An ARIMA model predicts a value in a response time series as a linear combination of its own past values, past errors, and current and past values of other time series. The ARIMA approach was first popularized by Box and Jenkins (1970), therefore, ARIMA models are also referred as Box-Jenkins models. Five different steps were followed in order to develop prediction model for the severity of stripe rust of wheat by univariate time series (ARIMA) model.

3.3.5.1 Unit Root Test

To check whether the univariate time series data of stripe rust of wheat was white noise (stationary) or not, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, in which the null hypothesis, that the series was non-stationary, was adopted. If the time series data was not stationary, it was transformed into stationary ones by differencing (by taking lag 1).

3.3.5.2 Parameter estimation

ARIMA model encompassed seven parameters, in which p and P were the orders of general and seasonal auto regression (AR), respectively; q and Q were the general and seasonal moving average (MA) orders, respectively; d and D were the numbers of general and seasonal differencing respectively; s denoted cyclicity in ARIMA(p,d,q) (P,D,Q)s model. Plotting of Auto correlation function (ACF) and partial auto correlation function (PACF) exhibited the structure of the models in which PACF decided values for p (AR), whereas, ACF gave value for q (MA).

3.3.5.3 Selection of model

Adding parameters or alterations, increased the likelihood of the model, but over-fitting of model could occur. Therefore, in order to reduce the error, the model with lower Akaike Information Criterion (AIC) “better” was employed (Brockwell and Davis 2009).

3.3.5.4 Diagnostic Checking

After the selection of model, we could test whether the residuals met white noise assumptions, as the residuals from the developed ARIMA model were assumed to be independent, homoskedastic and normally distributed. Various tests were performed to study the goodness of fit of the tentative model, such as, 'Ljung-Box Test for Autocorrelation test', to check the autocorrelation in the residual series (Ljung and Box, 1978), and 'Shapiro-Wilk Test', to check the Normality (Normally distribution of residuals in the model).

3.3.5.5 Validation of ARIMA model

To validate the developed model, it was used in the test datasets to predict the severity of stripe rust of wheat. If the model exhibited the minimum per cent deviation between the observed and predicted values, the model was used for the short-term prediction.

3.3.6 Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) Model

To develop the ARIMAX model, pre-whitening was conducted to reduce the association between linear autocorrelation. Cross-correlation function (CCF) between the severity and meteorological parameters, depicted the selection of lag regarding external variables (meteorological parameters). Selected meteorological parameters (with or without lag) were incorporated as covariates into the ARIMA to generate ARIMAX model. Finally, statistically significant regression coefficients and lower Akaike Information Criterion (AIC) value for the meteorological parameters gave the generation of model. The developed ARIMAX models were validated, once minimum per cent deviation was generated, and were used to predict the severity of stripe rust from 2020-2022. The prediction accuracy was evaluated by the root mean square error (RMSE) and mean square error (MSE).

3.3.7 Development of weather forecasting model based on multiple linear regression

Correlation analysis of stripe rust severity of wheat during 2005-2017 and 2017-2019 datasets were analyzed with individual weather variables like maximum and minimum temperatures, maximum and minimum relative humidity and rainfall. Higher correlation coefficient (r) showed the association between the parameters. To predict the severity under the influence of different weather parameters, models were generated by multiple linear regression. Coefficient of determination (R^2), root mean square error (RMSE) and mean square error (MSE) were worked out to find the impact of individual or combination of different abiotic factors on the disease development.

3.4 Quantification and temporal distribution of *Puccinia striiformis* f. sp. *tritici* inoculum

3.4.1 Collection of air borne inoculum

Spore traps (glass slides with grease) were hanged, at different locations over the experimental field, from December onwards to trap *P. striiformis* f. sp. *tritici* inoculum (urediospores). The slides were microscopically observed for counting of the spores. The correlation between the number of spores with the prevailing weather parameters (maximum and minimum temperatures, morning and evening relative humidity and rainfall) were computed. The spores were identified by using universal ITS primers (Bandral, 2020).

3.5 Statistical analysis

All statistical analyses were conducted using the software using the statistical package R software (R Core Team, 2013). The values of replication, which included number of infection cycles and duration of latent period of *P. striiformis* f. sp. *tritici* were assessed by One-way analysis of variance (ANOVA) and means were compared using least significant difference (LSD) at probability level of 5 per cent through “agricolae” packages (de Mendiburu, 2016).

Plate-1: Experimental Field

Plate-2: Symptoms of stripe rust of wheat

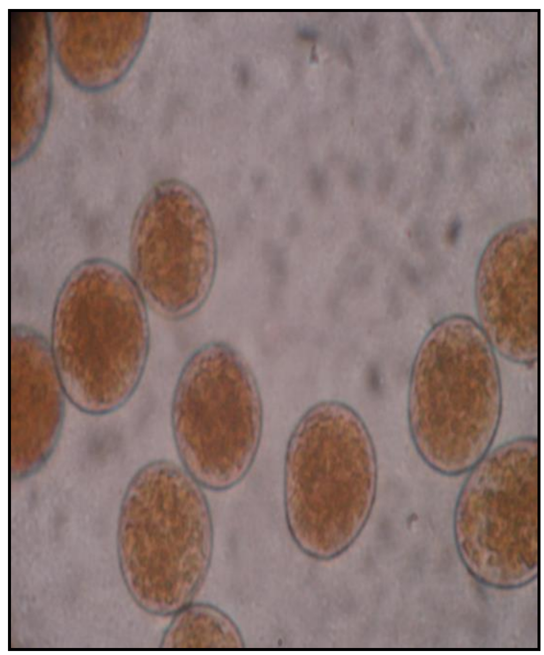


Plate-3: Spores of *Puccinia striiformis* f. sp. *tritici* under microscope

Results

CHAPTER-4

RESULTS

This chapter includes the research findings pertaining to the investigation entitled **"Comparative study of forecasting models for stripe rust of wheat"** conducted during *rabi* season of 2017-18 and 2018-19 as under:

4.1 Variation in projected temperatures among scenarios and models

Substantial variation in future maximum and minimum temperatures were predicted by the six adopted models (BCC, CSIRO, GFDL, IPSL, MIROC and GISS) when compared over four representative concentration pathways (RCPs), at four time periods (1975, 2020, 2050 and 2080) and six locations *viz*., Jammu, Ludhiana, Dhaulakuan, Hisar, Meerut and Leh. Data presented in Table 1 exhibit that maximum temperature would increase by 11.13, 6.56, 3.50°C, 7.64 and 5.18, in Jammu, Ludhiana, Dhaulakuan, Hisar and Meerut, respectively, whereas, it would decrease by 0.58°C in Leh, during the three future climate change periods (2020, 2050 and 2080), over baseline period (1975) of scenario RCP 8.5. Scenario RCP 2.6, exhibited slight variation in maximum temperature among the future time periods (2020, 2050 and 2080), whereas, RCP 4.5, 6.0 and 8.5 marked sharp fluctuations during 2050 and 2080, across the selected locations. Maximum temporal change in maximum temperature was predicted by model IPSL in 2020 and 2080, whereas, by GFDL in 2050, in all the scenarios during 2020, 2050 and 2080, in all the selected locations. Maximum fluctuations (increase) in maximum temperature recorded were in Jammu (6.26 to 11.13), followed by Hisar (2.78 to 7.64), Ludhiana (3.47 to 6.56), Dhaulakuan (0.65 to 3.50) and Leh (0.58 to 5.60), whereas, it was minimum in Meerut (1.34 to 5.18).

Similarly, data in Table 2 indicate that minimum temperature would increase by 11.58, 6.70, 6.01, 6.23, and 5.70°C in Jammu, Ludhiana, Dhaulakuan, Hisar and Meerut, respectively, whereas, it would decrease by 0.58°C in Leh, during 2080 as compared to 1975. Scenario RCP 8.5 exhibited highest fluctuations (maximum increase) in the minimum temperature in 2080 across the six locations. Maximum temporal change in minimum temperature was predicted by model IPSL in all the selected locations under four scenarios. Maximum variations in minimum temperature were recorded in Jammu (7.15 to 11.58), followed by Leh (0.58 to 5.85), Ludhiana (2.68 to 6.70), Hisar (2.16 to 6.23) and Dhaulakuan (1.68 to 6.01), whereas it was minimum in Meerut (1.81 to 5.70).

4.2 Latent period of *Puccinia striiformis* f. sp. *tritici*

Data in the Table 3 revealed that in the predicted future changes in climate during 2020, 2050 and 2080, over the baseline data of 1975, significant differences were observed in the duration of latent period (days) of *Puccinia striiformis* f. sp. *tritici*, under each climate change scenario (RCP), across the locations *viz*., Jammu, Ludhiana, Dhaulakuan, Hisar, Meerut and Leh. In the baseline period (1975), the duration of latent period (days) varies from 8.58±0.09 to 21.49±0.07, across all the locations. Maximum reduction in latent periods were observed during 2080 under RCP 8.5 scenario, which were 10.23±0.29, 10.23±0.29, 10.44±0.36, 9.88±0.19, 9.84±0.18 and 9.03±0.35 in Jammu, Ludhiana, Dhaulakuan, Hisar, Meerut and Leh, respectively. Whereas, maximum duration of 11.44±0.22, 11.34±0.14, 11.66±0.24 and 11.56±0.2 was recorded at Leh during 2020 under four scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5). Maximum reduction in latent period of 110.07, 49.27, 40.33, 35.32 and 35.87 per cent was observed in Jammu, Ludhiana, Dhaulakuan, Meerut and Hisar, respectively, during 2080 under RCP 8.5 scenario (Table 4). However, maximum per cent increase (26.41) in the latent period was observed at Leh under RCP 6.0 for 2020. All the scenarios showed maximum reduction in the latent period in all the three selected future periods at Jammu, followed by Ludhiana, Dhaulakuan, Meerut and Hisar, whereas, lowest increase was observed at Leh. Among all the models, CSIRO and IPSL indicated the maximum reduction in the duration of latent period of *P. striiformis* f. sp. *tritici* under each climate change scenario (RCPs), across all the locations in future climate periods over the baseline period (Fig. 1-4).

4.3 Number of infection cycles of *Puccinia striiformis* f. sp. *tritici*

The number of infection cycles generated by *Puccinia striiformis* f. sp. *tritici* is predicted to increase under all the RCP scenarios in the three future climate periods

Table 1: Variations in average maximum temperatures (°C) among four representative concentration pathway (RCP) scenarios across six wheat growing locations, during four time periods using MarkSim DSSAT weather file generator

Scenario	Time period	Locations					
		Jammu	**Ludhiana**	**Dhaulakuan**	**Hisar**	**Meerut**	**Leh**
	Baseline (1975)	25.25	29.43	30.84	31.11	30.85	19.70
RCP 2.6	2020	31.51±0.13 (6.26)	32.90±0.1 (3.47)	30.19±0.15 (0.65)	33.89±0.17 (2.78)	32.40±0.03 (1.55)	14.26±0.11 (5.44)
	2050	32.59±0.36 (7.34)	33.52±0.18 (4.09)	30.81±0.2 (0.03)	34.41±0.22 (3.3)	33.02±0.13 (2.17)	15.10±0.25 (4.6)
	2080	32.28±0.22 (7.03)	33.63±0.2 (4.20)	30.83±0.23 (0.01)	34.72±0.18 (3.61)	33.12±0.17 (2.27)	18.42±3.15 (1.28)
RCP 4.5	2020	31.77±0.21 (6.52)	33.01±0.08 (3.58)	30.33±0.2 (0.51)	33.74±0.19 (2.63)	32.36±0.05 (1.51)	14.26±0.09 (5.44)
	2050	32.64±0.19 (7.39)	34.32±0.2 (4.89)	31.30±0.18 (0.46)	35.06±0.11 (3.95)	33.41±0.13 (2.56)	15.70±0.16 (4)
	2080	34.08±0.46 (8.83)	35.23±0.3 (5.80)	32.26±0.24 (1.42)	35.94±0.28 (4.83)	34.15±0.3 (3.3)	16.71±0.45 (2.99)
RCP 6.0	2020	31.76±0.34 (6.51)	32.89±0.07 (3.46)	29.91±0.08 (0.93)	33.46±0.49 (2.35)	32.19±0.11 (1.34)	14.10±0.15 (5.6)
	2050	32.72±0.33 (7.47)	33.62±0.21 (4.19)	30.88±0.17 (0.04)	33.97±0.89 (2.86)	33.04±0.2 (2.19)	15.27±0.22 (4.43)
	2080	34.22±0.49 (8.97)	35.06±0.14 (5.63)	32.3±0.41 (1.86)	35.24±0.76 (4.13)	34.22±0.2 (3.37)	16.73±0.38 (2.97)
RCP 8.5	2020	31.84±0.32 (6.59)	33.04±0.2 (3.61)	30.04±0.1 (0.8)	33.86±0.16 (2.75)	32.35±0.06 (1.5)	14.33±0.17 (5.37)
	2050	33.86±0.48 (8.61)	34.91±0.22 (5.48)	31.96±0.19 (1.12)	34.98±0.55 (3.87)	34.13±0.25 (3.28)	16.36±0.27 (3.34)
	2080	36.38±0.66 (11.13)	37.67±0.28 (6.56)	34.34±0.41 (3.5)	37.07±0.61 (7.64)	36.03±0.25 (5.18)	19.12±0.64 (0.58)

± = Standard error.

Values in parentheses are percent increase in minimum temperature (°C) over the baseline period.

Table 2: Variations in average minimum temperature (°C) among four representative concentration pathway (RCP) scenarios, across six wheat growing locations, during four time periods using MarkSim DSSAT weather file generator

Scenario	Time period	Locations					
		Jammu	Ludhiana	Dhaulakuan	Hisar	Meerut	Leh
	Baseline (1975)	12.50	15.65	16.08	16.40	17.60	6.97
RCP 2.6	2020	19. 65±0.11 (7.15)	18.38±0.09 (2.73)	17.76±0.12 (1.68)	18.56±0.1 (2.16)	19.51±0.09 (1.91)	1.12±0.22 (5.85)
	2050	20.63±0.36 (8.13)	19.08±0.18 (3.43)	18.49±0.26 (2.41)	19.35±0.17 (2.95)	20.11±0.18 (2.51)	1.97±0.34 (5)
	2080	20.36±0.3 (7.86)	19.10±0.23 (3.45)	18.46±0.27 (2.38)	19.41±0.25 (3.01)	20.14±0.23 (2.54)	4.84±2.79 (2.13)
RCP 4.5	2020	19.70±0.13 (7.2)	18.43±0.08 (2.78)	17.96±0.28 (1.88)	18.67±0.1 (2.27)	19.49±0.08 (1.89)	1.15±0.15 (5.82)
	2050	20.74±0.22 (8.24)	19.74±0.24 (4.09)	19.05±0.25 (2.97)	19.87±0.19 (3.47)	20.63±0.2 (3.03)	2.58±0.35 (4.39)
	2080	21.83±0.38 (9.33)	20.52±0.28 (4.87)	20.04±0.3 (3.96)	20.64±0.26 (4.24)	21.35±0.27 (3.77)	3.47±0.48 (3.5)
RCP 6.0	2020	19.67±0.16 (7.17)	18.33±0.09 (2.68)	17.68±0.13 (1.6)	18.42±0.2 (2.02)	19.41±0.13 (1.81)	1.10±0.23 (5.87)
	2050	20.69±0.21 (8.19)	19.23±0.16 (3.58)	18.65±0.21 (2.57)	19.25±0.33 (2.85)	20.23±0.18 (2.63)	2.16±0.35 (4.81)
	2080	22.04±0.34 (9.54)	20.59±0.22 (4.94)	20.9±0.48 (3.14)	20.57±0.34 (4.17)	21.45±0.22 (1.94)	3.85±0.56 (2.73)
RCP 8.5	2020	19.83±0.18 (7.33)	18.46±0.11 (2.81)	17.80±0.13 (1.72)	18.65±0.08 (2.25)	19.59±0.1 (1.99)	1.22±0.21 (5.75)
	2050	21.74±0.35 (9.24)	20.41±0.26 (4.76)	19.74±0.29 (3.66)	20.40±0.19 (4)	21.07±0.15 (3.47)	3.37±0.49 (3.6)
	2080	24.08±0.54 (11.58)	22.35±0.53 (6.7)	22.09±0.48 (6.01)	22.63±0.3 (6.23)	23.30±0.32 (5.7)	6.39±0.9 (0.58)

± = Standard error.

Values in parentheses are percent increase in minimum temperature (°C) over the baseline period.

Table 3: Variation in the duration of latent period (days) of *Puccinia striiformis* f. sp. *tritici* in wheat, for four representative concentration pathway (RCP) scenarios, during four time periods

Scenario/ Time Period	Locations					
	Jammu	**Ludhiana**	**Dhaulakuan**	**Hisar**	**Meerut**	**Leh**
Baseline (1975)	$21.49\pm0.07^{a*}$	15.27 ± 0.093^{a}	14.65 ± 0.09^{a}	13.37 ± 0.08^{a}	13.370 ± 0.08^{a}	8.58 ± 0.09^{a}
RCP 2.6/2020	13.10 ± 0.03^{b}	13.10 ± 0.03^{ab}	13.42 ± 0.02^{b}	12.19 ± 0.19^{b}	11.91 ± 0.05^{ab}	11.44 ± 0.22^{b}
RCP 2.6/2050	12.40 ± 0.28^{b}	12.40 ± 0.28^{ab}	13.11 ± 0.36^{b}	11.22 ± 0.46^{b}	11.62 ± 0.03^{ab}	10.98 ± 0.24^{b}
RCP 2.6/2080	12.69 ± 0.20^{b}	12.69 ± 0.20^{ab}	13.09 ± 0.06^{b}	11.69 ± 0.06^{b}	11.63 ± 0.03^{ab}	10.08 ± 0.78^{b}
RCP 4.5/2020	13.14 ± 0.05^{b}	13.14 ± 0.05^{ab}	13.45 ± 0.03^{b}	12.38 ± 0.22^{b}	11.90 ± 0.05^{ab}	11.34 ± 0.14^{b}
RCP 4.5/2050	12.42 ± 0.26^{b}	12.42 ± 0.26^{ab}	12.79 ± 0.21^{b}	11.48 ± 0.13^{b}	11.34 ± 0.16^{ab}	10.62 ± 0.19^{b}
RCP 4.5/2080	11.64 ± 0.08^{b}	11.64 ± 0.08^{ab}	12.00 ± 0.22^{b}	10.82 ± 0.16^{b}	10.79 ± 0.17^{ab}	10.11 ± 0.31^{b}
RCP 6.0/2020	13.13 ± 0.05^{b}	13.13 ± 0.05^{ab}	14.07 ± 0.27^{b}	12.49 ± 0.46^{b}	11.94 ± 0.07^{ab}	11.66 ± 0.24^{b}
RCP 6.0/2050	12.44 ± 0.25^{b}	12.44 ± 0.25^{ab}	12.91 ± 0.21^{b}	12.17 ± 0.54^{b}	11.50 ± 0.13^{ab}	10.89 ± 0.19^{b}
RCP 6.0/2080	11.32 ± 0.21^{b}	11.32 ± 0.21^{ab}	11.74 ± 0.07^{b}	10.85 ± 0.15^{b}	10.67 ± 0.07^{ab}	10.17 ± 0.28^{b}
RCP 8.5/2020	13.07 ± 0.05^{b}	13.07 ± 0.05^{ab}	13.60 ± 0.23^{b}	12.19 ± 0.17^{b}	11.84 ± 0.06^{ab}	11.56 ± 0.22^{b}
RCP 8.5/2050	11.52 ± 0.21^{b}	11.52 ± 0.21^{ab}	12.13 ± 0.25^{b}	10.99 ± 0.20^{b}	11.08 ± 0.20^{ab}	10.31 ± 0.28^{b}
RCP 8.5/2080	10.23 ± 0.29^{b}	10.23 ± 0.29^{b}	10.44 ± 0.36^{b}	9.88 ± 0.19^{b}	9.84 ± 0.18^{b}	9.03 ± 0.35^{b}
P<0.001	$2.2e^{-16}$	$2.2e^{-16}$	$2.2e^{-16}$	$6.276e^{-13}$	$2e^{-16}$	$2.221e^{-12}$
F calculated	319.33	60.71	44.96	13.51	60.88	12.70
Error degree of freedom	60	60	60	60	60	60

Table 4: Per cent change in the duration of latent period (days) of *Puccinia striiformis* f. sp. *tritici* in wheat in four representative concentration pathway (RCP) scenarios during four time periods

Scenario/ Time Period	Locations					
	Jammu	**Ludhiana**	**Dhaulakuan**	**Hisar**	**Meerut**	**Leh**
RCP 2.6/2020	64.05	16.56	9.17	9.68	12.26	25.00
RCP 2.6/2050	73.31	23.15	11.75	19.16	15.06	21.85
RCP 2.6/2080	69.35	20.33	11.92	14.37	14.96	14.88
RCP 4.5/2020	63.55	16.21	8.92	7.99	12.35	24.34
RCP 4.5/2050	73.03	22.95	14.54	16.46	17.90	19.21
RCP 4.5/2080	84.62	31.19	22.08	23.57	23.91	15.13
RCP 6.0/2020	63.67	16.30	4.12	7.05	11.98	26.41
RCP 6.0/2050	72.75	22.75	13.48	9.86	16.26	21.21
RCP 6.0/2080	89.84	34.89	24.79	23.22	25.30	15.63
RCP 8.5/2020	64.42	16.83	7.72	9.68	12.92	25.78
RCP 8.5/2050	86.55	32.55	20.78	21.66	20.67	16.78
RCP 8.5/2080	110.07	49.27	40.33	35.32	35.87	4.98

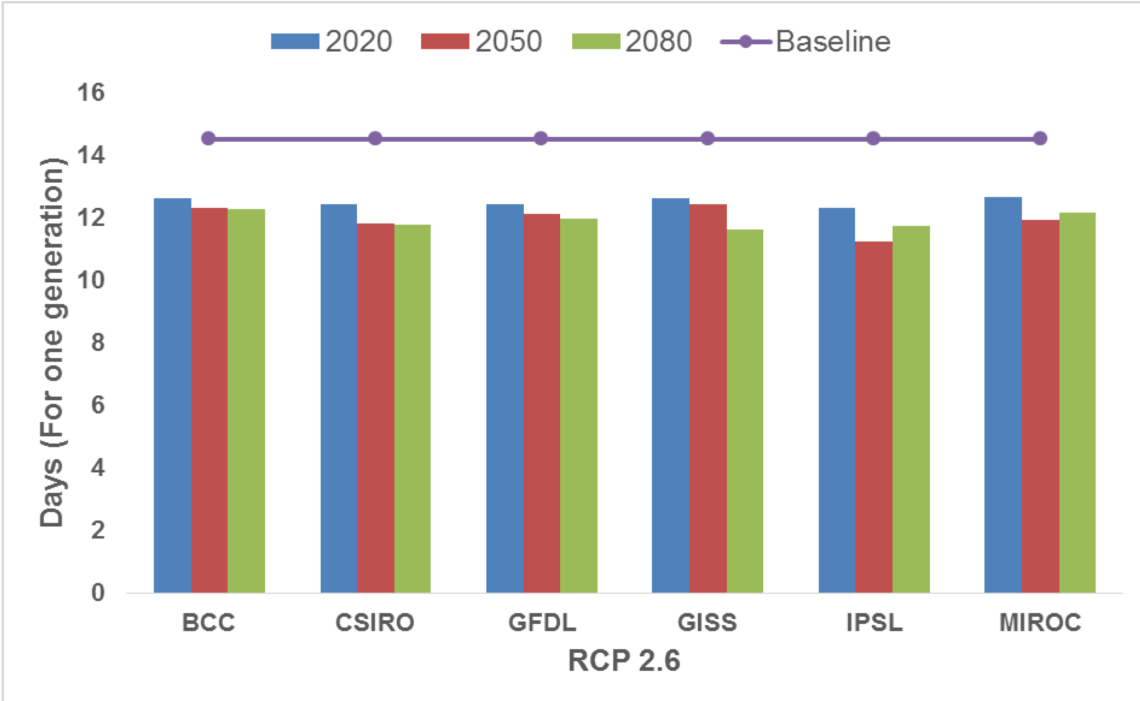


Fig. 1: Variation in the duration of latent period (days) of *Puccinia striiformis* f. sp. *tritici* in wheat, during four time periods for RCP 2.6

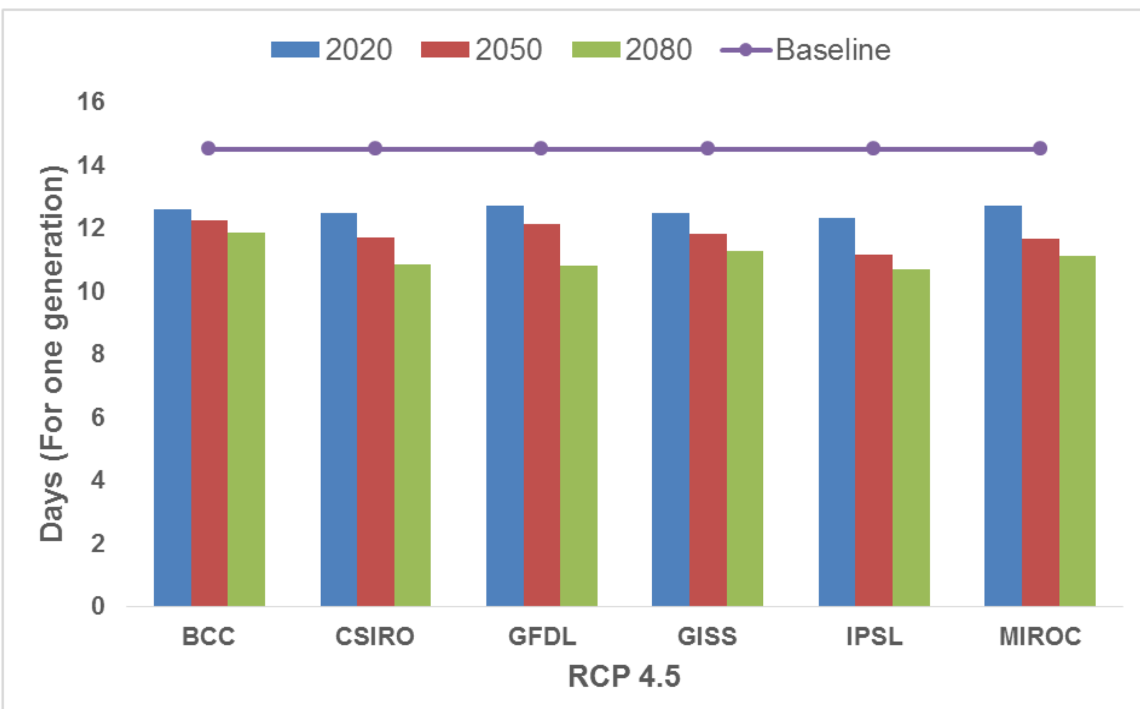


Fig. 2: Variation in the duration of latent period (days) of *Puccinia striiformis* f. sp. *tritici* in wheat, during four time periods for RCP 4.5

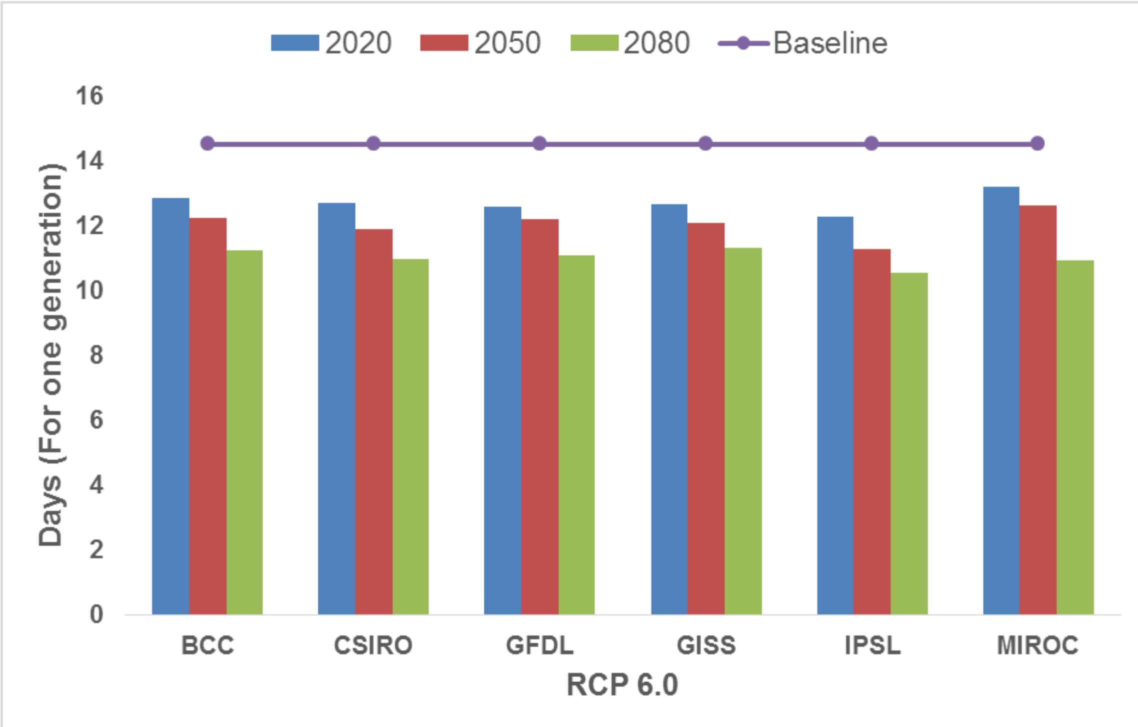


Fig. 3: Variation in the duration of latent period (days) of *Puccinia striiformis* f. sp. *tritici* in wheat, during four time periods for RCP 6.0

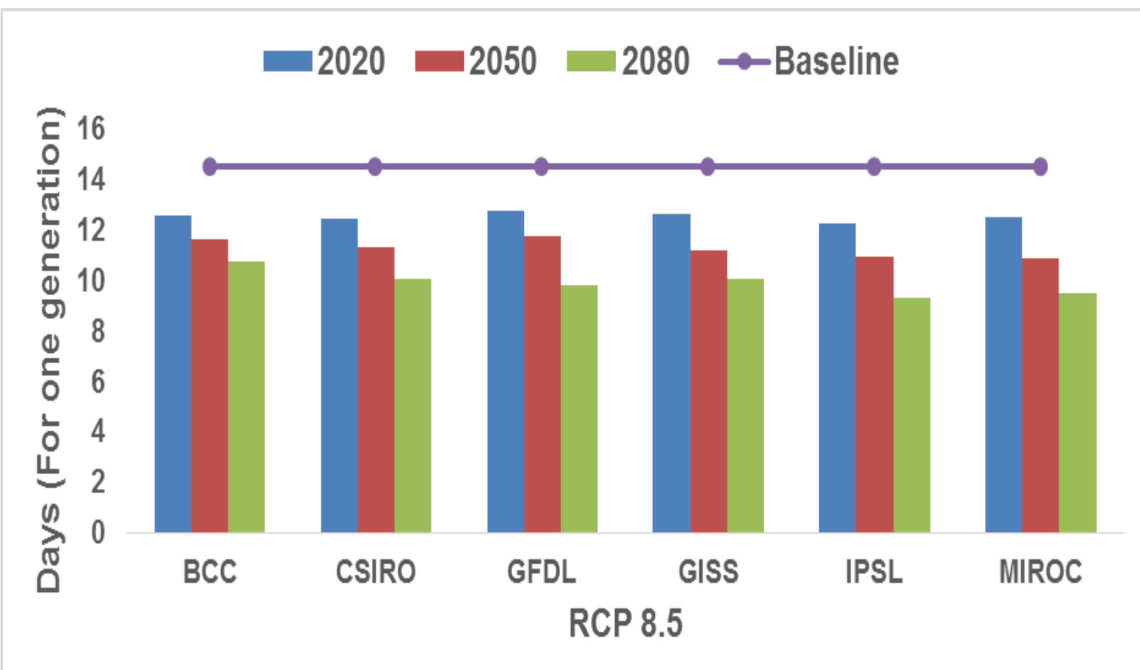


Fig. 4: Variation in the duration of latent period (days) of *Puccinia striiformis* f. sp. *tritici* in wheat, during four time periods for RCP 8.5

Table 5: Variations in the number of *Puccinia striiformis* f. sp. *tritici* infection cycles in wheat for four representative concentration pathway (RCP) scenarios during four time periods

Scenario/ Time Period	Locations					
	Jammu	**Ludhiana**	**Dhaula kuan**	**Hisar**	**Meerut**	**Leh**
Baseline (1975)	$4.56 \pm 0.09^{b*}$	6.42 ± 0.10^{b}	6.55 ± 0.12^{b}	7.45 ± 0.08^{b}	7.79 ± 0.07^{b}	7.62 ± 0.10^{a}
RCP 2.6/2020	7.74 ± 0.04^{a}	7.69 ± 0.05^{ab}	7.37 ± 0.04^{ab}	8.24 ± 0.10^{a}	8.52 ± 0.15^{a}	8.46 ± 0.01^{b}
RCP 2.6/2050	8.29 ± 0.10^{a}	8.10 ± 0.07^{ab}	7.86 ± 0.11^{ab}	9.14 ± 0.49^{a}	8.93 ± 0.20^{a}	8.85 ± 0.07^{b}
RCP 2.6/2080	8.11 ± 0.10^{a}	8.13 ± 0.10^{ab}	7.80 ± 0.12^{ab}	8.72 ± 0.07^{a}	10.12 ± 1.16^{a}	8.83 ± 0.07^{b}
RCP 4.5/2020	7.73 ± 0.06^{a}	7.67 ± 0.06^{ab}	7.38 ± 0.04^{ab}	8.20 ± 0.11^{a}	8.50 ± 0.10^{a}	8.47 ± 0.02^{b}
RCP 4.5/2050	8.26 ± 0.12^{a}	8.37 ± 0.13^{ab}	8.09 ± 0.12^{ab}	8.93 ± 0.10^{a}	9.29 ± 0.18^{a}	9.05 ± 0.10^{b}
RCP 4.5/2080	8.88 ± 0.14^{a}	8.86 ± 0.12^{ab}	8.56 ± 0.18^{ab}	9.39 ± 0.11^{a}	9.73 ± 0.28^{a}	9.45 ± 0.13^{b}
RCP 6.0/2020	7.75 ± 0.10^{a}	7.63 ± 0.07^{ab}	7.33 ± 0.05^{ab}	8.10 ± 0.21^{a}	8.41 ± 0.16^{a}	8.41 ± 0.06^{b}
RCP 6.0/2050	8.24 ± 0.10^{a}	8.08 ± 0.14^{ab}	7.87 ± 0.12^{ab}	8.46 ± 0.32^{a}	8.96 ± 0.19^{a}	8.84 ± 0.10^{b}
RCP 6.0/2080	9.01 ± 0.15^{a}	8.82 ± 0.11^{ab}	8.67 ± 0.15^{ab}	9.38 ± 0.09^{a}	9.74 ± 0.26^{a}	9.48 ± 0.07^{b}
RCP 8.5/2020	7.83 ± 0.08^{a}	7.76 ± 0.06^{ab}	7.42 ± 0.07^{ab}	8.28 ± 0.08^{a}	8.49 ± 0.15^{a}	8.51 ± 0.05^{b}
RCP 8.5/2050	8.85 ± 0.20^{a}	8.75 ± 0.16^{ab}	8.53 ± 0.14^{ab}	9.15 ± 0.16^{a}	9.58 ± 0.25^{a}	9.30 ± 0.10^{b}
RCP 8.5/2080	10.12 ± 0.23^{a}	9.91 ± 0.33^{a}	9.92 ± 0.29^{a}	10.36 ± 0.18^{a}	10.97 ± 0.42^{a}	10.50 ± 0.16^{b}
$P<0.001$	$2.2e^{-16}$	$2.2e^{-16}$	$2.2e^{-16}$	$5.092e^{-15}$	$2.2e^{-16}$	2.435e-06
F calculated	170.38	50.29	62.10	16.93	79.64	5.61
Error degree of freedom	60	60	60	60	60	60

Table 6: Per cent change in number of infection cycles of *Puccinia striiformis* f. sp. *tritici* in wheat in four representative concentration pathway (RCP) scenarios during four time periods

Scenario/ Time Period	Locations					
	Jammu	**Ludhiana**	**Dhaulakuan**	**Hisar**	**Meerut**	**Leh**
RCP 2.6/2020	44.99	20.74	12.77	18.50	16.67	13.89
RCP 2.6/2050	43.77	21.03	23.02	14.56	16.03	13.70
RCP 2.6/2080	41.01	16.29	8.35	9.15	11.25	10.03
RCP 4.5/2020	44.79	23.29	16.15	16.57	19.04	15.80
RCP 4.5/2050	48.65	27.54	19.94	20.66	23.48	19.37
RCP 4.5/2080	41.16	15.86	7.37	8.02	10.64	9.39
RCP 6.0/2020	44.66	20.54	13.06	11.94	16.77	13.80
RCP 6.0/2050	49.39	27.21	20.02	20.58	24.45	19.62
RCP 6.0/2080	41.76	17.27	0.35	0.48	0.67	0.59
RCP 8.5/2020	48.47	26.63	18.69	18.58	23.21	18.06
RCP 8.5/2050	54.94	35.22	28.99	28.09	33.97	27.43
RCP 8.5/2080	41.09	16.52	8.57	9.59	11.13	9.93

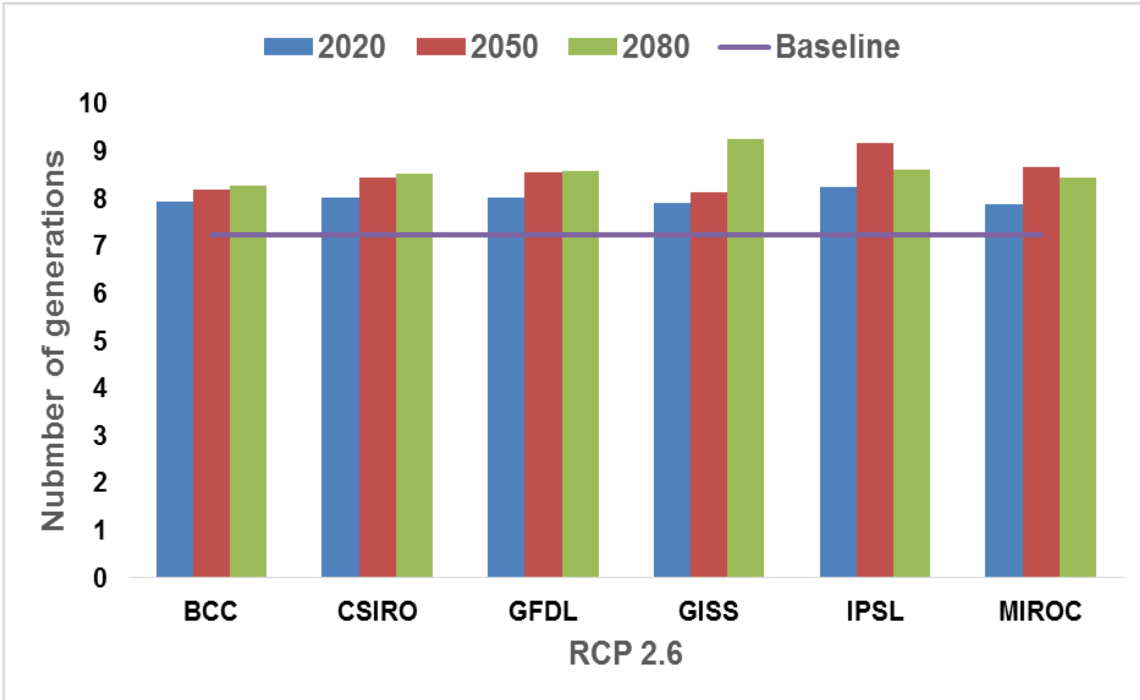


Fig. 5: Variations in the number of generations of *Puccinia striiformis* f. sp. *tritici* in wheat during four time periods for RCP 2.6

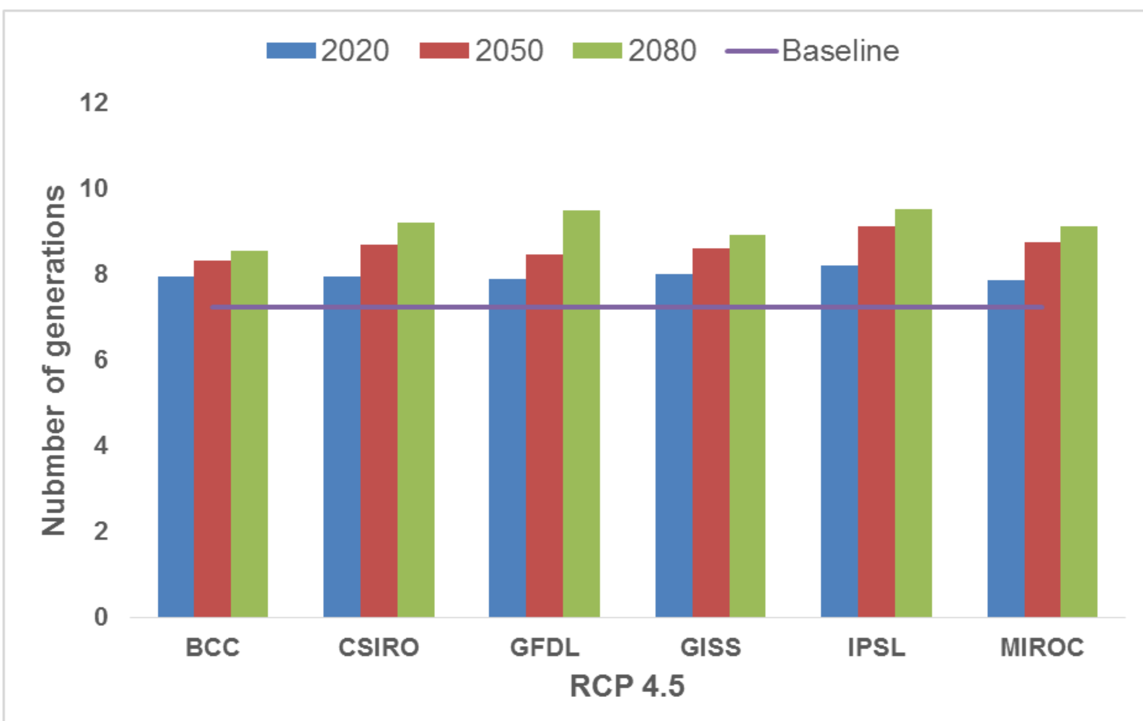


Fig. 6: Variations in the number of generations of *Puccinia striiformis* f. sp. *tritici* in wheat during four time periods for RCP 4.5

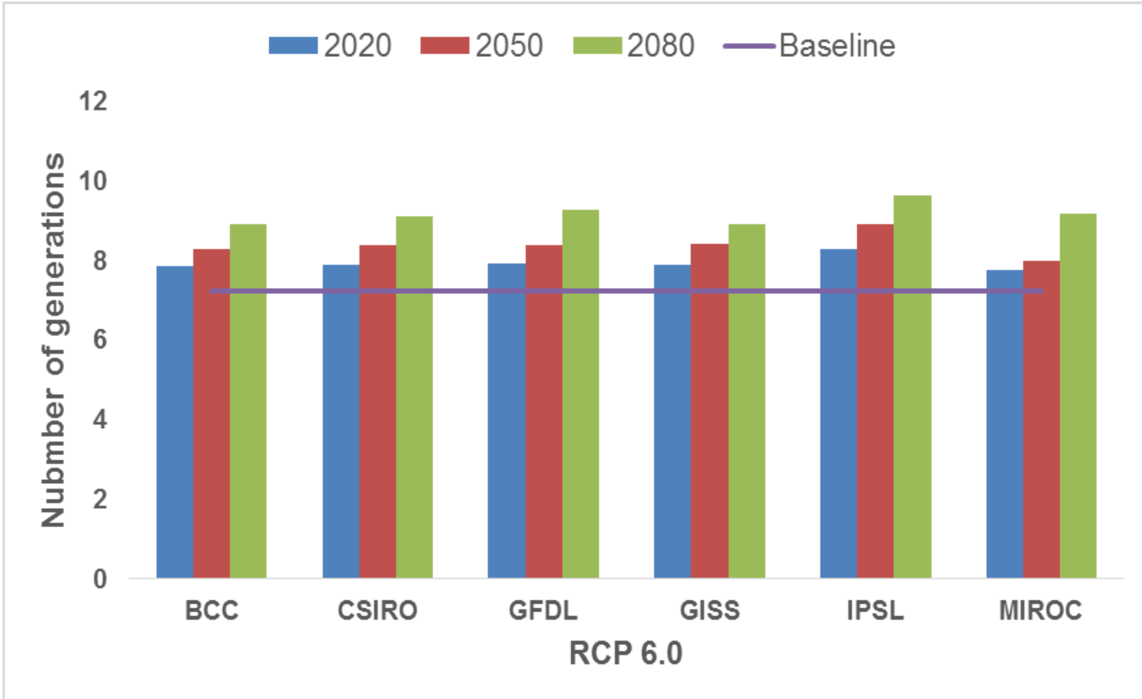


Fig. 7: Variations in the number of generations of *Puccinia striiformis* f. sp. *tritici* in wheat during four time periods for RCP 6.0

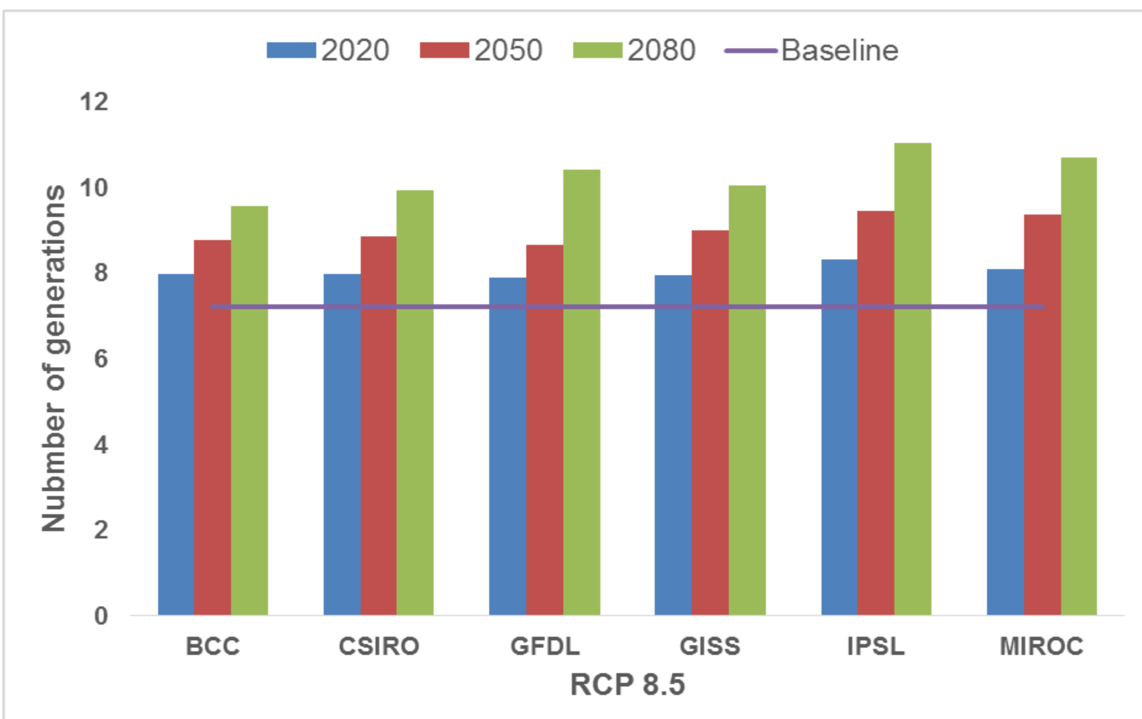


Fig. 8: Variations in the number of generations of *Puccinia striiformis* f. sp. *tritici* in wheat during four time periods for RCP 8.5

(2020, 2050 and 2080). The increase is predicted to be 9.91± 0.33 to 10.97± 0.42 under RCP 8.5 during the year 2080 (Table 5). Significant differences were observed in the number of infection cycles generated in all the selected locations under the four scenarios, for future time periods as compared to the baseline period (1975). However, there was no statistical difference among the scenarios, locations and future periods. Steady increase in number of generations was predicted in 2020 among the four RCP scenarios, which increased slightly in 2050 and sharply during 2080 period. Maximum per cent increase of 54.94, 35.22, 28.99, 28.09, 33.97 and 27.43 in number of *P. striiformis* f. sp. *tritici* infection cycles were recorded by RCP 8.5 scenario in Jammu, Ludhiana, Dhaulakuan, Hisar, Meerut and Leh, respectively during 2080 (Table 6). Model CSIRO and IPSL indicated the maximum number of *P. striiformis* f. sp. *tritici* generations under each climate change scenario (RCP), across all the locations in future climate periods over the baseline (Fig. 5-8).

4.4 Auto Regressive Integrated Moving Average (ARIMA) model for stripe rust of wheat

To predict the stripe rust of wheat, disease severity at weekly intervals from 2005 to 2019 was analysed to develop the Auto Regressive Integrated Moving Average (ARIMA) model, namely Box-Jenkins model. The stripe rust severity at weekly intervals from 2005 to 2017 was used as training data sets to build the ARIMA model which was validated to predict the severity of stripe rust of wheat during 2017-2019. The validated ARIMA model was fitted with the weekly interval meteorological factors as exogenous variables *viz.*, maximum and minimum temperatures, morning and evening relative humidity and rainfall, from 2005 to 2019 to develop ARIMAX model (Auto Regressive Integrated Moving Average with Exogenous Variables), in order to predict the severity of stripe rust of wheat from 2020-2022.

4.5 Descriptive statistics of meteorological factors and stripe rust of wheat

4.5.1 Severity of stripe rust of wheat

The mean, median, skewness, kurtosis, and maximum and minimum severity of stripe rust are presented in Table 7. During the study period (2005-19), overall mean disease severity was 35.30±1.41 per cent, whereas, minimum and maximum severity was 0.27 and 59.87 per cent, respectively. Skewness and kurtosis were -0.62 and -1.10, respectively, indicating that severity was negatively skewed with platykurtic distributions (Fig. 9).

4.5.2 Meteorological factors

During the period (2005-19), mean maximum temperature was 21.33±0.31^{0}C. The maximum and minimum values of maximum temperature were 35.40 and 10.85^{0}C, respectively (Table 7 and Fig. 10). Whereas, average minimum temperature during the period was 7.91±0.22^{0}C. The maximum and minimum values of minimum temperature were 16.30 and 1.47^{0}C, respectively.

Data in the Table 7 further exhibit that the average morning relative humidity (RH) was 89.30±0.37 per cent during 2015-2019. The maximum and minimum values of morning RH were 97.42 and 61.00 per cent, respectively. Whereas, in case of evening RH, the average was 52.45±0.72 per cent. The maximum and minimum values for minimum RH were 79.00 and 22.00 per cent, respectively (Fig. 11). During the period, average rainfall was 6.39±0.93mm with maximum of 80.66mm (Fig. 12).

4.6 Identification of forecasting model for stripe rust of wheat

To build-up ARIMA model (univariate), per cent severity of stripe rust of wheat from 2005-2019 was converted into time series frame, which analysed the past observations to make forecasts for the future. In order to understand underlying patterns of the severity of stripe rust of wheat, decomposition was computed. Data in the Fig. 13 exhibit upward and downward fluctuations in the observed data sets, indicating non-stationary nature which implies that the mean disease severity was increasing and decreasing with time among the selected years. The overall increasing trend of stripe rust, seasonal variations between year (upward and downward pattern) and unpredictable influences, which were not regular and also did not repeat in a particular pattern were observed after decomposing.

Table 7: Summary of weekly meteorological factors and severity of stripe rust of wheat in Jammu during 2005-2019

Epidemiological variable	Observation	Mean	Minimum	P_{25}	Median	P_{75}	Maximum	Skewness	Kurtosis
Disease severity (%)	180	35.30±1.41	0.27	20.70	42.65	50.78	59.87	-0.62	-1.10
Max. Temp. (ºC)	180	21.33±0.31	10.85	18.18	20.50	24.23	35.40	0.62	0.32
Min. Temp. (ºC)	180	7.91±0.22	1.47	5.475	7.70	9.800	16.30	0.29	-0.53
Morning RH (%)	180	89.30±0.37	61.00	86.67	90.43	92.71	97.42	-1.56	5.28
Evening RH (%)	180	52.45±0.72	22.00	46.00	52.43	58.14	79.00	0.00	0.26
Rainfall (mm)	180	6.39±0.93	0.00	0.000	3.46	6.855	80.66	3.37	13.50

P_{25} = Ist Quartile; P_{75} = 3rd Quartile; Max. Temp. = Maximum temperature (ºC); Min. Temp. = Minimum temperature (ºC);
RH = Relative humidity (%)

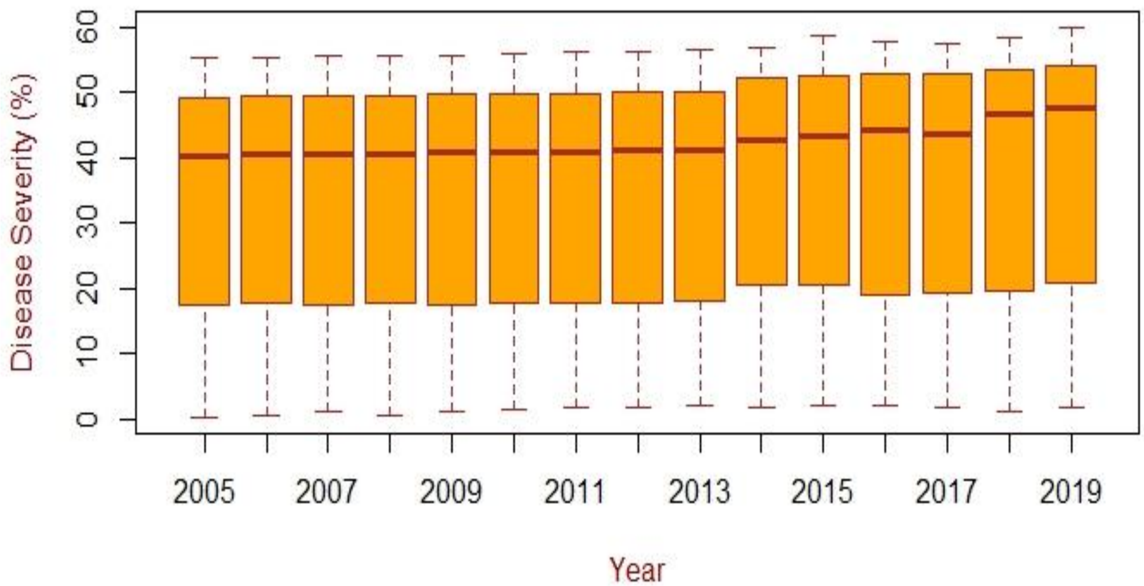


Fig. 9: Weekly severity (%) of stripe rust of wheat in Jammu during 2005 - 2019

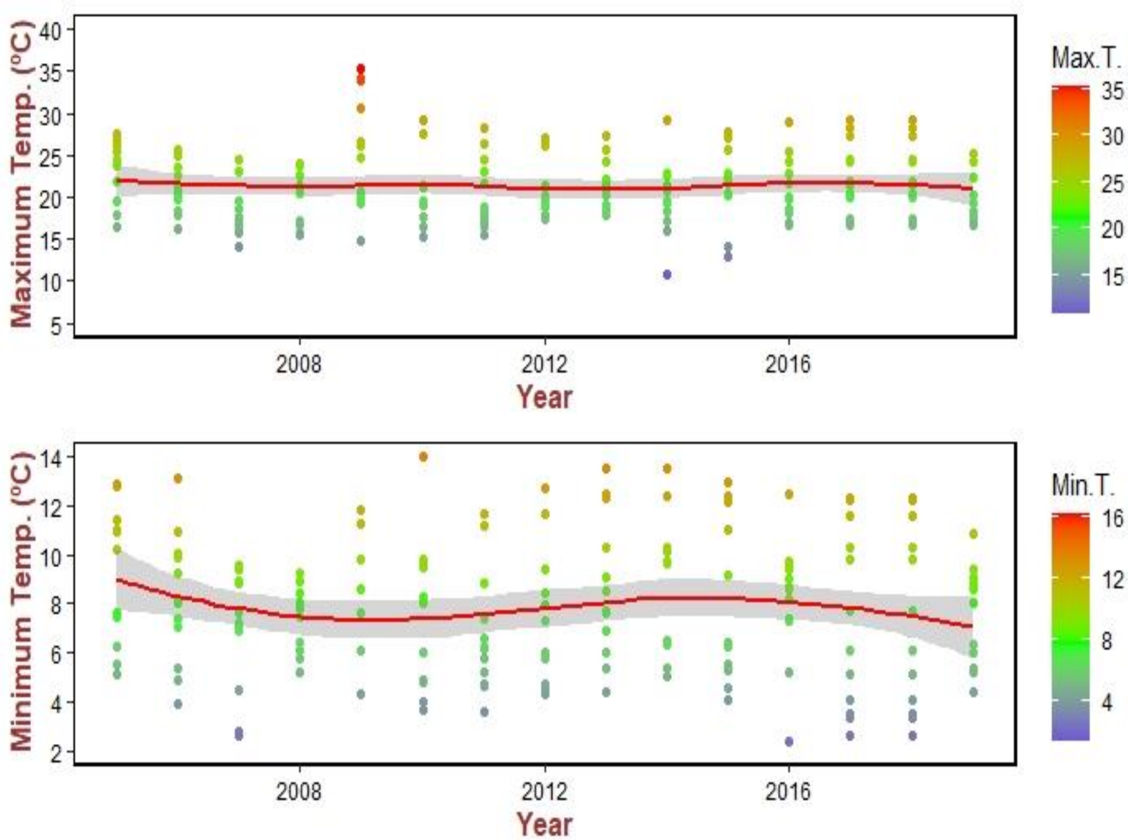


Fig. 10: Weekly mean temperature (maximum and minimum) in Jammu during 2005 - 2019

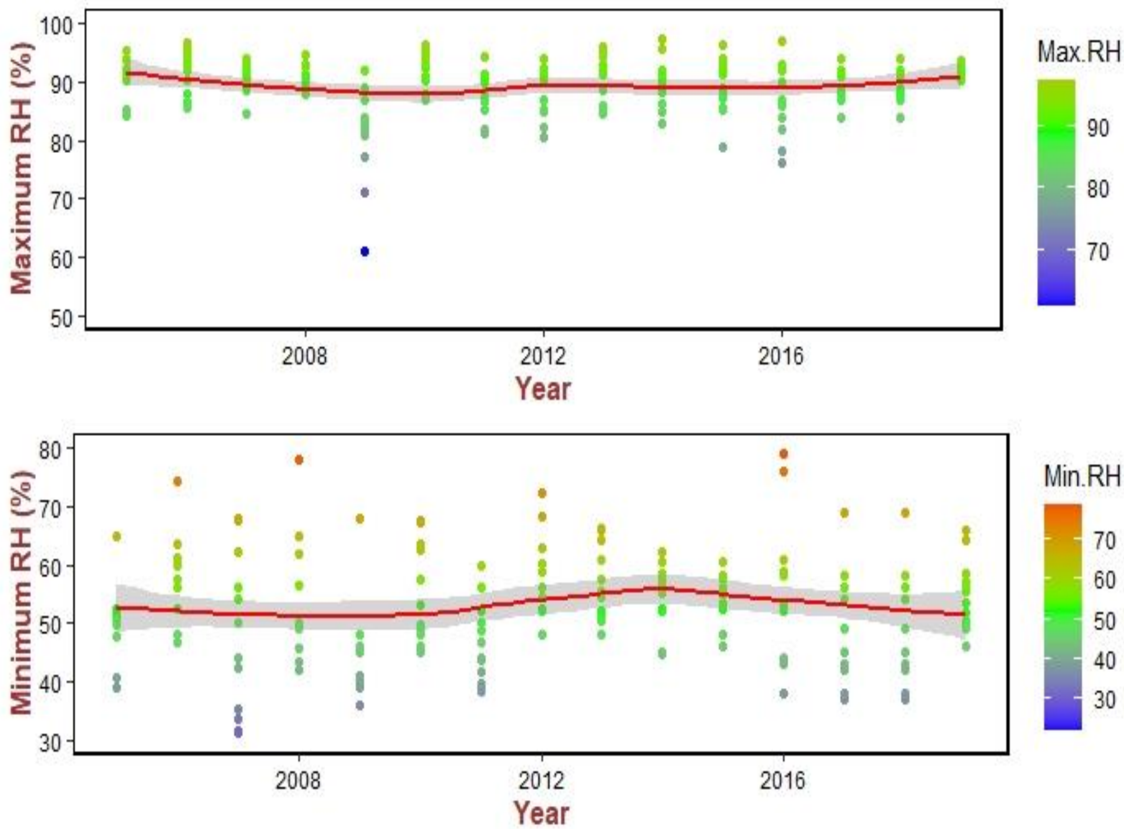


Fig. 11: Weekly mean relative humidity (maximum and minimum) in Jammu during 2005-2019

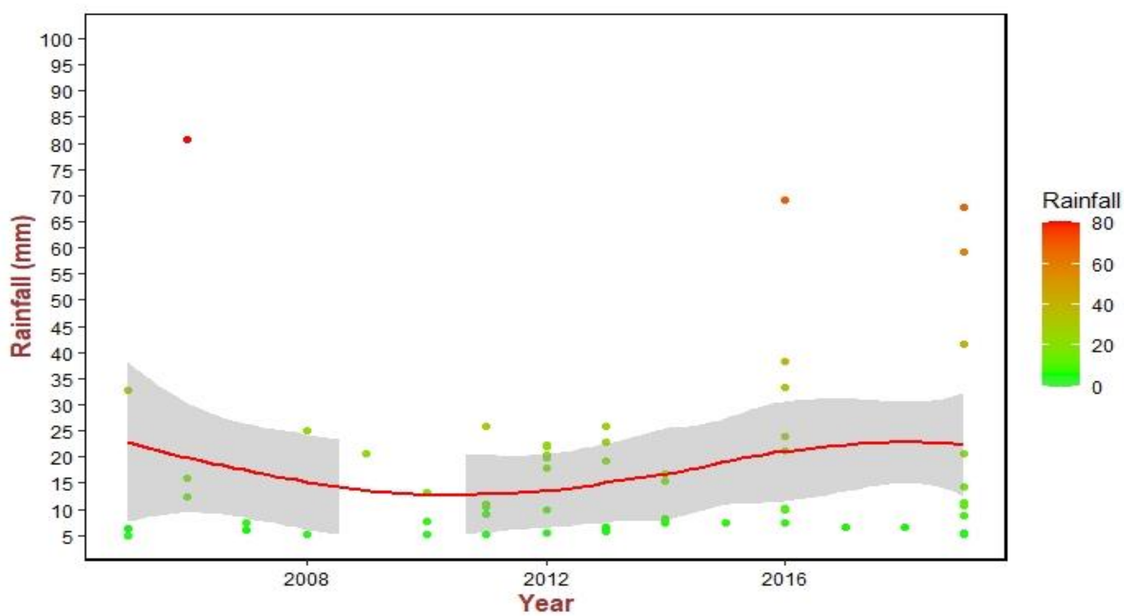


Fig. 12: Weekly mean rainfall (mm) in Jammu during 2005-2019

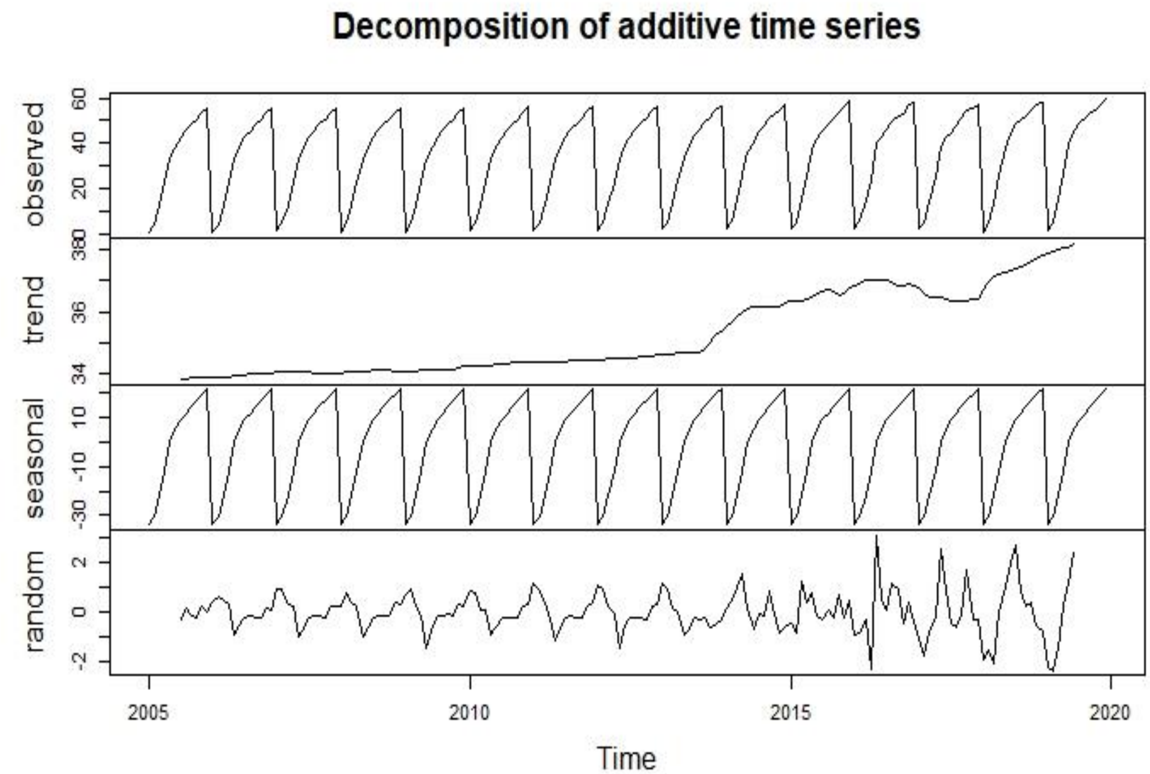


Fig. 13: Weekly severity (%) of stripe rust of wheat in Jammu during 2005-2019

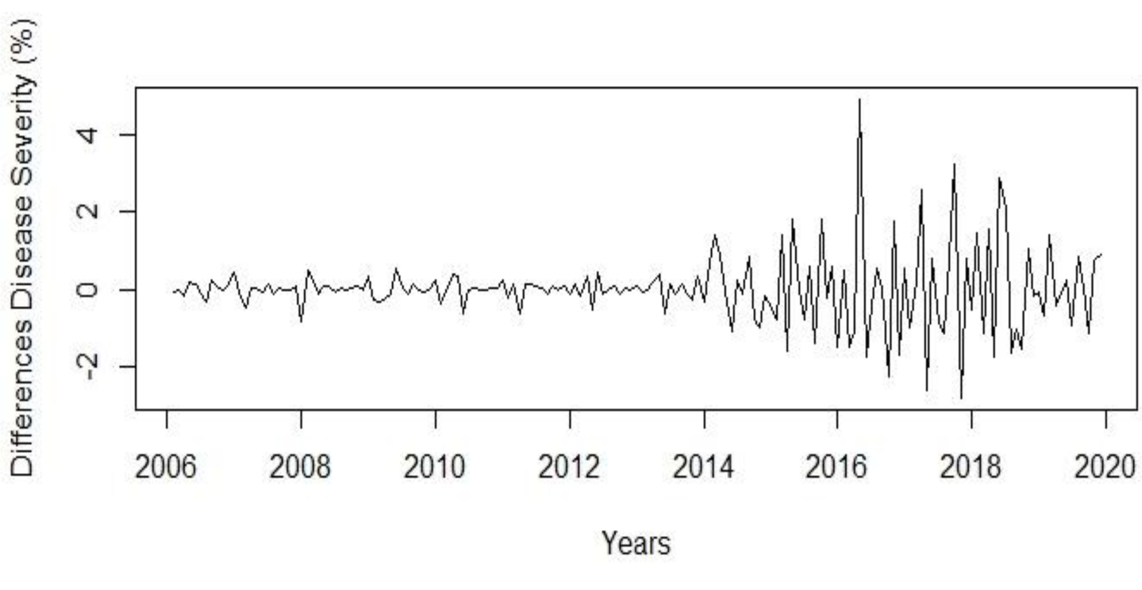


Fig. 14: 1st differencing of severity (%) of stripe rust of wheat in Jammu during 2005-2019

To make the data sets stationary (white-noise), 1st order differencing (lag 1) of severity data sets was performed (Fig. 14), resulting in both mean and variance constant and not dependent over time. In order to build ARIMA model, differencing of order one (d=1) was done to make the series stationary for severity of stripe rust of wheat.

4.6.1 Unit root test

After making the differencing (d=1) of time series of stripe rust of wheat, stationarity was checked through unit root tests *viz*., Augmented Dickey-Fuller (ADF) and Phillips-Perron tests (PP). Data in the Table 8 revealed that differenced series was stationary as Augmented Dickey-Fuller = -9.4802, $P < 0.01$, and Phillips-Perron = -71.347, $P < 0.01$ were significant.

4.6.2 Auto-correlation factor (ACF) and partial auto-correlation factor (PACF)

Plotting of auto-correlation factor **(**ACF) and partial auto-correlation factor (PACF) revealed the values of q (Moving Average**,** MA) and p (Auto-Regressive, AR) for the build up of ARIMA model. As only one significant spike in the ACF plot and two significant spikes in the PACF plot were outside the dotted horizontal lines, order of q (MA) was 1 and that of p (AR) was 2, respectively, resulting in AR=2 and MR=1 model (Fig. 15).

4.7 Model generation

In order to find out the most suitable model for prediction of stripe rust of wheat for future periods, five models were selected *viz*., ARIMA $(2,1,1)(1,1,1)_7$, ARIMA $(1,1,2)(1,1,1)_7$, ARIMA$(1,1,1)(1,1,1)_7$, ARIMA $(1,1,1)(1,1,2)_7$ and ARIMA $(1,1,1)(2,1,1)_7$, based on four different conditions p = 1 or 2, q = 1 or 2; P = 1 or 2; Q = 1 or 2 with I = 1, having minimum AIC (Akaike Information Criteria) values of 387.19, 387.62, 388.06, 389.95 and 389.89, respectively (Table 9). Simultaneously, through auto-ARIMA function, ninety-four ARIMA models were generated, of which ARIMA $(2,1,1)(1,1,1)_7$, ARIMA$(1,1,1)(1,1,1)_7$, ARIMA $(1,1,1)(1,1,2)_7$, ARIMA $(1,1,1)(2,1,1)_7$ and ARIMA $(1,1,2)(1,1,1)_7$ were selected having lowest AIC value (Table 10).

4.8 Estimation of model parameters

Data in the Table 9 exhibited the parameter statistics of selected ARIMA models for the prediction of stripe rust of wheat. The model $(2,1,1)(1,1,1)_7$ exhibited that estimation of 1st and 2nd order auto-regressive coefficient ϕ_1 and ϕ_2, 1st order moving average coefficient θ_1, 1st order seasonal auto-regressive coefficient φ_1 and1st order seasonal moving average coefficient Θ_1 were highly significant ($\phi_1 = 0.37$, p = 1.229e-05; $\phi_2 = 0.14$, p = 0.08; $\theta_1 = -0.96$, p = < 2.2e-16; $\varphi_1 = 0.40$, p = 0.02029 and $\Theta_1 = -0.71$, p = 1.033e-06, respectively).

In model ARIMA $(1,1,1)(1,1,1)_7$, estimate of 1st order of auto-regressive coefficient ϕ_1, moving average coefficient θ_1, seasonal auto-regressive coefficient φ_1 and seasonal moving average coefficient Θ_1 were highly significant ($\phi_1 = 0.39$, p = 0.0005437; $\theta_1 = -0.92$, p = < 2.2e-16; $\varphi_1 = 0.39$, p = 0.0199690 and $\Theta_1 = -0.72$, p = 4.92e-07, respectively). Whereas, in ARIMA (1,1,1) $(1,1,2)_7$ estimates of 1st order of auto-regressive coefficient ϕ_1 and moving average coefficient θ_1 were significant ($\phi_1 = 0.399$, p = 0.0003461; $\theta_1 = -0.92$, p = < 2.2e-16). In ARIMA (1,1,1) $(2,1,1)_7$, estimates of 1st order of auto-regressive coefficient ϕ_1 and moving average coefficient θ_1 along with 1st order of seasonal moving average coefficient Θ_1 were highly significant ($\phi_1 = 0.39$, p = 0.0002301; $\theta_1 = -0.93$, p = < 2.2e-16; $\Theta_1 = -0.66$, p = 0.0016030, respectively). The ARIMA (1,1,2) $(1,1,1)_7$ have estimates for 1st order of auto-regressive coefficient ϕ_1, moving average coefficient θ_1, seasonal auto-regressive φ_1 and moving average coefficient Θ_1 highly significant ($\phi_1 = 0.67$, p = 5.990e-06; $\theta_1 = -1.25$, p = 1.976e-11; $\varphi_1 = 0.39$, p =0.02871 and $\Theta_1 = -0.69$, p = 8.398e-06, respectively).

4.9 Performance of models

Data in the Table 11 show that ARIMA $(2,1,1)(1,1,1)_7$ had lowest Root mean square error (RMSE) and Mean absolute percentage error (MAPE) of 0.7071721 and 4.352807, respectively, along with maximum Mean absolute scaled error (MASE) of 0.04534878 with the accuracy of 95.65 per cent. ARIMA (1,1,1) $(1,1,1)_7$ depicted the RMSE, MAPE, MASE and accuracy of 0.7137975, 4.529791, 0.0453234 and 95.48 per cent, respectively. Whereas, ARIMA (1,1,1) $(1,1,2)_7$ showed RMSE, MAPE, MASE and

Table 8: Unit Root stationarity tests for stripe rust of wheat

Test	t-statistics	*P value*
Augmented Dickey-Fuller (ADF)	-9.480	0.01*
Phillips-Perron (PP)	-71.347	0.01*

*Significant at $p \leq 0.05$

Table 9: Estimates of the ARIMA models based on wheat stripe rust severity (%) parameters

Model	Coefficient	Estimate	Standard Error	t-test	*p-value*	AIC
ARIMA(2,1,1)(1,1,1)$_7$	ϕ_1(ar1)	0.37	0.09	4.37	1.229e-05 ***	387.19
	ϕ_2 (ar2)	0.14	0.08	1.74	0.08119 ·	
	θ_1 (ma1)	-0.96	0.03	-27.20	< 2.2e-16 ***	
	Φ_1 (sar1)	0.40	0.17	2.32	0.02029 *	
	Θ_1 (sma1)	-0.71	0.15	-4.89	1.033e-06 ***	
ARIMA (1,1,1)(1,1,1)$_7$	ϕ_1(ar1)	0.39	0.11	3.46	0.0005437 ***	388.06
	θ_1 (ma1)	-0.92	0.07	-14.10	< 2.2e-16 ***	
	Φ_1 (sar1)	0.39	0.17	2.33	0.0199690 *	
	Θ_1 (sma1)	-0.72	0.14	-5.03	4.92e-07 ***	
ARIMA (1,1,1)(1,1,2)$_7$	ϕ_1(ar1)	0.39	0.11	3.58	0.0003461 ***	389.95
	θ_1 (ma1)	-0.92	0.06	-14.52	< 2.2e-16 ***	
	Φ_1 (sar1)	0.28	0.37	0.73	0.4656950	
	Θ_1 (sma1)	-0.60	0.38	-1.59	0.1116735	
	Θ_2 (sma2)	-0.06	0.17	-0.35	0.7294539	
ARIMA (1,1,1)(2,1,1)$_7$	ϕ_1(ar1)	0.39	0.11	3.68	0.0002301 ***	389.89
	θ_1 (ma1)	-0.93	0.06	-14.96	< 2.2e-16 ***	
	Φ_1 (sar1)	0.34	0.22	1.56	0.1183378	
	Φ_2(sar2)	-0.05	0.12	-0.43	0.6694429	
	Θ_1 (sma1)	-0.66	0.21	-3.16	0.0016030 **	
ARIMA (1,1,2)(1,1,1)$_7$	ϕ_1(ar1)	0.67	0.15	4.53	5.990e-06 ***	387.62
	θ_1 (ma1)	-1.25	0.19	-6.71	1.976e-11 ***	
	θ_2(ma2)	0.28	0.17	1.64	0.10038	
	Φ_1 (sar1)	0.39	0.18	2.19	0.02871 *	
	Θ_1 (sma1)	-0.69	0.16	-4.45	8.398e-06 ***	

ϕ_1 and ϕ_2: 1-order and 2-order auto-regressive coefficient; θ_1 and θ_2: 1-order and 2-order moving average coefficient; Φ_1 and Φ_1: 1-order and 2-order seasonal auto-regressive coefficients; Θ_1 andΘ_2: 1-order and 2-order seasonal moving average coefficient

*** Significant at $p \leq 0.001$
** Significant at $p \leq 0.01$
* Significant at $p \leq 0.05$
· Significant at $p \leq 0.1$
AIC = Akaike Information Criterion

Table 10: ARIMA models generated through auto - ARIMA

S.No.	Model	AIC	S.No.	Model	AIC
1	ARIMA(0,1,0)(0,1,0)[7]	452.03	**48**	ARIMA(1,1,1)(0,1,2)[7]	388.84
2	ARIMA(0,1,0)(0,1,1)[7]	435.81	**49**	ARIMA(1,1,1)(1,1,0)[7]	393.03
3	ARIMA(0,1,0)(0,1,2)[7]	429.53	**50**	ARIMA(1,1,1)(1,1,1)[7]	388.43
4	ARIMA(0,1,0)(1,1,0)[7]	443.55	**51**	ARIMA(1,1,1)(1,1,2)[7]	390.48
5	ARIMA(0,1,0)(1,1,1)[7]	429.24	**52**	ARIMA(1,1,1)(2,1,0)[7]	392.61
6	ARIMA(0,1,0)(1,1,2)[7]	431.03	**53**	ARIMA(1,1,1)(2,1,1)[7]	390.42
7	ARIMA(0,1,0)(2,1,0)[7]	438.53	**54**	ARIMA(1,1,2)(0,1,0)[7]	397.74
8	ARIMA(0,1,0)(2,1,1)[7]	430.92	**55**	ARIMA(1,1,2)(0,1,1)[7]	389.25
9	ARIMA(0,1,0)(2,1,2)[7]	432.78	**56**	ARIMA(1,1,2)(0,1,2)[7]	388.33
10	ARIMA(0,1,1)(0,1,0)[7]	402.15	**57**	ARIMA(1,1,2)(1,1,0)[7]	391.81
11	ARIMA(0,1,1)(0,1,1)[7]	392.95	**58**	ARIMA(1,1,2)(1,1,1)[7]	388.14
12	ARIMA(0,1,1)(0,1,2)[7]	394.46	**59**	ARIMA(1,1,2)(2,1,0)[7]	390.92
13	ARIMA(0,1,1)(1,1,0)[7]	394.45	**60**	ARIMA(1,1,3)(0,1,0)[7]	399.85
14	ARIMA(0,1,1)(1,1,1)[7]	394.31	**61**	ARIMA(1,1,3)(0,1,1)[7]	391.40
15	ARIMA(0,1,1)(1,1,2)[7]	396.41	**62**	ARIMA(1,1,3)(1,1,0)[7]	393.85
16	ARIMA(0,1,1)(2,1,0)[7]	395.30	**63**	ARIMA(1,1,4)(0,1,0)[7]	401.82
17	ARIMA(0,1,1)(2,1,1)[7]	396.41	**64**	ARIMA(2,1,0)(0,1,0)[7]	415.09
18	ARIMA(0,1,1)(2,1,2)[7]	398.33	**65**	ARIMA(2,1,0)(0,1,1)[7]	404.73
19	ARIMA(0,1,2)(0,1,0)[7]	402.42	**66**	ARIMA(2,1,0)(0,1,2)[7]	405.18
20	ARIMA(0,1,2)(0,1,1)[7]	391.60	**67**	ARIMA(2,1,0)(1,1,0)[7]	407.02
21	ARIMA(0,1,2)(0,1,2)[7]	392.49	**68**	ARIMA(2,1,0)(1,1,1)[7]	404.84
22	ARIMA(0,1,2)(1,1,0)[7]	393.87	**69**	ARIMA(2,1,0)(1,1,2)[7]	406.99
23	ARIMA(0,1,2)(1,1,1)[7]	392.09	**70**	ARIMA(2,1,0)(2,1,0)[7]	406.84
24	ARIMA(0,1,2)(1,1,2)[7]	394.23	**71**	ARIMA(2,1,0)(2,1,1)[7]	406.99
25	ARIMA(0,1,2)(2,1,0)[7]	394.38	**72**	ARIMA(2,1,1)(0,1,0)[7]	398.91
26	ARIMA(0,1,2)(2,1,1)[7]	394.22	**73**	ARIMA(2,1,1)(0,1,1)[7]	389.72
27	ARIMA(0,1,3)(0,1,0)[7]	402.38	**74**	ARIMA(2,1,1)(0,1,2)[7]	387.73
28	ARIMA(0,1,3)(0,1,1)[7]	391.20	**75**	ARIMA(2,1,1)(1,1,0)[7]	393.36
29	ARIMA(0,1,3)(0,1,2)[7]	389.42	**76**	ARIMA(2,1,1)(1,1,1)[7]	387.72
30	ARIMA(0,1,3)(1,1,0)[7]	394.68	**77**	ARIMA(2,1,1)(2,1,0)[7]	390.75
31	ARIMA(0,1,3)(1,1,1)[7]	389.50	**78**	ARIMA(2,1,2)(0,1,0)[7]	399.85
32	ARIMA(0,1,3)(2,1,0)[7]	393.03	**79**	ARIMA(2,1,2)(0,1,1)[7]	391.39
33	ARIMA(0,1,4)(0,1,0)[7]	403.03	**80**	ARIMA(2,1,2)(1,1,0)[7]	393.82
34	ARIMA(0,1,4)(0,1,1)[7]	391.54	**81**	ARIMA(2,1,3)(0,1,0)[7]	401.99
35	ARIMA(0,1,4)(1,1,0)[7]	395.50	**82**	ARIMA(3,1,0)(0,1,0)[7]	412.97
36	ARIMA(0,1,5)(0,1,0)[7]	404.80	**83**	ARIMA(3,1,0)(0,1,1)[7]	404.50
37	ARIMA(1,1,0)(0,1,0)[7]	420.90	**84**	ARIMA(3,1,0)(0,1,2)[7]	404.62
38	ARIMA(1,1,0)(0,1,1)[7]	409.84	**85**	ARIMA(3,1,0)(1,1,0)[7]	406.61
39	ARIMA(1,1,0)(0,1,2)[7]	406.97	**86**	ARIMA(3,1,0)(1,1,1)[7]	404.42
40	ARIMA(1,1,0)(1,1,0)[7]	414.35	**87**	ARIMA(3,1,0)(2,1,0)[7]	406.27
41	ARIMA(1,1,0)(1,1,1)[7]	407.21	**88**	ARIMA(3,1,1)(0,1,0)[7]	400.43
42	ARIMA(1,1,0)(1,1,2)[7]	409.00	**89**	ARIMA(3,1,1)(0,1,1)[7]	391.50
43	ARIMA(1,1,0)(2,1,0)[7]	409.92	**90**	ARIMA(3,1,1)(1,1,0)[7]	394.41
44	ARIMA(1,1,0)(2,1,1)[7]	409.03	**91**	ARIMA(4,1,0)(0,1,0)[7]	411.30
45	ARIMA(1,1,0)(2,1,2)[7]	411.15	**92**	ARIMA(4,1,0)(0,1,1)[7]	400.53
46	ARIMA(1,1,1)(0,1,0)[7]	401.46	**93**	ARIMA(4,1,0)(1,1,0)[7]	402.73
47	ARIMA(1,1,1)(0,1,1)[7]	389.93	**94**	ARIMA(4,1,1)(0,1,0)[7]	402.35

Table 11: ARIMA models fit statistics of severity (%) of stripe rust of wheat

Model	Ljung-Box test			RMSE	MAPE	MASE	Accuracy
	Statistics	DF	Significance				
ARIMA(2,1,1)(1,1,1)$_7$	34.046	25	0.1069	0.7071721	4.352807	0.04534878	95.65
ARIMA(1,1,1)(1,1,1)$_7$	35.438	25	0.05216	0.7137975	4.529791	0.0453234	95.48
ARIMA 1,1,1)(1,1,2)$_7$	37.162	25	0.05573	0.713325	4.540096	0.0452683	95.46
ARIMA 1,1,1)(2,1,1)$_7$	37.034	25	0.05731	0.7130573	4.546114	0.0452238	95.46
ARIMA 1,1,2)(1,1,1)$_7$	33.713	25	0.1142	0.7083732	4.37238	0.04514377	95.63

RMSE = Root mean square error, MAPE = Mean absolute percentage error
MASE= Mean absolute scaled error

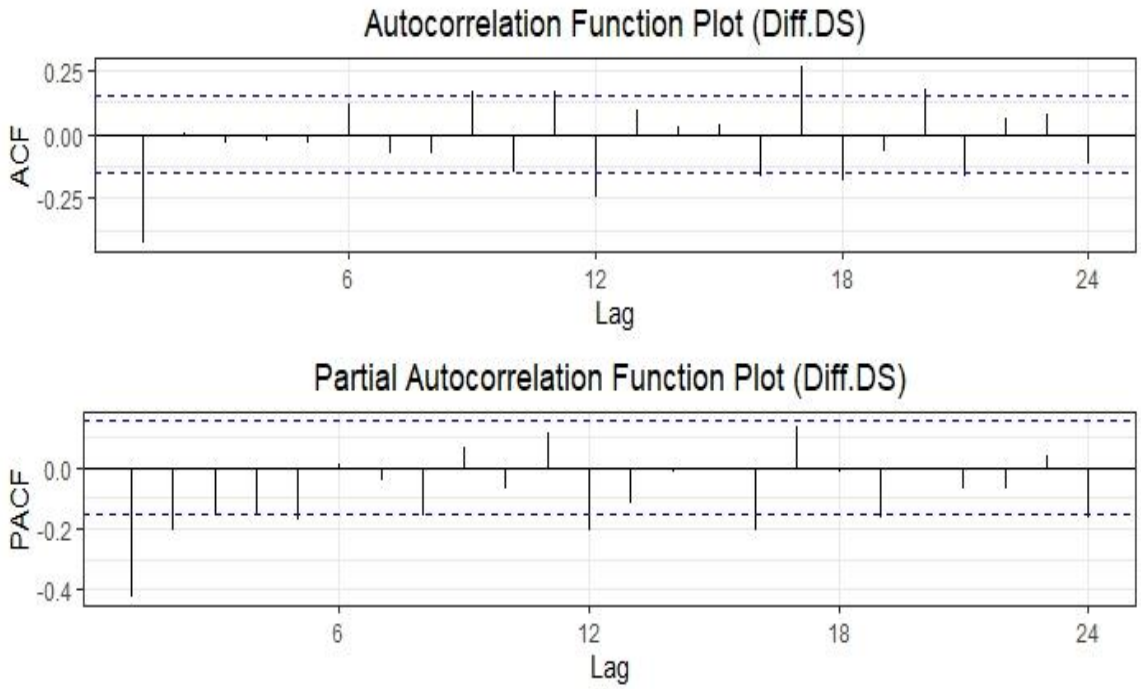


Fig. 15: Autocorrelation (ACF) and Partial-autocorrelation (PACF) plots of 1-step differences of severity (%) of stripe rust of wheat

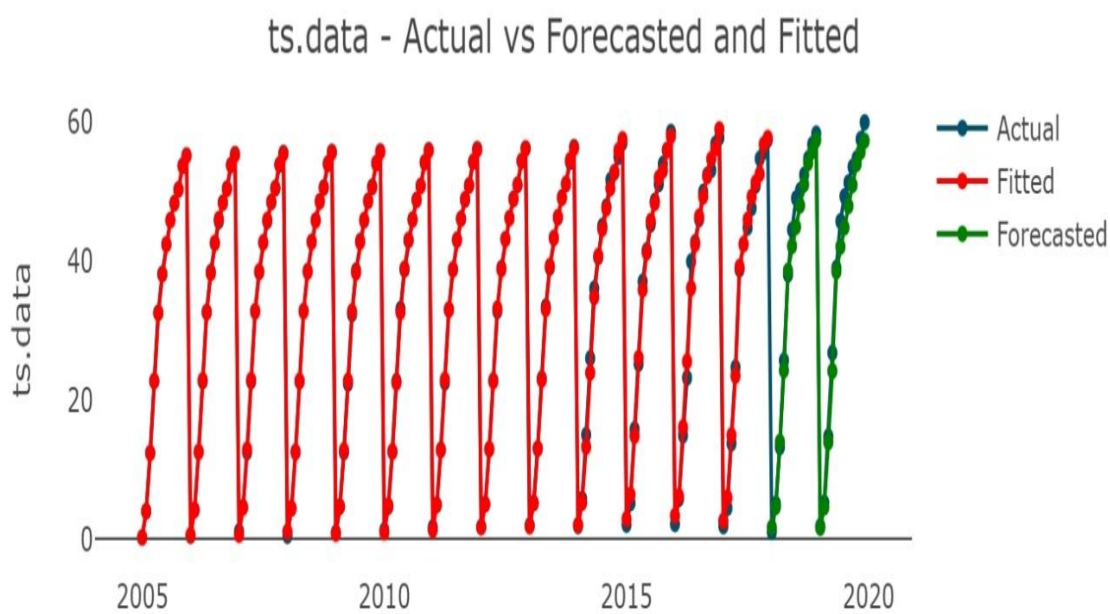


Fig. 16: Validation of the ARIMA model (2,1,1) $(1,1,1)_7$for severity (%) of stripe rust of wheat

Red lines = 2005-2017 and Green lines = 2018-2019

Table 12: Forecast accuracy of severity (%) of stripe rust of wheat by ARIMA model (2,1,1)(1,1,1)$_7$

Year	SMW	Observed severity (%)	Estimated severity (%)	Percent relative deviation (RD%)
2018	1st	1.05	1.41	25.53
	2nd	5.10	5.23	2.54
	3rd	13.24	13.64	3.20
	4th	25.67	25.44	0.89
	5th	38.00	38.43	1.13
	6th	44.45	42.28	4.88
	7th	48.97	44.98	8.14
	8th	50.12	47.91	4.40
	9th	52.33	50.99	2.56
	10th	54.67	54.28	0.71
	11th	56.71	55.78	1.64
	12th	58.25	57.47	1.34
2019	1st	1.89	1.60	15.34
	2nd	5.25	5.33	1.52
	3rd	14.78	13.84	6.36
	4th	26.78	25.44	5.00
	5th	38.98	38.53	1.15
	6th	45.67	42.34	7.29
	7th	49.25	45.08	8.46
	8th	51.23	48.07	6.17
	9th	53.47	51.11	4.41
	10th	54.68	54.18	0.91
	11th	57.45	55.88	2.73
	12th	59.87	57.57	3.84

Table 13: Prediction of severity (%) of stripe rust of wheat by ARIMA model $(2,1,1)(1,1,1)_7$

SMW	Year		
	2020	2021	2022
1st	3.22±0.73	3.83±1.052	4.37±1.28
2nd	6.53±0.79	7.17±1.087	7.73±1.32
3rd	15.72±0.83	16.30±1.11	16.85±1.34
4th	27.24±0.85	27.67±1.13	28.16±1.36
5th	39.57±0.86	40.07±1.14	40.58±1.37
6th	45.66±0.86	45.95±1.14	46.37±1.38
7th	49.29±0.87	49.60±1.15	50.03±1.39
8th	51.45±0.87	51.84±1.16	52.30±1.39
9th	53.84±0.88	54.28±1.16	54.77±1.40
10th	55.38±0.88	55.97±1.17	56.51±1.41
11th	58.01±0.88	58.54±1.17	59.06±1.42
12th	60.20±0.88	60.64±1.18	61.12±1.42

accuracy of 0.713325, 4.540096, 0.0452683 and 95.46 per cent, respectively. The RMSE, MAPE, MASE and accuracy of ARIMA (1,1,1) $(2,1,1)_7$ and ARIMA (1,1,2) $(1,1,1)_7$ were 0.7130573, 4.546114, 0.0452238 and 95.46 per cent; 0.7083732, 4.37238, 0.04514377 and 95.63 per cent, respectively. Box-Ljung test of all the developed models *viz*., ARIMA $(2,1,1)(1,1,1)_7$, ARIMA$(1,1,1)(1,1,1)_7$, ARIMA $(1,1,1)(1,1,2)_7$, ARIMA $(1,1,1)(2,1,1)_7$ and ARIMA $(1,1,2)(1,1,1)_7$ showed that the residuals are random and that the model provides an adequate fit to the data (χ^2 = = 34.046, p = 0.1069; χ^2 = = 35.438, p = 0.05216; χ^2= 37.162, p = 0.05573, χ^2 = 37.034 , p = 0.05731 and χ^2 = 33.713 , p = 0.1142).

Based on the lowest value of RMSE and MAPE and highest accuracy, ARIMA $(2,1,1)(1,1,1)_7$ was selected among the five developed models and was tested with the data sets of 2017-2019 (Fig. 16). Data in the Table 12 exhibited that the developed model predicted the severity of stripe rust of wheat in 2018-2019 with minimum per cent relative deviation (0.71 to 8.14; 0.91 to 8.46) except in the first week of both the tested years, favouring the use of ARIMA $(2,1,1)(1,1,1)_7$ for short-term forecasts. ARIMA $(2,1,1)(1,1,1)_7$ predicted the stripe rust severity of 3.22±0.73 to 60.20±0.88; 3.83±1.052 to 60.64±1.18 and 4.37±1.28 to 61.12±1.42 for the year 2020, 2021 and 2022, respectively (Table 13).

4.10 Diagnostic measures

After the selection and validation of ARIMA $(2,1,1)(1,1,1)_7$, for forecasting severity (%) of stripe rust of wheat, pattern in the residuals was tested whether the residuals could meet white noise assumptions, as the residuals from the ARIMA $(2,1,1)(1,1,1)_7$, assumed to be independent, homoscedastic, and usually normally distributed. Auto-correlation factor **(**ACF) and partial auto-correlation factor (PACF) plots of the residuals showed no significant auto-correlations since all the values were within the threshold limits, indicating that the residuals were behaving like white noise (Fig. 17a to 17c). Almost all the values were laid on the line in Normal QQ plot (Fig. 18); and the shape of the Histogram appeared "Bell Shaped" (Fig. 19) curve indicating that the residuals of the fitted model could be referred as normal. Box-Ljung test failed to reject the null hypothesis (model does not lack goodness of fit) of independence with a P-value of 0.1394 (Fig. 20).

4.11 Auto Regressive Integrated Moving Average with Exogenous Variables (ARIMAX)

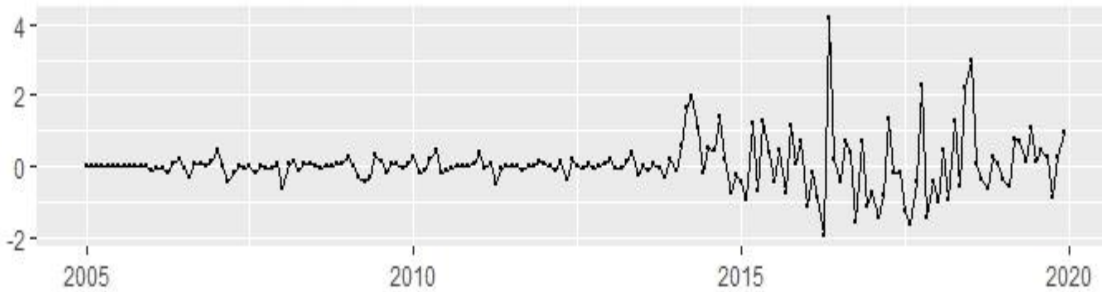
The Box-Jenkins methodology of specification, estimation of parameters, and diagnostic check was similar to both ARIMA as well as ARIMAX models. There was an additional step known as pre-whitening in ARIMAX applied to remove autocorrelations among meteorological factors *viz.,* maximum and minimum temperature, morning and evening relative humidity and rainfall which acted as exogenous variables in case of ARIMAX modelling

4.11.1 Selection of meteorological factors

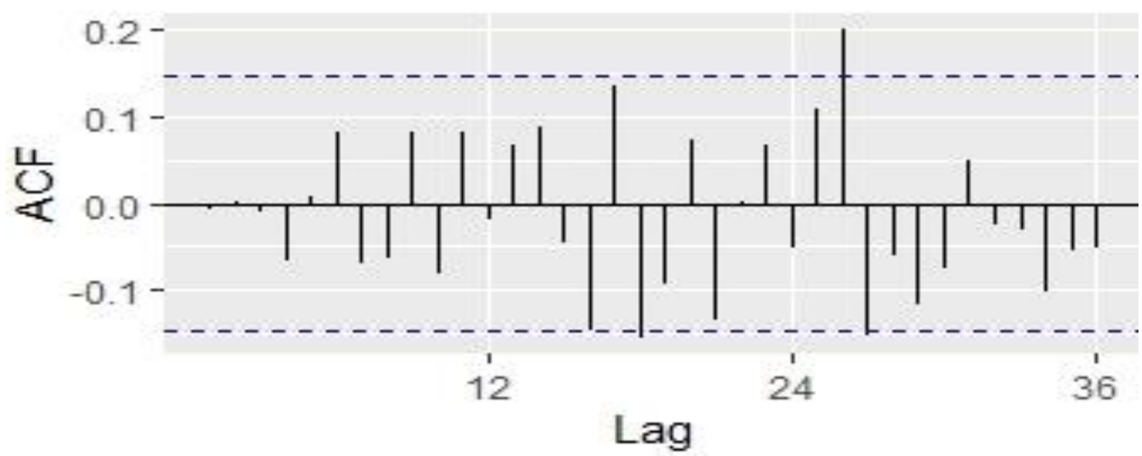
Cross-correlation factor (CCF) was explored to investigate the relationship between meteorological factors and per cent severity of stripe rust of wheat. Data on weekly intervals DS and meteorological factors during 2005-2019 were pre-whitened. Cross-correlation between the pre-whitened meteorological factors (maximum and minimum temperature, morning and evening relative humidity and rainfall) and DS exhibited that only minimum temperature showed the presence of relationship at one lag with DS. All the associations generated through CCF were used in establishing the ARIMAX model (Fig. 21a to 21e).

4.11.2 Developing ARIMAX model

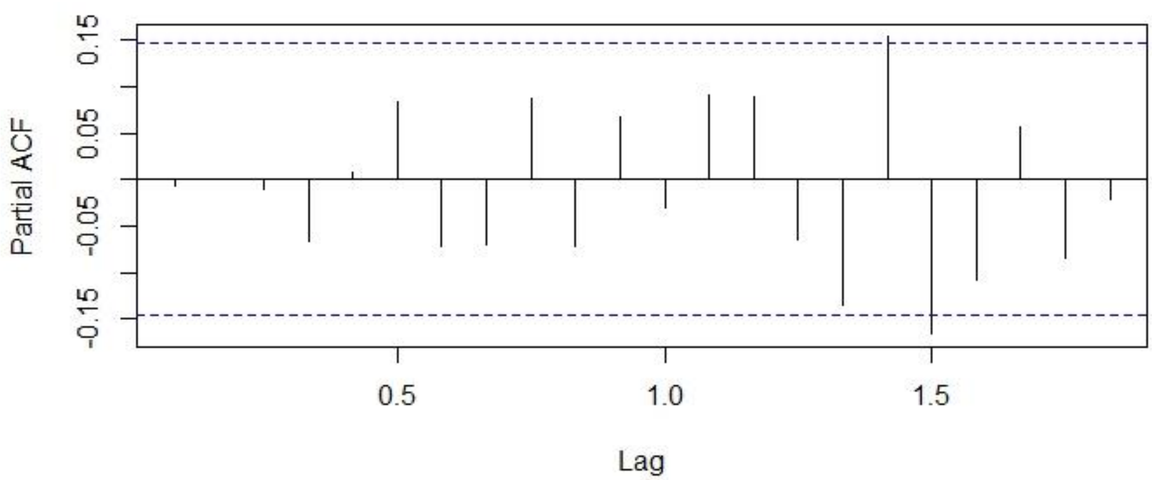
The meteorological factors *viz*., maximum temperature, morning and evening relative humidity at lag 0 and minimum temperature along with rainfall at lag 1 were used as covariates to fit in ARIMA model $(2,1,1)(1,1,1)_7$. Data in the Table 14 portray that ARIMA model with covariates of minimum temperature at lag 1 and rainfall at lag 1, along with the two covariates (minimum temperature and rainfall at lag 1), had statistically significant parameters and lower Akaike Information Criteria (AIC) value. Minimum temperature at lag 1 had AIC value of 382.68, rainfall at lag 1 had 381.66 and two covariates (minimum temperature and rainfall at lag 1) had 381.28 ($p = 0.02094$,



(a)



(b)



(c)

Fig. 17: Diagnostic plot of ARIMA model (2,1,1)(1,1,1)$_7$
a) Residuals, b) Residual ACF and c) Residual PACF

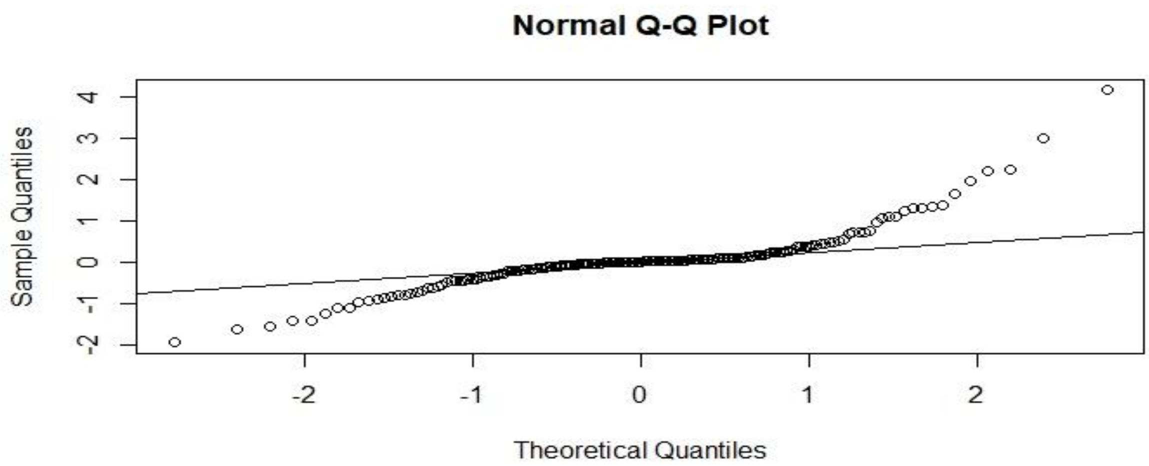


Fig. 18: Normality Q-Q Plot of residuals from ARIMA (2,1,1)(1,1,1)$_7$

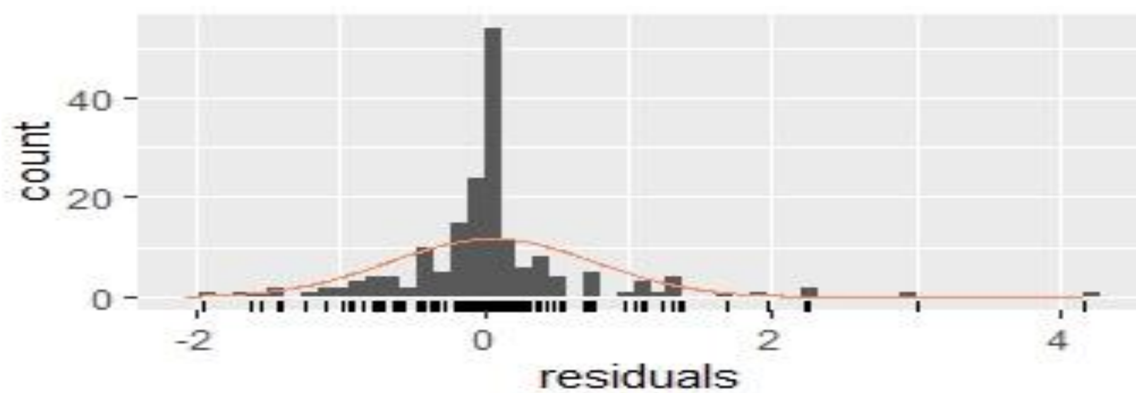


Fig. 19: Histogram of residuals from ARIMA (2,1,1)(1,1,1)$_7$

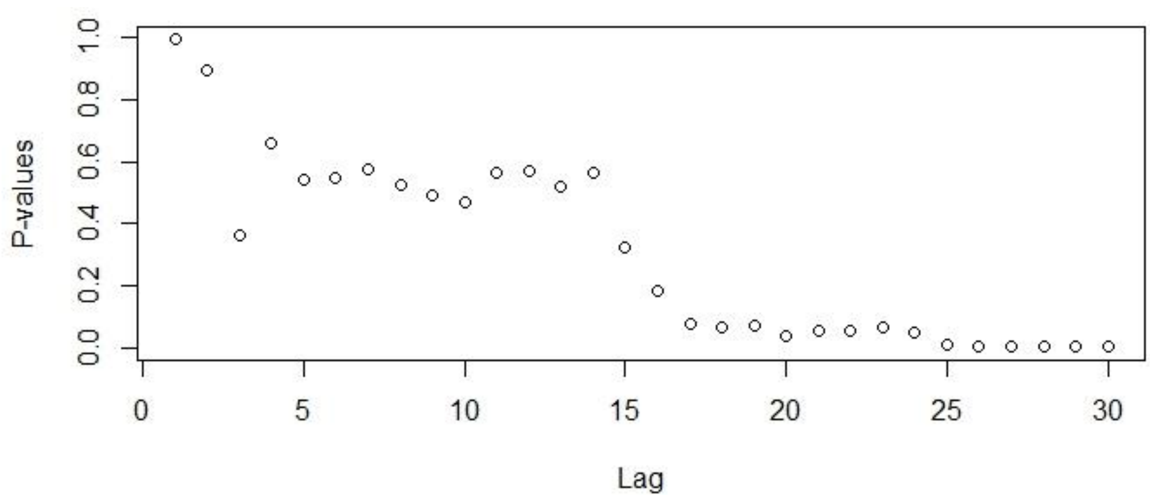
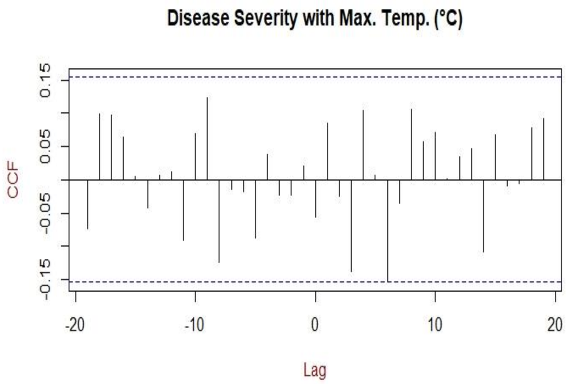
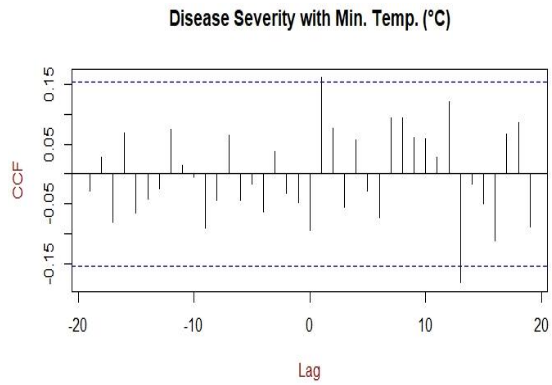


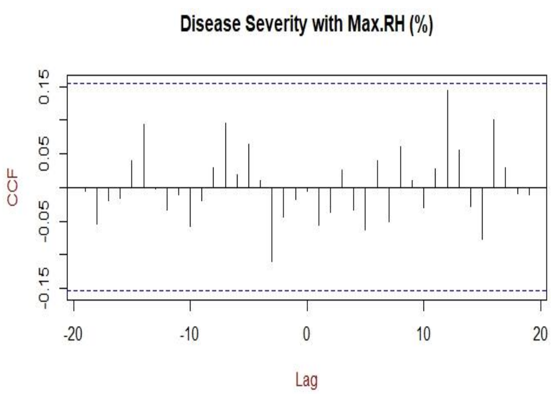
Fig. 20: Ljung-Box test plot of residuals from ARIMA (2,1,1)(1,1,1)$_7$



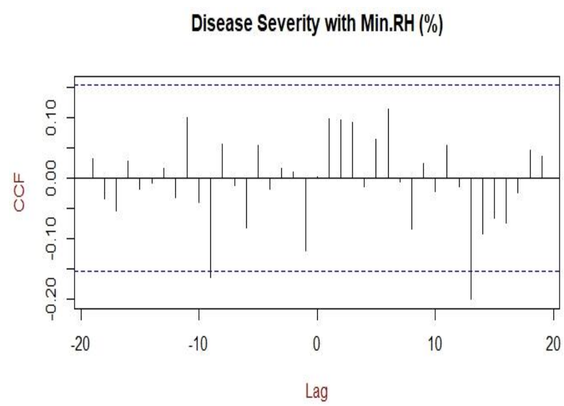
(a)



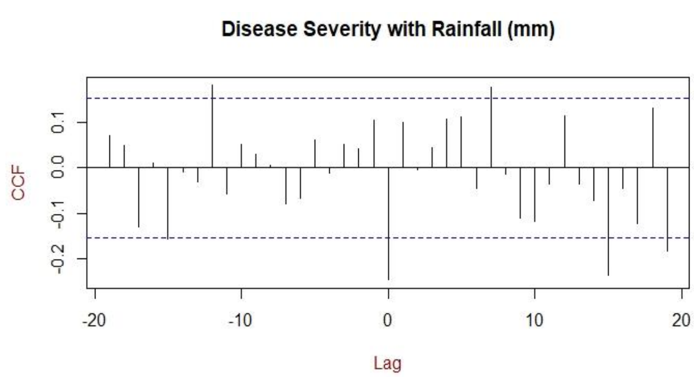
(b)



(c)



(d)



(e)

Fig. 21: Cross-Correlation Function of Disease severity with a) Maximum Temperature, b) Minimum Temperature, c) Morning Relative Humidity, d) Evening Relative Humidity and e) Rainfall

Table 14: ARIMAX (2,1,1) $(1,1,1)_7$ model with different meteorological factors

Model	Meteorological factors						AIC	RMSE	MAPE	MASE	Accuracy
	Meteorological factors	Lag	Estimate	Standard Error	t	*p*-value					
ARIMAX (2,1,1) $(1,1,1)_7$	Max. Temp. (°C)	0	-0.026	0.020	-1.30	0.19624	387.52	0.7035842	4.414205	0.04630282	95.59
	Min. Temp. (°C)	1	0.059	0.025	2.31	0.02094 *	382.68	0.6980256	4.192062	0.04746611	95.81
	Morning RH (%)	0	0.006	0.012	0.56	0.57716	388.88	0.7064467	4.284273	0.04536242	95.72
	Evening RH (%)	0	0.0006	0.0050	0.14	0.89009	389.17	0.7071308	4.36033	0.04540233	95.64
	Rainfall (mm)	1	-0.011	0.0040	-2.83	0.004651 **	381.66	0.6917779	4.186273	0.04651539	95.82
	Min. Temp. (°C)	1	-0.010	0.0039513	-2.65	0.00797 **	381.28	0.6831378	4.00381	0.04797156	96.00
	Rainfall (mm)	1									

Max. Temp. = Maximum temperature (°C); Min. Temp. = Minimum temperature (°C); RH = Relative humidity (%); AIC = Akaike Information Criterion; RMSE = Root mean square error, MAPE = Mean absolute percentage error; MASE= Mean absolute scaled error

** Significant at $p \leq 0.01$,
* Significant at $p \leq 0.05$

Table 15: Prediction of severity (%) of stripe rust of wheat by ARIMAX model (2,1,1)(1,1,1)$_7$

SMW	Year		
	2020	**2021**	**2022**
1st	4.02±0.71	4.04±1.06	4.66±1.32
2nd	6.75±0.78	7.55±1.10	8.09±1.35
3rd	15.94±0.82	16.67±1.13	17.27±1.38
4th	27.73±0.85	28.09±1.15	28.80±1.40
5th	39.89±0.86	40.25±1.16	40.75±1.41
6th	46.31±0.87	46.30±1.17	47.13±1.42
7th	49.75±0.87	50.01±1.18	50.26±1.43
8th	52.25±0.88	52.46±1.18	52.36±1.44
9th	54.11±0.88	54.44±1.19	54.66±1.45
10th	55.29±0.88	55.35±1.20	56.58±1.46
11th	58.35±0.89	58.55±1.20	58.92±1.46
12th	60.46±0.89	60.95±1.21	61.32±1.47

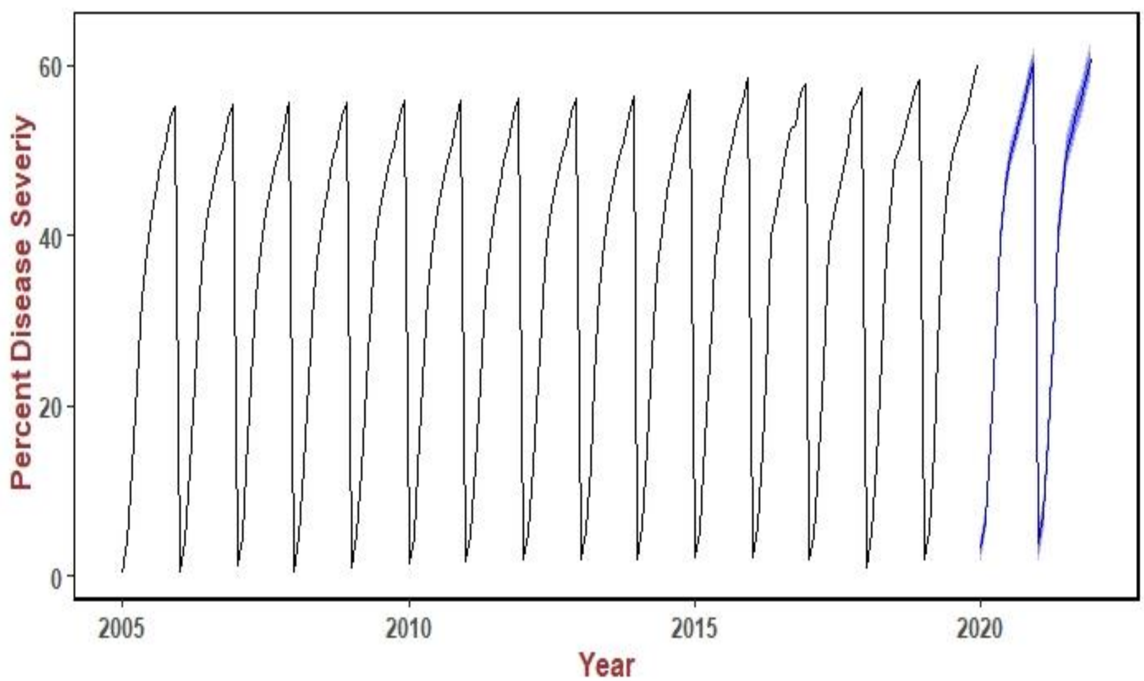
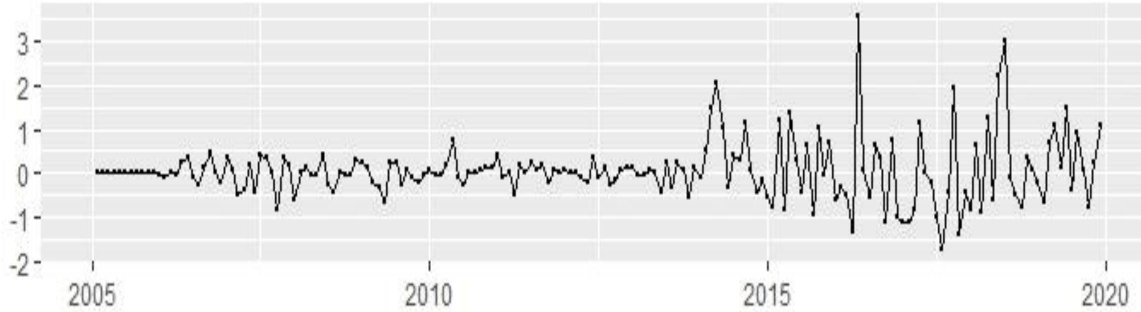
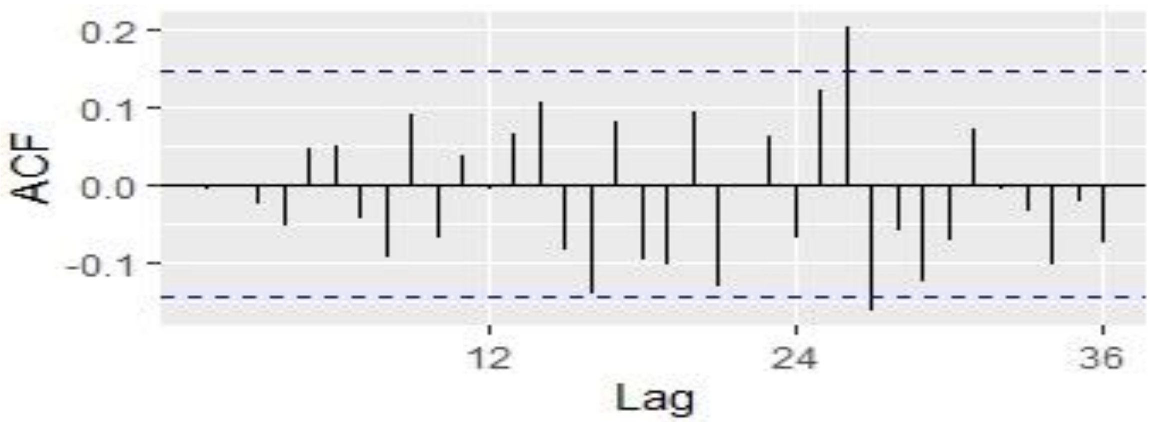


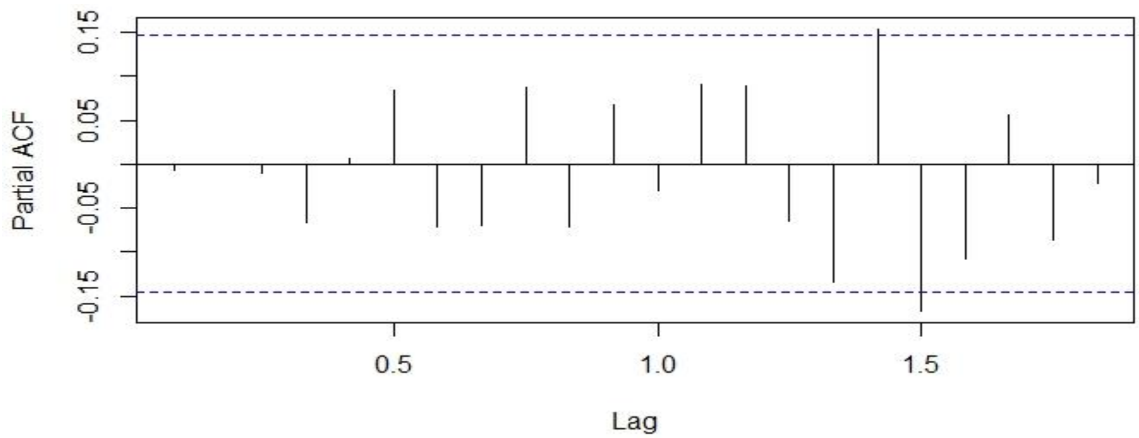
Fig. 22: Prediction of severity (%) of stripe rust of wheat by ARIMA model (2,1,1) (1,1,1)$_7$



(a)



(b)



(c)

Fig. 23: Diagnostic plot of ARIMAX model (2,1,1) $(1,1,1)_7$

a) Residuals, Residual ACF and c) Residual PACF

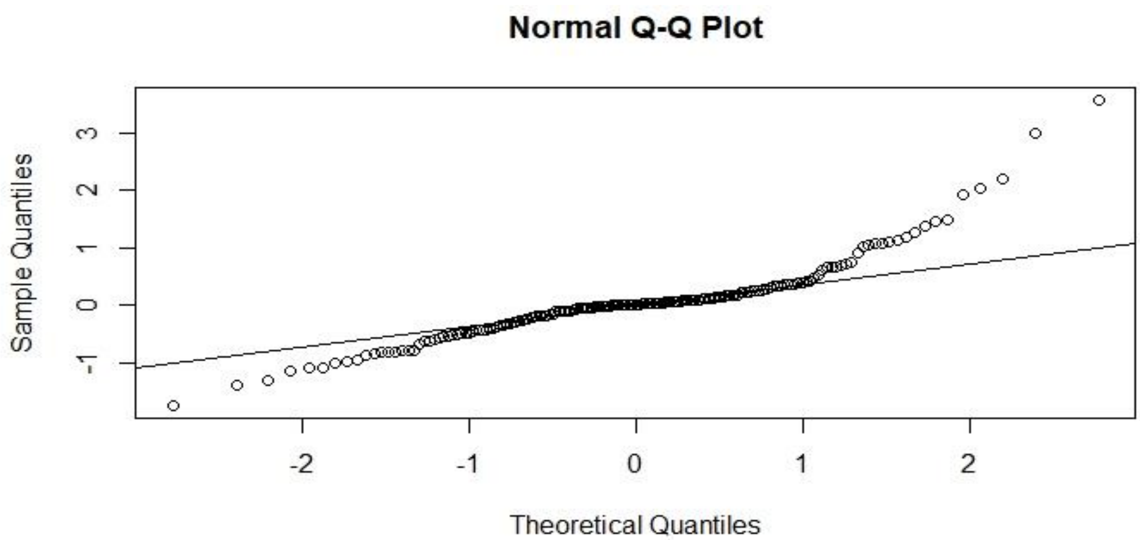


Fig. 24: Normality Q-Q Plot of residuals from ARIMAX (2,1,1)(1,1,1)$_7$

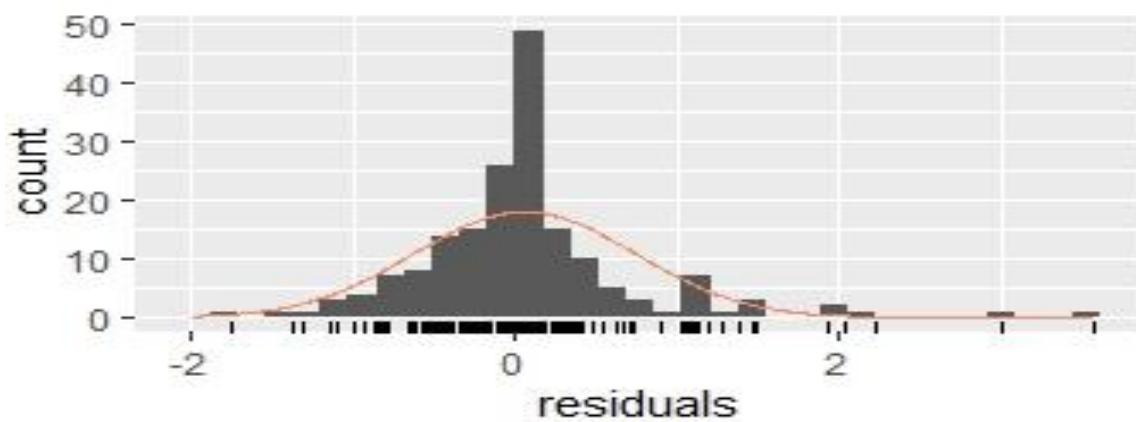


Fig. 25: Histogram of residuals from ARIMAX (2,1,1)(1,1,1)$_7$

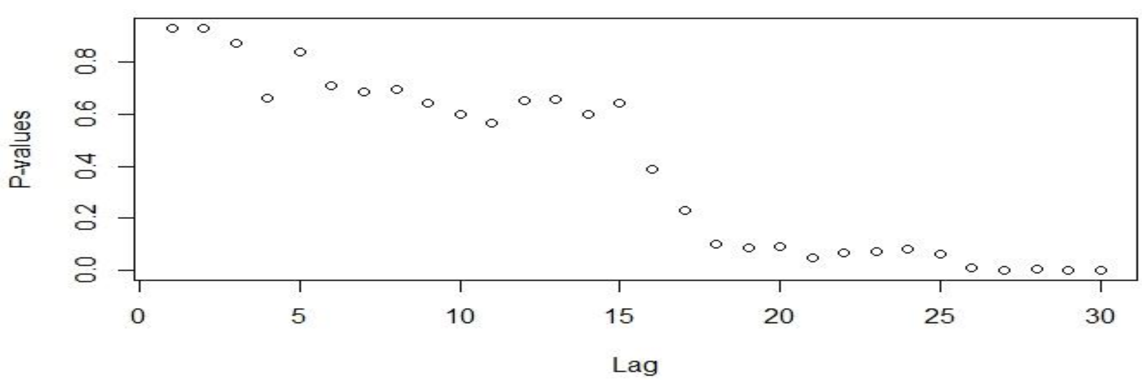


Fig. 26: Ljung-Box test plot of residuals from ARIMAX (2,1,1)(1,1,1)$_7$

0.004651 and 0.00797, respectively). Further, the two covariates (minimum temperature and rainfall at lag 1) together had lowest RMSE, MAPE (0.6831378 and 4.00381) and highest MASE and accuracy (0.04797156 and 96.00). Whereas, minimum temperature at lag 1 had RMSE, MAPE, MASE and accuracy of 0.6980256, 4.192062, 0.04746611 and 95.81, respectively. In rainfall at lag 1, RMSE, MAPE, MASE and accuracy were 0.6917779, 4.186273, 0.04651539 and 95.82, respectively.

Disease forecasting was done to predict weekly stripe rust for the year 2020, 2021 and 2022 based on the ARIMAX model. The predicted values of stripe rust by ARIMAX model (2,1,1) $(1,1,1)_7$ in the Table 15 predicted 4.02±0.71 to 60.46±0.89; 4.04±1.06 to 60.95±1.21 and 4.66±1.32 to 61.32±1.47 per cent severity of stripe rust in 2020, 2021 and 2022, respectively (Fig. 22).

4.11.3 Diagnostic check for ARIMAX model

After the generation of ARIMAX with minimum temperature and rainfall as external variable with lag 1, white noise assumptions of the residuals were tested. Residuals of ARIMAX $(2,1,1)(1,1,1)_7 – t_1r_1$ indicates that the ACF and PACF plots of the residuals of developed model exhibited no statistically significant correlation (Fig. 23a to 23c). Further, all the values were almost laying on the line in Normal QQ plot (Fig. 24), and the shape of the histogram appeared as a “Bell Shaped” curve (Fig. 25). So the residuals of the fitted model ARIMAX $(2,1,1)(1,1,1)_7$ – t_1r_1 was considered as normal. Box-Ljung test failed to reject the null hypothesis of independence ($\chi2$ = 30.666, p =0.2003) (Fig. 26). These observations confirm that the residuals from fitted model ARIMAX $(2,1,1)(1,1,1)_{7}$ -t_1r_1 were independent and normally distributed.

4.12 Multiple linear regression

4.12.1 Effect of meteorological factors on the severity of stripe rust of wheat during 2005-17

The data presented in Table 16 indicate that the initial symptoms of stripe rust were recorded on 1st Standard Meteorological Week (SMW) with the mean severity of 1.42 per cent, during 2005-2017. During the period average meteorological factors had maximum temperature of 17.34^0C, minimum temperature of 5.97^0C, morning relative humidity of 92.23 per cent, evening relative humidity of 55.08 per cent and rainfall of 5.40 mm. A steep increase in the mean severity occurred from 4.86 to 13.33 per cent during 2nd to 3rd SMW with corresponding mean maximum and minimum temperature of 18.07 and 5.52^{0}C, maximum and morning relative humidity of 90.73 and 53.76 per cent, and rainfall of 1.17 and 5.48 mm. Maximum mean disease severity of 56.31 per cent was recorded during 12th SMW, when average maximum temperature was 27.84^{0}C, minimum temperature 12.38^{0}C, morning relative humidity 83.21 per cent, evening relative humidity 44.14 per cent and rainfall 1.91mm.

4.12.2 Effect of meteorological factors on the severity of stripe rust of wheat during 2017-19

During 2017-2019, stripe rust (1.47%) appeared during the 1st SMW, when average meteorological factors had maximum temperature of 17.53^{0}C, minimum temperature of 4.35^{0}C, morning relative humidity of 93.64 per cent, evening relative humidity of 53.21 per cent and rainfall of 5.50 mm (Table 17). However, the mean disease severity increased sharply from 5.18 to 14.01 per cent from 2nd to 3rd SMW, when maximum temperature was 19.60^{0}C, minimum temperature 4.46^{0}C, morning relative humidity 91.36 per cent, evening relative humidity 53.21 per cent and rainfall 2.70 mm. Disease severity reached maximum (59.06%) at crop maturity stage when maximum temperature was 26.69^{0}C, minimum temperature 11.58^{0}C, morning relative humidity 87.93 per cent, evening relative humidity 48.29 per cent and rainfall 7.65 mm.

4.12.3 Correlation of meteorological factors with the severity of stripe rust of wheat

The data related to the correlation analysis, presented in Table 18 exhibit that the severity of stripe rust had positive and highly significant correlation with maximum and minimum temperatures, having correlation value (r) of 0.89 and 0.91 during 2005-2017; and 0.91 and 0.75 during 2017-2019, respectively. Whereas, morning relative humidity had significantly negative correlation with the disease severity, having r = -0.84 and -0.80, in 2005-17 and 2017-19, respectively. While evening relative humidity and rainfall

Table 16: Effect of meteorological factors on mean disease severity (%) of stripe rust of wheat during 2005-2017

SMW	Disease severity (%)	Max. Temp. (°C)	Min. Temp. (°C)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.42	17.34	5.97	92.23	55.08	5.40
2nd	4.86	17.60	5.33	92.15	53.81	1.71
3rd	13.33	18.07	5.52	90.73	53.76	5.48
4th	23.33	18.00	5.92	92.99	50.73	7.15
5th	34.38	19.84	6.76	90.91	56.10	4.52
6th	39.57	21.15	7.37	88.96	54.52	8.87
7th	43.56	21.80	7.92	89.71	55.92	2.81
8th	46.68	22.12	8.55	88.74	56.04	4.74
9th	49.49	22.91	9.68	86.88	52.63	6.78
10th	51.52	24.24	9.72	87.45	51.04	14.09
11th	54.55	25.33	11.00	85.15	46.67	4.59
12th	56.31	27.84	12.28	83.21	44.14	1.91

SMW = Standard meteorological week, Max. Temp. (°C)=Maximum temperature, Min. Temp. (°C) =Minimum temperature, RH = Relative humidity

Table 17: Effect of meteorological factors on mean disease severity (%) of stripe rust of wheat during 2017-19

SMW	Disease severity (%)	Max. Temp. (°C)	Min. Temp. (°C)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.47	17.53	4.35	93.64	53.21	5.50
2nd	5.18	19.11	3.88	93.21	45.93	2.60
3rd	14.01	19.60	4.46	91.36	53.21	2.70
4th	26.23	16.71	4.76	93.71	61.21	21.50
5th	38.49	19.86	6.07	90.71	52.21	4.40
6th	45.06	20.15	6.07	90.14	47.00	29.60
7th	49.11	19.87	8.54	92.79	59.93	13.65
8th	50.68	22.25	9.20	89.14	56.29	34.15
9th	52.90	21.23	9.23	88.15	57.32	6.00
10th	54.68	24.79	9.57	89.57	46.00	0.00
11th	57.08	26.74	10.36	87.64	42.07	5.40
12th	59.06	26.69	11.58	87.93	48.29	7.65

SMW = Standard meteorological week, Max. Temp. (°C)=Maximum temperature, Min. Temp. (°C) =Minimum temperature, RH = Relative humidity

Table 18: Correlation of meteorological factors with severity of stripe rust of wheat

Meteorological factors	2005-2017	2017-2019
Max. Temp. (^oC)	0.89***	0.91***
Min. Temp. (^oC)	0.91***	0.75**
Morning RH (%)	-0.84***	-0.80**
Evening RH (%)	-0.45	-0.12
Rainfall (mm)	0.21	0.22

Max. Temp. (^oC)=Maximum temperature, Min. Temp. (^oC) =Minimum temperature, RH = Relative humidity

Significant codes = '***'; 0.001 '**'; 0.01

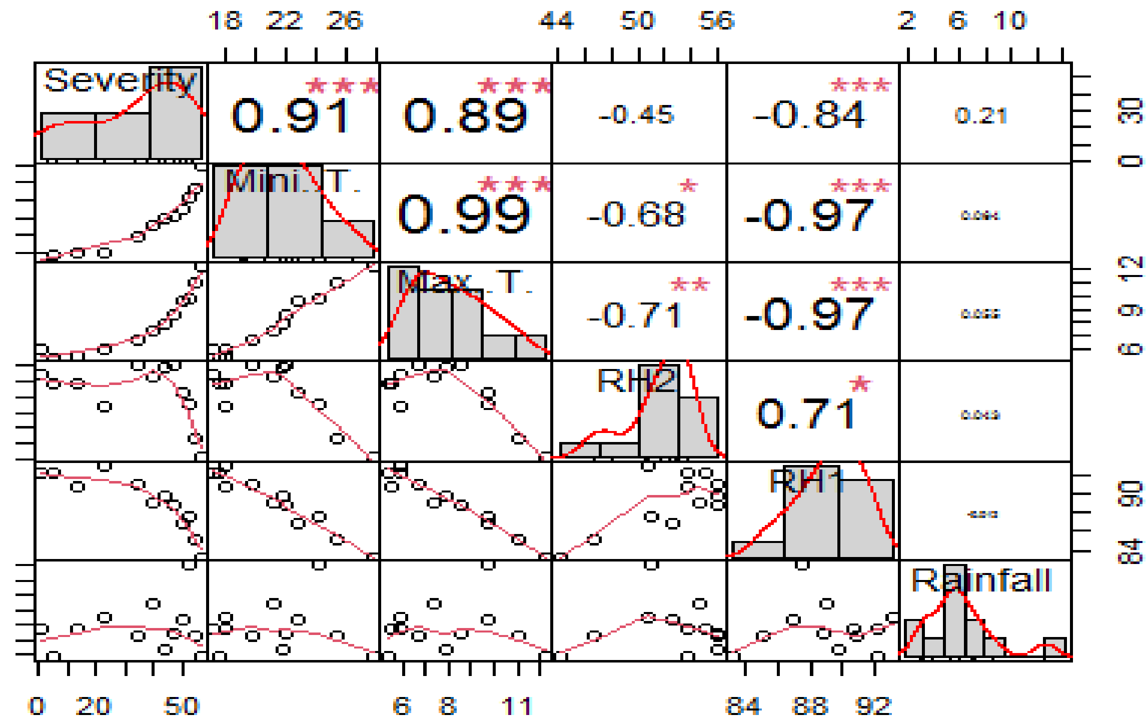


Fig. 27: **Correlation between meteorological factors and severity of stripe rust of wheat during 2005-2017**

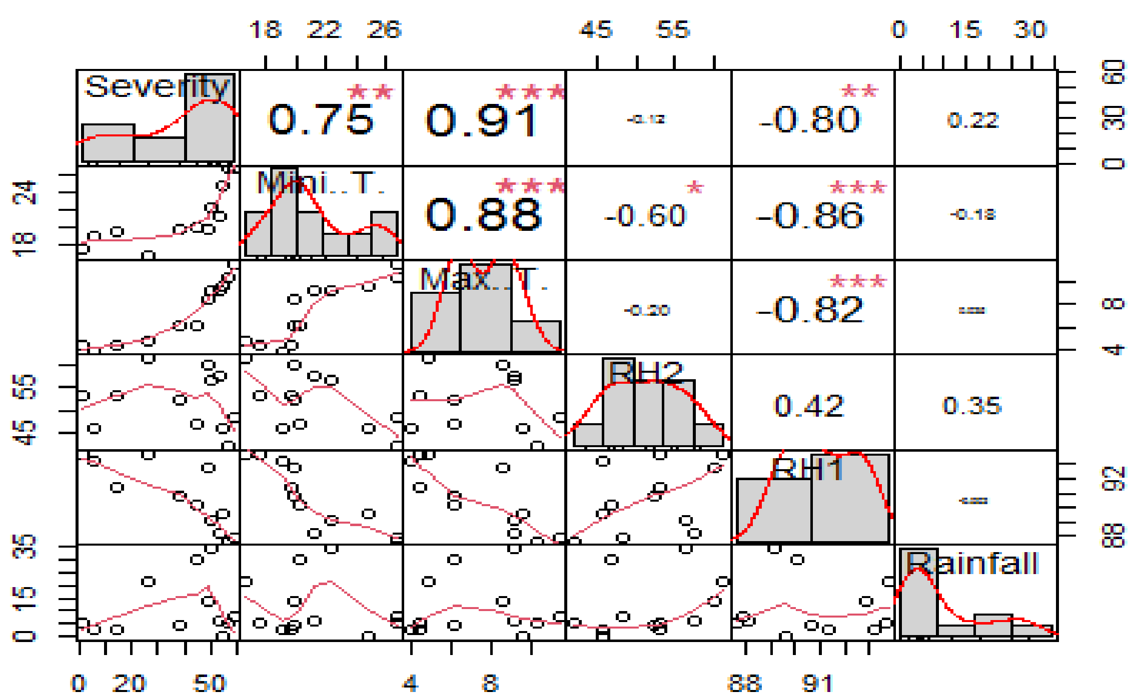


Fig. 28: **Correlation between meteorological factors and severity of stripe rust of wheat during 2017-2019**

during 2005-17 and 2017-19 had non-significant relationship with the disease severity (Fig. 27 and 28).

4.12.4 Multiple linear regressions of meteorological factors with the severity of stripe rust of wheat

To develop predictive model to forecast stripe rust of wheat, multiple linear regressions were performed to determine the contribution of different meteorological factors. Data in the Table 19 exhibited that the generated model (Y_1) was highly significant (p=0.003) in predicting the severity of stripe rust of wheat during 2005-2017, with the coefficient of determination (R^2) of 0.913. This explains that 91.3 per cent of the variation in the severity of stripe rust was influenced by the maximum and minimum temperature, maximum and evening relative humidity and rainfall. The root mean squared error (RMSE) of 5.5125 and mean absolute percentage error (MAPE) of 0.8106 indicate that developed model was effective in predicting per cent severity of stripe rust of wheat.

Further, data presented in Table 19 unveil that in the model developed, based on the data for the period of 2017-19, dependent and independent variables were highly significant (p= 0.006) in predicting the severity of stripe rust. The model had coefficient of determination (R^2) of 0.8952, which revealed that 89.52 per cent of the variation was influenced by the maximum and minimum temperature, maximum and evening relative humidity and rainfall. The root mean squared error (RMSE) and mean absolute percentage error (MAPE) values of 6.4525 and 0.9331, respectively, showed that the developed model was effective in predicting per cent disease intensity of stripe rust of wheat during 2017-2019.

4.12.5 Assumption of multiple linear regressions for stripe rust of wheat

The data regarding global test of model assumption (*gvlma*) presented in Table 20 divulged that all the assumptions were acceptable as the global stat, skewness, kurtosis, link function and heteroscedasticity test having p value of 0.9256, 0.4873, 0.6203, 0.7003 and 0.8968 for both data sets of 2005-17 and 2017-2019 (Fig. 29).

Perusal of the data presented in Table 20 indicate that Shapiro-wilk test for normality, Bonferroni outlier test for outlier's detection and non-constant variance (ncv) test for the homoscedasticity rejected the null hypothesis for the developed model of stripe rust of wheat. Shapiro-wilk test was having the p value of 0.1049 and 0.04132, Bonferroni outlier test had the p value of 0.24943 and 0.77744, whereas, ncv test had the value of 0.38693 and 0.36655 for 2005-2017 and 2017-19, respectively, which explains that the model was statistically good and effective for the prediction of stripe rust of wheat (Fig. 30).

4.12.6 Performance of MLR models

Both the models developed by multiple linear regressions for 2005-17 and 2017-2019 predicted the severity with minimum per cent deviation (Table 21 and 22).

4.13 Quantification of inoculum of *Puccinia striiformis* f. sp. *tritici*

Data presented in Table 23 revealed that spore concentration of *Puccinia striiformis* f. sp. *tritici* (0.25) was reported in the 51th Standard Meteorological Week, when the corresponding meteorological parameters had maximum temperature of 21.7^{0}C, minimum temperature of 4.95^{0}C, morning relative humidity of 86.50 per cent and evening relative humidity of 53 per cent. The spore concentration increased with time and 1.63 was observed in 7th SMW with maximum temperature of 19.65^{0}C, minimum temperature of 19.65^{0}C, morning relative humidity of 8.95 per cent, evening relative humidity of 57 per cent and rainfall of 11.15mm.

Correlation of spore concentration of *Puccinia striiformis* f. sp. *tritici* exhibited non-significant relationship with meteorological parameters having r = 0.20, -0.14, -0.43, 10 and -14 for maximum temperature, minimum temperature, morning relative humidity of 8.95 per cent, evening relative humidity and rainfall, respectively (Fig. 31).

Table 19: Multiple linear regression of meteorological factors with per cent severity of stripe rust of wheat during during 2005-17 and 2017-19

Years	Regression Equation	R^2	Adjusted R^2	RMSE	MAPE	P value
2005-17	$Y= -02.1392 + 0.6373X_1 + 8.5741X_2 + 3.0402X_3 + 1.4227X_4 + 0.5764X_5$	0.913	0.8405	5.512589	0.8106821	0.003905
2017-19	$Y= 322.5683 + 9.4103X_1 - 4.1446X_2 - 2.5589X_3 - 0.7089 + 0.2609X_5$	0.8952	0.8079	6.452588	0.9331274	0.006682

X_1= Maximum temperature; X_2= Minimum temperature; X_3= Morning relative humidity; X_4= Evening relative humidity; X_5= Rainfall; RMSE = root mean square error; MAPE = Mean absolute percentage error

Table 20: Assessment of the multiple linear model of stripe rust of wheat by global test of model assumptions (gvlma)

Test	**Data sets**	
	2005-2017	**2017-2019**
Global Stat	0.9256	0.9256
Skewness	0.4873	0.4873
Kurtosis	0.6203	0.6203
Link Function	0.7003	0.7003
Heteroscedasticity	0.8968	0.8968
Shapiro-Wilk normality test	0.1049	0.04132
Outlier Test	0.24943	0.77744
Non-constant Variance Score Test	0.38693	0.36655

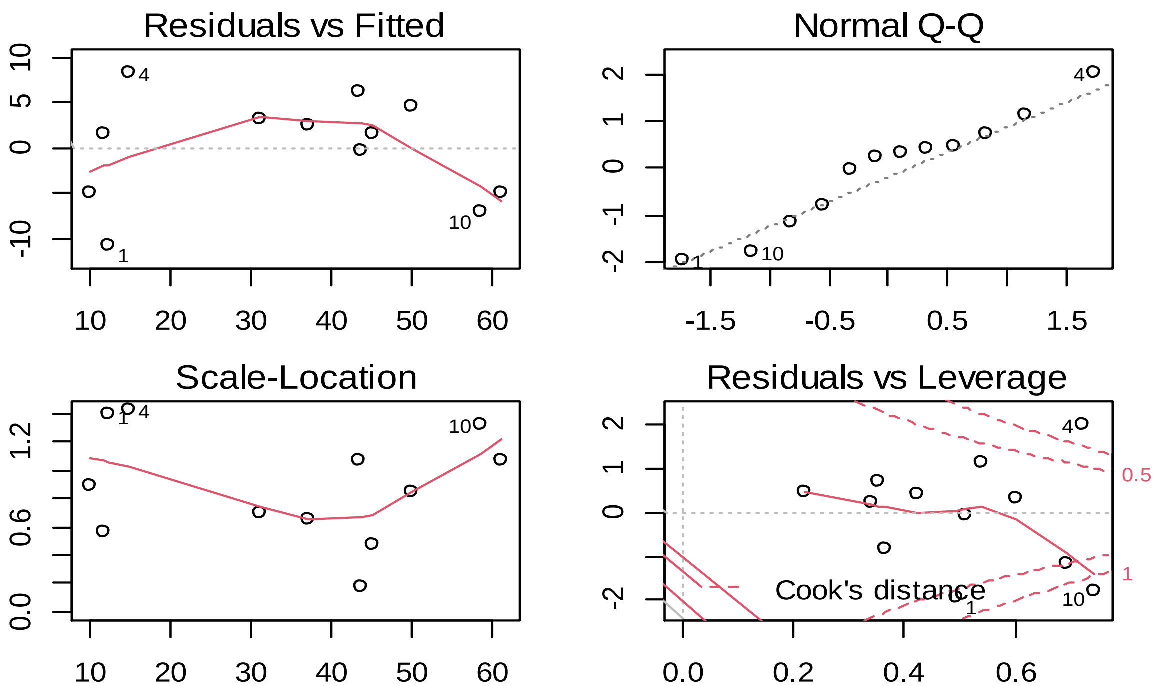


Fig. 29: Residual plots of multiple linear regressions for stripe rust of wheat during 2005-2017 and 2017-19

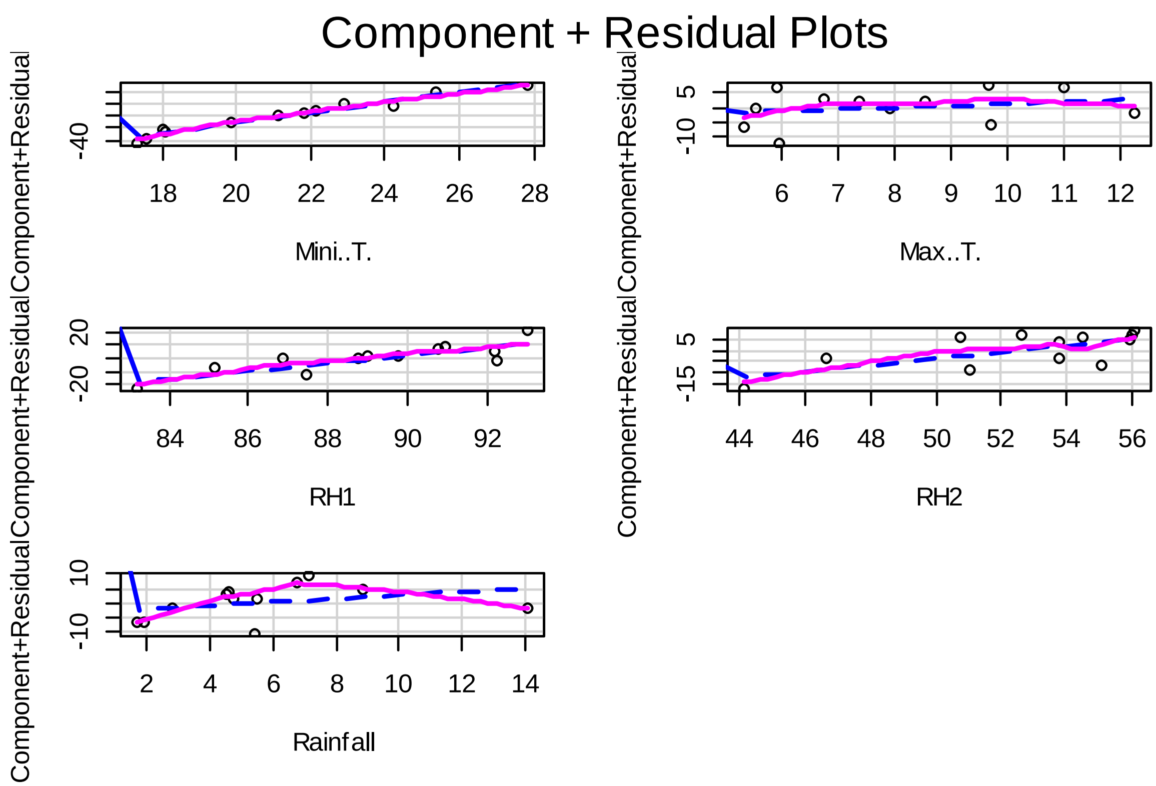


Fig. 30: Linearity graph for stripe rust of wheat during 2005-2017 and 2017-19

Table 21: Prediction of severity (%) of stripe rust of wheat by MLR model for 2005-2017

SMW	Per cent severity of stripe rust of wheat	
	Observed	Predicted
1st	1.42	12.21
2nd	4.86	9.86
3rd	13.33	11.79
4th	23.33	14.97
5th	34.38	31.08
6th	39.57	37.03
7th	43.56	43.74
8th	46.68	45.21
9th	49.49	43.38
10th	51.52	58.49
11th	54.55	49.97
12th	56.31	61.26

Table 22: Prediction of severity (%) of stripe rust of wheat by MLR model for 2017-2019

SMW	Per cent severity of stripe rust of wheat	
	Observed	Predicted
1st	1.47	14.95
2nd	5.18	9.48
3rd	14.01	12.51
4th	26.23	20.53
5th	38.49	29.40
6th	45.06	39.92
7th	49.11	44.22
8th	50.68	57.83
9th	52.9	56.80
10th	54.68	48.07
11th	57.08	56.56
12th	59.06	63.68

Table 23: Effect of meteorological factors on inoculum of *Puccinia striiformis* f. sp. *tritici* during 2017-19

SMW	Average no. of Urediospores	Max. Temp. (°C)	Min. Temp. (°C)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
50th	0	18.25	7.7	89	68	37.6
51st	0.25	21.7	4.95	86.5	53	0
52th	0.43	20.75	3.85	87.5	58.25	0
1st	0.95	18.1	4.6	91	59.5	3
2nd	1.07	19.2	4.8	90	52.5	0.75
3rd	1.21	20.35	4.85	88	54.5	1.3
4th	1.34	16.75	5.4	91	63	13.4
5th	1.5	19.7	6.25	88	54	5.05
6th	1.57	20.5	5.65	86	53	24.3
7th	1.63	19.65	8.95	89	57	11.15

SMW = Standard meteorological week, Max. Temp. (°C)=Maximum temperature, Min. Temp. (°C) =Minimum temperature, RH = Relative humidity

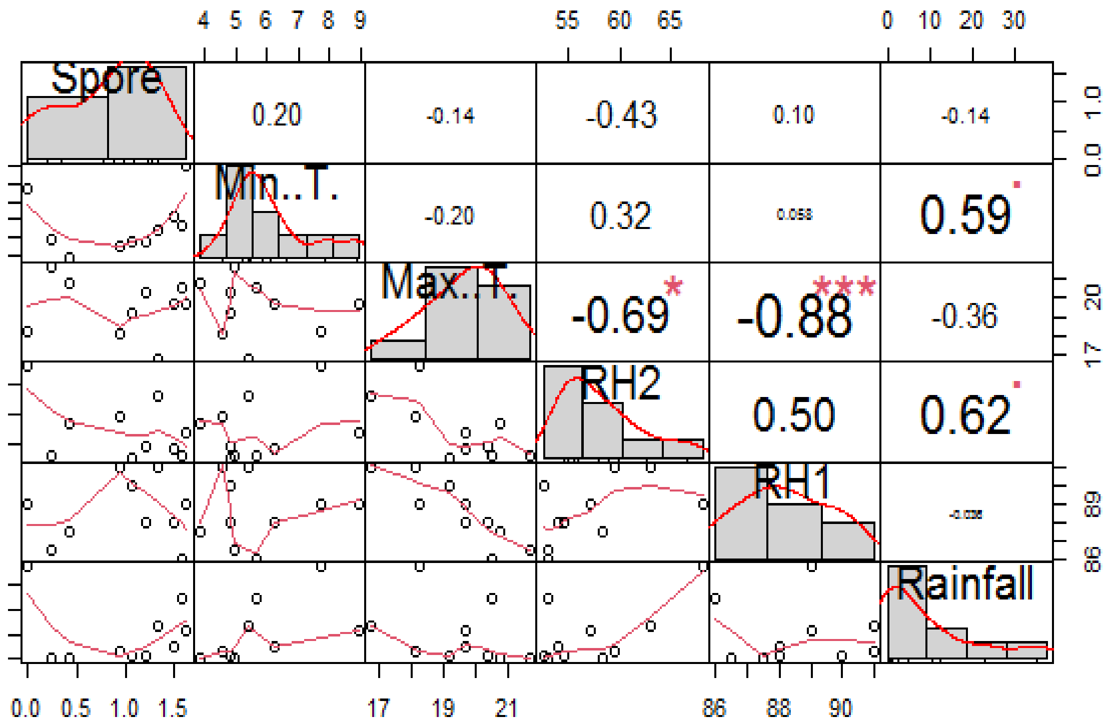


Fig. 31: Correlation of meteorological factors with spore concentration of *Puccinia striiformis* f. sp. *tritici* rust of wheat during 2017-2019

Discussion

CHAPTER-5

DISCUSSION

In the present study, all the six Generation Circulation Models (GCMs) predicted an increasing trend in the temperature projections (maximum and minimum), during future climate change periods (2020, 2050, 2080) in all the scenarios in Jammu, Hisar, Ludhiana, Dhaulakuan and Meerut. However, at Leh, decreasing trend in temperature projections (maximum and minimum) was observed. In the current study, maximum temperature increased by ±0.08 to ± 11.13°C and minimum temperature by ±1.88 to ±11.58°C during future climate change periods over the baseline of four scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) at selected locations except Leh, where maximum and minimum temperature decreased by ±5.60 and ±5.87°C, respectively. This indicates that average temperature at almost all the locations would increase significantly during the three future climate change periods under different scenarios. In India, mean temperature is projected to increase by 0.48 to 2.0°Cin *kharif* (summer) and 1.1 to 4.5°C in *rabi* (winter) by 2070 (Anonymous, 1996). Increase in maximum temperature at Ludhiana (+15%) and minimum nights at Raipur (+17%) and Akola (+22%), has exhibited sharp decline in wheat yield (Pramod *et al.*, 2017). Increasing trends of maximum and minimum temperature in different locations of India using MarkSim GCM multimodal has also been reported (Rao *et al.*, 2015; Rao *et al.*, 2016). Mean temperature is likely to increase by 1.7-2.0°C and 3.3-4.8°C during 2030s and 2080s, respectively, relative to preindustrial times in India (Chaturvedi *et al*., 2012).

The projected climate change fluctuations by the six models under four scenarios in the present study confirm the earlier reports (Kumar *et al*., 2013; Choudhary *et al*., 2017, 2019). India would witness a warming of 0.5ºC by the year 2030 and of 2-4ºC by the end of this century, with the maximum increase over northern India (Anonymous, 1996). Globally, temperature and CO_2 concentration may increase by 3.4°C and 1250 ppm, respectively, by 2095 (Savary *et al*., 2012). Global mean temperature has increased by 0.74±0.18°C during 1906–2005 and is predicted to increase by an additional 1.0-3.7°C by the end of this century, due to the accumulation of greenhouse gasses (Pachauri *et al*., 2014; Anderson *et al*., 2016; Huang *et al*., 2017)

In the present study, shorter duration of latent period of *Puccinia striiformis* f. sp. *tritici* was reported in Jammu, Ludhiana, Meerut, Hisar and Dhaulakuan, whereas, an increase was observed in Leh, under all scenarios in the three future time periods (2020, 2050, 2080) as compared to baseline period (1975). Maximum reduction of 110, 49, 36, 35 and 40 per cent was observed in the duration of latent period (days) of *P. striiformis* f. sp. *tritici* in Jammu, Ludhiana, Dhaulakuan, Meerut and Hisar, respectively, during 2080 under RCP 8.5 scenario. However, 26 per cent increase was observed in the latent period (days) of *P. striiformis* f. sp. *tritici* at Leh during 2020 under RCP 6.0 scenario. Under global warming conditions pathogens are expected to withstand new thermal fluctuations. Maximum per cent increase in number of infection cycles of 55, 36, 34, 29, 28 and 27 in *P. striiformis* f. sp. *tritici* were recorded by RCP 8.5 scenario in Jammu, Ludhiana, Meerut, Dhaulakuan, Hisar, and Leh, respectively, in three future time periods (2020, 2050, 2080) over the baseline period (1975). However, significant increase in the number of infection cycles was observed across all the locations under different scenario during three future periods. The shorter the latent period, the more aggressive the pathotypes due to more number of infection cycles. Changes in temperature have been reported to have significant effects on the initiation and epidemics of crop pests and diseases (Goudriaan and Zadoks, 1985; Coakley *et al*., 1999; Rosenzweig *et al.*, 2001; Jonnson *et al.*, 2009). *P. striiformis* f. sp. *tritici* infection process is mainly affected by temperature. Minimum, optimum, and maximum temperatures of 2, 9-13, 23°C are required for penetration of *P. striiformis* f. sp. *tritici*, whereas, 5, 12-15, 20°C is required for sporulation, respectively (Roelfs *et al*.,1992). Temperature more than 23°C, especially in the late season, halts the epidemics of stripe rust, by affecting infectious lesion (Gladders *et al.*, 2007).

For *Puccinia striiformis* f. sp. *tritici*, latent period of 11 days at 12-19°C has been reported by earlier workers (Zadoks 1961; Tollenaar and Houston, 1967; Burleigh and Hendrix, 1970). Temperature from 7 to 20°C shortened the latent period of *P. striiformis* f. sp. *tritici* which was mainly 9 to 20 days at 10-20°C (McGregor and Manners, 1985).

Maximum incubation period of 15 days and latent period 19 days was recorded in the month December during 2010-11. Whereas, incubation and latent period of 20 and 22 days and 16 and 19 days were recorded in January during 2011-12 and 2012-13, respectively (Sunil, 2013). An average latent period (13.5days) of *P. striiformis* f. sp. *tritici* was observed in Huixianhong's, high-susceptible and fast-developing variety of wheat during 2011-2013 (He *et al*., 2019). Aggressiveness of *P. striiformis* f. sp. *tritici* increases due to the prevalence of new races having affiliation to high temperature and shortening of latent period (de Vallavieille *et al*., 2018). Shift in climatic conditions such as warmer winter, intermittent and erratic rainfall has resulted in the modification of host phenology to synchronization life-cycle of pathogen, shift in population dynamics, more generation and risk of invasion of exotic races of the pathogen (Juroszek and Tiedemann, 2013). Temperature (maximum and minimum), had a significantly positive correlation with the severity of stripe rust of wheat in cultivar PBW 343 having correlation co-efficient (R) values of 0.83, and 0.83, respectively, under early sowing conditions (Gupta *et al*., 2017b). Increase in temperatures by 1°C for 2041-2050 and by 3.7°C for 2091-2100, as compared to 1991-2000, indicated positive trends in favourable infection of leaf rust in wheat (Junk *et al.,* 2016).

The appearance of stripe rust during the past decades has mainly been induced due to the susceptibility of cultivars growing in the field. Thus, a precise forecast of stripe rust based on predictive models is critical for researchers, growers, field functionaries and policy makers, to clearly comprehend the disease epidemic characteristics, track seasonal changes in advance, and prepare early response activities such as the surveillance and monitoring of the disease and deployment of alternative management strategies (Yang *et al*., 2018). Autoregressive integrated moving average (Box and Jenkins, 1970), a time series model has been widely employed as classical approach for the short-term prediction of insect pests (Aswathi and Duraisamy, 2018; Chiu *et a*l., 2019), plant diseases (Fernández-González *et al*., 2012, 2016; Ling *et al*., 2019; Singh *et al*., 2019), weather parameters (Powell and Reinhard, 2016), human diseases (Zhang *et al*., 2014; Yan *et al.*, 2017; Tian *et al.*, 2019) and crop production (Saeed *et al*., 2000; Suresh and Priya, 2011; Dash *et al*., 2020). The model (ARIMA) encompasses, regression between present and past values in the AR (Auto regressive) model, whereas, current value depends on the previous forecast errors in MA (Moving average) model.

In the present study, stripe rust of wheat, during 2005-2019, exhibited non-stationary nature of the data sets (trend and seasonality). In order to transform the time series data into stationary (mean and variance remains constant and do not change with time), differencing (lag 1), between successive observations was made, which was statistically proved by the unit root tests. Augmented Dickey-Fuller and Phillips-Perron exhibited = -9.4802, $P < 0.01$, and = -71.347, $P < 0.01$ values, respectively. Both these tests were applied to identify and check the stationary of the data sets (Mamun *et al.*, 2018). The generation of ARIMA model requires the differencing orders (d, D), general and seasonal operators (p, q, P, Q), as well as the assessment of structures in the auto regressive (AR) and moving average (MR) models. Autocorrelation (ACF) and Partial-autocorrelation (PACF) defined the parameters for general and seasonal AR and MR which in turn buildup five different ARIMA model *viz*., ARIMA (2,1,1) $(1,1,1)_7$, ARIMA (1,1,2) $(1,1,1)_7$, ARIMA (1,1,1) $(1,1,1)_7$, ARIMA (1,1,1) $(1,1,2)_7$ and ARIMA (1,1,1) $(2,1,1)_7$. Both ACF and PACF graphs were widely used for identification of the model structure (Zhang *et al*., 2008, 2016; Lin *et al*., 2012; Yan *et al*., 2017).

Although all the models had significant co-efficient ϕ_1 and ϕ_2: 1-order and 2-order auto-regressive coefficient; θ_1 and θ_2: 1-order and 2-order moving average coefficient; ϕ_1 and ϕ_1: 1-order and 2-order seasonal auto-regressive coefficients; Θ_1 andΘ_2: 1-order and 2-order seasonal moving average coefficient, ARIMA $(2,1,1)(1,1,1)_7$ was selected having lowest Akaike Information Criterion (AIC) value (387.19). Based on the predicting measured errors RMSE (0.7071721), MAPE (4.352807), MASE (0.04534878) and accuracy of 95.65 per cent, ARIMA $(2,1,1)(1,1,1)_7$ was used for stripe rust prediction during 2017-2019. Prediction of test data indicated minimum per cent relative deviation of 0.71 to 8.46 across the standard meteorological weeks except 1st week. Further, ARIMA $(2,1,1)(1,1,1)_7$ predicted the disease severity of 3.22±0.73 to 60.20±0.88, 3.83±1.052 to 60.64±1.18 and 4.37±1.28 to 61.12±1.42 during 2020, 2021 and 2022, respectively, irrespective of cultivars' response and environmental conditions. ARIMA (3,1,3) and (1,0,3) models have been employed for the prediction of for powdery mildew

(*Uncinula necator*) and downy mildew (*Plasmopara viticola*) in vineyards, as both the diseases are also caused by the obligate pathogens as in case of stripe rust (Fernández-González *et al*., 2016).

Further, ARIMA were explored in conjugation with X (meteorological factors) to increase the accuracy in prediction of stripe rust of wheat. The finest adjusted model was again ARIMA (2,1,1) $(1,1,1)_7$, including the minimum temperature (°C) and rainfall with lag 1 having maximum accuracy of 96.00 per cent. ARIMA (0,2,2), with relative humidity four days earlier, and ARIMA (1,2,3), having relative humidity three days earlier and rainfall two days earlier were best in predicting *Botrytis cinerea* spores in vineyards at Cenlle, and Amares (Fernández-González *et al*., 2012). Non-linear regression model with ARMA errors proficiently predicted the disease progress, with R^2 of 75·42 and 79·03 per cent for severity and incidence of brown eye spot in coffee (Souza *et al*., 2015).

ARIMA is widely used for the temporal assessment for the prediction of spore concentration of *Podosphaera leucotricha*, causing powdery mildew of apple (Xu *et al.*, 1995). Under timely and late sown conditions, ARIMA (1, 0, 1) was best fitted to predict the disease severity of spot blotch (SB) in wheat caused by *Bipolariss orokiniana*, with R^2 and RMSE of 0.88 and 7.61, and 0.86 and 5.48, respectively (Singh *et al.*, 2019). Whereas, ARIMAX model was best in the prediction of cocoa black pod incidence caused by *Phytophthora palmivora*, with the minimum values of MSE (0.00955), RMSE (0.09773) and MAE (0.07765) (Ling *et al.*, 2019).

Among the different epidemiological factors, weather played a major role in the onset of stripe rust epidemics in wheat, at regional and continental scales. The pathogen, *Puccinia striiformis* f. sp. *tritici* (*Pst*) responsible for the disease is very sensitive to environmental conditions. Out of different weather parameters, temperature, moisture and wind are mainly responsible for the epidemics of the disease (Chen, 2005). Temperature, leaf-wetness duration and light intensity influenced the sporulation capacity and infection efficiency of *P. striiformis* f. sp. *tritici* (de Vallavieille-Pope *et al.*, 1995). Various models have been developed for predicting the stripe rust of wheat (Kuang *et al*., 2013; Khajuria *et al*., 2016; Gupta *et al*., 2017a; 2017b; El Jarroudi *et al.*, 2017; Singh *et al.,* 2018; Naseri and Sharifi, 2019).

In the present study, the severity of 1.42 and 1.47 per cent were observed in Ist standard meteorological week (SMW), when the corresponding meteorological factors of maximum temperature of 17.34 and 17.53^{0}C, minimum temperature of 5.97 and 4.35^{0}C, maximum relative humidity of 92.23 and 93.64 per cent, minimum relative humidity of 55.08 and 53.21 per cent and rainfall of 5.40 and 5.50 mm were recorded during 2005-2017 and 2018-2019, respectively. Minimum, optimum and maximum temperature range of 0 and 3°C, 11 and 9°C, 23 and 18°C with continuous 6 hours of wetness period is required for the infection of stripe rust (Hoggs *et al.*, 1969; de Vallavieille-Pope *et al.*, 1995). For penetration and sporulation of *Pst*, minimum, optimum, and maximum temperature of 2°C, 9-13°C, 23°C and 5°C, 12- 15°C, 20°C are required, respectively (Roelfs *et al*., 1992). The disease (1%) was recorded in 1st standard meteorological week (SMW) during 2013-15, after 73 days after sowing (jointing stage), with corresponding maximum temperature of 17.5^{0}C, minimum temperature of 5^{0}C, maximum relative humidity of 92.50 per cent, minimum relative humidity of 59 per cent, mean wind velocity of 1.6 km h^{-1}, vapour pressure of 8.2 mmHg (morning) and 9.9 mmHg (evening), sunshine of 2.9 h day^{-1}, cloud cover of 3.5 (morning) and 6.0 okta (evening), soil temperature of 11.4^{0}C and canopy temperature of 11.7^{0}C, before one-week of disease appearance (Gupta *et al.*, 2017b). Rate of disease progress (r) varied from 0.09 to 0.32 in pathotype 78S84, during 2011-12, and from 0.00-0.32 during 2012-13, and was higher in the month of January and February (Sunil, 2013).

Maximum periodical progression in severity of 87 and 75 per cent were recorded during 3rd to 4th SMW during 2005-17 and 2017-2019, respectively. The prevailing meteorological parameters during the corresponding period helped in the aggravation of stripe rust disease. Average temperature of 11.4, 10.6, 14.1 and 15.5°C, during December to March, respectively, contributed in the development of epidemic of stripe rust of wheat (Wan *et al.,* 2002). At 12th SMW (end of the cropping season), the final severity reached to 56.31 and 59.06 per cent in 2005-17 and 2017-2019, respectively. Temperature >22 to 25ºC inhibited the growth and spread of the stripe rust (Sharp, 1965; Shaner and

Powelson, 1971). Although the maximum temperature started increasing in the month of March (>20ºC), the microclimatic conditions, leaf wetness, establishment of infection water logging conditions,e growth stage of the crop and aggressiveness and virulence of the prevailing pathotypes of *Puccinia striiformis* f. sp. *tritici* were the key factors contributing in the epidemics of the diseases. Amalgamation of relative humidity (>92%) and temperature (< 4°C to < 16°C) for 4 continuous hours, along with rainfall (≤0.1mm), were best for the progress of epidemic of stripe rust of wheat (El Jarroudi *et al*., 2017)

In the present, study, correlation between meteorological factors and severity of stripe rust of wheat revealed that maximum and minimum temperatures had positive and highly significant correlation (0.89 and 0.91; 0.91 and 0.75), whereas, morning relative humidity had significantly negative correlation (-0.84 and -0.80) in 2005-17 and 2017-2019, respectively. Evening relative humidity and rainfall had non-significant correction with the disease severity, during 2005-17 and 2017-19, respectively. Temperature and moisture had pronounced impact on the stripe rust of wheat, contributing towards the initiation and spread of the disease. Average of maximum and minimum temperature (Tavg), mean of maximum temperature (Tmax) and maximum temperature were found to have significantly positive correlation with the severity of pathotype 78S84, with correlation coefficient (r) of +0.779, +0.719 and +0.635, respectively, during 2011-12 season (Sunil, 2013). Disease incidence of stripe rust was positively and significantly correlated with maximum and minimum temperatures and sunshine hours during 2012-13 and 2013-14 cropping seasons (Sandhu and Dhaliwal, 2017). Morning and evening relative humidity had negative correlation with disease incidence and severity (Lemaire *et al.,* 2002; Gupta *et al*., 2017b; Sandhu and Dhaliwal, 2017). Though rainfall has no significant association with the disease severity but it indirectly promotes the favourable disease conditions (moisture and leaf wetness) for build-up of disease.

In the present study, the models developed by multiple linear regression during 2005-17 and 2017-19 for the prediction of stripe rust $Y= -502.1392+0.6373X_1 +8.5741X_2+3.0402X_3+1.4227X_4+0.5764X_5$ and $Y=322.5683 +9.4103X_1- 4.1446X_2- 2.5589X_3-0.7089+0.2609X_5$ were significant. Both the models exhibited that 91 and 89 per cent variation in the disease severity were influenced by maximum temperature, minimum temperature, maximum and minimum relative humidity and rainfall.

Association of various weather parameters *viz*., maximum and minimum temperatures, morning and evening relative humidity, rainfall and sunshine hours played important role in the development and spread of stripe rust of wheat (Khajuria *et al*., 2016; Rodríguez-Moreno *et al.*, 2020). Significant R^2 of 0.91 and 0.92 was recorded for multiple regression model of stripe rust, when maximum abiotic parameters were combined in cultivars, PBW 550 and PBW 343, respectively (Sandhu and Dhaliwal, 2017). Severity of stripe rust was best predicted in susceptible cultivars by the combination of temperature, humidity, and rain from April to June (Beest *et al*., 2008). First Chinese simulation modal (TXLX) of stripe rust was based on the daily temperature and dew period (Zeng and Zhang, 1990). Both these models, predicted the severity with minimum per cent deviation in both data sets. All the assumptions *viz*., linearity, reliability, homoscedasticity, normality, outlier's detection, non-constant variance and normality were fulfilled by the developed models signifying the stability and better performance of prediction of stripe rust of wheat at regional level. Various models generated by multiple linear regressions were used for the prediction of foliar plant diseases at regional scale (Eddy, 2009; Kumar, 2014; Gupta *et al.*, 2020).

In the present study, 84 per cent increase in spore concentration of *Puccinia striiformis* f. sp. *tritici* was observed from 51st to 7th SMW during 2017 - 2019. Nowadays, spore traps for the detection of inoculum are being increasingly used to quantify the airborne inoculum of plant pathogens and to improve precision in disease risk management and fungicide applications (Luo *et al*., 2007; Rogers *et al*., 2009; Dedeurwaerder *et al*., 2011; Duvivier *et al*., 2013, 2016; Wieczorek and Jørgensen, 2013; Almquist and Wallenhammar, 2014; Chandelier *et al*., 2014). Pan *et al*. (2010) established a real-time polymerase chain reaction (PCR) assay to quantify the inoculum level of *P. striiformis* f. sp. *tritici* in leaves by quantifying the latent infection levels and estimating potential disease intensity in the field. By targeting latent infection foci with fungicide applications, the initial inoculum was effectively lessened, reducing the build-up of rust epidemic.

Chapter-6

Summary and Conclusions

CHAPTER-6

SUMMARY AND CONCLUSIONS

The study was conducted to predict the population of *Puccinia striiformis* f. sp. *tritici*, responsible for stripe rust of wheat in the future time period under the influence of climate change, to develop forewarning model of the disease in relationship with meteorological factors, by the time series and multiple linear regression and quantification of *P. striiformis* f. sp. *tritici*.

The study revealed highest fluctuations (increase) in maximum temperature in Jammu (6.26 to 11.13^{0}C), followed by Hisar (2.78 to 7.64^{0}C), Ludhiana (3.46 to 6.56^{0}C), Dhaulakuan (0.65 to 3.50^{0}C) and Leh (2.97 to 5.44^{0}C), whereas minimum in Meerut (0.58 to 3.37^{0}C). Maximum variations in minimum temperatures were also recorded in Jammu (7.15 to 9.24^{0}C), followed by Leh (3.66 to 5.87^{0}C), Ludhiana (2.68 to 4.76^{0}C), Hisar (2.16 to 4.24^{0}C) and Dhaulakuan (1.68 to 3.66^{0}C), with minimum in Meerut (0.58 to 3.37^{0}C). Shortest latent period of *P. striiformis* f. sp. *tritici* infection was recorded in Jammu, followed by Ludhiana, Meerut, Hisar and Dhaulakuan, whereas, it was more in Leh, under all scenarios in three future time periods of 2020, 2050 and 2080 as compared to baseline period (1975). Maximum reduction in the latent period (days) of *P. striiformis* f. sp. *tritici* of 110, 49, 36, 35 and 40 per cent was observed in Jammu, Hisar, Ludhiana, Dhaulakuan and Meerut, respectively, during 2080, under RCP 8.5 scenario. However, 25 per cent increase was observed in the latent period was recorded at Leh. Maximum increase of 49, 27, 20, 21, 24 and 20 per cent in the number of *P. striiformis* f. sp. *tritici* generations were recorded by RCP 6.0 scenario in Jammu, Hisar, Ludhiana, Dhaulakuan, Meerut and Leh, respectively, whereas, minimum per cent increase of 41, 17, 9, 9, 11 and 9 were recorded by RCP 2.6 scenario in these locations, respectively.

Univariate time series (ARIMA) model was developed to predict the severity of stripe rust of wheat using 2005-2017 data set. The developed ARIMA (2,1,1) $(1,1,1)_7$ model was validated with test data sets (2007-2019) having highest accuracy of 95 per cent. The model ARIMA (2,1,1) $(1,1,1)_7$ predicted the disease severity of 3.22±0.73 to

60.20±0.88, 3.83±1.052 to 60.64±1.18 and 4.37±1.28 to 61.12±1.42 during 2020, 2021 and 2022, respectively, irrespective of cultivars response and environmental conditions. Further, after pre-whitening with meteorological factors, ARIMAX (2,1,1) $(1,1,1)_7$ with minimum temperature (^oC) and rainfall (mm) with lag 1, was adjusted best having maximum accuracy of 96.00 per cent in predicting stripe rust of wheat for short-term period.

In the study, the initiation of disease (1.42 and 1.47%) was observed in 1st standard meteorological week (SMW), when the corresponding meteorological factors of maximum temperatures were 17.34 and 17.53^{0}C, minimum temperatures of 5.97 and 4.35^{0}C, maximum relative humidity of 92.23 and 93.64 per cent, minimum relative humidity of 55.08 and 53.21 per cent and rainfall of 5.40 and 5.50 mm, during 2005-2017 and 2018-2019, respectively. Severity of stripe rust of wheat had positive and highly significant correlation with maximum and minimum temperatures (0.89 and 0.91; 0.91 and 0.75), whereas, morning relative humidity had significantly negative correlation (-0.84 and -0.80), in 2005-17 and 2017-2019, respectively. Rainfall had non-significant correction with the disease during 2005-17 and 2017-19, respectively. Models *viz*., $Y = -502.1392+0.6373X_1+8.5741X_2+ 3.0402X_3+ 1.4227X_4+ 0.5764X_5$ and $Y = 322.5683+9.4103X_1 - 4.1446X_2 - 2.5589X_3 - 0.7089+0.2609X_5$, developed by multiple regression for 2005-17 and 2017 and 2019, were highly significant in predicting stripe rust of wheat. Both the models exhibited that 91 and 89 per cent variation in the disease severity was influenced by maximum and minimum temperatures, maximum and minimum relative humidity and rainfall.

The following conclusions were drawn from the present investigations:

- Maximum temperature showed highest variations in Jammu (6.26 to 11.13^{0}C), followed by Hisar (2.78 to 7.64^{0}C), Ludhiana (3.46 to 6.56^{0}C), Dhaulakuan (0.65 to 3.50^{0}C) and Leh (2.97 to 5.44^{0}C), whereas it was minimum in Meerut (0.58 to 3.37^{0}C). Whereas, minimum temperature again exhibited maximum variation in Jammu (7.15 to 9.24^{0}C), followed by Leh (3.66 to 5.87^{0}C), Ludhiana (2.68 to 4.76^{0}C), Hisar (2.16 to 4.24^{0}C) and Dhaulakuan (1.68 to 3.66^{0}C), it was minimum in Meerut (0.58 to 3.37^{0}C) in future time periods (2020, 2050 and 2080).

- Reduction in latent period (days) of *Puccinia striiformis* f. sp. *tritici* was estimated in Jammu, Ludhiana, Meerut, Hisar and Dhaulakuan for future time periods (2020, 2050 and 2080). Whereas, increase in the latent period was envisaged in Leh for future time periods.

- Maximum increase of 49, 27, 20, 21, 24 and 20 per cent in the number of *P. striiformis* f. sp. *tritici* infection cycles were recorded by RCP 6.0 scenario in Jammu, Hisar, Ludhiana, Dhaulakuan, Meerut and Leh, respectively.

- ARIMA (2,1,1) $(1,1,1)_7$ with minimum temperature (^{o}C) and rainfall (mm) with lag 1 was found best for predicting stripe rust of wheat.

- The models generated for forewarning of stripe rust of wheat by multiple linear regression for 2005 and 2017 significantly influenced by maximum temperature, minimum temperature, maximum and minimum relative humidity and rainfall.

- The urediospore population (0.25) of *Puccinia striiformis* f. sp. *tritici* started recorded during 51st SMW during 2017-19.

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Appendix

WEATHER AND DISEASE SEVERITY DATA

Year - 2005

SMW	Disease severity (%)	Max. Temp. (ºC)	Min. Temp. (ºC)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	0.27	17.78	6.25	92.22	51.37	6.3
2nd	4.03	16.35	5.56	91.26	52.01	1.2
3rd	12.40	19.51	5.14	93.57	50.29	0
4th	22.73	21.84	7.46	94	52.57	0
5th	32.53	24.4	7.64	95.43	49.71	0
6th	38.10	25.51	11.41	90.43	52	3
7th	42.37	27.53	12.86	84.29	49.86	0
8th	45.83	26.17	11.41	91.43	52.43	5
9th	48.27	27.29	10.21	85.29	40.71	0
10th	50.23	23.73	12.83	91.57	64.86	32.6
11th	53.63	25.7	11	84.57	38.86	0
12th	55.10	26.74	10.96	84.86	47.86	0

Year - 2006

SMW	Disease severity (%)	Max. Temp. (ºC)	Min. Temp. (ºC)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	0.50	16.23	8.01	95.23	61.2	2.4
2nd	4.17	18.23	7.1	94.24	56.28	1.2
3rd	12.53	17.93	3.9	96.29	48	0
4th	22.67	20.36	4.89	96.86	46.57	0
5th	32.67	20.36	5.39	96.86	46.57	0
6th	38.40	24.91	9.26	85.71	52.57	12.37
7th	42.53	22.69	9.89	93.29	74.43	4.65
8th	45.67	19.7	7.39	92.14	60	4.7
9th	48.37	21.17	10.07	93	63.43	0
10th	50.37	23.46	8.19	87.86	52.43	80.66
11th	53.73	20.91	10.97	90.14	60.29	16
12th	55.33	25.63	13.1	86.71	57.43	0

Year - 2007

SMW	Disease severity (%)	Max. Temp. (ºC)	Min. Temp. (ºC)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.17	18.54	7.2	92.1	50.02	6.1
2nd	4.63	17.26	7.6	90.02	56.24	0.9
3rd	12.50	16.29	8.9	89	54.02	0
4th	22.67	19.43	4.5	91.57	31.57	0
5th	32.73	17.6	9.37	84.43	67.86	0
6th	38.37	16.31	7.16	94.14	67.57	0
7th	42.63	15.83	1.47	93	31.14	3.4
8th	45.67	16.79	2.59	92	35.29	7.4
9th	48.43	14.21	6.93	88.71	62.14	0
10th	50.40	19.51	2.79	93.57	33.43	0
11th	53.77	23.01	8.87	89.43	44.14	0
12th	55.47	24.47	9.57	90.57	42.29	0

Year - 2008

SMW	Disease severity (%)	Max. Temp. (ºC)	Min. Temp. (ºC)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	0.50	15.78	6.45	90.45	50.16	4.1
2nd	4.47	16.59	6.1	91.23	56.57	0.2
3rd	12.60	17.26	5.78	90.34	78.01	0.1
4th	22.67	15.56	5.23	90.64	49.06	0
5th	32.80	21.06	7.81	92.71	62	2.4
6th	38.53	20.46	8.03	87.86	64.86	25
7th	42.73	20.46	8.03	87.86	64.86	0
8th	45.80	21.39	7.44	94.71	61.71	0
9th	48.53	22.59	8.4	88.43	45.71	0
10th	50.53	21.01	9.27	90.43	62	0
11th	53.97	23.8	8.9	93	43.43	4.2
12th	55.63	25.04	8.41	89.14	42.14	5.13

Year - 2009

SMW	Disease severity (%)	Max. Temp. (°C)	Min. Temp. (°C)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.00	14.9	4.3	92	68	0
2nd	4.70	20.6	4.3	89	48	0
3rd	12.50	20.8	6.1	87	46	3.2
4th	22.33	19.4	9.8	87	84	20.7
5th	32.33	19.9	7.6	83	40	0
6th	38.60	24.8	8.6	84	46	0
7th	42.83	26.1	11.3	84	45	0
8th	45.77	26.5	9.8	81	46	0
9th	48.63	30.6	11.8	77	41	0
10th	50.63	34	15.1	82	39	0
11th	54.00	34.2	15.3	71	36	2.7
12th	55.70	35.4	16.3	61	22	0

Year - 2010

SMW	Disease severity (%)	Max. Temp. (°C)	Min. Temp. (°C)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.32	16.5	6	90.24	53	5.2
2nd	4.67	17.7	4.9	91.06	48	0.2
3rd	12.53	15.3	4.02	88.03	45.01	0.3
4th	22.73	19.47	3.63	96.43	46	0
5th	33.07	19.53	4.83	93.57	49.86	0
6th	38.70	21.23	9.81	93.29	63.43	13.2
7th	42.90	19.13	8.31	94.43	67.29	7.8
8th	45.90	19.04	8.07	95.43	67.71	2.9
9th	48.73	19.2	8.23	92.71	57.43	4.2
10th	50.73	21.46	9.47	94.43	62.71	5.2
11th	54.13	27.44	9.63	92.29	45.14	0
12th	55.87	29.14	14	86.86	48.86	0

Year - 2011

SMW	Disease severity (%)	Max. Temp. (ºC)	Min. Temp. (ºC)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.75	16.5	6.2	90.78	50.2	10.5
2nd	4.90	17.14	5.2	91.15	52.26	5.2
3rd	12.90	17.34	4.74	90.01	48.57	0
4th	22.50	15.6	3.59	88.14	46.57	0
5th	32.97	17.61	5.74	86.57	56	11
6th	38.73	18.11	4.67	87.14	44	9.1
7th	43.00	18.7	6.24	94.29	59.86	0
8th	46.03	21.53	6.54	87.86	43.71	0
9th	48.73	24.47	8.87	82.01	41.71	25.8
10th	50.80	23.13	7.4	85.29	38.57	2.8
11th	54.20	26.46	11.16	81.57	39.71	0
12th	56.03	28.23	11.64	81.14	38.14	0

Year - 2012

SMW	Disease severity (%)	Max. Temp. (ºC)	Min. Temp. (ºC)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.80	17.89	5.8	94	52.2	2.2
2nd	5.07	18.89	5.9	90.23	56.25	2.6
3rd	12.90	19.25	6.04	87	60.14	20.4
4th	22.83	17.37	4.44	91.14	60.28	0
5th	32.77	20.28	4.28	85.14	52.42	19.8
6th	38.97	19.42	7.3	92.28	63	22.4
7th	43.10	21.44	4.72	90.28	52.71	10
8th	46.10	19.3	7.95	90.28	72.42	21.93
9th	48.90	19.72	9.42	92.14	68.42	17.9
10th	50.87	26.1	8.45	84.85	54.57	0
11th	54.33	26.42	12.75	80.42	58.7	5.4
12th	56.13	27.15	11.65	82.14	48.14	17.85

Year - 2013

SMW	Disease severity (%)	Max. Temp. (°C)	Min. Temp. (°C)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	2.00	18	4.4	95	51.1	0
2nd	5.20	17.8	6	96.1	65.9	0
3rd	13.00	20.5	6.9	95.4	55.3	26
4th	23.10	18.7	8.5	94.3	27.7	0
5th	33.43	18.4	7.7	91.3	64.3	5.7
6th	39.00	19.1	5.4	92.3	50.3	5.8
7th	43.27	21.4	7.6	93.1	54.6	3.2
8th	46.17	20.3	9.1	92	66.1	2.6
9th	49.10	22.2	10.3	88.6	57.6	22.8
10th	50.97	25.6	12.3	84.9	52	19.2
11th	54.17	24.3	12.5	86	60.7	6.7
12th	56.33	27.2	13.5	84.6	47.9	0

Year - 2014-15

SMW	Disease severity (%)	Max. Temp. (°C)	Min. Temp. (°C)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.9	15.91	6.47	89.7	58.37	0
2nd	5.8	10.85	6.34	97.42	58.14	0.77
3rd	15	19.21	5.04	91.85	52.34	0.08
4th	26	17.28	6.41	95.57	55.02	1.6
5th	36	18.34	5.37	90.71	60.43	8.25
6th	40.5	21.4	6.42	86.14	52.5	0
7th	45	22.6	10.32	84.85	62.2	0.82
8th	47.8	22.81	12.37	88.57	56.56	7.32
9th	51.6	19.45	9.65	88.28	57.4	16.65
10th	52.7	20.6	9.7	91	51.94	3
11th	54.9	22.6	10.1	89	44.53	15.3
12th	56.9	29.1	13.5	83	45.1	0

Year - 2015-16

SMW	Disease severity (%)	Max. Temp. (ºC)	Min. Temp. (ºC)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	2.1	20.24	4.58	91.28	55.39	0.25
2nd	5.2	20.55	5.31	92.28	54.94	0
3rd	15.8	13.01	6.45	93	58.14	0
4th	25.2	14.15	4.04	96.28	48.1	0
5th	37	20.48	6.3	94.14	55.21	1.42
6th	41.5	21.64	6.25	88.14	57.5	0.4
7th	45.2	22.88	5.5	88.85	53.54	0
8th	48.6	25.57	9.14	85.14	60.56	1.82
9th	51	26.97	11.04	87.28	52.6	0
10th	53.9	27.68	12.4	79	56.02	1
11th	55.9	22.3	12.97	87.57	53.25	7.37
12th	58.5	27.7	12.15	85.71	45.9	0.77

Year - 2016-17

SMW	Disease severity (%)	Max. Temp. (ºC)	Min. Temp. (ºC)	Morning RH (%)	Evening RH (%)	Rainfall (mm)
1st	1.05	17.5	3.3	94	56	0
2nd	5.1	20	2.6	94	42	0
3rd	13.24	21.8	3.5	91	42	0
4th	25.67	16.8	5.1	94	69	1.4
5th	38	21.4	6.1	91	49	0
6th	44.45	21.9	4.1	89	37	0
7th	48.97	20.5	7.7	92	54	6.7
8th	50.12	24.2	9.8	87	54	0.5
9th	52.33	24.5	12.2	84	58	0.8
10th	54.67	27.2	10.3	88	43	0
11th	56.71	29.2	11.6	84	38	0
12th	58.25	28.2	12.3	84	45	1.1

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CERTIFICATE-IV

Certified that all the necessary corrections as suggested by external examiner and the advisory committee have been duly incorporated in the thesis entitled **"Comparative study of forecasting models for stripe rust of wheat"** submitted by **Ms. Sheikh Saima Khushboo**, Registration No. **J-16-D-289-A.**

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Place: Jammu

Dated: 18.03.2021

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