SIMULATING IMPACT OF CLIMATE CHANGE ON PRODUCTIVITY, CARBON SEQUESTRATION AND EROSION PROCESS IN AN AGRICULTURAL LANDSCAPE

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CERTIFICATE

This is to certify that **Mr. Akarsh. A** has carried out his research work entitled ***'Simulating Impact of Climate Change on Productivity, Carbon Sequestration and Erosion Process in an Agricultural Landscape'*** in partial fulfillment of the requirements for the award of **Master of Technology** (M. Tech.) in Remote Sensing and Geographic Information System by Andhra University,Visakhapatnam. The thesis has been carried out in Agriculture & Soils Department and is original work of the candidate under the guidance of Dr. N. R. Patel, Scientist/Engineer 'SF' and Dr. Suresh Kumar, Scientist 'SF' & Head Agriculture & Soils at Indian Institute of Remote Sensing, Dehradun, India.

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DEHRADUN **AKARSH. A**

Dedicated to

The Farmers of Doon Valley

ABSTRACT

"SIMULATING IMPACT OF CLIMATE CHANGE ON PRODUCTIVITY, CARBON SEQUESTRATION AND EROSION PROCESS IN AN AGRICULTURAL LANDSCAPE"

Climate change is already a reality to offset performance of Indian agriculture and posing a serious threat to food security. There are many approaches to investigate possible regional impact of climate change, however, biophysical models coupled with GIS environment have received wider acceptance in recent decades. Impact of climate change on productivity of major food crops is well understood at district level but studies on climate change impact on crop's productivity over high resolution grids are limited.

The current study depicts the impact of climate change on crop productivity, soil erosion and soil organic carbon sequestration in the Doon valley of Uttarakhand state, India with the help of GIS based Environmental Policy Integrated Climate model (GEPIC). The study area covers complex landscapes of the Himalayan region and the GIS based EPIC model is capable of taking into account the variability in topography soil and climatic conditions by incorporating high resolution data sets. The model can simulate crop yield as a combined effect of soil, weather and management practices.

The study was conducted in a spatial domain (1×1 km grid) to simulate and evaluate the potential productivity of major food grain crops under baseline and future climate change scenarios (2020s, 2050s, and 2080s). Model parameterization is done as per the local conditions. The calibration and validation of the model for crop productivity were done in selected sites with respect to ground measured yield data and daily weather data as input. The change in crop productivity under A2a and B2a scenarios with respect to baseline period were analyzed for rice and wheat crop. Simulations were performed to understand the effect of climate change on soil organic carbon sequestration and erosion process.

The model has performed well for both rice and wheat crop this is evidenced from very less RMSE of 0.38 and 0.24 t ha^{-1} respectively. For erosion assessment the model predicted rainfall erosivity index factor adjusted to the observed monthly values of the study area (R^2 =0.95).The current SOC stock for top 30 cm for three major agricultural soil series were assessed based on field data collected and Jussuvala series in the study area showed an improvement of 6.3 t.ha^{-1} SOC over 12 year period (2000 to 2012).

The model after calibration was used to assess climate change impact on crop productivity, soil erosion and SOC sequestration under different scenarios. The climate change impact on rice crop shows that with CO_2 fertilization there could be an improvement in yield (5%) during A2a50 scenarios and marginally declined afterwards. The study shows the vulnerability of wheat under un-irrigated conditions, as per the results obtained there could be a large decline in wheat productivity (42%) during 2080 without CO_2 fertilization but with CO_2 fertilization the reduction could be (23%).The climate change impact on SOC and erosion process under A2a scenario was assessed and the results shows in all time scales there is an increase in soil erosion due to increase in rainfall, and reduction in SOC content.

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1. AOGCMs: Atmosphere-Ocean General Circulation Models
2. CDF: Cumulative Distribution Function
3. CO_2: Carbon dioxide
4. CVF: Crop Management Factor
5. DEM: Digital Elevation Model
6. ^{o}C : Degree Centigrade
7. EPIC: Environmental Policy Integrated Climate
8. ENVI: Environment for Visualizing Images
9. EVI: Enhanced vegitation index
10. FACE: Free air CO_2 enrichment
11. FAO: Food and agriculture organization
12. GCM: Global climate model
13. GEPIC : GIS-based EPIC
14. GHG: Greenhouse gasses
15. GNP: Gross National Production
16. GPS: Global Positioning System
17. GIS: Geographic Information System
18. HadCM3: Hadley centre Climate model
19. HUI: Heat Unit Index value
20. ICIMOD: International Centre for Integrated Mountain Development
21. IIRS: Indian Institute of Remote Sensing
22. INCCA: Indian Network for Climate Change Assessment
23. IPCC : The Inter governmental Panel for Climate Change
24. LULC: Land Use Land Cover
25. LAI: Leaf Area Index
26. MAE: mean absolute error
27. MODAWEC: MOnthly to DAily WEather Convertor
28. MODIS: Moderate Resolution Imaging Spectroradiometer
29. NDVI: Normalised Difference Vegetation Index
30. NRSC: National Remote Sensing Centre
31. OTC: open-top field chamber
32. ppmv: parts per million volume
33. RCM : Regional climate models
34. RLAD: Leaf area decline rate
35. RMSE: Root Mean Square Error
36. SAVI: Soil adjusted vegitation index
37. SCE-UA: Shuffled Complex Evolution-university of Arizona
38. SOC: Soil organic Carbon
39. SOCS: Soil Organic Carbon Sequestration
40. SOM: Soil organic matter
41. SRES: Special Report on Emission Scenarios

42. SRTM: Shuttle Radar Topography Mission
43. TOC: Total Organic Carbon
44. UNEP: United Nations Environment Program
45. USDA: United States Department of Agriculture
46. USGS: United States Geological Survey
47. UTIL: Universal Text Integrated Language
48. VPD: Vapour Pressure Deficit
49. WGS84: World Geodetic System 1984
50. WMO: World Meteorological Organisation

1. INTRODUCTION

1.1. Background

Climate change is the most significant and alarming phenomenon that affects life and natural resources in the recent decades. The Green house effect is the major phenomenon behind the climate change and the increased concentration of major greenhouse gas, atmospheric CO_2 causes for the gradual increase of the atmospheric temperature. The changes in pattern and distributions of precipitation are the after effects of the climate change. The impact of these changes on agriculture and agricultural landscape is under great concern among the scientific community.

Agriculture is highly sensitive to short-term changes in weather and to seasonal, annual and long term variations in climate, (Khan *et al.,* 2009). It will affect all four dimensions of food security such as availability, accessibility and stability of food supply and the ability of the consumers to utilize food, (FAO, 2008). According to the reports of Food and agriculture organization (FAO), world population has been doubled (from 3 to 6.7 billion) in the last five decades and it will be around 9.1 billion in 2050. Increased population demands for immense productivity in agriculture and create more pressure on Agriculture. Another important phenomenon that affects agricultural landscape is the land degradation due to poor management practices. This will be accelerated due to changes in climatic patterns. The changes in land use and precipitation patterns lead to soil erosion, the key element in land degradation, will alter the fluxes of soil organic carbon (SOC). Soil act as the important source and sink of atmospheric CO_2 and the process of erosion affect the carbon dynamics due to detachment, transportation distribution and deposition, (Blanco and Lal, 2008). The disturbed SOC further contributes to greenhouse gases and thus global warming. . Hence the soil erosion and SOC flux demands for the continuous monitoring and modelling approach to assess the spatial distribution and variation of SOC under various management and landscape systems.

In order to achieve food security with limited resources, impact assessment is a must and it will help in evolving adaptation strategies for the development of climate-resilient agriculture. For The impact assessments under controlled experimental setups are expensive and other approaches which are useful in assessing climate change impact include: (1) Historical studies which asses past effect of climate change. (2) Short term climate event based analysis known as “forecasting by analogy”. (3) Assessment based on current changes. (4) Model based quantitative prediction of current and future impacts. (5) A judgment made by a group of field experts. Out of these, model based methods are most frequently used for the quantitative prediction of future changes, (Feenstra *et al.*, 1998).

1.2. Modelling Approach for climate change impact assessment

Models represent the mathematical formulation of a particular phenomenon or system etc. Impact assessment models can be broadly classified into biophysical models, socioeconomic models, and integrated system models, in which biophysical model assess the first order impact of climate change such as impact on crop yield, runoff etc, Socioeconomic models asses the second order impact on the economy due to first order changes and integrated system models assess interaction between different sectors, (Feenstra *et al.*, 1998).

Land use systems are generally represented using biophysical models, which are capable to simulate the interaction of climate with the exposure units (Rossiter, 2003). Based on the complexity biophysical models are classified into empirical statistical models and process based or mechanistic models. Empirical models are based on statistical or quantitative relationships developed between observed conditions (e.g.: weather parameters, soil properties etc.) with our area of interest (e.g.: crop yield, soil erosion, soil organic carbon etc.) whereas process based models are based on physical laws and scientific principles and hence they are universal in nature with a certain amount of calibration. Most of the process based models performs simulation (e.g.: crop growth, soil erosion etc.) in a daily time step based on daily input data (e.g.: weather), which are dynamic in nature and so these models are considered as dynamic simulation models.

The capabilities of dynamic simulation models to estimate the complex interaction of an ecosystem with weather or atmospheric parameters are utilized for climate change impact assessment. Earlier these models were used in site scale or watershed scale to assess the impact of climate change on crop productivity, soil processes etc. but in the current scenario the dynamic simulation models are applied to a larger extent such as regional or global level for a better assessment of the climate change impact. This will help the policy makers to evaluate the adaptation strategies and hence to identify the priority regions after considering vulnerability and socioeconomic aspects of that area.

Remote sensing and Geographical Information System (GIS) technologies provides the prominent information for the large scale climate change impact assessment using dynamic simulation models.

1.3. Integrated Use of GIS and Remote Sensing with biophysical models

The integrated use of GIS, remote sensing and Global Climate model (GCM) outputs with agro ecosystem model serve as a powerful tool for the spatial and temporal impact assessment of climate change.GIS provides a common platform for the input data preparation and database management for biophysical models, (Yang *et al.*, 2004; Hodson and White *et al.*, 2010). There are different methods to integrate GIS with simulation models such as embedding method, loose coupling, and tight coupling approach, in which loose coupling approach is preferred in most of the cases to avoid redundancy in programming, (Yang *et al.*, 2004). “Environmental Policy integrated climate” (EPIC) is coupled with GIS platform by Liu, (2009) termed as GIS based EPIC (GEPIC), and Priya, (2000) known as spatial EPIC, which are examples of the loose coupling approach of an agro ecosystem model.

The spatial impact assessment requires spatial variability in Land Use Land Cover (LULC), soil type, and topographic data. LULC map, Soil physiography and Digital Elevation Model (DEM) derived through remote sensing are suitable to incorporate the spatial heterogeneity of landscape units to agro ecosystem models. It helps to derive crop biophysical parameters from spectral indices for spatial calibration and validation of crop growth models. Radiometric observations can be incorporated to crop growth models in different ways such as direct use of driving variable estimated from remote sensing information; the updating of state variables of the model; the reinitialization of the model; and the recalibration of the model, (Mass, 1988; Delecolle *et al.*, 1992; Moulin *et al.*, 1998).

The output of GCMs from various global and regional climate models now-a-days available in GIS data formats and it helps to analyse the spatial variability of crop system performance in current and future scenario (Neelin *et al.,* 2006; Lobell *et al.,* 2008). Integration of all the above mentioned tools and concepts is required for an effective and large scale analysis of climate change impact on an agro ecosystem.

1.4. Problem Statement and Importance

Agricultural sector provides 23 % of Gross National Production (GNP) of our country and it is the important lively hood for nearly about 70 % of the population. (Khan *et al.,* 2009). The large variability in topography, climate, cultivation and management practices increase the complexity of the climate change analysis. The 4x4 assessment conducted by Indian Network for Climate Change Assessment (INCCA) shows the importance of sectoral and region vise assessment of climate change impact over India. If the ecosystem under consideration is mountainous, then it becomes more difficult to understand the impact of climate change due to its complexity in topography and orographic features, (ICIMOD, 2010).

To overcome this heterogeneity and complexity in climate and topography, high resolution spatial simulations have been performed by incorporating high resolution datasets with agro ecosystem models. This generates a quantitative and visual idea of spatial impact of climate change over a complex landscape. The present study considered mainly two aspects of impact of climate change over an agricultural landscape which includes: (1) Impact on crop productivity and (2) Impact on Soil organic carbon due to combined effect of soil erosion and climate change. Doon valley, a complex and fast growing mountainous ecosystem is selected as the current study area. The present research work carried out in a spatial resolution of 0.009^{o} X 0.009^{o} (~1km X 1km) which concern most of the spatial variabilities in soil type, topography and weather.

1.5. Research Objectives

1. To test the applicability of Environmental Policy Integrated Climate (EPIC) model to simulate crop productivity on grid basis.
2. To simulate EPIC model for soil erosion and soil carbon sequestration in the Agricultural landscapes.
3. To simulate potential impact of climate change on productivity of major food grain crops, carbon sequestration and erosion process in Doon valley.

1.6. Research Questions

1. How well the EPIC model can predict crop-specific productivity and erosion process?

2. What changes in crop productivity can we expect due to changes in climatic conditions?

3. What is the potential carbon sequestration in the study area?

1.7. Structure of the thesis

The present thesis titled “Simulating Impact of Climate Change on Productivity, Carbon Sequestration and Erosion Process in an Agricultural Landscape” concerns with the assessment of impact of climate change on a mountainous agro ecosystem. The whole thesis is divided into six chapters. Research objectives and the research questions through which the objectives are achieved are mentioned in the introductory chapter along with the problem statement. The second chapter examines the literature reviewed to explain the context and relevance of the present study. The third chapter provides a detailed description of the mountainous study area of Doon valley. Fourth chapter is meant for describing the materials and methodology adopted in the current research. Fifth chapter is dedicated for the results achieved through the project with their interpretation and discussion. The sixth and the final chapter conclude the thesis with some recommendations for the future works related to the current research.

2. LITERATURE REVIEW

2.1. Climate Change in General: 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 Organisation (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.” Meanwhile IPCC 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 CO_2 concentration from 280 ppm in the pre industrial era to 379 ppm in 2005 (35% increase).The global average temperature has increased about $0.74^{o}C \pm 0.18^{o}C$ over the last century (1906 to 2005).This happened in two phases from 1910 to 1940 ($0.34^{o}C$) and more strongly from 1940 to present($0.55^{o}C$). 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 $1^{o}C$ 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.”

2.1.1. 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 2.1 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 global projections in temperature, sea level rise and Hadley Coupled Atmosphere-Ocean General Circulation Model (HadCM3) used atmospheric CO_2 concentration for future predictions were given in Table 2.2.The expected estimate of future rise in temperature are 1.1 – 2.9^{o}C for low scenario and 2.4 – 6.4^{o}C for high scenario.

Table 2.1: Summary characteristics of the four SRES storylines (Adapted from Climate Change 2007: Working Group II)

	ECONOMIC		
GLOBAL	**A1 storyline** *World:* market oriented *Economy:* fast per capita growth. *Population:* 2050 peak, then decline. *Governance:* strong regional interactions; income convergence. *Technology:* three scenario groups: • A1F1: fossil Intensive. • A1T : non-fossil energy sources. • A1B : balanced across all sources.	**A2 storyline** *World:* differentiated. *Economy:* regional oriented; lowest per capita growth. *Population:* continuously increasing. *Governance*: self-reliance with preservation of local identities. *Technology:* slowest and most fragmented development.	***REGIONAL***
	B1 storyline *World:* convergent *Economy:* service and information based; lower growth than A1 *Population:* same as A1 *Governance*: global solutions to economic, social and environmental sustainability. *Technology:* clean and resource efficient.	**B2 storyline** *World:* local solutions *Economy:* intermediate growth. *Population:* continuously increasing at lower rate than A2. *Governance:* local and regional solutions to environmental protection and social equity. *Technology:* more rapid than A2;less rapid, more diverse than A1/B1	
	ENVIRONMENTAL		

Table 2.2: Global projections in temperature, sea level rise and atmospheric CO_2 concentration

Scenario	Temperature Change [a] (^oC)		Sea Level Rise [b] (cm)	Atmospheric CO_2 Concentration (ppmv)[c]			
	Optimal Estimation	Expected Range		1990s	2020s	2050s	2080s
A1F1	4.0	2.4~6.4	26~59	358	432	590	810
A1T	2.4	1.4~3.8	20~45	…….	…….	…….	…….
A1B	2.8	1.7~4.4	21~48	…….	…….	……..	…….
A2	3.4	2.0~5.4	23~51	358	432	549	709
B1	1.8	1.1~2.9	18~38	358	421	492	527
B2	2.4	1.4~3.8	20~43	358	422	488	561

(a) and (b) (IPCC., 2007) are the projections for 2100s (2090-2099), estimated using a hierarchy of models with respect to 1990s (1980-1999).(c) (Arnell *et al.*, 2004) Global CO_2 concentrations (ppmv) used in the SRES-driven HadCM3 climate change experiments.

2.2. Climate change Impact on Agro-eco systems

2.2.1. Climate change and crop productivity: Global experiences

Impact of climate change on crop productivity is closely related to regional climate variability and plant species. (1PCC, 2007).The outputs of crop simulation models and experimental studies show the sensitivity of crops towards the changes in atmospheric temperature, precipitation, CO_2 concentration and solar radiation. (Southworth *et al.*,2002)**.** The effect of these factors on crop productivity under changing climate may be positive or negative. The expected changes on crop productivity due to climate change are: changes in planting date, time to maturity, harvesting dates and crop yield.

The response of plans towards elevated atmospheric CO_2 ,the CO_2 fertilization effect, (Dhakhwa *et al.*, 1997) have been studied worldwide under different experimental setups such as Free air CO_2 enrichment(FACE),open-top field chamber(OTC),closed-top field chamber, greenhouse, laboratory chambers etc.(Amthor et.al,2001).It is observed that plants with C_3 photosynthesis pathways (small grain crops such as rice, wheet etc.) were more benefited than C_4 (maize, tropical grasses) since the current optimum CO_2 concentration is a limiting factor for C_3 plants,(Ziska and Bunce., 2006).The effects can be either positive or negative that depends on other factors governing plant growth such as temperature, water, solar radiation, salinity and nutrients (Bowes., 1993).The positive effects of CO_2 fertilization are increasing photosynthesis and water use efficiency and decreasing transpiration through stomatal conductance (Morison 1998; Long *et al.*, 2004).

The response of crops to temperature depends on crop specific optimum temperature for photosynthesis, growth and yield, (Canroy *et al.,* 1994). A slight increase in temperature will improve crop growth if the temperature is below the optimum temperature and vice versa if the temperature is close to maximum (Baker and Allen., 1993). IPCC, 2007 report states that there should be an increase in potential productivity of crops over 1- 3^o C rise in local average temperature and decrease thereafter. The expected reasons for this reduction in crop yield are poor vernalization (Trnka *et al.*, 2004), reduced photosynthesis and increased transpiration and stomatal conductance, (Nobel, 2005), shortened phonological stages, (Mitchell *et al.*, 1993).

2.2.2. 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; DES, 2004). 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'. '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, soyabean, 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^{o}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^{o}C in the 2050s and 4.5^{o}C by 2080s, and summer temperatures will increase by 2.2^{o}C in the 2050s and 3.2^{o}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 ^{o}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 2.3, 2.4 and 2.5 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 CO_2 and associated climatic change (Aggarwal and Sinha, 1993; Gangadhar Rao *et al.*, 1994; Lal *et al.*,1999; Rathore *et al.*, 2001; Mall and Aggarwal, 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 CO_2; the magnitude of these changes varied with crop, region and climate change scenario.

Sinha and Swaminathan (1991) showed that an increase of 2^{o}C in temperature could decrease the rice yield by about 0.75 ton/ha in the high yield areas; and a 0.5^{o}C increase in winter temperature would reduce wheat yield by 0.45 ton/ha. Gangadhar Rao and Sinha (1994) showed that wheat yields could decrease between 28 to 68% without considering the CO_2 fertilization effects; and would range between +4 to -34% after considering CO_2 fertilization effects. Aggarwal and Sinha (1993) using WTGROWS model showed that a 2^{o}C temperature rise would decrease wheat yields in most places. Lal *et al.*, (1999) 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 *et al.*, (2002) 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 ^{o}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 CO_2 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 CO_2 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 CO_2 could be nullified by 1.7, 3.5 and 5.0^{o}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.

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

Model used	Region	Temperature (°C)	CO_2 (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) -7 days (crop duration)	Sinha and Swaminathan, 1991
	Punjab	+1	Normal	-8.1%	Hundal and Kaur,1996
		+2		-18.7%	
		+3		-25.7%	
CERES	NW India	Normal	2 x CO_2	+28 %	Lal *et al.,* 1998
		+3	2 x CO_2	Cancels positive effect of elevated CO_2	

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

Model used	Region	Temperature (°C)	CO_2 (ppmv)	Impact on yield	Reference
	All India	+2	Normal	-0.75 t/ha (high yield areas) -0.06 t/ha (low yield coastal area)	Sinha and Swaminathan, 1991
CERES-rice	Punjab	+1	Normal	-5.4%	Hundal and Kaur,1996
		+2		-7.4%	
		+3		-25.1%	
CERES-rice	North West	Normal	2 x CO_2	+15%	Lal *et al.,* 1998
		+2	2 x CO_2	Cancels positive effect of elevated CO_2	
CERES-rice	Kerala	up to +5	Normal	-6%(for every +1°C)	Saseendran *et al.*, 2000.
CERES-rice &ORYZA1N		+0.1 +0.4 +0.3 +2.0	416 755 397 605	+3.5% +33.8% +1.0% +16.8%	Aggarwal and Mall(2002)

Table 2.5: Climate change impact on Indian maize

Model used	Region	Temperature (°C)	CO_2 (ppmv)	Impact on yield	Reference
	Punjab	+1	Normal	-10.4%	Hundal and Kaur,1996
		+2		-14.6%	
		+3		-21.4%	
CERES-maize	North India	up to +4	350	Continuous yield reduction	Sahoo,1999
		Normal	700	+ 9%	
		+ 0.6	700	Nullified the beneficial effect of CO_2 fertilization	

2.2.3. Soil erosion process

Soil, the fundamental and non-renewable natural resource act as the basic medium for plant growth and prone to rapid degradation over time due to human interventions (Blanco and Lal, 2008). Land degradation caused by soil erosion is categorized into geological and accelerated, the former is natural and act as the basis for soil formation while the later will be happened when the rate of erosion exceeds a threshold level.

Water erosion and wind erosion, the major ingredients of land degradation contribute 56% and 28% respectively to the worldwide land degradation (Oldeman, 1994). On behalf of the affecting extend and severity water erosion can be treated as more dangerous than wind erosion. The water erosion commonly occurs in a three step process namely detachment, transportation and deposition of soil particles. The magnitude and rate of erosion governed by the interactive effect of factors such as precipitation, vegetative cover, topography, and soil properties. The ability of rainfall to erode soil is termed as Rainfall erosivity, comes under water erosion and is affected by the following factors of amount, intensity, terminal velocity, drop size, and drop size distribution of rain (Lal *et al.,* 2004)

2.2.3.1. Climate change impact on soil erosion process

Local and regional conditions will devise the magnitude of the risk of soil erosion while the projected change in intensity and pattern of rainfall together with human activities will increase the risk of soil degradation (O'Neal et.al, 2005).The relation between rainfall change with water erosion is displayed in Fig:2.1. To analyze the risk of soil erosion a large number of studies are conducted all over the world from micro to global level through macro and regional levels (Peeters *et al.*, 2008). Rainfall act as the prominent natural driving force for soil erosion and run off and hence any change in amount, intensity and erosivity will affect water flow and erosion process significantly (Wei *et al.*, 2007).

Kosmas *et al.,* (2000) observed that the surface runoff volume produced from a single rain event is comparatively less, if the annual rainfall is less than 280 mm where as 700 mm above rainfall lead to higher runoff coefficient. Wei *et al.,* (2009) tabulated major findings regard with the rainfall change and water erosion dynamics around the world and are provided in Table 2.6, which helps to understand how the changes in precipitation affect the runoff and erosion process. Recent studies substantiate that the intensity, amount and seasonal variations of event precipitation are gradually increasing over the globe as an after effect of the climate change (Berhe *et al.*, 2007).

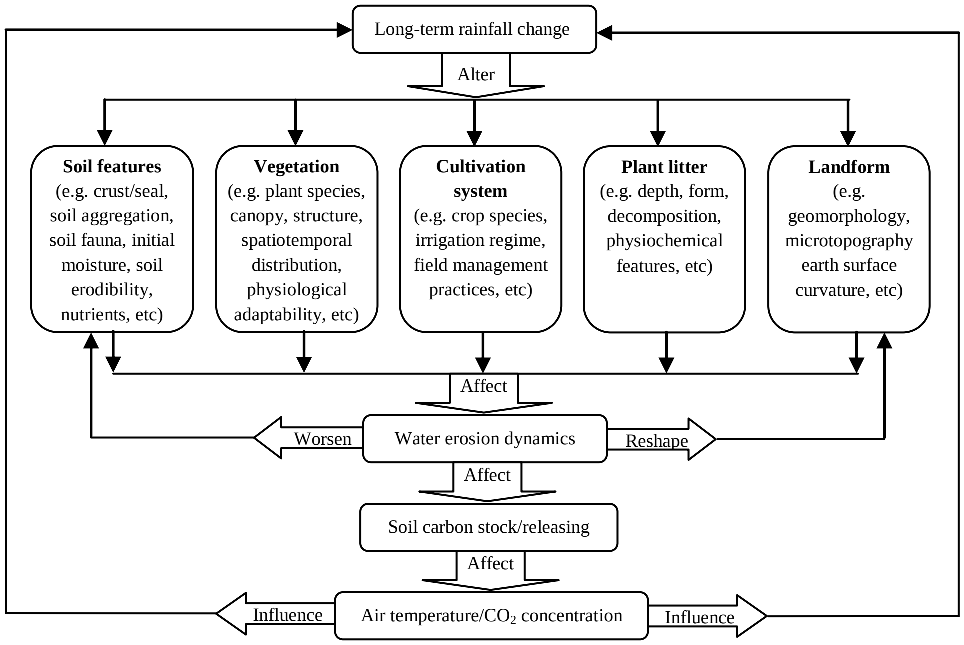


Figure 2.1: Relationship between rainfall change and water erosion process in terrestrial ecosystem (Wei *et al.*, 2009)

Table 2.6: Research findings of rainfall change and water erosion dynamics around the world (Wei *et al.*, 2009)

Covered geographical areas	Major conclusions/findings	Methodology
Midwest USA	10–310% increase in runoff and 33–274% increase in erosion due to increased rainfall and reduced land coverage.	Water Erosion Prediction Project (WEPP) model.
Meuse basin, Europe	3% increase in rain erosivity inducing 333% increase in water erosion.	WATEM/SEDEM model
South Korea	20% increase in storm depths and occurrence causing 54–60% and 27–62% increase in runoff and soil loss, respectively.	Climategenerator(CLIGEN); Water Erosion Prediction Project (WEPP) model.
Saxony, Germany	22–66% increase in erosion due to increased intensity and extreme events	ECHAM4-OPYC3 and EROSION2D mode.
Brazil	22–33% increase in mean annual sediment yield caused by 2% increase in annual rainfall.	Hadley Center climate model (HadCM2).
Different locations in USA	Each 1% change in rainfall may cause 2% and 1.7% changes in runoff and erosion, respectively	CLIGEN model and regression equations

Global scale	7% increase in rainfall during the twenty-first century	GCMs (general circulation Models)
South Downs, UK	7% increase in precipitation causing 26% increase in water erosion	Erosion Productivity Impact Calculator (EPIC) model
Changwu tableland, Loess hilly area, China	23–37% increase in annual rainfall, 29–79% increase in runoff and 2–81% increase in soil erosion	HadCM3, WEPP and stochastic weather generator (CLIGEN)
South Africa	A 10% increase in rainfall may lead to a 20–40% increase in runoff	CERES-Maize and ACRU models
Loess Plateau, China	4–18% increase in rainfall with runoff increasing from 6% to 112% and erosion increasing from –10% to +167 %	GCM
Greece	The length and frequency of flood are predicted to increase two fold and three fold, respectively	Goddard Institute for Space Studies climate change model
Dingxi, Gansu province, northwestern China	Runoff and erosion rates under rainfall extremes were 2.68 and 53.15 times the mean ordinary rates, respectively.	Statistics on long-term consecutive field data in situ
Global scale	About 40% erosion potential due to increased precipitation	GIS-based RUSLE model

2.2.3. Soil organic carbon and sequestration

The soil organic carbon is dominant component of soil organic matter, denoted as Soil organic carbon pool moderates all physical, chemical and biological processes of soil. The soil organic matter maintains soil structure, upgrades soil tilth, rejuvenates root development, boosts water retention and nutrient availability, and enhances microbial processes. The SOC reduces soil erosion by managing aggregates and reducing erodibility, upgrading water infiltration rate and decreasing the amount and rate of overland flow (Blanco and Lal, 2008).

Soils are the third largest pool of global carbon after oceans (38,400 Pg) and fossil fuels (4500 Pg). The Soil carbon pools are divided into two classes namely, organic carbon (1500- 2000 Pg) and Inorganic carbon (700 -1000 Pg) (Lal, 2004). Any increase in soil organic carbon content due to changes in land management, with the implication which increase soil carbon storage, mitigates climate change is known as Carbon sequestration (Powlson *et al.*, 2011). Generally it is a process of transferring carbon dioxide from the atmosphere into the soil through crop residues and other organic solids, and in a form that is not immediately re-emitted.

The SOC budget can be estimated from the difference between vertical inputs and outputs of Carbon, and avoiding the lateral components. The biomass C and organic amendments serve as vertical inputs and C emissions and leaching act as vertical outputs in the SOC budget estimation (Izaurralde *et al.*, 2007).

Soil organic matter (SOM) consists of different types of organic components, but for modeling purpose they are mainly divided into three pools based on their rate of mineralization and turnover period, (Parton *et al.*, 1987).They are, microbial biomass pool: comprises of 5 -15 % of total SOM, easily mineralizable with a turnover period of months to years; slow pools: comprises 20-40% of total

SOM with turnover period of years to decades and stable or recalcitrant pools: comprises 60-70 % of total SOM with turnover period of hundreds to thousands of years, (Rice, 2002).

Simulation models play an important role in soil organic carbon assessment in varying scales. This is helpful to understand the processes of carbon sequestration and to develop management practices, (Izaurralde *et al*., 1998).Process based multi-compartment models are widely used in SOC assessment and the important characteristics are: (i) sub division of SOM into different pools with unique decomposition rates with an assumption that the decomposition follow first-order kinetics, (ii) defined relationship between dynamics of C and N pools, (Paustian, 1994).

Soil erosion removes and redistributes the carbon sediment and accelerates the process of mineralization and alters the SOC flux. Out of the eroded carbon 10 % is transported to the ocean, 20- 30% is emitted to the atmosphere and 60- 70 % are redistributed over the landscape (Blanco and Lal, 2008). Various modelling approaches are used to measure the erosion induced changes in soil organic carbon pools by estimating the gains in carbon storage under different management scenarios. EPIC, Century, APEX, Ecosystem and CQESTER are the common and well known models used for soil organic carbon simulation studies.

2.3. Remote sensing Application in model calibration

Doraiswamy *et al.*, (2003) investigated the use of remotely sensed data to improve the regional level prediction accuracy and real time calibration of EPIC crop growth model. . In this study the EPIC model generated Leaf Area Index (LAI) for spring wheat was directly used in a radiative transfer model SAIL to simulate reflectance. NDVI derived from this reflectance was then compared with Landsat data derived NDVI. The EPIC model parameters such as potential LAI, leaf area decline rate (RLAD),and time when green LAI begins to decline (DLAI) were adjusted to obtain an NDVI within 20 percent of satellite data. The findings of Doraiswami *et al.*, (2003) strongly substantiate that remotely sensed data improve the consistency of yield predictions prior to crop harvest.

Ren *et al.*, (2010**)** has been conducted a study in China for regional estimation of summer maize yield by integrating EPIC model with MODIS NDVI derived LAI. Shuffled Complex Evolution-university of Arizona (SCE-UA) optimization algorithm with EPIC model is used in this study to minimize the objective function (see Eq. 2.1) to a value below 0.001.

$$y = \sum_{i=1}^{n} \left(\mathrm{LAI_{sim}} - \mathrm{LAI_{obs}}\right)^2 \tag{2.1}$$

Where $\mathrm{LAI_{sim}}$ is simulate LAI; $\mathrm{LAI_{obs}}$ is remotely sensed LAI; n is the number of mapping units.

2.4. Relevant Studies conducted world wide

Recent decades experienced with a large number of research works regard with the climate change and its impact on crop productivity, soil erosion and soil organic carbon sequestration to develop strategies for adaptation and mitigation. EPIC has used in climate change impact studies and is incorporated with enhanced carbon cycling routines based on the approach used in the Century model (Izaurralde *et al.*, 2001)

Touré *et al.,* (1994) recommended that EPIC had the best potential for analyzing climate change impacts on agricultural production by evaluating five well known models used at that time. Causarano *et al.* (2008) introduced EPIC model to study the impact of soil and crop management on SOC in corn and soybean crop lands of Iowa. The model estimated a decrease in of SOC (0-20 cm depth) with time due to soil erosion impact on soil depth.

Farina *et al.,* (2011) applied EPIC model to simulate the interactive effect of climate change, CO_2 enrichment, soil management and two crop rotations on crop yield and SOC (0-100 cm depth) in central Italy. The current study used GCM (general Circulation Model) derived future climatic conditions to study the climate change impact on crop productivity. Outcomes of the study concluded that conventional tillage practices led to massive C loss rate.

Zhang *et al.,* (2005) evaluated the potential impact of climate change under three emissions scenarios on hydrology soil loss and crop production .They used HadCM3 derived future climatic conditions in Chengwu tableland region of southern Loess Plateau of China. The study concluded that conservation tillage would be sufficient protect agro ecosystem under projected climate change.
Brown and Rosenberg (1999) used EPIC model to assess the impact of climate change on corn and wheat yields using GCM outputs in major wheat and corn growing regions of US and the predicted impacts on yields ranged from -20% to +5% for corn and -76% to +18% for wheat.

Thomson *et al.,* (2002) conducted a study by incorporating GCM output to EPIC model to interpret the CO_2 doubling effect on dry land wheat yield and predicted an increase in yield of 1 $t.ha^{-1}$. Global assessment of Tan and Shibasaki (2003) using EPIC model coined the harmful effects of global warming on most of the crops.

3. STUDY AREA

3.1. Introduction to Study Area

The current research mainly concerns with the impact of climate change over agricultural landscapes based on the impact on crop productivity as well as impact on soil organic carbon due to combined effect of soil erosion and climate change. To execute such a study, agricultural area with spatial variabilities in soil type, topography and weather should be a must. A mountainous ecosystem provides such a study area and hence Doon valley of Uttarakhand state in India is selected as the study area.3.1. Location and Extend

The mountainous agro eco system Doon valley lies in between 29°57’30”N to 30 °31’40”N latitudes and 77 ° 34’50”E to 78 °18’50”E longitudes. It is a long and wide valley which covers an area of 1870 km^2 bounded between Lesser Himalayan mountain range at north east and Sivalic hill range at south west. The holly rivers Ganga and Yamuna traverse through the North West and South East part of the valley respectively. Dehradun the capital city of the state Uttarakhand belong to Doon valley, which is also a part of the Dehradun district.

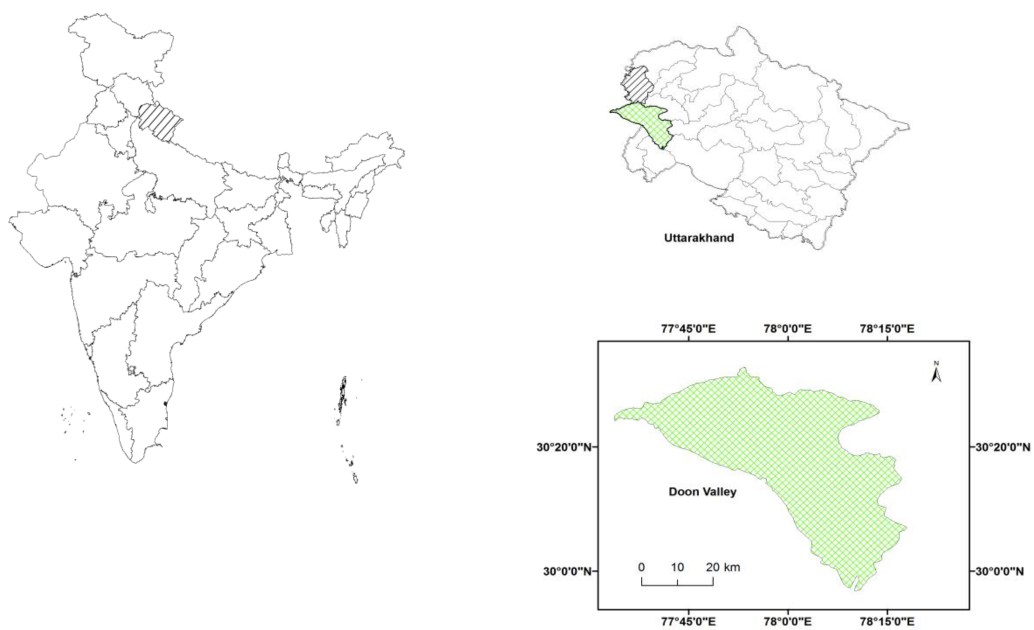


Figure 3.1: Study area: Doon valley

3.2. Climate

The climate of the Doon valley region is subtropical to temperate. Based on the altitude it varies from tropical to ice cold. As Doon valley is a hilly region, temperature variations according to elevation differences are considerable. Even though Doon valley is hilly area, heat is often intense but not as much as that in the plains of the adjoining district. In winter higher peaks of Doon valley are under snow while places like Dehradun are around freezing point. From June to September Doon valley suffers the Monsoon with an average annual rain fall of 2073.3 mm. July and August are the peak periods of monsoon. Monthly Climate data of Doon Valley on the basis of mean of last 25 years are given in Table 3.1

Table 3.1: Monthly Climate data of Doon Valley

Month	Rainfall (mm)	Relative Humidity (%)	Temperature Mean		
			Max	Min	Mean
January	46.9	91	19.3	3.6	10.9
February	54.9	83	22.4	5.6	13.3
March	52.4	69	26.2	9.1	17.5
April	21.2	53	32	13.3	22.7
May	54.2	49	35.3	16.8	25.4
June	230.2	65	34.4	29.4	27.1
July	630.7	86	30.5	22.6	25.1
August	627.4	89	29.7	22.3	25.3
September	261.4	83	29.8	19.7	24.2
October	32.0	74	28.5	13.3	20.5
November	10.9	82	24.8	7.6	15.7
December	2.8	89	21.9	4.0	12.0
Average Annual	**2051.4**	**76**	**27.8**	**13.3**	**20.0**

3.3. Physiography and Soils of Doon valley

The Doon valley comprises of Himalayan and Shiwalik mountainous terrains in north and south respectively act as a sloping terrain composed of Piedmont material, which has been continuously reworked by organic and fluvial process to form terraces of varying age and elevation. Weathering and erosion govern the soil formation of Doon valley. The major physiographic features seen on Doon valley can be classified into four types, which are given below.

1. Lesser Himalayan mountain ranges
2. Shiwalik hill ranges
3. Piedmont
4. Ganga alluvial Plain

Further subdivisions of these physiographic features are listed below.

1. Ganga river terrace

2. Yamuna river terrace
3. Piedmont
4. Residual hill
5. Shiwalik hill
6. Lesser Himalayan mountain – northern aspect
7. Lesser Himalayan mountain – sourthern aspect

Soil taxonomy of Doon valley reveals that Inceptisols, Entisols, Alfisols and Mollisols are the dominant soil types seen in this region. Soil moisture regime of Doon valley is classified from Ustic to Udic and soil temperature from hyper thermic to mesic.

3.4. Agriculture

Doon valley experience similar kinds of agriculture seen in the adjoining plains, except in the hilly regions. Agriculture of the mountainous region requires skill and hard labour. There are two harvests common in Doon valley, which are Kharif and Rabi. Paddy is the prominent crop of Kharif season followed by sugar cane and maize. The dominant crop of Rabi season is wheat.

4. MATERIALS AND METHODOLOGY

4.1. Materials used

4.1.1. Satellite Data

The satellite data used for this study are standard geo-referenced product of IRS P6 LISS-III sensor acquired from NRSC data centre and Standard Terrain Correction (Level 1T) product of Landsat 7 ETM+ sensor downloaded from U.S. Geological Survey(USGS) Earthexplorer (http://earthexplorer.usgs.gov/) archive. The details are given in table 5.1.

Table 4.1 Characteristics of satellite data used

Sl. No	Sensor	Path/ Row	Date of Acquisition	Spectral range (µm)	Resolution		
					Spatial (m)	Radio-metric	Temporal
1	Landsat 7 ETM+	146/39	15-MAR-2012 23-SEPT-2012 09-OCT-2012 18-MAR-2013	0.45-0.515 (B) 0.525-0.605 (G) 0.63-0.69 (R) 0.75-0.90 (NIR) 1.55-1.75 (SWIR1) 10.4-12.5 (TIR) 2.09-2.35 (SWIR2) 0.52-0.9 (PAN)	30 30 30 30 30 60 30 15	8 bit	16 days
2	IRS P6 LISS-III	96/50	08-OCT-2011	0.52 – 0.59 (G) 0.62 – 0.68 (R) 0.77 – 0.86 (NIR) 1.55 – 1.77 (MIR)	23.5	8 bit	24 days

4.1.2. Elevation data

Shuttle Radar Topography Mission (SRTM) void filled digital elevation data with 90 m spatial resolution were acquired from USGS earth explorer archive.

4.1.3. Weather data

The daily weather data for the study area was obtained from the Global Summary of the Day dataset of US National Climatic Data Center. This is the observed daily data for the study area from 2000-2012.

4.1.4. Spatial Climate data

The spatial monthly climate data of 30 arc-seconds (~1 km) for the baseline period and future projected scenarios were obtained from worldclim-global climate data archive. It consists of mean monthly maximum, minimum and means temperature and precipitation in generic or ESRI grid format with WGS84 datum. These data mainly results from interpolation of observed weather data obtained from different sources from 1950-2000 after strict quality controls with the help of thin-plate smoothing algorithm in ANUSPLIN package using latitude longitude, and elevation (SRTM DEM) as independent sources.

The HadCM3 model based future climate projections, calibrated and downscaled using current condition data of worldclim were used in this study. The scenarios used were HadCM3 A2a and B2a during the period viz. 2020(2010-2039), 2050(2040-2069) and 2080(2070 – 2099).

4.1.5. Soil and Land use/Land cover Map

The soil physiography map and land use/land cover maps prepared in 1:50000 scales, as part of NR-CENSUS prototype study for Dehradun district were obtained in ArcGIS shape file format. The soil analysis data for the study area were collected from NR-CENSUS report.

4.1.6. Use of field/laboratory Instruments

Table 4.2 Details of Instruments used

Sl No:	Instrument	Purpose
1	Globel 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 Knife	To collect soil sample from 0 – 30 cm depth.
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.

4.2. Methodology

The main focus of this research was to establish the biophysical model i.e., "Environmental Policy Integrated Climate (EPIC) Model" to assess the impact of climate change on productivity, soil erosion and soil organic carbon sequestration in an agricultural landscape of a mountain ecosystem. The present study has been conducted in Doon valley of Uttarakhnd 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 EPIC model, the Arc GIS interface for EPIC v0509 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 crop growing seasons. The calibrated model is implemented for base line scenario for whole Doon valley and then used for climate change impact assessment in a spatial resolution of 0.009° X 0.009° (~1km X 1km). The broad methodological framework for the study is given in Fig: 4.1.

4.2.1 EPIC Model: Concepts and Description

EPIC is a process based field scale model that operates in continuous basis using a daily time step and can perform long-term simulations of climate, soil and management interactions. This model has been developed by USDA modeling team since 1980 to provide an improved technology for evaluating the impacts of soil erosion on soil productivity.

According to Williams, (1990) EPIC is broad in terms of its components to model biophysical processes which include weather, hydrology, erosion, nutrients, soil temperature, plant growth, plant environment control, tillage, and economic budgets. The model is designed to simulate drainage areas which are characterized by homogeneous weather, soil, landscape, crop rotation, and management system parameters.

The EPIC model is being refined and expanded continuously since the original development, and in current scenario, it serve as the key in solving many agricultural management problems such as Crop Growth and Yield Studies, Irrigation Studies, Nutrient Cycling and Nutrient Loss Studies, Wind and Water Erosion Studies, Economic and Environmental Studies, Comprehensive Regional Assessments, Soil Carbon Sequestration, Climate Change Effects on Crop Yields assessment etc, (Gassman *et al.*, 2005). Due to this large variety of applications, the EPIC acronym now stands for 'Environmental Policy Integrated Climate', instead of earlier 'Erosion Productivity Impact Calculator'. GEPIC is a GIS-based EPIC model developed and maintained by the Swiss Federal Institute of Aquatic Science and Technology (Eawag). The GEPIC model treats each grid cell as a site, and which is capable to simulate biophysical processes for all predefined grid cells with any spatial resolution (Liu 2009).

The major EPIC model modules used for this study are crop simulation, soil erosion assessment and Soil organic carbon sequestration component. The detailed description of the model components used in current study is given in upcoming sections, (Williams, J.R., Sharpley, A.N., 1989; Williams *et al.*, 2008).

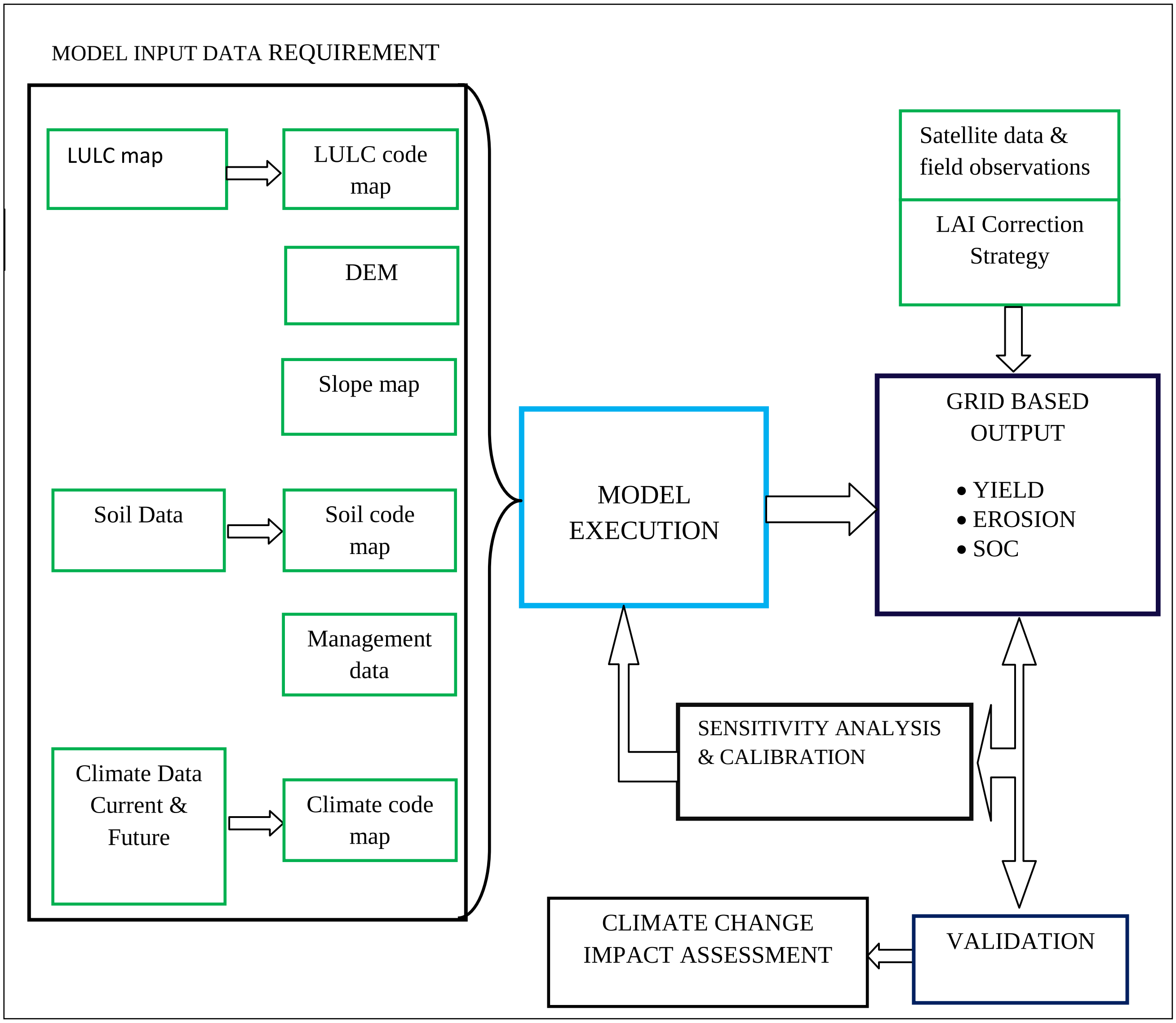


Figure 4.1: Methodological framework for the study.

4.2.1.1. Crop Growth Model

EPIC model has the capability to simulate growth of both annual and perennial crops based on a single crop growth model. Each crop is defined with unique model parameters that can be adjusted for the study area based on expert's opinion and experimental studies. Annual crop growth is from planting date to harvest date or until the accumulated heat unit reaches potential heat unit, defined for the crop. Crop growth constrains or stress factors are incorporated in the model which restricts the crop from achieving its potential growth. The stress factor value ranges from 0 to 1, and minimum of water, temperature, nutrient and aeration stresses were selected for further adjustment of biomass accumulation. These concepts have been implemented in EPIC model through the equations explained in the following section.

The phonological development of the crop is based on daily heat units accumulation and a Heat Unit Index value (HUI) is computed from 0 at planting to 1 at maturity.

$$HU_k = \frac{T_{mx,k}+T_{mn,k}}{2} - T_{b,j} \ ; \quad HU_k \geq 0 \tag{4.1}$$

$$\mathrm{HUI}_i = \frac{\sum_{k=1}^{i} \mathrm{HU_k}}{\mathrm{PHU_j}} \tag{4.2}$$

Where, HU, T_{mx} and T_{mn} are the heat unit, maximum temperature and minimum temperature in ^oC on day k. T_b and PHU are the base temperature and Potential heat units require for crop j.

Crop yield is considered as the amount of crop removed from the field and simulated as a function of above ground biomass accumulates at the end of crop growth and harvest index.

$$YLD_j = (HI_j) * (B_{AG})_j \tag{4.3}$$

Where, (HI_j) is the Harvest index and $(B_{AG})_j$ is the above ground biomass in t ha^{-1} for crop j.

Biomass simulation

The potential daily increase in biomass is estimated as follows,

$$\Delta B_{p,i} = 0.001 * (BE)_j * (PAR)_i \tag{4.4}$$

Where, $(BE)_j$ is the crop parameter for converting energy to biomass in $kg.ha^{-1}.MJ^{-1}.m^2$ and $(PAR)_i$ is the intercepted photosynthetic active radiation in $MJ.m^{-2}$ derived using Beer's law equation. In order to incorporate the effect changing atmospheric CO_2 and vapor pressure deficit, BE value is adjusted as follows.

$$BE^* = \frac{(100 * CO_2)}{(CO_2 + exp(bc_1 - bc_2(CO_2))} \tag{4.5}$$

$$BE = BE^* - bc_3 * (VPD - 1) \qquad \mathrm{VPD} > 0.5 \tag{4.6}$$

Where CO_2 is the atmospheric CO_2 level in ppm, VPD is the vapor pressure deficit in kPa and bc_1, bc_2 and bc_3 are the crop specific parameters.

$$PAR_i = 0.5 * (RA)_i * [1 - exp(-0.65 * LAI_i)] \tag{4.7}$$

Where, $(RA)_i$ is the solar radiation in $MJ.m^{-2}$ and LAI_i is the leaf area index in i^{th} day of the year. The constant 0.65 is the extinction coefficient.

LAI estimation

From emergence to start of leaf decline LAI is simulated using following equations.

$$HUF_i = \frac{HUI_i}{HUI_i + exp[ah_{j,1} - (ah_{j,2}) * (HUI_i)]} \tag{4.7}$$

$$LAI_i = LAI_{i-1} + \Delta LAI \tag{4.8}$$

$$\Delta LAI = (\Delta HUF) * (LAI_{mx}) * \{1.0 - exp[(5.0 * (LAI_{i-1} - LAI_{mx})]\} * \sqrt{REG_i} \tag{4.9}$$

4.2.1.2. Soil Erosion Model

$$Y = \chi * (EK) * (CVF) * (PE) * (SL) * (ROKF) \tag{4.10}$$

Where Y is the sediment yield (t ha-1), χ is the rain fall and runoff factor, EK is the soil erodibility factor, CVF is the crop management factor, PE is the erosion control practice factor, SL is the slope length and steepness factor and ROKF is the course fragment factor.

Rainfall and Runoff Factor (χ)

For USLE and RUSLE

$$\chi = EI \tag{4.11}$$

For Onstand-Foster

$$\chi = 0.646 * EI + 0.45 * \left(Q * q_p\right)^{0.33} \tag{4.12}$$

For MUSLE

$$\chi = 1.586 * \left(Q * q_p\right)^{0.56} * A^{0.12} \tag{4.13}$$

For MUST

$$\chi = 2.5 * (Q * q_p)^{0.5} \tag{4.14}$$

For MUSS

$$\chi = 0.79 * \left(Q * q_p\right)^{0.65} * A^{0.009} \tag{4.15}$$

Where, EI is the rainfall energy factor, Q is the runoff volume (mm), q_p peak runoff rate (mm h-1) and A is the watershed area (ha)

Soil Erodibility Factor (EK)

Soil erodibility factor represents the susceptibility of soil to erosion. EK is estimated for the top layer at the start of each year simulation as a function of sand, silt, clay and organic carbon present in the soil and it vary between 0 to 0.5.The equations for soil erodibilit estimation are described as follows.

$$EK = X1 * X2 * X3 * X4 \quad (4.16)$$

$$X1 = 0.2 + 0.3 * \exp\left(-0.0256 * SAN * \left(1 - \frac{SIL}{100}\right)\right) \quad (4.17)$$

$$X2 = \left(\frac{SIL}{CLA+SIL}\right)^{0.3} \quad (4.18)$$

$$X3 = 1.0 - \left(\frac{0.25*WOC}{WOC+exp(3.718-2.947*WOC)}\right) \quad (4.19)$$

$$X4 = 1.0 - \frac{0.7*SN1}{SN1+exp(-5.509+22.899*SN1)} \quad (4.20)$$

$$SN1 = 1.0 - \frac{SAN}{100} \quad (4.21)$$

Where SAN, SIL, CLA and WOC respectively the sand, silt, clay and organic carbon content of the top soil layer in %.

Crop Management Factor (CVF)

CVF is updated as a function of crop residue, crop height, standing live biomass of the crop and soil surface roughness, for all days when runoff occurs using the following equation.

$$CVF = (FRSD) * (FBIO) * (FRUF) \quad (4.22)$$

$$FRSD = \exp(-P23 * CVRS) \quad (4.23)$$

$$FBIO = 1 - \exp(-P26 * CPHT) * \frac{STL}{STL+exp(1.175-1.748*STL)} \quad (4.24)$$

$$FRUF = \exp\left(-0.026 * (RRUF - 6.1)\right) \quad (4.25)$$

Where FRSD is the crop residue factor, FBIO is the growing biomass factor, FRUF is the soil random roughness factor, CVRS is the above ground crop residue in t ha^{-1}, CPHT is the crop height in m, RRUF is the soil surface random roughness in mm, STL is the standing live biomass of the crop in t. ha^{-1}, P23 and P26 are coefficients in exponential functions.

Increasing P23 (0.50-1.50) and P26 (0.05-0.20) decrease FRSD and FBIO respectively and the combined effect of this will reduce CVF factor and thus the sediment yield.

Erosion Control Practice Factor (PE)

Erosion control practice factor indicates the effectiveness of support practices on erosion process, which includes contour farming, terracing, strip cropping etc. Normally erosion control practice factor varies in between 0.1 to 1.

Slope Length and Steepness Factor (SL)

The model is provided with USLE (Wischmeier and Smith, 1978) and RUSLE (Renard, *et al.*, 1997) methods for calculation of SL factor. The RULSE method applied in the current study as follows.

$$SL = RSF * RLF \tag{4.24}$$

$$RSF = 10.8 * STP + 0.03;\ \ SPLG > 4.57;\ STP < 0.09 \tag{4.25}$$

$$RSF = 16.8 * STP - 0.5;\quad SPLG > 4.57;\ STP > 0.09 \tag{4.26}$$

$$RSF = 3.0 * STP^{0.8} + 0.56;\ SPLG < 4.57 \tag{4.27}$$

$$RLF = \left(\frac{SPLG}{22.127}\right)^{RXM} \tag{4.28}$$

$$RXM = \frac{STP}{(0.2688 * STP^{0.8} + STP + 0.05)} \tag{4.29}$$

Where STP is the land surface slope in m m^{-1} and SPLG is the slope length in m.

Course Fragment Factor (ROKF)

$$ROKF = exp\,(-0.03 * ROK) \tag{4.30}$$

Where, ROK is the percentage of coarse fragments in the surface soil layer.

4.2.1.3. Soil Organic Carbon model

The soil organic carbon model in EPIC splits soil organic carbon and nitrogen in three components such as microbial biomass, slow humus and passive humus. These components have varying turnover time ranging from days to weeks for microbial biomass, 20-50 years for slow humus and hundreds of years for passive humus. The soil carbon routine in EPIC has recently been modified with equations from century model developed by Parton et.al in 1994. The organic residues such added to surface and below ground are fist split into structural and metabolic litters based on carbon and nitrogen content. Further these two litters are allocated to above mentioned three compartments as a function of soil moisture and temperature. Considerations are given in the model to take account for the portion of C and N that loss to atmosphere in gaseous form. The important feature that differ EPIC from other soil carbon simulation models is, its capability to estimate wind and water erosion induced SOC losses. It is also capable to estimate the changes in bulk density and soil depth due to change in SOC by soil erosion and respiration, (Izaurralde *et al.*, 2001, 2006).

4.2.2. Model Input data preparation

The GEPIC model simulations are performed on a grid basis, with a spatial resolution of 0.009 X 0.009^{o} (~1kmX1km). In GEPIC, an input data translation module integrated with ArcGIS is used to transform raster datasets to text input files. This capability has not been much explored and utilized due to availability of only low resolution spatial extraction (50 X 50 km). The text file consists of latitude, longitude, elevation (m), slope (%), LULC code, soil code, climate code, location code, Maximum fertilizer applied and maximum irrigation for each grid. It is generated using ArcGIS spatial analyst sample extraction toolkit and Microsoft Excel. The details of grid file generation are explained in the following sections. A Universal Text Integrated Language (UTIL) is used to create input files in EPIC format as mentioned in EPIC v.0509 user manual, (Williams *et al.*, 2006).

Table 4.3: Details of essential input parameters required for EPIC model.

Sl No	Input Data	Parameters
1	climate data	Monthly precipitation and number of wet days; mean monthly maximum and minimum temperature.
2	Soil data	Depth, Hydrologic Soil Group, Texture, Organic carbon (%), CaCO3, pH, EC, CEC, Bulk density, Coarse Fragment.
3	Crop management	Date of planting and harvesting, details of fertilization, irrigation, tillage practices, plant density, and potential heat unit requirement.
4	Topography	Elevation, slope, latitude-longitude.

(1) Grid and grid centroid file generation: Grids and grid centroid files are generated using Hawths analysis tool, an extension in ArcGIS. The grid file with above mentioned spatial resolution is kept as the base grid for further analysis. The study area is divided into 2155 grid cells. Grid centroid is used to extract grid wise information from different input layers mentioned below.

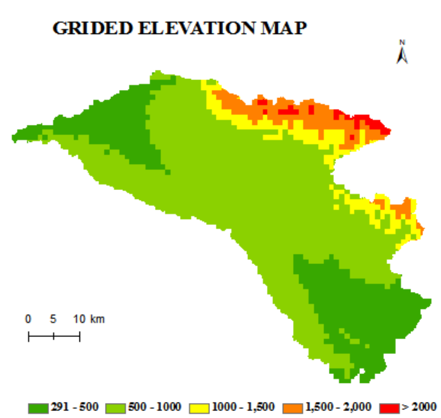
(2)Soil code map and soil file: The soil physiographic units are integrated with major soil series and codes are assigned to each series. To generate gridded soil code map Identity analysis are performed in Arcmap with grid file as the input feature and soil file as the identity feature. The output of identity analysis is then converted to soil code map by assigning maximum combined area to each grid. Soil files (.sol) are created using UTIL with soil code as the file name.

(3) LULC code map: There are three codes to represent the presence and absence of particular crop or crop rotation under consideration. 0 represents absence of the crop, 1 and 2 respectively represents crop under rain fed and irrigated conditions.

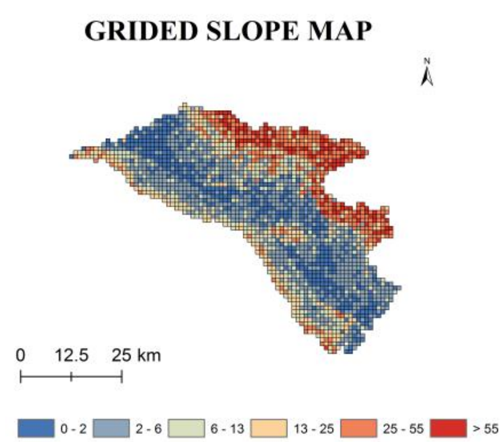
(4) Gridded elevation and slope map: The SRTM DEM with 90 m resolution is used to prepare slope map in %. Zonal statistics are performed both on elevation and slope map using grid file as zone data.

(5) Climate data preparation: This study has tested the applicability of high resolution (1kmX1km) climate datasets in EPIC model. The high resolution datasets available for Baseline period (1950-2000) and future scenarios (HadCM3 A2a and B2a) are mean monthly maximum temperature, minimum temperature; precipitation and number of wet days. The MOnthly to DAily WEather Convertor (MODAWEC), an inbuilt weather generator along with GEPIC model have the capability to generate daily weather data and weather statistics file in EPIC file formats, (Liu *et al.*, 2009). The acquired monthly data are processed and average monthly maximum and minimum temperatures, total monthly precipitation and numbers of wet days are extracted. The data extracted for 2155 grids are converted to MODWEC format using Excel VB macro programme developed during the study period.

(6) Crop Management file: The crop management information such as planting date, harvesting date fertilizer and manure application rates are collected from the farmer's during field visit besides the literatures. Management (operation schedule/.ops) file for rice, wheat and maize crops are prepared from the above gathered information.



(a)



(b)

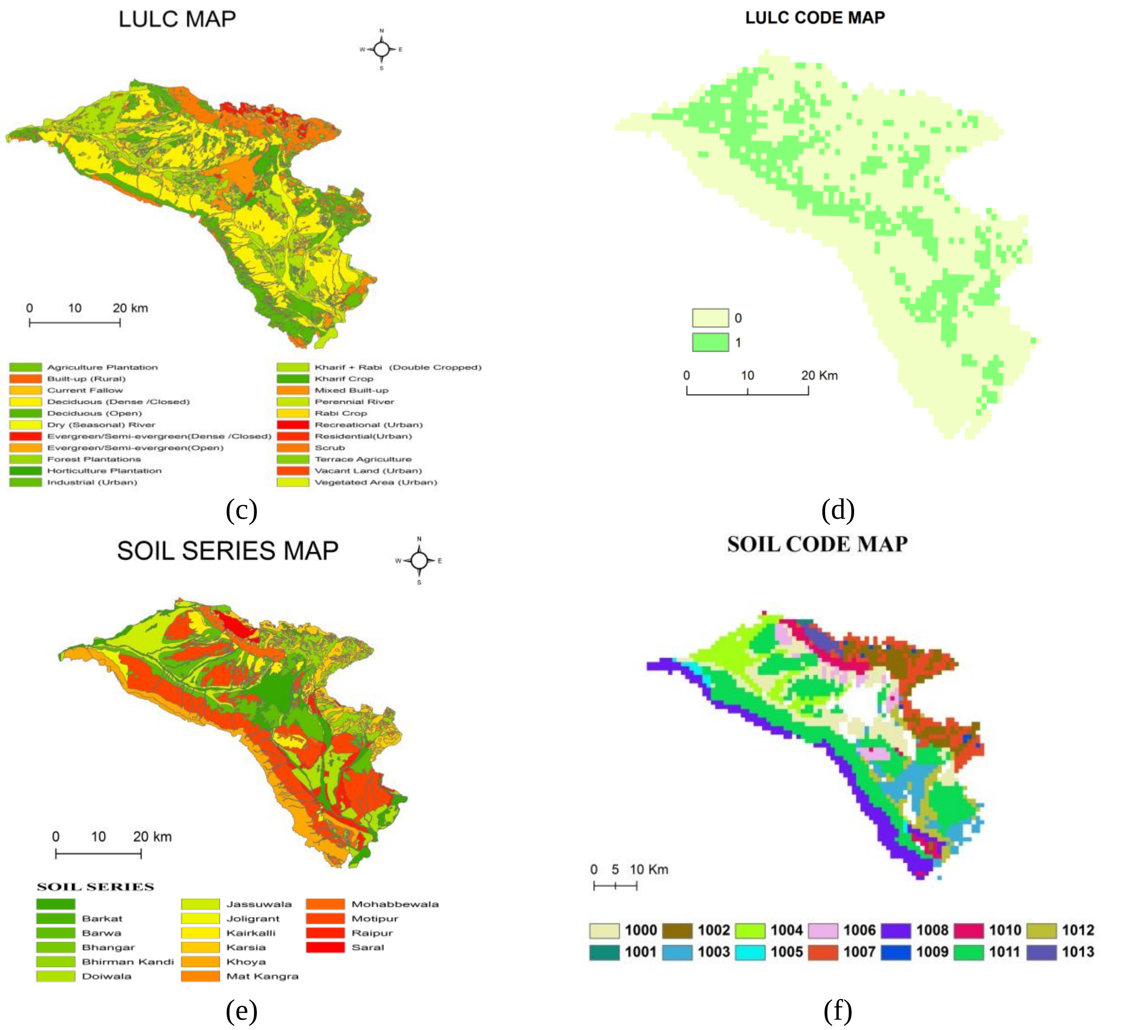


Figure 4.2: Input maps prepared for model simulation in gridded form (a) elevation (b) slope (d) LULC (f) soil code map; (f) LULC map and (e) soil series map in vector format.

4.2.3 Model simulations

Model simulations are performed on grid basis for crop yield, soil erosion and SOC assessments as explained in the following section.

4.2.3.1. Simulation for crop yield

Simulations are performed based on calibrated/adjusted parameter values of the most sensitive parameters ascertained by relative sensitivity index and gridded soil, weather and management input data prepared for the study area. Preliminary adjustments are performed as explained in EPIC user manual and Outputs are analyzed for further adjustments.

4.2.3.2. Simulation for Soil erosion

Revised universal soil loss equation (RUSLE) is selected for soil erosion simulation since the study area consists of steep slopes >20%. Model simulations are performed under maize-wheat rotation one of the most common practice in the study area. The erosion control practice factor selected 0.45 was selected. Preliminary runs were made to understand the trend in model simulations under baseline conditions and parameters were adjusted as mentioned in calibration section.

4.2.3.3. Soil organic carbon sequestration study

After adjusting crop yield and soil erosion within observed range, simulations are performed for soil organic carbon assessment. The number of years of cultivation at start of simulation is kept as 100 years. This factor governs the fraction of mineralizable organic nitrogen pool present in soil. Soils which are cultivated for a longer period have more stable organic nitrogen pool. For the spatial prediction of SOC a module is added to GEPIC as explained in the following section.

4.2.4. Updation of specific Modules of GEPIC

Two modules are being added to GEPIC model to achieve the study objective and to improve the spatial prediction of the model.

(1) *Module for Spatial Prediction of SOC*

To achieve high resolution spatial assessment of SOC, a module developed in VB programming language was added to GEPIC model. Which is capable to extract the information of Total Organic Carbon (TOC) from Annual cropman variable definition file (.ACM) produced during simulation. The output consists of a single text file with grid information (latitude, longitude and soil code) and year wise soil organic carbon present in total depth of the soil (here 2155 grids). This is useful for the spatial prediction of the rate of soil organic carbon changes under various management practices and climatic conditions. This module is utilized for Soil organic carbon sequestration (SOCS) assessment in the study area.

(2) *Module for spatial prediction of daily LAI*

LAI is the most important and useful parameter for crop growth assessment. For the large scale calibration and validation of the models spatially predicted LAI are adjusted with observed/satellite derived LAI .This is also useful to assess the physiological maturity process of plants under various climatic conditions. A module is added for the grid wise extraction of daily LAI from .OUT file generated during simulation. It is further utilized for model calibration and validation through integrating remote sensing derived LAI. The time series LAI helps to understand the impact of climate change on crop growth processes such as reduced crop duration , CO_2 fertilization effect etc,.

4.2.5. Field Data collection

The necessary data required for model initialization and calibration were collected from the study area through field observations performed during two crop growing seasons. Prior to filed visit the area was divided into 1km X 1 km grids and suitable grids were identified for field sampling based on land use/land cover, soil mapping units and accessibility to the area.The selected grids were marked on base map (topomap and satellite imagery /Bhuvan map/).The selected points were located in the field with the help of Google-earth overlayed study area map, features from the base map and GPS. After identifying the location necessary changes were made in plan based on current field conditions and presence of selected crop.

4.2.5.1. Crop data collection: The current study focus on major cereal crops, rice/maize and wheat which were respectively grown during Kharif and Rabi season. Field observations were made for these crops during respective growing seasons. The data collected are crop management practices, LAI and yield for rice and wheat crop. The crop management data is important for model initialization and management file preparation. The management data include date of planting and harvesting; rate of application of fertilizers, pesticides and irrigation; and field operations performed.LAI observations and yield data collections were performed in selected grids. It is observed that most of the farmers follow organic manuring and use of fertilizers is comparatively less. In Doon valley pesticides are rarely used. The use of fertilizers in plain areas (Tarai) is more than that in terrace cultivated areas. The ploughing operations are performed with the help of animal drawn Indigenous plough. Tractor drawn cultivators are also observed mainly in plain areas. Planting and harvesting operations were performed manually. LAI observations were made during peak growth stages using ceptometer. Crop cutting experiment was performed in selected plots (8 for paddy and 10 for wheat) using quadrat frame of size 0.5X0.5 m^2, to estimate crop yield and biomass per hectare.

Table 4.4: Field data collected for crops

Sl No.	operation	Crop	Date of Visit		No: of locations
			From	To	
1	Date of planting. Management practices.	Maize	01/08/12	10/08/12	10
		Rice			16
		Wheat	24/12/12	27/12/12	12
2	LAI,FPAR	Maize	01/08/12	10/08/12	10
		Rice	19/09/12	22/09/12	16
		Wheat	28/03/13	29/03/13	12
2	Crop Cutting (yield,biomass. PD)	Maize	19/09/12	22/09/12	05
		Rice	07/11/12	10/11/12	08
		Wheat	26/04/13	27/04/13	10

Sl No.	Crop	DOP	DOH	PD	Fertilization	Operations
1	Maize	15-Jun	20-Sept	7-12	FYM- 4 – 7 $t.ha^{-1}$	Ploughing –Animal drawn Indigenous
2	Paddy	10-Jul	10-Nov	25-40	Urea- 65-100 $kg.ha^{-1}$	plough/ tractor drawn cultivators,
3	Wheat	25-Dec	26-April	75-95	DAP – 30-40 $kg.ha^{-1}$	Planting& harvesting -Manual

DOP-Date of planting; DOH-Date of harvesting;PD-plant density (plants/m^2)

4.2.5.2. Soil data collection: soil samples were collected during the month of December, after kharif harvest and before field preparation for next season. Soil samples were collected based on soil physiographic units and major soil group found in that area. Main focus is given to agricultural landscapes and soil series. A total of 40 grids were identified for soil sample collection. From these locations samples were collected at 0-15, 15-30 and 30 - 50 cm depths at 3 locations in the grid for analyzing soil organic carbon. Soil moisture at various crop growth stages were observed using Theta probe. The locations were identified with the help of Garmin GPS and georeferenced with an accuracy of 5 m. Samples collection procedure include removal of surface debris, excavation of sampling pits, collection of samples at different depths in sample bags and proper labeling (sampling depth, location, date etc.), seal the bag and transport to laboratory for further analysis. The grids were characterized to assess soil erosion by field observation and soil erosion was calculated based on RUSLE model for the grid. The collected samples were air dried in laboratory and after sieving (2mm) stored in airtight containers for further analysis. Physio-chemical analysis were performed in IIRS central analytical laboratory to determine pH, EC, texture , bulk density, soil organic carbon, Total carbon and nitrogen. pH and EC meters were used for pH and EC analysis at 1:2 ratio. Soil bulk density was determined using clod method (Blake ,1965).Soil organic carbon were analysed using Walkley-Black dichromate extraction with titrimetric quantitation method and total carbon were assessed using CHNS analyzer.

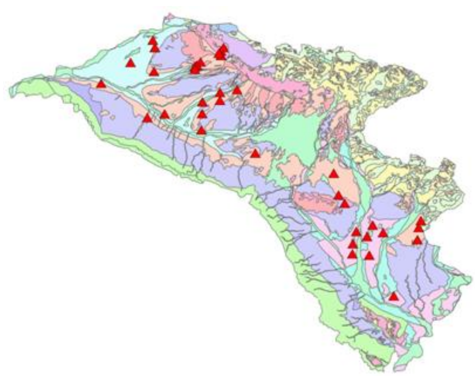


Figure 4.3: Soil sampling sites.

Table 4.5: Details of soil sample collected.

Sl No.	Soil series	Soil classification	No. of samples
1	Barwa	Dystric Eutrudepts	15
2	Doiwala	Typic Eutrudepts	9
3	Jassuwala	Typic Udifluvents	11
4	Kursia	Dystric Eutrudepts	2
5	Mohabbewala	Dystiric Eutrudpts	1
6	Motipur	Typic Hapludalfs	2
Total			40

4.2.6 Regionalization of EPIC model for the study area

Regionalization is the process of adjusting model parameters to perform regional analysis. Without proper adjustment the model may give erroneous outputs. The steps followed in the current study to regionalize EPIC model are field data collection, sensitivity analysis, calibration and validation of the model as explained in following sections.

4.2.6.1 Model Sensitivity Analysis

The basic objective of sensitivity analysis is to determine the magnitude of changes in the response of the model due to changes in the value of the specified parameter. This is helpful in calibration various model parameters. In this study a relative sensitivity index analysis is performed for crop yield, biomass production and LAI by varying selected parameters one at a time. A total of eight parameters are selected based on literature as given in Table 4.6.These parameters were varied ±10% of mean or model default value to assess the sensitivity using the equation given below, (adapted from Liu *et al.*, 2009).

$$S_i = \frac{\left|OUT_{1.1X_i} - OUT_{X_i}\right| + \left|OUT_{0.9X_i} - OUT_{X_i}\right|}{0.2 * OUT_{X_i}} \qquad (4.31)$$

Where, S_i is the sensitivity index of parameter X_i, OUT_{X_i} is the simulated outputs after setting all parameters to default model value, $OUT_{1.1X_i}$ and $OUT_{0.9X_i}$ are the outputs obtained after setting X_i value to 110 % and 90 % of its default values and other parameters kept default.

Sensitivity analysis for yield, biomass and LAI are performed based on selected parameters. The parameters with highest S_i values are identified as the most influential parameter, which are further adjusted during calibration process.

Table 4.6: Selected Parameters for model sensitivity analysis. (Doraiswamy *et al.*, 2003; Ren *et al.*, 2010; Wang *et al.*, 2011)

Sl No:	Parameter	Symbol	Mean	Range	model Set value		
					Maize	Wheat	Rice
I	*Crop File*						
1	Biomass Energy Ratio (kg ha^{-1} MJ^{-1} m^2)	WA	40	30 - 45	45	35	25
2	Harvest Index	HI	0.5	0.45 - 0.6	0.5	0.45	0.5
3	Maximum Potential Leaf Area Index	DMLA			6	6	6
4	Point in the growing season when the leaf area begins to decline due to leaf senescence	DLAI			0.8	0.6	0.8
5	Leaf Area Index decline rate parameter	RLAD			1	1	0.5
II	*Operation Schedule File*						
6	Potential Heat Units (^{0}C)	PHU	1500	1200-2400	1800	1600	1800
III	*Parameter File*						
7	Water stress HI	PARM(3)	0.5	0. 3 - 0.7	0.5		
8	SCS CN index coefficient	PARM(42)	1.5	0.5 – 2	1.5		

4.2.6.2. Model Calibration and Validation

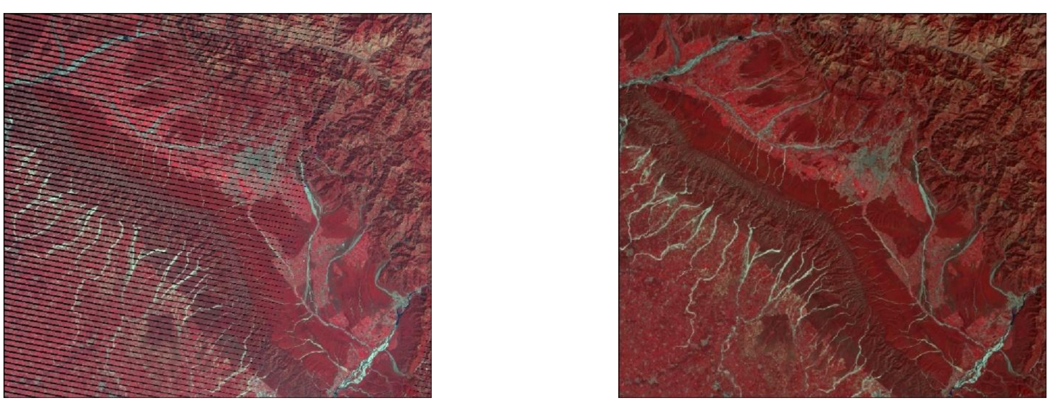
Crop yield: Model calibration is being perfomed for selected grids based on field observations. The crop yield is calibrated by adjusting selected parameters. The HUSC value is set in between 1-1.2 by adjusting the planting date, harvesting date and PHU. The fine tuning are performed by adjusting crop parameters such as harvet index(HI),Maximum LAI (DMLA),PPLP1,PPLP2, plant population etc. LAI correction strategy is performed only for wheat crop, due to the avalability of cloud free satellita data.After all adjustments the model is validated with observed yield and LAI.

Soil erosion process: The selected parameters are adjusted to keep the soil erosion with in the observed range.One of the important factor that govern RUSLE soil erosion is rainfall erosive enery factor(EI).The peak runoff rate-rainfall energy adjustment factro(apm) is adjusted to obtain EI value within the observed range of the study area.The site observations such as field length, slope,percentage cource fragment,erosion control practices,landuse, etc. along with laborator analysed textural parameters,soil organic carbon etc. were tabulated and site specific erosion were assessed using RUSLE model. The same equations as mentioned in section 4.2.1.2 were used for slope length factor and soil erodibility factor calculation.

4.2.6.3. LAI correction strategy for model calibration

LAI correction strategy is applied for the model calibration of wheat crop using landsat derieved LAI.The imporatan steps are as follows.

(1) Satellite data processing: The cloud free landsat data (18-March-2013) for the study area is radiometricaly corrected to retrive at sensor radiance.The ENVI landsat calibration utility is used for this purpose.Then ENVI atmospheric correction module Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) is applied to retrive surface refletance.The average sceen elevation for the study area is obtained by zonal statistics of SRTM digital elevation model.The Landsat images obtained after May 2003 have missing data(gaps) due to sensor failure.The strip errors were corrected by Local Linear Histogram Matching technique (LLHM) (Storey *et al.*,2005) in ENVI.After all these correction processess the study area is extracted for further analysis.



(a) (b)

Figure 4.4: Landsat image after correction (a) radiometric corrected (b) atmospspheric and striperror corrected.

(2) Selection of Vegitation Index: The vegitation indeces used for the estimation of LAI are
(i) Normalised differencevegitation index (NDVI), (Rouse *et al.*,1974).
(ii) Soil adjusted vegitation index (SAVI), (Huete *et al.*, 1984).
(iii) Enhanced vegitation index (EVI), (Huete *et al*., 2002).
The emperical relation with highest corelation with observed LAI is considered for LAI map generation for wheat.The LAI observations in the strip error corrected region were not considered to develop relationship.

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \tag{4.32}$$

$$SAVI = \frac{(\rho_{NIR} - \rho_R) * (1 + L)}{(\rho_{NIR} + \rho_R + L)} \tag{4.33}$$

$$EVI = \frac{G * (\rho_{NIR} - \rho_R)}{(\rho_{NIR} + C1 * \rho_R - C2 * \rho_B + L)} \tag{4.34}$$

Where, ρ_{NIR}, ρ_R and ρ_B are atmospherically corrected surface reflectance for Near infrared(band4),Red(band3) and Blue(band1) respectively of Landsat7 ETM+ data. In case of SAVI L is a correction factor whose values range from 0 (high vegetation cover) to 1(low vegetation).An L value of 0.5 is use in this study. In EVI equation the coefficients C1 and C2 are aerosol resistance term and blue band is introduced to correct aerosol influence on red band. G is the gain factor and L is the canopy background adjustment factor. The coefficients used are L=1, C1=6, C2=7.5 and G=2.5.

(3) Crop area mask generation: LULC map for the study area was prepared using the corrected landsat image by isodataclustering method. Except wheat area all other ares were masked by recoding the image with 1 for wheat area and 0 for other classes.

(4) LAI map generation: LAI map for wheat crop is prepared after performing masking operation using selected LAI-VI relationship.

(5) Calibration of the model with derieved LAI: This landsat derieved LAI is further utilized for model calibration process. Model LAI is corrected with derived LAI by adjusting parameters such as plant density,HI,PPLP1,PPLP2 etc.

4.2.6.4. Evaluation of model performance

The model perfomence is evaluated using statistical measures such as, root mean square error (RMSE) , index of agreement (d), model efficiency (EF), mean absolute error(MAE) and coefficient of determination(R^2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Ei - M_i)^2}{n}} \tag{4.35}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (E_i - M_i)^2}{\sum_{i=1}^{n} \left(|E_i - \overline{M}| + |M_i - \overline{M}| \right)^2} \tag{4.36}$$

$$EF = 1 - \frac{\sum_{i=1}^{n} (E_i - M_i)^2}{\sum_{i=1}^{n} \left(M_i - \overline{M} \right)^2} \tag{4.37}$$

$$MAE = \sum_{i=1}^{n} \frac{|Ei - M_i|}{n} \tag{4.38}$$

Where , E_i and M_i are respectively the simulated value and measured values of i^{th} grid; $\overline{M}$ is the mean of measured values; n is the sample number.MAE and RMSE values ranges between 0 and ∞ and values close to zero shows better prediction.EF value ranges between -∞ to +1, EF=1 shows perfect match of model predicted and observed values,0 shows that model predictions are as accurate as that of mean observed data and negative value shows that observed mean is a better predictor than the model.

4.2.7. Assessment of current SOC stock and SOCS

The current soil organic carbon stock of agricultural landscapes were assessed based on field measured samples and laboratory analysis performed as mentioned in section 4.2.5.2.Through geospatial analysis it is found that majority of the agricultural lands fall under three soil serieses named Barwa,Doiwala and Jassuwala.The analysis results of samples collected from each serieses were compiled and top 30 cm SOC were calculated in t.ha-1 using equation given below.

$$\text{SOC stock} = (OC * D * E)*100 \tag{4.39}$$

Where SOC stock, is the Soil organic carbon stock in $t.ha^{-1}$,OC is the SOC in % ,D is the bulk density in $g.cm^3$ and E is the thicknes of soil layer in m.

The SOC for top 30 cm were assessed for the year 2000 (NR-CENSUS report) and for the year 2012 (field measurement) and the soil organic carbon sequestration(SOCS) rate of three soil serieses (Barwa,Doiwala and Jassuwala) were determined.

4.2.8. Climate change impact assessment

This portion consists of climate data analysis to understand the projected changes in climate with respect to the baseline period and GEPIC model simulation to assess the possible impacts of climate change on crop productivity, soil erosion and soil organic carbon sequestration processes in the study area.

4.2.8.1 Climate data analysis

The climate data analysis are perfomed for baseline period and future A2a and B2a scenarios. World clime data for the baseline period and worldclim downscaled data for HadCM3 A2a and B2a scenarios are used for this analysis.Using the gridwise data extracted for mothly maximum and minimum temperatue the possible changes in mean temperature with respect to baseline period were assessed. The percentage chnge in rainfall also cosidered for the analysis. Crop season wise variation in ranfall and mean temperature for major food grain crops were also performed.

4.2.8.2 Model simulation under climate change scenarios

The regionalised model is used to perform climate change impact assessment under above mentioned scenarios.Simulations for the baseline(BL) period are performed and changes from BL are analysed under A2a and B2a scenarios in different time scales(2020s,2050s and 2080s).

(1) Climate change impact on crop productivity

Simulations are performed for rice and wheat for BL and future scenarios. Both crops were simulated under A2a scenario with and without considering futture trends in atmospheric CO_2 concentration to understand the effect of CO_2 fertilization effect on crop productivity.The CO_2 concentration for the BL period were kept at 360 ppm and future projections for A2a and B2a scenarios were used as mentioned in Table 2.2 ,(Arnell *et al.*, 2004).

The analysis were performed based on mean,standerd deviation (SD) and percentiles(5^{th},50^{th} and 95^{th}) as changes from baseline.The spatial prediction of model in grids with cultivation are also incorporate.Histogram and cumulative distribution function (CDF) of yield changes during 2020,2050 and 2080 under A2a and B2a scenarios were also derieved.

(2) Climate change impact on SOCS and soil erosion process

To assess the climate change impact on soil organic carbon sequestration simulations are performed under baseline climatic conditions and future A2a scenario over twelve year period. The rate of change over this period is assessed for the selected agricultural soil series named Barwa, Doiwalla and Jasssuwala. The changes from baseline were assessed to understand the effect of climate change on soil erosion and SOC sequestration.

5. RESULTS AND DISCUSSION

This chapter presents the results achieved from the thesis work as per the methodology. The major findings are presented with interpretation of results.

5.1. Dynamics of key climate change indicators

The analysis of the key climate change indicator such as mean temperature and average rainfall for the study area is performed for A2a and B2a scenarios and the results are given in Table5.1 and 5.2 respectively.

The analysis of mean temperature shows an increasing trend in annual mean temperature in both scnarios.Up to 2050s the increase is almost same under both scenarios but by 2080s the change is drastic under A2a(+4.1^{o}C) compared to B2a (+2.97^{o}C). The crop growing season wise analysis shows that the hike in temperature during Rabi season is almost double compared to that of Kharif under both scenarios.The results shows that the increase in temperature under A2a20,50 and 80 sceanrios during Kharif season could be 0.52 ^{o}C,1.67^{o}C and 2.94 ^{o}C and for Rabi season could be 1.41 ^{o}C,2.71 ^{o}C and 4.72 ^{o}C.Under B2a scenario also the trend will be same but the vigour is less compared to A2a scenario.

The analysis of rainfall shows an improvement from baseline period under both A2a and B2a scenarios.There coud be an increse in rainfall of about 25 %, 35 % and 70 % respetively during A2a20,A2a50 and A2a80 and 21%,41% and 54% during B2a20,B2a50 and B2a80 reapectively.The season wise analysis shows that during Rabi season the improvement is relatively low compared to Kharif season. The change in rainfall from baseline under A2a sceanrio, during Kharif season are:+25.46%,+40.30% and +85.76% and during Rabi season are:+5.26%,+20% and -13.70% for 2020s,2050s and 2080s. The same under B2a scenario during Kharif season are:+29.08%,+46.42% and +64.38% and during Rabi season are:-10.07%,-9.08% and -0.50% for 2020s,2050s and 2080s.

Table 5.1:Mean monthly temperature change from the baseline under A2a and B2a scenarios.

Month	BL temperature (^{o}C)	Mean monthly temperature Change from baseline(^{o}C)					
		A2a20	A2a50	A2a80	B2a20	B2a50	B2a80
Jan	12.16	1.52	3.02	4.65	1.27	3.00	3.83
feb	14.35	0.79	2.40	4.26	0.94	2.58	3.24
Mar	19.03	1.57	2.49	5.08	1.76	2.60	3.77
Apr	24.30	1.60	2.28	4.92	1.30	2.55	2.95
May	28.58	1.31	3.11	5.11	1.06	2.07	3.14
Jun	29.17	0.90	2.61	4.64	0.50	2.29	3.59
Jul	26.51	0.58	1.56	2.59	0.68	0.73	2.08
Aug	25.83	-0.10	1.05	1.66	-0.09	0.74	1.34
Sep	25.21	0.50	1.70	3.82	0.81	1.24	2.19
Oct	21.87	1.09	2.36	3.70	1.35	1.82	2.82
Nov	17.11	1.05	2.45	4.10	1.20	2.37	2.93

Dec	13.55	1.59	3.35	4.69	1.43	2.86	3.71
Average	**21.47**	**1.03**	**2.37**	**4.10**	**1.02**	**2.07**	**2.97**
Jul - oct	24.86	0.52	1.67	2.94	0.69	1.13	2.11
Dec -April	16.68	1.41	2.71	4.72	1.34	2.72	3.50

Table 5.2:Monthlty percentage change in rainfall from baseline under A2a and B2a scenarios.

Month	BL Rainfall-(mm)	Change in rainfall from baseline (%)					
		A2a20	A2a50	A2a80	B2a20	B2a50	B2a80
Jan	64.32	40.89	24.62	20.88	11.25	6.57	28.40
Feb	39.77	-25.49	15.24	-51.56	-12.46	-31.17	-0.50
Mar	47.21	3.77	36.46	-18.13	-26.40	2.27	-23.52
Apr	12.39	-6.27	57.67	-11.13	-8.50	-8.93	5.65
May	32.95	80.01	28.51	19.86	-13.03	33.39	6.27
Jun	134.39	35.67	1.31	20.36	-23.01	49.40	26.85
Jul	591.45	15.56	53.56	101.33	37.01	64.01	64.34
Aug	658.43	17.62	20.58	87.63	22.95	30.77	56.48
Sep	268.86	52.71	71.22	79.01	25.15	59.68	81.34
Oct	85.41	68.63	3.16	-15.18	33.83	3.46	72.16
Nov	13.10	0.01	0.13	14.80	17.73	-14.73	-12.82
Dec	24.98	-28.99	-34.14	-35.32	-31.03	-35.77	-34.49
Average	**1973.24**	**24.96**	**35.24**	**70.23**	**21.01**	**40.69**	**54.14**
Jul - Oct	1604.15	25.46	40.30	85.76	29.08	46.42	64.38
Dec -April	188.66	5.26	20.00	-13.70	-10.07	-9.08	-0.50

5.2. Crop productivity assessment

Crop productivity assessment part consits of sensitivity analysis and calibration of the model and climate change impact assesment on crop productivity.

5.2.1 Model Sensitivity analysis

Sensitivity analysis of eight selected parameters on crop yield,biomass and LAI were performed based on relative sensitivity index and the parameters are ranked in increasing order of there sensitivity.

5.2.1.1. Sensitivity analysis for rice crop

The sensitivity analysis for rice crop shows that PHU is the most sensitive parameter for yield, followed by HI and WA . For biomass (BM) and LAI, respectively WA and DMLA shows the highest sensitivity. The influence of other selected parameters on BM and LAI are relatively negligible.The results are presented in table 5.3.

Table 5.3:Sensitiviy analysis for rice crop

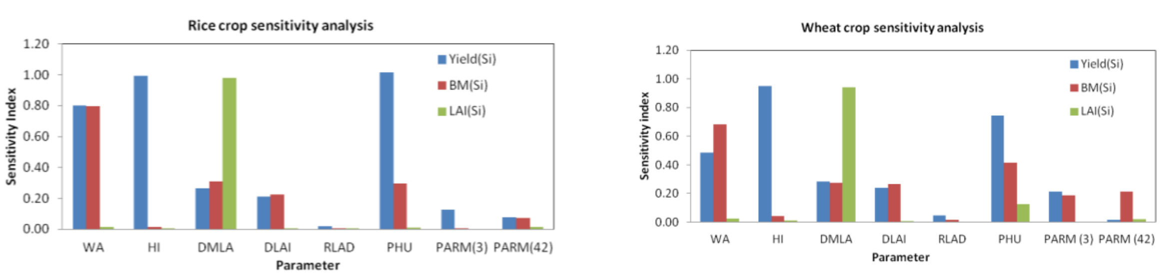
Sl No.	Parameter	Yield(Si)	Rank	BM(Si)	Rank	LAI(Si)	Rank
1	WA	0.801	3	0.797	1	0.016	2
2	HI	0.991	2	0.014	6	0.002	6
3	DMLA	0.265	4	0.308	2	0.979	1
4	DLAI	0.210	5	0.224	4	0.004	5
5	RLAD	0.018	8	0.007	7	0.001	7
6	PHU	1.017	1	0.296	3	0.011	4
7	PARM(3)	0.126	6	0.000	8	0.000	8
8	PARM(42)	0.075	7	0.074	5	0.014	3

5.2.1.2. Sensitivity analysis for wheat crop

The HI shows the highest sensitivity for wheat yield followed by PHU and WA. For bimass WA is the most influencing parameter next to PHU.Incase of LAI the most sensitive parameter is DMAL and other selected parameters show insignificant effects. The results are presented in table 5.4

Table 5.4:Sensitiviy analysis for Wheat crop

Sl No.	Parameter	Yield(Si)	Rank	BM(Si)	Rank	LAI(Si)	Rank
1	WA	0.485	3	0.682	1	0.023	3
2	HI	0.952	1	0.042	7	0.012	5
3	DMLA	0.285	4	0.274	3	0.942	1
4	DLAI	0.241	5	0.265	4	0.006	6
5	RLAD	0.045	7	0.014	8	0.003	7
6	PHU	0.742	2	0.413	2	0.124	2
7	PARM (3)	0.215	6	0.186	6	0	8
8	PARM (42)	0.015	8	0.215	5	0.018	4



(a) (b)

Figure 5.1 : realtive sensitivity index of yield,biomass and LAI for (a) rice crop (b) wheat crop

5.2.2 Calibration and validation of EPIC model

5.2.2.1 Calibration and validation of EPIC model for rice crop at site scale

The model was calibrated by adjusting the crop specific parameters such as PPLP1, PPLP2, PHU,Plant density and HI as mentioned in table 5.5**.** After performing the calibration steps model simulated LAI and yield were compared with observed values.EPIC model, predicted yield and LAI with an RMSE of 0.38 and 0.35 respectively.The values above 1:1 line shows the tendency of model to over estimate LAI and yield.The efiiciancy and index of agreement were 0.93 aand 0.78 respectively for yield and 0.85 and 0.56 respecctively for LAI.The EF value shows that model predicted values are better than the mean of observed data.

Table 5.5:Parameters adjusted to calibrate EPIC model for rice crop.

SL No:	Parameters Adjusted	Adjusted Value
1	PPLP1	25.45
2	PPLP2	90.95
3	PHU	1800
4	Plant Density	30-40
5	Harvest Index	0.35-0.45

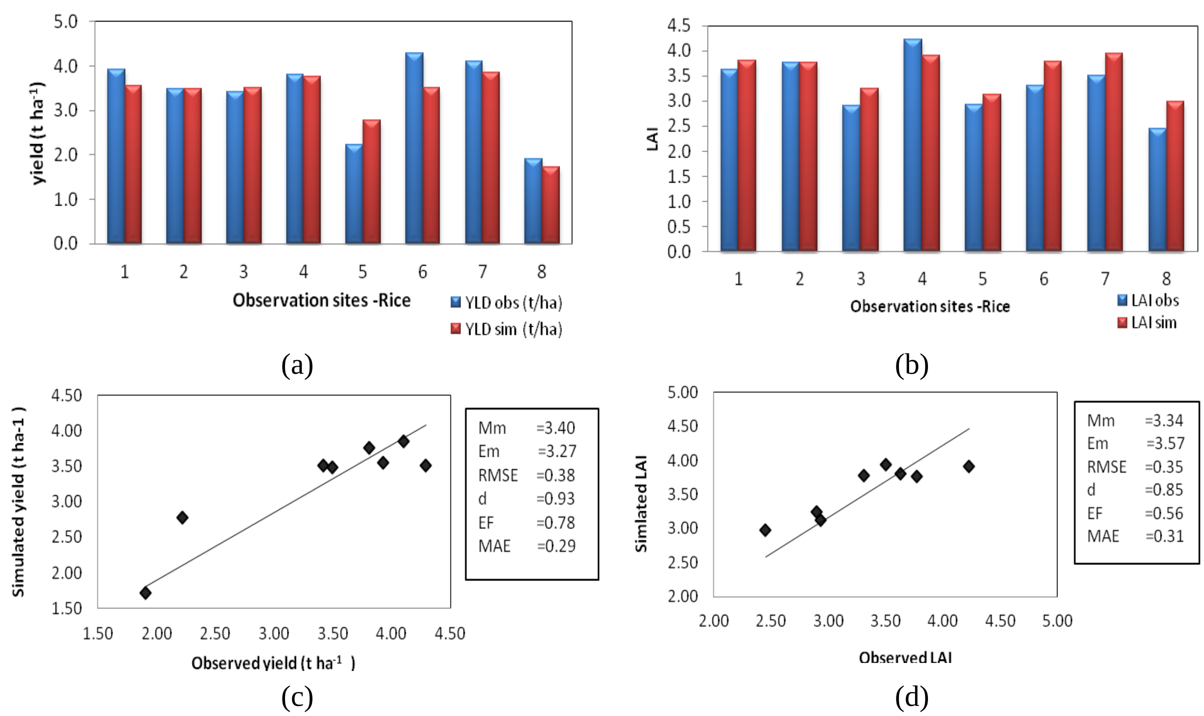
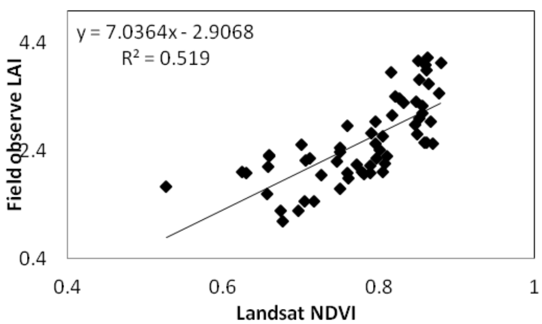


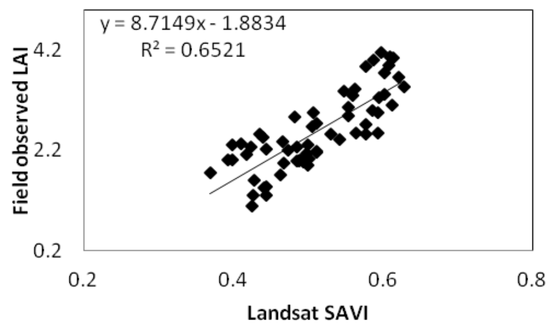
Figure 5.2 : Calibration results for rice crop: site scale validation of (a) crop yield and (b) LAI; The 1:1 line and statistics showing the obseved Vs simulated (c) yield and (d) LAI.

5.2.2.2. Derivation of Remotely sensed LAI for Validation of wheat crop

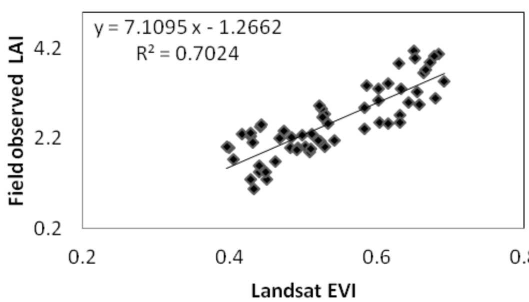
Vegetaion indices such as NDVI,SAVI and EVI were generated from landsat data after atmospheric correction.After extracting the VI values curresponding to groun measured LAI emperical relationships were developed. Amoung the relationships EVI-LAI give higehest coefficient of determination(R^2=0.70). SAVI and NDVI give an R^2 value of 0.65 and 0.51 respectively.Based on these analysis EVI-LAI relationship was selected to generate LAI map for wheat crop.



(a)



(b)



(c)

Figure 5.3:Relationship between (a) NDVI vs. LAI (b) SAVI vs. LAI and (c) EVI vs. LAI

Based on high corelation between LAI and EVI the following equation was used for wheat LAI map generation.

$$LAI = 7.1095 * EVI - 1.2662$$

Table 5.6: LAI vegitation index relationshps

Sl No:	Vegitation Index	Relationship	R^2
1	EVI	y = 7.1095x - 1.2662	0.70
2	SAVI	y = 8.7149x - 1.8834	0.65
3	NDVI	y = 7.0364x - 2.9068	0.52

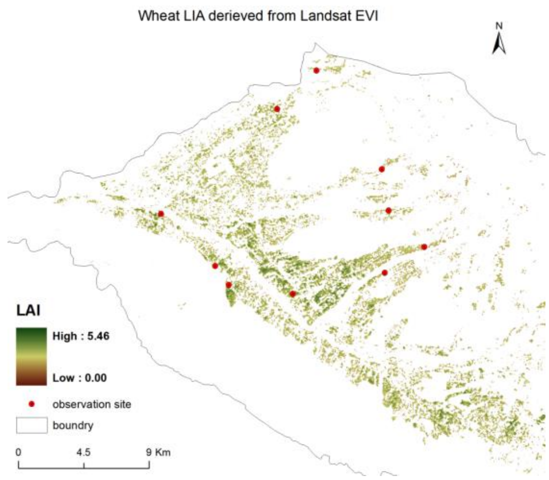
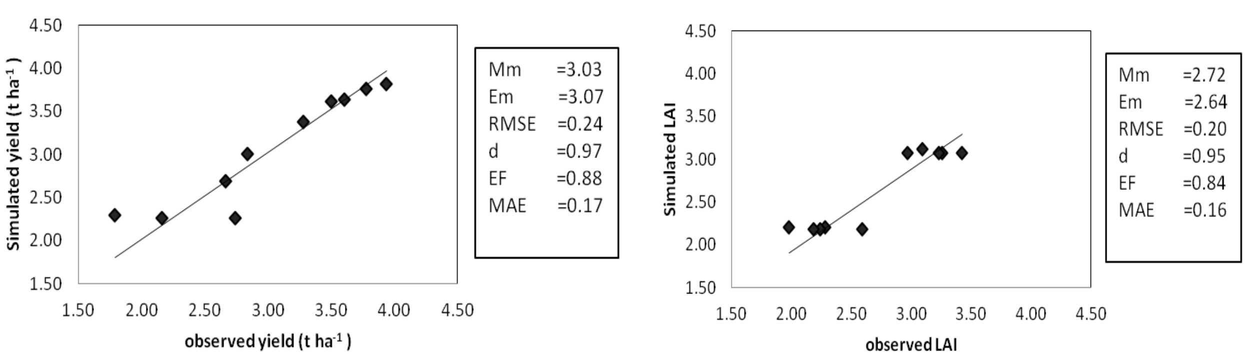


Figure 5.4 : Wheat LAI derievd from Landsat EVI

The landsat derived LAI has been used to correct model predicted peak LAI. As the first step the model predicted LAI is corrected by adjusting planting density of that site.After this adjustment the model predicted yield was corrected by adjusting Harvest index. The LAI obtained after correction is given in Fig 5.5 (b).This shows that the model, predicted LAI with an RMSE of 0.20 which shows better results compared to rice predictions.The modelling efficiency is 0.84 with a degree of agreement of 0.95. The model predicted yield after adjusting LAI and HI as given in Fig 5.5 shows an RMSE of 0.24 with a modelling efficiency of 0.88.The mean absolute error for the yield prediction is 0.17.



(a) (b)

Figure 5.5:Calibration results for wheat crop (a) The 1:1 line and statistics showing observed vs. simulated (a) yield and (b) LAI

5.3.3. Climate change impact on crop productivity

Climate change impact on major Kharif and Rabi (Rice and Wheat) crops were performed under A2a and B2a scenarios after baseline simulations.The changes from baseline period were given in terms of mean,standerd deviation (SD) and percentiles(5^{th},50^{th} and 95^{th}).The spatial prediction of model in grids with cultivation are shown with baseline yield and percetage changes from baseline. Histogram and cumulative distribution function (CDF) of yield changes during 2020s,2050s and 2080s under A2a and B2a scenarios were also derieved.The simulations were performed with and without considering changes in atmospheric CO_2 concentration to understand the effect of CO_2 fertilization effect on crops. The atmospheric CO_2 concentration as per table 2.2 (Arnell *et al.*, 2004) was considered in this study.

5.3.3.1. Impact of climate change on Rice productivity

The summery of climate change impact assessment done for rice crop is given in Table 5.7 which shows the changes in rice yield under A2a (with and without CO_2 fertilisation) and B2a scenario during 2020s,2050s and 2080s.

Table 5.7: Projected change in yield of rice crop in 2020s,2050s and 2080s from baseline period

Scenario	Period	Mean (%)	SD (%)	P5 (%)	P50 (%)	P95(%)
A2a(NF)	2020	-1.03	1.94	-4.76	-0.38	1.33
	2050	-9.01	2.01	-10.72	-9.49	-5.97
	2080	-19.22	3.12	-24.14	-20.00	-14.05
A2a	2020	5.22	4.02	-1.95	6.76	9.69
	2050	5.07	6.14	-4.63	6.98	12.96
	2080	-2.39	4.64	-8.55	-2.21	6.25
B2a	2020	-3.33	4.68	-9.61	-3.87	5.76
	2050	-3.30	4.01	-9.47	-2.49	2.11
	2080	1.29	4.72	-5.90	2.37	8.56

Where, A2a (NF)- A2a scenario with out considering CO_2 fertilzation

(1) A2a scenario without CO_2 fertilization: Under A2a scenario without considering CO_2 fertilisation the average reduction in yield could be 1.03 (A2a20), 9.01 (A2a50) and 19.22 (A2a80) percent with a SD of 1.94,2.01 and 3.12 percent, respectively. Results also reveals that the degree of projected changes in yield at 95% probability would be 1.33,-5.97 and -14.05 and with 95% probability intervals (5% - 95 %) the yield reduction could be with in (-4.76,1.33),(-10.72,-5.97) and (-24.14,-14.05) respectively during A2a20,50 and 80 scnarios. The cumulative disribution function(CDF) (Fig 5.7(a)) and histogram show that there is a 60% probability that the projected yield could reduce by 0.18% , 9.15% , 18.78% respetively during 20,50 and 80.

The spatial predictions (Fig 5.6) and histogram shows that maximum number of grid are coming in yield change class of 0 to -2 (Fig5.7(c)) ,-5 to -10 (Fig 5.7(d)) ,-20 to -22 (Fig 5.7(e)) during 2020,50 and 80 respectively.

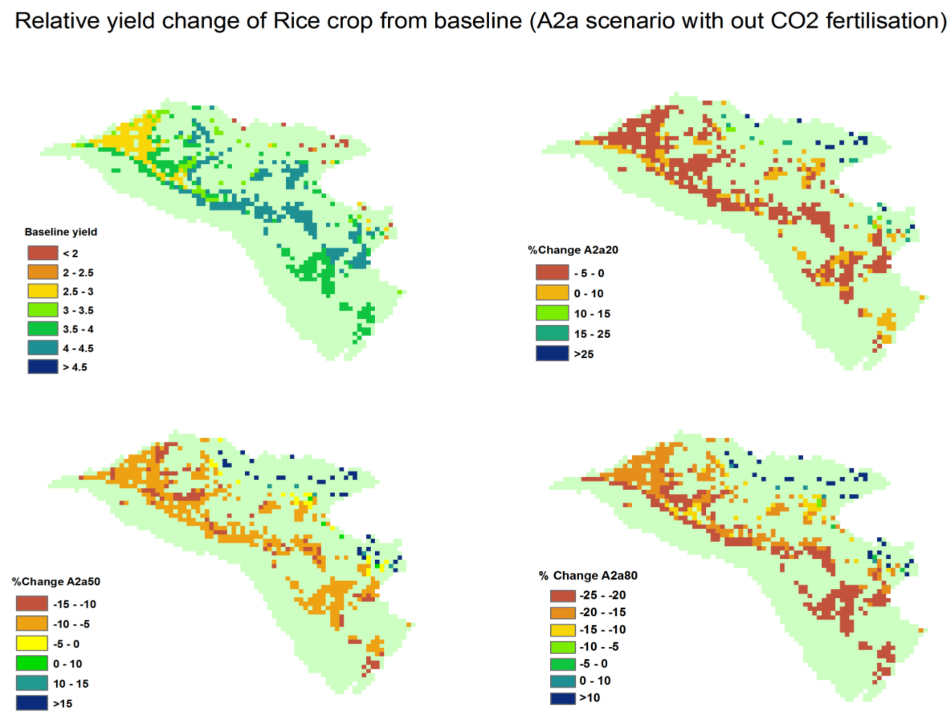
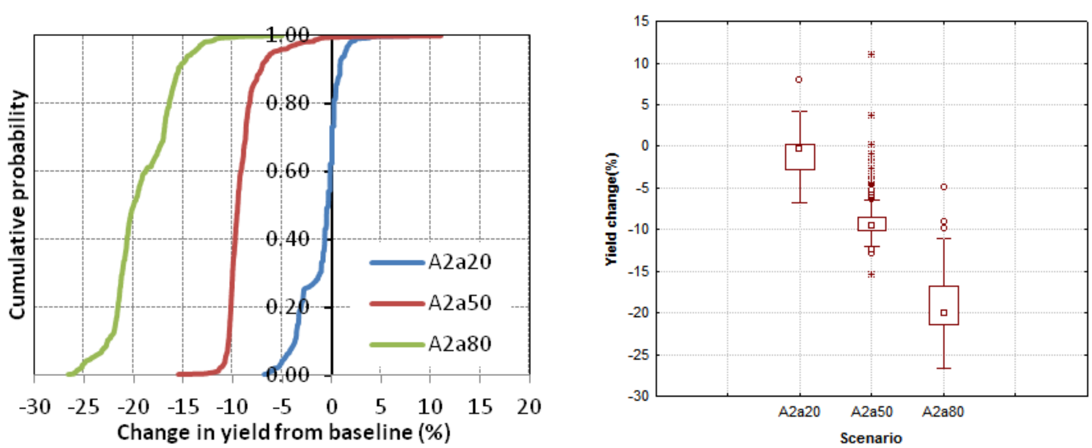
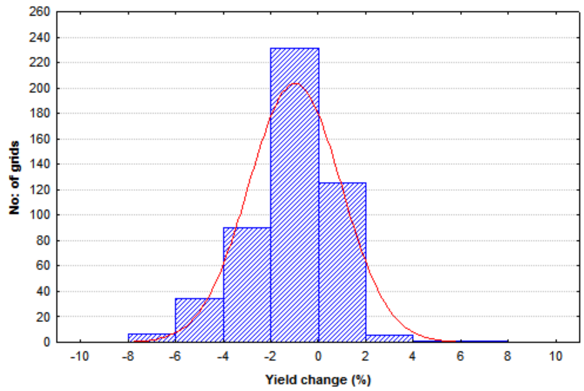


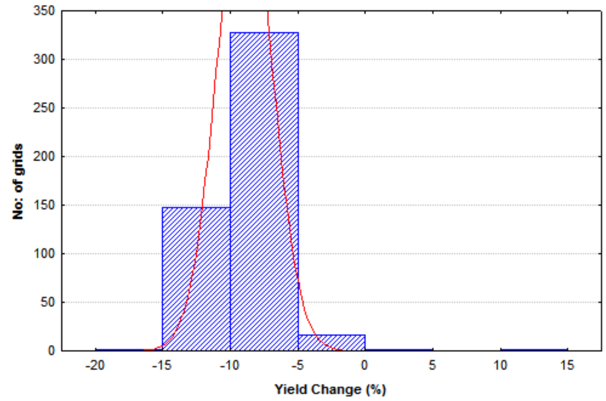
Figure 5.6: Relative yield change of rice crop from baseline under A2a scenario without CO_2 fertilization



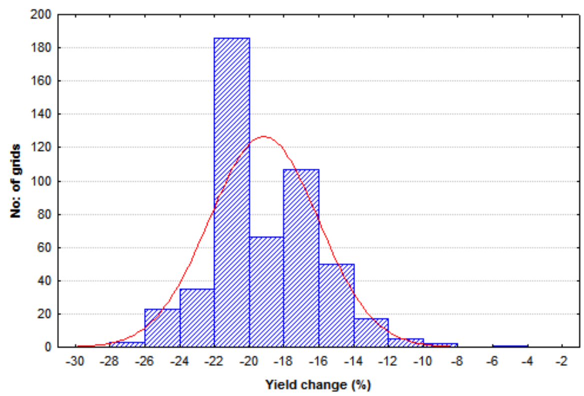
(a) (b)



(c)



(d)



(e)

Figure 5.7: Rice yield changes under A2a scenario without CO_2 fertilization. (a) Cumulative probability function and (b) box plot showing % change in yield in 2020s, 2050s and 2080s. (c), (d) and (e) respectively the histogram of rice yield change during 2020s, 2050s and 2080s.

(2) A2a scenario with CO_2 fertilization: A2a scenario with projected atmospheric CO_2 concentrstion the average change in yield for rice crop could be +5.22,+5.07 and -2.39 respectively with a SD of 4.02,6.14 and 4.64 in 2020s,2050s and 2080s respectively.With 95% probability interval the yield change could be with in (-1.95,9.63),(-4.63,12.96) and (-8.55,6.25) during respective time periods,(Table 5.7). From CDF (Fig 5.9 (a)) it is clear that at 60 % probability there could be a change in yield of +7.21,+7.96 and -1.48 % respectively during A2a20s,50s and 80s. The histogram shows that the yield change (%) in maximum number of grids is between +6 to +8 (Fig 5.9 (c)), +5 to +10 (Fig 5.9 (d)) and 0 to -5 (Fig 5.9 (e))

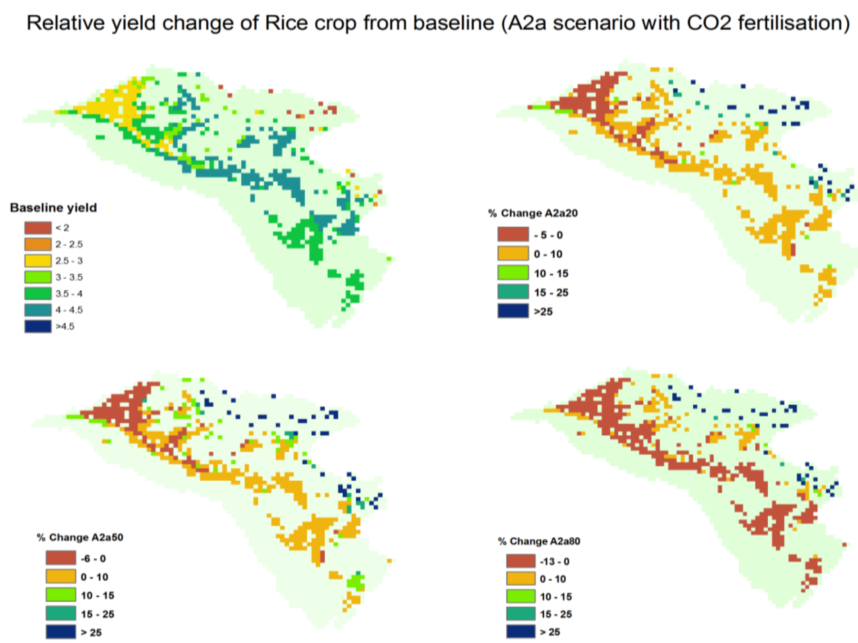
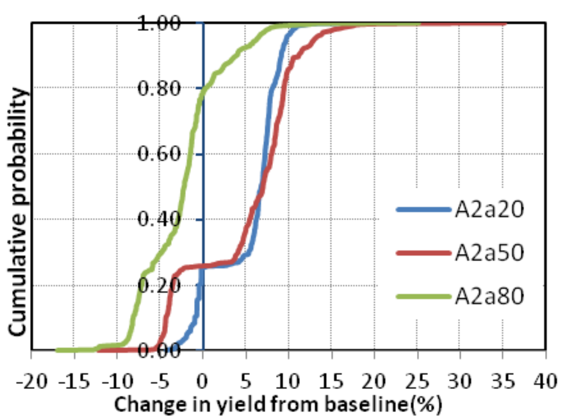
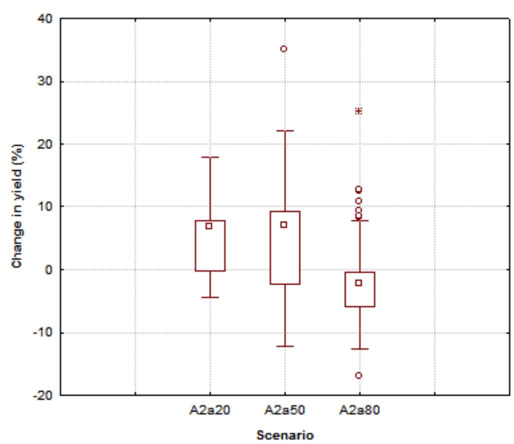


Figure 5.8: Relative yield change of rice crop from baseline under A2a scenario with CO_2 fertilization.



(a)



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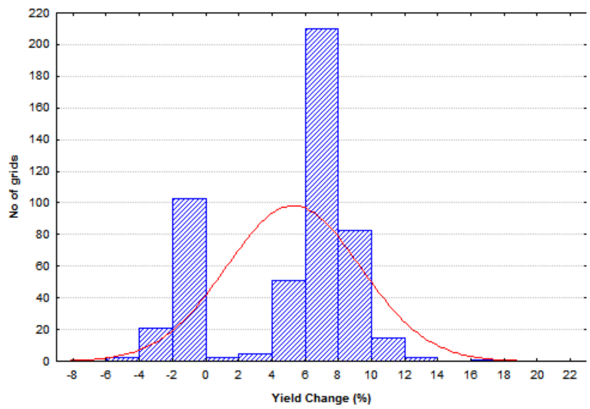

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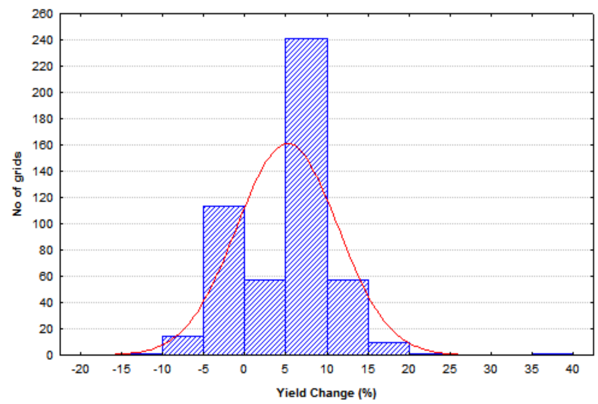
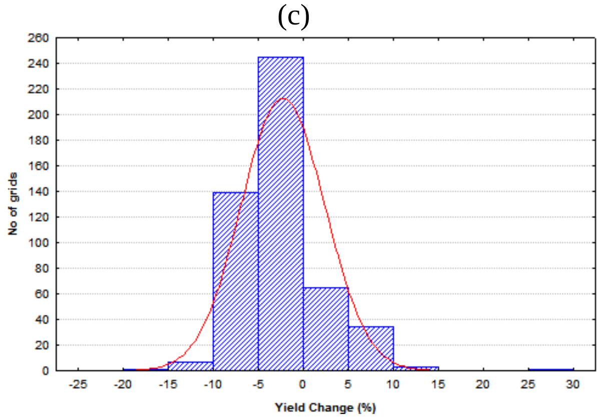


(d)

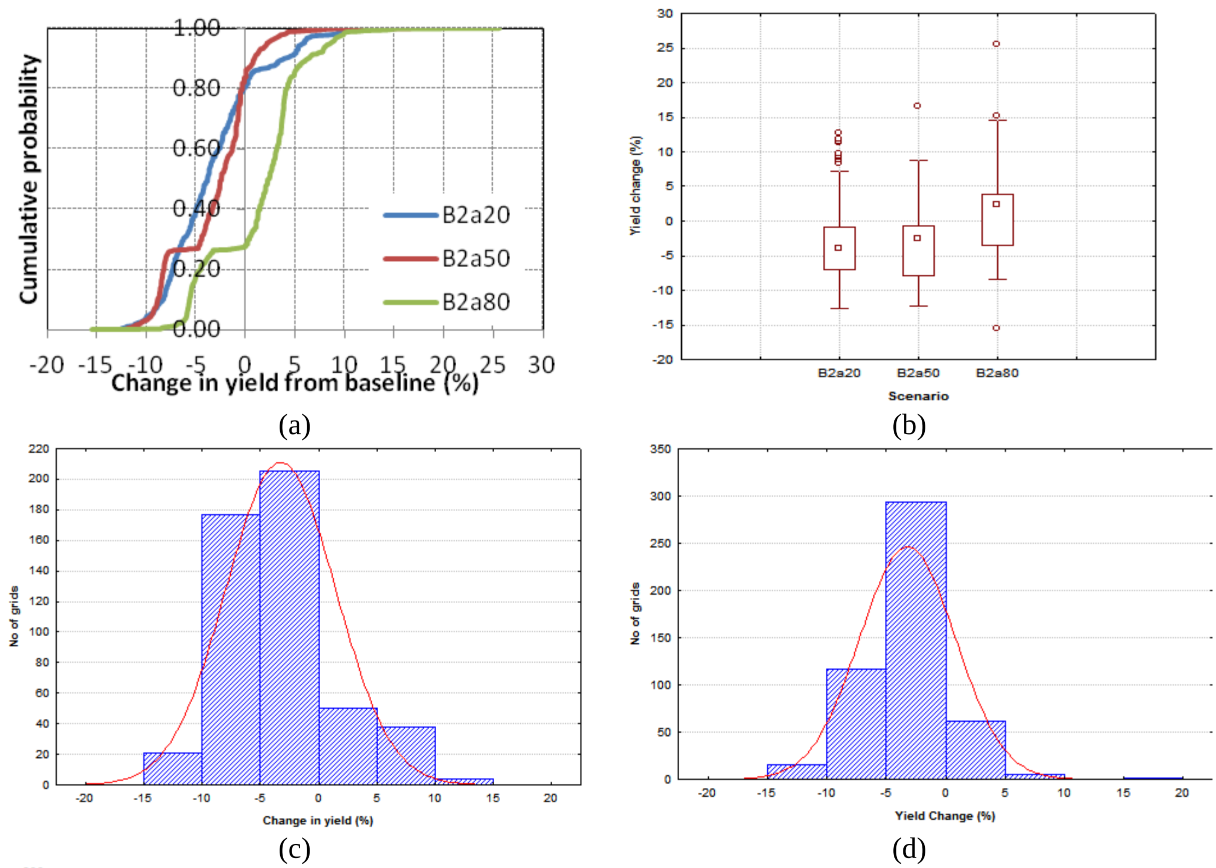


(e)

Figure 5.9: Rice yield changes under A2a scenario with CO_2 fertilization: (a) Cumulative probability function and (b) box plot showing % change in yield during 2020s, 2050s and 2080s. (c), (d) and (e) respectively the histogram of rice yield change during 2020s, 2050s and 2080s.

(3) B2a scenario with CO_2 fertilization: Under B2a scenario with CO_2 fertilisation the average reduction in yield could be -3.33(B2a20), -3.3 (B2a50) and +1.29 (B2a80) percent with a SD of 4.68,4.01 and 4.72 percent, respectively (Table 5.7). Results also reveals that the degree of projected changes in yield at 95% probability would be -9.61,-9.47 and -5.90 and with 95% probability intervals (5% - 95 %) the yield reduction could be with in (-9.61,5.76),(-9.47,2.11) and (-5.90,8.56) respectively during B2a20,50 and 80 scnarios. The cumulative disribution function(CDF) (Fig 5.10 (a)) and histogram show that there is a 60% probability that the projected yield could reduce by -2.77 % , -1.40 % , 3.15 % respetively during 20,50 and 80.

The spatial predictions and histogram shows that maximum number of grid are coming in yield change class of 0 to -5 (Fig5.10 (c)) ,0 to -5 (Fig 5.10 (d)) ,0 to +5 (Fig 5.10(e)) during 2020,50 and 80 respectively.



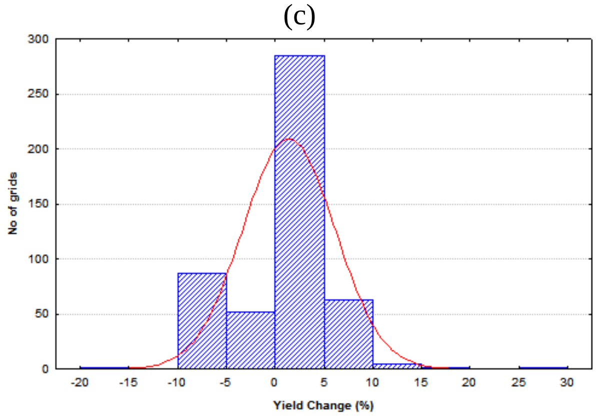


Figure 5.10: Rice yield changes under B2a scenario with CO_2 fertilization. (a) Cumulative probability function and (b) box plot showing % change in yield in 2020, 2050 and 2080. (c), (d) and (e) respectively the histogram of rice yield change during 2020, 2050 and 2080.

(4) Interpretation of climate change impact on Rice crop

Table 5.8: Mean temperature and total rainfall of the study area during rice growing season (July–October)

	BL	A2a20	A2a50	A2a80	B2a20	B2a50	B2a80
Tmean (°C)	24.86	25.37 (+0.52)	26.53 (+1.67)	27.80 (+2.94)	25.55 (+0.69)	25.99 (+1.13)	26.97 (+2.11)
Rainfall (mm)	1604.15	2012.51 (+25)	2250.64 (+40)	2979.89 (+85)	2070.65 (+29)	2348.73 (+46)	2636.92 (+64)

In parenthesis, increase in temperature and percent increase in rainfall from baseline is given.

The analysis shows that the there could be an average change in rice yield by -1.03, -9.01 and -19.22 percent during 2020s, 2050s and 2080s under A2a scenario without CO_2 fertilization effect and +5.22,+5.07 and -2.39 with CO_2 fertilization effect. The mean change in temperature during the same period is +0.52, +1.67 and +2.94 ^oC with respective atmospheric CO_2 concentration of 432,590 and 709 ppmv. This shows the effect of CO_2 fertilization on crop productivity. During initial periods there is an improvement in crop productivity due to CO_2 enrichment but this effect is cancelled due an increased temperature in A2a80.

The initial timescales of B2a scenario (B2a20 and B2a50) shows a reduction in crop yield compared to that of A2a.This is because of low concentration of atmospheric CO_2 (422 ppmv B2a20 and 50) with respect to A2a. The increase in temperature during the growth season for B2a20 is slightly higher (+0.69) than that of A2a20.From this we can interpret that the two factors that govern the yield reduction in the initial timescales of B2a scenario are the reduced concentration of atmospheric CO_2 which is not capable to compensate the increase in temperature.B2a80 scenario shows a slight improvement in average yield (+1.29 %) compared to A2a 80 (-2.39) this is due to comparatively less increase in temperature (+2.11^{o}C) compared to A2a 80.

The study conducted by Saseendran *et al.*, (1999) reported that there is a 6 % reduction in rice yield for every 1 ^oC increase in temperature with normal atmospheric CO_2.The study by Aggarwal and Mall (2002) shows that an increase in temperature of 2.7 ^OC cancels the positive effect of 550 ppmv atmospheric CO_2. The results obtained for A2a50 scenario supports this finding.

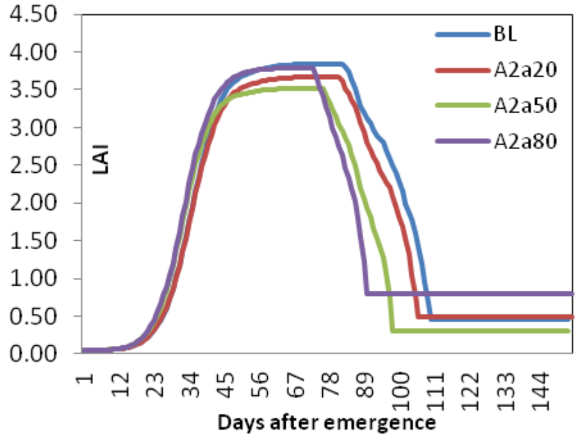
An analysis was made in selected grid to assess the impact of climate change on crop duration, maximum LAI and yield. There is a projected reduction of 21 days in crop duration under A2a80 scenario due to fast accumulation of growing degree days and elevated temperature. The projected mean temperature in the study area under A2a80 scenario would be 27.8^{o}C (BL+2.9^{o}C) and which is above the optimum temperature of rice crop (25^{o}C). The improvement in radiation use efficiency (RUE) and biomass accumulation under elevated CO_2 (CO_2 fertilization) can reduce this vulnerability to certain extend. The analysis shows that under A2a 80 scenario the reduction in crop productivity is comparatively less (8%) under elevated CO_2 conditions compared to that under the normal CO_2 concentration (16%). The results for other time periods are given in the table 5.9.

Table 5.9: Effect of climate change on crop duration, LAI and yield of rice crop (selected grid)

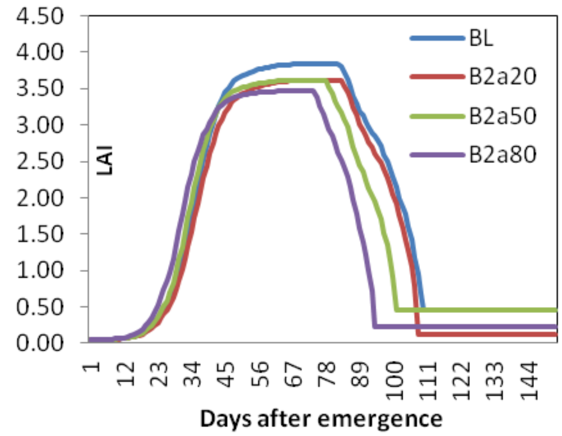
Scenario	DOP	DOM	Duration	Reduction in crop Duration	LAImax	LAImax	Yield change in %	
					Normal CO_2	Projected CO_2	Normal CO_2	Projected CO_2
BL	10-Jul	02-Nov	115	……	3.839	3.839	…….	……
A2a20	10-Jul	28-Oct	110	5	3.67	3.753	-3.14	-0.52
A2a50	10-Jul	21-Oct	103	12	3.519	3.728	-9.95	-3.93
A2a80	10-Jul	12-Oct	94	21	3.368	3.658	-16.75	-8.12
B2a20	10-Jul	31-Oct	113	2	3.617	3.651	…….	-1.57

B2a50	10-Jul	24-Oct	106	9	3.614	3.614	……..	-8.90
B2a80	10-Jul	17-Oct	99	16	3.469	3.469	……..	-5.50

Where, DOP-Date of planting; DOM- Date of maturity; LAImax-Maximum LAI



(a)



(b)

Figure 5.11: Model simulated course of LAI of rice crop under (a) A2a scenario and (b) B2a scenario.

5.3.3.2 Impact of climate change on wheat productivity

Impact of climate chnge on wheat crop in unirrigated conditions were assesed under A2a scenario with and with out considering CO_2 fertilization effect.The mean of simlated baseline yield of the study area is 3.17 t.ha-1 with a SD of 0.33.Based on this baseline yield the future changes were assessed and results are given in table 5.10.

Table 5.10:Projected change in yield of wheat crop in A2a 2020s,2050s and 2080s from baseline period.

Scenario	Period	Mean	SD	P5	P50	P95
Baseline yield (t.ha^{-1})		3.17	0.33	2.97	3.17	3.73
A2a(NF) (%)	2020	-21.15	13.53	-54.03	-16.51	-6.00
	2050	-15.72	15.41	-44.66	-14.68	-3.04
	2080	-42.34	10.81	-68.51	-39.76	-30.66
A2a (%)	2020	-13.93	14.76	-49.79	-8.84	2.48
	2050	4.13	19.00	-31.59	5.50	19.63
	2080	-23.72	14.27	-58.40	-20.19	-8.55

(1) A2a scenario without CO_2 fertilization: A2a scenario without considering CO_2 fertilisation the average change in yield for unirrigated wheat crop could be -21.5 (A2a20), -15.72 (A2a50) and -42.34 (A2a80) percent with a SD of 13.53,15.41 and 10.81 percent, respectively. Results also reveals that the degree of projected changes in yield at 95% probability would be -6.00,-3.04 and -30.66. The cumulative disribution function(CDF) (Fig 5.13 (a)) and histogram shows that there is a 60% probability that the projected change yield could be -15.67%, -13.75 % , -39.39 % respetively during 20,50 and 80.

The spatial predictions (Fig 5.12) and histogram shows that maximum number of grids are coming in yield change class of -10 to -20 (Fig5.13(c)) ,0 to -20 (Fig 5.13 (d)) ,-30 to -40 (Fig 5.13 (e)) during 2020,50 and 80 respectively.

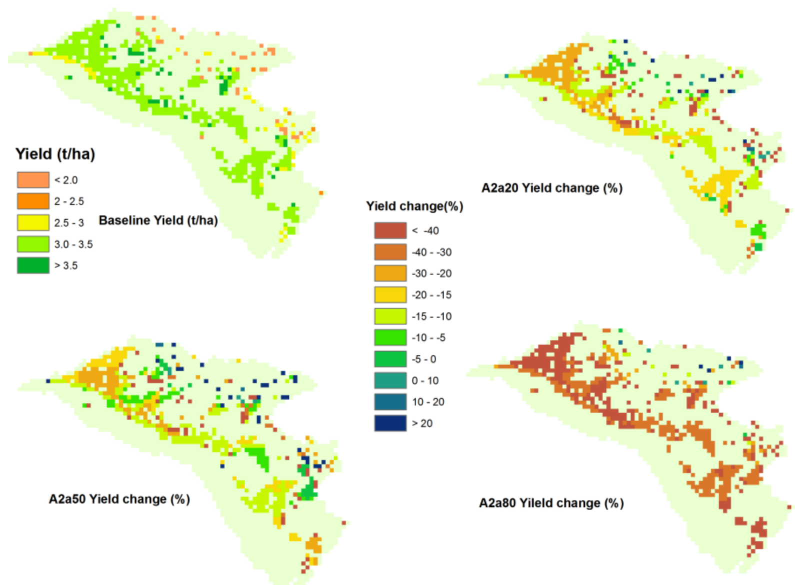
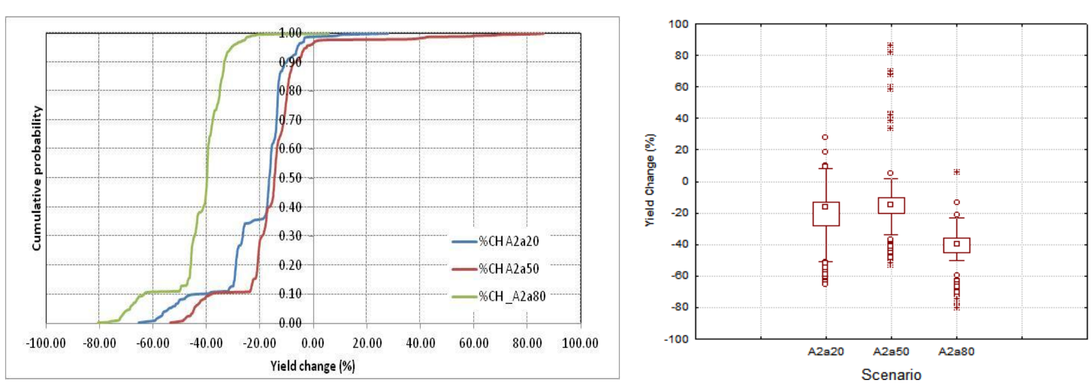
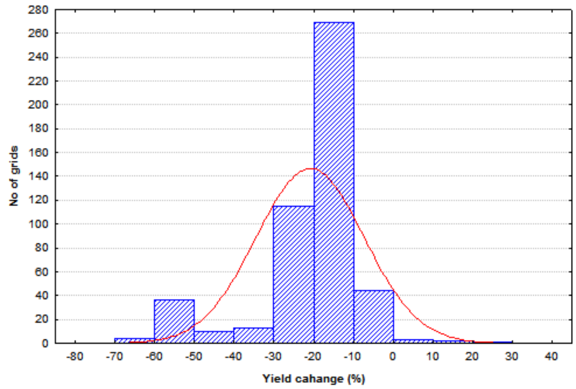


Figure 5.12: Relative yield change of Wheat crop from baseline under A2a scenario without CO_2 fertilization.



(a) (b)



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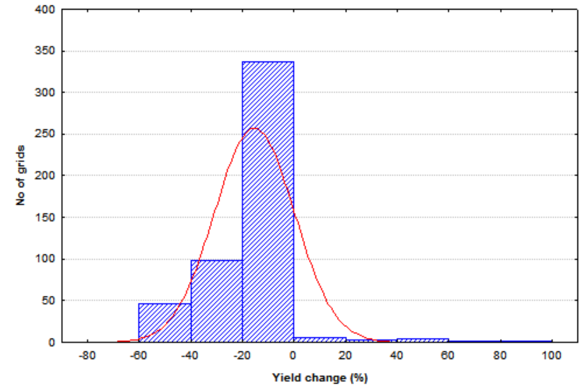

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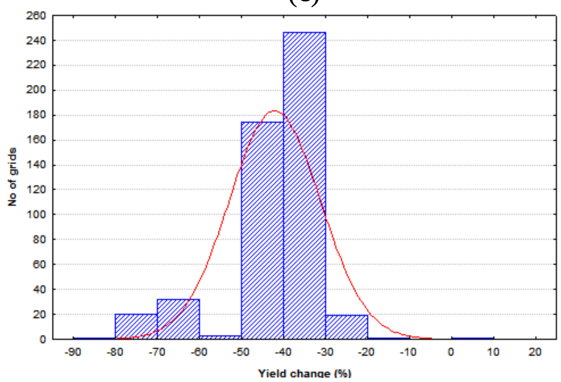


(e)

Figure 5.13: Wheat yield changes under A2a scenario without CO_2 fertilization. (a) Cumulative probability function and (b) box plot showing % change in yield during 2020, 2050 and 2080. (c), (d) and (e) respectively the grid wise distribution of wheat yield change (%) during 2020, 2050 and 2080.

(2) A2a scenario with CO_2 fertilization: A2a scenario with CO_2 fertilisation the average changes in yield for unirrigated wheat crop could be -13.93 (A2a20), +4.13 (A2a50) and -23.72 (A2a80) percent with a SD of 14.76,19.00 and 14.27 percent, respectively. Results also reveals that the degree of projected changes in yield at 95% probability would be 2.48,19.63 and -8.55. The cumulative disribution function(CDF) (Fig 5.15(a)) show that there is a 60% probability that the projected yield could change by -7.92 %, +6.65 % , -19.69 % respetively during 20,50 and 80.

The spatial predictions (Fig 5.14) and histogram shows that maximum number of grid are coming in yield change class of 0 to -10 (Fig5.15(c)),0 to +20 (Fig 5. (d)) ,-10 to -30 (Fig 5. (e)) during 2020,50 and 80 respectively.

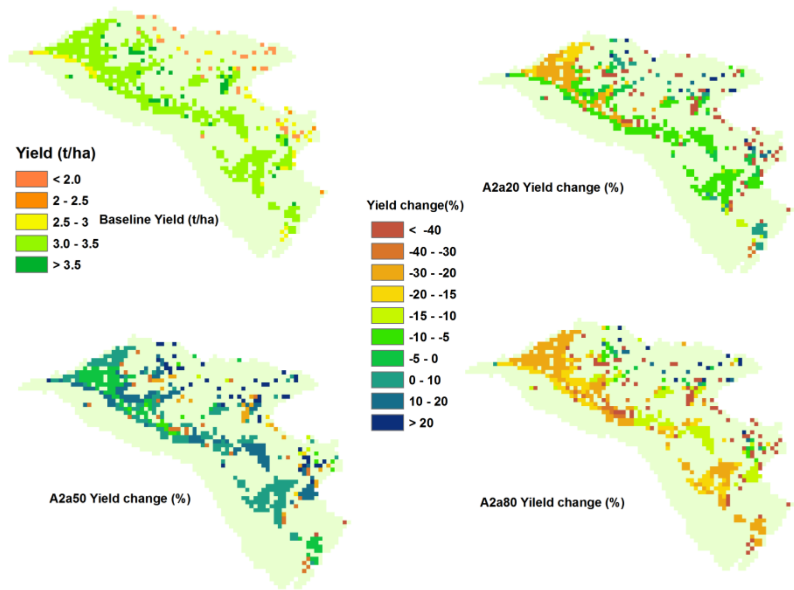
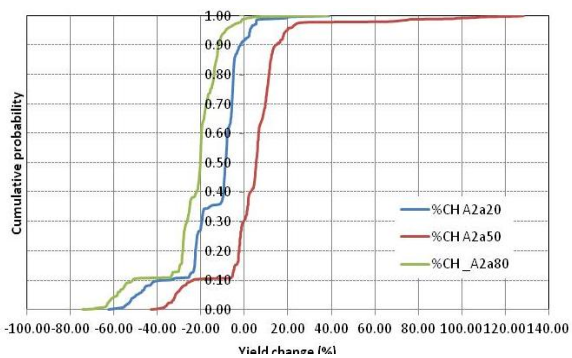
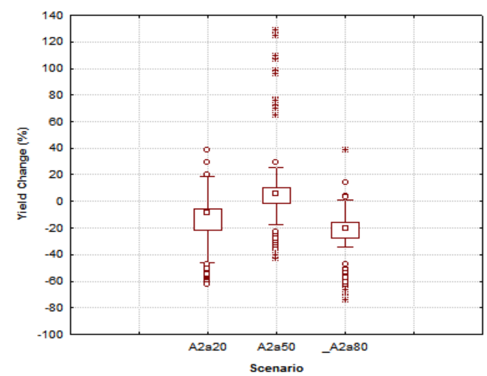


Figure 5.14: Relative yield change of Wheat crop from baseline under A2a scenario with CO_2 fertilization.



(a)



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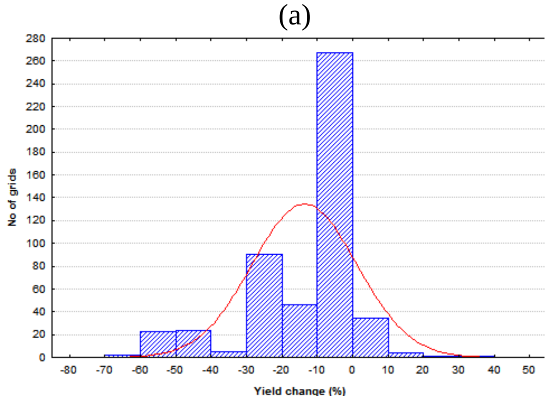
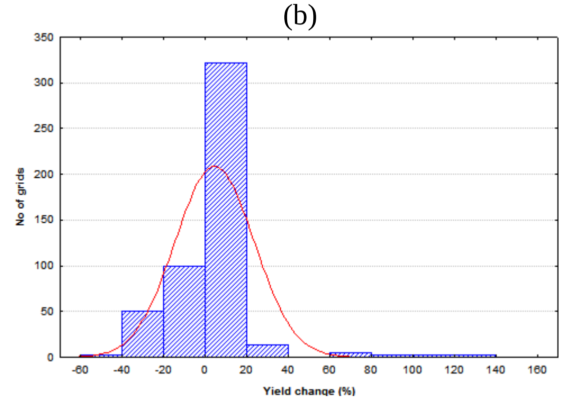


(c)



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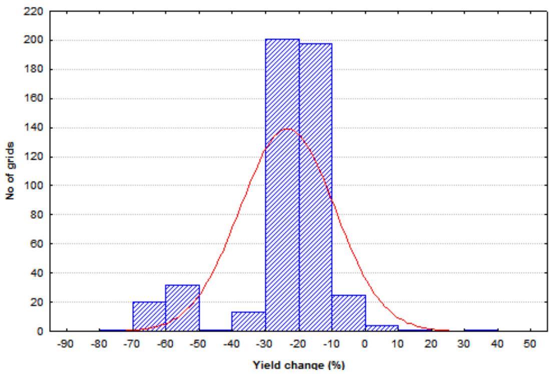


(e)

Figure 5.15: Wheat yield changes under A2a scenario with CO_2 fertilization. (a) Cumulative probability function and (b) box plot showing % change in yield in 2020, 2050 and 2080. (c), (d) and (e) respectively the grid wise distribution of wheat yield change (%) during 2020, 2050 and 2080.

(3) Interpretation of climate change impact on wheat crop

Table 5.11: Mean temperature and total rainfall of the study area during wheat growing season (December to April)

	BL	A2a20	A2a50	A2a80	B2a20	B2a50	B2a80
Tmean (^{o}C)	16.68	18.09 (+1.41)	19.39 (+2.71)	21.40 (+4.72)	18.02 (+1.34)	19.40 (+2.72)	20.18 (+3.50)
Rainfall (mm)	188.66	198.59 (+5.26)	226.39 (+20.00)	162.83 (-13.70)	169.67 (-10.07)	171.52 (-9.08)	187.71 (-0.50)

In parenthesis, increase in temperature and percent increase in rainfall from baseline is given.

The climate data analysis during the growing period reveals that the there is a continuous increase in mean temperature in different time scales but the increase in rainfall is comparatively less. The results show that there could be a decline in rainfall of 13.70% from the baseline. As per model simulation under A2a scenario without CO_2 fertilization there could be a huge reduction in average wheat productivity in the study area, ranging from -15% to -42%. The yield reduction in 2050 (-15.72) is less compared to 2020 (-21.50%) the possible reason for this is the improved rainfall and reduced number of water stress days.

A2a scenario with CO_2 fertilization shows a similar trend of yield reduction but with low vigor, except in 2050.In 2050s there could be a slight improvement in wheat productivity compared to baseline. The possible reason for this is the combined effect of improved rainfall and CO_2 fertilization. During A2a80 the positive effect of CO_2 fertilization cancels due to increased temperature. The study conducted by Lal *et al.*, (1998) shows that the a rise in temperature of 3 ^{o}C cancel the effect of doubled CO_2.The current shows similar results that, in 2050 the increase in temperature is 2.71 ^{o}C and yield change with CO_2 fertilization is +4.13 %. Were as in 2080 increase in temperature is 4.7^{o}C leads to a reduction in crop yield of 23.72 %. A study conducted by Hundal and Kaur, (1996) in Punjab shows that an increase in temperature by 1, 2 and 3 ^{o}C under normal CO_2 conditions will reduce wheat yield by 8.1%, 18.7% and 25.7 % respectively. The current study under A2a scenario without CO_2 fertilization follows the same trend but more vulnerable due to lack of irrigation. An analysis was performed to understand the effect of climate change on water stress days and the plant transpiration (actual to potential transpiration –T/Tp) .The results shows that the numbers of water stress days are more during A2a20 with reduced transpiration. This will leads to a reduction in crop productivity. This shows the requirement of improved irrigation facilities and optimum water management.

5.4. Soil erosion and SOC assessment

An attempt has been made to assess the soil erosion process and SOC in major agricultural soils of the study area. The current Soil organic carbon stock were assessed by laboratory analysis of field collected soil samples.Model Simulations are performed for 12 years period under current climatic conditions(2000-2012) for soil erosion with a spatial resolution of 1 km X 1 km. The simulation results for agricultural grids, based on soil series are compiled and model performance were evaluated based on field observed data. Three dominent soil serieses in the agricultural landscpes aer considered for the study.They are Barwa,Doiwala and Jassuwala, respectively represents soil physiographys pidmont (gentle to moderate slope),Ganga river terrace and Yamuna river terrace. The climate change impact on soil erosion and SOC were assessed under A2a scenario during 2020s, 2050s and 2080s for maize-wheat system. The important findings are given in following sections.

5.4.1. Model calibration for soil erosion process

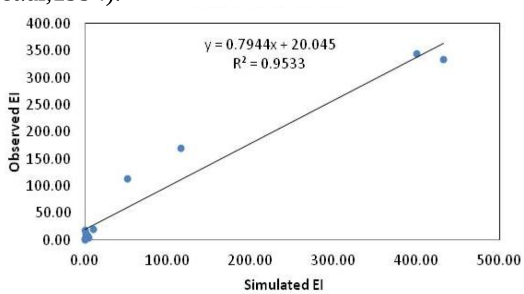
The factors governing soil erosions process, mainly rainfall erossivity is adjusted with reference to baseline rainfall erosivity value.

Rainfall erosivity adjustment: Rainfall erosivity index(EI) is one of the major factor that affects soil erosion.For proper estimation of soil erosion the model predictions for EI is adjusted for baseline period.the average monthly erosion index value for doon valley is used for EI correction. The peak runoff rate-rainfall energy adjustment factor (apm) in EPIC model is set to 0.6 instead of default value 1. EI value adjusted with an R^2 value of 0.95. The results after incorporating this correction is given in table 5.12.

Table 5.12: Model adjustment for rain fall erossivity.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
$EI_{simulated}$	4.0	1.0	3.0	0.0	0.0	51.0	400.0	432.0	115.0	10.0	0.0	1.0	**1017.0**
$EI_{observed}$	5.9	10.1	8.7	3.60	19.8	113.8	344.4	335.4	171.0	20.6	1.0	14.1	**1048.4**

Where, EI_{sim} is the simulated EI and EI_{obs} average observe value of EI for Doon valley from 1984-1992 (Narain et.al,1994).



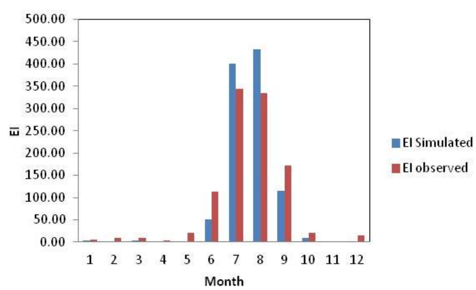


Figure 5.16:Model calibration for rainfall erosivity index in baseline simulations

5.4.2.Validation of Soil erosion based on field observations

Field observations were performed for field size, slope,course fragment, and erosion severity during soil data collection. Based on this observations RUSLE site specific erosion was calculated. The soil series wise aggragation were performe and average soil erosion for each soil series were assessed.This is then compared with EPIC simulated soil erosion for the same location and the results and comparable results were obtained and are given in table 5.13.

Table 5.13: Comparison of site specific and model simulate soil erosion

Sl No.	Soil series	No. of observations for aggragation	Soil erosion rate (t.ha^{-1})	
			Observed	Simulated
1	Barwa	12	16.06	19.86
2	Doilwala	9	16.78	14.70
3	Jassuwala	8	6.76	6.34

5.4.3. Assessment of curent soil organic carbon stock

The current soil organic carbon stock of agricultural landscapes were assessed based on field collected soil samples.Through geospatial analysis it is found that majority of the agricultural lands fall under three soil serieses named Barwa,Doiwala and Jassuwala.Soil series wise aggration of these samples were performed and the current SOC stock in top 30 cm were calculated. The results results are given in table 5.14.

Table 5.14:Current soil organic carbon stock of major agricultural soil serieses in top 30 cm.

Soil Series	SOC stock in top 30 cm (t ha^{-1})		Change in 12 years (t.ha^{-1})	Rate of SOC change (t ha^{-1} yr^{-1})	No. of profiles taken for averaging
	Year 2000	Year 2012			
Barwa	52.10	44.94	-7.16	-0.597	15
Doiwala	60.93	52.09	-8.84	-0.736	9
Jassuwala	28.06	34.36	6.30	0.525	11

Barwa and Doiwala soil series showed reduction in soil organic carbon stock (7.16 t.ha^{-1} and 8.84 t.ha^{-1}) where as Jassuwala series witness an increase of 6.3 t.ha^{-1} in top 30 cm over 12 year period.

5.4.4. Simulation for Soil organic carbon

For the spatial prediction of SOC a module is added to the GEPIC model.From the point scale out put (.ACM file) obtained from each grids were collected and the grid wise value for total organic carbon over 'n' year period is extracted to single OC file. This can be utilized to assess the impact of climate change on SOC sequestration under different croping systems over a large spatial scale. In current study soil organic carbon for the study area are simulated for 12 year period under maize-wheat rotation.10 t.ha^{-1}.yr^{-1} farmyard mannure applicatin and 100% residue removel is considered for the study.The number years of cultivation at start of simulation was set to 100 years.Operation schedule file was prepared based on common management practices followed in the study area. The combined effect of climate change and soil erosion was assessed and results are given in the following section.

5.4.5. Climate change impact on soil erosion and SOC sequestration

To understand the vulnerability of climate change on SOC and erosion process EPIC model simulations were performed (12 year period) under A2a scenario with maize-wheat cropping system for 2020, 2050 and 2080 timescales. The results obtained are given in table 5.15.

The results show that under all the three scenarios the soil erosion increases which is mainly due to increase in rainfall in future scenarios. The climate data analysis shows that under A2a scenario there could be an increase in rainfall of about 25%, 35 % and 70 % during 2020s, 2050s and 2080s (Table 5.2).This will result in increase in rainfall intensity and thus soil erosion. The analysis results are given in table 5.15.

The SOC shows a declining trend in all the scenarios for the three soil series studied. Under baseline A2a20, A2a50 and A2a80 scenarios, the rate of SOC changes for Barwa series are -0.68,-0.72, - 0.70 and -0.94 and for Doiwala series are -0.58,-0.62,-0.55 and -0.82 $t.ha^{-1}.yr^{-1}$. Jassuwala series shows SOC sequestration in all the time period but the rate of sequestration is declining over different time period. The analysis shows that the rate of sequestration for Jassuwala series under BL, 2020s, 2050s and 2080s are 0.42, 0.38, 0.37and 0.08 respectively.

Table 5.15: Climate change impact on SOC sequestration and soil erosion rate.

Soil Series	Scenario	SOC ($t.ha^{-1}$)		SOC change ($t.ha^{-1}$)	Rate of SOC change ($t.ha^{-1}.yr^{-1}$)	Average Soil erosion (t.ha-1)	Change in soil erosion from BL (%)
		Year 1	Year 12				
Barwa	BL	206.72	198.55	-8.17	-0.68	18.16	…….
	A2a20	206.54	197.91	-8.63	-0.72	24.72	36.14
	A2a50	206.00	197.54	-8.46	-0.70	31.64	74.27
	A2a80	205.79	194.53	-11.27	-0.94	44.60	145.61
Doiwalla	BL	185.84	178.92	-6.92	-0.58	8.63	…….
	A2a20	185.84	178.37	-7.47	-0.62	10.84	25.55
	A2a50	185.44	178.83	-6.60	-0.55	17.16	98.76
	A2a80	185.16	175.29	-9.87	-0.82	28.80	233.66
Jassuwala	BL	69.84	74.85	5.01	0.42	7.51	……..
	A2a20	69.53	74.11	4.58	0.38	11.43	52.22
	A2a50	69.26	73.67	4.41	0.37	16.39	118.15
	A2a80	68.63	69.59	0.95	0.08	29.05	286.70

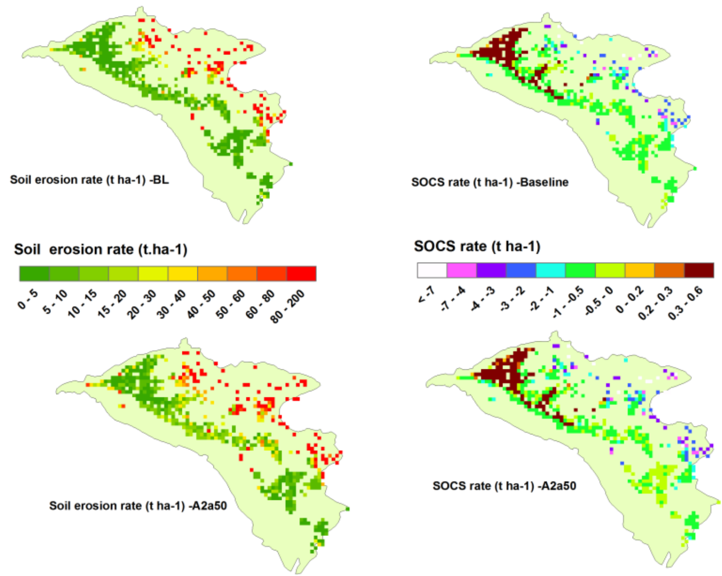


Figure5.17: Climate change impact on SOC sequestration rate under base line and A2a50 scenario

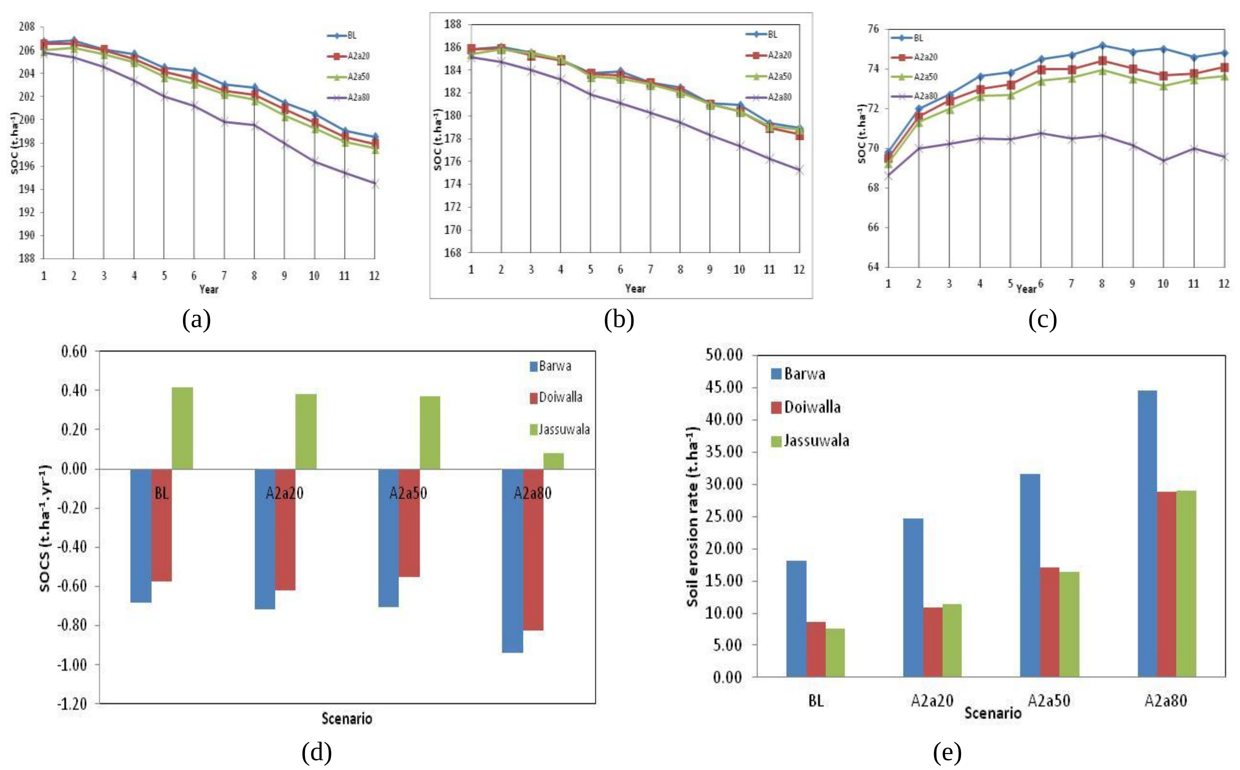


Figure 5.18: Climate change impact on Soil erosion and SOC sequestration under Baseline, A2a20, A2a50 and A2a80 scenarios. (a),(b) and (c): variation of SOC over 12 year period for Barwa, Doiwala and Jassuwala series (d): rate of SOC change and (e): Soil erosion rate for Barwa, Doiwala and Jassuwala series.

6. CONCLUSION AND RECOMENDATIONS

6.1. Conclusions

The analysis performed during entire study period and the result obtained as discussed in previous chapter conclusions were formulated and attempted to answer the research questions.

The current study was carried out to test the applicability of biophysical model EPIC in a regional scale, to assess the impact of climate change on crop productivity carbon sequestration and erosion process in an agricultural landscape of a mountain ecosystem. The study area selected was Doon valley, a perfect example for a mountainous agro ecosystem, due to its vulnerability towards extreme climatic conditions.

The first objective was achieved through model sensitivity analysis and calibration based on field observations. The site specific calibration and validation result shows the capability of the model to predict crop productivity based on local conditions. The calibration and validation of the model are performed for rice and wheat crop in the study area with an RMSE of 0.38 t ha^{-1} and modeling efficiency of 0.78 for rice. LAI correction strategy is performed for wheat crop calibration, which is showing better results than rice with the RMSE of 0.24 t ha^{-1} and a modeling efficiency of 0.88.

The applicability of the model to predict impact of climate change on crop productivity and soil erosion impact on soil organic carbon sequestration were investigated in the study area on grid basis. Due to large variability in topography climate and soils in the study area simulations are performed with a spatial resolution of 1 km X 1 km by incorporating same resolution datasets under baseline conditions and future scenarios. The results obtained were promising which shows the spatial variability with in a particular region. This is helpful for the policy makers to understand the future focus areas with in a region and planning can be done, such as for irrigation facilities, soil and water conservation measures, and identification of suitable crops etc.

The climate change impact on rice and wheat crops in the study area were performed under different scenarios. The study shows that there could be a continuous reduction in rice yield under A2a scenario without CO_2 fertilization ranging from -1.03% in 2020s to -19.22 % in 2080s.Under A2a scenario with CO_2 fertilization showcasing an improvement in yield of about 5 % till 2050 but a slight reduction of 2.4% afterwards. Under B2a scenario both in 2020s and 2050s there could be a reduction in yield of about 3 % because the atmospheric CO_2 concentration is not sufficient to compensate the increase in temperature. After 2050s there could be a slight improvement in yield of about 1.3 %. To assess the vulnerability, wheat crop simulations were performed by considering un-irrigated conditions. Under A2a scenario without CO_2 fertilization the results shows a large reduction in wheat yield with 42 % in 2080s. The vulnerability of wheat crop to climate change is less if we consider CO_2 fertilization which is showing an improvement in yield of about 4 % in 2050 due to increase in rainfall (+20%). But in 2020s and 2080s, there could be a reduction in productivity of about 13% and 23 % respectively. The results shows that even increasing CO_2 would not be able to offset losses incurred due to extreme rise in temperature in 2080s. Avoidance of such temperature effects could be mitigated with improved irrigation facilities and water conservation measures.

The soil organic carbon can act as a source or sink of atmospheric CO_2 based on the management practices we performed. The assessment of soil organic carbon stock is a must in this era of global warming and carbon trading. The focus is mainly towards agricultural landscapes because it is highly susceptible to land degradation due to varying management practices. This study attempted to assess current organic carbon stock and potential carbon sequestration of three major agricultural soil series of the study area. The current carbon stock has been assessed by the laboratory analysis of collected soil samples. Three soil series namely Barwa, Doiwala and Jassuwala representing dominant soil series in the agricultural landscape were assessed. Jussuvala series in the study area shows an improvement of 6.3 t ha^{-1} SOC over 12 year period (2000-2012). The GEPIC model simulations were performed to assess the impact of Climate change on SOCS affected by soil erosion. After thorough analysis it was noticed that soil erosion rate will increase under A2a scenario for all timescales. This is mainly due to increased rainfall and rainfall erossivity. Climate change impact analysis revealed that Barwa, Doiwala, Jssuvala soil series showed a decrease in soil carbon under A2a scenario for all time scales.

6.2. Recommendations

The difficulties faced and experiences obtained during the study leads to the formulation of following recommendation.

1. The model predictions can be improved with the help of agronomic experiments and incorporating region wise data base of crop parameters.
2. The current study conducted with statistically downscaled climate change scenario which may have inherent error in projection of climatic parameters. It is worthy now to use dynamic down-scaling with RCM model for generating high spatial resolution grid datasets.
3. There is an urgent requirement of meta-data analysis of multiple model performance in simulating climate change effect on crop productivity.
4. The soil sampling is a major factor that determining the assessment. There should be a common platform for sampling techniques, time of sampling and type of sampling (pedon /fixed depth) etc. The exact positioning of location of profiles is a must for time series analysis of SOC.

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