Modeling Disease Dynamics of Spring Wheat

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بسم الله الرحمن الرحيم

(IN THE NAME OF ALLAH, THE MOST GRACIOUS AND THE MOST BENEFICIAL)

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FINAL APPROVAL

It is certificate that we have read the thesis submitted by Ms. Zohra Bibi and it is our judgment that this project is of sufficient standard to warrant its acceptance by the International Islamic University, Islamabad for the M.S Degree in Bioinformatics

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degree of M.S in Bioinformatics

DEDICATION

This thesis is dedicated to my Parents for their love, endless support and encouragement and my Mamoo who have supported me all the way since the beginning of my studies

Are those who know equal to those who know not?

(Az-Zumar 39:09)

DECLARATION

I hereby declare that the work presented in the following thesis is my own effort, except where otherwise acknowledged, and that the thesis is my own composition. No part of the thesis has been previously presented for any other degree.

Dated: 27-09-12.

Zohra Bibi

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(Zohra Bibi)

LIST OF ABBREVIATIONS

Acronym	Abbreviation
^{o}C	Degree Centigrade
t/ha	Tonnes/hectare
ppm	parts per million
mm	Millimeter
CO_2	Carbon Dioxide
O_3	Ozone
CO	Carbon Monoxide
CH_4	Methane
SO_2	Sulphur Dioxide
N_2O	Nitrous Oxide
APSIM	*A*gricultural *P*roduction *Systems SIM*ulator
APSRU	Agricultural Production System Research Unit
IPCC	Intergovernmental Panel on Climate Change
NARC	National Agriculture Research Centre
CSM	Crop Simulation Model
PMD	Pakistan Meteorological Department
SRES	Special Report on Emission Scenarios
GCM	Global Climate Model
RCM	Regional Climate Model
MRM	Multiple Regression Model
LRM	Logistic Regression Model
QPM	Quadratic plateau Model
R^2	Coefficient of determination
d-stat	Index of Agreement

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ABSTRACT

Wheat (*Triticum aestivum* L.) is the main staple food crop, cultivated in most parts of the globe. The world demand for food will rise due to continuously increasing population. Reduction in agricultural productivity was due to variation in climate. The abrupt change in climate in response to global earth warming has led to reduced grain yield and productivity over the whole world. Food production and security are also affected by pests and pathogen-mediated changes that occur because of change in climate. *Alternaria triticina* and *Drechslera sorokiniana* leaf blight are most important diseases of wheat crop in Pakistan. The present studies were conducted in rainfed zone (Islamabad) to understand and monitor the impact of fungal diseases to wheat yield under climate change.

Statistical (Multiple Regression, Logistic Regression and Quadratic Plateau Model) and Dynamical model (APSIM) can help wheat producers to evaluate disease risk. Both models used weather (Temperature and Rainfall) information.

Biological processes are very hard to comprehend. Computer modeling gives an aid to elucidate biological complexity to make novel and abstract concepts. Crop simulation models was used as computational and bioinformatics tools to better analyze the performance of wheat crop in relation to fungal diseases under climate change and to depict strategic or tactical management options based on results.

Statistical model were evaluated using validation skill scores: R^2, RMSE (root mean square error) and d-stat (index of agreement). The values for pathogen occurrence for *Alternaria* leaf blight were 0.50 with RMSE 11.36 and d-stat 0.43 and for *Drechslera* leaf blight was 0.63 with RMSE 8.81 and d-stat 0.75. Similarly for Logistic Regression, the values for pathogen occurrence for *Alternaria* leaf blight (when Temperature is above 20°C) were 0.93 with RMSE 3.47 and d-stat 0.98 and non-significant results for *Drechslera* leaf blight. When Rainfall is above 10 mm, the values for pathogen occurrence for *Alternaria* leaf blight were 0.98 with RMSE 28.0 and d-stat 0.80 and for *Drechslera* leaf blight was 0.87 with RMSE 3.69 and d-stat 0.99. Quadratic Plateau Modelof statistical analysis was a good method for predicting the maximum point of disease called as plateau. Similar conclusion were made by Multiple, Logistic Regression and Quadratic Plateau Model. Outcomes of the statistical modeling depicted that

increase or decrease in temperature and rainfall has negative and positive impacts on fungal diseases of wheat respectively.

The second phase presents dynamic modeling to explain and understand the host-pathogen interaction. Hypothetical climate change scenarios were created and simulation was run in the framework of agriculture production system simulator (APSIM) model. The impacts of projections or future climatic variations (Temperature and Rainfall) under A2 emission scenarios on wheat yield and fungal diseases were analyzing. Impact of fungal diseases under A2 scenarios depicted that increase in climatic variants (temperature, humidity and CO_2) exerted positive impacts, which consequently depress wheat yield.

The outcomes of statistical models are linked intrinsically with dynamical model, depicted that the risk of wheat fungal diseases is projected to increase under climate change in selected area of Pakistan. The results indicated that APSIM model was able to simulate the wheat yield formation, capable for simulating the impact of temperature and rainfall and can aid in providing farmer with information for their management decision. Simulation results using APSIM model combined with historical record of climatic data (52 years), wheat infested with fungal pathogen (*Alternaria triticina* and *Drechslera sorokiniana*) and hypothetical scenarios depicted that increase or decrease in temperature and rainfall have negative and positive impacts on fungal diseases of wheat respectively. Climatic variability greatly affected crop yield and productivity. Therefore, APSIM model can assist in the development of a system approach to reduce the negative impact of pathogens on crops.

Further, it is suggested to link the temperature and rainfall variability on different locations in Pakistan and organize similar studies using simulation techniques as tool for forecasting of wheat yield in relation to fungal diseases to make tactical management decisions.

CHAPTER 1

INTRODUCTION

INTRODUCTION

In computer base information technology era, crop modeling and simulated technologies are increasingly seen and its usefulness in agricultural research as bioinformatics tools to understand crop physiology, development and to optimize the plant management strategies. Knowledge about crop research and development has been increasing and advancing at a rapid pace. Therefore, the multi-disciplinary knowledge about plant processes and crops have coupled or lumped together in the form of the Crop simulation models.

Crop simulation models (CSM) integrate available scientific knowledge in a way to explain and clarify the current understanding of plant processes. System biology, Bioinformatics tools and computational modeling, enable us to study the complex interactions of plant pathogens in a more realistic and convenient way (Andres *et al.*, 2009). Climatic variations that include daily minima and maxima temperature and rainfall have a greater influence on plant diseases, crop growth and development. However it is an important limitation to accessibility of the weather data in the developing world (Wilkens and Singh, 2001).

Besides global warming and climatic changes, Plant diseases represent major threats for crops around the world. It was noticed that 14.1% of crops are lost due to plant diseases alone. To address this objective, it is necessary to have some acceptable strategies to prevent the epidemic development of plant disease in order to reduce crop losses (Medina *et al.*, 2009).

1.1 Background and Related work

Dynamical models and computational simulation have been used to control and manage the plant diseases and to identify other factors that contribute to reduced agriculture production. In the second half of 20^{th} century, simulation of cropping system was carried out by several research groups.

There is always a need of quantitative representation and computational resources to build a mathematical description of multilevel biological processes toanalyze the complex biological system and their interaction with surrounding environment as well as agro-ecosystem (Mabrouk A and Sharkawy, 2011).

In the 1960's, the effort was initiated by pioneers of plant disease model at Mississippi State University build a dynamic simulation model of cotton crop as a tool to enhance crop management strategies as depicted in figure (1.1). Vanderplank (1963) proposed logistic model. Waggoner and Horsfall (1969) have developed a simulation model of tomato and potato blights. Challinor (2004) mentioned the need of process-based modeling approach to improve crop physiology and to capture the effect of climate changes on crop yields. It was found in the literature that early crop models addressed the yield and growth of individual crop. Later on (1996-2007) modeling and simulation technologies have been developed to simulate crop sequences and to find the interaction among them.

Pioneers of plant disease model: Mississipi State university (MSU) researchers in 1960 build a crop growth model for cotton

1981 Real time simulation approach has been applied to sorghum yield prediction by Arkin

1989 Rao proposed leaf rust development and yield loss caused by Puccinia recondita f.sp.tritici

1994 Kosman proposed modeling and qualitative analysis of fungal foliar plant pathogen epidemics

1997 Thomas proposed a winter wheat biomass and nitrogen dynamics

1999 Stochastic modeling of winter wheat yield

2001 Delden proposed a model for simulating increase in leaf area-index Evaluated for potato and wheat

2002 Ewert proposed crop simulation model- Effects of elevated CO_2 and drought on wheat for different experimental and climatic conditions

2003 Ziaei proposed a wheat yield simulation model under irrigated and dry land condition

2004 Asseng proposed a model for simulated the wheat growth effected by increased water deficit, rising temperature and elevated CO_2.

2005 Conor proposed a simulation model for predicting wheat growth

2006 Fabre proposed a Stochastic population dynamic model against Barley yellow dwarf virus

2007 Schaafsma proposed a climatic model to predict Fusarium occurrence in maize and wheat

2008 Langensiepen proposed a validating CERES-wheat under Environmental condition

2009 Mathematical modeling tendencies in Plant pathology

2010 Modeling the effects of climatic conditions and water management on crop water productivity in North China

2011 Adam proposed effects of modeling on simulated crop yields under climatic condition

Figure 1.1: History of Plant Disease Models

Mimic climatic deterioration and finding the best management options are two factors under consideration in agronomic research to enhance crop productivity. Peterson *et al.*, (1993) proposed that dynamic approach is useful to answer agricultural/crop management problems and identify spaces in basic research knowledge. Crop modeling and computational simulation has developed over many years in accordance with advances in crop ecology, crop physiology and computational technology (Amanullah *et al.*, 2007).

Crop simulation models proved to be valuable for agriculture research undervarying climatic conditions for sustainable and better agricultural production (Amanullah *et al.*, 2007). These models study the complex interaction between soil properties, weather, water and management options which influence on crop growth and performance. Modeling efficiency has been visualized in future with several opportunities including scientific inspection or analysis, decision making by yield manager and a key role in understanding and advancing the genetic regulation of plant improvement and plant performance (Ahmed and Fayyaz-ul-Hassan, 2011). The dynamics of the system can be better described by the concurrent computational models. Today Bioinformatics tools which integrate not only biological science fields but also mathematics, statistics and engineering have been used to understand the complex biological disease problems by modeling the epidemic dynamics.

Various models are used as a toolfor modeling/forecasting the fungal diseases of wheat including: CERES-Cropsim, WHEAT PEST, DONCAST, GIBSIM and FACODEM for *Fusarium* head blight. Foliar disease, PROCULTURE, Source-sink, Distrain and Dymex modeling software's are used for studies of interaction between wheat crop as host and fungal diseases including Rust diseases (stem, leaf and stripe), *Fusarium* stem rot, Powdery mildew and

Septoria leaf blotch (Fernandes *et al.*, 2004; White *et al.*, 2004; Willocquet *et al.*, 2008; AUDSLEY *et al.*, 2006; Ponte *et al.*, 2005; Bancal *et al.*, 2012; Jarroudi, 2012).

1.2 Motivation Factors

- Diseases are complex system. Modeling them is a quite demanding, multidimensional and multi scale process.
- A model is a mathematical/graphical representation of available knowledge.
- Models include guidance for validation.
- Models are a tool for communication.
- Modeling simplifies the reality.
- Models as tool to manage/run crop system.
- Through designing empirical model and running computer simulations, we expect a better understanding of our problem domain.
- Models provide a foundation for research planning, cost- effectiveness analysis, clinical trial analysis, policy making, and education.
- Crop Simulation models reduce the time consuming and expensive field experimentation while such studies need lot of money, time, several years and myriad man hours in real world.
- Crop simulation models provide a means to quantify the impact of soil, management and climate on crop productivity, growth and sustainability of agricultural production.

1.3 Climate change and their effects

The climate of earth has always changed or fluctuated in response to changes in hydrosphere, biosphere, cryosphere and other interacting and atmospheric factors. It is generally accepted that human interventions play a key role in increasingly changes in global climate. Increase in (man-made) CO_2 emission has come from industry as a result of use of carbon-based fuels. Temperature and CO_2 concentration are projected to increase under the IPCC A2 scenarios, associated by extreme weather related events and greater variation in climate (Pachauri and Reisinger, 2007).

Variation in climate over time due to human interventions or as a result of natural variability alters the global atmosphere composition (IPCC, 2007). In the face of climate changes, management of crop growth will be a major challenge. Climate change has dramatic consequences for ecosystem, economic stability, human health, water resources, food security and production as outlined in figure (1.2).

It is broadly accepted that human interventions are now increasingly inducing changes in global climate (Pachauri and Reisinger, 2007). Man-made increases in concentration of CO_2 emission have come from market/industry, particularly as a result of use of burning of fossil/carbon-based fuel. Over the last 150 years, atmospheric CO_2 concentration has increased 280 ppm to 385 ppm (Chakraborty and Newton, 2011).

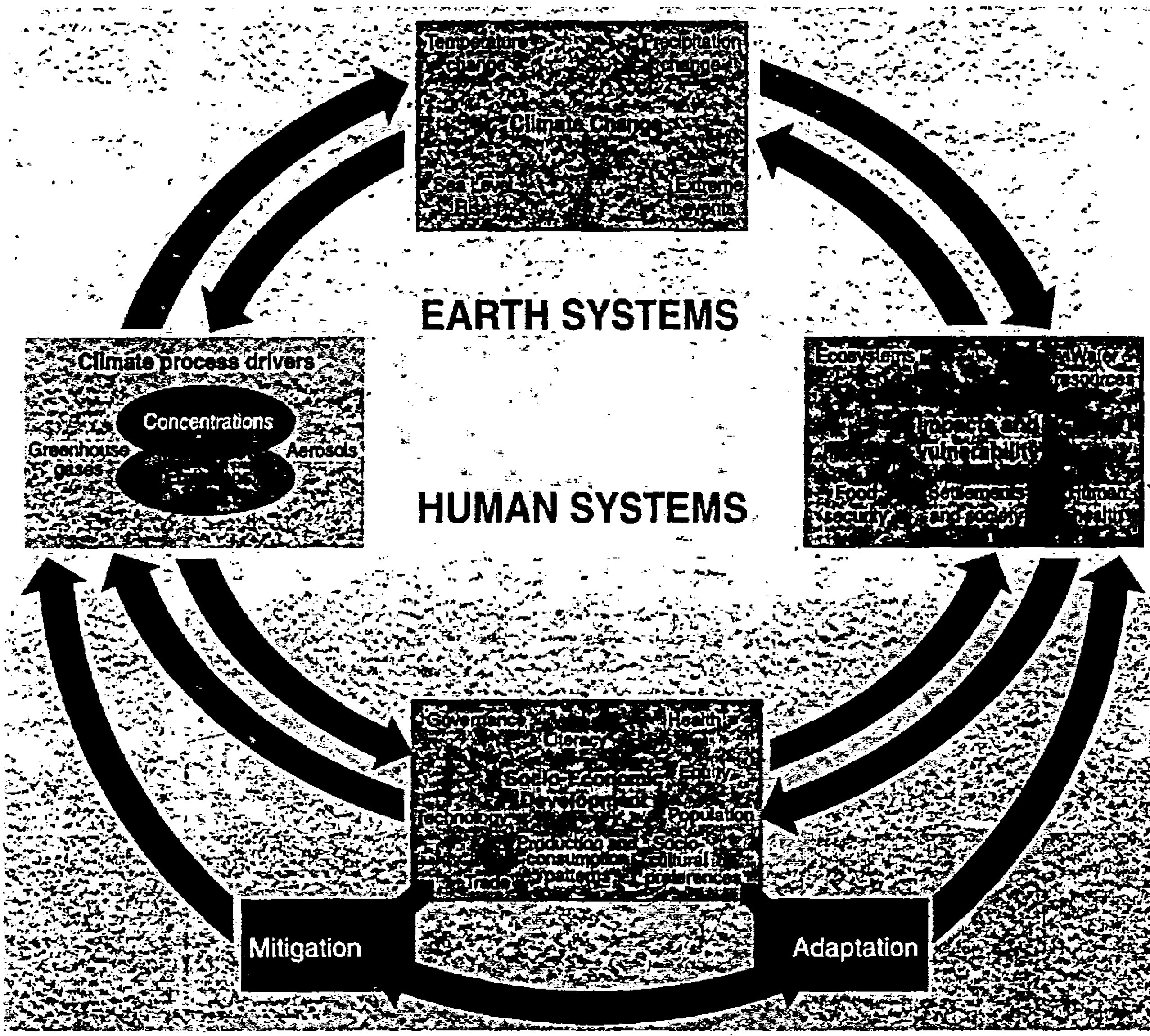


Figure 1.2: Schematic Representation of anthropogenic drivers, impacts and responses

(IPCC synthesis report, 2007)

1.4 Projections of future climate change

Climate change in IPCC usage refers to a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer. It refers to any change in climate over time, whetherdue to natural variability or as a result of human activity. Continued GHG emissions would cause further warming and induce many changes in the global climate system during the 21st century that would *very likely* be larger than those observed during the 20th century. The Intergovernmental panel for climate change (IPCC) provided strong clue of accelerated global warming. According to IPCC 4th assessment report (AR4), future climate projections to the late 21th century indicate an increase in temperature, increase in rainfall and higher CO_2 (anthropogenic greenhouse gas) concentration from present condition (IPCC, 2007).

- Global earth temperature is projected to rise between 1.8°C to 4.0°C (under the A2 low emission to high emission scenarios) up to end of this century
- More heat waves are expected
- More intense and extreme precipitation patterns are likely to occur on global scale (IPCC, 2007).

Change in climate is not linear, there is uncertainty about the future climate and this remains a key issue.

1.5 Climate variability, plant diseases and food security

Each process or mechanism is a complex, intricate biological system, with diverse components, influenced by climatic variants in different ways. The challenge, question is to rank the effects of both the key climatic and environmental processes in parallel in order to predict the effects of climatic variations on production system (Chakraborty and Newton, 2011).

1.5.1 Climate change and plant diseases

In the developing countries Plant diseases, pests, weeds and other environmental factors are major threats that alter agriculture production. Plant scientists have dedicated greater efforts to studying the impact of global climate changes on plant disease epidemics. The association of altered environmental conditions with climatic change has potential to alter the severity of plant disease epidemics. Climate importance has been observed to the plant diseases development for over 2000 years. Climatic variability may have contributed to global warming and this has particularly related to plant diseases. The changes in environmental factors such as rise in concentration of CO_2 and O_3 can also have direct effects on pathogen and host plant (Eastburn *et al.*, 2011).

Pathogens life cycle are directly affected by climate. The abiotic factors influences the dynamics of host-pathogen interaction and its environment; resulting to changes in plant disease occurrence/incidence and severity (Sturrock *et al.*, 2011). Luck *et al.*, (2011) stated that under elevated CO_2, growth of pathogens is increased. Rising CO_2 correlated with climate change may affect the performance, abundance and distribution of plant pathogens, modify the pathogen resistance and host susceptibility. Temperature has greater influence on crop growth, phasic development, photosynthesis and respiration. Warmer temperature reduced the grain yield by decreasing the length of growth cycle in grain filling phase and this is identified as the most important factor (Wilkens and Singh, 2001; White and Reynolds, 2001).

The considerable factors of climate change likely to influence severity of plant diseases and spread include:

- Unseasonal and Heavy Precipitation
- Increase in Atmospheric CO_2
- Higher Temperature
- Hurricanes
- Increased Humidity
- Cyclones
- Drought (Chakraborty *et al.*, 2000; Pimentel *et al.*, 2001; Rosenzweig *et al.*, 2001; Berry *et al.*, 2002; Anderson *et al.*, 2004).

Changes to all of these or any one climatic variant may influence the distribution and biology of pathogen with positive, negative or neutral effects (Fuhrer, 2003). Changes or increase in temperature and rainfall patterns may alter the use of land for food crops, subsequent in pest or plant-pathogen problems (Parker and Gilbert, 2004). Chakraborty *et al.*, (2008) stated that elevated CO_2 associated with change in climate may affect the abundance, distribution and performance of plant pests, insects and pathogens. Increased levels of CO_2 may modify aggressiveness of pathogen or host susceptibility, affecting the pathogen initial establishment on the host.

It also has been reported that under elevated CO_2 growthof fungal pathogens and fecundity is increased (Plessl *et al.*, 2005; Matros *et al.*, 2006; Chakraborty *et al.*, 2000). Increased in atmospheric CO_2 results in thickness of epidermal and leaf waxes increases (Fuhrer, 2003). Changes to the crop architecture due to increasing concentration of CO_2, may direct to or simulate increased humidity within the canopy and provides more favorable conditions for survival of pathogen (Chakraborty and Datta 2003; Pangga *et al.*, 2011). Under elevated levels of CO_2 photosynthetic rate increased could direct to the availability of pathogens to colonize and ultimately increase in plant biomass will results in pathogens larger reservoir to multiply in and colonize (Luck *et al.*, 2011).

1.5.2 Climate change and food security

Defining uncertainty is important or essential in all areas of global climate change research also in biological processes where understanding or knowledge is lacking. However, when variations of climate are considered on food security, uncertainties are arguably greater.

Food security can be described as "when at all times all people have economic and physical access to safe, nutritious and sufficient food to meet their food preferences and dietary needs for an healthy and active life'' (FAO, 2003).

OR

It can be defined as "choice, fair prices, access through competitive and open markets, continuous food safety improvements, environmentally sustainable or endurable food chain and transition to healthier diet'' (Anonymous, 2008a).

It is a combination of diverse or multiple food access, food utilization and food availability issues. All of these are influenced by many factors, including climate change, currency fluctuations, economic recession, political unrest, water pollution, poverty, education, property rights and unemployment and increase in food prices (Scholes and Biggs, 2004). The climatic variability, continuously increasing population, urbanization, growth income, and globalization are driven forces on food production, consumption, market infrastructure and new challengesinfluence of climate change on biotic constraints (pests and diseases) that have reduced the agricultural productivity worldwide (Newton *et al.*, 2010; Ahmed and Fayyaz-ul-Hassan, 2011). It is harder to attain/acquire food security over the coming decades; the opportunity exists to address the risk of poverty/scarcity (IPCC, 2007).

Food production and security are also affected by pathogen and pest-mediated changes that occur because of change in climate. Changes in the pathogen complex influence crop yield, safety and quality, therefore value and food security (Chakraborty and Newton, 2011). It has been expected that urban expansion, land degradation, combined with water scarcity will reduce the 8-20% of total global cropping area by 2050 (Nellemann *et al.*, 2009). This fact is already posing a challenge to meet the proposed demand of world's population by 2050 to increase food production by 50%. The condition will be even more severe in Asia if change in climate disturbs the monsoon pattern and increases flooding/drought results in melting of Himalayan glaciers, as this will influence 25% of the world's cereal production through increased uncertainty over the availability of water (for irrigation) and frequent floods affecting livelihoods and lives.

1.6 Modeling links the plant-pathogen interaction

By complex changes in agricultural practices and crops that may results from change in climate, pathogen and pest threats are determined. Use of forecasting models of disease based on climate data may assist in determining the meteorological factors which are closely related with the disease and help to identify the threats posed by pathogen under current and future climate changes (Legreve and Duveiller, 2010).

The modeling and simulation tools use variables that depend on the nature of the problem (Medina *et al.*, 2009). Various crop modeling and simulation tools provide analytical framework and predict the effects of climatic variants on pathogen's biology are increasingly able tointegrate quantitative relationship and account complex interaction between pathogen, host and its environment (Luck *et al.*, 2011). Biotic diseases are associated with abiotic stresses. Changes in atmospheric composition and physical climate influence plant diseases severity. Plant disease results in association of three elements: a susceptible host, virulent pathogen and suitable environment/climate (viewed/called as 'disease triangle').

The development of Plant disease requires three input variables (Medina *et al.*, 2009).

- A susceptible host
- A virulent pathogen
- A suitable environmental condition that include Temperature and Rainfall

These variables are used as input and related to plant disease development. (Figure 1.3) illustrated the variable classification according to host, its pathogen and environment.

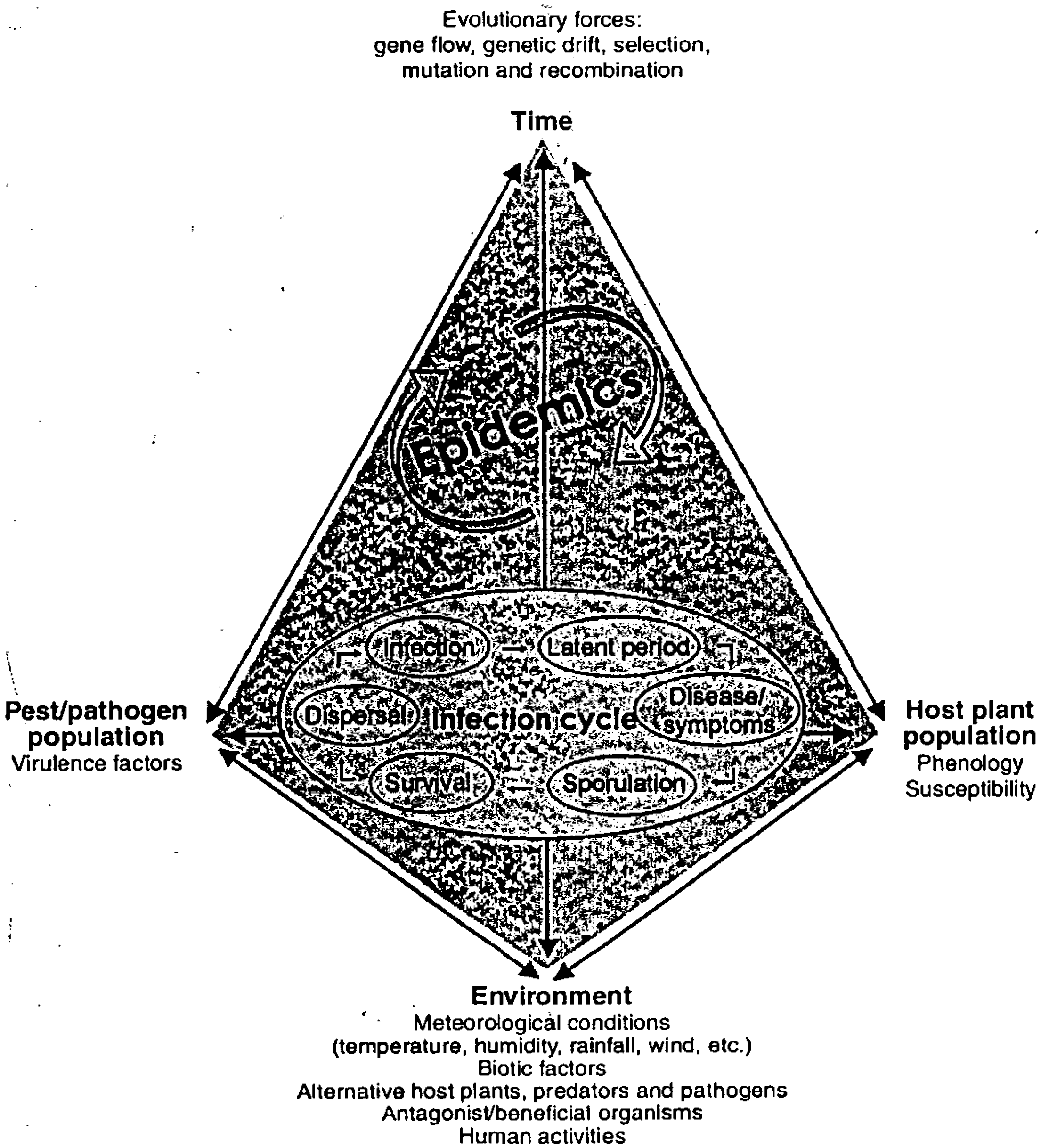


Figure 1.3: The complex interactive epidemic tetrahedron illustrating the multiple interactions between the three components of the 'disease triangle', the environment, the pest/pathogen and the host plant

1.7 Climate change in Pakistan

Pakistan (23° 35' – 37° 05'N and 60° 50' -77° 50'E) has a warm climate; it lies in a geographical region where increase in temperature is expected to be higher than global averages. Annual surface temperature has a constant trend in Pakistan since the beginning of the 20th century. Pakistan is also projected to experience a broad range of weather changes with its agricultural output in response to global warming.

Being a developing country, Pakistan is on number 12 among the vulnerable nations list in the world and is not contributing (Pakistan contribution is 135th part of other nations that are producing) much in increasing the concentration of greenhouse gases-CO_2, CO, SO_2, CH_4 and N_2O in the atmosphere. Climate variations have been analyzed in Pakistan. Temperature and rainfall have been key limits for climate analysis. The consequences of global warming and climate change include uncertainty in the intensity and occurrence of precipitation (IPCC, 2007). Rainfall is received in both winter and summer seasons however 59% of annual precipitation is due to summer monsoon rains. In Asian regions, the frequency and intensity of precipitation has increased. The rapidly receding of Himalayan glaciers and larger variability in monsoon rains resulted to extended droughts and large floods. Rise in mean temperature 0.6-1.0°C in arid mountains, hyper arid plains and arid coastal areas decrease 10-15% in both summer and winter rainfall in hyper arid plains and coastal belt, 18-32% increase in precipitation in monsoon zone (especially humid and sub humid areas) is observed (Farooqi *et al.*, 2005). Temperature increased at the rate of 0.057°C per decade in the last century. The annual maximum temperature from 1960-2010 of the country has boosted up by 0.89°C. The annual minimum temperature from 1960-2010 of the country has boosted up by 0.51°C. Change in climate is not linear; there is high variability (PMD, 2009).

Pakistan is an agricultural country, independent in wheat production. Out of country's total area, 24% area is cultivated, of which 80% area is irrigated.Wheat is grown in almost all over the country on an average of 2.52 t/ha yields. Punjab province (granary of country) contributes up to 72% of total wheat production. It is located in arid and semi-arid zone. Irrigation is key demand for agricultural production. The world demand for food due to continuously increasing population will rise to exploding figure (40% in 2030) in coming decades (Charmet, 2011). As an outcome there will be huge increase in the demand for food on our agricultural system. Pakistanis not only dependent on rainfall but also on irrigation water which comes from seasonal rainfall as well as melting of ice and snow for agro-based activities. Reduction in agricultural productivity and yieldwere visualized due to pest and pathogens and greater variability in climate and weather related extreme events.

Climate change increase water demand andbring serious stresses to farming system. Meeting this demand would require that stabilizes agricultural land together with an increase annual yield. Reduction in agricultural productivity was due to variation in rainfall pattern, intermittent floods, drought and dry spells. The abruptly change in climate in response to global earth warminghas led to reduced agricultural production over the whole world. By changing behavior and specific policies, the threats of climate change can be coped by determining its impact on socio-economic sector of the country that are important to public health, water availability and agricultural production (PMD, 2009).

1.8 Wheat as Host Crop and Fungal Pathogens

Pests and diseases are envisaged as one of the major yield constraints and are major hindrance, impediment to the quality and production of essential food stuffs and wheat fungal diseases like

Fusarium head blight, *Alternaria* leaf blight, *and Drechslera* leaf blight affect food safety. They also have direct impact on animals including human health.

In Pakistan, grain yield is low as compared to other wheat producing countries of the world. Yield is lowered due to reduction in tillering, plant vigor and emergence which might be because of biotic and abiotic stresses. Diseases are caused by viruses, bacteria and fungi. Among fungal diseases, foliar blight pathogens are examined to contribute considerably to reduce average yield loss of cereal crop in the developing world (Iftikhar *et al.*, 2006).Wheat (*Triticum aestivum* L.) is the main staple food crop, cultivated in most parts of the globe and single most important in the world in terms of amount and total harvested weight. It is used for human and animal nutrition as they are rich in protein, fat, carbohydrates, energy, dietary fibre, thiamine, folate, riboflavin, pantothenic acid, calcium, vitamin B6, iron, phosphorus, magnesium, zinc, manganese and potassium (Acharya *et al.*, 2011).

The wheat fungal pathogen *Alternaria triticina* and *Drechslera sorokiniana* (Sacc.) leaf blight infects a wide variety of wheat crop and cause severe yield loss in humid and warmer regions of Pakistan. In Pakistan, during a survey in 2000 of wheat field in Islamabad surroundings, foliar spots were observed but considered to be of minor importance (Iftikhar *et al.*, 2006).

1.8.1 *Drechslera sorokiniana* leaf blight

Diseases caused by *Drechslera sorokiniana* (Sacc.) and *Bipolaris sorokiniana* (Sacc.) were grouped together as *Helminthosporium sorokiniana* (Sacc.). Fungus act as causal organism for diseases like head blight, foliar blight, seedling blight, common root rot and black point of barley, wheat and small cereal grains. Among all diseases, foliar blight of wheat caused by pathogen is most important in environment/areas which are characterized by high humidity and high temperature (Acharya *et al.*, 2011).

1.8.1.1 Symptoms

Drechslera sorokiniana foliar blight reported in colder regions, infects top three (flag, second and third) leaves of wheat after ear emergence. Infection appears as irregular patches which enlarge to form dark blotches. Small, dark brown, purplish colored lesions appear on the leaves, fungus attacks during the weather of early spring and late fall. The lower leaves highly infected than flag leaves. Flag leaves infection cause severe yield loss while third leaves infection cause least yield loss. In the leaf spotting stages *Drechslera* sp. does not cause injury to the plant. The whole plant is killed when the root rot phase of the *Helminthosporium* disease develop (Danneberger, 2012).

1.8.1.2 Epidemiology

The pathogen causes crop grain yield loss up to 20% through leaf blight disease in south Asian countries which can be devastating for producers. It has been reported that 15% yield reduction due to spot blotch in Bangladesh and China. 18-22% grain yield losses reported in India. The pathogen causes grain yield reduction through seedling blight and common root rot 10% in Scotland, 15% in Canada and 20% in Brazil (Acharya *et al.*, 2011).

Spot blotch development and disease severity is directly related to irrigation, sowing density, low soil fertility, stage of crop growth, heat stress and late rain during grain filling and crop cycle respectively, high humidity and high temperature in the field (Acharya *et al.*, 2011). However, as the temperature increases, disease may occur in the crown, stem and roots where the plant eventually dies. Infection of new leaves may occur as long as temperatures are suitable and the weather remains moist (Danneberger, 2012). Fungus acts as pathogen when the climatic conditions (High humidity and temperature above 20°C) favor its development.

1.8.1.3 Disease cycle

The pathogen/causal organism perennates both as conidia (externally) and in the seeds as mycelium (internally), as well as in contaminated or infected crop residues. The infected seeds are primary source of inoculums of foliar blight pathogens. Along the diseased seeds germination, the perennating organs of pathogen become active called starting point of the disease. It germinates in four hours completely. Hypha produces conidiophores under suitable conditions which arise through host tissue stomata. The emerging or arising conidiophores produce a succession or series of conidia which are transmitted by wind and rain splashes, thus enhancing or promoting polycyclic disease epidemics (Acharya *et al.*, 2011) as illustrated in figure (1.5)

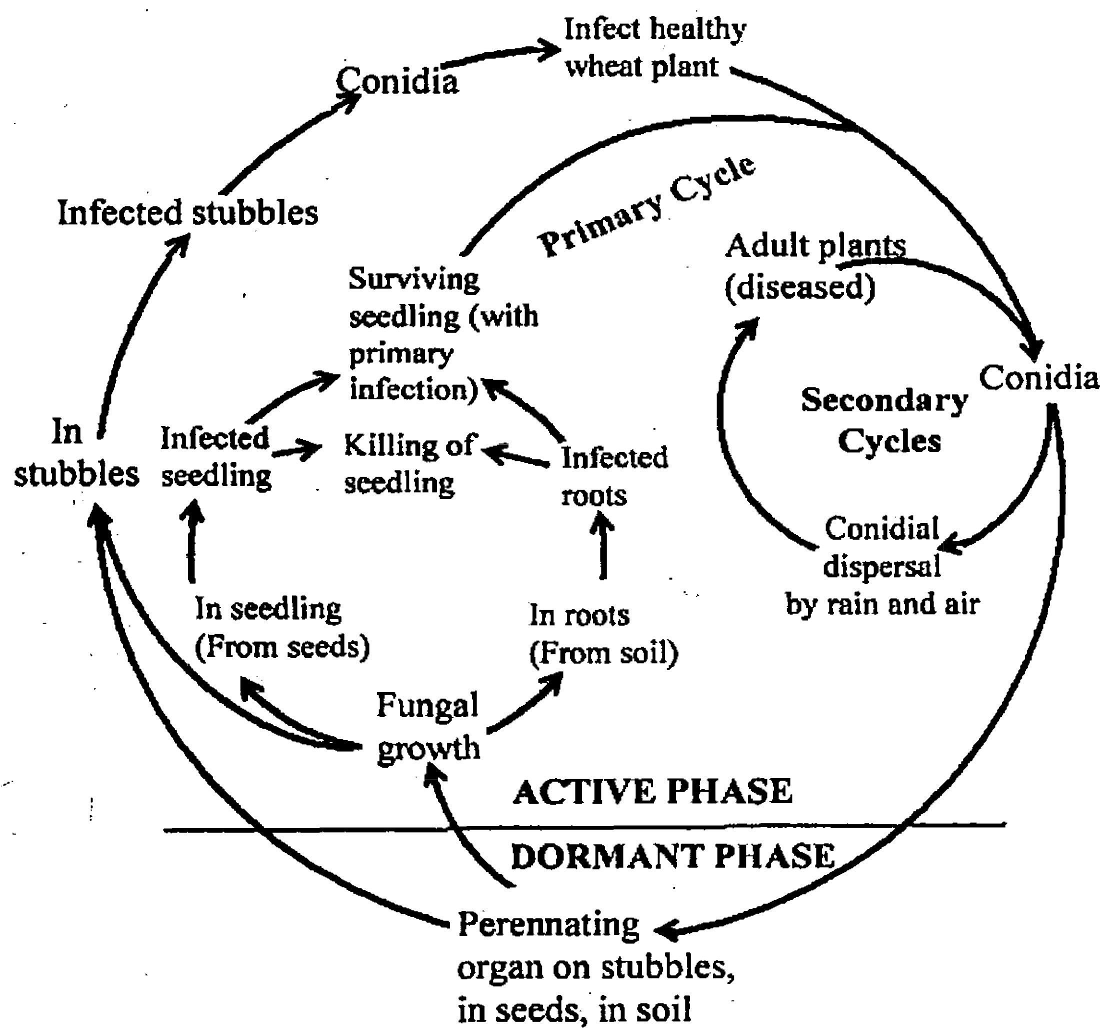


Figure 1.3: Disease cycle of *Bipolaris sorokiniana* (Acharya *et al.*, 2011).

1.8.2 *Alternaria triticina* leaf blight

Alternaria triticina is causal agent, first originated in the Indian subcontinents and has expanded/dispersed throughout the world (Perello and Sisterna, 2005). *Alternaria* blight epidemic were observed in Uttar Pradesh during 1964-66 (Ahlawat, 2007).

1.8.2.1 Symptoms

The *Alternaria triticina* leaf blight first appears on the lower most leaves and gradually progresses upward to the upper leaves. Initial symptoms consist of oval, yellow and small lesions scattered irregularly on leaves. As the disease spread the spots become irregular in shape, lesions enlarge with dark brown color surrounded by yellow bright margin as depicted in figure (1.6). Glumes and leaf sheath are also infected in case of severe attack (Ahlawat, 2007).

Figure 1.4: Symptoms of wheat blight and lesions with yellow margins caused by *A.triticina*

1.8.2.2 Epidemiology

Alternaria triticina leaf blight caused significant yield losses. Disease severity is enhanced due to new cultural practices such as nitrogen fertilization, irrigation, use of new germplasm, conservation tillage, high humidity and wet, warm weather with temperature between 20-25°C (Arya and Perello, 2010).

1.8.2.3 Disease Cycle

Alternaria leaf blight is soil as well as seed borne (Ahlawat, 2007). Barley, Triticale, bread and durum wheat are the primary host. The fungus survives as mycelia within seed or as conidia on seed. *A.triticina* infects foliar parts cause's necrotic leaf lesions, disease progresses upward as plant matures; sporulation provides inoculum on lower leaves that can be scattered by wind leading to secondary infection of the disease. The pathogen causedpremature death of heads and uppermost leaves. When crop is 45-50 days old, maximum infection takes place (Arya and Perello, 2010).

1.9 Objectives

Currently Quantitative analysis, Bioinformatics and Computational crop simulation models have been used as decision-support tool to elucidate plant processes, develop crop management system, and provide strategic guidance/options to improve crop growth, development, yield and optimize the crop management strategies for risk/ disease control.

Therefore, the present study was conducted to enhance the implementation of crop simulation and modeling techniques as bioinformatics tool to simplify, facilitate and promote agricultural research for tactical management decision.

Objectives of my research include:

1. To predict effects of climate change (Temperature and Rainfall) on wheat productivity
2. To develop a Multiple Regression, Logistic Regression and Quadratic Plateau Model for predicting disease dynamics of wheat crop
3. Generate climate projections using IPCC-A2 emission scenarios for near future (2011-2050) and far-future (2051-2100)
4. Determine the prevalence of fungal diseases (*Alternaria triticina* and *Drechslera sorokiniana* leaf blight of wheat) in projected/future climate
5. Predict the future management options by linking the future climate with host-pathogen interactions
6. To validate and parameterized APSIM (decision-support tool) under changing climate to allow meaningful analysis of problem domain

CHAPTER 2

MATERIALS AND METHODS

MATERIALS AND METHODS

The present studies were undertaken to predict the impact of fungal pathogens on wheat yield under changing climate. The study was divided into two phases: Statistical and Dynamical modeling. Statistical or Empirical models describe the relationship between multiple variables without elucidating the underlying physical or physiological causalities. Dynamical or mechanistic/explanatory models describe the relational causality explicitly between variables (Sridhara and Prasad, 2002).

In this information technology era, crop simulation techniques with various computational techniques and algorithms were used as bioinformatics tools to understand the agricultural and biological processes and has proven its efficiency. Therefore, in presented study crop simulation and modeling techniques in rainfed environment to better understand the dynamics of two wheat fungal diseases (*Alternaria triticina* and *Drechslera sorokiniana* leaf blight) and their impact on wheat yield.

The data (experimental and generated) was analyzed using various statistical methods and was used for simulation to parameterize the APSIM model using long-term weather data. The materials and methods details are given as follows:

2.1 Data Collection

The wheat crop data infested with fungal pathogens *Alternaria triticina* and *Drechslera sorokiniana* leaf blight were collected from field experiments conducted during 2008-09 at National Agriculture Research Centre (NARC), Islamabad (33° 43'N, 73° 06'E and 547 m Elevation) as depicted in Figure 2.1.

The dataset used in study included field experimental data (Year, Location and Months) and data regarding weather included Temperature, Rainfall and Humidity to predict the impact of changing climate on wheat fungal diseases *Alternaria triticina* and *Drechslera sorokiniana* leaf blight. Field survey was conducted at the study site and data was recorded by using standard Performa. This data was subjected to Statistical analysis.

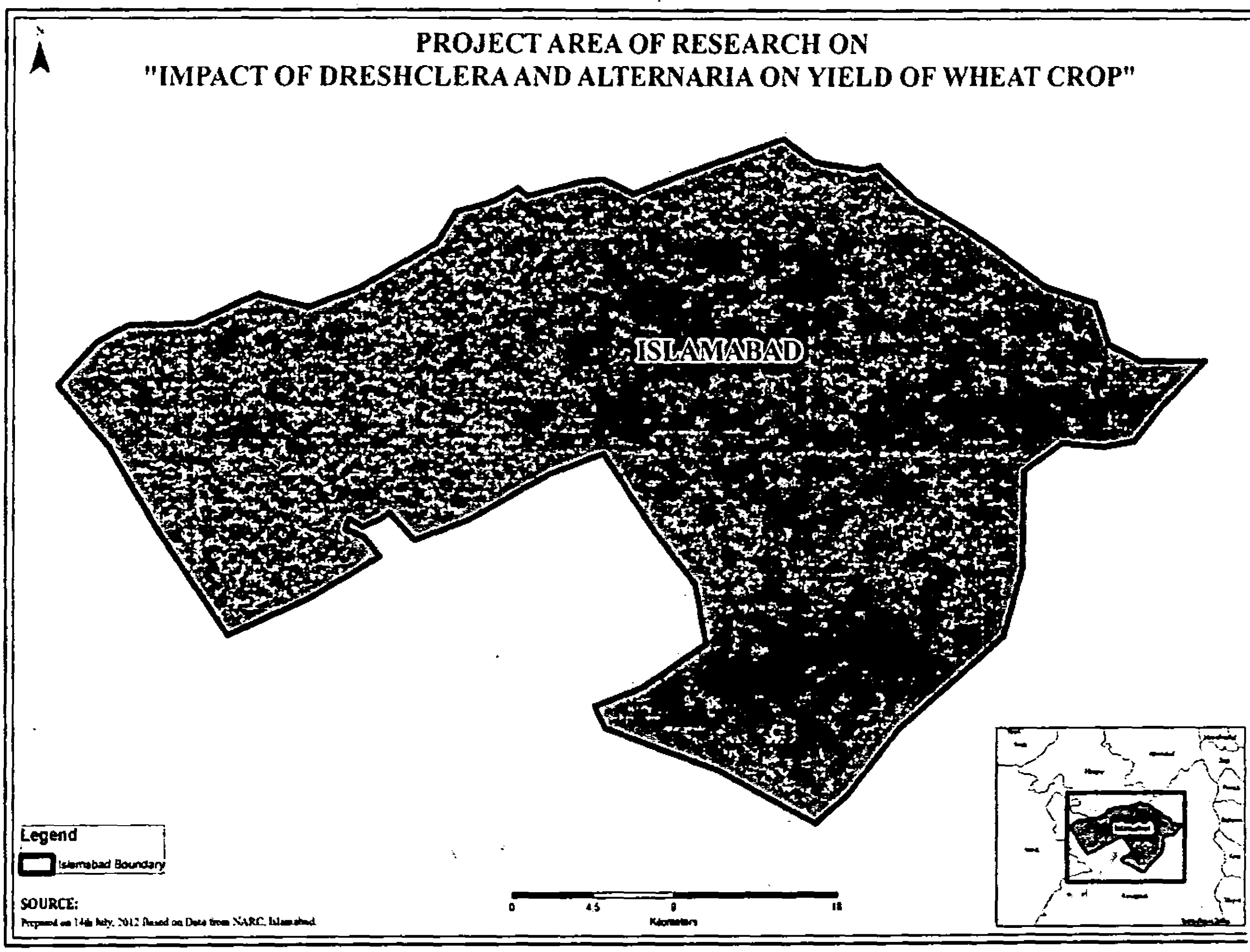


Figure 2.1: Diagrammatic Representation of research area to studies the impact of *Drechslera sorokiniana* and *Alternaria triticina* on Yield of Wheat Crop

2.2 Wheat Genotype

One wheat genotype (Chakwal 50) was included in the study, sown during mid of November until the mid of April.

2.3 Weather Data

The long-term historical climate data from 1961 to 2012 which included daily maximum temperature (°C), minimum temperature (°C), solar radiations (MJ/m^2) and rainfall (mm) were obtained from weather station, Pakistan Meteorological Department (PMD), to predict the effects of climatic variants on fungal diseases for dynamical modeling studies.

2.4 Statistical Modeling

The methods of statistical modeling have the advantage of being easy to analyze, interpret and implement by producing an equation that can be algebraically solved. R software was used for statistical modeling.

In the current study three statistical modeling methods have been used as illustrated in table (2.1).

2.4.1 Multiple Regression Method

Multiple regression model (MRM) is a mathematical modeling approach widely used when the target is on the relationship between dependent variable (fungal diseases *Alternaria triticina* and *Drechslera sorokiniana*) and two or more independent variables (Years, Location, Months, Humidity, Temperature and Rainfall) and how the value of dependent/disease variable is changed when anyone of the independent (temperature or rainfall) variable is fixed while others are varied. The results were significant statistically only if the p-value or probability is less than significance level 0.05 called alpha (α) ($p<0.05$) at 95% confidence level.

The equation generated by Multiple Linear Regression method for *Alternaria triticina* and *Drechslera sorokiniana* leaf blight is:

$$\boldsymbol{Alternaria\ triticina} = -7.399 - 0.596 * months + 0.685 * temperature + 0.289 * rainfall \quad \textbf{(1)}$$

$$\boldsymbol{Drechslera\ sorokiniana} = -9.77 - 1.0602 * months + 0.9005 * temperature \quad \textbf{(2)}$$

The Equation 1 represents *Alternaria triticina* disease as a linear function of the three predictor variables. Three of the one regression coefficients are negative. Years, Location and Humidity depicts non-significant results ($p>0.05$) as illustrated in Appendix 1. The multiple regression model would seem to imply that increasing months would reduce the *Alternaria triticina* disease while increasing temperature and rainfall exerted negative effect on disease. Similarly Equation 2 depicts *Drechslera sorokiniana* disease as a linear function of the two predictor variables. Two of the one regression coefficients are negative. Years, Location, Humidity and Rainfall depicts non-significant results ($p>0.05$) as illustrated in Appendix 2.

The model would seem to imply that increasing months would reduce the *Drechslera sorokiniana* disease while increasing temperature has exerted negative effect on disease. Multiple Regression Model of statistical analysis reveals that impact of temperature and rainfall were examined on diseases by varying climatic parameters. To predict disease incidence, disease index built. Disease index is taken as the average sample of wheat infected leaf and considering the percentage of each infected leaf.

2.4.2 Logistic Regression Method

Logistic Regression Method (LRM) is designed between two or more independent variables and dependent variable where dependent variable is a binary response variable expressed as a probability of the event (disease, where temperature is above 20°C and rainfall is above 10mm) hence, having disease (=1) / doesn't have disease (=0). The results were significant statistically only if the ($p<0.05$) at 95% confidence level.

In Logistic regression analysis probability of event is calculated as:

$$P\,(y\,=1)\,=[exp(a+bx)]/[1+exp(a+bx)]$$

Where a and b are parameters that can be solved using function.

The equation generated by Logistic Regression modeling method for *Alternaria triticina* diseasewhen temperature is above 20°C:

$$Eta=-23.97+1.076*Months+0.813*Temperature$$

$$\boldsymbol{Alternaria\ triticina}=\exp\,(eta)\div(1+\exp(eta)) \qquad \textbf{(3)}$$

The Equation 3 represents *Alternaria triticina* disease as a linear function of the two predictor variables. Years and Location depicts non-significant results ($p>0.05$) as illustrated in Appendix 3. The Logistic Regression model would seem to imply that increasing months and temperature would increase the *Alternaria triticina* disease. The Logistic Regression was not applied on *Drechslera sorokiniana* disease as their p-value depicts non-significant result illustrated in Appendix 4.

The equation generated by Logistic Regression modeling method for *Alternaria triticina* and *Drechslera sorokiniana* disease when Rainfall is above 10mm is:

$$Eta = -94.24 + 9.282 * rainfall$$

$$\boldsymbol{Alternaria\ triticina} = \exp(eta) \div (1 + \exp(eta)) \quad (4)$$

$$Eta = -6.288 - 0.8900 * months + 0.856 * rainfall$$

$$\boldsymbol{Drechslera\ sorokiniana} = \exp(eta) \div (1 + \exp(eta)) \quad (5)$$

The Equation 4 represents *Alternaria triticina* disease as a linear function of the one predictor variables. Years, Location and Months depicts non-significant results (p>0.05) as illustrated in Appendix 5. The Logistic Regression model would seem to imply that increasing rainfall would increase the *Alternaria triticina* disease. Similarly Equation 5 represents *Drechslera sorokiniana* disease as a linear function of the two predictor variables. Two of the one regression coefficients are negative. Years and Location depicts non-significant results (p>0.05) as illustrated in Appendix 6.

The Logistic Regression model would seem to imply that increasing rainfall would increase the *Alternaria triticina* disease while increasing months would reduce the disease. The Logistic Regression approach has been used in other studies of plant diseases such as to assess the risk of fusarium head blight (FHB) epidemic (De Wolf *et al.*, 2003).

2.4.3 Quadratic Plateau Model

Quadratic Plateau Model (QPM) of statistical analysis was a good method to predict the point at which impact of temperature and rainfall on wheat fungal pathogens will maximum. Quadratic model have ability to represent a plateau.

Table 2.1: Statistical Modeling Methods

Software used	Type of data	Method used	Significant results	Target variable
R	Weather data (daily temperature, daily rainfall and daily humidity), 1 location (Islamabad), months, years [2008-10] and disease information (field experiments)	Multiple Linear Regression	P-value<0.05 2 equations	Disease Index built
		Logistic Regression	P-value<0.05 3 equation, non-significant for *Drechslera sorokiniana* disease when temperature is above 20°C	Having disease =1/ doesn't have disease=0
		Quadratic Plateau Model	Determine the maximum point of disease called as plateau	

2.5 Validation of Statistical Modeling

Model validation is comparison between observed and simulated values. There are several statistical criteria's available to evaluate the association between observed and predicted values, among them are root mean square error (RMSE), d-stat (index of agreement) and coefficient of determination (R^2) as depicted in table (2.2).

RMSE is the best measure of model performance evaluation. It summarizes the mean difference in the units of simulated and observed values (Willmot 1982). It was computed as

$$\boldsymbol{RMSE} = \left[N^{-1}\sum_{i=1}^{n}(Pi - Oi)^2\right]^{0.5}, \quad 0 \le RMSE \le \infty$$

Where N is the number of cases/observed values and Pi and Oi are simulated and measured values for i^{-th} data pair. The value of RMSE ranged from 0 which indicates perfect accuracy to ∞ which means null result.

The index of agreement (d) is a relative and bounded measure, which can be used in order to make cross comparisons between models. The d-index was computed as

$$\boldsymbol{d} = 1 - \left[\sum_{i=0}^{n}(Pi - Oi)^2 \Big/ \sum_{i=0}^{n}[|P'i| + |O'i|]^2\right], \qquad 0 \le d \le 1$$

Where Pi and Oi are simulated and measured values for i^{-th} data pair, and O'i = Oi-O and P'i = Pi-O (average of the observed).The value of index (d) ranged from 0 which indicates null result to 1 which indicates best fit.

R^2 is the ratio of sum of squares of regression (SSR) and the total sum of squares (SST). R^2 is used to measure the agreement between measured and simulated values.

It is computed as

$$R^2 = \frac{SSR}{SST}, \quad 0 \leq R^2 \leq 1$$

The value of R^2 ranged from 0 which indicates null result to 1 which indicates best fit.

Table 2.2: Skill scores

	Formulas	*Value range*	*Best fit*	*Null result*
RMSE	$\left[N^{-1}\sum_{i=1}^{n}(Pi-Oi)^2\right]^{0.5}$	$0 \leq RMSE \leq \infty$	*0 (at lower values)*	∞
d	$1-\left[\sum_{i=0}^{n}(Pi-Oi)^2 \Big/ \sum_{i=0}^{n}[\lvert P'i\rvert + \lvert O'i\rvert]^2\right]$	$0 \leq d \leq 1$	*1*	*0*
$\boldsymbol{R^2}$	$\frac{SSR}{SST}$	$0 \leq R^2 \leq 1$	*1*	*0*

2.6 Dynamical Model

The dynamical model *Agricultural Production Systems SIMulator,* (APSIM) was used in the present study to simulate wheat yield in the absence of disease under historical climatic data and for forecasting of wheat crop in Pothwar region of Pakistan under A2 scenarios.

2.6.1 APSIM Model

The *A*gricultural *P*roduction *Systems SIM*ulator, (*APSIM)* version 7.4 model together with long-term (1961-2012) climate data was used for simulation of wheat crop.The APSIM modeling framework has been developed by Agricultural Production System Research Unit (APSRU) in Australia (Keating *et al.*, 2003).

The *A*gricultural *P*roduction *Systems SIM*ulator, APSIM is a software tool allows modules of crop, nutrient, erosion, soil PH, soil water, and management controlto be configured flexibly to simulate biophysical process as illustrated in figure (2.1). APSIM model has been successfully used in the agriculture research systemfor sustainable and efficient crop production and improved disease Management. APSIM simulates mechanistic growth of crops, range of management options and key soil processes considering cropping system perspective. The Met module in APSIM provided daily meteorological information to all modules within APSIM simulation (Keating *et al.*, 2003).

APSIM model predicts the management option and effects of abiotic constraints (Temperature and Rainfall) on crop performance while it doesn't account for pests and diseases control (Manschadi *et al.,* 2004). APSIM has been used for the development of waste management guidelines, issue analysis in agribusiness activities, assessment of seasonal climate forecasting, risk assessment for policy makers and as a guide for education and research activity (Keating *et al.*, 2003).

2.6.2 Model Data Requirements

APSIM Modules requires initialization and temporal data as the simulation proceeds. Initialization data is which defines the module for all simulation and parameter specific data for simulation such as site parameters (soil characteristics for soil module, climate parameters for meteorological module, surface residue definition and soil surface characteristics), cultivar and management (during simulation defines a set of rules, calculations that are used and messages to modules).

Data is stored in a specific format with parameters name and unit. Temporal data is climate and observed measurements (Keating *et al.*, 2003). Climate parameters include Temperature maximum, Temperature minimum, Rainfall and Solar radiations figure (2.2). Daily weather data was compiled as a met file under APSIM met module which provides this information to all APSIM modules that were used in simulation.

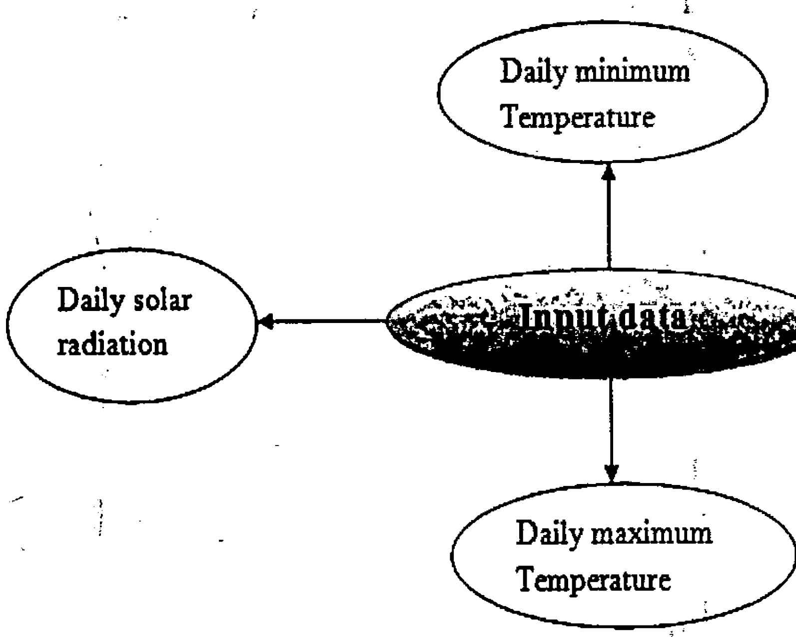


Figure 2.2: Weather data required for APSIM-wheat simulation

2.6.3 Parameterization and Validation of Dynamical Model

Crop simulation models (CSM) cannot be used in other areas until validated under local conditions. In late 90's model testing and parameterization initiated in Pakistan. The APSIM model was parameterized for wheat crop infested with fungal pathogens (*Alternaria triticina* and *Drechslera sorokiniana*) under local conditions and evaluated against climate/independent data (temperature and rainfall) from Pothwar region (Islamabad) of Pakistan. The data set on wheat crop fungal interaction were obtained from field experiment during 2008-09. Model evaluation acknowledged the farming system model APSIM's capability to simulate the yield formation for wheat crop exposed to biotic (fungal diseases) and various abiotic stresses.

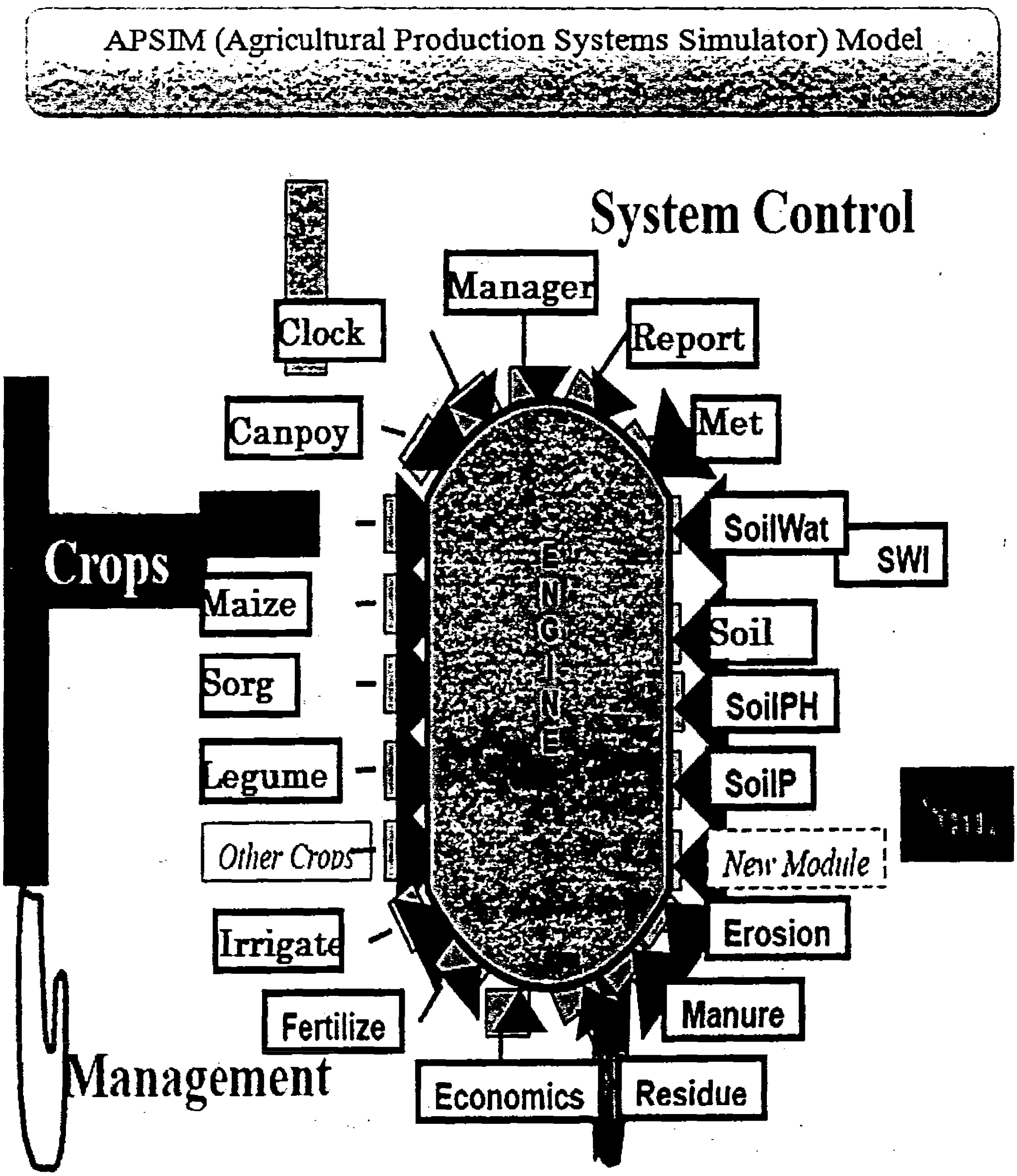


Figure 2.3: Schematic Representation of APSIM Model Working Mechanism with soil module, individual crop, simulation engine and module interfaces

CHAPTER 3

RESULTS AND DISCUSSIONS

RESULTS AND DISCUSSIONS

The presented are the study's results using statistical and computational simulation techniques to depict strategic management decisions. Using statistical and dynamical models under climate change, wheat crop and fungal diseases, projected the risk of wheat fungal diseases in selected area of Pakistan.

3.1 Statistical Models

For studying the impact of climatic variations on disease dynamics and their impact on spring wheat productivity we built models, which can predicts disease dynamics under changing climate. Statistical models were developed to observe the influence of meteorological parameters (temperature and rainfall) on wheat crop fungal diseases *Alternaria triticina* and *Drechslera sorokiniana*.

3.1.1 Analysis of climate variability from 2008-09 on wheat fungal diseases

In the initial analysis, short-term (2008-09) climatic variations of temperature and rainfall on wheat crop infested with fungal pathogens in Islamabad were studied by three statistical methods (Multiple Regression, Logistic Regression and Quadratic Plateau Model).

The figure (3.1 a & b) illustrated the effects of increasing temperature on *Alternaria triticina* leaf blight by Multiple Linear Regression and Quadratic Plateau Model. Increase in *Alternaria triticina* disease was from -3.92% at minimum observed temperature 15.2°C, to 8.0% at average temperature 28.41°C, to 34% at maximum temperature 36.9°C. The figure (3.2 a & b) depicted the results of variation in rainfall pattern on *Alternaria triticina* disease by Multiple Linear Regression and Quadratic Plateau Model. Increase in rainfall patterns also enhanced disease epidemics, ultimately lower production of wheat crop. Increase in *Alternaria triticina* disease was 46% when maximum observed precipitation recorded is 43.25 mm and minimum -0.29% when rainfall is 1.01 mm. However, least disease 0.03% was observed when rainfall is 11.07 mm. Similarly, the impact of varying temperature on *Drechslera sorokiniana* leaf blight were described in figure (3.3 a & b) by Multiple Linear Regression and Quadratic Plateau Model. Increase in *Drechslera sorokiniana* disease (46%) was observed from minimum observed temperature 15.2°C to maximum temperature 36.9°C.

The trend of changing weather (when observed temperature is above 20°C) by Logistic Regression and Quadratic Plateau Model for *Alternaria triticina* were illustrated in figure (3.4 a & b). Results depicted that impact of increasing temperature exerted a positive impact on disease as increase in *Alternaria triticina* disease (20%) was observed from minimum observed temperature 15.2°C to maximum temperature 36.9°C. The outcomes observed by Logistic Regression and Quadratic Plateau Model for *Alternaria triticina* disease (when observed rainfall is above 10 mm) were represented in figure (3.5 a & b). The analysis reveals that increase in rainfall exerted a positive impact on *Alternaria triticina* leaf blight. Increase in *Alternaria triticina* disease (67%) was observed from minimum observed precipitation (recorded) 1.01 mm to maximum observed precipitation (recorded) 43.25 mm.

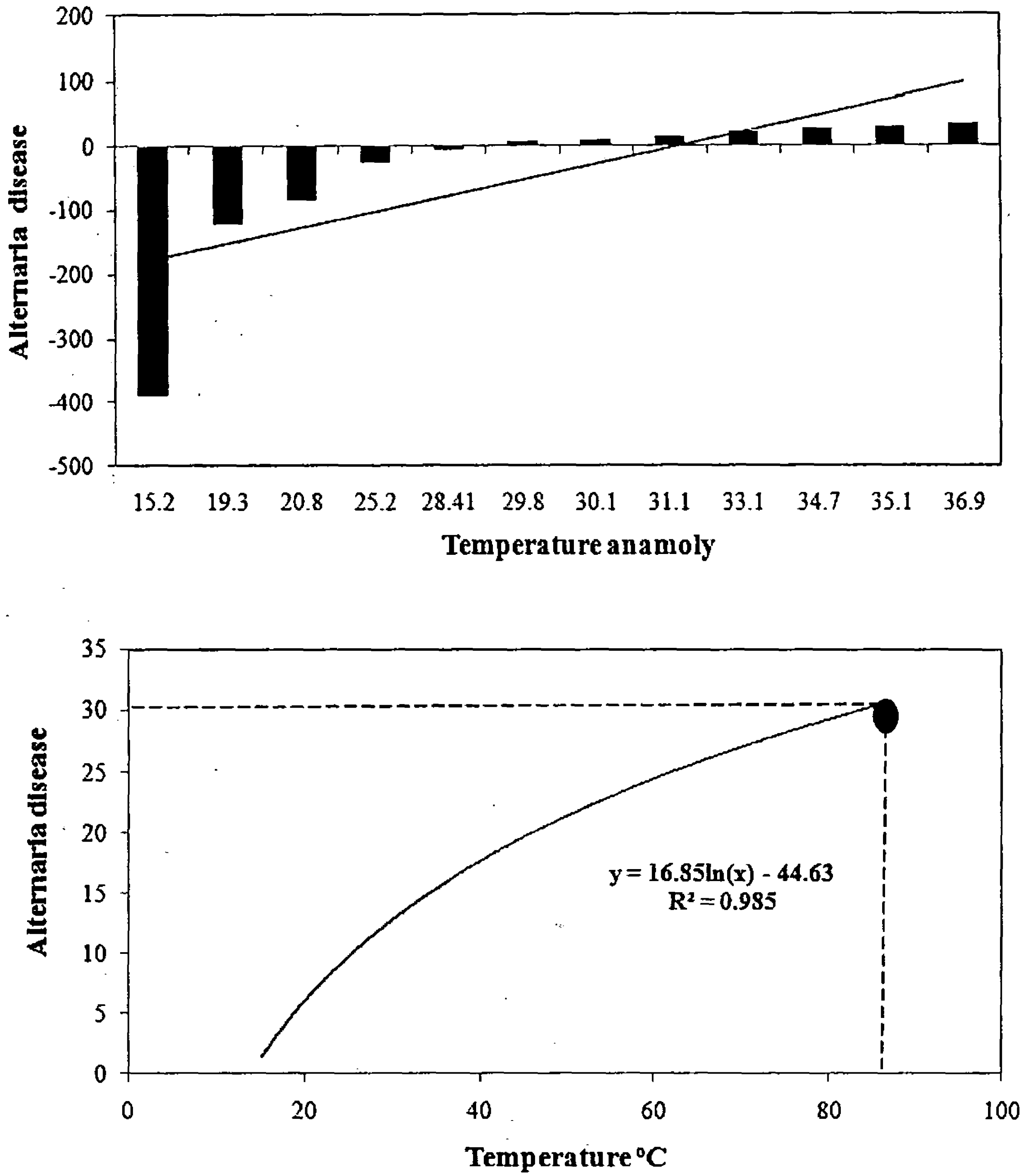
Similarly the trend observed in *Drechslera sorokiniana* disease due to variation in rainfall pattern by Logistic Regression and Quadratic Plateau Model (when rainfall is above 10 mm) were depicted in figure (3.6 a & b). The results revealed that increase in *Drechslera sorokiniana* leaf blight was observed from 74% when minimum observed precipitation 1.01 mm to when maximum observed precipitation 43.25 mm.

Results were analyzed using Multiple Regression, Logistic Regression and Quadratic Plateau Model. The same conclusions were observed by Multiple Regression, Logistic Regression and

Quadratic Plateau Model. A remarkable impact of climatic variations upon diseases was observed. Variations in climate have a significant impact on diseases. Therefore, the increasing trend for *Alternaria triticina* and *Drechslera sorokiniana* leaf blight of wheat was observed because of extreme rise in temperature and rainfall events.

The statistical analysis which revealed that fungal diseases increased due to increase in temperature and rainfall events, affected the wheat productivity. Availability of favorable climatic conditions during 2008-09 promoted fungal disease infection on wheat crop. Temperature and rainfall has greater influence on crop fungal diseases. It has been clearly described in literature that life cycle of fungal pathogens are directly affected by climate (Sturrock *et al.*, 2011). Disease severity is enhanced due to high humidity and warm weather with temperature between 20-25°C (Arya and Perello, 2010). With decreasing temperature and rainfall, reduction in fungal diseases was recorded. The outcomes depicted positive response of fungal diseases towards climatic variations, which led to decline in wheat grain yield. The current study clearly indicated that *Alternaria triticina* and *Drechslera sorokiniana* leaf blotch of wheat was strongly influenced under changing climatic variants, higher temperature and rainfall led to increase in fungal pathogen infection, adverse effects on crop development and growth which consequently decreased yield.

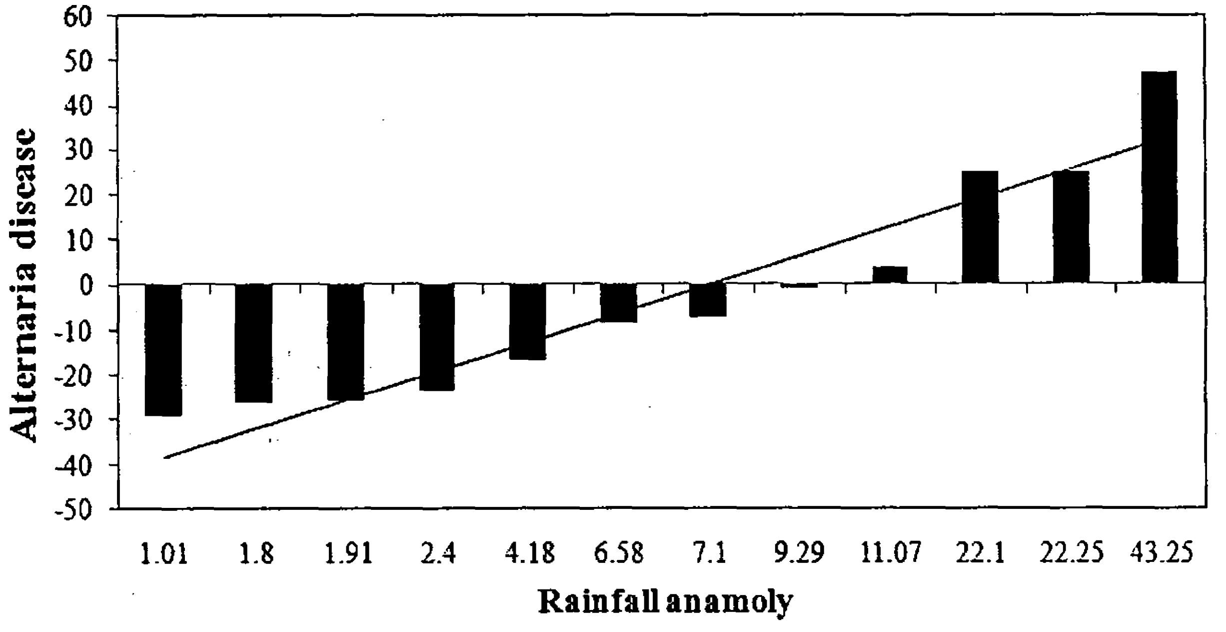
(a)



(b)

Figure 3.1: Impact of increased Temperature on *Alternaria triticina* disease by (a) Multiple regression and (b) Quadratic Plateau model

(a)



(b)

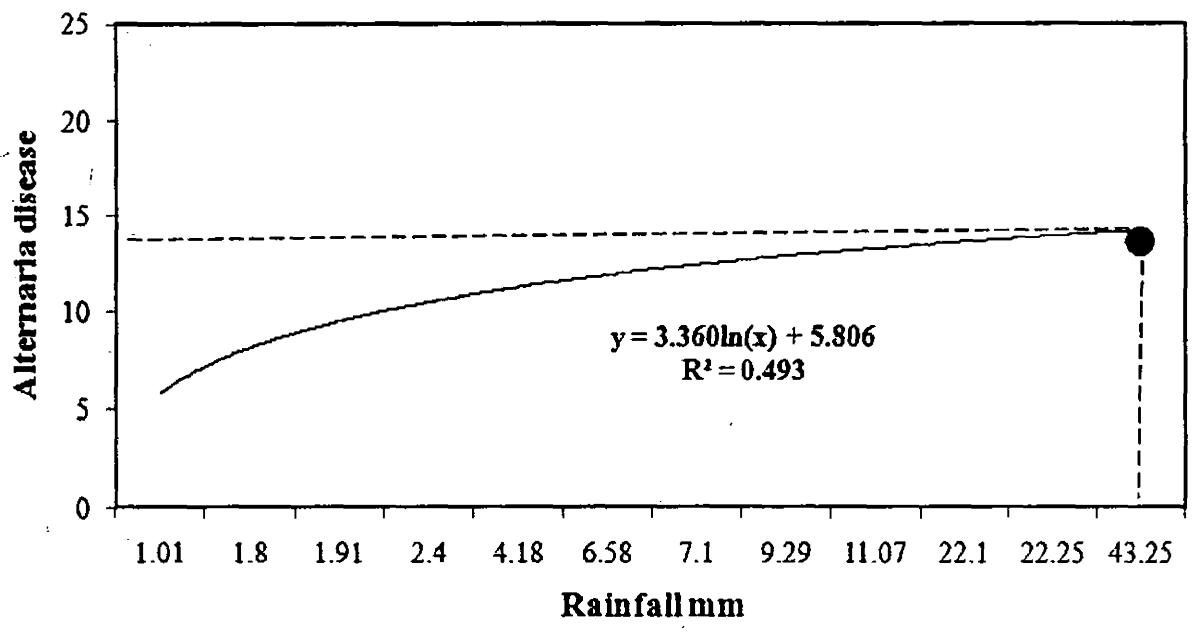
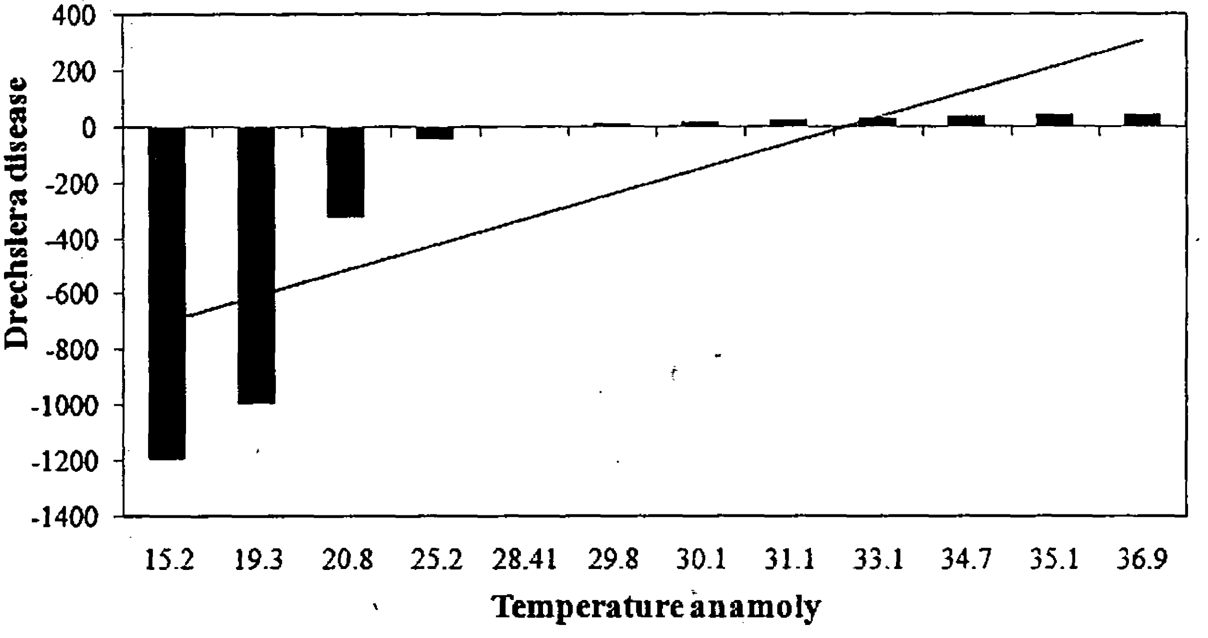


Figure 3.2: Impact of increased Rainfall on *Alternaria* disease by (a) Multiple Regression and (b) Quadratic Plateau Model

(a)



(b)

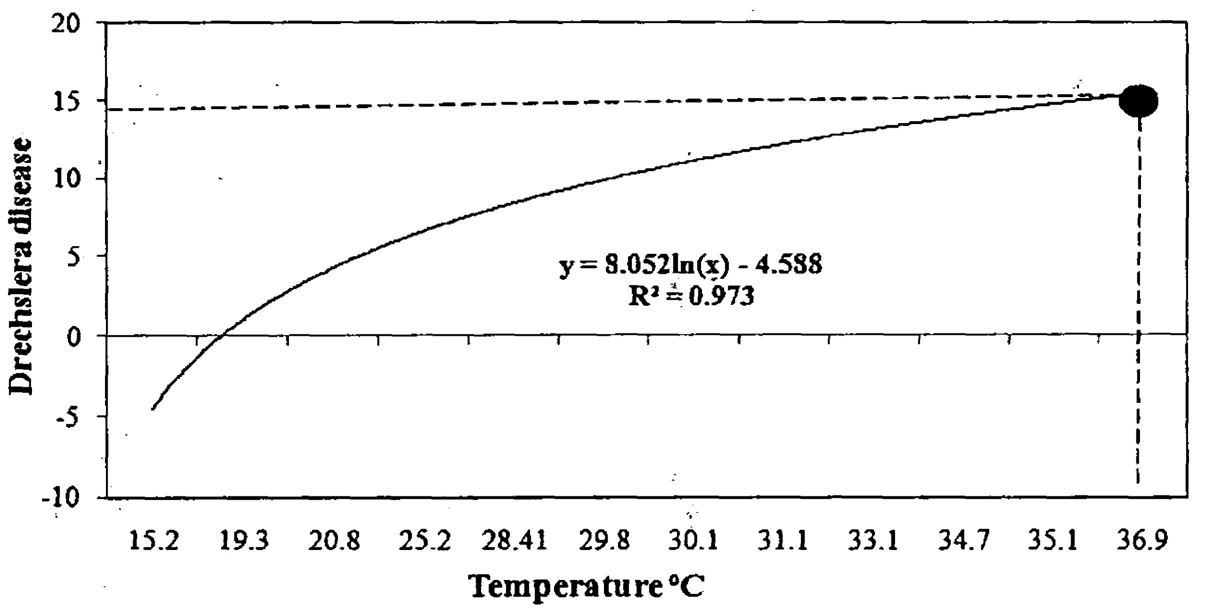
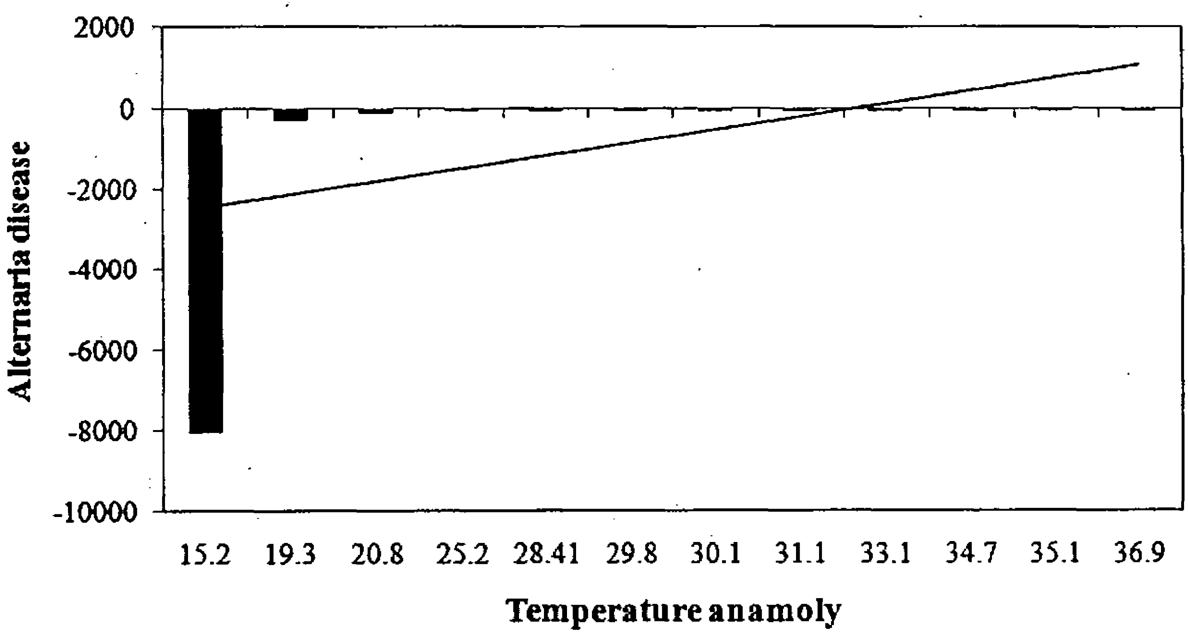


Figure 3.3: Impact of increased Temperature on *Drechslera sorokiniana* disease by (a) Multiple Regression and (b) Quadratic Plateau Model

(a)



(b)

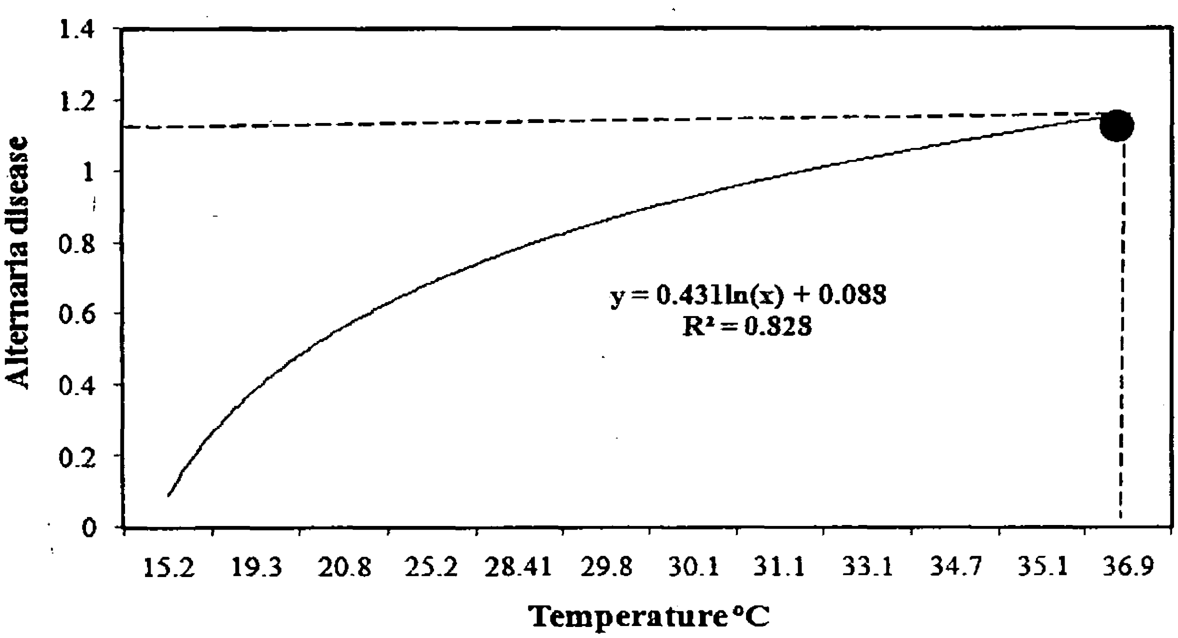
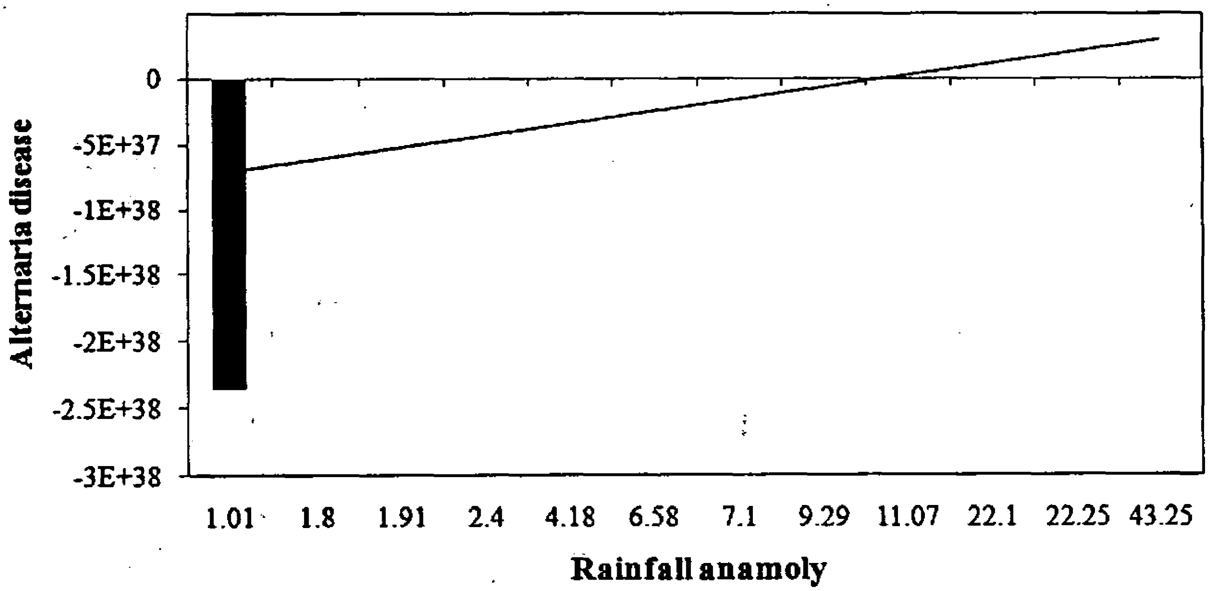


Figure 3.4: Impact of increased Temperature on *Alternaria triticina* disease by (a) Logistic Regression and (b) Quadratic Plateau Model

(a)



(b)

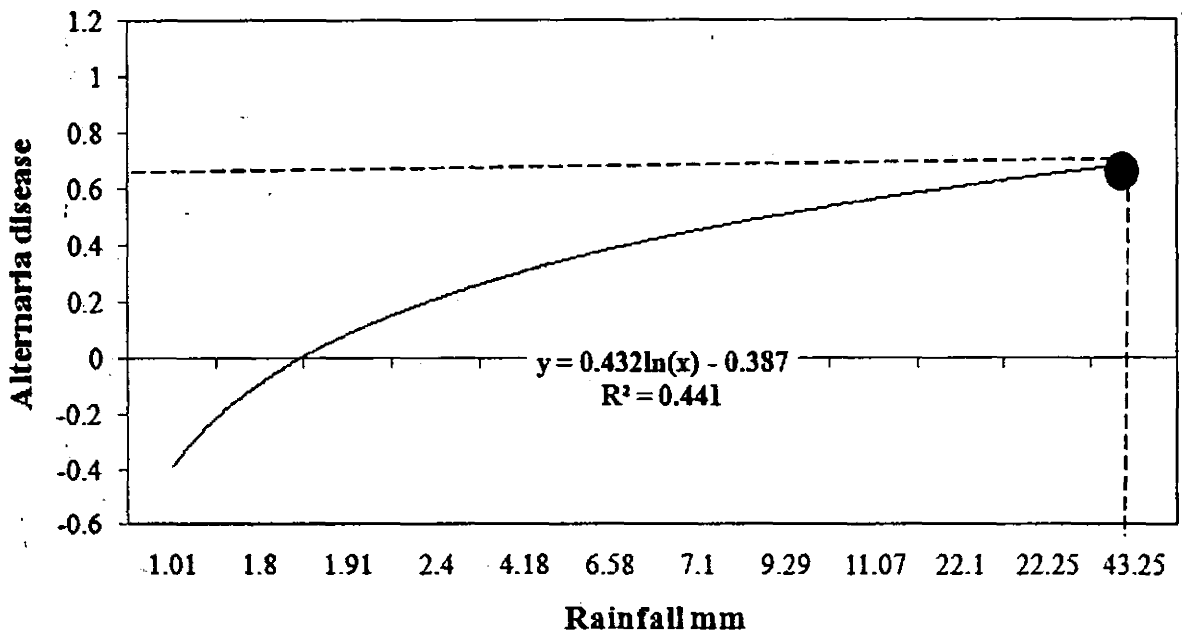
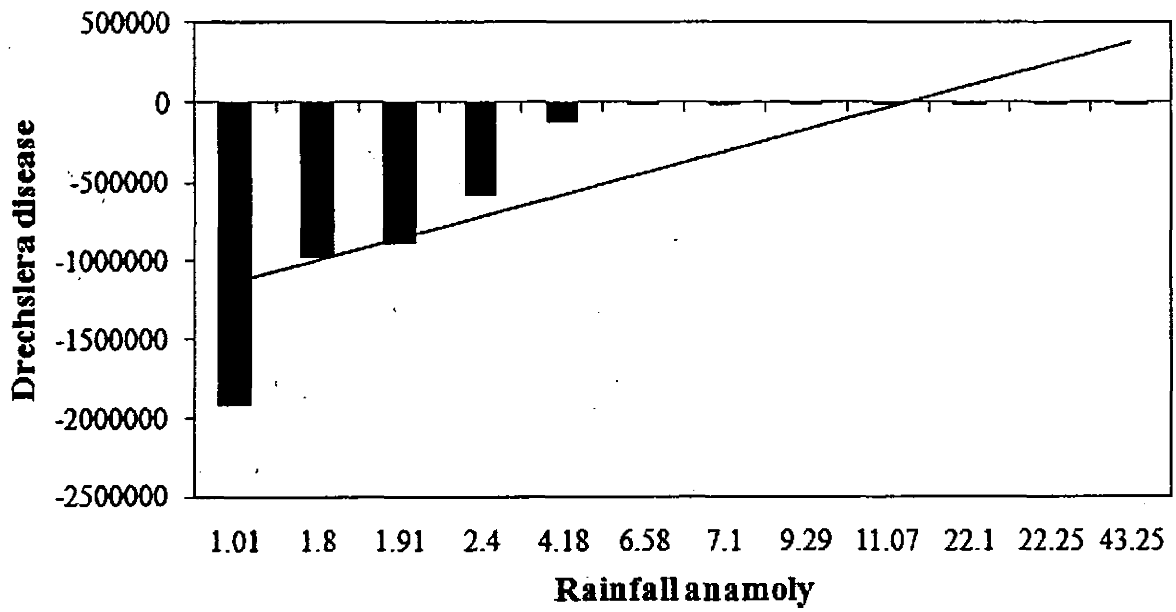


Figure 3.5: Impact of increased Rainfall on *Alternaria triticina* disease by (a) Logistic Regression and (b) Quadratic Plateau Model

(a)



(b)

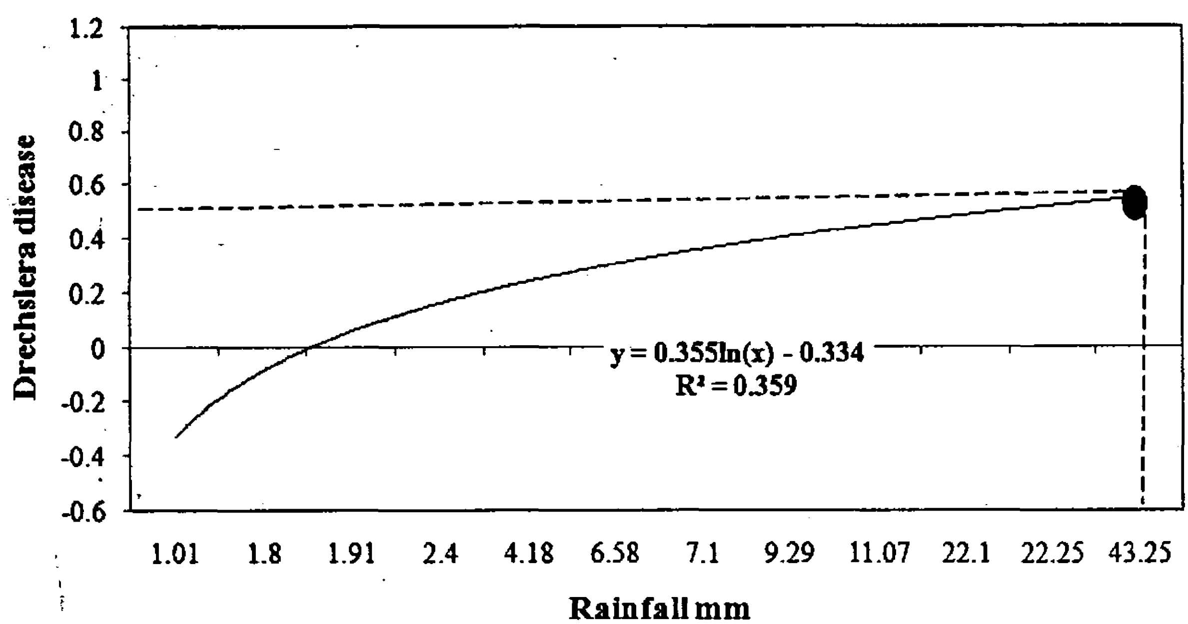


Figure 3.6: Impact of increased Rainfall on *Drechslera sorokiniana* disease by (a) Logistic Regression and (b) Quadratic Plateau Model

3.1.2 Statistical Model Validation

Evaluation is an important step for verifying the model. The validation skill scores like RMSE, d-stat and R^2 confirmed the efficiency of statistical models (Multiple and Logistic Regression Model). The table (3.1) depicted that Multiple and Logistic Regression Model could be used significantly to predict the fungal diseases occurrence with good validation skill scores. The values for pathogen occurrence for *Alternaria triticina* leaf blotch were 0.50 with RMSE 11.36 and d-stat 0.43 and for *Drechslera sorokiniana* leaf blotch was 0.63 with RMSE 8.81 and d-stat 0.75. Similarly for Logistic Regression, the values for pathogen occurrence for *Alternaria triticina* leaf blotch (when Temperature is above 20°C) were 0.93 with RMSE 3.47 and d-stat 0.98 and non-significant results for *Drechslera sorokiniana* blight of wheat. However, when Rainfall is above 10 mm, the values for pathogen occurrence for *Alternaria triticina* disease were 0.98 with RMSE 28.0 and d-stat 0.80 and for *Drechslera sorokiniana* disease; it was 0.87 with RMSE 3.69 and d-stat 0.99.

Table 3.1: Validation of Statistical Modeling

	Multiple linear regression		
	R^2	**RMSE**	**d-stat**
Alternaria	50.0%	11.36	0.43
Drechslera	63.1%	8.81	0.75
	Logistic regression (Temperature>20°C)		
Alternaria	93%	3.47	0.98
Drechslera		Non-significant	
	Logistic regression (Rainfall>10mm)		
Alternaria	98%	28.0	0.80
Drechslera	87%	3.69	0.99

3.2 Dynamical Model

Simulation model APSIM was used for simulating effects of changing climate and fungal pathogens on wheat yield. The key element in this field of research is being able to link statistical, dynamical model and field data of wheat crop fungal diseases. Results explore the impact of projected change in climate on *Alternaria triticina* and *Drechslera sorokiniana* leaf blight of wheat and how this may influence on wheat yield.

3.2.1 Studies climate influence on fungal pathogens andwheat productivity

Crop simulation models provide means to assess the effects of soil, climate and management factors on crop productivity, growth and sustainability of agricultural production. The development of decision-support tools and system approaches can help identify the detrimental environmental impacts. The APSIM model has been extensively used to quantify the impacts of climate change on agricultural production in different regions of the world.

The APSIM model was used for analyzing the impact of climate change on wheat productivity initially under hypothetical climate change scenarios table (3.2) and then under A2 scenarios table (3.3) developed by Pakistan meteorological department (PMD) from ECHAM5 Global Climate Model (GCM) output which can be downscaled using Regional Climate Model (RCM) to finer resolution.The host-pathogen module is under development in APSIM model. Therefore, the impact of climate change on *Alternaria triticina* and *Drechslera sorokiniana* was analyzed statistically and then under A2 scenarios and their effects on wheat grain yield were examined.

However, the impact of climate to crop fungal diseases supports the theory about variations in climate to wheat fungal disease and crop productivity. Temperature and precipitation shows increasing trend in coming years. Higher temperature, rainfall and humidity enhance leaf blight epidemics (Sharma *et al.*, 2007).

3.2.2 Past Trends of Wheat Yield (1960-2012)

Run from the APSIM simulation model on wheat yield for the past 52 years was presented in figure (3.7) which revealed a declining trend of wheat yield (statistically not significant) in Islamabad region.

These results illustrated that the aggregate impact of climatic parameters (changes in surface temperature, rainfall amounts and increase in CO_2 levels) exerted an overall adverse/negative impact on grain yield of wheat, the other management practices remaining the same during all the (52) study years. However, considerable variation in wheat grain yield was observed over the study years.

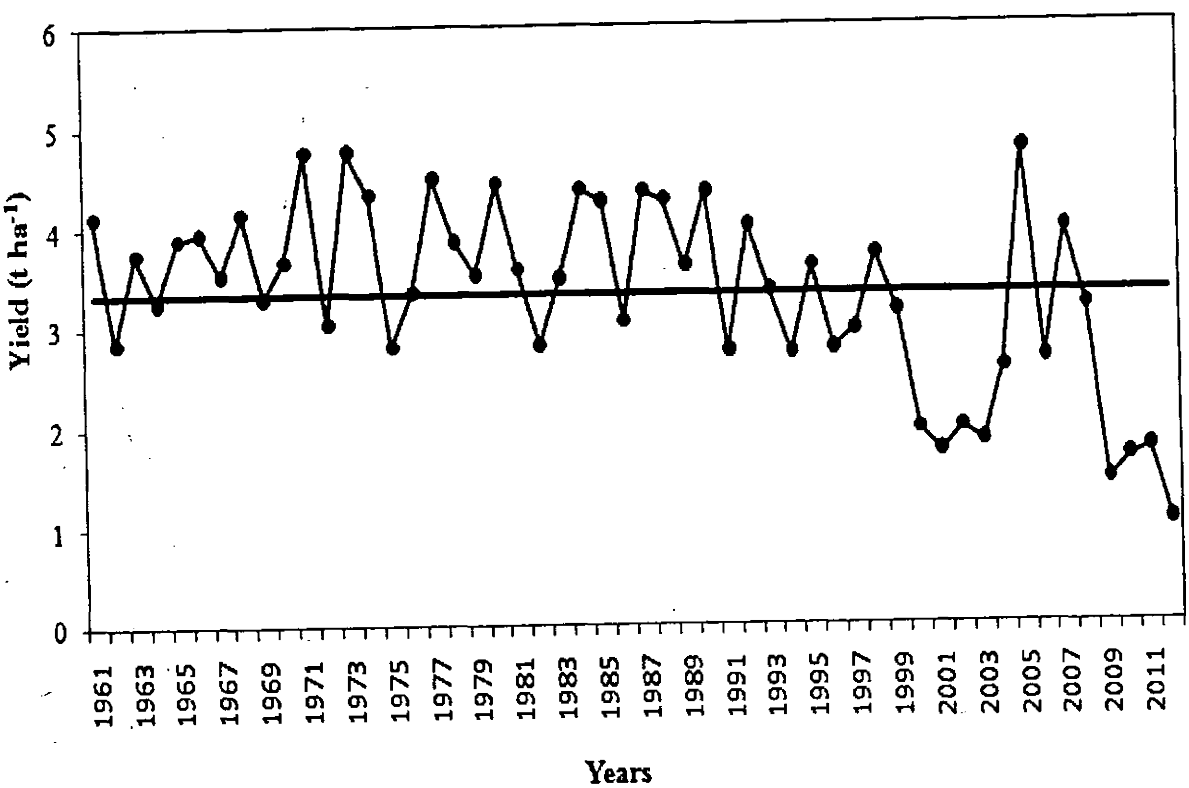


Figure 3.7: Past trends in wheat yield due to climate change

3.3 Hypothetical Climate Change Scenarios

Hypothetical scenarios is a widely accepted approach to analyze the possible effects of climate change attributes on crop yield to determine the incremental changes in precipitation, temperature, moisture and CO_2 and how to apply these changes to a baseline climate (Rosenzweig and Iglesias, 1994). The climate change attributes expected to affect crop yield in the present study were: increase in the surface temperature, changes in precipitation amount and increase in concentration of CO_2.

The scenarios that were used in the present study to analyze the impact of climate change on wheat yield were given in table (3.2). These were: (i) increased temperature (average of 52 years as the baseline temperature and increase in temperature by 1°C) (ii) increased CO_2 concentration in the atmosphere (370 as baseline and 550, 730, 910 and 1090 ppm as determined by IPCC scenario) and (iii) change in rainfall (10% to 50%). The impact of hypothetical climate change scenarios were examined on fungal pathogens and crop yield of wheat using APSIM model climate change module. Climate change may have negative and positive impact on crop yields. Since future climate changes are expected to pose serious danger to our agriculture. Therefore, the APSIM model was evaluated using above mentioned hypothetical scenarios.

The outcomes of statistical or regression analysis (Quadratic Plateau Model) are intrinsically linked with APSIM model to predict the effects of climate variants on crop fungal diseases *Alternaria triticina* and *Drechslera sorokiniana*.

Table 3.2: Hypothetical scenarios for impact Assessment on grain yield of wheat

Sr. No	Scenarios	Parameters
1	Baseline (1960-2012)	Daily observed Rainfall and temperature CO_2 level = 360 ppm during wheat growing season
2	If only Temperature changes	Temperature changes = 1 to 5 ^{0}C
3	If only Rainfall changes	Rainfall change: 10% to 50%
4	If only CO_2 level changes	CO_2 level = 370, 550, 730, 910 and 1090 ppm
5	If both Temperature and CO_2 changes	Temperature changes = 1 to 5 ^{0}C CO_2 level = 370, 550, 730, 910 and 1090 ppm

3.3.1 Impact of increased Temperature on wheat grain yield

APSIM model was evaluated and impact of temperature on wheat grain yield was assessed at five levels of temperature (1°C to 5°C) at CO_2 concentration 370 ppm (baseline) under continuously changing scenarios.

The results illustrated that any increase in temperature over the baseline (average of 52 years) exerted a negative impact on the Pothwar region which would led to declined wheat yield as described by APSIM model figure (3.8). Reduction in wheat yield was observed from 2.48t ha^{-1} at 1°C; to 2.44t ha^{-1} at 2°C, to 2.39t ha^{-1} at 3°C, to 2.35t ha^{-1} at 4°C to 2.33t ha^{-1} at 5°C. Increase in temperature will tend to reduce the growing period length, potentially depressing overall yield and biomass accumulation (Wilkens and Singh, 2001).

The *Alternaria triticina* and *Drechslera sorokiniana* leaf blotch are serious diseases of wheat included in this study. The effect of temperature on wheat fungal diseases was estimated by statistical modeling. Regression analysis inferred that by increasing temperature, disease continuously increases. The projected increase in temperature apparently will have a negative effect on wheat foliar pathogens and yield. There was an increasing trend for leaf blight and consequently a decreasing trend for grain yield (studied by dynamical modeling).

3.3.2 Impact of increased Rainfall on wheat grain yield

Increase in rainfall has positive impact on wheat grain yield but the magnitude of change is small. APSIM model was evaluated and impact of precipitation on wheat grain yield was assessed at five levels of rainfall (10 to 50%) at CO_2 concentration 370 ppm (baseline) under continuously changing scenarios.

The wheat yield increased from 131.70t ha^{-1} at 10% rainfall, to 131.709t ha^{-1} at 20% rainfall, to 131.713t ha^{-1} at 30% rainfall, to 131.717t ha^{-1} at 40% rainfall, to 131.722 t ha^{-1} at 50% rainfall as described by APSIM model figure (3.9). The results illustrated that any increase in rainfall over the baseline (average of 52 years) exerted a positive impact in the Pothwar region which would led to increase in wheat yield.

The effect of rainfall on fungal pathogens was examined by statistical modeling, predicted that higher rainfall and humidity increase pathogens survival, whereas lower humidity and rainfall would reduce the risk of infection by *Alternaria triticina* and *Drechslera sorokiniana* (Fuhrer, 2003).

3.3.3 Impact of increased CO_2 on wheat grain yield

An increase in wheat yield was recorded under increased concentration of CO_2 from 370 ppm to 1090 ppm by APSIM model. Simulation with elevated CO_2 indicated the impact of increase CO_2 concentration under A2 scenarios in the Pothwar region was positive as the yield increased from 2.53 t ha^{-1} under the CO_2 concentration 370 ppm to 3.13 t ha^{-1} under the CO_2 concentration 550 ppm, to 3.36 t ha^{-1} under the CO_2 concentration 730 ppm, to 3.53 t ha^{-1}under the CO_2 concentration 910 ppm, to 3.63 t ha^{-1} under the CO_2 concentration 1090 ppm. Our results also confirmed the evidence that enhanced CO_2 concentration has positive impact on wheat yield as depicted in figure (3.10).

Foliar pathogens have its own optimum N in its leaves. Thus, by elevated CO_2 caused changes in the C: N concentration ratio may have differential effects on fungal pathogens. The elevated atmospheric CO_2 concentration together with increased humidity increases leaf area index could promote expression of fungal diseases (Fuhrer, 2003). Elevated CO_2 level is known to stimulate the growth rate and aggressiveness of fungal pathogens. The increased in disease expression under elevated CO_2 have been attributed to altered host chemistry, leaf demography and canopy structure (McElrone *et al.*, 2010).

3.3.4 Impact of both increased Temperature and CO_2 on wheat grain yield

(Figure 3.11) revealed the results of increased temperature (1 to 5°C) on yield at five levels of CO_2concentration. The data from simulation results illustrated that wheat yield at temperature 1°C was 2.51t ha^{-1} under the CO_2 concentration 370 ppm to 3.63t ha^{-1} under the concentration of CO_2 1090 ppm, at 2°C yield was 2.27t ha^{-1} under CO_2 concentration 370 ppm to 3.46t ha^{-1} under the concentration of CO_2 1090 ppm, at 3°C yield was 2.17t ha^{-1} under CO_2 concentration 370 ppm to 3.29t ha^{-1} under the concentration of CO_2 1090 ppm, at 4°C yield was 2.00t ha^{-1} under CO_2 concentration 370 ppm to 3.11 t ha^{-1} under the concentration of CO_2 1090 ppm and at 5°C yield was 1.92 t ha^{-1} under the CO_2 concentration 370 ppm to 2.97t ha^{-1} under the concentration of CO_2 1090 ppm.

The analysis reveals that any increase in temperature over the baseline (average of 52 years) exerted a negative impact would lead to decline in wheat yield as described by APSIM model. The results depicted that reduction in wheat yield due to rise in temperature could be compensated if concentration of CO_2 increases.

It has been discussed that wheat yield is positively affected/increased (grain number produced per unit ground area) by CO_2. Elevated level of CO_2 exposure is well known to enhance the grain yield of wheat (Piiki *et al.*, 2008). Increased atmospheric CO_2 concentration tends to increase wheat growth and yield.

For doubling of CO_2 concentration from 350 ppm to 700 ppm, potential crop growth and productivity was to increase by 25 % for C3 crops (rice, wheat etc) by increasing water use efficiency and enhancing photosynthetic rates. The effect of elevated CO_2 concentration is to compensate the negative effects of rising temperature on yield but only to 4 %, it is unable to fully compensate (Anwar *et al.*, 2007). Similarly, elevated CO_2 is known to enhance the growth of fungal pathogens (Fuhrer, 2003).

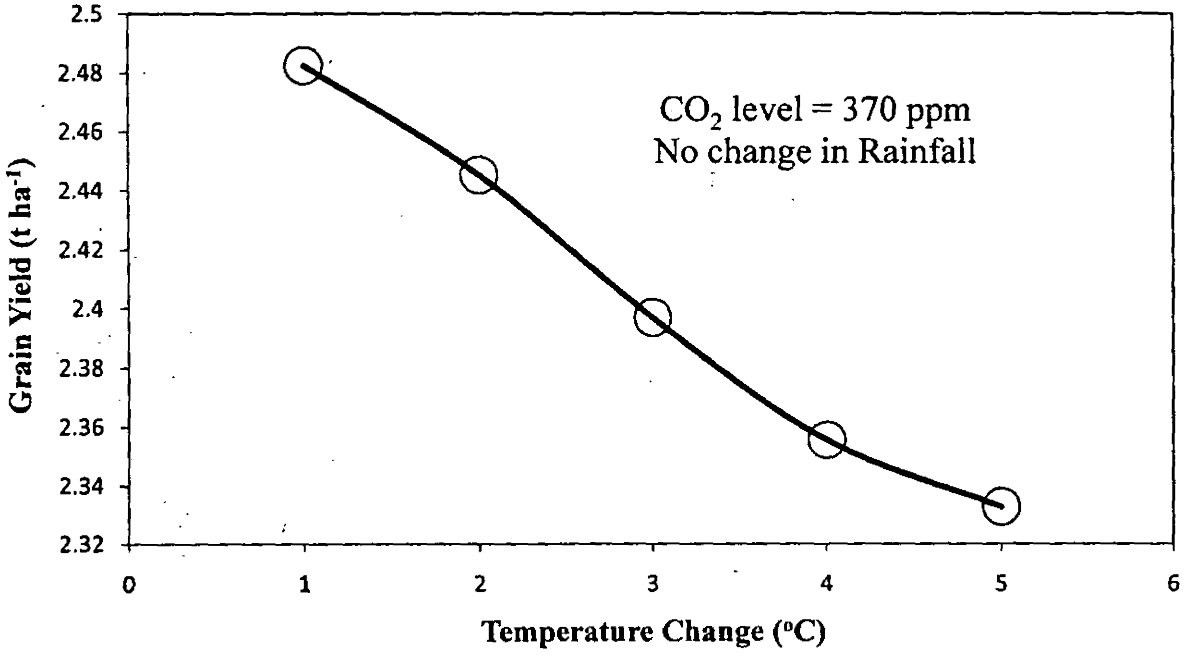


Figure 3.8: Impact of increased Temperature on grain yield of wheat simulated by APSIM

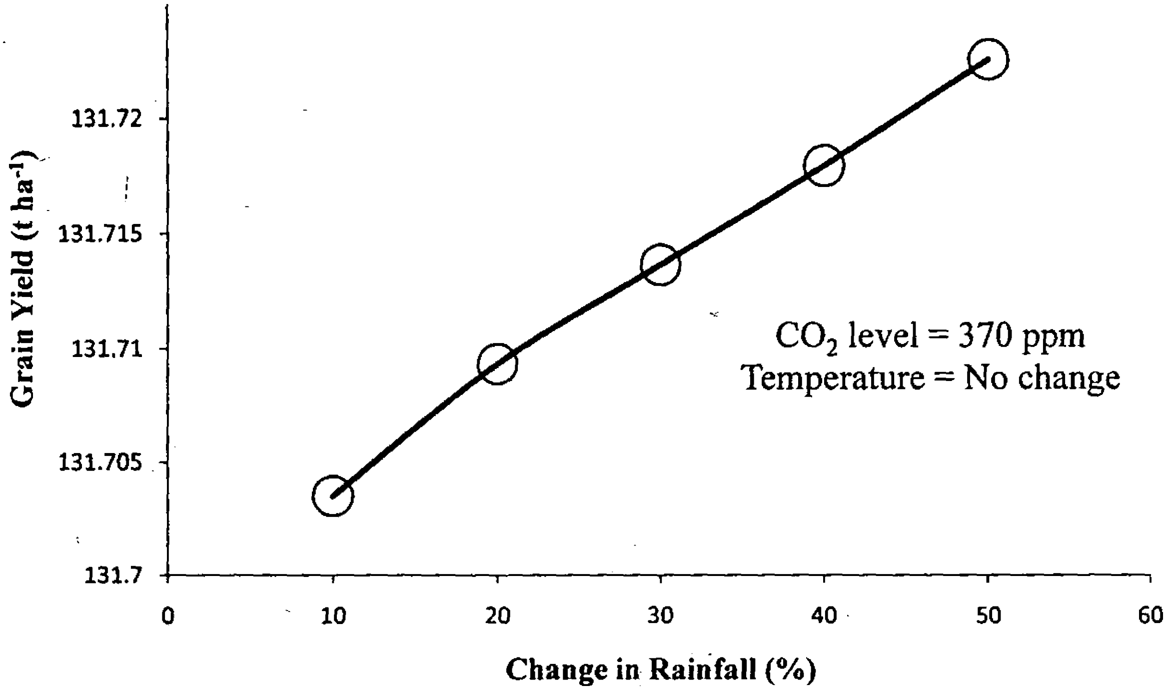


Figure 3.9: Impact of increased Rainfall on grain yield of wheat simulated by APSIM

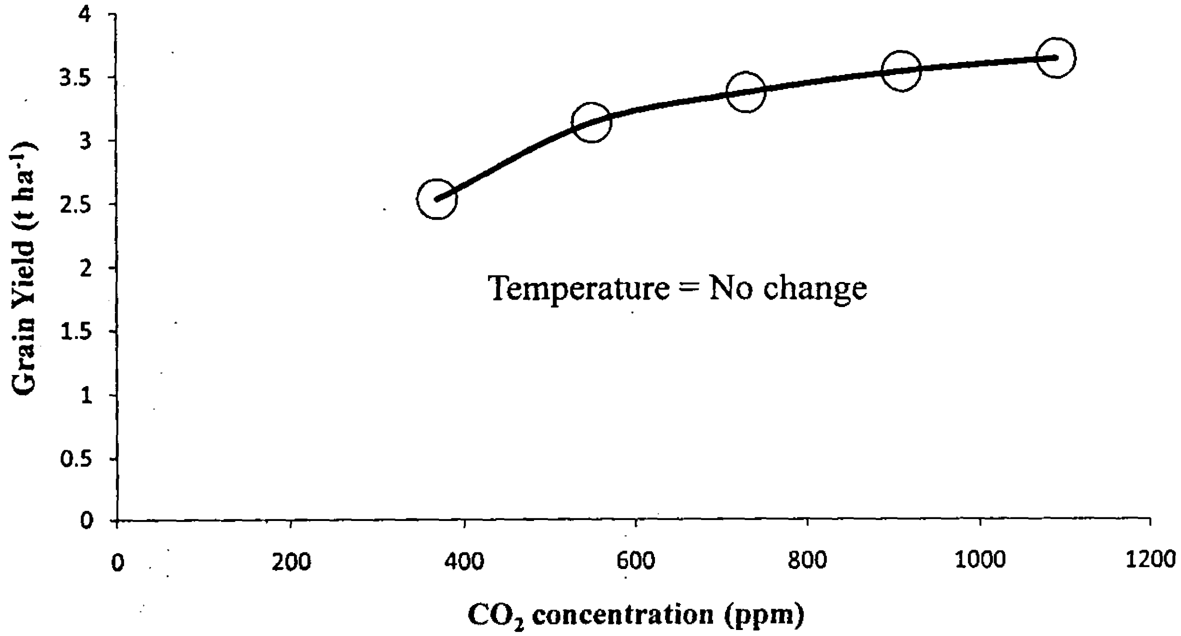


Figure 3.10: Impact of increased CO_2 concentration on grain yield of wheat simulated by APSIM

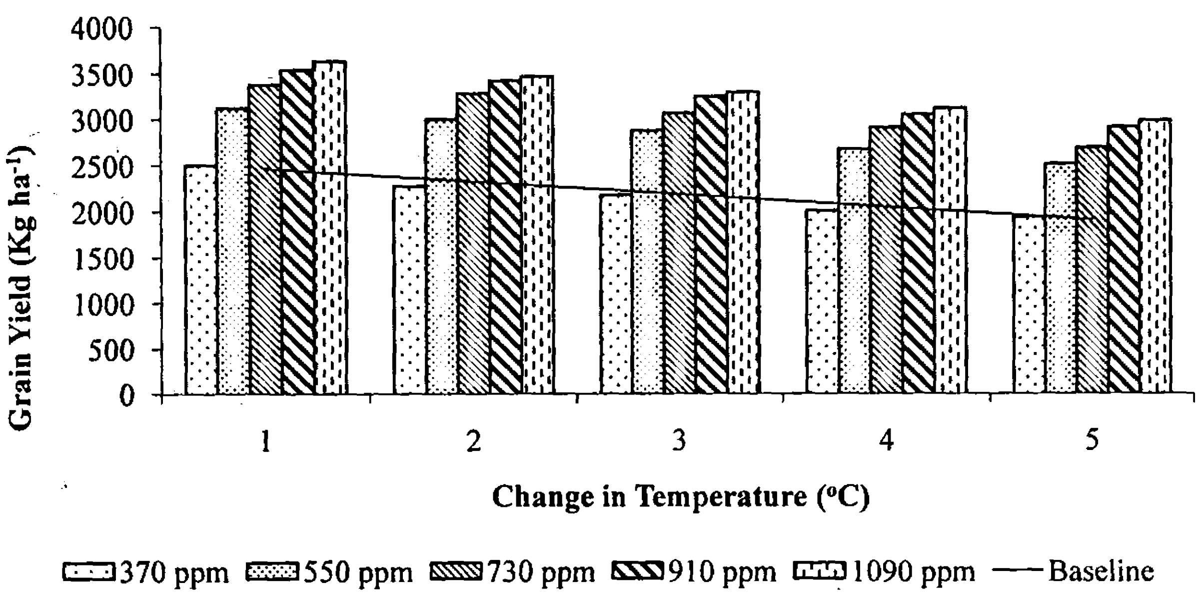


Figure 3.11: Impact of CO_2 concentration at five Temperature levels on grain yield of wheat simulated by APSIM

3.4 IPCC-A2 (Medium-High) EmissionScenarios

As part of statistical study, long-term climatic variations were also determined. The crop simulation studies for projecting future crop yield, requires weather data (rain, mint, maxt and solar radiation). The APSIM Model requires daily information of climate variables. The future climate change (Temperature and Rainfall) projection was developed in the light of historical climate (50 years trend) records as worked out by Pakistan Meteorological Department, (PMD) using ECHAM5 Global Climate Model (GCM) output which can be downscaled using Regional Climate Model (RCM) to finer resolution.

The projected increase in temperature is 0.01, 0.03 and 0.05°C; increase in precipitation is 6.1, 8.1 and 9.5 mm to the late 21th century in Pothwar area of Pakistan under A2 scenario based on IPCC special report on emission scenarios (SRES). The A2 scenario describes a future world of lowest economic growth. The underlying theme is regionally oriented; self-reliance with preservation of local identities, population is continuously increasing, technological change is slower and more fragmented. The expected climate change impacts of A2 scenario is given in table (3.3). How might this future climate projections effect foliar pathogens and crop productivity of the region? Simulation were performed under dynamic model APSIM module to study the impact of both fungal diseases on wheat yield for historical climatic data (1961-February 2012) and for nine future decades, namely March 2012-2020, 2021-2030, 2031-2040, 2041-2050, 2051-2060, 2061-2070, 2071-2080, 2081-2090 and 2091-2100. Impact of fungal diseases (*Alternaria triticina* and *Drechslera sorokiniana* leaf blight) was also studied on crop productivity. Shift in agricultural productivity can be the result of combined effect of biotic (diseases) and abiotic (climate) stress factors.

Table 2.3: Future Climate Projection (2012-2100) under IPCC-A2 (Medium-High) Emission Scenarios

Region	Time Horizon	CO_2 Concentration (ppm)	Rainfall (mm/decade)	Temperature (°C/decade)
	2011-2050	430-545	+6.1	+0.01
Pakistan	2080	720	+8.0	+0.03
(Islamabad)	2100	815	+9.5	+0.05

3.4.1 Impact of projected (2012-2100) climate change on wheat yield

Past change in climate has negative effect on wheat yield. The wheat sensitivity to climate change under the future climate change scenarios is more pronounced. The impact of changes in CO_2 concentration, precipitation and temperature level on wheat yield, under A2 emission scenario, was described in figure (3.13). Crop yield modeling based on climate change A2 scenarios predicted that increase in crop yield and productivity for 2100s are expected for Pothwar region.

The simulated data depicted that the impact in the Pothwar region was positive as the yield increased from 1.96 t ha^{-1} in 2001-2010 to 2.14 t ha^{-1} in 2011-2020, to 2.18 t ha^{-1} in 2050, to 2.86 t ha^{-1} in 2070, then there will be slightly reduction in yield 2.82 t ha^{-1} in 2080, 2.81t ha^{-1} in 2090 and 2.69t ha^{-1} in 2100 under A2 scenarios. Modeled yield is highly variable from decade to decade. Change in climate is likely to depress crop yield. The impact of increased decadal climate variability increases the risk to future wheat production, ultimately food production.

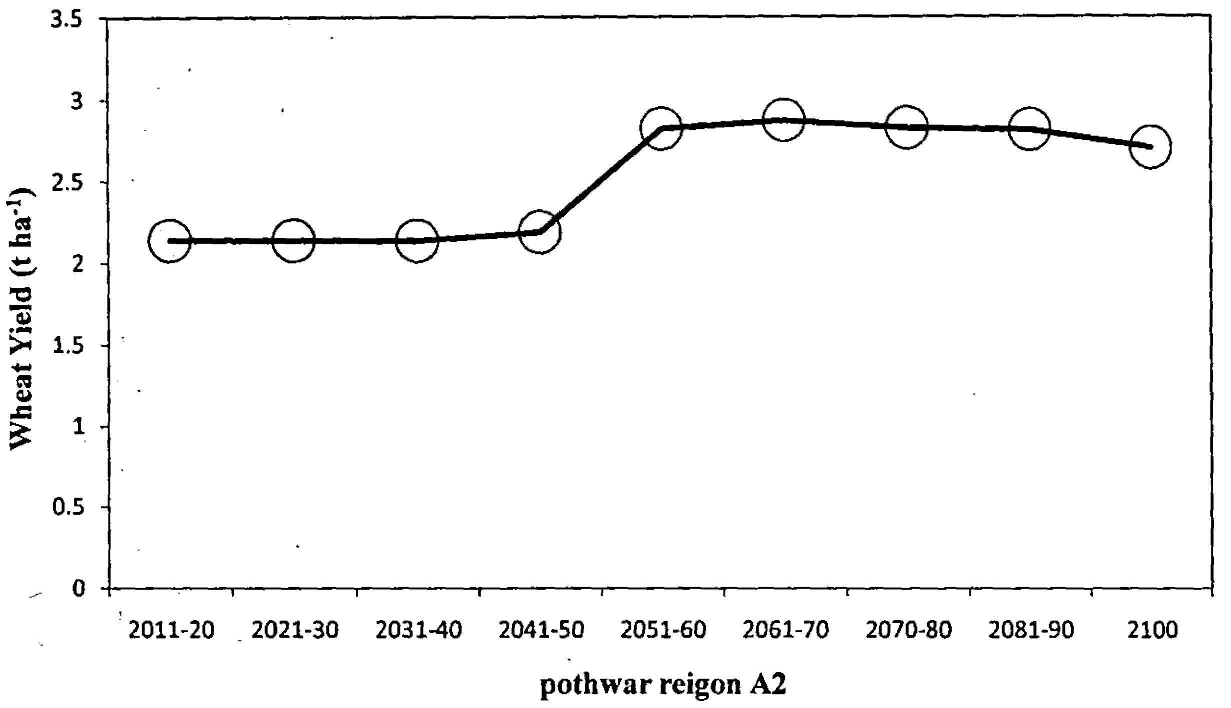


Figure 3.12: Impact of projected climate change (2012-2100) on wheat yield in Pothwar region (Islamabad) of Pakistan

3.4.2 Fungal pathogens prevalence under projected climate (2012-2100)

The outputs of farming system APSIM model with projected A2 scenarios and wheat yield for 21^{th} century were used as input to predict the influence of fungal diseases on wheat yield. Simulation was performed in the absence of fungal diseases. Dynamical results were linked with statistical models to study the impact of fugal pathogens on wheat growth and production under future climate scenarios. APSIM model was evaluated and impact of fungal diseases *Alternaria triticina* and *Drechslera sorokiniana* leaf blight on wheat grain yield was assessed under A2 future climate scenarios. The results illustrated that increase in temperature exerted a positive impact on both fungal diseases as described by figure (3.13 & 3.14).

The *Alternaria triticina* disease continuously increased as 13.32 in 1970 at temperature 31.14°C, 18.84 in 2000 at temperature 32.71°C, 19.25 in 2050 at temperature 33.62°C, 19.41 in 2080 at temperature 33.74°C and 19.59 in 2100 at temperature 34.48°C. Similarly, the *Drechslera sorokiniana* disease continuously increased due to rise in temperature as 8.73 in 1970 at temperature 31.14°C, 9.73 in 2000 at temperature 32.71°C, 10.32 in 2050 at temperature 33.62°C, 10.54 in 2080 at temperature 33.74°C and 10.74 in 2100 at temperature 34.48°C.

The present studies depicted that variation in climatic variants have a very strong effect on fungal disease. The increase in fungal diseases was due to variation in climate more specifically temperature as temperature has greater influence on fungal pathogens. It has been clearly described in the literature that disease severity is enhanced due to warm weather (temperature above 20°C). The current study revealed that variation in temperature has strong influential impact on wheat fungal diseases *Alternaria triticina* and *Drechslera sorokiniana*.

The results confirm an increasing tendency towards leaf blight severity in the study region. In the same period, there has been a decreasing trend in wheat yield. The outcomes of regression analysis are intrinsically linked with dynamical modeling. However, the effects of climate variants to crop fungal diseases through systematically designed study conducted at Islamabad region has been shown.

This supports the general speculations about climatic variations due to global warming and their specific relevance to wheat fungal disease and crop productivity. Temperature shows increasing trend in coming years. Similar trend was present for precipitation patterns.The "fertilization effect" of raising CO_2 increases grain yield, increasing the possibility of food production. However, higher temperature and rainfall reduced grain yield. The impact of fungal diseases in assessment of food production and security under changing climate, reverse or minimize benefit from fertilization effect of CO_2 (Butterworth *et al.*, 2004). Higher temperature, rainfall and humidity favor leaf blight severity (Sharma *et al.*, 2007).

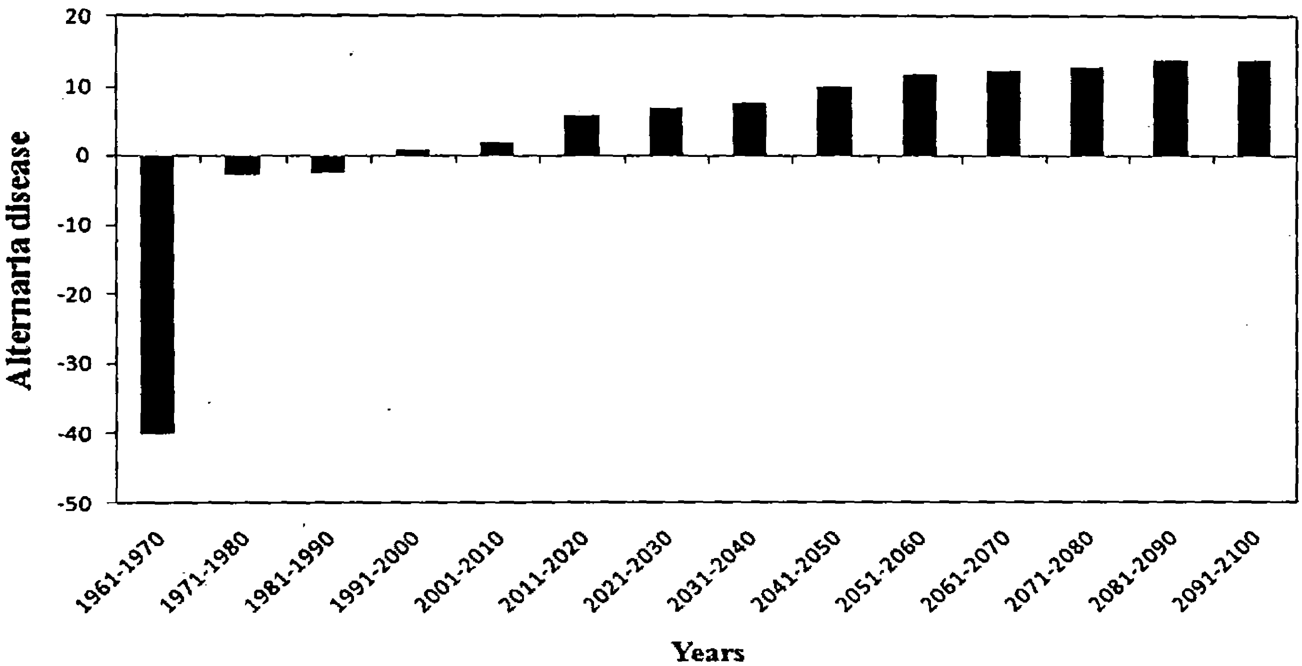


Figure 3.13: Impact of historical and projected climate change (2012-2100) on *Alternaria triticina* leaf blight of wheat

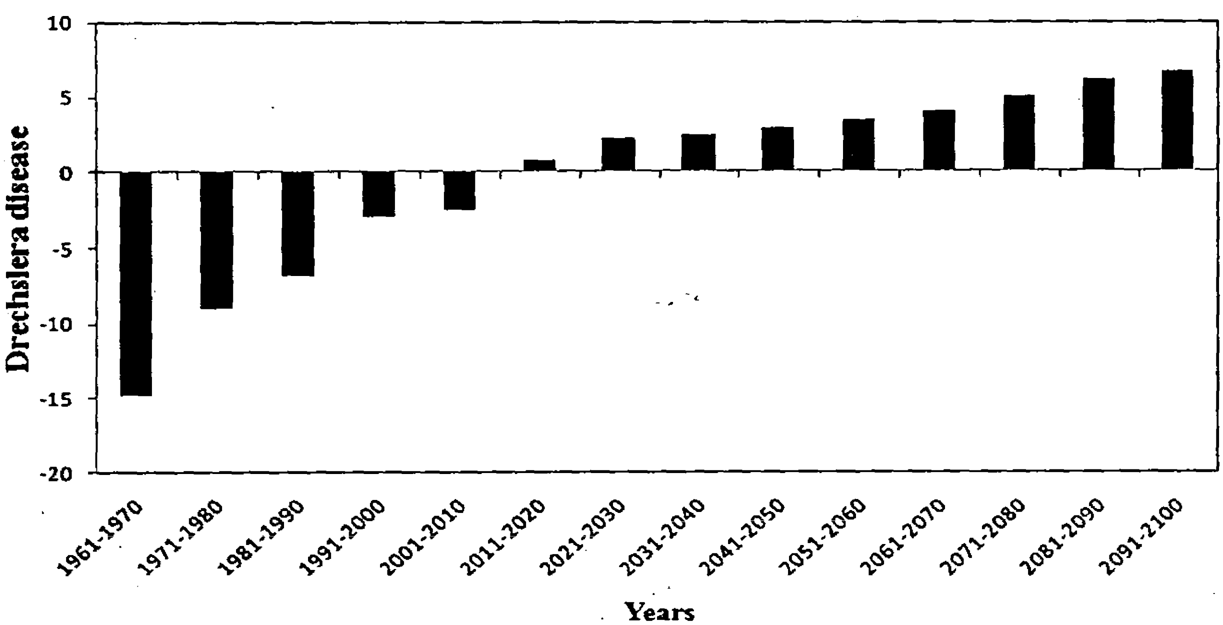


Figure 3.14: Impact of historical and projected climate change(2012-2100) on *Drechslera sorokiniana* leaf blight of wheat

3.4.3 Impact of fungal pathogens on wheat yield

(Figure 3.15 & 3.16) illustrated the effects of increased temperature under future scenarios on fungal diseases *Alternaria triticina* and *Drechslera sorokiniana* leaf blight. Based on statistical and dynamical climate-disease modeling predicted that an increase in temperature, combined with increase precipitation could increase *Alternaria triticina* and *Drechslera sorokiniana* leaf blight of wheat which would led to declined wheat production.

The simulated results depicted that the impact of *Alternaria triticina* disease on yield in the Pothwar region was negative as the yield decreased from 17 t ha^{-1} in 1960-1970, -17.9 t ha^{-1} in 2000, -11 t ha^{-1} in 2050, -19 t ha^{-1} in 2080 and -30 t ha^{-1} in 2091-2100. Similarly, the impact of *Drechslera sorokiniana* leaf blight on grain yield was also poor depicted that yield decreased from 9 t ha^{-1} in 1960-1970, -4 t ha^{-1} in 2000, -5.85 t ha^{-1} in 2050, -6 t ha^{-1} in 2080 and-8 t ha^{-1} in 2091-2100.

The impact of fungal pathogens on wheat production illustrated that reduction in wheat yield and productivity due to attack of *Alternaria triticina* was more severe as compared to *Drechslera sorokiniana*, because *Alternaria* leaf blotch is strongly influenced by variation in temperature as compared to *Drechslera* leaf blight. However, the prediction of yield for future (2100) was low, partly because wheat yield is strongly influenced by host-pathogen interaction. Similar conclusion had been documented that wheat fungal diseases such as stem rust, stripe rust and leaf rust inflict severe loss to crop yield. The pathogen life cycle and its interaction with host crop were strongly influenced by variations in weather attributes (temperature, rainfall and humidity) that were used in the simulation.

To model host-pathogen interaction, to better integrate and to be precisely representative of cropping systems it would be necessary to compile a set of phenological parameters for each of the cultivars (White *et al.*, 2004).

The present study verdict that grain yield is showing a decreasing trend while there is an increasing tendency of wheat leaf blight *Alternaria triticina* and *Drechslera sorokiniana*. The outcomes based on experimental and simulated data underlines a potential threat due to change in climate: the rise in temperature could destabilize grain yield and productivity in wheat growing parts in South Asia in agreement with the conclusion by (Garrett *et al.*, 2006).

The occurrence of fungal pathogens depends on weather. Pathogens life cycle are directly affected by climate. However, an earlier literature suggested that growth of fungal pathogens would increase with higher temperature and rainfall, potentially affect the wheat production. Climate (increase in temperature, humidity, rainfall and elevated CO_2) affect the growth of pathogen, spread of pathogen and resistance of host plant (Fuhrer, 2003).

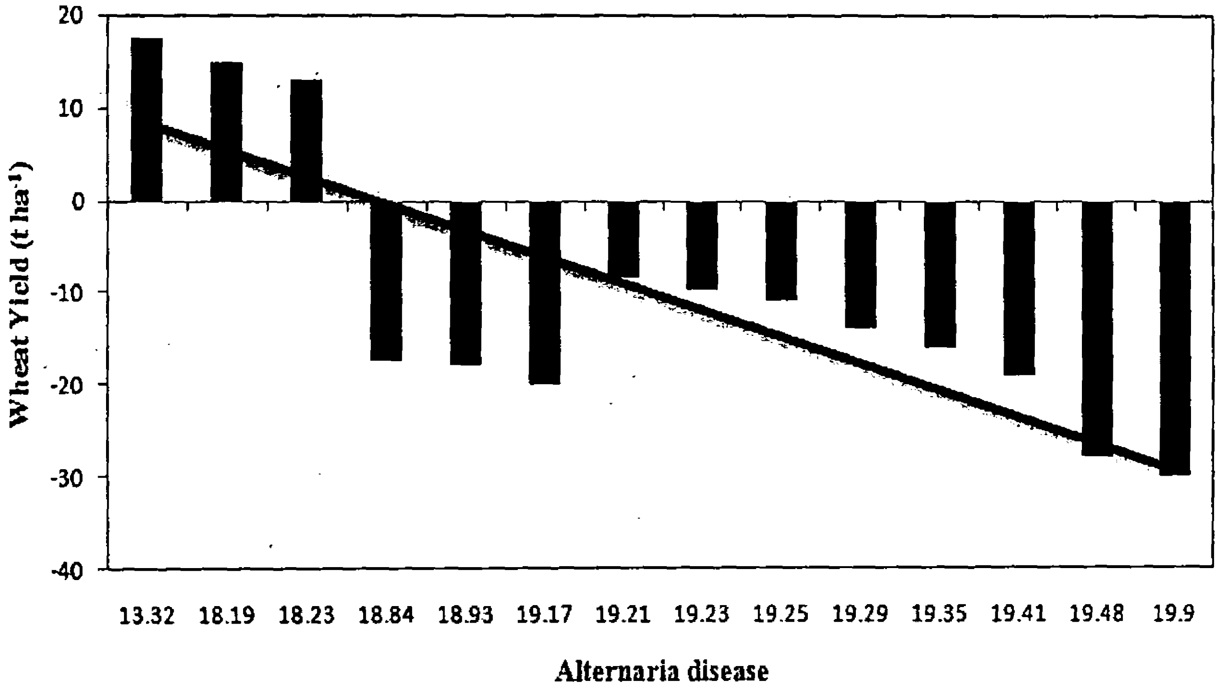


Figure 3.15: Impact of *Alternaria triticina* disease on wheat Yield

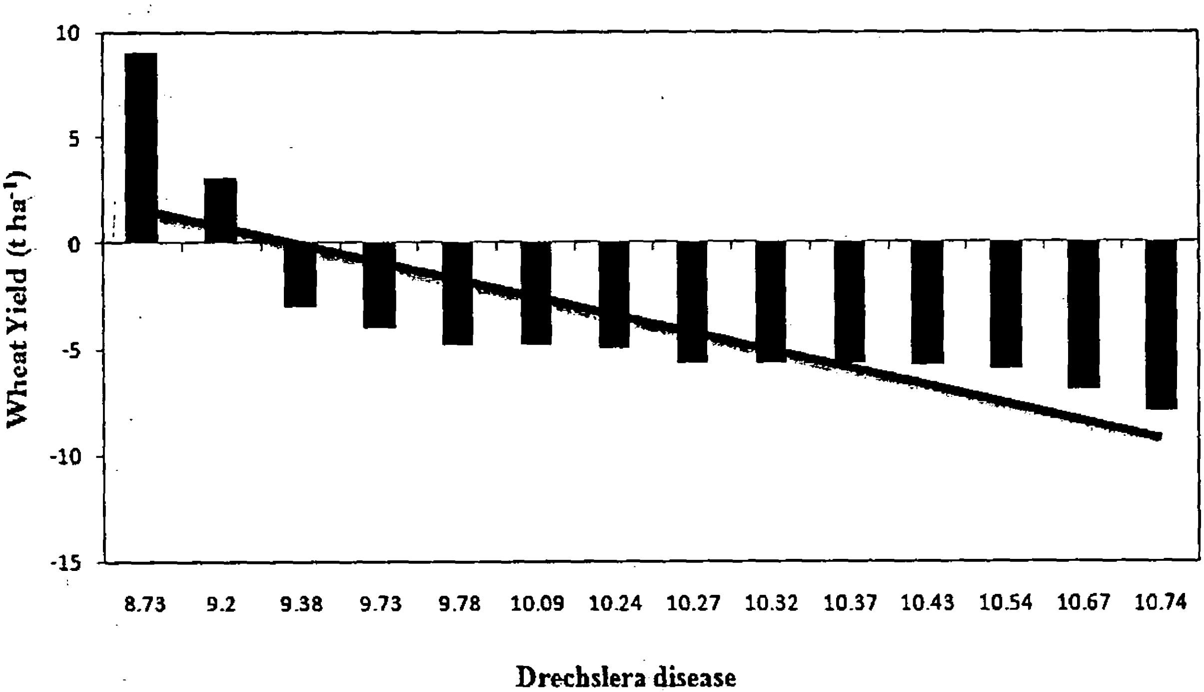


Figure 3.16: Impact of *Drechslera sorokiniana* disease on wheat Yield

Climate change, with its multiple effects on ecosystems, is likely to change the interactions between an infectious propagule, a susceptible host and favourable environmental conditions, leading to the development of new epidemics. The effect of fungal diseases on crop damage is recognized because agriculture is highly influenced by climatic factors. Climate change is expected to have major effects on population thresholds of microorganisms and disease vectors. The dynamics affecting host–pathogen interactions lead to the selection of new pathotypes or pathogens. They also determine the emergence of new diseases and pests.

Among these strategies, breeding for disease resistance is critical and will remain an essential part of germplasm improvement. Increases in yield per unit of area will continue to depend largely on more efficient control of (biotic) stresses rather than on an increase in yield potential. Integrated crop management is therefore the basis for sustainable agriculture. The range of options for adapting to the changes increases with technological advances. It is anticipated that modeling, remote sensing and spatial integration of critical climatic information and its access in near real time through the Internet will also contribute to precision agriculture (Legrève and Duveiller, 2010).

CONCLUSIONS

In the present studies outcome of statistical (Multiple Regression, Logistic Regression and Quadratic Plateau Model) and dynamical model (APSIM)depicted that increase or decrease in temperature and rainfall have negative and positive impacts on fungal diseases of wheat respectively. With the increase of temperature and rainfall, disease increases. This generally led to decline in crop yield and productivity.

APSIM model was parameterized and evaluated using historical data and future projections of Islamabad. The results indicated that APSIM model could simulate the wheat biomass growth and yield formation, capable for simulating the impact of temperature and rainfall. Simulation results using APSIM model combined with historical record of climatic data (52 years), wheat infested with fungal pathogen (*Alternaria triticina* and *Drechslera sorokiniana*) and hypothetical scenarios depicted that climatic variability (increase in temperature) greatly affected crop yield and productivity. Results from the scenarios have also clearly predicted that potential change in climate (especially temperature) will affect agricultural productivity, either positively or negatively (which may lead to food crisis).

The present studies depicted that proposed model could be successfully used as a risk management tools to understand host-pathogen interactions, bio dynamism of crop, climate and management options to explore potential grain yield of wheat in a given environment. The model evaluation over multiple locations will increase our knowledge and prove a better technique or tool for disease dynamics and yield forecasts of these areas.

It is also bear in mind when examining the forthcoming effects of plant diseases on crops that climate change is one driver, the other factors to envisage or examine include crop management practices (crop rotation, irrigation practices and planting time) and use of resistant cultivars.

KNOWLEDGE GAPS AND FUTURE ENHANCEMENTS

Overall, there has been limited research on diseases and pathogens of crops.These limited findings show that diseases caused by pathogens may increase. In some instances, a disease has been projected to increase or decrease depending on the region and / or the weather variables used. Given the number of interacting factors determining disease outcomes, modelingapproaches will offer the best approach for developing realistic projections (Scherm, 2004). Models used to predict the likely effects of climate change on a pathogen's distribution or biology are increasingly able to account for the complex interactions between a pathogen, its host and the environment. Despite this, there are critical gaps resulting from a fundamental lack of data (both spatial and temporal) at a field scale and at the cellular and genomic levels. Measuring how a pathogen is affected by climate change at a cellular or genetic level, such as at elevated CO2 levels (Matros *et al.*, 2006; Lake and Wade, 2009) will provide insight into the prevalence of the disease in future climates. The challenge will be in linking this data to host–pathogen interactions on a spatial scale in order to determine future management options.

As climate information is available in Pakistan for producers from a range of different sources for agricultural sector but deficit in providing the details information needed in order to affect or influence management decision. It is suggested to link the temperature and rainfall variability on different or multiple locations in Pakistan and organize similar studies using simulation techniques as tool for forecasting of wheat fungal diseases in relation towheat yield to make tactical management decisions.

To improve disease risk related decision building at farm level, producers and farmers need to have complete or better understanding of climate variants (especially temperature) that effect fungal diseases (*Alternaria triticina*and *Drechslera sorokiniana* leaf blight) in their environment and ultimately affect crop yield. This will confess decision makers to identify tactical management options based on climatic information (climate forecasts).

CHAPTER 4

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APPENDICES

APPENDICES

Appendix 2.1: P-values showing significance of Independent variables (*Alternaria triticina* disease) in the Multiple Linear Regression

Parameters	P-Value
Humidity	0.3465
Months	*0.0001
Rainfall	*0.0000
Temperature	*0.0001
Year	0.1316
Location	0.6026

Appendix 2.2: P-values showing significance of Independent variables (*Drechslera sorokiniana* Disease) in the Multiple Linear Regression

Parameters	P-Value
Humidity	0.8336
Months	*0.0000
Rainfall	0.7788
Temperature	*0.0000
Year	0.4016
Location	0.1084

Appendix 2.3: P-values showing significance of Independent variables (*Alternaria triticina* Disease) in the Logistic Regression when Temperature is above 20°C

Parameters	P-Value
Year	0.2851
Months	*0.0000
Temperature	*0.0003
Location	0.1851

Appendix 2.4: P-values showing significance of Independent variables (*Drechslera sorokiniana* Disease) in the Logistic Regression when Temperature is above 20°C

Parameters	P-Value
Year	0.6607
Months	0.7000
Temperature	0.1850
Location	1.0000

Appendix 2.5: P-values showing significance of Independent variables (*Alternaria triticina* Disease) in the Logistic Regression when Rainfall is above 10 mm

Parameters	P-Value
Year	1.0000
Months	0.8546
Rainfall	*0.0000
Location	1.0000

Appendix 2.6: P-values showing significance of Independent variables (*Drechslera sorokiniana* Disease) in the Logistic Regression when Rainfall is above 10 mm

Parameters	P-Value
Year	0.6607
Months	*0.0044
Rainfall	*0.0000
Location	1.0000