Downscaling Climate scenario and its impacts on food grains productivity in Himachal Pradesh

Thesis submitted to the Andhra University, Visakhapatnam in partial fulfilment of the requirement for the award of

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Dated: June16, 2014

CERTIFICATE

This is to certify that Mr. A.Ponraj has carried out the thesis entitled "Downscaling Climate scenario and its impacts on major food grains productivity in Himachal Pradesh" in partial fulfillment for the award of degree of Master of Technology (M. Tech.) in Remote Sensing and GIS. The thesis has been carried out in Agriculture and Soils Department and is the original work of the candidate under the guidance of Dr N.R.Patel, Scientist/Engineer-F, Agriculture and Soils Department, Indian Institute of Remote Sensing, Dehradun, India.

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Dedicated to the agrarian community

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ABSTRACT

Downscaling Climate scenario and its impact on major food grains Productivity in Himachal Pradesh

ABSTRACT

India's economy is most dependable on agriculture. India has a huge arable land area of 159.7 million hectares (394.6 million acres) standing second in the world after the United States. As per the statement of Food and Agricultural Organization (FAO), India is World's second largest producer of wheat, rice and major food staples and also ranked within five World's largest producers in cash crops like coffee and cotton. The agricultural history of India over the past four decades has been quite impressive and successive with a gross irrigated crop area of 82.6 million hectares (215.6 million acres).The montane ecosystem is critical for agricultural practices which is mostly found in the northern region of India.

Himachal Pradesh is the biggest montane ecosystem in India in which 65% people are depending on agriculture and 60% of GDP is coming from Agriculture sector. Nowadays, increasing temperatures and reducing rainfall is a major issue in global level which can directly affect the crop growth and crop production. As per IPCC report in South East Asian countries wheat and maize yield are going to reduce around 50 % in the upcoming decades and also the report states that in the next 50 years temperature is going to increase by 2.5 Degree Celsius than the current climate. This study is focusing on the impacts of climate change in wheat and maize productivity in Himachal Pradesh. Attempts were made to analyze the crop yield from 2001 to 2014 and to predict for the next 10 years i.e., till 2025.

In this study Regional Climate Model (RCM) named RegCM-4.3.5.6 is using for predicting the future climate (2001-2025) with Dynamic Downscaling for the IPPC scenario A1B, EH5OM-GCM (Global Circulation model) datasets. These output are validated with CRU Data sets. DSSAT is the crop model which is used in this study to predict the current and future yield. The outputs from the RegCM climate model are taken as inputs for the crop model. Maximum and Minimum Temperature, Rainfall, Solar Radiation are the inputs for crop model and these inputs are validated with CRU observed Data. Maximum Temperature is 90% correlated with CRU data while the minimum temperature is 92% and rainfall is 65% correlated with CRU observed datasets. Soil data is required for crop model simulation as well as crop management data, Cultivar data etc. This information is collected from field visit and from various Agriculture research stations in Himachal Pradesh.

Crop Model outputs are validated with observed datasets. Yield data is validated with yield statistics from Ministry of Agriculture. Yield is validated district wise. Overall correlation between observed and estimated yield for wheat is 72% and for maize is 61%. Maximum LAI is validated with MODIS LAI 8 day Composite images which showed 63% correlation.

Main Objective of this research is providing information about future climate and providing information about crop yield and techniques for adaptation in future.

Keywords: Dynamic Downscaling, Crop yield simulation, Future climate, adaptation

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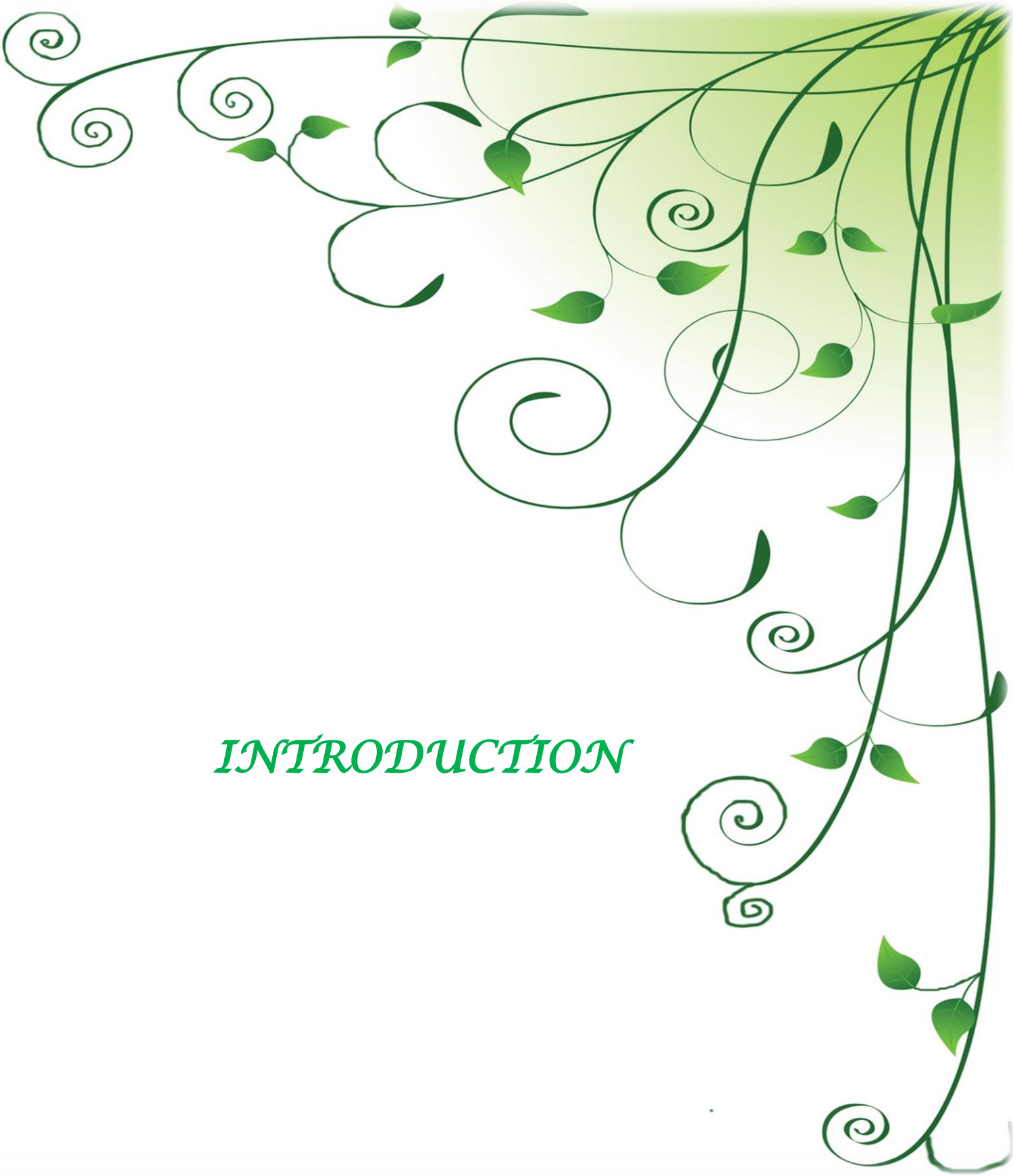
Abbrevations

IPCC	- Intergovernmental Panel for Climate Change
RegCM	- Regional Climate Model
GCM	- Global circulation models
NCAR	- National Center for Atmospheric Research
ESP	- Earth System Physics
RegCNET	- Regional Climate Research Network, or UNFCCC –
GCM	- Global Climate Models (s).
CERES	- Crop Environment Resource Synthesis
IBSNAT	- International Benchmark Sites Network for Agrotechnology Transfer
ICASA	- International Consortium for Agricultural Systems
DSSAT	- Decision Support System for Agro-technology Transfer
WRIS	- Water Resources Information System of India
RMSE	- Root Mean Square Error
MAPE	- Mean Absolute Percentage Error
MSE	- Mean squared error
ENVI	- Environmental Visualization



INTRODUCTION

INTRODUCTION CHAPTER 1

1.1. Problem statement and motivation

1.1.1 Agriculture in India

India has a huge arable land area of 159.7 million hectares (394.6 million acres) standing second in the world after the United States. The agricultural history of India over the past four decades has been quite impressive and successive with a gross irrigated crop area of 82.6 million hectares (215.6 million acres). Agriculture has played major role in improving the Indian economy and will continue to be the same in the future*(Abrol, 2002)*. As of 2012, India has a huge and various agricultural sectors, accounting, on average, for about 28% of GDP and 10% of export earnings and providing employment upto60 % of the total population. Innovation of new varieties and techniques in agricultural crops are increasing the productivity which in turn helped in improving the feeding capacity of the society. This dramatic productivity increase happened in 70s and 80s which is called as the "Green Revolution" era. India has second rank in agricultural productivity among the world countries and also has first rank in fisheries, fibrous crops, vegetables, major spices and fruits productivity. As per the statement of Food and Agricultural Organization (FAO), India is World's second largest producer of wheat, rice and major food staples and also ranked within five World's largest producers in cash crops like coffee and cotton.

1.1.1.2 Technological Needs and Future Agriculture

It is apparent that the tasks of meeting the consumption needs of the projected population are going to be more difficult given the higher productivity base than in 1960s. There is also a growing realization that previous strategies of generating and promoting technologies have contributed to serious and widespread problems of environmental and natural resource degradation. This implies that in future the technologies that are developed and promoted must result not only in increased productivity level but also ensure that the quality of natural resource base is preserved and enhanced. In short, they lead to sustainable improvements in agricultural production. Productivity gains during the 'Green Revolution' era were largely confined to relatively well endowed areas. Given the wide range of agro ecological setting and producers, Indian agriculture is faced with a great diversity of needs, opportunities and prospects. Future growth needs to be more rapid, more widely distributed and better targeted. Responding to these challenges will call for more efficient and sustainable use of increasingly scarce land water and germplasm resources. Technical solutions required to solve problems will be increasingly location-specific and matched to the huge agro ecological/climatic diversity. Detailed indigenous knowledge and greater skills in blending modern and traditional technologies to enhance productive efficiency will be more than ever before key to the farming success and sectorial growth. Most technological solutions will have to be generated and adapted locally to make them compatible with socio-economic conditions of farming community.

New technologies are needed to push the yield frontiers further, utilize inputs more efficiently and diversify to more sustainable and higher value cropping patterns. These are all knowledge intensive technologies that require not only a strong research and extension system and skilled farmers but also a reinvigorated interface where the emphasis is on mutual exchange of information bringing advantages to all. At the same time potential of less favored areas must be better exploited to meet the targets of growth and poverty alleviation. These challenges have profound implications for products of agricultural research. The way they are transferred to the farmers and indeed the way research is organized and conducted. One thing is, however, clear – the new generation of technologies will have to be much more site specific, based on high quality science and a heightened opportunity for end user participation in the identification of targets. These must be not only aimed at increasing farmers' technical knowledge and understanding of science based agriculture but also taking advantage of opportunities for full integration with indigenous knowledge. It will also need to take on the challenges of incorporating the socio-economic context and role of markets.

With the passage of time and accelerated by macro-economic reforms undertaken in recent years, the Institutional arrangements as well as the mode of functions of bodies responsible for providing technical underpinning to agricultural growth are proving increasingly inadequate. Changes are needed urgently to respond to new demands for agricultural technologies from several directions. Increasing pressure to maintain and enhance the integrity of degrading natural resources, changes in demands and opportunities arising from economic liberalization, unprecedented opportunities arising from advances in biotechnology, information revolution and most importantly the need and urgency to reach the poor and disadvantaged who have been by passed by the green revolution technologies. Another important implication of increasing globalization relates to the need for greater attention to the quality of produce and products both for the domestic and the foreign markets. This would imply that production must be tuned to actual rapidly changing product demand. Such adaptation to global markets would require state of the art research, which can be achieved only by setting global standards of research, focus on well-defined priorities and mechanisms which permit close interaction of farmers with researchers, the private sector and markets.

1.1.2 Climate change and agriculture

Climate change can affect crop productivity in both positive and negative way. There are many climatic factors that affect the agricultural productivity of which rainfall and temperature are considered to be more important. Variability in temperature, carbon sequestration and the frequency and significant changes in weather could have serious impact on crop productivity. For example, an increase in rainfall maximizes the productivity of the crop, but on the other hand it also prolongs the maturing period. At the same time increasing temperatures lead to excessive water requirement which increases the proneness to pest and diseases.

In the year 2007, IPCC (Intergovernmental Panel for Climate Change) in its fourth assessment has produced a report that gave a brief estimate of various past climatic scenarios and made a prediction of the future on various factors affecting the climate. As per this report, the earth's surface temperature has raised by 0.83°C since 1880 till now. It has also been stated that - by 2070, the mean temperatures in India are expected to rise up to 1.7°C in Kharif (July to October) and rise up to 3.2°C in Rabi (November to March) seasons. The mean precipitation is estimated to rise up to 10% by 2070. Thus from the overall estimates, IPCC concluded that there will be a rise in the agricultural productivity up to 20% in East and South East Asia but in the Central and South Asia productivity could decrease up to 30% by the end of 21st century.

1.1.3 Need for this Study

Climate change and agriculture processes are interrelated on the earth. Global warming - increasing temperature and upcoming water deficit are going to be greatly exacerbating and will have significant impact on agriculture in terms of their productivity, resistance to diseases etc. The effect in crop production is projected at 10-40% loss by 2100. So, we are in great necessity to adapt the future climate change for food security and socio- economic development.

The adaptation strategies may be short or long-term changes that respond to the effects of changes in climate. In agriculture, adaptation will require

- Cost-effective investments in water infrastructure,
- Emergency preparation to extreme weather events, development of resilient crop varieties that tolerate temperature and precipitation stresses, and
- Invention of new or improved land use and management practices.

Hence, in order to properly assess the strategies to be adapted, it is first necessary to understand the past and future climatic scenario. Climate modeling is one such source of getting the information about the climate scenario of regional and global scale. Hence, in this research various climate models have been used to give an idea about climate change impacts on agriculture and adaptation of future climate change.

1.2. Modeling approach for impact assessment

1.2.1 Climate Modeling

Modeling climate and Earth system processes on a regional scale is essential for projecting the impacts of climate change on society and our natural resources. Quantifying model biases is critical to characterizing the uncertainties associated with these climate change projections and is also an essential step in developing and improving Earth systems models. The Regional Climate Model Evaluation System (RCMES) is designed to greatly facilitate regional-scale evaluations of climate and Earth system model providing standardized access to a vast and comprehensive set of observations, as well as tools for performing common analysis and visualization tasks.

Eco-physiological models are generally used to forecast the potential impact of environmental factors on agricultural and natural ecosystem. Using quantitative methods, climate models will simulate the interactions of the land surface, ice, ocean and atmosphere. Climate models are used for getting high resolution climate scenario from the global level coarse resolution datasets. Compare with coarse resolution datasets we can get more information about them in high resolution datasets. High resolution datasets are mandatory for impact assessments.

Climate models are based on the dynamics and physics process. Climate models have been developed that consider social and economic factors (population and carbon emissions). By combining these factors with an understanding of global and regional climate science, experts have developed climate scenarios that express the potential for different behaviors to impact climate patterns. Climate scenarios have the ability to inform our choices about the likely impacts of temperature, precipitation, and seasonality on food production. They also allow us to guide agricultural sectors on the best methods to adapt to various climate consequences by evaluating impacts and identifying tradeoffs.

1.2.2 Crop Modeling

"Crop simulation models integrate current scientific knowledge from many different disciplines, including crop physiology, plant breeding, agronomy, agro meteorology, soil physics, soil chemistry, pathology and entomology". A crop model needs a season-long daily weather dataset to simulate the crop productivity. A skillful seasonal forecast in a monthly or seasonal average sense is recommended *(Pal et al., n.d.).*However, only mean values does not guarantee a good crop yield forecast*(Baigorria et al., 2007).*Operational climate season forecast generally focuses on seasonal mean rainfall while crop models are usually designed to assimilate daily rainfall values. Therefore, establishment of linkage between climate predictions with the crop simulation model can be an important tool for prediction of crop productivity for a season as well as to investigate suitable strategic options for crop management and food security.

Several researchers *(Tomei et al., 2009)* have used rainfall forecasts from different global circulation models (GCMs) for its application in crop simulation models with promising results. Grain productivity prediction using a crop simulation model requires weather input for entire growing season. When the availability of weather information is limited for certain period only, it becomes necessary to generate 'synthetic weather' for the remaining part of the season. This deficiency can be fulfilled by use of stochastic weather generator *(Hansen and Ines, 2005).*

1.3 Models in this Research

1.3.1. Regional Climate Model (RegCM 4.3.5.6)

National Center for Atmospheric Research (NCAR) developed the Regional Climate Model system initially and it is undertaken by the Earth System Physics (ESP) section of the ICTP. RegCM1 the initial version of model was developed in 1989.After that it has undergone major updates in 1993-RegCM2, 1999-RegCM2.5, and 2006-RegCM3 and now recently RegCM4-2010.

The newer version of the model, RegCM4, is now fully undertaken by the ESP, while previous versions are no longer available *(ICTP-2014)*. These upgrades include the structure of the code and its processors, along with the development of some new Dynamic Physics parameterizations. The model is easy to handle and can be used for any part of the World, with resolution up to about 10 km, and for a broad range of researches, from process studies to future climate simulation paleoclimate.

Model developments currently under way contains the development of a new microphysical cloud scheme that has to be released by the end of 2014, coupling with full gas-phase chemistry in regional ocean model, and upgrades of some physics schemes like convection, Planetary Boundary Layer, cloud microphysics and development of a non-hydrostatic dynamical core. Regional Climate Research Network, or RegCNET also supported by the ESP. The goal of RegCNET is to elaborate and strengthen the network of model utilizers and to improve collaborative researches across the network to improve the understanding of climate change at the high resolution. The RegCNET also supplies a forum for future and current model users to discuss related issues share their research experiences and make needs and importance for further model development and dissemination *(ICTP-2014)*.

1.3.2 Decision Support System for Agrotechnology Transfer (DSSAT)

DSSAT is a software application program that contains crop simulation models for over twenty eight crops which is being used for more than 20 years in over 100 countries over the world. It has to be functional and it can be used for processing the database management programs for weather, climate, soil, experimental data, utilities, crop management date and other application programs. The crop simulation models can simulate growth, development and productivity as a function of the soil, crop and atmospheric dynamics. DSSAT and its crop simulation models have been utilized for various applications ranging from on-farm and precision management to regional assessments of the impact of climate variability and climate change.

The inputs for these crop models include – daily weather data, soil surface and profile information, detailed crop management. Along with these some additional information about the crop genetics (provided in a crop species file by DSSAT) and info about the cultivar or variety should also be provided. The initiations are done at the planting or prior planting stage which is conducted as a daily step or in some cases as an hourly step depending on the crop model. Daily

updates of plant and soil water, nitrogen and carbon balances, as well as the crop's vegetative and reproductive development stage are made. \

As a part of simulating the multi - year crop management, DSSAT combines crop, soil, and weather data bases with crop models and application programs. DSSAT also provides an interactive environment by asking some conditional questions, thus reducing the processing time extensively compared to the real experiments. The application of a crop model mainly depends on the accuracy of the outputs, especially if real-world decisions or recommendations are based on modeled result. DSSAT also helps users to compare simulated outcomes with observed results thus evaluating the results of the model.

Evaluation process includes -running the model with minimum inputs and comparing the outputs with observed data. The upcoming release of DSSAT v4.6 will incorporate changes to both the structure of the crop models and the interface to the models and associated analysis and utility programs. Application programs for seasonal, spatial, sequence and crop rotation analyses that assess the economic risks and environmental impacts associated with irrigation, fertilizer and nutrient management, climate variability, climate change, soil carbon sequestration, and precision management are additional advantages of the upcoming DSSAT model.

1.4. Research Objectives

- Downscaling of Global Circulation Model (EH5OM) output by using regional climate model for creating high resolution climate change scenario
- Crop model (DSSAT) simulation and validation of Maize and wheat productivity in Himachal Pradesh under current climate
- Assessing magnitude and direction of regional productivity changes of Maize and Wheat crops under future climate scenario.

1.5 Research Questions

- How well models can predict the future climate, climate scenario and agricultural productivity of western Himalayan region?
- How well crop model can predicting crop productivity under current and future climate?
- What will be the impacts on productivity of major food grain crops due to climate change?

1.6 Structure of Thesis:

The thesis comprises 6 chapters. Chapter 1 gives an introduction of the study, its justification, objectives, and the general temperament of the research. Chapter 2 reviews the available literature on the study. A critical review of previous research work on related topics is performed. An in-depth description of variables key to the study is found in this chapter. Study area and the agronomic importance of wheat and maize are discussed in the Chapter 3. Chapter 4 lays out the materials and methodology used to accomplish the study. Chapter 5 documents the results obtained in statistical mode. The discussion of the results/ findings in the background of the scientific objectives and the research questions, as well as in the light of the chosen theoretical framework is also incorporated in this chapter. Chapter 6 gives the recommendations and conclusion with hints for future research and practical utility of the project.

REVIEW OF LITERATURE

REVIEW OF LITERATURE CHAPTER 2

India is agriculture dependent country and it has a significant history. India has second place in agriculture productivity among the world countries. Agriculture plays major role in India's GDP and economic growth of India. It provides direct and indirect employment. As per the FAO world statistics India is the largest producer of fruit crops, major spices fibrous crops, meat and vegetables. Climate change is major factor that can affect crop growth and productivity positively and negatively. Increase in rainfall will increase crop yield, and what is more, crop productivity is more sensitive to the precipitation than temperature. If water availability is reduced in the future, soils of high water holding capacity will be better to reduce the impact of drought while maintaining crop yield*(Kang et al., 2009)*. The study found that increases in temperature (by about 2°C) reduced potential grain yields in most places. "Temperature has risen by 0.6° C in the last 100 years and it is projected to rise by 3.5-5° C by 2100. Western Himalaya have experienced three time than whole Indian subcontinent in last 100 years *(4th assessment IPCC, 2007)".*Climate change induced by increasing greenhouse gases is likely to affect crops differently in every regions. Productivity of most cereals would loss due to increase in temperature and decrease in water availability, especially in Indo-Gangetic plains.

2.1. Modeling approach for Climate change simulation

2.1.1. Climate change and its impacts

Climate change: *"Climate change refers to a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer and it may be due to natural internal processes or external forcing such as modulations of the solar cycles, volcanic eruptions, and persistent anthropogenic changes in the composition of the atmosphere or in land use".*

Climate change is defined by UNFCCC is *"A change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods".*

Impacts: In this report, the term *impacts* are referred as how extreme weather and climate factors are affecting the natural and human systems. Impacts generally define to effects on, livelihoods, lives, social, ecosystems, economic, health status, cultural assets, services (including environmental), and infrastructure due to the climate change or hazardous climate events happening within a particular time period and the vulnerability of a society. Impacts are also defined to as "*consequences* and *outcomes*".

The impacts of climate change on geophysical systems including droughts, sea-level rise, and floods, and are a subset of impacts called physical impacts.

2.1.2. Climate Change - IPCC 2007

Climate change refers to any change in climate over time, whether due to natural variability or artificial disturbances due to human activities, (IPCC, 2007). The Inter-governmental Panel for Climate Change (IPCC), a combined initiative of the World Meteorological Organization (WMO) and United Nations Environment Program (UNEP) formed in 1988 to ―assess on a comprehensive, objective, open and transparent basis the scientific, technical and socioeconomic information relevant to understanding the scientific basis of risk of human-induced climate change, its potential impacts and options for adaptation and mitigation. IPCC has published four assessment reports regarding the global climate change and the fifth is under formulation.

The major findings of IPCC fourth Assessment report are explained in the following paragraphs. Climate is defined as the average weather (Temperature, Rainfall, wind speed, Relative Humidity, Solar radiation etc.) for a minimum period of 30 years. The change in climate occurs due to internal dynamics or external (forcing) factors. The forcing factors include natural phenomenon (volcanic eruption and solar variations) as well as anthropogenic effects. Human activities such as injudicious use of fossil fuels and removal of forest cover leads to the increased emission of Greenhouse gasses (GHG) to the atmosphere and that add to the global warming.

There is a significant increase in global atmospheric CO2 concentration from 280 ppm in the preindustrial era to 379 ppm in 2005 (35% increase).The global average temperature has increased about 0.74oC ± 0.18oC over the last century (1906 to 2005).This happened in two phases from 1910 to 1940 (0.34oC) and more strongly from 1940 to present (0.55oC). It is observed that since 1970s the warming over land mass is greater than that over the ocean.

The occurrence of precipitation shows large natural variability and mainly depends on temperature and atmospheric water vapor fed by weather systems. As per Clausius-Clapeyron relation, every 1oC rise in temperature leads to 7% increase in atmospheric water holding capacity. Thus the increase in atmospheric temperature will change the amount, intensity, frequency and type of precipitation. If there is no significant increase in precipitation the hike in temperature leads to increased drying of land surface. That is "The warmer climate therefore increases risks of both drought − where it is not raining − and floods − where it is − but at different times and/or places".

2.2. Vulnerability to climate change

The first step in our approach involves the creation of a climate change vulnerability profile. Vulnerability to climate change is generally understood to be a function of a range of biophysical and socioeconomic factors. The most recent report of the Intergovernmental Panel on Climate Change (IPCC) provides a useful typology suggesting that vulnerability may be characterized as a function of three components: adaptive capacity, sensitivity, and exposure. Adaptive capacity describes the ability of a system to adjust to actual or expected climate stresses, or to cope with the consequences. It is considered ''a function of wealth, technology, education, information, skills, infrastructure, access to resources, and stability and management capabilities''. Sensitivity refers to the degree to which a system will respond to a change in climate, either positively or negatively. Exposure relates to the degree of climate stress upon a particular unit of analysis; it may be represented as either long-term change in climate conditions, or by changes in climate variability, including the magnitude and frequency of extreme events.

In this study we focus on exposure to long-term climate change as projected by global climate models. Nevertheless, our measures of sensitivity and adaptive capacity can also be used to represent vulnerability to climate variability, as farmers will be adapting to changes in extreme temperatures and monsoon variability as much as to changes in mean conditions. Our approach applies the IPCC typology to develop measures of adaptive capacity, sensitivity and exposure. In effect, we are operationalizing the IPCC definition of vulnerability in a sub-national assessment to show how different factors that shape vulnerability vary within one country. While our approach represents only one interpretation of the IPCC typology, it does provide an important entry point for discussions and debates Related to the utility of vulnerability mapping at sub national levels. In developing our climate change vulnerability profile, we assumed that climate change exposure (i.e., ongoing and future exposure) will affect current sensitivity, either positively or negatively, and that farmers will respond to these changes in climate sensitivity if they have sufficient adaptive capacity. Thus the vulnerability profile is constructed by combining indices for adaptive capacity with sensitivity indices that take into account exposure to climate change. To measure adaptive capacity, we identified significant biophysical, socioeconomic, and technological factors that influence agricultural production. The biophysical indicators used in the profile consisted of soil conditions (quality and depth) and ground water availability. We selected these indicators based on the assumption that areas with more productive soil and more groundwater available for agriculture will be more adaptable to adverse climatic conditions and better able to compete and utilize the opportunities of trade.

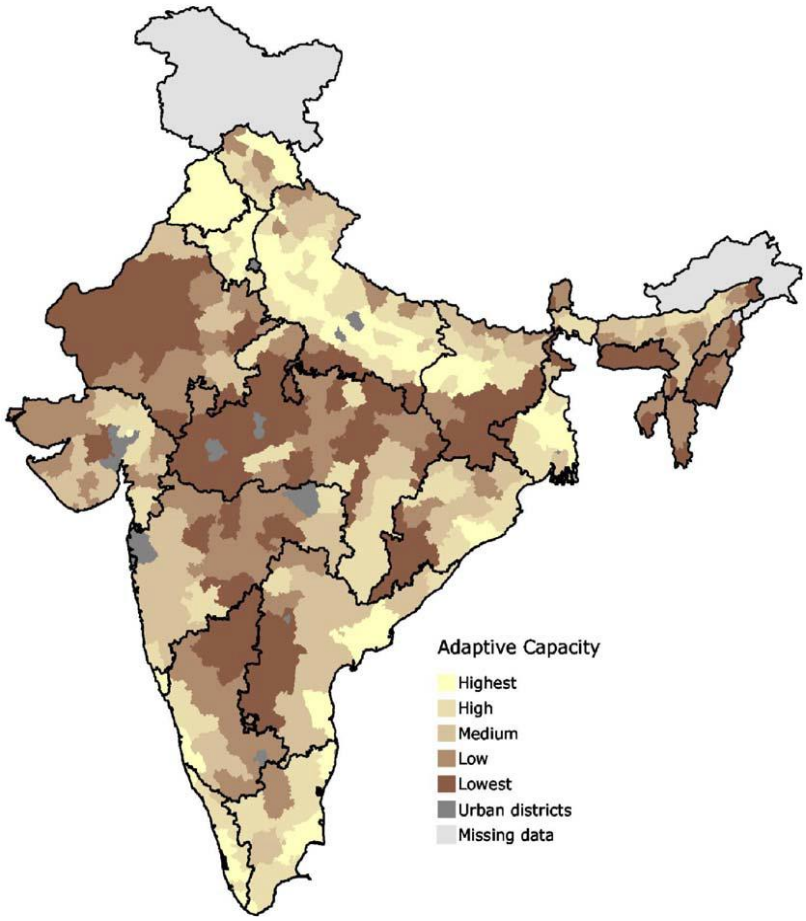


Fig. 2.1. District-level mapping of adaptive capacity in India. Adaptive capacity is measured here as a composite of biophysical, social, and technological indicators. Districts are ranked and presented as quintiles.

2.3. Present Climate Variability and Change in the Arid and Semi-Arid Tropics

Tropical Asia, including arid and semi-arid tropics, has a unique climatological distinction because of the pervasive influence of the monsoons. The summer southwest monsoon influences the climate of the region from May to September, and the winter northeast monsoon controls the climate from November to February. The monsoon brings most of the region's precipitation and is the most critical climatic factor in the provision of drinking water and water for rain-fed and irrigated agriculture.

Downscaling Climate scenario and its impact on major food grains Productivity in Himachal Pradesh

The El Ni˜no-Southern Oscillation (ENSO) phenomenon, which is geographically very extensive, has an especially important influence on the weather and inter-annual variability of climate and sea level, particularly in the western Pacific Ocean, South China Sea, Celebes Sea, and the northern Indian Ocean.*(Suppiah, 1997*)has found a strong correlation between the southern oscillation index (SOI) and seasonal rainfall in the dry zone of Sri Lanka; *(Clarke and Liu, 1994)*relate recent variations in south Asian sea-level records to zonal ENSO wind stress in the equatorial pacific. The influence of Indian Ocean sea-surface temperature on the large-scale Asian summer monsoon and hydrological cycle and the relationship between Eurasian snow cover and the Asian summer-monsoon also has been substantiated*(Zhu and Houghton, 1996)*.

Several countries in this region have reported increasing surface temperature trends in recent decades. The warming trend over India has been reported to be about 0.57 ◦C per 100 yr*(Kumar et al., 1997)*. In Pakistan, annual mean surface temperature has a consistent rising trend since the beginning of 20th century*(Sivakumar et al., 2005)*. In most of the Middle East, the long-time series of surface air temperature show a warming trend. In Vietnam, annual mean surface temperature has increased over the period 1895–1996, with mean warming estimated at 0.32 ◦C over the past three decades. Annual mean surface air temperature anomalies over Sri Lanka during the period 1869–1993 suggest a conspicuous and gradually increasing trend of about 0.30 ◦C per 100 yr *(Kumar et al., 1997)*.

In general, an increasing trend in temperature has been observed in southern and central India in recent decades in all seasons and over all of India in the post monsoon seasons. This warming has generally been accompanied by increases in diurnality except over northern India in the winter, pre-monsoon and post-monsoon seasons. *(Chattopadhyay and Hulme, 1997)*observed increase in trends of annual mean, maximum and minimum temperatures south of 23 ◦N and cooling trends north of 23 ◦N.The diurnal temperature range (DTR) shows an increasing trend in all the seasons over most of peninsular India. This is in contrast to many other land regions of the northern hemisphere*(Sivakumar et al., 2005)*.

Mean annual rainfall is considerably low in most parts of the arid and semiarid region of tropical Asia, and temporal variability quite high. In some places in the region, as much as 90% of the annual total is recorded in just two months of the year. Although, there is no definite trend discernible in the long-term mean for precipitation for the region or in individual countries during this time period, many countries have shown a decreasing trend in rainfall in the past three decades. In India, long-term time series of summer monsoon rainfall have no discernible trends, but decadal departures are found above and below the long-time averages alternatively for three consecutive decades*(Kothyari and Singh, 1996)*. Recent decades have exhibited an increase in extreme rainfall events over northwest India during the summer monsoon *(Mall et al., 2006)*.

Moreover, the number of rainy days during the monsoon along east coastal stations has declined in the past decade.

A long-term decreasing trend in rainfall in Thailand is reported (OEPP, 1996). In Pakistan, seven of 10 stations have shown a tendency toward increasing rainfall during monsoon season *(Sivakumar et al., 2005).(Sivakumar et al., 2005)* analyzed the trends in potential evapotranspiration (PE) for 10 stations in India including stations in arid and semi-arid tropics.

In the monsoon and post-monsoon seasons, PE was found to have decreased over the last 15 yr over the whole country, whereas in the winter and pre-monsoon seasons the trends are less consistent. The decreasing trend in PE is up to a maximum of about 0.3 mm day−1 decade−1 over west-central India in the monsoon and post-monsoon seasons (Figure 2.2). These trends are generally lower than for surface evapotranspiration (Ep) and represent a reduction in PE of less than 3% per decade. Changes in PE were most strongly associated with changes in relative humidity, particularly in the winter and pre-monsoon seasons. In the monsoon season, radiation was the dominant variable for regulating the PE variation at nearly all stations. Changes in both radiation and relative humidity are associated with decreases in PE in the post-monsoon season. No identifiable variability in the number, frequency, or intensity of tropical cyclones or depressions has been observed in the northern Indian Ocean cyclone region (Bay of Bengal and Arabian Sea) over the past 100 yr, though*(Gadgil, 1995)* has shown decadal-scale variations with a rising trend during 1950–1975 and a declining trend since that time. No conclusive increasing or decreasing trends in time series data of flooded areas has been noticed in various river basins of India and Bangladesh *(Kumar et al., 1997)*

Drought can reach devastating proportions in tropical Asia, though the incidence is variable in time and space. Drought or near-drought conditions occur in parts of Nepal, Papua New Guinea, and Indonesia, especially during El Ni˜no years. In India, Laos, the Philippines, and Vietnam drought disasters are more frequent during years following ENSO events. At least half of the severe failures of the Indian summer monsoon since 1871 have occurred during El Ni˜no years*(Kumar et al., 1997)*. When several decades were combined to provide an understanding of the decadal scale variability of drought occurrence in India, it is found that the 1891–1920 and 1961–80 periods witnessed frequent droughts while few droughts occurred during 1930–1960 and 1980–2000. This suggests some kind of low frequency oscillation of the monsoon system on the decadal scale.

(Sivakumar et al., 2005) observed that over arid and semi-arid regions of India, there have been periods in the last decades of the nineteenth century and first two decades of twentieth century when drought frequencies have been markedly higher than in recent years, though individual recent droughts may have been intense ones in some regions. There are also reports of an increase in thunderstorms over the land regions of tropical Asia*(Karl et al., 1995)*. The

frequency and severity of wild fires in grassland and rangelands in arid and semi-arid Asia have increased in recent decades*(Sivakumar et al., 2005)*.Low rainfall in arid and semi-arid regions dictates the formation of shallow soils, which are poor in organic matter and nutrients.

Coupled with the conversion of grazing lands to farming, the arid region of India is undergoing an aggravation of desertification through erosion of lands and aeolian shifting of soil particles. In some locations, there has been a rise of water table with simultaneous increase of salinity and deterioration of soil regime. The variation of the aridity index line, computed by Penman method, over arid regions of India reveals a possible spread of arid conditions in the southeast direction*(Sivakumar et al., 2005)*. Populations in arid or semi-arid areas of south Asia are most vulnerable because of their heavy dependence on agriculture and high population density.

Monsoon depressions and tropical storms are important features of the climate in this region from the agricultural production point of view. These storms can be destructive, but also are the main source of moisture. An estimated 31% of cropland is already irrigated, which may reduce vulnerability somewhat, provided water resources remain adequate. Chronic hunger remains a problem, however, for the poorer segments of the population particularly in semi-arid and arid parts of the region *(IPCC, 1995)*.

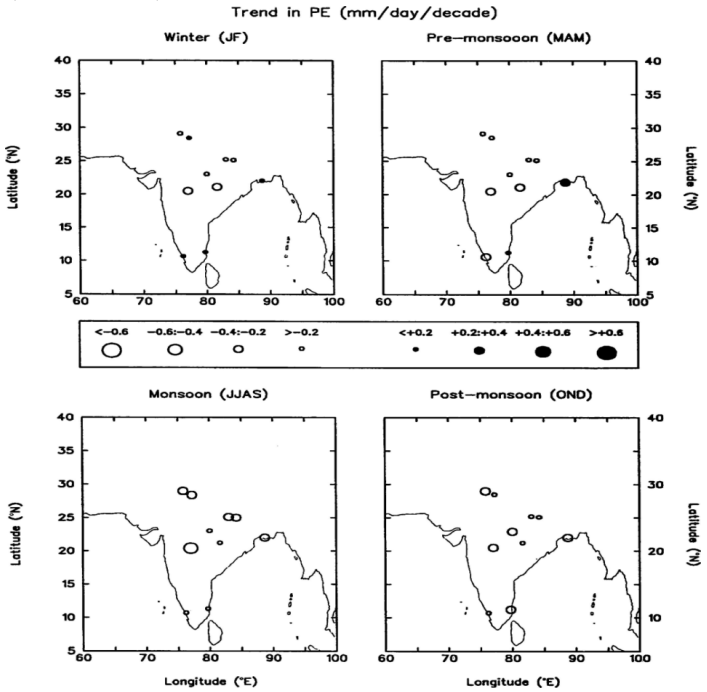


Figure 2.2. Mean linear trend (mm day−1 decade−1) in PEfor the period from 1976 to 1990 for different seasons over India based on ten stations data. Dot size is related to trend.

2.4. Downscaling

Downscaling is a method for obtaining high-resolution climate or climate change information from relatively coarse-resolution global climate models (GCMs). Typically, GCMs have a resolution of 150-300 km by 150-300 km. Many impacts models require information at scales of 50 km or less, so some method is needed to estimate the smaller-scale information. Downscaling techniques are two types:

1) Dynamic Downscaling
2) Statistical Downscaling

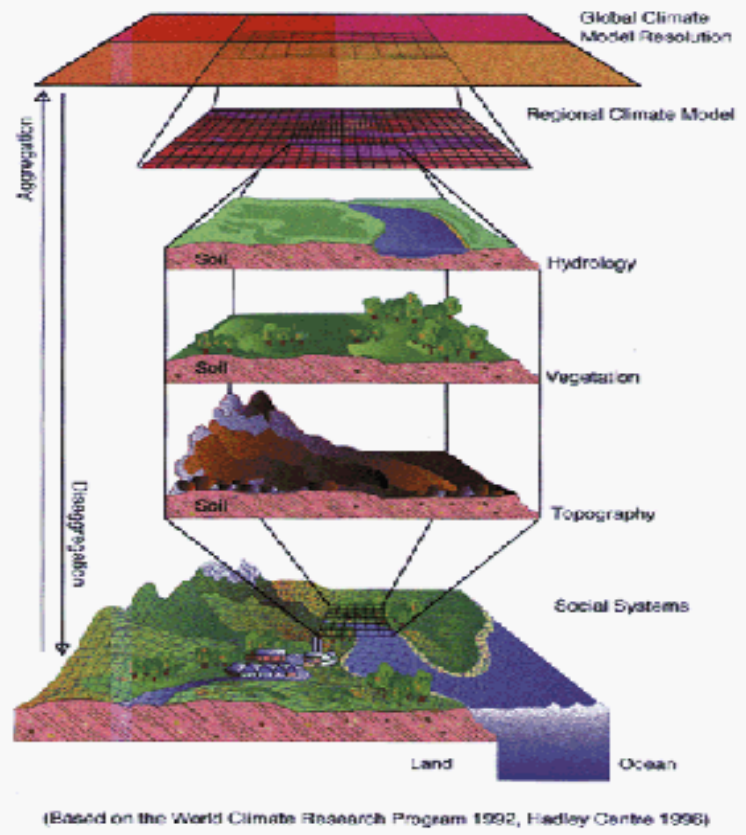


Figure 2.3 Dynamic Downscaling methodology

2.4.1 Dynamic and Statistical Downscaling

	Dynamical Downscaling	**Statistical Downscaling**
Description	Dynamical downscaling uses a limited-area, high-resolution model (a regional climate model, or RCM) driven by boundary conditions from a GCM to derive smaller-scale information. RCMs generally have a domain area of 106 to 107 km2 and a resolution of 20 to 60 km.	Statistical downscaling first derives statistical relationships between observed small-scale (often station level) variables and larger (GCM) scale variables, using either analogue methods (circulation typing), regression analysis, or neural network methods. Future values of the large-scale variables obtained from GCM projections of future climate are then used to drive the statistical relationships and so estimate the smaller-scale details of future climate (see also weather generators).
Appropriate Use	Dynamical downscaling can be used whenever impacts models require small-scale data.	Statistical downscaling may be used whenever impacts models require small-scale data, provide suitable observed data are available to derive the statistical relationships.
Scope	All locations.	All locations.
Key Output	Small-scale information on future climate or climate change.	Small scale information on future climate or climate change (maps, data, etc).
Key Input	Typically six-hourly, grid point GCM data for future climate to drive the RCM.	Appropriate observed data to calibrate and validate the statistical model(s). GCM data for future climate to drive the model(s).
Ease of Use	Requires considerable expertise in climate modeling — for specialists only.	Difficult to apply from first principles since it requires access to large data sets and considerable expertise to derive the statistical relationships. User-friendly software to facilitate use is available
Training Required	Considerable knowledge and experience required.	Considerable knowledge and experience is required to work from first principles.

		Use of packages like SDSM, however, requires relatively little training.
Training Available	No specific training courses available.	A training course for SDSM was held in late 2002, but there are no plans currently for future courses.
Computer Requirements	Same computer requirements as a GCM — i.e., high-level supercomputer or massively parallel computer.	Personal computer.
Documentation	Numerous publications in the scientific literature.	Numerous publications in the scientific literature. The SDSM package provides a list of the most useful such publications arranged by category.
Applications	Widely applied in many regions and over a range of climate impact sectors. For a specific example, see Hay and Clark (2003) in References below.	Widely applied in many regions and over a range of climate impact sectors.
Contacts for Framework, Documentation, Technical Assistance	None.	SDSM may be obtained by registering at https://co-public.lboro.ac.uk/cocwd/SDSM/
Cost	High. Impractical except for academic or government institutions.	SDSM is free.
References	*(Fowler et al., 2007), (Leung et al., 2003), (Hinzman et al., 2005)*	*(Wilby and Dettinger, 2000), (Hay et al., 2000), (Hansen and Ines, 2005).*

Table 2.1: Comparison between Dynamic and Statistical Downscaling

2.4.1.1. Dynamic Downscaling

With dynamic downscaling, a low resolution image is enhanced to a finer resolution using output from another higher resolution data product and a certain numerical procedure to drive a Mesoscale regional, numerical model, which therefore is able to simulate local conditions in higher spatial and temporal resolution *(Kim and Wold, 1985)*and *(Lenart et al., 2008)*).It fits output from GCMs into regional meteorological models. Rather than using equations to bring

global-scale projections down to a regional level, dynamic downscaling involves using numerical meteorological modeling to reflect how global patterns affect local weather conditions. The level of detail involved strains computer capabilities, so computations can only tackle individual GCM outputs and brief time slices. Yet climatologists generally consider three decades about the minimum for deducing climatic conditions from the vagaries of weather *(Lenart, n.d.)* All the atmospheric processes as we can put are governed by certain laws of physics which can be expressed mathematically in the form of various differential equations. These set of equations are put together to constitute a numerical model. Hence, a numerical model is a mathematical representative of a physical system and falls under the category of dynamic downscaling. Downscaling of extreme events at a larger resolution in numeric and physical based future regional climate model simulations will provide sufficient information at the spatial scale necessary for climate change decision making and adaptation *(Castro et al., 2010)*. Some refined form of dynamic downscaling simulation use a grid nesting. The model-level data needs to be interpolated on vertical pressure levels. The model grid data are projected to a horizontal latitude-longitude or to a polar stereographic grid; in the case of spectral models, the spectral coefficients have to be transformed into grid points. Both empirical and dynamical downscaling techniques have the potential to improve on large-scale forecasts of GCMs. Empirical techniques are easy to use and do not require lots of computational resources; climate might be unstable. Dynamical techniques are relatively complex and consume a lot of computational resources; skill limited by parameterization schemes, etc. To justify its operational use, dynamical techniques should outperform empirical techniques *(Castro et al., 2010)*.

2.4.2. Emission Scenarios

As per IPCC Special Report on Emission Scenarios (SRES) there are four storylines viz. A1, A2, B1 and B2 which represent different demographic, social, economic, technological and environmental developments. Concentration scenarios derived from emission scenarios are used as input to climate models to project future change in climate (IPCC, 2007). Table 2.6 Explains about how the storylines are divided under economical v/s environmental priorities and global v/s regional development. Atmosphere-Ocean General Circulation Models (AOGCMs) are the most advanced form of models available to simulate general circulation that is, "the large-scale motions of the atmosphere and the ocean as a consequence of differential heating on a rotating Earth".

The Global climate model (GCM) predictions are representative for a larger area (250 – 600 km) and in order to use it for regional level applications (10-100 km) downscaling is required. This can be achieved in two ways, either by dynamic downscaling using Regional climate models (RCM) or by empirical/statistical methods which link "large scale atmospheric variables with local/regional climate variables". The expected estimate of future rise in temperature is 1.1 – 2.9˚C for low scenario and 2.4 –6.4˚C for high scenario.

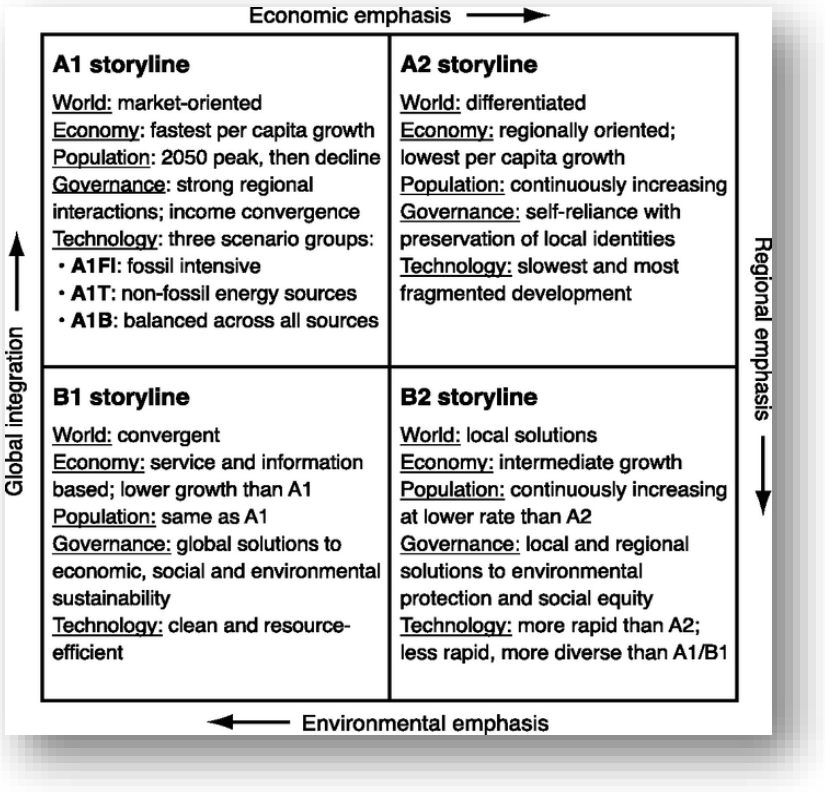


Table 2.2: Summary characteristics of the four SRES storylines (Adapted from Climate Change 2007: Working Group II)

2.5. Modelling approach for impact of climate change on crop productivity

2.5.1. Climate change and crop productivity: Indian Experiences

Agriculture plays a key role in overall economic and social well-being of India. Our country faces major challenges to increase its food production to the tune of 300 million tons by 2020 in order to feed its ever-growing population, which is likely to reach 1.30 billion by the year 2020. To meet the demand for food from this increased population, the country‘s farmers need to produce 50% more grain by 2020 *(Paroda and Kumar, 2000)* and*(Mall et al., 2006)*. Unfortunately, there are evidences of stagnation in yield growth rates of majority of food crops in recent decades. Climate change of some sort accompanied with rising temperature and altered pattern of precipitation would further negate the improvement in productivity by on-going genetic and other technological effort. In general, consequence of climate change may have serious implications for the country‘s food security and economy. Agricultural seasons naturally obtained in India are mainly divided into two, the summer or ‘Kharif’ and the winter or ‘Rabi’.

Downscaling Climate scenario and its impact on major food grains Productivity in Himachal Pradesh

'Kharif' season begins with the onset of south west monsoon (June - July) and end during the autumn (October –November) or winter (December –February) depending on crop duration. The major crops grown in this season are rice, maize, sugarcane, jute, cotton, soya bean, groundnut and bajra etc. This contributes more than 50% of the food-grain production and 65% of the oilseed production in the country. 'Rabi' season stars after the post /summer monsoon (October-November) and the major 'Rabi' crops are wheat, mustard, potato, onion, gram and barley. Summer monsoon provide essential soil moisture and often irrigation water for 'Rabi' crops*(Mall et al., 2006)*. In India about 60 % total cropped area is under rain fed conditions and any changes in precipitation pattern will affect the overall crop productivity.

The various studies conducted in India and abroad have shown that due to global warming, the surface air temperatures in India are going up at the rate of 0.4˚C per hundred years, particularly during the post-monsoon and winter seasons. It has been predicted with the help of Global Circulation (GCM) models that mean winter temperatures in India will increase by as much as 3.2˚C in the 2050s and 4.5˚C by 2080s, and summer temperatures will increase by 2.2˚C in the 2050s and 3.2˚C in the 2080s due to global warming. The expected increase in mean temperature in India during Kharif and Rabi season are respectively, 1.1 – 4.5 ˚C by 2070. Rainfall will increase up to 10% in both seasons by 2070.The details of various studies conducted in India using crop simulation models and experimental setups to assess the impact of climate change on wheat, rice and maize crop were compiled and are given in Table 2.7, 2.8 and 2.9 respectively.

There have been a few studies in India which aimed at understanding the nature and magnitude of yield gains or losses of crops at selected sites under elevated atmospheric CO2 and associated climatic change *(Gangadhar Rao et al., 1995), (Lal et al., 1998), (Rathore et al., 2001), (Aggarwal and Mall, 2002), (Attri and Rathore, 2003), (Mall et al., 2004).* Most of the simulation studies have shown a decrease in duration and yield of crops as temperature increased in different parts of India. Such reductions were, however, generally, offset by the increase in CO2; the magnitude of these changes varied with crop, region and climate change scenario.

(Sinha and Swaminathan, 1991) showed that an increase of 2˚C in temperature could decrease the rice yield by about 0.75 ton/ha in the high yield areas; and a 0.5˚C increase in winter temperature would reduce wheat yield by 0.45 ton/ha. *(Gangadhar Rao et al., 1995)* showed that wheat yields could decrease between 28 to 68% without considering the CO2 fertilization effects; and would range between +4 to -34% after considering CO2 fertilization effects. *(Aggarwal and Sinha, 1993)* using WTGROWS model showed that a 2oC temperature rise would decrease wheat yields in most places.*(Lal et al., 1998)*concluded that carbon fertilization effects would not be able to offset the negative impacts of high temperature on rice yields. *(Saseendran et al., 2000)* showed that for every one-degree rise in temperature the decline in rice yield would be about 6%.

*(Aggarwal, 2003)*using WTGROWS and recent climate change scenarios estimated impacts on wheat and other cereal crops.

In north India, irrigated wheat yields decreased as temperature increases, a 2 ˚C increase resulted in 17 % decrease in grain yield but beyond that the decrease was very high. The effect of climate change scenario of different periods can be positive or negative depending upon the magnitude of change in CO2 and temperature*(Aggarwal, 2003)*. He has crop simulation runs for two scenarios based on IPCC (2001) and pointed out that the irrigated wheat and rice yields in north India will not be significantly affected due to direct effect until 2050. It is only in 2070 when the temperature increases are very large, that the crops show large reduction in yield. The study conducted by *(Aggarwal and Mall, 2002)* shows the combined effect of atmospheric CO2 and temperature on rice crop in different Indian regions, showed that productivity gains possibly achieved in northern region through beneficial effect of 450,550 and 650 ppm CO2 could be nullified by 1.7, 3.5 and 5.0˚C increase in temperature.

It is projected that due to climate change, Kharif rainfall is going to increase and this might be positive for Kharif crops. Further, for Kharif crops, a one-degree rise in temperature may not have big implications for productivity. However, temperature rise in Rabi season will impact production of wheat, a critical food-grain crop. Productivity of most cereals would decrease due to increase in temperature and decrease in water availability, especially in Indo - Gangetic plains. The loss in crop production is projected at 10-40% by 2100. The impacts of the climate change on Indian agriculture would be small in near future, but in long run the Indian agriculture may be seriously affected depending upon season, level of management, and magnitude of climate change. Thus there is a need to investigate the impact of climate change on the important crops grown in specific regions for proper planning and adoption of different adaptation strategies.

Model used	**Region**	**Region Temperature (℃)**	**CO2 (ppmv)**	**Impact on yield**	**Reference**
WTGROWS	All India	+1	Normal	-0.43t/ha	*(Aggarwal and Kalra, 1994)*
	All India	+0.5(winter temperature)	Normal	-0.45 t/ha -10% (Punjab,Haryana,UP)	*(Sinha and Swaminathan, 1991)*

				-7 days (crop duration)	
	Punjab	+1	Normal	-8.1%	*(Mall et al., 2004)*
		+2		-18.7%	
		+3		-25.7%	
CERES	NW India	Normal	2 x CO2	+28 %	*(Lal et al., 1998)*
		+3	2 x CO2	Cancels positive effect of elevated CO2	

Table 2.3: Climate change impact on productivity of wheat in India: Past simulation studies

Model used	**Region**	**Region Temperature (℃)**	**CO2 (ppmv)**	**Impact on yield**	**Reference**
CERES-rice	All India	+2	Normal	-0.75 t/ha (high yield areas) -0.06 t/ha (low yield coastal area)	*(Sinha and Swaminathan, 1991)*
	Punjab	+1	Normal	-5.4%	*(Mall et al., 2004)*
		+2		-7.4%	
		+3		-25.1%	
	North West	Normal	2 x CO2	+15%	*(Lal et al., 1998)*
		+2	2 x CO2	Cancels positive effect of elevated CO2	
CERES-rice &ORYZA1N		up to +5	Normal	-6%(for every +1oC)	*(Saseendran et al., 2000)*
		+0.1	416	+3.5%	

	Kerala	+0.4	755	+33.8%	*(Aggarwal and Mall, 2002)*
		+0.3	397	+1.0%	
		+2.0	605	+16.8%	

Table 2.4: Climate change impact on productivity of rice in India: Past simulation studies

Model used	**Region**	**Region Temperature (℃)**	**CO2 (ppmv)**	**Impact on yield**	**Reference**
CERES maize	Punjab	+1	Normal	-10.4%	*(Mall et al., 2004)*
		+2		-14.6%	
		+3		-21.4%	
	North India	up to +4 350 Continuous	350	Continuous yield reduction	*(Khan et al., 2009*)
		Normal	700	+ 9%	
		+ 0.6	700	Nullified the beneficial effect of CO2 fertilization	

Table 2.5: Climate change impact on Indian maize

2.5.2 Climate change and Crop yield

Changes in crop yield will likely be affected from climatic variations. The likely impact from climate change on crop yield can be determined either by experimental data or by crop growth simulation models. A number of crop simulation models, such as CERES-Maize (Crop Environment Resource Synthesis), CERES-Wheat and SWAP (soil–water– atmosphere–plant), have been widely used to evaluate the possible impacts of climate variability on crop production, especially to analyze crop yield-climate sensitivity under different climate scenarios. Most studies related to role of climate change in wheat production are concerned with future CO2 concentration. Climate change impacts on wheat production with DSSAT 3.5 (Decision Support System for Agrotechnology Transfer) CERES-Wheat models has been discussed under all CO2 levels in Southern Australia for 2080s, and the result shows that wheat yield will increase under

all CO2 levels and the drier sites are more suitable for wheat production but are likely to have lower wheat quality*(Luo et al., 2007)*.

The temperature effect on the crop yield in India with the regional climate model PRECIS and the GLAM crop model under present (1961–1990) and future (2071– 2100) climate conditions was studied and the result shows that the mean and high temperature are not the main factors to decide the crop yield, but extreme temperature has a negative effect on crop yield when irrigation water is available for the extended growing period*(Challinor et al., 2009)*. Impact of climate change on crop yield is different for various areas. Depending on the latitude of the area and amount of irrigation applied, yield changes. The crop yield can increase with application of irrigation and precipitation increase during the crop growth however it is more sensitive to the precipitation than temperature. With climate change, the growing period will reduce, and the planting date also needs to change for higher crop production*(Kang et al., 2009)*.The positive effects of climate change on agriculture are concerned with the CO2 concentration, crop growth period increases in higher latitudes and montane ecosystems; the negative effects include the increasing incidence of pests and diseases, and soil degradation owing to temperature change*(Lal, 2004)*. This has urged scientists to develop crop varieties suiting climate change and degrading soil in order to obtain sufficient yield for the increasing population.

Crop model	Objective crop	Predicted impacts	Reference(s)
CERES-Maize	Maize	• Dry matter • Sustainable production • Planting date and different weather • Precise and deficit irrigation	*(LI et al., 2012)* (*Soler et al., 2013)* *(Popova et al., n.d.)*
CERES-Wheat	Wheat	• CO2 levels	*(Eitzinger et al., 2012)* *(Luo et al., 2007)*
CropSyst	Wheat	• Rainfall and warming temperature	*(Anwar et al., 2013)*
CERES-Rice	Rice	• CO2 levels	*(Yao et al., 2007)*
SWAP	Rice	• CO2 levels	

InFoCrop	Rice	• Elevated CO2and temperature • Climate change	*(Aggarwal, 2003)*
IBSNAT-ICASA	Cereal	• Climate change	*(Aggarwal, 2003)*
GLAM	Peanut	• Climate change	*(Challinor et al., 2009)*
GLYCIM	Soybean	• Temperature rainfall and CO2concentration	
SWAT	Maize	• Climate vulnerability	*(Xie et al., 2008)*

Table 2.6: List of crop models and its objectives

2.5.3 Climate change and crop water productivity

In the 21st century global agriculture must increase food production for the growing population under increasing scarce water resources, which can be met by improving crop water productivity. Water productivity is a concept to express the value or benefit derived from the use of water and includes essential aspects of water management such as production for arid and semi-arid regions*(Zwart and Bastiaanssen, 2004)*.Increasing water productivity means either to produce the same yield with less water resources or to obtain higher crop yields with the same water resources*(Zwart and Bastiaanssen, 2004)*.

2.6. Crop Yield Forecasting

On field surveying or so called judgmental forecasting systems is the earliest method of forecasting crop yields. This approach that uses sampling techniques at field level with inputs from farmers and extension workers could give better results but they can be more subjective and far from being time and cost effective *(for instance the "Delphi expert forecasting method" for coffee, (Eitzinger et al., 2012).* There is a need to develop sound objective forecasts of crop production. The main advantage of those developed models would be to provide objective forecasts of regional yields in advance of the harvest proper, and at the fraction of the cost of sampling techniques.

Through common sense one can infer the importance of weather on crop growth and yield. Plenty of research has been done to examine the impact of weather parameters on the crop growth and phenology *(Agrawal, n.d.).* Most of the techniques developed to forecast crop production validate this concept. Traditional statistical techniques are purely empirical being uni-variate or multi-variate. They relate crop yield either to the crop components that affect yield or consider the crop-weather relationships by developing statistical relationships between historical data. These models require a long series of weather data and reliable crop yield data for calibration of

the model. The data of one station is then used for large areas, which may not be representative of regional variability in weather conditions. Indian scenario has also seen such kind of models successfully used for forecasting yields of various crops at district level and agro climatic zone level *(Agrawal, 2012, n.d.)(Khan et al., 2009*). Some more sophisticated techniques also came as an improvement to the simple empirical models like complex polynomial approach, artificial neural network approach, semi-empirical approach, etc, were also tested in recent years *(Mehta et al., 2000)*. Most models do not respond well to extreme conditions in weather. The major disadvantage is that they work best when the weather conditions are within the range of the data that are used for fitting the models. While these methods may result in accurate predictions, they typically lack the interpretability of process-based models *(Barnett, 2004).* These models are known to often over-react due to their dependence on a too limited number of factors *(Selvaraju et al., 2011).* The data available for this purpose are often insufficient.

A practical problem is also scarcity of availability of key weather parameters driving the processes of crop growth and development (e.g. Temperature, Sunshine hours and Relative humidity etc.) A few techniques also valued the importance of plant characteristics (biometrics) on yield. Effects of weather and inputs on crop performance are manifested through crop stand, number of tillers, leaf area, and number of ear heads etc. which ultimately determine crop yield. As such, plant characters can be taken as the integrated effects of various weather parameters and crop inputs. In India, yield is directly regressed on plant counts and yield contributing characters for obtaining forecast model. Considerable work has been done at Indian Agricultural Statistics Research Institute (IASRI) using this approach *(Jain and Agrawal, 1992).* The data are collected at different periodic intervals through suitable sampling design for 3 to 4 years from farmers' fields. This technique is however not applicable in varieties that takes short interval to complete critical stages for example a country like India were the interval between the grain formation and harvest is less than even one month. Another popular approach in regional crop yield estimation is the use of Remote sensing data to demarcate the cropped area spatially and to identify the present vigor of the crop by certain indices and relate it to final yield. The primary assumption is that the spectral data has a strong correlation with canopy parameters. Several studies established good correlation between vegetation indices and grain yield *(Tucker et al., 1983*) *(Malingreau, 1986)(Doraiswamy et al., 2003).* In India the research at a larger scale started with Crop Acreage and Production Estimation *(Jones et al., 2003)(CAPE, 1987)* mission under the Remote Sensing Applications Mission by Department of Agriculture and Cooperation and Department of Space for state-level crop estimates. Such spectral based yield models also subject to uncertainty due to lack of accountability of abnormal weather conditions. Also the presence of clouds in the data increases the complexity in acquiring data at different time intervals which is essential to develop a robust model.

2.7. Regional Climate Model (RegCM) Vs Global Circulation Model (ECHAM)

2.7.1 Regional Climate Model (RegCM):

2.7.1.1 RegCM Model - Dynamic Physics and Schemes:

2.7.1.2 Components of RegCM:

Terrain, ICBC, RegCM and Postprocessor these are the components of RegCM modelling system. Terrain and ICBC are the RegCM preprocessor components. Terrestrial variables including elevation, land use and sea surface temperature and three-dimensional isobaric meteorological data are horizontally interpolated from a latitude longitude mesh to a high-resolution domain on either a Rotated (or Normal) Mercator, Lambert Conformal, or Polar Stereographic projection. Vertical interpolation from pressure levels to the σ coordinate system of RegCM is also performed. σ Surfaces near the ground closely follow the terrain, and the higher-level σ surfaces tend to approximate isobaric surfaces.

Since the vertical and horizontal resolution and domain size can vary, the modeling package programs employ parameterized dimensions requiring a variable amount of core memory, and the requisite hard-disk storage amount is varied accordingly.

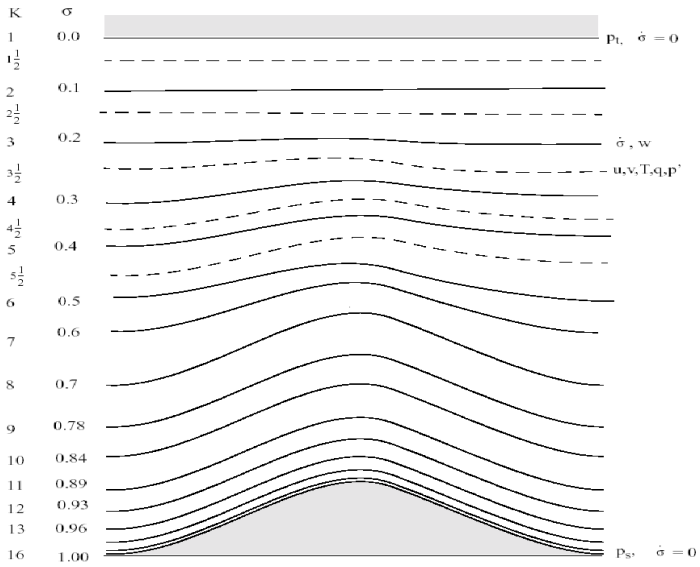


Figure 2.4: Schematic representation of the vertical structure of the model. This example is for 16 vertical Layers. Dashed lines denote half-sigma levels, solid lines denote full-sigma levels. (Adapted from the PSU/NCAR Mesoscale Modeling System Tutorial Class Notes and User's Guide.)

2.7.1.3 Horizontal and Vertical grids of RegCM:

It is useful to first introduce the model's grid configuration. The modeling system usually gets and analyzes its data on pressure surfaces, but these have to be interpolated to the model's vertical coordinate before input to the model. The vertical coordinate is terrain-following (Figure 2.1) meaning that the lower grid levels follow the terrain while the upper surface is flatter. Intermediate levels progressively flatten as the pressure decreases toward the top of the model. A dimensionless σ coordinate is used to define the model levels where p is the pressure, pt is a specified constant top pressure, and ps is the surface pressure.

$$\sigma = (p - pt)/(ps - pt) \quad \text{---------- (2.1)}$$

It can be seen from the equation and Figure 2.1 that σ is zero at the top and one at the surface, and each model level is defined by a value of σ. The model vertical resolution is defined by a list of values between zero and one that do not necessarily have to be evenly spaced. Commonly the resolution in the boundary layer is much finer than above, and the number of levels may vary upon the user demand.

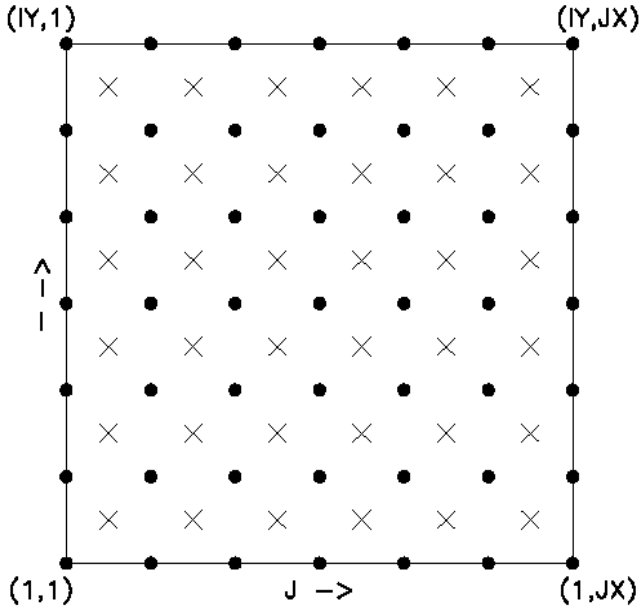


Figure 2.2: Schematic representation showing the horizontal Arakawa B-grid staggering of the dot and cross grid points.

The horizontal grid has an Arakawa-Lamb B-staggering of the velocity variables with respect to the scalar variables. This is shown in Figure 2.2 where it can be seen that the scalars (T, q, p, etc) are defined at the center of the grid box, while the eastward (u) and northward (v) velocity components are collocated at the corners. The center points of grid squares will be referred to as cross points, and the corner points are dot points. Hence horizontal velocity is defined at dot points. Data is input to the model, the preprocessors do the necessary interpolation to assure consistency with the grid.

All the above variables are defined in the middle of each model vertical layer, referred to as half-levels and represented by the dashed lines in Figure 2.1. Vertical velocity is carried at the full levels (solid lines). In defining the sigma levels it is the full levels that are listed, including levels at $\sigma = 0$ and 1. The number of model layers is therefore always one less than the number of full sigma levels. The finite differencing in the model is, of course, crucially dependent upon the grid staggering wherever gradients or averaging are represented terms in the equation.

2.7.1.4 Map Projections and map scale factors of RegCM:

The modeling system has a choice of four map projections. Lambert Conformal is suitable for mid-latitudes, Polar Stereographic for high latitudes, Normal Mercator for low latitudes, and Rotated Mercator for extra choice. The x and y directions in the model do not correspond to west-east and north-south except for the Normal Mercator projection, and therefore the observed wind generally has to be rotated to the model grid, and the model u and v components need to be rotated before comparison with observations. These transformations are accounted for in the model pre-processors that provide data on the model grid (Please note that model output of u and v components, raw or post processed, should be rotated to a lat/lon grid before comparing to observations). The map scale factor, m is defined by

$$m = \boxed{\text{(distance on grid) / (actual distance on earth)}}$$

and its value is usually close to one, varying with latitude. The projections in the model preserve the shape of small areas, so that dx=dy everywhere, but the grid length varies across the domain to allow a representation of a spherical surface on a plane surface. Map-scale factors need to be accounted for in the model equations wherever horizontal gradients are used.

2.7.1.4. Radiative Transfer Scheme:

Radiative transfer calculations in RegCM4 are carried out with the radiative transfer scheme of the global model CCM3 *(Kiehl et al., 1998),* as implemented by *(Giorgi et al., 1999)*. This contains both atmospheric gases and aerosols and calculations for the infrared and shortwave parts of the spectrum. The scheme includes contributions from all main greenhouse gases, i.e. H2O, CO2, O3, CH4, N2O, and CFCs, and solar radiative processes are treated using a delta-Eddington formulation *(Briegleb, 1992).* Aerosol's scattering and absorption of solar radiation

are also contained based on the aerosol optical properties (single scattering albedo and absorption coefficient). The cloud scattering and absorption parameterization follow that of *(Slingo, 1989)*, whereby the optical properties of the cloud droplets (extinction optical depth, single scattering albedo, and asymmetry parameter) are expressed in terms of the cloud liquid water content and an effective droplet radius. When cumulus clouds are formed, the grid point fractional cloud cover is such that the total cover for the column extending from the model-computed cloud-base level to the cloud-top level (calculated assuming random overlap) is a function of horizontal grid point spacing. The thickness of the cloud layer is assumed to be equal to that of the model layer, and a different cloud water content is specified for middle and low clouds.

2.7.1.5. Planetary boundary layer:

Two major developments have occurred in RegCM4 concerning the description of planetary boundary layer (PBL) processes. First, the scheme currently available in the RegCM system, that of *(Holtslag et al., 1990)*, underwent various modifications, and second a new PBL scheme, the University of Washington PBL *(Grenier and Bretherton, 2001)* and *(Bretherton et al., 2004)*, was implemented in the model. In the Holtslag scheme, a PBL height is first diagnostically calculated based on an iteration procedure employing a bulk critical Richardson number formulation *(Holtslag et al., 1990)*. Then a non-local vertical profile of eddy diffusivity for heat, moisture, and momentum is specified from the surface to the PBL height, and a counter gradient transport term is added for temperature and moisture. The eddy diffusivity depends on the friction velocity, height, Monin-Obhukov length, and PBL height *(Holtslag et al., 1990)*.

One of the deficiencies identified in RegCM3 has been the lack of simulation of low level stratus clouds, a problem clearly tied to the excessive vertical transport in the Holtslag PBL scheme *(T. A. O'Brien et al. unpubl.)*. To address this problem, *T. A. O'Brien et al. (unpubl.)* coupled the general turbulence closure parameterization of *(Grenier and Bretherton, 2001)*and *(Bretherton et al., 2004)*to the RegCM4, which we refer to as UW-PBL. This is a 1.5 order local, down-gradient diffusion parameterization in which the velocity scale is based on turbulent kinetic energy (TKE). The TKE is in turn calculated prognostically from the balance of buoyant production/destruction, shear production, dissipation vertical transport, and horizontal diffusion and advection. The scheme also parameterizes the entrainment process and its enhancement by evaporation of cloudy air into en trained air.

2.7.1.6. Cumulus Convection:

At present, RegCM4 includes 3 options for representing cumulus convection. The first is a simplified version of the Kuo-type scheme of *(Anthes, 1977)*, as described by *(Anthes et al., 1987)*. This scheme has been present since the earliest version RegCM1 and activates convection when the column moisture convergence exceeds a threshold value. This scheme, although still available, is used only very occasionally and generally provides poorer precipitation simulations

than the other available parameterizations. The second, and to date most used scheme, is that of *(Grell, 1993)* in the implementation of *(Giorgi et al., 1993)*. This is a mass flux deep convection parameterization in which clouds are considered as 2 steady state circulations including an updraft and a penetrative downdraft. The scheme is triggered when a parcel lifted in the updraft eventually reaches the moist convection level. A single cloud model is used with entrainment and detrainment only at the cloud bottom and top. Two different closures can be adopted: an Arakawa-Schubert type closure in which all buoyant energy is immediately released at each time step and a Fritsch-Chappell type closure in which the available buoyant energy is released with a time scale typically on the order of 30 min. A number of parameters present in the scheme can be used to optimize its performance, and *(Giorgi et al., 1993 b)* discussed a wide range of sensitivity experiments. We found that the parameter to which the scheme is most sensitive is by and large the fraction of precipitation evaporated in the downdraft (Peff, with values from 0 to 1), which essentially measures the precipitation efficiency. Larger values of Peff lead to reduced precipitation. The Grell scheme has been available in the RegCM system since its second version, RegCM2 *(Giorgi et al., 1993 b)*and it is currently the one most used. A third scheme was introduced in RegCM3 *(Pal et al., 2007)*, the so called MIT scheme *(Emanuel, 1991)* and *(Emanuel and Živković-Rothman, 1999)*. In this parameterization, convection is triggered when the level of buoyancy is higher than the cloud base level. Cloud mixing is considered to be episodic and in homogenous, and convective fluxes are based on a model of sub-cloud-scale updrafts and downdrafts. Precipitation is based on auto conversion of cloud water into rain water and accounts for simplified ice processes.

The MIT scheme is the most complex of the 3 and also includes a number of parameters that can be used to optimize the model performance in different climate regimes. Differently from the Grell scheme, however, test experiments did not identify a single parameter to which the model is most sensitive. A major augmentation in RegCM4 compared to previous versions of the model is the capability of running different convection schemes over land and ocean, a configuration which we refer to as 'mixed convection.' Extensive test experiments showed that different schemes have different performance over different regions, and in particular over land versus ocean areas. For example, the MIT scheme tends to produce excessive precipitation over land areas, especially through the occurrence of very intense individual precipitation events.

In other words, once the scheme is activated, it becomes difficult to 'decelerate.' Conversely, we found that the Grell scheme tends to produce excessively weak precipitation over tropical oceans. These preliminary tests suggested that a mixed convection approach by which, for example, the MIT scheme is used over oceans and the Grell scheme over land, might be the most suitable option to pursue, and therefore this option was added to the model. In the previous version (RegCM3) and many other schemes, these cumulus parameterizations tend to maximize rain in the early afternoon, essentially in response to the surface heating by the solar cycle. This often

leads to an earlier than observed diurnal precipitation maximum over tropical regions *(Diro et al., 2012).*

2.7.1.7. Resolved Scale Precipitation:

The resolved scale precipitation scheme was not significantly changed in RegCM4 compared to RegCM3, other than in some of the parameter settings. The scheme is essentially based on the SUBEX parameterization of *(Pal et al., 2000)* and includes a prognostic equation for cloud water. It first calculates fractional cloud cover at a given grid point based on the local relative humidity. Then, in the cloudy fraction it uses a Kessler-type bulk formulation in which cloud water is turned into precipitation via an auto conversion and an accretion term. Below-cloud evaporation of falling raindrops is also accounted for based on the local relative humidity and an evaporation rate coefficient. Key sensitivity parameters in this scheme are the in-cloud liquid water threshold for the activation of the auto conversion term (Qth) and the rate of sub-cloud evaporation (Cevap). Greater values of Qth and Cevap lead to decreased precipitation amounts. Traditionally, RegCM3 has shown a tendency to produce excessive precipitation, especially at high resolutions *(Im et al., 2010)* and optimizations of these parameters have proven effective in ameliorating this problem *(Im et al., 2010).* CLM and BATS surface schemes will be explained in the chapter 4.

2.8 Global Circulation Model

ECHAM is a computer- Fortran95 stand-alone general circulation atmospheric model (GCAM). The model can also run as part of a coupled atmosphere ocean GCM, or in assimilation mode by linear relaxation (nudging). This model is developed by the Max Planck Institute for Meteorology, one of the research organizations of the Max Planck Society. The model was given its name as combination of its origin the 'EC' being short for 'ECMWF') and the place of development of its parameterization package, Hamburg. Model MPI-ECHAM4 1996) is the fourth in a series of models developed at MPI that originally derive from cycle 17 of the European Centre for Medium-Range Weather Forecasts (ECMWF) model. The ECHAM4 model's immediate predecessor is AMIP baseline model MPI ECHAM3 (1992). ECHAM5 is currently the most recent version of the ECHAM model. Compared to its predecessor, ECHAM4, it is more portable and because of both major and minor changes to the parts of code that it uses, it produces a significantly different simulated climate. ECHAM5 hosts sub-models going beyond the usual meteorological processes of a GCM as, Interception of snow by the canopy, heat budget of the soil, Lake Mode, orbital variations, Sedimentation and cloud microphysics, etc.

The ECHAM5 core is constituted by a dynamical part, formulated in spherical harmonics, evaluated at a set of almost regularly distributed grid points – the Gaussian grid. The horizontal and representation, resolution and other important characteristics are in this model as follows (2005).

A. Atmosphere (ECHAM5 *(Roeckner et al., 2006)*)

1. Resolution: T63 L31, roughly equivalent to 2.8 x 2.8 degrees latitude-longitude.

2. Numerical scheme/grid (advective and time-stepping schemes; model top; vertical coordinate and number of layers above 200 hPa and below 850 hPa): Spectral, semi-implicit/leap-frog, flux form semi-Lagrangian scheme *(Lin and Rood, 1996)* for water components; top level at 10 hPa, 9 layers above 200 hPa, 5 layers below 850 hPa)

3. List of prognostic variables: Vorticity, divergence, temperature, log surface pressure, water vapor, cloud liquid water, cloud ice. Model output variable names are not needed, just a generic descriptive name (e.g., temperature, northward and eastward wind components, etc.): N/A

4. Name, terse descriptions, and references (journal articles, web pages) for all major parameterizations. Include, as appropriate, descriptions of:

   A. Clouds: Prognostic equations for the water phases (vapor, liquid and ice), bulk cloud microphysics *(Lohmann and Roeckner, 1996)*, and relative humidity based cloud cover parameterization. The microphysics scheme includes phase changes between water components and precipitation processes (auto conversion, accretion, aggregation). Evaporation/sublimation of rain/snow and melting of snow are considered as well as sedimentation of cloud ice.

   B. Convection: Mass flux scheme for shallow, mid-level and deep convection *(Tiedtke, 1989)* with modifications for deep convection according to *(Nordeng, 1994).* The scheme is based on steady state equations for mass, heat, moisture, cloud water and momentum for an ensemble of updrafts and downdrafts including turbulent and organized entrainment and detrainment. Cloud water detrainment in the upper part of the convective updrafts is used as source term in the strati form cloud water equations. For deep convection, an adjustment-type closure is used with convective activity expressed in terms of convective available potential energy.

   C. Boundary layer: Surface fluxes are computed from bulk relationships with transfer coefficients according to Monin-Obukhov similarity theory. Transpiration is limi ted by stomatal resistance and bare soil evaporation by the availability of soil water. Eddy viscosity and diffusivity are parameterized in terms of turbulent kinetic energy and length scales

involving the mixing length and stability functions for momentum and heat, respectively *(Brinkop and Roeckner, 1995).*

D. SW, LW radiation: The SW scheme *(Fouquart and Bonnel, 1980)* uses the Eddington approximation for the integration over zenith and azimuth angles and the delta-Eddington approximation for the reflectivity of a layer. The scheme includes Rayleigh scattering, absorption by water vapor, ozone, and well-mixed gases. The scheme has four spectral bands, one for visible+UV range, and three for the near infrared. (TAR = one for near infrared). Single scattering properties of clouds are determined on the basis of Mie calculations using idealized size distributions for cloud droplets and ice crystals. The LW (RRTM) scheme *(Mlawer et al., 1997)*, is based on the correlated-k method. Absorption coefficients were derived from the LBLRTM line-by-line model *(Clough and Bent, 1998)* and include the effect of the CKD2.2 water vapor continuum. The RRTM scheme computes fluxes in the spectral range 10 cm^{-1} to 3000 cm^{-1}. The computation is organized in 16 spectral bands and includes line absorption by water vapor, ozone and well-mixed gases. For cloud droplets, the mass absorption coefficient is a function of the respective effective radius with coefficients independent of wavenumber as obtained from a polynomial fit to the results of Mie calculations. For ice clouds, an inverse dependency of the mass absorption coefficient on the ice crystal effective radius is assumed and the coefficients vary with wave number *(Ebert and Curry, 1992).*

E. Any special handling of wind and temperature at top of model: Gradual increase of the horizontal diffusion coefficients in the top 5 layers.

F. Gravity wave drag: The scheme *(Lott and Miller, 1997)* takes into account two main mechanisms of interaction between sub grid-scale orography and the atmospheric flow: momentum transfer from the earth to the atmosphere accomplished by orographic gravity waves, and the drag exerted by the sub grid-scale mountain when the air flow is blocked at low levels.

Model	**RegCM 4.3.5.6**	**ECHAM**
Simulation period	2001-2025	2001-2025
Dynamics	MM5 hydrostatic *(Grell, 1993)*	spherical harmonics *(Simmons et al., 1989), (Orszag, 1970)*
Main prognostic variables	u, v, t, px, ts	u, v, t, px, ts
Central point of domain	Longitude: 71 ◦N latitude: 33◦E	Global Level
Number of horizontal grid points	91,85 grid points for x, y respectively	210, 140 grid points for x, y respectively
Horizontal grid distance	25 km	2.8˚X 2.8˚
Number of vertical levels	18 σ levels	24 σ levels
Horizontal grid scheme	Arakawa–Lamb B grid staggering	Spectral, Semi- implicit/leap-frog, flux form semi-lagrangian scheme *(Lin and Rood, 1996)*
Time integration scheme	Split explicit	
Lateral boundary conditions	EH5OM	-
Radiation scheme	CCM3 *(Kiehl et al., 1998)*	• The SW scheme *(Fouquart and Bonnel, 1980)* uses the Eddington approximation for the integration over zenith and azimuth angles and the delta – Eddington approximation for the reflectivity of a layer. • The LW scheme *(Mlawer et al., 1997)* is based on the correlated – k method

Planetary boundary layer parameterization schemes	Non-local, counter-gradient *(Grenier and Bretherton, 2001)*	Monin – Obukhov similarity theory *(Brinkop and Roeckner, 1995)*
Convective precipitation scheme	Grell *(Grell, 1993)* Fristch and Chappell closure assumptions	Mass flux Scheme for shallow, mid-level and deep convection *(Tiedtke, 1989)*
Soil model	High resolution soil model *(Dickinson et al., 1989)*	The Scheme *(Lott and Miller, 1997)* takes into account two main mechanisms of interaction between subgrid-scale orography and the atmospheric flow
Topography	GTOPO (USGS)	-
Surface parameters	BATS1E *(Dickinson, 1995)*	-
SST	OISST	-

Table 2.7 Comparison of schemes between Regional and Climate Model and Global Circulation Model

2.9. DSSAT for Crop Production Estimates

Decision Support System for Agro-technology Transfer (DSSAT) is in use for the last 15 years by researchers worldwide. This package incorporates models of 16 different crops with software that facilitates the evaluation and application of the crop models for different purposes. The models simulate the effects of weather, soil water, genotype, and soil and crop N dynamics on crop growth and yield *(Jones et al., 2003).* It is one of the best systems research tool for modeling crop, soil, weather and management or husbandry interactions and to assess the climate change impacts (Jones et al., 2003)(*Holden and Brereton, 2003).* It also standardizes the input format and brings lot of individual models in one platform which contributes in major to its popularity. *(Jones et al., 2003)* well amassed the applications also in reference to crop yield forecasting with DSSAT carried out world-wide.

2. 9.1. CERES Wheat for Wheat Simulations across Globe

CERES was developed for agricultural practice to simulate crop development and grain yield The model was designed for use under extremely different environments, including those with limited water availability *(Biernath et al., 2011),* concluded after comparing between four

simulation models, if only yield and total aboveground biomass are considered, the CERES simulations were high quality, and the model can therefore be recommended for up-scaling yield and total above ground biomass at regional levels and in climate change studies.

Numerous studies in Indian –context and worldwide revealed the adaptability of the model in predicting the wheat yield in several soil and climatic conditions. *(Fei et al., 1985)* used the CERES-Wheat model in southern Saskatchewan as an operational tool to predict yields. They initially tested the model with 25 years of historical data from the Saskatoon crop district. After correcting for a "technology trend" of 32 Kg/ha per year, they found that the CERES model was capable of simulating yields for 1960-84 with a correlation coefficient of 0.70. (Hundal, 1997) evaluated CERES-Wheat to simulate plant growth and yield in areas of Punjab, India. The results obtained with the model for the eight crop seasons showed satisfactory predictions of phenology, growth and yield of wheat. However, the biomass simulations indicated the need for further examination of the factors controlling the partitioning of photosynthates during crop growth. The results of this study reveal that the calibrated CERES–Wheat model can be used for the prediction of wheat growth and yield in the central irrigated plains of the Indian Punjab. The CERES Wheat model was validated for 13 representative locations in the main winter wheat producing regions in China to examine its suitability to model winter wheat production, using the agronomic, soil and daily weather data collected from each site concerned, by *(JiangMin et al., n.d.)'*

They suggested that the model's results were productive expect for places with extremities in rainfall. (*Popova* et al., n.d.) Briefed the applications using crop simulation models in Austria and Bulgaria. They had discussed on a specific application using CERES-Wheat in Austria winter wheat productivity. The simulated grain yields are in most cases in accord with the measured data, with predicted yield results mainly within acceptable limits of ±17 % of measured yields. Another attempt by *Xian Wang et al., 2008* to use CERES Wheat model for predicting the wheat yield in Beijing, China was made. The results of this study were positive and encouraged CERES-Wheat to be used for similar kind of studies.

2.9.2. Defining the limits of Crop Simulators

Though plentiful papers accredited the use of crop simulation models DSSAT-CERES-Wheat in specific, some of the papers critically state the limitation boundary of these models. Few crucial points that have to be considered while using crop models for yield simulations are listed in this section. The 'School of De Wit'*; (Bouman et al., 1996)* defines four levels with respect to the evolution of the crop growth simulators *(Vries, 1989).* The levels were to denote the complexity at which the model operates.

The Level1 models uses temperature and solar radiation to simulate growth and development and to calculate potential production. While Level 2 includes precipitation and irrigation as additional inputs for simulating soil and plant water balances. In Level 3, soil nitrogen is added as an input to simulate soil and plant nitrogen balance in addition. Level 4 is advanced stage where

soil minerals are also added along with pests, diseases and weed. The complete soil-plant-atmosphere system is simulated. At present we are in a transition period between level 3 and level 4. Input requirement of most of the models at present substantiate this point. Thus we are in a stage where process are not fully understood either fully ignored. The *technical documentation of CERES- (Ritchie et al., 1985)* documented the limitations in the development of methods to simulate the actual process. The development of the growth routine in conjunction with the rest of the model has been a major challenge in developing this model because the partitioning of assimilate is a dynamic process, requiring several feedback mechanisms. A major difficulty associated with verifying an intercepted radiation-biomass production relationship has been the lack of knowledge concerning the fraction of assimilates partitioned to the roots. Although several investigations were made to establish this relationship for use in CERES-Wheat by measuring roots or by approximating their weights compared to above ground biomass, there still remains considerable uncertainty in calculating the fraction of assimilate partitioned to the roots and tops. Also, the mechanisms of grain number determinations were not fully understood until now which is commonly agreed by (Fischer, 2008).

(Biernath et al., 2011), after inter-comparison between models stated that major weakness of CERES is the simple model of light absorption that does not consider diffuse and scattered light. As a consequence, biomass production was overestimated during the juvenile phase. They also documented this was due to low parameterization effect in certain methods used by CERES-Wheat.

The same group accepted that over-parameterization of another model also lead to unfavorable results. Thus models should be made simple, but not simpler. These problems with the methods and the parameterizations used in the model should be considered by model developers to manage the uncertainties associated with the crop simulation models.

Another aspect of limitation is with the uncertainties tied with input data. For rigorous use of these models for crop management decision in a given area, more carefully derived input environmental parameters are important *(Aggarwal and Kalra, 1994*), quantified the impact of uncertainty in inputs with the various simulated parameters of the model WTGROWS. The Monte Carlo simulation technique was used to analyze total uncertainty. The results showed that uncertainties in crop, soil and weather inputs resulted in uncertainty in simulated grain yield, ET and N uptake, which varied depending upon the production environment from potential to stressed condition. There was an 80% probability that the bias in the deterministic model outputs was always less than 10% in potential and irrigated production systems. In rainfed environments this bias was larger. He also stated that uncertainties are associated with weather variables since there might be some random errors and the systematic measurement errors. The missing weather data, the acceptance of direct face value from recorded data and the distance of the weather stations from the actual field pose a serious problem for simulating crop.

If case of prediction, the unavailability of a robust method for predicting the future weather at daily time-step comes as another issue in the usage of the model. *(Nonhebel, 1994),* has reported that simulated wheat yield was overestimated under potential conditions and underestimated under water-limiting conditions when generated meteorological data were used with SUCROS87. The uncertainty in other variables like soil initial condition, crop cultivar description in terms of genetic coefficients and management information has also got considerable effects on the yield simulation which was validated by *(Bouman et al., 1996)*. It is common in cropping systems to have large volumes of data relating to the above-ground crop growth and development, but data relating to root growth and soil characteristics are generally not as extensive. Using approximations may lead to erroneous results. Large variations in wheat yields (4.5 to 8.0 t ha^{-1}) attributable to within-field soil heterogeneity were reported by Hence, the use of average values of soil characteristics as model inputs could lead to some errors in simulated output.

(Gommes, 1998), explained that these simulation models are often not able to forecast the yield increase or drop due to a period of dry and sunny weather at unusual times of the crop cycle. He also explained that the models performance is not appreciable at times of extremities. Made clear that when a model is applied in a new situation, the calibration and validation steps are crucial for correct simulations. The need for model verification arises because all processes are not fully understood and even the best mechanistic model still contains some empirism making parameter adustments vital in a new situation.

One more concern is the application of the outputs from the simulation models –Spatial Sense. *(Moulin, 1999),* listed the serious issues in extrapolating the crop yield simulation from farm level to regional level. Though the models have a good predictive ability, their usefulness has been restricted to applicability at research plot scale due to high input data requirements. Their implementation at the scales of farmers' fields, district and province is restricted by the input data availability at corresponding scales. Desired accuracy is not also attained due to averaged input conditions.

STUDY AREA

STUDY AREA CHAPTER – 3

3.1 Region of study – Himachal Pradesh

3.1.1. Geographic extent

Himachal Pradesh is a state in northern India, especially in the western Himalayas which spreads over an area of 21,495km$^{2.}$ It is a mountainous region situated between 30º 22'40" to 33º 12' 20"north latitudes and 75º 45' 55" to 79º 04' 20" east longitudes. It is surrounded by Jammu and Kashmir in the north, Tibet on the north east, Haryana and Uttarakhand on the south-east and Punjab in the south west and west. It is divided into 12 districts with 55 sub divisions.

3.1.2. Relief

Himachal Pradesh is a mountainous state in the lap of Himalayas with the elevation ranging between 350 meters to 6975meters above the mean sea level. It is characterized by wide valleys imposing Snow Mountains, lakes, rivers and gushing streams. The major geographical divisions include – The Shivaliks or the outer Himalayas, the central zone or the lesser Himalayas and the northern zone or the great Himalayan and Zaskar.

3.1.3. Soil

There are 9 different soil types found in Himachal based on their physic – chemical and which include - (i) alluvial soils, (ii) brown hill soil, (iii) brown earth, (iv) grey brown podzolic soils, (v) grey wooded orpodzolic soils, (vi) brown forests soils, (vii) planosolic soils, (viii) humus and iron podzols (ix) alpine humus mountain speletal soils[1]. In a broader view the state comprises of brown, alluvial and grey brown podzolic soils in 7 districts (viz., Mandi, Kangra, Bilaspur, Una, Solan, Hamirpur and Sirmaur), grey wooded podzolic soils in two districts (Kullu and Shimla) and humus mountain speletal soils in three districts (Lahaul and Spiti and some parts of Chamba).

3.1.4. Water sources

About 90% of the Himachal's rivers systems are a part of Indus river system. The major river systems of the Himachal include Chandrabhaga or Chenab, Ravi, Beas, Sutllej to the west and Yamuna towards the east along with its tributaries – Tons, Pabbar and Giri. Out of these, the first three rivers actually have their origin in the state and flow through it while sutlaj has its origin in Tibet and flows through Himachal forming the largest catchment area of the state [Himachal Pradesh development report]. Snowfall and rainfall are the major sources that keep these rivers perennial. The state also comprises 15 natural lake in various districts along with four manmade lakes located in Bilaspur, kangra, Mandi and Chamba districts. The annual replenish able

groundwater resource in the state is 0.43BCM and the stage of ground water development is 30% (WRIS – Water Resources Information System of India).

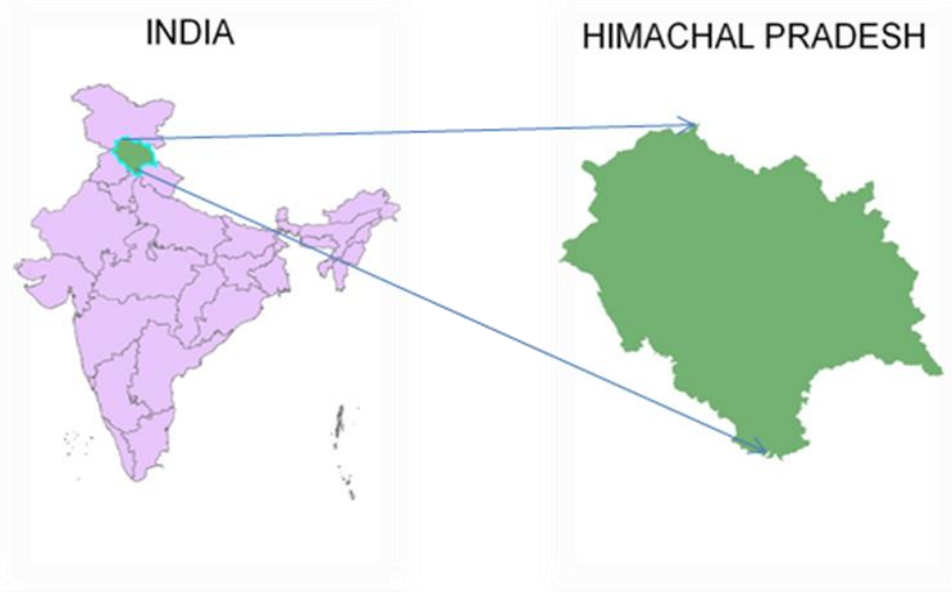


Figure 3.1 Himachal Pradesh – Study Area

3. 1.5. Climate

A great diversification is observed in the climatic conditions of Himachal Pradesh due to varying elevations. Physiographically, the state can be divided into five zones based on altitudes and moisture regime conditions. The climatic conditions, therefore, vary from wet humid sub-temperate situation to dry temperate alpine high lands in different parts of the state. The maximum temperature goes up to 22°C in the month of June–July and the minimum temperature around 3°C in the month of January. Average annual rainfall varies largely in the state with 454 mm in Lahul & Spiti and 1565mm in Kangra (WRIS – Water Resources Information System of India).

3.1.6. Agriculture

Agriculture is the mainstay of more than 75 per cent people in Himachal Pradesh. Most of farmers belongs to small and marginal category (about 83.7%). Major food crops are rice, wheat, jowar, bajra, potato etc. In the year 2006-2007, the state produced 123.5 thousand tonnes of kharif rice in 79.2 thousand hectares land, 501.6 thousand tonnes of Wheat produced from 362.2 thousand hectares land, 695.4 thousand tonnes of kharif Maize produced from 299.0 thousand hectares land, Total Food grains production 1,382.2 thousand tonnes in 806.4 thousand hectare of land and during the same period was Total Pulses production 28.9 thousand tonnes in 31.0

thousand hectare of land, 118.3 thousand tonnes of Potato produced from 12.7 thousand hectares land.

Diverse agro-climatic conditions afford excellent opportunities for horticulture and cash crops. Fruit cultivation is dominated by apples. Himachal's apples are world famous. Vegetables plays a notable part in the agriculture of Himachal Pradesh. Himachal has always been known for its potatoes and Shimla even gives its name to the vegetable paplwoca, popularly known in north India as Shimla mirch. Large scale expansion of mushroom cultivation has been undertaken. Farm activities are being supplemented by improvement in milch cattle through a cross-breeding programme, rabbitry, pisiculture and floriculture.

3.1.7 Flora and Fauna

Himachal Pradesh has a very rich Flora and Fauna. Due to varied elevation and humidity, the vegetation and forest cover is very rich. In the southern part we can find tropical and subtropical dry and wet broad leaf forest while in northern part deciduous and evergreen oaks are prominent. In pine family chir pine dominates it. Deodar, Sal, Blue pine, East Himalaya fir, shisham is also found here. It is also famous for its flowers and fruits yield. It has carnations, lilies, tulips, roses plantation for commercial use as well. It has around 359 animal and 1200 bird species which includes ghoral, musk deer, leopard etc.

MATERIALS AND METHODOLOGY

4.1. Objectives of the research and software and materials used in this research

The main focus of this research was to establish the biophysical model i.e., - Decision Support System Agrotechnology Transfer (DSSAT) to assess the impact of climate change on productivity using the outputs of Regional Climate Model (RCM), in an agricultural landscape of a mountain ecosystem. The present study has been conducted in Himachal Pradesh state, in India due to its vulnerable nature towards extreme climatic conditions and population growth. GeoInformatics tools such as remote sensing, Geographical information system (GIS), Global Positioning System (GPS), crop model namely DSSAT and RCM are used in the most integrated way to investigate influence of anticipated climate conditions on various crop system processes over space and time.

The model establishment parts constitute sensitivity analysis, calibration and validation of the model with site specific data under current conditions. The necessary data required for the model calibration were obtained from intensive field observations, conducted in two different crop growing seasons. The downscaled output for whole Himachal Pradesh is then used for climate change impact assessment at a spatial resolution of 25km*25km. The broad methodological framework for the study is given in Fig: 4.1.and the materials and models used in the present work and shown below in table 4.1.

Crop Models and Climate Models	Data Required for Crop Models	Data Required for Climate Models	Software
• RegCM 4.3 (Regional Climate Model) • DSSAT (Decision Support System Agrotechnology Transfer)	• Weather Data • Soil Data • Management Data • Experimental Data • Agricultural Land Cover • Digital Elevation Model • Crop statistics (2001-2009) for validation	• Global Circulation Model output • Current Climate Scenario • Land Use Land Cover • Digital Elevation Model	• ArcGIS 9.3 and ArcGIS10.0 • ERDAS IMAGINE 10 • ENVI 4.8

Table 4.1 Materials used in this research

4.2. Inputs and materials description of this research

4.2.1. Climate Model and Crop Model

4.2.1.1 Regional Climate Model (RegCM 4.3.5.6)

The Regional Climate Model (RegCM) is developed throughout the last decades, with a wide base of model developers and users. The idea that limited area models (LAMs) could be used for regional studies was originally proposed by *(Dickinson et al., 1989)* and *(Giorgi, 1990).* It has evolved from the first version (RegCM1) developed in the late eighties *(Dickinson et al., 1989)* and *(Giorgi, 1990)*, to later versions (RegCM2) in the early nineties *(Giorgi et al., 1993b)* and *(Giorgi, 1990c)*, RegCM2.5 in late nineties *(Giorgi and Mearns, 1999)* and in 2000s RegCM3*(Pal et al., 2000)*. The RegCM has been the first limited area model developed for long term regional climate simulation, it has participated to numerous regional model intercomparison projects, and it has been applied by a large community for a wide range of regional climate studies, from process studies to paleo-climate and future climate projections *(Giorgi and Mearns, 1999)* and *(Giorgi et al., 2006)*.

The RegCM system is a community model, and in particular it is designed for use by a varied community composed by scientists in industrialized countries as well as developing nations *(Pal et al., 2007)*. It is designed as user friendly, open source and portable code that can be used to any part of the earth. RegCM is supported through the Regional Climate research NETwork (RegCNET), a widespread network of scientists coordinated by the Earth System Physics section of the Abdus Salam International Centre for Theoretical Physics Abdus Salam International Centre for Theoretical Physics (ICTP), being the foster the growth of advanced studies and research in developing countries one of the main aims of the ICTP. Model can be downloaded from **http://users.ictp.it/RegCNET.** Using this network (currently subscribed by over 750 participants) scientists can interrogate through an email and scientific conferences and workshops, and they have been important for the evaluation and sequential developments of the model. Since the release of RegCM3 described by *(Pal et al., 2007)*, the model has undergone a substantial evolution both in terms of software code and physics representations, and this has led to the development of a fourth version of the model, RegCM4, which was released by the ICTP in June 2010 as a prototype version (RegCM4.0) and in May 2011 as a first complete version (RegCM4.1). Compared to previous versions, RegCM4 contains new land surface, PBL, a mixed convection and tropical band configuration, air-sea flux schemes, modifications to the pre-existing radiative transfer and boundary layer schemes and a full upgrade of the model code towards improved flexibility, portability and user friendliness. The model can be interactively coupled to a 1D lake model, a simplified aerosol scheme (including OC, BC, SO4, dust and sea spray) and a gas phase chemistry module (CBM-Z). Overall, RegCM4 shows an improved performance in several respects compared to previous versions, although further testing by the user community is needed to fully explore its sensitivities and range of applications. The RegCM

is available on the World Wide Web thanks to the Democritus Italy CNR group at **https://eforge.escience-lab.org/gf/project/regcm.**

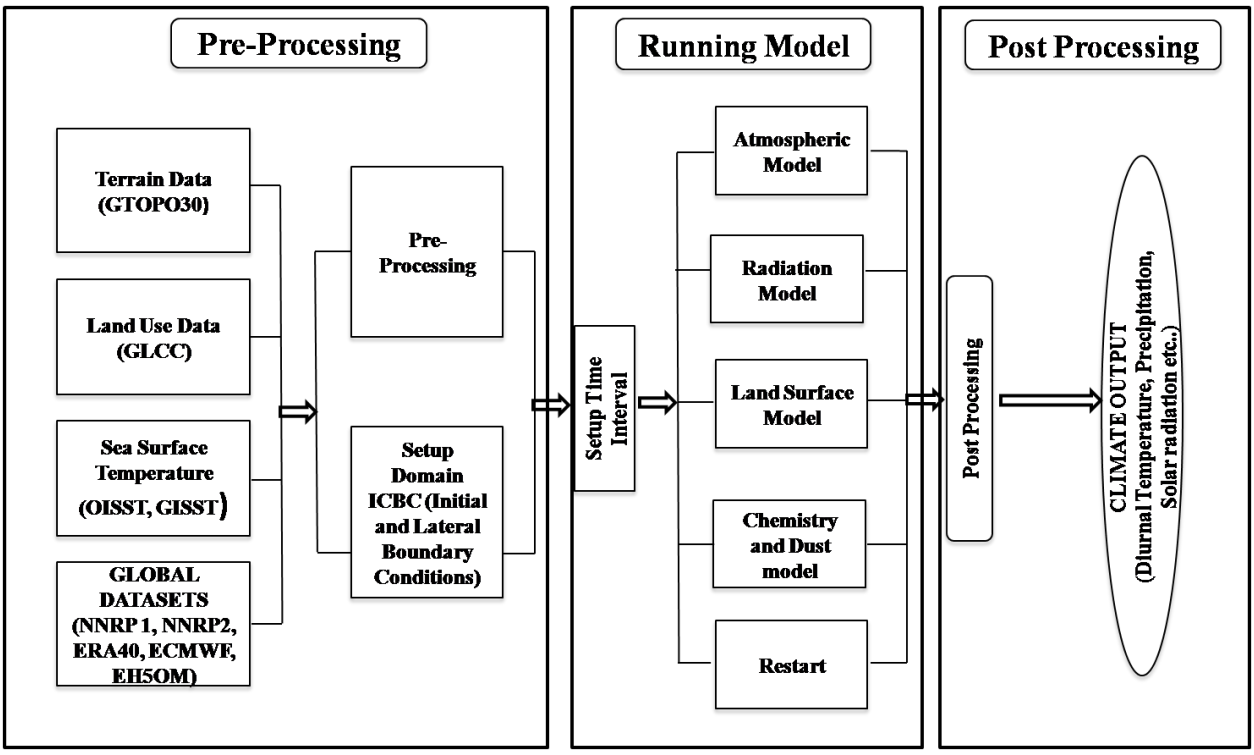


Figure4.1.Methodology for Regional Climate Model

4.1.1.2 Physics parameterizations:

Interest in regional climate modeling has been steadily increasing in the last 2 decades *(Giorgi et al., 2012).* Mesoscale meteorological models are the origin of Regional Climate Models (RCM) framework. Lot of physics parameterizations were upgraded for long term climate studies such as, radiative transfer, land surface physics, cloud parameterizations etc. Because of the huge publicity of Regional Climate Models, the model has developed extensively and continuously utilized. RegCM4 is advanced version of previous one (RegCM3). In the following table upgraded physics parameters are shown in the model.

Model aspects	Available options
Dynamics	• Hydrostatic, σ-vertical coordinate *(Giorgi et al., 1993)*
Radiative transfer	• Modified CCM3 *(Kiehl et al., 1998)*
PBL	• Modified Holtslag *(Holtslag et al., 1990)* • UW-PBL *(Bretherton et al., 2004)*
Cumulus convection	• Simplified Kuo *(Anthes et al., 1987)* • Grell *(Grell, 1993)* • MIT *(Emanuel and Živković-Rothman, 1999)* • Tiedtke *(Tiedtke, 1989)*
Resolved scale precipitation	• SUBEX *(Pal et al., 2000)*
Land surface	• BATS *(Dickinson et al., 1993)* • Sub-grid BATS *(Giorgi et al., 2003)* • CLM *(Steiner et al., 2009)*
Ocean fluxes	• Organic and black carbon, SO4 *(Solmon et al., 2006)* • Dust *(Zakey et al., 2006)* • Sea salt *(Zakey et al., 2008)*
Interactive lake	• 1D diffusion/convection *(Hostetler et al., 1994)*
Tropical band	• *(Coppola et al., 2012)*

Table 4.2 Physics parameters in RegCM4

4.2.1.2. Decision Support System Agrotechnology Transfer (DSSAT)

The decision support system for agrotechnology transfer (DSSAT) has been in use for the last 15 years by researchers worldwide *(Jones et al., 2003)*. This package facilitates the evaluation and application of the crop models for different purposes by incorporating models of 28 different crops. Thus, the DSSAT crop models have become very difficult to maintain due to the variation in the codes used for varying crop types and hence have been re-designed and programmed to facilitate more efficient incorporation of new scientific advances and applications and even for improving the maintenance capacity. The basis for the new DSSAT cropping system model

(CSM) design is a modular structure in which components separate along scientific discipline lines and are structured to allow easy replacement or addition of modules*(Jones et al., 2003)*. It includes one Soil module, a Crop Template module, a Weather module, and a module for dealing with competition for light and water among the soil, plants, and atmosphere. Crop Template module can help in simulating various crops by defining species input files. It is also provided with an interface to add individual crop models if they have the same design and interface. It is also designed for incorporation into various application packages, ranging from those that help researchers adapt and test the CSM to those that operate the DSSAT/CSM to simulate production over time and space for different purposes. The following flow chart in fig 4.2 describes the DSSAT process.

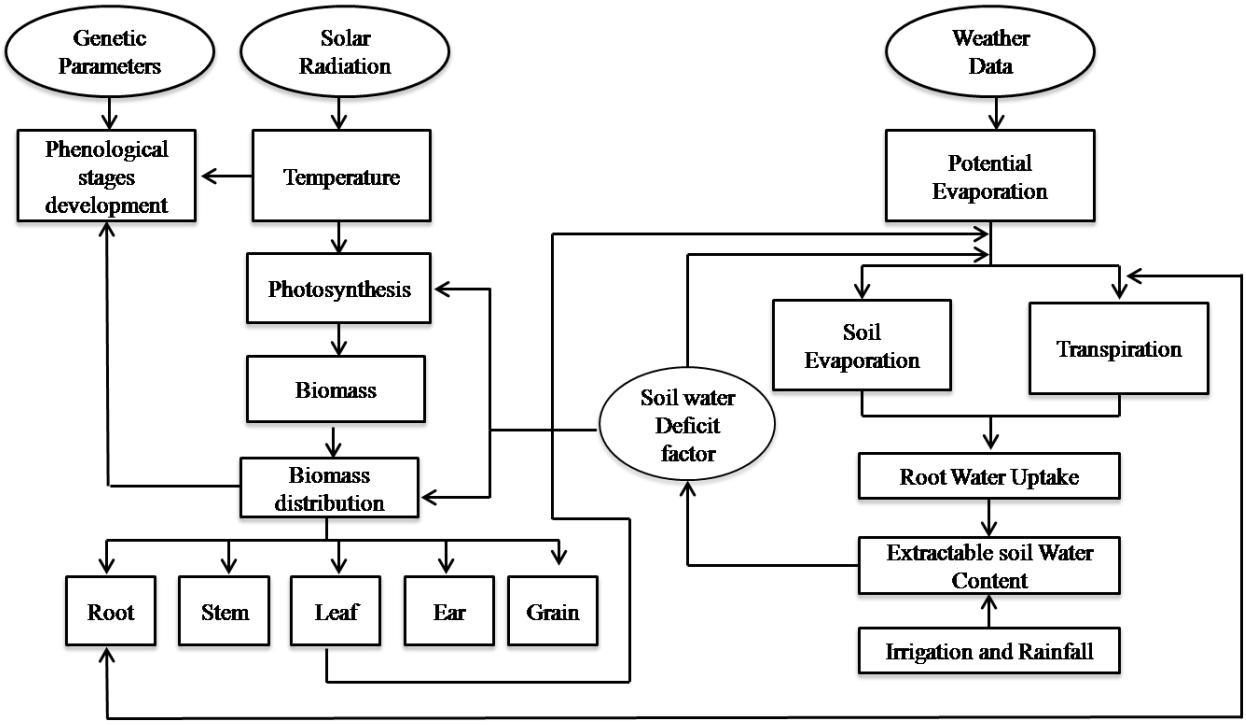


Fig 4.2. Methodolgy for DSSAT crop model

a) DSSAT for wheat (CERES wheat)

The CERES-Wheat model *(Ritchie et al., 1985) (Godwin et al., 1990; Ritchie and Otter, 1985)* simulation model describes the daily phenological development and growth of wheat according to the changing environmental factors (soils, weather and management). Modeled processes include phenological development, i.e. senescence of leaves, duration of growth stages, biomass production and partitioning among plant parts, growth of vegetative and reproductive plant parts,

extension growth of leaves and stems, and root system dynamics. The models have the capability to simulate the effects of nitrogen deficiency and soil water deficit on photosynthesis and pathways of carbohydrate movement in the plant by using the subroutines which can simulate the soil and nitrogen balance and crop water balance. Considering the phenology, the temperature is the primary factor that affects the phasic development rate. The thermal time for each phase of the crop is fine-tuned by coefficients that characterize the response of different genotypes.

b) DSSAT for maize (CERES maize)

CERES MAIZE is a process-oriented, management-level model of maize (*Zea mays L*) crop growth and development that also simulates nitrogen balance and soil water balance associated with the growth of maize *(Ritchie et al., 1992).* The model uses a minimum of readily available weather, soil and variety-specific genetic inputs. In the present work, the CERES-Maize of DSSAT v4.5 model was used to simulate nitrate leaching, nitrogen uptake, corn yield and soil moisture content in an acid sulphate soil.

4.3 Inputs for Models used in this research

4.3.1. Inputs for Regional Climate Model (RegCM)

4.3.1.1. Global Climate Model (GCM) inputs for downscaling

The input is EH5OM Atmospheric Ocean Global Circulation Model (AOGCM) consisting of ECHAM5 atmospheric model and MPI-OM oceanic model. ECHAM5 is a fifth generation ECHAM atmospheric GCM for climatic integration at T63L31 resolution (1.875° x 1.875°). MPI-OM is a global oceanic GCM with 40 vertical levels and horizontal resolution of 1.5°.The model includes parameters for additional wind mixing and calculation of sea ice. Atmospheric and oceanic models are coupled on a daily basis without flux adjustment *(Branković et al., 2010)*.

4.3.1.2. Climate Integration and Data Used

Three integrations for twentieth century climate 20C3M under IPCC A1B scenario were used. These integrations differ from each other in the initial condition that they are separated by 25 years and all were taken from pre-industrial control experiment (Branković et al., 2010). The 20C3M integrations cover the period 1860-2001 whereas SRESA1B experiment simply continue the three 20C3M run over the 2001-2100 period(.The data for this study were retrieved from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) archive of the Lawrence Livermore National Laboratory (LLNL) in Livermore, California, USA. To represent the twentieth century climate, the data from the period 1961–1991 are used, whereas the future climate has been estimated from the year 2001-2025. For the purpose of this study, the 1961–1990 modelling climate will be referred to as the "present climate". The two 25-year periods (20C3M and SRESA1B) represent a classical climatical time span required for representative, stable and statistically significant climatological samples.

It is sufficiently long to faithfully extract climatological parameters and compute variation in the climate scenario. For the 20C3M simulations, the concentration of CO2, CH4, N2O in EH5OM are specified at observed values (years 1860-2000), whereas anthropogenic ozone is specified as difference between the actual and pre-industrial values. For future climate, emission of greenhouse gases (GHG) is based on the A1B emission scenario including stratospheric ozone. Results are shown and discussed as daily values for the whole period of 2001-2025.

Most parameters of the EH5OM model systematic errors are calculated by comparing reference climate as defined from ERA-40. The ERA-40 daily values for the 1961–1990 period are defined at the same resolution as the EH5OM data, i.e. T63 (N48 Gaussian grid), however the original ERA-40 resolution is T159 (N80 Gaussian grid). For precipitation, the model results are compared against the Climatic Research Unit (CRU) data(*New et al., 2002*). The CRU precipitation is defined over the land points only and result from the original 0.5 × 0.5◦ regular latitude/longitude grid to the model N48 Gaussian grid was interpolated. Relatively high resolution CRU verification has an inappropriate disadvantage for the model. CRU precipitation covers the period 1961–1990, consistent for verification of other variables based on ERA-40 data.

4.3.1.3. Surface inputs for downscaling in the RegCM

The following surface inputs are given for downscaling using the RegCM model –

GTOPO30 for Topography: GTOPO is a DEM for the globe developed by USGS and it has 30 arc second resolution (approximately 1km resolution) *(eros.usgs.gov).* It is split into 33 tiles which are stored in the USGS DEM file format.

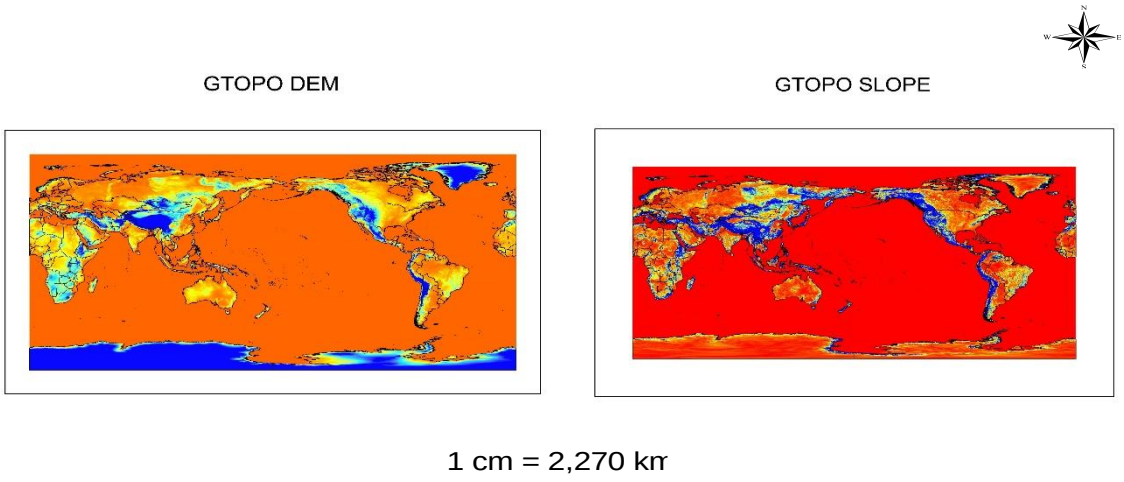


Fig 4.3. Global Level DEM and Slope map from GTOPO for downscaling

4.3.1.4. BATS (Bio - sphere-Atmosphere Transfer Scheme)

BATS (default): BATS is a surface package designed to describe the role of vegetation and interactive soil moisture In modifying the surface-atmosphere exchanges of momentum, energy, and water vapor *(Dickinson et al., 1993)*. The model has a vegetation layer, a snow layer, a surface soil layer, 10 cm thick, or root zone layer, 1-2 m thick, and a third deep soil layer 3 m thick. Prognostic equations are solved for the soil layer temperatures using a generalization of the force-restore method of *(Colburn et al., 1989)*. The temperature of the canopy and canopy foilage is calculated diagnostically via an energy balance formulation including sensible, radiative, and latent heat fluxes.

The soil hydrology calculations include predictive equations for the water content of the soil layers. These equations account for precipitation, snowmelt, canopy foiliage drip, evapotranspiration, surface runoff, infiltration below the root zone, and diffusive exchange of water between soil layers. The soil water movement formulation is obtained from a fit to results from a high-resolution soil model *(Dickinson, 1995)* and the surface runoff rates are expressed as functions of the precipitation rates and the degree of soil water saturation. Snow depth is prognostically calculated from snowfall, snowmelt, and sublimation. Precipitation is assumed to fall in the form of snow if the temperature of the lowest model level is below 271 K. Sensible heat, water vapor, and momentum fluxes at the surface are calculated using a standard surface drag coefficient formulation based on surface-layer similarity theory.

The drag coefficient depends on the surface roughness length and on the atmospheric stability in the surface layer. The surface evapotranspiration rates depend on the availability of soil water. Biosphere-Atmosphere Transfer Scheme (BATS) has 20 vegetation types (Table 2.3.; soil textures ranging from coarse (sand), to intermediate (loam), to fine (clay); and different soil colors (light to dark) for the soil albedo calculations. These are described in *(Pollard and Thompson, 1995)*. In the latest release version, additional modifications have been made to BATS in order to account for the sub grid variability of topography and land cover using a mosaic-type approach *(Giorgi et al., 2003)*.

GLCC BATS for land use: Global land Cover Characteristics Biosphere Atmosphere Transfer Scheme (GLCC BATS). This land cover maps are also developed by USGS globally at 1km resolution for various applications and environmental studies. The land cover characteristics differ from continent to continent. All continental databases have the same map projection – Interrupted Goode Homolosine and lambert azimuthal equal area projections.

BATS - LULC

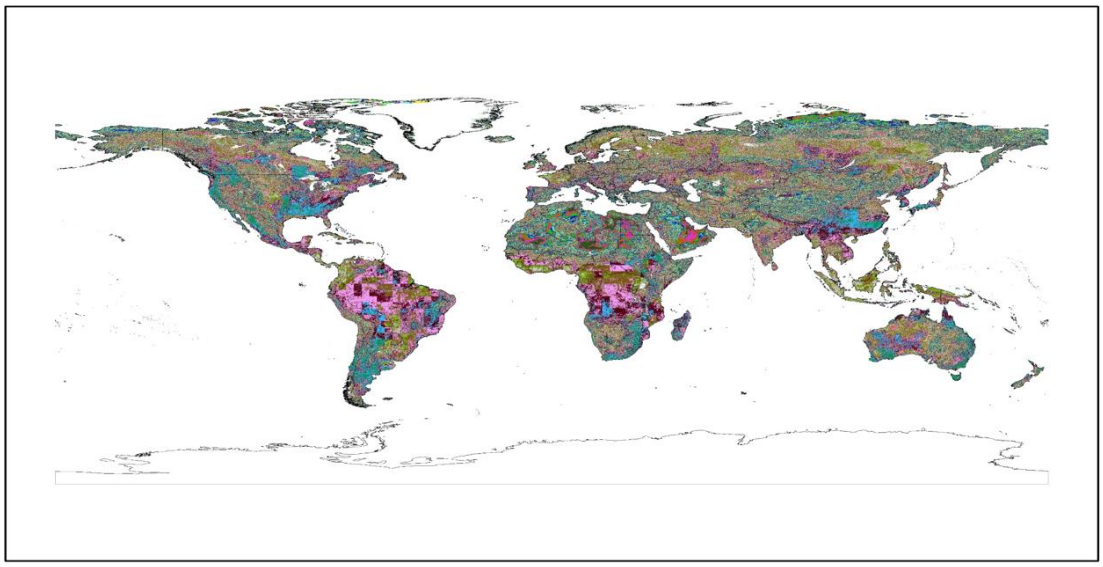


Fig 4.4. BATS- Land Use Land cover for Global Level

1	Crop/mixed farming
2	Short grass
3	Evergreen needleleaf tree
4	Deciduous needleleaf tree
5	Deciduous broadleaf tree
6	Evergreen broadleaf tree
7	Tall grass
8	Desert
9	Tundra
10	Irrigated Crop
11	Semi-desert

12	Ice cap/glacier
13	Bog or marsh
14	Inland water
15	Ocean
16	Evergreen shrub
17	Deciduous shrub
18	Mixed Woodland
19	Forest/Field mosaic
20	Water and Land mixture

Table 4.3: Land Cover/Vegetation classes of Model

This modification adopts a regular fine-scale surface sub grid for each coarse model grid cell. Meteorological variables are disaggregated from the coarse grid to the fine grid based on the elevation differences. The BATS calculations are then performed separately for each sub grid cell, and surface fluxes are re aggregated onto the coarse grid cell for input to the atmospheric model. This parameterization showed a marked improvement in the representation of the surface hydrological cycle in mountainous regions *(Giorgi et al., 2003)*. As a first augmentation, in REGional Climate Model version 4 (RegCM4) two new land use types were added to BATS to represent urban and sub-urban environments. Urban development not only modifies the surface albedo and alters the surface energy balance, but also creates impervious surfaces with large effects on runoff and evapotranspiration. These effects can be described by modifying relevant properties of the land surface types in the BATS package, such as maximum vegetation cover, roughness length, albedo, and soil characteristics.

4.3.1.5. CLM (The Community Land Model):

The Community Land Model *(Bonan et al., 2011)* is the land surface model developed by the National Center of Atmospheric Research (NCAR) as part of the Community Climate System Model (CCSM), described in detail in *(Collins et al., 2006)*. CLM version 3.5 was coupled to RegCM for a more detailed land surface description option. CLM contains five possible snow layers with an additional representation of trace snow and ten unevenly spaced soil layers with explicit solutions of temperature, liquid water and ice water in each layer. To account for land surface complexity within a climate model grid cell, CLM uses a tile or mosaic approach to capture surface heterogeneity. Each CLM grid cell contains up to four different land cover types (glacier, wetland, lake, and vegetated), where the vegetated fraction can be further divided into 17 different plant functional types. Hydrological and energy balance equations are solved for each

land cover type and aggregated back to the grid cell level. A detailed discussion of CLM version 3 implemented in RegCM3 and comparative analysis of land surface parameterization options is presented in *(Steiner et al., 2009).*

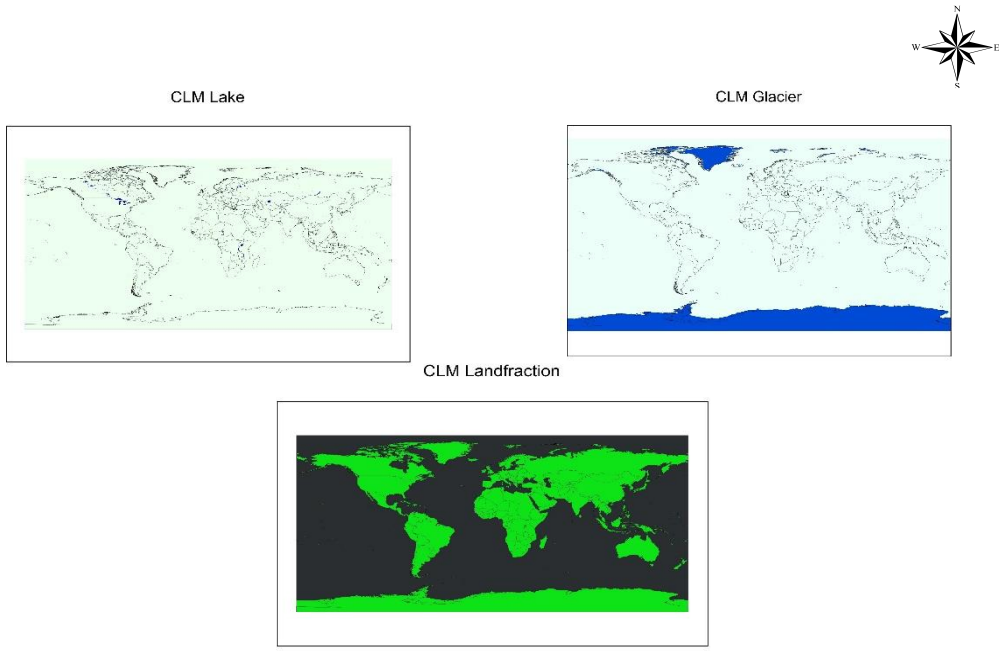


Fig 4.5. CLM- Community land model inputs for downscaling

Input data	Grid Spacing	Lon range	Lat range
Glacier	0.05◦ x 0.05◦	±179.975	±89.975
Lake	0.05◦ x 0.05◦	±179.975	±89.975
Wetland	0.05◦ x 0.05◦	±179.975	±89.975
Land fraction	0.05◦ x 0.05◦	±179.975	±89.975
LAI/SAI	0.5◦ x 0.5◦	±179.75	±89.75
PFT	0.5◦ x 0.5◦	±179.75	±89.75
Soil color	0.05◦ x 0.05◦	±179.975	±89.975
Soil texture	0.05◦ x 0.05◦	±179.975	±89.975
Max. sat. area	0.5◦ x 0.5◦	±179.75	±89.75

Table 4.4: Resolution for CLM input parameters

Since CLM was developed for the global scale, several input files and processes were modified to make it more appropriate for regional simulations, including (1) the use of high resolution input data, (2) soil moisture initialization, and (3) and an improved treatment of grid cells along coastlines. For the model input data, CLM requires several time-invariant surface input parameters: soil color, soil texture, percent cover of each land surface type, leaf and stem area indices, maximum saturation fraction, and land fraction *(Lawrence et al., 2011).* Table 2.4 shows the resolution for each input parameter used at the regional scale in RegCM-CLM compared to resolutions typically used for global simulations. The resolution of surface input parameters was increased for several parameters to capture surface heterogeneity when interpolating to the regional climate grid. Similar to *(Lawrence et al., 2011)* the number of soil colors was extended from 8 to 20 classes to resolve regional variations. The second modification was to update the soil moisture initialization based on a climatological soil moisture average *(Giorgi and Bates, 1989)* over the use of constant soil moisture content throughout the grid generally used for global CLM. By using a climatological average for soil moisture, model spin-up time is reduced with regards to deeper soil layers. The third modification to the CLM is the inclusion of a mosaic approach for grid cells that contain both land and ocean surface types. With this approach, a weighted average of necessary surface variables was calculated for land/ocean grid cells using the land fraction input dataset. This method provides a better representation of coastlines using the high-resolution land fraction data described in Table 2.4. For a more detailed description of CLM physics parameterizations see *(Oleson et al., 2008).*

\ ***Sea Surface Temperature (SST):*** OISST (Optimally Interpolated SST) datasets were used as inputs for downscaling in RegCM. This9km microwave + infrared SST product combines the through cloud capabilities of the microwave data with a high spatial resolution of the Infrared SST data which improves the accuracy of the inputs to RegCM.

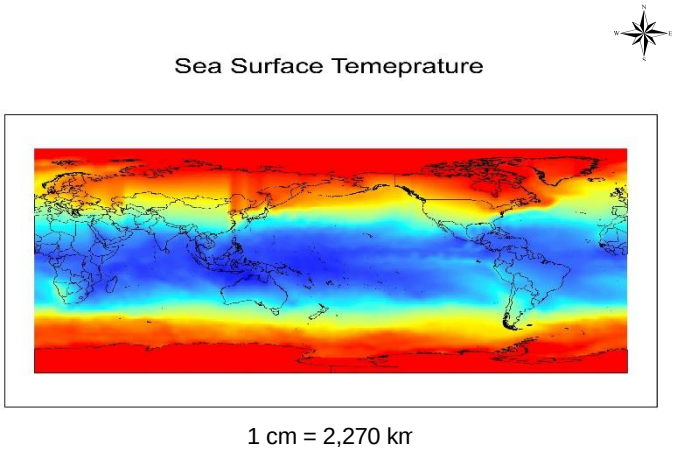


Fig 4.6. SST – Sea Surface Temperature from OISST for downscaling

4.4. Inputs for crop model

4.4.1. Weather data

The minimum required weather variable required for input into DSSAT crop model are Maximum temperature and minimum temperature in℃, solar radiation in MJ/m^2, and rainfall (mm^2) at a daily time scale. The relative humidity (percentage) and wind speed (km/hr) if available can also be used but are optional. It also requires latitude, longitude and elevation information. The sources of these data used in the present study are downscaled from the Regional Climate Model.

The RegCM outputs are obtained in NetCDF format which contains the daily based climate data for a period of 25 years – 2001 to 2025. The inputs for the DSSAT crop model which are required to have a particular supportable format are obtained from the outputs of RegCM model using python programming. This given inputs are at a resolution of 25km x 25km.

4.4.2. Soil Data

The soil resource database of India was produced based the soil map at 1:1 m published by NBSS&LUP was used. The soil attribute database on map unit id, soil depth, drainage, particle size, slope, erosion, surface stoniness, flooding, calcareousness, salinity and sodicity data was compiled and codified as per OGC standard and extended legend was prepared as per the INARIS data structure. The other attribute database like SRM map units, pedon no., colour, surface texture, soil temperature regime, parent material, land (surface) form, organic carbon (OC), cation, exchange capacity (CEC), soil reaction (pH) and mineralogy were compiled at respective regional centre from SRM data (1:250,000 scale) and was provided to enter in the main database as per the INARIS data structure. This depth wise soil data was collected through data collected from field visits and research stations in Himachal Pradesh which was later on strengthened by the data collected from the book *SOIL SERIES OF INDIA* published by NBSS and LUP.

Figure 4.7. Field photographs of soil data collection

4.4.3. Crop management data

The management data are collected from farmers and research associates from agriculture research stations of various districts during the field visit. The parameters derived are irrigation times and dates, depth of irrigation, type of irrigation, type, amount and date of fertilizer application, sowing depth, row spacing of plants, plant population, etc.

Management file for Wheat:

Soil textural class	Silty clay loam
Weather station name	Himachal Pradesh
Planting time	First fortnight of November
Population	120-130 plants /m2
Seeding depth	5cm
Row spacing	20-22 cm
Irrigation dates	25-30 DAS ; CRI- 1st 40-45 DAS; Tillering- 2nd 70-75 DAS Late jointing stage- 3rd 90-95 DAS; Flowering- 4th 125 DAS; Dough stage- 5th
Depth of irrigation	440-460 mm
Fertilizer	90:50:30 (N: P2O5: K2O) Kg/ha
Time	Half N + full P and K at sowing Half N at 1st irrigation

Table 4.5 Details of management data for wheat

Management file for Maize:

Field characteristics	**Weather station name:** Himachal Pradesh Soil textural class: Silty clay loam
Seed bed preparation and planting geometries	**Planting date**: 10th June **Plant population**:13.5/m^2 **Seedling depth** : 5 cm **Row spacing**: 75cm x 20cm
Fertilizer management	**Fertilizer date**:10th June

	Amount and type:90:40:40 i)Urea ii) SSP iii) MOP
Organic residue application : Nil	**Addition of staw, green manure and animal manure** : Nil

Table 4.6 Details of management data for maize

4.4.4. Crop cultivar data

Amongst the wheat, HPW-89 is the most sown variety in the districts of Himachal Pradesh which is a long duration crop that last s for 155 days. It has a height of 100cm with bold grains and hard and lustrous amber. Considering the maize variety, HPR- 927 is the most sown variety. The cultivar file contains the growth degree days, vernalization sensitivity, critical photo period and ancilliray information's which were collected from research stations during the field surveys.

Cultivar file for Wheat:

Name of cultivar	**HPW 89**
Days, optimum vernalizing temperature, required for vernalization	5 days
Photoperiod response (% reduction in rate/10 h drop in pp)	75
Grain filling (excluding lag) phase duration (oC.d)	450
Kernel number per unit canopy weight at anthesis (#/g)	30
Standard kernel size under optimum conditions (mg)	35
Standard, non-stressed mature tiller wt (incl grain) (g dwt)	1
Interval between successive leaf tip appearances (oC.d)	60

Table 4.7 Details of cultivar for wheat

Cultivar file for Maize:

Name of cultivar	**Parvati**
Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8°C) during which the plant is not responsive to changes in photoperiod.	160
Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours).	0.75
Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8°C).	780
Maximum possible number of kernels per plant.	750
Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day)	8.50
Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	49

Table 4.8 Details of cultivar for maize

4.4.5. Field visit

A field survey was conducted during the month of March for collecting the depth wise soil series, cultivar data information, crop management data information and other ancillary data. The various instruments used during the field visit and their corresponding purposes are given below in table 4.9.

Sl No:	**Instrument**	**Purpose**
1	Global Positioning System(GPS) Make: Garmin	Used to identify exact location of field data points for further access and analysis in geospatial environment.
2	Ceptometer AcuPAR-LP80(Decagon devices)	Is a PAR (Photo synthetically active radiation) sensor used for real time nondestructive measurement of LAI (leaf area index) in the field
3	Quadrat frame	A 50x50 cm metallic frame used for plot scale measurement of plant density, yield and biomass.
4	Spade, Pickaxe, Khurpi, Field	To collect soil sample from 0 – 30 cm depth.

	Knife	
5	Soil Auger (Edelman combination auger)	To collect soil sample from 30-50 cm depth.
6	Theta probe (Delta-T WET-2 Sensor kit)	To measure root zone % soil moisture, Electrical conductivity (EC) and temperature.
7	CHNS Analyser (Elementar)	To analyze Total organic carbon present in the soil.
8	pH and EC meter	To determine pH and electrical conductivity of collected soil samples.
9	Hydrometer (Bouyoucos)	Used for textural analysis of soil samples.

Table 4.9 Details of Instruments used in field Visit

4.5. Methodology

The stepwise methodology adopted for predicting the yield output using the climate and the crop models is given in figure 4.8.

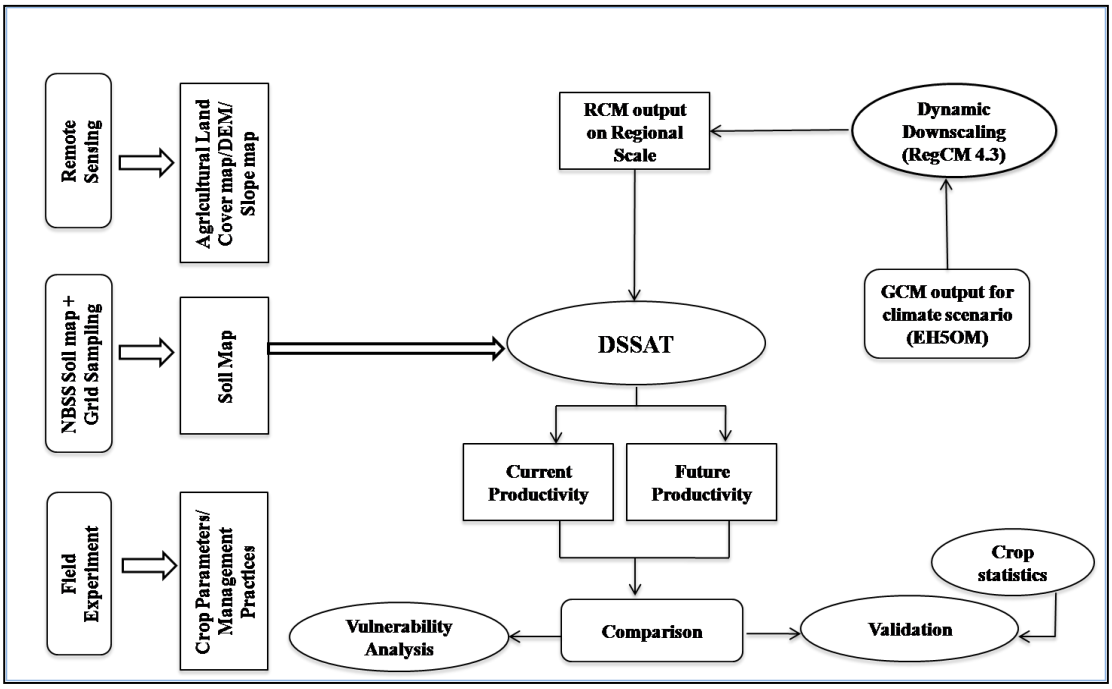


Figure 4.8. Methodology adapted for the preset work

The work starts with gathering the input datasets required for downscaling which are downloaded from http://users.ictp.it/~pubregcm/RegCM4/globedat.htm. The forcing input data listed in section 4.3 are acquired from this site which is stored in a system which is saved in a particular path that is accessible by the model.

4.5.1. Running the model

4.5.1.1. Pre-processing

a) Initial boundary conditions

The latitude and longitude of the study area, spatial grid size and the number of grids to be obtained after downscaling are given in the initial step. The duration of the period considered for analysis and the time interval are also set in this stage. The outputs of this step include terrain files, SST files, ICBC boundary files in which , for each lat/long the boundaries are created with the selected number of grids (150) at the required spatial resolution (25km). The output files are created in the format of ICBCYYYYMMDDHH.ctl and DOMAIN. ctl which is taken as an input for the next simulation.

The following code shows the input parameters given for RegCM climate model simulation

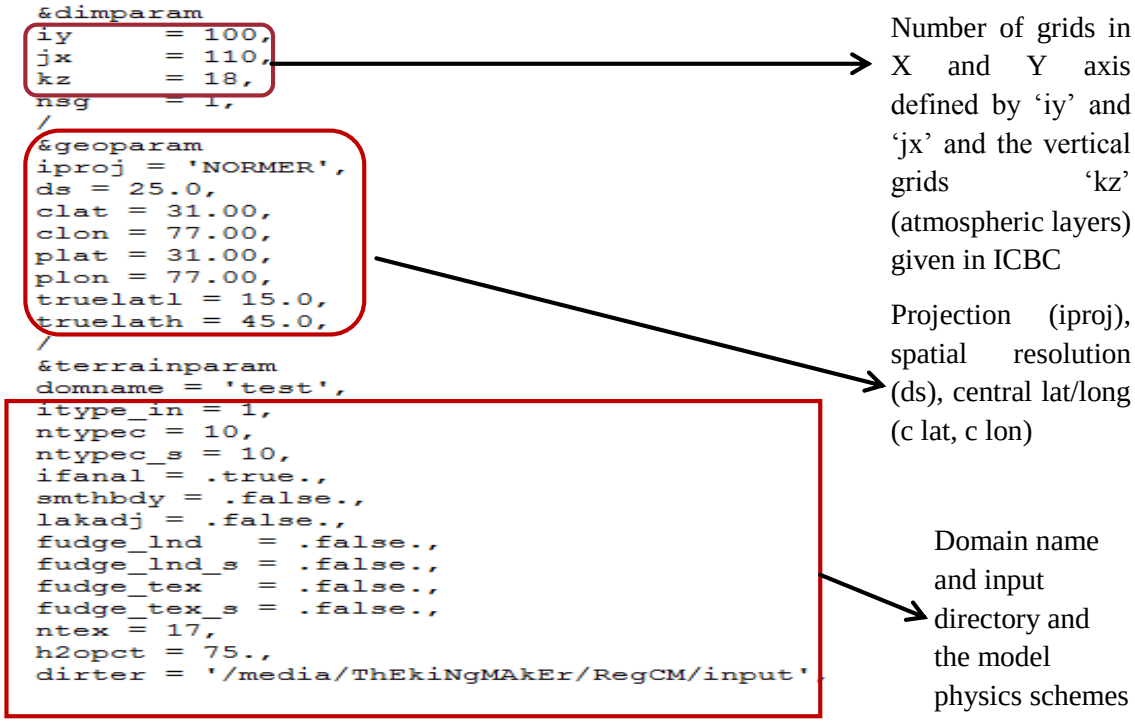


Fig 4.9. Input parameter for Resolution, grid size, domain name and input directory in RegCM simulation

```
&ioparam
igrads = 1,
ibigend = 1,
ibyte = 4,
iotyp = 1,
/
&debugparam
debug_level = 1
/
&boundaryparam
nspgx  = 12,
nspgd  = 12,
/
&modesparam
nsplit = 2,
/
&lakemodparam
lkpts  = 10,
/
&globdatparam
ssttyp = 'EHA1B',
dattyp = 'EH5OM',
ehso4 = .false.,
globidate1 = 2001010200,
globidate2 = 2001022818,
dirglob = '/media/ThEkiNgMAkEr/RegCM/input',
inpglob = '/media/ThEkiNgMAkEr/RegCM',
/
&lsmparam
lsmtyp = 'BATS',
/
```

→Data types and simulation start date, end date and input and output directory

Fig 4.10. Datatypes and simulation start date, end date and input and output directory

The variables contained in domain.ctl format are shown in table 4.10

Variables	Description	Variables	Description
ht	Surface elevation (m)	**dlon**	Longitude of dot points
landuse	Surface landuse type	**xmap**	Map factors of cross points
htsd	Surface landuse type	**dmap**	Map factors of dot points
xlat	Latitude of cross points	**coriol**	Coriolis force
xlon	Longitude of cross points	**snowam**	Initial snow amount
dlat	Latitude of dot points		

Table 4.10. Variables of DOMAIN.ctl format

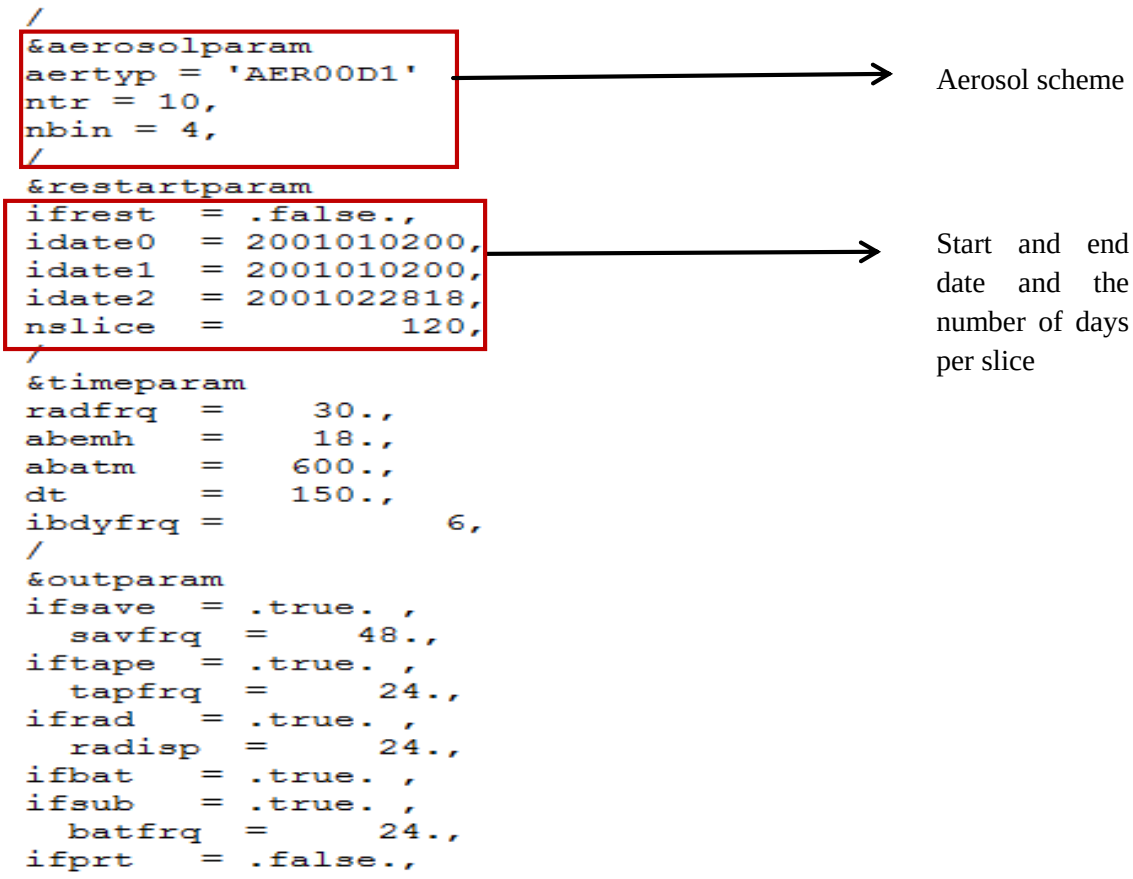


Figure 4.11. Aerosol scheme and dates of simulation

The variables contained in ICBCYYYYMMDDHH.ctl format are shown in table 4.11

Variables	Description
u	Westerly wind (m /s)
v	Southerly wind (m /s)
t	Air temperature (K)
q	Specific moisture (kg /kg)
px	Surface pressure (hPa)
ts	Surface air temperature (K)

Table 4.11. Variables contained in ICBCYYYYMMDDHH.ctl format

```
 iemiss  =           0,
 lakemod =           0,
 ichem   =           0,
 /
 &subexparam
 qck1land=   .250E-03,
 qck1oce =   .250E-03,
 cevap   =   .100E-02,
 caccr   =      3.000,
 /
 &grellparam
 /
 &emanparam
 /
  &chemparam
 idirect   =    2,
 inpchtrname  = 'DUST','DUST','DUST','DUST',
'SO2','SO4','BC_HB','BC_HL','OC_HB','OC_HL',
 inpchtrsol   =  0.10, 0.10, 0.10, 0.10, 0.20, 0.80, 0.05, 0.80,
0.05, 0.80
 inpchtrdpv(:,1) =0.,0.,0.,0.,
0.00300,0.00200,0.00025,0.00025,0.00025,0.00025
 inpchtrdpv(:,2) = 0.,0.,0.,0.,
0.00800,0.0020 ,0,0.00025,0.00250,0.00025,0.00250
 inpdustbsiz(:,1)  = 0.01, 1.00, 2.50, 5.00
 inpdustbsiz(:,2)= 1.00, 2.50, 5.00,20.00
 /
 &clmparam
 dirclm = '/media/ThEkiNgMAkEr/RegCM/input',
 imask  = 1,
 clmfrq = 0.,
```

Figure 4.12. Physics schemes and Output paths

4.5.1.2. Post processing

The post processor takes the outputs from ICBC and DOMAIN.ctl formats as inputs and generates the final outputs in NetCDF file format. The output monthly files which include 30 daily files each files saved in the name of

ATM.YYYYMMDDHH.nc – output from atmospheric model

RAD.YYYYMMDDHH.nc - output from radiation model

SRFYYYYMMDDHH.nc - output from land surface model.

STSYYYYMMDDHH.nc - out

The physics schemes and parameters processed by the RegCM model are shown in table 4.12.

Model aspects	**Available options**
Dynamics	• Hydrostatic, σ-vertical coordinate *(Giorgi et al., 1993)*
Radiative transfer	• Modified CCM3 *(Kiehl et al., 1998)*
PBL	• Modified Holtslag *(Holtslag et al., 1990)* • UW-PBL *(Bretherton et al., 2004)*
Cumulus convection	• Simplified Kuo *(Anthes et al., 1987)* • Grell *(Grell, 1993)* • MIT *(Emanuel and Živković-Rothman, 1999)* • Tiedtke *(Tiedtke, 1989)*
Resolved scale precipitation	• SUBEX *(Pal et al., 2000)*
Land surface	• BATS *(Dickinson et al., 1993)* • Sub-grid BATS *(Giorgi et al., 2003)* • CLM *(Steiner et al., 2009)*
Ocean fluxes	• Organic and black carbon, SO4 *(Solmon et al., 2006)* • Dust *(Zakey et al., 2006)* • Sea salt *(Zakey et al., 2008)*
Interactive lake	• 1D diffusion/convection *(Hostetler et al., 1994)*
Tropical band	• *(Coppola et al., 2012)*

Table 4.12. Physics schemes and parameters processed by the RegCM model

The model takes around 7 hours for simulating one month climate prediction and the final outputs are saved in heavy storage units. The outputs from RegCM models have the following parameters.

- ✓ Westerly wind at 10m (m/s)
- ✓ Southerly wind at 10m (m/s)
- ✓ Surface drag stress
- ✓ Ground temperature (degree)
- ✓ Temperature of foliage
- ✓ Air temperature at 2m (K)
- ✓ Water vapor mixing ratio at 2m(kg/kg
- ✓ Upper layer soil water
- ✓ Root zone soil water
- ✓ Total precipitation (mm/day)
- ✓ Evapotranspiration (mm/day)
- ✓ Runoff surface runoff (mm/day)

- ✓ Snow amount (mm, water equivalent)
- ✓ Sensible heat flux (W/m2)
- ✓ Net infrared energy flux (W/m2)
- ✓ Net absorbed solar energy flux (W/m2
- ✓ Downward infrared energy flux (W/m2)
- ✓ Incident solar energy flux (W/m2)
- ✓ Convective precipitation (mm/day)
- ✓ Surface pressure (hPa)
- ✓ PBL layer height
- ✓ Maximum ground temperature (K)
- ✓ Minimum ground temperature (K)
- ✓ Maximum 2m air temperature (K)
- ✓ Minimum 2m air temperature (K)
- ✓ Maximum 10m wind speed (m/s)
- ✓ Minimum surface pressure (hPa)

4.5.2. Analyzing and processing of the climate model output

Assessment of future climate scenario derived from EH5OM model was done using **inter-annual seasonal variability** study for year 2000-2025 in 25 km spatial resolution. In this process we have analyzed four main seasons in India – DJF (December, January, February - winter), MAM (March, April, May - spring), JJA (June, July, august – summer/ Monsoon), SON (September, October, November - autumn). The inputs for crop models mentioned in section 4.4.1 were extracted from the outputs of climate model in the format of -

Lat Long Date Solar radiation Max temperature Minimum temperature Rainfall Elevation

4.5.2.1. Software and package requirements for analyzing the outputs

The software required for analyzing the outputs of the climate model include

- GRADS
- NetCDF viewer
- ARC GIS
- ERDAS Imagine
- ENVI
- Python
- XL Stat

4.5.2.2. Procedure for analysis

Inter annual seasonal variability analysis was conducted in the variables of max temperature, min temperature and rainfall for various seasons. Analysis was also made on annual temperature and annual rainfall in the same way. The values of Lat, Long, Date, Solar radiation, Max temperature, Minimum temperature, Rainfall, Elevation were converted to DSSAT weather format using programming. The climate models thus obtained are validated with the CRU (Central research Unit) observed datasets. The accuracy of the predicted climate output were statistically analyzed using the RMSE, MAPE, MSE and agreement index.

4.6. Running the crop model

4.6.1. Input file creation

4.6.1.1. Weather data

The outputs obtained from the Regional climate model are used as inputs for the weather data. Himachal Pradesh contains 107 grids for a spatial resolution of 25km, which are extracted from the climate model. All these obtained 107 grids are imported as weather stations in to DSSAT model using DSSAT Weather Man. The outputs from weather man has daily wise weather data for 25 years which include Lat, long, Solar radiation, Max temperature, Minimum temperature, rainfall, elevation. The weather station name is saved as 'HPIIYYDD.WTH' format.

4.6.1.2. Soil data

The soil file is created by soil file generator in DSSAT. The depth wise details collected from field and other sources is given as input for the soil file generator which creates the soil files. The details include – soil depth, soil color, soil texture, silt, clay and sand content, organic carbon, P^H , EC (Electric conductivity), CEC(Carbon Exchange Cations). Each of these details are given for every soil layer (based on the depths). The soil data file is save in .SOL format. 13 soil files were generated in the present work for various soils distributed within the districts of Himachal Pradesh.

4.6.1.3. Crop Cultivar file

The crop cultivar file is created by DSSAT using genetic parameters of major varieties of wheat and maize in Himachal Pradesh. The cultivar file format for wheat is .WH and for maize is .MZ

4.6.1.4. Crop Management data

The crop management data included – plantation date, irrigation, cultivar file, weather stations, soil files, harvest information, tillage information, organic manure information, fertilizer information, plant sowing depth etc. Totally 107 simulations are created for each and every grid using these parameters which vary from grid to grid. The grids are grouped according to district

wise and the district wise information of the above mentioned parameters are given as inputs for the grids falling in the region of the respective districts.

4.6.1.5. Running the model

Using the information to the grids, the treatments will be created in DSSAT model when we opt to run the model. The final output file will be saved as .OSR format. These files contain anthesis date, Byproduct, harvest index, maximum leaf area index, grain yield and other information related to crop inventory.

4.6.1.6. Output extraction

The yield and maximum LAI are extracted from the .OSR file for each district. The yield is then calculated in Kilogram/Hectare. The yields are validated with the productivity statistics obtained from Ministry of Agriculture. Maximum LAI is validated with MODIS 8 day composite.

4.7. Validation

The obtained climate output is validated using the CRU datasets and the crop yield outputs are validated with the ministry of agriculture data and the maximum LAI is validated using the MODIS 8 day composite.

RESULTS AND DISCUSSIONS

RESULTS AND DISCUSSION CHAPTER 5

As discussed in methodology ECHAM GCM data sets were downscaled using dynamic downscaling after which we got climatic variables at finer resolution for 2001-2025 daily basis. Climate model outputs were extracted and validated with CRU observed datasets 2001-2010. These outputs were then used as inputs for DSSAT crop model for a period 2001-2025. DSSAT crop model yield outputs for Wheat and Maize were validated with district wise yield data (2001-2009) from Ministry of Agriculture and observed Maximum LAI from model were validated with MODIS LAI data sets.

5.1. Dynamic Downscaling:

To assess the future climate scenario, ECHAM GCM model was downscaled using RegCM-4.3.5.6 model. The RegCM has been the first limited area model developed for long term regional climate simulation, it has participated to numerous regional model intercomparison projects, and it has been applied by a large community for a wide range of regional climate studies, from process studies to paleo-climate and future climate projections *(Giorgi and Mearns, 1999)* and *(Giorgi et al., 2006)*. Downscaling is mainly categorized as statistical and dynamical. The differences between the two approaches are discussed in detail in chapter 2. In the present study, dynamical downscaling was adopted and applied over North West Himalayan region.

Dynamic downscaling of EH5OM future projections for the years 2001-2025 involved two processes:

- Spatial Downscaling.
- Temporal Downscaling.

5.1.1. Spatial Downscaling:

GCM forcing at a resolution of 2.5° X 3.75° was input into RegCM model. The coarse resolution GCM data was downscaled at a grid size of 25 km over the study area. The results showed that the regional details that were poorly simulated by GCM were now adequately distinguishable after downscaling to higher spatial resolution.

5.1.2. Temporal Downscaling:

GCM forcing at a temporal resolution of 6 Hour was input into climate model. This was used in RegCM model and we got daily climate prediction as 6 hourly changes as these temporal variation does not significantly alter plants biological processes. The model can predict 3 hour, 6 hour temporal interval also.

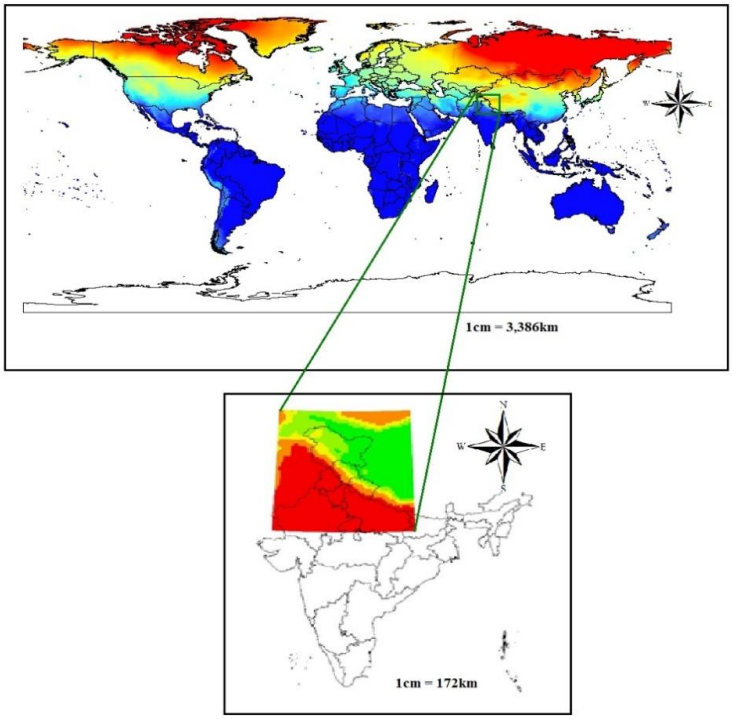


Figure5.1: Downscaling from GCM to RCM for northern Indian region

5.2. List of Outputs predicted from Regional Climate Model for crop model which are required and importance of crop growth and how it's important on crop growth.

5.2.1. Maximum Temperature

Maximum temperature output from RCM was used to predict its effect on crop yield as high temperature are known to decrease crop yield. The extent of the temperature determines the yield for the particular crop season as high temperature favors growth of pest and disease in plants and it also effect Mineral Nutrition, Shoot growth, Pollen development, Scorching, Physiological activities, Injury due to scorching sun, Burning off, Stem gridle etc.

5.2.2. Minimum Temperature

Minimum temperature out from RCM was used to predict the effect on crop yield. Low temperatures adversely affect pant growth because if the plants grown in hot temperature are exposed to low temperature, they will be killed (or) severely injured. When the night temperature is below 15°C field crops may show yellowing symptoms (e.g.) Tropical annuals. When the plants are exposed to how temperature, water freezes into ice crystals in the intercellular spaces. (e.g.) Cell dehydration. Formation of thick cover of ice/snow on the soil surface presents the entry of oxygen and crop suffers. This presents the respiration and lead to accumulation of harmful substance.

5.2.3. Solar Radiation

Along with water and nutrients, solar radiation (sunlight) is an essential input for plant growth. Solar radiation and crop yield have a direct relationship as it is an integral part of the photosynthesis process. Longer solar exposure at optimum temperature increases photosynthesis which in turn increases crop yield.

5.2.4. Rainfall

Precipitation, especially rain, has a dramatic effect on agriculture. All plants need at least some water to survive, therefore rain (being the most effective means of watering) is important to agriculture. While a regular rain pattern is usually vital to healthy plants, too much or too little rainfall can be harmful, even devastating to crops. Drought can kill crops and increase erosion, while overly wet weather can cause harmful fungus growth. Plants need varying amounts of rainfall to survive.

For example, certain cacti require small amounts of water, while tropical plants may need up to hundreds of inches of rain per year to survive. In areas with wet and dry seasons, soil nutrients diminish and erosion increases during the wet season. Animals have adaptation and survival strategies for the wetter regime. The previous dry season leads to food shortages into the wet season, as the crops have yet to mature. Developing countries have noted that their populations show seasonal weight fluctuations due to food shortages seen before the first harvest, which occurs late in the wet season. Rain may be harvested through the use of rainwater tanks; treated to potable use or for non-potable use indoors or for irrigation, Excessive rain during short periods of time can cause flash floods.

5.3. Analysis of Seasonal Maximum temperature, Minimum Temperature and Rainfall

With reference to the various discussions and work by researchers, the present study aims to understand the effect of the changing ICBCs on the winter (DJF) regional climate of the WH; also, to find out which reanalysis dataset as ICBC is showing more realistic results in simulating climatology and interannual variability of different meteorological parameters during IWM. This study also looks in to the explanation for the reason of the model biases which are inherent to the model simulated results.

The analysis of surface energy balance is taken into account which plays a major role in defining the surface temperature, evaporation and convective activities which are similar to the study of *(Krishnamurthy and VanderVeen, 2008)*where they analyzed the different phases of monsoon over central India. The WH is chosen as the study area because of its complexity in terrain and most of the RCMs are not able to capture the climatic processes over these regions. The climatic information from the RCM for DJF may contribute to the agricultural preparedness, tourism industry, transport, source of moisture to this region, defense as well as the water

resources management over this region. The methodology consisting model detail, experimental design and data used is explained in Chapter 2. This chapter provides results and discussion and the concluding remarks are given in chapter 6.

In India there are four main seasons:

- DJF – December, January, February (Winter Season)
- MAM – March, April, May (Spring Season/Summer)
- JJA – June, July, August (Monsoon/Summer)
- SON- September, October, November (Autumn)

Wheat is sown and harvested by November to May and Maize is sown and harvested by June to August/September. In Himachal Pradesh maize is mostly sowing under the rainfed condition.

As per the analysis done in the model for the period of 2001 – 2025, the predictions are as follows:

As can be seen in the graphs below, In DJF season – a maximum rainfall of 300mm was registered in the year 2007, and the maximum temperature records were shown in the years of 2016 and 2021 while the minimum temperatures observed in the year of 2019. In MAM season – a maximum rainfall was registered in the year 2005, and the maximum temperature records were shown in the years of 2005 and 2009 while the minimum temperatures were predicted in the year of 2016.

According to the results obtained for the JJA season – the rainfall was maximum in the year of 2006 and 2010 and a similar quantity is predicted in the year 2021. The maximum and minimum temperatures were recorded in the years of 2015 and 2010 respectively. For the SON season, the maximum rainfall was forecasted in the year of 2016 and maximum temperature was seen in the years of 2005, 2008 and a similar temperature was predicted in the year of 2018. The minimum temperature of 291 K was predicted in the year of 2016.

Seasonal wise Rainfall maps for 2001-2025- Northern India

Seasonal wise Minimum Temperature maps for 2001-2025- Northern India

Seasonal wise Maximum Temperature maps for 2001-2025- Northern India

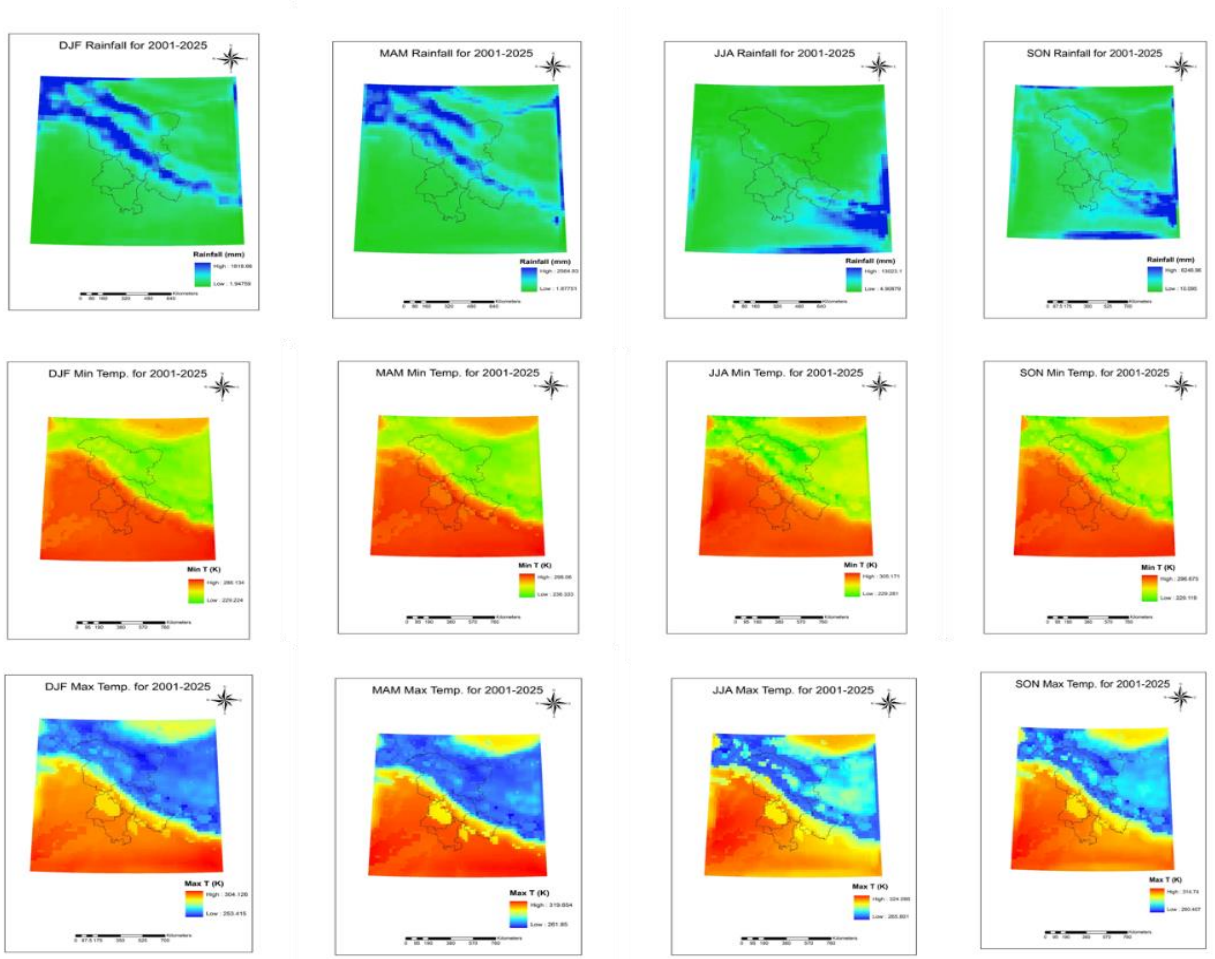


Figure 5.2 Seasonal Analysis of Maximum temperature, Minimum temperature, Rainfall

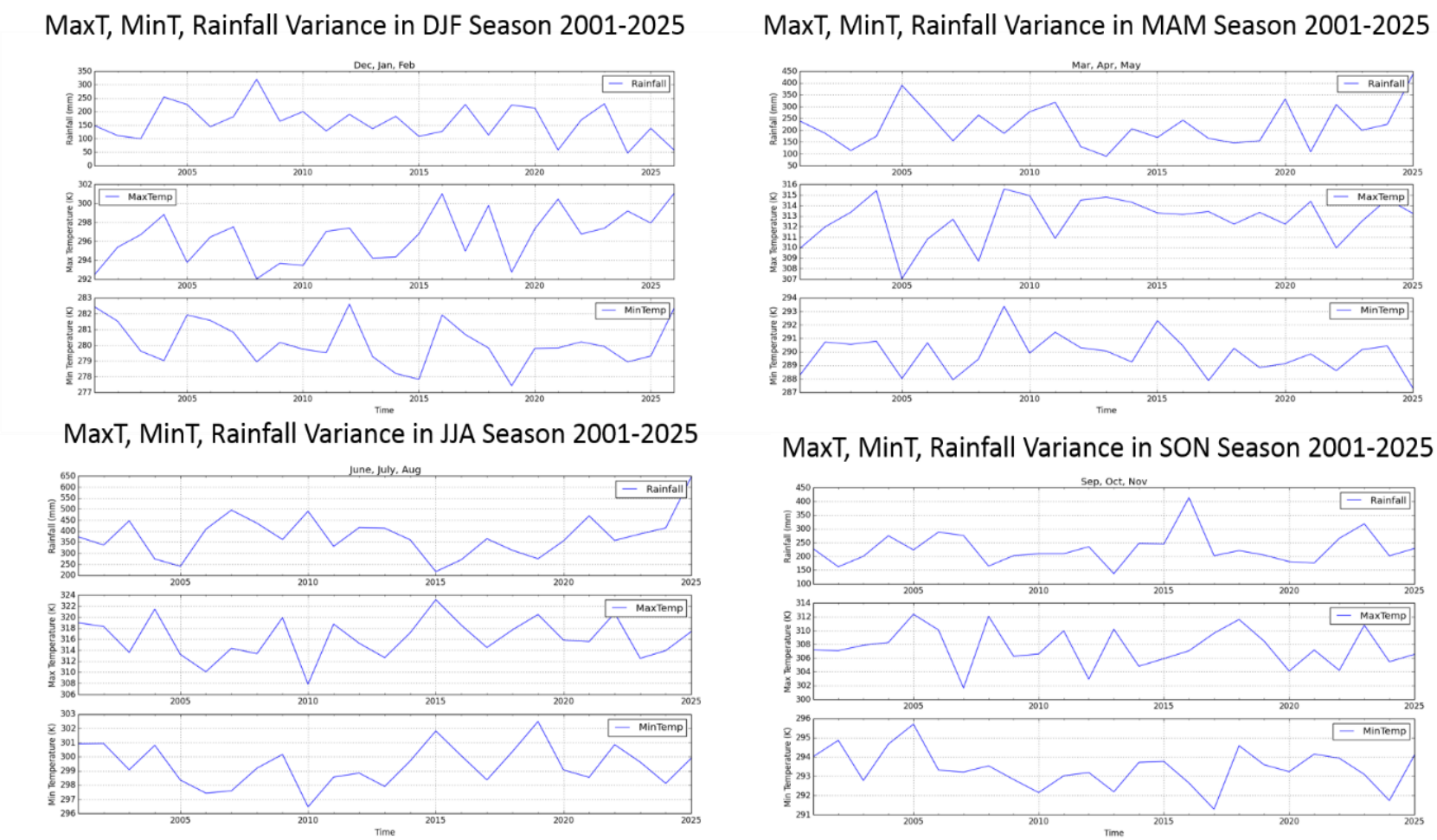


Figure 5.3 Graphical representation of various Seasons for Maximum temperature, Minimum temperature, Rainfall in Northern India

5.4. Validation of climatic data with CRU data (Monthly)

As per the Central Research Unit, the observed climate datasets were validated with the predicted datasets and the results are shown in the figure 5.4

	RMSE	MAPE	MSE	R^2
Maximum Temperature	14.134	61.635	71.24	0.82
Rainfall	60.134	96.5	198.590	0.52
Minimum Temperature	10.123	123.45	167.985	0.81

Table 5.1. Monthly RMSE between wise RegCM downscaled output and CRU observed datasets

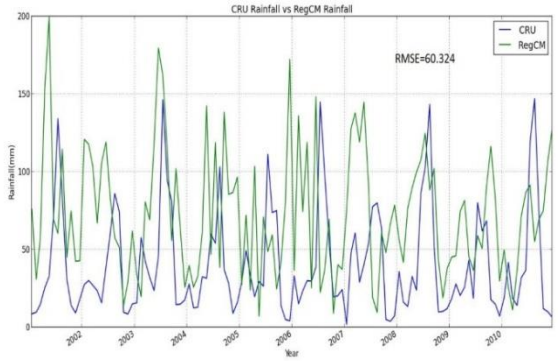
Climatic Research Unit (CRU) TS (time-series) datasets are month-by-month variations in climate over the last century or so. These are calculated on high-resolution (0.5x0.5 degree) grids, which are based on an archive of monthly mean temperatures provided by more than 4000 weather stations distributed around the world. They allow variations in climate to be studied, and include variables such as cloud cover, diurnal temperature range, frost day frequency, precipitation, daily mean temperature, monthly average daily maximum temperature, vapour pressure and wet day frequency. At present, the BADC holds the latest CRU TS version 3.21 spanning the period 1901-2012 as well as previous versions (3.00, 3.10 and 3.20). The CRU TS 3.20 data are monthly gridded fields based on daily values -hence the ASCII and netcdf files both contain monthly mean values for the various parameters.

The CRU TS data are stored in both ASCII and NetCDF formats:

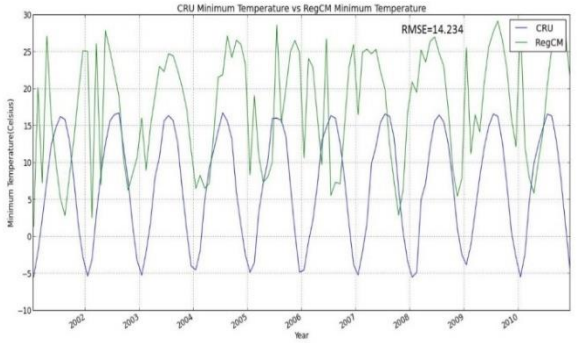
- ASCII data: The 360-lat x 720-long grid is presented exactly as 720 columns, and 360 rows per time step. The first row in each grid is the southernmost (centred on 89.75S). The first column is the westernmost (centred on 179.75W). There are scaling factors to be used in the data files (see Table below). One gets the whole global grid for the first time step, then the whole grid for the second, and so on. So the first 360 rows show the data for Jan 1901, next 360 rows the data for Feb 1901 and next 360 rows for March 1901 and so on.
- NetCDF data: CRU3.20 - There are no scale factors in the NetCDF files because the data is FLOAT instead of INT.
- Missing values are stored as -999.

Compared with CRU data, estimated data is overestimated for Minimum Temperature in the monthly basis section. Maximum Temperature is under estimated with CRU data. CRU minimum Temperature datasets are maintaining constant difference. But, estimated minimum temperatures are showing high variability. Rainfall is also under estimated with CRU observed datasets. Maximum and Minimum Temperature are correlated 82 and 81 percent respectively. But rainfall is correlated 52 percent only. Because of high variability topography, lot of annotations in Himalayan region rainfall can be under estimated by model. Based on the previous studies CRU data also can be more biased for the Indian sub-continent region. In table 5.1, statistical calculation between CRU and RegCM data sets are given.

Monthly Validation between RegCM Downscaled Rainfall and Observed CRU Rainfall



Monthly Validation between RegCM Downscaled Minimum Temperature and Observed CRU Minimum Temperature 2001-2010



Monthly Validation between RegCM Downscaled Maximum Temperature and Observed CRU Maximum Temperature 2001-2010

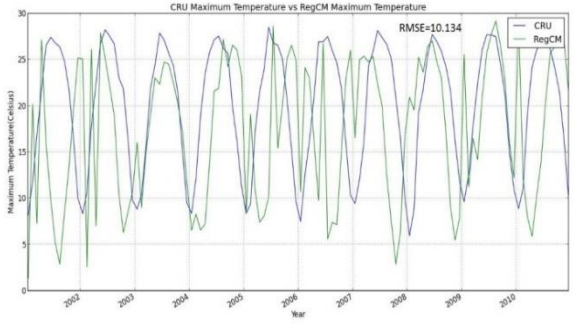


Figure 5.4.Month wise validation between RegCM downscaled output and CRU observed datasets

5.5. Validation of climatic data with CRU data (Seasonal)

As per the Central Research Unit, the observed climate datasets were validated with the predicted datasets and the results are shown in the figure 5.5, 5.6 and 5.7.

In this section climate parameters maximum temperature, minimum temperature and rainfall are validated with CRU observed data in the basis of seasonal (DJF – December, January and February, MAM – March, April and May, JJA – June, July and August, SON – September, October and November)

Parameters	Seasons	RMSE	MAPE	MSE	R^2
Maximum Temperature	DJF	3.371	47.807	11.365	0.866
	MAM	3.585	24.329	12.849	0.846
	JJA	3.985	15.479	15.877	0.766
	SON	4.825	40.165	23.728	0.812
Rainfall	DJF	71.762	96.145	24.789	0.678
	MAM	80.376	103.456	27.654	0.712
	JJA	76.543	97.843	26.865	0.724
	SON	82.458	99.321	27.987	0.675
Minimum Temperature	DJF	3.284	179.579	10.784	0.856
	MAM	3.651	198.131	13.333	0.867
	JJA	3.337	46.178	11.133	0.854
	SON	3.619	94.353	13.094	0.836

Table 5.2. Seasonal RMSE between wise RegCM downscaled output and CRU observed datasets

Table5.2 is showing the statistical relation between the estimated and observed data sets. In Maximum temperature in DJF season is showing 86 percent correlation with observed datasets, MAM season is showing 84 percent correlation with observed datasets, JJA season is showing 76 percent correlation with observed datasets, SON season is showing 81 percent correlation with observed datasets. Minimum temperature in DJF season is showing 85 percent of correlation with observed datasets, MAM season correlated 86 percent with observed datasets, JJA season is showing 85 percent with observed datasets, SON season is correlated with 83 percent with observed datasets. Rainfall in DJF season 67 percent correlated with observed datasets, MAM, JJA, SON seasons are correlated 71, 71, and 67 percent with observed datasets respectively. Overall correlation of Maximum temperature in various seasons are around 85 percent with

observed datasets. Minimum temperature in various seasons are around 86 percent with observed datasets. Rainfall in various seasons are around 70 percent with observed datasets.

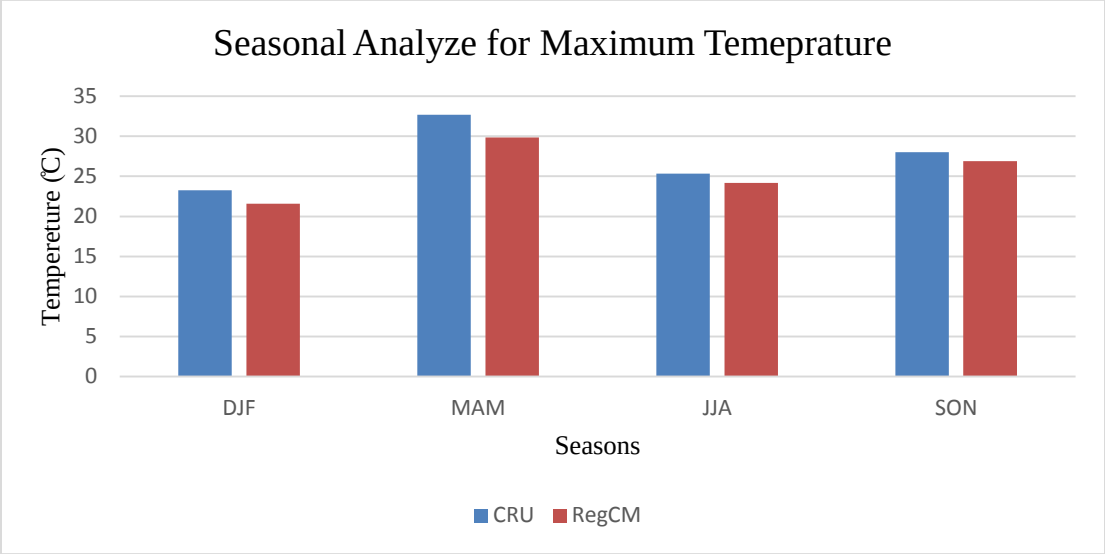


Figure 5.5 Seasonal Maximum Temperature validation between RegCM downscaled data and CRU Observed Datasets

Figure 5.5 showing variance of observed and estimated maximum temperature in different seasons. Observed maximum temperature in the season of DJF is showing 24 Degree Celsius and estimated maximum temperature is showing 22 Degree Celsius. In the season of MAM, observation is showing around 33 Degree Celsius and estimation is showing around 30 Degree Celsius. In the season of JJA observation is showing around 25 Degree Celsius and estimation is showing around 23 Degree Celsius. Observed maximum temperature in the season of SON is showing 28 Degree Celsius and estimated maximum temperature is showing 26 Degree Celsius. Overall correlation between the observed and estimated maximum temperature on the basis of season is around 85 percent. MAM is the summer season in India. So, it is showing high temperature values in analysis. DJF is the winter season in India. So, it is showing low temperature values in analysis.

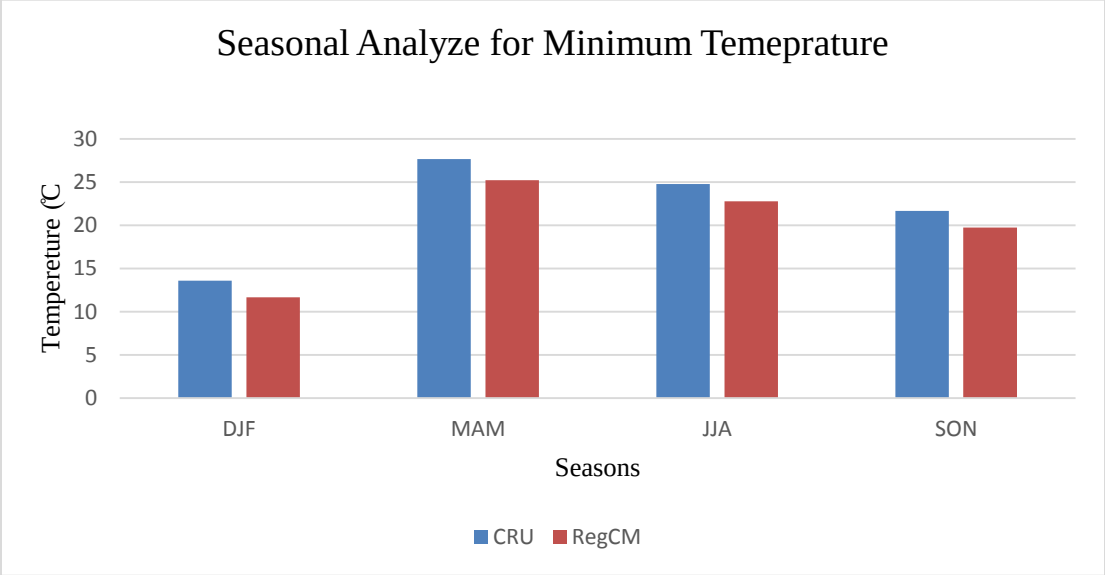


Figure 5.6 Seasonal Minimum Temperature validation between RegCM downscaled data and CRU Observed Datasets

Figure 5.6 showing variance of observed and estimated minimum temperature in different seasons. Observed minimum temperature in the season of DJF is showing 14 Degree Celsius and estimated minimum temperature is showing 12 Degree Celsius. In the season of MAM, observation is showing around 27 Degree Celsius and estimation is showing around 25 Degree Celsius. In the season of JJA observation is showing around 25 Degree Celsius and estimation is showing around 23 Degree Celsius. Observed minimum temperature in the season of SON is showing 21 Degree Celsius and estimated minimum temperature is showing 19 Degree Celsius. Overall correlation between the observed and estimated minimum temperature in the basis of seasonal is around 86 percent. MAM is the summer season in India. So, it is showing high temperature values in analysis. DJF is the winter season in India. So, it is showing low temperature values in analysis.

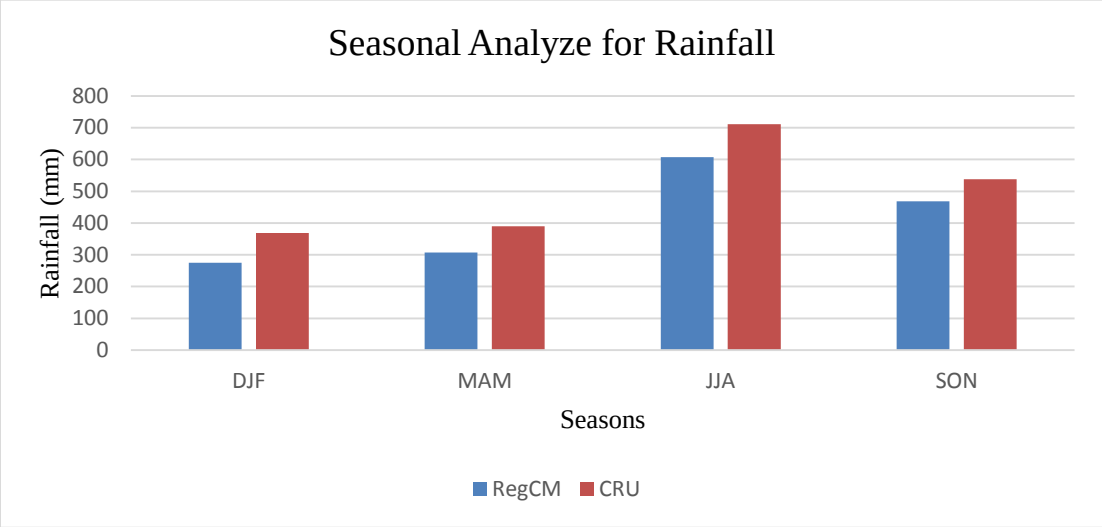


Figure 5.7 Seasonal Rainfall validation between RegCM downscaled data and CRU Observed Datasets

Figure 5.7 showing variance of observed and estimated minimum temperature in different seasons. Observed rainfall in the season of DJF is showing 360 mm and estimated rainfall is showing 280 mm. In the season of MAM, observation is showing around 380 mm and estimation is showing around 300 mm. In the season of JJA observation is showing around 720 mm and estimation is showing around 600 mm. Observed rainfall in the season of SON is showing 520 mm and estimated rainfall is showing 470 mm Celsius. Overall correlation between the observed and estimated rainfall in the basis of seasonal is around 72 percent. JJA is the monsoon season in India. So, it is showing high rainfall values in analysis.

5.6. Validation of climatic data with CRU data (Annual)

As per the Central Research Unit, the observed climate datasets were validated with the Predicted datasets and the results are shown in the figure

	RMSE	MAPE	MSE	R^2
Maximum Temperature	9.192	64.635	84.90	0.843
Rainfall	107.2133	91.04808	201.590	0.595
Minimum Temperature	13.190	143.123	173.985	0.876

Table 5.3. Annual RMSE between wise RegCM downscaled output and CRU observed datasets

Maximum and Minimum Temperature of RegCM downscaled output are 84 and 87 percent respectively correlated with observed datasets in the basis of Annual analysis. Rainfall estimated data is correlated with observed datasets 60 percent in the basis of annual. In every estimated parameters of climate are underestimated with CRU observed datasets. But maximum and minimum temperature parameters are more correlated than rainfall with observed datasets.

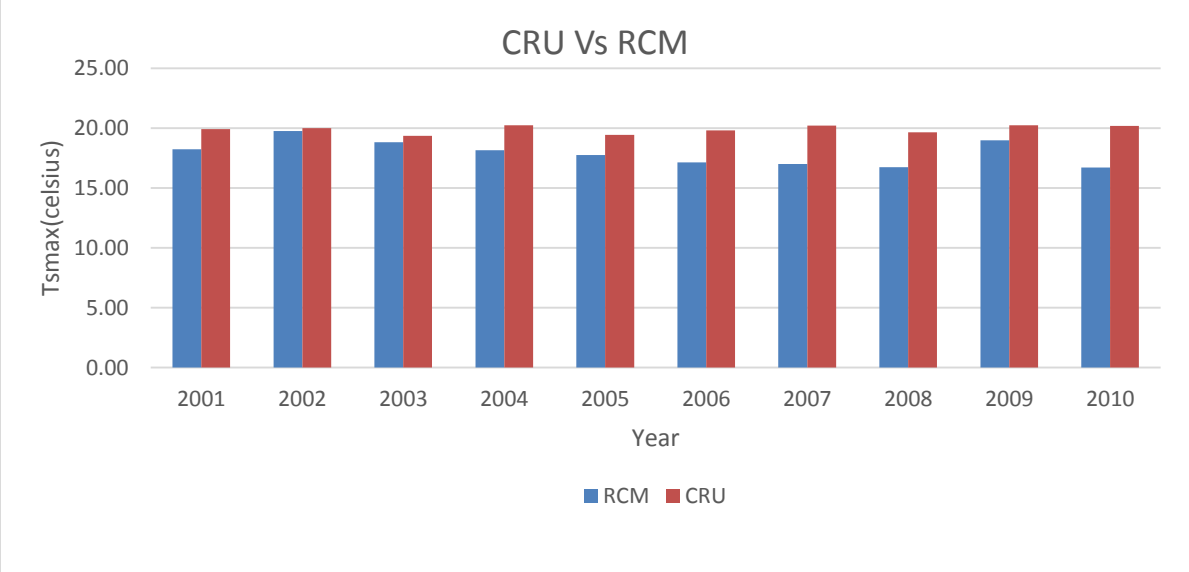


Figure 5.8 Annual Maximum Temperature validation between RegCM downscaled data and CRU Observed Datasets

Above figure 5.8 is showing annual variability in maximum temperature for observed and estimated datasets. In the year of 2001 maximum temperature of observed datasets is showing around 20 Degree Celsius. Almost every years for observed values are showing similar values around 20 Degree Celsius. But estimated datasets are showing variance in the years 2001 -2010. Anyways estimated datasets are underestimated with observed datasets. The correlation between the observed estimated datasets are 84 percent.

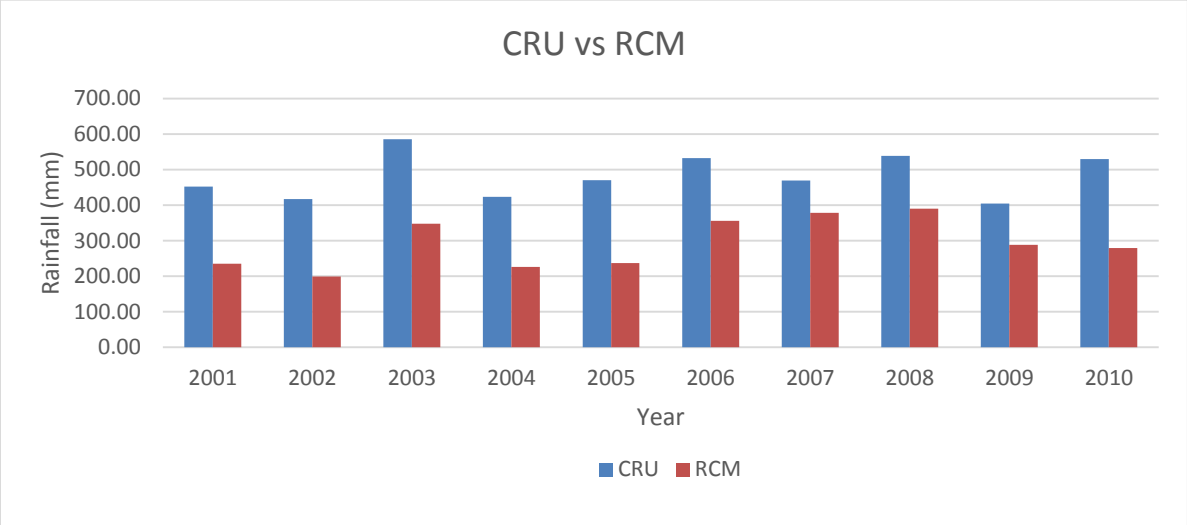


Figure 5.9 Annual Rainfall validation between RegCM downscaled data and CRU Observed Datasets

Above figure 5.9 is showing the validation between the observed and estimated annual rainfall. As per the previous studies 2002 is observed as the drought period having less rainfall coinciding with this thesis work. In this analysis 2002 is registered with less rainfall, year 2008 having high rainfall. The correlation between the observed and estimated rainfall is around 60 percent. This is having less correlation when compared with the correlation of maximum and minimum temperature.

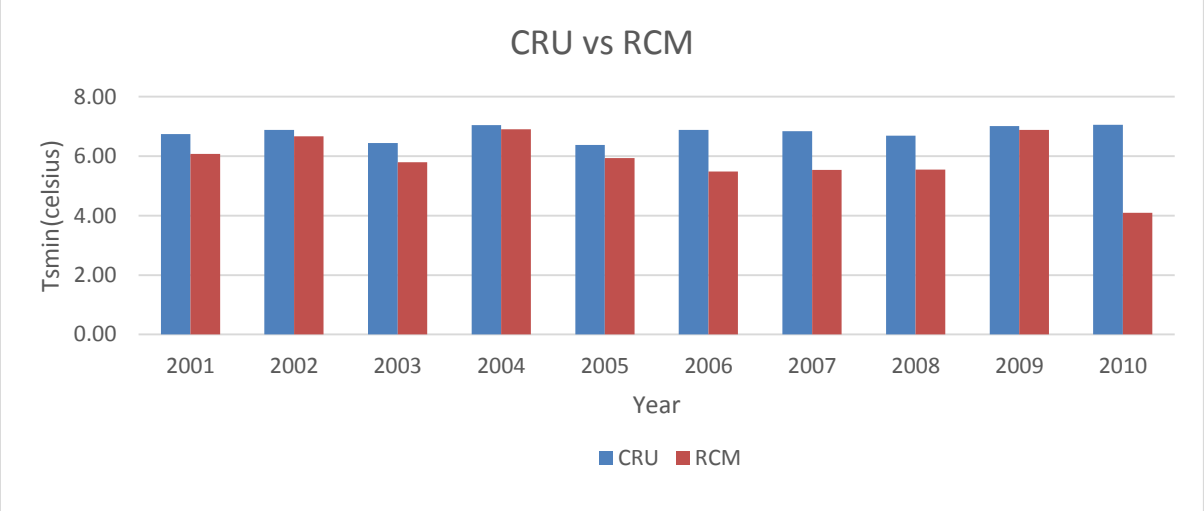


Figure 5.10 Annual Minimum Temperature validation between RegCM downscaled data and CRU Observed Datasets

Above figure 5.8 is showing annual variability in minimum temperature for observed and estimated datasets. In the year 2001 minimum temperature of observed dataset was showing around 7 Degree Celsius. Almost every year for observed values are showing similar values around 7 Degree Celsius. But estimated datasets are showing variance in the years 2001 -2010. Though estimated datasets are underestimated with observed datasets, the correlation between the observed estimated datasets is 87 percent.

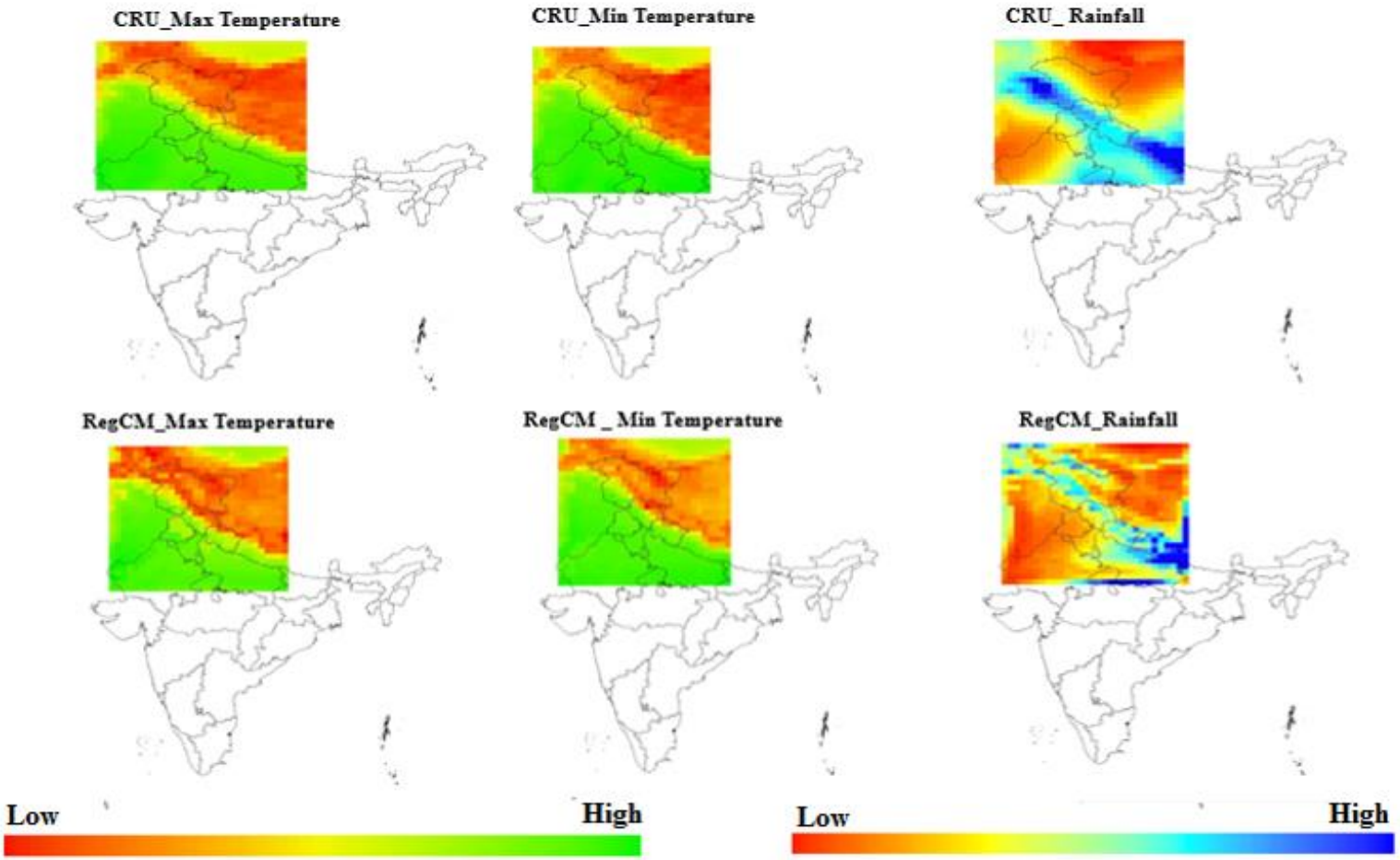


Figure 5.11. Validation between CRU and RegCM data from 2001 - 2010

5.7. Yield forecast

DSSAT model is run as per the procedure discussed in the methodology and the results obtained are shown below

5.7.1. Regional Wheat yield output

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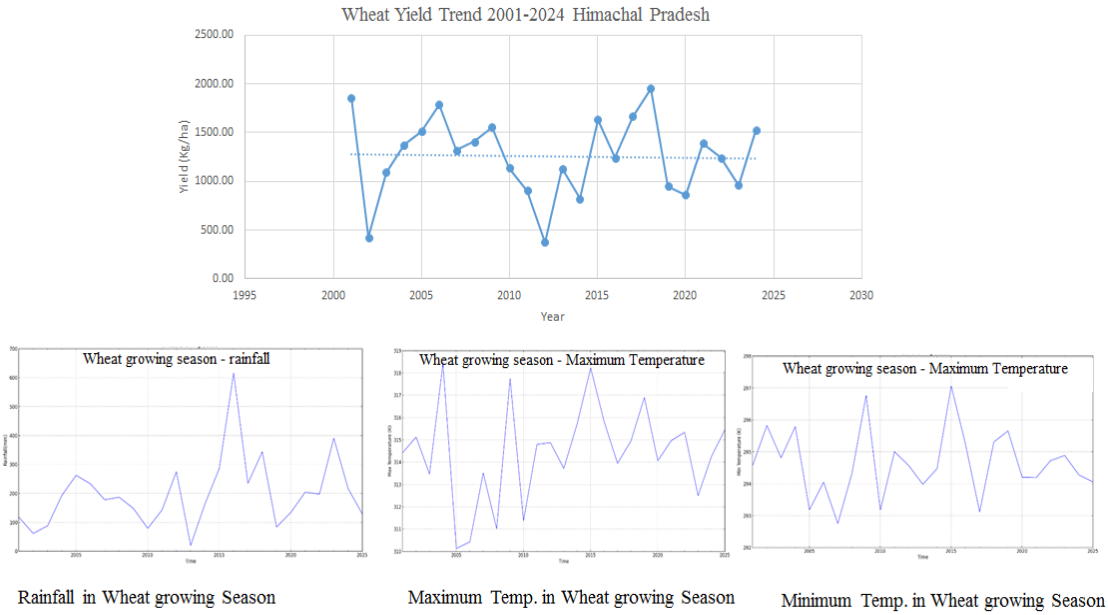

Fig 5.12. Trend analysis of predicted wheat yield and climate variables for the crop period

CERES-wheat model was calibrated and validated for variety HPW-89 for Himachal region and the genetic coefficients thus generated were used to simulate the wheat yield in different years starting from 2001-2025.

As per the IPCC report the wheat yield in the South East Asian countries is going to reduce to up to 50% during the next 50 years. The predicted trend observations also showed a decreasing trend line, which is showing a reduction in the wheat yield in the future. As per the graph, the maximum yield is expected in the year 2016, which was relating to an optimum forecasted weather conditions – like maximum rainfall of 600mm and optimum maximum and minimum temperatures. The crop yields in the years 2002 and 2012 were observed to be minimum during the entire 25 year period due to the abnormally low rainfall conditions that persisted during 2002 and 2012.The year wise wheat yield maps for the years 2001 to 2025 are presented in fig 5.13, 5.14, 5.15 and 5.16.

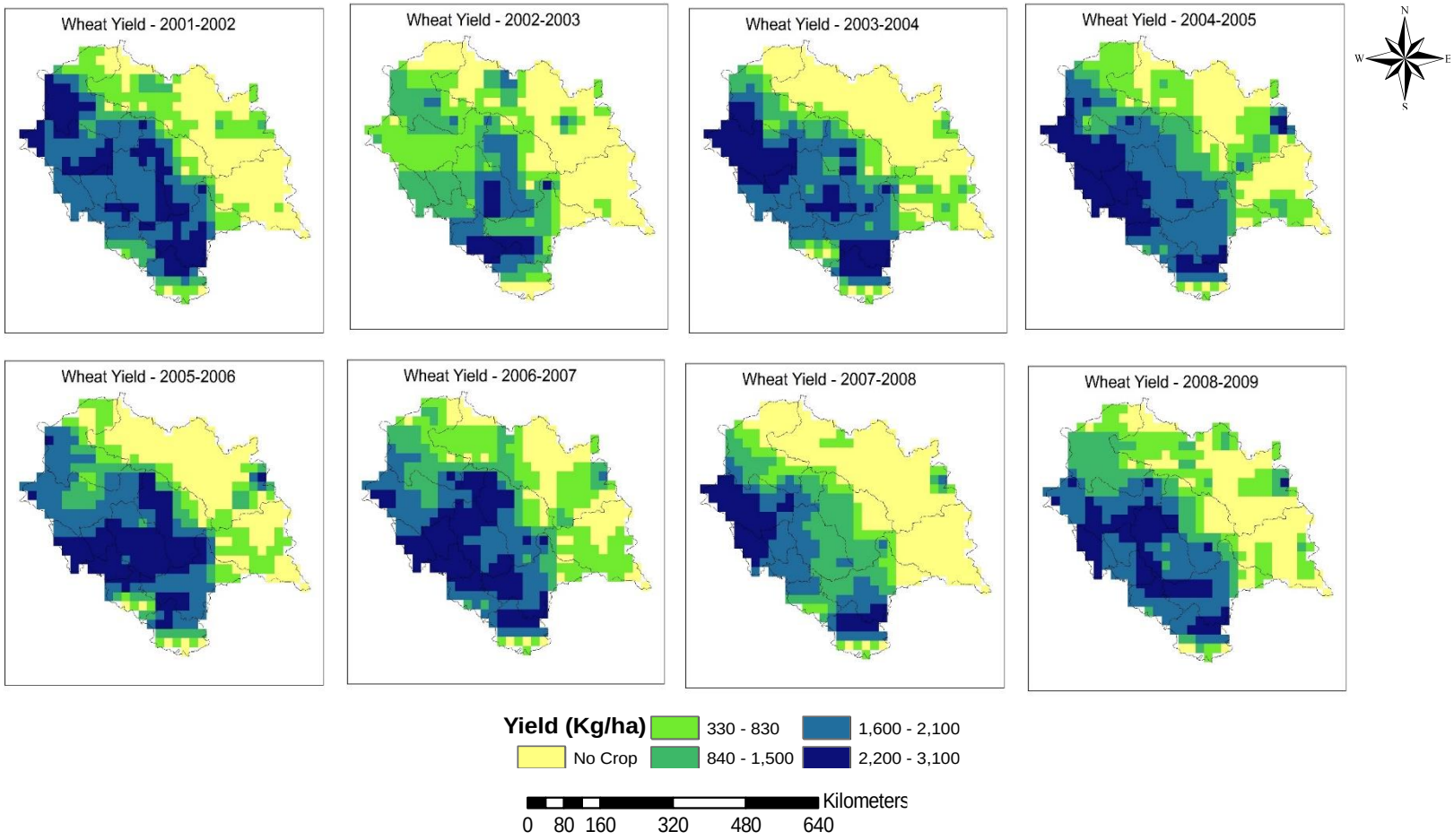

Fig. 5.13. Year wise current wheat yield maps from 2001 to 2009

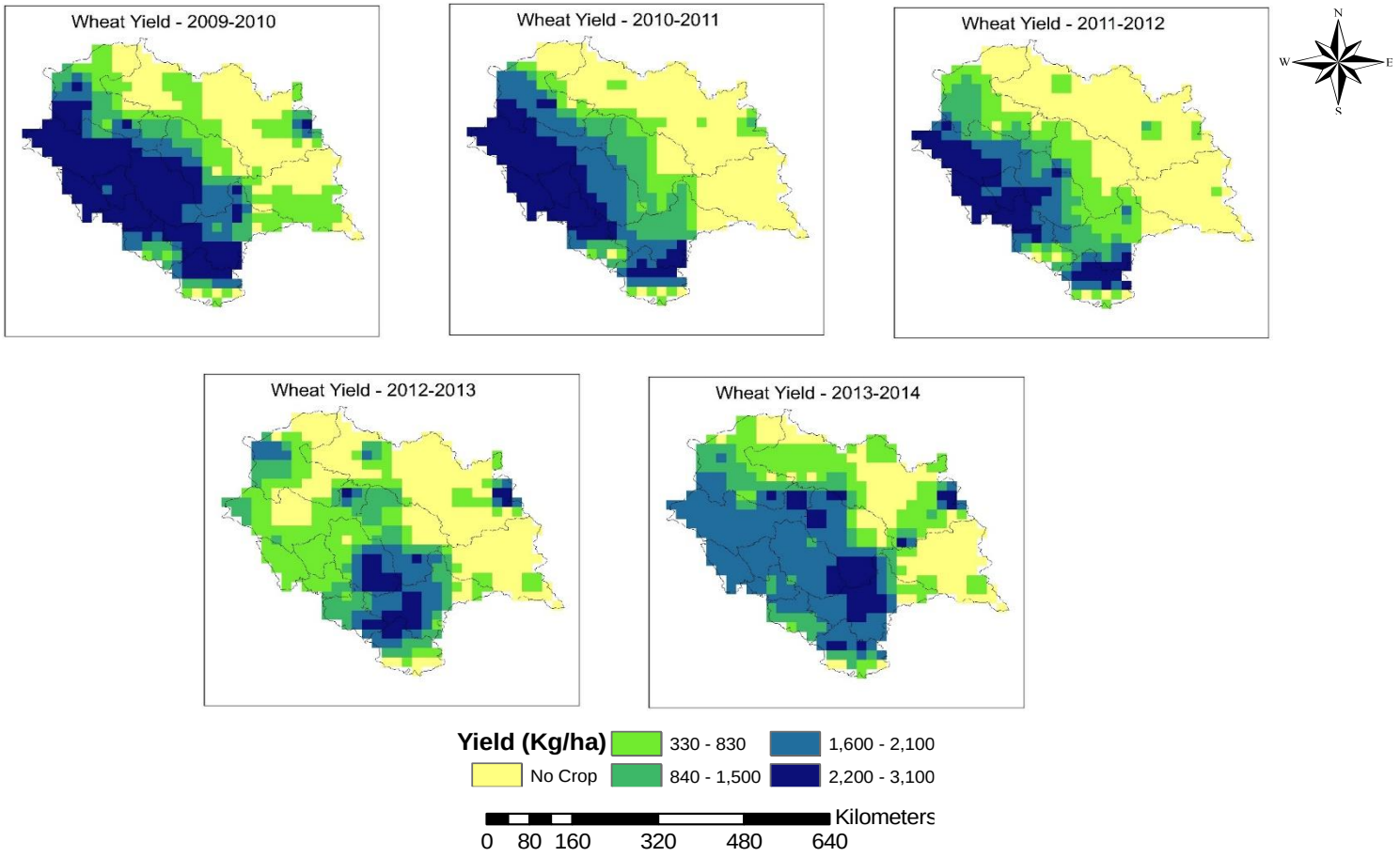

Fig. 5.14. Year wise current wheat yield maps from 2010 to 2014

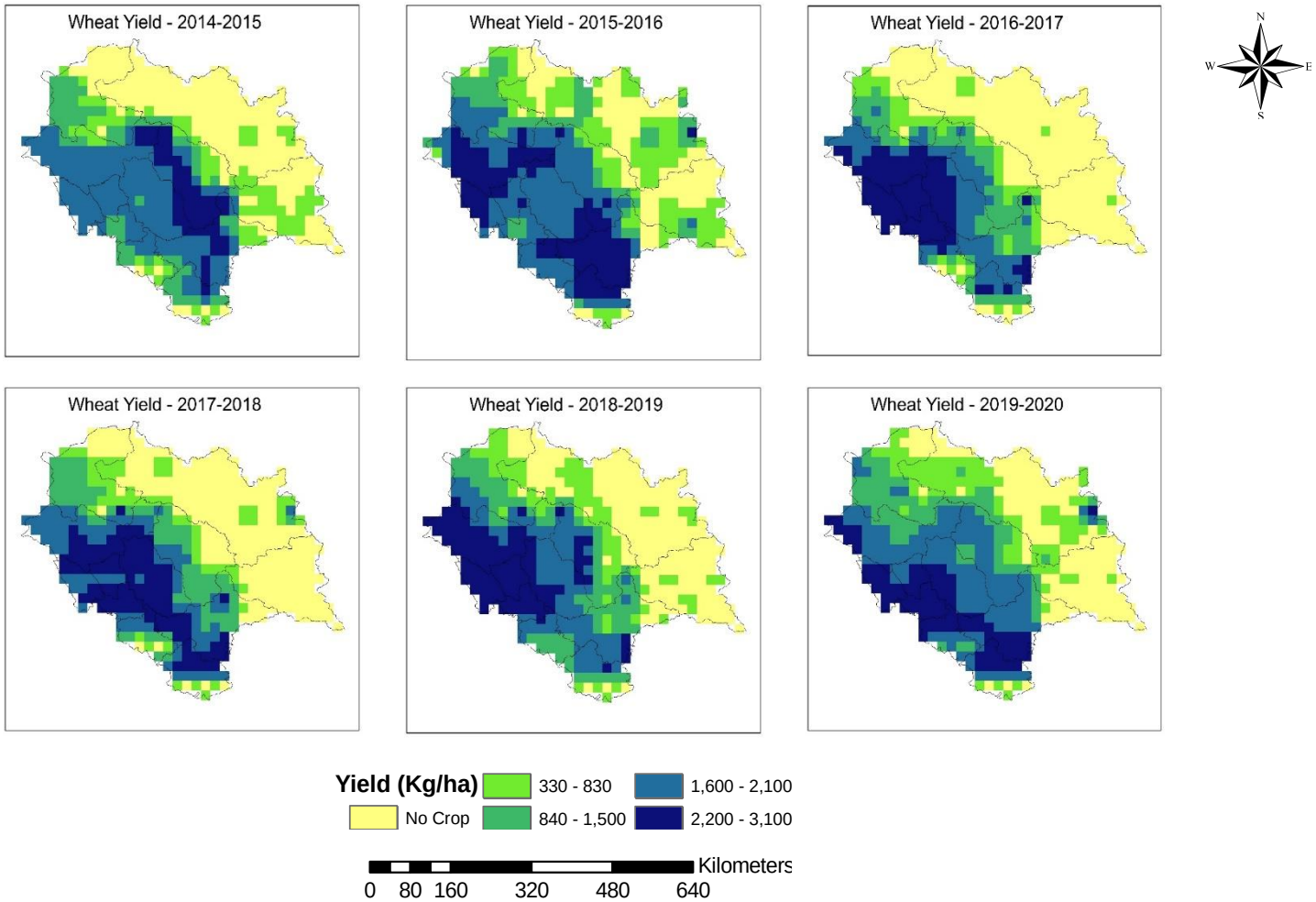

Fig. 5.15. Year wise future wheat yield maps from 2015 to 2020

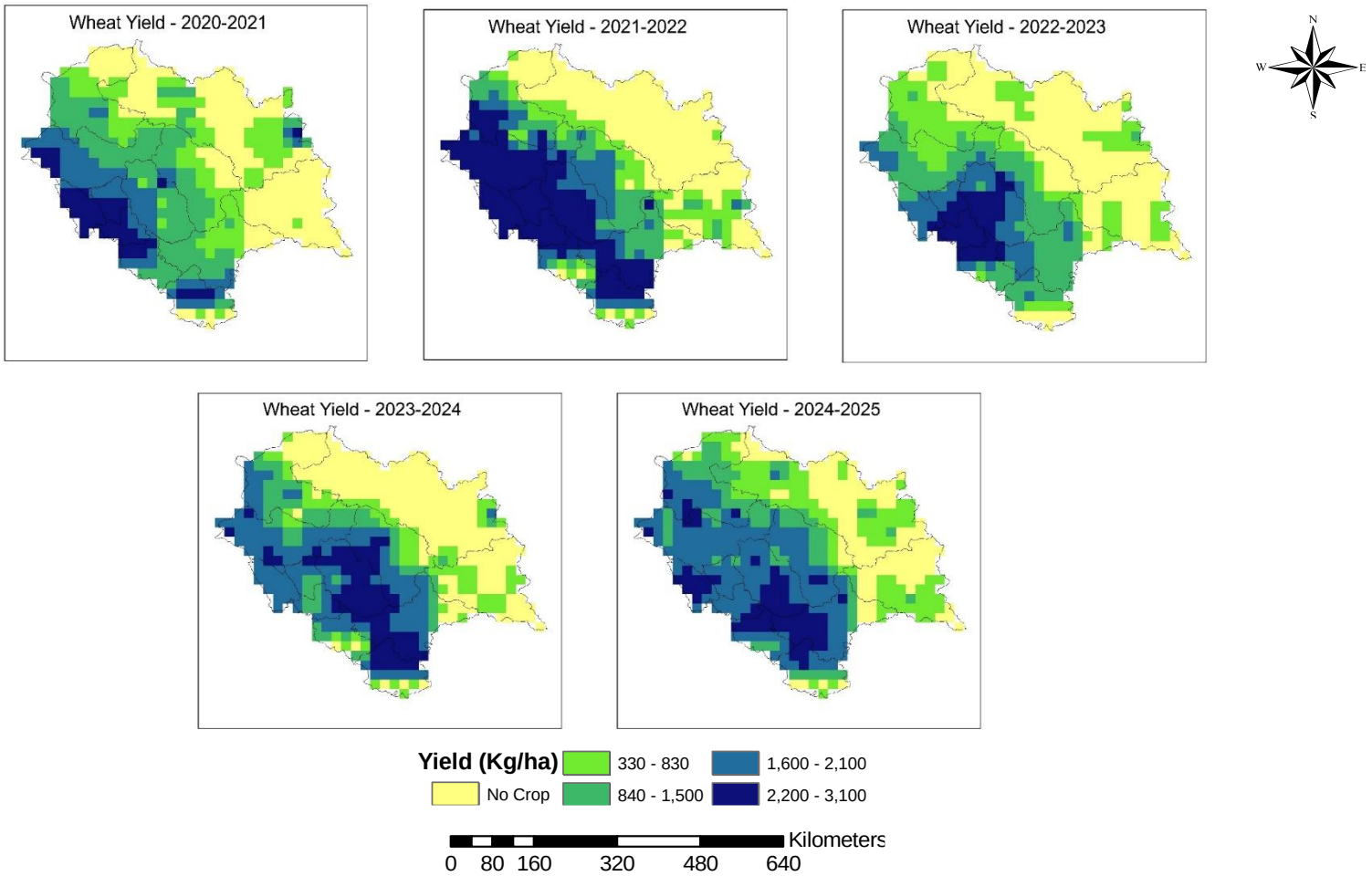

Fig. 5.16. Year wise future wheat yield maps from 2021 to 2025

5.7.2. Regional Maize yield output

CERES-maize model was calibrated and validated for variety Paravati for Himachal region and the genetic coefficients thus generated were used to simulate the wheat yield in different years starting from 2001-2025.

As per the IPCC report the maize yield in the South East Asian countries is going to decrease to up to 50% during the next 50 years. The predicted trend observations of maize have shown an increasing trend line, which resembles an increase the maize yield in the next 10 years i.e., by 2025.

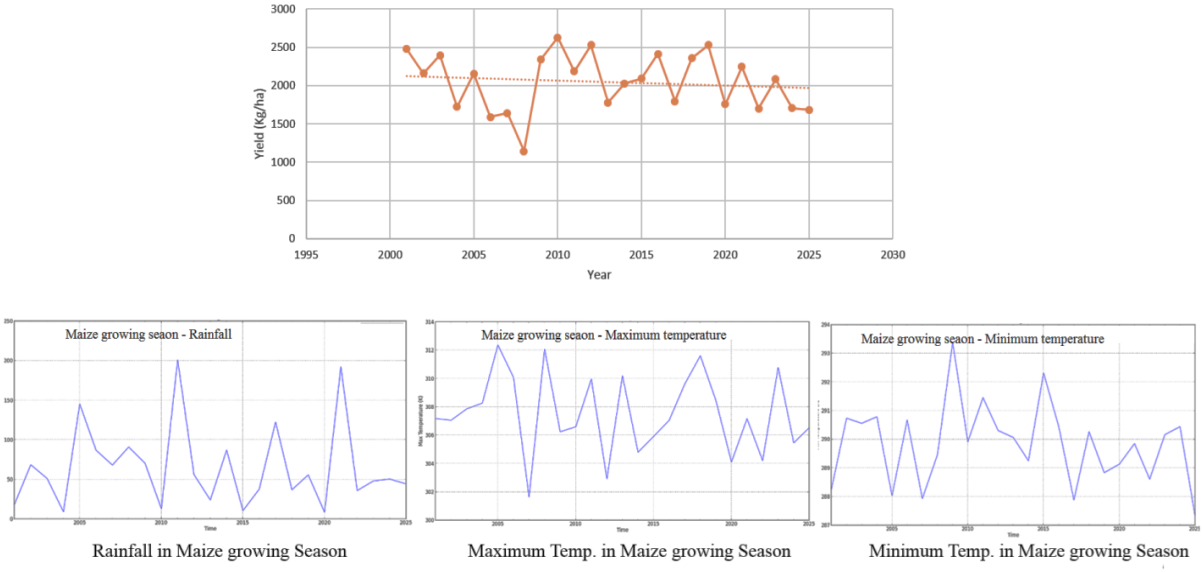

Figure 5.17 Trend analysis of predicted Maize yield and climate variables for the crop period

As per the graph, the maximum maize yield was obtained in the year 2010 and a same quantity is expected in the year 2019, the crop yield in the year 2008 was recorded to be the least during the whole 25 year period. The year wise maize yield maps for the years 2001 to 2025 are presented in fig 5.18, 5.19, 5.20 and 5.21

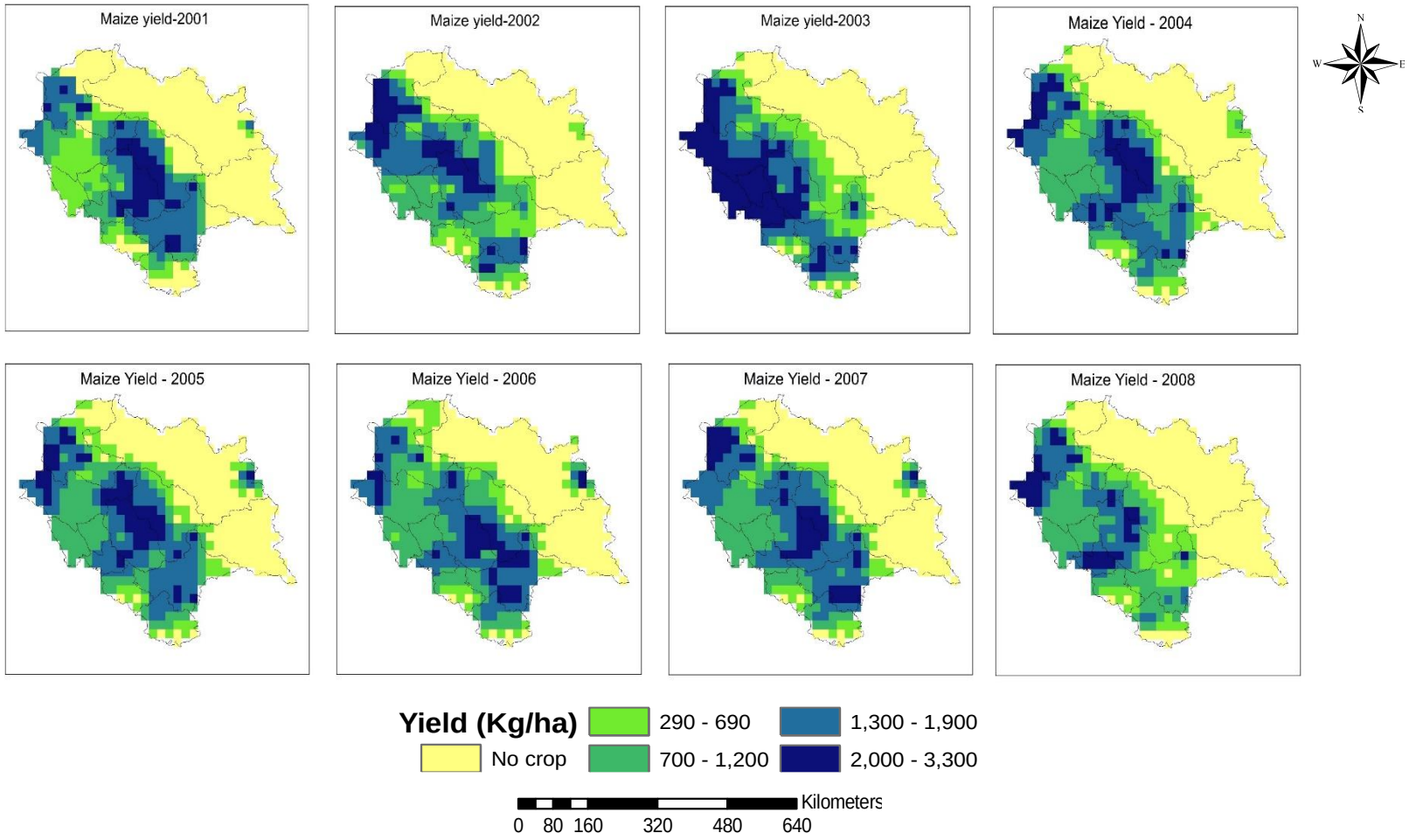

Fig. 5.18. Year wise current maize yield maps from 2001 to 2008

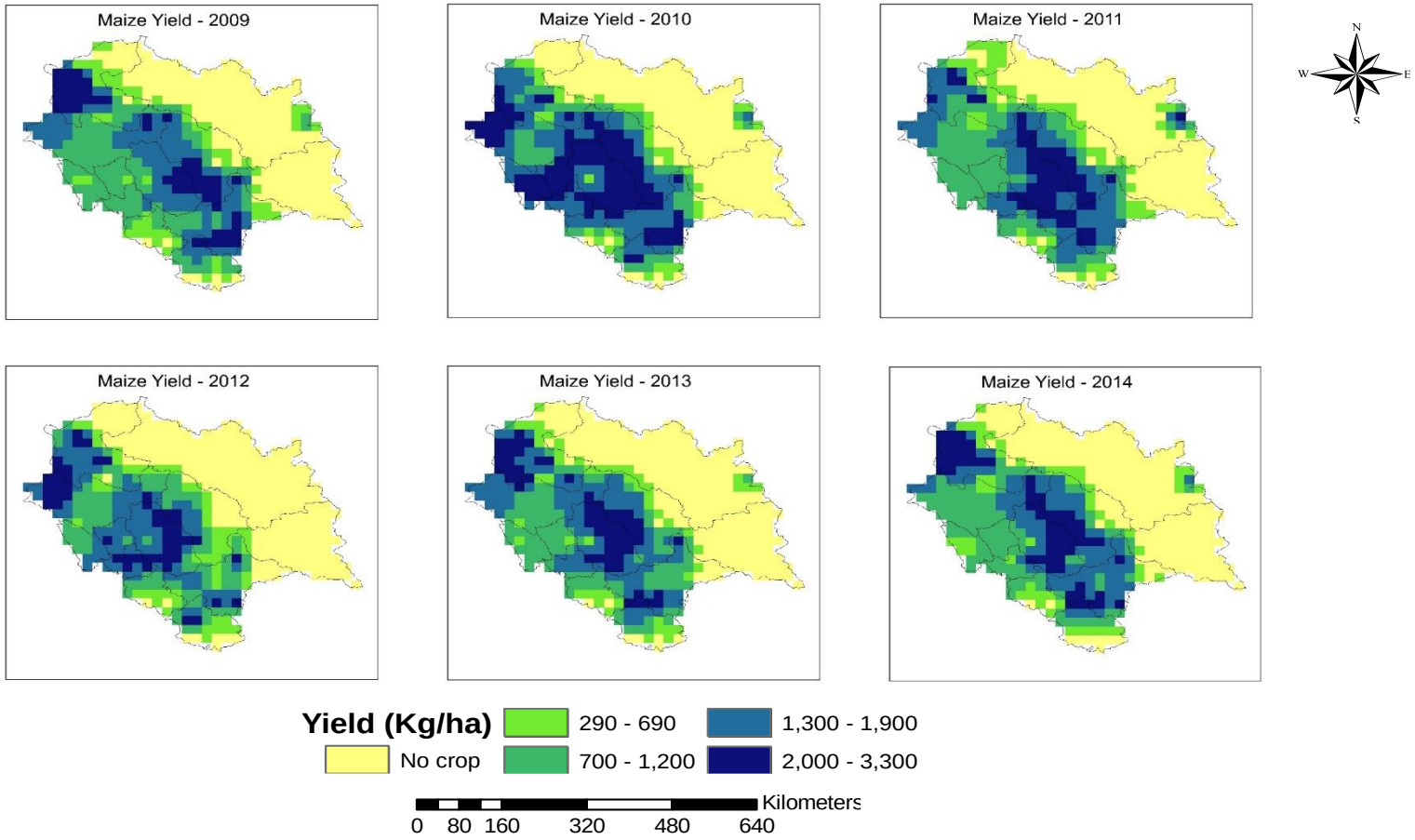

Fig. 5.19. Year wise current maize yield maps from 2009 to 2014

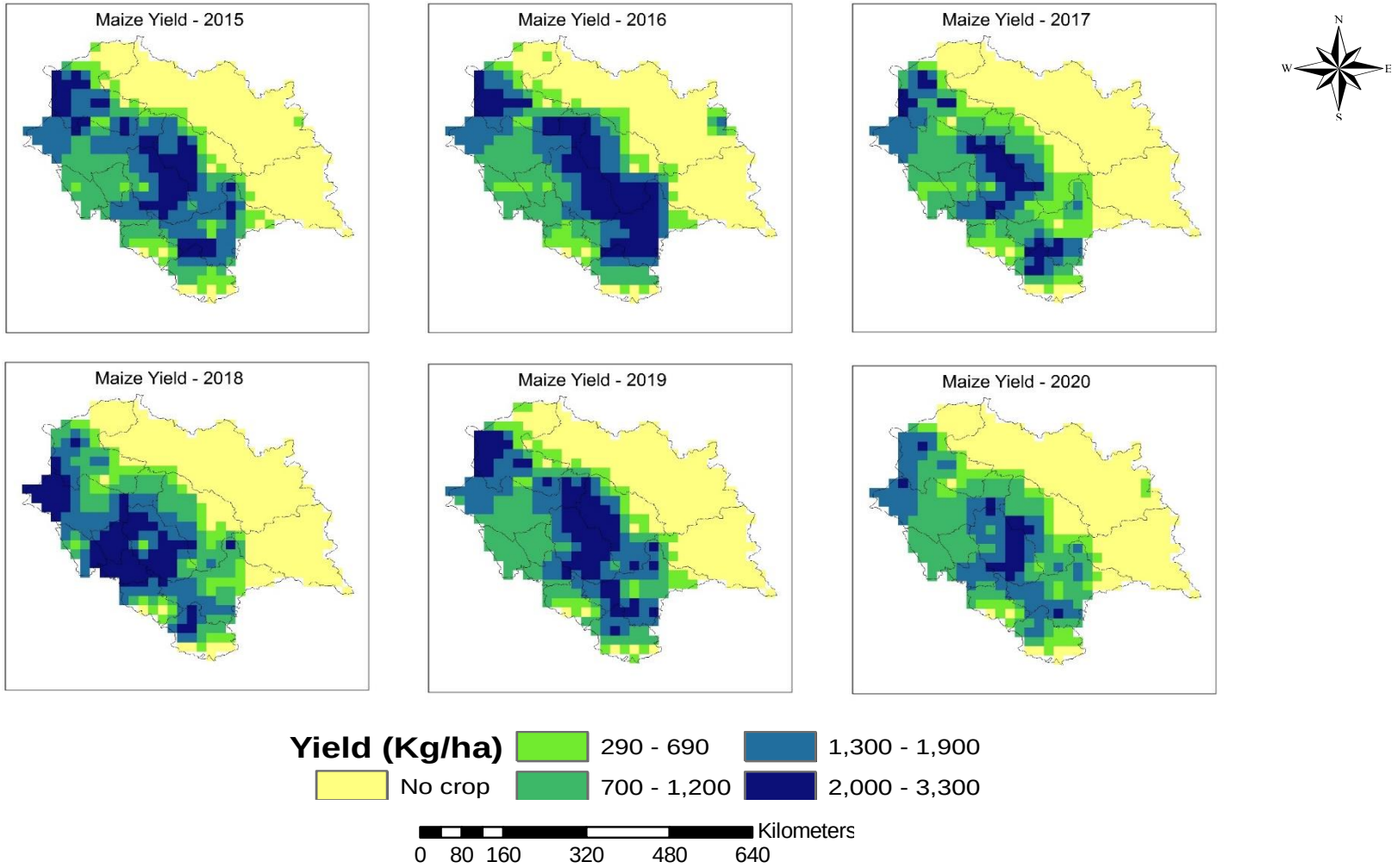

Fig. 5.20. Year wise future maize yield maps from 2015 to 2020

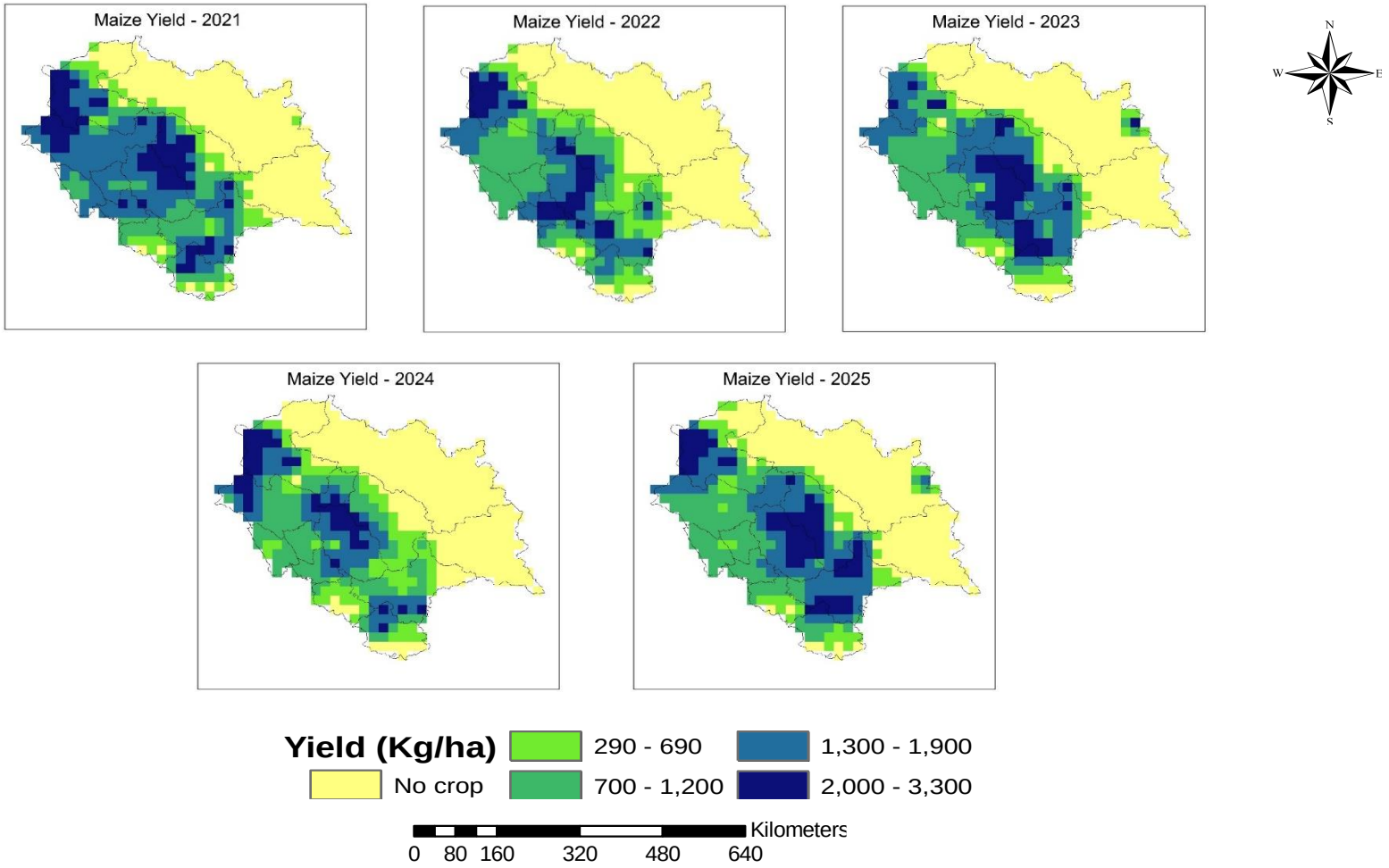

Fig. 5.21. Year wise future maize yield maps from 2021 to 2025

5.8. Validation

5.8.1. Yield Validation

5.8.1.1. District Wise Wheat Yield validation

A keen analysis has been made by comparing the observed yield data and the estimated yield data and the results of the analysis and their corresponding graphical representations are given in following graphs.

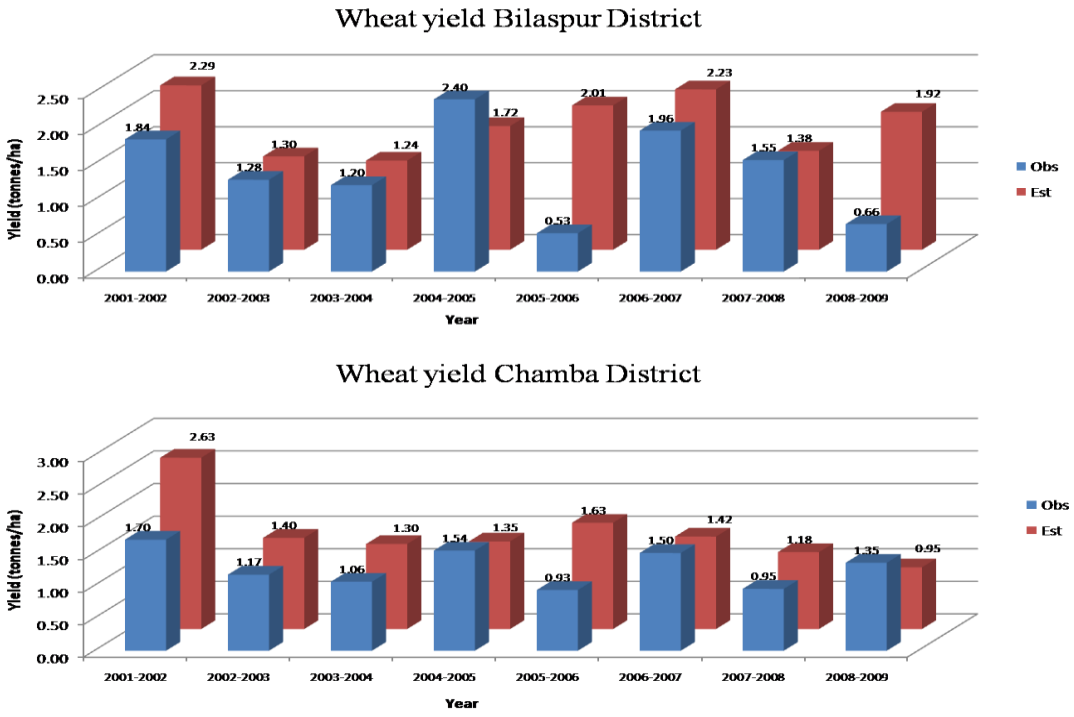

Fig. 5.22. Validation between observed and estimated wheat yield in Bilaspur and Chamba District

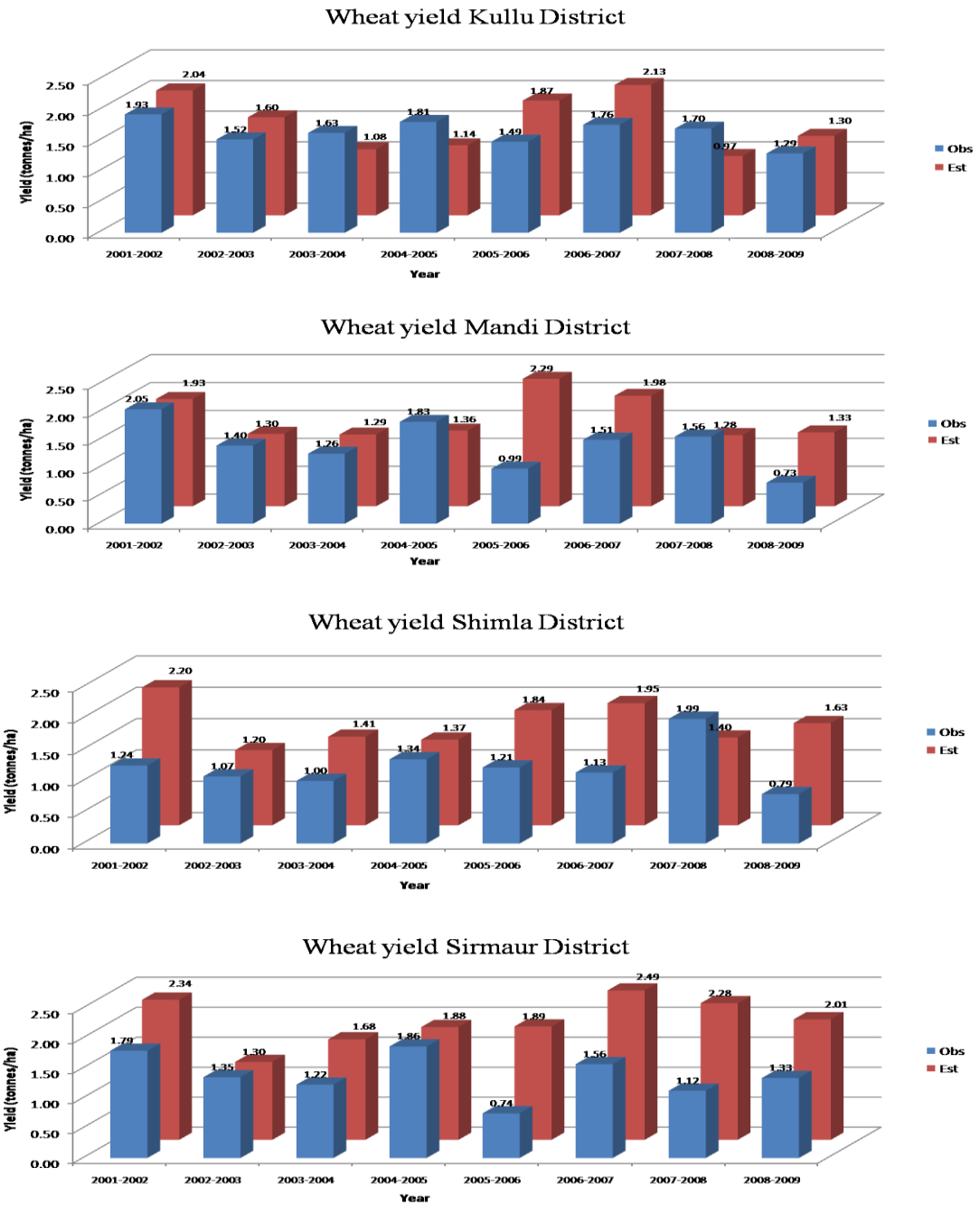

Fig. 5.23. Validation between observed and estimated wheat yield in Kullu, Mandi, Shimla and Sirmaur Districts

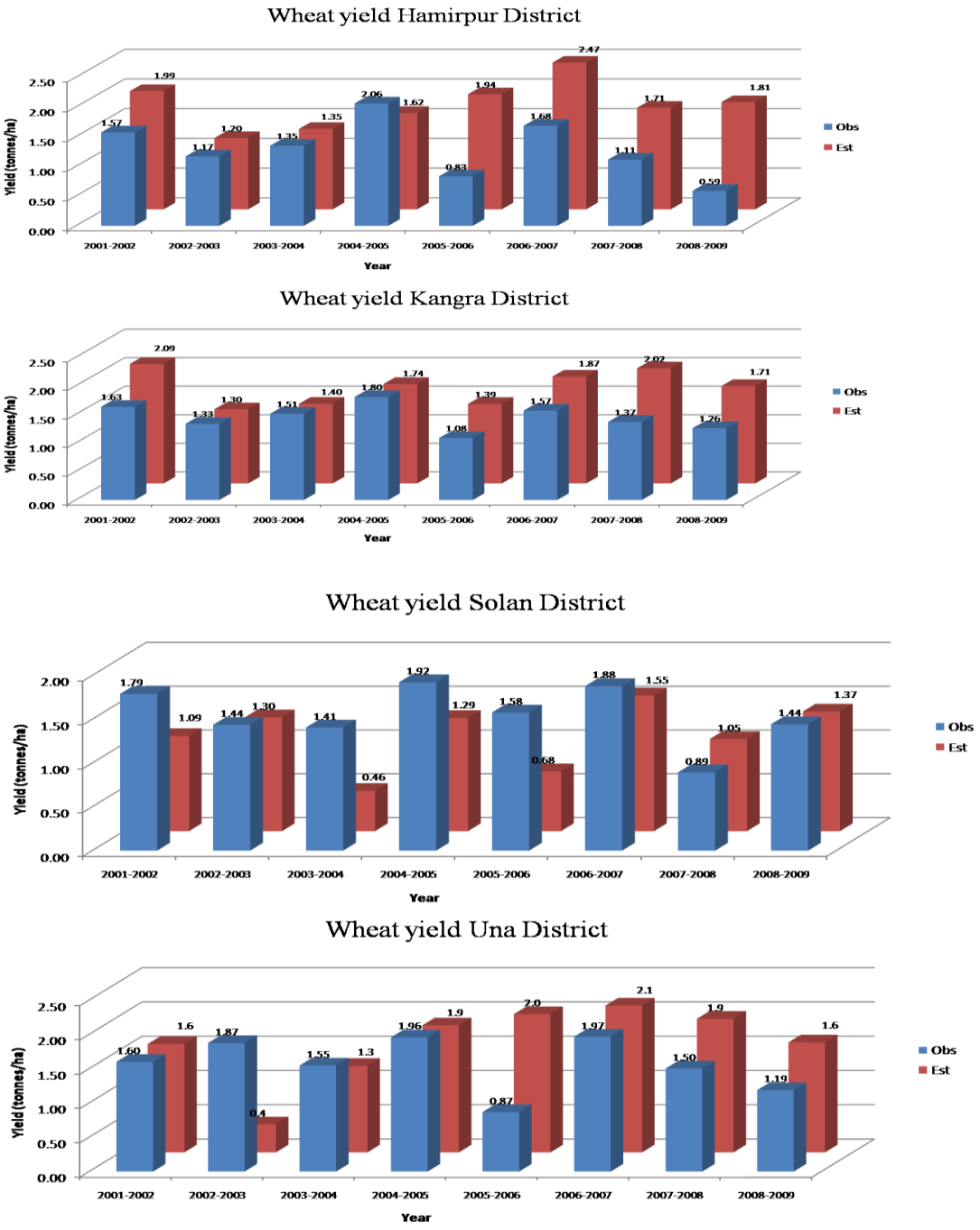

Fig. 5.24. Validation between observed and estimated wheat yield in Hamirpur, Kangra, Solan and Una Districts

District	Crop	RMSE	MAPE	MSE	Agreement Index
Kangra	Wheat	0.220	11.449	0.048	0.78
Solan		0.341	18.777	0.116	0.65
Hamirpur		0.507	34.603	0.257	0.5
Shimla		0.378	19.626	0.143	0.63
Chamba		0.275	18.565	0.075	0.64
Bilaspur		0.686	50.773	0.471	0.43
Sirmaur		0.382	22.566	0.146	0.59
Mandi		0.460	27.235	0.212	0.52
Una		0.405	20.529	0.164	0.61
Kullu		0.214	10.234	0.046	0.81

Table 5.4. Statistical validation of wheat

According to the observed charts, in the estimates of chamba district were good for the year 2006-2007 while a least match between observed and estimated yields for the years 2001-2002 and 2005-2006. In the bilaspur district, the yield results were very accurately matching with the observed yield in the years of 2002-2003 and 2003-2004 while for the years of 2005-2006 and 2008-2009, the estimated values were overestimated. The yields of hamirpur district were overestimated during the years 2005-2009 but the values were perfectly correlating in the years of 2002-2003 and 2006-2007. Coming to Kangra district, the yields were well estimated for the years of 2002-2003, 2003-2004 and 2004-2005 while a poor correlation was observed for the years of 2001-2002, 2007-2008 and 2008-2009. The estimated wheat yield values of kullu district were underestimated for 2003-2004 and 2007-2008 while 2001-2002 and 2002-2003 has good correlation. The values of 2008-2009 were excellently correlated while the 2005-2007 values are overestimated. For madi district, 2001-2004 were estimated well, 2004-2005 was underestimated while for 2005-2006 the yields were overestimated. The estimated yield values of solan district were almost underestimated. The estimates of una district were on the whole observed to be good except one or two years.

Validation was also done using some statistical measures like RMSE, MAPE, MSE and agreement index the results of which are shown in table 5.2.

5.8.1.2. District wise yield estimates for maize

A similar analysis was made by comparing the observed yield data and the estimated yield data for the maize crop and the results of the analysis are shown in the following graphs.

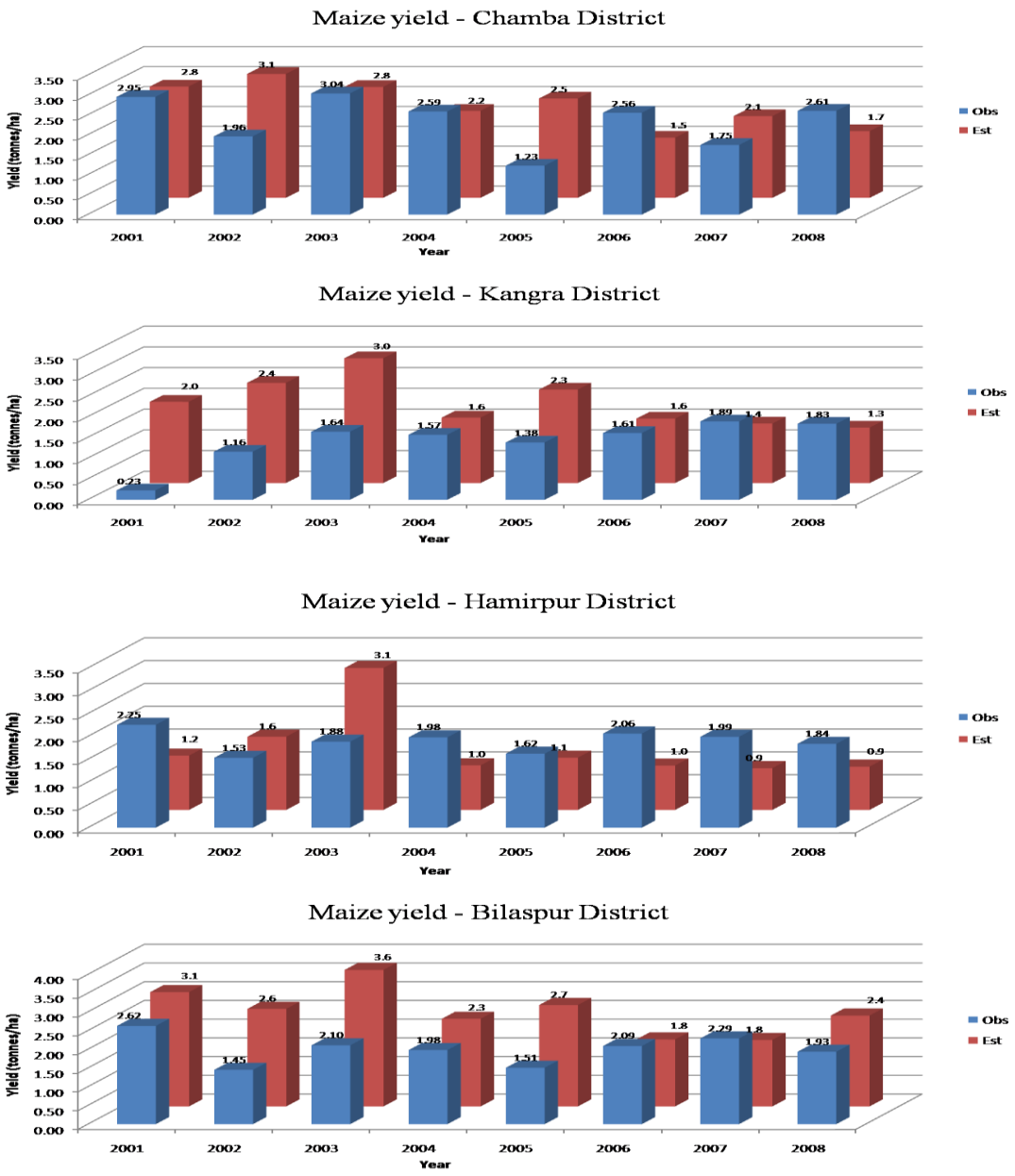

Fig. 5.25. Validation between observed and estimated Maize yield in Chamba, Kangra, Hamirpur and Bilaspur

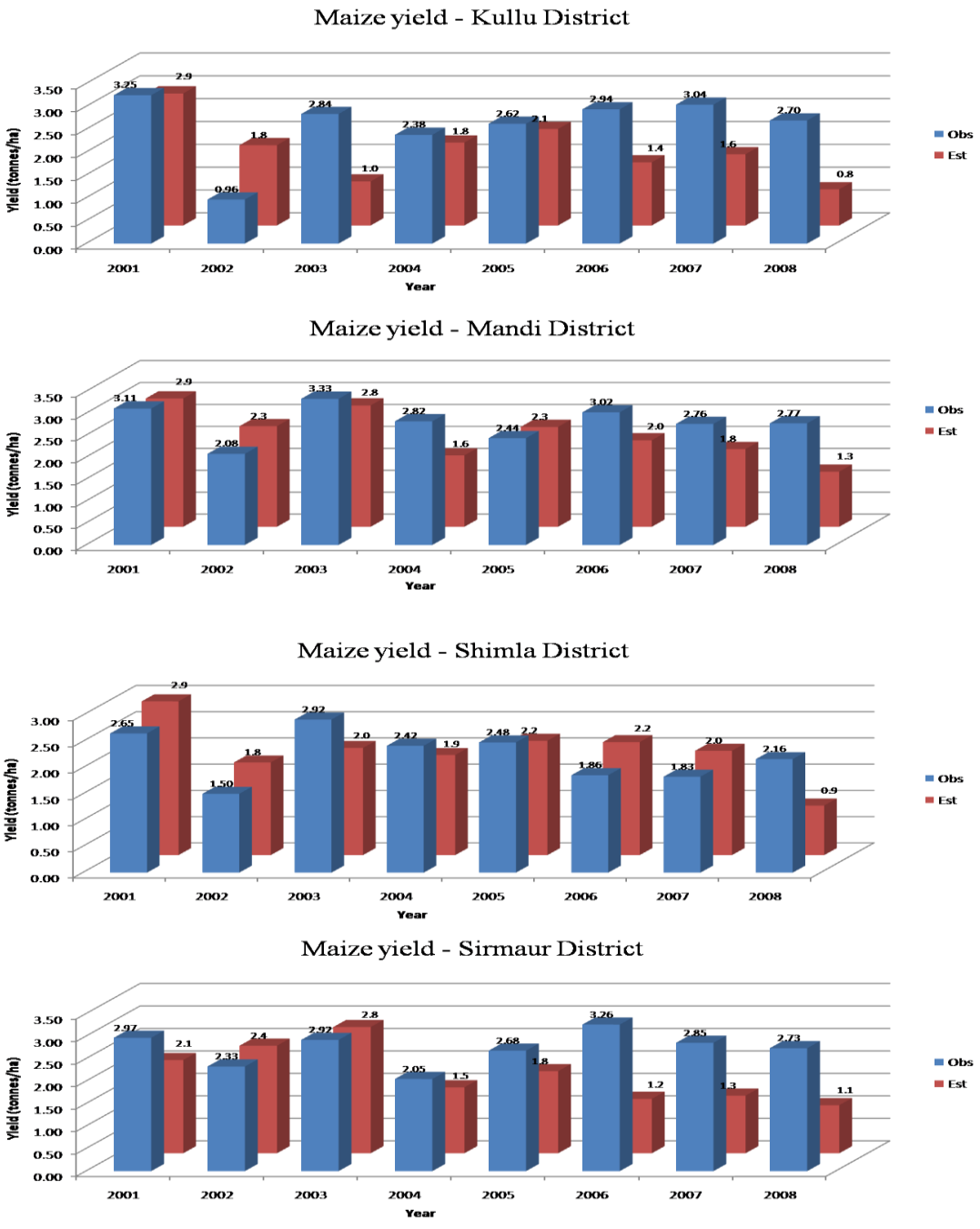

Fig. 5.26. Validation between observed and estimated Maize yield in Kullu, Mandi, Shimla and Sirmaur

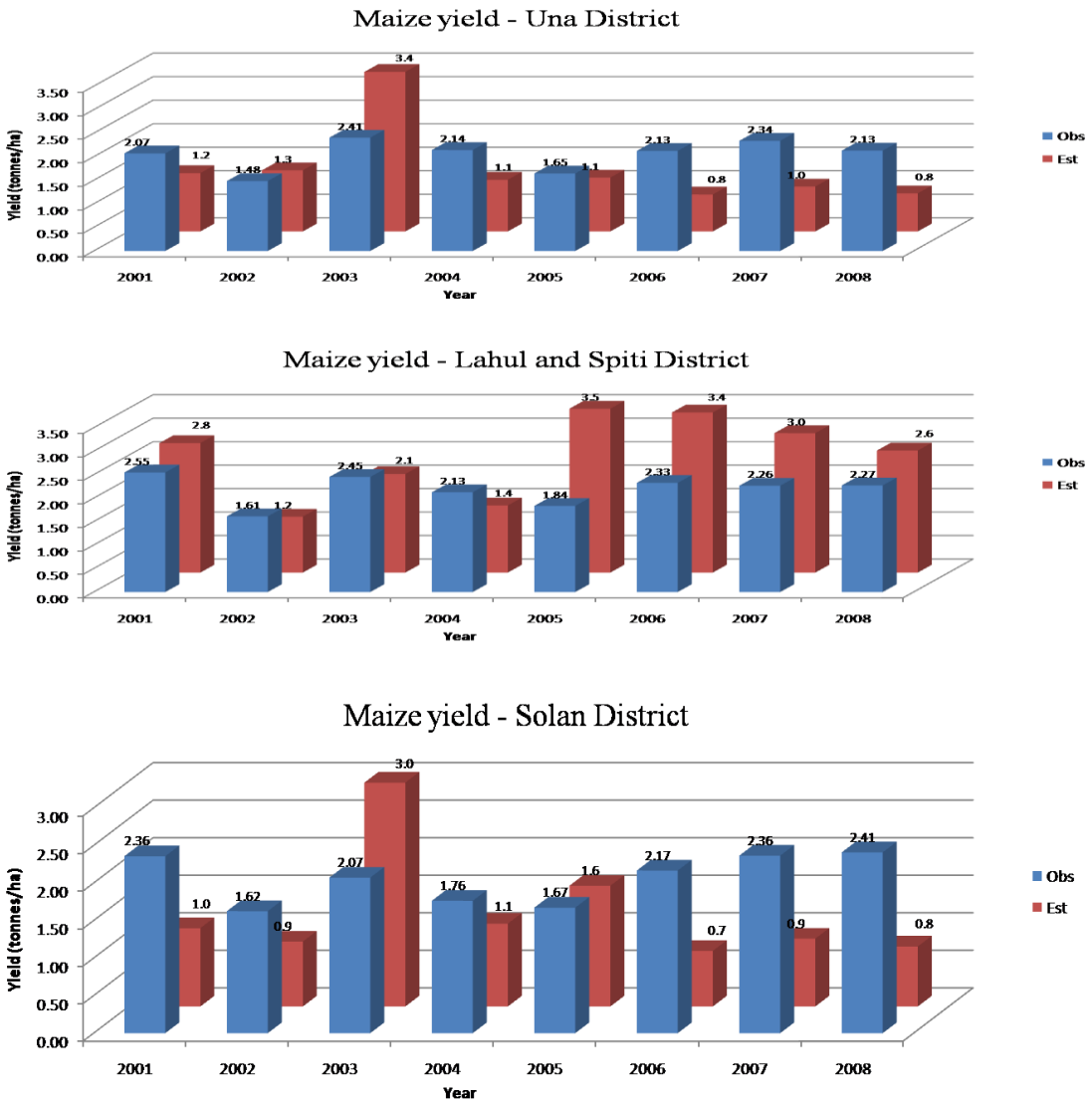

Fig. 5.27. Validation between observed and estimated Maize yield in Una, Lahul and Spiti and Solan

According to the observed charts, in the estimates of chamba district were good for the year 2001, 2003 and 2004 while a least match between observed and estimated yields for the years2002 and 2005. In the bilaspur district, the estimated yield values were overestimated for the years 2003 and 2002 while the rest were underestimated. The yields of hamirpur district were overestimated in 2003 but the values were more or less underestimated slightly in the rest of the years. Coming to Kangra district, very high differences were found in the estimated and observed values in 2001, 2002, 2003, 2005 while in the yields were well estimated for the years 2006 -2008. The estimated

wheat yield values of kullu district were underestimated for 2006-2009 while in 2001 the correlation was very high. For madi district, the estimates were good and showing a good correlation. The estimated yield values of solan district were almost underestimated in all the years except 2002 which was overestimated. The estimates of Una district were on the whole observed to be good except one or two years like 2003.

Validation was also done using some statistical measures like RMSE, MAPE, MSE and agreement index the results of which are shown in table 5.3.

District	**Crop**	**RMSE**	**MAPE**	**MSE**	**Agreement Index**
Kangra	Maize	0.558	76.820	0.312	0.34
Solan		0.347	14.327	0.120	0.72
Hamirpur		0.248	9.870	0.062	0.83
Shimla		0.482	18.141	0.232	0.61
Chamba		0.680	26.584	0.462	0.51
Bilaspur		0.417	15.055	0.174	0.61
Sirmaur		0.410	11.031	0.168	0.78
Mandi		0.411	11.070	0.169	0.78
Kullu		0.764	30.072	0.584	0.57
Lahul and Spiti		0.339	11.986	0.115	0.78
Una		0.327	12.699	0.107	0.72

Table 5.5. Statistical validation of maize

5.9. Impacts of future climate scenario in the productivity of food grain crops

According to the IPCC 4th Assessment Report, the Central Asia‘s environment, ecological and socio-economic systems are under serious threat of climate change and future increase in number of severe extreme weather events, particularly because of the semi-arid nature of the region. Agricultural production of the region has already decreased quantitatively, and water resources are at risk of climatic change *(Perelet, 2007).*

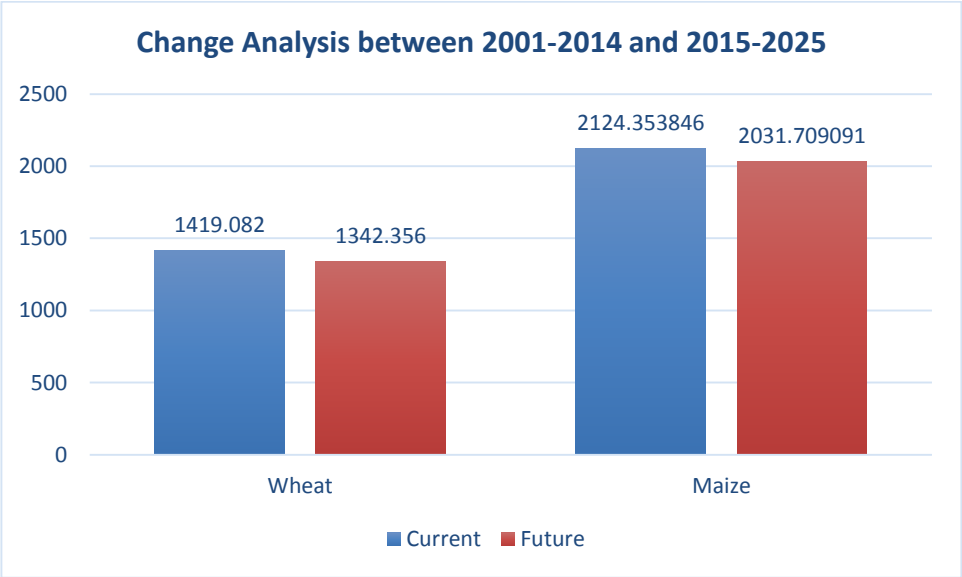

Fig. 5.28. Change analysis between current and future Yield

Crop	Yield change in Percentage
Wheat	-5.40673
Maize	-4.36108

Table 5.7. Yield change percentage for Wheat and Maize between current and future climate scenario

Table 5.7 shows a decrease in the expected yield for both wheat and maize. However yield change percentage shows a greater decrease in wheat productivity than maize. Quantitative yield for maize is greater than wheat for both current and future scenarios.

5.10. Validation of Leaf Area Index:

MODIS LAI datasets have nice correlation with the estimated maximum LAI of DSSAT. Maximum LAI is calculated from MODIS LAI for the cropping period of particular crops. After that the values of MODIS data sets are validated with observed datasets. MODIS datasets also includes forest features. So, we need to extract the cropping area and extract the LAI values, these values are validated with estimated maximum LAI of DSSAT model.

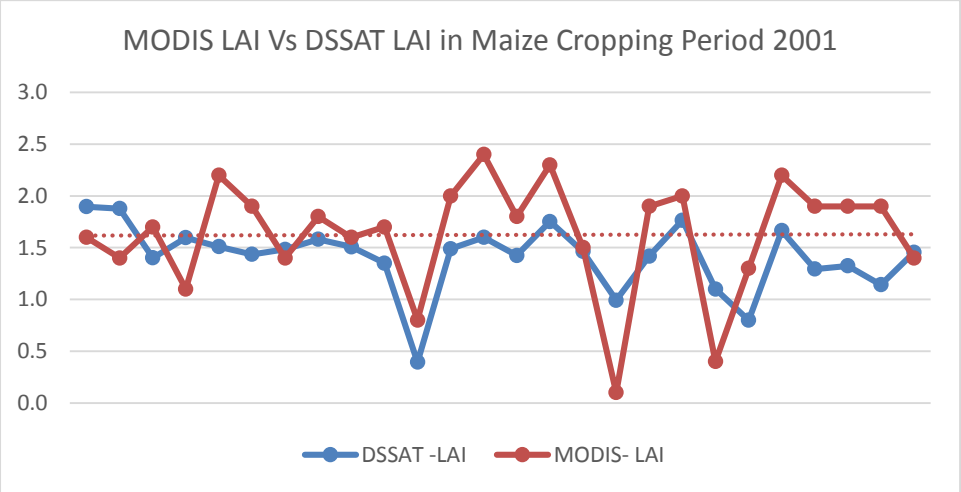

Fig. 5.29. Validation between the estimated maximum LAI and observed maximum MODIS LAI in the maize cropping period 2001

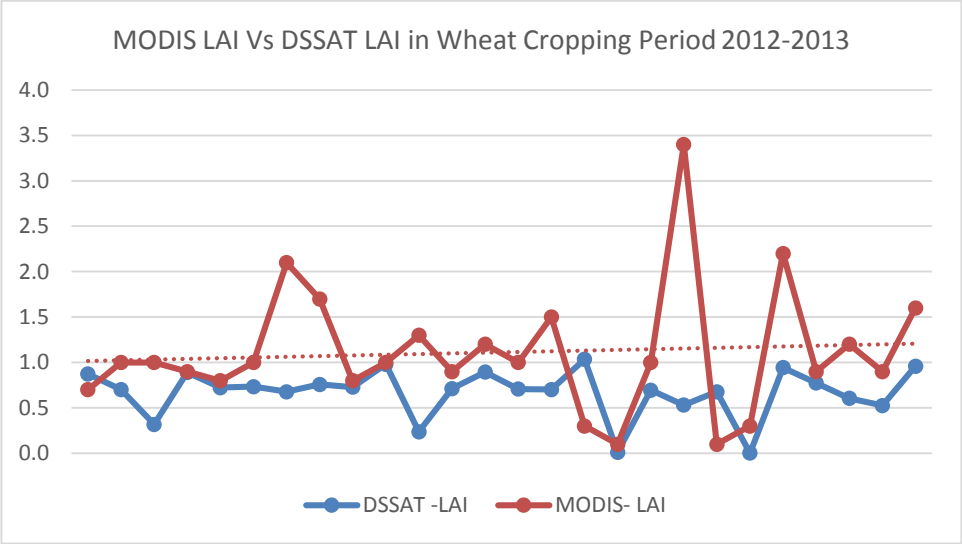

Fig. 5.30. Validation between the estimated maximum LAI and observed maximum MODIS LAI in the wheat cropping period 2012-2013

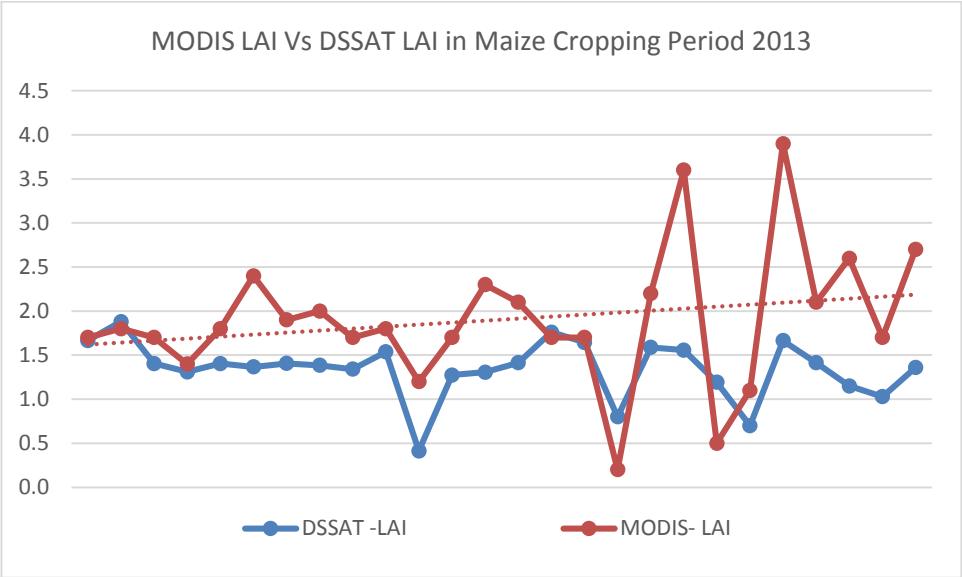

Fig. 5.31. Validation between the estimated maximum LAI and observed maximum MODIS LAI in the maize cropping period 2013

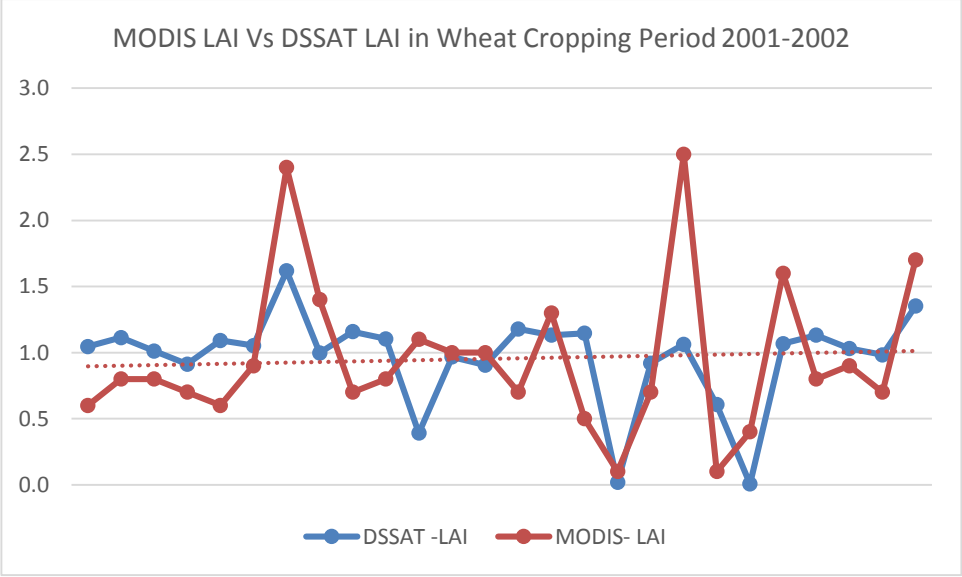

Fig. 5.32. Validation between the estimated maximum LAI and observed maximum MODIS LAI in the wheat cropping period 2001-2001

APPENDEX

District	2001-2002		2002-2003		2003-2004		2004-2005		2005-2006		2006-2007		2007-2008		2008-2009	
	Obs	Est	Obs	Est	Obs	Est	Obs	Est	Obs	Est	Obs	Est	Obs	Est	Obs	Est
Bilaspur	1.84	2.29	1.70	1.3	1.2	1.24	2.40	1.72	0.53	2.01	1.96	2.23	1.55	1.38	0.66	1.92
Chamba	1.70	2.63	1.17	1.40	1.06	1.30	1.54	1.35	0.93	1.63	1.50	1.42	0.95	1.18	1.35	0.95
Hamirpur	1.57	1.99	1.17	1.20	1.35	1.35	2.06	1.62	0.83	1.94	1.68	2.47	1.11	1.71	0.59	1.81
Kangra	1.63	2.09	1.33	1.30	1.51	1.40	1.80	1.74	1.08	1.39	1.57	1.87	1.37	2.02	1.26	1.71
Kullu	1.93	2.04	1.52	1.60	1.63	1.08	1.81	1.14	1.49	1.87	1.76	2.13	1.70	0.97	1.29	1.30
Mandi	2.05	1.93	1.40	1.30	1.26	1.29	1.83	1.36	0.99	2.29	1.51	1.98	1.56	1.28	0.73	1.33
Shimla	1.24	2.20	1.07	1.20	1.00	1.41	1.34	1.37	1.21	1.84	1.13	1.95	1.99	1.40	0.79	1.63
Sirmaur	1.79	2.34	1.35	1.30	1.22	1.68	1.86	1.88	0.74	1.89	1.56	2.49	1.12	2.28	1.33	2.01
Solan	1.79	1.09	1.44	1.30	1.41	0.46	1.92	1.29	1.58	0.68	1.88	1.55	0.89	1.05	1.44	1.37
Una	1.60	1.6	1.87	0.4	1.55	1.3	1.96	1.9	0.87	2.0	1.97	2.1	1.50	1.9	1.19	1.6
Himachal pradesh	1.72	2.02	1.40	1.23	1.32	1.25	1.85	1.53	1.03	1.76	1.65	2.02	1.38	1.52	1.06	1.56

Table 5.6. District wise observed and estimated yield for wheat crop

District	2001		2002		2003		2004		2005		2006		2007		2008	
	Obs	Est	Obs	Est	Obs	Est	Obs	Est	Obs	Est	Obs	Est	Obs	Est	Obs	Est
Bilaspur	2.62	3.1	1.45	2.6	2.10	3.6	1.98	2.3	1.51	2.7	2.09	1.8	2.29	1.8	1.93	2.4
Chamba	2.95	2.8	1.96	3.1	3.04	2.8	2.59	2.2	1.23	2.5	2.56	1.5	1.75	2.1	2.61	1.7
Hamirpur	2.25	1.2	1.53	1.6	1.88	3.1	1.98	1.0	1.62	1.1	2.06	1.0	1.99	0.9	1.84	0.9
Kangra	0.23	2.0	1.16	2.4	1.64	3.0	1.57	1.6	1.38	2.3	1.61	1.6	1.89	1.4	1.83	1.3
Kullu	3.25	2.9	0.96	1.8	2.84	1.0	2.38	1.8	2.62	2.1	2.94	1.4	3.04	1.6	2.70	0.8
Mandi	3.11	2.9	2.08	2.3	3.33	2.8	2.82	1.6	2.44	2.3	3.02	2.0	2.76	1.8	2.77	1.3
Shimla	2.65	2.9	1.50	1.8	2.92	2.0	2.42	1.9	2.48	2.2	1.86	2.2	1.83	2.0	2.16	0.9
Sirmaur	2.97	2.1	2.33	2.4	2.92	2.8	2.05	1.5	2.68	1.8	3.26	1.2	2.85	1.3	2.73	1.1
Solan	2.36	1.0	1.62	0.9	2.07	3.0	1.76	1.1	1.67	1.6	2.17	0.7	2.36	0.9	2.41	0.8
Una	2.07	1.2	1.48	1.3	2.41	3.4	2.14	1.1	1.65	1.1	2.13	0.8	2.34	1.0	2.13	0.8
Lahul and Spiti	2.55	2.8	1.61	1.2	2.45	2.1	2.13	1.4	1.84	3.5	2.33	3.4	2.26	3.0	2.27	2.6
Himachal Pradesh	2.46	2.3	1.61	1.9	2.51	2.7	2.16	1.6	1.92	2.1	2.37	1.6	2.31	1.6	2.31	1.3

Table 5.7. District wise observed and estimated yield for maize crop

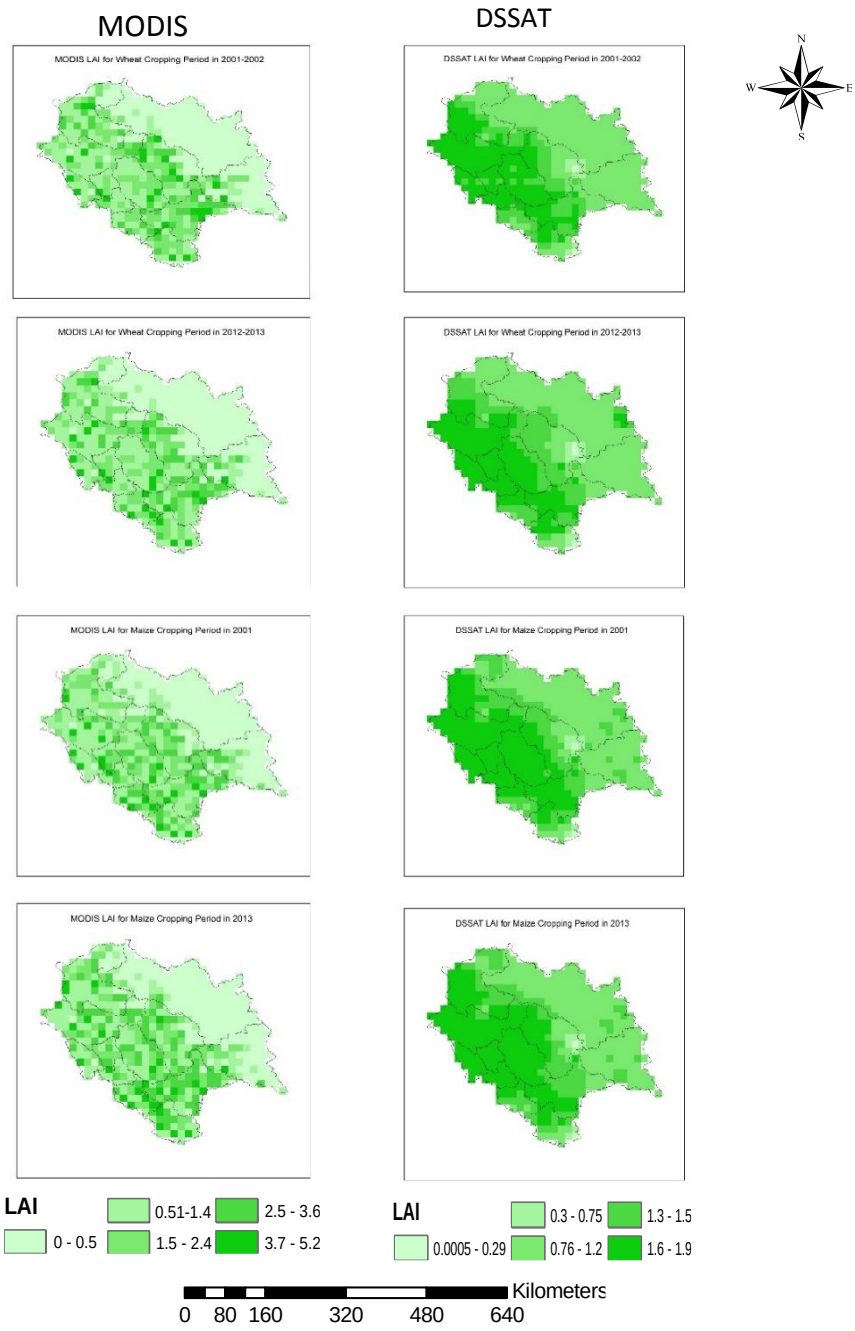

Figure 5.33 MODIS LAI and DSSAT simulated LAI in the crop periods

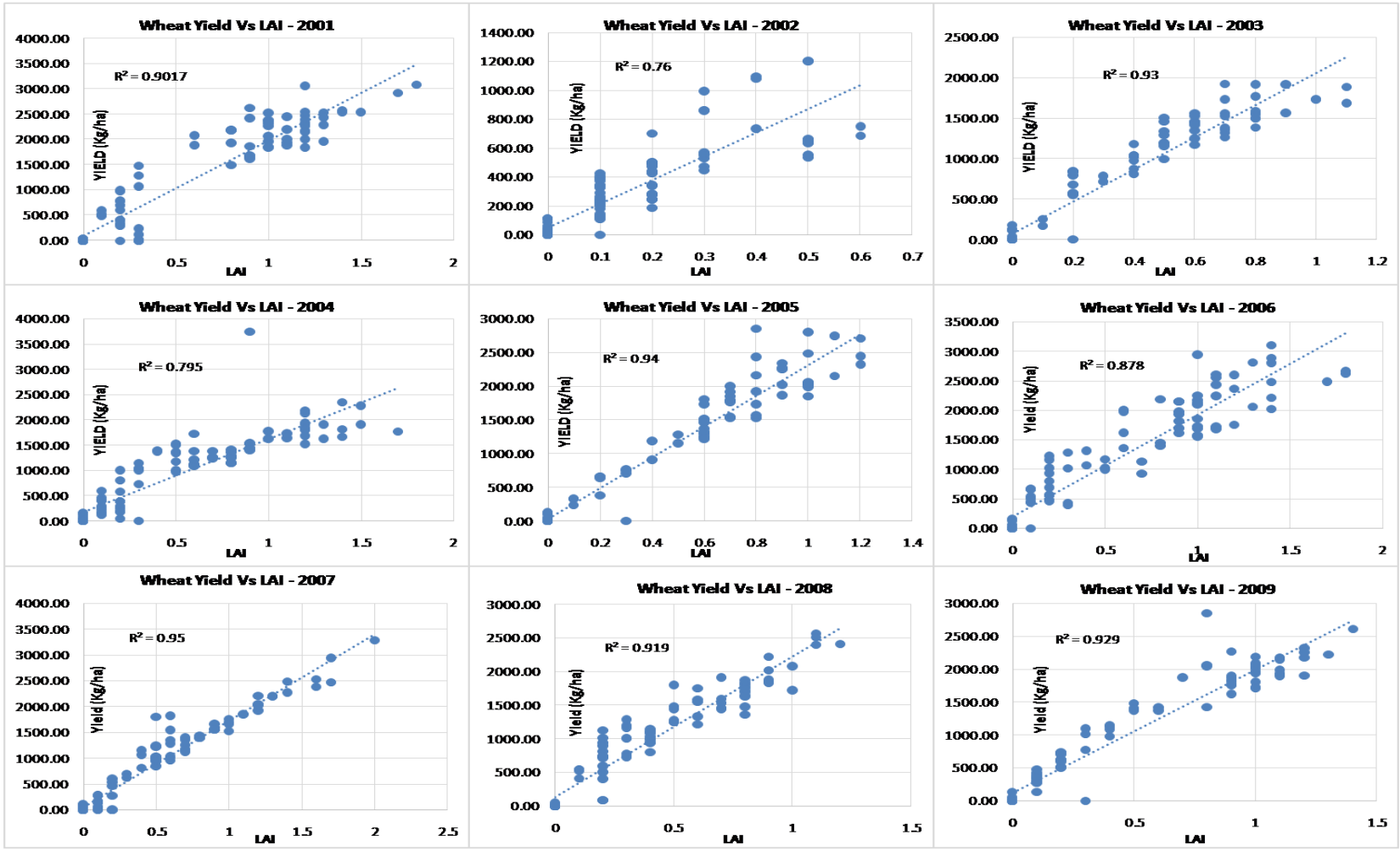

Figure 5.34. Validation of LAI and wheat yield – 2001 to 2009

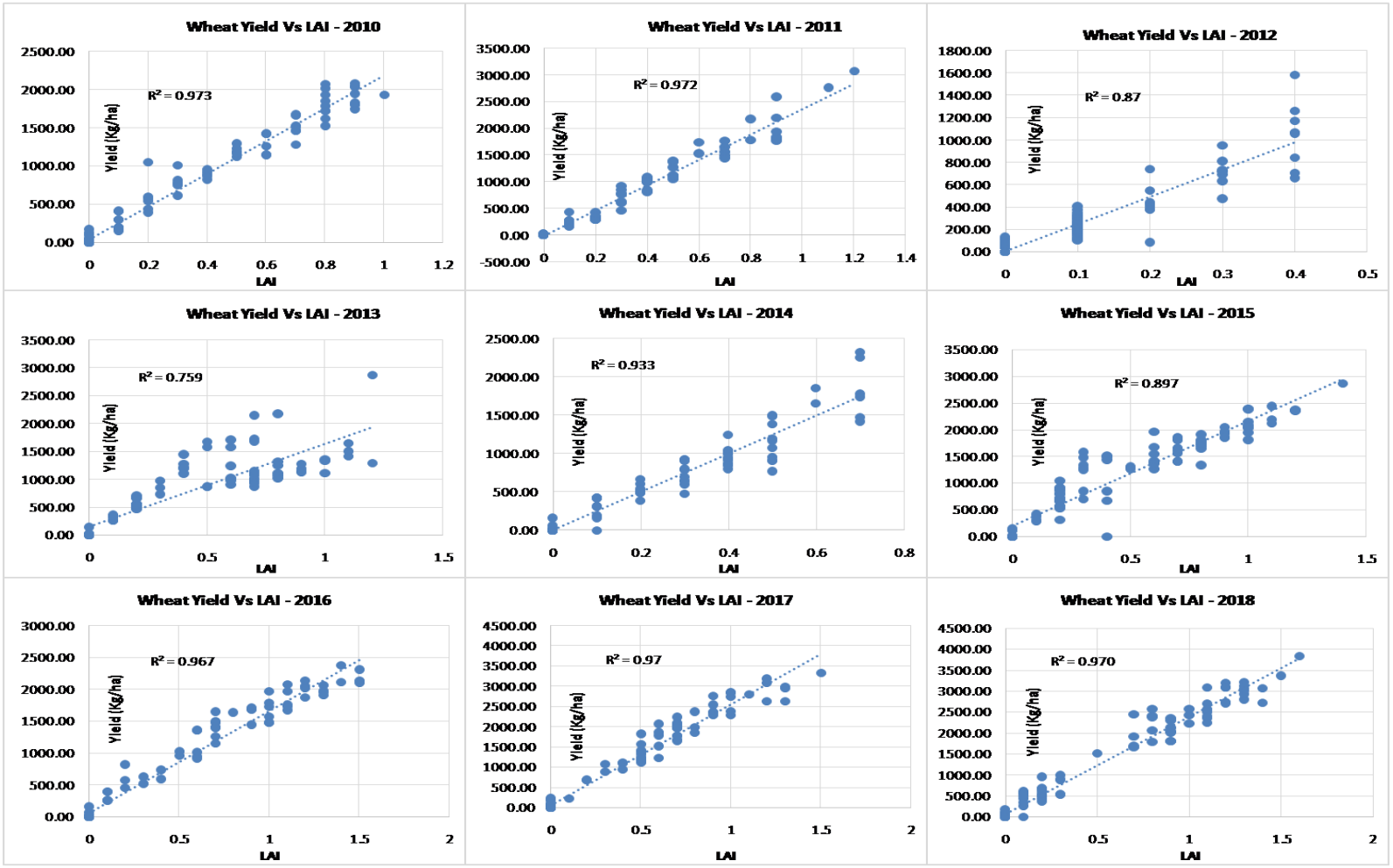

Figure 5.35. Validation of LAI and wheat yield – 2010 to 2018

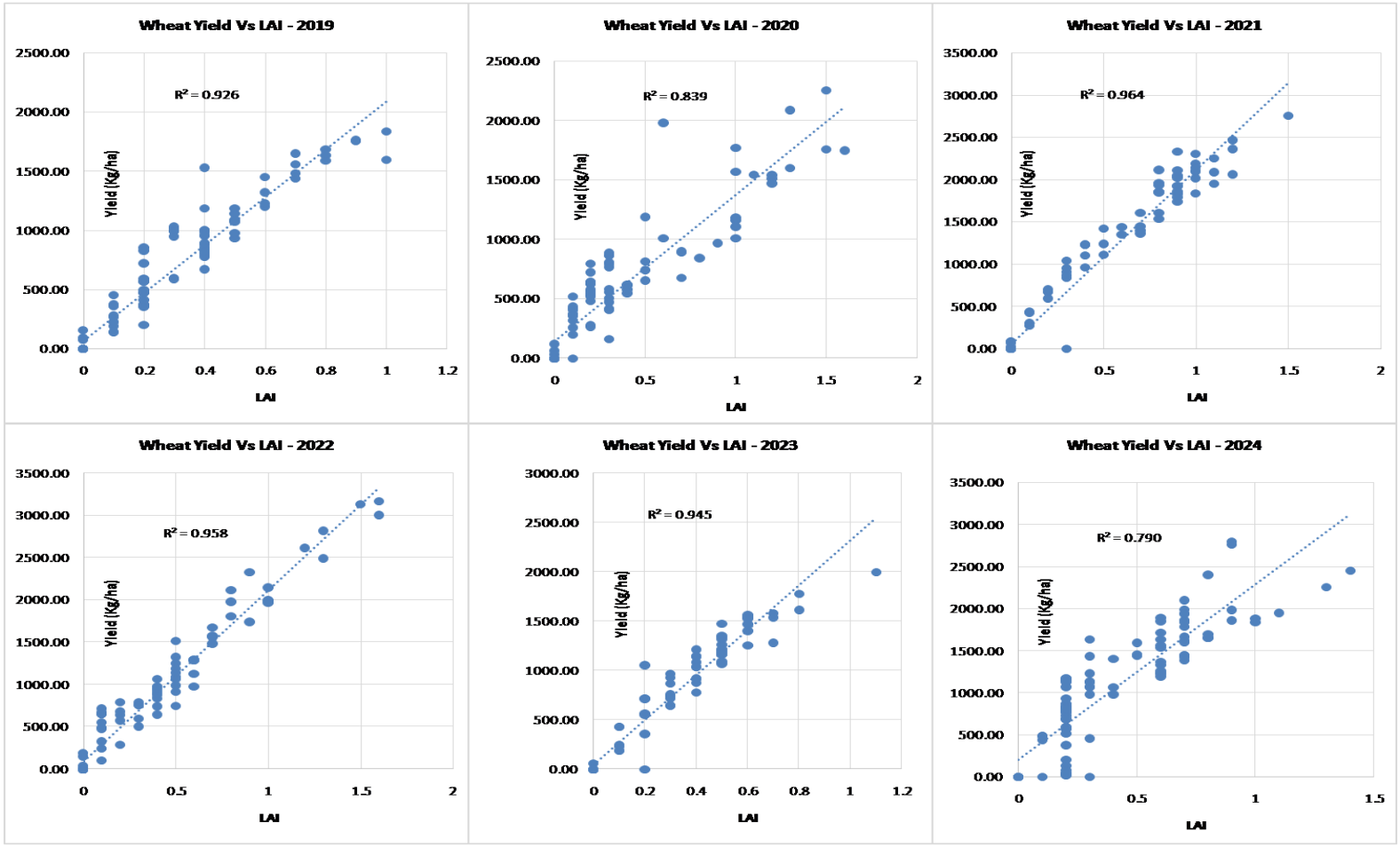

Figure 5.36. Validation of LAI and wheat yield – 2018 to 2024

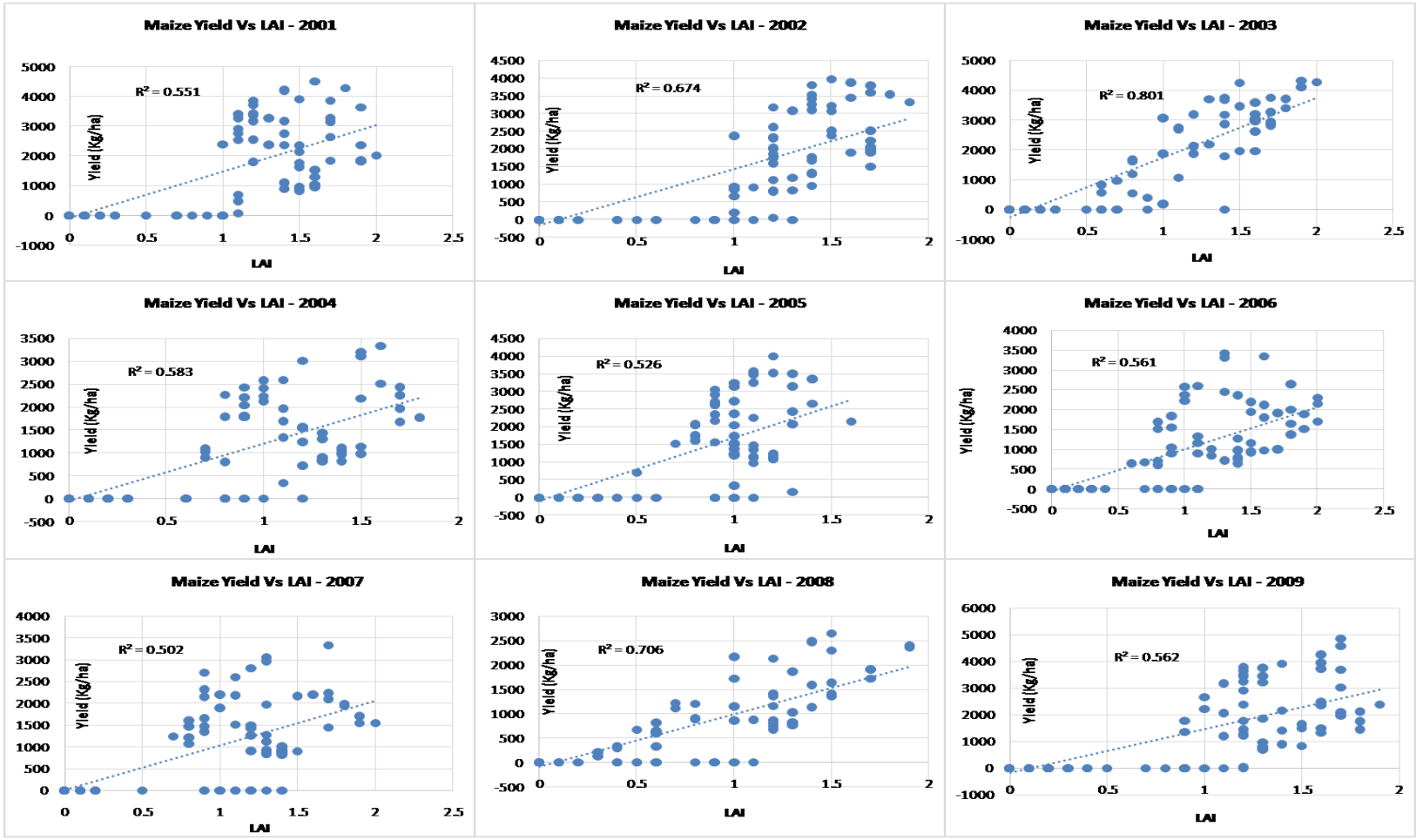

Figure 5.37. Validation of LAI and maize yield – 2001 to 2009

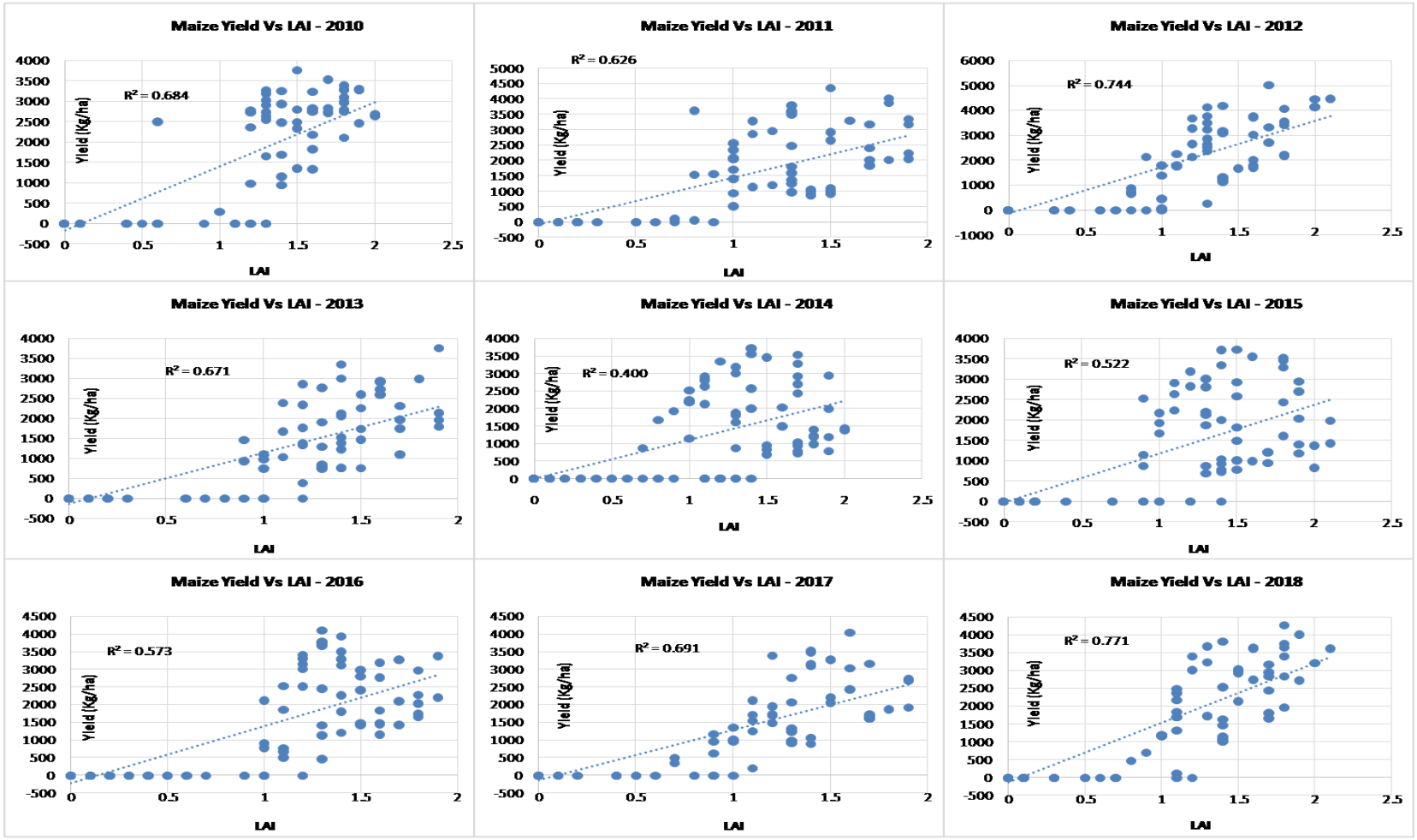

Figure 5.38. Validation of LAI and maize yield – 2001 to 2009

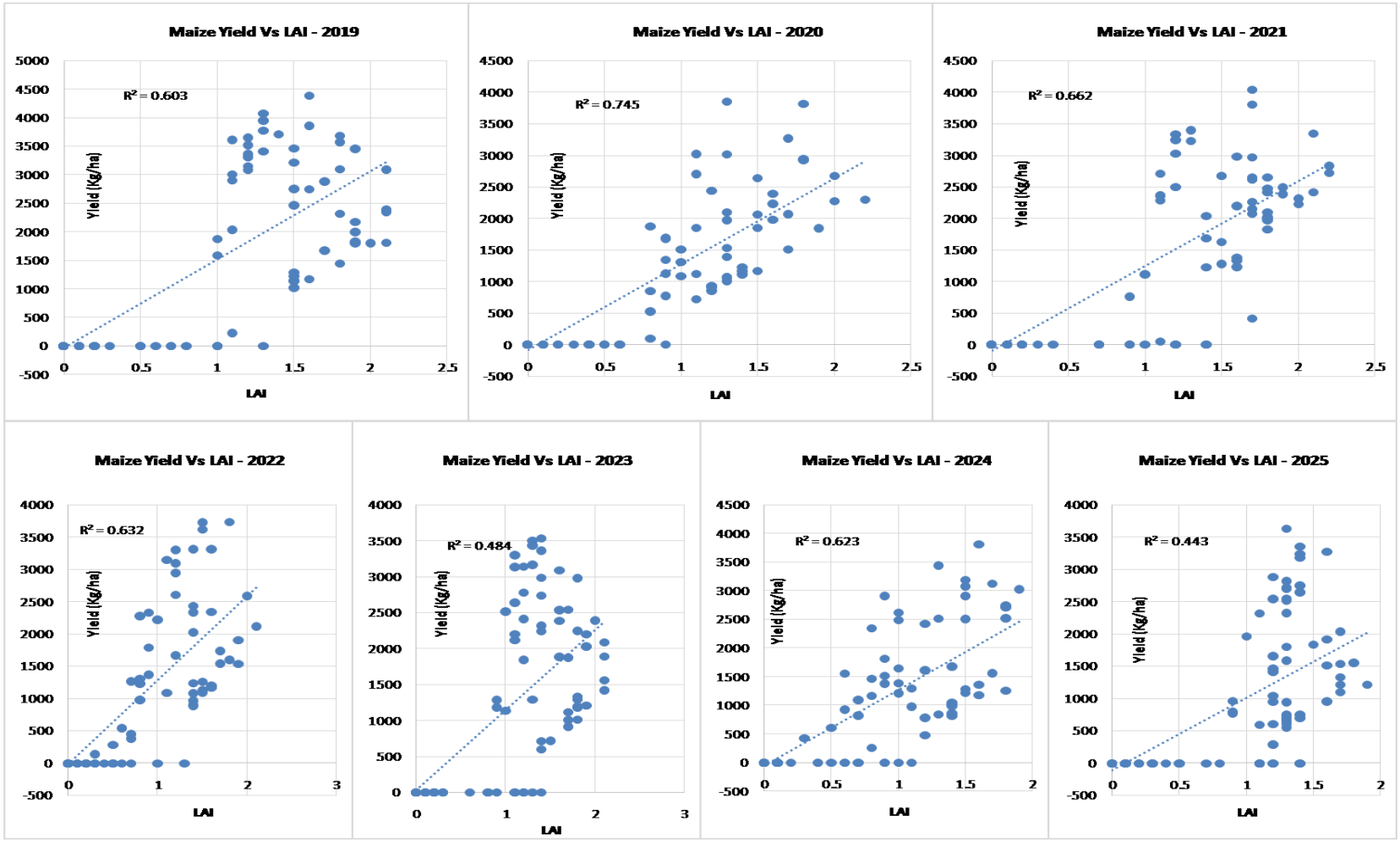

Figure 5.39. Validation of LAI and maize yield – 2019 to 2025

CONCLUSIONS AND RECCOMMENDATIONS

6. Conclusions and Recommendations

The main objective of the present study is to analyze the effect of changing climatic conditions on the yield percentage of wheat and maize crops. For this purpose we have used the climate and crop models for predicting the future climate scenario for a time span of 25 years (2001- 2025). The conclusions obtained from the present work are presented in this chapter. Also, certain recommendation on using the presently adopted methodology

6.1. Climate models

The RegCM climate model used in the present work is well suitable for modelling the climate scenarios. Although EH5OM datasets that we have used are older datasets, still RegCM model have given very god accuracies of 75- 80% due to the inbuilt dynamic physics processes like radiative scheme, planetary boundary scheme, sea surface temperature scheme, convective precipitation scheme etc. Hence, on using the updated new RegCM models which have many new physics schemes inbuilt in them, the accuracies of the outputs can be expected to improve further more. The 25 km resolution chosen for downscaling is well suitable for climate modelling at state levels as this resolution can well distinguish the boundaries between spatially varying climatic conditions.

Based on the RegCM climate model and according to the given inputs the following conclusions are derived from the present work.

- In the next decade, the temperature is going to increase by 0.75°C by 2025
- Rainfall would increase by 2016 but is expected to reduce in the later years.
- The temperature in the high elevated regions of the study area which cover a part of lower Himalayas are subjected to have an additional temperature increase of 0.1°C than the one expected on the usual elevated areas.
- Hence, certain adaptation strategies are to be made in order to overcome the upcoming climatic variations for producing good crop yields.

6.2. Crop modelling

As per the IPCC report, the crop yield is expected to decrease by 50% in the South East Asian countries. As per the literature study, DSSAT crop model adopted in the present work is one of the standard models available for modelling and predicting the crop biophysical parameters. Also, it has been observed that the downscaled outputs from the RegCM model are well suitable as inputs for DSSAT model which was justified by the very good RMSE obtained which recorded as around 80% for wheat and 72% for maize.

Based on the downscaled outputs obtained from RegCM model which are used as inputs into DSSAT model and the following conclusions are obtained from the crop model –

- Wheat is going to reduce at a faster rate by the year 2025 and
- Maize is also expected to reduce by 2025 but at small rate.

6.3. Limitations and Recommendations

- The EH5OM datasets are older datasets and does not include many upcoming physics phenomena which can closely map the present climate. New climate scenarios can be used for obtaining good and accurate results because there are many new physics schemes included in these upcoming scenarios.
- The study area considered has a highly varying topography and hence finds difficulty in modelling due to the lower spatial resolution of the DEM.
- High level computing systems are recommended for running the crop and climate models as these take a very high time of up to 7hrs for each month.
- The spatial variability of the soil is very high at a regional scale and hence we cannot expect a single value for the entire grid. This leads to certain discrepancies in the crop model. However this spatial variability is not a major issue in the climate model and hence the accuracies of climate model were good compared to the crop models.

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