Model based approach to study the impact of climate change on cotton crop

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by

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DEDICATE TO

ALL MY FAMILY AND FRIENDS

With Special thanks to

My Mother (Late Mrs. Asha Kumari)

My Father (Mr Rabindra Kumar)

My Brother (Ashish Shekhar)

Certificate

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Thesis title – **“ Model based approach to study the impact of climate change on cotton crop ”**

By *Anamika Shikha*

ABSTRACT

The present work aims to make a detailed assessment of the vulnerability and adaptability of climate change on the cotton crop. Cotton is one of the principal commercial fiber crops. India is among the leading producer of cotton, the highest in terms of area under production. India's decadal average productivity is 522 kg/ha, whereas the world's average is 765 kg/ha with a gap of 243 kg/ha. Abiotic and biotic stresses like weather erraticism and pest infestations are the paramount reasons for the productivity loss. This model-based study emphasizes the utilization of the crop simulation model to study the impact and reliability of climate model data for future projections. For the pest assessment, this study also highlights the application of remote sensing approach complementing weather-based statistical forewarning for taking effective Integrated Pest Management (IPM) measures. The cotton CROPGRO model incorporated under Decision Support System for Agro-technology Transfer (DSSAT) version 4.6 has been used in the study. The model input data taken from the field study were calibrated and validated with reasonable accuracy for the crop in the study region. In the first chapter, a brief review of the cotton crop is presented along with the valuable research carried out so far concerning crop modeling for cotton crops over various regions of India and the world. The chapter initially confers the historical existence and commercial significance of crop; further, it elaborates on the cotton physiology, conditions of growth, the impact of future climate on the crop yield, and physiology. It will then elucidate climate change and its future projections, climate model data, bias correction, and crop models. Then relevance and motivation behind selecting the topic

of research and the broad objectives are discussed. Finally, followed by a brief description of the study area and methodology applied to achieve the various objectives. In the second chapter, implications of increasing temperature and CO_2 concentrations on cotton yield and physiology are estimated over the Hisar region for the present climate with observation data both individually and taken together. The sensitivity of three cotton cultivars sown on three different dates were analyzed in the DSSAT model for the rising temperature by 1°C and 50 ppm each. In chapter three, the pest attack in the farm research area in Hisar is analyzed using LANDSAT images during 2013-18. After atmospheric corrections and cloud masking, the Vegetation indices(VIs) viz. NDVI and NDWI are calculated for the area of interest. The collected multi-temporal images are then composited in a time series plot. These indices were further analyzed along with the crop calendar and validated with the field observations.

Further, after assessment of the predominant biotic and abiotic stresses for the present future predictions are studied. But before using any future projections from the climate models, these models are to be carefully evaluated with the historical predictions. And the biases found in the model are to be corrected with acceptable precision over the study region. Various GCMs and RCMs have been used for similar studies earlier. And it has been found that RCMs have an advantage over GCMs due to higher resolution, which could potentially add benefits of accuracy and considerable details to outputs over courser resolution GCMs. It also helps to evaluate the model data against observations and strengthen our confidence for future projections. In chapter four, regional climate model RegCM4.0 data are evaluated for baseline-derived weather and its bias-corrected values, both for temperature and precipitation, with observed for diverse agroclimatic zones of cotton. Here, comparative study of the cotton crop for Akola (central) and Hisar (northern) agroclimatic zone of cotton for the period 1971 – 2005. Further, in chapter five, using the same model data for future projections from the CORDEX-SA experiment (GFDL-ESM2M- RegCM4) for RCP4.5 and RCP8.5 impact of climate on the cotton crop is studied for the study region. The model data was similarly bias-corrected using quantile mapping approach, and then both are employed in the cotton-CROPGRO model under DSSAT-CSM(v4.6). The RCM projected daily weather from 1971 to 2005, 2006 to 2035, 2036 to 2065, and 2066 to 2095 were average to represent projected climate centered at historical (1990), present (2020), and climate change scenario in the near future (2050) and far future (2080). The CO_2 concentrations were taken as 353, 415, 486, and 531 for RCP4.5 and 353, 415, 539, and 757 for RCP8.5, respectively. The crop model has been simulated for rainfed, irrigated, and potential conditions for three sowing dates. Finally, the significant results obtained from work are summarized with the main conclusions in the sixth chapter.

The evaluation of cotton for the present climate with the observation data shows that for the cultivar Pancham-541, a rise in 1°C of temperature with 50ppm CO_2 is beneficial, but further rise is harmful. Whereas for RCH-791 and SP-7007, productivity decreases gradually with increasing temperature and CO_2. Generally, yield decreases with an increase in temperature (by 1°C), but no significant effect was observed with increasing CO_2 (50ppm) cumulatively for the Hisar region. The adverse effects of rising temperatures are moderated due to increased CO2 due to an increase in photosynthesis when considered together. Again for the physiological aspect of the crop, the leaf area index and evapotranspiration rate increase with increasing temperature and CO_2 for all varieties in all sowing dates. Whereas, the harvest index and maturity dates decrease in general. Therefore, it can be concluded that increasing temperature at the present rate will be harmful for cotton productivity. Although this effect is abated with simultaneously rising CO_2 but yet the adversity due to the global rise in temperature is partially mitigated.

After analyzing the major abiotic constraint, the biotic constraints are examined. The DSSAT model is not able to forecast the pest attack. So statistical forecasts are prevalent in the study region along with remote sensing and GIS approach. In this study, vegetation indices has been evaluated after, along with the contemporary statistical approach. The NDVI and NDWI values are minimum for the years 2013, 2015, and 2018 compared to 2014, 2016, and 2017 respectively, reflecting the stress the crop was experiencing, which was corroborated as pest attack above Economic Threshold Level (ETL) as per field observations. The peak in the values is gained during September 2017, showing good plant health during the year. As per the field observations, in 2013 and 2015, the major threat was Cotton Leaf Curl Disease (CLCuD) transmitted through whitefly (Bemisia tabaci) and accompanied by other sucking pests like thrips, leafhopper, etc. And in the year 2018, the crop was majorly affected by the cotton leafhoppers Jassids. Thus it was found that the remote sensing approach is better reflective of crop health and stress. Therefore, for strengthening network programs monitoring the pest dynamics along with statistical forecasts, and this is needful.

Further, for analyzing future conditions, forecasting climate model data has to be used. But before using the projections for the future climate, they are validated for the region for the historical period (1971–2005). The model data and its bias-corrected data are evaluated in comparison to observations. The RCM model used in the study shows wet biases with high rainfall intensity. The model also suggests night warming due to a significant decline in maximum temperature and minimal decline in minimum temperature leading to reduced diurnal temperature difference in both the locations. Overall regional climate model underestimates the temperature and overestimates rainfall. A remarkable feature observed was less number of intense warm (maximum temperature ≥ 45 °C and ≥ 40 °C) and high cold events (minimum temperature ≤5 °C and ≤ 3 °C) is captured in the model. It is highly biased for rainfall>0mm/day and <5mm/day, and moderately biased for rainfall >5mm/day, which is because of the drizzling effects of the RCM model as various studies signify. The bias-correcting approach using ‘Quantile Mapping’ showed excellent agreement annually, but failed to correct daily and seasonal variability since it’s a 'distribution-based method.' The MBE and RMSE values of weather data show considerable improvement when bias-corrected. There are some limitations with the extreme weather, which could severely affect crop productivity and, therefore, be taken care of in future studies. Further, utilizing these weather data as an input for crop model simulations for outputs such as dry yield, Leaf Area Index (LAI), and ball Number at maturity/m^2 (NM), it was contemplated that with bias-corrected weather data they show excellent agreement with the corresponding observed weather than non-bias-corrected RCM model data for both regions. The percentage deviation has been reduced for bias-corrected variables. The I and RMSE values have also improved for the yields. The crop is performing better in the northern region for the present conditions with high potential and therefore has much scope of improvement with proper management strategies. Thus the study suggests the RCM outputs can be used explicitly for the analysis of the impact of climate change on crop productivity when complemented with reliable bias-correction techniques.

For future impact studies, the model predicts spatial and temporal variability in the precipitation patterns at different cotton-growing regions, which could possibly affect crop productivity. This approach also performed better in the arid Hisar region, which is irrigated, than the Akola region, which is rainfed. The detailed analysis of projections from the regional climate model for the study region for the temperature and rainfall variables signifies that the model predicts slightly increasing temperature from 1990 till 2080 and from RCP4.5 to RCP8.5. It is rising at higher rates at Hisar(northern) than Akola(central) agroclimatic zone of cotton. An overall increase in the amount of rainfall is observed in the northern region and decreasing in the central region at RCP8.5. It increases till 2050 and further reduces in 2080.

Crop model simulated outputs suggests, in Akola, the yields are higher for RCP8.5 than RCP4.5, whereas in Hisar, yields are lower in RCP8.5 than RCP4.5 for both model and bias-corrected data. The percent deviation of yield and LAI from the present(2020) signifies that future climate yields in the northern region (Hisar) are increasing for 2050 and 2080 at RCP4.5 and declining for 2050 and 2080 at RCP8.5. In the central region (Akola), it increases in 2050 and then 2080 as per both models and its bias-corrected data.

In the hot and dry northern agroclimatic cotton zone, the increasing temperature is detrimental. In contrast, in the cooler and wetter central zone, increasing temperature is not a hindrance, and at the same time, increased CO_2 is favoring the production. With temporal variability in the amount of precipitation and rising temperature, late sowing of the crop is favored. This can be due to various factors such as increased average precipitation during the cropping season, increase in CO_2, when the temperature is rising slightly for both RCPs from the baseline. So there is a scope of better productivity in the northern region at RCP4.5 and in the central region at RCP8.5 with the changing climate when proper irrigation is provided.

An adaptation measure such as alteration in sowing dates and irrigation and fertilizer scheduling will play a significant role. For cotton, late sowing is seen as beneficial to climate change. This delayed sowing owes its response due to the delayed onset of monsoon in the study region, where the rainfall intensity has increased during the cropping season. The growers and scientific communities have to about site-specific crop management and variability within the field for potential productivity with the changing climate. This can be done by modifying the sowing window, adopting stress-resistant varieties, developing new-age cultivars, improvising management, and implying climate forecasts in cropping decisions. Selecting weather tolerant varieties and pest-resistant crops can also help in the adaptation and sustainability of the crop. To enhance cotton productivity, sowing the plant at an optimum period will be helpful.

This study attempts to bring forward the impacts of regional climate change and its implications on cotton yield and physiology over the rainfed and irrigated cotton-growing regions of India. An increase in temperature and precipitation is expected with climate change in the study region, with an enormous increase in CO2 concentrations. The shift in the seasonal pattern will also disturb the crop-calendar. The complexity in the growth and developmental stages of cotton makes it more challenging to study the vulnerability of the crop for climate change. The central region acclimated to be fit for cotton because it has an ample amount of rainfall and black soil. But this study suggests that in the future climate, the rainfall in these regions is decreasing and increasing in the northern region. So the northern region can also be preferred for growing the crop, and it is also found that the alluvial soil in the Satluj-Ganga Plain is also suitable for cotton.

Apart from these abiotic constraints, the major concern for cotton productivity is with the pest for which proper Integrated Pest Management (IPM) measures has to be taken, wherever it is grown. Coupling the pest attributes with the crop modeling to forecast or estimate the climate-induced impacts on crops and pest need of the hour for cotton crop. Similarly, understanding the quantum and characteristic of pest and diseases are essential for predicting the infestation and take timely measures. Forecasting the pest along with real-time monitoring with the remote sensing approach could help the farmers and policymakers for better pest management.

The study embrace utilization of crop growth models for developing crop management strategies, yield forecasting, the sustainability of the crop, climate change impact assessment, economic analysis for bringing precision in agriculture. Uncertainty and variability in future climate may affect the growth and development of the crop. Future research could apply these model-simulated data to study the impact of climate change on crop productivity explicitly. This can also be complemented with more reliable model data and bias-correction techniques to complement the research. Understanding the ambiguous and unpredictable character of biases in climate models and bias-correction approaches is essential in studying the impacts of future climate. The development of physiology-linked economic models at the farm-level for decision-making under climate change scenarios is important.

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List of Abbreviations

AMFUs	**Agromet Field units**
AR4	Forth Assessment Report
ArcGIS	Aeronautical Reconnaissance Coverage Geographic Information System
CC	Climate Change
CCSHAU	Chaudhary Charan Singh Haryana Agricultural University
CERES	Crop Environment REsource Synthesis
CLCuD	Cotton Leaf Curl Disease
CMIP5	Coupled Model Intercomparison Project 5
CO_2	Carbon dioxide
CODEX-SA	Climate Downscaling Experiment over South Asia
CSM	Cropping System Models
CSM	Cropping System Model
DSSAT	Decision Support System for Agrotechnology Transfer
ESGF	Earth System Grid Federation
ET	Evapotranspiration
ETL	Economic Threshold Level
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization

FASAL	Forecasting Agricultural outputs using Space, Agrometeorology and Land based observations
Fig.	Figure
GCMs	General Circulation Models
GDP	Gross Domestic Product
GFDL	General Fluid Dynamics Laboratory
GKMS	Gramin Krishi Mausam Sewa
GLAM	General Large Area Model
HI	Harvest index
I	Index of agreement
IITM	Indian Institute of Tropical Meteorology
IMD	India Meteorological Department
InFoCrop	Information on Crop
IPCC	Intergovernmental Panel on Climate Change
IPM	Integrated Pest Management
LAI	Leaf Area Index
LAI	Leaf Area Index
LANDSAT	Land Remote Sensing Satellite (System)
MBE	Mean Bias Error
MD	Maturity date
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index

NDWI	Normalized Difference Water Index
NIR	Near infrared
NIR	Near Infrared
NM	Number at maturity (balls)
PDKV	Panjabrao Deshmukh Krishi Vidyapeeth
PREC	Precipitation
QM	Quantile Mapping
RCMs	Regional Climate Models
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
SRAD	Solar Radiation
SWIR	Short Wave infrared
TAVG	Average Temperature
TMAX	Maximum Temperature
TMIN	Minimum Temperature
USGS	United States Geological Survey
VIs	Vegetation Indices

Chapter- I

Introduction

INTRODUCTION

Cotton belongs to the family of Malvaceae and Tribe named Gossypieae. The Genus is Gossypium, which consists of about 50 species. Among them, four are cultivated, namely *Gossypium arboreum*, *Gossypium herbaceum*, *Gossypium hirsutum*, *and Gossypium barbadense*. The first two, known as old-world cotton and Asiatic cotton, are diploid (2n = 26) and are indigenous to Asia and Africa. The other two, also known as new world cotton or American cotton and upland cotton, are tetraploid (2n = 52) are confined to Egypt, Mexico, Central, and South America. The *G. hirsutum* is the predominant species and contributes almost 90% of global cotton production. The cotton fiber is a cellulosic polymer and hydrophobic in nature. Typically, the cotton fibres are composed of Cellulose (94%), Waxes (0.6%), Pectin (0.9%), Protein (1.3%), Mineral matters (1.2%), Organic compounds (0.8%), total Sugars (0.3%) and other substances (0.90%) (International Cotton Advisory Committee report, March 2017).

1.1 ABOUT COTTON CROP AND ITS IMPLICATIONS DUE TO CHANGING CLIMATE AND THE CLIMATE AND CROP MODELS

1.1.1 Cotton; Commercial Crop Of India

The economy of an agro-based country like India is predominantly based upon the Agriculture Sector. This includes the production of edible crops for food security and cash crops as well for economic empowerment. Cotton is the world's most significant fiber crop, and the second most important oilseed crop (Freeland et al., 2006). It is a source of fiber, oil for human consumption, protein meal for livestock feed, and potentially fuel for diverse industries. The waste after ginning can also be used as fertilizer and cellulose as paper and cardboard (Freeland et al., 2006). Cotton accounts for approximately 75% of total fiber production in the textile industry, which almost contributes to 4 % of GDP and 17% export earnings for India (India, C. E. I., 2007; Sankaranarayanan et al., 2010). It is grown worldwide with India as the highest producer accounting for 26% of the total world's cotton production and largest area under production as 38% to 41% as its share (International Cotton Advisory Committee report, March 2017). India also has the achieved highest acreage of cotton worldwide, with 9.5 million hectares and engaging around 5 to 5.5 million farmers (Sankaranarayanan et al., 2010). Due to its economic relevance, it is our priority to study the vulnerability and adaptability measures. And with the changing world, increasing temperature, monsoon unpredictability, and erraticism linked with rising global warming in the Indian Subcontinent, there is now a dire need to study the impact of weather on crops as well.

India was the leading cotton producer and second-largest cotton exporter in 2016-17 (Press Information Bureau, Government of India, Ministry of Textiles dated 09-March, 2017). But again, it slipped to the second position in 2018-19 as an estimated 27 million bales, which is 6.9 percent down from the preceding year. Harvested area fall marginally down as 1.6 percent from 2017-18, reduced monsoon rainfall and pest outbreak in the major crop-producing area like infestation by pink bollworm in Gujrat and Maharashtra truncated harvesting. (Cotton Outlook – USDA, 2019). Again in 2019-2020, India regained its position as per forecasts to come back as the leading cotton-growing country, surpassing China once again. It is projected to be 28.5 million bales, which is 10 percent above 2018-19 (FAO cotton report, 2019). In India, cotton is grown in three discrete agro-ecological zones: The Northern zone (Punjab, Haryana, and Rajasthan), the Central zone (Gujarat, Maharashtra, and Madhya Pradesh), and the Southern zone (Andhra Pradesh, Tamil Nadu, and Karnataka) Orissa and others. And all the four cultivable species of cotton such as Gossypium Arboretum, G. Herbaceum (Asian cotton), G. Barbadense (Egyptian cotton), and G. hirsutum (American Upland cotton) can be grown here. The majority of hybrids like Bt cotton produced in India are Gossypium Hirsutum, which is around 88% cotton. With the adoption of genetically modified (GM) crops in India since 2002, the cotton production and the farmer's income doubled. But the wild variety was more tolerant towards drought, whereas production of the Bacillus thuringiensis (Bt) cotton hybrids are influenced by the weather, especially monsoon patterns in the rainfed regions. Therefore, climate change could affect the yield cropping pattern of the crop. And the concern is the majority of the cotton is rainfed (approximately 62%). Also, there is a wide gap in the productivity of the crop where India (454.43 kgs/ha) ranks poorly when compared with USA (955 kgs/ha) and China (1764 Kgs/ha) (Ministry of textile, Cotton Updated by Fibre-I, Section on 12.9.2019).

1.1.2 Historical Existence Of Cotton

The cotton history is as old as human civilization itself. From the period of domestication of the cotton plant by several ancient civilizations till present times, this particular plant and it's by-products have given many things to the humankind. One of the most important contributions is the fabric that is received from it. The transition of cotton usage and its products can vary from purely functional decorative use of it to the shift in the manufacture of textiles from a highly individualized and specialized cottage craft to a mechanized and large-scale operation. This outcome of many persons' creative genius from all walks of life has contributed to the evolution of the particular material. These changes are closely interlaced with events in other spheres of human history. The cotton plant and the various factors starting from its birth until the crop's harvest undergo different stages. Moreover, several other physiological and climatic factors are deeply involved in the full-fledged growth of this particular crop. Therefore, the cotton plant, which comes under the category of cash crops, demands us to examine its economic value.

There has been a discovery of shreds of evidence of cotton under various aspects of civilization. It is traced that a single plant and its usage and the products are deeply connected in our day to day lives of every individual. An attempt is made to highlight the perks and importance of cotton, which is an essential part of society and the economy and the natural environment it is grown. For the last many centuries and several different time periods, it has served various services and also different purposes to mankind. And on the other hand, humankind has exploited this particular crop in multiple ways. A sincere emphasis is put to draw a nexus between historical, economic, physiological aspects of the cotton plant as a crop. This overall understanding is essential to help manage a view about the future where steps could be taken to protect the crop and enhance its production.

Cotton fabric has been found in the excavations of Mohenjodaro and pre- Inca cultures in America. In 1929, archaeologists recovered fragments of cotton textiles in Mohenjodaro, dating between 3250-2750 BC. This indicates the use of it to a very old period and, most probably, one of the earliest pieces of evidence. At the Indian Subcontinent, the by-products of the cotton plant and its history of usage date back to the ancient period, and many more other examples are found. In another instance, the Vedic scriptures, composed between 1500-1200 BC, also allude to cotton spinning and weaving (Hagge, 2013). Continuing the culture of cotton production and its uses in the 16th- 18th Century during the Mughal Empire, cotton production in India increased, both in terms of raw cotton and cotton as textiles. They also introduced agricultural reforms along with a revenue system that was in favor of commercial crops such as cotton, indigo, etc. They also supported the crop by providing them with incentives for growing these crops. (Richards, 1995).

The cotton industry has been highly dominated by India in the 18th Century and was taken over by the British. This industry faced challenges in the late 19th Century as it was not mechanized and due to American dominance for the export of raw cotton. India ceased to be a major exporter of cotton goods, becoming the major importer of British cotton textiles. During the 20th Century, when India's independence struggle began, Mahatma Gandhi believed that khadi i.e., cotton weaving, was closely tied to Indian sentiments for self-determination. Therefore, in the 1920s, he started the Khadi Movement. Again during World War II, shortages raised the demand for cotton cloths.

Further, in the latter half of the 20th Century, a downturn in the European cotton industry led to the Indian cotton industry's resurgence. India began to mechanize and was able to compete in the world market (Logan, 1958). Cotton has also played a vital role in the freedom struggle of the country. One single crop has seen many faces of transition in the ongoing centuries.

1.1.3 Cotton Physiology

The cotton plant belongs to the family Malvaceae and the genus Gossypium. They are either diploid species, e.g., *G. arboreum and G. herbaceum*, or tetraploid species, e.g., *G. barbadense and G. hirsutum*. It is an annual crop but has a xerophytic, woody perennial nature (Hearn, 1980). Among the major field crops, cotton possibly has the most complex structure. Also, it is susceptible to adverse environmental conditions (Oosterhuis, 1990). The stages of growth and development in the cotton plant are coinciding and overlapping upon each other. So its precise demarcation is not possible as in the case of other crops like wheat and rice. The growth stages consist of both vegetative and reproductive phases. After sowing, the vegetative phase starts, including seedling, emergence, and formation of the leaf.

Further, the reproductive stage starts with squares formation, followed by flowers and then the ball. In combination with hormonal influences, the nutritional hypothesis plays a crucial role in relation to changes in growth patterns during the cotton ontogeny, with a negative correlation between vegetative and reproductive growth (Guinn, 1986). Vegetative and reproductive growth could continue indefinitely under favorable conditions. However, due to demand for the resource supply by the reproductive organs, the vegetative growth ceases, which is called 'cut-out' as described by Hearn et al. (1994).

After planting, seedlings can emerge within 5 to 7 days under favorable conditions. Vegetative growth and development takes around 40-45 days after emergence. This includes development of root, stem and leaves system. After the vegetative growth, reproductive growth starts. It actually starts with the appearance of first floral-bud on the lowest fruiting branch after 30-35 days of emergence, depending upon prevailing environmental conditions. This is followed by coming up of other floral-buds at regular intervals until flowering ceases. Flowering can cease after the ball formation starts or due to and stress. During the period of peak flowering, the vegetative growth is almost contemptibly small in amount. Some shedding of squares is probable to happen, even under the best management practices.

The cotton plant may shed off 40% to 50% of all its squares, which is further benefitted during its ball formation and maturity. Extensive shedding may occur due to stress, which can upset the plant's vegetative and reproductive balance, which may also affect the yields. The plants response to "cutout" as shedding of squares is to consume the produced carbohydrates in maturing the balls. Yields can also be reduced if cutout occurs too early. Squares may also shed off either because of insects damaging the plant or due to the poor growing conditions. Both flowering and seed formation keeps occurring in the same plant at different branches. During this phase, fertilization of the flowers occurs. The cotton blossom is a perfect flower. It contains both female parts and the male parts in the same flower. These fertilized flowers finally result into seeds. This process of the first flower to the first seed formation generally takes 18-24 days. After fertilization has occurred, the flower drops, and a small ball is formed. It starts typically after 65 days of sowing. It takes 30 to 35 days for its formation phase. In a plant, at the same time the square is formed, the flower is blooming and the balls. Not every ball that is formed makes it up till maturity. Initially, the process of ball development is slow during its formation. Later, the growth rate enhances and reaches a steady phase of growth. Balls that set late in the season often take a longer time duration to mature compared to that set early and in the middle of the fruiting season. Balls that set in time have enough time to develop, mature, and open to produce quality lint, with good yield. Balls that appeared late are generally smaller, not mature properly, and may not open. Thus the quality of lint and yield is typically low.

After ball formation, four to five weeks are required for ball maturation. The first ball generally begins to open 100 to 110 days after cotton sowing. During this phase, the thickening of fiber occurs by the deposition of consecutive layers of cellulose in the inner walls. In this phase of ball maturation, fiber elongation can be impacted by numerous factors. The genetic code primarily controls the length and quality of the fiber. But, length could also be influenced by the environment. Stress during this period can cause fibers to be shorter than normal. Finally, after maturity, the crop is harvested for the final product. In general, the number of pickings is four (120, 140, 155, and 165 days after sowing) and varies according to labor availability. After the balls are matured, they are ready to be harvested.

1.1.4 Conditions Of Growth

Cotton is a deciduous plant, which is native to subtropical climates. To assure proper seed germination and crop emergence adequate soil temperature and moisture conditions are required at the time of planting (Oosterhuis, 2001). The production of cotton crop is directly influenced by temperature, photoperiod, total radiation, and precipitation. Processes leading to squaring, flowering and boll formation and maturation are temperature-dependent (Mauney, 1986). Minimum of 15ºC is required for germination, 21ºC-27ºC for vegetative growth, and 27ºC-32ºC during the fruiting period (Waddle, 1984; Freeland et al., 2006).

Since, germination is severely affected when the temperature fall below 14°C. Chilling injury is the damage brought about by near-freezing low temperatures in cotton plants at various growth stages. Chilling causes a disruption of metabolic activity leading to death of the plants. The stage of germination had been known to be important in determining the extent of injury (e.g., chilling of pre-emergence seedlings can cause delay in maturity). An optimum range of air temperatures for the process of photosynthesis is 25°C to 45°C; this process may drop to zero at 55°C. Cool nights are beneficial during fruiting period but extremes in temperature can result in delayed growth and aborted fruiting sites.

The placement of the first flowering branch gives an excellent indication to photosensitivity. In photosensitive varieties this position is much lower. For appearance of first flower, under comparatively cool day time temperature (28°C) with a 12-hour day, an upland variety may take 60-70 days from planting, while the same variety under warmer conditions (33°C) may take about 45 days. Excessively high air temperatures can result in an increase in square shedding. For ball production and retention, the sequential temperature of 45ºC or more for two or three consecutive days may be defined as an upper threshold, 16 ºC as a lower threshold, optimum as 27°C - 32°C and day time and night time temp range as 20°C - 24ºC. Mean temperature of 22°C - 27°C as optimum for the ball and fiber maturation. In general, rainfed cotton mature earlier than the irrigated ones. The absence of ball load on the plant, ball retention would be high in the range generally required for ball production irrespective of actual temperature and humidity experienced by the cotton plant. Ball retention is more dependent on fruit load on the plant rather than on temperature or relative humidity. An optimum day/night temperature of 27°C/22°C was suggested for optimum ball weight. Maximum temperatures greater than 38°C decreased yield considerably. If the daily mean temperature is below 20°C during the ball forming period, the fiber will stop thickening, and if it is below 15°C, the fiber will not elongate. For the elongation of fiber cells and thickening of secondary walls, the optimum temperature required was 25°C. With mean daily temperatures at 20°C - 25°C during ball development, 85% of seeds attain maturity while the percentage rapidly decreased at temperatures less than 25°C.

Extreme high temperature can result in delayed growth and shedding of fruiting bodies. High night temperatures cause poor or no pollen shed due to pollen sterility in cotton. Plants grown at 32ºC night temperature inhibit fruit setting. Temperatures below 20ºC and above 40ºC might result in pollen sterility and incomplete fertilization. Suppose temperatures are high during the night when the first flowers are due to open. In that case, the absence of early balls allows vegetative development further, resulting in a tendency to rank growth, which is found in areas or seasons where the minimum temperature exceeds 24°C. High temperature is disadvantageous to photosynthesis and often enhances photorespiration intensity, thus leading to carbohydrates in short supply, causing the abscission of balls. Gross photosynthesis declines when the temperature exceeds 32°C. But the photorespiration increases with temperature continuously, thus net photosynthesis decreasing with increasing temperature. At 32°C - 34°C, photorespiration reaches 50 percent of net photosynthesis. Too high or too low temperatures may affect the efficiency of plant protection chemicals.

Cotton is sensitive to day length. Early and mid-varieties of *G. hirsutum* can bud and blossom under normal conditions. However, late varieties of *G. hirsutum* and *G. barbadense* require short days. If the sunshine duration decreases appropriately, the first ball bearing branch's position will be lower, and the plant will be in compact conformation. But the output per plant will decrease. Cotton also requires plentiful light. The compensation point of irradiance for photosynthesis is 1000-2000 Lux, and the saturation point is 70000-80000 Lux. The intensity of photosynthesis has a close relation to irradiance. When irradiance ranges from 8000 to 70000 Lux, the photosynthesis increases with irradiance, and the peak appears at 70000 Lux. Over 80000 Lux, the intensity of photosynthesis will decrease. If irradiance is insufficient, photosynthesis will decrease, and the plants will put up excessive growth, thus leading to abscission of buds and balls.

Physiologists recognized the high ability of the cotton crop to utilize solar energy. Light rarely limits the growth of cotton plants under field conditions. In the temperate zone itself, the intensity of sunlight at midday is estimated to be four to five times more than that needed for the cotton plant's optimum growth. High light intensities are required for proper vegetative development. Abundant sunshine is essential to obtain good quality produce during the period of ball maturation and harvesting. Four hours of sunshine per day seems to be crucial for ball retention. However, no direct influence between cloudiness and ball shedding had been established with certainty as several factors interact in the process. A relatively dry period and good sunshine of at least four hours per day at the end of the season after ball opening ensures the right seasonal conditions for ripening and freedom from ball diseases and pests. The shedding percentage of young balls increases due to cloudy days; the result often appears about a week later.

If radiation is insufficient, photosynthesis will decrease, which may hamper the plants' vegetative growth, finally leading to buds' abscission. Light is essential for photosynthesis. During the late growth stage, the lower part of the plant accepts much less radiation and the photosynthates are in short supply, thus leading to the abscission of buds. Four hours of sunshine per day seems to be essential for ball retention; however, no direct influence between cloudiness and ball shedding had been established with certainty as several factors interact in the process.

Cotton requires approximately 550 mm to 950 mm for water not to be a limiting factor for the yield evenly distributed during the cropping season (Doorenbos et al., 1984). Adequate soil moisture during sowing is necessary for the growth and development of crop. Cumulative rainfall of 75-100 mm required for sowing of cotton to have better germination and crop establishment. Rainfall of 25 mm/week after onset of rains is optimum sowing time for rainfed regions. 400 mm of well-distributed rains in July and August are conducive for vigorous and luxuriant growth. Incessant rains or a long spell of dry weather may prevent the sowing of the crop at the proper time, hinder seed germination, or retard crop growth. Delayed germination could possibly expose the seed to fungal infections.

Heavy rainfall with intensity of more than 100 mm in 24 hours, cause flooding and waterlogging in cotton fields, damaging standing crop. Waterlogging is detrimental to growth of cotton crop due to poor aeration in the root zone. It has also been observed that the effect of waterlogging becomes evident after about a week's time when photosynthetic rates drastically decrease by about 86%. Heavy rains or excessive drought may cause heavy shedding of buds. Water deficit stress may result in stunted growth of plants due to reduced leaf area expansion.

Excess rainfall and high relative humidity during flowering can lower the value of the lint index. Heavy rains during peak flowering and ball formation (300-400 mm in September or continuous rains in October) increase ball shedding, which in turn leads to delay in maturity. Rainfall not only increases soil moisture but destroys the process of pollination and fertilization of cotton plants, leading to the abscission of buds and balls. When rainfall occurred during the daytime, the abscission rate was 80-90%, but with nighttime rainfall, it was 40-70%; and on dry and sunny days, it was 20-40%. When rainfall was less than 1 mm, the abscission rate was 49.3%; and when rainfall was 1-6 mm and more than 10 mm, the abscission rate was 52.9% and 80.4% respectively.

Precipitation or humid weather conditions during later stages of cotton growth can promote the pests or insects attack and disease such as boll rot (Boyd et al., 2004). Water stress can manifest reductions in photosynthetic activity and increases in leaf senescence (Gerik et al., 1996), the stunned plant with reduced leaf (Pettigrew, 2004b). Drought stress can cause severe shedding of small squares, resulting in a decrease in flowering reduce fiber length (Pettigrew, 2004a). Hence, a combination of warm and dry weather conditions along with abundant sunshine and sufficient moisture during the bolls opening till the harvest will maximize yield and quality potential (Freeland et al., 2006). For attaining its potential productivity, it requires long frost-free days, warm-season with a mean annual temperature of over 16°C, plenty of sunshine, and a moderate rainfall usually from 450 to 750 mm. Mono-cropping of cotton and heavy dependence on chemical fertilizers should be avoided in order to maintain the stability of cotton production. The cotton crop can be successfully cultivated on all soils (sandy loam, clay loam, loam, alluvial soils, black cotton soils, red sandy loams to loams, and lateritic soils) except the sandy, saline, and waterlogged soils. Cotton is semi-tolerant to salinity and sensitive to waterlogging and thus prefers well-drained soils. Cotton requires soil with excellent water-holding capacity, aeration, and good drainage since excessive moisture and waterlogging are detrimental to production.

1.1.5 Impact Of Changing Climate On Cotton Crop

Cotton belongs to the C_3 plant and requires warm days and cool nights for optimum growth and development. The crop encounters various biotic and antibiotic stresses, which disturbs its physiology and productivity during its growth and development. Among abiotic factors, moisture deficit, temperature extremes, and salinity due to changing climate are significant threats and account for a 50% reduction in the yield worldwide (Boyer, 1982). With the changing environment as the number of extremes will be amplified, it can negatively affect the crop. Studies indicate that the changing climate and environmental conditions will influence cotton productivity. These alterations can disturb the physiology of the crop. The response may vary according to the developmental stage, the severity of the impact, the climate of the location, and the cultivar's optimum range. The intricate pattern of the crop and indeterminate growth habit makes it more vulnerable towards stress (Loka and Oosterhuis, 2012; Reddey et al., 2005).

The impact of climate change and frequency and severity of extremes are essential for crop productivity assessment (Rosenzweig and Parry, 1994; Houghton et al., 1996; Rosenzweig and Iglesias, 1998). With increased carbon and higher temperature, the metabolic rate of the cotton crop is enhanced in the future (Reddy et al., 2002). Increased CO_2 has aggrieved the photosynthesis and abetted more squares, and then flowers, enhanced temperature above optimum has prompted ball abscission. It can also affect plant fitness and flowering related events by regulating flowering time (Jagadish et al., 2016). Among the climate variables, fluctuating temperature and rainfall predominantly affects the cotton (Reddy et al., 2005). The growing period has also been reduced by 11 days in the projected future in the Mississippi Delta region (Reddy et al., 2002). Severe sucking pests and related diseases and the dominance of weeds are expected in cotton (Sankaranarayanan et al., 2010).

Among the biotic effects, pests and diseases cause significant stress and yield reduction. Temperature and moisture have an impact on the host crop and the pathogen. So, the general increase in temperature induces increased ET and relative humidity, which favor the pest and associated disease (Rosenzweig and Hillel, 1998). Studies show increased biomass with increasing CO_2 also favors pathogens. On the contrary, with increased CO_2, host plants can also develop resistance due to physiological changes in the plant (Coakley et al., 1999). The pest populations in the cotton crop are also relatable with the weather variables. Studies indicate correlations of a different pest with the maximum and temperature, relative humidity, rainfall, etc. (Bishnoi et al., 1996; Janu et al., 2017). It is also found that increasing temperature also makes the crop vulnerable to pest attack, and in response, the crop may loose vegetative and fruiting bodies (ITC, 2011).

The impact of climate change also depends upon the area where the crop is sown and its present environmental conditions and crop's optimum range for tolerance. On the one hand, in arid and semi-arid cotton-growing regions where the temperature is near optimum, an increase in temperature has been found inducing fruit shedding (Brown, 2008). On the other hand, where the temperature is below the optimum range of tolerance, a slight rise is seen to be benefitting (Reddy et al., 1995). Apart from site-specific environmental conditions, the impact of stress could be dissimilar, conferring the cultivar's genetic constitution and is tolerance based on its enzymatic action conditions (Loveys et al., 2004; Reddy et al., 2005).

With the changing climate, crop responses varies from region to region based upon their regional weather, soil type, plant type, etc. Studies indicate the projected high temperature is better for cotton crops in the colder region with longer growing seasons, whereas in the warmer regions, hasted growth and development could reduce yield and quality of the crop (Rosenzweig and Hillel, 1998). The impact of changing climate on simulated cotton was pernicious in hot and dry years and was anodyne in a cold and wet year (Reddy et al., 2002). Among the three cotton growing zones changing climate have different implications, projected decreasing temperature and increasing precipitation in the northern zone can prolong the growth period and amplify the pest and disease susceptibility. Repercussions can be seen in sowing dates of the subsequent rabi crops. The central and southern zones region projected increasing temperature and decreasing rainfall with extremes in temperature and erratic distribution of rainfall characterized by recurring seasonal wet and dry spells. Therefore, escalated evapotranspiration demands may affect crop yield (Sankaranarayanan et al., 2010).

With the changing climate, erratic rainfall occurs, which is found to be disastrous for the cotton crop even in the irrigated regime. The flowering and ball formation is most sensitive towards water stress, which affects the yield and the fiber quality of the crop (Loka and Oosterhuis, 2012; Lokhande and Reddy, 2014; Shikha et al., 2018). Under irrigated conditions, cotton yields increased significantly with changing climate driven at RCPs 2.6, 4.5, and 6.0 in the years 2050 and 2080 with low to moderate emission levels. But, at RCP 8.5 and under the highest emission scenario, the cotton yield increased in 2050 but declined significantly in the year 2080. But under rainfed conditions, the yield declined in both 2050 and 2080 under all four RCP scenarios. However, the yield still increased when enough rainfall was received to meet the water requirements of the crop, in about 25% of the cases (Saseendran et al., 2016). The simulations show that change in meteorological parameters can influence crop productivity, which results from climate change. The increase in temperature would lead to reduced cotton yields in future scenarios. But while assessing with increased CO_2, the effects of rising temperature and decreased water availability get ameliorated to increase the yield attributes, also termed as 'CO_2 fertilisation effect'. Therefore, with increasing temperature, providing irrigation amounts by almost 50 % would help the plant sustain and enhance productivity by maintaining adequate soil moisture levels (Williams et al., 2015). Studies also suggest with an increasing ET, the crop water demand surging and supplemental irrigation will be required in the future to reduce canopy temperature and reduce ball abscission (Reddy et al., 2002).

1.1.6 Climate Change And Its Future Projections

As per IPCC, Climate is average of weather conditions and the statistical description of the weather variables in terms of mean and variability for around 30 years over a region. Climate change in the present era is mostly influenced by anthropogenic changes in the atmospheric constituents and land-use patterns. Historical climatic information can be utilized to understand its intricacies and take advantage and divert ill effects of weather. Future climate change scenarios can also be assessed based on modeling to mitigate its ill effects. Although with the changing climate, the intensity and frequency of intermittent rainfalls with longer periods of dry and wet spells and extreme hot and cold days are threatening for the crops across the globe (Liebig et al., 2012). With this still evolving climate change scenarios, our soil, water, and other natural resources are also deteriorating (Gurdak et al., 2012). For most crops, elevated temperature and carbon dioxide affect biological processes like respiration, photosynthesis, plant growth, reproduction, water use, etc. (Murthy, 2002). Also, policymakers and resource managers require information for future climate scenarios to understand and anticipate the potential impact of changing climate on agriculture and food security. So in order to formulate the policies, reliable climate projections are required. In addition, adaptation and development of response strategies strongly rely on regional effects.

1.1.7 Climate Models

Climate models are developed for understanding how the climate system works with the help of advanced computing systems. They work by resolving basic equations describing the energy, mass, momentum, and moisture at various grid points on, below, and above the surface (Sweeney, J. C. 2009). As defined by Sweeney (2009), GCMs are "Three-dimensional mathematical simulations of the processes that regulate the global climate system" and "Regional Climate Models (RCMs) are “To overcome the difficulties posed by coarse grid GCMs, RCMs with a higher resolution are constructed for smaller areas. These are driven at their boundaries by a parent GCM”. Several General Circulation Models (GCMs) and Regional Climate Models (RCMs) are utilized as a tool to obtain high-resolution climate information. For regional climate, GCMs are statistically and dynamically downscaled to enhance resolution based on digital elevation models (DEMs), representing the realistic topography. These synoptic-scale GCM fields can be nested for high-level fidelity with associated mesoscale resolution field with the RCM simulations. In the nesting technique, the output from GCMs is utilized to drive time-varying lateral (vertical profile for temperature, wind, humidity) and surface (sea surface temperature and pressure) boundary conditions to capture the atmospheric conditions over the region of interest. GCMs can do a reasonable job simulating global values of surface air temperature and precipitation (Goudriaan, 1977). They are mostly utilized for estimating variables such as temperature precipitation etc. for climate change scenarios but could not resolve regional small spatial scales (Sørland et al., 2018).

Although GCMs have so far produced reliable projections of changes in climate variability, such as alterations in the frequencies of drought and storms, etc. (Penning et al., 1974), which could significantly affect crop yields GCMs are the primary source of information on climate scenarios but still have the drawback of having high spatial resolution and inability to capture interannual variability which is rectified by RCM on regional scales (Metzger et al., 2005; Khan et al., 2008). The resolution of GCMs is too coarse to provide precise climate information over a particular region; RCMs are commonly nested over there GCMs to produce detailed data for climate realizations. Ensembles of GCMs and RCMs simulations are available with internationally coordinated projects like CMIP5 (Taylor *et al.*, 2012), CORDEX (Giorgi *et al.*, 2009), etc. RCMs improve the small scale features compared to its driving GCMs (Sørland et al., 2018). This improvement is not only the result of an added value of resolving large scale forcing over the complex terrain but due to better representation of underlying processes (Torma et al., 2015).

1.1.8 Bias Correction

The model projections from GCMs and RCMs have some degree of biases. It is essential to assess the performance of the model and with the observed data to identify the underlying shortcomings or bias, their strength before using its future projections, which are subjected to statistical bias-correction (Piani et al., 2010). This post-processing process corrects the systemic bias for improving the utility of model projections for end-users (Maraun et al., 2010). These biases can be induced due to 'systematic model errors,' 'boundary conditions' etc. Typically, preferences include innumerable wet days with low-intensity precipitation and erroneous assumptions for extreme temperature (Ines and Hansen, 2006; Teutschbein and Seibert, 2012).

Various methods to adjust the biases in RCM simulations include 'linear scaling, local intensity scaling, power transformation, variance scaling, distribution transfer approach as by probability mapping (Ines and Hansen, 2006), quantile mapping (Sun et al., 2011), statistical downscaling (Piani et al., 2010) and histogram equalization (Rojas et al., 2011). This study 'Distribution mapping of precipitation and temperatures by quantile mapping' method is utilized to reduce uncertainty linked with model data. Studies indicate that these bias-corrected weather variables of RCM are better fitted with the observed values than the model output (Mall et al., 2017). The change in temperature in these zones is most likely periodic expected to increase in the near future and far future as per the model.

The observations versus simulation and its bias-corrected version offer a comparatively viewpoint for credible information (Gudmundsson, 2014; Maraun, 2016). These models are trained and accustomed to understanding the process and simulating past, present, and future climatic conditions. Where these observations and simulation studies give a complementary prospect for any region (Gudmundsson et al., 2012; Gudmundsson, 2014; Thrasher et al., 2014).

1.1.9 Crop Simulation Model

Since the last decade, crop simulation models have been extensively used in agriculture to simulate crop responses towards different abiotic factors. Now they are also focusing upon developing a model that helps in the study of biotic stress too, such as pest. Crop models help us to assist in the synthesis of research. It provides us in inferring the interaction of genetics of the plant, its physiological and environmental interactions. For the evaluation of agronomic management strategies, the organization of data is an important tool (Mubeen et al., 2013; Wajid et al., 2013; Boote et al., 2010; Hoogenboom et al., 2004; Jones et al., 2003).

In this study, the DSSAT-CSM cropping system model: Version 4.6 is used. The Decision Support System for Agrotechnology Transfer- Cropping System Model (DSSAT-CSM), which includes the CROPGRO-Cotton model as an assemblage of independent programs that operate together. It aids in reducing the time, cost, and human resources required for analyzing the complexities and concluding for an alternative decision. This software helps users prepare the database and compare simulated results with observations to give them confidence in the model. This also assists in determining weather modifications are needed to improve accuracy or to achieve the potential yield. This way, it could be practically helpful for the cultivators to select the best management practice to raise production and productivity.

Parameters such as cultivar characteristics, maximum and minimum temperature, solar radiation, and crop management's factors are considered for crop growth models (Mahamood et al., 2003; Hoogenboom et al., 2011). The suite of crop simulation models encompassing the Decision Support System for Agrotechnology Transfer (DSSAT) includes the Cropping System Model (CSM)-CROPGRO-Cotton model (Jones et al., 2003; Hoogenboom et al., 2004). CROPGRO-Cotton is a recently developed crop model and consists of several parameters (Pathak et al., 2009). A study by Ortiz et al. (2009) states that the model simulates growth, development, and yield of cotton in correspondence to various factors like weather and soil conditions as well as management practices. Li et al. (2009) used the new semi-empirical model to simulate cotton leaf and concentration of ball nitrogen. They studied the direct indicator of nitrogen fertilizer and its effect on growth, development, and cottonseed. In terms of modifying weather simulation generators/or introducing a package to evaluate model performance for changing climate, the CROPGRO module under DSSAT can be used and was one of the first such package (Murthy, 2004).

Climate model data serve as input for the hydrological and crop simulation models to analyze the effect of changing climate on the crop ((Rauff, 2015; Mall and Aggarwal, 2002). These data are also applied as inputs in the crop simulation models to provide a more scientific approach for the study of climate change impact on cotton (Hebbar et al., 2013; Saseendran et al., 2016; Mall et al., 2018). Several crop simulation models are being utilized along with field studies to examine the crop yield and climate sensitivity under different scenarios (Aggarwal et al., 2006) like General Large Area Model (GLAM) (Sanai & Chun, 2017), Decision Support System for Agro-technology Transfer (DSSAT) (Saseendran et al., 2016; Mall et al., 2017), InFoCrop (Aggarwal et al., 2005), AquaCrop (Pareek et al., 2017), etc. (Anwar et al., 2007; Ortiz et al., 2008; Singh et al. 2017; Mall et al. 2018).

But the restraints while integrating these crop models are that the spatial scale is much smaller than those of the climate models (Hansen and Jones, 2000; Jagtap and Jones, 2002). So the weather data has to be downscaled as per the model requirements. However, using this process-based model such as DSSAT-CSM helps in analyzing some multifaceted relations (Dounias et al., 2002; Ortiz et al., 2009; Boote et al., 2010; Pathak et al., 2012; Thorp et al. 2014) by facilitating us for analyzing biotic and abiotic factors individually or in association with each other (White et al., 2005; Liu et al., 2010). Inputs from various and GCM are applied for the estimation of different crops like wheat (Pathak et al., 2003; Gourdji et al., 2013), rice (Kumar et al., 2013; Kumar and Aggarwal, 2014) cotton (Hebbar et al., 2013; Saseendran et al., 2016) and RCM models wheat and rice (Mall et al., 2018), etc.

1.2 RELEVANCE AND MOTIVATION

Due to the changing climate, agricultural productivity can be affected; therefore, it is a prerequisite to study its effect on the crop in the present and future climate in different regions. Studies indicate that the variability of our climate and especially the associated weather extremes, is currently one of the prime concerns for the general community (Murthy et al., 2002). Watson et al. (1998) have assessed various climate change scenarios according to which, increase in temperature in south Asia will range between 0.1–0.3 ºC and 0.4–2.0 ºC and CO_2 concentrations will be between 397–416 ppm and 397–416 ppm for 2010 and 2070 respectively. The changing climate will have a negative effect on agriculture and food security in many countries. Similarly, in many other studies observed that a relative increase in CO_2 concentrations at a higher rate and increase in temperatures at lower rates could be considered as an optimistic scenario since this is expected to favor crop growth. On the contrary, a high rate of increase in temperature and a low rate of increase in CO_2 can be assumed as pessimistic because of adverse effects on crop growth (Reddy et al., 2005; Anapalli et al., 2016). This study emphasizes the vulnerability of cotton due to climate change in the central rainfed and northern irrigated agroclimatic zone for cotton. This study also outlines the effect of changing temperature and CO_2 individually and together in the present climate to assess the crop response by modeling approach.

Cotton, as a principal commercial crop, has economic relevance for the country. India is at the first place in production and acreage and contributes 26.75 % (345.82 lakh bales and 38.13 % (118.81 lakh ha in 2015-2016 (Status of cotton report 2017). However, the average productivity is 522 kg/ha against the world average 765 kg/ha with a gap of 243 kg/ha. The reasons for low productivity are weather aberrations, which includes excess or deficit rain in the present scenario and variability of rain and temperature for future crop. Also, pest and disease incidence, especially sucking pest, is major concern for the crop. In the era of changing climate, cotton is projected to face diverse abiotic and biotic changes.

For estimating these earlier various studies are conducted based on field experiments. Now, this is complemented with computational methods such as modeling and remote sensing with an evolving era of digitization. Various agro-meteorological models have also been used, and optimal combinations of different parameters and meteorological derivatives have improvised to assess and predict the model outputs. These models have good potential for early crop yield assessment; the study of various type stresses at different phenological stages is necessary so that measures can be taken for its amelioration. All this give an insight into the productivity in advance. The model has an additional advantage of evaluating different permutations and combinations of management practices that could be evaluated through the model to find the most suitable for changing climate at different scenarios. The utilization of crop simulation models to study climate variability's impact provides a direct link between the field research with the models and meteorological variables that are concern forn the farmers and society.

Since climate change deals with future issues, the use of General Circulation Models (GCMs) and Regional Climate Models (RCMs) provide a more scientific approach to study the impact of climate change on agricultural production and world food security. CROPGRO is one of the frirst packages incorporated under DSSAT that modified the weather simulation generators and also introduced a package in the CSM to evaluate the performance of the model for climate change scenarios. The utilization of GCMs irrespective of the limitations are of the larger interest for the farming community of the world. The DSSAT modelers also find these GCMs to me for nearly accurate and, therefore, acceptable for weather generators in models. This can also help in finding solutions to crop production under climate change conditions, especially in underdeveloped and developing countries (Rauff, 2015).

The GCM projections in the Mississippi delta region exhibited a rise in 4°C in average temperature approximately and a decrease in the amount of precipitation during the cropping season. As per studies, the effect of climate change on cotton production was more drastic in a hot and dry year. They indicate that, if climate change occurs as projected, the production of fiber in the future will be compromised, and developing heat-cold-tolerant cultivars will be necessary to sustain cotton production (Anapalli et al., 2016). Cultural practices vested as climate-smart agriculture, such as planting earlier, can be practiced to prevent the flowering in cotton during high temperatures that occur during mid to late summer. This study, based upon two different agrometeorological cotton growing zones, signifies which zone is favorable for future climate cotton production and with what measures. This study also emphasizes the importance of planting dates as climate-smart agriculture measures.

General Circulatory Models (GCMs) have so far has produced projections for climate change and climate variability, with alterations in the frequencies of drought and storms, which could significantly affect crop yields (Penning et al., 1974). GCMs also does a reasonable job in simulating global surface air temperature and precipitation, but evaluate poorly at the regional scale (Goudriaan, 1977). General circulation models (GCMs) are used to study the variability in the climate projections, variable, and its magnitude of change on a regional basis (Mitchell et al., 1990). GCMs, provide us with data with a coarser resolution. So, Regional climate models (RCMs) could be preferably applied for regional scale data to study the impact on the crop, on a finer scale spatial data. RCMs are dynamically downscaled GCM outputs for regional scale (Sun et al. 2006). RCMs provide high-resolution data for regional scale with the influence of local heterogeneity compared to what can be obtained from GCMs. This study utilizes the RCM model output for the study, which is also bias corrected. In the study, the RCM model performance has been evaluated in the present climate for the study region. The bias corrected data has been compared to the observations for the present climate to see how reliable the model is for future projections. Further, the future projections from the evaluated best performing model data have been used to analyze the productivity and suitability of the crop at different scenarios with different agricultural practices to find the site specific best management practices for the future climate.

Apart from these abiotic constraints, there are some biotic constraints, also like the pest. Aphids, jassids, mites, bollworms, and whiteflies are major pests affecting the crop. So as to protect them, pesticides are widely used to such an extent that more than 50% of total production cost is attributed to pesticides alone (Sundaramurthy et al., 1998). Boyd et al. (2004) studied that humidity is a major contributor to pest and insect attacks, e.g., ball rot after ball opening. Hence, it can be concluded that the most suitable conditions for maximizing the yield include warm, dry weather conditions, abundant sunlight, and availability of soil moisture since the period when the balls start opening through harvest. Whitefly (Bemisia tabaci) is an insurgence of this insect species that has been noticed in recent years in the cotton system in India, resulting in heavy losses. During Kharif-2015 in Punjab, the pest damaged over 75 percent of the crop. It was considered the major reason for the suicide of more than 12 farmers. Haryana and farmers had suffered huge losses due to the white-fly attack (The Hindu, Oct 2016).

Whitefly-transmitted geminiviruses are a major constraint to the production of agricultural and vegetable crops in the tropical regions and subtropical regions of the world (Morales et al., 2004). It causes physiological damage resulting in considerable economic loss. Recent studies suggest that disease incidence CLCuD and whitefly have some correlations with the temperature (Wang et al., 1996), rainfall, and planting dates accordingly (Umar et al., 2003; Farooq et al., 2011). Thus pests has been found to have correlations with the weather, so various regression equations are utilized for their prediction, and recently this is accompanied by the remote sensing approach for real-time screening. In this study, various regression equations utilized for prediction are mentioned, and with the application of remote sensing the difference between infested and non-infested years are shown, which can help the growers to implement better pest management strategies on time for potential productivity.

The maintenance of critical agro-ecosystem functions requires proactive responses through the strategic application of management practices that mitigate greenhouse gas (GHG) emissions and/or adapt to impacts from climate change. The effects of climate change help scientists recommend farmers and growers to make proper crop management considerations such as selecting crops, cultivars, sowing dates, and irrigation scheduling to minimize the risks. The productivity can be enhanced, and the adaptation of crop to climate change can be brought through the changes in cropping patterns, farming practices, and harnessing of new technologies that will help ease its effect apart from the use of chemical fertilizers insecticides.

1.3 OBJECTIVES OF STUDY

This model-based study focuses on the vulnerability and adaptability of cotton crop with climate change in diverse agroclimatic zones with varied agricultural practices. Initially, it evaluates the present-day climatology based on station data with variations in temperature and CO_2 in the crop simulation model. Further, based upon the RCM projected data for the present climatology for the period 1970-2005 representing the present climate. Model data was bias corrected by the Quantile Mapping approach implemented with the help of ‘qmap' library written under R. Then for future climate for the period daily weather from 1971 to 2005, 2006 to 2035, 2036 to 2065, and 2066 to 2095 averaged to represent projected climate centered at historical (1990), present (2020) and climate change scenario at near future (2050) and far future (2080) for both RCP 4.5 and 8.5. The CO_2 concentrations are taken as 353, 415, 486, and 531 for RCP4.5 and 353, 415, 539, and 757 for RCP8.5, respectively (Vuuren et al., 2011; Anapalli et al., 2016; Dua et al., 2018). For pest assessment, the conventional forecasting approach based on developed regression equations with weather variables is mentioned along with advanced technological estimation with remote sensing for real-time monitoring approach for the pest attack above ETL between infested and non-infested years are shown along with field validation. The calibrated and validated and DSSAT model was utilized for simulating the impact on crop yield and physiology. The most widely used crop was considered for the study with three sowing dates and recommended packages and practices. The information about the impact on cotton at different climate scenarios could further contribute to the growers and scientific communities to have site-specific crop management and variability within the field for potential productivity with the changing climate. The study also focuses on the biotic stress, which is found to affect the productivity of cotton severely. The assessment of pest attack has been done by remote sensing for the year 2013-2018 to see the difference infestation status of the crop as per crop calendar. The study embrace utilization of climate models to study the vulnerability and adaptability of cotton crop in future climate change scenarios. And the application of crop growth models for developing site-specific crop management strategies, yield forecasting, and the sustainability of the crop, climate change impact assessment, and economic analysis for bringing precision in agriculture. Thus, broadly, the main objectives of this study are:

1. Model-based approach to study the response of Bt-cotton towards elevated temperature and carbon dioxide in the semi-arid region of Hisar.
2. Application of remote sensing for detection of stress in cotton induced by pest in Hisar.
3. Evaluating the performance of regional climate model for cotton production in rainfed and irrigated regions using DSSAT
4. Simulating the impacts of climate change on irrigated and rainfed cotton production in India.

1.4 STUDY REGION

The study region for Chapters II and III is Hisar (Figure 1.1), Haryana. Later, considering the fact that 58% of net cultivated area in India is rainfed and climate change will further exuberate the problems of rainfed agriculture (Turkhede et al., 2018), another location was added in chapter IV and V to assess the impact of climate change between the diverse environment and management conditions in India. Hisar has dry semi-arid climatic conditions and alluvial soil; the cotton crop grown here is mostly irrigated, whereas Akola (Figure 1.2) is located in Vidarbha in the region of Maharashtra with a moist semi-arid climate and black soil where rainfed agriculture.

Hisar, the westernmost district of Haryana, situated between 74°24' to76°18'E longitude and 28°54' to 29°59'N latitude at an elevation of 215.2 m. It is the westernmost district of Haryana, representative climatology of the northern irrigated cotton-growing region. It is basically a semi-arid region with a temperature range of 40°C to 44°C in summer months and between 4°C to 6°C in winter months. The annual average maximum temperature is 31.5°C, and the minimum temperature is 16.2°C and an average annual rainfall of approximately 450 mm, of which 75 to 80 percent of annual precipitation is received during the monsoon season (Shikha et al., 2018). Akola is located at latitude 20°42’ North and longitude 77°07’ East. The climate is characterized as tropical savannah type, with medium and deep clayey black soil. It has hot summers and dryness throughout the year. The average annual rainfall is approximately 846.5 mm, and it rains mostly in monsoon, with July as the rainiest month. May is the hottest with 42.4 °C to 27.3°C and December is the coldest, 29.5°C to 12.4°C as average maximum and minimum temperature (Ghosh et al., 2014).

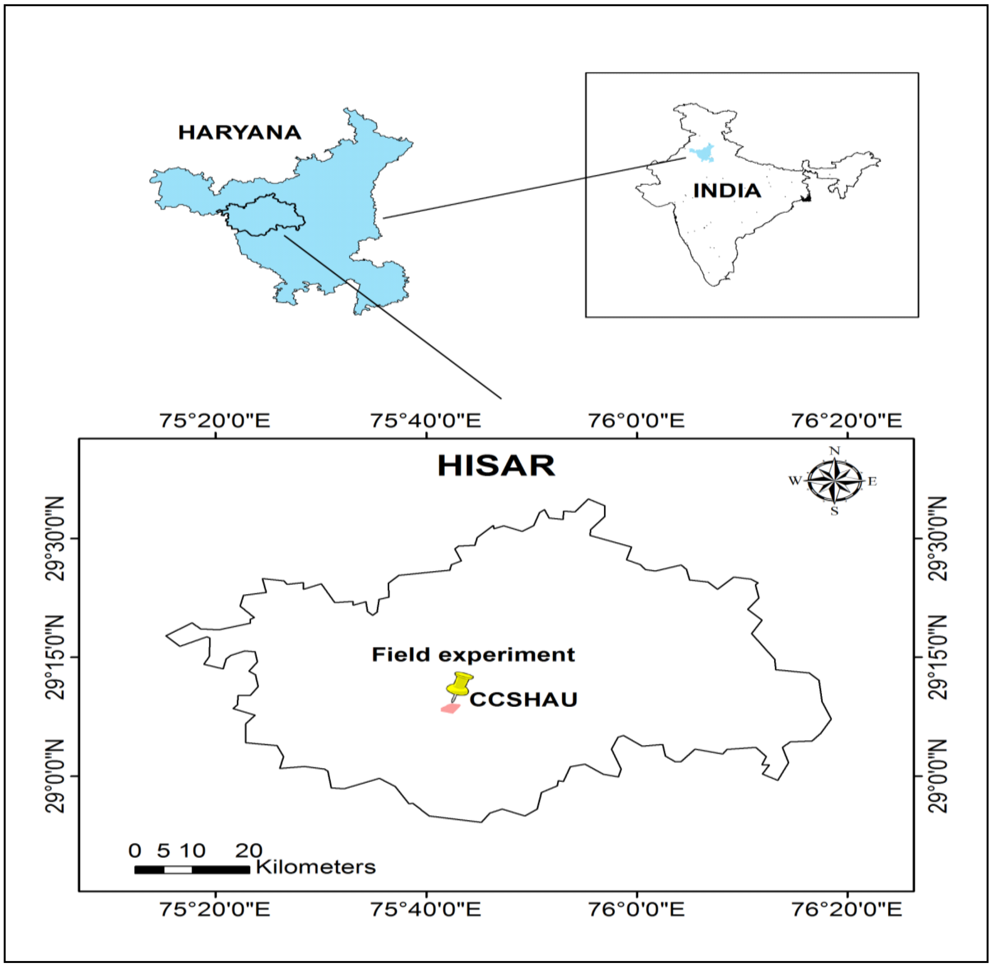

Figure 1.1 Area of study: Hisar, Haryana

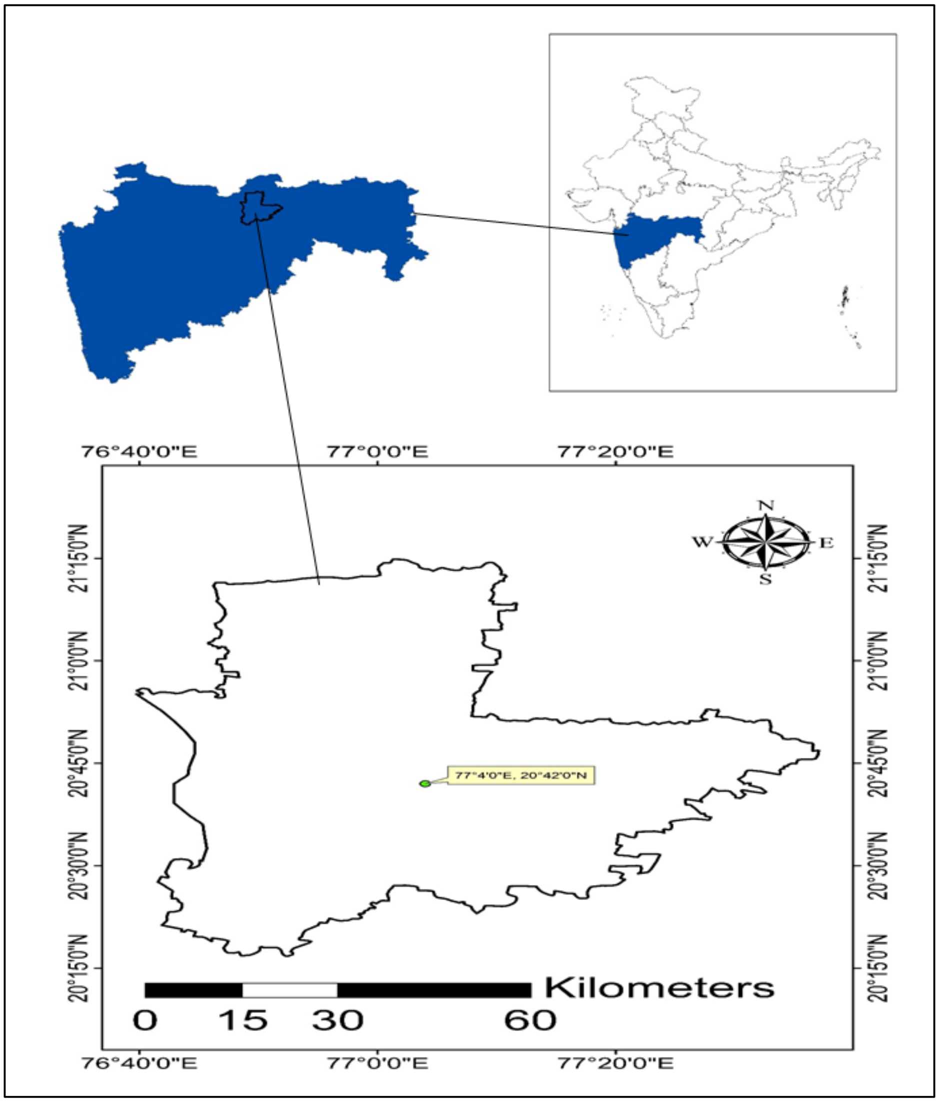

Figure 1.2 Area of study: Akola, Maharashtra

1.5 MODEL DESCRIPTION

Crop models are used to imitate or simulate the behaviour of real crop grown on the field. In this study, DSSAT-CSM cropping system model: Version 4.6 has been used. It is software application program that comprises dynamic crop growth simulation models for over 40 crops. The DSSAT-CSM is an assemblage of independent programs that operate together, which also includes the CROPGRO-Cotton model for fiber crop. It is capable of simulating the growth, development, yield and various other relevant parameters as a function of the soil-plant-atmosphere dynamics. It has a predefined input and output data format that has been developed and embedded in a software package. The datasets for management can be taken as per the field experiments conducted, considered to be grown over a uniform area of land and under prescribed management systems. It allows users to ask "what if" questions by conducting virtual simulation experiments on a desktop computer in minutes which would consume a significant part of an agronomist's career if conducted as real experiments. Changes and its effect could also be studied with the cropping system over time in soil, water, cultivars, carbon, and nitrogen that can take place. DSSAT also provides for evaluation of crop model outputs with experimental data, thus allowing users to calibrate and validate it (Hoogenboom et al., 2019) (https://DSSAT.net). It includes the following modules embedded for evaluation:

- **Weather module**: To read and generate daily weather data using WGEN or SIMMETEO.
- **Soil module**: Designed to read the soil properties as an input for the experiment.
- **Soil/plant/atmosphere module**: To compute daily soil evaporation, transpiration, and finally compute ET based on the Penman-FAO method (Doorenbos and Pruitt, 1977), LAI etc.
- **Template crop module (CROPGRO)**: To predict the growth of different crops such as cotton, soybean, chickpea, etc. from common source code (Boote et al., 1998a).
- **Individual crop module interface (plant module)**: Similar to CROPGRO, it links plants growth dynamics with other DSSAT-CSM modules.
- **Management module**: Includes input variables such as planting, applying nutrients, irrigating etc. specified as standard 'experiment' in input file (Hunt et al., 2001). It is then analysed with different years to see the impact of changing crop for different weather/year.
- **Pest module**: As an input, in-field observations to analyse insect populations or disease severity for specified pest and diseases infesting development and yield of the crop.

In the present study, the management practices are taken as per field experiments, which were based upon the prescribed package and practices for the respective area. Soil data are kept constant, with varying weather for analyzing the effects of changing weather and climate over the area.

1.6 DATA COLLECTION

The crop models require daily weather data, soil surface and profile information, and detailed crop management as input. Crop genetic information is defined in a crop species file that is provided by DSSAT and cultivar or variety information that should be provided by the user.

1.6.1 Field Experiment Data for Crop Model

For simulation of model three Bt-cotton crop varieties Pancham-541, RCH-791, SP-7007 in Hisar region of Haryana and AK 081 in Akola, Maharastra which is cultivated widely during the Kharif season. The genetic coefficient for this variety is already developed and reported by Dr. Ram Niwas (Swami et al., 2016; Sagar et al., 2017). Their sowing dates are 10^{th} May, 21^{st} May, and 06^{th} Jun which is widely practiced in this region. To achieve the objective, field experiment is conducted at AMFUs (Agromet Field units) at CCS University, Hisar and at Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola, Maharashtra during Kharif season under the Forecasting Agricultural outputs using Space, Agrometeorology and Land-based observations (FASAL) project by IMD (India Meteorological Department).

Daily agrometeorological observations are taken from the Agrometeorological Observatory under India Meteorological Department (IMD) situated near the experimental plots. Minimum weather data observed to be utilized for this study including daily maximum and minimum temperature, bright sunshine hours and rainfall were taken from here. There data was taken as baseline and observed datasets to compare with the model data and for bias corrections. Other management data such as nutrient, fertilizer and irrigation applications, plant spacing sowing dates etc., soil data and genetic coefficients has been obtained by field experiments conducted. These data had been earlier calibrated and validated for the DSSAT model over the region, Hisar (Swami et al., 2016, Shikha et al., 2018) and Akola (Nath et al., 2018; ICAR-CRIDA, Annual Report, 2017-18).

- ***Weather Module***

The weather module facilitates to read and generated daily weather data as per the model. It requires minimum data viz. daily weather data such as maximum and minimum temperatures, solar radiation and precipitation for the simulation.

- ***Soil module***

These input files include various information about the chemical and physical description of the soil profile. Distinct information for each soil horizon, its organic matter in the soil at the beginning of the experiment, soil water content initially, nitrogen concentration and the pH for each layer of the soil profile are important inputs. Sand, silt, and clay content information were collected from the station Hisar, Haryana.

- ***Crop data/cultivar module***

Crop cultivars for cotton are dominant varieties which include three Bt-cotton varieties grown by the cultivators of this region. Water and nitrogen management parameters considered in the model were as per agronomical recommendation widely accepted/practiced in these agro-climatic zones and field experiments conducted by AMFUs under FASAL scheme of IMD, India for different crops and cultivars.

- ***Genetic coefficient module***

This input data includes crop genetic coefficients, crop-specific characteristics, which explain how the life cycle of a Cotton cultivar, responds to its environment.

1.6.2 Climate Projections

For the impact of climate change in the Chapter IV and V the climate projections are taken from RCM experiments coming from institutions participating in the coordinated experiment under CORDEX-SA project. The data is available on CORDEX-SA databases maintained by Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), Pune, India which is the coordinating institution of this project and the Earth System Grid Federation (ESGF). In this study the best performing RCM weather data was obtained from GFDL-ESM2M-RegCM4 experiment of COordinated Regional Climate Downscaling Experiment (CORDEX). The regional model RegCM4 forced with global model GFDL-ESM2M experiment data is considered in the present study as it captures the seasonal precipitation (Choudhary and Dimri, 2017) and air temperature (Garg et al., 2015) with highest combined mean skill.

The Climate data is derived from Coordinated Regional Climate Downscaling Experiment (CORDEX) South Asia: (RegCM4- GFDL) with the host GCM (GFDL-ESM2M) as Regional Climate Model (RCM). RCMs are forced over the GCM data to improve the data explicitly and increase the resolution from 0.44 to 0.11◦ spatially and daily variability of the precipitation (Giorgi et al., 2013). These daily weather data sets are obtained from Coordinated Regional Climate Downscaling Experiment over South Asia (CORDEX- SA) and CMIP5 database, which is developed and maintained by Earth System Grid Federation (ESGF) (https://esgf-data.dkrz.de/projects/esgf-dkrz). The spatial resolution varies from 50 to 200 km (Taylor et al., 2012) which is enough to simulate the physical process that dominates the atmospheric dynamics on a large scale although it cannot resolve subgrid processes therefore need to be parameterised (Giorgi et al., 2013; Rajczak and Schär, 2017).

These data has been downloaded and extracted at the study region Hisar and Akola in the northern and central cotton-growing climate zones with the help of CDO (Climate Data Operator) in the format required for DSSAT. Minimum weather data required for the cropping model are daily maximum and minimum temperature, rainfall and sunshine duration. DSSAT generates site-specific weather data stochastically using built-in SIMMETEO software.

In Chapter IV, 1971 to 2005 is considered for the study, since it is available as a historical database after which different scenarios are inlaid as RCP 2.6, 4.5, 6.0 and 8.5. The GFDL-ESM2M shows the highest skill in capturing the seasonal mean precipitation

(Choudhary et al., 2018) and hence considered in the present study. Studies based on RCMs include CORDEX- SA (encompassing India) as a set of multiple RCM simulations under a common framework. These RCMs are driven by various GCMs from the Coupled Model Intercomparison Project Phase- 5 (CMIP5) (Taylor et al., 2012; Giorgi and Gutowski, 2015).

RegCM4 performs better in simulating the present climate over India and therefore it is preferable over the Indian Subcontinent (Gao and Giorigi, 2017). Still, conspicuous and systematic biases exist which attributes to limited process understanding in the dataset. To overcome this, post-processing is done by downscaling processes and bias-correction of the output. The underlying aim is to introduce statistical transformation so that the simulated model output distribution resembles the observation (Gudmundsson et al., 2012; Maraun 2016). In this study, the Quantile Mapping (QM) approach is used which calibrates the cumulative distribution function of model data for correction. It is implemented with the help of qmap library written for R statistical software (Gudmundsson et al., 2012; Zhao et al., 2017). Software packages based on R are developed and made available in public domain, which can be downloaded explicitly to downscale (https: //github.com/SantanderMetGroup/downscaleR, assessed on: 03rd Aug 2017).

1.6.3 Remote Sensing Data and its Field Observations

Satellite images from the LANDSAT 8 has been taken for the study. It was launched on 11th Feb 2013 by the National Aeronautics and Space Administration (NASA), which has 11 bands with a spatial resolution of 30 m, and 15 m for panchromatic band is 15-m. It has been upgraded from its previous Landsat satellite as the red, near-infrared, and shortwave infrared bands were narrowed. The radiation resolution was also increased to 16 bits. The signal-to-noise ratio was refined. These advances revamped its ability for vegetation discriminations. The LANDSAT data are available in the public domain on http://earthexplorer.usgs.gov/ and has contributed a lot is research and development purposes. For assessing the stress in the crop and quantifying the crop health VIs such as NDVI and NDWI are mostly used. The LANDSAT data downloaded from the 04th May

2013 to 16th Oct 2018 were obtained from the USGS Earth Explorer website. The data was combined with the high-resolution imagery from Google Earth™ taken for 5 sample points with coordinates 29.151562N -75.697045W, 29.151571N, -75.697218W, 29.151565N -75.697223W, 29.151526N-75.697155W, 29.15156N-75.69716W in the research field of HAU, Hisar, Haryana, India. It was further processed and subset was created as per the Area of Interest (AOI).

For validation filed observations were taken from the the study was conducted during the Kharif season of 2014 and 2015 on various cotton genotypes on the Research farm, Cotton Section of CCS Haryana Agricultural University, Hisar. The crops were grown unprotected with three replications. The plots consisted of 5 rows of 5 m each. Seeds of 23 genotypes were sown by hand dibbling method on May 2014-15. Observations were taken for the sucking pests on five randomly selected plants recorded weekly from 23rd to 41st Standard Meteorological Weeks on three leaves each from top, middle and bottom.

Figure 1.3 Area of field experiment and satellite data sampling point in Hisar farm field.

1.7 METHODOLOGY

The methodology applied to achieve the different objectives of this work is described briefly in this section in this section and elaborately in related the chapters.

1.7.1 Model-Based Approach to Study the Response of Bt-Cotton Towards Elevated Temperature and Carbon Dioxide in the Semi-Arid Region of Hisar

To assess the vulnerability of cotton, it's important to assess crop simulation model for the present data observed from the station. The calibrated and validated CROPGRO-cotton crop models under DSSAT vn.4.6 for different agro-climatic zones has been used for simulating the crop yields and physiology. With the changing climate temperature as well as CO_2 is rising, whereas the precipitation pattern is erratic with spacial and temporal variability at regional scale. Rising temperature and CO_2 is assessed separately and the together to assess the sensitivity of model. The climatology of thirty-five years daily weather data from IMD has been taken for Hisar station starting from 1981 to 2015 taken as normal. Seasonal simulations are carried out for that duration to assess present climatological impact of 35 years on the crop; Harvest index (HI) "Harvest index is defined as ratio of the reproductive yield with respect to total plant biomass", Evapotranspiration (ET; mm) "It is the sum of crop transpiration and transpiration from crop adjacent soil and water surface" , Leaf Area Index (LAI; Maximum) "It is generally defined as leaf area of one side per unit ground area for broadleaf canopies" and Maturity date (MD) "Days of physiological maturity of the crop from the planting date" .

To examine the impact of increasing temperature under changing climate; four different simulations are carried out taking Normal climatology, further by adding 1ºC, 2ºC and 3ºC to the climatological temperature value in the simulations. Similarly, another set of four simulations are made by increasing the CO_2 by 50ppm, 100ppm and 150ppm respectively to estimate the impact of increasing CO_2 on yield. Further, four new simulations are designed by changing the CO_2 concentration and temperature together in order to examine impacts on the productivity.

1.7.2 Application of Remote Sensing for Detection of Stress in Cotton Induced by Pest in Hisar.

The pest population and its relation with weather can also be assessed or forecasted from the empirical equations and models generated by statistical analysis based on the field observations. These generalised equations takes the meteorological parameters such as temperature, rainfall and humidity to forecast the frequency of pest. It can give a modest estimation about the different pest population. They are developed based upon the field experiments on the growing regions and then validating with its statistically significance. This can be complemented with remote sensing approach for real-time analysis and assess crop health. Many of the crop responds towards the stress are visually quantified with acceptable accuracy from reflected electromagnetic radiation from the plant canopies. Satellite images from the Landsat 8 has been taken and from that Vegetation indices (VIs) such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) are computed for the study region for 5 sample points. The multi-temporal LANDSAT images are then collected to composite a time series after cloud masking. These indices were further analysed with the crop calendar and validated with the field observations.

1.7.3 Simulating the Impacts of Climate Change On Irrigated and Rainfed Cotton Crop: Part-I- Present.

Analyzing the performance of model data in comparison to the actual observations and inspect the model biases and strengths is important before using their future projections. Thus validating the model and improving or bias-correcting the data aids in identifying the best performing model for the area of interest and strengthen the reliability for the model and its future projections. The minimum data required for crop simulation model as weather variable such as daily Maximum temperature (℃), Minimum temperature(℃), Solar radiation (MJ/m2), and Rainfall (mm2) are derived both from the station and derived from the model. The source data for the study is extracted and downscaled from the Regional Climate Model. These RegCM 4 outputs are availale in

NetCDF format and contains data on daily, monthly and yearly basis. The gridded data of the RCM are then extracted with the help of CDO for location. Since, the DSSAT crop model are required to have a particular supportable format.

The period considered for the study is from 1971 to 2005, since it is available as a historical database after which different scenarios are inlaid as RCP 2.6, 4.5, 6.0 and 8.5. Weather data were taken from the nearest agromet station of IMD during the field trial and from GFDL-ESM2M-RegCM4 experiment of Co-ordinated Regional Climate Downscaling Experiment (CORDEX). Under World Climate Research Program for the domain CORDEX-SA. The GFDL-ESM2M shows the highest skill in capturing the seasonal mean precipitation (Choudhary et al., 2018) and hence considered in the present study. Studies based on RCMs include CORDEX- SA (encompassing India) as a set of multiple RCM simulations under a common framework. Although, RegCM4 performs better in simulating the present climate over India and therefore it is preferable over the Indian Subcontinent (Gao and Giorigi, 2017). Still, conspicuous and systematic biases exist which attributes to limited process understanding in the dataset. To overcome this, post-processing is done by downscaling processes and bias-correction of the output. In this study, the Quatile Mapping (QM) approach is used which calibrates the cumulative distribution function of model data for correction. It is implemented with the help of qmap library written for R statistical software (Gudmundsson et al., 2012; Zhao et al., 2017). To analyse the sensitivity of crop model for different weather at different agroclimatic zones of cotton with different agricultural practices. The observed, RegCM and RegCM bias-corrected weather output was used for simulation of cotton in rainfed, irrigated and potential conditions. In the DSSAT model, the genetic coefficient and the management data were taken as per recommended package and practices. Three planting dates chiefly practiced in the region was considered for the study in both the northern region, Hisar and the central region, Akola. Further details for the description of the model and experimental design are described in Chapter IV.

1.7.4 Simulating the Impacts of Climate Change on Irrigated and Rainfed Cotton Crop: Part-II- Future.

Future climate change has been found to have critical implications on the agricultural productivity. Analysing the extremes and its impact on the crop is therefore very important. In this study an attempt is made to evaluate the future projections from the RCM model at two RCPs 4.5 and 8.5. The RCM projected daily weather from 1971 to 2005, 2006 to 2035, 2036 to 2065 and 2066 to 2095 were average to represent projected climate centred at historical (1990), present (2020) and climate change scenario at near future (2050) and far future (2080) and CO_2 concentration was also raised accordingly. Its impact on the cotton productivity is further evaluated with the crop model cotton-CROPGRO model under DSSAT-CSM v4.6. The crop growth model has been simulated for rainfed, irrigated, and potential conditions in both the regions for three sowing dates commonly practiced in these regions.

1.8 Significance /Deliverables

India presently is one of the major producer and exporter of the cotton crop. The cotton mostly cultivated in Indian land is Bt-cotton which is a Genetically Modified crop. With the introduction of Bt-cotton there has been revolutionary changes in its productivity. But unfortunately the cotton production is still facing challenges in enhancing the productivity due to biotic and abiotic stresses. Changing climate and the incidence of pests has put a question on the sustainability of the genetically modified crop. India has highest area of production for the cotton crop but there was a fall in cotton acreage in the year 2016 and thereafter and farmers are planning to switch on the alternatives. This is primarily because of cost of the GM seeds which fails to reap its benefit on the field.

This study focuses upon the impact of climate change on the cotton crop in the present and future scenarios and its effect on the growth and yield of the crop. With the changing world, climatic trends, monsoon unpredictability and erraticism linked with rising global warming in the Indian Subcontinent there is now a dire need for the study of impact of weather on crops as well. Despite the milestone achievement of highest production in 2018, the productivity has still not enhanced. This basically signifies that the country is not being able to achieve its potential productivity. Also the recent incidences of pests affecting the crop has prime concern which puts mark of interrogation on the effectiveness of Bt-cotton. The Bt-cotton, a genetically modified form of cotton crop as introduced in 2002 in India has brought to control the incidence of pest without the use of pesticide.

Earlier, we have quantified the sensitivity of the crop for water stress at different growth stages for excess and deficit years to see the impact of rainfall. In the present study, we have evaluated the impact of changing temperature and CO_2 on the crop for different planting dates. To assess the impact in the future climate change scenarios, best performing in this region RCM4 data has been considered which was bias corrected by Quantile mapping approach. Crop simulations are based upon the calibrated and validated DSSAT model which is a used worldwide. These models have good potential for early crop yield assessment, study of various type stresses at different phenological stages is necessary so that measures can be taken for its amelioration. They are calibrated and validated before the utilisation. They have a great significance for the purpose of research and improvement in the crop productivity on the field.

This study also focuses on the difference in productivity between the irrigated and rainfed cropping patterns and its future implications. This is based upon the model studies. But the model has some limitations regarding the assessment of pest. So for that remote sensing and GIS technique has been utilised. Primarily, these biotic stress caused by the cotton pest has relation with the weather variables. Which used to be visualised by some regression equations. This study evaluates the impact of stress utilising vegetation indices such as NDVI and NDWI for six years showing plant health as per crop calendar. It has been derived from the LANDSAT data over the region downloaded from the earth explorer. The study is verified with the field observation over the experimental field. This ability could be further devised to check the real-time crop health and biotic stresses if any.

These studies will give an insight about the impacts of climate change on different growing regions with different management practices and its improvement for affirming profitable production. The study will also help the farmers to implement timely and effective IPM measures to prevent its damage from the pest attacks. Thus can help to understand the biotic and abiotic stress on the cotton crop and draw site-specific management strategies.

The thesis consists of six chapters. In Chapter- I, a brief review of the cotton and its present status and important research carried out so far is presented. The unit has various subunits which emphasis the background or history of cotton, cotton physiology, seasonal requirements of cotton, stress in cotton, and a brief note about Bt-cotton. The motivation behind selecting the topic of research and the broad objectives of the work are discussed followed by a brief description of study area and methodology applied to achieve the various objectives are presented. Chapter-II presents the assessment of uncertainty and impact of changing climate on cotton crop using DSSAT model considering increasing temperature and CO_2 individually and then combined. After considering the abiotic factors such as moisture in the previous study and the temperature and CO_2 in Chapter III biotic factor i.e. effect of changing weather on the pest is considered. The relation of pest with weather variables has been represented is various studies with various regression equations developed in field studies. These equations are used for forecasting the pest populations and could be further analysed by using remote sensing techniques for early detection as the vegetation indices such as NDVI and NDWI falls below normal. This has been analysed parallel to the crop calendar to monitor the infestation. Then in Chapter IV again the abiotic variables are considered both from the observation station and the RCM4 model, to evaluate the performance the model before considering it for future studies or using its data of future projection in the cropping system model. This is done for three sowing dates as per recommended in these regions for both the rainfed and irrigated cotton crop in both the northern agroclimatic zone region at Hisar and central agroclimatic zone at Akola. Further, in Chapter V the crop is evaluated in the same region for the same soil and cultivar for future climate. The climate projections from the RCM4 model has been utilised to assess the cotton physiology and yield in future climate at both RCP 4.5 and RCP 8.5 in the near and far future. At the end, the important results obtained in Chapters II to IV are summarized with the main conclusions in Chapter VI.

1.9 Limitations of the Study

- These RCMs are computationally expensive are only justified when it significantly improves simulated data by its driving GCMs on regional scale (Sørland et al., 2018). It is also said that 'RCMs are merely producing uncertainty piled on top of uncertainty' (Kerr, 2011), and other studies state it as 'garbage in, garbage out' paradigm (Wilby and Dessai, 2010). It is also argued that the biases of GCMs and RCMs are not dependent and therefore the 'uncertainty would be increasing when the global data is translated into regional data also referred to as the cascade of uncertainty' (Wilby and Dessai, 2010).
- The DSSAT model represents the crop physiology and yield but fail to represent the damages due to pests (Batchelor et al., 1993). In some studies, the model sometimes exaggerates the yield responses for rainfed regions than irrigated due to precipitation variations when compared with observed. Studies also suggest while simulating the model with weather from climate models the crop model has limitations regarding the representation of effects of floods/ extreme precipitation and extreme heat.

Chapter- II

Model-based approach to study the response of Bt-cotton towards elevated temperature and carbon dioxide in the semi-arid region of Hisar

MODEL-BASED APPROACH TO STUDY THE RESPONSE OF BT-COTTON TOWARDS ELEVATED TEMPERATURE AND CARBON DIOXIDE IN THE SEMI-ARID REGION OF HISAR

ABSTRACT

Cotton is one of the principal commercial fibre crop. India is highest in terms of agricultural land involve in cotton production but second highest in production. Decadal yield data reveals that its productivity is 243kg/ha lesser than the global average. Weather aberrations is one of the paramount reasons for the productivity loss. The present study aims at estimating the implications of increasing temperature and CO_2 concentrations on cotton yield using a crop model DSSAT. Three different Bt-cotton varieties Pancham-541, RCH-791 and SP-7007 are considered for the study with three sowing dates 10th May, 21thMay and 06th June. For Pancham-541 variety, rise in 1°C of temperature with 50ppm CO_2 is beneficial, but further rise is harmful. Whereas for RCH-791 and SP-7007, productivity decreases gradually with increasing temperature and CO_2. Generally, yield decreases with increase in temperature (by 1°C), but no significant effect observed with increasing CO_2 (50ppm) cumulatively. The adverse effects of rising temperature is moderated due to increase of CO_2 with the increase in photosynthesis when considered together. The leaf area index as well as evapotranspiration rate increases with increasing temperature and CO_2 for all varieties in all sowing dates. Whereas, the harvest index and maturity dates decreases in general. Therefore, increasing temperature at the present rate will be harmful for the productivity of cotton with the changing climate. Although this effect is abated with simultaneously rising CO_2 but yet the adversity due to global rise in temperature is partially mitigated.

Key words: cotton, temperature, CO_2, climate change

2.1 INTRODUCTION

The global crop productivity is under threat due to the climate change. It is one of the potent challenges in the 21st century. Chemical composition of the atmosphere has been changing enormously with the beginning of industrial revolution due to anthropogenic activities. Burning of fossil fuel, vehicular emissions, and rapid deforestation resulted in an increase of atmospheric CO_2 levels. The gradual increase in the concentrations of greenhouse gases and hence leads to global temperature rise. Understanding its severity and its impact on various ecosystems, there are international climate treaties to control the global temperature. The Earth Summit and now Paris agreement addressing the problem of climate change; which aims at keeping the global temperature rise below 2°C and further try to limits it within 1.5°C.

Climate variability is one of the major factors, which influences the crop production even in high yielding and advanced technology regions (Kang et al., 2009). The impact of climate change on crop productivity has become a major area of scientific concern. Various studies are being conducted to assess the impact of climate change on crop productivity such as maize, wheat and rice (Howden et al., 1997; Hoogenboom, 2000; Gbetibouo et al., 2005; Aggarwal et al., 2006a; Aggarwal et al., 2006b; Dhungana et al., 2006; Challinor et al., 2008), forests (Lexer et al., 2002), industry (Harle et al., 2007) and native landscape (Dockerty et al., 2005, Dockerty et al., 2006). Crop and climate models are widely used by the research community to study the crop productivity and soil water balance in the changing climate (Kang et al., 2009).

Response of plant towards the climatic factor such as temperature on yield varies amongst species based upon crop's cardinal temperature requirements. The increasing global temperature will affect the plant physiology, growth cycle, and development along with yield (Kang et al., 2009). Crop yield is reported to be sensitive to both temperature and precipitation (Krause et al., 1997; Popova et al., 2005). The increase in the yield under future warming scenario is attributed to the elevated CO_2 concentration due enhanced photosynthesis which is termed as the 'fertilisation effect' that moderates the negative impacts of rising temperature as reported on rice yield in Kerala (Saseendran et al., 2000). It has also been found that with climate change, growing period will be reduced i.e. crop can mature earlier, therefore planting dates has to be advanced to improve the crop yield apart from introducing new resistant varieties (Cuculeanu et al., 2002). Temperature above the normal optimum levels are termed as 'heat stress'. It interferes with the normal homeostasis, growth retardation and even causes apoptosis (Mathur et al., 2014). Studies conducted to characterize energy use of cotton showed that latent heat flux was the major energy utilizing process which determines yield variation (Singh et al., 2008). Bt cotton cultivars in the semi- arid region of Punjab showed negative correlation of seed yield with temperature in reproductive phase (Sahoo et al., 2000, Singh, 2008; Liyong et al., 2007). As sessile organism, plants are exposed to various abiotic and biotic factors, such as temperature, CO_2 and precipitation which ultimately affect the yield.

Cotton is grown across 80 countries all over the world with an average productivity of 765 kg/ha. India ranks first in total area of land under cotton production with an average productivity of 522 kg/ha i.e. 23 percent of the world average. Where China ranks first in average production of cotton with an average productivity of 1352 kg/ha. (Status Paper of Indian Cotton report by Directorate of Cotton Development Government of India, Jan 2017). The reasons for this gap of 243 kg/ha in the productivity can be attributed as weather aberrations. This includes temperature extremes, inadequate or excess rain with uneven distribution, incidence of pest attack, especially sucking pest. Optimum temperature required for cotton growth and development of ball and its retention is around 28 °C (Reddy et al., 1991) but can continue to better yield till temperatures up to 32 °C, which is a critical threshold temperature for its yield. (Schlenker et al., 2009).

Increase in temperature above optimum i.e. the tolerable limit of the plant is found to negatively impact the yield of cotton due to increased ball abscission during flowering and smaller ball at maturity. Daily evaporative demand and crop water utilization are largely a function of the leaf area index and therefore yield of the crop. It is strongly influenced by the genetics and growing conditions (Reddy et al., 1997). Whereas increasing CO_2 above the present level will improve crop productivity due to improved carbon exchange rates (Reddy et al., 2005). These finding are also documented in an report by National cotton council of America as Cotton Physiology Today (1999). As CO_2 which helps to boost photosynthesis and therefore production also could not ameliorate the adverse effects of high temperature on some phenological phases like reproductive growth, boll formation and maturity that affects the quality of fibre. It is reported that in future climates, the yield and quality of fiber will decrease if increasing CO_2 is associated with increase in temperatures particularly in fields where present temperature are near to optimum for the crop (Reddy et al., 2005). Studies on the cotton crop of Stoneville region with future GCM projected data indicates, under rainfed conditions yield declined for all the RCP scenarios but under irrigated conditions yield declined only during extreme conditions. Yield partially increased with an increase in rainfall or supplementing the crop with water. As an adaptability measure planting crop earlier also somewhat compensated for yield losses (Anapalli et al., 2016).

Models such as Decision Support System for Agrotechnology Transfer (DSSAT) uses detailed location-specific data for physiological crop information, climate data, soil characteristics data etc. (Islam et al., 2016). It generally assesses under plausible future climate change scenarios taking other factors such as management practice and crop variety constant (Islam et al., 2016). Latest DSSAT Version 4.6.1 (Jones et al., 2003) is developed to simulate the growth and yield on 31 crops. It is an assemblage of various crop models in Crop Environment Resource Synthesis such as CERES CROPGRO etc., where CROPGRO assesses fibre crop cotton (Thorp et al., 2014; Hoogenboom et al., 2015).

Biophysical and socioeconomic factors are also studied with the combination of climate, crop, and economic models. It allows to estimate the difference in yields and other parameters with the changing climate. Historical data are utilized to analyze the climate of that location and field level experimental data are being used to calibrate and then validate the models for this structural framework. The set up can also be translated forward into looking at simulations for future scenarios. The Ministry of Agriculture use these modeling assessments in their FASAL and GKMS projects to improvise and assess the package and practices for the crop management and the crop production forecast. This is to help researchers, farmers and policy-makers to make strategies adapting climate change. The present study is based upon impact climate change on cotton crop using a DSSAT crop model. Specifically, it aims at finding the implications of increasing temperature and CO_2 individually and then combined to analyze the effect of climate change.

2.2 CLIMATIC CONDITION OF THE STUDY AREA

The study area considered for the present study is Hisar, Haryana, situated between 74°24' to 76°18'E longitude and 28°54' to 29°59'N latitude at an elevation of 215.2 amsl'. The district lies in alluvial plains of the Yamuna, which is a sub-basin of Ganga River. Soil texture is gradually changing from light sandy (bhur) to firm loamy (rausli), thus light and highly permeable. Semi-arid climate of Hisar owes to its continental location and on the margin of south-west monsoon. It can be further classified as tropical steppe type of climate (Singh et al., 2014). Annual temperature ranges from 3.5 to 48°C, which specifies that it has hot dry summer and chilling cold winter. Most of its precipitation (77%) occurs through the south-west monsoon during JJAS. Else from October to April weather remains dry, except with the wake of western disturbances. Occasional hailstorms also occur from February to April. Fog occurs during December and January. This region sometimes experiences thunderstorms during summer and post-monsoon (Singh et al., 2014).

Cotton is a kharif crop sown in the month of May-June and harvested in Sep-Oct. The climatological analysis of temperature (1970 – 2008) over the study region illustrates that mean monthly daily range of temperature during the sowing period of cotton are 31.5°C (May) and 26.0°C (June). Maximum and minimum temperatures during the cropping period are 40.2°C and 22.8°C, 39.8°C and 26.0°C, 36.2°C and 26.3°C, 34.8°C and 25.4°C, 34.8°C and 25.4°C, 34.8°C and 22.6°C, 33.5°C and 16.1°C in the month of May, June, July, August, September and October, respectively. Similarly, the cumulative rainfall during May, June, July, August, September, and October are 30.5, 56.1, 128.0, 109.1, 59.4 and 10.1 (mm) respectively. The bright sun shine hours during May, June, July, August, September, and October are 8.4, 6.7, 6.1, 7.1, 8.5, 8.8 (hrs.) respectively (Singh et al., 2014).

2.3 METHODOLOGY

2.3.1 Method for Raising Crop

For the present investigation on "impact of increasing temperature and CO_2 on the cotton crop" agronomic practices was carried out in experimental field of Chaudhary Charan Singh Haryana Agricultural University (CCSHAU), Haryana during the year 2013-14. Certified and delinted Bt-Cotton seeds for recommended varieties of Pancham-541, RCH-791, SP-7007 were sown during the Kharif season. Sowing was done by hand ploughing method, by keeping a distance of 60cm between the rows. All the management and agronomic practices were followed as per the recommended package of practices by the Haryana Agricultural University for growing the crop under irrigated conditions. The size and design of the experimental plot was 5.4m * 5.0m and split plot respectively.

2.3.2 Model Description

Crop models are used to imitate or simulate the behavior of real crop grown on the field. DSSAT-CSM Version 4.6.1 model has been employed for the present study. Decision Support System for Agrotechnology Transfer- Cropping System Model (DSSAT-CSM) suite includes the CROPGRO-cotton model for the simulation cropping systems based on cotton crop (Jones et al., 2003; Boote et al. 1998a). This model is utilized globally for about 40 crops (Jones et al., 2003). The DSSAT-CSM is a crop simulating model which contains the following components (Jones et al., 2003)

1. Weather module: To read and generate daily weather data using WGEN or SIMMETEO.
2. Soil module: Designed to read the soil properties as an input for the experiment.
3. Soil/plant/atmosphere module: To compute daily soil evaporation, transpiration and finally compute ET based on Penman-FAO method (Doorenbos and Pruitt, 1977), LAI etc.
4. Template crop module (CROPGRO): To predict growth of different crop such as cotton, soybean, chickpea etc. from a common source code (Boote et al. 1998a).
5. Individual crop module interface (plant module): Similar to CROPGRO, it links plants growth dynamics with other DSSAT-CSM modules.

6. Management module: Includes input variables such as planting, applying nutrients, irrigating etc. specified as standard ‘experiment’ in input file (Hunt et al., 2001). It is then analysed with different years to see the impact of changing crop for different weather/year.
7. Pest module: As an input in field observations to analyse insect populations or disease severity for specified pest and diseases infesting development and yield of the crop.

In this experiment, the seasonal management practices and soil modules are kept the same for the entire simulation, while the changes in the weather module is considered during the period of entire model integration.

2.3.3 Data for the Analysis

Daily agrometeorological observations are taken from the Agrometeorological Observatory under India Meteorological Department (IMD) situated about 0.5 km away from the experimental plot. Weather data utilized for this study includes daily maximum and minimum temperature, bright sunshine hours and rainfall. Three sowing (planting) dates are considered in the study, such as 10th May, 21st May, and 06th June which are widely practiced. The genetic coefficient of the cotton crop is employed in the model, which has been adopted from Swami et al. (2016). The model has been calibrated and validated for these cultivars with the actual production for simulating cotton production under Hisar region (Shikha et al., 2018).

2.3.4 Experimental Design

The climatology of thirty-five years daily weather data from IMD has been taken for Hisar station starting from 1981 to 2015. Seasonal simulation has been carried out for that duration to assess the climatological impact of 35 years of data. The final output for yield, LAI, ET, MD are all 35 years mean for this duration. The experiment has been replicated thrice for minimizing errors. To examine the impact of increasing temperature under changing climate; four different simulations are carried out taking Normal climatology, further by adding 1ºC, 2ºC and 3ºC to the climatological temperature value in the simulations. Similarly, another set of four simulations are made by increasing the CO_2 by 50ppm, 100ppm and 150ppm respectively to estimate the impact of increasing CO_2 on yield. Further, four new simulations are designed by changing the CO_2 concentration and temperature together in order to examine impacts on the productivity. It is important to mention that the increment of temperature and CO_2 are done on the climatological data of the 35 years in the model to observe changes w.r.t. the present mean behavior. Observed climatology has been taken as normal in the study, depicted as N. The climate change simulations for temperature are denoted as N+1°C, N+2°C and N+3°C. The experiments with change in CO_2 concentration are represented as N for normal CO_2, N+50 ppm, N+ 100ppm and N+150ppm. Model simulates various phenological and physiological parameters such as anthesis date, harvest index, dry matter, maturity date etc. (Jones et al., 2011). From these simulated output, four different physiological parameters are examined to assess the impact of the possible climate change. These parameters considered for this study are

1. Evapotranspiration (ET; mm) (It is the sum of crop transpiration and transpiration from crop adjacent soil and water surface) (Shih et al., 1993)
2. Leaf Area Index (LAI; Maximum) (It is generally defined as leaf area of one side per unit ground area for broadleaf canopies) (Myneni et al., 1997).
3. Maturity date (MD) (Days of physiological maturity of the crop from the planting date) (Corbeels et al., 2016)
4. Harvest index (HI) (Harvest index is defined as ratio of the reproductive yield with respect to total plant biomass) (Gur et at., 2010)

2.4 RESULTS AND DISCUSSION

This section deals with the sensitivity in the yield and four different physiogical characters (ET, LAI, MD and HI) of the three different cotton varieties in response towards the change in temperature, CO_2 concentration and combined at three different sowing dates.

2.4.1 Sensitivity of Yield Towards Change in Temperature

The model simulation shows that Pancham- 541 sown on 6th June is most sensitive to changes in temperature (Figure 2.1a), as the decrease in yield is maximum for 3°C rise in temperature. However, it has a high optimum range of temperature for tolerance, which is evident from the rise in yield with a temperature rise of 1°C. Further rise in temperature reduces the crop yield for all sowing dates. Interestingly, the decline in production is more for the crop sown in June as compared to the one sown during May. The varieties like Pancham- 541, RCH-791 also shows a gradual reduction in yield with temperature rise (Figure 1b). RCH-791 also shows higher sensitivity (decreasing yield) towards increasing temperature for crop sown on 06th June as compared to the other sowing dates considered in the study. This indicates that the present day temperature is the critical temperature for the crop and it could not withstand any further increase in temperature. This is the reason for decrease in crop yield beyond the present climatological temperature value. The sensitivity of SP-7007 towards the rise in temperature is least as compared to the other two varieties (Figure 2.1c). Interestingly, the decrease in crop yield is least for N+3°C for the crop sown on 06th June than the earlier sowing dates. Therefore, the results indicates that the early sowing (during May) relatively reduces the impact of rising temperature as compared to the varieties sown late (during June) in the agricultural practices. Higher the temperature rise, more is the severity and its impact on the crop yield.

The earlier studies indicates that the temperature significantly affected the crop phenology, leaf expansion, biomass production, internode elongation, and distribution of the assimilates to the different parts of the plant (Reddy et al., 1991; Reddy et al., 1996; Reddy et al., 1999) . Similar decline in yield with rise of temperature is reported (Jalotaa et al., 2009). They examined yield of Bt-cotton under semi-arid conditions and illustrated that the cotton seed yield declines from 4700kg/ha to 2300kg/ha with an increase in temperature from 28°C to 32°C and the reduction is high during sowing to flowering stage (Jalotaa et al., 2009). Similarly, the findings from this study shows that the simulated yield for Pancham-541 sown on 10th May compared to normal climate has reduced to 2737.54kg/ha from 2598.31kg/ha.

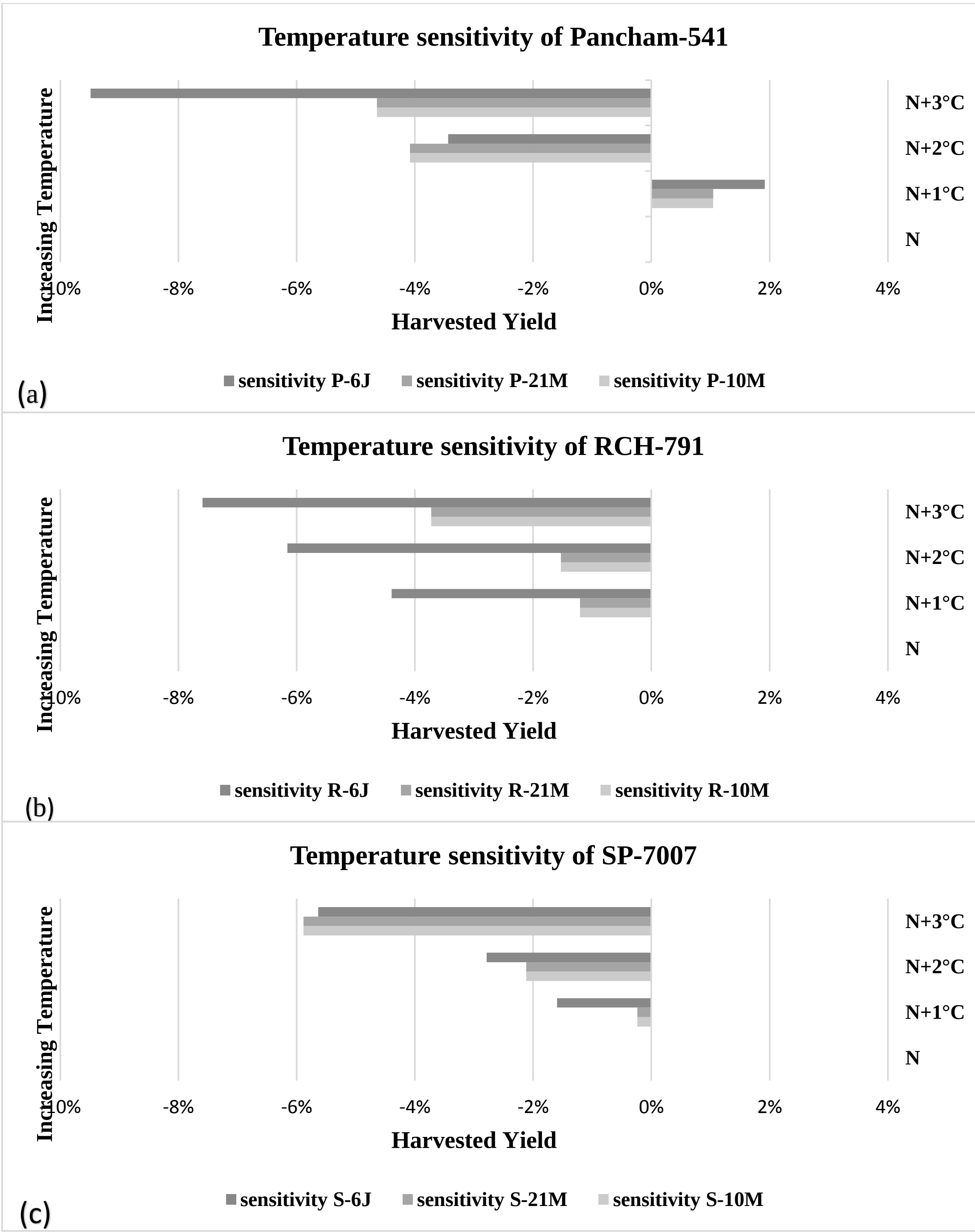

Figure 2.1 Temperature sensitivity of cotton cultivars for three different sowing dates 10th May, 21thMay and 06th June for (a) Pancham-541 (b) RCH- 791 (c) SP- 7007.

The negative impact associated with rising temperature could be potentially due to reduction in vegetative growth period, increased fruit shedding due to enhanced temperature stress and loss of reproductive capacity because of reduced boll filling (Luo et al., 2014). Similar studies based on field experiments showed strong positive correlation of temperature with cotton seed, cotton lint, ball opening and negative correlation with leaf area index (Tripathi, 2005; Pouresia and Nabipour, 2007; Singh et al., 2008).

Maximum temperature, minimum temperature and vapour pressure deficit showed a strong positive correlation with cotton seed, cotton lint and bolls per plant during boll opening stage, whereas morning and evening relative humidity showed negative correlation with seed cotton, cotton seed, cotton lint and bolls per plant during vegetative, flowering and boll opening stages. A negative correlation between air temperature and sunshine hours during seed development phase with leaf area index (Tripathi, 2005; Pouresia and Nabipour, 2007). Negative correlations between temperatures during two later phenophases and seed yield were due to higher temperatures during reproductive phase. Such results were also reported by various researchers (Sahoo et al., 2000; Singh, 2005; Singh, 2010; Pouresia and Nabipour, 2007; and Liyong et al., 2007.

2.4.2 Sensitivity of Yield Towards Change in CO_2

It is interesting here to observe that Pancham-541 sown on May is positively impacted by an increase in CO_2 concentration in the atmosphere; while the opposite is found for cases with sowing date during June (Figure 2.2a). Surprisingly, the RCH-791 variety shows exactly opposite behavior as compared to Pancham-541 (Figure 2.2b), where the increasing CO_2 has decline the yield except for variety sown in June. The sensitivity of SP-7007 is reported to be least as compared to other two varieties considered in the study (Figure 2.2c). However, the yield increase (decrease) for the variety shown in June (May) with increase in CO_2 concentration. The present analysis found that Pancham-541 (SP-7007) variety is most (least) sensitive to increase in CO_2. However, for RCH- 791 and SP-7007 varieties, the increase in CO_2 has negatively impacted to crop sown in May than the variety sown in June.

In cotton an increase in ball size is also evident due to elevated CO_2 (Ruiz- Vera et al., 2018). Sowing dates also play greater role for the plan to increase productivity, the improvement in cotton yield for early-sown crop is around 10% higher as comparison to late sown crop. This may be due to the lower cutout/abortion rate of the fruit that results in holding greater number of bolls for the plant (Pettigrew et al., 2002). Further, the positive influence on the crop due to sowing dates can also be attributed to early emergence and therefore increase in reproductive period which results in earlier onset of first square and delayed last square (Bange et al., 2004).

2.4.3 Sensitivity of Yield Towards Change in Combined Temperature and CO_2

As discussed earlier, the Pancham-541 has a high optimum range of temperature tolerance with respect to present temperature climatology, which is reflected from the rise in yield with 1°C rise but subsequently yield decreases with temperature rise of 2°C and 3°C. Similar finding are also observed from the combined rise of temperature and CO_2 (Figure 2.3a). The pattern is very close to the change in temperature but with a moderated effect. Similar declining yield is also observed for RCH-791variety (Figure 2.3b). For SP-7007 variety, the crop sown during May shows a positive effect in terms of yield with an increase in 50ppm and 1°C rise in temperature, which further decreases with increase in the concentration of both (Figure 2.3c). The yield decreases with increasing temperature, which is partially but not totally moderated by increasing CO_2. The crop still imitates the same behavior as increasing temperature but with lesser intensity. This moderation can be because of increasing CO_2 concentrations called the fertilization effect and reported in other crops as well (Saseendran et al., 2000). In general, rise in temperature and CO_2 negatively impacted the yield for all the planting dates.

Similar studies conducted for cotton crop, based upon field trials, showed that the vegetative growth is increased by increasing temperature and CO_2 together (Reddy et al., 2005). This could be because of the pretext that vegetative growth may require lesser time to support more fruit loads (Jalotaa et al., 2009). Therefore, reduced vegetative growth ‘cutout’ may occur forthwith and consequently reduce potential of crop yield (Lawlor et al., 2014; Pettigrew, et al., 2002). Further curtailment in time for 'cutout' can advance maturity, therefore decrease the yield (Bange et al., 2004b).

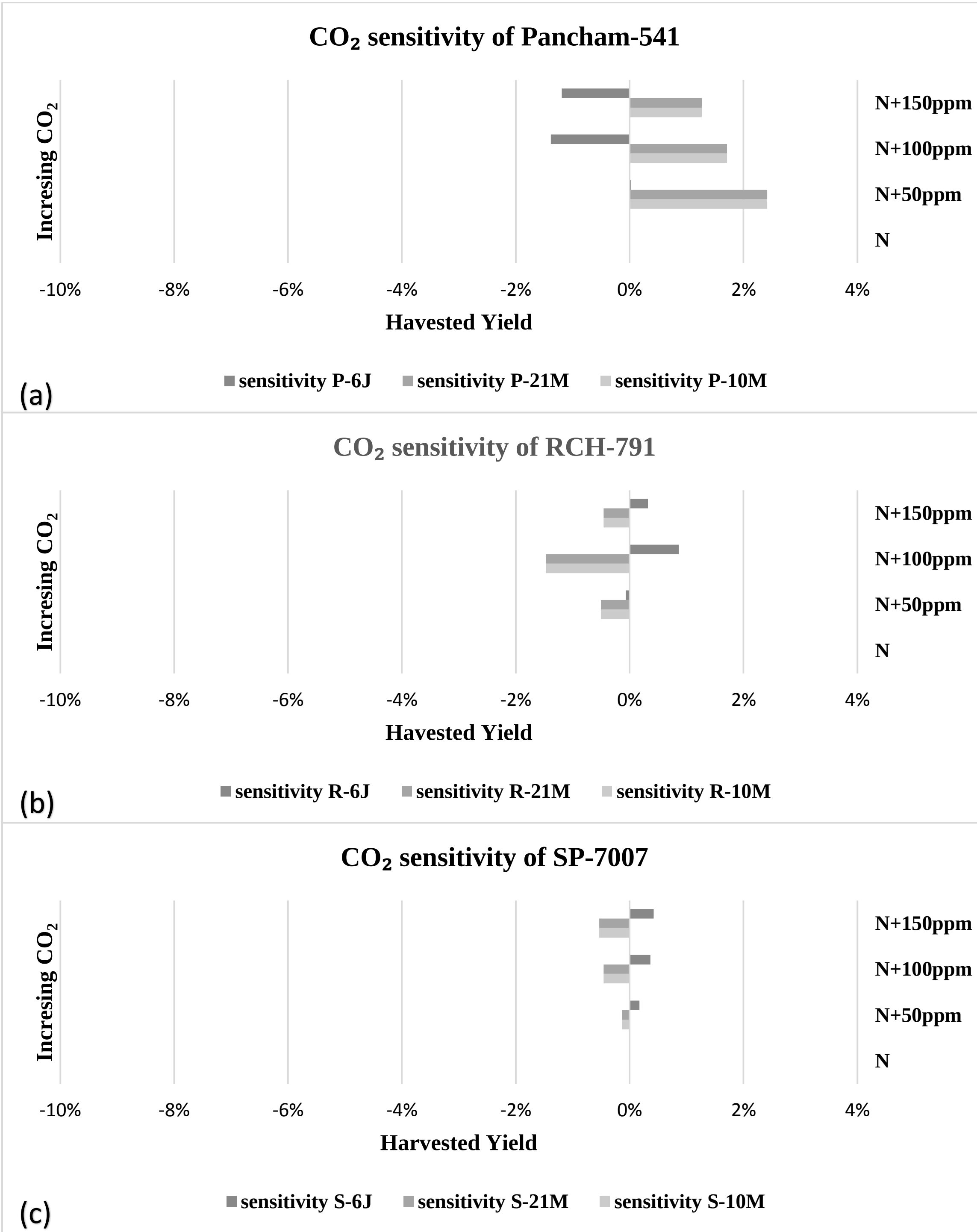

Figure 2.2 Same as Figure 2.1, but for Carbon dioxide.

It is also reported that higher vegetative growth is good to support yield of transgenic cotton with additional and early fruiting bodies (Constable et al., 2006). The effect of elevated CO_2 masked the apparent high temperature injury that limited the growth of all plant organs, especially reproductive system (Reddy et al., 1991; Reddy et al., 1996; Reddy et al., 1999). Studies also indicate that bolling periods will be shorter under warming climate (Reddy et al., 1999; Luo et al., 2014). Therefore, the fibre quality is compromised and boll size are reduced despite potentially increased fruiting periods and more fruit. This reduction in yield may be due to cutout in vegetative phase or reduction in boll size in reproductive phase (Lawlor et al., 1991).

In this section, the mean of the four major phenological parameters for the crop Such as Evapotranspiration (ET), Leaf Area Index (maximum) (LAI), Harvest Index (HI) and Maturity Date (MD) are analyzed. As discussed earlier, ET has positive correlation with LAI and HI with MD; they are plotted together (Ruiz- Vera et al., 2018; Reddy et al., 2005; Anapalli et al., 2016, Reddy et al., 2005).

A gradual increase in ET and LAI with increase in temperature is observed for Pancham-541 (Figure 2.4a) but interestingly, no significant change is observed under experiments with gradual increase of CO_2 (Figure 2.4b). However, the ET and LAI both increases gradually with the rise of both temperature and CO_2 rise from 1°C and 50ppm cumulatively to further higher values (Figure 2.4c). The simulation shows higher ET and LAI for the crop sown during June than that sown in May, with an increase in 1°C temperature and 50ppm CO_2 concentrations cumulatively. For Pancham-541, the HI is higher for 1°C rise as compared to the present climatology for all sowing dates (Figure 2.4d). The MD decreases slightly with increase in temperature and highest for the crop sown during June (Figure 2.4a). It also decreases slightly for combined increase of temperature and CO_2 concentrations. Similar studies indicate that low temperatures and prolonged growing period are advantageous for cotton productivity (Reddy et al., 1999).
It is observed that the HI is approximately same for all the sowing dates for Pancham-541 variety for present temperature climatology and N+1°C. However, it decreases with further rise of temperature.

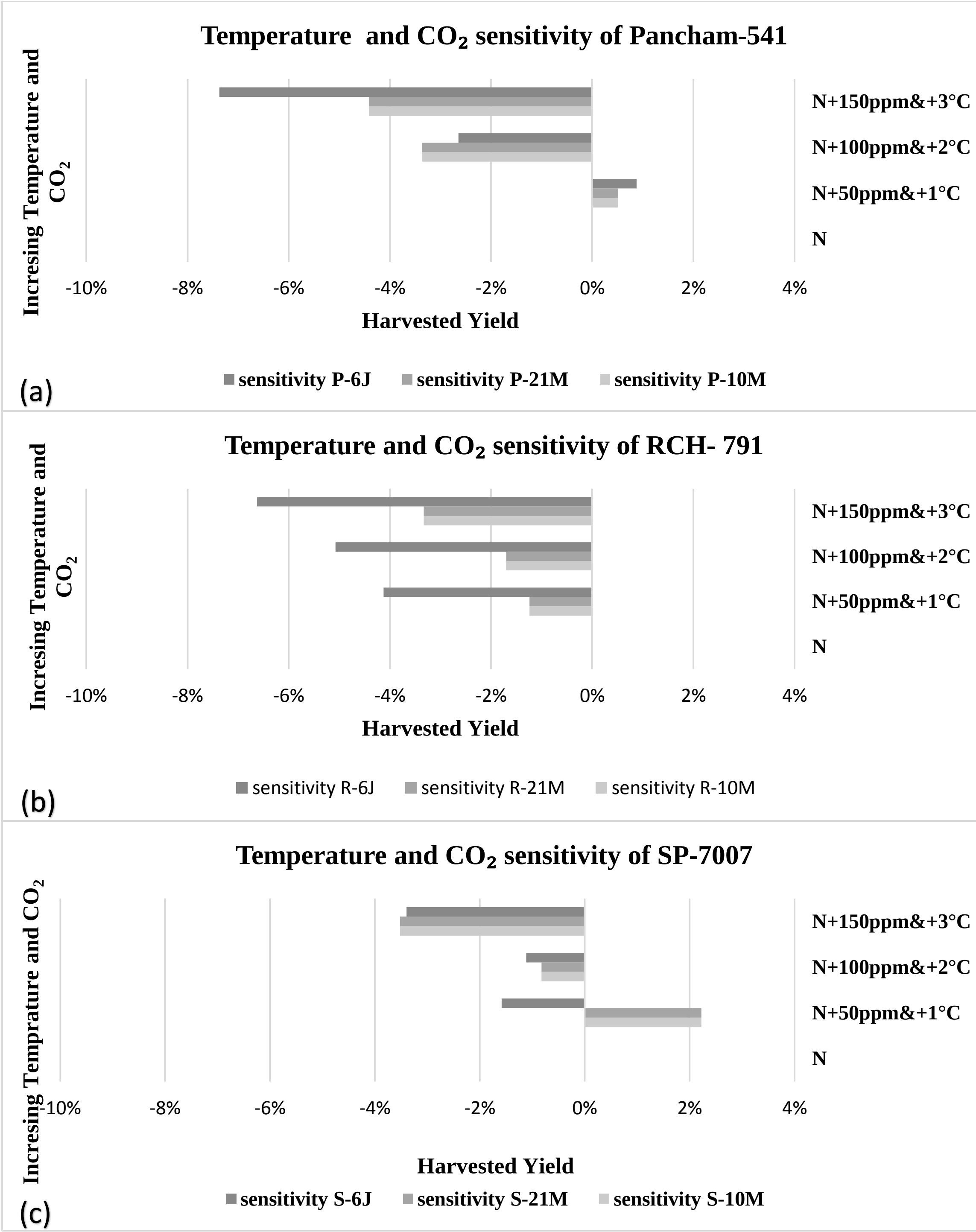

Figure 2.3 Same as Figure 2.1, but for Temperature and Carbon Dioxide combined.

2.4.4 Sensitivity of Yield Towards Phenological Characters

Interestingly, the sowing dates also play a major role is deciding the productivity. For example, June (May) shows higher productivity for temperature rise of 2°C (3°C). Moreover, the HI as well as MD do not show any significant change for 50ppm increase in CO_2 w.r.t. the climatological value. HI decrease faintly with further rise of in CO_2 concentration mostly for crop sown in June (Figure 2.4e). The crop under combined rise of temperature and CO_2 concentrations mimics similar behaviour as with rising temperature but with less intensity for N+2°C and N+3°C along with 100ppm and 150ppm CO_2 concentrations (Figure 2.4f). However, for 2°C (3°C) temperature rise with 100ppm (150ppm) $CO_{2,}$ June (May) is showing better yield.

For the cultivar RCH-791, ET and LAI shows similar response as Pancham-541. The increasing temperature leads to gradual increase in both ET and LAI (Figure 2.5a). But with increasing CO_2 concentrations, there is no significant impact observed upon them (Figure 2.5b). The fertilization effect dominates under combined increase of temperature and CO_2 leading to lesser impact (Figure 2.5c). However, the HI and MD slightly increases with 1°C rise of temperature for crops sown in May; which further reduces under N+2°C and N+3°C. The crop sown in June shows gradual reduction in its yield with gradual temperature rise from 1°C to 3°C(Figure 2.5d). HI and MD are almost insensitive (shows no change) towards 50ppm increase of the CO_2 concentrations; but there is a slight reduction in HI with further rise of CO2 w.r.t climatological value for the crop sown in May (Figure 2.5e). Again, the fertilization effect dominates for increasing CO_2 together with temperature rise leading to a small change in the mean values (Figure 2.5f). The change of temperature, CO_2 and combined has a little effect on MD which reduces by 1 – 2 days; while the change is maximum for the crop sown during June (Figure 2.5d-e-f). HI (0.37 to 0.34) and MD (1- 2 days) is also least affected by these changes for this particular variety. This cultivar is found to be least affected and better performing in terms of yield with the changing climate. Similar studies indicated that early sowing increases the MD up to 1 – 2days while late sown crop reduces it by 0–3 days, which is comparable with the present finding (Luo et al., 2014).

The ET and LAI means, for the cultivar SP-7007, is gradually increasing with the cumulative increase in temperature by 1°C (Figure 2.6a). For all experiments, the crop sown on 06th June has the highest ET and LAI mean values among all the sowing dates. Like other two varieties, the increasing CO_2 does not bring any significant change in the ET and LAI means (Figure 2.6b). Partial moderation in the increase in ET and LAI is observed for combined increase in temperature and CO_2 concentration (Figure 2.6c). The HI is almost insensitive to almost 1°C temperature rise and further decline slightly under N+2°C and the lowest is observed for late sown crop of 06th June (Figure 2.6d). This indicates that, this crop sown in May (early) provides better performance than sown in June (late) under future warming climate. Under 3°C rise in temperature, the yield has significantly reduced for the crops sown in May while the production is relatively higher for late sown crop on 06th June. Similar pattern is also observed for increase in CO_2 concentration (Figure 2.6e). But the maturity date is not much impacted with increasing temperature and CO_2 and both combined (Figure 2.6d-e-f). The HI mean slightly decreases with increase in CO_2 with lowest values for the crop sown on 06th June. Again, the increase in temperature and CO_2 combined mimic the similar behavior as with rise in temperature but the effect has been partially moderated (Figure 2.6f).

It is observed from the present analysis that the increasing temperature has more impact on the ET and LAI as compared to the increasing CO_2 in general. Pancham-541variety is found to be most tolerant towards increasing temperature till 1°C temperature rise. The mean values are higher for ET and LAI for varieties sown late (06th June) for all the conditions. Combining the effect of temperature and CO_2, the higher impact of the increasing temperature is moderated by increasing CO_2 for all the cultivar with all sowing dates in the experiment. The cotton being a C_3 plant is impacted by an increase in CO_2, which influences the photosynthesis, yield and dry matter production substantially (Lawlor et al., 1991). In some crops such as maize, vegetative and reproductive growth can be accelerated by rising temperature whereas increasing CO_2 concentrations has no apparent effect (Ruiz-Vera et al., 2018). Further, another study advocates an increase in productivity with doubling CO_2 concentration which is related to the higher leaf area (Reddy et al., 2005). With increased incidences of heat stress, there is a rapid crop development and maturity if the management strategies are not adjusted (Luo et al., 2014).

In general, higher Maturity Date (MD) are observed in crop sown on 06th June. This signifies that the crop sown late take more time to mature. As observed, crops sown in May are performing better under warming climate, which is also supported by earlier studies. Therefore, early planting is one good remedy to maintain a good yield for the future climate (Anapalli et al., 2016; Reddy et al., 2005). With increase of temperature, CO_2 and both, the harvested yield and maturity period decreases. ET and LAI are found to directly (indirectly) proportional to HI (MD) for all three varieties considered for the study. Crop sown during May seems to better performing in terms of HI with increasing temperature and CO_2 for Pancham-541 and RCH-791. But, the SP-7007 variety have least HI for the crop sown during June. The positive impacts of early sowing in productivity and development are related to early emergence and increase in reproductive period which results into earlier First Square and delayed last Effective Square (Anapalli et al., 2016; Reddy et al., 2005). Some degree of loss of fruiting bodies (decrease in yield) due to rise of temperature can be compensated by greater resources like irrigation and nutrition (Constable et al., 2006).

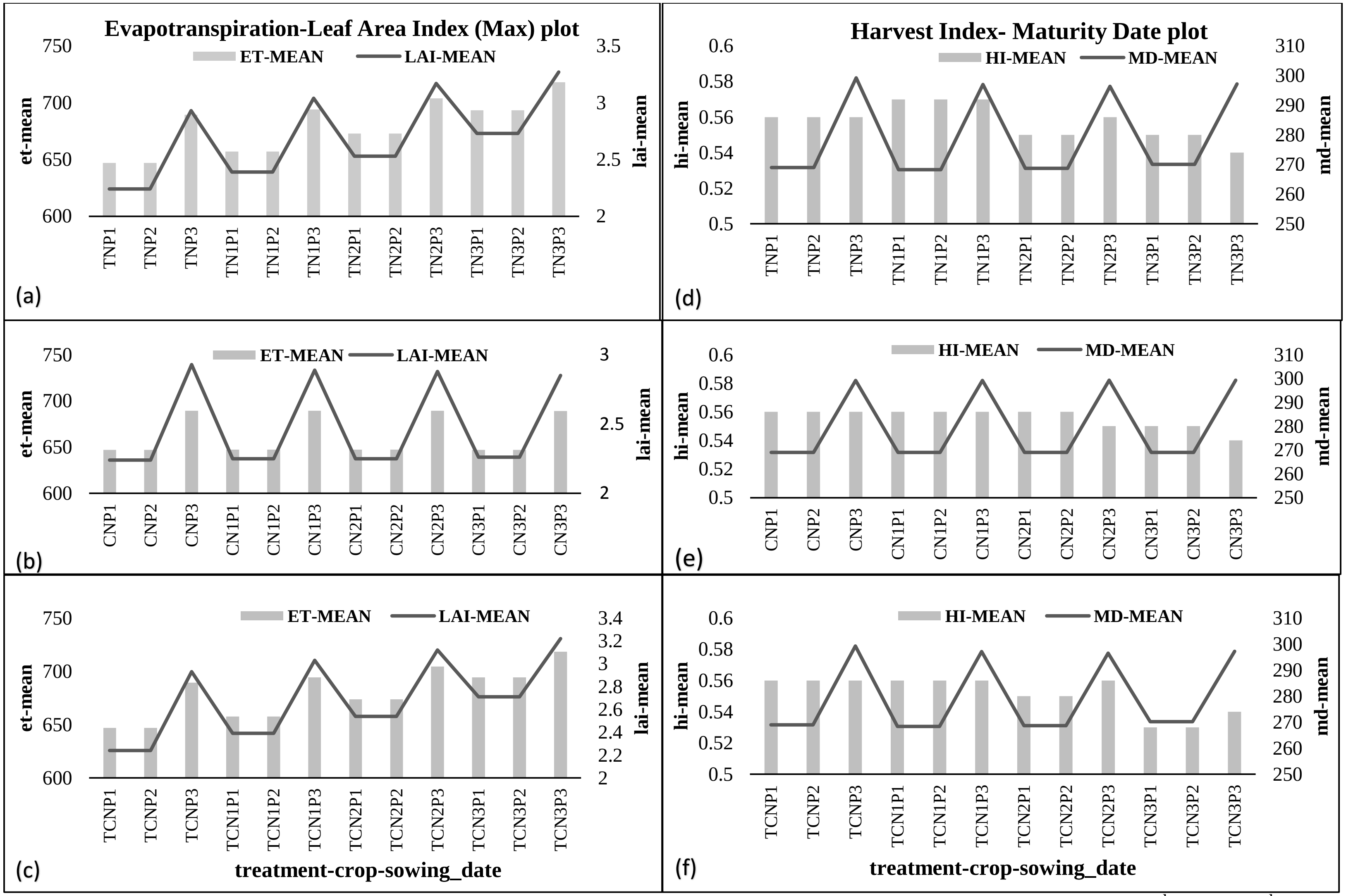

Figure 2.4 Cotton variety Pancham- 541, physiological parameters taken combined for three sowing dates 10th May, 21th May and 06th June (a) Evapotranspiration and Leaf Area Index (Maximum) with increasing temperature (b) Same as (a), but for increasing CO_2 (c) Same as (a) but for temperature and CO_2 (d) Harvest Index and Maturity date with increasing temperature (e) Same as (d), but for increasing CO_2 (f) Same as (d), but for temperature and CO_2.

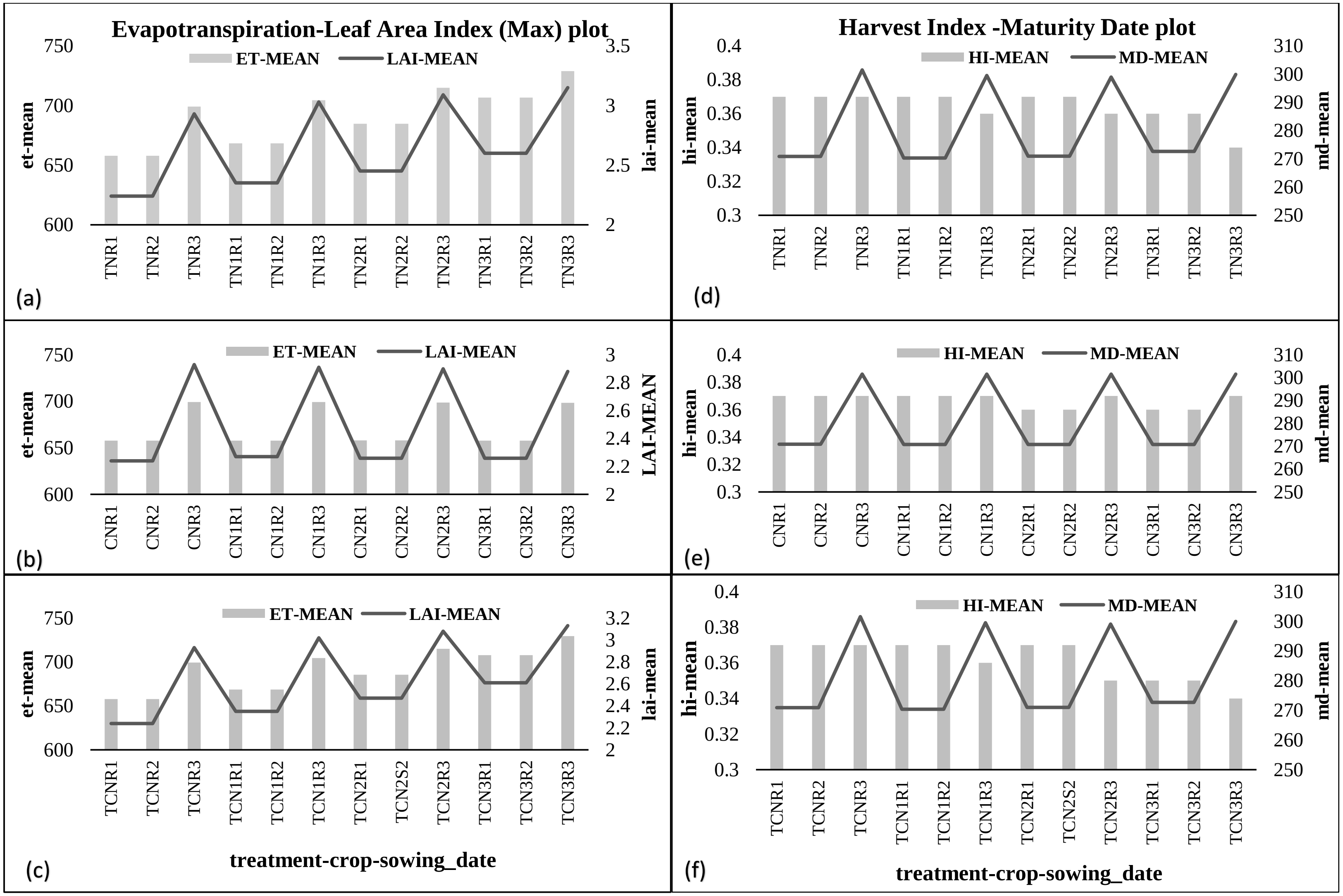

Figure 2.5 Same as Figure 4 but for cotton variety RCH – 791.

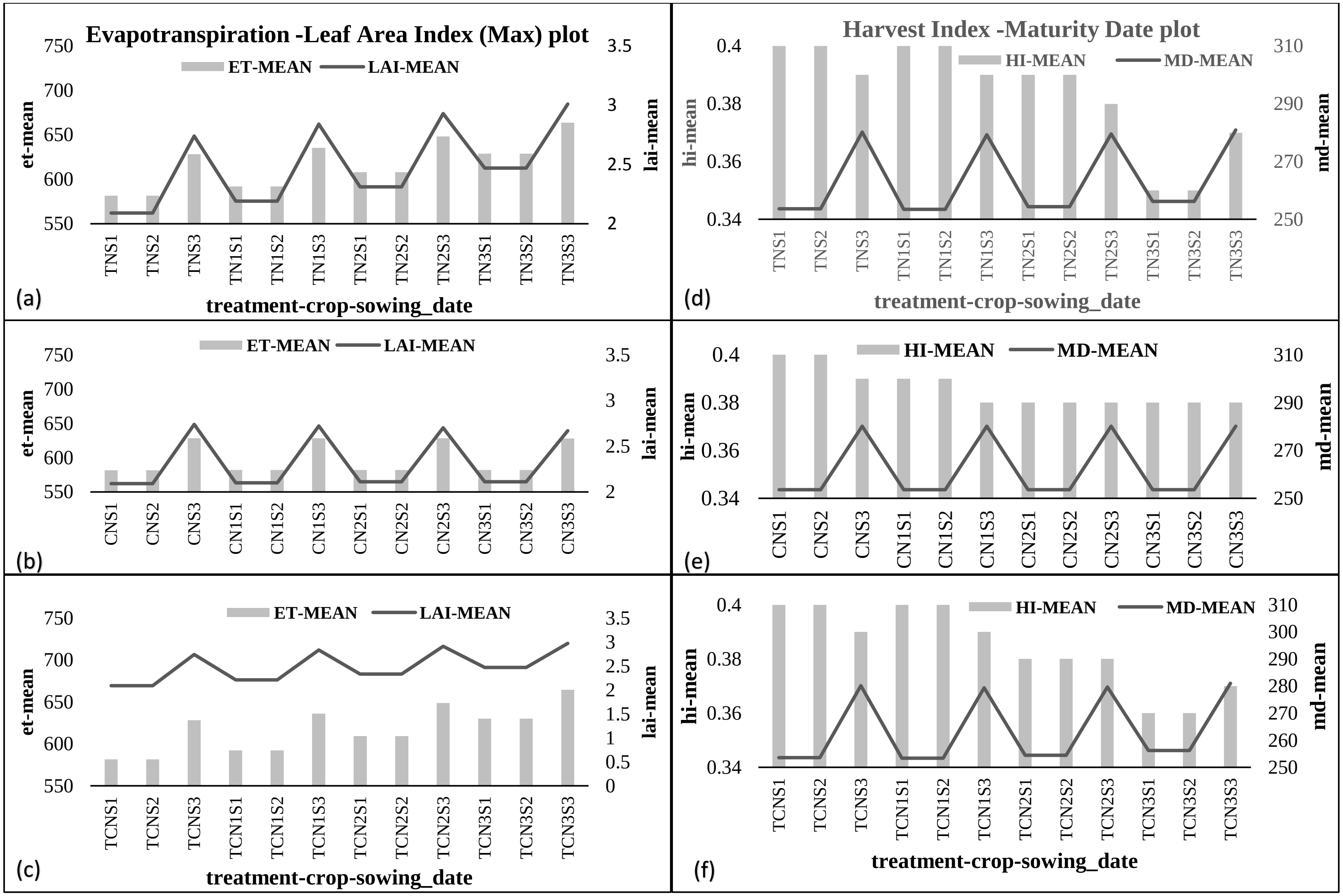

Figure 2.6: Same as Figure 4 but for cotton variety SP- 7007.

Abbreviations used in the Figure 2.4

TNP1	Evaluating temperature sensitivity with respect to(w.r.t) normal climate for Pancham-541 with sowing date(SD) 10th May
TNP2	Evaluating temperature sensitivity w.r.t normal climate for Pancham-541 with SD 21st May
TNP3	Evaluating temperature sensitivity w.r.t. normal climate for Pancham-541 with SD 06th June
TN1P1	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 10th May
TN1P2	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 21st May
TN1P3	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 06th June
TN2P1	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 10th May
TN2P2	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 21st May

TN2P3	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 06th June
TN3P1	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 10th May
TN3P2	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 21st May
TN3P3	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for Pancham-541 with SD 06th June
CNP1	Evaluating CO_2 sensitivity w.r.t. to normal climate for Pancham-541 with SD 10th May
CNP2	Evaluating CO_2 sensitivity w.r.t normal climate for Pancham-541 with SD 21st May
CNP3	Evaluating CO_2 sensitivity w.r.t. normal climate for Pancham-541 with SD 06th June
CN1P1	Evaluating CO_2 sensitivity for 50ppm increase in CO_2 w.r.t. normal climate for Pancham-541 with SD 10th May
CN1P2	Evaluating CO_2 sensitivity for 50ppm increase in CO_2 w.r.t. normal climate for Pancham-541 with SD 21st May

CN1P3	Evaluating CO_2 sensitivity for 50ppm increase in CO_2w.r.t. normal climate for Pancham-541 with SD 06th June
CN2P1	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for Pancham-541 with SD 10th May
CN2P2	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for Pancham-541 with SD 21st May
CN2P3	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for Pancham-541 with SD 06th June
CN3P1	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for Pancham-541 with SD 10th May
CN3P2	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for Pancham-541 with SD 21st May
CN3P3	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for Pancham-541 with SD 06th June
TCNP1	Evaluating temperature and CO_2 sensitivity w.r.t. normal climate for Pancham-541 with SD 10th May
TCNP2	Evaluating temperature and CO_2 sensitivity w.r.t normal climate for Pancham-541 with SD 21st May

TCNP3	Evaluating temperature and CO_2 sensitivity w.r.t. normal climate for Pancham-541 with SD 06th June
TCN1P1	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for Pancham-541 with SD 10th May
TCN1P2	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for Pancham-541 with SD 21st May
TCN1P3	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for Pancham-541 with SD 06th June
TCN2P1	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for Pancham-541 with SD 10th May
TCN2P2	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for Pancham-541 with SD 21st May
TCN2P3	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for Pancham-541 with SD 06th June
TCN3P1	Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for Pancham-541 with SD 10th May
TCN3P2	Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for Pancham-541 with SD 21st May

TCN3P3 Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for Pancham-541 with SD 06th June

Abbreviations used in the Figure 2.5

TNR1	Evaluating temperature sensitivity with respect to(w.r.t) normal climate for RCH-791 with sowing date(SD) 10th May
TNR2	Evaluating temperature sensitivity w.r.t normal climate for RCH-791 with SD 21st May
TNR3	Evaluating temperature sensitivity w.r.t. normal climate for RCH-791 with SD 06th June
TN1R1	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 10th May
TN1R2	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 21st May
TN1R3	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 06th June
TN2R1	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 10th May

TN2R2	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 21st May
TN2R3	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 06th June
TN3R1	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 10th May
TN3R2	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 21st May
TN3R3	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for RCH-791 with SD 06th June
TNR1	Evaluating CO_2 sensitivity w.r.t. to normal climate for RCH-791 with SD 10th May
TNR2	Evaluating CO_2 sensitivity w.r.t normal climate for RCH-791 with SD 21st May
TNR3	Evaluating CO_2 sensitivity w.r.t. normal climate for RCH-791 with SD 06th June
CN1R1	Evaluating CO_2 sensitivity for 50ppm increase in CO_2 w.r.t. normal climate for RCH-791 with SD 10th May
CN1R2	Evaluating CO_2 sensitivity for 50ppm increase in CO_2 w.r.t. normal climate for RCH-791 with SD 21st May
CN1R3	Evaluating CO_2 sensitivity for 50ppm increase in CO_2w.r.t. normal climate for RCH-791 with SD 06th June

CN2R1	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for RCH-791 with SD 10th May
CN2R2	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for RCH-791 with SD 21st May
CN2R3	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for RCH-791 with SD 06th June
CN3R1	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for RCH-791 with SD 10th May
CN3R2	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for RCH-791 with SD 21st May
CN3R3	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for RCH-791 with SD 06th June
TCNR1	Evaluating temperature and CO_2 sensitivity w.r.t. normal climate for RCH-791 with SD 10th May
TCNR2	Evaluating temperature and CO_2 sensitivity w.r.t normal climate for RCH-791 with SD 21st May
TCNR3	Evaluating temperature and CO_2 sensitivity w.r.t. normal climate for RCH-791 with SD 06th June

TCN1R1	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for RCH-791 with SD 10th May
TCN1R2	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for RCH-791 with SD 21st May
TCN1R3	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for RCH-791 with SD 06th June
TCN2R1	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for RCH-791 with SD 10th May
TCN2R2	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for RCH-791 with SD 21st May
TCN2R3	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for RCH-791 with SD 06th June
TCN3R1	Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for RCH-791 with SD 10th May
TCN3R2	Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for RCH-791 with SD 21st May

TCN3R3	Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for RCH-791 with SD 06th June

Abbreviations used in the Figure 2.6

TNS1	Evaluating temperature sensitivity with respect to(w.r.t) normal climate for SP-7007 with sowing date(SD) 10th May
TNS2	Evaluating temperature sensitivity w.r.t normal climate for SP-7007 with SD 21st May
TNS3	Evaluating temperature sensitivity w.r.t. normal climate for SP-7007 with SD 06th June
TN1S1	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 10th May
TN1S2	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 21st May
TN1S3	Evaluating temperature sensitivity for 1°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 06th June

TN2S1	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 10th May
TN2S2	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 21st May
TN2S3	Evaluating temperature sensitivity for 2°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 06th June
TN3S1	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 10th May
TN3S2	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 21st May
TN3S3	Evaluating temperature sensitivity for 3°C increase in Temperature w.r.t. to normal climate for SP-7007 with SD 06th June
TNS1	Evaluating CO_2 sensitivity w.r.t. to normal climate for SP-7007 with SD 10th May
TNS2	Evaluating CO_2 sensitivity w.r.t normal climate for SP-7007 with SD 21st May
TNS3	Evaluating CO_2 sensitivity w.r.t. normal climate for SP-7007 with SD 06th June
CN1S1	Evaluating CO_2 sensitivity for 50ppm increase in CO_2 w.r.t. normal climate for SP-7007 with SD 10th May

CN1S2	Evaluating CO_2 sensitivity for 50ppm increase in CO_2 w.r.t. normal climate for SP-7007 with SD 21st May
CN1S3	Evaluating CO_2 sensitivity for 50ppm increase in CO_2w.r.t. normal climate for SP-7007 with SD 06th June
CN2S1	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for SP-7007 with SD 10th May
CN2S2	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for SP-7007 with SD 21st May
CN2S3	Evaluating CO_2 sensitivity for 100ppm increase in CO_2 w.r.t. normal climate for SP-7007 with SD 06th June
CN3S1	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for SP-7007 with SD 10th May
CN3S2	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for SP-7007 with SD 21st May
CN3S3	Evaluating CO_2 sensitivity for 150ppm increase in CO_2 w.r.t. normal climate for SP-7007 with SD 06th June
TCNS1	Evaluating temperature and CO_2 sensitivity w.r.t. normal climate for SP-7007 with SD 10th May
TCNS2	Evaluating temperature and CO_2 sensitivity w.r.t normal climate for SP-7007 with SD 21st May
TCNS3	Evaluating temperature and CO_2 sensitivity w.r.t. normal climate for SP-7007 with SD 06th June
TCN1S1	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for SP-7007 with SD 10th May
TCN1S2	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for SP-7007 with SD 21st May

TCN1S3	Evaluating temperature and CO_2 sensitivity for 1°C+50ppm increase w.r.t. normal climate for SP-7007 with SD 06th June
TCN2S1	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for SP-7007 with SD 10th May
TCN2S2	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for SP-7007 with SD 21st May
TCN2S3	Evaluating temperature and CO_2 sensitivity for 2°C+100ppm increase w.r.t. normal climate for SP-7007 with SD 06th June
TCN3S1	Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for SP-7007 with SD 10th May
TCN3S2	Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for SP-7007 with SD 21st May
TCN3S3	Evaluating temperature and CO_2 sensitivity for 3°C+150ppm increase w.r.t. normal climate for SP-7007 with SD 06th June

Chapter- III

Application of remote sensing for detection of stress in cotton induced by pest in Hisar

APPLICATION OF REMOTE SENSING FOR DETECTION OF STRESS IN COTTON INDUCED BY PEST IN HISAR

Abstract

Pest is cardinal threat for cotton crop productivity. This study emphasizes the application of remote sensing approach in complement with weather based statistical forewarning for taking effective Integrated Pest Management (IPM) measures. Forecasts based on meteorological parameters and crop phenology help to prepare pest weather calendar for predicting the pest attack in advance and this can be monitored with the remote sensing technique on real-time basis. In this study pest infestation in the research field in Hisar is assessed with the help of LANDSAT images for the year 2013-18. Vegetation indices such as NDVI and NDWI is calculated for area of interest after cloud masking. The multi-temporal LANDSAT images are then collected to composite a time series. These indices were further analysed with the crop calendar and validated with the field observations. The NDVI and NDWI values is minimum for the year 2013, 2015 and 2018 in comparison to 2014, 2016 and 2017 respectively, which is reflective of stress the crop was experiencing which was corroborated as pest attack above Economic Threshold Level (ETL) as per field observations. The peak in the values are gained during the September 2017 showing good plant health during the year. As observed in the year 2013 and 2015 the major threat was Cotton Leaf Curl Disease (CLCuD) transmitted through whitefly (Bemisia tabaci) and accompanied by other sucking pests like thrips, leafhopper etc. And in the year 2018 the crop was majorly affected by the cotton leafhoppers Jassids. Thus, for strengthening network programs monitoring the pest dynamics along with statistical forecasts and pest models is needful.

Key words: Forewarning, Pest forecasting, Remote sensing, Vegetation indices, NDVI, NDWI

3.1 INTRODUCTION

Pest has been a major challenge for entomologist in cotton crop. Worldwide more than 1326 species of pest has been reported in cotton crop (Hargreaves, 1948). Among these insect pest is the major source of crop losses (Kumar et al., 2008). Bollworm was utmost cause of concern before the introduction of *Bt* cotton. But, even after revolutionary introduction and consequently enhancement of *Bt* cotton production, now sucking pest is burning issue. Since its introduction there has been reduction in conventional insecticides and higher doses of nitrogenous fertilizers leading to enhanced quantum of amino in the plant system has made it more conducive for fast development and fertility of sucking pests (Jain and Bhargava, 2007). Cotton sucking insect pests which if found to be major threat in the present are whitefly (*Bemisia tabaci* Gennadius), aphid (*Aphis gossypii* Glover) leafhopper (*Amrasca biguttula biguttula* Ishida) and thrips (*Thrips tabaci* Lindemann). So as to protect them pesticides are widely used to such an extent that more than 50% of total production cost is attributed to pesticides alone (Sundaramurthy et al., 1998).

Various field studies are being conducted to study the influence of pest on the crop. It has also been reported that the pest population is also influenced by abiotic factors such as temperature rainfall and relative humidity. When the number of pests grow above Economic Threshold Level (ETL) level it can cause huge devastation in the cropland. One such example is, huge loss in cotton productivity during the year 2014-15 is Hisar, northwest cotton growing belt due to attack of sucking pest, prominently whitefly (Weekly Advisory for Cotton Cultivation No. 18/2015) (Janu et al., 2017). And due to Jassids cotton leafhoppers also a sap sucking pest in the year 2018 (CAI, August 2018). The whitefly infestation and favourable weather conditions also triggered severe Cotton leaf curl virus (CLCuV) disease. The sucking pest population increases with advancement of vegetative stage and during the maximum leaf area index (Bishnoi et al., 1996). With the introduction of Bt-Hybrids over and above 90% of area the concern has shifted towards sucking pest. The meteorological parameters play a significant role in the development and build up on insect species. Among the major weather factors temperature and humidity are most influential attribute (Janu et al., 2017). Boyd et al. (2004) studied that humidity is a major contributor to pest and insect attacks, for e.g. ball rot after ball opening. The most suitable conditions for maximizing the yield include warm, dry weather conditions, abundant sunlight and availability of soil moisture since the period when the balls start opening through harvest.

The whitefly is a prominent pest for cotton (Brown and Bird, 1992) which caused devastation of crop during the year 2014-2015 in the Punjab and Haryana region. And it was also found that whitefly was significantly correlated with maximum temperature and rainfall whereas it is positively correlated with relative humidity (Janu et al., 2017). It is a sap sucking pest, highly polyphagous and serious cause of heavy loss. It has potential to reduce the phloem sap resulting in loss of plant vigour (Byrne et al., 1990). It infects the plant in two ways, either by reducing the vitality of plant of affecting the cell sap or by interfering the normal photosynthesis with the growth of sooty mold on honeydew extracted by it. These mold affects the quality of the fibre and leave a pale patches the leaves. These pale patches and obtrusion is plant health can be traced in reflectance as well. It is often accompanied by Cotton leaf curl virus (CLCuV) disease, causing upward curling of leaves and thickening of veins and enations (minute foliar outgrowth) pronounced at the lower surface of the leaves. It turns it into abnormally dark green which seems opaque beneath the surface (Watkins, 1981). This is transmitted through the white fly (ELNur, 1967). It also has significant impact on the yield and physiological components like stunted plant, reduced number of balls and ball weight (Tanveer and Mirza, 1996; Brown, 2001).
Some pests supply sufficient stress to the plant altering their physical structure and photosynthesis. Which distorts the reflectance signal and consequently detected by remote sensing (Moran et al., 1997). Remote sensing techniques the for detecting the pest activity are usually based upon the detection of damage caused by the pest rather than the actual organism (Riley, 1989). Likewise, the type of damage caused by the deposits of sooty mold from the honeydew producing pests resulting in defoliation and colour changes is detectable (Payne et al., 1971; Harris et al., 1976).

The different response of vegetation attributes for spectral regions have been articulated to various arithmetic formulae also known as vegetation Indices (VI). They deduce the multispectral responses to single numbers to signify characteristics such as biomass, leaf area index, stress etc. They have been found functionally and quantitatively related to canopy temperature, chlorophyll content other pigment availability etc. These VIs have also been utilised for assessing the crop health and have potential to monitor pests and diseases (Ray et al., 2010). Some of the widely used VIs are normalized difference vegetation index (NDVI), normalized difference water index (NDWI), enhanced vegetation index (EVI) etc.

The present study aims to analyse the crop health with the remote sensing approach. The field observations validate the stress during the study period due to the pest infestation. The behaviour of the pest are also correlated with the meteorological variables in the for pest forewarning. Conventionally to analyse and forecast the yield and pest attack on the crop was based upon field experiments and statistical correlation. But this now supplement with crop simulation modeling and remote sensing approach. These complementary approach for the study along with ground based validation has helped researchers is yield forecasting and can also play vital role in early detection of severity, quantum and distribution of pest incidence in the crop. Future research could apply these methods explicitly to study the impact of climate on pest. Which can also be complemented with more reliable data and various pest models and remote sensing techniques to complement the research.

3.1.1 Complementary Approaches for Pest Assessment

3.1.1.1 Statistical

The pest population and its relation with weather can also be assessed or forecasted from the empirical equations generated by statistical analysis based on the field observations. These generalised equations takes the meteorological parameters such as temperature, rainfall and humidity to forecast the frequency of pest. It can give a modest estimation about the different pest population. They are developed based upon the field experiments on the growing regions and then validating with it's statistically significance (Bishnoi et al., 1996). Regression analysis are done and relationships are developed to forecast the pest population of Aphids, Jassids, leafhopper and whitefly population build-up with weather variables (Janu et al., 2017). Below there are mentioned some of the equations to interpret the weather correlation with the major pests in the study region Hisar as studied by Bishnoi et al. (1996).

$$Jassid\ Pop. = \frac{1}{0.0019(\text{T mean}-30)^2+0457} \qquad (R^2=0.97)$$

$$Whitefly\ Pop. = -71.86 + 5.633\text{Tmean} - 0.1042\text{Tmean}^2 \qquad (R^2=0.98)$$

$$\text{Heliothis Pop.} = -9.24 + \frac{300.8}{\text{Tmean}} \qquad (R^2=0.77)$$

$$Pink\ Bollworm = \frac{1}{0.2494 + 0.0369(Tmean)^2} \qquad (R^2=0.77)$$

3.1.1.2 Remote sensing

Many of the crop responses towards the stress are difficult to visually quantify with acceptable accuracy and speed and the same responses can be observed for reflected electromagnetic radiation from the plant canopies and assesses by GIS and remote sensing techniques. This was used to quantify the crop health and nowadays are utilised to quantify and early detection of pests to take timely and precise Integrated Pest Management (IPM) measures (Ray et al., 2011). Since the pest affects the plant health thus can be calibrated with the help of vegetation indices to a certain degree. Studies are conducted for the behaviour of these indices with the biotic and abiotic stress on the crop (Pinter et al., 2003; Prabhakar, 2011; Wojtowicz et al., 2016). The most commonly preferred are NDVI and NDWI, which has been selected for the study.

3.2 MATERIALS AND METHODS

3.2.1 Study Region

The study has been conducted at Hisar, Haryana which come under northern cotton crop growing region of India (Figure 3.1). The area lies in alluvial plains of the Yamuna, a sub-basin of Ganga River system. The climate here is semi- arid due its continental location. The majority of rainfall occurs during the south-west monsoon in JJAS. Summers are hot and dry and winters are chilling cold with an annual range in temperature of 3.5°C to 48°C. From October to April the weather remains dry, except with the wake of western disturbances (Singh et al., 2014). Cotton here is sown in May-June during the Kharif season. Aphids, jassids, mites, bollworms, and whiteflies are major pests affecting the crop. Presently cotton genotypes has been reported with resistant to CLCuV (Burewala strain) which attacks late sown crop. As it is reported that sowing date has significant effect on the yield and its physiological components (Iqbal and Khan, 2010). So the only option available presently to minimize loss is management strategies like early sowing.

Figure 3.2 Area of field experiment and satellite data sampling point in Hisar farm field.

3.2.2 Field Observations

The study was conducted during the Kharif season of 2014 and 2015 on various cotton genotypes on the Research farm, Cotton Section of CCS Haryana Agricultural University, Hisar. The crops were grown unprotected with three replications. The plots consisted of 5 rows of 5 m each. Seeds of 23 genotypes were sown by hand dibbling method on May 2014-15. Observations were taken for the sucking pests on five randomly selected plants recorded weekly from 23rd to 41st Standard Meteorological Weeks on three leaves each from top, middle and bottom.

3.2.3 Collection of Spectral Data

Satellite images from the Landsat 8 has been taken for the study. It was launched on 11th Feb 2013 by the National Aeronautics and Space Administration (NASA), which has 11 bands with spacial resolution of 30 m and 15 m for panchromatic band is 15-m. It has been upgraded from its previous Landsat satellite as the red, near-infrared, and shortwave infrared bands were narrowed. The radiation resolution was also increased to 16 bits. The signal-to-noise ratio was refined. These advances revamped its ability for vegetation discriminations. The LANDSAT data are available in the public domain on **http://earthexplorer.usgs.gov/** and has contributed a lot is research and development purposes.

3.2.4 Computation of Vegetation Indices

Vegetation indices are the mathematical transformations which are designed to evaluate the spectral contribution of vegetation and other multispectral observations. For assessing the stress in the crop and quantifying the crop health VIs such as NDVI and NDWI are mostly used. The LANDSAT data downloaded from the 04 May 2013 to 16 October 2018 were obtained from the USGS Earth Explorer website. The data was combined with the high-resolution imagery from Google Earth™ taken for 5 sample points with coordinates 29.151562N -75.697045W, 29.151571N, -75.697218W, 29.151565N -75.697223W, 29.151526N-75.697155W, 29.15156N-75.69716W in the research field of

HAU, Hisar, Haryana, India. It was further processed and subset was created as per the Area of Interest (AOI), followed by pre-processing. Further, atmospheric corrections and cloud masking was done using procedure described in USGS website and atmospheric effects was removed for better representation and calculation. VIs are calculated using raster calculator in ArcGIS. These Vegetation indices derived using the equations given in Table 3.1. Multi-temporal LANDSAT images are then collected to composite a time series. These indices were further analysed with the crop calendar. The procedure is well depicted the flowchart given in Figure 3.2.

Table 3.1 Calculation of vegetation indices namely NDVI and NDWI from LANDSAT data

Index	Computation	Application	Reference
NDVI (Normalized Difference Vegetation Index)	NDVI= $(\rho_n - \rho_r)/(\rho_n + \rho_r)$ $(\rho_{(0.86\ \mu m)} - \rho_r)/(\rho_{(0.66\ \mu m)} + \rho_{(0.66\ \mu m)})$ $NDVI = \frac{NIR - RED}{NIR + RED}$	Determine the condition, developmental stages and biomass of cultivated plants and to forecasts their yields.	Rouse et al. (1973); Tucker et al. (1986)
NDWI (Normalized Difference Water Index)	NDVI= $(\rho_n - \rho_s)/(\rho_n + \rho_s)$ $(\rho_{(0.86\ \mu m)} - \rho_{(1.24\ \mu m)})/(\rho_{(1.24\ \mu m)} + \rho_{(0.86\ \mu m)})$ $NDWI = \frac{NIR - SWIR}{NIR + SWIR}$	Estimation of plant water content in canopies	Gao et al. (1996); Zarco-Tejada et al. (2003)

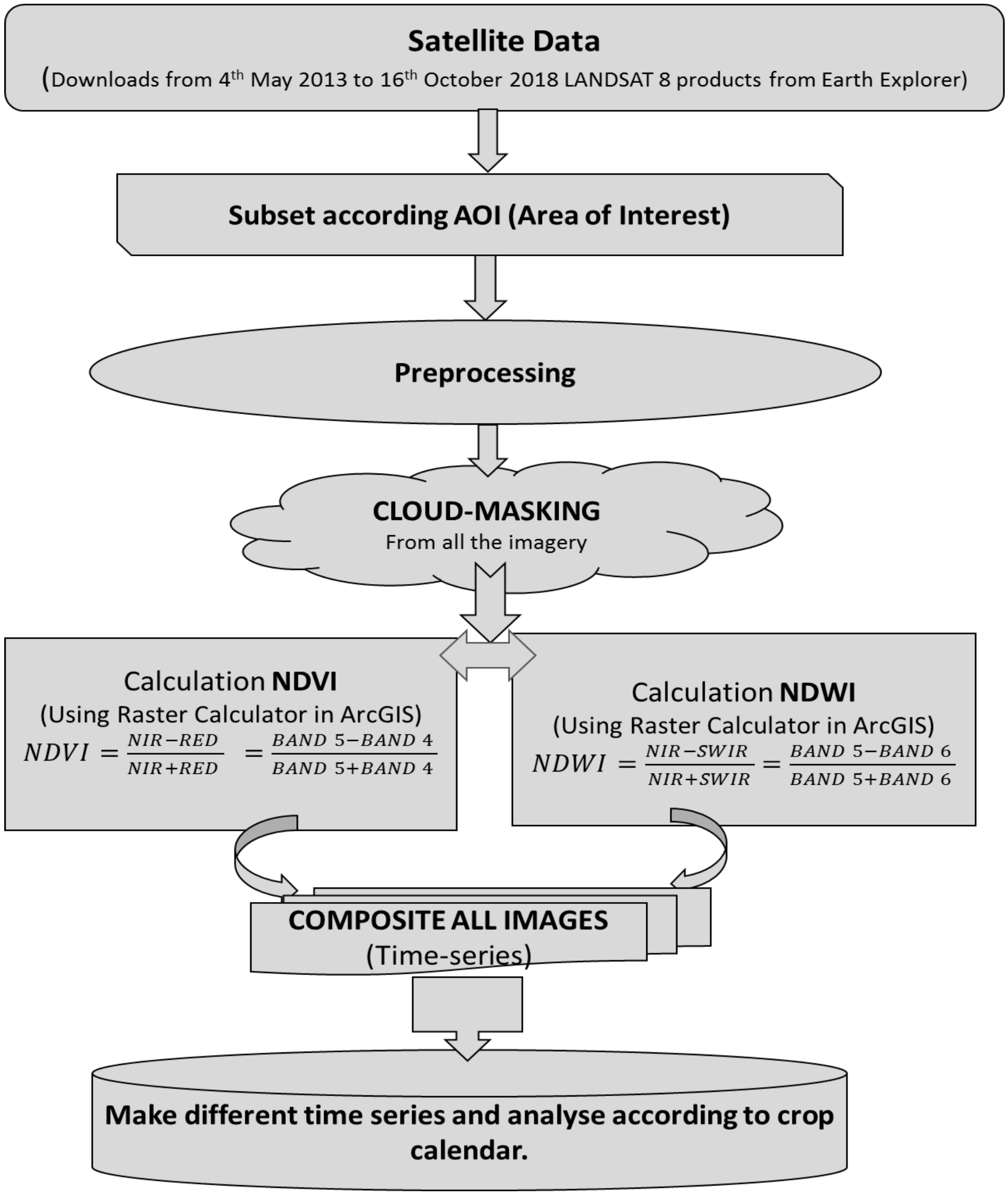

Figure 3.3 Flowchart for the computation of vegetation indices from the LANDSAT data and LAI from the crop model DSSAT.

3.3 RESULTS

The composite time-series of the vegetation indices study region are plotted to determine the crop health for kahrif season from 2013 to 2018 (Figure 3.3). The crop sown in the study site was cotton for the experimental purposes. The temporal pattern for NDVI and NDWI values portrayed together with the crop growth curve for each season with average in Figure 3.3a and with summation values of the sampling site in Figure 3.3b for better representation. These are the average five sample points of the farm field from where the field observations are collected for monthly (Figure 3.3) and annual (Figure 3.4) cropping season. The whole crop growing seasons for 6 years are analysed to see the overall impact of pest during the outbreak and its response captured remote sensing and crop model.

The annual average NDWI value during the cropping (Kharif) season was above 0.3 every year with minimum values for 2013 and 2015 showing the occurrence stress in crop which was corroborated as pest attack as per field observations. The sum of NDVI and NDWI values as shown in (Figure 3.3b) is minimum for the year 2013, 2015 and 2018 in comparison to 2014, 2016 and 2017 respectively, which is reflective of stress the crop was experiencing. The peak in the values are gained during the September 2017 showing good plant health during the year. The field studies are conducted on the Research farm of department of Agricultural Meteorology, CCS HAU, Hisar Haryana on various cultivars of cotton suggest invasion of pest on the field above the economic threshold levels. In the year 2013 and 2015 the major threat was Cotton Leaf Curl Disease (CLCuD) transmitted through whitefly (Bemisia tabaci) crop in the year 2018 which was also affected by the cotton leafhoppers Jassids above ETL. In 2015 again the whitefly population was again found to be increasing above the ETL levels in the field accompanied by other sucking pests like thrips (*Thrips tabaci* Lindeman), leafhopper (*Amrasca bigutulla bigutulla)* etc. Negative NDVI during May and some part of June signifies cropping to emergence period of the crop. As it is also found in many similar studies that late sowing of cotton in these regions makes it vulnerable for pest attack. Again in the year 2014 the incidence was stable and below ETL in comparison to 2013 and 2015. These infestation is also reported in the survey of nearby fields as reported by Weekly Advisory for Cotton Cultivation, ICAR-Central Institute for Cotton Research.

The value of NDVI ranges from -1 to 0, higher value signifies high Near Infrared (NIR) reflectance and dense greenery or healthy vegetation. In the Figure 3.3b for summation of NVDI, we observe value rises after emergence and is maximum for the mid-season flowering stage in 2014, whereas for the other years the maximum NDVI was observed during the ball forming and maturation period. This can be due to the complex and intricate development stages of cotton which is intersecting each other. Maximum NDVI was observed for the year 2017 the followed by 2016 and 2014, which is observed productive in terms of plant health. The maximum pest infestation is observed from the 24^{th} to 41^{st} standard meteorological week (SMW), with a peak around 30^{th} week depending upon the pest as shown in Table 3.2. Whereas in Figure 3.3a for mean NDVI we find minimum for the year 2015 which concludes the maximum crop damage during this year which is also validate with the field observations, and the reason for stress as pest outbreak. The NDVI and NDWI values also supported by the field data shows falling NDVI and NDWI values for the year 2013 and 2015 where the pest infestation was above ETL. Further, as per reports and sample surveys in the study regions for the year 2016-18 reports the infestation of Jassids also a sap sucking pest in the year 2018 above ETL (CAI, August 2018), which can also be observed in the NDVI and NDWI values.

The study indicates that the NDWI and NDVI calculated using LANDSAT 8 data and the field observations has very strong resemblance with the pest infestation in the study region. The stress in cotton crop caused by the pest attack are clearly visible in derived NDWI and NDVI outputs. Thus, these vegetation indices can be used as an indicator to perceive the threshold for zoning the outbreaks. Also, when the crops are affected above the ETL they can be identified and therefore forecasted by modelling approaches.

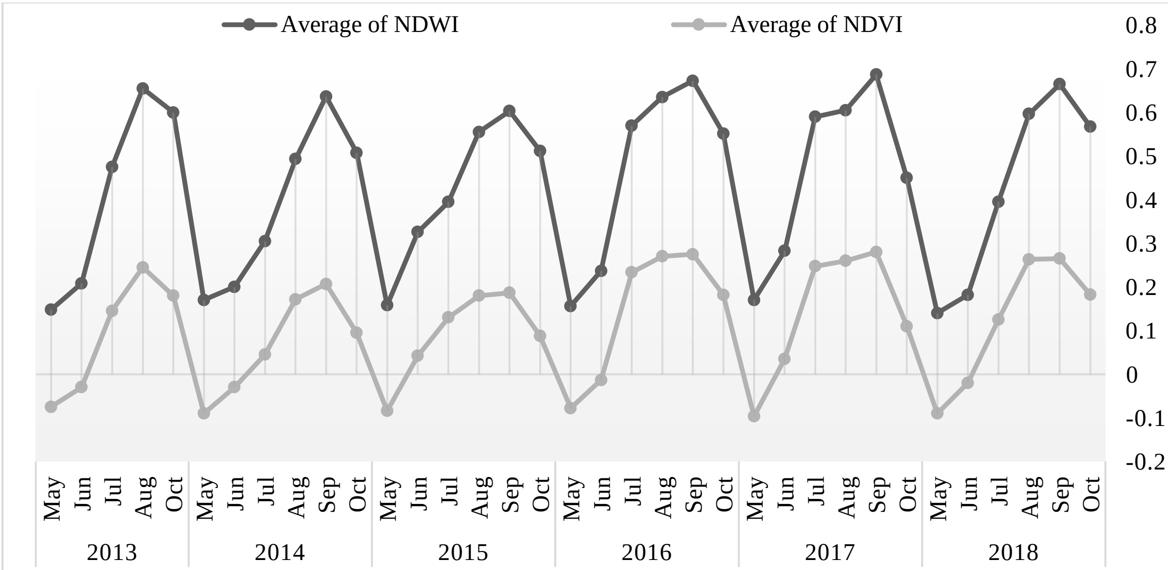

Figure 4.3a. Average of NDVI and NDWI of the five sampling sites.

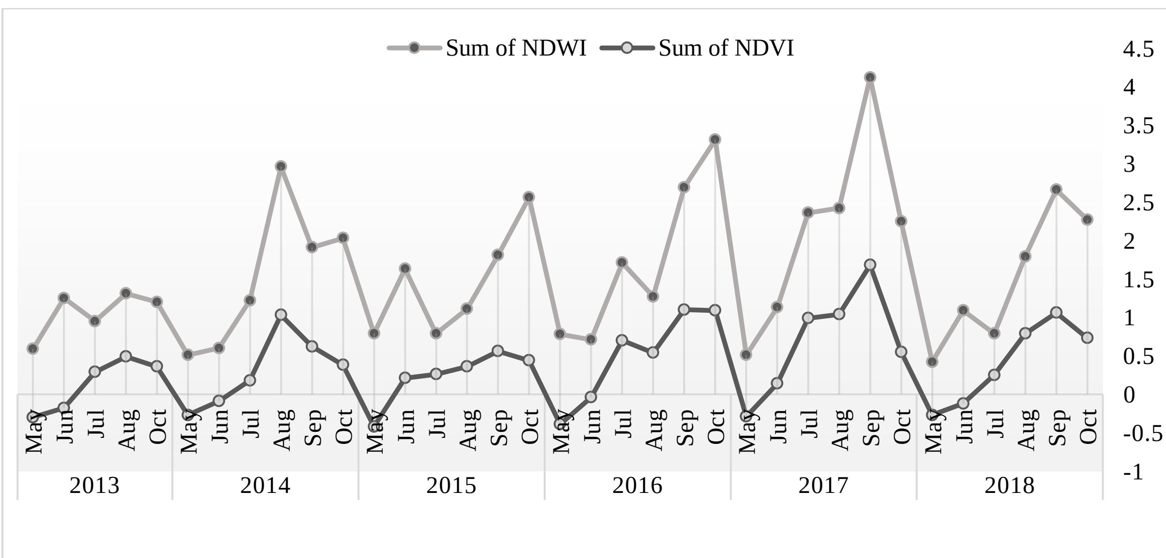

Figure 5.3b Summation of NDVI and NDWI of the five sampling sites.

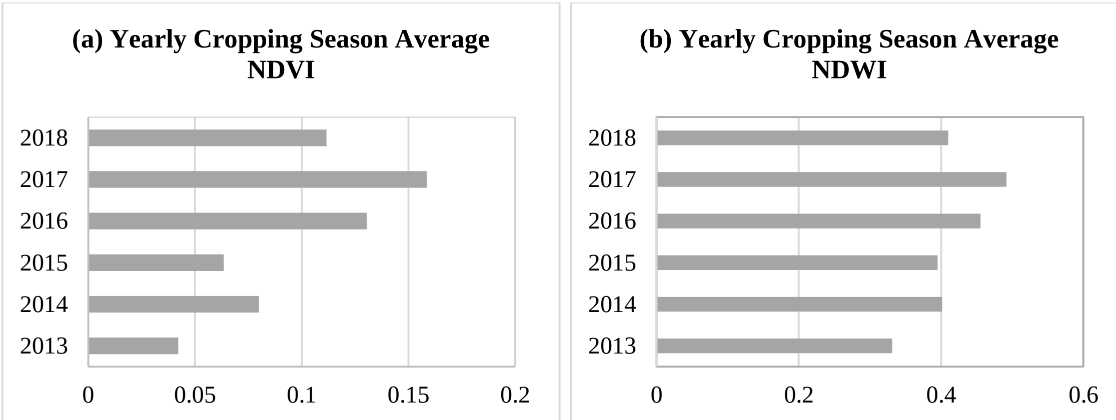

Figure 3.4 Annual average of (a) mean NDVI and (b) mean NDWI for the five sampling sites within the experimental field.

Table 3.2 Population dynamics of Sucking Pests in cotton sown in May 2014-2015 as observed between 23 to 41 Standard Meteorological Week (SMW)

Pest	***Year***	***First Appearance*** (SMW)	***Peak*** (SMW)	***Declined till*** (SMW)
White fly	2014	24	34	41
	2015	23	31	41
Thrips	2014	24	33	41
	2015	23	29	41
Leaf hopper	2014	27	31	41
	2015	27	33	41

3.4 DISCUSSION

Although the utility of satellite remote sensing techniques for the pest and disease detection has been suggested long ago (Cline, 1970), but its utility is still inadequate quantitatively in spite of immense potential in controlling the disease (Ray et al., 2011). Tucker (1979) introduced NDVI which most frequently used to characterize vegetation quality from the space and could be used for assessing the crop health and crop growth and development. Gao (1996) proposed an index related to liquid water content called NDWI to monitor changes in water content in the leaves using NIR and SWIR.

Statistical evaluation helps to assess the crop health by forecasting its population with relation to with weather variables and in the real-time basis by remote sensing. It has been found very successful in evaluating the abiotic stresses like temperature CO_2 and water availably (Shikha et al., 2018) and recently they are updated to capture the biotic stress as well with various pest models and induction of pest module in crop models like DSSAT (Ortiz et al., 2009; Hoogenboom et al., 2010). Monitoring the crop stress by remote sensing approach widely carried out at various parts of the world (Yang et al., 2011). They are also utilized for early detection of the pests (Ray et al., 2011). Studies in various parts of India on other crops such as wheat, rice, potato etc. (Panigrahy et al., 2001; Singh et al., 2002; Arora et al., 2004), is based on utilization of the satellite remote sensing technique has been demonstrated for crop area estimation, assessment of pest and diseases detection.

Cotton is grown as a monocrop in the various parts of the country like Hisar, Akola, Sirsa etc. The succulent leaves, bright and attractive flowers, floral nectars, large number of fruiting bodies available most of the time during the growing season exhibit that cotton is specifically designed by nature and thus attracts whole range of pest and disease. Among 145 insect pests affecting cotton major sucking pests are jassids, aphids, whitefly and thrips (Janu et al., 2017). The pest attack during the cropping season on the study area is also correlated with the weather variables such as maximum and minimum temperature, relative humidity etc. for the year 2013 (Swami et al., 2017) 2014 (Janu et al., 2017) 2015 (Janu et al., 2018).

These insect pests have been reported 57.9 percent reduction in yield (Sharma, 1998), thus need lot of attention for enhancing productivity. It is also reported that weather and sowing window have significant role in the pest population (Bishnoi et al., 1996). As reported in various studies, temperature and humidity favors the pest and diseases. There are various studies to assess correlations between the weather factors such as maximum and minimum temperature, precipitation and relative humidity with pests on the study region (Janu et al., 2017, Swami et al., 2017). The Gemini virus CLCuV carried by the whitefly vector affects the plants as stunted growth, less number of balls, reduction in ball size and deterioration in fiber quality in upland cotton (Tanveer and Mirza, 1996).

For the assessment of pest population and its correlation with weather attributes various field experiments are conducted. Swami et al. (2017) studied the leaf curl disease (CLCuD) transmitted by whitefly (Bemisica tabaci) in Bt-cotton cultivars of highly cotton productive area in North India. The study site selected for experiment/investigation was Research farm of department of Agricultural Meteorology CCS HAU, Hisar during 2013. Correlation analysis reveals that per cent CLCuD incidence and whitefly population shows a significant negative correlation with temperature maximum and minimum and rainfall while positively correlated with relative humidity morning and evening and sunshine hours. The significant observation using the study is that the maximum incidence of CLCuD occurs due to variations in minimum temperature. Janu et al. (2017) explore the population dynamics and the impact of abiotic factors like maximum temperature, minimum temperature, morning relative humidity, evening relative humidity, average weed speed, sunshine hours and rainfall on the population of thrips, (*Thrips tabaci* Lindeman) for twenty Bt cotton genotypes at Research Farm, Cotton Section, Department of Genetics and Plant Breeding, CCS Haryana Agricultural University, Hisar during *kharif 2014* and 2015. The results revealed that the impact on the fluctuation of thrips population increases with the addition of the influence of weather parameters in both the years. He further utilized standard meteorological week weather data for studying the dynamics of thrips, *Thrips tabaci* Lindemann along with their correlation with abiotic factors. The correlation results indicated that during 1st season all the weather parameters were non-significantly correlated with the thrips population whereas, during 2nd season maximum temperature correlated significantly negative with thrips population while minimum temperature, morning and evening relative humidity correlated significantly positive (Janu et al., 2017b). Janu et al. (2017c) also quantified the whitefly dynamics on Bt Cotton with prevailed weather conditions using the regression (linear, multiple and stepwise) analysis in SPSS Software. The simple regression results indicated higher incidence of whitefly with positive correlation with morning relative humidity (RHm) during 2014 and 2015 whereas multiple regression shows that weather factors exerted 64.90 % in 2014 and 79.50% in 2015 influence on whitefly disease incidence in Bt Cotton and finally stepwise regression again indicated that morning relative humidity (RHm) exerted (37.70 and 28.90 per cent) more influence on whitefly population.

Applying modern technologies along with conventional assessment techniques for yield forecasting and pest detection can be applied in various fields. They are found beneficial in bringing precision in agriculture. Remote sensing can also be used for crop classification, examining the crop health and crop viability. Nowadays is also used successfully for monitoring and mapping stress, quality of crop, crop growth and developmental phases, nutrient deficiencies and predicting and detecting the pest and diseases (Riley, 1989; Neteler et al., 2011; Gooshbor et al., 2016).

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Chapter- IV

Evaluating the performance of regional climate model for cotton production in rainfed and irrigated regions using DSSAT

EVALUATING THE PERFORMANCE OF REGIONAL CLIMATE MODEL FOR COTTON PRODUCTION IN RAINFED AND IRRIGATED REGIONS USING DSSAT

ABSTRACT

High resolution RCMs have potential to improve outputs of courser resolution GCMs. To identify suitable RCMs for area of interest, historical simulations are evaluated against corresponding observations. Successful representations, increase confidence for using future simulations. Present study evaluates RegCM4.0 historical simulations having baseline-derived information and its bias corrected data. Here, comparative study of the cotton crop for Akola (central) and Hisar (northern) agroclimatic zone of cotton for the period 1971–2005 is presented. RCM shows wet biases with high rainfall intensity. The model also evinces night warming due to a significant (minimal) decline in maximum (minimum) temperature leading to reduced diurnal temperature difference in both the locations. Overall model underestimate temperature and overestimate rainfall. In addition, strikingly low number of intense warm and cold events are simulated. Model is highly biased for rainfalls >0mm/day and <5mm/day; and moderately biased for rainfall >5mm/day. The bias-correction using quantile mapping approach shows excellent agreement annually, but drastically failed to correct variability as it is a ‘distribution-based method'. Also, this approach worked well in the arid Hisar region than rainfed Akola region. Further, utilising these data in Decision Support System for Agro-technology Transfer (DSSAT) simulated output for cotton yields, Leaf Area Index (LAI) and ball Number at maturity/m^2 (NM) with bias-corrected RCM outputs shows good agreement with corresponding observation than non-bias-corrected RCM outputs in both regions. The study suggests the RCM outputs can be used explicitly for the study of the impact of climate change on crop productivity when complemented with reliable bias-correction techniques.

Keywords: Climate change, cotton, RegCM4, Bias-correction, Quantile mapping, DSSAT, irrigated, rainfed

4.1 INTRODUCTION

Agricultural productivity is threatened due to climate change (IPCC AR5, 2014). So mitigation and adaptation strategies have to be applied for the crops as per changing climate. Therefore, the understanding of the inlying processes by which it is affected is important for the researchers and policymakers (Nelsona and Shively, 2013). In the light of which extensive researches are done both in the field experiments and modeling (Reddy et al., 2005, Saseendran et al., 2016; Ozturk et al., 2017). Projected changes in temperature, rainfall and carbon dioxides affect the agroecosystem and its processes. Understanding the impact of a regional warming trend on the phenological and growth stages of the crop may assist in optimizing the management practices and therefore increasing the productivity of the crop.

To assess the impact of climate change upon the crop, having reliable climate data is essential. Climatic projections from various global climate models (GCMs) and regional climate models (RCMs) still have significant errors and biases. While GCMs are the primary source of information on climate scenarios, but still have the drawback of having coarse special resolution and inability to capture inter-annual variability which is rectified by downscaling with RCMs on regional scales (Metzger et al., 2005). GCMs can also be used with various downscaling approaches (Thomas et al. 2008) for these purposes. These GCMs and RCMs data can be further bias-corrected by various methodologies viz., Linear Scaling, Delta change approach, Quantile Mapping (QM), etc. (Qian et al., 2016). These models help in understanding the processes while simulating the past, present and future climate. These observations versus simulations and their bias-corrected version offer a comparatively viewpoint for credible information (Gudmundsson, 2014; Maraun, 2016). These climate models' outputs serve as an input for the hydrological and crop simulation models. A number of crop simulation models are being utilized along with field studies to examine the crop yield and climate sensitivity under different scenarios (Aggarwal et al., 2006) like General Large Area Model (GLAM) (Sanai and Chun, 2017), Decision Support System for Agro-technology Transfer (DSSAT) (Saseendran et al., 2016; Mall et al., 2017), InFoCrop (Aggarwal et al., 2005), AquaCrop (Pareek et al., 2017) etc. (Anwar et al., 2007; Ortiz et al., 2008; Singh et al., 2017; Mall et al., 2018). But the restraints while integrating these crop models are that the spatial scale is much smaller than those of the climate models (Hansen and Jones, 2000). So the weather inputs have to be downscaled as per the model requirements. However, using this process-based model such as DSSAT-CSM helps in analyzing some multifaceted relations (Boote et al., 2010; Pathak et al., 2012; Thorp et al., 2014) by analyzing biotic and abiotic factors individually or in association with each other (White et al., 2005; Liu et al., 2010).

The growth and developmental rates of crops are accelerating with an increasing warming trend in the majority of the crops. This is due to the increase in biomass and reduction in maturity date (Menzel et al., 2006; Xiao et al., 2014; Ahmad et al., 2017). Crop yield, Leaf area index (LAI), evapotranspiration (ET) and various other phenological processes are also affected by weather conditions, variety assortments, sowing dates, nutrient availability and other management practices (Beamish et al., 2016; Ahmad et al., 2017).

Inputs from various and GCMs and RCMs are applied for the yield estimation of different crops like wheat (Pathak et al., 2003; Gourdji et al., 2013; Mall et al., 2018), rice (Kumar et al., 2013; (Kumar and Aggarwal, 2014; Mall et al., 2018), cotton (Hebbar et al., 2013; Saseendran et al., 2016). Cotton belongs to the C3 plant and requires warm days and cool nights for optimum growth and development. At high-temperature regime cotton loses its reproductive capacity more than its biomass production (Sankaranarayanan et al., 2010). The daily weather datasets required for the model are obtained from Coordinated Regional Climate Downscaling Experiment over South Asia (CORDEX- SA) and Coupled Model Intercomparison Project 5 (CMIP5) database, which are developed and maintained by Earth System Grid Federation (ESGF) (https://esgf-data.dkrz.de/projects/esgf-dkrz). The spatial resolution varies from 50 to 200 km (Taylor et al., 2012) which is enough to simulate the physical processes that dominate the atmospheric dynamics on a large scale although it cannot resolve subgrid processes; therefore, need to be parameterized (Giorgi et al., 2013; Rajczak and Schär, 2017). RCMs are forced over with the GCMs data to improve the data explicitly and increase the spatial resolution (Giorgi et al., 2013). The regional climate model (RegCM4) forced with the outputs from global model GFDL-ESM2M experiment data is considered in the present study as it captures the seasonal precipitation (Choudhary and Dimri, 2018) and air temperature (Garg et al., 2015) with highest combined mean skill. Reddy et al. (1992) reported that the effect of elevated temperature on cotton depends upon the genetic constitution like *Gossypium barbadense* is more sensitive than *G. hirsutum*. Among abiotic stresses, 60% yield loss is recorded in cotton as compared to 30% in other crops like cereals (Dason, 1996). Saseendran et al. (2016) using cotton model within RZWQM2 showed that until the mid-21st-century yield is found to be increased in low to moderate emission levels and declined in high emissions levels but further it declined significantly at all levels in irrigated conditions. Although in rainfed conditions yield declined in all emission scenarios. However, when the water requirements are met the yield increased in 25% of cases; while, Hebbar et al. (2007) using InfoCrop model implied that with an increase by 3.95°C (3.20°C) in mean temperature yield declined by 477 kg/ha (268 kg/ha). As due to high temperature, crop duration and ball retention and ball weight reduced. Reddy et al. (2005) suggested that an increase in cotton crop productivity depends upon the regional climate as well. So for places with lower mean temperature, an increase in temperature will be beneficial and regions having a temperature close to 40°C will be deleterious (ICAC, 2009). Heavy rain is pernicious for germination in the regions of black soil due to poor aeration quality (Raj and Dasan, 1975). Studies indicate that this perturbance on the crop phenology can be truncated by adopting new cultivars with higher growing degree days and by making few changes in management practices such as a different planting window or adding more nutrients at required time (Liu e al., 2006; Singh et al., 2007; Anwar et al., 2015; Shikha et al., 2017).

This present work aims to analyze the performance of RegCM4 model data and its bias-corrected data during the historical period (1971–2005) in comparison with the observed for the sensitivity analysis of the models of different regions. Weather parameters such as sunshine duration, maximum and minimum temperature, temperature extremes, rainfall, number of rainy days, extremes in rainfall, rainfall intensity are taken for the study.

Comparison of model performance and its bias-correctbias-corrected weather variables is introduced in the crop simulation models for the northern semi-arid region (Hisar) and central rainfed region (Akola) cotton-growing regions in India. Further sensitivity analysis of the DSSAT cropping model for evaluating the potential, irrigated, and rainfed conditions on cotton crop over the northern semi-arid region and rainfed region. The following section 2 deals with the data and methodology adopted for the study. Section 3 illustrates the results and discussion under the subsections regional climatic study with observation, model and bias-corrected weather data, then extremes in climate and crop simulation. Finally followed by the summary and conclusions of the study in section 4.

4.2 DATA AND METHODOLOGY

4.2.1 Study Area and its Climatic Conditions

In India, all four species of cotton are grown in three zones namely Northern zone, Central zone, and South zone. The northern zone is mostly irrigated; therefore, the increasing trend in rainfall has less influence, also decreasing temperature has prolonged the vegetative growth and thus crop duration. Central and South zones are mostly rainfed with expected increasing temperature and erratic rainfall which leads to a shortening of growth period of the crop (Sankaranarayanan et al., 2010). The northern zone includes Haryana, Punjab, and Rajasthan, Central zone includes Madhya Pradesh, Maharashtra, and Gujarat and southern zone comprising Karnataka, Andhra Pradesh, and Tamil Nadu. For this study, two regions with different climatic conditions and soil types are selected where the availability of water is different. This is further stimulated by crop model with different sources of weather data for cotton productivity. The selected sites for cultivation are Akola from Maharashtra region with rainfed agricultural practices and Hisar from Haryana with irrigated agricultural practices.

4.2.2 Crop Management Data And Crop Simulation

For the present study, the Decision Support System for Agrotechnology Transfer-Cropping System Model (DSSAT-CSM) Version 4.6.1 crop model has been used. DSSAT-

CSM is a set of various dynamic crop simulation models taken together like CERES, CROPGRO for over 40 crops (Shikha et al., 2018). The DSSAT-CSM is structured employing modular approach. Model input includes experimental details file and genotype data file under the crop management module, weather data file in weather module and soil data file in soil module (Hoogenboom et at., 2019). The model has in-built tool called GBuild, which displays graphs of simulated and observed data and are also able to compute statistical graphic interface.

Climate and soil data for Akola has been collected from Agromet observatory, Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola, Maharashtra. Similarly, Climate and soil data for Hisar is collected from Agromet observatory, Chaudhary Charan Singh Haryana Agricultural University (CCSHAU), Hisar, Haryana. Field experiment was carried out for the management data for the model in both the regions. These are taken from of northern and central agroclimatic zone for cotton respectively. Approved package and practices for the irrigation and fertilizers were applied in the field experiments which was taken as an input in the model in the management model. Crop management inputs employed in the model like genetic coefficients, planting dates, sowing depth and space, seed number application strategy of irrigation and fertiliser, etc. are also taken as per the field experiment conducted. Soil input parameters include soil texture and thickness, soil pH, bulk density, soil organic carbon, hydraulic conductivity, soil's water holding capacity, the slope of the field, etc. The cotton CROPGRO model under DSSAT was simulated for the study which was calibrated and validated using data from field experiment with reasonable accuracy for the cotton production in both the regions Hisar (Swami et al., 2016, Shikha et al., 2018) and Akola (Nath et al., 2018; ICAR-CRIDA, Annual Report, 2017-18) region.

4.2.3 Climate Model Output And The Bias-Corrected Data

The minimum data required as weather variable for input in the DSSAT model are daily Maximum temperature (℃), Minimum temperature (℃), Solar radiation (MJ/m^2), and Rainfall (mm^2). Few optional inputs are Relative humidity (%) and Wind speed (km/hr).

Apart from this model also requires the latitude, longitude and the elevation information of the site. The source data for the study is extracted and downscaled from the Regional Climate Model. These RegCM 4 outputs are available in NetCDF format and contains data on daily, monthly and yearly basis. The gridded data of the RCM are then extracted with the help of CDO for location. Since, the DSSAT crop model are required to have a particular supportable format.

The period considered for the study is from 1971 to 2005, since it is available as a historical database after which different scenarios are inlaid as RCP 2.6, 4.5, 6.0 and 8.5. Weather data taken during the field trial and long-term weather data were obtained from GFDL-ESM2M-RegCM4 experiment of Coordinated Regional Climate Downscaling Experiment (CORDEX), a World Climate Research Program for the domain CORDEX-SA. The GFDL-ESM2M shows the highest skill in capturing the seasonal mean precipitation (Choudhary et al., 2018) and hence considered in the present study. Studies based on RCMs include CORDEX- SA (encompassing India) as a set of multiple RCM simulations under a common framework. These RCMs are driven by various GCMs from the Coupled Model Intercomparison Project Phase- 5 (CMIP5) (Taylor et al., 2012; Giorgi and Gutowski, 2015).

RegCM4 performs better in simulating the present climate over India and therefore it is preferable over the Indian subcontinent (Gao and Giorigi, 2017). Still, conspicuous and systematic biases exist which attributes to limited process understanding in the dataset. To overcome this, post-processing is done by downscaling processes and bias-correction of the output. The underlying aim is to introduce statistical transformation so that the simulated model output distribution resembles the observation (Gudmundsson et al., 2012; Maraun, 2016). In this study, the Quatile Mapping (QM) approach is used which calibrates the cumulative distribution function of model data for correction. It is implemented with the help of qmap library written for R statistical software (Gudmundsson et al., 2012; Zhao et al., 2017). Software packages based on R are developed and are made available in public domain, which can be specifically downloaded used to downscale (https: //github.com/SantanderMetGroup/downscaleR, assessed on: 03 August 2017).

4.2.4 Experimental Outline

Detailed analysis and inter-comparison are done for the climate of the region based on the observations, model and bias-corrected data for the year 1971-2005. This is to evaluate how close the model predicts the data and how efficiently the extremes are captured in with the model at different regions.

To evaluate the impact of climate change on the cotton crop, weather data derived from RegCM4.0 were incorporated in the weather module of DSSAT vn.4.6. The observed, RegCM and RegCM bias-corrected weather output was used for simulation of the cotton rainfed, irrigated and potential conditions mentioned below. The genetic coefficient and the management data was constant for the simulation. Three planting dates chiefly practiced in the region was considered for the study viz. 10^{th} May (EPn), 21st May (MPn) and 06^{th} Jun (LPn) in the northern region, Hisar and 20^{th} Jun (EPc), 06^{th} Jul (MPc) and 21^{st} Jul (LPc) in the central region, Akola.

Three seasonal simulations were done for three sowing dates with three rainfed, irrigated and potential conditions (3* 3=9 treatments) in Hisar irrigated region and three sowing dates with rainfed, potential conditions (3* 2=6 treatments) in Akola rainfed region. The simulated output dry yield (Kg/ha), leaf area index (LAI) and ball number at maturity was derived to assess the phenology and impact of different climate.

Hisar:

1. Potential run assuming no water and nitrogen stress.
2. Irrigated cotton with the recommended application of 5-6 times every 20 days from the 60th day of planting and nutrients such as (N: P: K in the ratio 70:24:24)
3. Rainfed productivity applying no irrigation with the same nutrient levels.

Akola:

1. Potential run assuming no water and nitrogen stress.
2. Rainfed productivity applying no irrigation with nutrients such as (N: P: K in the ratio 60:30:30) as per recommended practices in the form of single super phosphate, potassium chloride, and urea.

4.2.5 Estimation Of Biases and Correction in Weather Data

4.2.5.1 Mean bias error

For the estimation of biases in RCM climate data, the average of observed has been deduced from the average of forecast or simulated. Bias estimation of RCM climate output was done by comparing its mean and standard deviation for the annual with observed climate (Willmot, 1981; Chai and Draxler, 2014).

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(S - O)$$

4.2.5.2 Root mean square error (RMSE) is utilized to measure the errors in a model predicting the data as, how spread the data is around the line of best fit. Its spread is between 0 to 1 and close to 0 indicates better performance. S and O are simulated and observed (Chai and Draxler, 2014).

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(S - O)^2}{n}}$$

4.2.6 Estimation of Biases and Correction in Simulated Yield

4.2.6.1 Percentage deviation (D%)

The goodness of fit statistics used to calculate the discrepancy between observed, model and bias-corrected was used. This is done by comparing the mean and standard deviation of the simulated versus expected. Si and Oi are simulated and observed yield. The magnitude of D% close to zero shows good agreement them (Araya et al., 2015).

$$D\% = \left(\frac{Si - Oi}{Oi}\right) \times 100$$

4.2.6.2 Index of agreement (I)

Sm and Om are the means for simulated and observed yield. It varies from 0 and 1 and where 1 shows perfect match value close to 1 shows better agreement (Willmot, 2012).

$$I = 1 - \frac{\sum_{i=1}^{n}(Si - Oi)^2}{\sum_{i=1}^{n}(|Si - Om| + |Oi - Om|)^2}$$

4.2.6.3 Root mean square error (RMSE) for the yield

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Si - Oi)^2}{n}}$$

4.3 RESULTS

4.3.1 Regional Climatic Study with Observation, Model and Bias-Corrected Weather Data

The RCM highly underestimates the average maximum temperature and slightly underestimates the average minimum temperature annually. Whereas it highly overestimates the sunshine duration and slightly overestimates the annual precipitation. Bias-correction satisfactorily improves the annual rainfall of RCM data to complement with the observed data precipitation (Figure 4.1a-h).

Rainfall indicates large heterogeneity in the distribution and intensity as per the model output. RCM shows wet bias in the annual precipitation in both the regions particularly over the northern region. The annual mean precipitation for 35 years during 1971 - 2005 as per observations are 451 ± 161 and 779 ± 202 mm and the model data shows 548 ± 128 and 889 ± 183 mm for Hisar and Akola region respectively. While, bias-corrected annual precipitation are 437 ± 112 mm and 764 ± 184 mm respectively, which is close to the actual observed value (Figure 4.1a-b). These results indicate that although the model overestimated rainfall intensity (collective of the amount of rainfall and rainy days); however, after bias-correction of model output the distribution was normalized.

The annual maximum temperature ranges from 31.4 ± 0.67°C and 34.1 ± 0.53°C as per observation, 26.1 ± 0.78°C and 28.8°C ± 0.68°C as per model for Hisar and Akola respectively. This reveals that the speculations as per simulations are lower than the actual with an approximation of 4-5°C. When bias-corrected the values came up to 31.4 ± 0.75 and 34.12 ± 0.75, which is very close to the actual observations (Figure 4.1c-d). Again annual minimum temperature ranges from 16.2 ± 0.59°C and 19.4± 0.68°C as per observation and 15.8 ± 0.73 and 19.1 ± 0.6 as per model. Here also the speculations as per simulations are approximately 1 - 2°C lower than actual. And the bias-corrected values are 16.18 ± 0.72 and 19.42 ± 0.81 which is also very close to the actual observations (Figure 4.1e-f). This indicates the bias-correction techniques work appreciably good for the temperature.

Sunshine duration is another important factor in plants for photosynthesis. RCM here shows the enhanced duration of sunshine with approximately similar variability in both the regions. The model estimates 9.8 ± 0.05 and 9.8 ± 0.06, but the actual is 7.72 ± 0.51 and 7.75 ± 0.74 hours which indicates an overestimation of approximately 2 hours at both the regions with almost similar conditions. This gap is minimized with bias-correcting the data where the average sunshine duration for the period is 7.78 ± 0.12 and 7.82 ± 0.17 for the Hisar and Akola region respectively (Figure 4.1g-h). Apparently, this is also very close to the actual duration of sunshine (hour).

A remarkable feature worth mentioning is that while the RCM model manifests a considerable decline in maximum temperature and trivial decline in minimum temperature as compared to observation (Figure 4.1). Hence it is observed that the diurnal temperature is found decreasing and the model shows night warming. This is evident in both the cotton-growing regions. But this phenomenon is more prominent in the northern zone than in the central zone. So, it's apparent that the northern zone is more susceptible in comparison to central zone. The model overestimates the count of rainy days in both the regions i.e., they show a considerably high number of rainy days which is > 0 and <1 mm (Table 4.1). This is due to the ‘drizzling effect' as shown by these models. This has been considerably corrected with the bias-correction.

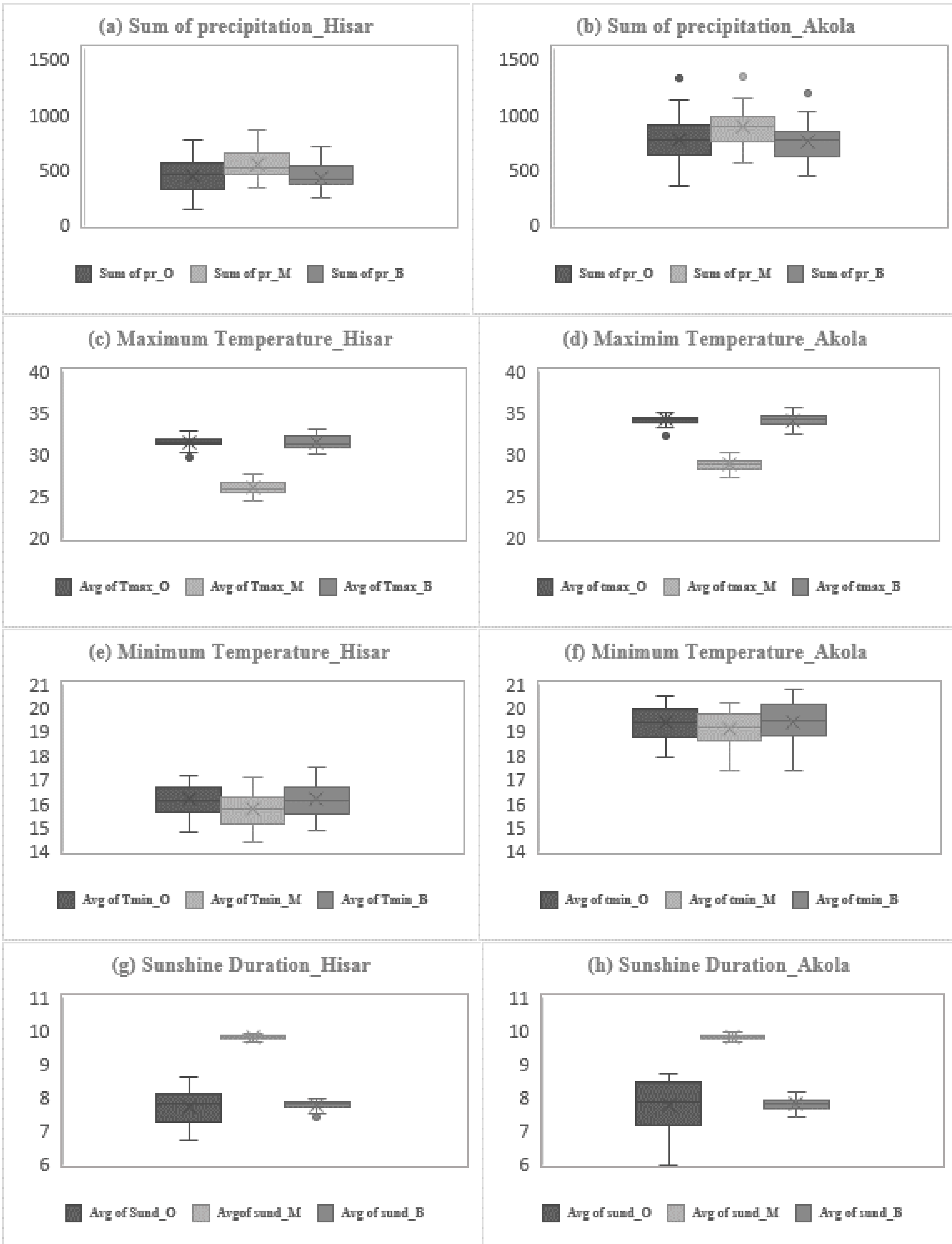

Figure 4.1 Comparison between observed (O), RCM/RegCM 4.0 (M) and RCM Bias corrected (B) sum of precipitation, maximum temperature, minimum temperature and sunshine duration during the period 1971 to 2005 for Hisar (a, c, e, g) and Akola (b, d, f, h) respectively.

Table 4.1 Comparison between observed (O), RCM/RegCM 4.0(M) and RCM Bias corrected (B) count of rainy days (CRD) for the period 1971 to 2005 for Hisar(h) and Akola(a).

	CRD (> 0 mm)						CRD (> 5 mm)						CRD (> 10 mm)					
Years	Oh	Oa	Mh	Ma	Bh	Ba	Oh	Oa	Mh	Ma	Bh	Ba	Oh	Oa	Mh	Ma	Bh	Ba
1971	44	60	302	298	41	48	22	24	19	32	18	29	13	16	7	16	7	15
1972	31	44	310	281	41	57	17	30	26	46	24	41	9	23	11	26	11	26
1973	29	68	338	284	24	62	17	33	15	44	13	42	13	24	8	26	8	24
1974	27	51	309	231	54	63	14	24	32	53	30	50	9	17	20	25	17	24
1975	37	63	340	243	43	69	22	34	24	63	22	57	16	21	13	38	11	35
1976	53	54	327	234	46	45	29	33	26	35	26	32	22	23	19	24	17	23
1977	53	65	300	216	39	62	29	40	21	55	20	48	19	25	15	32	13	32
1978	48	70	319	249	37	44	24	43	25	33	24	31	17	27	16	19	14	16
1979	39	67	327	241	39	57	17	36	20	46	19	42	12	24	13	28	9	28
1980	39	54	343	274	32	65	19	31	18	50	18	42	7	19	10	27	9	25
1981	51	63	321	232	44	50	24	38	27	34	25	31	14	27	18	18	18	18
1982	49	53	310	270	55	43	17	21	28	34	27	31	13	15	15	21	13	20
1983	57	57	324	264	49	56	26	46	32	43	31	40	17	31	22	25	20	23
1984	37	43	305	263	38	61	13	24	21	51	20	47	10	19	13	32	12	29
1985	51	38	305	297	48	66	13	23	27	50	24	47	8	21	14	27	13	27
1986	41	49	302	239	50	71	20	24	35	58	35	52	13	21	25	31	24	28
1987	31	56	313	281	38	51	10	34	19	38	18	36	4	20	12	16	11	16
1988	50	70	311	320	47	52	24	42	32	45	30	36	18	34	22	20	20	18
1989	33	56	309	299	45	78	12	29	34	59	33	52	6	20	21	23	19	21
1990	42	67	317	296	34	72	19	34	19	59	17	49	13	26	8	33	8	31
1991	34	38	337	252	51	59	16	21	26	45	26	39	13	12	15	29	13	28
1992	47	50	297	234	29	56	23	31	18	42	18	38	12	25	15	26	12	25
1993	44	58	298	269	39	48	18	36	25	35	25	27	8	28	14	14	11	12
1994	45	69	291	269	68	81	23	42	43	70	40	67	16	26	22	44	18	40
1995	46	55	294	230	38	60	23	28	28	47	27	41	20	14	11	28	10	26
1996	44	59	316	248	30	56	22	35	21	47	21	43	12	18	11	25	10	22
1997	61	68	322	246	34	44	32	35	20	34	19	32	20	24	15	20	11	18
1998	48	64	337	274	37	47	28	36	23	38	22	35	19	23	12	22	10	22
1999	27	69	325	269	42	56	13	32	31	47	31	44	9	25	18	27	17	24
2000	20	45	311	282	33	59	13	20	24	45	23	40	4	15	16	26	16	24
2001	41	55	334	282	51	64	28	30	30	48	29	44	18	19	16	23	15	22
2002	25	53	305	262	29	38	11	26	18	29	17	24	5	20	11	13	10	13
2003	37	58	292	287	37	60	25	20	23	40	22	37	20	11	16	19	13	16
2004	32	63	334	270	29	73	13	23	17	60	16	55	9	12	11	35	10	34
2005	43	67	343	292	40	45	25	38	22	40	21	37	17	25	16	25	16	24
Grand Total	**1436**	**2019**	**11068**	**9278**	**1431**	**2018**	**701**	**1096**	**869**	**1595**	**831**	**1438**	**455**	**750**	**521**	**883**	**466**	**829**

4.3.2 Extremes in Climate

Further detailed analysis upon the model output is done to visualize if it captures the weather extremes. This is important since the agricultural crops like cotton has a certain threshold temperature up to which it can sustain. Rainy days for the northern and central (Table 4.1) region, as captured by the model are; when the rainfall is above 0 mm and below 1mm (11068 and 9278), which is not the actual case as observed data reveals (1436 and 2019) respectively. This resembles the ‘drizzling effect’ of the model as discussed earlier. But it is also noticed that the model performs better when it comes to capturing the extremes in rainfall above 5mm and 10mm. The model also speculates 869 and 1595 days with more than 5mm rainfall which is 831 and 1438 days with bias-correction, where the observation was 701 and 1096 respectively. In the same way, 521 and 883 days of rainfall more than 10 mm which is 466 and 829 with bias-correction approach, it was observed 455 and 750 days.

Number of days with maximum temperature as observed ≥ 40ºC (Northern -1639 and central - 2285) (Table 4.2 and 4.3) was remarkably higher than the model (Northern -152 and central - 20) and for ≥ 45ºC also was higher in actual (Northern -120 and central -172) then model (Northern -2 and central - 0). Bias-correction though satisfactorily corrected the errors and the count went up to (Northern -1712 and central - 1368) and (Northern -140 and central - 50). Similarly, observed number of days with minimum temperature ≤ 5ºC (Northern - 1677 and central -59 days) is lower than the model (Northern -1810 and central -111) and bias-corrected (Northern -1732 and central - 321). And for ≤ 3ºC model estimated values (Northern -1104 and central -26) were higher than the observed (Northern -819 and 10) and when bias-corrected (Northern -1032 and central -125) values reduced in northern and escalated in the central region.

It can also be observed that the number of rainy days for the period 1971-2005 was higher in the central region (2019) than the northern (1436) region. And considerably high in the model (Northern - 11068 and central - 9278) when compared with the observed and bias-corrected (Northern -1431 and central - 2018). This implies, bias-corrected data shows good agreement with the observed. However, when extremes in temperature are concerned the model is not able to represent the maximum and minimum temperatures. The model underestimates temperature ≥ 40ºC and ≥ 45ºC in both the regions. It slightly overestimated minimum temperature ≤ 5ºC and ≤ 3ºC in the northern and overestimated in the central region. It can also be noted that the bias-correction approach although performs well for minimum temperature in Hisar but not in Akola. Further, Table 4.4 signifies that the model depicts the observation nicely but with some biases. These biases are remarkably corrected by the QM approach in this study. The Mean Bias Error (MBE) and Root mean squared error (RMSE) are lower for the bias-corrected data in comparison to the model in both the regions.

Finally, In Table 4.4, it is observed that the mean bias error (MBE) and Root mean squared error (RMSE) values have improved considerably with bias-correction. Since, the quantile mapping approach is equates the cumulative distribution function. So to capture extremes the downscaling approach or bias-correction techniques still needs to be refined for daily variables.

Table 4.2 Same as Table 4.1 but for extremes in maximum temperatures (≥40°C and ≥45°C) and minimum (≤5°C and ≤3°C) temperatures

Years	**Max Temp ≥40°C**			**Max Temp ≥45°C**			**Min Temp≤5°C**			**Min Temp≤3°C**		
Hisar	**C-O**	**C-M**	**C-B**	**C-O**	**C-M**	**C-B**	**C-O**	**C-M**	**C-B**	**C-O**	**C-M**	**C-B**
1971	32	1	48	0	0	1	47	63	59	18	27	24
1972	54	0	50	1	0	0	48	73	69	31	52	51
1973	59	6	73	0	0	5	59	49	49	34	18	17
1974	50	4	35	1	0	4	75	65	64	49	44	41
1975	47	1	40	0	0	1	67	46	40	29	21	20
1976	43	0	27	1	0	0	42	57	49	22	24	23
1977	33	1	58	4	0	1	45	69	65	20	55	52
1978	51	5	39	14	2	5	53	68	65	26	43	39
1979	52	3	48	7	0	3	34	27	25	10	13	12
1980	57	11	69	2	0	10	48	73	73	26	50	46
1981	57	9	53	8	0	7	38	58	54	7	23	20
1982	33	0	27	0	0	0	41	67	63	7	48	47
1983	22	0	21	0	0	0	48	56	56	23	38	37
1984	56	5	55	9	0	5	61	50	50	43	30	27
1985	57	2	47	1	0	2	36	46	43	13	17	15
1986	34	0	20	2	0	0	54	60	60	36	48	47
1987	66	2	33	2	0	2	37	66	65	8	49	44
1988	54	11	58	10	0	10	41	43	42	12	25	24
1989	43	1	40	4	0	1	53	27	27	31	16	13
1990	45	0	57	0	0	0	34	39	35	8	15	11
1991	46	0	49	0	0	0	41	60	58	18	38	34
1992	30	8	67	1	0	7	42	41	37	12	22	21
1993	56	6	31	7	0	6	36	66	64	25	38	35
1994	46	5	65	9	0	5	43	74	70	17	47	45
1995	55	1	37	11	0	1	39	74	74	8	48	45
1996	34	15	80	2	0	13	66	37	35	39	30	27
1997	26	10	46	0	0	8	57	21	20	39	15	14
1998	50	7	51	10	0	7	31	56	56	16	44	42
1999	62	3	35	2	0	3	37	46	44	14	31	30
2000	58	0	40	1	0	0	60	43	40	32	25	23
2001	30	2	42	2	0	2	51	32	30	34	16	14
2002	74	14	83	5	0	13	47	33	32	24	20	20
2003	47	10	54	2	0	10	58	65	63	34	46	46
2004	42	5	70	0	0	4	39	43	40	11	21	20
2005	38	4	64	2	0	4	69	17	16	43	7	6
Grand Total	**1639**	**152**	**1712**	**120**	**2**	**140**	**1677**	**1810**	**1732**	**819**	**1104**	**1032**

Table 4.3 Same as Table 4.2 but for Akola

Years Akola	Max Temp ≥40°C C-O	C-M	C-B	Max Temp ≥45°C C-O	C-M	C-B	Min Temp≤5°C C-O	C-M	C-B	Min Temp≤3°C C-O	C-M	C-B
1971	47	0	38	0	0	2	0	0	0	0	0	0
1972	90	0	29	3	0	0	0	2	10	0	0	2
1973	81	0	49	20	0	2	0	0	2	0	0	0
1974	53	2	37	0	0	3	2	19	33	0	3	20
1975	69	0	27	0	0	0	3	0	1	0	0	0
1976	57	0	39	0	0	0	0	7	13	0	4	7
1977	75	0	22	0	0	0	1	20	32	0	8	20
1978	56	0	47	7	0	0	1	9	25	1	2	10
1979	72	0	33	9	0	0	0	2	3	0	0	2
1980	66	0	18	7	0	0	0	10	26	0	0	12
1981	72	2	53	3	0	4	1	0	7	0	0	1
1982	60	0	26	0	0	0	0	1	3	0	0	1
1983	77	0	36	7	0	1	2	9	26	1	3	9
1984	71	3	77	11	0	12	1	1	8	0	0	2
1985	78	0	44	5	0	2	0	0	3	0	0	0
1986	70	1	32	3	0	1	0	2	9	0	0	3
1987	57	0	48	0	0	0	1	0	5	0	0	1
1988	76	1	72	13	0	2	0	2	10	0	0	2
1989	56	0	13	12	0	0	1	0	0	0	0	0
1990	39	0	17	2	0	0	0	0	0	0	0	0
1991	66	0	10	10	0	0	4	0	4	3	0	0
1992	87	0	54	6	0	0	13	2	12	2	0	2
1993	62	0	37	8	0	0	13	5	9	1	2	5
1994	73	0	27	5	0	1	9	4	12	2	1	4
1995	59	0	30	8	0	0	4	1	6	0	0	3
1996	87	3	70	6	0	8	0	5	12	0	3	5
1997	42	0	34	0	0	0	0	0	3	0	0	0
1998	71	2	61	10	0	5	0	4	13	0	0	5
1999	54	0	46	1	0	0	3	2	7	0	0	3
2000	50	0	52	3	0	2	0	0	1	0	0	0
2001	47	0	24	3	0	0	0	0	2	0	0	0
2002	66	6	83	5	0	9	0	0	0	0	0	0
2003	64	0	45	2	0	3	0	3	11	0	0	3
2004	68	0	17	0	0	1	0	1	4	0	0	2
2005	67	0	21	3	0	2	0	0	9	0	0	1
Grand Total	2285	20	1368	172	0	60	59	111	321	10	26	125

4.3.3 Crop simulation

The deviation of simulated yield, Leaf Area Index (LAI) and Number at maturity/m^2 (NM) are higher for the model derived weather data then the bias-corrected data in general when compared with observations (Figure 4.2). Similarly, in Table 4.5, we observe the overall percentage deviation is higher for the model data than the bias-corrected data in both the regions. Also, the overall Index of agreement and RMSE values has improved for the yields with bias-corrected data. This can be also be related to the correction in values and improvement in data quality for the study (Table 4.5). The simulated yield output as plotted graphilcally by G-build supported by the model DSSAT are shown in Figure 4.3 and 4.4. The model simulated potential output without water and nitrogen stress shows maximum productivity in terms of yield, LAI and NM (Figure 4.3). The variability is highest in for the model weather as the rainfed and irrigated yield LAI and NM are least in contrary to potential production. Although when bias-corrected data were used the variables was found close to the observation. Also, the potential yield in the northern irrigated region for LPn is the maximum for both observation and bias-corrected approach, whereas it has decreased slightly for model data. As per observed wearther, the high yield in irrigated EPn shows that early sowing was favourable here. And the yield could increase for late sowing for irrigated cotton in the northern region. This is not captured when the crop model is simulated with model data, whereas as after bias-correction this is comparatively depicted better. The yield gap is highest in the model data but the bias-corrected data outputs are closer to the observations. Irrigation strategy is seen best suited for the crop sown in June, this can be for the preventing moisture stress during the ball formation and maturation stage which is most susceptible.

Table 4.4 Mean bias error (MBE) and Root mean squared error (RMSE) of weather data for RCM model and its bias corrected values during the period 1971 to 2005 for Hisar and Akola

Annual values for Region	Hisar		Akola	
MEAN BIAS ERROR				
(Average Forecast- Average Observed)	**Model**	**Bias Corrected**	**Model**	**Bias Corrected**
Rainfall (mm)	0.267	-0.037	0.3	-0.04
Bright Sunshine (hr)	2.089	0.057	2.061	0.057
Minimum Temperature(°C)	-0.397	-0.013	-0.255	0.053
Maximum Temperature(°C)	-5.423	-0.003	-5.31	-0.017
Root mean squared error (RMSE)	**Model**	**Bias Corrected**	**Model**	**Bias Corrected**
Rainfall (mm)	0.0451	0.0063	0.0507	0.0068
Bright Sunshine (hr)	0.3531	0.0096	0.3484	0.0096
Minimum Temperature(°C)	0.0671	0.0022	0.0431	0.009
Maximum Temperature(°C)	0.9167	0.0005	0.8976	0.0029

Table 4.5 Percentage of Harvested yield deviation (D%), index of agreement (I), and root mean squared error (RMSE) of the RCM model and its bias corrected values from the observed weather variables as simulated by DSSAT4.6 during the period 1971 to 2005 for different treatments in both Hisar and Akola

Sl. No.	Hisar Treatment	Deviation % Model	 B Corr.	Index of Agreement Model	 B Corr.	Root mean square error Model	 B Corr.
1	10-May_Rainfed	-5.26	-10.73	0.99	0.96	68.06	138.92
2	10-May_Irrigated	-10.01	2.2	0.97	1	128.91	28.32
3	10-May_Potential	59.65	0.08	0.57	1	1123.37	1.54
4	21-May_Rainfed	-4.73	-8.98	0.99	0.96	63.11	119.77
5	21-May_Irrigated	-9.42	2.04	0.95	1	127.51	27.63
6	21-May_Potential	51.24	-5.95	0.71	0.98	1041.57	121
7	06-Jun_Rainfed	-2.36	-6.67	0.99	0.97	32.49	91.77
8	06-Jun_Irrigated	-10.17	-0.29	0.87	1	147.68	4.28
9	06-Jun_Potential	37.88	-14.84	0.85	0.89	857.83	336.2
	Average of all conditions	**11.87**	**-4.79**	**0.77**	**0.95**	**398.95**	**96.6**
Sl. No.	**Akola Treatment**	**Deviation % Model**	** B Corr.**	**Index of Agreement Model**	** B Corr.**	**Root mean square error Model**	** B Corr.**
1	20-Jun_Rainfed	32.01	25.45	0	0	253.97	201.91
2	20-Jun_Potential	112.4	22.81	0.09	0.34	982.91	199.4
3	06-Jul_Rainfed	26.83	23.55	0	0	204.37	179.43
4	06-Jul_Potential	95.96	8.63	0.31	0.91	905.98	81.46
5	21-Jul_Rainfed	14.7	20.36	0	0	109.2	151.26
6	21-Jul_Potential	74.01	-1.53	0.47	1	731.6	15.12
	Average of all conditions	**59.32**	**16.55**	**0.28**	**0.52**	**531.34**	**138.1**

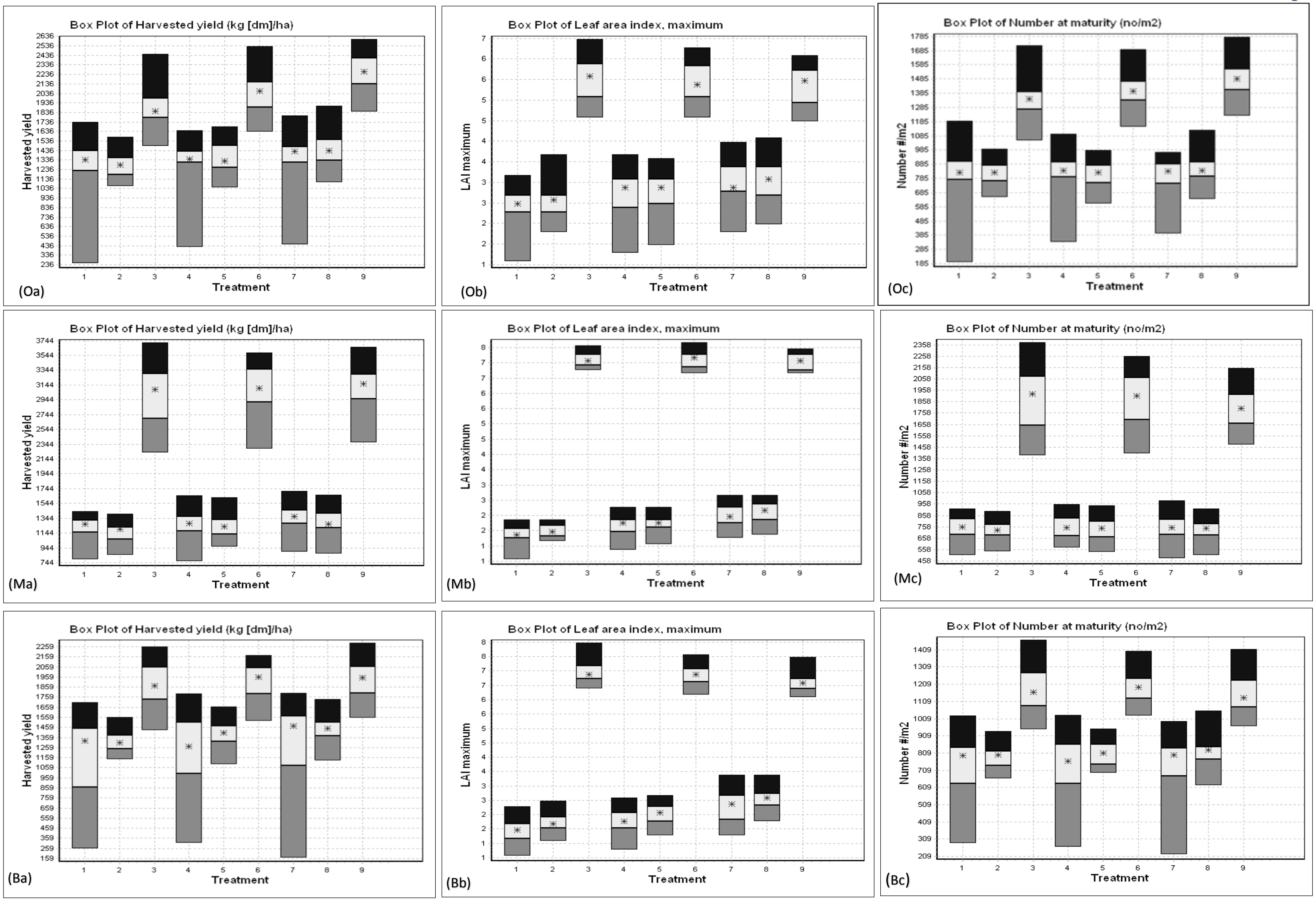

Figure 4.2 Box plot for crop phenologies based on observed (O) weather variables for (Oa) Harvested Yield (Kg/ha) (Ob) LAI, maximum and (Oc) Number at maturity/ m² in Hisar for the period 1971 to 2005 with nine field treatments. (Ma, Mb, Mc) are same as (Oa, Ob, Oc) but from RCM model (M). (Ba, Bb, Bc) are same as (Oa, Ob, Oc) but RCM Bias corrected (B)

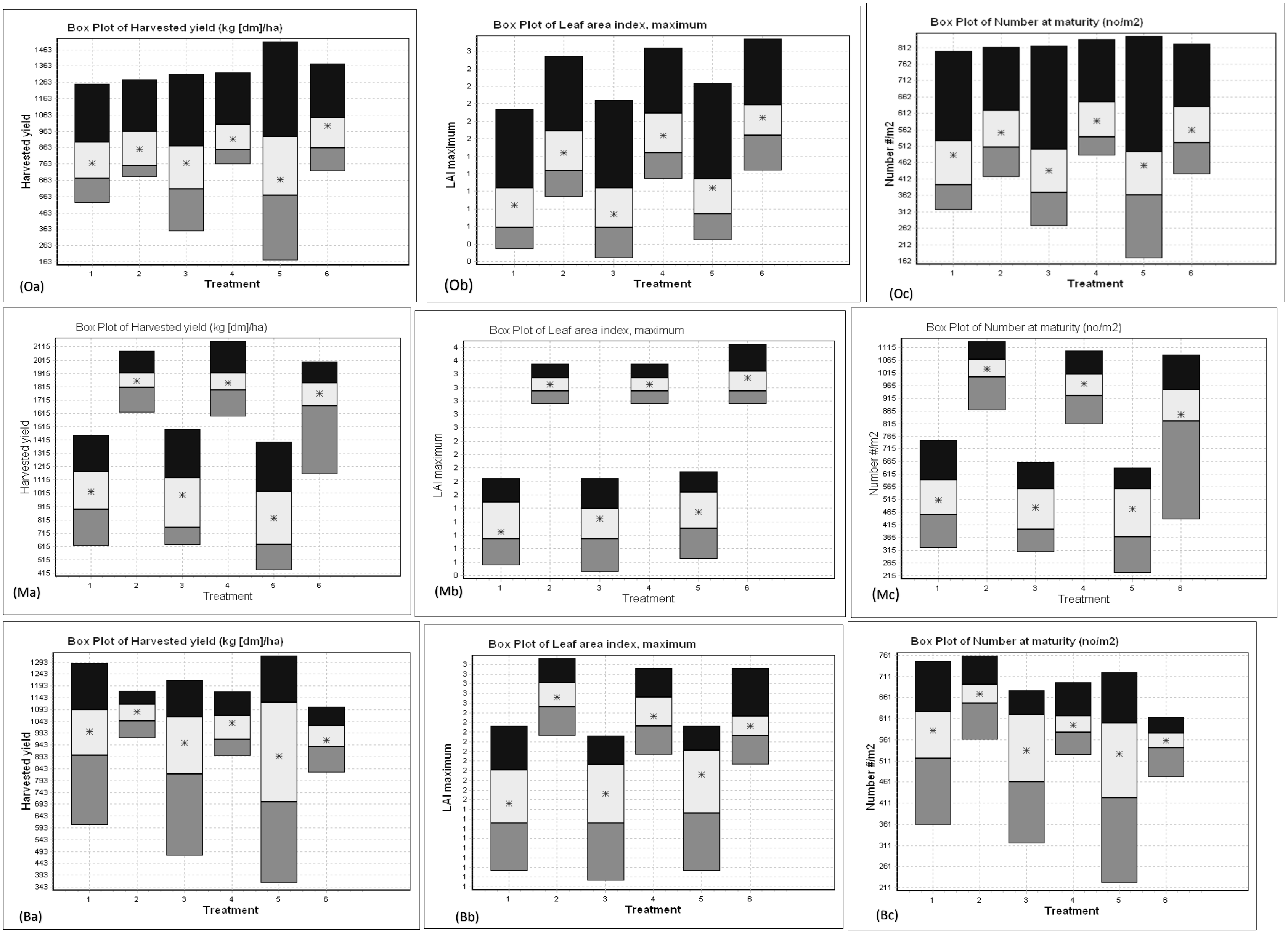

Figure 4.3 Same as Figure 4.3, but in Akola for the period 1971 to 2005 with six field treatments

Similarly, in the central rainfed region we observe that the potential yield, LAI and NM are slightly higher than the rain-fed cotton (Figure 4.4).The mean yield of the crop sown LPc is lower than that sown in LPc and MPc, indicating that early sown crop is favoured in this region. All these variables are much intensified with the same trend for model weather data. The variability among the rainfed and potential productivity also higher for model data in central region also. Late sown cotton has highest variability for rainfed cotton which shows the requirement proper strategy to enhance productivity. For bias-corrected data the crop simulated outputs are closer to observation but the rainfed cotton is higher than potential, which is not the case as oservation. The yield, LAI and number (ball) at maturity variability are higher in rainfed conditions than in potential. This can be attributed to variability in the monsoon trend which shows up in yield and physiology.

4.4 DISCUSSION

Climate change may have serious impacts on agriculture and food security. The use of climate models pertinent for assessments of future changes. Agro-ecosystem models often use the GCM projections. However some aspects of cliamte change is still uncertain at regional scale. So adequate downscaling is crutial at reginal scales. Dynamically downscaled RCMs are therefore pre-eminent is such studies (Yano et al., 2007).

The RCM of International Centre for Theoretical Physics (ICTP) has been successfully used for the study of the Indian summer monsoon (Dash et al., 2015; Maharana and Dimri, 2014; 2016; Pattnayak et al., 2018). And similar studies over the Indian subcontinent found an overestimation of rainfall in the western ghats, northeast India and Peninsular region and underestimation in the central India and over Rajasthan (Dash et al., 2013; Pattnayak et al., 2013; Pattnayak et al., 2018).

As per the RCM projections diurnal temperature is found decreasing and therefore the model shows night warming. But this phenomenon is more prominent in the northern zone than in the central zone. So, it's apparent that the northern zone is more susceptible in comparison to central zone (Pattnayak et al., 2013a; Pattnayak et al., 2013b; Chaudhary et al., 2017).

Apart from improving the regional scale predictions, RCMs has its own paramererization physics such as convection, assumption of planetary boundry, land surface scheme etc. Which supplement uncertanities in the projections and makes is necessary to study the dicrepencies and improve biasess (Chaudhary et al., 2017). A prevailing frailty in the dynamic RCM models is, it overestimates the number of rainy days with a little amount of precipitation (Teutschbein and Seibert, 2012). This is due to small-sized raster cells in combination with convection of moist air and as the air gets saturated at a certain height when temperature decreases for rising air, rainfall is induced in that area within the RCM, referred to as process 'drizzle-effect' (Dai, 2006). He also pointed out that in actual conditions this phenomenon could not occur due to atmospheric instabilities. So this bias has to be removed before applications.

Studies indicate that RCM outputs may have certain statistical mismatch from the meteorological observations also known as bias. Therefore, for its application purposes, various bias-correction methods have been developed which transform the algorithms to statistically match with the observations (Gudmundsson et al., 2012; Teutschbein and Seibert, 2012; Maraun, 2016). The most preffered are distribution- wise techniques where the fuction for corrections are derived from simulated and observed distibutions (Turco et al., 2017). One such approach, the quantile mapping approach equates the cumulative distribution function. It is proven to be superior to local intensity scaling and linear scaling, so recommend to assess the impact in agriculature (Mall et al., 2018) and on catchment hydrology (Willkofer et al., 2018). But the drawback with thi is it poorly represents the extremes. So to capture extremes the downscaling approach or bias-correction techniques still needs to be refined for daily variables applicable in agriculture (Casanueva et al., 2018).

So we can utilize the model simulated data for future projections of the crop yield and growth at different regions and assess the suitability of the crop growing region. Studies have been conducted incorporating different GCMs (Hebbar et al., 2012; Saseendran et al., 2016) and RCMs (Mall et al., 2018) data at various places. And this is done for variety of crops like rice (Auffhammer et al., 2014; Kumar et al., 2013), wheat

(Chattaraj et al., 2014; Saxena et al., 2014; Mall et al., 2018), maize (Araya et al., 2015) etc. in different regions of the world. Based on these outputs management practices can also be strategized as per the changing climate. Like on irrigation measures, sowing dates, nutrient availability, etc.

Cotton is a warm-season crop. Air temperatures are required throughout the growing season but are most critical at the time of planting. Throughout the growing season, it needs a mean annual temperature of over 16°C. The temperature favourable to growth and development is 25 to 30°C (Oosterhuis et al., 1999; Stewart et al., 2009). An increase in atmospheric CO_2, also increased the photosynthetic rate and further delayed cutout by 10 days, by providing more sugars (Mauney et al., 1978). For water not to be a limiting factor in terms of yield, cotton needs between 550 mm and 950 mm during the season in a consistent and regular pattern (FAO, Rome, 1977). Cotton also requires plentiful light. The position of the first boll bearing branch will be lower if the duration of sunshine properly decreases also the plant will be in compact conformation and also the output per plant will decrease (Mauney, 1986; Stewart et al., 2009). Cotton crop has been found susceptible to increasing temperature changes (Reddy et al., 2002; Reddy et al., 2005; Saseendran et al., 2016). Moisture availability is also an important factor for crop growth and productivity. Some variety of cotton requires water mostly during the ball growth and maturity phase and some during the peak flowering stage (Pettigrew et al., 2004; Loka et al., 2011; Loka, 2012; Shikha et al., 2018). Moreover, water-deficit stress affects nutrient supply to the reproductive organs, which inhibits the development of reproductive structures causing fruit abortion (McLaughlin and Boyer, 2004).

Cotton in India is grown in three diverse agro-climatic zones. Predominetly in central region as rainfed crop in black soil or vertisols, in the northern region cotton is grown in alluvial soil with irrigation. In the southern region in the red soil and vertisols for both rainfed and irrigated cotton. The northern region has highest Mean Seed Cotton Yield kg/ha) and highest potential yield for cotton. Productivity is found to improve by using Bt-cotton at suitable planting window. This is its effect on microclimate on the plant growth stage and reproductive bodies. Studies indicate early sowing was proved beneficial in the northern region (Kumar et al., 2014; Shikha et al., 2018) and central region (Hebbar et al., 2002). However, it was found yield reduction for rainfed cotton for late sown crop. Whereas irrigated cotton is benefitted. But when planting dates are advanced the crop water denamnd increase which raise irrigation requirements (Anapalli et al., 2016). Therefore, with proper irrigation late sown can be benefitted. Irrigation strategy is seen best suited for the crop sown in June, as the rainfed crop yield in May is observed higher than that of irrigated. This can be because of the high water requirement in the early flowering period (Turner et al., 1986; Pettigrew et al., 2004), when meiosis is taking place (Loka et al., 2011) fulfilled by monsoon and ball development and maturity by irrigation. Although all stages are sensitive to drought, but mostly the ball development are found to be the most water-sensitive stage (Shikha et al., 2018).

The leaf area tends to be decreasing with late sowing whereas the yield is increasing, which can be because of increase in nutrients during the reproductive phase of the crop (Guinn, 1979) and also due to cutout which favours the yield (Mauney, 1986; Stewart et al., 2009). On one hand adequate moisture availability delays cutout, on the other hand drought fastens it considerably (Hearn, 1975). Drought year and excess years have its effect on crop productivity as crops, as discussed in various studies (Shikha et al., 2018). The moisture deficit stress effects also depend on factors like duration and severity of drought and growth stage and genotype (Kramer and Boyer, 1995). Studies indicate cotton yields in the U.S. has exhibit year-to-year variability depending on the weather conditions (USDA, 2015), which may be related to plant genetic diversity and the physiological responses towards environmental stresses (Robertson, 2001).

Thus for the predicting the cotton production for future climate change it is important to know the behaviour of the crop for historical period. Also for precise projections, bias-correcting the model outputs are important. These data then has to be fed in the calibrated and validated crop models for assessment to authenticate the credibility of future projections and its impact on the crop in different conditions.

Chapter- V

Simulating the impacts of climate change on irrigated and rainfed cotton production in India

SIMULATING THE IMPACTS OF CLIMATE CHANGE ON IRRIGATED AND RAINFED COTTON PRODUCTION IN INDIA

ABSTRACT

Predicting the impacts of future climate on the food and fiber production are essential for devising suitable adaptations strategy. This study aims to study the impact of climate on cotton crop change using RCM data from CORDEX-SA experiment (GFDL-ESM2M-RegCM4) at RCP4.5 and RCP8.5. The model data was bias-corrected using quantile mapping approach and then both are employed in the cotton-CROPGRO model under DSSAT-CSM (v4.6). The study region Hisar (northern) and Akola (central) agro-ecological zones for cotton. The RCM projected daily weather from 1971-2005 (1990), 2006-2035 (2020), 2036-2065 (2050) and 2066-2095 (2080) were taken. The crop model has been simulated for rainfed, irrigated, and potential conditions for three sowing dates. The model predicts slightly increasing temperature from 1990 till 2080 and from RCP4.5 to RCP8.5. It is rising at higher rates at Hisar than Akola. An overall increase in amount of rainfall is observed in the northern region and decreasing in the central region at RCP8.5. It increases till 2050 and further reduces in 2080. In Akola, the yields are higher for RCP8.5 than RCP4.5, whereas in Hisar yields are lower in RCP8.5 than RCP4.5 for both model and bias-corrected data. Late sown crops with proper irrigation strategies are found beneficial in both regions. In the hot and dry northern agroclimatic cotton zone increasing temperature is detrimental, whereas in the cooler and wetter central zone increasing temperature is not a hindrance and at the same time increased CO_2 is favouring the production. The study embrace utilization of RCMs to study the vulnerability of crop with climate change.

Keywords: climate change; cotton; impacts; RegCM4; DSSAT; Bias correction; Quantile mapping

4.4 INTRODUCTION

Climate models predict an increase in global average temperature for future climate change. With increasing temperature comes higher evapotranspiration rates, potentially contributing to the duration and intensity droughts (IPCC, AR5, 2014). These changes will also have immediate effects on precipitation (Loo et al., 2015) and agricultural productivity (Anapalli et al., 2016). Frequent shifts in monsoon are predicted with increasing temperature in the late 21st century and early 22nd century (Schewe and Levermann, 2012). With changing climate there is a shift in the hydrological regime by intra and inter-seasonal precipitation patterns and crop water regime may also be affected (O'Brien, 2000). The increasing temperature could arouse the loss of soil moisture and elevate irrigation demands. This can be a challenge where mostly rainfed agriculture is practiced. Changes are likely not to be uniform everywhere and can increase in the future with intensified active and break cycles (Turner, 2013). Besides that, individual locations can also be benefitted due to changes at a regional scale, whereas for other locations it can be unfavorable. As reported by the International Food Policy Research Institute (IFPRI) Food Policy Report (2010), climate change will also alter the planting dates at some locations, shifting the sowing dates. These shifts in cropping patterns and sowing windows are also location-specific as per regional change in climatology (Bhatti et al., 2016). Such location-specific differences in climate change scenarios necessitate the study of its impact on agriculture to strategize proper mitigation and adaptation measures for sustained productivity.

Among various crops produced in India, cotton is a major commercial crop often termed as white gold. It is grown for fiber, oil and animal feed, therefore an integral part of commerce. Cotton is a warm-season crop, which requires plenty of sunshine, long frost-free period and rainfall between 450 to 750mm. For vegetative growth, the minimum temperature required is 21- 27°C, and during the fruiting period 27-32°C. For the development and maturation of the ball, the optimum temperature has to be between 27-32°C. The maximum capacity of the crop is to tolerate temperatures as high as 43°C with proper water availability (FAO, 1984; Reddy et al., 2005). When the temperature goes above 38°C the balls are damaged and therefore the yields are reduced. For the development of good quality boll and fiber, it requires warm days and cool nights with large diurnal variations at the fruiting period (Freeland et al., 2006). The fiber stop thickening if the daily mean temperature is below 20°C during the period of ball formation and below 15°C, the fiber stops to elongate. Moisture deficit stress promotes stunted growth in cotton with reduced leaf area expansion (McMichael and Hesketh, 1982; Turner et al., 1986; Gerik et al., 1996). The increasing temperature could accelerate ball abscission and reduce its size affecting the cotton yield. Whereas increasing CO_2 could promote vegetative and reproductive growth by improving carbon exchange rates and the number of reproductive organs (balls) (Reddy et al., 2005).

Studies based on climate models can also help to assess the site-specific adaptive potential and mitigation measures in future climate. Although, GCMs are the primary source of information and have so far able to produce reliable projections of climate variables and help in projecting in the frequencies of droughts (Penning et al., 1974) which could significantly affect crop yields. Still, they have drawbacks such as high spatial resolution and inability to capture interannual variability on regional scales (Metzger et al., 2005). Therefore, GCMs are statistically and dynamically downscaled to enhance the resolution at a regional scale. Ensembles of GCMs and RCMs are available under internationally coordinated projects like CMIP5 (Taylor et al., 2012) and CORDEX (Giorgi et al., 2009). The dynamically downscaled RCMs are found to improve the small scale features compared to its driving GCMs and therefore are more reliable (Sørland et al., 2018). Still, these climate projections are often associated with some systemic model errors or biases often conveyed by the GCMs. Bias-corrections are frequently used to improve the RCM projections to match with the observed (Qian et al., 2016). Therefore, besides using GCM data to drive crop models, RCM data can also be used. Large variations are estimated in sorghum yields using ten RCMs in crop model, but after applying bias-correction to RCM outputs, promising results were obtained (Oettli et al., 2011).

Some model-based studies based on GCM projections on cotton crops indicate that the projected high temperature is better for cotton crops in the colder region with longer growing seasons, whereas in the warmer regions hasted growth and development could reduce yield and quality of the crop (Rosenzweig and Hillel, 1998). Thus in future climates, the cotton yield and quality may decrease where the present temperature is near optimum. A study by Sankaranarayanan et al. (2010) over India reveals that projected decreasing temperature and increasing precipitation in the northern zone can prolong the growth period and amplify the pest and disease susceptibility and repercussions can be seen in sowing dates of the subsequent rabi crops. In the central and southern zones region projected increasing temperature and decreasing rainfall with extremes in temperature and erratic distribution of rainfall characterized by recurring seasonal wet and dry spells could affect the cotton yield. Another study by Hebbar et al. (2013) using GCM projections in the INFOCROP model for three agro-ecological zones of cotton in India shows changing climate has different implications at different locations. The productivity in northern India may decline marginally while in the central and southern India it may increase or remain the same as the present. Thus, the impact of changing climate on simulated cotton was detrimental for the hot and dry region and beneficial for the comparatively cold and wet region. In a study by Anapalli et al. (2016) over Mississippi Delta region, USA using spatially downscaled and bias-corrected ensemble of multiple GCMs at four Representative Concentration Pathways (RCP) in cotton RZWQM2 model for irrigated and rainfed practices observed that yield increased in irrigated conditions under low to moderate emissions and declined during high emissions, whereas during rainfed conditions yield declined in all four conditions. However, planting six weeks earlier partially compensated for yield losses and supplemental irrigation upto 10cm compensated for all yield losses. So rainfed systems are considered more vulnerable than irrigated for climate change. But the irrigated regions are also effected as observed is studies on cotton crops in the northern cotton-growing region, Hisar (Shikha et al., 2018).

This study aims to study the vulnerability of rainfed and irrigated cotton crop during climate change scenarios as projected by RCM for RCP4.5 and 8.5 both for near future and far future with the present as the baseline in the central and northern cotton-growing region of India, wherein the central zone mostly rainfed agriculture is practiced and in the northern zone irrigated agriculture is practiced. We also investigated different agricultural conditions like rainfed, irrigated and potential and three sowing dates on both the regions to assess the adaptability of cotton for future climates. The results can be useful for understanding the uncertainties with climate change and strategize associated mitigation measures.

4.5 DATA AND METHODOLOGY

4.5.1 Study Area

Two locations have been selected in the northern and central cotton growing zones where mostly irrigated and rainfed agriculture are practiced respectively. Hisar the westernmost district of Haryana representative climatology of the northern irrigated cotton-growing region. It is a semi-arid region with the average temperature range between 40°C to 44°C in summer months and between 4°C to 6°C in winter months. The annual average maximum and minimum temperature are 31.5°C and 16.2°C respectively; while the average annual rainfall is approximately 450 mm of which 75 to 80 percent is received during monsoon season (Shikha et al., 2018). Akola climate is characterized by hot summer and dryness throughout the year. The average annual rainfall is approximately 846.5 mm and it rains mostly in monsoon with July as the rainiest month. May is hottest with maximum temperature ranging from 27.3°C to 42.4 °C and December is coldest with minimum temperature ranging from 12.4°C to 29.5°C (Ghosh et al., 2014).

4.5.2 Model Description

Crop models are utilized to imitate the behavior of real field crops as grown. It aids to reduce the time, cost and human resources required for analyzing the complexities and concluding for an alternative decision. This software helps users to prepare the database and compare simulated results with observations to give them the confidence in the model. This also assists to determine weather modifications are needed to improve accuracy or to achieve the potential yield. It is capable of simulating the growth, development, yield and various other relevant parameters as a function of the soil-plant-atmosphere dynamics. In the present study, DSSAT-CSM: Version 4.6 has been employed. The Decision Support System for Agrotechnology Transfer- Cropping System Model (DSSAT-CSM), which includes the CROPGRO-Cotton model as an assemblage of independent programs that operate together. Apart from CERES it also CSM-CROPGRO model for simulating cotton cropping system (Pathak et al., 2007). It has a predefined input and output data format that has been developed and embedded in a software package. Changes and its effect could also be studied with the cropping system over time in soil, water, cultivars, carbon, and nitrogen that can take place. DSSAT also provides for the evaluation of crop model outputs with experimental data, thus allowing users to calibrate and validate it (Hoogenboom et al., 2019).

4.5.3 Data

4.5.3.1 Management and soil data

The crop models require daily weather data, soil surface and profile information, and detailed crop management as input. Crop genetic information is defined in a crop species file that is provided by DSSAT and cultivar or a variety of information that should be provided by the user. To achieve the objective, field experiment is conducted at AMFUs (Agromet Field units) at CCS University, Hisar and at Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola, Maharashtra during Kharif season under the Forecasting Agricultural outputs using Space, Agrometeorology and Land-based observations (FASAL) project by IMD (India Meteorological Department). The variety analyzed in this study is RCH-791 in Hisar and AK 081 in Akola, Maharastra which is cultivated widely during the Kharif season. Other management data such as nutrient, fertilizer and irrigation applications, plant spacing sowing dates etc., soil data and genetic coefficients has been obtained by field experiments conducted. These data had been earlier calibrated and validated for the DSSAT model over the region, Hisar (Swami et al., 2016, Shikha et al., 2018) and Akola (Nath et al., 2018; ICAR-CRIDA, Annual Report, 2017-18).

4.5.3.2 Weather data

The Climate data has been derived from the Coordinated Regional Climate Downscaling Experiment (CORDEX) South Asia. The forcings from the host GCM

(GFDL- ESM2M) as is dynamically downscaled using a Regional Climate Model (RegCM4) and the combination is termed as RegCM4- GFDL. This data has been considered for the present study as is best performing RCM in the Indian subcontinent (Chaudhary et al., 2018). These daily weather data sets are obtained from Coordinated Regional Climate Downscaling Experiment over South Asia (CORDEX- SA) and CMIP5 database, which is developed and maintained by Earth System Grid Federation (ESGF) (https://esgf-data.dkrz.de/projects/esgf-dkrz). These data have been extracted at the study region production with the help of CDO (Climate Data Operator). The study area includes. Hisar and Akola lying in the northern and central agro-ecological zones of cotton. This is to extract the weather data in the required format as desired as input in the cropping model, which requires the minimum dataset as daily maximum and minimum temperature(°C), rainfall(mm) and sunshine duration/ solar radiation (MJ m^2). DSSAT generates site-specific weather data stochastically using built-in SIMMETEO software.

Although the models provide reliable data but still some biases exist on a regional scale. So it is important to assess the performance of the models against real observations to identify the underlying biases, strengths or shortcomings before using them for future projections. In this study, the Quantile Mapping (QM) approach is used which calibrates the cumulative distribution function of model data for correction. It is implemented with the help of 'qmap' library written for R statistical software (Gudmundsson et al., 2012; Zhao et al., 2017). Daily agrometeorological observations taken from the Agrometeorological Observatory under India Meteorological Department (IMD) situated near the experimental fields were used for bias corrections of the climate projections.

4.5.3.3 Experimental design

In order to examine the impact of climate change, time series analysis for temperature and precipitation variables is done for a period of 30 years. The weather data includes both model and its bias-corrected datasets with RCP scenarios RCP4.5 and RCP8.5. In this procedure, the RCM projected daily weather from 1971 to 2005, 2006 to 2035, 2036 to 2065 and 2066 to 2095 were average to represent projected climate centered at historical

(1990), present (2020) and climate change scenario at near future (2050) and far future (2080). The CO_2 concentrations as 353, 415, 486 and 531 for RCP4.5 and 353, 415, 539 and 757 for RCP8.5 respectively (Vuuren et al., 2011; Anapalli et al., 2016; Dua et al., 2018). Model data was bias corrected by the Quantile Mapping approach implemented with the help of 'qmap' library written under R developed and are made available in the public domain, which can be specifically downloaded used to downscale (https: //github.com/SantanderMetGroup/downscaleR, assessed on: 03 August 2017). These data were incorporated in the weather module of the DSSAT vn4.6. Management and soil modules were the same as per the field trials. Three planting dates considered as 10th May (D1) 21st May (D2) and 06th Jun (D3) for the northern region and 20th Jun (D1), 06th Jul (D2) and 21st Jul (D3) for the central region. The crop growth model has been simulated for rainfed, irrigated and potential conditions in both the regions. Keeping the genetic coefficient, management strategy, soil as constant, the sensitivity of the crops was analyzed for different weather scenarios and sowing dates. Thus creating nine types of treatments region for all climatic conditions mentioned above. Dry yield (Kg/ha) and leaf area index (LAI) are derived as an output.

4.6 RESULTS

4.6.1 Climate Model Outputs

4.6.1.1 Maximum temperature

The monthly average maximum temperature for Hisar region during 1990 is 26.05°C and 31.44°C, 2020 is 27.51°C and 33.03°C, 2050 is 28.23°C and 33.58°C, 2080 is 28.55°C and 33.87°C in 4.5 RCP scenario for the model and after bias correction respectively (Table 5.1). Whereas, in RCP8.5 for 1990, 2020, 2050 and 2080 the annual average for the model is 26.05°C, 27.68°C, 28.68°C and 30.13°C and for bias-corrected is 31.47°C, 32.53°C, 34.01°C and 35.41°C respectively. Thus we can observe increasing maximum temperature from 1990 to 2020 and then in 2050 and 2080 in both model and bias-corrected values for this region. There is only a slight difference between RCP4.5 and RCP8.5 observed in the study. Further analyzing the deviation of climate variables from present 2020 as projected by model and its bias-corrected values, for 2050 it could be 0.72 and 0.55 at RCP4.5 and 1.00 and 1.47 at RCP8.5. And for 2080, 1.04 and 0.85 as per model and 2.44 and 2.87 as per bias-corrected values for RCP4.5 and RCP8.5 respectively. Same is the case with percentage deviation (%Dev) which is lower in RCP4.5 than RCP8.5. This shows that in RCP8.5 the deviation can be higher than what is projected in present in comparison to the present and this deviation is more prominent in 2080 than 2050 i.e. in the far future.

Similarly, the monthly average for Akola region (Table 5.2) as per model projections are 28.82°C, 30.71°C, 31.33°C and 31.58°C at RCP4.5 and its bias-corrected values are 26.22°C,35.62°C, 36.76°C and 37.00°C for HPNF (1990, 2020, 2050, 2080). And at RCP8.5 model projected 28.82°C, 30.74°C, 31.33°C and 31.58°C, and 26.22°C, 36.11°C, 36.77°C and 37.04°C during HPNF. The deviation from the present is slighter when compared with the northern Hisar region. But the striking feature which can be observed here is in Akola there is negligible difference in the RCP4.5 and RCP8.5 scenarios. Thus the deviation in RCP8.5 from the present is observed lower than RCP4.5 when compared with Hisar climate. So with the changing climate, the rise in maximum temperature is more prominent in the Hisar than in Akola.

The observed maximum for the Hisar region is 31.49°C so the model highly underestimates the maximum temperature and bias-correction performs well in this region. Similarly, the model in the Akola also highly underestimates the maximum temperature which is observed to be 34.12°C. And bias correction performed well for this region as well except for the historical data. This is for both the RCPs with slightly higher values for the RCP8.5 than 4.5 and increasing temperature from 1990 to 2080.

Table 5.1 Monthly average maximum temperature as projected by model and bias-corrected data for RCP 4.5 and RCP 8.5 and during 1990(historical), 2020(present), 2050(near future), 2080(far future) at Hisar

Maximum Temperature								
	Hisar model 4.5				**Hisar bias corrected 4.5**			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	15.33	16.26	17.68	18.25	21.15	22.77	23.36	23.98
Feb	17.74	19.49	20.01	21.19	23.47	25.28	25.73	26.81
Mar	23.30	24.10	25.82	26.08	28.82	30.57	31.24	31.44
Apr	27.96	30.03	31.10	31.48	33.31	35.73	36.31	36.64
May	32.64	33.05	34.18	35.08	37.81	39.19	39.31	40.09
Jun	34.59	36.26	36.71	36.71	39.68	41.39	41.70	41.68
Jul	33.80	35.85	36.55	35.42	38.92	40.71	41.57	40.54
Aug	32.03	33.77	33.81	33.44	37.22	38.46	38.89	38.63
Sep	30.55	32.04	31.60	32.36	35.80	37.22	36.98	37.59
Oct	26.76	28.79	28.74	28.86	32.15	33.10	34.16	34.19
Nov	21.57	22.81	23.99	23.87	27.16	28.14	29.52	29.47
Dec	16.29	17.63	18.52	19.79	21.73	23.73	24.14	25.39
Average	26.05	27.51	28.23	28.55	31.44	33.03	33.58	33.87
Deviation			0.72	1.04			0.55	0.85
%Dev			2.62	3.77			1.67	2.56
RMSE			0.72	1.04			0.55	0.85
	Hisar model 8.5				**Hisar bias corrected 8.5**			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	15.33	16.96	18.68	20.18	21.15	22.28	24.46	25.48
Feb	17.74	19.41	21.23	22.70	23.47	24.61	26.74	28.12
Mar	23.30	25.03	26.22	27.70	28.82	30.12	31.64	33.13
Apr	27.96	30.41	30.79	33.21	33.31	35.32	36.05	38.43
May	32.64	33.92	34.82	36.35	37.81	38.70	39.75	41.46
Jun	34.59	36.44	36.80	37.91	39.68	40.93	41.83	42.87
Jul	33.80	35.64	35.48	36.69	38.92	40.19	40.55	41.74
Aug	32.03	33.40	34.00	35.20	37.22	38.01	39.24	40.26
Sep	30.55	32.21	32.67	33.68	35.80	36.73	38.02	38.82
Oct	26.76	27.92	29.03	30.08	32.15	32.62	34.32	35.33
Nov	21.57	22.71	24.68	26.31	27.16	27.64	30.10	31.79
Dec	16.29	18.17	19.82	21.52	22.08	23.26	25.40	27.46
Average	26.05	27.68	28.68	30.13	31.47	32.53	34.01	35.41
Deviation			1.00	2.44			1.47	2.87
%Dev			3.61	8.83			4.53	8.83
RMSE			1.00	2.44			1.47	2.87

Table 5.2 Same as Table 5.1for Akola

Maximum Temperature								
	Akola model 4.5				Akola bias corrected 4.5			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	22.54	26.15	26.39	26.81	21.03	30.70	31.46	32.11
Feb	25.63	27.28	28.78	29.08	15.28	31.82	34.04	34.28
Mar	29.60	31.01	32.69	32.76	16.37	35.80	38.23	38.25
Apr	32.82	34.70	35.20	35.74	18.51	39.77	40.94	41.38
May	34.14	35.61	36.45	36.88	28.34	40.85	42.30	42.55
Jun	32.80	34.55	35.09	35.41	33.60	39.89	40.68	40.98
Jul	30.51	31.38	32.00	32.12	34.01	36.45	37.49	37.62
Aug	28.95	30.42	31.02	30.54	33.28	35.29	36.43	35.90
Sep	28.49	30.26	30.43	30.68	33.47	35.14	35.85	36.06
Oct	28.50	30.23	30.12	30.54	29.65	35.14	35.38	35.88
Nov	27.49	29.96	30.67	30.85	26.28	34.92	36.01	36.30
Dec	24.41	26.97	27.14	27.51	24.78	31.68	32.28	32.63
Average	28.82	30.71	31.33	31.58	26.22	35.62	36.76	37.00
Deviation			0.62	0.87			1.14	1.38
%Dev			2.02	2.82			3.19	3.86
RMSE			0.62	0.87			1.14	1.38
	Akola model 8.5				Akola bias corrected 8.5			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	22.54	26.06	26.43	26.83	21.03	31.22	31.57	32.07
Feb	25.63	27.24	28.78	29.18	15.28	32.33	34.09	34.49
Mar	29.60	31.03	32.74	32.74	16.37	36.44	38.17	38.32
Apr	32.82	34.87	35.19	35.77	18.51	40.33	40.85	41.44
May	34.14	35.67	36.45	36.83	28.34	41.29	42.25	42.75
Jun	32.80	34.61	35.05	35.41	33.60	40.34	40.71	41.07
Jul	30.51	31.41	32.11	32.16	34.01	36.76	37.62	37.61
Aug	28.95	30.42	30.95	30.55	33.28	35.78	36.44	35.77
Sep	28.49	30.31	30.46	30.71	33.47	35.63	35.82	36.05
Oct	28.50	30.30	30.16	30.44	29.65	35.66	35.47	35.88
Nov	27.49	29.95	30.53	30.87	26.28	35.31	35.97	36.34
Dec	24.41	27.05	27.15	27.42	24.78	32.21	32.26	32.64
Average	28.82	30.74	31.33	31.58	26.22	36.11	36.77	37.04
Deviation			0.59	0.83			0.66	0.93
%Dev			1.92	2.71			1.83	2.57
RMSE			0.59	0.83			0.66	0.93

4.6.1.2 Minimum temperature

The annual average minimum temperature of Hisar is 15.77°C and 16.12°C (1990), 17.26°C and 17.91°C (2020), 18.08°C and 18.45°C (2050), 18.50°C and 18.89°C (2080) at RCP4.5 and 15.77°C and 16.22°C (1990), 17.50°C and 17.40°C (2020), 18.76°C and 19.12°C (2050), 20.34°C and 20.75°C (2080) in RCP8.5 for model and bias-corrected respectively (Table 5.3). In Akola region, it is 19.10°C and 19.32°C (1990), 20.96°C and 21.47°C (2020), 21.63°C and 22.31°C (2050), 22.01°C and 22.74°C (2080) at RCP4.5 and 19.10°C and 19.32°C (1990), 20.95°C and 20.97°C (2020), 21.67°C and 20.97°C (2050), 22.00°C and 22.26°C (2080) at RCP8.5 for model and bias-corrected respectively (Table 4). The annual average as observed over Hisar is 16.20°C and Akola is 19.36°C as per observed climatology, which is closer to the model assessment. Thus the model slightly underestimates the minimum temperature in both and the bias correction region performs very well for minimum temperature in both the region. With the changing climate, the model predicts slightly increasing minimum temperature from historical to far future and from RCP4.5 to RCP8.5. The deviation is higher in the Hisar region than the Akola region. Thus there is a possibility of increasing temperature at a higher rate in the northern than the central cotton-growing region.

Table 5.3 Monthly average minimum temperature as projected by model and bias-corrected data for RCP 4.5 and RCP 8.5 and during 1990(historical), 2020(present), 2050(near future), 2080(far future) at Hisar

Minimum Temperature								
	Hisar model 4.5				**Hisar bias corrected 4.5**			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	3.91	5.03	6.80	7.44	4.27	6.33	7.10	7.57
Feb	4.87	6.62	7.28	8.28	5.16	7.03	7.55	8.57
Mar	10.06	10.95	12.36	12.86	10.34	12.18	12.60	13.24
Apr	15.71	17.60	18.31	19.06	16.06	18.54	18.65	19.37
May	21.56	22.43	23.28	23.99	21.98	23.84	23.83	24.43
Jun	25.00	26.56	26.94	27.19	25.46	27.33	27.35	27.62
Jul	25.86	27.59	28.22	27.40	26.33	27.83	28.78	27.84
Aug	24.52	26.18	26.11	26.03	24.98	26.17	26.58	26.63
Sep	22.31	23.74	24.17	24.40	22.75	24.36	24.57	24.88
Oct	17.55	19.64	20.13	20.31	17.92	19.67	20.57	20.94
Nov	11.76	13.26	14.41	14.77	12.06	13.26	14.75	15.02
Dec	6.09	7.56	8.92	10.31	6.07	8.41	9.07	10.59
Average	15.77	17.26	18.08	18.50	16.12	17.91	18.45	18.89
Deviation			0.81	1.24			0.54	0.98
%Dev			4.72	7.19			3.00	5.48
RMSE			0.81	1.24			0.54	0.98
	Hisar model 8.5				**Hisar bias corrected 8.5**			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	3.91	6.08	7.89	9.62	4.63	5.90	8.16	9.68
Feb	4.87	6.38	8.90	9.96	5.37	6.37	9.13	10.24
Mar	10.06	11.61	13.18	14.37	10.35	11.62	13.35	14.74
Apr	15.71	18.04	18.42	21.10	16.06	18.07	18.86	21.49
May	21.56	23.22	23.91	25.87	21.98	23.35	24.33	26.35
Jun	25.00	26.73	27.29	28.85	25.46	26.83	27.75	29.37
Jul	25.86	27.38	27.56	28.75	26.33	27.34	28.06	29.36
Aug	24.52	25.75	26.62	27.79	24.98	25.68	27.07	28.22
Sep	22.31	23.98	24.85	26.02	22.75	23.86	25.22	26.33
Oct	17.55	19.41	20.75	21.98	17.92	19.12	21.11	22.53
Nov	11.76	13.18	15.31	17.42	12.06	12.76	15.70	17.75
Dec	6.09	8.23	10.49	12.40	6.73	7.90	10.73	12.97
Average	15.77	17.50	18.76	20.34	16.22	17.40	19.12	20.75
Deviation			1.27	2.84			1.72	3.36
%Dev			7.23	16.26			9.91	19.29
RMSE			1.27	2.84			1.72	3.36

Table 5.4. Same as Table 5.3 for Akola

Minimum Temperature								
	Akola model 4.5				Akola bias corrected 4.5			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	10.97	14.20	14.55	15.30	12.90	13.70	14.01	14.80
Feb	13.32	14.95	16.90	16.61	16.05	14.43	16.78	16.38
Mar	17.55	18.85	20.60	20.70	20.11	18.99	21.16	21.20
Apr	21.62	23.60	24.04	24.77	23.40	24.65	25.05	25.96
May	24.45	26.07	26.65	27.17	24.74	27.34	28.09	28.87
Jun	24.61	26.34	26.84	27.10	23.38	27.64	28.37	28.77
Jul	23.54	24.76	25.30	25.43	21.04	26.00	26.72	26.86
Aug	22.34	23.95	24.37	24.32	19.45	24.88	25.53	25.47
Sep	21.38	23.00	23.37	23.80	18.98	23.88	24.43	24.83
Oct	19.26	20.99	21.37	21.83	18.99	21.55	21.91	22.46
Nov	16.78	19.00	19.69	20.24	17.96	19.18	20.09	20.60
Dec	13.37	15.80	15.95	16.89	14.81	15.46	15.54	16.66
Average	19.10	20.96	21.63	22.01	19.32	21.47	22.31	22.74
Deviation			0.68	1.05			0.83	1.26
%Dev			3.22	5.03			3.87	5.89
RMSE			0.68	1.05			0.83	1.26
	Akola model 8.5				Akola bias corrected 8.5			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	10.97	14.33	14.52	15.41	12.90	13.16	13.73	14.64
Feb	13.32	14.99	16.95	16.69	16.05	13.89	16.12	15.71
Mar	17.55	18.77	20.69	20.66	20.11	18.32	20.54	20.40
Apr	21.62	23.68	23.99	24.63	23.40	23.99	24.48	25.05
May	24.45	25.98	26.69	27.12	24.74	26.91	27.63	28.26
Jun	24.61	26.29	26.79	27.12	23.38	27.23	27.87	28.34
Jul	23.54	24.70	25.28	25.42	21.04	25.47	26.22	26.43
Aug	22.34	23.79	24.35	24.36	19.45	24.42	24.97	24.92
Sep	21.38	23.01	23.59	23.71	18.98	23.45	24.10	24.43
Oct	19.26	21.03	21.44	21.89	18.99	21.18	21.54	22.20
Nov	16.78	18.96	19.80	20.10	17.96	18.76	19.69	20.21
Dec	13.37	15.89	16.00	16.89	14.81	14.87	15.15	16.53
Average	19.10	20.95	21.67	22.00	19.32	20.97	21.84	22.26
Deviation			0.72	1.05			0.87	1.29
%Dev			3.44	5.01			4.13	6.14
RMSE			0.72	1.05			0.87	1.29

4.6.1.3 Precipitation

The annual average precipitation for Hisar as per model projections are 1.496 and 1.496 (1990), 1.921 and 2.058(2020), 1.981 and 2.103(2050), 1.973 and 2.052 (2080) and its bias-corrected values as 1.19 and 1.19(1990), 1.723 and 1.242(2020), 1.687 and 1.791 (2050), 1.692 and 1.750 (2080) at RCP4.5 and RCP8.5 respectively (Table 5.5). The average precipitation in Hisar is increasing from 1990 till 2050 then it declines in 2080 in both the RCPs as per model projections. Whereas, when bias-corrected, at RCP4.5 it increases till 2020 and then falls for 2050 and 2080 and at RCP8.5 it increases till 2050 and falls for 2080. The model predicts more rainfall 1.54 then its observed 1.24 mm which suggests that the model is wet. Bias- correction has performed better in this region bringing it near the observation. With the changing climate, the model suggests there will be an increase in the amount of precipitation till the near future and it may decline further in the far future. This characteristic is depicted with the amount of precipitation during the cropping season too.

In Akola region, the model projected 2.437 and 2.437(1990), 1.505 and 2.336(2020), 1.704 and 2.238(2050), 1.578 and 1.842(2080) and its bias-corrected values are 2.434 and 2.434(1990), 1.794 and 1.990 (2020), 1.789 and 1.881(2050), 1.756 and 1.472(2080) at RCP4.5 and RCP8.5 respectively (Table 5.6). Although, the amount of rainfall in the central rainfed region is presently more than the northern region. But the model predicts decreasing precipitation from 1990 to 2080 in this region. The model is found to be overestimating rainfall amount as 2.437 whereas 2.13 is observed here. Bias correction slightly reduces the amount to 2.434 which is closer to the observed values. Thus predicts very less precipitation from 2020 to 2080 at RCP4.5 than RCP8.5.

Table 5.5 Monthly average precipitation as projected by model and bias-corrected data for RCP 4.5 and RCP 8.5 and during 1990 (historical), 2020 (present), 2050 (near future), 2080 (far future) at Hisar

Precipitation								
	Hisar model 4.5				Hisar bias corrected 4.5			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	0.38	1.03	0.88	0.80	0.29	0.92	0.76	0.63
Feb	0.23	0.79	0.82	0.67	0.17	0.63	0.85	0.60
Mar	0.51	0.85	0.71	0.88	0.40	0.79	0.73	0.94
Apr	0.70	1.24	0.90	1.17	0.52	1.19	0.84	1.08
May	0.80	1.57	1.57	1.47	0.58	1.13	1.32	1.31
Jun	2.12	2.37	2.05	2.78	1.67	1.92	1.68	2.20
Jul	4.34	3.22	3.47	3.60	3.58	3.32	2.83	3.01
Aug	3.26	3.73	4.19	4.04	2.63	3.45	3.50	3.44
Sep	2.20	2.79	3.39	2.77	1.75	2.64	2.95	2.34
Oct	1.73	2.51	2.66	2.64	1.39	2.48	2.30	2.30
Nov	0.83	1.68	1.59	1.58	0.65	1.15	1.17	1.39
Dec	0.84	1.26	1.52	1.28	0.66	1.04	1.30	1.07
Average	1.496	1.921	1.981	1.973	1.192	1.723	1.687	1.692
Deviation			0.060	0.052			-0.037	-0.031
%Dev			3.082	2.778			-2.081	-1.694
RMSE			0.060	0.052			0.037	0.031
	Hisar model 8.5				**Hisar bias corrected 8.5**			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	0.38	1.02	1.02	0.80	0.29	0.42	0.98	0.61
Feb	0.23	0.84	0.95	0.57	0.17	0.15	0.87	0.67
Mar	0.51	0.87	0.90	0.81	0.40	0.30	0.84	0.74
Apr	0.70	1.31	1.08	1.00	0.52	0.59	0.89	0.89
May	0.80	1.48	1.38	1.50	0.58	0.76	1.16	1.28
Jun	2.12	2.29	2.32	2.64	1.67	1.50	1.90	2.06
Jul	4.34	3.83	3.91	4.25	3.58	2.83	3.27	3.60
Aug	3.26	4.12	4.57	3.52	2.63	2.93	3.76	3.03
Sep	2.20	3.18	3.24	3.57	1.75	2.17	2.86	3.02
Oct	1.73	3.10	2.76	3.17	1.39	1.98	2.28	2.57
Nov	0.83	1.38	1.67	1.61	0.65	0.75	1.47	1.35
Dec	0.84	1.29	1.45	1.19	0.67	0.53	1.21	1.18
Average	1.496	2.058	2.103	2.052	1.193	1.242	1.791	1.750
Deviation			0.045	-0.007			0.549	0.508
%Dev			2.185	-0.324			44.131	40.845
RMSE			0.045	0.007			0.549	0.508

Table 5.6 Same as Table 5.5 for Akola.

Precipitation								
	Akola model 4.5				Akola bias corrected 4.5			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	0.78	0.46	0.30	0.30	0.00	0.38	0.25	0.25
Feb	0.29	0.35	0.33	0.32	0.00	0.24	0.26	0.25
Mar	0.67	0.47	0.45	0.38	0.15	0.35	0.34	0.38
Apr	1.09	0.91	1.03	0.94	2.27	0.74	0.98	0.71
May	1.91	1.56	1.60	1.30	12.45	1.22	1.35	1.06
Jun	4.67	3.54	3.12	3.04	11.29	3.24	3.13	2.95
Jul	7.03	2.42	4.16	3.40	2.76	5.78	5.36	5.25
Aug	5.98	3.35	2.79	3.95	0.21	5.12	3.93	5.16
Sep	3.54	3.08	3.93	2.52	0.00	2.90	3.65	2.69
Oct	1.16	0.89	1.24	1.00	0.00	0.69	0.87	0.77
Nov	1.18	0.55	0.75	0.57	0.00	0.42	0.71	0.66
Dec	0.82	0.48	0.74	1.21	0.08	0.40	0.63	0.94
Average	2.437	1.505	1.704	1.578	2.434	1.794	1.789	1.756
Deviation			0.199	0.072			-0.002	-0.035
%Dev			13.214	4.817			-0.128	-1.959
RMSE			0.199	0.072			0.002	0.035
	Akola model 8.5				Akola bias corrected 8.5			
Months	**Historical**	**Present**	**Near Future**	**Far Future**	**Historical**	**Present**	**Near Future**	**Far Future**
Jan	0.78	0.40	0.49	0.26	0.00	0.31	0.40	0.14
Feb	0.29	0.37	0.35	0.37	0.00	0.29	0.29	0.26
Mar	0.67	0.44	0.40	0.48	0.15	0.34	0.30	0.36
Apr	1.09	1.01	0.87	1.11	2.27	0.82	0.68	0.89
May	1.91	1.95	1.64	1.90	12.45	1.55	1.30	1.48
Jun	4.67	4.03	4.31	3.76	11.29	3.47	3.64	3.09
Jul	7.03	6.77	5.89	5.28	2.76	6.06	5.17	4.57
Aug	5.98	5.93	5.93	3.97	0.21	5.25	5.16	3.29
Sep	3.54	3.79	3.60	2.43	0.00	3.10	2.88	1.73
Oct	1.16	1.62	1.95	1.70	0.00	1.23	1.56	1.27
Nov	1.18	0.97	0.87	0.36	0.00	0.82	0.74	0.23
Dec	0.82	0.76	0.55	0.47	0.08	0.64	0.45	0.35
Average	2.437	2.336	2.238	1.842	2.434	1.990	1.881	1.472
Deviation			-0.098	-0.494			-0.109	-0.518
%Dev			-4.191	-21.151			-5.484	-26.026
RMSE			0.098	0.494			0.109	0.518

Therefore, the model slightly overestimates the rainfall in these regions, where the bias-correction method is found very reliable for historical conditions. The amount of rainfall is increasing in the northern region whereas decreasing in the central region at RCP8.5. The amount of rainfall during the cropping season is also decreasing but higher than the non-cropping season this could be due to monsoon variability. Whereas, the spatial variability can also be observed as the rainfall amount is increasing in the northern irrigated region and decreasing in the central rainfed region. The combined effect of increasing temperature and decreasing annual rainfall during the cropping season in the central rainfed region from 1990 to 2080 can also have a negative influence over the crop productivity in these regions. So it is observed that there will be spacial and temporal variability in the rainfall patterns in both the regions, which can affect crop productivity.

4.6.2 Crop Simulation Outputs

The sensitivity of cotton productivity is analyzed in the study with the changing climate. In the central region (Figure 5.1a&b) the yield increased from 2020 to 2050 and then 2080 for model data in both the RCPs for all sowing dates. But, for D1 the rainfed and irrigated practices show negligible variations. The weather is cooler in comparison to the northern cotton-growing region so the increasing temperature is not much affecting the yield, whereas increasing CO_2 in also favoring the crop. For bias-corrected data, there is a slight difference in yield (Figure1c&d) between the rainfed and irrigated practices. This can be because of better water availability as the model is wet and underestimate maximum temperature. As mentioned earlier the bias-corrected is a better representative of the weather data since the bias-correction method is found performing better. While considering the bias-corrected value, we observe in both the RCPs irrigated conditions has better productivity than rainfed with changing climate. The yield increased 4% to 5.3% at RCP4.5 and 13.3% to 37.7% in 2050 and 2080 respectively from the present as per model data. The yield for bias-corrected data increased 14.7% to 5.8% at RCP4.5 and 16.2% and 44.3% at RCP8.5. Similarly, the LAI increased by 3.1% to 9.6% at RCP4.5 and 16.2% to 40% in 2050 and 2080 respectively as per model data (Figure 1e&f). And for bias-corrected data increased 16.7% to 16.7% at RCP4.5 and 18.8% and 45.1% at RCP8.5 (Figure

5.1g&h). The yield is increasing with late sowing and irrigated is performing better than the rainfed. Therefore, in this region, late sowing with proper irrigation strategy can be beneficial. The relationship of crop yield and LAI if not simple and varies with crop to crop and with developmental stages. However, this study suggests that the higher LAI of cotton produced a higher yield. Thus LAI plots show a similar tendency as yield. An increasing yield signifies that changing climate and with late sowing is beneficial if the Akola region.

In the northern region (Figure 5.2a&b), the dry yield for the model projected data is higher for 1990 then 2020 in both the RCPs and increases with the changing climate in 2050 and 2080. There is a slight variation in yield with irrigated higher than the rainfed practices and slighter variation between the two RCPs. The yield for the model projected weather data in higher than its bias-corrected values (Figure 5.2c&d). This could be again due to the wet bias of the model in this region underestimation of maximum temperature. The yield increased 12.5% to 23.3% at RCP4.5 and 3.7% to 2.7% in 2050 and 2080 respectively from 2020 as per model data. The yield for bias-corrected data increased by 10.1% to 18.1% at RCP4.5 and declined by 4.7% and 7.6% at RCP8.5. Similarly, the LAI increased 9.7% to 22.0% at RCP4.5 and 4.5% to 16.3% in 2050 and 2080 respectively as per model data. And for bias-corrected data increased 10.5% to 19.3% at RCP4.5 (Figure 5.2e&f) and declined 6.6% and 18.1% at RCP8.5 (Figure 5.2g&h). Again for both RCPs late crop shows better yield. Rainfed and irrigated crops show better yield in RCP4.5 than RCP8.5 in all sowing dates with model data. On the contrary for bias-corrected data, there is a reduction in yield from 2020 to 2050 and further, it increases in 2080. An almost similar trend is followed by LAI as well. Late sowing is found beneficial in future climate as per model projections as well as with the bias-corrected data for both the regions. This can be because the crop is able the escape the harsh summer season with the rising temperature. It has to be balanced as such is also prevented from the frost days of winter to prevent damage. Thus sowing dates are to be carefully strategized here.

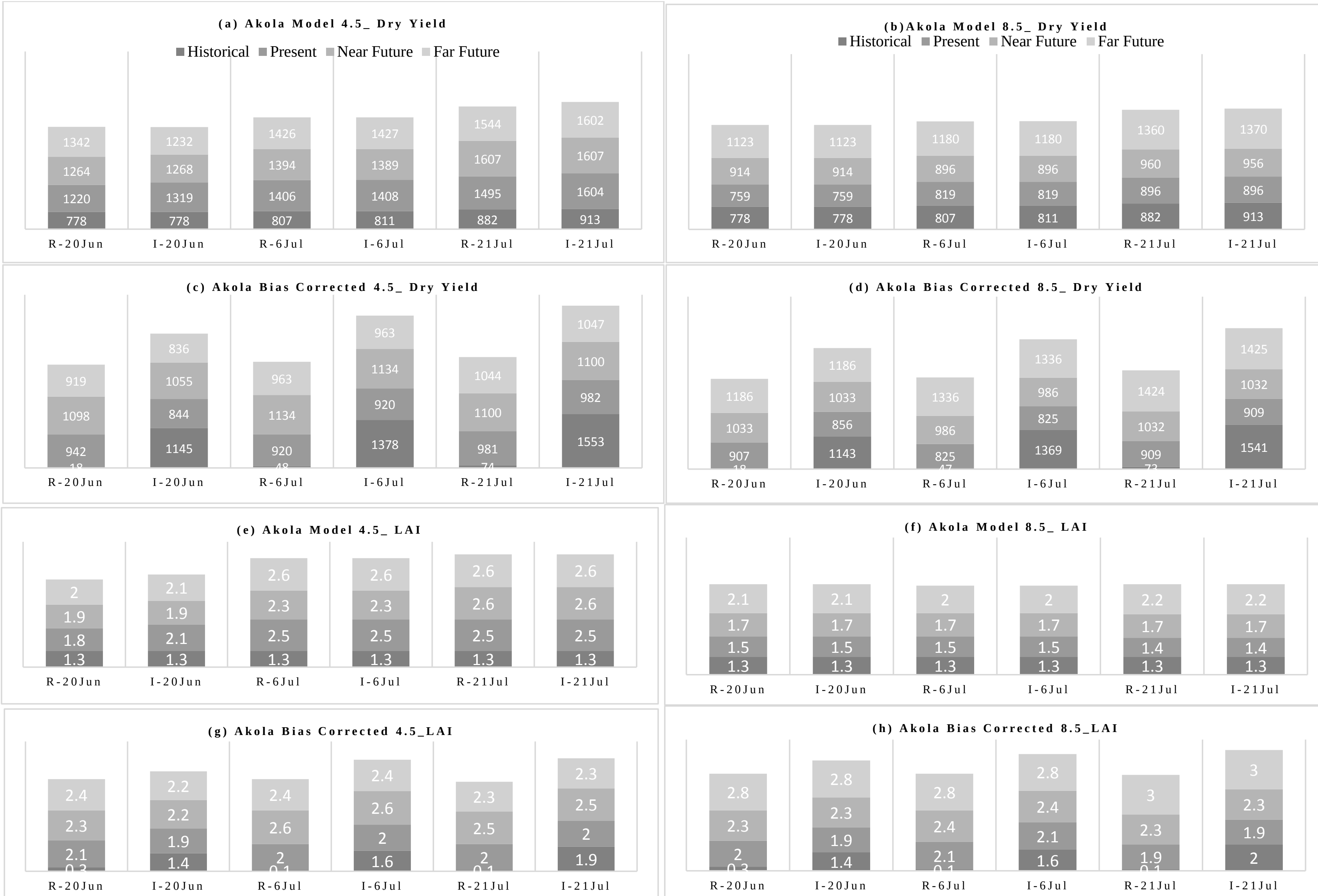

Figure 5.1 Simulated dry yield (Kg/ha) for historical (1990), present (2020), near future (2050) and far future (2080) for rainfed irrigated and potential productivity for three sowing dates in Akola (central) cotton producing region.

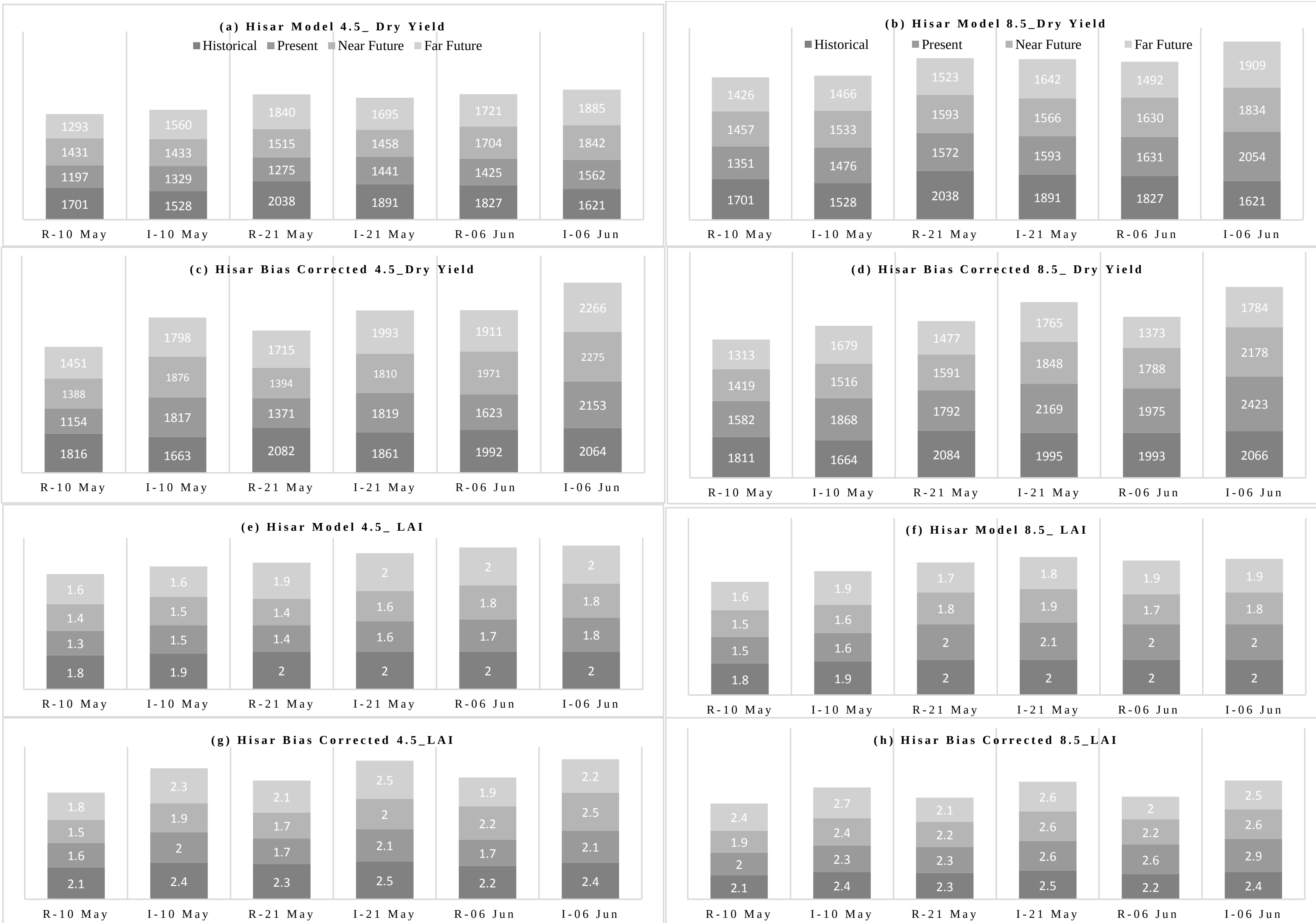

Figure 5.2 Same as Figure 5.1 for Hisar (northern) cotton producing region.

In the box plot of percent deviation of yields (Figure 5.3a&b) and LAI (Figure 5.3c&d) for Akola and Hisar are different at different RCPs from baseline 2020 to 2050 and 2080. As in Akola, the yields are higher for RCP8.5 than RCP4.5, whereas in Hisar yields are lower in RCP8.5 than RCP4.5 for both model and bias-corrected data. In Akola (central) at RCP4.5, the highest positive deviation is for bias-corrected data in 2050, whereas for RCP8.5 2080 climate production has much variability with positive deviation than 2050 (Figure 5.3a&c). The LAI also follows similar deviations as yield. Whereas in the Hisar (northern) region for the bias-corrected RCP8.5 climate maximum variability with negative deviation is observed for both yield (Figure 5.3b&d) and LAI. The yield is also higher in the far future more prominently in RCP 4.5. For model and bias-corrected data in RCP4.5 positive deviations are higher for 2080 than 2050, so in Hisar, the crop yield improves in RCP4.5. Which is not the case in RCP8.5, where if falls for both 2050 and 2080. With a maximum decline in yield and LAI for RCP8.5 in 2080. The reason can be, the crop has achieved maximum tolerance for the temperature at RCP4.5 in the hot and dry northern cotton-growing region and further increase even with increasing CO_2 is detrimental. Whereas in the central region which is cooler and wetter increasing temperature is not a hindrance and at the same time increased CO_2 is favoring the production.

In the (Figure 5.4) percentage deviation in yields from the baseline 2020 to 2050 and 2080 is plotted for three different sowing dates practiced widely in Akola and Hisar region for rained, irrigated and potential conditions. The deviation for potential productivity positive in both the regions higher values in RCP8.5 than RCP4.5 in Akola and RCP4.5 than RCP8.5 in Hisar. The sowing date D1 is most favored as per model data and D2 as per bias-corrected data in rainfed condition and D2 in irrigated conditions (Figure 5.4a&b). Whereas D1 has higher yield potential in RCP4.5 (Figure4c). At RCP8.5, 2080 has a higher positive deviation than 2050. In rainfed condition, D1 and irrigated condition D2 is beneficial in 2080 at RCP8.5 (Figure 5.4d&e). Again the D1 has higher yield potential in RCP8.5 (Figure 5.4f). Therefore, irrigation strategy has played a beneficial role for D2, whereas not it has not much impacted other sowing dates, especially for the late sown crop.

In the northern region at RCP4.5 in rainfed conditions yield is higher in D2 as per model data and D1 as per bias-corrected data for both 2050 and 2080, whereas late sown crop has a higher positive deviation in irrigated conditions (Figure 5.4g&h). And the yield for potential conditions are higher in D2 in both 2050 and 2080 (Figure4i). Again at RCP8.5 yield is better for D1 with a slight positive deviation as per model data and least negative deviation as per bias-corrected data in rainfed and irrigated conditions (Figure 5.4j&k). The difference is deviation is negligible for potential productivity among the sowing dates (Figure 5.4l). In this study generally, the late sowing D3 is found beneficial with the climate change scenarios in both the regions. And the percentage change from the present is higher for D1 and D2 with model and its bias-corrected data in Akola and D2 and D1 with model and its bias-corrected data respectively in Hisar. So with the changing climate positive variation is also higher for the early sown crop from the present.

As per climate observations, during RCP 8.5 there is a slight rise in temperature in this region with increased rainfall and CO_2. This could suitable for the crop in the central region. Therefore, the yield has increased to a larger extent. This signifies the suitably of crop in this region at the RCP8.5 emission scenario here. Whereas in the northern region the temperature slightly rises form present in RCP4.5 and then RCP8.5 and the precipitation increases till RCP4.5 and then reduces in RCP8.5. Thus the crop could stand an increase in temperature till RCP4.5 and increased CO_2 and precipitation also benefitted the productivity. But, beyond that at RCP8.5 the plant could not tolerate increased temperatures with reduced precipitation. So, productivity increased in RCP4.5 and declined in RCP8.5. Therefore, in the future at RCP4.5 northern regions and RCP8.5 central regions can facilitate cotton production with proper management strategy.

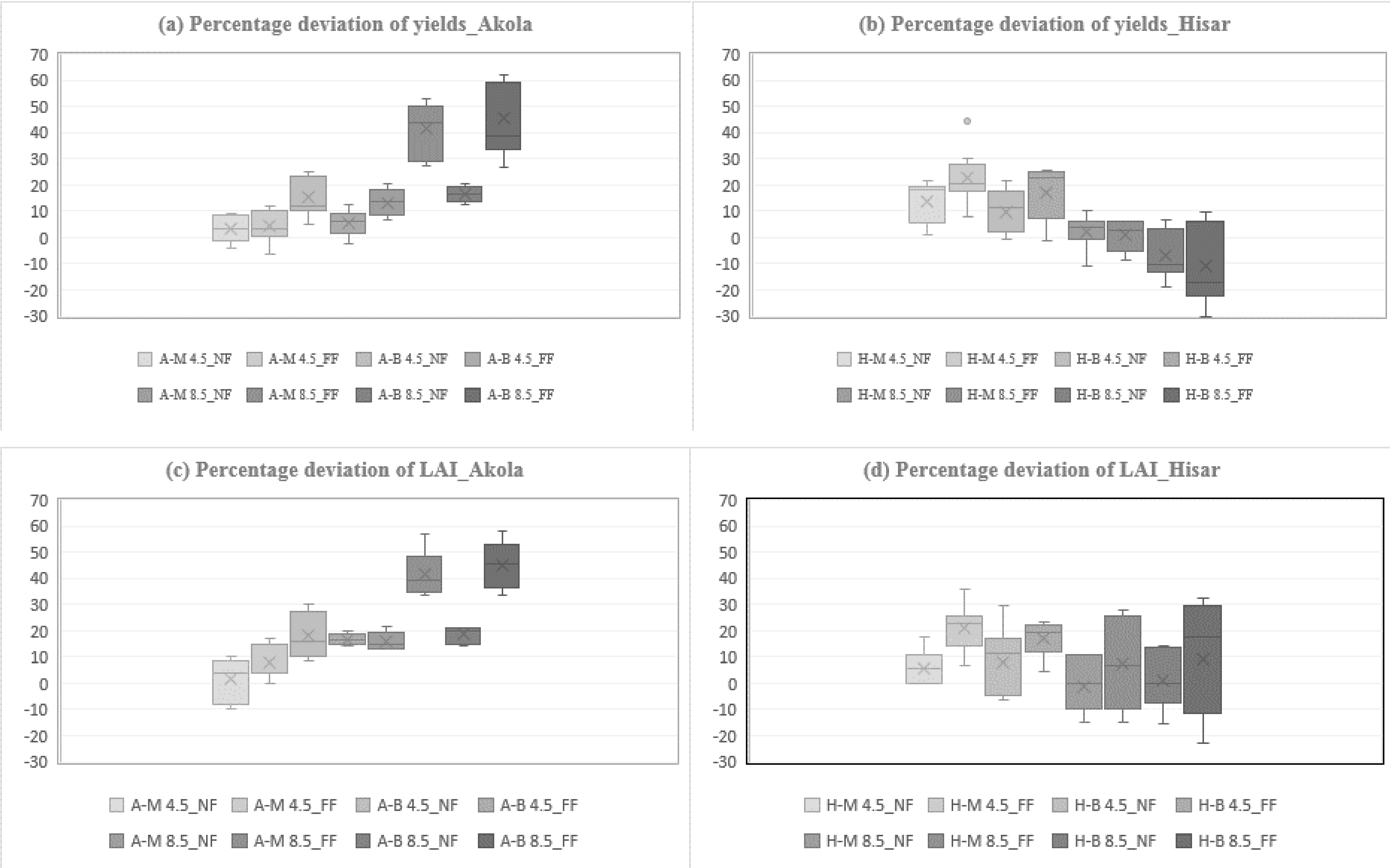

Figure 5.3 Box-plot for percentage deviation in yields and LAI from the present to near future (NF) and far future (FF) for the three sowing dates in different climatic conditions in both RCP4.5 and RCP8.5 both for model (M) its bias-corrected (B) climate data.

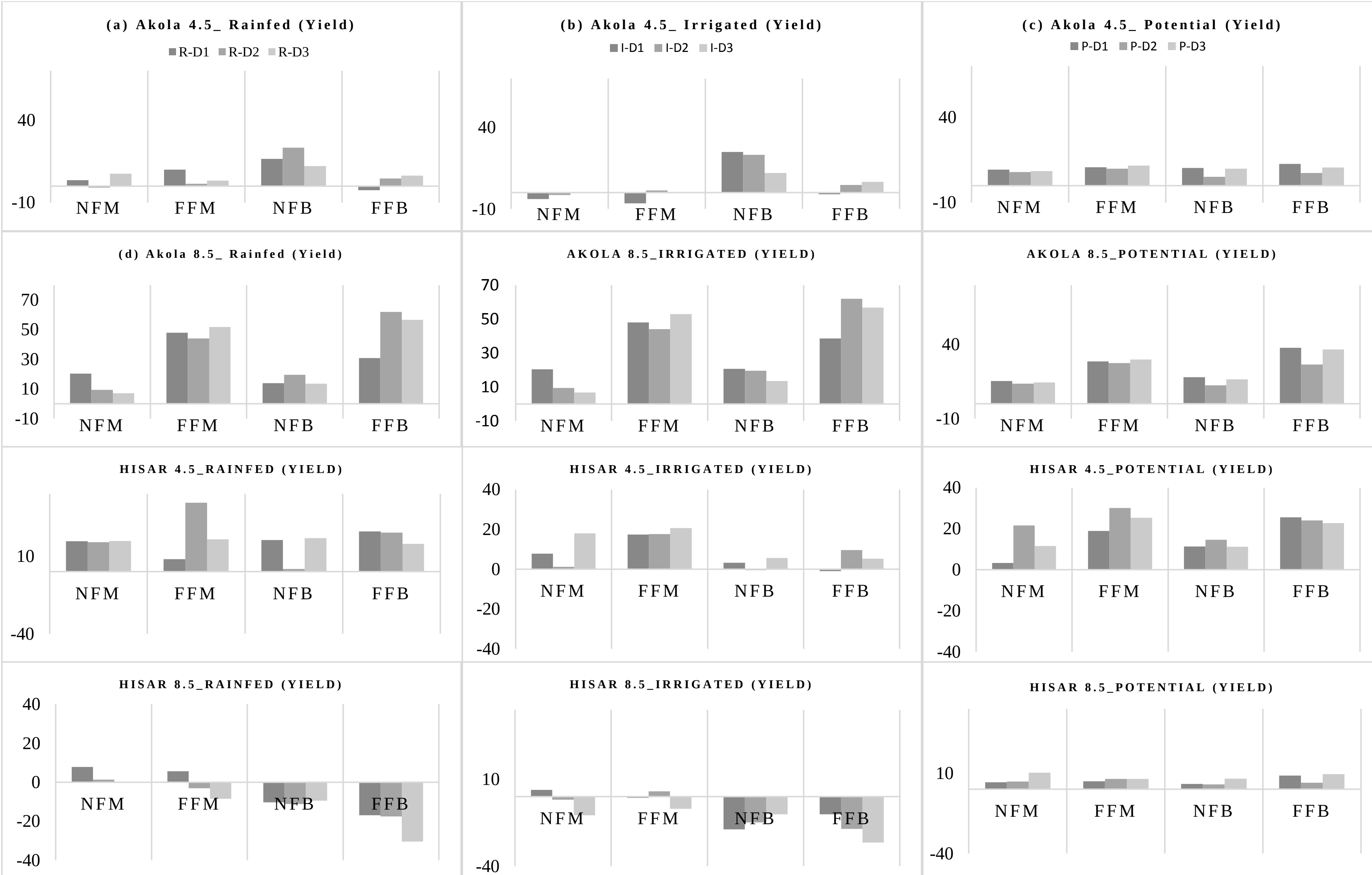

Figure 5.4. Percentage deviation of yields from the 2020 present to near future 2050 (NF) and far future 2080 (FF) both for model (M) and bias-corrected (B) climate data for three sowing dates in Akola region as 20th Jun (D1), 06th Jul (D2) and 21st Jul (D3) and in Hisar region as 10th May (D1) 21st May (D2) and 06th Jun (D3).

4.7 DISCUSSIONS

Climate change is projected to have a significant impact on agricultural productivity. So for the assessment of vulnerability and adaptability various GCM and RCM projections are used. Where RCMs has the potential to improve the representation of the climate information and therefore more useful than the GCMs (Zacharias et al., 2015). Various studies are conducted based on GCMs projections to assess the impact of cotton with climate change. The climate data was extracted from a regional model RegCM4 forced with global model GFDL-ESM2M which captures seasonal precipitation (Choudhary et al., 2018) and temperature (Garg et al., 2015) best combined mean skill. Significant dry bias is observed over a greater part of India which appears to be more pronounced in central India and wet bias in parts of northern India (Mall et al., 2018). These biases can be induced due to 'systematic model errors', 'boundary conditions' etc. So, before applying it in hydrological modeling and crop modeling, these biases has to be reduced with some statistical transformations and then calibrated with the observation data. Typically, biases include innumerable wet days with low-intensity precipitation and erroneous assumptions for extreme temperature (Ines and Hansen, 2006; Teutschbein and Seibert, 2012). Various methods to adjust the biases in RCM simulations include 'linear scaling, local intensity scaling, power transformation, variance scaling, distribution transfer approach as by probability mapping (Ines and Hansen, 2006), quantile mapping (Sun et al., 2011), statistical downscaling (Piani et al., 2010) and histogram equalization (Rojas et al., 2011). In this study 'Distribution mapping of precipitation and temperatures by quantile mapping' method is utilized to reduce uncertainty linked with model data The change in temperature in these zones is most likely periodic that is expected to increase in the near future and far future as per model. The increase in temperature is not well depicted at different RCP scenarios with the model and exhibits cool bias (Rana et al., 2018).

Climate variability will affect the crop yields by causing climatic stress during the growth stages of the plant life cycle. Crop growth models are able to capture the climatic stress for crops such as cotton (Hebbar et al., 2008; Anapalli et al., 2016) as a credible prediction too. This also helps to strategize the mitigation and adaptation measures. Studies indicate that increased temperature in future scenarios could adversely affect the yields. However, elevated CO_2 during the projected climate change could partially compensate for yield reduction due to the fertilization effect (Hebbar et al., 2008; Anapalli et al., 2016). The enhancement in photosynthetic responses in the crop is due to increased CO_2 concentration in future emission scenarios and this effect is found more pronounced in C3 plants such as cotton than other C4 plants (Leaky et al., 2009). Availability of moisture also plays a vital role in productivity for cotton even with the availability of irrigated water during the excess and deficit year (Shikha et al., 2018). Also, all the cotton-growing regions are not likely to be affected by some degree as projected by climate models, neither the crop physiology is affected in a similar pattern.

In a study by Anapallai et al. (2016) over the Mississippi Delta region (USA) with climate projections based on an ensemble of multiple GCMs (Global Climate Models/General Circulation Models) at all RCP scenarios and crop growing model 'CSM-CROPGRO-cotton v4.6 module within RZWQM2 model'. It was observed that under irrigated conditions yield increased in RCP 2.6, 4.5, and 6.0 for the years 2050 and 2080 and RCP 8.5 2050 but reduced in RCP 8.5 in 2080. Under rainfed conditions, yield declined for all RCP scenarios in both the years 2050 and 2080. Although the rainfed crop is found most vulnerable towards seasonal variations. However, after some extent irrigation is also found incompetent when yield and fiber properties of cotton are concerned and throughout the experiment the response of fiber quality and strength to irrigation was inconsistent (Pettigrew, 2004b; Karademir et al., 2011). Similar studies in the cotton-growing regions of India by Hebbar et al. (2013) using GCM projections in the INFOCROP cropping model suggested that with climate change and increased temperature and rainfall, cotton productivity is favored in southern and central zones which is comparatively cooler. And in the northern zone where the cotton is grown at relatively higher temperatures, the yield declined due to climate-induced high temperatures. This study also corroborates with this study stating that in the future climate, the Hisar (northern) region if favored at RCP4.5 and detrimental at RCP8.5 for the cotton. Whereas in the Akola (central) region with a relatively cooler climate the productivity is favored at RCP 8.5 than 4.5.

A projected increase in temperature and erratic behavior of precipitation with climate change will shift the seasonal regime are impeding the crop-calendar (Bhatti et al., 2016). The response of crops such as wheat (Sultana et al., 2009), rice (Mall et al., 2018), cotton (Hebbar et al., 2008; Gwimbi, 2009; Shikha et al., 2019) etc. towards elevated temperature and CO_2 will also be affected. Precipitation is the limiting factor that plays a vital role by changing or altering the crop water requirements. As an adaptive measure changing the planting time of wheat (rabi crop) showed a decrease in crop water requirements for an early sown crop, whereas for cotton (Kharif crop) late sowing was found beneficial due to reduced crop water requirement when compared with baseline data (Bhatti et al., 2018) that corroborates with this study. In the semi-arid zones of wheat and cotton cropping systems of Pakistan yield is higher for the late sown crops than the earlier ones (Sultana et al., 2009). Studies also indicated improvement in fiber quality (i.e. micronaire) with delayed sowing if future (Luo et al., 2016). Similarly, other crops such as rice and wheat delay in sowing by 15-21 days can be a mitigation option for the rise in temperature by 5.1°C in the Punjab region (Jalota et al., 2013). In some studies, it is also evident that early planting (six weeks earlier than the normal/ historical average) was beneficial for irrigated cotton and in climate change scenarios. It helped to boost the yield compensate for loss for irrigated crops and partially for the rainfed crop (Anapallai et al., 2016).

The physiological complexity of the cotton crop makes scheduling of the irrigation and nutrients also too difficult to assess in comparison to other field crops (Loka and Oosterhuis, 2010; Singh et al., 2014; Shikha et al., 2017). Hybrid cotton is a nutrient exhaustive and long duration crop (Nehra et al., 2004). Erratic rainfall is a primary constraint for the management of nutrients in rainfed crops affecting the physiological growth during both the vegetative and reproductive phases (Blaise, 2006). It has a remarkable ability to produce 'repeated flushes fruiting parts' which helps in compensating early-season damage due to stress (Singh et al., 2014). Temperature controls the rate of plant growth, flowering, ball maturation and developmental events in cotton (Baker, 1965) Temperature stress above optimum can induce ball abscission, reduced ball size and yield (Reddy et al., 2005). With elevated CO_2 it was observed that carbon exchange rates, reproductive bodies improved (Reddy et al., 2005) and increased plant height and leaf number, reduced square and ball shedding and delayed leaf senescence occurred (Singh et al., 2014). In the regions where the present temperature is optimum, the doubling of CO_2 also could not efficiently ameliorate the effect of high temperature (Reddy et al., 2005). When cotton plants are grown under moisture deficit conditions, infestations can be seen in leaf photosynthesis as it gets reduced with the combination of stomatal and nonstomatal limitations (Turner et al., 1986; Pettigrew, 2004a). Lint yield is generally reduced because of reduced boll production, primarily because of fewer flowers but also because of increased boll abortions when the stress is extreme and when it occurs during reproductive growth (Pettigrew, 2004b). Some studies suggest, as in most plants, leaf water potential is reduced under drought conditions, but cotton has the ability to osmotically adjust and maintain a higher leaf turgor potential (Nepomuceno et al., 1998; Karademir et al., 2011).

Chapter- VI

Conclusions

CONCLUSIONS

The objective of this study is to analyze the impact of climate change on cotton crop. An increase in temperature and precipitation is expected with climate change with an enormous increase in CO_2 concentrations. Although with changing climate, weather almost remains similar to the average. But the intensity and frequency of intermittent precipitation varies with longer periods of dry spells and extreme hot and cold days. Which is threatening for the crop productivity across the globe (Liebig et al., 2012). With this still evolving climate change scenarios, our soil, water and other natural resources are deteriorating (Gurdak et al., 2012). Elevated temperature and carbon dioxide affects the biological processes like respiration, photosynthesis, plant growth, reproduction, water use etc (Murthy, 2002). The shift in the seasonal pattern will also disturb the crop-calendar.

The economy of an agro based country like India is predominantly based upon the agriculture sector. This includes the production of edible crops for food security and commercial crop as well for economic empowerment. India has highest cotton production and also at the first place in terms of acreage in 2015-2016 (Status of cotton report 2017). However, the average productivity in India is 522 kg/ha with a gap of 243 kg/ha which is lower than the world average 765 kg/ha. The reasons behind this was observed as abiotic stress due to weather aberrations and biotic stress due to pest infestation. The incidence of pest and disease specially sucking pest is major concern nowadays after the introduction of Bt-cotton.

Cotton is world's most important fibre crop and second most important oil seed crop (Freeland et al., 2006). It is a source of fibre, oil for human consumption, protein meal for livestock feed and potentially a fuel for diverse industries. The waste after ginning can also be used as fertilizer and cellulose as paper and cardboard (Freeland et al., 2006). Cotton is a fibre crop and the oldest among the commercial crops of global significance. It belongs to Gossypium genus of family Malvaceae. It is warm season crop and grown worldwide with narrow temperature range. The plant is unique because it's a perennial plant with an indeterminate growth habit and has perhaps the most complex structure of any major field crop. Due to its complex growth habit is extremely sensitivity to adverse environmental conditions. Better understanding of cotton physiology and its response towards changing environment is significant for the commercial production of the crop. The combination of warm and dry weather conditions along with abundant sunshine and sufficient moisture during the bolls opening till the harvest will maximize yield and quality potential (Freeland et al., 2006). Therefore, for attaining its potential productivity, it requires long frost-free days, warm season with ambient temperature, plenty of sunshine, and a moderate rainfall usually from 450 to 750 mm.

Along with experimental field studies, crop and climate are also widely used for research purposes to study the crop productivity and soil water balance with the changing climate. Modeling studies nowadays are essential for the effect of elevated CO_2, increasing temperature, both together water balance and nutrition with the crop simulation models as they give good overview about the crop development which is further designed for the tests and the predictions (Schlenker et al., 2009). It helps in assimilating field experiment based knowledge for computation. It benefits scientific communities for interdisciplinary research to solve problems at the farm level. It gives us cost-benefit approach for experimentation of different management strategies (Jones el al., 2003; Hoogenboom et al., 2015).

Field studies conducted for cotton crop, showed that the vegetative growth is increased by increasing temperature and CO_2 together (Reddy et al., 2005). This could be because of the pretext that vegetative growth may require lesser time to support more fruit loads (Jalotaa et al., 2009). Therefore, reduced vegetative growth 'cutout' may occur forthwith and consequently reduce potential of crop yield (Lawlor et al., 2014; Pettigrew, et al., 2002). Further curtailment in time for 'cutout' can advance maturity, therefore decrease the yield (Bange et al., 2004b). It is also reported that higher vegetative growth is good to support yield of transgenic cotton with additional and early fruiting bodies (Constable et al., 2006). The effect of elevated CO_2 masked the apparent high temperature injury that limited the growth of all plant organs, especially reproductive system (Reddy et al., 1991; Reddy et al., 1996; Reddy et al., 1999). Studies also indicate that bolling periods will be shorter under warming climate (Reddy et al., 1999; Luo et al., 2014). Therefore, the fibre quality is compromised and boll size are reduced despite potentially increased fruiting periods and more fruit. This reduction in yield may be due to cut out in vegetative phase or reduction in boll size in reproductive phase (Lawlor et al., 1991).

In this study, while estimating the implications of increasing temperature and CO_2 concentrations on cotton yield using a crop model DSSAT. Three different Bt-cotton varieties Pancham-541, RCH-791 and SP-7007 are considered with three sowing dates 10th May, 21thMay and 06th June. The modeling output suggests that increasing temperature and CO_2 has a major role to play in the cotton productivity. Increase in temperature negatively impacted the crop productivity in general, but this effect was moderated by increasing CO_2. For Pancham-541 increasing 1°C of temperature and 50ppm CO_2 was beneficial but further 2°C and 3°C is harmful, which was not the case with RCH and SP varieties. For SP-7007, increase in temperature without an increase in CO_2 is harmful but when increasing 1°C combined with 50ppm and 2°C with 100ppm are beneficial but further 3°C with 150ppm are harmful.

The ET rate and LAI has been increasing with increasing temperature and CO_2 for all the varieties for all the sowing dates. Whereas, Harvest index and maturity period were decreasing in general for all temperatures above optimum. This reduces the number of retained bolls, boll-cellulose filling during maturation period and its rate of filling thus affecting the size of the boll under ambient and elevated CO_2. Elevated CO_2 helps to increase the total biomass chiefly due to increased photosynthesis simulated and increased boll weights because of increased branching, leaf area and increased fruiting sites every branch. It is observed from the study that with 1°C rise in temperature and corresponding $CO_{2,}$ the yield of Pancham-541 and SP-7007 has increased, when sown in May. Therefore, early planting of these two crop varieties can be recommended in near future. Further SP-7007 variety is found to be least sensitive to the increase in temperature by 2°C. Thus, it is concluded that the increasing temperature at the present rate will be harmful for the productivity of cotton under changing climate; particularly over a semi-arid region like Hisar for all three varieties. Therefore, productivity of cotton will reduce in future where the temperature is near optimum for the existing variety. The present study suggests necessary management practices such as using heat tolerant cultivars and changing the sowing time (early) will be needed in future to overcome the climatic constraints.

These modeling studies can also be applied to analyse the influence of weather on crop performance. The model takes care of the interaction of crop in a complex way for soil and management interactions to assess its vulnerability and adaptability. Thus, the study helps in understanding the uncertainty in crop production with the changing climate and associated economic risks. Presently, attempts are made by the government for providing farmers with management strategies through extension services using the crop models. Further our objective is to integrate the study with future climate data from the climate models to analyse the vulnerability of crop with the changing climate. Which will be a move towards sustainable agriculture by the means of Climate-Smart-Agriculture (CSA).

But before we analyse the future climate in this study we tried to examine the biotic stress due to stress. These pests can reduce the yield upto 57.9 % in cotton field (Sharma, 1998). The meteorological parameters and sowing window have been reported to have significant influence in the pest population (Bishnoi et al., 1996). Temperature and humidity has found to favour the pest and diseases (Janu et al., 2018). The pest population can be influenced by weather variables such as maximum and minimum temperature, precipitation and relative humidity with pests on the study region (Janu et al., 2017, Swami et al., 2017). Statistical correlation and regression analysis can be used to predict the pest infestation and population for area of interest. These 'Weather-based pest forecast models' are termed as 'Forecasters' in crop protection parlance. Recently, for real-time assessment remote sensing and GIS approaches are used widely. This can help the researchers' farmers and policy makers to design the Integrated Pest Management (IPM) strategies. Remote sensing approach can help to quantify the crop health and for the early detection of pests

(Ray et al., 2011). It is utilised as a tool for monitoring and mapping stress, yield, quality of crop, crop development, nutrient deficiencies, predicting or detecting the pest and diseases etc. (Riley, 1989; Neteler et al., 2011; Gooshbor et al., 2016). The pest can be identified and validated further with the field observations.

The study indicates that the NDWI and NDVI calculated using LANDSAT images and the field observations has very strong resemblance for the pest infestation in the study region. The stress in cotton crop caused by the pest attack are clearly visible in derived NDWI and NDVI outputs. Thus, these vegetation indices can be used as an indicator to perceive the threshold for zoning the outbreaks. Also, when the crops are affected above the ETL they can be identified and therefore forecasted by modelling approaches. This can help the researchers' farmers and policy makers to design the Integrated Pest Management (IPM) strategies. The improvement in statistical approach and models could further help to analyse the impact of climate change on the pest population and regional distribution. These calibrations and forecast can be validated with the observed populations and remote sensing applications for more precision and real-time monitoring. For better productivity, there is need to broaden the scope and evaluate the capabilities of pest and disease models and compliment it with remote sensing technique for monitoring the damage and take timely IPM measures.

This analyse the vulnerability of cotton crop due to changing climate in different agroclimatic zones of cotton the central rainfed and northern irrigated is chosen for the study. For this having reliable climate data is essential. Climatic projections from various global climate models (GCMs) and regional climate models (RCMs) are being utilised for this purpose. But they still have significant errors and biases. While GCMs are the primary source of information on climate scenarios, but still have the drawback of having coarser spacial resolution and inability to capture inter-annual variability which is rectified by downscaling with RCMs on regional scales (Metzger et al., 2005). GCMs can also be used with various downscaling approaches (Thomas et al., 2008) for these purposes. Climate change scenarios and historical data GFDL-ESM2M-IITM-RegCM4 are downloaded from archives of ESGF for the CORDEX-South Asia experiment (RegCM4-GFDL) with the host GCM (GFDL-ESM2M). These GCMs and RCMs data can be further bias-corrected by various methodologies viz., Linear Scaling, Delta change approach, Quantile Mapping (QM), etc. (Qian et al., 2016). In this study Quantile Mapping (QM) approach is utilised since it is reported to perform better in India for precipitation and temperature both (Mall et al., 2017). The observations versus simulations and their bias-corrected version offer a comparatively viewpoint for credible information (Gudmundsson, 2014; Maraun, 2016). These climate model outputs serve as an input for the hydrological and crop simulation models.

The performance of RegCM climate model is therefore assessed further at different climatic regimes and its applications in crop simulation models. It is observed that the RCM model is wet and shows high rainfall intensity in terms of frequency and number of rainy days. A notable decline in maximum temperature and minimal decline in minimum temperature is observed in RCM data. So we can say that the model shows night-time warming with reduced diurnal temperature. Less number of intense warm (maximum temperature ≥ 45 °C and ≥ 40 °C) and high cold events (minimum temperature ≤5 °C and ≤ 3 °C) is captured in the model. The model also captures numerous days with rainfall > 0 mm/day also referred to as 'drizzle effect'. However, it rainfall > 5 mm/day and > 10 mm/day values were very close to the observed. RCM model highly underestimates temperature and overestimates rainfall which resulted in biasness when compared with observed station data.

Bias-correction through QM approach showed good agreement with the observation annually but failed to correct daily variability as it is 'distribution-based method'. The QM approach also performed better in the semi-arid northern (Hisar) region than in central (Akola). The MBE and RMSE values of weather data show considerable improvement when bias-corrected. Simulating these weather data in DSSAT, the deviation in the yield, LAI and NM is observed higher for the model then the bias-corrected in general when compared with observations in both the regions. The percentage deviation has reduced for bias-corrected variables. The I and RMSE values have also improved for the yields. The bias-corrected yield and other physiologies show good agreement with observed. The yield, LAI and NM are higher for the crops in the northern region which is also evident from the actual observations. Therefore, we can say the crop is performing better in the northern region and there is much scope of improvement in the productivity with the management practices.

Climate models predict an increase in global average temperature for future climate change which could affect the crop productivity (IPCC, AR5, 2014). Therefore, predicting the impacts of future climate on the food and fiber production are essential for devising suitable adaptations strategy. So, in this study impact of climate on cotton crop change using RCM data from CORDEX-SA experiment (GFDL-ESM2M- RegCM4) at RCP4.5 and RCP8.5 are studied at different regions. And the period considered for the study are 1971-2005 (1990), 2006-2035 (2020), 2036-2065 (2050) and 2066-2095 (2080). The RCM projected daily weather from were downloaded and extracted.

With the changing climate, the model predicts slightly increasing minimum temperature from historical to far future and from RCP4.5 to RCP8.5. The deviation is higher in the Hisar region than the Akola region. Thus there is a possibility of increasing temperature at a higher rate in the northern than the central cotton-growing region. Again, the model suggests there will be an increase in the amount of precipitation in Hisar till the near future and it may decline further in the far future. This characteristic is depicted with the amount of precipitation during the cropping season too. The model slightly overestimates the rainfall in these regions, where the bias-correction method is found very reliable for historical conditions. Although, the amount of rainfall in the central rainfed region is presently more than the northern region. But the model predicts decreasing precipitation from 1990 to 2080 in this region. The amount of rainfall is increasing in the northern region whereas decreasing in the central region at RCP8.5. The combined effect of increasing temperature and decreasing annual rainfall during the cropping season in the central rainfed region from 1990 to 2080 can also have a negative influence over the crop productivity in these regions.

In the central region (Akola) the yield increased from 2020 to 2050 and then 2080 for model data in both the RCPs for all sowing dates. The weather is cooler in comparison to the northern cotton-growing region so the increasing temperature is not much affecting the yield, whereas increasing CO_2 in also favoring the crop. While considering the bias-corrected value, we observe in both the RCPs irrigated conditions has better productivity than rainfed with changing climate. This can be because of better water availability as the model is wet and underestimate maximum temperature. The yield is increasing with late sowing and irrigated is performing better than the rainfed. Whereas in the northern region dry yield for the model projected data is higher for 1990 then 2020 in both the RCPs and increases with the changing climate in 2050 and 2080. Rainfed and irrigated crops show better yield in RCP4.5 than RCP8.5 in all sowing dates with model data. For bias-corrected data, there is a reduction in yield in RCP 8.5. Again late sowing is found beneficial in future climate for in this region too. This can be because the crop is able the escape the harsh summer season with the rising temperature.

As per the deviation from present climate is concerned on the Akola region, the yields are higher for RCP8.5 than RCP4.5, whereas in Hisar yields are lower in RCP8.5 than RCP4.5 for both model and bias-corrected data. So in Hisar, the may crop yield improve far future in RCP4.5. Whereas in RCP8.5, it falls for both near and far future. The reason can be, the crop has achieved maximum tolerance for the temperature at RCP4.5 in the hot and dry northern cotton-growing region and further increase (as in RCP8.5) even with increasing CO_2 is detrimental. Whereas in the central region which is cooler and wetter the slight increase in temperature is not a hindrance and at the same time increased CO2 is favoring the production. In this study generally, the late sowing D3 is found beneficial with the climate change scenarios in both the regions. And the percentage change from the present is higher for D1 and D2 with model and its bias-corrected data in Akola and D2 and D1 with model and its bias-corrected data respectively in Hisar. So with the changing climate positive variation is also higher for the early sown crop from the present.

As per climate observations, during RCP 8.5 there is a slight rise in temperature in this region with increased rainfall and CO2. This could suitable for the crop in the central region. Therefore, the yield has increased to a larger extent. This signifies the suitably of crop in this region at the RCP8.5 emission scenario here. Whereas in the northern region the temperature slightly rises form present in RCP4.5 and then RCP8.5 and the precipitation increases till RCP4.5 and then reduces in RCP8.5. Thus the crop could stand an increase in temperature till RCP4.5 and increased CO_2 and precipitation also benefitted the productivity. But, beyond that at RCP8.5 the plant could not tolerate increased temperatures with reduced precipitation. So, productivity increased in RCP4.5 and declined in RCP8.5. Therefore, in the future at RCP4.5 northern regions and RCP8.5 central regions can facilitate cotton production with proper management strategy.

As an adaptation measure alteration in sowing dates and irrigation and fertilizer scheduling will play a significant role. For cotton, late sowing is seen as beneficial with climate change. This delayed sowing owes its response due to delayed onset of monsoon in the study region where the rainfall intensity has increased during the cropping season. The percent deviation of yield and LAI from present signifies in future climate in the northern region (Hisar) is increasing for near future and far future at RCP4.5 and declining for near future and far future at RCP8.5. In the central region (Akola) it increases in near future and then far future as per both model and its bias-corrected data. So the is a scope of better productivity in the northern region at RCP4.5 and in the central region at RCP8.5 with the changing climate when proper irrigation is provided. To influence the yield of cotton, it is required to go for timely sowing of the plant which means that sowing should be carried during the most optimum period.

The study embrace utilization of crop growth models for developing crop management strategies, yield forecasting, and the sustainability of the crop, climate change impact assessment, and economic analysis for bringing precision in agriculture. The growers and scientific communities have to about site-specific crop management and variability within the field for potential productivity with the changing climate. This can be done by modifying the sowing window, adopting stress-resistant varieties, developing new-age cultivars, improvising management and implying climate forecasts in cropping decisions. Selecting weather tolerant varieties and pest-resistant crops can also help in the adaptation and sustainability of the crop. To influence the yield of cotton, it is required to go for timely sowing of the plant which means that sowing should be carried during the most optimum period.

Uncertainty and variability in future climate may affect the growth and development of crop. The quantum and distribution of temperature and moisture conditions for the crop is predominant for researchers and farming communities for climate-smart agriculture, especially in the rainfed regions. Future research could apply these model-simulated data to explicitly study the impact of climate change on crop productivity. This can also be complemented with more reliable model data and bias-correction techniques to complement the research. Although, the model bias-corrected data showed a better representation of the actual weather of a region, but still, there are some limitations and a lot needs to be done for its improvement in the approach. Understanding the ambiguous and unpredictable character of biases in climate models and bias-correction approaches is essential in studying the impacts of future climate. Development of physiology linked economic models at the farm-level for decision-making under climate change scenarios are important. Coupling the pest attributes with the crop modeling to forecast or estimate the climate-induced impacts on crops and pest need of the hour for cotton crop. Similarly understanding the quantum and characteristic of pest and diseases are important to for predicting the infestation and take timely measures. Forecasting the pest along with real-time monitoring with the remote sensing approach could help the farmers and policy makers for better pest management.

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